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Optimizing Low Impact Development Controls for Sustainable Urban Flood Risk Management

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By

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Abstract

Increased urbanization and a changing climate are contributing to an increased urban flood risk. Low Impact Development (LID) is a green infrastructure approach to help mitigate this risk. Analysis of flooding potential and socioeconomic factors of an urban area are essential in determining how to best implement these controls. The objectives of the study was to identify the most prominent areas for LID implementation and develop a framework for identifying LID controls within a multiobjective optimization framework. Coupled risk assessment and socioeconomic analysis was used to determine the potential areas to implement LID controls to achieve continuous benefits. A risk assessment methodology was developed to delineate the greatest flooding risk areas in sewersheds. A socioeconomic analysis framework was then adapted to assess the areas that would be most likely to adopt and successfully maintain LID controls. A simulation-optimization framework was then developed by coupling Stormwater Management Model (SWMM 5) with the Borg Multiobjective Evolutionary Algorithm (MOEA). This methodology analyzed different LID implementation solutions with a cost function to determine the most cost effective LID solutions. The PCSWMM interface was used to create the model for a large urban sewershed in Windsor, Ontario, Canada. The model tested LID measures against eight different scenarios consisting of both historical climate data and future predicted climate change data with the objectives of reducing peak flows in the sewer system, reducing total runoff across the sewershed and minimizing the cost of LID implementation. The results provide stormwater management professionals and decision makers cost-benefit information for different LID implementation scenarios to help assess the feasibility of LID in this area and to make infrastructure investment decisions.

Dedication

This thesis is dedicated to my parents for their unconditional love and encouragement throughout all my endeavors. Without them none of this would be possible and I thank them for all that they do for me.

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List of Abbreviations

BMP – Best management practice

BMPDSS – Best management practice decision support tool

BR - Bioretention

CN – Curve number

CSO – combined sewer overflow

EA – Evolutionary algorithm

EPA – United States Environmental Protection Agency

GA – Genetic algorithm

GIS – Global information system

IDF – Intensity-duration-frequency

IPCC – Intergovernmental panel on climate change

IT – Infiltration trench

IUSM – Integrated urban stormwater management

IUWM – Integrated urban water management

LID – Low impact development

LIUDD – Low impact urban design and development

MOEA – Multiobjective evolutionary algorithm

PP – Permeable pavement

RB – Rain barrel

RCP – Representative Concentration Pathway

SCS – Soil Conservation Society

SuDS – Sustainable drainage system

SWM – Stormwater management

SWMM – Stormwater Management Model

WQV – Water quality volume

WSUD – Water sensitive urban design

Chapter 1 Introduction

1.1 Background and Justification

The transformation towards more sustainable urban development is not moving at a sufficient pace (Frame and Vale, 2006). The rapid increase in urbanization, environmental deterioration and ecological destruction in urban areas has had a major impact on sustainability of developments (Chen et al., 2016). Rapid urbanization and growing effects of climate change are contributing to the insufficiency of conventional stormwater management systems and are expected to only further increase flooding risk and drainage disasters in urban drainage systems (Duan et al., 2016; Stovin et al., 2013; Visitacion et al., 2009; Wang et al., 2016). Urbanization tends to cluster population and assets, which increases the likelihood of damage in urban areas (Morita, 2014). Urban stormwater management (SWM) is essential to mitigating these effects and current methods for urban stormwater management must evolve in order to handle the increased demands that come with urbanization and climate change.

Conventional stormwater management has the main objective of removing water from a site as quickly as possible (Ahiablame et al., 2012). To achieve this and to reduce the risk of flooding, curbs, gutters and other grey infrastructure are used in conjunction with sewers. Once water is collected, it is discharged to the nearest stream or lake. Though this method prevents local flooding, it can cause increased erosion and flooding downstream (Barkdoll et al., 2016). Since this method of stormwater management is designed to move water off-site as quickly as possible, it changes the hydrology of the site being developed (Holman-Dodds et al., 2003). The addition of impervious surfaces reduces infiltration that would have occurred at a site in its natural state, this contributes to increases in the peak runoff going to the receiving waters (Hood et al., 2007). Other than the increase in water quantity, the stormwater runoff carries suspended solids and pollutants from the site into the receiving water (Davis et al., 2009). Urbanization is causing increased runoff to enter sewer systems that are not adequately designed for this additional stormwater and impacts of a changing climate only amplify these consequences. Continuing to manage stormwater with this "out of sight out of mind" mentality will not contribute to sustainable developments (Wong and Eadie, 2000).

Climate change can have adverse impacts on hydrology and water quality (Liu et al., 2016) and thus, it has the potential to affect all aspects of stormwater infrastructure (Watt et al., 2003). As such, climate change should be a vital consideration for new systems and for the rehabilitation of existing systems. As extreme storm events become more frequent, the drainage system designs based on current design storm events become much less effective making sizing of drainage components to have to be reconsidered to reflect new design storms (Eckart, 2015, Zahmatkesh et al., 2015). Adding Low Impact Development (LID) controls to current stormwater management systems may provide, in addition to runoff volume and water quality benefits, climate impact mitigation benefits for stormwater runoff (Zahmatkesh et al., 2015).

As the objectives of modern stormwater management evolve to include maintaining the health of aquatic ecosystems, protecting water quality, and capturing and using stormwater as a resource for a more sustainable development (van Roon, 2007). Investment in conventional piped stormwater management systems will not, by itself, reduce the adverse effects on a region's receiving environments of stormwater discharges (Frame and Vale, 2006; Hoang and Fenner, 2016; Kandasamy and Sinha, 2017; Porse, 2013). A sense of ownership towards stormwater assets is necessary in order to encourage adoption in the community. This can reduce the reliance on government funding for stormwater system maintenance as the community will be more willing to maintain and manage assets. Stormwater management systems should be designed to incorporate landscape features and the promotion of the ecological, recreational and aesthetic benefits of LID measures can accomplish this (Wong and Eadie, 2000).

LID practices provide an increase in the replenishment of groundwater, rainwater reuse, and on-site water balance, while lessening downstream flooding (Pyke et al., 2011). LID, with its intent to return a site to its pre-development hydrologic condition, aims to remediate water quantity and quality issues and may even reverse biodiversity loss (Bullock et al., 2011). The implementation of LID controls into urban drainage systems is often considered a better alternative for cost-effective, environmentally beneficial stormwater management. There have been a number of studies that have shown LID measures to be an effective means for managing runoff while also providing numerous social, environmental and economic benefits (Chen and Hobbs, 2013; Green Nylen and Kiparsky, 2015; Nature Conservancy, 2013; Roseen et al., 2015; U.S EPA, 2007, 2013; Vogel et al., 2015). However, implementing LID to manage urban hydrologic processes has had a major focus on controlling stormwater and thus, the design and implementation of LID has had a main focus on local rainfall patterns and physical site characteristics while generally ignoring the human or social dimensions that are also involved. This conventional approach leads to highly centralized stormwater management in a disconnected urban landscape and can down play the secondary benefits of LID, such as increased property value, aesthetics, reduced heat island effect, carbon sequestration, and habitat for biodiversity (Schifman et al., 2017).

Identifying all social economic barriers towards LID is necessary to improve adoption (Carter and Fowler, 2008; Earles et al., 2009; Rodriguez et al., 2009). Understanding the socioeconomic factors of a sewershed's population that may affect their willingness to implement LID controls on their property can provide a better understanding of the best locations for LID implementation. This was a major issue looked at in this study to help contribute to the most beneficial implementation scenarios being developed. The variability and uncertainty that comes with LID implementation further complicates investment decisions, and requires the need to assess a wide range of different design scenarios before making a decision (Behr and Montalto, 2008) which creates a need for simulation tools that can optimize design and placement of LID controls in a sewershed to further encourage the implementation of LID measures.

1.2 Research Objectives

The objective of this study was to develop a multiobjective optimization framework capable of outlining the best combinations of LID measures and their placement to manage urban flooding. To do this, a coupled urban flood risk assessment and socioeconomic analysis methodology was adapted to prioritize the subwatersheds for placement of LID controls throughout an urban area. Once the critical areas were determined the next step was to develop an optimization-simulation model that can be used to generate important information about LID. The model was created by linking the stormwater management model (SWMM 5) to the Borg Multi-Objective Evolutionary Algorithm (MOEA) (Hadka and Reed, 2013) by adapting the procedure outlined in Eckart et al. (2018). The model was used to develop cost-benefit information for implementing LID controls in a large sewershed in Windsor, ON. The use of this model allows for the secondary objective of learning about the capabilities of LID in this area and the benefits of implementing them in high flood risk areas.

Chapter 2 Literature Review

2.1 Introduction

This chapter provides an overview of two major impacts contributing to the failure of traditional urban stormwater management systems. The content here provides an in depth look into Low Impact Development (LID) and how it can help mitigate against the impacts affecting stormwater systems in order to contribute to more sustainable developments.

2.2 Urbanization and its Impacts on Stormwater

2.2.1 Effects of Urbanization on Water Quantity

Urbanization produces numerous changes to the natural environment it replaces putting more stresses on conventional stormwater management systems. The rapid increase of urbanization, environmental deterioration and ecological destruction in urban areas have caused a serious roadblock towards sustainable urban growth (Chen et al., 2016). Urbanization drastically changes hydrological patterns and flow regimes. These changes often include peak flows, reduced times of concentration, redistribution of the water balance and flashier flows in urban streams (Chui et al., 2016; Konrad and Booth, 2005; Li et al., 2017; Paule-Mercado et al., 2017; Todeschini, 2016). The rapid urbanization and the corresponding increase in impervious area causes a decrease in infiltration and groundwater recharge thus increasing runoff and floods during storms and also decreasing environmental flow and groundwater storage during dry periods (Liu et al., 2015).

There are a multitude of factors that contribute to the amount of runoff, but Rose and Peters (2001) showed that peak flows in urbanized catchments can be from 30% to more than 100% greater than the peak flows in less urbanized and non-urbanized catchments. The replacement of vegetated areas that provide rainwater capture and storage often results in an increase in the rate and volume of stormwater runoff (Chen et al., 2016). Urban flooding with increased frequency and severity is intensified by climate change, which has caused rainfall intensity to be amplified (Dore, 2005).

2.2.2 Effects of Urbanization on Water Quality

It has been reported that urbanization significantly degrades aquatic ecosystems and water quality (Chen et al., 2016; Chui et al., 2016; McGrane, 2016). The damage to the ecosystem and property from flooding, often exceeds the cost of stormwater management (Visitacion et al., 2009). Urbanization, loss of biodiversity, and degradation of ecological systems have caused increasing concern for the current state of the environment. The changing of ecosystems for direct human benefit are one of the largest causes of biodiversity loss and ecosystem degradation (Bullock et al., 2011). The effect of a changing climate only amplifies these impacts.

2.3 Climate Change and its Impacts on Stormwater

The climate is made up of the meteorological elements in a region that characterize average and extreme weather over a long period of time and impacts the life of all living creatures. Generally, the climate of a region can be assumed to be constant since it changes very slowly over time. However, recently climate change has become an increasing area of concern. A changing climate could potentially cause many manmade structures (including stormwater infrastructure) that were designed to minimize the natural environment’s impact on human settlements to become ineffective (Cobbina, 2007). Due to the worry that climate change is impending, understanding the dynamics of climate change and predicting the possible impacts are critical. Present day climate change is a major concern especially since a large part of it seems to be a result of human activity. The combustion of fossil fuels, land use changes and agricultural practices have all contributed to increasing levels of greenhouse gases and aerosols in the atmosphere (IPCC, 2001). The increased concentrations of greenhouse gases trap outgoing solar radiation. While retaining solar energy is essential to sustaining life on earth, the increased amounts of these gases has greatly increased the capacity of the atmosphere to retain heat. In the twentieth century, the global mean air temperature increased by 0.6°C (±0.2°C) (IPCC, 2001).

The hydrologic cycle is influenced by changes in climate and thus, climate change has some impact on global precipitation patterns (Cobbina, 2007). Characteristics of urban watersheds, such as high percentage of imperviousness, intensify the impacts of climate change on the hydrologic cycle. A slight change in rainfall intensity and duration can cause severe floods (Karamouz and Nazif, 2013). The IPCC reports varying precipitation changes but has found that heavy precipitation events have increased and the frequency of these events is likely to also increase (IPCC, 2008).

Changes in average precipitation are not the only cause for concern. The concerns about the hydrologic disturbance align with what has been observed and predicted climate change impacts. It is expected that the intensity of the global water cycle is likely to increase as a result of climate change. One consequence of this is that it is widely expected that runoff will increase throughout the 21st century (Huntington, 2006). Franczyk and Chang (2009), while modeling the Rock Creek Basin in Oregon U.S., determined that the combination of land-use change and climate change would intensify runoff even compared to what was found in studies that looked at only one of those factors (Franczyk and Chang, 2009).

2.4 Low Impact Development (LID)

Low impact development was first introduced in Maryland as a way to help mitigate the effects of increased impervious areas (Prince George's County, 1999), although some individual systems had been implemented before the term "low impact development" came to be. Low impact development is the North American terminology for a design philosophy that has become popular in many areas around the world. Similar design philosophies include water sensitive urban design and development (WSUD) in Australia, urban design and development (LIUDD) in New Zealand, and sustainable urban drainage systems (SuDS) in Europe. LID aims to reduce the cost of stormwater management by considering a site's natural features in design. LID controls can be described as small scale stormwater treatment devices that encourage infiltration and evaporation that are located at or near the runoff source. WSUD is a methodology that attempts to manage water balance, improve water quality, encourage conservation of water and maintain environmental opportunities related to water. Similar to LID, it aims to minimize the hydrological impacts of urban development. SuDS is a variety of technologies and techniques that are applied to drain stormwater in a more sustainable manner than traditional stormwater management systems. Best Management Practice (BMP) is a term that is used to describe a practice or technique that is implemented to prevent pollution. Green Infrastructure (GI) attempts to include as much green space as possible in urban planning with the intention of maximizing the benefit from these green spaces (Fletcher et al., 2014).

2.4.1 Concept of LID

At its most ambitious, low impact development strategies aim to return a developed watershed to its pre-development hydrological conditions (i.e., to imitate natural water cycles or attain hydrologic neutrality) (Damodaram et al., 2010; Shuster et al., 2008; van Roon, 2005, 2007). It is common for LIDs to be implemented as a retrofit designed to lessen the stress on urban stormwater infrastructure and/or create the resiliency to adapt to climate changes. The success of LID depends heavily on infiltration and evapotranspiration as it attempts to incorporate the natural landscape into design in order to achieve stormwater objectives. Compared to traditional urban stormwater management patterns, LID alternatives have the function of returning the runoff to the natural hydrologic cycle, including reduction in runoff volume (Ahiablame et al., 2013; Jia et al., 2012), infiltration improvement (Ahiablame et al., 2012), reduction in peak flow (Drake et al., 2013), extending lag time, reduction in pollutant loads (Liu et al., 2015), and increase in baseflow (Hamel et al., 2013).

It may be most feasible to retrofit existing infrastructure, such as parking lots, sidewalks, roads and buildings with LID in heavily urbanized areas (Damodaram et al., 2010). Pervious areas that already exists, such as gardens, lawns, and parks, could provide additional infiltration capacity in urban areas depending on the site conditions (Shuster et al., 2008). LID measures can often be added to these public spaces without affecting their primary function (CVC, 2010). Directing runoff from impervious surfaces to pervious areas or retention facilities before diverting the runoff to catch basins/storm sewers is another infiltration strategy (Brander et al., 2004). An effective non-structural LID practice is to cluster development more densely to leave more natural land open that is capable of being used for infiltration and evapotranspiration (van Roon, 2005; Williams and Wise, 2006). LID solutions connected in series or parallel is known as a treatment train and can be effective in managing runoff (Brown et al., 2012; CVC, 2010). Implementing a combination of LID and piped systems or BMPs, such as detention ponds, will often be the best option for meeting stormwater control objectives (Ashley et al., 2011; Damodaram et al., 2010; Damodaram and Zechman, 2013).

2.4.2 LID Practices

Fletcher et al., (2013) categorized stormwater management technologies into infiltration-based technologies and retention-based technologies, both groups of technologies contribute to reducing the "effective impervious area" of a watershed, or the area that is directly connected to the stormwater system (Booth and Jackson, 1997). Infiltration-based and retention-based technologies may be applied close to or at a source, or at the end of the catchment (Fletcher et al., 2013). The combination of both infiltration and retention-based techniques is required to successfully achieve key elements of the natural flow regime (Burns et al., 2012)

2.4.2.1 Infiltration Techniques

Infiltration-based LIDs can be described as techniques that contribute to restoring baseflows through recharging of subsurface flows and groundwater (Fletcher et al., 2013). These techniques depend highly on site conditions, which is why there is such a wide range of performance reported for infiltration-based techniques. Infiltration-based LID controls include swales, basins, infiltration trenches, rain gardens, porous pavements, and sand filters.

Swale systems are shallow open channels with mild side slopes and filled with erosion and flood resistant vegetation. Swales are designed to control, convey, and improve stormwater through infiltration, sedimentation, and filtration (Kirby et al., 2005; U.S EPA, 2000). Swales are implemented to enhance or replace traditional curbs and gutters for stormwater transport in urban settings (Ahiablame et al., 2012) and are able to function efficiently in diverse seasonal conditions (Fach et al., 2011).

Infiltration trenches usually consist of a channel made of gravel that is covered with soil and vegetation and underlain by a geotextile fabric to help prevent clogging. The gravel allows for maximum infiltration and can assist with significant storage in the pore spaces. The design of infiltration trenches is based on the volume of stormwater to be captured and soil characteristics, which are used to understand the amount of water entering the trench and traveling through the topsoil layer and storage medium. Infiltration trenches use storage and filtration to slow the velocity of stormwater runoff, the reduced runoff velocity and meandering flow path can also remove suspended and solids and other contaminants from the stormwater (Barkdoll et al., 2016).

Bioretention areas or rain gardens are lowered areas in the landscape used to reduce and treat stormwater runoff at the site and to reduce peak flows (Shafique and Kim, 2015; U.S EPA, 1999), they can be beneficial when used in both residential and commercial settings (Dietz, 2007). The design of bioretention systems depends on the soil type, site conditions, and land use. An arrangement of different components, each performing separate functions in the removal of pollutants and reduction of stormwater runoff can be considered a bioretention area (U.S EPA, 2000). These areas generally consist of perennials, trees, or shrubs, and covered with bark mulch (Shafique and Kim, 2015). Bioretention systems can be effectively implemented to capture runoff, encourage infiltration, recharge groundwater, promote evapotranspiration, reduce peak flow, reduce pollutant loads, and protect stream channels since they act similar to natural and undeveloped watersheds (Ahiablame et al., 2012; Davis, 2005; Dietz, 2007; Dietz and Clausen, 2008).

Sand filters have progressed into multiple different variations, such as surface sand filter, underground sand filter, perimeter sand filter, organic filter, and pocket sand filter. Each of these variations follows the same principle with minor difference. The surface sand filters consist of two chambers: a flow splitter diverts runoff into a sedimentation chamber where pretreatment occurs. Runoff then continues into the second chamber where pollutants are strained out at the surface of the filter bed. Underground sand filters are useful at sites that have limited space. The design consists of the sand filter being placed in an underground vault that can be accessed through manholes. The perimeter sand filter consists of two parallel trenches that are generally installed around the perimeter of a parking lot. The organic filter is similar to the surface sand filter except that the compost is used as the filter material. Finally, the pocket sand filter is a cheaper and more simplified design that can be implemented at smaller sites (Claytor and Schueler, 1996).

Permeable pavements can retain storm runoff, to allow for infiltration into the subsoil (U.S EPA, 2000). Different types of permeable pavement include porous asphalt, porous concretes, block pavers, and plastic grid systems (Dietz, 2007). Permeable pavements are used to reduce runoff, though they can also be used to eliminate the generation of runoff (Bean et al., 2007) even during intense rainfall events (Brattebo and Booth, 2003). Permeable surfaces can be easily retrofitted to existing residential properties or installed in new residential developments (CVC, 2010; Yong et al., 2013). Urban municipalities can minimize wastewater capital and operating costs, manage their legislative obligations, and reduce negative environmental impacts by encouraging the widespread implementation of permeable pavements (Coffman et al., 1999; CVC, 2010). The runoff reduction capabilities of permeable pavements have demonstrated that pre-development hydrology is possible with the use of such technologies (Fassman and Blackbourn, 2010).

2.4.2.2 Retention Techniques

LID Techniques that retain stormwater in order to reduce outflow can be characterized as stormwater-retention based LIDs (Fletcher et al., 2013). LID controls considered as retention-based technologies include green roofs, ponds and wetlands, and rainwater harvesting (tanks, storage basins).

Green roofs are an efficient way of reducing stormwater runoff by lowering the percentage of impervious surface in urban areas (U.S EPA, 2000). A green roof is a building rooftop that is partially or entirely covered with vegetation on high quality waterproof membranes to offset the vegetation that was removed during the construction of the building (Rowe, 2011; Shafique and Kim, 2015; U.S EPA, 2000). The use of green roofs in urban areas can help extend the life of roofs, reduce energy costs and conserve valuable land that would otherwise be necessary for stormwater runoff controls (U.S EPA, 2000). Green roofs can also be designed to be added to existing rooftops without additional reinforcement or structural design requirements. The reduction in runoff provided by green roofs is directly related to the design rainfall event used during the design process. The design of green roofs should use storm events that have the most significant impacts on the hydraulic infrastructure of the area (U.S EPA, 2000).

Wetlands and ponds have extensively used for a long time. They have proven to be effective for pollutant removal, however they have a limited ability to reduce runoff volumes, since their only losses are from evapotranspiration (Fletcher et al., 2013). These techniques can have significant influences on the flow regime as the can cause both hydrologic and hydraulic consequences, for example detention-based techniques that reduce peak flows by storage may result in an increase of the duration of flow above a critical discharge (Burns et al., 2012).

Stormwater harvesting controls can significantly improve the ability of stormwater retention systems to reduce annual runoff volumes (Fletcher et al., 2007). Stormwater harvesting systems that supply regular daily demands are more efficient in terms of runoff reduction than those that supply seasonal demands. The use of stormwater harvesting for processes, such as irrigation, however, should not be ignored as this could be significant component of managing urban hydrology (Fletcher et al., 2013).

2.5 LID Performance

2.5.1 Overview

LID effectiveness can be determined by analyzing their hydrological function and pollutant removal capabilities (U.S EPA, 2000). Evaluating the changes to hydrological properties of a site can be more difficult than the changes in pollutant concentration due the complexity of the changes that need to consider factors that are not immediately observable such as groundwater flow (Jacobson, 2011). There have been a variety of studies that have analyzed the hydrological performance of LIDs in various different climates, this section discusses some of the research carried out.

2.5.2 Hydrology

A demonstration project by Lloyd et al. (2002) looked at the timing of flows in Lynbrook Estate, Melbourne. The project included 32 ha made up of 271 medium density residential lots and parklands. Roof and road runoff systems were collected by grassed swales underlain by gravel trenches. This system eventually fed into wetlands. A paired catchment storm even monitoring program was established in neighboring sub-catchments in order to compare the traditional piped system to the new LID system. It was determined that the LID catchment produced 51% to 100% less runoff as well as consistently lower peak discharges. It was also noticed that the stormwater was delayed by an average of 10 minutes and the LID system had continuously had a shorter duration stormwater discharge (Lloyd et al., 2002).

Jackisch and Weiler (2017) monitored precipitation, discharge, and stream flow in Freiburg, Germany for 30 months in order to analyze the hydrologic performance of an LID site. The study demonstrated that site-level LIDs can work as an alternative to conventional stormwater management techniques even when subjected to unfavorable conditions like weak performance related to prior conditions, underground storage, seasonal freezing periods, and storm characteristics.

Another study compared bioretention outflow from four cells to stream flow from three small, undeveloped watersheds in the Piedmont region of North Carolina. Debusk and Hunt (2011) found that the bioretention cells produced flow rates and patterns similar to the natural watersheds. A study by Lenhart and Hunt III (2010) showed that a 0.14 ha stormwater treatment wetland reduced runoff volumes by 54% and peak flows by 80% in River Bend, North Carolina. These results suggested that stormwater wetlands should be considered a practical LID option.

An LID subdivision in Watford, Connecticut was compared against a conventional stormwater management system. The LID controls included using permeable pavement to replace existing asphalt roads and some driveways, rain gardens were implemented, grass swales were used to replace gutters, a bioretention cul-de-sac was added, finally the construction of houses took place in a cluster layout. After monitoring and analyzing the area it was shown that the LID controls implemented proved to counteract the increased runoff that comes with increased impervious area. The runoff from the site did not increase despite increasing the impervious area from zero to 21% (Dietz and Clausen, 2008). In the Shepherd Creek watershed in Ohio, a six-year study that monitored before and after LID implementation was conducted on the 1.8 km^2 area. Mayer et al. (2012) observed the hydrological and ecological indicators in the watershed. With the installation of 176 rain barrels and 83 rain gardens on over 30% of the properties they were able to determine that the LID controls were able to have a "small but statistically significant effect of decreasing stormwater quantity at the sub-watershed scale" (Mayer et al., 2012). This is an important conclusion because the majority of the research in this area has focused on a smaller scale and the evaluation of the cumulative LID impacts on a watershed is not commonly looked at. Shuster and Rhea (2013) noted from the study by Mayer et al. (2012) that the LID measures were able to increase the system's detention capacity. They also pointed how important it should be to consider the transportation surfaces in order to maximize the efficiency of additional retrofits, swales are a good way to implement this retrofit (Shuster and Rhea, 2013).

A comparison of several LID controls was carried out by Damodaram et al. (2010). Permeable pavement, rainwater harvesting and green roofs were all compared to a detention pond, a traditional best management practice (BMP) and a scenario combining LID with traditional BMP practices for a watershed on the campus of Texas A&M University. The study concluded that the BMPs were more effective for the larger storms, but infiltration based LID measures were more effective than storage based BMPs for smaller storms. Under two 114 mm design storms the LID controls were able to create flow timings that were similar to the sites pre-development conditions (Damodaram et al., 2010). For each case it was found that the hybrid scenario performed the most efficient and demonstrated about 50% peak flow reductions for 10-year and 100-year events. It was observed, though, that for large storm events the majority of these flow reductions can be attributed to the detention pond. This study was expanded by Damodaram and Zechman

(2013) and they were able to conclude that LID/BMP hybrids work best for peak flow reduction but noted that the peak flow metrics are not the only factor, and may not be the best when looking at sustainability.

Line et al. (2012) compared three commercial sites in the Piedmont and Coastal Plain regions of North Carolina, one with a detention basin, one with LID measures and one with no stormwater control measures. The LID site had eight bioretention cells, 0.53 ha of permeable concrete and two constructed stormwater wetlands. The LID controls showed to have a lack of a drawdown orifice in the stormwater wetland and the bioretention cells were undersized and clogged, though these issues reduced the ability of the LIDs to reduce runoff they still had some positive impact. Bergman et al. (2011) analyzed two infiltration trenches over a 15-year period and noticed a significant decrease in infiltration rate that was likely caused mainly by clogging from fine particles. A model to simulate clogging and infiltration was also developed, it was used to predict that the infiltration rates will decrease at a rate inversely proportional to time.

The effectiveness of LID measures can be increased by using them in treatment trains (Brown et al., 2012; CVC, 2010). Brown et al. (2012) compared using bioretention cells to a treatment train consisting of 0.53 ha of permeable concrete and a 0.05 ha bioretention cell. The treatment train significantly outperformed the use of only the bioretention cell and effectively reduced peak flow, runoff volume and the duration of elevated outflow rates. Jia et al. (2015) studied a treatment train in China and its effectiveness of controlling urban runoff. The treatment train consisted of a bioretention cell, three grassed swales, two infiltration pits, a buffer strip and a constructed wetland all connected in series. The study showed that the bioretention reduced peak flow by 50-84% and runoff volume by 47-80%. The grassed swales reduced peak flows by 17-79% and runoff volume by 9-74%.

2.5.3 Water Quality

A major ecological benefit claimed of LID is the capability to reduce water pollution and contributing to the regulation of biogeochemical cycles. Dietz and Clausen, (2008), in their study in Watford CT previously mentioned, also looked at nutrient export. For the traditional development case, NO_3-N, NH_3N, TN, and TP export increased logarithmically as the impervious area increased. For the LID site there was no change to the NO_3-N, the NH_3-N export decreased significantly and both TN and TP remained very low. Wilson et al. (2015) looked at the water quality benefits of a commercial lot with LID controls implemented compared to a conventional one. The study showed that the water quality performance of the LID development was much greater than the conventional development but it should be noted that some of the stormwater LID controls were over-designed. Lloyd et al. (2002) conducted a field study in Lynwood Estates, Melbourne that looked at the water quality of an LID demonstration project. The system lowered the total suspended solids (TSS) with a positive relationship between dose and removal. The pollutant load reductions from the entire LID system in the subdivision exceeded the efficiencies of sing LID measures (Lloyd et al., 2002). Hunt et al., (2008) examined factors that affect the performance of LID controls and found reductions in TP but mentioned that the fill soil's low cation exchange capacity would restrict long-term TP reductions. Bioretention units located in areas with seasonally high water tables only reduced total ammoniacal nitrogen and TSS concentrations while nitrate, nitrite and TN all increased by two to four times due to contributions from baseflow. Draining groundwater through a bioretention cell should be avoided as it could also damage local hydrology (Brown et al., 2012). Jia et al. (2015)

demonstrated the effectiveness of treatment trains for pollutant removal with the train in their study removing 73% of NH_3-N, 74% of TN, 95% of TP, 19% of COD and 35% of TSS.

LID controls can also be effective in reducing concentrations of metals (Hunt et al., 2008) and bacteria (Hathaway et al., 2009; Hunt et al., 2008). In Cheonan Korea, Maniquiz-Redillas and Kim (2016) monitored six LID systems that included tree box filters, infiltration trenches, rain gardens and hybrid constructed wetlands implemented for the managing road, parking lot and roof runoff for a four year period to evaluate the efficiency of the systems for removing heavy metals, Zn, Cr, Pb, Cd, Cu, Ni, and Fe, from runoff. The heavy metal concentration increased proportionally with the total suspended solids concentration. It was determined that the systems were more efficient for larger storms. A bioretention cell performed well in reducing Cu, PB and Zn effluent concentrations but Fe increased immensely, likely due to high iron concentrations in the soil (Hunt et al., 2008). Bioretention units can also be an efficient way of reducing fecal coliform and E. Coli bacteria (Hathaway et al., 2009). Wetlands can also be effective in reducing the effluent concentrations of indicator bacteria, particularly shallow wetlands and ones with low vegetative cover. It should be noted that the environmental conditions found in some LID projects can actually produce bacteria (Hathaway et al., 2009). Hathaway et al. (2009) and Hunt et al. (2008) warned about generalizing their results as both studies are limited in scope and there are few other studies that test the bacterial removal abilities of LID measures.

2.6 Computer Modeling of LID

2.6.1 Overview

Computer modelling is the most effective tool for the design and optimization of sewer systems (Freni et al., 2010). Elliott and Trowsdale (2007) presented an early review on modelling and the ability of using it to evaluate LID measures. At the time they found that the current models did not incorporate a sufficient number of contaminants relating to water quality and that it was difficult to link hydrologic models to outside processes like toxicity and habitat models. Since that review has been published, the gaps in model capabilities have been continuously narrowed. There is a wide range of literature providing monitoring information that covers the beneficial uses of LID controls. Monitoring methods are limited to certain conditions and periods due to the expensive associated costs, simulation modelling provides a valuable method of determining spatial and temporal information for a variety of scales (Ahiablame et al., 2012). Generally, water quantity is more commonly modelled than water quality as the water quality data, necessary for model calibration, is more difficult to obtain than hydrological data (Imteaz et al., 2013). Urban stormwater quality models were reviewed in Obropta and Kardos (2007) where comparisons were made between deterministic, stochastic, and hybrid modelling approaches and it was suggested that hybrid approaches might reduce prediction error and uncertainty.

An in depth review of the models ANSWERS, CASC2D, DR3M, HEC-HMS, HSPF, KINEROS2, and SWMM is laid out in the thesis of Bosley II (2008). Zhou (2014) also provided a review on modelling and found that the open source models can be difficult to use and are often lacking in user support whereas proprietary models offer greater support but are often too expensive for many potential users. GIS integration reduces the amount of work required in processing data to input into the models (Viavattene et al., 2010;

Viavattene et al., 2008). Commercial software, such as PCSWMM provide LID modelling along with GIS integration. A GIS interface may also assist users that are familiar with GIS to overcome some of the current technical complexities of many current models. Bacchin et al. (2014) introduced a tool that integrates ArcGIS and SWMM to analyze the spatial composition and configuration of the urbanized area. Some non-proprietary models like HEC-HMS (Scharffenberg, 2013) and L-THIA (Park et al., 2013) now provide GIS extensions.

There is little literature that has quantified the impacts of LID at a watershed scale (Ahiablame et al., 2013). This is important for furthering the use of models as results are able to be simulated from a lot scale to a watershed scale and across various temporal scales, whereas it can be impractical to apply field studies at larger scales (Ahiablame et al., 2012).

The use of multiple models to evaluate the impact of stormwater management alternatives is also common. Sharma et al. (2008) used three models, Aquacycle for the urban water balance; PURRS for peak stormwater flows from properties; and Model for Urban Stormwater Improvement Conceptualization (MUSIC) for the stormwater flows, contaminants, and treatment options in order to analyze stormwater management options in Canberra, Australia. Damodaram et al. (2010) use HEC-HMS as a hydrological model while also using SWMM to compute hydraulic routing for a study on the campus of Texas A&M University. MIKE SHE has also been used to evaluate hydrological impacts of urbanization and to study the possible benefits resulting from implementing LID methods (Trinh and Chui, 2013).

Another method to evaluate the performance of LIDs is for researchers to develop their own model. Chen et al. (2016) developed a new computer model called Rainwater+, which uses the Natural Resource Conservation Service (NRCS) Curve Number method to calculate runoff depth. Rainwater+ is an intuitive and interactive tool for use in the early design process, it can be used for decision making, design evaluation, rough cost estimation, and compliance checking. StormWISE is a model developed by McGarity (2011) and was used as a screening method to optimize improvements to water quality.

Despite the availability of a variety of popular and widely used software dedicated to urban hydrology and stormwater drainage, such as HEC-HMS, SWMM, MOUSE, and MUSIC, rainfall-runoff modelling still needs further research (Fletcher et al., 2013). There are multiple studies that demonstrate a variety of techniques to analyze the effectiveness of LID controls in stormwater management (Ahiablame et al., 2012). Model sensitivity analysis, uncertainty analysis, and calibration are all important areas in determining the strength and accuracy of the results produced by the model (Fletcher et al., 2013). These issues all impact the modelling of LIDs with hydrologic models. The subsequent sections review some ways LID controls have been simulated and the capabilities of hydrologic models to demonstrate LID practices.

2.6.2 Representation of LID in Models

LID stormwater controls can be represented in models in a variety of ways. For example, it is possible to represent the physical processes within the LID control or they could be demonstrated by using aggregate properties such as curve number (CN) (Ahiablame et al., 2012). Another method is to develop a model for LID measures and integrate them into open-source models as shown in Damodaram et al. (2010) who did this using curve numbers and Zhang (2009) who created physically based algorithms to represent green roofs, porous pavement, and bioretention in SWMM. Many models such as SWMM now include a built in LID toolbox for simulating LID controls. Zhou (2014) illustrates the importance of representing LID accurately in modelling and in physical design. They pointed out that underestimating the complexity of LID functionality can lead to underachieving LID performance and failed performance expectations.

2.6.2.1 Hydrology

The following section looks at the findings of some studies that used computer models to analyze the hydrological process in LID measures. Xiao et al. (2007) looked at lot level controls with a model they developed. It was reported that increased percolation to groundwater had a bigger impact that evapotranspiration, which could help with groundwater recharge but care is required not to contaminate groundwater when runoff is routed to LID controls from paved surfaces in areas with highly permeable soil. Using Matlab language Gilroy and McCuen (2009) developed a model to simulate spatial and temporal features of rainfall and runoff to study the effectiveness of bioretention cells and cisterns on lot-sized watershed. For a one-year storm the LID controls studied performed much better than they did under a two-year storm. In order to increase the available storage for these events the LID controls could be placed in series along the same flow path. The design of LID controls impacts peak flow rate and runoff volume differently. Both timing and runoff volume are necessary to be looked at during the design. It is also important to realize optimal LID performance as greatly diminished returns can become apparent when adding additional LID measures (Gilroy and McCuen, 2009).

Using SWMM, Qin et al. (2013) compared swales, permeable pavements and green roofs in a catchment in China where heavy rainfall is common during the summer months. They determined that the swales were not able to efficiently reduce flood volumes since they received runoff from an area that was too large and thus overflowed quickly. Permeable pavements and green roofs, however, were found to effectively reduce flood volumes for precipitation events between 70 mm and 140 mm. Li et al. (2017) used SWMM simulations to compare bioretention units, green roofs, permeable pavement, low-elevation greenbelt, and rain barrels. Their study showed bioretention cells were able to reduce peak flow by 36% and total runoff by 39%, greenroofs reduced peak flow by 25% and total runoff by 30%, permeable pavement reduced peak flow by 18% and total runoff by 23%, low-elevation greenbelt reduced peak flow by 26% and total runoff by 30% and rain barrels were able to reduce peak flow and total runoff by 6% and 11%, respectively. Palla and Gnecco (2015) studied LID controls at the catchment scale using SWMM and found that the hydrological performance was linearly dependent on the reduction of impervious area. They reported that a reduction greater than 5% was necessary to achieve noticeable benefits. The retention capacity of LID measures drive improvements in hydrological performance. Simpson and Roesner (2018) used SWMM to assess if LID measures alone could maintain predevelopment hydrology. It was determined that LID can restore predevelopment hydrology however extensive implementation is necessary to manage a 100-year storm making it uneconomic to do so.

Hydrological effects of common LID controls were estimated in Zhang et al. (2016) by using the Soil Conservation Service (SCS) method to simulate runoff-generating processes for various rainfall frequencies. They were able to use the results from these simulations to look at the relevant factors affecting LID performance, such the impact of the LID controls on reducing runoff and increasing baseflow. Trinh and Chui (2013) used MIKE SHE for simulations and noted that groundwater and evapotranspiration have a key role in the hydrological systems. The proper planning and design of LID controls in an urban catchment can change the shape of outlet hydrograph. Stewart et al. (2017) developed a HYDRUS-2D/3D model of a bioretention cell and used the model to determine a mass balance to establish stormwater return flow reduction, assess LID effects on subsurface water dynamics, and to determine the model sensitivity to measured soil properties. The model demonstrated the bioretention cell reduced stormwater return flows into the sewer system and that the addition of the exfiltration from the bioretention unit activated a new groundwater dynamic.

Schmitter et al. (2016) created an integrated model to analyze the impacts of green roof implementation in Singapore and demonstrated positive effects on flood protection. This study shows the ability of green roofs in climatic conditions consisting of two monsoon seasons. Sun et al. (2014) modelled and analyzed the use of LID controls in a parking lot in Kansas, demonstrating that LID provided significant stormwater control during small rainfall events, but performed more poorly for flooding events. Chaosakul et al. (2013) modelled single and multiple LID controls in an urban village in Thailand to evaluate stormwater quantity and quality benefits. The combination of rain barrel and bioretention cells provided the greatest reduction in surface flooding however, the implementation costs for this strategy were likely not feasible for the region.

Semadeni-Davies et al. (2008) used the commercial Danish Hydrological Institute's Model of Urban Sewers (MOUSE) to model the combined sewer system in Helsingborg, Sweden. They were able to show under future climate scenarios the possibility of reducing or eliminating combined sewer overflows (CSO) by implementing LID controls in combination with disconnecting stormwater from combined sewers. To compare the effectiveness of decentralized LID controls to more traditional centralized stormwater controls and to analyze methods of improving stormwater management practices, Freni et al. (2010) developed their own model. They studied an urban catchment at the University of Palermo in Italy and found storage tanks that were connected to centralized systems were more effective at reducing CSO volume and pollutant load since storage tanks directly act on would-be CSO volume. Distributed infiltration techniques can be more effective for high infiltration soils, however, clogging can be an important factor in reducing the efficiency of these controls over time and regular maintenance may be required. Using a combination of distributed and centralized stormwater management controls can be feasible and effective. Massoudieh et al. (2017) also developed their own modelling framework assess the hydrological and water quality processes in LID controls and demonstrated it on various LID studies.

Stovin et al. (2013) created a GIS-based tool to model and analyze retrofit LID controls. LID measures were modeled by disconnecting areas of catchments from the sewer system by routing to pervious area or developing pervious area rather than modelling LID measures individually. They tested the model on three catchments in the London Tideway Improvements area. Modelling scenarios, such as disconnecting downspouts from sewers that remove stormwater from stormsewers is an efficient means to determine LID implementation potential. They determined that large-scale disconnection would be difficult and costly to implement and suggested LID controls be used as a tool implemented alongside conventional sewer systems (Stovin et al., 2013). Satellite imagery can be a very useful tool for GIS-based models. WorldView-2 high-resolution satellite imagery was used along with a two stage classification method to obtain land use cover types and to derive hydrologic parameters to model LID performance in Khin et al. (2016). Using satellite imagery provided an automated means to retrieve land cover information for modelling LID techniques with the urban drainage system. The classified image was used to develop three LID scenarios of detailed distributed hydrologic models in PCSWMM. Critical hydrologic parameters of each subcatchment, such as width, area, percent imperviousness, overland flow path, Manning's n value and depression storage value were determined from the classified results and employed in the GIS software. This method could be very beneficial when there is no high-quality GIS data for land cover type.

Computer modelling tools are required to support the selection and assessment of practical LID options. Modelling can help determine LID placement options in a watershed in a cost-effective way while addressing environmental quality restoration and protection needs in developed and developing urban areas (Lee et al., 2012). Chui et al. (2016) coupled SWMM with Matlab to evaluate the hydrological performance and cost effectiveness of bioretention, green roofs, and porous pavements to determine the optimal designs. LID controls were represented as vertical layers, whose movements and water balances are computed for each layer during the simulation. Matlab was coded to automate the large number of SWMM output files. The unit costs and dimensions of the optimal designs of various LID measures were than able to be calculated. Using L-THIA-LID 2.1 and linking it to an optimization tool, Liu et al. (2016) modelled the impacts of climate change and land use change on hydrology and water quality for a watershed in Indiana to determine the optimal selection and placement of LID practices. The authors determined that the land use changes by 2050 had more of an impact on runoff volume and pollutant loads than the consequences of predicted climate change. They also noted that the same runoff volumes and pollutant loads from 2001 could be achieved in 2050 by implementing green infrastructure. Son et al. (2017) created a LID-based district unit planning model (LID-DP). They verified the model with simulation tests for a city in Korea that demonstrated the role of LIDs in reducing runoff and having positive impacts on water quality. This area experiences torrential rainfall events during summer months.

