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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 combined sewer overflow (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 reductions resulting from GSI installations. This paper further extends StormWISE's hydrology components using a more detailed SWMM model and using its sewer flow rate time series to calculate annual CSO volume reductions. Analysis of results reveals a nonlinear hydrological response that is explained by exploring three different underlying physical processes that can cause nonlinearity. A nonlinear statistical model is developed through regression analysis of the simulation results. The StormWISE model is revised to incorporate the statistical model in a case study of Philadelphia's Wingohocking sewershed. Cost minimizing GSI deployment strategies are generated for achieving specified CSO reduction targets.

INTRODUCTION

The Storm Water Investment Strategy Evaluation (StormWISE) model (McGarity, 2012, 2013) 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 minimizing objective function subject to lower bounds on multiple GSI benefits and upper bounds that limit GSI deployments to realistic levels:

$$\begin{aligned} &Minimize\ c(\boldsymbol{x}) \\ &\text{subject to:} \\ &B_t(\boldsymbol{x}) \geq B_t^{min} \text{ for } t \in T \\ &0 \leq \boldsymbol{x} \leq \boldsymbol{u} \end{aligned} \qquad \text{Formulation (1)}$$

or

(2) multiobjective maximization of benefits subject to a budget constraint on total investment costs and upper bounds that limit GSI deployments to realistic levels:

$$Maximize\ [B_t(\boldsymbol{x}) \text{ for } t \in T]$$
subject to:
$$c(\boldsymbol{x}) \le c^{max}$$
$$0 \le \boldsymbol{x} \le \boldsymbol{u} \qquad \text{Formulation (2)}$$

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 total investment cost of any feasible GSI solution vector $\boldsymbol{x}$,

c^{max}= an upper bound (budget limit) 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 vector solution $\boldsymbol{x}$,

B_t^{min} = a lower bound (benefit target) for each kind of 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 results require many hours to generate, 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, et al., 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.

Treatment Train Nonlinearity. 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.

Hydrograph Modification Nonlinearity. 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."

Hydrograph Threshold 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.

Scale Economy Nonlinearity. 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 (PWD) 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, PWD 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. 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 GSI installation sites in the Wingohocking sewershed and running a three-dimensional subsurface model (Parflow-CLM) at site and watershed scales (Andino-Nolasco and Welty, 2016).

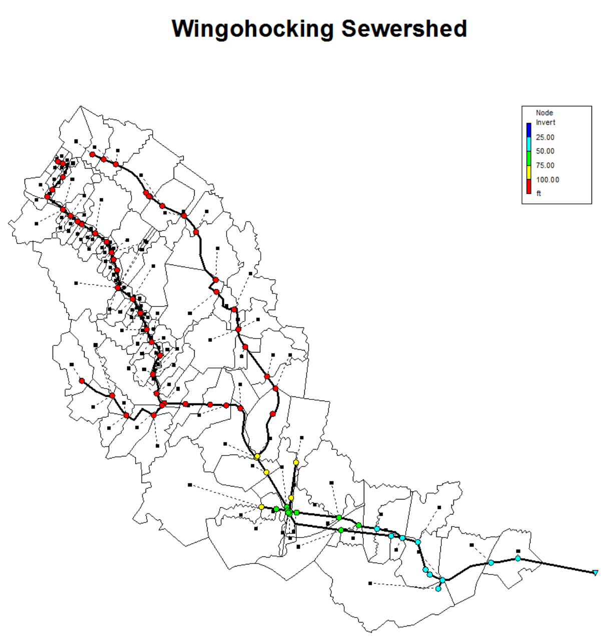


Figure 1. 145 Subcatchment SWMM Model with Sewer Mains Added

We have also extended PWD 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. We developed a Python wrapper for SWMM 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. We programed the wrapper code to execute a series of SWMM runs, each with a different configuration of GSI placements varied by GSI type (LID_CONTROL) and number of each GSI type deployed in each of the subcatchments. Output text files are parsed and relevant results are extracted and stored in a database for later analysis. Continuous annual simulations were run with a time step of 15 minutes. Each simulation took about 3 minutes to complete.

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 defined 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 50-gallon rain barrels serving multiple rooftops that can store 0.1 acre-in (2715 gallons) of roof runoff (approximately 54 rain barrels per RB unit). The stored volume drains to the pervious section of the subcatchment over a period of six days (if the rain barrels are full). The designs for the infiltration tree trenches and rain gardens are based on specifications widely used by PWD. The ITT unit is based on a one-block section of Lowber Avenue at PWD'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 PWD'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. It is also one of our research team's subsurface monitoring sites.

