Prepared in cooperation with the Milwaukee Metropolitan Sewerage District

Use of Real-Time Monitoring to Predict Concentrations of Select Constituents in the Menomonee River Drainage Basin, Southeast Wisconsin, 2008–9

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

Cover. Water-quality sonde deployment at Underwood Creek at Wauwatosa, Wisconsin, October 27, 2009. (Photograph by Austin K. Baldwin, U.S. Geological Survey.)

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Conversion Factors and Abbreviations

Inch/Pound to SI

Multiply	By	To obtain
	Length	
foot (ft)	0.3048	meter (m)
mile (mi)	1.609	kilometer (km)
	Area	
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)

Temperature in degrees Celsius (°C) may be converted to degrees Fahrenheit (°F) as follows:
°F=(1.8×°C)+32

Horizontal coordinate information is referenced to the Wisconsin Transverse Mercator (WTM) Projection and the North American Datum of 1983 (NAD 83), with 1991 adjustment.

Concentrations of chemical constituents in water are given in milligrams per liter (mg/L), micrograms per liter (µg/L), most probable number per 100 milliliters (MPN/100 mL), or colony forming units per 100 milliliters (CFU/100 mL).

Abbreviations used in this report

ADCP	acoustic Doppler current profiler
EPA	U.S. Environmental Protection Agency
EWI	equal-width increment
MLR	multiple linear regression
MMSD	Milwaukee Metropolitan Sewerage District
MSPE	model standard percent error
NTU	nephelometric turbidity units
NWIS	National Water Information System
PRESS	prediction error sum of squares
PVC	polyvinyl chloride
QA/QC	quality assurance/quality control
RMSE	root-mean-squared error
RPD	relative percent difference
SLR	simple linear regression
SSE	sum of squared error
USGS	U.S. Geological Survey

Use of Real-Time Monitoring to Predict Concentrations of Select Constituents in the Menomonee River Drainage Basin, Southeast Wisconsin, 2008–9

By Austin K. Baldwin,[1] David J. Graczyk,[1] Dale M. Robertson,[1] David A. Saad,[1] and Christopher Magruder[2]

Abstract

The Menomonee River drainage basin in southeast Wisconsin is undergoing changes that may affect water quality. Several rehabilitation and flood-management projects are underway, including removal of concrete channels and the construction of floodwater retention basins. The city of Waukesha may begin discharging treated wastewater into Underwood Creek, thus approximately doubling the current base-flow discharge. In addition, the headwater basins, historically dominated by agriculture and natural areas, are becoming increasingly urbanized.

In an effort to monitor these and future changes to the basin, the U.S. Geological Survey and the Milwaukee Metropolitan Sewerage District initiated a study in 2008 to develop regression models to estimate real-time concentrations and loads of selected water-quality constituents. Water-quality sensors and automated samplers were installed at five sites in the Menomonee River drainage basin. The sensors continuously measured four explanatory variables: water temperature, specific conductance, dissolved oxygen, and turbidity. Discrete water-quality samples were collected and analyzed for five response variables: chloride, total suspended solids, total phosphorus, *Escherichia coli* bacteria, and fecal coliform bacteria. Regression models were developed to continuously estimate the response variables on the basis of the explanatory variables.

The models to estimate chloride concentrations all used specific conductance as the explanatory variable, except for the model for the Little Menomonee River near Freistadt, which used both specific conductance and turbidity as explanatory variables. Adjusted R^2 values for the chloride models ranged from 0.74 to 0.97. Models to estimate total suspended solids and total phosphorus used turbidity as the only explanatory variable. Adjusted R^2 values ranged from 0.77 to 0.94 for the total suspended solids models and from 0.55 to 0.75 for the total phosphorus models. Models to estimate indicator bacteria used water temperature and turbidity as the explanatory variables, with adjusted R^2 values from 0.54 to 0.69 for *Escherichia coli* bacteria models and from 0.54 to 0.74 for fecal coliform bacteria models. Dissolved oxygen was not used in any of the final models. These models may help managers measure the effects of land-use changes and improvement projects, establish total maximum daily loads, estimate important water-quality indicators such as bacteria concentrations, and enable informed decision making in the future.

Introduction

Increasingly, real-time water-quality monitors are being used to estimate continuous concentrations of water-quality constituents. Certain water-quality constituents, such as bacteria concentrations, cannot easily be measured in real-time because of limitations in cost and sensor technology. However, studies have demonstrated that water-quality constituents can be estimated based on more easily measured surrogates, such as water temperature and turbidity (Christensen and others, 2000; Rasmussen and others, 2005). Using surrogates allows for continuous concentration estimates of the constituent(s) of interest and, when combined with discharges, constituent loads.

There are several advantages of load estimation with continuous concentration over traditional constituent load estimation methods. Traditional studies rely heavily on discrete sampling, which provides only snapshots of water-quality concentrations; therefore, the vast majority of the water-quality record is entirely unknown and must be estimated. Traditional estimation methods, such as the Graphical Constituent Loading Analysis System (Koltun and others, 2006), can be subjective, and results can vary from one estimate to the next. Daily, monthly, and annual fluctuations in concentrations, as well as concentration changes during a storm event, may not be accurately described. By providing a continuous record (for example, measurements every 5 minutes) of surrogates, real-time monitoring captures the variability in water-quality concentrations and reduces estimation errors associated with methods that do not use real-time data.

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[2] Milwaukee Metropolitan Sewerage District

In November 2008, the U.S. Geological Survey (USGS) and the Milwaukee Metropolitan Sewerage District (MMSD) began a cooperative study to develop regression models to estimate continuous real-time concentrations of selected water-quality constituents. Continuous real-time sensors and water-quality samplers were installed at five sites in the Menomonee River drainage basin. The real-time sensors measured four explanatory variables as surrogates: water temperature, turbidity, dissolved oxygen, and specific conductance. Discrete water-quality samples were collected for a range of streamflows and seasons and were analyzed for five response variables: chloride, total suspended solids, total phosphorus, *Escherichia coli* (*E. coli*) bacteria, and fecal coliform bacteria. A set of concurrently measured explanatory variables was used to develop regression equations for each of the response variables. These regressions between explanatory and response variables were then used to calculate continuous estimates of each of the water-quality constituents of interest.

Real-time water-quality information can be beneficial in public and ecosystem health management and facilitate water-resource management. For example, managers can use real-time estimates of chloride to determine if elevated levels are toxic to aquatic organisms (Corsi and others, 2010). Real-time estimates can be used for public health notices, such as whether fecal coliform concentrations may be above water-quality standards that may present public health risks (Francy and Darner, 2007). Real-time concentration estimates in conjunction with stream discharge data can be used to calculate loads of water-quality constituents of interest. Load estimates can then be used in the development of total maximum daily loads (TMDLs). Long-term continuous monitoring of surrogate explanatory variables and estimation of water-quality constituents may be used to evaluate the effects of land-use changes, improvement projects, and implementation of best-management practices.

Purpose and Scope

The purpose of this report is to describe the process used to create regression models to estimate real-time concentrations and loads of selected water-quality constituents based on data from real-time water-quality monitors. The regression models presented in this report may help provide MMSD with a means to document improvements in water quality related to capital projects, assist with basin planning efforts, and provide water-quality information to communities served by MMSD and the general public.

Description of the Study Area

The Menomonee River Basin drains 146 square miles (mi^2) in southeast Wisconsin (fig. 1). The basin is within the MMSD planning and service area and includes parts of Milwaukee, Waukesha, Ozaukee, and Washington Counties. The largest tributaries within the basin include Underwood Creek, Honey Creek, and the Little Menomonee River. The Menomonee River joins the Milwaukee and Kinnickinnic Rivers to form the Milwaukee estuary in Lake Michigan near downtown Milwaukee.

The Menomonee River drainage basin is currently (2007) 64 percent urban, an increase from 51 percent urban in 1970 (Southeastern Wisconsin Regional Planning Commission, 2007). Although the northern third of the basin is dominated by agriculture (fig. 1*B*), the area has experienced recent urban growth. Between 1990 and 2000, the population in the basin remained nearly stable at 322,000, although the number of households rose by 3.5 percent (Southeastern Wisconsin Regional Planning Commission, 2007).