Non-structural LID practices like clustered development has also been studied with computer simulation. Conventional curvilinear, urban cluster, coving, and new urbanism development methods, with and without infiltration based LID controls were compared in Brander et al. (2004). Their model is a spreadsheet based model called Infiltration Patch, which is an expansion of the National Resources Conservation Services SCS CN method. Similar to many other studies on LID controls, the LID measures implemented here were more effective for smaller storms. The cluster development, where there is more room left for open spaces, was the most effective for reducing runoff. Williams and Wise (2006) determined that cluster development useful to reduce peak flows and runoff volume, and to use LID controls to help preserve natural hydrological patterns.

2.6.2.2 Water Quality

As mentioned earlier, water quality relating to LIDs is not modelled as commonly as hydrology and is often studied more though experimentation. Ahiablame et al. (2012) draws attention to the fact that more research on the characterization of runoff water quality is necessary for different land uses. The Water Quality Capture Optimization and Statistic Model (WQ-COSM) was developed by Guo et al. (2014) to help determine the water quality capture volume for the design of LID controls. Chen and Lin, (2015) modelled LID measures and water quality performance for a watershed in Taiwan using SUSTAIN to establish best practices to be applied to the watershed. The effectiveness of grass swales, bioretention, and pervious pavements were compared for removing TP, SS, TN and BOD. The study demonstrated that the permeable pavements provided the largest reduction in pollution and runoff. Mao et al. (2017) also used SUSTAIN to evaluate the ecological benefits of LID measures for a city in China. They assessed the annual pollutant loads of COD, SS, TN and TP and found LIDs were able to reduce pollutant loads by over 60%. Seo et al. (2017) developed a procedure for representing LID practices in SWAT and were able to model the impacts LIDs had on water quantity and quality. Their model showed how LID controls can reduce pollutant loads for various different land uses. Carbone et al. (2014) used laboratory experiments to validate their k-C* model that was used to simulate permeable pavement systems. The model was able to predict accurately TSS concentration in runoff through a variety of permeable pavement types. Li et al. (2017) used SWMM to analyze LID pollutant removal capabilities and found that bioretention reduced COD, SS, TN, and TP by 28.3%, 34.5%, 36.1%, and 33.7%, respectively. Green roofs reduced COD, SS, TN, and TP by 19.1%, 22.9%, 24.6%, and 22.6%, respectively while the permeable pavements reduced these same pollutants by 13.3%, 16.0%, 17.4% and 15.8%.

2.6.2.3 Multi-criteria Modelling

Spatial multi-criteria analysis is necessary in the planning and implementation of LIDs. There is abundant literature on different methods and models to aid with LID selection, sizing and placement. Jia et al. (2013) developed a multi-criteria index system for the selection of LID controls during planning. The criteria consider specific site characteristics and site suitability, economic feasibility of LID implementation, and performance of runoff controls. In terms of models that contribute to the selection of LID controls Charlesworth et al. (2016) developed a large scale site specific model to determine the optimal treatment train. The model incorporates ArcGIS maps to better assist with the decision of suitable LID controls. This model can be beneficial in the early planning stages and can identify the best locations for LID implementation. Johnson and Sample (2017) developed the BMP Checker to assist in simplifying the site locations for BMP devices. The checker uses site characteristics, such as slope, seasonal high water table depth, soil types and catchment size and compares them to constraints. By doing this the model can provide suitable and unsuitable BMPs to be implemented. Joyce et al. (2017) used scale dependent data combined with the Interconnected Channel and Pond Routing model to develop a multi-scale modelling platform that evaluates drainage infrastructure. This model was developed specifically for coastal regions and demonstrated that rainfall type, sub-daily rainfall patterns and groundwater analysis are all necessary for proper evaluation of LID implementation.

2.6.3 LID Scenario Optimization

There are many selection factors when implementing LID controls, such as number of controls, sizes, combinations and locations of controls and there are many other possibilities at the watershed scale due to the variety of characteristics depending on the watershed. Budget is a major limiting factor in stormwater management projects, which makes the optimal selection and placement of LID measures is required to achieve the maximum runoff/peak flow reductions in the most cost effective manner. To properly assess and compare LID scenarios in watershed optimization it is necessary to develop the proper tools. The approach used by Zhen et al. (2004) took a scatter search in a single-objective constrained optimization. When using single objective optimization additional objectives, which might otherwise by optimized, are often simply constrained to a target range. In water resources one of the most common methods of optimization is to use genetic algorithms. These algorithms can be linked with simulation models and can optimize one or more objectives (Eckart et al., 2017). Jia et al., (2012) used Best Management Practice Decision Support System (BMPDSS), an optimization tool that assists with the design and placement of BMPs. BMPDSS requires the user to specify assessment points and evaluation factors, decision variables, cost functions, and management targets. Cano and Barkdoll, (2017) developed the Multi-Objective, Socio-Economic, Boundary-Emanation, Nearest Distance (MOSEBEND) algorithm that aims to provide the optimal BMPs to implement for different subcatchments. The algorithm tries to provide solutions considering the highest runoff reduction, lowest cost, and highest likelihood of private-owner maintenance. The System for Urban Stormwater Treatment and Analysis Integration Model (SUSTAIN) (Lai et al., 2007) is another model that uses a genetic algorithm, GIS integration, and some of the SWMM computational methods. Lee et al. (2012) carried out a case study using the SUSTAIN model, however since then the EPA no longer supports SUSTAIN and it only runs on Windows XP and ArcGIS 9.x. Innoyze® has since released InfoSWMM Sustain, a decision support tool that can analyze the costs and benefits associated with installing various LID measures (Innoyze, 2015). This model can provide hydrological modelling of LID measures and identify the most cost effective options based on the goals of a particular site, however, the current commercial license is expensive. Ellis and Viavattene (2014) developed SUDSLOC, which is another GIS-integrated decision support system. There is also an optimization model developed by McGarity (2011) that can help determine investment in LIDs to improve water quality in watersheds.

One of the most common genetic algorithms is NSGA-II (Deb, 2001). This algorithm, or variations of it, are used in many studies including in the SUSTAIN model. Karamouz and Nazif (2013) used SWMM and NSGA-II along with data envelopment analysis to optimize stormwater management practices for flood control under climate change conditions for a watershed in Tehran, Iran. Based on reliability criteria related to flood reduction and cost reduction, the authors optimized simulated BMPs. Hooshyaripor and Yazdi (2017) used NSGA-II with SWMM to determine the optimal layout and capacity of retention ponds to reduce surcharge from manholes in a small city in Iran. Maharjan et al. (2009) similarly linked a genetic algorithm with SWMM to optimize strategies to respond to changes in land use over time and climate change. Giacomoni and Joseph (2017) used SWMM linked with NSGA-II and Monte Carlo simulation approaches to determine near-optimal placement of permeable pavement and green roofs. NSGA-II was linked to SWMM in order to determine the location of controls and analyze the tradeoffs between performance and implementation costs. Damodaram and Zechman (2013) used a genetic algorithm to determine the optimal placement of permeable pavement, rainwater harvesting, and detention ponds to reduce peak flows in a cost effective manner. The optimization process allowed the authors to determine which stormwater control methods were the most flexible in effective designs. Yazdi and Salehi Neyshabouri (2014) used NSGA-II, multi-criteria selection, fuzzy set theorem and an artificial neural network (ANN) to develop cost-benefit information relating to LID implementation.

Using SWMM and a multi-objective optimization model has been common practice for evaluating LIDs. Baek et al. (2015) combined Matlab and SWMM along with the pattern search algorithm for the optimization of LID sizes to mitigate the First Flush Effect (FFE). Duan et al. (2016) looked at the multi-objective optimal design of urban stormwater drainage systems by LID controls and detention tanks. They applied the modified Particle Swarm Optimization (NPSO) scheme and linked it to SWMM. SWMM performed the numerical simulation while the NPSO scheme solve the multi-objective optimization problem. To validate their developed framework, the optimal design was applied to a real-life case and found the proposed method to be feasible. Xu et al. (2017) used SWMM with the global optimal algorithm and Matlab to optimize the layout of LID controls. They were able to develop an optimal layout that reduced runoff by 65% and provided a suspended solids pollutant load reduction efficiency of 65.6%. Jung et al., (2016) used the Harmony Search algorithm coupled with SWMM to develop and optimization model. The model was then used to determine the optimal design of permeable pavements. The HS algorithm selects locations for the permeable pavement to be implemented and determines which pavement size and type should be used to meet each condition for the selected locations. HS algorithm reduces repeated processes to search for the optimal solution. SWMM provides the rainfall-runoff analysis using the parameters found by the HS algorithm and returns the runoff results to the HS algorithm, which uses it to generate the more optimal solution.

Limbrunner et al. (2013) suggested linear and dynamic programming could be as efficient at finding optimal solutions as a genetic algorithm and could do so in less time. Zhang (2009) used an elitist version of NSGA-II, ε-NSGA-II, combined with SWMM for the cost effectiveness optimization of various LID controls. Eckart et al. (2018) provides a method that couples a genetic algorithm (Borg MOEA) with SWMM. This model provides users a means to evaluate the significance of various LID design parameters and is capable of performing multi-objective optimization to analyze potential LID measures by minimizing the peak flow in stormsewers. The model also provides important information on the cost-effectiveness of different LID controls. There have been many different methods developed and tested for the optimization of LID design but further research in this area will help encourage the implementation of LID systems to aid with stormwater management.

2.7 Costs of LID Scenarios

Stormwater management can accrue significant costs. Though costs vary depending on location, it is evident that implementing source controls like LIDs can be more cost effective than traditional stormwater management systems. The most significant costs associated with stormwater management come from efforts to improve drainage and reduce flooding (Visitacion et al., 2009). Reducing the burden on the conveyance network by implementing LID strategies can cause significant cost savings (Roy et al., 2008). In densely populated urban areas, upgrading the existing subterranean stormwater management infrastructure can be disruptive, difficult, and costly (Ashley et al., 2011). For areas served by combined sewer systems, LID might be able to reduce cost of regulatory compliance for areas, such as CSOs (Smullen et al., 2008). Despite the economic significance, very few jurisdictions have conducted economic analysis for their LID programs (U.S EPA, 2013).

Finding and implementing new, more economic ways to manage stormwater is becoming necessary. U.S EPA (2007) looks at 17 case studies of developments where LID practices have been implemented and was able to conclude that applying LID strategies can reduce costs while also improving environmental performance. Capital cost savings from these studies ranged from 15% to 80% when LID was used and significant savings were attributed to reduced costs for stormwater infrastructure, site grading and preparation, landscaping and site paving. U.S EPA released another study in 2013 on 13 case studies in order to promote the use of LID practices in the United States to improve traditional grey stormwater infrastructure. The report includes multiple economic analysis methods and concludes the use of economic analyses of LID programs can contribute to significant cost savings. One case study looked at was by Lenexa Public Works Department in Kansas, who used a capital cost assessment to determine the cost savings in site work and infrastructure costs associated with implementing LID strategies in various developments. In general, they found that the saving more than offset the associated costs for development fees (U.S EPA, 2013).

Economic analysis of implementing LID has provided important information associated with cost effectiveness of LID practices. Wright et al., (2016) analyzed the LID costs in four neighborhoods in Lafayette, Indiana. They found that the cost per cubic meter of runoff reduction varied from \$3 to \$600 and reported that as adoption for LID practices increased in an area, the associated implementation costs decreased. Stovin and Swan, (2007) ranked LID measures based on costs from least to most expensive as infiltration basins, soakaways, ponds, infiltration trenches, and porous pavements, however, some factors such as land acquisition were not considered in their analysis. The city of Lancaster, Pa. developed a green infrastructure calculator to estimate benefits and costs of implementing LID. They found that their program would cost \$141 million (in 2010 dollars), \$77 million of that would be increased cost incorporating LID initiatives into infrastructure and development projects. These costs work out to a marginal cost of \$0.03/L of stormwater which is cheaper than the estimated \$0.05/L for building grey infrastructure and the \$0.06/L for a large storage tank to remediate combined sewer overflows and water pollution issues (Katzenmoyer et al., 2013). In terms of implementing treatment train options, Brown et al. (2012) found that creating a treatment train with pervious concrete and a bioretention cell would increase the cost of the LID project to five times the costs of only using the bioretention cell. Uda et al. (2013) analyzed capital and life cycle costs of various LID controls for a 50 year time period. They found that bioretention, infiltration trenches, infiltration chambers and vegetative swales are some of the least expensive measures to implement when only considering the cost of the control. Permeable pavements were determined to be comparably more expensive than these other practices but green roofs were determined to be the most expensive to implement.

In areas recognized for their implementation of LID practices have seen increases in property values (van Roon, 2005). One drawback that may concern stormwater managers or property owner is lost opportunity costs. That is losing potential other uses of land due to designating land for green infrastructure project (Roy et al., 2008). It is important to consider a site carefully when implementing LID, another variable that effects the cost is how effectively LID controls are implemented, especially when considering location and quantity (Gilroy and McCuen, 2009). Williams and Wise (2009) found reducing lot sizes to include more open space and swales reduced the sale prices but also reduce the cost of construction. The ratio of sale price to construction cost was much better for developments with LIDs for part of the study period and worse for another part of the study period. They also noted that clustered development consistently outperformed traditional development (Williams and Wise, 2009).

Studies on LIDs that have included an optimization aspect have also been able to provide some information related to the costs of LID. Karamouz and Nazif (2013) determined the cost of BMPs was a critical factor in the reliability of flood control systems. Jia et al. (2012) found that LID controls optimized for cost effectiveness in runoff reduction generally had smaller dimensions than what was recommended in plans. Optimization for stormwater system intervention over time, however, allowed for cost savings (Maharjan et al., 2009).

A significant portion of the infrastructure costs in LID projects occurs early in the implementation, however, the full environmental benefits might not become apparent for years (van Roon, 2011). This is the reason improved life-cycle cost benefit analysis can be a more accurate comparison with traditional stormwater management systems (Wise et al., 2010). Further research should be done to quantify and monetize some social and environmental benefits like improved downstream environmental protection, aesthetics and recreation, flooding damage, and other factors that could develop cost savings over the lifetime of LID projects (U.S EPA, 2007). Houdeshel et al. (2011) developed a set of spreadsheet tools to conduct life-cycle cost analysis for various LID measures. Sample et al. (2003) created a costing approach based on land parcels and reported the importance of accurate unit cost data.

2.8 LID Barriers

2.8.1 Limitations of LID

To achieve desired flow mitigation and pollutant reduction, multiple stormwater management practices are necessary. Due to the variance from one area to another there is no one standard solution that can be effective in all locations. Factors such as human activities, watershed size, scale, and natural characteristics can vary significantly from one place to another (Lee et al., 2012). The suitability of LID controls depends more on site conditions rather than just available space. Soil permeability, water table depth, and slope should all be evaluated in order to effectively implement LID measures (U.S EPA, 2000).

Groundwater contamination concerns have been raised where infiltration practices, such as bioretention or permeable pavement, have been implemented. A research project carried out by Pitt et al. (1999) found that for light commercial and residential applications, the pollutants of concern are generally petroleum residue from automobile traffic, some nutrients, heavy metals, pathogens and possibly pesticides. Normally these pollutants are found in low concentrations in stormwater runoff and soils can retain them well, therefore contamination potential is low or moderate for LID controls.

2.8.2 Community Engagement

To ensure its adoption rate, new innovative technologies must demonstrate their ability to meet society's needs, norms and values (Rogers, 1983). In terms of LID there are numerous barriers to the adoption that have been identified (Barnhill and Smardon, 2012; Earles et al., 2009; Hood et al., 2007). Some of the potential barriers posed by society include the adopter's physical capacity, knowledge, awareness, attitudes, and perceptions; expense; and risk levels associated with LID uncertainty (Barnhill and Smardon, 2012; Earles et al., 2009; Hood, 2007). To increase and encourage LID adoption these social barriers must be alleviated (Earles et al., 2009; Zhao et al., 2012).

Implementing a decentralized, source control stormwater management approach requires the cooperation and involvement of the community. Community perception of LID may restrict or prevent its implementation. Homeowner's have now become accustomed to large lots and wide streets and may consider reduction of these as undesirable and unsafe. It has also become common belief that without curbs and gutters and other conventional stormwater management infrastructure, people will be dealing with flooded basements and surface structural damage (U.S EPA, 2000). To represent property owners decision making and stochastically simulate LID adoption Montalto et al., (2013) developed an agent-based model. They applied their model to 175 ha. neighbourhood in South Philadelphia and were able to show the importance of stakeholder engagement and the consideration of physical and social characteristics of an area targets for LID adoption.

Cote and Wolfe (2014) provided some insight to LID implementation barriers to urban stormwater management practices to the academic and applied literatures by studying the social and economic doubts of permeable surfaces in Kitchener, Ontario, Canada. They noted that less than half (44%) of residents who responded to their survey knew what permeable surfaces were before taking the survey. They also noted that there was a lack of awareness of the impacts that stormwater can cause. Decentralized stormwater management should be accomplished through guided public participation and local partnerships (Shuster et al., 2008). Measures such as rain barrels, rain gardens, and downspout disconnection require widespread public participation to be beneficial. Achieving this can be difficult as it may take a great deal of education to convince citizens of the long-term effects of stormwater on human health, quality of life, and ecology (Visitacion et al., 2009).

One way to increase public adoption that has become more common is financial incentive programs, such as fees or rebates. Cote and Wolfe (2014) found that residents were more willing to spend money on LID if there was a municipal incentive program available. Any kind of financial incentive, even at low levels, can often encourage implementation of new environmental technologies (Carter and Fowler, 2008; Dolnicar and Hurlimann, 2010; Mayer et al., 2012). Shuster et al. (2008) studied this method by using reverse auctions to encourage residents to adopt LID controls, such as rain gardens and rain barrels, where they paid people to take parcels while people bid down the amount they would receive as an incentive. There was a 25% response rate during the auction, with 60% of that being bids for $0 meaning those citizens did not require the added incentive but would implement the LID controls because they valued the impacts they could have. Shuster and Rhea (2013) built on this study and concluded that novel economic incentive programs could successfully encourage the adoption of distributed LID controls in suburban areas. Resident participation for a stormwater retrofit program in Mt. Evelyn, a residential suburb near Melbourne, Australia, was evaluated by Brown et al. (2016). This study used an economic incentive program to encourage change in stormwater runoff management from properties. The financial incentives and personal co-benefits, such as receiving future financial savings on water bills from installing rainwater tanks, were motivators whereas distrust and process complexity were barriers. An approach combining education, with financial incentives can help change public attitude towards a more sustainable stormwater management system (Eckart et al., 2017).

Lloyd et al. (2002) conducted a survey of 300 property owners and potential buyers from four LID developments in Melbourne and reported that over 90% of the respondents' favoured landscaped and grassed bio-filtration systems for management of stormwater and more the two-thirds believed they improve the aesthetics of the neighborhood. However, overall the responses showed there was still a lack of understanding of the benefits of implementing LID measures. In Kitchener, Ontario (Cote and Wolfe, 2014) surveyed property owners about the use of permeable pavements and determined that the greatest barriers were cost, awareness, and technological acceptance. To increase and encourage LID adoption these social barriers must be alleviated (Earles et al., 2009; Zhao et al., 2012). Some of these barriers can be mitigated through the efforts of private and public groups such as private firms, community non-governmental organizations, and watershed groups such as conservation authorities (Earles et al., 2009; Genskow and Wood, 2011; Vachon and Menz, 2006). However, government support is crucial to encouraging LID adoption and implementation (Rodriguez et al., 2009). Frame and Vale, (2006) suggested that social or political factors are larger barriers to sustainable developments than technical challenges.

2.8.3 Municipal and Consulting Professionals

There are significant barriers to LID practices becoming more widely accepted by professionals in risk adverse fields like engineering, public planning, and utility operation and management. Some of these risks include a lack of familiarity with new practices, uncertainty about maintenance and who is responsible for maintenance, liability issues, and a lack of experienced contractors (Binstock, 2011; Line et al., 2012; Roy et al., 2008; van Roon, 2007). Roy et al. (2008) also pointed out problems with distributing responsibility and authority over water management in many watersheds. It may also be difficult to quantify the value additions from LID implementation (Stovin et al., 2013). In order to move forward with resolving these issues there needs to be a commonly agreed upon framework or method for examining potential social, economic, and environmental costs and benefits of different water management alternative over different time periods (Mitchell, 2006).

In surveying stormwater professionals on which LID barriers have highest importance Lloyd et al. (2002) found that a lack of effective regulatory and operating environment was the most important issue, followed by the lack of quantitative data on the long-term performance and best practices, limited information on operation and maintenance and structural best practices, institutional fragmentation of responsibilities, lacking technical an culture skills within local governments and water corporations, a lack of ability to factor externality costs into life cycle costs analysis, insufficient information on market acceptance of residential properties with LID, and poor construction management leading to reduced efficiency (Lloyd et al., 2002).

Often times managers of stormwater programs lack benefit and cost information necessary to make rational funding decisions (Visitacion et al., 2009). Binstock (2011) recommended that funding provided from higher levels of government would be an effective way to reduce the risk for municipalities experimenting with LID, however, budgetary constraints of governments with smaller tax bases can limit implementation (Vogel et al., 2015). There are a lack of strict regulatory directives regarding LID (Roy et al., 2008), Washington and Maryland have requirements for LID use; however, regulations should be flexible (Binstock, 2011). In some cases, engineering standards and guidelines prevent LID adoption (Roy et al., 2008), for example some locations may require roads to have continuous curbs, detention basins may be required, and any kind of ponding might be discouraged. Many communities also have their own development rules that can make implementing innovative practices to reduce impervious area difficult. A mix of zoning regulations, parking and street standards, subdivision codes, and other local ordinances that determine how development happens are all examples of documentation restricting LID implementation (CWP, 1998). Wide streets, large-lot subdivisions, and expansive parking lots that reduce open space and natural features are a result of these documents and these obstacles are often difficult to overcome (U.S EPA, 2000). Policy and regulatory changes that support LID implementation are some of the most important requirements to expand LID application (Vogel et al., 2015). The successful implementation of LID controls requires a multidisciplinary approach and the proper coordination between different government agencies, private sector, and community groups (Brown et al., 2016; Roy et al., 2008; Wong and Eadie, 2000).

2.8.4 Monitoring and Evaluation Shortcomings

One of the greatest barriers to the implementation of LID practices is the lack of data regarding their performance in different situations (Roy et al., 2008), making the monitoring and evaluation of LID projects particularly important. There is not adequate long-term data to support any meaningful conclusions about the claimed benefits of LID measures (Clary et al., 2011; Shuster et al., 2008). Mitchell (2006) reviewed LID adoption in Australia and determined that monitoring was normally limited to what was required for operation as indicated by regulations. Mayer et al. (2012) conducted a six year study on the ecological effects of LID controls and suggested that six years may still be too short of a time frame to see the ecological impacts of distributed LID measures. They also emphasized the importance of quantifying ecosystem services and environmental benefits. Lengthier monitoring periods may be necessary to view the potential issues with degrading LID performance and maintenance.

Aside from a few research projects, systemic performance monitoring was lacking and there was a lack of long term monitoring and evaluation of LID projects, likely due to a lack of resources (Mitchell, 2006). For example, resources for demonstration projects may be used for gathering data but these same projects lack proper scientific oversight which has a negative impact on the quality of monitoring and evaluation. Most demonstration projects' short time period is not sufficient to run meaningful statistical comparisons (Shuster et al., 2008). The main objective of LID is to recreate predevelopment hydrological conditions, therefor before and after studies may be necessary to gauge performance (Clary et al., 2011). Generally, parallel or reference watershed studies have been conducted more often. Visitacion et al. (2009) also mentioned that there is a lack of monitoring and evaluation data for stormwater projects and thus it is hard to accurately evaluate benefits, risks and costs. In terms of modelling, performance data of LID controls at the sewershed level would be beneficial to calibrate LIDs incorporated in models.

It is necessary to understand the operating conditions and unique physiographic characteristics as part of the monitoring process, this is known as the location dependence of LID (Shuster et al., 2008). One major obstacle in monitoring and evaluation of LID is that large urban areas can make it very difficult to effectively detect the impacts of LID controls on receiving watersheds (Walsh and Fletcher, 2006). Modelling LID performance at larger scales, such as regions, watershed, or large cities, may even be difficult compared to individual LID controls (Clary et al., 2011; Wise et al., 2010). To assist with the need for cost effective methods for long-term monitoring and performance evaluation of LIDs Hakimdavar et al. (2016) showed how their Soil Water Apportioning Method (SWAM) can provide a low-cost long term monitoring approach for green roofs.

Further research on the spacing and location of stormwater alternatives is necessary. Additional research is also required on the quantity of stormwater controls, specifically in order to determine any diminishing returns (Gilroy and McCuen, 2009). Brown et al. (2012) suggested that it is important to determine how large should LID projects be, relative to the drainage area to effectively reduce runoff. As more information on LID comes available it should be included in decision making frameworks (Goonrey et al., 2009)

2.9 Conclusions

Continuous urbanization, climate change, and changing regulatory environments are some of the main factors driving the development of new, innovative stormwater management approaches. Low impact development has become a popular method to face these challenges. LID controls have now been included as part of stormwater management plans in many major cities around the world and green infrastructure is being encouraged by many regulatory agencies, such as the EPA in the U.S. In academics, new stormwater management practices have become a popular research topic.

The majority of research concludes that LID benefits include reduction of peak flows, runoff and the improvement of water quality; however, LID implemented by itself is not able to replicate predevelopment conditions in most watersheds. The level of benefit from LID is dependent on many factors including location dependencies, meaning that performance information of LID measures under different environmental conditions is necessary. It has also been commonly found that LID controls seem to perform better for controlling the hydrological impacts during shorter return period events. LID controls perform best for larger rainfall events when used in combination with traditional stormwater BMPs, such as detention ponds. In general, it appears that LID practices are a tool that works best in combination with more conventional stormwater management practices.

Improved design tools and continued research will only encourage the implementation of LID amongst stormwater professionals. Remaining areas of uncertainty that need to be addressed include the assessment of long term LID performance and the ability of LID to impact hydrology and water quality at a watershed scale. Continued monitoring and generation of performance data as well as the development of design tools for specific environments is important to make LID more accessible for stormwater managers.

Chapter 3 Study Area

3.1 Introduction

An urban watershed in Windsor, Ontario, Canada was the focus for this study. This watershed encompasses a large portion of Ward 6 (Fig 3-1) in the city and has been faced with major flooding in recent years. The sewershed was modelled using CHI Water's PCSWMM. The model was used to evaluate low impact development controls under historical and climate change conditions and was linked with an optimization methodology to determine the most suitable LID implementation options. This chapter describes the relevant study area properties.

3.2 Location and Land Use

The sewershed in question has an area of about 536 ha. and stretches from the Little River to Jefferson Blvd (Figure 3-1). The sewershed has three outlets, two that release surface runoff directly to the Detroit River and one to the Little River, which eventually flows into the Detroit River.

The sewershed consists mainly of residential properties with a high density of homes, roadways and many paved driveways. The sewershed includes a large area of commercial buildings with large impervious areas including high rise buildings and parking lots. There are a few green spaces including parks, school yards, baseball fields and a small undeveloped area. A 2017 Google Earth image of study area is shown in Figure 3-2, there has been no significant change in development or land use in the last 20 years.

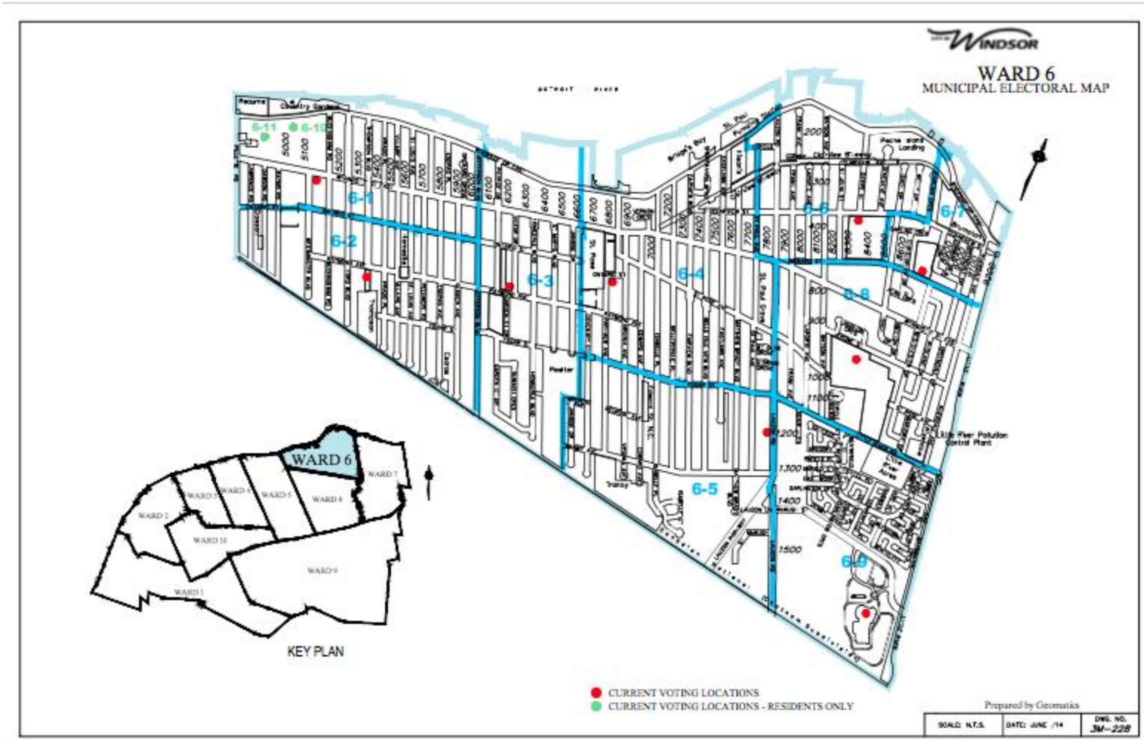

Figure 3-1 Ward 6 location in Windsor, ON

Figure 3-2 Location and land use of study area

3.3 Geology and Soils

Similar to much of Windsor and Essex County, the soils underlying the sewershed are mainly clayey with poor hydrological properties. The majority of the sewershed consists of Brookston Clay, with smaller areas consisting of Clyde Clay, or Colwood Fine Sandy Loam (Richards et al., 1949). All three of these soils are classified as hydrological soil Group D. Richards et al (1949) provides detailed information on these soils and their make-up. For the PCSWMM model (refer to Chapter 4), the soil parameters are encompassed in the curve number property since the SCS curve number method was chosen for infiltration calculations. This emphasizes the importance of determining accurate curve numbers for each subcatchment in the model.

The underlying soils of the study area are shown in Figure 3-3. It can be seen from the figure that the sewershed is encompassed by soils with poor drainage characteristics. Figure 3-3 was created in ESRI ArcMap from files obtained from the University of Windsor's Scholar Geoportal and from information from Richards et al. (1949). It is not clear whether or not development has impacted the underlying soil characteristics in any meaningful way. An important factor affecting the soils infiltration behaviour is the initial moisture content as saturated soils would reduce infiltration rates. An area where saturated soils are common would have an impact on the effectiveness of LID measures and may cause the need for LIDs to have underdrains as retained runoff would not infiltrate as designed.

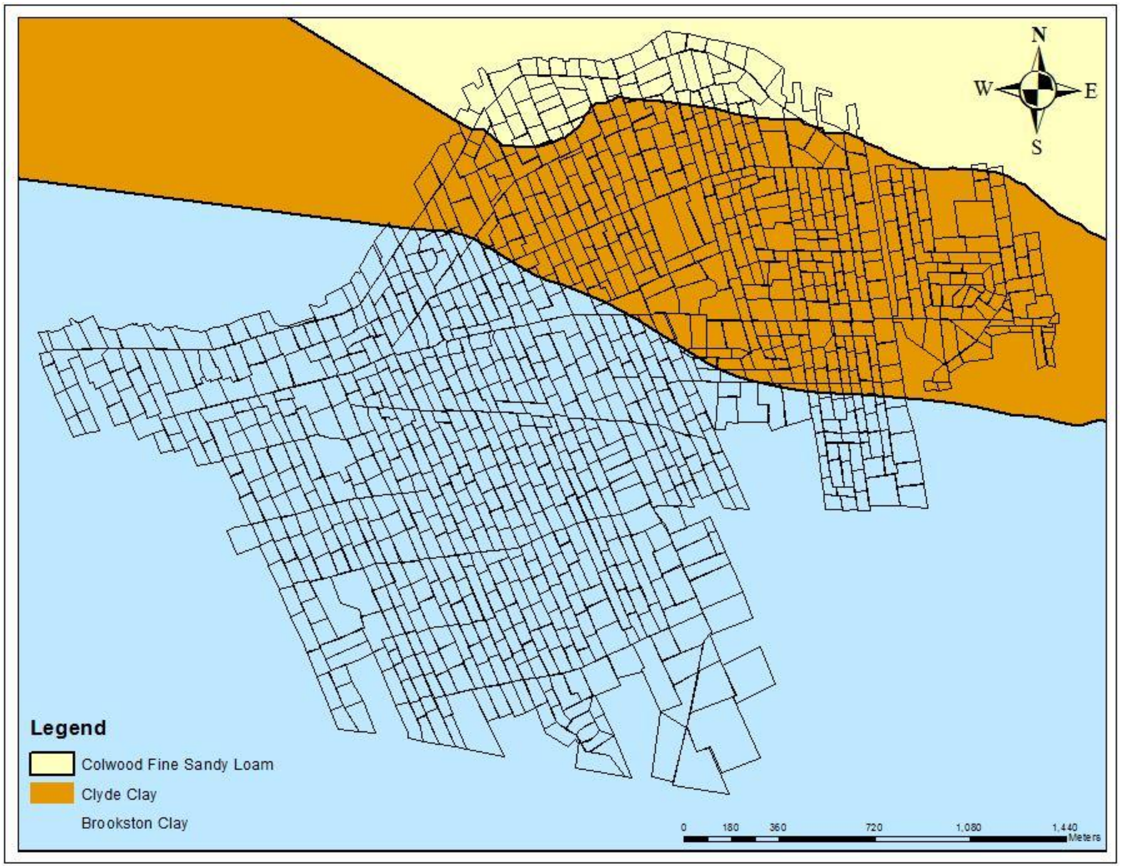

Figure 3-3 Native soils underlying the sewershed.

The sewershed is relatively flat, similar to most of Essex County. Figure 3-4 shows the elevations of the sewershed and was created in ESRI ArcMap from a digital elevation model retrieved from the University of Windsor's Scholar Geoportal. The variance in elevation is shown to be rather small and demonstrates that the slopes in the sewershed are generally very low.

Figure 3-4 Elevations across the sewershed

3.4 Climate

Windsor, Ontario is the southernmost city in Canada located on the Detroit River at the southwestern tip of Ontario. Its latitude and longitude are 42°17 N, 83°00 W and has an average elevation of about 190 m above sea level. It has a humid continental climate. In addition to the Detroit River, Windsor is bordered by Lake St. Clair and Lake Erie. The summer months are characterized as hot and humid and it experiences the most thunderstorms in Canada. From the Canadian climate normals for Windsor Airport Station that provide data between 1981 to 2010, June, July and September experience the most days with greater than 25 mm of rain. Windsor has mild winters compared to most of Canada. According to Canadian climate normals there are three months (December, January and February) with temperatures below freezing and snow depths greater than 10 mm are seen on about 53 days per year. Evaporation information for Windsor was not available but pan evaporation values for nearby Dearborn, Michigan, United States are shown in Table 3-1 (Farnsworth and Thompson, 1983).

Table 3-1 Monthly pan evaporation in mm

APRIL	MAY	JUNE	JULY	AUG	SEPTEMBER	OCTOBER
98.6	148.8	175.5	186.7	157.0	78.7	76.0

3.5 Sewer Network

The majority of the study area has a fully separated sewer system with only a small section (approximately 284 m) of combined sewer present. This study only focusses on the stormsewer system and the small section of combined sewer which connects to the stormsewer network. Runoff is directed into stormsewers through a curb and gutter system and there does not currently appear to be any kind of low impact development measures within the sewershed. Due to the recent flooding events the City of Windsor is implementing a mandatory downspout disconnection policy, though it is likely that some homes in his area still have eave troughs connected to the stormsewer system.

3.6 Stormwater Control Concerns

Street and basement flooding challenges have become common in some areas of Windsor. Windsor is experiencing heavier rainfall events facing two 100 year return period storms in back to back years (2016 and 2017), which have caused excessive flooding and millions of dollars in damages. One event in September 2016 saw up to 230 mm of rain in the hardest hit areas, which is 144% of the amount of precipitation normally received during the month of September (The City of Windsor, 2017). The second event occurred in August of 2017 and saw 285 mm in 32 hours in the hardest hit areas. This event saw over 200% of the normal monthly rainfall and put Windsor on Environment Canada's national list of Top 10 weather events in 2017 (Kotsis, 2017). During these two extreme events the City's sewers, drains, ponds and outlets performed as designed but the excessive volume of rainwater overwhelmed them leading to flooded roads, basements and ponds spilling onto adjacent properties. Other passed rainfall events that caused major flooding were experienced in 2010 and 2011. The City experienced 90 mm of rain in 14 hours over June 5 and June 6, 2010 and 75 mm of rain on November 29, 2011 (The City of Windsor, 2013b). This shows just how severe the storms that the City experienced in 2016 and 2017 were. Figures 3-5, 3-6 and 3-7 show the reported flooded basement calls received by the City after the storm in 2010, 2016 and 2017, the study area is highlighted in each figure. The City is currently in the process of developing their Sewer Master Plan which will identify improvement projects to be undertaken in order to improve sewer efficiency and reduce the flooding risk caused by these heavy rainfall events.

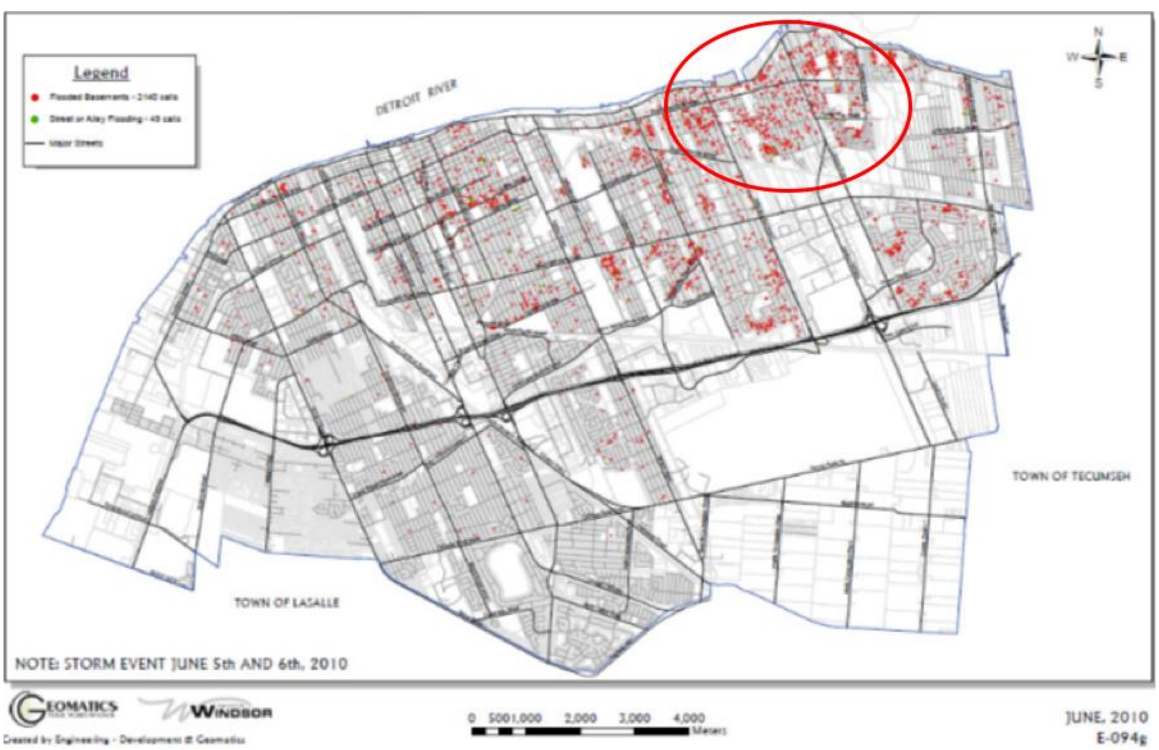

Figure 3-5 Reported basement flooding after storm event in 2010 (The City of Windsor, 2013b).

Figure 3-6 Reported basement flooding after storm event in 2016 (The City of Windsor, 2017).

