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EVALUATION OF A REGIONALIZATION APPROACH FOR DAILY FLOW DURATION CURVES IN CENTRAL AND SOUTHERN CALIFORNIA WATERSHEDS[1]

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ABSTRACT: Discontinuities in flow regimes of ephemeral rivers in California make the modeling of daily flow duration curves (FDCs) in ungauged watersheds challenging. A regionalization approach previously developed for perennial and ephemeral watersheds in Portugal was tested in central and southern California. This approach, which is based on the theory of total probability, requires the prediction of three key flow variables in ungauged watersheds: the percentage of time the river is dry, the nonzero flow equalled or exceeded 80% of the time, and the mean daily flow for nonzero flows. Data from 41 watersheds in California were used to develop and validate regression equations for these three metrics. The methodology included an "all possible models" regression approach, an extensive set of watershed descriptors as potential independent variables, and two different methods for constructing observed FDCs. Suitable regression models could not be identified for predicting any of the required flow metrics. The contrasting results from the studies in Portugal and California were primarily attributed to differences in the aridity of watersheds in the two samples.

(KEY TERMS: surface water hydrology; watersheds; statistics; flow duration curve; regionalization; theory of total probability.)

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INTRODUCTION

Flow duration curves (FDCs) relate river flow magnitude (e.g., daily or monthly) to the percentage of time that it is exceeded in a record (Cole *et al.*, 2003). The FDC is one of the most informative methods for displaying the complete range of river flow discharges (Smakhtin, 2001). These curves are widely used for hydrologic applications that include flood control, hydro-power, river and reservoir sedimentation, water quality management, and water use engineering (Vogel and Fennessey, 1995). Variations in FDC properties over time have also been used to characterize the effects of land-cover change on river flow regimes (e.g., Lane *et al.*, 2005; Shao *et al.*, 2009).

While empirical FDCs are constructed using gauged river flow data, many hydrologic applications require synthetic curves in ungauged watersheds. The development of regionalization procedures for estimating FDCs in ungauged watersheds is consistent with the goals of the International Association of Hydrological Sciences initiative, Predictions in Ungauged Basins (Sivapalan *et al.*, 2003). These procedures are generally developed using flow information from a network of gauged sites. A widely

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used regionalization methodology describes the FDC in terms of a mathematical model and relates the parameters of the model to watershed morphological and/or climatic variables using regression analysis (Niadas, 2005). The FDC can also be described using probabilistic models, with regression models developed for estimating the parameters of the distribution (Castellarin *et al.*, 2007). Synthetic FDCs can also be constructed by developing regional regression equations to predict the discharge for selected exceedance percentages (e.g., 5, 10, 20,…, 95%) from watershed physical characteristics (Yu and Yang, 2000; Mohamoud, 2008; Archfield *et al.*, 2010).

Rainfall discharge relationships in arid and semiarid watersheds are characterized by strong nonlinearities and low yields (Ye *et al.*, 1998). It is common for rivers in these dry environments to have extensive periods of zero river flow. Discontinuities in the flow regime of ephemeral rivers make the modeling of FDCs challenging (Croker *et al.*, 2003). Errors in the measurement of low flows and prediction of the point at which flows cease, contribute to this challenge. An approach based on the theory of total probability has been proposed by Croker *et al.* (2003) to derive daily FDCs for both perennial and ephemeral rivers in Portugal. This approach includes a model to predict the percentage of time the river is dry and a model to predict a FDC for the nonzero flow period, with flows normalized by the mean daily flow of nonzero flows. As many rivers in central and southern California are ephemeral, the FDC regionalization approach of Croker *et al.* (2003) was considered to be potentially suitable for this region.

FLOW DURATION CURVE APPROACH BASED ON TOTAL PROBABILITY THEORY

The regional FDC approach presented by Croker *et al.* (2003) has three components. First, it is necessary to determine the probability of zero flows occurring (p_{dry}) so that the threshold exceedance probability above which flows are nonzero (p_{nz}) can be derived ($1 - p_{\mathrm{dry}}$). The second component involves a procedure to estimate a FDC for nonzero flows ($\mathrm{FDC}_{\mathrm{nz}}$). As p_{dry} and $\mathrm{FDC}_{\mathrm{nz}}$ are each scaled from zero to one in the first two steps, the final step combines and rescales the derived distributions over a common probability interval [0,1].

