

TISBURY MA IMPERVIOUS COVER DISCONNECTION (ICD) PROJECT: AN INTEGRATED STORMWATER MANAGEMENT APPROACH FOR PROMOTING URBAN COMMUNITY SUSTAINABILITY AND RESILIENCE

A TECHNICAL DIRECT ASSISTANCE PROJECT FUNDED BY THE U.S. EPA SOUTHEAST NEW ENGLAND PROGRAM (SNEP)

TASK 4D. DEVELOP PLANNING LEVEL GI SCM PERFORMANCE CURVES FOR ESTIMATING CUMULATIVE REDUCTIONS IN SW-RELATED INDICATOR BACTERIA

Prepared for:

U.S. EPA Region 1



In Cooperation With:

Town of Tisbury, MA
Tisbury Waterways
Martha's Vineyard Commission
Massachusetts Department of Transportation

Prepared by:

Paradigm Environmental
University of New Hampshire Stormwater Center
Great Lakes Environmental Center

Under Contract:

Blanket Purchase Agreement: BPA-68HE0118A0001-0003
Requisition Number: PR-R1-18-00375
Order: 68HE0118F0011

September 30, 2019

To: Ray Cody, Mark Voorhees (US EPA Region 1)
From: Khalid Alvi, David Rosa, Ryan Murphy (Paradigm Environmental)
CC: Project Technical Team
Date: 9/30/2019
Re: Develop Planning Level Green Infrastructure (**GI**) Stormwater Control Measure (**SCM**) Performance Curves for Estimating Cumulative Reductions in SW-Related Indicator Bacteria (Task 4D)

1 EXECUTIVE SUMMARY

This memorandum presents the technical approach for developing planning-level green infrastructure (**GI**) stormwater control measure (**SCM**) performance curves for indicator bacteria load reduction for use within Opti-Tool (U.S. EPA, 2016). The resulting curves provide estimates of relative cumulative bacteria load reductions that can be expected from the implementation of various SCMs. Consistent with the other performance curves previously developed for the New England region (EPA Region 1), the cumulative indicator bacteria performance curves provide estimates of the overall net reductions accomplished by SCMs for all storm events that have occurred over an extended period of time (1998–2018). Consequently, the curves reflect the known primary dynamic processes involved with both the generation of stormwater runoff pollution including the build-up of pollutants on impervious surfaces and the frequency and intensity of precipitation, as well as the continuous routing of runoff flow and pollutants through treatment processes in SCMs. While these curves provide reasonable long-term performance (in terms of annual average load reduction and should not be substituted with event mean concentration reduction) expectations of various SCM types and sizes, they are not suitable for estimating SCM bacteria load reductions for a single design storm event or for quantifying expected changes in indicator bacteria concentrations.

When applying these curves to specific sites and watersheds, baseline bacteria loading should be estimated from local monitoring data if available. Otherwise, the bacteria loading rates provided in Opti-Tool could be used to estimate cumulative bacteria loads to assist users in developing planning level information that quantifies the expected overall long-term benefits of various SCMs for addressing waterbody bacteria impairments. Use of these curves is especially encouraged in cases where quantification of SCM benefits otherwise rely on a single published SCM removal rate for a specific design storm or water quality volume that may not be applicable to the size or type of SCMs being assessed.

The Storm Water Management Model (SWMM) (U.S. EPA. 2015) and the System for Urban Stormwater Treatment and Analysis Integration (SUSTAIN) GI simulation engine (U.S. EPA. 2009) were utilized in curve development to estimate stormwater quantity and quality boundary conditions and establish relationships between SCM storage capacity and bacteria load reduction, respectively. A literature review identified event mean concentration (EMC), unit area loading values, and SWMM buildup/washoff values used to establish boundary conditions. The SCM efficiency values were also derived from values in the literature review.

Several factors may contribute to bacteria removal efficiency within an SCM with the major mechanisms being physical processes including sedimentation, sorption, and filtration. However, other factors impacting bacteria removal include SCM holding time, temperature, sunlight, salinity, and predation. Careful consideration of SCM types and associated processes is necessary when applying these curves to specific sites and watersheds. For example, it is well documented that infiltration practices are highly effective at achieving bacterial reductions as runoff exfiltrates through subsoils. Consequently, practitioners may confidently select infiltration SCMs to address excessive SW bacteria loading wherever site conditions are favorable for infiltration. However, there is greater uncertainty in bacteria removal performances associated

with flow-through SCMs that rely primarily on sedimentation or vegetative filtering because of the potential bacterial regrowth and subsequent entrainment during storm events resulting in the SCM becoming a source of bacteria to surface waters. Generally, users should first consider infiltration SCMs followed by filtering systems and last other SCMs to address excessive SW bacterial loading.

While such due diligence can help facilitate the implementation of SCMs that can achieve the estimated bacteria load reductions given local conditions, there is still a large amount of uncertainty involved in estimating both bacterial loading and long-term cumulative performances of SCMs especially for flow-through SCMs. The removal curves provide estimates of bacterial load removal efficiency based on the literature rather than detailed model calibrations of individual SCMs with extensive performance data. Consequently, the curves represent planning level information for developing management plans and quantifying potential benefits. SCMs intended to achieve the reductions presented in Opti-Tool should be installed and maintained in a manner that promotes the identified bacteria removal processes and mechanisms. Regular inspections and ambient water quality monitoring are recommended to help ensure that the SCMs are operating as expected.

2 INTRODUCTION

Performance curves representing indicator bacteria (*E. coli*) load reductions that may be achieved by SCM treatment of stormwater were developed based on simulated runoff from impervious Hydrologic Response Units (**HRUs**). The curves may also be applied to other indicator bacteria, such as *Enterococcus* load reductions if the underlying mechanisms for the SCM performance are similar to other indicator bacteria. The SCM performance curves represent long-term average annual indicator bacteria load reductions (as a percent) that can be expected for a wide range of SCM storage capacities. Rainfall-runoff response timeseries from impervious HRUs were simulated using the **SWMM** hydrology model (U.S. EPA. 2015). The SCM performance curves were developed using the **SUSTAIN** GI simulation engine (U.S. EPA. 2009) through Opti-Tool (U.S. EPA. 2016). This modeling approach has previously been used to provide performance curves for total nitrogen (TN), total phosphorus (TP), sediments (Total Suspended Sediment (TSS)), and zinc (Zn). Both models (SWMM and SUSTAIN) for Opti-Tool were calibrated using New England's regional monitoring data, observed pollutant event mean concentrations (**EMCs**) in stormwater runoff and observed inflow/outflow pollutant concentrations from stormwater SCMs that were studied to assess pollutant reduction performances. HRU timeseries for bacteria were developed for the impervious surfaces of the urbanized New England community of Tisbury, MA, located on Martha's Vineyard. A literature review identified concentration, loading, and buildup/washoff values used to develop the timeseries. The resulting concentrations and loadings represent generalized conditions for purposes of SCM performance curve development and do not reflect the specific bacteria loading conditions in Tisbury, MA. A literature review was also completed to identify SCM efficiency values to include in SUSTAIN GI simulation. For a given depth of runoff volume storage capacity from the impervious cover by an SCM, the curves provide an estimated bacteria load reduction given as a percentage of total loading. Due to a lack of literature values for SCM removal efficiencies for *Enterococcus*, the rates for *E. coli* were used for both fecal bacteria indicators.

3 IMPERVIOUS HRU TIMESERIES FOR INDICATOR BACTERIA

The SUSTAIN model requires hourly timeseries of flow and pollutant load as a boundary condition to run. To develop impervious HRU timeseries, the HRU SWMM hydrology model, developed previously for Opti-Tool, was used for hourly flow simulation. The same model was updated for water quality by adding two fecal bacteria indicators (*E. coli* and *Enterococcus*). The hourly precipitation timeseries and daily air temperature data collected at the Martha's Vineyard Airport was used in the HRU SWMM model to represent the local patterns of precipitation, including dry periods between storm events when pollutants accumulate on impervious surfaces. The output timeseries from the SWMM model were formatted for the Opti-Tool using a utility tool, *SWMM2Opti-Tool*, available in the Opti-Tool package. The following subsections describe the steps for developing the impervious HRU timeseries for indicator bacteria.

3.1 Literature Review

3.1.1 Introduction

A literature review was conducted to find stormwater related EMCs (MPN¹/100 ml) and average annual export rates (MPN/ac/yr) for *E. coli* and *Enterococcus* from impervious land cover. Recent journal publications, conference papers, and data from the national stormwater quality database (NSQD) were reviewed to obtain information specific to these types of indicator bacteria. Several published sources of bacteria EMCs from urban areas were identified and summarized. A limited number of observed average annual export rates were found, therefore the literature review was expanded to include published export rates for fecal coliform. The literature review also included an evaluation of previous SWMM models and associated buildup/washoff values for *E. coli* and *Enterococcus*.

3.1.2 Event Mean Concentrations

An EMC is a flow proportional concentration of a pollutant, when applied to bacteria it is calculated as the total constituent number of bacteria divided by total runoff volume for a single event. Several physical, biological, and chemical factors can impact the fate and transport of microbes within a watershed, including temperature, moisture, sunlight, nutrients, settling, adsorption/desorption processes, hydrologic processes and predation (Ferguson et al., 2003). While sanitary sewage pollution contamination can contribute to high bacteria concentrations, elevated levels are often observed in areas not impacted by sewage (Shergill and Pitt, 2004). Unsurprisingly, monitoring studies often show tremendous variability in bacteria concentrations (Table 1-1). Figure 1-1 and Figure 1-2 summarize the EMCs for residential, commercial, industrial, and transportation land uses. Residential areas generally had the highest *E. coli* EMCs, followed by commercial, industrial, and transportation. While residential EMS were also relatively high for *Enterococcus*, the highest observed EMC (Stein et al., 2008) was from commercial land. Additionally, transportation had a higher EMC than industrial land uses. However, care should be taken in drawing conclusions about the relative bacteria loading from different impervious surfaces given the limited and highly variable data.

Because of the uncertainty associated with bacteria EMCs, models such as the water treatment model (WTM) use the median urban runoff value for fecal coliform from National Urban Runoff Program (NURP) data (Pitt, 1998) of 20,000 MPN/100 ml as the default model value for bacteria (Caraco, 2013). Table 1-1 presents published EMC for *E. coli* and *Enterococcus* from developed land uses. Values with associated error, designated with a ± in Table 1-1 indicate EMCs reported as a mean of multiple events, potentially from multiple sites of the same land use. EMCs from six studies as well as the NSQD were found for *E. coli*. Only three studies were identified that reported EMCs for *Enterococcus*.

EMCs for *E. coli* ranged from a low of 5/100 ml from a parking lot (transportation land use) in Maryland (Li and Davis, 2009) to a high of $(5.3 \pm 1.7) \times 10^5$ /100 ml from recreational land in California (Stein et al., 2008). Hathaway and Hunt (2010) found a mean *E. coli* EMC of 2.5671×10^3 /100 ml from an urban watershed in Raleigh, North Carolina, although individual samples ranged from 0.71×10^3 to 85.233×10^3 /100 ml. Additionally, Hathaway and Hunt (2010) found a mean *Enterococcus* EMC of 2.155×10^3 /100 ml from the same urban watershed, although individual samples ranged from 1.306×10^3 to 181.846×10^3 /100 ml. *Enterococcus* EMCs from urban land uses in California ranged from $(8.9 \pm 4.4) \times 10^3$ from transportation to $(1.4 \pm 0.82) \times 10^5$ from recreational areas (Stein, 2008).

¹ where, MPN refers to “most probable number”. Fecal coliform and *E. coli* in compost or leachate is usually reported in MPN per g compost or MPN per 100 mL water (or leachate). MPN/100ml is a statistical probability of the number of organisms. Refer to, American Public Health Association, American Water Works Association, Water Environment Federation (2012), Standard Methods for the Examination of Water and Waste Water. Depending on circumstances, US EPA may prefer MPN rather than Colony Forming Units (CFU) (actual plate count) “because a colony in a CFU test might have originated from a clump of bacteria instead of an individual, the count is not necessarily a count of separate individuals.” Environmental Regulations and Technology. Control of Pathogens and Vector Attraction in Sewage Sludge (Including Domestic Septage) Under 40 CFR Part 503, EPA/625/R-92/013 (https://www.epa.gov/sites/production/files/2015-04/documents/control_of_pathogens_and_vector_attraction_in_sewage_sludge_july_2003.pdf).

3.1.3 Export rates

Studies of bacteria export from urban areas relied on stream sampling for estimates. Therefore, there is additionally uncertainty associated with applying these rates to areas such as Tisbury, MA where stormwater is not conveyed to a receiving stream or river but is instead discharged directly into a coastal ecosystem. Line et al. (2008) monitored stream concentrations of fecal coliform from industrial and residential sites in North Carolina. Loading from these urban areas ranged from 180,024 to 477,654 million MPN/ac/yr. These values were higher than observed *E. coli* loading estimated in Maryland from a watershed consisting of medium-to-high density residential and open urban land uses resulted (EA Engineering, 2010) (Table 1-2). CDM (2012) estimated loading from several sites in Boston's municipal separate storm sewer system (MS4). Export was highly variable, *E. coli* ranged from 22 billion CFU/ac/yr to 1.4 trillion CFU/ac/yr. Site imperviousness ranged from 25% to 94%, although the loading estimates did not distinguish between urban land use types.

3.1.4 Buildup/Washoff Values

The pollutant buildup and washoff functions in SWMM are similar to the equations developed for the accumulation and washoff of dust and dirt on street surfaces (APWA, 1969; Sartor et al., 1974). Previous applications of SWMM to simulate the buildup and washoff of *E. coli* and *Enterococcus* were reviewed and summarized. Two studies were identified, one for Boston's MS4 (CMD Smith, 2012) and another for the city of Lakewood, Ohio (CT Consultants, 2016). Both studies relied on local bacteria monitoring data to calibrate the models. The calibrated parameter values for both studies are presented in Table 1-3.

