Accepted: 8 January 2018
DOI: 10.1111/fwb.13074

SPECIAL ISSUE

WILEY Freshwater Biology

Tools for managing hydrologic alteration on a regional scale: Estimating changes in flow characteristics at ungauged sites

Ashmita Sengupta[1] | Stephen K. Adams[2] | Brian P. Bledsoe[3] | Eric D. Stein[1] | Kenneth S. McCune[1] | Raphael D. Mazor[1,4]

[1]Southern California Coastal Water Research Project, Costa Mesa, CA, USA
[2]Colorado State University, Fort Collins, CO, USA
[3]College of Engineering, University of Georgia, Athens, GA, USA
[4]CA Department of Fish and Wildlife, Rancho Cordova, CA, USA

Correspondence
Ashmita Sengupta, Southern California Coastal Water Research Project, Costa Mesa, CA, USA.
Email: ashmitas@sccwrp.org

Funding information
California State Water Resources Control Board, Grant/Award Number: SWCRB 12-430-550

Abstract

1. Hydrologic alteration is a predominant stressor for biological resources in streams. This stress is further aggravated by competing human and ecological demands for limited water resources. Understanding flow–ecology relationships and establishing relevant and implementable flow targets are essential to protect biological communities.
2. Estimating degree of ecologically relevant hydrologic alteration depends on the availability of long-term flow data at sites with biological information. However, measured flow data are seldom available at sufficient density to support large-scale analyses of the biological effects of hydrologic alterations. The ability to accurately simulate flows and estimate flow metrics at many ungauged locations across a broad geographical area remains a fundamental challenge.
3. We address this challenge by applying a novel technique to simulate flow regimes at any stream reach of interest by first developing an ensemble of regionally calibrated and validated hydrological models, and then using a selection tool to match the "best-fit" model to ungauged stream reaches. An ensemble of 26 HEC-HMS rainfall–runoff models were calibrated to represent the range of catchment conditions in the southern California region.
4. We developed current and historical flow regimes and a suite of flow metrics at 572 ungauged sites in southern California with bioassessment monitoring data. The flow metrics represent hydrograph characteristics of magnitude, timing, frequency, duration and variability. The flow metrics were estimated under three precipitation conditions—dry, wet and average. In addition, we estimated aggregated flow metrics for (dry + wet + average) condition. Hydrologic alteration was estimated as the deviation between the modelled current and historical flow metrics.
5. Approximately 79% of the region shows some degree of hydrologic alteration, and approximately 40% of the sites are estimated to be severely altered. Magnitude metrics tend to increase in response to urban and agricultural land uses, whereas the timing and duration metrics are mostly unchanged.
6. This mechanistic modelling approach demonstrates the feasibility of estimating flow alterations for ungauged catchments with relative ease of transferability over a broad geographical region. The continuous granular flow data allow for

computation and consideration of metrics that may be applicable to a variety of ecological endpoints and consideration of a range of management trade-offs.

KEYWORDS
ELOHA, Environmental flows, Hydrologic alteration, ungauged basins, regional hydrology, ensemble model

1 | INTRODUCTION

The influence of hydrologic alterations on the structure and function of stream ecosystems is widespread and expected to increase with increasing urbanisation and climate change (Malmqvist & Rundle, 2002; Poff & Zimmerman, 2010; Postel & Richter, 2012; Rosenberg, McCully, & Pringle, 2000). Well-informed water resource management is required to protect in-stream habitats and ecosystem services from hydrologic alterations while meeting increasing human demands. This balance requires an understanding of relationships between hydrologic alteration and biological responses. Based on these relationships, ecologically important in-stream flow targets need to be identified and managed (DeGasperi et al., 2009; Poff & Zimmerman, 2010). However, setting regionally applicable flow targets is challenging for two primary reasons, lack of gauged flow data at sites with existing biological data and difficulty in estimating historical/reference flow conditions (Puckridge, Sheldon, Walker, & Boulton, 1998; Poff, Bledsoe, & Cuhaciyan, 2006).

The Ecological Limits to Hydrologic Alteration (ELOHA) framework emphasises the importance of establishing a regional hydrologic foundation to estimate alteration in streamflows (Poff et al., 2010). Typically, approaches to predict streamflow behaviour in ungauged basins are based on transferring gauge data at drainage basin scales (Sivapalan et al., 2003). This can be performed by regressing flow metrics against basin characteristics or by estimating hydrologic model parameters at gauged sites similar to the sites of interest (Post & Jakeman, 1999; Sivapalan et al., 2003; Wagener & Wheater, 2006; Sanborn & Bledsoe, 2006; Yadav, Wagener, & Gupta, 2007; Parajka et al., 2013). Historic (i.e. reference or minimally altered) conditions are sometimes estimated by developing models from gauges in relatively unaltered settings in a space for time substitution. This concept of using physical characteristics of gauged basins to predict flows at ungauged basins has been explored in many studies with some success (Kokkonen, Jakeman, Young, & Koivusalo, 2003; Moretti & Montanari, 2008; Samaniego, Kumar, & Attinger, 2010).

Simple regression models can be developed to predict daily flows and flow metrics. However, they can be limited in their ability to evaluate future scenarios associated with changing climate, water use, and land use, including the effect of water management, such as water recycling and stormwater retention and detention. Robust hydrological models that can be transferred to any stream reach of interest to estimate streamflow and flow metrics provide a potential mechanism for developing regional flow data necessary for developing flow–ecology relationships. Detailed and highly parameterised models can be computationally expensive and complicated to parameterise in larger catchments (Sivapalan et al., 2003; Caldwell et al., 2015). These models cannot be easily transferred to new ungauged reaches due to limited availability of the data required to parameterise the model. Buchanan, Moltz, Haywood, Palmer, and Griggs (2013) applied the complex mechanistic model HSPF (Hydrologic Simulation Program—Fortran) to simulate historical and current conditions at gauged sites; however, their study was limited to ungauged sites in the subcatchments of a single catchment. In comparison, lumped regional models might lack the capacity to represent subcatchment processes but can be useful in assessing flow alterations at larger scale (Caldwell et al., 2015). Ultimately, a new modelling approach is necessary that parsimoniously and reliably predicts current and historic streamflow and ecologically relevant flow metrics across a broad range of sites in a region of interest.

In this study, we present a novel technique to estimate hydrologic alteration at ungauged stream reaches across a large and heterogeneous region of southern California. We apply an ensemble of simple yet regionally representative hydrological models that can be easily transferred to any ungauged location in the region. We evaluate the ability of these models to estimate potential biologically relevant flow metrics for current and historic conditions at ungauged sites, and provide a regional understanding of the nature and extent of hydrological alteration in southern California.

2 | METHODS

The overall modelling process is somewhat complex with a number of interdependent and sequential steps. We provide a process diagram to facilitate navigation through the methods (Figure 1). Briefly, hydrological models were developed for a set of sites for which high-quality flow and precipitation data were available. These models were then assigned to a larger number of ungauged catchments and used to estimate streamflow and hydrological alteration.

2.1 | Study area

Southern coastal California has a Mediterranean climate, with hot, dry summers, and cool, wet winters. Ephemeral streams are typical of the region. Much of the coastal, lower elevation areas have been converted to agricultural or urban lands, where water importation, runoff and effluent discharges have perennialised many naturally

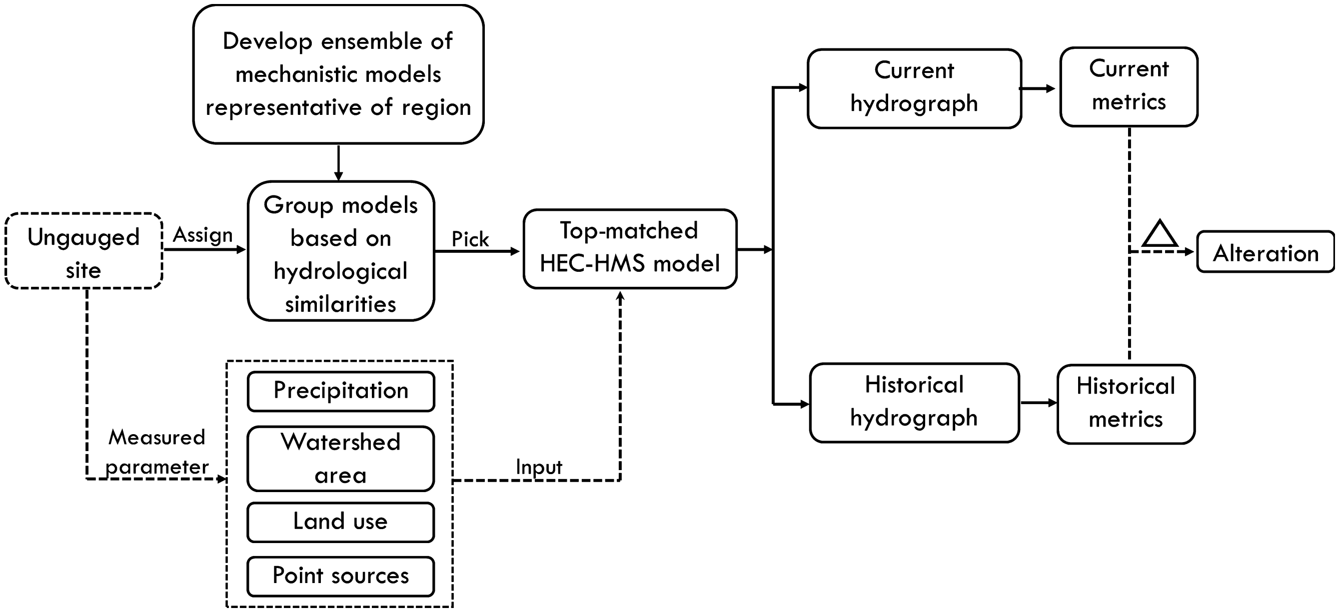

FIGURE 1 Process to estimate hydrologic alteration at ungauged sites by assigned hydrologic model from a gauged site

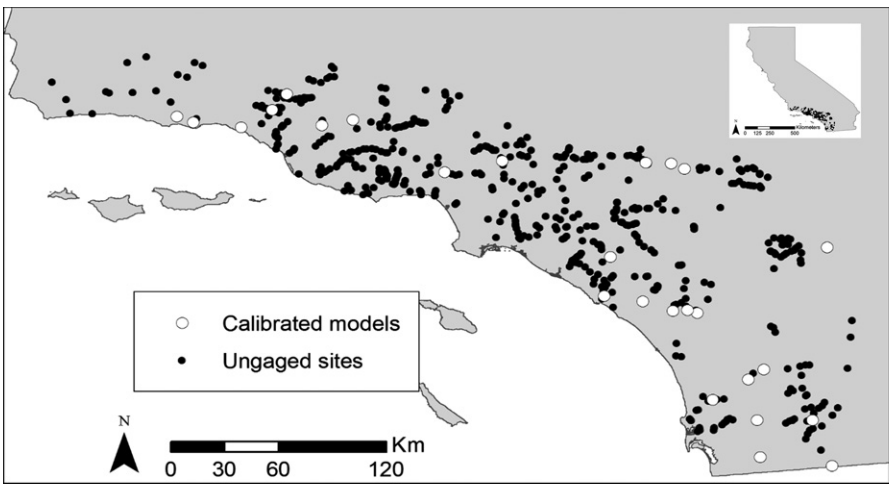

FIGURE 2 Sites showing 26 calibrated models (white dots) and 572 ungauged bioassessment sites (black dots) in southern California. Inset shows the map of California

intermittent or ephemeral streams (Mazor, Stein, Ode, & Schiff, 2014). Most of the upper elevations of catchments remain undeveloped, with chaparral, grassland and oak or pine forest land cover. Pyne, Carlisle, Konrad, and Stein (2017) grouped the streams for the state of California in seven classes based on landscape and climate variables. There are three (of the seven) main types of streams in the southern region; class one, high-elevation mountain streams, which regularly receive snowmelt for a few months in most years; class two, lower elevation streams are primarily driven by rainfall and ground water; and finally, class four which comprises of larger lowland rivers representative of ground water, transitional snowmelt and rainfall-driven rivers.

