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Statistics for Stochastic Modeling of Volume Reduction, Hydrograph Extension, and Water-Quality Treatment by Structural Stormwater Runoff Best Management Practices (BMPs)

Scientific Investigations Report 2014–5037

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SALLY JEWELL, Secretary

U.S. Geological Survey
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Conversion Factors and Abbreviations

Inch/Pound to International System of Units (SI)

Multiply	By	To obtain
	Length	
inch (in.)	2.54	centimeter (cm)
foot (ft)	0.3048	meter (m)
	Area	
acre	4,047	square meter (m^2)
acre	0.4047	hectare (ha)
square foot (ft^2)	0.09290	square meter (m^2)
	Flow rate	
cubic foot per second (ft^3/s)	0.02832	cubic meter per second (m^3/s)
cubic foot per second (ft^3/s)	0.01093	liter per second (l/s)

Concentrations of chemical constituents in water are given either in milligrams per liter (mg/L) or micrograms per liter (µg/L). Milligrams per liter are equivalent to “parts per million.” Micrograms per liter are equivalent to “parts per billion.”

For water-quality loads, 28.32 liters per second (L/s) = 1 cubic foot per second (ft^3/s).

Abbreviations

BMPs	best management practices
BMPSE	Best Management Practices Statistical Estimator
CDF	cumulative distribution function
EMC	Event Mean Concentration
EPA	U.S. Environmental Protection Agency
FHWA	Federal Highway Administration
LBMPV	lower bound of the most probable value
MIC	minimum irreducible concentration
MIC0	the minimum of the minimum values of the positive MIC estimates
MIC1	the 25th percentile of the minimum values of the positive MIC estimates
MIC2	the median of the minimum values of the positive MIC estimates
MIC3	the median of the median values of the positive MIC estimates
MIC4	median of the positive MIC estimates for an individual monitoring site
MQLBE	modified quantile lower-bound estimator
NWIS	National Water Information System
r	Pearson’s correlation coefficient
r(log)	Pearson’s correlation coefficient for the common logarithms of concentrations

ROS	Regression on Order Statistics
SELDM	Stochastic Empirical Loading and Dilution Model
SSC	suspended sediment concentrations
TCu	total copper
TP	total phosphorus
TSS	total suspended solids
UBMPV	upper bound of the most probable value
USGS	U.S. Geological Survey
VBA	Microsoft Visual Basic for Applications®

Statistics for Stochastic Modeling of Volume Reduction, Hydrograph Extension, and Water-Quality Treatment by Structural Stormwater Runoff Best Management Practices (BMPs)

By Gregory E. Granato

Abstract

The U.S. Geological Survey (USGS) developed the Stochastic Empirical Loading and Dilution Model (SELDM) in cooperation with the Federal Highway Administration (FHWA) to indicate the risk for stormwater concentrations, flows, and loads to be above user-selected water-quality goals and the potential effectiveness of mitigation measures to reduce such risks. SELDM models the potential effect of mitigation measures by using Monte Carlo methods with statistics that approximate the net effects of structural and nonstructural best management practices (BMPs). In this report, structural BMPs are defined as the components of the drainage pathway between the source of runoff and a stormwater discharge location that affect the volume, timing, or quality of runoff. SELDM uses a simple stochastic statistical model of BMP performance to develop planning-level estimates of runoff-event characteristics. This statistical approach can be used to represent a single BMP or an assemblage of BMPs. The SELDM BMP-treatment module has provisions for stochastic modeling of three stormwater treatments: volume reduction, hydrograph extension, and water-quality treatment. In SELDM, these three treatment variables are modeled by using the trapezoidal distribution and the rank correlation with the associated highway-runoff variables. This report describes methods for calculating the trapezoidal-distribution statistics and rank correlation coefficients for stochastic modeling of volume reduction, hydrograph extension, and water-quality treatment by structural stormwater BMPs and provides the calculated values for these variables. This report also provides robust methods for estimating the minimum irreducible concentration (MIC), which is the lowest expected effluent concentration from a particular BMP site or a class of BMPs. These statistics are different from the statistics commonly used to characterize or compare BMPs. They are designed to provide a stochastic transfer function to approximate the quantity, duration, and quality of BMP effluent given the associated inflow values for a population of storm events. A database application and several spreadsheet tools are included in the digital media accompanying this report for further documentation of methods and for future use.

In this study, analyses were done with data extracted from a modified copy of the January 2012 version of International Stormwater Best Management Practices Database, designated herein as the January 2012a version. Statistics for volume reduction, hydrograph extension, and water-quality treatment were developed with selected data. Sufficient data were available to estimate statistics for 5 to 10 BMP categories by using data from 40 to more than 165 monitoring sites. Water-quality treatment statistics were developed for 13 runoff-quality constituents commonly measured in highway and urban runoff studies including turbidity, sediment and solids; nutrients; total metals; organic carbon; and fecal coliforms. The medians of the best-fit statistics for each category were selected to construct generalized cumulative distribution functions for the three treatment variables. For volume reduction and hydrograph extension, interpretation of available data indicates that selection of a Spearman's rho value that is the average of the median and maximum values for the BMP category may help generate realistic simulation results in SELDM. The median rho value may be selected to help generate realistic simulation results for water-quality treatment variables.

MIC statistics were developed for 12 runoff-quality constituents commonly measured in highway and urban runoff studies by using data from 11 BMP categories and more than 167 monitoring sites. Four statistical techniques were applied for estimating MIC values with monitoring data from each site. These techniques produce a range of lower-bound estimates for each site. Four MIC estimators are proposed as alternatives for selecting a value from among the estimates from multiple sites. Correlation analysis indicates that the MIC estimates from multiple sites were weakly correlated with the geometric mean of inflow values, which indicates that there may be a qualitative or semiquantitative link between the inflow quality and the MIC. Correlations probably are weak because the MIC is influenced by the inflow water quality and the capability of each individual BMP site to reduce inflow concentrations.

Introduction

The U.S. Geological Survey (USGS) developed the Stochastic Empirical Loading and Dilution Model (SELDM) in cooperation with the Federal Highway Administration (FHWA) to indicate the risk for stormwater concentrations, flows, and loads to be above user-selected water-quality goals and the potential effectiveness of mitigation measures to reduce such risks (Granato, 2013). SELDM is designed to be a tool that can be used to transform disparate and complex scientific data into meaningful information about the risk for adverse effects of runoff on receiving waters, the potential need for mitigation measures, and the potential effectiveness of such measures for reducing these risks. SELDM was designed to help inform water-management decisions for streams and lakes receiving highway runoff. SELDM is a stochastic model because it uses Monte Carlo methods to produce the random populations needed to generate the values for each component variable. SELDM is designed to facilitate an iterative approach that is consistent with environmental risk-management methods used by the FHWA and the U.S. Environmental Protection Agency (EPA) (Sevin, 1987; Cazenas and others, 1996; FHWA, 1998; U.S. Environmental Protection Agency, 1996).

SELDM models the potential effect of mitigation measures by using Monte Carlo methods with statistics approximating the net effects of structural and nonstructural best management practices (BMPs). In this report, structural BMPs are defined as the components of the drainage pathway between the source of runoff and a stormwater discharge location that affect the volume, timing, or quality of runoff. Use of the term BMP in this report, and much of the literature on stormwater treatment, does not imply that these mitigation measures represent an optimal solution for any particular site. The potential effects of nonstructural BMPs, such as street sweeping, can be modeled implicitly by modifying input statistics to reflect the effect of such measures on the quantity and quality of runoff from the site of interest. SELDM also can explicitly model potential effects of structural and nonstructural BMPs on the volume, timing, and quality of runoff (Granato, 2013).

SELDM uses a simple stochastic statistical model of BMP performance to develop planning-level estimates of runoff-event characteristics rather than a complex theoretical or physical model. Planning-level estimates are defined as the results of analyses used to evaluate alternative management measures; planning-level estimates are recognized to include substantial uncertainties, commonly orders of magnitude (Granato, 2013). The statistical approach used to model BMPs in SELDM can be used to represent a single BMP or an assemblage of BMPs. The SELDM BMP-treatment module has provisions for stochastic modeling of three stormwater treatments: volume reduction, hydrograph extension, and water-quality treatment. Statistics for the ratios of inflow to outflow are used to model volume reduction and water-quality treatment, and statistics characterizing difference between outflow and inflow durations are used to model hydrograph extension. The BMP runoff-control options alter the highway, upstream, and downstream outputs from the model. If BMP volume-reduction statistics are specified, the highway-runoff flows and loads will be affected accordingly. If BMP volume-reduction statistics are specified but water-quality treatment statistics are not, then the highway-runoff and BMP discharge concentrations will be the same, but the BMP discharge loads and the concurrent downstream loads and concentrations will all be different. If BMP hydrograph extension is specified, the concurrent upstream and downstream flows and loads will be different than for the untreated runoff because the discharge period will be extended to include more of the upstream flow and loads. If BMP water-quality treatment statistics are specified, BMP discharge concentrations and loads will be affected as well as downstream concentrations and loads.

SELDM provides methods to model potential effects of BMPs on concentrations, flows, and loads in runoff and receiving waters, but methods for calculating the trapezoidal-distribution statistics, rank correlation coefficients, and minimum irreducible concentration (MIC) values used by SELDM are not familiar to many potential SELDM users. Commonly used software such as spreadsheets and statistical packages do not have predefined algorithms for estimating the minimum value, upper and lower bound of the most probable value, and maximum value of the trapezoidal distribution. Many statistical packages have predefined algorithms for estimating rank correlation coefficients, but commonly used spreadsheets do not. The MIC concept is recognized in the literature, but a systematic method for estimating the MIC is not. During the SELDM beta-test process, members of the team, which included stormwater engineers, planners, decisionmakers, and regulators, indicated that they wanted standard methods for calculating BMP treatment variables and representative values to be used as the defaults for modeling widely used BMP categories.

Purpose and Scope

This report describes methods for calculating input statistics for stochastic modeling of volume reduction, hydrograph extension, and water-quality treatment by structural stormwater BMPs and provides BMP performance statistics for these variables. This study was done by the USGS in cooperation with the FHWA to inform professional judgments for stochastic modeling of volume, timing, and quality of BMP effluent given a stochastic population of inflows from a user-defined site of interest. Specifically, this study was done to establish methods for estimating the trapezoidal-distribution statistics, rank correlation coefficients, and MIC values used by SELDM and to develop default values for commonly used BMP categories. The data, information, and statistics developed in this analysis are intended to facilitate stochastic planning-level analysis of the potential effects of stormwater runoff on receiving waters at unmonitored sites (or sites with limited monitoring data). The methods and statistics described in this report were designed for use with SELDM, but may be used with other methods or models. These methods and statistics are designed to help evaluate the risk for adverse effects of runoff on receiving waters, the potential need for mitigation measures, and the potential effectiveness of such management measures for reducing these risks.

The methods and statistics in this report are not intended to replace accepted methods for evaluating and comparing different types of BMPs. Such methods include the effluent probability method (EPM) (Strecker and others, 2001; Geosyntec Consultants and Wright Water Engineers, 2009) and theoretical-analytical time-series analyses (Clar and others, 2004a; Huber and others, 2006; National Cooperative Highway Research Program, 2006). Existing methods for BMP comparison provide information about BMP performance at previously studied sites, which may or may not represent the volume, timing, and quality of runoff from a site of interest. The methods described in this report, however, do provide statistics for estimating expected BMP effluent characteristics and the reduction of risk for adverse effects of runoff in receiving waters given user-defined site properties, runoff quality, BMP performance statistics, and receiving-water characteristics.

Runoff Volume Reduction

Volume reduction by BMPs is the practice of retaining, detaining, or routing runoff flows to increase the amount of infiltration, evapotranspiration, or diversion between the pavement and the outfall (Goforth and others, 1983; Schueler, 1987; Urbonas and Roesner, 1993; Wanielista and Yousef, 1993; Young and others, 1996; Adams and Papa, 2000; Burton and Pitt, 2002; National Cooperative Highway Research Program, 2006; Poresky and others, 2011; Granato, 2013). Volume reduction commonly is a design criterion for BMPs to reduce flood flows, instream erosion, and runoff loads. Features such as flow lengths (for swales) or design volumes commonly are used with moisture-retention estimates and data on local infiltration rates to estimate the volume-reduction capacity of BMPs. Expected storm-event characteristics also are considered in BMP designs because the volume, intensity, and duration of events and the time between storms affect the capacity of the BMP to reduce runoff volumes. Although the term “volume reduction” is used to describe this process, outflows can exceed inflows and therefore volume-reduction ratios may be larger than one. Outflows may exceed inflows if there is carryover in BMP storage from one runoff event to the next or if there is groundwater discharge into the BMP during or between some events.

SELDM uses a simple stochastic representation of the net volume reduction from a BMP or series of BMPs (Granato, 2013). Volume reduction is modeled to represent how BMPs can affect flows and loads from the highway site. SELDM models the potential effects of BMPs on the volume of runoff by generating a stochastic population of the ratios of outflow to inflow volumes and applying these ratios to the stochastic population of inflow volumes from the site of interest. SELDM generates these ratios by using the trapezoidal distribution and the rank correlation with the highway stormflow volume. Rank correlation coefficients (Spearman’s rho) are used by SELDM to help generate the volume-reduction ratios associated with input runoff volumes, which helps to preserve the structure of BMP monitoring data (Granato, 2013). Volume-reduction statistics for the trapezoidal distribution can be estimated by using expert judgment or by fitting the distribution to data.

Hydrograph Extension

Hydrograph extension by BMPs is the practice of slowing the discharge of runoff flows and releasing these flows to the stream over an extended period of time (Granato, 2013). Hydrograph extension is defined as the duration in hours of discharge from the BMP that occurs after runoff from the highway site has ceased. Hydrograph extension commonly is a design criterion for BMPs to reduce flood flows, to reduce instream erosion and, more recently, to mimic predevelopment stormflow hydrographs. Historically, attempts to optimize detention were done to maximize sediment settling time while minimizing the chance of untreated overflows from subsequent storms (Goforth and others, 1983; Driscoll and others, 1986; Schueler, 1987; Wanielista and Yousef, 1993; Adams and Papa, 2000; Chen and Adams, 2005, 2007; National Cooperative Highway Research Program, 2006). These efforts commonly resulted in extension of the outflow hydrograph. Hydrograph extension also has the added benefit of increasing dilution of runoff from small, highly impervious sites. Extending the duration of the highway-runoff hydrograph can make a substantial difference in the amount of dilution in a receiving stream, especially in the rising limb of the upstream storm-event hydrograph.

SELDM calculates hydrograph-extension times (in hours) from a BMP or series of BMPs (Granato, 2013). Hydrograph extension is modeled to represent how BMPs can increase dilution in receiving waters by extending the duration of runoff from the highway site. SELDM models the potential effects of structural BMPs on the timing of runoff by generating a population of BMP flow-extension durations and adding these durations to the runoff duration from the site of interest. SELDM generates these flow-extension durations by using the trapezoidal distribution and the rank correlation with the highway stormflow volume. Rank correlation coefficients (Spearman’s rho) are used by SELDM to help generate the flow-extension durations associated with input runoff volumes, which helps to preserve the structure of BMP monitoring data (Granato, 2013). Hydrograph-extension times can be estimated by using expert judgment or by fitting the distribution to data.

Water-Quality Treatment

Water-quality treatment is the practice of using physical and chemical processes in an attempt to reduce the concentration of runoff constituents in stormflow (Granato, 2013). Hundreds of BMP studies have focused on water-quality treatment during the past 40 years. Historically, process modeling (for example, methods described by Huber and others, 2006; and Park and others, 2011), theoretical statistical modeling (for example, Adams and Papa, 2000), and data analysis (for example, Strecker and others, 2001; Barrett, 2005, 2008; and Leisenring and others, 2010, 2011) have been used to examine BMP performance. Settling and filtration commonly are the primary water-quality treatment mechanisms that form the basis for reductions in influent concentrations for many constituents in commonly used BMP designs (National Cooperative Highway Research Program, 2006; Clary and others, 2010, 2011; Leisenring and others, 2010, 2011). Increasingly, however, chemical and biological processes are being incorporated into BMP designs to enhance treatment of runoff constituents. Although the term “concentration reduction” is commonly used to describe these processes, concentrations in outflows can exceed inflows and therefore concentration-reduction ratios may be larger than one. Outflow concentrations may exceed inflow concentrations if there is carryover in BMP storage from one runoff event to the next; if physical, chemical, or biological processes mobilize constituents between storms; or if flow through the BMP mobilizes previously retained constituents during some events.

SELDM uses a simple stochastic representation of the net change in concentration from a BMP or series of BMPs (Granato, 2013). Water-quality treatment is modeled to represent changes in constituent concentrations that may result from different treatment options. SELDM models the potential effects of BMPs on the concentrations of constituents in runoff by generating a stochastic population of the ratios of outflow to inflow concentrations and applying these ratios to the stochastic population of inflow concentrations from the site of interest. SELDM generates these ratios by using the trapezoidal distribution and the rank correlation with the highway stormflow concentrations. Rank correlation coefficients (Spearman’s rho) are used by SELDM to help generate the concentration-reduction ratios associated with input runoff concentrations, which helps to preserve the structure of BMP monitoring data (Granato, 2013). Concentration-reduction statistics for the trapezoidal distribution can be estimated by using expert judgment or by fitting the distribution to data.

The Minimum Irreducible Concentration

The minimum irreducible concentration (MIC) is commonly defined as the lowest concentration achievable for a well-designed example of each type of BMP (Schueler, 1996; Barrett and others, 2004; Barrett, 2005, 2008; Geosyntec Consultants and Wright Water Engineers, 2009; Granato, 2013). The MIC also has been defined as a background concentration (Wong and Geiger, 1997; Huber and others, 2006), the lower bound of first-order decay models (Kadlec and Knight, 1996; Wong and Geiger, 1997; Huber and others, 2006), or the intercept of regression equations relating outflow to inflow concentrations (Barrett, 2005, 2008; Barrett and others, 2013). Use of a MIC reflects the fact that most BMPs will not produce effluent that is free of sediment, solutes, and bacteria; so there will be some lower limit to the effluent concentrations that can be achieved with normal BMP unit operations. In SELDM, the MIC estimate is used to replace low concentrations calculated from stochastic influent and concentration-ratio values for thousands of storm events that may occur over one or more decades. If the MIC estimate is set too high (based on results of short-term monitoring studies with relatively small sample sizes), then the model results may overestimate the risk for exceeding water-quality targets, which may lead to use of the limited resources available for mitigation at sites where such measures may not be warranted. If the MIC estimate is set too low, however, model results may underestimate the risks for exceeding water-quality targets.

Although the concept of the MIC is sound, determining such a value from data may be difficult especially if data are limited, the selected BMP is not characteristic of design standards, or a substantial proportion of the effluent concentrations are below historical detection limits. Two of the most widely cited articles on the subject in studies of urban and highway runoff are by Schueler (1996) and by Barrett (2005). Schueler (1996) examined available data and settling times to estimate MICs for different types of BMPs. Barrett (2005) developed regression relations between influent and effluent concentrations and interpreted the intercept as a good estimate of the MIC. The most widely cited report on MICs in studies of wastewater treatment is Kadlec and Knight (1996), who added a lower bound to the first-order decay models commonly used to model concentrations in wetland systems, and increasingly, in stormwater BMPs (Wong and Geiger, 1997; Huber and others, 2006; Park and Roesner, 2012; Barrett and others, 2013). These modified first-order decay models are commonly known as k-C* models.

In some cases it is assumed that the MIC values represent local background water quality (Kadlec and Knight, 1996; Wong and Geiger, 1997; Huber and others, 2006). If this assumption will be used, then SELDM modelers may want to develop local MIC estimates using available water-quality data. Granato and others (2009) developed and implemented methods for data mining from the online version of the U.S. Geological Survey National Water Information System database, known as NWIS Web. They also collected and published 1,876,000 paired discharge and water-quality measurements that include 24 constituents commonly measured in highway- and urban-runoff studies. Such data may be used to characterize background concentrations in an area of interest.

SELDM uses a simple deterministic representation of the net MIC from a BMP or series of BMPs (Granato, 2013). Water-quality treatment ratios are modeled to represent changes in constituent concentrations that may result from different treatment options; the MIC provides a lower bound to the modeled reductions. The MIC can be estimated by using expert judgment, from literature values, or by statistical analysis of available data.

Methods of Analysis

Quantitative methods were needed to estimate values of the trapezoidal-distribution statistics and to develop a robust estimator for the MIC from available data. The methods and analysis tools were designed to analyze currently available data and to replicate the analysis with user-supplied data in the future. The triangular and rectangular distributions are in use for risk analysis, but the trapezoidal distribution, which is a more general and flexible form of both distributions, is not widely used for risk analysis. Therefore, quantitative methods were needed to estimate trapezoidal-distribution statistics for analysis of BMP performance. Similarly, quantitative methods for developing MIC estimates were needed. Standard methods (Press and others, 1992; Helsel and Hirsch, 2002) were used to estimate rank correlations because SELDM generates correlated random BMP performance variables to help preserve the structure of monitoring data (Granato, 2013). Properly modeling the performance of structural BMPs is a complex endeavor and there are many explanatory variables that are difficult to quantify, especially with limited monitoring data. Therefore, available data are sufficient for planning-level estimates, but there is great uncertainty in the representativeness and transferability of many available datasets.

