Modeling Functional Flows in California's Rivers

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Environmental flows are critical to the recovery and conservation of freshwater ecosystems worldwide. However, estimating the flows needed to sustain ecosystem health across large, diverse landscapes is challenging. To advance protections of environmental flows for streams in California, United States, we developed a statewide modeling approach focused on functional components of the natural flow regime. Functional flow components in California streams—fall pulse flows, wet season peak flows and base flows, spring recession flows, and dry season baseflows—support essential physical and ecological processes in riverine ecosystems. These functional flow components can be represented by functional flow metrics (FFMs) and quantified by their magnitude, timing, frequency, duration, and rate-of-change from daily streamflow records. After calculating FFMs at reference-quality streamflow gages in California, we used machine-learning methods to estimate their natural range of values for all stream reaches in the state based on physical watershed characteristics, and climatic factors. We found that the models performed well in predicting FFMs in streams across a diversity of landscape and climate contexts, according to a suite of model performance criteria. Using the predicted FFM values, we established initial estimates of ecological flows that are expected to support critical ecosystem functions and be broadly protective of ecosystem health. Modeling functional flows at large regional scales offers a pathway for increasing the pace and scale of environmental flow protections in California and beyond.

Keywords: environmental flows, flow metrics, hydrologic modeling, holistic method, California environmental flows framework, natural flow regime

INTRODUCTION

The protection of environmental flows—water needed to sustain biodiversity and the services that healthy freshwater ecosystems support—is essential to reversing worldwide trends in freshwater ecosystem degradation (Reid et al., 2019; Tickner et al., 2020). To address this need, river scientists have developed a broad suite of environmental flow assessment tools (Horne et al., 2017), and advanced policy agendas for environmental flows (Arthington et al., 2018). Yet, most environmental

flow programs are limited in spatial scale (Poff et al., 2010) and are narrowly focused on species of management concern. For example, environmental flow protections in the western US have primarily focused on major rivers supporting Pacific salmon and trout (*Oncorhynchus* spp.), and other threatened fish species listed under the federal Endangered Species Act (Gillilan and Brown, 1997; Obester et al., 2022). As pressures on water resources intensify at a global scale (Grill et al., 2019), the vast majority of rivers and streams still lack environmental flow protections. New environmental flow approaches are needed to broaden the pace, scope, and scale of flow protections across diverse river types and geographies.

Recently, river scientists have argued that a functional flows approach offers a promising framework for establishing holistic environmental flow protections at regional scales (Grantham et al., 2020; Yarnell et al., 2020). Functional flows are components of the natural flow regime that sustain the biological, chemical, and physical processes upon which native freshwater species depend (Escobar-Arias and Pasternack, 2010; Yarnell et al., 2015). The functional flows concept is founded on the principles of the natural flow regime paradigm (Poff et al., 1997), but recognizes specific dimensions of flow variability, and their interactions with the landscape, as being particularly important for supporting ecosystem processes. For mediterranean-montane rivers, *functional flow components* include fall pulse flows, wet season peak flows, wet season baseflows, spring recession flows, and dry season baseflows (Yarnell et al., 2020). By focusing environmental water allocations on these functional flow components, the maintenance of their associated physical and biological processes is expected to be broadly protective of ecosystem needs. Furthermore, there is evidence that functional flows can be managed to accommodate human water demands and deliver benefits to both people and nature (Grantham et al., 2020).

The California Environmental Flows Framework (CEFF) is a technical approach for developing environmental flow recommendations in California, United States, and relies on the functional flows concept (Stein et al., 2021). The purpose of CEFF is to provide a consistent, scientifically-defensible, and holistic approach for assessing environmental flow needs statewide. To support this goal, models are used to predict the natural range of functional flows in all rivers and streams in the state at the resolution of individual stream segments. If there are no physical modifications, water quality impairments, or invasive species present in focal streams, the habitat needs of native aquatic species are assumed to be supported by the natural range of functional flows (Stein et al., 2021). Therefore, under CEFF, predicted natural values of functional flows are considered an initial estimate of ecological flow needs and can be used to develop environmental flow recommendations without the need of further resource-intensive studies. CEFF allows for more detailed evaluation of ecological flow needs in contexts where there are physical habitat modifications or other local environmental factors that could limit the effectiveness of natural functional flows in supporting ecosystem functions and the habitat requirements of native species. Once ecological flow needs are defined as quantitative targets, CEFF also includes

a series of steps to evaluate tradeoffs between ecological and other water management objectives, and to develop environmental flow recommendations that balance human and ecosystem needs (Stein et al., 2021).

Here, we present a data-driven modeling approach to predict functional flows in California rivers, a 424,000-km^2 region that encompasses a diversity of river types, human pressures, and water management objectives. We describe data requirements and model training procedures and assess the influence of model predictor variables on distinct functional flow metrics. We also evaluate the predictive performance of the models by metric and stream type, using a suite of model performance criteria. Finally, we use the models to predict the natural range of functional metrics at all stream reaches (over 140,000) in the state, serving as a foundation for CEFF and other environmental flow management efforts. By estimating functional flows statewide, this modeling approach can support development of holistic environmental flow programs at large spatial scales and across diverse geographies, jurisdictions, and management contexts.

METHODS

Modeling Approach Overview

We calculated observed annual values of 24 functional flow metrics (FFMs) describing 5 functional flow components (fall pulse flows, wet season baseflows, wet season peak flows, spring recession flows, and dry season baseflows) from reference gage records in California (**Figure 1**). We then characterized the watershed above each reference gage using a suite of physical and climatic variables from publicly available data sources. Next, we used a machine learning approach to relate the watershed variables to functional flow metrics, developing a total of 24 models (one for each functional flow metric). The predictive performance of each model was then evaluated by comparing predictions of functional flow metrics with observations at gages excluded from model training. Finally, we used the models to predict the natural range of values of each FFM at all stream reaches in California's stream network, using the same set of predictor variables calculated for the catchment of each stream reach. The details of each step are provided below.

