Prepared in cooperation with the U.S. Environmental Protection Agency Chesapeake Bay Program and the Virginia Department of Environmental Quality

A Comparison of Turbidity-Based and Streamflow-Based Estimates of Suspended-Sediment Concentrations in Three Chesapeake Bay Tributaries

Scientific Investigations Report 2009–5165

U.S. Department of the Interior
U.S. Geological Survey

Front Cover. The James River at Cartersville, Virginia, during stormflow conditions *(photograph by John Jastram, U.S. Geological Survey).*

Inset—U.S. Geological Survey personnel sampling the Rappahannock River near Fredericksburg, Virginia, from a cableway during stormflow conditions *(photograph by Douglas Moyer, U.S. Geological Survey).*

Back Cover. The shadow created by U.S. Geological Survey personnel sampling the Rappahannock River near Fredericksburg, Virginia, from a cableway during stormflow conditions *(photograph by Douglas Moyer, U.S. Geological Survey).*

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Conversion Factors

Multiply	By	To obtain
	Length	
foot (ft)	0.3048	meter (m)
	Area	
square mile (mi^2)	259.0	hectare (ha)
square mile (mi^2)	2.590	square kilometer (km^2)
	Flow rate	
cubic foot per second (ft^3/s)	0.02832	cubic meter per second (m^3/s)
	Mass	
ton, short (2,000 lb)	0.9072	megagram (Mg)
kilogram (kg)	2.205	pound avoirdupois (lb)

Temperature in degrees Celsius (°C) may be converted to degrees Fahrenheit (°F) as follows:

$$°F = (1.8 \times °C) + 32$$

Specific conductance is given in microsiemens per centimeter at 25 degrees Celsius (µS/cm at 25 °C).

Concentrations of chemical constituents in water are given in milligrams per liter (mg/L).

Abbreviations and Acronyms

AMLE	adjusted maximum likelihood estimator
BMP	best management practice
CBP	Chesapeake Bay Program
CDF	cumulative distribution frequency
CV	coefficient of variation
FNU	formazin nephelometric units
GOES	Geostationary Operational Environmental Satellites
MAE	mean absolute error
MSE	mean squared error
NWISWeb	National Water Information System Web site
RIM	River Input Monitoring Program
SSC	suspended-sediment concentration
SSE	sum of squared errors
SSL	suspended-sediment load
TMDL	total maximum daily load
TN	total nitrogen
TP	total phosphorus
TTS	turbidity threshold sampling
US EPA	U.S. Environmental Protection Agency
USGS	U.S. Geological Survey
VA DEQ	Virginia Department of Environmental Quality
VA WSC	Virginia Water Science Center
VIF	variance inflation factor

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Abstract

Fluvial transport of sediment into the Chesapeake Bay estuary is a persistent water-quality issue with major implications for the overall health of the bay ecosystem. Accurately and precisely estimating the suspended-sediment concentrations (SSC) and loads that are delivered to the bay, however, remains challenging. Although manual sampling of SSC produces an accurate series of point-in-time measurements, robust extrapolation to unmeasured periods (especially high-flow periods) has proven to be difficult. Sediment concentrations typically have been estimated using regression relations between individual SSC values and associated streamflow values; however, suspended-sediment transport during storm events is extremely variable, and it is often difficult to relate a unique SSC to a given streamflow. With this limitation for estimating SSC, innovative approaches for generating detailed records of suspended-sediment transport are needed.

One effective method for improved suspended-sediment determination involves the continuous monitoring of turbidity as a surrogate for SSC. Turbidity measurements are theoretically well correlated to SSC because turbidity represents a measure of water clarity that is directly influenced by suspended sediments; thus, turbidity-based estimation models typically are effective tools for generating SSC data. The U.S. Geological Survey, in cooperation with the U.S. Environmental Protection Agency Chesapeake Bay Program and Virginia Department of Environmental Quality, initiated continuous turbidity monitoring on three major tributaries of the bay—the James, Rappahannock, and North Fork Shenandoah Rivers—to evaluate the use of turbidity as a sediment surrogate in rivers that deliver sediment to the bay. Results of this surrogate approach were compared to the traditionally applied streamflow-based approach for estimating SSC. Additionally, evaluation and comparison of these two approaches were conducted for nutrient estimations.

Results demonstrate that the application of turbidity-based estimation models provides an improved method for generating a continuous record of SSC, relative to the classical approach that uses streamflow as a surrogate for SSC. Turbidity-based estimates of SSC were found to be more accurate and precise than SSC estimates from streamflow-based approaches. The turbidity-based SSC estimation models explained 92 to 98 percent of the variability in SSC, while streamflow-based models explained 74 to 88 percent of the variability in SSC. Furthermore, the mean absolute error of turbidity-based SSC estimates was 50 to 87 percent less than the corresponding values from the streamflow-based models. Statistically significant differences were detected between the distributions of residual errors and estimates from the two approaches, indicating that the turbidity-based approach yields estimates of SSC with greater precision than the streamflow-based approach.

Similar improvements were identified for turbidity-based estimates of total phosphorus, which is strongly related to turbidity because total phosphorus occurs predominantly in particulate form. Total nitrogen estimation models based on turbidity and streamflow generated estimates of similar quality, with the turbidity-based models providing slight improvements in the quality of estimations. This result is attributed to the understanding that nitrogen transport is dominated by dissolved forms that relate less directly to streamflow and turbidity. Improvements in concentration estimation resulted in improved estimates of load. Turbidity-based suspended-sediment loads estimated for the James River at Cartersville, VA, monitoring station exhibited tighter confidence interval bounds and a coefficient of variation of 12 percent, compared with a coefficient of variation of 38 percent for the streamflow-based load.

Introduction

Elevated suspended-sediment concentrations (SSC) are major water-pollution concerns in the Chesapeake Bay watershed, as they are in many sensitive ecosystems throughout the world. Nationwide, siltation ranked second on the U.S. Environmental Protection Agency's (USEPA) 305b list of stressors causing stream impairments (U.S. Environmental Protection Agency, 2002). The Chesapeake Bay (hereafter referred to as the bay), the Nation's largest estuary, has been degraded through declines in water-quality conditions and loss of habitat. Excess sediment has an adverse effect on the living resources and associated habitat of the bay and its watershed. The bay was listed as an impaired water body in 1998 under the Clean Water Act because of excess nutrient and sediment levels (Chesapeake Bay Program, 2008). The USEPA Chesapeake Bay Program (CBP) needs information with which to evaluate current conditions and assess progress toward meeting sediment-reduction goals.

Background

The detrimental effects of sediment transport are apparent in the terrestrial environments that serve as sediment sources and in the aquatic environments to which the sediments are delivered. Terrestrial effects of soil erosion (the source of most fluvial sediments) include the erosion of surficial soil, loss of soil nutrients, degradation of soil structure, reduction of tillable land, and the ultimate reduction of agricultural productivity (Walling and Collins, 2000). The effects of excessive sedimentation to the aquatic systems receiving the eroded sediments range from ecological degradation to economic expenses. Ecologically, suspended sediments harm aquatic ecosystems by decreasing light penetration into the water column (reducing photosynthesis), smothering benthic habitats, delivering excess nutrients, and potentially delivering soil-bound contaminants, such as phosphorus and bacteria (Christensen, 2001; Davies-Colley and Smith, 2001). Furthermore, toxic materials, including pesticides, metals, and radionuclides, may adsorb strongly to sediment particles; thus, introduction of excessive amounts of sediment to a water body from source areas where such materials are present may lead to toxic conditions for the biota that use the resource (Meade and Parker, 1984).

Economically, accelerated transport of suspended sediments increases the costs of water treatment for human use and may decrease profits from waterways used for recreational purposes because people typically perceive sediment-laden or turbid water as less desirable for recreation than clearer waters (Davies-Colley and Smith, 2001). Also, sediment accumulation within channels increases streambed elevation, leading to more damaging and life-threatening floods as the stormflow carrying capacity of the channel is decreased (Meade and Parker, 1984). Yet another economic cost related to sediment is the increased maintenance needs of structures within waterways carrying elevated sediment concentrations; most reservoirs in the United States trap at least half of the sediment transported by the impounded river, with larger dams trapping virtually the entire sediment load carried by the river (Meade and Parker, 1984). The reduction of reservoir capacity as sediment accumulates introduces multiple expenses: an aggrading reservoir may no longer serve the intended purpose, and the costs of maintenance may be compounded by contaminated sediments, preventing removal or making sediment removal extremely costly. The cost of sediment-transport related damages is estimated to range from $20 to $50 billion annually in North America (Pimentel and others, 1995; Osterkamp and others, 1998, 2004). Globally, erosion of soils and sediment transport are major issues, most notably in developing nations where the demands on marginal farmland and water resources are greatest (Walling and Collins, 2000).

Previous Studies

Given the consequences of elevated SSC and the need for accurate and precise data to aid management strategies aiming to reduce the problems associated with accelerated erosion and sediment transport, the scientific community has sought to understand and characterize the fluvial transport of sediment. Understanding and managing movement of suspended sediment has been challenging, however, because sediment transport is highly variable in time, across landscapes, and within stream channels. In order to quantify suspended-sediment transport within a stream channel at a given point in time, personnel must be onsite sampling with specialized equipment and proper methods during the sediment transport event. This effort can be especially difficult because most sediment transport is triggered and sustained by stormflow events (Wolman and Miller, 1960). Previous studies have demonstrated that as much as 98 percent of a river's sediment load can be transported during just 10 percent of the time of record, and as much as 60 percent of the load can be discharged in only 1 percent of the time of record (Meade and others, 1990). Thus, monitoring programs must quantify sediment transport during stormflow events, which generally is the time when the fewest data are collected.

Although manual sampling of SSC can produce an accurate series of point-in-time measurements, robust extrapolation to the many unmeasured periods (especially high-flow periods) has proven difficult because of the inherently complex nature of suspended-sediment transport. A fundamental link exists between streamflow and sediment transport because the runoff responsible for increasing streamflow is typically responsible for a large portion of the soil erosion that contributes to sediment transport. This relation has been used in traditional methods for calculating sediment transport; however, suspended-sediment transport during stormflow events is extremely variable, and relating a unique concentration to a given streamflow is difficult. As a result of the variability in sediment transport, using streamflow as the sole predictor of suspended-sediment concentration may provide results with large error terms when applied without regard for the complex nature of the relation and the underlying fundamental concepts (Walling, 1977). For example, Horowitz (2003) found that for multiple watersheds in the United States and Europe ranging from less than 385 square miles (mi^2) to greater than 385,000 mi^2, high sediment concentrations are often underpredicted and low sediment concentrations are often overpredicted, partly as a result of the differing relation between SSC and streamflow on the rising and falling limbs of the stormflow hydrograph (often referred to as hysteresis). Although short-duration studies applying the rating curve method are subject to the largest errors, longer-duration studies calculating annual suspended-sediment loads (SSL) have been reported to have errors as high as 280 percent (Walling, 1977). In addition to the potential for large error terms associated with transport estimates generated in this fashion, some studies have documented the inability to detect statistically significant correlations between streamflow and SSC. For example, Christensen and others (2002) identified that only four of their eight study stations actually had significant correlations between suspended sediment and streamflow.

Furthermore, studies that use discrete water-quality samples will generally suffer from several challenges that are inherent to discrete sampling, including:

- A relatively limited number of samples are used to develop interpretations.
- The delay between sample collection and reporting laboratory results, especially when the objective is to detect violations of a water-quality standard and(or) to protect public health, may expose the public to unnecessary risks.
- Detailed understanding of in-stream variability (diurnal patterns, for example) is difficult to develop.
- The time and cost associated with collecting representative water-quality samples can be considerable.
- Sampling designs for loading studies, which usually require targeted storm-runoff sampling, conflict with sampling designs for trend analyses, which typically require fixed-frequency sampling.

With the current limitations of discrete water-quality sampling and the challenges associated with predicting suspended-sediment levels solely from streamflow, innovative approaches for generating detailed records of SSC are needed.

A potentially more effective technology for improved suspended-sediment determination involves the continuous monitoring of turbidity as a surrogate for SSC. Turbidity measurements are well correlated to SSC because turbidity is an optical measure of water clarity, and the presence of suspended particles directly influences this measurement. Using turbidity values as a surrogate for estimating SSC is not new, but until recently, technological limitations have made this approach largely unreasonable. As early as 1977, Walling described this surrogate approach using turbidity and demonstrated a sharp reduction in suspended-sediment prediction error using a turbidity-sediment relation relative to a streamflow-sediment approach. In the earlier-mentioned study by Christensen and others (2002), which demonstrated poor correlation between suspended-sediment concentrations and streamflow, all of their research stations demonstrated significant correlations between SSC and turbidity measurements. The development of continuous turbidity records to estimate SSC is now inherently more feasible because of technical improvements to in situ water-quality sensors and data telemetry. Continuous turbidity measurement has become a common field approach because it provides more detailed and more precise information on sediment transport than was previously possible (Christensen and others, 2000; Christensen, 2001).

Purpose and Scope

Efforts by CBP and the U.S. Geological Survey (USGS) to quantify sediment transport to the bay from major tributaries have traditionally relied on streamflow-based regression methods, such as the seven-parameter ESTIMATOR model introduced by Cohn and others (1992). This streamflow-based model incorporates variables to explain flow dependence, seasonal variability, and trends over time. In recognition of previous successful use of continuous turbidity monitoring and surrogate approaches to estimating concentrations of suspended sediment, the USGS, in cooperation with the CBP and the Virginia Department of Environmental Quality (VA DEQ), began an evaluation of the use of a turbidity-based approach to estimate sediment transport to the bay. The purpose of this report is to present a comparison of turbidity-based and streamflow-based estimates of suspended-sediment concentrations in three major tributaries to the bay: the James, Rappahannock, and North Fork Shenandoah Rivers. Specifically, the objectives of this investigation were to:

1. Evaluate the use of turbidity as a surrogate for estimating SSC in the James, Rappahannock, and North Fork Shenandoah Rivers, each of which drain into the Chesapeake Bay; and
2. Compare two methods of estimating SSC: turbidity-based and streamflow-based regression models.

These study objectives were expanded to include the evaluation of turbidity-based models to estimate nutrient concentrations, specifically total nitrogen (TN) and total phosphorous (TP).

Study sites for this project were identified primarily on the basis of existing water-quality data that indicated which of the major rivers in Virginia had the greatest suspended-sediment transport to the bay. Based on the available long-term data, the James, Rappahannock, and North Fork Shenandoah Rivers were selected for this study (Langland and others, 2004). To enhance the efficiency of this data collection, continuous water-quality monitors were collocated with an existing water-quality sampling and streamgaging station on each river—the James River at Cartersville, VA (USGS station number 02035000), Rappahannock River near Fredericksburg, VA (USGS station number 01668000), and North Fork Shenandoah River near Strasburg, VA (USGS station number 01634000; fig. 1).

