Revealing the diversity of natural hydrologic regimes in California with relevance for environmental flows applications

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Abstract: Alterations to flow regimes for water management objectives have degraded river ecosystems worldwide. These alterations are particularly profound in Mediterranean climate regions such as California with strong climatic variability and riverine species highly adapted to the resulting flooding and drought disturbances. However, defining environmental flow targets for Mediterranean rivers is complicated by extreme hydrologic variability and often intensive water management legacies. Improved understanding of the diversity of natural streamflow patterns and their spatial arrangement across Mediterranean regions is needed to support the future development of effective flow targets at appropriate scales for management applications with minimal resource and data requirements. Our study addresses this need through the development of a spatially explicit reach-scale hydrologic classification for California. Dominant hydrologic regimes and their physio-climatic controls are revealed using available unimpaired and naturalized streamflow time-series and generally available geospatial datasets. This methodology identifies eight natural flow classes representing distinct flow sources, hydrologic characteristics, and catchment controls over rainfall-runoff response. The study provides a broad-scale hydrologic framework upon which flow – ecology relationships could subsequently be established towards reach-scale environmental flows applications in a complex, highly altered Mediterranean region.

(**Key Terms**: hydrologic classification; natural flow regime; California.)

INTRODUCTION

Alterations to natural flow regimes for human water management objectives have degraded river ecosystems worldwide. These alterations are particularly profound in Mediterranean regions such as California with strong climatic variability and aquatic and riparian species highly adapted to the resulting flooding and drought disturbances (Gasith and Resh 1999). The modification of reservoir operations to control the timing, magnitude, and duration of flow releases for environmental benefits (i.e., environmental flows) is an emerging approach for mitigating the negative ecological impacts of dams while preserving essential water management functions

(Richter et al. 1996; Richter and Thomas 2007; Arthington 2012; Ai et al. 2013; Lane et al. 2014). However, defining effective environmental flows targets has proven very challenging (Konrad et al. 2012; Meitzen et al. 2013) due to natural complexity and heterogeneity as well as widespread human intervention (Benda and Dunne 1997; Egger et al. 2012; Wyrick et al. 2014). These challenges are often exaggerated in Mediterranean regions by extreme hydrologic variability and intensive water management legacies (Bejerano et al. 2010).

Hydrologic classification is one strategy to improve our understanding of complex catchment function (Pardé 1933; Dooge 1986; Sauquet et al. 2000; Sivapalan 2005; Wagener et al. 2007) and to ascribe catchments to empirically-based functional groups (e.g., Rosgen 1994; Brandt 2000; Montgomery and Buffington 1997). By identifying and categorizing dominant catchment functions as revealed through a suite of hydrologic response characteristics (e.g., streamflow indices) and catchment attributes (e.g., climate, topography, geology), hydrologic classification allows for the regional transfer of hydrologic information. This ultimately improves the predictive power and process basis of flow — ecology relationships towards the future development of effective environmental flow targets with minimal data and resource requirements (e.g., Richter et al. 1996; Poff et al. 2010; Liermann et al. 2011; Olden et al. 2012).

Hydrologic classification has established a central role in environmental flows science (Olden et al. 2012) to support the assessment of baseline conditions (e.g., Tavassoli et al. 2014; Hersh and Maidment 2010; Richter et al. 1996) and the development of flow — ecology relationships (Apse et al. 2008; Kennen et al. 2007; Carlisle et al. 2010). In the past decade, such regional classifications have been developed for New Zealand (Snelder et al. 2005), Turkey (Kahya et al. 2008), France (Snelder et al. 2009), Australia (Kennard et al. 2010), Canada (Monk et al. 2011), various basins in Spain (Baeza Sanz and García de Jalón 2005; Bejarano et al 2010; Belmar et al. 2011) and in the United States for Colorado (Sanborn and Bledsoe 2006), Michigan (Seelbach et al. 1997, Brenden et al. 2008), Texas (Hersh and Maidment 2010), New Jersey (Kennen et al. 2007), Pennsylvania (Apse et al. 2008), Missouri (Kennen et al. 2009), Washington (Liermann et al. 2011), and Oregon (Wigington et al. 2013).

In spite of the marked value of hydrologic classification as an environmental water management tool and the evident need for such a tool in Mediterranean regions, relatively few hydrologic classifications have been developed for this climate setting. An evaluation by the authors indicated that, of 50 regional hydrologic classifications developed in the past 40 years [based on the subset of regional hydrologic classifications reviewed by Olden et al. (2012)], only 10% fell within dominantly Mediterranean regions (Köppen climate classes Csa and Csb) (Köppen and Geiger 1930) (Turkey, Kahya et al. 2008; Spain, Baeza and García de Jalón 2005; Washington State, Liermann et al. 2011; Oregon State, Wigington et al. 2013). Furthermore, 71% of studies were based in fully humid regions while only 10% fell within seasonally dry climates [*see supplemental materials*]. While based on a subset of regional classifications, these findings emphasize the need for further classification of Mediterranean rivers and streams to inform the development of environmental flow targets given their disproportionate regulation and degradation and underrepresentation in the literature.

Study objectives

The goal of this study is to develop a hydrologic classification for the Mediterranean region of California by applying established hydrologic and ecological techniques at appropriate scales for environmental flows applications with minimal resource and data requirements. To the best of the authors' knowledge, this study represents the first attempt at a statewide hydrologic classification for the State of California, supporting the future development of environmental flow targets for the region's severely degraded river ecosystems at a time of increasing sociopolitical impetus to address these problems (Magilligan and Nislow 2005; Moyle et al. 2011; Hanak et al. 2011). This study advances scientific understanding of the diversity and spatial distribution of dominant hydrologic regimes and catchment controls present in a large Mediterranean region. To achieve these goals this study aims to address four key questions: (1) What distinct dominant hydrologic regimes can be distinguished within the study region? (2) Do physical catchment attributes help to explain the distinguished hydrologic regimes? (3) How do the identified hydrologic regimes compare to those found in existing California-based and national or global hydrologic classifications? (4) What insights does the resulting hydrologic classification provide for environmental flows applications in California?

STUDY REGION

The study region comprises the State of California (425,000 km^2), a highly heterogeneous region with respect to physical and climatic characteristics that contains both the highest (4,418 m) and lowest (-86 m) points in the contiguous United States and extends from 32° to 42° latitude. California primarily exhibits a Mediterranean climate with cold, wet winters (Oct - Apr) and warm, dry summers (May - Sep). Within the state, climate is determined by the interactions between atmospheric circulation, ocean proximity, and topography (Leung et al. 2003). For example, ocean-derived moisture from the west causes the western slopes of the Sierra Nevada to be generally wetter than the eastern slopes, with winter precipitation at higher elevations falling as snow. High inter-annual variability associated with large-scale circulation patterns [e.g., El Niño Southern Oscillation (Cayan et al. 1999) and the Pacific Decadal Oscillation (Mantua and Hare 2002)] adds additional complexity to regional rainfall-runoff patterns. California's geologic setting is highly heterogeneous, ranging from the volcanic dominated Modoc Plateau to the thick sedimentary strata of the Coastal Range, and is often organized into eleven geomorphic provinces consisting of prominent tectonics, lithology, and topographic relief (CGS 2002). Soils composition also varies widely based on soil texture, depth, and rock fragment content. A statewide range of soil water storage capacity from 0 to 71 cm highlights this variability and is expected to influence the region's hydrology (CSRL 2010).

California's legacy of intensive and widespread hydrologic alteration for mining, water supply, flood control, land use change, and hydropower has severely degraded the state's river ecosystems (Healey et al. 2008; Hanak et al. 2011), emphasizing the need for a broad-scale hydrologic framework for environmental flows management. Less than 2% of California's total streamflow remains unaltered (Mailligan and Nislow 2005), while over 80% of the native fish species are now imperiled or extinct (Moyle et al. 2011). Further, most of the state's approximately 1,400 jurisdictional dams and 10,000 smaller impoundments are currently operated with minimal consideration for their effects on river ecosystems (Viers 2011; Grantham et al. 2014). Releasing environmental flows has been shown to substantially improve environmental conditions below dams while preserving essential water management functions. For instance, adjusting the timing of flow releases to correspond with natural seasonal fish spawning and rearing cues in a California stream promoted the expansion and maintenance of native-dominated fish assemblages without reducing the annual volume of water delivered to downstream irrigators (Kiernan et al. 2012).

