OPTIMAL DISTRIBUTION OF BEST MANAGEMENT PRACTICES (BMPS) FOR URBAN STORMWATER RUNOFF QUANTITY AND QUALITY CONTROL

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INSTITUTE FOR ADVANCED STUDIES
UNIVERSITY OF MALAYA
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OPTIMAL DISTRIBUTION OF BEST MANAGEMENT PRACTICES (BMPS) FOR URBAN STORMWATER RUNOFF QUANTITY AND QUALITY CONTROL

ABSTRACT

The vast development of urban areas throughout the world has substantially impacted the natural landscapes, leading to more imperviousness. Urbanization typically results in a larger amount of runoff volume, increase in flow frequency, duration and peak runoff, faster time of concentration as well as lower infiltration which will affect groundwater recharge. The stormwater runoff quality is also adversely affected in urban areas due to the pollutant loads in stormwater runoff. Best Management Practices (BMPs) and Low Impact Development (LID) have been widely applied to urban impervious surfaces to reduce urban stormwater runoff and improve water quality. In order to achieve the maximum runoff and pollutant concentration reduction with the lowest cost, it is vital to find the optimal number and combination of LID controls implemented on impervious surfaces. In this study, a simulation-optimization model was developed by linking the US Environmental Protection Agency Stormwater Management Model (US EPA SWMM) to the Multi-Objective Particle Swarm Optimization (MOPSO) using MATLAB. The coupled model is able to carry out multi-objective optimization and find potential solutions to the optimization objectives by using the SWMM simulation model outputs. The SWMM model was developed by calibrating and validating the model using real quantity and quality data from BUNUS catchment in Kuala Lumpur, Malaysia. The rainfall-flow data and quality data were collected through sampling rainfall events and the Malaysian Department of Irrigation and Drainage (DID). The Total Suspended Solids (TSS) and Total Nitrogen (TN) were selected as pollutants to be used in the simulation model. The LID controls were designed using the catchment characteristics, applied to the model and the performance of the simulation model was tested with real rainfall-flow data from the catchment. The target objectives were to investigate the hydrological performance of LIDs at the catchment scale, to minimize the peak runoff, TSS and TN with the minimum number of LID controls applied, and to minimize the vulnerability of urban areas against flood. This study applied vegetated swale and rain garden to assess the model performance at a catchment scale. The selected LIDs occupied 7% of each sub-catchment (of which 40% was swale and 30% was rain garden, respectively). The stormwater runoff substantially reduced, and the runoff quality was also greatly improved by applying the LIDs into the simulation model. The LID removal efficiency was up to 40.42% for TN and 61.60% for TSS, respectively. The peak runoff reduction was also up to 27.44%. The outputs of the simulation model were, then, optimized with the MOPSO model to identify the final best LID types and combination to achieve the maximum peak runoff and pollutant concentration reductions with the minimum number of LIDs. Based on the results achieved from the optimization model, the peak runoff, TSS and TN were found to reduce by 13%, 38% and 24%, respectively. The optimal number of LID controls for the BUNUS catchment was also found to be 25. The LID cost analysis was also performed using MOPSO to find out the best combination of LIDs in the catchment for the maximum runoff and pollutants reduction with the minimum cost. It can be concluded that urbanization will greatly affect both peak discharge and the quality of surface runoff. Applying LID and redirecting the surface runoff to the LID units can greatly reduce the surface runoff and improve the water quality. Hence, the significant role of LIDs in peak runoff reduction and water quality improvement could not be ignored.

Keywords: Urbanization, Stormwater, Simulation-Optimization Modelling, LID-BMP, MOPSO

TABURAN OPTIMAL AMALAN PENGURUSAN TERBAIK (BMPS) UNTUK KAWALAN KUANTITI DAN KUALITI ALIRAN AIR RIBUT DI KAWASAN BANDAR

ABSTRAK

Pembangunan rancak kawasan bandar di seluruh dunia sebahagian besarnya telah memberi kesan terhadap landskap semulajadi seterusnya membawa kepada kekedapan. Urbanisasi lazimnya mengakibatkan jumlah isi padu air larian yang lebih besar, peningkatan frekuensi aliran, tempoh dan larian puncak, masa kepekatan yang lebih cepat serta penyerapan yang lebih rendah akhirnya akan menjejaskan pengimbuhan air bawah tanah. Kualiti larian air ribut juga terjejas teruk di kawasan bandar disebabkan oleh kandungan bahan pencemaran di dalam larian air ribut. Amalan Pengurusan Terbaik (BMPs) dan Pembangunan Impak Rendah (LID) telah digunakan secara meluas terhadap permukaan kedap di bandar bagi mengurangkan larian air ribut bandar dan meningkatkan kualiti air. Adalah mustahak untuk mencari bilangan optimal dan kombinasi kawalan LID dilakukan terhadap permukaan kedap bagi mencapai larian maksimum di samping mengurangkan kepekatan bahan pencemaran dengan kos yang terendah. Menerusi kajian ini, model pengoptimuman-simulasi telah dibangunkan dengan menghubungkan Model Pengurusan Air Ribut Agensi Perlindungan Alam Sekitar Amerika Syarikat (US EPA SWMM) kepada Pengoptimuman Kerumunan Zarah Multi-Objektif (MOPSO) menggunakan aplikasi MATLAB. Kombinasi model ini mampu menjalankan pengoptimuman multi-objektif serta mencari penyelesaian berpotensi kepada pengoptimuman objektif dengan menggunakan hasil pengeluaran model simulasi SWMM. Model SWMM dibangunkan dengan penentukuran dan pengesahan menggunakan data kuantiti dan kualiti sebenar dari tadahan BUNUS di Kuala Lumpur, Malaysia. Data aliran hujan dan kualiti dikumpul melalui pensampelan kejadian hujan dan juga dari Jabatan Pengairan dan Saliran Malaysia (JPS). Endapan Ampai Total (TSS) dan Nitrogen Total (TN) dipilih sebagai bahan pencemaran yang telah digunakan dalam model simulasi. Kawalan LID direka bentuk menggunakan ciri tadahan, diaplikasikan pada model dan prestasi model simulasi diuji dengan data aliran hujan sebenar dari tadahan. Objektif sasaran adalah untuk menyiasat prestasi hidrologikal LID pada skala tadahan, untuk meminimumkan larian puncak, TSS dan TN dengan bilangan minimum kawalan LID yang digunakan, selain mengurangkan kerentanan kawasan bandar terhadap banjir. Kajian ini menggunakan alur bertumbuhan dan taman hujan untuk menilai prestasi model pada skala tadahan. LID yang dipilih merangkumi 7% daripada setiap subtadahan (di mana masing-masing adalah 40% saliran berumput dan 30% taman hujan). Larian air ribut sebahagian besarnya telah berjaya dikurangkan dan kualiti aliran juga meningkat secara mendadak dengan menggunakan LID pada model simulasi. Kecekapan penyingkiran LID adalah sehingga 40.42% untuk TN dan 61.60% untuk TSS. Pengurangan larian puncak juga mencapai sehingga 27.44%. Hasil pengeluaran model simulasi kemudiannya dioptimumkan melalui model MOPSO untuk mengenal pasti jenis dan kombinasi LID yang terbaik bagi mencapai larian puncak maksimum serta mengurangkan kepekatan bahan pencemaran dengan bilangan minimum LID. Berdasarkan keputusan yang diperoleh dari pengoptimuman model, larian puncak, TSS dan TN masing-masing didapati menurun sebanyak 13%, 38% dan 24%. Bilangan optimal kawalan LID untuk tadahan BUNUS yang diperolehi juga adalah sebanyak 25. Selain itu juga, analisa kos LID turut dilakukan menggunakan MOPSO untuk mengetahui kombinasi terbaik LID di dalam tadahan untuk aliran maksimum dan pengurangan bahan pencemaran dengan kos yang minimum. Dapat disimpulkan bahawa urbanisasi dilihat sangat mempengaruhi kedua-dua pelepasan puncak dan kualiti larian permukaan. Penerapan LID dan pengalihan larian permukaan ke unit LID mampu mengurangkan

larian permukaan dan meningkatkan kualiti air. Oleh itu, peranan penting LID dalam mengurangi larian puncak serta menambah baik kualiti air tidak boleh diabaikan.

Kata kunci: Urbanisasi, Air Ribut, Pemodelan Pengoptimuman-Simulasi, LID-BMP, MOPSO

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LIST OF SYMBOLS AND ABBREVIATIONS

$	:	Dollar sign
E	:	East longitude
e	:	Base-10 exponent symbol
N	:	North latitude
r^2	:	Coefficient of determination
T	:	Return period
^	:	exponentiation operator
Al	:	Aluminum
AN	:	Ammoniacal Nitrogen
As	:	Arsenic
Ba	:	Barium
BMP	:	Best Management Practices
BOD	:	Biochemical Oxygen Demand
Ca	:	Calcium
Cd	:	Cadmium
CM	:	Cubic meter
cm	:	Centimeter
CMS	:	Cubic meter per second
COD	:	Chemical Oxygen Demand
Cond	:	Conductivity
Cr	:	Chromium
Cu	:	Copper
DCIA	:	Directly Connected Impervious Area
DEM	:	Digital Elevation Model

DID	:	Department of Irrigation and Drainage
DIN	:	Dissolved Inorganic Nitrogen
DO	:	Dissolved Oxygen
D_v	:	Deviation Volume Coefficient
e.g.	:	For example
EIA	:	Effective Impervious Area
EMC	:	Event Mean Concentration
EPA	:	Environmental Protection Agency
ET	:	Evapotranspiration
Fe	:	Iron
GA	:	Genetic Algorithm
GIS	:	Geographical Information System
GSA	:	Global Sensitivity Analysis
ha	:	Hectare
Hg	:	Mercury
hr	:	Hour
IMPs	:	Integrated Management Practices
Kg	:	Kilogram
KL	:	Kuala Lumpur
Km	:	Kilometer
km^2	:	Square kilometer
L	:	Liter
ltr	:	Liter
LID	:	Low Impact Development
m	:	Meter
m^3/s	:	Cubic meter per second

MATLAB	:	Matrix Laboratory
Mg	:	Magnesium
mg	:	milligram
mm	:	millimeter
Mn	:	Manganese
MOPSO	:	Multi-Objective Particle Swarm Optimization
MSMA	:	Urban Stormwater Management Manual for Malaysia
NH3	:	Ammoniacal Nitrogen
NO2	:	Nitrite
NO3	:	Nitrate
NOF	:	Normalized Objective Function
NOx	:	Nitrate and/or Nitrite
NSC	:	Nash–Sutcliffe Coefficient
O&M	:	Operation and Maintenance
Pb	:	Lead
PO4	:	Phosphate
PR	:	Peak runoff
PSO	:	Particle Swarm Optimization
RG	:	Rain Garden
RMSE	:	Root Mean Square Error
S1	:	Station1
S2	:	Station2
SA	:	Sensitivity Analysis
SCE-UA	:	Shuffled Complex Evolution Algorithm
SMART	:	Stormwater Management and Road Tunnel
Sr	:	Strontium

SUDS	:	Sustainable Urban Drainage Systems
SW	:	Swale
SWMM	:	Stormwater Management Model
TDS	:	Total Dissolved Solids
TIA	:	Total Imperviousness Area
TN	:	Total Nitrogen
TP	:	Total Phosphorous
TSS	:	Total Suspended Solids
TV	:	Total Volume
UHI	:	Urban Heat Island
USEPA	:	United States Environmental Protection Agency
UTM	:	University Technology Malaysia
V_m	:	Modeled total runoff volume
V_o	:	Observed total runoff volume
WSUD	:	Water Sensitive Urban Design
WWCs		Wet weather controls
Zn	:	Zinc

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CHAPTER 1: INTRODUCTION

1.1 Introduction

In a natural watershed, there is a unique climate, topography, vegetation and coverage which results in a natural water cycle and hydrological response. Different factors can affect this unique natural hydrological process and cause adverse effects to the urban catchment. Although geomorphological features of the urban areas, such as topography, geology, soil characteristics, slope and roughness have profound impact on the runoff generation of the urban catchment, the anthropogenic effects are specifically important in this respect. The continuous growing population and large human activities in urban areas have led to some issues in different parts of the world Yang et al. (2008). The main reason for many alterations in the natural hydrological processes in urban areas is population growth and the pertinent human activities changing the natural features of urban catchments and leading to more imperviousness. Based on the United Nations reports, a great deal of people are residing in urban or urban-like areas throughout the world (UnitedNations, 2010). Also, based on the population projections, urban population will reach 80% of the total population by the year 2030, with growth or migration, especially concentrated in megacities and developing countries (Salvadore et al., 2015). Population growth and urbanization reinforce the pressure on the environment and is usually a threat to water resources sustainability (Carle et al., 2005; Lee & Heaney, 2003). Land use changes in the process of increase in urbanization can have a severe impact on the runoff generation (DeFries & Eshleman, 2004). Hydrological processes are also significantly affected by human activities in urban catchments (Kuchment, 2004). Climate change also plays an important role on the hydrologic cycle in urban areas by changing rainfall patterns and consequently increasing runoff volume and peak flow.

Due to the growing population and the resultant impact on the urban hydrology, it is of high interest to understand how various factors, including the human activities, influence the hydrologic variables in urban areas and how to mitigate these effects (Ahn & Merwade, 2014).

When the runoff volume and peak flow increase in urban areas, the ecosystem, human and property as well as the water quality will be adversely affected. Urbanization is the most significant factor leading to higher runoff volume and peak runoff, and therefore causes flood disaster (Shi et al., 2007).

1.2 Urban runoff generation

Part of the rainfall does not neither retain on the surface nor infiltrate deep into the soil. This part of the rainfall is known as excess rainfall, or effective rainfall. Excess rainfall flows over the surface and turns into direct runoff at the catchment outlet (Chow et al., 1988). The flow regimes in a watershed are determined by watershed characteristics which are typically inclusive of climate, geology, topography, soil vegetation and human activities (Brilly et al., 2006). Different factors might impact the amount and extent of surface runoff generation.

1.3 Urban stormwater runoff generation

Different factors contribute to urban runoff generation. Human activities is one of the most significant factor contributing to the runoff generation in urban catchments which have gained a great deal of attention in the past years (Wang S. et al., 2015). Anthropogenic impacts (sometimes integrated with climatic impact) on runoff alterations have been the focus of many studies by researchers recently, e.g., (Ma et al., 2008; Milliman et al., 2008). Urban development has largely resulted in the catchment land use/land cover modifications which have influenced the runoff variability (Wang et al., 2011). Anthropogenic effects along with urbanization lead to the extreme modification of urban pathways (Price, 2011). Urbanization is the most significant aspect of anthropogenic impact in urban areas affecting surface runoff. Urbanization, imperviousness and land use/land cover changes are the results of anthropogenic activities in urban areas affecting the runoff generation.

Urbanization usually results in the modification of natural landscapes and eventually vegetated surfaces are replaced with impermeable surfaces (Shuster et al., 2005). The artificial coverage used in the process of urbanization encompass a wide range of sealed surfaces such as paved roads, parking lots and roofs, that typically clear the vegetation and compact the soil (Brilly et al., 2006). The main results of urbanization include: increasing of road surface area (Forman 2000); reducing drainage capacity (Hicks & Larson, 1997a); and land modification for agriculture (Pringle, 2001).

Impervious surfaces are the result of urbanization which are generally known as material with natural or anthropogenic sources preventing the infiltration of surface water into the sub-layer soils (Slonecker et al., 2001). Human activities and habitation are the main reasons for the growth of impervious surfaces in urban areas by construction of structures such as roofs, parking lots and roads. Imperviousness decreases infiltration capacity, increases the direct runoff, improves the connectivity of flow and leads to the reduction of groundwater recharge paths (Brabec et al., 2002; Shuster et al., 2005). These alterations will ultimately result in the modification of the magnitude and duration of urban catchment floods (Yang et al., 2015).

Climate change has gained a lot of attentions recently because of its significant influence, particularly on the urban hydrology. Thus, understanding the rainfall behavior alteration at urban scales is urgently vital. We also need to assess the effects of such alterations on the efficiency and stormwater management systems reliability for controlling flood, hygiene as well as environmental protection (Fletcher et al., 2013). It is usually anticipated that the climate change will alter the timing and magnitude of runoff, which is a significant factor in the water resources management (Zhang et al., 2012). In addition, the precipitation intensity might also be modified by climate change.

Another factor affecting urban runoff generation is soil characteristics in urban areas. When the topsoil is removed from pervious areas of urban catchments and it is combined with soil compaction (because of construction, traffic, loss of organic matters and vegetation), rainfall-runoff will have uncertain behavior (Gregory et al., 2006; Shuster & Pappas, 2010). Antecedent soil moisture also contributes to urban runoff generation. In wet soil condition, the runoff is averagely two times higher compared to dry soil condition (Shi et al., 2007).

Precipitation is another significant meteorological factor affecting the hydrological process (Li et al., 2008). The alteration of both precipitation and temperature significantly affect urban runoff. Studies have proved that if precipitation changes 10%, it will possibly result in about 15 to 25% alterations in runoff (Fu et al., 2007b; Liuzzo et al., 2009; Notter et al., 2007; Wang et al., 2011; Zhang et al., 2009b).

Apart from precipitation, temperature is a significant meteorological factor affecting hydrological process (Li et al., 2008). It is estimated that when the temperature is increased by 2-degree, the runoff will be reduced by 5 to 12% (Fu et al., 2007b; Liuzzo et al., 2009; Notter et al., 2007; Zhang et al., 2009b). Evaporation from land surface is also another major component of surface runoff even for the surfaces which are nominally impervious (Mansell & Rollet, 2009).

1.4 Problem statement

Urbanization, land use/land cover and imperviousness can be considered as the most significant factors impacting the rainfall-runoff behavior in urban catchments. Urbanization results in considerable runoff volume and peak discharge increase as well as base flow reduction which is due to the alteration in the percentage of imperviousness and the decrease of infiltration rates (Bedan & Clausen, 2009; Burns et al., 2012; Dietz & Clausen, 2008). Excess runoff can lead to urban flooding, economic losses, pollution and health issues, which can considerably threaten local residents and urban development.

Impervious surfaces substantially affect the infiltration of precipitation and runoff is rapidly conveyed into stream channels that will change the natural hydrologic cycle. This process will increase the velocity, volume and peak runoff of the storm events. Erosion will also cause some problems to the surface and streams due to the high velocity of runoff on impervious surfaces. Urban runoff and associated erosion resulted from storms can have significant adverse effects on catchment health and ecosystem habitats (Gilroy & McCuen, 2009). Due to imperviousness in urbanized watersheds, floods also occur with greater magnitude and frequency. This will make flood damage mitigation and water quality improvement more challenging.

Apart from runoff peaks and volume, surface water quality is also a great concern in urban areas due to pollutant loads in stormwater runoff. Studies have quantified a huge amount of pollutants in stormwater which may affect aquatic systems adversely (Björklund, 2011).

1.5 Purpose and scope of the study

Traditionally, urban drainage networks have been used to direct and collect urban excess runoff to prevent the consequences. Urban stormwater runoff problems have typically been mitigated using Best Management Practices (BMPs), such as constructed wetlands and ponds which have traditionally been implemented in a centralized manner. The newly developed source control techniques, such as rain gardens, permeable pavements, vegetated swales, and bioretention systems have been widely used recently to manage urban stormwater. Collectively, these best management practices techniques have been termed Low Impact Development (LID) (Qin et al., 2013). These techniques are usually implemented at the source and are often referred to as distributed, source control or decentralized systems. Best management practices (BMPs) and low impact development (LID) strategies are widely used to mitigate the impacts of urbanization on water quantity and quality (Dietz, 2007). Particularly, the LID techniques have been developed to mimic the pre-development hydrologic conditions and promote the storage, infiltration and evapotranspiration processes (Ahiablame et al., 2012).

Stormwater engineers apply hydrological modeling to determine the most useful places for LID facilities as well as the required level of stormwater management through the selected facilities. Several studies have proved the suitability and effectiveness of modeling approaches to evaluate the impact of stormwater strategies on receiving waters (Elliott & Trowsdale, 2007; German et al., 2005a).

In order to achieve the maximum runoff and pollutant reduction with the lowest cost, it is vital to find the optimal number and combination of LID controls implemented on impervious surfaces. This could be achieved by developing a simulation-optimization model to achieve the maximum runoff and pollutant concentration reduction with the lowest cost. Coupling a hydrological model with an optimization model would be the best method to achieve the optimal number and combination of LIDs in the catchment with the minimum cost. The idea of optimization is to achieve the optimal number and combination of LIDs so that the runoff/peak runoff and pollutants are optimally reduced while the LID implementation is also cost-beneficial.

The purpose of the study was to find the optimal number and combination of LID controls implemented on impervious surfaces by developing a simulation-optimization model to achieve the maximum runoff and pollutants reduction with the minimum cost.

