Is it worthwhile to invest in learning? A stormwater management case study with green infrastructure using Bayesian-based optimization

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Key Points:

- We propose an adaptive green infrastructure planning framework that combines stochastic optimization and hydrological simulation
- The Bayesian-based model considers learning-by-doing and that experience learned is transferable between locations
- We quantify the economic value of learning that can support the use of adaptive planning approaches

Abstract

To cope with the uncertainty of green infrastructure planning at city scale, many cities take an adaptive approach and use learning-by-doing to improve understanding of the urban systems. However, whether that learning is worth it has been a challenge to adaptive management practitioners. In this paper, we propose an evaluation and planning framework for green infrastructure (GI) to address this issue and demonstrate its use by an application to the Wingohocking watershed, Philadelphia, PA, USA. The framework allows users to specify possible knowledge gains from near-term actions and assess the impacts of this learning on subsequent decisions, which enables evaluation of the net benefits of alternative investment plans. In the case study, we consider two types of learning: learning to reduce uncertainty and learning to improve performance. This learning can happen through investments or knowledge transfer from experience at other locations. Estimates of cost, performance, and deterioration over time of GI and the prediction of possible knowledge gains are based on the literature and expert opinions. The results propose optimal investment strategies over a 25-year planning horizon and describe tradeoffs between the risk of poor performance and reductions in expected annual stormwater runoff. Finally, by calculating differences in expected total costs between non-adaptive, passive adaptive, and active adaptive decision-making, we quantify the economic value of learning and adaptability.

Plain Language Summary

How much can stormwater plans be improved by investing in learning? Is that investment worthwhile? This paper presents an adaptive green infrastructure (GI) investment planning and evaluation framework to address these questions, and an application to the Wingohocking sewershed in Philadelphia, PA, USA. The proposed framework includes two components: the evaluation of GI's capability to reduce stormwater, and the optimization of a portfolio of near-term and subsequent investments. The evaluation quantifies stormwater reduction capacity for GI types at different locations and the uncertainty associated with them, whereas the optimization

also considers deterioration in the performance of installed GI and improved GI cost-efficiency of future installations due to improved designs, materials, and installation. Results of modeling experiments show the optimal timing and type of GI investments, the expected stormwater reduction, and the associated risk levels. The results highlight that assumptions concerning deterioration and learning can change which near-term GI investments are optimal. Furthermore, we calculate the value of adaptability as the difference between the cost of non-adaptive (no learning) and passive adaptive (trial-and-error) management, and the value of learning as the difference between passive and active adaptive (active experimentation) management solutions.

1. Introduction

Green infrastructure (GI) or Low Impact Development (LID) utilizes engineering design with soil and vegetation to mimic natural hydrological processes to remove pollutant, detain runoff and harvest rainwater for non-potable uses, which has been considered as a more sustainable solution to urban stormwater pollution comparing to “gray infrastructure” (i.e. conventional engineering solutions, such as underground storage tunnels) (Askarizadeh et al., 2015; Copeland, 2014; Dhakal & Chevalier, 2017). GI consists of one or more independent distributed systems, called stormwater management practices (SMPs), which are designed to treat stormwater on-site and could be adjusted for the site conditions. SMPs have evolved into a broad spectrum of designs according to the typology of the urban impervious surface (Askarizadeh et al., 2015; Lee et al., 2012). For example, rain gardens and infiltration trenches are often installed to treat runoff from roads and other paved areas; green roofs and rain barrels are for treating rooftop runoff; and permeable pavers can replace impermeable surfaces such as sidewalks, parking lots, and playgrounds.

The effectiveness of SMPs can vary with the designs, the spatial alignment, the climate and the underlying watershed characteristics (Avellaneda et al., 2017; Dietz, 2007; Jackisch & Weiler, 2017; Jarden et al., 2016; Rossman & Huber, 2016). Studies have pointed out that the flexibility and diversity of SMPs can complicate GI investment planning for their cost and performance uncertainty, and this has become a barrier for GI adoption (Copeland, 2014; Dhakal & Chevalier, 2017). For example, in the analysis of Wright et al., (2016), runoff reductions vary from 10% to 70% depending on SMPs, while cost per cubic meter of reduction ranges from $3 to almost $600 depending on SMPs types and land use.

Another layer of complexity comes from the maintenance of GI (Asleson et al., 2009; Avellaneda et al., 2017; Eckart et al., 2017; Freni et al., 2010). Cities sometimes share the maintenance responsibility of GI with the communities and residents by retrofit and community engagement programs (Eckart et al., 2017; Jarden et al., 2016). These programs are desirable for cost savings, but they could also increase the difficulty for assuring maintenance quality and the uncertainty of SMPs’ long-term efficacy. Depending on the quality of the maintenance, SMPs may fail during storms or become less effective over time. The deterioration in SMP performance could result in increasing of disturbance of water uses and violations of regulatory requirements. In contrast, traditional centralized engineering solutions, such as underground storage tunnels, can provide massive storage to reduce peak flow, which are usually operated and maintained by professionals and are less likely to fail during storms or suffer the deterioration in performance over time. As a result, many cities implements GI only at small scale or by pilot projects (US EPA, 2010), even though GI has been proven to be a viable alternative to conventional engineering approaches as well as providing ancillary benefits that enhance residents' quality of life (Copeland, 2014; Dietz, 2007; Wise et al., 2010).

Adaptive management (AM) is a framework for resolving key uncertainties that has been applied mostly in natural resource and water management (Holling, 1978; Medema et al., 2008; Rist et al., 2013; Williams & Brown, 2014). However, the literature of AM has pointed out that most AM projects failed to evaluate costs and benefits of the monitoring and research plans, which may improve the scientific understanding but not necessarily contribute to decision making (Failing et al., 2004; Williams, 2011; Williams & Johnson, 2015). More recently, researchers have recognized the need to evaluate the value of learning to justify the costs and resources required for monitoring and research actions, and they have applied the concept of value of perfect information (VPI) (also called Expected Value of Perfect Information) to assess the expected improvement resulting from AM (Johnson et al., 2017; Probert et al., 2011; Runge et al., 2011; Williams & Johnson, 2015). Although traditional VPI approach can provide information about the best case learning scenario, the real-world data seldom provides perfect information and the state of nature could also be non-stationary, further complicating the analysis (Runge et al., 2011; Williams & Brown, 2014).

The model of this paper extends the simple framework we have previously proposed (Hung & Hobbs, 2019) for adaptive GI investment planning. Unlike the studies mentioned earlier that assume perfect information and only look at expected value, the framework can quantify tradeoffs between expected benefit and the risk of undesirable outcomes, test assumptions about what and how we can learn, and assess the value of learning resulting from near-term investments. Although the framework has these features that stormwater managers desired, its potential is not fully explored in our previous paper other than the expected value-risk tradeoff. This paper shows an application of the framework with the emphasis on how learning works (modeling) and how it can improve the outcome (optimal objective value).

Specifically, this paper interviews experts about their thoughts on learning and SMPs' cost uncertainty, evaluates SMP efficacy by hydrological simulation, and assesses the value of learning imperfect information, accounting for non-stationarity of the future states. We compare the optimal solution with learning with traditional planning approaches (one-time master planning), with passive adaptive management (plan without considering in learning and the subsequent ability to adapt later, if there is a surprise), and also with active adaptive management (consideration of investments in learning, and how the resulting information can be used to optimally adapt plans). The research questions we have are the following.

- Where, when, and how much should be invested in what types of SMP?
- How does the inclusion of GI performance deterioration and learning processes change near-term and subsequent optimal investments?
- Is it worthwhile to invest in learning?

Learning is defined as the updating of prior distributions by Bayes' law based on the knowledge gains from implementing the investments. Investments can yield different levels and types of "learning." More specifically, in the case study where we have three subcatchments to account for spatial heterogeneity, we model learning by updating distribution parameters when investments in one location exceed predetermined thresholds or by sharing experience learned at other locations. Theoretically, learning can lead to perfect information with a high investment threshold, but it is often not cost-effective if not infeasible for financial and technical issues. Therefore, it is more important to explore learning imperfect information and the tradeoffs between invest in learning and invest in immediate stormwater benefits.

Figure 1 shows the conceptual diagram of the proposed framework, which consists of a hydrologic simulation and an adaptive GI planning model. The adaptive GI investment planning considers multiple subcatchments and decisions about siting GIs, budget of the GI program.

The remainder of this paper is organized as follows. Section 2 introduces the case study area as well as the hydrologic model used to evaluate SMP performance in reducing stormwater runoff and the associated uncertainty. In Section 3, we summarize assumptions about the dynamics of performance and cost (performance deterioration due to aging, improved characterization of performance and cost due to learning, and technological improvements resulting from cumulative investment) and modification of the model formulation in Hung and Hobbs' (2019). Section 4 discusses the results of the optimization of adaptive investment strategies and the economic value of learning and adaptability. Finally, Section 5 presents our summary and conclusions .

2. Evaluation of SMP Cost-effectiveness

In this section, we focus on integrating various sources of uncertainty in SMP cost-effectiveness. The purpose of this section is not to develop a calibrated model to evaluate the uncertainty of SMP performance in the study area as the data for calibration and validation are not available, but to demonstrate the use of modeling tools to evaluate the uncertainty using our best knowledge. The improvement in modeling techniques is viewed as a kind of learning in the adaptive planning scheme.

2.1. Evaluation of SMP Performance in Reducing Stormwater

Among existing rainfall-runoff simulation products, USEPA's Storm Water Management Model (SWMM) is one of a few models with functions for modeling GI (called LID in SWMM) (www.epa.gov/water-research/storm-water-management-model-swmm). SWMM is widely applied to urban stormwater management studies around the world (Avellaneda et al., 2017; Dong et al., 2017; McGarity, 2013; Palla & Gnecco, 2015; Petrucci & Tassin, 2015; Sebti et al., 2016). Although it is a highly parameterized hydrologic model, its GI module makes it a convenient tool for preparing SMP performance and uncertainty estimates for the adaptive optimization framework of Section 3. For simplicity, we only focus on runoff generation processes and SMP response to precipitation events.

For most input parameters for the SWMM simulations, values needed for the simulations cannot be obtained by direct measurement but are instead inferred from observed hydrographs or based on numbers reported in the literature (Bates & Campbell, 2001; Stow et al., 2007). Unfortunately, for our study area, we have neither direct measurements nor runoff hydrographs to calibrate the model, which limits our ability to make precise predictions regarding the dynamic interactions between GI, the urban sewershed, and the climate. However, it is more important to have a consistent assessment of possible SMPs using the best information available, given that the main value of the investment planning models is to screen candidate investments, to identify the most attractive near-term installation, and to understand how assumptions concerning learning, adaptation, and performance changes could impact those recommendations. Therefore, the evaluation is based on the most relevant parameter values we could find in the literature, the GI/LID design guides (Hinman & Wulkan, 2012; Philadelphia Water Department, 2015;

Schueler & Claytor, 2009), and consultation with a local expert (a GI design and installation contractor with extensive experience in Philadelphia) (S. Szalay, personal communication, 2018),. There are methods to improve parameterization in the literature (Dong et al., 2017; Muleta et al., 2013; Sadegh & Vrugt, 2014) if monitoring data are available, but their use is beyond the scope of this study.

2.1.1. Study Area

The study area is located at North Philadelphia where the original Wingohocking Creek watershed was before it was integrated into the sewer system. Figure 2 shows the location and coverage of the Wingohocking sewershed, which has a total area of 2,076 ha and a length of approximately 10 km, and the location of the sewer overflow outlet to Frankford Creek.

