WATERSHED-SCALE LIFE CYCLE ASSESSMENT OF RAINWATER HARVESTING SYSTEMS TO CONTROL COMBINED SEWER OVERFLOWS

by

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STATEMENT OF DISSERTATION APPROVAL

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ABSTRACT

Controlling combined sewer overflows (CSOs) is one of the greatest urban drainage challenges in more than 700 communities in the United States. Traditional drainage design typically leads to centralized, costly and energy-intensive infrastructure solutions. Recently, however, application of decentralized techniques to reduce the costs and environmental impacts is gaining popularity. Rainwater harvesting (RWH) is a decentralized technique being used more often today, but its sustainability evaluation has been limited to a building scale, without considering hydrologic implications at the watershed scale. Therefore, the goal of this research is to study watershed-scale life cycle effects of RWH on controlling CSOs. To achieve this goal, (i) the life cycle costs (LCC) and long-term hydrologic performance are combined to evaluate the cost-effectiveness of control plans, (ii) the life cycle assessment (LCA) and hydrologic analysis were integrated into a framework to evaluate environmental sustainability of control plans, and (iii) the major sources of uncertainty in the integrated framework with relative impacts were identified and quantified, respectively. A case study of the City of Toledo, Ohio serves as the platform to investigate these approaches and to compare RWH with centralized infrastructure strategies. LCC evaluation shows that incorporating RWH into centralized control plans could noticeably improve the cost-effectiveness over the life cycle of drainage infrastructure. According to the results of the integrated framework, incorporating RWH could reduce Eco-toxicity Water (ETW) impacts, but caused an increase in the

Global Warming Potential (GWP). In fact, incorporating RWH contributes to avoidance of untreated discharges into water bodies (thus reducing ETW) and additional combined sewage delivered to treatment facilities (thus increasing GWP). The uncertainty analysis suggests that rainfall data (as a hydrologic parameter) could be a significant source of the uncertainty in outputs of the integrated framework. Conversely, parameters of LCIA (life cycle impact assessment) could have trivial impacts on the outputs. This supports the need for robust hydrologic data and associated analyses to increase the reliability of LCA-based urban drainage design. In addition, results suggest that such an uncertainty analysis is capable of rendering optimal RWH system capacity as a function of annual rainfall depth to lead to minimized life cycle impacts. Capacities smaller than the optimal size would likely result in loss of RWH potable water savings and CSO control benefits, while capacities larger than optimal would probably incur excessive wastewater treatment burden and construction phase impacts.

I dedicate this dissertation to my parents, my brother and to my best friend for their unconditional love.

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CHAPTER 1

INTRODUCTION

Stormwater runoff and sanitary sewage in more than 700 communities (about 40 million people in total) located in the North Eastern, Pacific Northwest and Great Lakes regions of the United States are transmitted together by combined sewer systems to treatment facilities (U.S. EPA 2008). For many of these communities, controlling combined sewer overflows (CSOs) is one of the greatest drainage challenges (U.S. EPA 2014a). During wet weather, treatment or conveyance systems might be overwhelmed by stormwater entering the combined sewers. This condition leads to point source discharges of diluted sewage directly into adjacent water bodies in order to relieve the system (U.S. EPA 2014a). Referred to as combined sewer overflows (CSOs), these discharges contain domestic, commercial, industrial, and stormwater pollution. They may cause serious environmental problems, such as contamination of drinking water supplies, occasional fish kills, beach closures, and aesthetic degradation (Figure 1.1) (U.S. EPA 1999; Alliance for the Great Lakes 2012; U.S. EPA 2014a). To eliminate these impacts, U.S. communities have been mandated by the Clean Water Act amendment (2000) to design and implement appropriate drainage plans. Designing economically and environmentally sustainable control plans is of a great concern for the CSO communities, many of which are still

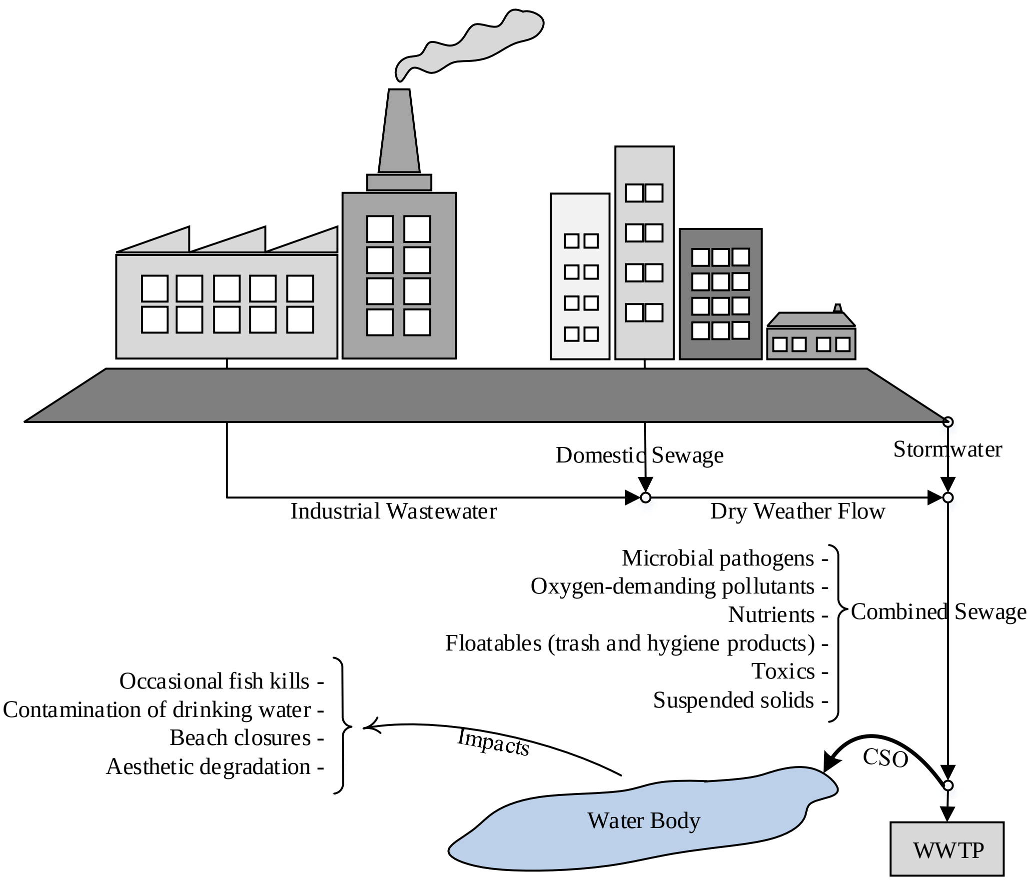

Figure 1.1. Pollutants of combined sewage and environmental impacts of CSOs to receiving water bodies.

evaluating the feasibility of different control alternatives (U.S. EPA 2014a). Meanwhile, around 3.2 billion cubic meters of CSOs taint U.S. water bodies every year on average (U.S. EPA 2004).

1.1 Background

Designing sustainable urban water infrastructure according to economic and environmental criteria is a new area of study in urban water management. Traditional design approaches rely on hydrologic considerations (Guo 2001; Haan et al. 1994; Hsu et al. 2000), which typically lead to centralized infrastructure solutions. Historically, as urbanization has intensified the demand for urban water infrastructure, several centralized measures are taken (Burian et al. 1999; Burian et al. 2000). The higher pace of urbanization growth in comparison with the development potential of centralized water infrastructure (American Rivers 2014; Carruthers 2003; Coyne 2003; Natural Resources Defense Council 1998) is urging the urban water managers to use decentralized infrastructure in recent decades (Montalto and Rothstein 2008). Subsequently, application of sustainability evaluation methods, e.g. life cycle costs estimation (LCC) and life cycle assessment (LCA), is gaining popularity to quantify the benefits of decentralization for urban water infrastructure (Zhou 2014).

Hydrologic analysis in traditional urban drainage design is limited to the operation phase and may represent different development scenarios (Lucas 2010; Shadeed and Lange 2010). LCC and LCA can provide a complement to hydrologic analysis for supporting more holistic decisions with regard to sustainability criteria. As illustrated in Figure 1.2 with a tripod schematic, LCC and LCA can assist in achieving urban water designs being sustainable in terms of economic and environmental criteria. A balanced tripod (shown with the balancer bubble located in the middle of gage) conceptually represents an economically and environmentally sustainable design for water infrastructure. However, the literature of LCA applications for urban water infrastructure analysis is limited to building-scale infrastructure, without considering the hydrologic implications at the watershed scale (Devkota et al. 2015; Ghimire et al. 2014; Malinowski et al. 2015; Morales-Pinzon et al. 2015; Vargas-Parra et al. 2013; Vieira et al. 2014; Vineyard et al. 2015). Building-scale analyses often lead to policies that are useful for a developer or facility manager, but limited when considering watershed-scale impacts. Policies may be

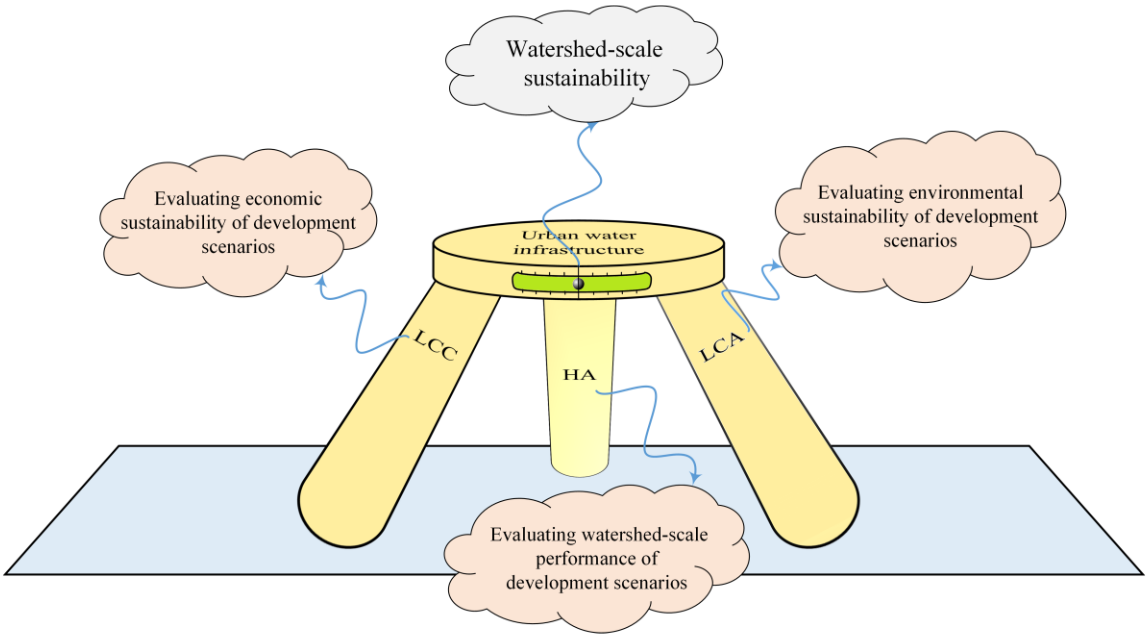

Figure 1.2. A tripod schematic that conceptually illustrates the contribution of LCC and LCA to hydrologic analysis (HA) for achieving a watershed-scale sustainable design. A balanced tripod, shown with the balancer bubble in the middle of gage, represents a sustainable design according to economic and environmental criteria.

different in case of dealing with broader systemic impacts and benefits in an urban watershed. The concern stems from the inefficiencies of building-scale analyses to be extrapolated to the watershed, and to be considered in terms of their interconnection to watershed-scale hydrologic, hydraulic, economic, and environmental processes for different locations.

Thus, given the large number of watershed-scale LCC studies in the literature, developing a study framework to integrate hydrologic analysis and LCA criteria seems to be of a higher priority. Such a framework may assist in appropriately informing LCA to reflect system operation at the proper time-space scales over a life cycle of a drainage infrastructure. Performing hydrologic analyses while defining appropriate LCA system boundaries, functional units and life cycle inventories requires an interdisciplinary study.

Given the fact that few studies have carried an interdisciplinary vision on the issue, there still remains uncertainty about the sustainability benefits of decentralized approaches for urban water management, although decentralization is taking place in practice. A critical need remains to continue advancing approaches to effectively integrate hydrologic analysis and LCA. These advancements would help to compare centralized and decentralized urban water management approaches, and to design hybrid systems that maximize benefits.

Improving the comprehension of uncertainty and its impacts on urban drainage design may provide insight into effective ways of integrating hydrologic analysis and LCA. Life cycle impact assessment (LCIA) data are subject to uncertainties from several sources, depending on the quality of the data (Yoshida et al. 2014). Use of hydrologic data amplifies the uncertainty because these data introduce natural variability and thus additional uncertainty that cannot be reduced by more measurements. Reporting LCA results may be misleading if potential sources of uncertainty are not addressed, especially in the case of comparing design alternatives for decision making (Baker and Lepech 2009; U.S. EPA 2014b). Consequently, identifying major sources of uncertainty with their relative impacts on final LCA results is indispensable (Cowell et al. 2002; Harder et al. 2015; Huijbregts 1998a,b) for effective integration of hydrologic analysis and LCA for sustainable, watershed-scale design of urban drainage systems.

1.2 Research Goal and Scope

This research investigates watershed-scale sustainability benefits of decentralized CSO control infrastructure in terms of economic and environmental criteria, and compares them with centralized solutions. The goal is to contribute to advancing the capacity of designing decentralized CSO control infrastructure at a watershed scale in order to promote urban sustainability. A particular outcome of this study is to present a framework merging hydrologic and LCA criteria into the sustainability evaluation of urban water infrastructure, considering sources and effects of uncertainty. This framework constitutes the main contribution of the present research to the body of urban infrastructure sustainability literature, including those describing uncertainty studies.

Rainwater harvesting (RWH) is selected in the scope of the present research as the decentralized infrastructure. This selection is related to the unique capability of RWH to supplement water demand, attracting a widespread interest and emphasizing the need to further consider sustainability. A case study of the City of Toledo, Ohio serves as the platform to conduct the research due to its noticeable CSO discharges to the Great Lakes of the U.S. This city is the fifth highest CSO contributor to the lakes among all the U.S. cities surrounding the Great Lakes, yet there have been no studies on decentralized CSO control infrastructure for this city. Additional information about RWH applications and the study area is presented in Chapter 2.

1.3 Research Questions and Hypotheses

Following the research goal and scope, three research questions are formulated to guide the study, each of which includes a testable hypothesis.

1.3.1 Research Question 1

- What is the relative benefit and threshold of impacts of RWH in terms of life cycle costs and performance, when used as a supplement to centralized CSO control infrastructure in Toledo?

$$\mathrm{CPR}_{\mathrm{Hybrid}} \approx \mathrm{CPR}_{\mathrm{Centralized}} \qquad \text{(Hypothesis 1)}$$

where CPR is a proposed metric denoting the life cycle costs per reduced one unit volume of CSOs. The lower the CPR for a scenario, the higher the desirability for that scenario in terms of cost-effectiveness over its life cycle. This metric is calculated for each control scenario separately. Hypothesis 1 assumes that a hybrid RWH-centralized plan does not noticeably improve the cost-effectiveness compared to a solely centralized scenario. For making a general rule out of this hypothesis, several test cases in different locations with various system specifications have to be evaluated. However, if Hypothesis 1 is rejected for the case of Toledo by a $\mathrm{CPR}_{\mathrm{Hybrid}}$ noticeably lower than the $\mathrm{CPR}_{\mathrm{Centralized}}$, an interesting area for further investigations into hybrid plans in different regions will emerge. In addition, a comprehensive approach to conduct such studies will be available as the outcome of the present study. A detailed methodology to test this hypothesis is presented in Chapter 2, with discussions on the results. Since financial criteria have a higher importance for stakeholders, studying environmental sustainability in Toledo will be of interest for them only when a lower CPR by hybrid solutions can be achieved in the study area.

1.3.2 Research Question 2

- Can extrapolating the life cycle environmental impacts of RWH from a building-scale to a watershed-scale lead to a reliable decision?

$$\mathrm{LCEI}_{\mathrm{Watershed}}(\mathrm{RWH}) \approx \mathrm{n} \cdot \mathrm{LCEI}_{\mathrm{Building}}(\mathrm{RWH}) \qquad \text{(Hypothesis 2)}$$

where LCEI stands for life cycle environmental impacts as a result of implementing a water infrastructure, such as RWH. $\mathrm{LCEI}_{\mathrm{Watershed}}$ and $\mathrm{LCEI}_{\mathrm{Building}}$ respectively denote the watershed-scale and building-scale LCEI, and n indicates the number of buildings in the watershed that use RWH. Hypothesis 2 assumes that extrapolating the life cycle environmental impacts of RWH, from a building to a watershed, leads to a reliable approximation. Similar to Hypothesis 1, several test cases have to be evaluated before making a general conclusion based on Hypothesis 2. However, if Hypothesis 2 is rejected for Toledo with sufficient proof, the need for developing an integrated LCA and hydrologic analysis framework for this case will be emphasized for this system. Testing this framework for other systems can contribute to the verification of the conclusions drawn for Toledo's case study. A detailed procedure to test this hypothesis with descriptions of results and conclusions are presented in Chapter 3.

1.3.3 Research Question 3

- Can a life cycle assessment of RWH remain reliable if the uncertainties in hydrologic data are neglected?

$$\mathrm{Var}_{\mathrm{Hydrologic\ data}}(\mathrm{LCEI}\ (\mathrm{RWH})) \approx 0 \qquad \text{(Hypothesis 3)}$$

where Var denotes variance (as a basic indicator of uncertainty), and $\mathrm{Var}_{\mathrm{Hydrologic\ data}}$ indicates the contribution of hydrologic data to the variance of a dependent variable.

Hypothesis 3 assumes that for RWH design, the contribution of hydrologic data in the variance of LCEI outputs is negligible. If Hypothesis 3 is rejected, it means an LCA-based design of RWH is contingent upon robust hydrologic data and associated analyses. Testing this hypothesis for various cases is required before generalization. Indeed, the results of testing this hypothesis for Toledo will be valid only for that case. However, these results will provide insight into interesting research areas for future work in the field of LCA-based design of water infrastructure. Chapter 4 comprehensively presents the approach used to test this hypothesis as well as the results, findings, conclusions.

1.4 Research Plan

To direct the flow of the research and organize the efforts to answer the research questions, a conceptual research plan is compiled (Figure 1.3) according to the deficiencies in the literature and possible answers to each question. The research plan consists of several intermediate tasks representing the technical accomplishments that can be achieved through this research. Each of the three major steps illustrated Figure 1.3 corresponds to one research question.

In step (i), appropriate CSO control scenarios are designed based on the available recommendations and existing studies in the area of interest. Then, scenarios are characterized to enable the analysis of life cycle costs and hydrologic performance. After that, CPR is calculated for each scenario, and then scenarios are ranked accordingly. Lastly, conclusions regarding Research Question 1 are provided based on the results and observations.

In step (ii), first, Hypothesis 2 is tested in order to find an appropriate LCA framework

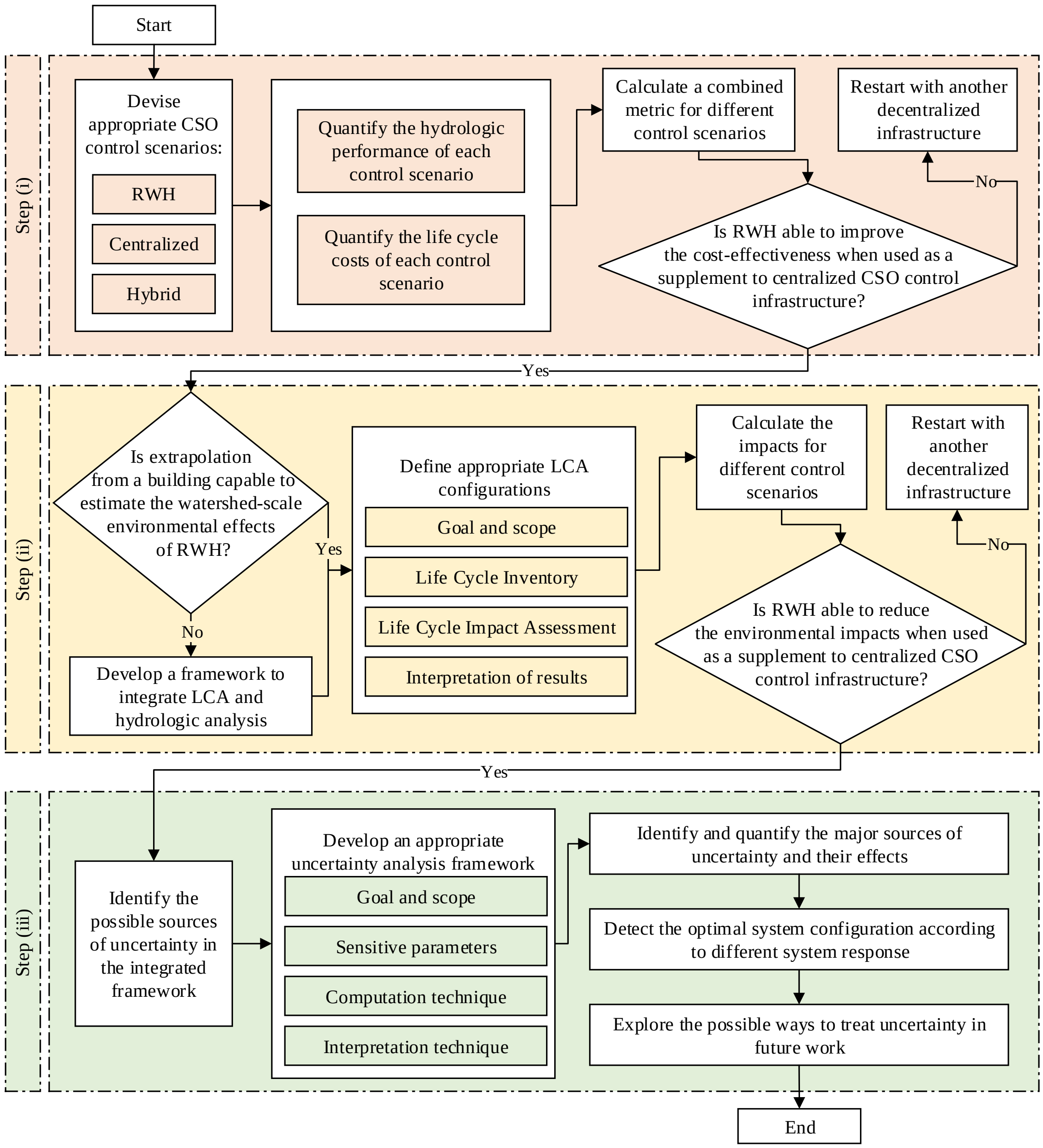

Figure 1.3. Conceptual schematic of the research plan, its three major steps and intermediate tasks.

for comparing CSO control scenarios in terms of watershed-scale life cycle environmental impacts. Only the scenarios that had a satisfactory performance based on the analysis in step (i) are analyzed in step (ii). Lastly, the relative effectiveness of studied scenarios is discussed and major drivers for the observed impacts are explored.

In step (iii), all the possible sources of uncertainty in the framework of the previous step are gathered. Then, using a sensitivity analysis, the sensitive parameters are extracted. Next, an appropriate uncertainty analysis framework with respect to computational and interpretational demands is set up. Lastly, results are analyzed in order to identify the major sources of uncertainty to find an answer for Research Question 3. Furthermore, this step is organized to assist with inferring the optimal system behavior according to its different response identified by the uncertainty analysis.

1.5 Dissertation Outline

Each hypothesis is tested in a separate chapter of the dissertation. The methods and intermediate tasks are briefly presented in this subchapter.

1.5.1 Chapter 2 (Answering Research Question 1)

The goal of this chapter is to compare the implementation of RWH systems to centralized approaches previously designed as a part of the Long Term Control Plan (LTCP). This comparison helps investigate the performance of hybrid solutions to control CSOs in Toledo. Two RWH system capacities, i.e., 2.65 m^3 (700 gal.) and 5.68 m^3 (1,500 gal.), two RWH system functions, i.e., supplying toilet flushing demand and distributed detention (24 h and 48 h release), and two participation rates to RWH plans, i.e., 50% and

100%, are considered. This chapter employs long-term continuous Hydrologic and Hydraulic (H&H) simulations using the US EPA Storm Water Management Model (SWMM) and Net Present Value (NPV) analysis to quantify hydrologic performance and life cycle costs, respectively. Lastly, the CPR metric to calculate the life cycle costs per reduced unit volume of CSOs is presented for each scenario in order to compare them in terms of life cycle cost-effectiveness.

1.5.2 Chapter 3 (Answering Research Question 2)

The goal of this chapter is to present a study of merging hydrologic and LCA criteria into the evaluation of the environmental sustainability of RWH to control CSOs. In this chapter, the scenarios with a satisfactory performance based on analyses in the previous chapter are studied. These scenarios are RHW with 2.65 m^3 capacity for toilet flushing and 5.68 m^3 for distributed detention, both with a 50% participation. In addition, the combination of these scenarios with centralized infrastructure are considered. TRACI (the Tool for the Reduction and Assessment of Chemical and other environmental Impact) method is used for life cycle impact assessment (LCIA). The LCA system boundary includes the operational phases of the WTP and WWTP because both would be affected by RWH. To represent the environmental and water quality impacts caused by the studied scenarios, four impact categories are selected as follows: Global Warming Potential (GWP), Eco-toxicity Water (ETW), Eutrophication Potential (EP) and Ozone Depletion Potential (ODP). At the first step, the results of extrapolating the life cycle environmental impacts of RWH, from a building to a watershed, are compared with an integrated hydrologic-LCA framework. Then, the appropriate framework is used to compare the different scenarios.

1.5.3 Chapter 4 (Answering Research Question 3)

The goal of this chapter is to identify major sources of uncertainty of an environmentally sustainable urban drainage infrastructure design, based on hydrologic analysis and LCA. The uncertainty analysis is intended to characterize and compare relative roles of unreliability, incompleteness, technological difference, spatial and temporal variations in life cycle impact assessment (LCIA) data (model parameters), as well as natural variability in hydrologic data (input parameters). Specifically, this chapter attempts to reconcile model-induced uncertainty versus uncertainty stemming from data. Uncertainties are analyzed using a robust Monte Carlo (MC) simulation approach, performed by High Throughput Computing (HTC) and interpreted by topology-inspired maps based on the Morse-Smale regression. The uncertainty analysis platform is applied to a watershed-scale LCA of RWH to control CSOs. To take the watershed-scale implications into consideration, RWH is simulated to serve for both water supply and CSO control.

1.5.4 Chapter 5 (Conclusion)

This concluding chapter summarizes the author's findings from conducting this research and analyzing the results. Areas for performing future work based on the findings are also presented in Chapter 5.

CHAPTER 2

PERFORMANCE AND COST-BASED COMPARISON OF RAINWATER HARVESTING AND CENTRALIZED INFRASTRUCTURE TO CONTROL COMBINED SEWER OVERFLOWS

2.1 Introduction

Stormwater runoff and sanitary sewage in more than 700 communities (about 40 million people total) located in the Northeastern, Pacific Northwest, and Great Lakes regions of the United States are transmitted together by combined sewer systems to treatment facilities (U.S. EPA 2008). For many of these communities, combined sewer overflows (CSOs) are one of the greatest challenges in meeting water quality standards (U.S. EPA 2014a). During wet weather, wastewater treatment plants (WWTP) or conveyance systems may be overwhelmed by stormwater runoff entering the combined sewers. This condition leads to point discharges of untreated or partially treated sewage to receiving water bodies, i.e., rivers, streams, lakes, or oceans, to relieve the system (U.S. EPA 2004). Since CSOs contain domestic, commercial, industrial, and stormwater pollution (e.g., microbial pathogens, oxygen-demanding pollutants, nutrients, floatables, toxics, and suspended solids), they can cause serious environmental problems and public-health risks, such as shellfish bed closures, occasional fish kills, contamination of drinking water supplies, beach closures, and aesthetic degradation (Alliance for the Great Lakes 2012; U.S. EPA 1999; U.S. EPA 2014a). To mitigate these CSO-caused problems, U.S. communities have been required to design and implement long-term control plans (LTCPs) under the Clean Water Act amendment (2000). However, many communities are still studying cost effectiveness of the alternatives in their LTCPs (U.S. EPA 2014a).

There are four types of CSO control techniques: storage facilities, operation and maintenance, pollution prevention, and collection system controls (U.S. EPA 1993, 2014a). Storage facilities enhance conveyance capacity and manage timing of combined sewage arrival at treatment facilities to coincide with treatment capacity; operation and maintenance techniques improve the existing system and optimize available capacity; pollution prevention practices reduce pollutants entering the system; and collection system controls reduce the volume of stormwater runoff entering the system (U.S. EPA 2014a). This study focuses on storage facilities, operation and maintenance, and collection system controls techniques.

