Turbidity-controlled sampling for suspended sediment load estimation

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Abstract Automated data collection is essential to effectively measure suspended sediment loads in storm events, particularly in small basins. Continuous turbidity measurements can be used, along with discharge, in an automated system that makes real-time sampling decisions to facilitate sediment load estimation. The Turbidity Threshold Sampling method distributes sample collection over the range of rising and falling turbidity values and attempts to sample all significant turbidity episodes. A data logger activates a pumping sampler when specified turbidity conditions are met. The resulting set of samples can be used to accurately determine suspended sediment loads by establishing a relation between sediment concentration and turbidity for any sampled period with significant sediment transport. Relations between turbidity, concentration, and particle size are examined at five sites in northern California, USA. Despite the influence of particle size, turbidity is in all cases superior to flow as a surrogate for sediment concentration.

Key words particle size; regression; sampling; suspended sediment; turbidity

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 the full range (submicron to 2 mm) of 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, USA, since 1996 (Lewis & Eads, 2001). Its design objectives are to:

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

The sampling 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, sediment, algae, and macroinvertebrates, but larger debris must be manually removed. Fouling from larger debris is best controlled by overhead suspension of the sensor on an articulating boom (Eads & Lewis, 2001, 2002). Data affected by fouling are in many cases difficult to distinguish from episodes of sediment transport. Some types of fouling can be readily identified on data plots 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. Thresholds are chosen so that the square roots are evenly spaced to adequately define loads for small storms without oversampling large storms. A programmable data logger, recording at 10 or 15-min intervals, instructs an automatic pumping sampler to collect a sample whenever a threshold is crossed. To avoid sampling ephemeral turbidity spikes caused by passing debris, a threshold must be met for two intervals before signaling the sampler. Because most sediment is discharged while turbidity is in recession, more thresholds are utilized 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 user can modify the specific thresholds and numerical parameters mentioned here.

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. Remote telemetry provides the most effective means of detection.

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 the 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 RMS errors 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, RMS was generally no more than 5% of the load. Estimates based on log-log discharge-SSC rating curves had RMS 1.9-7.5 times larger than those based on linear turbidity-SSC regressions, fitting a single curve 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 representing the turbidity-SSC relation based on log-log fits were less prone to extrapolation error than polynomials. Log-log 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) residual variance is often less dependent on turbidity. This last feature can improve estimation of the variance of the sediment load.

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-log regressions by Gilroy *et al*. (1990). Lewis investigated the errors associated with applying linear regressions to realistic SSC data generated with log-normal error 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 log-log models had little bias, but its RMS error ranged from 52 to 110%. The variance estimator associated with linear models performed even worse, with RMS from 73 to 244%. In contrast, both models produced very good load estimates, with RMS from 5.2 to 7.9% for log-log models and 5.6 to 8.3% for linear models fit to the log-normal data. For larger sample sizes, variance estimation would improve, and the log-log 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 (Fig. 1). 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 24 791 kg. The difference is small, but a log-log model that avoids
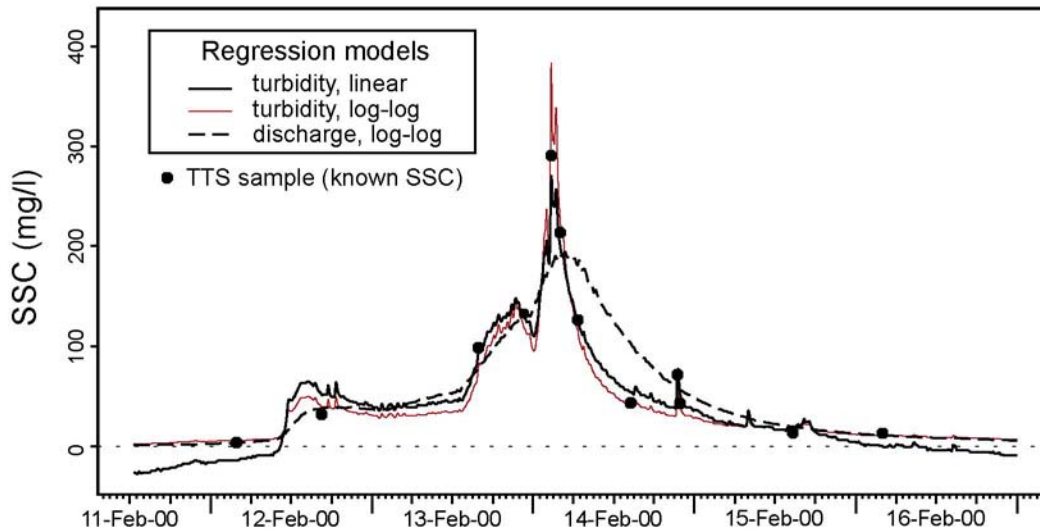
Figure 1. Estimated SSC at Caspar Creek from 3 models based on TTS sample data