Data from gauged watersheds in Portugal were used by Croker *et al.* (2003) to develop a regional regression model to estimate p_{dry} in ungauged watersheds from mean annual rainfall (MAR). These authors then used all nonzero flows in the period-of-record to construct the $\mathrm{FDC}_{\mathrm{nz}}$ for each gauged watershed. Flow duration statistics were standardized by the mean flow of nonzero days ($\mathrm{MF}_{\mathrm{nz}}$) as standardized statistics have a strong relationship with hydrogeology and tend to minimize the influence of watershed area (Croker *et al.*, 2003). Each standardized $\mathrm{FDC}_{\mathrm{nz}}$ was transformed so that the exceedance interval $[0,p_{\mathrm{nz}}]$ was rescaled to [0,1]. The standardized and rescaled FDCs for nonzero flows ($\mathrm{SFDC}_{\mathrm{nz}}$) in gauged watersheds were grouped into 1 of 12 equally spaced flow classes. The class divisions were based on the flow equalled or exceeded 80% of the time in the $\mathrm{SFDC}_{\mathrm{nz}}$ ($\mathrm{SQ80}_{\mathrm{nz}}$). An average curve was derived for each class, which Croker *et al.* (2003) referred to as nonzero flow duration type curves. These average curves were used as the $\mathrm{SFDC}_{\mathrm{nz}}$ in ungauged watersheds with the selection of the appropriate curve being based on the predicted value of $\mathrm{SQ80}_{\mathrm{nz}}$ for a specified watershed.

To obtain $\mathrm{SQ80}_{\mathrm{nz}}$ in ungauged watersheds, Croker *et al.* (2003) developed a regional regression model that included base-flow index (BFI) and MAR as independent variables. A separate multivariate regression model was used to derive BFI from the fractional extent of different soil groups (Croker *et al.*, 2003). The regional regression model for $\mathrm{SQ80}_{\mathrm{nz}}$ explained 63% of the variance in the observed values but no validation results are provided by Croker *et al.* (2003) for independent watersheds.

As p_{nz} and the $\mathrm{SFDC}_{\mathrm{nz}}$ each have exceedance probability intervals of [0,1], the final step in the Croker *et al.* (2003) method was to rescale the distributions over a common probability interval [0,1]. They applied the theory of total probability so that:

$$p(i)_t = p(i)_{\mathrm{nz}} p_{\mathrm{nz}}, \tag{1}$$

where $p(i)_t$ is the transformed exceedance probability over the interval [0,1] and $p(i)_{\mathrm{nz}}$ is the exceedance probability of a specific nonzero flow (i).

RESEARCH OBJECTIVES

Regionalization approaches for predicting FDCs in central and southern California watersheds need to accommodate discontinuities in the flow regimes which characterize many rivers in this region. Consequently, the Croker *et al.* (2003) approach was considered to be a potentially suitable FDC regionalization procedure for central and southern California. Successful implementation of this approach requires the prediction of two key FDC metrics, namely, p_{dry}

and $SQ80_{nz}$. An additional FDC metric used in this approach, MF_{nz}, also needs to be predicted in ungauged watersheds if the actual flows (not standardized by MF_{nz}) are to be calculated from the synthetic FDC. The goal of this study was to develop and test regional regression equations to predict p_{dry}, $SQ80_{nz}$, and MF_{nz} in central and southern California to ascertain whether the Croker *et al.* (2003) approach would be suitable for this region.

Two methodological objectives were included in the design of the experiment. The first methodological objective addressed potential uncertainties in the approach used by Croker *et al.* (2003) to derive empirical FDCs in gauged watersheds. The traditional "period-of-record" FDCs used by Croker *et al.* (2003) are sensitive to extreme values in the data record, particularly the lower tail of the FDC (Vogel and Fennessey, 1994). The use of annual FDCs to derive a median annual FDC has been proposed as a method to reduce this uncertainty (Vogel and Fennessey, 1994). An annual FDC is constructed for each year of record and the median flow at each exceedance percentage is used to derive the median FDC to represent the typical frequency and magnitude of daily river flow. Consequently, the study investigated whether there would be differences in the uncertainty associated with regional regression equations to predict p_{dry} and $SQ80_{nz}$ when these metrics were derived from the median annual FDC approach and the period-of-record approach.

Croker *et al.* (2003) used a single variable (MAR) to predict p_{dry} and two variables (BFI, MAR) to predict $SQ80_{nz}$. The second methodological objective in the California study was to test a more comprehensive set of watershed descriptors (independent variables) in regional models to predict the required FDC metrics. Variables were selected to represent watershed soils, climate, and physiography as well as remotely sensed measures of vegetation cover.

APPROACH

Watershed Selection

The northern extent of the central and southern California region was taken as latitude 39°N and the United States (U.S.)-Mexico border was the southern extent. River flow data for this region were obtained from the surface water daily dataset of the U.S. Geological Survey (USGS) (National Water Information System, http://waterdata.usgs.gov/nwis). All gauged rivers in this region with watershed areas between 50 and 1,000 km^2 were identified as potential candidates for the study. Larger watersheds were excluded in this proof-of-concept study since they are more prone to having dams, development, and water abstractions than smaller watersheds. A set of elimination criteria were applied to identify the final set of study watersheds and to minimize uncertainties in the derivation of FDC indices. Watersheds were required to have a minimum of 10 years of high quality daily river flow record. In a FDC regionalization study in Italy, Castellarin *et al.* (2007) concluded that five years of observed river flow data was sufficient to obtain consistent estimates of the long-term FDC. Data quality was determined using the USGS quality rating and our examination of the flow records. Watersheds with impoundments (e.g., dams) or water diversions documented by the USGS in the surface water daily dataset were excluded. Watershed boundaries were projected onto 1:100,000 toposheets and Google Earth for visual examination so that other dams, and impoundments not documented by the USGS could be identified. This procedure was also used to help identify and exclude watersheds with significant urbanization or agriculture (>5% of watershed area).