Data Collection

The analyses documented in this report were done with data that were extracted from the January 2012 version of the International BMP Database (accessed at www.bmpdatabase.org). These data were modified in cooperation with Jane Clary, the project manager of the International BMP database project to resolve a number of issues with data in the January 2012 version of that database as they were uncovered in this analysis. This modified copy is designated herein as the January 2012a version. These data modifications appear in subsequent versions of the official International BMP Database. The International BMP Database was selected as the source of data for this analysis because it is extensive. The January 2012 version has data for 356 sites, 1,687 monitoring stations, 11,962 runoff events, 20,795 flow measurements, and 283,559 water-quality measurements. This compilation represents continuing efforts of the project team to collect, format, check, and enter data over a 17-year period from 1996 to 2012. In many cases, the data have been vetted for use in various BMP performance summaries (for example, Clary and others, 2011; Leisenring and others, 2011; Poresky and others, 2011). In some cases, however, the data used in this analysis are different from the data found in the January 2012 version because the author worked closely with Jane Clary, the Project Manager of the BMP database, to resolve a number of issues that were identified during the process for extracting, checking, and manipulating the data for this analysis. These changes, however, are reflected in subsequent versions of the International BMP Database available at www.bmpdatabase.org (Jane Clary, Wright Water Engineers, Inc., oral commun., 2012).

The results of analyses presented in this report are organized by using the categories specified in the international BMP database (table 1). The 2012 version of this database contains 16 types of structural BMPs; for this analysis, 11 types of BMP were selected on the basis of available data and applicability for modeling the quality and quantity of stormwater runoff with SELDM. The selected BMPs are designed to treat the quality and (or) quantity of runoff between the source area and the discharge area. The selected BMPs also are commonly used to treat highway and urban runoff. The 2012 version of this database also contains 40 subcategories of BMP, but this analysis was done using the categories in table 1. Despite the large amount of data in the database, the availability of paired inflow and outflow data from BMP sites for some categories and many subcategories is not sufficient for quantitative characterization of BMP performance. Data for BMP sites, monitoring sites, runoff volumes, runoff durations, and constituent concentrations were obtained from the BMP database using a series of queries that were designed to obtain paired input and output values. Although it is recognized that the outflow for one event may represent the effects of inflows from one or more prior events (Strecker and others, 2001), building a large dataset of paired values for each category should provide the statistics necessary to stochastically generate the wide variations in output values that may occur over a large number of storms.

The extracted data were loaded into a derivative Microsoft Access® database to facilitate retrieval and analysis of the data. This database application, named the Best Management Practices Statistical Estimator (BMPSE) tool, is in the file BMPAnalysisDBver1.0.0.mdb on the digital media accompanying this report. The BMPSE has commented open-source code that documents the methods used in the database. The BMPSE includes interface forms and Microsoft Visual Basic for Applications® (VBA) modules to manipulate the data, calculate summary statistics, and output the resultant values for further analysis. Because SELDM uses rank correlation to preserve the structure of inflow and outflow data, these database modules also calculate the Spearman's rho and Kendall's tau correlation coefficients with their respective 95-percent confidence limits and the probability that each correlation coefficient value is not significantly different from zero (Fisher, 1924; Hann, 1977; Press and others, 1992; Caruso and Cliff, 1997; Helsel and Hirsch, 2002). This database includes the VBA subroutines and functions that were developed to implement the Regression on Order Statistics (ROS) analysis to estimate summary statistics for left-censored data developed for use in the highway-runoff database (Granato and Cazenas, 2009).

Table 1. Explanation of structural best management practice (BMP) categories used in the International BMP Database (www.bmpdatabase.org).

Code	Name	Description
BR	Bioretention	Bioretention BMPs are shallow depressions lined with mulch or amended soils and vegetation. These BMPs drain either to groundwater or to an underdrain that discharges to sewers or surface water bodies. These BMPs are also known as rain gardens.
CO	Composite	Composite BMPs are treatment trains that include different BMP categories in series that use a variety of treatment methods.
DB	Detention basin	Detention basins are normally dry ponds designed to empty after storm events by drainage over a weir and through an orifice that controls the rate of release. This category also includes concrete-lined basins and underground concrete vaults.
GS	Biofilter (swale)	Biofilters are dry, grassy strips and swales designed to convey overland flow.
IB	Infiltration basin	Infiltration basins are dry ponds that are not designed with a surface-water drainage structure. Infiltration basins may have overflow drains for large storms. Some infiltration basins may have underdrains that discharge to sewers or surface water bodies.
LD	Low impact development	In the BMP database, low impact development (LID) BMPs are site-scale combinations of small dry and wet BMPs used in attempt to mimic the natural hydrology of an area.
MD	Manufactured device	Manufactured devices are prefabricated stormwater treatment methods. This category includes catchbasins, oil and grit seperators, hydrodynamic devices, baffle boxes, filter inserts, and other devices.
MF	Media filter	Media filters are self-contained infiltration BMPs with overflow structures and underdrains. Media filters use sand, peat, perlite, zeolite, and (or) compost to treat infiltrating stormwater.
RP	Retention pond	Retention ponds, also known as wet ponds, are artifical lakes designed to maintain a permanent pool and a water-quality treatment volume. An orifice or weir commonly is used to drain the pool to the level of the permanent pool between storms.
WB	Wetland basin	Wetland basins are either surface wetlands with a semipermanent pool or wetland meadows that fill during storms and drain between storms. The groundwater level in wetland meadows commonly is within the root zone.
WC	Wetland channel	Wetland channels are normally wet swales designed to convey overland flow.

Fitting the Trapezoidal Distribution to Duration and Ratio Data

In SELDM, volume-reduction, hydrograph-extension, and concentration-reduction variables are modeled by using the trapezoidal distribution and the rank correlation with the associated highway-runoff variables. This family of distributions was selected for modeling BMP performance measures because it can be parameterized by using expert judgment or by fitting the distribution to data if good data are available (Johnson, 1997; Back and others, 2000; U.S. Environmental Protection Agency, 2001; Scherer, 2003; Kacker and Lawrence, 2007). The triangular distribution, which is a special case of the trapezoidal distribution, commonly is suggested when uncertainties in input data that may be used to define a parametric distribution are large (U.S. Environmental Protection Agency, 2001). The trapezoidal distribution is bounded by a selected minimum and maximum value. When data are uncertain or are limited in scope, use of a bounded distribution reduces the chance that unrealistic output values will be generated by extrapolating a distribution beyond the range of available data.

SELDM generates random numbers that follow trapezoidal distributions by using the inverse cumulative distribution function (CDF) with an algorithm developed by Kacker and Lawrence (2007). The trapezoidal distribution is defined by four location variables: the lower bound (the minimum value), the lower bound of the most probable value (LBMPV), the upper bound of the most probable value (UBMPV), and the upper bound (the maximum value), all of which are shown in figure 1. The trapezoidal distribution is very flexible and can assume a variety of shapes, including a positive-skewed triangular distribution, a negative-skewed triangular distribution, a symmetric (isosceles) triangular distribution, and a rectangular (uniform) distribution (fig. 1). SELDM will produce stochastic data that fit the triangular distribution if the LBMPV and UBMPV are specified as being equal. SELDM will produce stochastic data that fit the rectangular distribution if the LBMPV is set equal to the minimum and UBMPV is set equal to the maximum. The triangular distribution is commonly used in environmental risk analysis, but the rectangular distribution is not (U.S. Environmental Protection Agency, 2001).

Least-squares optimization was used to fit the BMP monitoring data to the parameters of the trapezoidal distribution.

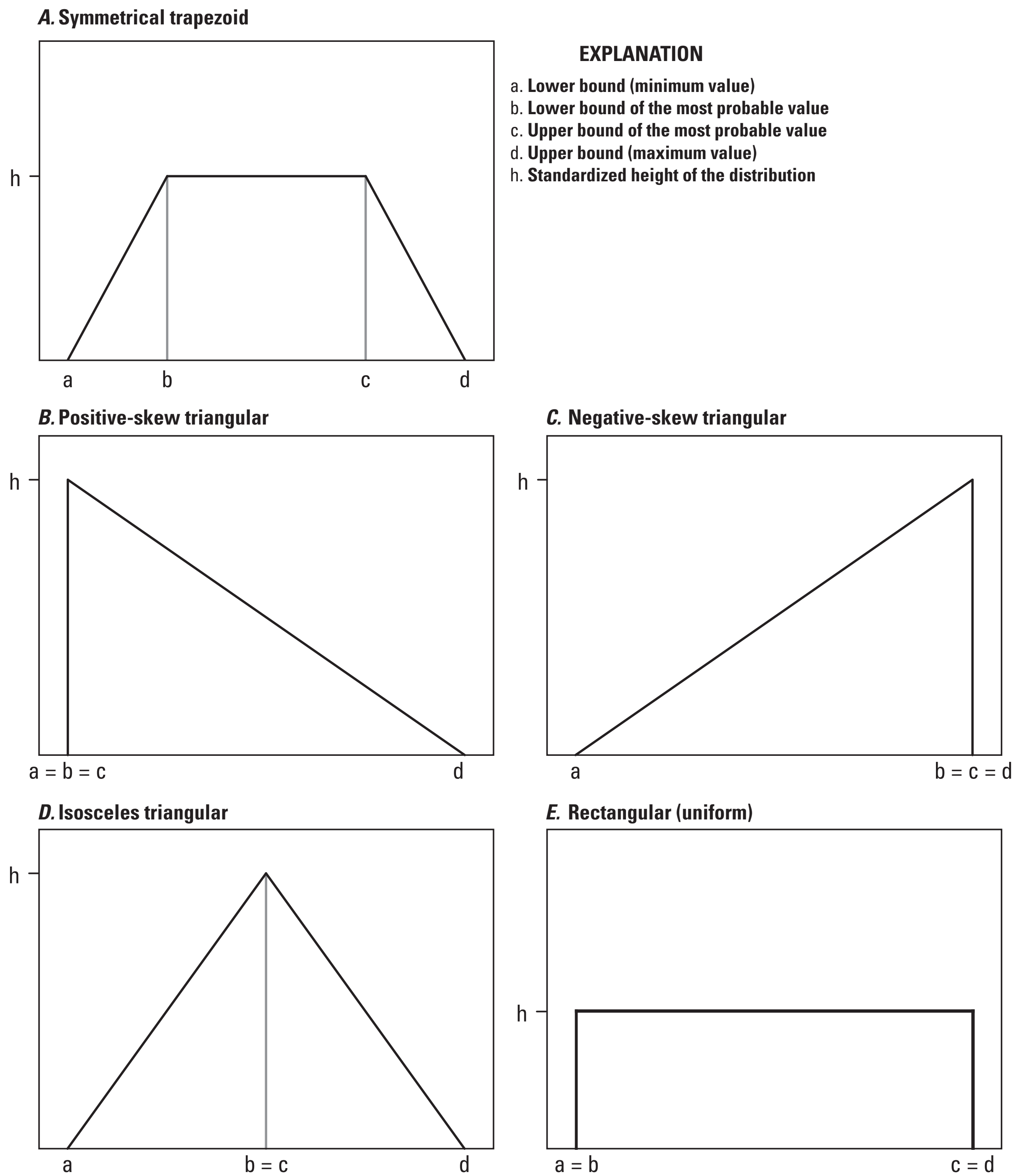

Figure 1. Five possible probability-density functions of the trapezoidal distribution as defined by the location variables. The height of each trapezoid is calculated to normalize the area under the probability-density function to equal one (Granato, 2013).

Least-squares optimization was used because it has been shown to be effective for fitting data to the triangular distribution (Johnson, 1997; Back and others, 2000; Joo and Casella, 2001; van Straalen, 2002). Least-squares methods have been used in hydrology and other sciences to fit statistical distributions to data for more than 40 years (Snyder, 1972; Benšic, 2014). In the absence of reliable data, it is easier to estimate the parameters of the trapezoidal distribution by using professional judgment than it is to estimate the parameters of other commonly used distributions. More importantly, it is easier to avoid generation of extreme outliers when large stochastic datasets are generated because the trapezoidal distributions are bounded. However, it is more difficult to estimate the parameters of the trapezoidal distribution using available data than to estimate the parameters of other distributions commonly used in hydrologic studies such as the exponential, normal, lognormal, Pearson Type III, and log Pearson Type III because these distributions commonly are parameterized by using summary statistics such as the mean, standard deviation, and skew (Stedinger and others, 1993).

The optimal fit to the trapezoidal distribution was calculated by minimizing the least-squares difference between the cumulative distributions of the flow-reduction ratios, the flow-extension times, and the water-quality treatment ratios. In each case the data were sorted, ranked, and assigned plotting positions by using the Cunnane (1978) plotting-position formula. The value for each data point was compared to the value of the same plotting position for the theoretical trapezoidal distribution with the input minimum, LBMPV, UBMPV, and maximum values, and the difference and squared difference were calculated. The sum of squared differences was used as the measure of fit.

The Microsoft Excel® solver tool available in the analysis tool pack was used to find the optimal fit of the cumulative distribution of a trapezoidal distribution to each dataset. The Microsoft Excel® solver tool should be installed with Excel®, but this tool must be activated using the Microsoft Excel® "Add-Ins" menu. The solver was set up with the generalized reduced gradient nonlinear solving package to minimize the sum of squared errors between the data and the fitted distribution by varying the input statistics. The solver manipulated the values of the minimum, LBMPV, UBMPV, and the maximum values to do this optimization. The constraints on the solver were that the values must be greater than or equal to zero, the LBMPV must be greater than or equal to the minimum, the UBMPV must be greater than or equal to the LBMPV, and the maximum must be greater than or equal to the UBMPV. By definition, the maximum must be greater than the minimum; this criterion is not available in the solver, but it represents a trivial solution that was not encountered in this study.

To prepare for optimization, the BMPSE tool was used to sort and rank the data, calculate plotting positions, calculate initial estimates, and calculate potential correlations. For the flow-extension and volume-reduction variables, initial estimates were calculated by using the approximation equations for the triangular distribution developed by Johnson (1997). These values were adjusted to ensure the minimum was greater than or equal to zero, the most probable value was greater than or equal to the minimum, the maximum was greater than or equal to the most probable value, and the maximum was greater than the minimum. For the water-quality treatment ratios, initial estimates were calculated from the median ratio because the prior analyses indicated that the estimates based on Johnson's (1997) equations did not facilitate rapid convergence to a final solution.

The solver was restarted with different input values several times for each analysis to find the most optimal solution. In some cases, there are multiple combinations of input variables that may produce what appears to be an optimal fit to the generalized reduced gradient non-linear solving package. The situation is analogous to the problem of finding the highest peak in a mountain range in the fog by following an uphill gradient. Starting in different locations may result in discovery of different peaks; selecting different starting locations should help find the tallest peak. In an effort to find the most optimal fit, the values calculated from the first solution were modified and the solver was rerun. This was done several times and the most optimum solution (having the smallest sum of square errors) was selected. In many cases, there seemed to be only one optimal solution.

For the volume-reduction ratio and the flow-extension ratio runs, which were done manually, at least two additional conditions were tested. In one run, the minimum was set equal to zero; the LBMPV minimum was set equal to 50 percent of the average; the UBMPV minimum was set equal to twice the average; and the maximum was set equal to four times the average. In another run, the values for the solution with the lowest sum of square errors were adjusted. The minimum was set equal to 0; the LBMPV minimum was reduced by 10 to 20 percent; the UBMPV minimum was increased by 10 to 20 percent; and the maximum was increased by 20 percent. For these variables, the analyst evaluated the stability of the solution and either picked the best solution if the results were stable or continued to modify the starting points if the solution seemed unstable. Finally, the solution with the lowest value of the sum of square errors was selected as the final result. The Microsoft Excel® spreadsheets used to do these analyses named FitTriangleToBMP01v1.0.3.xls and FitTrapezoidToBMP01v1.0.3.xls are available on the digital media accompanying this report. Sufficient data were available to do the flow-reduction analyses on 94 BMP monitoring sites and the flow-extension analyses on 40 BMP monitoring sites.

The trapezoidal-fit spreadsheet was automated to do the analyses of the concentration ratios because 1,075 datasets had to be optimized to determine trapezoidal fit statistics for each site within the 10 BMP categories that had sufficient data for analysis for one or more of the 13 commonly measured highway- and urban-runoff constituents. The BMPSE generates the input files and the list of filenames for each constituent within the Graphical User Interface (GUI). For the water-quality treatment ratios, the minimum was set equal to one third of the median; the LBMPV minimum was set equal to 65 percent of the median; the UBMPV minimum was set equal to median; and the maximum was set equal to three times the median to do the initial optimization run. If a solution was reached, then the minimum was set equal to 50 percent of the initial estimate; the LBMPV was reduced to 75 percent of the initial estimate; the UBMPV was increased to 1.1 times the initial estimate; and the maximum was increased to 2 times the initial estimate, and the solver was rerun. If a solution was reached, then the minimum was set equal to 50 percent of the first-solution minimum; the LBMPV was reduced to 75 percent of the first-solution LBMPV; the UBMPV was increased to 1.1 times the first-solution UBMPV; and the maximum was increased to 2 times the first-solution maximum, and the solver was rerun. In the final trial, the values of the minimum, LBMPV, UBMPV, and maximum were changed to 0, 0.75, 0.75 and 1.5, respectively. If one of the trial solutions failed to converge, the minimum was set equal to 0; the LBMPV was set equal to 10 percent of the measured maximum; the UBMPV was set equal to 25 percent of the measured maximum; and the maximum was increased to 1.5 times the measured maximum ratio, and the solver was rerun. The concentration-ratio solver program then sorted results to identify the solution with the smallest sum of squared errors, and this solution was identified as the final result for that monitoring site. The Microsoft Excel® spreadsheet used to do these analyses is named ConcentrationRatioFitv1.0.0.xls and is available on the digital media accompanying this report.

Methods for Estimating the Minimum Irreducible Concentrations

Four statistical estimators were used to calculate MICs from available BMP effluent-concentration-sample data. These estimators are the measured minimum, the log-triangular lower-bound estimator, Stedinger's (1980) quantile lower-bound estimator, and a modified quantile lower-bound estimator. Two other lower-bound estimators, the measured 25th percentile estimate used by Job and Smith (2010) and the measured 10th percentile estimate used by Susilo and others (2008) and Chapman and Horner (2010 were not used in this analysis. Although these two percentile estimators represent a conservative assessment of outflow concentrations, these values are not robust estimators for long-term MIC values because most available BMP monitoring datasets are small.

The four selected statistical estimators for the MIC are consistent with the theory that the effluent concentrations are approximately lognormal. Stormwater-quality data and BMP effluent-quality data commonly are characterized and modeled as being from a lognormal distribution, but other distributions also are used (Athayed and others, 1983; DiToro, 1984; Driscoll, and others, 1989; Driscoll and others, 1990; Van Buren and others, 1997; Novotny, 2004; Burton and Pitt, 2002; Maestre and others, 2004; Maestre and others, 2005; National Cooperative Highway Research Program, 2006; National Research Council, 2008). The four lower-bound estimators selected for use in this study are based on the assumption of lognormality, but are not constrained to this assumption. Four different estimators were selected for use because each estimator has several potential advantages and disadvantages.

The Measured Minimum Value

The measured minimum value is the simplest method for estimating the MIC and is commonly used for this purpose in the literature (see the spreadsheet LiteratureMIC.xls on the digital media accompanying this report). The measured minimum value method has three advantages and two disadvantages.

The advantages are:

- it is simple to calculate;
- it is generally accepted because it is commonly used; and
- it is completely nonparametric because the result does not depend on the assumption that the data fit any given probability distribution.

The disadvantages are:

- the probability that the measured minimum is representative of the MIC may be low especially if sample sizes are small; and
- it may not be possible to quantify the measured minimum value because there may be one or more censored values below one or more detection limits.

The probability that the measured minimum value is representative of the MIC is low because most BMP monitoring studies collect relatively few samples. The probability that the measured minimum value is representative of the MIC depends on sample size, and the difference between the actual MIC and the median value. If sample sizes are large or the difference between the median effluent concentration and the actual MIC is small, then the measured minimum may be a good approximation for the MIC for a given BMP at the data collection site. Queries of the January 2012 version of the International BMP database indicate that in many cases, the sample sizes are small. For example, about 30 percent of datasets for total suspended solids (TSS), total copper (TCu) and total phosphorus (TP) have fewer than 10 samples, and about 70 percent of these datasets have fewer than 20 samples.

If the measured minimum is censored, then the value may be estimated by using half the lowest detection limit or by using statistical methods, but neither method is recommended for estimating an individual value to replace a censored measurement (Helsel and Hirsch, 2002; Helsel, 2005). The robust regression ROS method (Helsel and Hirsch, 2002; Helsel, 2005) was used to estimate values below detection limits for all the MIC estimates. When necessary, the measured minimum value was estimated from the minimum percentile calculated by using the selected plotting-position formula. The Blom, Cunnane, Gringorten, Hazen, or Weibull plotting-position formulas (Helsel and Hirsch, 2002) may be selected for calculating this minimum percentile by using the BMPSE tool in the file BMPAnalysisDBver1.0.0.mdb on the digital media accompanying this report. There is, however, substantial uncertainty in the exact minimum value if estimates are made using ROS or other methods.

The Log-Triangular Lower-Bound Estimator

Scherer and others (2003) developed the triangular lower-bound estimator to provide a simple algebraic solution for calculating values of the CDF for data that could be approximated using a normal distribution. They note that the triangular distribution has a fixed upper and lower bound, which may be more realistic for many data than the upper and lower bounds of plus or minus infinity that are characteristic of the normal distribution. For the lognormal distribution, the lack of a lower bound results in values that are infinitely close to zero. To develop the estimator, Scherer and others (2003) optimized the fit of the triangular CDF to the standard-normal CDF and calculated the lower bound by using the method of moments. To estimate the MIC, calculate the lower bound as

$$LB = 10^{\left(\bar{Y} - \sigma_y \times \sqrt{6}\right)} \tag{1}$$

where

LB is the triangular lower-bound estimate;
$\bar{Y}$ is the average of the logarithms of the BMP effluent data; and
σ_Y is the standard deviation of the logarithms of the BMP effluent data.