1.6 Objectives of the study

Based on the literature review and the gap found, we aimed to develop a simulation-optimization model to improve the urban stormwater runoff quantity and quality. Thus, the study was derived from the following main objectives:

1. To investigate the hydrological performance (peak runoff reduction) of LID-BMPs at the catchment scale.
2. To evaluate the removal efficiency of LID-BMPs at the catchment scale.
3. To develop a simulation- optimization model that can integrate both quantity and quality control of urban runoff.
4. To determine the optimal placement (type, number and combination) of LID-BMPs for maximum runoff and pollutant loads reduction with the minimum cost.

1.7 Thesis outline

The thesis has been organized in 6 chapters as follows:

- Chapter 1 is an introduction to the subject and contains the main points of the research as well as problem statement, purpose and the objectives to be achieved in the study.
- Chapter 2 encompasses a wide variety of literature review related to this study which have been carried out recently throughout the world. It contains some basic definitions and theories related to the subject performed by other researchers. The literature has mainly been selected from the most prominent and specialized journals and some relevant books.
- Chapter 3 includes the materials and methods of the research, the study area as well as the software and models used in the study. The data collection methods and data analysis have also been explained in this chapter.

- Chapter 4 explains the results of the study. This chapter contains the modeling process of the study area, simulation and optimization of the best management practices for the study area as well as the best outcome of the simulation-optimization model for the LID-BMPs to be implemented in the study area.
- Chapter 5 discusses the results and major findings obtained from this study and explains the significance of the findings by comparing them with the previous studies.
- Chapter 6 will present the conclusions of the study as well as some suggestions for the future research directions of similar studies in this area.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Urbanization causes substantial disturbance to the natural landscapes and as a result, natural vegetated surfaces are replaced by impermeable surfaces. This increase in the impervious surfaces are the main reason responsible for the hydrologic changes resulting from urbanization Process (Shuster et al., 2005). Impervious surfaces dramatically affect the infiltration of precipitation, and runoff is rapidly conveyed into stream channels which will change the natural hydrologic cycle. This will increase the volume and peak rate of runoff resulting from storm events. Impervious surfaces also facilitate the delivery of pollutants directly into streams (Palmer et al., 2004). Roads and parking lots are the main sources of impervious surfaces of different catchments. These impervious surfaces cause runoff and poor water quality problems imposed by vehicles residues (Moglen, 2009). Thus, with that large number of roadways in urban areas, the amount of surface runoff produced is significant as well. As a result, traditional ways of stormwater management practices will not be practical nowadays. By controlling stormwater at source, the damages to the natural water cycle will be controlled for both pre and post development.

Although the runoff increase in urbanized areas is considered a danger to both humans and receiving water bodies, it can be viewed as an opportunity as well. Harvesting excess surface runoff water in urban areas, not only is helpful for ecosystem protection but also can be used as a new source of water for residential areas (Fletcher et al., 2013). In semi-arid areas, stormwater runoff is considered as an important potential source of water supply for providing base flow in urban streams (Read et al., 2019).

A number of methods are used to control the quantity and quality of urban stormwater runoff. Traditionally, the urban drainage has been used to direct and harvest the urban stormwater runoff. Low Impact Development (LID) and Best Management Practices

(BMP) are broadly used, nowadays, to mitigate the devastating impacts of stormwater runoff. They have been widely studied in the past years by different researchers. For instance, (Damodaram et al., 2010; Elliott & Trowsdale, 2007; Jia et al., 2013; Liu et al., 2014) are few examples to be mentioned in this respect.

2.2 Watershed and Urban catchment

The terms "watershed" and urban "catchment" are often used interchangeably in urban areas for hydrologic modeling. The main difference between watershed hydrologic models and urban catchment hydrologic models are their time and space relative scales. (Blöschl & Sivapalan, 1995). Natural watersheds usually have time scales in the range of minutes to years, while time scales in urban catchments often lie in the range of minutes to hours. Likewise, the space scales of urban catchments are typically smaller, and generally they are in the range of meters to kilometers. Urban catchments land uses are also highly impervious, being predominantly residential, commercial, and industrial. Whereas, the perviousness of natural watersheds is high, and their land use types are typically meadows, forest, pasture, crop land, and other types of agricultural land cover.

The runoff is subject to natural hydrological processes on the normal surfaces, while impervious surfaces produce more runoff because they are less permeable and smoother. Imperviousness is a significant environmental indicator (Arnold Jr & Gibbons, 1996) which plays an important role in hydrological analysis. The spatial distribution and connectivity of impervious surfaces are the most important factor in determining the surface runoff volume and velocity (Jacobson, 2011; Shuster et al., 2005; Zhou et al., 2010). Connectivity to stormwater system is the most significant factor impacting the surface runoff amount and its dynamics (Brabec et al., 2002; Lee & Heaney, 2003; Roy & Shuster, 2009). When the flow velocity increases, it will decrease the lag time, which is the time interval between the center of mass of the storm and the center of the resultant hydrograph (Huang et al., 2008a; Paul & Meyer, 2001). This high runoff velocity will also impact the flood peaks compared to the pre-urbanized conditions (Burns et al., 2005). This high flood peak will increase erosion, resulting in the slope stability reduction and production of more suspended sediments (Fletcher et al., 2013), which ultimately leads to higher flood risk and severity (Chen et al., 2009). Urbanization and imperviousness can also decrease base flow (Rumman et al., 2005), although some studies found no significant alteration in base flow because of urbanization (Meyer, 2005). If the flow regime in natural catchments changes, e.g. because of velocity increase, the channel will adjust itself to the new flow conditions (Leopold, 1968). The water streams in urban catchments are usually modified, such as a closed pipe system replaces an open channel. Therefore, the natural adaptability of flow is limited, resulting in the increase of flood frequency and magnitude (Salvadore et al., 2015).

2.3 The Natural Hydrologic Cycle

The natural hydrologic cycle is a cycle involving the processes of precipitation, interception, runoff, infiltration, interflow, percolation, groundwater recharge, evapotranspiration, and back to the atmosphere, etc. When precipitation falls onto land surfaces, part of it is intercepted by vegetation, part of it is stored in surface depressions, part of it is infiltrated into the ground, and part of the precipitation is discharged over land to rivers that eventually lead back to the oceans. Precipitation held by vegetation eventually evaporates into the atmosphere; water held by depression storages either evaporates into the atmosphere or infiltrates into the ground; and the infiltrated water recharges the subsurface, where it can be utilized by plants, return to streams as interflow or base flow, or serve to recharge ground water aquifers (Chin et al., 2000). It is estimated that about 40% of the precipitation is intercepted by vegetation and depression storages in a natural landscape, and the intercepted precipitation eventually goes back to the atmosphere through evapotranspiration (FISRWG, 1998). About 25% of the precipitation infiltrates into the ground and becomes interflow/base flow back to the stream, and another 25% of the precipitation percolates into the ground and becomes ground water. The other 10% of precipitation becomes surface runoff (FISRWG, 1998).

2.4 Water cycle in urbanized areas

The water cycle concept is a complicated issue in urban areas because water can easily enter from one catchment to another via water distribution and sewer networks. An urban catchment is a heterogeneous natural environment consisting of both natural and artificial surfaces. It should also be noted that the natural and artificial processes interact with each other in urban catchments (Figure 2.1). Therefore, achieving a standard definition for the urban water cycle is difficult. However, even in the disturbed natural network, water still follows the natural hydrological pathways of the catchment. For instance, infiltration will happen on locations in which the soil has not been sealed. Even in the subsurface, the water movement is under the influence of urban unnatural soils composition. Groundwater discharge is also impacted if the surface and the groundwater systems are not naturally connected. Other parts of the water cycle flow in an urban catchment includes: waste water, water supply, stormwater, leakage from pipes, irrigation, infiltration of water through artificial ponds and septic tanks, and wastewater release into surface water (Salvadore et al., 2015).

Figure 2.1 gives a summary of a wide range of hydrologic processes which could possibly take place in a normal urban catchment system. Each one of these variables has a different unique complexity and has been investigated separately in different studies in the past years. The scales of time and space noticed in urban catchments, precipitation, overland flow, infiltration, depression storage, and surface runoff are widely known as the main hydrologic variables to be deeply comprehended and simulated in urban areas (Cantone & Schmidt, 2011).

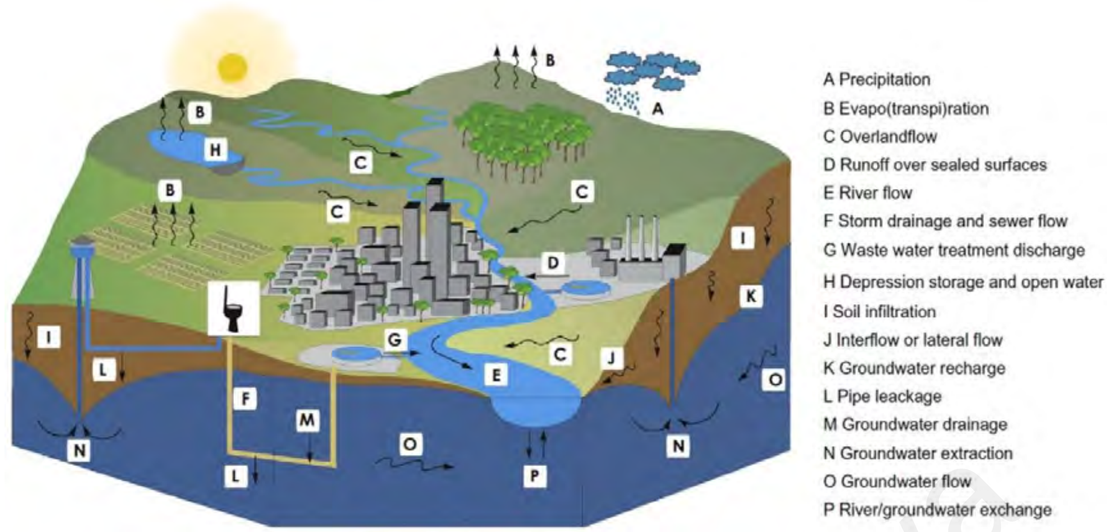

Figure 2.1: Water cycle in an urban catchment (Salvadore et al., 2015).

2.5 Hydrological processes in urban environments

Mejía and Moglen (2010) proved that the patterns and distribution of imperviousness can affect the hydrological response of the catchment remarkably. Therefore, an urban catchment is the one that the local anthropogenic activities significantly disturb the hydrological fluxes; then the hydrological assessment can be performed in the area (Salvadore et al., 2015).

The hydrological systems are usually different from one city to another one, the population and sealed surfaces of urban areas can have different impacts on the water resources. The policies in different areas can also affect the water resources and population. What is more, the catchment boundaries of urban catchments could not be very clear as water can cross the boundaries. An urban catchment consists of both natural and artificial surfaces (Salvadore et al., 2015).

2.5.1 Precipitation

Fletcher et al. (2013) stated that the studies regarding urban effects on precipitation have been of high interest for researchers since the 1970s. These impacts have been quantified in many studies by comparing the conditions of pre and post urbanization and found that the precipitation changed between 5% and 15% by seasonal changes (Shepherd, 2006; Shepherd et al., 2002; Taha, 1997). However, the uncertainties originating from data scarcity and other atmospheric processes have greatly impacted these findings. Therefore, the U.S. Weather Research Program considered these studies uncertain (Dabberdt et al., 2000). However, urbanization can generally affect atmospheric processes, particularly the intensity and patterns of precipitation (Salvadore et al., 2015).

2.5.2 Evaporation and Transpiration

Evapotranspiration (ET) can significantly be affected by urbanization, so it is crucial to accurately estimate ET as it is an important component of water balance (Cheng et al., 2011). Because of lack of vegetation, ET might be substantially less in urban catchments compared to rural areas (Chen et al., 2009; Taha, 1997). Many studies found that ET can reach up to 40% and in extreme cases up to 80% in urban areas annually, so it cannot be ignored (Berthier et al., 2006; Rodriguez et al., 2008). The green areas are often over irrigated in urban zones in both dry and wet periods (Salvador et al., 2011). In these cases, the plants transpiration can be more than normal conditions. The phenomenon of urban heat island (UHI), or the increase in temperature of urban centers, is the most common studied impact of urbanization on local climatic conditions (Arnfield, 2003; Dixon & Mote, 2003). As higher temperature increases the evaporation of surface stored water, plant canopy, artificial and natural water reservoirs, and it can enhance vegetation growth, so the impacts of UHI are hydrologically relevant (Salvadore et al., 2015).

2.5.3 Depression storage, overland flow and runoff

The urban precipitation falls on natural or impervious surfaces, flows on pervious or impervious surfaces or ends in water bodies and stormwater collectors. Depression storage is part of the surface runoff retained in small ponds of the surface until it infiltrates or evaporates. Sometimes, the wetting abstractions (water needed for the initial wetting of the catchment surface) and the depression storage are combined and are collectively called the initial abstraction (Geiger et al., 1987). Part of the rainfall which is not intercepted or infiltrated (known as excess rainfall, or effective rainfall) flows over the surface and is called overland flow and turns into direct runoff at the catchment outlet (Chow et al., 1988).

On natural surfaces, the depression storage capacity normally ranges from 0.5 mm to 15 mm, and this amount for impervious surfaces is between 0.2 mm to 3.2 mm (Marsalek et al., 2008). It should be noted that depression storage is usually more influential at low rainfall intensities, whereas in heavy storms its impact is marginal. The depressions filling process is relatively fast and depends on precipitation, evaporation and infiltration rates and generally is in the order of seconds to minutes (Salvadore et al., 2015).

2.5.4 Infiltration and subsurface processes

When the water moves into the soil under gravity and capillary forces, the process is called infiltration. Infiltration process recharges shallow aquifers, and during dry periods the shallow aquifers contribute to surface water and streamflow (Marsalek et al., 2008) .

In urban hydrology, understanding the effect of urbanization on ground water systems plays a significant role (Changming et al., 2001; Schirmer et al., 2013). The volume and quality of groundwater recharge are affected by anthropogenic activities in very short time spans (Garcia-Fresca & Sharp, 2005). Urbanization usually modifies the natural recharge mechanisms, and new mechanisms will replace (Foster, 1990b). Imperviousness decreases infiltration and direct recharge, which ultimately reduces groundwater resources. Urbanization will also generally increase groundwater recharge due mainly to indirect recharge from mains leakage (Lerner, 2002). Therefore, evaluating the anthropogenic effects on groundwater systems is a challenging issue (Salvadore et al., 2015).

In residential areas, surface sealing can be more than 50%, whereas it can easily reach 70–80% in industrial areas (Foster, 1990b). However, urban paved surfaces are not totally impervious, and runoff losses can go up to 30–40% (Ramier et al., 2011). Also, the infiltration on roads of residential areas have been measured 6–9% of the total annual rainfall (Ragab et al., 2003a). The infiltration on urban pavements could be due mainly to the abundant fractures observed (Salvadore et al., 2015).

The decrease of infiltration rates in urban areas is mainly due to the following factors (Marsalek et al., 2008):

- Imperviousness in urban catchments (pavements, rooftops, parking lots, etc.).
- Soil compaction in urban areas.
- The artificial drainage system that can quickly removes ponded water, without allowing water infiltrating into the ground.

2.6 Factors affecting urban stormwater runoff

A wide range of factors impact the natural hydrologic process and flow regime in urban catchment. An increasing amount of studies have been performed to investigate these factors. However, the focus of this study is on the most important factors contributing to the direct urban runoff.

2.6.1 Urbanization

Stormwater is rainwater that runs off impervious surfaces in urban areas, such as roofs, sidewalks, streets and parking lots. One of the most significant effects of urbanization is the changes of runoff regime. Urbanization impacts surface runoff in three ways:

- By increasing runoff volumes due to the reduction of infiltration and evapotranspiration.

- By increasing the runoff speed due to the hydraulic improvements of conveyance channels.
- By reducing the catchment response time which increases the maximum runoff intensity that causes the peak runoff discharge.

Thus, urbanization changes the catchment hydrologic regime. Stormwater is drained by sewers or open channels from urban areas to avoid flooding. The stormwater becomes polluted during this process, and its discharge into receiving waters causes environmental concerns (Marsalek et al., 2008).

Urbanization is increasing vastly and rapidly all over the world (Han et al., 2014; Long et al., 2014). This massive increase in urbanization coupled with the increasing climate change are the two main factors contributing to urban stormwater runoff that could not be handled properly by applying conventional stormwater management (Chen et al., 2016; Eckart et al., 2017). Many urban areas are undergoing rapid development around the world and the urbanization process is gaining more interest. This has profoundly modified the natural environment in urban areas (Long et al., 2014).

The alteration of Land use in urban areas will change the hydrological processes such as interception, infiltration and evaporation which can influence the runoff generation and flow patterns. This will result in the alteration of intensity and frequency of surface runoff as well as flooding (Chen et al., 2009; Wang et al., 2007; Weng, 2001). Numerous studies have proved that land-use alterations will have significant effects on watershed hydrology, especially by changing the frequency of flood (Brath et al., 2006), base flow (Wang et al., 2007) and annual discharge (Costa et al., 2003).

Urbanization usually results in the modification of natural landscapes and eventually vegetated surfaces are replaced with impermeable surfaces (Shuster et al., 2005). Future projections show that it will rise from 75% in 2000 to 83% in 2030 in developed countries, whereas, at the same period, it is estimated to rise from 40% to 50% in developing countries (Cohen, 2003). The artificial coverage used in the process of urbanization encompass a wide range of sealed surfaces such as paved roads, parking lots and roofs, that typically clear the vegetation and compact the soil (Brilly et al., 2006).

The main results of urbanization include: increasing of road surface area (Forman, 2000; Jones et al., 2000); reducing drainage capacity (Hicks & Larson, 1997b); channelization and engineered water exchanges especially among major surface waters (Simmons & Reynolds, 1982); as well as land modification for agriculture (Pringle, 2001). Another consequence of the urbanization alterations is that the runoff pathways in urban catchment will be altered (Cairns Jr, 1995). This would significantly affect urban hydrologic cycles (Niemczynowicz, 1999). Urbanization will also change the hydrological response of a catchment to precipitation (Figures 2.2 and 2.3), i.e. the volume, peak flow, flood risk and pollution will be increased, and the low flow will be decreased (Bedan & Clausen, 2009; Burns et al., 2012; Dietz & Clausen, 2008).

The impacts of urbanization on runoff processes are mainly dependent not only on the urban area but also on the extent of urban catchment development. The small-sized and heavily urbanized river basins are more prone to the urban runoff rather than large river basins which flow through cities. In the large-sized river basins, the runoff peaks constitute only a small portion of the flow (Maksimovic & Tucci, 2001). Therefore, to study the hydrological response of a catchment to rainfall, small urban rivers would be more suitable (Foster et al., 1995). Figure 2.2 shows how runoff will be varied if the impervious surfaces are increased.

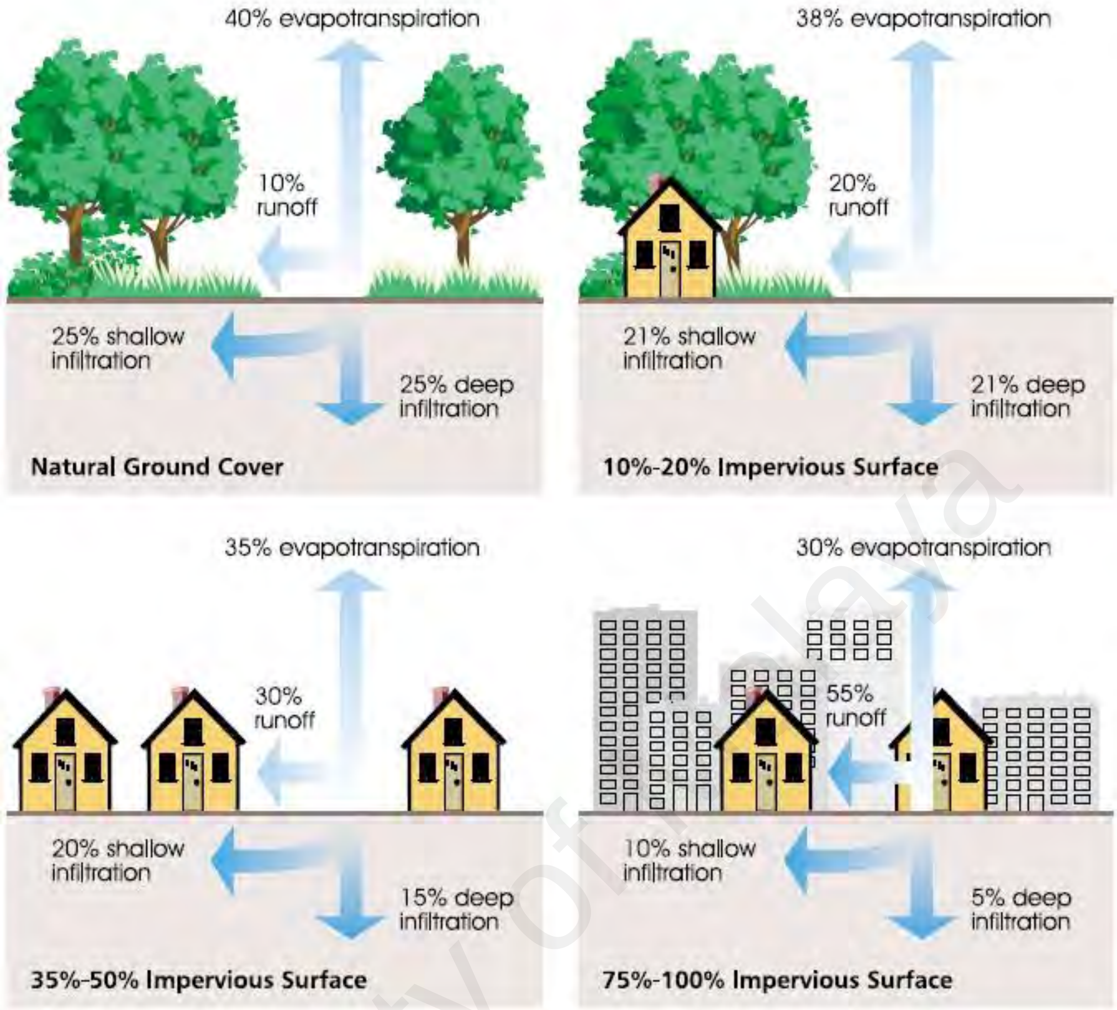

Figure 2.2: Runoff Variability with Increased Impervious Surfaces (FISRWG, 1998).