Table 1-1 Observed Event Mean Concentration (EMC) for *E. coli* and *Enterococci* by land use type

Land use	EMC (MPN/100ml)			location	Source
	Residential	Recreational	Commercial		
<i>E. coli</i>	(3.0 ± 1.8) × 10 ⁴ (Low Residential)	(5.3 ± 1.7) × 10 ⁵	(1.1 ± 0.88) × 10 ⁴	CA	Stein, 2008
	(8.2 ± 7.7) × 10 ³ (High Residential)	-	-	CA	Stein, 2008
	2.938 × 10 ³	-	-	NC	Krometis et al., 2009
	1 × 10 ¹ – 3.5 × 10 ⁴	-	-	MA	NSQD
	25.671 × 10 ³ (Medium Residential)	-	-	NC	Hathaway and Hunt, 2010
<i>Enterococcus</i>	2.166 × 10 ⁴	-	-	NC	Krometis et al., 2009
	(5.5 ± 3.7) × 10 ⁴ (Low Residential)	(1.4 ± 0.82) × 10 ⁵	(7.7 ± 9.2) × 10 ⁴	CA	Stein et al, 2008
	(2.7 ± 3.6) × 10 ⁴ (High Residential)	-	-	CA	Stein et al, 2008
	25.155 × 10 ³ (Medium Residential)	-	-	NC	Hathaway and Hunt, 2010
	18.00 × 10 ³ (Multifamily)		13.00 × 10 ³	MA	Breault et al., 2002
	27.00 × 10 ³ (Single Family)			MA	Breault et al., 2002
EMC (MPN/100ml)					
Land use	Urban	Industrial	Transportation	location	Source
<i>E. coli</i>	-	(3.8 ± 2.3) × 10 ³	(1.4 ± 2.7) × 10 ³	CA	Stein, 2008
	10.846 × 10 ³	-	-	TN, TX, WA, WI	Schueler, 2000
	15.01 × 10 ³	-	-	NC	McCarthy et al., 2012
	-	-	5	MD	Li and Davis, 2009
	-	-	92	MD	Li and Davis, 2009
	25.671 × 10 ³ ± 24.393 × 10 ³	-	-	NC	Hathaway and Hunt, 2010
<i>Enterococcus</i>	-	(2.1 ± 2.2) × 10 ⁴	(8.9 ± 4.4) × 10 ³	CA	Stein et al, 2008

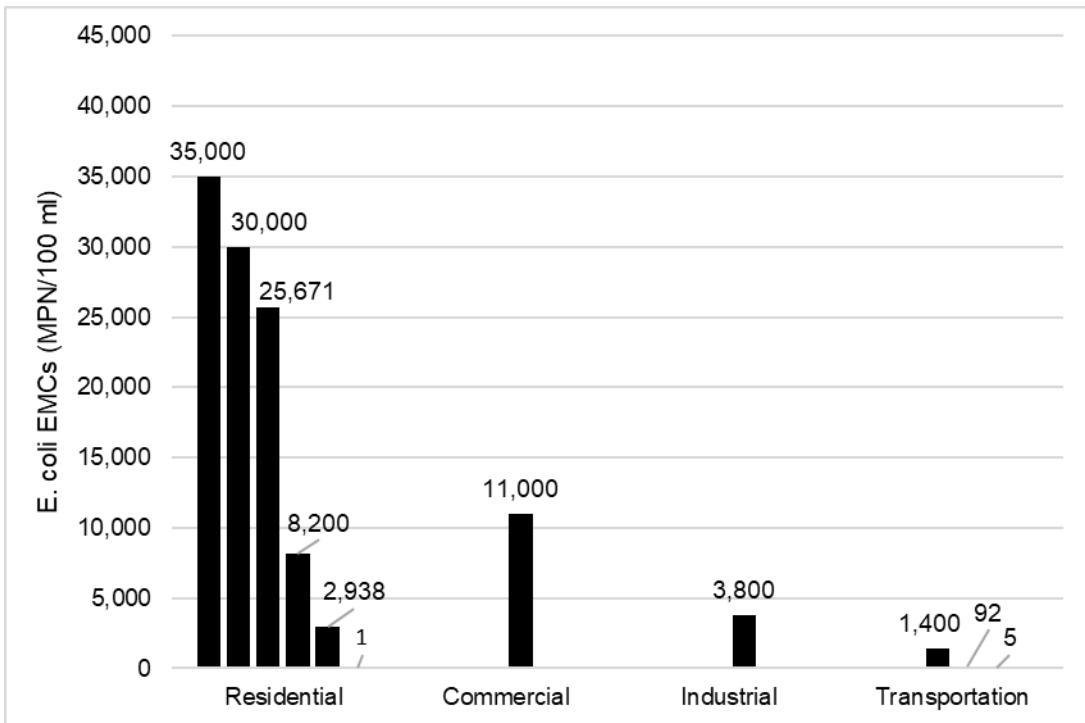


Figure 1-1. Mean observed EMCs for *E. coli* from literature (See Table 1-1)

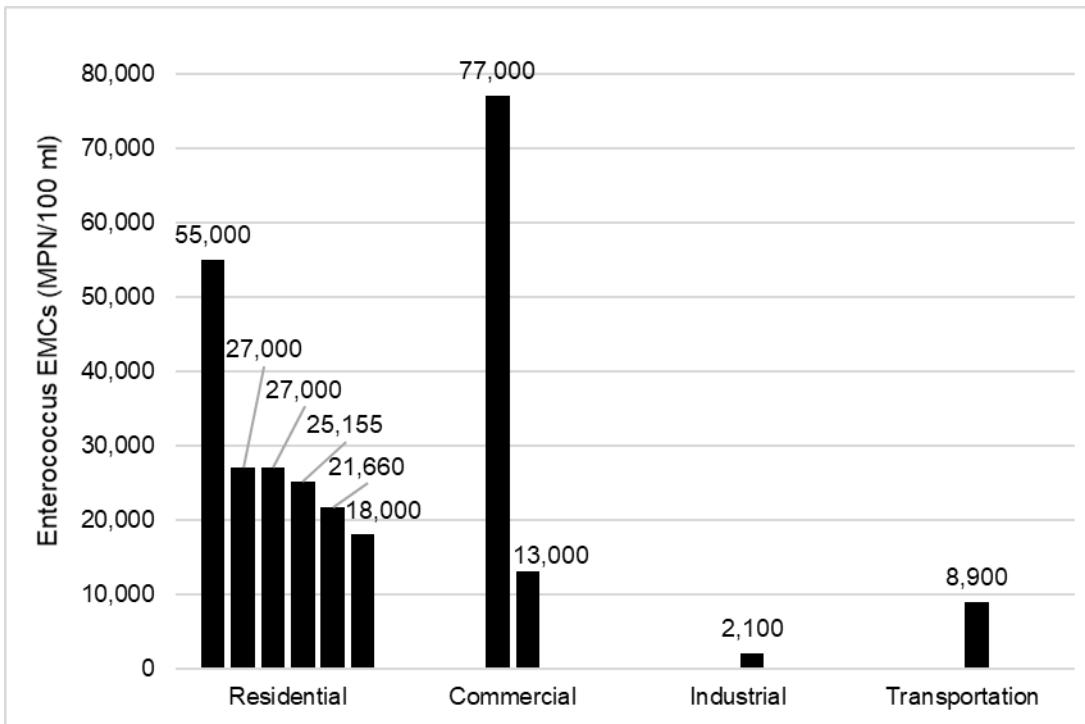


Figure 1-2. Mean observed EMCs for *Enterococcus* from literature (See Table 1-1)

Table 1-2 . Observed Bacteria Loading from urban areas

	Land use	Billion MPN/ac/yr	Source
Fecal Coliform	Urban	190.024 – 477.654	(Line et al, 2008)
<i>E. coli</i>	Open Urban	13.789 – 60.482	(EA Engineering, 2010)
	Residential/Commercial	9.00 – 3.80	
	Various	22 - 1,397	CDM Smith, 2012*
<i>Enterococcus</i>	Various	64 – 930	CDM Smith, 2012*

*Units in CFUs, not MPN

Table 1-3 Summary of previously calibration SWMM buildup and washoff values for *E. coli* and *Enterococcus*

Study Location			
(Single-family) Low-density residential			
Buildup Equation		Exponential	Saturation
Max per acre (C1)	<i>E. coli</i>	85.6×10^9	6.9×10^{11}
	Enterococci	26.6×10^9	-
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	<i>E. coli</i>	2	10
	Enterococci	2	-
Washoff Equation		Exponential	Exponential
Coefficient – C1	<i>E. coli</i>	18	10
	Enterococci	18	-
Exponent – C2	<i>E. coli</i>	2.2	0.5
	Enterococci	2.2	-
(Multi- family) Medium density residential			
Buildup Equation		Exponential	Saturation
Max per acre (C1)	<i>E. coli</i>	85.6×10^9	2.5×10^{10}
	Enterococci	25.6×10^9	-
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	<i>E. coli</i>	2	10
	Enterococci	2	-
Washoff Equation		Exponential	Exponential
Coefficient – C1	<i>E. coli</i>	18	10
	Enterococci	18	-
Exponent – C2	<i>E. coli</i>	2.2	0.5
	Enterococci	2.2	-
High density residential			
Buildup Equation		Exponential	Saturation
Max per acre (C1)	<i>E. coli</i>	-	1.41×10^{11}
	Enterococci	-	-
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	<i>E. coli</i>	-	10
	Enterococci	-	-
Washoff Equation		Exponential	Exponential
Coefficient – C1	<i>E. coli</i>	-	10
	Enterococci	-	-
Exponent – C2	<i>E. coli</i>	-	0.5
	Enterococci	-	-
Commercial			
Buildup Equation		Exponential	Saturation
Max per acre (C1)	<i>E. coli</i>	0.42×10^9	1.4×10^{12}
	Enterococci	0.72×10^9	-
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	<i>E. coli</i>	2	10
	Enterococci	2	-

Study Location			
	Boston, MA	Lakewood, OH	
Washoff Equation		Exponential	Exponential
Coefficient – C1	E. coli Enterococci	18 18	10 -
Exponent – C2	E. coli Enterococci	2.2 2.2	0.5 -
Industrial			
Buildup Equation		Exponential	Saturation
Max per acre (C1)	E. coli Enterococci	1.26×10^9 2.12×10^9	1.4×10^{12} -
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	E. coli Enterococci	2 2	10 -
Washoff Equation		Exponential	Exponential
Coefficient – C1	E. coli Enterococci	18 18	10 -
Exponent – C2	E. coli Enterococci	2.2 2.2	0.5 -
Transportation			
Buildup Equation		Exponential	NA
Max per acre (C1)	E. coli Enterococci	0.001×10^9 0.002×10^9	- -
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	E. coli Enterococci	2 2	- -
Washoff Equation		Exponential	NA
Coefficient – C1	E. coli Enterococci	18 18	- -
Exponent – C2	E. coli Enterococci	2.2 2.2	- -
Open Space			
Buildup Equation		Exponential	Saturation
Max per acre (C1)	E. coli Enterococci	126×10^9 214×10^9	$1.25 \times 10^{10*}$ -
C2 - Buildup rate constant (1/days) or Days to $\frac{1}{2}$ max buildup	E. coli Enterococci	2 2	10^* -
Washoff Equation		Exponential	Exponential
Coefficient – C1	E. coli Enterococci	18 18	10^* -
Exponent – C2	E. coli Enterococci	2.2 2.2	0.5 -

Buildup in SWMM can occur as either a mass per unit of sub catchment area or per unit of curb length (Rossman, 2010). The amount of buildup is a function of antecedent dry weather days. The user can choose a power, exponential, or saturation function to compute buildup, or use an external time series to describe the rate of buildup per day as a function of time (Rossman, 2010). CMD Smith (2012) used an exponential buildup and a rate constant (1/days) of 2, which is equivalent to 0.3 days to reach $\frac{1}{2}$ max buildup. Alternatively, CT Consultants (2016) used the saturation function and a value of 10 days to reach $\frac{1}{2}$ max buildup. The exponential function builds up pollutants very rapidly, then slows down to the maximum value while the saturation function has a less rapid buildup and a more gradual approach to the maximum value. Additionally, CMD Smith (2012) also added a term to represent bed load growth of bacteria to account for the potential for rapid population changes within the collection system, although this had minimal impact on overall model results.

SWMM can simulate washoff on user-defined land use categories using exponential, rating curve, or EMC functions. Exponential functions have been used to describe the washoff of dust and dirt from streets (Sartor et al., 1974). SWMM relies on user defined values for washoff coefficients and exponents, the runoff rate per unit area and the pollutant buildup in mass units to calculate exponential washoff. Both CDM Smith (2012) and CT Consultants (2016) used the exponential function to simulate washoff, with coefficients ranging from 10 to 18 and exponents ranging from 0.5 to 2.2.

3.1.5 Conclusions

Results of studies on the export of bacteria from urban watersheds had highly variable results; observed EMCs range over orders of magnitude. Fewer studies evaluated *Enterococcus* than *E. coli* and limited data was found on observed bacteria loading from urban areas. Previous studies using SWMM to model bacteria buildup and washoff relied on both exponential and saturation buildup functions. Using functions originally developed for the buildup and washoff of dust and dirt on streets to simulate the export of organisms is a simplified approach to a complex phenomenon. Several factors that can influence the propagation and die-off of bacteria in a watershed are necessarily omitted. For any bacteria export modeling effort, robust local monitoring data can help to inform model calibration and increase confidence in modeling results.

3.2 Climate Data (Precipitation and Air Temperature)

Historical climate data for the latest 21 years (1998 – 2018) from local gages at Martha’s Vineyard airport was used for impervious HRU timeseries development. The climate data included:

- Hourly continuous precipitation timeseries (in/hr)
- Daily minimum and maximum temperature timeseries (°F)

The climate data was reviewed for its completeness and quality. After QA/QC was complete, the annual and monthly summary statistics were estimated to review and identify any data gaps/issues. The data was then formatted to the required input format for the HRU SWMM model. Additional discussion of climate data can be found in the task 4B memo “Opti-Tool Analyses for Quantifying Stormwater Runoff Volume and Pollutant Loadings from Watershed Source Areas (Task 4B)”.

3.3 HRU SWMM Model (Initial Setup and Run)

Local climate data was used to update the boundary conditions in the Opti-Tool HRU SWMM model. Buildup/wash off parameters for modeling indicator bacteria load on the impervious HRU were initially set to the calibrated parameters used for Boston’s MS₄ (CMD Smith, 2012). The model output timeseries was used to statistically summarize the predicted indicator bacteria EMC distributions and average annual pollutant export rates. For further analysis, box and whisker plots and bar graphs were created to compare these model timeseries to literature values.

3.4 HRU Timeseries (Hourly Flow and Bacteria Concentration and Load Estimates)

SWMM model output timeseries were structured into the required format for the SUSTAIN model using a spreadsheet-based utility tool, SWMM2Opti-Tool, available in Opti-Tool (Figure 3-3). The HRU timeseries format for the Opti-Tool is identical to the format needed in SUSTAIN (the Opti-Tool uses the SUSTAIN model as a backend GI simulation engine).