Storage facilities are the most conventionally implemented CSO controls (Montalto et al. 2007; U.S. EPA 2014a). These facilities can store excess combined sewage flows in a reservoir (e.g., tunnels, tanks, or basins) when the WWTP is overwhelmed. A storage tunnel is an attractive option in dense urban areas since they are able to share the storage capacity between many CSO outfalls underneath the urban lands. Another storage technology is storage basins, which can provide attenuation in peak flows and removal of pathogens, solids, floatables, etc. Although it could be less costly than storage tunnels in terms of implementation, it might be very challenging to site storage basins in cities (U.S. EPA 1993). Proper operation and maintenance practices improve the ability of the system to capture wet-weather flows and transport them to the treatment plants. These practices vary from simple physical improvements of the aged system components to devising optimized, real-time operation control plans (Ruggaber 2006; U.S. EPA 1993). Lastly, collection system controls include sewer separation and green infrastructure (GI). Sewer separation is perceived as a highly effective solution because it eliminates the combined sewer overflows (U.S. EPA 1993). Yet, separate stormwater runoff still may transport sediments, bacteria, floatables, and city-surface materials such as metals and oils to the receiving water bodies (U.S. EPA 1993). GI are vegetated or sustainability-based practices, such as rainwater harvesting (RWH), green roofs, bioswales, bioretention cells, and porous pavements, that reduce the amount of stormwater entering the system (American Rivers 2014). GI are a recently devised option to traditional collection system controls termed gray infrastructure. Gray infrastructure is composed predominantly of concrete and steel (thus the gray part of the term) and installed as part of the collection system (U.S. EPA 2014a, b). Generally, costs and energy consumption associated with implementation and operation of GIs are perceived to be lower than gray infrastructure due to GIs' simple structure, small size, and passive operation (U.S. EPA 2014a). However, studies are needed to confirm this for a range of cases and conditions.

Numerous CSO control projects have been implemented in the United States during the last several decades. Primarily, these projects have been based on gray infrastructure approaches, especially those initially implemented. An example of a gray project is the South Boston CSO Storage Tunnel implemented by Massachusetts Water Resources Authority (MWRA). By investing $868 million, this project also included sewer separation and system optimization, and reduced 79% of CSOs compared to the 1988 condition of

12.4 million cubic meters (MCM) of CSO (MWRA 2011). In another gray project, with $2.4 billion investment, the Southeast Michigan Council of Governments (SEMCOG) reduced CSOs by 85% through implementation of storage facilities, improving the sewer system and WWTP, and sewer separation (SEMCOG 2008). Prior to the SEMCOG project (before 1990), more than 113 MCM of CSOs were entering the water bodies each year.

Recently, there has been a tendency to green the previously designed gray infrastructures with GIs (U.S. EPA 2014a). For instance, the District of Columbia Water and Sewer Authority (DC Water) is studying ways to implement a $90 million GI control strategy that addresses 30% of the impervious area (DC Water 2014). The DCWater project will reduce the size of a storage tunnel formerly designed as a part of the LTCP (a $2.6 billion project) to decrease 98% of CSO volume into the Anacostia River by 2018 (DCWater 2011). Seattle Public Utilities is also planning to capture 99% of CSOs through adding storage capacity, optimizing existing infrastructure, and implementing GIs. Since the 1970s, CSO volume has been reduced by around 75.7 MCM through different projects. Preliminary studies on GIs in pilot basins showed that implementation of RWH cisterns, roadside raingardens, and permeable pavement alleys are able to reduce the CSO volume up to 80%. Seattle is currently studying the economical and physical feasibility of a watershed-scale GI plan (Tetra Tech 2010). Many other municipalities in the United States, such as New York, NY; Milwaukee, WI; Pittsburgh, PA; Cincinnati, OH; San Francisco, CA; Portland, OR; Philadelphia, PA; and Kansas City, MO, are exploring the benefits of mixing GIs with the formerly designed gray infrastructures (Behm 2014; City of New York 2014; Landers 2013; Lucas 2010; Montalto et al. 2007; The Pittsburgh Water and Sewer Authority 2014; U.S. EPA 2014a).

Similar to these mentioned cases across the United States, CSOs from the Toledo, Ohio, collection system also need to be controlled, specifically due to their substantial impact on the water quality of the Great Lakes. In 2011, 9% of the combined sewage discharged to the Great Lakes was generated in Toledo (6.4 MCM), hence, this city was ranked the fifth highest CSO volume contributor to the lakes among the nine major U.S. cities surrounding the Great Lakes (Alliance for the Great Lakes 2012). Table 2.1 summarizes the CSO volume generated by the nine major U.S. cities next to the Great Lakes, as well as the details of their gray control plans.

Table 2.2 shows the recent popularity of incorporating GI implementation and the associated lower capital costs for GIs compared to gray techniques. Table 2.2 also indicates that the City of Toledo has not yet considered GIs in its LTCP (although there are few test models of bioswales and pervious concrete sidewalks performed by Brescol et al. 2011). Therefore, there is an urgent need to investigate the potential of GI incorporation into the Toledo CSO control plan, called Toledo LTCP.

Despite the necessity of understanding GI performance in controlling CSOs, there have been only a few studies on this topic. Montalto et al. (2007), for example, studied the cost-effectiveness of investments in GIs (e.g., green roofs, porous pavement, and a constructed wetland) in a CSO interceptor in Brooklyn, NY. The study applied life cycle cost analysis of control scenarios and found that GIs could be a cost-effective solution for public agencies via a subsidy to encourage installation. Although not directly linked to CSO control, several studies have proven GI ability for stormwater control (Damodaram et al. 2010; Khastagir and Jayasuriya 2010, 2011; Mehrabadi et al. 2013; Sample and Liu 2014; Steffen et al. 2013; Vargas 2009; Walsh et al. 2014).

Table 2.1. U.S. cities discharging CSOs to the Great Lakes and their LTCP details for gray infrastructure to control CSO (Adapted from Alliance for the Great Lakes 2012; Behm 2014; City of Toledo 2009b; Detroit Water and Sewerage Department 2011; Northeast Ohio Regional Sewer District 2012).

City (sorted alphabetically)	**Annual CSO Volume (MCM)**	**Future Gray Infrastructures**		
		Type(s)	**Cost per capacity ($/m^3)**	**Year of Operation**
Buffalo	6.6	Interceptor relief sewer, supplemental storage capacity	1,500	2031
Chicago	16.8	Storage tunnel and reservoir, etc.	Under Study	2029
Cleveland	17.0	Storage tunnels and tanks, increase in treatment capacity, etc.	2,523	2019
Detroit	14.7	Storage tunnel, first flush capture basins, disinfection system, etc.	682	2035
Grand Rapids	0.1	Sewer separation, etc.	Under Study	2019
Hammond	6.2	Catch basin, pump maintenance, interceptor improvements	1,754	Under study
Milwaukee	5.7	Increase pump station capacity, tunnel optimization, etc.	Under Study	2035
Rochester	0.3	-	-	-
Toledo	4.4	Sewer separation, transport and storage, tunnel disinfection	1,574	2020

Table 2.2. U.S. cities discharging CSOs to the Great Lakes and their LTCP details for green infrastructure to control CSO (Adapted from Alliance for the Great Lakes 2012; Behm 2014; City of Toledo 2009b; Detroit Water and Sewerage Department 2011).

City (sorted alphabetically)	**Future Green Infrastructures**			**Control level with future infrastructure (%)**
	Type(s)	**Cost per capacity ($/m^3)**	**Year of Operation**	
Buffalo	Rain gardens, pervious pavements, rain barrels, etc.	Under study	2031	97
Chicago	Rain barrels, etc.	Under study	2027	100†
Cleveland	Infiltration basins, green roof, bio-retention, etc.	251	2023	98
Detroit	Downspout disconnection, parking lot bio-swale, tree planting, etc.	Under study	2029	100
Grand Rapids	-	-	-	100
Hammond	-	-	-	Under study
Milwaukee	Rain garden, RWH, green roofs, etc.	460	2035	100
Rochester	green roofs, tree boxes and porous pavements	Under study	Under study	100
Toledo	-	-	-	92

The goal of the study reported in this chapter is to explore the benefits of GIs to control CSO through continuous hydrologic and hydraulic (H&H) modeling and simulation. U.S. EPA Stormwater Management Model (SWMM) (Rossman 2015) is employed for this purpose. Then, the benefits of GI implementation are analyzed and compared to the previously designed gray solution as a part of Toledo's LTCP. Performance of the hybrid integration of green and gray infrastructures is also studied. Suggestions for further improvement are proposed lastly. The following sections explain the approach and results of the study.

2.2 Methodology

2.2.1 Study Area

The City of Toledo's collection system is the study area of this research. This system is located in northwest Ohio, on the western bank of Lake Erie, and at the mouths of the Maumee and Ottawa Rivers. Swan Creek also passes through the city and enters the Maumee River (Figure 2.1). Toledo is ranked fourth in the state of Ohio in terms of population (U.S. Census Bureau 2014), and its collection system serves approximately 340,000 people (City of Toledo 2009b). Toledo, with an average annual precipitation of 85.2 cm and annual high, average, and low temperatures of 16.4, 11.9, and 7.3°C, respectively, follows the typical upper Ohio Valley climate, which can be represented as Koppen group Dfa climate class (U.S. Climate Data 2014). The collection system construction began in the late 1800s. At that time, it had only consisted of underground brick sewers carrying both sewage types (sanitary and stormwater), then emptied directly into the water bodies—like the other growing industrial communities at that time (City of Toledo 2014b). Currently, the Toledo collection system consists of more than 1,600 km of sewers and storage tunnels, and it serves around 310 km^2 of mostly residential and commercial land use (City of Toledo 2009a). The collection system includes legacy combined sewers, which serve 12% of the drainage area (hatched area in Figure 2.2). Separate sewers serve the rest (City of Toledo 2005). The boundaries on Figure 2.2 also represent the city of Toledo limits.

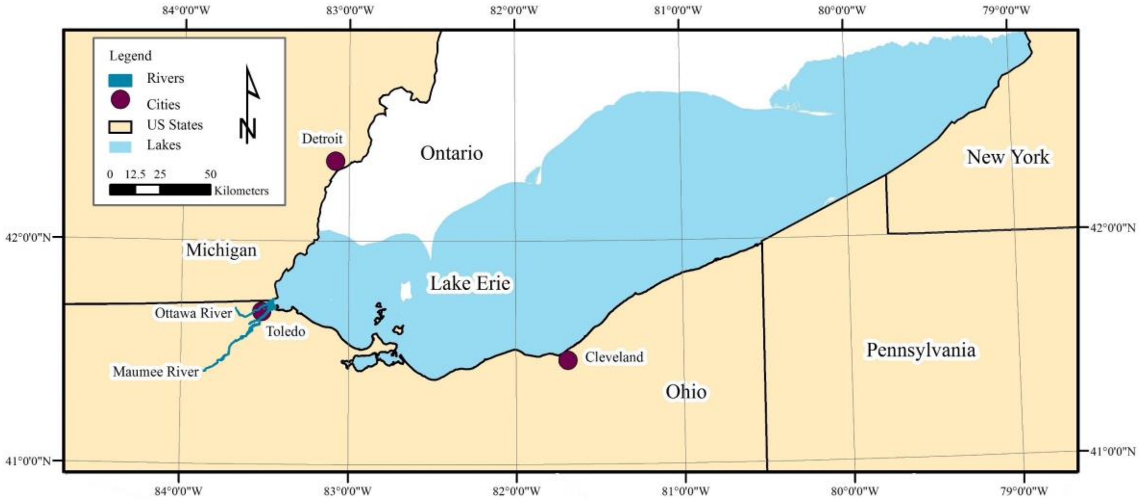

Figure 2.1. Location map of the City of Toledo as well as the rivers passing through it. Data are taken from the Ohio Geographically Referenced Information Program (OGRIP) and Auditors Real Estate Information System (ARIES).

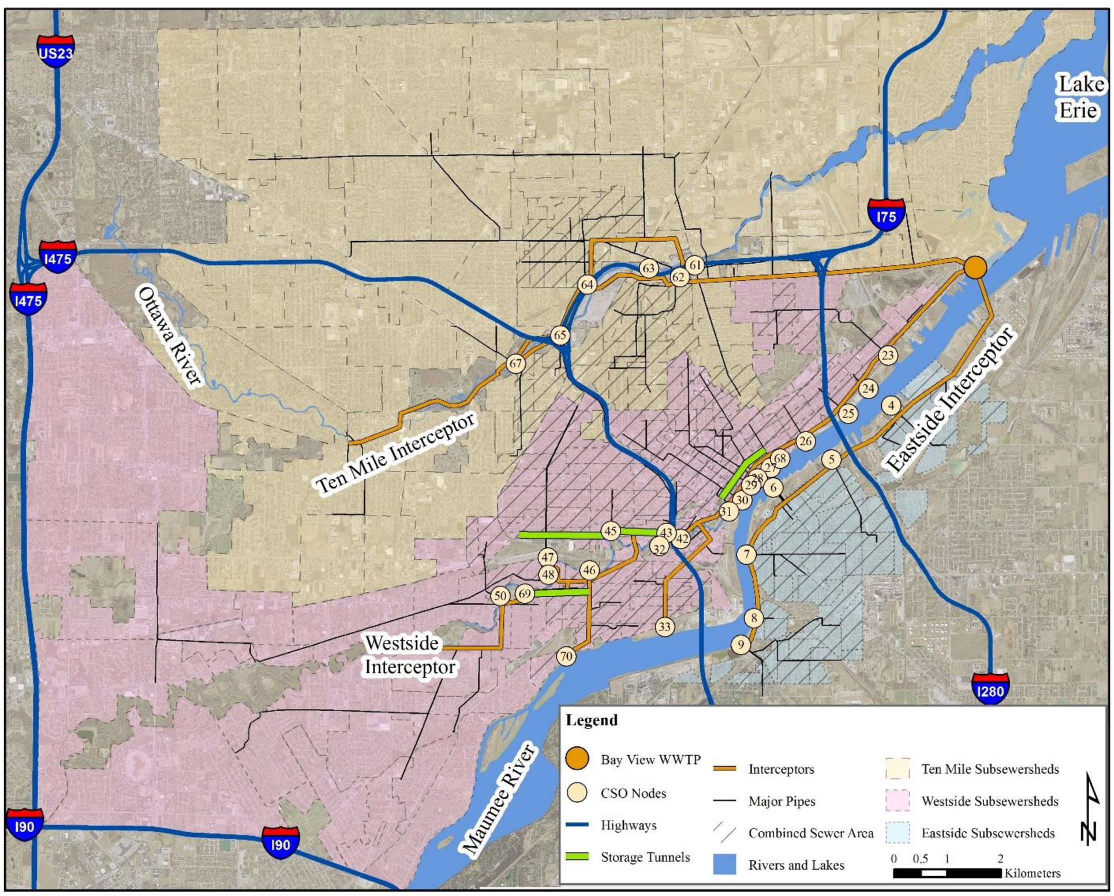

Figure 2.2. Studied area, tributary sewersheds, and collection system elements (data from City of Toledo and ARIES).

An average of 0.26 MCM/day is delivered by the collection system and treated by the Bay View WWTP. During wet weather, Bay View WWTP throughput may increase up to 1.5 MCM/day (City of Toledo 2014b). The collection system has three sewersheds, namely Ten Mile Creek, West Side, and East Side, which generate 26, 14, and 60% of total CSO volume, respectively. These watersheds are illustrated in Figure 2.2. Each sewershed has an interceptor (a pipe that takes combined sewage to a treatment plant) conveying the combined sewage to the Bay View WWTP. The capacities of the interceptors are 0.32, 0.33 and 0.25 MCM/day, respectively. For the East Side Interceptor, there is a pump station, called East Side Pump Station, which pumps combined sewage to an inverted siphon that crosses under the Maumee River (Figure 2.2). Each interceptor collects sanitary sewage from both separate and combined subsewersheds (City of Toledo 2005). There are a total of 33 permitted CSO discharge outfalls in the collection system (Figure 2.2). In order to reduce CSO discharges to the Maumee River and Swan Creek, three CSO Control Tunnels were constructed in the West Side Interceptor system by 1993 with total storage capacity of 74.2 MCM (19.6 million gal.) (Figure 2.2). Tunnels serve 40% of the total combined area. They are pumped back into the interceptor sewer when capacity is available for treatment (City of Toledo 2005).

2.2.2 CSO Control Scenarios

CSO control scenarios in this study were classified based on their use of green and gray infrastructures. The existing SWMM model for the Toledo LTCP Phase 2 was called the Gray scenario because storage facilities, system improvement, and sewer separation comprise this scenario. Three additional scenarios were developed in this study. The Green scenario was designed only based on GI implementation, and then the Gray+Green and Hybrid scenarios were defined based on combinations of the Gray and Green scenarios. The following subsections explain the details of the scenarios.

2.2.2.1 Gray Scenario

Negotiations between the U.S. EPA and Ohio EPA about Toledo's LTCP led to its last version in 2009 (also called Phase Two). In this study, all activities in the Toledo LTCP Phase Two were considered as one scenario, namely the Gray scenario. Twenty-five activities, including sewer separation, storage pipeline implementation, WWTP improvement, storage basin implementation, storage tunnel construction, and existing storage tunnel extension, make up this scenario. In general, sewer separation and storage basins will serve outfalls far from the downtown area, while the storage tunnels will serve downtown outfalls. The target benefits of this scenario are shown in Table 2.3. More information, e.g., location, capacity, and status of the subprojects, can be found at http://www.toledowaterwaysinitiative.com. All the activities are planned for completion by the year 2020.

2.2.2.2 Green Scenario

Acquiring private properties' agreement for GI implementation at appropriate locations (e.g., residential and commercial rooftops, parking lots, and driveways) might be a challenge due to the perception that GIs could be costly to retrofit (DC Water 2011; Montalto et al. 2007). Apart from this, implementing GIs only in public lands does not lead to a system-wide CSO control; therefore, incentives might be required to urge private

Table 2.3. Projected Benefits of the Gray scenario (Adapted from City of Toledo 2009b).

Receiving water body	**CSO storage capacity (MCM)**	**Percent Capture**
Ottawa River	0.102	92%
Maumee River’s east side	0.045	92%
Maumee River’s west side	0.045	92%
Swan Creek	0.010	93%

owners to enable GI implementation (Heaney et al. 2002; Montalto et al. 2007). RWH provides a solution to overcome these issues. Not only does RWH reduce the stormwater runoff volume and consequently reduce the CSOs (stormwater control function), but also the captured water could be used as a supplement to potable water from the distribution network, which leads to savings in water bills (water supply function). Dual benefits of RWH have been recently proved in different locations (Khastagir and Jayasuriya 2011; Mehrabadi et al. 2013; Sample and Liu 2014; Steffen et al. 2013; Vargas 2009; Walsh et al. 2014). RWH can be designed to capture rainwater for different indoor (e.g., toilet flushing, laundry, and drinking) and outdoor (e.g., lawn irrigation) uses that reduce the water conveyance needs and enhances the infiltration. Therefore, among the various GIs, this study focuses on RWH.

Among the different indoor water uses, this study focuses on toilet flushing (TF). This demand has been selected to be supplied by RWH in different studies due to the lower cost and higher simplicity in their implementation and operation rather than purposes that require partial or full treatment (Crettaz et al. 2002; Wang and Zimmerman 2015).

Two participation rates for RWH implementation were considered: 100 and 50%. The former represents the upper bound of the Green scenario's control ability based on implementing one RWH system per building in the combined sewer area (35,062 buildings), although it has a low likelihood. The latter represents a reasonable anticipated participation rate. In order to count the number of buildings in each subsewershed, GIS data of the buildings footprints were obtained from Auditor's Real Estate Information System (AREIS) (2014) of City of Toledo. These data were also used to calculate the building rooftop area treated by RWH in each subsewershed.

Additionally, high release rate (HRR) conditions that represent a 24 and 48 h release of the entire harvested rainwater were considered for the different participation rates. In this condition, cisterns operate as distributed detention basins and have more capacity prior to events. Although water supply capacity is lost this way, it increases the drainage benefits (Sample and Liu 2014).

Uniform RWH scenarios were considered for different buildings in this study because of modeling simplicity and due to the fact that considering a uniform cistern size designed based on the typical building specifications may not compromise city-scale results since SWMM is a lump model in subsewershed scale. In this study, 2.65 m^3 (700 gal.) cisterns were considered based on the recommendation of Steffen et al. (2013) for a typical residential parcel in Midwest cities, with 186 m^2 roof area that can lead to up to 92% saving in toilet-flushing water supply for a single household in this area.

Although Steffen's approach provides a useful guideline based on the yield before spill (YBS) method (Fewkes and Butler 2000), it does not explore the optimization tradeoffs of dual-benefits RWH discussed by Sample and Liu (2014). The present study followed the recommendation of Steffen et al. (2013) because analysis of optimized control plans is beyond its scope. The 2.65 m^3 cisterns may provide 1.42 cm rainfall collection of rooftop rainfall for a typical residential building. Furthermore, it provides around 0.092 MCM storage capacity for the city, which is 46% of the Gray scenario capacity presented in Table 2.3.

The cistern capacity for the HRR conditions was chosen as 5.68 m^3 (1,500 gal.) to provide a high stormwater capture capacity. This capacity was also considered as another TF scenario (called TF 5.68 m^3). Details of the selected cisterns are shown Table 2.4. These options were in the middle of the price range in the market and were selected to avoid the high maintenance costs of cheap options and the low cost-effectiveness of expensive ones. Cisterns were assumed to be located above ground with a foundation (Table 2.4). TF scenarios also require piping and connections between the cistern and the toilets. Furthermore, a pump is needed to keep the required water pressure to ensure proper toilet functionality. The labor and materials in Table 2.4 consider the cost of retrofitting the buildings (putting in new plumbing features, punching holes in walls, etc.), thus a cost of $1500 was considered to take engineering services fee into account for retrofitting and inspection cost, based on Devkota et al. (2015).

This study assumed priority in consuming the harvested rainwater rather than water in the distribution network for TF. In other words, water from the distribution network will be used only when there is not enough harvested water in cisterns. This approach leads to a higher level of savings on water bills and provides capacity for the next storm more quickly compared to the condition that harvested water has low priority to supply toilet flushing demand.

Table 2.4. RWH unit characterization and cost estimation.

Scenario	Item	Sub-Item	Quantity	Unit	Unit cost	Capital cost
TF (2.65 m^3)	Cistern	2.65 m^3 Dura-Cast Vertical Water Tank	1	ct	$569.9	$569.9
		First flush diverter	1	ct	$30.0	$30.0
	Foundation	Concrete	2.3	m^2	$32.3	$75.0
	Installation	Downspout elbows	2	ct	$4.0	$8.0
		9.5 mm sheet metal screws	8	ct	$0.1	$0.8
		Silicone or gutter sealer	1	tube	$6.5	$6.5
		Securing strap	1	ct	$5.0	$5.0
	Piping	2 cm Sch. 40 PVC Pipe	45.7	m	$0.8	$37.5
		2 cm PVC Elbows	15	ct	$0.4	$6.3
		Garden hose splitter	3	ct	$6.0	$18.0
		Pipe fittings to toilet	6	ct	$2.50	$15.0
		30 cm Braided nylon toilet hose	3	ct	$5.26	$15.8
	Pumping	Pump (1 hp pump, 275 kPa, 57 lit/min)	1	ct	$200.00	$200.0
		Pump controller	1	ct	$150.00	$150.0
	Labor	RWH installation	8	h	$18.00	$144.0
		Foundation construction	2.3	m^2	$86.9	$200.0
		Engineering services fee (for retrofitting and inspection cost)	N/A	N/A	N/A	$1500.0
		Piping permitting fee	1	ct	$64.00	$64.0
HRR	Cistern	5.68 m^3 Snyder Vertical Water Tank	1	ct	$785.95	$785.9
		First flush diverter	1	ct	$30.00	$30.0
	Foundation	Concrete	7.5	m^2	$32.3	$243.0
	Materials	Downspout elbows	2	ct	$4.00	$8.0
		9.5 mm sheet metal screws	8	ct	$0.10	$0.8
		Silicone or gutter sealer	1	tube	$6.50	$6.5
		Securing strap	1	ct	$5.00	$5.0
	Labor	RWH installation	8	h	$18.00	$144.0
		Foundation construction	7.5	m^2	86.9	$648.0

As discussed in this section, this Green scenario does not represent an optimized GI solution based on watershed-scale performance of RWH. In other words, it just represents the effects of applying the overall recommendation of Steffen et al. (2013) for the Midwest region in the studied sewershed in order to provide a basis for further studies, i.e., combined scenarios. Furthermore, this scenario analysis will enable future sensitivity/optimization analyses to seek to maximize GI performance benefits by varying RWH configurations and adding in more GI to address beyond rooftop control.

2.2.2.3 Gray+Green Scenario

Similar to the recent greening LTCP studies (summarized in Section 2.1), this study also evaluated the benefits of combined use of Green and Gray infrastructures in the studied area. The Gray+Green scenario was defined to consider simultaneous implementation of both the Gray and Green scenarios (all of the activities in the Gray scenario and all of the Green scenario). In other words, this scenario estimates how much increased control could be obtained in case of adding GIs to the existing LTCP plan.

2.2.2.4 Hybrid Scenario

As another combined scenario, the Hybrid scenario was developed to simulate what would happen in case of replacing some of the Gray activities in the Gray scenario with RWH. This scenario was derived based on engineering judgment to achieve the improved hydrologic functionality and lower life cycle costs at the same time. To do this, different permutations of implementing either the RWH or Gray activities in the three sewersheds were analyzed (2^3=8 permutations total). Consequently, the Hybrid scenario was defined based on the Gray activities in the East Side sewershed and RWH in the West Side and Ten Mile (25,169 buildings) because it led to the lowest simultaneous life cycle costs and CSO volume (explained in Section 2.3) compared to the other seven permutations. Similar to the Gray+Green scenario, different participation and release rates were also analyzed for this scenario.

2.2.3 Modeling

2.2.3.1 Hydrologic and Hydraulic (H&H) Modeling Approach

U.S. EPA SWMM was employed for H&H modeling of the system-wide combined sewer network in this study (shown in Figure 2.2). In order to model CSOs in SWMM, hydrologic characteristics of subsewersheds (i.e., slope, percent of impervious area, Manning's n, and infiltration capacity) as well as hydraulic specifications of the drainage process (i.e., dry weather flows, flow regulators, diversion structures, pump stations, combined sewer pipes, interceptors, storage facilities, junctions, and outfalls) should be introduced to the software (Gironas et al. 2009). Figure 2.3 illustrates the conceptual CSO modeling framework in SWMM. This figure illustrates how rainfall over a subsewershed transforms to stormwater and combines with the dry-weather flows in the combined sewer network.

A SWMM model was developed as a part of Toledo LTCP that includes separate sanitary sewers (30 cm diameter and larger) and combined sewers (91.44 cm diameter and larger) to represent the condition in 2009, referred as Business As Usual (BAU). Combinations of orifices, weirs, and pipes were used to simulate the flow regulators for the CSO outfalls. Impervious and pervious area characteristics in each subsewershed were

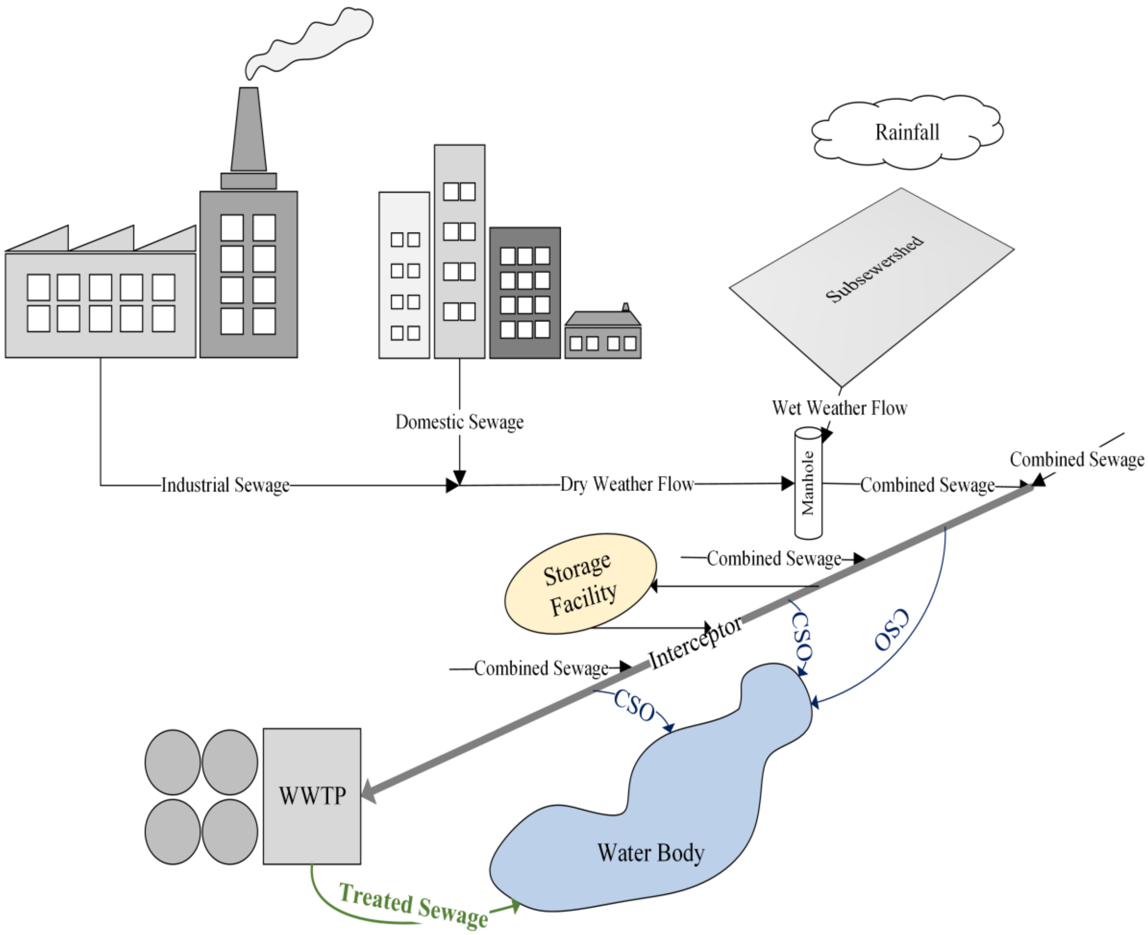

Figure 2.3. Schematic of CSO modeling framework in SWMM 5.1 from subsewersheds to WWTP (adapted from Gironas et al. 2009)

defined by analyzing specifications of buildings, streets, parking lots, lawns, etc. through GIS data. The model has been calibrated to flow metering data through different subprojects in different areas (City of Toledo 2010). Another model, also as a part of the LTCP, was developed to simulate CSO reduction through the LTCP 2009 recommendations. Details of the model have been presented in Table 2.5. More than 10,000 pipes and nodes in these models show their sophistication level. The dynamic wave approach was used for flow routing for higher accuracy. In the present study, the five models were used in SWMM 5.1. All of these models are shown in Table 2.5.

