JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

Vol. 47, No. 2 AMERICAN WATER RESOURCES ASSOCIATION April 2011

SURROGATE MEASURES FOR PROVIDING HIGH FREQUENCY ESTIMATES OF TOTAL SUSPENDED SOLIDS AND TOTAL PHOSPHORUS CONCENTRATIONS[1]

Amber Spackman Jones, David K. Stevens, Jeffery S. Horsburgh, and Nancy O. Mesner[2]

ABSTRACT: Surrogate measures like turbidity, which can be observed with high frequency *in situ*, have potential for generating high frequency estimates of total suspended solids (TSS) and total phosphorus (TP) concentrations. In the semiarid, snowmelt-driven, and irrigation-regulated Little Bear River watershed of northern Utah, high frequency *in situ* water quality measurements were recorded in conjunction with periodic chemistry sampling. Site-specific relationships were developed using turbidity as a surrogate for TP and TSS at two monitoring locations. Methods are presented for employing censored data and for investigating categorical explanatory variables (e.g., hydrologic conditions). Turbidity was a significant explanatory variable for TP and TSS at both sites, which differ in hydrologic and water quality characteristics. The relationship between turbidity and TP was stronger at the upper watershed site where TP is predominantly particulate. At both sites, the relationships between turbidity and TP varied between spring snowmelt and base flow conditions while the relationships between TSS and turbidity were consistent across hydrological conditions. This approach enables the calculation of high frequency time series of TP and TSS concentrations previously unavailable using traditional monitoring approaches. These methods have broad application for situations that require accurate characterization of fluxes of these constituents over a range of hydrologic conditions.

(KEY TERMS: surrogate measures; total phosphorus; suspended sediment; turbidity; surface water quality; monitoring; regression.)

Spackman Jones, Amber, David K. Stevens, Jeffery S. Horsburgh, and Nancy O. Mesner, 2011. Surrogate Measures for Providing High Frequency Estimates of Total Suspended Solids and Total Phosphorus Concentrations. *Journal of the American Water Resources Association* (JAWRA) 47(2):239-253. DOI: 10.1111/j.1752-1688.2010.00505.x

INTRODUCTION

Traditional water quality monitoring programs rely on the analysis of grab samples that are typically collected at a frequency too low to fully characterize water quality constituent concentrations and to calculate loads of those constituents over time (de Vries and Klavers, 1994; Scholefield *et al.*, 2005). Additionally, concentrations of solids and nutrients are often greater during storm events because of nonpoint source runoff (Nolan *et al.*, 1995; Correll *et al.*, 1999; Houser *et al.*, 2006; Jordan *et al.*, 2007). Routine monitoring programs often miss these important events. High frequency monitoring with *in situ* sensors offers a number of advantages to traditional

[1]Paper No. JAWRA-09-0118-P of the *Journal of the American Water Resources Association* (JAWRA). Received August 10, 2009; accepted October 13, 2010. **Discussions are open until six months from print publication**.

[2]Respectively, Research Assistant, Professor, Research Assistant Professor, Utah Water Research Laboratory, Utah State University, Logan, Utah, 8200 Old Main Hill Logan, Utah 84322; and Associate Dean, College of Natural Resources, Utah State University, Logan, Utah 84322 (E-Mail/Spackman Jones: amber.s@aggiemail.usu.edu).

monitoring methods. High frequency monitoring can capture time periods and characterize seasonal trends that may be omitted by traditional periodic grab sampling (Christensen *et al.*, 2002; Tomlinson and De Carlo, 2003; Kirchner *et al.*, 2004; Jordan *et al.*, 2007). Monitoring equipment that measures continuously can simplify the logistics and personnel required for grab sampling to be representative (Grayson *et al.*, 1997), can reduce errors in transcription and delays in obtaining data (Vivoni and Camilli, 2003), and can be closely linked with water quality models to help refine parameters and results (Vivoni and Richards, 2005). Variables commonly measured *in situ* include water level, pH, specific conductance, dissolved oxygen, and turbidity. Additionally, UV-VIS spectroscopy and ion-specific sensors can be used *in situ* to quantify constituents such as nitrate, nitrite, chlorophyll, and chemical oxygen demand, although caution should be exercised because interfering substances (e.g., dissolved organic matter) can affect the validity of *in situ* colorimetric measurements for parameters such as nitrate.

Despite developments in sensor technology, there are still important water quality constituents that are either impossible or impractical to measure *in situ* or in real time for extended periods. For example, total phosphorus (TP) samples are most often digested and analyzed in a lab. Some commonly used, high frequency measurements have the powerful potential to be used as surrogates to estimate other properties such as constituent concentrations. A common surrogate used for this purpose is turbidity, which is an optical measure of the scattering of light passing through a sample of water because of colloidal and suspended matter. In many situations, turbidity can be used as a surrogate for suspended solids as well as constituents such as phosphorus that may be associated with suspended matter (Grayson *et al.*, 1996; Kronvang *et al.*, 1997; Stubblefield *et al.*, 2007).

The objective of this study is to develop a method for estimating TP and total suspended solid (TSS) concentrations with high frequency. This paper examines turbidity as a surrogate measure for TP and TSS in the Little Bear River, Utah. As a result of concerns with algal growth, aquatic habitat, and downstream water quality impairments, TP and TSS are water quality constituents of interest in the Little Bear River (Utah DEQ, 2000, 2009). Water borne phosphorus occurs in both dissolved and particulate forms. Particulate phosphorus is generally less bio-available than dissolved phosphorus but more readily estimated using turbidity as a surrogate. TP, which is the sum of dissolved and particulate phosphorus, is examined in this paper because it is regulated in the Little Bear River. Moreover, phosphorus may cycle between its various forms, and TP accounts for all phosphorus loading (Utah DEQ, 2009). We use linear relationships between turbidity and TSS and between turbidity and TP to allow prediction of TP and TSS concentrations as functions of turbidity, enabling the generation of high frequency, long-term estimates of their concentration.

Considerable research is available demonstrating the potential for accurately relating suspended sediment concentrations to turbidity measurements (Gippel, 1995; Kronvang *et al.*, 1997; Brasington and Richards, 2000; Christensen *et al.*, 2000; Tomlinson and De Carlo, 2003). There is also evidence that turbidity can be used as a surrogate for phosphorus. Grayson *et al.* (1996), Christensen *et al.* (2002), Rasmussen *et al.* (2008), Ryberg (2006), and Stubblefield *et al.* (2007) found statistically significant correlations between turbidity and TP in watersheds of differing characteristics exhibiting a range of turbidity values. In these studies, turbidity was the principal explanatory variable for TP and TSS. As the nature of turbidity depends greatly on the source of sediment (Gippel, 1995), the surrogate relationships are site-specific (Grayson *et al.*, 1996; Christensen *et al.*, 2002; Tomlinson and De Carlo, 2003), limiting the general applicability of previous studies to targeted locations.

Surrogate relationships for estimating water quality constituent concentrations such as those presented in this paper allow for the generation of concentration estimates at a much higher temporal resolution than most traditional water quality monitoring programs have achieved. Although many aspects of water quality monitoring have improved, sampling frequency remains a limiting factor in the estimation of water quality constituent loads (de Vries and Klavers, 1994; Johnes, 2007). High frequency estimates of concentration can overcome some problems encountered when constituent loads are calculated (e.g., complicated load estimation equations and situations where discharge and concentration are measured at different frequencies). Water quality models also suffer from a general paucity of water quality observations and would be improved by high frequency estimates of concentration (Neilson and Chapra, 2003; Kirchner *et al.*, 2004; Johnes, 2007). The results of applying surrogate relationships may also assist water quality regulators to target locations and time periods of interest for water quality monitoring.

Surrogate measures can be an important component of water quality monitoring programs and environmental observatory design as a relatively inexpensive method for producing high frequency time series of water quality constituent concentrations over extended time periods. The Little Bear River is 1 of 11 National Science Foundation environmental observatory test bed projects tasked with developing techniques and technologies for environmental observatory design. These applications range from innovative implementation of environmental sensors to publishing observations data in common formats and making those data widely accessible (Montgomery *et al.*, 2007).