Each SWMM run consisted of a continuous full-year simulation. We selected precipitation data from the period July 1, 2012 through June 30, 2013 to correspond with the PWD's 2013 fiscal year, for which annual flows for its CSO outfalls are published (Philadelphia Water Department, 2013). The Wingohocking sewershed outfall spilling into Tacony Creek is labeled T-14 in published reports. The published annual CSO flow volume for this period is 1565 million gallons.

Annual CSO volumes were calculated by postprocessing the stored sewer outfall flow rate time series for each run. We determined the threshold flow rate for the T-14 outfall to be 275 ft^3/sec, which produced the best agreement between the calculated annual CSO volume and the published value of 1565 million gallons. This rate was subtracted from the simulated 15-minute sewer outfall flow rate time series to generate the simulated CSO flow rate time series, which was integrated to produce our estimates of annual CSO volumes. The threshold flow rate indicates the maximum flow that can be directed to the treatment plant on the Delaware River that serves this sewershed, and it corresponds to 0.088 ft^3/sec/impervious acre in the sewershed. PWD's engineers call this ratio the "wet weather treatment rate," and we have been advised that the Philadelphia sewer system has an overall rate of 0.05 ft^3/sec/impervious acre.

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

For our analyses, we adopt PWD's metric, the "greened acre" (GA), for characterizing the magnitude of GSI development. A greened acre manages an inch of precipitation over an acre of directly connected impervious surface. It is used by PWD as the primary metric to track progress towards their regulatory obligations, and it is a measure of the *volume* of stormwater managed. Each GA provided by GSI manages one acre-inch of runoff. 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.

SWMM Simulation Results for a Single GSI. Figure 2 shows reductions in total annual wet-weather flow volumes at the sewershed outlet versus greened acres for each of the three selected GSI technologies for series of runs for which *only one type of GSI practice* was installed throughout the watershed. For each of these runs, an integer number of GSI units were placed in each subcatchment so as to treat a specified percentage of the subcatchment's impervious surface ranging from 10% to 100% in increments of 10%. The response of runoff volume to CSO deployment is fairly linear. SWMM calculates the wet weather flow volume with no GSI to be 3759 MGal/yr, so reductions in the range of 67% (rain barrels) to 77% (rain gardens) are achieved at 100% deployment.

