Relating low-flow characteristics to the base flow recession time constant at partial record stream gauges

Ken Eng[1] and P. C. D. Milly[2]

Received 27 June 2006; revised 18 September 2006; accepted 10 October 2006; published 5 January 2007.

[1] Base flow recession information is helpful for regional estimation of low-flow characteristics. However, analyses that exploit such information generally require a continuous record of streamflow at the estimation site to characterize base flow recession. Here we propose a simple method for characterizing base flow recession at low-flow partial record stream gauges (i.e., sites with very few streamflow measurements under low-streamflow conditions), and we use that characterization as the basis for a practical new approach to low-flow regression. In a case study the introduction of a base flow recession time constant, estimated from a single pair of strategically timed streamflow measurements, approximately halves the root-mean-square estimation error relative to that of a conventional drainage area regression. Additional streamflow measurements can be used to reduce the error further.

Citation: Eng, K., and P. C. D. Milly (2007), Relating low-flow characteristics to the base flow recession time constant at partial record stream gauges, *Water Resour. Res.*, *43*, W01201, doi:10.1029/2006WR005293.

1. Introduction

[2] Periods of low streamflow are a challenge to water managers, who must balance competing demands for water. Low flows also are associated with low dissolved oxygen and/or high contaminant concentrations, with negative consequences for aquatic habitat. For these reasons, state and local municipalities establish regulatory limits on the basis of estimated low-flow characteristics, such as the estimated 7-day, 10-year low flow, $\hat{Q}_{7,10}$ [*Riggs*, 1980]. The $\hat{Q}_{7,10}$ is defined as the estimated annual minimum 7-day average flow that is expected to be exceeded on average in 9 out of 10 years and, equivalently, as the 10th percentile of the distribution of annual minimum 7-day average streamflows. The $\hat{Q}_{7,10}$ commonly is used as an indicator of drought conditions and as an indirect regulatory control on water quality and aquatic habitat in the United States.

[3] Low-flow characteristics determined at continuously observed streamflow-gauging stations (henceforth referred to either as continuous gauges or simply as gauges) can be used to define regional regression models that use basin attributes, such as drainage area, as predictors [e.g., *Thomas and Benson*, 1970; *Bingham*, 1986]. These models then can be used to estimate low-flow characteristics at locations without continuous gauges. Table 1 summarizes the types of basin attributes that have been used in a representative sample of recent studies, and it identifies basin attributes found to be statistically significant in those studies. The definitions of the performance metrics are not readily generalized across these studies, so they are not presented in Table 1.

[4] The only statistically significant predictor of low-flow characteristics common to all studies in Table 1 is basin area. The other predictors are significant in some studies and not in others. In some cases these differences across studies might be explained by correlations among the predictors used, with one predictor serving as a surrogate for another. In other cases, the differences across studies might reflect regional differences in sensitivity to, or variability of, the predictors.

[5] In studies where base flow recession and/or streamflow variability have been used to define predictors, one of the two generally is statistically significant (Table 1). Although *Giese and Mason* [1993] did not find either of these to be significant within their "low-flow hydrologic areas," the definitions of those areas themselves presumably reflected spatial variations of such predictors. Streamflow variability can be characterized by the streamflow variability index (standard deviation of the logarithm of daily flows) [*Lane and Lei*, 1950]. Base flow recession can be characterized either by ratios of flows on successive days [*Vogel and Kroll*, 1992] or by the characteristic time constant of decay of the base flow rate [*Brutsaert and Lopez*, 1998]. The rate of base flow recession is closely related to the streamflow variability index; rapid base flow recession implies a wide range of flow values.

[6] In applications to date (Table 1) [see also *Brutsaert and Nieber*, 1977], both the streamflow variability index and the measures of base flow recession have been estimated from continuous streamflow records. This prevents their use as predictors of low-flow characteristics at sites without continuous streamflow records. Because continuous streamflow measurements are expensive, it is desirable to develop similar methods that would require only sporadic streamflow measurements; this would enable low-flow estimation at low-flow "partial record" gauges (henceforth referred to as partial record gauges). Our objectives here are (1) to propose a

[1]U.S. Geological Survey, Reston, Virginia, USA.
[2]U.S. Geological Survey and Geophysical Fluid Dynamics Laboratory, NOAA, Princeton, New Jersey, USA.

