THE VALUE OF CONTINUOUS TURBIDITY MONITORING IN TMDL PROGRAMS

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Abstract: The Federal Clean Water Act requires States to establish total maximum daily loads (TMDLs) to meet water-quality criteria and to attain designated beneficial uses for each water body. Sediment and sediment-associated constituents, such as total nutrients and bacteria, are among the most common water-quality impairments in the Nation. The load of a contaminant introduced to a water body varies with both concentration and streamflow, requiring reliable information for both when implementing an effective TMDL program. In most TMDL programs, discrete water samples collected at periodic intervals are used to determine whether established criteria are being met and to determine loads from contributing sources. However, discrete samples do not adequately describe daily, monthly, or annual variability in load characteristics because both concentration and streamflow can fluctuate substantially between samples.

The ability to continuously measure water-quality constituents such as sediment, nutrients, and bacteria frequently is limited by technical and financial constraints. However, turbidity, which often is strongly correlated with sediment, nutrients, and bacteria, can be measured in-stream and on a continuous basis. By developing regression models to establish statistical relations between laboratory-analyzed samples and in-stream turbidity measurements, it is possible to provide continuous estimates of concentration and load under changing streamflow and seasonal conditions.

The information is valuable to State water-quality programs for several reasons. Continuous turbidity data lead to an improved understanding of in-stream processes affecting sediment and sediment-associated constituents. Regression models using turbidity to estimate sediment-associated constituents are better than those using streamflow because there is a better correlation between turbidity and sediment than between streamflow and sediment. Load and yield estimates that are based on continuous data may be more accurate than estimates that are based on discrete samples because the continuous data better capture variability. Continuous concentration estimates can be used to construct duration curves to determine the percentage of time that estimated concentrations exceed existing water-quality criteria or established goals. Because the full range of conditions are displayed, duration curves are a convenient tool for evaluating conditions during any selected time period and making comparisons between sites, seasons, years, and even particular periods of rainfall. In addition, when continuous data are transmitted in near real-time, the information can be used to optimize efforts to collect discrete samples. Continuous data collected over the long term may be used to help identify changes in water-quality conditions resulting from land-use changes and implementation of best-management practices in the watershed. Finally, continuous data lead to more effective strategies for developing and implementing TMDLs to protect water quality.

INTRODUCTION

The Federal Clean Water Act as amended in 1977 requires States to establish total maximum daily loads (TMDLs) to meet water-quality criteria and to attain designated beneficial uses for each water body. A TMDL is the maximum quantity of a contaminant that a water body can receive and still meet water-quality criteria (Kansas Department of Health and Environment, 2004). The load of a contaminant introduced to a water body varies with both concentration and streamflow, requiring reliable information for both when implementing an effective TMDL program. Typically, TMDLs are developed for water bodies identified by each State as impaired and included in the section 303(d) list required by the Clean Water Act. Sediment and sediment-associated constituents, such as total nutrients and bacteria, are among the most common water-quality impairments in the Nation (U.S. Environmental Protection Agency, 2005a).

Most State TMDL programs rely on analysis of discrete samples for constituent concentration information (Stiles, 2002). Although discrete samples are valuable for determining instantaneous constituent concentrations, they do not describe daily, monthly, or annual variability in constituent load characteristics because both concentration and streamflow can fluctuate substantially between samples. Continuous monitoring, on the other hand, does capture temporal variability and has become more common for many water-quality applications, including TMDL programs.

In-stream instruments designed to continuously measure specific conductance, pH, water temperature, turbidity, and dissolved oxygen are readily available. However, the ability to continuously measure water-quality constituents that are most commonly associated with impairments, such as sediment, nutrients, and bacteria, often is limited by technical and financial constraints. Fortunately, turbidity data can be used as a surrogate because it is strongly correlated with sediment, nutrients, and bacteria, and can be measured in-stream on a continuous basis. Turbidity is caused by the presence of suspended and dissolved matter such as clay, silt, organic matter, and microscopic organisms (ASTM International, 2003). These particulates in water provide attachment sites for nutrients, bacteria, and other potential contaminants (U.S. Environmental Protection Agency, 2005b). By developing regression models to establish statistical relations between laboratory-analyzed samples and in-stream turbidity measurements, it is possible to provide continuous estimates of concentration and load for sediment-related constituents under changing conditions.