The triangular lower-bound estimator has five advantages and two potential disadvantages.
The advantages are:

- it is simple to calculate;
- it is robust because it will always produce a value that is greater than zero;
- it is robust to presence of data below one or more detection limits because it is calculated using the average and standard deviation of the logarithms of data, which can be calculated using commonly accepted standard methods for censored data (Helsel and Hirsch, 2002; Helsel, 2005);
- it provides an empirical solution to BMP effluent data that can be approximated using the lognormal distribution because the triangular distribution provides a good fit to the standard normal distribution; and
- it can be adapted to data such as pH, which cannot be modeled using a lognormal distribution, by using the average and standard deviation of the untransformed data.

The disadvantages of the triangular lower-bound estimator are:

- it may not be the best estimator if the CDF of the logarithms of the BMP effluent data is substantially asymmetrical above and below the geometric mean because the estimator developed by Scherer and others (2003) is based on a symmetrical distribution; and
- the triangular distribution is empirical, whereas the lognormal distribution is supported by the multiplicative environmental processes that give rise to data that fit a lognormal distribution (Chow, 1954; Chow and others, 1988; Stedinger and others, 1993).

Stedinger's Quantile Lower-Bound Estimator

Stedinger (1980) developed the quantile lower-bound estimator to calculate the minimum value of the three-parameter lognormal distribution. The three-parameter lognormal distribution commonly is used to model environmental data that are well approximated by a lognormal distribution, but do not have a lower-bound value of zero (Stedinger, 1980; Hoshi and others, 1984; Stedinger and others, 1993). To develop the estimator, Stedinger (1980) used the theoretical properties of the three-parameter lognormal distribution to formulate the quantile lower-bound estimator and Monte Carlo methods to optimize the fit of the selected quantiles. Stedinger (1980) and Hoshi and others (1984) demonstrated that this method consistently outperformed many of the alternate parametric methods using different input values and varying (generated) sample sizes. The equation for estimating the MIC using this estimator is

$$LB = \frac{\left(X_1 \times X_n\right) - X_{med}^2}{X_1 + X_n - 2X_{med}} \tag{2}$$

where

LB is the quantile lower-bound estimate;
X_1 is the minimum of the BMP effluent data values;
X_n is the maximum of the BMP effluent data values;
X_{med} is the median of the BMP effluent data values; and
n is the number of values in the dataset.

Stedinger's quantile lower-bound estimator has four advantages and four potential disadvantages.
The advantages are:

- it is simple to calculate;
- the three-parameter lognormal distribution is well accepted in theory and in practice (Stedinger and others, 1993; Maestre and others, 2005);

- the quantile lower bound can be used to estimate the MIC for BMP effluent data that can be approximated using the lognormal distribution; and
- the three-parameter lognormal distribution will fit data that are not symmetrical above and below the geometric mean.

The disadvantages of Stedinger's quantile lower-bound estimator are:

- it is not robust because it can produce a lower-bound value that is less than zero;
- it is not robust to presence of data below one or more detection limits because it is calculated using the minimum value;
- the minimum value can be estimated using commonly accepted standard methods, but use of individual censored-value estimates below one or more detection limits are not commonly recommended (Helsel and Hirsch, 2002; Helsel, 2005); and
- the lower-bound estimated using the three-parameter lognormal distribution cannot be adapted to data that cannot be modeled using a lognormal distribution (pH for example).

The Modified Quantile Lower-Bound Estimator

The Iwai quantile lower-bound estimator is not used to estimate the MIC, but this estimator forms the basis for the modified quantile lower-bound estimator (MQLBE) that is used to estimate the MIC in this report. The Iwai quantile lower-bound estimator commonly is used to calculate the minimum value of the three-parameter lognormal distribution used for flood frequency analysis in Japan (Hoshi and others, 1984). The Iwai quantile lower-bound estimator is similar to the Stedinger (1980) estimator, but an average of the extreme values is used instead of the minimum and maximum value. Hoshi and others, (1984) used Monte Carlo methods to demonstrate that the Iwai method outperformed many of the alternate parametric methods and was as good or almost as good as the Stedinger method in many cases. The equation for estimating the MIC using the Iwai quantile lower-bound estimator is

$$LB = \frac{\left(\bar{X}_{(i=1 \text{ to } m)} \times \bar{X}_{(i=n-m+1 \text{ to } n)}\right) - X_{med}^2}{\bar{X}_{(i=1 \text{ to } m)} + \bar{X}_{(i=n-m+1 \text{ to } n)} - 2X_{med}} \quad (3)$$

where

LB is the quantile lower-bound estimate;

$\bar{X}_{(i=1 \text{ to } m)}$ is the average of the m lowest BMP effluent data values;

$\bar{X}_{(i=n-m+1 \text{ to } n)}$ is the average of the m highest BMP effluent data values;

X_{med} is the median of the BMP effluent data values;

i is the index number of a given values in the dataset;

n is the number of values in the dataset; and

m is the number of values used to calculate the upper and lower average values, which commonly is the integer closest to one-tenth of the n values.

Iwai's quantile lower-bound estimator has four advantages and three potential disadvantages.
The advantages are:

- it is relatively simple to calculate;
- the three-parameter distribution is well accepted in theory and in practice (Stedinger and others, 1993; Maestre and others, 2005);
- the quantile lower bound can be used to estimate the MIC for BMP effluent data that can be approximated using the lognormal distribution; and
- the three-parameter lognormal distribution will fit data that are not symmetrical above and below the geometric mean.

The disadvantages of Iwai's quantile lower-bound estimator are:

- it is not robust because it can produce a lower-bound value that is less than zero;
- it may not be robust to presence of data below one or more detection limits (however, the Iwai estimator may be more robust than the Stedinger's method in this respect because the Iwai estimator is calculated using the average of lower values rather than just one minimum value); and
- the lower-bound value estimated using the three-parameter lognormal distribution cannot be adapted to data that cannot be modeled using a lognormal distribution.

The MQLBE was developed to estimate MIC values using an iterative process. This estimator was developed because the Stedinger and Iwai estimators produced negative-value estimates for about 30 percent of the TSS effluent datasets in the International BMP Database that have 20 or more storm events. The modified quantile lower-bound estimator is hybrid of the Stedinger and Iwai estimator calculated using the equation:

$$LB = \frac{\left(\bar{X}_{(i=1 \text{ to } m)} \times X_n\right) - X_{med}^2}{\bar{X}_{(i=1 \text{ to } m)} + X_n - 2X_{med}} \quad (4)$$

The variables in equation 4 are the same as those defined for equations 2 and 3. The modified quantile lower-bound estimator is calculated by setting m to two and then incrementing the value of *m* until *LB* is greater than zero. In the worst case scenario, *m* may increase to include values that are greater than the median value.

The modified quantile lower-bound estimator has six advantages and three disadvantages.
The advantages are:

- the three-parameter distribution is well accepted in theory and in practice (Stedinger and others, 1993; Maestre and others, 2005);
- it can be used to estimate the MIC for BMP effluent data that can be approximated using the lognormal distribution;
- the three-parameter lognormal distribution will fit data that are not symmetrical above and below the geometric mean;
- it is robust because it will produce a lower-bound value that is greater than zero;
- it is more robust to the effects of censored data than the minimum value or Stedinger's methods because the minimum value used in the equation is the average of two or more values; and
- using an average of selected lower values incorporates more information about the entire sample than selecting a single estimated minimum value.

The disadvantages are:

- because it is iterative, this estimator is not as easy to calculate as some of the other estimators used to estimate the MIC values;
- the lower-bound value estimated using the three-parameter lognormal distribution cannot be adapted to data that cannot be modeled using a lognormal distribution; and
- although potential adverse effects of using one or more censored-value estimates is reduced by averaging two or more of the lowest values, use of individual censored estimates is not highly recommended (Helsel and Hirsch, 2002; Helsel, 2005).

Selecting Minimum Irreducible Concentrations from Lower-Bound Estimates

Application of these lower-bound estimators to monitoring data indicates that there is wide variation in lower-bound estimates for each monitoring site and among the lower-bound estimates for different monitoring sites. Figure 2 shows the distribution of site-specific minimum and median MIC estimates for TSS concentrations calculated from data collected at 202 study sites. Among the individual BMPs, ratios of the median of MIC estimate to the minimum of MIC estimate for individual sites (documented in the spreadsheet SiteValues-MIC.xlsx in the digital media accompanying this report) range from 1 to 37 with an average of 3.7 and a median of 2. The absolute difference between median of MIC estimates and minimum of MIC estimates ranges from 0 to 61 mg/L with an average of 4.1 and a median of 1.24 mg/L. Among the 202 sites, about 48 percent of these alternate MIC estimates differ by less than 1 mg/L and about 63 percent differ by less than 2 mg/L. Data in figure 2 also indicate that the at-site MIC estimates can range over 2 to 4 orders of magnitude for BMP categories with more than a few monitoring sites.

Four methods (denoted as MIC0 through MIC3) were chosen for selecting representative MIC values from among the four statistical lower-bound estimators for each category of BMP, and one method (denoted as MIC4) was chosen for selecting a representative MIC for an individual monitoring site from among the four methods for calculating a statistical lower-bound estimate. In both cases, only the BMP monitoring sites with enough data points above the detection limits to calculate the four statistical MIC estimators (minimum, log-triangular, Stedinger, and MQLBE) were used to develop the three representative MIC values for each category (fig. 2). The first category-level method (MIC0) is to use the minimum of the minimum values of the positive MIC estimates. The second category-level method (MIC1) is to use the 25th percentile of the minimum values of the positive MIC estimates. The third category-level method (MIC2) is to use the median of the minimum values of the positive MIC estimates. The fourth category-level method (MIC3) is to use the median of the median values of the positive MIC estimates. The median of the positive MIC estimates for an individual monitoring site (MIC4) was chosen for selecting a representative MIC for that site because many of the datasets include one or more values below detection limits, which means that an individual minimum MIC estimate may be uncertain for any one site. However, the MIC1 and MIC2 estimates from all available sites were chosen as the primary methods for estimating the MIC for a category or group of BMP sites because the MIC3 estimates may be biased high and the MIC0 may be biased low if the objective is to select a representative MIC for a class of BMPs.

The more conservative MIC estimates based on relatively small sample sizes may not be representative of long-term performance in BMP simulations. SELDM generates stochastic populations with about 800 to 2,300 storms. All BMP effluent concentrations calculated as being below the MIC will be set equal to the MIC. In large long-term simulations, a substantial proportion of effluent concentrations may equal the MIC estimate generated from small short-term studies, which will result in a seemingly unrealistic distribution of effluent concentrations. SELDM was designed with the MIC as a constant variable, whereas further research indicates that it may be a stochastic variable that varies at a site and between sites. Selection of the MIC1 estimate or a lower percentile value will allow for more variation in low-end concentrations. Selection of a lower MIC estimate will reduce the proportion of

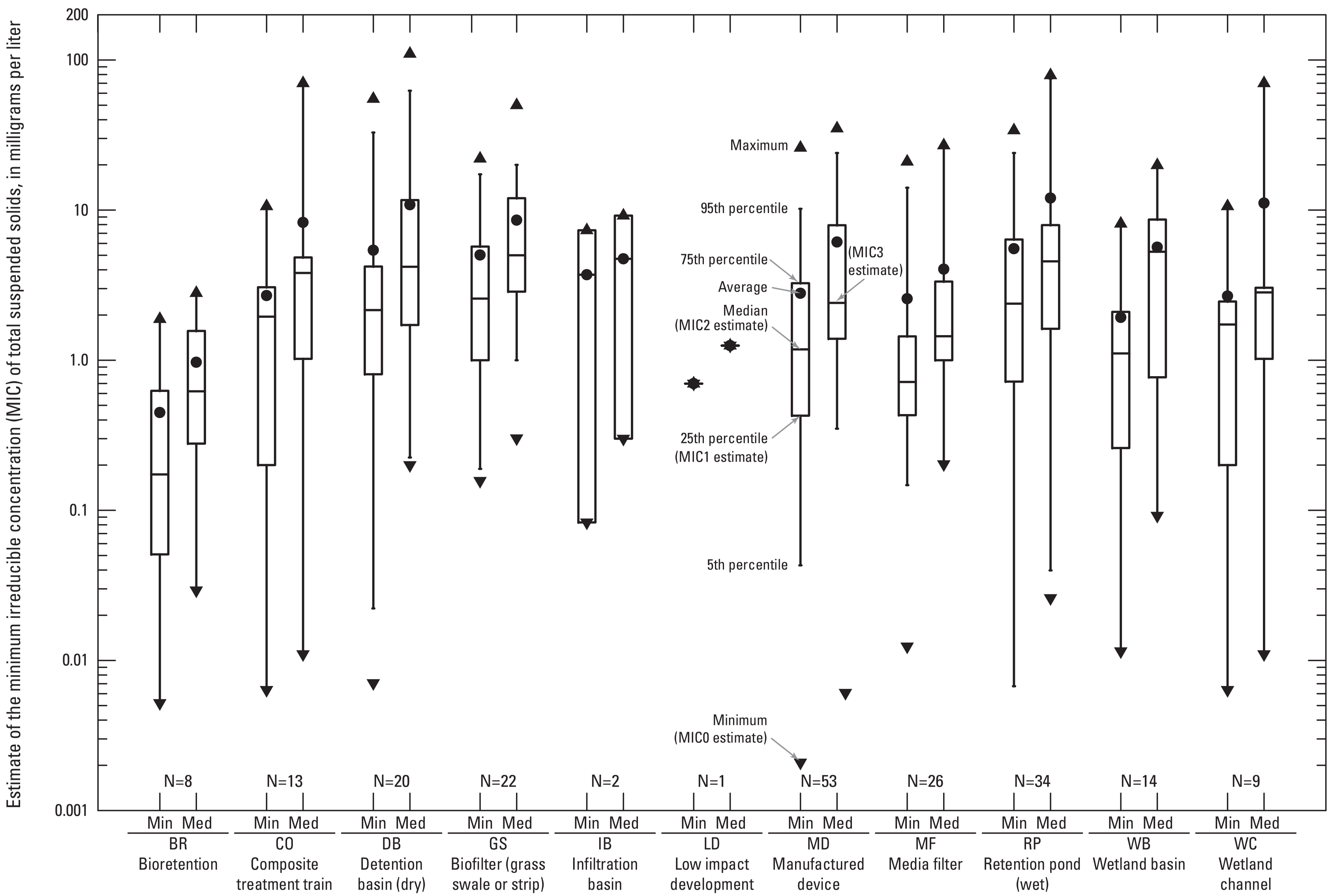

Figure 2. The variation in estimates of the minimum irreducible concentrations (MIC) among different structural best management practice (BMP) monitoring sites by BMP category. The Min and Med estimates are the minimum and median of the positive values of four statistical lower-bound estimators for each individual monitoring site. The MIC0, MIC1, MIC2, and MIC3 are the category-level MIC estimates. N is the number of sites.

constant-value lower-end concentrations, but is not expected to substantially change the proportion of water-quality excursions or total annual loads in most cases because absolute differences in MIC values are small in comparison to the range of BMP effluent concentrations.

Correlation Coefficients

Correlation coefficients were calculated for the volume-reduction ratios, flow-extension durations, concentration-reduction ratios, and MIC values. Rank correlations were calculated by using Spearman’s rho and Kendall’s tau, and data correlations were calculated using Pearson’s R (Haan, 1977; Helsel and Hirsch, 2002). Correlation coefficients and associated 95-percent confidence intervals and probability values were calculated by use of standard methods (Fisher, 1924; Haan, 1977; Press and others, 1992; Caruso and Cliff, 1997; Helsel and Hirsch, 2002). Inflow volumes were used to calculate nonparametric correlation coefficients for the volume-reduction ratios and flow-extension durations. Inflow concentrations were used to calculate rank correlation coefficients for the water-quality treatment ratios. The geometric means of inflow concentrations were used to calculate rank- and Pearson’s R-correlation coefficients for the MIC values. Rank correlations for volume reduction, flow extension, and water-quality treatment ratios were calculated to provide input for the Monte Carlo analyses in SELDM (Granato, 2013). The Spearman’s rho values are provided in this report; the values of Kendall’s tau and the confidence intervals and probability values are provided in the “SiteValues” spreadsheets within the compressed archive file “SiteValues.zip” in the digital media accompanying this report. The rank correlations and Pearson’s linear correlation coefficients on the arithmetic and logarithmic values of the geometric mean inflow concentration and the estimated MIC value were calculated to help inform the choice of MIC values and to explore the feasibility of predictive equations for these variables. These values of the correlation coefficients are provided in this report.

The rank correlation between the inflow volume and the ratio of outflow to inflow volume or the inflow concentration to the concentration ratios should not be used for statistical inference. Because the inflow concentration and runoff are included in the ratios, the correlations are spurious (Haan, 1977). However, these rank correlations can be used in a Monte Carlo analysis to help preserve the structure of the input data (Granato, 2013). Thus, for example, if the rank correlations between inflow volumes and ratios are positive, then large inflows would be associated with large ratios and small inflows would be associated with small ratios when the performance data were generated. Conversely, if the rank correlations are negative, large inflows would be associated with small ratios and small inflows would be associated with large ratios when the performance data were generated.

Sample sizes of seven or more storms per BMP monitoring site were selected for calculating correlation coefficients for the volume-reduction ratios, flow-extension durations, and concentration ratios. This sample-size criterion was applied for selection of datasets to estimate correlation coefficients because Abdel-Megeed (1984) determined that at least 5 data pairs were necessary to begin to quantify the correlation. A minimum sample size of seven was selected to improve on the minimum estimate of five storms while retaining two or more datasets for each BMP category.

Limitations of the BMP Performance Analyses

The BMP performance estimates identified in this study are based on several assumptions about available data in the international BMP database and the methods used for analysis, which may or may not be robust for some applications. These assumptions are:

- the BMPs in the database are representative of the category;
- the monitored BMPs were properly designed for local conditions;
- the designs, and therefore performance, are transferable to other sites and other areas if the designs are rescaled for local hydrology;
- monitoring protocols and data management protocols result in valid and representative data;
- short-term monitoring results characteristic of most datasets are representative for long-term performance statistics; and
- the statistical methods chosen to estimate the performance metrics are sufficient approximations for characterizing long-term BMP effluent characteristics.

Application of results from BMP monitoring studies is highly uncertain; few studies provide reliable predictions of treatment performance even with large datasets and complex models (Strecker and others, 2001; Wong and others, 2006; Park and others, 2011). Uncertainties arise because of the many categories of BMPs, wide variations in design and construction of BMPs within each category, and wide variations in the operation and maintenance of BMPs once they are installed. Similar BMPs are used at sites with widely varying site characteristics including different precipitation, site hydraulics, constituent characteristics and loads, and total stormwater loads. For example, local soil characteristics can influence the amount of runoff generated by a given storm, the concentrations of sediment in runoff, and the settling rate of the sediments within a BMP. Variations in BMP design also can affect actual and modeled BMP effectiveness. For example, BMP structures may have overflow or bypass structures that have a substantial effect on performance once the BMP volume has been filled. These design features may affect performance only during large storms or storms that occur in rapid succession (Strecker others, 2001). Uncertainties in effectiveness also arise because BMP monitoring is a complex endeavor that requires a high degree of expertise. Although BMP monitoring protocols have become more standardized, many BMP studies still are conducted individually with different protocols and data-reporting standards rather than as part of a large consistent and coordinated monitoring effort (Jane Clary, Civil Engineer, International BMP Database Project, written commun., May 2011).

Uncertainties in results also are compounded by available sample sizes. Driscoll and others (1979) recommend the collection of 20 to 40 Event Mean Concentration (EMC) samples to characterize runoff on the basis of the variability of commonly measured runoff constituents. Similarly, Burton and Pitt (2002) indicate that, at a minimum, 25 to 50 EMC samples may be needed. The California Department of Transportation (2009) provides examples in their BMP monitoring handbook indicating that 50 to 113 paired samples may be needed just to detect differences in mean concentrations. In comparison, Leisenring and others (2011) looked at TSS data for 10 types of BMPs in a recent summary of solids-removal data in studies in the International BMP Database. Although TSS is one of the most widely monitored constituents in BMP studies, the average number of paired samples per category ranged from 6 to 16 with a median of about 12 per study. Schneider and McCuen (2006) calculated that monitoring data from about 90 storms would be necessary to fully quantify the hydraulic performance of a stormwater-detention cistern in Maryland on the basis of local precipitation-event characteristics. In comparison, Poresky and others (2011) looked at volume-reduction data from the International BMP Database; they found that the number of storm events ranged from 5 to 173 with a median of about 11 per study. As with other hydrologic data, uncertainty in data related to BMP performance increases when data from one site are extrapolated to estimate conditions at a different site. The confidence intervals of correlation coefficients are strongly influenced by sample size; the true value may substantially depart from the estimated value when sample sizes are smaller than 20 values (Fisher, 1924; Haan, 1977; Caruso and Cliff, 1997). In addition, small sample sizes limit the ability to select and parameterize statistical distributions for modeling BMPs with data.

Despite decades of BMP-monitoring efforts, data are limited for some BMP categories, and substantial uncertainties in the volume-reduction and flow-extension performance of many BMPs remain. In an analysis of flow data in the International BMP Database, Poresky and others (2011) noted that because many older studies were designed to monitor reductions in concentration instead of volume, measurements of volume were made only during the collection of flow-weighted water samples. Thus, flow-duration and volume data may include only the period used for water-quality sampling rather than the complete duration of inflows and outflows. They also noted that the inflow and outflow data from some BMP studies could not be truly paired because these studies measured BMP inputs at only one of many inlets to the BMP or at a reference site that was not associated with the monitored BMP outlet. Poresky and others (2011) emphasize that data are not available for many types of BMPs and that the level of uncertainty of the available data is high.