Table 1. Types of Basin Attributes Examined in Previous Low-Flow Regression Studies[a]

Study	Region	Types of Basin Attributes: Area A	Slope S	Basin Shape Sp	Location Ln	Elevation Z	Precipitation P	Temperature T	Surface Water Storage St	Snow Cover Sn	Forest Cover F	Soil Sl	Flow Variability FV	Base Flow Recession BR	Average Flow Fl
Kroll et al. [2004]	Conterminous United States	S	S	S		S	S	S				S		S	
Flynn [2002]	New Hampshire and Vermont	S	ns	ns	ns	S	S	S	ns	ns	S	ns			
Yu et al. [2002]	Southern Taiwan	S	S						S			S		S	
Waltemeyer [2001]	New Mexico	S	ns		ns	ns	S								
Ries and Friesz [2000]	Massachusetts	S	S	ns		ns			ns			S			
Rifai et al. [2000]	Texas	S	S	ns			S					S			
Giese and Mason [1993][b]	North Carolina	S	ns	ns			ns	ns			ns	ns	ns	ns	S
Ludwig and Tasker [1993]	Arkansas	S										S			
Vogel and Kroll [1992]	Massachusetts	S	S											S	
Arihood and Glatfelter [1991]	Indiana	S	ns	ns			ns		ns		ns	S	S	ns	
Ruhl and Martin [1991]	Kentucky	S	ns	ns		ns	ns						S	ns	

[a]Because the exact definitions of predictors vary across studies, any column heading may indicate multiple definitions based on a common physical property. An entry in the table indicates that at least one predictor of the given type was tested in that study; S indicates a finding of statistical significance, and ns indicates no significance.

[b]In the case of *Giese and Mason* [1993], the analyses were performed on "low-flow hydrologic areas" that were based on visual correlations among low-flow characteristics, topography, mean annual precipitation, mean annual runoff, soil type, and yields of wells by rock type; here nonsignificance refers to variability within the low-flow hydrologic areas.

practical new method for estimation of the base flow recession time constant from a small number (two to eight) of streamflow measurements, and (2) to evaluate the ability of that time constant to predict $\hat{Q}_{7,10}$ at partial record gauges. The evaluation is based on synthetic partial records generated by use of data from 93 continuous gauges in the southeast United States. The proposed method requires at least two measurements during the same recession period; this currently is not common practice on partial record networks.

2. Exponential-Decay Model for Base Flow

[7] *Boussinesq* [1903] formulated the idealized problem of outflow from a horizontal, unconfined aquifer discharging into a fully penetrating stream. *Brutsaert and Nieber* [1977] showed that several available solutions of the Boussinesq problem follow the general power relation

$$\frac{dQ}{dt} = -aQ^b, \tag{1}$$

where Q [L^3T^{-1}] (where L and T are length and time, respectively) is streamflow, t [T] is time, and a [$L^{3(1-b)}$ T^{b-2}] and b (dimensionless) are constants. For application to the low-flow problem addressed herein, we shall focus on the large-time behavior, which generally is associated with a value of b equal to 1 [*Brutsaert and Lopez*, 1998; *Eng and Brutsaert*, 1999]. For the large-time solution, we can write

$$a = \frac{\pi^2 KpdL_s^2}{fA_d^2}, \tag{2}$$

and thus

$$Q_{t+\Delta t} = Q_t e^{-\Delta t/\tau}, \tag{3}$$

where Q_t is the streamflow at time t, and $Q_{t+\Delta t}$ is the streamflow at time $t + \Delta t$, τ [T] is the reciprocal of a, K [LT^{-1}] is the hydraulic conductivity, f (dimensionless) is the drainable porosity, d [L] is the aquifer thickness, L_s [L] is the upstream stream length, A_d [L^2] is the drainage area, and p (dimensionless) is approximately 0.3465 [*Brutsaert and Nieber*, 1977]. The parameter τ is a long-term aquifer time constant, which characterizes the rate of recession of base flow [*Brutsaert and Lopez*, 1998; *Eng and Brutsaert*, 1999] according to this Boussinesq conceptual model. Because (3) is based solely on consideration of the groundwater system, it can be used to describe streamflow only in the absence of substantial surface water storage, diversion, and return flows within the basin. Even relatively small alterations of streamflow can have relatively large impact on low-flow characteristics. Additionally, (3) neglects the contributions to streamflow from more rapid direct runoff processes shortly after storm events. Finally, (3) ignores direct evaporative losses from groundwater.

[8] In principle, one could use (2) to estimate $\tau = a^{-1}$. In practice, it is not possible to obtain sufficiently accurate estimates of the parameters in (2), and real basins, although they typically follow (3) quite closely, generally depart greatly from the conceptual model underlying (3). Instead of using (2), here we infer an effective value of τ from streamflow measurements by use of (3).

3. Basin Selection

[9] We chose the southeastern United States for this analysis. From the basins for which continuous streamflow records were available for the study, we chose those that we judged to have minimal streamflow alterations relative to natural conditions. Gauges for which more than 25% of the gauged basin area drains through a dam were excluded. Also excluded were basins that contain water or wastewater treatment plants, fish farms, strip mines, or artificial (lined) channels. All of the abovementioned exclusions were made on the basis of U. S. Geological Survey (USGS) 7.5-min series topographic maps and annual USGS Water Resources Data–Surface Water Data reports. In addition, an upper limit of 1,000 km^2 was set for basin drainage area.