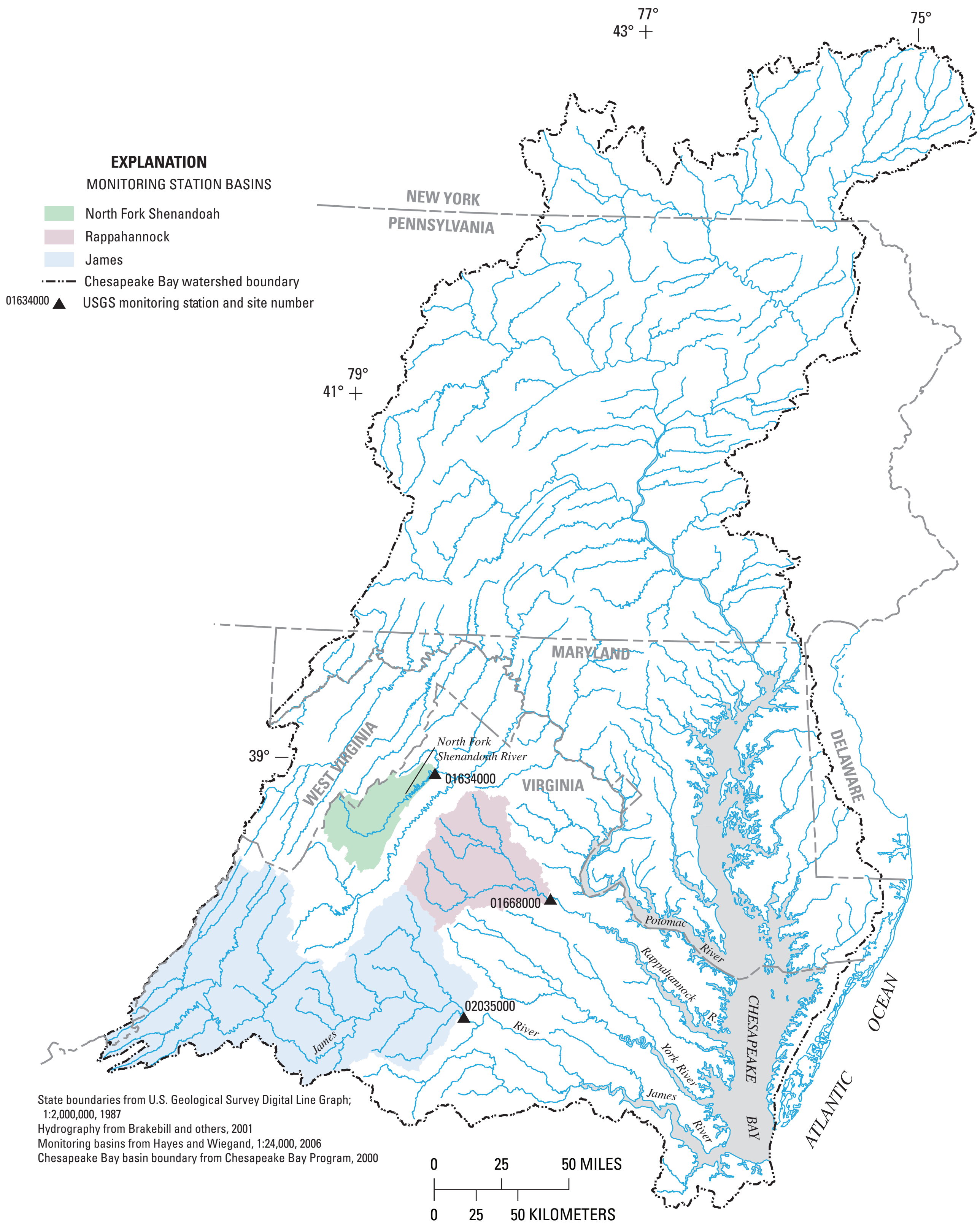

Figure 1. Chesapeake Bay watershed and the James River near Cartersville, Virginia, Rappahannock River near Fredericksburg, Virginia, and North Fork Shenandoah River near Strasburg, Virginia, basins.

In late 2003 and early 2004, the USGS initiated a continuous water-quality monitoring effort on the James and Rappahannock Rivers with the intent of generating a time-series dataset for use in the estimation of SSC and nutrient concentrations. The network was expanded to a third river, the North Fork Shenandoah River, in 2006. This effort was augmented by ongoing discrete sample collection in support of the USGS Chesapeake Bay River Input Monitoring (RIM) Program.

Multivariate regression models to estimate SSC and nutrients were constructed using the datasets generated by the continuous water-quality monitoring and discrete sample-collection activities. Additionally, streamflow-based estimation models were generated using the ESTIMATOR program, which is the approach currently used for estimating nutrient and sediment concentrations and loads transported to the bay from its major tributaries. These two approaches for generating estimates of SSC and nutrients were compared using graphical, statistical, and hypothesis testing methods to determine if either provides greater accuracy or precision.

Description of Study Area

The James River watershed encompasses 10,200 mi^2, making it the third-largest tributary basin in the bay watershed. Originating in the Appalachian Mountains near the West Virginia–Virginia border, the James River flows through the Valley and Ridge, Blue Ridge, Piedmont, and Coastal Plain Physiographic Provinces before flowing into the bay in southeastern Virginia. The drainage area of the James River at Cartersville monitoring station encompasses over 60 percent (6,252 mi^2; Hayes and Wiegand, 2006) of the James River basin, has a long-term annual mean streamflow of 7,082 cubic feet per second (ft^3/s), and a median annual suspended-solids yield of approximately 9.1 x 10^4 kilograms per square mile (kg/mi^2; U.S. Geological Survey, 2007). Dominant land uses in the drainage area for this monitoring station are forest (80 percent) and agriculture (16 percent; Belval and Sprague, 1999).

The Rappahannock River is the fourth largest tributary in the bay watershed, draining an area of 2,800 mi^2. Originating in the Blue Ridge Physiographic Province, the Rappahannock River flows through the Piedmont and Coastal Plain Physiographic Provinces before entering the bay. The drainage area of the Rappahannock River near Fredericksburg monitoring station encompasses 57 percent (1,595 mi^2) of the Rappahannock River basin (Hayes and Wiegand, 2006) and has a long-term annual mean streamflow of 1,686 ft^3/s and a median annual suspended-solids yield of approximately 1.4 x 10^5 kg/mi^2 (U.S. Geological Survey, 2007). Dominant land uses in the drainage area for this monitoring station are forest (61 percent) and agriculture (36 percent; Belval and Sprague, 1999).

The North Fork Shenandoah River, a branch of the Shenandoah River, drains 1,034 mi^2 of the 3,058 mi^2 Shenandoah River watershed (Hayes and Wiegand, 2006). The Shenandoah River flows through the Valley and Ridge Physiographic Province and into the Potomac River near Harpers Ferry, WV. The drainage area of the North Fork Shenandoah River near Strasburg monitoring station encompasses 74 percent (770 mi^2) of the North Fork Shenandoah River Basin (Hayes and Wiegand, 2006) and has a long-term annual mean streamflow of 608 ft^3/s and a median annual suspended-solids yield of approximately 4.2 x 10^4 kg/mi^2 (U.S. Geological Survey, 2007). Dominant land uses in the drainage area for this monitoring station are forest (59 percent) and agriculture (38 percent; Johnson and Belval, 1998).

Approach and Methods

The study approach relied on continuous water-quality data collected by an in-situ water-quality monitoring device, discrete water-quality data collected using manual sample-collection methods, and statistical analyses performed using various computing platforms for generation and evaluation of estimation models.

Continuous Monitoring of Water Quality

YSI 6920 multiparameter water-quality monitoring sondes (manufactured by YSI, Inc.) were selected for field deployment. These particular instruments were selected because the equipment seemed sufficiently rugged for the task and because YSI water-quality monitors were already being used for the collection of field data in several ongoing studies. Using the YSI 6920, the field parameters of water temperature, specific conductance, pH, and turbidity were measured at 15-minute intervals. The YSI 6136 turbidity sensor was used for turbidity measurements. This turbidity sensor uses near-infrared wavelengths with 90-degree detector geometry and is calibrated using formazin-based standards; therefore, data are expressed in formazin nephelometric units (FNUs; Anderson, 2005).

The water-quality monitors were deployed in such a way that the data recorded by the instruments would be representative of the stream cross section being monitored and not just the single point where the monitor was deployed. Because of specific site conditions, different deployment approaches were required for each of the study sites. At the James River and North Fork Shenandoah River monitoring stations, bridges were used as monitoring platforms. A water-quality monitor was suspended from the bridge and configured to make water-quality measurements approximately 1–2 feet below the water surface. Weights were added to the bottom of the water-quality monitor to ensure that the monitor remained underwater during high-velocity stormflow events. A 2-foot-long section of schedule 80 polyvinyl chloride piping with 1-inch holes drilled into the lower section of the pipe was used to shield the monitor from debris during flood events while still permitting a flow-through environment and good contact between the monitor and the river water. A braided steel cable was used to connect the water-quality monitor to the bridge, and all the supporting electronics were installed in a weather-proof box that was attached to the topside of the bridge. Using this approach, the water-quality monitor was securely deployed into a portion of the river that responded uniformly to various flow conditions; an example of this type of deployment is presented in figure 2.

Figure 2. A typical bridge-mounted deployment of a continuous water-quality monitoring station.

At the Rappahannock River monitoring station, no bridge was available to use as a monitoring platform. Various bank-mounted deployment systems were considered; however, none of these were used because of the concern that water-quality conditions at the edge of the river might not be representative of the average water-quality conditions throughout the cross section of the river. Consequently, a buoy-mounted system was developed to permit measurements from the approximate center of the streamflow. An estuarine monitoring buoy from Apprise Technology, Inc., was modified with minor welding work to allow the monitoring equipment to be deployed on the outside of the buoy (fig. 3). The buoy was moored in the river to a portion of exposed bedrock. Using this setup, the water-quality monitor was deployed approximately 1.5 feet below the water surface, under all flow conditions. The particular monitoring buoy used had a hollow internal cylinder that held all the necessary electronics for data logging. During a high-flow event, the buoy was damaged beyond repair. In June 2007 the water-quality monitor was relocated, and a new approach of directly attaching the monitor to a large, stable boulder was employed. Data from the old monitor location were compared with data from the new monitor location, and data were found to be similar.

The water-quality monitors were programmed to make measurements of water temperature, specific conductance, pH, and turbidity every 15 minutes. These data were then stored in a Campbell Scientific CR10 data logger and transferred by telephone modem every 3 hours to the USGS Virginia Water Science Center (VA WSC), or the data were stored on a Sutron Satlink II and transferred hourly to the VA WSC by Geostationary Operational Environmental Satellites (GOES). Upon arrival at the USGS office, the data were processed by a quality-control data-review program to screen possible problems with the data, and then data were made available to the public on the National Water Information System Web site (NWISWeb; http://waterdata.usgs.gov/nwis/rt).

Approximately every 4 weeks, the water-quality monitors were serviced in the field to clean the sensors, evaluate the quality of the data collected, and recalibrate the instrument (if necessary). This monitor servicing was performed in accordance with the USGS guidelines for the operation and maintenance of continuous water-quality monitors (Wagner and others, 2000). Because these guidelines were followed, only a summary of the maintenance steps are presented here. In all cases, parameters were measured before and after the instrument was cleaned of any silt, debris, algae, or bio-film that may have accumulated. The differences before and after this cleaning were used to determine the need for, and the magnitude of, corrections for instrument fouling. Following this fouling check, calibrations of the pH, specific

Figure 3. The monitoring buoy deployed in the Rappahannock River.

conductance, and turbidity sensors were checked using known standards. Discrepancies between the known values of the check standards and the readings from the sonde were used to determine whether the data needed to be corrected for a drift in instrument calibration. Following the fouling and calibration checks, any sensor out of tolerance was recalibrated (Wagner and others, 2000). After the maintenance visit, any necessary data corrections were made, the database was updated with the corrected data, and the original values were archived.

In addition to the monthly monitor maintenance, the entire water-quality record for each parameter was reviewed and finalized at the end of each water year[1]. This annual review involved evaluation of all the fouling and calibration drift checks, screening the data for anomalous values, and rating the quality of the record as excellent, good, fair, or poor. These ratings were determined on the basis of the corrections that had been applied to the record, and the criteria used for the ratings were those provided by Wagner and others (2000).

Collection of Discrete Water-Quality Samples

In addition to the continuous water-quality monitoring at each sampling site, discrete water-quality samples were collected at these sites. These discrete water-quality samples were collected as part of a joint effort by USGS, VA DEQ, and the CBP to understand sediment and nutrient inputs to the bay from major tributaries in Virginia. These discrete samples were collected during a broad range of environmental conditions through scheduled monthly sampling and targeted storm sampling.

The discrete water-quality samples were collected using standard USGS sampling protocols for the collection of representative water-quality samples (U.S. Geological Survey, 1998). These protocols for representative sampling involve the collection of depth- and width-integrated water-quality samples, and the use of isokinetic samplers when required by the water depth or velocity. Water-quality samples were sent to the USGS Kentucky Sediment Laboratory for analysis of SSC using analytical methods from Sholar and Shreve (1998). Nutrient analyses were performed by the Virginia Division of Consolidated Laboratory Services. All results from these two laboratories were reviewed and quality assured by USGS VA WSC staff before the data were entered into the USGS database (http://va.water.usgs.gov/chesbay/RIMP/index.html).

Generation of Turbidity-Based Regression Models

Using data from the continuous water-quality monitors and from laboratory analysis of the discrete samples, multivariate turbidity-based SSC estimation models were generated such that the general form of the model was:

$$SSC = f^{-1}[\hat{\beta}_0 + \hat{\beta}_1 f(turbidity) + \hat{\beta}_j f(x_j) ... \hat{\beta}_k f(x_k) + \varepsilon] \quad (1)$$

where

SSC is suspended-sediment concentration, in milligrams per liter;

f^{-1} is the inverse of the transformation selected for the response variable (SSC);

$\hat{\beta}_i$ are coefficients estimated by ordinary least squares;

$\hat{\beta}_0$ is a constant;

f is the transformation function selected for the explanatory variables (such as natural logarithm or square root);

$\hat{\beta}_1$ describes the relation between SSC and turbidity;

$x_j ... x_k$ are additional site-specific explanatory variables (such as streamflow, water temperature, and specific conductance) evaluated for inclusion using best-subsets regression;

$\hat{\beta}_j ... \hat{\beta}_k$ describe the relations between concentration and $x_j ... x_k$; and

ε is residual error, assumed to be normally distributed with zero mean and variance σ_ε^2.

[1] Water year is the period October 1 through September 30 and is identified by the year in which the period ends.

Turbidity-based estimation models were developed and compared using SAS (version 9.1.3) for Windows and JMP 7.0 software (SAS Institute, Cary, NC). Multivariate models were generated using best-subsets regression, which ranks all 2^k possible regressions (where k is the number of explanatory variables evaluated) according to user-specified statistics; Mallows' Cp was used in this study. Selecting a model with the smallest Mallows' Cp value provides a compromise between explaining the most variance possible in the response through incorporation of all relevant regressors and minimizing the variance of the estimates by minimizing the number of regressors (Helsel and Hirsch, 2002). Additionally, the adjusted R^2 was used to evaluate the proportion of variability explained by the models selected by the best-subsets procedure. R^2, or coefficient of determination, is a measure of the fraction of the variability in the response variable explained by the model, and the adjusted R^2 is a similar measure corrected for the number of explanatory variables in the model (Helsel and Hirsch, 2002). This adjustment is necessary to determine an accurate measure of explained variability in multiple regression because R^2 will increase with each additional explanatory variable, regardless of explanatory power (Helsel and Hirsch, 2002). The additional explanatory variables evaluated for inclusion in the turbidity-based model include streamflow and water-quality parameters (water temperature and specific conductance) that were measured at the same temporal scale as turbidity and have the potential to explain variance induced by processes related to sediment transport. Variables selected by the best-subsets regression procedure were evaluated for multicollinearity and to ensure that sound reasoning existed for inclusion of the variables. Multicollinearity occurs when one explanatory variable is closely related to one or more other explanatory variables and results in errors in the estimation of model coefficients (Helsel and Hirsch, 2002; Montgomery and others, 2006). Each variable was tested for multicollinearity using the variance inflation factor (VIF; Marquardt, 1970), calculated as:

$$VIF_j = \frac{1}{(1-R_j^2)}\ , \qquad (2)$$

where

VIF_j is the variance inflation factor for the j^{th} variable, and

R_j^2 is the coefficient of determination (R^2) of a regression of the j^{th} variable on all other explanatory variables.

Ideally, $VIF \cong 1$ for all explanatory variables, indicating the absence of multicollinearity ($R_j^2 = 0$), but $VIF_j > 10$ ($R_j^2 > 0.9$) indicates serious problems with multicollinearity (Helsel and Hirsch, 2002; Montgomery and others, 2006). This threshold value ($VIF_j > 10$) is used in this study because the purpose of the models is to generate estimates of concentration; multicollinearity is of lesser concern when the model is used only for estimations, and interpretations of the model coefficients are not made (Helsel and Hirsch, 2002; Montgomery and others, 2006). Furthermore, the concern over multicollinearity is reduced when estimates are generated from the same range of explanatory variables as is used in the specification of the model, as is the case in this study (Helsel and Hirsch, 2002; Montgomery and others, 2006).

