Prepared in cooperation with the Federal Highway Administration

Statistical Methods for Simulating Structural Stormwater Runoff Best Management Practices (BMPs) With the Stochastic Empirical Loading and Dilution Model (SELDM)

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Conversion Factors

International System of Units to U.S. customary units

Multiply	By	To obtain
centimeter (cm)	0.3937	inch (in.)
meter (m)	3.281	foot (ft)
kilometer (km)	0.6214	mile (mi)
square kilometer (km^2)	0.3861	square mile (mi^2)
liter (L)	0.2642	gallon (gal)

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

$$°F = (1.8 \times °C) + 32.$$

Supplemental Information

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

Concentrations of chemical constituents in water are given either in milligrams per liter (mg/L), micrograms per liter (μg/L), or nanograms per liter (ng/L). Milligrams per liter are equivalent to parts per million, micrograms per liter are equivalent to parts per billion, and nanograms per liter are equivalent to parts per trillion.

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

Abbreviations

BMP	best management practice
BMPDB	International Stormwater Best Management Practices Database
BMPSE	Best Management Practices Statistical Estimator
CDF	cumulative distribution function
FHWA	Federal Highway Administration
LBMPV	lower bound of the most probable value
MIC	minimum irreducible concentration
MIC0	minimum of the minimum values of the positive MIC estimates
MIC1	25th percentile of the minimum values of the positive MIC estimates
MIC2	median of the minimum values of the positive MIC estimates
MIC3	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 concentration
TMDL	total maximum daily load
TSS	total suspended solids
UBMPV	upper bound of the most probable value
USGS	U.S. Geological Survey

Statistical Methods for Simulating Structural Stormwater Runoff Best Management Practices (BMPs) With the Stochastic Empirical Loading and Dilution Model (SELDM)

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Abstract

This report documents statistics for simulating structural stormwater runoff best management practices (BMPs) with the Stochastic Empirical Loading and Dilution Model (SELDM). The U.S. Geological Survey developed SELDM and the statistics documented in this report in cooperation with the Federal Highway Administration to indicate the risk for stormwater flows, concentrations, and loads to exceed user-selected water-quality goals and the potential effectiveness of mitigation measures to reduce such risks. In SELDM, three treatment variables—hydrograph extension, volume reduction, and water-quality treatment—are simulated by using the trapezoidal distribution and the rank correlation with the associated runoff variables. This report describes methods for calculating the trapezoidal distribution statistics and rank correlation coefficients for these treatment variables and methods for estimating the minimum irreducible concentration (MIC), which is the lowest expected effluent concentration from a BMP site or a category 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.

Analyses for this study were done with data extracted from a modified copy of the December 2019 version of the International Stormwater Best Management Practices Database. Statistics for volume reduction, hydrograph extension, and water-quality treatment were developed with selected data. The medians of the best-fit statistics for selected constituents were used to construct generalized cumulative distribution functions for the three treatment variables. For volume reduction and hydrograph extension, selection of a Spearman's rank correlation coefficient (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.

Water-quality treatment statistics, including trapezoidal ratios and MIC values, were developed for 51 runoff-quality constituents commonly measured in highway and urban runoff studies. Statistics were calculated for water-quality properties, sediment and solids, nutrients, major and trace inorganic elements, organic compounds, and biologic constituents.

Analysis of MIC values provides information to guide professional judgement for selecting values for simulating water quality at sites of interest. The MIC is a lower bound for BMP discharge concentrations and will therefore replace simulated BMP discharge concentrations below the selected value. A new method for estimating MIC values, the lognormal variate of inflow concentrations, was developed in this report and these statistics were calculated for individual constituents and constituent categories. Inflow quality is correlated to MIC values for some constituents, but regional soil concentrations were not strongly correlated to MIC values.

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 flows, concentrations, and loads to be above user-selected water-quality goals and to evaluate the potential effectiveness of mitigation measures to reduce such risks (Granato, 2013, 2014). 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 simulates the potential effect of mitigation measures by using 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 timing, volume, 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. SELDM can be used to explicitly simulate the effects of structural BMPs on the timing, volume, and quality of runoff by using professional judgment or by fitting the trapezoidal distribution to available data (Granato, 2013, 2014). SELDM can be used to implicitly simulate the potential effects of nonstructural BMPs, such as street sweeping, by modifying input statistics to reflect the effect of such measures on the quantity and quality of runoff from the site of interest (Granato, 2013, 2014).

Hydrograph extension is the practice of slowing the discharge of runoff flows and releasing these flows to the receiving water body over an extended period (Granato, 2014). SELDM simulates hydrograph extension times (in hours) from a BMP or series of BMPs as a stochastic variable (Granato, 2013, 2014). In theory, hydrograph extension provides extended treatment time within the BMP. Although SELDM does not alter the water-quality treatment statistics with the hydrograph extension variable, 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 (Granato, 2013; Granato and Jones, 2014, 2019; Risley and Granato, 2014; Stonewall and others, 2019; Weaver and others, 2019; Jeznach and Granato, 2020). SELDM simulates the potential effects of structural BMPs on the timing of runoff by generating a population of BMP hydrograph extension durations and adding these durations to the runoff duration from the site of interest. SELDM preserves the structure of hydrograph extension monitoring data in simulation results by using the trapezoidal distribution and the rank correlation with the highway stormflow volume (Granato, 2013, 2014).

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 (Granato, 2014). SELDM simulations indicate that runoff volume reduction can substantially reduce downstream flows and constituent loads to receiving waters (Granato and Jones, 2014, 2017, 2019; Risley and Granato, 2014; Smith and others, 2018; Stonewall and others, 2018, 2019; Weaver and others, 2019; Jeznach and Granato, 2020). SELDM simulates 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 (Granato, 2013, 2014). SELDM generates these ratios by using the trapezoidal distribution and the rank correlation with the highway stormflow volume. Rank correlation coefficients (Spearman's rho values) 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, 2014). Although this variable is described as volume reduction, the BMP may increase storm discharge volumes during some runoff events if there is carryover from one storm to another or if groundwater discharges to the BMP during or between storm events (Granato, 2014). Groundwater discharge is more common for normally wet BMPs, but it can occur intermittently at many sites.

Water-quality treatment is the practice of using physical, chemical, and biological processes in an attempt to reduce the concentration of runoff constituents in stormflow (Granato, 2014). Although the term "concentration reduction" is commonly used to describe these processes, concentrations in outflows can exceed inflows and therefore water quality-treatment ratios may be larger than 1. 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 simulates 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 by using the trapezoidal distribution and rank correlation to inflow concentration and applying these ratios to the stochastic population of inflow concentrations from the site of interest (Granato, 2013, 2014). SELDM simulations indicate that water-quality treatment can substantially reduce constituent loads to receiving waters even if some concentration ratios are greater than 1 (Granato and Jones, 2014, 2017, 2019; Risley and Granato, 2014; Smith and others, 2018; Stonewall and others, 2018, 2019; Weaver and others, 2019; Jeznach and Granato, 2020).

Water-quality treatment by BMPs is limited because there will be some lower limit to the effluent concentrations that can be achieved with normal BMP unit operations (Granato, 2014). The lowest concentration achievable for a well-designed example of each type of BMP is known as the minimum irreducible concentration (MIC). The MIC also has been defined as a background concentration, the lower bound of first-order decay processes, or the intercept of regression equations relating outflow to inflow concentrations (Granato, 2014). In SELDM, the MIC estimate is used to replace concentrations calculated from stochastic influent and concentration-ratio values for simulated events that are lower than the MIC (Granato, 2013, 2014). As such, the MIC provides a lower bound to the simulated population of BMP discharge concentrations.

Granato (2014) used data from the 2012 version of the International Stormwater Best Management Practices Database (BMPDB; Leisenring and others, 2013) to calculate BMP treatment statistics. Those treatment statistics have been used to estimate the risks for adverse effects of runoff on receiving waters and the potential for BMPs to reduce those risks (Granato and Jones, 2014, 2019; Risley and Granato, 2014; Stonewall and others, 2019; Weaver and others, 2019; Jeznach and Granato, 2020). Those treatment statistics also have been used for runoff-loading analyses, which can be used to calculate total maximum daily loads (TMDLs) for watersheds of interest (Granato and Jones, 2017; Smith and others, 2018; Stonewall and others, 2018, 2019). Although the existing statistics have been widely used, Granato (2014) published water-quality treatment statistics for only 12 commonly measured highway and urban runoff constituents. State departments of transportation and municipalities are facing

TMDL requirements for many more constituents (Lantin and others, 2019), and the December 2019 version of the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019) has been improved and expanded during the period after the analyses in Granato (2014) were complete.

Purpose and scope.—This report documents BMP performance statistics calculated from publicly available data from the December 2019 version of the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019) by using methods developed by Granato (2014). This report provides an updated and expanded set of BMP statistics but does not provide the detailed description of analytical and numerical methods provided by Granato (2014). This study was done by the USGS in cooperation with the FHWA to provide national statistics for stochastic modeling of the timing, volume, and quality of BMP effluent given a stochastic population of inflows from a user-defined site of interest. The purpose of the analyses in this report is to update and expand statistics developed by Granato (2014) by using the expanded and refined December 2019 version of the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). 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 (Strecker and others, 2001; Geosyntec Consultants and Wright Water Engineers, Inc., 2009), regression analysis between influent and effluent concentrations (Taylor and others, 2014), and theoretical-analytical time-series analyses (Clar and others, 2004; 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, 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.

Methods

Granato (2014) developed quantitative methods to estimate values of the trapezoidal distribution statistics, correlation coefficients, and the MIC from available data. The methods and analysis tools were designed to analyze data from the 2012 version of the BMPDB and to replicate the analysis with user-supplied data in the future. Granato (2014) developed a Microsoft Access database application named the Best Management Practices Statistical Estimator (BMPSE) to facilitate retrieval and analysis of data from the BMPDB and potentially other datasets. Granato (2014) also developed spreadsheets to fit BMP monitoring data retrieved from the BMPSE to the trapezoidal distribution. As part of the current study, the BMPSE was improved to facilitate the use and calculation of additional statistics (Granato, 2021). The spreadsheets also were updated and improved to work as macro-enabled Microsoft Excel spreadsheets (Granato and others, 2021).

Data Collection

The analyses documented in this report were done with data extracted from the December 2019 version of the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). The BMPDB was selected as the source of data for this analysis because it is extensive and is available to the public for research purposes. The 2019 version of the BMPDB has data for 526 test sites, 771 BMPs, 2,371 monitoring stations, 19,547 runoff events, 30,682 flow measurements, and 374,643 water-quality measurements. The 2019 compilation represents continuing efforts of the BMPDB project team to collect, format, check, and enter data over a 24-year period from 1996 through 2019. In many cases, the data have been vetted for use in various BMP performance summaries (for example, Leisenring and others, 2013, 2020; Clary and others, 2017). Data for BMP sites, monitoring sites, runoff volumes, runoff durations, and constituent concentrations were retrieved from the BMP database using a series of queries that were designed to obtain paired input and output values. Although 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.

Data from the December 2019 version of the BMPDB were screened for import into the BMPSE (Granato, 2021), in consultation with the project team that supports and maintains the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). Modifications included identifying water-quality constituents, making measurement units consistent, identifying paired inflow and outflow values, and converting water-quality values that were set in the BMPDB as half the detection limit back to the detection limit. Total polycyclic aromatic hydrocarbon (PAH) values were calculated from individual PAH measurements at sites with enough data to calculate totals. The screened data are available in the BMPSE database application (Granato, 2021).

The results of analyses presented in this report are organized by using the categories specified in the December 2019 version of the BMPDB. This version of the database contains 19 categories of structural BMPs. For this analysis, 12 categories of BMP were selected on the basis of available data and applicability for modeling the quality and quantity of stormwater runoff with SELDM (table 1). Analyses were not done for BMPs listed as "permeable friction course" because of insufficient paired data; BMP data classified as "Other" were not analyzed because statistics for this category would not be meaningful for a set of unrelated BMPs. 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 December 2019 version of this database also contains 40 subcategories of structural BMPs, but the analysis documented in this report 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.

Fitting the Trapezoidal Distribution to Duration and Ratio Data

In SELDM, volume reduction ratios, hydrograph extension times, and water-quality treatment ratios are simulated by using the trapezoidal distribution and the rank correlation with the associated highway runoff variables (Granato, 2013, 2014). The trapezoidal 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 and others, 2003; Kacker and Lawrence, 2007;

Table 1. Explanation of selected structural best management practice categories used in the International Stormwater Best Management Practices Database.

[The International Stormwater Best Management Practices Database is documented by Leisenring and others (2020). BMP, best management practice]

Code	Name	Description
BI	Grass strip (biofilter)	Grass strips are vegetated areas designed to receive laterally distributed sheet flow from adjacent impervious areas; also called buffer strips or vegetated buffers.
BR	Bioretention	Bioretention BMPs are shallow, vegetated basins with a variety of planting/filtration media and often include underdrains. Also called rain gardens when underdrains are not present and biofiltration when underdrains are present.
BS	Grass swale (bioswale)	Grass swales are shallow, vegetated channels; also called bioswales or vegetated swales, which are designed to convey overland flow.
CO	Composite	Composite BMPs include different BMP categories in a 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 (or) through an orifice that controls the rate of release. This category also includes concrete-lined basins and underground concrete vaults.
IB	Infiltration basin	Infiltration basins are dry ponds that are not designed to include 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.
MD	Manufactured device	Manufactured devices are prefabricated stormwater treatment methods. This category includes catch basins, oil and grit separators, 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.
PP	Porous pavement	Porous pavement BMPs are full-depth, pervious concrete, porous asphalt, paving stones or bricks, reinforced turf rings, and other permeable surfaces designed to replace traditional pavement.
RP	Retention pond	Retention ponds, also known as wet ponds, are artificial 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 semi-permanent 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.

Granato, 2013, 2014). 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 (fig. 1): 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). 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. 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 the 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). 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. Furthermore, it is easier to avoid generation of extreme outliers when large stochastic datasets are generated because the trapezoidal distributions are bounded.

Least-squares optimization was used to fit the BMP monitoring data to the parameters of the trapezoidal distribution (Granato, 2014). The optimal fit to the trapezoidal distribution was calculated by minimizing the least-squares difference between the cumulative distributions of the volume reduction ratios, the hydrograph 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 with 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 (Granato, 2014; Granato and others, 2021). The Microsoft Excel solver tool should be installed with Microsoft 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 optimized the minimum, LBMPV, UBMPV, and the maximum values. The constraints on the solver were that the values must be greater than or equal to 0, 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 (Granato, 2014). 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 (Granato, 2014, 2021). For the hydrograph 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 0, 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 the Johnson (1997) equations did not facilitate rapid convergence to a final solution (Granato, 2014, 2021).

