Green Stormwater Infrastructure Investment Model

for Philadelphia's Wingohocking Sewershed

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ABSTRACT

Municipalities are turning to Green Infrastructure (GI) as an attractive solution for combined sewer overflow (CSO) control. Given the myriad combinations of GI implementation options, decision makers need tools to optimize investments. Multiobjective models hold significant promise for developing GI investment portfolios, but need to be developed and tested under real world conditions. We present models for estimating GI costs and for optimizing deployment of GI practices applied to a Piedmont sewershed in Philadelphia's CSO area.

INTRODUCTION

The City of Philadelphia is one of many cities in the U.S. that is undertaking long range capital programs to control combined sewer overflows (CSOs). The Philadelphia Water Department's (PWD) approved Long Term Control Plan Update, called "Green City, Clean Waters," has outlined strategies to manage some 10,000 impervious acres over 25 years to meet requirements of the Clean Water Act through the use of green infrastructure (Green City, Clean Waters, 2011). PWD is pursuing implementation of green infrastructure within the right-of-way and on both public and private lands to meet their regulatory obligations with the Pennsylvania Department of Environmental Protection (PADEP) and the United States Environmental Protection Agency (EPA).

Philadelphia's Wingohocking sewershed is being monitored and modeled by the GreenPhilly Research Group, based at Swarthmore College, as a case study of Piedmont sewersheds in the city's CSO area (www.greenphilly.net). As part of this effort, the Storm Water Investment Strategy Evaluation (StormWISE) model (McGarity, 2012) has been adapted and applied to prioritize deployment of GI practices. A multiobjective screening optimization generates Pareto optimal solutions that achieve required runoff reductions at minimum cost. In this paper, we examine optimal deployment of two GI practices, rain gardens and infiltraton tree trenches, in subcatchments of the sewershed. EPA's Storm Water Management Model (SWMM) is used to model the hydrological performance of the GI practices.

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 would 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 details a preliminary analysis of built green infrastructure project data in Philadelphia using linear regression analysis. This work demonstrates the type of cost analysis that could be used to develop localized cost models to drive green infrastructure planning. Future work will refine the cost models using additional predictors and demonstrate how cost models of this type could be used to inform optimization modeling.

METHODOLOGY

Construction cost data for green infrastructure projects built in the City of Philadelphia were compiled and analyzed using a linear regression model (Minitab 14). The cost data set included both projects in the right-of-way or within publically-owned lands that were designed and built through direct contracts with PWD (public projects), and projects on privately owned property that were designed and built through PWD's Stormwater Management Incentive Program (SMIP) and Greened Acre Incentive Program (GARP), which provides grant monies to private property owners (in the case of SMIP) or to third party "developers" (in the case of GARP).

Construction costs for public projects were sourced from the PWD FY15 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 prior to 2015 to 2015 costs.

Project Variables

Several predictor variables were evaluated to determine the best linear model for predicting green infrastructure costs. Unit cost (as construction cost per greened acre) was used as the primary response variable rather than raw construction costs. Greened acres, defined as an inch of precipitation over an acre of directly connected impervious surface, is a primary metric used by PWD to track progress towards their regulatory obligations and it relates to the volume of stormwater managed. Predictor variables tested during model development were as follows:

- Typology
  - Typology 1: Stormwater Management Practices (SMPs) on public property managing public runoff (i.e., runoff from the right-of-way).
  - Typology 2: SMPs on private property managing public runoff.
  - Typology 3: SMPs on private property managing private runoff (i.e. runoff from impervious areas on private property)
- Project Type
  - Public: SMPs on public/private property managing public runoff.
  - Private: SMPs on private property managing private runoff.
- Year Built

- Impervious Drainage Area, DA
- Greened Acres, GA (impervious drainage area x storm depth managed)
- Number of SMPs

Note: PWD "public" projects are submitted for contractor bid by a group of projects, which can be comprised of multiple SMPs and multiple SMP types. Because of this, SMP type could not be used as a predictive variable in the cost model.