Table 2.5. SWMM models details (Adapted from City of Toledo 2010).

SWMM model parameter	**Value**
No. of Subsewersheds	279
No. of Rain Gages	45
Rainfall data time step	hourly
Rainfall period	1/1/1997 to 12/31/2001
Infiltration method	Green Ampt
Flow Routing	Dynamic Wave
Dry weather time step	1 day
Wet weather time step	15 min
Routing time step	5 min
No. of Dry Weather inflows	3443

- Business As Usual (BAU): The SWMM model developed through LTCP to represent the drainage condition in 2009 was used as the BAU;
- Gray: The SWMM model developed through LTCP to simulate the LTCP 2009 recommendations was used as the Gray;
- Green: It was developed as a part of the present study by adding RWH to the BAU model;
- Gray+Green: It was developed as a part of this study by adding RWH to the Gray model; and
- Hybrid: It was developed a part of the present study by combining Green model for the West Side and Ten Mile sewersheds to the Gray model for the East Side sewershed.

Since SWMM is a lump model, each sewershed needs to be divided into smaller subsewersheds in order to simulate spatial variability of the hydrologic parameters. Each subsewershed consists of pervious and impervious areas. An impervious area is the part of a subsewershed that may be partially or fully served by GIs. For the purpose of this study, RWH was simulated using the low-impact development (LID) routines in SWMM. Rain barrels were selected as the desired LID to capture rainfall from rooftops. There are two kinds of outflows from a rain barrel: overflow and underdrain. The former happens due to the inadequate storage capacity during extreme events, and the latter represents the gradual use/leakage of the stored water.

For the Green, Gray+Green, and Hybrid scenarios, the percentage of impervious area treated by the RWH system in each subsewershed was calculated based on the total served rooftop area divided by the total impervious area in that subsewershed. In order to simulate the process of supplying toilet flushing demands by cisterns, underdrain flows of cisterns were matched to the toilet flushing demand. SWMM uses Equation 2.1 to calculate underdrain flow, U (cm/h):

$$\mathrm{U} = \mathrm{C} \cdot \mathrm{h}^{\mathrm{n}} \tag{2.1}$$

where C = underdrain coefficient; n = drain exponent; and h = water height from the drain offset (cm). Values of C and n should be given to the model, and h is calculated by SWMM at each time step. To estimate C in each subsewershed, Equation 2.1 and typical values of n, h, and U are required. For n, 0.5 was considered as a typical value based on SWMM manual suggestion (Rossman 2010). h was considered as the tank height (assuming a full tank and no drain offset). To obtain typical values of U, first, the dominant building type in each subsewersheds (residential or commercial) was identified through GIS data. Then, based on the flushing demand and occupant data in Table 2.6, average daily flushing demand volume was calculated in terms of volume per day (lit/day) for a typical building in each subsewershed. Next, based on the cistern area section, it was converted to depth per hour (cm/h), then used as typical value of U. Finally, using Equation 2.1., C was obtained for different subsewersheds.

The RWH process may be simulated through different approaches in SWMM (e.g., discretizing subsewersheds, using pump routine for demand simulation, etc.). The approach used in this study was selected because of modeling simplicity. Representation of the individual details of each rooftop and rain barrel is not critical to assess the response at the city scale.

For the HRR condition, C was calculated based on Equation 2.2 (Rossman 2010):

$$C = \frac{2\sqrt{D}}{T} \tag{2.2}$$

where D = depth of stored water; and T = drain duration. D was considered as the cistern

Table 2.6. Toilet flushing demand details in the studied area.

Item	**Value**	**Reference**
No. of flush/person/day in residential buildings	5.1	Vickers (2001)
No. of flush/person/day in commercial buildings	4.0	Vickers (2001)
Average number of occupants per building	2.4	U.S. Census Bureau (2014)
Flush water demand (lit/flush)	6	Vickers (2001)

height. T was considered as 24 and 48 h, which led to C as 1.75 and 0.89 cm/h, respectively, which are several times higher than the average toilet flushing underdrain rate (0.23 cm/h). No drain delay was assumed because toilet demand was simulated as a gradual constant underdrain release, and the high release rate condition was considered a no-control, passive release policy. RWH overflows were assumed to be discharged to pervious areas in the subsewersheds. The feasibility of this assumption was verified through inspection of aerial imagery. Underdrain flows in TF scenarios were directed to the WWTP. For the HRR scenarios, underdrain flows were also directed to pervious areas.

2.2.3.2 Life Cycle Costs (LCC)

The capital costs for the Gray scenario were achieved from the cost estimations developed by the Toledo LTCP (City of Toledo 2009b). These capital costs were generated by taking into account the total construction cost for each project component, the engineering, legal, and administrative fees and costs associated with each project, as well as a contingency factor, which was incorporated to account for any unforeseen project costs (City of Toledo 2009a). Operation and maintenance (O/M) costs of CSO controls are highly site-specific (U.S. EPA 1993), but for the purposes of this study, the annual O/M costs were determined using, as reference, historic costs from similar facilities because of lack of data in the studied area. The replacement parts for each project were determined by considering the different lifespans of components, ranging between 20 years (equipment), 40 years (structure), and 50 years (sewers) (City of Toledo 2009a).

In order to analyze the cost-effectiveness of the RWH units, the itemized costs in Table 2.4 were considered. The cost of each component of the RWH unit was estimated by looking up the cost from different online sources (Conservation Technology 2008; Office of the Ohio Consumers' Counsel 2014; RainHarvest Systems 2014). For the O/M costs of cisterns and pumps, their replacement in 30 and 10 years were considered, respectively (Florida Rainwater Harvesting Initiative 2009). For the electricity demand of pumping, \$1.45/year was considered based on \$0.0739/kwh (Office of the Ohio Consumers' Counsel 2014), 60% pump efficiency, and 5 m height difference to toilet. To consider the dual piping permitting fee in the study area, an average value of \$64 was used based on residential and commercial permitting fees in Lucas County, Ohio (Lucas County 2015). For the O/M costs of other items, 10% of their capital costs were considered (Schueler 1987). Although the 10% (of capital cost) for O/M costs of these RWH components might represent a relatively high rate, it was considered a safety factor because RWH in modern style is still a new practice, and O/M cost data in different locations are still uncertain. In addition to the RWH unit characteristics in Table 2.4, each building's owner will have to perform some amount of standard maintenance every year that does not contribute to maintenance costs. This includes regular cleaning of the catchment area, gutters, filters, and the tank to avoid sediment buildup in the tank.

To provide a basis for comparing the life cycle costs of the projects, the present value of life cycle costs for each scenario was estimated. For this purpose, this study considered 75 years as the life cycle of the both gray and green facilities with regular replacement of the components, as explained earlier. Then, capital, O/M, and replacement costs were listed for each year of the life cycle. The total costs for each year were then converted to the equivalent present cost according to Equation 2.3, assuming an annual rate of return of 5.375% (City of Toledo 2009a):

$$\mathrm{PV} = \mathrm{FV}(1+\mathrm{r})^{-n} \tag{2.3}$$

where PV = present value; FV is future value; r = rate of return; and n = number of years from present. Finally, the present value of life cycle costs was obtained as the summation of present value of costs in each year of the 75-year life cycle.

A unique part of RWH to supply toilet flushing demand is that part of the O/M costs will be offset due to savings on each monthly water bill since rainwater is being use in the place of municipal water. To take this into account, the present value of water bill cost savings was also calculated through Equation 2.3. Then, to obtain the present value of the LCC of the scenarios that use RWH to supplement toilet flushing demand, present value of savings was subtracted from present value of cost, as shown in Equation 2.4:

$$\mathrm{PV_{LCC}} = \mathrm{PV_{Costs}} - \mathrm{PV_{Water\ Bill\ Savings}} \tag{2.4}$$

2.2.3.3 Combined Hydrologic and Economic Analysis

To combine the hydrologic performance and the LCC of the scenarios, this study proposed an indicator, namely Costs Per Reduction (CPR), as Equation 2.5:

$$\mathrm{CPR(scenario_x)} = \frac{\text{present value of life cycle costs of scenario}_\mathrm{x}}{\text{annual CSO volume reduction under scenario}_\mathrm{x}} \tag{2.5}$$

where $\mathrm{scenario_x}$ denotes a given CSO control scenario. To calculate CPR, present value of life cycle costs and annual CSO volume reduction are expressed in \$million and

MCM/year, respectively.

The lower the values of CPR for a scenario, the higher the desirability of that scenario in terms of dual performance and economic criteria. This indicator was calculated for the scenarios of this study and is discussed in the next section.

2.3 Results and Discussions

The results validated the Gray scenario ability in long-term CSO volume reduction. Over the simulation period, the BAU scenario led to 1.94 MCM/year of CSOs, and the Gray scenario could reduce it to 0.25 MCM/year. Figure 2.4 illustrates the CSO volume under different scenarios. This figure shows that for the scenarios that use RWH, the four TF subscenarios had higher CSO control abilities than the four HRR subscenarios on average. Further analysis of the data revealed that rainfall events that caused overflows had a 1.86 day duration on average. This high duration made the HRRs ineffective since underdrain flows were sent to the pervious areas, and these flows contributed the CSOs because the pervious areas were saturated in case of long rainfall events. Figure 2.4 also demonstrates that increasing the cistern capacity from 2.65 to 5.68 m^3 (or doubling the number of RWH units) could not add a meaningful ability to the TF subscenarios. The increased ability is just slightly higher than the added cisterns' capacity, which shows how cisterns are quickly filled up and unable to provide further reduction because of the slow underdrain rate that causes a lack of pre-rainfall event capacity. For the HRR subscenarios, the performance of the additional cisterns was again restricted by the long rainfall events. These results highlight the possible hydrologic usefulness of supplying more indoor demands (e.g., laundry) that could empty the cisterns faster but not send the underdrain

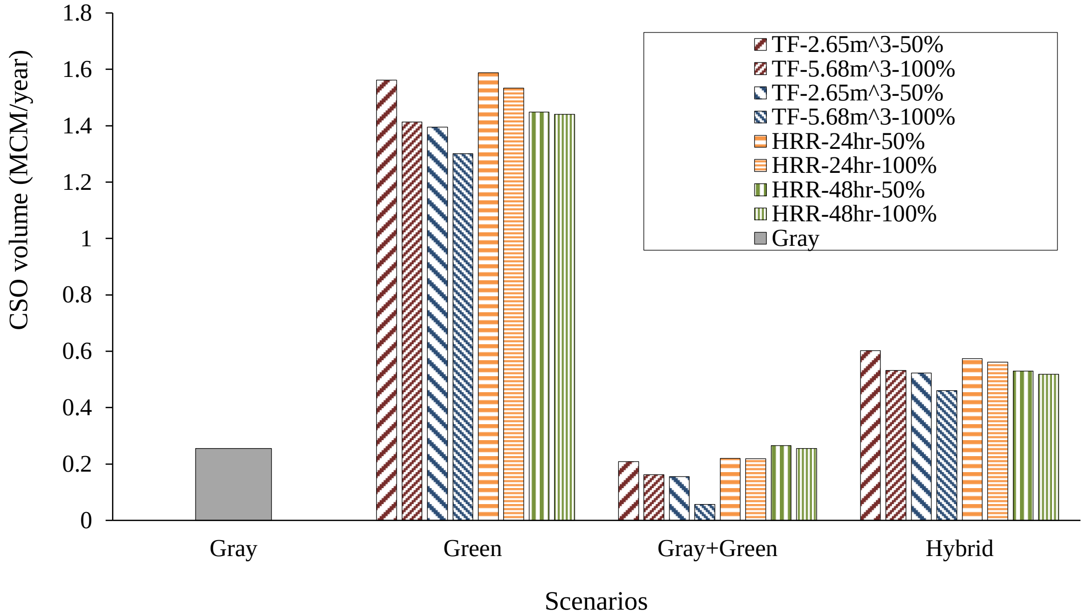

Figure 2.4. Annual CSO volume under different control scenarios. (In figure legend: for TF subscenarios, the first number shows the system capacity and the second number shows the participation rate; and for HRR subscenarios, the first number shows the release duration and the second number shows the participation rate).

flow to the drainage system. Although the Green and Gray+Green scenarios did not present significant CSO reduction with respect to the scale of the projects, the Hybrid scenario showed a meaningful reduction aligned with the recent studies on replacing some of the previously designed CSO control with GIs (reviewed in Section 2.1).

The effectiveness of the Hybrid scenario was further approved by the LCC results. To quantify this, the present value of the life cycle costs for different scenarios was calculated. Results show both the Green and Hybrid scenarios led to lower life cycle costs than the Gray (Figure 2.5). The cheapest subscenario was the HRR-50% under the Green scenario (HRR signifies the RWH function and 50% represents the participation rate). For the Gray scenario, capital cost and the present value of the O/M costs were calculated as \$315.7 million and \$79.72 million, respectively.

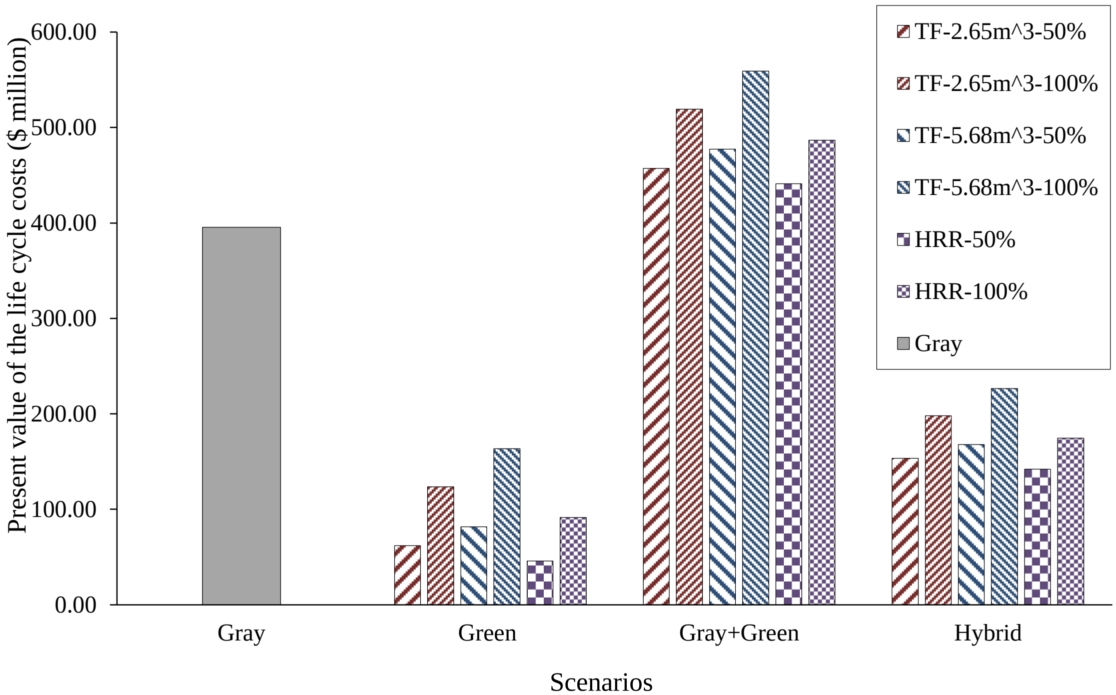

Figure 2.5. Present value of life cycle costs of different control scenarios. Different release rates for the HRR have the same life cycle costs, thus they are not separately shown in this figure.

Capital cost for a 2.65 m^3 TF unit, a 5.68 m^3 TF unit, and a HRR unit (5.68 m^3) were calculated as $3,045, $3,877, and $1,871 respectively, while the present value of the O/M costs (including water bill cost benefits) for these units were obtained as $480, $787, and $697 correspondingly. According to this economic findings, the 2.65 m^3 TF unit showed the highest level of offsetting costs by harvesting benefits. Pump replacement cost was the major component of the O/M costs for the TF RWH units (more than 30%), whereas the electricity cost (for pumping) was trivial (less than 1%).

The CPR indicator was calculated for all the scenarios of this study. The Gray led to a CPR of 235. CPRs for the other scenarios are also calculated. Results generally show that the Hybrid subscenarios lead to the lowest CPR. On average, this indicator for the Hybrid subscenarios was around 48% lower than the Gray (Table 2.7). Based on this table and Figure 2.4, the Hybrid's TF-2.56m^3-50% subscenario suggests a cost-effective CSO control with a reasonable participation rate and the ability of supply decentralization (the first number shows the system capacity and the second number shows the participation rate). This subscenario appeared to be able to supply the entire modeled toilet flushing demand in the buildings with RWH (which are located in the West Side and Ten Mile sewersheds). Although the Green's HRR-48hr-50% led to a lower CPR, it did not represent an accepted level of control according to Figure 2.4. Thus, Hybrid's TF-2.56m^3-50% is considered for further analysis. For the Hybrid's TF-2.56m^3-50%, the total amount of rainwater collected by RWH systems (1.32 MCM/year) was averaged across all 25,169 buildings, giving 52.43 m^3 of water saved per building per year. This amount of the harvested rainfall could meet the entire toilet flushing demand. Using an average water rate of \$2.1989 per 3.78 m^3 (1,000 gal.) (City of Toledo 2014a), the average cost savings each year are \$30 per building.

Table 2.7. CPR indicator for different scenarios. The Gray scenario led to a CPR of 235. The TF and HRR subscenarios with the highest performance concerning the CPR indicator are marked in dark and light gray, respectively.

CPR (\$/m^3)	**Participation**	**TF-2.65m^3**	**TF-2.65m^3**	**HRR-24hr**	**HRR-48hr**
Green	50%	165	151	129	92
	100%	236	257	223	182
Gray+Green	50%	265	268	257	264
	100%	293	297	283	289
Hybrid	50%	115	119	104	101
	100%	141	153	126	122

The CSO event series for Hybrid's TF-2.56m^3-50% were achieved from the continuous SWMM simulations for calculating nonexceedance probabilities of an event's volume using the Weibull plotting position (Figure 2.6). This figure shows that the Gray scenario had a higher control ability for almost all the ranges of CSO events' magnitudes. For larger CSO events, both scenarios showed around the same control level because the Hybrid scenario benefits from the large-scale gray facilities in the East Side sewershed. Analysis of the system revealed that major CSO events happen in this area (especially at outfalls #7 and #9 in Figure 2.2). For smaller CSO events (more frequent events), the superior performance of the Gray scenario is related to the sewer separation activities. These activities are planned to be implemented in areas of the network that had CSO events with low magnitudes, e.g., Ten Mile sewershed. Therefore, under the gray scenario, a majority of these events were eliminated, as presented in Figure 2.2.

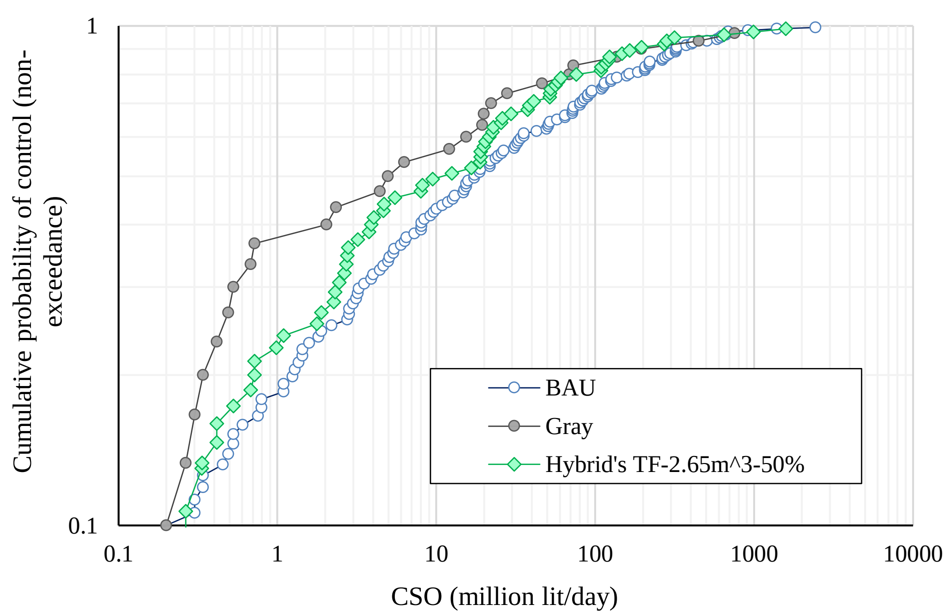

Figure 2.6. Cumulative probability of controls (nonexceedance) for the selected hybrid scenario, compared with Gray and BAU scenarios.

2.4 Conclusions

Through H&H simulation, this study showed the limited benefits of system-wide RWH in CSO control when it is implemented alone. Combining RWH with gray facilities improved the performance; however, the control level in the Hybrid scenario was still lower than the costly Gray scenario. Taking life cycle costs into account affirmed the noticeably lower costs of GIs, and led to an enhanced combined hydrologic–economic performance for the Hybrid scenario compared to the other scenarios evaluated in this study. This study did not explore the maximized design of RWH system in the studied area. Further sensitivity/optimization studies on RWH system characteristics may improve the performance of the RWH and reduce the costs.

The benefits of RWH for both toilet flushing and CSO control could be generalizable for other combined sewer systems with similar climate in terms of rainfall characteristics. In such areas, capturing rainwater could lead to remarkable cost saving on water bills, if used to supply many nonpotable indoor demands. The following limitations in this chapter could be considered as future studies:

- This research did not study a maximized level of combined Green and Gray infrastructure controls. It only showed that combing conventional gray techniques with GIs can improve the cost-effectiveness. A maximized level of control may be achieved through linking the model to optimization algorithms.
- Life cycle cost boundaries considered in this study were limited to implementation, operation, and maintenance costs of the facilities. Reduced potable water consumption in the case of using RWH systems was also considered. However, this study did not consider the changes in volume and

characteristics of combined sewage sent to the WWTP, and their associated costs in the case of using RWH systems.

- For better urban drainage performance, RWH cisterns should be kept empty prior to storm events; on the other hand, they should always have a minimum stored water volume for reliable water-supply purposes. This issue raises the effectiveness of a cistern with two storages: retention and detention. In this case, the captured water volume is stopped at a certain level to cover demands. Life cycle cost-effectiveness of such RWH systems could be studied in future work.

CHAPTER 3

WATERSHED-SCALE LIFE CYCLE ASSESSMENT OF RAINWATER HARVESTING TO CONTROL COMBINED SEWER OVERFLOWS

3.1 Introduction

Current practices in urban water management favor decentralized practices for stormwater control (Damodaram et al. 2010; Lynch and Deborah 2010; Montalto and Rothstein 2008; Zahmatkesh et al. 2014), combined sewer overflow (CSO) reduction (Carbone et al. 2014; Montalto et al. 2007; U.S. EPA 2014a; Water Environment Research Foundation 2009), and wastewater management (Chung et al. 2008; Hwang et al. 2014; Sitzenfrei et al. 2013; Wang 2014). Historically, as urbanization has increased the demand for urban water infrastructure, several actions, such as expanding centralized treatment facilities and extending potable, stormwater, and wastewater networks, were taken (Burian et al. 1999; Burian et al. 2000). Since the development potential of centralized water infrastructure cannot keep up with the pace of recent urbanization, especially of sprawl (American Rivers 2014; Carruthers 2003; Coyne 2003; Natural Resources Defense Council 1998), decentralized urban water infrastructure is being increasingly deployed to decrease costs and energy requirements (Montalto and Rothstein 2008) and to increase system reliability (Piratla and Goverdhanam 2015), security (Daigger and Crawford 2007), resilience (Chelleri et al. 2015), flexibility, and expandability (Cayuela and Pilon 2015).

The use of rainwater harvesting (RWH) as a decentralized urban water management practice has recently gained widespread attention due to its ability to supplement domestic water demand (Burian and Jones 2010; Jones and Hunt 2010; Mehrabadi et al. 2013; Sample and Liu 2014; Steffen et al. 2013; Thomas et al. 2014), manage stormwater (Khastagir and Jayasuriya 2010; Sample and Liu 2014; Steffen et al. 2013; Vargas 2009; Walsh et al. 2014), and to control CSOs (Tavakol-Davani et al. 2015; Vaes and Berlamont 1999). Researchers have investigated the potential of RWH to achieve urban water management objectives at the building scale and watershed scales. Methods employed for building-scale analyses include water balance analysis (Campisano et al. 2014; Campisano and Modica 2014; Fewkes and Butler 2000; Okoye et al. 2015; Ward et al. 2010; Youn et al. 2012), life cycle cost (LCC) estimation (Farreny et al. 2011; Ghisi et al. 2009; Ghisi et al. 2014; Liang and Van Dijk 2011; Silva et al. 2015) and life cycle assessment (LCA) (Devkota et al. 2015; Ghimire et al. 2014; Morales-Pinzon et al. 2015; Vargas-Parra et al. 2013; Vieira et al. 2014). For watershed-scale analysis, methods included hydrologic and hydraulic (H&H) modeling (Ghimire and Johnston 2015; Shadeed and Lange 2010; Walsh et al. 2014), and planning studies (Jha et al. 2014; Makropoulos et al. 2008; Newton et al. 2014).

Building-scale LCA analyses often lead to policies that are useful for a developer or facility manager to guide environmentally friendly implementation of RWH for buildings. While being helpful for building stakeholders, these studies are limited when considering watershed-scale impacts. Policies may be different when considering the broader systemic impacts and benefits in an urban watershed. The concern lies in the inability of building-scale performance analyses to be extrapolated to the watershed, and to be considered in terms of their interconnection to watershed-scale hydrologic, hydraulic, and environmental processes. For example, nonlinearities in RWH processes have been taken into account in several RWH studies (Shadeed and Lange 2010; Tavakol-Davani et al. 2015; Walsh et al. 2014). In an urban watershed, although LCA can factor environmental sustainability into the design, it must be appropriately informed by watershed-scale considerations and hydrologic analysis to accurately reflect performance at the appropriate time-space scales over a life cycle of a project.

Although needed, few studies have sought to bring together analysis approaches to provide a comprehensive environmental sustainability evaluation of urban water infrastructure that considers hydrologic analysis and LCA. Performing long-term hydrologic analyses while defining appropriate LCA system boundaries, functional units and life cycle inventories – especially for a combined sewer system transmitting both stormwater and sanitary sewage to treatment facilities – requires an interdisciplinary study. De Sousa et al. (2012) used H&H modeling to propose CSO strategies with an equivalent degree of annual volume reduction, and employed LCA to compare them in terms of life cycle impacts. In De Sousa et al. (2012), the impacts and benefits of the implementation, operation and maintenance phases of the strategies as well as the wastewater treatment plant (WWTP) operation were included. However, the environmental benefits of avoiding CSOs were not considered (since the studied scenarios led to an "equivalent" level of CSO reduction). Thus, the approach of De Sousa et al. (2012) is neither applicable for comparing those CSO control strategies that do not necessarily lead to equivalent CSO reductions, nor for comparing a proposed strategy with the existing condition. Essentially, ignoring the effects of avoided CSOs may result in inconsistency with hydrology, explained by the following example. Storage facilities provide gradual release of stormwater, which decreases CSO volume and increases the combined sewage volume delivered to the WWTP. Therefore, if CSO impacts were ignored, two storage scenarios that are identical, except for release rates, would produce incorrect conclusions because the storage scenario with a superior CSO storage ability would be reported as inferior in terms of life cycle impacts (because of the higher treatment impacts). This would not consider the significant impacts of CSOs on human health and aquatic life (Alliance for the Great Lakes 2012; U.S. EPA 2014a). An example of a study integrating water quality impacts in LCA of CSO control plans is presented by Wang et al. (2013); however, this study did not include H&H analysis of CSO control strategies.

Given the relatively few studies that have used comprehensive analyses, there remains uncertainty about the environmental sustainability benefits of using decentralized approaches for urban water management. A critical need remains to continue advancing approaches to effectively integrate hydrologic analysis and LCA. These advances are necessary to compare centralized and decentralized urban water management approaches, and to design hybrid systems that maximize benefits. This chapter presents such an approach. Of particular note is a novel approach to conduct watershed-scale LCA that can provide an improved estimate of performance compared to approaches that merely extrapolate building analysis up to the watershed. The environmental sustainability evaluation framework is applied to investigate the potential for RWH as a CSO control infrastructure in Toledo, Ohio. RWH is compared to a centralized gray infrastructure approach, and is used as a part of hybrid control strategies. This chapter represents a large watershed-scale (310 km^2) study of water supply and stormwater management benefits of RWH that builds on past studies of De Sousa et al. (2012) and Wang et al. (2013) that were at the subwatershed scale (7.84 and 0.004 km^2, respectively).

3.2 Methodology

This section introduces a framework, called uWISE (urban Water Infrastructure Sustainability Evaluation), to integrate hydrologic analysis and LCA to analyze centralized, decentralized, and hybrid urban water management approaches in a city-scale combined sewer network. Characteristics of the analysis framework, information about the study area and the proposed management scenarios are provided next.