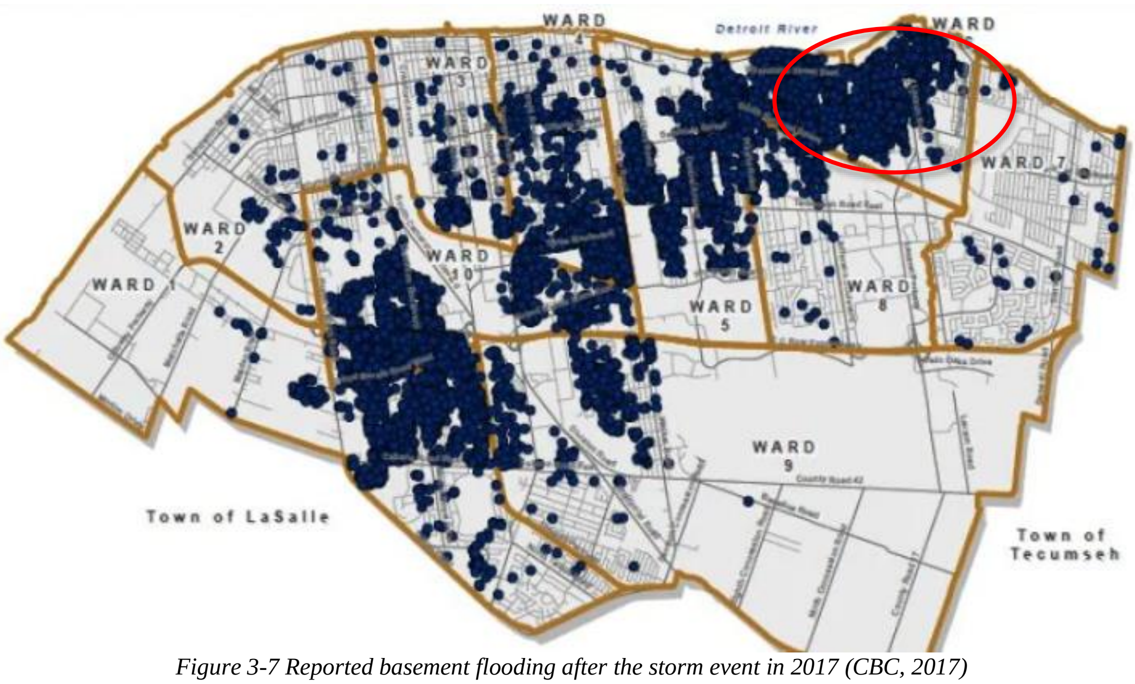

Figure 3-7 Reported basement flooding after the storm event in 2017 (CBC, 2017)

Chapter 4 Hydrological Model

4.1 PCSWMM

4.1.1 Background

PCSWMM is a derivative of the U.S Environmental Protection Agencies' Stormwater Management Model (SWMM). PCSWMM enhances the capabilities of the EPA SWMM hydrology and hydraulics engine with multiple decision support tools that improve the professional and scientific use of SWMM. Since PCSWMM includes a variety of techniques that can uncover errors and uncertainties it is well suited for research as well as for professionals (James et al., 2010).

The USEPA SWMM is an open source computer model that is often used in the planning, design, and analysis of urban water systems (Rossman, 2015). It calculates dynamic rainfall-runoff for single event and long-term, single event or continuous, runoff quality and quantity from urban and rural areas. The runoff element of SWMM functions on a number of subcatchment areas that generate runoff and pollutant loads based off of precipitation data. The routing component of SWMM models a system of pipes, storage and treatment devices, channels, pumps, and regulators to transport this runoff overland and underground. During a simulation period, made up of various time steps, SWMM determines the runoff quantity and quality within each subcatchment, and the flow depth, flow rate, and water quality in each pipe and channel (James et al., 2010). SWMM has been commonly used as a tool for evaluating low impact development (Damodaram et al., 2010; Damodaram and Zechman, 2013; Elliott and Trowsdale, 2007; Karamouz and Nazif, 2013; McGarity, 2011; Palla and Gnecco, 2015; Qin et al., 2013; Zahmatkesh et al., 2015; Zhang, 2009). SWMM has also been a commonly used simulation model to link with genetic algorithms in order to optimize multiple objectives for LID evaluation such as in Baek et al. (2015), Duan et al. (2016), Eckart et al. (2018), Hooshyaripor and Yazdi (2017) Jung et al. (2016) Karamouz and Nazif (2013). These and other examples of optimization-simulation models are discussed in Section 2.6.3. Gironás et al. (2009) also provides more examples of SWMM applications.

PCSWMM is a physically based distributed model, meaning that the objects in the model have a spatial representation and the parameters of various objects can be edited independently of all other objects. These objects' subcatchments, conduits, and nodes, parameters are used by the process equations. The physical processes represented in PCSWMM include flow routing, surface runoff, groundwater, water quality routing, surface ponding, snowmelt, and infiltration. The equations used for these processes are derived from the conservations of energy, mass, and momentum (Rossman, 2015).

4.1.2 Infiltration and Runoff

In a PCSWMM model the generation of runoff is one of the most important hydrologic processes. Subcatchments are treated as nonlinear reservoirs where the input is run-on, precipitation, or snowmelt that is either stored in surface depressions, infiltrated, evaporated, or becomes runoff (Rossman, 2015). The storage capacity of the subcatchment is determined by the maximum depression storage from ponding, surface wetting, and interception. Subcatchments consist of pervious and impervious subareas where runoff can infiltrate into the upper soil zone of the pervious area but cannot infiltrate the impervious area. Runoff can be routed from one subarea to the other, or both subareas can drain to the outlet (Rossman, 2015). Infiltration is a key consideration for determining runoff. No runoff will be generated until the depression storage and infiltration is exceeded by water depth (Zhang, 2009). For the calculation of infiltration there are three methods available in PCSWMM; Horton's equation, Green-Ampt method, or SCS curve number method, descriptions of each of these methods can be found in the SWMM manual (Rossman, 2015). Evaporation from a subcatchment can be determined using either an evaporation rate time series, or climate files. Subcatchments can also receive run-on from other subcatchments if they are routed to each other. Considering all these factors runoff is then calculated and Manning's equating can be used to determine its flow (Rossman, 2015).

The curve number method was chosen for infiltration calculations as it has been previously used for urban stormwater system studies that also incorporated genetic algorithms (Eckart et al., 2018; Maharjan et al., 2009). The SCS method was determined most suitable for this study because the data that was available is the data necessary for determining curve numbers. Though the Green-Ampt method is the most recommended method, the curve number method was originally developed for determining runoff in small urban watersheds similar to the sewershed looked at in this study.

4.1.3 Flow Routing

One of the benefits of using PCSWMM is the ability to design complicated routing networks for urban water systems. PCSWMM provides options to include a variety of conduit shapes, such as culverts and open channels, manholes and other non-conduit structures that act as nodes in the routing network (Eckart, 2015). Once the flow network is delineated and parameterized for the model flow routing can be carried out. Inflows that enter nodes (manholes or other non-conduit structures) can come from subcatchment runoff or by hydrographs entered by the user (Nix, 1994). Flow routing through the network is governed by the conservation or mass and momentum equations for gradually varied, unsteady flow. These equations can be solved by selecting either kinematic wave routing, steady flow routing, or dynamic wave routing. Manning's equation is used in all three methods to relate flow depth to flow rate but when considering force mains under pressure either the Hazen-Williams or Darcy-Weisbach equations are used (Rossman, 2015).

The dynamic wave routing method was chosen for this study as it is the most complete and complex method since it can account for entrance/exit losses, channel storage, backwater effects, pressurized flow, and flow reversal. Dynamic wave routing solves the one-dimensional Saint-Venant equations using the continuity equation and a complete form of the momentum equation (Nix, 1994; Rossman, 2017). The routing network information was developed from My Windsor Sewer System, an interactive sewer atlas provided on http://www.mappmycity.ca/.

4.1.4 LID Representation

PCSWMM includes an LID toolbox that provides the user the ability to define LID controls such as rain gardens, bioretention cells, infiltration trenches, vegetative swales, green roofs, permeable pavements, roof disconnection and rain barrels. This study considers rain barrels, bioretention units, infiltration trenches and permeable pavement.

LID controls in PCSWMM are made up of a combination of vertical layers that have properties defined on a per-unit-area basis which allows LIDs with the same design but different area to be easily implemented in different subcatchments. Not all LIDs consider all the layers. Figure 4-1 below demonstrates the representation of the different layers and the flow pathways between them.

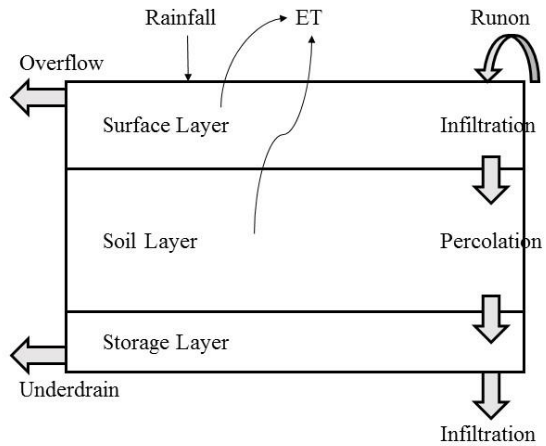

Figure 4-1 SWMM LID representation (adapted from Rossman, 2015)

Run-off gets directed from the impervious area of the subcatchment to the LID measures, as shown in Figure 4-2. LIDs can be implemented on existing subcatchments, or a new subcatchment can be created specifically for implementing a LID control, where run-on can then be routed to this new LID subcatchment from the existing subcatchments. It is also possible to route LID subcatchments to other LID subcatchments, creating a treatment train. This is the only way to develop treatment trains in PCSWMM since runoff from impervious areas is divided among LID controls and to the outlet or to pervious areas. There currently is no option to route flow from one LID to another in the same subcatchment.

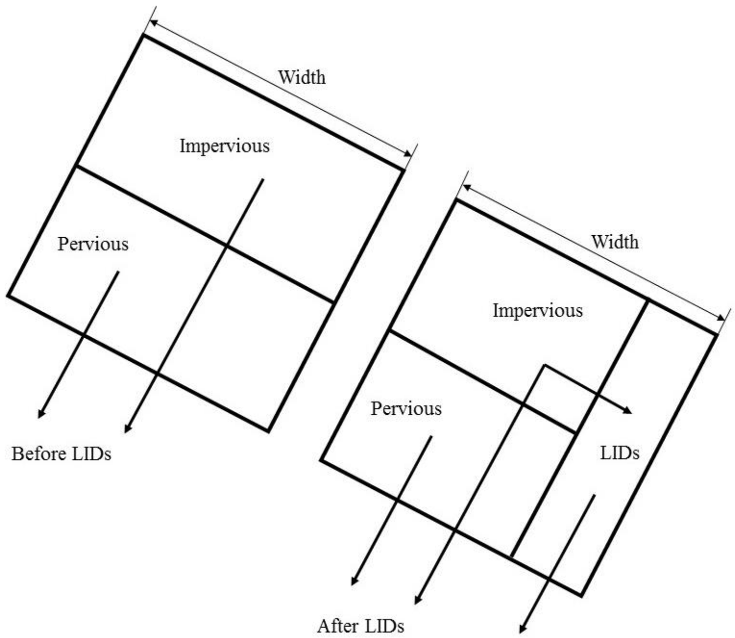

Figure 4-2 LID flow routing (adapted from Rossman, 2015)

4.2 Model Development

4.2.1 Model Development Objectives

The main objective of the model development was to represent the hydrologic conditions of the sewershed discussed in Chapter 3 as a computer simulation model. The model allows evaluation of LID performance, development of cost-benefit relationships, and optimal LID combinations to be evaluated for this sewershed.

4.2.2 Subcatchments

The model contains 1125 subcatchments. Subcatchments were created to remain a reasonable size and to delineate similar land uses. For example, each subcatchment contains only residential areas, or only commercial areas, or only green space, this allows for easier analysis when determining the curve number. Each lot was assumed to drain to the nearest inlet or to the nearest downstream node as drainage maps were not available. Each subcatchment was generally made up of four to five residential lots around each node.

In PCSWMM the main parameters that need to be defined for subcatchments include area, width, slope, percent impervious area, Manning's n for overland flow on pervious and impervious surfaces, depression storage depth for impervious and pervious surfaces, infiltration parameters, internal routing parameters, and percent zero. Since PCSWMM is GIS-integrated, the area was determined using the satellite map provided in PCSWWM and the auto-length tool. As suggested in Gironás et al. (2009), the width was set as the distance from the back of the subcatchment to the street. The purpose of the width parameter is to determine the overland flow distance that runoff travels before it enters a channel. The slope parameter was determined using Digital Elevation Model (DEM) data obtained from the Scholars GeoPortal (Scholars Geoportal, 2018). PCSWMM can use the DEM data to automatically calculate slopes within subcatchments. The DEM file was resampled in order to provide a more accurate slope across the subcatchment as suggested on PCSWMM forum (CHI Water, 2018). The percent impervious area was found by using four-band aerial photographs (USGS, n.d.) and ArcGIS (Esri, n.d.). Manning's n values, storage depths and the required infiltration parameters were determined from the tables provided in Rossman (2015) and the sewershed information outlined in Chapter 3. The possibility that runoff from impervious areas is routed to pervious areas before the outlet of the subcatchment is considered in the internal routing parameters. These parameters also cover the percent of the runoff that gets routed from impervious area to pervious area. Generally, these values were set based on inspection of the sewershed. Finally, the percent zero parameter is the percent of the impervious area that has no surface storage, mainly roofs. Appendix A outlines the complete list of parameters and the corresponding values.

4.2.3 Conduits

The conduits in the PCSWMM model were designed from sewer maps (MapMyCity.com) and sewer data provided by the City of Windsor. Other required parameters, such as loss coefficients and Manning's n were determined from the tables in the SWMM manual (Rossman, 2015). Appendix A provides a complete list of parameters and the values used.

4.2.4 Nodes

The nodes were also determined from sewer maps and sewer data provided by the City of Windsor. For nodes that did not have elevation data available, the invert elevations were estimated from the inverts of connecting sewers or from other surrounding nodes. The depth of each node was calculated automatically in PCSWMM from the elevation data. The surcharge depth and initial depth were both set to zero and the ponding area, the surface area of the puddle above the node if it backed up, varies between zero and ten square meters.

4.2.5 Other Properties

Additional input parameters in the PCSWMM model describe some of the general simulation options. Evaporation was set to only occur during dry periods and based on the pan evaporation values in Table 3-1. Since this is pan evaporation it is necessary to multiply the values by 0.7 in order to convert to potential evaporation. The potential evaporation values were used in the model. The force main equation selected was the Darcy-Weisbach equation. The start and end times were selected to include the entirety of the precipitation events as well as some time before and after the event where there is no precipitation occurring. Time controls include the reporting interval, wet calculation time step, dry calculation time step, and routing time step. These were set to 5 minutes, 20 seconds, 40 seconds and 3 seconds, respectively. These values are set based on the rainfall recording intervals and the choice of dynamic wave routing. A complete list of parameters and corresponding values are shown in Appendix A.

Chapter 5 LID Controls

5.1 Design Strategy

The representation of LID measures in PCSWMM has already been discussed, however, here the design of the LID controls is discussed including their placement, size and physical characteristics that are required in PCSWMM. Constraints needed to be determined for the LID parameters that were to be optimized. Most of the LID defining parameters were not selected to be optimized; therefore, these parameters needed to be set according to design standards. Multiple LID design guidelines were required as there currently is not a single guideline that outlines all the necessary parameters required by PCSWMM. The focus of this study was on water quantity and thus a common design principle, water quality volume (WQV), was not used for sizing LID controls. Another reason why this parameter was not used was because for the optimization process it was required to develop general designs that could be placed in varying numbers and sizes into subcatchments. Sewershed properties were another important factor in the design of LID controls, for example, the soils in the study area have very poor hydrological properties and this has a major impact on LID designs. Some cross-sectional sketches of various LIDs are included in Appendix B for reference.

5.2 Rain Barrels

Most commercially available rain barrels range from 200L to 300L. A common size used in Windsor is 200L (50 USG) and thus this was selected for this study. Rain barrels require a spigot, which often is included with the barrel, and downspout adapter for directing flow into the barrel. Other optional additions include an overflow pipe to direct overflow, soaker hose to allow the rain barrel to be used for watering lawns or gardens, and a filter to ensure no debris enters the rain barrel. From online retailers it was determined that the height of the rain barrel would be 864 mm, which corresponds to a 200L barrel.

In PCSWMM all of LID underdrains are represented in the same way. The flow from underdrains is governed by Equation 5-1. For rain barrels the design of the underdrain is the design of the outflow from the rain barrel.

$$q = C(h - H_d)^n \qquad \textit{(5-1)}$$

where q is the velocity of the outflow through the underdrain in mm/hr, h is the stored water height in the drainage layers in mm, and H_d height of the drain in mm. For rain barrels the drainage layer is simply the rain barrel and it is important that h and H_d are taken from the same zero (Rossman, 2015). The C and n parameters are used to determine the flow rate and can be adjusted. Rossman (2015) gives values for these parameters and states 0.5 as a typical n value for a rain barrel. The underdrain coefficient, C, for a rain barrel can be determined from Toricelli's law.

Torricelli's law is a case of the Bernoulli Principle for fluid exiting a reservoir or tank and is shown in Equation 5-2.

$$v = (2gh)^{\frac{1}{2}} \qquad \textit{(5-2)}$$

where v is the flow velocity exiting the orifice, g is the gravitational constant, and h is the water depth in the tank. By multiplying v by the orifice area, the flow through the orifice, Q, can be determined. Q may also be determined by multiplying q by the area of the tank, as shown in Equation 5-3.

$$Q = qA_{\text{tank}} = A_{\text{orifice}}(2g\hbar)^{\frac{1}{2}} \qquad \textit{(5-3)}$$

where the area of the tank and area of orifice are the cross-sectional areas. Using $n = 0.5$, as mentioned above, Equation 5-3 can be rearranged with Equation 5-1 as shown in Equation 5-4.

$$q = \frac{A_{orifice}}{A_{tank}}(2gh)^{\frac{1}{2}} \tag{5-4}$$

In Equations 5-3 and 5-4, the value of h is the same as $h - H_d$. Considering all these factors, C can be determined by rearranging to get equation 5-5.

$$C = \frac{A_{orifice}}{A_{tank}}(2g)^{\frac{1}{2}} \tag{5-5}$$

Using the specified rain barrel size from earlier, which has an orifice area of 0.045 m^2, and Equation 5-5, C was determined to be 4407. Since this value does not consider any head loss in outflow pipes or from clogging and it was found to be high (Eckart, 2015), it was divided by two and 2204 was used for C. Assuming that home owners are unlikely to drain their rain barrels within 24 hours after a rainfall event, the drain delay parameter was set to 24 hours. Table 5-1 provides the parameters for each layer for the rain barrel design in PCSWMM.

In terms of rain barrel implementation, the parameters for adding rain barrels to each subcatchment are shown in Table 5-2. The parameter optimized is the number of units per house. The number of units in a given subcatchment can then be determined by multiplying the number of units per house by the number of houses that implement rain barrels in that subcatchment.

Table 5-1 Rain barrel design parameters

Parameter	Description	Value	Source
Storage Layer			
Height (mm)	The height of the rain barrel	864	City of Windsor and online retailers
Underdrain			
Drain coefficient (C)	Parameter that can be adjusted and determine the flow rate. Equation 5-1.	2204	Equation 5-5
Drain exponent (n)	Parameter that can be adjusted and determine the flow rate. Equation 5-1.	0.5	Rossman (2015)
Drain offset height (mm)	The height of the drain above the bottom of the storage layer, H_d	0	Design choice
Drain delay (hours)	The dry period time required for the normal rain barrel to be opened	24	Estimate

Table 5-2 Rain barrel implementation parameters

Parameter	Description	Value Selected	Source
No. of units	The number of units in the subcatchment	optimized	N/A
Area of each unit (m^2)	Total surface area of each unit	0.231	Vol. divided by height
Percent Impervious area treated	The percentage of the impervious area in a subcatchment that is directed to the LID	Depends on LID combinations	Table 5-12
Percent Initially saturated	At the start of the simulation, the percent of the rain barrel filled	0	N/A
Top width of each unit (m)	The width of the side of the LID where outflow gets directed	N/A	N/A
Overflow routed to pervious (Y/N)	If outflow gets routed to subcatchment pervious area (Y), or to the outlet (N)	Y	Design choice

5.3 Bioretention and Rain Gardens

Rain gardens are very similar to bioretention units except that they do not include an underlying drainage layer. The design and construction of bioretention units is much more complex than a rain garden and it is likely that homeowners would not implement a bioretention system as a retrofit option, however, due to the poor drainage of underlying soils in the study area an underdrain is likely necessary and due to this bioretention cells were chosen to be implemented instead of rain gardens. Bioretention is much easier to implement in a new development area where it can be designed into the landscape with the design of the development and implemented during home construction. The study area is well developed and there are not many areas where new development might take place, however, bioretention units were still designed and implemented as a retrofit in this study in order to show comparison of the effectiveness of this control. The Credit Valley Conservation LID Planning and Design Guide (2010) provides a detailed design guide for different LID controls and was followed for the design of the bioretention units in this study. PCSWMM provides a different editor for both bioretention and rain gardens and thus they can be analyzed as separate LIDs. In earlier versions of SWMM rain gardens needed to be designed as bioretention units with some altered parameters such as storage depth being set to zero (see Eckart (2015) for more details about this).

Rain gardens are designed to be slightly depressed relative to the landscapes around them which increases the surface storage. Rain gardens are designed this way to provide a larger depression storage and cause runoff from surround surfaces to flow into them. The SWMM manual (Rossman, 2015) was used to determine the roughness coefficient based on the ground cover that would be used in the rain garden. Since bioretention and rain gardens are not used to transmit overland flow their roughness and slope can be set to zero (CHI Support, 2018).

The values used for the soil layer parameters are the same for bioretention cells and rain gardens in this case since soil should be imported due to the poor drainage characteristics of the current underlying soil. Rossman (2015) was used to determine these parameters.

The storage layer parameters represent the properties of the crushed stone or gravel layer used as a bottom storage/drainage layer. For rain gardens the seepage rate, or the saturated hydraulic conductivity of the surrounding area, is the only parameter that can be set. For bioretention cells all the storage layer parameters must be defined. CVC (2010) and Richards et al. (1949) were consulted for the design of this layer. Due to the short simulations conducted in this study clogging factors were set to zero because they would not be a significant factor in that length of time.

The final layer that was designed is the underdrain. Since rain gardens do not have an underdrain layer all these parameters are set to zero. The bioretention parameters for this layer are explained through the following equations. Since outflow flows through aggregate Torricelli's Law cannot be used and thus the previous equation (Equation 5-5) cannot be used to determine the outflow. Studies focused on the flow through perforated pipes that are surrounded by aggregate (Murphy et al., 2014; Murphy, 2013) were consulted to determine the underdrain coefficient. Equation 5-6 was used to determine the time required to drain a given depth of water, a detailed procedure to arrive at this equation is provided in (Eckart, 2015). The underdrain that was designed used a 200 mm perforated pipe in order to accommodate freezing conditions as suggested in CVC (2010).

$$t = \frac{2A_{surface}H^{\frac{1}{2}}}{A_{pipe}(\frac{2g}{N})^{\frac{1}{2}}} \tag{5-6}$$

where $A_{surface}$ is the LID surface area, H is the water surface elevation, A_{pipe} is the cross-sectional area of the underdrain pipe, g is the gravitational constant, and

$$N = 1 + \frac{fL}{D} + C_L \frac{A_{pipe}^2}{(A_{inlet}^2 \Theta_{agg}^2)} \quad (5\text{-}7)$$

where f is the friction factor, L is the length of the pipe, D is the pipe diameter, A_{inlet} is the inlet hole area into the perforated pipe, $C_L = \frac{1-C_d^2}{C_d^2}$ and C_d is the orifice coefficient of contraction. Subsequently, Equation 5-8 that is provided in the SWMM manual (Rossman, 2015) was used to estimate the outflow coefficient.

$$C = \frac{2D^{\frac{1}{2}}}{T} \quad (5\text{-}8)$$

Table 5-3 summarizes the design parameters for each layer used in the PCSWMM model for both rain gardens and bioretention units.

Table 5-3 Summary of design parameters for rain gardens and bioretention units

Parameter	**Description**	**Value for Rain Garden**	**Value for Bioretention Unit**	**Source**
Surface Layer				
Storage depth (mm)	The height of the surface depression storage	200	200	CVC (2010); Uda et al. (2013)
Vegetation volume (fraction)	The fraction of the volume within the storage depth which is occupied by vegetation	0.15	0.15	CHI Support (2018)
Surface roughness (Manning's n)	Roughness for overland flow on the surface of the LID	0	0	CHI Support (2018)
Surface slope (%)	Slope of the LID surface	0	0	CHI Support (2018)
Soil Layer				
Thickness (mm)	Height of soil layer	optimized	optimized	CVC (2010)
Porosity (volume fraction)	The volume of pore space divided by the total volume	0.4	0.4	CVC (2010)

Field Capacity (volume fraction)	The volume of pore water remaining in the soil after the soil has drained fully	0.25	0.25	Rossman (2015)
Wilting point (volume fraction)	The volume of pore water relative to the total volume of well dried soil.	0.15	0.15	Rossman (2015)
Conductivity (mm/hr)	Saturated hydraulic conductivity for the soil layer	40	40	Eckart (2015)
Conductivity slope	Slope of the curve of the log graph of conductivity versus the soil moisture content	6	6	Rossman (2015)
Suction Head (mm)	The average soil capillary suction along the wetting front	75	75	Rossman (2015)
Storage Layer				
Height (mm)	Height of the storage layer	N/A	680	Uda et al. (2013)
Void ratio (V voids/V solids)	The volume of void space relative to the volume of soils layer	N/A	0.5	Murphy (2013)
Seepage rate (mm/hr)	The maximum rate that water is allowed to infiltrate into native soils	2.27	1.44	Rahman (2007); Richards et al. (1949)
Clogging factor	The volume of runoff needed to clog the bottom layer divided by the void volume.	N/A	0	Based on scenario
Underdrain parameter				
Drain coefficient (C)	Used to determine the flow rate through the underdrain as a function of stored water height	0	15.8	Murphy (2013); Rossman (2015)
Drain exponent (n)	Makes the drain act as an orifice	0	0.5	Rossman (2015)
Drain offset height (mm)	Height of underdrain piping about the bottom of the storage layer	0	50	Design choice

Table 5-4 describes the parameters for implementation of rain gardens and bioretention units in PCSWMM. Soils are important for the effectiveness of rain gardens and bioretention cells which is why it is suggested that soils with good hydrological performance be imported during construction of these measures in the study area. The initial saturation values in the table below is based on these soils. In a bioretention unit the soil is layered on top of drain rock and an underdrain allowing for lower saturation, and thus better drainage, than the rain garden as it does not have an underdrain and lays directly on the native clay soils. In order to meet the requirements of keeping units back from building foundations by at least 4 m but also within 10 m of the area that directs runoff to the bioretention cell or rain garden, the unit width was determined based on the average available space in subcatchments (Center for Watershed Protection, 2015).

Table 5-4 Rain garden and bioretention implementation parameters

Subcatchment parameters				
No. of units	Number of equal sized units in a given subcatchment	optimized	optimized	N/A
Area of each unit (m^2)	The total surface area of each LID unit	optimized	optimized	N/A
Surface width of each unit (m)	The width of the outflow side of each LID unit	5	5	Design choice based on available space
Percent Initially saturated	The initial condition of the unit's soil in terms of water content. The underlying storage zone is assumed to be dry	50	20	Eckart (2015)
Percent Impervious area treated	The percentage of the impervious area in a given subcatchment whose runoff is directed to this LID type	Depends on LID combinations	Depends on LID combinations	Table 5-12

Send drain flow to:	Specify location to send underdrain flow if it is to be routed to another subcatchment or node. Leave blank if use subcatchment outlet.	N	N	Design choice
Return all outflow to pervious area	Select if all outflow is returned to the subcatchments pervious area rather than going to the outlet.	N	N	Design choice

5.4 Infiltration Trench

Infiltration trenches are shallow depressions in the landscape that are filled with stone for temporary storage of runoff in order to facilitate infiltration. Infiltration trenches can be easily incorporated into an area's landscape to capture and allow stormwater to infiltrate to the surrounding soils significantly reducing runoff volumes and flow rates (Woods-Ballard et al., 2007). Similar to bioretention units, it is suggested trenches have at least a 4 m set back from building foundations but they are very useful in implementing densely populated housing where multiple lots can drain to the same infiltration trench (CVC, 2010). For these reasons this study implemented infiltration trenches in shared backyard spaces where multiple rows of houses can drain to them. Constructing underdrains allows infiltration trenches to be implemented in areas where underlying soils have poor hydrologic properties (CVC, 2010), similar to the study area in question.

The surface layer of the infiltration trench was designed from the process outlined in OMOE (2003) design manual and the SWMM Manual (Rossman, 2015). The storage layer was designed based off of the designs in CVC (2010) and Woods-Ballard et al. (2007). These two design manuals suggest ranges of common design values to be used for the various layers of the trench, the infiltration depth was chosen based on these suggestions.

The underdrain was placed 150 mm from the bottom of the infiltration trench in order to drain runoff more rapidly to reduce the risk of flooding. The poor infiltration rates of the underlying soil will impact the performance of the infiltration trench but the design of the underdrain and addition of a sand base can help facilitate some additional infiltration. The underdrain coefficient was determined using the equations discussed in Section 5.3 as was done for the bioretention unit.

Table 5-5 Summary of design parameters for infiltration trench

Parameter	Description	Value	Source
Surface Layer			
Storage depth (mm)	The height of the surface depression storage	64	OMOE (2003); Rossman (2015)
Vegetation volume (fraction)	The fraction of the volume within the storage depth which is occupied by vegetation	0	Rossman (2015)
Surface roughness (Manning's n)	Roughness for overland flow on the surface of the LID	0	CHI Support (2018)
Surface slope (%)	Slope of the LID surface	0	CHI Support (2018)
Storage Layer			
Height (mm)	Height of the storage layer	1500	CVC (2010); Woods-Ballard et al. (2007)
Void ratio (V voids/V solids)	The volume of void space relative to the volume of soils layer	0.4	CVC (2010); OMOE (2003)
Seepage rate (mm/hr)	The maximum rate that water is allowed to infiltrate into native soils	1.44	Rahman (2007); Richards et al. (1949)
Clogging factor	The volume of runoff needed to clog the bottom layer divided by the void volume.	0	Based on scenario
Underdrain			
Drain coefficient (C)	Used to determine the flow rate through the underdrain as a function of stored water height	0.83	Equation 5-8
Drain exponent (n)	Makes the drain act as an orifice	0.5	Rossman (2015)
Drain offset height (mm)	Height of underdrain piping about the bottom of the storage layer	150	CVC (2010)

The parameters for implementing infiltration trenches in subcatchments are outlined in Table 5-6 below. There are two parameters to be optimized for infiltration trenches, the number of units (0 or 1) and the area each replica unit (Eckart, 2015). Subcatchments can only have one or no infiltration trenches implemented and thus all the lots within that subcatchment will send runoff to that trench. CVC (2010) outlines that infiltration trenches should be designed with a ratio of impervious drainage area to treatment trench area between 5:1 and 20:1, with a maximum ratio of 10:1 if the trench receives runoff from roads or parking lots. For this reason, a range of 10 m^2 to 300 m^2 was set for the infiltration trench areas.

Table 5-6 Infiltration trench implementation parameters

Subcatchment			
No. of units	Number of equal sized units in a given subcatchment	optimized	N/A
Area of each unit (m^2)	The total surface area of each LID unit	optimized	N/A
Surface width of each unit (m)	The width of the outflow side of each LID unit	2	CVC (2010)
Percent Initially saturated	The initial condition of the unit's soil in terms of water content. The underlying storage zone is assumed to be dry	10	Eckart (2015)
Percent Impervious area treated	The percentage of the impervious area in a given subcatchment whose runoff is directed to this LID type	Depends on combinations	Table 5-12
Send drain flow to:	Specify location to send underdrain flow if it is to be routed to another subcatchment or node. Leave blank if use subcatchment outlet.	N	Design choice
Return all outflow to pervious area	Select if all outflow is returned to the subcatchments pervious area rather than going to the outlet.	N	Design choice

5.5 Permeable Pavement

Permeable pavement provides a means for stormwater to drain into underlying soils rather than become runoff as is the case with conventional impervious pavement. Permeable pavement can be implemented for low traffic roads, driveways, parking lots, sidewalks/walkways (CVC, 2010). In this case permeable pavement was looked at as a retrofit to paved driveways. Large, paved driveways are the norm in the majority of this sewershed. Google Earth was used to estimate the average driveway size as about 85 m^2 in the study area which is relatively large. Center for Watershed Protection (2015) suggests minimizing driveway areas to reduce overall imperviousness so as part of the permeable pavement implementation it was determined that reducing the driveway size by 20 m^2 to 65 m^2 of permeable pavement and the remaining area be converted back to pervious area would allow for a larger reduction in runoff and also saves money as less permeable pavement area is required. Eckart (2015) reduced the average driveway size from 73 m^2 to 50 m^2 when implementing permeable pavement in his study area and reported doing so provided a greater reduction in peak flow than permeable pavement alone.

Porous pavement has an additional layer to be defined in PCSWMM compared to other LIDs. This layer, the pavement layer, provides the parameters for the permeable pavement layer. Interlocking concrete paving stones with a thickness of 80 mm was selected for this study as suggested in CVC (2010). Infiltration only takes place in the space between pavers which is filled with small aggregate (5 mm clear crush open graded bedding course is commonly used), thus the infiltration rate specified only applies to these gaps. Since clogging is a frequent concern with permeable pavers one was specified, however it still will not have much of an effect due to the short simulation time in this study.

The storage layer is made up of three layers, the first is 50 mm of bedding for the permeable pavement driveway, followed by 100 mm of stone base and finally the remaining 350 mm is a stone sub base providing a total depth of 500 mm. The clogging factor of the storage layer remained zero as seen in the design of the other LID controls since the simulations are not long enough for this to be a serious factor. The infiltration rate was set as the lowest rate of any underlying soils. As shown in bioretention units and infiltration trenches an underdrain is necessary for permeable pavements in this study area. Equation 5-8 was once again used to determine the drain coefficient following the procedure outline in Section 5-3.

Table 5-7 Summary of design parameters for permeable pavement driveways

Parameter	Description	Value	Source
Surface Layer			
Storage depth (mm)	The height of the surface depression storage	4	Rossman (2015)
Vegetation volume (fraction)	The fraction of the volume within the storage depth which is occupied by vegetation	0	Design choice
Surface roughness (Manning's n)	Roughness for overland flow on the surface of the LID	0.014	Rossman (2015)
Surface slope (%)	Slope of the LID surface	2	CVC (2010)
Pavement Layer			
Thickness (mm)	Thickness of the permeable pavement surface	80	CVC (2010); Uda et al. (2013); Woods-Ballard et al. (2007)
Void ratio (V voids/V solids)	Related to materials used	0.4	CVC (2010); OMOE (2003)
Impervious surface fraction	The fraction of the area of the permeable pavement that is impervious	0.9	Center for Watershed Protection (2015)
Permeability (mm/hr)	Permeability through the paving joints	4000	Woods-Ballard et al. (2007)
Clogging factor	The amount of pavement void volumes of runoff to completely clog the pavement	100	Based on scenario
Storage Layer			

Height (mm)	Height of the storage layer	500	CVC (2010)
Void ratio (V voids/V solids)	The volume of void space relative to the volume of soils layer	0.4	CVC (2010); OMOE (2003)
Seepage Rate (mm/hr)	The maximum rate that water is allowed to infiltrate into native soils	2.21	Rahman (2007); Richards et al. (1949)
Clogging factor	The volume of runoff needed to clog the bottom layer divided by the void volume.	0	Based on scenario
Underdrain			
Drain coefficient (C)	Used to determine the flow rate through the underdrain as a function of stored water height	12	Equation 5-8
Drain exponent (n)	Makes the drain act as an orifice	0.5	Rossman (2015)
Drain offset height (mm)	Height of underdrain piping about the bottom of the storage layer	50	Design choice

The implementation parameters for permeable pavement in subcatchments are provided in Table 5-8. The number of units in a subcatchment is the parameter optimized and is equal to the number of houses adopting permeable pavement in that subcatchment. The addition of an underdrain allows the storage layer to drain quickly and therefore there should not be a large quantity of water being stored for an extended period of time; this is why the initial saturation rate was set so low.

Table 5-8 Permeable pavement implementation parameters

Subcatchment			
No. of units	Number of units in a given subcatchment	optimized	N/A
Area of each unit (m^2)	Total surface area of each unit	65	Design choice
Surface width of each unit (m)	The width of the outflow side of each LID unit	6	Google Earth Estimate

Percent Initially saturated	Percent of the rain barrel filled at the beginning of a simulation	10	Eckart (2015)
Percent Impervious area treated	The percentage of the impervious area in a given subcatchment which is directed to this LID type	Depends on LID combinations	Table 5-12
Send drain flow to:	Specify location to send underdrain flow if it is to be routed to another subcatchment or node. Leave blank if use subcatchment outlet.	N	Design choice
Return all outflow to pervious area	Select if all outflow is returned to the subcatchments pervious area rather than going to the outlet.	N	Design choice

5.6 Cost of LID Controls

The costs of the LID measures discussed in the preceding sections are compared here. The designs explained in Tables 5-1 to 5-8 were used to determine the costs, parameters that are to be optimized were set based on common designs in order to provide a total cost for comparing the LID controls. The cost breakdown from Uda et al. (2013) was adopted and updated based on the designs used in this study. The RSMeans database ("RSMeans Cost Data," 2018) for Windsor, ON, personal communication with a contact in the construction field and Uda et al. 2013 were consulted in order to put together a reliable cost estimate for the different LIDs being looked at in this study. The RSMeans database provides unit material, labour and equipment costs and is widely used for construction cost estimates. In this study the costs marked "O&P" were used. These costs represent the contractor's price including overhead and profit. Where the data from RSMeans were not available personal contacts and construction suppliers were consulted. Table 5-9 shows a summary of the associated costs for a common LID design for each control used in this study. Table 5-10 shows a summary of maintenance and rehabilitation costs for each LID control. It should be noted that in the optimization model only construction costs were considered, engineering, design and maintenance costs were not included. Rain barrels' maintenance costs were assumed negligible as they are a simple LID control that can be easily maintained by the homeowner with minimal effort. Maintenance and rehabilitation costs were based on the time frame and activities outlined in CVC (2010) and Uda et al. (2013). Detailed cost breakdowns can be found in the supplemental files.

Table 5-9 Summary of costs associated with each LID for a typical design

Capital Costs				
Parameter	**Rain Garden**	**Bioretention**	**Infiltration Trench**	**Permeable Pavement**
	($130m^2$)	**($130m^2$)**	**($101.8m^2$)**	**($85m^2$)**
Planning & Site Preparation	$ 1,167	$ 1,189	$ 5,287	$ 3,367
Excavation	$ 2,841	$ 3,274	$ 2,679	$ 3,545
Materials & Installation	$ 23,316	$ 30,861	$ 13,389	$ 15,597
TOTAL	$ 27,324	$ 35,323	$ 21,355	$ 22,509

Table 5-10 Maintenance and Rehabilitation costs associated with each LID control

Life Cycle Costs				
Parameter	**Rain Garden**	**Bioretention**	**Infiltration Trench**	**Permeable Pavement**
Life Span (years)	25	25	50+	30
Capital Cost	$ 27,324	$ 35,324	$ 21,355	$ 22,509
Rehabilitation/ Replacement Cost	$ 6,881	$ 6,881	N/A	$ 8,764
Annual Maintenance	$ 1,025	$ 1,032	$ 74.00	$ 473
NPV at 50 years, 5% discount rate	$ 52,916	$ 61,054	$ 21,429	$ 39,906

In the model, Borg uses cost functions as one of the fitness functions and the different LID costs depend on different design parameters such as surface area and depth. Table 5-11 below shows how the different costs for each LID control was represented in the code's cost function.

Table 5-11 Summary of cost function breakdown for each LID type

	Rain Barrel	**Rain Garden**	**Bioretention**	**Infiltration Trench**	**Permeable Pavement**
Per unit	$ 216	$ 7,609	$ 9,099	$ 6,154	$ 6,289
Per m	N/A	$ 253	$ 309	$ 1,330	$ 100
Per m^2	N/A	$ 71	$ 72	$ 8	$ 92
Per m^3	N/A	$ 465	$ 580	$ 236	$ 224

5.7 LID Combinations

The percent impervious treated parameter in the LID implementation options can be found from Table 5-12. This table breaks down the percentage of runoff that is routed to each LID type based on the combination of controls present in the subcatchment. This percentage of runoff, along with the rainfall that falls on the LIDs, is the inflow to each LID measure. Overflow from the LIDs can be directed to pervious areas, or to the outlet of the subcatchment, but cannot be directed to other LID controls meaning there are no treatment trains in a single subcatchment.

Google Earth measurements were used to determine the breakdown of impervious surfaces in each subcatchment and this was used to calculate how much runoff each LID would receive. Estimates were made for all possible LID implementation combinations. It is impossible for the LID controls to capture all of the runoff in a subcatchment, for example runoff from streets and sidewalks should not be flowing into yards, where the LID controls are present. This is why none of the total percentages in Table 5-12 are equal to 100%.

The values in Table 5-12 are included in arrays in the optimization-simulation model. Code was developed from Eckart (2015) to determine which LIDs are present in a subcatchment and then the corresponding runoff percentages are taken from the arrays.

Table 5-12 Percentages of runoff routed to LID controls from impervious areas

	Maximum Percent Impervious Treated					Notes
Combination	RB	BR	IT	PP	SUM	
RB	30	0	0	0	30	Capturing entire roof area
BR		27.5			27.5	Capturing 1/2 roof area and 1/4 driveway
IT			34		34	From Google Earth
PP				14.2	14.2	Capturing 1/4 roof and some addition area from walkways
RB + BR	18.3	15			33.3	Rain barrels are routed to pervious area. Bioretention captures 1/4 roof runoff
RB + IT	15		25.2		40.2	Infiltration trench captures 1/2 of roof area
RB + PP	56			2	58	Permeable pavement catches very little from roof since rain barrels collect much of roof runoff
BR + IT		27.5	34		61.5	Infiltration trench captures 1/2 of roof area; Bioretention captures 1/2 roof runoff and 1/4 driveway runoff
BR + PP		28.4		2	30.4	Bioretention captures 1/2 roof runoff as permeable pavement does not take much flow from other areas
IT + PP			34	14.2	48.2	Do not interfere with eachother
RB + BR + IT	11.5	19.3	26		56.8	Infiltration trench captures 1/2 roof, bioretention and rain barells collect 1/4 roof runoff each
RB + BR + PP	27.2	15.3		2	44.5	Bioretention captures just over 1/4 of roof
RB + IT + PP	19		31	2	52	Infiltration trench captures 1/2 roof runoff
BR + IT + PP		28.4	34	2	64.4	Bioretention and infiltration trench each can capture 1/2 roof runoff
RB + BR + IT + PP	19	20	23.1	2	64.1	Roof runoff is split between bioretention, rain barrels and infiltration trench.

*RB = Rain Barrel; BR = Bioretention; IT = Infiltration Trench; RB = Rain Barrel

Chapter 6 Subcatchment LID Placement Ranking

6.1 Introduction

In order for the model to optimize where LIDs should be placed in the sewershed, subcatchments were divided into groups based on a risk score and a social economic score. Subcatchments were given a total score by combining the risk score and social economic score and then, based on this total, divided into five groups which relate to the decision variables used in the optimization framework.