Many studies have been done to measure and model volume reduction, but accurate categorical determination is hampered by the stochastic nature of antecedent conditions, precipitation, and runoff (Goforth and Heany, 1983; Adams and others, 1986; Driscoll and others, 1986; Schueler, 1987; Driscoll, and others, 1989; Urbonas and Roesner, 1993; Wanielista and Yousef, 1993; Young and others, 1996; Adams and Papa, 2000; Huber and others, 2006; Poresky and others, 2011). For example, Emerson and Traver (2008) attributed seasonal two-fold variations in infiltration rates during a 4-year period at BMPs in Maryland to changes in the viscosity of ponded water with changes in temperature.

Although hydrograph extension is a BMP design variable, it is not well defined or well characterized in the literature describing BMP monitoring results. In theory, runoff from a highway site or a BMP may continue to trickle forth for an extended period of time. In practice, however, the duration of runoff should be defined so that it is truncated at some measurable and meaningful value. For example, minimum precipitation-monitoring depths commonly are about 0.01 inches (in.) per hour, which would yield about 0.01 cubic feet per second per acre ($ft^3/s/acre$) (Church and others, 2003). This threshold, however, may not be measurable at small sites. For example, Smith and Granato (2010) used a storm-monitoring threshold of about 0.009 ft^3/s to distinguish the presence of flow because it was the minimum value that was reliably discernible for a level sensor to detect the presence of flow in 8-in. pipes draining 12,000 to 24,000 square feet (ft^2) of pavement (about 0.03 and 0.016 $ft^3/s/acre$, respectively).

The stochastic approach used in SELDM is warranted because there are large uncertainties in available information, and the level of effort required to develop detailed simulation models may be beyond the scope of an initial planning-level estimate. If, however, the initial analysis done with SELDM indicates the potential need for mitigation, then detailed simulation models such as those described by Huber and others (2006) or detailed statistical models such as those described by Adams and Papa (2000) may be used to develop the performance statistics used by SELDM. Furthermore, if the initial analysis without BMP treatment indicates the potential need for mitigation, then SELDM can easily be used to develop the BMP-performance statistics needed to reduce storm loads or the frequencies of water-quality excursions in receiving waters to an acceptable level. This analysis can be done by varying BMP flow-reduction statistics to meet water-quality objectives. Such an analysis may indicate that it is impossible to meet water-quality objectives by using the treatment capabilities of feasible BMP designs.

Results of Analyses

SELDM uses the trapezoidal distribution to model runoff volume-reduction ratios, hydrograph extension values, and water-quality treatment ratios stochastically and models the MIC used for the lower bound of effluent concentrations deterministically (Granato, 2013). SELDM uses rank correlation coefficients between inflow values and the runoff volume-reduction ratios, hydrograph extension values, and water-quality treatment ratios to model the structure of environmental datasets. After data from many monitoring sites were analyzed for these variables, it was determined that the median of best-fit statistics would be the most robust approach for selecting BMP-performance statistics. Analysis of MIC values for 12 water-quality constituents that are commonly measured in highway and urban-runoff studies provides several options depending on whether a category of BMPs is being modeled or if data from an individual monitoring site are being modeled.

Runoff Volume Reduction

In this study, volume-reduction statistics were developed for 7 BMP categories using data from 94 BMP monitoring sites with 3 or more storm events (table 2). There was insufficient paired inflow and outflow data for composite BMPs, infiltration basins, and low impact development sites. Net volume reductions for composite BMPs can be estimated from reductions of the component BMPs. The lack of data for infiltration basins and low impact development sites could be interpreted as complete reductions, but many of these designs have overflow or bypass structures and therefore will produce some outflows (Northern Virginia Planning District Commission, 1992, 1996; Young and others, 1996; Clar and others, 2004a, b; National Cooperative Highway Research Program, 2006; Denver Urban Drainage and Flood Control District, 2008, 2010). Manufactured devices were not included in the analysis; although they may lose water to leakage or evapotranspiration, they are not commonly designed for volume reduction and therefore the reductions observed for some sites may be the result of sampling artifacts. Volume reduction statistics for individual BMP monitoring sites are available in the spreadsheet “SiteValues-VR.xlsx” within the compressed archive file “SiteValues.zip” in the digital media accompanying this report.

The median volume-reduction statistics in table 2 indicate that outflows range from about 6 percent of inflows (for swales) to about 185 percent of inflows (for wetland channels). With the exception of Bioretention, all the BMP categories have some outflows that exceed inflows for some storms. Among the other BMP categories, the percentage of storms in which outflows exceed inflows ranges from 1 percent for swales to 40 percent for retention ponds.

Examples of the cumulative distribution functions for the trapezoidal distribution of volume-reduction ratios for 29 biofilter (grass swale) sites and 13 detention-basin sites are shown with the cumulative distribution functions constructed

Table 2. Median of stormflow volume-reduction statistics for the trapezoidal distribution and Spearman’s rho correlation coefficient statistics for best management practices (BMPs) by category.

[NR, number of sites with at least three storms used to calculate the median ratio statistics; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; Pct GT 1, the percentage of storms in which outflows exceed inflows and thus, ratio is greater than 1; NS, number of sites with at least seven storms used to calculate the Spearman’s rho statistics; NA, not applicable; --, insufficient data. The volume-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow volume. The Spearman’s rho correlation coefficients are calculated using the ranks of the inflow volumes and the associated ratios of outflow to inflow volumes]

International BMP category		Volume-reduction statistics						Spearman’s rho correlation coefficients			
		NR	Minimum	LBMPV	UBMPV	Maximum	Pct GT 1	NS	Median	Minimum	Maximum
BR	Bioretention	8	0.0000	0.0185	0.1518	0.9467	0	8	0.61	-0.72	0.81
CO	Composite	--	--	--	--	--	--	--	--	--	--
DB	Detention basin	13	0.1466	0.1466	0.6570	1.2315	5.9	8	0.07	-0.57	0.48
GS	Biofilter (swale)	29	0.0602	0.3059	0.4948	1.0845	1	17	0.29	-0.27	0.90
IB	Infiltration basin	--	--	--	--	--	--	--	--	--	--
LD	Low impact development	--	--	--	--	--	--	--	--	--	--
MD	Manufactured device	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
MF	Media filter	4	0.1125	0.7424	0.7424	1.2623	12	3	-0.04	-0.15	0.57
RP	Retention pond	31	0.2080	0.6652	0.9026	1.8322	40	23	-0.06	-0.72	0.79
WB	Wetland basin	6	0.1355	0.9342	0.9342	1.2325	17	5	0.21	-0.20	0.61
WC	Wetland channel	3	0.1160	0.5478	0.5478	1.8492	32	3	0.27	0.04	0.50

using the medians of the best fit statistics in figure 3. The graph indicates the large range in performance of each type of BMP among the different studies. In both cases, use of the medians of each of the trapezoidal statistics among sites shown in table 2 produces a seemingly reasonable CDF for the category. Volume-reduction ratio statistics for the other types of BMPs also show similar patterns with wide variations in the CDFs within each category and representative CDFs constructed from the median values. The CDF constructed with the medians of statistics have outflows that exceed inflows for about 1 percent of runoff events for the grassy swale CDF and about 6 percent of runoff events for the detention basin CDF (fig. 3).

In this study, rank correlation coefficients between volume-reduction ratios and inflow volumes were calculated for use in the Monte Carlo analysis to help preserve the structure of the input data (Granato, 2013). Rank correlation statistics were developed for 7 BMP categories using data from 67 BMP monitoring sites with 7 or more storm events (table 2). The rank correlation coefficients (Spearman's rho) were ambiguous for six of the seven BMP categories with correlations ranging from positive to negative values. The rank correlation coefficients for the seventh category (wetland channels) were consistently positive but rather weak (from 0.04 to 0.5). The potential for wide variations in correlation coefficients is expected for small sample sizes; it is highly likely that the sample correlation coefficient may be substantially different from the actual correlation coefficient for a given site (Haan, 1977; Caruso and Cliff, 1997). In theory, the ratio of outflow to inflow volumes would be expected to increase with increasing storm volumes because it is reasonable to assume that a smaller fraction of the total inflow may be lost to infiltration or evapotranspiration for large storms than for small storms. Therefore, positive rank correlation coefficients would be expected. However, if the number of storms is small and the range of monitored storm volumes is not large in comparison to the expected range of precipitation volumes, then the fact that the inflow volume is in the denominator of the flow-reduction ratio may explain the negative correlations between inflow volumes and ratios. Alternatively because the maximum ratios are substantially greater than 1 and it is unlikely that a large storm will result in a large surplus outflow volume, the largest storms may not be associated with the largest ratios. Given these factors, selecting a Spearman's rho value that is the average of the median and maximum values in table 2 for use in SELDM may help generate realistic simulation results.

Hydrograph Extension

In this study, hydrograph-extension statistics were developed for 5 BMP categories using data from 40 BMP monitoring sites with 3 or more storm events (table 3). The median values of the minimum, LBMPV, and UBMPV of the trapezoidal distributions were equal to zero for all 5 BMP categories with sufficient data to do the analysis. Therefore, these distributions are the positive-skew triangular distributions shown in figure 1B, which means that most of the values generated will be substantially greater than zero. As indicated in table 3, 44 to 97 percent of flow extensions generated by using these trapezoidal-distribution statistics will be greater than or equal to 1 hour. A decreasing number of generated flow-extension values will be greater than 6, 12 and 24 hours. Only the media filter and retention pond categories have flow extension in excess of 24 hours; only the media filters exceed the 72 hour threshold. Hydrograph-extension statistics for individual BMP monitoring sites are available in the spreadsheet "SiteValues-HE.xlsx" within the compressed archive file "SiteValues.zip" in the digital media accompanying this report.

The cumulative distribution functions of the fitted hydrograph-extension results for individual BMP sites are shown with the category median CDF for the biofilters (grass swales) and detention basins (dry ponds) in figure 4. Although the biofilter results seem plausible and the upper bound of the detention basin seems correct, less variation in the hydrograph-extensions from an engineered basin would be expected. However, the hydrograph extensions are the drain times from the end of the inflow hydrograph rather than a full-basin or full water-quality treatment-volume drain time and therefore, may be shorter than the design-storm drainage duration.

Hydrograph-extension estimates made using data from the International BMP Database may underrepresent actual BMP performance because, as Poresky and others (2011) noted, measurements of volume were made only during the collection of flow-weighted water samples in many older studies. Thus, flow-duration data may include only the period used for water-quality sampling rather than the complete duration of inflow and outflow hydrographs. Although the values in table 3 provide initial and conservative flow-extension statistics that can be used for a preliminary runoff-quality analysis, simple hydraulic analysis and use of professional judgment for estimating flow extension ratios as described by Granato (2013) to develop SELDM input may, currently (2013), be more reliable than use of the duration data from the international BMP database.

Queries of the design tables in the BMP database indicate that design-flow durations for BMPs in the database (table 4) may exceed many of the durations that would be modeled using the statistics developed from the monitoring data (table 3). The values in table 4 represent at-site estimates of the brim-full and half-full drain times rather than the trapezoidal performance statistics shown in table 3. About 52 percent of the 371 BMP sites in the database with design information include values of variables that can be used to estimate design drain-down times for that BMP (table 4). Drawdown times for bioretention BMPs are estimated by using the ponding depths and infiltration rates. Drawdown times for biofilters (swales) and wetland channels are estimated by using the length and longitudinal slope values with the basin lagtime equation (Granato, 2012), which provide a simple plug-flow estimate. These minimum

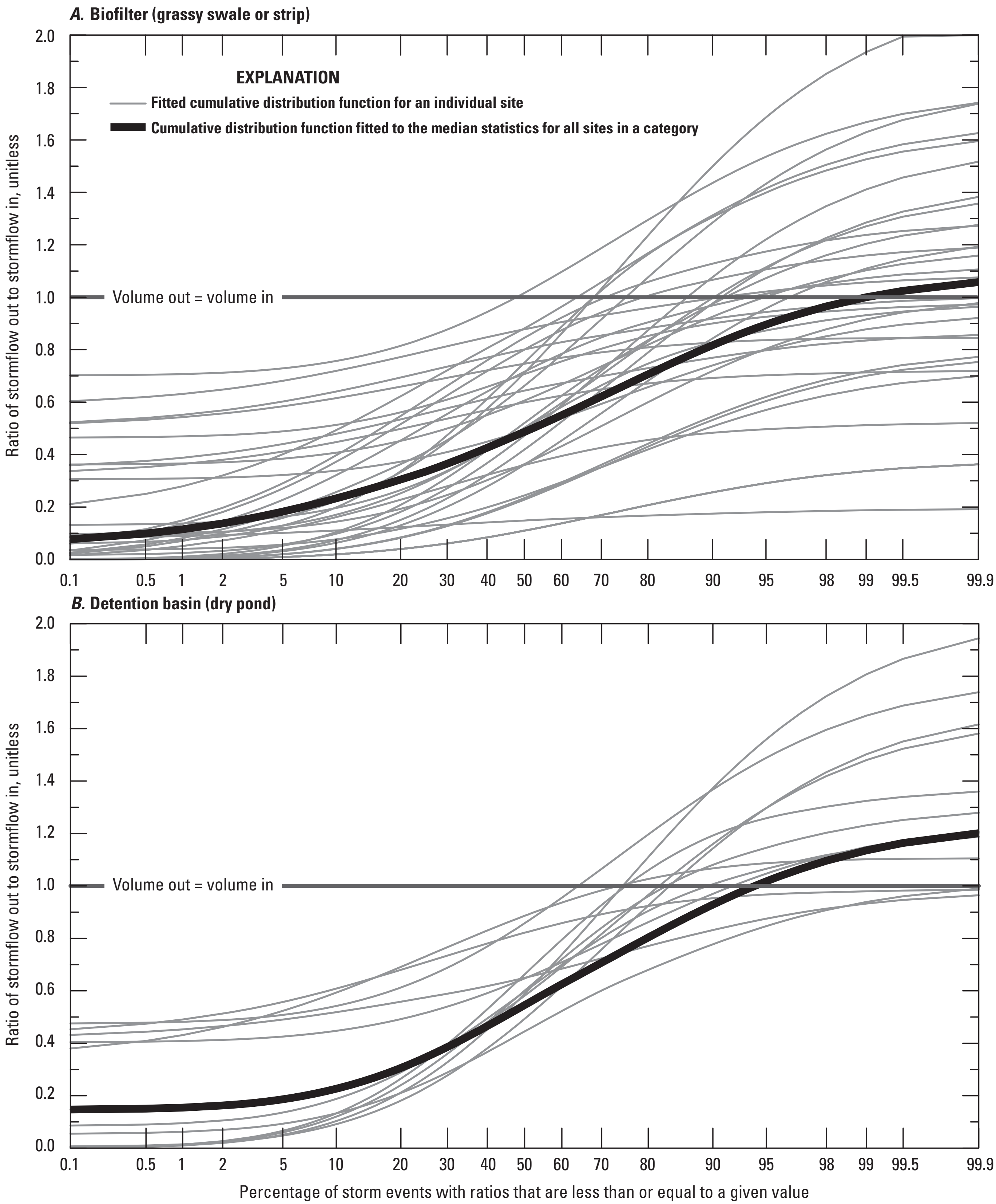

Figure 3. Fitted cumulative trapezoidal-distribution functions of the flow-reduction statistics for *A,* 29 biofilter (grassy swale or strip) monitoring sites and *B,* 13 detention-basin monitoring sites. The graphs also show cumulative distribution functions that are fitted to the median of the flow-reduction statistics for each category.

Table 3. Median of stormflow-extension statistics for the trapezoidal distribution and Spearman’s rho correlation coefficient statistics for best management practices (BMPs) by category.

[NR, number of sites with at least three storms used to calculate the median ratio statistics; Min, minimum value; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; Max, maximum; h, hour(s); NS, number of sites with at least seven storms used to calculate the Spearman’s rho statistics; Med, Median; NA, not applicable; --, insufficient data. The flow-extension statistics are for the trapezoidal distribution of the number of hours that outflows exceed inflows. The Spearman’s rho correlation coefficients are calculated using the ranks of the inflow volumes and the associated flow-extension values]

International BMP category		Stormflow-extension statistics, in hours					Percentage of outflows greater than				Spearman’s rho correlation coefficients			
		NR	Min	LBMPV	UBMPV	Max	1 h	6 h	12 h	24 h	NS	Med	Min	Max
BR	Bioretention	--	--	--	--	--	--	--	--	--	--	--	--	--
CO	Composite	--	--	--	--	--	--	--	--	--	--	--	--	--
DB	Detention basin	12	0	0	0	18	89	44	11	0	7	0.42	-0.59	0.71
GS	Biofilter (swale)	11	0	0	0	3	44	0	0	0	11	0.04	-0.23	0.41
IB	Infiltration basin	--	--	--	--	--	--	--	--	--	--	--	--	--
LD	Low impact development	--	--	--	--	--	--	--	--	--	--	--	--	--
MD	Manufactured device	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
MF	Media filter	4	0	0	0	77	97	85	71	47	1	0.41	--	--
RP	Retention pond	10	0	0	0	40	95	72	49	16	4	0.3	-0.17	0.59
WB	Wetland basin	3	0	0	0	8	76	6	0	0	3	0.15	-0.43	0.24
WC	Wetland channel	--	--	--	--	--	--	--	--	--	--	--	--	--

estimates are comparable to minimum recommended contact times documented by Young and others (1996). If the 6-minute contact-time estimate from table 4 is substituted into the minimum, LBMPV, and UBMPV values of the swale statistics in table 3, then about 46 percent of flow-extension values will exceed 1 hour rather than the 44 percent in table 3. If the 9-minute contact-time value recommended by Young and others (1996) is used, then 49 percent of flow-extension values will exceed 1 hour. Detention basins commonly are designed to drain the water-quality volumes over 24 hours or more (Northern Virginia Planning District Commission, 1992, 1996; Young and others, 1996; Clar and others, 2004a, b; Denver Urban Drainage and Flood Control District, 2008, 2010). If, for example, the maximum brimful drain time from table 4 is substituted into the maximum value of the detention-basin statistics for table 3, then about 97, 85, 71, and 46 percent of flow-extension values will exceed 1, 6, 12, and 24 hours, respectively. Although the statistics in table 4 are not best-fit trapezoidal-distribution statistics, they may help inform professional judgment for adjusting values modeled with the statistics in table 3.

Increasingly, structural BMPs are designed to process a water-quality volume for a relatively frequent design storm and an excess urban runoff volume, which is used to process larger, less frequent storms (American Society of Civil Engineers and Water Environment Federation, 1992, 1998; Northern Virginia Planning District Commission, 1992, 1996; Clar and others, 2004a, b; Denver Urban Drainage and Flood Control District, 2008, 2010; Wyoming Department of Environmental Quality, 2013). In many areas of the country, BMPs commonly are designed to process a water-quality design volume within 12 to 48 hours. BMPs are sized and outlet structures are designed to meet these criteria so as to maximize the water-quality treatment without the need to bypass flows in subsequent storms. BMPs commonly are designed with one or more secondary drainage structures to handle higher flows from larger storms. These structures commonly are designed to accommodate high flow rates and to draw down the excess urban runoff volume to the water-quality control volume relatively rapidly. The water-quality outflow structures are designed to have lower flow rates to meet the extended holding times. Figure 5A is an example of a stage-discharge hydrograph for a detention basin from FHWA Hydraulic Engineering Circular 22 (Brown and others, 2009). At low water depths, discharge from the pond is controlled by the low-flow orifice design. As the water depth rises, the larger riser-orifice design increases the rate of outflows. Once the water depth reaches the emergency spillway, the spillway further increases the rate of outflows. The volume in the basin exhibits an exponential decay once inflows cease and the pond stage and associated outflow discharges decrease (fig. 5B).