In this paper, we begin with a description of the Little Bear River watershed. We then detail the data collection and statistical procedures that were used to obtain surrogate relationships at two monitoring locations in the Little Bear River, which differ with regard to hydrology and water quality. Finally, we describe the resulting surrogate equations and discuss the explanatory variables, differences between the two sites, the applicability of the surrogate approach, and potential improvements to our approach.

STUDY AREA

The Little Bear River watershed is located in northern Utah and is a major tributary of the Bear River, which flows into the Great Salt Lake. The Little Bear watershed encompasses an area of approximately 740 km^2. The headwaters are in the Bear River Mountain Range, and elevations range from 1,340 m to 2,700 m. The upper watershed drains higher elevation forest and range land. Most of the land adjacent to the river is agricultural, including crops and livestock grazing, and there are a number of irrigation diversions from the river. Near the town of Hyrum, the river is stored behind Hyrum Dam, which is operated to supply summer irrigation water. Below Hyrum Dam, the river flows through lower gradient agricultural land and a few towns before draining into an arm of Cutler Reservoir, which impounds the Bear River. The watershed and local towns are shown in Figure 1. There are concerns with low dissolved oxygen levels in Cutler Reservoir resulting from algae growth attributed to high levels of phosphorus in the reservoir (Utah DEQ, 2009). Phosphorus may be contributed by fertilized fields, animal waste, wastewater treatment plants, and industries as well as natural sources such as phosphorus-rich soils.

The average annual precipitation is around 430 mm in the lower watershed and on the order of 1,000 mm in the upper watershed, demonstrating significant variability with elevation. Most of the precipitation occurs as snow, and the flow regime in the watershed is driven by snowmelt with hydrograph peaks occurring in late spring. The magnitude, timing, and duration of the peaks are dictated by the winter snowpack and spring weather conditions. In the upper watershed, where an active U.S. Geological Survey (USGS) gage is located, discharge ranges from

FIGURE 1. Little Bear River Watershed.

0.50 to 12 m^3/s with an average annual discharge of 2.5 m^3/s.

Seven sites have been instrumented within the Little Bear River for the collection of high frequency water quality monitoring data. General characteristics of the monitoring system and data collected at these locations are described in detail by Horsburgh *et al.* (2010). Two of these sites were chosen for analysis in this paper and are indicated in Figure 1. The first site is the Little Bear River at Paradise, located in the upper watershed above Hyrum Reservoir. The second site is the Little Bear River at Mendon, located in the lower watershed near the river's terminus at Cutler Reservoir. The two sites were selected for their distinct characteristics. Above Paradise, there are agricultural diversions and the river passes through some agricultural land, but relative to Mendon, the river is less regulated, is of higher gradient, and less impacted by human activity. In contrast, above Mendon, the river is controlled by Hyrum Reservoir releases and influenced by agricultural return flows, a wastewater treatment plant, and an increasingly agricultural landscape. Approximately 4% of the land above Paradise is agricultural whereas between Paradise and Mendon, about 50% of the land is used for agriculture. Additionally, at Mendon, the river is lower gradient and groundwater levels are closer to the surface than at Paradise. Soil characteristics and instream sediment dynamics also differ between the two sites. Mendon is located in a lacustrine valley with finer soils that tend to remain in suspension while the suspended matter at Paradise is coarser and more likely to settle [Soil Survey Staff, National Resource Conservation Service (NRCS), United States Department of Agriculture (USDA), 2008].

MATERIALS AND METHODS

Instrumentation and Monitoring

Each site was equipped with continuous monitoring and telemetry instrumentation. The water quality monitoring equipment includes a Forest Technology Systems (Victoria, BC, Canada) DTS-12 SDI-12 Turbidity Sensor. The turbidity sensor uses an infrared light beam and optical backscatter with a detector at 90° to the emitted light to determine turbidity in nephelometric turbidity units (NTU) (Forest Technology Systems Ltd, 2007). The turbidity sensor also measures water temperature. Turbidity and water temperature measurements were recorded at half hour intervals. At Paradise, there is an active USGS gage (USGS 10105900 Little Bear River at Paradise, Utah) adjacent to the real-time water quality sensors for which records of 15 min instantaneous and daily average discharge were obtained. At Mendon, water level is measured continuously by a KWK Technologies (Spokane, Washington) SPXD-600 SDI-12 pressure transducer. The water level measurements were paired with manually measured discharges to develop a stage-discharge relationship. Discharges were measured using either a Teledyne RD Instruments (Poway, CA) Acoustic Doppler Current Profiler or a velocity meter attached to a wading rod or a bridge cart. The stage-discharge relationship was then used to generate continuous, half-hourly estimates of discharge.

Water quality samples were collected at the two sites either by grab sampling conducted by a field crew or using automated samplers. All samples were collected in the thalweg of the channel as near to the *in situ* probes as possible. These methods are consistent with those outlined by Eaton *et al.* (2005) and Utah DEQ (2006). The automated samplers operate by pumping water from the river through tubing into sample bottles held within the main chamber, allowing for the collection of multiple samples during an event such as a storm or a period of snowmelt. In general, samplers were deployed when precipitation was expected. Each sample was split for TSS and TP analysis, with a portion of the sample filtered using a 0.45 μm filter for the analysis of total dissolved phosphorus (TDP). Manually collected samples were split in the field immediately upon collection, and automatically collected samples were split after being returned to the lab and agitated to insure homogeneity. Analyses of duplicates of split samples indicate no significant loss of homogeneity. TDP measurements were used to obtain values of particulate phosphorus to understand the speciation of phosphorus at each location.

Laboratory analyses were performed by labs affiliated with Utah State University and with the State of Utah Division of Water Quality. This study also used historic data, so labs and their associated methods changed over the time period examined. In principle, the results from the labs should produce consistent results, and quality assurance/quality control samples sent to multiple labs confirmed this assumption. For TSS analyses, some samples were analyzed under EPA Method 340.2, Total Suspended Solids, Mass Balance, while the remaining samples were analyzed according to EPA Method 160.2, Residue Nonfilterable Total Suspended Solids. For TP and TDP analyses, some samples were analyzed according to EPA Method 200.8, Determination of Trace Elements in Water and Waste by Inductively Coupled Mass Spectroscopy, and the remaining samples were analyzed as directed by EPA Method 365.2, Orthophosphate Ascorbic Acid Manual Single Reagent, preceded by an acid digestion of the sample.

Database Procedures

All of the referenced datasets were stored and managed using a database at the Utah Water Research Laboratory (http://littlebearriver.usu.edu/). The turbidity, water temperature, and water level data were transmitted via a spread spectrum radio network from the monitoring sites and imported directly to the database, the USGS discharge data were obtained from the USGS National Water Information System and incorporated into the database, and the lab results were entered into the database by hand. The time period under examination extended from the installation of *in situ* sensors in August 2005 through April 2008 resulting in datasets of 145-175 samples of TP, TDP, and TSS collected at each site (Table 1). For each observation of TP and TSS, associated continuous measurements of turbidity, water temperature, and discharge were extracted from the database and matched in time with the lab results. When the timing of a manual sample did not exactly correspond to the timing of continuous measurements, the values of turbidity, water temperature, and discharge that bracketed the sample were interpolated accordingly. The resulting datasets and summary statistics for each site and each variable are summarized in Table 1.

Statistical Methods

Our objective was to develop correlations to estimate TP and TSS as functions of turbidity using simple regression, following the general form given in Equation (1).

$$y_i = \alpha_0 + \alpha_1 x_i + e_i, \quad i = 1, 2, \ldots n, \tag{1}$$

where y_i represents the ith observation of the response variable, α_0 and α_1 are parameters estimated by regression, x_i is the ith observation of an explanatory variable, e_i represents the error for the ith observation, and n is the number of samples. Using techniques described subsequently, regression parameters unique to each response variable were estimated based on the observation datasets. In evaluating the regressions, we examined the errors, or residuals, to determine whether they demonstrated constant variance, were independent, had a mean of zero, and were normally distributed, all of which are characteristics of a reasonable linear model (Draper and Smith, 1998; Berthouex and Brown, 2002).