Urbanization causes enormous effects on the watershed and many factors affect the specific stream response (Doyle et al., 2000). Urbanization will cause water to more quickly flow across the catchments because the land surfaces have less hydraulic resistance which are mainly due to the sealed surfaces, compacted soils and subsurface drainage (Price, 2011). As a result of urbanization, the landscape capacity to infiltrate precipitation runoff will be significantly reduced because the runoff will be increased (Booth, 1991; Hsu et al., 2000), lag times or concentration times will be shortened (Rhoads, 1995) and the water table recharge will be decreased which leads to the decline of base flows (Smakhtin, 2001). Heavily urbanized areas can also alter evapotranspiration regimes of the catchment because of vegetation removal as well as precipitation patterns and intensity of 'heat island' effects (Carlson & Arthur, 2000; Dale et al., 2000). Apart from the local and regional environment, urbanization brings about different challenges to the wider environment as well. The biological and physical characteristics of the hydrological systems will significantly be affected (Fletcher et al., 2013; Jacobson, 2011).

On natural surfaces, water encounters the natural hydrological processes of catchments. Impervious surfaces have low permeability and smooth surface which leads to the production of higher amount of runoff. Therefore, imperviousness is a significant environmental index (Arnold Jr & Gibbons, 1996). It should also be mentioned that impervious surfaces are considered as substantially important in hydrological analysis because their spatial distribution and connectivity is a very important factor to determine the velocity and volume of surface runoff (Jacobson, 2011; Shuster et al., 2005; Zhou et al., 2010).

Connectivity to stormwater system has a high effect on the amount and the running of surface runoff (Brabec et al., 2002; Lee & Heaney, 2003; Roy & Shuster, 2009). In post developed surfaces (Figure 2.2), the lag time, time interval between the center of storm mass and the center of the resultant hydrograph mass, is decreased due to the high flow velocity (Huang et al., 2008b; Paul & Meyer, 2001). This high velocity results in higher flood peaks compared to pre-urbanized conditions (Burns et al., 2005) and amplify erosion, which brings about slope instability and produces more suspended sediments (Fletcher et al., 2013).

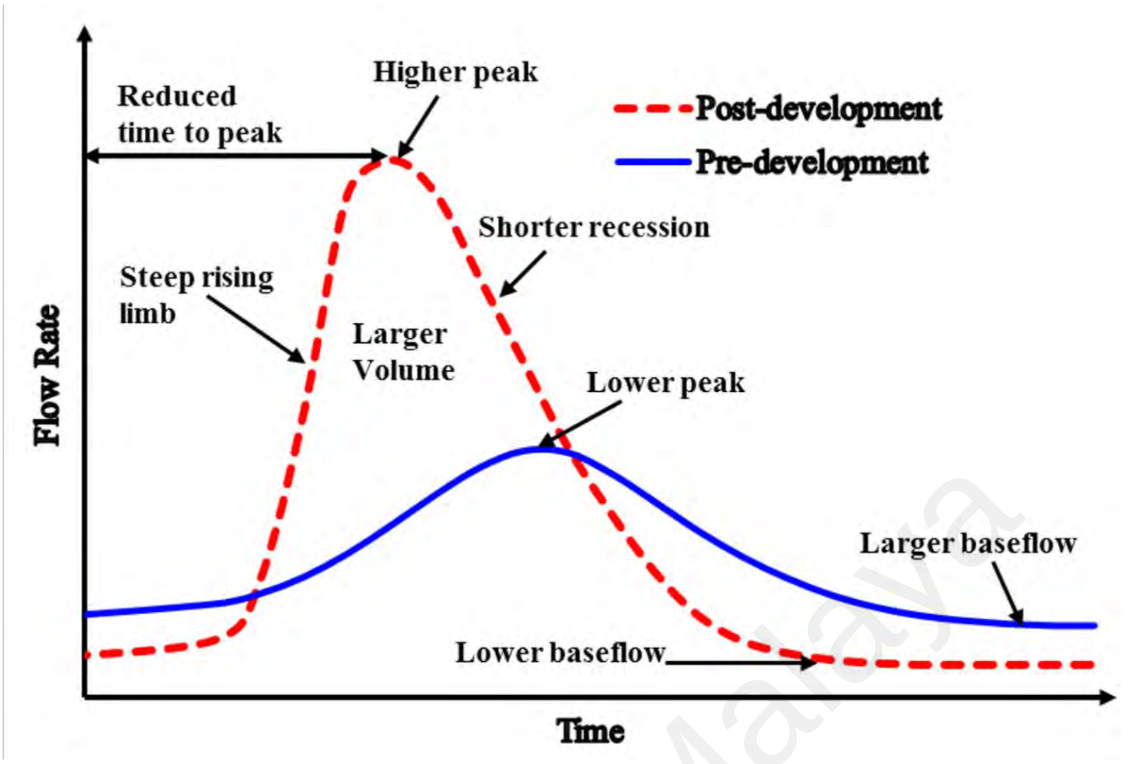

Figure 2.3: Schematic graph of the relative effects of urbanization on catchment hydrology; adapted from: Marsalek et al. (2008).

Figure 2.3 depicts the relative effects of urbanization on catchment hydrology. According to Figure 2.3, we can perform an assessment of urbanization effects on hydrological analysis using the modified outlet hydrographs that results in the reduction of flow time (Huang et al., 2012), increase of volume (Guo, 2008), peak flow (Beighley et al., 2009; Huang et al., 2008a), and total discharge (Kliment & Matoušková, 2009; Moramarco et al., 2005). Urban development and the pertinent increase in the surface imperviousness will change the typical hydrologic regime which can be summarized as follows (Field & Sullivan, 2002):

- The increase in the runoff volume
- Increase in flow frequency, duration and peak runoff
- Reduction in the infiltration (groundwater recharge)
- Flow pattern alteration
- Time to peak will be faster
- Storage loss

Yang et al. (2014) investigated the hydrologic response of a catchment to urbanization in tropical areas. They applied a hydrologic model (MOBIDIC) to a catchment in Singapore which was in the process of urban land use transformation. Their findings confirmed that base flow, interflow and evaporation decreased with urbanization and at the same time, streamflow, surface runoff and peak streamflow increased relative to the urban change. All the changes happened at varying rates.

Similarly, Miller et al. (2014) explored the effect of urbanization on runoff using a peri-urban catchment. Their findings showed that increasing the imperviousness in rural catchments will result in higher effect on peak flows and flood duration compared to the previously existing urban catchment. They specifically figured out that the peak flows will be much greater while the impervious surfaces and all storm runoff routing through the network of storm drainage are combined.

Sillanpää and Koivusalo (2015) investigated the impacts of urban area development on the characteristics of runoff event in both warm and cold seasons in two control sub catchments of 0.31 km^2 and 0.13 km^2 of an urban catchment. They found out that depending on the season, urbanization can have dissimilar impacts on the runoff generation. They found that urbanization can increase runoff volume and depth, peak flows as well as runoff intensities and reduce catchment lag time in warm season. While during the cold period, alterations in the cumulative total runoff production due to the urbanization were not noticeable, but its temporal occurrence was affected.

Impervious surfaces have natural or anthropogenic sources that prevent water to infiltrate into the sub-layer soils (Slonecker et al., 2001). Human activities and habitation are the main reasons for the growth of impervious surfaces in urban areas by construction of structures such as roofs, parking lots and roads. When the impervious surfaces increase, the hydraulic efficiency can be enhanced and the infiltration of rainwater into the sub-layers is decreased; the runoff generation in urban catchments is also increased (Mejía & Moglen, 2010). Therefore, the hydrologic performance of imperviousness is of high interest in urban rainwater management studies (Yao et al., 2016). Although pavements and Streets are generally known as impervious surfaces, their hydrologic behavior is directly affected by the intensity and duration of rainfall in the real situations (Ragab et al., 2003a).

The runoff generation can usually be augmented with the increase of smaller rainfall events which is caused by the increase of the imperviousness (Sheeder et al., 2002). Booth (2000) showed that if the imperviousness is increased by 10%, the increase in runoff generation amount was to the same extent as a 2-year storm in the post development could possibly produce in a pre-development 10-year storm.

Imperviousness is a simple index that can easily be measured, and this has made it to be widely recognized and accepted as a key index to predict the urban impacts on rainfall-runoff process (Arnold Jr & Gibbons, 1996). Previous studies have generally proved that the surface runoff volume and velocity will be increased when the impervious coverage is increased (Jacobson, 2011; Shuster et al., 2005).

Total impervious area (TIA) is the most well-known imperviousness type used in these studies, which is stated as the total impervious area in an urban catchment (Yao et al., 2016). Schueler et al. (2009) pointed out that runoff volume can increase with the increase of TIA. The magnitude of urbanization is also directly related to this quantity. However, TIA does not illustrate the relationship between impervious surfaces and the drainage system, which may result in unexpected approximation between TIA and runoff parameters (Shuster et al., 2005). As an example, rooftops drain onto pervious areas, so do not have much contribution to runoff compared to roadways that are directly connected to the drainage system. On the other hand, directly connected impervious area (DCIA) accounts for the part of TIA which is connected to a drainage network hydraulically, such as streets with gutters drained to an outlet (Yao et al., 2016). Table 2.1 summarizes some of the studies investigated the effect of imperviousness increase on the amount of runoff generation.

There have been enormous studies in the past years, investigating the impact of various types of imperviousness on the catchment hydrological processes. Yao et al. (2016) conducted a research to analyze the effect of different types of imperviousness on rainfall–runoff process, such as runoff depth, peak discharge and lag time. They reported that TIA is a more significant factor affecting total runoff rather than DCIA and under different storm condition its impact remains relatively stable. Moreover, they found that using a combination with TIA and DCIA as indicators can lead to a more effective prediction of peak runoff, compared to using one single measure.

Lee and Heaney (2003) carried out a hydrologic modeling to study the hydrologic performance of DCIA and found out that DCIA has the most significant effect on urban hydrology. Yang et al. (2011) and Burns et al. (2015) also pointed out that the majority of hydrologic modification in urbanized areas is due to DCIA. The DCIA are directly responsible for harming streams, rivers, and lakes in urban areas (Obropta & Del Monaco, 2018). Similarly, a disconnected or ineffective impervious layer (Booth & Jackson, 1997) drains runoff to pervious areas (Walesh, 1989). It should be noted that total imperviousness of a catchment is an index which is widely used to measure the hydrologic effects of urbanization (Campana & Tucci, 2001; Choi, 2008).

Table 2.1: Impact of imperviousness on the stormwater runoff generation in urban catchments.

Reference	Type of catchment	Catchment area	Increase in Imperviousness (%)	Runoff Response (%)
Wang Y.-m. et al. (2015)	urban catchment	-	-	Peak discharge 40% increased
Yang et al. (2010)	urban catchment	-	10	Flow frequency increased by 19%
Albrecht (1974)	urban catchment	-	20 to 100%	50% increase in total runoff
Cook and Dickinson (1985)	urban catchment	-	after a period of urbanization	Runoff coefficients increased by 50%, the maximum peak discharge increased three-fold
Hollis (1975)	urban catchment	-	30% increase in imperviousness	100-year flood peaks would be doubled
Sajikumar and Remya (2015)	urban catchment	145 km^2	-	15% increase in discharge peaks
Ozdemir and Elbaşı (2014)	urban catchment	9.33 km^2	-	Runoff increased Significantly
Rose and Peters (2001)	urban catchment	50 km^2	-	Peak flows were from 30% to more than 100% greater
Kong et al. (2017)	urban catchment	8.38 km^2	33.3%	Runoff and runoff coefficients increased 92.9% and 90.9%, respectively

Wang Y.-m. et al. (2015) carried out a research to evaluate the spatial-temporal effects of imperviousness on the hydrological response of different parts of an urbanized watershed. The results showed that the time to peak will be decreased by nearly 15% if the modifications of downstream imperviousness (marked urbanization) is large, while the increase in peak discharge was found to be more than 40%. However, in another research performed in Dead Run watershed ($14.3km^2$), Maryland, Ogden et al. (2011) reported that for extreme rainfall, imperviousness was not significantly important to cause a noticeable change in runoff peak.

In another research Yang et al. (2010), conducted a research on 16 small watersheds in Indiana, USA. They reported that when impervious surface area increases by 10%, the flow variation and flow frequency can be increased by 15% and 19%, respectively. They found a 19% and 12% increase in the frequency of the simulated high-flow and flow variability, respectively which is due to the development of the urban areas in the basin. They concluded that impervious cover was the key significant factor in the selected hydrologic measures trend.

Most recently, Wang et al. (2019) developed a probabilistic model that can distinguish the difference between directly-connected and disconnected impervious areas and can also calculate analytically the effects of the runoff reduction produced by the impervious area disconnection. In another recent study, Ebrahimian et al. (2018) develop a method to estimate the effective impervious area (EIA) portion of urban catchments to assess the impact of EIA on the hydrology of urban watersheds.

There are various types of land use alterations in urban areas which typically have different percentage of imperviousness including residential, industrial, and commercial. Surface coverage in residential and industrial areas are different and can be more than 50% in residential areas and can often reach 70-80% in industrial areas (Foster, 1990a). Nevertheless, Urban paved surfaces are not fully impervious and runoff losses can go up to 30-40% of the total runoff (Ramier et al., 2011), and the infiltration on roads of residential areas has been measured about 6-9% of the total annual rainfall (Ragab et al., 2003b). Depending on the given rainfall event, the surface area contributing to the runoff generation will reportedly be varied (Ramier et al., 2011). However, the sizes and complexities of landscapes in large urban catchments are always greater than that of the small catchments, which lead to varied runoff discharges and travel times (Walsh et al., 2005; Yang et al., 2011).

Li et al. (2011) explored the effects of land-use modification on the nature of runoff generation in a basin of 10,190km^2. They investigated farmland, wood land and paddy field. They stated that land-use alteration is the reason of modification in the rainfall-runoff relationship. They also found out that with similar rainfall event, the maximum runoff will be for farmland and the least runoff will be for woodland, whereas the paddy field is between the two.

Similarly, Sajikumar and Remya (2015) conducted a research on two watersheds with the area of 145 km^2 and 322.5km^2, respectively to evaluate the influence of local land cover and land use on the runoff nature over the past few decades. They observed a 15% increase in discharge peaks whereas the flows during dry seasons were decreased, which shows the reduction in percolation and the resultant decrease in base flow.

It has been proved that the runoff generation resulted from different land use types would be different. A recent research was conducted by Wang et al. (2014) on the two sub basins with the area of 1469 km^2 and 1151km^2, respectively. They intended to quantify the effect of land use alterations on the runoff generation. They compared forest, pasture and paddy fields runoff coefficient to study the impact of different land use type on runoff. They found out that forest and pastureland use have a positive impact, while paddy fields were found to have negative effects on runoff generation.

Very recently, Algeet-Abarquero et al. (2015) also studied the effect of land use on runoff generation at the plot scale in a humid tropic experimental catchment. They investigated various land use types such as main land covers, forest plantations, grassland

and oil palm plantations. Runoff response of these land covers was analyzed at two spatial plot scales: 1- the plot of ($150m^2$) under natural rainfall conditions and 2- simulation of runoff on micro plots ($0.0625m^2$). They found that land use alterations have a profound effect on surface flow generation. For example, they observed the highest runoff response in oil palm plantations, which was 20-fold higher than secondary forests in natural storm conditions and went up to 75% runoff coefficient in extreme rainfall intensity.

2.6.2 Climate change effects

The climate change has a significant influence on urban hydrology. The combination of climate change, with the geologic, topographic, and vegetative characteristics of a catchment generate a unique hydrological regime. Thus, understanding the rainfall behavior alteration at urban scale is urgently vital. We also need to assess the effects of such alterations on the efficiency and stormwater management systems reliability for controlling flood, hygiene and environmental protection (Fletcher et al., 2013). It is usually anticipated that the climate change will alter the timing and magnitude of runoff, which is a significant factor in the water resources management (Zhang et al., 2012). In addition, the precipitation intensity might also be modified by climate change that can be augmented hydrologically by land-use alteration and soil compaction which typically leads to higher impervious surface sealing. Easterling et al. (2000) proved that nearly all precipitation increases resulted from global climate change are due largely to the rainfall intensity increase.

Based on the literature review conducted, although urbanization almost always affects the urban runoff directly, by increasing the magnitude of runoff in urbanized areas, the effect of climate change on urban runoff can be both positive and negative. Zhang et al. (2012) used a hydrologic simulation model to study the effects of climate change on runoff generation. They found out that alterations in precipitation has a more significant effect on runoff than alterations in the temperature. Their findings also generally showed that the whole basin runoff might also increase in the future, although the runoff alterations will not be spatially distributed consistently over the basin. However, climate change can sometimes have a negative influence on the runoff generation by decreasing the amount of surface runoff which can adversely affect the water resources availability.

As an example, Xu et al. (2013) explored the climate change effect on the hydrology of a river basin. They aimed to study both the effect of climate change on hydrology and the uncertainties related to river runoff projections. They found out that the river runoff in the basin will considerably be reduced in the future with some uncertainties in the analysis.

On the other hand, some studies found the positive effect of climate change on runoff generation. Wagesho et al. (2012) investigated two agricultural watersheds in a semi-arid tropical climate in Ethiopia. Their simulation of future runoff showed increased daily extreme events at both stations that will result in the increase of annual runoff.

The effect of climate change combined with urbanization on runoff has also been investigated in different studies (Chung et al., 2011; Poelmans et al., 2011); it seems that both topics will be important in the future research (Fletcher et al., 2013). Wang and Cai (2010) indicated that we can use the recession characteristics to assess the relative impacts of climate change and land use modification. The basin surface and/or subsurface topography might attenuate or augment the impact of climate change and land-use alteration on streamflow, and generally speaking, we should consider these factors in the evaluation of streamflow response to human activities (Dubé et al., 1995; Iroumé et al., 2005).

Studies that have evaluated hydrologic response to land-use modification considering the long-term variations in climate, have proved that hydrologic response to land-use alteration is much more severe than climate fluctuations (Knox, 2001; Leigh, 2008; Smakhtin, 2001). The results of these studies are in consistent with Tomer and Schilling (2009) research who indicated that the effects of climate change resulted from human activities are more delicate than continuous climate fluctuations.

On the contrary, some investigations have found climate change more significant on surface runoff than land use/land cover alteration. Liu et al. (2011) studied the effects of climate change and land use on the hydrologic cycle of a large basin. They found that climate change was more effective on hydrologic processes than land-use, which reduced the surface water and base flow. They also found that the effect of climate change on surface runoff variation was more noticeable compared to other hydrologic alterations.

2.6.3 Other influential factors

Topography and slope are other factors affecting surface runoff. The rate that water moves downslope in the soil is controlled by topographic gradients which indicates whether the stormwater is flushed to the drainage network or remains in soil (Price, 2011). The runoff volume is directly related to slope; steep slopes result in larger overland flow, whereas gentle slopes lead to more infiltration (Liu et al., 2006).

The amount of depression storage also influences urban runoff generation. Part of precipitation will retain on the land surface in ponds, puddles and ditches. It is typically known as depression storage. The rest of overland flow will transform into surface runoff. One of the features which describes hydrological losses in the process of rainfall-runoff is depression storage. It accounts for the retention of rainfall in the ground local depressions. If the runoff is generated by the impervious areas of the watershed, then the depression storage is usually representative of all types of hydrological losses including evaporation and wetting losses (Skotnicki & Sowiński, 2015). The depression storage is mainly considered as effective on outflow of a catchment, which has small depth rainfalls (Barco et al., 2008; Dayaratne & Perera, 2004). The depression storage is significantly important in the computations of small outflows from a catchment surface as well as the flushing of pollutant loads (Tsihrintzis & Hamid, 1998), particularly in the first flush effect.