The methodology used to group parameters into one of five groups for each of the different categories looked at during the risk and socioeconomic analysis was a z-score analysis. A z-score is a statistical measure that converts data to a standard score. The resulting z-score can be defined as a measurement of a data point's relationship to the mean of the data set. It can be determined by Equation 6-1. The overall mean of the data set is subtracted from an individual data point (x) and then divided by the standard deviation of the data set. Equation 6-1 provides either a positive or negative z-score that shows if data point 'x' is above, below, or equal to the mean of the data set and by how many standard deviations. For example, a z-score equal to zero means the data point is equal to the mean, a z-score of -1 means the data point is 1 standard deviation below the mean. Similarly, a z-score of 1 means the data point is 1 standard deviation above the mean (NBLC, 2012).

$$Z = \frac{x - MEAN}{STDEV} \tag{6-1}$$

6.2 Subcatchment Risk Assessment

Risk analysis provides a cost effective way to address increasing infrastructure needs and budget constraints by focusing investments on the most critical assets (Van Auken et al., 2016). To do this there needs to be a way to quantitatively measure risk. Measuring risk quantitatively is now commonly accomplished by multiplying the probability of occurrence by the consequence or impact of that event (National Research Council, 1989). A flood risk is defined in Klijn et al. (2008) as multiplying the probability of a flood occurring with the corresponding consequences (Equation 6-2). This definition allows the evaluation of flood risk on an economic basis and focusses flood risk assessment on the severity and frequency of flooding (Davis, 2003; Morita, 2008). Urbanization tends to cluster population and assets, which increases the likelihood of damage in urban areas (Morita, 2014). This emphasizes the importance of quantifying flood risk as it allows for the evaluation of flood mitigation techniques and provides a basis for making stormwater management decisions (Plate, 2002).

The failure of stormwater management systems can have significant effects on the surrounding area, such as flooding, traffic disruptions, road cave-ins and environmental issues. To assess the risk of flooding, the likelihood and consequence of the failure of stormsewers is required (Kandasamy and Sinha, 2017). For assessing the probability of failure of stormsewers, the following factors should be considered; physical condition, soil profile, functional/operational performance and hydraulic capacity (Kandasamy and Sinha, 2017). Due to a lack of available widespread condition assessment data for the stormsewer pipes in the study area, age is considered a relevant indicator of condition (The City of Windsor, 2013a).

The development of a specific ranking criteria is a way of determining current asset conditions. Generally a score of 1 to 5 is used to define the physical condition of assets as well as the performance capacity of assets and the worse score of the two is taken as the probability of failure (WERF, 2009). Van Auken et al. (2016) used a rating system from 1, being very good, to 5, being severe/failing. An example of this system is if a culvert had a score of 2 for its physical condition and a score of 5 for performance, then that culvert has a probability of failure (POF) score of 5.

The second part of asset risk assessment is evaluating the consequence of failure (COF). The consequence of failure can be used to determine the asset's criticality. This process considers economic damage, social issues such as impacts to human life or property, and environmental impacts (Van Auken et al., 2016). Van Auken et al. (2016) used a COF score from 1 to 3 as 1 being low consequence and 3 being highest consequence. The combination of POF and COF provides a risk calculation as shown in Equation 6-2 and Figure 6-1. Once a risk score has been determined a stormwater asset risk registry can be made, as seen in the supplemental files provided with this thesis.

$$Risk = probability\ of\ failure\ x\ consequence\ of\ failure \qquad (6\text{-}2)$$

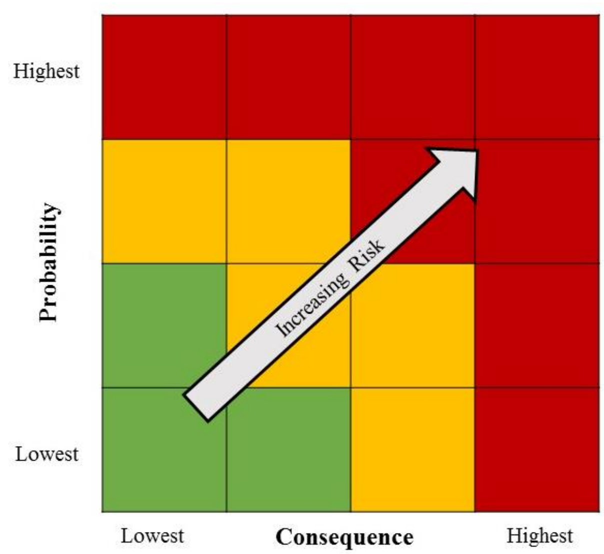

Figure 6-1 Risk matrix indicating increasing risk based on equation 6-2 (adapted from Van Auken et al., 2016)

6.2.1 Probability of Failure

To determine a numerical value for the likelihood of failure the following procedure was carried out. First, a test run of the PCSWMM model was done without any LID implementation under a historic five-year design storm to determine the risk of flooding. Nodes in the model were analyzed to determine which ones were already showing flooding under this storm and the corresponding subcatchments that contribute to those nodes were determined. The corresponding sewers for each subcatchment were analyzed by looking at the capacity of the sewers, age of the sewers, as well as the max flow volume from the PCSWMM test to determine the risk of sewer failure and the sewer's capability to handle the runoff from subcatchments. To normalize max flow through the sewers all flows were divided by the corresponding sewer diameter. The runoff coefficient for each subcatchment was then looked at to determine the subcatchments that were contributing the most runoff to the sewers and compared to the sewer capabilities. The sewer capacity, max flow volume and runoff coefficient was used to analyze the sewers performance while age was the main indicator for the sewers condition (The City of Windsor, 2013a). Each of these factors provided a score from 1 to 5 based on z-scores as shown in Table 6-1, one being the least likely of flood and five being the highest probability of flooding. As was done in Van Auken et al. (2016), the worst score from these factors was taken as the probability of flooding for that subcatchment.

Table 6-1 Corresponding z-scores and subcatchment scores for parameters analyzed

Z-Score	**Score**
$Z \leq -0.75$	1
$-0.75 < Z \leq -0.25$	2
$-0.25 < Z \leq 0.25$	3
$0.25 < Z \leq 0.75$	4
$Z > 0.75$	5

6.2.2 Consequence of Failure

To determine the consequence of failure the land use of each subcatchment was looked at. Each subcatchment was determined as high, medium, or low residential, apartment complex, schools, open space or commercial properties. These land uses were then analyzed to determine where flooding would cause the greatest impact/ most damage by considering environmental and economic factors. Data from the 2016 and 2017 floods in Windsor was used to determine which land uses see the most damage during floods and the cost of that damage. For example, flooding in 2017 resulted in 6,200 insurance claims totaling more than $154 million (Kotsis, 2017); this averages out to about $24,800 per claim, therefore if a high density residential subcatchment with seven or eight homes on it floods it will have a much more significant economic impact than a low residential area having one or two homes flooding. Each subcatchment was given a score from 1 to 5 based on land use with one having the lowest negative impact and five having the most damage from flooding.

6.2.3 Final Risk Rating

The above risk analysis provides the information on whether and where LID could be successful. Detailed flood risk analysis spreadsheets are provided in the supplemental files. Subcatchments with High POFs and COFs are prioritized as those where LID should be addressed first.

Once each subcatchment was given a numeric value for probability of flooding and consequence of flooding, Equation 6-2 was used to determine the total risk score for each subcatchment with 25 being the highest possible score. Each subcatchment was then ranked based on the areas that would likely see the most benefit from LID placement. Table 6-2 shows how the subcatchments were placed in one of five groups. Figure 6-2 below shows a map of each subcatchments final risk ranking.

Table 6-2 Final subcatchment flood risk scores

Subcatchment Group	Risk Score (Eq. 6-2)
1	Score ≤5
2	5 < Score ≤10
3	10 < Score ≤15
4	15 < Score ≤20
5	Score >20

Figure 6-2 Map of subcatchment risk ratings

6.3 Subcatchment Socioeconomic Analysis

In order to analyze the practicality of different LID design alternatives, and long term maintenance strategies Engel-Yan et al. (2005) suggested that at the beginning of planning a sustainable neighborhood project an inventory of its socioeconomic characteristics such as its population, income distribution, and distribution of land uses should be taken.

Since there are numerous possible LID measures, and the majority of implementation areas contain multiple subcatchments to be considered, it is necessary to carefully select which LIDs to implement in each subcatchment and where to place these controls in order to minimize cost, but also to give the highest chance of the property owner providing the LID maintenance. For the most effective solutions LID controls are often required to be constructed on private land and thus maintenance can fall at the owner's expense which makes it not guaranteed. One of the major concerns towards LID implementation is whether or not landowners will implement and maintain the LID controls installed on their land. An LID could be a cost-effective way to reduce runoff from a site back to near pre-development conditions but if the land owner is not willing to maintain the LID control than there is no point in investing in this area (Cano and Barkdoll, 2017).

Cote and Wolfe (2014) found that households with higher incomes were willing to spend a greater percentage than were those with low or medium household incomes. They also determined through a survey that residents indicated 42% of respondents would be "very likely" and another 34% replied with "somewhat likely" to performing annual LID maintenance. Median household income plays an important role in demonstrating how incomes are distributed within a city, the spending capability of households, and the probability that a household is likely to maintain and reinvest in their property (NBLC, 2012).

6.3.1 Socioeconomic Rating

The socio-economic aspect in this study is contained in the likelihood that the landowners in each subcatchment will maintain the LID control once it is implemented on their property. Household income becomes important because it has been noted that households with higher incomes were willing to spend a greater percentage than those with low or medium household incomes (Cote and Wolfe, 2014). The probability of LID maintenance was found based on the community's social attitudes towards property maintenance and subcatchments were scored based on two factors; land use and median household income.

Each subcatchment was categorized based on its land use similar to Cano and Barkdoll (2017). There were five categories used to categorize each subcatchment by land use: open space/parking lots, apartment complex, medium residential density, low residential density and commercial/institutional. Each of these categories was then given a score of 1 for open space/parking lot subcatchments, 2 for apartment complexes, 3 for medium-density residential, 4 for low-density residential and 5 for institutional/ commercial. These values are used to assign a quantitative value to each land use with 1 being unlikely to maintain controls to 5 having the highest probability of maintenance. They are not used in the sense that a value of 2 would be twice as likely to maintain LID controls as subcatchments categorized with a value of 1. Instead, they help to give each subcatchment a value by which to gauge the probability of maintenance per case (Cano and Barkdoll, 2017).

Using 2016 Canadian census data (Government of Canada, 2016) at the dissemination area level, as shown in Figure 6-3, median household income was determined to find out the subcatchments that are more financially capable of contributing to maintenance costs of LID controls. This was considered as a way of determining subcatchments that would be more open to adopting LID strategies (Cote and Wolfe, 2014) and each subcatchment was scored 1 to 5 based on the z-score calculated from the median household income data. Table 6-1 shows how the subcatchments were scored using household income z-scores. Again 1 represents the lowest median household income and thus least likely to maintain and 5 represents the highest median household income meaning highest probability of maintenance.

A final socioeconomic score was then found based on the land use and median household incomes by adding the two scores, therefore a score of 10 would be the maximum. Figure 6-4 shows the final socioeconomic ranks for each subcatchment throughout the study area based on Table 6-3. Detailed excel sheets of each subcatchment scoring is provided in the supplemental files provided with this thesis. To better quantify property owner's willingness to maintain LID controls, detailed social surveys could be carried out (Cano and Barkdoll, 2017).

Table 6-3 Final socioeconomic rankings for subcatchments

Subcatchment Group	Socioeconomic Score
1	Score ≤2
2	2 < Score ≤4
3	4 < Score ≤6
4	6 < Score ≤8
5	Score >8

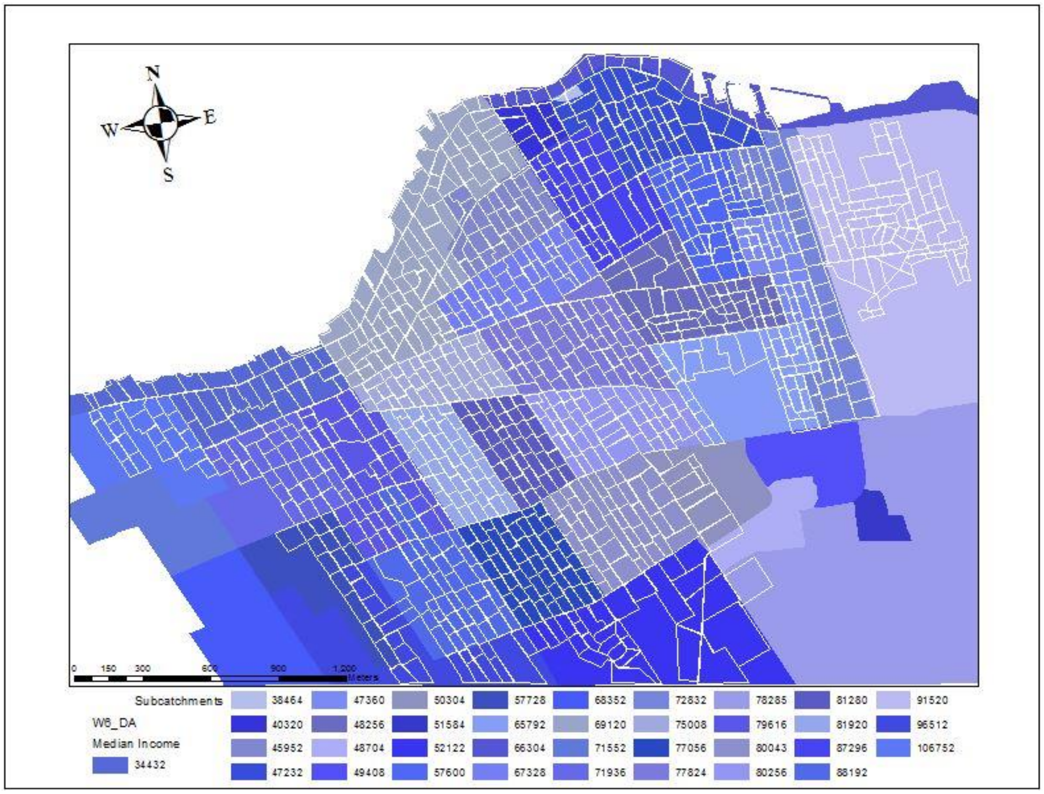

Figure 6-3 Dissemination areas in the sewershed based on census data

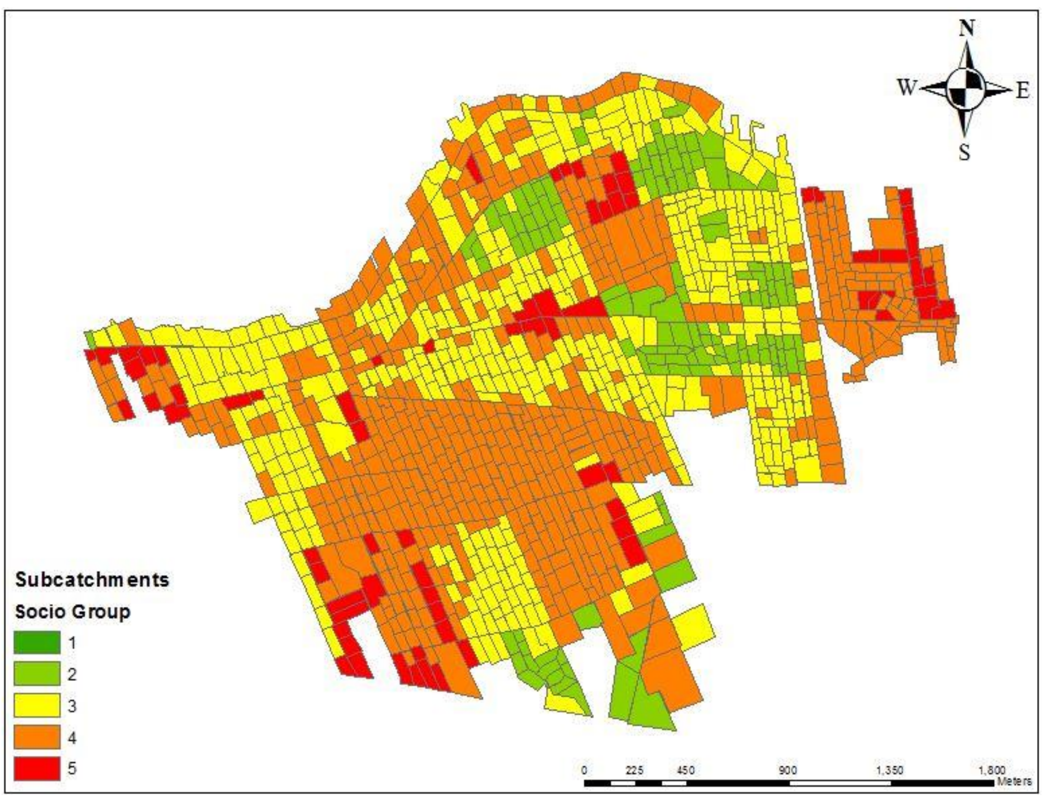

Figure 6-4 Map of subcatchment socioeconomic rankings

6.4 Final Subcatchment Rankings

It’s important to understand not only where in an urban area the flooding risk is the highest but also the socioeconomic impacts in that area. A final score was determined by combining the risk scores and socioeconomic scores to divide the subcatchments into one of 5 groups as seen in Table 6-4. Each group is given a score by adding the risk score and socioeconomic score together, therefore the maximum possible score would be 35. Doing so penalizes areas that have high flood risk but are unlikely to accept and maintain LID controls but also benefits areas that have lower flood risk but a higher probability of maintaining LID measures and vice versa as continually maintained LID controls would contribute more to flood management over the entire area. Group 1 represented the areas where the least impact of LID would be seen and each group getting progressively better to Group 5. Group 5 represents the subcatchments that will see the greatest impact from LID implementation based on flooding risk and have the highest likelihood that LID will continue to be accepted and maintained ensuring the most benefit from investment. Figure 6-5 below maps the final rankings of each subcatchment.

Table 6-4 Final rankings for subcatchments

Subcatchment Group	Socioeconomic Score
1	Score ≤ 7
2	7 < Score ≤ 14
3	14 < Score ≤ 21
4	21 < Score ≤ 28
5	28 < Score ≤ 35

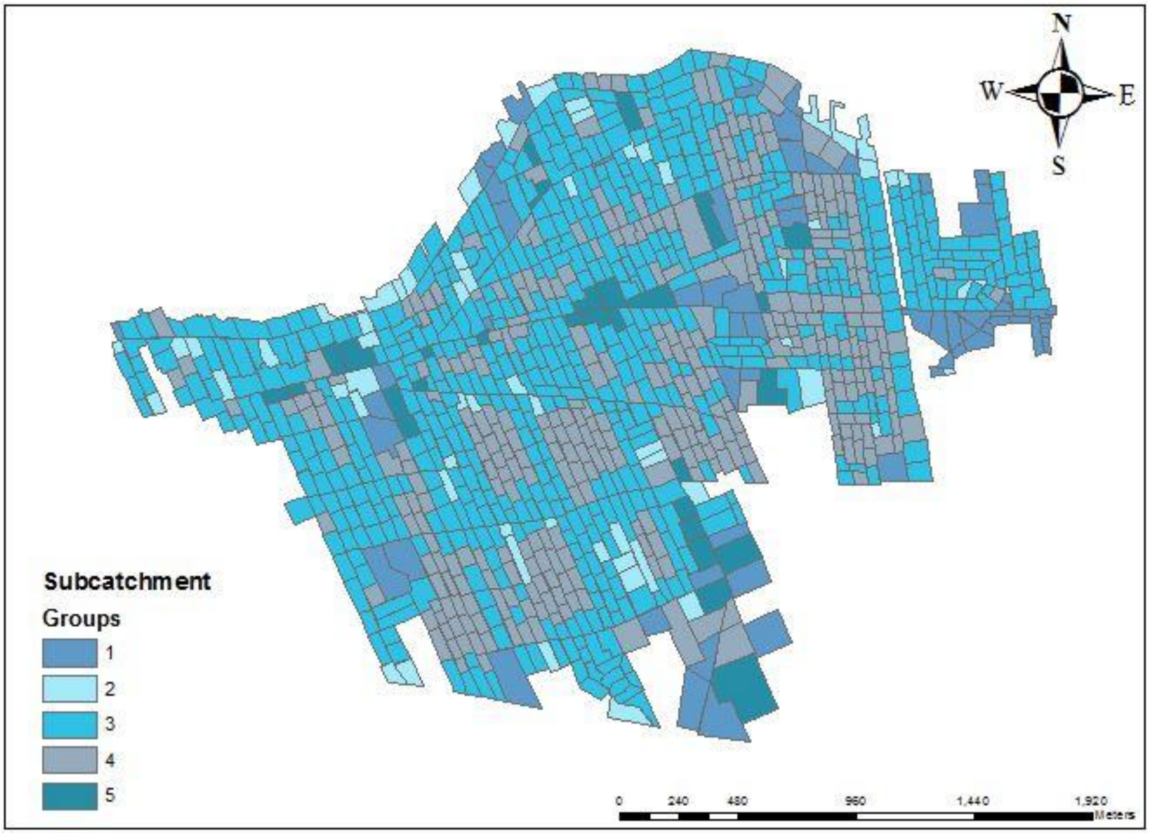

Figure 6-5 Map of final subcatchment rankings for LID placement

Chapter 7 Optimization

7.1 Introduction

When considering implementing LID controls in an urban or sub-urban area, there is a number of variables that are involved. There is an abundance of different possible combinations of controls, as well as the number of controls, the size of controls and where in a subcatchment each control should be placed in order to see maximum benefit. The hydrologic properties can vary drastically across an urban area which coincidently makes the performance of LID measures vary as well based on where they are placed. Therefore, a primary objective of the optimization process is to determine the right combination and placement of LIDs that maximizes runoff reduction. With stormwater management budgets continually being restricted it is important to determine the maximum benefit from LID measures at the lowest cost. Another primary objective is to determine the least cost solutions. Thus, the goal of optimization is to determine the most beneficial combinations of controls at various cost levels so decision makers have the opportunity to decide which solution best fits their needs and capabilities.

7.2 Multi-Objective Optimization

Single-objective optimization aims to find the maximum or minimum values for one objective. Single objective optimization techniques include linear programming, stochastic hill climbing and gradient searches (Zhang, 2009). Caramia and Dell'Olmo (2008) provide the formulation of a basic single objective problem as:

$$\begin{gathered} \min f(x) \\ x \in S, \end{gathered} \tag{7-1}$$

where f is a scalar function and S is a set of constraints defined as

$$S = \{x \in R^m : \hbar(x) = 0, g(x) \geq 0\}. \tag{7-2}$$

Multi-objective optimization aims to optimize a number of different objectives simultaneously. In mathematical terms multi-objective optimization can be described as:

$$\min[f_1(x), f_2(x), \dots, f_n(x)] \\ x \in S, \tag{7-3}$$

where S is a set of constraints (as defined above), and n > 1. The objective space is the space that the objective vector belongs, and the image of the feasible set under F is known as the attained set (Caramia and Dell'Olmo, 2008). This set can be denoted as

$$C = \{y \in R^n : y = f(x), x \in S\} \tag{7-4}$$

Generally, there is no one optimal solution in multi-objective optimization problems, instead there is a set of alternative solutions referred to as the Pareto optimal set. There is a vector $x^* \in S$ which is said to be the Pareto optimal if all other vectors $x \in S$ have a higher value for at least one objective function, f_i, where $i = 1, \dots, n$, or have the same value for all objective functions in the multi-objective problem (Caramia and Dell'Olmo, 2008). Basically, if a vector *u* is said to "pareto dominate" another vector *v*, then all values of *u* are less than or equal to their corresponding values of *v* and at least one component of *u* is strictly less than the corresponding component of *v*. Multi-objective solutions with lower values are considered dominant since the objectives are being minimized (Eckart, 2015).

The image of all efficient solutions is known as the Pareto front or Pareto surface (Caramia and Dell'Olmo, 2008). The Pareto front is defined by the Pareto optimal set and its shape specifies the nature of the trade-offs between objective functions (Caramia and Dell'Olmo, 2008; Hadka and Reed, 2013). The Pareto optimal set $\mathcal{P}^*$ for a given multi-objective problem can be defined as

$$\mathcal{P}^* = \{x \in \Lambda \mid \neg\exists x' \in \Lambda, F(x') \prec F(x)\} \qquad (7\text{-}5)$$

meaning solutions “x” are part of the Pareto optimal set and there does not exist any solution in the set of feasible solutions that would dominate “x” (Hadka and Reed, 2013).

The image of the Pareto optimal set is referred to as the Pareto front. The shape of the Pareto front demonstrates the trade-offs between objective functions (Caramia and Dell’Olmo, 2008). Hadka and Reed (2013) define the Pareto front for a Pareto optimal set $\mathcal{P}^*$as

$$\mathcal{P}\mathcal{F}^* = \{F(x) \mid x \in \mathcal{P}^*\} \qquad (7\text{-}6)$$

Methods of solving multi-objective optimization problems include tabu searches, simulated annealing, scatter searches and genetic or evolutionary algorithms. A genetic algorithm is a common type of evolutionary algorithm that is advantageous over the other techniques and is very common in water resource multi-objective problems (Sivanandam and Deepa, 2007; U.S EPA, 2006). Genetic algorithms (GA) use a population based approach where multiple solutions participate in an iteration and a new population of solutions evolves from each iteration.

7.2.1 Genetic Algorithms

For the purpose of solving multi-objective optimization problems, genetic algorithms are found to be more effective than traditional techniques like gradient searches and linear programming (Fonseca and Fleming, 1995). They are popular in solving multi-objective optimization problems since derivative information is not necessary, they are relatively simple and they are flexible and can be applied to a wide range of problems (Deb, 2011).

Since all objectives in a multi-objective optimization problem are important the principle of determining the optimum solution cannot only be applied to one objective.

Different solutions often produce trade-offs between different objectives. A solution that may perform well for one objective likely requires compromise in other objectives (Deb, 2011). This restricts the ability to select a solution that is optimal in only one objective which leads to the goals of multi-objective optimization to determine a solution set that lies on the Pareto front and determine a solution set that is diverse enough to represent all of the Pareto front (Deb, 2011).

Genetic algorithms are stochastic search techniques that imitate the natural selection process in that positive traits of a solution set are continued on with newly-added random solutions (U.S EPA, 2006). GA's are particularly good for large optimization problems as a set of solutions is processed in parallel and similarities in solutions are exploited through crossover (Zhang, 2009; Zitzler and Thiele, 1999). Each new generation provides a set of solutions by selecting individuals based on their fitness. The crossover and mutation operators are then applied to create a child generation of solutions. This process is continually repeated, evolving the individual's population and the respective level of fitness to the problem increases, similar to natural adaptation (Eshelman, 1991).

Genetic algorithms have been a common multi-objective optimization tool used to analyze low impact developments. GAs are can easily be linked to simulation models like SWMM, Baek et al. (2015), Duan et al. (2016), Eckart et al. (2018), Jung et al. (2016), Karamouz and Nazif (2013) are all examples of studies where this has been carried out in order to run simulation-optimization models capable of solving multiple objectives.

7.2.1.1 Crossover

Crossover is a reproduction operator where random information changes occur between two solutions. It is the process of taking from two solutions to produce a new solution. Once selection process occurs, the population is enhanced with improved solutions. Selection creates copies of good strings but no new ones are created. The crossover operator is applied to create improved offspring (Sivanandam and Deepa, 2007).

7.2.1.2 Mutation

Mutation proceeds after crossover in order to prevent the algorithm from converging to a local minimum. If the crossover process is meant to expose the current solution in order to produce improved solutions, mutation is meant to assist with ensuring the entire search space is looked at. Mutation is used to help maintain a genetic diversity in the population and, by randomly altering some of its building blocks, it introduces new genetic structures (Sivanandam and Deepa, 2007).

7.2.2 Borg MOEA

The Borg Multi-Objective Evolutionary Algorithm (MOEA) (Hadka and Reed, 2013) was used as the optimization technique in this study as shown in Eckart (2015). Borg is specifically designed to handle many-objective problems by assimilating and enhancing several design principles from past GAs. Hadka and Reed (2012) tested Borg against other state-of-the-art MOEAs for multiple different test problems and determined that Borg was able to meet or exceed the performance of the other algorithms on the majority of the problems.

Borg is an elitist genetic algorithm, meaning that an elite archive of solutions is stored in addition to the population. This archive's acceptance criterion is stricter than the population and the elite archive is what ends up being the output of a Borg run. A new solution gets added to the population if it dominates at least one member of the population and the dominated member is replaced. For a solution to be added to the elite archive it must ε-box dominate at least one of the solutions already in the elite archive and all solutions that are in the elite archive that are ε-box dominated are discarded (Hadka and

Reed, 2013). Essentially, ε-box dominance is a system in the Borg MOEA that provides a minimum criteria for improvement to help ensure that any new solutions that are technically improvements but are close to any existing solutions in the objective space are not added (Eckart, 2015). Hadka and Reed (2013) define ε-box dominance as for a given $\varepsilon > 0$, a vector u = (u_1, u_2, ..., u_M) ε-box dominates another vector v = (v_1, v_2, ... , v_M) if, and only if, $\left\lfloor \frac{u}{\varepsilon} \right\rfloor \prec \left\lfloor \frac{v}{\varepsilon} \right\rfloor$, or $\left\lfloor \frac{u}{\varepsilon} \right\rfloor = \left\lfloor \frac{v}{\varepsilon} \right\rfloor$ and $\left\| u - \varepsilon \left\lfloor \frac{u}{\varepsilon} \right\rfloor \right\| < \left\| v - \varepsilon \left\lfloor \frac{v}{\varepsilon} \right\rfloor \right\|$.

As mentioned above, new solutions are created by taking from two parent solutions. The elite archive provides one of those parent solutions and the other is selected from the population. The number of solutions chosen from the population to be potential parent solutions is adaptive in Borg in order to maintain selection pressure. This means that the number of potential parent solutions chosen changes with the population size to ensure that a non-dominated solution from the population that is chosen to participate will not be dropped (Hadka and Reed, 2013).

After parent solutions have been determined, Borg uses AMALGAM, an adaptive multi-operator recombination process (Vrugt and Robinson, 2007), to combine the parent genes into a new solution. Six operators are available to recombine parent genes and over the course of a run the probability of any of these operators being selected is updated based upon the number of solutions created by each recombination operator that have been added to the elite archive (Hadka and Reed, 2013).

7.3 Optimization Methodology

7.3.1 Overview

The optimization goal of the model set-up is to determine the pareto-optimal front for the objectives of reducing peak flow in the stormsewer network and total runoff in the sewershed while also looking at minimizing the costs of doing so. The following sections discuss the optimization-simulation framework for the method studied.

7.3.2 Borg Optimization Set-up

7.3.2.1 Optimization-Simulation System

The PCSWMM model and cost functions are the fitness functions used to evaluate solutions by taking the decision variables and returning objective values. The entire system was developed by linking SWMM 5 (the same engine is used in PCSWMM) with the Borg MOEA such that a feedback process is created which allows Borg to alter SWMM parameters and then receive the model outputs. Figures 7-1 and 7-2 show flow charts of how SWMM 5 and Borg are linked together. Borg was coded into the SWMM 5 source code essentially turning SWMM into a fitness function for the Borg MOEA. Figure 7-1 shows the broad transfer of data between SWMM and Borg. Figure 7-2 provides more details to better illustrate the Borg procedure. The PCSWMM input file is updated from read-write functions that change targeted portions of the input file by parsing the file. Borg decision variables, various subcatchment properties, and arrays of unaltered subcatchment parameters are used by the parsing functions to calculate the values required for the targeted string in the PCSWMM input file (Eckart, 2015).

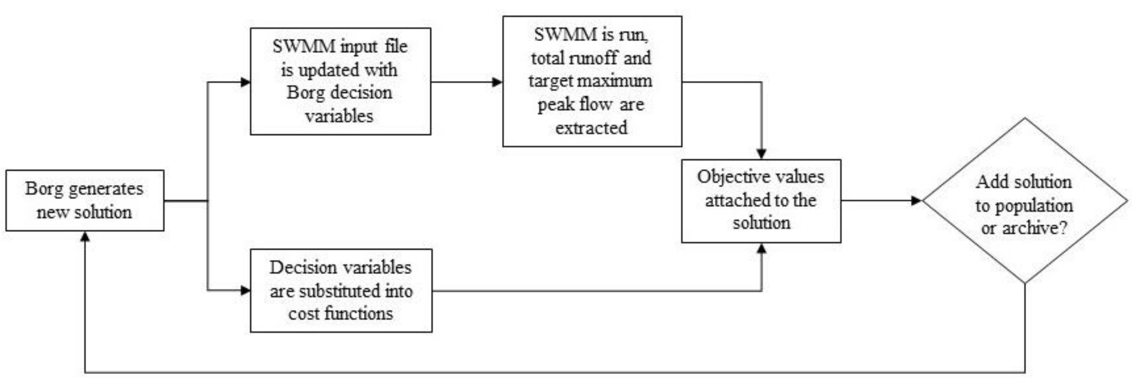

Figure 7-1 Generalized Borg-SWMM model framework (adapted from Eckart, 2015)

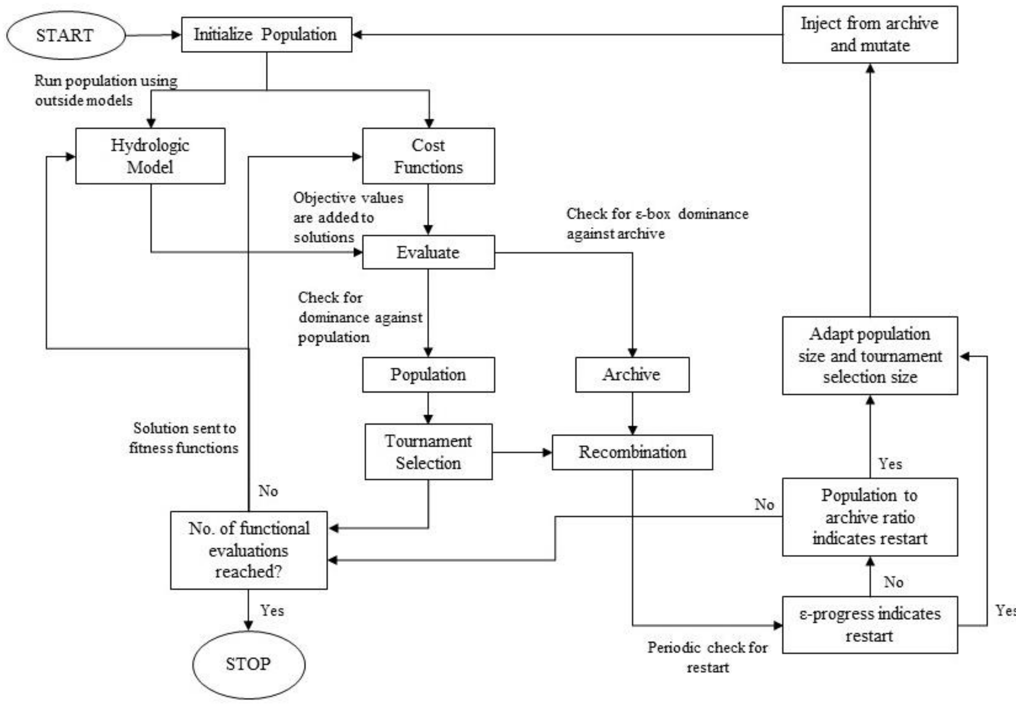

Figure 7-2 Borg-SWMM optimization-simulation scheme (adapted from Eckart, 2015)

7.3.2.2 Objective Functions

There are three objective functions being optimized by the Borg algorithm; minimize cost, reduce peak flow in the sewers, and reduce the total runoff. All three of the objectives are minimized. These objective functions can be seen in equations 7-7 through 7-9. The cost function is based on the type, size and number of LID controls in a subcatchment. Using the costing information provided in Chapter 5 and the groups discussed above the costs for each scenario is determined. Minimizing peak flow rate and runoff are closely related but in this study are set as two separate objectives to make the results easier to interpret. In order to combine these two objectives into a single objective normalization and weighting would be necessary causing the output to be less instinctive. The results from Eckart (2015) confirm that keeping these two factors as separate objectives can be beneficial as the importance of timing in peak flow is evident.

$$\min \sum_{i=1}^{m} \sum_{j=1}^{n} C_i^j (S, N) \tag{7-7}$$

where,

C_i^j = cost of LID type j in subcatchment i,
S = LID size,
N = number of LID units in a given subcatchment

$$\min(Q_P) \tag{7-8}$$

where,

Q_P = maximum flow rate during the duration of simulation through the point of interest in a stormsewer.

$$\min \sum_{t=0}^{k} \sum_{i=1}^{n} R_i^t \tag{7-9}$$

where,

R_i^t = runoff from subcatchment i at time t,
k = end point of the simulation.

7.3.2.3 Decision Variables

There are 30 decision variables used in this study. The decision variables used have a focus on the types of LID controls being selected, the size of LID measures and their corresponding location. The combination of LIDs implemented in a subcatchment influences the percent of impervious area in that subcatchment. The percent of impervious area in a subcatchment is what routes runoff to each LID. Table 7-1 lists the decision variables used, the first decision variable is numbered "0" in order to keep consistency with C programming.

To optimize the placement of LIDs, subcatchments were divided into five groups as explained in Chapter 6. These groups are related to the implementation of decision variables. Subcatchment Group 1 consists of 153 subcatchments and 557 houses. This group contains a large portion of open space and LID adoption is not a high priority. Group 2 has 145 subcatchments and 485 houses, this group has a higher priority than Group 1 but still has a low probability of seeing consistent LID maintenance and thus is still a lower priority for implementation. Group 3 contains 537 subcatchments with a total of 2290 houses. This is the largest group with a large amount of residential area which would benefit from LID implementation. Group 4 consists of 174 subcatchments and 684 houses. This is the second largest group and has a higher priority for LID implementation than Group 3. Group 5 has 117 subcatchments with 307 houses. This is the group with the highest priority, it consists mostly of high flood risk areas and commercial properties that would be more likely to adopt and maintain LID controls. The purpose of dividing the subcatchments into groups is to achieve cost-benefit information as a result of investing in these designated areas that are likely to see the most success from LID. These groups can also be individually optimized. Due to the high number of subcatchments in the model, subcatchments were not optimized individually and thus LID placement is dependent on the groups.

Table 7-1 Decision variables used for optimization

Decision Variable	**Explanation**	**Range**	**Change by**
0, 1, 2, 3, 4	Number of rain barrels per house in groups 1, 2, 3, 4, and 5	0 - 4	1
5, 6, 7, 8, 9	The implementation of an infiltration trench in groups 1, 2, 3, 4, and 5	0 or 1	1
10, 11, 12, 13, 14	The implementation of an permeable pavement driveways in groups 1, 2, 3, 4, and 5	0 or 1	1
15, 16, 17, 18, 19	The implementation of bioretention units in groups 1, 2, 3, 4, and 5	0 or 1	1
20, 21, 22, 23, 24	Surface area in m^2 of infiltration trenches in groups 1, 2, 3, 4, and 5	20 - 300	10
25, 26, 27, 28, 29	Surface area in m^2 of bioretention units in groups 1, 2, 3, 4, and 5	4 - 28	4

The decision variables are acted on by the floor function in order to set them to whole numbers and setting the constraints determined the margins by which decision variables are changed by. The constraints are divided by that margin, however, the decision variable is multiplied by that value when it is written into the input file or used in the cost function (Eckart, 2015).

7.3.3 Parameter Settings for the Optimization Process

Borg has several parameters required for running the optimization framework. These parameters are set to defaults but can be altered by the user. The altered parameters are shown in Table 7-2 and are mostly based on values used in Eckart et al. (2018) for a similar optimization set up.

The parameters that are generally required to be altered based on the test are the epsilon (ε) values for each objective and the maximum number of functional evaluations. Objective values are evaluated at a resolution set out by the epsilon values. A larger epsilon value provides a coarser resolution which means there is a greater distance separating output solutions in the objective space. The epsilon values are a required input for the Borg MOEA (Hadka and Reed, 2014). Final epsilon values are shown in Table 7-2. Values are kept smaller to ensure diversity of the solutions explored. Other optimization parameters that were not updated and used the default values include minimum population, maximum populations, and selection ratio. Appendix C includes all parameters for the Borg set up.

Table 7-2 Changes made to Borg parameters

Parameter	**Notes**	**Default Value**	**New Value**
Epsilon Values	(Q_p, R_T, \$)	N/A	(0.01, 0,01, 1000)
Window Size	Minimum evaluations between ε-progress checks.	50	100
Maximum Window Size	Maximum evaluations between ε-progress checks.	20,000	200
Initial Population	Number of solutions in the initial population.	100	1500
Population Ratio	Population to archive ratio.	4	5
Update Interval	Determines the frequency properties are updated	100	50

To determine the number of functional evaluations necessary for convergence, test runs were carried out to see the pareto front under different numbers of evaluations. Figure 7-3 and 7-4 show the results of these tests. The numbers in the legend represent the number of functional evaluations tested. The tests shown are independent from each other meaning that a test may not have the same solution after the same amount of evaluations as another test unless the pareto front has already been identified at that point. Overlapping solutions mean that two separate runs have reached the same solution. Some of the solutions in the graphs may appear to be dominated but these solutions are non-dominated in the objective not shown.

The optimization process is used to determine a wide variety of diverse solutions that are as close to the pareto optimal front as possible. In the figures it is shown that there is no longer much improvement between 9000 and 10000 evaluations meaning better solutions are not being acknowledged by increasing the number of functional evaluations. The number of simulations used in this study was thus 10,000. In similar optimization studies, Zhang (2009) used 10,000 evaluations and Eckart et al. (2018) used 12,500.