To be consistent with the analysis of Croker *et al.* (2003), watersheds that had persistent snow cover in the winter months were identified using Moderate Resolution Imaging Spectrometer (MODIS) satellite imagery and excluded from the dataset. From the original pool of over 200 candidate watersheds, 41 were selected for the study. The area of these watersheds ranged from 52 to 632 km^2 and the mean annual streamflow from 316 to 1,318 mm. The time at which river flow ceased varied widely from watershed to watershed between late spring and early fall. The average number of zero flow days for all watersheds was 25.1% and ranged from 0% to a maximum of 72.9%. A random sample of 8 watersheds was removed for model validation, leaving 33 for model development. The watersheds used for model development and validation are indicated in Figure 1.

Watershed Variables

Daily river flow data were used to construct period-of-record and median annual FDCs for each watershed and to calculate MF_{nz}. These FDCs were used to derive values of p_{dry} and $SQ80_{nz}$. For all analyses, river flows <1% of the daily average flow were assumed to be zero because of uncertainties in low-flow measurements (Best *et al.*, 2003). The corresponding flow rates for this threshold ranged between 0.0004 and 0.053 m^3/s depending on the watershed area and rainfall characteristics.

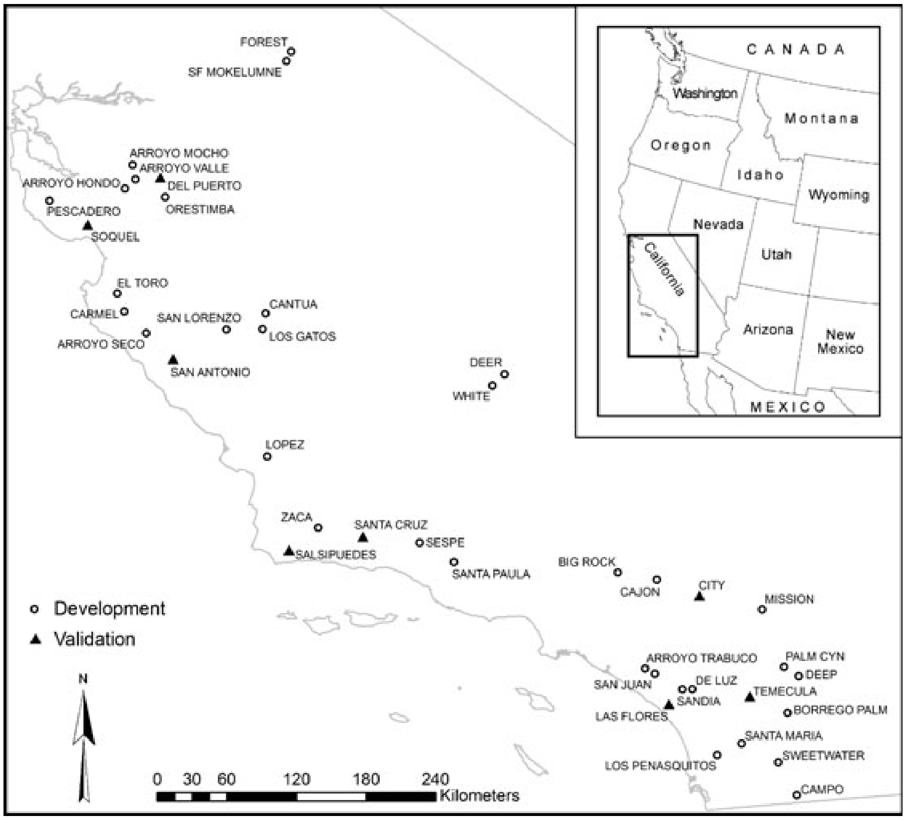

FIGURE 1. Location of Watersheds Used for Model Development and Model Validation.

Watershed characteristics used as predictor variables in regression models for p_{dry}, $SQ80_{nz}$, and MF_{nz} are summarized in Table 1. Vegetation descriptors were based on MODIS satellite data from the Terra satellite launched in 1999 by the U.S. National Aeronautics and Space Administration (NASA). MODIS vegetation indices have been shown to relate to watershed actual evapotranspiration in southern California (Fitch *et al.*, 2010) and these data are readily available for hydrologic predictions in ungauged watersheds. MODIS data are converted on a systematic basis into derived terrestrial products, including indices that quantify vegetation cover (Justice *et al.*, 2002). These products are archived and distributed by the USGS Land Processes (LP) Distributed Active Archive Center (DAAC) at the Earth Resources Observation and Science (EROS) Data Center. Three MODIS vegetation products were used in this study, two spectral vegetation indices and Leaf Area Index (LAI). The two spectral vegetation indices were the Normalized Difference Vegetation Index (NDVI) described by Tucker (1979) and the Enhanced Vegetation Index (EVI) described by Huete *et al.* (2002). Both indices are based on near infrared to red reflectance ratios and the EVI also includes blue reflectance and weights to correct for different atmospheric aerosol concentrations (Huete *et al.*, 2002). LAI is estimated by inversion of a radiative transfer model which uses MODIS spectral reflectance data (Myneni *et al.*, 2002).