Although the example in figure 5 is for a detention pond, many types of structural BMPs may have a combination of hydraulic outflow mechanisms. For example, flow controls

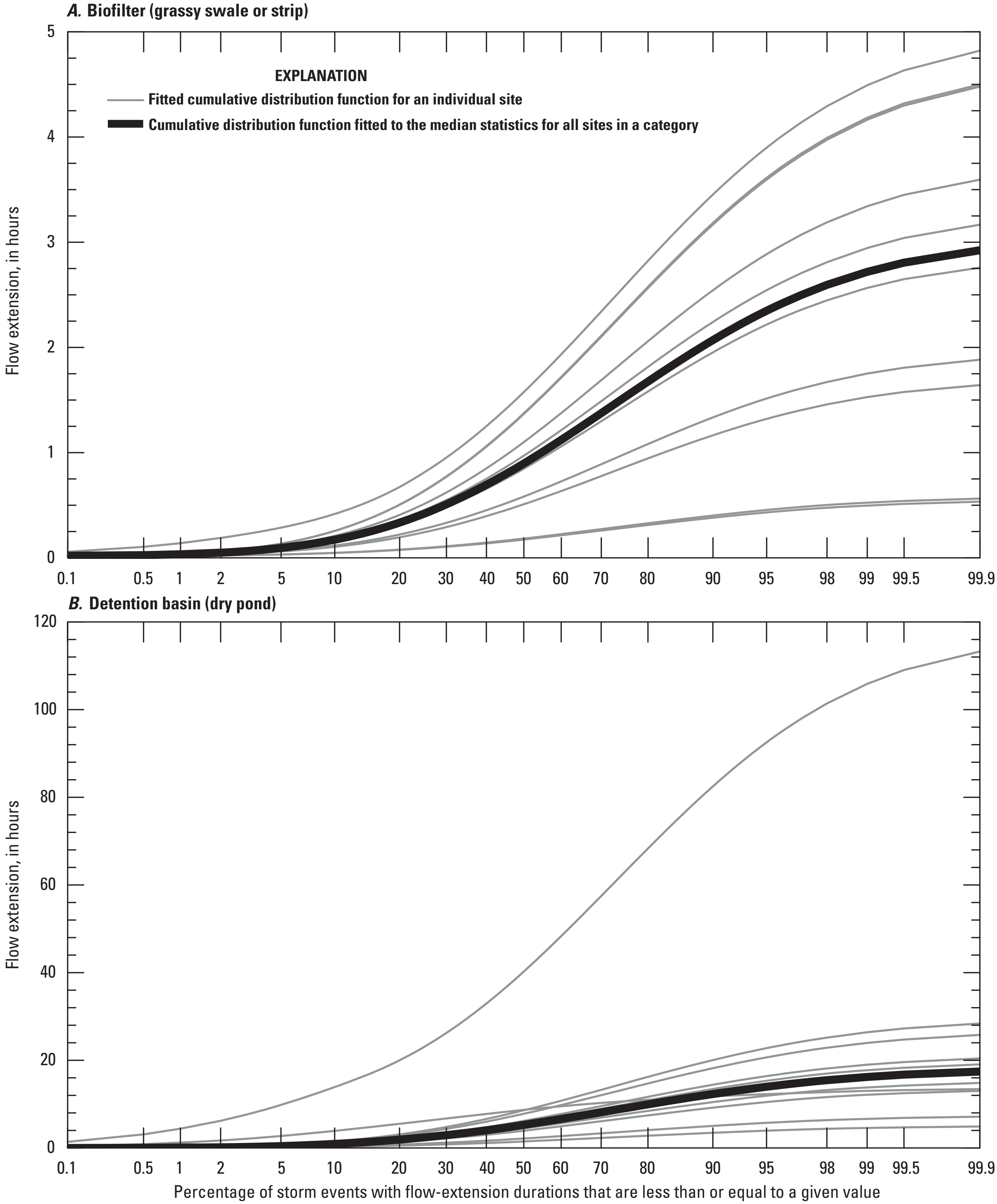

Figure 4. Fitted cumulative trapezoidal-distribution functions of the flow-extension statistics for *A,* 11 biofilter (grassy swale or strip) monitoring sites and *B,* 12 detention-basin monitoring sites. The graphs also show cumulative distribution functions that are fitted to the median of the flow-reduction statistics for each category.

Table 4. Summary of water-quality volume drawdown times from design tables in the January 2012 version of the International BMP Database (www.bmpdatabase.org).

[The number of sites is the number in the design information table for each best management practice (BMP); No., is the number of sites with the specified emptying time; ND, not documented]

International BMP category		Number of sites	Brim-full emptying time, in hours				Half-full emptying time, in hours			
			No.	Minimum	Median	Maximum	No.	Minimum	Median	Maximum
BR	Bioretention[1]	31	6	5	6.4	6.6	ND	ND	ND	ND
CO	Composite	25	ND	ND	ND	ND	ND	ND	ND	ND
DB	Detention basin	29	19	0	24	75	11	0	6.4	30
GS	Biofilter (swale)[2]	79	77	0.1	0.6	1.83	ND	ND	ND	ND
IB	Infiltration basin	1	ND	ND	ND	ND	ND	ND	ND	ND
LD	Low impact development	2	ND	ND	ND	ND	ND	ND	ND	ND
MD	Manufactured device	82	23	0	0	6	15	0	0	4.2
MF	Media filter	26	16	0	56	72	ND	ND	ND	ND
RP	Retention pond	55	19	0	40	768	16	0	34.5	624
WB	Wetland basin	25	8	0	7	600	8	0	3.5	360
WC	Wetland channel[2]	16	9	0.05	0.46	2.6	ND	ND	ND	ND

[1]The emptying time is estimated by dividing the average ponding depth above bioretention media surface by the design infiltration rate.

[2]The emptying time is estimated by using the basin lagtime equation (Granato, 2012) from length and longitudinal slope values with the assumption that the basin development factor is three, because the swale is an engineered channel and the recession ratio is equal to 1.

through a swale with rip-rap check dams may be constrained by the roughness of the channel, weir discharge over the check dam, then Darcian flow through the rip-rap (Haan and others 1994, Flanagan and Nearing, 1995). Similarly, swales, bioretention BMPs, infiltration basins, low impact development designs, and media filters may be designed with an underdrain that produces head-dependent Darcian flow, which discharges to a sewer system or surface water body (Northern Virginia Planning District Commission, 1996; Young and others, 1996; Denver Urban Drainage and Flood Control District, 2010). BMP designs commonly have bypass or overflow structures to handle high flows. If the hydraulic controls are not obstructed, the combination of flow rates from the different controls provides a deterministic relation between the BMP stage at the end of the inflow hydrograph and the remaining duration of outflows (for example, fig. 5B). Outlet designs can be complex, but practitioners have designed spreadsheets to facilitate many of the calculations (for example, Denver Urban Drainage and Flood Control District, 2012; Guo and MacKenzie, 2013).

Although the designs are deterministic, the performance of the BMPs is stochastic because the volume produced by each storm and the time between storms (and therefore the residual volume from the previous storm) result in a random pattern of drain-down times. To calculate hydrograph-extension statistics SELDM modelers can:

- run the model to produce a stochastic series of inflow volumes and runoff durations;
- use local BMP design standards to define stage storage outflow relations for a BMP;
- apply the stage storage outflow relations for prospective BMPs to the series of SELDM runoff volumes;
- calculate the resulting hydrograph extension times;
- fit the population of hydrograph extension times to the trapezoidal distribution by using the spreadsheets provided with this report; and
- calculate the rank correlation coefficient between the runoff volumes and the flow extension durations.

Rank correlation coefficients between hydrograph-extension durations and inflow volumes were calculated for use in the Monte Carlo analysis to help preserve the structure of the input data (table 3). The rank correlation coefficients were ambiguous, with correlations ranging from positive to negative values for five of the six BMP categories that had data for more than one site. As with the volume-reduction statistics, small sample sizes are expected to produce wide variation in correlation coefficients (Haan, 1977; Caruso and Cliff, 1997). In theory, hydrograph extension times would be expected to increase with increasing storm volumes because

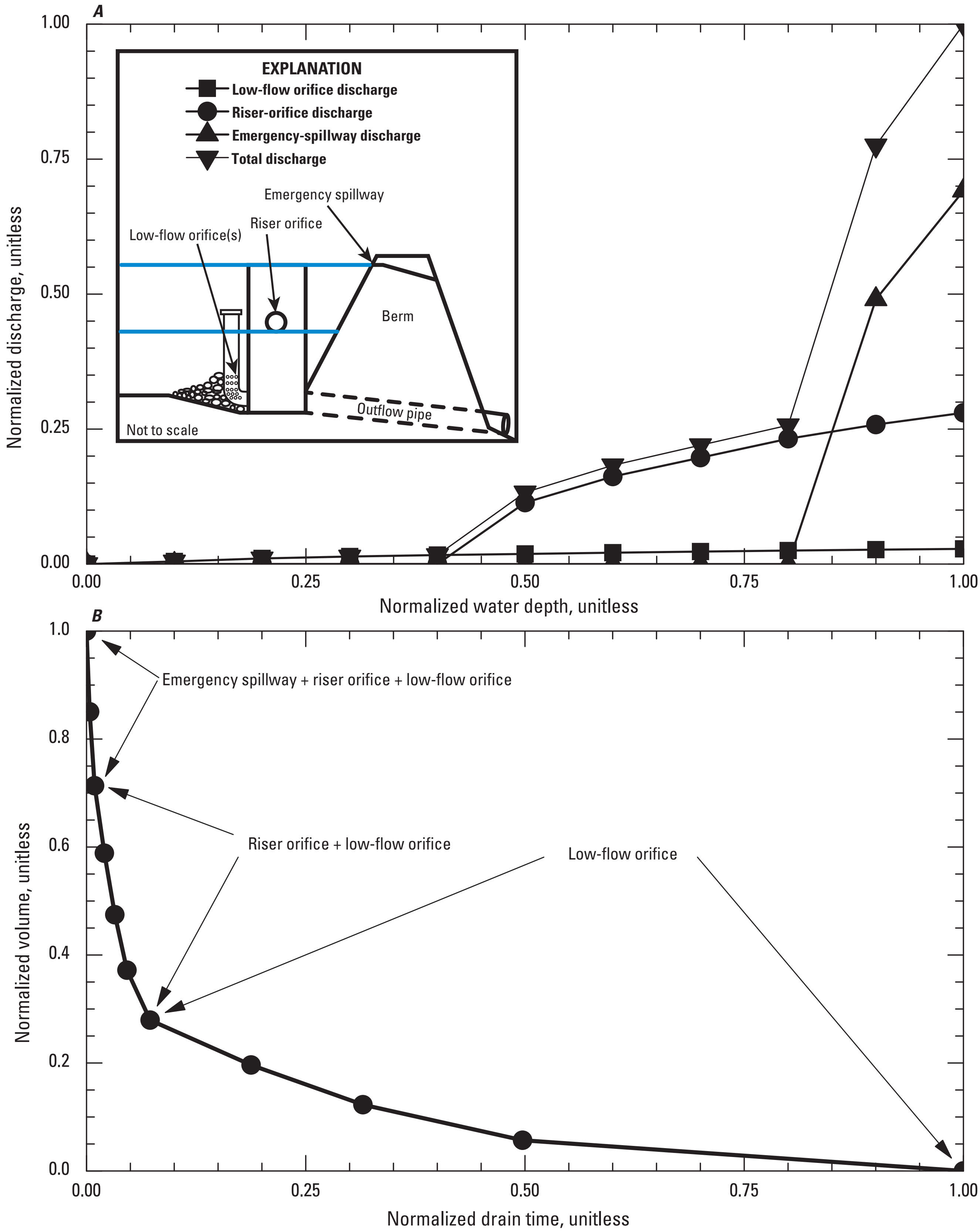

Figure 5. Normalized *A,* depth-discharge and *B,* drain-time volume graphs showing the contribution of a low-flow orifice, a riser orifice, and an emergency spillway to the drawdown time for a brim-full detention pond (example values from Brown and others, 2009; diagram in *A* modified from Young and others, 1996).

larger storms would tend to fill the water-quality and excess runoff volumes in the BMP. Therefore, one would expect positive rank correlation coefficients. However, as indicated by the diagrams in figure 5, initial drawdowns are rapid. The total drawdown time may depend on antecedent conditions; for example, the duration and intensity of storms may affect hydrograph extension beyond the duration of inflows. Given these factors, selecting a Spearman's rho value that is the average of the median and maximum values in table 3 for use in SELDM may help generate realistic simulation results.

Water-Quality Treatment

In this study, water-quality treatment statistics were developed for 13 commonly measured runoff-quality constituents by using data from more than 165 monitoring sites (representing 10 BMP categories) with paired inflow and outflow concentrations from 7 or more storm events (table 5). The constituents included turbidity, sediment, and solids; nutrients; total metals; organic carbon, and fecal coliforms. Constituents were selected on the basis of available data, potential transferability, and the perceived quality of data in the database. The median of best-fit concentration ratios for all 10 BMP categories in table 5 range from 0 to values greater than 1 for one or more runoff-quality constituents. Because of the form of the equations for the cumulative distribution function of the trapezoidal distribution (Kacker and Lawrence, 2007), the maximum value has the largest influence on the proportion of ratios that are greater than 1. As the maximum value increases from 1 to 2, the percentage of generated values that are greater than one increases from zero to about 40 percent. As the maximum value increases from 2 to 4, the percentage of generated values that are greater than one increases from about 40 to 60 percent. Water-quality treatment statistics for individual BMP monitoring sites are available in the spreadsheet "SiteValues-WQT.xlsx" within the compressed archive file "SiteValues.zip" in the digital media accompanying this report.

Performance statistics for suspended-sediment concentrations (SSC) were estimated from total suspended solids (TSS) data in the international database because many studies have shown that TSS is an unreliable measure of sediment if sand-size particles are present (Granato, 2013) and there are very few SSC samples in the International BMP Database. The relation between TSS and SSC developed by Granato and Cazenas (2009) was used to estimate inflow concentrations. TSS concentrations were used as estimates for concentrations of SSC in BMP outflows on the assumption that most BMPs could remove the coarse sediment fractions that cannot be effectively measured by using TSS measurement methods. Several studies have shown that SSC and TSS values tend to converge as the percentage of large diameter particles decreases (Gray and others, 2000; Guo, 2006).

The cumulative distribution functions of the fitted suspended-sediment concentration-reduction results for individual BMP sites are shown with the category median CDF for the biofilters (grass swales, fig. 6A) and detention basins (dry ponds, fig. 6B). As with the other treatment statistics, there are wide variations among the CDFs for each type of BMP. The CDFs constructed with the median of best-fit statistics (shown in table 5) provide reasonable models for the BMPs in each category. The graph indicates that about 13 percent of biofilter effluent concentrations and about 1 percent of detention basin effluent concentrations will exceed the inflow concentrations if these CDF values are used.

In this study, rank correlation coefficients between concentration-reduction ratios and inflow concentration were calculated for use in the Monte Carlo analysis to help preserve the structure of the input data (Granato, 2013). With only a few exceptions, the rank correlation coefficients in table 5 are negative, indicating that the larger ratios are associated with the smaller concentrations. The fact that BMPs are not good at reducing concentrations when input concentrations are low is one of the primary criticisms made against the use of ratios (Strecker and others, 2001; Leisenring and others, 2010, 2011). Use of rank correlation for generating data helps to represent such low-concentration effects. The rank correlations generally are moderate (most are between -0.3 and -0.7), so there may be some higher inflow concentrations that are greater than effluent concentrations. This situation is not uncommon for many BMPs in the International BMP database.

Minimum Irreducible Concentrations

In this report, it is assumed that the MIC is a property of the type of BMP, the design and implementation of each type for the local hydrologic conditions, and, potentially, the quality of water entering the BMP. In this study, MIC statistics were developed for 12 runoff-quality constituents commonly measured in highway and urban runoff studies by using data from 11 BMP categories and more than 167 monitoring sites. Table 6 shows the category-level MIC0, MIC1, MIC2, and MIC3 estimates for TSS and the 11 other water-quality constituents that are commonly measured in highway- and urban-runoff studies. For TSS, the MIC0 estimates range from 0.002 to 0.7 mg/L, the MIC1 estimates range from 0.06 to 1.9 mg/L, the MIC2 estimates range from 0.17 to 3.7 mg/L, and the MIC3 estimates range from 0.62 to 5.3 mg/L. In comparison, the MIC estimates for TSS from the literature (please see the spreadsheet LiteratureMIC.xls on the digital media accompanying this report) range from 1 to 40 mg/L (fig. 7). Most of the MIC estimates in table 6 are within or below the lowest quartile of values from the literature (fig. 7). This is to be expected because many of the values in figure 7 were based on values at or above the measured minimums from studies with relatively small sample sizes, whereas the values in table 6 are statistical estimates that are meant to represent expected minimums over hundreds or thousands of storms. Furthermore, values in figure 7 (and in

Table 5. Median of water-quality treatment statistics for the trapezoidal distribution and Spearman's rho correlation coefficients for best management practices (BMPs) by category.

[N, number of sites with paired inflow and outflow concentrations for at least seven storms used to calculate the median ratio statistics; LBMPV, lower bound of the most probable value; Max, maximum; Min, minimum; Rho, Spearman's correlation coefficient; UBMPV, upper bound of the most probable value; --, insufficient data. The concentration-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow concentration. The Spearman's rho correlation coefficients are calculated by using the ranks of the inflow concentrations and the associated ratios of outflow to inflow concentrations. The water-quality parameter code in parentheses is denoted by the letter p and the five-digit identification number]

International BMP category		TSS (p00530)[1]						TN (p00600)[2]						NO2NO3 (p00630)[3]					
		N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho
BR	Bioretention	8	0	0	0	1.232	-0.563	8	0.148	0.4	0.593	2.01	-0.636	3	0	0.286	0.939	1.769	0.002
CO	Composite	12	0.02	0.029	0.06	1.205	-0.588	4	0.222	0.372	0.372	1.088	-0.081	5	0.061	0.061	0.214	2.214	-0.571
DB	Detention basin	16	0.056	0.073	0.11	1.682	-0.514	2	0.141	0.417	1.998	3.121	-0.548	4	0.107	0.649	0.743	2.083	-0.309
GS	Biofilter (swale)	17	0	0.024	0.205	1.966	-0.5	9	0.174	0.642	0.642	2.27	-0.552	8	0.145	0.687	0.814	2.264	-0.265
IB	Infiltration basin	2	0	0	0	1.784	-0.675	1	0.052	0.052	0.158	2.598	-0.6	--	--	--	--	--	--
MD	Manufactured device	45	0.042	0.091	0.204	1.587	-0.515	4	0.677	0.908	0.908	1.419	-0.309	16	0.096	0.526	1.039	2.029	-0.472
MF	Media filter	24	0.035	0.068	0.104	0.906	-0.482	6	0.126	0.391	0.536	1.703	-0.318	9	0.177	1.068	1.09	2.925	-0.455
RP	Retention pond	24	0	0	0	1.254	-0.589	11	0.332	0.693	0.693	1.522	-0.508	12	0	0.004	0.076	1.24	-0.477
WB	Wetland basin	8	0.001	0.047	0.073	2.368	-0.646	3	0.272	0.394	0.394	2.181	-0.437	5	0	0	0	2.253	-0.63
WC	Wetland channel	9	0	0	0	3.539	-0.386	6	0.346	0.367	0.539	1.705	-0.595	1	0.199	0.199	0.213	1.316	-0.111

International BMP category		TP (p00665)[4]						Cd (p01027)[5]						Cu (p01042)[6]					
		N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho
BR	Bioretention	14	0.013	0.176	0.325	2.339	-0.42	--	--	--	--	--	--	4	0.067	0.071	0.073	1.336	-0.653
CO	Composite	11	0	0.126	0.17	1.562	-0.571	2	0.421	0.455	0.859	1.709	-0.346	7	0.045	0.052	0.064	1.544	-0.766
DB	Detention basin	14	0.24	0.415	0.561	1.55	-0.498	6	0.203	0.444	0.569	1.761	-0.465	11	0.151	0.415	0.628	1.221	-0.366
GS	Biofilter (swale)	17	0.105	0.669	0.827	3.556	-0.669	1	0.022	0.079	0.094	0.583		7	0.071	0.127	0.626	1.468	-0.583
IB	Infiltration basin	1	0.002	0.002	0.031	3.649	-0.292	1	0	0	0	1.036	-0.879	1	0.009	0.009	0.113	1.193	-0.806
MD	Manufactured device	29	0.286	0.445	0.664	1.533	-0.212	6	0.153	0.332	0.548	1.561	0.059	22	0.227	0.435	0.739	1.494	-0.489
MF	Media filter	24	0.161	0.21	0.228	1.597	-0.555	7	0.103	0.103	0.174	1.271	-0.808	19	0.112	0.245	0.43	1.36	-0.357
RP	Retention pond	25	0.053	0.199	0.38	1.653	-0.606	9	0	0.046	0.162	1.142	-0.646	16	0.042	0.2	0.219	1.421	-0.642
WB	Wetland basin	9	0.056	0.512	0.88	2.158	-0.517	1	0	0	0	2.415	0	3	0.123	0.305	0.323	1.333	-0.667
WC	Wetland channel	9	0.171	0.226	0.623	2.203	-0.401	1	0.073	1.254	1.254	1.401	-0.268	3	0.156	0.607	0.67	2.113	-0.775

International BMP category		Pb (p01051)[7]						Zn (p01092)[8]						Turbidity (p00076)[9]					
		N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho
BR	Bioretention	2	0.363	0.642	0.72	1.506	-0.736	6	0	0	0	1.372	-0.555	1	0.185	0.185	0.321	11.429	-0.654
CO	Composite	6	0	0	0	1.557	-0.581	8	0.071	0.117	0.164	1.522	-0.381	1	0	0	0	0.889	0.2
DB	Detention basin	9	0.058	0.278	0.335	1.168	-0.289	12	0.06	0.102	0.213	1.074	-0.56	2	0.118	0.118	0.118	1.842	-0.755
GS	Biofilter (swale)	7	0	0.094	0.14	1.995	-0.524	8	0.112	0.173	0.177	1.05	-0.337	1	0.096	0.473	0.473	1.786	-0.952
IB	Infiltration basin	1	0	0	0	0.867	-0.855	1	0	0	0	1.056	-0.842	1	0.195	0.195	0.224	1.258	-0.539
MD	Manufactured device	9	0.011	0.231	0.231	1.44	-0.394	33	0.144	0.304	0.499	1.444	-0.515	4	0.147	0.507	0.507	1.701	-0.434
MF	Media filter	18	0.008	0.008	0.008	1.066	-0.722	23	0	0.029	0.069	0.818	-0.493	2	0.042	0.042	0.27	0.504	-0.231
RP	Retention pond	22	0	0	0.03	1.341	-0.705	19	0	0.056	0.165	1.036	-0.538	4	0.034	0.035	0.049	0.975	-0.558
WB	Wetland basin	2	0.126	0.303	0.36	0.984	-0.464	5	0.076	0.276	0.528	1.336	-0.714	--	--	--	--	--	--
WC	Wetland channel	4	0	0	0	2.795	-0.381	4	0.081	0.144	0.202	2.123	-0.609	1	0.007	0.037	0.49	1.802	-0.321

Table 5. Median of water-quality treatment statistics for the trapezoidal distribution and Spearman's rho correlation coefficients for best management practices (BMPs) by category.—Continued

[N, number of sites with paired inflow and outflow concentrations for at least seven storms used to calculate the median ratio statistics; LBMPV, lower bound of the most probable value; Max, maximum; Min, minimum; Rho, Spearman's correlation coefficient; UBMPV, upper bound of the most probable value; --, insufficient data. The concentration-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow concentration. The Spearman's rho correlation coefficients are calculated by using the ranks of the inflow concentrations and the associated ratios of outflow to inflow concentrations. The water-quality parameter code in parentheses is denoted by the letter p and the five-digit identification number]

International BMP category		COD (p00340)[10]						TOC (p00680)[11]						FC (p31613)[12]					
		N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho	N	Min	LBMPV	UBMPV	Max	Rho
BR	Bioretention	2	0.103	0.177	0.54	2.034	-0.616	--	--	--	--	--	--	2	0.009	0.009	0.022	0.643	-0.677
CO	Composite	5	0.017	0.235	0.25	1.36	-0.595	6	0.166	0.47	0.581	1.713	-0.484	1	0.005	0.019	1.187	1.844	-0.234
DB	Detention basin	3	0.382	0.382	0.403	2.02	-0.37	7	0.587	0.854	0.977	1.78	-0.107	6	0	0	0	2.154	-0.187
GS	Biofilter (swale)	2	0.449	0.951	0.951	1.931	-0.415	3	0.484	0.995	0.995	1.363	-0.465	1	0	0	0	3.839	-0.58
IB	Infiltration basin	--	--	--	--	--	--	--	--	--	--	--	--	1	0	0	0	1.998	-0.155
MD	Manufactured device	15	0.136	0.349	0.454	1.462	-0.309	10	0.607	0.731	0.964	1.55	-0.191	6	0	0.165	0.407	3.265	-0.284
MF	Media filter	7	0.069	0.343	0.343	1.505	-0.476	10	0.34	0.54	0.847	1.442	-0.307	10	0	0	0	2.323	-0.595
RP	Retention pond	11	0.074	0.257	0.268	1.349	-0.723	10	0.376	0.643	0.913	1.764	-0.678	5	0	0	0	1.421	-0.151
WB	Wetland basin	1	0.393	0.855	0.855	1.357	-0.595	1	0.35	1.259	1.35	1.596	-0.524	2	0.16	0.896	0.929	1.781	-0.059
WC	Wetland channel	3	0.05	0.436	1.022	1.234	-0.399	2	0.674	0.779	0.779	1.784	-0.315	--	--	--	--	--	--

International BMP category		SSC (p80154)[13]					
		N	Min	LBMPV	UBMPV	Max	Rho
BR	Bioretention	8	0	0	0	0.885	-0.635
CO	Composite	12	0	0	0	0.791	-0.626
DB	Detention basin	16	0	0	0	1.158	-0.631
GS	Biofilter (swale)	17	0	0	0	1.545	-0.569
IB	Infiltration basin	2	0	0	0	0.902	-0.738
MD	Manufactured device	45	0.001	0.011	0.062	1.089	-0.589
MF	Media filter	24	0	0	0	0.652	-0.604
RP	Retention pond	24	0	0	0	0.822	-0.721
WB	Wetland basin	8	0	0	0	1.681	-0.759
WC	Wetland channel	9	0	0	0	2.21	-0.446

[1]Solids, suspended, water, milligrams per liter (parameter code p00530).