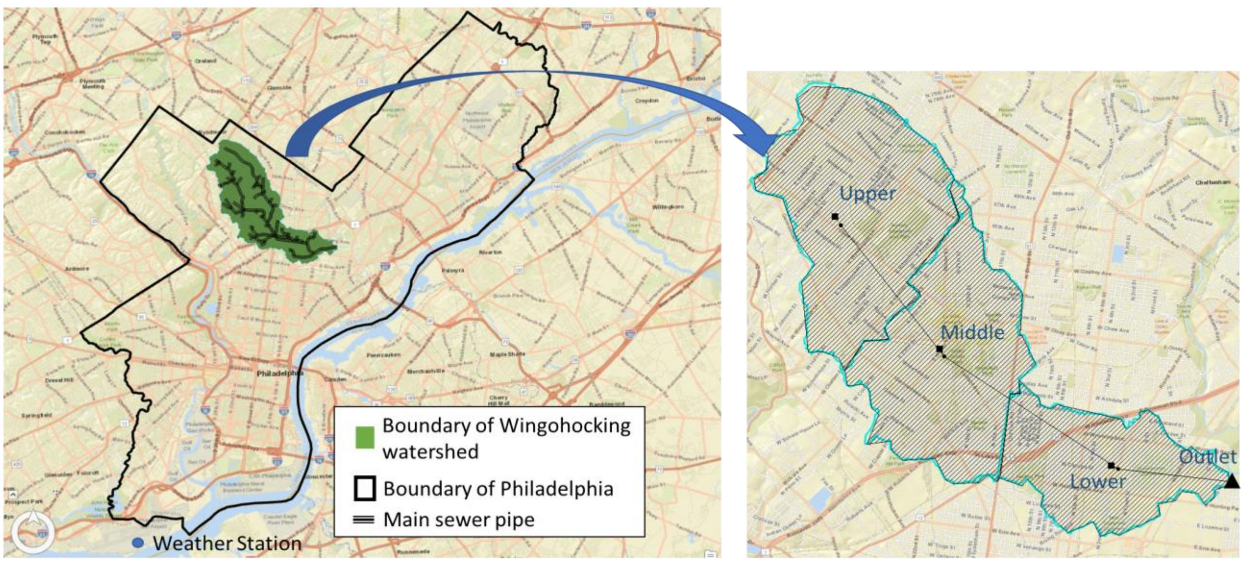

Figure 2. Boundaries of Philadelphia and the Wingohocking watershed, the main sewer pipes, and three subcatchments

Commonly used modeling approaches tend to involve significant geographical aggregation of the study area because including all processes in a fine scale would result in complex models with high data needs and computing requirements (Jefferson et al., 2017). Due to the limited data available, we simplified the processes by dividing the Wingohocking sewershed into three subcatchments, called Upper, Middle, and Lower, based on the distance to the overflow outlet and the layout of the main sewer pipes (Figure 2). For the same reason, the hydrologic model simplifies the sewer system to only one conveyance channel which collects only stormwater runoff (i.e., wastewater generation and treatment are not included), under the assumption that runoff dominates flows in the system in the events of greatest concern to planners. These simplifications expedite computation and allow us to estimate output uncertainty by simulating a large number of scenarios based on random samples of model inputs and parameters from assumed distributions.

2.1.2. Watershed Characteristics

The Wingohocking watershed is a highly developed area (100% developed). Land uses in the Upper subcatchment are mostly residential, while the Middle and Lower subcatchments are primarily residential mixed with commercial and industrial uses (Table 1). The Lower and Middle also have higher vacant properties (6% and 7%, respectively) than the Upper (3%). The imperviousness is about 55% and is fairly uniformly distributed across Wingohocking sewershed. The average slope is about 6% and is slightly lower in the Lower sewershed (4.7%), where the original Wingohocking Creek transitioned from the Piedmont Region to the Atlantic Coastal Plain. The average catchment widths of the subcatchments are estimated on the digital map by the ArcGIS measure tool. The characteristics of the three subcatchments calculated are summarized in Table 1, and data for the calculation are from publicly available geospatial data, of which the sources are listed in the Appendix.

Table 1.
Subcatchment Characteristics and Land Use

	Slope (%)	Imperviousness (%)	Area (ha)	Width (m)	Land use (%)			
					Residential	Commercial	Industrial	Others
Upper	6.2	53.9	850	3,800	50%	11%	5%	34%
Middle	6.5	56	733	3,800	37%	17%	7%	39%
Lower	4.7	55.6	493	3,000	23%	10%	19%	53%

The soil in Wingohocking sewershed is mostly (>95%) categorized as urban land in USDA's soil survey, meaning that the soil is largely covered by impervious materials and its permeability is unknown. However, the soil on Atlantic Coastal Plain (the physiographic region where most of Philadelphia is located) generally is highly permeable (Markewich et al., 1990). Infiltration of permeable surfaces is modeled by the Green-Ampt method (Chow et al., 1988) in our SWMM simulation, where the saturated infiltration rate is chosen based on loam (25 mm/hr). The depression storage for the pervious and impervious areas are 4 mm and 1.3 mm, respectively.

The conveyance channel collecting stormwater is modeled as a 9 m-wide by 3 m-high rectangular channel with a length of 7.8 km and a Manning roughness coefficient of 0.013. For other parameters for SWMM modeling not discussed here, we use default values from the SWMM user manuals (Rossman, 2015; Rossman & Huber, 2016).

2.1.3. SMP design parameters

The five distinct types of SMPs evaluated in this paper include the following. *Rain gardens* (RGs) are vegetated SMPs that detain stormwater to infiltrate and recharge groundwater. *Infiltration trenches* (ITs) and *permeable pavement* (PP) are both non-vegetated infiltration SMPs. ITs are often installed for retaining stormwater from transportation right-of-ways, while PP holds stormwater directly on its surface and increases permeability to the underlying soil, relative to the impermeable pavement. RG, IT, and PP are characterized as infiltration SMPs because they divert a portion of surface runoff to soil moisture and groundwater. *Green roofs* (GRs) and *rain barrels* (RBs) can retain or reduce stormwater from rooftops and, therefore, are characterized as roof SMPs. However, a GR utilizes the evapotranspiration to deplete water after storms, while an RB is generally designed to delay but not reduce discharges, unless it drains primarily onto permeable surfaces.

We assume that all SMP installations are in parallel so that the stormwater reductions are additive if multiple installations are made. In actual GI plans, some SMPs may be installed downstream of others (e.g., rain gardens downslope from permeable pavement); we assume that such installations in series are the exception rather than the rule. By the assumption of additivity, the SMP installations can be combined into single synthetic SMP to represent the overall performance. Then we can apply the hydrologic model to assess the performance of the SMPs, in which the parameter values are assumed uncertain due to the variability of the designs, and the quality of the installations. The design parameters of SMPs and the assumptions regarding their uncertainty are presented in Supporting Information (Text S1).

2.1.4. Evaluation of SMP Efficacy and Its Uncertainty

We apply Monte Carlo method coupled with SWMM to estimate distributions of the stormwater reduction for each SMP type. Recent studies have applied the same method to evaluate SWMM's prediction uncertainty by comparing monitoring data with the modeling results (Avellaneda et al., 2017) and SMP efficacy uncertainty under future climate and land use change uncertainty (Dong et al., 2017). Our work is distinguished from these analyses in that our estimation focuses on the overall performance uncertainty of individual SMP type at watershed scale concerning the design variability and installation quality among the installations., whereas their analyses emphasis on the uncertainty from model selection and calibration contributed to SMP performance. Although our analysis does not include the model and calibration uncertainty due to lack of data, the results can still provide a basis for comparison to inform investment decision making. Model uncertainty can be incorporated in our framework when sufficient data become available, but it is beyond the scope of this paper.

We chose reduced stormwater volume as the performance metric for simplicity and because we lack sufficient information to model the CSO generation process (e.g., data of sewer network and characteristics, capacities of wastewater treatment plants and their operation rules). In addition, we use the same parameter distributions for SMP efficacy in all three subcatchments due to our limited knowledge of site conditions in the subcatchments. These assumptions are not a limitation of our framework for the following reasons: lack of data is common in stormwater management for the high costs of monitoring and the missing sewer system information. Moreover, our framework can accommodate different metrics and differentiated assumptions for each subcatchment, which could, for example, be implemented after the initial (first stage) investments are made.

The Monte Carlo simulation is described as follows. In order to quantify the mean and standard deviation (SD) of stormwater reductions for each SMP, we draw one sample from each of the parameter distributions, simulate the resulting annual stormwater reduction with one-year precipitation data (from Jan. 1 to Dec 31), and repeat this process 30 times for each year from 1980 to 2013 using SWMM. The precipitation data applied in this analysis are presented in Supporting Information (Text S2).

The simulation assumes that a 200 ha impervious area is treated by the SMP and that the random parameters are statistically independent. The simulation results are summarized in Table 2, where the unit is in m/yr (m^3 stormwater reduction per m^2 SMP per year). The coefficient of variation (CV) is a measure of dispersion (risk) relative to the mean.

Table 2
Statistical Summary of SMP Annual Stormwater Reductions

	Upper			Middle		Lower	
SMP	Mean	SD	CV ($\frac{\mu}{\sigma}$)	Mean	SD	Mean	SD

	(m/yr)	(m/yr)		(m/yr)	(m/yr)	(m/yr)	(m/yr)
Rain Garden (RG)	14.71	2.27	0.15	14.75	2.22	14.57	2.20
Infil. Trench (IT)	19.15	3.21	0.17	19.01	3.09	19.08	3.07
Permeable Pavement (PP)	2.03	0.49	0.24	2.04	0.48	2.06	0.49
Rain Barrel (RB)	33.36	3.08	0.09	33.27	2.95	33.41	3.09
Green Roof (GR)	0.66	0.08	0.12	0.67	0.08	0.62	0.07

From Table 2, we can see that the SMPs' performances are only slightly different in the three subcatchments, which is the result of watershed geometry and rainfall pattern. Generally speaking, SMPs performs at locations of which the treated area collects water faster, if no overflows (SMPs's storage are not full during the storms) and at locations of which the treated area collects water slower, if SMPs overflow. The former is the case of RG and IT in the Middle subcatchment and the latter is the case of PP and RB in the Lower subcatchment. Since the effects only happen at site scale, the difference of the means and standard deviaions of the SMPs' performance in the three catchments should not be viewed as real differences in distribution but rather the errors from our modeling assumption. Therefore, we assume that the SMP efficacy distributions in the Middle and Lower subcatchments are the same as the results in the Upper Subcatchment.

Moreover, we can see that IT can provide the highest expected annual stormwater reduction per m^2-installation, but it is also relatively risky, as its CV being the second-highest among the SMPs. PP is the riskiest (the highest CV) and the second lowest in stormwater reduction per m^2-installation. For the roof SMPs, RB is better than GR for the higher stormwater reduction per m^2-installation and lower uncertainty (lower CV).

2.2. Evaluation of Cost Uncertainty

The previous section described uncertainty in SMP performance in terms of annual water storage per unit area (m/yr). This section describes the derivation of uncertainty in SMP cost ($/yr/m^2). The ratio of performance to cost (in m^3/$) and its uncertainty can then be derived.

Our cost analysis is based on the cost information summarized in the Center for Neighborhood Technology's "Green Values – National Stormwater Management Calculator" (greenvalues.cnt.org/national/cost_detail.php, accessed June 2018), including capital and maintenance costs, installation lifespans, and cost uncertainty ranges of the SMPs. Because this cost information came from various sources, the values are adjusted to accommodate the local conditions based on the discussion with our Philadelphia expert (S. Szalay, personal communication, 2018).