TABLE 1. Watershed Characteristics Used as Potential Independent Variables in Regression Models to Predict p_{dry}, $SQ80_{nz}$, and MF_{nz}.

Symbol	Variable Description	Units
MODIS vegetation indices		
LAI	Leaf Area Index	-
NDVI	Normalized Difference Vegetation Index	-
EVI	Enhanced Vegetation Index	-
Geomorphology		
AREA	Drainage area	km^2
ELEV	Mean elevation	m
SLP	Mean slope	%
MCL	Main channel length	km
DD	Drainage density	km/km^2
Soils and lithology		
SDP	Soil depth	m
SP	Soil porosity	%
SED	Percent sedimentary rock	%
Climatology and hydrology		
MAR	Mean annual rainfall	mm
SDAR	Standard deviation of annual rainfall	mm
ADXT	Average daily maximum temperature	°C
ADMT	Average daily mean temperature	°C
BFI	Base-flow index	-

Note: MODIS, Moderate Resolution Imaging Spectrometer.

The NDVI, EVI, and LAI products were obtained from the EROS Data Center DAAC for the five-year period from October 2000 through September 2005. The data have a ground resolution of 1 km and values are provided at 16-day intervals for NDVI and EVI and every 8 days for LAI. Average NDVI, EVI, and LAI values were calculated for each watershed over the five-year period.

Digital elevation model data (30 m) were obtained from the USGS (http://seamless.usgs.gov/) and used to calculate the geomorphologic variables listed in Table 1. Average soil depth and soil porosity of the top 100 cm for each watershed were derived from a geospatial dataset of soil properties for the conterminous U.S. compiled by the Pennsylvania State University, Earth System Science Center (http://www.soilinfo.psu.edu) (Miller and White, 1998). Watershed boundaries were intersected with a California Department of Conservation digital geology map (http://www.consrv.ca.gov/CGS/information/publications/pub_index/Pages/gis_data.aspx) and used to calculate the fraction of each watershed underlain by sedimentary rocks.

Annual rainfall totals were derived from gridded monthly rainfall data (4 km spatial resolution) produced by the Precipitation-Elevation Regressions on Independent Slopes Model (PRISM) project (http://www.prismclimate.org). This dataset was generated by interpolating rain gauge data and adjusting estimates for elevation using an expert system and statistical methods (Daly *et al.*, 2002). Values for each watershed were calculated as the average of all grid cells within the watershed boundary (weighted by the fractional area of a cell inside the watershed boundary). Gridded maximum and minimum daily air temperature at 0.5° resolution were obtained from the U.S. National Center for Environmental Prediction, Climate Prediction Center (ftp://ftp.cpc.ncep.noaa.gov/precip/daily_grids/). Average daily mean and average daily maximum temperatures were calculated for each watershed.

Base-flow index is defined as the volume of base flow divided by the volume of total river flow (Wolock, 2003). The USGS has developed a 1 km resolution raster BFI dataset for the conterminous U.S. (http://water.usgs.gov/lookup/getspatial?bfi48grd). This USGS product was produced by interpolating BFI values from river flow data collected at 8,249 river gauges and is described by Wolock (2003). Separation of base flow from total flow and the calculation of BFI followed the UK Institute of Hydrology (1980) method.

Regression Models

The development of multiple regression models may have two distinct purposes, to produce the single "best" model for prediction or to infer causal influences of selected independent variables on the dependent variable (Mac Nally, 2000). While the stepwise regression technique is often used to identify predictive models, Mac Nally (2000) states that it is widely regarded as a highly flawed approach that is likely to yield spurious results. This view was echoed by Keith (2006) who concluded that the technique frequently does not choose the best model predictors and is prone to producing inflated coefficient of determination values which contribute to poor model performance in validation.

Given current computer power, it is now generally feasible to conduct an exhaustive search of all possible independent variable combinations ("all-models") to identify the best model (Mac Nally, 2000). Model selection criteria need to be defined to provide a compromise between model "fit" and model "complexity" (Mac Nally, 2000). Model fit is usually evaluated by an objective function based on the residual sum of squares while model complexity is indicated by the number of model terms.