3.2.1 uWISE (urban Water Infrastructure Sustainability Evaluation)

The uWISE framework uses a dynamic urban H&H model to simulate the effects of control strategies on hydrologic components, such as characteristics of CSOs, untreated stormwater discharges to water bodies, combined sewage volume delivered to WWTPs and adjusted potable water demand volume (Figure 3.1). Model inputs include characteristics of control strategies (centralized, decentralized or hybrid), subwatersheds (delineated boundaries, area, slope, roughness, imperviousness, infiltration capacity, etc.), drainage network (pipes, junctions, pumps, storage units, etc.) and water fluxes (rainfall, dry weather flow (DWF), rainfall derived infiltration inflow (RDII) and groundwater flow). The hydrologic modeling component simulates nonlinear hydrologic inputs and functions in a combined sewer network. The importance of H&H modeling is brought further to the fore

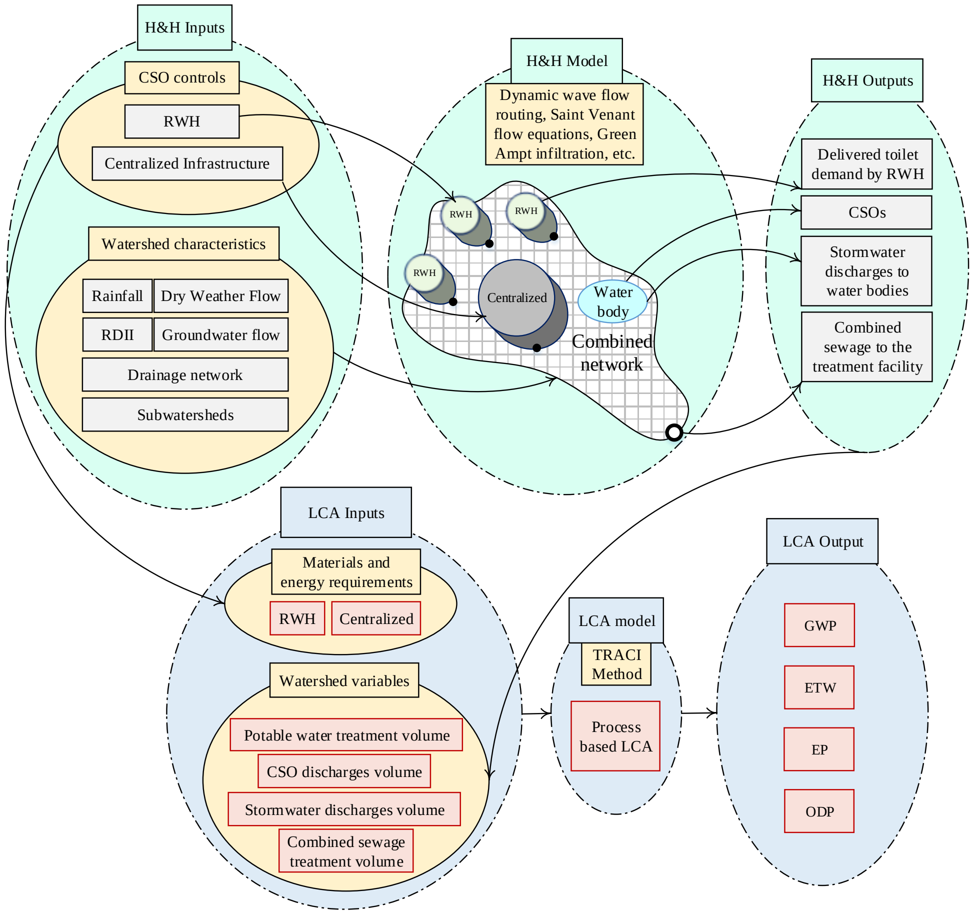

Figure 3.1. The uWISE framework. Upper row shows the H&H model components, and lower row shows the LCA model components. RWH to supply toilet flushing demand is shown as an example of decentralized methods.

when considering the fact that different CSO control infrastructure has dissimilar effects on CSOs and combined sewage volume delivered to the WWTP. For instance, sewer separation decreases CSOs and combined sewage volume delivered to the WWTP, while implementing storage facilities (including RWH) may decrease the former and increase the latter. Sewer separation is implemented for a combined sewer system to discretize it into separate sanitary and stormwater sewers. The uWISE approach can be implemented with any appropriate H&H model, but for this study the U.S. Environmental Protection Agency Model (SWMM) is used as described in Section 3.2.2.2.

The second step of the uWISE framework is to use a process-based LCA model, which translates the quantity and consumed energy of the inputs into life cycle impacts. This step consists of combining the H&H model results (e.g., volumes of combined sewage delivered to the WWTP, CSOs, untreated stormwater discharges to water bodies, and toilet flushing demand delivered by RWH) with the characteristics of construction, operation and maintenance phases of CSO control practices. Similar to the choice of the H&H model, the LCA model used in the uWISE framework can vary. Common process-based LCA software (e.g., SimaPro and GaBi) and impact assessment methods (e.g., ReCiPe for Europe and TRACI for the U.S.) are some possibilities. Methods used for this study are described in Section 3.2.2.3. A key advance presented in this research is the integration of the H&H modeling with LCA for watershed-scale analysis using uWISE. Instead of H&H modeling, LCA results from a decentralized CSO control unit may be extrapolated in order to achieve watershed-scale LCA results. In the present study, this method was called "Extrapolation" for simplicity, and was used for comparison with the uWISE framework. Although water supply and detention functionalities of decentralized infrastructure can be simulated without H&H modeling, the aggregated results would not be able to take into account the effects of watershed and conveyance system hydraulics on CSOs. Figure 3.2 illustrates the steps of the Extrapolation approach in this study. Extrapolation applies LCA to analyze decentralized water infrastructure (e.g., RWH) performance at their implementation scale (e.g., building scale). Then, the results for one unit are multiplied by the total number of units in the area. Figure 3.2 also shows the simpler structure and lower computational demands of this method, compared to the uWISE framework. Additional information is discussed in Section 3.2.3.2.

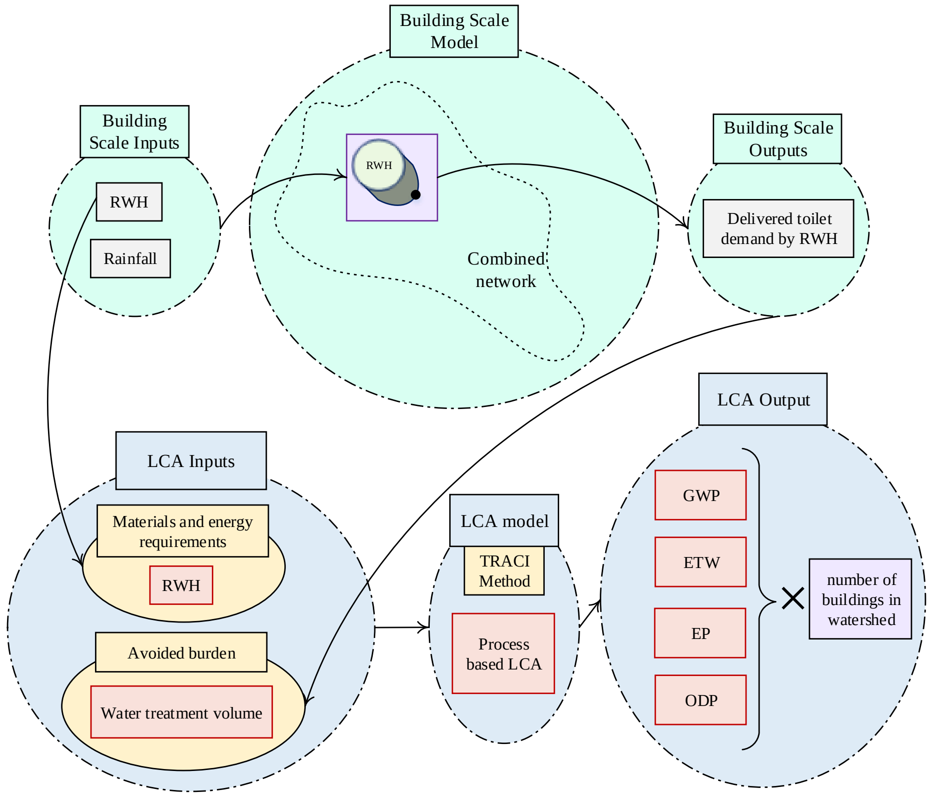

Figure 3.2. The Extrapolation framework. This framework achieves LCA results without H&H modeling.

3.2.2 Application of the uWISE Framework

3.2.2.1 Study Area

The uWISE framework was applied to study the City of Toledo’s combined sewer system. The collection system serves approximately 310 km^2 of predominantly residential and commercial land uses (City of Toledo 2009a). As illustrated in Figure 2.1, Toledo is located on the western shore of Lake Erie, and at the mouths of the Maumee and Ottawa Rivers. According to the U.S. Census Bureau (2014), Toledo is the fourth most populated Ohio city, with 340,000 inhabitants. This city has an average annual precipitation of 85.2 cm. IDF curves for different return periods of precipitation in Toledo are analyzed in this study. According to this analysis, the 10-yr, 24-hr precipitation, which is conventionally used in single storm event analyses, has a 3.7 mm/hr intensity that shows the relatively high magnitude of the storm events in Toledo (Figure 3.3). This figure shows the relatively high frequency of precipitation events with long duration (e.g., 48-hr duration of 1.5 mm/hr with 2 years return period) in Toledo. Currently, the collection system of Toledo includes both the combined sewer network (12% of the drainage area, the hatched region in Figure 2.2) and separate sewer network (City of Toledo 2005). On average, 0.26 million cubic meters (MCM) of combined sewage is transmitted to the Bay View WWTP (also depicted in Figure 2.2) per day. By including a bypassing technique (primary treatment only), Bay View WWTP capacity may increase up to 1.5 MCM/day (City of Toledo 2014a). Three watersheds, namely Ten Mile Creek, Westside, and Eastside constitute the collection system, each of which has both separate and combined subwatersheds (City of Toledo 2005). The 33 nodes illustrated in Figure 2.2 are the permitted CSO outfalls.

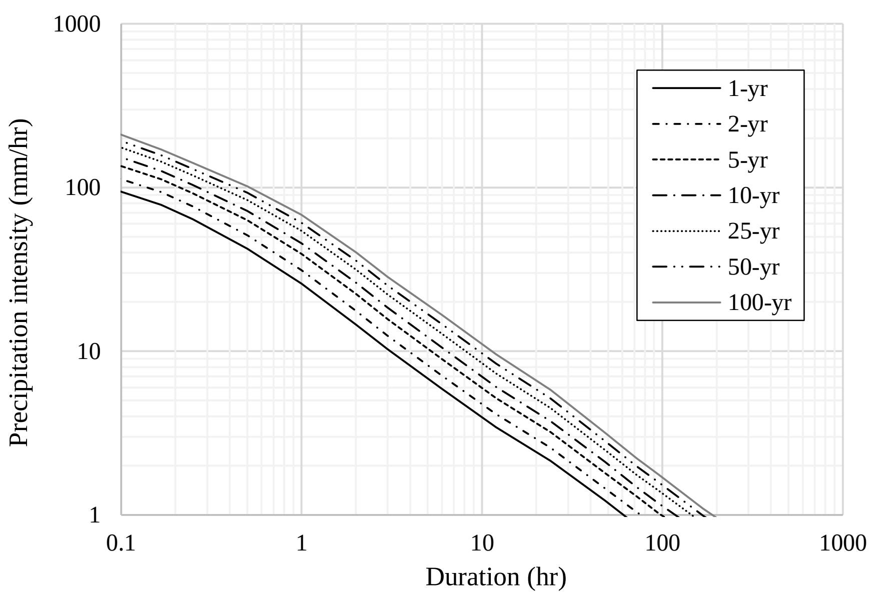

Figure 3.3. Intensity-Duration-Frequency (IDF) curves for different return periods of precipitation in Toledo (data from NOAA Atlas 14, Volume 2, Version 3)

3.2.2.2 H&H Model

In this study, the U.S. EPA SWMM 5.1 (Rossman 2015) has been used to develop an H&H model of the three watersheds constituting Toledo's collection system. SWMM discretizes the land surface into subwatersheds, each represented hydrologically as a nonlinear reservoir with outflow governed by Manning's equation for overland flow. Figure 3.4 shows the schematic of a subwatershed module in SWMM. Each subwatershed may contain pervious and impervious areas. RWH systems typically serve impervious areas, partially or fully. SWMM also has a hydraulic module for conduit flow that solves the one-dimensional Saint Venant flow equation at each time step using the Dynamic Wave approximation for flow routing (Gironas et al. 2009). In SWMM, Low-Impact Development (LID) practices can simulate runoff capture and detention, infiltration, evapotranspiration (or a combination of these processes) (Gironas et al. 2009).

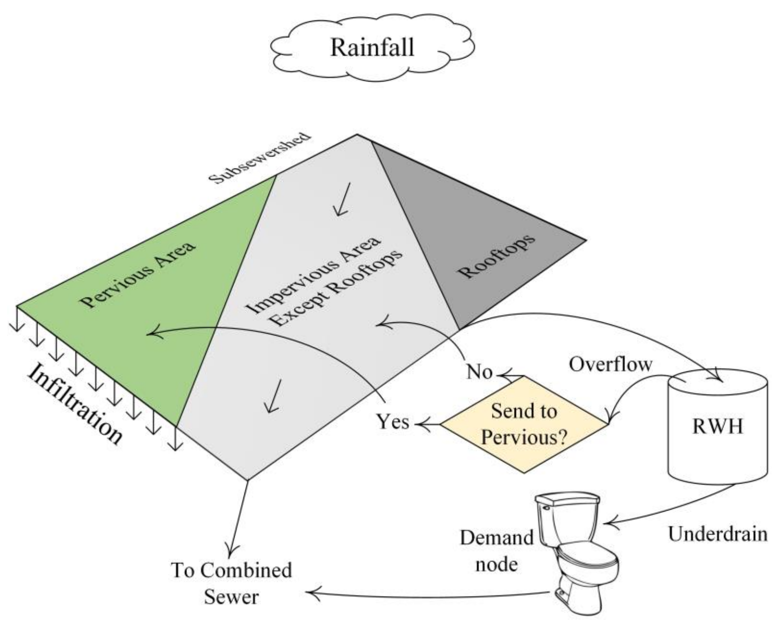

Figure 3.4. Schematic of subsewersheds and RWH modeling process in SWMM model for the present research (adapted from Walsh et al. 2014).

The model of the City of Toledo's collection system was originally created and calibrated for the development of the Toledo CSO Long-Term Control Plan (LTCP). It was updated and applied by Tavakol-Davani et al. (2015) to study RWH implementation in the collection system. The Toledo model consists of 279 subwatersheds, 45 rainfall stations, and more than 10,000 pipe and node elements. Here, the Green Ampt model was used to simulate infiltration. Furthermore, the Rain Barrel LID template in SWMM was used to simulate the capture of rainfall from rooftops (see Figure 3.4) for the scenarios with RWH. In SWMM, a cistern can have both underdrain flow and overflow. Underdrain flow represents either the planned, gradual release of the harvested rainfall for different end uses (TF in this research), or simply allowing the tank to gradually empty prior to the next storm event (48 h release in this research). Overflow happens when storage capacity is exceeded. Overflows were assumed to be discharged to pervious areas of subwatersheds, based on site visits and inspection of aerial imagery, and thus the presence of the RWH disconnects the upstream impervious area. The excess runoff from pervious areas enters the combined sewers.

The RDII, DWF, and groundwater flows were simulated as inflows using pipe elements. The RDII into the sewer system was simulated using three separate unit hydrographs for short-term, intermediate-term and long-term responses. These hydrographs were calibrated as a part of Toledo's LTCP using measurements made in 2003 (City of Toledo 2005). DWF and groundwater flows were modeled as inflow nodes using hourly average values (measured for 37 sites in 2003) and monthly average values (measured for 7 sites in 2003), respectively (City of Toledo 2005).

Five years of hourly continuous precipitation data from 1/1/1997 to 12/31/2001 were used in concordance with the LTCP baseline. The wet weather time step and the routing time step were respectively set at 15 and 5 minutes. CSO outfalls were simulated via a set of orifice, weir and pipe elements. All the storage units were assumed empty at the beginning of simulation. Additional information about RWH modeling is explained in Section 3.2.3.2.

3.2.2.3 LCA Model

Life cycle assessment (LCA) is a scientific, internationally standardized (ISO 14044 2006) procedure to estimate the environmental performance of a product or service, including all stages of its life cycle (Comas and Morera 2012). LCA is particularly acknowledged for comparing alternative product or service systems that provide the same function (Vineyard et al 2015). While early LCA studies focused on consumer goods and services, recent ones have extended its application to include built infrastructure (Racoviceanu et al. 2007; De Sousa et al. 2012; Wang et al. 2013; Ghimire et al. 2014; Uche et al. 2015). According to ISO 14044 (2006), LCA has four steps: outlining the goal and scope of the analysis; gathering the data needed for all life cycle stages to create a life cycle inventory (LCI); quantifying the impacts via life cycle impact assessment (LCIA) methods; and interpretation of results.

The goal of the LCA for this study was to compare the watershed-scale life cycle impacts of different options of CSO control infrastructure. In LCA, “functional unit (FU) is a measure of the performance of the functional outputs” of the system, and it is used as the comparison basis for all results (ISO 14044 2006). In LCA studies of water and wastewater treatment plants, 1 m^3 of treated water (Barrios et al. 2008; Bonton et al. 2012) or wastewater (Roushdi et al. 2012; U.S. EPA 2014b) is often used as the FU. Drainage area has been used as the FU in prior watershed-scale LCAs (De Sousa et al. 2012; Wang et al. 2013). In this study, since the goal of the analyzed facilities is to reduce CSOs, the FU was defined as 1 m^3 reduction of CSO volume over the life cycle of facilities. The selected FU sets the system boundaries of the LCA as conceptually diagrammed in Figure 3.5. This boundary includes the operational phases of the WTP and WWTP because both would be affected by RWH. CSOs and untreated stormwater discharges were also included because they would be significantly affected by the control infrastructure.

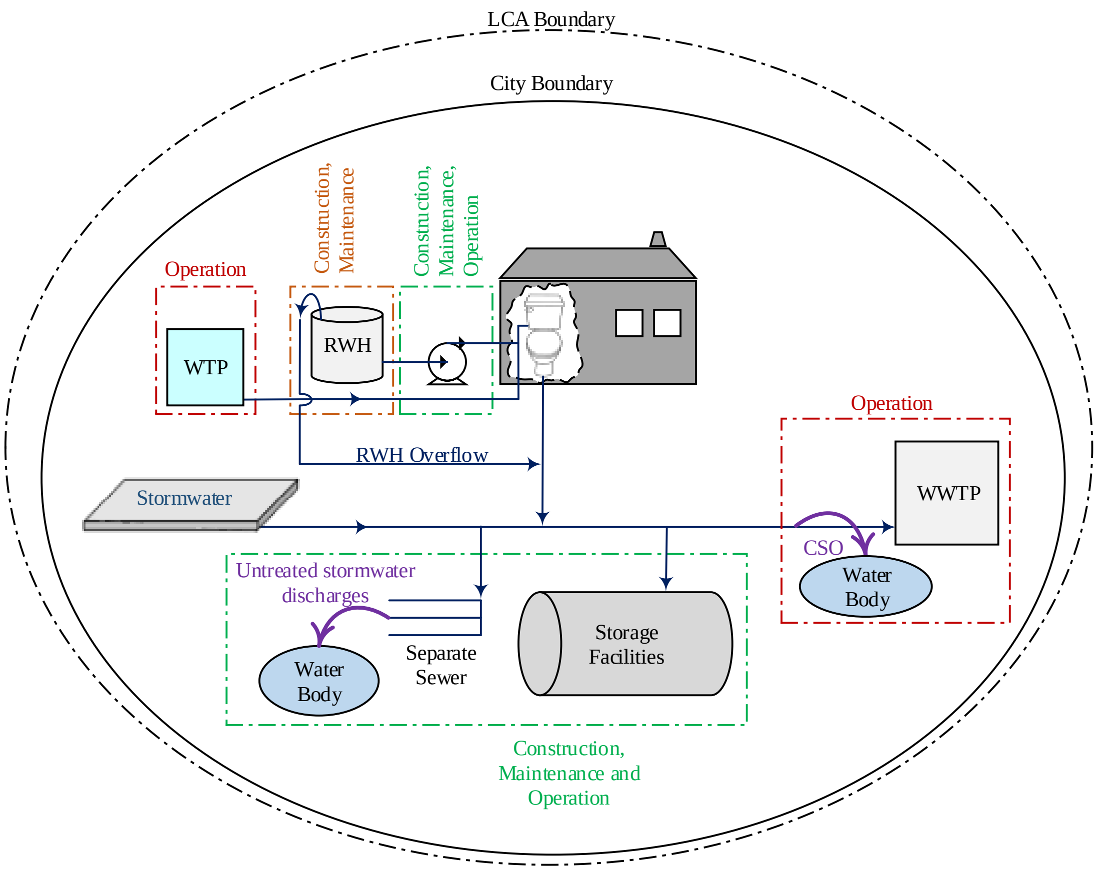

Figure 3.5. LCA system boundary. Boundaries for analyzing all RWH, gray, and hybrid elements are illustrated.

The construction phase of the scenarios represented in the LCA included manufacturing and transportation of CSO control components. The operation phase included the operation of water and wastewater treatment plants, CSO/stormwater discharges impacts, and pump operation for both RWH and gray infrastructure facilities. The maintenance phase included replacement of pumps and cisterns. A 75-year analysis period was considered after discussions with the City of Toledo Engineering personnel. A 50-year period was considered by De Sousa et al. (2012) to study strategies composed of porous pavements, bio-retention cells, and rain gardens.

The Life Cycle Inventory (LCI) analysis is, in fact, creating an inventory of flows to and from nature for a product system (ISO 14040 2006). Inventory flows comprise inputs of water, energy, and raw materials; and releases to air, land, and water (ISO 14040 2006). The system boundary shown in Figure 3.5 directed the LCI as presented in Table 3.1 and Table 3.2. The input quantities for each scenario are explained in Section 3.2.3. The data for the environmental impacts of processes included in Table 3.1 and Table 3.2 were taken from Ecoinvent database (Ecoinvent, 2.2) using GaBi 6 (PE International 2014) and the Ecoinvent database (Ecoinvent 2.2). In Table 3.1 and Table 3.2, values for potable water treatment, CSOs, and combined sewage treatment are differences from the existing condition (BAU). A process for pumping does not exist in Ecoinvent. Quantities of steel and plastic included within a pump were estimated to model the impacts of manufacturing a pump. Both CSOs and untreated stormwater discharges contain pollutants that impact the environment once released to surface water bodies. To inventory these flows, the concentrations of pollutants were obtained from City of Toledo engineering personnel and U.S. National Stormwater Quality Database (Maestre and Pitt 2005), respectively.

Table 3.1. Components and energy consumption of scenarios using the TRACI method.

Scenario	Phase	Component	Input quantity	Unit	Energy (kwh)
TF	Construction	Concrete	3.9E+3	m^3	3.3E+6
		Galvanized steel	1.8E+6	kg	1.4E+7
		Pump	2.4E+5	kg	7.0E+5
		PVC pipes	2.6E+5	kg	5.3E+6
		Materials transportation	1.2E+9	kg-km	3.4E+5
	Operation	Pump energy	1.5E+7	MJ	1.5E+7
		Potable water treatment	-6.7E+7	m^3	-2.3E+8
		CSOs	-2.8E+7	m^3	-
		Combined sewage treatment	3.2E+7	m^3	1.0E+8
	Maintenance	Cistern and pump replacement	Mixed	-	3.3E+7
HRR	Construction	Concrete	1.3E+4	m^3	1.1E+7
		Galvanized steel	1.9E+6	kg	1.5E+7
		Materials transportation	3.3E+9	kg-km	9.6E+5
	Operation	CSOs	-3.7E+7	m^3	-
		Combined sewage treatment	3.8E+7	m^3	1.2E+8
	Maintenance	Cistern replacement	Mixed	-	3.0E+7
HybTF	Construction	Concrete	4.1E+3	m^3	3.5E+6
		Galvanized steel	1.3E+6	kg	1.0E+7
		Pump	1.8E+5	kg	5.1E+5
		PVC pipes	1.9E+5	kg	3.8E+6
		Materials transportation	1.1E+9	kg-km	3.4E+5
		Reinforced Steel	9.4E+4	kg	1.1E+6
	Operation	Pump energy	1.1E+7	MJ	1.1E+7
		Potable water treatment	-4.8E+7	m^3	-1.7E+8
		CSOs	-1.0E+8	m^3	-
		Stormwater discharges	-7.2E+6	m^3	-
		Combined sewage treatment	1.1E+8	m^3	3.4E+8
	Maintenance	Cistern and pump replacement	Mixed	-	2.4E+7
HybHRR	Construction	Concrete	1.0E+4	m^3	8.8E+6
		Galvanized steel	1.4E+6	kg	1.1E+7
		Pump	2.2E+3	kg	6.4E+3
		Materials transportation	2.6E+9	kg-km	7.8E+5
		Reinforced Steel	9.4E+4	kg	1.1E+6
	Operation	Pump energy	4.3E+5	MJ	4.3E+5
		CSOs	-1.1E+8	m^3	-
		Stormwater discharges	-6.9E+6	m^3	-
		Combined sewage treatment	1.1E+8	m^3	3.6E+8
	Maintenance	Cistern and pump replacement	Mixed	-	2.2E+7
Gray	Construction	Concrete	8.5E+4	m^3	7.2E+7
		Pump	7.5E+4	kg	2.2E+5
		Reinforced steel	9.9E+5	kg	1.2E+7
		Materials transportation	2.0E+10	kg-km	6.0E+6
	Operation	Pump energy	3.7E+6	MJ	3.7E+6
		CSOs	-1.3E+8	m^3	-
		Stormwater discharges	5.8E+8	m^3	-
		Combined sewage treatment	-4.6E+8	m^3	-1.5E+9
	Maintenance	Pump replacement	Mixed	-	1.5E+6

Table 3.2. Environmental impacts of scenarios using the TRACI method.

Scenario	Component	GWP (kg CO_2e)	ETW (CTU eco)	EP (kg Neq)	ODP (kg CFC 11eq)
TF	Concrete (pad)	1.1E+6	1.1E+6	5.6E+2	4.6E-2
	Cistern (galvanized steel)	4.8E+6	-4.3E+6	-1.5E+4	1.3E-2
	Pump	2.2E+5	-2.6E+5	-9.1E+2	4.0E-4
	PVC pipes	7.4E+5	5.3E+4	9.6E+1	1.0E-4
	Materials transportation	8.6E+4	5.2E+4	2.6E+4	1.4E+1
	Pump energy	1.1E+7	3.9E+5	1.4E+3	4.7E-3
	Potable water treatment	-2.7E+7	-1.9E+8	-1.0E+5	-1.4E+0
	CSOs	-	-7.3E+8	-1.6E+2	-
	Combined sewage treatment	1.9E+7	2.0E+8	7.5E+5	1.0E+0
	Cistern and pump replacement	1.1E+7	-1.0E+7	-2.5E+4	6.1E+0
HRR	Concrete (pad)	3.4E+6	3.7E+6	1.8E+3	1.5E-1
	Cistern (galvanized steel)	5.2E+6	-4.6E+6	-1.6E+4	1.4E-2
	Materials transportation	2.4E+5	1.5E+5	7.2E+4	3.8E+1
	CSOs	-	-9.5E+8	-2.0E+2	-
	Combined sewage treatment	2.2E+7	2.4E+8	8.7E+5	1.2E+0
	Cistern replacement	1.0E+7	-9.2E+6	-2.4E+4	4.5E+0
HybTF	Concrete	1.1E+6	1.2E+6	5.8E+2	4.8E-2
	Cistern (galvanized steel)	3.4E+6	-3.1E+6	-1.1E+4	9.5E-3
	Pump	1.6E+5	-1.9E+5	-6.7E+2	3.0E-4
	PVC pipes	5.3E+5	3.8E+4	6.9E+1	1.0E-4
	Materials transportation	8.4E+4	5.1E+4	2.5E+4	1.3E+1
	Reinforced Steel	1.4E+5	2.4E+6	6.4E+2	7.0E-3
	Pump energy	7.8E+6	2.9E+5	1.0E+3	3.5E-3
	Potable water treatment	-1.9E+7	-1.4E+8	-7.3E+4	-1.0E+0
	CSOs	-	-2.6E+9	-5.5E+2	-
	Stormwater discharges	-	-5.6E+7	-3.4E+4	-
	Combined sewage treatment	6.3E+7	6.7E+8	2.5E+6	3.4E+0
	Cistern and pump replacement	8.0E+6	-7.4E+6	-1.8E+4	4.4E+0
HybHRR	Concrete	2.8E+6	3.0E+6	1.5E+3	1.2E-1
	Cistern (galvanized steel)	3.7E+6	-3.3E+6	-1.2E+4	1.0E-2
	Pump	2.0E+3	-2.4E+3	-8.0E+0	0.0E+0
	Materials transportation	1.9E+5	1.2E+5	5.8E+4	3.1E+1
	Reinforced Steel	1.4E+5	2.4E+6	6.4E+2	7.0E-3
	Pump energy	3.0E+5	1.1E+4	3.9E+1	1.0E-4
	CSOs	-	-2.7E+9	-5.8E+2	-
	Stormwater discharges	-	-5.4E+7	-3.3E+4	-
	Combined sewage treatment	6.5E+7	7.0E+8	2.6E+6	3.6E+0
	Cistern and pump replacement	7.5E+6	-6.6E+6	-1.7E+4	3.2E+0
Gray	Concrete (pavement, storage)	2.3E+7	2.4E+7	1.2E+4	9.9E-1
	Pump	6.8E+4	-8.0E+4	-2.8E+2	1.0E-4
	Reinforced steel	1.4E+6	2.5E+7	6.7E+3	7.3E-2
	Materials transportation	1.5E+6	9.1E+5	4.5E+5	2.4E+2
	Pump energy	2.6E+6	9.7E+4	3.4E+2	1.1E-3
	CSOs	-	-3.3E+9	-6.9E+2	-
	Stormwater discharges	-	4.6E+9	2.8E+6	-
	Combined sewage treatment	-2.7E+8	-2.9E+9	-1.1E+7	-1.5E+1
	Pump replacement	4.8E+5	-5.6E+5	-8.2E+2	6.1E-1

Being based on U.S. impact data, TRACI (the Tool for the Reduction and Assessment of Chemical and other environmental Impact) assessment method was used in this study to best represent environmental impacts in Toledo. Among the TRACI impact categories, Global Warming Potential (GWP), Eco-toxicity Water (ETW), Eutrophication Potential (EP), and Ozone Depletion Potential (ODP) were selected to represent the environmental and water quality impacts caused by the studied scenarios.