Prior to model development, outliers on unit costs were identified using a box and whisker plot. These projects were removed from the dataset on a case-by-case basis based on a review of project construction documents or other project information available to the authors. Linear models were developed by adding predictor variables and inspecting regression plots to identify significant predictors. Interactive effects among main predictors were also evaluated. Based on initial inspection of preliminary model data, a transformation was required to stabilize residuals and meet normality requirements. It was determined that both the response and predictor variables would need to be transformed. A logarithmic base 10 transformation was performed on all continuous data used. Figure 1 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.

COST MODEL RESULTS

From initial analyses, it was determined that typology, drainage area, year built were not statistically significant predictor variables. Interactive effects between predictor variables were also determined to be non-significant.

The final linear model included greened acres per SMP (a measure of the average SMP size) and project type (refer to Table 1) as significant predictor variables.

Explanation of Predictor Variables

GA/SMP – 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.

Project Type – 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	$Log_{10}(Cost/GA) = 4.98 - 0.24*Log_{10}(GA/SMP)$	49.1%	46.9%	39.8%
Public	$Log_{10}(Cost/GA) = 5.25 - 0.24*Log_{10}(GA/SMP)$			

DISCUSSION

Analysis of model results reveals an interesting interaction between project scale and type. The model showed that project type was a significant predictor of cost, even when project scale variables were included. Thus the effect of project type includes effects not captured by scale predictor. Specifically, private projects tended to be significantly less expensive than public projects, regardless of scale. There are a variety of reasons why this might be the case. First, private projects are funded through the SMIP and GARP programs, both of which establish a funding cap on total project costs. Second, since the SMIP and GARP programs are competitive, construction costs may be driven down by competitive market forces. Third, public and private projects are subjected to different design standards. More exacting design standards associated with public projects may increase costs relative to private projects. Finally, private projects may be located on sites that are less constrained than public projects, many of which are located in the public right-of-way.

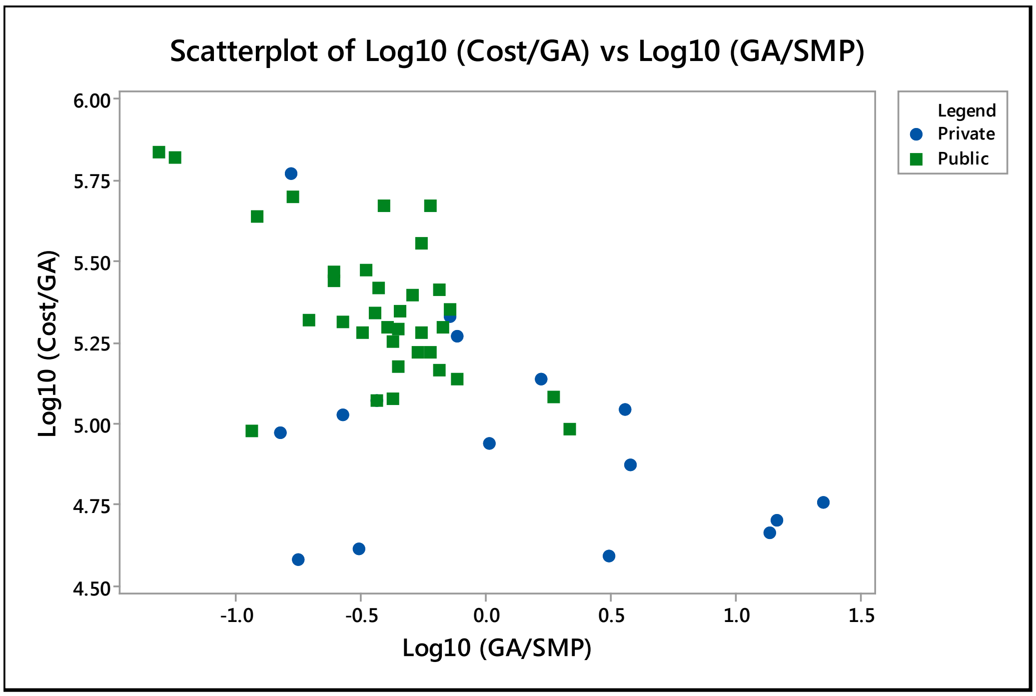

Figure 1: Scatterplot of transformed data.