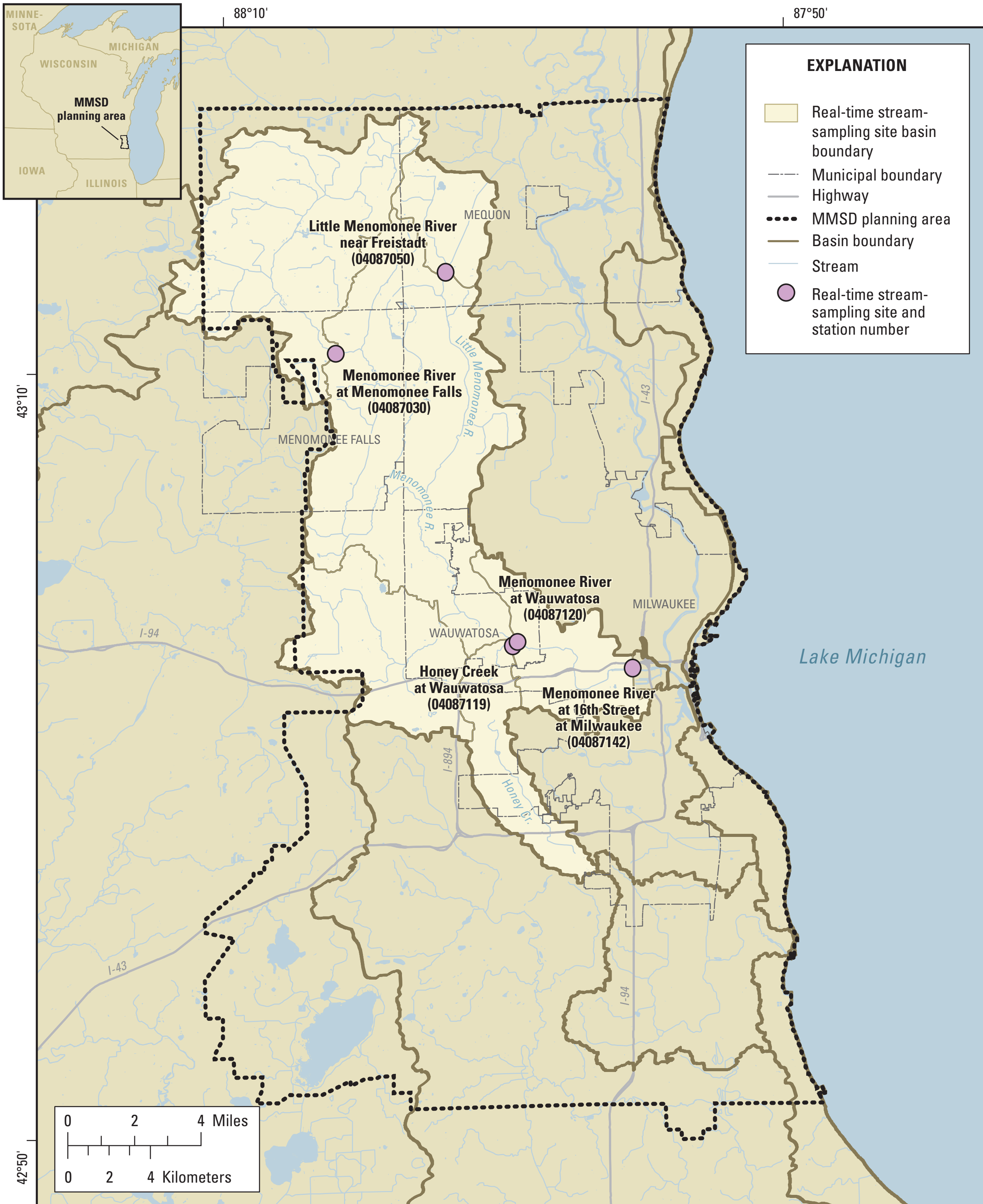
Five sites within the basin were monitored and sampled as part of this study: the Little Menomonee River near Freistadt, the Menomonee River at Menomonee Falls, Honey Creek at Wauwatosa, the Menomonee River at Wauwatosa, and the Menomonee River at Milwaukee (fig. 1). General basin characteristics upstream of these sites, including land use, are listed in table 1. The basin with the smallest urban area is the Little Menomonee River (20 percent); the basin with the largest urban area is Honey Creek (96 percent).

Data Collection

Data for the regression model development were collected from November 2008 to September 2009. Types of data collected included continuous real-time data and discrete water-quality samples. Quality assurance/quality control (QA/QC) samples were collected, as well.

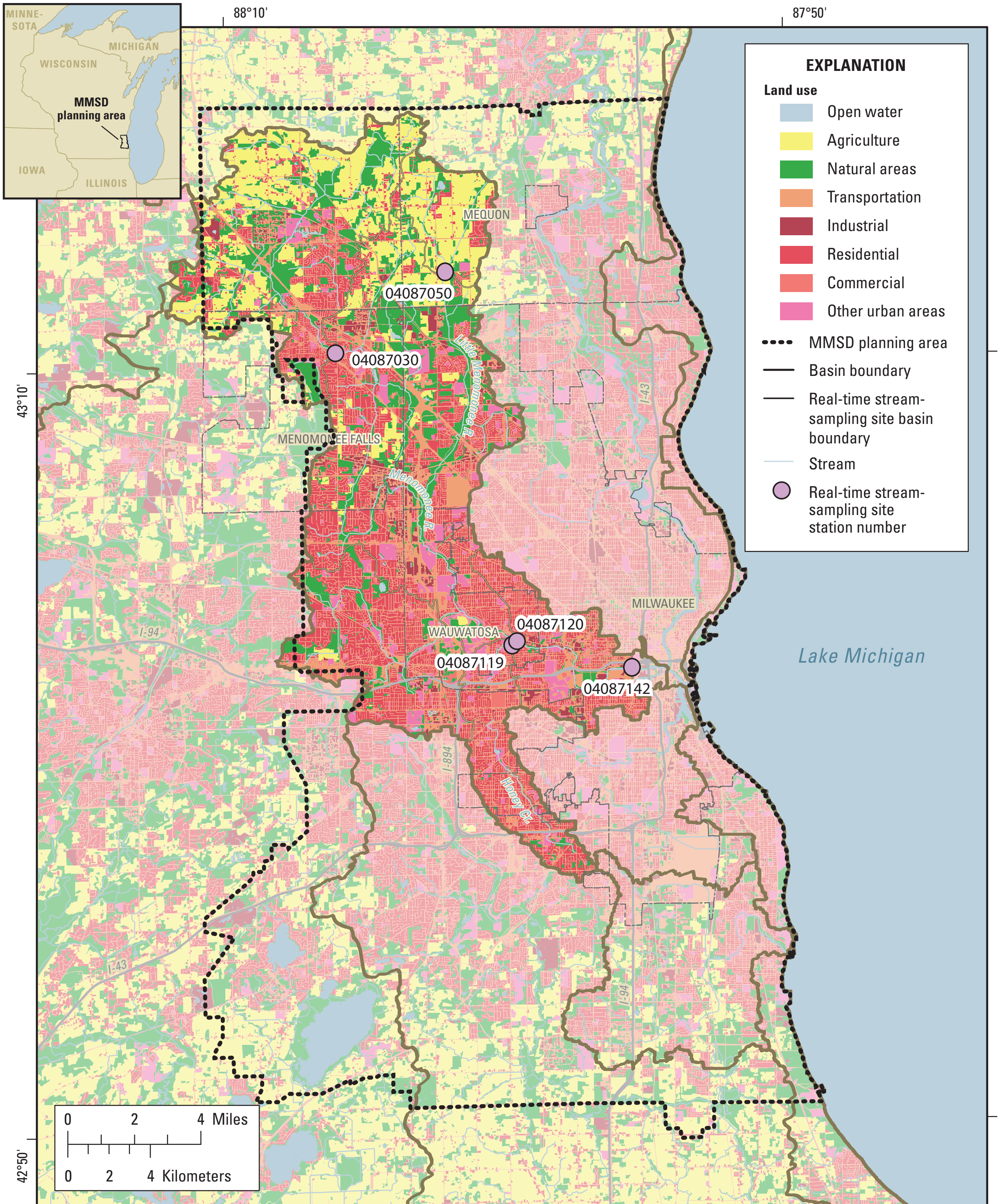
Continuous Real-Time Data

At four of the five sites, stream stage was measured every 5 minutes and was used to calculate stream discharge (Rantz and others, 1982). These four sites are the Menomonee River at Menomonee Falls, Little Menomonee River, Honey Creek, and Menomonee River at Wauwatosa. Stream stages were measured by a gas-purge-pressure system and recorded on a datalogger. Discharge measurements at these sites were made according to standard USGS methods (Turnipseed and Sauer, 2010) every 4 to 6 weeks and more frequently during high flows to define the stage-discharge relation for each site. At the fifth site, the Menomonee River at Milwaukee (16th Street), an acoustic Doppler current profiler (ADCP) was installed to measure water velocities because this site is affected by backwater and seiche effects from Lake Michigan. Water velocities and the cross-sectional area were used to determine the discharge at this site (Laenen, 1985; Oberg and others, 2005; Ruhl and Simpson, 2005).



Base composited from Southeastern Wisconsin Regional Planning Commission regional base map, 1:2,000, 1995; U.S. Geological Survey digital line graph hydrography, 1:100,000, 1989; Wisconsin Department of Natural Resources minor civil divisions, 1:100,000, 1998; Wisconsin Department of Natural Resources state trunk highways, 1:100,000, 1998; Wisconsin Department of Natural Resources version 2 hydrography, 1:24,000, 2002. Wisconsin Transverse Mercator Projection, referenced to North American Datum of 1983, 1991 adjustment.

Figure 1*A*. Location of real-time water-quality monitoring sites and drainage basins in the Menomonee River Basin. Dotted line demarcates the Milwaukee Metropolitan Sewerage District (MMSD) planning area.



Base composited from Southeastern Wisconsin Regional Planning Commission digital land use inventory, 1:4,800, 2000; Southeastern Wisconsin Regional Planning Commission regional base map, 1:2,000, 1995; U.S. Geological Survey digital line graph hydrography, 1:100,000, 1989; Wisconsin Department of Natural Resources version 2 hydrography, 1:24,000, 2002. Wisconsin Transverse Mercator Projection, referenced to North American Datum of 1983, 1991 adjustment.

Figure 1*B*. Location of real-time water-quality monitoring sites and land use in the Menomonee River Basin. Dotted line demarcates the Milwaukee Metropolitan Sewerage District (MMSD) planning area.

Table 1. Basin characteristics of monitoring sites, Menomonee River Basin, Southeast Wisconsin.