3.2.3 CSO Control Scenarios

CSO control scenarios in this study were classified based on their use of RWH and gray infrastructure. The gray scenario was selected to match the City of Toledo's existing LTCP. Two RWH-only scenarios were considered based on cistern outflows: supplying toilet flushing (TF) demand and incorporating extended detention with a high release rate (HRR). The TF and HRR scenarios were developed to evaluate the local and regional recommendations via the uWISE framework. Two hybrid scenarios (HybTF and HybHRR) were also modeled based on the combinations of gray infrastructure and RWH to find a compromise between high performance and low impact. The scenarios were not equivalent in terms of degree of control, but this issue is taken care of when all results are normalized to the FU. In order to calculate the changes from existing conditions, a scenario with no CSO control was considered additionally.

3.2.3.1 Gray Scenario

Toledo's last version of the LTCP (2009), also known as Phase Two, was selected to be the gray infrastructure-only scenario (Gray scenario) in this study. All of the control practices implemented are so-called gray infrastructure components.

This scenario is composed of several components shown in Table 3.3, including sewer separation, storage pipelines, storage basins, new storage tunnels and existing storage tunnel extensions. In general, storage tunnels will serve outfalls close to the city downtown (located at the center of the hatched area in Figure 2.2). On the other hand, sewer separation and storage basins will serve outfalls far from the downtown area. The location of the elements of this scenario is presented in Table 3.3.

Table 3.3. Major components of the Gray scenario (adapted from City of Toledo 2009b).

Item	Project type	Receiving water body	Location
1	Sewer Separation	Ottawa River	Tributary area of outfalls 63 and 64
2		Maumee River's east side	Northern part of the Eastside watershed
3		Swan Creek	Tributary area of outfalls 50
4		Maumee River's west side	Tributary area of outfalls 25
5	Storage Basin	Ottawa River	Tributary area of outfalls 61, 62, 65 and 67
6		Maumee River's west side	Tributary area of outfall 33
7		Maumee River's east side	Tributary area of outfall 9
8		Maumee River's east side	Tributary area of outfall 5
9	Storage Tunnel	Ottawa River	Tributary area of outfalls 61, 62, 65 and 67
10		Maumee River's west side	The existing Downtown Tunnel
11		Swan Creek	Extending existing Swan Creek North Tunnel
12	Storage Pipeline	Maumee River's west side	Tributary area of outfalls 23, 24 and 25
13		Maumee River's east side	Tributary area of outfalls 6 and 7

All the components are planned for completion by 2020. Additional information of subprojects, e.g., location, capacity, and current status, can be found at http://www.toledowaterwaysinitiative.com. Table 3.1 shows the estimated quantities of concrete, steel, and pumps needed for constructing the Gray scenario. These quantities were derived from the construction plans and data provided by the City of Toledo engineering personnel. According to these data, concrete was the major component for storage facilities, and steel was the major component for sewer separation. The storage capacity of this scenario is presented in Table 3.4.

Pumping was required to dewater the storage facilities. Material transportation requirements were estimated based on the weight of materials and an assumed 100 *km* average distance from plant to installation point (Sanjuan-Delmas 2014). As shown in Figure 3.1, SWMM results provide the volumes of CSOs, the stormwater discharges to water bodies (through the hypothetical, new separate sewers), and the combined sewage delivered to the WWTP. Then this model is linked to the LCA model.

Table 3.4. CSO control scenarios and their capacity.

	RWH		**Hybrid**		
Scenarios	**TF**	**HRR**	**HybTF**	**HybHRR**	**Gray**
Control strategy	Only RWH for all the 3 watersheds	Only RWH for all the 3 watersheds	RWH in West Side and Ten Mile, and Gray in East Side	RWH in West Side and Ten Mile, and Gray in East Side	All the items in Table 3.3
RWH cap.	2.65m^3	5.68m^3	2.65m^3	5.68m^3	-
RWH release	Toilet flushing	48 hr release	Toilet flushing	48 hr release	-
Total cap.	46,457m^3	99,576m^3	78,017m^3	116,151m^3	201,384m^3

3.2.3.2 RWH Scenarios

Table 3.4 lists the details of the RWH scenarios in this study: TF and HRR. A 50% participation rate was assumed for these scenarios to represent a target participation rate after discussions with the City of Toledo Engineering personnel, which means that 50% of the total buildings (residential and commercial) in the combined sewer area were equipped with an RWH cistern. The total number of buildings with the RWH systems in this scenario is 17,531, installed at buildings located in the combined area. To count the number of buildings in each subsewershed, GIS data of the buildings' footprints were obtained from Auditor's Real Estate Information System (AREIS) (2014). These data were also used to calculate the building rooftop area treated by RWH in each subsewershed.

Among the various GI types, this study focused on RWH due to its ability to provide dual benefits of runoff reduction and offsetting indoor water demands (Sample and Liu 2014; Steffen et al. 2013; Walsh et al. 2014). Different indoor (e.g., TF, laundry, and drinking) and outdoor (e.g., lawn irrigation) end uses can be supplied by RWH. In this study, two types of RWH release were considered.

For the first RWH scenario, TF was selected because of its feasibility as a reasonable indoor end use for harvested rainfall without requiring the need for full treatment to drinking water standards (Crettaz et al. 1999; Wang and Zimmerman 2014). The TF scenario comprised a uniform implementation of 2.65 m^3 cisterns throughout the city. The size of the cisterns was based on previous studies and discussions with the City of Toledo Engineering personnel. Steffen et al. (2013) recommended this cistern size for a typical residential parcel (186 m^2) in Midwest cities based on the yield before spill (Fewkes and Butler 2000) to save up to 92% in TF supply. The selected cistern size is sufficient to capture 1.4 cm rainfall on a typical residential building rooftop (with a pitched roof). To estimate the toilet flushing demand, we assumed 5.1 and 4.0 flushes/person/day for residential and commercial buildings, respectively (Vickers 2001). The average number of people in buildings was set at 2.4, according to the U.S. Census Bureau (2014). In order to simulate the releases from RWH units, underdrain flows in SWMM (governed by the orifice equation) were matched to supply (residential and commercial) TF demands. To obtain an underdrain coefficient for each subwatershed, first, the dominant building type in each subsewershed (residential or commercial) was identified using the GIS data. Then, based on the flushing demand and average number of building occupants, average daily flushing demand volume was calculated in terms of volume per day for a typical building in each subsewershed. The complete details of the modeling procedure and data were explained in Chapter 2.

The second scenario, namely HRR, implemented a larger cistern size – 5.68 m^3 – with a release rate related to a 48-hour drain time performing extended detention. Although this function is partially different than the classic definition of RWH (since the captured water is not used to meet any indoor demand), it is considered a member of RWH family functions in some recent studies, e.g., Walsh et al. (2014). The selected cistern size for this scenario is sufficient to capture 3 cm rainfall on a typical residential building rooftop. The complete details of 48-hour drainage modeling were explained in Chapter 2. According to Table 3.4, RWH scenarios do not represent an equivalent storage capacity to the Gray scenario because achieving a total storage capacity as high as the Gray scenario through RWH in buildings required infeasible tank sizes in the studied area. This is due to the large capacity of infrastructure in the Gray scenario.

Table 3.1 shows the estimated quantities of concrete and steel needed for constructing the TF and HRR scenarios as the major components in their construction phase. For the TF scenario, pumping and PVC pipes were required to supply the TF demand. All quantities and the energy required for pump operation were taken from Chapter 2. Material transportation requirements were estimated using the same approach for the Gray scenario. According to Figure 3.1, SWMM results provided the volume of TF demand delivered, the CSOs, and the combined sewage delivered to the WWTP. However, since the available SWMM model only simulates the CSO outfalls (not stormwater outfalls), RWH potential in decreasing stormwater discharges to water bodies was not considered in this study.

The TF scenario was used as a basis for comparing the uWISE with the Extrapolation method. The TF scenario was selected for this purpose because it suggests a benefit at the building-scale, i.e., avoiding potable water utilization for TF. Since the HRR was not designed to supply any indoor or outdoor building demand, the Extrapolation method is not applicable to this scenario, as it would only show negative impacts in the present framework. In order to analyze the TF via the Extrapolation method, the following are required to calculate the TF demands met by the RWH (according to Figure 3.2): RWH system details, rainfall data, and TF demand in buildings. Due to the lack of H&H modeling, the effects of RWH implementation on CSOs cannot be assessed using the Extrapolation method. Furthermore, in case of studying the TF scenario in a combined sewer network via the Extrapolation method, effects of RWH implementation on the volume of combined sewage delivered to the WWTP cannot be observed. This is because, in a combined network, both the stormwater and wastewater go to the same network, so the Extrapolation method assumes all captured stormwater volume by RWH (except the final storage, which is trivial) is either overflowed or flushed through toilets. Both enter the combined sewage network through the storm drain inlets or through the sanitary sewer connections. Therefore, the total combined sewage volume is unaffected. This inconsistency is resolved by the uWISE framework.

3.2.3.3 Hybrid Scenarios

Two hybrid scenarios were designed to combine gray infrastructure and RWH: HybTF and HybHRR. The former is based on the combination of the TF and Gray scenarios, and the latter is based on the combination of the HRR and Gray scenarios. Table 3.4 describes these scenarios. HybTF and HybHRR were chosen for this study to determine the effect of replacing some gray infrastructure in the LTCP by RWH. The HybTF scenario was derived based on engineering judgment to find a compromise between high performance and low impacts provided by the Gray and TF scenarios, respectively. To accomplish this, different permutations of implementing either the TF or Gray components in the three watersheds were analyzed ($2^3 = 8$ permutations total). As a result, the HybTF scenario was defined based on the Gray activities in the Eastside watershed and RWH in the Westside and Ten Mile watersheds (Table 3.4) since it led to the lowest life cycle costs per CSO volume reduction compared to the other seven permutations (see Chapter 2). For the HybHRR scenario, HRR components were considered instead of TF components to compare the performance of these functionalities of RWH in a hybrid manner (Table 3.4).

In summary, five scenarios were studied: one Gray, two RWHs, and two hybrids (Table 3.4). For each scenario, five years of hourly continuous simulation from 1/1/1997 to 12/31/2001 was performed in concordance with the LTCP baseline. This period is identified as the representative interval of 1972 to 2001 by the City of Toledo (2005). To achieve the operation phase results for the 75 years analysis period, repetition of the five years of simulation was executed 15 times. Incorporating the possible future changes on rainfall intensity, regimes, and other characteristics of rainfall into account was beyond the scope of the present study.

3.3 Results and Discussions

3.3.1 H&H Results

Figure 3.6 shows the results for the four H&H outputs listed in Figure 3.1. In order to present the overall hydrologic effects provided by each scenario, the results are not normalized to the FU at this step. Figure 3.6 indicates that the extended detention function of RWH (considered in HRR and HybHRR scenarios) did not lead to a significant improvement in CSO control ability compared to the supplying toilet flushing demand function (TF and HybTF scenarios respectively). Further analysis revealed that the CSOs are likely caused by the long duration of the rainfall events in the studied area, which lead to the cisterns being filled during each storm. The long rainfall events also lead to saturated pervious areas. Therefore, the high release rate of HRR and HybHRR scenarios contributed to CSO events through the stormwater drainage network. For the TF and HybTF scenarios, the proposed cistern size could lead to around 52 m^3 of captured water per building per year that could meet the entire assumed flushing demand. In summary, given the dual benefits of water supply and CSO reductions observed in the TF and HybTF scenarios (depicted with a light hatch fill in Figure 3.6), it can be stated that these scenarios outperformed the HRR and HybHRR scenarios.

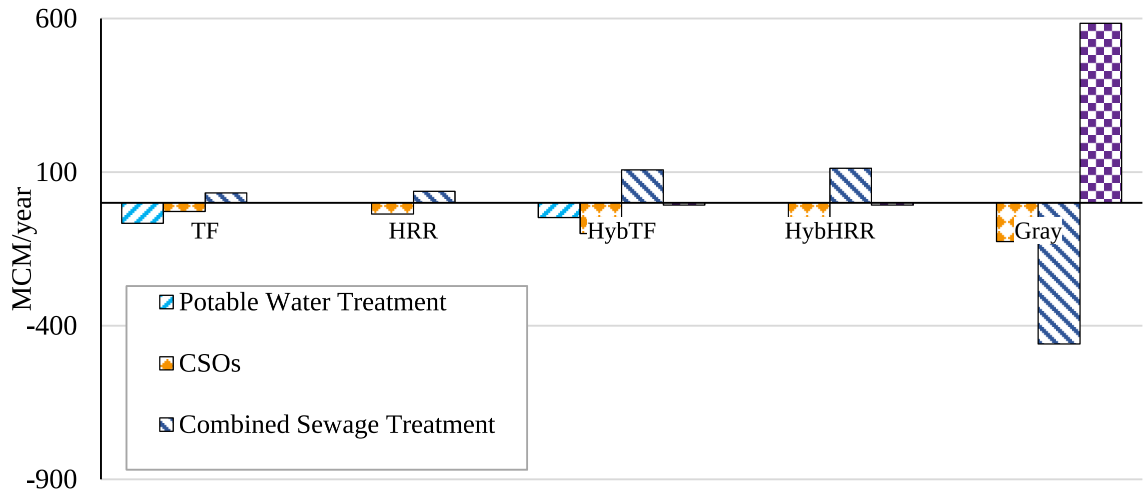

Figure 3.6. H&H results for all the scenarios. Values indicate changes from existing conditions.

Apart from the above point, Figure 3.6 indicates that the Gray scenario shows a substantial decrease in combined sewage volume delivered to the WWTP and an increase in untreated stormwater discharges. This indicates the significant role of the four sewer separation projects in this scenario (items 1 to 4 in Table 3.3). The other four scenarios led to an increase in the combined sewage volume delivered to WWTP due to the decentralized detention effect of the RWH units. This increase is the highest for the hybrid scenarios due to the large-scale storage facilities in the Eastside (items 7, 8 and 13 in Table 3.3).

Lastly, the CSO control ability of the hybrid scenarios (HybTF and HybHRR) was considerably higher than the RWH-only scenarios (TF and HRR) and slightly lower than the Gray scenario. This suggests the superior hydrological efficiency of the hybrid scenarios compared to the nonhybrid scenarios. Considering the dual water supply and CSO control criteria, the HybTF scenario is the highest performing scenario. All scenarios led to a daily combined sewage volume lower than the capacity of the Bay View WWTP, so all met the global performance goal.

3.3.2 uWISE Framework vs. Extrapolation Method

The performance of the uWISE and Extrapolation methods for the TF scenario is shown in Figure 3.7. Here, the results are not normalized to the FU, since the Extrapolation method is unable to model the CSOs. Note that only the TF scenario can be compared with the Extrapolation method, as explained in Section 3.2.3.2. Figure 3.7a shows that the impacts of increased combined sewage treatment volume (that was considered in uWISE and ignored in Extrapolation) are significant. As explained in Section 3.3.1, this increase is because of the detention effect of the decentralized RWH units. According to Figure 3.7a, the Extrapolation method shows an approximate balance between the added and avoided burdens of the TF scenario components. Without considering the increased combined sewage treatment volume, the avoided burden can almost compensate for the added burden of the new system implementation, performance and maintenance – which could be referred to as a sustainable equilibrium. However, according to the uWISE results in Figure 3.7a, the added burden caused by the additional combined sewage treatment volume (18.9 million kg CO_2e) – now captured instead of being discharged as a CSO – could approach 66% of total from the other components (28.5 million kg CO_2e). Further analyses confirmed that the high energy consumption for treating combined sewage is the main cause of this observation.

Figure 3.7b and 3.7c show the importance of watershed-scale hydrologic components (e.g. CSOs and combined sewage volume delivered to WWTPs) to estimate the life cycle environmental impacts for the categories related to the water quality, i.e., ETW and EP. These figures indicate that the Extrapolation method was incapable of estimating the watershed-scale life cycle impacts. For the uWISE results, in terms of ETW

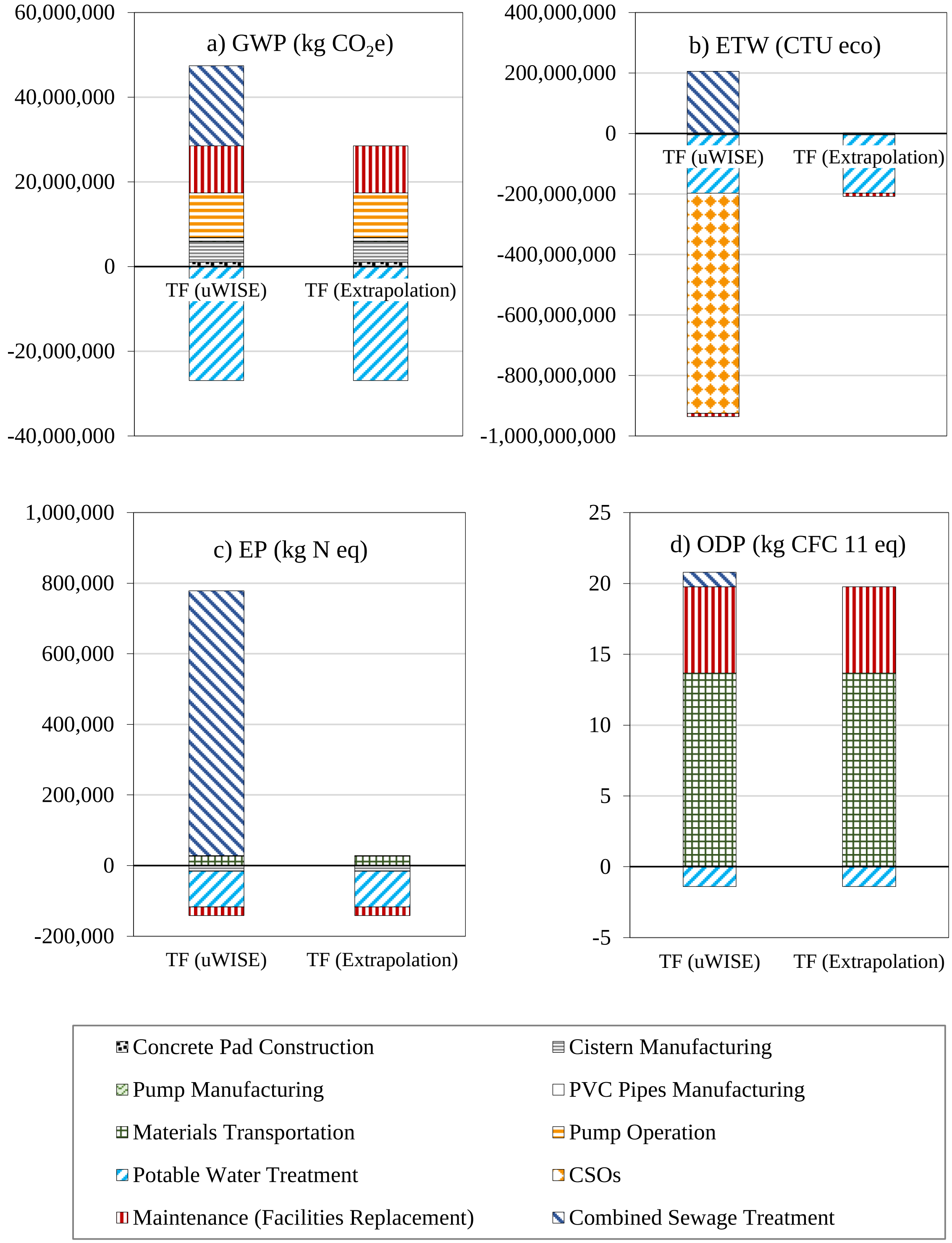

Figure 3.7. Comparison of the uWISE and Extrapolation results for the TF scenario over the entire (75 years) life cycle of facilities (not normalized). Volumes of potable water treatment, wastewater treatment, and CSOs indicate changes from existing conditions.

(Figure 3.7b), the reduced CSO volume could avoid 727 million CTU eco, while the added burden of combined sewage treatment and avoided burden of potable water treatment were in equilibrium (≈200 million CTU eco). CSO discharges were the most effective driving force for the uWISE results in terms of ETW, which can be explained by the high toxicity of CSO pollutants obtained from the LCA model. Figure 3.7c reveals the noticeable adverse impacts of increased combined sewage treatment volume via the uWISE framework in terms of EP. None of the avoided burdens in the uWISE framework (i.e. reduced potable water treatment and CSOs) could alleviate this impact. This is due to the significantly high eutrophication impacts of wastewater effluents obtained from the LCA model.

Lastly, Figure 3.7d shows materials transportation and replacement were the most important factors for ODP through both the uWISE framework and the Extrapolation method. In other words, the impacts of the hydrologic factors – i.e., CSO discharges, untreated stormwater discharges, potable water treatment, and wastewater treatment – were insignificant for this particular impact category. This is because of the high effect of fossil fuel consumption (compared to other components of the scenarios) on ozone depletion. Therefore, the Extrapolation method exhibited an acceptable estimation (95% accuracy).

3.3.3 RWH, Gray and Hybrid Scenarios

Results of comparing all five scenarios (gray, two RWH, and two hybrid) are shown in Figure 3.8. All the results shown in Figure 3.8 are normalized to the FU. The GWP for all scenarios is presented in Figure 3.8a. This figure indicates that the Gray scenario had the lowest GWP during its life cycle. This is because of the significant avoided burden

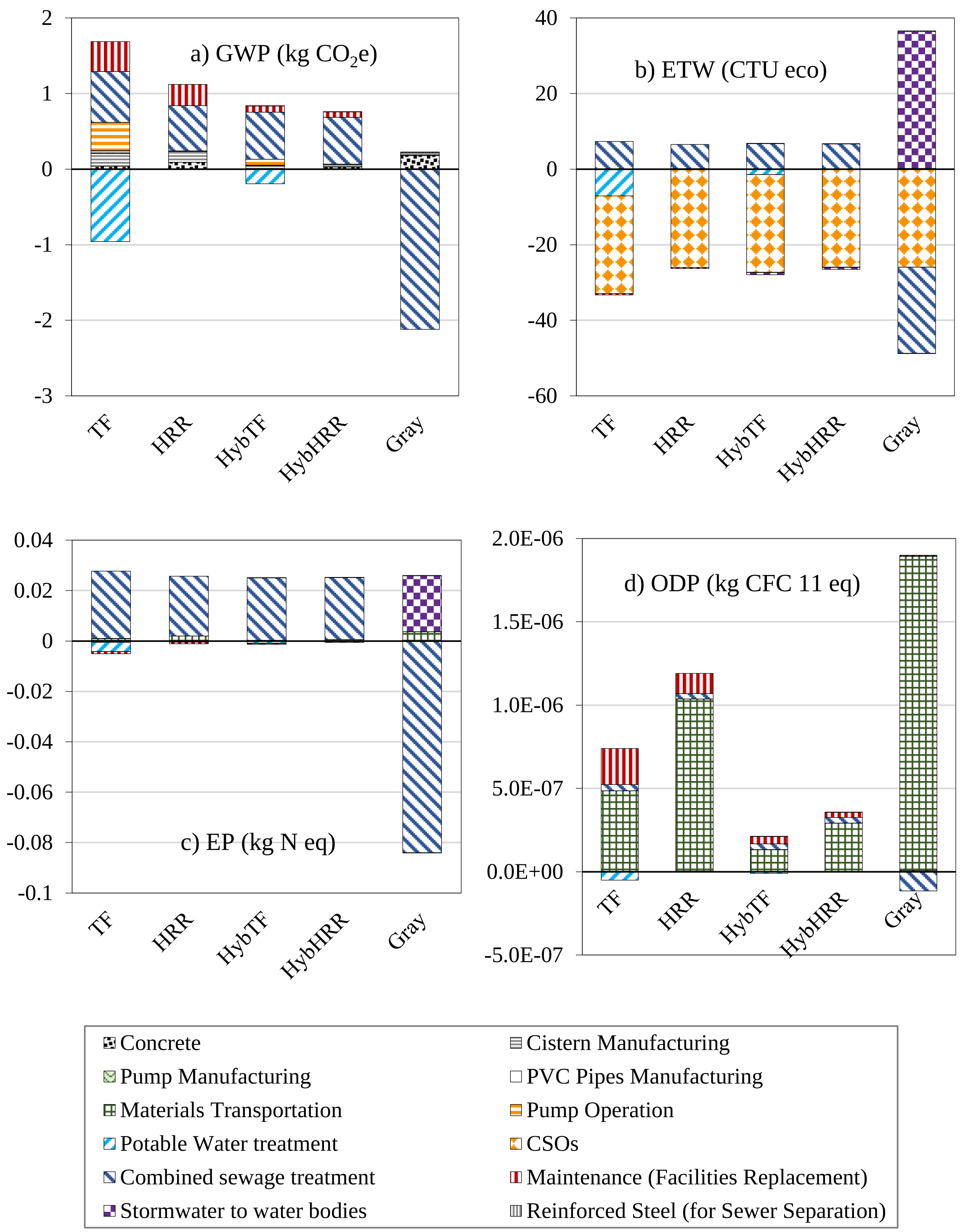

Figure 3.8. Comparison of the studied CSO control scenarios using the uWISE framework (normalized to the FU). Volumes of potable water treatment, wastewater treatment, CSOs, and stormwater discharges to water bodies represent changes from existing conditions.

from combined sewage treatment caused by the proposed separate sewers. Without performing the uWISE analyses, the above conclusion could be counter-intuitive to the general perception about gray CSO infrastructure: They necessarily lead to a higher GWP compared to decentralized techniques. Figure 3.8a shows that although the GWP impacts of concrete structure construction in the Gray scenario (0.18 kg CO_2e/m^3) were higher than the other scenarios, these impacts were trivial compared to the other components.

Figure 3.8a also indicates the TF had lower life cycle impacts in terms of GWP (0.73 kg CO_2e/m^3) compared to the HRR (1.12 kg CO_2e/m^3). This is mainly because the HRR does not realize the potable water treatment benefit (0.95 kg CO_2e/m^3). Although HRR avoided the impacts of pump operation (0.37 kg CO_2e/m^3) and maintenance (0.11 kg CO_2e/m^3), such benefits were negligible. Regarding the hybrid scenarios, similar to the previous point, HybTF had lower life cycle impacts in terms of GWP compared to the HybHRR. In general, hybrid scenarios presented lower potable water treatment benefits and lower maintenance impacts compared to the RWH-only scenarios, since in hybrid scenarios RWH implementation had a smaller scale.

Figure 3.8b shows all the scenarios could reduce ETW. Best performance was related to the TF scenario (-26.0 CTU eco/m^3) due to the avoided potable water treatment. The Gray scenario had the lowest performance (-12.1 CTU eco/m^3) because of the untreated stormwater discharges to water bodies. Since the results are normalized to the total CSO volume discharges, the avoided burdens from all the CSO control strategies were within a similar range (-25.9 CTU eco/m^3). Figure 3.8c shows that for the EP, the RWH scenarios led to an adverse life cycle impact (0.023 kg N eq/m^3 on average for the four scenarios), mainly because CSO discharges do not appear to increase long-term loading for constituents such as nitrogen and phosphorus. On the other hand, wastewater effluents increased the EP. Hence, the Gray scenario had the best performance for this category (-0.058 kg N eq/m^3).

Figure 3.8d shows that the Gray had the highest negative impacts (1.88 10^{-6} kg CFC 11 eq/m^3) regarding the ODP. Further analyses showed this is because the ODP is mostly related to the weight of the materials for their transportation needs. TF scenarios had smaller tanks and concrete foundation compared to the HRR scenarios. It is noted that since CSO impacts were almost zero for this impact category, normalization to the FU did not cause a similar pattern for different scenarios, as was the case for the previous categories.

For all the impact categories except ODP, the operation phase had the highest impacts compared to the other phases. For ODP, the highest impact was related to the material transportation. These mean that the impact of choice of materials on LCA results was trivial for all the scenarios (e.g., choosing plastic tanks instead of steel tanks).

3.4 Conclusions

This chapter combined hydrologic and LCA considerations into the evaluation of the environmental sustainability of RWH, gray, and hybrid strategies to control combined sewer overflows. For this purpose, an integrated watershed-scale assessment approach called uWISE was developed to explore the benefits versus extrapolating from a building to the watershed. Compared to a gray-only strategy, RWH could lead to lower life cycle impacts in terms of ETW and ODP, and higher impacts in terms of GWP and EP according to the uWISE results. Extrapolating from a building to the watershed was unable to properly estimate the impacts of the one scenario considered for the GWP, ETW, and EP categories (less than 28% of the estimated values by the uWISE framework). The only impact category where the linear extrapolation is similar to the uWISE results was the ODP (95% of the estimated values by the uWISE framework).

Moreover, results of projected GWP indicated that RWH could lead to higher impacts than gray strategies. Ordinarily, a detention facility (including RWH) avoids overflows, and so leads to a higher combined sewage treatment demand with elevated global warming impacts, while sewer separation (a gray activity) eliminates this impact. Instead, sewer separation may lead to comparatively high ETW impacts through untreated stormwater discharges to water bodies. Results showed that the ODP is mostly affected by transportation needs of materials during the construction and maintenance phases of the scenarios.