[2]Total nitrogen, water, unfiltered, milligrams per liter (parameter code p00600).

[3]Nitrite plus nitrate, water, unfiltered, milligrams per liter as nitrogen (parameter code p00630).

[4]Phosphorus, water, unfiltered, milligrams per liter (parameter code p00665).

[5]Cadmium, water, unfiltered, recoverable, micrograms per liter (parameter code p01027).

[6]Copper, water, unfiltered, recoverable, micrograms per liter (parameter code p01042).

[7]Lead, water, unfiltered, recoverable, micrograms per liter (parameter code p01051).

[8]Zinc, water, unfiltered, recoverable, micrograms per liter (parameter code p01092).

[9]Turbidity, water, unfiltered, nephelometric turbidity units (parameter code p00076).

[10]Chemical oxygen demand, water, unfiltered, milligrams per liter (parameter code p00340).

[11]Organic carbon, water, unfiltered, milligrams per liter (parameter code p00680).

[12]Fecal coliform, water, colonies per 100 milliliters (parameter code p31613).

[13]Suspended sediment concentration (estimated), water, milligrams per liter (parameter code p80154).

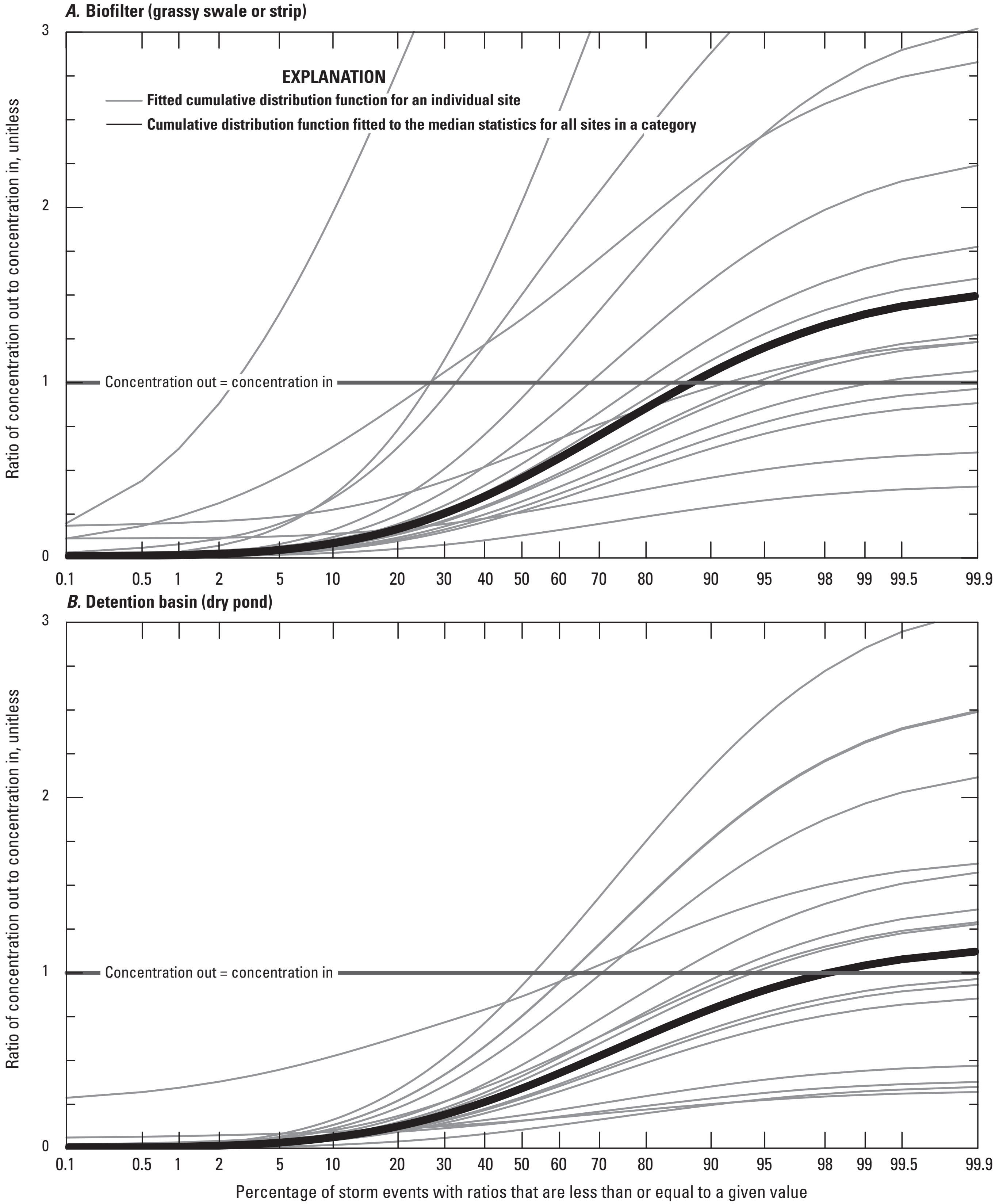

Figure 6. Fitted cumulative trapezoidal-distribution functions of the suspended sediment water-quality treatment statistics for *A,* 17 biofilter (swale) monitoring sites and *B,* 16 detention-basin monitoring sites. The graphs also show cumulative distribution functions that are fitted to the median of the flow-reduction statistics for each category.

the spreadsheet LiteratureMIC.xls) may represent analytical detection limits, one-half of the analytical detection limits, or some other substitute value, whereas the MIC estimates in this report are designed to estimate actual minimum values, which may fall below current and historic detection limits. MIC statistics for individual BMP monitoring sites are available in the spreadsheet "SiteValues-MIC.xlsx" within the compressed archive file "SiteValues.zip" in the digital media accompanying this report.

There were variations in which of the four lower-bound estimators (minimum, log-triangular, Stedinger, or MQLBE) were used for the MIC estimates shown in table 6 because the relative values of the estimators changed from dataset to dataset. The MIC0, MIC1 and MIC2 estimates are based on the minimum of the positive MIC estimates. The value of Stedinger's quantile lower-bound estimator for TSS was less than or equal to zero for 41 percent of the 202 BMP monitoring sites with TSS data; these values were therefore disqualified from further consideration. The value of the log-triangular lower-bound estimate, which is by definition greater than zero, was most commonly the minimum value among the positive-value estimators. The percentages of values that were the minimum positive value among the estimates were: 3 percent for the minimum measured value, 48 percent for the log-triangular lower bound estimate, 31 percent for the modified quantile lower-bound estimate, and, 18 percent for Stedinger's quantile lower-bound estimator. The MIC3 estimates are based on the median of positive MIC estimates; 50 percent of MIC3 estimates were the average of two different estimators and 9 percent were tied values. When cases of tied values are ignored, the percentages for each type of estimator were 12.6 percent for the minimum measured value, 21 percent for the log-triangular lower-bound estimate, 9.7 percent for the modified quantile lower-bound estimate, and, 6.7 percent for Stedinger's quantile lower-bound estimator.

Because the MIC commonly is thought to represent a local background concentration rather than an absolute limit for a BMP design, it may be desirable to adjust the expected MIC to reflect the conditions at a site by using expected inflow concentrations. The effect of the contributing area is described by Leisenring and others (2010, 2011) as the "clean water in = clean water out" phenomenon. The MIC estimates shown in table 6 for a given BMP category do not account for the effect of the surrounding area, which may not be known. In theory, comparison of the geometric mean inflow concentrations from site to site should represent variations in inflow concentrations that may be used to adjust MIC estimates on the basis of the background conditions at a given site. If correlations between the MIC estimators and the geometric mean inflow concentrations are robust, regression equations may be used to refine category estimates based on influent water quality. Pearson's r for the concentrations and common logarithms of concentrations (denoted as r(log)) and Spearman's rho on the ranks of the concentrations for the MIC3 estimators of TSS and 11 other constituents are shown in table 6. In this analysis, each site that has a geometric-mean inflow concentration and a MIC value is used as a single data point. This table includes 11 types of BMPs and 12 different water-quality constituents; 45 percent of these combinations do not have the proper data at enough sites to calculate a correlation coefficient. Among the absolute values of the calculated Pearson's r, 36 percent are less than 0.5 (defined herein as weak correlations), 29 percent are greater than or equal to 0.5 and less than 0.75 (defined herein as moderate correlations), 16 percent are greater than or equal to 0.75 and less than 0.85 (defined herein as semistrong correlations), and 19 percent are greater than or equal to 0.85 (defined herein as strong correlations). Among the absolute values of the Pearson's r for the logarithms of data r(log), 29 percent are weak correlations, 42 percent are moderate correlations, 18 percent are semistrong correlations, and 11 percent are strong correlations. Among the absolute values of Spearman's rho, 44 percent are weak correlations, 39 percent are moderate correlations, 12 percent are semistrong correlations, and 5 percent are strong correlations.

Spearman's rho is a robust estimator of a monotonic relation between two variables that is resistant to outliers (Helsel and Hirsch, 2002). If a rho value is equivalent to one or more of the associated r values, then it may be assumed that the representative linear relation also is robust. If the rho value is greater than one or more of the associated r values, it may be assumed that a different transformation of either the geometric mean or MIC estimates (or both) may produce a linear relation that corresponds to the rho estimate. However, if one or more r value is substantially greater than the associated rho value, it may be assumed that one or more far outliers are responsible for artificially inflating the r values. Taking the logarithms of the values tends to decrease the leverage of high outliers, but this increases the leverage of small outliers. Among the 80 entries in table 6 that have correlation coefficients, only 2 entries have the r, r(log), and rho values that are the strong correlations, which would provide highly quantitative estimates of MIC values from the geometric mean of inflow values. Only 9 entries have semistrong r and rho values, 10 entries have semistrong r(log) and rho values and 8 have semistrong r, r(log), and rho values that would provide semiquantitative estimates of MIC values from the geometric mean of inflow values. Twenty-seven entries have moderate r and rho values, 40 entries have moderate r(log) and rho values, and 19 have moderate r, r(log), and rho values that would provide qualitative estimates of MIC values from the geometric mean of inflow values. These values indicate that regression relations developed by using the logarithms of the MIC estimates and the geometric mean of inflows may provide better predictive power than the untransformed alternative. However, development of regression equations may be limited by the number of data points or the range of available geometric mean influent concentrations.

Figure 8 shows the different MIC estimates for TSS from biofilters (grass strips or swales) from 22 sites with geometric mean influent concentrations that range from 9.9 to 165 mg/L. Although there is some trend and the slope of the regression line for estimating the median and minimum of MIC values

Table 6. Estimates of the minimum irreducible concentration (MIC) and correlations between the geometric mean concentration of inflows and the median of MIC estimates for individual best management practice (BMP) monitoring sites for each selected BMP category.

[N, the number of BMP sites with data with an influent geometric mean; R, Pearson's correlation coefficient; R(log), Pearson's correlation coefficient for the common logarithms of data; Rho, Spearman's rank correlation coefficient; Each MIC0 estimate is the category minimum of the minimum of positive MIC estimates from available sites. Each MIC1 estimate is the 25th percentile. Each MIC 2 estimate is the category median of the minimum of MIC estimates from available sites. Each MIC 3 estimate is the category median of the median MIC of the minimum of MIC estimates from available sites. The correlation coefficients were calculated using the MIC3 estimates and and the geometric mean of influents. Small values are expressed in scientific notation. The MIC estimates for total suspended solids (p00530) are applicable for estimating the MIC of suspended sediment concentration (p80154) because differences in the results of these analytical methods are small once the large grain-size fractions are removed]

International BMP category		TSS (p00530)[1]								TN (p00600)[2]								NO2NO3 (p00630)[3]							
		MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho
BR	Bioretention	0.005	0.06	0.17	0.62	8/8	-0.27	0.07	0.00	0.007	0.09	0.26	0.38	8/8	0.68	0.73	0.72	0.001	0.004	0.006	0.01	3/3	--	--	--
CO	Composite	0.006	0.2	1.9	3.8	13/13	-0.30	0.03	-0.01	0.043	0.06	0.17	0.57	5/4	0.46	0.80	0.40	0.002	0.05	0.09	0.17	7/7	0.67	0.60	0.29
DB	Detention basin	0.007	0.89	2.2	4.2	20/20	0.51	0.76	0.74	0.049	0.1	0.15	0.50	3/3	--	--	--	3.E-04	0.02	0.12	0.19	7/6	0.94	0.85	0.89
GS	Biofilter (swale)	0.16	1.0	2.6	5.0	22/22	0.50	0.44	0.49	0.098	0.17	0.23	0.37	9/9	0.70	0.75	0.73	9.E-04	0.008	0.01	0.03	8/8	0.92	0.58	0.42
IB	Infiltration basin	0.08	1.9	3.7	4.7	2/2	--	--	--	0.38	0.38	0.38	0.76	1/1	--	--	--	--	--	--	--	0/0	--	--	--
LD	Low impact development	0.7	0.7	0.7	1.3	1/1	--	--	--	--	--	--	--	0/0	--	--	--	--	--	--	--	0/0	--	--	--
MD	Manufactured device	0.002	0.43	1.2	2.4	53/46	0.76	0.53	0.62	0.046	0.21	0.66	1.150	4/4	0.98	0.97	0.95	0.002	0.005	0.02	0.04	16/15	0.43	0.50	0.30
MF	Media filter	0.12	0.43	0.72	1.4	26/25	0.58	0.22	0.09	0.001	0.05	0.12	0.149	6/6	0.94	0.81	0.83	6.E-04	0.01	0.04	0.14	10/10	0.82	0.57	0.85
RP	Retention pond	0.007	0.74	2.4	4.6	34/31	0.24	0.27	0.12	0.03	0.14	0.23	0.521	12/12	0.39	0.66	0.62	2.E-06	0.008	0.02	0.03	16/15	0.66	0.85	0.50
WB	Wetland basin	0.012	0.28	1.1	5.3	14/10	0.36	0.30	0.26	0.007	0.04	0.12	0.387	5/3	--	--	--	4.E-05	0.001	0.009	0.02	7/5	0.64	0.75	0.30
WC	Wetland channel	0.006	0.2	1.7	2.8	9/9	0.90	0.64	0.40	0.043	0.11	0.38	0.565	7/6	0.87	0.96	0.66	0.57	0.57	0.57	0.76	1/0	--	--	--
International BMP category		TP (p00665)[4]								Cd (p01027)[5]								Cu (p01042)[6]							
		MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho
BR	Bioretention	9.E-04	0.01	0.02	0.04	15/14	-0.09	-0.07	0.02	0.40	0.40	0.40	0.65	1/1	--	--	--	1.4	2.3	3.1	3.8	3/3	--	--	--
CO	Composite	0.002	0.005	0.007	0.03	13/12	0.33	0.39	0.34	0.02	0.04	0.06	0.07	3/3	--	--	--	0.09	0.4	0.58	1.4	9/8	0.51	0.81	0.83
DB	Detention basin	0.007	0.03	0.04	0.06	21/17	0.29	0.34	0.24	0.05	0.08	0.08	0.20	7/7	0.73	0.63	0.68	0.14	1.1	3.5	5.0	13/12	0.58	0.82	0.87
GS	Biofilter (swale)	1.E-04	0.01	0.05	0.12	22/22	0.63	0.74	0.68	0.07	0.08	0.10	0.20	6/6	0.42	0.33	0.49	0.5	1.7	3.3	4.3	12/12	0.29	0.68	0.48
IB	Infiltration basin	0.002	0.002	0.002	0.00	1/1	--	--	--	0.02	0.02	0.02	0.08	1/1	--	--	--	3.4	3.4	3.4	6.9	1/1	--	--	--
LD	Low impact development	0.03	0.03	0.03	0.04	1/1	--	--	--	--	--	--	--	0/0	--	--	--	0.95	0.95	0.95	1.2	1/0	--	--	--
MD	Manufactured device	2.E-04	0.003	0.01	0.02	40/33	0.78	0.67	0.67	0.00	0.004	0.05	0.14	11/8	0.86	0.43	0.21	0.12	0.6	1.2	2.6	31/24	0.49	0.64	0.60
MF	Media filter	7.E-04	0.005	0.01	0.03	26/25	0.63	0.65	0.76	0.02	0.06	0.09	0.20	10/9	0.99	0.94	0.73	0.26	0.28	0.40	1.4	20/20	0.90	0.73	0.57
RP	Retention pond	5.E-04	0.006	0.01	0.03	35/33	0.63	0.53	0.52	0.002	0.008	0.02	0.07	9/7	0.73	0.68	0.68	0.13	0.48	0.99	1.7	19/16	0.16	0.44	0.46
WB	Wetland basin	9.E-04	0.008	0.02	0.04	16/12	0.84	0.43	0.24	0.002	0.004	0.006	0.02	2/2	--	--	--	0.11	0.26	1.6	2.7	4/4	0.88	0.64	0.20
WC	Wetland channel	2.E-04	0.007	0.02	0.04	10/10	0.82	0.62	0.58	0.02	0.02	0.02	0.04	1/1	--	--	--	0.30	0.43	0.56	0.88	3/3	--	--	--

Table 6. Estimates of the minimum irreducible concentration (MIC) and correlations between the geometric mean concentration of inflows and the median of MIC estimates for individual best management practice (BMP) monitoring sites for each selected BMP category.—Continued

[N, the number of BMP sites with data with an influent geometric mean; R, Pearson's correlation coefficient; R(log), Pearson's correlation coefficient for the common logarithms of data; Rho, Spearman's rank correlation coefficient; Each MIC0 estimate is the category minimum of the minimum of positive MIC estimates from available sites. Each MIC1 estimate is the 25th percentile. Each MIC 2 estimate is the category median of the minimum of MIC estimates from available sites. Each MIC 3 estimate is the category median of the median MIC of the minimum of MIC estimates from available sites. The correlation coefficients were calculated using the MIC3 estimates and and the geometric mean of influents. Small values are expressed in scientific notation. The MIC estimates for total suspended solids (p00530) are applicable for estimating the MIC of suspended sediment concentration (p80154) because differences in the results of these analytical methods are small once the large grain-size fractions are removed]

