Tang, C.J., Zheng, P., Hu, B.L., Chen, J.W., and Wang, C.H. (2010). Influence of substrates on nitrogen removal performance and microbiology of anaerobic ammonium oxidation by operating two UASB reactors fed with different substrate levels. *J. Hazard. Mater.,* 181(1-3), 19-26.

Vela, J.D., Lauren, S.B., Martin, K.J., Raskin, L., Bott, C.B., and Love, N.G. (2015). Prospects for Biological Nitrogen Removal from Anaerobic Effluents during Mainstream Wastewater Treatment. *Environ. Sci. Technol. Letters,* 2(9), 234-244.

Wett, B., Omari, S.M., Podmiserg, M.H., Akintayo, M., G., Murthy, S., Bott, C., Hell, M., Takács, I., Nyhuis, G., and O'Shaughnessy, M. (2013). Going for mainstream deammonification from bench to full scale for maximized resource efficiency. *Water Sci. Technol.,* 68(2), 283-289.

Xu, G., Zhou, Y., Yang, Q., Lee, Z.M., Gu, J., Lay, W., Cao, Y., and Liu, Y. (2015). The challenges of mainstream deammonification process for municipal used water treatment. *Appl. Microbiol. Biotechnology,* 99, 2485-2490.

StormWISE Model Using Green Infrastructure to Achieve Philadelphia's CSO Volume Reductions at Minimum Cost

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Abstract

The Storm Water Investment Strategy Evaluation (StormWISE) model is applied in Philadelphia as a case study in deploying green stormwater infrastructure (GSI) to reduce CSO flows. Previous work reported on revisions to StormWISE's hydrology and cost components to adapt the optimization model for intense urbanization in Philadelphia using EPA's SWMM model to calculate runoff volume reduction from deploying GSI. This paper further extends StormWISE's hydrology components using a more detailed SWMM model and using it's sewer flow rate time series to calculate annual CSO volume reductions. Analysis of results shows nonlinear hydrological response that be explained by exploring three different underlying physical processes that cause nonlinearities. A nonlinear statistical model is developed through regression analysis of the simulation results. A revised StormWISE model incorporates the statistical model and applies it to Philadelphia's Wingohocking sewershed to generate cost minimizing GSI deployment strategiesto achieve CSO reduction targets.

INTRODUCTION

The Storm Water Investment Strategy Evaluation (StormWISE) model (McGarity, 2012) can be used to develop optimal stormwater management strategies at the watershed or sewershed scale. In this paper, we use StormWISE to examine optimal reduction of combined sewer overflows (CSOs). We present a case study in Philadelphia, where the city's Green City Clean Waters Program is installing green stormwater infrastructure (GSI) practices to reduce CSO flows for compliance with the federal Clean Water Act. Our case study involves Philadelphia's Wingohocking sewershed, which drains into the city's largest CSO outfall that spills overflows into Tacony Creek, a tributary of the Delaware Estuary.

MATHEMATICAL FORMULATIONS OF THE OPTIMAL GSI INVESTMENT PROBLEM

Several different methods have been proposed in the literature for selecting GSI technologies and deciding where to place them. The problems they are solving can be expressed generally using one of two mathematical formulations:

(1) a single cost minimization objective subject to lower bounds on multiple GSI benefits:

$$Minimize\ c(\boldsymbol{x})$$

subject to:

$$B_t(\boldsymbol{x}) \geq B_t^{min} \text{ for } t \in T$$

$$0 \leq \boldsymbol{x} \leq \boldsymbol{u}$$

or

(2) multiobjective maximization of benefits subject to a budget constraint total cost:

$$Maximize\ [B_t(\boldsymbol{x}) \text{ for } t \in T]$$

subject to:

$$c(\boldsymbol{x}) \leq c^{max}$$

$$0 \leq \boldsymbol{x} \leq \boldsymbol{u}$$

where:

$\boldsymbol{x}$ = a vector of decision variable solutions specifying how much of different types of GSI to install in the watershed and where to place them,

$\boldsymbol{u}$ = a vector of upper bounds on the GSI decision variables based on realistic constraints within the watershed

$c(\boldsymbol{x})$ = a function calculating the total cost of any feasible GSI solution vector $\boldsymbol{x}$,

c^{max}= an upper bound on watershed-wide GSI investments

T = the set of all types of GSI benefits, hydrological, environmental, societal, etc.,