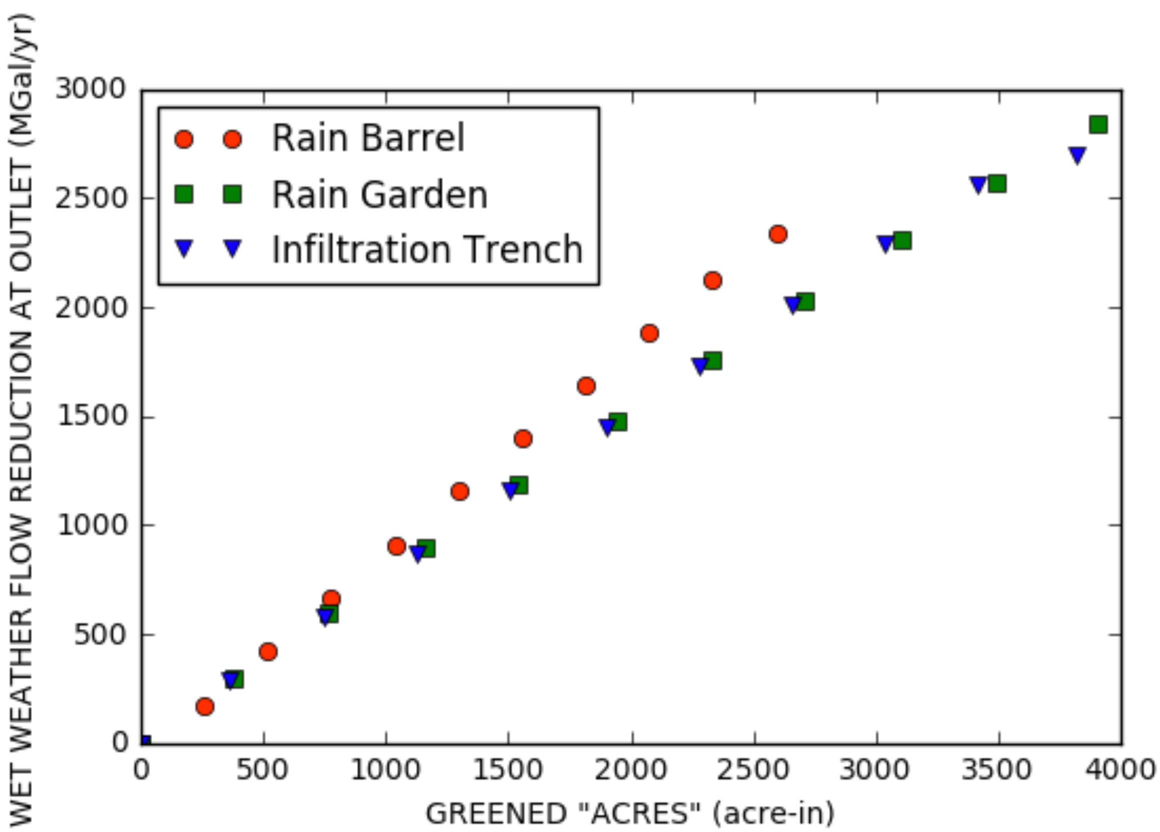


Figure 2. Results from multiple SWMM simulations: reductions in total annual wet-weather flow volumes at the sewershed outlet versus greened acres for increasing numbers of a single GSI technology deployed in the 45 larger subcatchment.

Figure 3 shows CSO annual volume reductions versus greened acres for each of the three GSI practices. Reductions in the range of 60% (rain barrels) to 89% (rain gardens) are achieved at 100% deployment. All three demonstrate mild nonlinearity. This behavior in the infiltration tree trench and the rain garden is believed to be due primarily to hydrograph threshold nonlinearity. However, examination of sewer outfall hydrographs in Figure 4 generated by two of the runs deploying rain barrels only indicate that hydrograph modification nonlinearities are also present. A precipitation event having three pulses within 20 hours is shown. The first pulse (0.6") began with empty rain barrels, but it was followed by a 1.6" pulse that filled the rain barrels to capacity. None of the runoff from the third pulse (1.0") was captured in the rain barrels, producing the same CSO flows as if no rain barrels were present in the sewershed. This behavior results in more rapidly diminishing returns to scale and it also limits the maximum CSO reduction achievable at 100% deployment.

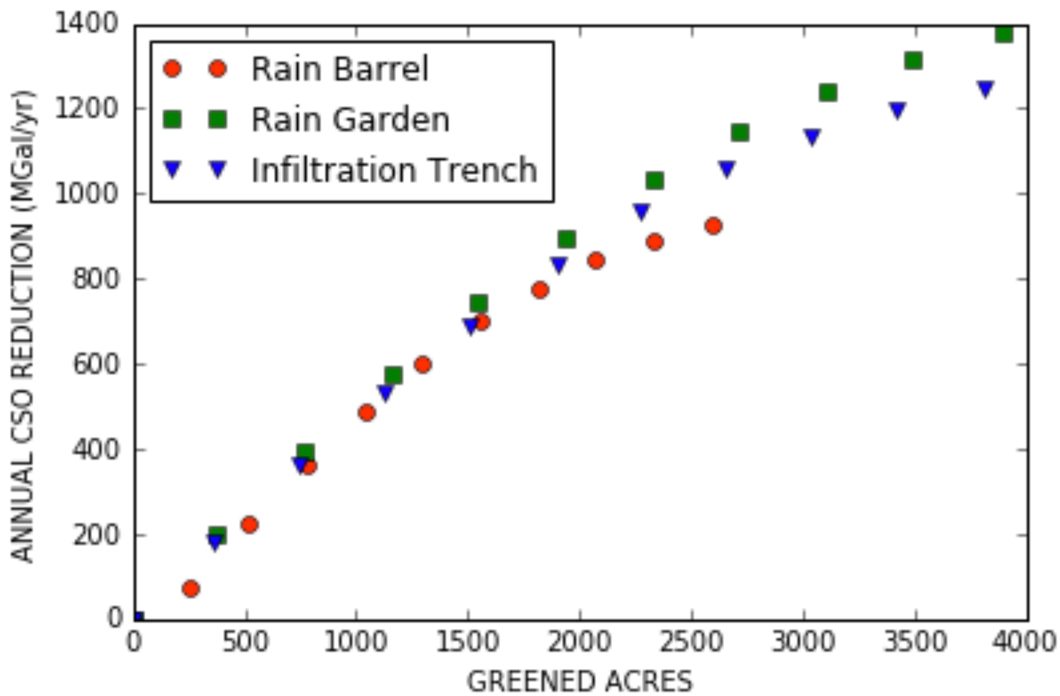


Figure 3. Further results from the multiple SWMM simulations: reductions in total CSO flow volumes at the sewershed outlet versus greened acres for increasing numbers of a single GSI technology deployed in the 45 larger subcatchments