To assess the potential of the surrogate approach, we initially examined plots of turbidity against the response variables. This allowed for the visual identification and subsequent removal of a few extreme data points (no more than 3.5% of a single dataset). These points were unusually high turbidity measurements corresponding to low TP or TSS measurements and low turbidity corresponding to high TP or TSS, relative to the majority of observation pairs. It is assumed that these observations are a consequence of inconsistency between grab samples and the water that passes in the range of the turbidity sensor. Although efforts were made to collect samples near the turbidity

TABLE 1. Summary Statistics for Observed Variables. Total phosphorus (TP) and total suspended solid (TSS) values are the results of water quality grab samples whereas turbidity, discharge, and temperature are values extracted from continuous datasets corresponding in time to the TSS or TP sample. At Paradise, the discharge values are obtained from the U.S. Geological Survey. At Mendon, discharge was derived from stage measured simultaneously with the TP and TSS samples. Note that the maximum likelihood estimation mean and standard deviation are reported for TP because of the censored values (Helsel, 2005).

Site	Variable	Count	Mean	Standard Deviation	Range	Count Censored
Paradise	TP (mg/l)	172	0.256	1.23	<0.01-0.954	55
	Turbidity (NTU)	172	151	217	1.99-861	
	Discharge (m^3/s)	172	5.09	5.19	0.736-26.2	
	Temperature (°C)	172	7.00	2.96	0.30-16.9	
	TSS (mg/l)	175	240	390	0.86-2,280	
	Turbidity (NTU)	175	180	284	1.99-1,670	
	Discharge (m^3/s)	175	5.36	5.48	0.736-26.2	
	Temperature (°C)	175	6.96	2.86	0.30-15.8	
Mendon	TP (mg/l)	152	0.0791	0.0742	<0.01-0.20	21
	Turbidity (NTU)	152	21.1	11.1	4.33-55.1	
	Discharge (m^3/s)	152	3.81	3.05	0.232-10.4	
	Temperature (°C)	152	9.16	3.97	0.10-21.1	
	TSS (mg/l)	148	30.4	19.6	3.33-92.0	
	Turbidity (NTU)	148	21.3	11.6	4.33-55.1	
	Discharge (m^3/s)	148	3.94	2.92	0.655-10.4	
	Temperature (°C)	148	8.83	3.77	0.10-21.1	

sensors, there could still be discrepancies between the collected sample and the water measured by the turbidity sensor. The potential of these points to unduly influence the regressions was verified using a jackknife procedure, and our results were consistent with the findings of Christensen *et al.* (2000) and Tomlinson and De Carlo (2003) that removal of outliers may be justified in the development of surrogate relationships.

While turbidity was the target explanatory variable, other variables (e.g., discharge, water temperature, day of year, and hour of day) were considered for inclusion in the regression equations and were tested for significance in describing some of the variability in the response variables. Categorical variables associated with the hydrological conditions at the time of sample collection were also examined, as seasonal differences in surrogate relationships have been suggested by Grayson *et al.* (1996), Christensen *et al.* (2002), and Ryberg (2006). Categorical variables are qualitative descriptors of data that can be used in regression models (Berthouex and Brown, 2002). For each observation, a categorical variable is assigned a value to designate whether or not the observation falls into a particular category (e.g., seasons, laboratory methods). Equation (2) shows the general form of a regression equation with the inclusion of two categorical variables, Z_1 and Z_2.

$$y_i = \alpha_0 + \alpha_1 x_i + Z_1(\beta_0 + \beta_1 x_i) + Z_2(\gamma_0 + \gamma_1 x_i) + e_i, \quad i = 1, 2, \ldots n, \tag{2}$$

where β_0, β_1, γ_1, and γ_2 are parameters estimated by regression, and y_i, α_0, α_1, x_i, e_i, and n are as defined in Equation (1). The categorical variables, Z_1 and Z_2, are set as 0 or 1 to indicate the occurrence of the associated category.

We investigated two categorical variables associated with hydrological conditions: one to represent spring snowmelt *vs.* base flow conditions and one to represent the occurrence of a storm. Because the flow regime of the Little Bear is primarily snowmelt-driven, we hypothesized that the relationships between TP or TSS and turbidity might be significantly different during spring snowmelt *vs.* groundwater-dominated base flow conditions. Observations identified to occur during the period of spring snowmelt were assigned a value of 1 for this variable while the remaining observations were assigned a value of 0. As runoff resulting from precipitation events also has the potential to carry significant amounts of sediment and associated phosphorus into the river, the other categorical variable that was hypothesized to be significant was whether a sample was collected during a storm event. Storm events were identified by examining a number of factors including the incidence of precipitation and hydrograph response. Observations identified as occurring during a storm event were assigned a value of 1 for this variable, while observations collected during interstorm periods were assigned a value of 0.

A significant portion of the TP concentrations was censored, or reported as below detection limit (30% at Paradise and 13% at Mendon; see Table 1). We needed a regression method with the capability to properly include censored data. Historically, censored data have either been omitted from analyses or substituted with some value at or below the detection limit. These methods are known to introduce bias and variability into descriptive statistics that are calculated from datasets with censored values (Helsel, 2005). To preserve the censored values in the dataset without using substitution, regression with maximum likelihood estimation (MLE) was used on the matched datasets within the framework of the R statistical computing environment (http://www.r-project.org/) using techniques developed and described by Helsel and Lee (2006). MLE estimates a mean and a standard deviation for the response variable that is most likely to result in the values above the detection limit and the proportion of values below the detection limit. The mean and standard deviation are then used to produce values for the regression parameters that account for censored data. The TSS datasets do not include a large number of censored data, so associated regressions were developed using standard least squares regression within the R framework.

To determine which variables were important predictors, regression was performed several times for each response variable by adding and removing potential explanatory variables. A number of techniques were employed to address the appropriateness of each resulting regression model and to compare between them. For each explanatory variable in the regression, a *p*-value was calculated, which indicates the probability that the value of the regression parameter is not different from 0. A *p*-value greater than a specified threshold (commonly 0.05) indicates that the relationship between the explanatory variable and response variable is not statistically significant. If a *p*-value was less than 0.05, the associated variable was considered significant. For MLE regression, overall log-likelihood tests assist in determining whether the regression is better than no regression at all, and the parallel partial log-likelihood test was used to discern whether the addition of a variable improved the regression as compared with the equation without that variable (Helsel, 2005). The partial log-likelihood was compared with a chi-square distribution with the associated degrees of freedom to determine the

p-value, which represents the probability that the regression with the additional variable was different than without it. Again, 0.05 was used as the criterion for significance. Finally, residuals were examined to assess the error in each regression model. The root mean square error (RMSE) given by Equation (3) was used to compare regressions. A lower RMSE indicates a reduction in overall error.

$$\mathrm{RMSE} = \sqrt{\frac{\sum e^2}{\upsilon}}, \tag{3}$$

where *RMSE* is the root mean square error, e represents each residual value, and υ corresponds to the degrees of freedom. A variable was included in the final regression equation if it provided a reduction in the RMSE, had a p-value less than 0.05, and was significant according to the partial log-likelihood test (Helsel, 2005). Plots of the residuals were also examined to verify randomness and independence from other factors as well as to assess whether the residuals exhibited constant variance and approached a normal distribution. Log transformations of the data were examined, but did not provide significant improvement in the prediction of any of the response variables or in the behavior of the residuals, so untransformed datasets were used in all cases.