DATA

For this study we considered all gauge stations with >15 years of continuous daily unimpaired or naturalized streamflow records (see Kennard et al. 2010 for definition of unimpaired and naturalized). For the 20-year time period from 1968-1988, 75 unimpaired gauge stations were identified from the Hydro-Climate Data Network GAGESII database based on an index of cumulative upstream disturbance by anthropogenic stressors (Falcone et al. 2010). An unimpaired streamflow record refers to a time series that is minimally influenced by upstream disturbances of infrastructure, land use change, or water diversions. An additional 16 gauge stations for which simulated non-regulated (i.e., naturalized) streamflow time-series are available [20-year period (1989-2009)] were added to the analysis to increase both sample size and physiographic range of reference gauge stations (CDWR 2007). The resulting 91 reference gauge stations ranged in elevation from 7 to 2,286 m above sea level (a.s.l.) and in drainage area from 54 to 8,063 km^2, covering a wide range of physical and climatic catchment characteristics (Fig. 1). It should be noted that no reference gauge stations were available for the southeastern desert part of California. Results of trend tests for climate non-stationarity (Kendall 1975) and autocorrelation (Durbin and Watson, 1950) in the streamflow records indicated minimal monotonic climate trends over the time periods considered in this analysis, supporting the use of selected streamflow records for the calculation of hydrologic indices and subsequent classification development [*see supplementary materials*].

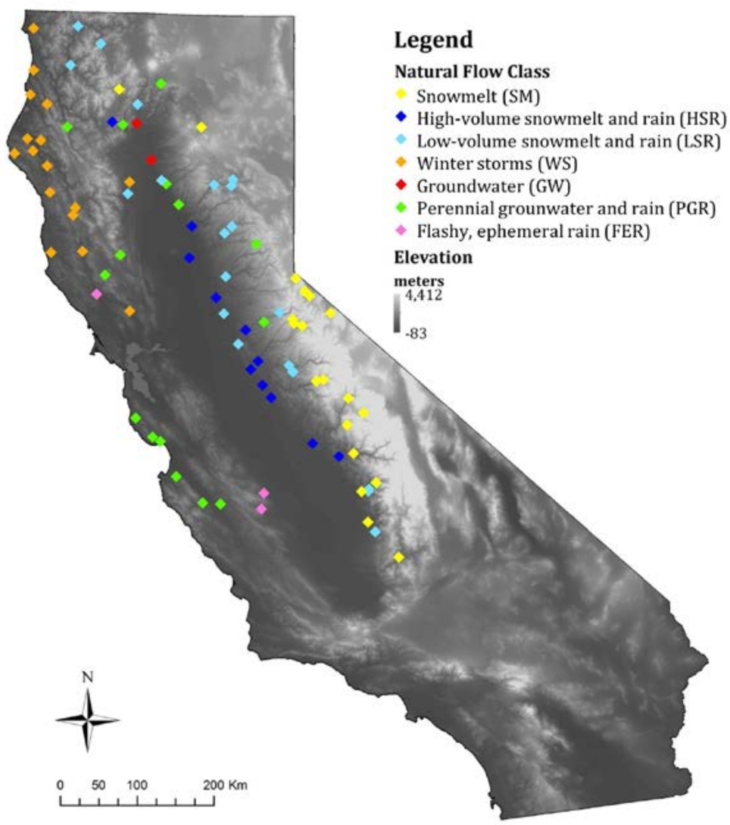

Figure 1. Reference Gauge Stations Considered in Development of Hydrologic Classification.

Geospatial data for 27 catchment attributes were considered in the hydrologic classification to derive physical explanations for the dominant hydrologic regimes. These attributes were also used to transfer the dominant hydrologic regimes from gauged reference catchments to ungauged catchments (Table 1). The 27 attributes represent three primary controls on hydrologic behavior: topography, geology, and climate (Wolock et al. 2004). Topographic attributes included upstream contributing area, elevation, drainage density, basin geometry, and numerous other terrain indices; geologic attributes included dominant geology, surficial geologic materials, underlying aquifers, and riparian soils composition; and climatic attributes consisted of measures of precipitation, temperature, and seasonality (Markham 1970). In an effort to capture flow regime seasonality, the months of January and August were chosen to represent the peak of the wet and dry seasons, respectively. July climatic attributes were considered in addition to August attributes to capture the expected difference in late spring recession rates across the state. All catchment attributes were calculated for each reference gauge station or reach based on its entire upstream watershed. Table 1 provides a complete list of catchment attributes considered, including their spatial resolution, data source, and method of derivation.

Table 1. Catchment Attributes Considered in This Study as Potential Controls on Hydrologic Response.

Variable	Description	Units	Time period	Resolution	Citation
Basin-scale topographic					
ELEV_MEAN*[a]	Mean basin elevation	m	N/A	10-m grid	USGS 2008
AREA*[a]	Drainage area	km^2	N/A	10-m grid	USGS 2008
SLOPE_PCT*[a]	Mean slope	%	N/A	100-m grid	USGS 2008
STRAHLER[a]	Mean Strahler stream order	N/A	N/A	10-m grid	USGS 2008
STRAHLER_MAX[a]	Maximum Strahler stream order	N/A	N/A	10-m grid	USGS 2008
STRM_DENSITY*[a]	Stream density, length of streams per watershed area	km/ km^2	N/A	10-m grid	USGS 2008
1ST_ORDER*[a]	Percent of watershed stream lengths which are Strahler first-order	%	N/A	10-m grid	USGS 2008
BAS_COMPACT	Watershed compactness ratio = area/perimeter^2 * 100	N/A	N/A	1:24,000 - 1:100,000	USGS 2008
RRMEDIAN	Dimensionless elevation to relief ratio, calculated as (median elev – min elev)/(max elev – min elev)	N/A	N/A	100-m grid	USGS 2008
TOPWET	Topographic wetness index, ln(a/S); a is the upslope area per unit contour length and s is the slope at that point	N/A	N/A	1-km grid	Wolock and McCabe 1995
MAINSTEM_SIN	Sinuosity of mainstem stream line	N/A	N/A	10-m grid	USGS 2008; Rosgen 1994
Basin-scale climatic					
JUL_TMP	Mean July temperature	C°	1971-2000	800-m grid	PRISM
T_AVG_BASIN	Mean annual air temperature	C°	1971-2000	800-m grid	PRISM
T_MAXSTD	Mean maximum monthly air temperature	C°	1971-2000	800-m grid	PRISM
T_MINSTD	Mean minimum monthly air temperature	C°	1971-2000	800-m grid	PRISM
JUN_PPT*	Mean June precipitation	cm	1971-2000	800-m grid	PRISM
AUG_PPT*	Mean August precipitation	cm	1971-2000	800-m grid	PRISM
PPTAVG_BASIN	Mean annual precipitation	cm	1971-2000	800-m grid	PRISM
PRECIP_SEAS_IND	Precipitation seasonality index; measure of how much annual precipitation falls seasonally (high values) or is spread out over the year (low values)	N/A	1971-2000	800-m grid	Markham 1970; PRISM
SNOW_PCT_PRECIP	Percent of total precipitation as snow	%	1901-2000	1-km grid	McCabe and Wolock 2009
WD_BASIN	Mean annual number of days of measurable precipitation	days	1961-1990	2-km grid	PRISM
WDMAX_BASIN	Mean monthly maximum number of days of measurable precipitation	days	1961-1990	2-km grid	PRISM
Reach-scale channel					
SAND_AVE	Mean sand content in riparian soils	%	N/A	200 m	Wolock 1997
SILT_AVE	Mean silt content in riparian soils	%	N/A	200 m	Wolock 1997
CLAY_AVE*	Mean clay content in riparian soils	%	N/A	200 m	Wolock 1997

METHODOLOGY

The hydrologic classification was developed in four steps: (1) statistical analysis of streamflow data, (2) cluster analysis of hydrologic indices to identify distinct dominant hydrologic regimes, (3) classification of dominant hydrologic regimes based on physical and climatic catchment attributes, and (4) prediction of natural flow classes for ungauged reaches (Fig. 2). Steps 1 and 2 address the first study question, and steps 3 and 4 address the second question. The third and fourth study questions are considered in the subsequent discussion.