The uWISE framework provided broader information on the CSO control strategies and indicated the strengths and weaknesses of each scenario. Although the hybrid scenarios outperformed the other scenarios considering the hydrologic criteria, the uWISE results were mixed. Selecting the best scenario considering all hydrologic and LCA criteria using multicriteria decision making (MCDM) in conjunction with stakeholders is recommended as a follow-up study.

Other limitations that could be addressed by future studies include:

- Among the three spheres of sustainability – i.e., economic, environmental, and social – only environmental aspects were discussed in this study. Economic aspects were studied in Chapter 2, and social aspects could be the subject of a future study.
- This study used average values for water quality of combined sewage, CSOs

and stormwater. For higher accuracy, the H&H model could be extended to include a water quality module to simulate the pollutant concentration for combined sewage, CSOs, and stormwater.

- In this study, future values of system inputs and components, e.g., rainfall and water demand, were assumed to be the same as the current condition. However, for a more accurate estimate, future changes could be projected through appropriate research, e.g., climate and demographic change studies.

CHAPTER 4

WATERSHED-SCALE LIFE CYCLE ASSESSMENT OF RAINWATER HARVESTING: AN UNCERTAINTY ANALYSIS

4.1 Introduction

Designing and retrofitting urban drainage infrastructure to meet water quality standards is a challenge for more than 700 combined sewer communities in the U.S. (U.S. EPA 2014a). These communities discharge diluted (and in some cases partially treated) sewage directly into adjacent water bodies when the drainage system is overwhelmed (U.S. EPA 2014a). These point sources of discharge are referred to as combined sewer overflows (CSOs). Traditional drainage infrastructure design relies on hydrologic considerations (Guo 2001; Haan et al. 1994; Hsu et al. 2000), which typically lead to centralized, energy-intensive infrastructure solutions. Recently, however, application of life cycle assessment (LCA) that contributes to environmentally sensitive designs is gaining popularity (Flynn and Traver 2013; Ghimire et al. 2014; Stokes and Horvath 2011; Vineyard et al. 2015). Incorporating LCA into design and planning helps identify and quantify the relative environmental benefits of distributed infrastructure compared to centralized solutions for urban drainage (Zhou 2014), including CSO control (De Sousa et al. 2012; Wang et al.

2013).

Hydrologic analysis in traditional urban drainage design focuses on the operation phase, thus it may represent watershed-scale outcomes of different climatic, anthropogenic, and other scenario conditions (Lucas 2010; Ghimire and Johnston 2015; Shadeed and Lange 2010). As illustrated in Figure 4.1, LCA can provide a complement to hydrologic analysis to enable more holistic decision making by modeling all life cycle phases of the infrastructure (e.g., manufacturing of the materials and operation of the infrastructure) and by considering a broader set of sustainability criteria. However, most studies are limited to building-scale infrastructure without including hydrologic assessment at the watershed scale (Devkota et al. 2015; Ghimire et al. 2014; Malinowski et al. 2015; Morales-Pinzon

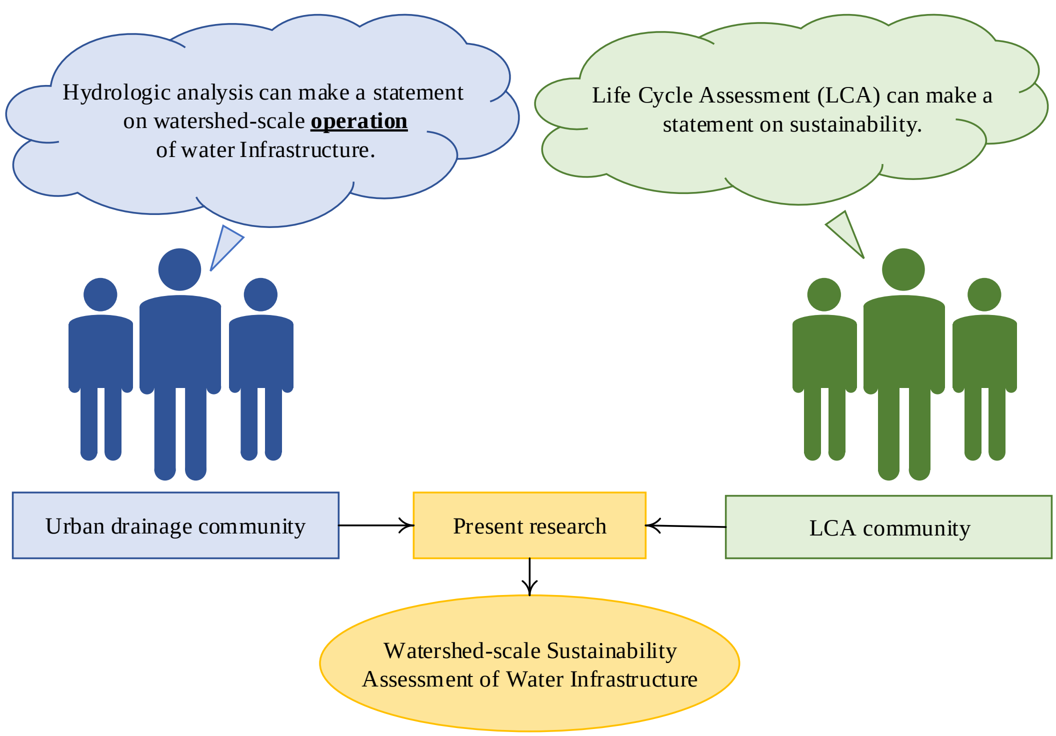

Figure 4.1. Contribution of the present research to watershed-scale, environmentally sustainable design of urban water infrastructure by combining hydrologic analysis and life cycle assessment.

et al. 2015; Vargas-Parra et al. 2013; Vieira et al. 2014; Vineyard et al. 2015). Given the recent movement toward the watershed-scale LCA of urban drainage practices (De Sousa et al. 2012; Philadelphia's Green City Clean Waters program 2015), making a transition to a more cohesive hydrologic-LCA analysis is appropriate. Improving the comprehension of uncertainty and how it may influence system specifications and design can guide this transition.

Life cycle impact assessment (LCIA) data are subject to uncertainties from several sources, depending on the quality of the data (Yoshida et al. 2014). These sources of uncertainty are highlighted by Weidema et al. (2013): unreliability, incompleteness, technological difference, spatial and temporal variation. Unreliability refers to data that are partly or completely estimated rather than measured. Incompleteness is the condition that representative data are not obtained from all relevant sites. Technological, spatial, and temporal variations exist in datasets obtained from different technologies, locations, time periods, and technologies. Use of hydrologic data amplifies these uncertainties because these data introduce natural variability and thus additional uncertainty that cannot be reduced by more measurements. Apart from uncertainties caused by data, incomplete or biased model structure also propagates uncertainties into outputs (Harder et al. 2015). Reported LCA results may be misleading if potential sources of uncertainty are not addressed, especially in the case of comparing design alternatives for decision making (Baker and Lepech 2009; EPA 2014b). Identifying major sources of uncertainties with relative impacts on final LCA results is indispensable (Cowell et al. 2002; Harder et al. 2015; Huijbregts 1998a,b) for effective application of hydrologic analysis and LCA for sustainable, watershed-scale design of urban drainage systems.

Uncertainty quantification aims find ways to increase the reliability of LCA-based conclusions (Heijungs and Huijbregts 2004), and they help support interpretation of LCA results according to the ISO 14040 (2006). Such statistically based analysis determines the density of plausible outputs around an expected value based on uncertainty propagated from different sources, instead of inflexible outputs of deterministic (nonstatistical) methods. Despite numerous uncertainty studies of LCA applications in different fields, including energy systems (Dones et al. 2005; Grant 2005; Sonneman et al. 2003), electronic devices (Andrae et al. 2004), farming (Basset-Mens et al. 2004; Ferret et al. 2004); transportation systems (Contadini et al. 2002) and building materials (Zhang and Vidakovic 2005), uncertainty analysis of LCA in water infrastructure evaluation has been studied by only a few researchers recently (Hongxiang and Wei 2013; Niero et al. 2014; Yoshida et al. 2014). Monte Carlo simulation appears to be the most commonly utilized and recommended technique for uncertainty analysis by LCA scientists (Baker and Lepech 2009; Contadini et al. 2002; Ciroth et al. 2004; Guo and Murphy 2012; Hongxiang and Wei 2013; Hung and Ma 2009; Niero et al. 2014; Yoshida et al. 2014). However, two recently published LCA studies on CSO control infrastructure (De Sousa et al. 2012; Wang et al. 2013) only investigated the possible range of LCA results using sensitivity analysis, without identifying the sources and relative effects of the different specific uncertainty components.

Therefore, this present research is intended to augment the body of urban drainage sustainability literature, including uncertainty studies, because it identifies and quantifies the sources and effects of uncertainties. Decentralized (or distributed) water infrastructure, specifically rainwater harvesting (RWH), is a primary focus of this research because of widespread interest of RWH and the need to consider environmental sustainability in addition to cost and traditional performance criteria for stormwater control and water supply (Burian and Jones 2010; Jones and Hunt 2010; Mehrabadi et al. 2013; Sample and Liu 2014; Steffen et al. 2013; Tavakol-Davani et al. 2015; Thomas et al. 2014).

An integrated hydrologic and LCA modeling framework is presented. Then, using Monte Carlo simulation, a comprehensive uncertainty analysis is conducted to investigate and quantify the major sources of uncertainties and their relative impacts. To perform the uncertainty analysis and interpret the results, two computational techniques are employed: high throughput computing (HTC) and partition-based, topology-inspired maps based on Morse-Smale regression (Gerber et al. 2013; Maljovec et al. 2016). The former provides the computational resource for iterative time-consuming simulations and the latter assists in detecting main drivers within local regions of the results to identify different system responses.

4.2 Methodology

This section presents (1) the goal and scope of the uncertainty analysis, (2) an integrated hydrologic analysis and LCA framework for the application of the uncertainty analysis, (3) the approach used to quantify the relative impacts of uncertainty components identified in the integrated framework, and (4) details of the case study application.

4.2.1 The Goal and Scope of Uncertainty Analysis

This subsection describes the sources of uncertainties in an integrated hydrologic-LCA design and then delineates the specific sources studied in this research. Based on merging previous relevant studies (Baker and Lepech 2009; Cellura et al. 2011; Dotto et al. 2012; Huijbregts 1998a; Leta et al. 2015; Loucks et al. 2005; Weidema et al. 2013), sources of uncertainties pertinent to integrated hydrologic-LCA design include

(i) Data uncertainty:

   a. Input parameter uncertainty, i.e., Life Cycle Inventory (LCI) data, which includes construction phase data, hydrologic data for the operation phase, and maintenance phase data. These data are subject to uncertainty arising from inaccurate measurements as well as natural variability.

   b. Model parameter uncertainty, i.e., LCIA data, which are subject to unreliability, incompleteness, technological difference, spatial and temporal variability.

(ii) Model structural uncertainty, which is either due to the incomplete structure of the model or unavoidable methodological choices, such as the functional unit and system boundaries. The incomplete structure of the model may include uncertainty in a future physical system, relative to the designed system.

(iii) Human-based uncertainty, which is caused by a lack of knowledge concerning human preferences from time to time or choices of analysts regarding modeling of preferences. Design objectives have been traditionally limited to hydrologic criteria, currently include environmental criteria, and might consider other objectives in future, e.g., social aspects.

The goal of the present study is to compare the effects of uncertainty in hydrologic data (input parameter) versus the effects of uncertainty in LCIA data (model parameter) in LCA-based urban water infrastructure design. Analyzing model structural and decision uncertainty is beyond the scope of this study because we believe that studying those uncertainty sources is of a lower priority compared to the goal of this research. This is because the present research examines the necessity of developing integrated frameworks. Studying the structural or design uncertainty of such frameworks may be performed as a follow-up study.

4.2.2 uWISE (urban Water Infrastructure Sustainability Evaluation)

We selected the uWISE approach (Figure 4.2 and Chapter 3), an integrated hydrologic analysis and LCA framework, for the uncertainty analysis application. The

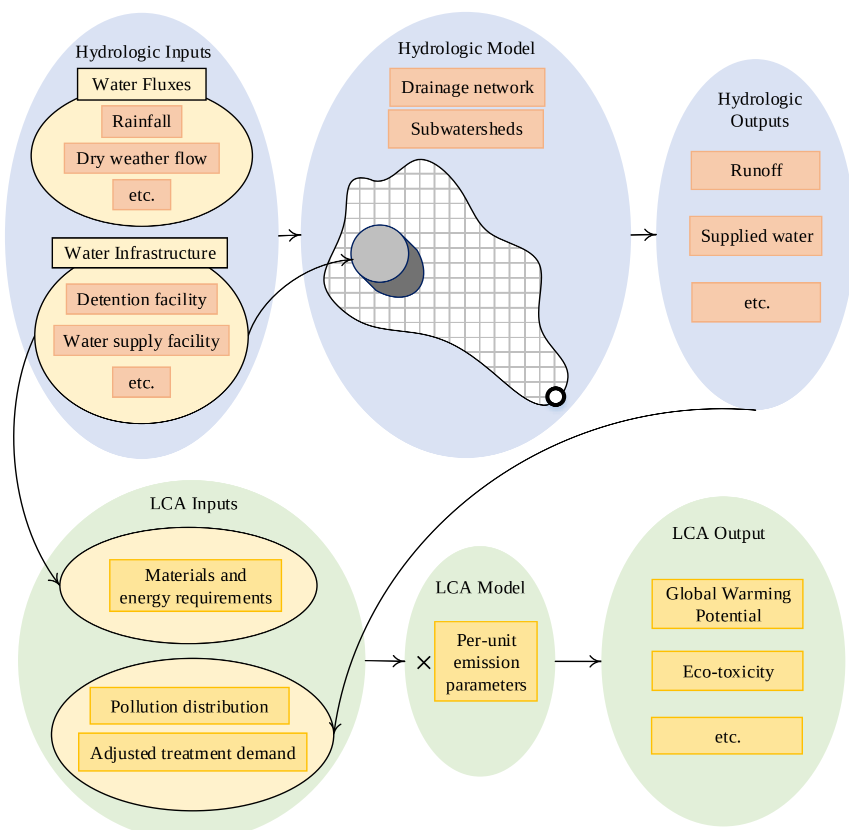

Figure 4.2. Summary of the uWISE framework. The upper row shows the H&H model components and the lower row shows the LCA model components.

uWISE framework uses a hydrologic model to simulate the effects of water infrastructure on the hydrology of the watershed in terms of supplied water through new infrastructure and stormwater. The model inputs include the characteristics of the water infrastructure components studied as well as hydrologic inputs, e.g., rainfall and dry weather flow (DWF). The hydrologic module computes the hydrologic response of subwatersheds and the hydraulic response of conveyance networks, explained in Section 4.2.2.1. Then, uWISE utilizes a process-based LCA model (Section 4.2.2.2) to translate the quantity of materials and energy consumption – over the life cycle of drainage facilities – into environmental impacts. To compute the LCA model calculations, uWISE combines hydrologic model outputs from the operation phase with the materials and energy from the construction and maintenance phases. In sum, uWISE forecasts the life cycle impacts for selected impact categories.

4.2.2.1 H&H Model

The U.S. EPA Storm Water Management Model version 5 (Rossman 2015) was employed in this study for continuous simulation of the representative year. The SWMM simulates the land surface as delineated subwatersheds, governed by the nonlinear reservoir equation as well as Manning's equation for overland flow. Water transport in conduits is addressed with the Dynamic Wave method, and SWMM solves the one-dimensional Saint Venant flow equation at each time step. The capture of rainfall from rooftops by RWH is simulated using the Rain Barrel Low Impact Development (LID) module in SWMM. To mimic the release from RWH units, underdrain flows from rain barrels (governed by the orifice equation) are matched to supply indoor demands. Among numerous hydrologic model outputs, the following were selected for the uWISE framework: CSO volume, CSD (combined sewage delivered to treatment plant) volume, and SDR (supplied demand by RWH) volume. It is noteworthy that SDR is conceptually similar to the volumetric reliability, which is a ratio defined as the total volume of rainwater supplied divided by total target demand during the entire simulation period. This research chose SDR rather than volumetric reliability, since SDR presents the actual volume that is needed for environmental impact assessment.

4.2.2.2 LCA Model

Life Cycle Assessment is a standard approach to estimate consumption of resources and emissions associated with the life cycle of a product, process or infrastructure (ISO 14044 2006). The LCA has four steps: outlining the goal and scope of the analysis (described in Section 4.2.1); gathering the data needed for all life cycle stages to create a life cycle inventory (LCI); quantifying the impacts via life cycle impact assessment (LCIA) methods; and interpretation of results. Since the goal of the drainage infrastructure in this study is to reduce CSOs, the functional unit (FU) is defined as 1 m^3 reduction of CSO volume over the life cycle of facilities. The selected FU sets the system boundaries of the LCA as depicted in a conceptual schematic (Figure 4.3). This boundary includes the operational phases of the WTP (water treatment plant) and WWTP (wastewater treatment plant) because both would be affected by RWH. The SWMM does not include a water distribution module. Therefore, to capture the effects on WTP, supplied demand by RWH was considered as an avoided burden from the WTP. A 75-year analysis period was considered since it is recommended as the average building life cycle and is used in other

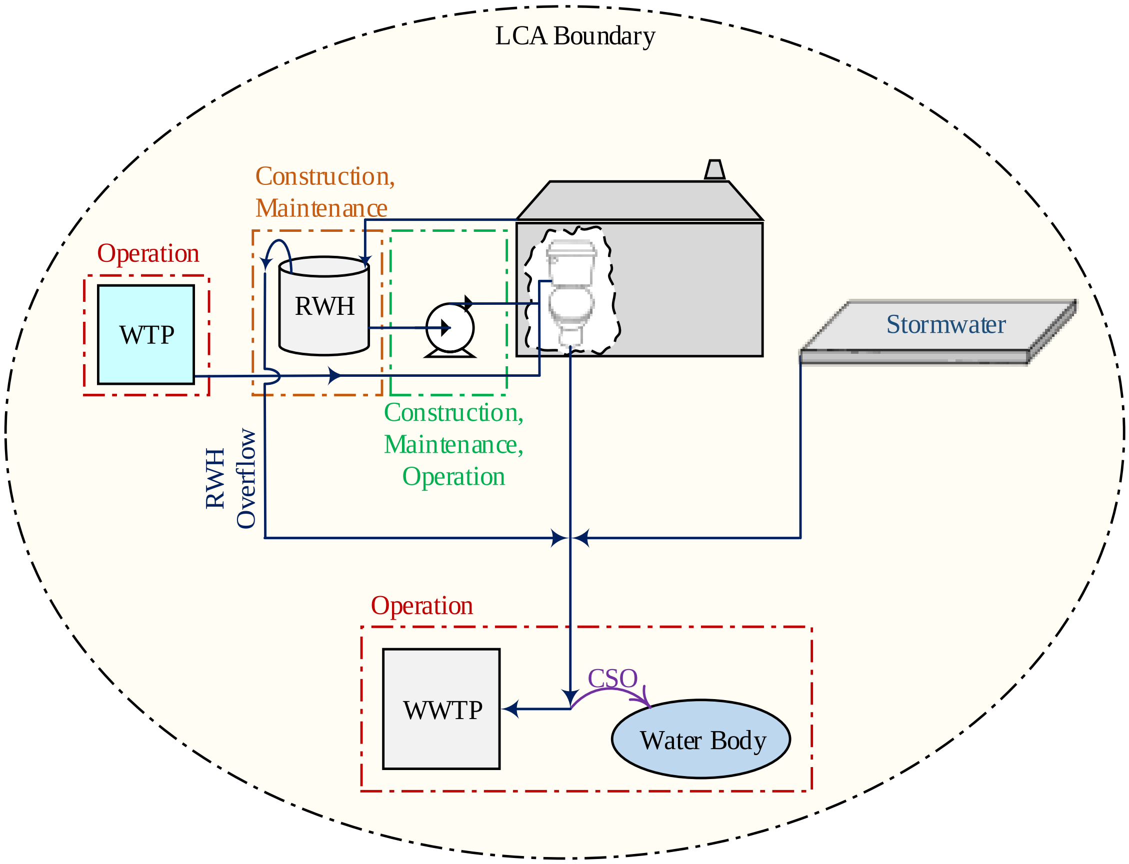

Figure 4.3. LCA system boundary. Operation phases of both WTP and WWTP would be affected by watershed-scale RWH implementation, and are thus included.

RWH studies (Devkota et al. 2015). Replacement of RWH components during this analysis period was considered in the present study.

The data for the environmental impacts of processes in this study were adapted from the Ecoinvent database (Ecoinvent, 2.2) using GaBi 6 (PE International 2014). The components of construction and maintenance phases are summarized in Table 4.1. The operation phase components will be varied through the uncertainty analysis process. The TRACI (Tool for the Reduction and Assessment of Chemical and other environmental Impact) method was used in this study since TRACI method and database is based on U.S. impact data.

Table 4.1. Components and impacts of RWH system for one building using the TRACI method. Impacts of construction and maintenance phases are provided in this table, and the values of operation phase components are provided by the hydrologic models that are varied in each MC run.

Phase	**Component**	**Input quantity**	**Input unit**	**Energy (kwh)**	**GWP (k CO_2 e)**	**ETW (CTU eco)**
Construction	Concrete (pad)	0.23	m^3	190.6	60.3	64.6
	Cistern (galvanized steel)	100.5	kg	799.5	272.5	-243.4
	Pump	13.9	kg	39.9	12.5	-14.8
	PVC pipes	14.8	kg	304.1	42.0	3.0
	Materials transportation	66,926.1	kg-km	19.7	4.9	2.9
Maintenance	Cistern and pump replacement	Mixed	-	1,887.2	634.5	-589.2

Among the TRACI impact categories, Global Warming Potential (GWP) and Eco-toxicity Water (ETW) were selected to represent the environmental and water quality effects of the studied urban water infrastructure.

4.2.3Uncertainty Analysis Procedure

4.2.3.1 Selected Parameters

Major sources of uncertainty in the parameters of uWISE are detailed in Table 4.2; selected parameters are marked in gray (Table 4.2). Two hydrologic input parameters and two LCIA model parameters were selected based on preanalysis tests.

Table 4.2. Major uncertainty sources of the uWISE. Selected components for uncertainty analysis in this research are marked with a gray background.

Sub-model	Component	Uncertainty type	Data source
Hydrologic	Rainfall (**R**). Illustrated as a part of water fluxes in Figure 4.2.	Input parameter	Sampled from a normal distribution for annual rainfall depth (Figure 4.4).
	Combined network water fluxes (e.g. Dry Weather Flow, groundwater flow)	Input parameter	Measured data.
	Capacity (**C**) of RWH (referred to as water infrastructure in Figure 4.2)	Input parameter	Sampled from a gamma distribution (Figure 4.4).
	RWH release rate	Model parameter	Toilet flushing demand data for a typical residential building (Tavakol-Davani et al. 2015).
	Subwatershed characteristics (e.g. slope, imperviousness, roughness, infiltration capacity)	Model parameters	Measured data.
	Conveyance network characteristics (e.g. details of pipes, regulators, pumps, outfalls)	Model parameters	Measured data.
LCA	Materials and energy requirement for construction and maintenance phase of RWH	Input parameter	Table 4.1
	Materials and energy requirements for performance phase of RWH	Input parameter	Hydrologic model output
	GWP impacts for per unit of CSD (GWP_{CSD}) – referred to as per unit emission parameter in Figure 4.2.	Model parameter	Sampled from a lognormal distribution (Figure 4.4)
	ETW impacts for per unit CSO (ETW_{CSO}) – referred to as per unit emission parameter in Figure 4.2.	Model parameter	Sampled from a lognormal distribution (Figure 4.4)

Hydrologic input parameters were selected based on a local sensitivity analysis, i.e., by identifying the model response to one parameter variation while other parameters held constant (Hamby 1995). Parameters whose variation (over the respective possible range) resulted in more than 30% change in the annual CSO volume were picked for the uncertainty analysis, leading to the selection of rainfall (R) and RWH capacity (C).

The importance of R and C as significant sources of uncertainty was also confirmed in previous hydrologic studies that focused on rainfall-runoff modeling (Leta et al. 2015; Zahmatkesh et al. 2015) and RWH design (Chilton et al. 2000; Lash et al. 2014; Matos et al. 2013; Ward et al. 2010), respectively.

LCIA model parameters were selected based on an LCA study of RWH scenarios at a watershed scale presented in Chapter 3. In that chapter, global warming potential (GWP) and Eco-toxicity Water (ETW) were reported as the impact categories that would be highly affected by RWH implementation in a combined sewer network.

Furthermore, the main drivers for increasing GWP and decreasing ETW were respectively found to be CSD and CSO, each of which were responsible for more than 40% of added/avoided impacts according to Chapter 3. Thus, in this study, GWP per unit of CSD was selected as one of the LCIA model parameters for uncertainty analysis (denoted by GWP_{CSD} for simplicity). The second parameter selected was the ETW per unit of CSOs (ETW_{CSO}). Although the choice of probability distribution for parameters has a limited influence on the overall uncertainty of LCA results (Weidema et al. 2013), an effort was made to extract accurate representative distributions based on the available data. For rainfall (R), the annual depth was sampled from a normal distribution fitted to the historical annual records of 54 years (Figure 4.4). Since the H&H model works with hourly data, the

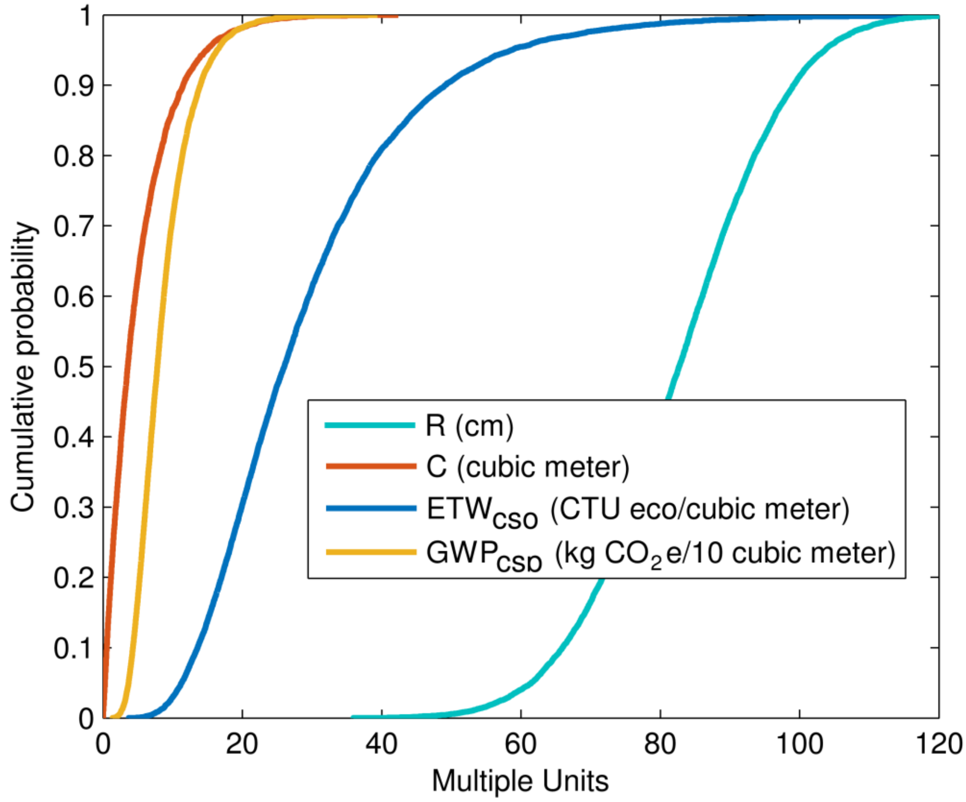

Figure 4.4. Cumulative probably density functions for parameters selected to perform the uncertainty analysis. A normal distribution for R (μ = 82.8, σ = 12.8), Gamma for C (α = 1, β = 0.2), lognormal for GWP_{CSD} (μ = -0.2, σ = 0.5), and lognormal for ETW_{CSO} (μ = 32.5, σ = 5.0) are considered.

hourly pattern of the representative year was applied to the sampled annual depth. The available C data were not as extensive as the available R data. Therefore, based on engineering judgment and consultation with RWH planners (from the City of San Diego, California), a gamma distribution was considered to reflect the higher possibility of installing smaller RWH systems and the unlikelihood of installing cisterns larger than 50 m^3. This distribution considers the demands of different buildings in the area (estimated based on size of buildings) as well as building owners' willingness to participate in the RWH program (estimated based on available RWH plan experiences). The uncertainty analysis approach in the present study considered RWH implementation for every building at the watershed with the same C, although C may get a value of zero that is equivalent to no RWH implementation. Lastly, LCIA model parameters were sampled from lognormal distributions based on the Ecoinvent data quality guideline (Weidema et al. 2013). Additionally, the pedigree matrix approach adapted by this guideline was used to calculate the variance of the distributions. The highest level of recommended uncertainties for the pedigree matrix was considered in order to comprehend the threshold of their effects compared to hydrologic data. Specifically, the variances of the underlying normal distributions for reliability, completeness, temporal correlation, geographical correlation, and technological correlation were considered as 0.04, 0.008, 0.04, 0.002, and 0.12, respectively. Considering the highest recommended uncertainty in the LCIA parameters allows us to make a statement on areas to advance the LCA-based design of urban water infrastructure, especially if we find the effect of this uncertainty insignificant.