When fitting the distribution in Microsoft Excel, 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 nonlinear solving package. The situation is analogous to the problem of finding the highest peak of a mountain range in the fog by following an uphill gradient (Granato, 2014). 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 and hydrograph extension ratio solver runs, which were done manually, at least two additional conditions were tested. In one solver run, the minimum was set equal to 0, 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 solver 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 of the prior estimate the UBMPV minimum was increased by 10 to 20 percent of the

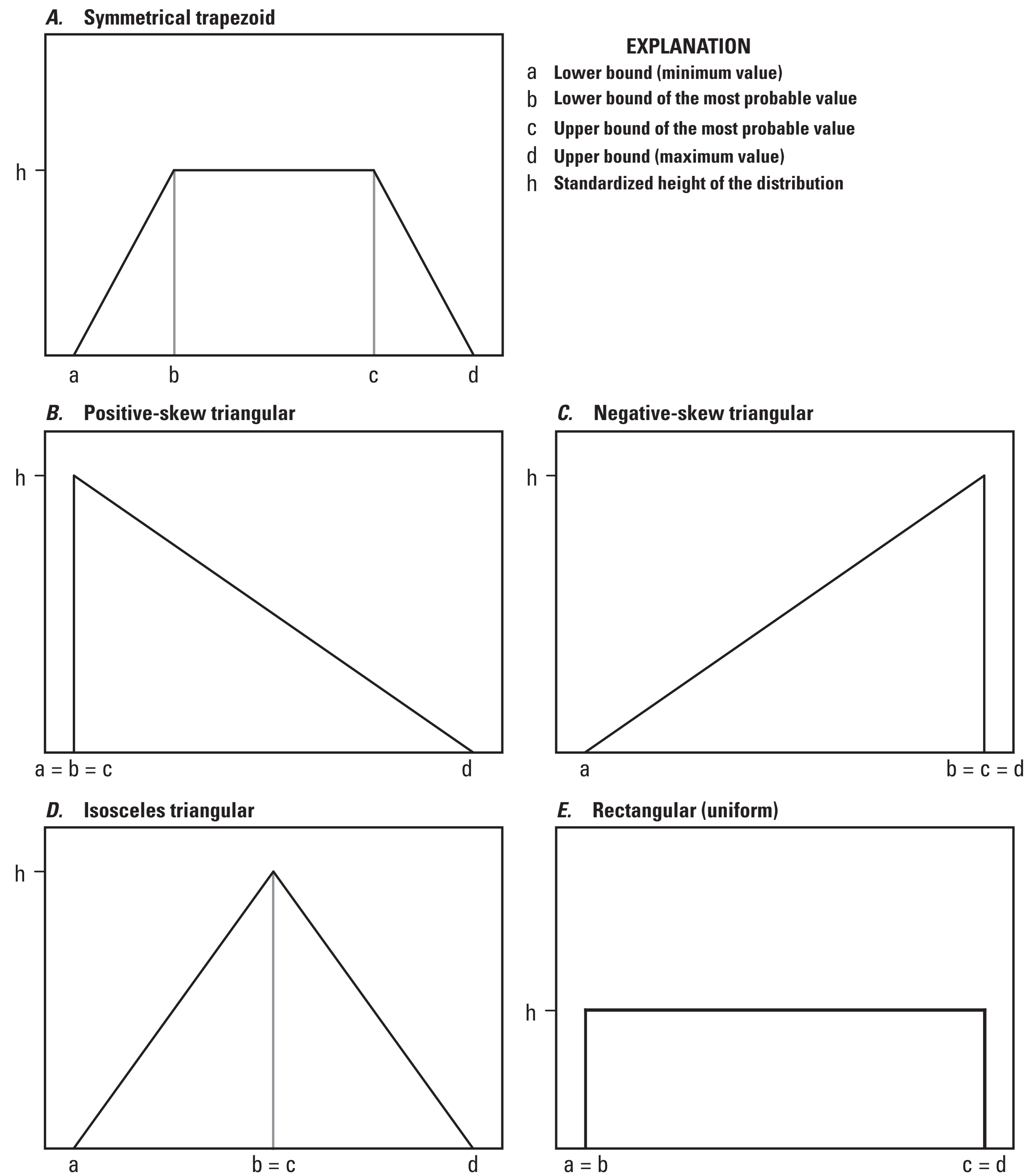

Figure 1. Schematic diagram showing five possible probability density functions of the trapezoidal distribution for simulating structural stormwater runoff best management practices with the stochastic empirical loading and dilution model as defined by the location variables (from Granato, 2014). *A*, symmetrical trapezoid; *B*, positive-skew triangular; *C*, negative-skew triangular; *D*, isosceles triangular; and *E*, rectangular (uniform). The height of each trapezoid is calculated to normalize the area under the probability-density function to equal one (Granato, 2013, 2014).

prior estimate, and the maximum was increased by 20 percent of the prior estimate. For these variables, the stability of the least-squares solution was evaluated, and the best solution was picked if the results were stable or the starting points were modified if the solution seemed unstable. The solution with the lowest value of the sum of square errors was selected as the final result. The Microsoft Excel spreadsheet used to do these analyses (FitTrapezoidToBMP01v1.0.3.xlsx) is provided in the data release by Granato and others (2021).

In this study, water-quality measurements from 2,017 datasets were optimized to determine trapezoidal fit statistics for concentration ratios for each site within the 10 BMP categories that had sufficient data for analysis for one or more of the 51 highway- and urban-runoff constituents. The trapezoidal-fit spreadsheet for concentration ratios was automated by Granato (2014) to analyze concentration ratios because of the large number of water-quality datasets. The BMPSE generates the input files and the list of filenames for each constituent within the graphical user interface (Granato, 2014, 2021).

For the initial optimization run 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 the median, and the maximum was set equal to three times the median. 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 with the second run, 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 run for a third time. 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 (FitConcentrationRatiov1.1.0.xlsm) is provided in the data release by Granato and others (2021).

Calculating Rank Correlation Coefficients for Duration and Ratio Data

SELDM uses rank correlation to preserve the structure of inflow and outflow data (Granato, 2013, 2014). The BMPSE (Granato, 2021) calculates 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 0 by using standard methods (Fisher, 1924; Haan, 1977; Press and others, 1992; Caruso and Cliff, 1997; Helsel and Hirsch, 2002). If the 95-percent confidence limit values are of the same sign, then the correlation coefficient is statistically different from 0. The range of the 95-percent confidence limit values, which depends on the strength of correlation and the number of data points, indicates the potential precision of the correlation value. For hydrograph extension, the BMPSE calculates rho and tau between the inflow volume and the hydrograph extension values (Granato, 2014, 2021). For volume reduction, the BMPSE calculates rho and tau between the inflow volume and the ratio of outflow to inflow volumes (Granato, 2014, 2021). For water-quality treatment, the BMPSE calculates rho and tau between the inflow concentrations and the ratio of outflow to inflow concentrations (Granato, 2014, 2021). The BMPSE also calculates rho between the inflow and the outflow concentrations when a water-quality treatment analysis is done.

The rank correlation between the paired inflow volume and the ratio of outflow to inflow volume or the paired inflow concentration and the ratio of outflow to inflow concentration should not be used for statistical inference (Granato, 2014). 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, 2014). Figure 2 shows the results of an example Monte Carlo analysis to demonstrate the pattern of uniform random numbers generated by using four positive correlation values. These patterns show that as the correlation-coefficient increases, the likelihood that the paired numbers will be similar also increases (fig. 2; Granato, 2013). With positive correlations, higher input values will tend to produce higher ratios. If correlations are negative, then the patterns will be mirrored diagonally from the top left to bottom right of each graph panel. With negative correlations, higher input values will tend to produce lower ratios. Thus, 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 are 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 are generated. The absolute value of the correlation determines the magnitude of the scatter of the points.

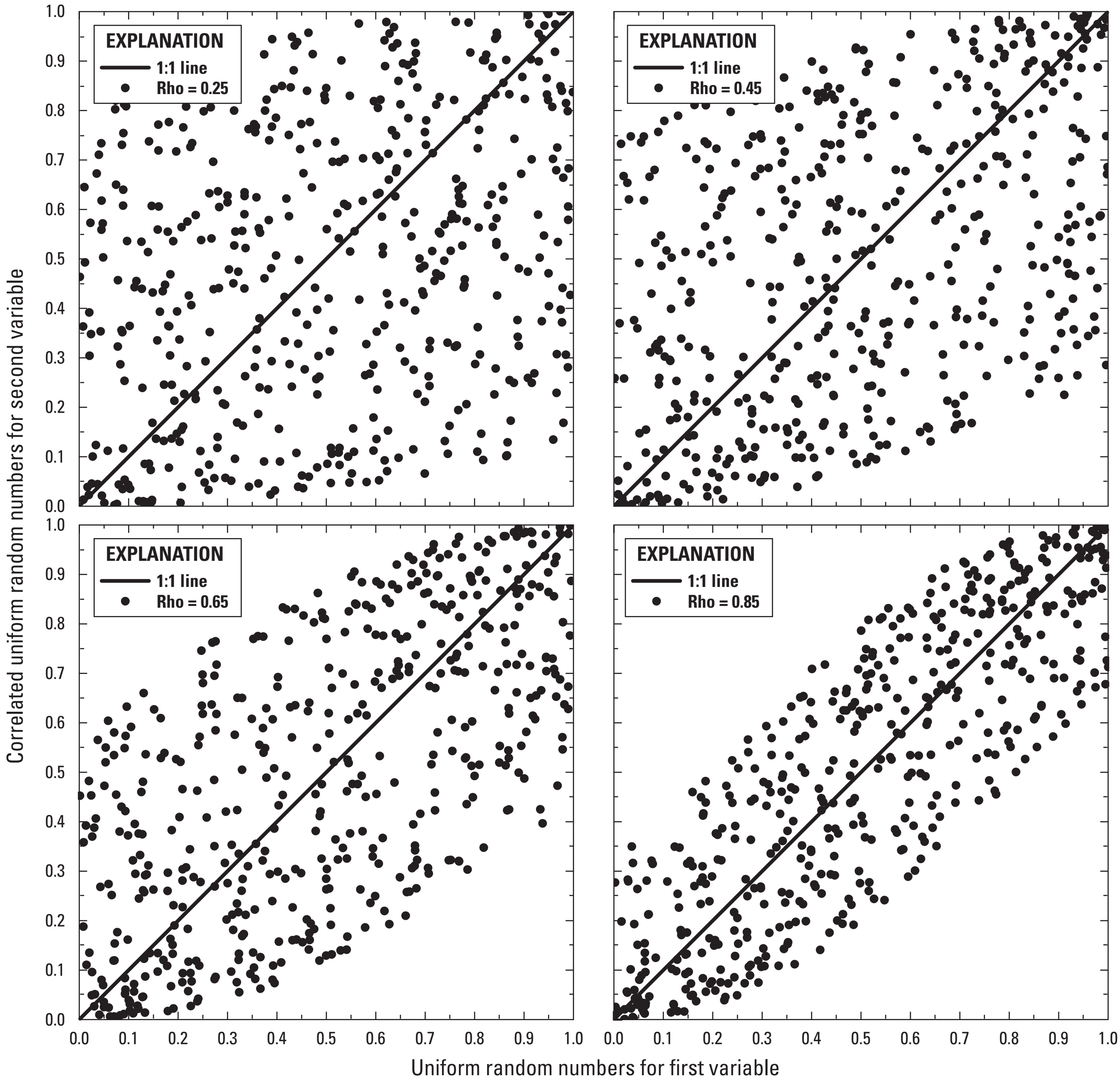

Figure 2. Scatter plots of results of a Monte Carlo analysis to demonstrate scatter of paired uniform random-number samples around a one-to-one relation for four different values of the rank correlation coefficient (Spearman's rho). Each sample consists of 500 paired uniform random numbers in the range between 0 and 1. Modified from Granato (2013).

Sample sizes of seven or more storms per BMP monitoring site were selected for calculating correlation coefficients for the volume reduction ratios, hydrograph extension durations, and concentration ratios (Granato, 2014). This sample-size criterion was applied for selection of datasets to estimate correlation coefficients because Abdel-Megeed (1984) determined that at least five 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.

Estimating the MIC Values

Granato (2014) used four statistical estimators to calculate MICs from available BMP effluent-concentration sample data and then used these estimators to select representative MIC values. These estimators are the measured minimum, the log-triangular lower-bound estimator, Stedinger's quantile lower-bound estimator, and a modified quantile lower-bound estimator. The four lower-bound estimators selected for estimating the MIC in this study are based on the theory that the effluent concentrations are approximately lognormal but are not constrained to this assumption. These four different estimators were selected for use because each estimator has several potential advantages and disadvantages. Granato (2014) ranked the estimated MIC values that were greater than 0 and used various percentiles from all sites with sufficient data to provide several MIC values for the constituents of interest that stormwater practitioners could use to simulate BMP discharges to estimate potential effects of runoff on receiving waters or to calculate TMDLs.

Calculating Statistical Estimators

The measured minimum value is the simplest method for estimating the MIC and is commonly used for this purpose in the literature (Granato, 2014). The measured minimum value is commonly used because it is simple to calculate, it is generally accepted, and it is completely nonparametric. Limitations to the measured minimum value as an estimator for the MIC are that 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 (Granato, 2014). For example, among sites in the BMPSE from the 2019 dataset with 5 or more samples, about 35 percent of datasets for total suspended solids, total zinc, total copper and total phosphorus have fewer than 10 samples, and about 77 percent of these datasets have fewer than 20 samples (Granato, 2021). In the BMPDB and in many studies, a value of half the detection limit may be substituted if the measured minimum is censored (Granato, 2014). In this study, however, the robust regression on order statistics method 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. There is substantial uncertainty in the exact minimum value if estimates are made using regression on order statistics or other methods (Granato, 2014).

The log-triangular lower-bound estimator also is a simple and robust method to estimate a MIC value (Granato, 2014). Although the lognormal distribution is commonly used, the lack of a lower bound in log space may produce estimates that are infinitely close to 0. Using the log-triangular lower-bound estimator puts a finite lower limit to the estimated MIC. Scherer and others (2003) found that the best fit lower limit could be calculated by subtracting a value of the standard deviation multiplied by the square root of 6 from the mean value. The log-triangular lower-bound estimator is advantageous because it is simple to calculate, it will always produce a value that is greater than 0, it can be calculated by using accepted standard methods for censored data, and it provides a good fit to the standard normal distribution (Granato, 2014). For data such as pH, which cannot be simulated using a lognormal distribution, the triangular lower bound estimator can be calculated by using the average and standard deviation of the untransformed data. However, the triangular lower-bound estimator may not be the best estimator if the logarithms of the BMP effluent data are substantially asymmetrical above and below the geometric mean.

Granato (2014) also used Stedinger's quantile lower-bound estimator of the three-parameter lognormal distribution to estimate the MIC. 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 0. Stedinger's quantile lower-bound estimator is simple to calculate and will fit data that are not symmetrical above and below the geometric mean (Granato, 2014). However, this estimate of the MIC is not robust because it can produce a lower-bound value that is less than 0, it is very sensitive to the presence of data below one or more detection limits because it is calculated using the minimum measured (or censored) value, and the lower-bound estimated using the three-parameter lognormal distribution cannot be adapted to data that cannot be simulated using a lognormal distribution (such as pH, for example).

Because of the limitations of Stedinger's lower-bound estimator, Granato (2014) also used a modified quantile lower-bound estimator (MQLBE) to estimate the MIC. The MQLBE also is simple to calculate and will fit data that are not symmetrical above and below the geometric mean. To avoid MQLBE values that were less than or equal to 0, Granato (2014) developed an iterative method that would adjust the parameters of the equation until the MIC estimate was greater than 0. In some cases, however, this method could produce MIC estimates that exceeded the median measured value. Because it uses the average of the smallest measured or censored values, the MQLBE is more robust to the presence of censored values than Stedinger's lower bound estimator but may be affected by a high proportion of censored values. Because it is iterative, the MQLBE is not as easy to calculate as some of the other estimators used by Granato (2014) for MIC values The MQLBE will not produce valid MIC estimates for constituents that cannot be approximated by a lognormal distribution.

Selecting Representative MIC values

Four statistics (denoted as MIC0 through MIC3) were chosen for selecting representative MIC values from among the four statistical lower-bound estimators (minimum, log-triangular, Stedinger, and MQLBE) for each BMP category. Another statistic, 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. Only the BMP monitoring sites with five or more samples above the detection limits were used to calculate the four MIC statistics. The first category-level method (MIC0) uses the minimum of the minimum values of the positive MIC estimates. The second category-level method (MIC1) uses the 25th percentile of the minimum values of the positive MIC estimates. The third category-level method (MIC2) uses the median of the minimum values of the positive MIC estimates. The fourth category-level method (MIC3) uses the median of the median values of the positive MIC estimates. The median of the positive statistical lower-bound estimators 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 category 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 should allow for more variation in low-end concentrations. Selection of a lower MIC estimate should reduce the proportion of constant-value low-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.

Estimating MIC Values From Inflow-Concentration Statistics

Inflow concentration statistics were used to help inform MIC estimates because inflow concentrations can have a substantial effect on the outflow concentrations (Leisenring and others, 2013; Granato, 2014). The geometric means of inflow concentrations were used to calculate the rank and Pearson's r correlation coefficients for the MIC values (Granato, 2014). The rank and Pearson's r 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. The geometric means and standard deviations of inflow concentrations also were used to refine MIC estimates based on inflow concentration statistics.

To evaluate the potential for developing quantitative relations between the geometric mean inflow concentration and the MIC values, Granato (2014) defined correlation strengths based on the value of the correlation coefficient. Granato (2014) defined weak correlations as having correlation coefficient values less than 0.5, moderate correlations having values greater than or equal to 0.5 and less than 0.75, semistrong correlations having values greater than or equal to 0.75 and less than 0.85, and strong correlations having values greater than or equal to 0.85. Granato (2014) found that few constituents had correlations strong enough to provide quantitative relations between geometric mean inflow concentrations and representative MIC values.

Comparisons of the three correlation coefficients can inform the true relations between variables (Granato, 2014). 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, a different transformation of either the geometric mean or MIC estimates (or both) may be assumed to 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, one or more far outliers may be assumed to be responsible for artificially inflating the r values. Using the logarithms of the values tends to decrease the leverage of high outliers, but this increases the leverage of small outliers.

The lognormal variate (K) for the MIC values also were calculated from BMP inflow-concentration statistics to help estimate a site-specific MIC value. The lognormal variate is calculated as follows:

$$K = \frac{\log(MIC) - \log(GeometricMean)}{\log(GeometricStandardDeviation)}. \quad (1)$$

Once K is estimated from input datasets, it can be used to estimate a MIC value from simulated inflow concentrations at a site of interest with the equation:

$$\mathrm{MIC} = 10^{(\log(GeometricMean) + K \times \log(GeometricStandardDeviation))}. \quad (2)$$

The resulting MIC estimate will be an estimate of a constituent concentration or parameter value that is a fraction of the geometric mean of inflow concentrations.

Limitations of the BMP Performance Analysis

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. For example, Leisenring and others (2013) analyzed the effects of structural BMP design parameters on achievable effluent concentrations by using data from 530 monitoring sites in the BMPDB and found that BMP design variables had weak correlation to performance. Leisenring and others (2013) found the strongest correlations were between inflow and outflow concentrations. Few studies provide reliable predictions of treatment performance even with large datasets and complex models (Strecker and others, 2001; Granato, 2014). Uncertainties in volume reduction, hydrograph extension, water-quality treatment, and the MICs 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 (Granato, 2014).