In terms of scale effects, we found that the predictor variable greened acres/SMP was a significant model predictor even when project type (i.e. public vs. private) was included in the model. This suggests a unifying scale effect that occurs regardless of project type. It is interesting to note that the scaling variable greened acres/SMP refers to the scale of the SMP, not of the project. We did evaluate a project specific variable, namely greened acres, which was not significant. This finding suggests that economies of scale associated with both public and private installations may be more related to the scale of the SMP rather than the scale of the project.

There are many reasons why SMP scale may be inversely related to construction costs. For instance, smaller SMPs may be more difficult to build, requiring the use of smaller, less efficient machinery and finesse installation in tight quarters. By contrast larger SMPs may be built with larger earth moving equipment with less emphasis on precise placement of material. Larger SMPs may also be located, by necessity, on less constrained properties where there is more room to build a larger installation.

Finally, it is interesting to note that final model predicted only 40% of the total variability in the data set. Many other site specific and project specific factors may affect project costs. 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.

Linear modeling of built cost data can help inform planners about the most cost-effective allocations of funds for managing stormwater through the use of green infrastructure. Continual refinements to model parameters can help to identify factors that can drive down future project costs through intelligent project selection and help to benchmark program performance.

Many of the public projects in the data set consist of tree trenches on city blocks. These projects have an upper limit on the number of greened acres they can manage per SMP because of space constraints. Thus, much of the data is concentrated in the lower GA/SMP range (refer to Figure 2). The model may not accurately predict future public projects in the higher GA/SMP range as the data set did not include any projects with GA/SMP above 2.2. The model can be improved by adding additional built data, including several public projects with larger SMPs that are currently in design.

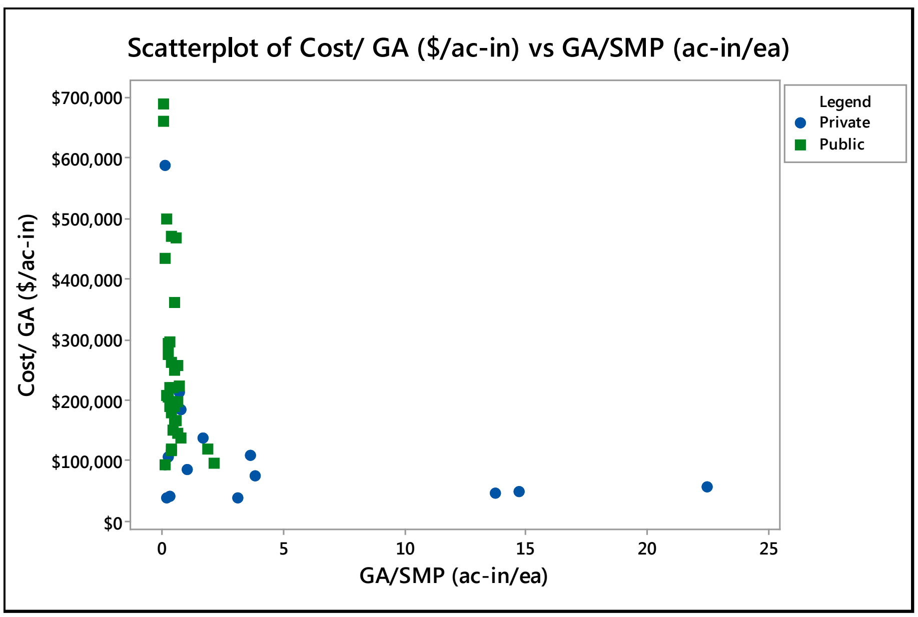

Figure 2: Scatterplot of unit cost and greened acres per SMP.

While the linear model developed shows a statistically significant relationship between project type and project scale on unit cost, additional data, especially with SMPs managing a larger number of greened acres, is required for further analysis in order to better predict unit cost of project. Additional site and/or SMP characteristics, such as on-site vs. off-site disposal, pavement removal, and SMP type, could also help create a model with greater predictive ability.