The cost uncertainty needed for basin planning is the uncertainty in the average cost of many installations rather than the cost variability of one installation. So instead of using the cost range summary from the calculator, we adjust those ranges in order to obtain plausible ranges of average cost based on two criteria:

1. the construction complexity of the SMP; and
2. the portion of the installation cost that serves the purpose of stormwater control. There are other costs that are sometimes incurred (such as the cost of landscaping) to enhance GI's social benefits; these are highly variable and are not directly related to the purpose of the installation, and so for a basin-level analysis are not included.

Table 3 shows our estimates of the five SMPs' capital costs, including their lifespans and the ranges of the annualized capital costs, and the annual maintenance costs. The values of the average capital and maintenance costs are chosen based on the ranges in CNT's cost summary and expert judgment (S. Szalay, personal communication, 2018). The annualized costs are calculated by assuming a 5% interest rate and their lifespans. We can see that RB has the highest annualized capital cost per m^2-installation because the surface area of RB provides a 91cm (3 ft) storage depth and the cost estimation is based on the aggregation of rain barrels, each with 227 liters storage (60 gallons). With economies of scale, the cost could be lower, which is not directly modeled as a function of investment size; however, such effects are at least partially captured by our modeling of learning as a function of total investment since learning can reduce SMP costs.

Table 3

SMP Capital and Maintenance Costs and Uncertainty Ranges

SMP	Avg. Capital Cost ($/m^2)	Life Span (yr)	Assumed Annualized Capital Cost Range			Assumed Annual Maintenance Cost Range		
			Lower Bound ($/m^2/yr)	Mean ($/m^2/yr)	Upper Bound ($/m^2/yr)	Lower Bound ($/m^2/yr)	Mean ($/m^2/yr)	Upper Bound ($/m^2/yr)
RG	100	30	15.1	21.6	28.1	3.5	5	6.5
IT	150	20	13.9	19.9	25.9	5.6	8	10.4
PP	80	15	6.7	8.3	10	3.2	4	4.8
RB	200	20	25.2	26.5	27.9	1	1	1.1
GR	80	30	13.8	17.3	20.7	3.2	4	4.8

The SMPs' annual maintenance cost ranges (Table 3) are assigned based on the frequency and complexity of maintenance. For example, the infiltration SMPs (RG, IT, and PP) require frequent inspection to avoiding clogging (Avellaneda et al., 2017; Fletcher et al., 2013), while RB can be inspected less often and only rarely needs replacement (US EPA, 2013). However, maintenance of the RB often requires manual emptying of storage after storms (other designs may come with a drain hose at the bottom and discharge slowly). We assume that the attention paid to RB maintenance and emptying would affect rain barrels' capacity to store stormwater, which adds to the uncertainty in performance.

The annualized costs per installation area in Table 4 combine the annualized capital costs and maintenance costs under the assumption that the two costs are perfectly correlated (unexpectedly high capital costs are likely to be accompanied by higher maintenance costs as well). Table 4 also shows the annualized cost per treated area (the annualized costs per installation area divided by the average drainage area ratio), which are the costs for treating the impervious surface. It appears that the annualized cost per treated area is mostly determined by the SMP's treated area to surface area ratio (drainage area ratio). RG and PP are expensive because of their low treatment ratios, whereas RB becomes the cheapest SMP because of its high treatment ratio even though they are the most expensive SMP per m^2-installation.

Table 4

SMP Annualized Costs per m^2-installation and per m^2-treated

SMP	Annualized Cost per Installation Area			Avg. Drainage	Annualized Cost per Treated Area		
	Lower	Mean	Upper		Lower	Mean	Upper Bound

	Bound ($/m^2/yr)	($/m^2/yr)	Bound ($/m^2/yr)	area ratio	Bound ($/m^2/yr)	($/m^2/yr)	($/m^2/yr)
RG	18.6	26.6	34.6	24	0.78	1.11	1.44
IT	19.5	27.9	36.3	30	0.65	0.93	1.21
PP	9.9	12.3	14.8	1.5	6.57	8.21	9.85
RB	26.2	27.5	28.9	108	0.24	0.25	0.27
GR	17.0	21.3	25.5	1	17.03	21.29	25.55

We calculate the distribution of each SMP's cost-effectiveness using Monte Carlo simulation by drawing samples from the annualized cost (per treated area) distributions (assumed to be uniform between the lower and upper bounds of Table 4) and from the results of SWMM performance simulations (Table 2). Costs and stormwater reductions are assumed to be independent. In addition, we assumed that the costs in the Middle and Lower subcatchments are 5% and 10% less than the values shown in Table 4 because of the lower property values in those areas, which provides an incentive to invest in the Lower and Middle over the Upper subcatchments. Table 5 shows the statistical summary of the SMP's cost-effectiveness in m^3/$ of the subcatchments, where IT is the most cost-effective SMP while GR is the least. The values of CV indicate that PP is the most uncertain SMP and RB is the least risky one. The CV values of the SMPs are the same for the subcatchments because the cost adjustment would cancel out.

Table 5

SMP Cost-effectiveness and Uncertainty per Unit Installation Areas by Subcatchment (based on Tables 2 and 4)

SMP	Upper			Middle		Lower		Stormwater Reduction (m^3/ha)	
	Mean (m^3/$)	SD (m^3/$/yr)	CV	Mean (m^3/$)	SD (m^3/$/yr)	Mean (m^3/$)	SD (m^3/$/yr)	Per ha of Drainage Area	Per ha of Instal-lation
RG	0.437	0.106	0.243	0.460	0.112	0.486	0.118	4,851	147,090
IT	0.537	0.127	0.236	0.565	0.134	0.597	0.141	4,994	191,523
PP	0.127	0.036	0.283	0.134	0.038	0.141	0.040	10,427	20,258
RB	0.927	0.087	0.094	0.976	0.092	1.030	0.097	2,318	333,581
GR	0.024	0.004	0.167	0.025	0.004	0.027	0.004	5,110	6,620

From the values of the SMP cost-effectiveness per ha installation (next to the last column in Table 5), we can see that a low-cost investment strategy would be to install IT for impervious ground surfaces and RB for impervious roofs. However, the relatively low amount of stormwater reduction per ha of drainage area for IT and RB means that if a large amount of reduction is desired, these measures will not be as effective as other approaches (namely PP and GR, respectively). For instance, for a given roof drainage area, GRs will reduce more stormwater than RBs (as indicated by the last column of Table 5), even though RBs are more cost-effective (in m^3/$).

3. Modeling GI Investment Planning and Learning

Our GI investment planning model is an extension of the basic method proposed by Hung and Hobbs (2019). The basic approach accounts for the following characteristics of the GI decision framework:

- optimization of stormwater reduction over multiple years subject to monetary budget limitations and the acceptable risk level specified by users;
- uncertainty in SMP performance and cost that changes from one investment decision stage to the next as a result of learning and investment; and
- adaptive investment planning framework, including multiple investment decision stages (e.g., years 0 and 5) and consideration of the value of learning for improving decisions in later stages.

The method is structured as a two-stage stochastic program with recourse, in which uncertainties are characterized by discrete scenarios with probabilities. The uncertain coefficients are the SMP cost-effectiveness, which follow some distributions representing the current understanding of the SMPs cost-effectiveness. Based on the learning assumptions, the distribution parameters would be updated if the first-stage investments exceed the learning thresholds. For example, the multi-stage learning model with technology improvement assumes that, if learning criteria are met, the mean values of the cost-effectiveness distributions will increase by γ%, and the standard deviation would be reduced by β%. Our GI investment planning model is developed based on this variant.

The differences of our method compared to the original method presented in Hung and Hobbs (2019) are as follows. The highly simplified hypothetical example presented in that reference considers a single subcatchment, disregards the possibility of deterioration over time of performance of existing installations, and does not consider that learning about SMPs at one location is transferable to SMPs at other locations. In this paper, we incorporate these considerations into our model by introducing new random variables for deterioration and constraints for modeling knowledge transfer. We also test the system based on SWMM hydrological simulations and cost estimates for an actual case study, the Wingohocking watershed, rather than a simple hypothetical illustration.

3.1. Assumptions and Problem Settings

Following the Philadelphia's Green City Clean Waters (GCCW) program, the total planning horizon is set to 25 years where the first stage starts at year 0 and the second stage starts at year 5. Although the planning and review cycle of the GCCW program is every 5 years, which means 5 planning stages in total, we only model the first stage decisions (the near-term decisions) and combine the rest into the second decision stage (the long-term decisions).

Therefore, the objective of the planning model is to maximize the expected stormwater reduction over a 25-year time horizon by making investments in the SMPs in the subcatchments while considering constraints representing the total budget (which limits investment amounts), impervious roof and ground area of each subcatchment (which limit installation opportunities), risks of realizing a low stormwater reduction (in the form of a conditional value of risk,CVAR), and learning (which use Bayes Law to update distributions of the SMP cost-effectiveness). This is essentially a multi-objective optimization where the objectives are (1) maximizing expectation of the stormwater reduction over the horizon, (2) maximizing CVAR (defined as the conditional expectation of the stormwater reduction for the poorest 10% of realizations), or (3) minimizing cost. We use the epsilon constraint method of multi-objective optimization, in which the problem is solved repeatedly as single-objective optimization while treating the other objectives as constraints with various user-specified upper bounds (for maximization objectives) or lower bounds (for minimization objectives) (Deb, 2014), to search for the Pareto-optimal solutions. By applying the epsilon constraint method, we can describe tradeoffs among these three objectives.

Uncertainty is characterized using the magnitude of the standard deviation of a distribution, and we assume that learning would cause a decrease in the standard deviation. In addition, if learning contributes to technological progress, it could also lead to an increase in the expected value in the SMPs' cost-effectiveness. More details of the learning assumptions are presented below.

3.1.1. Basic Learning (BL) and Advanced Learning (AL)

In this case study, we assume that the learning for an SMP has two levels, which are triggered if cumulative investment in that SMP in the first (year 0) decision stage exceeds predefined learning thresholds. The lower level of learning, basic learning (BL), has a lower investment threshold and can result in the second stage (here, year 5) realizing both (1) a reduction in uncertainty concerning the SMP's cost-effectiveness (standard deviation) and (2) technological progress, reflected in an increase in an expected SMP's cost-effectiveness over what it would have been otherwise. Meanwhile, the higher level of learning, advanced learning (AL), has a higher investment threshold and can provide a greater boost in the cost-effectiveness of second stage SMP investment and a larger uncertainty reduction. On the other hand, if the first stage investment in an SMP does not reach the BL thresholds, the cost-effectiveness distribution would remain unchanged in the second stage, called no learning (NL).

Based on consultations with our local expert (S. Szalay, personal communication, 2018), the assumptions concerning learning thresholds for each of the SMPs and the corresponding changes in the SMPs' cost-effectiveness distributions in the second stage are summarized in Table 6. Refinement of the learning thresholds and changes in distributions could be a subject for future study based on consultation with multiple experts or statistical analysis of actual experience.