International BMP category		Pb (p01051)[7]								Zn (p01092)[8]								Turbidity (p00076)[9]							
		MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho
BR	Bioretention	1.6	1.6	1.6	2.4	1/1	--	--	--	0.04	0.30	0.52	1.3	6/6	0.08	0.52	0.54	8	8.0	8.0	15	1/1	--	--	--
CO	Composite	0.77	0.21	0.49	1.8	8/7	0.16	0.54	0.36	0.08	0.14	8.8	14	9/9	0.84	0.48	0.52	0.03	0.03	0.03	0.50	1/1	--	--	--
DB	Detention basin	0.55	0.76	1.1	5.1	12/10	0.68	0.87	0.74	0.55	2.8	13	22	17/14	0.79	0.76	0.82	0.15	2.1	2.5	4.1	5/4	0.22	0.64	0.20
GS	Biofilter (swale)	0.03	0.62	0.87	1.6	12/12	0.88	0.76	0.66	0.39	2.1	5.1	18	9/9	0.47	0.69	0.61	2.5	2.5	2.5	4.8	1/1	--	--	--
IB	Infiltration basin	2.7	2.7	2.7	4.1	1/1	--	--	--	35	35	35	41	1/1	--	--	--	1.0	1.0	1.0	3.2	1/1	--	--	--
LD	Low impact development	0.02	0.02	0.02	0.07	1/0	--	--	--	2.0	2.0	2.0	4.0	1/0	--	--	--	--	--	--	--	0/0	--	--	--
MD	Manufactured device	2.E-05	0.08	0.36	0.65	20/13	0.06	0.55	0.19	0.17	4.5	8.6	18	41/34	0.81	0.65	0.67	0.04	0.04	0.09	0.86	4/4	-0.29	0.26	0.32
MF	Media filter	0.05	0.22	0.40	1.0	18/18	0.72	0.45	0.23	0.04	0.74	1.3	5.5	24/24	0.76	0.45	0.2	0.35	0.40	0.44	2.1	3/2	--	--	--
RP	Retention pond	0.008	0.18	0.40	0.91	24/22	0.03	0.53	0.45	0.1	1.7	5.0	8.0	27/24	0.14	0.50	0.40	0.20	0.20	0.49	1.7	5/5	-0.28	-0.10	0.30
WB	Wetland basin	0.19	1.0	1.3	1.9	4/4	-0.11	-0.20	-0.60	0.1	8.7	9.8	19	7/6	0.76	0.75	0.77	0.11	0.50	0.83	2.9	2/1	--	--	--
WC	Wetland channel	0.13	0.20	0.22	0.22	4/4	0.91	0.88	0.80	0.08	0.39	1.2	3.5	4/4	0.89	0.36	0.40	0.03	0.03	0.03	0.50	1/1	--	--	--

International BMP category		COD (p00340)[10]								TOC (p00680)[11]								FC (p31613)[12]							
		MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho	MIC0	MIC1	MIC2	MIC3	N	R	R(log)	Rho
BR	Bioretention	0.77	1.1	1.5	1.8	3/2	--	--	--	--	--	--	--	--	--	--	--	0.01	57	114	1100	2/2	--	--	--
CO	Composite	0.45	2.3	2.9	8.5	7/6	0.09	0.26	0.20	0.25	0.89	1.1	4.4	8/7	0.76	0.82	0.71	171	320	430	1300	4/3	--	--	--
DB	Detention basin	0.26	2.1	4.7	14	7/4	0.75	0.91	0.80	0.19	1.5	3.1	5.5	10/8	0.55	0.77	0.05	0.18	4.0	27	88	10/14	0.64	0.58	0.52
GS	Biofilter (swale)	2.5	5.6	9.7	19	4/4	0.59	0.65	0.63	0.75	1.7	3.9	6.0	6/6	0.75	0.79	0.77	4.2	5.0	48	300	5/3	--	--	--
IB	Infiltration basin	--	--	--	--	0/0	--	--	--	--	--	--	--	0/0	--	--	--	--	--	--	--	0/0	--	--	--
LD	Low impact development	1.0	1.0	1.0	4.4	1/0	--	--	--	--	--	--	--	0/0	--	--	--	--	--	--	--	0/0	--	--	--
MD	Manufactured device	0.15	3.2	5.0	13	17/17	0.67	0.69	0.68	0.27	1.1	2.0	4.4	14/11	0.74	0.65	0.58	0.01	0.18	1.0	9.0	11/10	0.95	0.79	0.78
MF	Media filter	0.65	1.7	2.4	5.8	8/8	0.44	0.51	0.50	0.25	0.68	2.0	4.7	16/16	0.39	0.58	0.54	0.01	1.5	5.0	34	16/14	0.05	0.28	0.32
RP	Retention pond	0.006	2.3	5.1	10	16/12	0.03	0.18	0.07	0.61	1.6	3.0	5.2	13/12	0.68	0.62	0.73	0.00	1.0	6.0	18	9/7	0.93	0.88	0.76
WB	Wetland basin	3.2	9.0	9.1	13	5/3	--	--	--	1.6	3.7	5.7	7.8	2/2	--	--	--	3.0	150	290	1700	2/2	--	--	--
WC	Wetland channel	2.5	2.7	2.9	16	3/3	--	--	--	0.25	0.45	0.66	5.7	2/2	--	--	--	--	--	--	--	--	--	--	--

[1]Solids, suspended, water, milligrams per liter (parameter code p00530).

[2]Total nitrogen, water, unfiltered, milligrams per liter (parameter code p00600).

[3]Nitrite plus nitrate, water, unfiltered, milligrams per liter as nitrogen (parameter code p00630).

[4]Phosphorus, water, unfiltered, milligrams per liter (parameter code p00665).

[5]Cadmium, water, unfiltered, recoverable, micrograms per liter (parameter code p01027).

[6]Copper, water, unfiltered, recoverable, micrograms per liter (parameter code p01042).

[7]Lead, water, unfiltered, recoverable, micrograms per liter (parameter code p01051).

[8]Zinc, water, unfiltered, recoverable, micrograms per liter (parameter code p01092).

[9]Turbidity, water, unfiltered, nephelometric turbidity units (parameter code p00076).

[10]Chemical oxygen demand, water, unfiltered, milligrams per liter (parameter code p00340).

[11]Organic carbon, water, unfiltered, milligrams per liter (parameter code p00680).

[12]Fecal coliform, water, colonies per 100 milliliters (parameter code p31613).

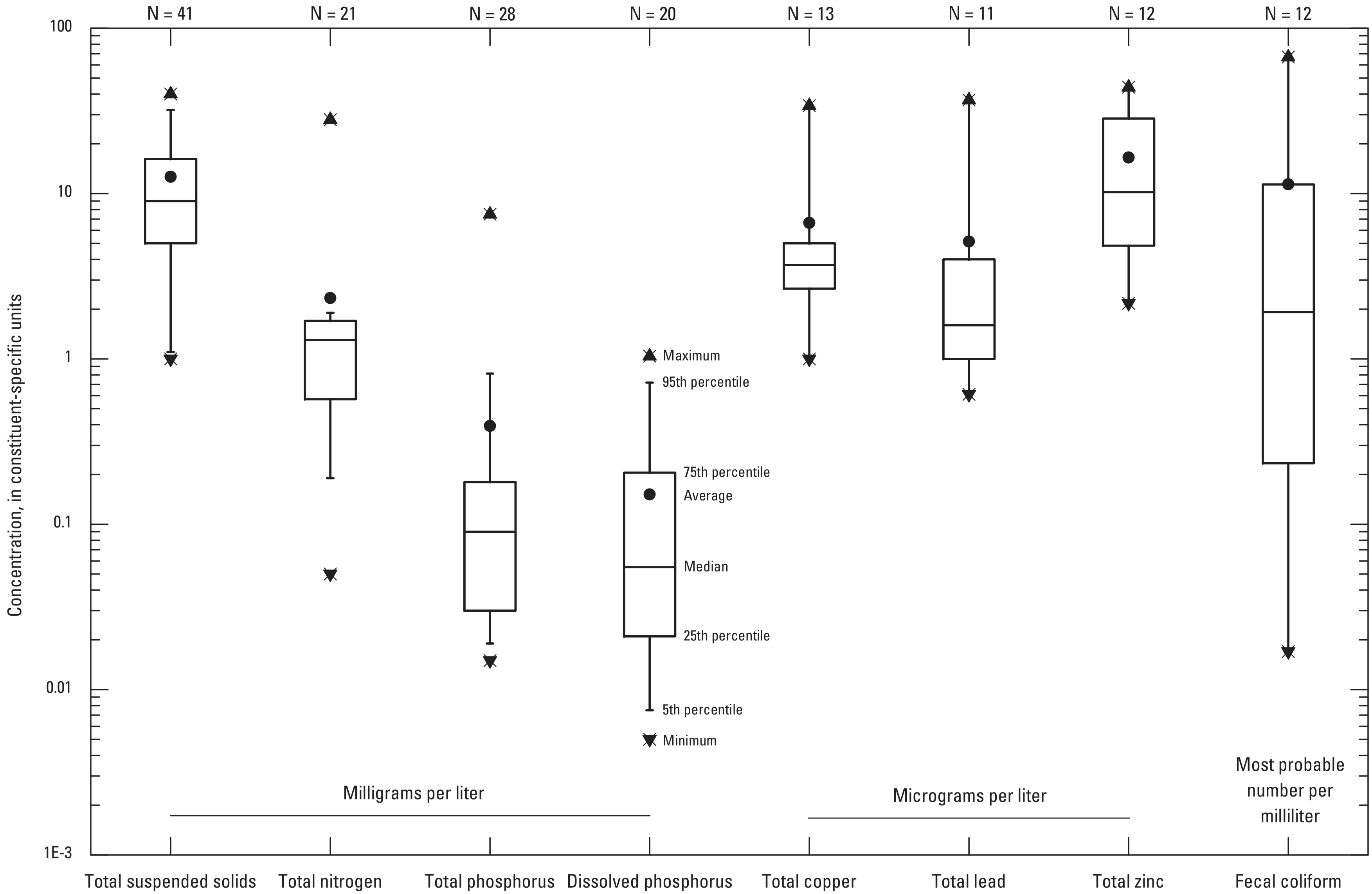

Figure 7. The populations of minimum irreducible concentration (MIC) estimates from the literature for selected runoff-quality constituents (please see the spreadsheet LiteratureMIC.xls on the digital media accompanying this report for individual values of these and other constituents). N is the number of sites.

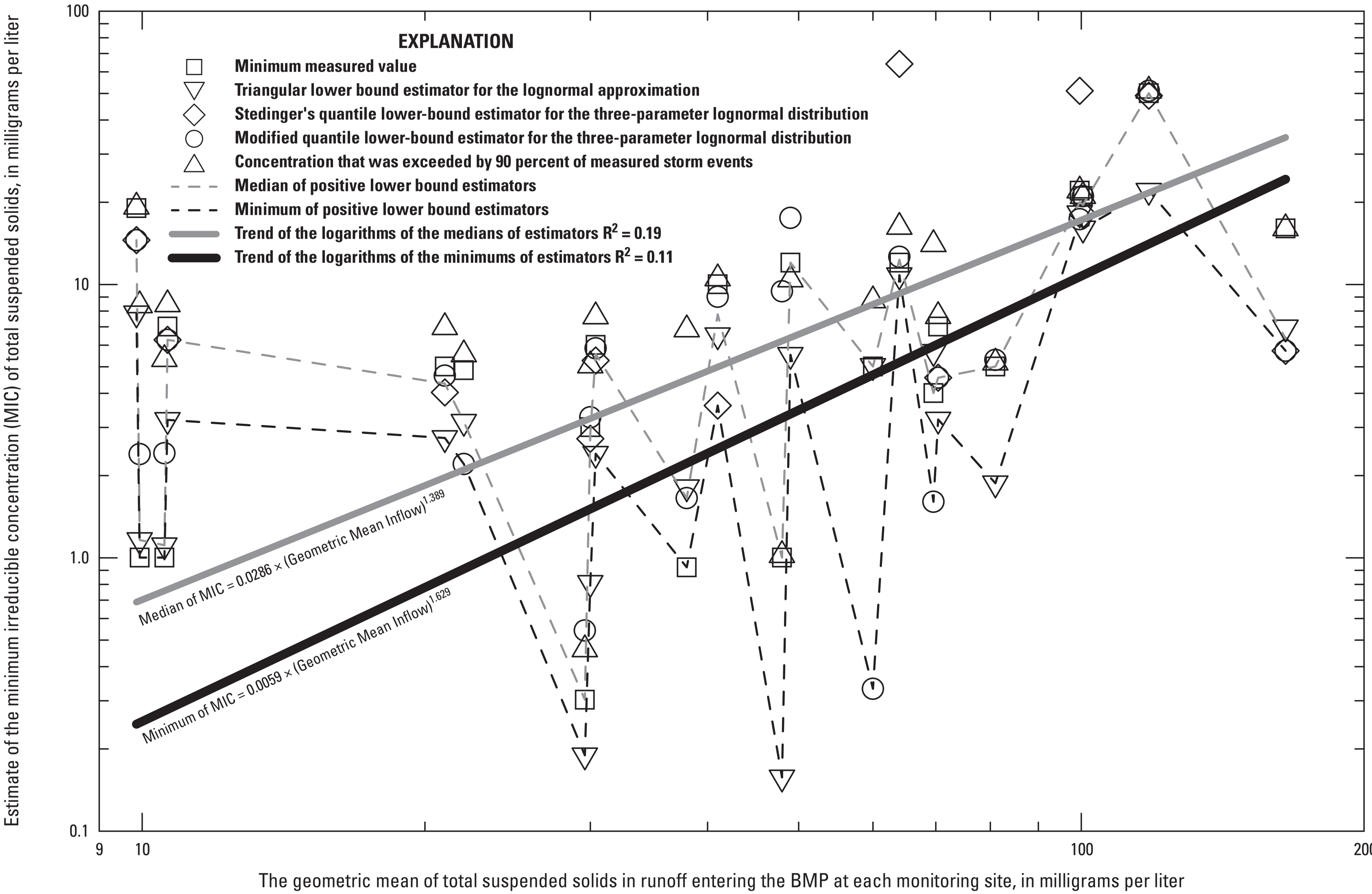

Figure 8. The variation in estimators of the minimum irreducible concentrations (MICs) of total suspended solids in effluents from biofilters (grass strips and grass swales) with respect to the geometric means of inflow concentrations measured at 22 sites. Ten of the values of Stedinger's quantile lower-bound estimator for the three-parameter lognormal distribution are less than zero.

at each site is positive, these relations are very weak with R^2 values of 0.19 and 0.11, respectively. The correlation coefficients for this group of sites are less than or equal to 0.5, so the regression lines shown on the graph are qualitative at best. These equations, which were developed by using the Kendall-Theil Robust line, seem to produce estimates that are much too low for sites with geometric-mean influent concentrations less than 20 mg/L. These equations, however, do seem to produce reasonable estimates for sites with higher influent concentrations. Ignoring geometric mean influent concentrations below 30 mg/L increases the R^2 values to about 0.4, which is still qualitative at best. Although the lines are nonquantitative, the positive slopes would indicate that it would be prudent to select higher MIC values for modeling sites with higher inflow concentrations.

All the original MIC estimates used to calculate the statistics in table 6 are included in the spreadsheet “SiteValues-MIC.xlsx” on the digital media accompanying this report. A value of -9999 for the influent geometric mean indicates that there were no influent data available. A value of -8888 for the influent geometric mean indicates that fewer than five values measured above one or more detection limits were available. The values in the spreadsheet include the four MIC estimators (minimum, log-triangular, Stedinger, and MQLBE) described in this report and the 10th percentile of measured values for each BMP monitoring site. The spreadsheet also contains information about the dataset, the site, and the number of available concentrations above and below detection limits.

Summary

The U.S. Geological Survey (USGS) developed the Stochastic Empirical Loading and Dilution Model (SELDM) in cooperation with the Federal Highway Administration (FHWA) to indicate the risk for stormwater concentrations, flows, and loads to be above user-selected water-quality goals and the potential effectiveness of mitigation measures to reduce such risks (Granato, 2013). SELDM models the potential effect of mitigation measures by using Monte Carlo methods with statistics approximating the net effects of structural best management practices (BMPs). In this report, structural BMPs are defined as the components of the drainage pathway between the source of runoff and a stormwater discharge location that affect the volume, timing, or quality of runoff. SELDM uses a simple stochastic statistical model of BMP performance to develop planning-level estimates of runoff-event characteristics rather than a complex theoretical or physical model. This statistical approach can be used to represent a single BMP or an assemblage of BMPs. The SELDM BMP-treatment module has provisions for stochastic modeling of three stormwater treatments: volume reduction, hydrograph extension, and water-quality treatment. The BMP runoff-control options alter the highway, upstream, and downstream outputs from the model. If BMP volume-reduction statistics are specified, the highway-runoff flows and loads will be affected accordingly. If BMP volume reductions are specified but concentration changes are not, then the highway-runoff and BMP discharge concentrations will be the same, but the BMP discharge loads and the concurrent downstream loads and concentrations will all be different. If BMP hydrograph extension is specified, the concurrent upstream and downstream flows and loads will be different than those for the untreated runoff because the discharge period will be extended to include more of the upstream flow and loads. If BMP water-quality treatment statistics are specified, BMP discharge concentrations and loads will be affected as well as downstream concentrations and loads.

This report describes methods for calculating the trapezoidal-distribution statistics and rank correlation coefficients for stochastic modeling of volume reduction, hydrograph extension, and water-quality treatment by structural stormwater BMPs and provides BMP performance statistics for these variables. The trapezoidal-distribution statistics and rank correlation coefficients are different from the statistics commonly used to characterize or compare BMPs. They are designed to provide a stochastic transfer function to approximate the quantity, quality, and duration of BMP effluents given a population of inflow values. This report also provides robust methods for estimating the minimum irreducible concentration (MIC), which is the lowest expected effluent concentration from a particular BMP site or a class of BMPs. This study was done to inform professional judgments for stochastic modeling of volume, timing, and quality of BMP effluent given a stochastic population of inflows from a user-defined site of interest. The data, information, and statistics developed in this analysis are intended to facilitate stochastic planning-level analysis of the potential effects of stormwater runoff on receiving waters at unmonitored sites (or sites with limited monitoring data). The methods and statistics described in this report were designed for use with SELDM, but may be used with other methods or models. The methods and statistics described in this report are designed to help evaluate the risk for adverse effects of runoff on receiving waters, the potential need for mitigation measures, and the potential effectiveness of such management measures for reducing these risks. A Microsoft Access® database application and several Microsoft Excel® Spreadsheet tools that were used to estimate these statistics are included in the digital media accompanying this report for further documentation of methods and for future use.

In SELDM, volume-reduction, hydrograph-extension, and water-quality treatment variables are modeled by using the trapezoidal distribution and the rank correlation with the associated highway-runoff variables. This family of distributions was selected for modeling BMP performance measures because it can be parameterized by using expert judgment or by fitting the distribution to data. The triangular distribution, which is a special case of the trapezoidal distribution, commonly is suggested when uncertainties in input data that may be used to define a parametric distribution are large. The trapezoidal distribution is bounded by a selected minimum and maximum value. The trapezoidal distribution is further defined by the lower and upper most probable values. When data are uncertain or are limited in scope, use of a bounded distribution reduces the chance that unrealistic output values will be generated by extrapolating a distribution beyond the range of available data.

Volume reduction by BMPs is the practice of retaining, detaining, or routing runoff flows to increase the amount of infiltration, evapotranspiration, or diversion between the pavement and the outfall. Although the term “volume reduction” is used to describe this process, outflows can exceed inflows, and therefore volume-reduction ratios may be larger than one. Outflows may exceed inflows if there is carryover in BMP storage from one runoff event to the next or if there is groundwater discharge into the BMP during some events. SELDM models the potential effects of BMPs on the volume of runoff by generating a stochastic population of the ratios of outflow to inflow volumes and applying these ratios to the stochastic population of inflow volumes from the site of interest. In this study, volume-reduction statistics were developed for 7 BMP categories using data from 94 BMP monitoring sites with 3 or more storm events. The medians of the best-fit statistics for each category were selected to construct generalized cumulative distribution functions for volume reductions. Rank correlation statistics were developed for 7 BMP categories using data from 67 BMP monitoring sites with 7 or more storm events. Interpretation of the correlation coefficients indicates that selection of a Spearman’s rho value that is the average of the median and maximum values for the BMP category may help generate realistic simulation results in SELDM.

Hydrograph extension by BMPs is the practice of slowing the discharge of runoff flows and releasing these flows to the stream over an extended period of time. Hydrograph extension is defined as the duration in hours of discharge from the BMP that occurs after runoff from the highway site has ceased. SELDM calculates hydrograph-extension times (in hours) from a BMP or series of BMPs (Granato, 2013). Hydrograph extension is modeled to represent how BMPs can increase dilution in receiving waters by extending the duration of runoff from the highway site. In this study, hydrograph-extension statistics were developed for 5 BMP categories using data from 40 BMP monitoring sites with 3 or more storm events. The medians of the best-fit statistics for each category were selected to construct generalized cumulative distribution functions for hydrograph extensions, but professional judgment for estimating flow extension ratios may be warranted because measurements of flow volume were made only during the collection of flow-weighted water samples in many older studies. Rank correlation statistics were developed for 5 BMP categories using data from 26 BMP monitoring sites with 7 or more storm events. As with volume reduction, interpretation of available data indicates that selection of a Spearman’s rho value that is the average of the median and maximum values for the BMP category may help generate realistic simulation results in SELDM.

Water-quality treatment is the practice of using physical and chemical processes in an attempt to reduce the concentration of runoff constituents in stormflow. Although the term “concentration reduction” commonly is used to describe this process, concentrations in outflows can exceed inflows, and therefore water-quality treatment ratios may be larger than one. Outflow concentrations may exceed inflow concentrations if there is carryover in BMP storage from one runoff event to the next; if physical, chemical, or biological processes mobilize constituents between storms; or if flow through the BMP mobilizes previously retained constituents during some events. Outflow concentrations also may exceed inflow concentrations if the concentrations in runoff entering the BMP are less than minimum background concentrations produced by the BMP. These low background concentrations are known as minimum irreducible concentrations (MIC). In this study, water-quality treatment statistics were developed for 13 commonly measured runoff-quality constituents by using data from more than 165 monitoring sites (representing 10 BMP categories) with paired inflow and outflow concentrations from 7 or more storm events. The selected constituents included turbidity, sediment, and solids; nutrients; total metals; organic carbon; and fecal coliforms. The median of the best-fit statistics for each category was selected to construct generalized cumulative distribution functions for water-quality treatment ratios. With only a few exceptions, the rank correlation coefficients calculated for water-quality treatment ratios are negative, indicating that the larger ratios are associated with the smaller concentrations. The rank correlations generally are moderate (most are between -0.3 and -0.7), so there may be some higher inflow concentrations that are greater than effluent concentrations.