4.2.3.2 Uncertainty Analysis Technique

Following recommendations in the literature (Baker and Lepech 2009; Contadini et al. 2002; Ciroth et al. 2004; Guo and Murphy 2012; Hongxiang and Wei 2013; Hung and Ma 2009; Niero et al. 2014; Yoshida et al. 2014), a Monte Carlo method (MC) was employed in this study for comparing the effects of input parameter uncertainty (hydrologic data) versus model parameter uncertainty (LCIA data). Since the initiation of MC (e.g., Metropolis and Ulam 1949), it has been globally utilized to obtain a statistical description of the system performance uncertainty (Loucks and Van Beek 2005). An interesting aspect of the MC application for this study is its nondependency on calculus-based characteristics in contrast to analytical methods, such as the first-order second-moment (FOSM) method (e.g., Elishakoff et al. 1987). The MC simply evaluates the uWISE function with diffident sets of parameters in an iterative manner. This is of importance for the present study due to the mathematical complexities of the uWISE, specifically in the hydrologic module. This module consists of several implicit, nonlinear functions (e.g., the Saint Venant flow equation) for transporting rainfall through conveyance network elements.

Some extensions to the MC have been proposed specifically to enhance its mathematical efficiency, such as Markov Chain Monte Carlo (MCMC) with the Metropolis-Hastings algorithm (Metropolis et al. 1953; Hastings 1970). Although these algorithms are widely used in hydrologic modeling to facilitate analysis of complex spaces (e.g., Vrugt et al. 2009; Zahmatkesh et al. 2015), some researchers disagree about convergence requirements (Gelman and Shirley 2011; Cowles and Carlin 1996).

The present study followed a fundamental MC instead, both for simplicity and to avoid these requirements, because a High Throughput Computing (HTC) resource was able to provide sufficient iterations for simulations. A freely available HTC resource, namely HTCondor (2015), was chosen in lieu of other available distributed computing resources, such as High Performance Computing (HPC) and Graphics Processing Unit (GPU). Our selection was due to significantly lower setup costs, platform-independent structure (cloud-based computing), and the high processing speed of HTCondor. Additional information on these resources and their examples in water engineering are presented in the Appendix.

The steps of the MC simulation for this study are diagrammed in Figure 4.5. Specifically, random sampling of individual parameter space from prior probability distributions is employed to extract a set of parameter values. Then, the parameters are

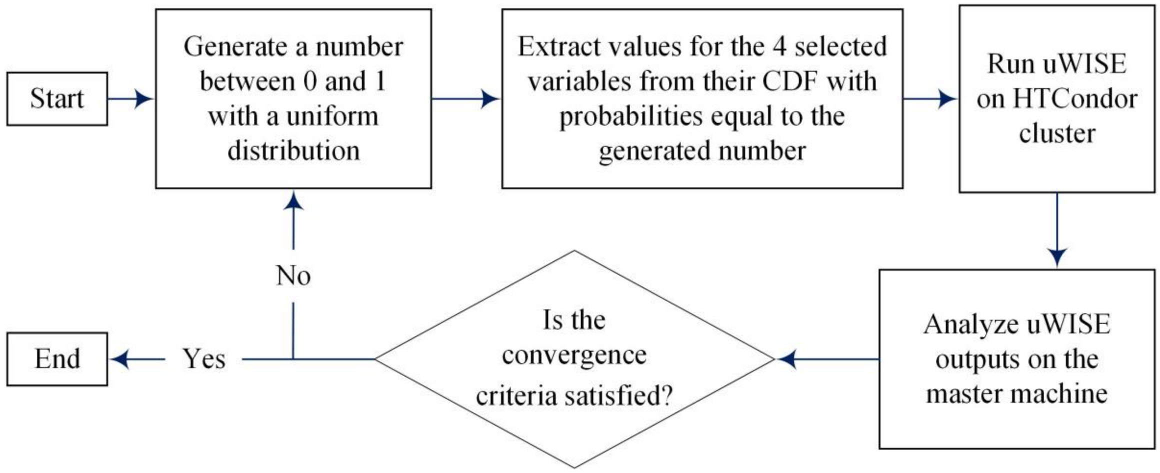

Figure 4.5. The steps of Monte Carlo simulation to analyze the uncertainties in results of the uWISE framework using HTCondor.

utilized to run the uWISE framework on an HTCondor v.7.8.8 cluster. Next, the changes in outputs are tracked and compared with a convergence threshold. When the convergence criterion is satisfied, probability density of outputs is presented. The convergence criterion was selected according to the Central Limit Theorem. For MC simulations, such a theorem states that the term $\frac{\sqrt{n}}{\sigma}(E(Y) - \overline{Y})$ converges to a Gaussian random variable with a mean of 0 and a variance of 1, where n and σ respectively denote the number and standard deviation of samples, E(Y) is the expected values of the selected output, and $\overline{Y}$ represents the average of the sampled outputs through Monte Carlo iterations. Since it is impossible to bound a random term, an inequality form of the above theorem is utilized in this research, considering a confidence level of 95%. With a probability of 95% and for large values of n, convergence occurs when the absolute value of $E(Y) - \overline{Y}$ approaches values smaller than $1.96\frac{\sigma}{\sqrt{n}}$ (Lapeyre 2007). This criterion is used for each model output studied in this research, separately.

4.2.3.3 Interpreting the Results

After performing the MC simulation, the portion of uncertainty propagated by each parameter was calculated using the First-Order Sensitivity Analysis method for the MC results as (Loucks and Van Beek 2005):

$$\mathrm{Var}(O) = \sum_{i=1}^{n} \left(\frac{\delta F}{\delta X_i}\right)^2 \times \mathrm{Var}(X_i) \tag{4.1}$$

where F is the uWISE model, X denotes the parameters, O represents the model output and n is the number of considered parameters (4 in this study). This equation is applicable only when all the parameters are independent of each other. In such case, the term $\left(\frac{\delta F}{\delta X_i}\right)^2 \times \mathrm{Var}(X_i)$ presents the portion of uncertainty propagated by variable X. In this study, independence of parameters was verified using the Mutual Information (MI) index (e.g., Cover and Thomas 1991). Values of MI close to zero show the statistical independence of studied variables, while higher values (e.g., higher than 1) may represent a meaningful dependency. MI for LCIA model parameters presented the highest value among all the permutations of the parameters in this study. However, this value was as 6.4×10^{-6}, which represent an insignificant dependency. In addition, $\frac{\delta F}{\delta X_i}$ was estimated using a numerical approximation, $\frac{\Delta F}{\Delta X_i}$, according to points adjacent to the output expected value. To control the accuracy of this approximation, the output variance calculated by Equation 4.1 was compared with the variance of the MC simulation for the uWISE outputs.

Furthermore, a partition-based, topology-inspired model based on the Morse-Smale regression (MSR) technique (Gerber et al. 2013) was adopted to assist in visual interpretation of the MC results. The MSR performs a domain partitioning induced by an approximated version of the topological structure known as the Morse-Smale complex (MSC). The MSC decomposes a space based on gradient flow. That is, each partition in the MSC represents data whose integral line begins at a specific local minimum and terminates at a specific local maximum. This minimum-maximum pair uniquely identifies the partitions of the MSC. Thus, the MSC can be approximated on the MC results by imposing a graph structure and approximating gradient flow as occurring on edges of the graph. An important property of the decomposed results is that within each partition, the data are assumed to be monotonic. As such, a linear model can be satisfactorily fitted within each partition. Additional information about this method and its application for the present research are presented in the Appendix.

4.2.4 Details of the Case Study Application

A combined sewer watershed in the City of Toledo, Ohio was used to conduct the uncertainty analysis. The annual average precipitation in Toledo is 85 cm (U.S. Climate Data 2014). The year 1998 is identified as the representative year for Toledo's rainfall. This identification is based on analysis of rainfall depth and intensity for 1972 to 2001 records by the City of Toledo (2005). The studied watershed, Eastside, consists of 41 subwatersheds with a total area of 9.54 km^2 (Figure 4.6). There are 9,892 buildings, predominantly residential, in this watershed (AREIS 2014). Financial and engineering aspects of RWH plans in this watershed are summarized in Chapter 2. In that chapter, RWH was reported as a cost-effective solution to supply toilet flushing demand and control CSOs

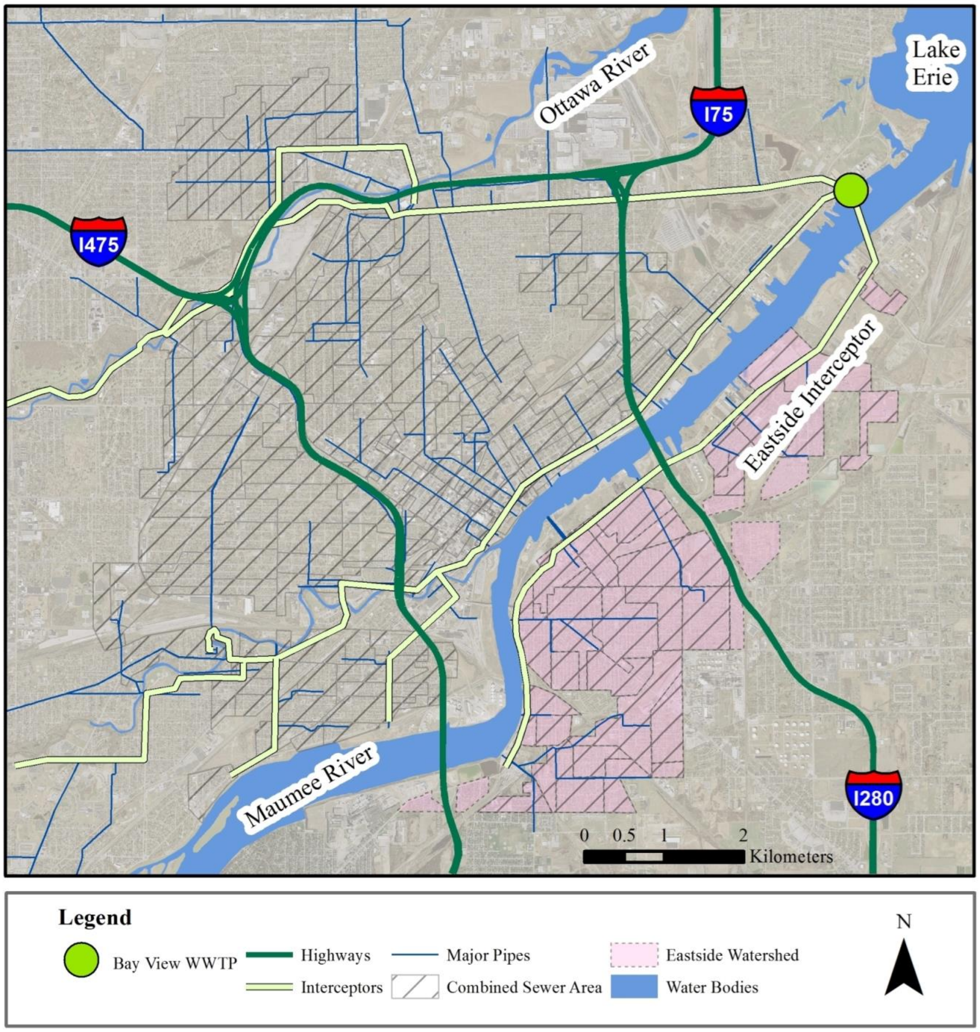

Figure 4.6. Tributary subwatersheds, major pipes, and the interceptor at the case study. This figure also shows the water bodies adjacent to the combined sewer drainage network (i.e., Maumee River and Lake Erie).

(48% cheaper than centralized solutions). Therefore, the uncertainty analysis considered toilet flushing as the end use of interest (Table 2.1). Eastside generates on average 1.3 MCM of CSOs annually, which is on average approximately 60% of the total annual CSO volume in Toledo. On average, the interceptor conveys 0.16 MCM/day of combined sewage from the combined and separate subwatersheds to the wastewater treatment plant located at the shore of Lake Erie.

4.3 Results and Discussions

4.3.1 H&H Results

Figure 4.7 presents the scatter plots of MC simulation for the hydrologic outputs based on 10,000 iterations, which was sufficient to satisfy the convergence criteria. Figure 4.7a reveals the nonlinear response of supplied demand by RWH (SDR) to a change in RWH system capacity (C). This finding challenges the efficacy of linear approximation of decentralized infrastructure performance for different capacities, e.g., methods that are based on the linear summation of capture depths. In fact, an increase in C will not cause a proportional increase in SDR because as C increases, the chance of a system becoming partially filled (by nonextreme rainfall events) also increases. Eventually, SDR will converge to a horizontal asymptote when C reaches the maximum possible capture of rooftop rainwater for each value of annual rainfall (R). Figure 4.7a also illustrates that increasing values of C increase the range of possible SDR values. Therefore, for larger systems, variability in R brings a higher uncertainty to SDR. This is because small systems would likely react similarly to various rainfall events (become completely full regardless of the rainwater level), while large systems would be filled to different levels in various rainfall events. Figure 4.7b shows that C has a comparatively small effect on CSO, although a slight nonlinear response of CSO to a change in C is observed (specifically for high values of R, illustrated with light green to red). This result is attributed to the limited capability of RWH to control CSOs given the existence of other CSO-causing components, e.g., DWF, groundwater flow, RDII (rainfall derived infiltration inflows), and the runoff from other impervious areas in subwatersheds. For low values of R, relative contribution of rainfall in generating CSOs is low, thus RWH is ineffective to control CSOs.

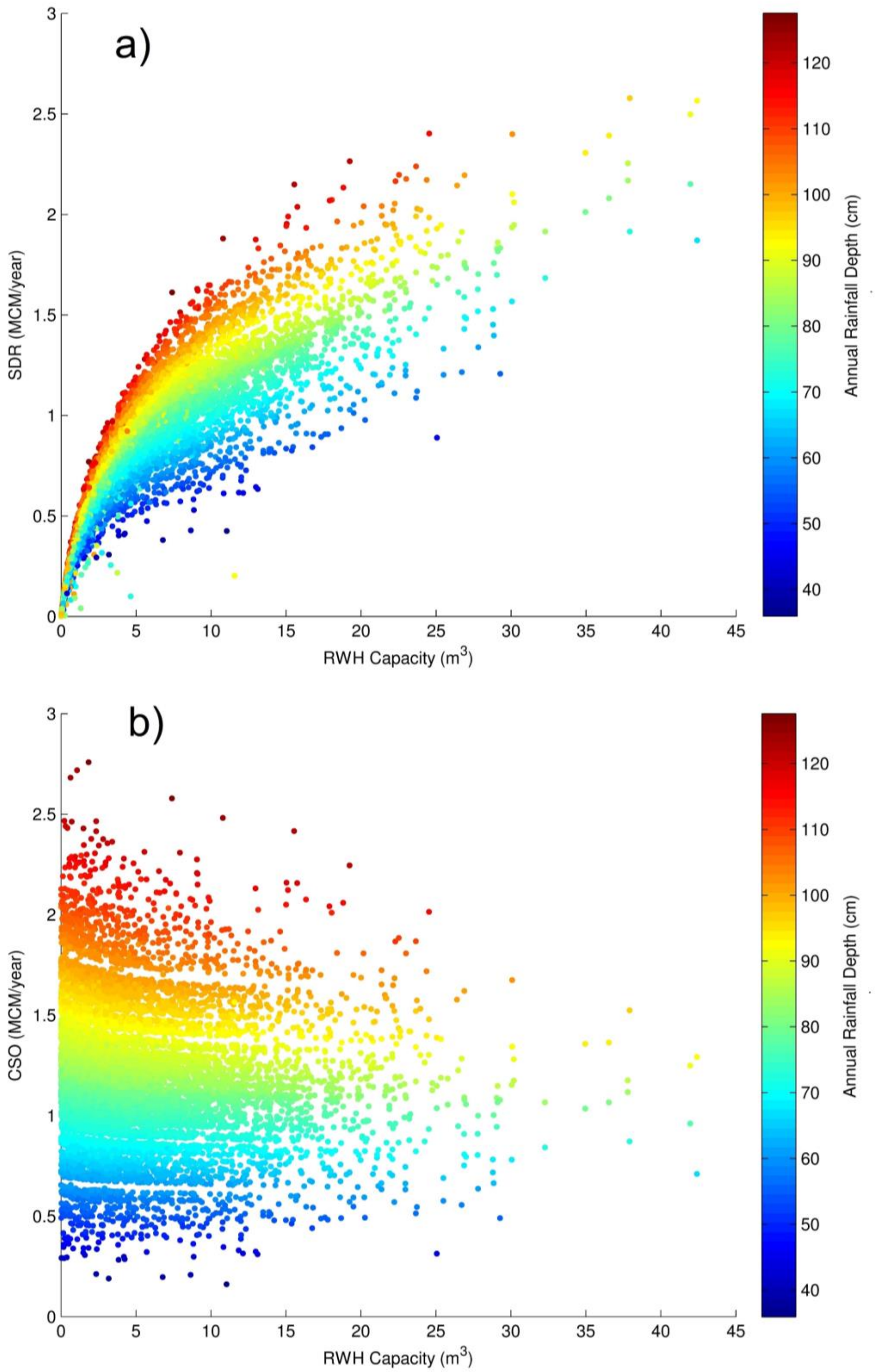

Figure 4.7. Scatter plots of the MC simulation results for SDR and CSO. Different values for annual rainfall depth are depicted with a blue to red color range.

Figure 4.8 exhibits the probability density of the MC simulation for the hydrologic outputs. According to this figure, the highest probability (mode) of SDR and CSO are associated with 0.7-0.8 and 1.1-1.2 MCM/year, respectively. According to Figure 4.8 and the CSO volume of 1.3 MCM/year without RWH implementation (as explained in Section 4.2), a low CSO reduction from the RWH system is expected. On the other hand, a noticeable SDR is expected for supplying indoor demands (compared to a null SDR without RWH implementation). Figure 4.8 also indicates a higher variance (as a measure for uncertainty) in SDR than CSO (variance is 0.16 MCM/year for SDR and 0.12 MCM/year for CSO). This higher variance in SDR reflects the entire variance in R and C, while these two parameters have limited effects on CSO due to the existence of other factors, such as DWF, groundwater flow, and RDII.

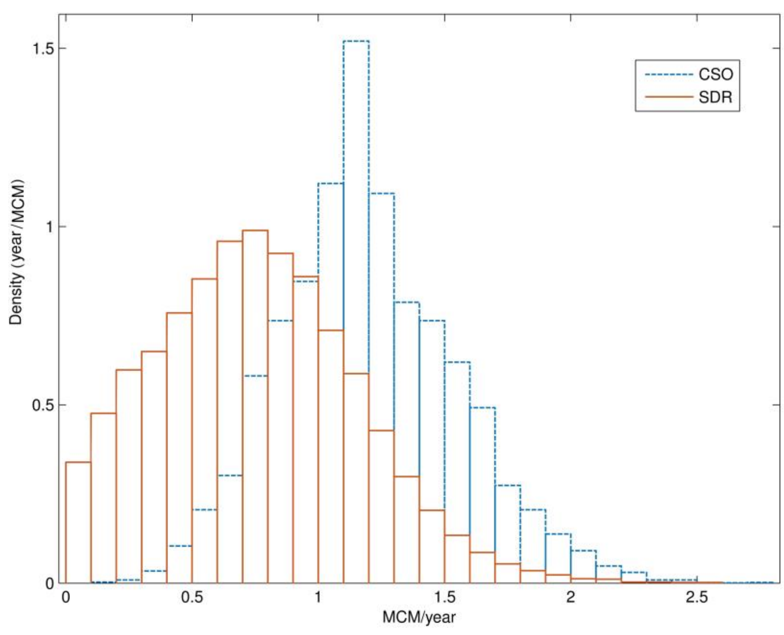

Figure 4.8. Probability density of the 10,000 MC simulation results for SDR and CSO. This figure illustrates that SDR and CSO have successfully converged to normal distributions.

4.3.2 uWISE Results

The topology-inspired model detected two partitions for GWP response based on 10,000 outputs, which was sufficient to satisfy the convergence criteria. Figure 4.9 was assembled to explore the implication of GWP results concerning the two partitions. Analysis of these results suggested that the left partition in Figure 4.9a is driven by the water supply benefits of RWH, contributing to the avoidance (reduction) of the potable water treatment burden in WTP, and thus has a descending trend. The right partition in Figure 4.9a is driven by increased wastewater treatment burden in WWTP as a result of detention effects of RWH, so exhibits an ascending trend. The detention effect of RWH leads to collecting stormwater and transmitting it to WWTP (instead of discharging it as a CSO to water bodies), thus it increases the wastewater treatment burden.

A linear line was fitted to the points located at the boundary of partitions (shown by a dash-dot line in Figure 4.9a). Such a line represents an equilibrium between the added and avoided GWP impacts by RWH. This line connects the local minima for different rainfall depths, and thus may be interpreted as the optimal system design as a function of R. An interesting point about this line concerns its suggested relationship between C and R: the optimal system capacity proportionally increases with the increase in annual rainfall depth.

The optimal RWH system capacity (in m^3) for each rainfall annual depth could be calculated by multiplying the annual rainfall depth (in m) by 5 (according to the dash-dot line in Figure 4.9a). This capacity is sufficient to capture 1/40 of annual depth in each rainfall event, assuming a typical rooftop of 200 m^2 area. Figure 4.9b suggests that high impacts per volume of CSD amplifies the final LCA outputs; however, this effect appears to be trivial compared to the strong observed correlation between GWP and R.

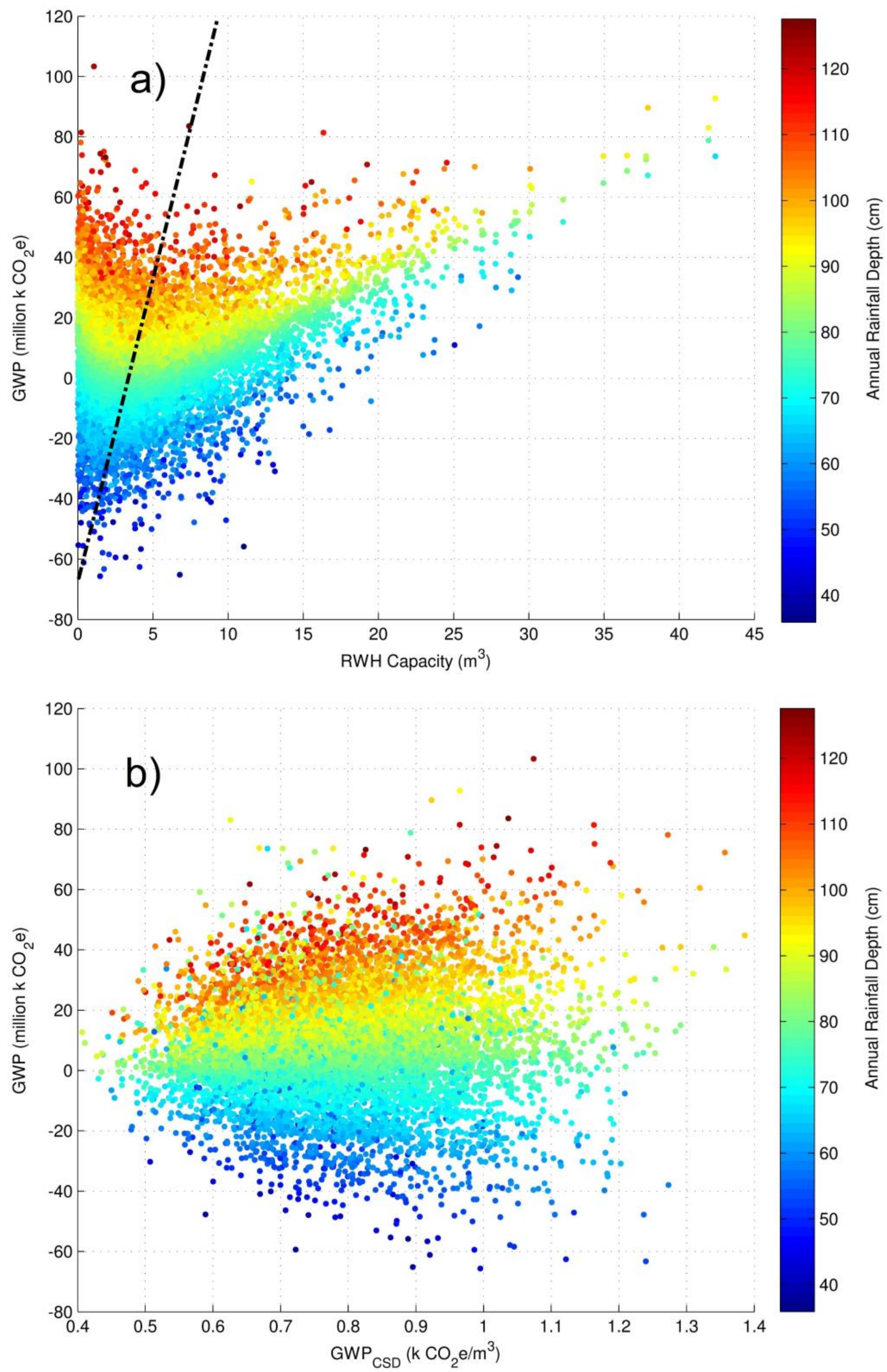

Figure 4.9. Scatter plots of the MC simulation results for GWP. The dash-dot line shows a linear line fitted to the partitions boundary.

Figure 4.10a indicates a slight nonlinear response of ETW to changes in C for high values of R (illustrated in light green to red) based on 10,000 iterations, which was sufficient to satisfy the convergence criteria. For other values of R, no significant response was observed. These correspond to the observations plotted in Figure 4.7b, suggesting that ETW is primarily driven by CSO. The minimal GWP line is also demonstrated in Figure 4.10a. This line indicates no noticeable reduction in ETW for capacities larger than the dash-dot line plotted (Figure 4.10a). This observation affirms the optimal behavior of the dash-dot line in terms of ETW in addition to GWP. Figure 4.10b shows the amplifying effect of high ETW_{CSD} values in providing high ETW outputs. However, this effect was insignificant compared to the observed correlation between ETW and R.

Figure 4.11 shows the probability density of the MC simulation for the final uWISE outputs. According to this figure, the highest probability of GWP and ETW is approximately associated with 0-5 million kg CO_2e and -500-zero million CTU eco, respectively. Since these results are based on change from existing conditions, they indicate that RWH implementation is likely to lead to an increase in GWP and a decrease in ETW. In addition, a higher variance was observed in GWP than ETW, which can be explained through the dependency of GWP to SDR and dependency of ETW to CSO.

Lastly, the First Order Sensitivity Analysis method identified the relative roles of uncertainty sources to fulfill the goal of uncertainty analysis for the present study. Table 4.3 summarizes estimates of the portion of uncertainty brought by each parameter. This table indicates that R is the most significant source of uncertainty, with more than 86% of contribution in propagating the uncertainty. C was ranked second, with around an order of magnitude lower effect.

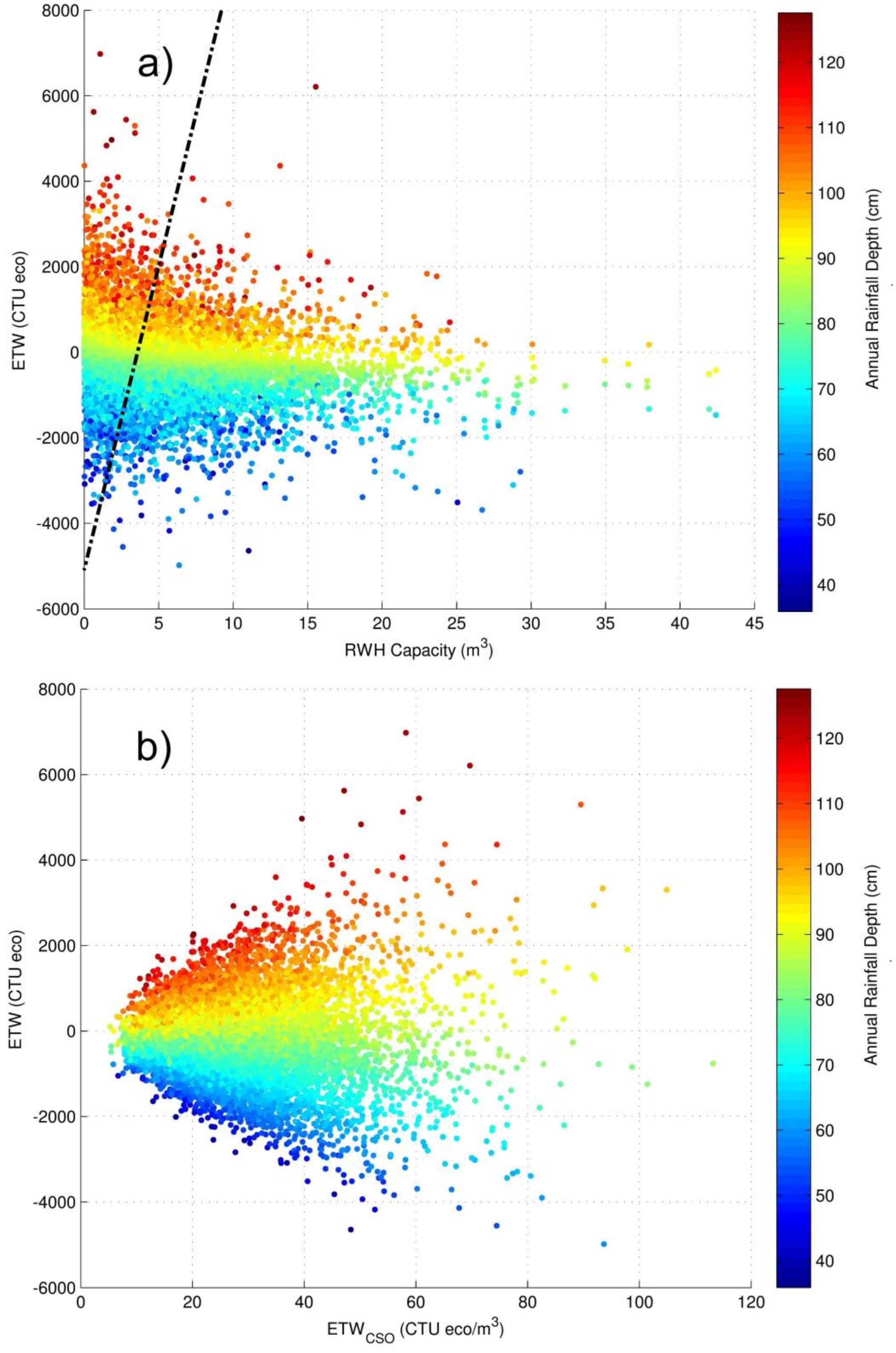

Figure 4.10. Scatter plots of the MC simulation results for ETW. The dash-dot line shows the partitions boundary obtained from analysis of GWP in Figure 4.9.