[Periods of record for annual mean discharge range from 4 years at Menomonee River at 16th Street (2008 to present) to 51 years at Menomonee River at Wauwatosa (1961 to present). Land use percentages are from 2007 (Southeastern Wisconsin Regional Planning Commission); USGS, U.S. Geological Survey; mi^2, square mile; ft^3/s, cubic foot per second]

Monitoring site	USGS station number	Drainage area (mi^2)	Annual mean discharge (ft^3/s)	Percent urban	Percent agriculture	Percent natural areas
Menomonee River at Menomonee Falls	04087030	34.7	31.5	35	38	27
Little Menomonee River near Freistadt	04087050	8.0	7.3	20	63	16
Honey Creek at Wauwatosa	04087119	10.3	11.4	96	0	4
Menomonee River at Wauwatosa	04087120	123.0	106.0	60	19	20
Menomonee River at 16th Street at Milwaukee	04087142	146.0	184.5	64	17	19

A multiparameter water-quality sonde was installed at each site in November 2008. Each sonde was equipped with an optical dissolved-oxygen sensor, an optical turbidity sensor, and a specific conductivity and temperature sensor. The sonde was installed in a polyvinyl chloride (PVC) tube in a fixed position in the stream, and water-quality measurements were made every 5 minutes. Sonde maintenance, data correction, and reporting procedures followed standard USGS protocol (Wagner and others, 2006). Sites were visited approximately every 2 weeks during the open-water period (March through November) and monthly in the winter when the streams were usually ice covered. Extensive fouling at some sites during the summer necessitated weekly visits.

Continuous monitoring data for use in the regression models was downloaded from the USGS National Water Information System database on January 25, 2010. For most sites and water-quality measurements, the continuous monitoring record was at least 95 percent complete (table 2). Reasons for missing records include equipment malfunctions, flood damage to equipment, and excessive fouling. The quality of the continuous monitoring data was rated according to criteria outlined in Wagner and others (2006). This rating scheme is based on the combined fouling and calibration drift corrections applied to the data. For example, specific conductance data are considered excellent if the combined fouling and drift corrections are less than or equal to +/– 3 percent of the specific conductance value. The quality of the continuous monitoring data was mostly considered good to excellent, but varied substantially by site and water-quality measurements. The water temperature record was considered excellent at all five sites. The percentage of the specific conductance record rated as either good or excellent ranged from 77 percent at Honey Creek to 96 percent at the Little Menomonee River and the Menomonee River at Wauwatosa. The percentage of the dissolved oxygen record rated as either good or excellent ranged from 67 percent at the Menomonee River at Menomonee Falls to 95 percent at Honey Creek. The percentage of the turbidity record rated as either good or excellent ranged from 48 percent at Honey Creek to 82 percent at the Little Menomonee River. For dissolved oxygen, turbidity, specific conductivity, and temperature, the measured values were within the ranges of sensor operation.

Table 2. Water-quality sonde ratings (as percentages of the record) at the continuous water-quality monitoring sites in the Menomonee River drainage basin, Southeast Wisconsin.

[Ratings based on criteria outlined in Wagner and others, 2006, table 18]

	Excellent	Good	Fair	Poor or missing
Menomonee River at Menomonee Falls, WI 04087030				
Water temperature	99	0	0	1
Specific conductance	50	45	5	1
Dissolved oxygen	43	24	10	24
Turbidity	73	5	0	23
Little Menomonee River near Freistadt, WI 04087050				
Water temperature	99	0	0	1
Specific conductance	64	32	0	5
Dissolved oxygen	48	24	19	9
Turbidity	68	14	0	18
Honey Creek at Wauwatosa, WI 04087119				
Water temperature	95	0	0	5
Specific conductance	68	9	3	20
Dissolved oxygen	85	10	1	4
Turbidity	35	13	14	39
Menomonee River at Wauwatosa, WI 04087120				
Water temperature	95	0	0	5
Specific conductance	82	14	2	2
Dissolved oxygen	75	10	8	7
Turbidity	32	21	13	34
Menomonee River at 16th Street at Milwaukee, WI 04087142				
Water temperature	99	0	0	1
Specific conductance	78	11	5	6
Dissolved oxygen	71	15	8	6
Turbidity	57	12	8	23

Continuous in-stream water-quality monitor data were compared to cross-sectional data at the monitor location to determine if the continuous data were representative of the water-quality conditions across the stream. Four to five cross-sectional surveys were conducted at each site during both base-flow and stormflow conditions. The cross-sectional surveys show that the streams at all sites are generally well mixed, with no consistent differences from one side of the channel to the other. No corrections were made to the continuous water-quality monitor record. Continuous streamflow and water-quality data are available at the USGS Web site at *http://waterdata.usgs.gov/wi/nwis* (accessed February 2012).

Discrete Water-Quality Samples

Each site was equipped with a stage-activated, refrigerated automated sampler for the collection of water samples over a full range of hydrologic conditions. These samplers were controlled using dataloggers that were programmed to collect a sample with each 0.5 foot (ft) increase in stage once the stage reached an initial sampling threshold. The initial sampling threshold varied at each site and changed seasonally. After the stage peaked, samples were collected with each 1.0 ft decrease in stage. This sampling strategy was designed to maximize the number of samples collected during each event and to collect more samples on the rising limb of the hydrograph when water-quality constituents typically change the most. At the Menomonee River at 16th Street, the sampler was activated by turbidity rather than stage because of backwater and reverse flows from the seiche effects of Lake Michigan. Once the turbidity reached a predefined threshold, sampling would begin, and samples would be collected at set time intervals until the turbidity dropped below the threshold. The turbidity threshold was changed as needed depending on current turbidity and season.

For most sites and constituents (chloride, total suspended solids, total phosphorus, *E. coli* bacteria, and fecal coliform bacteria), between 50 and 100 samples were collected and analyzed. At some of the sites between one and four samples were not used in the final regression models because of fouling on the water-quality meter. Fewer samples were collected at the Little Menomonee River: 39 samples for chloride, total suspended solids, and total phosphorus; 37 samples for *E. coli* bacteria; and 32 samples for fecal coliform bacteria. The Little Menomonee River site is the most rural of the sampling sites and high-flow events were less frequent. Christensen and others (2000) found that 35 to 55 samples, collected throughout 90 to 95 percent of the stream's flow duration, were sufficient to define relations between constituents and surrogates for two Kansas streams.

The distribution of samples over the range of observed hydrologic conditions is at least as important in creating a regression model as is the total number of samples (Rasmussen and others, 2009). To evaluate whether the collected samples adequately represent the range of observed hydrologic conditions, the samples were plotted on duration curves of associated time-series data for each site and constituent. The turbidity duration curve in figure 2 was developed from 5-minute data from the Menomonee River at Menomonee Falls for the period from November 2008 to September 2010. The samples plotting on top of the curve are associated total suspended solids samples. The plot shows very good sample coverage for the observed turbidity values between 10 and 220 nephelometric turbidity units (NTU) and good coverage for turbidity values between 2 and 10 NTU. Duration curves showing sample coverage for all sites and constituents are provided in the appendixes.

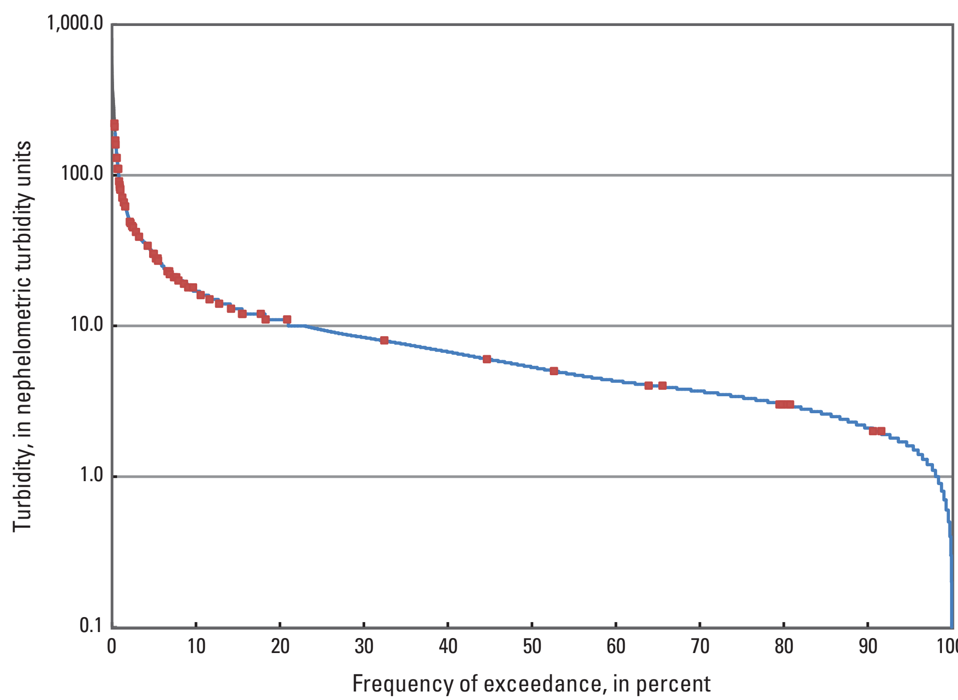


Figure 2. Turbidity duration curve developed from 5-minute data from November 2008 to September 2010, with associated samples used in the total suspended solids regression model, Menomonee River at Menomonee Falls, Wisconsin.