[10] As noted in the Data section, some of the basins had $\hat{Q}_{7,10}$ values equal to zero. These basins were excluded to avoid the additional complexity of zero values (e.g., no generally accepted performance measure for regressions). In principle, prediction of zero values could be addressed by use of logistic regression [e.g., *Ludwig and Tasker*, 1993] or censored 'Tobit' regression [e.g., *Judge et al.*, 1985; *Kroll and Stedinger*, 1999].

[11] Presence of log linearity in the base flow recession process was not used as a criterion for basin selection. However, as described in the Data section, we did estimate and review values of the exponent b in (1) to assess the overall consistency of the data with the log linear assumption.

[12] The basin selection criteria resulted in a set of 109 continuously gauged basins, some of which had $\hat{Q}_{7,10}$ values equal to zero. Exclusion of the zero-value cases reduced the number of basins to 93 (Figure 1), and these were used in the remainder of the analysis. Drainage areas range in size from 4 to 829 km^2, with a median value of 177 km^2. The lengths of streamflow records range from 7 to 100 y, with a median value of 35 y.

4. Data

[13] Because $\hat{Q}_{7,10}$ was estimated by regression against drainage area and τ, the analysis required estimates of these three variables for each basin. Estimates of $\hat{Q}_{7,10}$ were derived from daily streamflow data obtained from the USGS National Water Information System (NWISWeb, http://nwis.waterdata.usgs.gov/usa/nwis/discharge), which also provides the drainage areas.

[14] For each gauge, the annual time series of minimum consecutive 7-day average streamflow was computed from the daily records. This time series was assumed to follow the log-Pearson Type III distribution [*Kroll and Vogel*, 2002; *Tasker*, 1987], with conditional probability adjustment to allow annual 7-day low flow values that equal zero [*U.S. Geological Survey*, 1969]. This adjustment was used at the 16 gauges for which at least one of the annual 7-day minimum flows was zero. At each of these 16 gauges, the resultant $\hat{Q}_{7,10}$ was zero. The 93 nonzero $\hat{Q}_{7,10}$ values ranged from 3×10^{-3} to 3.6 m^3/s (0.1 to 128 ft^3/s), with a median value of 1.4×10^{-1} m^3/s (5 ft^3/s).

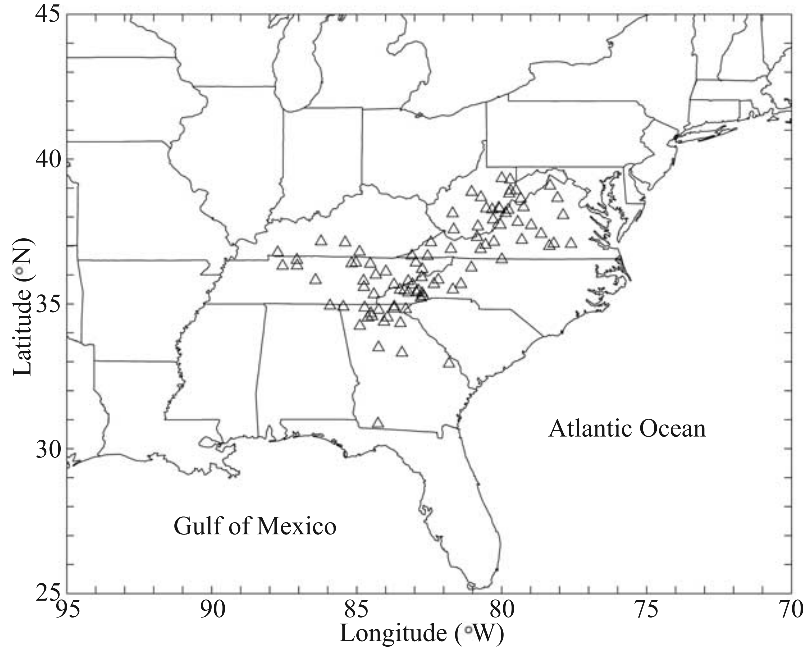

Figure 1. Southeastern United States. Triangles represent the 93 continuous gauges used in this study.

[15] From (3) we have

$$\tau = \frac{J\Delta t}{\ln Q_j - \ln Q_{j+J}}, \tag{4}$$

where Q_j is the daily streamflow on day j, Q_{j+J} is the streamflow on day $j + J$, J (dimensionless) is a positive integer representing the time difference in days between the two streamflow measurements, Δt [T] is the length of one day, and both streamflow values are on a single recession segment of the hydrograph. Use of (4) requires the identification of distinct recession segments.