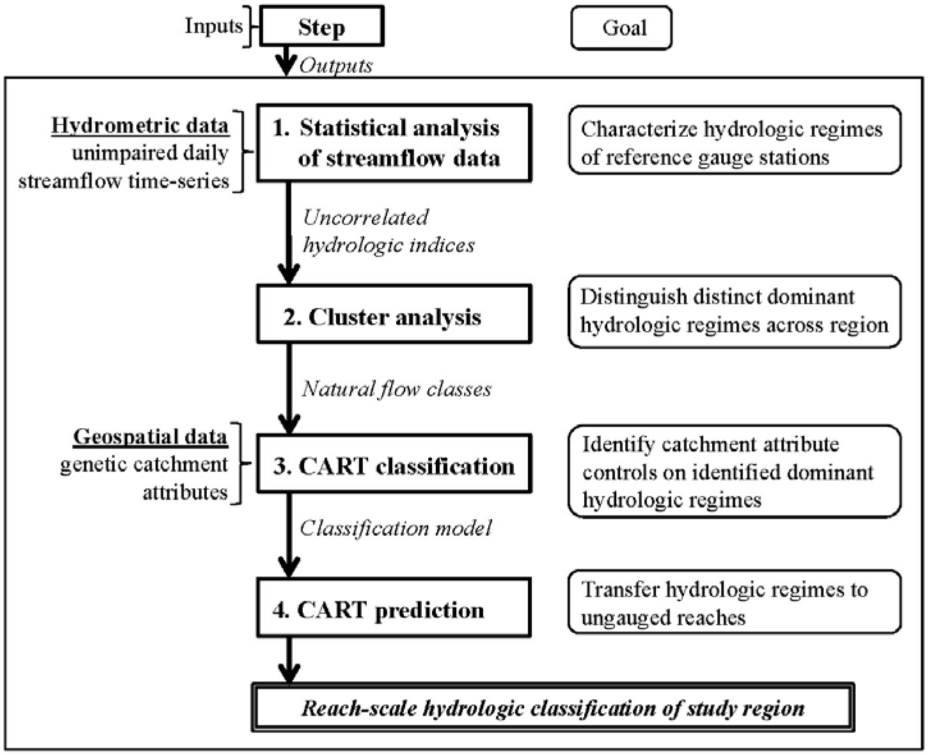

Figure 2. Hydrologic Classification Methodology, Including Key Steps and Associated Goals. CART, classification and regression trees.

Identification of dominant hydrologic regimes

Statistical analysis of streamflow data.

Using the publicly available Indicators of Hydrologic Alteration (IHA) software (Richter et al. 1996; Matthews and Richter 2007), ecologically-relevant hydrologic indices were calculated for the 75 unimpaired gauge stations for the 1968-1988 period and for the 16 naturalized gauge stations for the 1989-2009 period. A normalized subset of hydrologic indices meeting probabilistic independence was used for subsequent cluster analysis (Table 2). First, calculated indices were normalized with feature scaling to range from 0 to 1 to remove potential differences in index magnitudes leading to differential weighting in the cluster analysis. The coefficient of correlation was then used to identify an independent subset of indices ($r < 0.8$) with the objective of reducing the dimensionality of the dataset while retaining as much of the variation inherent in the original streamflow data as possible; hydrologic indices supported by the literature to be of particular ecological importance (e.g., mean annual flow and high flow duration) were excluded from this selection process and included in the analysis regardless of their correlation (Postel and Richter

2003). Finally, a principal components analysis (PCA) based on correlations between hydrologic indices was used to evaluate the loadings of indices on the first four PCs in order to examine which variables explained the majority of variation between natural flow classes (Jolliffe 1986).

Table 2. Hydrologic Indices Used in the Cluster Analysis to Distinguish Dominant Hydrologic Regimes across California Based on the 91

Hydrologic Index	Type	Description
Mean annual flow	Summary	Mean daily streamflow value over period of record
Annual C.V.	Summary	Coefficient of inter-annual variation, defined as the standard deviation divided by the mean daily streamflow
Flow predictability	Summary	Standard deviation of daily streamflow
% of floods in 60d period	Summary	Percentage of floods that occur during a given 60 day period in all years
med_Oct	IHA	Median daily October streamflow over period of record
med_May	IHA	Median daily May streamflow over period of record
1-day minimum	IHA	Median of 1-day minimum annual flows
Date of minimum	IHA	Median Julian date of 1-day minimum annual flows
Date of maximum	IHA	Median Julian date of 1-day maximum annual flows
Low pulse duration	IHA	Median number of days of low flow pulses per year
High pulse count	IHA	Median number of high flow pulses per year
Extreme low duration	EFC	Median number of days of extreme low flow pulses per year
Extreme low timing	EFC	Median Julian date of minimum extreme low flow
High flow duration	EFC	Median number of days of high flow pulses per year
High flow timing	EFC	Median Julian date of peak high flow
Small flood duration	EFC	Median number of days of small flood events per year
Small flood frequency	EFC	Median frequency of small flood events per year
Large flood duration	EFC	Median number of days of large flood events per year
Large flood timing	EFC	Median Julian date of peak large flood
Large flood fall rate	EFC	Median daily rate of negative change in large flood events

Cluster analysis.

To identify dominant hydrologic regimes (i.e., natural flow classes) among the 91 reference gauge stations, a non-hierarchical *k*-means cluster analysis was performed on the hydrologic indices (Hartigan and Wong 1979; Kaufman and Rousseeuw 1990) (Table 2, Fig. 2). *K*-means is known for its efficiency to handle large datasets, sensitivity to noise (Purviya et al. 2014), and repeated successful application in hydrologic classification studies (e.g., Poff and Ward 1989; Dettinger and Diaz 2000; Liermann et al. 2011). A hierarchical "Ward's linkage" algorithm was first applied to evaluate the natural data partitioning (Johnson 1967) (Fig. 3) and *k*-means was then applied for $k = 2 – 9$ *k*-values. The optimal *k* was determined by the Davies-Bouldin internal clustering validation index (DBI) (Davies and Bouldin 1979). The stability of the identified natural flow classes was assessed with the cluster stability index (CSI) (Hennig 2007), calculated as the average proportion of gauges reassigned to their original clusters based on nonparametric bootstrapping with replacement (50 replications, leave out 10) (Hubert and Arabie 1985). CSI values <0.5 represent dissolved clusters whereas values >0.6 indicate true patterns (Hennig 2007). An additional cross-validation assessed the classification’s robustness to the addition of naturalized gauge stations based on the adjusted Rand index (Hubert and Arabie 1985; Santos and Embrechts 2009).

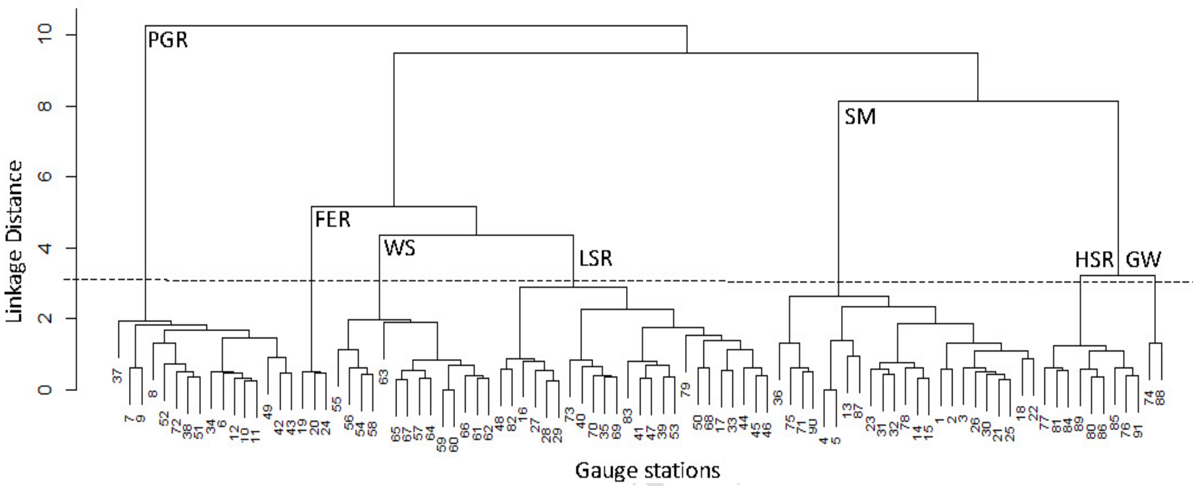

Figure 3. Hierarchical Cluster Diagram Shows Commonalities among 91 Reference Gauge Stations Based on Their Hydrologic Indices, Corroborating the Identification of Seven Distinct Clusters (defined in text) as Distinguished by the Nonhierarchical k-Mean Cluster Analysis. SM, snowmelt; HSR, high-volume snowmelt and rain; LSR, low-volume snowmelt and rain; WS, winter storms; GW, groundwater; PGR, perennial groundwater and rain; FER, flashy ephemeral rain.