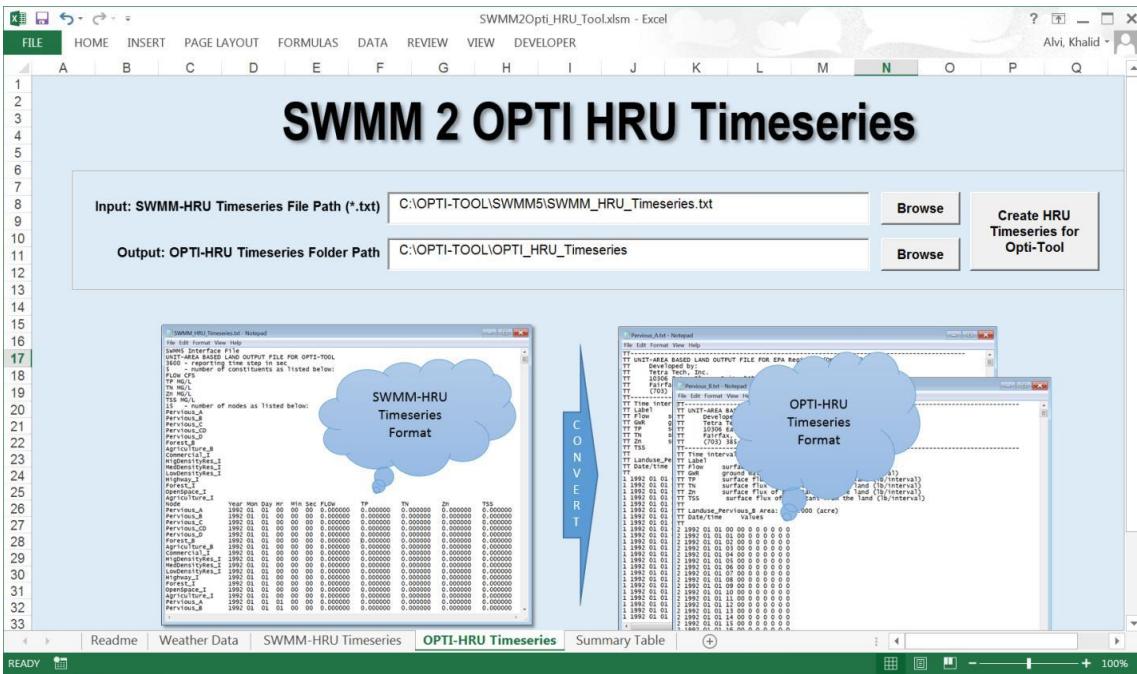


Figure 3-3. The user interfaces for SWMM2Opti-Tool, a utility to reformat SWMM output to Opti-Tool HRU timeseries.

Figure 3-4 and Figure 3-5 present simulated *E. coli* and *Enterococci* concentrations, respectfully, based on the calibrated buildup/washoff values from CDM Smith (2012). Bacteria concentrations were highest from residential land uses and lowest from transportation. These results are reflective of the maximum buildup values attributed to each land use (Table 1-3). Maximum buildup for residential land uses was set to 85.6×10^9 MPN/acre while the maximum buildup on transportation land uses was set to 0.001×10^9 MPN/acre. Sources of *E. coli* and *Enterococcus* include both human and animal sources. Therefore, it is not surprising that bacteria export is lower from transportation land uses than from other land uses where it is more likely to find warm blooded animals interacting with the land surface. Additionally, this pattern is representative of the EMCs presented in Figure 1-1. The median simulated *E. coli* concentrations from residential areas of 33,651/100ml is similar to observed EMCs found in the literature. Based on NSWD data, the highest *E. coli* EMC from residential land uses in Massachusetts was 35,000 MPN/100ml. Relatively high EMCs were also observed by Stein (2008) who found *E. coli* EMCs of $30,000 \pm 18,000$ MPN/100ml from residential areas in California. Simulated concentrations of *Enterococcus* were generally lower than observed EMCs presented in Table 1-1. Data from Breault et al. (2002) was included in Figure 3-5 since median and upper and lower quartiles were reported and therefore allowed for visual comparison with the distribution of the simulated data. Observed values included data from single family and multifamily residential land uses as well as the entire Charles River Watershed. The median simulated concentration for residential land use was 10,456 MPN/100ml, which was lower than the median observed values. The lowest observed EMC was 13,000 CFU/100 ml observed in the Charles River watershed (Breault et al., 2002) while the highest was $55,000 \pm 37,000$ CFU/100 ml (Stein et al., 2008).

Figure 3-6 and Figure 3-7 present simulated *E. coli* and *Enterococci* unit area loading, respectfully, based on the calibrated buildup/washoff values from CDM Smith (2012). The values are generally in good agreement with observed data. The mean simulated *E. coli* unit area loading ranged from 0.32 to 1,753 billion/ac/yr while CDM Smith (2012) observed an *E. coli* export of 22 - 1,397 billion/ac/yr from Boston's MS₄. Simulated *Enterococcus* unit area loading ranged from 0.04 to 544.84 Billion/ac/yr, while observed loading from the Boston's MS₄ ranged from 64 – 930 Billion/ac/yr (Table 1-2). The unit area loadings for bacteria show the same trend as the concentrations. For example, *E. coli* has highest concentrations and loadings from residential land uses, followed by industrial, commercial, then transportation. This is expected given that loading was calculated as concentration multiplied by volume. While the four land uses have different build up-washoff values for bacteria, they all represent an impervious surface which converts the same amount of rainfall to runoff. The same stormwater volume applied to different concentrations will result in the same pattern of loading compared to concentration.

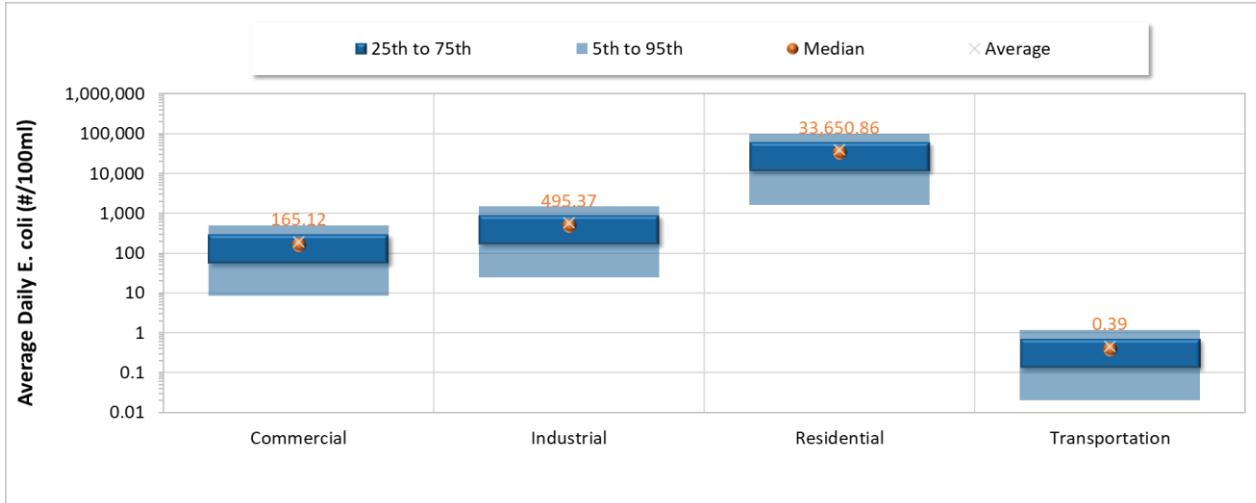


Figure 3-4. Simulated average daily *E. coli* concentrations from developed land uses in Tisbury, MA for the period 1998-2018.

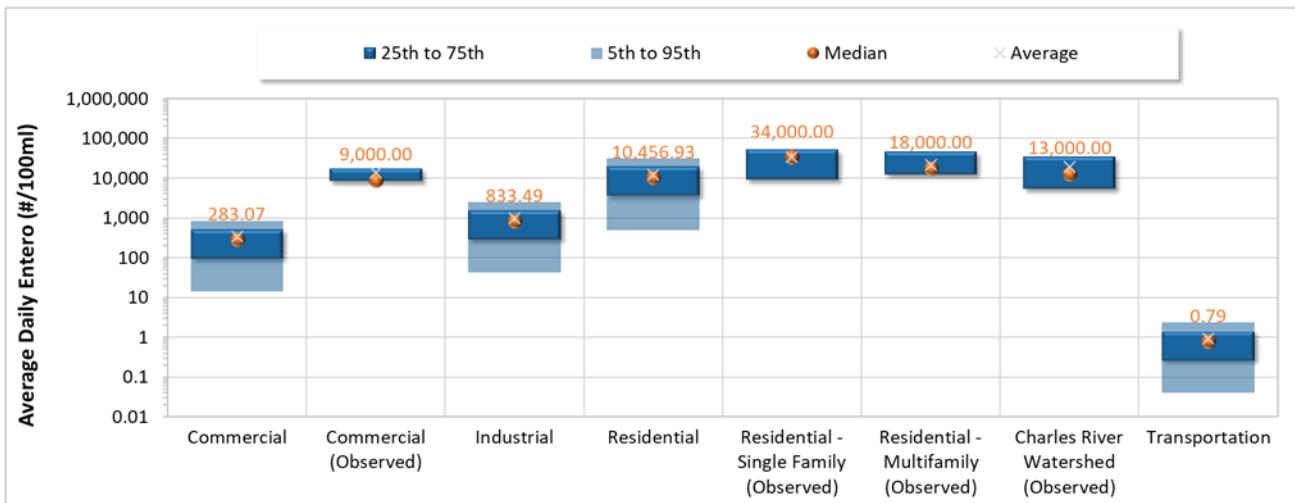


Figure 3-5. Simulated average daily Enterococci concentrations from developed land uses in Tisbury, MA for the period 1998-2018. (Observed data source: Breault et al., 2002)

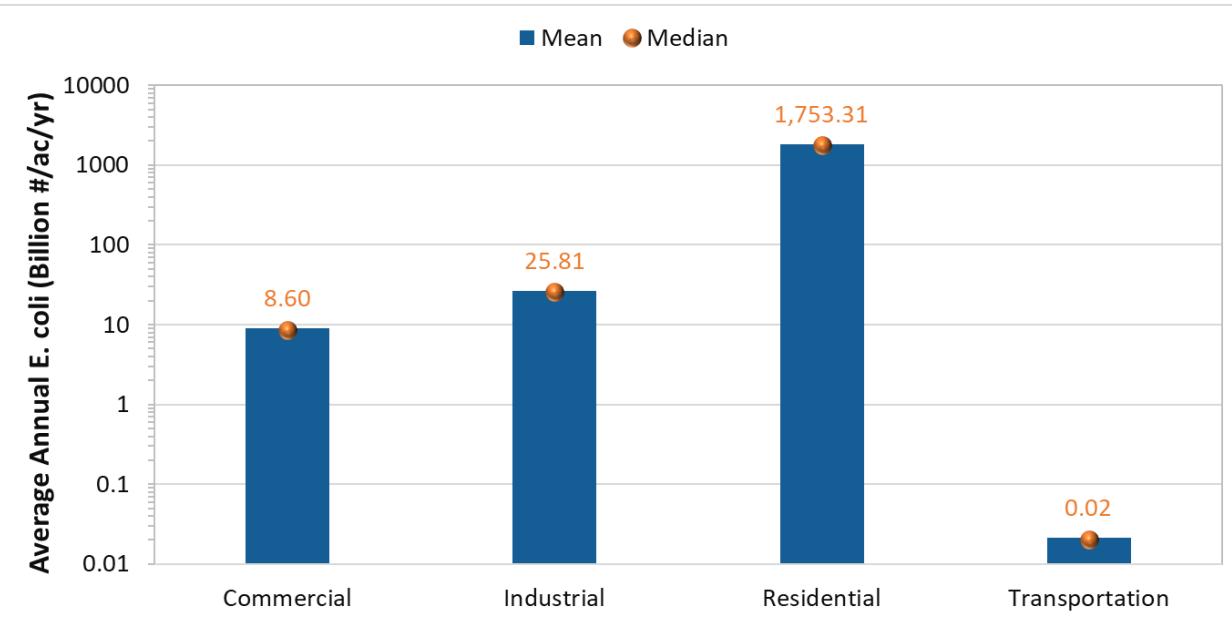


Figure 3-6. Average annual *E. coli* export from developed land uses in Tisbury, MA for the period 1998-2018.

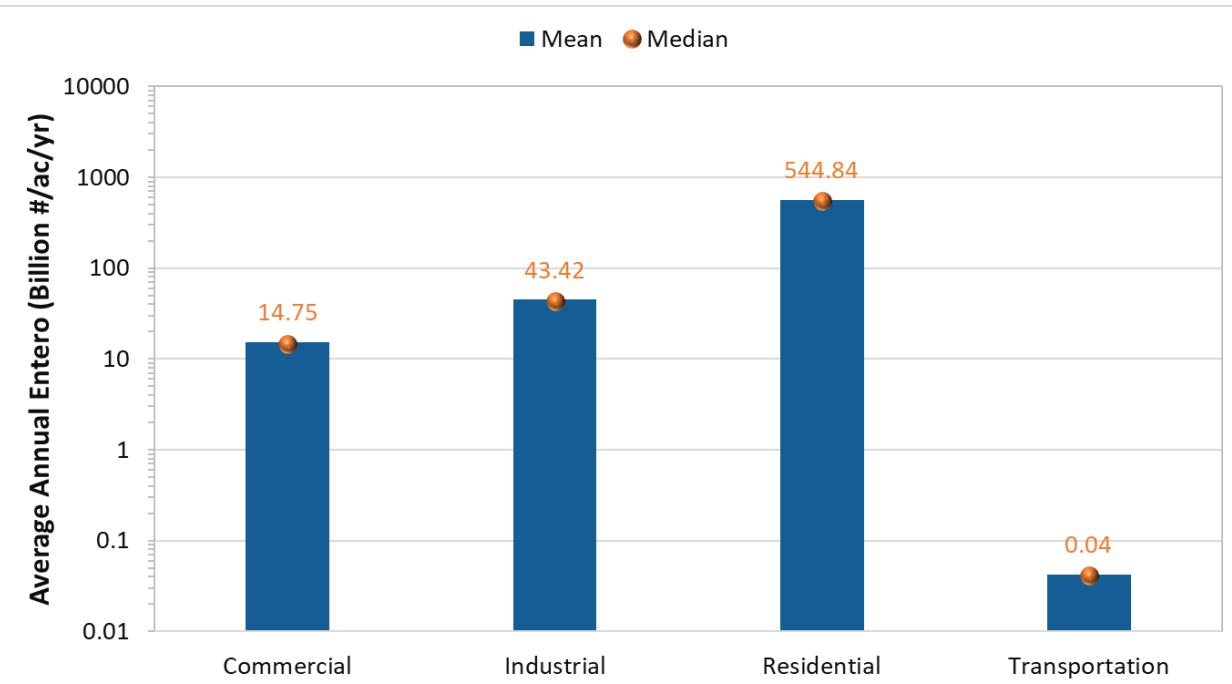


Figure 3-7. Average annual *Enterococcus* export from developed land uses in Tisbury, MA for the period 1998-2018.