[16] Recession segments were chosen only from the period from 1 April to 31 October, because low streamflow values generally occur at this time of year in the study region. This time period also avoids potential effects of seasonality in plant phenology, river ice, and soil freezing. To identify the recession segments, we first located all sequences of 8 or more daily streamflows that (1) starts with a peak daily streamflow that exceeds the median daily flow value and (2) ends with the first day j for which both Q_{j+1} and Q_{j+2} exceed Q_j. Single increases in daily flows, which can occur as a result of measurement error, especially under low-flow conditions, were allowed. The requirement for the peak to exceed the median flow was made to avoid inclusion of segments that followed only minor storm events. To avoid direct runoff contributions to streamflow and early time groundwater response [*Brutsaert and Lopez*, 1998; *Eng and Brutsaert*, 1999], the first five daily values were removed from the segments identified above. The number of resulting recession segments (three days or longer in duration) ranged across gauges from 124 to 1,417, with a median value of 718.

[17] To quantify the degree of agreement of the data with the log linear approximation used here (i.e., the assumption that $b = 1$), we determined the form of the characteristic recession behavior of each basin by fitting the logarithmic transform of (1) with organic correlation regression [*Helsel and Hirsch*, 1992] applied to all recession segments simultaneously. The line of organic correlation minimizes the sum of areas of right triangles formed by horizontal and vertical line segments extending from data points to the fitted line. Organic correlation provides a robust estimate of slope. The 93 values of b determined in this way ranged from 0.72 to 1.46 with a median value of 1.1.

[18] We used two strategies to obtain estimates of τ, and these correspond to the two partial record sampling strategies that are described in section 5. With either strategy, we calculated the estimate, $\hat{\tau}$, for each basin as the average of 400 values obtained from application of (4) to 400 randomly chosen recession segments for that basin. Sampling was performed with replacement, because not all gauges had 400 recession segments. With the first (the "random") strategy, the two days used for application of (4) within a given segment were chosen randomly with equal probability, with rejection of the choice if the two days were the same or were only one day apart. With the second (the "deterministic") strategy, we simply used the first and fourth days of the segment; if the segment had fewer than four days, it was discarded, and a new segment was chosen. In some cases, because of roundoff of reported daily streamflow values, the two streamflows chosen for application of (4) were equal; in such cases, the sample was rejected.

[19] The $\hat{\tau}$ values from the random strategy range from 5 days to 44 days, with a median value of 14 days. The 400 values whose average is $\hat{\tau}$ have a coefficient of variation that ranges, across basins, from 0.1 to 0.5, with a median value of 0.3. Not surprisingly, systematic differences in segment sampling strategy (i.e., random versus deterministic), in conjunction with an imperfect model, lead to systematic differences in estimates $\hat{\tau}$ (Figure 2). However, results from the two strategies are well correlated. Herein we present results obtained with both

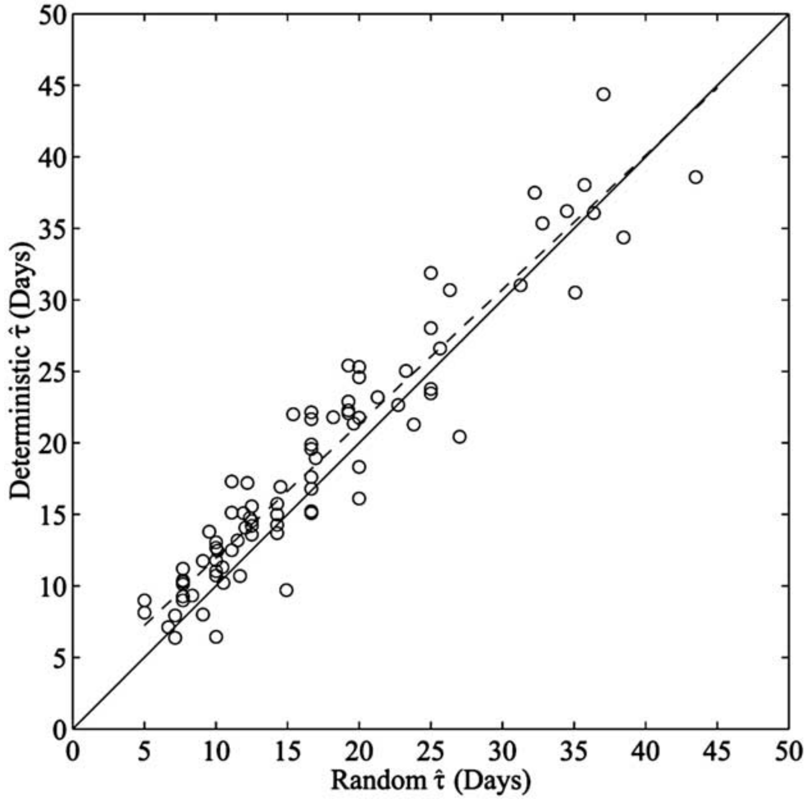

Figure 2. Comparison of long-term aquifer time constant, $\hat{\tau}$, calculated from random and deterministic sampling strategies. The dashed line is the best fit line (R^2 = 0.90), and the solid line is the 1:1 line.

strategies. The $\hat{\tau}$ values were found to follow a lognormal distribution, as illustrated for the random strategy in Figure 3.