RESULTS

Correlations

The relationships between TP and TSS and potential explanatory variables are shown as matrices of correlation plots in Figure 2. At Paradise, there is a strong correlation between turbidity and both TP and TSS (Pearson's correlation coefficient, r, of 0.95). Both response variables exhibit some correlation with

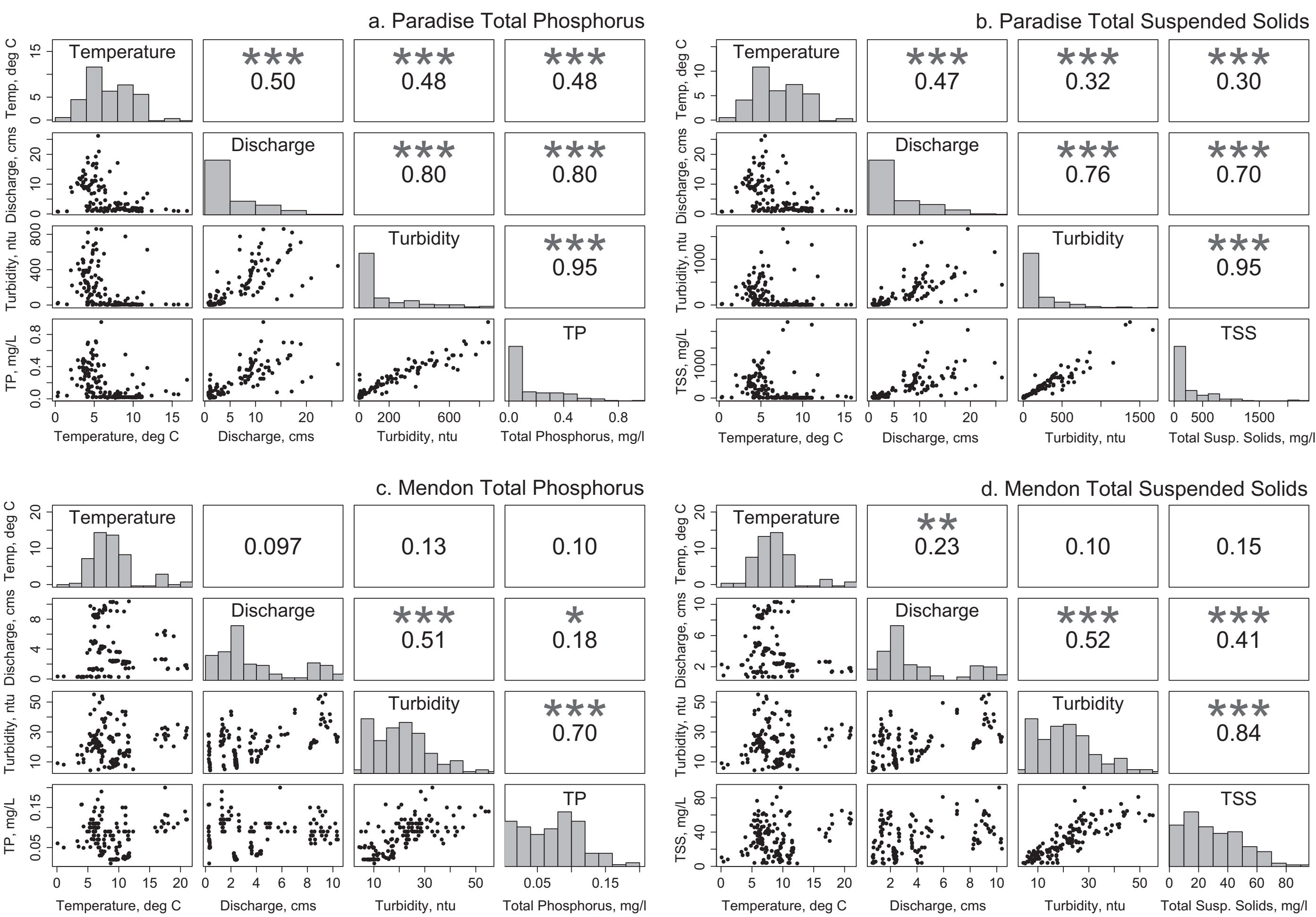

FIGURE 2. Correlation Matrices for Paradise Total Phosphorus (TP) (a) and Total Suspended Solids (TSS) (b) and Mendon TP (c) and TSS (d). Stars indicate the significance of the Pearson's correlation coefficient (***, 0.001; **, 0.01; *, 0.05).

discharge (TP: r = 0.80; TSS: r = 0.70) and water temperature (TP: r = 0.48; TSS: r = 0.70). At Mendon, the correlation between TP and turbidity is significant (r = 0.70), though not as strong as that at Paradise nor as strong as the correlation between turbidity and TSS at Mendon (r = 0.84). TSS at Mendon is also correlated with discharge (r = 0.41). Discharge can influence TP and TSS concentrations, so correlation is expected between discharge and the response variables. Correlation with temperature could reflect cyclical, seasonal variations in TP or TSS as suggested by Christensen *et al.* (2002). Discharge at Mendon is highly regulated by releases from Hyrum Reservoir and includes considerable groundwater contribution, factors that may explain the stronger correlations with discharge and temperature at Paradise than at Mendon. Although Porcupine Reservoir is located upstream of Paradise, its releases are diverted into agricultural canals for most of the year. Because turbidity is hypothesized to be a significant surrogate for TP and TSS, Figure 3 shows an enlarged view of the plots of turbidity related to TP and TSS at both sites, highlighting the strength of these relationships.

Regression Results

Turbidity, discharge, temperature, day of year, hour of day, and the two hydrologic categorical variables (spring snowmelt and storm event) were considered as explanatory variables for TSS and TP at each location. A variable was only retained if it was found to be significant according to the criteria described in the "Materials and Methods." The resulting equations are found in Table 2. Table 2 also gives the p-values for all the explanatory variables and the RMSE values for the regressions. The RMSE for the TP regression at Paradise is 0.069 mg/l TP, and the RMSE for the TP regression at Mendon is 0.027 mg/l TP. These values are within the range of RMSE values resulting from the turbidity and TP correlations reported by Christensen *et al.* (2002) over a similar turbidity range. For the TSS regressions, the RMSE for Paradise is 117 mg/l TSS and the Mendon RMSE is 10.8 mg/l TSS. The Paradise RMSE is relatively high because of the influence of a few large residuals; 2% of the residuals account for 38% of the variance, and another 3% of the residuals are responsible for an additional 32% of the variance. Removal of these anomalous values would reduce the RMSE to 64 mg/l TSS.

Figures 4 and 5 contain plots of observed and estimated TP and TSS at Paradise and Mendon, respectively. Estimated values were generated using the equations in Table 2. In these figures, panels (a) and (c) show time series of estimated TP or TSS along with points of observed TP or TSS for the entire period used to generate the regression equations. However, the time-series plots are dense and do not permit direct comparison between each point as do panels (b) and (d), which contain only corresponding

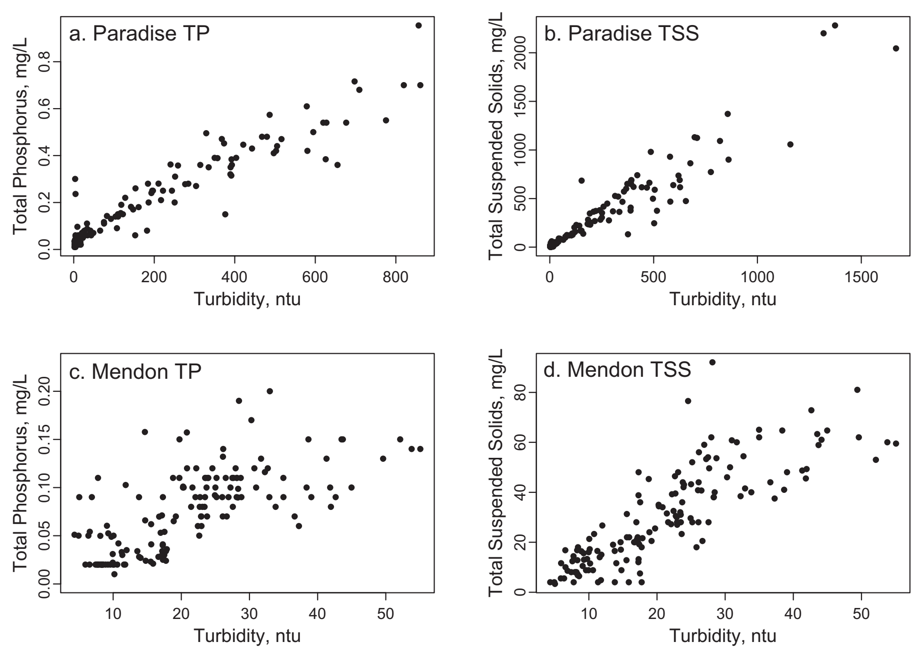

FIGURE 3. Correlation Plots for Turbidity and Total Phosphorus (TP) at Paradise (a), Total Suspended Solids (TSS) at Paradise (b), TP at Mendon (c), and TSS at Mendon (d).