Transformations of the explanatory and response variables were required to generate normally distributed residual errors (residuals = observed concentration – estimated concentration) with approximately constant variance (homoscedasticity) because these are assumptions inherent in linear regression (Helsel and Hirsch, 2002). Logarithmic (natural log) and square-root transformations were investigated; logarithmic transformations are commonly applied for turbidity-based estimations of SSC (Christensen and others, 2000; Rasmussen and others, 2005, 2008; Miller and others, 2007), and the square-root transformation is another commonly applied transformation for right-skewed hydrologic data (Helsel and Hirsch, 2002). The natural logarithm was used in this study instead of the base-10 logarithm because the natural logarithm is used by the ESTIMATOR and LOADEST applications. A transformation-bias-correction procedure was applied to the re-transformed estimates of SSC. In the case of the logarithmic transform, re-transforming estimates into original units produces estimates of the geometric mean concentration (which approximates the median concentration), rather than estimates of the mean concentration. This bias typically results in underestimating the mean concentration, which must be corrected using a bias-correcting procedure. The Duan (1983) smearing factor, which "smears" the average estimation error over all estimates, was used to correct transformation bias in the turbidity-based models in this study. The Duan smearing factor, as presented by Helsel and Hirsch (2002), is the mean of the re-transformed residuals when a log-based transformation is used; thus, bias-corrected concentration estimates are computed from natural-logarithm-transformed data as:

$$\hat{c}_D = \exp[\hat{y}] \bullet \frac{\sum_{i=1}^{n} \exp[e_i]}{n}\ , \qquad (3)$$

where

$\hat{c}_D$ is the smeared, or bias-corrected, estimation of concentration;

exp is the inverse of the natural-logarithm function;

$\hat{y}$ is the re-transformed estimate of concentration from the turbidity-based model;

e_i are the residual errors; and

n is the number of observations in the turbidity-based estimation model.

The same factor is applied to all values to be corrected.

In the case of non-logarithmic transformations, such as the square-root transformation used in this study, application of the Duan smearing correction requires the use of spreadsheet software or scripting programs when a large number of observations are used to specify models because the correction for a single value is calculated using all of the residuals from the model specification dataset. For example, the smearing correction for the square-root transformation is calculated as:

$$\hat{c}_D = \frac{\sum_{i=1}^{n} (\hat{y} + e_i)^2}{n} , \tag{4}$$

where

$\hat{c}_D$ is the smeared, or bias-corrected, estimation of concentration;

$\hat{y}$ is the re-transformed estimate of concentration from the turbidity-based model;

e_i are the residual errors; and

n is the number of observations in the turbidity-based estimation model.

The Duan approach corrects only the transformation bias. Potential bias in the coefficient estimations resulting from sample error was expected to be negligible (sample error goes to zero with large samples), and final estimations were graphically evaluated for the presence of bias.

The determination of which transformation to apply at each site was made through assessment of the distribution of residual errors, relation between the residuals and each explanatory variable in the model, and the relation between the residuals and the estimated values. When both transformations provided equally acceptable residuals, the analysis was expanded to directly compare the error in the estimates of SSC, and consequently instantaneous SSL, provided by each transform. This comparison was accomplished using the sum of squared errors (SSE), mean squared error (MSE), and mean absolute error (MAE) for the re-transformed and bias-corrected estimates. The SSE, MSE, and MAE are expressions of the error of the estimates in concentration units (milligrams per liter), calculated as:

$$SSE = \sum_{i=1}^{n} e_i^2 , \tag{5}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \text{ , and} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| e_i \right| , \tag{7}$$

where

n is the number of observations used in the regression,

e_i is the residual error of the i^{th} estimate, and

$|e_i|$ is the absolute value of the i^{th} residual (e).

Evaluating these statistics for instantaneous SSL provides error measures that give greater weight to concentration errors at high streamflow. Concentration errors during high streamflow are the critical errors to minimize because the majority of the SSL is transported during periods of elevated streamflow. Instantaneous SSL was computed using the equation presented by Porterfield (1972):

$$SSL_{inst} = Q_w \times C_s \times k , \tag{8}$$

where

SSL_{inst} is the instantaneous suspended-sediment load, in tons per day;

Q_w is the instantaneous streamflow, in cubic feet per second;

C_s is the concentration of suspended sediment, in milligrams per liter; and

k is a coefficient based on the unit of measurement of water discharge, which equals 0.0027 in this instance.

Streamflow-Based Regression Models

The seven-parameter log-linear ESTIMATOR model developed by Cohn and others (1992) is used by the RIM Program to estimate loads of sediment at multiple sites on tributaries of the bay, including the three sites used in this study. The ESTIMATOR model is a streamflow-based model that estimates the natural logarithm of sediment concentration using the model:

$$\begin{aligned} \ln(c) &= \hat{\beta}_0 + \hat{\beta}_1 \ln(q/q_c) + \hat{\beta}_2[\ln(q/q_c)]^2 \\ &+ \hat{\beta}_3(t-t_c) + \hat{\beta}_4(t-t_c)^2 + \hat{\beta}_5 \sin(2\pi t) \\ &+ \hat{\beta}_6 \cos(2\pi t) + \varepsilon, \end{aligned} \tag{9}$$

where

ln is the natural-logarithm function;

c is measured SSC, in milligrams per liter;

q is measured daily-mean streamflow, in cubic feet per second;

t is time, in decimal years;

q_c, t_c are centering variables for streamflow and time, respectively;

$\hat{\beta}_i$ are coefficients estimated by ordinary least squares;

$\hat{\beta}_0$ is a constant;

$\hat{\beta}_1, \hat{\beta}_2$ describe the relation between concentration and streamflow;

$\hat{\beta}_3, \hat{\beta}_4$ describe the relation between concentration and time, independent of flow;

$\hat{\beta}_5, \hat{\beta}_6$ describe seasonal variation in concentration data; and

ε is residual error, assumed to be normally distributed with zero mean and variance σ_ε^2 .

The adjusted maximum likelihood estimator (AMLE) is used to assign a concentration value to those samples with observed concentration values below the detection limit to eliminate sample bias in the estimation of model coefficients (Cohn, 1988). This model estimates the natural logarithm of concentration; thus, the estimated concentrations are subject to re-transformation bias when transformed back into original units. This bias is corrected using the Bradu and Mundlak (1970) minimum variance unbiased estimator as described by Gilroy and others (1990).

For the purpose of estimating nutrient and suspended-sediment loadings to the bay, the ESTIMATOR model is typically run on a 9-year moving window of data, as described by Yochum (2000). This 9-year period of data was used to generate the streamflow-based concentration estimates for the James, Rappahannock, and North Fork Shenandoah Rivers for the comparison in this study. For this study, streamflow-based models also were generated using the same data period that was used to generate the turbidity-based estimation models.

Comparison of Turbidity-Based and Streamflow-Based Estimates of Suspended-Sediment Concentrations

The turbidity-based approach was compared with two iterations of the streamflow-based approach: one model generated from the 9-year dataset used by the CBP and a second model generated from a dataset containing only the data collected during the period of the dataset used to generate the turbidity-based model. Using the 9-year dataset allowed a comparison of overall approaches, and using the two models built using the same period of data allowed a direct comparison of the models.

Comparison of the accuracy of estimates from the streamflow-based and turbidity-based estimation models was achieved through measures of the difference between estimated and observed concentrations for those observations included in each of the three estimation models. Multiple plots of the residuals of the re-transformed bias-corrected estimates from both approaches were evaluated, and SSE, MSE, and MAE values were compared. Comparison of the precision of the two approaches was achieved using a squared-ranks test for equal variance (Conover, 1980) on the estimates and the residuals of the re-transformed bias-corrected estimates of SSC; estimates and residuals with lesser variance are more precise than those with greater variance. The squared-ranks test for equal variance is a non-parametric test in which the variance of two populations is compared using the absolute deviations from the means of the populations (Conover, 1980). These deviations are then ranked, and the ranks are squared for calculation of the test statistic. This test can be constructed as a two-tailed test of the null hypothesis that the variances of the two populations are the same, or as a one-tailed test of the null hypothesis that the variance of one population is greater than the variance of the other population. The one-tailed test is used in this study to test the null hypothesis that the variances of the streamflow-based estimates and errors are greater than those from the turbidity-based model.

Water-Quality Monitoring Data

Continuous water-quality monitoring was initiated on different dates for each site depending on instrument deployment requirements (table 1). Although there were no long-term gaps in monitoring, short periods of data are missing as a result of instrument malfunction, ice, or fouling. These periods of missing data typically span less than 1 week and cause the records to be less than 100 percent complete.

Table 1. Summary of continuous water-quality monitoring data at the monitoring stations at the James River near Cartersville, Rappahannock River near Fredericksburg, and North Fork Shenandoah River near Strasburg, Virginia.

[°C, degrees Celsius; FNU, formazin nephelometric units; µS/cm, microsiemens per centimeter]

Period of record	Parameter	Percentage of record complete	Minimum	Maximum	Median
James River at Cartersville, VA					
12/11/2003	Water temperature (°C)	96	0.0	34.8	16.6
to	Turbidity (FNU)	92	0.0	720	5.7
9/30/2007	Specific conductance (µS/cm)	96	43	412	139
Rappahannock River near Fredericksburg, VA					
3/4/2004	Water temperature (°C)	93	0.0	34.4	17.0
to	Turbidity (FNU)	79	0.0	1,316	5.6
9/30/2007	Specific conductance (µS/cm)	88	42	146	87
North Fork Shenandoah River near Strasburg, VA					
2/3/2006	Water temperature (°C)	96	0.0	31.4	16.9
to	Turbidity (FNU)	88	0.0	660	1
2/3/2008	Specific conductance (µS/cm)	94	119	467	363

Width- and depth-integrated samples of SSC were collected at each monitoring station to represent the range of hydrologic conditions observed during the monitoring period. The observed range of turbidity and streamflow was adequately sampled, as demonstrated by the distribution of sampled points on the cumulative distribution frequency (CDF) plots of the continuous turbidity and streamflow data (fig. 4).

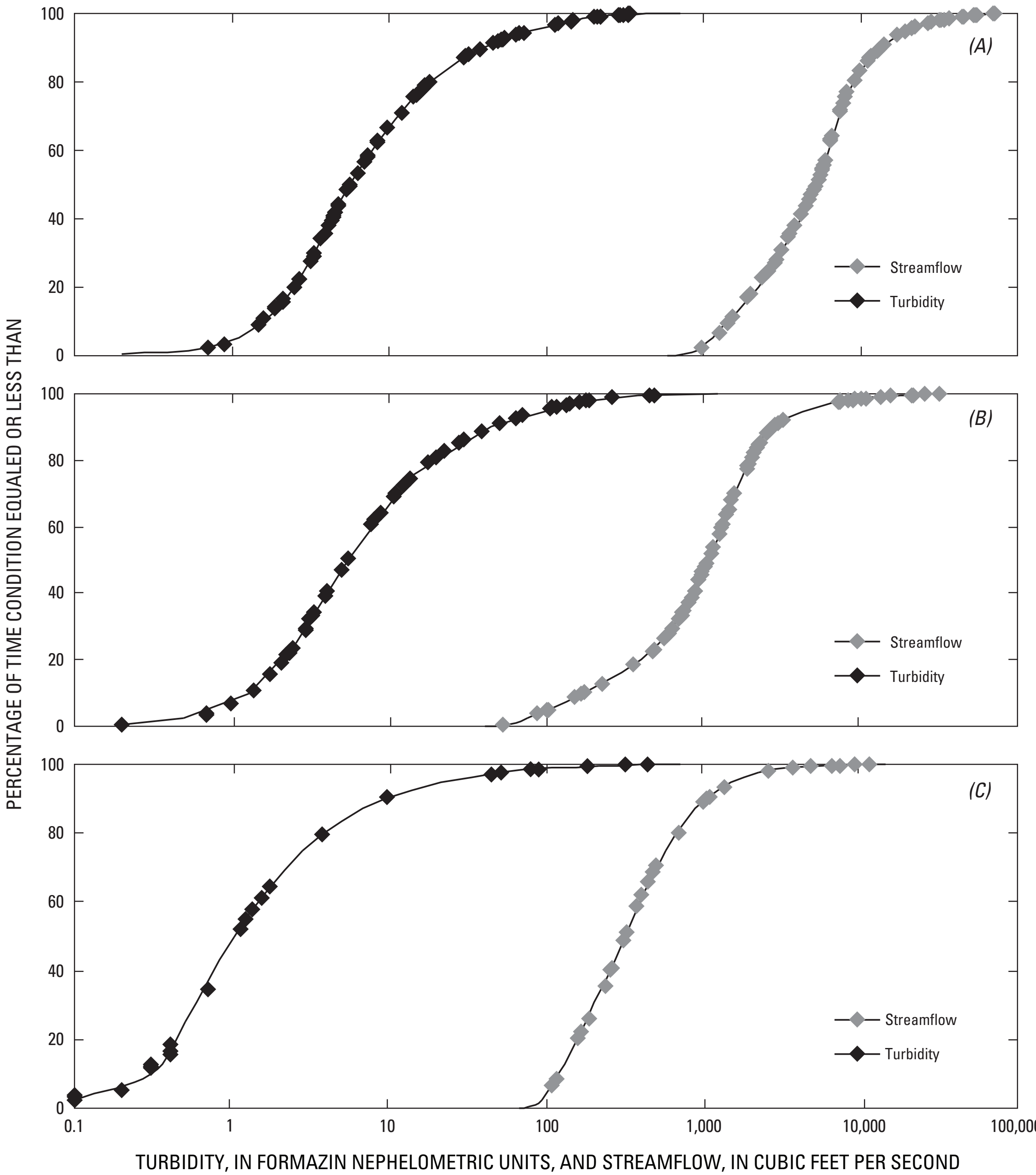

Figure 4. Cumulative distribution frequency plot of continuous turbidity and streamflow measurements with sampled points at *(A)* James River at Cartersville, Virginia, *(B)* Rappahannock River near Fredericksburg, Virginia, and *(C)* North Fork Shenandoah River near Strasburg, Virginia.

Turbidity-Based Models

Site-specific turbidity-based SSC estimation models were developed for each site using the aforementioned procedures and datasets. Model specification is site-specific because the distribution of observed SSC and water-quality parameter data varies in response to watershed characteristics and hydrologic regime during the period of study.

James River at Cartersville, Virginia

The best-subsets regression procedure was used to rank potential formulations of the turbidity-based estimation model for the James River at Cartersville (table 2). Only models with a smaller Mallows' Cp than the single-variable (turbidity only) model are presented, and a single-variable model using streamflow as the explanatory variable did not outperform the single-variable turbidity model. The top-ranked model (according to Mallows' Cp) for both the natural-logarithm and square-root transformations included transformed turbidity, streamflow, and water temperature. All coefficients were significant at the 0.05 α-level with attained significance levels (p-values) less than 0.05 (table 3). There were no problems with multicollinearity according to the specified criteria (table 3; fig. 4). Partial residual plots reveal that each transformation provides a model with residuals having approximately constant variance (fig. 5), as is required to meet the assumption of normally distributed residuals in linear regression (Helsel and Hirsch, 2002).

These two models (natural-logarithm and square-root transformations) were evaluated to determine which transformation provided estimates of SSC and SSL with the least amount of error. The values of SSE, MSE, and MAE (table 4) were calculated using the residuals of the re-transformed bias-corrected estimates for each model, and these calculations were compared. The magnitude of errors is greater for the natural-logarithm transformed model than for the square-root transformed model, as indicated by the error statistics. With greater error in the estimates from the natural-logarithm model, the square-root model was selected as the best possible estimation model for this dataset.

Table 2. Results of best-subsets regression for turbidity-based suspended-sediment concentration estimation models for the monitoring station at the James River at Cartersville, Virginia.

[ln, natural logarithm; Q, streamflow; WT, water temperature; SC, specific conductance; √, square root]

Explanatory variables	Mallows' Cp[1]	Adjusted coefficient of determination
Natural-logarithm transformation models		
ln(Turbidity) ln(Q) ln(WT)	3.00	0.925
ln(Turbidity) ln(SC) ln(Q) ln(WT)	5.00	0.924
ln(Turbidity) ln(Q)	8.23	0.918
ln(Turbidity) ln(SC) ln(Q)	9.98	0.917
ln(Turbidity) ln(SC) ln(WT)	33.82	0.889
ln(Turbidity) ln(SC)	34.94	0.888
ln(Turbidity)	37.08	0.885
ln(Q)	63.88	0.854
Square-root transformation models		
√(Turbidity) √(Q) √(WT)	3.55	0.971
√(Turbidity) √(SC) √(Q) √(WT)	5.00	0.971
√(Turbidity) √(SC) √(Q)	7.56	0.970
√(Turbidity) √(Q)	8.28	0.969
√(Turbidity)	43.39	0.953
√(Q)	164.14	0.901

[1]Mallows' Cp values are only comparable for models using the same transformation.

Table 3. Details of top-ranked turbidity-based suspended-sediment concentration estimation models for the monitoring station at the James River at Cartersville, Virginia.