Physical and climatic catchment controls on hydrologic regimes

In order to identify physical and climatic controls on the flow regime of a catchment and to predict the flow regime (i.e., natural flow class) of ungauged reaches, we applied Classification and Regression Trees (CART), a recursive-partitioning algorithm that classifies the data space defined by the input variables (catchment attributes) based on the output variable (natural flow class) (Breiman et al. 1984) (Step 3, Fig. 2). The CART analysis was conducted using the statistical R package ‘rpart’ (Therneau et al. 2010). Input variables for the CART analysis consisted of the 27 catchment attributes (see Table 1). The Gini impurity criterion was used to determine optimal variable splits (minimum parent node size: n=5; minimal terminal node size: n = 2) (De’ath and Fabricus, 2000), and optimal tree size was based on a ten-fold cross-validation (Therneau et al. 2010). The fitted misclassification rate (Breiman et al. 1984) was used to assess how well the catchment attributes explain the spatial variability of natural flow classes across reference gauge stations. The random forest classifier out-of-bag error rate (Breiman 2001) provided a probabilistic measure of model accuracy that compared model predictions of natural flow class with randomized subsets of reference gauges withheld.

Prediction of natural flow classes

The classification model was then used to transfer the identified natural flow classes to over 100,000 National Hydrography Dataset [(NHD, 1:100,000 scale, Simley and Carswell (2009)] stream reaches in California based on their upstream catchment attributes (Step 4, Fig. 2). Prediction of natural flow classes was conducted for reaches with a Strahler order of two or higher derived from the NHD (average reach length 2 km); Strahler first-order reaches were excluded to improve processing time. All catchment attributes were calculated for each reach based on its entire upstream watershed using the Catchment Attribute Allocation and Accumulation Tool in ArcGIS (version 10.2, ESRI Inc.) (Horizon System Corporation 2008).

RESULTS

Eight natural flow classes were distinguished across California, representing statistically distinct and physically interpretable dominant hydrologic regimes and physical and climatic catchment controls. Both the hierarchical and *k*-means cluster analyses identified seven distinct hydrologic regimes as the most probable classification (DBI=1.45) (Fig. 1). However, further analysis of classification results indicated that one of the seven classes was better distinguished by splitting it into two sub-classes, resulting in eight final natural flow classes. This splitting process is described later in this section.

Identification of dominant hydrologic regimes

Both the hierarchical and *k*-means cluster analyses identified seven clusters as the most probable classification (DBI=1.45) (Fig. 1). Probability of cluster membership ranged from 60 to 99%, with an average of 80%, suggesting strong support for the seven-tier classification. The bootstrapping test produced CSI values >0.5 for all seven clusters (mean=0.71), indicating a parsimonious clustering solution (Hennig 2007). An adjusted Rand index of 1 between cluster analysis results using only unimpaired gauge stations and using both unimpaired and naturalized gauge stations further corroborates the stability of the seven-tier clustering solution to the dataset augmentation.

The standardized annual hydrographs (Fig. 4) and range of hydrologic indices of each natural flow class (Fig. 5) illustrate the clear differences in seasonal and annual streamflow patterns as well as streamflow timing, magnitude, duration, frequency, and rate-of-change characteristics (Table 2) exhibited by each flow regime. The annual hydrographs illustrate the median of the standardized average monthly streamflow volumes across all years and gauges within each flow class. Loadings of hydrologic indices on the first four PCs indicate that the components (and associated hydrologic indices) of the flow regime best capable of distinguishing between natural flow classes are (i) low flow characteristics (flood-free season, number of zero-flow days, and extreme low flow timing), (ii) high flow characteristics (date of maximum, high flow timing and frequency, large flood duration), (iii) seasonality (flood-free season, high and low flow timing, duration, and frequency), and (iv) predictability (flow predictability, constancy/predictability, base flow index, low and high flow duration) (Table 3).

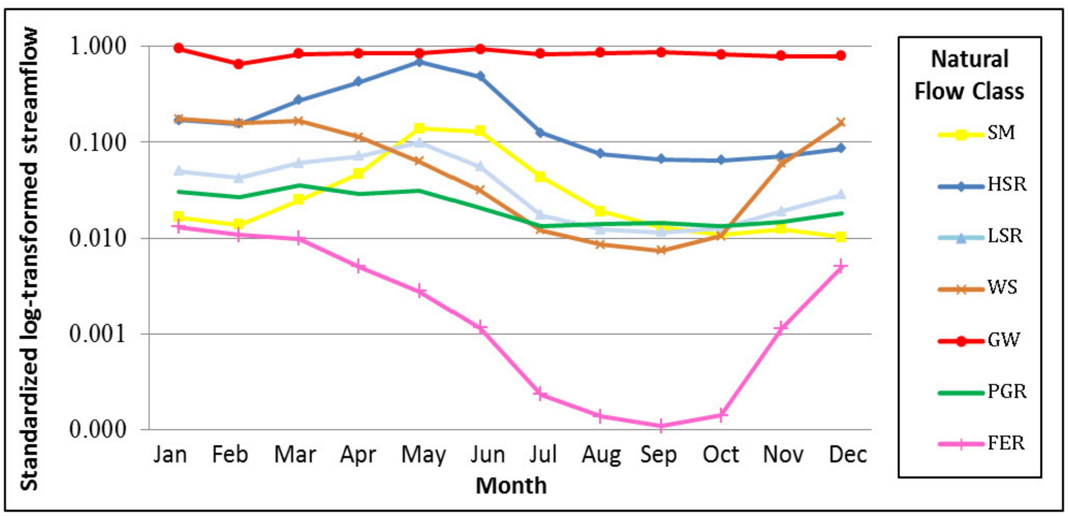

Figure 4. Standardized Log-Transformed (log(Q)) Annual Hydrographs of the Initial Seven Hydrologic Regimes Identified in the Cluster Analysis. The annual hydrographs illustrate the median of the standardized average monthly streamflow volumes across all years and gauges within each flow class. Classes are defined as follows: SM, snowmelt; HSR, high-volume snowmelt and rain; LSR, low-volume snowmelt and rain; WS, winter storms; GW, groundwater; PGR, perennial groundwater and rain; FER, flashy ephemeral rain.

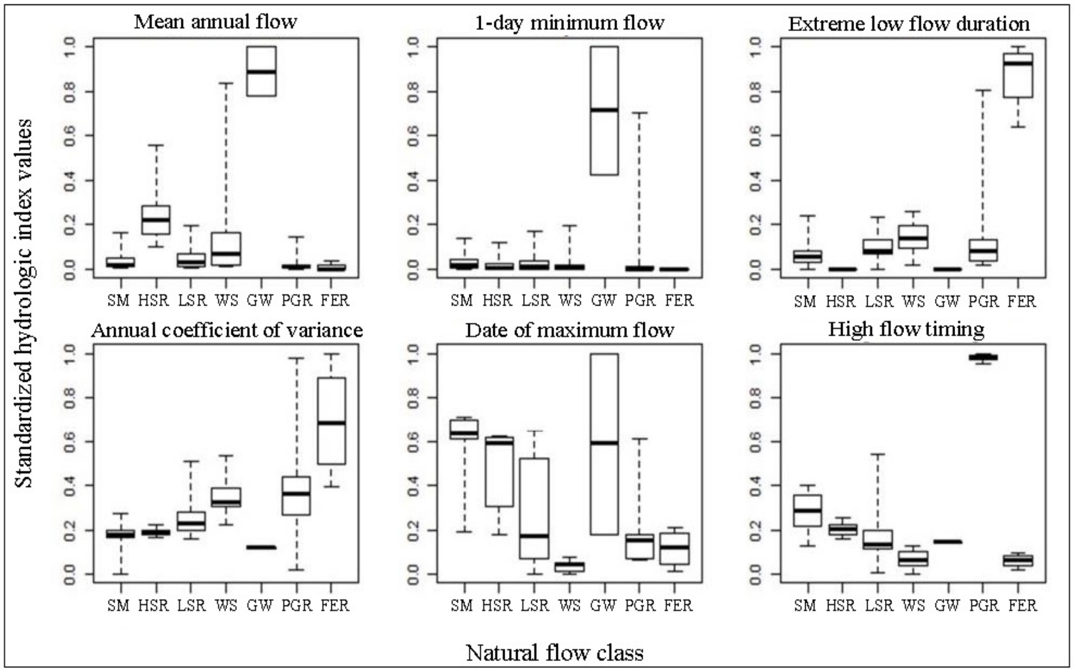

Figure 5. Box-and-Whisker Plots of Selected Hydrologic Indices Used in the Cluster Analysis to Separate the Initial Seven Hydrologic Regimes Based on Daily Streamflow Data from the 91 Reference Gauge Stations. Classes are defined as follows: SM, snowmelt; HSR, high volume snowmelt and rain; LSR, low-volume snowmelt and rain; WS, winter storms; GW, groundwater; PGR, perennial groundwater and rain; FER, flashy ephemeral rain.