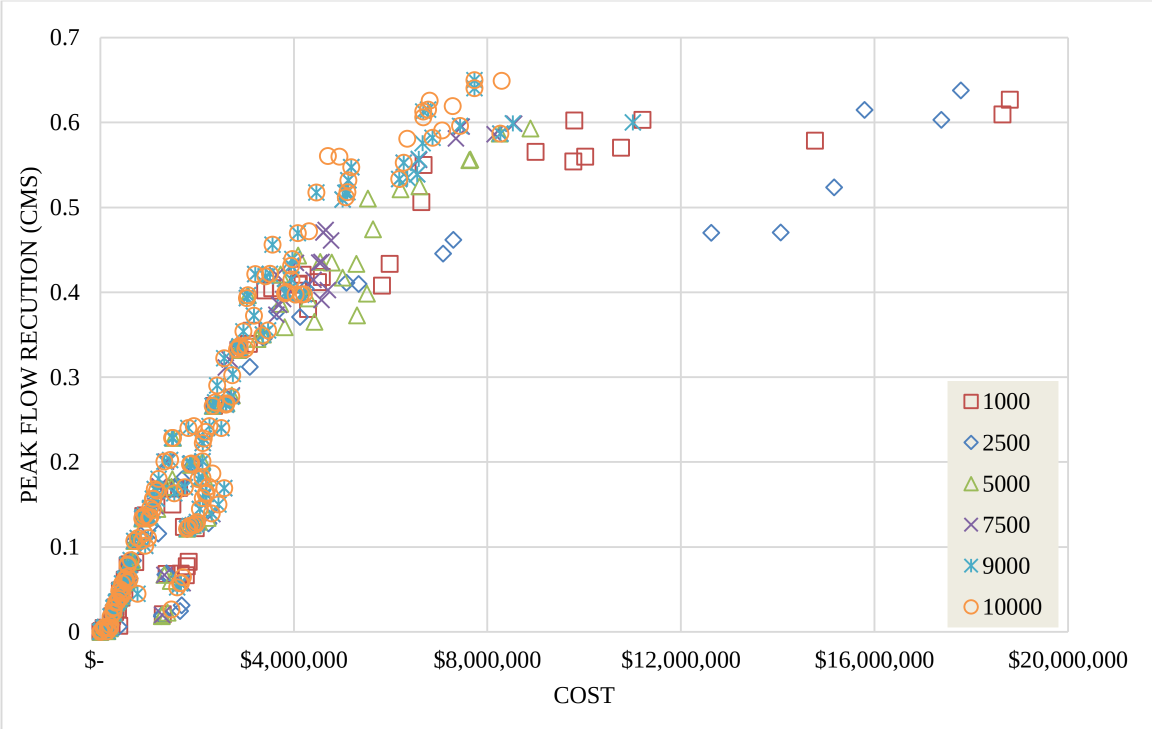

Figure 7-3 Peak flow reductions during convergence test

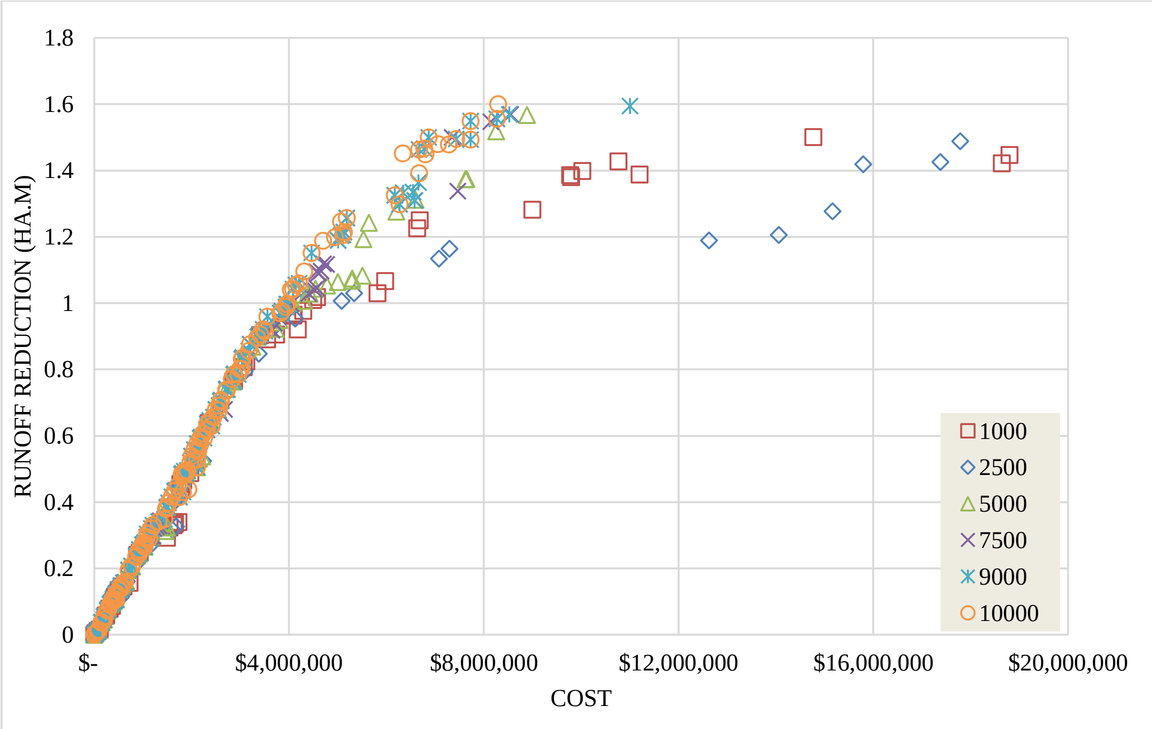

Figure 7-4 Total runoff reductions during convergence test

7.4 Scenario Development

The different scenarios tested by the optimization-simulation model are discussed here. The different scenarios used allow the performance of LID controls to be compared under different conditions. Comparing the scenarios to one another can contribute to an improved understanding how LID design and performance is impacted by changing factors.

There are eight different scenarios used for evaluation. There are two different LID implementation scenarios that are tested under four different storm events. The storm events are 5-year and 100-year return period design storms for both historic climate data and predicted future climate change data.

7.4.1 Design Storm Distributions

7.4.1.1 Climate Change

The four different design storms are used to compare LID performance against historical climate conditions and predicted future climate change conditions. They are created using intensity-duration-frequency (IDF) curves for historical recorded data and future climate change predicted data. One of the main driving forces behind LID is its use for climate change adaptation. Many cities now have climate change adaptation plans as they are trying to deal with the increased frequency of heavy rainfall events. In their climate change adaptation plan, Windsor, Ontario has included LID as a stormwater management strategy (The City of Windsor, 2012), they have also been looking LID controls as part of their sewer master plan (Dillon Consulting and Aquafor Beech Limited, 2018).

In this study the climate change component is based on IDF curves that have been updated to include predicted climate change data. Researchers at the University of Western Ontario have developed an online tool that generates new IDF curves. The IDF Climate Change Tool allows the user to choose climate stations in Canada as well as select data from climate models (Schardong et al., 2018). The Windsor Airport climate station was selected for this study. It provides 60 years of historical data that can be used to generate historical IDF curves. The IDF Climate Change Tool used climate change data from 22 climate models for a period of 2006 to 2100 to create the future predicted climate change IDF curves. For the design storms created the RCP 8.5 emissions scenario was used as it is the worst case emissions scenario and has the greatest difference to the historical IDF curve data. Appendix D shows the IDF curves used in this research.

7.4.1.2 Design Storm Development

The design storms used in this research were created for use by the PCSWMM model. They were developed by selecting precipitation values for a 24-hour storm event from IDF curves for both a 5 and 100 year return period for the historical and climate change scenario. An SCS Type II rainfall distribution was then used to convert the total rainfall into a 24-hour rainfall, providing the fraction of the total rainfall at 12 minute intervals. Precipitation files for the design storms are shown in Appendix E. The cumulative rainfall distributions are shown in Figure 7-5.

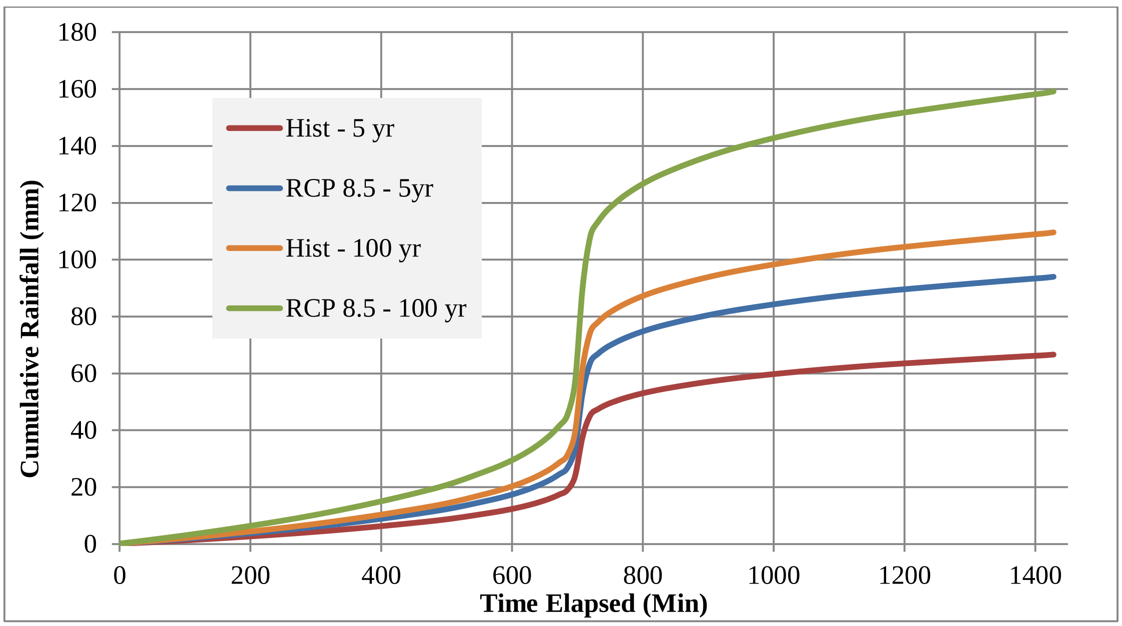

Figure 7-5 Cumulative rainfall distributions for the four design storms used for this study

7.4.2 LID Implementation Scenarios

There are two different LID implementation scenarios. The study area does not have much available area for further development and thus the LID controls were considered to be implemented as retrofit options in the sewershed as it currently exists under two different LID adoption rates. Table 7-3 shows the percentage of LID adoption for both a low and high adoption scenario. The adoption rates are selected to replicate what might be possible in reality based on values recorded in past literature (Eckart et al., 2018; Lloyd et al., 2002; Mayer et al., 2012; Shuster et al., 2008), while also ensuring the ability to study the benefits of LID at different adoption rates. The adoption of infiltration trenches increased the most between the two scenarios because it does not rely on public adoption, assuming there is available land, as it is a centralized LID control.

Table 7-3 Adoption rates by percent of houses or subcatchments for each LID control

	Adoption Rate (%)	
LID Control	**Low**	**High**
Rain barrel	5	10
Bioretention	5	10
Permeable pavement	2	5
Infiltration trench	5	25

The LID adoption rates shown in Table 7-3 are the maximum possible for each scenario, if some LIDs are not used in a solution then the implementation rate would be lower. LID adoption rates vary for each control. There is only one infiltration trench implemented per subcatchment, thus the number of eligible subcatchmnets was reduced accordingly. The subcatchments deemed suitable for infiltration trenches were also eligible for the other LID controls to ensure the routing dynamics that inform the user which LID combinations are most effective remain unchanged. If it was required that more subcatchments were necessary for the other LID controls to meet its corresponding adoption than the remaining number of required subcatchments were assigned based on inspection of the PCSWMM model.

For rain barrels, bioretention units, and permeable pavement driveways the LID adoption was dependent on the number of adopting houses. The number of units for each LID control in each subcatchment are written into the PCSWMM input file. This is done by multiplying the number of houses in the subcatchment by the decision variable (or the number of units per house). To limit LID adoption to the required adoption rate, arrays were developed with reduced number of houses to align with the necessary adoption rate. Runoff routing is handled by multiplying the runoff from impervious surfaces to each LID control by the number of adopting houses in a subcatchment and dividing it by the total number of houses in that subcatchment. This is done because in real life it would be unlikely that a control on one property would receive runoff from several additional properties and it prevents the LID controls from being overloaded prematurely. Changes to the subcatchments' percent imperviousness and changes to internal routing were calculated using similar methods.

Chapter 8 Results and Discussion

8.1 Overview

The optimization-simulation framework was applied to the study area to determine tradeoffs between LID's cost, peak flow rate and total runoff volume in order to identify the cost-benefit for a variety of different LID implementation scenarios. These solutions placed various LID types and varying number of LID controls in subcatchments that are likely to achieve the most benefit from continued LID maintenance. The model also produced valuable information for optimal LID designs in areas with low infiltration characteristics. LID performance was analyzed for all four design storms and both adoption scenarios. All the solutions from the tests are shown in three dimensions (all objectives graphed at once) in Figures 8-1 and 8-6 for the low adoption and high adoption scenarios, respectively. Figures 8-2, 8-3, 8-7, and 8-8 graph the three dimensional results (Figures 8-1 and 8-6) in two dimensions to show peak flow reduction versus cost and to show total runoff reduction versus cost. Some solutions in these graphs may appear to be dominated but those solutions are actually non-dominated for the other objective not shown (peak flow or total runoff). Due to this, solutions were then broken down to develop tradeoff curves between total LID cost and peak flow reduction (Figures 8-4 and 8-9) as well as total LID cost and total runoff reduction (Figures 8-5, 8-10). These separate graphs show all the solutions for each storm non-dominated in the peak flow objective and non-dominated in the total runoff objective to allow the solutions for each objective to be more easily analyzed as graphing all three objectives in three dimensions makes the solutions difficult to interpret. For a solution to be non-dominated means none of the other solutions perform as well in the two objectives being looked at.

Cost analysis of some of the most cost effective solutions for each case were looked at and analyzed. Some of these solutions were then also tested for the flooding events in Windsor from 2016 and 2017 to evaluate the impact that having these LID scenarios implemented could have had on the floods. The raw optimization results are available in the supplemental files. Solutions were also looked at to determine the investment in each subcatchment group. It was evident that there was benefit to investing in the groups with the highest flood risk and the highest probability of LID maintenance as the average investment per subcatchment was highest in these regions.

8.2 Low Adoption Scenario

8.2.1 All Solutions

The results for each storm under the low LID adoption scenario are displayed in Figures 8-1, Figure 8-2 and Figure 8-3. The graphs display the objective values for each solution stored in Borg's elite archive. Figure 8-1 demonstrates the solutions with all three objectives graphed in three dimensions. If this surface is rotated to display two objectives the non-dominated solutions can be seen for those two objectives, these are the graphs displayed in Figures 8-4 and 8-5. When testing this low of a level of implementation, changes that are made to the decision variables provide very minor changes to the peak flow and total runoff which can make results difficult to interpret as many of the solutions are bunched together as seen in Figures 8-2 and 8-3. As mentioned above in order to see the true pareto front the optimization-simulation results have to be graphed in three dimensions (Figure 8-1) but the results graphed this way are difficult to interpret and thus are separated into the two different graphs shown in Figure 8-2 and 8-3. These graphs may not appear to show a true pareto front but they allow the different solutions be evaluated more easily. Due to the large study area and the resultant large volume of runoff leaving subcatchments, runoff reduction levels significantly outweigh the peak flow reductions achieved.

The low adoption level makes the reduction capacity for both peak flow and total runoff quite low as shown in Figures 8-2 and 8-3. Under all four design storms LID implementation scenarios demonstrate an overall reduction percentage for total runoff greater than the percentage of peak flow reduction. This was also the case when LID adoption was increased in the high adoption scenario. The low adoption scenario demonstrates solutions that are much less expensive to implement but can still provide benefit, in fact the amount of reduction per money spent is similar in both low LID adoption and high LID adoption scenarios. The achieved reduction percentages decrease with higher intensity storms and are clearly the worst for the climate change 100-year storm, the most intense precipitation event looked at. Though the low adoption scenario provides some benefit and a cost-effectiveness similar to the high adoption scenario, the results provide questions as to if this level of LID implementation is worth investing in for this study area to limit peak flow rates and total runoff, especially for larger rainfall events.

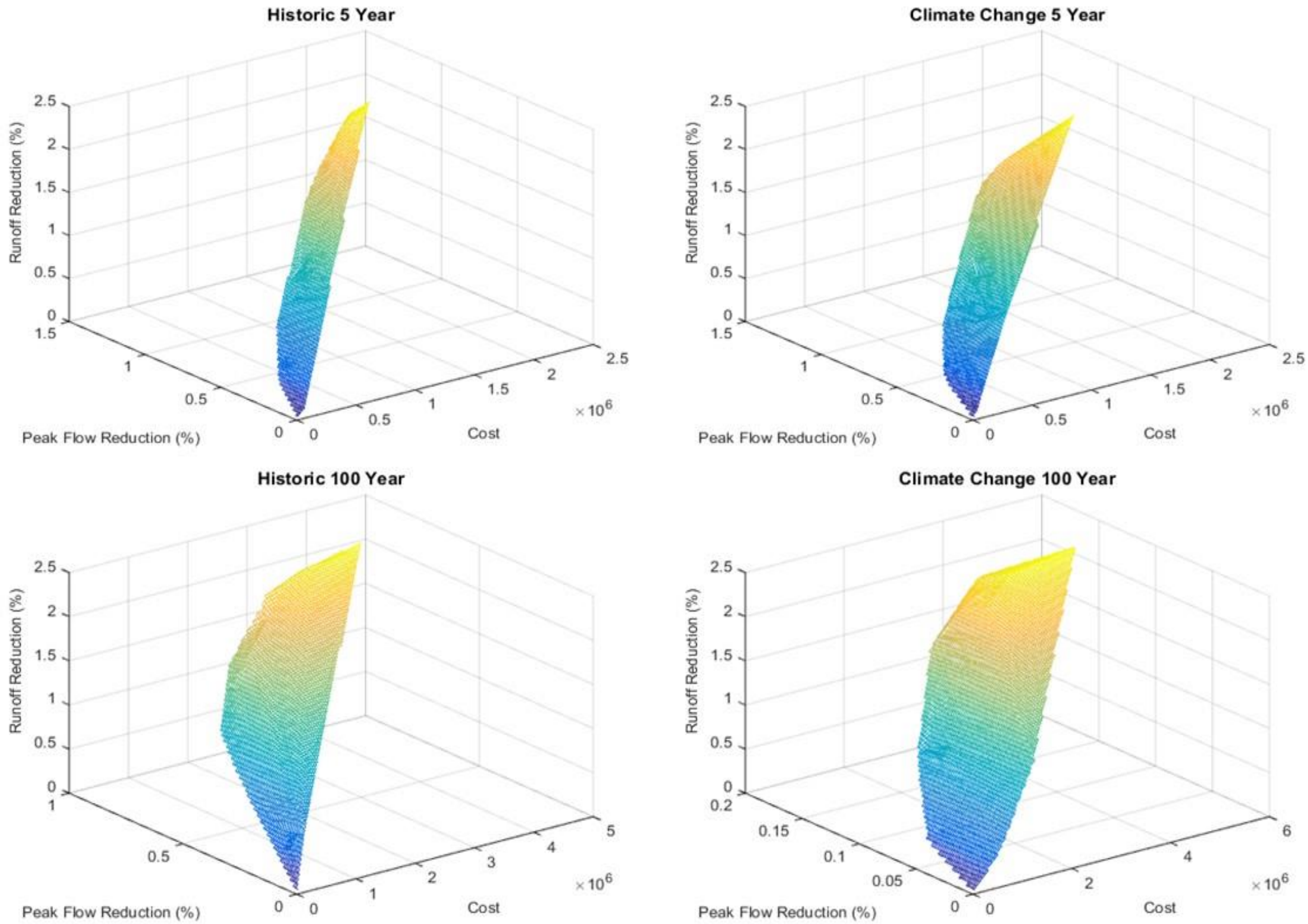

Figure 8-1 Pareto optimal surfaces achieved for each storm event under the low adoption scenario

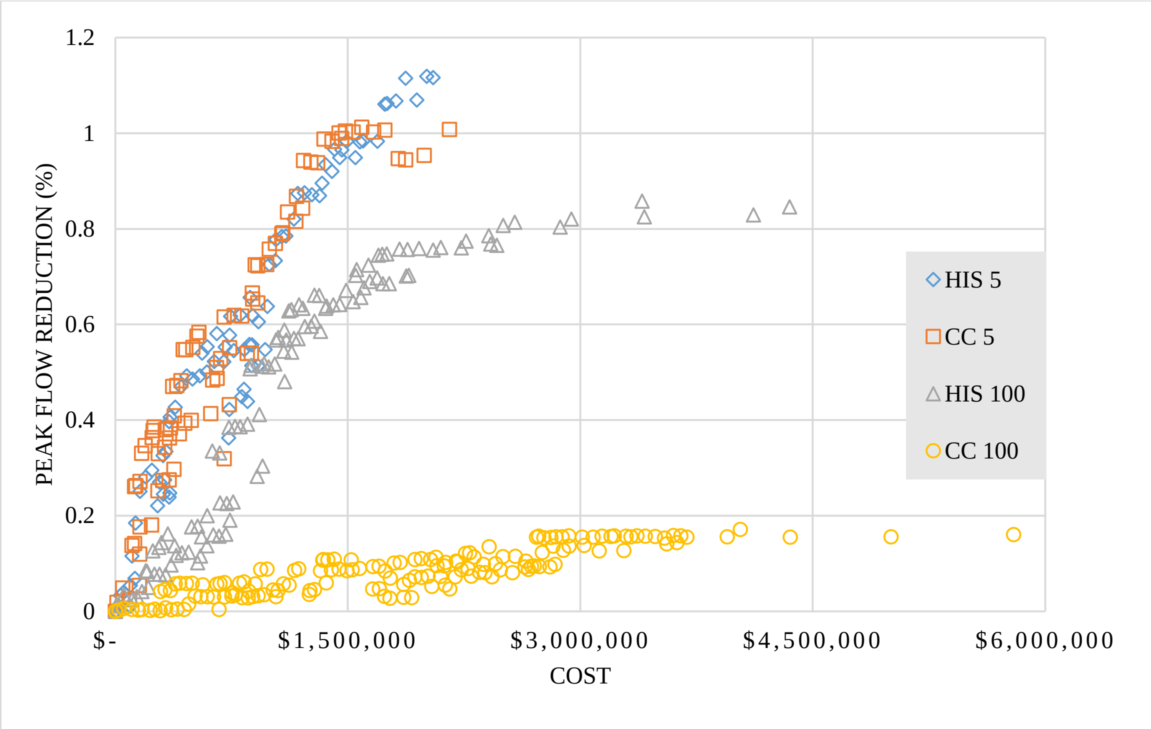

Figure 8-2 Peak flow percent reduction for the low adoption scenario

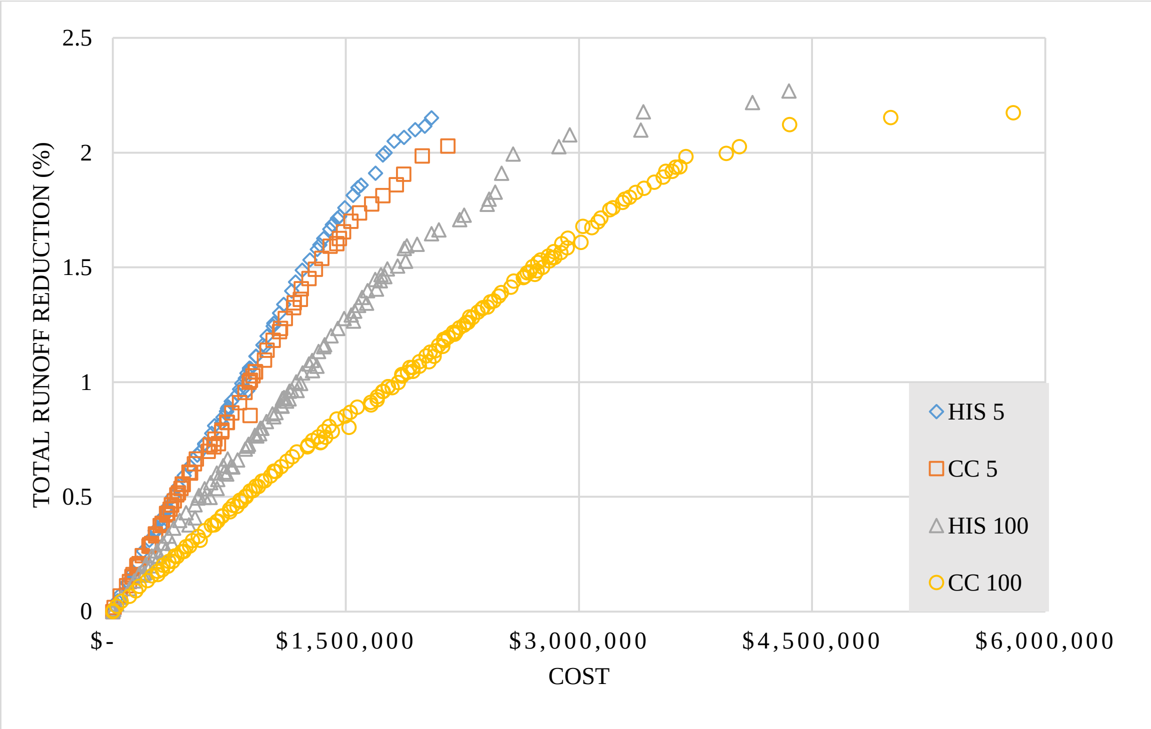

Figure 8-3 Total runoff percent reduction for the low adoption scenario

8.2.2 Solutions Non-Dominated Peak Flow and Cost

The solutions for each storm event that are non-dominated in peak flow reduction and cost minimization are shown in Figure 8-4. To highlight some of the most cost effective solutions a star is used to mark these solutions on the graphs. These cost effective solutions are further evaluated in Section 8.5. In Figure 8-4 peak flow reduction is now demonstrated as a quantity rather than a percentage as was demonstrated in Figure 8-2, but the LID performance for peak flow reductions is still worse for the two larger storms and very poor for the climate change 100-year event. The highest total peak flow reduction was achieved for the historic and climate change 5-year storms but then declines significantly as the total rainfall increases during the two 100-year storm events. The poor performance of LID scenarios for peak flow reduction under the larger precipitation events can be attributed to flow timing. When the water depth stored in some LIDs hits a certain level, the flow rate through the underdrains can be large enough to cause water to flow through the LID and underdrain and reach stormsewers faster, or at a similar rate, as if it was to travel over land to the subcatchment's outlet. This is emphasized in the poor results achieved under the 100-year climate change storm as the generalized designs used are not adequate to deal with that high volume of precipitation and thus quickly became overloaded.

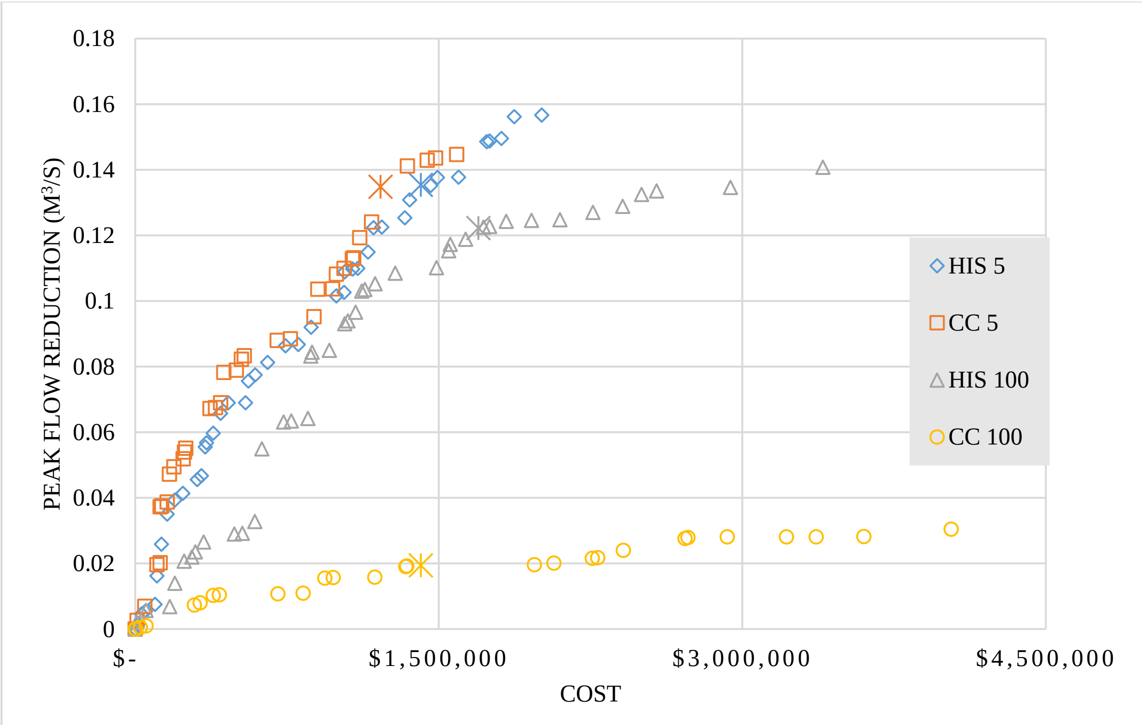

Figure 8-4 Low adoption solutions non-dominated in peak flow reduction and cost

The different changes between solutions, such as changes to infiltration trench and/or bioretention area, changes in present LID combinations, or changes in the number of LID controls, all impact the efficiency of solutions differently. This is why the slopes of the series presented in Figure 8-4 are not uniform and where the concept of diminishing returns on investment becomes apparent. The diminishing returns on investment for each storm happens when the best performing LID type can no longer be further implemented and the only way to continue to reduce peak flow rates is to invest in less efficient LID controls. This means that adoption constraints on the most effective LID types, in this case infiltration trenches, play an important role in how much peak flow reduction can be achieved before a point of diminishing returns occurs. The most effective solutions all contain infiltration trenches and bioretention units were often added for improved peak flow reduction, though these two LID types increased the costs. Rain barrels were a common LID control implemented in most solutions especially in the low cost solutions.

Rain barrels, however, are not as significant for reducing peak flow as they are for runoff reduction as they often become full before the most intense part of the precipitation events and thus are not contributing during the times where the largest peak flow rates are present. In real LID design, routing as much runoff as possible to the most efficient LID controls is important in achieving maximum benefit. In this study this was not done as LIDs cannot be routed to other LIDs in PCSWMM and so runoff from impervious surfaces that may be routed to less efficient LID controls is prevented from flowing to more efficient LID types.

8.2.3 Non-Dominated Total Runoff and Cost

The patterns shown in Figure 8-5 for the objectives of runoff reduction and cost minimization vary significantly from those seen in the peak flow reduction graphs. The series' slopes for total runoff reduction are much more constant than the slopes seen in peak flow reduction meaning runoff reductions continue to increase at a fairly steady rate. The point of diminishing returns for reducing runoff also comes much later in the series than for peak flow reduction with total reductions nearly reaching the maximum before investing starts to lose significance. Another major difference between the runoff reduction objective and peak flow reduction is LIDs are still able to reduce runoff during the larger precipitation events and effectiveness does not fall off as much as with peak flows. As shown in Figure 8-5, the largest runoff reductions are achieved during the climate change 100-year storm, though for the relatively lower cost solutions, the reduction totals remain similar for all four storms. Similar to the most cost effective solutions for reducing peak flows, infiltration trenches are a prominent LID type in the runoff reduction solutions. The main difference, however, is that bioretention units and rain barrels are also more prominent in solutions than they were in the non-dominated peak flow solutions.

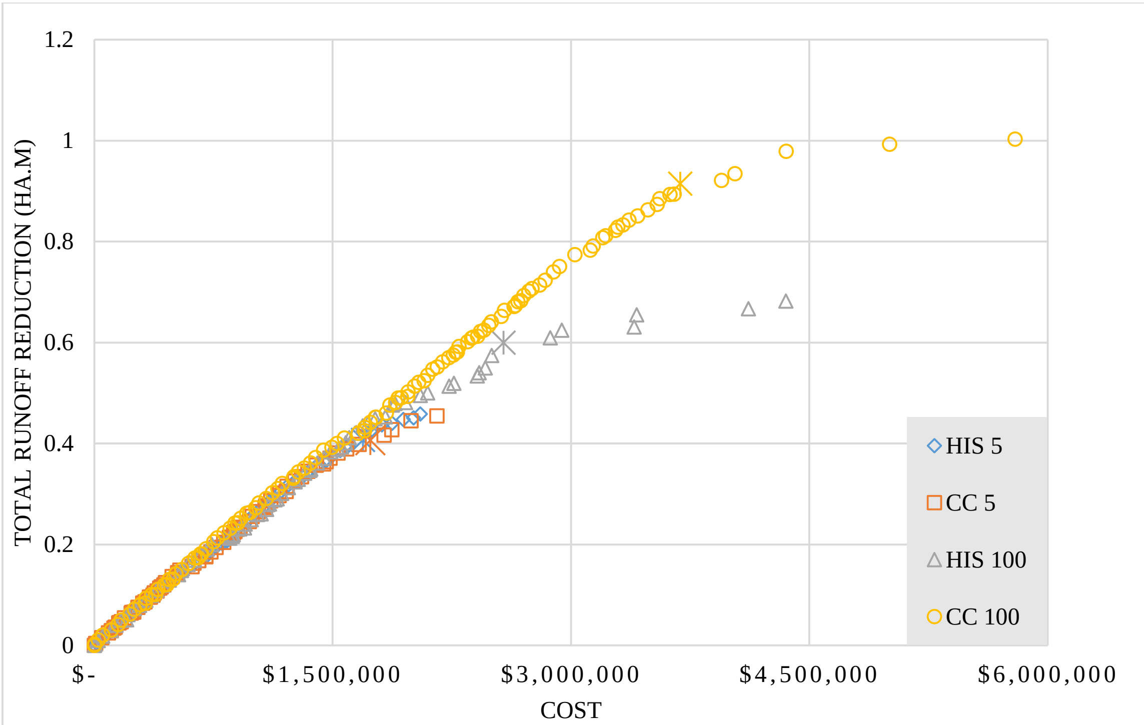

Figure 8-5 Low adoption solutions non-dominated in total runoff reduction and cost

8.3 High Adoption Scenario

8.3.1 All Solutions

The results for each precipitation event under the high LID adoption scenario are displayed in Figures 8-7 to 8-9. It is clear that the increased number of adopting households allows for the maximum reduction percentages for both peak flow and total runoff to be higher compared to the low LID adoption scenario. The improvement in peak flow reduction is greater than the increase in runoff reduction between the two scenarios. This is likely due to the decrease in infiltration trench restrictions which also improves the efficiency of the reduction percentage increases. The number of feasible subcatchments for infiltration trenches implementation increased from 5% to 25% from the low to high adoption scenario, which is the largest increase for all LID types (Table 7-3 lists all maximum adoption rates for each scenario). As was the case in the low adoption scenario, infiltration trenches were the dominant LID control shown in the solutions.

Similar to the low adoption scenario, both peak flow and total runoff reduction percentages decrease as the storm intensities increase with the climate change 100-year event seeing the lowest reduction percentages. The runoff reduction volume, however, is the greatest for the 100-year climate change storm as shown in Figure 8-10. This is because the more intense the storm the larger the volume of runoff that is produced and thus the larger the volume that is routed to the LIDs. This allows for a greater volume of total runoff to be reduced. The actual percent reduction however, ends up decreasing because the much larger total volume of runoff that is created during the larger storms outweighs the increased LID reduction volume. The gaps that appear in the solution are resultant of changing factors. Where there are a group of solutions bunched together then it is likely that those solutions are made up of the same LID controls and only the number of controls and/or the area of controls vary between the solutions. This provides only slight differences in performance. Where there is a gap between series is where the combination of LID controls have been altered.

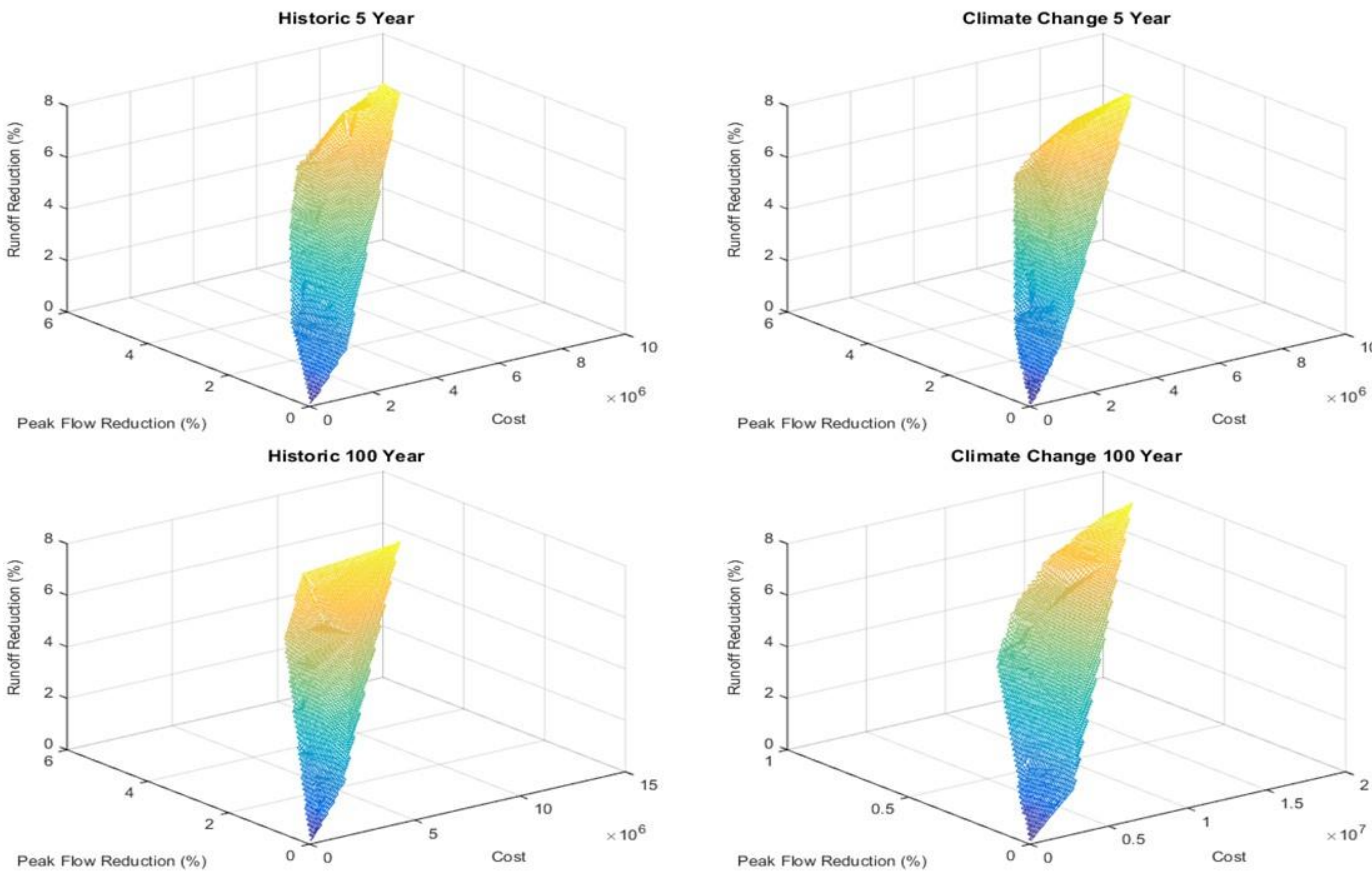

Figure 8-6 Pareto optimal surfaces achieved for each storm event under the high adoption scenario

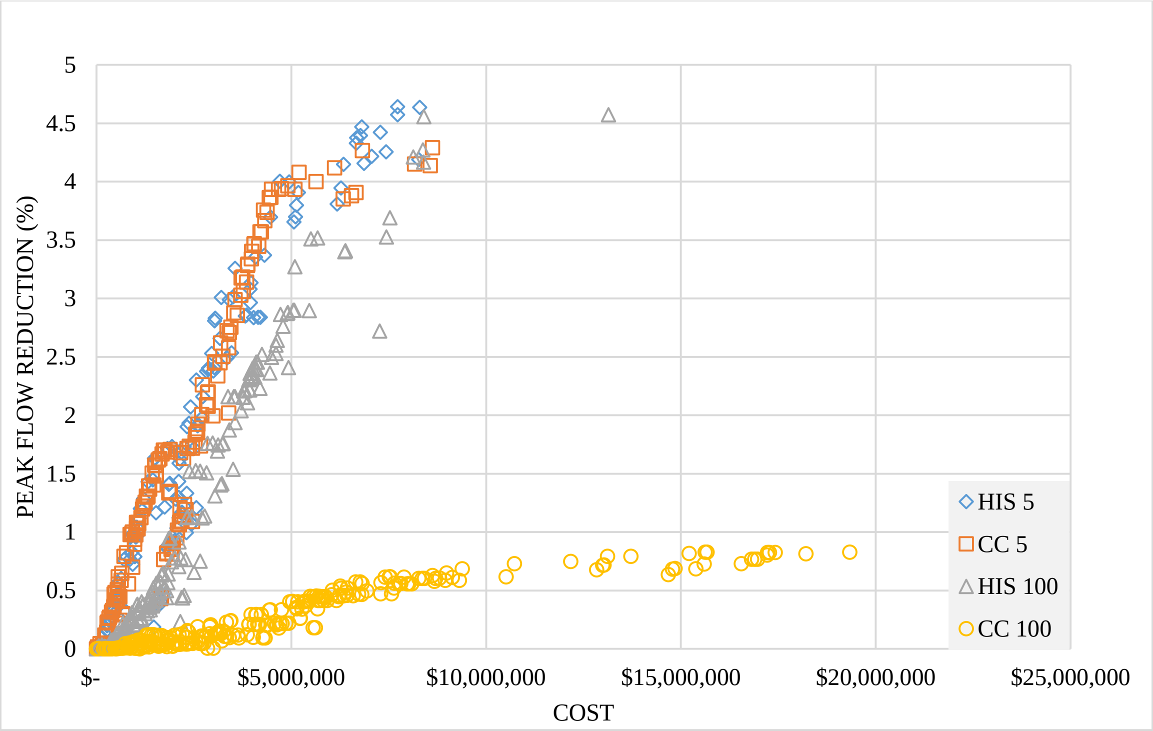

Figure 8-7 Peak flow reduction percentage for high adoption scenario

Figure 8-8 Total runoff reduction percentage for high adoption scenario

8.3.2 Non-Dominated Peak Flow and Cost

The high adoption scenario produced patterns that are similar to the low adoption scenario for the non-dominated peak flow solutions. The LID scenarios performed best under the historic and climate change 5-year storm events and performance decreased with the larger events. The climate change 100-year storm received the least benefit from LIDs in limiting peak flow rates. Relaxing the LID adoption constraints in this scenario allows for greater implementation of the most efficient controls, such as infiltration trenches. This can help explain why there is an improvement in the peak flow reductions for all the storm events when compared against the low adoption scenario. Figure 8-9 demonstrates the improved peak flow reduction in the high adoption scenario with points of diminishing returns being much greater (between four and six times) than seen in the low adoption scenario.