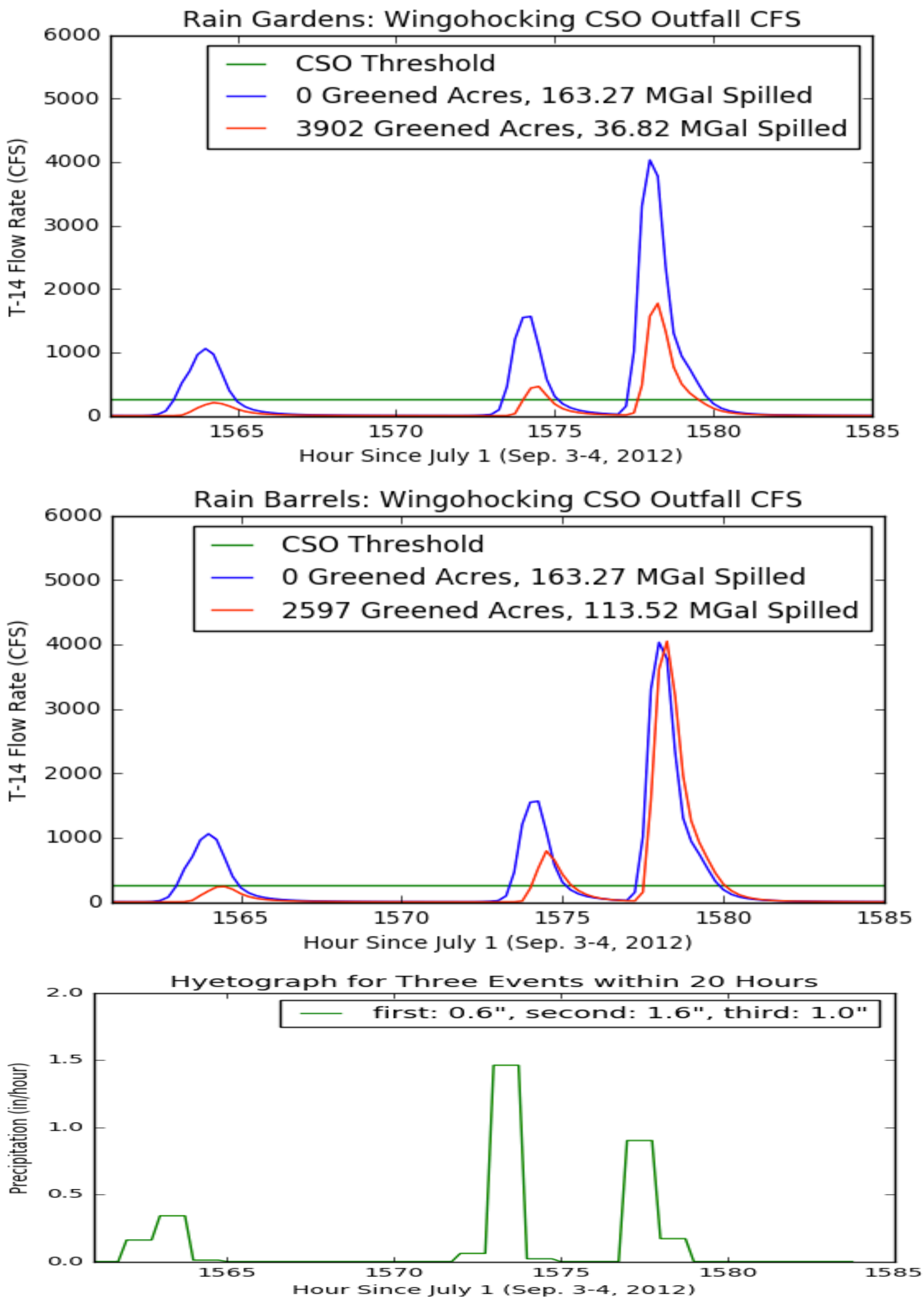
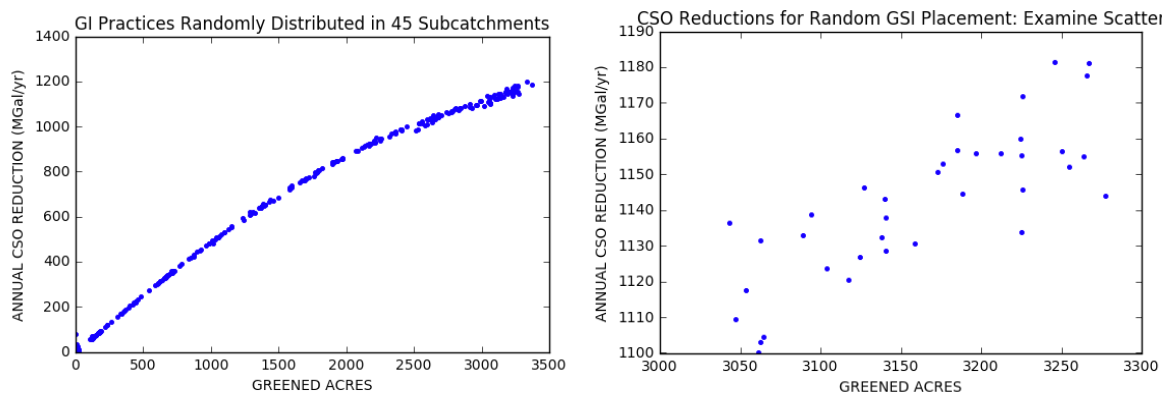