negative predictions seems preferable. The log-log 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 fixed-interval sampling. The rating curve was unusually good for this stream (r^2=0.92), but inferior to the turbidity models. Percentage standard errors (defined as $s\% = 100\,[\exp(s) – 1]$, where s is the residual standard error) were 46% for the discharge-SSC rating curve *vs* 25% for the log-log turbidity-SSC model.

PARTICLE-SIZE INFLUENCE ON TURBIDITY

It is well-known that turbidity is strongly influenced by particle size, among other factors. Therefore, when particle sizes are changing, one might expect the usefulness of turbidity as a surrogate for SSC to be limited. Variability in particle size can result from changes in source materials or streamflow.

If source materials are changing, there could be considerable variability in turbidity for a given SSC. This situation can occur in drainage basins with spatially heterogeneous geology and soils. Heterogeneous soils can contribute to geographic variability in source areas if the timing of erosion is desynchronized among the different soil types, a scenario that is most probable in large basins where rainfall patterns are also spatially heterogeneous. However, unless source areas change very rapidly, i.e. within runoff events, the event-wise calibrations of turbidity to SSC used in TTS are still likely to be adequate for reliably estimating sediment loads. Studies need to be conducted in large, geologically and climatically heterogeneous basins to determine the actual importance of this issue.

If the sediment load coarsens with increasing streamflow, then at higher flows one should expect smaller changes in turbidity for a given change in concentration, resulting in a curvilinear relation between SSC and turbidity. However, as long as mean turbidity is monotonically related

to concentration, curvilinearity should be no obstacle to using turbidity as an SSC surrogate. Nonlinear or log-log models can be employed. In practice, the degree of curvature is usually very minor. Linear models perform quite well in estimating loads from slightly nonlinear data when the variance of the relation is low.

Fig. 2 shows relationships between turbidity and SSC for five streams in northern California. At three of the five stations, negative curvature is apparent. Although the relation is nonlinear at Freshwater Creek, linear regression results in a load estimate only 1.7% higher than the loess model developed from the same samples. At Caspar and Freshwater Creeks, the curvature is associated with positive trends in sand fraction with SSC. At the other stations, sand fractions indicate little or no coarsening of the load at higher SSC. There is some concern that, because of its elevation above the stream bed, the pumping sampler at Mad River did not operate efficiently in the sand ranges (Rand Eads, personal communication), but the observed curvature could still be indicative of a coarsening of the load within the sub-sand size ranges that were reliably sampled.

At the Miller Creek site, which had the most complete data set (203 matched measurements), turbidity (t) was related to SSC (c) and sand fraction (*sand*)

$$\ln(t) = 0.408 + 0.818 \ln(c) - 1.260\, sand$$

(r^2=0.95, s=0.13). The model implies that a 20% absolute decrease in sand fraction is equivalent to a 36% increase in SSC ($0.20 \times 1.260/0.818 = \ln(1.36)$)—i.e. either one would result in the same 0.252 increase in $\ln(t)$, a 29% increase in turbidity. Not all of the sites had matching measurements on all three variables, but the variability in turbidity for a given SSC can be compared to the variability in sand fraction for a given SSC (Table 1) by relating the residual standard errors, s, of linear regressions of *sand* and $\ln(t)$ on $\ln(c)$. The log transformations stabilize the variance, improving estimation of s. Although the sample size of five stations is small, a correlation of 0.88 between the two standard errors suggests that the variability in *sand* and $\ln(t)$ for a given SSC may be related among sites. That is, the variability in the turbidity-SSC relation is determined in part by variability in sand fractions for a given SSC.