StormWISE Model APPLICATION IN THE PHILADELPHIA CSO AREA

The Storm Water Investment Strategy Evaluation (StormWISE) model (McGarity, 2012) uses multiobjective optimization to prioritize the deployment of GI practices in urban watersheds. It is presently being modified for managing CSO overflows in densely urbanized settings using Philadelphia as a case study.

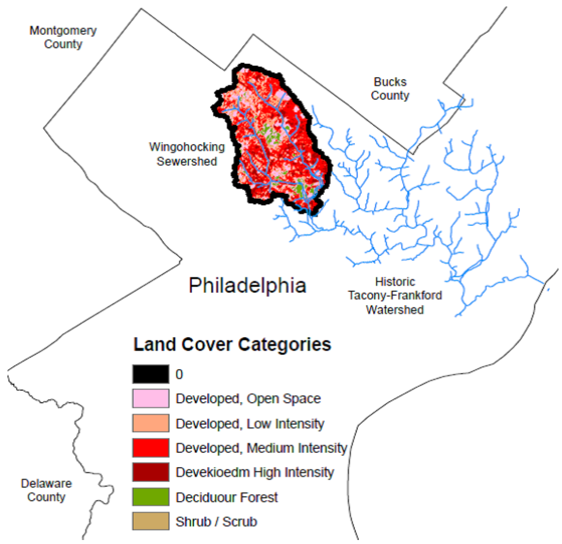

Figure 3. Philadelphia and the Wingohocking Sewershed

Philadelphia's historical Wingohocking Creek, shown in Figure 3, was completely enclosed in the late 19th and early 20th centuries to create one of the major sewersheds in the CSO area. A 2970 acre portion of the upper reaches of the sewershed in the Piedmont has been selected for applying the StormWISE model with the cost model discussed above. In order to obtain annual hydrological performance of the area, the sewershed were modeled using EPA's SWMM. Seven subcatchments were delineated and the model was run for an entire year. Recently added features of SWMM (version 5.1.010) are used to model the deployment of GI practices.

Two GI practices were chosen for our initial runs of StormWISE in the Wingohocking, rain gardens and infiltrating tree trenches. The design parameters used in the model for each GI were based on actual PWD installations on public property in the area. Several runs of SWMM were made for different numbers of each GI deployed in the seven subcatchments. *The annual total of stormwater runoff was observed to decrease linearly as the number of GI deployments increased, but the rates of decrease differed significantly among the subcatchments and with type of GI practice.* These rates, along with corresponding GI costs, obtained from the cost model, were used to generate parameters for optimization runs with StormWISE.

Figure 4 shows one of the primary outputs of StormWISE obtained by running the optimization 37 times by specifying the runoff volume reductions required and then finding the optimal number of greened acres for each GI practice (rain garden or infiltration tree trench) in each subcatchment, and on each type of land ownership (private or public) while minimizing the total watershed-wide investment required to achieve each specified runoff volume reduction. Runoff volume reductions were specified in increments of 10 MGal/yr with values ranging between zero and 370 MGal/yr, which is the maximum total reduction achievable with these two GI practices as determined by SWMM. Figure 4 plots the resulting runoff volume reductions on the vertical axis and the minimum investment levels on the horizontal axis so that for each level of investment, the maximum possible reduction in annual runoff volume is shown resulting from optimal combinations of rain gardens and infiltration tree trenches deployed in the seven subcatchments. Figure 5 shows how the solutions minimizing total investment split the investment among the different subcatchments as the specified watershed-wide runoff reductions are increased to the maximum possible.