Streamflow Data and Functional Flow Metric Calculations

All gages operated by the U.S. Geological Survey (USGS) in California were screened to identify those considered to be reference-quality, following methods described by Zimmerman et al. (2018). Briefly, the watershed above each gage was evaluated using GIS-based methods and visual inspection of aerial imagery to exclude sites with evidence of significant human activities, including water diversions and storage reservoirs, intensive agriculture and forestry practices, dense road networks, and extensive impervious surfaces. We also reviewed USGS published annual data reports for each gage that note the influence of significant anthropogenic activities on observed flow records (Falcone et al., 2010). Through a subsequent
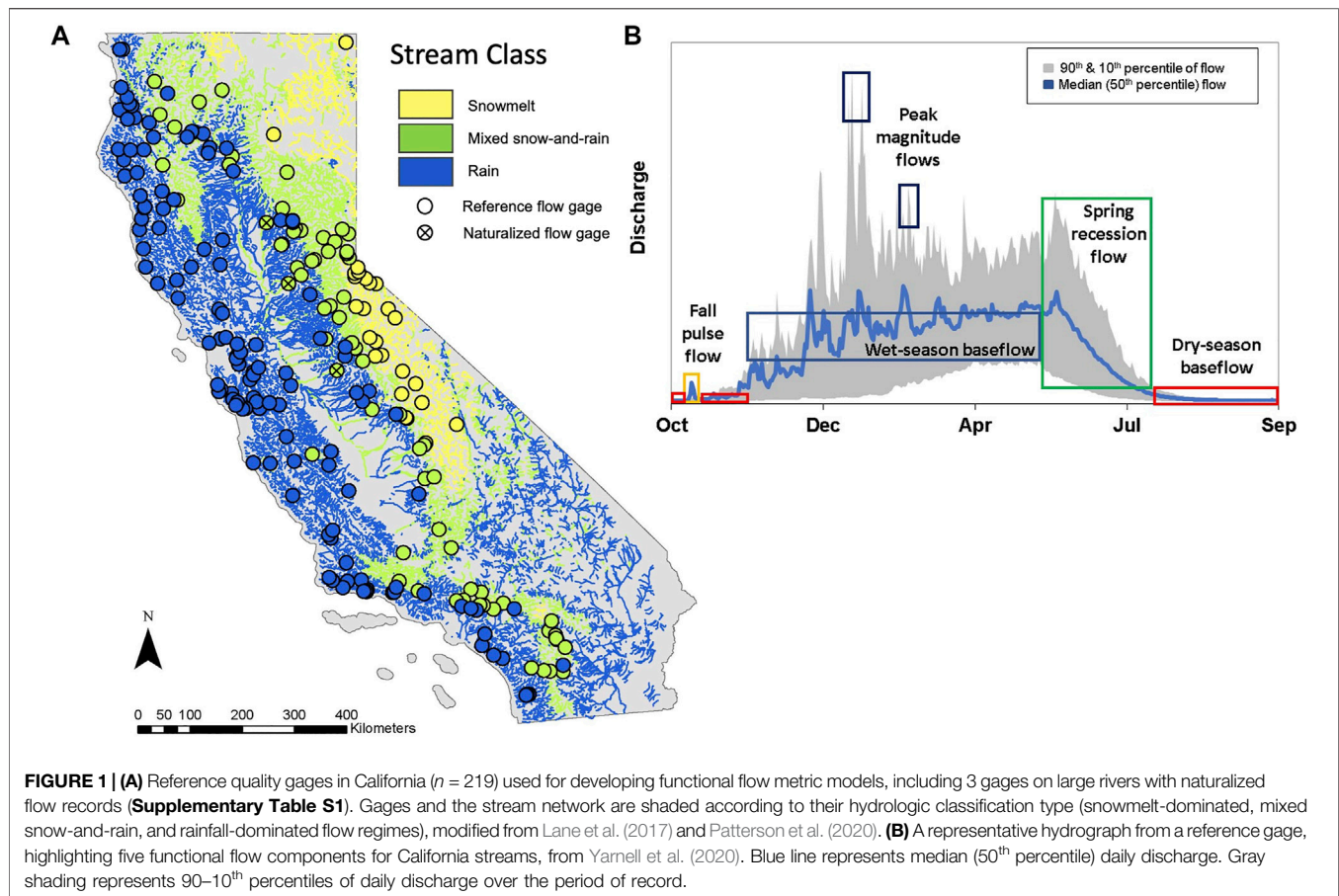
FIGURE 1 | (A) Reference quality gages in California (n = 219) used for developing functional flow metric models, including 3 gages on large rivers with naturalized flow records (**Supplementary Table S1**). Gages and the stream network are shaded according to their hydrologic classification type (snowmelt-dominated, mixed snow-and-rain, and rainfall-dominated flow regimes), modified from Lane et al. (2017) and Patterson et al. (2020). (B) A representative hydrograph from a reference gage, highlighting five functional flow components for California streams, from Yarnell et al. (2020). Blue line represents median (50th percentile) daily discharge. Gray shading represents 90–10th percentiles of daily discharge over the period of record.

manual screening process, several gages were removed from the analysis that exhibited irregular, impaired, and or aseasonal flow patterns. In total, we identified 216 reference gages in California, which included both active stations located on relatively pristine streams and gages with historical observations that pre-dated significant anthropogenic disturbances (e.g., prior to dam construction). We included an additional 3 gages located below dams for which reconstructed unimpaired flow data were available in order to increase the physiographic range represented in the dataset (California Department of Water Resources [DWR], 2007), bringing the total number of reference gages to 219 (**Figure 1**; **Supplementary Table S1**).