TABLE 2. Final Surrogate Equations.

Site	Constituent	Equation	RMSE (mg/l)	*p*-value	Standard Error
Paradise	Total phosphorus	TP = 0.0209 + 0.000798 × Turb + 0.0386 × Z	0.069	Turb: $<10^{-6}$ Z: 8.71×10^{-4}	Turb: 2.67×10^{-5} Z: 1.16×10^{-2}
	Total suspended solids	TSS = 3.58 + 1.31 × Turb	117	Turb: $<10^{-6}$	Turb: 3.12×10^{-2}
Mendon	Total phosphorus	TP = −0.0341 + 0.0053 × Turb + 0.0949 × Z − 0.00404 × Turb × Z + 0.0832 × Y −0.000871 × Turb × Y	0.027	Turb: $<10^{-6}$ Z: $<10^{-6}$ Turb × Z: $<10^{-6}$ Y: 1.38×10^{-3} Turb × Y: 5.24×10^{-3}	Turb: 4.39×10^{-4} Z: 1.13×10^{-2} Turb × Z: 4.86×10^{-4} Y: 2.60×10^{-2} Turb × Y: 3.12×10^{-3}
	Total suspended solids	TSS = 0.341 + 1.41 × Turb	10.8	Turb: $<10^{-6}$	Turb: 7.70×10^{-2}

Variable	Description
TP	Total phosphorus (mg/l)
TSS	Total suspended solids (mg/l)
Turb	Turbidity (NTU)
Z	Categorical variable for spring snowmelt (Z = 1) *vs.* base flow (Z = 0)
Y	Categorical variable for Turb < 10 NTU (Y = 1) *vs.* Turb > 10 NTU (Y = 0)

RMSE, root mean square error.

estimated and observed values connected by vertical lines.

The vertical lines in Figures 4b, 4d, 5b, and 5d represent the residuals of the regressions. More detailed plots of the residuals can be found in Spackman Jones (2008). For TP and TSS at both locations, no significant relationships between the residuals and any measured properties were observed, and the residuals did not show any correlation with temporal variables such as day of year or hour of day. For the Mendon TP regression, the residuals exhibited constant variance and were approximately normally distributed (Figure 5b). For TP at Paradise, Figure 4b suggests that some residuals may be greater at greater values of TP, but there are also small residuals at high TP levels. Although transformations can sometimes correct this pattern, transforming data did not improve TP estimations nor did it provide constant variance in the residuals.

As mentioned before, the Paradise TSS regression resulted in several large residual values (Figure 4d). Transformations were considered in an attempt to account for the large range of TSS residual values, but neither the TSS estimates nor the retransformed RMSE were improved. For the Mendon TSS regression, Figure 5d shows a greater difference in estimated and observed values at higher values of TSS, though there are exceptions to this generalization, and the residuals were approximately normally distributed. Again, transformations were examined, but did not improve TSS estimates. For all cases, untransformed data were used to simplify interpretation of results and to maintain consistency between the regressions.

DISCUSSION

Explanatory Variables

Although turbidity, discharge, temperature, day of year, hour of day, and hydrologic categorical variables were considered, turbidity was the only explanatory variable that was a significant predictor of TSS at both sites, suggesting that turbidity alone is sufficient to estimate TSS across hydrologic conditions at these locations. Though there is correlation between TSS and discharge at both Paradise and Mendon and between TSS and water temperature at Paradise, including discharge or water temperature did not explain a significant proportion of the variance, so neither variable was retained. This is likely because of colinearity with turbidity as shown in Figures 2b and d. The relationships between TSS and discharge and between TSS and water temperature are very similar to the relationships between turbidity and discharge and between turbidity and water temperature.

For TP at both sites, only turbidity and the spring snowmelt/base flow categorical variable were significant. Although TP was correlated with both discharge and water temperature at Paradise, turbidity was correlated with these variables to a similar degree (see Figure 2a). The presence of turbidity in the final regression equation accounts for the information provided by discharge and water temperature, making their inclusion unnecessary. The categorical variable indicating whether observations were collected during a storm event was not significant at either site,

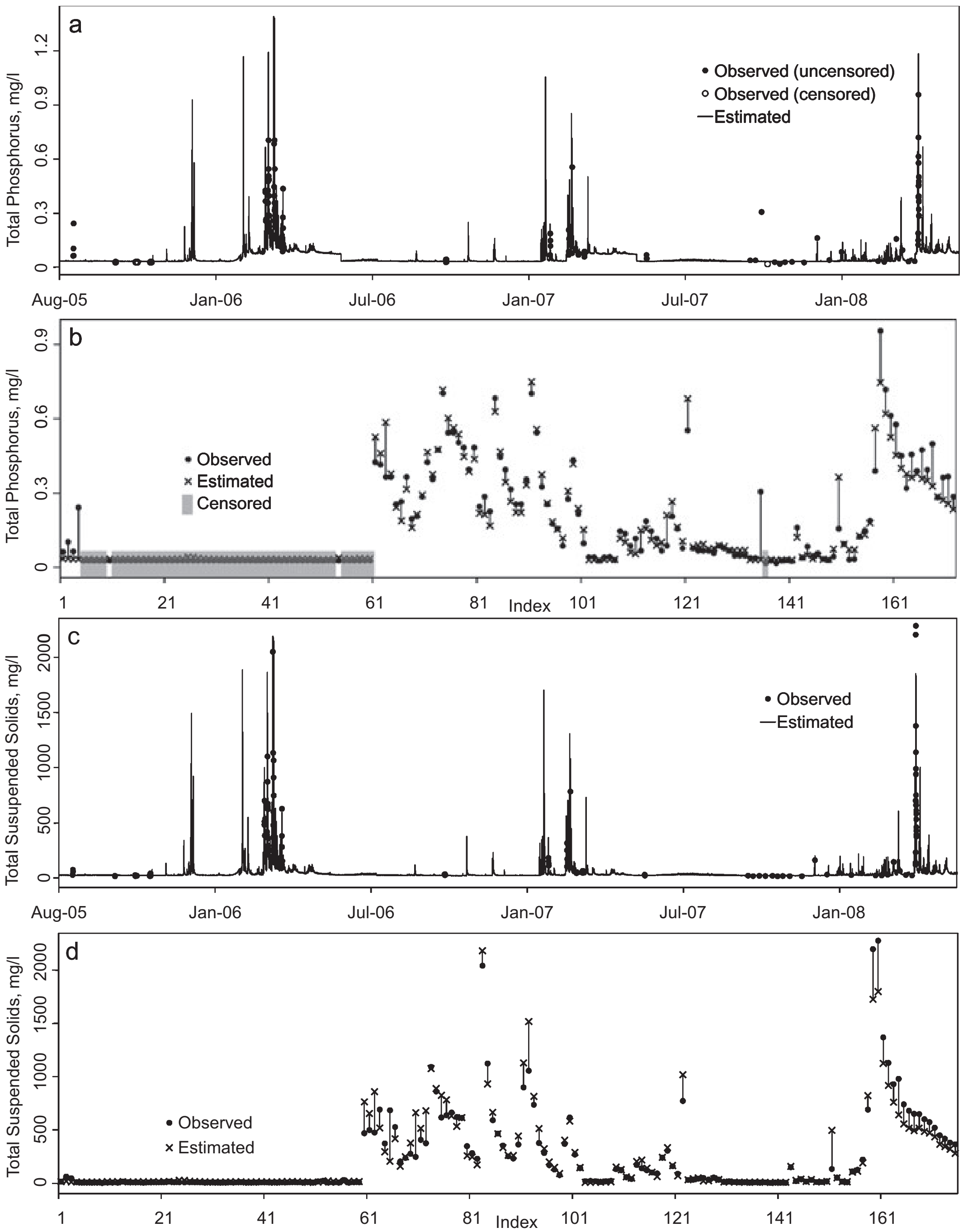

FIGURE 4. Plot of Observed and Estimated Total Phosphorus (a, b) and Total Suspended Solids (c, d) at Paradise. For censored data, points are plotted at the detection limit. As many of the observations in the full time series (a, c) are obscured, panels (b) and (d) only contain estimated results with each corresponding observation. Observed and estimated values are connected by vertical lines. The *x*-axis is an index that represents the order in which observations were made.

implying that the relationships between turbidity and TP are consistent throughout storm events. There is a distinction between periods of spring snowmelt and periods of base flow at both Paradise and Mendon. This observed correlation with season or hydrologic regime is consistent with the results of Christensen *et al.* (2002) and Ryberg (2006).