The purpose of this paper is to describe methods for developing regression models that are used to continuously estimate concentration and load for sediment-related water-quality constituents and to demonstrate the utility of the resulting data for State water-quality monitoring efforts such as TMDL programs. Examples will be provided using water-quality data collected at three sites on the Kansas River in northeast Kansas from 2000 through 2004. Additional information can be found in Rasmussen et al. (2005), available at http://pubs.usgs.gov/sir/2005/5165, and on the U.S. Geological Survey Kansas Water Science Center Website at http://ks.water.usgs.gov/Kansas/rtqw/.

APPROACH

Data Collection: Three USGS streamflow-gaging stations on the Kansas River in northeast Kansas were equipped with water-quality monitors that provided continuous (hourly) measurements of turbidity. Monitor maintenance and data reporting followed standard procedures described in Wagner et al. (2000). In addition, about 20 discrete water samples were collected from each site throughout the range of recorded streamflow and turbidity conditions according to methods described by Wilde et al. (1999) and analyzed for suspended sediment, total nitrogen and phosphorus, *Escherichia coli* (*E. coli)* bacteria, and other selected constituents. Duration curves for streamflow and turbidity were used to evaluate sample distribution and adapt sampling strategies to fill voids in data along the curves. Continuous in-stream sensor data were compared to average cross-section data at the monitor locations to verify that the continuous data were representative of cross-section conditions.

Regression Models: Regression analysis through an overall model-building method (Helsel and Hirsch, 1992) was used to develop relations between the continuous turbidity measurements, streamflow, time, and discretely sampled constituent concentrations. Models were evaluated by using plots of each possible explanatory (independent) variable and the response (dependent) variable and visually and statistically examining the residual plots for patterns. The prediction error sum of squares (PRESS), which is a measure of goodness of fit of a regression model, coefficient of determination (R^2), which is the fraction of the variance explained by the regression, and the mean square error (MSE), which is a measure of the variance between the estimated and measured values, were used to evaluate the models. Explanatory and response variables (except time) were log transformed, if necessary, to develop linear relations. Although many possible models were evaluated, this paper focuses on the model that use turbidity as the explanatory variable because they generally were the best overall models for the Kansas River monitoring stations.

For variables that were log-transformed, retransformation of regression-estimated concentrations was necessary. Retransformation can cause bias (underestimation) in the constituent loads when adding individual load estimates over a period of time (Helsel and Hirsch, 1992). Therefore, the estimated hourly concentration and density values were multiplied by a log-transformation bias correction factor, or smear factor, to correct for this underestimation. Duan's smearing estimator (Duan, 1983) was used because it is the least complex and most easily applied correction method (Cohn and Gilroy, 1991).

Uncertainty of the estimates for the regression models was determined using 90-percent prediction intervals (Helsel and Hirsch, 1992). For a given explanatory variable, the 90-percent prediction interval represents the range of values expected for the response variable 90 percent of the time. Probabilities of exceeding water-quality standards, recommended criteria, or State and U.S. Environmental Protection Agency (USEPA) guidelines also can be used to evaluate uncertainty of the estimated values (Rasmussen and Ziegler, 2003).

Estimation of Loads and Yields: Constituent loads were calculated by multiplying hourly regression-estimated concentrations and densities by a bias correction factor (Duan smear factor; Duan, 1983) and by streamflow and then summing over the appropriate period of time. Constituent yields were calculated by dividing loads by corresponding drainage areas to determine constituent load per acre. Yields can be used to compare relative contributions of each drainage basin.

VALUE OF CONTINUOUS TURBIDITY DATA

Continuous Turbidity Data Lead to an Improved Understanding of In-Stream Processes: A fundamental knowledge of in-stream turbidity fluctuations leads to an improved understanding of processes affecting sediment and sediment-related constituents such as nutrients and bacteria. Streamflow data alone do not accurately characterize turbidity. For example, hourly turbidity measurements from the Kansas River at Wamego during the spring of 2001 (Figure 1A) indicate that turbidity peaks did not coincide with streamflow peaks. In fact, the turbidity peak occurred 4 days after the June 1 streamflow peak, but it preceded the streamflow peak 4 days later on June 5. In addition, the magnitude of the streamflow peak was not indicative of the magnitude of the corresponding turbidity peak. Turbidity values may be larger during either the rising or falling limb of the streamflow hydrograph, depending on the source of the suspended material. Sediment originating from the stream channel typically causes larger turbidity values as streamflow increases, and sediment originating from more distant basin sources may cause larger turbidity values as streamflow decreases because of the timing of the tributary inflows (Asselman, 1999). In addition, changes in turbidity often were much more abrupt than changes in streamflow. The increase in streamflow at the Kansas River at DeSoto that began on July 12, 2001 (Figure 1B), and peaked on July 14, 2001, occurred over about a 60-hour period. In contrast, the associated change in turbidity that peaked on July 13 increased within a 5-hour period and had nearly recovered about 7 hours later.