The resulting reference gage set includes periods of record as early as 1950 and as recent as 2015, with an average period of record of 33 years and ranging from 6 to 65 years (**Supplementary Table S1**). These gages are well distributed across the diversity of river types in California, including snowmelt (n = 25), rain (n = 125), and mixed snow-and-rain (n = 69) hydrologic regimes, following a simplified version of a stream classification scheme developed by Lane et al. (2017). The gages are located on streams with drainage areas ranging from 5 to 9,340 square kilometers and are distributed throughout California, with the exception of the arid southeastern corner of the state (**Figure 1**), where most streams are ephemeral and no reference gages are present. We confirmed that reference gages

located in close proximity were separated by intervening tributaries or had distinct periods of record.

Complete years of daily flow data for all reference gages were downloaded from the USGS National Water Information System (USGS, 2017). Annual FFMs were then calculated from daily flow records using signal processing algorithms designed to characterize seasonal flow features of the annual hydrograph. The approach to calculate annual timing metrics detailed by Patterson et al. (2020) is as follows: A high standard deviation Gaussian filter was applied to daily streamflow time series to detect dominant peaks and valleys from the annual hydrograph. Localized search windows were set around hydrologic features of interest (e.g., annual peak flow). A low standard deviation Gaussian filter was then applied to the observed daily flow in the search window to identify seasonal shifts in the hydrograph, based on slope breaks in the derivative of a fitted spline curve. Break points were used to quantify the timing metrics for the wet season, dry season, and spring recession periods, from which seasonal magnitude, duration, frequency, and rate of change metrics could then be calculated. The spring recession rate was calculated as the median daily rate of change in flow from the start date of the spring recession until the start of the dry season, considering only days with negative change to omit storm events during the recession period. Peak flow magnitudes were calculated as the long-term annual flood exceedance flow

TABLE 1 | Functional flow metrics for which machine learning models were developed and their corresponding functional flow components and characteristics. There are a total of 24 metrics that represent five functional flow components. Note that there are 2 metrics describing the magnitudes of wet season baseflow and dry season baseflow and 3 metrics describing each of the peak flow characteristics (2-, 5-, and 10-years recurrence interval floods) in the wet season.

Functional flow component	Flow characteristic	Functional flow metric
Fall pulse flow	Magnitude (cms)	Peak magnitude of fall season pulse event (maximum daily peak flow) in years when it occurs
	Timing (date)	Start date of fall pulse event
	Duration (days)	Duration of fall pulse event (# of days start to end)
Wet season baseflow	Magnitude (cms)	Magnitude of wet season baseflow and wet season median flow (10th and 50th percentile of daily flows, respectively, during the wet season)
	Timing (date)	Start date of wet season
	Duration (days)	Wet season baseflow duration (# of days from start of wet season to start of spring season)
Wet season peak flows	Magnitude (cms) Duration (days)	Peak flow magnitude (annual peak flows for 2-, 5-, and 10-years recurrence intervals) Duration of peak flows over wet season (number of days in which a given peak flow recurrence interval is exceeded, in years when it occurs)
	Frequency	Frequency of peak flow events over wet season (number of times in which a given peak flow recurrence interval flow is exceeded, in years when occurs)
Spring recession flow	Magnitude (cms)	Spring peak magnitude (daily flow on start date of spring recession-flow period)
	Timing (date)	Start date of spring recession
	Duration (days)	Spring recession flow duration (# of days from start of spring to start of summer base flow period)
	Rate of change (%)	Spring recession flow rate (percent decrease per day over spring recession period)
Dry season baseflow	Magnitude (cms)	Dry season baseflow and high baseflow magnitude (metrics for the 50th and 90th percentile of daily flow, respectively, during the dry season)
	Timing (date)	Start date of dry season
	Duration (days)	Dry season baseflow duration (# of days from start of dry season to start of wet season)

associated with the 2-, 5-, and 10-years recurrence intervals. We also calculated peak flow duration (cumulative number of days in which this peak flow magnitude is exceeded) and frequency (number of times the flow magnitude is exceeded), in each of the years in which a flood of a given recurrence interval occurred. Following these methods, we calculated the values of 24 FFMs, describing 5 functional flow components, at each reference gage (**Table 1**; **Figure 1**).

Next, we used a GIS-based approach to calculate over 150 variables related to physical attributes of the watershed above each reference gage using publicly available geospatial datasets (**Supplementary Table S1**). These included variables related to topography (e.g., elevation, slope, and aspect, etc.), dominant geology and soil types (e.g., granitic, volcanic, or sedimentary, and mean content of clay, sand, and silt, etc.), and watershed hydraulic properties (e.g., topographic wetness index, baseflow index, mean depth to water table, etc.). We also included time-varying climatic variables including mean monthly temperature and precipitation from the 800-m PRISM dataset from Daly et al. (2008), as well as expected monthly runoff from McCabe and Wolock (2011). These climate variables were expressed as monthly, seasonal, and annual values for each year of FFM observations at a reference site, as well as for years preceding the FFM observations (**Supplementary Table S2**).

Functional Flow Metric Modeling

Random forest (RF) models (Cutler et al., 2012) were developed for each FFM. For most FFMs, observed values were calculated for each year of the reference period of each gage. For peak flow magnitude FFMs, single values for the 2-, 5-, and 10-years recurrence interval flood were estimated at each gage. Each RF model specified a FFM as the response variable and a total of 182 watershed and climate variables as predictor variables (**Supplementary Table S2**; Carlisle, 2022). All models were run using 2000 trees and default parameters with the randomForest function in the randomForest package, version 4.6 (Liaw and Wiener, 2018) in R (R Core Team, 2020).