Table 3. Key Flow Components Distinguishing Natural Flow Classes with Expected Significance for Setting Environmental Flow Targets Including: (1) Low Flow Characteristics, (2) High Flow Characteristics, (3) Seasonality, and (4) Predictability.

Class	Low Flow Characteristics	High Flow Characteristics	Seasonality	Predictability
SM	Many zero-flow days; Extended extreme low flow duration	Latest peak flows; Short flood duration	Very high	Very high
HSR	Long flood-free season; Very short extreme low flow duration; No zero-flow days	Longest flood duration; Early spring peak flows	High	High
LSR	Extended extreme low flow duration	Late spring peak flows	Very high	Very high
RGW	High one-day minimum flow; No zero-flow days	Early summer peak flows	Low	Mid
WS	Extended extreme low flow duration	Winter peak flows; Frequent wet season high flows	High	High
GW	Extremely high one-day minimum flow; No zero-flow days	No floods	Very low	High
PGR	High one-day minimum flow	Winter peak flows	Low	Mid
FER	Most zero-flow days; Longest extreme low flow duration	Short large flood duration; Winter peak flows	Mid	Very low

By qualitatively interpreting classification results, clusters (i.e., groups of reference gauge stations) were characterized by their dominant flow sources and subsequently referred to as follows (Table 4): snowmelt (SM), high-volume snowmelt and rain (HSR), low-volume snowmelt and rain (LSR), winter storms (WS), groundwater (GW), perennial groundwater and rain (PGR), and flashy ephemeral rain (FER). Of the 91 reference gauge stations, 20 were classified as SM (22%), 11 as HSR (12%), 22 as LSR (24%), 16 as WS (18%), 2 as GW (2%), 16 as PGR (18%), and 4 as FER (4%). SM sites exhibit highly seasonal hydrologic regimes with spring snowmelt peak flows, predictable recession curves, very low summer flows, and minimal winter rain influence. These sites exist along the crest of the Sierra Nevada with most sites in the southern, higher elevation portion of the mountain range. LSR and HSR sites exhibit similar seasonality but illustrate a transition towards earlier snowmelt peak and increasing winter rain contributions which follows their general downstream transition towards the Central Valley lowlands. WS sites exhibit distinct duration and timing of high flows from the snowmelt influenced sites, driven by winter rain storms. These sites are characterized by high interannual flow variance due to the variability of winter storm patterns, and generally follow the spatial distribution of strong orographic precipitation in the north coast region. GW sites are distinguished by significantly higher and more stable flows year-round, despite uncertainty associated with the fact that only two reference gauge stations were used to distinguish this flow class. PGR sites combine the stable, base flow-driven conditions of GW sites with the winter rain dominated conditions of WS sites in catchments with low annual streamflow. FER reaches are characterized by the highest interannual flow variance, extended extreme low flows and large floods, and the lowest average daily streamflows of any class, although this class is also limited by reference gauge availability (n=3).

Class	Name	Hydrologic Characteristics	Physical and Climatic Catchment Controls
SM	Snowmelt	• Large spring snowmelt pulse (~May 24) • Very high streamflow seasonality index • Extreme low flows (<10th percentile) Sep-Feb	• High elevation catchments (>2,293 m), major snow influence and minimal rain influence
LSR	Low-volume snowmelt and rain	• Transition between Classes SM and HSR • Bimodal snow—rain hydrograph driven by spring snowmelt pulse and winter rain	• Mid-elevation catchments with limited area (<2,144 km^2) (low winter temperatures [Jan temp <−5°C], high stream density [>0.65 km/km^2])
HSR	High-volume snowmelt and rain	• Spring snowmelt pulse (~May 4) • High seasonality but larger winter storm contributions • Retain high base flow throughout summer low flow season • Bimodal snow-rain hydrograph	• Mid-elevation catchments (1,126-2,293 m), large contributing area (>2,144 km^2) *not* underlain by volcanic geology (high stream density [>0.65 km/km^2], mild winter temperatures [Jan temp >−5°C]) **OR** • Low elevation (<1,125 m) with very large contributing area (>15,420 km^2) and high riparian soils clay content (>17% clay) (substantial winter precipitation [Jan precip 16-28 cm])
RSG	Rain and seasonal groundwater	• Bimodal hydrograph driven by winter rain pulse and percolating winter rain appearing as base flow pulse later in year	• Low elevation catchments (<1,126 m) with limited winter precipitation (Jan precip <28 cm) and low slopes (<24%) **AND** • Underlain by igneous and metamorphic rock materials **AND** • Coastal catchments with small aquifers driving short residence times
WS	Winter storms	• Predictable large fall and winter storms • Earliest peak flows (in January)	• Low elevation catchments with substantial winter precipitation (Jan precip >28 cm) **OR** • Low elevation, mid-slope (31-24%) catchments with low winter precipitation but high riparian soils clay content (>23%), underlain by unconsolidated sand and gravel aquifers covered by thick alluvial sediments
GW	Groundwater	• Highest mean annual flows and minimum flows • Low seasonality and high predictability	• Mid-elevation catchments with large area (>2,144 km^2) underlain by volcanic (basaltic and andesitic) geology (low stream density [<0.65 km/km^2]) **OR** • Low elevation catchments with limited winter precipitation, very large contributing area (>15,420 km^2) with low riparian soils clay content (<17%), underlain by igneous and metamorphic-rock aquifers
PGR	Perennial groundwater and rain	• Low seasonality and mean annual flow • Transition between WS and GW, with winter storms but generally stable flows	• Low elevation catchments with low riparian soils clay content (<23%) (low stream density [<1.1 km/km^2]) **AND** • Catchments primarily underlain by residual sedimentary rock materials
FER	Flashy, ephemeral rain	• Lowest mean annual flows • Highest coefficient of annual variation, lowest predictability • Longest extreme low flow duration	• Low elevation catchments with high riparian soils clay content (>23%) and high slopes (>31%) (high stream density [>1.15 km/km^2])

Table 4. Summary of Dominant Hydrologic Characteristics and Physical and Climatic Catchment Controls on Hydrologic Regimes for the Natural Flow Classes Identified in California.

The prediction of numerous LSR reaches throughout southern California, the central coast, and the central valley despite the evident lack of snowmelt influence indicated an inability of the classification model to accurately distinguish hydrologic regimes in these areas. This is not surprising given the lack of reference gauge stations in southern California (Fig. 1). Recognizing the disparity between class predictions and known physiographic and climatic patterns (NRCS 2015) as well as the large spatial footprint of LSR reaches compared to other natural flow classes, the LSR flow class was further split into two sub-classes. The classification tree indicated that two distinct groups of catchment attributes were capable of producing an LSR type hydrologic regime and that these functional groups could be distinguished on the basis of elevation. Thus LSR reaches were manually split into LSR and low-volume rain and seasonal groundwater (RGW), representing LSR reaches with average catchment elevations greater than and less than 1,126 m a.s.l., respectively.

Physical and climatic catchment controls on hydrologic regimes

Our classification model identified a combination of topographic, geologic, and climatic attributes as controls on the distinguished hydrologic response (Table 4). Specifically, the following six catchment attributes were found to be the predictor variables with the greatest explanatory power for the seven identified hydrologic regimes: mean catchment elevation, contributing area, mean upstream January precipitation, dominant rock type, percent clay content in riparian soils, and mean catchment slope (Fig. 6, Table 1). Mean catchment elevation was the primary splitting variable, distinguishing the SM sites (>2,293 m a.s.l.) from the other six flow classes (Fig. 6). Contributing area differentiated high-volume HSR and GW reaches from other reaches, and acted with elevation to define the transition from a highly seasonal snowmelt-dominated to a bimodal snow-rain regime. Climatic setting characterized by average winter precipitation distinguished WS reaches from other low-elevation reaches in California. Slope (and drainage density as a proxy variable) was identified as first-order control over the rate and duration of low-elevation catchment response to precipitation. The delayed response to winter storms characterized in the hydrograph as a long spring base flow pulse in LSR reaches can be distinguished from the large, rapid hydrograph response exhibited by FER reaches based on slope. The classification model also identified geologic rock type and soil permeability as major controls in distinguishing groundwater-dominated from snowmelt- and rain-dominated hydrologic regimes. Underlying fractured volcanic bedrock distinguished high volume GW reaches from seasonal, high-volume HSR reaches, while high clay-content (low permeability) soils distinguished more stable flow PGR reaches from highly seasonal WS reaches in low-elevation catchments. In selecting natural flow classes (HSR, WS, GW), two alternative combinations of catchment attributes were capable of driving a similar hydrologic response. In these cases, Table 4 describes both potential catchment attribute combinations.

