Turbidity-controlled sampling for suspended sediment load estimation

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INTRODUCTION

Accurate measurement and estimation of suspended sediment transport is dependent on the timing and frequency of data collection. It is common in streams and rivers for most of the annual suspended sediment to be transported during a few, large runoff events. Automated data collection is essential to effectively capture such events. Although it is possible to rely solely on manual measurements, important flows are infrequent, unpredictable, and when they do occur, trained personnel may not be available to collect the required information.

There is currently no practical method to directly measure total (submicron to 2 mm) suspended sediment concentration (SSC) in the field. Pumped or manual samples must be transported to a laboratory for analysis. However, a number of companies offer turbidity sensors that can be deployed on a continuous basis in streams. While turbidity cannot replace SSC, it can be of great benefit as an auxiliary measurement. The continuous turbidity record can reveal sediment pulses unrelated to flow, providing information about the timing and magnitude of sediment inputs. And turbidity can be used in an automated system that makes real-time sampling decisions to facilitate sediment load estimation. Such a system, called Turbidity Threshold Sampling (TTS) has been used at a growing number of gaging stations in northern California since 1996 (Lewis and Eads, 2001). Its design objectives are to:

(1) Facilitate accurate estimation of suspended sediment loads at a reasonable cost.
(2) Provide an adequate number and distribution of physical samples to
    (a) validate every significant rise in turbidity, and
    (b) calibrate turbidity against SSC for each period being estimated.
(3) Provide a continuous estimate of sediment concentration and flux based upon turbidity.

The algorithm ensures that a wide range of SSC is sampled in each transport event, so that reliable turbidity-SSC relations can be developed. These are then applied to the near-continuous turbidity data to produce a corresponding time series of estimated SSC.

While turbidity is virtually always a better SSC surrogate than flow, its quality is less consistent due to fouling from biological organisms, detritus, and waterborne debris. Mechanical wipers can prevent fouling from small contaminants such as fine organics and sediment, algae, and macroinvertebrates, but larger debris must be manually removed. Data affected by fouling is in many cases difficult to distinguish from episodes of sediment transport. Some types of fouling can be readily identified on graphical displays with experience. However, fouling that occurs during storm events can often be identified only by plotting the turbidity against SSC from corresponding physical samples, or by comparing the turbidity with independent readings from a second sensor. By activating a pumping sampler during each significant change in turbidity, TTS provides physical samples that can be used to validate the turbidity.

SAMPLING PROTOCOL

The TTS algorithm attempts to collect physical samples at specific turbidity thresholds. The scaling of thresholds is designed to adequately define loads for small storms without oversampling large storms. This is most often accomplished by evenly spacing the square roots of thresholds so that threshold density decreases with increasing turbidity. A programmable data logger instructs an automatic pumping sampler to collect a sample when a threshold is crossed. To avoid sampling ephemeral turbidity spikes caused by passing debris, a threshold must be met for two intervals before signalling the sampler. Because more sediment is discharged while turbidity is in a recession mode, more thresholds are needed while turbidity is falling than when it is rising. Reversals are detected when the turbidity drops 10% below the preceding peak, or rises 20% above the preceding trough. In addition, the change must be at least 5 NTU, and the new course must continue for at least two intervals before declaring a reversal. At the time a reversal is detected, a sample is collected if a threshold has been crossed since the preceding peak or trough unless that threshold has already been utilized in the past five intervals. The program has been implemented on two brands of data loggers. The specific thresholds and sampling parameters described above are all set by the user.

The above rules provide reasonable assurance of avoiding extraneous sampling in the presence of normal turbidity fluctuations. However, it will not prevent oversampling when debris snags on the sensor or its mounting apparatus, causing extended fluctuations. Oversampling due to fouling can cause a pumping sampler to quickly reach its bottle capacity and fail to sample the next important event. Sites experiencing fouling require more frequent field visits. Telemetry provides the most effective means of detection. A warning can be issued remotely from the gaging station when sampler capacity is approached.

SIMULATIONS

Lewis (1996) simulated the above sampling protocol with varying threshold scales, fitting procedures, and sample sizes to evaluate the effectiveness of TTS and associated regression models for load estimation. The sampled populations consisted of five Caspar Creek (north coastal California) storm events for which both turbidity and SSC were measured at 10-min intervals. Sampling based on a square-root threshold scale generally produced more accurate results than cube-root or logarithmic scales; and regression variable transformations (square root, cube root, and logarithm) tended to increase estimation errors. But there was not a great deal of sensitivity to either the threshold scale type or the choice of regression model. The most important result was that root mean square errors (r.m.s.e.) were small, less than 10% in nearly every combination simulated, with mean sample sizes of 4-13 per storm. For samples sizes of at least five, r.m.s.e. was generally no more than 5% of the load. Estimates based on log-linear discharge-SSC rating curves had r.m.s.e. 1.9-7.5 times larger than those based on linear turbidity-SSC regressions when a single curve was fit to each storm.