2.2 | Developing the hydrological model ensemble

We selected the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) to predict flows. We developed hydrological models at 32 locations with measured hourly flow and precipitation data, although only 26 of the gauged sites were selected for the final ensemble (Figure 2; Table 1) and the remaining six models were

TABLE 1 List of sites used for the final ensemble, associated characteristics (size, imperviousness and elevation) and flow gauges used to calibrate the Hydrologic Engineering Center Hydrologic Modeling System models. Performance of models for Nash–Sutcliffe efficiency (NSE), per cent low-flow error (LFE) and per cent error for Richards–Baker Index (RBI E). Number of ungauged sites (bioassessment) assigned to each of the gauged models from the ensemble

Site name	Area (mi^2)	% Imp	Elev (ft)	USGS Gauge ID	NSE	LFE	RBI E	No. of ungauged sites assigned
Andreas	8.65	0	800	10259000	0.58	5.3	8.1	44
Arroyo Seco	16	0.46	1,398	11098000	0.42	19.4	5.2	9
Arroyo Trabuco	54.12	19.06	80	11047300	0.73	15.7	33.2	60
Campo	84.11	0.55	2,179	11012500	0.49	7.4	55.3	10
Carpinteria	13.1	0.1	130	11119500	0.83	0.3	0.1	0
De Luz	33	0.32	270	11044800	0.9	6.4	8.3	4
Devil Canyon	5.49	0.74	2,080	11063680	0.57	59.5	27.8	33
East Twin	8.8	0.64	1,590	11058500	0.4	33.4	4.9	16
Jamul	70.11	0.54	512	11014000	0.46	15.8	13.8	60
Los Angeles	158	27.34	663	11092450	0.95	0	23.1	22
Los Coches	12.17	9.39	560	11022200	0.79	4.5	22.2	15
Poway	42.44	20.66	300	11023340	0.91	18.8	20.7	38
Lytle	46.6	0.33	2,380	11062000	0.44	18.9	6.3	64
Matilija	47.8	0.01	1,380	11114495	0.84	16.7	18.8	36
Mission	8.38	4.77	140	11119750	0.83	8	26.6	26
Rainbow	10.21	3.7	500	11044250	0.73	10.7	8.3	18
San Jose	5.51	0.4	96	11120500	0.81	5.5	25	1
San Mateo	80.8	0.13	405	11046300	0.75	2.5	50.7	14
Santa Maria	57.6	2.52	1,294	11028500	0.73	1.3	23.4	7
Santa Paula	38.4	0.14	619	11113500	0.53	0	17.8	19
Santa Ysabel	111.43	0.1	848	11025500	0.72	3.4	16	21
Santiago	12.5	0.21	1,340	11075800	0.58	0.1	27.6	19
Sespe Fillmore	252	0.05	565	11113000	0.61	0	22.6	1
Sespe Wheeler Springs	49.5	0.09	3,500	11111500	0.58	5.2	47.2	28
Sandia	19.67	1.27	380	11044350	0.63	0	24	6
Sweetwater	45.4	0.28	3,269	11015000	0.57	2.9	71	1

rejected due to poor calibration performance. At the 26 gauged sites, HEC-HMS models were calibrated using eight measured catchment parameters and optimised to estimate nine modelling parameters (Table S1). At each gauge, the HEC-HMS model was sequentially calibrated for overall fit, runoff during low-flow periods and streamflow flashiness. We used the generalisation of Nash–Sutcliffe efficiency (NSE, Equation 1) as a measure of overall model fit.

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (Q_{\mathrm{obs}i} - Q_{\mathrm{pred}})^2}{\sum_{i=1}^{n} (Q_{\mathrm{obs}i} - \bar{Q}_{\mathrm{obs}})^2}, \tag{1}$$

where Q_{obs} is observed and Q_{pred} is predicted values of flow. NSE ranges from $-\infty$ to 1.

We added two separate calibration endpoints, which could potentially be important for southern California in-stream biological communities: runoff during low-flow periods (hereafter referred to as low flows) and streamflow flashiness. We define low-flow days as those with flows <0.03 m^3/s. For low-flow days, we estimated a per cent low-flow error (LFE) between model output and measured flow using Equation 2.

$$\mathrm{LFE} = \frac{(\%\ \text{days} < 0.03\ \mathrm{m^3/s})_{\ \mathrm{pred}} - (\%\text{days} < 0.03\ \mathrm{m^3/s})_{\mathrm{Obs}}}{(\%\ \text{days} < 0.03\ \mathrm{m^3/s})_{\mathrm{Obs}}} \times 100. \tag{2}$$

Finally, we estimated the Richards–Baker Index (RBI, Equation 3) as a measure of flashiness and estimated the per cent model error using Equation 4.

$$\mathrm{RBI} = \frac{\sum_{i=1}^{n} (Q_i - Q_{i-1})}{\sum_{i=1}^{n} (Q_i)} \tag{3}$$

Q_i is flow on a given day i, and Q_{i-1} is flow on the previous day. The RBI per cent error (RBI E) is

$$\mathrm{RBI}\ E = \frac{(\mathrm{RBI})_{\ \mathrm{pred}} - (\mathrm{RBI})_{\mathrm{Obs}}}{(\mathrm{RBI})_{\mathrm{Obs}}} \times 100. \tag{4}$$

For each model at a gauged location, we first calibrated to the highest NSE value achievable, then optimised to reduce the LFE and

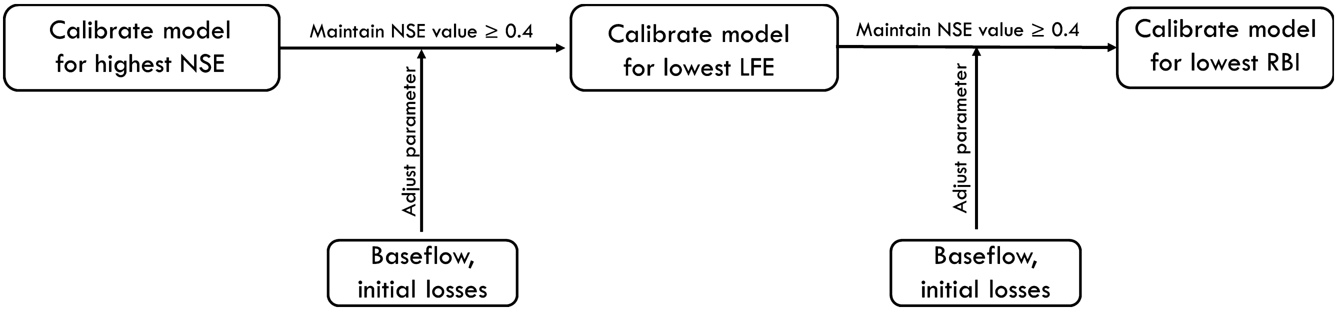

FIGURE 3 Sequential calibration of Nash–Sutcliffe efficiency (NSE), low-flow error (LFE) and Richards–Baker Index error (RBI E)

RBI E (Figure 3) by changing the nine modelling parameters (Table S1). At all times, the NSE values were maintained at ≥0.40.

Flow data used for calibrating the model ensemble were sourced from United States Geological Survey (USGS) gauges, while the precipitation data were obtained from national databases, such as the National Oceanic and Atmospheric Administration (NOAA), National Weather Service Automated Local Evaluation in Real Time (*ALERT*); state databases, such as California Irrigation Management Information System (CIMIS) and California Data Exchange Center (CDEC); and local databases, such as San Diego Regional (SDRCD) and Ventura County Watershed Protection District (VCWPD). Models were developed for the period of 2005, 2006 and 2007 representing a wet, average and dry year, respectively.

To test transferability of models to sites that have limited or no-flow data, we applied a jackknifing resampling technique. Each gauged site was treated as an ungauged site and the remaining 25 models were used to predict flows at that site, and the three calibration values were estimated. In addition, we validated the models spatially and temporally. The temporal validation consisted of simulating flow for 10 gauges for time periods outside the calibration period with reliable precipitation and measured flow data. A drop in NSE higher than 50% between calibration and the validation run was considered poor validation. Spatial validation consisted of simulating the models at a subset (n = 15) of the 572 bioassessment sites (Figure 2) with limited measured flows. The predicted flows were then compared to limited observed flows from local gauges. We used a simple coefficient of determination (r^2) to quantify model performance.

2.3 | Assigning a Gauged HEC-HMS Model to an Ungauged Site

To assign a HEC-HMS model from the ensemble to an ungauged site, cluster analysis was used to identify groups of hydrologically similar calibration gauges. First, a suite of flow metrics was calculated from observed daily flow data at the 26 calibration gauges during the calibration period (Table 2). Flow metric values were then rank-transformed to eliminate the influence of different metric scales. The ranks were used as input into a principal components analysis group metrics and minimise the influence of redundancy. The first eight components (representing 95% of the total variance) were then used in a flexible-beta cluster analysis (beta: −.25) based on Euclidean distance to produce a dendrogram. Flexible-beta is a common clustering method in community ecology that provides more interpretable dendrogram with less distortion than those produced by nearest-neighbour or farthest-neighbour methods (Milligan, 1989). Eight clusters of gauges were identified by visual inspection of the dendrogram. Next, a random forest model was developed to predict cluster membership of novel ungauged sites based on catchment characteristics (e.g. impervious cover, urban and agricultural land cover, soil erodibility and road density). This random forest model was then used to estimate the statistical proximity between a new, ungauged site and each calibration gauge within the eight clusters. Statistical proximity was calculated as the frequency that the ungauged site and the calibration gauge are assigned to the same cluster by the random forest model. The HEC-HMS model associated with the most proximal gauge was then assigned to each ungauged site.