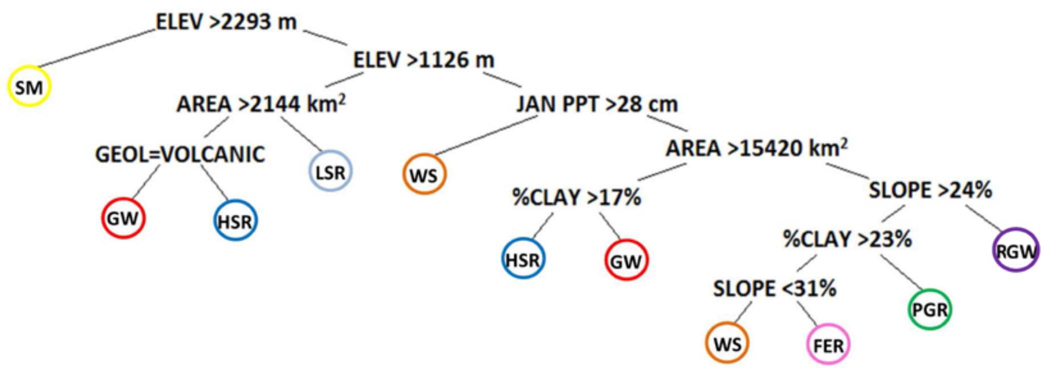

Figure 6. Classification Tree Model Identifying the Eight Natural Flow Classes Based on Physical and Climatic Catchment Attributes. If the stated condition is true, the left branch is followed, otherwise the right branch is followed (see Table 1 for variable definitions). Classes are defined as follows: SM, snowmelt; HSR, high-volume snowmelt and rain; LSR, low-volume snowmelt and rain; RSG, rain and seasonal groundwater; WS, winter storms; GW, groundwater; PGR, perennial groundwater and rain; FER, flashy ephemeral rain.

A fitted misclassification rate of 12% indicates that 80 of the 91 reference stations were correctly classified based on the six catchment attributes described above (Fig. 6) relative to their known hydrological regimes from statistical analysis. An out-of-bag error rate of 23% (Cohen's $\kappa=0.66$, $Z=13.7$, $p<0.001$; Landis and Koch 1977) indicates that natural flow classes were accurately predicted for 77% of the reference gauge stations. The model achieved highest classification accuracy for the most strongly seasonal annual hydrograph endmembers, WS (88%) and SM (82%), and the lowest accuracy for the classes with the least number of reference gauge stations, GW (50%, n=2) and FER (33%, n=4), which were primarily misclassified as HSR and PGR, respectively. The model misclassified at least one gauge into every natural flow class except GW, with the highest misclassification into LSR (n=8).

Final hydrologic classification

The predicted distribution of the eight natural flow classes across California stream reaches (Figs. 7 and 8) generally corresponds with expectations given known physio-climatic and hydrologic patterns [*see supplemental materials for full description of each natural flow class*].

Most mountain basins demonstrate a downstream progression from SM to LSR to HSR with decreasing elevation. WS reaches are generally located along the Pacific coast where the vast majority of the state's rainfall occurs or in small lowland basins lacking snowmelt influence, and GW reaches are generally underlain by fractured volcanic geologic settings expected to produce stable, high-volume hydrologic regimes.

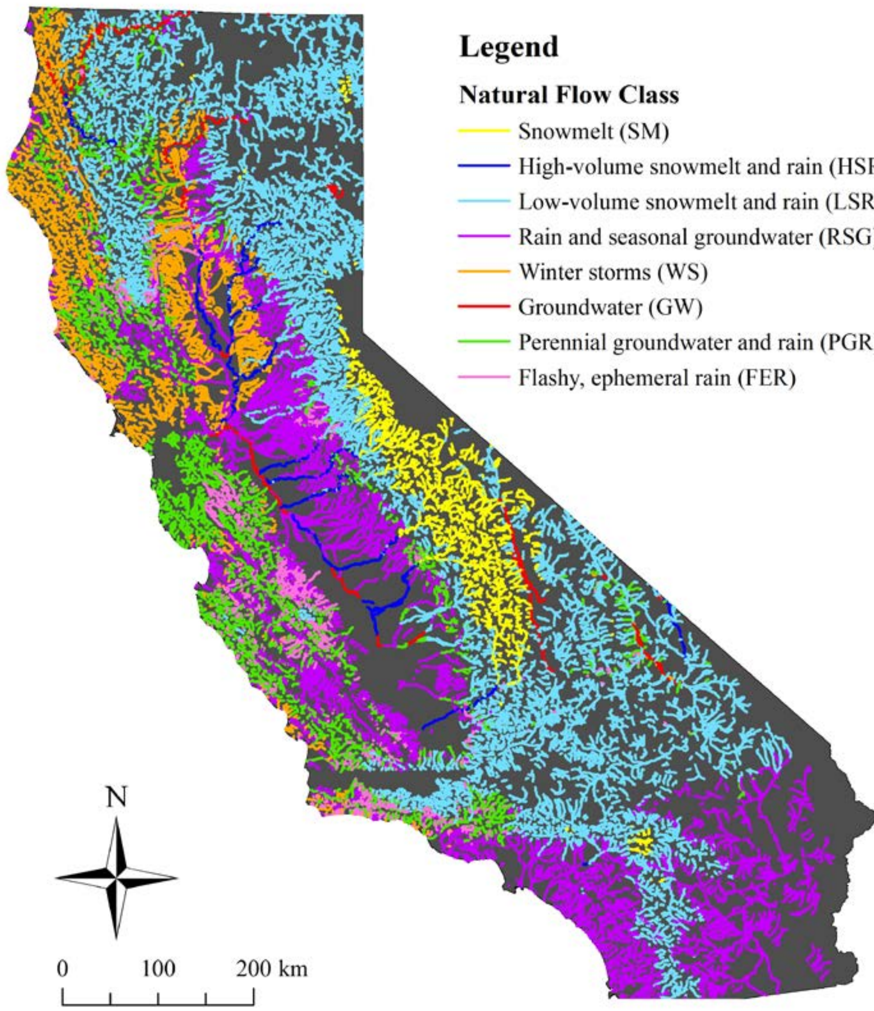

Figure 7. Map of the Reach-Scale Hydrologic Classification of California National Hydrography Dataset Streams (excluding Strahler first order streams) Resulting from the Natural Flow Class Transfer Based on the Classification Tree Model.