For the TP regression at Mendon, the interaction between turbidity and the spring snowmelt/base flow variable was found to improve the regression significantly, indicating that the combined effect of the two variables is different from the sum of their individual contributions. In this case, TP is decreased during spring snowmelt periods by a factor

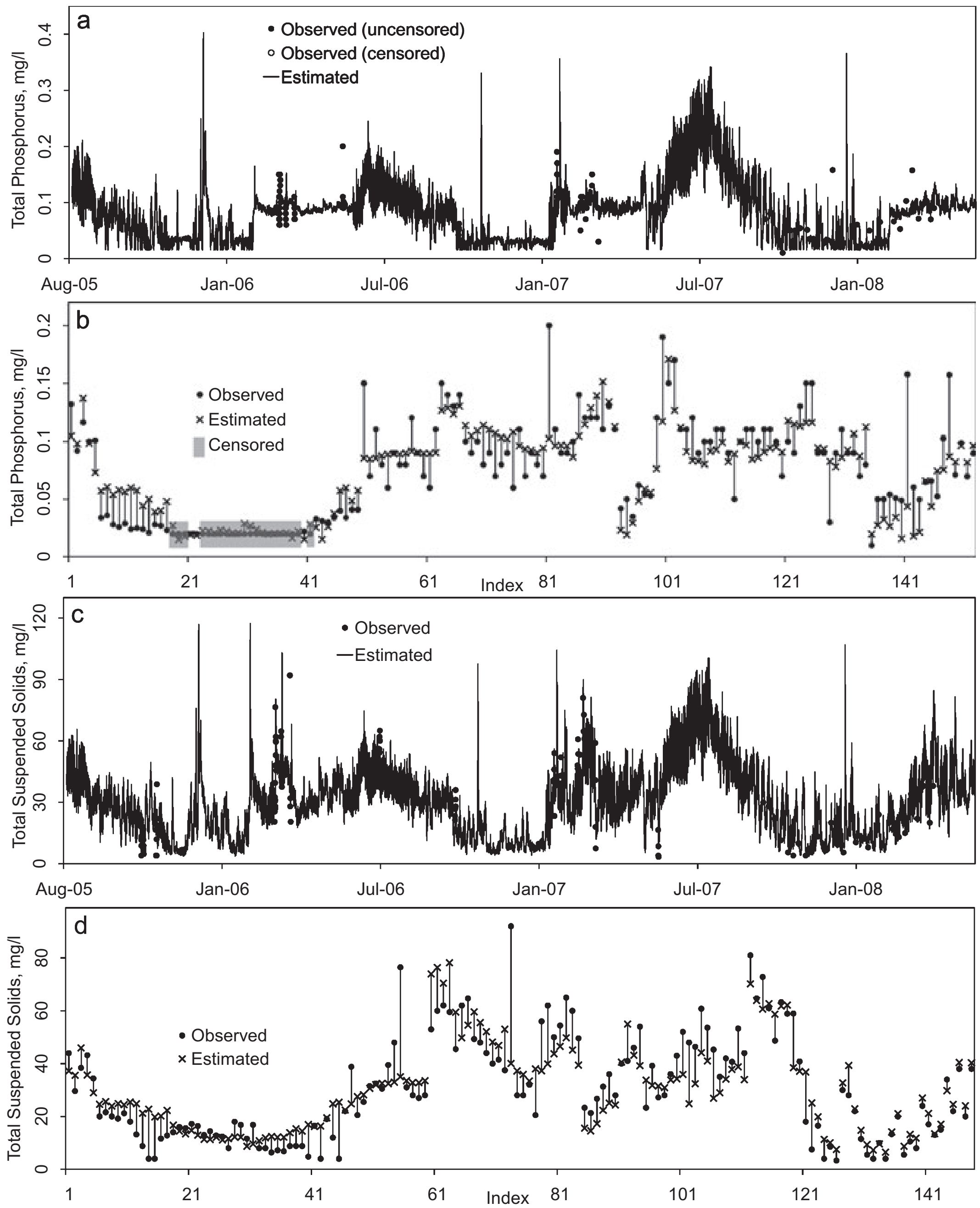

FIGURE 5. Plot of Observed and Estimated Total Phosphorus (a, b) and Total Suspended Solids (c, d) at Mendon. See Figure 4 for description of panels.

of $0.00404 \times$ turbidity. The negative term in the equation, however, resulted in some negative predicted concentrations, so an additional categorical variable, Y, was added to distinguish the relationship at low *vs.* high levels of turbidity. The categorical variable differentiating low from high turbidity levels (Y) was found to be significant and improved the regression results. The regression parameters reported in Table 2 for Mendon TP have been adjusted to account for Y. The inclusion of this variable implies that the relationship between turbidity and TP is different at low values of turbidity, corresponding to low TP measurements. Distinctions in surrogate relationships at low turbidity levels have been suggested by Grayson *et al.* (1996) and Stubblefield *et al.* (2007).

Site Comparison

Paradise and Mendon were selected as sampling sites for analyses in this work because of their differing characteristics, which are reflected in the differences in the resulting surrogate relationships. The RMSE values for both TP and TSS are greater at Paradise than Mendon, which is a result of the larger range of observed values at that site (Paradise: 0.01-0.95 mg/l TP and 0.86-2,280 mg/l TSS; Mendon: 0.01-0.20 mg/l TP and 3.33-92 mg/l TSS). Figures 2 and 3 indicate stronger correlations at Paradise than Mendon between turbidity and both TP and TSS, and the final TP equation at Paradise appears to better track trends through a greater range than does the Mendon relationship. Moreover, the Mendon TP regression is more complex as it includes the interaction between turbidity and the spring snowmelt/base flow categorical variable and requires an additional variable to account for different behaviors between turbidity and TP at low concentrations.

We surmise that these differences are a result of the varying composition of TP between the two sites. At Mendon, an overall average of 60% of the TP was dissolved, leaving 40% as particulate. The average composition of TP measured at Paradise was the opposite, 40% dissolved and 60% particulate. These ratios are comparable with those reported by Johnes (2007) for sites with higher base flow and more groundwater influence (65-75% dissolved) *vs.* those with lower base flow (40-50% dissolved). As dissolved phosphorus is not associated with particles, the correlation between TP and turbidity at Mendon would not be as strong as the correlation at Paradise where the TP is primarily comprised of particulate phosphorus. Indeed, in this study, TDP and turbidity were not significantly correlated at either site. This is corroborated by Stubblefield *et al.* (2007) who found no relationship between soluble reactive phosphorus and turbidity.

Patterns of dissolved phosphorus were further examined to address the possibility of relating the portion of TP that was dissolved to the results of the regression model. No trends in the fraction of dissolved phosphorus were found with respect to season, and there was no relationship with the regression residuals at either site. During periods of spring snowmelt at both sites, the fraction of dissolved phosphorus was slightly higher than during base flow periods, but the difference was not significant at the 95% confidence level. This potential difference will be investigated more thoroughly as more data are obtained. The TP relationships do not explicitly include the speciation of phosphorus, but we suspect that stronger TP-turbidity relationships result when the TP is predominantly particulate. Although there is generally more of dissolved phosphorus than particulate phosphorus at Mendon, the TP-turbidity relationship is still useful for comparing between sites and between time periods.