5. Regional Regression Models of Low-Flow Characteristics

[20] On the basis of the literature review in the Introduction, we focus here on A_d and τ as potential predictors of $\hat{Q}_{7,10}$. Thus we consider four forms of regression models,

$$\log\left(\hat{Q}_{7,10}\right) = \xi_0 + \varepsilon, \tag{5}$$

$$\log\left(\hat{Q}_{7,10}\right) = \xi_0 + \xi_{A_d} \log(A_d) + \varepsilon, \tag{6}$$

$$\log\left(\hat{Q}_{7,10}\right) = \xi_0 + \xi_{\hat{\tau}} \log(\hat{\tau}) + \varepsilon, \tag{7}$$

$$\log\left(\hat{Q}_{7,10}\right) = \xi_0 + \xi_{A_d} \log(A_d) + \xi_{\hat{\tau}} \log(\hat{\tau}) + \varepsilon, \tag{8}$$

where ξ_0, ξ_{A_d}, and $\xi_{\hat{\tau}}$ are constants, and ε is model error; the first of these four models is simply a constant model, which provides a baseline for comparison of estimation errors.

[21] We defined 93 versions of the model (5), each time holding back one gauge to simulate a prediction site and using the remaining 92 gauges to determine the constant parameter, which was then used as the predicted value for that site. Similarly, to apply (6), we performed 93 different linear regressions, each time holding back one gauge to simulate a prediction site and using the remaining 92 gauges to determine the two regression constants, which were then used together with drainage area to generate a prediction for each site.

[22] To apply (7) or (8), we performed 93 different regressions, in each case using one of the gauges to simulate a partial record gauge (i.e., a prediction site), and the remaining 92 gauges to determine the regression constants. For each of the 93 simulated partial record gauges, (7) or (8) was then applied 100 times to estimate $\log(\hat{Q}_{7,10})$. The 100 estimates of τ used in the predictions were calculated as averages of 1, 2, 3, or 4 of the 400 values whose average had been used earlier to determine $\hat{\tau}$. Any one of the 100 estimates in this approach is meant to simulate the practical situation in which anywhere from one to four pairs of streamflow measurements might be available at a partial record gauge.

[23] The root-mean-square error (RMSE) of estimation of $\hat{Q}_{7,10}$ is used to evaluate model performance. In percentage terms (*Aitchison and Brown* [1957], modified for use of common logarithms),

$$\mathrm{RMSE} = 100\left\{e^{\left[(\ln 10)^2 \sigma_\varepsilon^2\right]} - 1\right\}^{1/2}, \tag{9}$$

where σ_ε^2 is the mean squared error,

$$\sigma_\varepsilon^2 = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[\log\left(\hat{Q}_{7,10}\right)_j - \log\left(\hat{Q}_{7,10}\right)_{R,ij}\right]^2, \tag{10}$$

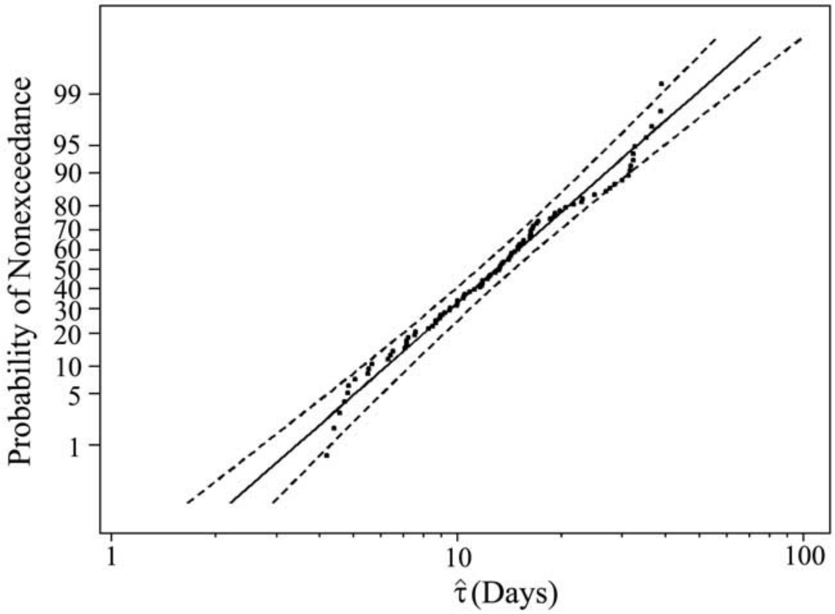

Figure 3. Lognormal (base 10) probability plot of the average long-term aquifer time constant, $\hat{\tau}$, at 93 continuous gauges. The $\hat{\tau}$ values are computed from the mean of the 400 individual τ values at each gauge using the random strategy. The solid line is the median, and the dashed lines are the 95% confidence intervals.