Random forest models include a resampling routine that provides estimates of model performance comparable to what is obtained from independent validation data. However, because our dataset included repeated observations of FFM values from each of the 219 reference sites, the replicate datasets generated from RF's internal sampling could produce overly optimistic estimates of model performance. We therefore used a leave-one-out cross-validation approach to estimate model performance, in which each reference site (including observations for all years of record) was excluded in turn from a calibration dataset, following methods by Eng et al. (2017); Zimmerman et al. (2018). The trained model was subsequently used to predict FFM values at the excluded reference site. We

retained the 10th, 25th, 50th, 75th, and 90th percentiles of the predictions generated by the 2000 trees for each excluded reference site. For each model iteration, we also identified the most influential predictor variables, based on their Gini index (Cutler et al., 2007), which measures the loss of model predictive accuracy when that variable is excluded. Higher values indicate greater importance in contributing to the accuracy of the models.

To assess model performance, we compared predicted FFM values with observations at sites excluded from model training. We restricted the assessment to sites with 20 or more observations (i.e., 20 years of record) and calculated several model performance criteria to limit the risk of flawed interpretation resulting from the use of a single performance metric (Clark et al., 2021). We calculated performance criteria that provided measures of both the dispersion and central tendency of model predictions in comparison to observed values. First, we compared the distribution of observed to predicted values of FFMs by calculating the percent of annual observed values at a site that fell within the predicted interquartile range (IQR, range between the 25th to 75th percentile values) and the inter-80th percentile range (I80R, range between the 10th to 90th percentile values) for that site. The mean of these percentage values across all sites was used to assess the overall degree to which the distribution of observations aligned with the predicted range of each metric. Models with perfect performance would have percentage values of 50% for the IQR criterion and 80% for the I80R criterion, indicating that, on average, 50% and 80% of the observed values fall within the predicted IQR and I80R, respectively. Models that under-estimate the natural range of variation in FFMs would have values below 50% and 80%, respectively, and models that over-estimate the range of variation would exceed these values.

To evaluate accuracy for the central tendency of model predictions, we also compared the median value of observations to the median value of predictions at each site. The paired values were used to calculate several "goodness-of-fit" criteria commonly used in hydrologic model performance assessment (Moriasi et al., 2007; Eng et al., 2017): the observed-to-expected ratio (O/E), the coefficient of determination (r^2), percent bias, and Nash-Sutcliffe Efficiency (NSE). We then calculated the mean value of each performance criterion across all sites. For the peak flow magnitude metrics, we only calculated the performance measures of central tendency because only single values were available for each site (i.e., 2-, 5-, and 10-years recurrence interval peak flows). Due to the skewed distribution of peak flow frequency and duration metrics to low values, measures of central tendency were unreliable. For those metrics, we excluded observations with zero values and considered only the distribution of observations relative to the predicted range of values, by calculating the percentage of observations falling within the predicted IQR and I80R, as described above.

To evaluate model performance across all criteria, we standardized the values of all calculated criteria between 0 (poor performance) and 1 (perfect performance). To scale O/E values, we retained values less than 1 and calculated the inverse of those greater than 1. To scale percent bias, we subtracted values

from 100 and then divided by 100. NSE values less than 0 were set to 0 and no changes were made to the r^2 values. To scale the IQR criterion, the absolute value of difference between the calculated value and 50 was divided by 50 and subtracted from 1. Similarly for I80R, the absolute value of difference between the calculated value and 80 was divided by 80 and subtracted from 1. We then developed a composite performance index by averaging the values of all six criteria. We assigned a qualitative performance rating to the composite performance index values excellent (>0.9), very good (0.81–0.9), good (0.65–0.8), satisfactory (0.5–0.64), and poor (<0.5) model performance, following guidelines similar to Moriasi et al. (2007).

Finally, we evaluated spatial bias in model performance by separating reference gages into stream classes (Lane et al., 2017). We grouped gages into one of three classes based on their dominant hydrologic characteristics: snowmelt, rain, and mixed snow-and-rain. We then compared model predictions and observed data from reference gages occurring within each stream class, using the same set of performance criteria, and again calculated the composite performance index for each metric.

Predicting Functional Flows Across the Stream Network

After the model performance evaluation, we used the RF models to predict the natural range of functional flows for all stream reaches in California. We trained final models (n = 2000 trees) with the full set of reference gages to include the maximum amount of information possible. We then calculated the same set of watershed and climate variables used in model training, obtained from Wieczorek et al. (2018), for 142,509 natural stream reaches (mean length = 2.1 km; sd length = 2.0 km) represented by the National Hydrography Dataset for California (NHDPlus, Version2) (Horizon Systems Corporation, 2012). These data were used to predict FFM values from 1950 to 2015 at each stream reach from the trained RF models. The 10th, 50th, and 90th percentiles of model predictions for each FFM were calculated for each stream reach. Predicted ranges were compiled for all years (1950–2015) and for all dry, moderate, and wet water years and made available on a public website (California Environmental Flows Working Group [CWFWG], 2021). Reported values represent the expected natural range of FFMs at each stream, also accounting for model prediction uncertainty.

RESULTS

Variable Influences on Functional Flow Metrics

Climate variables were generally the most influential predictors in the FFM models, although physical catchment variables were important for some metrics (**Table 2**; **Supplementary Table S3**). For the fall pulse metrics, climate variables including precipitation, temperature, and runoff for fall season months

TABLE 2 | Most influential variables for each functional flow metric model, as determined by the Gini index. Only the most influential variable is reported, unless the next most influential variable was within the 10% of its Gini index value. See **Supplementary Table S2** for predictor variable descriptions and **Supplementary Table S3** for the Gini index values for all variables in each model.