$B_t(\boldsymbol{x})$ = benefit functions expressing the level of each benefit t achieved for each decision variable solution $\boldsymbol{x}$,

B_t^{min} = a lower bound for each benefit $t \in T$

The fundamental differences among the methods applied to solve the optimization problem have to do with how the benefit functions $B_t(\boldsymbol{x})$ are expressed and evaluated. One approach is to limit consideration of GSI benefits to those associated with the reduction of runoff and nonpoint pollutant loads. Among these, some rely exclusively on simulation software to model the response of the watershed to installation of GSI (for example, Zhen, et. al, 2004 and Liu, et al., 2016). These couple an evolutionary optimization engine to the simulation along with routines that calculate GSI costs, and solution requires many hours, even in a parallel-processor computing environment, limiting their application to research studies. Another approach is to represent benefits and costs with mathematical functions that enable rapid solution of the problem using linear or nonlinear programming algorithms (for example, Perez-Pedini, 2005 and McGarity, 2012 and 2013).

Progress is currently being made in quantifying ancillary benefits realized by neighborhoods where GSI practices are installed such as increases in green canopy, aesthetics, green jobs, and reduced stormwater fees, and mathematical benefit functions are being developed to enable solution of the multiobjective optimization problem (Hung, et al., 2016). The StormWater Investment Strategy Evaluation (StormWISE) model that we are using to model CSO management in Philadelphia builds on the work of McGarity and Hung, et al.

StormWISE Formulations. The StormWISE method can be used to solve problems for which GSI benefits and costs can be expressed as linear or mildly nonlinear functions. Optimal solutions are obtained rapidly using widely available software such as Microsoft Excel or modeling languages such as AMPL and GAMS. These features enable the kinds of interactions with decision makers and stakeholders that are necessary for examining tradeoffs in a multiobjective context. However, the approach is limited to applications for which suitable functions can be derived either from theoretical considerations or, as we show in this paper, from statistical analyses of GSI cost data and simulation model results.

NONLINEARITIES IN BENEFIT AND COST FUNCTIONS

Before attempting to apply optimization to a GSI investment problem, it is necessary first to understand how benefits and costs vary as different numbers and sizes of different types of GSI are deployed to serve different kinds of landscapes. Nonlinearities always complicate the analysis, so it is important to understand the types of nonlinearities that arise as well as their underlying causes. We identify four different types of nonlinearities affecting optimization of CSO management problems.

Installation of two or more GSI practices in series can create "treatment train nonlinearities" that are particularly difficult for optimization when it is desired to vary the features of each practice independently. Treatment trains are common in treating agricultural lands to remove nutrient pollution, and they may occur in urban or suburban settings as well. However, if treatment trains occur in a limited number of well-specified sizes and configurations in the watershed, then each combination can be designated as a separate GSI practice, increasing the number of decision variables, but greatly decreasing the severity of the nonlinearity. Also, in intensely urbanized areas such as Philadelphia, where runoff is routed to streets served by storm sewers with intakes every block or so, GSI practices tend to operate in parallel making interaction nonlinearities uncommon and therefore of minor importance.

When GSI is used to reduce overflow spills from combined sewer systems, and one of the objectives is to maximize the reduction in annual CSO volumes, a different mechanism can create nonlinearities, even when GSI practices operate in parallel. CSO spills into receiving waters occur when flow rates at CSO outfalls exceed a threshold. These flow rates depend on arrival times of runoff flows originating at the various stormwater intakes throughout the sewershed. CSO deployment at varying magnitudes in subcatchments at different distances from the outfall may significantly alter the shape of the hydrograph arriving at the outfall thereby changing the relationship between runoff volumes and CSO spill volumes. This effect may be particularly pronounced when CSO practices such as rain barrels are widely used to store runoff and then overflow when capacities are exceeded. A large precipitation event or two smaller events that occur within a short period of time can produce excessive spill flows leading to high peaks at the outfall. We show in this paper that when large numbers of rain barrels are deployed throughout a sewershed, multiple overflows are likely to occur within a brief time interval leading to peak flows at the outfall that generate CSO spills, thereby diminishing the rain barrels' marginal effectiveness and, in extreme cases, actually creating *increases* in CSO volumes, when additional rain barrels are added. This effect is a type of "hydrograph modification nonlinearity."