[<, less than; N/A, not applicable; ln, natural logarithm; Q, streamflow; WT, water temperature; √, square root]

Variable	Model coefficient (β)	p-value	Variance inflation factor	Number of observations	Adjusted coefficient of determination
Natural-logarithm model					
Intercept	–6.125	<0.0001	N/A	69	0.925
ln(Turbidity)	0.545	<0.0001	5.21		
ln(Q)	0.799	<0.0001	5.44		
ln(WT)	0.199	0.0086	1.10		
Square-root model					
Intercept	–3.514	<0.0001	N/A	69	0.971
√(Turbidity)	0.825	<0.0001	7.52		
√(Q)	0.044	<0.0001	7.91		
√(WT)	0.336	0.0114	1.18		

Table 4. Sum of squared errors (SSE), mean squared error (MSE), and mean absolute error (MAE) for turbidity-based suspended-sediment concentration (SSC) and instantaneous suspended-sediment load (in parentheses) estimations using the natural-logarithm transformation model and the square-root transformation model for the monitoring station at the James River at Cartersville, Virginia.

Statistic	Natural-logarithm model	Square-root model
SSE	220,492 (6.5×10^9)	66,265 (1.2×10^9)
MSE	3,196 (9.5×10^7)	960 (1.8×10^7)
MAE	23.2 (2.8×10^3)	14.3 (1.4×10^3)

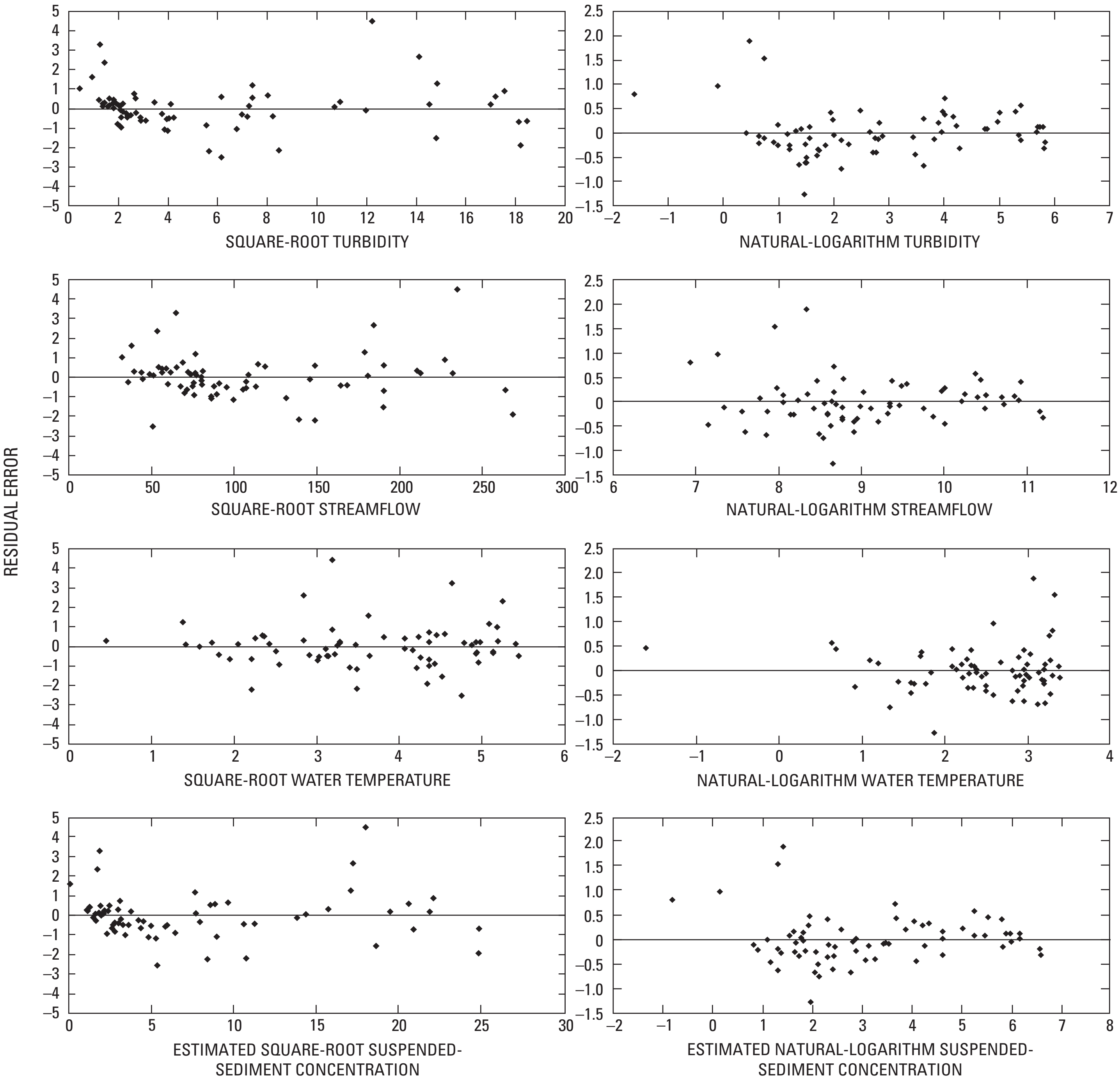

Figure 5. Partial residual plots for turbidity-based suspended-sediment concentration estimation models using square-root and natural-logarithm transformations for the James River at Cartersville, Virginia.

Rappahannock River near Fredericksburg, Virginia

The results of the best-subsets regression procedure were used to rank potential formulations of the estimation model for the Rappahannock River near Fredericksburg monitoring station (table 5). Only models with a smaller Mallows' Cp than the single-variable (turbidity only) model are listed in table 5, and a single-variable model using streamflow as the explanatory variable did not outperform the single-variable turbidity model.

Evaluation of partial residual plots for the models containing the natural-logarithm transformed variables revealed undesirable patterns in the residuals, indicating non-constant variance (fig. 6); therefore, only the models containing square-root transformed variables were considered for use. Two of the top-ranked square-root transformed models included water temperature; however, this variable was not statistically significant (for $\alpha = 0.05$) in either case, so these models were deemed unacceptable. The details about the highest-ranked model with acceptable variables in terms of significance, multicollinearity, and residual distributions are given in table 6 and figure 6.

Table 5. Results of best-subsets regression for turbidity-based suspended-sediment concentration estimation models for the monitoring station at the Rappahannock River near Fredericksburg, Virginia.

[ln, natural logarithm; Q, streamflow; WT, water temperature; SC, specific conductance; √, square root]

Explanatory variables	Mallows' Cp[1]	Adjusted coefficient of determination
Natural-logarithm transformation models		
ln(Turbidity) ln(Q) ln(WT)	4.97	0.863
ln(Turbidity) ln(SC) ln(Q) ln(WT)	5.00	0.866
ln(Turbidity) ln(Q)	8.97	0.848
ln(Turbidity) ln(SC) ln(Q)	9.67	0.849
ln(Turbidity)	14.57	0.830
ln(Q)	56.09	0.711
Square-root transformation models		
√(Turbidity) √(SC) √(Q) √(WT)	5.00	0.929
√(Turbidity) √(SC) √(Q)	6.28	0.925
√(Turbidity) √(Q) √(WT)	9.97	0.920
√(Turbidity) √(Q)	11.47	0.916
√(Turbidity)	25.64	0.893
√(Q)	47.74	0.859

[1]Mallows' Cp values are only comparable for models using the same transformation.

Table 6. Details of top-ranked turbidity-based suspended-sediment concentration estimation model for the monitoring station at the Rappahannock River near Fredericksburg, Virginia.

[N/A, not applicable; √, square root; <, less than; SC, specific conductance; Q, streamflow]

Variable	Model coefficient (β)	p-value	Variance inflation factor	Number of observations	Adjusted coefficient of determination
Square-root model					
Intercept	–15.807	0.005	N/A	50	0.925
√(Turbidity)	0.774	<0.0001	6.22		
√(SC)	1.426	<0.0001	1.61		
√(Q)	0.105	0.0121	6.96		

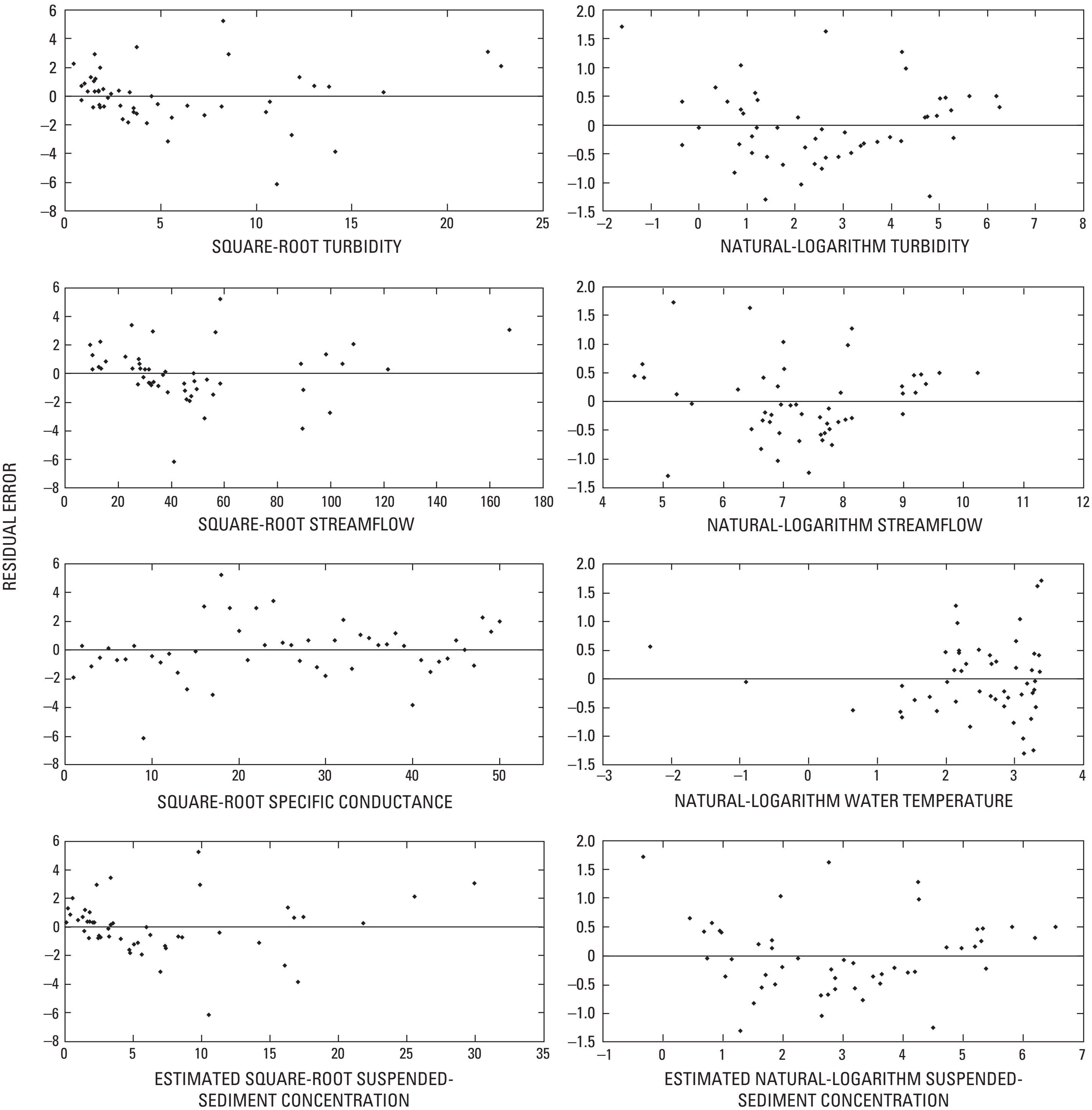

Figure 6. Partial residual plots for turbidity-based suspended-sediment concentration estimation models using square-root and natural-logarithm transformations for the Rappahannock River near Fredericksburg, Virginia.

North Fork Shenandoah River near Strasburg, Virginia

The best-subsets regression procedure was used to rank potential formulations of the estimation model for the North Fork Shenandoah River near Strasburg monitoring station (table 7). Only models that ranked higher than the single-variable (turbidity only) model are listed in table 7, and in the case of the square-root transformation, the single-variable model using streamflow as the explanatory variable did not outperform the single-variable turbidity model. In the best-subsets results for the natural-logarithm transformation, however, the single-variable model using streamflow as the only explanatory variable ranked above the single-variable model using turbidity as the only explanatory variable.

The natural-logarithm transformation did not produce any satisfactory estimation models because all possible formulations had problems with significance of variables and non-constant variance in the residuals. Each of the multivariate models using the square-root transformation were unsatisfactory because of multicollinearity, non-significant variables, or non-constant variance in the residuals. These results likely can be attributed to the small sample size used to specify the model because the variance of parameter estimates increases with decreased sample size, leading to elevated VIF values and issues with detecting significance (O'Brien, 2007). The single-variable (turbidity only) model using the square-root transformation was determined to be an acceptable model and was used as the estimation model for this site; the coefficients and summary statistics for this model are given in table 8, with the partial residual plots shown in figure 7.

Streamflow-Based Models

Two versions of the streamflow-based model were generated for each station. One used the data period used for generation of the turbidity-based model, and a second version of the model was generated using data from the 9-year period (water years 1999 through 2007), as is used by the CBP for estimates at the RIM Program stations. The parameter coefficients (βs) and coefficient of determination (R^2) for each model formulation are given in table 9. The streamflow-based ESTIMATOR model is applied consistently by the RIM Program at all monitoring stations in the bay watershed using all seven explanatory variables regardless of their statistical significance. The estimation model therefore may include explanatory variables that do not explain a significant amount of the variability in SSC. An evaluation of the goodness of the fit of these models is presented later in this report.

Table 7. Results of best-subsets regression for turbidity-based suspended-sediment concentration estimation models for the monitoring station at the North Fork Shenandoah River near Strasburg, Virginia.

[ln, natural logarithm; SC, specific conductance; Q, streamflow; WT, water temperature; √, square root]

Explanatory variables	Mallows' Cp[1]	Adjusted coefficient of determination
Natural-logarithm transformation models		
ln(Turbidity) ln(SC) ln(Q)	3.70	0.921
ln(Turbidity) ln(SC) ln(Q) ln(WT)	5.00	0.919
ln(Turbidity) ln(Q)	5.72	0.909
ln(Turbidity) ln(Q) ln(WT)	7.38	0.906
ln(Turbidity) ln(WT)	18.86	0.858
ln(Q)	19.29	0.856
ln(Turbidity)	20.25	0.852
Square-root transformation models		
√(Turbidity) √(SC) √(Q) √(WT)	5.00	0.993
√(Turbidity) √(SC) √(Q)	5.71	0.992
√(Turbidity) √(SC) √(WT)	23.77	0.985
√(Turbidity) √(SC)	23.85	0.985
√(Turbidity) √(Q)	28.80	0.984
√(Turbidity) √(Q) √(WT)	30.76	0.983
√(Turbidity) √(WT)	32.33	0.982
√(Turbidity)	32.37	0.982
√(Q)	183.67	0.931

[1]Mallows' Cp values are only comparable for models using the same transformation.

Table 8. Details of turbidity-based suspended-sediment concentration estimation model for the monitoring station at the North Fork Shenandoah River near Strasburg, Virginia.