4 SCM PERFORMANCE CURVES FOR INDICATOR BACTERIA

The Opti-Tool previously included SCM performance curves (U.S. EPA. 2010) for estimating the cumulative pollutant load reductions from infiltration, filtration, and detention practices for nutrients (TP, TN), sediments (TSS) and Zn. The Opti-Tool performance curves for indicator bacteria were developed for the SCM types shown in Table 4-1. The SCM efficiencies for *E.coli* and *Enterococcus* in Table 4-1 are based on an analysis of published data presented in Table 4-2. Since some of the SCMs used in Opti-Tool did not have published information on their bacteria load reduction efficiencies, it was necessary to equate the SCMs without data to those that did in Table 4-2. For example, the efficiencies attributed to Infiltration Basin, Infiltration Trench, and Sand Filter in Table 4-1 are based on data for media filters (Table 4-2) obtained from the International Stormwater BMP database (Clary et al., 2017). Additionally, only three studies with SCM efficiencies of *Enterococcus* were identified. Due to insufficient data, efficiencies for *E. coli* were used for *Enterococcus*. Since removal efficiencies were assumed to be identical, only curves for *E. coli* were developed.

Table 4-1. SCM types and associated removal efficiencies for developing indicator bacteria performance curves

SCM Type	Underdrain Option	<i>E. coli</i> Efficiency	<i>Enterococcus</i> Efficiency	Major Processes for Bacteria Removal
Biofiltration	Yes	0.76	0.76	Adsorption, filtration
Biofiltration with ISR	Yes	0.76	0.76	Adsorption, filtration
Dry Pond	No	0.64	0.64	Settling
Infiltration Basin	No	0.76	0.76	Adsorption, filtration
Infiltration Trench	No	0.76	0.76	Adsorption, filtration
Sand Filter	Yes	0.76	0.76	Filtration
Subsurface Gravel Wetland	Yes	0.60	0.60	Adsorption, filtration
Wet Pond	No	0.96	0.96	Settling

Table 4-1 includes the major processes that are assumed to be responsible for bacteria removal. However, the major mechanisms which remove bacteria in SCMs are not fully understood. While dominant removal processes include settling, filtration and adsorption, there are other biological and physical processes occurring in SCMs that may reduce bacteria concentrations as well as increase them. Settling is likely the dominant removal process occurring within the water column. Bacteria may enter a SCM ‘free’, existing as individual organisms/groups, or may be associated with particles. Bacteria attached to denser particles will tend to settle out of the water column more quickly than free phase organisms or those associated with less dense, more mobile particles. Characklis et al. (2005) found that an average of 30-55% of *E. Coli* and *Enterococcus* organisms were associated with settleable particles in stormwater samples. *E. coli* is a rod-shaped bacteria with a diameter ranging from 2-6 μm and a length ranging from 1.1-1.5 μm . Within porous soil media, adsorption is likely a major removal mechanism due to the small size of *E. coli* (Lan et al., 2010). Sorption rates can be affected by several factors, including media texture, organic matter, temperature, flow rate, ionic strength, pH, hydrophobicity, chemotaxis and electrostatic charge (Stevik et al., 2004). Temperature has also been cited as an important environmental factor for bacteria die-off, with increasing temperatures associated with higher removal rates (USEPA, 2006). Additionally, sun exposure can result in increased pathogen inactivation and removal through treatment by ultraviolet light.

The wet, nutrient rich environments found in many stormwater SCMs can limit their ability to reduce bacteria loading (Hathaway et al., 2008). Rusciano and Obropta (2007) found viable bacteria retained in the soil substrate of a bioretention column 36 days after performing the last stormwater simulation. SCMs can result in increased bacteria concentrations, indicated by negative values in Table 4-2. Performance data of infiltration SCMs only represents removal processes that occur within the infiltration SCM as filtered runoff is captured by an underdrain to assess performance of an in-system removal. Consequently, these data do not reflect the additional removal accomplished as exfiltrate flows through subsoils beyond the performance

monitoring collection system. Runoff events that are completely captured and infiltrated achieve 100% removal of bacteria.

Unpublished research (Houle, et al., 2014) evaluated SCMs in New Hampshire whose primary treatment mechanisms included settling, enhanced settling using a hydrodynamic separator, and filtration. The results suggest SCMs using conventional settling techniques were often a source of bacteria, having higher outflow concentrations compared to inflow, especially during summer months when concentrations were highest and conditions for regrowth are most favorable. The study also found that systems using filtration and infiltration performed better, generally having lower concentrations in the outflow compared to inflow. Periods of high influent flow rates can cause turbulent conditions within SCMs, resuspending sediment and associated bacteria, resulting in possible increases in effluent concentrations. Sediment resuspension is more likely to occur in SCMs that are poorly designed, not well maintained, or have reached their design life (EPA, 2006). Zarriello et al (2002) estimated the effect of SCMs and street sweeping on reducing fecal coliform in the Lower Charles River, MA watershed. The SCMs treated runoff depths ranging from 0.25 to 1.0 and had a median removal efficiency for fecal coliform of 13%.

Bioretention areas, wet ponds and infiltration-based SCMs appear to be the most effective at reducing bacteria concentrations (Table 4-2). EPA (2006) found that settling was a contributing but not primary factor in bacteria removal and that bacteria concentrations decreased with time in a constructed wetland and dry pond. Bacteria load reduction may be higher in SCMs which limit the opportunity for sediment resuspension, such as infiltration based SCMs.

Table 4-2. – Observed SCM efficiencies for *E. coli* and Enterococcus

	SCM with published efficiency data							Location	Source
	Bioretention	Grass swale	Dry detention	Media Filter	Wet Pond	Wetland	Wetland/ Retention Pond		
	Opti-Tool equivalent								
	Biofiltration Biofiltration with ISR	NA	Dry Pond	Infiltration Basin/Trench, Sand Filter	Wet Pond	Subsurface gravel wetland	Wet Pond		
<i>E. coli</i>	0.71							NC	Hunt et al., 2008
	0.48 – 0.97							TX	Kim et al., 2012
	0.72 – 0.97							Laboratory & synthetic stormwater	Zhang et al., 2011
	0.71		0.05 - 0.14		0.18	0.22-0.92		North Carolina	Hathaway et al. 2008
	0.80	-0.26	0.64*	0.76*	0.96	0.64	0.80 – 0.96	National	Clary et al., 2017
<i>Enterococcus</i>	-0.76 – 0.01				0.49	0.06-0.93		NC	Hunt et al., 2008
			0.63			0.61	0.78	National	Clary et al., 2017
		-0.60	-1.96			0.21	0.78	NH	Houle et al., 2014 unpublished

*Data for fecal coliform

The following subsections describe the steps for developing the SCM performance curves for the indicator bacteria.

4.1 SUSTAIN SCM Model (Setup and Run)

The SUSTAIN GI module is a process-based continuous simulation model that requires two performance parameters to estimate cumulative load reduction: 1) a first-order decay rate in the ponded water column and 2) an underdrain pollutant removal rate to account for the filtration mechanism. These parameters were adjusted to predict SCM performance comparable to SCM efficiency numbers reported in the literature. A value of 0.1 was used as a default decay rate for *E.coli* for all SCMs. The model output timeseries were summarized into average annual pollutant loads with and without SCM simulation to estimate long-term pollutant load reductions. The SCM scenarios for a wide range of storage capacities, up to 2 inches of runoff depth from the impervious area, were developed for each SCM type listed in Table 4-1. Three hundred and sixty SCM simulation scenarios for 8 SCM types and a range of infiltration rates for infiltration-based SCMs were developed and a continuous hourly flow and pollutant load simulation for 20 years were performed. Each SCM was sized to have a physical capacity to instantaneously store 20 runoff depths ranging from 0.1 to 2.0 inches from a 100% impervious drainage area. A wilting point of 0.01 was included in the representation of each SCM's soil layer to account for unavailable storage due to strongly retained water.

4.2 SCM Performance Curves (Storage Capacity versus Pollutant Load Reduction)

The SUSTAIN model output for each scenario was processed to estimate the indicator bacteria load reduction for modeled storage capacity to develop performance curves for SCMs listed in Table 4-1. Performance curves for SCMs from the Opti-Tool for *E. coli* are shown in Figure 4-1 - Figure 4-20. Appendix-A1, Appendix-A2, and Appendix-A3 contain the tabular data for the curves. The infiltration practices were the most effective SCMs for bacteria load reduction due to the infiltration mechanism of water loss through background soil. The wet pond was the least effective due to the bottom sealed without any infiltration loss from the available storage. The performance curves reflect the effectiveness of infiltration techniques compared to ones relying on settling and filtration mechanism. Appendix-B shows SCMs design specifications modeled in the Opti-Tool to develop the performance curves. Appendix-C shows methods for determining stormwater control design volume for using the SCMs performance curves and provides crosswalk between stormwater control types and the SCMs available in Opti-Tool.

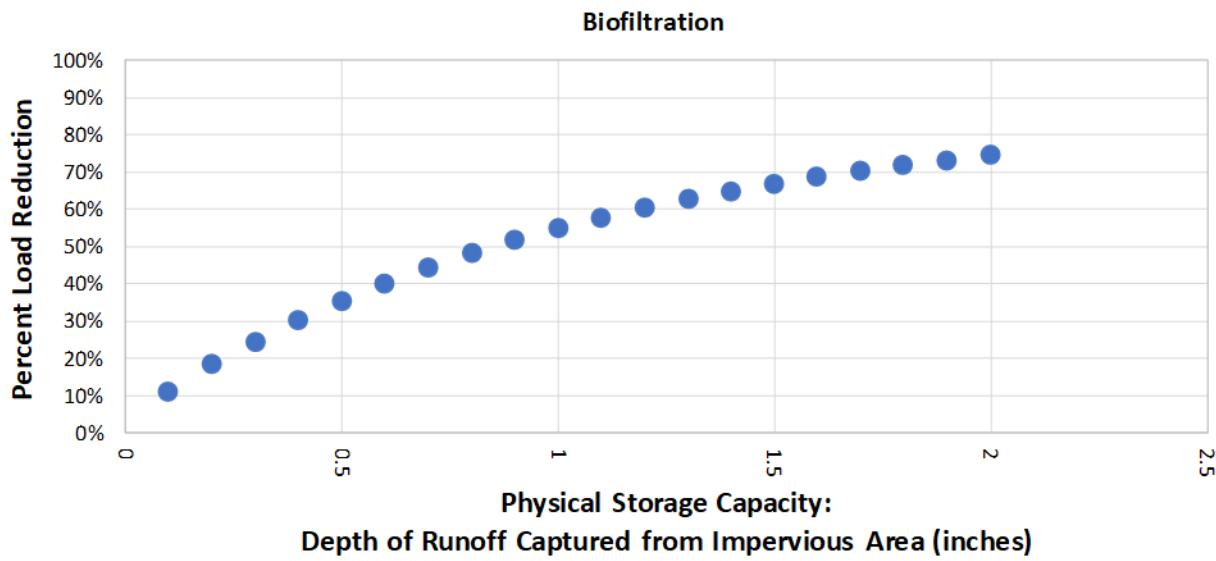


Figure 4-1. Biofiltration performance curve for annual average E. coli load reduction.

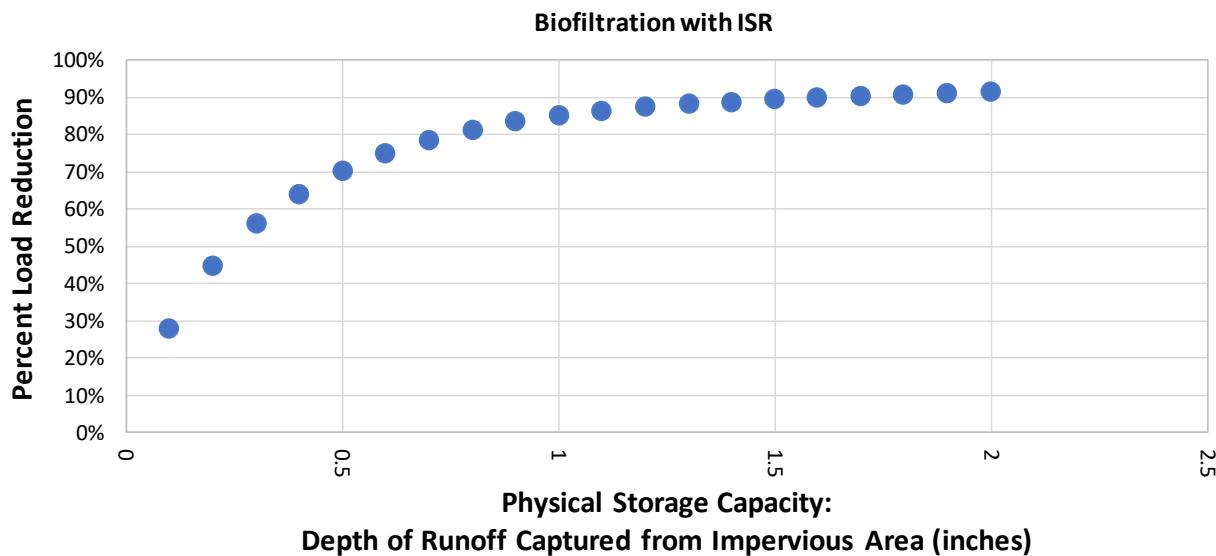


Figure 4-2. Biofiltration with ISR performance curve for annual average E. coli load reduction.

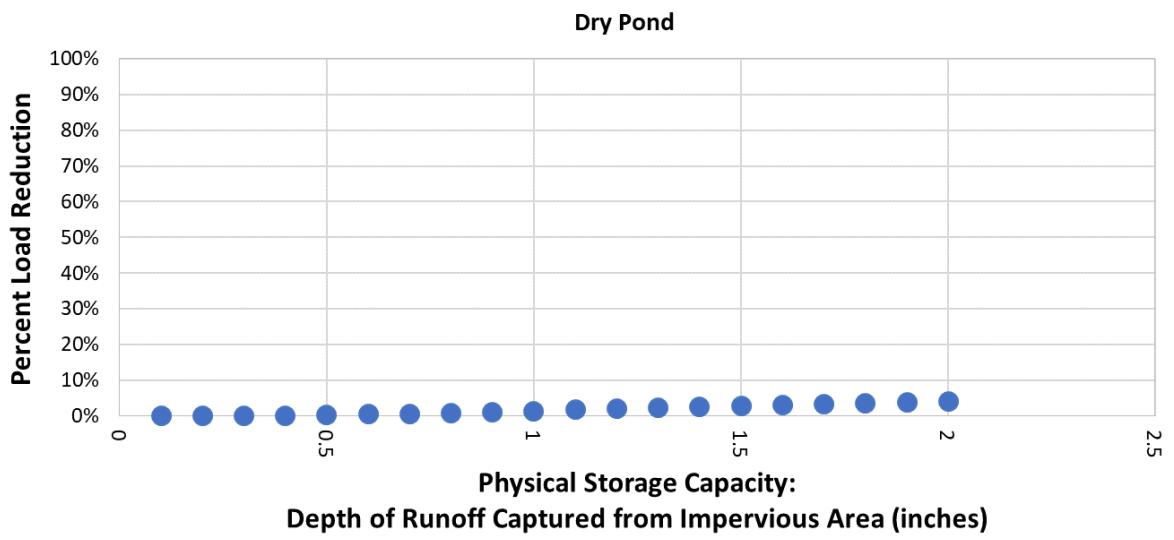


Figure 4-3. Dry Pond performance curve for annual average E. coli load reduction.