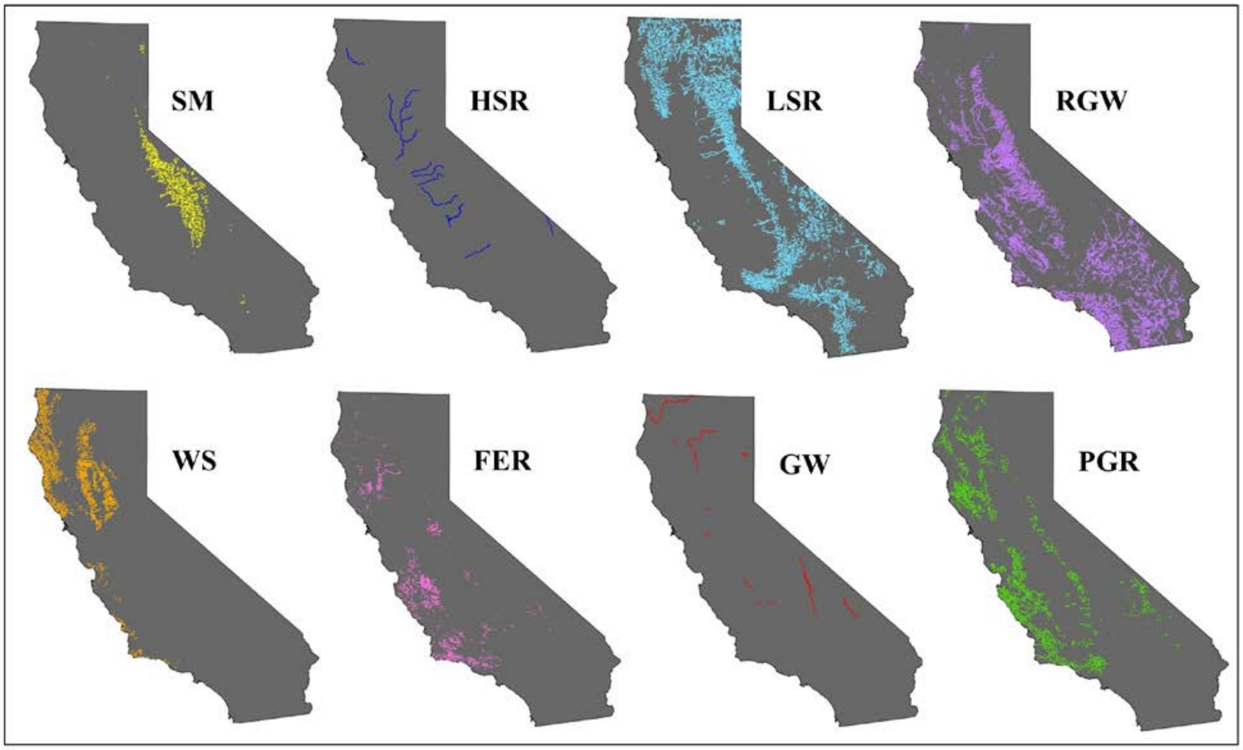

Figure 8. Spatial Footprint of the Final Eight Natural Flow Classes within California (excluding Strahler first-order streams and canals). Classes are defined as follows: SM, snowmelt; HSR, high-volume snowmelt and rain; LSR, low-volume snowmelt and rain; RGW, rain and seasonal groundwater; WS, winter storms; GW, groundwater; PGR, perennial groundwater and rain; FER, flashy ephemeral rain

DISCUSSION

Can distinct hydrologic regimes be distinguished within the study region?

Study results indicate that our hydrologic classification is capable of distinguishing dominant hydrologic regimes and their physical and climatic catchment controls across California. Seven hydrologic regimes were identified, characterized by distinct combinations of snowmelt, rain, and groundwater flow sources and resulting streamflow patterns (Fig. 4; Fig. 5). The high performance of the cluster analysis (DBI=1.45, CSI=0.71) and classification model (77% accuracy, κ =0.66) achieved in this study compared to other similar studies (e.g., Liermann et al. 2011; Snelder et al. 2009; Chinnayakanahalli et al. 2011; McManamay et al. 2014) is very encouraging. This provides some confidence that the identified dominant hydrologic regimes are derived from similarities in the hydrologic function of catchments characterized by similar catchment attributes. However, the focus on streamflow means that we are limited in the degree of detail regarding hydrologic function that can be extracted from such an integrated measure.

Despite overall high performance, limited FER and GW reference gauge stations and the lack of reference gauge stations in southern California somewhat constrain the classification's ability to accurately predict hydrologic regimes of these classes and parts of California. By considering gauge stations with both unimpaired (n=75) and naturalized (n=16) streamflow time-series, we were able to increase the number and distribution of reference gauge stations and reduce the systematic bias towards small, high elevation basins. However, the minimum record length required (> 15 years) and the choice of hydrologic impairment thresholds substantially limited reference gauge station availability, thus constraining classification performance (Olden et al. 2012). The final classification is therefore expected to better predict hydrologic regimes in the regions of the state with more reference gauge stations and should be applied with caution in regions with insufficient reference gauge stations. Future work could improve the performance of the classification by incorporating more gauges stations in these regions by loosening the minimum time series length and impairment threshold requirements.

Can identified explanatory catchment attributes help reveal the dominant processes distinguishing distinct hydrologic regimes?

The explanatory catchment attributes identified in our study showed wide agreement with existing hydrologic classification studies. For instance, elevation was also found by Singh et al. (2014) and Liermann et al. (2011) to be the primary control distinguishing snowmelt- from rain-dominated hydrologic regimes. Contributing area was found by Sawicz et al. (2011) and Belmar et al. (2011) to differentiate reaches of high versus low flow magnitudes, supporting its identification as the foremost control distinguishing HSR reaches from lower volume SM and LSR reaches in California. Sawicz et al. (2011) also found climate to exert a strong influence on catchment function and response in the eastern United States. Thus, although hydrology has not yet established a common catchment classification system (Wagener et al. 2007; Sawicz et al. 2011), the similarities in hydrologic regimes and catchment controls identified in our and the above studies suggest that a first-order classification of reaches based on upstream catchment attributes is warranted for California.

Only six of the 27 catchment attributes were found to be of significant explanatory value in predicting the seven natural flow classes with high accuracy. To our surprise, despite their known influence on catchment hydrologic response, the CART model did not select basin shape, relief, and surficial geology as explanatory variables in the classification tree. Similarly, no climatic attributes (e.g., temperature, precipitation) other than January precipitation were recognized as explanatory variables. The significance of topography and geology in addition to climate for distinguishing flow regimes in California contrasts with findings of other classifications (e.g., Liermann et al. 2011; Chinnayakanahalli et al. 2011; Alba Solans and Poff 2013) that identified climate as the sole controlling attribute on hydrologic response. From a process perspective, this indicates that the dominant hydrologic regimes found in California are controlled by physical catchment attributes that influence runoff generation processes in addition to climate, highlighting the need to consider local controls (e.g., topography, soil, geology) in hydrologic classification that might act on the sub-catchment or reach-scale hydrology of a basin.

The inability of our classification to distinguish between LSR and RSG hydrologic regimes highlights a significant limitation of the use of automatic, data-driven classifications for hydrologic analysis. While numerous clustering and regression algorithms have been applied in hydrologic classification, with the best algorithm depending primarily on the study objectives (Olden et al. 2012), we found an additional need for expert validation of the classification given external limitations on input data. Our approach of manually splitting a natural flow class because the classification model was incapable of resolving evident differences in catchment controls and hydrologic responses dramatically improved classification results in terms of the model's agreement with known physiographic and hydrologic patterns. Using the structure of the classification model in addition to regional expertise to define a splitting criterion (in our case elevation) increased the objectivity of the process and provided additional information regarding the differences in the driving catchment processes of the two sub-classes. Alternatively, adding other catchment attributes, such as glacial history or soil-to-bedrock ratio (Peterson et al. 2008), may further improve our classification's ability to capture distinct catchment processes and their effect on the hydrologic response of California catchments.

How do the identified dominant hydrologic regimes compare with those found in California field and modeling studies and in other hydrologic classifications?

Comparison with California field and modeling studies.

In the absence of a statewide hydrologic classification, existing field and modeling studies can be used to evaluate our results for selected physiographic regions within California. Overall we found that the identified hydrologic regimes and catchment controls were generally consistent with prior, local knowledge of rainfall-runoff processes in California (e.g., Mount 1995; Yarnell et al. 2010; Hunsaker et al. 2012). The transition from a highly seasonal SM regime to a high baseflow, bimodal HSR regime closely tracks the elevation gradient from the Sierra Nevada to the Central Valley. This is consistent with Hunsaker et al.'s (2012) finding that mixed rain-snow and snowmelt-dominated flow regimes could be differentiated solely on the basis of elevation for eight headwater catchments of the Kings River. Furthermore, their elevation threshold for distinguishing between these flow regimes (2,287 m a.s.l.) almost exactly matches the threshold identified by our classification model (2,293 m) for distinguishing SM from LSR reaches. Also similar to our study, annual discharge was found to increase with elevation over the eight catchments, indicative of a higher snow-rainfall ratio and a lesser role of evapotranspiration in snowmelt-dominated vs. mixed rain-snow catchments (Hunsaker et al. 2012). An estimate of water balance components along an elevation gradient in the American River basin suggests that runoff and evapotranspiration are about equal at 1,200 m a.s.l. (40% of total water balance each), whereas runoff increases to 68% at 2,100 m as the evapotranspiration effect decreases (Armstrong and Stidd 1967). These topographic controls over catchment function are profoundly similar to the two elevation thresholds identified in our study (1,126 and 2,293 m), indicating that the empirical classification model is in fact identifying similar catchment controls on rainfall-runoff response.