A third source of hydrological nonlinearity affecting CSO reduction benefits is also linked to sewer outfall hydrographs, but it will be active whether or not the shape of the hydrograph is modified by GSI installations, and it can occur whenever total GSI deployments begin to produce substantial reductions in annual CSO volumes. The area underneath the outfall's annual hydrograph and above the CSO threshold flow rate is used to calculate CSO volume for a particular year. As the number of GSI installations increases, the hydrograph shrinks with each GSI increment reducing the area above the threshold, but the *marginal* reduction in this area becomes less for each increment because of the hydrograph's peaked shape. This "hydrograph threshold nonlinearity" will interact with hydrograph modification nonlinearities and will also depend strongly on the nature of the precipitation hyetograph that is typical in the climate where the watershed is located.

The final nonlinearity we highlight has to do with the cost function $c(\boldsymbol{x})$. As with most water quality treatment processes, GIS practices experience economies of scale. Previous work by the authors (McGarity, et. al, 2016), based on cost data from recent public and private installations in Philadelphia, demonstrates substantial decreases in marginal costs with increasing amounts of impervious areas served.

In the remainder of this paper, we investigate nature and magnitude of these nonlinearities in Philadelphia's Wingohocking sewershed and develop methods to handle them within the StormWISE framework to enable solution of the optimal GSI investment problem.

HYDROLOGICAL RESPONSE TO GSI INSTALLATIONS IN THE WINGOHOCKING SEWERSHED

Philadelphia's historical Wingohocking Creek was completely enclosed in the late 19th and early 20th centuries to create one of the largest sewersheds in the city's CSO area. The watershed is 58% impervious, and it occupies 5414 acres (2191 ha) in North Central Philadelphia. The Philadelphia Water Department (Philadelphia Water) implements its watershed and wastewater conveyance model (Philadelphia Water Department, 2017) using the Storm Water Management Model (SWMM) developed by the U.S. Environmental Protection Agency (USEPA). For this study, Philadelphia Water provided to the authors a version of their SWMM model for the Wingohocking watershed without sewers that can be used to calculate time series of stormwater runoff as well as annual totals of runoff volumes. We extended the model by adding major sewer lines using publicly available data. This extension enables the model to calculate time series of wet-weather spill flow rates at the watershed's single CSO overflow into Tacony Creek. The model represents the hydrology of the watershed using a total of 145 subcatchments. Figure 1 shows a map of the watershed with the subcatchments and placements of the major sewer lines. In addition to watershed-scale modeling with SWMM, other researchers in the authors' GreenPhilly Research Group (www.greenphilly.net) are monitoring subsurface tension pressure and water table levels at three sites in the Wingohocking sewershed and running a three-dimensional subsurface model (Parflow-CLM) at site and watershed scales (Andino-Nolasco and Welty, 2016).

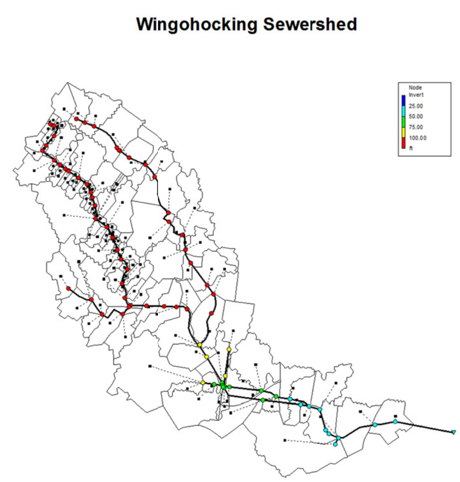


Figure 1. Philadelphia Water's 145 Subcatchment SWMM Model with Sewer Mains Added

We have also extended Philadelphia Water's SWMM model by adding GSI using SWMM's "low impact development" (LID) components. We used SWMM's convenient default method of handling GSI by placing entries in the [LID_CONTROLS] and [LID_USAGE] sections of the input file using a Python script we wrote that reads and edits input files, executes the command-line SWMM engine program (compiled from C), and processes the report file to extract selected results. The script installs a random number of GSI practices of different types into selected subcatchments. The 45 largest subcatchments in the model were selected to receive GSI practices. Note that SWMM's default method treats multiple GSI in each subcatchment as operating in parallel and not in treatment trains (EPA, 2015). Thus treatment train nonlinearities are not present in our analyses, which is appropriate in intensely developed Philadelphia neighborhoods for reasons discussed above.