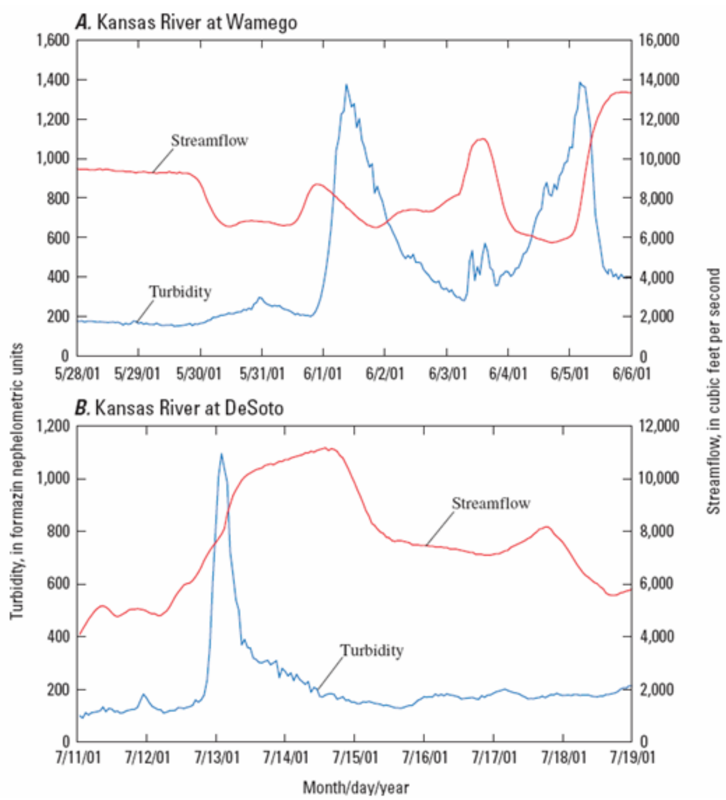

Figure 1 Comparisons of streamflow and turbidity for Kansas River at Wamego and DeSoto during the summer of 2001 (Rasmussen et al., 2005).

Regression Models Using Turbidity to Estimate Sediment-Related Constituents are Better than Those Using Streamflow: Regression models were developed for each of the three Kansas River sites to estimate suspended sediment using turbidity (Rasmussen et al., 2005). For comparison, regression models also were developed using streamflow to estimate suspended sediment. In each case, turbidity was a better explanatory variable for sediment-associated constituents than streamflow as indicated by larger R^2 values and smaller MSE values. For example, the turbidity model for estimating sediment at Wamego had an R^2 of 0.95 and MSE of 0.0158, compared to the streamflow model for sediment, which had an R^2 of 0.66 and MSE of 0.1361 (Rasmussen et al., 2005). Better statistical models result in better estimated values.

Regression models also provide information about relations between constituents of concern and variables that affect them. Generally, there was a one-to-one relation between turbidity and suspended sediment at the three Kansas River monitoring sites (Figure 2). The Topeka regression line had a steeper slope than the others, indicating that the relation between turbidity and suspended sediment at that site was different from the other sites. When turbidity was low, suspended sediment at Topeka was smaller than at the other two sites, and when turbidity was high, suspended sediment was larger than at the other two sites. In this river system, the different relation between turbidity and sediment may indicate a difference in sediment sources related to reservoir contributions (Rasmussen et al., 2005).