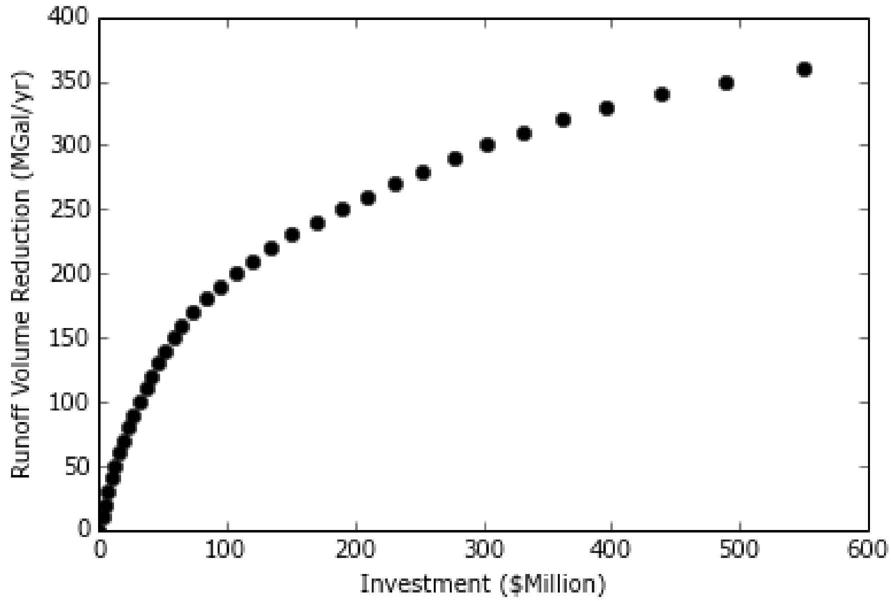

Figure 4. StormWISE model output showing Pareto Optimal solutions maximizing reductions in annual runoff volume as the level of GI investment throughout the sewershed increases

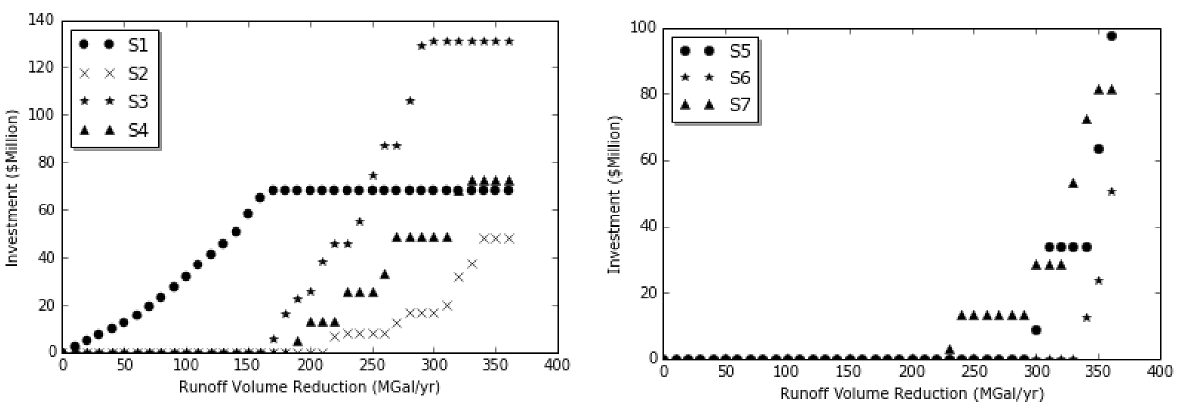

Figure 5. Optimal Investment levels in each Subcatchment

The cost model has determined that costs are strongly influenced by the ownership of the land on which GI practices are installed. Figure 6 shows StormWISE results for how total GI investment would be optimally partitioned between private and public installations as the total runoff volume is increased. The less expensive private investments optimally attract the greater total investment when lower runoff reductions are specified, but at higher runoff reduction levels, the more expensive public projects must also be implemented.