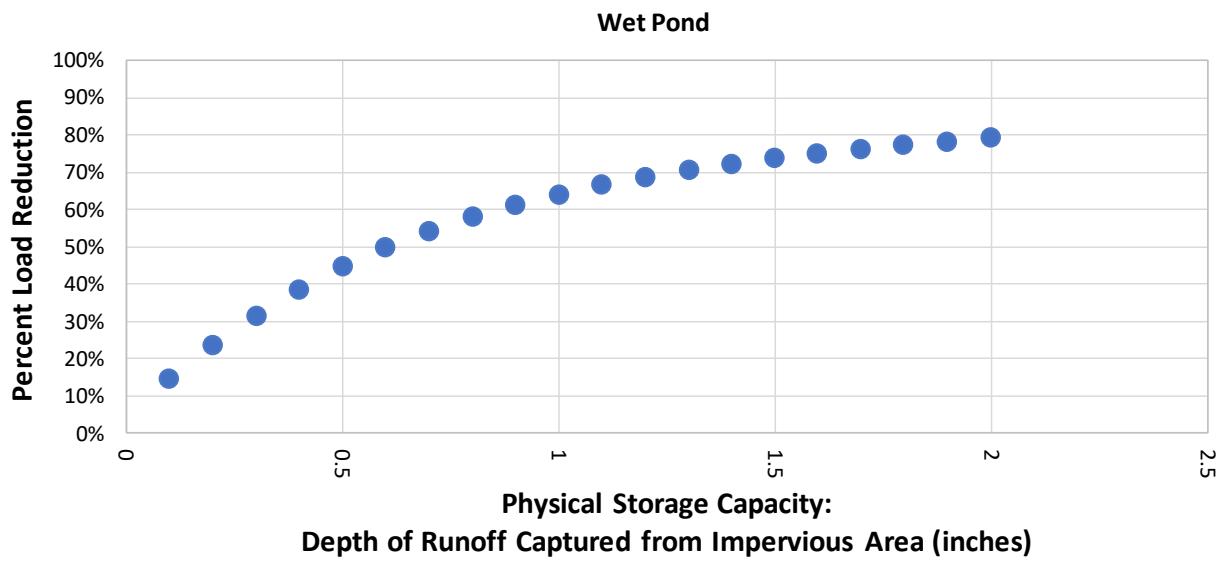


Figure 4-4. Wet Pond performance curve for annual average E. coli load reduction.

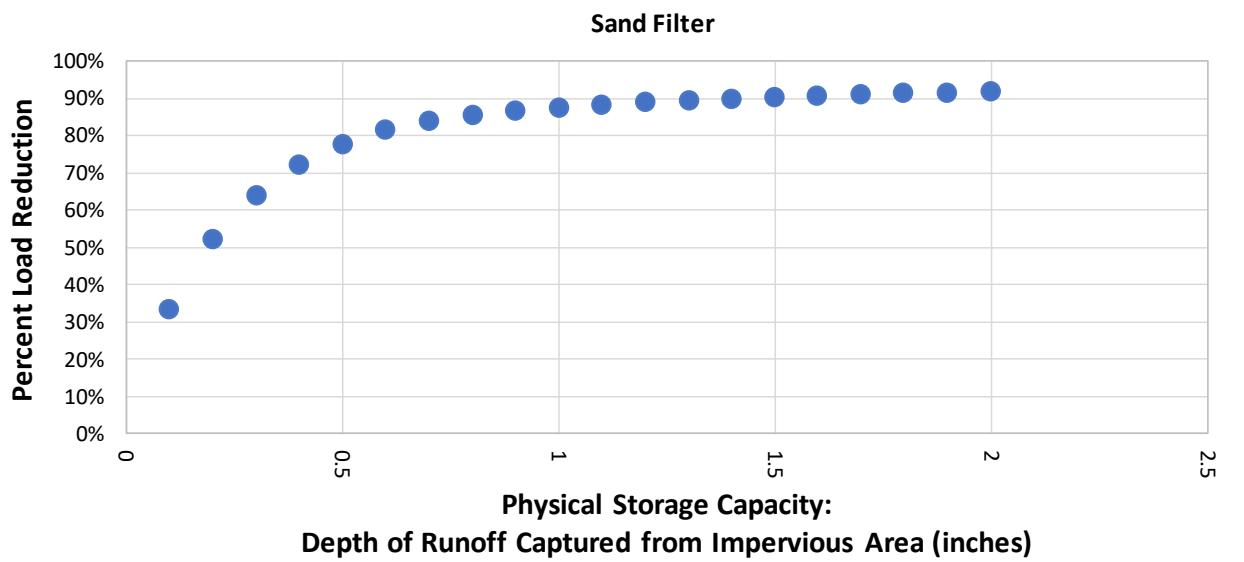


Figure 4-5. Sand Filter performance curve for annual average E. coli load reduction.

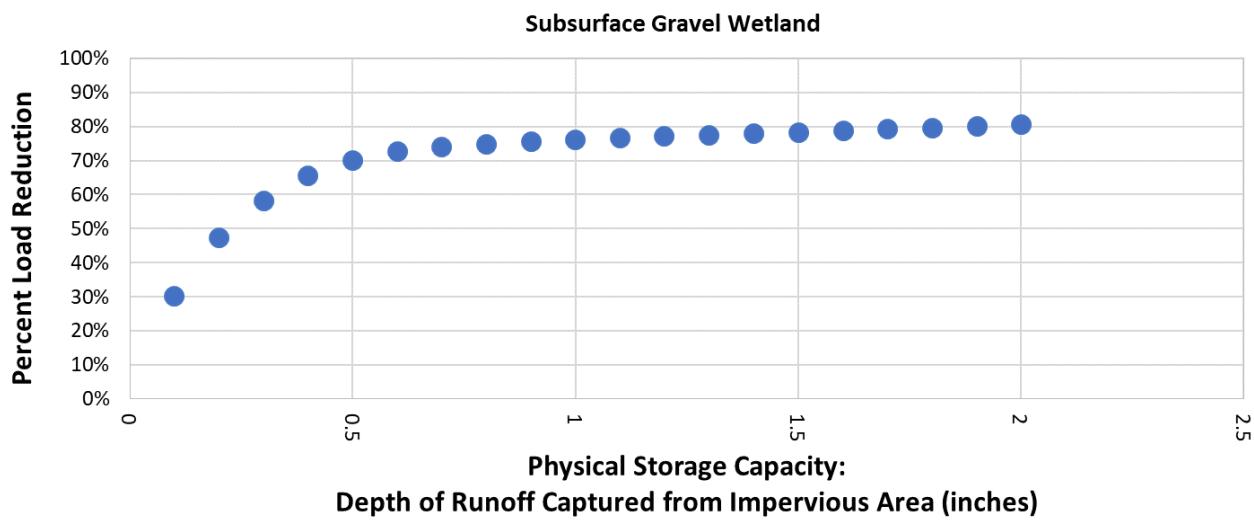


Figure 4-6. Subsurface Gravel Wetland performance curve for annual average E. coli load reduction.

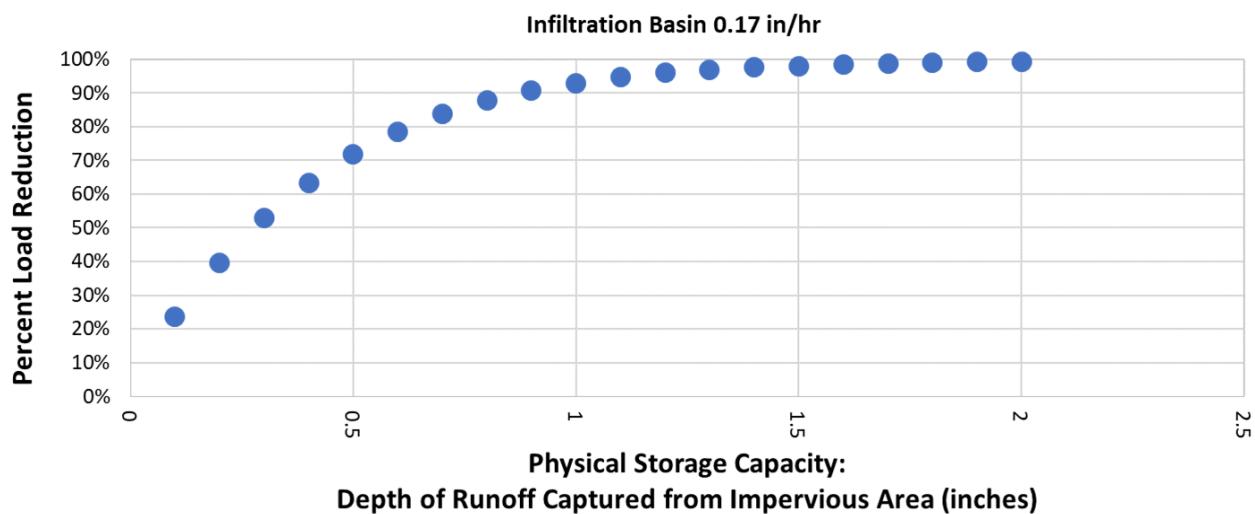


Figure 4-7. Infiltration Basin (0.17 in/hr) performance curve for annual average E. coli load reduction.

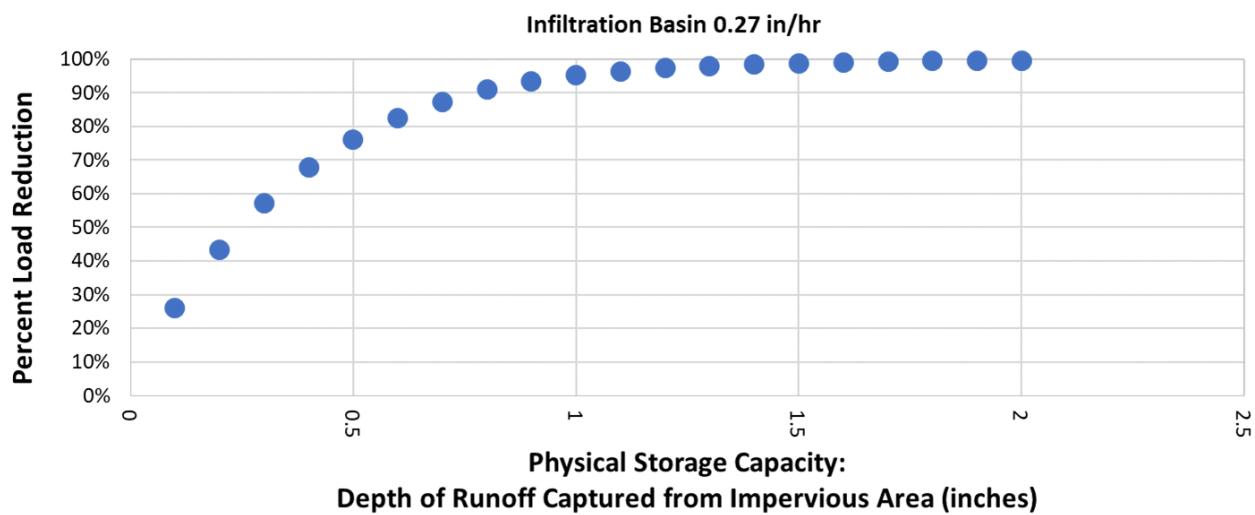


Figure 4-8. Infiltration Basin (0.27 in/hr) performance curve for annual average E. coli load reduction.

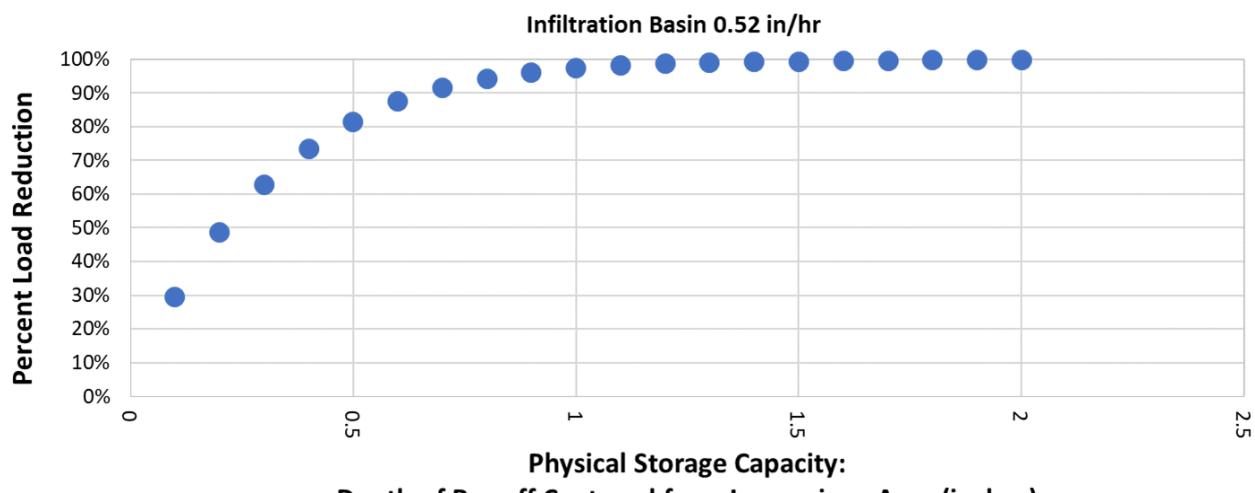


Figure 4-9. Infiltration Basin (0.52 in/hr) performance curve for annual average E. coli load reduction.

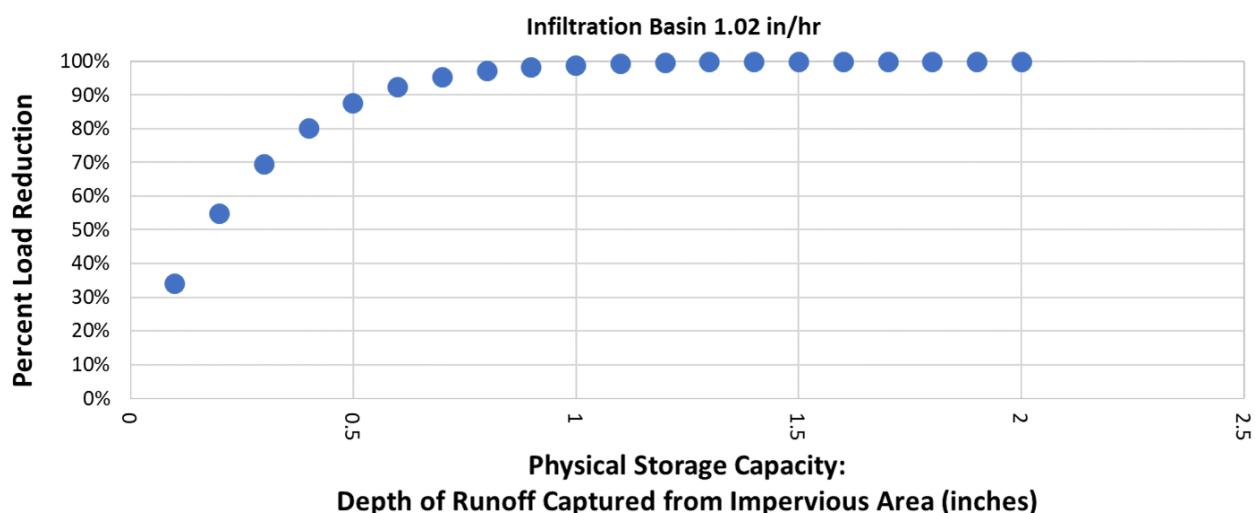


Figure 4-10. Infiltration Basin (1.02 in/hr) performance curve for annual average E. coli load reduction.