Uncertainties in results also are compounded by available sample sizes (Driscoll and others, 1979; Burton and Pitt, 2002; California Department of Transportation, 2009; Granato, 2014; Leutnant and others, 2018). 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 that indicate that 50 to 113 paired EMC samples may be needed just to detect differences in mean concentrations. Leutnant and others (2018) determined that 40 EMC samples would need to be collected to characterize total suspended solids (TSS) concentrations. By comparison, the paired data table of the 2019 version of the BMPDB has an average of about 16 samples per BMP for TSS and total phosphorus (TP); the most commonly measured constituents. Only about 6 percent of these BMPs have 40 or more samples for these constituents.

BMP statistics presented in this report are category medians from sites with 7 or more monitoring events: 248 of 446 BMP sites have 7 or more TSS samples, and 319 of 424 BMP sites have 7 or more TP samples. Although this is a seemingly large number of sites, the number of sites per category with sufficient data for analysis can be small for some BMP categories and some BMP performance variables. The category median is selected on the principal of the wisdom of the crowd; the median is selected rather than the mean to reduce the potential effect of far outliers (Granato, 2014; Wallis, 2014). However, the (approximate) 95-percent confidence limit of the median can encompass a large portion of a dataset (table 2).

Professional judgement may be needed to apply analysis of data from short-term studies to long-term simulations. Although the methods described in this report will reproduce the data used for analysis when used to simulate BMP performance, the results of analyses are only as good as the underlying data. The BMPDB includes many small datasets, and many studies do not include the effects of year-round weather conditions. The number of runoff-generating events per year among the 15 U.S. Environmental Protection Agency rain zones defined by the ranges from 17 in arid areas to 62 in areas with wet climates; the average among the rain zones is 40 events per year (Granato, 2010). By comparison, about 36, 10, and 4 percent of studies with paired flow data for 7 or more storms have 20, 40, or 60 events, respectively. Similarly, the variation in precipitation volume for most sites approximates typical annual variations but not long-term variations in precipitation volumes. Many datasets have outflow to inflow ratios that greatly exceed 1; these values may represent site-specific conditions or problems in the measurements. 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 effect 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 1 increases from 0 to about 40 percent. As the maximum value increases from 2 to 4, the percentage of generated values that are greater than 1 increases from about 40 to 60 percent. Although the median of at-site statistics should not reflect extreme values from individual sites, the selected medians may be biased upward by the presence of multiple sites with high outliers. These limitations may be overcome by selecting trapezoidal statistics from among selected sites and correlation coefficients that reduce the risk for large ratios with large flows or concentrations.

Planning-level estimates are defined as the results of analyses used to evaluate alternative management measures and are recognized to include substantial uncertainties (Barnwell and Krenkel, 1982; Marsalek and Ng, 1989; Marsalek, 1991; Granato, 2014). 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 (Granato, 2013, 2014). Even if data in the BMPDB were more comprehensive, there is always substantial uncertainty when using hydrologic data at one location to estimate conditions at another location. However, if the initial analysis done with SELDM indicates the potential need for mitigation, then detailed simulation or statistical models may be used to develop more refined performance statistics for use with SELDM (Granato, 2014). 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 (Granato, 2014). This analysis can be done by varying BMP treatment statistics to meet water-quality objectives. Such an analysis may indicate that it is impossible in practice to meet water-quality objectives by using the treatment capabilities of feasible BMP designs.

Table 2. Minimum and maximum ranks of a dataset of a given size that encompass the approximate 95-percent confidence interval for the median based on the binomial distribution.

[Equation for the binomial distribution is from Bland (2015)]

Sample size	Median value	
	Lower-bound rank	Upper-bound rank
3	1	3
4	1	4
5	1	5
6	1	6
7	1	7
8	2	7
9	2	8
10	2	9
11	3	9
12	3	10
13	3	11
14	4	11
15	4	12
16	5	12
17	5	13
18	5	14
19	6	14
20	6	15
21	7	15
22	7	16
23	7	17
24	8	17
25	8	18
26	9	18
27	9	19
28	9	20
29	10	20
30	10	21
31	11	21
32	11	22
33	11	23
34	12	23
35	12	24
36	13	24
37	13	25
38	13	26
39	14	26
40	14	27
41	15	27
42	15	28
43	16	28
44	16	29
45	16	30
46	17	30
47	17	31
48	18	31
49	18	32
50	19	32
51	19	33
52	19	34
53	20	34
54	20	35
55	21	35
56	21	36
57	22	36
58	22	37
59	22	38
60	23	38
61	23	39
62	24	39
63	24	40
64	25	40
65	25	41
66	26	41
67	26	42
68	26	43
69	27	43
70	27	44
71	28	44
72	28	45
73	29	45
74	29	46
75	30	46
76	30	47
77	30	48
78	31	48
79	31	49
80	32	49
85	34	52
90	36	55
100	41	60
125	52	74
150	63	88
175	75	101
200	87	114
250	110	141
300	134	167
400	181	220

Results of Analyses

This study produced statistics for hydrograph extension, volume reduction, and water-quality treatment. The minimum, LBMPV, UBMPV, and maximum of the trapezoidal distribution were calculated for every site in the 2019 version of the BMPDB with seven or more paired events. Correlations between inflow and outflow values also were calculated for these three variables. This report documents the medians of individual statistics because Granato (2014) determined that the median of best-fit statistics would be the most robust approach for selecting BMP-performance statistics after analyzing data from many monitoring sites. Individual at-site statistics for all the sites are listed in Granato and others (2021).

Hydrograph Extension

In this study, hydrograph extension statistics were developed for 8 BMP categories using data from 44 BMP monitoring sites with 7 or more storm events (table 3). The median values of the minimum, LBMPV, and UBMPV of the trapezoidal distributions were equal to 0 for four BMP categories (grass strip, detention basin, manufactured device, and wetland channel) with sufficient data to do the analysis. Therefore, these distributions are the positive-skew triangular distributions shown in figure 1*B*. The grass swale BMP category has values that also produce a positively skewed triangular distribution, and the rest of the BMP categories have values that produce trapezoidal distributions with a vertical lower bound. Hydrograph extension statistics for individual BMP monitoring sites are provided in a runoff hydrograph extension file (USGS-SIR-2020-5136-HydrographExtension-SiteResults.txt) published by Granato and others (2021). The statistics in table 3 also are published in SELDM input file format (SELDM-tblBMPHydraulicsTable.csv) by Granato and others (2021). In comparison to the values developed by Granato (2014), hydrograph extension values increased substantially for detention basins and media filters and decreased substantially for grassy swales. In the 2012 BMPDB, however, which is the version of the BMPDB that was used for the analysis in Granato (2014), grass strips and swales were combined in one category. SELDM users should apply hydrograph extension results carefully, especially for categories with data from only a few monitoring sites. As Granato (2014) indicated, hydraulic design information may help establish the critical upper bound limits for the trapezoidal distribution to be used in SELDM modeling studies, especially since so few studies in the BMPDB have reliably documented hydrograph extension values.

Examination of results for individual BMP sites indicates that there may be large variations in performance within all the categories (fig. 3). Some of these variations may represent limitations in monitoring data, site-specific conditions such as groundwater discharge, or specific design features. For example, the median of the maximum extension values for the grass strip and manufactured device (8.63 and 8.58 hours, respectively; table 3) are greater than what professional judgement might suggest, but these categories have the largest number of monitoring sites (fig. 3). When results for individual sites are examined, it is apparent that hydrograph extension for the multichambered treatment trains in the manufactured device category are much longer than for the much smaller hydrodynamic devices (Granato and others, 2021). Thus, the medians may straddle different designs within the same BMP category. Although category-median values, which provide robust planning level estimates, are documented in table 3, some professional judgement may be needed to select statistics from among the individual sites based on design information for the individual sites. The BMPDB, however, does not contain a full set of design values for every BMP, and Leisenring and others (2013) did not find strong correlations between design and performance variables.

In SELDM, the rank correlation between inflow volume and hydrograph extension can be used to condition the stochastic generation of extension values based on the exceedance percentile of flow volume (Granato, 2013; 2014). However, only 7 of the 44 BMP monitoring sites included in the hydrograph extension analyses documented in this report had statistically significant (95th percentile) rank correlations between hydrograph extension and inflow volumes. Among the 44 BMPs with sufficient data, 29 had positive, 14 had negative, and 1 had a 0-rho value. These rho values ranged from about −0.93 to about 0.71 (table 3). This indicates that antecedent conditions rather than within-event runoff volumes may account for a substantial amount of the variability in measured hydrograph extension values (Granato, 2014). Only the detention basin and retention pond, which are designed primarily as storage volumes with specified drain times (Granato, 2014) had consistent correlations between hydrograph extension and inflow volumes. Because hydrograph extension is simulated as a duration in hours rather than being a ratio to an inflow variable, correlation to the inflow value is unlikely to produce anomalous values; therefore, the correlation coefficient is not crucial for simulating reasonable BMP discharge durations.

Runoff Volume Reduction

In this study, volume reduction statistics were developed for 12 BMP categories using data from 135 BMP monitoring sites with 7 or more storm events (table 4). BMP monitoring sites with equivalent ratios of outflow to inflow volumes across all events were excluded. Volume reduction statistics for individual BMP monitoring sites are provided in a runoff-volume reduction file (USGS-SIR-2020-5136-VolumeReduction-SiteResults.txt) published by Granato and others (2021). In comparison to the values developed by Granato (2014), the percent of events with ratios exceeding 1 (outflow volume exceeds inflow volume) increased for grass strips, bioretention, detention basins, and wetland basins; the percent exceedance was about the same

Table 3. Medians of hydrograph extension statistics for the trapezoidal distribution and Spearman’s rank correlation coefficient statistics for structural best management practices, by category.

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). BMPDB category codes and names are listed in table 1. The hydrograph extension statistics are for the trapezoidal distribution of the number of hours that outflows exceed inflows. Spearman’s rank correlation coefficients (rho) are calculated by using the ranks of the inflow volumes and the associated hydrograph extension values. The percentage of outflow hydrograph extensions greater than each hour threshold are calculated by using the extension statistics in this table. N, number of sites with at least seven storms used to calculate the statistics; min, minimum value; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; max, maximum; med, median; est, rho estimate for simulation, which is the average of the median and maximum rho values; —, insufficient data]

BMPDB category		N	Hydrograph extension statistics, in hours				Percentage of outflow hydrograph extensions greater than				rho correlation coefficients			
Code	Name		Min	LBMPV	UBMPV	Max	1 hour	6 hours	12 hours	24 hours	Min	Med	Max	Est
BI	Grass strip	14	0	0	0	8.63	78.2	9.3	0	0	−0.93	0.04	0.57	0.31
BR	Bioretention	6	0.068	0.94	1.45	8.46	88.8	9.7	0	0	−0.27	0.11	0.53	0.32
BS	Grass swale	3	0	0.41	0.41	1.59	18.8	0	0	0	0.07	0.18	0.28	0.23
CO	Composite	—	—	—	—	—	—	—	—	—	—	—	—	—
DB	Detention basin	5	0	0	0	46.3	95.7	75.8	54.9	23.2	0.27	0.58	0.71	0.65
IB	Infiltration basin	—	—	—	—	—	—	—	—	—	—	—	—	—
MD	Manufactured device	7	0	0	0	8.58	78.1	9.1	0	0	−0.62	0.15	0.61	0.38
MF	Media filter	7	0	0	12.6	117	98.5	90.8	81.5	64	−0.69	0.02	0.54	0.28
PP	Porous pavement	—	—	—	—	—	—	—	—	—	—	—	—	—
RP	Retention pond	1	0	0	41.2	41.2	97.6	85.4	70.9	41.7	0.51	0.51	0.51	0.51
WB	Wetland basin	—	—	—	—	—	—	—	—	—	—	—	—	—
WC	Wetland channel	1	0	0	0	1.81	20.1	0	0	0	−0.22	−0.22	−0.22	−0.22
	Parameter values	44	0	0	0.21	8.61	78.2	9.2	0	0	−0.25	0.13	0.54	0.34

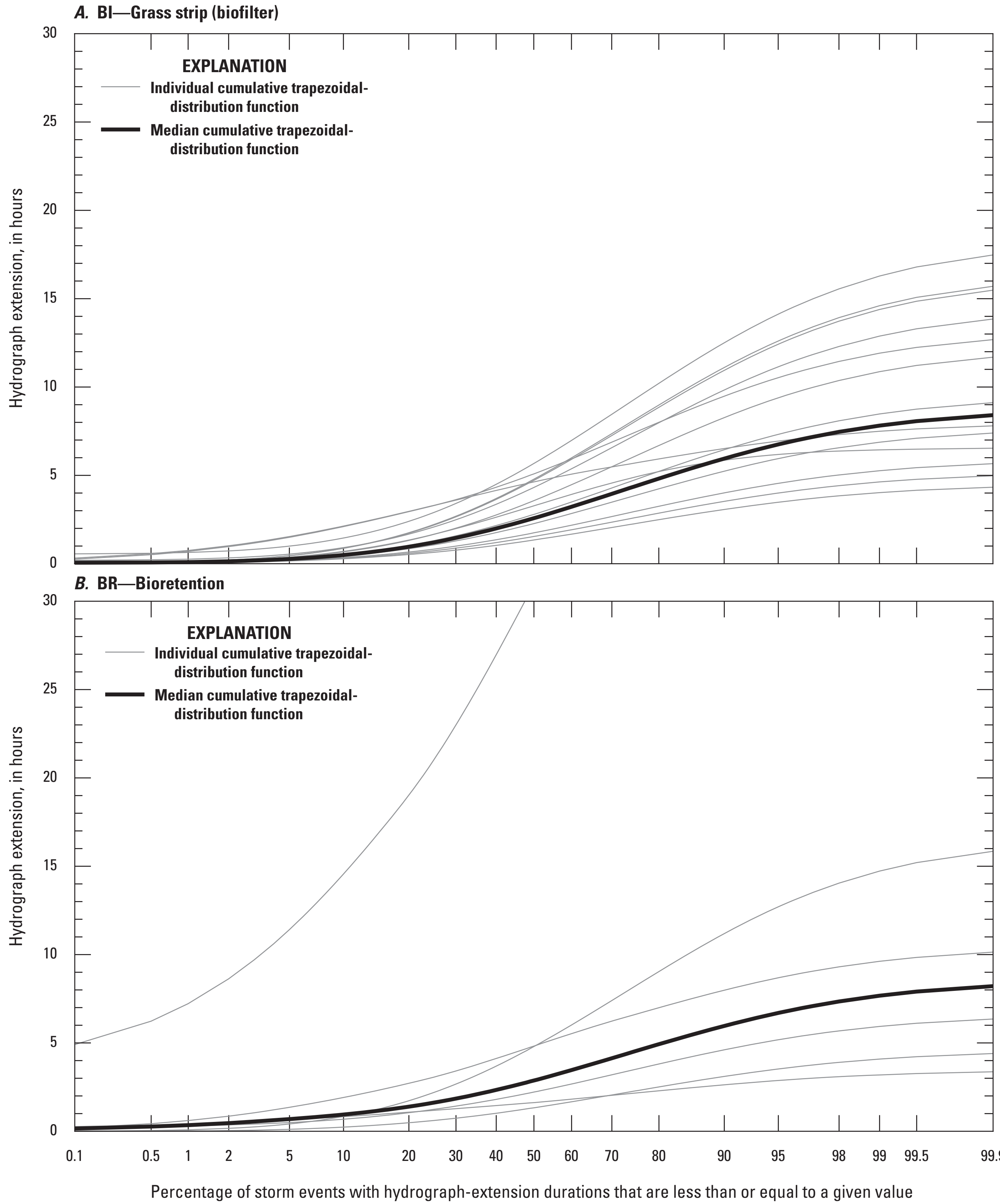

Figure 3. Line graphs showing fitted cumulative trapezoidal distribution functions of the hydrograph extension statistics for *A*, 14 grass strip (biofilter) monitoring sites, *B*, 6 bioretention monitoring sites, *C*, 7 manufactured device monitoring sites, and *D*, 7 media filter monitoring sites. The graphs also show cumulative distribution functions that are fitted to the median of the hydrograph extension statistics for each category.