Design specifications for units of three different types of GSI: rain barrels (RB), infiltration tree trenches (ITT), and rain gardens (RG), were established for the SWMM model and inserted into the [LID_CONTROLS] section of the input file. We define one RB unit as a collection of several 50 gallon rain barrels that store the runoff from approximately five residences during a 1-inch rain event before overflowing. The stored volume drains slowly to the pervious section of the subcatchment in which the rain barrels are installed. The designs for the infiltration tree trenches and rain gardens are based on specifications widely used by Philadelphia Water. The ITT unit is based on a one-block section of Lowber Avenue at Philadelphia Water's GSI installation at Morris Leeds School, which is one of our subsurface monitoring sites. The installation's footprint is 2272 ft^2 and the contributing impervious area is 26,850 ft^2. The RG unit is based on Philadelphia Water's installation at Wakefield Park on Ogontz Ave. The installation's footprint is 3315 ft^2 and the contributing impervious area is 21,009 ft^2.

For our analyses, we have adopted Philadelphia Water's metric, the "greened acre" (GA) for characterizing the magnitude of GSI development. Each greened acre can manage the runoff from one impervious acre resulting from 1-inch of rainfall. This metric is convenient for combining different types of GSI into a single measure. Each RB unit provides 0.1 GA, each ITT unit is 0.94 GA, and each RG unit is 0.747 GA.

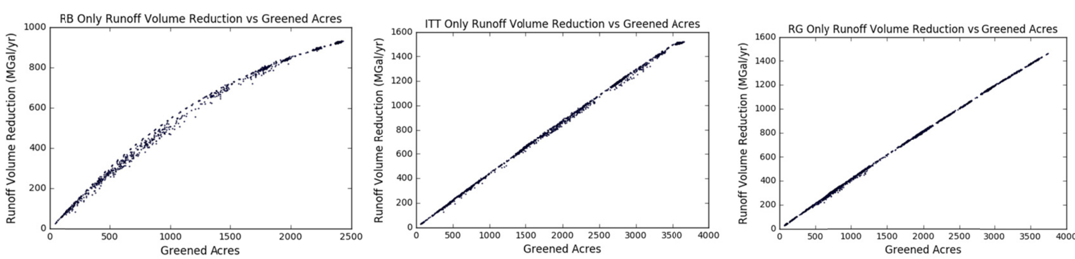
For this study, more than 5000 SWMM simulation runs were made. Multiple instances of SWMM were run in parallel on multicore CPUs on desktops and on elastic computing "cloud instances" set up on Amazon Web Services. Results from each run on the various CPUs were stored together in a MongoDB database running on one of the cloud instances. Each run consisted of a full-year simulation for a single GSI configuration. We selected, arbitrarily, Philadelphia precipitation data for the year 2008 to run continuous annual simulations with a time step of 15 minutes. Each simulation took about 3 minutes to complete.

Each GSI configuration was generated by assigning random numbers of RB, ITT, and RG to each of the 45 larger subcatchments. The numbers were assigned so that the total contributing impervious area could not exceed the actual impervious area in each subcatchment. Also, as GSI placements were made, each subcatchment's percent impervious parameters in SWMM were adjusted accordingly by subtracting each GSI's footprint from the total impervious area.

Annual CSO volumes were calculated by postprocessing the stored sewer outfall flow rate time series for each run. We obtained an estimate of the threshold flow rate from engineers at Philadelphia Water who advised calculating this threshold by multiplying the total impervious area in the watershed by the sewer system's average "wet weather treatment rate" which is 0.05 ft^3/sec per impervious acre. This resulted in a threshold flow rate of 156 ft^3/sec. This rate was subtracted from the 15 minute sewer outfall flow rate time series to generate the CSO flow rate time series, which was integrated to produce annual CSO volumes.