Quality Assurance/Quality Control

Quality-assurance and quality-control (QA/QC) samples collected during this study accounted for about 6 percent of the water-quality samples. Sampler blanks were collected at each site to check for sampler contamination by pumping Milli-Q® water through the entire sample line and into a sample bottle. The sample was split into bottles and analyzed at the MMSD laboratory. None of the constituents had concentrations above the detection limit except for one total suspended solids sample that had a concentration of 2.8 milligrams per liter (mg/L). Splitter blanks were also collected to check for contamination from the sample processing equipment. The splitter blanks were collected by running Milli-Q water through a decaport sample splitter, then collecting and analyzing that water. All of the constituents analyzed for the splitter blanks were below the detection limit.

Multiple pairs of concurrent automated sampler and equal-width-increment (EWI) samples were collected at each site to evaluate whether the automated sampler samples were chemically and physically representative of the stream cross section. The EWI sampling method is designed to accurately represent the discharge-weighted concentrations of the stream (Edwards and Glysson, 1999). Relative percent differences (RPDs) were calculated between the EWI and automated sampler sample concentrations. Median RDPs for chloride, total suspended solids, and total phosphorus were all less than 10 percent. Median RDPs for fecal coliform bacteria and *E. coli* bacteria were 36 and 18 percent, respectively. The higher variability in the bacteria samples may be the result of rapidly changing flows in these urban basins and the inherent variability of bacteria concentrations in the stream. No corrections were applied on the basis of the EWI results.

Preparation and analysis of the water samples were performed by the MMSD laboratory. The preparatory steps included dividing samples into representative subsamples using a splitting device developed for aqueous matrices and preserving the subsamples according to U.S. Environmental Protection Agency (EPA) protocols. The subsamples were analyzed for chloride, total suspended solids, total phosphorus, and *E. coli* and fecal coliform bacteria. The analytical methods used by MMSD are based on procedures described by the U.S. Environmental Protection Agency (1993) or by Clesceri and others (1998). Specific procedure references are listed in appendix 1. The MMSD follows extensive QA/QC guidelines set forth in the 2003 National Environmental Laboratory Accreditation Conference NELAC Standard (National Environmental Laboratory Accreditation Conference, 2003).

Regression Model Development

Simple and multiple linear regression (SLR and MLR) models were developed to estimate chloride, total suspended solids, total phosphorus, *E. coli* bacteria, and fecal coliform bacteria by using continuous in-stream temperature, specific conductance, dissolved oxygen, and turbidity sensor measurements. These models were used to calculate continuous (5-minute) estimates of chloride, total suspended solids, total phosphorus, *E. coli bacteria*, and fecal coliform bacteria suitable for evaluating exceedance criteria in the sampled streams. A detailed description of the process used to develop the regression models using continuously measured sensor data can be found in Rasmussen and others (2009). A brief description of the methods used for this study follows.

Regression models were developed using a two-step approach: (1) initial model development and (2) final model selection. Initial regression models were developed for each of the response variables by using stepwise regression with all of the continuous in-stream sensor measurements as explanatory variables. Initial models were developed with $\log_{10}$-transformed response variables. Untransformed and $\log_{10}$-transformed explanatory variables, as well as seasonal variables (sine Julian day and cosine Julian day), were considered during model development by using the SAS software PROC REG command (SAS Institute Inc., 2004). An alpha value of 0.05 was used for the stepwise selection (for both entry into and removal from the model). Final models were selected manually and typically included a subset of the explanatory variables chosen during initial model development. Considerations for selecting the final models included (1) simplicity of the model (preference for fewer variables), (2) consistency between models (preference for a consistent set of variables), and (3) similar fit and explanatory power as the initial model while including considerations (1) and (2). For example, in the initial models for total suspended solids, one of the five models found sine Julian day to be a significant variable, and another model found water temperature to be significant. Because each of these variables was found to be significant in only one of the five models and because they lacked explanatory power, both of these variables were omitted from the final regression models.

Initial models used between one and six explanatory variables. All final models used one or two variables. Final models for chloride included specific conductance as the only explanatory variable, except for the Little Menomonee River model, which used both specific conductance and turbidity as explanatory variables. Final models for both total suspended solids and total phosphorus included turbidity as the only explanatory variable. Final models for *E. coli* and fecal coliform bacteria included both water temperature and turbidity as explanatory variables. Dissolved oxygen was not used in any of the final models. Although dissolved oxygen was significant in some of the initial models, it was not included in the final models to maintain simplicity and consistency between models, and because it lacked explanatory power.

Similar fit and explanatory power between the initial and final models were compared primarily using plots of observed versus computed values and the adjusted coefficient of determination (adj R^2). Plots of observed versus computed values appeared to have similar fit. Adj R^2 values of the final models were typically within 5 to 15 percent of the initial models. The adj R^2 and additional regression model statistics considered in model development are described in more detail below. Statistics and graphs describing the final models are included in the appendixes.

Regression models were evaluated for fit and explanatory power by using graphs and several measures of variance between computed and observed values. Plots of observed versus computed values were evaluated for fit relative to a 1:1 line and distribution across the range of observed values. Plots of residuals versus computed values, date, and a normal quantile distribution were evaluated for bias and normality. Measures of variance between computed and observed values used include the sum of squared errors (SSE), root-mean-squared error (RMSE), adjusted coefficient of determination (adj R^2), and prediction error sum of squares (PRESS). The SSE represents the total model error, and the RMSE is a measure of the average error between computed and observed values. The SSE and RMSE have the same units as the response variable. Smaller values of SSE and RMSE indicate better fit for a particular model. The model standard percent error (MSPE) is the RMSE expressed as a percentage and allows regression model comparison. The adj R^2 is adjusted for the number of explanatory variables in the model and represents the fraction of variability in the response variable that is explained by the model. Adj R^2 ranges from 0 to 1, where 1 represents 100 percent of variability explained. PRESS is a validation-type estimator of error based on regression with one observation left out of the regression and repeated for each observation.

All models developed in this study were based on $\log_{10}$-transformed response variables. Retransforming the computed values back into the original units introduces a bias because regression estimates are the mean of y given x in logarithmic units, and retransformation of these estimates is not equal to the mean of y given x in linear space. Therefore, the retransformation bias of these models was corrected by applying a bias correction factor (Duan, 1983). Bias correction factors for each model are included in the appendixes. Also provided in the appendixes are 90-percent prediction, or confidence, intervals. These confidence intervals can be used for evaluating uncertainty of the computed values. Smaller prediction intervals indicate less uncertainty associated with the computed value.

Regression Model Results

Chloride

Chloride occurs naturally in streams, but at high concentrations chloride poses a significant threat to aquatic ecosystems. According to the EPA, chronic chloride concentrations above 230 mg/L, and acute chloride concentrations above 860 mg/L, pose a potential threat to aquatic life (U.S. Environmental Protection Agency, 1988). Road-salt runoff, caused by melting snow and ice that contains road salt, is a common source of elevated chloride concentrations in urban areas. Samples collected from 7 of 13 streams in the Milwaukee area during road-salt runoff periods exhibited toxicity in bioassays (Corsi and others, 2010). Chloride increases the conductivity of water and is, therefore, directly related to specific conductivity (Christensen and others, 2000). The relation between chloride concentrations and specific conductivity should make specific conductivity an effective surrogate for estimating chloride concentrations in streams.

Chloride regression models for four of the five sites use specific conductance as the only explanatory variable, with adjusted R^2 values between 0.81 and 0.97 and RMSE values between 0.07 and 0.23 (table 3). The model for the fifth site, the Little Menomonee River, uses both specific conductance and turbidity as explanatory variables, with an R^2 of 0.74 and an RMSE of 0.1. Figure 3 is an example from the Honey Creek at Wauwatosa monitoring site, showing predicted chloride values with 90-percent confidence intervals as well as the measured chloride values used in the regression model. The model-calibration dataset, model summary, summary statistics, plots of the explanatory and response variables, and residual plots are provided in appendix 2.

Table 3. Regression models and summary statistics for estimating chloride concentrations in water at five water-quality monitoring sites in the Menomonee River Basin, Southeast Wisconsin, November 2008–September 2009.