Figure 8-9 High adoption solutions non-dominated in peak flow and cost

8.3.3 Non-Dominated Total Runoff and Cost

The non-dominated solutions in total runoff reduction and cost for the high adoption scenario are again similar to the patterns seen in the low adoption scenario with a steady increase in reduction for all four storm events. Again, it can be seen from Figure 8-10 that the runoff reduction solutions do not demonstrate a very clear point of diminishing returns as the LID controls' capability to reduce runoff does not drop off as storm intensity increases as it does in the peak flow reduction solutions. Another similarity to the low adoption scenario is the closeness of the series of solutions for each storm, except now in the high adoption scenario the reduction volumes are much higher.

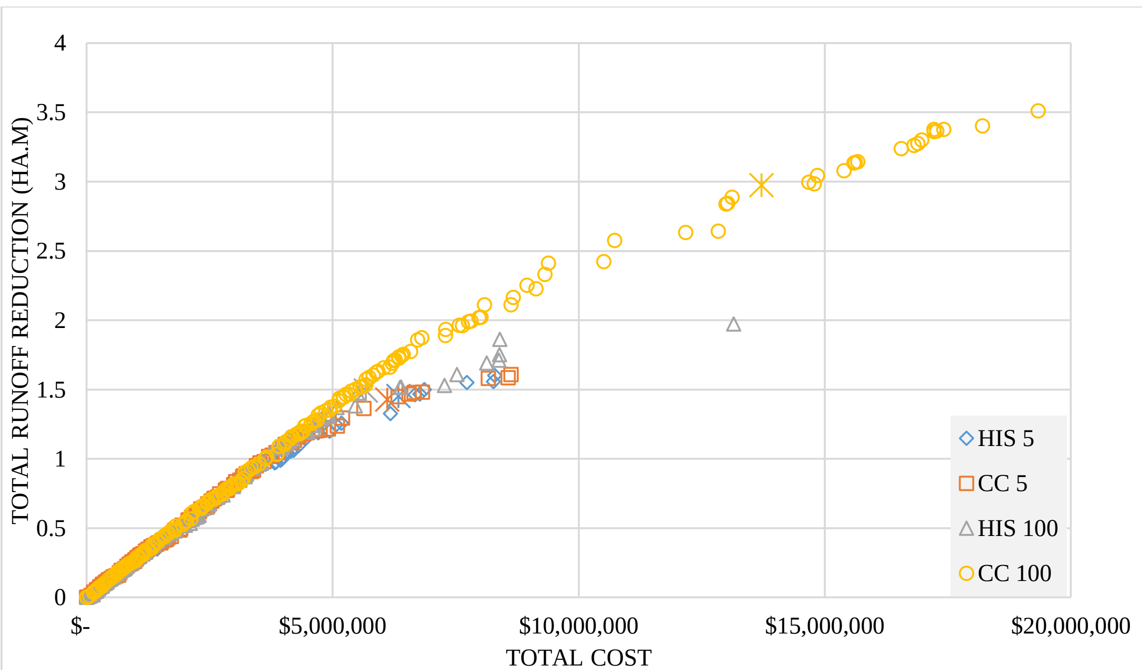

Figure 8-10 High adoption solutions non-dominated in total runoff and cost

8.4 Scenario Comparison

The previous sections show comparisons for each storm event for a given adoption scenario, however comparing the two adoption scenarios against one another allow for some more important observations to be made. The maximum reductions for each scenario and the associated costs are summarized in Table 8-1. The historical 100-year storm results for both adoption scenarios were compared. Figure 8-11 shows the solutions that are non-dominated in peak flow and cost minimization while Figure 8-12 shows the solutions that are non-dominated total runoff and cost minimization. The cost effectiveness, or reduction achieved per investment, is similar between the two scenarios for the low cost solutions. It is clear, however, that the amount of reduction in the peak flow and total runoff achieved in the high adoption scenario is much greater as the additional LID controls being implemented are able to contribute much more runoff retention. It should be noted that both these cases are for retrofitting the current conditions of the study area. If new development was to take place it would be much easier to implement LID controls during construction and improve the reduction capacity. For example, during the planning of a new development infiltration trenches and bioretention units, two of the most prominent LID types found in the solutions, can be incorporated into the design and included on shared green spaces which eliminates the need for homeowners to have to individually adopt these controls.

Table 8-1 Max reductions achieved for each scenario

	Peak Flow Reduction (m^3/s)	Peak Flow Reduction (%)	Total Runoff Reduction (ha.m)	Total Runoff Reduction (%)	Cost (average peak flow and runoff solutions)
Low Adoption Scenario					
His 5 year	0.16	1.12	0.46	2.15	$ 2,030,222
CC 5 year	0.15	1.01	0.46	2.03	$ 1,872,606
His 100 year	0.14	0.86	0.68	2.27	$ 3,874,903
CC 100 year	0.03	0.17	1.00	2.17	$ 4,913,997
High Adoption Scenario					
His 5 year	0.65	4.64	1.60	7.51	$ 8,011,859
CC 5 year	0.61	4.29	1.61	7.17	$ 8,626,029
His 100 year	0.75	4.57	1.97	6.56	$ 13,145,518
CC 100 year	0.15	0.83	3.51	7.61	$ 17,503,571

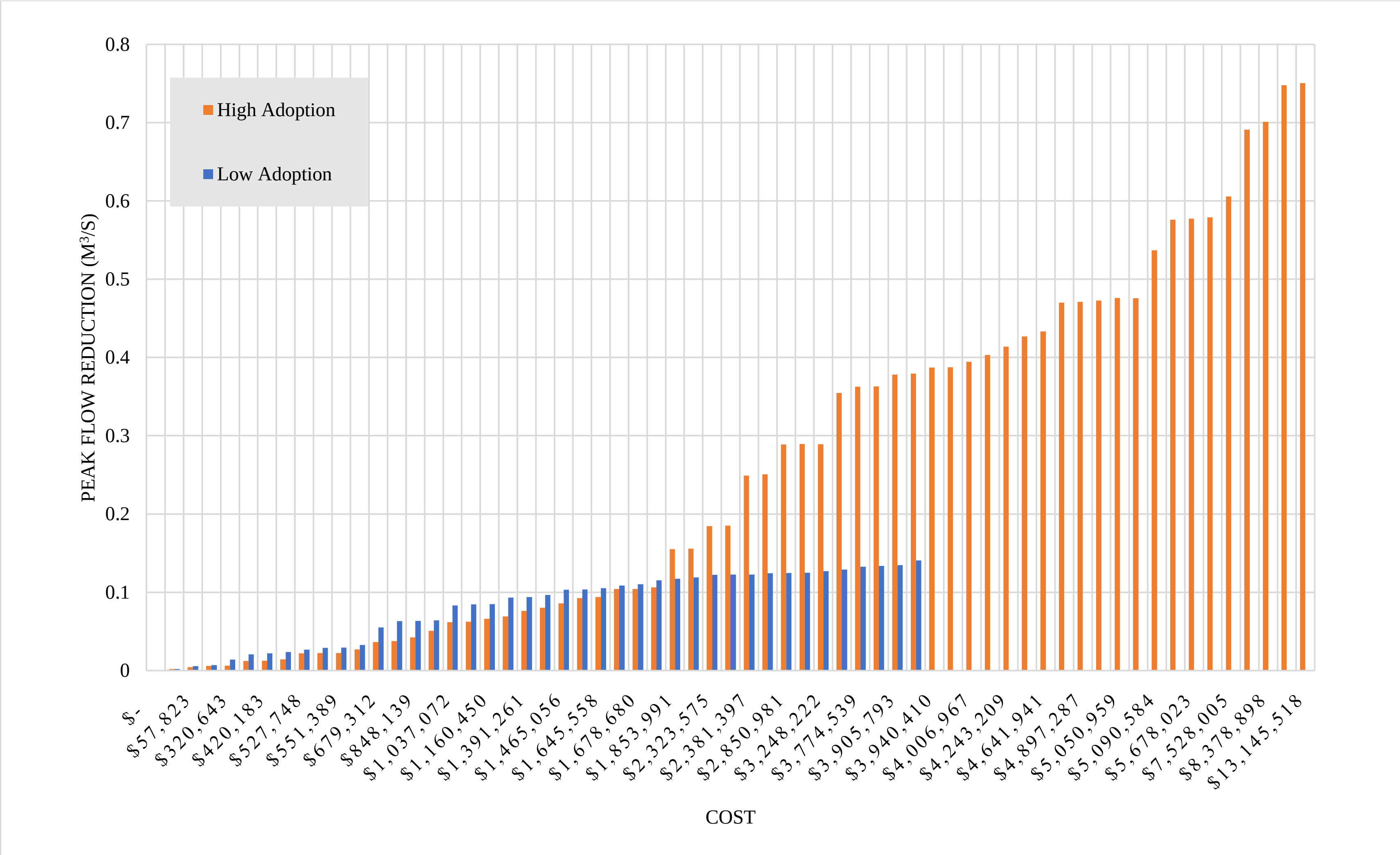

Figure 8-11 Comparison of LID costs for solutions non-dominated in peak flow reduction and cost

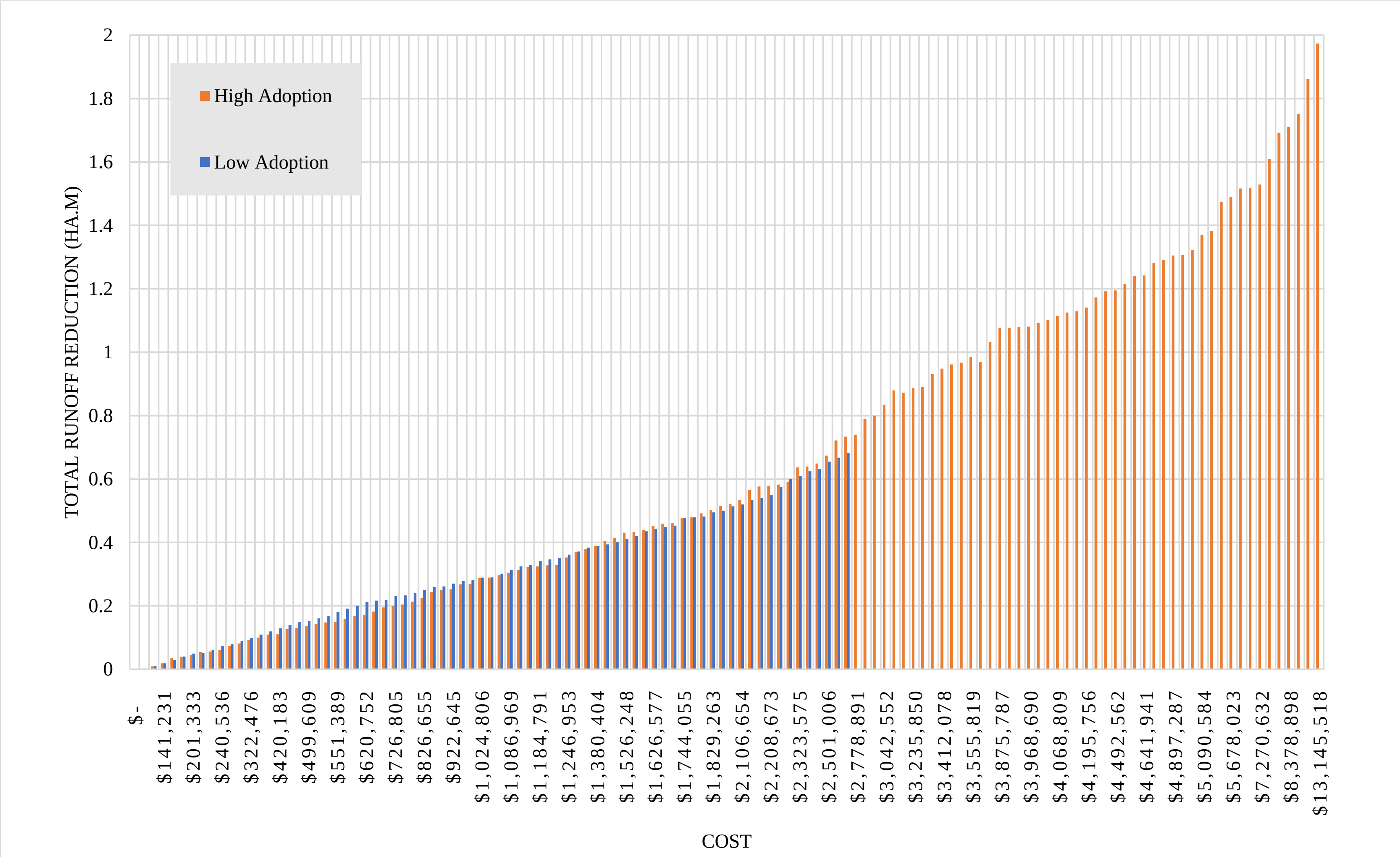

Figure 8-12 Comparison of LID costs for solutions non-dominated in total runoff reduction and cost

8.5 Scenario Costing

The most cost effective solutions for each scenario are compared in this section. The comparison of solutions demonstrates the distribution of investment into LID types for different rainfall events. The cost effective solutions were chosen from the data sets and highlighted on Figures 8-4 and 8-5 for the low adoption scenario and on Figures 8-9 and 8-10 for the high adoption scenario. These solutions are considered cost effective only compared against other LID scenarios, no non-LID stormwater control measures were considered in this study. The number of controls for each LID type, size of infiltration trenches and bioretention units, and the performance of each solution can be found in Appendix F.

8.5.1 Cost Effective Solutions for Peak Flow Reduction

The cost effective solutions chosen from the non-dominated peak flow data sets are shown in this section. The most cost effective solution for each rainfall event was chosen and further analyzed to show the cost breakdown of the solutions and how the size of the precipitation event affected the investment.

8.5.1.1 Low LID Adoption

Figure 8-13 compares the investment in each LID type for the cost effective peak flow solution for each storm event. It can be seen that infiltration trenches are the most prominent LID type with rain barrels being the only other LID type included in solutions but in a much lesser extent. The increase in total cost is essentially due to larger infiltration trench areas between solutions and the cost for these solutions is almost entirely from infiltration trench costs. The largest infiltration trench areas were found in the solution for the historic 100-year storm with a total area of 0.119 ha throughout the study area. Cost breakdown of solutions for each storm are shown in Figure 8-14. This figure further emphasizes the observations seen in Figure 8-13 but more clearly shows the investment in each LID type under each storm event.

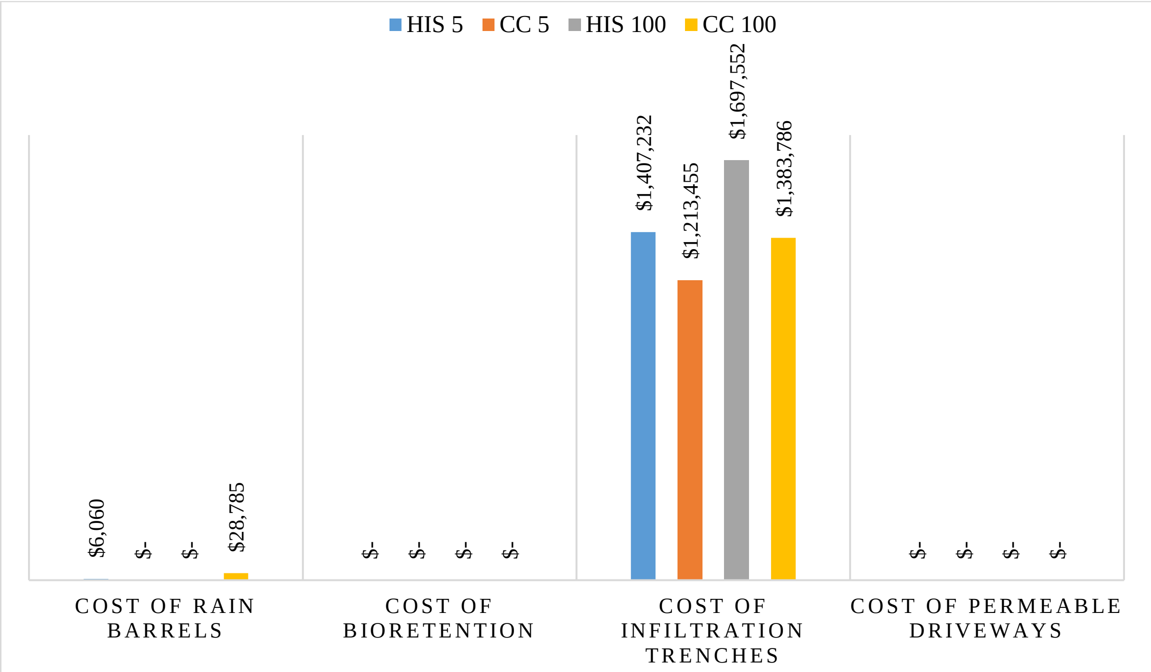

Figure 8-13 LID investment in the low adoption scenario for cost effective peak flow solutions

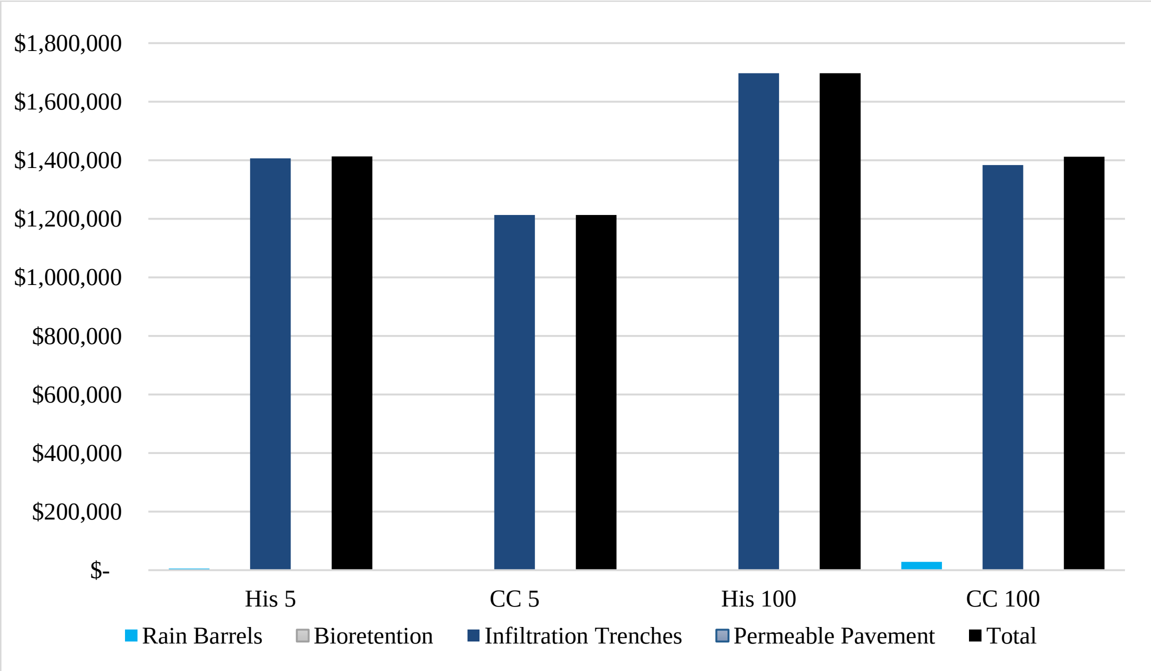

Figure 8-14 LID cost breakdown for low adoption, peak flow solutions for each storm event

8.5.1.2 High LID Adoption

The most cost effective solutions for peak flow reduction in the high adoption scenario have similar patterns to that of the low adoption scenario. Infiltration trenches are again the dominant LID type as shown in Figure 8-15, with rain barrels only being present in the 100-year climate change storm solution. Increasing costs are again attributed to larger infiltration trench areas, and/or an increased number of units. As expected, solutions in the high adoption scenario have a much higher cost than the low adoption solutions.

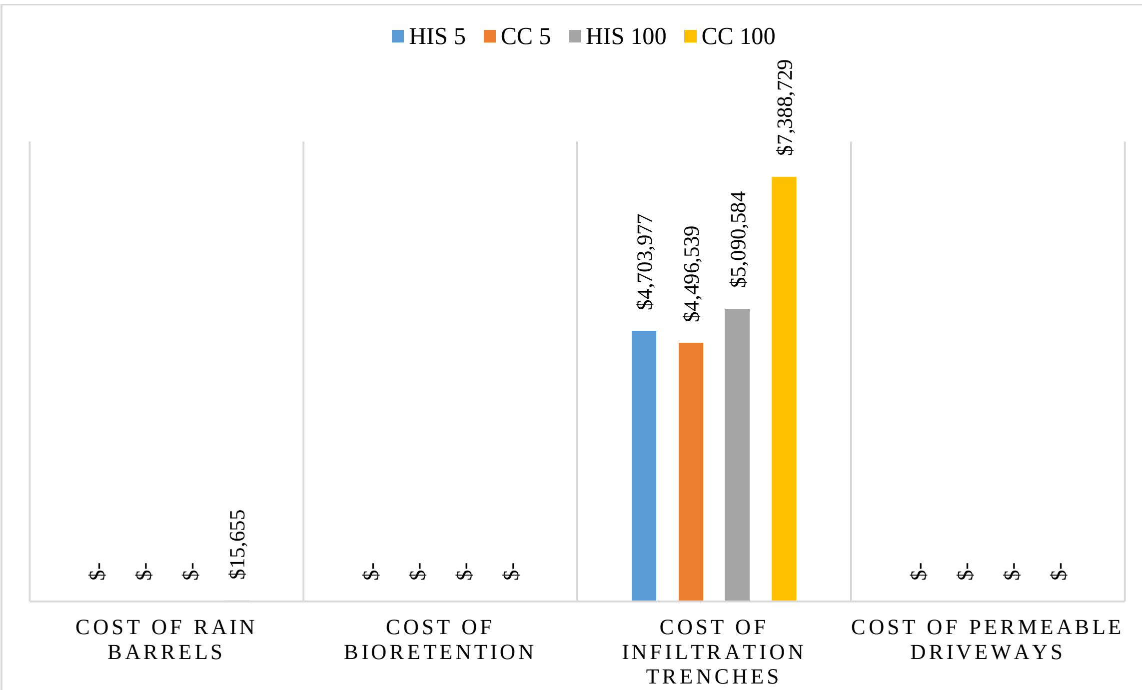

Figure 8-15 LID investment in the high adoption scenario for cost effective peak flow solutions

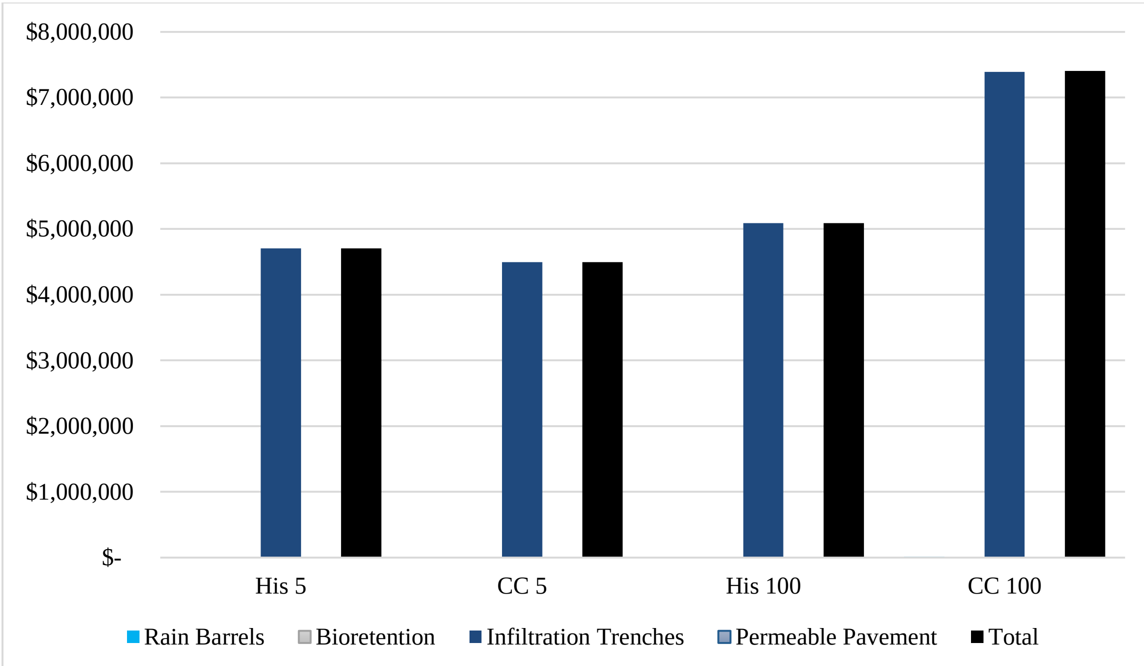

Figure 8-16 LID cost breakdown for high adoption, peak flow solutions for each storm event

8.5.2 Cost Effective Solutions for Total Runoff Reduction

8.5.2.1 Low LID Adoption

The cost effective solutions chosen from the total runoff non-dominated dataset have more variation to the LID controls implemented compared to the solutions non-dominated in peak flow, however, infiltration trenches remain the most prominent LID type selected. Figure 8-17 shows rain barrels and bioretention units also present in solutions. Bioretention units are an effective means to reduce runoff because they provide a larger infiltration rate than the other LID controls. Again infiltration trench area increases with increasing storm intensities and are the main reason for the increases in total cost.

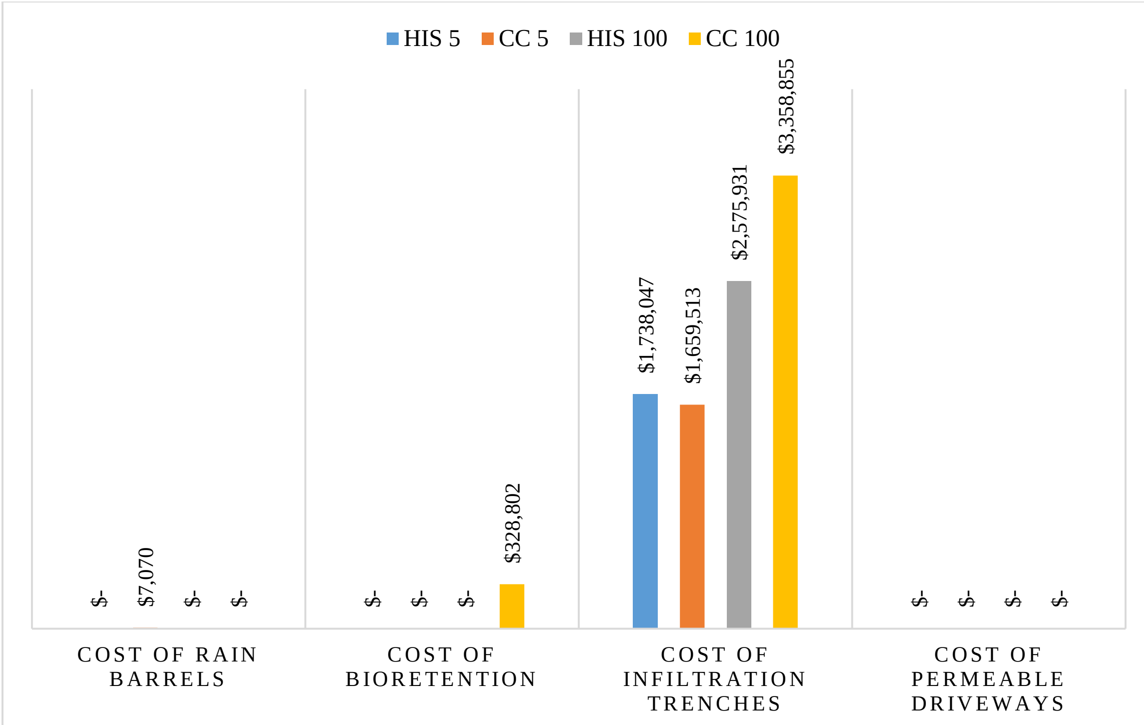

Figure 8-17 LID investment in the low adoption scenario for cost effective runoff solutions

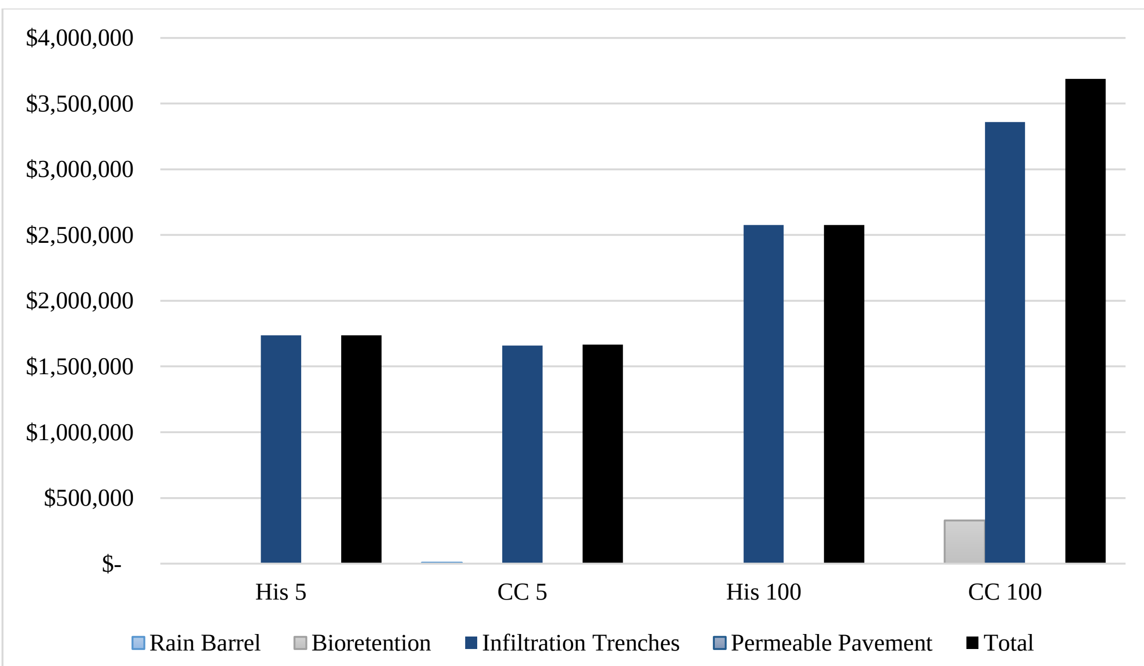

Figure 8-18 LID cost breakdown for low adoption, runoff solutions for each storm event

8.5.2.2 High LID Adoption

The high LID adoption scenario solutions non-dominated for runoff reduction have the most LID types selected with the cost effective solution for the 100-year climate change storm contains all four LID type. The historic 5 year cost effective solution here is the only cost effective solution chosen where bioretention investment exceeds that of infiltration trenches, however overall infiltration trenches are still the most common LID control despite not being selected for subcatchment group 1 for the climate change 5-year and historic 100-year storm events. The areas of bioretention units selected in both the historic 5-year and climate change 100-year storm events are in the higher range allowed with the maximum allowable size ($28m^2$) being selected for subcatchment group 1 for the historic 5-year storm and for subcatchment groups 2 and 3 for the 100-year climate change storm.

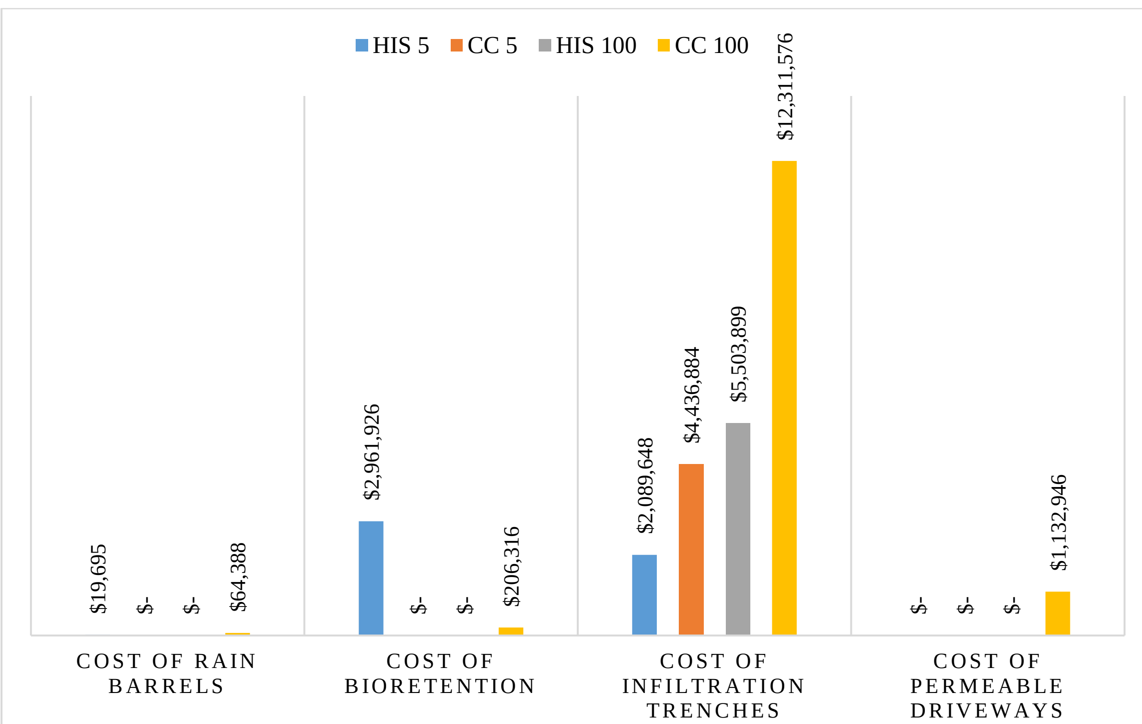

Figure 8-19 LID investment in the high adoption scenario for cost effective runoff solutions

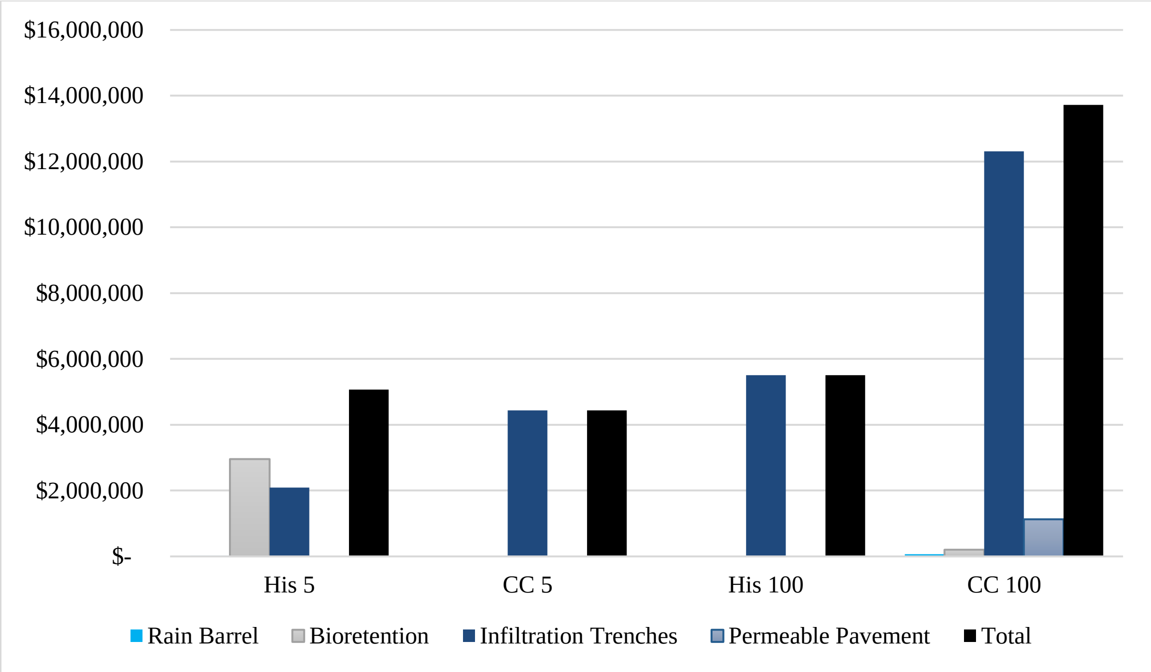

Figure 8-20 LID cost breakdown for high adoption, runoff solutions for each storm event

8.6 LID Implementation in Subcatchment Groups

As discussed in Chapter 6, all 1125 subcatchments were separated into five groups based on flooding potential and the probability of continued LID maintenance. This was done to prioritize where LID should be placed during the optimization-simulation tests to ensure the most benefit from LID controls. This section summarizes how investment in LID controls was divided between the groups. The investment into each individual LID type for each group can be found in Appendix F.

8.6.1 Non-dominated Peak Flow Solutions

The average total investment for all LID types for the solutions that are non-dominated in peak flow and cost minimization are summarized in Table 8-2. Total LID investment clearly increases with storm intensity. The largest investment was in Group 3 as this group is substantially larger than the other groups and thus presents the most opportunity for LID adoption. Group 3 is also in the middle for prioritization and thus would see substantial benefit from LID controls as well as would be likely to receive some LID maintenance by homeowners. Group 4 is the second largest group and the second highest rank for LID placement for this reason it is consistently the group with the second highest investment for reducing peak flow. Group 1 and 2 are often the lowest invested areas as these are the groups that were ranked the lowest for LID placement based on the procedure outlined in Chapter 6. Group 5 is the group deemed to be the best for LID placement as it has high risk of flooding and also has a high probability of LID maintenance. This is why Group 5 often has the third highest investment despite containing the smallest number of subcatchments and houses of all the groups. Figure 8-21 is helpful in easily displaying the division of investment to the groups in the optimal LID solutions for peak flow reduction. The numbers in the legend in Figure 8-21 correspond with the subcatchment group 1 through 5.

Table 8-2 Average total LID investment in each group for peak flow solutions

		Peak Flow Solutions				
		Group 1	Group 2	Group 3	Group 4	Group 5
Low Adoption	HIS 5	$ 11,312	$ 104,469	$ 663,498	$ 262,034	$ 171,950
	CC 5	$ 8,080	$ 43,575	$ 530,362	$ 220,215	$ 164,455
	HIS 100	$ 21,300	$ 242,718	$ 830,922	$ 390,229	$ 146,918
	CC 100	$ 380,423	$ 129,000	$ 927,912	$ 523,710	$ 255,870
High Adoption	HIS 5	$ 111,315	$ 773,642	$ 1,891,845	$ 835,253	$ 395,933
	CC 5	$ 337,388	$ 20,371	$ 2,210,409	$ 847,956	$ 412,860
	HIS 100	$ 92,903	$ 432,557	$ 2,874,851	$ 1,323,279	$ 390,490
	CC 100	$ 823,884	$ 1,251,326	$ 4,181,016	$ 1,803,235	$ 392,185

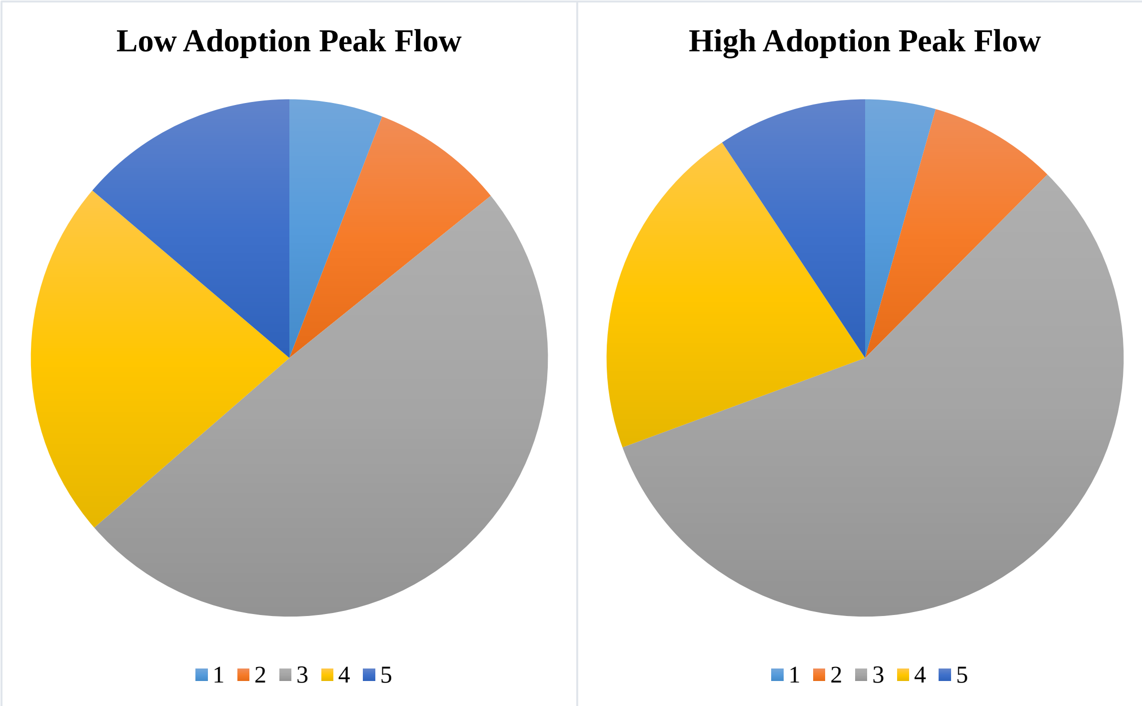

Figure 8-21 Total LID investment by percent for solutions non-dominated in peak flow reduction

8.6.2 Non-dominated Total Runoff Solutions

The average total investment for each subcatchment group for the solutions non-dominated in runoff reduction and cost minimization are summarized in Table 8-3 and Figure 8-22. These results follow similar trends as the solutions non-dominated in peak flow in that total investment increases with storm intensity and that groups 3 and 4 receive the most investment. Group 5 again commonly sees the third highest investment despite being the smallest group, these results support the LID ranking procedure. Comparing Figure 8-22 to Figure 8-21 shows that the percentage of investment in Groups 1 and 2 is less for runoff reduction solutions. This is likely due to permeable pavement becoming more common in some of the solutions and it being more widely implemented into the more beneficial areas of the sewershed. There is also an increase in the implementation of bioretention units in groups 4 and 5 for the runoff reduction solutions. This increase in permeable pavement and bioretention brings with it increased costs to groups 4 and 5 and thus taking some investment away from groups 1 and 2. Similar to Figure 8-21, the numbers in the legend on Figure 8-22 correspond to each subcatchment group.