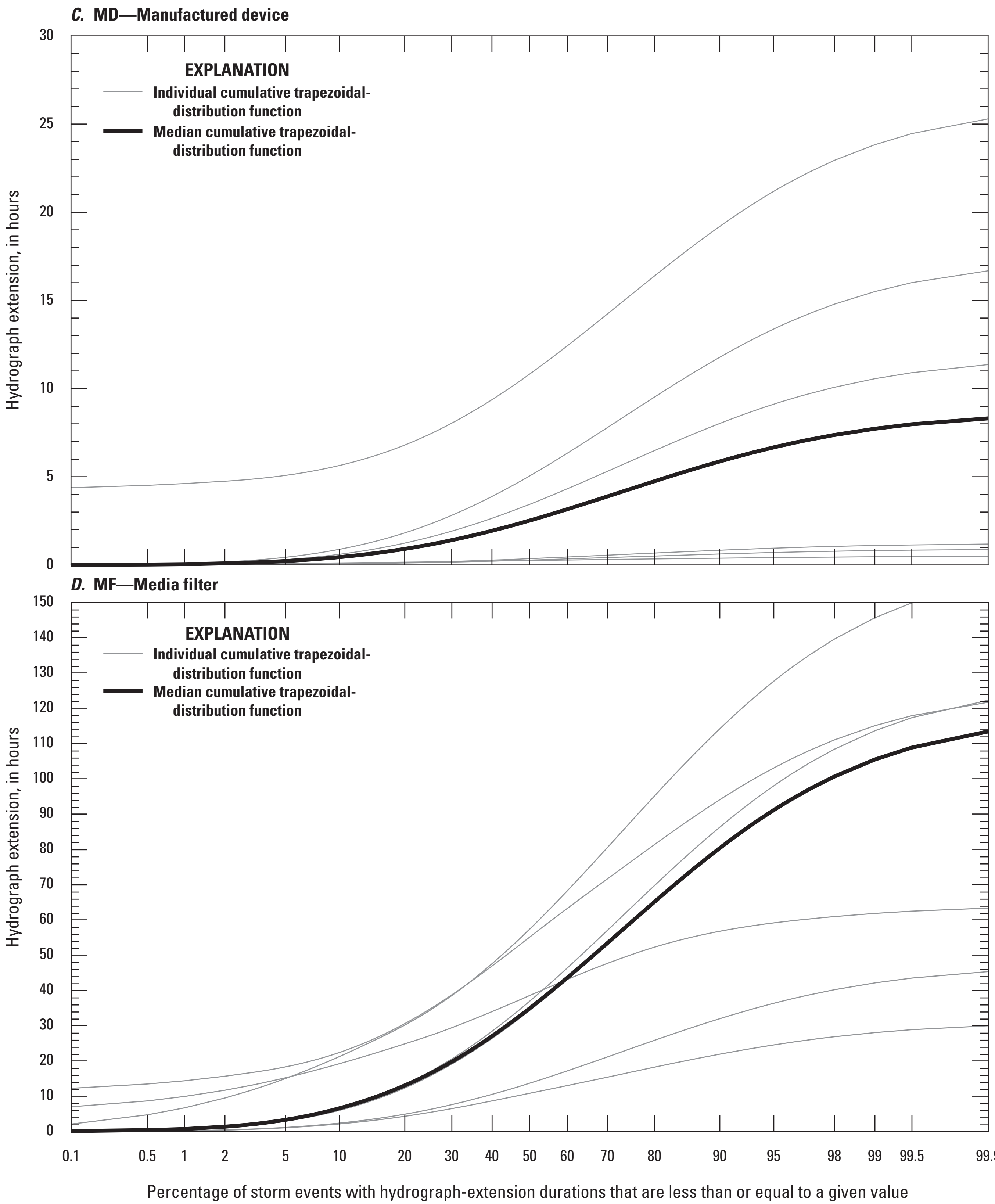

Figure 3. —Continued

Table 4. Medians of stormflow volume reduction statistics for the trapezoidal distribution and Spearman's rho correlation coefficient statistics for structural stormwater runoff best management practices by category.

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). BMPDB category codes and names are listed in table 1. The percentage of outflow ratios greater than 1 are calculated by using the volume reduction statistics in this table. The volume reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow volume. Spearman's rank correlation coefficients (rho) are calculated by using the ranks of the inflow volumes and the associated ratios of outflow to inflow volumes. N, number of sites with at least seven storms used to calculate the median ratio statistics and Spearman's rho statistics; min, minimum; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; max, maximum; Pct GT 1, the theoretical percentage of storms in which outflows exceed inflows and thus, the ratio is greater than 1; med, median; —, insufficient data]

BMPDB category		N	Volume reduction statistics, ratio					Spearman's rho correlation coefficients		
Code	Name		Min	LBMPV	UBMPV	Max	Pct GT 1	Min	Med	Max
BI	Grass strip	31	0	0.0137	0.0324	1.9511	23.9	−0.72	−0.10	0.90
BR	Bioretention	22	0.0043	0.0720	0.2051	1.1318	1.49	−0.70	0.27	0.78
BS	Grass swale	12	0.0671	0.1969	0.6720	0.9732	0.0	−0.60	0.24	0.84
CO	Composite	4	0	0.7815	1.0377	1.5961	34.2	−0.72	−0.40	0.70
DB	Detention basin	15	0.0658	0.1411	0.6570	1.8986	27.7	−0.76	−0.26	0.48
IB	Infiltration basin	1	0.2277	1.0584	1.0605	1.0605	14.0	0.84	0.84	0.84
MD	Manufactured device	8	0.3745	0.8024	0.9502	1.3533	27.5	−0.71	−0.15	0.10
MF	Media filter	6	0.2551	0.2648	0.2746	1.3979	12.2	−0.15	0.00	0.57
PP	Porous pavement	2	0	0	0	0.4008	0.0	0.28	0.53	0.77
RP	Retention pond	25	0.1462	0.6207	0.8907	1.6295	30.6	−0.72	−0.01	0.79
WB	Wetland basin	4	0.2843	0.9028	0.9028	2.0932	55.5	−0.57	−0.18	0.61
WC	Wetland channel	5	0.4378	0.4378	0.9530	1.5623	31.6	−0.60	0.04	0.70
	Parameter values	135	0.1067	0.3513	0.7814	1.4801	18.3	−0.65	−0.01	0.74

as in Granato (2014) for media filters and wetland channels, and smaller for swales and retention ponds. The values for grassy strips and swales may be different because these two categories were separated in the 2019 version of the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). SELDM users should apply runoff-volume reduction statistics carefully, especially for categories with data from only a few monitoring sites.

The median volume reduction statistics in table 4 indicate that outflows range from about 0.4 percent of inflows (for bioretention) to about 209 percent of outflows (for wetland basins). Only the median for the grass swale and porous pavement category result in BMPs that do not have some outflows that exceed inflows for some storm events. Among the other BMP categories in table 4, the percentage of storms in which outflows exceed inflows ranges from 1.5 percent for bioretention to 56 percent for wetland basins. Outflows may exceed inflows if flows retained during one event are released during a subsequent event, if precipitation on the BMP is a substantial component of flow, if groundwater discharge occurs, if monitoring instruments are miscalibrated, or if flow is otherwise erroneously measured. Groundwater discharge may occur as saturation overland flow, throughflow, or near-channel groundwater ridging (Granato, 2010); these types of flow may be especially prevalent for normally wet BMPs, such as detention ponds or wetland BMPs.

Examples of the CDFs for the trapezoidal distribution of volume reduction ratios for 31 grass strip (biofilter), 22 bioretention, 8 manufactured device, and 6 media-filter sites are shown with the CDFs constructed using the medians of the best fit statistics in figure 4. The graphs indicate the large range in performance of each type of BMP among the different studies. The BMP categories for the other 68 sites not included in figure 4 also have 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 24 percent of runoff events for the grass strip CDF, about 1 percent of runoff events for the bioretention CDF, about 28 percent for the manufactured device CDF, and about 12 percent of runoff events for the media filter CDF (fig. 4).

The CDFs in figure 4 indicate that the median values provided in table 4 may produce robust estimates for some BMPs but professional judgement may be necessary for selecting statistics for other categories. Although there are 31 grass-strip monitoring sites, many of the CDFs for grass strips indicate the presence of groundwater discharge (Granato, 2010) or other sources of stormflow because outflows greatly exceed inflows for a large proportion of runoff events. If the median of grass-strip values that do not exceed 2 is selected, then the maximum trapezoidal statistic would equal 1.36, and only about 7 percent of events would exceed a ratio of 1. Granato

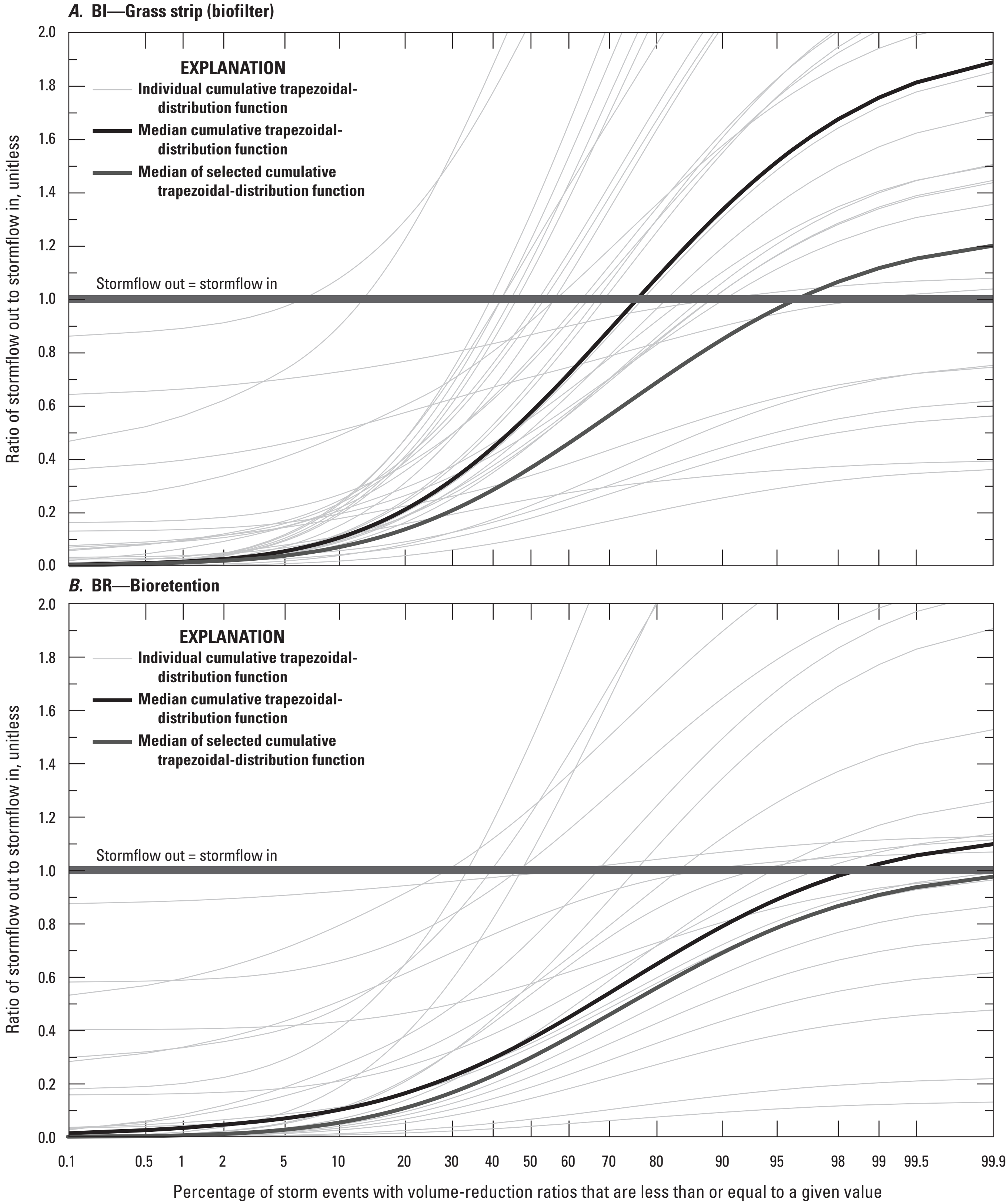

Figure 4. Line graphs showing fitted cumulative trapezoidal distribution functions of the volume reduction ratio statistics for *A*, 31 grass strip (biofilter), *B*, 22 bioretention, *C*, 8 manufactured device, and *D*, 6 media filter monitoring sites. The graphs also show cumulative distribution functions that are fitted to the median and selected-median statistics.

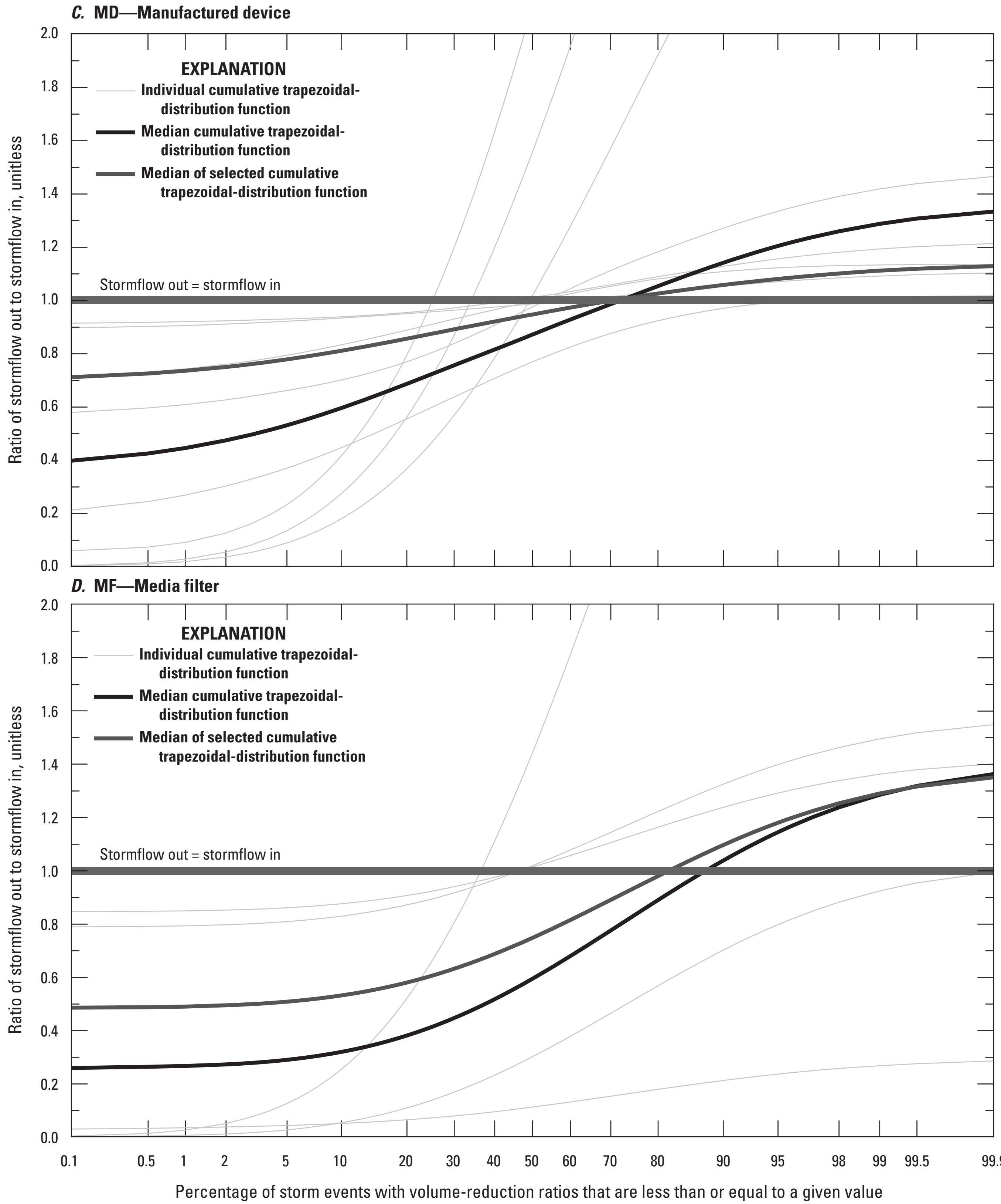

Figure 4. —Continued

(2014) did not analyze manufactured devices because volume reduction is not a design feature for many of these devices. The CDFs for manufactured device and media filter sites (fig. 4*C* and *D*) indicate the potential for volume changes caused by both infiltration into and leakage from manufactured devices and media filters. Infiltration is evidenced by the CDFs with a substantial percentage of events with ratios that substantially exceed 1. Leakage is evidenced by the CDFs with a substantial percentage of events with ratios that are substantially less than 1. Although some evaporation or leakage may be expected from such devices from storm to storm, thereby reducing the outflow from the next event, it may be prudent not to simulate volume reduction for BMPs that are not designed for this purpose. This is because volume reductions observed in the data for some BMPs that are not commonly designed for volume reduction may be the result of sampling artifacts.

To address the potential for simulated mass balance problems for BMPs without unmonitored inflows, median statistics were recalculated by using only the sites with maximum volume reduction ratios that are less than 2 (table 5). Although this resulted in a substantial reduction in the number of sites used in the calculations for several BMPs, it also substantially reduced the risk for exceeding a volume reduction ratio of one and reduced the magnitude for most BMP categories (tables 4 and 5). Results for closed-volume BMPs such as manufactured devices and media filters remain higher than may be expected, but the normally wet BMPs (including retention ponds, wetland basins, and wetland channels) that commonly are in contact with groundwater may reflect the effect of rising groundwater levels during storm events. Using only selected BMPs also reduced the magnitude of excess flows for all BMP categories in these tables. The selected median CDFs in figure 4 can be used to demonstrate the potential effects of the selection criteria on simulated long-term volume reduction populations. The statistics in table 5 also are published in SELDM input-file format (SELDM-tblBMPHydraulicsTable.csv) by Granato and others (2021).