Soil characteristics is another effective factor. When the topsoil is removed from pervious areas of urban catchments and it is combined with soil compaction (because of construction, traffic, loss of organic matter and vegetation), rainfall-runoff will have uncertain behavior (Gregory et al., 2006; Shuster & Pappas, 2010). Another factor affecting the surface runoff response to rainfall is antecedent soil moisture. In wet soil condition, the runoff is averagely two times higher compared to dry soil condition (Shi et al., 2007). In their research, Shi et al. (2007) investigated the influence of land use/land cover alteration on surface runoff. They calculated the runoff coefficient using SCS model. Based on their findings, the runoff coefficient will increase with the increase of antecedent soil moisture content. They concluded that the land use alteration will be less effective on runoff, if antecedent soil moisture increases.

Precipitation is a significant meteorological factor affecting hydrological process (Li et al., 2008). The alteration of both precipitation and temperature significantly affect the runoff. Studies have proved that a 10% change in precipitation will possibly result in about 15 to 25% alterations in runoff; e.g., (Fu et al., 2007a; Liuzzo et al., 2009; Notter et al., 2007; Wang et al., 2011; Zhang et al., 2009a). Moreover, the effect of climate change on runoff in arid or semi-arid areas is much stronger compared to humid areas (Zhang & Wang, 2007).

Apart from precipitation, temperature is another significant meteorological factor affecting the hydrological process (Li et al., 2008). It is estimated that when the temperature increases by 2-degree, the runoff will reduce by 5% to 12% (Fu et al., 2007a; Liuzzo et al., 2009; Notter et al., 2007; Zhang et al., 2009a). Evaporation from land surface is also another major component of surface runoff even for the surfaces which are nominally impervious (Mansell & Rollet, 2009).

2.7 Urban stormwater quality

Urban surface water quality is also a great concern in urban areas due to pollutant loads in stormwater runoff. There are different types of pollutants on the urban surfaces that are washed off and transported by runoff to the surface and ground water bodies. For instance, urban stormwater runoff is the largest source of metals to the local water bodies (Characklis & Wiesner, 1997). The metals from anthropogenic sources include As, Pb, Zn, Ba, Cd, Fe and Cr. Whereas Al, Ca, Mg, Sr, Hg and Mn are usually from natural sources (Zartman et al., 2001).

Urban runoff transports a great deal of nutrients as well, such as nitrogen and phosphorous (Abustan & Ball, 2000). Nutrients have various sources, such as fertilizers, roof runoff, various household chemicals and street runoff. Other types of water quality parameters in urban stormwater runoff include: Heavy metals, such as zinc (Zn), lead (Pb) and copper (Cu), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Suspended Solids (TSS), Ammoniacal Nitrogen (AN), Nitrate (NO3) and Nitrite (NO2).

2.7.1 Sources of pollutants in urban runoff

Pollutants enter stormwater runoff from various sources, including atmospheric fallout, automobile emissions and corrosion, land surface erosion, pavement degradation, vegetation and leaf litter, etc. These sources, including streets, roofs, parking lots, vehicle service areas, and loading docks may contribute a wide range of pollutants to stormwater runoff (Chen, 2004). Regarding atmospheric pollution, conveyed in wet form with precipitation and dry form as gases and particulates, Novotny and Olem (1994) found that the major pollutants are as acidity (originating from nitrogen and Sulphur oxides), trace metals, mercury and agricultural chemicals (particularly pesticides and herbicides). These chemicals may enter directly into receiving waters or be deposited on catchment surfaces and washed off into receiving waters during wet weather (Marsalek et al., 2008).

There are other pollution sources, such as inappropriate land use activities and poor housekeeping, and also transportation, construction activities, use of building materials, road maintenance, soil erosion, urban wildlife (particularly birds) and pets and poor waste collection are among others to be mentioned. These pollutants may be washed off and transported by urban runoff as dissolved or suspended loads, or as a bedload. These processes are often more intense during the first flush effect (Marsalek et al., 2008).

2.8 Urban stormwater management

The conventional approach for stormwater management use gutters and a system of sewers and canals to convey the stormwater out of the city as fast as possible. This traditional approach could not contribute to the sustainable urban development (Chen et al., 2016; Paule-Mercado et al., 2017).

Historically, the main targets of stormwater management have been excess runoff drainage and flood control. It is related to larger storms and larger watersheds. For designing drainage systems, the minor storms of 5- to 10-year return period are usually used and for flood control purposes, 50- to 100-year major storms are used. However, it has been found that the two-year or less return period micro storms might be the most contaminated urban runoff (Guo & Urbonas, 1996; Pitt, 1999). Guo and Urbonas (1996) in a study on runoff event in Denver, Colorado proved that nearly 95 percent of runoff producing events may be smaller than a two-year storm. The rainfall-runoff events that are small but frequent should be evaluated for stormwater quality management practices.

Although difficult to implement, source control measures are the best methods for pollution control. Maximizing infiltration and minimizing runoff are the main function of BMPs. Swales and filter strips can be used to filter and infiltrate stormwater in urban impervious areas. When the flow travel time on pervious surfaces is longer, more pollutants will be removed by sedimentation and transformation (Lee, 2003).

Controlling stormwater at the source is the best measure to solve urban runoff problem (Dunne & Leopold, 1978). The strategies for designing distributed wet weather controls (WWCs) are summarized as follows (Lee, 2003):

- Maximizing depression storage and infiltration and minimizing runoff.
- Minimizing directly connected impervious areas (DCIA).
- Maximizing time of concentration runoff paths.
- Controlling small storms and maintaining conventional drainage systems and flood control measures.
- Controlling both runoff quantity and quality problems.
- Making the urban hydrologic cycle more visible for both aesthetic and ecology purposes.

There are different measures to deal with stormwater problems, such as strategic approaches, political decisions; source control or end-of-pipe measures (German et al., 2005b). The source control approach has been used more in the past decades, followed by conventional or separated sewer systems (Martin et al., 2007). The decentralized solutions for urban stormwater problems have different denominations based on the focus and where they were first developed. The most common names are (Barbosa et al., 2012):

“Best Management Practices – BMPs” (Shoemaker et al., 2000); “Low Impact Development - LID” (Elliott & Trowsdale, 2007) which is the North American terminology; “Water Sensitive Urban Design - WSUD” used in Australia; “Sustainable Urban Drainage Systems - SUDS” (used more in Europe; (Eckart et al., 2017; Elliott & Trowsdale, 2007)); “Innovative Stormwater Management” (which is more common in Canada; (Marsalek & Schreier, 2009)). It should be mentioned that BMP is a more general word than LID and is used worldwide, while LID is mostly used in north America. LID is a newly developed type of BMPs. In other words, LID is a subset of BMPs.

2.8.1 Best Management Practices (BMPs)

The problems of urban stormwater runoff have been tackled using stormwater best management practices (BMPs), which are techniques, measures, or structural controls used to control both the quantity and quality of stormwater runoff as much as practicable (Loperfido et al., 2014). In the traditional methods, BMPs (primarily wet and dry ponds) have been implemented in a centralized manner (a few large BMPs in or adjacent to stream channels), focusing on mitigating peak discharge and minimizing hydrologic alterations as compared to pre-urbanized conditions. However, BMPs have recently been applied in a decentralized (distributed) manner to control stormwater runoff at or closer to the source, emphasizing on infiltration, retention on the green space and integration with urban design (Davis, 2005; Loperfido et al., 2014; Roy et al., 2008).

There are different types of Best Management Practices (BMPs) used to manage urban stormwater, namely constructed wetlands, stormwater ponds, extended detention/retention basins, and buffer strips, which are the most popular types (Ahiablame & Shakya, 2016; Edwards et al., 2016; Leitão et al., 2018; Marques et al., 2017). BMPs can be structural (built systems), such as rainwater retention, or non-structural, such as preventing pollution or cleaning street (Martin et al., 2007). This approach deals with stormwater considering both future needs and the protection of natural resources (Hvitved-Jacobsen et al., 2011).

2.8.2 Low Impact Development (LID)

Some new stormwater management strategies have been developed to manage the urban runoff at or near the source, such as green roofs, permeable pavements, vegetated swales, bioretention systems, infiltration trenches, and rain barrels. Collectively, these best management practices techniques have been termed as Low Impact Development (LID) (Qin et al., 2013). Low impact development was first introduced in Maryland, USA to mitigate the effects of increased impervious surfaces (Eckart et al., 2017; Prince George's County, 1999). Low impact development is a common terminology for the North America for a philosophy of BMP design that has become popular in many parts of the world (Eckart et al., 2017). These techniques are usually implemented upstream of the catchment at or near the source of runoff, and are often referred to as distributed, source control or decentralized systems.

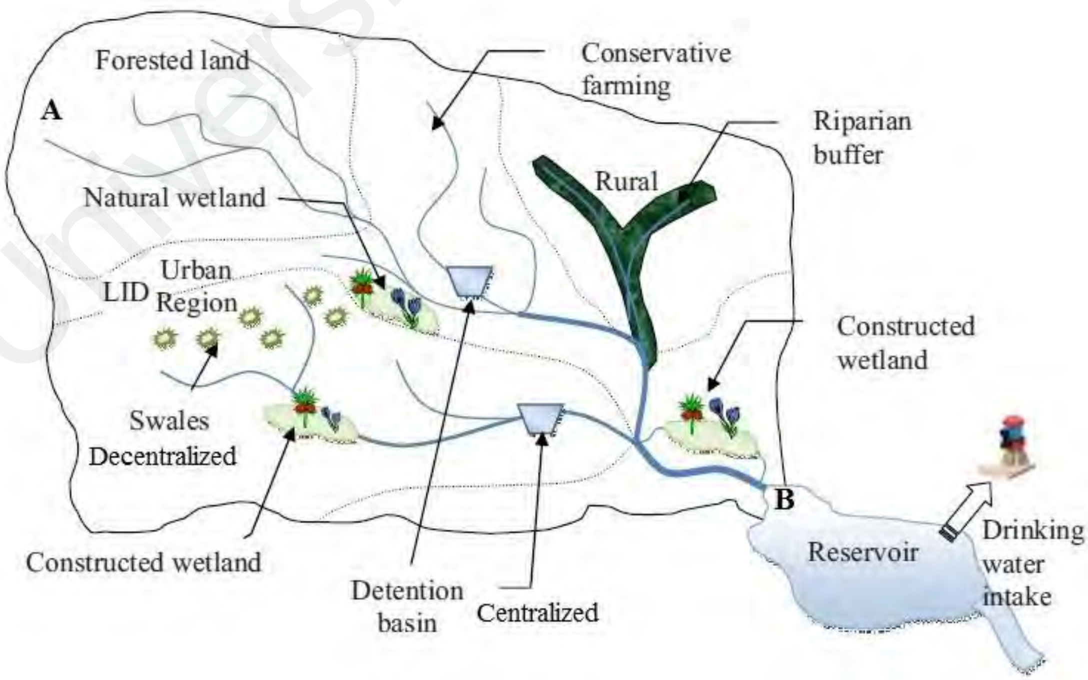

Figure 2.4: Simplified schematic of centralized and decentralized LIDs in a watershed; adapted from Chang (2010).

Figure 2.4 depicts the two different types of LIDs, namely source control (decentralized) and end of pipe (centralized). In comparison with the traditional stormwater management methods, the low impact development (LID) method considers the stormwater as a resource to be more efficiently used (USEPA, 2004b).

The LID methods emphasize detaining, infiltrating, evaporating, and treating stormwater runoff at the source, instead of delivering it quickly offsite. To achieve this target, the low impact development systems apply many onsite integrated management practices (IMPs) to reach the source control. IMPs can be integrated into site design at or near the source of runoff generation. Typical management practices, suitable for to be integrated into an LID design layout, include bio-retention areas, grass swales, green roofs, porous pavements, rain barrels, infiltration trenches, etc. (Zhang, 2009).

Low Impact Development (LID) practices are alternative approaches to manage stormwater using decentralized designs, where stormwater is controlled at or near the source. Low Impact Development (LID) practices have been developed to mitigate the effect of imperviousness on stormwater runoff in urban areas for both quantity and quality. Particularly, LIDs have been designed to mimic the pre-development hydrologic conditions to promote retention, infiltration, and evapotranspiration processes (Ahiablame et al., 2012).

Various studies that have tried to investigate the effectiveness of LID practices have largely directed their focus on the evaluation of bioretention systems, green roofs, vegetated swales, permeable pavements, and other LID practices (Berndtsson, 2010; Davis et al., 2009; Dietz, 2007; Rowe, 2011; Roy-Poirier et al., 2010; Scholz & Grabowiecki, 2007). LID techniques have been credited in these studies as best management practices which are capable of reducing runoff and improving water quality

(Collins et al., 2008; Fassman & Blackbourn, 2010; Gregoire & Clausen, 2011; Myers et al., 2011).

The main purposes of LID practices are runoff reduction (peak and volume), infiltration increase, groundwater recharge, stream protection, and water quality enhancement by removing pollutants through different mechanics, such as filtration, chemical sorption, and biological processes (Hunt et al., 2010a).

Studies have shown that the performance of LIDs on runoff will be different when the rainfall intensities change. Lee J.-m. et al. (2012) studied the LID performance in a demonstration district of Asan Tangjung New Town and found that LIDs can reduce the flood peak by about 7-15% in rainfall of 50- and 100-year return periods. They also found out that LIDs have better reduction performance in smaller storms with shorter durations. Damodaram et al. (2010) estimated the effects of LID on a watershed flow using a hydrologic model at the campus of Texas A&M University, Texas. They found that LID has better performance on stormwater resulted from small storms, while for flooding events of large storms it is not as effective compared to conventional detention ponds. Therefore, it would be more effective to incorporate LID strategies into the conventional drainage systems to handle large storm events (Damodaram et al., 2010).

Two types of LIDs we investigated in our study are bio-retention/rain garden and vegetated swale. These two LIDs have the advantage of controlling the stormwater quantity and quality at the source, and are able to reduce the flow volume, and thus delay the hydrologic response and reduce the pollutant load washed-off from urban surfaces (Eckart et al., 2017). Rain garden (bioretention) is relatively highly efficient for both runoff and pollutant reduction (Dietz, 2007). For example, bioretention cells reduced the average peak flows by at least 45% in Maryland and North Carolina during a series of rainfall events (Hunt et al., 2008). It has also been proved that bioretention are capable of reducing sediment and nutrient from 0% to 99% (Dietz, 2007). Swales have also been shown to have an average retention of 14 % to 98 % for nutrients and TSS, and up to 93 % for metals (Ahiablame et al., 2012).

2.8.2.1 Bio-retention/Rain garden systems

The Bio-retention/Rain Garden area is a structural stormwater control practice collecting and detaining temporarily the stormwater runoff. It also reduces the pollutant discharge using soil and vegetation treatment in the basin area (Debo & Reese, 2003).

Bioretention systems are made up of small areas excavated and backfilled with a mixture of high-permeability soil and organic matter designed to improve infiltration and vegetative growth which are covered with native terrestrial vegetation (Roy-Poirier et al., 2010). The vegetation type can usually resist the environmental stresses and can range from small plants to large trees, depending on the size of bioretention facility. To cover the soil media and retain solids, a layer of mulch is often added. An inlet structure routes urban runoff from the surrounding area to the unit and an overflow structure bypasses the excess flows of the unit. In regions where the soil permeability is low, an underdrain structure is installed at the bottom to prevent water from standing in the unit for extended time. Bioretention, like wetlands, relies on ecological interactions in a natural system to provide storm-water retention and pollutant removal (Roy-Poirier et al., 2010). Figure 2.5 shows a typical rain garden in urban areas (Edmonton, 2011).

Figure 2.5: Typical Rain garden in an urban area.

Although bioretention systems are efficient for both runoff and pollutant mitigation, their main focus is usually on surface pollutant removal (Yang & Chui, 2018). Based on the USEPA (2000a) report on the results of three field studies, the bio-retention areas were able to remove 70 to 97% of lead, 43 to 97% percent of copper, and 64 to 98% of zinc. The removal rates for nutrients also ranged from 0 to 87% for phosphorus, 37 to 80% for total Kjeldahl Nitrogen, <0 to 92% for ammonium and <0 to 26% for nitrate, which were more variable than others.

2.8.2.2 Vegetated Swales (Bio-Swales or Swales)

Bioswales, are open channels with dense vegetation which are specifically designed to mitigate, treat, and transport stormwater runoff. The topsoil in bioswales is amended and selected plants are used for vegetation. They may also include an infiltration layer for water quality treatment and infiltration promotion. Bioswales are designed to grab particulates from the water, slow the flow velocity, and reduce runoff volume through infiltration and evapo-transpiration (Edmonton, 2011).

Figure 2.6: Typical vegetated swale in urban areas.

The vegetation coverage in bioswale improves surface infiltration and soil moisture which improves evapotranspiration. The vegetation also improves stormwater quality through settling particulates, deep infiltration, biodegradation from soil microbes, and filtration through soil layers. By using check dams and increasing the retention time, the water quality treatment efficiency can be improved (Edmonton, 2011). Figure 2.6 shows a typical swale in urban areas.

Bioswales can be applied to most post-development situations, such as residential areas, office complexes, along roadways, parking lots, parks, and other green spaces. Bioswales are suitable to treat roadway runoff as they are constructed along roads and are able to receive sheet flows. Using bioswales to replace traditional drainage systems is a common retrofit opportunity. The traditional stormwater systems, such as ditches are designed only to convey stormwater away from roads. (Edmonton, 2011).

2.9 LID Technology Efficiency

Debo and Reese (2003) stated that the LID technology is able to satisfy the following performances:

1. The hydrology will be approximately acceptable;
2. The natural diversity and beauty will be improved;
3. The economic growth and development will be balanced with ecological preservation;
4. The systems will be more sustainable and maintainable;
5. They work at small scales and achieve accumulated results; and
6. The stormwater quality will be improved as a valuable resource.

According to Lai et al. (2003), the LID technology is also capable of replicating the pre-development hydrology via on-site control and can sometimes work without the need for the large scale, centralized BMPs such as retention ponds. Financially, the LID techniques can also reduce the development and related maintenance costs through site planning, such as reducing sidewalks, sharing drive-ways, removing gutters, etc. (USEPA, 2004b). Bioretention systems, Vegetated Swales, green roofs and permeable pavements are very effective in managing stormwater quantity and quality problems, and promote the reduction of outflow volume, delay the hydrologic response, and control the pollutant loads washed-off and transported from urban surfaces. Table 2.2 presents the LID-BMP systems efficiency.

Research has also shown that the characteristics of rainfall (e.g., total amount, duration and location of intensity peak) can significantly affect the flood risk management of traditional drainage systems (Fu et al., 2011). Therefore, the LID can have a significant contribution to the flood control in urban areas.

Table 2.2: Typical BMP Removal efficiency (MSMA, 2012).

Pollutant	Expected Removal	Comments
Litter	>90%	Expected to trap all gross pollutants
Total Suspended Solids	65-99%	Pre-treatment is required
Total Nitrogen	50-70%	Depend on nitrogen speciation and state
Total Phosphorous	40-80%	Depend on Phosphorous speciation and state
Heavy Metals	50-95%	Depend on state (Soluble or particulate)

Qin et al. (2013) analyzed the effectiveness of an urban drainage system in Shenzhen, China, where some LIDs were implemented for flood reduction purposes. The performance of urban drainage system was assessed using total flood volume during a storm event. They used three different LIDs, namely permeable pavement, green roof and swale. Their evaluation showed that the designed LIDs successfully reduced flood during heavier and shorter rainfall events. They stated that to control the urban flooding resulted from heavier and longer rainfalls, it would be more effective to integrate LID practices with the conventional flood control measures. Zhu et al. (2019) developed an approach to evaluate the effectiveness of LID practices to manage runoff with different objectives and land use. They selected porous pavement and bio-retention cell as their target LIDs for their research. Their approach could auto-optimize runoff management strategies based on LID practices and land use.

2.10 Cost of LIDs

Implementing LID practices is usually more cost effective than traditional stormwater management systems (Eckart et al., 2017). The most important costs of stormwater management are related to reducing flooding and improving drainage (Visitacion et al., 2009). If LID implementation can reduce the load on the drainage network and the resultant flooding in urban areas, then the cost savings would be significant (Roy et al., 2008).

USEPA (2007) studied 17 cases with the LID implementation practices and found out that LID development in urban areas can reduce costs and improve environmental performance. Based on their study, the range of capital cost savings were between 15% to 80% when Lid techniques were applied. Significant savings were achieved through site preparation, infrastructure, paving, and landscaping reduced costs. Wright et al. (2016) conducted a study in Indiana and reported that the more LID practices are implemented in an area, the less the cost of implementation will be. They also concluded that the cost per cubic meter of runoff reduction when LID strategies are adopted varied from around $3 to $600.