Table 6

Assumptions about Changes in Mean and Standard Deviation (SD) of SMP Cost-effectiveness Realized in the Second Stage (year 5) as a Result of Learning, and the Investment Thresholds for Learning

SMP	Basic Learning			Advanced Learning		
	Mean adjustment (γ_{BL})	SD adjustment (β_{BL})	Threshold ($K)	Mean adjustment (γ_{AL})	SD adjustment (β_{AL})	Threshold ($K)
RG	+10 %	-30 %	2,200	+30 %	-50 %	10,000
IT	+10 %	-30 %	1,000	+20 %	-50 %	4,000
PP	+10 %	-30 %	160	+20 %	-50 %	350
RB	+5 %	-30 %	30	+10 %	-50 %	60
GR	+10 %	-30 %	350	+30 %	-50 %	700

3.1.2. Partially Transferable Learning

When learning happens, the knowledge gains from one SMP in a subcatchment may be partially applicable to the other subcatchments. For example, if we learned about the rain gardens in the Lower subcatchment, we may expect the rain gardens in the Middle and Upper subcatchment to perform similarly. However, we may not know the costs of the SMPs in the Middle and Upper subcatchment if we did not invest there. Therefore, we assume the learning is only partially transferrable across locations. That is, if the investment in one SMP triggers AL in one subcatchment, the same SMP in the other subcatchment would have BL even though the investments there are below the BL investment thresholds.

Similarly, the knowledge transfer could happen between different types of SMPs in a subcatchment. For example, RG and IT are both infiltration practices treating stormwater runoff from the ground impervious area, so learning about one of them may also teach us about the other. It is not difficult to model both types of learning, but in this case study, we only model the former (learning transfers between subcatchments) for simplicity.

3.1.3. Performance deterioration

Studies have shown that the performance of installations of infiltration SMPs (RG, IT, and PP) would deteriorate over time due to clogging, with the rate depending on the inflow water quality, pretreatment, and maintenance (Bergman et al., 2011; Drake & Bradford, 2013). Deterioration may also happen to roof practices (RB and GR). Unfortunately, data to support estimates of deterioration rates is unavailable. Nonetheless, we believe that it is important to consider the deterioration process in a long-term planning problem, in part because practitioners believe that different SMPs are likely to experience different rates of deterioration. To model deterioration, we assume that the stormwater reduction (and thus cost-effectiveness) of an SMP installed in the first stage would, on average, decrease by a fraction, D_I, on average over the 5 years (denoted T_I) between the first and second decision stages, and by D_{II} over the 20 years (denoted T_{II}) following the second stage. For second stage installations, we assume that the deterioration rate is also D_{II}. This simplification could result in a slight disadvantage for second stage installations, but sensitivity tests showed that the exact value used for those installations did not appreciably affect the solutions.

The local GI expert gave quantitative judgments of the distributions of the values of D_I and D_{II} shown in Table 7; we assume that uniform distributions with the means and ranges shown in Table 7. These distributions represent parameter uncertainty concerning the mean over many installations over the time horizon, and not the variability among individual facilities, which would be expected to be much greater.

Table 7

Assumptions Concerning Performance Deterioration of Stage I and Stage II Installations

SMP	Stage I			Stage II		
	Lower Bound	Mean	Upper Bound	Lower Bound	Mean	Upper Bound
RG	0.9	0.95	1	0.7	0.8	0.9
IT	0.9	0.95	1	0.6	0.75	0.9
PP	0.7	0.85	1	0.5	0.6	0.7
RB	0.9	0.95	1	0.7	0.8	0.9

GR	0.95	0.975	1	0.9	0.93	0.95

3.1.4. Prior and Posterior Distributions of SMP Cost-effectiveness

The first stage cost-effectiveness values (denoted as vector C_I in m^3/\$) have a prior probability distribution that represents our current understanding of the SMPs' cost-effectiveness; if no learning occurs, then that same distribution applies to the second stage cost-effectiveness, independent of what C_I occurred (realized). But if learning occurs, then the prior distribution would be updated to a posterior distribution of C_{II}. For the mathematical formulation, we generate scenarios to represent the uncertainty, as explained in Section 3.1.5. The updated distribution in scenario s is the posterior distribution, conditioned on the scenario s, which is denoted C_{IINs}, C_{IIBs}, or C_{IIAs}, if no learning, BL, or AL happens, respectively. Depending on which s occurs, the posterior mean cost-effectiveness may be high or low; when this deviates from the prior expected value, this indicates that learning has occurred that indicates that the performance is either better or worse than what was originally expected.

For ease of computation, when learning occurs, the distribution of the posterior expected values, across s, is assumed to be adequately approximated by a normal distribution. (If no learning occurs, then the posterior expected value is just the prior expected value.) For the cases of BL and AL, this distribution may deviate from the prior if it is also assumed that there is a technological improvement as a result of learning, in which case, the mean cost-effectiveness is increased. Table 6 shows that the mean adjustments are 10% (γ_{BL}) for BL and 30% (γ_{AL}) for AL for most technologies, except for the simpler technologies of rain barrels and infiltration trenches, where less improvement is expected.

Each posterior has a reduced standard deviation equal to $((1+\beta)\sigma$, where β is the uncertainty adjustment (negative values; either β_{BL} or β_{AL} in Table 6, depending on the amount of investment), and σ is the standard deviation of the prior distribution. The standard deviation of the expected posterior value is $\sqrt{(1-(1+\beta)^2)}\sigma$, which can be derived from the Law of Total Variance (Hung and Hobbs, 2019)

To represent the prior distributions, we simply use the sets of Monte Carlo samples ("sampling distribution") generated for the cost-effectiveness assessment of the SMPs in Section 2, based on the assumed prior means and standard deviations (Table 5). The samples are saved and reused in the scenario generation process. By recycling the samples, we need to make neither assumptions about the distributions of the SMPs' cost-effectiveness nor to perform distribution fitting. The posterior distributions are also sampling distributions where the means and standard deviations are adjusted based on the learning assumptions, which are explained next.

3.1.5. Scenario Generation Procedure

Our mathematical formulation below (Section 3.2.) requires m_I scenarios of SMP cost-effectiveness in the first stage and, for each first stage scenario, m_{II} scenarios of second stage cost-effectiveness for each of the learning cases (NL, BL, and AL), where m_I and m_{II} are user-specified. Figure 3 provides a decision tree to illustrate the structure of the model and the scenarios, where the squares are the decision nodes, the circles are the chance nodes, the lines emitting from chance nodes are the scenarios, and the end of each branch is an outcome ($f_{s,r}$, $s \in m_I$ and $r \in m_{II}$ are the indices of the first and second stage scenarios, respectively). At this point, let us simplify the explanation by imagining that the decision tree represents just the investment decision for one SMP on one subcatchment. First, a decision is made about the amount of Stage I investment (year 0, left-most node). The state of knowledge at that point in time about that SMP's effectiveness is represented by the prior distribution. Following the investment, then only one of the three learning cases can happen for that SMP; if investment in the first stage is high enough, then either BL or AL can occur, otherwise NL occurs. The first chance node then represents possible realizations (m_I distinct scenarios s) of C_I for that SMP as well as what is learned (i.e., whether one learns that the SMP's effectiveness per $ is likely to be higher or lower than the prior expected value). The decision tree shows that the next thing to happen is that a Stage II decision about investment in that SMP (year 6 in our case study, represented by the second set of decision nodes). The state of knowledge at that point in time is the posterior distribution of effectiveness; if learning takes place then the variance of possible outcomes is narrowed relative to the prior, and depending on which scenario s occurred (i.e., what exactly is learned), the expected value changes relative to the prior. Following that investment, the actual effectiveness $f_{s,r}$ of the SMP is realized, depending on which of the m_{II} second stage scenarios r occurs. At this point, we know what decisions have been made in the two stages and the resulting precise impact on stormwater.

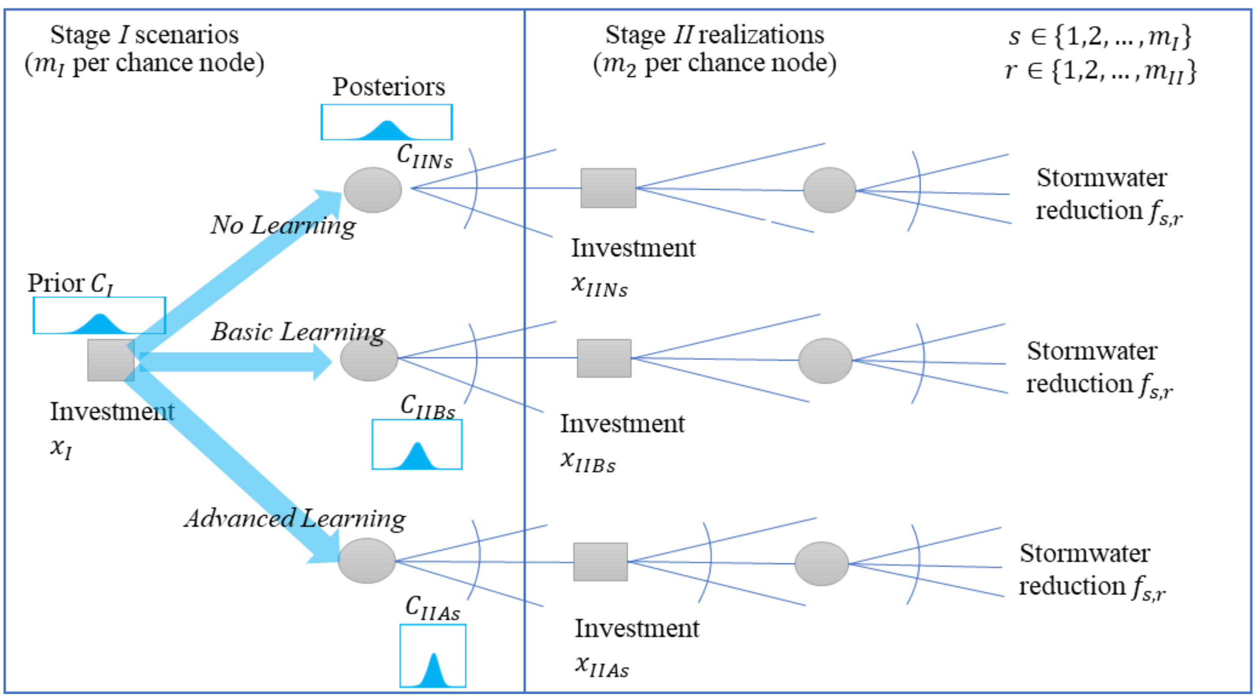

Figure 3. Decision tree representation of the prior, posteriors, and scenarios, in the adaptive GI investment planning model

In contrast to the decision process just described, the optimization model actually considers five SMPs and three subcatchments. Consequently, the investment decisions at each stage are a vector length 15, one element per SMP and catchment. Similarly, a scenario of C_I or C_{II} for a particular stage also consists of a vector of length 15 (15 values of cost-effectiveness, one for each combination of SMP technology and subcatchment). The probabilities of these scenarios s and r reflect any assumptions about joint distributions across SMPs and subcatchments. Posterior joint distributions reflect the learning that occurs for each SMP, based on the first stage investments, as well as assumptions about how learning about one SMP affects learning about others. The total number of paths in the scenario tree equals $m_I * m_{II}$ multiplying by the combinations of learning outcomes (3^{15}). The first stage scenario is indexed by $s \in S_I$ and the second stage scenario is indexed by $r \in S_{II}$. The mathematical formulation in Section 3.2 is more complicated for the risk and physical constraints and the consideration of transferable learnings.