[R^2, coefficient of determination; RMSE, root mean square error; PRESS, prediction error sum of squares; n, number of discrete samples; mg/L, milligrams per liter; SC, specific conductance, in microsiemens per centimeter at 25 degrees Celsius; CL, chloride, dissolved, in mg/L; Turb, turbidity, in nephelometric turbidity units]

Monitoring site	Regression model	Model diagnostics				Model inputs			
		Adjusted R^2	RMSE	PRESS	n	Range of values in variable measurements	Mean	Median	Standard deviation
Menomonee River at Menomonee Falls, Wis. 04087030	$Log_{10}CL = -1.63 + 1.28log_{10}(SC)$	0.94	0.07	0.32	59	CL 24–960 SC 252–3,700	171 960	120 784	167 643
Little Menomonee River near Freistadt, Wis. 04087050	$Log_{10}CL = -4.16 + 1.99log_{10}(SC) + 0.1511log_{10}(Turb)$	.74	.10	.38	39	CL 23–130 SC 384–1,123 Turb 0.7–290	54 698 72	50 676 46	26 192 78
Honey Creek at Wauwatosa, Wis. 04087119	$Log_{10}CL = -0.984 + 1.12log_{10}(SC)$	.81	.23	3.88	70	CL 11–1,700 SC 124–5,930	297 1,150	235 629	321 1,186
Menomonee River at Wauwatosa, Wis. 04087120	$Log_{10}CL = -1.41 + 1.23log_{10}(SC)$	.92	.12	1.35	101	CL 29–2,300 SC 235–6,890	334 1,429	190 970	418 1,295
Menomonee River at Milwaukee, Wis. 04087142	$Log_{10}CL = -1.50 + 1.26log_{10}(SC)$	.97	.07	.44	79	CL 18–1,400 SC 174–4,763	249 1,180	160 938	254 910

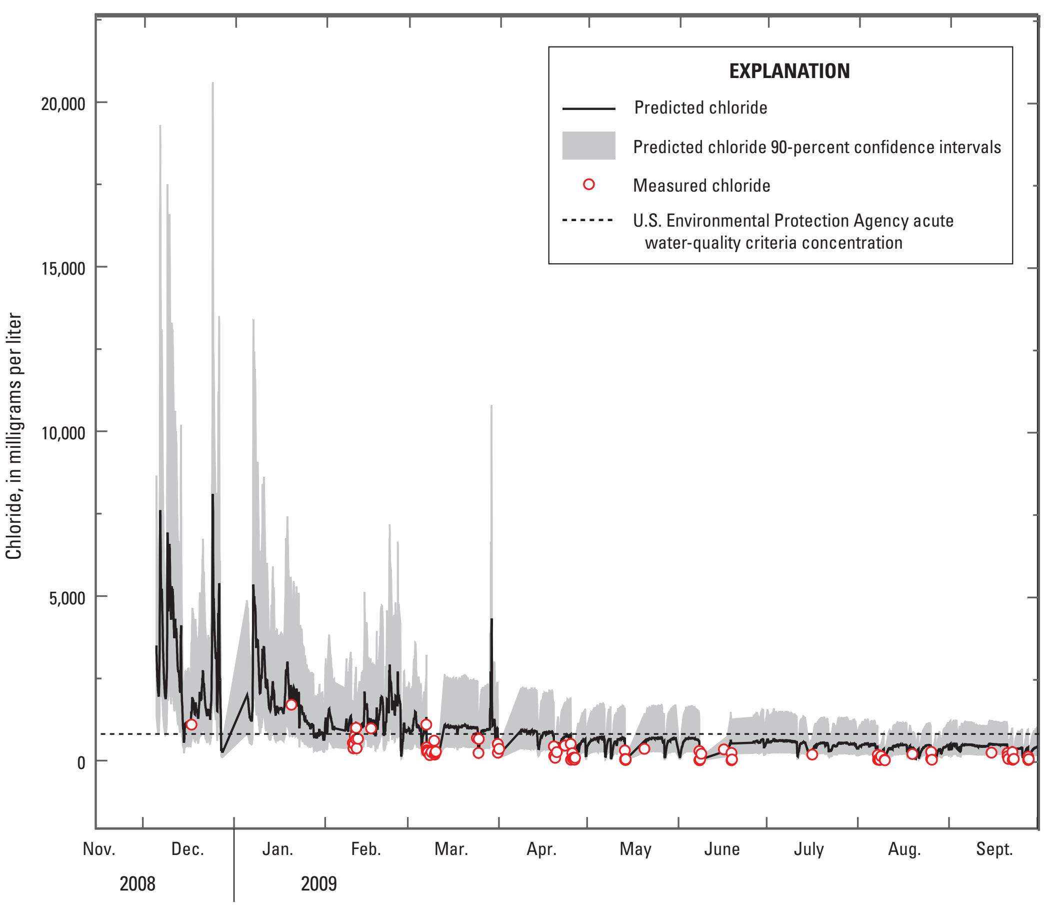


Figure 3. Predicted and measured chloride concentrations at the U.S. Geological Survey streamgage on Honey Creek at Wauwatosa, Wisconsin, December 2008–September 2009.

Total Suspended Solids

Total suspended solids are a combination of suspended sediment and organic matter. Because total suspended solids have numerous adverse effects on stream ecosystems, it is often considered a major pollutant (Ritchie, 1972). Total suspended solids may be detrimental to stream communities by reducing light penetration and oxygen levels, smothering, scouring, reducing habitat through deposition, and introduction of absorbed pollutants (Lenat and others, 1981; Alabaster and Lloyd, 1982). Effects on fish include mechanical abrasion, gill damage, fin rot, reduced survival of eggs, and death by clogging gills (Ritchie, 1972). Turbidity, caused by dissolved and suspended material such as clay, silt, fine organic material, microscopic organisms, organic acids, and dyes (ASTM International, 2003), is often used as a surrogate for total suspended solids.

The regression models for total suspended solids at all five sites use turbidity as the explanatory variable (table 4). The adjusted R^2 ranged from 0.77 at the Menomonee River at Wauwatosa to 0.94 at the Little Menomonee River. The RMSE ranged from 0.16 at the Menomonee River at Menomonee Falls to 0.25 at Honey Creek (table 4). Figure 4 is an example from Honey Creek at Wauwatosa, showing predicted total suspended solids values with 90-percent confidence intervals as well as the measured total suspended solids values used in the regression model. The model-calibration dataset, model summary, summary statistics, plots of the explanatory and response variables, and residual plots are provided in appendix 3.

Table 4. Regression models and summary statistics for estimating total suspended solids concentrations in water at five water-quality monitoring sites in the Menomonee River Basin, Southeast Wisconsin, November 2008–September 2009.

[R^2, coefficient of determination; RMSE, root mean square error; PRESS, prediction error sum of squares; n, number of discrete samples; mg/L, milligrams per liter; SS, suspended solids; Turb, turbidity, in nephelometric turbidity units]

Monitoring site	Regression model	Model diagnostics				Model inputs			
		Adjusted R^2	RMSE	PRESS	n	Range of values in variable measurements	Mean	Median	Standard deviation
Menomonee River at Menomonee Falls, Wis. 04087030	$Log_{10}SS = 0.256 + 0.953log_{10}(Turb)$	0.92	0.16	1.54	59	SS 4–500 Turb 2.3–220	81 47	46 25	95 52
Little Menomonee River near Freistadt, Wis. 04087050	$Log_{10}SS = 0.334 + 0.910log_{10}(Turb)$	.94	.17	1.25	39	SS 1.6–410 Turb 0.7–290	108 72	71 46	121 78
Honey Creek at Wauwatosa, Wis. 04087119	$Log_{10}SS = 0.160 + 0.967log_{10}(Turb)$	.86	.25	4.25	66	SS 1–530 Turb 1.3–390	136 95	73 57	147 91
Menomonee River at Wauwatosa, Wis. 04087120	$Log_{10}SS = 0.567 + 0.779log_{10}(Turb)$	.77	.22	4.92	95	SS 5.2–390 Turb 1.1–210	105 66	76 53	93 52
Menomonee River at Milwaukee, Wis. 04087142	$Log_{10}SS = 0.108 + 0.974log_{10}(Turb)$	.85	.21	3.61	79	SS 5–1,800 Turb 2.9–530	105 64	35 35	249 88

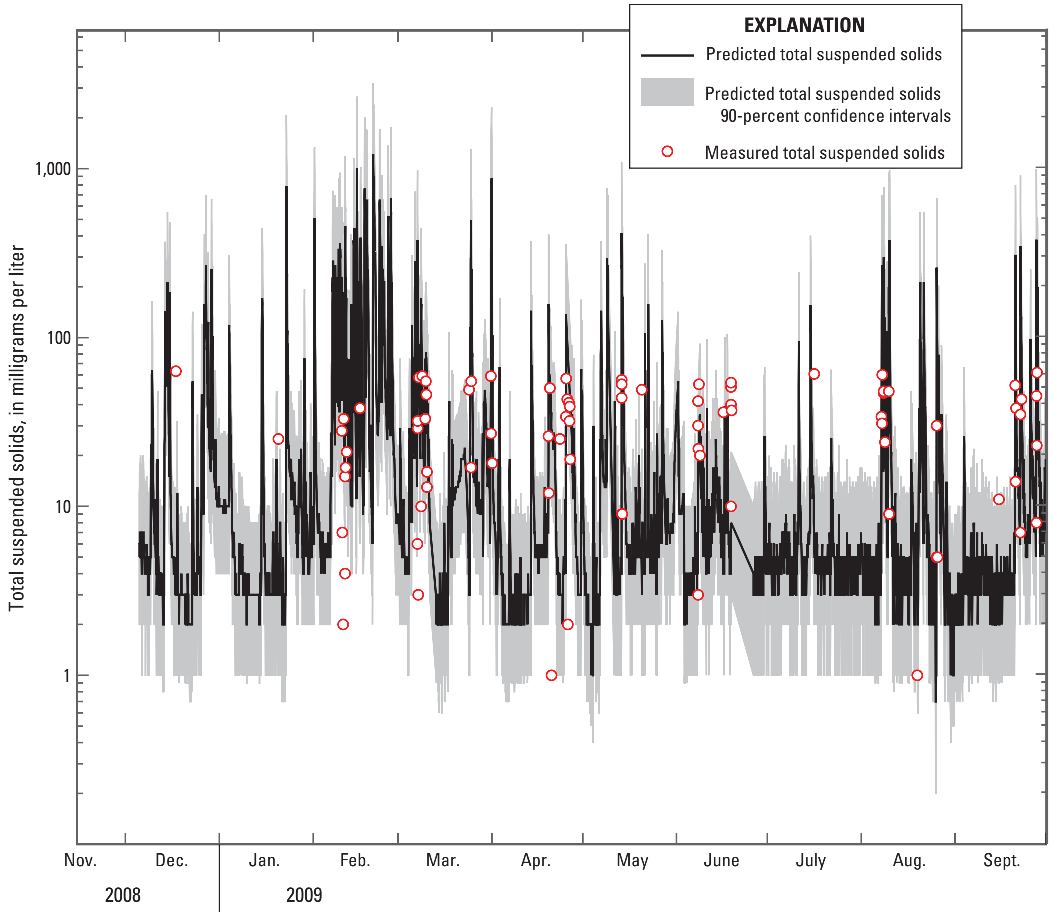


Figure 4. Predicted and measured total suspended solids concentrations at the U.S. Geological Survey streamgage on Honey Creek at Wauwatosa, Wisconsin, December 2008–September 2009.