Functional flow component	Flow metric	Most influential Variable(s) in model
Fall pulse flow	Fall pulse magnitude	October precipitation
	Fall pulse timing	October precipitation
	Fall pulse duration	Rainfall-runoff erosivity index (R factor)[a]; October runoff; November precipitation
Wet season baseflow	Wet season baseflow magnitude	Four-year mean annual precipitation; Three-year mean annual precipitation
	Wet season median baseflow magnitude	Three-year mean annual runoff[b]
	Wet season timing	Three-year mean annual temperature
	Wet season duration	December runoff[b]
Wet season peak flows	2-years flood magnitude	Long-term mean annual runoff[b]
	2-years flood duration[c]	Mean catchment elevation
	2-years flood frequency[c]	Rainfall-runoff erosivity index (R factor)[a]
	5-years flood magnitude	Long-term mean annual runoff[b]
	5-years flood duration[c]	Proportion of catchment with in HLR 18[c]; July precipitation in previous water year; winter precipitation
	5-years flood frequency[c]	Rainfall-runoff erosivity index (R factor)[a]
	10-years flood magnitude	Long-term mean annual runoff[b]
	10-years flood duration[c]	July precipitation in previous water year
	10-years flood frequency[c]	January and December precipitation
Spring recession flow	Spring recession magnitude	Total annual precipitation
	Spring recession timing	Mean spring temperature
	Spring recession duration	Mean catchment elevation
	Spring recession rate of change	Four-year mean annual runoff[b]
Dry season baseflow	Dry season baseflow	Summer runoff[b]; September runoff[b]
	Dry season high baseflow	Natural groundwater recharge index[e]
	Dry season timing	Maximum catchment elevation
	Dry season duration	Difference between maximum and minimum catchment elevation

[a]*From the Universal Soil Loss Equation, calculated mean value for each watershed (Falcone et al., 2010).*

[b]*Monthly, seasonal, and annual catchment runoff estimated from water-balance models, developed by McCabe and Wolock (2011). Long-term annual runoff values (1951–1980) are derived from rainfall-runoff models, developed by Gebert et al. (1987).*

[c]*Flood duration is the total number of days a flood of a given recurrence value is exceeded in a year, when it occurs, and frequency is the number of discrete events within a season when a flood occurs.*

[d]*Hydrologic Landscape Regions delineate watersheds in the United States with similar land-surface form, geological texture, and climate characteristics. HLR 18 includes watersheds in semiarid mountains with permeable soils and impermeable bedrock (Wolock, 2003a).*
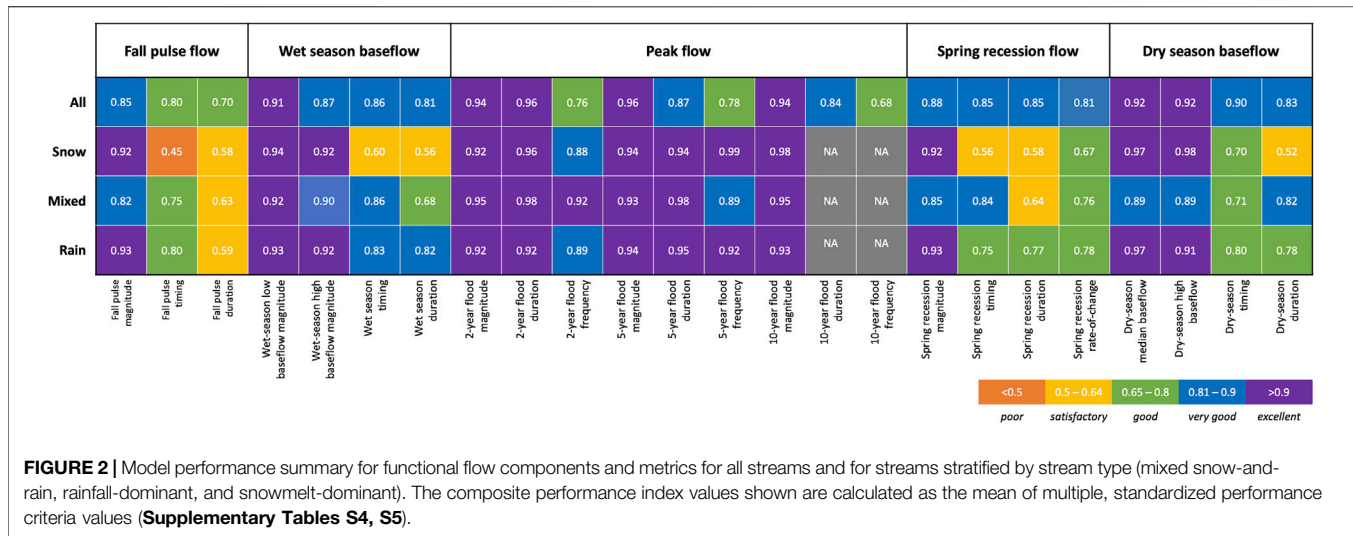
[e]*Mean annual natural groundwater recharge (1951–1980) for catchments in the conterminous United States (Wolock, 2003b).*

(e.g., Oct, Nov) were consistently among the most influential variables. The rainfall-runoff erosivity index, which reflects the estimated amount and rate of runoff produced by a storm (Renard et al., 1997), was also influential in predicting fall pulse flow duration. Wet season baseflow metrics were strongly influenced by monthly climate variables corresponding to winter months (e.g., December runoff) and multi-annual antecedent precipitation, runoff, and temperature variables were generally the most important variables in the models. Precipitation and runoff had a stronger influence on wet season baseflow magnitudes and duration, whereas temperature had a stronger influence on wet season baseflow timing.