Table 8-3 Average total LID investment in each group for total runoff solutions

		Runoff Solutions				
		Group 1	Group 2	Group 3	Group 4	Group 5
Low Adoption	HIS 5	$ 9,595	$ 87,378	$ 639,919	$ 276,940	$ 170,037
	CC 5	$ 50,891	$ 65,095	$ 602,232	$ 221,038	$ 169,605
	HIS 100	$ 40,294	$ 152,333	$ 916,605	$ 382,261	$ 211,857
	CC 100	$ 327,569	$ 62,977	$ 1,006,855	$ 592,870	$ 321,449
High Adoption	HIS 5	$ 228,869	$ 500,141	$ 2,283,878	$ 736,399	$ 322,030
	CC 5	$ 645,708	$ 155,213	$ 2,278,555	$ 897,320	$ 360,678
	HIS 100	$ 60,822	$ 309,380	$ 2,574,115	$ 1,004,814	$ 363,453
	CC 100	$ 521,705	$ 989,959	$ 5,109,609	$ 1,363,420	$ 622,453

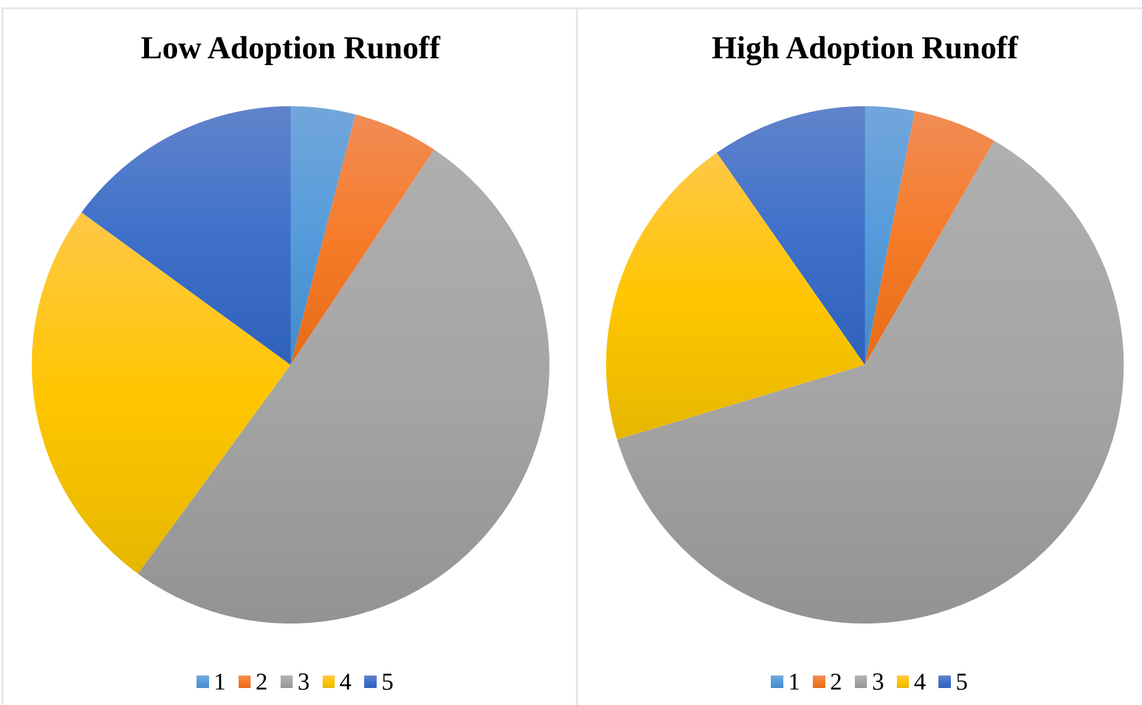

Figure 8-22 Total LID investment by percent for solutions non-dominated in total runoff reduction

8.7 Windsor Flooding Events

The cost effective solutions evaluated above were tested against the two most recent major flooding events in Windsor, Ontario from September of 2016 and August of 2017. The 2016 and 2017 storms exceed but are most closely related to a 100-year historical design storm and thus the most cost effective solutions found for these storms were implemented in the model to determine the impact they could have had on the flooding in the study area. The most cost effective solutions non-dominated in peak flow and non-dominated in total runoff for the historic 100-year storm event for both the low adoption and high adoption cases were evaluated and the most common LID characteristics from the two solutions were used to develop the LID implementation scenario tested for the 2016 and 2017 flooding events.

The results for these tests show similar performance under both storms. The hydrographs shown in Figures 8-23 and 8-25 demonstrate that the LID solutions did not substantially reduce the peak flows in the sewer system, consistent with the results shown in Sections 8.2 and 8.3 where peak flow reduction decreased drastically as storm intensity increased into the larger 100-year climate change storm. The high adoption solution performed, as expected, better than the low adoption case and was able to not only reduce peak flows but slightly delay them as well, which is beneficial in flooding events to retain and reduce the sewer flow as much as possible. Where the LID scenarios were more beneficial in these large storms was runoff reduction. Again, similar to the results shown in Sections 8.2 and 8.3, Figures 8-24 and 8-26 show how the cost effective solutions were able to contribute to total runoff reduction in the study area. The high adoption case was able to improve infiltration by about 3% across the study area which for both storms results to over 400 mm of retained runoff being infiltrated and kept out of the sewer system. The results for the two major flooding events encourage the consideration for LID as the solutions developed were able to help control some runoff, even with generalized LID designs across the study area. More specific LID designs for subcatchments could improve the performance of these solutions, this is further discussed in Section 8.8.

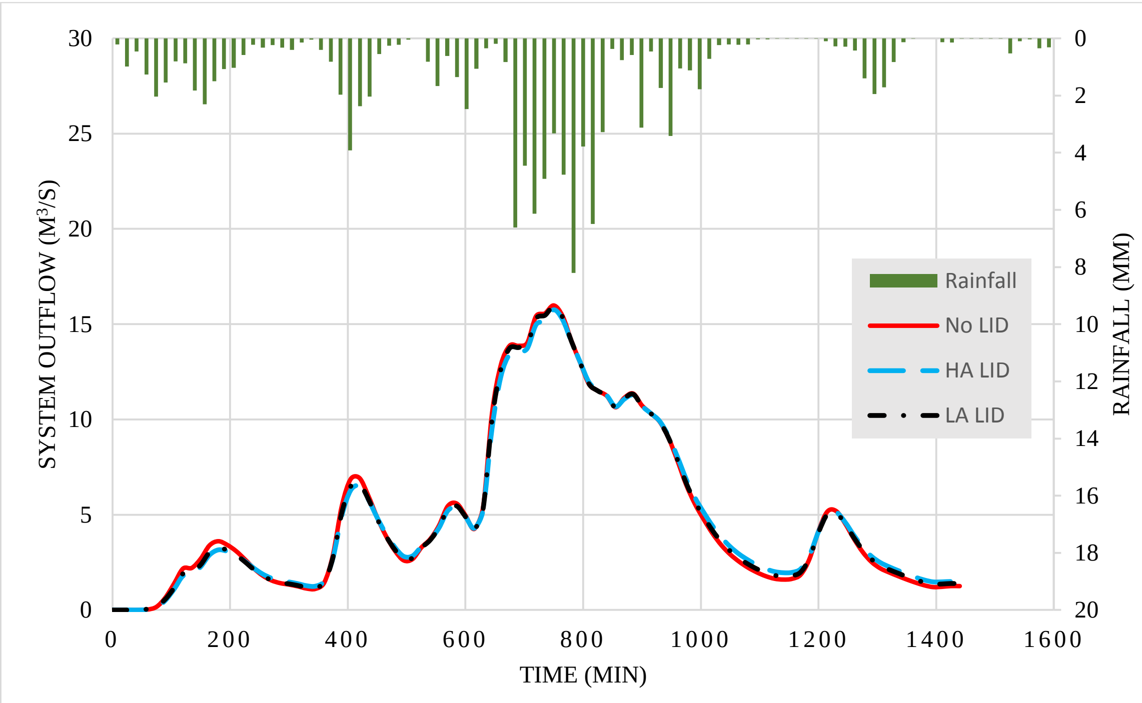

Figure 8-23 Hydrographs of peak flow reduction for cost effective solutions tested for the September 2016 storm event

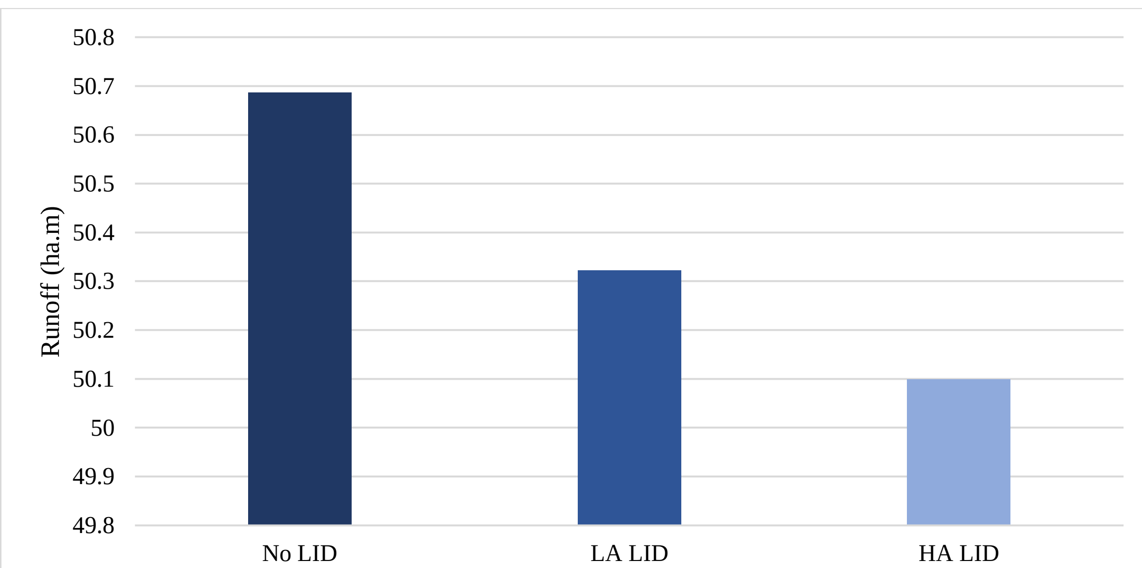

Figure 8-24 Total runoff for each scenario tested for the September 2016 storm

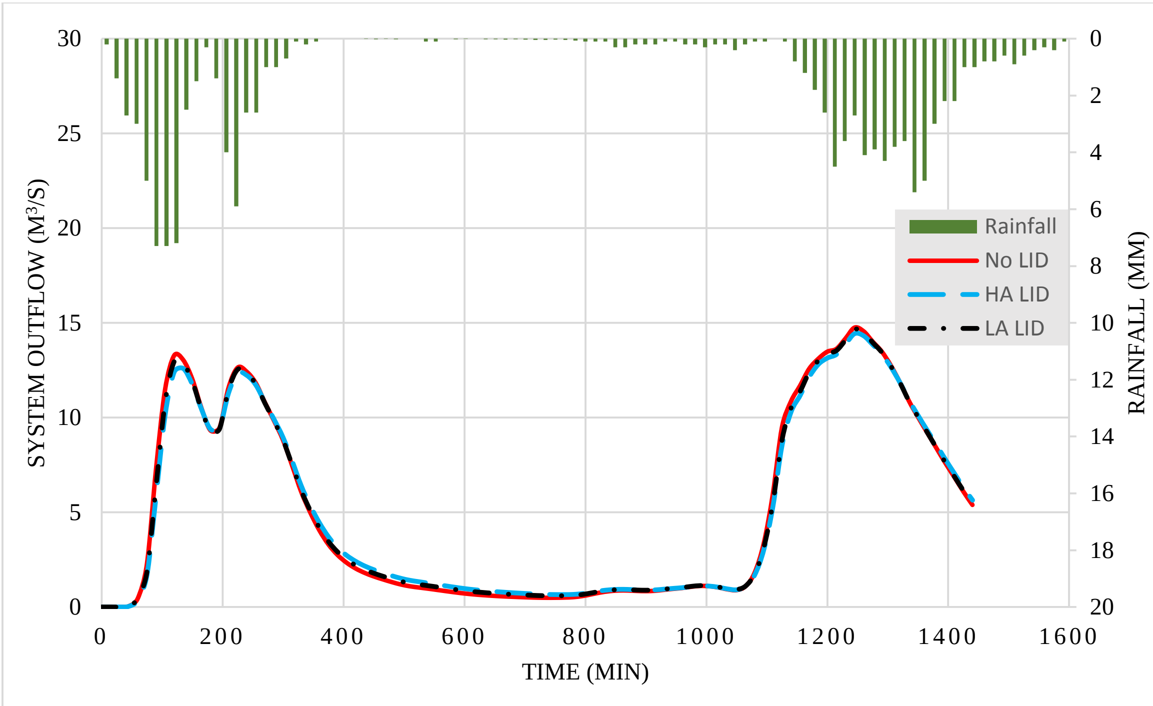

Figure 8-25 Hydrographs of peak flow reduction for cost effective solutions tested for the August 2017storm event

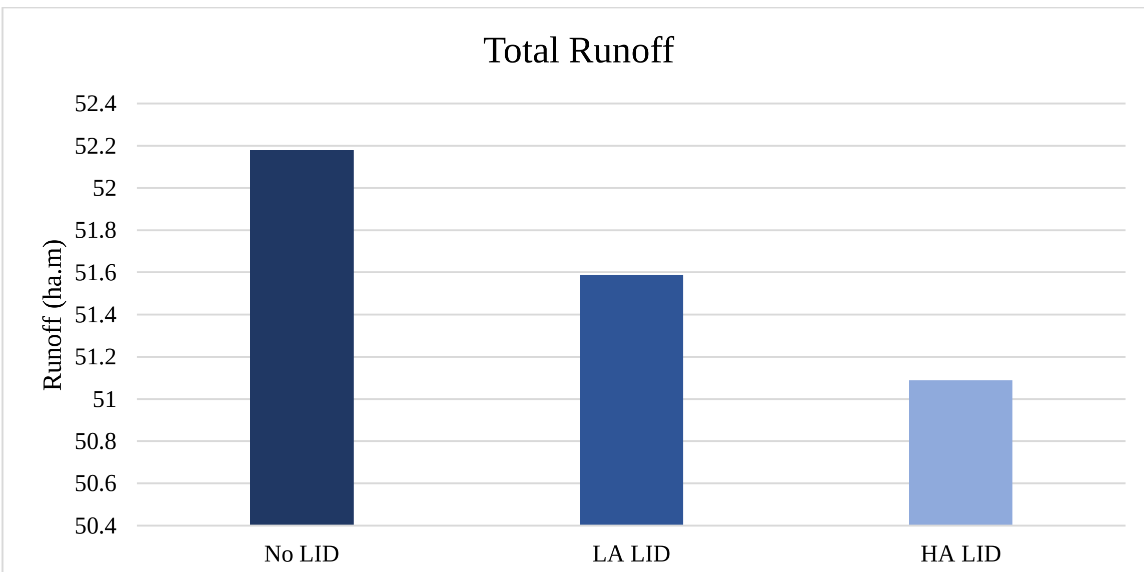

Figure 8-26 Total runoff for each scenario tested for the August 2017 storm

8.8 Limitations

There are some limitations that may impact the LID controls' performance in this study. For example, the LID designs are widely generalized for use in the optimization-simulation model but each subcatchment's size and properties vary throughout the study area and thus these generalized designs may cause certain LID controls to be designed too small for some areas causing poorer hydraulic performance whereas LIDs may be over-designed for other areas causing unnecessary increased costs. Another factor that could limit the performance of LIDs is the routing limitations in PCSWMM that does not allow LIDs to route to each other. One issue that was not considered in this study but could impact LID performance in real life is groundwater flow into LID controls, for example, if the LID control is implemented in an area with a high water table. An issue with the PCSWMM model that most likely had an impact on the hydrologic characteristics of the study area was a lack of available data for calibration. Due to this the model was not properly calibrated and some properties were dependent on a study area from another part of Windsor (Eckart et al., 2018), where data was available for calibration.

Chapter 9 Summary, Conclusions, and Recommendations

9.1 Summary

The motivation for this study was to determine where, or if, low impact development stormwater controls could provide the most benefit in an urban area by analyzing the flood risks and socioeconomic factors in that area. The second main part of this study was to take that information and develop an optimization-simulation model that could evaluate the ability of LID controls in managing the urban flood risk. A flood risk assessment of the study area was carried out to determine where the likelihood of flooding during storm events is the greatest. A socioeconomic analysis was carried out for the study area to determine the areas that would have the highest probability of supporting LID maintenance. Based on these two assessments the entire study area was divided into five groups that would then be optimized in the model to determine ideal LID placement scenarios. The model was created by coupling the Borg multiobjective evolutionary algorithm (MOEA) with a stormwater management model (SWMM 5). Borg is able to pass solutions to the SWMM model which analyzes them and returns the simulation outputs back to Borg. Borg then determines each solution's effectiveness. Solutions are comprised of decision variables that can be set as any parameter from the SWMM 5 input file. The decision variables were based on LID implementation in the model as this study focused on the evaluation of LID performance.

The PCSWMM model for this study represented a 536 ha. urban sewershed in Windsor, Ontario. The model contains 1125 subcatchments, 4321 homes and over 62,000 meters of stormsewer. Some of the study area characteristics, such as its poor underlying soil infiltration, would reduce the efficiency of LID controls. The optimization-simulation model evaluates LID effectiveness in the sewershed and can help determine their feasibility.

There were four low impact development controls that were determined to be the most suitable for optimization in the sewershed. These LID measures include rain barrels, infiltration trenches, bioretention units, and permeable pavement. The LIDs were evaluated as if they were implemented as retrofit solutions to the study area in its current condition and were assessed against eight different scenarios. There were two different implementation scenarios; a high LID adoption scenario and a low LID adoption scenario. These two scenarios represented typical household adoption rates for LIDs implemented as retrofit solutions that were found in past studies that surveyed urban areas similar to the one in question. For each of these implementation scenarios the LID controls' performance was tested for four different design storms. These storms represented 5-year and 100-year return period design storms based on historical climate data and future predicted climate change data.

There were 30 decision variables used in setting up the optimization problem. Twenty of the decision variables controlled how many of each LID type were implemented in each of the five subcatchment groups. The remaining ten decision variables represented the surface area of bioretention cells and infiltration trenches in each subcatchment group. The multiobjective problem was defined by three objectives: reduction of peak flow in the storm sewers, reduction of total runoff, and the minimization of LID costs. Each scenario above was run for 10,000 functional evaluations in order to determine the pareto optimal front.

The model results were able to provide some insights into the feasibility of LID in this study area. The solutions are made up of a value for each of the 30 decision variables, representing a specific LID implementation scenario. Most of the solutions varied in their ability to reduce peak flows and their ability to reduce runoff. It was found that some solutions may improve runoff reduction over other solutions but then have decreased peak flow reductions when compared with those same solutions. Overall, solutions were much better at reducing runoff than peak flows with maximum runoff reduction percentages being higher than peak flow reduction percentages for each of the scenarios looked at. Some solutions provided almost no peak flow reduction because some LID configurations actually allowed runoff to reach stormsewers faster through the LID controls and their underdrains than if it was to flow overland. This is due to the generalized LID designs throughout the study area and factors like subcatchment width that have influence on the surface travel time.

9.2 Conclusions

It was concluded that the performance of the LID measures studied would decrease with climate change as both the peak flow reduction percentages and total runoff reduction percentages decreased as the storm intensities increased. The decrease in reduction percentage was generally gradual for runoff reduction under both adoption levels, however, the decrease was drastic for peak flow reduction percentage for the 100-year climate change storm. The 100-year return period event due to climate change had the lowest peak flow reduction percentage and the lowest reduction quantity by a significant margin for both the high and low level adoption rates. Due to the intensity of that event being so much larger than the other storms tested it overwhelmed more LID controls and caused the phenomenon discussed earlier where water was reaching sewers faster by flowing through the LID controls.

It was apparent that LID implementation was most cost-effective when controls were placed in areas with high flood risk first. This was best demonstrated by Group 5, which has the highest risk of flooding, generally having the third highest investment in LID controls despite being much smaller than the other groups. The two groups that exceeded investment were not only much larger but also had the next highest flood risk. It was also evident that investment into larger infiltration trench and bioretention areas was necessary as storm intensity increased in order to improve reduction.

Overall, the sewershed characteristics played a critical role in limiting the performance of LID measures, however, the implementation of LID controls could still be considered beneficial. The maximum peak flow reductions were: 0.157 m^3/s for the low adoption scenario, and 0.751 m^3/s for the high adoption scenario. The maximum total runoff reductions were: 1.00 ha-m for the low adoption scenario and 3.51 ha-m for the high adoption scenario. In determining the most cost-effective means to manage urban flood risk all alternatives should be carefully looked at but LID is a tool that could contribute to reducing the load on the stormsewer system and extend the useful life of the sewers. The information gained from this modelling study can be beneficial in deciding if implementing LID controls is a viable option and, if so, the best implementation strategies for doing so as this methodology provides LID solutions that are cost-effective, high benefit, and have the highest probability to be adopted and maintained.

9.3 Recommendations

This study demonstrated the usefulness in identifying the areas that have the highest flood risk as well as the areas that have the highest likelihood of LID maintenance. The optimization framework could be valuable to decision makers and engineers for analyzing a wide range of solutions and identifying a portfolio of solutions to consider for actual design. It is recommended that LID should be considered as a possible option to reduce the flood risk in the study area. At the very least this study demonstrated that strategically placing LID measures in the sewershed can reduce the load on the stormsewer system. Ways to encourage adoption across the community should be looked into as increasing the amount of controls will only improve the performance of solutions. These solutions could also be analyzed in conjunction with other stormwater management methodologies to determine the most cost effective way to reduce the urban flood risk as climate change impacts continue to increase that risk. These solutions and the methodology developed could be considered a starting point to analyzing stormwater management approaches and their efficiency in different areas.

The framework used here allows for easy extension of the work. Additional objectives could be included into the optimization model to achieve more benefit from the LID measures. For example, water quality objectives could be added to assess the ability of LID controls to remove pollutants from stormwater. One way to extend this study and improve on its effectiveness would be to carry out a survey of the area to help better understand how the public actually responds to the idea of LID on their properties. Finally, studies should be done to assess the uncertainty in the data. It is important to understand the data uncertainty when dealing with large datasets, such as the ones achieved in this study.

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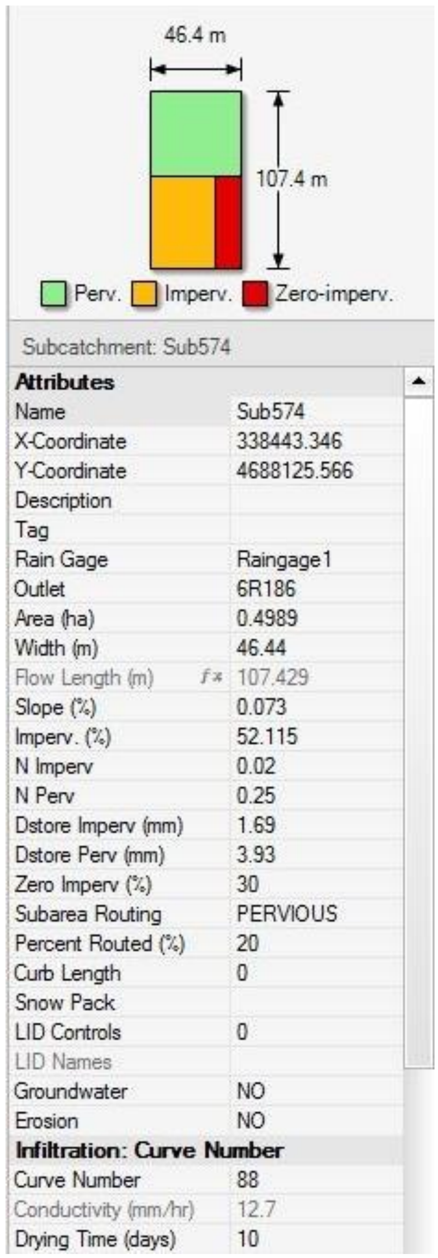
Appendix A: PCSWMM Parameters

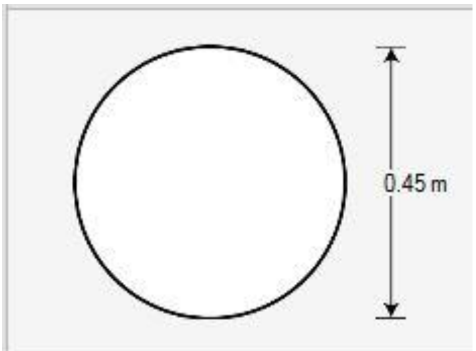
The parameters for implementing subcatchments, conduits, and nodes are provided here. Any additional parameters that are required for running the PCSWMM model are also included.

Subcatchment Parameters



Attributes	
Name	Sub574
X-Coordinate	338443.346
Y-Coordinate	4688125.566
Description	
Tag	
Rain Gage	Raingage1
Outlet	6R186
Area (ha)	0.4989
Width (m)	46.44
Flow Length (m)	107.429
Slope (%)	0.073
Imperv. (%)	52.115
N Imperv	0.02
N Perv	0.25
Dstore Imperv (mm)	1.69
Dstore Perv (mm)	3.93
Zero Imperv (%)	30
Subarea Routing	PERVIOUS
Percent Routed (%)	20
Curb Length	0
Snow Pack	
LID Controls	0
LID Names	
Groundwater	NO
Erosion	NO
Infiltration: Curve Number	
Curve Number	88
Conductivity (mm/hr)	12.7
Drying Time (days)	10

Conduit Parameters



Conduit: 20804

Attributes	
Name	20804
Inlet Node	6R204
Outlet Node	6R205
Description	AC
Tag	
Length (m)	190.4
Roughness	0.011
Inlet Elev. (m)	174.156
Outlet Elev. (m)	173.043
Initial Flow (m^3/s)	0
Flow Limit (m^3/s)	0
Entry Loss Coeff.	0.5
Exit Loss Coeff.	1
Avg. Loss Coeff.	0.1
Seepage Rate (mm/hr)	0
Flap Gate	NO
Cross-Section	CIRCULAR
Geom1 (m)	0.45
Geom2 (m)	0
Geom3	0
Geom4	0
Barrels	1
Transect	
Shape Curve	
Culvert Code	

Node Parameters

Junction: 6R206

Attributes	
Name	6R206
X-Coordinate	338772.59
Y-Coordinate	4688585
Description	6R206
Tag	
Inflows	NO
Treatment	NO
Invert Elev. (m)	173.138
Rim Elev. (m) *fx*	175.97
Depth (m)	2.832
Initial Depth (m)	0
Surcharge Depth (m)	0
Ponded Area (m²)	0
Inflows	
Baseline (m³/s)	0
Baseline Pattern	
Time Series	
Scale Factor	1
Average Value (m³/s)	0
Time Pattern 1	
Time Pattern 2	
Time Pattern 3	
Time Pattern 4	
Hydrograph	
Sewershed Area (ha)	0

Simulation Parameters

```
[OPTIONS]
;; Options           Value
;;------------------ ------------
FLOW_UNITS           CMS
INFILTRATION         CURVE_NUMBER
FLOW_ROUTING         DYNWAVE
START_DATE           09/29/2016
START_TIME           00:00:00
REPORT_START_DATE    09/29/2016
REPORT_START_TIME    00:00:00
END_DATE             09/30/2016
END_TIME             00:00:00
SWEEP_START          01/01
SWEEP_END            12/31
DRY_DAYS             5
REPORT_STEP          00:05:00
WET_STEP             00:00:45
DRY_STEP             00:02:00
ROUTING_STEP         10
ALLOW_PONDING        YES
INERTIAL_DAMPING     PARTIAL
VARIABLE_STEP        0.4
LENGTHENING_STEP     0
MIN_SURFAREA         1.14
NORMAL_FLOW_LIMITED BOTH
SKIP_STEADY_STATE    NO
FORCE_MAIN_EQUATION D-W
LINK_OFFSETS         ELEVATION
MIN_SLOPE            0
MAX_TRIALS           8
HEAD_TOLERANCE       0.0015
SYS_FLOW_TOL         5
LAT_FLOW_TOL         5
MINIMUM_STEP         0.5
THREADS              4
```

Appendix B: LID Sketches

Figures to assist with the LID designs laid out in Chapter 5 are included here. Other LID controls that were not included in this study but were considered during the design section and discussed in the literature review are also included in this appendix.

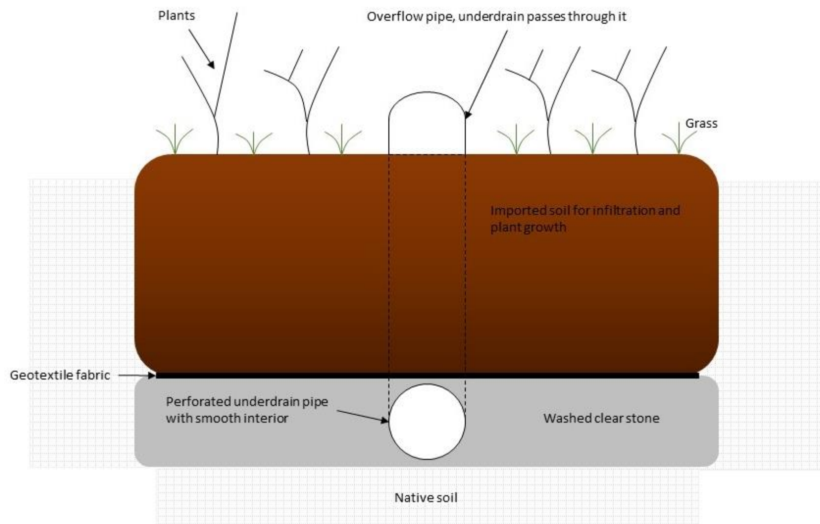


Figure B 1 Profile of a typical bioretention cell

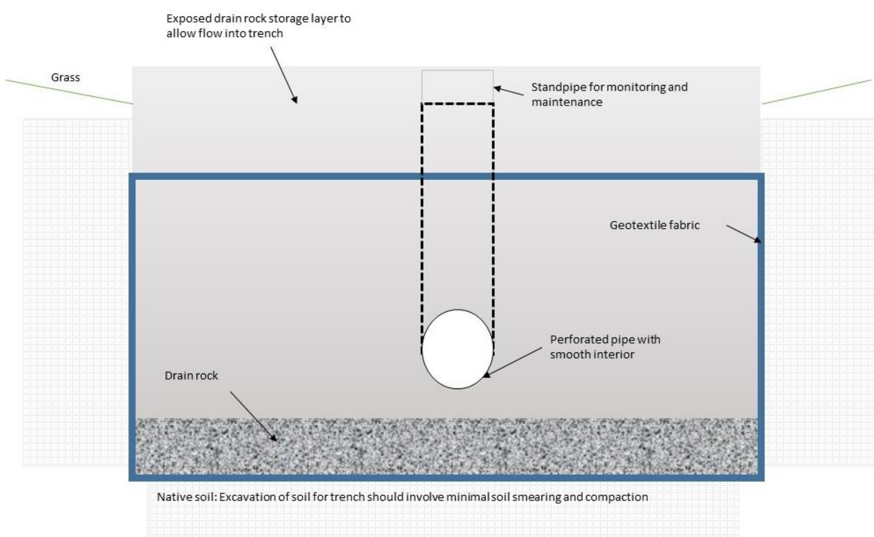


Figure B 2 Profile of a typical infiltration trench

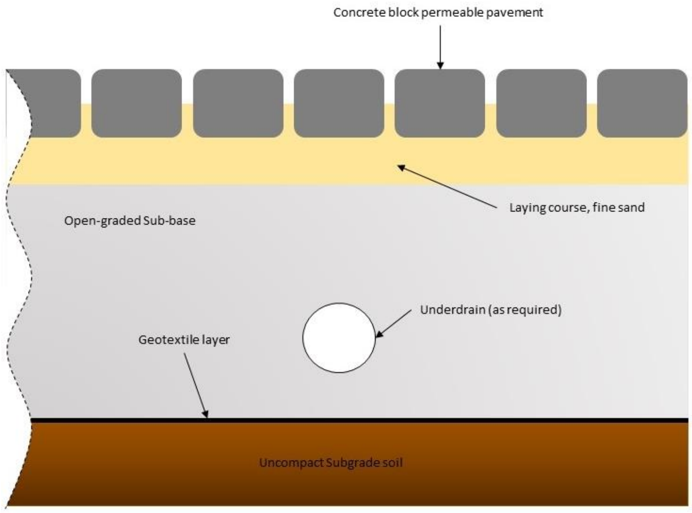


Figure B 3 Profile of a typical permeable pavement driveway

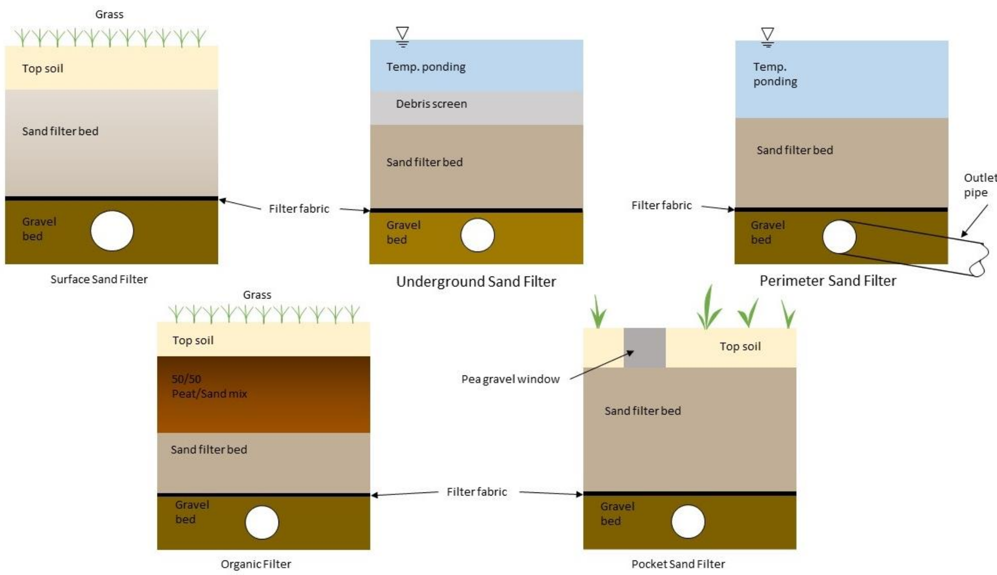


Figure B 4 Profile of various sand filters

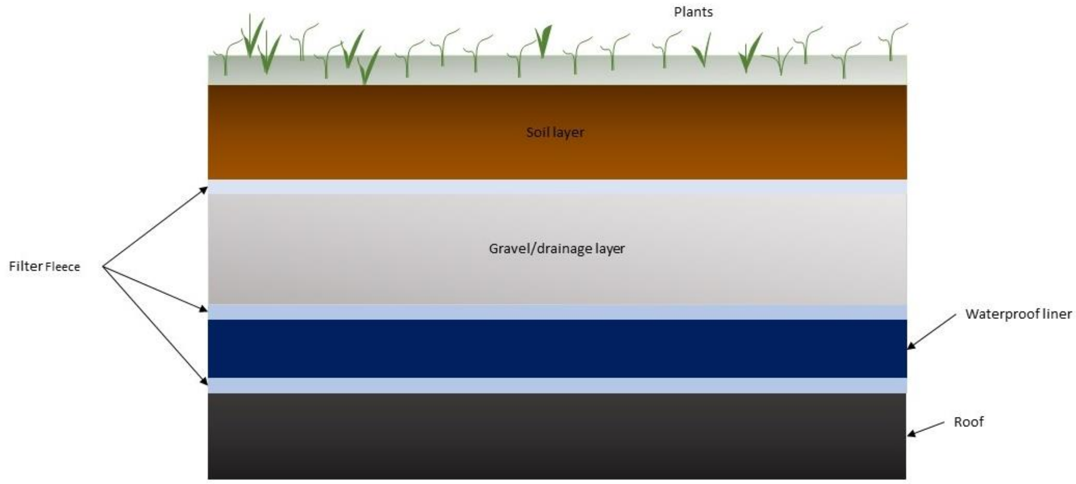


Figure B 5 Profile of a typical green roof

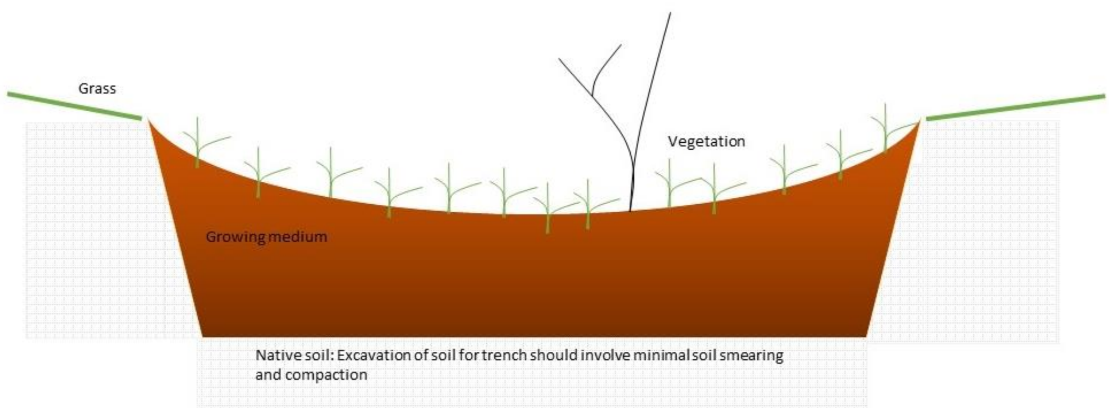


Figure B 6 Profile of a typical grassed swale

Appendix C: Optimization Problem Set Up

```
int nvars = 30;
int nobjs = 3;
void borg_fitness(double* vars, double* objs, double* constrs) {
        vars[0] = (int)floor(vars[0]) ;
        vars[1] = (int)floor(vars[1]) ;
        vars[2] = (int)floor(vars[2]) ;
        vars[3] = (int)floor(vars[3]) ;
        vars[4] = (int)floor(vars[4]) ;
        vars[5] = (int)floor(vars[5]) ;
        vars[6] = (int)floor(vars[6]) ;
        vars[7] = (int)floor(vars[7]) ;
        vars[8] = (int)floor(vars[8]) ;
        vars[9] = (int)floor(vars[9]) ;
        vars[10] = (int)floor(vars[10]) ;
        vars[11] = (int)floor(vars[11]) ;
        vars[12] = (int)floor(vars[12]) ;
        vars[13] = (int)floor(vars[13]) ;
        vars[14] = (int)floor(vars[14]) ;
        vars[15] = (int)floor(vars[15]) ;
        vars[16] = (int)floor(vars[16]) ;
        vars[17] = (int)floor(vars[17]) ;
        vars[18] = (int)floor(vars[18]) ;
        vars[19] = (int)floor(vars[19]) ;
        vars[20] = (int)floor(vars[20]) ;
        vars[21] = (int)floor(vars[21]) ;
        vars[22] = (int)floor(vars[22]) ;
        vars[23] = (int)floor(vars[23]) ;
        vars[24] = (int)floor(vars[24]) ;
        vars[25] = (int)floor(vars[25]) ;
        vars[26] = (int)floor(vars[26]) ;
        vars[27] = (int)floor(vars[27]) ;
        vars[28] = (int)floor(vars[28]) ;
        vars[29] = (int)floor(vars[29]) ;

swmm_fitness("W6_scenario2.inp",vars,output);
        objs[0] = output[0]; //peak flow
        objs[1] = output[1]; //total runoff
        //cost
    objs[2] = 216*(vars[0]*56 +vars[1]*49 + vars[2]*229 + vars[3]*68 + vars[4]*31)

        + 10394*(vars[10]*28 + vars[11]*24 + vars[12]*114 + vars[13]*34 +
    vars[14]*15)
```

```
                + (vars[5]*83)*(92*vars[20]*10 + 550 + 410*vars[20] +
        6*(2.3*vars[20]+2*vars[20]))
                + (vars[6]*91)*(92*vars[21]*10 + 550 + 410*vars[21] +
        6*(2.3*vars[21]+2*vars[21]))
                + (vars[7]*389)*(92*vars[22]*10 + 550 + 410*vars[22] +
        6*(2.3*vars[22]+2*vars[22]))
                + (vars[8]*118)*(92*vars[23]*10 + 550 + 410*vars[23] +
6*(2.3*vars[23]+2*vars[23]))
                + (vars[9]*44)*(92*vars[24]*10 + 550 + 410*vars[24] +
6*(2.3*vars[24]+2*vars[24]))
                + (vars[15]*56)*(40*vars[25]*(5*4/10) + 50 + 107*vars[25]*4*(0.7 +
(0.3*5/5)) + 1.5*vars[25]*4)
                + (vars[16]*49)*(40*vars[26]*(5*4/10) + 50 + 107*vars[26]*4*(0.7 +
(0.3*5/5)) + 1.5*vars[26]*4)
                + (vars[17]*229)*(40*vars[27]*(5*4/10) + 50 + 107*vars[27]*4*(0.7 +
(0.3*5/5)) + 1.5*vars[27]*4)
                + (vars[18]*68)*(40*vars[28]*(5*4/10) + 50 + 107*vars[28]*4*(0.7 +
(0.3*5/5)) + 1.5*vars[28]*4)
                + (vars[19]*31)*(40*vars[29]*(5*4/10) + 50 + 107*vars[29]*4*(0.7 +
(0.3*5/5)) + 1.5*vars[29]*4);


                    //constrs[0] = objs[0] >= 0.0?0.0:10;
                    //constrs[1] = objs[1] >= 0.0?0.0:10;

        }

problem = BORG_Problem_create(nvars, nobjs, 0, borg_fitness);


//The variables 0-2 & 6-11 will also be multiplied by the number of houses in each
subcatchmemnt before writing to the LID usage section.
        BORG_Problem_set_bounds(problem, 0, 0.0, 4.1);
        BORG_Problem_set_bounds(problem, 1, 0.0, 4.1);
        BORG_Problem_set_bounds(problem, 2, 0.0, 4.1);
        BORG_Problem_set_bounds(problem, 3, 0.0, 4.1);
        BORG_Problem_set_bounds(problem, 4, 0.0, 4.1);
        BORG_Problem_set_bounds(problem, 5, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 6, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 7, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 8, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 9, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 10, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 11, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 12, 0.0, 1.1);
        BORG_Problem_set_bounds(problem, 13, 0.0, 1.1);
```

```
            BORG_Problem_set_bounds(problem, 14, 0.0, 1.1);
            BORG_Problem_set_bounds(problem, 15, 0.0, 1.1);
            BORG_Problem_set_bounds(problem, 16, 0.0, 1.1);
            BORG_Problem_set_bounds(problem, 17, 0.0, 1.1);
            BORG_Problem_set_bounds(problem, 18, 0.0, 1.1);
            BORG_Problem_set_bounds(problem, 19, 0.0, 1.1);

            BORG_Problem_set_bounds(problem, 20, 2, 30.1); //x10
            BORG_Problem_set_bounds(problem, 21, 2, 30.1); //x10
            BORG_Problem_set_bounds(problem, 22, 2, 30.1); //x10
            BORG_Problem_set_bounds(problem, 23, 2, 30.1); //x10
            BORG_Problem_set_bounds(problem, 24, 2, 30.1); //x10
            BORG_Problem_set_bounds(problem, 25, 1, 7.1); //x4
            BORG_Problem_set_bounds(problem, 26, 1, 7.1); //x4
            BORG_Problem_set_bounds(problem, 27, 1, 7.1); //x4
            BORG_Problem_set_bounds(problem, 28, 1, 7.1); //x4
            BORG_Problem_set_bounds(problem, 29, 1, 7.1); //x4

BORG_Problem_set_epsilon(problem, 0, 0.01);
            BORG_Problem_set_epsilon(problem, 1, 0.01);
            BORG_Problem_set_epsilon(problem, 2, 1000);
            result = BORG_Algorithm_run(problem, 10000);
            BORG_Archive_print(result, stdout);
            BORG_Archive_destroy(result);
        BORG_Problem_destroy(problem);
```