The all-models approach was adopted in this study to identify the best predictive models for p_{dry}, $\mathrm{SQ80_{nz}}$, and $\mathrm{MF_{nz}}$. Untransformed and log-transformed variables were used in the exhaustive search to allow for linear and nonlinear relationships between dependent and independent variables as well as additive and multiplicative model structures (Berger, 2004). Considering the sample size for model development ($n = 33$), models were limited to five terms and the best model representing each of the five levels of model complexity (one to five terms) was identified. A two-step strategy was implemented to select the best model for each level of complexity. The first step screened all models for multicollinearity and the remaining models were then ranked according to their adjusted coefficient of determination (R^2) to identify the best model.

The degree of multicollinearity was quantified in step 1 using the condition index (CI) which is given by:

$$\mathrm{CI} = \sqrt{\lambda_{\max}/\lambda_{\min}}, \tag{2}$$

where for a given set of independent variables, λ are the eigenvalues of the rescaled crossproduct X′X matrix (Belsley *et al.*, 1980). The index value increases with increasing collinearity and since the index is considered situational, only rules of thumb exist to reject models. Belsley *et al.* (1980) suggest that weak dependencies are associated with CI values around 5 or 10 and strong relations are associated with values above 30. Following the approach of Greene (1997), models with CI >20 were rejected. Independent validation of the regression models used data from the eight randomly selected watersheds not included in model development. To be consistent with the approach used by Croker *et al.* (2003), predictive error was quantified using the "bias" and is defined as the differences between observed and predicted values expressed as a percentage of the observed value.

RESULTS AND DISCUSSION

Values for $SQ80_{nz}$ and p_{dry} were determined for each watershed using the period-of-record and median annual FDC approaches. Relationships between the period-of-record and median annual $SQ80_{nz}$ and p_{dry} values are illustrated in Figure 2. Some systematic differences were observed when p_{dry} was <40% (Figure 2a). Though overall, the two FDC methodologies yielded similar values of $SQ80_{nz}$ and p_{dry}, with most points in the scatter plots being close to the 1:1 line (Figure 2).

Variables that entered the five regression models to predict $SQ80_{nz}$ along with their adjusted R^2 and CI values are summarized in Table 2. Corresponding validation results for these equations are given in Table 3. Models to predict $SQ80_{nz}$ were generally poor with all adjusted R^2 values being <0.466 regardless of the FDC method used to estimate $SQ80_{nz}$ (Table 2). Variables selected for the two sets of $SQ80_{nz}$ models (models 1-5 for the two FDC methodologies) were the same, an outcome that could be expected given that the $SQ80_{nz}$ values were similar. BFI was the only watershed variable to be included in all five models. This variable along with MAR was also used by Croker *et al.* (2003) to estimate $SQ80_{nz}$ in Portugal. In contrast to the models developed for central and southern California, the model for Portugal explained most of the variance in $SQ80_{nz}$ ($R^2 = 0.63$). However, Croker *et al.* (2003) indicated that prediction errors were particularly large in southern Portugal where MAR was <800 mm and observed flow volumes were smaller than those in the northern, wetter watersheds. These are conditions that are more typical of our study region.

Given that most of the variance in observed $SQ80_{nz}$ could not be explained by the regression models (adjusted $R^2 < 0.5$), large predictive errors (bias) were anticipated in the validation watersheds and confirmed by the results summarized in Table 3. Although these biases were large, Croker *et al.* (2003) point out that they translate into small absolute errors in flow volumes in dry watersheds. The validation results obtained for $SQ80_{nz}$ in California need to be evaluated in light of the results reported by Croker *et al.* (2003) for Portugal. These authors reported bias values >75% in 11 out of the 67 test watersheds, with some values close to 300%. Most of these watersheds were in the southern half of the study area. It should be noted that Croker *et al.* (2003) did not test their model for $SQ80_{nz}$ using an independent set of validation watersheds to evaluate predictive errors. As most of the bias values in the California validation watersheds were <75% (Table 3), it was concluded that the regression models were no less reliable predictors of standardized $SQ80_{nz}$ than the model proposed by Croker *et al.* (2003) for Portugal.

In most validation watersheds, the single variable models (model 1) were the best predictors for period-of-record and median annual standardized $SQ80_{nz}$ (Table 3). Model validation errors were generally smaller for predicting the $SQ80_{nz}$ from the period-of-record than from the median annual FDC which

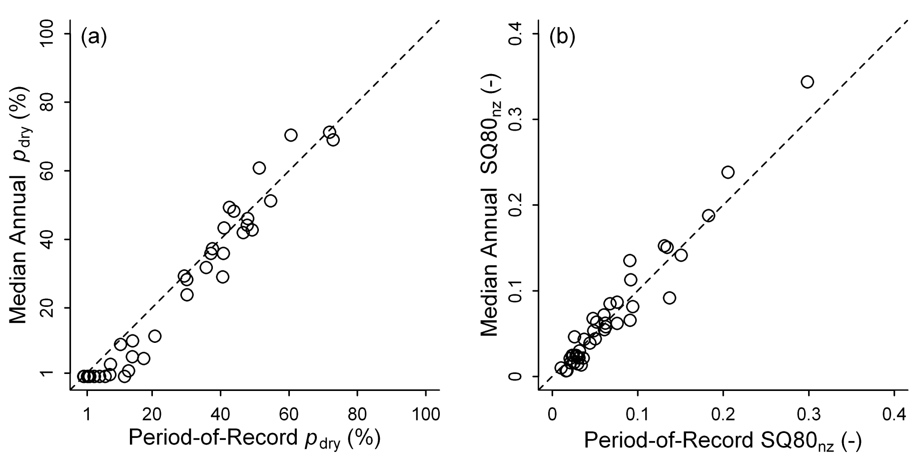

FIGURE 2. Relationship Between the Period-of-Record and Median Annual Flow Duration Curve (FDC) Flow Metrics (a) p_{dry} and (b) $SQ80_{nz}$. The broken line indicates perfect agreement.