In SELDM, the rank correlation between inflow volumes and the volume reduction ratios can be used to condition the stochastic generation of the ratios based on the exceedance percentile of flow volume (Granato, 2013, 2014). Because volume reduction is simulated as a ratio of the inflow volume, the correlation coefficient can be used to reduce the probability that a small ratio would be applied to a very large runoff volume. A strong positive correlation between inflow volume and the volume reduction ratio would tend to result in low ratios (larger proportional reductions) for small runoff volumes and high ratios (smaller proportional reductions) for large runoff volumes. This is consistent with what would be expected, but strong positive correlations could create large excess flows if the maximum volume reduction value greatly exceeds 1.

Table 5. Medians of selected stormflow volume reduction statistics for the trapezoidal distribution and Spearman’s rho correlation coefficient statistics for structural stormwater runoff best management practices, by category.

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). BMPDB category codes and names are listed in table 1. The medians were calculated by using statistics from sites with maximum ratios that are less than two. The percentage of outflow ratios greater than 1 are calculated by using the volume reduction statistics in this table. The volume reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow volume. Spearman’s rank correlation coefficients (rho) are calculated by using the ranks of the inflow volumes and the associated ratios of outflow to inflow volumes. N, number of sites with at least seven storms used to calculate the median ratio statistics and Spearman's rho statistics; min, minimum; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; max, maximum; pct GT 1, the theoretical percentage of storms in which outflows exceed inflows; med, median; est, estimate for simulation, which is the average of the median and maximum rho values]

BMPDB category		N	Volume reduction statistics, ratio					Spearman’s rho correlation coefficients			
Code	Name		Min	LBMPV	UBMPV	Max	Pct GT 1	Min	Med	Max	Est
BI	Grass strip	16	0	0.0202	0.0317	1.2428	3.9	−0.61	−0.06	0.90	0.42
BR	Bioretention	16	0	0	0.0492	1.0067	0.0	−0.70	0.43	0.78	0.61
BS	Grass swale	8	0.0671	0.0671	0.4966	0.8882	0.0	−0.14	0.51	0.84	0.68
CO	Composite	3	0	0.5561	1.0161	1.3593	20.6	−0.72	−0.72	0.70	−0.01
DB	Detention basin	8	0.2486	0.3649	0.6229	0.9973	0.0	−0.76	−0.04	0.48	0.22
IB	Infiltration basin	1	0.2277	1.0584	1.0605	1.0605	14.0	0.84	0.84	0.84	0.84
MD	Manufactured device	5	0.6993	0.9320	1.0158	1.1350	29.0	−0.29	−0.06	0.10	0.02
MF	Media filter	5	0.4836	0.4836	0.5033	1.3773	17.8	−0.15	−0.02	0.57	0.28
PP	Porous pavement	2	0	0	0	0.4008	0.0	0.28	0.53	0.77	0.65
RP	Retention pond	17	0.4150	0.8726	0.9878	1.3992	35.2	−0.72	0.07	0.79	0.43
WB	Wetland basin	2	0.2843	0.9028	0.9028	1.5797	38.3	−0.20	0.20	0.61	0.41
WC	Wetland channel	3	0.4777	0.9530	1.1223	1.3803	46.9	0.04	0.50	0.70	0.60
	Parameter values	86	0.2382	0.5199	0.7629	1.1889	7.0	−0.25	0.14	0.74	0.44

Unless there is reason to believe that groundwater discharges are occurring at a site of interest, use of a semistrong-to-strong positive correlation (greater than 0.75) with a maximum volume reduction ratio that is much greater than 1 may result in unrealistic mass-balance values for some large events. Use of a negative correlation, however, could lead to excess flows for small runoff volumes and large reductions (small ratios) for large runoff volumes.

Rank correlations calculated from available data in the BMPDB were not definitive indicators of quantitative relations between inflow volumes and volume reduction ratios. Only 35 of the 135 BMP monitoring sites with 7 or more storm events included in the volume reduction analyses documented in this report had statistically significant (95th percentile) rank correlations between volume reduction and inflow volumes. Among the 35 BMPs with statistically significant rho values, 21 had positive and 14 had negative rho values. Among the 135 BMP monitoring sites with data for 7 or more storm events, 68 had positive, 66 had negative, and 1 had a 0 rho value. These rho values ranged from about −0.76 to about 0.90. These correlation coefficients indicate that a combination of different antecedent conditions, rather than within-event runoff volumes, may account for a substantial amount of the variability in measured volume reduction values (Granato, 2014).

Water-Quality Treatment

In this study, water-quality treatment statistics were developed for 10 BMP categories by using data from 206 BMP monitoring sites with paired inflow and outflow concentrations from 7 or more storm events (table 6). Water-quality treatment statistics were developed for 51 selected runoff-quality constituents of interest to State departments of transportation. Constituents were selected for inclusion in this report on the basis of available data, potential transferability, and the perceived quality of data in the database. Water-quality treatment statistics from individual BMP monitoring sites for all the water-quality properties and constituents in table 6 are provided in a water-quality treatment file (USGS-SIR-2020-5136-WaterQuality-SiteResults.txt) published by Granato and others (2021). Median water-quality treatment statistics, by BMP category, for eight constituent groups are provided in table 7. Median water-quality treatment statistics, by BMP category, for 48 individual water-quality constituents are provided in appendix table 1.1 of this report; these statistics also are published in SELDM input-file format (SELDM-tadBMPTreatmentTable.csv) by Granato and others (2021). The constituent-group statistics in table 7 are estimated as the median of statistics from related constituents in table 1.1. There are variations among constituents and groups, but the water-quality treatment statistics in this report are by-and-large similar to the values developed by Granato (2014). The updated statistics are more robust because the 2012 dataset contained about 80 percent of the sites available in the updated 2019 dataset and the BMPDB team improved the quality of data between 2012 and 2019. The analysis in this report also includes data for many more runoff-quality constituents than Granato (2014).

For many constituent groups (table 7) and constituents (table 1.1), the theoretical percentage of events with water-quality treatment ratios that are greater than 1 is substantial. In some cases, the percentage of events in which the outflow concentrations exceed the inflow concentrations exceed 50 percent. There are many physicochemical processes that may cause increases in concentrations during some events, especially for dissolved constituents that can partition from stormwater solids. 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 effect 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 1 increases from 0 to about 40 percent. As the maximum value increases from 2 to 4, the percentage of generated values that are greater than 1 increases from about 40 to 60 percent. Although the ratios may exceed 1, indicating higher concentrations in the outflows than in the inflows, the negative correlations prevalent for most constituents indicate that small inflow concentrations may tend to increase within the BMPs, whereas large concentrations decrease. Because concentrations of highway and urban runoff commonly vary logarithmically over one or more orders of magnitude, an equivalent percentage change for a low concentration is usually much smaller than for a large concentration (Granato and Jones, 2014, 2019; Risley and Granato, 2014; Smith and others, 2018; Stonewall and others, 2019; Weaver and others, 2019; Jeznach and Granato, 2020).

Tables 7 and 1.1 contain statistics for individual BMP types and for “parameter values.” These “parameter values” statistics are estimated from multiple BMP categories for each property, constituent, or constituent group. The trapezoidal statistics are the median of values in the tables for the BMP categories. The cumulative distribution functions for the parameter value statistics in table 7 are shown in figure 5. The percentages of values exceeding a ratio of 1 for these estimates are the theoretical percent of events calculated by using the trapezoidal parameter value statistics. The rho values for the parameter value estimates were selected as the smallest rho values from among the category values; these minimum of median rho values were selected to minimize simulations in which large concentrations would be paired with large ratios (Granato, 2013, 2014). The probability that this would occur increases as the absolute value correlation coefficient increases (Granato, 2013).

The parameter value statistics may be used as planning-level estimates of treatment statistics for constituents with insufficient data to produce robust estimates for a given BMP category or for a given constituent. These statistics also may be used to provide planning-level treatment estimates for TMDL analyses in receiving-water basins where multiple BMPs may be in use or for analyses at actual or hypothetical sites without a particular BMP (Granato and Jones, 2017;

Table 6. Runoff-quality constituents analyzed with counts of the number of sites, number of International Stormwater Best Management Practice Database categories, and number of paired samples used to analyze structural stormwater runoff best management practices.

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). Pcode is the water-quality parameter code is denoted by the letter p and the five-digit identification number from the U.S. Geological Survey (2020) National Water Information System (NWIS); abbreviation is the short name used in tables and figures in this report; name is the constituent name in NWIS; fraction is the sampled fraction (filtered water or unfiltered (whole) water); and number of sites are the sites with seven or more uncensored paired samples]

Pcode	Abbrev-iation	Name	Fraction	Number of sites	Number of BMPDB catego-ries	Total number of paired samples
Water-quality properties						
p00076	TUR	Turbidity, water, unfiltered, nephelometric turbidity units	Whole	31	9	501
p00094	SpC	Specific conductance, water, unfiltered, field, microsiemens per centimeter at 25 degrees Celsius	Whole	35	6	487
p00400	pH	pH, water, unfiltered, field, standard units	Whole	70	8	1,038
Sediment and related constituents						
p00530	TSS	Solids, suspended, water, milligrams per liter	Whole	206	12	3,587
p80154	SSC	Suspended sediment concentration, milligrams per liter	Whole	23	6	516
p99409	SSCest	Suspended sediment concentration, milligrams per liter (estimated from TSS)	Whole	206	12	3,587
Nutrient constituents, filtered						
p00602	FN	Total nitrogen, water, filtered, milligrams per liter	Filtered	4	3	555
p00618	FNO_3	Nitrate, water, filtered, milligrams per liter as nitrogen	Filtered	1	1	11
p00666	FP	Phosphorus, water, filtered, milligrams per liter	Filtered	56	8	1,454
p00671	FPO_4	Orthophosphate, water, filtered, milligrams per liter as phosphorus	Filtered	22	5	410
Nutrient constituents, unfiltered						
p00600	TN	Total nitrogen, water, unfiltered, milligrams per liter	Whole	59	9	1,490
p00615	TNO_2	Nitrite, water, unfiltered, milligrams per liter as nitrogen	Whole	5	2	65
p00620	TNO_3	Nitrate, water, unfiltered, milligrams per liter as nitrogen	Whole	46	9	643
p00625	TKN	Ammonia plus organic nitrogen, water, unfiltered, milligrams per liter as nitrogen	Whole	93	8	1,393
p00630	$TNO_2{}^3$	Nitrite plus nitrate, water, unfiltered, milligrams per liter as nitrogen	Whole	51	10	862
p00665	TP	Phosphorus, water, unfiltered, milligrams per liter	Whole	167	12	3,152
p70507	TPO_4	Orthophosphate, water, unfiltered, milligrams per liter as phosphorus	Whole	12	4	108
Minor and trace inorganics, filtered						
p01030	FCr	Chromium, water, filtered, micrograms per liter	Filtered	16	5	198
p01040	FCu	Copper, water, filtered, micrograms per liter	Filtered	71	9	1,033
p01046	FFe	Iron, water, filtered, micrograms per liter	Filtered	4	4	72
p01049	FPb	Lead, water, filtered, micrograms per liter	Filtered	35	8	411
p01065	FNi	Nickel, water, filtered, micrograms per liter	Filtered	19	5	246
p01090	FZn	Zinc, water, filtered, micrograms per liter	Filtered	71	9	1,040
p01106	FAl	Aluminum, water, filtered, micrograms per liter	Filtered	1	1	24
Minor and trace inorganics, unfiltered						
p01002	TAs	Arsenic, water, unfiltered, micrograms per liter	Whole	17	5	193
p01027	TCd	Cadmium, water, unfiltered, micrograms per liter	Whole	37	8	546
p01034	TCr	Chromium, water, unfiltered, recoverable, micrograms per liter	Whole	22	6	330
p01042	TCu	Copper, water, unfiltered, recoverable, micrograms per liter	Whole	112	10	1,818

Table 6. Runoff-quality constituents analyzed with counts of the number of sites, number of International Stormwater Best Management Practice Database categories, and number of paired samples used to analyze structural stormwater runoff best management practices.—Continued

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). Pcode is the water-quality parameter code is denoted by the letter p and the five-digit identification number from the U.S. Geological Survey (2020) National Water Information System (NWIS); abbreviation is the short name used in tables and figures in this report; name is the constituent name in NWIS; fraction is the sampled fraction (filtered water or unfiltered (whole) water); and number of sites are the sites with seven or more uncensored paired samples]

Pcode	Abbrev-iation	Name	Fraction	Number of sites	Number of BMPDB catego-ries	Total number of paired samples
		Minor and trace inorganics, unfiltered—Continued				
p01045	TFe	Iron, water, unfiltered, recoverable, micrograms per liter	Whole	20	6	329
p01051	TPb	Lead, water, unfiltered, recoverable, micrograms per liter	Whole	75	10	1,119
p01067	TNi	Nickel, water, unfiltered, recoverable, micrograms per liter	Whole	29	7	406
p01092	TZn	Zinc, water, unfiltered, recoverable, micrograms per liter	Whole	137	12	2,169
p01104	TAl	Aluminum, water, unfiltered, recoverable, micrograms per liter	Whole	4	3	42
p50286	THg	Mercury, water, unfiltered, nanograms per liter	Whole	1	1	8
		Organic constituents				
p00310	TBOD	Biochemical oxygen demand, water, unfiltered, 5 days at 20 degrees Celsius, milligrams per liter	Whole	2	2	36
p00340	TCOD	Chemical oxygen demand, high level, water, unfiltered, milligrams per liter	Whole	11	4	187
p00550	TOG	Oil and grease, water, unfiltered, recoverable, milligrams per liter	Whole	5	1	72
p00680	TOC	Organic carbon, water, unfiltered, milligrams per liter	Whole	43	6	604
p04585	TDRH	Diesel range hydrocarbons, water, unfiltered, recoverable, micrograms per liter	Whole	10	3	95
p75984	TPCB	PCBs, water, unfiltered, recoverable, nanograms per liter (sum of congeners)	Whole	1	1	8
pXXX05	TPAH	PAHs EPA 8310, water, unfiltered, micrograms per liter, (sum of 16 PAHs not censored)	Whole	3	1	42
		Biological constituents				
p50468	Ecoli	*Escherichia coli*, colilert quantitray method, water, most probable number per 100 milliliters	Whole	10	5	176
p31616	Fcoli	Fecal coliform, M–FC MF (0.45-micrometer) method, water, colonies per 100 milliliters	Whole	20	4	236
p31507	Tcoli	Total coliform, completed test, water, most probable number per 100 milliliters	Whole	7	2	79
		Major ionic constituents and properties				
p00500	TS	Residue on total evaporation at 105 degrees Celsius, water, unfiltered, milligrams per liter	Whole	11	6	194
p00515	TDS	Residue, water, filtered, dried at 105 degrees Celsius, milligrams per liter	Filtered	46	10	675
p00900	Hard	Hardness, water, unfiltered, milligrams per liter as calcium carbonate	Whole	8	4	127
p00915	FCa	Calcium, water, filtered, milligrams per liter	Filtered	7	2	104
p00923	TNa	Sodium, water, unfiltered, recoverable, milligrams per liter	Whole	5	4	100
p00925	FMg	Magnesium, water, filtered, milligrams per liter	Filtered	7	2	104
p00940	FCl	Chloride, water, filtered, milligrams per liter	Filtered	63	12	917

Table 7. Medians of selected water-quality treatment statistics for selected parameter groups including the trapezoidal distribution and Spearman's rank correlation coefficient statistics for structural stormwater runoff best management practices, by category.