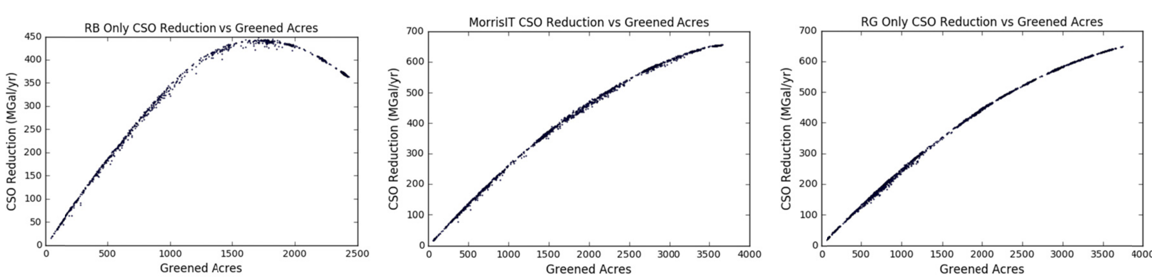
SWMM Simulation Results For a Single GSI. Figure 2 shows annual runoff volume reductions versus greened acres for each of the three selected GSI technologies for series of runs for which only the indicated GSI practice was installed throughout the watershed. Each GSI was deployed to the maximum extent possible. Runoff volume reductions respond linearly for infiltration tree trenches and rain gardens. This behavior is expected because SWMM treats multiple GSIs in a single subcatchment in parallel. The response for rain barrels demonstrates hydrograph modification nonlinearity, which is a possibility for this type of GSI.

Figure 3 shows CSO annual volume reductions versus greened acres for each of the three GSI practices. The total CSO volume calculated by the SWMM model for 2008 with no GSI was 687 MGal, so we see that CSOs can be virtually eliminated with full deployment of either infiltration tree trenches or rain gardens, but not with rain barrels alone. All three demonstrate nonlinearity. This behavior in the infiltration tree trench and the rain garden is believed to be due primarily to hydrograph threshold nonlinearity because of the strongly linear behavior in these GSIs' runoff reduction responses. The unusual behavior of the rain barrel response, indicated by decreasing CSO reductions (i.e. increasing CSO volumes) with increasing GSI installation after peaking at a reduction of almost 450 MGal/yr, is most likely caused by the combined effects of hydrograph modification and hydrograph threshold nonlinearities. This behavior is further explored by examining the sewer outfall hydrographs from the rain barrel only case for two different simulations, one at a total of 1783 greened acres and a CSO reduction volume of 440 MGal, and the other at a total of 2326 greened acres and a CSO reduction volume of 380 MGal. Figure 4 shows two precipitation events that occurred on Julian dates 136 and 137 within 22 hours of each other. The first event began with empty rain barrels, but the second event began before the rain barrels had drained. We can see from the much larger peak associated with the larger number of rain barrels in place that simultaneous overflows from those rain barrels created a peak sewer outfall flow that produced a significantly higher CSO volume for these two events than the CSO volume produced by a smaller number of rain barrels.



a. Rain Barrels Only b. Infiltration Tree Trenches Only c. Rain Gardens Only

Figure 2. Results from multiple SWMM simulations: Runoff Volume Reduction vs. Greened Acres with random placement of a single GSI technology in 45 subcatchments



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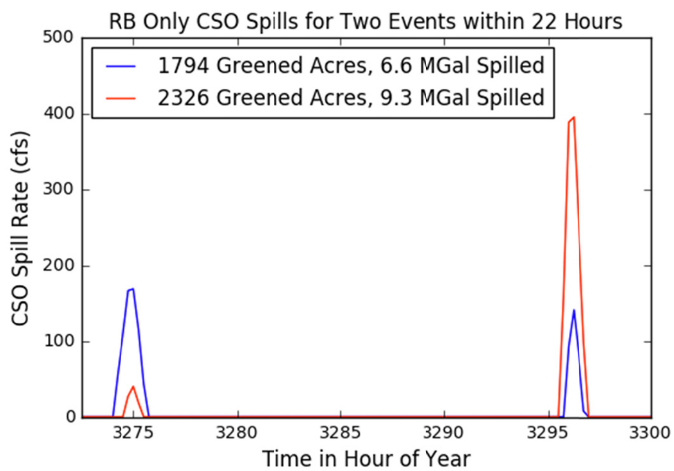
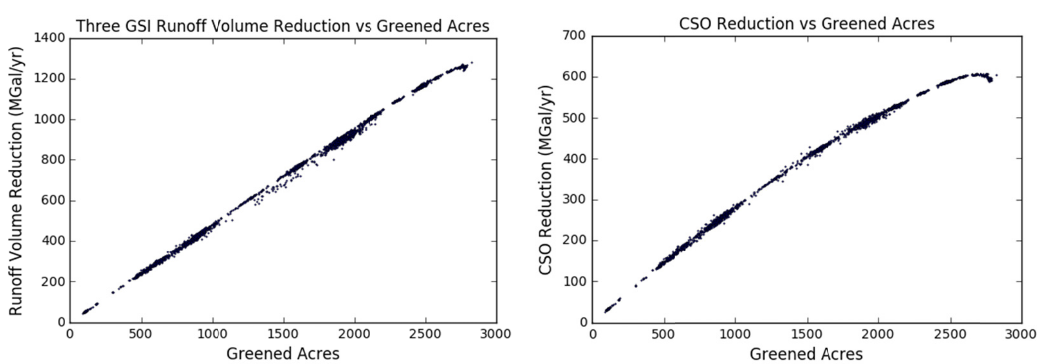