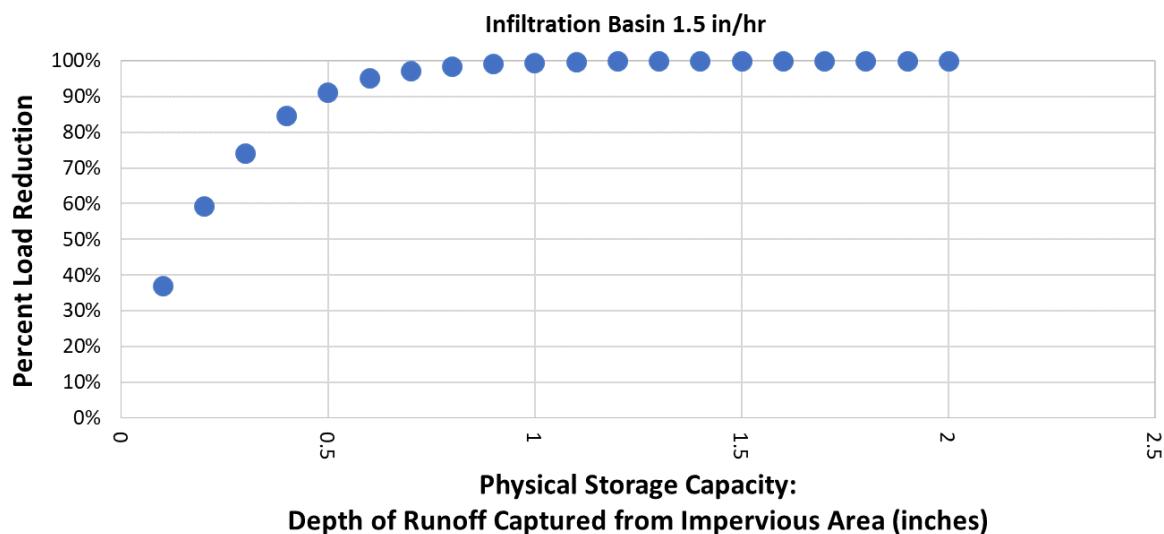


Figure 4-11. Infiltration Basin (1.50 in/hr) performance curve for annual average E. coli load reduction.

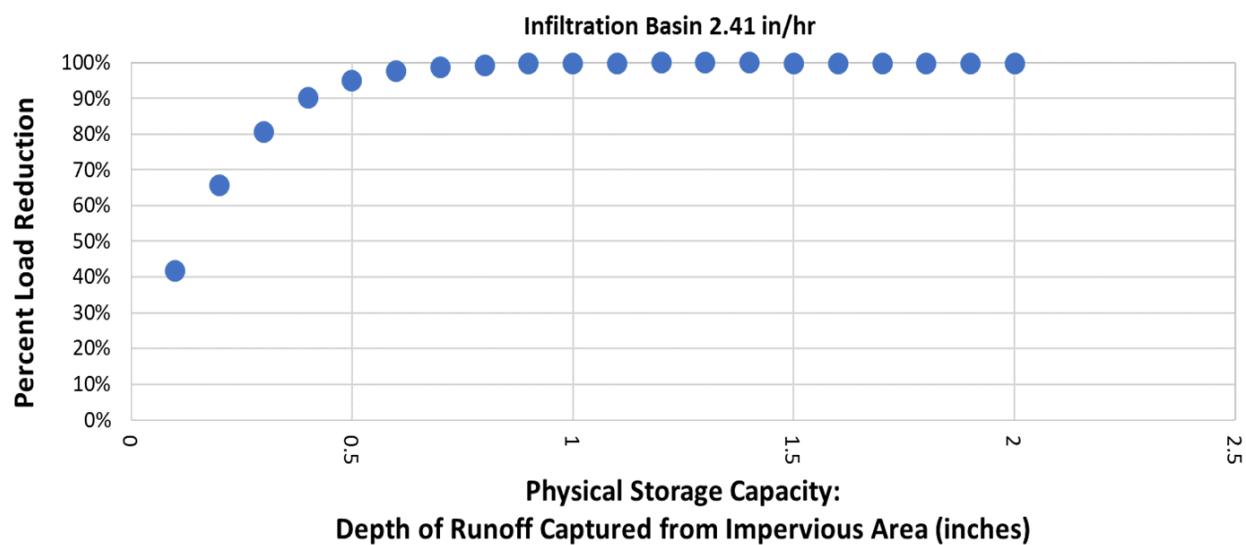


Figure 4-12. Infiltration Basin (2.41 in/hr) performance curve for annual average E. coli load reduction.

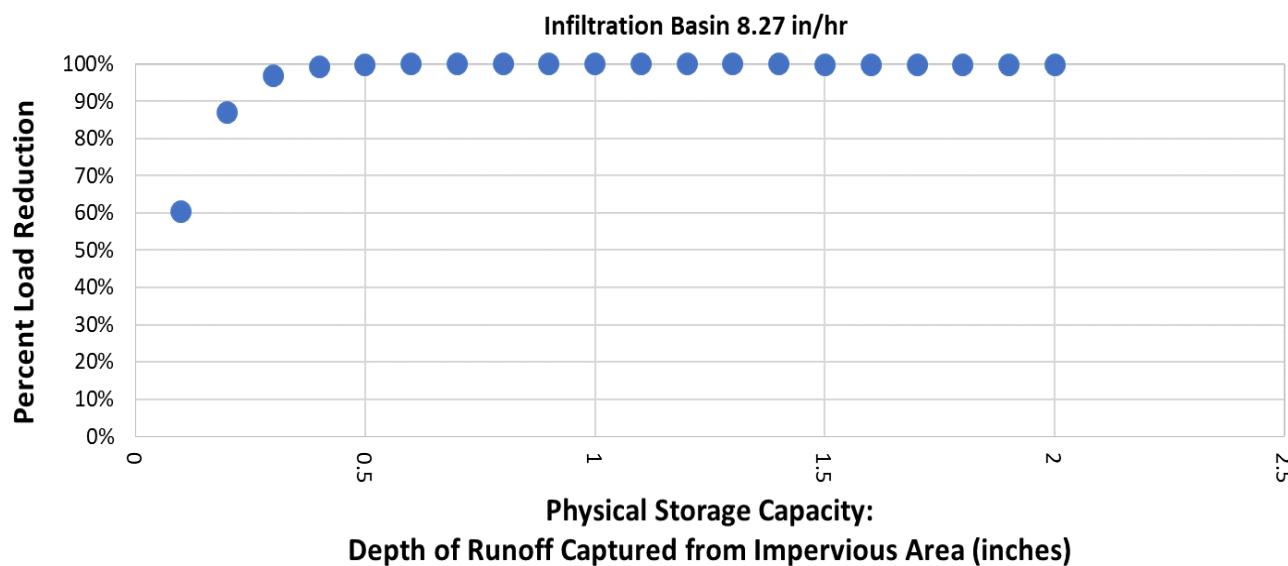


Figure 4-13. Infiltration Basin (8.27 in/hr) performance curve for annual average E. coli load reduction.

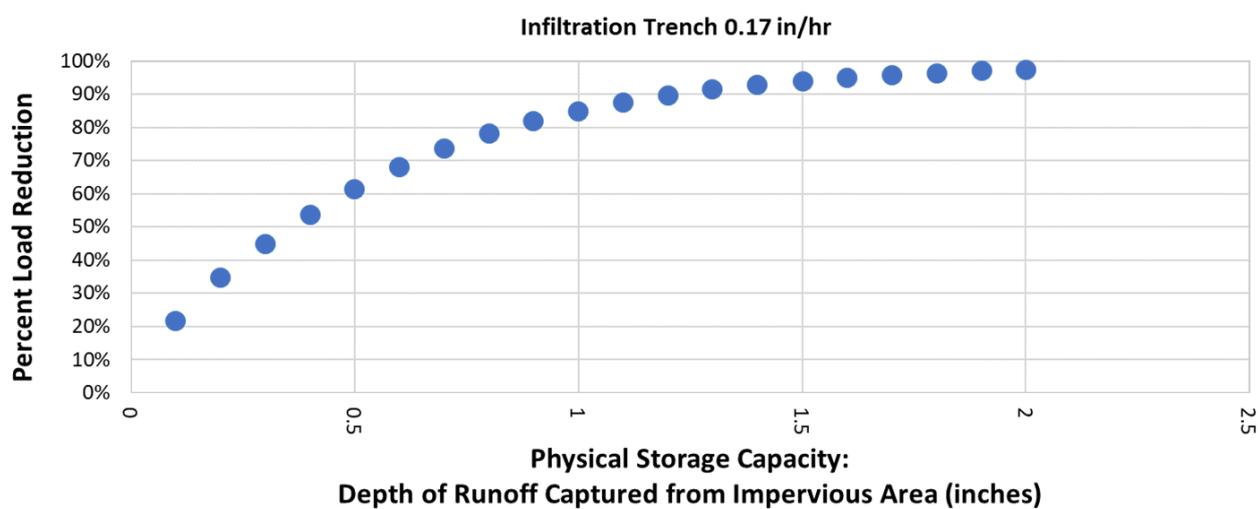


Figure 4-14. Infiltration Trench (0.17 in/hr) performance curve for annual average E. coli load reduction.

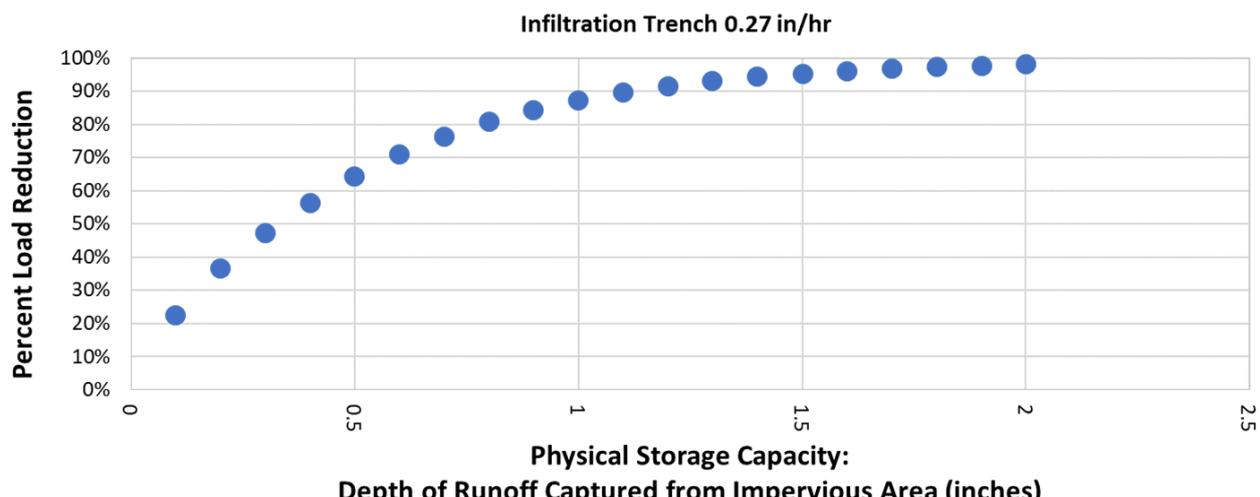


Figure 4-15. Infiltration Trench (0.27 in/hr) performance curve for annual average E. coli load reduction.

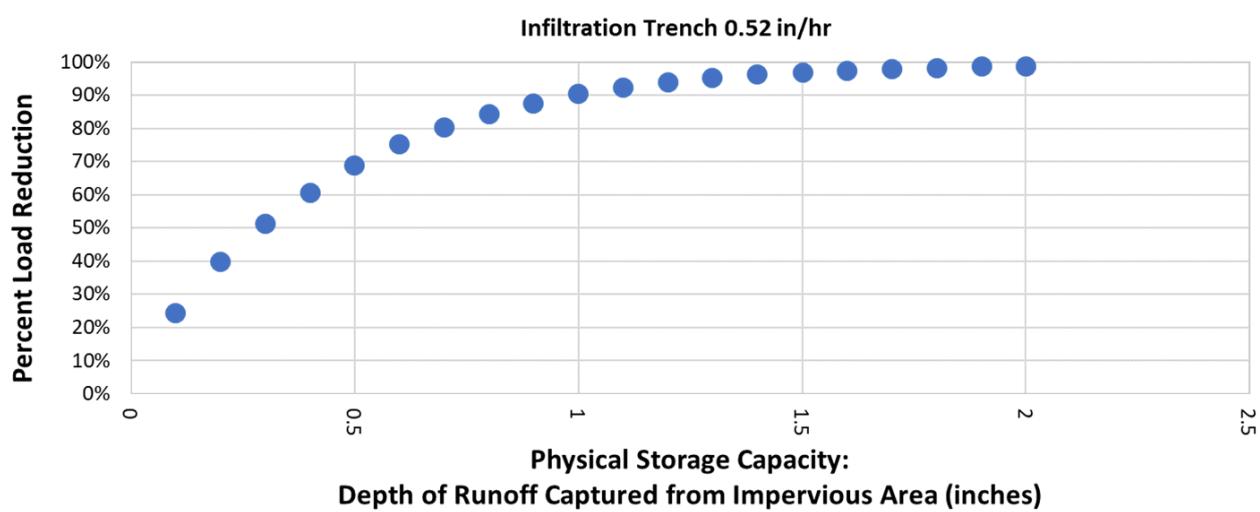


Figure 4-16. Infiltration Trench (0.52 in/hr) performance curve for annual average E. coli load reduction.