[√, square root; N/A, not applicable]

Variable	Model coefficient (β)	p-value	Variance inflation factor	Number of observations	Adjusted coefficient of determination
Square-root model					
Intercept	0.510	0.0294	N/A	27	0.982
√(Turbidity)	1.159	<0.0001	N/A		

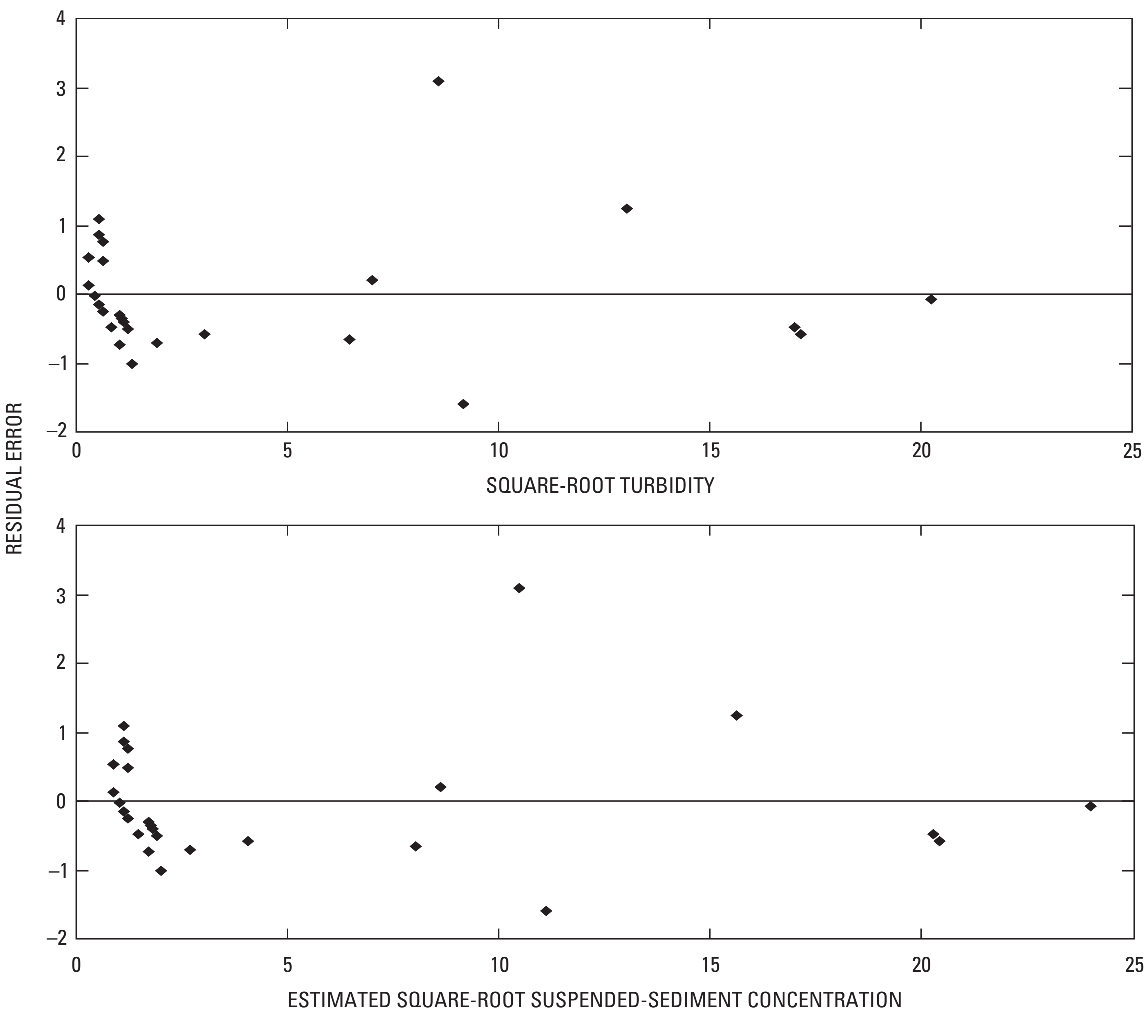

Figure 7. Partial residual plots for turbidity-based suspended-sediment concentration estimation model for the North Fork Shenandoah River near Strasburg, Virginia.

Table 9. Coefficients for streamflow-based suspended-sediment concentration estimation models generated for the monitoring stations at the James River near Cartersville, Rappahannock River near Fredericksburg, and North Fork Shenandoah River near Strasburg, Virginia.

[ln, natural logarithm; *q*, streamflow in cubic feet per second; q_c, centered streamflow (streamflow – mean streamflow); *t*, decimal time; t_c, centered decimal time (decimal time – mean decimal time); sin, sine function; cos, cosine function; π, pi]

Dataset	Coefficient *(p-value)*							Number of observations	Adjusted coefficient of determination
	Intercept	$\ln(q/q_c)$	$[\ln(q/q_c)]^2$	$(t-t_c)$	$(t-t_c)^2$	$\sin(2\pi t)$	$\cos(2\pi t)$		
James River near Cartersville, VA									
9-year window	2.776 *(<0.01)*	1.583 *(<0.01)*	0.077 *(0.03)*	–0.022 *(0.38)*	0.012 *(0.33)*	–0.015 *(0.85)*	–0.0422 *(<0.01)*	195	0.851
Study period	3.125 *(<0.01)*	1.624 *(<0.01)*	0.078 *(0.17)*	0.039 *(0.54)*	–0.002 *(0.98)*	–0.206 *(0.05)*	–0.504 *(<0.01)*	80	0.883
Rappahannock River near Fredericksburg, VA									
9-year window	2.480 *(<0.01)*	1.182 *(<0.01)*	0.170 *(<0.01)*	–0.063 *(0.06)*	0.009 *(0.65)*	–0.019 *(0.85)*	–0.530 *(<0.01)*	174	0.781
Study period	2.555 *(<0.01)*	1.165 *(<0.01)*	0.232 *(0.17)*	–0.115 *(0.26)*	–0.098 *(0.37)*	0.132 *(0.40)*	–0.484 *(<0.01)*	72	0.791
North Fork Shenandoah River near Strasburg, VA									
9-year window	1.518 *(<0.01)*	1.258 *(<0.01)*	0.430 *(<0.01)*	–0.106 *(<0.01)*	0.006 (0.70)	0.152 (0.22)	–0.346 *(<0.01)*	124	0.742
Study period	2.091 *(<0.01)*	1.572 *(<0.01)*	0.218 *(0.03)*	0.249 *(0.39)*	–0.117 *(0.88)*	0.020 *(0.92)*	–0.687 *(<0.01)*	31	0.878

Comparison of Turbidity-Based and Streamflow-Based Suspended-Sediment Concentration Estimates

Comparison of the two methods for estimating SSC focused on the precision and accuracy of the estimates by testing for differences in the variance of the estimates and associated residual errors and comparing the estimated values to the observed values. One-way squared-ranks tests for homogeneity of variance were used to test the null hypothesis that the variance of the estimates and residuals from the streamflow-based models was greater than the variance of the values generated by the turbidity-based models. The squared-ranks tests revealed significantly greater variance (less precision) in the estimates generated with the streamflow-based model for all comparisons (p-values < 0.01; table 10). All squared-ranks tests on the residuals revealed significantly greater variance (less precision) in the residuals from the streamflow-based models than from the turbidity-based models, except for the study-period streamflow-based model at the North Fork Shenandoah River. The lack of significance for the test on residuals when a significant result was obtained on the test of the estimates may be attributed to the smaller dataset used for this comparison.

Three measures of uncertainty were calculated to describe the accuracy of each of the models, SSE, MSE, and MAE, with these values given in table 11. To allow comparison, these values were calculated using the re-transformed bias-corrected estimates of SSC associated with those observations that were included in all three models. In every instance, the accuracy of the turbidity-based SSC and SSL estimations is greater than the accuracy of the corresponding streamflow-based estimations, with the exception of the SSL estimations at the North Fork Shenandoah River. The error statistics for SSL for the turbidity-based and study-period streamflow-based models at the North Fork Shenandoah River are nearly identical (MSE of the turbidity-based estimation is slightly higher than the streamflow-based MSE), but error in the estimates of SSL from the 9-year streamflow-based model are greater than the error terms for the estimations from the other two models.

In addition to the aforementioned statistics, graphical evaluations of the data were performed to compare the accuracy of each approach. Plots of observed SSC and estimated SSC (fig. 8) were generated to depict how accurately the models replicate the observed concentrations. A perfect estimation model would generate estimates along the 1:1 line; departures from this line indicate error in the estimations. At each of the three sites, the turbidity-based estimates have a greater degree of accuracy than the streamflow-based estimates, exhibited by a generally tighter fit along the 1:1 line than the streamflow-based estimates. This result becomes more apparent as SSC values increase, where departures of the streamflow-based estimates from the 1:1 line increase

Table 10. P-values for one-way squared-ranks tests on the variance of estimates and residuals comparing turbidity-based models to two streamflow-based models for the monitoring stations at the James River near Cartersville, Rappahannock River near Fredericksburg, and North Fork Shenandoah River near Strasburg, Virginia.

	Streamflow-based p-values (using 9-year dataset)	Streamflow-based p-values (using study-period dataset)
James River near Cartersville		
Estimates	<0.01	<0.01
Residuals	<0.01	<0.01
Rappahannock River near Fredericksburg		
Estimates	<0.01	<0.01
Residual	<0.01	<0.01
North Fork Shenandoah River near Strasburg		
Estimates	<0.01	<0.01
Residual	<0.01	0.645

Table 11. Error statistics for turbidity-based and streamflow-based estimates of suspended-sediment concentrations and instantaneous suspended-sediment load (in parentheses) for the monitoring stations at the James River near Cartersville, Rappahannock River near Fredericksburg, and North Fork Shenandoah River near Strasburg, Virginia.

[n, number of observations/estimations used to compute statistics; SSE, sum of squared errors; MSE, mean squared error; MAE, mean absolute error]

	Turbidity-based error statistics	Streamflow-based error statistics (using 9-year dataset)	Streamflow-based error statistics (using study-period dataset)
James River near Cartersville (n = 67)			
SSE	57,551 (9.5×10^8)	377,496 (6.6×10^9)	566,794 (1.3×10^{10})
MSE	846 (1.4×10^7)	5,634 (9.9×10^7)	8,460 (2.0×10^8)
MAE	13 (1.2×10^3)	36 (3.6×10^3)	38 (4.1×10^3)
Rappahannock River near Fredericksburg (n = 49)			
SSE	115,565 (2.5×10^8)	1,077,044 (4.0×10^9)	836,820 (2.8×10^9)
MSE	2,358 (5.1×10^6)	21,980 (8.1×10^7)	17,078 (5.8×10^7)
MAE	25 (6.2×10^2)	56 (2.1×10^3)	50 (1.8×10^3)
North Fork Shenandoah River near Strasburg (n = 27)			
SSE	9,241 (3.9×10^8)	1,017,429 (1.6×10^9)	134,158 (3.9×10^8)
MSE	342 (1.5×10^7)	37,683 (5.8×10^7)	4,969 (1.4×10^7)
MAE	9 (1.4×10^3)	68 (2.7×10^3)	30 (1.4×10^3)

greatly. Additionally, the departures from the 1:1 line for the streamflow-based models at the Rappahannock River indicate bias resulting in increased underestimation as SSC concentrations increase. Large errors in the estimation of SSC at these higher values are of great concern because the majority of the sediment load is transported during the short periods of time when concentrations are in this upper range; thus, accurately characterizing these periods is critical.

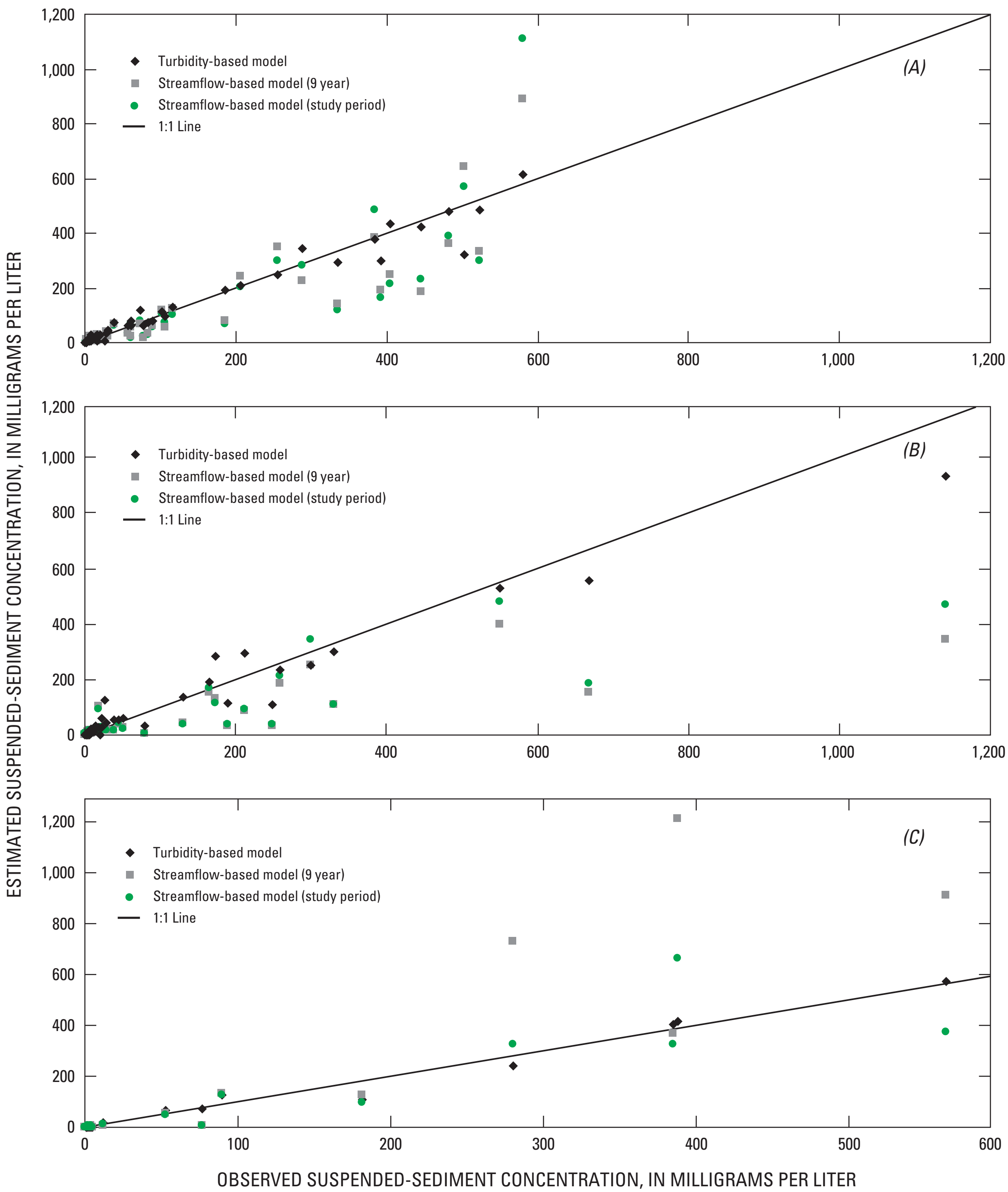

Figure 8. Observed suspended-sediment concentration and estimated suspended-sediment concentration for the turbidity-based model and two streamflow-based models for *(A)* James River at Cartersville, Virginia, *(B)* Rappahannock River near Fredericksburg, Virginia, and *(C)* North Fork Shenandoah River near Strasburg, Virginia.

Exceedance-probability plots of the absolute value of the residuals for each model show that divergence in the distribution of residuals from the turbidity- and streamflow-based models generally occurs between the 20- and 30-percent exceedance levels (fig. 9). At the 10-percent exceedance level, the residual error in the streamflow-based estimates is 1.5 to more than 10 times the residual error in the turbidity-based estimates.

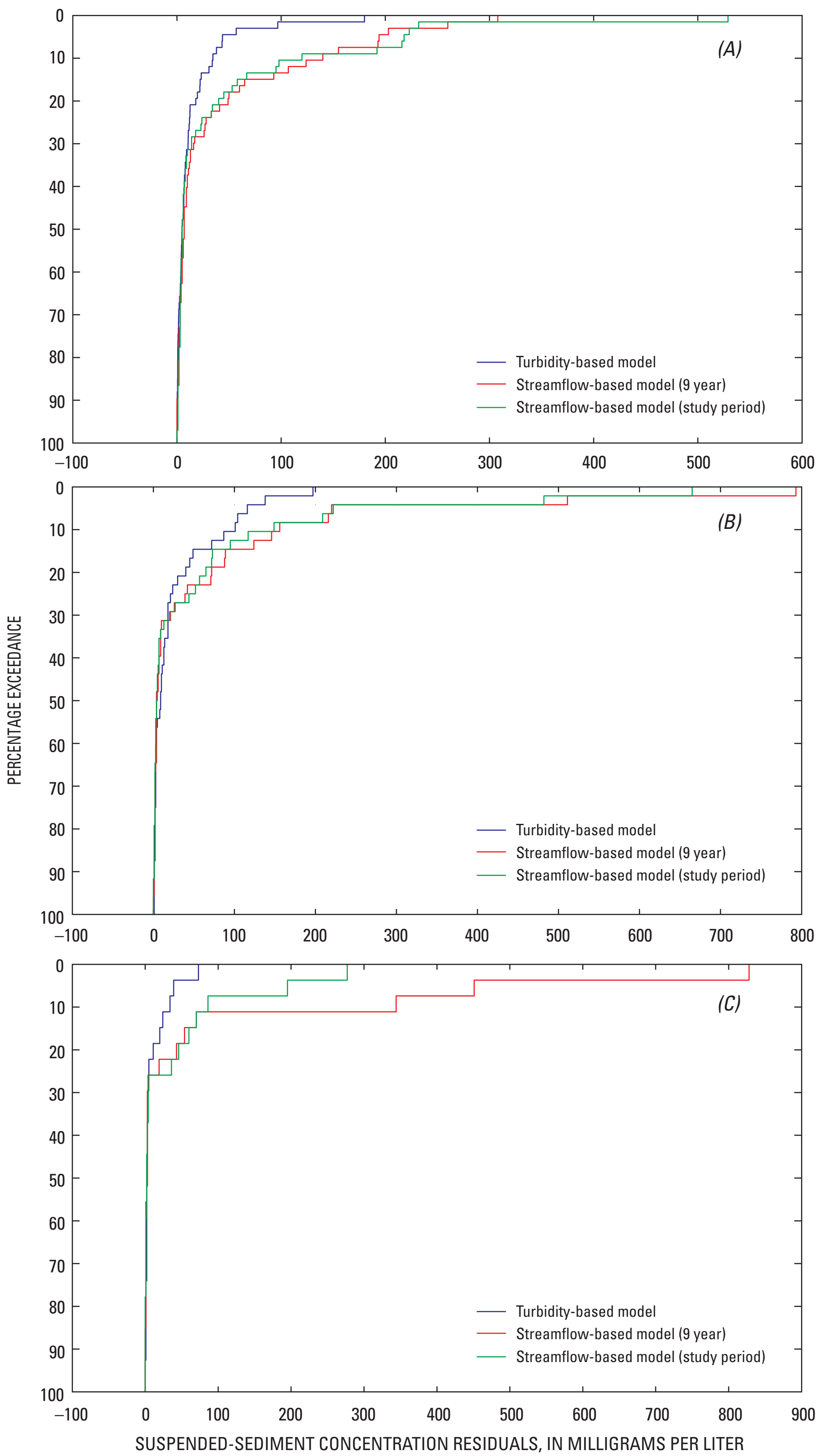

Figure 9. Percentage of exceedance plots of the absolute value of residuals from the turbidity-based suspended-sediment concentration model and the two streamflow-based suspended-sediment concentration models for *(A)* James River at Cartersville, Virginia, *(B)* Rappahannock River near Fredericksburg, Virginia, and *(C)* North Fork Shenandoah River near Strasburg, Virginia.