TABLE 2. Independent Variables Selected for the Five Models to Predict $SQ80_{nz}$ Based on Period-of-Record and Median Annual FDCs, Along With the Adjusted R^2 and CI Values for Each Model.

Model	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Adjusted R^2	CI
Period-of-record FDC							
1	BFI					0.238	-
2	BFI	L-AREA				0.335	17.7
3	BFI	L-AREA	L-SED			0.433	19.0
4	BFI	MCL	L-SED	DD		0.466	14.1
5	BFI	MCL	L-SED	DD	SP	0.459	15.6
Median annual FDC							
1	BFI					0.211	-
2	BFI	L-AREA				0.340	17.7
3	BFI	L-AREA	L-SED			0.437	19.0
4	BFI	MCL	L-SED	DD		0.444	14.1
5	BFI	MCL	L-SED	DD	SP	0.436	15.6

Notes: L, log-transformed variables; FDC, flow duration curve; BFI, base-flow index; AREA, drainage area; SED, percent sedimentary rock; MCL, main channel length; DD, drainage density; SP, soil porosity.

TABLE 3. Model Bias Values (%) for Predicting $SQ80_{nz}$ in the Validation Watersheds Along With Their Observed $SQ80_{nz}$ Values.

Watershed	$SQ80_{nz}$ (–)	Model 1	Model 2	Model 3	Model 4	Model 5
Period-of-record FDC						
City Creek	0.091	−41.4	−5.0	−10.8	−31.9	−36.5
Del Puerto Creek	0.052	−6.2	−16.4	−8.6	22.1	27.0
Las Flores Creek	0.017	57.1	203.8	207.3	159.7	212.3
Salsipuedes Creek	0.044	11.7	29.5	50.5	81.7	92.2
San Antonio River	0.063	−11.1	−72.0	−70.1	−66.1	−61.7
Santa Cruz Creek	0.049	−41.6	−51.8	−57.3	−42.5	−27.8
Soquel Creek	0.062	11.4	30.5	60.6	53.0	69.3
Temecula Creek	0.076	−23.1	−53.7	−77.3	−58.3	−68.1
Median annual FDC						
City Creek	0.065	−17.2	49.1	39.7	5.7	−1.7
Del Puerto Creek	0.063	−22.2	−33.2	−25.8	3.6	8.2
Las Flores Creek	0.007	268.4	747.2	757.2	613.2	763.0
Salsipuedes Creek	0.039	28.4	54.7	82.2	122.3	135.9
San Antonio River	0.058	−1.7	−87.9	−85.6	−75.1	−69.7
Santa Cruz Creek	0.053	−49.8	−61.9	−67.7	−51.2	−36.0
Soquel Creek	0.062	15.3	40.2	74.9	65.7	84.3
Temecula Creek	0.062	−3.6	−52.5	−85.9	−53.6	−67.2

Note: FDC, flow duration curve.

was contrary to what was expected initially given potential uncertainties in the period-of-record FDC discussed previously.

Results of the p_{dry} regression models were worse than those for $SQ80_{nz}$ and are summarized in Table 4. The maximum adjusted R^2 was 0.313 for models to predict p_{dry} based on the period-of-record FDC approach and 0.269 based on the median annual FDC approach. The single variable models included MAR as the independent variable, the same variable used by Croker *et al.* (2003) to predict p_{dry} in Portugal. As most of the MAR values in our study region were <1,000 mm, these small adjusted R^2 values may be a product of the smaller range of rainfall in California compared to Portugal. It is also unclear how the zero flow threshold of 1% of daily average flow may have affected the prediction of p_{dry}.

The higher order models in Table 4 include LAI in place of MAR. Since LAI is an average value over five years of MODIS data and the watersheds are largely undisturbed, the mean LAI was probably a partial surrogate for MAR and possibly included a degree of vegetation control over river flows. Regression of LAI on MAR confirms the strong relationship between these two variables ($R^2 = 0.707$).

Validation errors for p_{dry} based on the period-of-record and median annual FDC approaches were large, confirming the inadequacy of these models for use in ungauged watersheds (Table 5). Bias values for p_{dry} using the period-of-record FDC ranged from 18.1 to 470.9% and from 25.7 to 331.8% with the

TABLE 4. Independent Variables Selected for the Five Models to Predict p_{dry} Based on Period-of-Record and Median Annual FDCs, Along With the Adjusted R^2 and CI Values for Each Model.