Stormwater managers or land owners might be concerned about lost opportunity costs because of allocating land for LID development projects (Roy et al., 2008). Another issue impacting the cost is whether LID techniques are effectively and optimally implemented regarding the location and number of LIDs (Gilroy & McCuen, 2009). The significant LID costs appear in the early stage of implementation; however, the full benefits of BMP practices might not show up for years (van Roon, 2011). For this reason, the USEPA (2007) suggests that comprehensive research to be performed to quantify social and environmental benefits of LID projects during the life cycle, such as environmental protection, flooding damage, aesthetics and recreation cost savings.

2.11 Modeling overview

A model is a concept (or object) that is used to represent something else. It is a simple view of a complex natural reality which helps us to comprehend it. In other words, a model helps us to deal with complexity (James, 2003). To put it simply, a model can be defined as a simplified representation of a complex system and consequently, it always describes the basic and most important components of a complex system.

2.11.1 Hydrological modeling

Similar to the definition of a model, a hydrologic system model is an approximation of the actual hydrologic system (Xu, 2002). In hydrological modeling, abstraction is necessary to understand and control their behavior because most hydrologic systems are very complex. As a matter of fact, abstraction is required to understand and predict the behavior of any part of the environment. There have been many different reasons to develop the catchment hydrologic models. One reason for catchment modelling is to have a better understanding of the hydrologic phenomena occurring in a catchment and how these phenomena may be affected by changes in the catchment. Another aim of modelling of catchment is to generate synthetic sequences of hydrologic data to design facilities for forecasting purposes. The hydrological modeling is also valuable to study the potential impacts of land use alterations or climate changes (Xu, 2002).

In order to apply a hydrologic model successfully, its parameters should be selected carefully. A model usually consists of many parameters which cannot be directly determined from field measurement or watershed characteristics; so, to determine the model parameters, it should be calibrated (Jakeman et al., 2006). By calibrating a hydrological model using local observational data, their predictability is improved. To do the calibration and select the parameters, many optimization methods have been proposed and im proved. Some important optimization methods for this purpose are: Genetic Algorithm (GA) (Cheng et al., 2002), SCE-UA (Vrugt et al., 2003) and particle swarm optimization (PSO) (Jiang et al., 2010; Krauße et al., 2011; Kuok et al., 2010; Zhang, 2009).

2.11.2 Urban hydrological modeling

The primarily application of urban hydrological models are: (1) to assess the impact of urbanization on the water cycle in natural environment and to satisfy the knowledge of this system; (2) to make up for the data deficit; because the urban environment is heterogeneous and measurements are even more complicated than in the natural environment; and (3) to predict the future phenomena, such as flooding, land use, and climate changes, and other issues that impact the urban ecosystem. The primary needs of urban areas are the clean fresh water supply and the waste evacuation. Thus, the basic requirements to fulfil these needs are designing water supply and sewer networks. The issue of flood and pollution risk assessment were addressed by scientists later by developing hydraulic and transport models (Price & Vojinovic, 2011).

O'Loughlin et al. (1996) and Mitchell et al. (2007) stated that when simulating the water system in catchments, the stability of model integration is the main issue for models. The spatial and temporal analysis capability of models are the main criteria for the classification of hydrological models. The urban hydrological modeling is usually conducted at the catchment or city scale (Salvadore et al., 2015).

2.12 LID - BMP modeling for urban stormwater runoff

The replacement of natural soil and vegetation with impervious surfaces in urban catchments remarkably affects the hydrologic cycle; the runoff peaks and volumes are increased, and evapotranspiration is limited (Jacobson, 2011). The Effective Impervious Area (EIA) is part of the impervious area which is directly connected to the drainage system. EIA is the part that contributes to the increase of stormwater volume and peak runoff (Shuster et al., 2005). Studies have shown that reducing EIA could make up for the adverse impact of climate change on urban hydrology and on the effectiveness of urban drainage systems; e.g., (Damodaram et al., 2010; Liu et al., 2014; Lucas & Sample, 2015).

LID-BMP modeling are widely used for urban stormwater both quantity and quality aspects to reduce the runoff volume, delay the hydrologic response and control the pollutant loads on urban surfaces. Therefore, the EPA Stormwater Management Model (SWMM) (Rossman, 2010) is used for urban catchment hydrologic modeling. SWMM is a dynamic model, capable of performing both hydrology-hydraulic and water quality simulation. The urban catchment consists of some sub catchment areas receiving rainfall and generating different hydrologic components, such as surface runoff, infiltration and evaporation; the rainfall-runoff process is a nonlinear approach (Palla & Gnecco, 2015).

The LID controls module has been integrated into SWMM (from v. 5.1.007) to simulate the hydrologic performance of source control strategies, such as rain gardens, green roofs, infiltration trenches and permeable pavements. A combination of vertical layers represents LID systems and their properties, such as thickness, void volume, hydraulic conductivity, and underdrain characteristics are defined on a per-unit-area basis. LIDs are applied within sub catchments by defining their areal coverage (Palla & Gnecco, 2015).

2.13 Applications of SWMM model

The SWMM model has been used widely in water quantity and quality problems in different parts of the world (Huber et al., 1988). The model is capable of performing complex hydraulic analysis for combined sewer and stormwater management planning studies, and pollution controls (Huber et al., 1988; Tsihrintzis & Hamid, 1998). For example, Chen et al. (2002) applied the SWMM model to the Castro Valley Creek catchment in California, to simulate the decay, wash off, and transport of diazinon. Heier and Starrett (2005) used the SWMM model on a 416-hectare golf course in Kansas to predict the total suspended solids, total nitrogen, and total phosphorous during the golf course construction and operation. The SWMM model was also used in four planned development areas of Korea to assess and compare the pre-and post-development runoff conditions (Jang et al., 2007). Barco et al. (2008) carried out an auto calibration to the SWMM model in a large urban catchment in California. Qin et al. (2013) applied the EPA SWMM model to evaluate the effects of low impact development on urban flooding under different rainfalls on a 156-km^2 area in Shenzhen, China. The evaluation was performed on three typical types of LIDs, namely swales, permeable pavements, and green roofs. The SWMM model was used by Palla and Gnecco (2015) to model the low impact development systems at the catchment scale to restore the natural flow regime in the catchment. Green roofs and permeable pavements were used as source control systems in a 5.5-hectare catchment in Genoa, Italy. Tuomela et al. (2019) applied SWMM to model total suspended solids, total phosphorus, total nitrogen, lead, copper and zinc, based on event mean concentrations (EMCs) for different types of land cover and on-site rainfall and flow data to investigate the use of constant source concentrations in modeling pollutant loads. The study was carried out in a residential area in southern Finland.

2.14 Evaluation of urban hydrological models

There are several areas of uncertainty in the application of hydrologic models originated from the input data (rainfall time series); the model parameters and structure, and calibration and validation of models with the observed data. Model calibration, validation and sensitivity analysis are important issues to assess the accuracy and robustness of the results (Fletcher et al., 2013).

The urban hydrological models are substantially more complex than the classical ones as there are more spatio-temporal processes to be simulated in urban catchments. Moreover, the number of parameters and data requirement for urban catchment modeling considerably increase compared to classical models (Hamel & Fletcher, 2014; Mackay & Last, 2010). Therefore, care should be taken about the reliability of the results achieved from these kind of models (Petrucci & Bonhomme, 2014; Vrebos et al., 2014).

Sometimes, there are not enough data available to fulfill the model requirements and perform proper calibration and validation (Aronica & Lanza, 2005). Furthermore, more accurate spatio-temporal measurements will improve modeling results (Dotto et al., 2011). The manual calibration is often preferred to increase model performance (Hamel & Fletcher, 2014; Pan et al., 2011). However, in some cases both manual and automated calibration are applied (Berezowski et al., 2012) or different automatic calibration strategies are explored (Mejía & Moglen, 2010; Petrucci & Bonhomme, 2014). A number of approaches are used to deal with the complexity of parameters in urban modeling. The most important ones are: 1- Parameter reduction (sensitivity analysis), 2- Calibration/Validation (Salvadore et al., 2015).

2.15 Optimization in stormwater management

Many problems in real life are characterized with competing and conflicting objectives which result in systematic analysis and economic optimization applications during the process of decision-making (Zitzler & Thiele, 1998).

As far as the stormwater management is concerned, a catchment level optimization approach can help identify the most cost-effective management alternatives (USEPA, 2006). The U.S. EPA has encouraged and supported the development and implementation of stormwater management on a catchment basis over the past ten years (USEPA, 2004a). A catchment level approach concerns the tradeoff between peak flow and total runoff volume control, total cost, and pollution prevention. The location and sizes of the stormwater management systems can be optimized against objectives of pollution, flood, and erosion-sedimentation control (USEPA, 2004a).

Simulation and optimization of LID practices has been of high interest in the study of stormwater management strategies (Liu et al., 2019). Linking SWMM with a multi objective optimization model has been a widely used method for analyzing LIDs in many studies. For example, Baek et al. (2015) coupled SWMM with MATLAB to optimize LID sizes using the pattern search algorithm. Duan et al. (2016) used the multi-objective optimal model to design urban stormwater drainage systems by using detention tanks and LID devices. The SWMM was used for the numerical simulation, and the modified Particle Swarm Optimization (NPSO) scheme was applied to solve the multi-objective optimization problem. Jung et al. (2016) coupled the Harmony Search (HS) algorithm with SWMM and developed an optimization model to determine the optimal design of permeable pavement. Eckart et al. (2018) developed a simulation-optimization model by linking the EPA SWMM to the Borg Multi objective Evolutionary Algorithm to optimize LIDs for stormwater control. The SWMM model was calibrated, and validated for a catchment in Windsor, Ontario, Canada and the LID stormwater controls were tested for three different return periods.

Optimizing multiple objectives could be very helpful for the implementation of LID controls. In order to maximize the cost-effectiveness and fully assess the planning control effects, the optimal design and placement of LID-BMPs is very essential. (You et al., 2019). The optimization models have the ability to help optimize various aspects of LID implementation, such as the selection, placement, and sizing of many LID controls throughout a catchment (Eckart et al., 2017).

Overall, LID practices have the capacity to alleviate the adverse effects of imperviousness on stormwater runoff quantity and quality. They have been particularly developed to imitate the pre-development hydrologic conditions and improve the infiltration and evapotranspiration in urban areas (Ahiablame et al., 2012). Numerous studies have proved the positive effects of LID-BMPs on urban runoff reduction and water quality improvement (Autixier et al., 2014; Kok et al., 2013; Newcomer et al., 2014; Vezzaro et al., 2011).

However, there are many factors to be considered while implementing the LID controls, such as number of controls, locations and combinations of LID controls, which are due mainly to the variation in catchment characteristics. In order to lower the implementation costs and identify the best implementation scenarios, optimization tools are vital so that the maximum runoff and pollutants reduction is achieved (Eckart et al., 2017).

As the catchment characteristics are complex, it would not be easy to find out the best LID combination performances without comparing different scenarios by using optimization. However, the type of optimization algorithm to be selected is also important to make sure the objective functions are satisfied (Liu et al., 2016).

The Multi-Objective Particle Swarm Optimization (MOPSO) is a multi-objective form of PSO, which was developed by Coello et al. (2004). The idea behind most multi-objective optimization is to find a set of optimal solutions representing the optimal surface between different criteria (Liu et al., 2016). This trade-off surface is widely known as the Pareto front which is used to differentiate between the conflicting solutions. The goal of multi-objective optimization is to identify the Pareto-optimal solution (or Pareto-optimal front) for the problem (or an approximation sample) (Montalvo et al., 2010).

Optimizing multi objectives could be very helpful for the implementation of LID controls. The optimization models have the ability to help optimize various aspects of LID implementation, such as the selection, placement, and sizing of many LID controls throughout a catchment (Eckart et al., 2017).

In this study, two types of LIDs, namely rain garden and vegetated swale were selected, and a simulation-optimization model was developed accordingly to find the best combination of LIDs at the catchment scale. This study used EPA SWMM and MOPSO algorithm to find the type, number, and best combination of LIDs in order to minimize the peak runoff and improve the water quality in urban areas with the optimal number of LIDs applied.

The objective was to achieve the optimal number and combination of LIDs in order to have the maximum reduction of peak runoff, total suspended solids (TSS), and total nitrogen (TN) with the minimum cost using a simulation-optimization model. In order to achieve the maximum flow and pollutants reduction, the cost of LIDs should also be investigated. The simulation-optimization model developed was also able to calculate the minimum cost for LID practices implemented in the catchment to achieve the optimal reduction of peak runoff, total runoff volume, TSS, and TN.

CHAPTER 3: METHODOLOGY

3.1 Study area

The study has been carried out in the Bunus river subcatchment located in Kuala Lumpur city, Malaysia. The Bunus river subcatchment is part of the bigger catchment, Klang river catchment.

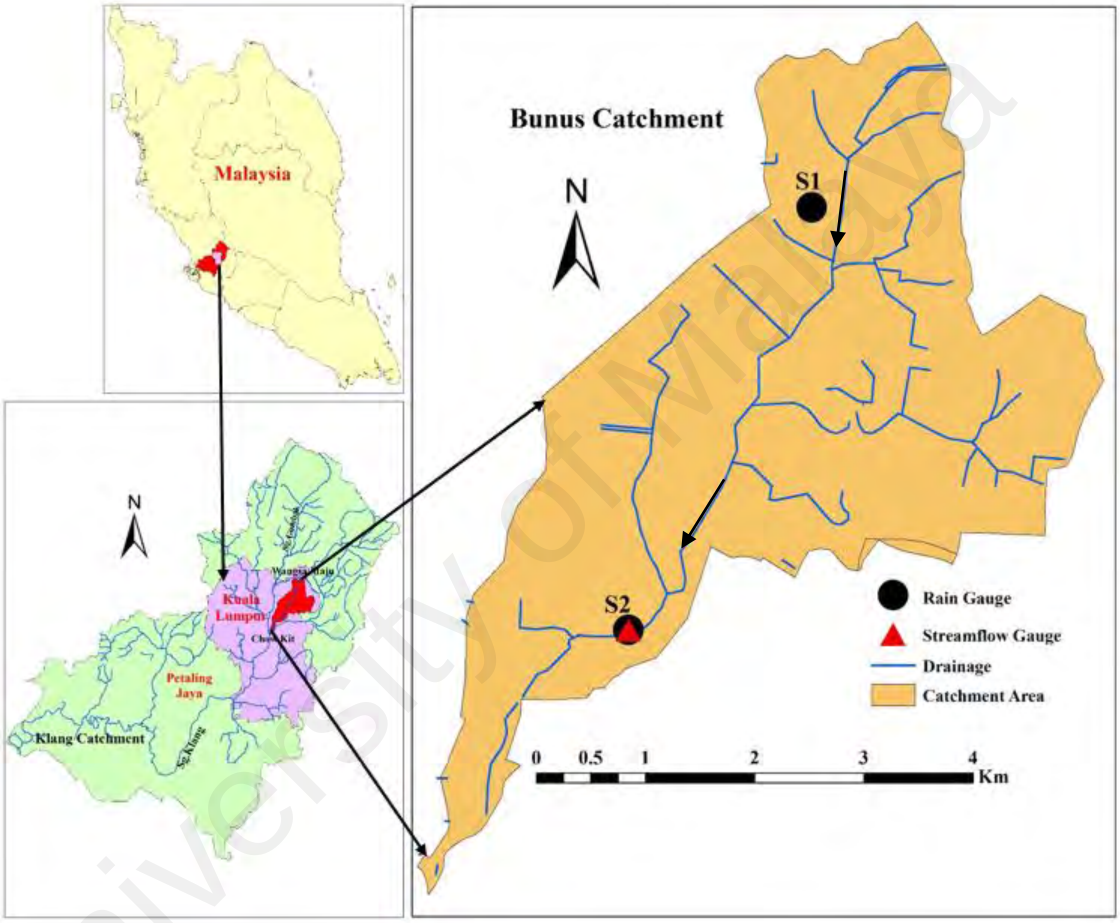

Figure 3.1: Bunus subcatchment within Klang catchment.

The Bunus subcatchment area is about 18 sq km in terms of total size, with the main river stretching about 9.5 km, originating from Wangsa Maju (3.212 N and 101.735 E) and joining Klang river next to Jalan Munshi Abdullah (3.153 N and 101.698 E). The catchment has two hydrological stations (S1 and S2 in Figure 3.1) and one automated streamflow monitoring point (S2) run by the SMART (Stormwater Management And

Road Tunnel) control center which is under the Malaysian Department of Irrigation and Drainage (DID).

The city of Kuala Lumpur is undergoing remarkable development which has widely resulted in the vast urbanization and urban runoff. As Bunus river subcatchment is one of the most densely populated areas within the region, the urban runoff quantity and quality is a major issue in the area. Figure 3.1 depicts the Bunus river subcatchment within the Klang catchment.

The catchment consists of Wangsa Maju, Setapak, Jalan Genting Kelang, KL Festival Mall, Pulapol, UTM Kuala Lumpur Campus, Kampung Ayer Panas, Jalan Tun Razak, Taman Tasik Titiwangsa, Kampung Baru, Chow Kit, Dang Wangi and Jalan Tunku Abdul Rahman.

3.2 Data collection

The main data for this study to perform was the historical rainfall and flow data, topography, land use data, soil groups, catchment drainage networks, GIS maps and Digital Elevation Model (DEM). The required data was collected from the Department of Irrigation and Drainage (DID) and SMART (Stormwater Management And Road Tunnel) control center which is under DID as well. Figure 3.1 depicts the hydrological stations in Bunus catchment.

The rainfall data and the relevant discharges were collected from the SMART Control center. There are two rain gauges within the Bunus catchment located at Jalan Genting Klang (S1) and at Jalan Tun Razak area (S2). Both stations have been depicted in Figure 3.1. The catchment has also one automated monitoring gauge (S2) located at Jalan Tun Razak. The DID office also provided us with relevant GIS maps of Klang catchment and Bunus subcatchment consisted of the main Klang river and the tributaries which were very helpful. Figure 3.1 gives more details of hydrological characteristics of Bunus subcatchment.

For the purpose of the calibration and validation of our model, we also collected one event rainfall sampling at Jalan Tun Razaq Hydrological station on 20-09-2018 rainfall event. Later, the SMART control center provided us with the rainfall and flow data of the same event as well. We collected a total of 17 samples and analyzed them in the Environmental Laboratory at the University of Malaya for the quality parameters. The parameters we analyzed consisted of BOD, COD, TSS, TDS, Turbidity, DO, Ammonia-N, Nitrate, Nitrite and Phosphate. We used the water quality parameters to calibrate our quality model for the purpose of our modeling.

3.3 Bunus catchment drainage networks

The Bunus subcatchment has a network of drainage to collect the runoff and drain it to the main collector. The GIS maps and site inspection showed that the drainage networks and river tributaries are the same in most parts of the catchment. The main Bunus river serves as the main collector in the catchment and drains the runoff and wastewater out of the catchment. The direction of the runoff is from north east to the south west. Figure 3.1 depicts the drainage networks and the runoff direction.

3.4 Bunus catchment land use

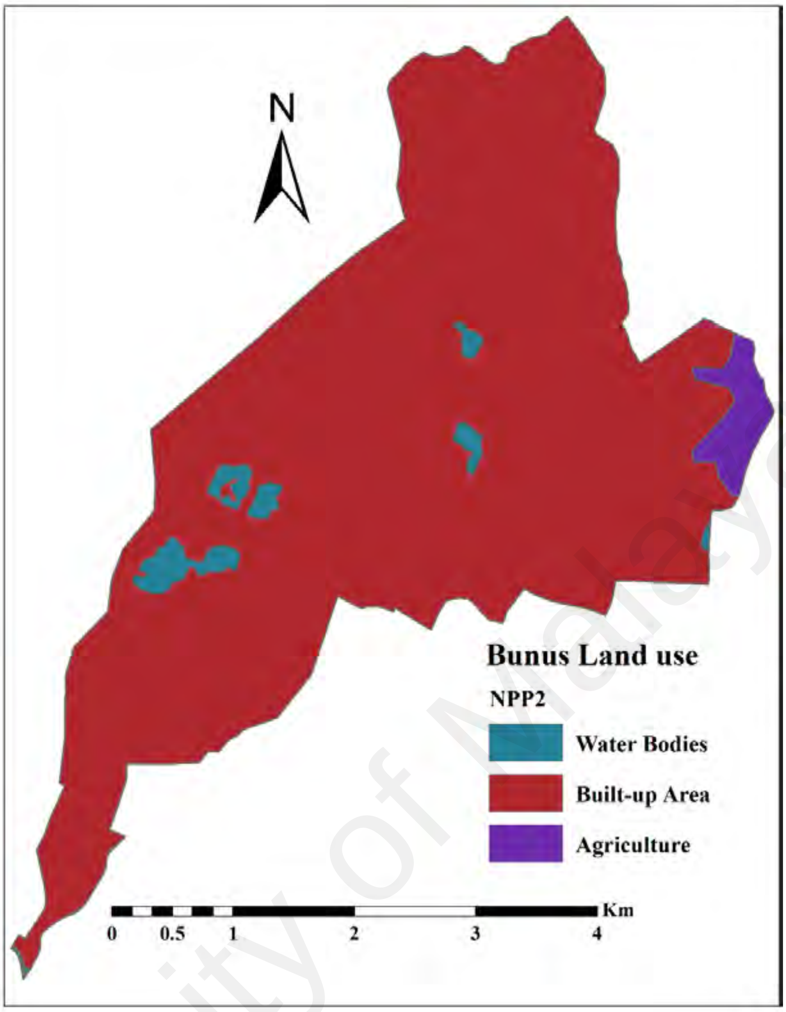

Figure 3.2: Bunus catchment land use.