Peak flow magnitudes, including 2-, 5-, and 10-years recurrence interval peak flow metrics, were most influenced by the catchment's long-term mean annual runoff (Gebert et al., 1987) as well as mean maximum and mean annual precipitation (**Table 2**; **Supplementary Table S3**). Peak flow duration–the number of days in a year in which flows exceeded a peak flow threshold–was most influenced by monthly precipitation variables in the winter months and the previous water year, catchment mean elevation, and the hydrologic landscape region in which the catchment predominately occurs (Wolock, 2003a). Peak flow frequency—the number of peak flow events in a year of a given recurrence interval—was also most influenced by precipitation in winter months and antecedent year, as well as the catchment's rainfall-runoff erosivity index and groundwater recharge index (Wolock, 2003b).

Annual precipitation and runoff had the greatest influence on spring recession magnitude, whereas mean temperatures in the spring months and spring season had the greatest influence on spring recession timing (**Table 2**; **Supplementary Table S3**). The duration of the spring recession flow period was most influenced by catchment elevation, the clay content of catchment soils, winter precipitation, and monthly runoff in December and June, near the start, and end of the wet season, respectively and the rate-of-change by mean runoff observed over the most recent four-year period. Spring rate-of-change was most

FIGURE 2 | Model performance summary for functional flow components and metrics for all streams and for streams stratified by stream type (mixed snow-and-rain, rainfall-dominant, and snowmelt-dominant). The composite performance index values shown are calculated as the mean of multiple, standardized performance criteria values (**Supplementary Tables S4, S5**).

influenced by runoff variables, including annual runoff for the water year and multi-annual antecedent periods.

Runoff variables were also influential in predicting dry season baseflow characteristics. Runoff in the summer months and seasonally-averaged runoff were both important in predicting dry season baseflow magnitudes. The catchment groundwater recharge index was also influential for the dry season high baseflow metric. Catchment variables were most important in predicting the timing of the dry season. Influential variables included the mean and max catchment elevation, the baseflow index, and soil properties (**Supplementary Table S3**). Similar to the fall and spring duration metrics, duration of the dry season was most influenced by catchment properties, including elevation, spring precipitation, and the catchment erodibility index (K-factor).

Model Performance

Overall, the FFM models had high predictive accuracy, with all 24 metrics exhibiting excellent (composite performance index [CPI] > 0.9 for 7 metrics), very good (0.8 < CPI ≤0.9 for 12 metrics) or good (0.65 < CPI ≤0.8 for 5 metrics) performance (**Figure 2**; **Supplementary Table S4**). The models performed well in predicting fall pulse flows, including the magnitude (CPI = 0.85), timing (CPI = 0.80), and duration (CPI = 0.70). The slightly lower CPI for fall pulse duration was driven by low NSE and r^2 performance criteria values (<0.25). This was the result of the limited range of whole number values in the observation record (median fall pulse duration of 2–7 days among all sites), such that slight deviation of predictions (i.e., 1 or 2 days) caused NSE and r^2 values to substantially decrease.

The models for wet season baseflow accurately predicted all metrics, especially the wet season low magnitude metric (CPI = 0.91), and exhibited excellent performance (CPI >0.9) in predicting peak flow magnitudes for 2-, 5-, and 10-years flood recurrence intervals. Model performance for within-year flood

frequency and duration were also considered good, very good, or excellent. The model for the 10-years flood frequency tended to overestimate the observed range of variation (i.e., a higher proportion of observed values fell within the predicted interquartile range than expected; **Supplementary Table S4**), although overall model performance was still good. Model performance was very good (CPI >0.8) for spring recession flow magnitude, timing, duration, and rate-of-change. The models were very good or excellent in predicting all dry season baseflow metrics, including the median (CPI = 0.92) and high baseflow magnitudes (CPI = 0.92), dry season timing (CPI = 0.90), and dry season duration (CPI = 0.83).

When model performance was assessed by stream class, the CPI deviated from those obtained when all streams were evaluated together (**Figure 2**). For snowmelt-dominated streams, the models performed less well in predicting timing and duration metrics, including for the fall pulse, wet season, spring recession, and dry season. However, only the fall pulse timing model was considered "poor" performing for the snowmelt stream class. Model performance declined for some metrics in the mixed snow-and-rain and rainfall-dominated classes, but all models were considered at least satisfactory and most were very good or excellent (**Figure 2**). Stream gage records were insufficient to evaluate the performance of the 10-years flood duration and frequency metrics by stream class.