It should be remembered, however, that turbidity depends on the entire particle size distribution and is not a simple function of sand fraction or D_{50}. Thus, an increase in D_{50}, if also accompanied by an increase in variance, could actually result in higher turbidity (Fig. 3). The attenuation coefficient, T_a, was calculated for Fig. 3 as a mass-weighted sum using the equation $T_a = 8.599 D_{50}^{-1.313}$ for the Partech S1000 sensor (Foster *et al*., 1992). If variance and central tendency both increase with streamflow, their offsetting influences would tend to reduce departures from linearity of the turbidity-SSC relation.

Historically, the only available surrogate for SSC has been flow. Therefore, in practice, evaluations of turbidity as a surrogate will be made on the basis of comparisons with flow. Ranges of variability in SSC as high as 100:1 for a given flow are not unusual. Table 1 compares variability in SSC for a given turbidity (t) with that for a given flow (q) for the northern California streams, using percentage standard errors from log-log regressions (Table 1). Among these streams, the maximum range of variability in SSC for a given flow is about 40:1 (Panther Creek). The residual standard error (s%) was 1.8-4.3 times greater using flow as a surrogate than using turbidity and, on average, flow increases the error by a factor of 2.6.
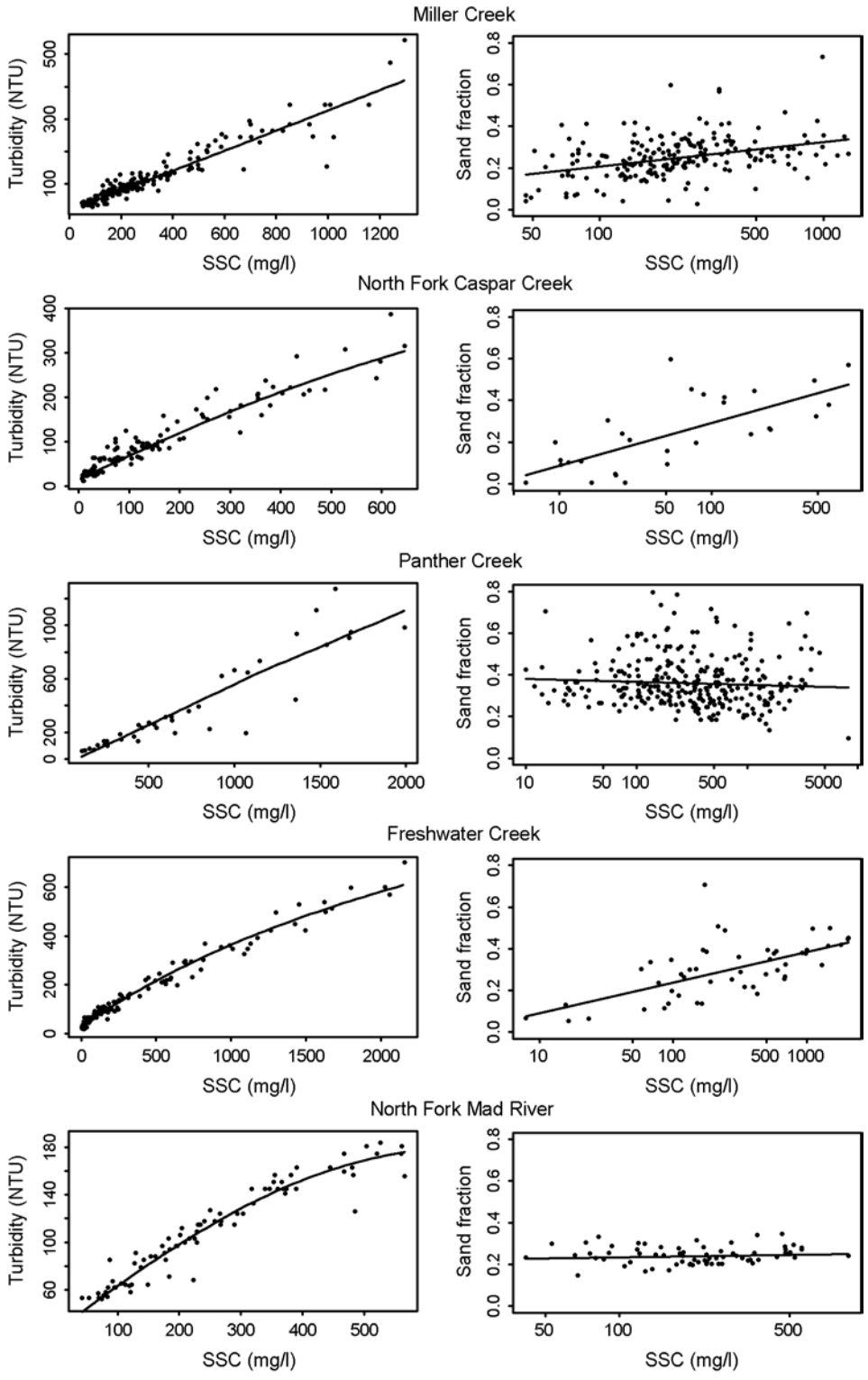
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Figure 2. Relationships of turbidity and sand fraction to suspended sediment concentration (SSC) in five northern California streams