Total Phosphorus

Elevated concentrations of nutrients, especially phosphorus, are some of the most common stressors affecting rivers and streams throughout the United States (Robertson and others, 2006). High nutrient concentrations may cause excessive aquatic plant growth, which may result in low dissolved-oxygen concentrations from respiration and decomposing plants. Excessive nutrients may also cause nuisance algal blooms in receiving waters. Because phosphorus is likely to adsorb to suspended sediment, turbidity is often used as a surrogate for the estimation of total phosphorus.

The regression models for total phosphorus at each site all used turbidity as the explanatory variable (table 5). The adjusted R^2 ranged from 0.55 at the Menomonee River at Wauwatosa to 0.75 at the Little Menomonee River. The RMSE ranged from 0.19 at the Little Menomonee River to 0.22 at Honey Creek at Wauwatosa. Figure 5 is an example from Honey Creek at Wauwatosa, showing predicted total phosphorus values with 90-percent confidence intervals as well as the measured total phosphorus values used in the regression model. The model-calibration dataset, model summary, summary statistics, plots of the explanatory and response variables, and residual plots are provided in appendix 4.

Indicator Bacteria

Wastewater may enter surface waters through leaking sewage lines or septic tanks, wastewater-treatment plants, or runoff from agricultural sources. *E. coli* and fecal coliform are common types of bacteria used as wastewater indicators. The presence of these bacteria suggests the presence of fecal wastes from either humans or other warm-blooded animals (Dufour, 1977). Pathogens that may be present in waters contaminated by fecal waste include *Cryptosporidium* spp., *Giardia* spp., Hepatitis A, enteric adenovirus, Norwalk-like viruses, and rotavirus (Craun and Calderon, 1999). Exposure to these and other pathogens is a serious human health risk. Because suspended material is a medium for bacterial accumulation and transport, turbidity is often used as a surrogate for bacteria. In addition to turbidity, water temperature was determined to be a significant variable in the indicator bacteria regression models, likely because *E. coli* and fecal coliform bacteria grow better in warmer temperatures than in cold (Madigan and others, 1997).

Table 5. Regression models and summary statistics for estimating total phosphorus concentrations in water at five water-quality monitoring sites in the Menomonee River Basin, Southeast Wisconsin, November 2008–September 2009.

[R^2, coefficient of determination; RMSE, root mean square error; PRESS, prediction error sum of squares; n, number of discrete samples; mg/L, milligrams per liter; TP, total phosphorus, in mg/L; Turb, turbidity, in nephelometric turbidity units]

Monitoring site	Regression model	Model diagnostics				Model inputs			
		Adjusted R^2	RMSE	PRESS	n	Range of values in variable measurements	Mean	Median	Standard deviation
Menomonee River at Menomonee Falls, Wis. 04087030	$Log_{10}TP = -1.55 + 0.492log_{10}(Turb)$	0.62	0.21	2.67	59	TP 0.034–0.78 Turb 2.3–220	0.19 47	0.17 25	0.15 52
Little Menomonee River near Freistadt, Wis. 04087050	$Log_{10}TP = -1.37 + 0.486log_{10}(Turb)$	.75	.19	1.75	39	TP 0.038–0.83 Turb 0.7–290	.30 72	.26 46	.21 78
Honey Creek at Wauwatosa, Wis. 04087119	$Log_{10}TP = -1.45 + 0.451log_{10}(Turb)$	.64	.22	3.35	66	TP 0.03–0.88 Turb 1.3–390	.28 95	.24 57	.21 91
Menomonee River at Wauwatosa, Wis. 04087120	$Log_{10}TP = -1.42 + 0.431log_{10}(Turb)$	.55	.20	3.96	91	TP 0.035–0.66 Turb 1.1–210	.66 65	.23 52	.20 51
Menomonee River at Milwaukee, Wis. 04087142	$Log_{10}TP = -1.51 + 0.462log_{10}(Turb)$	.61	.19	2.97	77	TP 0.039–1.8 Turb 2.9–530	.21 64	.14 35	.26 88

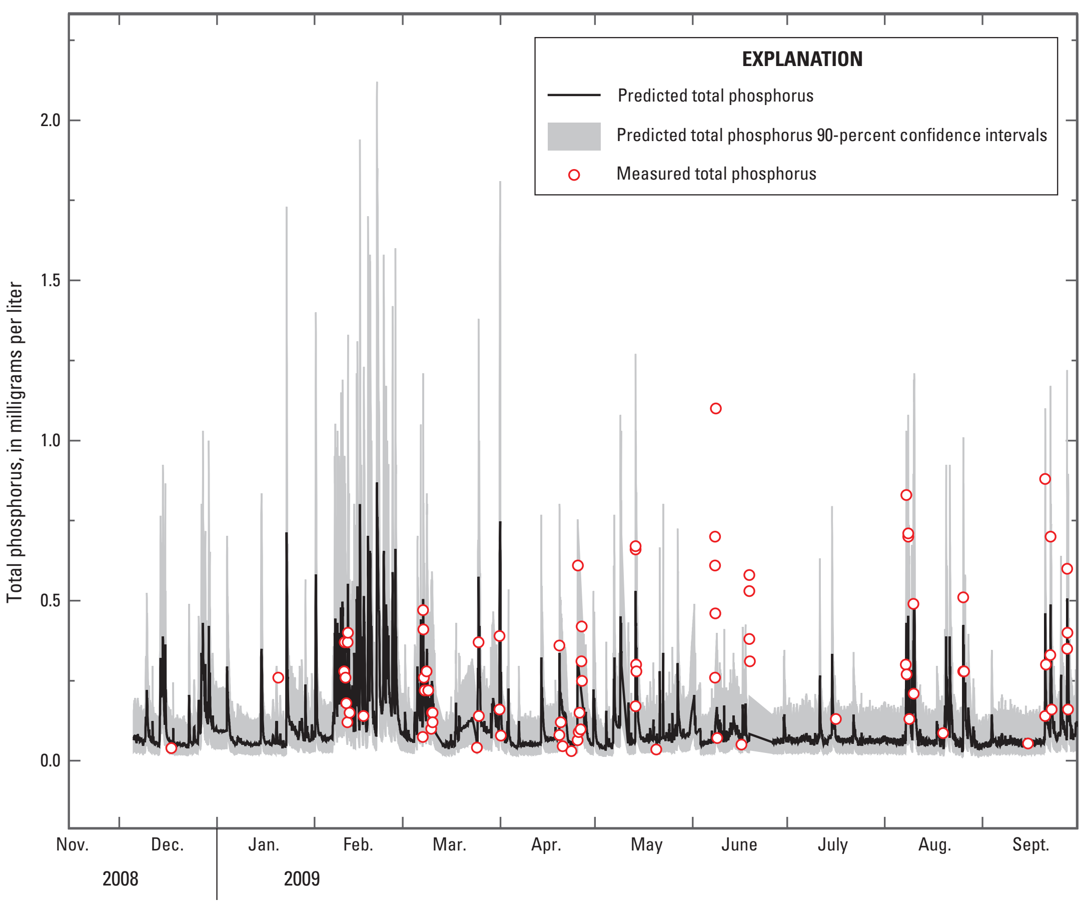


Figure 5. Predicted and measured total phosphorus concentrations at the U.S. Geological Survey streamgage on Honey Creek at Wauwatosa, Wisconsin, December 2008–September 2009.

Escherichia coli

The regression model for *E. coli* bacteria for each site used water temperature and turbidity as explanatory variables (table 6). The adjusted R^2 ranged from 0.54 at the Menomonee River at Milwaukee to 0.69 at Honey Creek. The RMSE ranged from 0.45 at the Little Menomonee to 0.56 at the Menomonee River at Menomonee Falls. Figure 6 is an example from Honey Creek at Wauwatosa, showing predicted *E. coli* values with 90-percent confidence intervals as well as the measured *E. coli* values used in the regression model. The model-calibration dataset, model summary, summary statistics, plots of the explanatory and response variables, and residual plots are provided in appendix 5.

Fecal Coliform

The regression model for fecal coliform bacteria at each site used water temperature and turbidity as the explanatory variables (table 7). The adjusted R^2 ranged from 0.54 at the Menomonee River at Milwaukee to 0.74 at Honey Creek and Menomonee River at Wauwatosa. The RMSE ranged from 0.49 at the Menomonee River at Wauwatosa to 0.65 at Menomonee River at Milwaukee. Figure 7 is an example from Honey Creek at Wauwatosa, showing predicted fecal coliform values with 90-percent confidence intervals as well as the measured fecal coliform values used in the regression model. The model-calibration dataset, model summary, summary statistics, plots of the explanatory and response variables, and residual plots are provided in appendix 6.