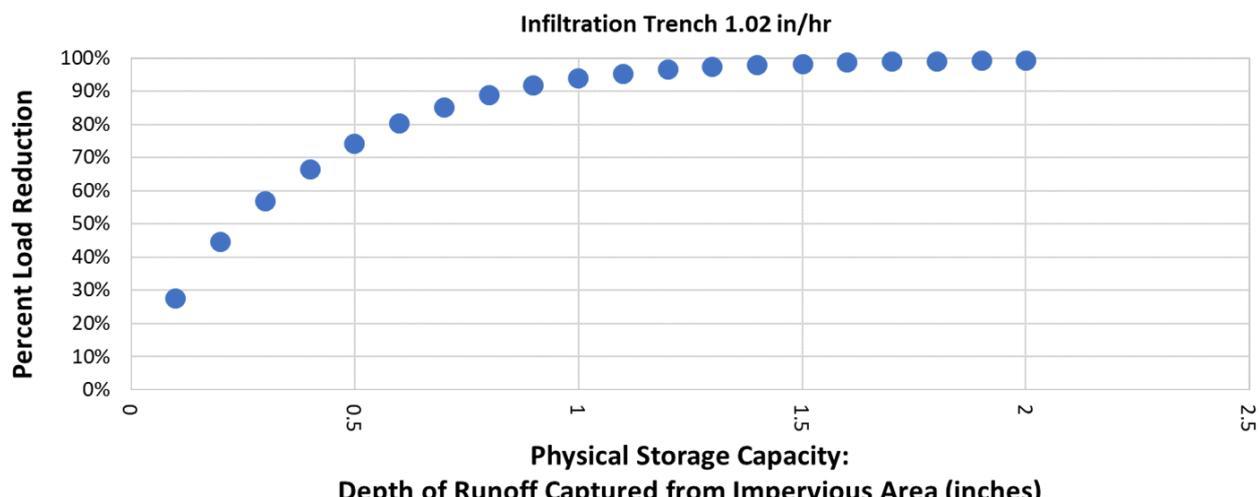


Figure 4-17. Infiltration Trench (1.02 in/hr) performance curve for annual average E. coli load reduction.

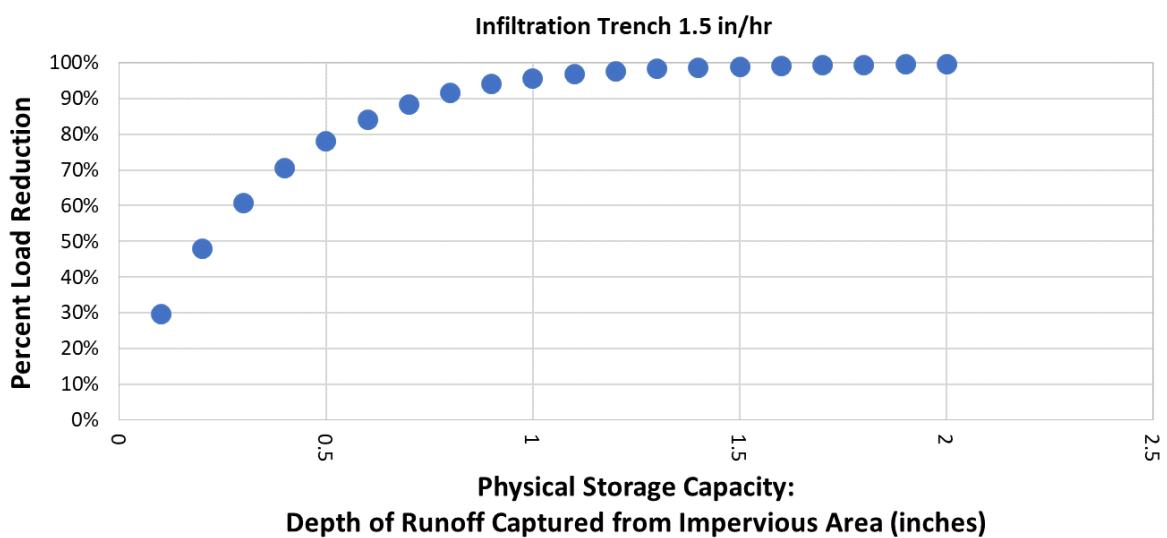


Figure 4-18. Infiltration Trench (1.50 in/hr) performance curve for annual average E. coli load reduction.

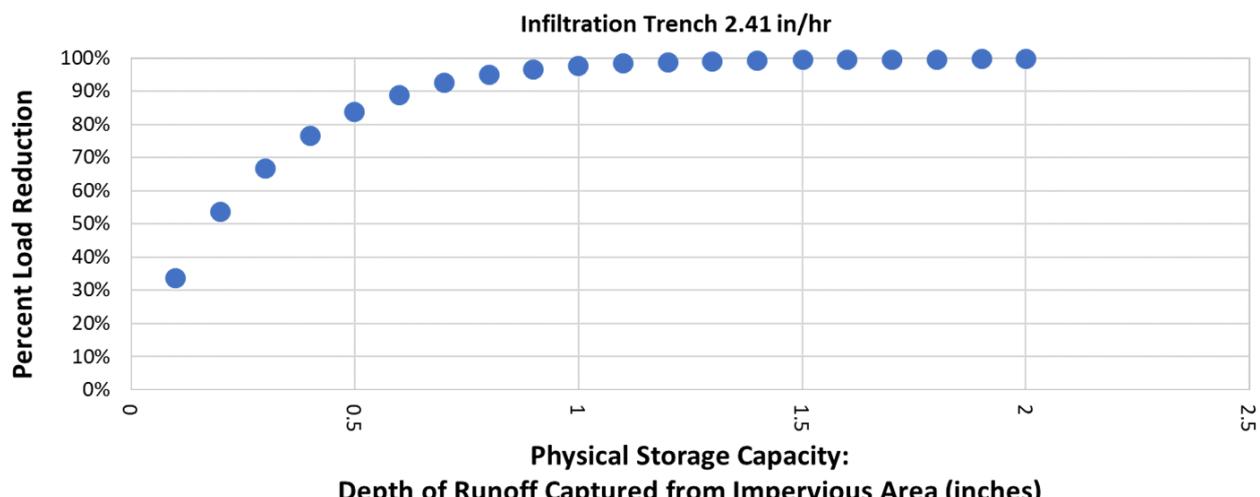


Figure 4-19. Infiltration Trench (2.41 in/hr) performance curve for annual average E. coli load reduction.

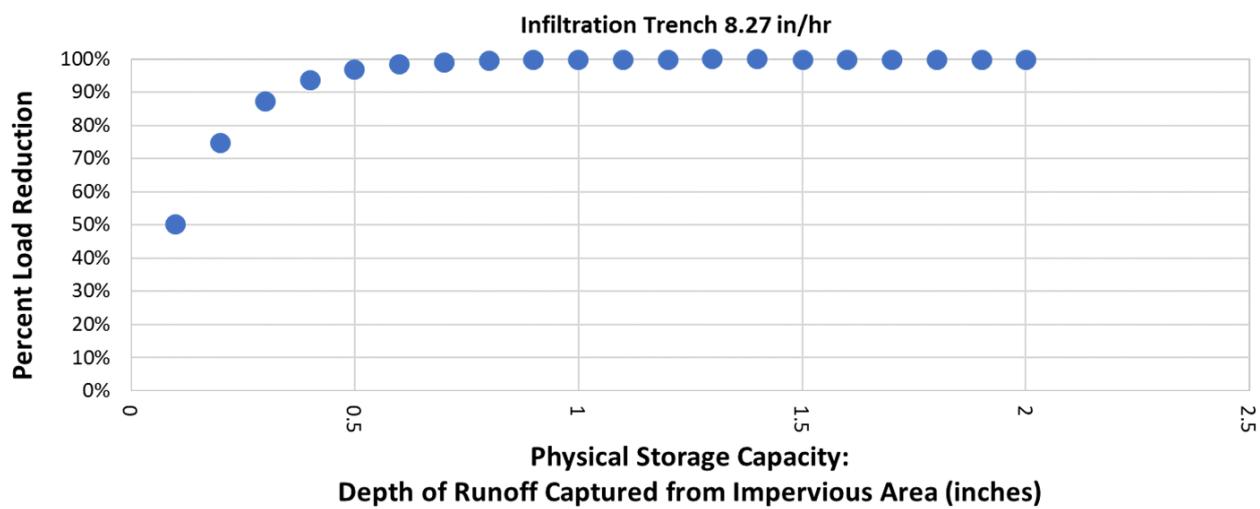


Figure 4-20. Infiltration Trench (8.27 in/hr) performance curve for annual average E. coli load reduction.

REFERENCES

- APWA (American Public Works Association), 1969. Water Pollution Aspects of Urban Runoff. U.S. Department of the Interior, Federal Water Pollution Control Administration.
- Breault, R. F., Sorenson, J.R., and P.K. Weiskel. 2002. Streamflow, Water Quality, and Contaminant Loads in the Lower Charles River Watershed, Massachusetts, 1999-2000
- Caraco, D. 2013. Water Treatment Model (WTM) 2013 Documentation. Center for Watershed Protection.
- CDM. 2012. 2012 Stormwater Model Report. Boston Water and Sewer Commission.
- Characklis, G.W., Dilts, M.J., Simmons, O.D., Likidopoulos, C.A., Krometis, L.A.H., and Sobsey, M.D. (2005) Microbial partitioning to settleable particles in stormwater. *Water Research* 39 (9), 1773- 1782.
- Clary, J., J. Jones, M. Leisenring, P. Hobson, and E Strecker. International Stormwater SCM Database 2016 Summary Statistics Final Report.
- Clary, J. R. Pitt, B Streets. 2014. Pathogens in Urban Stormwater. Urban Water Resources Research Council Pathogens in Wet Weather Flows Technical Committee. Environmental and Water Resources Institute, American Society of Civil Engineers.
- EA Engineering, Science and Technology, Inc. 2010. Chemical Data Analysis Ambient Station/Unnamed Tributary to Winters Run Harford County, Maryland. Prepared for Harford County Department of Public Works Division of Highways and Water Resources.
- Hathaway, J.M. and W. F. Hunt. (2010). Evaluation of indicator bacteria export from an urban watershed. World Environmental and water Resource Congress 2010: Challenges of Change.
- Hathaway, J.M., W.F. Hunt, J.D. Wright, and S Jadlocki. 2008. An Evaluation of Pathogen Removal in Stormwater Best Management Practices in Charlotte and Wilmington, North Carolina. Paper Number 084330. 2008 ASABE Annual International Meeting. Providence, RI.
- Hathaway, J.M., W.F. Hunt, and S Jadlocki. 2009. Indicatory Bacteria Removal in Storm-Water Best Management Practices in Charlotte, North Carolina. *Journal of Enviormentl Engineering*. 135(12) pp 1275-1285.
- Lan, Z., Seagren, E. Davis, A., and J. Karns. The capture and destruction of escherichia coli from simulated urban runoff using conventional bioretention media and iron oxide-coated sand. *Water Environ. Res.*, 82 (2010), pp. 701-7.
- Line, D.E. D.E. Line, N.M. White, W.W. Kirby-Smith, J.D. Potts. Fecal coliform export from four coastal North Carolina areas. *Journal of the American Water Resources Association*, 44 (3) (2008), pp. 606-617
- Pitt, R. 1998. "Epidemiology and Stormwater Management." *Stormwater Quality Management*. CRC Lewis Publishers. New York, NY.
- Rossman, L.A., 2010. Storm Water Management Model User's Manual Version 5.0. United States Environmental Protection Agency, Water Supply and Water Resources Division, National Risk Management Research Laboratory, Cincinnati, Ohio.
- Rusciano, G. M., & Obropta, C. C. (2007). Bioretention column study: fecal coliform and total suspended solids reductions. *Transactions of the ASABE*, 50(4), 1261–1269.

Sartor, J.D., G.B. Boyd, and F.J. Agardy, 1974. Water Pollution Aspects of Street Surface Contaminants. Journal (Water Pollution Control Federation) 46(3):458-467.

Stevik, T. K., K. Aa, G. Ausland, and J. F. Hanssen. 2004. Retention and removal of pathogenic bacteria in wastewater percolating through porous media: A review. Water Res. 38(6): 1355-1367.

Shergill, S. S. and R Pitt. 2004. Quantification of Escherichia coli and enterococci levels in wet weather and dry weather flows. Proceedings of the Water Environment Federation 2004, (10), 746-774

United States Environmental Protection Agency (U.S. EPA). (2006). "Performance of storm water retention ponds and constructed wetlands in reducing microbial concentration." EPA-600-R-06-102, Office of Research and Development, Washington, DC.

U.S. EPA. 2016. *Opti-Tool – Opti-Tool for Stormwater and Nutrient Management User's Guide*. Prepared for: U.S. EPA Region 1, Boston, MA. Prepared by: Tetra Tech, Inc. Fairfax, VA.

U.S. EPA. 2015. *SWMM – Storm Water Management Model User's Manual Version 5.1*. (Publication No. EPA/600/R-14/413b, Revised September 2015)

U.S. EPA. 2010. *Stormwater Best Management Practices (SCM) Performance Analysis*. Prepared for: U.S. EPA Region 1, Boston, MA. Prepared by: Tetra Tech, Inc. Fairfax, VA.

U.S. EPA. 2009. *SUSTAIN – A Framework for Placement of Best Management Practices in Urban Watersheds to Protect Water Quality*. (Publication No. EPA/600/R-09/095, September 2009)

Zarriello, P.J., Breault, R.F., and P. K. Weiskel. 2002. Potential Effects of Structural Controls and Street Sweeping on Stormwater Loads to the Lower Charles River, Massachusetts. USGS Water-Resources Investigations Report 02-4220.