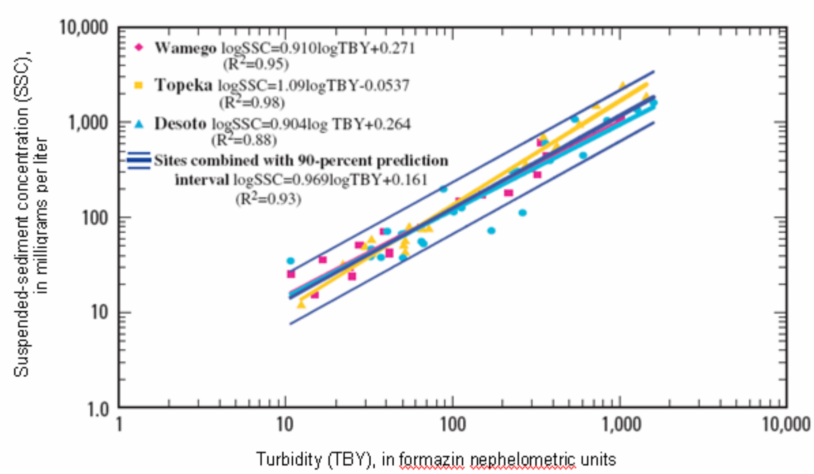

Figure 2 Comparison of turbidity (explanatory variable) and suspended-sediment concentration (response variable) in regression models developed for three Kansas River monitoring sites (Rasmussen et al., 2005).

Continuous Estimates, with Defined Statistical Uncertainty, Describe Variability of Water-Quality Constituents That Often Cause Impairments: Often, water-quality constituents that cause impairments, like sediment, nutrients, and bacteria, cannot be measured easily in-stream because of financial and technological limitations. In lieu of direct measurements, regression-estimated values provide important information about constituent variability throughout the year. Continuous monitoring helps identify climatic, seasonal, and hydrologic conditions during which sediment-related water-quality impairments occur. It is especially useful for characterizing nonpoint-source contributions associated with stormwater because it describes conditions throughout the duration of each runoff occurrence. Load and yield estimates that are based on continuous data may be more accurate than estimates made on the basis of discrete samples because the continuous data better capture temporal variability.

Hourly estimates of *E. coli* in the Kansas River at DeSoto in 2004 (Figure 3) indicate that, during normal flow conditions, water-quality criteria were not likely to be exceeded unless there was an unusual point source release upstream that increased *E. coli* load without increasing turbidity. *E. coli* densities were elevated during increased streamflow in March and June through August. Peaks in *E. coli* density tend to fall more quickly than corresponding streamflow peaks. *E. coli* densities can increase by several orders of magnitude within a short time. Statistical uncertainty of the estimates for the regression model is displayed in gray using 90-percent prediction intervals (Helsel and Hirsch, 1992). Probabilities of exceeding water-quality standards, recommended criteria, or guidelines also can be used as an alternative method of expressing statistical uncertainty. Examples can be found on the Web at http://ks.water.usgs.gov/Kansas/rtqw/.

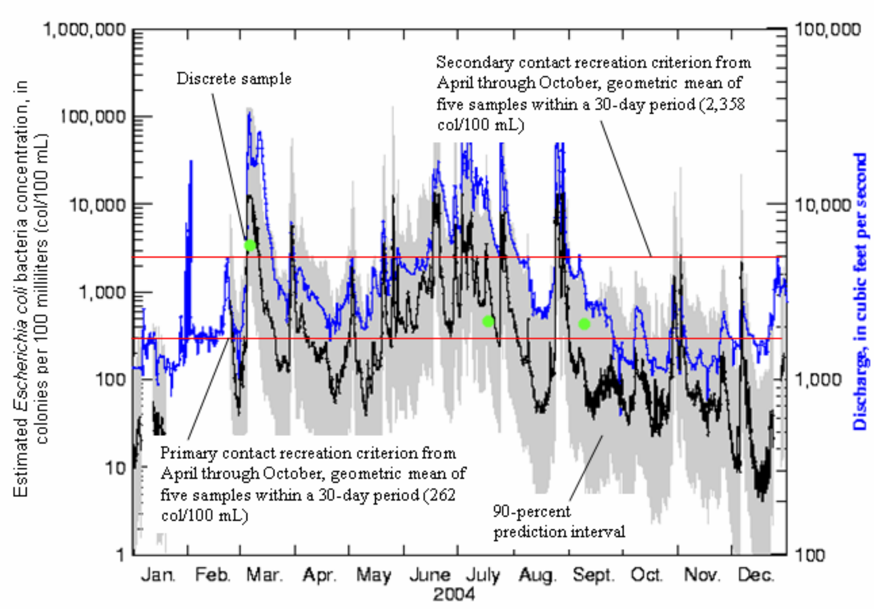

Figure 3 Estimated *Escherichia coli (E. coli)* bacteria densities at the Kansas River at DeSoto, Kansas monitoring site, 2004 (http://ks.water.usgs.gov/Kansas/rtqw/). Water-quality criteria from Kansas Department of Health and Environment (2003).