Figure 4. Time series showing hydrograph modification caused by excessive deployment of rain barrels resulting in increasing CSO spill volumes with increasing rain barrel greened acres.

SWMM Simulation Results For a Simultaneous Multiple GSIs. The next series of runs was made for simultaneous deployments of all three GSIs throughout the watershed. Figure 5 plots both annual runoff volumes and annual CSO volumes versus total combined greened acres. Clearly, installation of more than 1600 greened acres of rain barrels will never be part of an optimal solution, so combined runs having more than this level of rain barrels were eliminated from the analysis. This results is a quite linear response in the runoff volume reduction plot, and the mild nonlinearity in the CSO volume reduction plot is expected to be caused mainly by hydrograph threshold nonlinearity. The scatter in both parts of Figure 5 is most likely caused by randomly distributing greened acres of the GSI practices across 45 different subcatchments. Variations in the SWMM subcatchment parameters will cause some variation across the subcatchments in the response to GSI installation. However, the scatter is fairly small, suggesting that the subcatchments where GSI are installed may have only a minor effect on runoff and CSO volume reductions in the Wingohocking.



a. Runoff Volume vs. Combined Greened Acres b. CSO Volume vs. Combined Greened Acres

Figure 5. Results from multiple SWMM simulations with random placement of all three GSI technologies in 45 subcatchments

Nonlinear Statistical Model for Simultaneous Multiple GSIs. The runs shown plotted in Figure 5b were used as data in a second-order polynomial multivariable regression analysis to determine the parameters for the equation:

$$y = \beta_0 + \beta_{11}x_1 + \beta_{12}x_1^2 + \beta_{21}x_2 + \beta_{22}x_2^2 + \beta_{31}x_3 + \beta_{32}x_3^2$$

where x_1, x_2, x_3 are the number of greened acres deployed in rain barrels, infiltration tree trenches, and rain gardens, respectively, β_0 is an intercept coefficient, β_{ij} for *j* = 1,2,3 and *I* = 1,2 are the associated regression slope coefficients. The regression analysis produced R^2 near 1.0 and a residuals standard deviation of only 2.35 MGal.

STORMWISE OPTIMIZATION

Mathematical Formulation. The statistical model developed above was incorporated into a StormWISE optimization formulation to solve for optimal combinations of the three GSI technologies that achieve the entire range of CSO reductions at minimum cost. We use the first mathematical formulation of the optimal GSI investment problem shown above. The decision variables are x_1, x_2, x_3, defined above.

The objective function minimizes total GSI investment cost. A linear GSI cost function multiplies each decision variable by a cost coefficient obtained from regression analysis of recent data from GSI installations on private and public properties in Philadelphia. This model, developed by our consultants AKRF, Inc. was fully explained in a previous paper (McGarity, et al., 2016). The formulas for the cost model are repeated here in Table 1.