Variations in the speciation of phosphorus at the two sites reflect differing sources of phosphorus and differing stream dynamics. Factors that may increase the amount of TDP at Mendon include more concentrated agricultural activity than above Paradise, impact from wastewater treatment lagoons, and manure or fertilizer that is transported to canals and into the river before being incorporated by plants or adsorbed to the soil. In contrast, the phosphorus entering the river above Paradise is primarily related to soil erosion and particulate matter. Additionally, between the two sites is Hyrum Reservoir. Phosphorus (primarily particulate) enters the reservoir from the upper watershed and accumulates in the sediment. Over time, the phosphorus can be released from the sediment and carried out of the reservoir in its dissolved form through reservoir releases (Utah DEQ, 2000, 2009), which might also carry algae that contain phosphorus. Other than releases from Hyrum Reservoir, the sources of discharge at Mendon include agricultural return flows, which have the potential to contribute dissolved phosphorus from crop runoff, and some groundwater influence. It is possible that dissolved phosphorus enters the river via the groundwater (Burkart *et al.*, 2004), however, we have no specific evidence that this is occurring in the Little Bear River.

Despite the differing characteristics of the two sites, some aspects of the surrogate relationships are consistent between Paradise and Mendon. Both TSS surrogate relationships are functions only of turbidity with similar slopes (1.31 mg/l TSS/NTU at Paradise and 1.41 mg/l TSS/NTU at Mendon), although the suspended matter varied between the two locations. The intercepts of the TSS regressions differ between the two sites (3.58 mg/l TSS at Paradise and 0.341 mg/l TSS at Mendon), but the difference is comparable with variations in duplicate TSS samples. For both sites, the TP relationships include a variable to account for base flow *vs.* spring snowmelt. This is similar to the differences between the suspended sediment and TP surrogate relationships determined by Ryberg (2006). Another similarity is the lack of significance of the storm event term in all the regressions. Although storms can be important periods for TSS and TP transport, in this watershed the relationships between turbidity and TP and between turbidity and TSS did not vary during storms.

Applicability

Surrogate relationships like those described in this paper can be used to provide high frequency estimates of TP and TSS concentrations. Until robust *in situ* sensors for TP and TSS are developed, surrogate measures allow for the characterization of fluxes at varying time scales (e.g., from individual events to entire seasons or years) and also provide a better means for comparison between monitoring sites. The use of surrogate measures for estimating water quality constituents has widespread implications for water quality monitoring programs and the design of environmental observatories. For water quality models, improved quantification of constituent concentrations will facilitate the refinement of model parameters that represent pollutant loading drivers such as land use, management practices, and hydrologic characteristics. It will also support the testing of underlying model assumptions. For large-scale environmental observatories, the use of surrogate measures will be necessary as a logistically and economically feasible means to characterize the variability in constituent fluxes on high temporal and spatial resolutions over extended time periods.

Although surrogate relationships may be appropriate to address scientific questions (e.g., how and when constituents move through a watershed), the adequacy of surrogate methods for regulatory purposes will be determined by policy makers. The uncertainty in surrogate relationships may be considered by regulators to be too great for determining compliance with a concentration or load threshold. However, because high frequency concentrations can provide an improved perspective of the spatial and temporal behavior of constituents, surrogate methods could assist regulators in targeting locations and time periods of interest for additional monitoring and to determine what sampling frequency is optimal. Furthermore, knowledge of the spatial and temporal distributions of constituent loading could assist in targeting specific sources or source areas for water quality management projects.

Improving Surrogate Relationships

The surrogate relationships described in this paper provide improved understanding of TP and TSS transport in the Little Bear watershed, but steps may be taken in the future to improve these relationships. We anticipate that just as there are differences in the relationships during different times of the year (as represented by the categorical variable in the TP-turbidity relationships), there may also be changes in the relationships as the watershed changes over time (e.g., as land use changes or with changes in water management, etc.). Just as the USGS periodically updates its stage-discharge relationships at streamflow gages (Wahl *et al.*, 1995), the TP and TSS surrogate relationships should be reviewed as new data are collected. Although this study included adequate data to develop regression equations, the equations may be revised or adjusted to improve the fit with additional observations as conditions in the watershed change.

In this paper, we have shown that turbidity can be used as a surrogate for TSS and TP. However, turbidity is an optical measure, whereas TSS and TP are based on the mass of particulate matter in a sample volume and the total mass of phosphorus in a sample, respectively. Turbidity can be affected by the size and characteristics of the particulate matter (Gippel, 1995), as can the distribution of phosphorus between dissolved and particulate forms, which may contribute to the site specificity of the surrogate relationships. Examination of particle size distributions of suspended sediment at different sites and over time may provide additional information that could be used to determine why surrogate relationships are site-specific and why these relationships are seasonal (e.g., spring snowmelt *vs.* base flow conditions) (Pfannkuche and Schmidt, 2003).

The surrogate relationships might be improved by the inclusion of water quality variables in addition to turbidity. As mentioned previously, a significant fraction of the TP is in dissolved form at Mendon. Part way into this study, *in situ* sensors were installed to measure pH, specific conductance, and dissolved oxygen. Although TDP likely makes up a very small fraction of the total dissolved constituents (as reflected in specific conductance), changes in specific conductance may be the result of changes in discharge sources (Covino and McGlynn, 2007; Stewart *et al.*, 2007) that may indicate resulting changes in TDP. Thus, a correlation with specific conductance may help to refine the regression where the majority of TP is dissolved, similar to relationships developed by Christensen *et al.* (2000) and Rasmussen *et al.* (2008) for other dissolved constituents. A method for using surrogate measures to estimate dissolved phosphorus would be valuable because, although TP is the form of phosphorus that is generally regulated, dissolved phosphorus is the form that is actually available for biological uptake.

SUMMARY AND CONCLUSIONS

Regression equations incorporating censored observations were developed for TP and TSS as functions of turbidity at two sites in the Little Bear River. For TSS, the relationships with turbidity were consistent across hydrological conditions while for TP, there was a distinction in the relationships between spring snowmelt and base flow periods. The overall RMSE in the regression models was optimized, and visual examinations of the observed and estimated concentrations indicate that the equations track observed trends. The surrogate relationships between turbidity and TSS at both sites were similar. The differences in the surrogate relationships between turbidity and TP at the upper and lower watershed sites are a result of the predominant form of phosphorus at each site. The fraction of phosphorus in dissolved and particulate forms at each site reflects the differences in the sources of phosphorus within the upper and lower watershed.

Coupled with high frequency measurements of explanatory variables, surrogate relationships can be used to calculate high frequency estimates of concentration for extended time periods. Loads derived from high frequency, continuous concentration records provide a number of advantages to loads calculated from traditionally sampled concentration. Increased loading during events such as storms or spring snowmelt, which are often missed by routine sampling programs, is considered without skewing load estimates high as collecting samples disproportionately during storm events can do. Also, there is no need to use complicated load estimation equations that account for long periods between concentration measurements or discharge measured more frequently than concentration.

ACKNOWLEDGMENTS

This work was supported by the National Science Foundation grant CBET 0610075 and by the United States Department of Agriculture's Conservation Effects Assessment Program (CEAP) grant UTAW-2004-05671. The authors gratefully acknowledge field technicians, namely Michael Stevens and Sandra Guerrero, private land owners within the Little Bear River watershed who have graciously provided them access to their property, and Mountain Crest High School and Willow Valley Middle School for providing internet connectivity for their remote base stations. Any opinions, findings and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation or the United States Department of Agriculture. Mention of trade names or commercial products within this paper is for identification purposes only and does not constitute endorsement or recommendation for use by the National Science Foundation, the United States Department of Agriculture, or Utah State University.

LITERATURE CITED

Berthouex, P.M. and L.C. Brown, 2002. Statistics for Environmental Engineers. Lewis Publishers, New York.

Brasington, J. and K. Richards, 2000. Turbidity and Suspended Sediment Dynamics in Small Catchments in the Nepal Middle Hills. Hydrological Processes 14:2559-2574.

Burkart, M.R., W.W. Simpkins, A.J. Morrow, and J.M. Gannon, 2004. Occurrence of Total Dissolved Phosphorus in Unconsolidated Aquifers and Aquitards in Iowa. Journal of the American Water Resources Association 40:827-834.