Model Predictability

The fit of the regression models, on the basis of the adjusted R^2, RMSE, and PRESS statistics, varies by constituent. This variability in fit is demonstrated by the varied width of the confidence limits in each of the time series plots (figs. 3–7). The models for chloride, total suspended solids, and total phosphorus have better fits (higher adj. R^2 values and lower RMSE and PRESS values) than those for the indicator bacteria (fig. 8). In general, the fits for each of these constituents are comparable to those found in similar regression studies (Christensen and others, 2001; Rasmussen and others, 2009). There is no apparent relation between model fit and percentage of urban area in the respective basins, nor between model fit and number of samples collected at each site. The site with the fewest number of samples, the Little Menomonee River, had some of the better fitting models.

Turbidity was the most frequently used explanatory variable of the continuous variables examined and was used in 21 of the 25 developed models. This frequency is likely because turbidity is a measure of particulates, and indicator bacteria and total phosphorus attach to particulates. All chloride models used specific conductance as the only explanatory variable, except for the Little Menomonee River model, which also included turbidity. This may be related to the fact that the Little Menomonee River is the most rural site and, therefore, the least affected by road-salt runoff. None of the models found season to be a significant factor, but water temperature was significant in all of the indicator bacteria models.

Table 6. Regression models and summary statistics for estimating *Escherichia coli* (*E. coli*) bacteria concentrations in water at five water-quality monitoring sites in the Menomonee River Basin, Southeast Wisconsin, November 2008–September 2009.

[R^2, coefficient of determination; RMSE, root mean square error; PRESS, prediction error sum of squares; n, number of discrete samples; mg/L, milligrams per liter; EC, *E. coli*, in colonies per 100 milliliters; WT, water temperature in degrees Celsius (°C); Turb, turbidity, in nephelometric turbidity units]

Monitoring site	Regression model	Model diagnostics				Model inputs			
		Adjusted R^2	RMSE	PRESS	n	Range of values in variable measurements	Mean	Median	Standard deviation
Menomonee River at Menomonee Falls, Wis. 04087030	$\log_{10}EC = 1.30 + 0.057(WT) + 0.674\log_{10}(Turb)$	0.60	0.56	17.84	55	EC 10–52,000 WT 0–23.1 Turb 2.3–220	4,778 11 47	520 13 25	9,252 8 52
Little Menomonee River near Freistadt, Wis. 04087050	$\log_{10}EC = 1.81 + 0.025(WT) + 0.693\log_{10}(Turb)$	.58	.45	8.17	37	EC 10–25,000 WT 0–18.8 Turb 0.70–290	2,840 6 72	1,100 2 46	4,870 7 78
Honey Creek at Wauwatosa, Wis. 04087119	$\log_{10}EC = 1.68 + 0.071(WT) + 0.626\log_{10}(Turb)$	.69	.48	16.22	66	EC 200–200,000 WT 0–21.9 Turb 1.3–390	19,239 11 95	1,850 9 57	41,203 8 91
Menomonee River at Wauwatosa, Wis. 04087120	$\log_{10}EC = 1.28 + 0.063(WT) + 0.884\log_{10}(Turb)$	.66	.53	23.37	81	EC 60–200,000 WT 0–22.4 Turb 1.1–190	16,476 10 64	1,700 10 52	40,762 8 50
Menomonee River at Milwaukee, Wis. 04087142	$\log_{10}EC = 1.29 + 0.059(WT) + 0.886\log_{10}(Turb)$	.54	.54	24.05	76	EC 41–140,000 WT 0–26.0 Turb 2.9–530	7,936 10 64	1,550 10 35	19,897 8 88

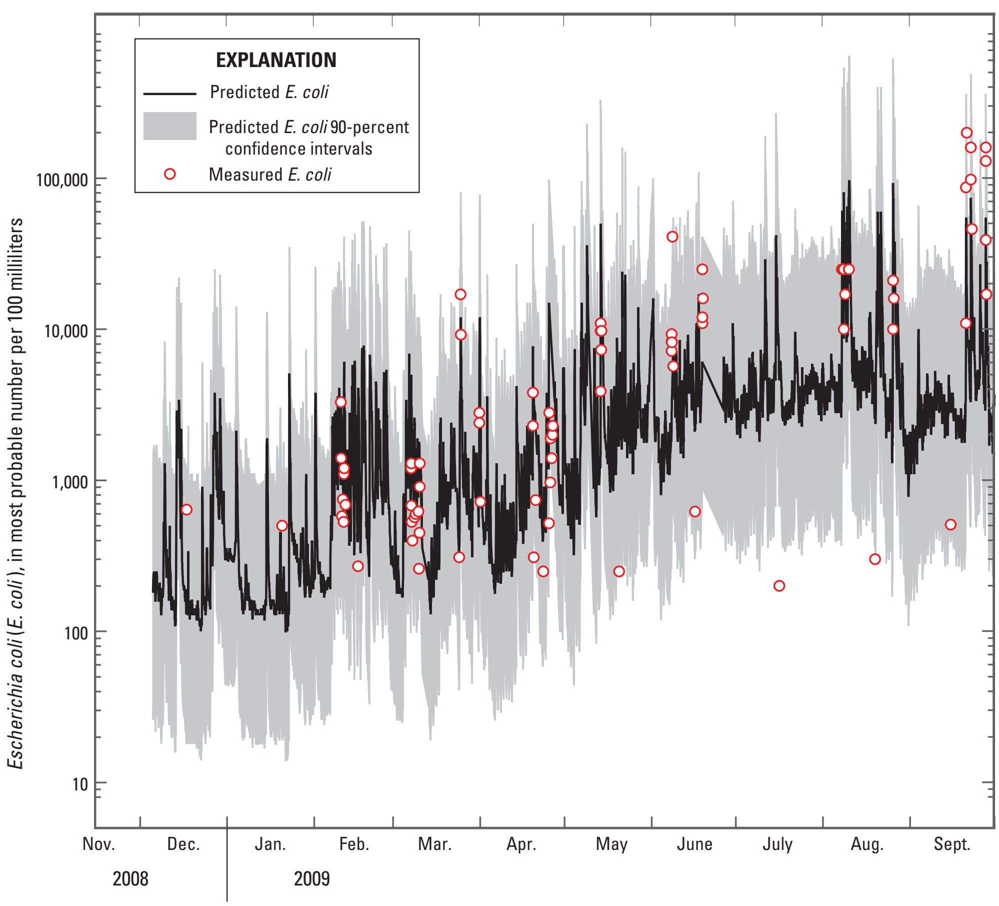


Figure 6. Predicted and measured *Escherichia coli* (*E. coli*) bacteria concentrations at the U.S. Geological Survey streamgage on Honey Creek at Wauwatosa, Wisconsin, December 2008–September 2009.

Table 7. Regression models and summary statistics for estimating fecal coliform bacteria concentrations in water at five water-quality monitoring sites in the Menomonee River Basin, Southeast Wisconsin, November 2008–September 2009.

[R^2, coefficient of determination; RMSE, root mean square error; PRESS, prediction error sum of squares; n, number of discrete samples; mg/L, milligrams per liter; FC, fecal coliform, in colonies per 100 milliliters; WT, water temperature in degrees Celsius (°C); Turb, turbidity, in nephelometric turbidity units]

Monitoring site	Regression model	Model diagnostics: Adjusted R^2	RMSE	PRESS	n	Model inputs: Range of values in variable measurements	Mean	Median	Standard deviation
Menomonee River at Menomonee Falls, Wis. 04087030	$Log_{10}FC = 1.07 + 0.063(WT) + 0.834log_{10}(Turb)$	0.68	0.54	14.99	49	FC 10–46,000	6,975	570	11,911
						WT 0–23.1	13	15	8
						Turb 2.2–220	47	23	52
Little Menomonee River near Freistadt, Wis. 04087050	$Log_{10}FC = 1.49 + 0.035(WT) + 0.777log_{10}(Turb)$	.58	.51	8.97	32	FC 10–30,000	2,912	740	5,533
						WT 0–18.8	7	7	7
						Turb 0.70–290	77	52	80
Honey Creek at Wauwatosa, Wis. 04087119	$Log_{10}FC = 1.46 + 0.089(WT) + 0.648log_{10}(Turb)$	.74	.50	17.81	65	FC 95–17,000	25,116	1,600	44,560
						WT 0–21.9	11	10	7
						Turb 1.3–390	95	57	91
Menomonee River at Wauwatosa, Wis. 04087120	$Log_{10}FC = 1.38 + 0.078(WT) + 0.79log_{10}(Turb)$	.74	.49	17.10	68	FC 48–180,000	22,956	3,300	36,566
						WT 0–22.4	12	15	8
						Turb 1.1–210	70	62	52
Menomonee River at Milwaukee, Wis. 04087142	$Log_{10}FC = 1.07 + 0.062(WT) + 1.001log_{10}(Turb)$	.54	.65	25.56	56	FC 24–110,000	12,128	2,150	23,421
						WT 0–26.0	10	10	8
						Turb 2.9–530	64	35	88