Table 1: Cost Model Formulas from McGarity, et al., 2016

Project Type	Regression Model	R^2	$R^2_{adjusted}$	$R^2_{predictive}$
Private	$Log_{10}(Cost/GA) = 4.98 - 0.24*Log_{10}(GA/GSI)$	49.1%	46.9%	39.8%
Public	$Log_{10}(Cost/GA) = 5.25 - 0.24*Log_{10}(GA/GSI)$			

This model is currently being revised and updated using additional data that has become available as GSI installations in Philadelphia continue to grow. We applied this model to obtain cost coefficients for the specific GSI that we used in the simulation studies. The greened acres per GSI (GA/GSI) values shown above were used to in the cost model assuming that rain barrels are installed on private property and that infiltration tree trenches and rain gardens are installed on public property. The resulting cost coefficients are $166 thousand/GA for rain barrels, $181 thousand/GA for infiltration tree trenches, and $190 thousand/GA for rain gardens.

The constraints consist of lower bounds of zero for all decision variables and a single inequality that places a lower bound on the annual CSO volume reduction using the second-order polynomial regression formula developed from statistical analysis of our SWMM simulations.

Optimal Solutions Over All Feasible CSO Reduction Targets. The StormWISE model was run 121 times for lower bounds on annual CSO volume ranging from zero to 600 MGal in increments of 5 MGal. All 121 solutions were obtained in less than 5 seconds on a laptop computer. Figure 6 shows plots of the results indicating how total GSI investment costs increase as the CSO reduction target is increased. Also, we see that the combination of CSO reduction performance factors and cost factors favor rain barrels such that they are selected exclusively to provide the first 135 MGal of annual CSO volume reductions. Combinations of rain barrels and infiltration tree trenches are selected up to a total CSO reduction of 245 MGal/yr, and then all three GSI types are required to achieve cost minimizing solutions up to the point where CSOs are virtually eliminated at an annual reduction of 600 MGal.

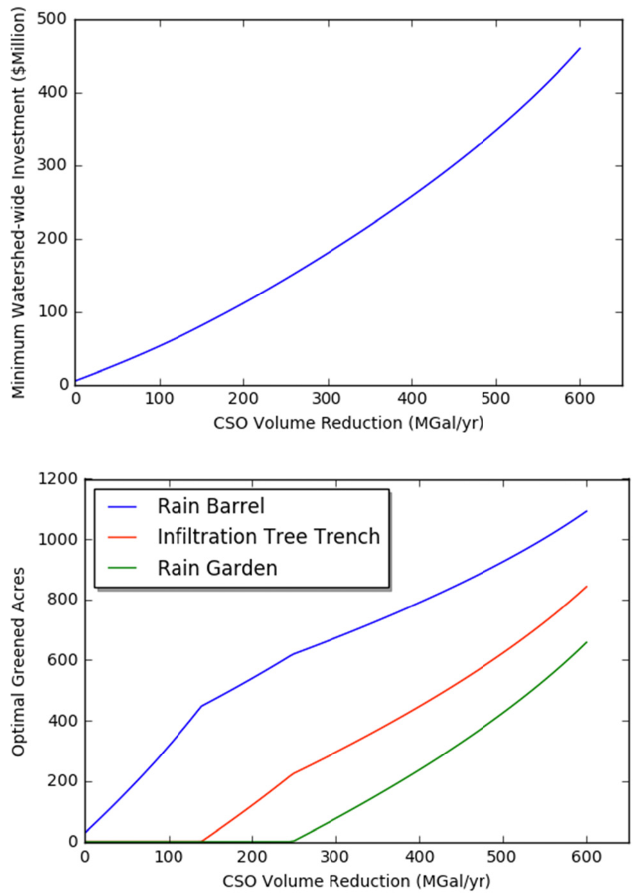


Figure 6. StormWISE optimization runs for Philadelphia's Wingohocking sewershed for the case of three GSI technologies.

Caveats Regarding Watershed Specific Constraints and Other Limitations. The analysis presented here makes no attempt to account for the many practical and realistic constraints that are specific to the Wingohocking watershed. Although realistic cost parameters are used, the CSO reduction response to GSI deployments derive exclusively from subcatchment scale hydrological considerations. We have in this paper made no attempt to evaluate how many suitable sites exist in the watershed for rain barrels, infiltration tree trenches, and rain gardens. A complete analysis would most certainly have to consider such information. Furthermore, our results show how GSI deployments affect *simulated* hydrology as calculated by EPA's SWMM model. Future work will attempt to evaluate the accuracy of these simulations when results from our monitoring and 3-D modeling research in the Wingohocking watershed are available. Furthermore, our finding of apparent insensitivity to subcatchment placements of GSI should be further examined to determine whether this behavior is common across watersheds in Philadelphia.