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). BMPDB category codes and names are listed in table 1. The constituents included in the parameter categories are listed in table 6. The percentage of outflow ratios greater than 1 are calculated by using the treatment statistics in this table. The concentration-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow concentration. Spearman's rank correlation coefficients (rho) are calculated by using the ranks of the inflow concentrations and the associated ratios of outflow to inflow concentrations. The selected rho value is closest to minus one among at-site rho values. The water-quality parameter groups are listed and defined in table 6. N, number of sites with paired inflow and outflow concentrations for at least seven storms used to calculate the median ratio statistics; min, minimum; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; max, maximum; Pct GT 1, theoretical percentage of storms in which outflows exceed inflows and thus, the ratio is greater than 1; —, insufficient data]

BMPDB category		N	Trapezoidal distribution statistics					
Code	Name		Min	LBMPV	UBMPV	Max	Pct GT 1	rho
			Suspended sediment and solids					
BI	Grass strip	12	0	0.003	0.021	1.031	0.09	−0.82
BR	Bioretention	29	0	0	0	1.418	8.7	−0.96
BS	Grass swale	12	0.017	0.044	0.092	1.373	7.7	−0.99
DB	Detention basin	27	0	0	0	1.682	16.4	−0.96
IB	Infiltration basin	1	0	0	0	0.671	0	−0.89
MD	Manufactured device	79	0.001	0.015	0.072	1.129	1.33	−0.88
MF	Media filter	21	0	0	0	0.801	0	−0.87
RP	Retention pond	27	0	0	0	1.064	0.36	−0.97
WB	Wetland basin	14	0	0	0	2.191	29.5	−0.89
WC	Wetland channel	2	0.016	0.016	0.123	2.72	40.5	−0.49
	Parameter values	224	0	0	0	1.251	4	−0.99
			Nutrients, nitrogen constituents, filtered					
BI	Grass strip	—	—	—	—	—	—	—
BR	Bioretention	—	—	—	—	—	—	—
BS	Grass swale	—	—	—	—	—	—	—
DB	Detention basin	—	—	—	—	—	—	—
IB	Infiltration basin	—	—	—	—	—	—	—
MD	Manufactured device	2	0.28	0.317	0.543	1.581	21.3	−0.79
MF	Media filter	—	—	—	—	—	—	—
RP	Retention pond	1	0.275	0.818	0.818	1.57	33.4	−0.43
WB	Wetland basin	2	0.591	1.007	1.007	1.648	62	−0.31
WC	Wetland channel	—	—	—	—	—	—	—
	Parameter values	5	0.28	0.818	0.818	1.581	34	−0.43
			Nutrients, nitrogen constituents, unfiltered					
BI	Grass strip	12	0.121	0.228	0.494	2.313	38.6	−0.39
BR	Bioretention	31	0.022	0.177	0.269	2.962	47.1	−0.53
BS	Grass swale	9	0.311	0.591	0.601	2.211	47.7	−0.53
DB	Detention basin	50	0.154	0.555	0.729	1.981	38.4	−0.38
IB	Infiltration basin	—	—	—	—	—	—	—
MD	Manufactured device	43	0.153	0.446	0.752	1.79	30.9	−0.63
MF	Media filter	37	0.123	0.421	0.448	2.851	51.7	−0.63
RP	Retention pond	50	0.088	0.176	0.328	1.794	23.1	−0.51
WB	Wetland basin	14	0.114	0.114	0.175	2.687	43	−0.64
WC	Wetland channel	1	0	1.175	1.175	1.269	32.9	−0.29
	Parameter values	247	0.121	0.421	0.494	2.211	39.5	−0.53

Table 7. Medians of selected water-quality treatment statistics for selected parameter groups including the trapezoidal distribution and Spearman's rank correlation coefficient statistics for structural stormwater runoff best management practices, by category. —Continued

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). BMPDB category codes and names are listed in table 1. The constituents included in the parameter categories are listed in table 6. The percentage of outflow ratios greater than 1 are calculated by using the treatment statistics in this table. The concentration-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow concentration. Spearman's rank correlation coefficients (rho) are calculated by using the ranks of the inflow concentrations and the associated ratios of outflow to inflow concentrations. The selected rho value is closest to minus one among at-site rho values. The water-quality parameter groups are listed and defined in table 6. N, number of sites with paired inflow and outflow concentrations for at least seven storms used to calculate the median ratio statistics; min, minimum; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; max, maximum; Pct GT 1, theoretical percentage of storms in which outflows exceed inflows and thus, the ratio is greater than 1; —, insufficient data]

BMPDB category		N	Trapezoidal distribution statistics					
Code	Name		Min	LBMPV	UBMPV	Max	Pct GT 1	rho
	Nutrients, phosphorus constituents, filtered							
BI	Grass strip	5	0.273	0.692	0.731	3.769	71.4	−0.52
BR	Bioretention	2	0.016	0.383	0.383	1.216	4.7	0.04
BS	Grass swale	4	0.256	0.382	0.418	4.899	72.5	−0.62
DB	Detention basin	9	0.189	0.189	0.21	2.037	31.5	−0.34
IB	Infiltration basin	—	—	—	—	—	—	—
MD	Manufactured device	25	0.092	0.379	0.666	1.801	28.3	−0.44
MF	Media filter	6	0	0.672	0.676	1.588	23.8	−0.6
RP	Retention pond	19	0	0	0	2.161	28.9	−0.57
WB	Wetland basin	8	0.184	0.248	0.302	3.817	61.2	−0.3
WC	Wetland channel	—	—	—	—	—	—	—
	Parameter values	78	0.13775	0.38025	0.4005	2.09875	35.9	−0.48
	Nutrients, phosphorus constituents, unfiltered							
BI	Grass strip	7	0.015	0.075	0.129	2.598	39.2	−0.59
BR	Bioretention	22	0	0.01	0.077	4.433	60.1	−0.64
BS	Grass swale	10	0.052	0.565	0.784	3.4	61.7	−0.63
DB	Detention basin	33	0.062	0.18	0.456	2.744	44.9	−0.54
IB	Infiltration basin	41	0.207	0.521	0.569	1.568	22.9	−0.34
MD	Manufactured device	21	0.266	0.338	0.356	2.085	37	−0.57
MF	Media filter	2	0.007	0.007	0.007	1.849	21.2	−0.92
RP	Retention pond	27	0.155	0.209	0.765	2.35	41.8	−0.55
WB	Wetland basin	12	0.09	0.157	0.212	2.489	39.7	−0.47
WC	Wetland channel	2	0.29	0.556	0.835	2.08	45.3	0.13
	Parameter values	177	0.076	0.194	0.406	2.419	39.1	−0.56
	Minor and trace inorganics, filtered							
BI	Grass strip	24	0.057	0.1785	0.2665	1.3555	8.4	−0.89
BR	Bioretention	6	0.005	0.153	0.182	1.191	3	−0.35
BS	Grass swale	11	0.15	0.169	0.659	1.837	27.3	−0.49
DB	Detention basin	30	0.2345	0.609	0.6885	1.886	37.9	−0.73
IB	Infiltration basin	2	0.563	0.563	0.584	2.933	66.5	−0.62
MD	Manufactured device	79	0.225	0.765	0.8925	1.815	41.9	−0.79
MF	Media filter	39	0.183	0.544	0.89	1.44	22	−0.79
RP	Retention pond	17	0.09	0.116	0.396	2.114	31.4	−0.94
WB	Wetland basin	4	0.198	0.371	0.371	2.289	41.4	−0.86
WC	Wetland channel	—	—	—	—	—	—	—
	Parameter values	212	0.183	0.371	0.584	1.837	29.9	−0.79

Table 7. Medians of selected water-quality treatment statistics for selected parameter groups including the trapezoidal distribution and Spearman's rank correlation coefficient statistics for structural stormwater runoff best management practices, by category. —Continued

[The International Stormflow Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). BMPDB category codes and names are listed in table 1. The constituents included in the parameter categories are listed in table 6. The percentage of outflow ratios greater than 1 are calculated by using the treatment statistics in this table. The concentration-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow concentration. Spearman's rank correlation coefficients (rho) are calculated by using the ranks of the inflow concentrations and the associated ratios of outflow to inflow concentrations. The selected rho value is closest to minus one among at-site rho values. The water-quality parameter groups are listed and defined in table 6. N, number of sites with paired inflow and outflow concentrations for at least seven storms used to calculate the median ratio statistics; min, minimum; LBMPV, lower bound of the most probable value; UBMPV, upper bound of the most probable value; max, maximum; Pct GT 1, theoretical percentage of storms in which outflows exceed inflows and thus, the ratio is greater than 1; —, insufficient data]

BMPDB category		N	Trapezoidal distribution statistics					
Code	Name		Min	LBMPV	UBMPV	Max	Pct GT 1	rho
			Minor and trace inorganics, unfiltered					
BI	Grass strip	33	0.0055	0.0475	0.0785	1.4215	9.1	−0.85
BR	Bioretention	35	0	0	0	1.529	12	−0.89
BS	Grass swale	14	0	0.1275	0.2365	1.364	8	−0.79
DB	Detention basin	54	0.1005	0.3555	0.411	1.367	10.7	−0.66
IB	Infiltration basin	5	0	0	0	1.036	0.1	−0.88
MD	Manufactured device	136	0.1905	0.482	0.639	1.3815	14.5	−0.67
MF	Media filter	66	0.029	0.074	0.263	1.471	11.3	−0.9
RP	Retention pond	83	0.024	0.0765	0.1315	1.4315	9.8	−0.77
WB	Wetland basin	11	0.019	0.07	0.07	1.895	23.4	−0.89
WC	Wetland channel	5	0.102	0.4605	0.822	1.687	28	−0.73
	Parameter values	442	0.0215	0.07525	0.184	1.4265	9.7	−0.82
			Organic constituents, unfiltered					
BI	Grass strip	6	0.146	0.388	0.414	1.671	23.1	−0.58
BR	Bioretention	4	0	0	0	1.559	12.9	−1
BS	Grass swale	—	—	—	—	—	—	—
DB	Detention basin	9	0.442	0.74	0.912	1.918	50.8	−0.54
IB	Infiltration basin	—	—	—	—	—	—	—
MD	Manufactured device	33	0.18	0.438	0.605	1.475	17.7	−0.65
MF	Media filter	12	0.209	0.503	0.513	1.327	11.6	−0.52
RP	Retention pond	9	0.232	0.376	0.675	1.426	16.2	−0.69
WB	Wetland basin	—	—	—	—	—	—	—
WC	Wetland channel	—	—	—	—	—	—	—
	Parameter values	73	0.194	0.413	0.559	1.517	19	−0.62
			Biological constituents, unfiltered					
BI	Grass strip	—	—	—	—	—	—	—
BR	Bioretention	1	0	0	0	0.206	0	−0.1
BS	Grass swale	—	—	—	—	—	—	—
DB	Detention basin	8	0	0	0	2.746	40.4	−0.69
IB	Infiltration basin	—	—	—	—	—	—	—
MD	Manufactured device	10	0	0	0	2.948	43.7	−0.38
MF	Media filter	6	0	0	0	3.378	49.6	−0.55
RP	Retention pond	8	0	0	0	3.14	46.4	−0.51
WB	Wetland basin	1	0	0	0	0.711	0	0.14
WC	Wetland channel	—	—	—	—	—	—	—
	Parameter values	34	0	0	0	2.847	42.1	−0.45

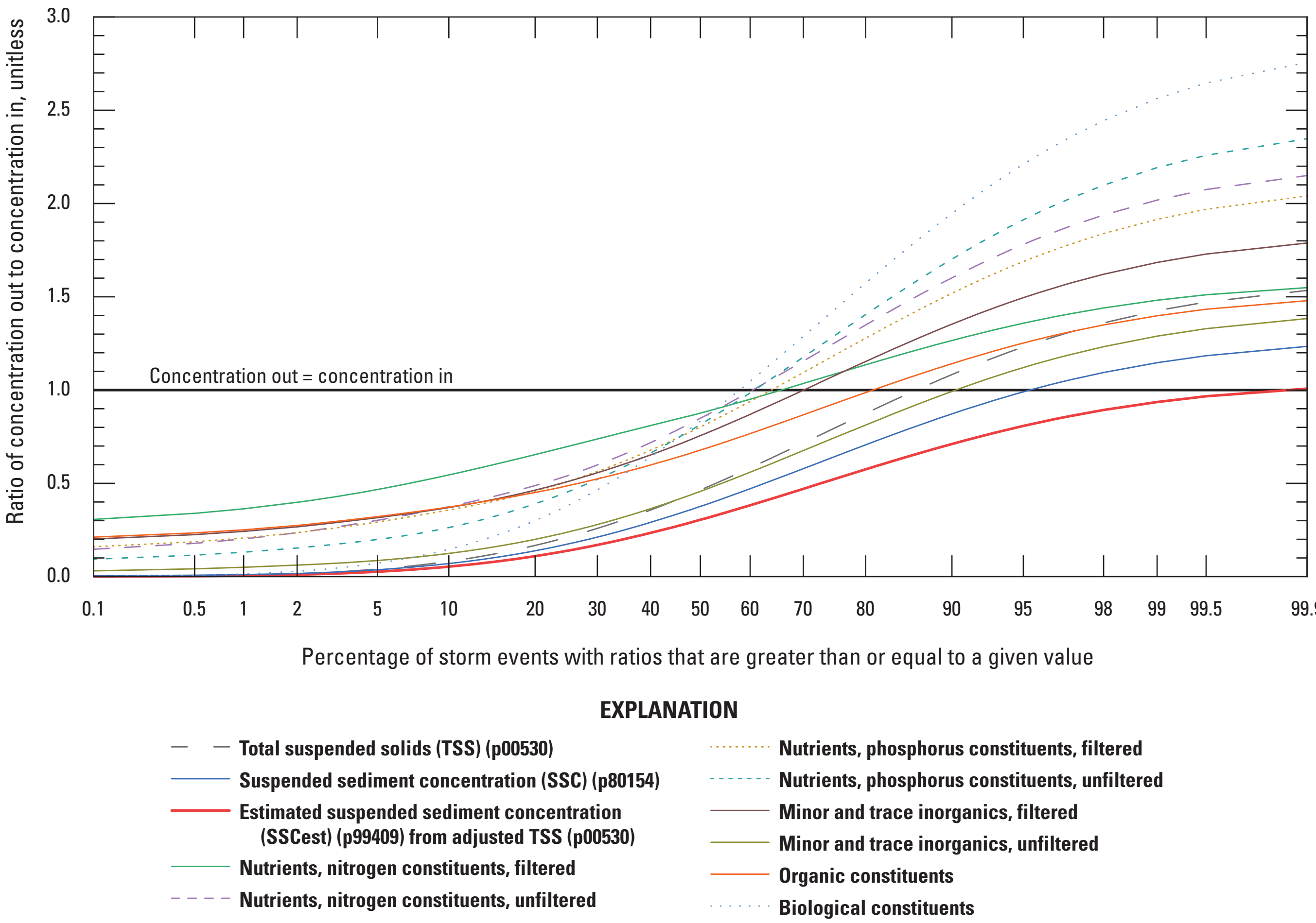

Figure 5. Line graphs showing fitted cumulative trapezoidal distribution functions for the parameter value estimates for sediment, solids, nutrients, minor and trace inorganic, organic, and biological constituents.

Smith and others, 2018; Stonewall and others, 2018, 2019; Jeznach and Granato, 2020). For many constituent groups (table 7) and constituents (table 1.1), these parameter value statistics may be used instead of category-specific statistics for constituents without sufficient data to calculate treatment statistics for one or more BMP categories. Only 4 of 41 constituents analyzed (table 1.1) have sufficient data for all 10 BMP categories. Because of the wide range in BMP performance statistics from site to site that are observed for constituents with plentiful data (such as total suspended solids, total phosphorus, or total zinc), use of the parameter value statistics may be more robust than use of category-specific statistics based on data collected at a small number of monitoring sites.

Granato (2014) estimated water-quality statistics for suspended sediment concentrations (SSCs) from TSS data in the BMPDB because many studies have shown that TSS is an unreliable measure of sediment if sand-sized particles are present. Granato (2014) had used the relation between TSS and SSC developed by Granato and Cazenas (2009) to estimate inflow concentrations of SSC and used TSS effluent concentrations as estimates for concentrations of SSC in BMP outflows based on the assumption that most BMPs could remove the coarse sediment fractions that cannot be effectively measured by using TSS measurement methods. This analysis was repeated with the 2019 data from the BMPDB to refine the SSC treatment statistics with additional data; these results are shown as “SSCest (p99409) from adjusted TSS (p00530)” in table 1.1. These results, when compared to the TSS statistics, demonstrate how use of the TSS analysis method may be underrepresenting the true effectiveness of many BMPs for sediment removal (fig. 5). For example, the parameter values calculated from TSS data indicate that about 14 percent of outflow concentrations may exceed inflow concentrations, but only 0.1 percent of outflow concentrations for the SSC values estimated from TSS may exceed inflow concentrations (table 1.1). This is because the estimated SSC concentrations include the sand-size fraction of SSC in the inflows that are not captured by the TSS method (Granato and Cazenas, 2009). It is difficult to compare the estimated SSC treatment statistics with the measured SSC treatment statistics directly because relatively few sites include sufficient SSC data for a definitive comparison. However, only 1.3 percent of measured SSC concentrations exceed inflow concentrations for the only BMP category (manufactured devices) with data from more than one monitoring site. The categorical “Suspended Sediment and Solids” statistics in table 7 are the medians of the TSS, SSC and SSCest statistics.

Summary water-quality treatment statistics for total solids, total dissolved solids, total sodium and filtered chloride are not provided in table 1.1 because these statistics may be misinterpreted when effects of sodium chloride deicing salt are simulated. Statistics for filtered calcium and filtered magnesium, which also are deicing-chemical constituents that are not readily reduced by structural BMPs, are provided to evaluate potential changes in total hardness that may occur as a byproduct of flow through a structural BMP. Total hardness is of special concern because it can affect the partitioning and toxicity of trace elements in the BMP discharge and receiving stream. These treatment statistics should not be used for simulating treatment of deicing chemicals. Treatment statistics from individual BMP monitoring sites for TNa (p00923) and FCl (p00940) are provided in the water-quality treatment file (USGS-SIR-2020-5136-WaterQuality-SiteResults.txt) published by Granato and others (2021) but should not be used to simulate the effects of structural BMP in deicing-chemical analyses. Analyses for unfiltered selenium (p01147), silver (p01077), dieldrin (p39380), and methylmercury (p50284), which are constituents of concern in TMDLs for the California Department of Transportation, were examined, but not enough uncensored data were available to calculate statistics for a single site. Unless additional data are collected and stored in the BMPDB (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019) and the BMPSE (Granato, 2021), it may be necessary to use statistics for unfiltered minor and trace inorganics to develop planning-level estimates for unfiltered selenium and silver and statistics for unfiltered organic constituents to develop planning-level estimates for dieldrin and methylmercury.