Appendix D: IDF Curves

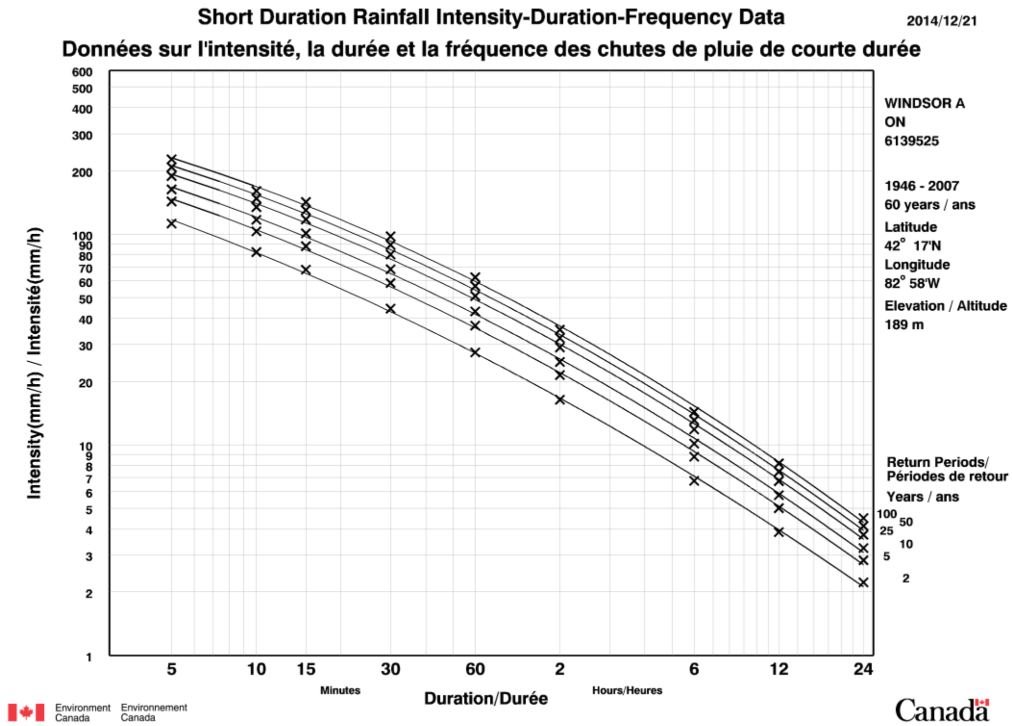


Figure H 1 IDF curves for Windsor Airport based on historical data

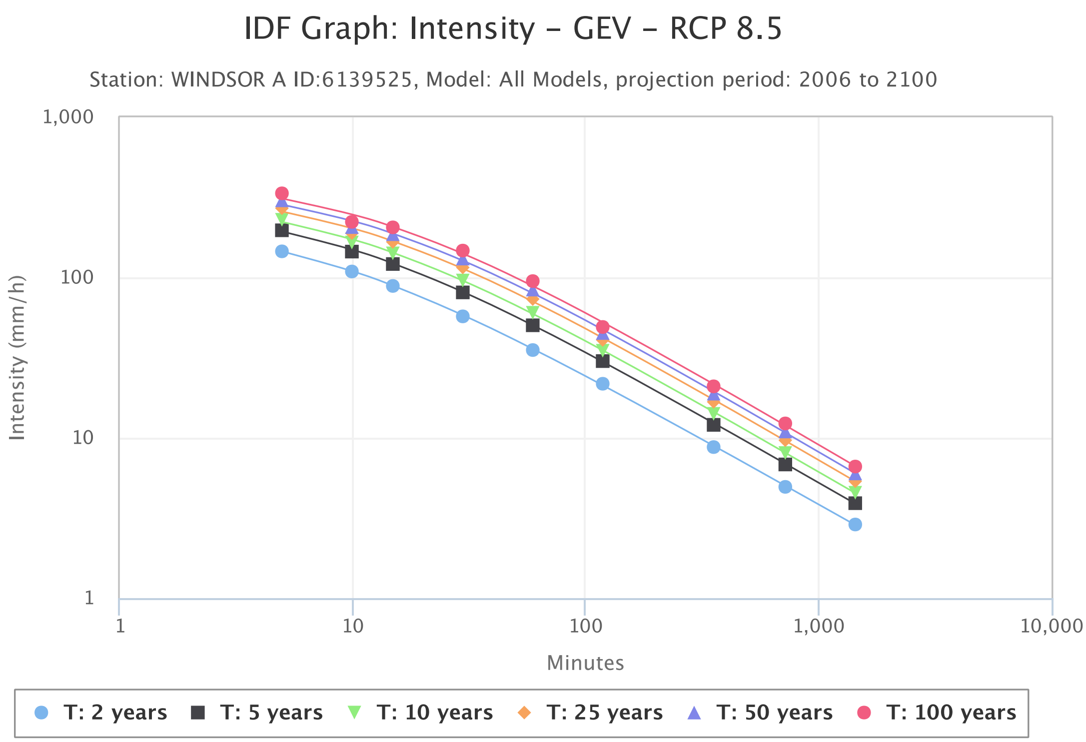


Figure H 2 Future predicted IDF curves for climate change for Windsor Airport

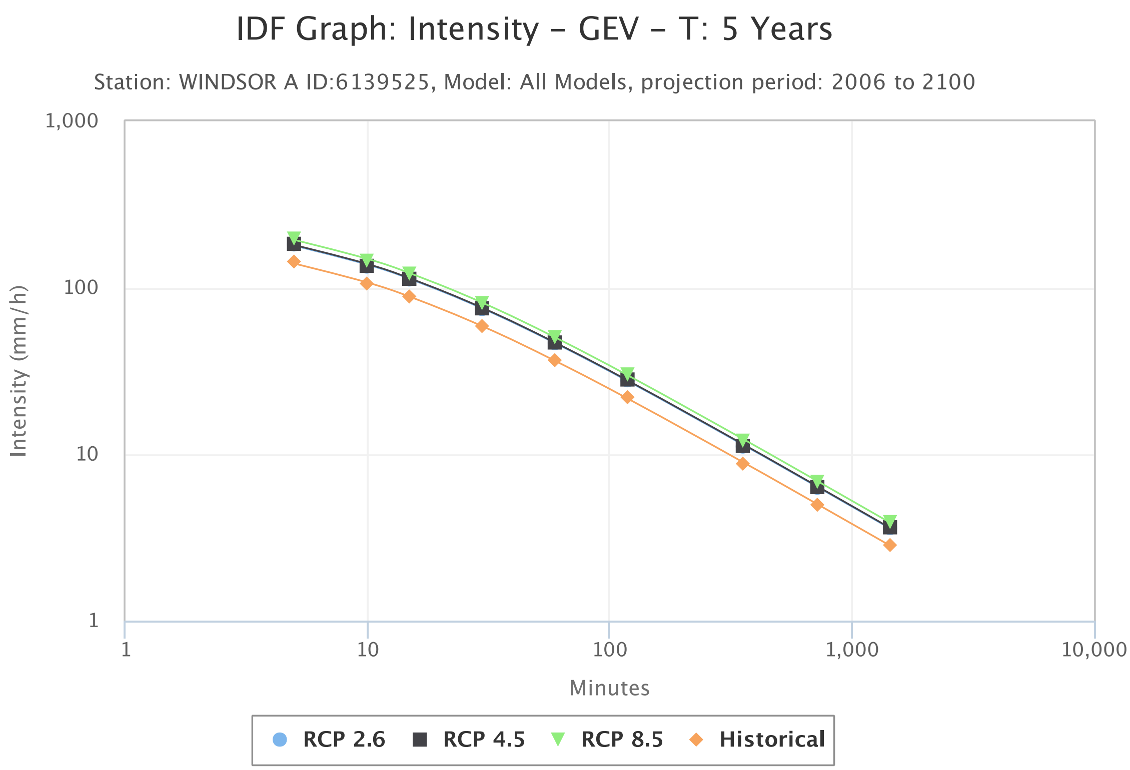


Figure H 3 Comparison of 5-year return period scenarios IDF curves

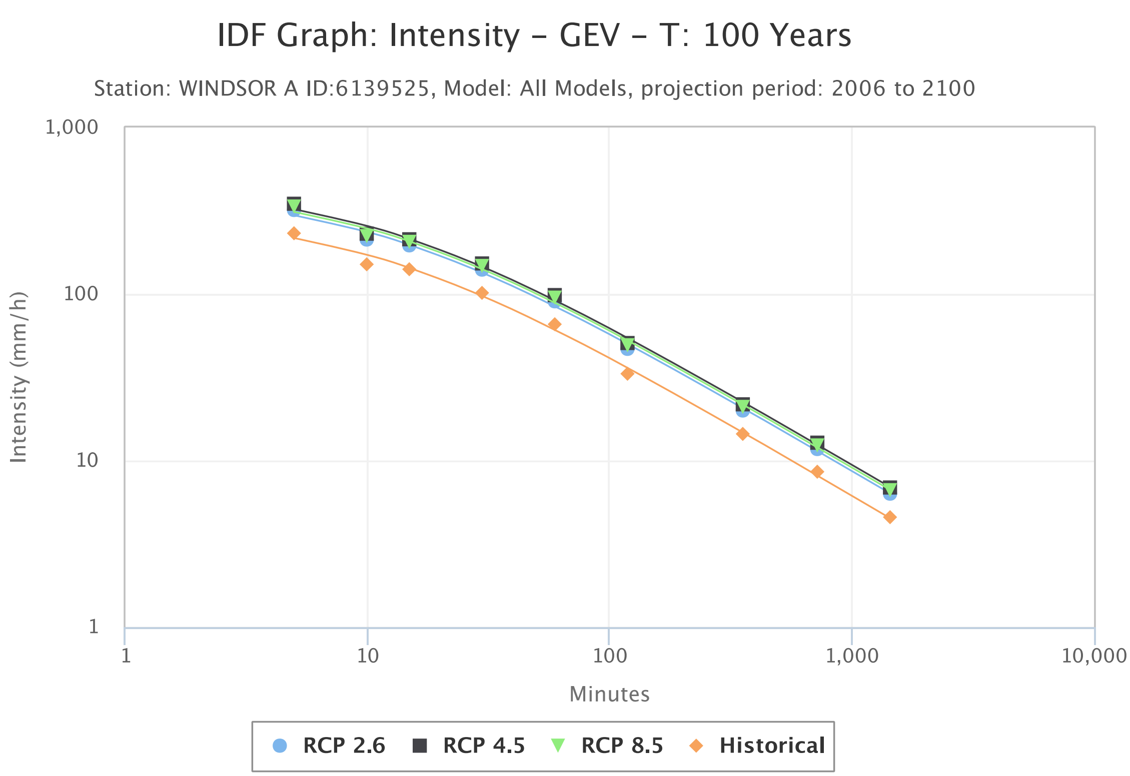


Figure H 4 Comparison of 100-year return period scenarios IDF curves

Appendix E: Precipitation Files

Historical 5-year storm

[Station][Year][Month][Day][Hour][Minute][Rain, mm, 12min interval]

STA1	2016	9	29	0	12	0.0673
STA1	2016	9	29	0	24	0.1359
STA1	2016	9	29	0	36	0.1386
STA1	2016	9	29	0	48	0.1413
STA1	2016	9	29	1	0	0.1439
STA1	2016	9	29	1	12	0.1466
STA1	2016	9	29	1	24	0.1493
STA1	2016	9	29	1	36	0.1519
STA1	2016	9	29	1	48	0.1546
STA1	2016	9	29	2	0	0.1572
STA1	2016	9	29	2	12	0.1599
STA1	2016	9	29	2	24	0.1626
STA1	2016	9	29	2	36	0.1652
STA1	2016	9	29	2	48	0.1679
STA1	2016	9	29	3	0	0.1706
STA1	2016	9	29	3	12	0.1732
STA1	2016	9	29	3	24	0.1759
STA1	2016	9	29	3	36	0.1786
STA1	2016	9	29	3	48	0.1812
STA1	2016	9	29	4	0	0.1839
STA1	2016	9	29	4	12	0.1866
STA1	2016	9	29	4	24	0.1919
STA1	2016	9	29	4	36	0.1972
STA1	2016	9	29	4	48	0.2026
STA1	2016	9	29	5	0	0.2079
STA1	2016	9	29	5	12	0.2132
STA1	2016	9	29	5	24	0.2185
STA1	2016	9	29	5	36	0.2239
STA1	2016	9	29	5	48	0.2292
STA1	2016	9	29	6	0	0.2345
STA1	2016	9	29	6	12	0.2399
STA1	2016	9	29	6	24	0.2452
STA1	2016	9	29	6	36	0.2505
STA1	2016	9	29	6	48	0.2559
STA1	2016	9	29	7	0	0.2612
STA1	2016	9	29	7	12	0.2665
STA1	2016	9	29	7	24	0.2719
STA1	2016	9	29	7	36	0.2772
STA1	2016	9	29	7	48	0.2825
STA1	2016	9	29	8	0	0.2878
STA1	2016	9	29	8	12	0.2958
STA1	2016	9	29	8	24	0.3198

STA1	2016	9	29	8	36	0.3465
STA1	2016	9	29	8	48	0.3731
STA1	2016	9	29	9	0	0.3998
STA1	2016	9	29	9	12	0.4231
STA1	2016	9	29	9	24	0.4264
STA1	2016	9	29	9	36	0.4264
STA1	2016	9	29	9	48	0.4478
STA1	2016	9	29	10	0	0.4904
STA1	2016	9	29	10	12	0.5357
STA1	2016	9	29	10	24	0.5970
STA1	2016	9	29	10	36	0.6610
STA1	2016	9	29	10	48	0.7463
STA1	2016	9	29	11	0	0.8529
STA1	2016	9	29	11	12	0.9781
STA1	2016	9	29	11	24	1.2153
STA1	2016	9	29	11	36	1.4712
STA1	2016	9	29	11	48	4.7547
STA1	2016	9	29	12	0	14.2255
STA1	2016	9	29	12	12	7.6025
STA1	2016	9	29	12	24	2.0709
STA1	2016	9	29	12	36	1.4632
STA1	2016	9	29	12	48	1.0901
STA1	2016	9	29	13	0	0.9515
STA1	2016	9	29	13	12	0.8209
STA1	2016	9	29	13	24	0.7383
STA1	2016	9	29	13	36	0.6636
STA1	2016	9	29	13	48	0.5997
STA1	2016	9	29	14	0	0.5464
STA1	2016	9	29	14	12	0.4977
STA1	2016	9	29	14	24	0.4744
STA1	2016	9	29	14	36	0.4557
STA1	2016	9	29	14	48	0.4371
STA1	2016	9	29	15	0	0.4184
STA1	2016	9	29	15	12	0.3998
STA1	2016	9	29	15	24	0.3811
STA1	2016	9	29	15	36	0.3625
STA1	2016	9	29	15	48	0.3438
STA1	2016	9	29	16	0	0.3252
STA1	2016	9	29	16	12	0.3078
STA1	2016	9	29	16	24	0.2998
STA1	2016	9	29	16	36	0.2932
STA1	2016	9	29	16	48	0.2865
STA1	2016	9	29	17	0	0.2798
STA1	2016	9	29	17	12	0.2732
STA1	2016	9	29	17	24	0.2665
STA1	2016	9	29	17	36	0.2599

STA1	2016	9	29	17	48	0.2532
STA1	2016	9	29	18	0	0.2465
STA1	2016	9	29	18	12	0.2399
STA1	2016	9	29	18	24	0.2332
STA1	2016	9	29	18	36	0.2265
STA1	2016	9	29	18	48	0.2199
STA1	2016	9	29	19	0	0.2132
STA1	2016	9	29	19	12	0.2066
STA1	2016	9	29	19	24	0.1999
STA1	2016	9	29	19	36	0.1932
STA1	2016	9	29	19	48	0.1866
STA1	2016	9	29	20	0	0.1799
STA1	2016	9	29	20	12	0.1739
STA1	2016	9	29	20	24	0.1719
STA1	2016	9	29	20	36	0.1706
STA1	2016	9	29	20	48	0.1692
STA1	2016	9	29	21	0	0.1679
STA1	2016	9	29	21	12	0.1666
STA1	2016	9	29	21	24	0.1652
STA1	2016	9	29	21	36	0.1639
STA1	2016	9	29	21	48	0.1626
STA1	2016	9	29	22	0	0.1612
STA1	2016	9	29	22	12	0.1599
STA1	2016	9	29	22	24	0.1586
STA1	2016	9	29	22	36	0.1572
STA1	2016	9	29	22	48	0.1559
STA1	2016	9	29	23	0	0.1546
STA1	2016	9	29	23	12	0.1532
STA1	2016	9	29	23	24	0.1519
STA1	2016	9	29	23	36	0.1506
STA1	2016	9	29	23	48	0.1493
STA1	2016	9	30	0	0	0.2212

Climate Change 5-year storm

[Station][Year][Month][Day][Hour][Minute][Rain, mm, 12min interval]

STA1	2016	9	29	0	12	0.0949
STA1	2016	9	29	0	24	0.1917
STA1	2016	9	29	0	36	0.1955
STA1	2016	9	29	0	48	0.1992
STA1	2016	9	29	1	0	0.2030
STA1	2016	9	29	1	12	0.2068
STA1	2016	9	29	1	24	0.2105
STA1	2016	9	29	1	36	0.2143
STA1	2016	9	29	1	48	0.2180
STA1	2016	9	29	2	0	0.2218
STA1	2016	9	29	2	12	0.2256

STA1	2016	9	29	2	24	0.2293
STA1	2016	9	29	2	36	0.2331
STA1	2016	9	29	2	48	0.2368
STA1	2016	9	29	3	0	0.2406
STA1	2016	9	29	3	12	0.2443
STA1	2016	9	29	3	24	0.2481
STA1	2016	9	29	3	36	0.2519
STA1	2016	9	29	3	48	0.2556
STA1	2016	9	29	4	0	0.2594
STA1	2016	9	29	4	12	0.2631
STA1	2016	9	29	4	24	0.2707
STA1	2016	9	29	4	36	0.2782
STA1	2016	9	29	4	48	0.2857
STA1	2016	9	29	5	0	0.2932
STA1	2016	9	29	5	12	0.3007
STA1	2016	9	29	5	24	0.3083
STA1	2016	9	29	5	36	0.3158
STA1	2016	9	29	5	48	0.3233
STA1	2016	9	29	6	0	0.3308
STA1	2016	9	29	6	12	0.3383
STA1	2016	9	29	6	24	0.3458
STA1	2016	9	29	6	36	0.3534
STA1	2016	9	29	6	48	0.3609
STA1	2016	9	29	7	0	0.3684
STA1	2016	9	29	7	12	0.3759
STA1	2016	9	29	7	24	0.3834
STA1	2016	9	29	7	36	0.3910
STA1	2016	9	29	7	48	0.3985
STA1	2016	9	29	8	0	0.4060
STA1	2016	9	29	8	12	0.4173
STA1	2016	9	29	8	24	0.4511
STA1	2016	9	29	8	36	0.4887
STA1	2016	9	29	8	48	0.5263
STA1	2016	9	29	9	0	0.5639
STA1	2016	9	29	9	12	0.5968
STA1	2016	9	29	9	24	0.6015
STA1	2016	9	29	9	36	0.6015
STA1	2016	9	29	9	48	0.6315
STA1	2016	9	29	10	0	0.6917
STA1	2016	9	29	10	12	0.7556
STA1	2016	9	29	10	24	0.8421
STA1	2016	9	29	10	36	0.9323
STA1	2016	9	29	10	48	1.0526
STA1	2016	9	29	11	0	1.2029
STA1	2016	9	29	11	12	1.3796
STA1	2016	9	29	11	24	1.7142

STA1	2016	9	29	11	36	2.0751
STA1	2016	9	29	11	48	6.7064
STA1	2016	9	29	12	0	20.0647
STA1	2016	9	29	12	12	10.7231
STA1	2016	9	29	12	24	2.9209
STA1	2016	9	29	12	36	2.0638
STA1	2016	9	29	12	48	1.5375
STA1	2016	9	29	13	0	1.3420
STA1	2016	9	29	13	12	1.1578
STA1	2016	9	29	13	24	1.0413
STA1	2016	9	29	13	36	0.9360
STA1	2016	9	29	13	48	0.8458
STA1	2016	9	29	14	0	0.7706
STA1	2016	9	29	14	12	0.7020
STA1	2016	9	29	14	24	0.6691
STA1	2016	9	29	14	36	0.6428
STA1	2016	9	29	14	48	0.6165
STA1	2016	9	29	15	0	0.5902
STA1	2016	9	29	15	12	0.5639
STA1	2016	9	29	15	24	0.5376
STA1	2016	9	29	15	36	0.5113
STA1	2016	9	29	15	48	0.4849
STA1	2016	9	29	16	0	0.4586
STA1	2016	9	29	16	12	0.4342
STA1	2016	9	29	16	24	0.4229
STA1	2016	9	29	16	36	0.4135
STA1	2016	9	29	16	48	0.4041
STA1	2016	9	29	17	0	0.3947
STA1	2016	9	29	17	12	0.3853
STA1	2016	9	29	17	24	0.3759
STA1	2016	9	29	17	36	0.3665
STA1	2016	9	29	17	48	0.3571
STA1	2016	9	29	18	0	0.3477
STA1	2016	9	29	18	12	0.3383
STA1	2016	9	29	18	24	0.3289
STA1	2016	9	29	18	36	0.3195
STA1	2016	9	29	18	48	0.3101
STA1	2016	9	29	19	0	0.3007
STA1	2016	9	29	19	12	0.2913
STA1	2016	9	29	19	24	0.2819
STA1	2016	9	29	19	36	0.2725
STA1	2016	9	29	19	48	0.2631
STA1	2016	9	29	20	0	0.2537
STA1	2016	9	29	20	12	0.2453
STA1	2016	9	29	20	24	0.2425
STA1	2016	9	29	20	36	0.2406

STA1	2016	9	29	20	48	0.2387
STA1	2016	9	29	21	0	0.2368
STA1	2016	9	29	21	12	0.2349
STA1	2016	9	29	21	24	0.2331
STA1	2016	9	29	21	36	0.2312
STA1	2016	9	29	21	48	0.2293
STA1	2016	9	29	22	0	0.2274
STA1	2016	9	29	22	12	0.2256
STA1	2016	9	29	22	24	0.2237
STA1	2016	9	29	22	36	0.2218
STA1	2016	9	29	22	48	0.2199
STA1	2016	9	29	23	0	0.2180
STA1	2016	9	29	23	12	0.2162
STA1	2016	9	29	23	24	0.2143
STA1	2016	9	29	23	36	0.2124
STA1	2016	9	29	23	48	0.2105
STA1	2016	9	30	0	0	0.3120

Historical 100-year storm

[Station][Year][Month][Day][Hour][Minute][Rain, mm, 12min interval]

STA1	2016	9	29	0	12	0.1107
STA1	2016	9	29	0	24	0.2236
STA1	2016	9	29	0	36	0.2280
STA1	2016	9	29	0	48	0.2324
STA1	2016	9	29	1	0	0.2368
STA1	2016	9	29	1	12	0.2412
STA1	2016	9	29	1	24	0.2455
STA1	2016	9	29	1	36	0.2499
STA1	2016	9	29	1	48	0.2543
STA1	2016	9	29	2	0	0.2587
STA1	2016	9	29	2	12	0.2631
STA1	2016	9	29	2	24	0.2675
STA1	2016	9	29	2	36	0.2719
STA1	2016	9	29	2	48	0.2762
STA1	2016	9	29	3	0	0.2806
STA1	2016	9	29	3	12	0.2850
STA1	2016	9	29	3	24	0.2894
STA1	2016	9	29	3	36	0.2938
STA1	2016	9	29	3	48	0.2982
STA1	2016	9	29	4	0	0.3026
STA1	2016	9	29	4	12	0.3069
STA1	2016	9	29	4	24	0.3157
STA1	2016	9	29	4	36	0.3245
STA1	2016	9	29	4	48	0.3332
STA1	2016	9	29	5	0	0.3420
STA1	2016	9	29	5	12	0.3508

STA1	2016	9	29	5	24	0.3596
STA1	2016	9	29	5	36	0.3683
STA1	2016	9	29	5	48	0.3771
STA1	2016	9	29	6	0	0.3859
STA1	2016	9	29	6	12	0.3946
STA1	2016	9	29	6	24	0.4034
STA1	2016	9	29	6	36	0.4122
STA1	2016	9	29	6	48	0.4209
STA1	2016	9	29	7	0	0.4297
STA1	2016	9	29	7	12	0.4385
STA1	2016	9	29	7	24	0.4472
STA1	2016	9	29	7	36	0.4560
STA1	2016	9	29	7	48	0.4648
STA1	2016	9	29	8	0	0.4736
STA1	2016	9	29	8	12	0.4867
STA1	2016	9	29	8	24	0.5262
STA1	2016	9	29	8	36	0.5700
STA1	2016	9	29	8	48	0.6139
STA1	2016	9	29	9	0	0.6577
STA1	2016	9	29	9	12	0.6961
STA1	2016	9	29	9	24	0.7016
STA1	2016	9	29	9	36	0.7016
STA1	2016	9	29	9	48	0.7366
STA1	2016	9	29	10	0	0.8068
STA1	2016	9	29	10	12	0.8813
STA1	2016	9	29	10	24	0.9822
STA1	2016	9	29	10	36	1.0874
STA1	2016	9	29	10	48	1.2277
STA1	2016	9	29	11	0	1.4031
STA1	2016	9	29	11	12	1.6092
STA1	2016	9	29	11	24	1.9995
STA1	2016	9	29	11	36	2.4204
STA1	2016	9	29	11	48	7.8225
STA1	2016	9	29	12	0	23.4039
STA1	2016	9	29	12	12	12.5076
STA1	2016	9	29	12	24	3.4070
STA1	2016	9	29	12	36	2.4073
STA1	2016	9	29	12	48	1.7934
STA1	2016	9	29	13	0	1.5654
STA1	2016	9	29	13	12	1.3505
STA1	2016	9	29	13	24	1.2146
STA1	2016	9	29	13	36	1.0918
STA1	2016	9	29	13	48	0.9866
STA1	2016	9	29	14	0	0.8989
STA1	2016	9	29	14	12	0.8189
STA1	2016	9	29	14	24	0.7805

STA1	2016	9	29	14	36	0.7498
STA1	2016	9	29	14	48	0.7191
STA1	2016	9	29	15	0	0.6884
STA1	2016	9	29	15	12	0.6577
STA1	2016	9	29	15	24	0.6270
STA1	2016	9	29	15	36	0.5963
STA1	2016	9	29	15	48	0.5656
STA1	2016	9	29	16	0	0.5349
STA1	2016	9	29	16	12	0.5064
STA1	2016	9	29	16	24	0.4933
STA1	2016	9	29	16	36	0.4823
STA1	2016	9	29	16	48	0.4714
STA1	2016	9	29	17	0	0.4604
STA1	2016	9	29	17	12	0.4494
STA1	2016	9	29	17	24	0.4385
STA1	2016	9	29	17	36	0.4275
STA1	2016	9	29	17	48	0.4166
STA1	2016	9	29	18	0	0.4056
STA1	2016	9	29	18	12	0.3946
STA1	2016	9	29	18	24	0.3837
STA1	2016	9	29	18	36	0.3727
STA1	2016	9	29	18	48	0.3617
STA1	2016	9	29	19	0	0.3508
STA1	2016	9	29	19	12	0.3398
STA1	2016	9	29	19	24	0.3289
STA1	2016	9	29	19	36	0.3179
STA1	2016	9	29	19	48	0.3069
STA1	2016	9	29	20	0	0.2960
STA1	2016	9	29	20	12	0.2861
STA1	2016	9	29	20	24	0.2828
STA1	2016	9	29	20	36	0.2806
STA1	2016	9	29	20	48	0.2784
STA1	2016	9	29	21	0	0.2762
STA1	2016	9	29	21	12	0.2740
STA1	2016	9	29	21	24	0.2719
STA1	2016	9	29	21	36	0.2697
STA1	2016	9	29	21	48	0.2675
STA1	2016	9	29	22	0	0.2653
STA1	2016	9	29	22	12	0.2631
STA1	2016	9	29	22	24	0.2609
STA1	2016	9	29	22	36	0.2587
STA1	2016	9	29	22	48	0.2565
STA1	2016	9	29	23	0	0.2543
STA1	2016	9	29	23	12	0.2521
STA1	2016	9	29	23	24	0.2499
STA1	2016	9	29	23	36	0.2477

STA1	2016	9	29	23	48	0.2455
STA1	2016	9	30	0	0	0.3639

Climate Change 100-year storm

[Station][Year][Month][Day][Hour][Minute][Rain, mm, 12min interval]

STA1	2016	9	29	0	12	0.1608
STA1	2016	9	29	0	24	0.3247
STA1	2016	9	29	0	36	0.3311
STA1	2016	9	29	0	48	0.3375
STA1	2016	9	29	1	0	0.3438
STA1	2016	9	29	1	12	0.3502
STA1	2016	9	29	1	24	0.3566
STA1	2016	9	29	1	36	0.3629
STA1	2016	9	29	1	48	0.3693
STA1	2016	9	29	2	0	0.3757
STA1	2016	9	29	2	12	0.3820
STA1	2016	9	29	2	24	0.3884
STA1	2016	9	29	2	36	0.3948
STA1	2016	9	29	2	48	0.4011
STA1	2016	9	29	3	0	0.4075
STA1	2016	9	29	3	12	0.4139
STA1	2016	9	29	3	24	0.4202
STA1	2016	9	29	3	36	0.4266
STA1	2016	9	29	3	48	0.4330
STA1	2016	9	29	4	0	0.4393
STA1	2016	9	29	4	12	0.4457
STA1	2016	9	29	4	24	0.4584
STA1	2016	9	29	4	36	0.4712
STA1	2016	9	29	4	48	0.4839
STA1	2016	9	29	5	0	0.4966
STA1	2016	9	29	5	12	0.5094
STA1	2016	9	29	5	24	0.5221
STA1	2016	9	29	5	36	0.5348
STA1	2016	9	29	5	48	0.5476
STA1	2016	9	29	6	0	0.5603
STA1	2016	9	29	6	12	0.5730
STA1	2016	9	29	6	24	0.5858
STA1	2016	9	29	6	36	0.5985
STA1	2016	9	29	6	48	0.6113
STA1	2016	9	29	7	0	0.6240
STA1	2016	9	29	7	12	0.6367
STA1	2016	9	29	7	24	0.6495
STA1	2016	9	29	7	36	0.6622
STA1	2016	9	29	7	48	0.6749
STA1	2016	9	29	8	0	0.6877
STA1	2016	9	29	8	12	0.7068

STA1	2016	9	29	8	24	0.7641
STA1	2016	9	29	8	36	0.8277
STA1	2016	9	29	8	48	0.8914
STA1	2016	9	29	9	0	0.9551
STA1	2016	9	29	9	12	1.0108
STA1	2016	9	29	9	24	1.0188
STA1	2016	9	29	9	36	1.0188
STA1	2016	9	29	9	48	1.0697
STA1	2016	9	29	10	0	1.1716
STA1	2016	9	29	10	12	1.2798
STA1	2016	9	29	10	24	1.4263
STA1	2016	9	29	10	36	1.5791
STA1	2016	9	29	10	48	1.7828
STA1	2016	9	29	11	0	2.0375
STA1	2016	9	29	11	12	2.3368
STA1	2016	9	29	11	24	2.9034
STA1	2016	9	29	11	36	3.5147
STA1	2016	9	29	11	48	11.3591
STA1	2016	9	29	12	0	33.9849
STA1	2016	9	29	12	12	18.1624
STA1	2016	9	29	12	24	4.9473
STA1	2016	9	29	12	36	3.4956
STA1	2016	9	29	12	48	2.6042
STA1	2016	9	29	13	0	2.2731
STA1	2016	9	29	13	12	1.9611
STA1	2016	9	29	13	24	1.7637
STA1	2016	9	29	13	36	1.5854
STA1	2016	9	29	13	48	1.4326
STA1	2016	9	29	14	0	1.3053
STA1	2016	9	29	14	12	1.1891
STA1	2016	9	29	14	24	1.1334
STA1	2016	9	29	14	36	1.0888
STA1	2016	9	29	14	48	1.0442
STA1	2016	9	29	15	0	0.9997
STA1	2016	9	29	15	12	0.9551
STA1	2016	9	29	15	24	0.9105
STA1	2016	9	29	15	36	0.8659
STA1	2016	9	29	15	48	0.8214
STA1	2016	9	29	16	0	0.7768
STA1	2016	9	29	16	12	0.7354
STA1	2016	9	29	16	24	0.7163
STA1	2016	9	29	16	36	0.7004
STA1	2016	9	29	16	48	0.6845
STA1	2016	9	29	17	0	0.6686
STA1	2016	9	29	17	12	0.6526
STA1	2016	9	29	17	24	0.6367

STA1	2016	9	29	17	36	0.6208
STA1	2016	9	29	17	48	0.6049
STA1	2016	9	29	18	0	0.5890
STA1	2016	9	29	18	12	0.5730
STA1	2016	9	29	18	24	0.5571
STA1	2016	9	29	18	36	0.5412
STA1	2016	9	29	18	48	0.5253
STA1	2016	9	29	19	0	0.5094
STA1	2016	9	29	19	12	0.4935
STA1	2016	9	29	19	24	0.4775
STA1	2016	9	29	19	36	0.4616
STA1	2016	9	29	19	48	0.4457
STA1	2016	9	29	20	0	0.4298
STA1	2016	9	29	20	12	0.4155
STA1	2016	9	29	20	24	0.4107
STA1	2016	9	29	20	36	0.4075
STA1	2016	9	29	20	48	0.4043
STA1	2016	9	29	21	0	0.4011
STA1	2016	9	29	21	12	0.3979
STA1	2016	9	29	21	24	0.3948
STA1	2016	9	29	21	36	0.3916
STA1	2016	9	29	21	48	0.3884
STA1	2016	9	29	22	0	0.3852
STA1	2016	9	29	22	12	0.3820
STA1	2016	9	29	22	24	0.3788
STA1	2016	9	29	22	36	0.3757
STA1	2016	9	29	22	48	0.3725
STA1	2016	9	29	23	0	0.3693
STA1	2016	9	29	23	12	0.3661
STA1	2016	9	29	23	24	0.3629
STA1	2016	9	29	23	36	0.3597
STA1	2016	9	29	23	48	0.3566
STA1	2016	9	30	0	0	0.5285

Appendix F: Individual LID Investment

The tables in this section show the investment into each LID control type in each subcatchment group.

Table J 1 Rain barrel investment in each subcatchment group

		Average Rain Barrel Investment							
		Low Adoption				High Adoption			
		HIS 5	CC 5	HIS 100	CC 100	HIS 5	CC 5	HIS 100	CC 100
Peak Flow Solutions	Group 1	$ 11,312	$ 8,080	$ 9,090	$ 9,898	$ 14,140	$ 19,796	$ 15,451	$ 28,953
	Group 2	$ 6,526	$ 6,565	$ 6,060	$ 7,070	$ 12,373	$ 12,373	$ 12,864	$ 13,324
	Group 3	$ 28,785	$ 25,912	$ 28,785	$ 28,785	$ 69,387	$ 57,823	$ 54,732	$ 57,823
	Group 4	$ 8,585	$ 8,585	$ 10,302	$ 8,585	$ 17,170	$ 22,076	$ 20,604	$ 24,038
	Group 5	$ 3,788	$ 631	$ 4,545	$ 3,788	$ 9,295	$ 9,784	$ 9,102	$ 18,063
Runoff Solutions	Group 1	$ 9,595	$ 8,186	$ 8,838	$ 11,110	$ 17,170	$ 20,424	$ 16,161	$ 31,815
	Group 2	$ 6,318	$ 6,587	$ 6,262	$ 6,611	$ 12,991	$ 12,976	$ 14,636	$ 13,919
	Group 3	$ 28,785	$ 27,952	$ 28,785	$ 28,785	$ 66,083	$ 57,823	$ 56,573	$ 57,823
	Group 4	$ 8,585	$ 10,302	$ 9,365	$ 8,585	$ 17,170	$ 27,472	$ 25,095	$ 36,629
	Group 5	$ 3,788	$ 3,788	$ 4,870	$ 3,788	$ 9,063	$ 7,828	$ 11,016	$ 18,482

Table J 2 Bioretention investment in each subcatchment group

		Average Bioretention Investment							
		Low Adoption				High Adoption			
		HIS 5	CC 5	HIS 100	CC 100	HIS 5	CC 5	HIS 100	CC 100
Peak Flow Solutions	Group 1	$ -	$ -	$ 46,528	$ -	$ -	$ -	$ 398,852	$ -
	Group 2	$ -	$ -	$ 25,568	$ -	$ 1,516,516	$ 78,174	$ -	$ -
	Group 3	$ -	$ -	$ 921,380	$ -	$ -	$ -	$ 1,721,096	$ 715,854
	Group 4	$ -	$ 76,769	$ 358,172	$ 266,458	$ -	$ 1,328,160	$ 1,586,044	$ 1,766,665
	Group 5	$ -	$ -	$ -	$ 34,890	$ -	$ -	$ 665	$ 765,266
Runoff Solutions	Group 1	$ -	$ -	$ -	$ 66,528	$ 134,928	$ -	$ 50,056	$ 134,928
	Group 2	$ -	$ -	$ -	$ -	$ 636,916	$ 262,942	$ 53,174	$ -
	Group 3	$ -	$ 175,644	$ 708,289	$ -	$ -	$ -	$ -	$ 1,641,302
	Group 4	$ -	$ 50,908	$ 195,226	$ 229,771	$ 278,648	$ 322,493	$ 383,805	$ 506,652
	Group 5	$ -	$ 17,070	$ -	$ 21,890	$ -	$ 17,906	$ 21,906	$ 414,128

Table J 3 Infiltration trench investment in each subcatchment group

		Average Infiltration Trench Investment							
		Low Adoption				High Adoption			
		HIS 5	CC 5	HIS 100	CC 100	HIS 5	CC 5	HIS 100	CC 100
Peak Flow Solutions	Group 1	$ -	$ -	$ 81,540	$ 410,062	$ 289,468	$ 1,396,027	$ -	$ 1,275,817
	Group 2	$ 205,102	$265,635	$ 282,286	$ 370,031	$ 776,600	$ -	$ 708,065	$ 1,694,875
	Group 3	$ 797,122	$746,554	$ 949,831	$ 1,602,258	$ 2,519,709	$ 2,662,063	$ 3,334,271	$ 5,149,820
	Group 4	$ 284,990	$271,330	$ 436,879	$ 553,682	$ 903,412	$ 899,976	$ 1,319,442	$ 1,531,424
	Group 5	$ 175,971	$173,733	$ 218,105	$ 358,921	$ 468,788	$ 439,554	$ 623,892	$ 635,666
Runoff Solutions	Group 1	$ -	$241,015	$ 183,225	$ 377,309	$ 419,977	$ 1,270,992	$ 608,307	$ 1,145,644
	Group 2	$ 176,704	$233,307	$ 339,243	$ 390,911	$ 891,814	$ 670,277	$ 646,376	$ 1,442,724
	Group 3	$ 768,579	$789,421	$ 1,083,840	$ 1,473,826	$ 2,534,274	$ 2,483,510	$ 3,245,459	$ 5,689,280
	Group 4	$ 290,612	$279,480	$ 422,524	$ 588,655	$ 841,361	$ 905,582	$ 1,034,412	$ 1,646,681
	Group 5	$ 180,580	$174,595	$ 254,472	$ 332,029	$ 373,093	$ 406,656	$ 469,987	$ 687,270

Table J 4 Permeable pavement investment in each subcatchment group

		Average Permeable Pavement Investment							
		Low Adoption				High Adoption			
		HIS 5	CC 5	HIS 100	CC 100	HIS 5	CC 5	HIS 100	CC 100
Peak Flow Solutions	Group 1	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
	Group 2	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
	Group 3	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 1,010,700
	Group 4	$ -	$ -	$ -	$ -	$ -	$ -	$ 353,396	$ -
	Group 5	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Runoff Solutions	Group 1	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
	Group 2	$ -	$ -	$ -	$ -	$ 249,456	$ -	$ -	$ 249,456
	Group 3	$ -	$ -	$ -	$ 478,124	$ -	$ -	$ -	$ 1,184,916
	Group 4	$ -	$ -	$ -	$ -	$ -	$ -	$ 353,396	$ -
	Group 5	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ 155,910

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Eckart, K., McPhee, Z., & Bolisetti, T. (2017). Performance and implementation of low impact development – A review. *Science of the Total Environment*, *607–608*, 413–432. https://doi.org/10.1016/j.scitotenv.2017.06.254

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