The scenario generation procedure is as follows. For each first-stage scenario *s*, SMP *i*, and subcatchment *j:*

- Generate one cost-effectiveness realization for each SMP from the prior distributions (resample from the sampling distributions), denoted by the vector C_{Is}, of which the elements are the cost-effectiveness realizations of SMP *i* and subcatchment *j*, denoted $C_{Is(i,j)}$
- Generate one sample (vector) from the expected value distributions of BL and AL each, denoted C_{IBs} and C_{IAs}, respectively. This is assumed independent to the C_{Is} realization. This assumption is based on the idea that learning of the expected value may not necessarily come from just data. It could be the information extracted from modeling and monitoring data, personal experience or something else. For example, the stormwater manager may learn that the poor performance in the first-stage installations was the results of some design flaws, which could be corrected easily to improve the performance, or that the high performance in the first stage installations was due to siting on the best sites and would expect a decline in average performance with more installation in the second stage.
- Generate m_{II} samples from the prior for no learning case, denoted $C_{IINs,r}$
- Generate m_{II} samples from the posterior distribution of the BL case (denoted $C_{IIBs,r}$), where the mean is equal to C_{IBs} and the standard deviation is equal to $\sqrt{(1-(1+\beta_{BL})^2)}\sigma$
- Generate m_{II} samples from the posterior distribution of the AL case (denoted $C_{IIAs,r}$), where the mean is equal to C_{IAs} and the standard deviation is equal to $\sqrt{(1-(1+\beta_{AL})^2)}\sigma$
- This sampling procedure does not need to make assumptions about the posterior distributions but simply resample and adjust the mean and variance based on the learnings. This allows the user to work with empirical distributions and data for the distributions in real-world cases that are often difficult to characterize.

3.2. Mathematical Formulation

In this section, we present only our modification of the original formulation in the following order: decisions, objectives, learning constraints, risk constraints, and physical constraints. Please refer to Hung and Hobbs (2019) for the complete formulation.

3.2.1. The Decisions

The decisions are the annualized investments ($/yr) in the SMPs (denoted by x_I for the investment decisions in the first stage and x_{II} for the decisions in the second stage). x_I and x_{II} are decision vectors that contain 15 elements representing the investment in the five SMPs at the three locations. The investment in SMP i at subcatchment j in the first stage is denoted $x_{I,(i,j)}$ and the investment in the second stage, scenario s, is denoted $x_{IIs,(i,j)}$. The sets of SMPs and the subcatchments are denoted as $SMP = \{RG, IT, PP, RB, GR\}$ and $Sub = \{Upper, Middle, Lower\}$.

The second-stage investment decisions (x_{IIs}) in scenario s consist of the decisions under three learning cases: no learning (x_{IINs}), basic learning (x_{IIBs}), and advanced learning (x_{IIAs}). That is, $x_{IIs} = (x_{IINs}, x_{IIBs}, x_{IIAs})$. The investments are assumed non-negative.

$$x_I, x_{IINs}, x_{IIBs}, x_{IIAs} \geq 0, \forall s \in S_I \quad (1)$$

One caveat is that if investments are made in the first stage, some SMPs may reach their service life before the end of the planning horizon. We assume that the replacement would be installed immediately at the end of an SMP's service life and the average cost-effectiveness would remain unchanged throughout the planning horizon. This allows us to model the investment problems as a two-stage programming (now and later) to avoid the curse of dimensionality. The replacement problem can be a future direction, but it is beyond the scope of this paper.

3.2.2. The Objective – Maximizing Expected Annual Stormwater Reduction

The objective (f) is the expected annual stormwater reduction as shown in Eq. 2, where $\mathrm{E}[C_I]$ is the vector of the expected values of the SMPs' annual stormwater reduction per \$ investment based on our current understanding (i.e., the prior); C_{IBs} and C_{IAs} are the vectors of our prediction on the SMPs' expected performance for basic learning and advanced learning, respectively (i.e., the posteriors); D_I and D_{II} are fractions representing the average loss of the SMPs' capacity in stormwater reduction in the first stage and the second stage, respectively; and $T_I$and T_{II} are the time horizons of the first and second stages, respectively.

$$Max\ f = \frac{T_I}{T_I+T_{II}} \mathrm{E}[D_I C_I] x_I + \frac{T_{II}}{T_I+T_{II}} (E[D_I D_{II} C_I] x_I + E[D_{II}(C_I x_{IINs} + C_{IBs} x_{IIBs} + C_{IAs} x_{IIAs})]) \quad (2)$$

Multiplying the objective by the planning horizon ($\frac{1}{T_I+T_{II}}$), we can get the annual average stormwater reduction over that time period. That is, the objective is essentially to maximize the total stormwater reduction over the planning horizon. As a result, deferring investments to the second stage would mean an opportunity cost is incurred, in the form of giving up of stormwater reductions for the years in the first stage. Another way to interpret the objective is to view $\frac{T_{II}}{T_I+T_{II}}$ as a discount factor for the worth of future benefits. This formulation allows the user to manipulate the values of T_I and T_{II} and assess how the decisions change with the discount factor.

3.2.3. Learning Constraints

Eqs. 3 and 4 are the constraints for modeling the investment – learning relationship, where $Th^{BL}_{(i,j)}$ and $Th^{AL}_{(i,j)}$ are the learning thresholds of SMP i at subcatchment j for basic learning and advanced learning, respectively; $L_{NL,(i,j)}, L_{BL,(i,j)}$, and $L_{AL,(i,j)}$ are binary variables that indicate whether learning happens or not; and M is an arbitrarily large number (e.g., 10^8).

$$\begin{cases} (a): L_{N,(i,j)} + L_{B,(i,j)} + L_{A,(i,j)} = 1 \\ (b): -x_{I,(i,j)} + Th^{AL}_{(i,j)} L_{A,(i,j)} \leq 0 \\ (c): x_{I,(i,j)} - M L_{A,(i,j)} \leq Th^{AL}_{(i,j)} \\ (d): x_{I,(i,j)} - M\big(L_{B,(i,j)} + L_{A,(i,j)}\big) \leq Th^{BL}_{(i,j)} \\ (e): -x_{I,(i,j)} + Th^{BL}_{(i,j)}\big(L_{B,(i,j)} - \sum_{k \in Sub, k \neq j} L_{A,(i,k)}\big) \leq 0 \\ (f): L_{A,(i,j)} - L_{A,(i,k)} - L_{B,(i,k)} \leq 0\ ,\ k \in Sub, k \neq j \end{cases} \quad , \forall i \in SMP, j \in Sub$$

(3)

$$\begin{cases} x_{IINs,(i,j)} - ML_{NL,(i,j)} \leq 0 \\ x_{IIBs,(i,j)} - ML_{BL,(i,j)} \leq 0 \\ x_{IIAs,(i,j)} - ML_{AL,(i,j)} \leq 0 \end{cases} \quad , \forall i \in SMP, j \in Sub \text{ and } \forall\ s \in S_I \tag{4}$$

The constraints of Eq. 3 forcing only one of the situations (NL, BL, and AL) can happen to an SMP, based on the first-stage investment. The corresponding binary learning variable would be set to 1, and the rest would remain 0. In addition, as discussed in Section 3.1.1, we assume that for an SMP i in the subcatchment j, if AL happens, it will also update the cost-effectiveness distribution of SMP i in other subcatchments with BL. This transferrable learning is modeled as Eq. 3(e) and 3(f).

Once we know which case (NL, BL, or AL) we are in, the corresponding second stage decision variables would be activated (allows to be non-zero), and the decision variables of other situations would be set to 0 (Eq. 4).

3.2.4. Risk Metric

The risk matric applied in this formulation is the conditional value at risk (CVaR). The CVaR value of a random variable, *f*, is the expected value of the left tail below the value of the α-th quantile, denoted $CVaR_\alpha(f)$, and the value at the α-th quantile is called the value at risk (VaR), denoted $VaR_\alpha(f)$. For example, a $CVaR_{0.1}(f)$ value of 1-million-ton stormwater reduction means that the average of the lowest 10% outcomes is 1 million tons. Therefore, a higher CVaR value is more desirable. More discussion of this risk metric and its mathematical properties is available in Artzner et al. (1999) and Rockafellar & Uryasev (2000). The mathematical definitions of VaR and CVaR are as follows.

VaR: VaR_α(f) = ArgMin_y $\{ Prob(f \leq y) \geq \alpha\}$

CVaR: $CVaR_\alpha(f) = \frac{1}{\alpha}\int_0^\alpha VaR_t(f)dt$

We adopted the method proposed by Krokhmal et al. (2001) for our formulation, where the CVaR can be calculated using linear constraints in an optimization. The method is based on discretizing the random distributions by drawing sample sets. Each sample set represents a scenario with probability *1/m*, where *m* is the number of the sample sets.

The mathematical formulation is as follows.

$$\begin{cases} z_{s,r} \geq \tau - f_{IIs,r}, \forall s \in S_I, r \in S_{II} \\ \tau - \frac{1}{\alpha * m_I m_{II}} \sum_{s=1}^{m_I} \sum_{r=1}^{m_{II}} z_{s,r} \geq CVaR_\alpha\ , \end{cases} \tag{5}$$

$$f_{IIs} = D_{Is}C_{Is}x_I + D_{IIs}(D_{Is}C_{Is}x_I + C_{IINs,r}x_{IINs} + C_{IIBs}x_{IIBs} + C_{IIAs,r}x_{IIAs}), \forall s \in S_I, r \in S_{II} \tag{6}$$

where $z_{s,r}$ is the auxiliary variable for CVaR calculation, τ is a variable representing VaR_α, $f_{IIs,r}$ is a linear objective function with the coefficient set equal to the sample set of cost-effectiveness values in scenario (*s,r*), and $CVaR_\alpha$ is the target CVaR value specified by the user (i.e., the least acceptable outcome having a chance of α).

3.2.5. Total Budget and Impervious Area

We assume a total budget (denoted *B*) in the study area for the 25-year planning horizon. The impervious areas of the three subcatchments are divided into the ground (*60%*) and roof (*40%)*

areas, which is approximated by visual inspection and randomly sampling points on the aerial photographs on Google Map. These numbers could be updated if further information is available for the sewershed. Eq. 7 is the total budget constraint; for each scenario, this limits the sum of annual expenditures *x* on each SMP within each subcatchment over the time horizon to *B*. Eqs. 8 and 9 are the constraints imposed by the amount of impervious surface of the ground and rooftop area, respectively, upon the amounts of SMP investment of each type that can be made. The notation includes the following: $G = \{RG, IT, PP\}$ is the set of the ground SMPs; $R = \{RB, GR\}$ is the set of the roof SMPs; $T_{A,(i,j)}$ is drainage area ratio; $E_{c,(i,j)}$ is the prior expected cost per m^2 per year of SMP i at subcatchment j; and $A_{G,j}$ $A_{R,j}$ are the total impervious surface area and total impervious roof area, respectively, in subcatchment j.

$$\sum_{i\in SMP}\sum_{j\in Sub}\{(T_I+T_{II})x_{I,(i,j)}+T_{II}(x_{IINs,(i,j)}+x_{IIBs,(i,j)}+x_{IIAs,(i,j)})\}-B\le 0, \forall s\in S_I \quad (7)$$

$$\sum_{i\in G}\frac{T_{A,(i,j)}}{E_{c,(i,j)}}(x_{I,(i,j)}+x_{IINs,(i,j)}+x_{IIBs,(i,j)}+x_{IIAs,(i,j)})-A_{G,j}\le 0,\ \forall j\in Sub, s\in S_I \quad (8)$$

$$\sum_{i\in R}\frac{T_{A,(i,j)}}{E_{c,(i,j)}}(x_{I,(i,j)}+x_{IINs,(i,j)}+x_{IIBs,(i,j)}+x_{IIAs,(i,j)})-A_{R,j}\le 0,\ \forall j\in Sub, s\in S_I \quad (9)$$

4. Results and Discussion

In this section, we describe tradeoffs between the three objectives–total stormwater reductions, total cost, and risk–by changing constraints on two of the objectives (budget and CVaR/risk) and noting their effect on the optimal decisions and resulting stormwater reductions. Increasing the budget gives us an estimate of the incremental cost of stormwater reductions using GI, while increasing the risk target will show how becoming more averse to the possibility of particularly bad stormwater performance has a cost in terms of worsening the expected (probability-weighted) performance. As we will show, changing the risk target favors different SMPs, and affects the attractiveness of investment in learning and deferring investment until more is known about the performance of SMPs.