In one of the storm events, applying separate turbidity-SSC regressions to periods of rising and falling turbidity significantly improved the estimation. In another storm, quadratic regression had a slight 1-2% edge over linear regression. But, in most cases, a single linear regression performed nearly as well or better than other methods, and caution should be exercised in applying nonlinear fits or multiple fits, particularly in the presence of outliers.

Extrapolating nonlinear curves can lead to large errors and dividing the data is inefficient unless there clearly are multiple relations.

Power functions based on log-linear fits were less prone to extrapolation error than polynomials. Log-linear models performed nearly as well as linear models in estimating sediment load; and they have two advantages over linear models: (1) predictions are always positive, and (2) the residuals are often more homoscedastic. This last feature can improve variance estimation.

The variance of the load estimate can be estimated without bias if the regression model assumptions are satisfied. Formulas are given for the linear regression model by Lewis (1996) and for log-linear regressions by Gilroy *et al*. (1990). Lewis investigated the errors associated with applying linear regressions to realistic SSC data generated from log-linear models and concluded that, for typical TTS sample sizes of 4-11 samples per storm, variance estimation was unreliable regardless of the model applied. The variance estimator associated with the log-linear model had little bias, but its r.m.s.e. ranged from 52 to 110%. The variance estimator associated with the linear model performed even worse, with r.m.s.e. from 73 to 244%. In contrast, both models produced very good load estimates, with r.m.s.e. from 5.2 to 7.9% for log-linear models and 5.6 to 8.3% for linear models fit to the log-linear data. For larger sample sizes, variance estimation would improve, and the log-linear model should produce reliable estimates if the residuals can be normalized by log-transformation.

EXAMPLE

The TTS method is illustrated by a February 2000 storm event at Caspar Creek. The range of turbidity measured during the 5.5-day storm was 14-199 NTU. Thresholds were 20, 77, and 170 NTU during rising turbidities and 159, 105, 62, and 30 NTU during falling turbidities. During the course of the event turbidity rose and fell four times, resulting in 12 samples. SSC was well-correlated with turbidity on both natural (r^2= 0.98) and log-transformed (r^2= 0.97) scales. The untransformed model predicts a sediment load of 24 519 kg, with an estimated coefficient of variation (CV) of 5.2%. However, the model predicts negative SSC at the beginning and ending of the storm (Fig. 1). If the negative predictions are set to zero, the estimated load increases to 24791 kg. The difference is small, but a log-linear model that avoids negative predictions seems preferable. The log-linear model predicts a sediment load of 23 343 kg with estimated CV of 7.3%. For comparison, a discharge-SSC rating curve predicts a sediment load of 28 447 kg with an estimated CV of 13.2%. The TTS sample selection likely improved the rating curve estimate considerably (relative to, say, sampling at 12-hour intervals). The rating curve was unusually good for this stream (r^2=0.92), but inferior to the turbidity models. Standard errors in predicting SSC were 46% for the discharge-SSC rating curve versus 25% for the turbidity model. To aid interpretation, the standard errors from these log-linear regressions are expressed as percentage errors, $s\% = 100(\exp(s) - 1)$

PARTICLE-SIZE INFLUENCE ON TURBIDITY

It is well-known that turbidity is strongly influenced by particle size (e.g. Foster *et al*., 1992), among other factors. Therefore, when particle sizes are changing, one might expect the usefulness of turbidity as a surrogate for SSC to be limited. But how much error is acceptable in