where $\log(\hat{Q}_{7,10})_{R,ij}$ is the estimate of $\log(\hat{Q}_{7,10})$ for sample i calculated from a regression model at site j, n (=1 in the case of (5) or (6); = 100 in the case of (7) or (8)) is the number of predictions per gauge, and m (=93) is the number of gauges.

[24] As discussed in the Introduction, most previous applications of base flow recession metrics in low-flow regressions have assumed the availability of continuous streamflow records in order to estimate the relevant metric. The prediction strategy analyzed above assumes the availability only of one to four pairs of measurements, with each pair collected on a single recession segment. To facilitate a comparison of our analysis with some previous analyses [*Kroll et al.*, 2004; *Yu et al.*, 2002; *Vogel and Kroll*, 1992], we repeated the computations described above, with the exception that $\hat{\tau}$ (the average of 400 sample estimates) was used as the predictor and only one prediction was made for each gauge.

6. Results

[25] Model parameter estimates are summarized in Table 2. For each combination of predictor variables, 93 sets of model parameters were estimated, one for each simulated partial record gauge. Entries in Table 2 give the median and range of each estimated model parameter across the 93 models. Not surprisingly, the range of estimated parameters varies little from one simulated partial record gauge to another, because the data sets for model estimation overlap greatly from one model to the next. When only drainage area is used as a predictor, its regression coefficient is slightly greater than 1, indicating a nearly linear dependence of $\hat{Q}_{7,10}$ on drainage area. When both drainage area and recession time constant are used as predictors, the drainage area coefficient changes substantially because of a correlation between the two predictors. When only the recession time constant is used as a predictor, its coefficient is positive, indicating that relatively slow rates of recession are associated with relatively large values of characteristic low flows; results from the two-parameter model indicate that this dependence is present even after allowance for differences in drainage area.

[26] Results of model evaluation are summarized in Table 3. Given that the values of $\hat{Q}_{7,10}$ range over three orders of magnitude, it is not surprising that the constant model (5) has such a large RMSE (617%). As mentioned

Table 2. Median Values and Ranges of Parameters From the Regression Models

Predictor Variables	Regression Parameters								
	ξ_0			ξ_{A_d}			$\xi_{\hat{\tau}}$		
	Median	Minimum	Maximum	Median	Minimum	Maximum	Median	Minimum	Maximum
Constant	−0.9	−0.9	−0.8	-	-	-	-	-	-
A_d	−3.4	−3.6	−3.3	1.1	1.1	1.2	-	-	-
$\hat{\tau}$	−4.9	−5.0	−4.8	-	-	-	3.5	3.4	3.6
A_d, $\hat{\tau}$	−3.9	−4.0	−3.7	0.5	0.5	0.6	3.0	2.7	3.0

Table 3. Summary of the Evaluation Results From the Regression Models

Sample Size for $\hat{\tau}$ Estimate at Evaluation Site	Predictor Variables	RMSE, %		R^2, %	
		Random	Deterministic	Random	Deterministic
—	—	617	617	—	—
—	A_d	479	479	41	41
1	$\hat{\tau}$	363	359	52	43
2	$\hat{\tau}$	278	302	58	46
3	$\hat{\tau}$	251	277	61	53
4	$\hat{\tau}$	232	265	66	56
400	$\hat{\tau}$	128	137	82	79
1	A_d, $\hat{\tau}$	266	261	70	59
2	A_d, $\hat{\tau}$	210	214	73	65
3	A_d, $\hat{\tau}$	180	193	76	68
4	A_d, $\hat{\tau}$	177	186	77	72
400	A_d, $\hat{\tau}$	105	100	87	82

in the Introduction, drainage area is the predictor most commonly used in low-flow regressions. In our study, the use of drainage area as the only predictor (6) explains a substantial fraction of the variance (R^2 = 0.41), but produces large estimation errors; the 479% RMSE indicates that estimated values are commonly in error by a factor of about 5. Such a large estimation error is consistent with previous findings [e.g., *Thomas and Benson*, 1970]. The addition of any estimate of $\hat{\tau}$ as a second predictor (8) substantially reduces the estimation error. Even when $\hat{\tau}$ is estimated from a single pair of measurements, the RMSE decreases to 266% or 261% and R^2 rises from 41% to 70% or 59%, depending on sampling strategy. Availability of additional pairs of measurements reduces RMSE and increases R^2 further, although with diminishing returns. The improvement in model performance with increase in the number of measurements is a result of the improvement in the estimate of the base flow recession time constant. The median coefficient of variation of the 100 averages of 1, 2, 3, and 4 τ values are 0.5 (ranges from 0.2 to 1.5 across 93 simulated partial record gauges), 0.3 (0.1 to 0.6), 0.3 (0.1 to 0.6), and 0.2 (0.1 to 0.5), respectively. The results for 400 samples in Table 3 are representative of how well this approach could perform with perfect knowledge of the recession constant. Despite the diminishing returns mentioned above, the benefit to be gained from further measurements is not negligible.