4.1. Effect of the Budget on Stormwater Reductions, Optimal GI Investment Mix, and Learning

In order to focus on cost-expected stormwater reduction tradeoffs, we first did a series of runs with the CVaR constraint dropped from the model. Section 4.2, which follows, instead explores how changing our risk tolerance, as measured by the CVaR constraint, affects the results.

We solved the model forty times with a range of budgets for the 25-year planning horizon, varying from \$0.08 billion to \$3.2 billion. The impacts on decisions and stormwater are organized in Figure 4. Part (a) shows how investments allocated among subcatchments, (b) shows the investments grouped by SMP type (the left *y*-axis) and how much they reduce expected annual runoff (the right *y*-axis), (c) shows how investment commitments are divided between the first and the second stages, and (d) is an enlargement of (b) providing more detail on how investments are allocated among SMP types.

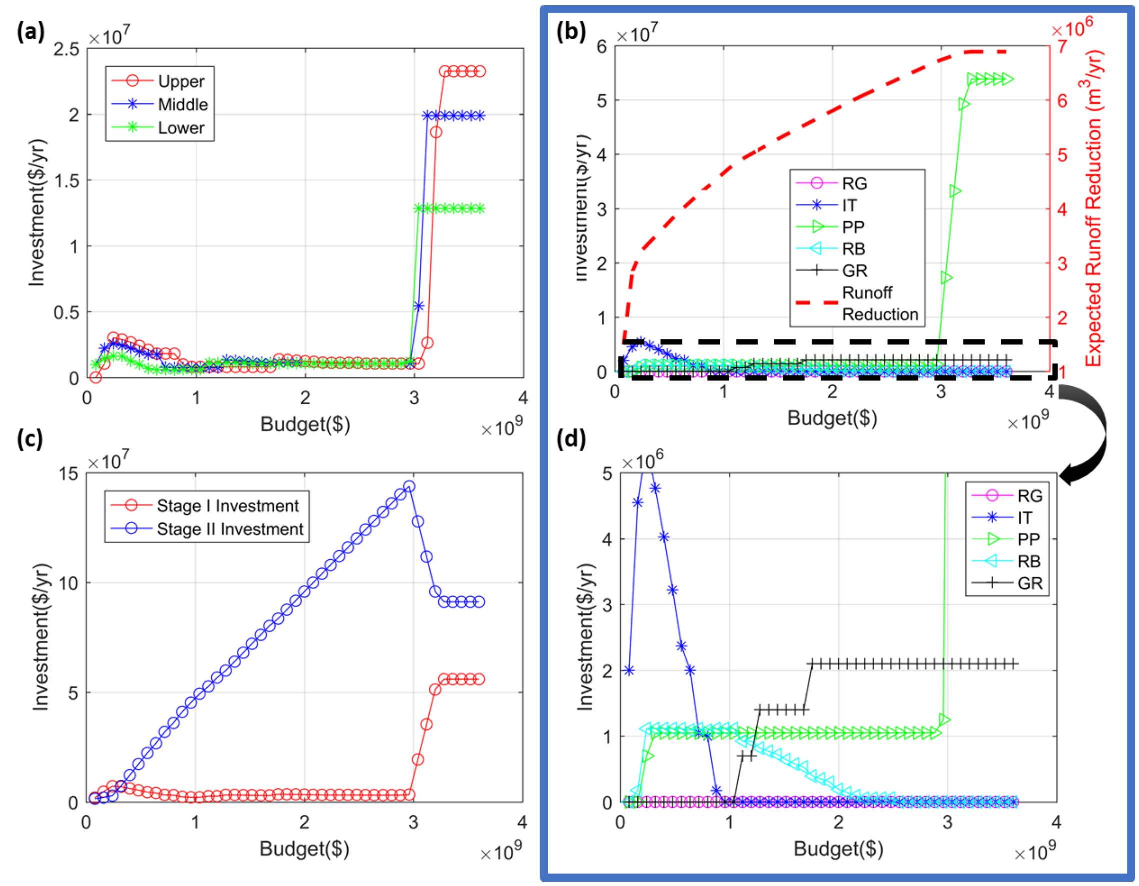

Figure 4. First stage investments as a function of budget; (a) optimal GI investment allocations among three subcatchments; (b) the objective (expected annual stormwater runoff reduction; red dashed line, right y-axis [from 1 million m^3/yr to 7 million m^3/yr]) and the optimal GI investment allocations among SMPs (solid lines, right left y-axis), (c) split of the budget between investments in the first and second stages, and (d) expanded view of the optimal GI investment allocations among the SMPs

Generally, the results show strongly diminishing returns as the budget is increased (Figure 4b). Of the total possible reduction of 6.9 million m^3/yr that can be achieved by spending \$3.6 billion, one-quarter of that reduction can be achieved by spending just over \$100 million, while one-half requires only \$300 million. This is because the most cost-efficient SMP types (IT and RB) are installed first until all impervious area is treated. Then, if extra money is available, the optimal solution is to replace some low-cost SMPs with more expansive and higher reduction SMPs or to invest for learning. As a result, the expected stormwater reduction gradually flattens as the marginal stormwater reduction per dollar investment diminishes. Figure 4 also shows that expanding the budget changes the decisions in several specific respects: in terms of location, technology choice, timing, and emphasis on learning to improve technologies. We discuss each in turn below. In addition to numerical results, some general relationships are established as to when particular strategies are best.

4.1.1. Location: Does It Matter Where the GI Go?

In Figure 4a, we can see that when the total budget is low ($0.08 billion, the leftmost point in Figure 4a), the optimal first-stage investment portfolio is to invest in Middle and Lower subcatchments for $10 million/yr each (both are investments in IT from Figure 4b) because of the low SMP costs in those locations. As more money becomes available, the Upper subcatchment starts to receive IT investment. When the budget is low (< $0.16 billion, the second point from the left in Figure 4a), early investment in the most cost-efficient SMP (IT) provides the highest expected stormwater reductions, since there will not have much money left to make investments to improve planning even if learning happens (Figure 4c). For the same reason, we can see that with the total budget reaches $3.0 billion, first stage investment suddenly increases, first in the Lower subcatchment and then the Middle and Upper subcatchments. Occasionally, the model may suggest investments in the Upper subcatchment for learning (AL) for its largest impervious area and the higher improvement in expected stormwater reduction. By doing so, the knowledge learned in the Upper subcatchment will be partially transferred to the other subcatchments so that we can also improve the second stage investments in these areas. This effect is most obvious when the budget is between $0.7 and $0.8 billion in Figure 4a.

4.1.2. Technology: Which GI?

From Figure 4d, we can see that increasing the total budget shifts the mix of technologies chosen. For example, under a low budget (≤ $0.16 billion, the first two points from the left in Figure 4d), IT dominates, but as the budget increases (beyond $0.24 billion to $0.9 billion), IT is then displaced by PP. Similarly, investment in RB is emphasized for treating impervious roof area when the budget is low but gradually replaced by GR when the total budget climbs beyond $1.1 billion. As mentioned above, this occurs because the technology with the greatest reduction per dollar is chosen first, even if its overall effectiveness (per unit surface area) is less. But when the budget is large enough such that the watershed's impervious area is fully treated, then further reductions are only possible by replacing technology that is the cheapest in terms of $/unit stormwater reduction with a more costly technology that yields more stormwater reduction per unit area. Among the SMPs, PP and GR have the highest stormwater reduction per treated area (Table 5, "Per ha of Drainage Area") for the ground and roof areas, respectively, as a result of having the highest ratio of storage to total impervious area draining into the SMP. Therefore, when budgets are ample (above $3.2 billion), the optimal solutions consist of PP and GR only.

4.1.3. Timing: Invest All Now, or Invest in Learning and Wait?

From Figure 4b, we can see that the expected stormwater reduction (red dashed line; right y-axis) increases with the increase in the total budget and reaches its maximum (6.9 million-m^3/yr) when the total budget equals $3.2 billion, after which the budget is no longer a limiting factor because no further investment opportunities remain. Under that ample budget (Figure 4b), we can see that the PP investment ($54 million/yr) treats all the impervious ground area in the first stage (invest all now) whereas the GR investment ($2.1 million/yr) is only for advanced learning in the three subcatchments (invest in learning and wait). The PP investment occurs now because that GI has a relatively high deterioration rate and low potential for learning. Consequently, stormwater reductions that could result from potential improvement in its cost-effectiveness (either via reduced costs or increased effectiveness) cannot make up for the loss of the potential stormwater benefits in the first stage. In contrast, GR is the opposite, and waiting for potential cost-effectiveness improvements is well worthwhile.

We can derive a general relationship for determining whether to invest all or to invest just enough for learning in the first stage by calculating the difference in objective value (Eq. 2) of those two strategies. The objective values (expected stormwater reductions) of the two strategies are as follows.

- Invest all now: $\frac{T_I}{T_I+T_{II}}E[D_I C_I]X+\frac{T_{II}}{T_I+T_{II}}E[D_I D_{II} C_I]X$
- Invest just enough for learning in the first stage (AL, in this derivation) and invest the rest in the second stage to exploit the cost-effectiveness improvement:
  $\frac{T_I}{T_I+T_{II}}E[D_I C_I](Th^{AL})+\frac{T_{II}}{T_I+T_{II}}E[D_I D_{II} C_I](Th^{AL})+\frac{T_{II}}{T_I+T_{II}}\mathrm{E}[(D_{IIs}C_{IAs}](X-Th^{AL})$

where X is a vector of fixed investments (not a decision variable), C_I is the prior distribution of SMP cost-effectiveness, Th^{AL} is the investment threshold for AL, D_I and D_{II} are random variables for the performance deterioration in the first and the second stages, respectively, and D_{IIs} and C_{IAs} are random samples drawn from D_{II} and C_I, respectively. If the difference between the two objective values below is positive, then investing now is best:

$$\frac{T_I}{T_I+T_{II}}E[D_I C_I](X-Th^{AL})+\frac{T_{II}}{T_I+T_{II}}E[D_I D_{II} C_I](X-Th^{AL})-\frac{T_{II}}{T_I+T_{II}}\mathrm{E}[D_{IIs}C_{IAs}](X-Th^{AL})>0 \qquad (10)$$

Because we assume independence, the average of $D_{IIs}C_{IAs}$ is the product of the mean of the random variables, D_{II} and C_I, and since $E[C_{IAs}]$ equals $(1+\gamma)E[C_I]$, we can rewrite Eq. 10 as:

$$\frac{T_I}{T_I+T_{II}}E[D_I C_I](X-Th^{AL}) \quad + \quad \frac{T_{II}}{T_I+T_{II}}E[D_I D_{II} C_I](X-Th^{AL})>\frac{T_{II}}{T_I+T_{II}}E[D_{II}](1+\gamma)E[C_I](X-Th^{AL})$$
(11)

By multiplying both sides of Eq. 11 by ($\frac{T_I+T_{II}}{E[C_I](X-Th^{AL})}$) and reorganizing, we get the following inequality:

$$\frac{E[D_I]}{E[D_{II}]}\frac{T_I}{T_{II}}+E[D_I]-1>\gamma$$
(12)

If Eq. 12 holds, then making the entire investment in the first stage and none in the second stage can reduce more runoff in terms of expectation, otherwise to invest for learning would be optimal. In our specific case, a $3.2 billion budget results in the inequality test being satisfied for PP but not for GR, as shown in Table 8, which explains why the best timing for each of those GIs differs.