Model	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Adjusted R^2	CI
Period-of-record FDC							
1	L-MAR					0.277	-
2	LAI	SDAR				0.313	8.2
3	L-LAI	SDAR	L-AREA			0.304	19.6
4	L-LAI	SDAR	DD	MCL		0.290	15.3
5	L-LAI	SDAR	DD	MCL	BFI	0.272	16.9
Median annual FDC							
1	L-MAR					0.257	-
2	L-LAI	SDAR				0.269	8.1
3	L-LAI	SDAR	SDP			0.258	10.3
4	L-LAI	SDAR	SDP	DD		0.246	15.4
5	L-LAI	SDAR	SDP	MCL	AREA	0.228	13.5

Notes: L, log-transformed variables; FDC, flow duration curve; MAR, mean annual rainfall; LAI, Leaf Area Index; SDAR, standard deviation of annual rainfall; AREA, drainage area; BFI, base-flow index; MCL, main channel length; DD, drainage density; SDP, soil depth.

TABLE 5. Model Bias Values (%) for Predicting p_{dry} in the Validation Watersheds Along With the Observed p_{dry} Values.

Watershed	p_{dry} (%)	Model 1	Model 2	Model 3	Model 4	Model 5
Period-of-record FDC						
City Creek	3.1	320.0	226.1	38.9	18.1	111.4
Del Puerto Creek	47.9	−29.2	−22.0	−22.2	−24.0	−23.4
Las Flores Creek	51.3	−21.7	−28.2	−34.4	−31.6	−27.5
Salsipuedes Creek	14.3	94.1	56.5	37.6	18.5	27.8
San Antonio River	46.7	−49.7	−45.9	−39.2	−40.1	−38.5
Santa Cruz Creek	37.2	−64.7	−87.3	−89.1	−103.2	−91.5
Soquel Creek	3.0	−19.3	−408.8	−309.4	−405.8	−340.8
Temecula Creek	6.3	364.6	411.4	470.9	450.5	460.8
Median annual FDC						
City Creek	0.0	10.0*	6.6*	9.4*	8.8*	6.8*
Del Puerto Creek	46.0	−32.0	−28.2	−25.9	−25.9	−25.7
Las Flores Creek	60.8	−38.0	−44.7	−52.6	−53.0	−55.8
Salsipuedes Creek	5.8	331.8	197.5	204.4	171.3	173.4
San Antonio River	41.9	−51.0	−51.6	−55.1	−53.8	−63.3
Santa Cruz Creek	35.9	−72.3	−96.1	−90.1	−100.6	−88.1
Soquel Creek	0.0	−1.1*	−7.8*	−8.5*	−11.1*	−9.0*
Temecula Creek	0.0	26.5*	30.8*	31.6*	32.4*	29.6*

Notes: FDC, flow duration curve. Asterisks indicate actual predicted values of p_{dry} (%) and are given in watersheds where the observed values were zero.

median annual FDC. As observed p_{dry} based on the median annual FDC was zero in three watersheds, the bias could not be calculated (division by zero). The actual p_{dry} values predicted by the models are given in place of bias in Table 5. Large differences between estimated p_{dry} and observed values (zero) were consistent with the poor results obtained in the other validation watersheds (Table 5).

The development of regression models to predict MF_{nz} using watershed descriptors was more promising. The adjusted R^2 values for the five regression models ranged between 0.366 and 0.688 (Table 6). Watershed area (AREA) and MAR were expected to be important explanatory variables for the observed variability in MF_{nz}. Model 1 included AREA as the independent variable and it explained 36.6% of the variance in MF_{nz} (Table 6). The four remaining higher order models all included LAI. The validation results for MF_{nz} presented in Table 7 were less encouraging and revealed substantial predictive errors (large bias) in some test watersheds. No single model could be identified as preferable for use in this region; different models were superior in different validation watersheds. Representative examples of the observed and predicted FDCs for two of the validation watersheds, Temecula Creek and San Antonio River, are given in Figure 3. These examples illustrate how prediction errors may be large for both high and low flows.

Given the uncertainties in predicting key FDC components required for implementing the Croker

TABLE 6. Independent Variables Selected for the Five Models to Predict MF_{nz} Along With the Adjusted R^2 and CI Values for Each Model.

Model	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Adjusted R^2	CI
1	AREA					0.366	-
2	AREA	L-LAI				0.479	3.3
3	AREA	L-LAI	MCL			0.617	9.9
4	AREA	L-LAI	MCL	DD		0.645	15.4
5	AREA	L-LAI	MCL	DD	SP	0.688	17.4

Notes: AREA, drainage area; L, log-transformed variables; LAI, Leaf Area Index; MCL, main channel length; DD, drainage density; SP, soil porosity.

TABLE 7. Model Bias Values (%) for Predicting MF_{nz} in the Validation Watersheds Along With the Observed MF_{nz} Values.