In this study, MIC statistics were developed for 12 runoff-quality constituents commonly measured in highway and urban runoff studies by using data from 11 BMP categories and more than 167 monitoring sites. The primary MIC variable selected for each category is the MIC1 estimate, which is the 25th percentile of the minimum of MIC estimates from available sites. Alternatives are the MIC0 estimate, which is the category minimum of minimum MIC estimates; the MIC2 estimate, which is the category median of the minimum of MIC estimates; and the MIC3 estimate, which is the category median of the median of MIC estimates from available sites. For an individual site the MIC4 estimate, which is based on the median of MIC estimates at that site, may be most representative. The MIC estimates developed in this study are generally less than or equal to values compiled from the literature because the MIC values in this study are estimates of the population minimums rather than sample minimums. Correlation analysis indicates that the MIC estimates were weakly correlated with the geometric mean of inflow values, which indicates that there may be a qualitative or semiquantitative link between the inflow quality and the MIC. Correlations are weak because the MIC is influenced by the inflow water quality and the capability of each BMP to reduce inflow concentrations.

References Cited

Abdel-Megeed, S.M., 1984, Accuracy of correlation coefficient with limited number of points: The Journal of Experimental Education, v. 52, no. 4, p. 188–191.

Adams, B.J., Fraser, H.G., Howard, C.D.D., and Hanafy, M.S., 1986, Meteorological data analysis for drainage system design: Journal of Environmental Engineering, v. 112, no. 5, p. 827–848.

Adams, B.J., and Papa, Fabian, 2000, Urban stormwater management planning with analytical probabilistic models: New York, John Wiley & Sons, Inc., 358 p.

American Society of Civil Engineers and Water Environment Federation, 1992, Design and construction of urban stormwater management systems: New York, American Society of Civil Engineers, Manuals and Report of Engineering Practice no. 77, (also published as Alexandria, Va., Water Environment Federation, Manual of Practice no. FD–20) [variously paged].

American Society of Civil Engineers and Water Environment Federation, 1998, Urban runoff quality management: New York, American Society of Civil Engineers, Manuals and Report of Engineering Practice no. 87, (also published as Alexandria, Va., Water Environment Federation, Manual of Practice no. 23) [variously paged].

Athayde, D.N., Shelley, P.E., Driscoll, E.D., and Boyd, G.B., 1983, Results of the nationwide urban runoff program: v. 1, final report: U.S. Environmental Protection Agency, Water Planning Division, WH–554, 186 p.

Back, W.E., Boles, W.W., and Fry, G.T., 2000, Defining triangular probability distributions from historical cost data: Journal of Construction Engineering, v. 126, no. 1, p. 29–37.

Barrett, M.E., 2005, Performance comparison of structural stormwater best management practices: Water Environment Research, v. 77, no. 6, p. 78–86.

Barrett, M.E., 2008, Comparison of BMP performance using the International BMP Database: Journal of Irrigation and Drainage Engineering, v. 134, no. 5, p. 556–561.

Barrett, Michael, Lantin, Anna, and Austrheim-Smith, Steve, 2004, Stormwater pollutant removal in roadside vegetated buffer strips: Transportation Research Record 1890, p. 129–140.

Barrett, Michael, Leisenring, Marc, Pomeroy, Christine, Poresky, Aaron, Roesner, Larry, Rowney, A.C., and Strecker, Eric, 2013, Linking BMP systems performance to receiving water protection—BMP performance algorithms: Alexandria, Va., Water Environment Research Foundation, Report 06–SW–1, 150 p.

Benšic, Mirta, 2014, Fitting distribution to data by a generalized nonlinear least squares method: Communications in Statistics-Simulation and Computation, v. 43, no. 4, p. 687–705.

Brown, S.A., Schall, J.D., Morris, J.L., Doherty, C.L., Stein, S.M., and Warner, J.C., 2009, Urban drainage design manual—Hydraulic Engineering Circular 22 (3d ed.): Federal Highway Administration Report FHWA–NHI–10–009 HEC–22, 478 p.

Burton, G.A., Jr., and Pitt, R., 2002, Stormwater effects handbook—A tool box for watershed managers, scientists, and engineers: Boca Raton, Fla., Lewis Publishers, CRC Press, 911 p.

California Department of Transportation, 2009, BMP pilot study guidance manual: California Department of Transportation, Division of Environmental Analysis, Stormwater Program, CTSW–RT–06–171.02.1, 368 p.

Caruso, J.C., and Cliff, Norman, 1997, Empirical size, coverage, and power of confidence intervals for Spearman's rho: Educational and Psychological Measurement, v. 57, no. 4, p. 637–654.

Cazenas, P.A., Bank, F.G., and Shrouds, J.M., 1996, Guidance on developing water-quality action plans: Federal Highway Administration, Office of Natural Environment, 9 p.

Chapman, Cameron, and Horner, R.R., 2010, Performance assessment of a street-drainage bioretention system: Water Environment Research, v. 82, no. 2, p. 109–119.

Chen, Jieyun, and Adams, B.J., 2005, Analysis of storage facilities for urban stormwater quantity control: Advances in Water Resources, v. 28, p. 377–392.

Chen, Jieyun, and Adams, B.J., 2007, Development of analytical models for estimation of urban stormwater runoff: Journal of Hydrology, v. 336, p. 458–469.

Chow, V.T., 1954, The log-probability law and its engineering applications: Proceedings of the American Society of Civil Engineers, v. 80, no. 536, 25 p.

Chow, V.T., Maidment, D.R., and Mays, L.W., 1988, Applied hydrology: New York, McGraw-Hill, Inc., 572 p.

Church, P.E., Granato, G.E., and Owens, D.W., 2003, Basic requirements for collecting, documenting, and reporting precipitation and stormwater-flow measurements, *in* Granato, G.E., Zenone, Chester, and Cazenas, P.A., eds., National highway runoff water-quality data and methodology synthesis, v. 1—Technical issues for monitoring highway runoff and urban stormwater: Federal Highway Administration Report FHWA–EP–03–054, p. 47–79.

Clar, M.L., Barfield, B.J., and O'Connor, T.P., 2004a, Stormwater best management practice design guide, v. 1, General considerations: U.S. Environmental Protection Agency Report EPA/600/R–04/121, 179 p.

Clar, M.L., Barfield, B.J., and O'Connor, T.P., 2004b, Stormwater best management practice design guide, v. 2, Vegetative biofilters: U.S. Environmental Protection Agency Report EPA/600/R–04/121A, 194 p.

Clary, Jane, Leisenring, Marc, and Hobson, Paul, 2011, International stormwater best management practices (BMP) database pollutant category summary—Metals: Water Environment Research Foundation, accessed January 1, 2012, at http://www.bmpdatabase.org/.

Clary, Jane, Leisenring, Marc, and Jeray, Joe, 2010, International stormwater best management practices (BMP) database pollutant category summary—Fecal indicator bacteria: Water Environment Research Foundation, accessed January 1, 2012, at http://www.bmpdatabase.org/.

Cunnane, C., 1978, Unbiased plotting positions—A review: Journal of Hydrology, v. 37, p. 205–222.

Denver Urban Drainage and Flood Control District, 2008, Urban storm drainage, criteria manual, v. 2: Denver, Urban Drainage and Flood Control District, 434 p., http://www.udfcd.org/.

Denver Urban Drainage and Flood Control District, 2010, Urban storm drainage, criteria manual, v. 3-Best management practices: Denver, Urban Drainage and Flood Control District, 434 p., http://www.udfcd.org/.

Denver Urban Drainage and Flood Control District, 2012, Stormwater best management practice design workbook—ver. 3.02: Denver, Denver Urban Drainage and Flood Control District, accessed August 4, 2013, at http://www.udfcd.org/.

Di Toro, D.M., 1984, Probability model of stream quality due to runoff: Journal of Environmental Engineering, v. 110, no. 3, p. 607–628.

Driscoll, E.D., Di Toro, D.M., Gaboury, D.R., and Shelley, P.E., 1986, Methodology for analysis of detention basins for control of urban runoff quality: U.S. Environmental Protection Agency Report EPA440/5–87–001, 74 p.

Driscoll, E.D., Di Toro, D.M., and Thomann, R.V., 1979, A statistical method for assessment of urban runoff: U.S. Environmental Protection Agency Report EPA 440/3–79–023, 200 p.

Driscoll, E.D., Shelley, P.E., Gaboury, D.R., and Salhotra, Atul, 1989, A probabilistic methodology for analyzing water quality effects of urban runoff on rivers and streams: U.S. Environmental Protection Agency Report EPA 841–R89–101, 128 p.

Driscoll, E.D., Shelley, P.E., and Strecker, E.W., 1990, Pollutant loadings and impacts from highway stormwater runoff, v. III—Analytical investigation and research report: Federal Highway Administration Report FHWA–RD–88–008, 160 p.

Emerson, C.H., and Traver, R.G., 2008, Multiyear and seasonal variation of infiltration from storm-water best management practices: Journal of Irrigation and Drainage Engineering, v. 134, no. 5, p. 598–605.

Federal Highway Administration, 1998, Environmental flow charts: Federal Highway Administration, Office of Natural Environment, 45 p.

Fisher, R.A., 1924, On a distribution yielding the error functions of several well known statistics: Toronto, Proceedings of the International Congress of Mathematics, v. 2, p. 805–813.

Flanagan, D.C., and Nearing, M.A., (eds.) 1995, Water erosion prediction project (WEPP) hillslope profile and watershed model documentation: U.S. Department of Agriculture-Agricultural Research Service, National Soil Erosion Research Laboratory, Report no. 10, variously paged, accessed August 5, 2013, at http://www.ars.usda.gov/Research/docs.htm?docid=18073.

Geosyntec Consultants and Wright Water Engineers, 2009, Urban stormwater BMP performance monitoring: accessed February 22, 2013, at http://www.bmpdatabase.org/monitoring-guidance.html.

Goforth, G.F., Heaney, J.P., and Huber, W.C., 1983, Comparison of basin modeling techniques: Journal of Environmental Engineering, v. 109, no. 5, p. 1082–1098.

Granato, G.E., 2012, Estimating basin lagtime and hydrograph-timing indexes used to characterize stormflows for runoff-quality analysis: U.S. Geological Survey Scientific Investigations Report 2012–5110, 47 p.

Granato, G.E., 2013, Stochastic empirical loading and dilution model (SELDM) version 1.0.0: U.S. Geological Survey Techniques and Methods, book 4, chap. C3, 112 p., CD–ROM.

Granato, G.E., Carlson, C.S., and Sniderman, B.S., 2009, Methods for development of planning-level estimates of water quality at unmonitored stream sites in the conterminous United States: Federal Highway Administration Report FHWA–HEP–09–003, 53 p., CD–ROM.

Granato, G.E., and Cazenas, P.A., 2009, Highway-runoff database (HRDB version 1.0)—A data warehouse and preprocessor for the stochastic empirical loading and dilution model: Federal Highway Administration Report FHWA–HEP–09–004, 57 p.

Gray, J.R., Glysson, G.D., Turcios, L.M., and Schwarz, G.E., 2000, Comparability of suspended-sediment concentration and total suspended solids data: U.S. Geological Survey Water-Resources Investigations Report 00–4191, 14 p.

Guo, J.C.Y., and MacKenzie, Ken, 2013, Detention basin volume estimating workbook—ver. 2.32: Denver, Denver Urban Drainage and Flood Control District, accessed August 4, 2013, at http://www.udfcd.org/.

Guo, Q.G., 2006, Correlation of total suspended solids (TSS) and suspended sediment concentration (SSC) test methods: New Jersey Department of Environmental Protection Division of Science, Research, and Technology Contract no. SR05–005, 52 p.

Haan, C.T., 1977, Statistical methods in hydrology: Ames, Iowa State University Press, 378 p.

Haan, C.T., Barfield, B.J., and Hayes, J.C., 1994, Design hydrology and sedimentology for small catchments: San Diego, Calif., Academic Press, 588 p.

Helsel, D.R., 2005, Nondetects and data analysis—Statistics for censored environmental data: Hoboken, N.J., John Wiley & Sons Publishing, Inc., 250 p.

Helsel, D.R., and Hirsch, R.M., 2002, Statistical methods in water resources—Hydrologic analysis and interpretation: U.S. Geological Survey Techniques of Water-Resources Investigations, book 4, chap. A3, 510 p.

Hoshi, Kiyoshi, Stedinger, J.R., and Burges, S.J., 1984, Estimation of log-normal quantiles: Monte Carlo results and first-order approximations: Journal of Hydrology, v. 71, no. 1–2, p. 1–30.

Huber, W.C., Cannon, LaMarr, and Stouder, Matt, 2006, BMP modeling concepts and simulation: U.S. Environmental Protection Agency EPA/600/R–06/033, 166 p.

Job, Scott, and Smith, J.T., 2010, Moving beyond the percent removal paradigm: Using lower limit effluent concentrations in design guidance and evaluation, *in* Struck, Scott, and Lichten, Keith, (eds), 2010 Proceedings of the Low Impact Development 2010—Redefining Water in the City: San Francisco, April 11–14, 2010, American Society of Civil Engineers, 13 p.

Johnson, David, 1997, The triangular distribution as a proxy for the beta distribution in risk analysis: The Statistician, v. 46, no. 3, p. 387–398.

Joo, Yongsung, and Casella, George, 2001, Predictive distributions in risk analysis and estimation for the triangular distribution: Environmetrics, v. 12, p. 647–658.

Kacker, R.N., and Lawrence, J.F., 2007, Trapezoidal and triangular distributions for Type B evaluation of standard uncertainty: Metrologia, v. 44, no. 2, p. 117–127.

Kadlec, R.H., and Knight, R.L., 1996, Treatment wetlands: Boca Raton, Fla., CRC Press, 893 p.

Leisenring, Marc, Clary, Jane, Lawler, Ken, and Hobson, Paul, 2011, International stormwater best management practices (BMP) database pollutant category summary—Solids: Water Environment Research Foundation, accessed January 1, 2012, at http://www.bmpdatabase.org/.

Leisenring, Marc, Clary, Jane, Stephenson, Julie, and Hobson, Paul, 2010, International stormwater best management practices (BMP) database pollutant category summary—Nutrients: Water Environment Research Foundation, accessed January 1, 2012, at http://www.bmpdatabase.org/.

Maestre, Alexander, Pitt, R.E., Durrans, S.R., and Chakraborti, S.R., 2005, Stormwater quality descriptions using the three parameter lognormal distribution, *in* James, William, Irvine, K.N., McBean, E.A., and Pitt, R.E. (eds.), Effective modeling of urban water systems: Guelph, Ontario, Computational Hydraulics International Monograph 13, p. 247–274.

Maestre, Alexander, Pitt, R.E., and Williamson, Derek, 2004, Nonparametric statistical tests comparing first flush and composite samples from the National Stormwater Quality Database, *in* James, W., ed., Models and applications to urban water systems: Guelph, Ontario, CHI Publications, v. 12, p. 317–338.

National Cooperative Highway Research Program, 2006, Evaluation of best management practices for highway runoff control: Washington, D.C., Transportation Research Board NCHRP Report 565, 143 p.

National Research Council, 2008, Urban stormwater management in the United States: Washington, D.C., National Academy of Sciences Committee on Reducing Stormwater Discharge Contributions to Water Pollution, 610 p.

Northern Virginia Planning District Commission, 1992, Northern Virginia BMP handbook—A guide to planning and designing best management practices in northern Virginia: Annandale, Va., Northern Virginia Planning District Commission, 302 p.

Northern Virginia Planning District Commission, 1996, Northern Virginia BMP handbook addendum—Sand filtration systems: Annandale, Va., Northern Virginia Planning District Commission, 63 p.

Novotny, Vladimir, 2004, Simplified data based total maximum daily loads, or the world is log-normal: Journal of Environmental Engineering, v. 130, no. 6, p. 674–683.

Park, Daeryong, Loftis, J.C., and Roesner, L.A., 2011, Modeling performance of storm water best management practices with uncertainty analysis: Journal of Hydrologic Engineering, v. 16, no. 4, p. 332–344.

Park, Daeryong, and Roesner, L.A., 2012, Evaluation of pollutant loads from stormwater BMPs to receiving water using load frequency curves with uncertainty analysis: Water Research, v. 46, p. 6836–6856.

Poresky, Aaron, Clary, Jane, Strecker, Eric, and Earles, Andrew, 2011, International stormwater best management practices (BMP) database technical summary—Volume reduction: Water Environment Research Foundation, accessed January 1, 2012, at http://www.bmpdatabase.org/.

Press, W.H., Flannery, B.P., Teukolsky, S.A., and Vetterling, W.T., 1992, Numerical recipes in Fortran 77—The art of scientific computing (2d ed.): New York, Cambridge University Press, 992 p.

Scherer, W.T., Pomroy, T.A., and Fuller, D.N., 2003, The triangular density to approximate the normal density—Decision rules-of-thumb: Reliability Engineering and System Safety, v. 82, p. 331–341.

Schneider, L.E., and McCuen, R.H., 2006, Assessing the hydrologic performance of best management practices: Journal of Hydrologic Engineering, v. 11, no. 3, p. 278–281.

Schueler, T.R., 1987, Controlling urban runoff—A practical manual for planning and designing urban BMPs: Washington, D.C., Metropolitan Washington Council of Governments, Department of Environmental Programs, no. 87703, 275 p.

Schueler, T.R., 1996, Irreducible pollutant concentrations discharged from stormwater practices: Watershed Protection Techniques, v. 2, no. 2, p. 361–363.

Sevin, A.F., 1987, Guidance for preparing and processing environmental and section 4(f) documents: Washington, D.C., Department of Transportation, Federal Highway Administration, Technical Advisory T–6640.8A, 62 p., accessed August 13, 2012, at http://environment.fhwa.dot.gov/projdev/impta6640.asp.

Smith, K.P., and Granato, G.E., 2010, Quality of stormwater runoff discharged from Massachusetts highways, 2005–2007: U.S. Geological Survey Scientific Investigations Report 2009–5269, 198 p. with CD–ROM, at http://pubs.usgs.gov/sir/2009/5269.

Snyder, W.M., 1972, Fitting of distribution functions by nonlinear least squares: Water Resources Research, v. 8, no. 6, p. 1423–1432.

Stedinger, J.R., 1980, Fitting log normal distributions to hydrologic data: Water Resources Research, v. 16, no. 3, p. 481–490.

Stedinger, J.R., Vogel, R.M., and Foufoula-Georgiou, Efi, 1993—Frequency analysis of extreme events, chap. 18, *in* Maidment, D.R., ed., Handbook of hydrology: New York, McGraw-Hill, Inc., p. 18.1–18.66.

Strecker, E.W., Quigley, M.M., Urbonas, B.R., Jones, J.E., and Clary, J.K., 2001, Determining urban storm water BMP effectiveness: Journal of Water Resources Planning and Management, v. 127, no. 3, p. 144–149.

Susilo, K.J., Steets, Brandon, Leisenring, Marc, and Strecker, Eric, 2008, A user's guide for the structural BMP prioritization and analysis tool (SBPAT v1.0)—Technical appendices: Los Angeles, Geosyntec Consultants, Project Report LA0104, 229 p.

Urbonas, B.R., and Roesner, L.A., 1993, Chapter 28—Hydrologic design for urban drainage control, *in* Maidment, D.R., ed., Handbook of hydrology: New York, McGraw-Hill, Inc., p. 28.1–28.52.

U.S. Environmental Protection Agency, 1996, Guidance for data quality assessment—Practical methods for data analysis, EPA QA/G–9, Final report: U.S. Environmental Protection Agency Report EPA/600/R–96/084, 164 p.

U.S. Environmental Protection Agency, 2001, Risk assessment guidance for Superfund, v. 3, part A, Process for conducting probabilistic risk assessment: U.S. Environmental Protection Agency Report EPA 540–R–02–002, 385 p.

Van Buren, M.A., Watt, W.E., and Marsalek, Jiri, 1997, Applications of the log-normal and normal distributions to stormwater quality parameters: Water Research, v. 31, no. 1, p. 95–104.

van Straalen, N.M., 2002, Threshold models for species sensitivity distributions applied to aquatic risk assessment for zinc: Environmental Toxicology and Pharmacology, v. 11, p. 167–172.

Wanielista, M.P., and Yousef, Y.A., 1993, Stormwater management: New York, John Wiley and Sons, 579 p.

Wong, T.H.F., Fletcher, T.D., Duncan, H.P., and Jenkins, G.A., 2006, Modelling urban stormwater treatment—A unified approach: Ecological Engineering, v. 27, p. 58–70.

Wong, T.H.F., and Geiger, W.F., 1997, Adaptation of wastewater surface flow wetland formulae for application in constructed stormwater wetlands: Ecological Engineering, v. 9, p. 187–202.

Wyoming Department of Environmental Quality, 2013, Urban best management practice manual—Conservation practices to protect surface and ground water: Wyoming Department of Environmental Quality, Document #13-0037, 88 p.

Young, G.K., Stein, Stuart, Cole, Pamela, Kammer, Traci, Graziano, Frank, and Bank, F.G., 1996, Evaluation and management of highway runoff water quality: Federal Highway Administration Report FHWA–PD–96–032, 480 p.

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