Twenty-seven candidate catchment characteristics were evaluated for use in the random forest model, including both natural (e.g. climate, geology, elevation) and anthropogenic (e.g. road density, per cent impervious) gradients (Table S2). Recursive feature elimination (RFE), as implemented by the caret package in R (Kuhn et al., 2012), was used to select the variables that were most useful for predicting cluster membership. RFE attempts to find the simplest model whose accuracy is within 1% of the most accurate model; thus, if the model with the best accuracy has 10 predictor variables, but an eight-variable model was nearly as accurate, the eight-variable model was selected. The selected variables were used to calibrate the final 1,000-tree assignment model using the random forest package in R (Liaw & Wiener, 2002). This final model was then used to assign an HEC-HMS model to each of the 572 bioassessment sites.

2.4 | Estimating Flows under Current and Historic Conditions

We estimated hydrologic alteration as the change in flow between the current and historical conditions. The initial losses/abstraction is estimated using curve numbers (CNs) based on soil type (Woodward et al., 2003). When the catchment has mixed land use including developed portions, we estimate a CN composite using Equation 5, using the area A_i and curve number CN_i associated with each land use in the catchment. For historical conditions, CN composite is

TABLE 2 Description of flow metrics (n = 39) grouped into categories (n = 5). Hydrologic alteration is estimated as the extent of deviation between the current (C) and historical (H). Four italic metrics require threshold adjustment

Metric	Unit	Description	Alteration
Duration			
HighDur	Days/event	Median annual longest number of consecutive days that flow was greater than the high-flow threshold	C-H
Hydroperiod	Proportion	Fraction of period of analysis with flows	C-H
LowDur	Days/event	Median annual longest number of consecutive days that flow was less than or equal to the low-flow threshold	C-H
NoDisturb	Days	Median annual longest number of consecutive days that flow between the low- and high-flow threshold	C-H
Per_LowFlow	Proportion	Per cent of time with flow below 0.0283 m^3/s	C-H
Frequency			
FracYearsNoFlow	Proportion	Fraction of years with at least one no-flow day	C-H
LowNum	Events/year	Median annual number of continuous events that flow was lesser than the low-flow threshold	
HighNum	Events/year	Median annual number of continuous events that flow was greater than the high-flow threshold	C-H
MedianNoFlowDays	Days/year	Median annual number of no-flow days	C-H
Magnitude			
MaxMonthQ	m^3/s	Maximum mean monthly streamflow	(C-H/H)
MinMonthQ	m^3/s	Minimum mean monthly streamflow	(C-H/H)
Q01	m^3/s	1st percentile of daily streamflow	(C-H/H)
Q05	m^3/s	5th percentile of daily streamflow	(C-H/H)
Q10	m^3/s	10th percentile of daily streamflow	(C-H/H)
Q25	m^3/s	25th percentile of daily streamflow	(C-H/H)
Q50	m^3/s	50th percentile of daily streamflow	(C-H/H)
Q75	m^3/s	75th percentile of daily streamflow	(C-H/H)
Q90	m^3/s	90th percentile of daily streamflow	(C-H/H)
Q95	m^3/s	95th percentile of daily streamflow	(C-H/H)
Q99	m^3/s	99th percentile of daily streamflow	(C-H/H)
Qmax	m^3/s	Median annual maximum daily streamflow	(C-H/H)
Qmean	m^3/s	Mean streamflow for the period of analysis	(C-H/H)
QmeanMEDIAN	m^3/s	Median annual mean daily streamflow	(C-H/H)
Qmed	m^3/s	Median annual median daily streamflow	(C-H/H)
Qmin	m^3/s	Median annual minimum daily streamflow	(C-H/H)
Timing			
C_C	Ratio	Colwell's constancy (C) a measure of flow uniformity.	C-H
C_CP	Ratio	Colwell's maximised constancy (C/P). Likelihood that flow is constant throughout the year	C-H
C_M	Ratio	Colwell's contingency (M). Repeatability of seasonal patterns.	C-H
C_MP	Ratio	Colwell's maximised contingency (M/P). Likelihood that the pattern of high- and low-flow events is repeated across years.	C-H
C_P	Ratio	Colwell's predictability (P = C + M). Likelihood of being able to predict high- and low-flow events	C-H
MaxMonth	Month	Month of maximum mean monthly streamflow	C-H
MinMonth	Month	Month of minimum mean monthly streamflow	C-H
Variability			
QmaxIDR	m^3/s	Interdecile range (IDR) of annual maximum flow	C-H
QmeanIDR	m^3/s	Interdecile range (IDR) of annual mean flow	C-H
QminIDR	m^3/s	Interdecile range (IDR) of annual minimum flow	C-H

(Continues)

TABLE 2 (Continued)

Metric	Unit	Description	Alteration
PDC50	Unitless	50th percentile of absolute value of per cent daily change	C-H
BFR	Unitless	Baseflow recession rate	C-H
RBI	Unitless	Richards–Baker Index (flashiness)	C-H
SFR	Proportion	90th percentile of per cent daily change in streamflow on days when streamflow is receding (storm-flow recession)	C-H

estimated assuming there is no developed land and imperviousness is zero. In HEC-HMS, the net initial loss is set to a limit of 0.2S for both current and historical conditions, where S is the maximum retention in each catchment dependent on the CN (Equation 6).

$$\mathrm{CN}_{\mathrm{composite}} = \frac{\sum A_i CN_i}{\sum A_i} \quad (5)$$

$$S = \left(\frac{1{,}000}{\mathrm{CN}}\right) - 100 \quad (6)$$

Flows were estimated for a 23-year period (1990–2013) over which the biological sampling spanned. Hourly precipitation was estimated for each of the 572 sites using an inverse distance weighting (IDW) interpolation method using data from 206 precipitation gauges (Table S3). Since historical precipitation records are not available, the precipitation data from 1990 to 2013 were used to model both current and historical scenarios.

Within the 23 years, a subset of six years comprising two wet, two dry and two average precipitation years were selected for each site. The choice of 6 years at the 572 sites is driven by availability of reliable precipitation data over a range of climates (i.e. wet, dry and average). Each IDW data set was checked for consistency with raw data from nearby rain gauges, and inconsistent gauges were removed. Anomalously large or small yearly precipitation sums were eliminated by setting upper and lower bounds using the measured maximum and minimum yearly precipitation for each county. Dry years were defined as precipitation below the 30th percentile, average years between the 30th and 60th percentiles and wet years exceeding the 60th percentile of the annual precipitation between 1990 and 2013.

2.5 | Estimating hydrologic alteration

A suite 39 flow metrics was calculated for current and historical flows for selected 6 years at each site. These metrics were estimated for four climatic conditions—wet, dry, average and aggregated across all conditions. This resulted in a total of 156 (39 × 4) flow precipitation combinations. Metrics estimated under current conditions were then compared to historical flow metrics to estimate hydrologic alterations (ΔH). These metrics grouped into duration (n = 5), frequency (n = 4), magnitude (n = 16), timing (n = 7) and variability (n = 7) are listed in Table 2. Two modifications were applied to estimate hydrologic alteration. First, for streams with no flows in the reference condition, a minimal flow of 0.03 m^3/s was assigned to ensure that the magnitude metrics could be estimated. Second, four metrics (highlighted in Table 2) are based on high-flow or low-flow thresholds (e.g. low flows are identified as flow below the 10th percentile), and these threshold values can change between historic and current conditions (e.g. the 10th percentile may decrease as a catchment undergoes urbanisation). To deal with this changing baseline effect, we applied an alternative approach of using the value derived for historic conditions to calculate hydrologic alterations for duration and frequency metrics. The method used to estimate hydrologic alteration for each metric is also shown in Table 2.

3 | RESULTS

3.1 | Performance of model ensemble

The ensemble of 26 models had NSE values in the range 0.40–0.95 with an average NSE value of 0.67 and 22 of the 26 models had values higher than 0.50 (Table 1). The LFE ranged from 0 to 59.5% with lower values indicating better performance with an average LFE of 10% and 24 of the 26 models had <25% error. The RBI E ranged from 0.1% to 55.3%, and a >25% error for 18 of the 26 models.

Temporal validation at 10 gauged sites from the HEC-HMS ensemble showed that the performance was comparable to calibration for four gauges: Los Angeles, Arroyo Trabuco, Sandia and Santa Paula; however, validation is generally poor at mountainous sites subject to greater orographic effects (e.g. Campo and Santiago). Six of the models had less than a 50% drop in performance between the calibration and validation. The per cent error and the NSE values are listed in Table 3.