[27] Results for prediction based on $\hat{\tau}$ alone are included in Table 3 simply for comparison; not unexpectedly, exclusion of area as a predictor degrades results. Qualitatively, whether or not drainage area is used as a predictor, the results are similar for the two sampling strategies, although the RMSE values tend to be smaller (and the R^2 values tend to be larger) with random sampling than with deterministic sampling.

7. Discussion

[28] This study confirms the findings of other studies that the use of a base flow recession or streamflow variability predictor greatly reduces the error of estimation of low-flow characteristics [*Kroll et al.*, 2004; *Yu et al.*, 2002; *Vogel and Kroll*, 1992]. A serious disadvantage of such methods is that they require a continuous streamflow record at the estimation site. Here we show that a base flow recession index (the characteristic time constant of exponential decay of streamflow long after a storm), estimated readily from as few as two measurements of streamflow, provides much of the predictive power found with the more data-intensive methods.

[29] In view of the strength of the base flow recession time constant as a predictor of a low-flow characteristic over a multistate region, and in recognition of the physical basis for such strength, further exploration of the value of this predictor appears warranted. Regional relations based on this predictor might yield more consistency within and across regions than regional relations based on other basin attributes that are only indirect and/or region-specific correlates of base flow recession.

[30] This study uses the simplest dynamic exponential decay model of base flow recession, treated statistically through random sampling, to improve the accuracy of estimated low-flow characteristics at partial record gauges. As noted in the Results, the apparent value of b for a given basin can differ substantially from 1, suggesting the potential for increased predictive power by use of a more accurate recession model. For example, *Brutsaert and Nieber*'s [1977] characterization of recession in terms of both long and short timescales might be useful in the analysis of shorter return periods than that studied here (e.g., the median annual 7-day low flow).

[31] Our analysis did not address the complicating factor of zero flows, although we noted that statistical methods exist for generalization of standard techniques. From a physical viewpoint, we suggest that the problem of zero flow is related to the problem of direct evaporative losses from groundwater. Accordingly, the use of a model that considers the evaporative influence on base flow recession might yield predictive benefits. Such an approach would also allow a more physical treatment of the possible seasonal variation in recession behavior and its influence on low-flow characteristics.

[32] On conventional low-flow partial record gauge networks, streamflow measurements may be taken a few times a year during drought periods for a few years. The number of streamflow measurements at a partial record site can typically range from two to twenty. Generally, however, only one measurement is made on any given recession segment at a given location, so the data currently available from such networks are not suited for the methods outlined in this study. Thus the benefits of the technique demon-

strated herein can be realized only with a change in sampling strategies used on low-flow networks. By strategically timing the sampling of low streamflows in this way, we minimize the data requirements for any given site, thereby allowing maximization of the number of sites that can be included in a network. Additionally, as shown here, simulated sampling of continuous streamflow records can be used to evaluate the value of multiple pairs of base flow recession measurements on a partial record network. Our results suggested possible superiority of a random temporal sampling strategy over a deterministic strategy. However, it is not at all clear how in practice the former could be implemented without a great increase in the ability to forecast the duration of storm-free periods. Nevertheless, the difference in errors between the two strategies apparently is small, and the practical appeal of a deterministic strategy probably outweighs the associated slight decrease in predictive power.

[33] **Acknowledgments.** The authors thank Michael Gooseff and an anonymous reviewer for their helpful comments on this paper.

References

Aitchison, J., and J. A. C. Brown (1957), *The Lognormal Distribution*, 176 pp., Cambridge Univ. Press, New York.

Arihood, L. D., and D. R. Glatfelter (1991), Method for estimating low-flow characteristics of ungaged streams in Indiana, *U.S. Geol. Surv. Water Supply Pap.*, *2372*, 18 pp.

Bingham, R. H. (1986), Regionalization of low-flow characteristics of Tennessee streams, *U.S. Geol. Surv. Water Resour. Invest. Rep.*, *85-4191*, 63 pp.

Boussinesq, J. (1903), Sur le débit, en temps de sécheresse, d'une source allimentée par une nappe d'eaux d'infiltration, *C. R. Acad. Sci.*, *136*, 1511–1517.