Minimum Irreducible Concentrations

Granato (2014) calculated MIC values on the assumption 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. The analysis in this report is based on the same assumptions and includes an analysis of background soil chemistry to assess potential effects of this variable on MIC values. In this study, MIC statistics were developed for 51 runoff-quality constituents commonly measured in highway and urban runoff studies (tables 6 and 1.2) by using data from 10 BMP categories and 265 monitoring sites (Granato and others, 2021). Correlations between the geometric mean of inflow concentrations and MIC values were calculated by using data from 164 sites with inflow and outflow concentrations for 7 or more storm events. MIC statistics from individual BMP monitoring sites for all the water-quality properties and constituents in table 6 are provided in a MIC file (USGS-SIR-2020-5136-MICs-SiteResults.txt) published by Granato and others (2021). Selected MIC0 values also are published in SELDM input-file format (SELDM-tadBMPTreatmentTable.csv) by Granato and others (2021). However, MIC values for chloride and sodium are not included in this report because these constituents are not changed by commonly used BMP treatment processes, and MIC values for SSCest are not provided because the outflow concentrations were equal to TSS outflow concentrations for the SSCest analyses.

Category-level MIC statistics for individual water-quality constituents are published in appendix 1 of this report. Table 1.2 in appendix 1 lists the category-level MIC0, MIC1, MIC2, and MIC3 estimates; table 1.3 lists the category-level lognormal-variate (K) estimates (eq. 1) for the four MIC estimates (KMIC0, KMIC1, KMIC2, and KMIC3); and table 1.4 lists the correlation coefficients between the geometric mean of inflows and the MIC0 and MIC2 estimates for each constituent. MIC estimates for each type of BMP and parameter estimates, which are the median of the BMP type estimates in the table are provided for each constituent. Only 5 of the 48 runoff-quality constituents have sufficient data (concentrations from 7 or more storm events from 1 or more sites) to calculate MIC values for all 10 BMP categories. The parameter estimates were developed, therefore, to guide professional judgement in the selection of MICs for BMP categories that do not have MIC estimates for a given constituent. There are variations among MIC estimates for different constituents and categories, but the water-quality treatment statistics in this report are by-and-large similar to the values developed by Granato (2014). The updated MIC estimates in this report are more robust because the 2012 dataset contained about 80 percent of the sites available in the newer 2019 dataset and the BMPDB team improved the quality of data in the intervening time. The analysis in this report also includes MIC estimates for many more runoff-quality constituents than Granato (2014).

The lognormal variates (eq. 1; table 1.3) provide information to guide professional judgement for selecting MIC values based on simulated BMP inflow statistics. Use of the lognormal variates is based on the idea that inflow concentrations will reflect the background conditions at a site of interest that may affect the MIC at a given site. A MIC value can be estimated from a lognormal variate by using equation 2 in this report. When used in simulations, this method could reduce the probability that a high proportion of outflow concentrations would be replaced by a single MIC value.

The potential accuracy of the lognormal-variate-based estimates can be inferred from the correlation coefficients in table 1.4. The table includes Pearson’s R and Spearman’s rho correlations between the selected MIC estimates and the geometric mean of inflow concentrations and Pearson’s R correlations between the logarithms of selected MIC estimates and the geometric mean of inflow concentrations. Correlation coefficients are calculated when data are available from five or more sites (Abdel-Megeed, 1984). About 11 percent of MIC0 and 14 percent of MIC2 rho values in table 1.4 indicate strong correlations (an absolute value greater than or equal to 0.85). About 41 percent of MIC0 and 32 percent of MIC2 rho values in table 1.4 indicate weak correlations (an absolute value less than 0.5). In most cases, therefore, the lognormal-variate-based estimates of the MIC derived from table 1.3 should be viewed as a qualitative rather than a quantitative method for estimating a MIC value for a site of interest.

Lognormal variates also were estimated for nine constituent categories because data were lacking for individual constituents of concern (table 8). These variates were calculated by taking the median of available statistics for each BMP category with one or more constituent values in table 1.2. The categories include sediment, filtered and unfiltered nutrients, filtered and unfiltered minor and trace inorganic constituents, and unfiltered organic and biological constituents. Table 8 also includes a parameter estimate for each constituent category, which is the median of values for each constituent group in table 8. The lognormal variates (table 8) can be used with BMP inflow statistics to guide professional judgement on the selection of MIC values using equation 2. If the BMPs inflow concentrations are lognormally distributed, then it may be assumed that variate (K) values of −1, −2, −3, and −4 would produce MIC estimates that are less than about 84.1, 97.7, 99.987, and 99.997 percent of simulated inflow concentrations, respectively. The percentages of unmodified outflow concentrations that are converted to the MIC value, however, also depend on the water-quality treatment ratios and the rank correlation between inflow concentrations and outflow ratio values.

Potential correlations between the median of MIC estimates of selected constituents and the concentrations of the associated elements in the top 5 centimeters of soil (Smith and others, 2014) were calculated to see if this national-scale soil-chemistry dataset could be used with the BMP database data to refine MIC estimates at sites of interest (table 9). This analysis was done because few of the correlations between the MIC values and inflow concentrations were strong and because the MIC has been described as a background concentration in the literature such as Kadlec and Knight (1996), Wong and Geiger (1997), Huber and others (2006), and Granato (2014). The MIC2 values at individual monitoring sites were correlated with the soil concentration calculated as weighted average of concentration values for all data points within 75 kilometers of the center of each 444-square-kilometer grid cell as calculated by Smith and others (2014). No strong correlations emerged from the analysis (table 9), which may be because the coarse resolution of the national-scale soil-chemistry dataset does not capture small-scale variations in concentrations that could affect BMP discharge quality. The soil-chemistry dataset collection effort was designed to characterize natural soils, and thus efforts were made to minimize the local anthropogenic influences on soil chemistry (Smith and others, 2014). These local anthropogenic influences may help define the MIC in BMP discharge at a given site. In the absence of a national- or international-scale dataset of paired BMP discharge and site-specific soil-chemistry data, the BMP inflow concentrations may have to suffice to guide professional judgement for adjusting local MIC estimates.

Table 8. Lognormal variate (K) values for the minimum irreducible concentration estimates of selected parameter categories.

[The International Stormwater Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019); BMPDB category codes and names are listed in table 1. The constituents included in the parameter categories are listed in table 6. The lognormal variates (K) are calculated by subtracting the geometric mean from each minimum irreducible concentration (MIC) estimate and dividing by the geometric standard deviation in logarithmic space (eq. 1). To use the lognormal variate (KMIC) values, add the geometric mean of simulated inflow concentrations to the product of the geometric standard deviation of simulated inflow concentrations in logarithmic space and then retransform the resultant MIC estimate to arithmetic space (eq. 2). KMIC0, the lognormal variate for the minimum of the minimum values of the positive MIC estimates; KMIC1, the lognormal variate for the 25th percentile of the minimum values of the positive MIC estimates; KMIC2, the lognormal variate for the median of the minimum values of the positive MIC estimates; KMIC3, the lognormal variate for the median of the median values of the positive MIC estimates; —, no data]

BMPDB category		Number of sites	Number of samples	Lognormal variate (K)			
Code	Name			KMIC0	KMIC1	KMIC2	KMIC3
			Suspended sediment and solids				
BI	Grass strip	15	302	−11.4	−7.44	−6.2	−4.46
BR	Bioretention	34	715	−6.91	−3.54	−2.78	−1.85
BS	Grass swale	19	282	−8.84	−5.02	−3.35	−2.53
DB	Detention basin	33	524	−7.31	−3.79	−3.48	−2.7
IB	Infiltration basin	1	10	−2.28	−2.28	−2.28	−2.13
MD	Manufactured device	91	1,713	−12.39	−5.43	−4.3	−3.27
MF	Media filter	25	448	−10.64	−7.06	−5.62	−4.57
RP	Retention pond	45	1,053	−58.52	−4.87	−3.72	−3.16
WB	Wetland basin	23	610	−5.6	−4.01	−2.77	−1.89
WC	Wetland channel	2	55	−6.38	−5.61	−4.84	−3.79
	Parameter values	288	5,712	−8.07	−4.95	−3.6	−2.93
			Nutrients, nitrogen constituents, filtered				
BI	Grass strip	0	0	—	—	—	—
BR	Bioretention	0	0	—	—	—	—
BS	Grass swale	0	0	—	—	—	—
DB	Detention basin	0	0	—	—	—	—
IB	Infiltration basin	0	0	—	—	—	—
MD	Manufactured device	2	59	−2.51	−2.51	−2.51	−2.17
MF	Media filter	0	0	—	—	—	—
RP	Retention pond	1	8	−2.62	−2.62	−2.62	−1.75
WB	Wetland basin	2	560	−7.12	−6.53	−5.95	−3.24
WC	Wetland channel	0	0	—	—	—	—
	Parameter values	5	627	−2.62	−2.62	−2.62	−2.17
			Nutrients, nitrogen constituents, unfiltered				
BI	Grass strip	18	315	−5.11	−4.01	−2.99	−2.23
BR	Bioretention	35	697	−5.4	−4.33	−3.45	−2.98
BS	Grass swale	22	266	−3.61	−3.02	−3.01	−1.97
DB	Detention basin	57	849	−5.58	−4	−3.17	−2.15
IB	Infiltration basin	0	0	—	—	—	—
MD	Manufactured device	61	984	−6.63	−4.22	−3.29	−2.21
MF	Media filter	47	828	−6.89	−5.58	−3.62	−1.65
RP	Retention pond	70	1,582	−12.05	−5.88	−3.69	−2.8
WB	Wetland basin	18	1,023	−9.01	−7.91	−3.96	−2.64
WC	Wetland channel	1	7	−4.67	−4.67	−4.67	−3.42
	Parameter values	329	6,551	−5.58	−4.33	−3.45	−2.23

Table 8. Lognormal variate (K) values for the minimum irreducible concentration estimates of selected parameter categories. —Continued

[The International Stormwater Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019); BMPDB category codes and names are listed in table 1. The constituents included in the parameter categories are listed in table 6. The lognormal variates (K) are calculated by subtracting the geometric mean from each minimum irreducible concentration (MIC) estimate and dividing by the geometric standard deviation in logarithmic space (eq. 1). To use the lognormal variate (KMIC) values, add the geometric mean of simulated inflow concentrations to the product of the geometric standard deviation of simulated inflow concentrations in logarithmic space and then retransform the resultant MIC estimate to arithmetic space (eq. 2). KMIC0, the lognormal variate for the minimum of the minimum values of the positive MIC estimates; KMIC1, the lognormal variate for the 25th percentile of the minimum values of the positive MIC estimates; KMIC2, the lognormal variate for the median of the minimum values of the positive MIC estimates; KMIC3, the lognormal variate for the median of the median values of the positive MIC estimates; —, no data]

BMPDB category		Number of sites	Number of samples	Lognormal variate (K)			
Code	Name			KMIC0	KMIC1	KMIC2	KMIC3
	Nutrients, phosphorus constituents, filtered						
BI	Grass strip	8	173	−4.09	−2.34	−2.19	−1.13
BR	Bioretention	6	154	−15.9	−12.81	−9.72	−4.94
BS	Grass swale	9	147	−2.33	−1.47	−0.99	0.25
DB	Detention basin	12	169	−7.66	−5.04	−2.97	−2.06
IB	Infiltration basin	0	0	—	—	—	—
MD	Manufactured device	25	414	−6.15	−3.48	−2.73	−2.15
MF	Media filter	13	237	−6.74	−4.23	−3.5	−2.23
RP	Retention pond	25	627	−8.72	−7.72	−6.77	−4.37
WB	Wetland basin	10	807	−10.25	−7.47	−5.3	−2.96
WC	Wetland channel	0	0	—	—	—	—
	Parameter values	108	2,728	−7.2	−4.63	−3.23	−2.19
	Nutrients, phosphorus constituents, unfiltered						
BI	Grass strip	10	215	−3.78	−2.76	−2.16	−1.55
BR	Bioretention	29	624	−9.29	−3.38	−2.28	−1.04
BS	Grass swale	17	253	−5.54	−3.44	−1.54	−0.55
DB	Detention basin	39	561	−4.85	−3.78	−3.01	−2.03
IB	Infiltration basin	0	0	—	—	—	—
MD	Manufactured device	63	963	−31.21	−6.21	−5.22	−3.33
MF	Media filter	26	464	−7.31	−5.8	−4.45	−2.95
RP	Retention pond	47	1,070	−8.66	−4.76	−3.19	−2.35
WB	Wetland basin	15	885	−9.89	−6.18	−3.44	−2.41
WC	Wetland channel	2	56	−3.85	−3.52	−3.18	−1.82
	Parameter values	248	5,091	−7.31	−3.78	−3.18	−2.03
	Minor and trace inorganics, filtered						
BI	Grass strip	38	857	−8	−5.75	−3.66	−2.5
BR	Bioretention	20	773	−9.12	−7.67	−6.2	−2.84
BS	Grass swale	32	287	−5.82	−3.52	−3.29	−1.86
DB	Detention basin	33	589	−4.43	−3.33	−2.86	−1.84
IB	Infiltration basin	3	30	−2.45	−2.45	−2.45	−1.52
MD	Manufactured device	118	1,631	−8.3	−3.96	−2.63	−1.97
MF	Media filter	47	793	−8.49	−2.97	−2.32	−1.14
RP	Retention pond	44	1,026	−3.32	−3.32	−2.95	−1.65
WB	Wetland basin	11	146	−6.65	−6.49	−5.67	−4.27
WC	Wetland channel	0	0	—	—	—	—
	Parameter values	346	6,132	−6.65	−3.52	−2.95	−1.86

Table 8. Lognormal variate (K) values for the minimum irreducible concentration estimates of selected parameter categories.—Continued

[The International Stormwater Best Management Practices Database (BMPDB) data are from the 2019 version of the database (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019); BMPDB category codes and names are listed in table 1. The constituents included in the parameter categories are listed in table 6. The lognormal variates (K) are calculated by subtracting the geometric mean from each minimum irreducible concentration (MIC) estimate and dividing by the geometric standard deviation in logarithmic space (eq. 1). To use the lognormal variate (KMIC) values, add the geometric mean of simulated inflow concentrations to the product of the geometric standard deviation of simulated inflow concentrations in logarithmic space and then retransform the resultant MIC estimate to arithmetic space (eq. 2). KMIC0, the lognormal variate for the minimum of the minimum values of the positive MIC estimates; KMIC1, the lognormal variate for the 25th percentile of the minimum values of the positive MIC estimates; KMIC2, the lognormal variate for the median of the minimum values of the positive MIC estimates; KMIC3, the lognormal variate for the median of the median values of the positive MIC estimates; —, no data]

BMPDB category		Number of sites	Number of samples	Lognormal variate (K)			
Code	Name			KMIC0	KMIC1	KMIC2	KMIC3
Minor and trace inorganics, unfiltered							
BI	Grass strip	54	1,270	−8.69	−6.21	−5.5	−4
BR	Bioretention	63	1,516	−5.09	−3.87	−3.06	−2.15
BS	Grass swale	43	399	−5.12	−4.09	−3.28	−2.33
DB	Detention basin	67	948	−6.55	−4.97	−3.25	−2.43
IB	Infiltration basin	5	50	−2.77	−2.77	−2.77	−2.49
MD	Manufactured device	194	2,672	−11.93	−4.96	−3.5	−2.48
MF	Media filter	89	1,548	−4.38	−4.01	−2.82	−1.68
RP	Retention pond	127	3,228	−10.36	−4.93	−3.93	−2.67
WB	Wetland basin	22	352	−6.42	−5.65	−3.96	−3.13
WC	Wetland channel	8	266	−5.33	−4.94	−4.55	−2.96
	Parameter values	672	12,249	−5.88	−4.94	−4.94	−2.49
Organic constituents, unfiltered							
BI	Grass strip	7	178	−5.77	−4.63	−2.66	−1.88
BR	Bioretention	8	136	−3.82	−4.18	−3.79	−2.71
BS	Grass swale	4	74	−1.62	−1.58	−1.53	−0.9
DB	Detention basin	15	177	−3.81	−3.07	−3.03	−2.18
IB	Infiltration basin	0	0	—	—	—	—
MD	Manufactured device	44	558	−6.45	−5.02	−3.52	−2.56
MF	Media filter	22	387	−4.4	−4.14	−3.94	−2.63
RP	Retention pond	16	419	−10.24	−4.87	−3.68	−2.29
WB	Wetland basin	1	16	—	—	—	—
WC	Wetland channel	0	0	—	—	—	—
	Parameter values	117	1,945	−4.4	−4.18	−3.52	−2.29
Biological constituents, unfiltered							
BI	Grass strip	2	16	−2.82	−2.82	−2.82	−1.48
BR	Bioretention	3	91	−8.84	−7.85	−6.85	−3.58
BS	Grass swale	1	5	−2.59	−2.59	−2.59	−0.84
DB	Detention basin	11	158	−5.5	−4.81	−4.38	−3.24
IB	Infiltration basin	0	0	—	—	—	—
MD	Manufactured device	14	209	−3.41	−3.03	−2.86	−1.97
MF	Media filter	12	135	−6.67	−3.41	−2.9	−2.01
RP	Retention pond	13	204	−3.88	−3.87	−3.86	−3.42
WB	Wetland basin	4	47	−7.37	−7.37	−7.37	−5.65
WC	Wetland channel	0	0	—	—	—	—
	Parameter values	60	865	−4.69	−3.64	−3.38	−2.63

Table 9. Correlation between the median of minimum irreducible concentration estimates of selected constituents at individual monitoring sites and the concentration of the associated elements in the top 5 centimeters of soil.