Spatial validation using jackknifing for the 26 gauged HEC-HMS models showed that 75% of the sites had a matched model that

TABLE 3 Temporal validation (Nash–Sutcliffe efficiency, NSE) at 10 calibration gauges

Model	Validation period	Calibration NSE	Validation NSE
Arroyo Trabuco	2007–2010	0.75	0.34
Arroyo Seco	2007–2010	0.58	−0.90
Campo	2007–2010	0.46	−0.85
Los Angeles	2007–2010	0.89	0.75
Lytle	1990–2004	0.78	0.54
Sandia	1991–2004	0.85	0.80
Santiago	2007–2010	0.69	−0.05
San Mateo	1992–2004	0.82	0.70
Santa Paula	1993–2004	0.67	0.56
Sespe Fillmore	1994–2004	0.59	0.47

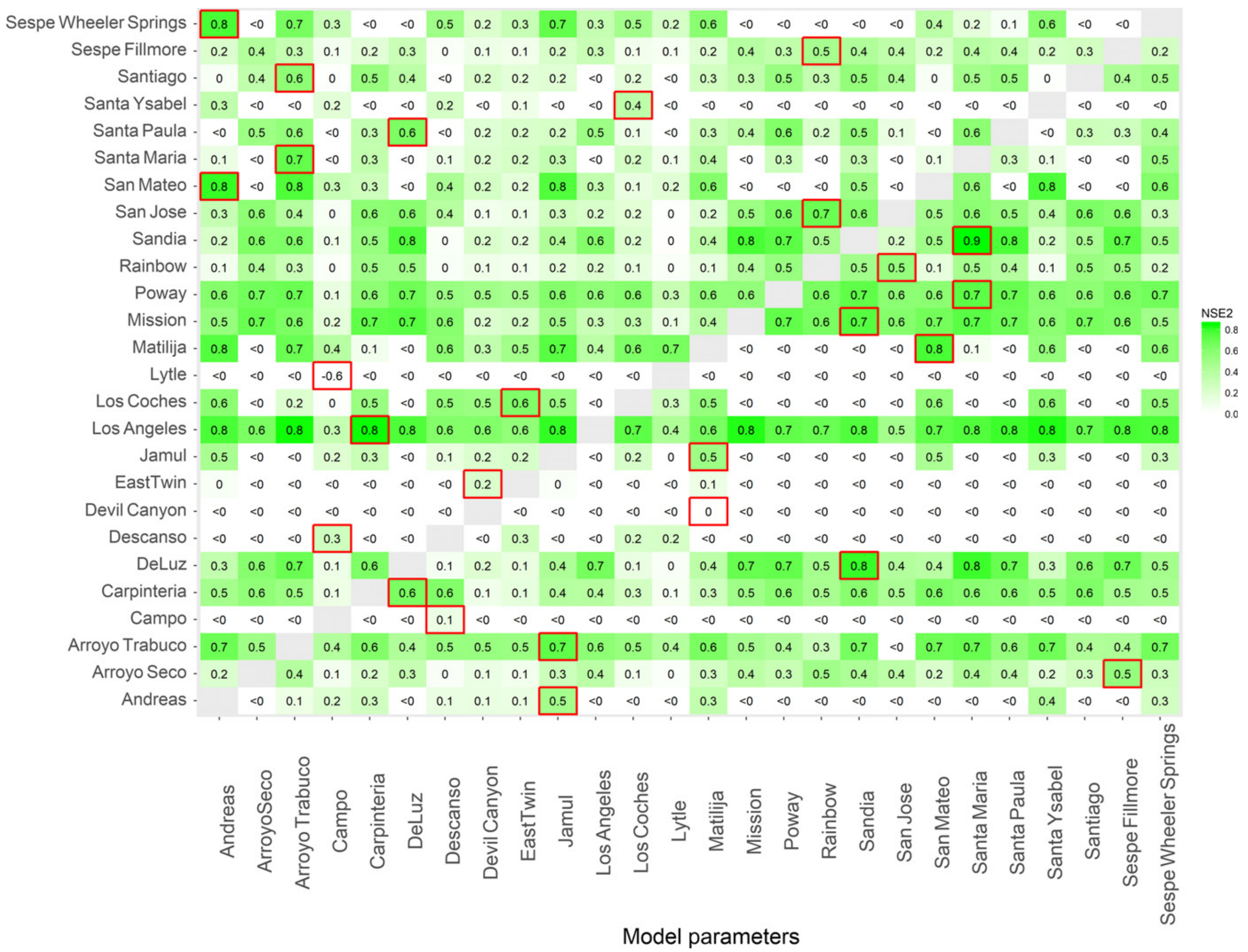

FIGURE 4 Jackknifing at the 16 gauged sites with Nash–Sutcliffe efficiency (NSE) values. Green cells show acceptable model performance. Red outlined box shows best value [Colour figure can be viewed at wileyonlinelibrary.com]

predicted flows at the site with NSE > 0.50 (Figure 4). Models that calibrate poorly (e.g. Campo: NSE = 0.49, LFE = 7.4, RBI E = 55.3; Lytle: NSE = 0.44, LFE = 18.9, RBI E = 6.3) also perform poorly during the jackknifing (i.e. Campo parameters did not transfer well to other sites, and the performance at Campo using other model parameters remains low).

Flow predictions at bioassessment sites with measured flow data had an average r^2 of .45 (Table 4). Seven of the 15 sites had a coefficient of determination (r^2) higher than .50. The performance was primarily driven by the quality of precipitation data at the site for a specific year. The impact of precipitation on model performance can be seen in the interannual variation at a given site; that is, for Site 1, the worst year (1996) has r^2 value of 0, but the best year (1998) has r^2 value of .96.

3.2 | Cluster analysis and model assignment

Cluster analysis of calibration gauges did not show strong geographic clustering, as even the small clusters included gauges that were spatially dispersed. Of the 29 candidate predictor variables, seven ranked highest in predicting group membership, with all but one variable (i.e. soil erodibility) representing anthropogenic factors (Figure 5).

Gauged models from the ensemble were best matched with between 1 and 64 ungauged sites, with the top five models in the ensemble being matched to 46% of the 572 ungauged sites (Table 1). These five gauged models are representative of a wide range of catchment area and imperviousness. Three gauged models (Campo, Lytle and Devil Canyon) that performed poorly during validation were assigned a total of only 26 ungauged sites, which comprise only 4% of the total ungauged sites (n = 572).

3.3 | Ability to predict metrics

In general, the metrics calibrated and validated reasonably well, but results vary by metric category (magnitude, duration, frequency, timing and variability) and precipitation conditions, dry, wet, average and aggregated (Table 5). Metrics estimated for aggregated and dry precipitation conditions validated better than for the average and wet conditions. Among the metric categories, magnitude had the

TABLE 4 Annual coefficient of determination (r^2) values for validation gauges, showing worst, best and average r^2 values, along with regression slope

Validation sites	Worst Year r^2	Slope	Best Year r^2	Slope	Average r^2
Site 1	0	0.21	.96	1.62	.21
Site 2	0	0	.08	0.07	.03
Site 3	.14	0.49	.50	0.42	.32
Site 4	.29	−0.12	.73	1.6	.49
Site 5	.37	0.24	.95	0.61	.72
Site 6	.03	0.08	.52	0	.14
Site 7	.02	0.16	.52	0.49	.24
Site 8	.01	0.02	.81	0.78	.52
Site 9	.03	0.09	.44	0.51	.21
Site 10	.12	0.19	.16	0.22	.14
Site 11	.49	0.7	.71	0.25	.61
Site 12	.54	1.14	.91	1.62	.67
Site 13	.64	0.47	.86	0.29	.77
Site 14	.08	1.98	.63	13.92	.31
Site 15	.27	0.01	.95	0.01	.62

highest coefficient of determination (r^2) values for both calibration and validation. For example, all 16 of the magnitude metrics had a range of r^2 between .39 and .99 under aggregated condition, and .34 and .99 for dry. Approximately 65% of the magnitude and duration metrics had r^2 values higher than .25, followed by 44% of frequency and 40% of the variability metrics. Only 21% of the timing metrics had r^2 higher than .25.

3.4 | Assessing hydrologic alteration

Approximately 79% of the region showed some degree of hydrologic alteration, and approximately 40% of the sites were estimated to be severely altered, defined as having at least 10 metrics in the top quartile of change in flow metric values (Figure 6). Among the five metric categories (timing, frequency, magnitude, duration and variability), the magnitude metrics were typically the most altered at the severely impacted sites (number of altered metrics in the top 25th quartile > 10). The influence of anthropogenic actions on flow alteration varied by metric category (Table 6). Magnitude metrics values tend to increase in response to urban and agricultural land uses, whereas the timing and duration metrics are impacted less. We

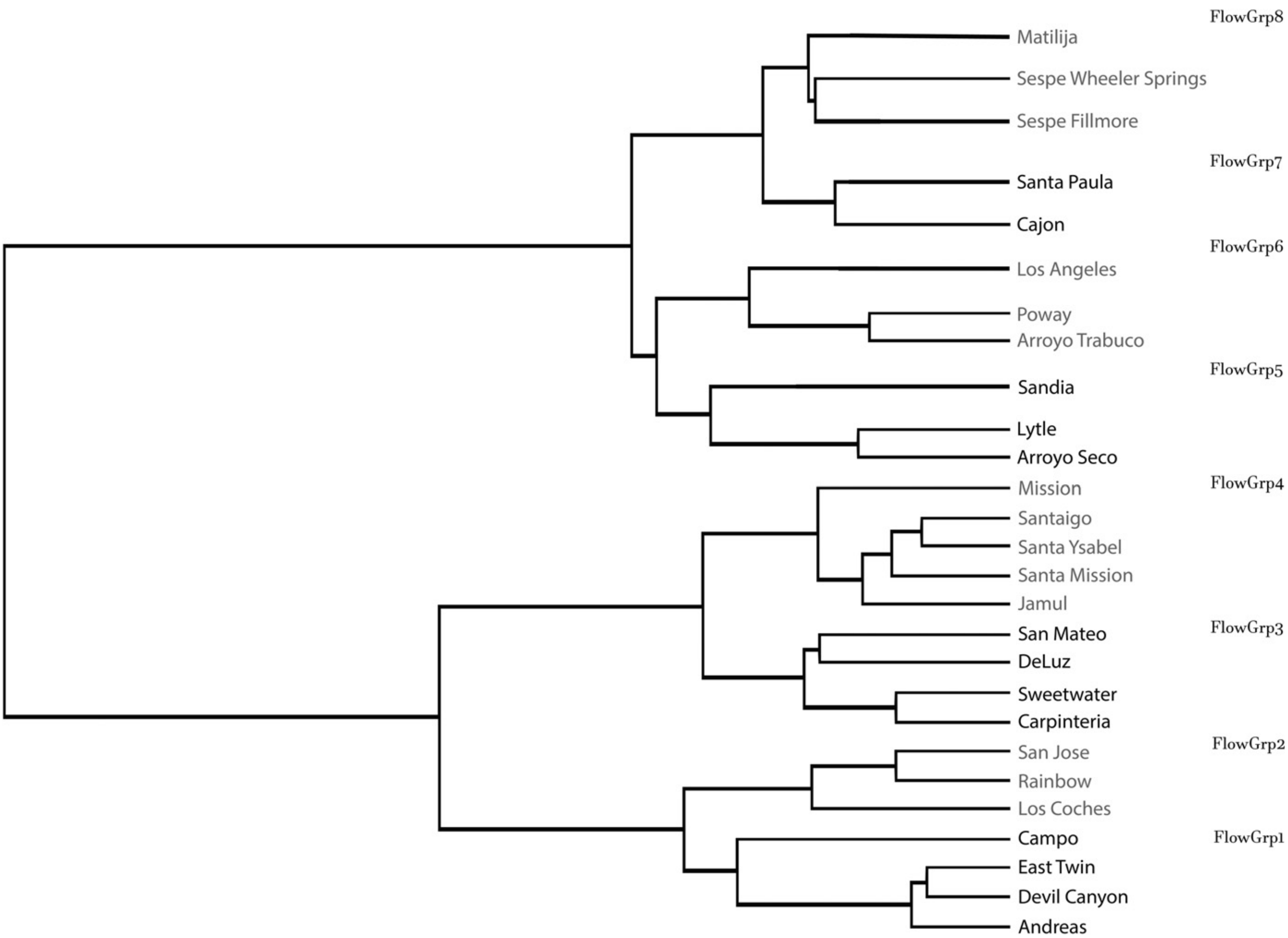

FIGURE 5 Cluster analysis showing eight groups of hydrologically similar calibration gauges from the ensemble. Ungauged sites are assigned to a gauged model in one of the clusters