Comparison of Turbidity-Based and Streamflow-Based Nutrient Concentration Estimates

After the main objectives of this study were completed, additional analysis of the data indicated that the methods developed for SSC estimation also applied well to estimation of nutrients. Other investigators have successfully generated estimation models for nutrients and other chemical constituents using continuous water-quality data (Christensen and others, 2000, 2002; Rasmussen and others, 2005, 2008; Miller and others, 2007). The objective of this additional analysis was to demonstrate the applicability of this approach in major tributaries of the bay and to compare this approach with the streamflow-based estimation approach typically used for estimation of nutrient transport in these tributaries.

The approach for data collection and analysis used at monitoring stations at the James and Rappahannock Rivers was the same as the approach used for generation of the SSC estimation models. The approach was not attempted at the North Fork Shenandoah River station because of the smaller nutrient dataset available for this station. Nutrient samples were collected concurrently with the SSC samples; thus, the nutrient dataset is representative of conditions observed during the period of study (fig. 4). Nutrient analyses were conducted by the Virginia Department of Consolidated Laboratory Services in Richmond, VA; this effort focused on the total phosphorus (TP) and total nitrogen (TN) analyses. The same continuous water-quality and streamflow datasets were used for generation of the nutrient estimation models as were used in the SSC estimation models.

The TP and TN estimation models were selected from the best-subsets regression procedure and subsequent residual evaluation for the two monitoring stations (tables 12 and 13). These estimation models were the highest ranked (lowest Mallows' CP) models with acceptable residuals and summary statistics. The nutrient estimation models explain 83–94 percent of the variability in the nutrient concentrations, depending on the site and nutrient species, as indicated by the adjusted R^2 values.

The variance explained by the streamflow-based TP estimation models ranged from approximately 57–85 percent, according to the adjusted R^2 values (table 14). For the two monitoring stations investigated, the model using the study period dataset explained a greater portion of the variability in TP than the model generated using the 9-year window dataset, presumably because these smaller datasets contained less variability in the TP concentrations.

Table 12. Details of turbidity-based estimation models for total phosphorus for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[N/A, not applicable; √, square root]

Variable	Model coefficient (β)	p-value	Variance inflation factor	Number of observations	Adjusted coefficient of determination
James River at Cartersville					
Intercept	–0.5883	0.042	N/A		
√Turbidity	0.0268	<0.001	7.94		
√Streamflow	0.0007	0.006	7.43	61	0.942
√Water temperature	0.0149	0.003	1.35		
√pH	0.2217	0.035	2.03		
Rappahannock River near Fredericksburg					
Intercept	–0.5473	0.026	N/A		
√Turbidity	0.0197	0.004	8.59	42	0.851
√Streamflow	0.0031	0.006	9.08		
√Specific conductance	0.0631	0.012	1.83		

Table 13. Details of turbidity-based estimation models for total nitrogen for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[N/A, not applicable; √, square root]

Variable	Model coefficient (β)	p-value	Variance inflation factor	Number of observations	Adjusted coefficient of determination
James River at Cartersville					
Intercept	0.5481	<0.001	N/A	61	0.847
√Turbidity	0.0419	<0.001	1		
Rappahannock River near Fredericksburg					
Intercept	0.0421	0.906	N/A	42	0.834
√Turbidity	0.0510	<0.001	1.72		
√Water temperature	–0.074	<0.001	1.08		
√Specific conductance	0.0961	0.014	1.79		

Table 14. Coefficients for streamflow-based total phosphorus estimation models for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[ln, natural logarithm; q, streamflow in cubic feet per second; q_c, centered streamflow (streamflow – mean streamflow); t, decimal time, t_c, centered decimal time (decimal time – mean decimal time); sin, sine function; cos, cosine function; π, pi]

Dataset	Coefficient *(p-value)*							Number of observations	Adjusted coefficient of determination
	Intercept	$\ln(q/q_c)$	$[\ln(q/q_c)]^2$	$(t-t_c)$	$(t-t_c)^2$	$\sin(2\pi t)$	$\cos(2\pi t)$		
James River at Cartersville									
9-year window	–2.623 *(<0.01)*	0.412 *(<0.01)*	0.234 *(<0.01)*	–0.072 *(<0.01)*	–0.019 *(<0.01)*	–0.065 *(0.20)*	–0.107 *(0.04)*	224	0.575
Study period	–2.768 *(<0.01)*	0.766 *(<0.01)*	0.224 *(<0.01)*	–0.004 *(0.91)*	–0.091 *(0.02)*	–0.172 *<0.01)*	–0.299 *(<0.01)*	73	0.849
Rappahannock River near Fredericksburg									
9-year window	–3.276 *(<0.01)*	0.635 *(<0.01)*	0.105 *(<0.01)*	–0.032 *(0.04)*	0.009 *(0.13)*	–0.176 *(<0.01)*	–0.254 *(<0.01)*	196	0.759
Study period	–3.047 *(<0.01)*	0.690 *(<0.01)*	0.199 *(<0.01)*	0.054 *(0.36)*	–0.154 *(0.01)*	0.030 *(0.74)*	–0.282 *(<0.01)*	65	0.837

Comparison of TP estimations from the streamflow-based models and the turbidity-based models revealed that greater accuracy was achieved using the turbidity-based model at each of the two monitoring stations, as indicated by the fit of the estimates around the 1:1 line in figure 10. Additionally, the streamflow-based models tend to underestimate TP, but there is no indication of bias in the turbidity-based estimates of TP. Error statistics, MSE, SSE, and MAE, calculated from the re-transformed and bias-corrected estimates of TP and instantaneous TP load further exemplify the greater accuracy of the turbidity-based approach (table 15). Also, a significant difference in the variance of the estimates and residuals from the turbidity-based and streamflow-based models, as demonstrated by the squared-ranks test (table 16), indicates that the turbidity-based model provides estimates of TP with greater precision than the streamflow-based model.

Overall, these results demonstrate that the turbidity-based approach generates estimates of TP that are more accurate and precise than those estimated using the streamflow-based approach. This result is likely attributable to the characteristics of phosphorous transport because the majority of phosphorous transported in these rivers is in particulate form (fig. 11) and turbidity is a better estimator of particulate material than streamflow, as demonstrated by the results presented for SSC estimation.

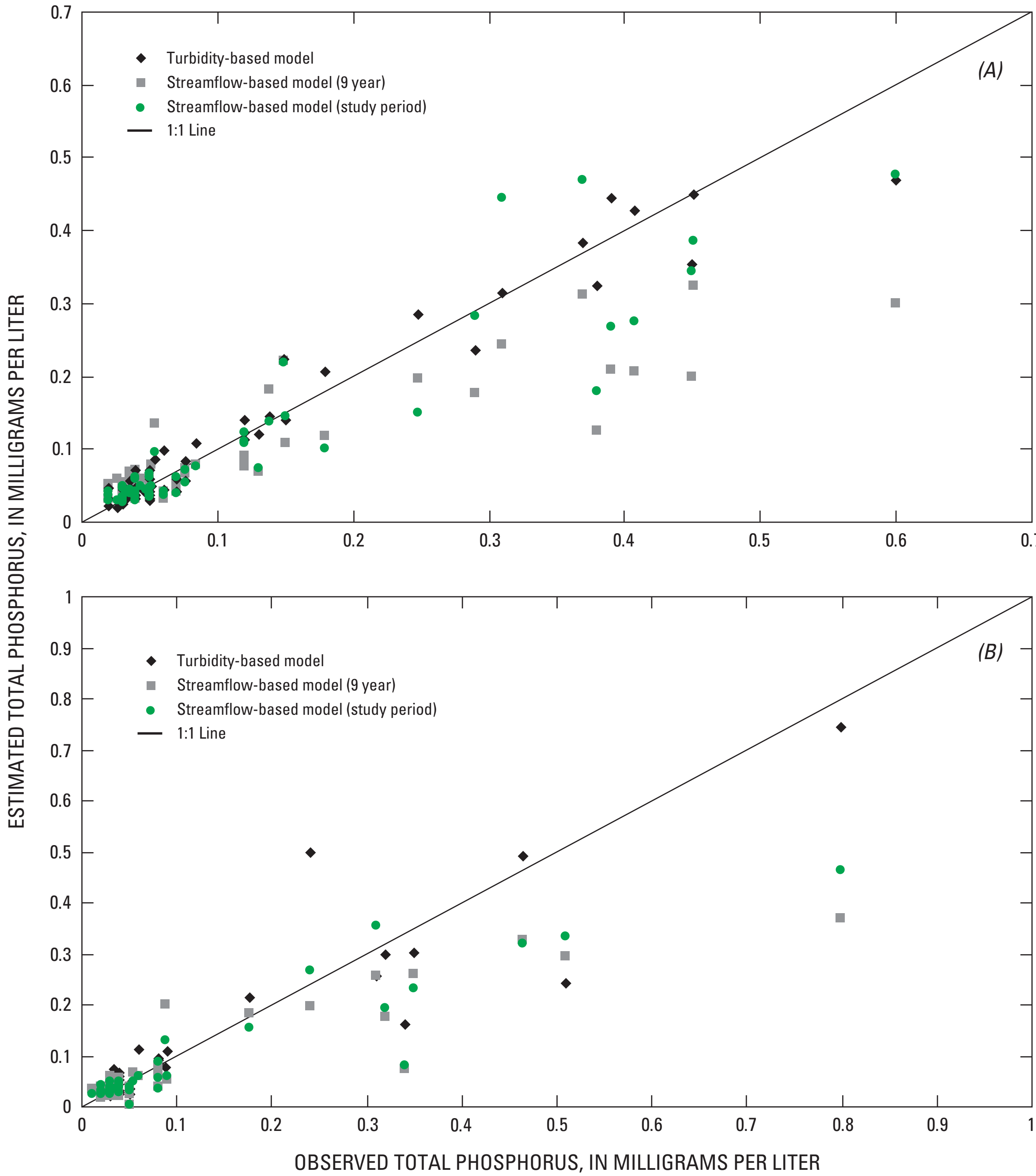

Figure 10. Observed total phosphorus and estimated total phosphorus for the turbidity-based model and two streamflow-based models for *(A)* James River at Cartersville, Virginia, and *(B)* Rappahannock River near Fredericksburg, Virginia.

Table 15. Error statistics for turbidity-based and streamflow-based estimates of total phosphorus concentration and instantaneous load (in parentheses) for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[n, number of observations/estimations used to compute statistics; SSE, sum of squared errors; MSE, mean squared error; MAE, mean absolute error]

	Turbidity-based error statistics	Streamflow-based error statistics (using 9-year dataset)	Streamflow-based error statistics (using study-period dataset)
James River at Cartersville (n = 61)			
SSE	0.055 (626.3)	0.370 (4,568.6)	0.164 (1,868.7)
MSE	0.001 (10.3)	0.006 (74.9)	0.003 (30.6)
MAE	0.019 (1.2)	0.044 (3.6)	0.030 (2.4)
Rappahannock River near Fredericksburg (n = 42)			
SSE	0.191 (124.4)	0.376 (1,135.7)	0.276 (718.7)
MSE	0.005 (3.0)	0.009 (27.0)	0.007 (17.1)
MAE	0.035 (0.6)	0.046 (1.3)	0.039 (1.1)

Table 16. P-values for one-way squared-ranks tests on the variance of estimates and residuals for turbidity-based and streamflow-based total phosphorus estimation models for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[<, less than]

	Streamflow-based p-values (using 9-year dataset)	Streamflow-based p-values (using study-period dataset)
James River at Cartersville		
Estimates	<0.01	<0.01
Residuals	<0.01	0.119
Rappahannock River near Fredericksburg		
Estimates	0.02	<0.01
Residuals	<0.01	<0.01

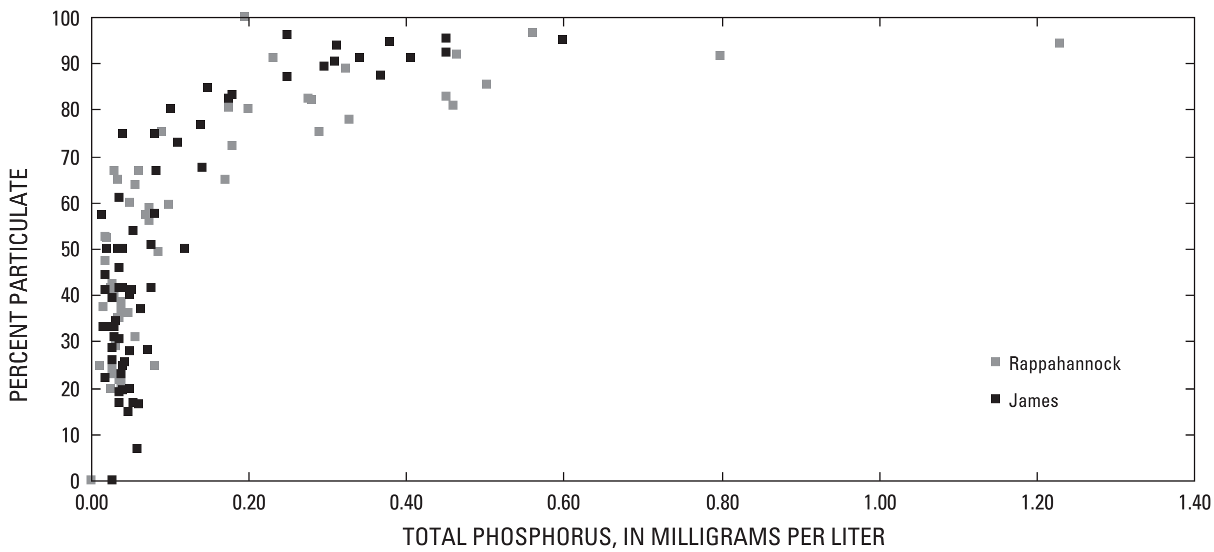

Figure 11. Total phosphorus concentrations and percent particulate phosphorus for the James River at Cartersville, Virginia, and Rappahannock River near Fredericksburg, Virginia.

The streamflow-based TN estimation models were not as efficient at explaining variability as the streamflow-based TP estimation models; the TN estimation models explained only about 60–68 percent of the variability in TN (table 17). As with the TP estimation models, the streamflow-based model generated using the study-period dataset explained a greater portion of the variance in TN than did the model specified using the 9-year window dataset, likely because the shorter dataset contains less variability in the TN concentrations.

Results of the comparison of TN estimates from the streamflow-based model and from the turbidity-based model indicate that both methods provide similar results, with the turbidity-based approach providing only slightly improved accuracy (fig. 12). Although the fit of the streamflow-based TN estimates at the James River at Cartersville monitoring station is comparable to the fit of the turbidity-based estimates, a slightly better fit is observed in the turbidity-based estimates at the Rappahannock River monitoring station.