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

Data sources: RSL=US 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.
s = residual standard error, *s*% = $100 (\exp(s) - 1)$.
[†]At Caspar Creek, sand fraction data were from 1986-1988, turbidity data from 1998.
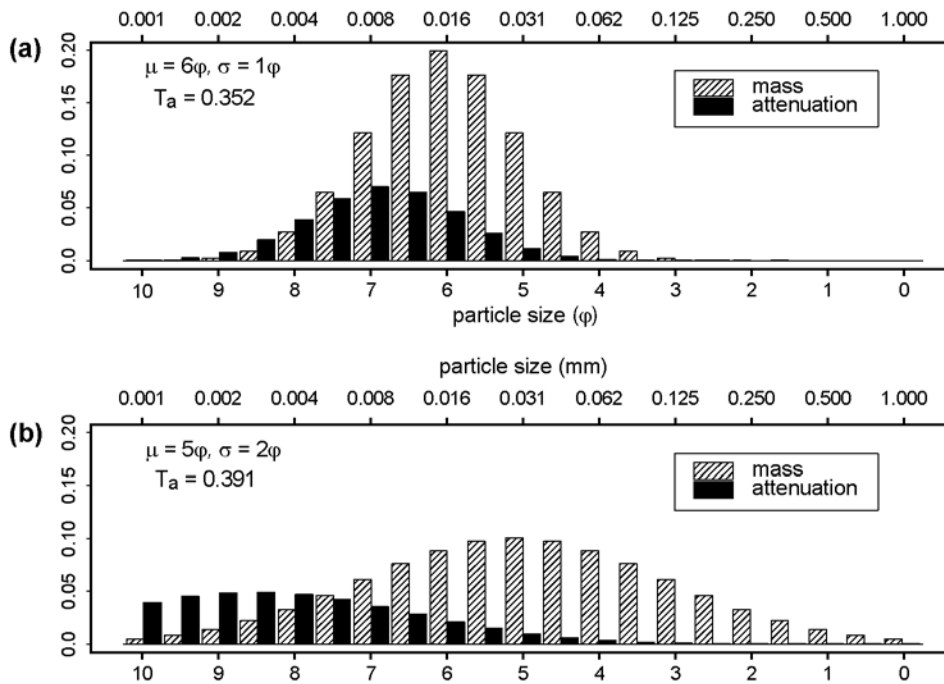[‡]Loess regression was applied to curvilinear relations.

Figure 3. Comparison of light attenuation for two hypothetical grain size distributions. Distribution (b) attenuates more light despite its greater D_{50}, because, having greater variance, it is richer in fine particles below 0.004 mm. The symbols μ and σ denote the mean and standard deviation expressed in φ-units. T_a is the light attenuation, summed over all particle sizes.

CONCLUSION

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.

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