Bunus subcatchment is one of the most densely populated districts in Kuala Lumpur. As can be seen in Figure 3.2, only a very small part of the catchment is agricultural lands or water bodies. The whole subcatchment lands are almost covered by buildings and as a result, by other forms of impervious surfaces, such as roofs, streets and roads. This makes the catchment vulnerable to runoff and consequently to flash floods.

3.5 Bunus catchment topography

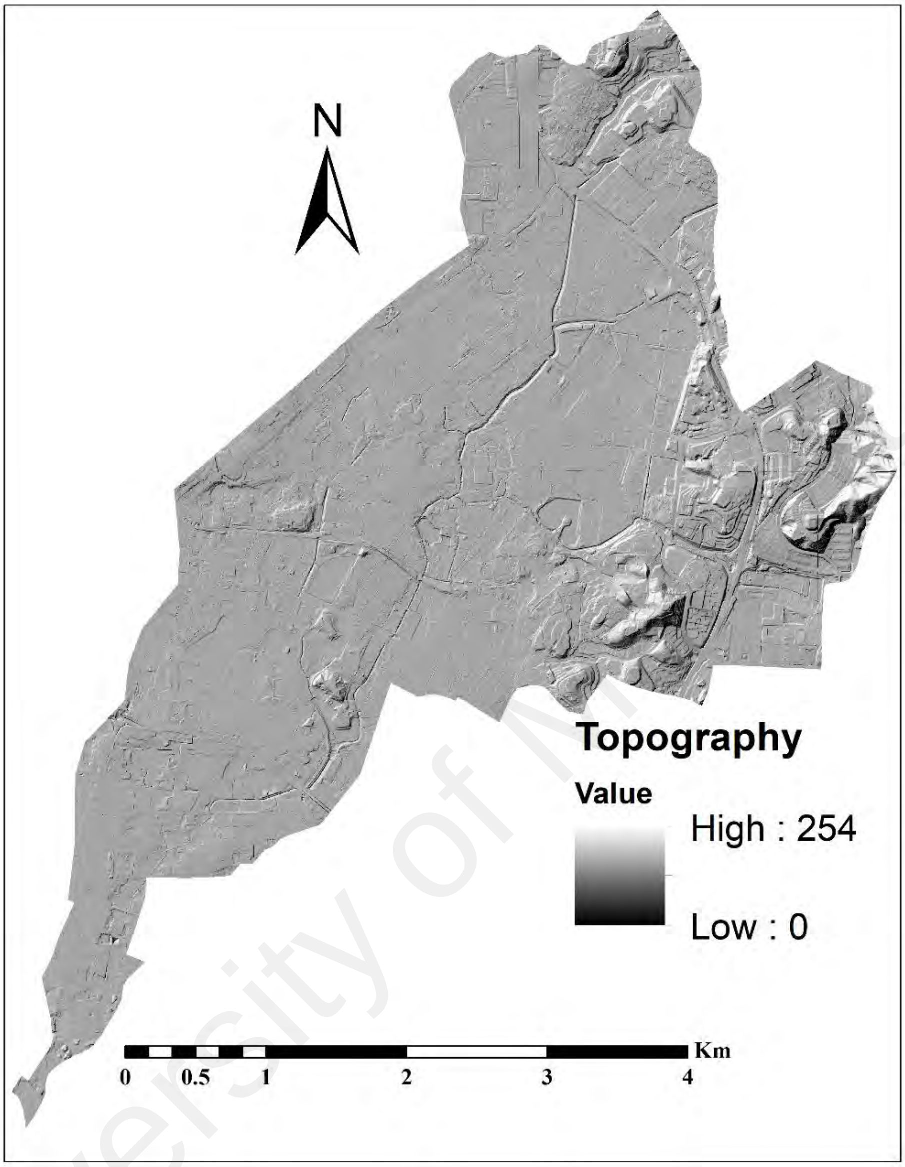

Figure 3.3: Bunus catchment topography.

The Bunus catchment is naturally steep, and the slope of the catchment is from borders towards the main river located in the middle of the catchment. The highest point in the catchment measured was 252 located at the east part of the catchment and the lowest point measured was about 2 located in the middle, down the main river. The topographic map was used to calculate the slopes for each subcatchment to be used in SWMM model. Figure 3.3 illustrates the topographic map for the Bunus catchment.

3.6 Modeling procedure

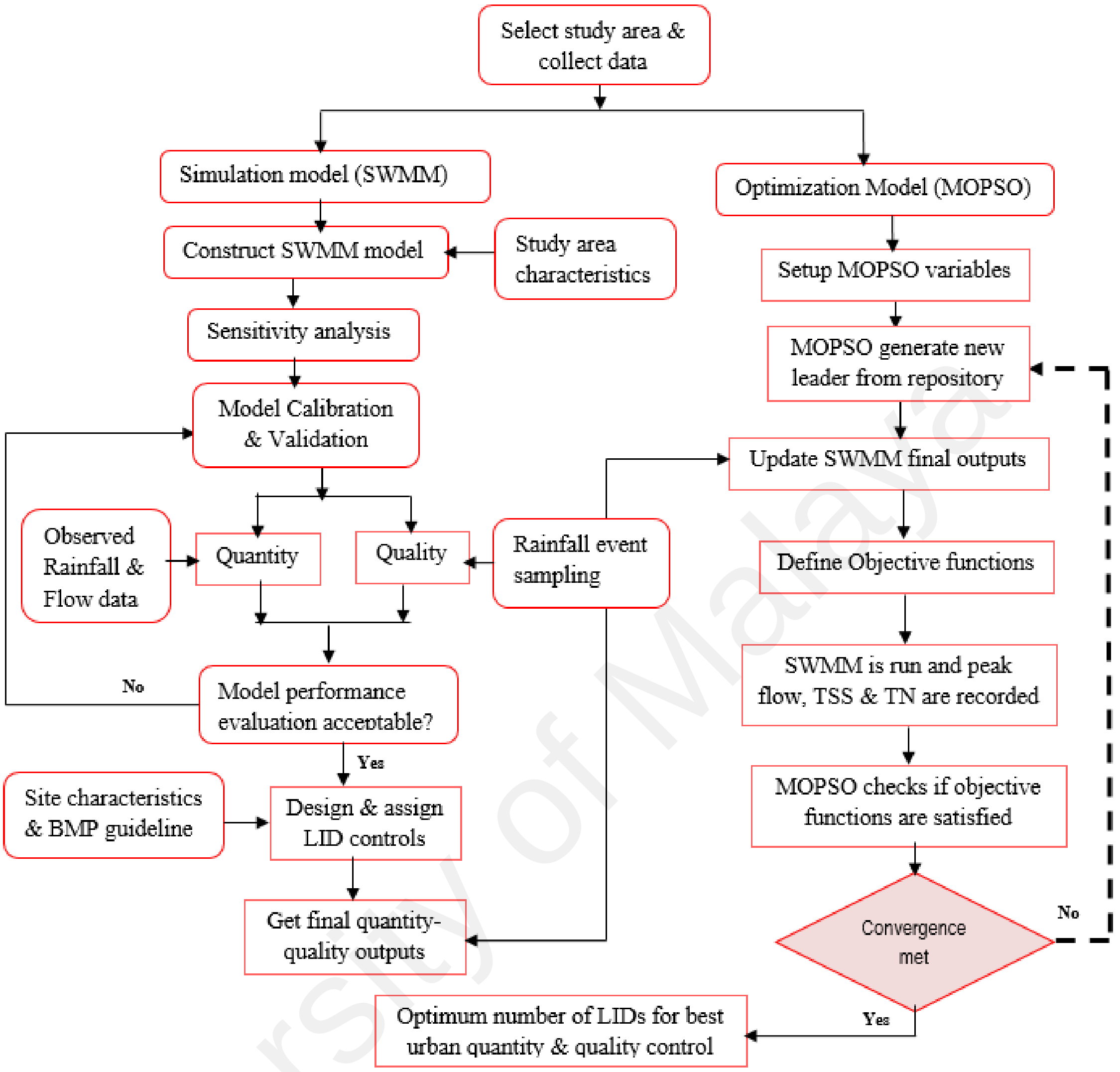

Figure 3.4: Schematic flow chart of the modeling procedure.

Compared with the traditional stormwater management practices, the LID method uses distributed, on-site integrated management practices (IMPs) to control the runoff at the source. By encouraging on-site infiltration and treating the surface runoff through IMPs, the LID technique has the potential to bring the post-development runoff conditions to the pre-development level.

Watershed models are very helpful for evaluating runoff conditions from both future development schemes and possible stormwater management practices. The USEPA SWMM model can be used for making water quantity and quality predictions.

In this study a simulation-optimization model was developed to find the optimal number and implementation of LID controls at the catchment scale in order to achieve the maximum runoff and pollutants reductions. Figure 3.4 depicts the general simulation-optimization model setup and required data to construct it.

The modeling approach has two different but related parts; simulation modeling using SWMM and optimization modeling using multi objective particle swarm optimization (MOPSO). The following sections describe all the components of the simulation-optimization model in more details.

3.7 Simulation model development

The simulation model, SWMM, is used as the base model for the optimization model to provide the necessary input data for the optimization modeling.

3.7.1 Stormwater Management Model (SWMM)

The USEPA Stormwater Management Model (EPA SWMM) (Rossman, 2010) has been selected to evaluate the effects of LID on runoff reduction and water quality improvement in the study area. A dynamic rainfall-runoff module and a hydraulic module are included in SWMM for piped systems. An LID control module has been provided to the model from version (5.1.010), which can precisely model the hydrologic performance of LID controls in urban areas. The EPA SWMM is used for single event or continuous simulation of urban runoff quantity and quality aspects. A collection of sub catchment areas receive precipitation and generate runoff and pollutant loads which constitute the runoff components of SWMM. The model transports this runoff using the routing part through a system of pipes, channels, storage/treatment devices, pumps, and regulators. The quantity and quality of runoff produced within each sub catchment, the flow rate, flow depth, and quality of water in each pipe and channel are tracked by SWMM during a simulation period. Each simulation period consists of multiple time steps. In addition to modeling the generation and transport of runoff flows, SWMM can also estimate the amount of pollutant loads related to this runoff (Rossman, 2010).

SWMM is a deterministic and spatially distributed hydrological model, which is able to simulate the hydrological cycle mainly within urban areas (Huber et al., 1988; Rossman, 2010). SWMM uses the continuity equation along with the Manning's equation to simulate hydrological outflows (Huber et al., 1988).

To apply SWMM in urban areas, hourly, or sub-hourly, rainfall data, topographic slope and elevation, soil, land use data, sewer system network map, and storm sewer discharge data are required for calibration and validation of the model (Sun, 2012). Input parameters required by the SWMM model to simulate stormwater runoff include rainfall and climatology data (for continuous modeling), parameters for hydrologic components (sub-catchments, pipes, storage units, etc.), and run time controls (time step, starting and ending time, etc.).

3.7.2 Simulation model setup

In this study the USEPA Stormwater Management Model (SWMM) (Rossman, 2010) has been used to assess the effects of LID controls on runoff reduction and water quality improvement in the study catchment. SWMM is able to simulate runoff quantity and quality mainly from urban areas. The SWMM model has been successfully applied to many studies investigating the effects of LID-BMPs on stormwater. Few examples are: (Elliott & Trowsdale, 2007; Palla & Gnecco, 2015; Qin et al., 2013; Zhang et al., 2009a).

The data required to set up the SWMM model consists of: rainfall and flow data, topographic data, river and catchment characteristics, catchment drainage networks, catchment slope, land use and soil type.

The catchment map is applied to SWMM model and the subcatchments are derived following the contour lines. The system of nodes and conduits are also added to the model. Totally, the study area was divided into 35 subcatchments and 10 junctions in the model. The sub-catchments characteristics were determined through GIS data and site inspection. The percent impervious area was determined using Google Earth. Figure 3.5 depicts the drainage system in the base case in SWMM with subcatchments.

In the hydrologic module of SWMM, the Green-Ampt model was employed in the infiltration model, which calculates the amount of rainfalls infiltrated into the unsaturated upper soil, while Manning's equation is used to compute the surface runoff (Rossman, 2004).

For the model time control, the reporting time interval was set to 10 minutes as the rainfall data time step was the same. The routing time set up was also set to 10s. The time interval for analysis was set to report after 4.5 hours so that the model has enough time to analyze the data properly based on the catchment time of concentration.

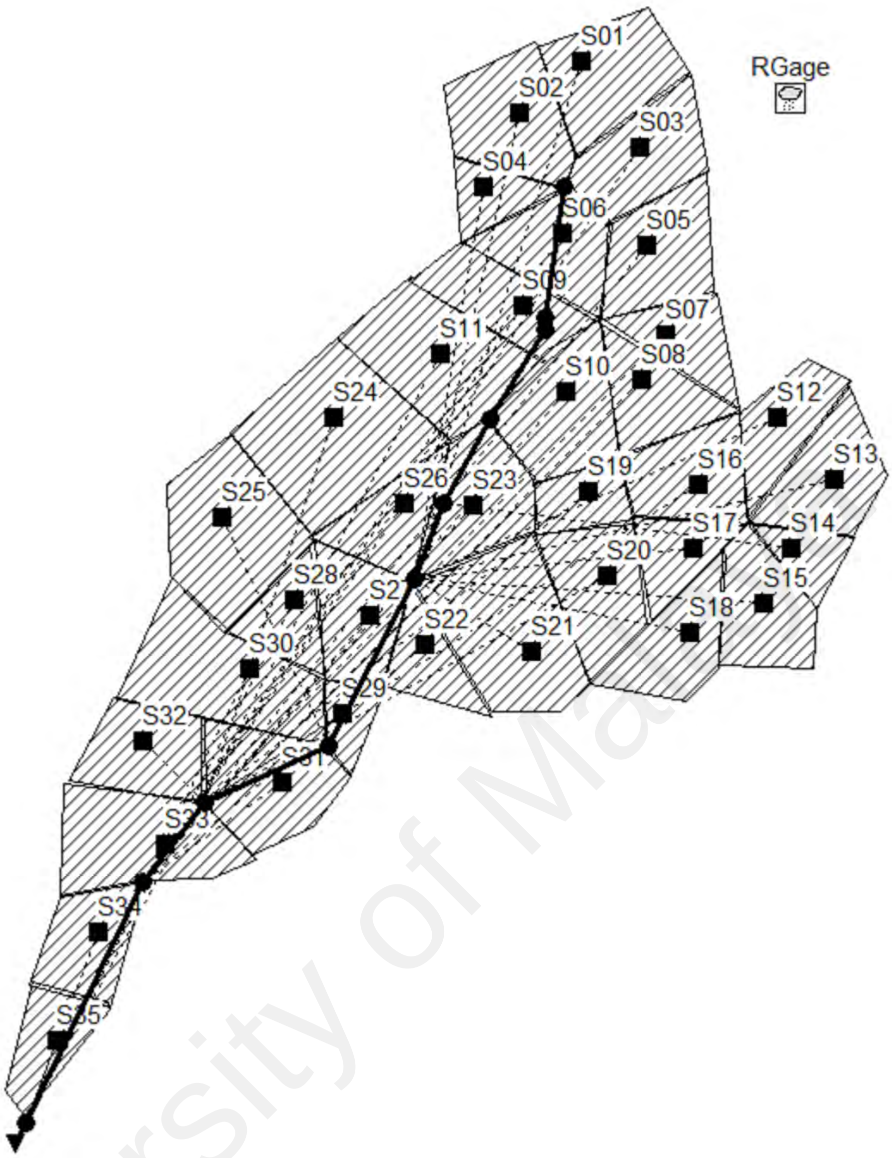

Figure 3.5: Drainage system in the base case in SWMM with sub-catchments.

3.7.3 Input Parameters for SWMM

SWMM requires some initial parameters for model set up including area, width, slope, imperviousness, and some more for each subcatchment in the model. Other input parameters required by the SWMM model to simulate stormwater runoff include rainfall and climatology data (for continuous modeling), parameters for hydrologic components (subcatchments, pipes, storage units, etc.), and run time controls (time step, starting and ending time, etc.). Table 3.1 illustrates some initial parameters required for each subcatchment in order to set up the model. A more detailed introduction regarding the model and user inputs can be found in the USEPA SWMM User's Manual (Rossman, 2004).

Table 3.1: The initial parameters for each sub-catchment to construct the SWMM model.

Model initial parameters									
Sub-Catchment	**Area**	**Width**	**%Slope**	**%Imperv**	**N-Imper**	**N-Perv**	**Dstore-Imprv**	**Dstore-Perv**	**%Zero-Imperv**
S1	66	658	1.176	55	0.01	0.02	1.3	2.5	27
S2	61	763	1.275	55	0.01	0.02	1.3	2.5	27
S3	56	551	1.043	70	0.01	0.02	1.3	2.5	35

3.7.4 Rainfall and Climatology Data

Rainfall is the driving force for SWMM simulations. Rainfall data intervals can vary from one minute to twenty-four hours, and the data can be in the format of intensity or cumulative amount. The SWMM model accepts rainfall data stored in external files. User specified rainfall hyetographs can also be entered in SWMM (Rossman, 2004). Weather data are used in continuous simulations to account for evaporation effects. Required climatology data include daily average air temperature, evaporation, and wind speed. When only monthly average evaporation and wind speed data are available, SWMM uses an internal interpolation algorithm to estimate daily values.

3.7.5 Parameters for Hydrologic Components

Input parameters for subcatchments in SWMM encompass the area, average land slope, percentage of impervious area, width of flow path (calculated as the subcatchment area divided by the longest flow path), Manning's n for impervious area and pervious area, depths of depression storage on impervious and pervious areas, and the method to calculate infiltration losses. The three main methods available for calculating infiltration losses in SWMM are: Green-Ampt method, Classical Horton method, and Curve Number method.

The input parameters required by SWMM for Green-Ampt infiltration equation are soil capillary suction head (cm), soil saturated hydraulic conductivity (cm/hr), and the initial soil water deficit (a fraction value between 0 and 1). Horton's equation also needs input for the maximum and minimum infiltration rates on Horton's infiltration curve (cm/hr), the decay constant for the Horton's infiltration curve (hr^{-1}), time for a saturated soil to completely dry (days), and the maximum infiltration volume possible (cm). For the curve number method, the input parameters for calculating infiltration include the curve number, saturated hydraulic conductivity (cm/hr), and the time for a fully saturated soil to dry (days) (Zhang, 2009).

In this study, the Green-Ampt method was used to calculate the infiltration. The soil type in the catchment area were mostly clay loam. Based on the soil type, the parameters for Green-Ampt method, namely soil capillary suction head, soil saturated hydraulic conductivity, and the initial soil water deficit were derived for the simulation (SWMM) modeling requirements.

3.7.6 SWMM System Parameter Settings

Common stormwater system components include conduits (pipes) and non-conduit structures such as open channels, junctions, storage units, flow dividers, orifices, weirs, etc.

3.7.6.1 Conduits

Conduits (pipes): Input parameters for conduits include the inlet and outlet non-conduit structure numbers, shape of the conduit, maximum depth of the conduit cross-section (m), length of conduit (m), and the Manning's n for the conduit. The SWMM model has 23 different conduit shapes to choose from, including common shapes of circular, rectangular, parabolic, trapezoidal, and horseshoe.

3.7.6.2 Open channels

The SWMM model does not provide a separate element type for open channels. Instead, open channels are represented using the same set of parameters as are used with conduits. Usually open channels use the trapezoidal shape (or other appropriate shape) and different Manning's n values according to different lining materials.

3.7.6.3 Junctions

Input parameters for junctions include the invert elevation (m), maximum water depth at the junction (m), initial water depth (m), depth in excess of the maximum water depth before flooding occurs (m), area of ponding water when flooded (m^2), and the external inflow hydrograph received by the junction.

3.7.6.4 Storage units

Input parameters for storage units include the invert elevation of the storage unit (m), the maximum depth of water within the storage unit (m), initial water depth (m), area of ponding water when flooded (m^2), fraction of evaporation realized (between 0 and 1), and the stage-storage relationship for the storage unit. The storage unit also allows the input of an external inflow hydrograph to the storage unit.