Duration Curves Have Many Uses: Continuous concentration or load estimates can be used to construct cumulative frequency distribution (duration) curves to estimate the frequency, duration, and magnitude of potential water-quality degradation. Because the full range of conditions are displayed, duration curves are a convenient tool for evaluating conditions during any selected time period and for making comparisons between sites, seasons, years, and even particular periods of rainfall. They also can be used to determine the percentage of time that estimated concentrations or densities exceed existing water-quality criteria, proposed criteria, and established goals.

Examination of differences in concentrations, densities, and loads at a series of sensor stations along a stream allows the analysis of upstream-to-downstream changes in water quality. Estimated *E. coli* densities at Topeka, the middle Kansas River monitoring site, were larger than estimated densities at the other two sites about 90 percent of the time (Figure 4). Duration curves also may be used to differentiate between base-flow and runoff conditions. The three *E. coli* duration curves in Figure 4 diverge at about 80-percent exceedance, which corresponds to about 50 col/100 mL (colonies per 100 milliliters of water). This also may be indicative of when stormwater runoff begins to affect base-flow conditions.

By summing hourly load values from a selected portion of the load duration curve or period of time and converting the calculated load to a percentage of the total load, it is possible to determine how much of the total annual load occurred during specified periods of time. For example, by summing hourly loads within the upper 10 percent of the load duration curve and converting to a percentage of the total load, it was found that, on average, 83 percent of the annual bacteria load in the Kansas River at DeSoto during 2000–03 occurred during 10 percent of the time in conjunction with the most intense runoff. The same method was used to estimate that 64 percent of the annual suspended-sediment load at the same site occurred during 10 percent of the time (Rasmussen et al., 2005).

Sampling Efforts Can Be Optimized: When continuous data are transmitted in near real-time, the information can be used to efficiently time discrete sampling efforts to collect important data during targeted water-quality conditions. In situations where discrete samples and constituent concentration or density data are necessary for regulatory requirements, monitoring by continuous sensor data allows regulatory agencies to optimize sampling efforts. In some cases it may be more cost effective to use continuous monitors for critical constituent monitoring rather than intensive discrete sampling.

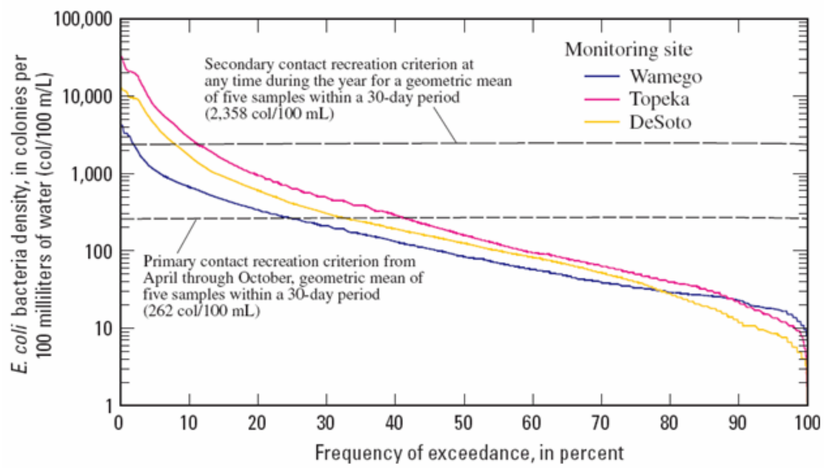

Figure 4 Duration curves for estimated *Escherichia coli (E. coli)* bacteria densities at three Kansas River monitoring sites, January 2000-December 2003 (Rasmussen et al., 2005). Water-quality criteria from Kansas Department of Health and Environment (2003).