TABLE 5 Flow metric validation (r^2) for four climatic condition at gauged Hydrologic Engineering Center Hydrologic Modeling System model sites (calibration gauges N = 26) and bioassessment sites with measured flow data (validation gauges N = 15)

	Calibration gauges				Validation gauges			
Metrics	Overall	Dry	Average	Wet	Overall	Dry	Average	Wet
Duration								
HighDur	.25	.26	.1	.47	.11	.09	.09	.4
Hydroperiod	.49	.48	.38	.2	.33	.47	.3	.61
LowDur	.54	.51	.32	.22	.33	.43	.4	.37
NoDisturb	.33	.44	.38	.37	.33	.43	.43	.36
Per_Low Flow	.96	.92	.89	.49	.01	.1	.11	.1
Frequency								
FracYearsNoFlow	.33	.25	.1	.28	.08	.2	.05	0
LowNum	−.04	.21	−.04	.01	.004	.16	.001	.05
HighNum	.7	.33	.47	.7	.51	.34	.31	.37
MedianNoFlowDays	.37	.57	.37	.2	.34	.5	.31	0
Magnitude								
MaxMonthQ	.69	.95	.83	.82	.6	.11	.14	.69
MinMonthQ	.39	.34	.24	.03	0	0	0	0
Q01	.99	.99	.75	.99	.07	.14	.05	.1
Q05	.99	.99	.73	.89	.16	.32	.05	.08
Q10	.99	.99	.71	.72	.25	.5	.04	.07
Q25	.97	1	.73	.31	.4	.73	.02	.03
Q50	.69	.97	.68	.27	.37	.8	.02	.01
Q75	.56	.97	.74	.7	.21	.82	.12	.1
Q90	.71	.92	.72	.73	.55	.81	.4	.55
Q95	.77	.9	.45	.8	.66	.71	.63	.65
Q99	.94	.98	.95	.86	.23	.51	.02	.15
Qmax	.91	.95	.91	.85	.4	.67	0	.34
Qmean	.9	.99	.9	.89	.4	.74	.31	.61
QmeanMEDIAN	.9	.99	.9	.89	.43	.74	.61	.31
Qmed	.57	.99	.68	.27	.59	.76	.37	0
Qmin	.99	1	.74	.44	.83	.92	.08	.07
Timing								
C_C	.81	.66	.57	.33	.09	.17	.09	.05
C_CP	.81	.63	.55	.41	.01	.02	.04	.07
C_M	.76	.61	.54	.46	.04	.01	.01	.02
C_MP	.81	.62	.54	.41	.01	0	.04	.07
C_P	.71	.61	.41	.33	.28	.28	.39	.31
MaxMonth	0	−.04	.19	.77	.08	.01	.25	.01
MinMonth	.24	.34	.39	.03	.25	.08	.08	.16
Variability								
QmaxIDR	.85	NA	NA	NA	.65	.53	.09	.64
QminIDR	.71	NA	NA	NA	0	.03	0	0
QmeanIDR	.88	NA	NA	NA	.45	.28	.95	.37
PDC50	−.04	.14	.25	−.04	.06	.06	.07	.006
BFR	−.04	.05	.18	−.04	.02	.006	.04	.75
RBI	.72	.64	.32	.72	.06	.03	.02	.07
SFR	−.01	.19	.75	−.03	.8	.05	.84	.51

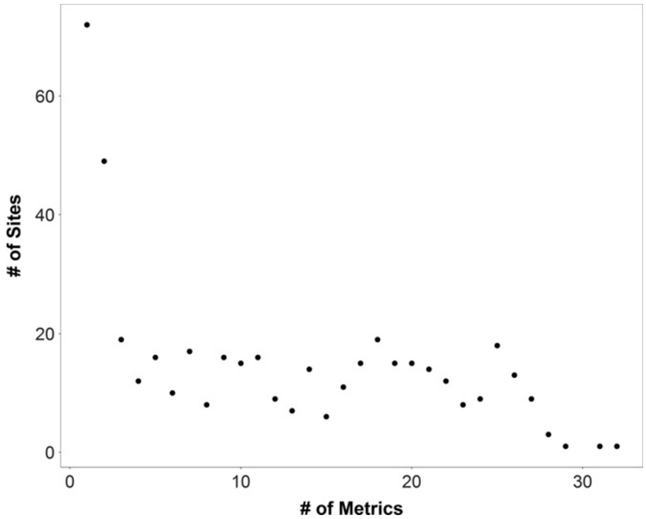

FIGURE 6 Number of sites with metrics in the top quartile of alteration depicting highly altered state. At each ungauged site, we estimated the hydrologic alteration for the 39 metrics. The sites were grouped by the number of metrics in the top quartile

observed a decrease in the duration metrics values under agricultural and urban land use, especially the number of no disturbance days and per cent low-flow days. Duration metrics were not significantly altered in the streams in undeveloped areas. Agricultural and urban land use causes a decrease in the timing metrics.

4 | DISCUSSION

By applying an ensemble of simple mechanistic models, this paper addresses the challenge of estimating regional hydrologic alteration at hundreds of ungauged sites. The study shows that 79% of stream-miles in southern California are hydrologically altered. This is comparable the estimates presented in Carlisle, Wolock, and Meador (2011) where a statistical approach was used and shows that 86% of the streams assessed throughout the conterminous United States are altered and Zimmerman et al. (2017) that showed a 55% alteration in California streams.

4.1 | Mechanistic approach provides an alternative to estimating hydrographs and flow metrics at ungauged sites

There are several options for estimating hydrologic alteration, including mechanistic models, statistical models and neural networks. Application of a mechanistic model ensemble to predict regional hydrologic alteration provides some advantages over statistical methods that are typically applied at the regional or national scale (Vis, Knight, Pool, Wolfe, & Seibert, 2015; Carlisle et al., 2011). Because this approach is based on physical processes, it allows for consideration of a broad suite of flow metrics that are derived from hourly flow data and represent all aspects of the hydrograph. Statistical methods, such as regression based models (Carlisle, Falcone, Wolock, Meador, & Norris, 2010), neural networks (Besaw, Rizzo, Bierman, & Hackett, 2010) and flow duration curves (Holmes, Young, Gustard, & Grew, 2002), provide a static flow characterisation at ungauged sites for a pre-determined set of flow metrics (i.e. whatever is modelled). Although less data intensive and computationally easier, the static nature makes it difficult to apply model output to address new questions involving different species of concern or different management considerations. Mechanistic models are more versatile, but may be limited by calibration and validation performance. Whereas our models failed to estimate hydrologic alteration at some bioassessment sites with insufficient precipitation data, an empirical model would likely be successful at those locations. Other mechanistic studies have also reported validation failures at proportion of sites modelled (e.g. Buchanan et al., 2013). Another advantage of empirical models is that their underlying statistical techniques tend to be more widely understood by non-hydrologists. This familiarity may facilitate their adoption by resource managers and researchers in broader disciplines.

Nevertheless, the mechanistic approach generates continuous granular flow data (hourly time step) at ungauged locations allowing for computation and consideration of metrics that may be applicable to a variety of ecological endpoints (e.g. fish versus invertebrates), different life history requirements (e.g. breeding versus migrations) and the consideration of a range of management trade-offs (e.g. diversions or discharges). Moreover, once the models are established, they can be applied to new management questions or locations in a straightforward manner. The subdaily flow data can be useful for managing flow regimes to maintain ecological function (Richter, Baumgartner, Wigington, & Braun, 1997; Richter, Warner, Meyer, & Lutz, 2006; Poff et al., 2003), especially where precipitation patterns are extremely variable (Gasith & Resh, 1999; Nezlin & Stein, 2005). The regional ensemble allows for rapid application to new sites of interest with minimal effort on model parameterisation and no additional calibration or validation requirements. This approach can allow managers to explore the impact of land use conversion on the receiving waters. Similarly, these models can be easily adapted to consider site best management practices aimed at managing flow alteration on an ongoing basis.

4.2 | Model calibration using multiple calibration measures improves performance

The three calibration criteria selected in this study emphasise different components of a flow regime, especially low-flow frequency and flashiness. Relying on a simple overall fit, as depicted by NSE is insufficient for representing low-flow periods, intermittency and flashiness in southern California streams. For example, the models calibrated for only NSE tend to have high LFE. However, multi-objective calibration comes with its own set of caveats (Price, Purucker, Kraemer, & Babendreier, 2012) and can result in a decrease in the NSE values. For example, at the Lytle Creek site, NSE decreases from 0.78 (single objective calibration for NSE) to 0.42 in the multi-objective calibration model. Therefore, it is essential to ensure that

TABLE 6 Percent of hydrologic alteration by stream length in the region, by land use and by the three main stream classes in southern California