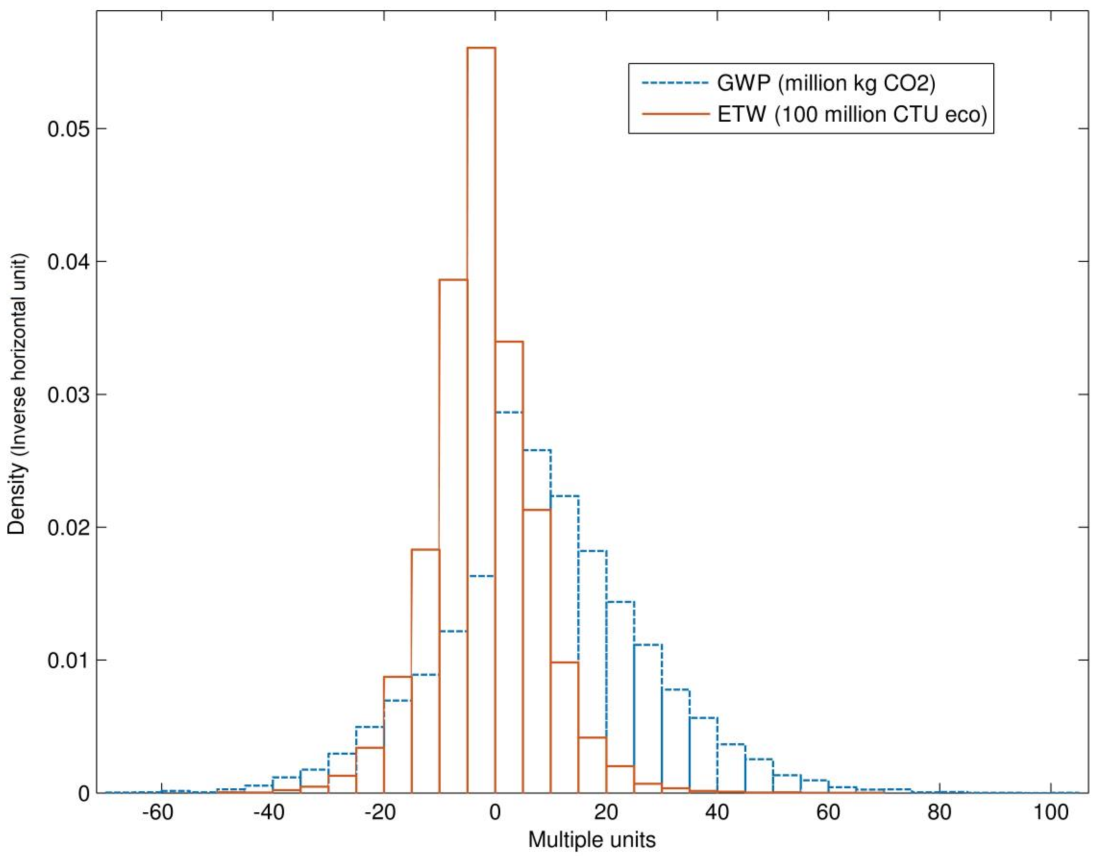

Figure 4.11. Probability density of the MC simulation results for GWP and ETW.

Table 4.3. Estimating sensitivity coefficient of variables using the First Order Sensitivity Analysis method.

Function (F)	**Variable (X)**	**Unit**	$\frac{\partial F}{\partial X}$	$\mathrm{Var}(X)$	$(\frac{\partial F}{\partial X})^2 \times \mathrm{Var}(X)$	**Portion of uncertainty propagated by X (%)**
GWP	R	cm	0.9	165.9	152.0	86.1%
	C	m^3	0.7	24.3	12.5	7.1%
	GWP_{CSD}	k CO_2 e/m^3	8.5	0.2	12.1	6.8%
ETW	R	cm	66.6	165.9	736,617.1	94.4%
	C	m^3	-38.7	24.3	36,366.4	4.7%
	ETW_{CSO}	CTU eco/m^3	-5.6	242.8	7,524.3	0.9%

The effects of uncertainties in GWP_{CSD} and ETW_{CSO} were the lowest. Furthermore, these results (Table 4.3) indicate that uncertainty in R provides a higher contribution in uncertainty in ETW (94.4%) than GWP (86.1%), which stems from the great dependency of ETW to CSO and CSO to rainfall (Figure 4.7b). These led to a higher effect of C and LCIA parameter on GWP compared to ETW.

4.4 Conclusions

This chapter identified the major sources of uncertainty in an integrated framework for environmentally sustainable design of urban drainage infrastructure based on hydrologic analysis and life cycle assessment (LCA). The study compared the uncertainty effects of inaccuracy in LCIA model parameters with variability in hydrologic data as input parameters. The uncertainty analysis platform was applied to a watershed-scale LCA of RWH to supply indoor demands and control CSOs. Rainfall, as a hydrologic input parameter, appeared to be the most significant source of uncertainty. Therefore:

(i) For a reliable LCA-based urban water infrastructure design, it is necessary to adopt robust hydrologic analysis to inform the operation phase of the LCA. This analysis allows understanding the possible responses of watersheds to variability in rainfall during the life cycle of a water infrastructure. Without hydrologic analysis, the LCA results may not represent the actual impacts of the water infrastructure governed by variability in rainfall. Moreover, analyzing the operation impacts for a short period and projecting it to the entire life cycle may be inappropriate.

(ii) This study considered the highest recommended uncertainty in the LCIA parameters and still found the effect of this uncertainty insignificant. To advance the LCA-based design of urban water infrastructure, increasing the accuracy in compiling LCI may be of a higher importance than defining LCIA parameters. This statement is in need of further corroboration with additional studies on different urban water infrastructure.

(iii) The case study application suggested that the optimal RWH system capacity could be defined as a linear function of annual rainfall depth. This optimal design would lead to minimized life cycle impacts in terms of global warming potential (GWP) and Eco-Toxicity Water (ETW). Capacities smaller than the optimal would make the RWH system lose potable water treatment savings and CSO control benefits, while capacitates larger than the optimal would cause additional wastewater treatment burden and construction phase impacts. However, the annual rainfall depth varies each year and may not provide a practical design guideline. Thus, to achieve the minimized impacts, this study suggests RWH capacities be designed for short periods (e.g., 10 years) through robust analysis of the future annual rainfall, considering possible changes and anomalies. This statement is in need of further corroboration with additional tests of the presented method for different drainage system capacities and climates.

The present study had limitations that could be addressed by future studies, including the following:

- Other sources of uncertainty, i.e., structural and human-based uncertainties, may be studied to provide insight into the overall status of uncertainty of the integrated framework. Such analysis may identify the areas to improve the results reliability, and thus lead to advances in the integration of hydrologic and LCA models for urban water infrastructure assessment.

- Other urban drainage infrastructure, e.g., separate sewers, detention basins, and pervious pavements, may be studied in future to understand their optimal LCA-based design with a consideration to the existing uncertainties.
- A broader hydrologic representation of urban drainage systems can be considered as a follow up study, including water quality simulation modules.

CHAPTER 5

SUMMARY AND CONCLUSION

In this dissertation, three research questions were formulated, and then modeling efforts were organized to answer the questions. This section summarizes the answers and other findings.

5.1 Summary of Research Findings

5.1.1 Testing Hypothesis 1

Testing Hypothesis 1 suggests that $\mathrm{CPR}_{\mathrm{Hybrid}} \ll \mathrm{CPR}_{\mathrm{Centralized}}$ for the Toledo case study. The results show that a hybrid scenario based on 2.65 m^3 RWH for toilet flushing (50% participation) and centralized infrastructure could reduce the CPR of LTCP by up to 48% while meeting the entire toilet flushing demand via RWH. For making a general rule out of Hypothesis 1, several test cases in different locations with various system specifications need to be evaluated. The framework presented in Chapter 2 can be used for this purpose.

Furthermore, the results show that for large CSO events, the hybrid scenario has a high control ability because it benefits from the large-scale detention facilities in sensitive areas. For smaller CSO events, the hybrid scenario presented an inferior performance compared to the LTCP plan due to the lack of separate sewers in areas that generate small CSO discharges. Moreover, the results show that the RWH scenarios with distributed detention function did not perform satisfactorily, because their underdrain flows contributed to CSOs. Such a phenomenon is attributed to the long duration of the storms in the studied area.

5.1.2 Testing Hypothesis 2

Testing Hypothesis 2 suggests that $\mathrm{LCEI}_{\mathrm{Watershed}}(\mathrm{RWH}) \neq \mathrm{n} \cdot \mathrm{LCEI}_{\mathrm{Building}}(\mathrm{RWH})$ for the Toledo case study. The results show that extrapolating the impacts from a building scale to a watershed scale could lead to inaccurate results because major components of environmental impacts were ignored in this case, e.g., effects of RWH on combined sewage volumes delivered to wastewater treatment plants. Without considering the increased combined sewage volume, the avoided potable water treatment burden (as a result of water supply function of RWH) could almost compensate for the added burden of the new system implementation, performance, and maintenance. However, the proposed integrated framework, namely uWISE, discovered that increased combined sewage treatment burden would cause significant GWP impacts (66% of total GWP impacts from the other components). For the categories related to water quality, e.g., ETW and EP, results also suggest the importance of watershed-scale hydrologic components to estimate the life cycle environmental impacts. Overall, extrapolating was unable to properly estimate the impacts for GWP, ETW, and EP categories (led to less than 28% of the estimated values by the uWISE framework). The only impact category, for which the linear extrapolation offered acceptable results was ODP (95% of the estimated values by the uWISE framework) because this category was mostly driven by the transportation demand, which is a part of the construction phase and does not deal with hydrologic performance. Testing Hypothesis 2 for various cases is required before generalization, and the uWISE framework can be used for this purpose.

Results of comparing different scenarios using the uWISE framework show that the RWH scenarios delivered higher combined sewage volumes to wastewater treatment facilities compared to the LTCP. This resulted in elevated GWP impacts for the RWH scenarios. The LTCP reduced GWP impacts because it included sewer separation, leading to lowered amounts of combined sewage treated. But, due to the untreated stormwater discharges to receiving waters, the LTCP led to a higher ETW impact compared to the RWH scenarios. For EP, RWH scenarios led to higher impacts than LTCP, mainly because CSO discharges did not appear to increase long-term loading for constituents such as nitrogen and phosphorus, while wastewater effluents increased the EP. On the other hand, LTCP suggested higher negative impacts regarding the ODP, which is related to the high weight of the materials leading to increased transportation needs. Lastly, the results indicate that the effect of material choice (e.g., choosing plastic tanks instead of steel tanks) on life cycle environmental impacts was trivial for all the scenarios.

5.1.3 Testing Hypothesis 3

Testing Hypothesis 3 suggests that $\mathrm{Var}_{\mathrm{Hydrologic\ data}}(\mathrm{LCEI\ (RWH)}) \gg 0$ for the Toledo case study. Results show that among the studied parameters, rainfall data (as a hydrologic parameter) were responsible for more than 86% of the uncertainty of the integrated framework, while the LCIA model data were responsible for less than 7%. This emphasizes the necessity of robust hydrologic data and associated analyses to increase the reliability of LCA-based urban water infrastructure design, and affirms the importance of integrated hydrologic-LCA frameworks, such as uWISE. In other words, the results indicate that the performance phase is responsible for the majority of the life cycle environmental impacts from CSO control infrastructure. Hydrologic analysis allows understanding the different responses of water systems to the variability of input parameters. Several cases have to be tested for generalizing the conclusion for Hypothesis 3. Such studies may use the framework developed in this research.

In addition, results suggest that such a topology-inspired model is capable of rendering optimal RWH system capacity as a function of annual rainfall depth, at least in general. Specifically, the RWH system would be optimal, and thus lead to minimized life cycle impacts – in terms of GWP and ETW – if the system could capture 1/40 of annual rainfall depth in each event from rooftops. This capture depth would be around 2.1 cm for Toledo (given an 85 cm/year rainfall), which could be achieved by an RWH system with 4.25 m^3 capacity. Capacities smaller than this suggested optimal value would likely result in loss of RWH potable water treatment savings and CSO control benefits, while capacities larger than the optimal would probably incur excessive wastewater treatment burden and construction phase impacts.

5.2 Summary of Technical Findings

Several modeling techniques were used in this research as explained in the previous chapters. Here, a few recommendations for future users of the employed models are presented:

- US EPA SWMM was employed in this study to simulate the combined sewer networks, implementation of RWH, and centralized infrastructure. This model provided appropriate features to accomplish the simulation of CSO elements, e.g., Rainfall Derived Infiltration Inflows through unit hydrographs, Dry Weather Flow with hourly variations, groundwater flow with monthly variations, CSO outfalls via a set of weirs, pumps and orifices. However, this model was unable to accurately simulate the water supply process via actual time series of demands. Toilet flushing demand is not constant at different times of a day. Adding demand time-series feature to the SWMM source is suggested as a future project. In addition, SWMM is unable to consider freezing of the stored water in RWH cisterns during cold seasons. This inability neglects the interruptions in water supply process. Finding solutions for this inability can be also addressed in future work.

- Net Present Value (NPV) method was used in this study to translate the life cycle costs to the current basis. The CPR metric was defined as costs per reduced volume to provide a tangible measure for stakeholders. However, this metric was unable to consider the additional desirability of achieving high levels of control for engineers. Therefore, more sophisticated ways of combining LCC and hydrologic performance may be considered in future work. For example, they may consider a credit weight for plans that have a control level above a predefined threshold, or may adopt nonlinear combinations.
- The new watershed-scale LCA framework, uWISE, led to more information on the CSO control strategies compared to hydrologic-only analysis, but created a more complicated decision. Information from water stakeholders must be taken into account before nominating a scenario as the one that globally outperforms the

others according to the multihydrologic-LCA criteria. Multi Criteria Decision Making (MCDM) may be used to facilitate this process and can be studied as a future research.

- For life cycle assessment, the tool for the reduction and assessment of chemical and other environmental impacts (TRACI), developed by the U.S. EPA, was satisfactorily used to facilitate the characterization of potential environmental stressors. In TRACI, impact assessment methodologies estimate the relative impacts at a midpoint (e.g., ozone depletion potential) rather than an endpoints (e.g., skin cancer), within the cause-effect chain. Performing additional modeling and data collection is needed for estimating the endpoint impacts, which may be done as a future study.
- Performing a life cycle assessment for all the potential effects of infrastructure at the highest level of disaggregation is in need of spending substantially large amounts of time and compiling extensive datasets; the present study is no exception. A follow-up study may be performed to increase the level of disaggregation for the proposed scenarios and the number of studied impact categories in this research.
- HTCondor was able to provide a free, reliable computational resource for the Monte Carlo simulation. This resource does not have the problem of mixing the shared memories, which is reported in some GPU applications. The platform-independent structure of HTCondor also allowed different operation systems to join the pool, even without installing the US EPA SWMM. The executable version of the software was being transmitted through the pool during the simulations. MATLAB

software was used to run the Monte Carlo algorithm and link it to SWMM and HTCondor. The compatibility of such a framework for other water engineering models, such as US EPANET, might be tested in future work.

- A topology-inspired model based on the Morse-Smale regression was adopted to assist in visual interpretation of the Monte Carlo results. This tool was effectively able to detect different system responses within the results. However, due to the sparse nature of sampling, it is often the case that extraneous local minima and maxima occur. Therefore, the topological notion of persistence simplification was utilized in order to filter out such insignificant features occurring in the data. Such analysis is recommended for future applications of this model in other fields to avoid obtaining clusters with no physical significance.
- A case study of the City of Toledo, Ohio combined sewer system served as the platform to investigate the economic and environmental sustainability approaches and to compare RWH with centralized gray infrastructure for controlling CSOs. Based on the findings in this research, engineering recommendations for the urban drainage decision makers of Toledo are summarized as follows:
  - Incorporating RWH into the Toledo LTCP can improve the life cycle cost-effectiveness significantly.
  - Due to the abundance of rainfall in Toledo, RWH can be used as a reliable tool to supply nonpotable building demands in a decentralized manner.
  - RWH has a noticeable potential to reduce the toxicity of water bodies caused by CSOs. However, overdesigned RWH may increase combined sewage treatment burden and consequently Global Warming Potential.

APPENDIX

APPLICATION OF COMPUTER SCIENCE TOOLS

A.1 Distributed Computing Resources

Performing iterative hydrologic simulations requires substantial computational resources. In some cases, it could take months to run an uncertainty analysis or evolutionary optimization algorithm in series on a regular, stand-alone computer. High-Performance Computing (HPC), High Throughput Computing (HTC) and Graphical Processor Units (GPUs) can provide extensive computational resources in a distributed manner. Table A.1 summarizes the advantages and disadvantages of the above mentioned distributed computing resources.

Table A.1. Comparison of HPC, HTC and GPU to provide distributed computational resource

Computational resource specification	**HPC**	**HTC**	**GPU**
Cost	High	Low	Low
Setting up effort	High	Low	High
Job transmission speed	High	Low	High
Unit processing speed	High	High	Low

According to this table, for those iterative calculations in which objective function evaluation is taking a noticeably longer time than running the main algorithm (for example more than a hundred times), HTC provides a cheap, user-friendly and fast computational resource. An example of such calculations is the subject of the current study, where the long-term continuous modeling of the combined sewers takes much longer than calculations within the uncertainty analysis algorithm. In this case, low job transmission speed of HTC does not play an important role. Examples of the application of distributed computing resources in water engineering problems are provided in this section.

A.1.1 High Performance Computing (HPC)

HPC integrates computer architecture design principles, operating systems, heterogeneous hardware components, programs, algorithms, and specialized computational approaches to address the handling of tasks not possible or practical with a single computer workstation (Foster and Kesselman 1997; Foster et al., 2002; Pijanowsky et al. 2014). A self-contained HPC (i.e., a group of computers) is often referred to as a high performance compute cluster (HPCC) (Cheung and Reeves 1992; Buyya 1999; Reinefeld and Lindenstruth 2001). A main feature of HPCs is the integration of hardware and software systems that are configured to parse large processing jobs into smaller parallel tasks. Hardware resources can be managed at the level of cores (a single processing unit capable of performing work), sockets (a group of cores that have direct access to memory) and nodes (individual servers or computers that contain one or more sockets). An HPCC is managed by an administrator with hardware and software services accessible to many users. HPCCs are systems smaller than supercomputers, although the terms HPC and supercomputer are often used interchangeably (Pijanowsky et al. 2014).

Although there is no past HPC research in the area of current research, there are a few applications of distributed computing in other water engineering-related fields. For instance, Pijanowsky et al. (2014) employed a Land Transformation Model (LTM), a Land Use Land Cover Change (LUCC) model, which was originally developed to simulate local scale LUCC patterns. The model uses a commercial windows-based GIS program to process and manage spatial data and an artificial neural network (ANN) program within a series of batch routines to learn about spatial patterns in data. They provided an overview of a redesigned LTM capable of running at continental scales and at a fine (30m) resolution using a new architecture that employs a windows-based High-Performance Computing (HPC) cluster. They provided an overview of the new architecture within the context of modeling LUCC that requires: (1) using an HPC to run a modified version of LTM; (2) managing large datasets in terms of size and quantity of files; (3) integration of tools that are executed using different scripting languages; and (4) a large number of steps necessitating several aspects of job management.

A.1.2 High Throughput Computing (HTC)

The High-Performance Computing Cloud or Science Cloud (SC) provides the resources to applications in an on-demand and stand-alone manner that means jobs can be performed on the slave machines without any preconfigurations for slave machines, which is called High-Throughput Computing (HTC). HTCondor is an open-source HTC workload management software framework for a cluster of distributed computer resources. It consists of a set of software tools which implement and deploy HTC on distributed computers. Distributed computing powers can be effectively integrated through HTCondor into one computing environment for simulation-based optimization tasks. Furthermore, the distributed ownership and low price make an HTC environment more convenient for users than the supercomputers (Yang et al. 2014).

Examples of HTCondor application in water engineering is limited. One of them is the efforts of Yang et al. (2014) that presented a master-slave synchronous single population parallel NSGA-II. Originally, NSGA-II is a nondomination asynchronous sequel genetic algorithm. The parallel NSGA-II inherits the original NSGA-II's population topology, search strategy and basic sketch. The main difference between the two algorithms is that the parallel NSGA-II parallelizes the calculations of the individuals' fitness values in HTCondor distributed computation environment. The optimization framework has been utilized in an EU FP7 project – SportE2 (Energy Efficiency for Sport Facilities) to conduct large-scale buildings' energy consumption optimizations. The optimization results achieved for a testing building, KUBIK in Spain, showed a significant computation time deduction while still producing acceptable results.

In another example, Gitau et al. (2012) used HTCondor for watershed modeling using Soil and Water Assessment Tool (SWAT) to provide a framework for evaluating the impacts of 172 different watershed management decisions combined with weather uncertainty. The framework significantly reduced the model run time from 2.5 years to 18 days. Given the newness of distributed computing strategies, there has been no documented application of distributed computing to provide the computational power necessary to permit LCA and long-term urban hydrologic simulation to be integrated within a multiobjective analysis.

A.1.3 Graphical Processor Units (GPUs)

Recent capability of GPUs can also be used to perform parallel computing. GPUs enable the parallel computation on one personal computer. When compared to traditional clusters and supercomputers, the remarkable difference offered by GPUs is the low (and quickly decreasing) cost per processor and the fact that thousands of parallel tasks can be performed in parallel on the same card. The GPUs were originally designed for rendering complex 3D scenes, which basically involve a high degree of parallel computations. The particular feature of these operations is that the same instructions (e.g., matrix multiplications) can be performed in parallel over different data. This particular type of parallelism, named Single Instruction Multiple Thread (SIMT), has been implemented on the GPUs with dedicated hardware. A GPU contains a large set of Arithmetic Logic Units (ALUs) (that can perform their tasks concurrently) controlled by some Control Units that apply the same instruction in parallel to different operands on the corresponding ALUs. Only recently, the video cards allowed a General Purpose programming of the hardware (therefore the acronym GPGPU), making it possible to exploit the multicore architecture for user-defined tasks, rather than graphical rendering and processing of images. The main competitor, NVIDIA, released a framework named CUDA that allows one to program the GPU with conventional programming languages (Vacondio et al. 2014). An example of employing GPUs for parallelizing water engineering-related tasks is the research of Vacondio et al. (2014), which developed a parallelization of a Shallow Water numerical scheme suitable for architectures under the NVIDIA’s Compute Unified Device Architecture (CUDA) framework. In order to provide simulations of flood events, the system featured a Finite Volume explicit discretization technique. GPU led to speedups of two orders of magnitude with respect to a single-core CPU.

A.2 Topology-Inspired Regression

After performing iterative simulations for uncertainty/sensitivity analysis, engineers are usually interested in understanding different gradient behavior of system responses by means of scatter plot analysis. A traditional approach to perform such analysis is manually dividing the domains of the scatter plots achieved from uncertainty/sensitivity analyses. The Morse-Smale complex decomposition suggests a scientific solution for this need, since it can routinely divide the domain into regions of uniform gradient flow, as each partition is associated with exactly one minimum and one maximum on the partition's boundary. In sum, the goal of Morse-Smale complex decomposition is to capture the geometry of the regression surface, instead of focusing on a quality of fit measure for splitting the domain that pays low attention to the geometry outputs of the studied system (Gerber et al. 2013). Complete details of Morse-Smale complex decomposition is presented by Gerber et al. (2013).

Therefore, the results of Morse-Smale complex decomposition consist of regions of uniform gradient flow that may be satisfactorily represented by linear regression models (Morse-Smale regression), if model simplification is the goal of study. The other results are a set of local optimal points that can provide insight into interesting system responses. Compared to global optima, local optima are of greater interest for system response analysis because global optima are only two points (one global minimum and one global maximum) that are unable to provide information on different system responses. In the case of this research, global optima happen with extrema in rainfall data because rainfall appeared to be the most sensitive dimension. However, we are unable to govern the rainfall to achieve minimized impacts. Thus, we are interested in understanding the effects of other system components, e.g., RWH system, on life cycle environmental impacts. The values of RWH system capacity that lead to optimal impacts are, in fact, local optima in our case.

However, due to the sparse nature of sampling, it is often the case that extraneous local minima and maxima may occur in the data when Morse-Smale decomposition is used. In order to filter out such insignificant features occurring in the data, a measure, called “persistence”, is presented by Gerber et al. (2013). Persistence is a measure of the amount of change in the function (uWISE in this case) required to remove a topological feature (i.e., local minimum or maximum), and thus merge two (or more) partitions. Low values of persistence are referred to as “noise” in order to emphasize the insignificance of such points (Figure A.1). On the other hand, high persistence values are named “pattern” (Figure A.1). In order to filter out insignificant local optima, those that have a persistence lower than a user-defined threshold are discarded. Using this technique, the main drivers within local regions of the uWISE domain were discovered, as illustrated in Figure A.1. The results of this analysis were two partitions, with significant optima shown in gold and blue. In Figure A.1a, x-axis is persistence and y-axis is Global Warming Potential (GWP). Red triangles show the maxima and blue triangles show the minima. For optima that have a persistence higher than the threshold, the triangles are shown with a bigger size to emphasize their significance. The two partitions had the same minimum but different maxima. Analysis showed that the gold partition resulted in loss of RWH potable water savings and CSO control benefits, while the blue partition incurred excessive wastewater treatment burden.

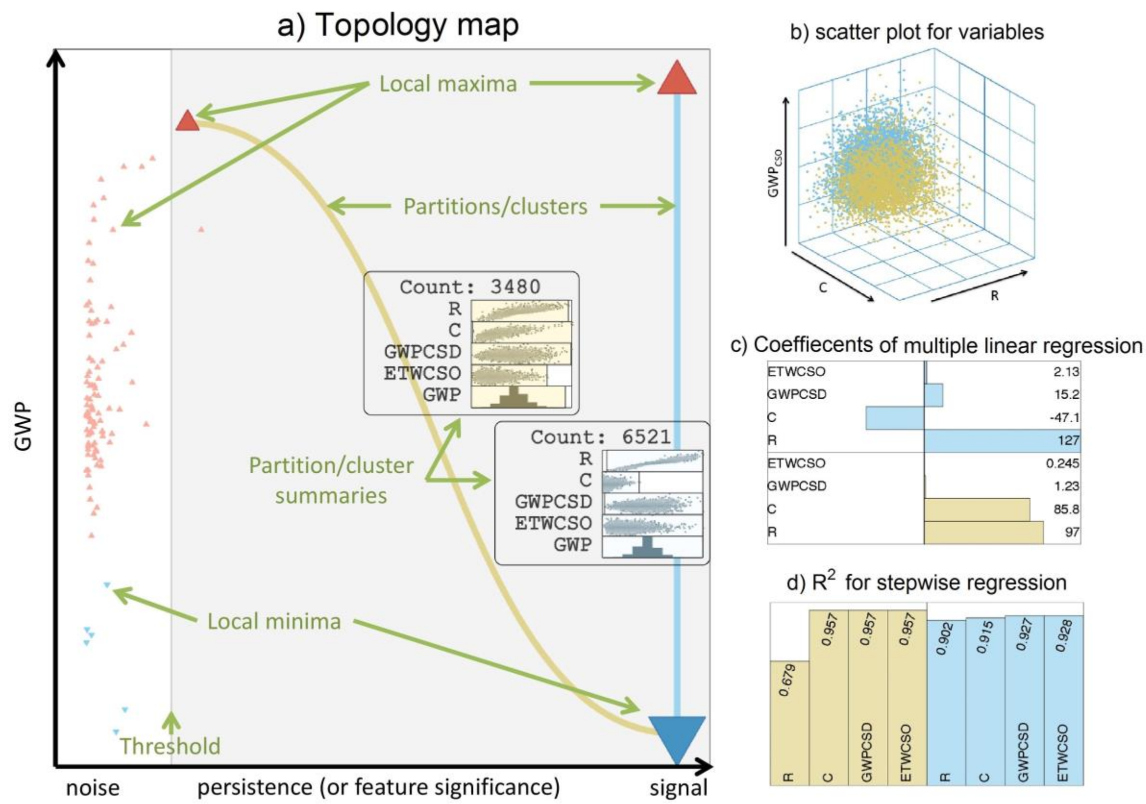

Figure A.1. Results of topology-inspired regression model: (a) topology map and detected partitions, (b) scatter plot on variable space for the detected partitions, (c) coefficient of determination for linear regression in each partition.

The number of points in each partition is also presented in this figure. Note that the sum of counts is 10,001 because the two clusters share one point (a minimum). Curvature of the gold partition is only used for aesthetics and does not have a value.

Additional information was also provided by the Morse-Smale regression tool. The partitions' boundary appeared to be predominantly governed by C, which is RWH capacity (Figure A.1b). The partitions exhibited the strongest linear regression parameters to R (annual rainfall depth), then to C, and lastly to GWP_{CSD} (Figure A.1c), where CSD denotes the combined sewage volume delivered to WWTP. The partitions had two different responses to C, i.e., a direct correlation in the gold partition and an inverse correlation in the blue (Figure A.1c). Figure A.1d shows the R^2 coefficients for stepwise regression, i.e., adding the parameters one by to a linear model (from left to right as presented in Figure A.1d). This figure shows after adding C that the improvement in R^2 is trivial, which affirms the results of Figure A.1c.

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