Figure 4. Time series showing hydrograph modification in the case of only rain barrels (middle graph) compared to only rain gardens (upper graph) when multiple precipitation pulses occur within 20 hours (lower graph) because rain barrels overflow when they can not fully drain.

SWMM Simulation Results For Simultaneous Multiple GSIs. The next series of runs was made for simultaneous deployments of all three GSIs throughout the watershed. Now, a random number of units of rain barrels, infiltration tree trenches, and rain gardens are deployed in each subcatchment such that the total treated area never exceeds the total impervious area. 265 runs of SWMM were made, each with a different GSI configuration. Figure 5 plots annual CSO volume reduction versus total combined greened acres. The scatter in Figure 5 is caused by randomly distributing greened acres of different GSI practices across 45 different subcatchments. Also, 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 choice of subcatchments where GSI are installed may have only a minor effect on CSO volume reductions in the Wingohocking. Part b of Figure 5 shows a zoomed view of the high range of the plot where the scatter is greatest. The greatest difference between the highest and lowest CSO reduction at a particular level of greened acres is only about 40 MGal/year or about 3.5%.



a. CSO Reduction vs. Combined Greened Acres

b. Zoom to show scatter at high range

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 5a were used as data in a second-order polynomial multivariable regression analysis to determine the parameters for the equation:

$$y = \beta_0 + \beta_{11}x_1 + \beta_{12}x_1^2 + \beta_{21}x_2 + \beta_{22}x_2^2 + \beta_{31}x_3 + \beta_{32}x_3^2 \qquad \text{Equation (1)}$$

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 *i* = 1,2 and *j* = 1,2,3 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. The following values were obtained: β_0= 16.4 MGal, β_{11}=0.2237 MGal/GA, β_{12} = 0.0 MGal/GA^2, β_{21}=0.7535 MGal/GA, β_{12}=-2.258x10^{-4} MGal/GA^2, β_{31}=0.4650 MGal/GA, β_{12}=-1.173x10^{-4} MGal/GA^2. An R^2 value of 0.996 was obtained, and the 95% confidence intervals associated with the first order terms do not overlap, indicating that the marginal CSO reduction benefits of the three different GSI practices are significantly different. However, our cost model, shown below, produces different marginal costs, as well. A cost-benefit optimization analysis is necessary to prioritize deployment of different GSI practices, which is provided by the StormWISE framework.

UPDATED COST MODEL

Costs associated with green infrastructure implementation can vary according to a wide range of potential factors ranging from practice type (e.g. rain gardens, infiltration trenches, porous pavement, green roofs, etc.), locational and site specific variables, and design-related variables. Municipal planners undertaking green infrastructure programs benefit from planning tools that allow for the evaluation of various green infrastructure investment scenarios in terms of both projected cost and benefits. Early in program implementation, planners may rely largely on literature estimates or studies to benchmark expected costs. However, as implementation proceeds, data from built projects can be collected and analyzed to develop localized cost models. These cost models can in turn be used within optimization models to assist planners in forecasting the cost and benefit tradeoffs with future implementation scenarios.

This paper updates a previously published analysis of built green infrastructure project data in Philadelphia using linear regression analysis (McGarity et al., 2016). The previous work details the methodology (log-transformed linear regression), statistical tests of potential predictor variables, and results obtained using data available through 2015. For the updated model presented here, construction costs for public projects were sourced from the PWD FY16 Combined Sewer Management Program Annual Report. Construction costs for PWD private projects were provided by PWD's Office of Watersheds. Construction costs were adjusted to account for inflation by adjusting costs for projects constructed in prior years to 2017 costs.