Comparison of the magnitude (absolute value) of the residuals at each site is shown in figure 13, where points plotting above the 1:1 indicate greater error in the streamflow-based estimates and points below the 1:1 line indicate greater error in the turbidity-based estimates. Although not as apparent in figure 12, the magnitude of residuals at the James River monitoring station tends to be less for the turbidity-based estimates, and the magnitude of residuals at the Rappahannock River monitoring station tends to be greater for the streamflow-based estimates. These findings are supported

Table 17. Coefficients for streamflow-based total nitrogen estimation models for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[ln, natural logarithm; *q*, streamflow in cubic feet per second; q_c, centered streamflow (streamflow – mean streamflow); *t*, decimal time; t_c, centered decimal time (decimal time – mean decimal time); sin, sine function; cos, cosine function; π, pi]

Dataset	Coefficient *(p-value)*							Number of observations	Adjusted coefficient of determination
	Intercept	$\ln(q/q_c)$	$[\ln(q/q_c)]^2$	$(t-t_c)$	$(t-t_c)^2$	$\sin(2\pi t)$	$\cos(2\pi t)$		
James River at Cartersville									
9-year window	–0.670 *(<0.01)*	0.404 *(<0.01)*	0.084 *(<0.01)*	–0.014 *(0.15)*	–0.001 *(0.75)*	–0.061 *(0.09)*	–0.078 *(0.03)*	222	0.618
Study period	–0.622 *(<0.01)*	0.407 *(<0.01)*	0.101 *(<0.01)*	–0.017 *(0.61)*	–0.035 *(0.30)*	–0.107 *(0.05)*	–0.119 *(0.03)*	77	0.677
Rappahannock River near Fredericksburg									
9-year window	–0.328 *(<0.01)*	0.360 *(<0.01)*	0.031 *(<0.01)*	–0.018 *(0.18)*	–0.003 *(0.65)*	–0.002 *(0.97)*	0.024 *(0.64)*	194	0.596
Study period	–0.292 *(<0.01)*	0.330 *(<0.01)*	0.036 *(0.08)*	–0.005 *(0.91)*	0.013 *(0.80)*	0.009 *(0.90)*	0.107 *(0.20)*	74	0.627

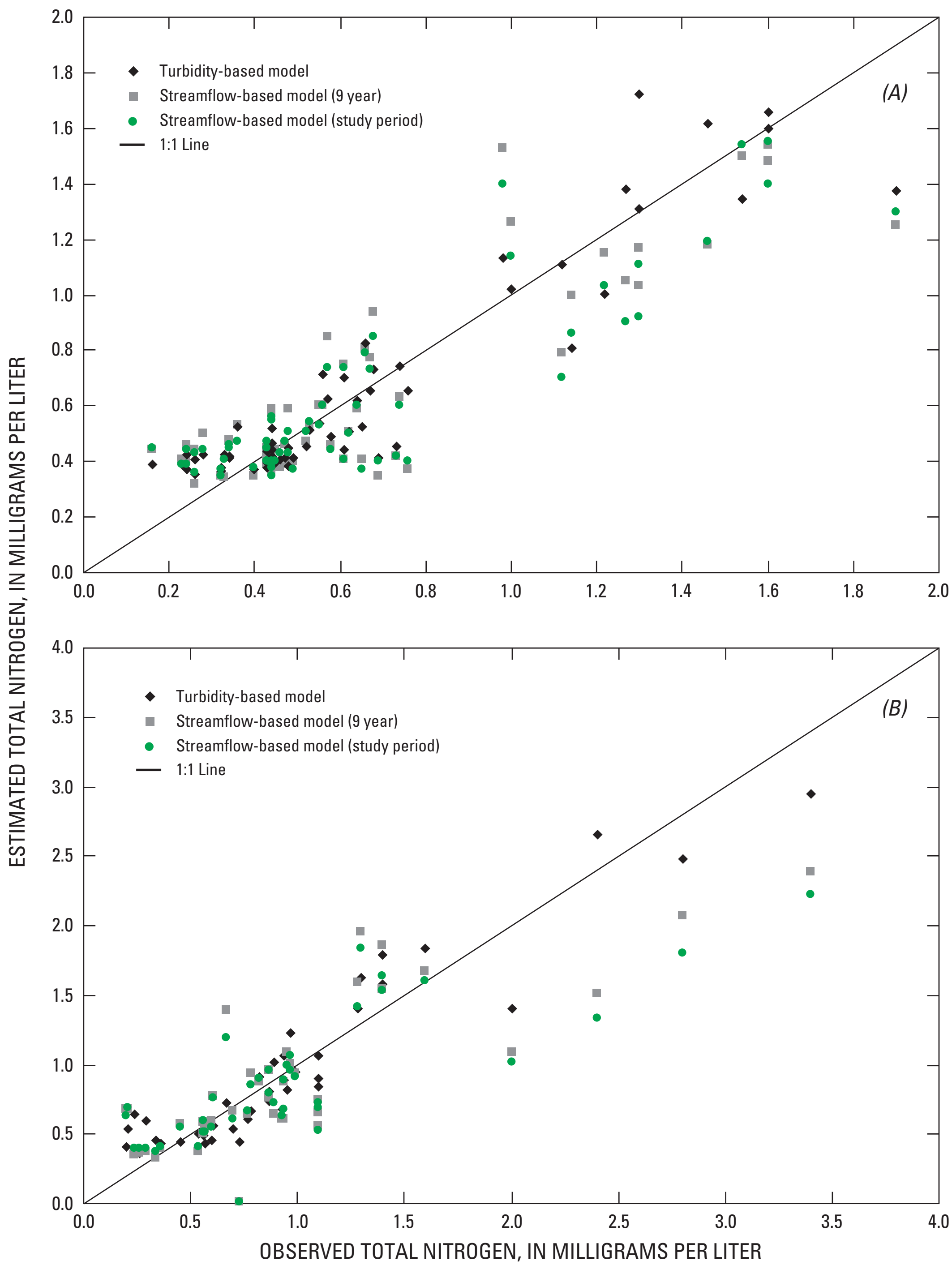

Figure 12. Observed total nitrogen and estimated total nitrogen for the turbidity-based model and two streamflow-based models for *(A)* James River at Cartersville, Virginia, and *(B)* Rappahannock River near Fredericksburg, Virginia.

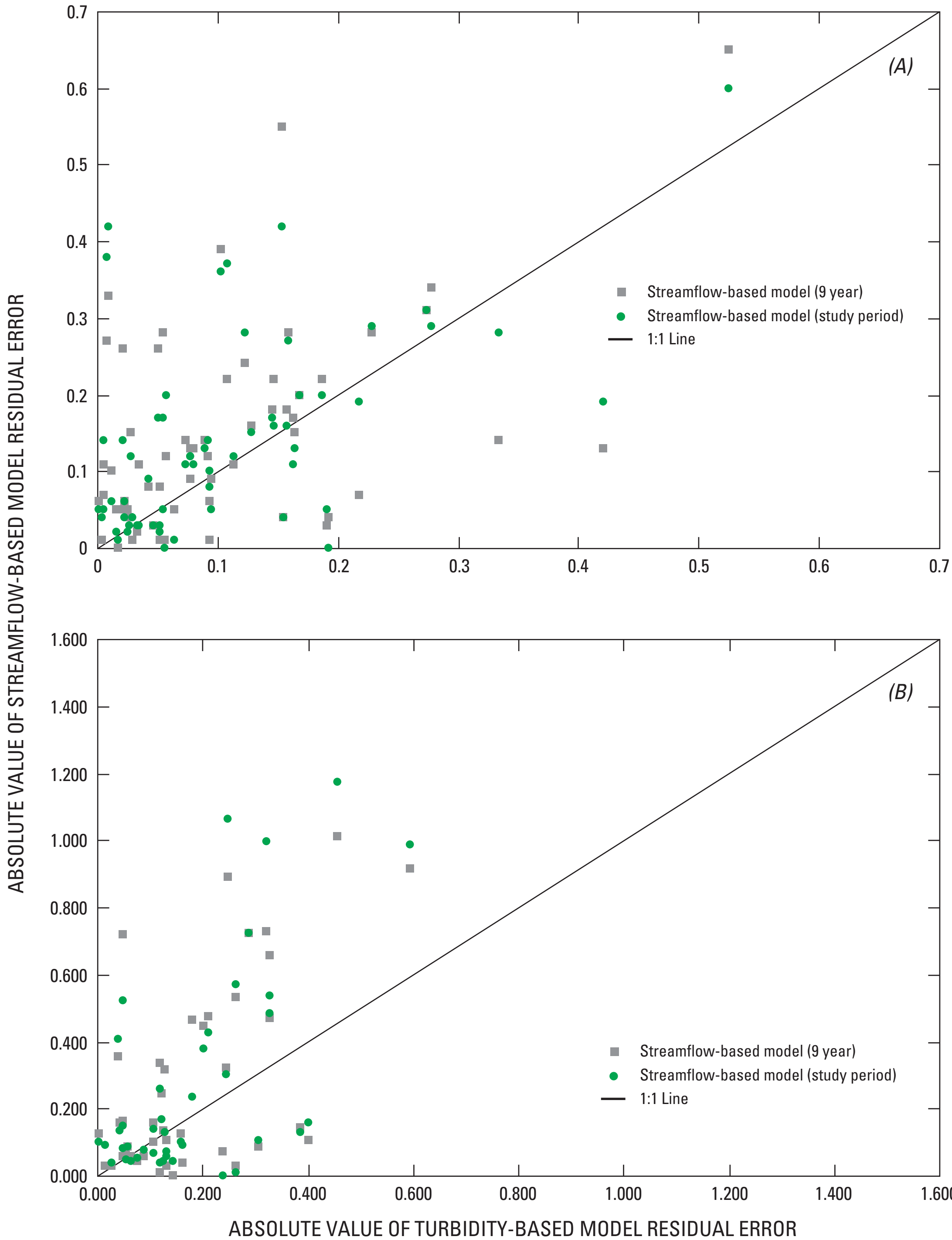

Figure 13. The absolute value of residuals from the turbidity-based total nitrogen estimation model and absolute value of residuals from the two streamflow-based total nitrogen estimation models for *(A)* James River at Cartersville, Virginia, and *(B)* Rappahannock River near Fredericksburg, Virginia.

by the error statistics for the models at each site, which also demonstrate less error (greater accuracy) in the turbidity-based estimates compared to the streamflow-based estimates of TN and instantaneous TN load (table 18).

The squared-ranks test performed on the TN estimates and residuals at each site yielded mixed results, with most outcomes failing to detect significant differences in the precision of the two estimation approaches (table 19). The exception to this lack of significance is that the variance of the residuals from the turbidity-based TN estimation at the James River monitoring station is significantly less than that of the streamflow-based estimation models. The results of the test of residuals at the Rappahannock River monitoring station are not significant using the significance level established for this study (α-level = 0.05).

The finding that there is generally no major difference in the accuracy and precision of TN estimates from turbidity-based and streamflow-based approaches is reasonable because nitrogen transport is dominated by dissolved species. This results in generally low percent-particulate values, which are not well represented by these methods (fig. 14).

Table 18. Error statistics for turbidity-based and streamflow-based estimates of total nitrogen concentration and instantaneous load (in parentheses) for monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

[n, number of observations/estimations used to compute statistics; SSE, sum of squared errors; MSE, mean squared error; MAE, mean absolute error]

	Turbidity-based error statistics	Streamflow-based error statistics (using 9-year dataset)	Streamflow-based error statistics (using study-period dataset)
James River at Cartersville (n = 61)			
SSE	1.28 (7,105.4)	2.30 (1,5606.0)	2.21(13,699.6)
MSE	0.021 (116.5)	0.038 (255.8)	0.036 (224.6)
MAE	0.106 (4.8)	0.146 (7.5)	0.143 (7.4)
Rappahannock River near Fredericksburg (n = 42)			
SSE	2.04 (1,691.3)	6.52 (8,008.4)	7.06 (10,899.3)
MSE	0.049 (40.3)	0.155 (190.7)	0.168 (259.5)
MAE	0.177 (2.5)	0.276 (4.7)	0.27 (5.0)

Table 19. P-values for one-way squared-ranks tests on the variance of estimates and residuals for turbidity-based and streamflow-based total nitrogen estimation models for the monitoring stations at the James River at Cartersville and Rappahannock River near Fredericksburg, Virginia.

	Streamflow-based p-values (using 9-year dataset)	Streamflow-based p-values (using study-period dataset)
James River at Cartersville		
Estimates	0.789	0.063
Residuals	0.035	0.022
Rappahannock River near Fredericksburg		
Estimates	0.766	0.250
Residuals	0.078	0.095

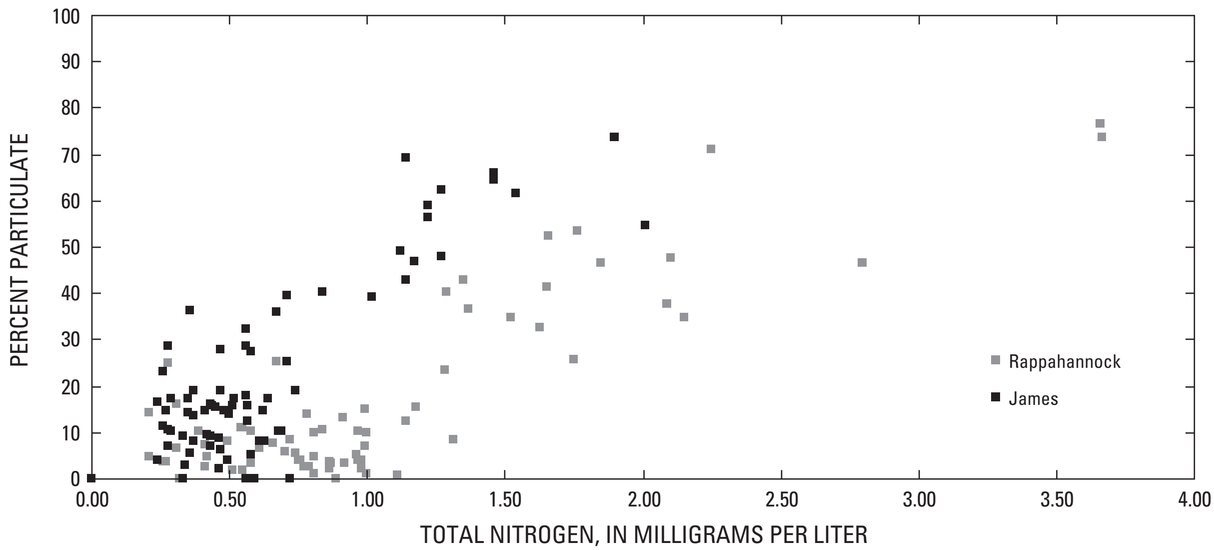

Figure 14. Total nitrogen concentration and percent particulate nitrogen for the James River at Cartersville, Virginia, and Rappahannock River near Fredericksburg, Virginia.

Limitations and Challenges of the Turbidity-Based Method

Although the turbidity-based approach of estimating suspended-sediment and nutrient concentrations provides greater accuracy and precision than the traditional streamflow-based approach, the method is not without limitations. These limitations range from data collection challenges to limitations in the tools available for data analysis.

Collection of continuous water-quality data, such as turbidity, presents challenges similar to those associated with operating continuous-record streamgages, as well as challenges unique to continuous water-quality sensors. As with streamgages, consideration must be given to site-specific conditions to ensure the water-quality monitor and associated components are adequately protected from high water, high velocities, and any associated debris, while maintaining acceptable in-stream performance. Unlike streamgages, sensors on continuous water-quality monitors (particularly optical turbidity sensors) are susceptible to fouling by biological growth, siltation, and entangled debris. These effects may be minimized through careful sensor placement and other creative solutions, but ultimately, successful operation of continuous water-quality monitors requires flexibility in staffing to perform unscheduled site maintenance when such fouling occurs. These episodes of sensor fouling create a data-analysis challenge because discarded data from fouled sensors result in data gaps that must be addressed prior to data analysis. Resolving data gaps requires consideration of study objectives and effects on end products (such as loads and yields). In some circumstances, filling in missing periods of data using the existing data as a guide may be acceptable; in other cases, using an alternative method to make inferences about conditions during gaps in the continuous water-quality monitor data may be necessary.