3.7.7 Sensitivity analysis

Sensitivity depicts the effect of input parameters uncertainties (e.g. sub-catchment width, slopes, and infiltration parameters) on model responses (e.g. peak runoff). The purpose of sensitivity analysis is to assess the rate of change in the response of a model with respect to changes in model input parameters. Such knowledge is important for

1. Evaluating the applicability of the model,

2. Determining parameters which are important to have more accurate values, and
3. Understanding the behavior of the system which is being modeled (James, 2003).

Before carrying out the calibration, a sensitivity analysis was performed to figure out the most influential parameters in the model. Several parameters impact the model calibration. Based on previous researches, the main parameters affecting the model calibration are: sub-catchments area, percent impervious area, width, slope, infiltration parameters, Manning's roughness coefficients for pervious and impervious surfaces, depression storage depth for pervious and impervious surfaces, percent zero, and internal routing parameters (Eckart et al., 2018).

In order to achieve the best match between the observed and modeled flow, these parameters need to be adjusted in the model. To carry out sensitivity analysis, the parameters are checked one by one. For each parameter to be analyzed, it is changed in the model, while keeping all other parameters fixed. The model is executed, and the results of the simulated outflow hydrograph is compared with the observed one. The process is repeated several times to identify the most effective parameters for model calibration.

3.7.8 Calibration and validation

There are always some unknown constants representing the physical process, no matter what the model form is. Fixed numerical values should be assigned to these model parameters before the model is used to predict runoff. In other words, these parameters need to be estimated in such a way that the best agreement between modelled and observed values can be achieved. The process of selecting the model parameters is called model "calibration". There are two main methods to adjust the model parameters, namely manual calibration and automatic calibration (Xu, 2002).

After the values of the model parameters are estimated, the third stage of model analysis is called verification or validation or simply testing of the model. With regard to this, to evaluate the model calibration and validation performance, the goodness-of-fit test (model performance evaluation) was performed to compare the modelled discharge volume against the observed discharged volume for a specific analysis period (Palla & Gnecco, 2015). The calibration and validation for the quantity model were conducted twice in this study to get more accurate results.

3.7.9 Water quality modeling

Modeling of stormwater quantity normally focuses on the prediction of stormwater runoff volumes, hydrographs and peak discharge rates to mitigate the runoff peak and volume in urban areas. Modeling of urban stormwater quality usually aims for pollution prevention and impact assessment resulted from urban stormwater.

Table 3.2: Most common pollutants in urban areas (Water, 2005).

Land use	**Gross Pollutants**	**Total Suspended Solids (TSS)**	**Nutrients (TN&TP)**
Roads and Highways	Low	High	Low
Residential	**High**	**High**	**High**
Commercial	High	Medium	Medium
Industrial	Medium	Medium	Low
Parks and Agriculture	Low	Medium	High

Having calibrated and validated the quantity model, then the quality model was also calibrated using the data achieved from the 20-9-2018 rainfall event. The parameters selected for quality modelling were Total Suspended Solids (TSS) and Total Nitrogen

(TN). According to (Water, 2005), TSS and TN are the most common pollutants in urban areas (Table 3.2).

3.7.10 LID control assigning

Having finished the calibration and validation of the model, the selected LIDs were assigned to the model. The types of LIDs selected in this study were rain garden and vegetated swale. The model, then, was executed for the same rainfall event that was calibrated (20-9-2018). The aim was to check the performance of the model after assigning the LIDs.

3.8 Common measures to assess model performance

Four different goodness-of-fit tests have been used for measuring the accuracy of the predicted stormwater runoff against the observed values. One method was the deviation volume coefficient (D_V), which can be used for the total runoff volume comparison. A second approach has been the root mean square error (RMSE), which can be used for comparing the predicted and observed hydrographs (Zhang, 2009). A third technique was the Nash–Sutcliffe coefficient (NSC) and the fourth one has been the regression method.

3.8.1 The Deviation Volume Coefficient (D_V) for Total Runoff Volume

The deviation volume coefficient (D_v) is defined by (Yen, 1993) to compare the predicted discharge volume against the observed discharge volume for a particular period of analysis. The D_v coefficient represents the fraction by which the predicted total volume over- or under-estimates the total observed volume (Eq. 3.1).

$$D_v = \frac{V_o - V_m}{V_o} * 100 \qquad (3.1)$$

Where:

D_v = Deviation volume coefficient,

V_o = Observed total runoff volume (m^3), and

V_m = Modeled total runoff volume (m^3).

A value of D_v closer to zero indicates a better match of the predicted total runoff volume to the observed total runoff volume. If the value of D_v is positive, the total runoff volume is under-estimated by the model. A negative D_v value indicates that the total runoff volume is over-estimated by the model (Yen, 1993). In their study conducted at the Upper Bukit Timah watershed in Singapore, Liong et al. (1991) used the D_v parameter to compare the stormwater runoff volumes predicted by the SWMM model to the observed volumes. A similar use of the D_v parameter was found in several other studies involving the comparison between predicted and observed values of total runoff volume (Warwick & Tadepalli, 1991). The ideal value for D_v is between 5% to 20% (James, 2003). The lower the D_v value is, the better the match between the predicted and the observed values will be.

3.8.2 The Root Mean Square Error (RMSE) for Hydrograph Comparisons

The Root Mean Square Error (RMSE) (Willmott, 1984) is a measure of difference between paired predicted and observed values. The Normalized Objective Function (NOF) can be used for the root mean square error. The RMSE and NOF are explained as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \tag{3.2}$$

$$NOF = \frac{RMSE}{\bar{O}} \tag{3.3}$$

Where P_i and O_i are predicted and observed values at time step i, respectively and N is the number of observations during the flow period. $\bar{O}$ is the mean of observed values.

The value of the RMSE index ranges from 0 to ∞, and the match between the predicted value and the observed value gets better when RMSE is closer to zero. An RMSE equal to 0 indicates a perfect match between the predicted and observed flow (Zhang, 2009).

The ideal value for NOF is 0, however, it cannot be expected to occur, otherwise it would be a perfect model if it did. So, values between 0 and 1 are acceptable for NOF when field specific data are available for calibration (Kornecki et al., 1999).

Smith and Wheater (2004) used the RMSE as a measurement of the agreement between the observed and simulated flow hydrographs when conducting a study in the Welland Watershed, UK.

3.8.3 Nash–Sutcliffe Coefficient (NSC)

Nash–Sutcliffe coefficient (NSC) is explained as follows (Nash & Sutcliffe, 1970):

$$NSC = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{3.4}$$

Where P_i is the predicted value, O_i is the observed value for the n observations, and $\bar{O}$ is the mean of observed values. The acceptable range for NSC is values between 0 and 1. The optimal condition for the model occurs when the NSC is 1. For the purposes of evaluation, a satisfactory NSC is higher than 0.5 (Tan et al., 2008; Worqlul et al., 2018).

3.8.4 Regression method

The regression method is defined as:

$$P_i = rO_i \tag{3.5}$$

In the regression method, the linear regression line (Eq. 3.5) is fitted between the modelled and observed values and the slope r is compared with the 1:1 slope (perfect match). Generally, the best calibration requires that both slope r and coefficient of determination r^2 be as close to 1.0 as possible (Chow et al., 2012).

Overall, for the purposes of evaluation, a satisfactory NSC is higher than 0.5 and a good Dv is lower than 20% (Tan et al., 2008). In another study, Yazdi et al. (2019) mentioned that when r^2 and NSC are higher than 0.6 and 0.5, respectively, and D_V is lower than 25%, the model calibration is considered satisfactory.

3.9 Optimization modeling

Multi objective optimization is widely known as the maximizing, or the minimizing of multiple objectives $F(x) = [f_1(x), f_2(x),\ldots, f_n(x)]$. where $x=x_1, x_2,\ldots,x_n$ are the decision variables. The decision variables refer to the decision space in which the possible region is the set of solutions in the space that would satisfy the constraints placed on the decision variables (Eckart et al., 2018; Kalyanmoy, 2001).

3.9.1 Multi Objective Particle Swarm Optimization (MOPSO)

The Multi-Objective Particle Swarm Optimization (MOPSO), which was developed by Coello et al. (2004), is a multi-objective form of the single objective particle swarm (PSO). The particle swarm optimization was developed by Eberhart and Kennedy (1995) based on the swarming animals analogy, such as a flock of birds or school of fish. In each iteration, each particle is updated based on two ‘‘best” values: “pbest” is the best solution (in terms of fitness) each particle obtained so far, while “gbest” is the best solution each particle in the population achieved globally so far. By using the current positions, the current velocities, the distance between the current position and pbest, and the distance between the current position and gbest, each particle tries to change its position to a new one. PSO does not have many parameters to be tuned, compared to genetic algorithm optimization. The parameters are the number of particles; weighting factors; and the maximum change for a particle. It has been identified that the PSO operation is not very sensitive to parameter settings (Liu, 2009).

PSO has been widely used in various optimization problems as it has unique searching mechanism, excellent convergence and simple implementation. These features make PSO particularly suitable for multi-objective optimization especially because of its high speed of convergence for single-objective optimization (Coello et al., 2004; Yang et al., 2005). Many studies have been carried out in recent years using multi-objective particle swarm optimization (MOPSO) in various fields (Coello et al., 2004; Yang et al., 2009). In MOPSO, the global optimal solutions are a set of non-dominated solutions known as Pareto optimal front. It should be noted that choosing pbest and gbest from the set of Pareto-optimal solutions for each particle to direct its flight is still a challenge, although it is of high importance to achieve convergence and diversity of solutions (Yang et al., 2009).

In multi objective optimization approach, the non-dominated solutions are used to represent the Pareto optimal front. A solution A dominates solution B when A is better than B in at least one objective, and not worse in others. If two solutions do not dominate each other, they are called indifferent or incomparable. The multi-objective optimization aims at finding the Pareto-optimal set or front (or an approximation sample). The final solutions are selected using the front of non-dominated solutions produced by a multi-objective algorithm based on different criteria (Montalvo et al., 2010).

The multi objective optimization algorithm produces non-dominated solutions in each iteration. These solutions are stored in a special space called repository. Repository members are the best non-dominated agents of the problem achieved during different stages of optimization algorithm process (Hosseini et al., 2015). The repository members dominate the whole population members; however, none of them dominate each other in the repository. In the final stage, the members with least distance from each other are selected for the ultimate optimal solutions (Hosseini et al., 2015); which are known as Pareto optimal or non-dominated solutions.

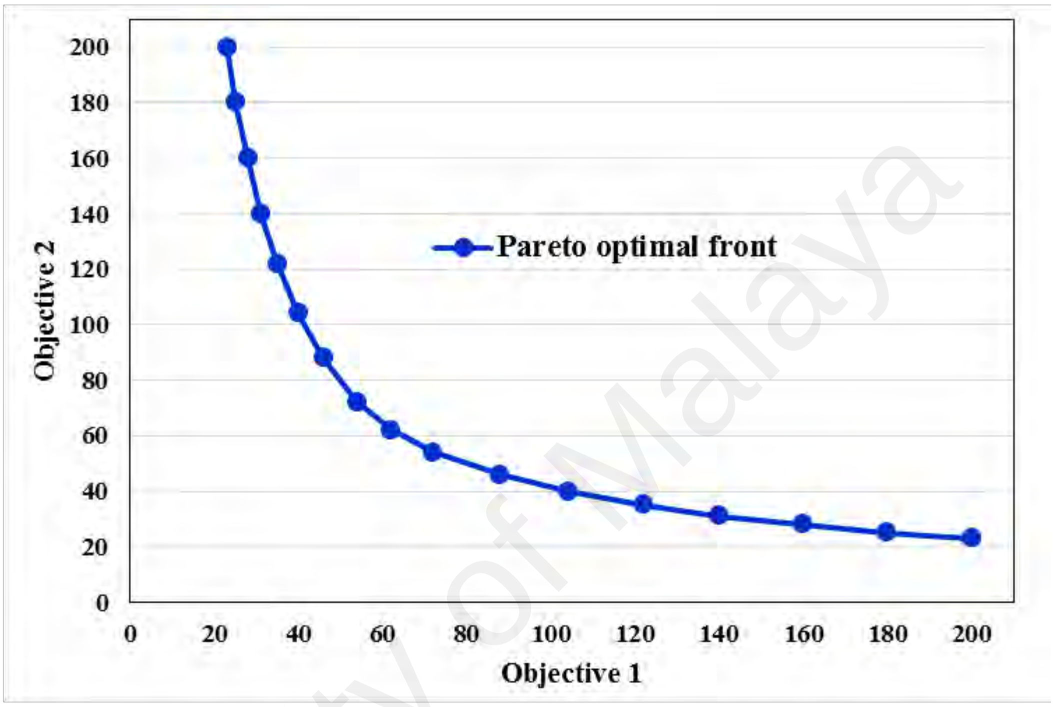

Figure 3.6: Typical form of Pareto optimal front in MOPSO.

When there is not adequate information, deciding on one unique pareto solutions to be objectively better than any others with respect to all the objectives involved is not possible (i.e. there is no uniquely ''best'' solution); hence, any one of them is a plausible solution (Liu, 2009). Thus, unlike single objective optimization, the multi objective optimization answer will be a set of solutions, presented as a curve, instead of a single point. These solutions never dominate each other but are superior to the rest of the population. They will be optimized based on the problem objective criteria. These points are known as Pareto optimal front and any one of them can be considered as an acceptable solution (Hosseini et al., 2015; Liu, 2009). Figure 3.6 depicts a typical form of Pareto optimal front in MOPSO.

The Multi Objective Particle Swarm Optimization (MOPSO) was used for the optimization modelling in this study. The idea behind most multi-objective optimization is to find a set of optimal solutions representing the optimal surface between different criteria (Liu et al., 2016). The optimization target for the objectives of this study was to find the Pareto-optimal front to minimize the peak runoff and maximize the water quality in the catchment with the minimum number of LIDs applied to the sub-catchments. The results might appear as runoff/pollutants reductions-number of LIDs curves. The decision variables are the number of sub-catchments and the number of LIDs in each one as well as the design parameters defined in the SWMM simulation model. The SWMM base file and the defined parameters for the LIDs is the input file for the optimization process. Such a procedure is possible to carry out by linking the SWMM model to the relevant defined sub routine through the MOPSO algorithm using MATLAB. The MOPSO receives the output from SWMM and alters some parameters so that the objective functions are satisfied and generate the results as graphs and matrices. Compared to similar algorithms, the MOPSO is easy to use and converges faster with the minimum number of parameters required.

3.9.2 MOPSO Objectives

In the process of selection and implementation of BMP/LIDs in urban catchments, there are definitely various combinations of LIDs to place in order to minimize the runoff and maximize the water quality. Potentially, the best way to have the minimum runoff and best water quality in the catchment is to implement as many LIDs as possible. However, the aim of optimization is to identify the minimum number of BMP/LIDs (N_{LID}) to be implemented in the catchment so that the peak runoff/pollutants are optimally reduced while the implementation is cost-effective. In other words, the ideal aim of optimization for the urban stormwater quantity and quality control is to get the maximum performance of BMP/LIDs in the catchment with the lowest cost.

Thus, to achieve the above-mentioned goals, the following equations represent the objectives to be satisfied by the MOPSO algorithm in this study.

Objective 1:

$$\begin{cases} F_1 = \min \ N_{LID} \\ F_2 = \min \ Q_{\max} \end{cases} \tag{3.6}$$

Where N_{LID} denotes the number of LIDs applied to each sub-catchment throughout the catchment and $Q_{\max}$ is the peak runoff generated at the catchment outlet (CMS).

Objective 2:

$$\begin{cases} G_1 = \min \ N_{LID} \\ G_2 = \min \ C_1 \end{cases} \tag{3.7}$$

Objective 3:

$$\begin{cases} Z_1 = \min \ N_{LID} \\ Z_2 = \min \ C_2 \end{cases} \tag{3.8}$$

Where C_1 and $C2$ are mean concentration of TSS and TN washed of through the catchment outlet, respectively (Kg).

The objective of equations (3.6), (3.7) and (3.8) is to find the minimum number of each LID in each sub-catchment so that the peak runoff, TSS and TN are optimally reduced. The MOPSO algorithm generates the results in the form Pareto optimal front curve in which various combinations could be achieved.

Objective 4:

$$\begin{cases} S_1 = \min \ N_{LID} \\ S_2 = \min \left(Q_{\max} \ , C_1 \,\&\, C_2 \right) \end{cases} \tag{3.9}$$

The objective of equation (3.9) is to achieve the minimum number LID in each sub-catchment so that all three parameters, namely, peak runoff, TSS and TN are optimally reduced. This equation was not defined in the MOPSO sub routine as it is complicated and needs more time and efforts. However, it was achieved through defining some scenarios of LID combinations in SWMM and comparing the results after executing the simulation model for different defined LID combination scenarios. The LID combination scenarios have been presented in the following sections.

3.9.3 Simulation-Optimization model

The simulation model was first set up by various input data required; calibrated and validated. The LID controls were then designed and applied to the model. The most important part of LID control design in the model is to obtain the necessary parameters of each LID unit such as soil characteristics, number of units, surface width per unit, berm height, surface roughness and slope. Having designed and applied the LID units in the simulation model, it is ready to be linked to the optimization model.

The decision variables for the optimization algorithm and subroutine function should be first defined. The maximum iteration for the algorithm and the initial size of particle population and repository were other variables to be set. These variables should be selected based on several times trial and error.

The two models are then linked to each other using MATLAB through the subroutine programmed in MATLAB for the study. The optimization process aims to find the Pareto optimal front so that the maximum runoff/peak runoff and pollutants reductions is achieved. The results are presented in the form of matrices and reduction-number of LID units graphs. The variables are those designed parameters for the SWMM in the simulation process. The functions are the SWMM and the subroutine function prepared for the optimization model. By linking the simulation and the optimization models, MOPSO algorithm starts the optimization process by changing some parameters in the SWMM and get the output as the new optimization input parameters. The process repeats until the runoff/peak runoff and the pollutants are optimally reduced and the best combination of LID units is achieved. Figure 2 depicts the optimization process and how the simulation-optimization models are linked with each other.

3.10 MATLAB

MATLAB is used for technical computing. This high-performance language combines computation, visualization, and programming environment. Moreover, MATLAB is a modern programming language environment which has complicated data structures, contains built-in editing and debugging tools, and supports object-oriented programming. These unique features have made MATLAB a state-of-the-art tool for teaching and research.

Compared to conventional computer languages (e.g., C, FORTRAN) MATLAB has many advanced features to solve technical problems. As an interactive system, the basic data element of MATLAB is an array that does not require dimensioning. MATLAB package has been commercialized since 1984 and is now considered as a standard programming language at many universities and industries all over the world.

In this study, MATLAB was used to write the coding in order to link MOPSO algorithm with the simulation model (SWMM). In addition, all the procedure of running the optimization model to achieve the required results was also performed using MATLAB.

3.11 Overview of GIS

GIS is a computer-based technology with a general-purpose for applying geographical data in digital form. The main purpose of GIS is to capture, store, manipulate, analyze, and display various collections of spatial or geo-referenced data. Both sets of geometry data (coordinates and topological information) and attribute data (i.e., information that describes the features of geometrical objects, such as points, lines and areas) are included in GIS. Goodchild (1993) illustrated that the GIS technology is capable of performing a variety of tasks, such as: (1) data preprocessing from large stores into a form which is appropriate for analysis represented by reformatting, change of projection, resampling, and generalization; (2) analysis and modeling support, such as forms of analysis, models calibration, forecasting, and prediction; and (3) post processing of results by reformatting, tabulation, report generation, and mapping. According to Mark and Gould (1991), in any operation that GIS is involved, the user specifies the requirement and communicates with the system via a "user-friendly" intuitive interface making use of such contemporary concepts such as graphic icons and desktop images (Singh & Fiorentino, 2013).

3.11.1 Applications of GIS

There are four areas that GIS can be applied successfully: (1) mapping, (2) data preprocessing, (3) modeling, and (4) policy formulation. GIS consists of the capability of digital cartography in the input and output subsystem, and more abilities for storing and handling relationship between entities as well as representing entities with multiple attributes. GIS has the ability to deal with digital representation of continuous variables in many various ways (Singh & Fiorentino, 2013).

3.11.2 ArcGIS

ArcGIS is part of the geographic information system (GIS) for handling maps and geographic information. The main applications of ArcGIS are creating and using maps; geographic data compilation; analyzing information from maps; sharing and discovering geographic information; using maps and geographic information in a range of applications; and managing geographic information in a database.

ArcGIS was used to manage our case study maps for delineating data, producing topography, drainage and land use maps for the study area, calculating the sub-catchments slopes, calculating the catchment area and the required distances, locating the hydrological stations on the maps and producing the study area maps.

3.12 Cost analysis

The cost of LID techniques is usually the initial capital cost as well as the operation and maintenance (O&M) costs through the whole life cycle of LIDs in place (Sample et al., 2003). The capital cost also includes the land cost, planning and design (engineering) cost, construction cost, and the environmental cost. As the land, engineering and environmental costs are site specific, the construction cost is usually used for analysis purposes (Sample et al., 2003).

Table 3.3: Life cycle costs of different LID-BMP facilities (Edmonton, 2011).