Continuous Data Can Be Used to Monitor and Evaluate Changes Over Time: Temporal changes may be observed by evaluating hourly values over time and by evaluating changes in relations between explanatory and response variables in the regression models. Turbidity duration curves for the Kansas River at DeSoto during 2000-03 (Figure 5) indicate that turbidity generally was largest in 2001 and smallest in 2002. During low turbidity conditions corresponding with low streamflow, about 25 percent of the time, annual duration curves were similar from 1 year to the next. For the remaining 75 percent of the time, turbidity in 2001 was largest. Because duration curves show the entire range of conditions, they are more useful for evaluating changes than merely using summary statistics such as maximum, median, and minimum values. When continuous data are considered over the long term, it may be possible to identify changes in water-quality conditions resulting from land-use changes and implementation of best-management practices in the watershed (Rasmussen et al., 2005).

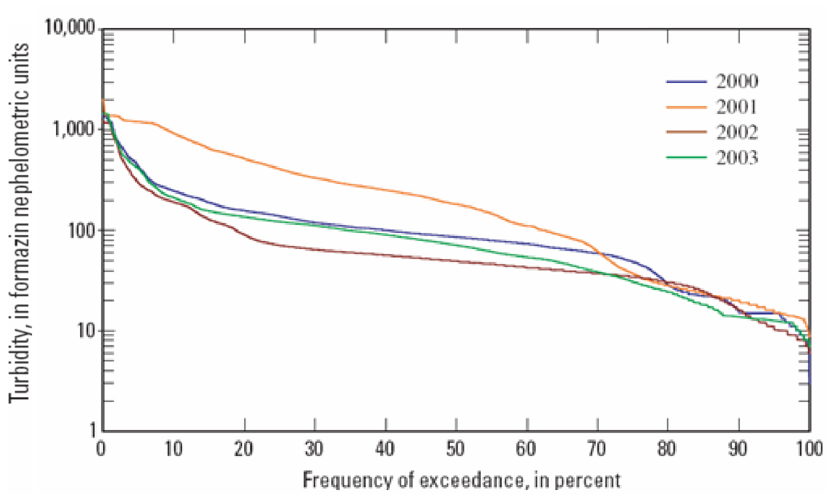

Figure 5 Annual duration curves for measured turbidity at Kansas River at DeSoto monitoring site, January 2000 through December 2003 (Rasmussen et al., 2005).

Continuous Data Lead to More Effective Strategies for Developing and Implementing TMDLs to Protect Water Quality: Understanding a particular stream system is the foundation for developing effective water-quality management plans. By knowing when conditions are likely to exceed criteria and what factors contribute to stream degradation, cost-effective strategies can be developed to target particular conditions in each stream system rather than treating all systems uniformly.

CONCLUSIONS

The ability to continuously measure water-quality constituents such as sediment, nutrients, and bacteria, often is limited by technical and financial constraints. However, turbidity, which usually is strongly correlated with sediment, nutrients, and bacteria, can be measured in-stream and on a continuous basis. By developing regression models to establish statistical relations between laboratory-analyzed samples and in-stream sensor measurements, it is possible to provide continuous estimates of concentration and load under changing streamflow and seasonal conditions. The information is valuable to State water-quality management programs for the following reasons:

- Continuous turbidity data lead to an improved understanding of in-stream processes affecting sediment and sediment-related constituents such as nutrients and bacteria. Streamflow data alone do not accurately characterize turbidity because turbidity fluctuations do not coincide directly with streamflow fluctuations.
- Regression models using turbidity to estimate sediment-associated constituents are better than those using streamflow because there is a better correlation between turbidity and sediment than between streamflow and sediment.
- Continuous estimates, with defined statistical uncertainty, describe variability of water-quality constituents causing impairments. In addition, load and yield estimates that are based on continuous data may be more accurate than estimates that are based on discrete samples because the continuous data better capture variability.
- Continuous concentration and load duration curves have many uses for State water-quality monitoring programs. Because the full range of conditions are displayed, duration curves are a convenient tool for evaluating conditions during any selected time period and making comparisons between sites, seasons, years, and even particular periods of rainfall. They also can be used to determine the percentage of time that estimated concentrations or densities exceed existing water-quality criteria, proposed criteria, and established goals.
- When continuous data are transmitted in near real-time, the information can be used to optimize efforts to collect discrete samples.
- Continuous data can be used to monitor and evaluate changes by examining hourly values over time and by evaluating changes in statistical relations between explanatory and response variables.
- Continuous data lead to more effective strategies for developing and implementing TMDLs to protect water quality.

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