APPENDIX-A1: E. COLI AVERAGE ANNUAL LOAD REDUCTIONS (%) FOR BIOFILTRATION, BIOFILTRATION WITH ISR, DRY POND, WET POND, SAND FILTER, AND SUBSURFACE GRAVEL WETLAND

Runoff Capture Depth (inches)	E. coli Average Annual Load Reduction (%)					
	Biofiltration	Biofiltration with ISR	Dry Pond	Wet Pond	Sand Filter	Subsurface Gravel Wetland
0.1	10.99%	27.89%	0.00%	14.52%	33.64%	30.29%
0.2	18.50%	44.92%	0.00%	23.70%	52.20%	47.21%
0.3	24.54%	56.12%	0.02%	31.56%	64.01%	58.14%
0.4	30.21%	64.16%	0.07%	38.59%	72.22%	65.51%
0.5	35.44%	70.24%	0.20%	44.69%	77.86%	70.07%
0.6	40.15%	74.98%	0.40%	49.94%	81.68%	72.63%
0.7	44.44%	78.61%	0.61%	54.40%	84.11%	74.00%
0.8	48.36%	81.41%	0.85%	58.17%	85.74%	74.80%
0.9	51.92%	83.50%	1.10%	61.39%	86.84%	75.51%
1.0	55.04%	85.14%	1.37%	64.16%	87.68%	76.07%
1.1	57.86%	86.36%	1.65%	66.57%	88.32%	76.51%
1.2	60.49%	87.38%	1.95%	68.68%	88.91%	77.06%
1.3	62.79%	88.19%	2.23%	70.54%	89.38%	77.52%
1.4	64.93%	88.85%	2.51%	72.21%	89.84%	77.92%
1.5	66.81%	89.39%	2.80%	73.69%	90.22%	78.39%
1.6	68.57%	89.86%	3.09%	75.01%	90.58%	78.87%
1.7	70.20%	90.27%	3.37%	76.22%	90.94%	79.31%
1.8	71.69%	90.65%	3.65%	77.29%	91.28%	79.77%
1.9	73.15%	91.00%	3.96%	78.27%	91.60%	80.22%
2.0	74.70%	91.29%	4.26%	79.20%	91.90%	80.67%

APPENDIX-A2: E. COLI AVERAGE ANNUAL LOAD REDUCTIONS (%) FOR INFILTRATION BASIN

Runoff Capture Depth (inches)	E. coli Average Annual Load Reduction (%) for Background Infiltration Rates						
	0.17 (in/hr)	0.27 (in/hr)	0.52 (in/hr)	1.02 (in/hr)	1.50 (in/hr)	2.41 (in/hr)	8.27 (in/hr)
0.1	23.58%	25.88%	29.56%	33.99%	36.93%	41.68%	60.24%
0.2	39.65%	43.40%	48.64%	54.79%	59.17%	65.64%	87.09%
0.3	52.82%	57.15%	62.71%	69.39%	74.05%	80.66%	96.90%
0.4	63.39%	67.71%	73.38%	80.00%	84.44%	90.06%	99.20%
0.5	71.91%	76.09%	81.52%	87.49%	91.08%	95.08%	99.76%
0.6	78.52%	82.48%	87.41%	92.30%	94.99%	97.59%	99.94%
0.7	83.76%	87.34%	91.44%	95.32%	97.20%	98.74%	99.99%
0.8	87.78%	90.86%	94.21%	97.12%	98.31%	99.34%	100.00%
0.9	90.70%	93.36%	96.05%	98.16%	98.98%	99.64%	100.00%
1.0	92.94%	95.16%	97.28%	98.77%	99.36%	99.82%	100.00%
1.1	94.65%	96.43%	98.08%	99.19%	99.62%	99.89%	100.00%
1.2	95.93%	97.34%	98.63%	99.46%	99.76%	99.93%	100.00%
1.3	96.87%	98.00%	99.01%	99.64%	99.83%	99.97%	100.00%
1.4	97.56%	98.49%	99.28%	99.74%	99.89%	99.99%	100.00%
1.5	98.10%	98.86%	99.47%	99.82%	99.94%	100.00%	100.00%
1.6	98.50%	99.14%	99.60%	99.88%	99.97%	100.00%	100.00%
1.7	98.81%	99.35%	99.70%	99.93%	99.98%	100.00%	100.00%
1.8	99.07%	99.51%	99.79%	99.95%	99.99%	100.00%	100.00%
1.9	99.28%	99.63%	99.85%	99.97%	100.00%	100.00%	100.00%
2.0	99.45%	99.72%	99.89%	99.98%	100.00%	100.00%	100.00%

APPENDIX-A3: E. COLI AVERAGE ANNUAL LOAD REDUCTIONS (%) FOR INFILTRATION TRENCH

Runoff Capture Depth (inches)	E. coli Average Annual Load Reduction (%) for Background Infiltration Rates						
	0.17 (in/hr)	0.27 (in/hr)	0.52 (in/hr)	1.02 (in/hr)	1.50 (in/hr)	2.41 (in/hr)	8.27 (in/hr)
0.1	21.59%	22.40%	24.42%	27.49%	29.70%	33.56%	50.19%
0.2	34.63%	36.48%	39.88%	44.54%	48.02%	53.55%	74.76%
0.3	44.86%	47.32%	51.17%	56.74%	60.77%	66.74%	87.14%
0.4	53.68%	56.34%	60.69%	66.50%	70.55%	76.44%	93.67%
0.5	61.44%	64.24%	68.73%	74.27%	78.13%	83.70%	96.77%
0.6	68.09%	70.95%	75.15%	80.39%	84.00%	88.83%	98.37%
0.7	73.54%	76.33%	80.17%	85.09%	88.39%	92.45%	99.07%
0.8	78.04%	80.69%	84.28%	88.85%	91.64%	94.90%	99.44%
0.9	81.79%	84.26%	87.60%	91.68%	93.99%	96.57%	99.64%
1.0	84.91%	87.18%	90.30%	93.77%	95.67%	97.59%	99.74%
1.1	87.49%	89.57%	92.38%	95.34%	96.84%	98.29%	99.81%
1.2	89.62%	91.52%	93.97%	96.47%	97.65%	98.75%	99.88%
1.3	91.36%	93.09%	95.24%	97.30%	98.24%	99.08%	99.93%
1.4	92.80%	94.38%	96.24%	97.93%	98.65%	99.33%	99.95%
1.5	94.03%	95.42%	97.01%	98.37%	98.96%	99.50%	99.96%
1.6	95.03%	96.26%	97.60%	98.71%	99.20%	99.61%	99.97%
1.7	95.85%	96.90%	98.05%	98.98%	99.37%	99.68%	99.98%
1.8	96.52%	97.44%	98.40%	99.19%	99.50%	99.74%	99.98%
1.9	97.08%	97.88%	98.70%	99.34%	99.60%	99.79%	99.99%
2.0	97.55%	98.22%	98.92%	99.46%	99.67%	99.83%	99.99%

APPENDIX-B: SCM DESIGN CONFIURATION FOR THE PERFORMANCE CURVES

General Information	BMP Parameters	Biofiltration	Biofiltration with ISR	Infiltration Basin	Infiltration Trench	Dry Pond	Wet Pond	Sand Filter	Subsurface Gravel Wetland
Surface Storage Configuration	Orifice Height (ft)	0	0	0	0	0	0	0	0
	Orifice Diameter (in.)	0	0	0	0	4	0	0	0
	Rectangular or Triangular Weir	Rectangular	Rectangular	Rectangular	Rectangular	Rectangular	Rectangular	Rectangular	Rectangular
	Weir Height (ft)/Ponding Depth (ft)	0.5	0.33	2	0.5	6.0	6.0	0.5	2.2
	Crest Width (ft)	30	30	30	30	30	30	30	6
Soil Properties	Depth of Soil (ft)	2.5	2.0	0.001	6.0	0.001	0.001	2.5	0.67
	Soil Porosity (0-1)	0.2	0.45	0.4	0.4	0.3	0.3	0.3	0.4
	Vegetative Parameter A	0.9	0.6	0.9	0.9	0.1	0.1	0.8	0.9
	Soil Infiltration (in/hr)	2.5	4.5	background infiltration	background infiltration	0	0	2.5	4.4
Underdrain Properties	Consider Underdrain Structure?	Yes	Yes	No	No	No	No	Yes	Yes
	Storage Depth (ft)	1	2.5	0	0	0	0	1	2
	Media Void Fraction (0-1)	0.40	0.42	0	0	0	0	0.40	0.4
	Background Infiltration (in/hr)	0	0	see Appendix A2	see Appendix A3	0	0	0	0
Decay Rates	<i>E.coli</i> (1/hr)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Underdrain Removal Rates	<i>E.coli</i> (%), 0-1)	0.76	0.76	0.96	0.76	0.64	0.96	0.76	0.60

APPENDIX-C: METHOD FOR DETERMINING STORMWATER CONTROL DESIGN VOLUME (DSV) (I.E., CAPACITY) USING LONG-TERM CUMULATIVE PERFORMANCE CURVES

Stormwater Control Type	Description	Applicable Structural Stormwater Control Performance Curve	Equation for calculating Design Storage Capacity for Estimating Cumulative Reductions using Performances Curves
Infiltration Trench	Provides temporary storage of runoff using the void spaces within the soil/sand/gravel mixture that is used to backfill the trench for subsequent infiltration into the surrounding sub-soils.	Infiltration Trench (6 infiltration rates: 0.17, 0.27, 0.52, 1.02, 2.41 and 8.27 inches per hour)	$DSV = \text{void space volumes of gravel and sand layers}$ $DSV = (L \times W \times D_{stone} \times n_{stone})^+ (L \times W \times D_{sand} \times n_{sand})$
Subsurface Infiltration	Provides temporary storage of runoff using the combination of storage structures (e.g., galleries, chambers, pipes, etc.) and void spaces within the soil/sand/gravel mixture that is used to backfill the system for subsequent infiltration into the surrounding sub-soils.	Infiltration Trench (6 infiltration rates: 0.17, 0.27, 0.52, 1.02, 2.41 and 8.27 inches per hour)	$DSV = \text{Water storage volume of storage units and void space volumes of backfill materials. Example for subsurface galleries}$ $DSV = (L \times W \times D_{galler})^+ (L \times W \times D_{stone} \times n_{stone})$
Surface Infiltration	Provides temporary storage of runoff through surface ponding storage structures (e.g., basin or swale) for subsequent infiltration into the underlying soils.	Infiltration Basin (6 infiltration rates: 0.17, 0.27, 0.52, 1.02, 2.41 and 8.27 inches per hour)	$DSV = \text{Water volume of storage structure before bypass.}$ $\text{Example for linear trapezoidal vegetated swale}$ $DSV = (L \times ((W_{bottom} + W_{top})/2) \times D)$
Rain Garden/Bio-retention (no underdrains)	Provides temporary storage of runoff through surface ponding and possibly void spaces within the soil/sand/gravel mixture that is used to filter runoff prior to infiltration into underlying soils.	Infiltration Basin (6 infiltration rates: 0.17, 0.27, 0.52, 1.02, 2.41 and 8.27 inches per hour)	$DSV = \text{Ponding water storage volume and void space volumes of soil filter media. Example for rangarden:}$ $DSV = (A_{pond} \times D_{pond}) + (A_{soil} \times D_{soil} \times n_{soil \text{ mix}})$
Tree Filter (no underdrain)	Provides temporary storage of runoff through surface ponding and void spaces within the soil/sand/gravel mixture that is used to filter runoff prior to infiltration into underlying soils.	Infiltration Trench (6 infiltration rates: 0.17, 0.27, 0.52, 1.02, 2.41 and 8.27 inches per hour)	$DSV = \text{Ponding water storage volume and void space volumes of soil filter media.}$ $DSV = (L \times W \times D_{ponding}) + (L \times W \times D_{soil} \times n_{soil \text{ mix}})$
Bio-Filtration (w/underdrain)	Provides temporary storage of runoff for filtering through an engineered soil media. The storage capacity includes void spaces in the filter media and temporary ponding at the surface. After runoff has passed through the filter media it is collected by an under-drain pipe for discharge. Manufactured or packaged bio-filter systems such as tree box filters may be suitable for using the bio-filtration performance results.	Bio-filtration	$DSV = \text{Ponding water storage volume and void space volume of soil filter media. Example of a linear biofilter:}$ $DSV = (L \times W \times D_{ponding})^+ (L \times W \times D_{soil} \times n_{soil})$
Enhanced Bio-filtration w/ Internal Storage Reservoir (ISR) (no infiltration)	Based on design by the UNH Stormwater Center (UNHSC). Provides temporary storage of runoff for filtering through an engineered soil media, augmented for enhanced phosphorus removal, followed by detention and denitrification in a subsurface internal storage reservoir (ISR) comprised of gravel. An elevated outlet control at the top of the ISR is designed to provide a retention time of at least 24 hours in the system to allow for sufficient time for denitrification and nitrogen reduction to occur prior to discharge. The design storage capacity for using the cumulative performance curves is comprised of void spaces in the filter media, temporary ponding at the surface of the practice and the void spaces in the gravel ISR.	Enhanced Bio-filtration w/ISR	$DSV = \text{Ponding water storage volume and void space volume of soil filter media and gravel ISR.}$ $DSV = (A_{bed} \times D_{ponding}) + (A_{bed} \times D_{soil} \times n_{soil}) + (A_{ISR} \times D_{gravel} \times n_{gravel})$
Gravel Wetland	Provides temporary surface ponding storage of runoff in a vegetated wetland cell that is eventually routed to an underlying saturated gravel internal storage reservoir (ISR) for nitrogen treatment. Outflow is controlled by an elevated orifice that has its invert elevation equal to the top of the ISR layer and provides a retention time of at least 24 hours.	Gravel Wetland	$DSV = \text{pretreatment volume} + \text{ponding volume} + \text{void space volume of gravel ISR.}$ $DSV = (A_{pretreatment} \times D_{preTreatment})^+ (A_{wetland} \times D_{ponding}) + (A_{ISR} \times D_{gravel} \times n_{gravel})$
Porous Pavement with subsurface infiltration	Provides filtering of runoff through a filter course and temporary storage of runoff within the void spaces of a subsurface gravel reservoir prior to infiltration into subsoils.	Infiltration Trench (6 infiltration rates: 0.17, 0.27, 0.52, 1.02, 2.41 and 8.27 inches per hour)	$DSV = \text{void space volumes of gravel layer}$ $DSV = (L \times W \times D_{stone} \times n_{stone})$
Porous pavement w/ impermeable underliner w/underdrain	Provides filtering of runoff through a filter course and temporary storage of runoff within the void spaces prior to discharge by way of an underdrain.	Porous Pavement	$\text{Depth of Filter Course} = D_{fc}$
Sand Filter w/underdrain	Provides filtering of runoff through a sand filter course and temporary storage of runoff through surface ponding and within void spaces of the sand and washed stone layers prior to discharge by way of an underdrain.	Sand Filter	$DSV = \text{pretreatment volume} + \text{ponding volume} + \text{void space volume of sand and washed stone layers.}$ $DSV = (A_{pretreatment} \times D_{preTreatment}) + (A_{bed} \times D_{ponding}) + (A_{bed} \times D_{sand} \times n_{sand}) + (A_{bed} \times D_{stone} \times n_{stone})$
Wet Pond	Provides treatment of runoff through routing through permanent pool.	Wet Pond	$DSV = \text{Permanent pool volume prior to high flow bypass}$ $DSV = A_{pond} \times D_{pond}$ (does not include pretreatment volume)
Extended Dry Detention Basin	Provides temporary detention storage for the design storage volume to drain in 24 hours through multiple outlet controls.	Dry Pond	$DSV = \text{Ponding volume prior to high flow bypass}$ $DSV = A_{pond} \times D_{pond}$ (does not include pretreatment volume)
Dry Water Quality Swale/Grass Swale	Based on MA design standards. Provides temporary surface ponding storage of runoff in an open vegetated channel through permeable check dams. Treatment is provided by filtering of runoff by vegetation and check dams and infiltration into subsurface soils.	Water Quality Grass swale	$DSV = \text{Volume of swale at full design depth}$ $DSV = L_{swale} \times A_{swale} \times D_{ponding \text{ swale}}$

Definitions: DSV= Design Storage Volume = physical storage capacity to hold water; VSV = Void Space Volume; L = length, W = width, D = depth at design capacity before bypass, n = porosity fill material, A= average surface area for calculating volume; Infiltration rate = saturated soil hydraulic conductivity