				Land use									Stream class								
	Region			Agricultural			Undeveloped			Urban			Class 1			Class 2			Class 4		
Flow metrics	Dec	NC	Inc	Dec	NC	Inc	Dec	NC	Inc	Dec	NC	Inc	Dec	NC	Inc	Dec	NC	Inc	Dec	NC	Inc
HighDur	30	43	27	45	20	36	10	57	33	72	5	22	15	49	36	33	15	52	33	36	31
Hydroperiod	1	71	27	5	52	44	1	78	22	1	46	53	0	83	16	2	29	68	0	33	67
LowDur	18	62	19	18	45	37	10	78	11	31	20	49	21	73	7	20	24	56	17	18	65
NoDisturb	55	35	10	89	8	3	37	44	18	91	5	3	44	32	24	56	5	39	64	8	27
Per_LowFlow	42	47	10	86	10	4	34	62	3	68	18	15	30	59	11	44	8	48	53	4	43
FracYearsNoFlow																					
LowNum																					
HighNum	0	56	44	2	6	92	0	79	21	0	4	96	0	69	31	0	39	61	0	61	39
MedianNoFlowDays	22	78	0	22	78	0	15	85	0	38	62	0	12	88	0	27	0	73	21	0	79
MaxMonthQ	5	3	91	1	3	96	15	7	78	0	0	100	13	3	84	4	95	2	1	93	6
MinMonthQ	36	23	41	27	6	67	44	27	29	34	12	54	40	33	27	41	49	10	18	46	37
Q01	32	57	11	36	31	33	32	52	16	51	44	6	18	65	17	38	8	54	39	6	55
Q05	20	47	34	16	38	46	17	55	28	40	47	13	9	66	25	20	47	33	17	30	53
Q10	31	47	22	35	53	12	32	39	28	51	38	10	16	48	35	38	14	47	34	13	53
Q25	38	32	30	34	21	45	35	33	33	51	23	26	19	45	37	58	22	21	24	42	35
Q50	29	22	49	12	5	83	25	24	51	37	6	56	16	46	38	43	50	7	14	56	30
Q75	47	17	36	32	6	62	40	27	33	43	4	53	27	29	44	66	27	7	26	45	29
Q90	38	11	51	33	5	63	39	19	42	22	4	74	34	16	50	53	42	5	20	55	26
Q95	32	15	54	22	3	76	39	25	36	7	2	92	20	39	41	46	49	6	20	68	12
Q99	20	20	60	8	3	89	40	26	34	1	6	94	24	40	36	26	69	6	14	63	23
Qmax	3	2	95	10	3	88	8	5	86	0	0	99	7	2	91	2	97	2	2	94	5
Qmean	2	0	98	0	3	97	7	1	92	0	0	100	4	0	95	2	98	0	0	99	1
QmeanMEDIAN	59	2	39	35	3	63	74	3	24	11	4	85	75	2	22	55	44	1	58	39	3
Qmed	49	2	49	56	4	40	36	4	60	63	6	32	24	2	73	66	32	2	38	58	4
Qmin	58	12	29	44	12	44	35	11	54	74	19	7	44	12	44	66	22	11	49	36	15
C_C	35	58	7	63	29	8	17	71	12	92	7	2	18	75	7	36	5	59	40	6	54
C_CP	42	52	7	65	22	13	20	63	17	94	4	2	25	66	9	46	3	51	43	8	48
C_M	8	53	38	41	20	40	16	68	16	5	6	89	10	68	22	3	43	54	10	41	48
C_MP	7	51	42	15	20	65	18	62	20	2	5	93	10	65	25	3	45	51	8	45	48
C_P	21	67	12	40	45	15	7	90	3	59	16	25	7	86	7	24	11	65	20	16	63
MaxMonth	7	86	7	8	78	15	0	92	8	22	68	10	1	93	5	5	4	91	9	6	85
MinMonth	12	79	8	5	90	5	2	97	2	30	45	26	3	94	3	15	10	75	16	8	76
QmaxIDR	9	5	86	24	3	73	13	6	81	13	0	86	19	11	70	6	92	2	7	87	6
QminIDR	67	26	6	62	34	4	52	31	17	78	17	5	55	40	6	77	8	15	60	6	34
QmeanIDR	26	0	74	5	3	93	19	1	80	3	0	97	27	1	71	31	69	0	22	77	0
PDC50																					
BFR																					
RBI	19	3	78	4	3	93	28	4	68	0	4	96	40	4	56	7	92	1	29	67	4
SFR	75	20	6	94	6	0	57	21	22	93	6	1	54	36	10	90	4	6	67	6	27

the multi-objective calibration is within acceptable range of confidence.

The performance of the HEC-HMS models is primarily dictated by the quality of precipitation estimates, precipitation patterns, model parameters assigned, and the presence of flow control or diversion structures. As expected, the model predictions are better for years with good precipitation data inputs compared to years with missing data. The predictions are also affected at sites with extreme topography and significant orographic effects. Challenges of predicting flow in relatively steep streams with fast-rising hydrographs can

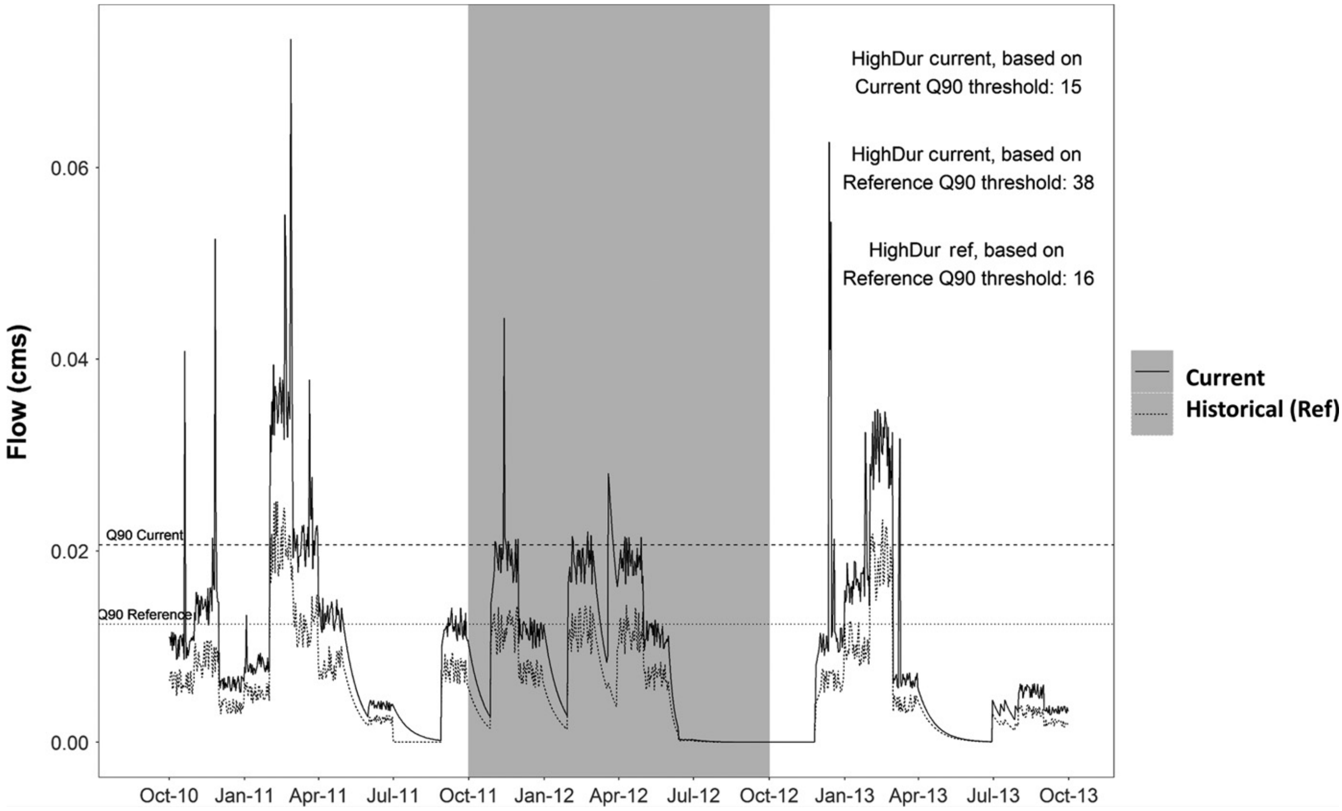

FIGURE 7 Change in the metric values (high duration) when current and historical thresholds are implemented. HighDur Current is the shift from High Dur Ref which represents historical condition. HighDur Current estimated using the current baseline shows a value lower than HighDur Ref implying minimal or no alteration (numbers counted for the selected period highlighted with a grey bar)

be addressed by selecting a different routing method, such as the Muskingum-Cunge in HEC-HMS. In future, this can be addressed by weighting the stream slope higher during the clustering and model assignment process.

4.3 | Lessons learned from the ensemble model approach

The mechanistic model ensemble provides a calibrated template that represents hydrological processes in different catchments within a region. The model assignments are based on catchment characteristics easily available for ungauged sites. We believe this approach is reasonable and parsimonious for regional application. However, alternative approaches are possible (or have been used by others) and should be evaluated in future studies. An alternate approach of assigning a gauged model from the ensemble to an ungauged site could be by clustering the gauged models based on the errors from the jackknife validation exercise. With this approach, the error matrix is used as a dissimilarity matrix in cluster analysis rather than clustering them based on observed flow metrics. This approach may be better at identifying mutually transferable pairs of models, rather than hydrologically similar models. Additionally, our model assignment was largely based on stressor gradients, even though variables related to natural factors had a chance for selection. Given that our goal is to use these models to simulate both current and historic conditions, it may be reasonable to restrict future model selection to natural factors. Finally, we selected just a single HEC-HMS model for each ungauged location, rather than combining several models with good matches (perhaps weighting by Euclidian proximity). We did not find much benefit to using multiple models, but these alternative approaches to model extrapolation should be explored through future studies to determine whether adding complexity provides measurable benefit in model performance at assigned ungauged sites for specific applications.

This study addresses difficulties with evaluating hydrologic change for duration metrics involving a shifting baseline. Duration metrics are based on benchmark discharge values used to identify high- or low-flow events (typically, the 90th or 10th percentile). Comparisons between historic and current conditions can be complicated and counter-intuitive when this benchmark changes dramatically (e.g. under certain conditions, large reductions in flow may appear to increase the frequency and duration of high-flow events). An example is illustrated in Figure 7, where the Current HighDur metric has a value of 15 days using current threshold and 38 days when estimated using historic Q90 threshold value. This indicates that the high-flow days are lower under the current conditions even though the catchment has undergone land use change, a finding that seems counter-intuitive. Cassin et al. (2005) in a study based in