Relationships between natural flow classes and watershed-specific model parameters estimated for a hydrologic model of the western Sierra Nevada (Young et al. 2009) further corroborate the physical basis of our hydrologic classification. Of the 15 watersheds considered by Young et al. (2009), all but five are classified at their outlet as HSR by our hydrologic classification; four watersheds (Cosumnes, Calaveras, Kaweah, and Tule) are classified as LSR and one (Kern) as SM. The SM watershed exhibits much higher soil water storage capacity (1,181 mm) and lower hydraulic conductivity (30 mm/week) than the other watersheds based on model parameters; the LSR watersheds exhibit similar but less extreme trends. The high storage capacity and low hydraulic conductivity of SM and LSR watersheds implicate saturation overland flow as the dominant runoff process in these reaches, as infiltration rates far exceed precipitation intensities (Dunne and Black 1970; Dahlke et al. 2012).

Comparison with other regional hydrologic classifications.

Our catchment classification model was highly accurate (77%) and exceeded the predictive capacities of classification models reported elsewhere (e.g., 75%, Liermann et al. 2011; 61%, Snelder et al. 2009; 70%, Chinnayakanahalli et al. 2011; 75% McManamay et al. 2014). We hypothesize that the high performance of our hydrologic classification may be attributable to the suggestion by Sawicz et al. (2011) that classification results are largely controlled by the particular gradients present and datasets analyzed in the study region. Sawicz et al. (2011) found that catchment attributes exhibiting steep gradients across regions tend to emerge as dominant controls over hydrologic response in regional hydrologic classifications, exerting a stronger control on separating the catchments into different classes than more spatially homogeneous attributes. Similar results were obtained by Sanborn and Bledsoe (2006) and Liermann et al. (2011) that identified climate as the only dominant control over hydrologic response in regions with steep climatic gradients, while topographic and geologic attributes exhibited minimal influence. The fact that California exhibits steep gradients across all three catchment variables representing primary controls on hydrologic behavior (Wolock et al. 2004) ensures that no single variable dominates the classification. The significance of topographic (elevation, area, slope), geologic (rock type, soil type), and climatic (winter precipitation) attributes for explaining differences in identified hydrologic regimes corroborates the theory that watersheds should be grouped by similarity in topography, geology, and climate (Winter 2001; Wolock et al. 2004). Thus, the influence of dominant environmental gradients on hydrologic classification and the regionalization of hydrologic regimes need not necessarily discourage its application or require the splitting up of a region into smaller subregions, as suggested by Sawicz et al. (2011). Rather, it may indicate that hydrologic classification could provide a tool better suited for Mediterranean regions, which generally exhibit steep gradients across climate, topography, and geology (Peel et al. 2007), than regions with a single dominant environmental gradient.

Insights for environmental flows setting in California

Hydrologic classifications form the template for developing hypothetical relationships between hydrologic characteristics and ecological responses (Arthington 2012; Poff et al. 2010; McManamay et al. 2015). The significance of the natural flow regime for native river ecosystems (Richter et al. 1996; Poff et al. 1997) has generally been considered as appropriate for California rivers and streams (Marchetti and Moyle 2001; Brown and Bauer 2010). A recent ecological assessment of hydrologic alterations on large California rivers (Brown and Bauer 2010) indicated that changes to key components of the natural flow regime (e.g., spring high flows, summer low flows) had major implications for native and alien fish species assemblages. However, relating ecological measures to hydrologic regimes is currently limited in California because unimpaired streamflow records are unavailable for many locations of interest where biological data exists (e.g. Ode 2007; Santos et al. 2014). The spatial extent and reach scale of the proposed hydrologic classification are expected to substantially improve the coincidence of biological and hydrologic datasets statewide. Future comparisons of ecological patterns between natural and hydrologically altered streams within each of the eight natural flow class distinguished by our study are therefore expected to yield flow–ecological response relationships which can provide the basis for statewide environmental flow standards (see Poff et al. 2010).

The four flow components identified here as best capable of distinguishing natural hydrologic regimes (low flow characteristics, high flow characteristics, seasonality, and predictability, Table 3) highlight key characteristics of Mediterranean rivers [e.g., extreme high and low flows, high seasonality, and inter-annual variability (Gasith and Resh 1999)]. The hydrologic regimes distinguished in this study are therefore expected to be capturing ecologically significant distinctions rather than purely empirical groupings. Native Mediterranean biota have established life history traits providing resilience to the predictable and periodic extremes of these dynamic systems (Gasith and Resh 1999; Bonada et al. 2007), but these adaptations may make them particularly vulnerable to flow alterations (Lytle and Poff 2004). Improving understanding of the role of these key Mediterranean flow components in promoting natural ecosystem functions (Arthington 2012; Yarnell et al. 2015) in each of the distinguished natural flow classes would help to identify opportunities for environmental flow releases and link flow targets directly to driving ecosystem functions in stream reaches of each natural flow class. This would support the development of ecological performance metrics for regional adaptive management.

Stratification of California streams by natural flow class is expected to support the development of mechanistic associations between hydrologic classes and ecological characteristics and constrain the data and resource requirements of such efforts (e.g. Monk et al., 2006; Chinnayakanahalli et al., 2011; Rolls and Arthington, 2014; McManamay et al. 2015). For example, based on the established ecological significance of dry-season low flow duration and magnitude for native species in LSR-dominated streams (Gasith and Resh 1999; Yarnell et al. 2015), the archetypal LSR low flow characteristics distinguished by our classification (Fig. 5; Table 3) could be used to develop preliminary flow targets for classified LSR reaches of interest for restoration. Flow targets could be based on expected ranges of unimpaired streamflow timing, magnitude, duration, frequency, and rate-of-change. For instance, the natural range of extreme low flow duration exhibited by unimpaired LSR rivers (Fig. 5) could be used as an initial flow threshold for water abstractions to support imperiled native biota over large areas in the absence of sufficient reach-specific data. In this manner, highly regulated LSR stream reaches in California could be targeted for recovery of these natural low flow characteristics or for a large-scale evaluation of the ecological impacts of removing this functional flow component (Brown and Bauer 2010).

The ultimate ecological value of the proposed classification lies in its ability to reduce natural hydrologic variability to a level at which functionally similar groups of stream reaches can be identified for future flow – ecology analysis. Future research that extends the organizational framework presented here by further stratifying natural flow classes based on ecologically relevant hydrologic distinctions will increase the predictive power of discriminant relationships between specific flow regime components and biotic and abiotic functions for each class. For example, further dividing streamflow records within a natural flow class based on season (e.g., fall vs. winter) or geomorphic setting (i.e., confined vs. unconfined) would allow for the separate analysis of streamflow patterns with respect to factors of known ecological significance not addressed here (Junk et al. 1989; Wohl et al. 2015; Yarnell et al. 2015). Stratifying biomonitoring campaigns with respect to natural flow classes and proposed sub-classes to obtain ecohydrologic information would support the development and testing of physically-based, statistically defensible relationships between hydrologic characteristics and flow-driven geomorphic and ecological functions.

CONCLUSIONS

This study presents a hydrologic classification for the State of California to meet the recognized need for improved broad-scale environmental management of the state's many impaired rivers. The classification evaluates the diversity and distribution of natural hydrologic regimes present in a large, heterogeneous Mediterranean region using available unimpaired streamflow and geospatial datasets. From a management perspective, the hydrologic classification provides a footprint of the locations of distinct dominant hydrologic regions across California. This classification, combined with ecological and geomorphic information, could be used to design functional flow targets that could then be incorporated with current human water management objectives through an adaptive management framework. The ultimate utility of this classification is demonstrated by its ability to distinguish distinct hydrologic regimes and characterize dominant physical and climatic catchment controls on hydrology with a strong physical basis and expected ecological relevance. Eight natural flow classes were distinguished for California and results were corroborated by high predictive accuracy and regional performance. Our analyses revealed that topographic, geologic, and climatic attributes all explained significant variation in these hydrologic regimes. This supports the view that spatial variation in hydrology is determined by interactions among these factors at multiple spatial and temporal scales (Snelder et al. 2005; Sanborn and Bledsoe 2006; Kennard et al. 2010) and the need to consider local hydrologic controls acting at the reach scale by means of a spatially-explicit hydrologic classification.

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: A climate-based literature review of existing hydrologic classifications, a full description of the hydrologic time-series uncertainty analysis with gauge station specific results, and additional details on each of the identified natural flow classes.

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