Figure 6 shows a scatterplot of the transformed unit cost and greened acres per SMP variables for the final model. The scatterplot shows that the transformed variables have a linear relationship with significant scatter indicating the existence of unknown factors that significantly affect costs. With updated data, we determined, once again, that drainage area, year built, and SMP type grouping are not statistically significant predictor variables and that interactive effects between predictor variables are non-significant. The final linear model continues to use greened acres per SMP (a measure of the average SMP size) and project type as significant predictor variables.

Table 1 shows the updated regression coefficients, which differ somewhat from the previous values. The predictive ability of the model as measured by $R^2_{predictive}$ has increased significantly from 39.8% to 46.5%. But the model still predicts less than 50% of the total variability in the data set. Clearly, other site specific and project specific factors are affecting project costs, but data on these factors are not available. These include disposal method for excavated material (i.e. on vs. off-site), project specific costs such as utility relocations, prevailing economic factors that may affect contractor bids, and other factors.

Explanation of Predictor Variables

<u>GA/SMP</u> – Greened acres per SMP was calculated by dividing the total greened acres managed by the project by the total number of SMPs in that project.

<u>Project Type</u> – As described above, the project type variable refers to whether the project primarily manages private or public drainage area. This predictor captures the differences between PWD's public and private programs.

Table 1: Model Results Summary

Project Type	Regression Model	R^2	$R^2_{adjusted}$	$R^2_{predictive}$
Private	$Log_{10}(Cost/GA) = 5.0109 - 0.2708 * Log_{10}(GA/SMP)$	50.4%	49.1%	46.5%
Public	$Log_{10}(Cost/GA) = 5.1817 - 0.2708 * Log_{10}(GA/SMP)$			

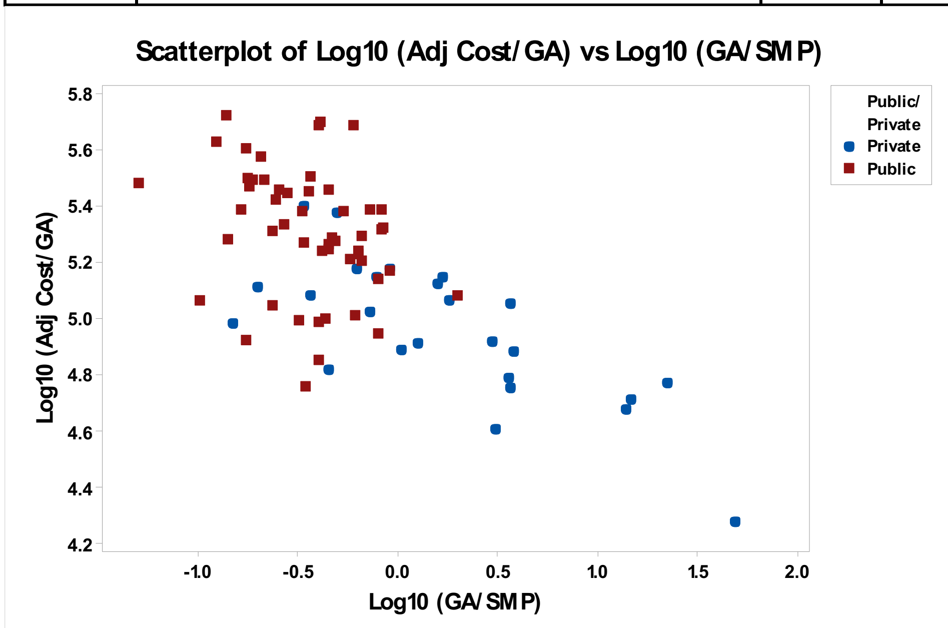


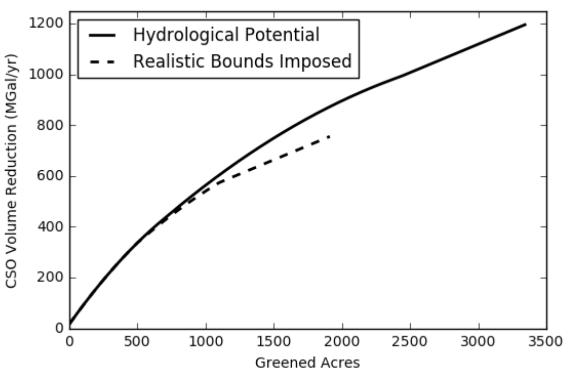
Figure 6: Scatterplot of transformed cost data used to update coefficients in our cost model.