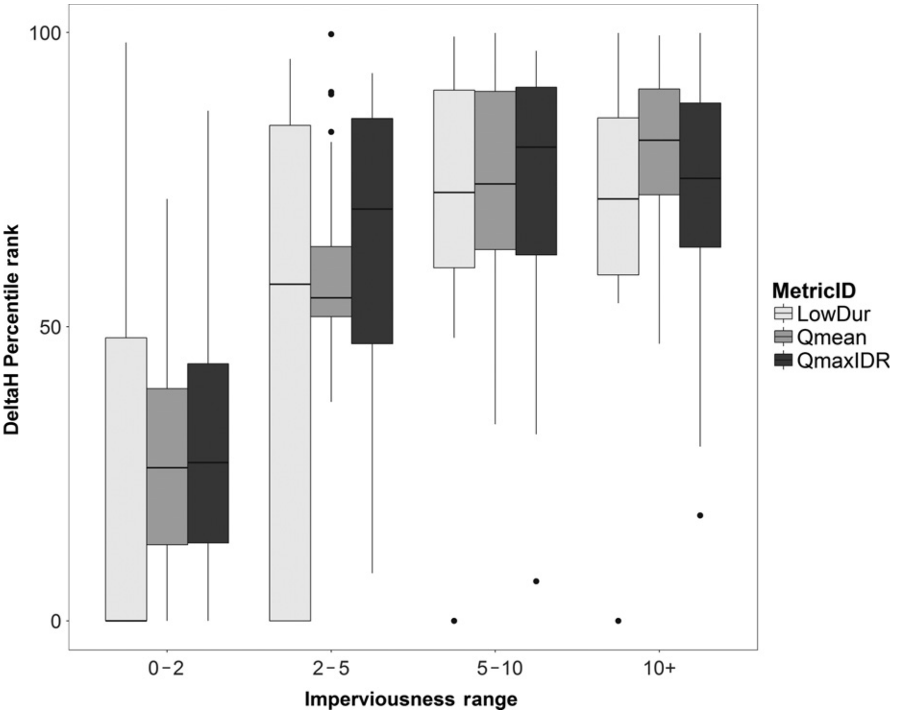

FIGURE 8 Hydrologic alterations (ΔH) for three selected metrics LowDur (duration), Qmean (magnitude) and QmaxIDR (variability) with changing imperviousness at the 572 sites. Horizontal box lines, from lower to upper, represent 25th, 50th and 75th percentiles. Whiskers lengths are 1.5 multiplied by the interquartile range

Puget Sound Lowland streams reports similar issue and set the flow thresholds at 50% of the average flow-rate under forested conditions over full period of record. We propose that the approach applied in this study of using single historic benchmark for both current and historic condition metric estimation addresses the "changing baseline" issue and allows for more accurate evaluation of hydrologic change.

4.4 | Hydrologic alterations in southern California

The degree of hydrologic alteration for our southern California study area varies seasonally, which has potential management implications. For example, a site could fail to meet target conditions in the dry years but not in the wet years. Limiting predictions of alteration to overall climatic conditions could mask the interannual variability in the metric alterations.

The impact of anthropogenic land use on increasing magnitude metrics and decreasing duration and timing metrics is observed regionally. This effect of increasing streamflow due to irrigation practices has been reported in other studies (Raymond, Oh, Turner, & Broussard, 2008) and other land use (Stohlgren, Chase, Pielke, Kittel, & Baron, 1998; Yan, Fang, Zhang, & Shi, 2013). Further analysis of the effect of increasing imperviousness on the metrics shows that imperviousness is positively correlated with increasing alteration. Comparing the degree of alteration for three representative metrics, LowDur (duration), Qmean (magnitude) and QmaxIDR (variability) show that hydrologic alteration is pervasive in catchments (48% of sites) with impervious cover higher than 5% (Figure 8). Hydrologic and biological responses can occur at low levels of imperviousness (King, Baker, Kazyak, & Weller, 2011; Booth, Hartley, & Jackson, 2002), but most studies report a threshold of around 8%–10% (Wang, Lyons, Kanehl, & Bannerman, 2001; Brabec, Schulte, & Richards, 2002). Hawley and Bledsoe (2013) report hydrologic responses in southern California at low imperviousness (<5%). Hydrologic response to very low imperviousness is usually driven by high degree of connectivity through stormwater drainage infrastructure in the catchment (Walsh et al., 2005) or due to steep gradient in the catchment or presence of erodible substratum. For example, precipitation falling on disconnected impervious surface will infiltrate resulting in an increase in the baseflow but not an increase in the peaks or the overall flashiness in the streams (Alley & Veenhuis, 1983). Currently, most of the sites used in this study are undeveloped (0%–2%), and as noted in the previous section, many of these sites show signs of existing alteration, implying that further urbanisation might easily tip the sites towards severe alteration and potential impacts on the biological assemblages in the streams.

5 | CONCLUSION AND FUTURE WORK

Our goal is to provide a regional understanding of the hydrologic alteration that can be used in combination with multiple robust biological datasets to develop a broad suite of flow–ecology relationships to foster sustainable management decisions. The modelling approach we describe successfully predicts the flows, and a range of flow metrics at many sites spread over a wide geographical region. Relative ease of transferability and applicability makes this a useful tool for assessing new sites throughout the region, and the approach should also be transferable to other regions. A distinct advantage of the mechanistic approach over statistical approaches is the ability to generate site-specific scenarios such as flow responses to the implementation of stormwater control measures or rapid urban development in a catchment (Stein et al., 2017). However, we recommend that flow-ecology researchers consider both statistical and mechanistic approaches, as each brings a different set of costs and benefits. This will aid managers in understanding the implications of regional flow–ecology relationships specific to their case.

In future, we anticipate the application of these tools for predicting changes in the hydrologic regimes under various management options and climate change, and for developing future scenarios and informing risk analyses (Poff et al., 2003; Stewardson & Gippel, 2003; Richter et al., 2006). This is particularly applicable to southern California given the impetus to reuse and recycle treated effluent and storm water in the region (California Water Action Plan 2016; Hering, Waite, Luthy, Drewes, & Sedlak, 2013). Impacts of climate change in southern California will manifest in the form of flooding and shifts in precipitation patterns (Hanak & Lund, 2012). Forecasting the impact of these factors on the hydrologic regimes in the region and proactively developing management strategies to mitigate the impacts is advisable.

Finally, our assessment of general hydrologic alteration did not consider its relevance to any specific biological endpoint. Biological endpoints such as amphibians, fish, benthic invertebrates, or algae are often used to inform regulatory or management decisions. The tools and approach developed in this study can be readily applied to numerous biological endpoints by computing a subset of flow metrics that potentially affect the ecology, site suitability or life history requirements of biological assemblages of interest. These can be adapted to estimate other components of the flow regime as knowledge is updated over time. One such application for regional assessment of benthic macroinvertebrate community composition is presented in the companion paper (Mazor et al., this issue).

ACKNOWLEDGEMENTS

We thank our technical advisory and stakeholder workgroups for their participation throughout this project. Their input and critical review improved both the technical quality and the management applicability of this work. Funding for this project has been provided in full or in part through an agreement with the California State Water Resources Control Board. The contents of this document do not necessarily reflect the views and policies of the State Water Resources Control Board, nor do mention of trade names or commercial products constitute endorsement or recommendation for use.

ORCID

Ashmita Sengupta http://orcid.org/0000-0003-4057-452X
Brian P. Bledsoe http://orcid.org/0000-0002-0779-0127
Eric D. Stein http://orcid.org/0000-0002-4729-809X
Kenneth S. McCune http://orcid.org/0000-0002-0737-5169
Raphael D. Mazor http://orcid.org/0000-0003-2439-3710

REFERENCES

Alley, W. M., & Veenhuis, J. E. (1983). Effective impervious area in urban runoff modeling. *Journal of Hydraulic Engineering*, *109*, 313–319. https://doi.org/10.1061/(ASCE)0733-9429(1983)109:2(313)

Besaw, L. E., Rizzo, D. M., Bierman, P. R., & Hackett, W. R. (2010). Advances in ungauged streamflow prediction using artificial neural networks. *Journal of Hydrology*, *386*, 27–37. https://doi.org/10.1016/j.jhydrol.2010.02.037

Booth, D. B., Hartley, D., & Jackson, R. (2002). Forest cover, impervious-surface area, and the mitigation of stormwater impacts. *JAWRA Journal of the American Water Resources Association*, *38*, 835–845. https://doi.org/10.1111/j.1752-1688.2002.tb01000.x

Brabec, E., Schulte, S., & Richards, P. L. (2002). Impervious surfaces and water quality: A review of current literature and its implications for watershed planning. *CPL Bibliography*, *16*, 499–514.

Buchanan, C., Moltz, H. L., Haywood, H. C., Palmer, J. B., & Griggs, A. N. (2013). A test of The Ecological Limits of Hydrologic Alteration (ELOHA) method for determining environmental flows in the Potomac River basin, USA. *Freshwater Biology*, *58*(12), 2632–2647. https://doi.org/10.1111/fwb.12240

Caldwell, P. V., Kennen, J. G., Sun, G., Kiang, J. E., Butcher, J. B., Eddy, M. C., . . . McNulty, S. G. (2015). A comparison of hydrologic models for ecological flows and water availability. *Ecohydrology*, *8*, 1525–1546. https://doi.org/10.1002/eco.1602

California Water Action Plan (2016). Welcome to the New California Water Plan Website. Retrieved from http://www.water.ca.gov/waterplan/

Carlisle, D. M., Falcone, J., Wolock, D. M., Meador, M. R., & Norris, R. H. (2010). Predicting the natural flow regime: Models for assessing hydrological alteration in streams. *River Research and Applications*, *26*, 118–136.

Carlisle, D. M., Wolock, D. M., & Meador, M. R. (2011). Alteration of streamflow magnitudes and potential ecological consequences: A multiregional assessment. *Frontiers in Ecology and the Environment*, *9*, 264–270. https://doi.org/10.1890/100053

Cassin, J., Fuerstenberg, R., Tear, L., Whiting, K., John, D. S., Murray, B., & Burkey, J. (2005). *Development of hydrological and biological indicators o flow alteration in Puget Sound Lowland streams*. Seattle, WA: King County DNRP.

DeGasperi, C. L., Berge, H. B., Whiting, K. R., Burkey, J. J., Cassin, J. L., & Fuerstenberg, R. R. (2009). Linking hydrologic alteration to biological impairment in urbanizing streams of the Puget Lowland, Washington, USA. *JAWRA Journal of the American Water Resources Association*, *45*, 512–533. https://doi.org/10.1111/j.1752-1688.2009.00306.x

Gasith, A., & Resh, V. H. (1999). Streams in Mediterranean climate regions: Abiotic influences and biotic responses to predictable seasonal events. *Annual Review of Ecology and Systematics*, *30*, 51–81. https://doi.org/10.1146/annurev.ecolsys.30.1.51

Hanak, E., & Lund, J. R. (2012). Adapting California's water management to climate change. *Climatic Change*, *111*, 17–44. https://doi.org/10.1007/s10584-011-0241-3

Hawley, R. J., & Bledsoe, B. P. (2013). Channel enlargement in semiarid suburbanizing watersheds: A southern California case study. *Journal of Hydrology*, *496*, 17–30. https://doi.org/10.1016/j.jhydrol.2013.05.010

Hering, J. G., Waite, T. D., Luthy, R. G., Drewes, J. E., & Sedlak, D. L. (2013). A changing framework for urban water systems. *Environmental Science & Technology*, *47*, 10721–10726. https://doi.org/10.1021/es4007096

Holmes, M. G. R., Young, A. R., Gustard, A., & Grew, R. (2002). A region of influence approach to predicting flow duration curves within ungauged catchments. *Hydrology and Earth System Sciences Discussions*, *6*, 721–731. https://doi.org/10.5194/hess-6-721-2002

King, R. S., Baker, M. E., Kazyak, P. F., & Weller, D. E. (2011). How novel is too novel? Stream community thresholds at exceptionally low levels of catchment urbanization. *Ecological Applications*, *21*, 1659–1678. https://doi.org/10.1890/10-1357.1

Kokkonen, T. S., Jakeman, A. J., Young, P. C., & Koivusalo, H. J. (2003). Predicting daily flows in ungauged catchments: Model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina. *Hydrological Processes*, *17*, 2219–2238. https://doi.org/10.1002/(ISSN)1099-1085

Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., & Engelhardt, A. (2012) *Caret: Classification and regression training*. R package version 5.15-045. Vienna, Austria: R Project for Statistical Computing. Retrieved from http://www.epa.gov/nheerl/arm

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, *2*, 18–22.