Model Predictions

Based on the overall satisfactory performance of the FFM models, predictions of expected, natural FFM values were generated for all stream reaches in California using models calibrated with the full set of reference gages. Model predictions were compiled in a geospatial database and made available through an online mapping tool to allow users to visualize and download estimates of natural FFM values for any stream reach in the state CEFWG, 2021 (**Figure 3**).
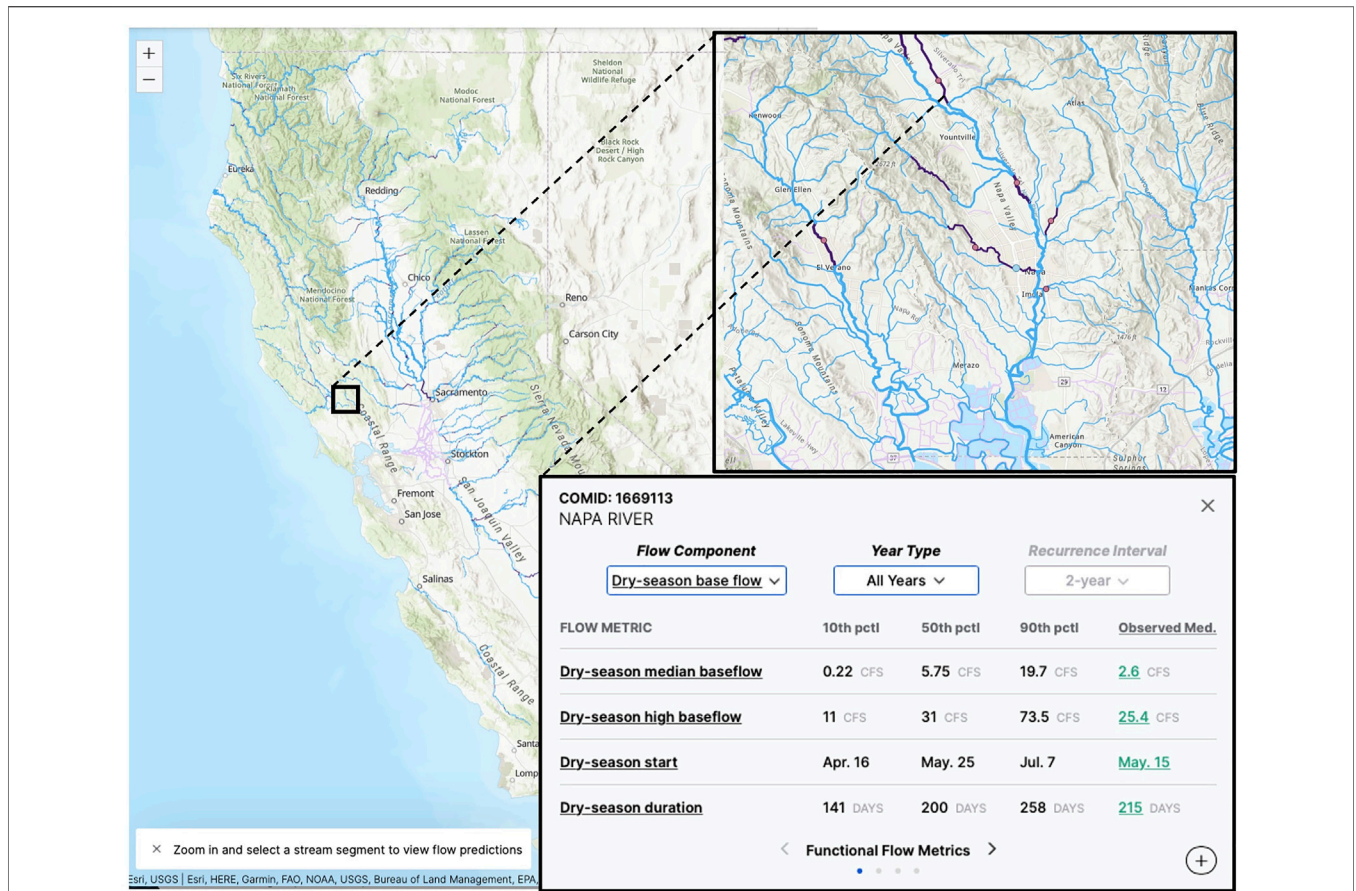
FIGURE 3 | Screenshot of online mapping tool developed to explore, visualize, and download modeled natural functional flow metrics for streams in California, displaying dry season baseflow metrics at a gaged stream reach of the Napa River. Available at: https://rivers.codefornature.org.

DISCUSSION

Here we applied a machine learning modeling approach to estimate functional flows for over 140,000 stream reaches exceeding 250,000 km in total length in California, United States. Our evaluation of model performance indicated that natural hydrologic signatures describing the magnitude, timing, duration, frequency, and rate-of-change of functional components of the flow regime could be accurately predicted across a large region with high geographic variability. For every stream reach in the state, we generated predictions for the expected natural range of five functional flow components, including fall pulse flows, wet season baseflows, peak flows, spring recession flows, and dry season baseflows. By predicting the range of flows that are expected to support essential ecosystem functions under natural landscape conditions, these estimates can serve as a foundation for assessing ecological flow needs, quantifying flow alteration, and guiding development of environmental flow recommendations in the state, through the California Environmental Flows Framework (Stein et al., 2021) or other environmental flow assessment approaches.

The models relied on a network of reference-quality gages and a broad suite of watershed variables to predict functional flow

metrics. For most metrics, these variables appeared to capture the effects of dominant physical processes that control seasonal flow dynamics. In particular, the models were highly accurate in predicting the magnitudes of fall pulse and wet season peak flows, as well as wet and dry season baseflows. In contrast, the models did not perform as well in predicting the timing and duration of flow components. This likely relates to the monthly scale of the climate predictor variables, which fail to represent physical processes that control the timing and duration of functional flow components at shorter timescales. These deficiencies were more pronounced when evaluating model performance by stream class. For example, model performance was substantially lower for timing and duration metrics in the snow-dominated stream class, which might relate to the inability of the model to capture snow accumulation and snowmelt runoff dynamics. Nevertheless, model performance remained satisfactory or better for all but one metric: fall pulse timing in the snow class.

The modeling approach used in this study differs from physically-based hydrologic models (i.e., rainfall-runoff models) that are commonly used in environmental flow applications. First, rainfall-runoff models are generally trained and calibrated using a small sample of streamflow gaging records

to estimate streamflow 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. Model calibration procedures also differ. Rainfall-runoff models are often run on daily or sub-daily timescales and are calibrated to generate the best fit with observed streamflow data. This means that model parameters are generally tuned to minimize deviation in all elements of the flow regime and, as a result, there may be tradeoffs associated with improving predictive accuracy in some flow components (e.g., peak flows) at the expense of others (e.g., low flows). In contrast, the modeling approach described here calibrates to specific aspects of the flow regime, avoiding such tradeoffs, and likely increasing model predictive accuracy of functional flow metrics.