STORMWISE OPTIMIZATION

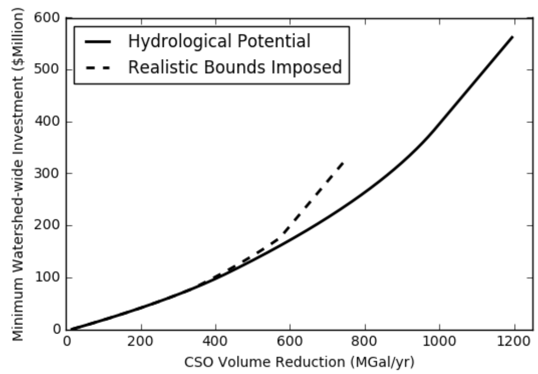
Mathematical Formulation. The statistical model for predicting annual CSO reductions resulting from GSI deployment for the Wingohocking sewershed is now incorporated into a StormWISE optimization formulation to solve for optimal combinations of the three GSI technologies that achieve CSO reductions, over the entire feasible range, at minimum investment cost. We use mathematical formulation (1) of the optimal GSI investment problem shown above. The decision variables are greened acres x_1, x_2, x_3, defined above. Upper bounds on these variables can be used to specify realistic limits imposed on each type of GSI practice by the prevailing land uses. We have not yet determined appropriate upper bounds for the Wingohocking. The optimization results presented here will first impose no upper bounds, thereby indicating the best that can be achieved given constraints imposed only by the watershed's hydrological processes as modeled by SWMM. We call this the "hydrological potential" case. Then, we set hypothetical bounds on infiltration tree trenches and rain gardens to demonstrate how the solutions change when realistic constraints are imposed. Hypothetical upper bounds imposed for rain barrels, infiltration tree trenches, and rain gardens are 800, 500, and 600 greened acres, respectively.

We apply the updated cost model to obtain cost coefficients for the specific GSI that were used in the simulation studies. The specific number of greened acres per GSI unit for each of the three GSI practices (GA/GSI), listed earlier in this paper, is used in the cost model. We assume 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 $191,000/GA for rain barrels, $155,000/GA for infiltration tree trenches, and $164,000/GA for rain gardens. Note: installed costs for rain barrels were not included in the database used to develop our cost model. However, the cost/GA obtained from the model is equivalent to $19,000 for 54 rain barrels or $354 installed cost per rain barrel, which is not unreasonable for a professionally installed rain barrel with the necessary guttering and drain system installed in an urban setting.

Optimal Solutions Over All Feasible CSO Reduction Targets. The StormWISE model was run multiple times for lower bounds on annual CSO volume ranging from zero to 1200 MGal in increments of 5 MGal. Less that 5 seconds were necessary to obtain all solutions on a laptop computer using the default nonlinear solver Minos in the AMPL modeling language (Fourer, et al., 2003). Figure 7 shows plots of the results indicating how total GSI investment costs increase as the CSO reduction target is increased. Marginal costs increase as CSO volume reductions increase, which is consistent with diminishing returns shown in Figures 3 and 5b and a linear cost increase with each greened acre added.



a. CSO Reduction vs. Combined Greened Acres



b. Total Cost vs. Annual CSO Volume Reductions Achieved

Figure 7: StormWISE results for the entire range of possible annual CSO reductions: overall CSO reduction performance and costs, comparing the case of no GSI bounds (Hydrological Potential) with hypothesized realistic bounds imposed on deployment of each GSI practice.

Observe that for the hydrological potential case, optimal solutions shown in the plot of CSO reductions versus greened acres closely follows the SWMM simulation results shown in Figure 5a, indicating the accuracy of the multivariable polynomial regression formula used to fit the SWMM results. Also, observe that imposition of realistic bounds on GSI deployment decreases the achievable CSO volume reductions and increases the investment levels required to achieve specified CSO reductions. With bounds imposed, maximum GA = 1900 acre-inches and maximum CSO reduction = 750 MGal, with a cost of 330 $Million. This CSO reduction represents 48% of the original untreated CSO flow of 1565 MGal. On the other hand, with no bounds and GSI deployments achieving their full hydrological potential, maximum GA = 3400 acre-inches and maximum CSO reduction = 1200 MGal, which is 77% of the untreated CSO flow, at a cost of 562 $million.

Figure 8 shows the optimal values of each GSI type's greened acres (x_1, x_2, x_3) to reveal how GSI benefits and costs combine to produce solutions yielding the lowest cost for the particular level of CSO volume reduction specified for each run of the optimization model. We can also use these results to reveal that particular combination of GSI deployments that maximizes the annual CSO reduction benefit for each level of total watershed investment, when Figure 7b is combined with Figure 8.

When no upper bounds are placed on individual GSI's, we see that the combination of CSO reduction performance factors and cost factors favor infiltration tree trenches such that they are selected exclusively to provide the first 400 MGal of annual CSO volume reductions. Combinations of rain gardens and infiltration tree trenches are selected up to a total CSO reduction of 990 MGal/yr, and then all three GSI types participate in the cost minimizing solutions up to the point where 77% of annual CSO volume is eliminated at an annual reduction of 1200 MGal.