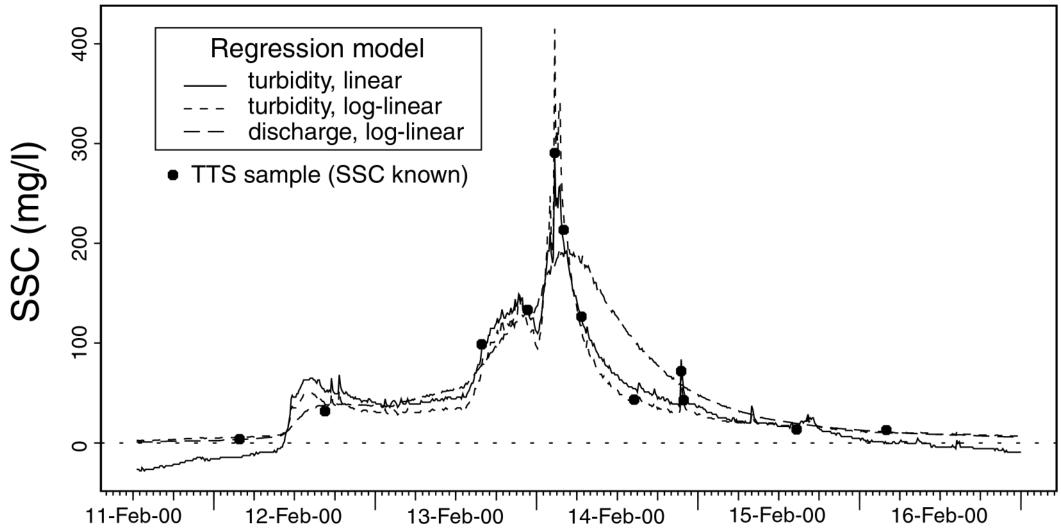

Figure 1. Estimated SSC from 3 models derived from TTS sample data

a given SSC estimate? Historically, the only available surrogate for SSC has been flow, and ranges of variability as high as 100:1 for a given flow have been routinely accepted.

To evaluate the influence of particle size on the relation between SSC and turbidity, historical data sets that included turbidity, SSC, sand fraction, and flow were obtained from five streams in northern California (Table 1). Variability in sand fractions (*sand*) and turbidity (t) for a given SSC (c) were related using the residual standard errors, s, of linear regressions of *sand* and $\ln(t)$ on $\ln(c)$. Although the sample size of five stations is small, a 0.88 correlation between the two standard errors suggests that the variability in *sand* and $\ln(t)$ may be related.

Also compared were variability in SSC for a given turbidity (t) or flow (q), again using standard errors from log-linear regressions (Table 1). The percentage error (s%) was 1.8-4.2 times greater using flow as a surrogate than using turbidity.

If the particle size distribution coarsens with increasing SSC, then one would expect to see an increase in the slope of the relation between SSC and turbidity at higher turbidity and SSC levels. None of the streams exhibited a strong trend in *sand* versus $\ln(c)$ (Table 1, maximum r^2=0.502). Minor upward curvature was apparent at Caspar and Freshwater Creeks, the two streams with the strongest relations between sand fraction and SSC. But linear models perform quite well in estimating loads from slightly nonlinear data when the variance of the relation is low. For example, at Freshwater Creek in water year 2000, a linear regression resulted in a load estimate only 1.7% higher than a loess model developed from the same 181 samples.

While the relation between SSC and turbidity depends on several factors, it is typically nearly linear with low variance. There is growing recognition (Glysson & Gray, 2002) that optical sediment surrogates have the potential to improve sediment load estimation. By controlling sampling using TTS, very accurate load estimation is possible with a moderate number of physical samples. Because it collects samples during each rise in turbidity, TTS also overcomes the difficulty of interpreting turbidity spikes that may be caused by fouling. The TTS method should work well in any stream where a pumping sampler can collect samples that are representative or can be reliably adjusted to cross-sectional mean SSC.

Table 1. Characterizations of variability in relationships among sand fraction (*sand*), SSC (*c*), turbidity (*t*), and flow (*q*) in five streams in northern California

	Miller	Caspar, NF	Mad, NF	Freshwater	Panther
Data source	RSL	RSL	RSL	SF	RNP
Basin area (km^2)	2.3	3.8	104.6	34.4	15.7
Water year	1982	1986-1988 1998[a]	1986	2000	2000
Turbidity sensor	DRT, lab	OBS, in situ	DRT, lab	OBS, in situ	Hach, lab
Mean sand fraction	0.25	0.24	0.24	0.30	0.32
r^2: *sand* v. ln(*c*)	0.137 (203)	0.502 (29)	0.010 (69)	0.391 (50)	0.005 (298)
s: *sand* v. ln(*c*)	0.093 (203)	0.126 (29)	0.042 (69)	0.106 (50)	0.118 (298)
s: ln(*t*) v. ln(*c*)	0.190 (203)	0.241 (173)	0.117 (80)	0.195[b] (181)	0.299 (38)
s%: ln(*c*) v. ln(*q*)	67.0 (169)	122.8 (171)	42.3 (80)	111.1 (181)	126.6 (272)
s%: ln(*c*) v. ln(*t*)	26.9 (203)	45.1 (173)	21.9 (80)	61.3[b] (181)	30.0 (38)

Data sources: RSL=U.S. Forest Service, SF=Salmon Forever, RNP=Redwood National Park
Turbidity sensors: Fisher model DRT-1000, D&A Instruments Co. model OBS-3, Hach model 2100-P
Parenthetical numbers indicate sample sizes
[a]At Caspar Creek, the sand fraction data were from 1986-1988, turbidity data from 1998
[b]Loess regression was applied to curvilinear relations

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