Table 8
The Results of the Investment Timing Test of the SMPs (Eq. 12)

	E[$\boldsymbol{D_I}$]	E[$\boldsymbol{D_{II}}$]	$\boldsymbol{T_I}$	$\boldsymbol{T_{II}}$	$\frac{\boldsymbol{E[D_I]}}{\boldsymbol{E[D_{II}]}}\frac{\boldsymbol{T_I}}{\boldsymbol{T_{II}}}+\boldsymbol{E[D_I]-1}$		$\boldsymbol{\gamma_{AL}}$	Major Investment Timing
RG	0.95	0.8	5	20	24.7%	<	30%	Stage II
IT	0.95	0.75	5	20	26.7%	>	20%	Stage I
PP	0.85	0.6	5	20	20.4%	>	20%	Stage I
RB	0.95	0.8	5	20	24.7%	>	10%	Stage I
GR	0.975	0.93	5	20	23.7%	<	30%	Stage II

4.1.4. Learning: When is It Worthwhile to Stimulate Technological Improvement?

In this section's series of model runs, we did not impose the risk constraint, so the jumps in SMP investments (e.g., GR, Figure 4d) are motivated by the potential benefits of learning for improving SMP cost-effectiveness, not for reducing uncertainty. However, the uncertainty in the cost-effectiveness improvement also provides an incentive for the investor to hedge the strategy. This is because the outcome of the first stage investments can be to learn which SMPs will perform better than expected *a priori* (and thus should are attractive for second-stage investment) and which SMPs will perform more poorly (and therefore should perhaps be shunned in the second stage). If there is sufficient potential to learn, then stormwater management investments in the second stage will benefit from the improved SMPs' cost-effectiveness and the knowledge gained about which SMPs will perform better than expected. That benefit can be higher than the foregone stormwater reductions in the first stage resulting from delaying investment.

This effect is illustrated by the increased PP investment in Figure 4d that occurs when the budget expands from \$0.4 to \$0.8 billion. In these cases, the PP investment in the first stage enables the stormwater manager to learn whether PP can reduce more stormwater than IT (both are for ground impervious surface) in the second stage. If that turns out to be the case, the manager can switch to invest in PP at that time, and obtain more stormwater reductions for the dollars spent.

4.2. Effect of Risk Aversion upon Expected Stormwater Reduction Tradeoff and SMP Choices

Based on the above results, the best strategy under a modest budget without a risk constraint is to invest in IT and RB in the first stage. But because those SMPs have some risk of performing more poorly than expected, we anticipate that if risk aversion is considered then this strategy will change to one that has less probability of a poor stormwater performance. This hedging can be accomplished either by diversifying investment in the first stage, or by investing in learning and deferring investment until the second stage when more is known. Tightening the CVaR constraint allows us to calculate how much the strategy shifts as we become more risk averse, and how the expected reduction as well as the risk of poor performance changes. In particular, the model quantifies how much we need to give up in expected stormwater reduction in order to reduce the possibility of poor performance as measured by CVaR.

Therefore, we constrain the model results such that the average of the 10% worst stormwater outcomes (i.e., CVaR with α=0.1) meets or exceeds a stated target, and then vary that target. The total budget is set to \$180 million, which is the amount of money needed to treat all the impervious surfaces with the least-cost SMPs (IT and RB) for the 25-year planning horizon.

The results in Figure 5 summarizes how the investment changes as the CVaR target increased from 2.2 million to 2.74 million m^3/yr of stormwater reduction, which represent 74% to 92% of the overall expected reduction of 2.97 million m^3/yr if there is no CVaR constraint. If the CVaR target is below 2.2 million, the constraint no longer binds, and the optimal investment strategy is the risk neutral strategy – to invest in only IT and RB. The results we show in Figure 5 include: (a) the expected stormwater reduction over the 25-year planning horizon (the right y-axis in Figure 5a) and the optimal mix of first stage SMP investments, (b) the expected stormwater reduction over all years and the expected annual stormwater reduction in just the second stage (the last 20 years, including reductions during that time yielded by both the first and second stage investments), (c) how investments are allocated among the three subcatchments, and (d) how investment is distributed between the first and second stages (years 0-4 and 5-24, respectively). In all the solutions, the full \$180 million budget is completely spent on SMPs.

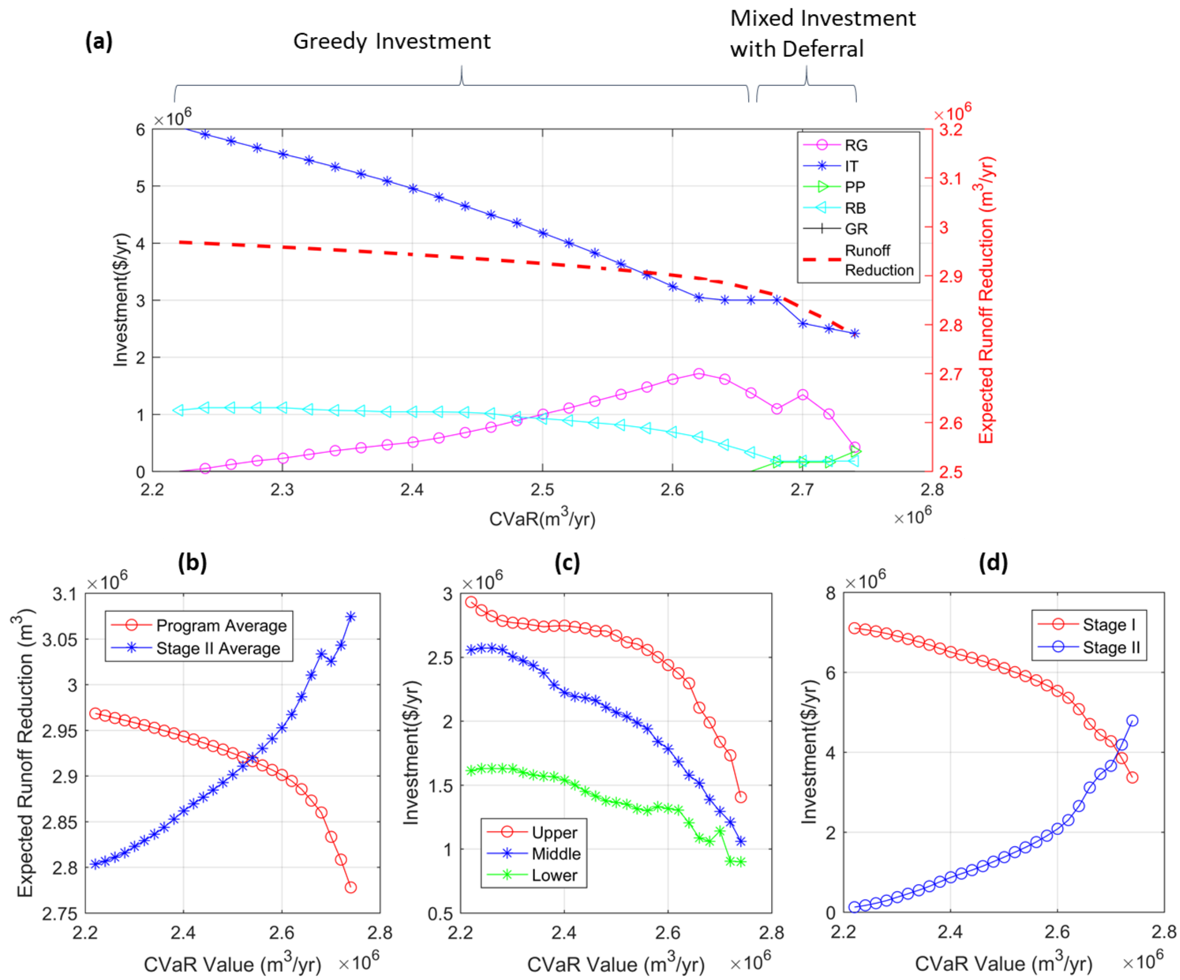

Figure 5. The results of simulations with different CVaR targets: (a) the expected stormwater runoff reduction and the optimal first stage investments; (b) the expected stormwater runoff reduction and the expected runoff reduction in just the second stage; (c) investment allocations among subcatchments; and (d) split of the budget between investments in the first and second stages

We now focus on how investment strategies shift as the manager becomes more risk averse, as represented by an increased CVaR target. Two types of strategies are identified to manage risk, one (which we call the “greedy strategy”) dominating when risk aversion is mild, and the other (“mixed investment with deferral”) being chosen for higher CVaR targets. These two strategies are summarized in Sections 4.2.1 and 4.2.2, respectively.

4.2.1. First Risk-averse Strategy: Greedy Investment (CVaR between 2.2 to 2.6 million m^3/yr)

From Figure 5a, we can see that by changing the composition of the investment portfolio in the first stage, the CVaR value can increase from 2.2 million m^3/yr to 2.60 million m^3/yr (17% increase) with a minimal (0.067 million m^3/yr, or 2.3%) deterioration in the objective value (expected stormwater reduction). We dub this strategy “greedy investment” because the majority of the investment is made right away in cost-effective measures IT, RG and RB (Figures 5a and d). Since RG has a slightly lower standard deviation in its cost-effectiveness and less deterioration in the second stage compared to IT, the investment portfolio shifts to the less risky RG from the riskier IT as the CVaR target increases within this range. Also, a small portion of the investment (about 2 to 20%) is deferred to the second stage as another way or lessening risk.

4.2.2. Second Risk-averse Strategy: Mixed Investment with Deferral (CVaR is between 2.6 and 2.74 million m^3/yr).

A further increase in the risk target from 2.6 million m^3/yr to 2.74 million m^3/yr (representing an increased aversion to poor stormwater reduction outcomes) causes the model to suggest diversifying the mix of first stage investments in RG, IT, PP and RB (Figure 5a). 2.74 million m^3/yr is the highest CVAR value that is achievable under the $180 million budget. It also recommends reducing first stage investment (Figure 5d). This strategy takes advantage of learning in second-stage decisions in order to lower the risk of very poor stormwater reduction outcomes, but at the expense of lower expected stormwater reductions over the entire time horizon.

From Figure 5b, we can see that as the CVaR target increases, the expected stormwater reduction in the second stage (“Stage *II* average”) increases but the objective (“program average”) decreases. This means that much less of the stormwater reduction is happening in the first five years. Moreover, we can see in Figure 5c that the reduction from the first stage investment is most pronounced in the Lower subcatchment. This is because the greater original cost-effectiveness in the Lower catchment means that the learning-based improvement would be worth more in both expected stormwater reduction and CVaR.

Meanwhile, for the most extreme risk aversion (CVaR target = 2.74 million m^3/yr), the investment in PP ($0.35 million) is for advanced learning in the Lower subcatchment. That learning would also provide a basic level of learning for the other subcatchments, so that the investment in the second stage in any subcatchment can provide higher stormwater reduction with lower uncertainty. Under this strategy, there is very little risk, since the CVaR of 2.74 million m^3/yr is very close to the overall expected value of 2.78. Thus, a 6.4% sacrifice in expected value (compared the 2.97 million m^3/yr if there is no CVaR constraint) has increased the expected performance of the 10% worse outcomes by 24.5% (from 2.2 million m^3/yr to 2.74 million m^3/yr).