Brutsaert, W., and J. P. Lopez (1998), Basin-scale geohydrologic drought flow features of riparian aquifers in the southern Great Plains, *Water Resour. Res.*, *34*(2), 233–240.

Brutsaert, W., and J. L. Nieber (1977), Regionalized drought flow hydrographs from a mature glaciated plateau, *Water Resour. Res.*, *13*(3), 637–643.

Eng, K., and W. Brutsaert (1999), Generality of drought flow characteristics within the Arkansas River basin, *J. Geophys. Res.*, *104*(D16), 19,435–19,441.

Flynn, R. H. (2002), Development of regression equations to estimate flow durations and low-flow frequency statistics in New Hampshire streams, *U.S. Geol. Surv. Water Resour. Invest. Rep.*, *02-4298*, 66 pp.

Giese, G. L., and R. R. Mason Jr. (1993), Low-flow characteristics of streams in North Carolina, *U.S. Geol. Surv. Water Supply Pap.*, *2403*, 29 pp.

Helsel, D. R., and R. M. Hirsch (1992), *Statistical Methods in Water Resources*, 522 pp., Elsevier, New York.

Judge, G. G., W. E. Griffiths, R. C. Hill, H. Lütkepohl, and T.-C. Lee (1985), Qualitative and limited dependent variable models, in *The Theory and Practice of Econometrics*, 2nd edition, chap.18, pp. 779–785, John Wiley, Hoboken, N. J.

Kroll, C. N., and J. R. Stedinger (1999), Development of regional regression relationships with censored data, *Water Resour. Res.*, *35*(3), 775–784.

Kroll, C. N., and R. M. Vogel (2002), Probability distribution of low streamflow series in the United States, *J. Hydrol. Eng.*, *7*(2), 137–146.

Kroll, C. N., J. Luz, B. Allen, and R. M. Vogel (2004), Developing a watershed characteristics database to improve low streamflow prediction, *J. Hydrol. Eng.*, *9*(2), 116–125.

Lane, E. W., and K. Lei (1950), Stream flow variability, *Proc. Am. Soc. Civ. Eng.*, *115*, 1084–1098.

Ludwig, A. H., and G. D. Tasker (1993), Regionalization of low-flow characteristics of Arkansas streams, *U.S. Geol. Surv. Water Resour. Invest. Rep.*, *93-4013*, 19 pp.

Ries, K. G., III, and P. J. Friesz (2000), Methods for estimating low-flow statistics for Massachusetts streams, *U.S. Geol. Surv. Water Resour. Invest. Rep.*, *00-4135*, 81 pp.

Rifai, H. S., S. M. Brock, K. B. Ensor, and P. B. Bedient (2000), Determination of low-flow characteristics for Texas streams, *J. Water Resour. Plann. Manage.*, *126*(5), 310–319.

Riggs, H. C. (1980), Characteristics of low flows, *J. Hydraul. Div. Am. Soc. Civ. Eng.*, *106*(HY5), 717–731.

Ruhl, K. J., and G. R. Martin (1991), Low-flow characteristics of Kentucky streams, *U.S. Geol. Surv. Water Resour. Invest. Rep.*, *91-4097*, 50 pp.

Tasker, G. D. (1987), A comparison of methods for estimating low flow characteristics of streams, *Water Resour. Bull.*, *23*(6), 1077–1083.

Thomas, D. M., and M. A. Benson (1970), Generalization of streamflow characteristics from drainage-basin characteristics, *U.S. Geol. Surv. Water Supply Pap.*, *1975*, 55 pp.

U.S. Geological Survey (1969), Programs and plans—Study of surface-water data programs—Adjustments for zero-flow items, *Surf. Water Branch Tech. Memo. 70.07*, Reston, Va. (Available at http://water.usgs.gov/admin/memo/SW/sw70.07.html)

Vogel, R. M., and C. N. Kroll (1992), Regional geohydrologic-geomorphic relationships for the estimation of low-flow statistics, *Water Resour. Res.*, *28*(9), 2451–2458.

Waltemeyer, S. D. (2001), Analysis of the magnitude and frequency of the 4-day annual low flow and regression equations for estimating the 4-day, 3-year low-flow frequency at ungaged sites on unregulated streams in New Mexico, *U.S. Geol. Surv. Water Resour. Invest. Rep.*, *01-4271*, 22 pp.

Yu, P.-S., T.-C. Yang, and C.-W. Liu (2002), A regional model of low flow for southern Taiwan, *Hydrol. Processes*, *16*, 2017–2034.

K. Eng, U.S. Geological Survey, 12201 Sunrise Valley Drive, Mail Stop 430, Reston, VA 20192, USA. (keng@usgs.gov)

P. C. D. Milly, U.S. Geological Survey, Route 1, Forrestal Campus, Princeton, NJ 08542, USA. (cmilly@usgs.gov)