Christensen, V.G., X. Jian, and A.C. Ziegler, 2000. Regression Analysis and Real-Time Water-Quality Monitoring to Estimate Constituent Concentrations, Loads, and Yields in the Little Arkansas River, South-Central Kansas, 1995-99. U.S. Geological Survey Water Resources Investigations Report 2000-4126, Reston, Virginia, 36 pp.

Christensen, V.G., P.P. Rasmussen, and A.C. Ziegler, 2002. Real-Time Water Quality Monitoring and Regression Analysis to Estimate Nutrient and Bacteria Concentrations in Kansas Streams. Water Science and Technology 45:205-211.

Correll, D.L., T.E. Jordan, and D.E. Weller, 1999. Transport of Nitrogen and Phosphorus from Rhode River Watersheds During Storm Events. Water Resources Research 35:2513-2521.

Covino, T.P. and B.L. McGlynn, 2007. Stream Gains and Losses Across a Mountain-to-Valley Transition: Impacts on Watershed Hydrology and Stream Water Chemistry. Water Resources Research 43:W10431, 14 pp.

Draper, N. and H. Smith, 1998. Applied Regression Analysis. Wiley, New York.

Eaton, A.D., L.S. Clesceri, E.W. Rice, and A.E. Greenberg, 2005. Standard Methods for the Examination of Water and Wastewater (21st Edition). American Public Health Association, American Water Works Association and Water Environment Federation, Washington, DC.

Forest Technology Systems, Ltd., 2007. DTS-12 SDI-12 Turbidity Sensor Operating Manual. Forest Technology Systems, Victoria, BC.

Gippel, C.J., 1995. Potential of Turbidity Monitoring for Measuring the Transport of Suspended Solids in Streams. Hydrological Processes 9:83-97.

Grayson, R.B., B.L. Finlayson, C.J. Gippel, and B.T. Hart, 1996. The Potential of Field Turbidity Measurements for the Computation of Total Phosphorus and Suspended Solids Loads. Journal of Environmental Management 47:257-267.

Grayson, R.B., C.J. Gippel, B.L. Finlayson, and B.T. Hart, 1997. Catchment-wide Impacts on Water Quality: The Use of 'Snapshot' Sampling During Stable Flow. Journal of Hydrology 199:121-134.

Helsel, D.R., 2005. Nondetects and Data Analysis: Statistics for Censored Environmental Data. Wiley-Interscience, Hoboken, New Jersey.

Helsel, D. and L. Lee, 2006. Analysis of Environmental Data with Nondetects. Continuing Education Workshop at the Joint Statistical Meetings. American Statistical Association, Seattle, Washington, 30 pp.

Horsburgh, J.S., A. Spackman Jones, D.G. Tarboton, D.K. Stevens, and N.O. Mesner, 2010. A Sensor Network for High Frequency Estimation of Water Quality Constituent Fluxes Using Surrogates. Environmental Modelling and Software 25:1031-1044.

Houser, J.N., P.J. Mulholland, and K.O. Maloney, 2006. Upland Disturbance Affects Headwater Stream Nutrients and Suspended Sediments During Baseflow and Stormflow. Journal of Environmental Quality 35:352-365.

Johnes, P.J., 2007. Uncertainties in Annual Riverine Phosphorus Load Estimation: Impact of Load Estimation Methodology, Sampling Frequency, Baseflow Index and Catchment Population Density. Journal of Hydrology 332:241-258.

Jordan, P., A. Arnscheidt, H. McGrogan, and S. McCormick, 2007. Characterising Phosphorus Transfers in Rural Catchments Using a Continuous Bank-side Analyser. Hydrology and Earth System Sciences 11:372-381.

Kirchner, J.W., X.H. Feng, C. Neal, and A.J. Robson, 2004. The Fine Structure of Water-Quality Dynamics: The (High-Frequency) Wave of the Future. Hydrological Processes 18:1353-1359.

Kronvang, B., A. Laubel, and R. Grant, 1997. Suspended Sediment and Particulate Phosphorus Transport and Delivery Pathways in an Arable Catchment, Gelbaek Stream, Denmark. Hydrological Processes 11:627-642.

Montgomery, J.L., T. Harmon, W. Kaiser, A. Sanderson, C.N. Haas, R. Hooper, B. Minsker, J. Schnoor, N.L. Clesceri, W. Graham, and P. Brezonik, 2007. The WATERS Network: An Integrated Environmental Observatory Network for Water Research. Environmental Science & Technology 41:6642-6647.

Neilson, B.T. and S.C. Chapra, 2003. Integration of Water Quality Monitoring and Modeling for TMDL Development. Water Resources Impact 5:9-11.

Nolan, A.L., G.A. Lawrence, and M. Maeder, 1995. Phosphorus Speciation in the Williams River, New South Wales: Eutrophication and a Chemometric Analysis of Relationships with Other Water Quality Parameters. Marine and Freshwater Research 46:1055-1064.

Pfannkuche, J. and A. Schmidt, 2003. Determination of Suspended Particulate Matter Concentration From Turbidity Measurements: Particle Size Effects and Calibration Procedures. Hydrological Processes 17:1951-1963.

Rasmussen, T.J., C.J. Lee, and A.C. Siegler, 2008. Estimation of Constituent Concentrations, Loads, and Yields in Streams of Johnson County, Northeast Kansas, Using Continuous Water-Quality Monitoring and Regression Models, October 2002 through December 2006. U.S. Geological Survey Scientific Investigations Report 2008-5014, Reston, Virginia, 103 pp.

Ryberg, K.R., 2006. Continuous Water-Quality Monitoring and Regression Analysis to Estimate Constituent Concentrations and Loads in the Red River of the North, Fargo, North Dakota, 2003-05. U.S. Geological Survey Scientific Investigation Report 2006-5241, Reston, Virginia, 35 pp.

Scholefield, D., T. Le Goff, J. Braven, L. Ebdon, T. Long, and M. Butler, 2005. Concerted Diurnal Patterns in Riverine Nutrient Concentrations and Physical Conditions. Science of the Total Environment 344:201-210.

Soil Survey Staff, National Resource Conservation Service (NRCS), United States Department of Agriculture (USDA), 2008. Web Soil Survey. http://websoilsurvey.nrcs.usda.gov, *accessed* November 2008.

Spackman Jones, A., 2008. Estimating Total Phosphorus and Total Suspended Solids Loads from High Frequency Data. M.S. Thesis, Utah State University, Logan, Utah.

Stewart, M., J. Cimino, and M. Ross, 2007. Calibration of Base Flow Separation Methods with Streamflow Conductivity. Ground Water 45:17-27.

Stubblefield, A.P., J.E. Reuter, R.A. Dahlgren, and C.R. Goldman, 2007. Use of Turbidometry to Characterize Suspended Sediment and Phosphorus Fluxes in the Lake Tahoe Basin, California, USA. Hydrological Processes 21:281-291.

Tomlinson, M.S. and E.H. De Carlo, 2003. The Need for High Resolution Time Series Data to Characterize Hawaiian Streams. Journal of the American Water Resources Association 39:113-123.

Utah Department of Environmental Quality (Utah DEQ), 2000. Little Bear River Watershed TMDL. Division of Water Quality, Salt Lake City, Utah.

Utah Department of Environmental Quality (Utah DEQ), 2006. Monitoring Manual. Division of Water Quality, Salt Lake City, Utah.

Utah Department of Environmental Quality (Utah DEQ), 2009. Middle Bear River and Cutler Reservoir TMDLs – Public Draft. Division of Water Quality, Salt Lake City, Utah.

Vivoni, E.R. and R. Camilli, 2003. Real-Time Streaming of Environmental Field Data. Computers & Geosciences 29:457-468.

Vivoni, E.R. and K.T. Richards, 2005. Integrated Use of GIS-Based Field Sampling and Modeling for Hydrologic and Water Quality Studies. Journal of Hydroinformatics 7:235-250.

de Vries, A. and H.C. Klavers, 1994. Riverine Fluxes of Pollutants: Monitoring Strategy First, Calculation Methods Second. European Water Pollution Control 4:12-17.

Wahl, K.L., W.O. Thomas, and R.M. Hirsch, 1995. The Stream-Gaging Program of the U.S. Geological Survey. U.S. Geological Survey Circular 1123, Reston, Virginia, 22 pp.