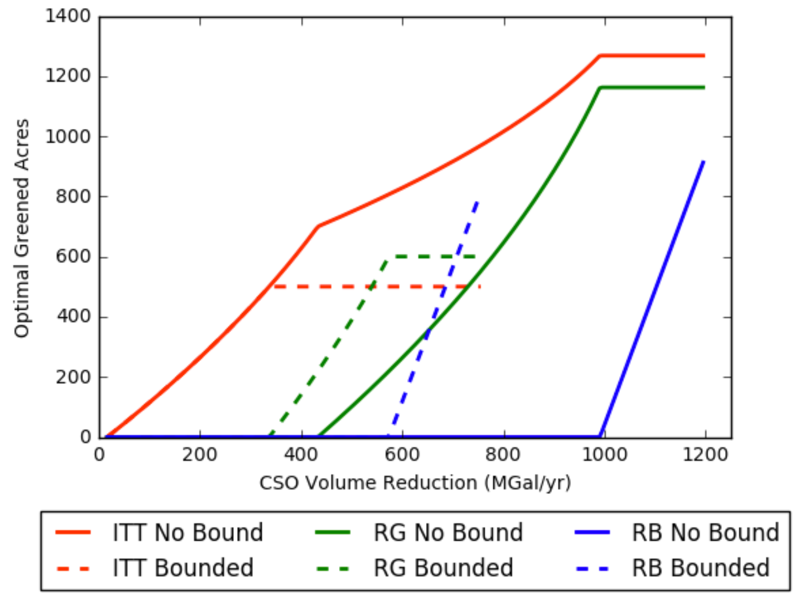


Figure 8. StormWISE results for the entire range of possible annual CSO reductions: showing greened acres to deploy of each GSI practice to *minimize total investment cost* comparing the case of no GSI bounds (Hydrological Potential) with hypothesized realistic bounds imposed on deployment of each GSI practice. Bounds assumed for these runs: ITT = 500 GA, RG = 600 GA, RB = 800 GA.

When realistic upper bounds are placed on total greened acres for each type of GSI, the priorities are similar, but the optimal greened acres can never exceed the specified bounds. Thus, at the point where the top priority GSI type reaches its bound, the second priority GSI activates and increases its greened acres until its bound is reached, at which point the third priority GSI activates. When the third priority GSI reaches its upper bound, no further CSO reduction can be achieved using these three GSI types.

Caveats Regarding Watershed Specific Constraints and Other Limitations. Although realistic cost parameters and calibrated measures of GSI performance from SWMM modeling are used, the analysis presented here makes *no attempt to accurately account for the many practical and realistic constraints* that are specific to the Wingohocking watershed. Realistic constraints are either ignored (hydrological potential) or they are imposed at arbitrary levels in order to demonstrate the methodology to be used when more site-specific data on factors affecting these constraints, such as land use, are analyzed. A more complete analysis is in progress to obtain and consider such information. Furthermore, our results show how simulated GSI deployments affect sewershed hydrology as calculated by EPA's SWMM model. Future work will attempt to evaluate the accuracy of these simulations when complete results from our monitoring and 3-D modeling research in the Wingohocking watershed are available. Moreover, our finding of apparent insensitivity to subcatchment placements of GSI will be further examined to determine whether this behavior is common across watersheds in Philadelphia.

CONCLUSIONS

This paper explores fundamental hydrological characteristics of large-scale application of green stormwater infrastructure practices to control combined sewer overflows as they relate to the problem of identifying optimal strategies for deploying these practices throughout a watershed. Results are obtained using EPA's SWMM hydrological simulation model in its default mode of parallel GSI operation when multiple practices are installed in a subcatchment. Three different kinds of potential nonlinearities in hydrological performance are defined and explored in the simulation results. A multivariable nonlinear statistical model is used to extract parameters from simulation model runs using randomly assigned placements of three different GSI types in subcatchments throughout a Philadelphia combined sewershed. The statistically derived parameters are used in a StormWISE optimization model to minimize total investment costs over the entire range of possible annual CSO volume reductions. The optimization model runs also indicate how the three GSI practices can be prioritized over the range of CSO reduction targets, and how realistic constraints imposing upper bounds on GSI deployment can affect the optimal solutions. Future work will address the several caveats raised above by testing the methodology in different watersheds and by incorporating site-specific data for different land use categories to accurately incorporate realistic limits on the extent to which each GSI practice can be installed in a watershed.

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