Watershed	MF_{nz} (m^3/s)	Model 1	Model 2	Model 3	Model 4	Model 5
City Creek	0.404	−37.4	29.5	141.4	144.9	217.6
Del Puerto Creek	0.435	98.7	63.2	60.3	43.2	9.2
Las Flores Creek	0.164	103.2	−37.7	80.0	95.4	−171.1
Salsipuedes Creek	0.474	19.0	81.1	134.3	96.8	76.7
San Antonio River	5.870	−57.0	−56.6	−50.1	−47.1	−50.7
Santa Cruz Creek	1.168	−25.0	5.5	3.5	−20.1	−28.8
Soquel Creek	1.275	−62.1	10.4	18.3	3.7	−8.7
Temecula Creek	0.280	447.6	297.0	391.8	445.2	509.8

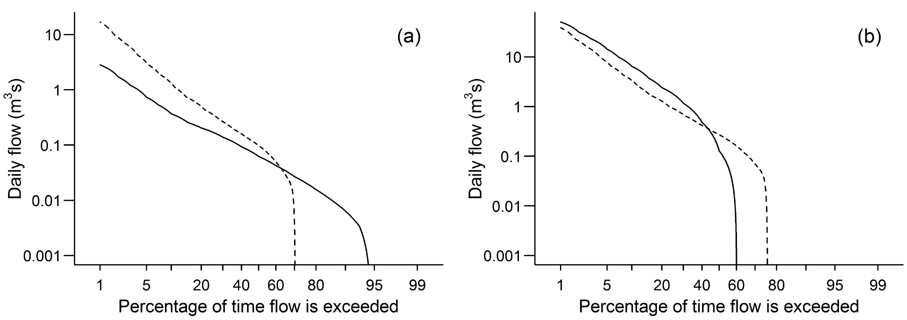

FIGURE 3. Observed (solid line) and Estimated (broken line) Flow Duration Curves (FDCs) for (a) Temecula Creek and (b) San Antonio River.

et al. (2003) regionalization approach in central and southern California, results of this study indicated that the approach is likely to lead to significant uncertainty in the prediction of FDCs. The apparently better results reported by Croker *et al.* (2003) may be attributed to differences in the characteristics of watersheds used in each study. While watersheds selected for our study were generally smaller than those used by Croker *et al.* (2003), the most significant difference between the two regions may have been the greater aridity (smaller MAR and river flow) of the California sample. Watersheds used by Croker *et al.* (2003) had MAR ranging from 500 to 2,000 mm but almost half of our watersheds had MAR <500 mm, with only four having MAR >1,000 mm (maximum = 1,318 mm).

As stated earlier, hydrologic predictions in semiarid environments are challenging due to the acute nonlinearities in hydrologic processes. Low-flow predictions may be expected to be particularly prone to these uncertainties. Two of the three FDC metrics required for the Croker *et al.* (2003) regionalization approach are low-flow metrics ($SQ80_{nz}$ and p_{dry}). Following this reasoning, the prediction of high and intermediate magnitude FDC quantities may be expected to be more successful than these low-flow quantities. When the model development experiment was repeated for two additional metrics representing intermediate ($SQ50_{nz}$) and high flows ($SQ20_{nz}$), the results supported this argument. The best adjusted R^2 values for $SQ50_{nz}$ and $SQ20_{nz}$ were 0.657 and 0.808 respectively, compared to 0.466 for $SQ80_{nz}$. Consequently, a regionalization approach based on individual regression equations for selected exceedance percentages may be considered in future research (e.g., Yu and Yang, 2000; Mohamoud, 2008), though it is likely that such an approach would also be prone to large predictive uncertainties in low-flow metrics.

CONCLUSIONS

The regression models developed in this study to predict $SQ80_{nz}$, p_{dry}, and MF_{nz} were associated with large predictive uncertainty. They are not suitable for implementing the Croker *et al.* (2003) theory of total probability approach for FDC estimation in central and southern California. Although more watershed variables were tested in the California regression models than those used by Croker *et al.* (2003) in Portugal, the regression results were poor in both the development and validation phases of the study. Use of the median annual FDC did not present an advantage over the period-of-record approach. Extreme wet or dry periods in the period-of-record did not appear to have a critical effect on the magnitude of $SQ80_{nz}$ and p_{dry}.

The poor performance of the Croker *et al.* (2003) approach in California compared to the more promising results in Portugal may be a consequence of the more arid conditions typical of watersheds in central and southern California. Despite the large number of variables used to characterize watersheds, it was not possible to identify controls over the number of zero flow days in the California watersheds. Understanding these controls and formulating equations to predict low-flow metrics may be one of the most critical challenges in establishing a regionalization procedure for FDCs in this region. Furthermore, future studies may examine mathematical models to describe the FDCs with regression equations based on watershed morphological and/or climatic variables to predict the parameters of these models (Best *et al.*, 2003; Niadas, 2005).

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