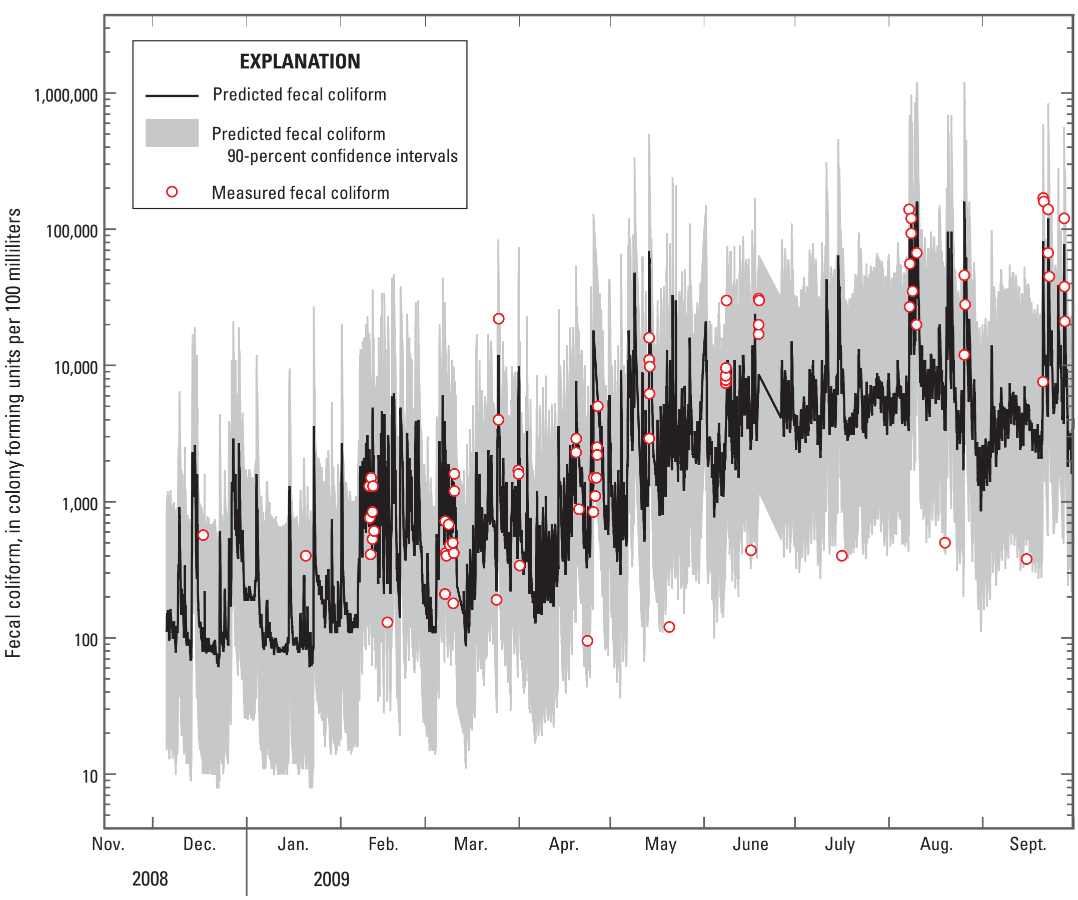


Figure 7. Predicted and measured fecal coliform bacteria concentrations at the U.S. Geological Survey streamgage on Honey Creek at Wauwatosa, Wisconsin, December 2008–September 2009.

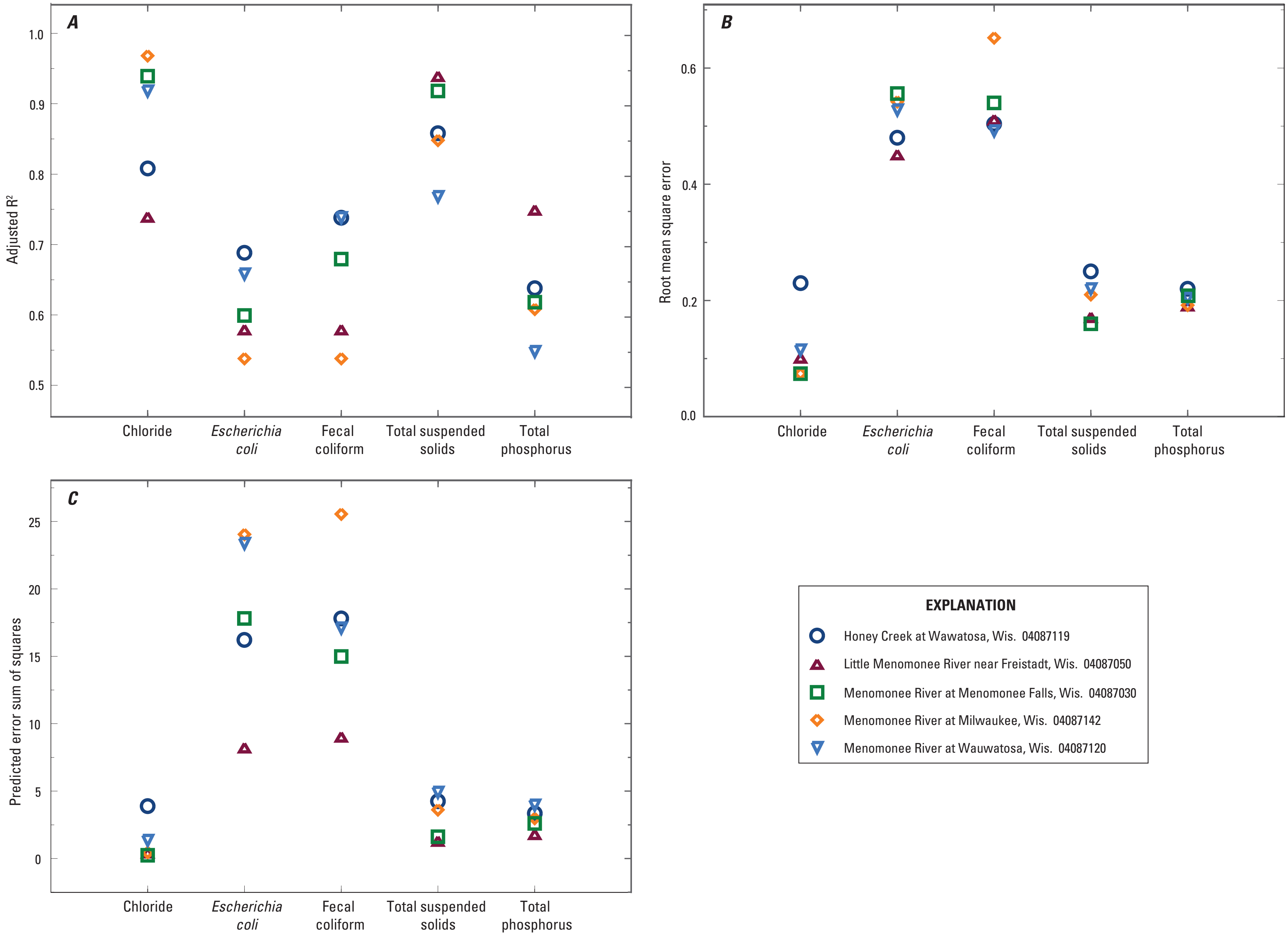


Figure 8. Statistics by constituent and monitoring site in the Menomonee River Basin, Wisconsin. *A*, Adjusted R^2. *B*, root mean square error (RMSE). *C*, prediction error sum of squares (PRESS).

Summary and Conclusions

With increasing headwater urbanization, channel restorations, and implementation of best management practices, the Menomonee River drainage basin in southeast Wisconsin faces changes which may affect water quality in the coming years. In an effort to monitor these and future changes to the basin, the U.S. Geological Survey and the Milwaukee Metropolitan Sewerage District (MMSD) initiated a study in 2008 to develop regression models to estimate real-time concentrations and loads of selected water-quality constituents. Water-quality sensors and automated samplers were installed at five sites in the Menomonee River drainage basin. The sensors continuously measured four explanatory variables: water temperature, specific conductance, dissolved oxygen, and turbidity. Discrete water-quality samples were collected and analyzed for five response variables: chloride, total suspended solids, total phosphorus, *Escherichia coli* (*E. coli*) bacteria, and fecal coliform bacteria.

Regression models were developed to estimate the response variables on the basis of the explanatory variables. The models to estimate chloride concentrations all used specific conductance as the explanatory variable, except for the model for the Little Menomonee River near Freistadt, which used both specific conductance and turbidity. Adj. R^2 values for the chloride models ranged from 0.74 to 0.97. Models to estimate total suspended solids and total phosphorus used turbidity as the only explanatory variable. Adj. R^2 values ranged from 0.77 to 0.94 for the total suspended solids models and from 0.55 to 0.75 for the total phosphorus models. Models to estimate indicator bacteria used water temperature and turbidity as the explanatory variables, with adj. R^2 ranges from 0.54 to 0.69 for *E. coli* bacteria models and 0.54 to 0.74 for fecal coliform bacteria models. Dissolved oxygen was not used in any of the final models. Although there was a significant correlation between dissolved oxygen and the modeled constituent in a few of the bacteria models, dissolved oxygen was not used because it lacked explanatory power and because we wanted consistency among the sites.

The regression models can be used to continuously estimate concentrations of chloride, total suspended solids, total phosphorus, *E. coli* bacteria, and fecal coliform bacteria. Managers can use the resulting data to estimate important water-quality indicators such as bacteria concentrations, understand variability in constituent concentrations, develop total maximum daily loads, assess the effects of improvement projects and land-use changes, provide water-quality information to communities served by MMSD and the general public, and focus where future improvement projects could be implemented to maximize benefits.

Continued periodic sampling will be important to test the validity of the models in the future. Annual and longer-term climate variability, changes in land use, and improvements to infrastructure may necessitate making future model adjustments.

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