[The International Stormwater Best Management Practices (BMP) Database (BMPDB) is from (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). The concentrations of elements in the top 5 centimeters of soil are reported by Smith and others (2014) and are a weighted average of concentration values for all data points within 75 kilometers of the center of a 444-square-kilometer grid cell. The number in parentheses after each constituent is the water-quality parameter code from the National Water Information System and is denoted by "p" followed by a five-digit identification number; parameters are listed in table 6. N, number of sites with sufficient data to calculate the median of the minimum values of the positive minimum irreducible concentration estimate (MIC2) values; R, Pearson correlation coefficient; R(log), Pearson correlation coefficient for the common logarithms of data; Rho, Spearman's correlation coefficient; —, no data]

BMPDB category		Correlation to soil chemistry			
Code	**Name**	**N**	**R**	**R(log)**	**Rho**
	Phosphorus, water, unfiltered (TP, p00665)				
BI	Grass strip	10	0.44	0.41	0.66
BR	Bioretention	29	0.06	−0.02	0.1
BS	Grass swale	17	0.08	0.23	0.2
DB	Detention basin	32	−0.13	−0.28	−0.32
IB	Infiltration basin	58	−0.3	−0.34	−0.36
MD	Manufactured device	23	0.02	−0.09	−0.04
MF	Media filter	1	—	—	—
RP	Retention pond	44	0.08	0.12	0.11
WB	Wetland basin	15	0.47	0.4	0.3
WC	Wetland channel	2	—	—	—
	Cadmium, water, unfiltered (TCd, p01027)				
BI	Grass strip	6	0.59	0.65	0.46
BR	Bioretention	3	—	—	—
BS	Grass swale	4	—	—	—
DB	Detention basin	6	0.18	0.11	−0.03
IB	Infiltration basin	1	—	—	—
MD	Manufactured device	19	0.04	0.12	−0.01
MF	Media filter	7	—	—	—
RP	Retention pond	10	−0.25	−0.57	−0.46
WB	Wetland basin	1	—	—	—
WC	Wetland channel	1	—	—	—
	Copper, water, unfiltered (TCu, p01042)				
BI	Grass strip	9	0.05	0.18	0
BR	Bioretention	19	0.18	0.02	−0.06
BS	Grass swale	11	−0.09	−0.05	0.03
DB	Detention basin	14	0.17	0.24	0.14
IB	Infiltration basin	1	—	—	—
MD	Manufactured device	52	−0.22	−0.24	−0.3
MF	Media filter	18	0.27	0.31	0.46
RP	Retention pond	26	0.1	0.16	0.14
WB	Wetland basin	5	0.62	0.66	0.6
WC	Wetland channel	2	—	—	—

Table 9. Correlation between the median of minimum irreducible concentration estimates of selected constituents at individual monitoring sites and the concentration of the associated elements in the top 5 centimeters of soil.—Continued

[The International Stormwater Best Management Practices (BMP) Database (BMPDB) is from (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). The concentrations of elements in the top 5 centimeters of soil are reported by Smith and others (2014) and are a weighted average of concentration values for all data points within 75 kilometers of the center of a 444-square-kilometer grid cell. The number in parentheses after each constituent is the water-quality parameter code from the National Water Information System and is denoted by "p" followed by a five-digit identification number; parameters are listed in table 6. N, number of sites with sufficient data to calculate the median of the minimum values of the positive minimum irreducible concentration estimate (MIC2) values; R, Pearson correlation coefficient; R(log), Pearson correlation coefficient for the common logarithms of data; Rho, Spearman's correlation coefficient; —, no data]

BMPDB category		Correlation to soil chemistry			
Code	**Name**	**N**	**R**	**R(log)**	**Rho**
	Lead, water, unfiltered (TPb, p01051)				
BI	Grass strip	9	−0.12	−0.04	0.16
BR	Bioretention	8	−0.67	−0.43	−0.65
BS	Grass swale	8	0.18	0.08	−0.18
DB	Detention basin	10	0.42	0.33	0.45
IB	Infiltration basin	1	—	—	—
MD	Manufactured device	30	−0.12	−0.13	0.02
MF	Media filter	14	−0.36	−0.48	0.11
RP	Retention pond	24	0.35	0.47	0.53
WB	Wetland basin	3	—	—	—
WC	Wetland channel	2	—	—	—
	Zinc, water, unfiltered (TZn, p01092)				
BI	Grass strip	9	0.61	0.52	0.49
BR	Bioretention	18	0.29	0.56	0.57
BS	Grass swale	11	−0.11	0.19	−0.27
DB	Detention basin	18	0.25	0.34	0.25
IB	Infiltration basin	62	0.15	0.2	0.22
MD	Manufactured device	21	0.19	0.17	0.38
MF	Media filter	1	—	—	—
RP	Retention pond	34	0.14	0.22	0.1
WB	Wetland basin	9	−0.06	0.11	0.08
WC	Wetland channel	2	—	—	—
	Phosphorus, water, filtered (FP, p00666)				
BI	Grass strip	3	—	—	—
BR	Bioretention	5	−0.29	−0.35	−0.56
BS	Grass swale	8	−0.33	−0.46	−0.39
DB	Detention basin	9	0.69	0.66	0.54
IB	Infiltration basin	25	−0.13	−0.06	−0.05
MD	Manufactured device	9	−0.35	−0.26	−0.4
MF	Media filter	0	—	—	—
RP	Retention pond	10	0.28	0.68	0.15
WB	Wetland basin	7	0.7	0.63	0.81
WC	Wetland channel	—	—	—	—

Table 9. Correlation between the median of minimum irreducible concentration estimates of selected constituents at individual monitoring sites and the concentration of the associated elements in the top 5 centimeters of soil.—Continued

[The International Stormwater Best Management Practices (BMP) Database (BMPDB) is from (Wright Water Engineers, Inc. and Geosyntec Consultants, 2019). The concentrations of elements in the top 5 centimeters of soil are reported by Smith and others (2014) and are a weighted average of concentration values for all data points within 75 kilometers of the center of a 444-square-kilometer grid cell. The number in parentheses after each constituent is the water-quality parameter code from the National Water Information System and is denoted by "p" followed by a five-digit identification number; parameters are listed in table 6. N, number of sites with sufficient data to calculate the median of the minimum values of the positive minimum irreducible concentration estimate (MIC2) values; R, Pearson correlation coefficient; R(log), Pearson correlation coefficient for the common logarithms of data; Rho, Spearman's correlation coefficient; —, no data]

BMPDB category		Correlation to soil chemistry			
Code	**Name**	**N**	**R**	**R(log)**	**Rho**
		Copper, water, filtered (FCu, p01040)			
BI	Grass strip	11	0.04	0.08	−0.17
BR	Bioretention	9	0.27	0.24	0.05
BS	Grass swale	11	0.08	0.06	0.21
DB	Detention basin	9	0.01	0.07	0.02
IB	Infiltration basin	1	—	—	—
MD	Manufactured device	41	−0.08	−0.2	−0.2
MF	Media filter	11	0.08	0.08	0.14
RP	Retention pond	15	−0.2	−0.31	−0.21
WB	Wetland basin	3	—	—	—
WC	Wetland channel	—	—	—	—
		Lead, water, filtered (FPb, p01049)			
BI	Grass strip	6	0.5	0.27	0.29
BR	Bioretention	3	—	—	—
BS	Grass swale	8	0.46	0.6	0.78
DB	Detention basin	5	0.58	0.52	0.9
IB	Infiltration basin	1	—	—	—
MD	Manufactured device	19	0.06	0.17	0.19
MF	Media filter	8	−0.19	−0.19	−0.45
RP	Retention pond	6	0.61	0.41	0.49
WB	Wetland basin	2	—	—	—
WC	Wetland channel	—	—	—	—
		Zinc, water, filtered (FZn, p01090)			
BI	Grass strip	9	0.19	0.3	−0.03
BR	Bioretention	5	−0.54	−0.49	−0.36
BS	Grass swale	9	−0.19	−0.26	−0.16
DB	Detention basin	10	0.43	0.56	0.57
IB	Infiltration basin	40	0.07	0.15	0.05
MD	Manufactured device	11	−0.01	−0.44	0.05
MF	Media filter	—	—	—	—
RP	Retention pond	15	0.37	0.54	0.12
WB	Wetland basin	5	0.54	0.41	0.1
WC	Wetland channel	—	—	—	—

Summary

Decisionmakers need information 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. Structural stormwater control measures, commonly known as best management practices (BMPs), are used as the primary mitigation measures for reducing adverse effects of runoff on receiving waters. Decisionmakers also need information about the flows and concentrations of runoff and stormwater discharges from BMPs to calculate Total Maximum Daily Loads (TMDLs) for impaired receiving-water basins. 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 timing, volume, or quality of runoff.

The U.S. Geological Survey, in cooperation with the Federal Highway Administration, developed the Stochastic Empirical Loading and Dilution Model (SELDM) to indicate the risk for stormwater flows, concentrations, and loads to be above user-selected water-quality goals and the potential effectiveness of mitigation measures to reduce such risks. 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. In SELDM, three treatment variables, hydrograph extension, volume reduction, and water-quality treatment are simulated by using the trapezoidal distribution and the rank correlation with the associated highway-runoff variables.

This report documents statistics for simulating structural stormwater runoff best management practices. The trapezoidal-distribution statistics and rank correlation coefficients documented in this report provide a stochastic transfer function to approximate the quantity, quality, and duration of BMP effluents given a population of inflow values. This statistical approach can be used to represent a single BMP or an assemblage of BMPs. If hydrograph extension is specified for a simulated BMP, then 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 volume reductions are specified but concentration changes are not, then the stormwater-runoff and BMP discharge concentrations will be the same, but the BMP discharge loads and the concurrent downstream loads and concentrations will be different. If BMP water-quality treatment statistics are specified, then BMP discharge concentrations and loads will be affected as well as downstream concentrations and loads. The water-quality treatment statistics also include estimates for the minimum irreducible concentrations (MIC), which represents the lower bound of outflow concentrations that can be achieved with commonly used BMP designs.

In this study, data extracted from a modified copy of the December 2019 version of International Stormwater Best Management Practices Database were used for the analyses. Sufficient data were available to estimate statistics for 8 to 12 BMP categories by using data from 44 to more than 265 monitoring sites. The medians of the best-fit statistics were used to construct generalized cumulative distribution functions for the three treatment variables. In cases where data are not available for a category of interest or a stream basin with multiple BMPs is being simulated, then the parameter values, which are the medians of categorical medians, may guide professional judgement in these cases.

A parameter value estimate, which represents a generic BMP for watershed-wide simulations, was also calculated for each BMP treatment variable. For hydrograph extension, data were available from 44 monitoring sites with 7 or more storm events; statistics for 8 BMP categories were calculated. For volume reduction, data were available from 87 monitoring sites with 7 or more storm events; statistics for 12 BMP categories were calculated. For water-quality treatment ratios, data were available from 206 monitoring sites with paired inflow and outflow concentrations from 7 or more storm events. Water-quality treatment ratio statistics were calculated for 51 runoff-quality constituents commonly measured in highway and urban runoff studies. Statistics were calculated for water-quality properties, sediment and solids, nutrients, major and trace inorganic elements, organic compounds, and biologic constituents. However, the amount of available data was substantially different for various constituents. Statistics from 1 to 10 BMP categories and parameter-level estimates were calculated for the different constituents and constituent categories analyzed in this report. For the MIC values, data were available from 265 monitoring sites with outflow concentrations from 7 or more storm events. The amount of data available to calculate MIC values also was substantially different for various constituents. Analysis of MIC values indicates that the inflow concentration statistics may be used to guide selection of representative MIC values, but regional soil chemistry is not a strong predictor for this variable. Water-quality statistics for constituent categories are provided in tables within this report; constituent-specific statistics are provided in tables within appendix 1.

SELDM uses rank correlation to the inflow variable to condition the treatment variables to better represent the structure of actual BMP data. 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. Interpretation of available data also indicates that the median rho value may be selected to help generate realistic simulation results for water-quality treatment ratios and the MIC values.

The planning-level estimates for BMP categories are recognized to include substantial uncertainties when applied to any particular site. Therefore, statistics for individual monitoring sites are available in the U.S. Geological Survey data release by Granato and others (2021) so that analysts may use their own professional judgement to select statistics that are most representative of a particular site of interest. However,

practitioners may need to combine statistics from multiple sites to represent a site of interest because sample sizes are small, monitoring artifacts are present in many BMP datasets, and previous studies have not demonstrated predictive correlations between BMP design characteristics and BMP performance statistics.

Although site-specific estimates for all 51 constituents are available in the U.S. Geological Survey data release (Granato and others, 2021), summary statistics for constituents in deicing salts (including sodium, chloride, and total solids) were not included in the analyses in this report. Calcium and magnesium, however, were included because statistics for these constituents may be used to estimate the hardness of BMP discharges, which may be used to estimate potential effects of trace elements on receiving-water quality. Statistics for constituents in deicing salts should not be used for analysis of the effects of deicing chemicals on water quality, however, because most datasets do not include deicing-salt data and these constituents are not substantially affected by commonly used BMP treatment methods at concentrations found in winter runoff.

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Appendix 1. Water-Quality Treatment Statistics for Individual Constituents

Table 1.1. Median of selected treatment statistics for individual constituents including the trapezoidal distribution parameters and Spearman's rank correlation coefficients for structural stormwater best management practices, by category.

[The table is available for download as a tab-separated value file at https://doi.org/10.3133/sir20205136. The concentration-reduction statistics are for the trapezoidal distribution of the ratio of outflow to inflow concentration. The Spearman's rank correlation coefficients (rho values) are calculated by using the ranks of the inflow concentrations and the associated ratios of outflow to inflow concentrations; selected value is closest to −1 among at-site rho values. The water-quality parameter code in parentheses is denoted by the letter p and the five-digit identification number, the full name of each parameter is listed in table 6; properties and constituents are listed in parameter-code order. N, number of sites with paired inflow and outflow concentrations for at least seven storms used to calculate the median ratio statistics; *, statistic based on values from selected sites; **, statistics based on selected data from the available site(s); LBMPV, lower bound of the most probable value; max, maximum; min, minimum; parameter values are the medians of values in this table; UBMPV, upper bound of the most probable value; Pct GT 1, theoretical percentage of event ratios that may equal or exceed a value of 1; —, insufficient data]

Table 1.2. Estimates of the minimum irreducible concentration for each selected structural stormwater best management practice category for constituents of concern.

[The table is available for download as a tab-separated value file at https://doi.org/10.3133/sir20205136. Each MIC0 estimate is the category minimum of the minimum of positive minimum irreducible concentration (MIC) estimates from available sites. Each MIC1 estimate is the 25th percentile of the minimum of positive MIC estimates from available sites. Each MIC2 estimate is the category median of the minimum of positive MIC estimates from available sites. Each MIC3 estimate is the category median of the median of positive MIC estimates from available sites. International Stormwater Best Management Practices Database (BMPDB) category codes and names are described in table 1; the constituents included in the parameter categories are listed in table 6]

Table 1.3. Estimates of the lognormal variate (K) values of selected minimum irreducible concentrations (MICs) for each selected structural stormwater best management practice category for constituents of concern.

[The table is available for download as a tab-separated value file at https://doi.org/10.3133/sir20205136. The KMIC values are the lognormal variate (K) for the associated minimum irreducible concentration (MIC) values, which are calculated by subtracting the geometric mean from the MIC estimate and dividing by the geometric standard deviation in logarithmic space (eq. 1). To use the KMIC values add the geometric mean of simulated inflow concentrations to the product of the geometric standard deviation of simulated inflow concentrations in logarithmic space and then retransform the resultant MIC estimate to arithmetic space (eq. 2). International Stormwater Best Management Practices Database (BMPDB) category codes and names are described in table 1; the constituents included in the parameter categories are listed in table 6; the MIC values are listed in table 1.2]

Table 1.4. Estimates of correlations between the geometric mean concentration of inflows and selected minimum irreducible concentration (MIC) estimates for each selected best management practices category for constituents of concern.

[The table is available for download as a tab-separated value file at https://doi.org/10.3133/sir20205136. Spearman's rank correlation coefficients (rho) were calculated using the MIC0 and MIC2 estimates and the geometric mean of influents. 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 Stormwater Best Management Practices Database (BMPDB) category codes and names are described in table 1; the constituents included in the parameter categories are listed in table 6; the MIC values are listed in table 1.2. *R*, Pearson's correlation coefficient; *R*(log), Pearson's correlation coefficient for the common logarithms of data, MIC0, the minimum of the minimum values of the positive MIC estimates; MIC2, the median of the minimum values of the positive MIC estimates]

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