Application of methods using continuous water-quality data for the estimation of constituent loadings has one apparent major limitation—methods and tools for estimating loads and associated variance require further development. Currently available tools, such as ESTIMATOR, LOADEST (Runkel and others, 2004), and the turbidity threshold sampling (TTS) software developed by Lewis and Eads (2008), do not contain the functionality required to calculate the variance of loads estimated from concentration-estimation models using transformations of the response variable other than the natural-logarithm. This is a major limitation; this study has demonstrated that estimation models using natural-logarithm transformations may not produce the best possible concentration estimates, and in some circumstances, models using the natural-logarithm transformation do not meet the assumptions of linear regression. This limitation is a result of the lack of development of statistical methods for estimating the variance of loads generated from models using non-logarithm transformations (C.G. Crawford, D.L. Lorenz, and G.E. Schwarz, U.S. Geological Survey, oral commun., 2008). Derivation of the statistical methods and development of a tool for application of such procedures would require a concerted effort. The statistical methods for calculation of the variance of load estimates using natural-logarithm transformations developed by Gilroy and others (1990) require calculation of the variance and covariance of all variables, which is a computationally intensive process available in software packages designed for load estimation. A similar effort would be required to develop these procedures for use with non-logarithm transformations. A further limitation of LOADEST for use with continuous water-quality data is that the finest temporal resolution achievable is hourly; with continuous water-quality data typically collected at 15-minute intervals, software capable of using data at this resolution is needed. The TTS software package was developed by investigators working in flashy headwater streams and was designed for use with data collected at 10-minute intervals (Lewis and Eads, 2008).

Potential Applications of Turbidity-Based Estimation Models

Continuous turbidity data and estimations of constituent concentrations based on continuous turbidity data represent an accurate and temporally dense dataset that can provide a valuable tool for resource managers, policy makers, academics, and others to apply to a wide range of water-resource problems. As demonstrated by this investigation, these data can be used to effectively estimate sediment and nutrient concentrations; in addition, effective turbidity-based estimation models may be generated for other particulate or particulate-associated constituents such as bacteria and sediment-bound contaminants. These estimation models may provide the foundational data needed for process-level transport studies, watershed modeling, time-series analysis, trend analysis, total maximum daily load (TMDL) studies, public health investigations and warning systems, and many additional applications at scales ranging from individual best management practice (BMP) structures to large rivers.

One possibility for applying turbidity-based estimation models in public health matters is the development of real-time beach-closure programs. Currently, most beach-closure programs operate on a lag, typically 24 hours, because of the incubation time required for bacteria analysis (Francy and Darner, 2002; Francy and others, 2006). Coupling realtime turbidity measurements with turbidity-based bacteria estimation models can provide a means for basing beach-closure decisions on current conditions, rather than on conditions from the previous day (Francy and Darner, 2002; Francy and others, 2006). This approach could greatly reduce beachgoers risk of exposure to pathogens and potentially reduce the economic impact of beach closures in resort areas as periods of risk would be more accurately defined.

Another possible application of turbidity-based estimation models, when coupled with real-time data collection, is for the detection of changing or impaired water-quality conditions. Real-time water-quality alone may be used to detect changes in, or impairments from, those measured parameters. Furthermore, estimation models may be coupled with those data to detect changes in, or impairments from, constituents that can be effectively estimated. In addition to these methods for instantaneous detections, frequency distributions of measured parameters or estimated constituents may be used to detect impairments when impairment criteria are based on exceeding a given value for a given period of time, or to detect change over time. Such changes over time may be in the form of declining water quality in response to detrimental near-stream or landscape-level activities, or in the form of improving water-quality conditions in response to BMP implementation or stream-restoration activities.

Many investigations seek to quantify the total mass of a constituent transported by a river of interest in order to determine the loading to receiving waters (such as the bay) or to assist in the development of TMDLs for regulatory purposes. Using concentration estimates generated from regression models on continuous water-quality data to estimate constituent loading is an obvious application of the data. This study has demonstrated that these models are capable of estimating constituent concentrations and instantaneous loads with greater precision and accuracy than streamflow-based approaches, and summed load estimates based on these concentration estimates will also have greater accuracy and precision than those based on streamflow.

Total monthly and annual suspended-sediment loads for water year 2007 have been estimated for the James River at Cartersville monitoring station using streamflow- and turbidity-based concentration estimation models presented earlier in this report. These estimations were generated to demonstrate the load estimation application and the improvement over the streamflow-based approach. Current software packages do not permit the use of transformations other than natural logarithm for the response variable; thus, the turbidity-based estimation model using the natural-logarithm transformation (table 3) was used in the LOADEST program to estimate turbidity-based loads. Although the natural-logarithm model was determined to provide estimates of SSC with greater error than the square-root transformed model, the natural-logarithm model was found to be an acceptable model because the assumptions of linear regression were not violated. Hourly turbidity, water temperature, and streamflow values were extracted from the 15-minute-interval datasets for use in LOADEST. Short periods (approximately 8 hours or less) of missing values for all parameters were estimated as the average of nearest neighbors. The turbidity dataset contained two periods of missing data that were longer in duration, occurring as a result of biological fouling during extended periods of low streamflow and turbidity. Because no storm event occurred during these periods, resulting in negligible sediment transport, these periods were assigned estimated turbidity values equal to the 25th percentile of the observed turbidity dataset; graphical analysis of the resulting dataset indicated that this was a reasonable approximation. Finally, all turbidity values equal to zero were assigned a value of 0.1 to permit the use of the natural-logarithm transform. These modifications to the dataset are not expected to adversely alter the load estimates. The streamflow-based estimates of SSL were calculated using the 9-year-window model in the ESTIMATOR program.

Results of the load estimation procedures demonstrate that although the streamflow- and turbidity-based methods typically generate similar estimates of SSL, the turbidity-based approach provides estimates of load with reduced uncertainty (fig. 15), which is expected given the results of the comparison

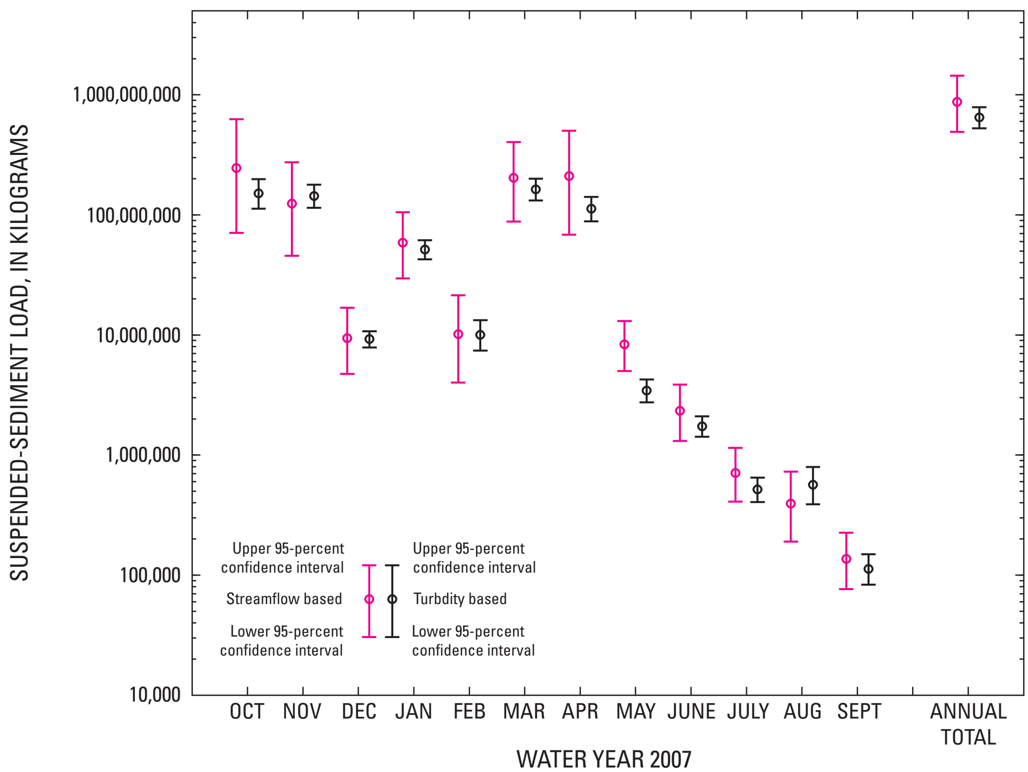

Figure 15. Monthly and annual suspended-sediment load estimations for the 2007 water year at the James River at Cartersville, Virginia, estimated using turbidity-based and streamflow-based methods.

of concentration models and instantaneous SSL. This reduced uncertainty is quantified by the mean monthly coefficient of variation (CV), or standard error of prediction as a percentage of the load. The CV is 38 percent for the streamflow-based load estimates and 12 percent for the turbidity-based load estimates. These results are consistent with those presented by Miller and others (2007) for a similar analysis on the Anacostia River in Maryland. The improved precision in the turbidity-based loads is a direct effect of the improved precision in the turbidity-based concentration estimates. With the square-root transformed model generating SSC estimates with even less uncertainty than the natural-logarithm transformed model, uncertainty in load estimations is expected to be further reduced if a tool could be developed for use with such models.

The reduction of uncertainty in load estimates has numerous practical implications. Primarily, reduced uncertainty in the load estimates will facilitate change or trend detection, as smaller changes in load will be necessary to detect statistically significant differences. This may lead to more accurate and timely detection of trends resulting from management practices on the landscape, which ultimately leads to an improved understanding of processes affecting sediment and nutrient transport from the terrestrial environment to, and through, fluvial systems.

Summary and Conclusions

Elevated suspended-sediment concentrations (SSC) and nutrient concentrations are major water-quality concerns in the Chesapeake Bay, the Nation's largest estuary. Excess sediment is having an adverse effect on the living resources and associated habitat of the bay and its watershed. Because of excess nutrient and sediment levels, the bay was listed as an impaired water body in 1998 under the Clean Water Act. The USEPA Chesapeake Bay Program (CBP) needs information with which to evaluate current conditions and assess progress toward meeting sediment-reduction goals.

Implementation of recent technological and methodological advances in continuous water-quality monitoring and surrogate approaches has helped to generate estimates of SSC and suspended-sediment loads (SSL) with improved precision as compared with traditional approaches. The U.S. Geological Survey, in cooperation with the Chesapeake Bay Program and the Virginia Department of Environmental Quality, evaluated this approach in three major tributaries to the bay and compared the results with the conventionally applied approach using streamflow as the primary regressor for SSC estimation. Specifically, the objectives of this investigation were to

1. Evaluate the use of turbidity as a surrogate for estimating SSC in the James, Rappahannock, and North Fork Shenandoah Rivers, each of which drain into the Chesapeake Bay; and
2. Compare two methods of estimating SSC: turbidity-based and streamflow-based regression models.

These study objectives were expanded to include the evaluation of turbidity-based models to estimate nutrient concentrations, specifically total nitrogen (TN) and total phosphorous (TP).

Multivariate turbidity-based estimation models were generated using best-subsets regression procedures, with potential explanatory variables including continuously measured water-quality and streamflow parameters. Natural-logarithm and square-root transformations of the explanatory and response variables were evaluated, and in all instances, the square-root transformation provided estimates of constituent concentration with the least uncertainty. Turbidity-based models using the square-root transform explained 92–98 percent of the variability in SSC, 85–94 percent of the variability in TP, and 83–85 percent of the variability in TN. With one exception, a single-variable model using turbidity as the explanatory variable outperformed a single-variable model using streamflow as the explanatory variable. Furthermore, the use of a square-root transformation was shown to produce the most statistically acceptable models. In the case of similar levels of acceptability between the square-root and log-based transformations, the square-root transformation was shown to produce estimates of SSC and SSL with the least unexplained variance.

Two iterations of the streamflow-based estimation models were generated using the ESTIMATOR program. One was generated using a 9-year window of data because this is the dataset used by the CBP to estimate nutrient and sediment loadings to the bay. The second model was generated using the data from the same time period that was used to generate the turbidity-based models. These two models were generated so that comparisons of both the streamflow-based model and the approach used by the CBP could be compared with the turbidity-based models. Each of the streamflow-based estimation models explained a large portion of the variance in the estimated constituent, describing 74–88 percent of the variability in SSC, 58–85 percent of the variability in TP, and 60–68 percent of the variability in TN. The streamflow-based estimation models specified using the study-period dataset consistently described a greater portion of the variance than the model generated from the 9-year window; this result is attributed to the shorter datasets having less variability in the constituent concentrations.

Comparison of the streamflow-based and turbidity-based methods focused on the accuracy and precision of the two methods. Accuracy was evaluated through graphical and statistical comparison of the error in the re-transformed bias-corrected concentration estimates. Precision was compared using a squared-ranks test of equal variance on the estimates and the residual errors in those estimates. Using these multiple lines of evidence, results of this study indicate that the turbidity-based modeling approach is capable of generating estimates of the concentration of particulate constituents with greater precision and accuracy than the streamflow-based modeling approach. Interpretation of the accuracy of the turbidity-based approach using graphical analysis of the model fit and residual error distributions is supported by the summary statistics calculated from the re-transformed and bias-corrected estimates of SSC, where the mean absolute error (MAE) of the turbidity-based estimates is found to be 50–87 percent less than the corresponding value from the streamflow-based approach. The magnitude of error for the turbidity-based estimates of TP also was generally smaller, with MAE values 10–57 percent less than those from the streamflow-based estimates. Improvements in precision over the streamflow-based approach are typically evident through significant results from the squared-ranks test on the distribution of SSC estimates and associated residual errors. While the turbidity-based approach yields estimates of SSC and TP with greater accuracy and precision, the streamflow-based approach remains practicable.

The accuracy and precision of estimates of particulate concentrations using turbidity as an explanatory variable are improved because of the strong relation between turbidity and particulate material, and the lesser relation between streamflow and particulate concentrations. Turbidity is a measure of the optical properties of water, and those optical properties are directly influenced by suspended particulate matter. Therefore, the relation between turbidity and suspended matter stays the same, regardless of flow conditions. In contrast, streamflow influences suspension and transport of particulate material, so a relation exists between the two, but many confounding factors (such as variable source area contribution, variations in runoff intensity, and other non-constant variables) degrade the strength of the relation between streamflow and particulate concentrations.

Results from the estimation of TN, a primarily dissolved constituent, did not indicate that either approach provided a definite advantage for estimating concentrations. Both approaches were found to provide acceptable estimates of TN. The turbidity-based model generated slightly more accurate concentration estimates, and precision tests gave mixed results about the significance of differences in variance of the estimates and residuals. Although the results were not typically statistically separable, the turbidity-based approach appears to provide more desirable results than the streamflow-based approach. The finding that neither approach yielded appreciably better estimates of TN follows the understanding that TN occurs mostly as nitrogen in the dissolved form; thus, neither turbidity nor streamflow are measures of TN that may be influenced by either predictor.

Improvements in the concentration estimates were shown to translate into similar improvements in load estimates. Monthly and annual suspended-sediment loads estimated for the James River at Cartersville monitoring station were shown to be more precise when estimated using the turbidity-based approach, with an average monthly coefficient of variation of 12 percent compared with the average monthly coefficient of variation of 38 percent for the streamflow-based approach. The demonstrated improvements reveal the desirable characteristics of turbidity-based estimations; however, the streamflow-based approach remains a viable practical methodology.

Results of this effort demonstrate that use of continuous water-quality data and turbidity-based regression models to estimate SSC and nutrients is viable for use in tributaries to the bay. Furthermore, this investigation identified advantages of using the turbidity-based methodology relative to the currently applied streamflow-based approach. The advantages are that

1. The use of continuously monitored water-quality data coupled with turbidity-based regression models permits generation of a dense time-series dataset of accurate SSC and nutrient estimations, and

2. The precision of turbidity-based SSC and nutrient estimates, and consequently loads calculated from those estimates, is often significantly greater than the precision of those values estimated using the streamflow-based approach.

Although the turbidity-based approach has been shown to provide a more effective means for estimating constituent concentrations and loads, the approach requires further development to take full advantage of the improved precision in load estimates. Currently available statistical methods and load-calculation tools do not permit the use of response variable transformations other than natural logarithm because the tools to calculate estimates of the variance of the load have not been developed for other transformations. With the development of such statistical procedures and software to apply these procedures, reductions in the uncertainty of load estimations are expected to be greater than the reductions observed in this investigation.

In conclusion, the model based on continuous turbidity data has been found to be capable of providing more precise estimates of sediment and nutrient concentrations and loads for the Chesapeake Bay tributaries than a model based on continuous streamflow data. These findings are important to many groups, including scientists, resource managers, policy makers, and the general public because application of this new methodology could promote an enhanced understanding of trends and transport processes.

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