Hydrologic models are typically evaluated using a limited set of "goodness of fit" (GOF) criteria, such as r-squared and NSE, to compare predictions with paired observations (Clark et al., 2021). The performance assessment approach used in this study used a broader suite of criteria, including both GOF and measures that evaluate the degree to which the distributions of predictions align with observations. We found there was notable variation in the performance criteria values for several metrics (**Supplementary Tables S4, S5**). This indicates that interpretation of model accuracy can be highly influenced by the selection of performance criteria and suggests that multiple criteria should be used to assess hydrologic model performance where possible.

One of the shortcomings of statistical models is that they do not explicitly represent the mechanisms that control streamflow generation and variability. Although the variable importance rankings can provide some insight into the physical controls on specific flow components, factors contributing to model accuracy can be difficult to ascertain. For example, the relationship between seasonal precipitation (and runoff) volumes and the magnitudes of functional flow components was evident in the variable important plots of the RF models. In the dry season, the importance of the groundwater recharge index (Wolock, 2003b) suggested that this variable was, at least in part, effective in representing groundwater-surface interactions that influence baseflow. The strong influence of spring temperature on the timing of the spring flow recession was also consistent with understanding of the physical controls on spring snowmelt dynamics (Yarnell et al., 2010). However, the influences of other variables on functional flow metrics were more difficult to interpret. For example, catchment elevation was important in predicting the duration of the 2-years flood, spring recession duration, and dry season duration, but the physical basis for these relationships is less clear. Additional studies that offer robust comparisons between statistical and physically-based models, such as performed by Hodgkins et al. (2020), would be helpful for evaluating the benefits and limitations of different hydrologic modeling approaches in predicting functional flows and supporting environmental flow applications.

One important limitation in our modeling approach is the network of available reference gages. The USGS stream gaging network is biased towards larger, perennial streams of management interest (Kiang et al., 2013), and these biases are also evident in our study area. In particular, there is poor

representation of intermittent and ephemeral streams among reference gages (Hammond et al., 2021), especially in the arid southeastern region of California. Similarly, spring-fed streams and those highly dependent on groundwater interactions are poorly represented in the reference gage network. In addition, most large streams and rivers in the state have been altered by dams, diversions, and land use change, among other human activities (Zimmerman et al., 2018), so there are few locations that are considered reference-quality in these larger rivers. We addressed this limitation, in part, by including reconstructed natural flow records from a few major rivers below dams (DWR, 2007). However, we recognize that predictions of FFMs are likely less reliable in these and other poorly gaged systems compared to better-gaged portions of the stream network. Unfortunately, the degree to which model performance is affected by gage network gaps is difficult to quantify because the absence of gages for model training also means there are no gages for model validation. Strategically installing new gages in reference-quality streams that represent these unique hydrologic contexts would help improve the accuracy, aid quantification of uncertainty, and enhance the utility of the models in environmental flow management applications across a broader range of stream types. Limiting human catchment disturbance would also help ensure streams remain as reference-quality in the future.

In addition to obtaining data from a wider representation of reference-quality streams, the performance of functional flow models could be improved with new geospatial data that describe hydrologically relevant watershed characteristics. In particular, improved characterization of watershed lithology, which has a strong effect on subsurface flow dynamics, is likely to be helpful in predicting flow recession patterns and baseflow conditions (Lovill et al., 2018). Advancements in satellite sensing products for assessing vegetation dynamics, surface water, and groundwater levels (Tang et al., 2009) also hold enormous potential for improving the characterization of watersheds and enhancing model performance. We acknowledge that more work is needed to understand how changing climatic conditions will influence flow regimes and supported functions (Grantham et al., 2018). The current modeling approach estimates the range of variation in functional flow metrics based on historical (1950–2015) climate, watershed conditions, and flow responses. As California and the world experience novel climate conditions, retraining models with contemporary data will be necessary to generate new predictions for the flow regime and to evaluate whether critical ecosystem functions will continue to be supported as flow components shift in response to climate change.

CONCLUSION

The modeling approach presented here can be used to develop an initial estimate of flows required to sustain essential ecological functions and establish a foundation upon which subsequent analyses can be performed. These modeled natural functional flow predictions provide a reference condition against which to evaluate potential alterations to critical ecosystem functions due

to human management activities or climate changes. For systems with specific management objectives or where ecosystems have been highly altered, more intensive studies will likely be needed to determine if the functional flows estimated by the models are appropriate for quantifying ecological flow needs (e.g.,Taniguchi-Quan et al., 2022). In addition, support and guidance for adaptively managing environmental flows to maximize their effectiveness will help sustain ecosystem functions and health, particularly in a changing climate (John et al., 2020). Efforts to integrate the functional flows modeling approach in an environmental flow program in California are promising (Stein et al., 2021). As a relatively simple and cost-effective means for supporting regional environmental flow programs, there is also potential to adapt the approach for use in other geographic contexts, including data-poor regions of the world. Together with other advances in environmental flow science, functional flows models could play an important role in accelerating much-needed protections of environmental flows at a global scale.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories, which are cited in this article or provided as **supplementary material**. Questions regarding the data and code used in the analysis can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

TG led the preparation of this manuscript. TG, DC, JZ, BL, and KT-Q contributed to model development and evaluation. TG, JH, BL, RL, AO, SS-S, BS, ES, SY, JZ, and KT-Q contributed to the development of the California Environmental Flows Framework, theoretical concepts guiding the modeling approach, and to writing, review, and editing of this manuscript.

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SUPPLEMENTARY MATERIAL

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