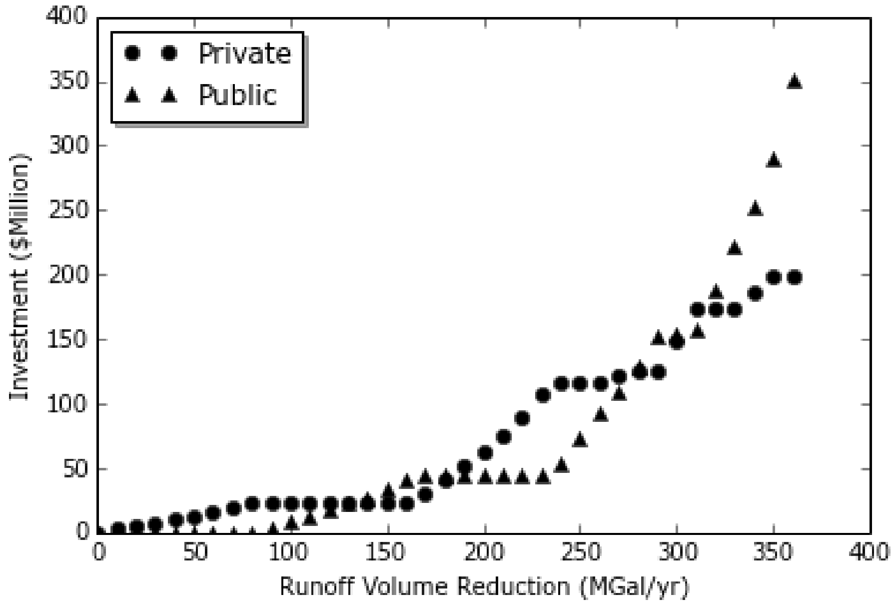

Figure 6. Optimal investment levels by ownership of land where GI practices are deployed, public and private.

Finally, we show in Figure 7 how the total investment would be optimally partitioned between the two different GI practices at different total runoff reduction levels. These two GI practices appear to have quite similar benefit/cost performance overall, with some noticeable differences in certain subcatchments.

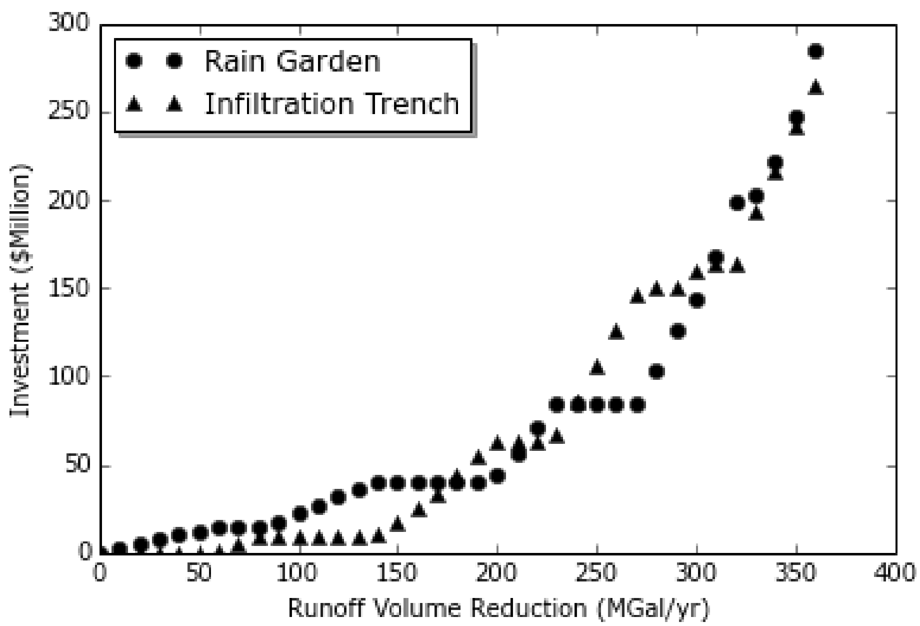

Figure 7. Optimal investment levels by Green Infrastructure type

CONCLUSIONS

This paper reports progress on research on the development of methodologies for guiding investments in green stormwater infrastructure for controlling combined sewer overflows in densely urbanized areas. Philadelphia serves as a case study in innovative public programs to promote the adoption of green infrastructure. A cost model has been developed using data from recently constructed GI installations in Philadelphia. The StormWISE model has been modified to incorporate parameters that are best suited for modeling CSO problems and the necessary hydrological parameters are obtained from multiple runs of SWMM.

Future work will include incorporation of ancillary community benefits of green infrastructure into the multiobjective framework used by StormWISE. Much progress is being made on quantifying these benefits as detailed by a companion paper in these proceedings by Hung et al. (2016). Improvements in hydrological modeling of GI practices are also being pursued by our research team through application of the Parflow coupled surface-subsurface model by Andino-Nolasco and Welty (2016), also in this proceedings.

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