Malmqvist, B., & Rundle, S. (2002). Threats to the running water ecosystems of the world. *Environmental Conservation*, *29*, 134–153.

Mazor, R. D., May, J. T., Sengupta, A., McCune, K. S., Bledsoe, B. P., & Stein, E. D. (In reviewthis issue). Tools for managing hydrologic alteration on a regional scale II: Setting targets to protect stream health. *Freshwater Biology*, *00*, 1–18. https://doi.org/10.1111/fwb.13062

Mazor, R. D., Stein, E. D., Ode, P. R., & Schiff, K. (2014). Integrating intermittent streams into watershed assessments: Applicability of an index of biotic integrity. *Freshwater Science*, *33*, 459–474. https://doi.org/10.1086/675683

Milligan, G. W. (1989). A study of the beta-flexible clustering method. *Multivariate Behavioral Research*, *24*, 163–176. https://doi.org/10.1207/s15327906mbr2402_2

Moretti, G., & Montanari, A. (2008). Inferring the flood frequency distribution for an ungauged basin using a spatially distributed rainfall-runoff model. *Hydrology and Earth System Sciences*, *12*, 1141–1152. https://doi.org/10.5194/hess-12-1141-2008

Nezlin, N. P., & Stein, E. D. (2005). Spatial and temporal patterns of remotely-sensed and field-measured rainfall in southern California. *Remote Sensing of Environment*, *96*, 228–245. https://doi.org/10.1016/j.rse.2005.02.005

Parajka, J., Viglione, A., Rogger, M., Salinas, J. L., Sivapalan, M., & Blöschl, G. (2013). Comparative assessment of predictions in ungauged basins-Part 1: Runoff-hydrograph studies. *Hydrology and Earth System Sciences*, *17*, 1783. https://doi.org/10.5194/hess-17-1783-2013

Poff, N. L., Allan, J. D., Palmer, M. A., Hart, D. D., Richter, B. D., Arthington, A. H., … Stanford, J. A. (2003). River flows and water wars: Emerging science for environmental decision making. *Frontiers in Ecology and the Environment*, *1*, 298–306. https://doi.org/10.1890/1540-9295(2003)001[0298:RFAWWE]2.0.CO;2

Poff, N. L., Bledsoe, B. P., & Cuhaciyan, C. O. (2006). Hydrologic variation with land use across the contiguous United States: Geomorphic and ecological consequences for stream ecosystems. *Geomorphology*, *79*, 264–285. https://doi.org/10.1016/j.geomorph.2006.06.032

Poff, N. L., Richter, B. D., Arthington, A. H., Bunn, S. E., Naiman, R. J., Kendy, E., … Henriksen, J. (2010). The ecological limits of hydrologic alteration (ELOHA): A new framework for developing regional environmental flow standards. *Freshwater Biology*, *55*, 147–170. https://doi.org/10.1111/j.1365-2427.2009.02204.x

Poff, N. L., & Zimmerman, J. K. (2010). Ecological responses to altered flow regimes: A literature review to inform the science and management of environmental flows. *Freshwater Biology*, *55*, 194–205. https://doi.org/10.1111/j.1365-2427.2009.02272.x

Post, D. A., & Jakeman, A. J. (1999). Predicting the daily streamflow of ungauged catchments in SE Australia by regionalising the parameters of a lumped conceptual rainfall-runoff model. *Ecological Modelling*, *123*, 91–104. https://doi.org/10.1016/S0304-3800(99)00125-8

Postel, S., & Richter, B. (2012). *Rivers for life: Managing water for people and nature*. Washington, DC: Island Press.

Price, K., Purucker, S. T., Kraemer, S. R., & Babendreier, J. E. (2012). Tradeoffs among watershed model calibration targets for parameter estimation. *Water Resources Research*, *48*, W10542.

Puckridge, J. T., Sheldon, F., Walker, K. F., & Boulton, A. J. (1998). Flow variability and the ecology of large rivers. *Marine and Freshwater Research*, *49*, 55–72. https://doi.org/10.1071/MF94161

Pyne, M. I., Carlisle, D. M., Konrad, C. P., & Stein, E. D. (2017). Classification of California streams using combined deductive and inductive approaches: Setting the foundation for analysis of hydrologic alteration. *Ecohydrology*, *10*, e1802. https://doi.org/10.1002/eco.1802

Raymond, P. A., Oh, N.-H., Turner, R. E., & Broussard, W. (2008). Anthropogenically enhanced fluxes of water and carbon from the Mississippi River. *Nature*, *451*, 449–452. https://doi.org/10.1038/nature06505

Richter, B., Baumgartner, J., Wigington, R., & Braun, D. (1997). How much water does a river need? *Freshwater Biology*, *37*, 231–249. https://doi.org/10.1046/j.1365-2427.1997.00153.x

Richter, B. D., Warner, A. T., Meyer, J. L., & Lutz, K. (2006). A collaborative and adaptive process for developing environmental flow recommendations. *River Research and Applications*, *22*, 297–318. https://doi.org/10.1002/(ISSN)1535-1467

Rosenberg, D. M., McCully, P., & Pringle, C. M. (2000). Global-scale environmental effects of hydrological alterations: Introduction. *BioScience*, *50*, 746–751. https://doi.org/10.1641/0006-3568(2000)050[0746:GSEEOH]2.0.CO;2

Samaniego, L., Kumar, R., & Attinger, S. (2010). Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *Water Resources Research*, *46*, W05523. https://doi.org/10.1029/2008WR007327

Sanborn, S. C., & Bledsoe, B. P. (2006). Predicting streamflow regime metrics for ungauged streams in Colorado, Washington, and Oregon. *Journal of Hydrology*, *325*, 241–261. https://doi.org/10.1016/j.jhydrol.2005.10.018

Sivapalan, M., Takeuchi, K., Franks, S. W., Gupta, V. K., Karambiri, H., Lakshmi, V., … Oki, T. (2003). IAHS decade on predictions in ungauged basins (PUB), 2003–2012: Shaping an exciting future for the hydrological sciences. *Hydrological Sciences Journal*, *48*, 857–880. https://doi.org/10.1623/hysj.48.6.857.51421

Stein, E. D., Sengupta, A., Mazor, R. D., McCune, K., Bledsoe, B. P., & Adams, S. (2017). Application of regional flow-ecology relationships to inform watershed management decisions: Application of the ELOHA framework in the San Diego River watershed, California, USA. *Ecohydrology*, *40*, e1869. https://doi.org/10.1002/eco.1869

Stewardson, M. J., & Gippel, C. J. (2003). Incorporating flow variability into environmental flow regimes using the flow events method. *River Research and Applications*, *19*, 459–472. https://doi.org/10.1002/(ISSN)1535-1467

Stohlgren, T. J., Chase, T. N., Pielke, R. A., Kittel, T. G., & Baron, J. (1998). Evidence that local land use practices influence regional climate, vegetation, and stream flow patterns in adjacent natural areas. *Global Change Biology*, *4*, 495–504. https://doi.org/10.1046/j.1365-2486.1998.t01-1-00182.x

Vis, M., Knight, R., Pool, S., Wolfe, W., & Seibert, J. (2015). Model calibration criteria for estimating ecological flow characteristics. *Water*, *7*, 2358–2381. https://doi.org/10.3390/w7052358

Wagener, T., & Wheater, H. S. (2006). Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty. *Journal of Hydrology*, *320*, 132–154. https://doi.org/10.1016/j.jhydrol.2005.07.015

Walsh, C. J., Roy, A. H., Feminella, J. W., Cottingham, P. D., Groffman, P. M., & Morgan II, R. P. (2005). The urban stream syndrome: Current knowledge and the search for a cure. *Journal of the North American Benthological Society*, *24*, 706–723. https://doi.org/10.1899/04-028.1

Wang, L., Lyons, J., Kanehl, P., & Bannerman, R. (2001). Impacts of urbanization on stream habitat and fish across multiple spatial scales.

Environmental Management, 28, 255–266. https://doi.org/10.1007/s0026702409
Woodward, D. E., Hawkins, R. H., Jiang, R., Hjelmfelt Jr, A. T., Van Mullem, J. A., & Quan, Q. D. (2003). Runoff curve number method: Examination of the initial abstraction ratio. In *World water & environmental resources congress 2003* (pp. 1–10). Pennsylvania, United States. https://doi.org/10.1061/40685(2003)308
Yadav, M., Wagener, T., & Gupta, H. (2007). Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins. *Advances in Water Resources*, *30*, 1756–1774. https://doi.org/10.1016/j.advwatres.2007.01.005
Yan, B., Fang, N. F., Zhang, P. C., & Shi, Z. H. (2013). Impacts of land use change on watershed streamflow and sediment yield: An assessment using hydrologic modelling and partial least squares regression. *Journal of Hydrology*, *484*, 26–37. https://doi.org/10.1016/j.jhydrol.2013.01.008
Zimmerman, J., Carlisle, D., May, J., Klausmeyer, K., Grantham, T., Brown, L., & Howard, J. (2017, current issue) Patterns and magnitude of flow alternation in California, USA. *Freshwater Biology*, *00*, 1–15. https://doi.org/10.1111/fwb.13058. Special issue.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

How to cite this article: Sengupta A, Adams SK, Bledsoe BP, Stein ED, McCune KS, Mazor RD. Tools for managing hydrologic alteration on a regional scale: Estimating changes in flow characteristics at ungauged sites. *Freshwater Biol*. 2018;63:769–785. https://doi.org/10.1111/fwb.13074