Finally, Figure 6 shows the histograms of the first and last solutions of our simulations (CVaR = 2.2 million m^3/yr and 2.74 million m^3/yr, respectively) and their CVaR values as examples to illustrate CVaR calculation. We can see that the spread of the greedy investment distribution is wider than the mixed investment with deferral distribution and, therefore, is riskier.

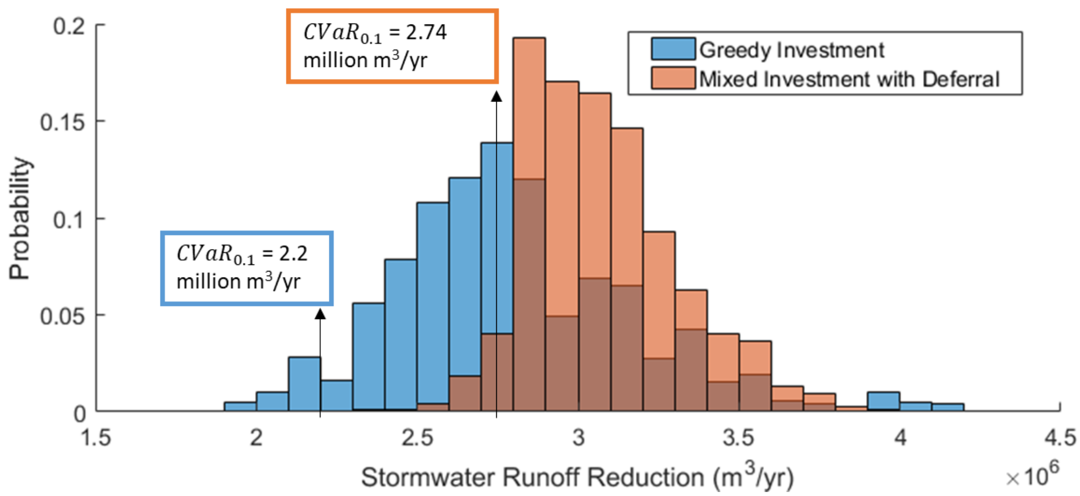

Figure 6. The stormwater reduction distributions of the greedy investment strategy (CVaR = 2.2 million m^3/yr) and mixed investment with deferral (2.74 million m^3/yr)

4.3. The Value of Learning

To justify use of adaptive planning, we can calculate how decisions change and how much the objective improves when we consider learning, compared to a solution chosen without considering learning. Although this calculation can be in terms of any of three objectives (stormwater reduction, cost, and risk), here we use the monetary metric (minimize expected total cost, Eq. 13) to provide a more intuitive comparison. The original objective of the model (expected annual stormwater reduction) is then treated as a constraint in this model (Eq. 14).

Objective: Minimize total cost

$$\sum_{s\in S_I}\sum_{i\in SMP}\sum_{j\in Sub}\{(T_I+T_{II})x_{I,(i,j)}+T_{II}(x_{IINs,(i,j)}+x_{IIBs,(i,j)}+x_{IIAs,(i,j)})\}/m_I \tag{13}$$

Subject to: Expected total stormwater reduction constraint:

$$\frac{T_I}{T_I+T_{II}}\mathrm{E}[D_I C_I]x_I+\frac{T_{II}}{T_I+T_{II}}(E[D_I D_{II} C_I]x_I+E[D_{II}(C_I x_{IINs}+C_{IBs}x_{IIBs}+C_{IAs}x_{IIAs})])\geq ESR \tag{14}$$

where *ESR* is the target for the expected annual reduction over the 25-year life of the program. As a consequence, learning in this case reduces the expected cost of meeting a given stormwater target. To characterize the value of learning, we define and compare three types of decision making: non-adaptive, passive adaptive, and active adaptive:

- **Non-adaptive**: The decision maker recognizes that recourse actions are possible in the future but neglects to consider learning by disregarding any information generated from the first-stage investment when making the subsequent second-stage investment decisions. That is, the prior probabilities are the basis of decisions in the second stage rather than the posterior probabilities. After making a Stage *I* decision, the cost-effectiveness of just those investments is randomly selected; then in Stage *II*, the optimization assumes that the performance of the later investments is also random, with the same distribution and independent of what cost-effectiveness occurred in Stage *I*.

- **Passive adaptive**: The decision maker does not consider learning in making the immediate investment but when learning takes place in stage II, the investment plan is adapted based on what is learned (i.e., based on the posterior rather than prior probabilities).
- **Active adaptive**: The decision maker knows that investments can result in learning, and evaluates first stage investments, fully recognizing the value of what might be learned in the second stage.

To calculate the total cost of the non-adaptive case, we simply set the learning thresholds to a large number (e.g., total budget) so that the model cannot take actions in Stage *I* to learn. For the passive adaptive case, we restrict the model to take just the optimal Stage *I* investment from the non-adaptive case as an additional equality constraint (i.e., $x_I = x_{I,non-adaptive}$). As a result, that model is forced to be ignorant in the first stage but can adapt the investment plan in the second stage based on what has been learned (posterior rather than prior probabilities). Finally, the total cost of the active adaptive case is obtained by relaxing the just-mentioned first-stage investment constraint to allow the model to recognize how first-stage investments might affect the second stage's learning when making first-stage investment decisions.

We define the difference in the objective between the non-adaptive and the passive adaptive cases the **value of adaptivity** and the difference between the passive and the active adaptive cases the **value of learning**. Table 9 shows an example of the calculation of the values with the total expected stormwater (*ESR*) set to 80 million $\mathrm{m}^3$and the minimum annual stormwater reduction after the program ($CVaR_{0.1}$) set to 3 million m^3/yr. The resulting expected total costs are $452 million, $407 million, and $303 million for non-adaptive, passive adaptive and active adaptive cases, respectively.

Table 9

The Calculation of the Value of Adaptivity and the Value of Learning

Unit: $ Million	Objective (Total Cost)	Value of Adaptivity Calculation	Value of Learning Calculation
Non-adaptive	452	452	-
Passive Adaptive	407	-407	407
Active Adaptive	303	-	-303
Sum	-	**+45**	**+104**

The value of adaptivity means that if planning is flexible such that second-stage decisions can adapt to information gained, then second-stage choices will improve, saving $45 million. Whereas the value of learning means that the planning process can save an additional $104 million if first-stage decisions are made by recognizing how such decisions affect learning and how that learning will affect second-stage decisions. Although the definitions of the two values resemble in some respects the well-known concepts of the value of stochastic solutions (VSS) and the value of perfect information (VPI) (Birge, 1982), there are important differences that we blieve are more realistic and useful for decision making. In particular, unlike the calculation of VSS, the non-adaptive solution is also a stochastic solution with recourse but no learning. Further, unlike VPI calculations, the passive and active adaptive solutions only learn imperfect rather than perfect information. This example shows that the adaptive approaches can save 9.7% to 33.0 % of the total cost compared to the non-adaptive solution.

These savings are, of course, case-dependent, varying considerably depending on the prior knowledge about SMP performance, risk aversion levels, and watershed and climate characteristics. Nonetheless, our framework provides a way of evaluating the use of adaptive approaches while managing the risk of failing to meet management goals. The intent is to lessen the barriers that uncertain performance present to adoption of GI.

5. Summary and Conclusion

We propose an adaptive management framework for GI evaluation and investment planning that consists of technology efficacy assessment, optimization, and risk characterization and management. The assessment of individual SMP cost-effectiveness involves cost estimation, use of hydrologic modeling to account for each SMP's stormwater reduction capacity, and consideration of performance deterioration as investments age. The methodology's goal is not to provide highly precise results for detailed design, as data for calibration and validation often not available. Rather, the intent is to provide insights on the magnitude of uncertainties and the value of adaptation and learning in GI planning.

We rely on EPA SWMM to assess the SMPs' efficacy in reducing stormwater runoff because of its GI functionality and its wide use in urban stormwater management. By applying Monte Carlo methods, the SWMM hydrological simulation can be used to characterize the uncertainty of the SMPs' capabilities to control stormwater. Although our SWMM parameter calibration relies on values from the literature and expert judgment rather than field validation, the results generated from this method are traceable and are consistent among the SMPs of interest.

Our estimates of uncertainty in capital and maintenance costs and performance deterioration also rely on expert opinion and the literature. These estimates are combined with the results of SWMM simulations to calculate the SMPs' cost-effectiveness (in m^3/\$/yr). The results are then used in the adaptive GI investment model, which is structured as a decision tree. The decision tree includes prior probabilities that feed into first-stage decisions (year 0). Those first-stage ("here-and-now") decisions result in learning while second-stage (year 5, "wait and see") decisions take advantage of that learning to adjust the mix of GIs. The learning consists of updated probabilities (posterior) based on opportunities to learn from experience (investment) as well as learning curve-type uncertainty reductions and performance improvement.

The adaptive GI investment model is solved using two-stage stochastic programming. The objective that is maximized is the probability-weighted stormwater reduction. This maximization is subject to constraints on two other objectives: an upper limit to the amount spent over the time horizon, and a lower limit on stormwater reduction under the worst possible outcomes of the uncertain variables, quantified as the Conditional Value at Risk ($CVaR_{\alpha}$).

The study area is the Wingohocking sewershed in Philadelphia, Pennsylvania, which we divide into three subcatchments to capture the spatial variability of sewershed characteristics. The modeling results presented in Section 4 show how the framework can be used to develop investment strategies and provide the economic justification of the adaptive approach (*value of learning*). In the first modeling experiment (Section 4.1), we show how decisions to invest immediately or wait until the second stage depend on how much is learned, and whether that learning would affect later decisions. We also see that as the total budget increases, the optimal investment portfolio would change in one or more of three ways (Figure 4): diversification of types of GIs at intermediate budget levels (*hedging*), switching from the most cost-efficient SMPs to the SMPs with a higher stormwater reduction per treated area (*technology switch*), and, eventually, increased first-stage investment in order to learn (*learning for stimulating technology improvement*).

In the second modeling experiment (Section 4.2), we identified two strategies that are resorted to as the manager becomes more risk averse. Under a moderately stringent CVaR constraint, a *greedy investment* strategy is adopted. It devotes most of its investment to SMPs with the highest expected stormwater reduction in the first stage, and the remainder is either invested immediately in other SMPs or deferred until the second stage in order to manage risks. A more risk averse manager would specify a higher CVaR lower bound, which yields a *mixed investment with deferral strategy*. That strategy improves the CVaR value by deferring major investments to the second stage, investing mainly for learning in the first stage. The result is a pronounced tradeoff between the expected performance objective and CVaR, in which the CVaR value can be increased from 2.2 million m^3/yr to 2.74 million m^3/yr stormwater reduction at a cost of sacrificing 6% expected stormwater reduction objective.

The final experiments quantify the economic values of adaptivity and learning. These can inform stormwater manager about how performance can be improved by adaptive management, and the tradeoffs between costs and benefits of deliberate learning through research and monitoring (Walters, 1997; Williams, 2011). If the net value of learning is positive (its benefits exceed its cost), the stormwater manager should consider options for learning when planning, which may result in investments in diversification, monitoring, or deliberate experimentation. The value of adaptivity, on the other hand, represents the expected total cost saving by recognizing and taking advantage of flexibility to modify plans over time in response to changing circumstances. The decision tree/stochastic programming framework we propose can quantify these values, which are considerable in our GI case study.

Future research can make our adaptive GI investment model more realistic and more reflective of long-term costs by, for instance, considering how the dynamics of maintenance and deterioration affect decisions concerning SMP renovation or replacement in later stages. Consideration should also be given to additional objectives of GI planning, such as the “ancillary benefits” of energy savings, environmental amenities, and heat island mitigation(CNT, 2009).

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