LID Facilities	Cost (USD)		Life cycle (year)
	Construction	Annual maintenance	
Bioretention	30-250/m^2	13-30/m^3	>20
Swales	11-35/m^2	0.20-1/m^2	>20
Permeable pavement	340-500/m^2	0.15-0.30/m^2	>20
Green Roofs	230-3000/m^2	3-44/m^2	30-50
Box Planter	30-350/m^2	13-30/m^3	25-50
Naturalized Drainage Ways	25-250/m^2	1-18/m^2	>20-100+

Table 3.3 presents different types of LID-BMP facilities costs, including bioretention and swales. In this study, the construction cost was considered as the total cost of LID-BMP techniques implemented. As the cost is usually site specific, the cost was set \$60/m^2 and \$20/m^2 for bioretention and swale, respectively for the analysis purposes of the study area. To do the cost analysis against peak flow, total flow volume, TSS, and TN reduction, the coding was conducted accordingly, and the function was optimized using MOPSO algorithm and MATLAB.

CHAPTER 4: RESULTS

4.1 Simulation model development

For the simulation modeling, Stormwater Management Model (SWMM) was used for this study. The model was first set up with the required collected data and then the necessary steps to construct the simulation model were taken. Then, the sensitivity analysis was conducted to find out the most sensitive parameters to the model and after the model was calibrated and validated twice, to make sure the simulation model was precise enough to proceed to the optimization modeling.

4.2 Sensitivity analysis results

Before conducting the calibration and validation, the sensitivity analysis was performed. Figure 4.1 depicts the results of the sensitivity analysis.

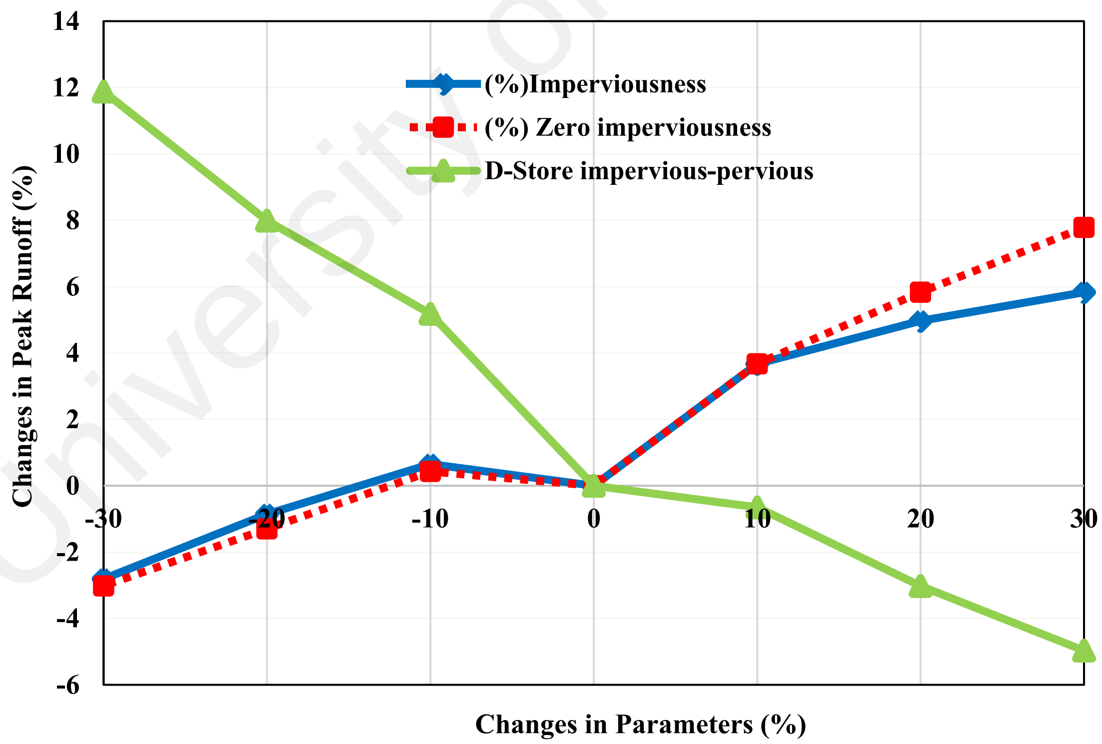

Figure 4.1: Sensitivity analysis results for SWMM model.

As can be observed, the most sensitive parameters for the model are: % imperviousness (Percent of the land area which is impervious), % zero imperviousness (Percent of the impervious area with no depression storage), Dstore-impervious (Depth of depression storage on the impervious portion of the sub-catchment) and Dstore-pervious (Depth of depression storage on the pervious portion of the sub-catchment) which have been shortened as D-Store impervious-pervious. This means that the model is mostly sensitive to these three parameters and they need to be adjusted accordingly to get a good calibration. However, care should be taken that the sensitivity of the model to the three parameters is not the same. The model is more sensitive to the D-Store impervious-pervious, especially when it decreases.

4.3 Quantity model calibration and validation

The model was calibrated and validated twice; once with the rainfall events of the Bunus catchment collected from SMART control center. The data collected are time series data of 10 minutes, 20 minutes and hourly basis data from 2008 to 2018, both from hydrological station 1 (S1) and hydrological station 2 (S2). However, as station S2 has also got flow monitoring gauge, the rainfall and flow data of S2 were used for model calibration and validation. For the second time, the model was calibrated with the rainfall event of 20-09-2018 as the rainfall sampling was done from S2 station for water quality analysis. The rainfall and flow data of the same date was collected from SMART control center and the model was calibrated for both quantity and quality.

To calibrate the model, some rainfall-runoff events were selected, and the data series were input into the model. The model was then run with all the initial parameters entered into the model at the beginning and adjust the parameters after each trial. The model performance evaluation was also performed and checked the error after each run. The process continued until the error was minimal and the best model performance was achieved.

For a good calibration and validation result, it is required that the general shape of both hydrographs follow each other, and the results of goodness-of-fit criteria are satisfactory. The parameters used in this study for the model calibration and validation evaluation test are D_v, NOF, NSC, and r^2. The ideal value for D_v is between 5% to 20% (James, 2003). The lower the D_v value is, the better the match between the predicted and the observed values will be. For the NOF, NSC, and r^2, the acceptable range is values between 0 and 1. For NOF, the closer it is to 0, the better match between the two hydrographs will be achieved. As for NSC and r^2, the closer they are to 1, the better the match between the predicted and the observed values will be. It should also be stated that for the purposes of evaluation, a good NSC is higher than 0.5 and a good D_v is lower than 20% (Tan et al., 2008). In another study, Yazdi et al. (2019) mentioned that when r^2 and NSC are higher than 0.6 and 0.5, respectively, and D_v is lower than 25%, the model calibration is considered satisfactory.

Based on the sensitivity analysis, there were several parameters to be adjusted for the model calibration. The most significant parameters influencing the model calibration were: %imperviousness, manning's n coefficient, D-Store impervious-pervious, %zero imperviousness and the outlet for each sub-catchment.

4.3.1 Model calibration for the data on the 05-12-2015 event

To construct the model, it was calibrated and validated with the rainfall and flow data of years 2015 and 2016. The model was run many times and the parameters were adjusted for the data on 05-12-2015. Figure 4.2 depicts the model calibration for the data of 05-12-2015. In another study, Yazdi et al. (2019) mentioned that when r^2 and NSC are higher than 0.6 and 0.5, respectively, and D_v is lower than 25%, the model calibration is considered satisfactory.

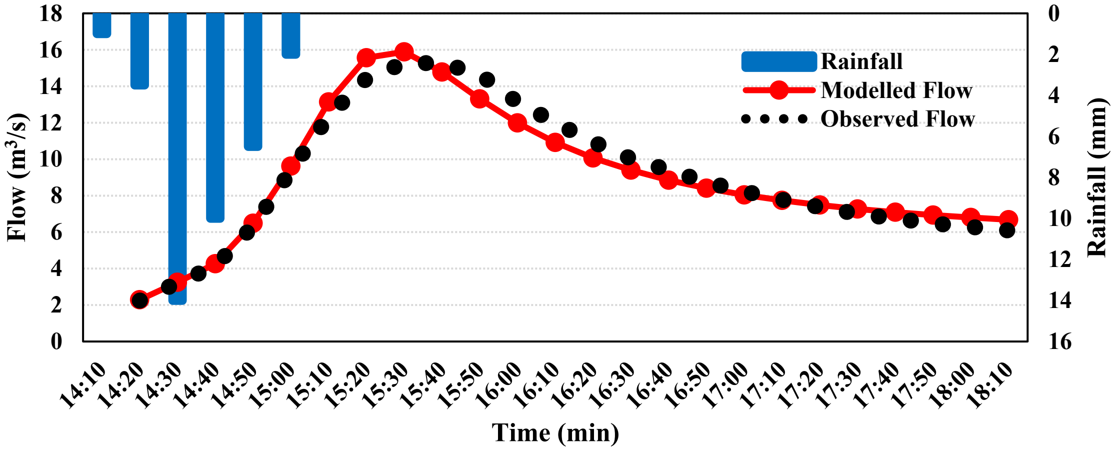

Figure 4.2: Model calibration for the 05-12-2015 event.

Overall, the modeled and observed hydrographs for calibration follow each other and are a very good match. This could also be confirmed by the results of model evaluation test (Table 4.3). They are all very satisfactory. The evaluation parameters, namely D_v, NOF, NSC, and r^2 are 5%, 0.07, 0.97, and 0.97, respectively, which show a very good match between the modeled and observed values for the calibration. Figure 4.3 also shows that the coefficient of determination r^2 is very close to 1 and is as high as 0.97, which confirms that the model has been well calibrated.

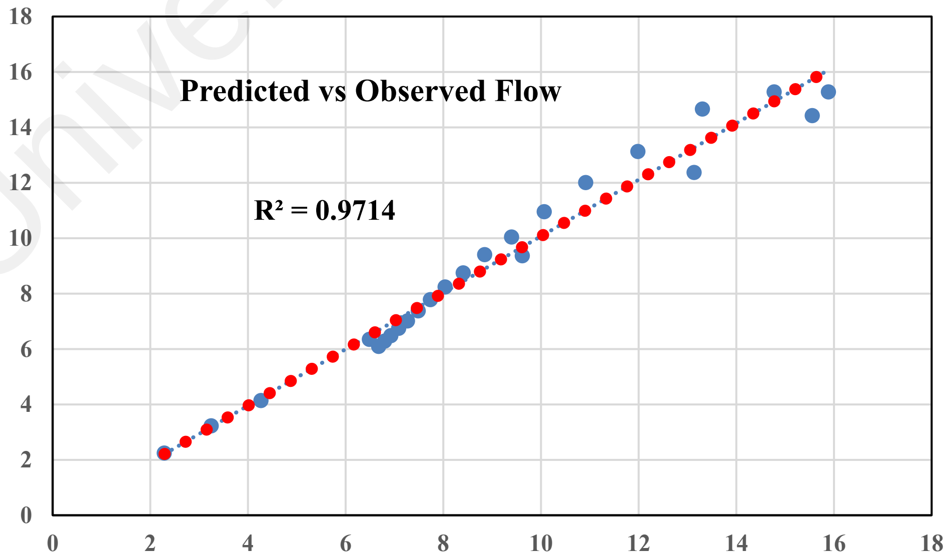

Figure 4.3: Coefficient of determination for the model calibration on the 05-12-2015 event.

4.3.2 Model Validation

In order to check the validity of the model after calibration, it should be validated with different rainfall events to see whether the output results are acceptable. Thus, we verified the calibrated model using two different rainfall events of the study area and compared the observed and modelled hydrographs to see whether they match or not. The rainfall-flow data on the 10-06-2015 and on the 21-04-2016 events were selected for the model validation, respectively. Figures 4.4 and 4.5 depict the model validation results.

As can be seen from the figures, the modelled and observed hydrographs follow each other and the results of model evaluation test are satisfactory. For Figure 4.4, the evaluation parameters, namely NOF, NSC, and r^2 are 0.21, 0.85, and 0.88, respectively, and for Figure 4.5, NOF, NSC, and r^2 are 0.2, 0.82, and 0.87, respectively, which show an acceptable match between the modeled and observed values Both hydrographs are in a very good match, except for some discrepancies at the peak for Figure 4.5, but overall, they are both quite satisfactory.

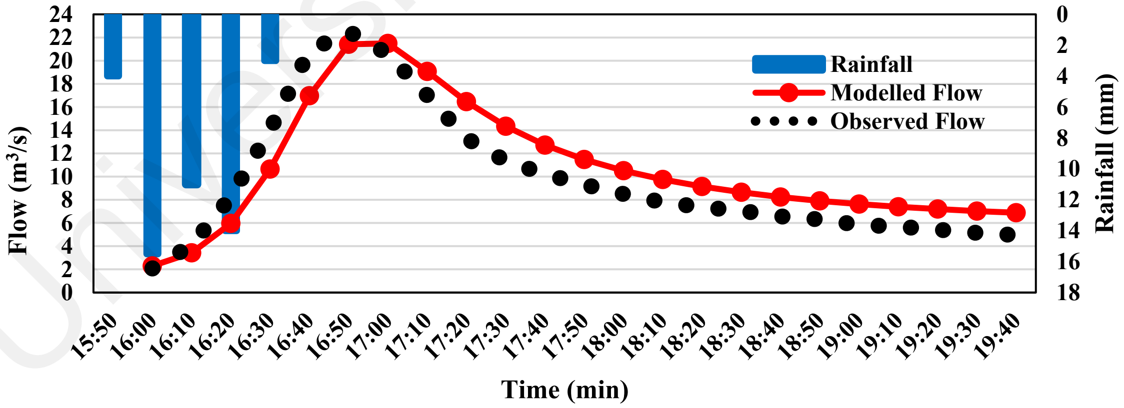

Figure 4.4: Model validation for the 10-06-2015 event.

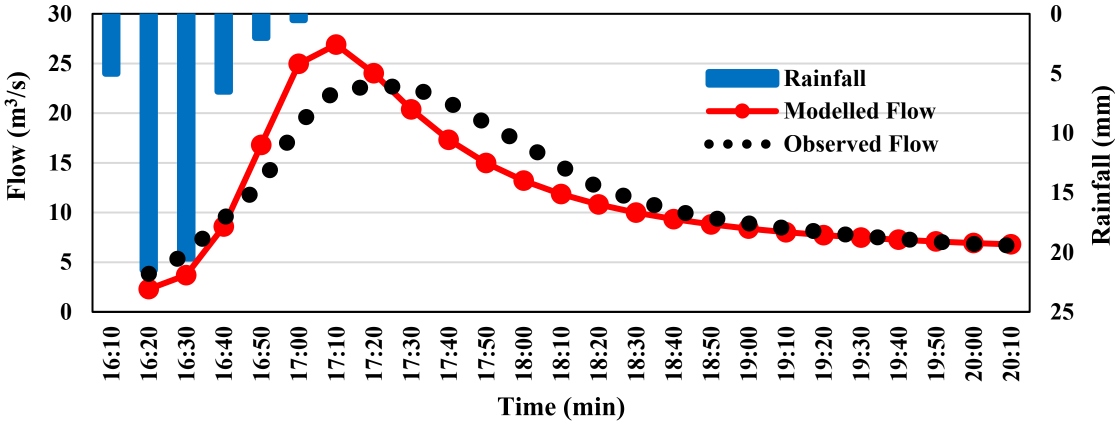

Figure 4.5: Model validation for the 21-04-2016 event.

Having calibrated and validated the constructed model, we got confident that the model was working properly, and the parameters were well adjusted. After that, we used the model for the main data we got through sampling from the S2 hydrological station of the catchment from the 20-09-2018 rainfall event. To do so, we calibrated and validated the model again with the new data to enhance the accuracy of the model.

4.3.3 Model calibration for the sampling data of the 20-09-2018 rainfall event

In order to calibrate the simulation model, both quantity and quality, more accurately and prepare it for the main purpose of the research, we did runoff sampling from a rainfall event on 20-09-2018. A total of 17 samples were collected from the Bunus river at Jalan Tun Razak (S2 monitoring point) during the rainfall event. The samples were collected every 10 minutes for a duration of three hours. Based on the catchment time of concentration, the samples were taken in a proper period of time to be at least twice as the time of concentration to make sure we have collected enough samples to accurately calibrate the model for water quality parameters as well. Having finished the sampling, the rainfall and flow data of the same event were also collected from SMART control center to be able to calibrate the quantity and quality model.

4.3.4 Quantity model calibration for the 20-09-2018 rainfall event

First, the model was calibrated again with the rainfall and flow data collected from the 20-09-2018 event to make sure the model works accurately and prepare the model for quality calibration and LID control assignment.

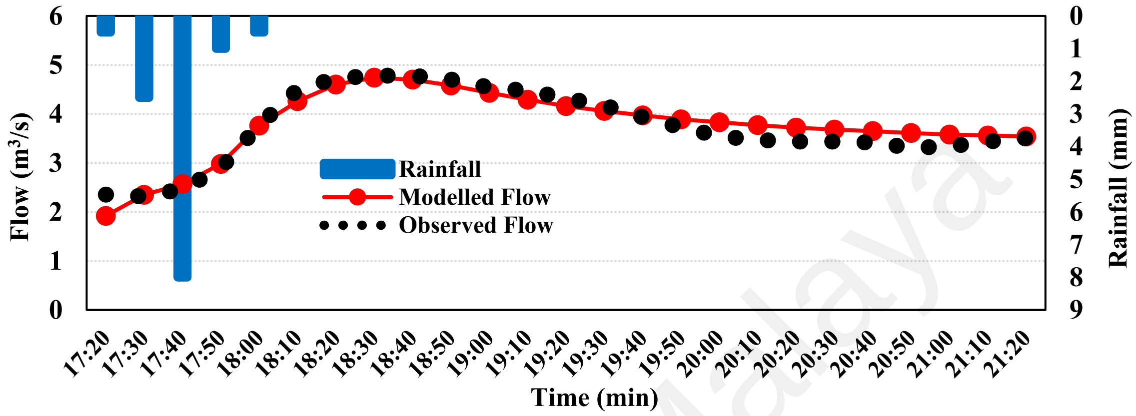

Figure 4.6: Model calibration for the 20-09-2018 event.

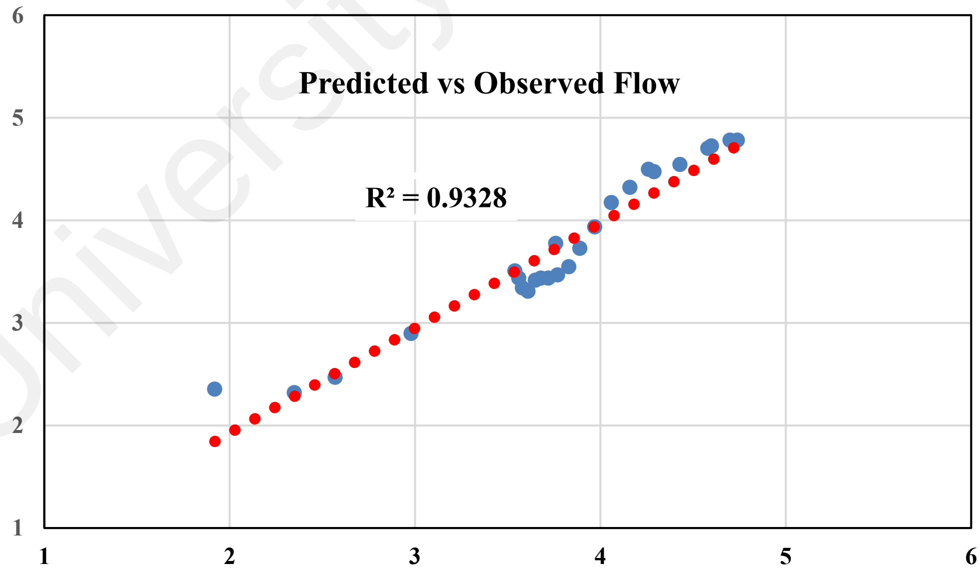

Figure 4.7: Coefficient of determination for the model calibration on the 20-09-2018 event.

Based on the sensitivity analysis, the same procedure for calibration and validation was carried out. The model parameters needed to be adjusted again to get the best results. After many runs and adjusting the same parameters, the results of calibration were quite satisfactory.

Figure 4.6 compares the modelled flow against the observed flow for the 20-09-2018 rainfall event. It is obvious from Figure 4.6 that, overall, the modeled flow closely follows the observed flow and the errors are minimal. The results of model evaluation criteria are very satisfactory which could also be confirmed by the results of goodness-of-fit test (Table 4.3). The evaluation parameters for the second calibration, namely D_V, NOF, NSC, and r^2 are 4.7%, 0.05, 0.93, and 0.93, respectively. This means that the model could be used for the validation process and the LID control assignment. Figure 4.7 depicts the coefficient of determination (r^2) which is close to 1 and is as high as 0.93. This confirms that the model has been well calibrated.

4.3.5 Validation of the quantity model for the 20-09-2018 event

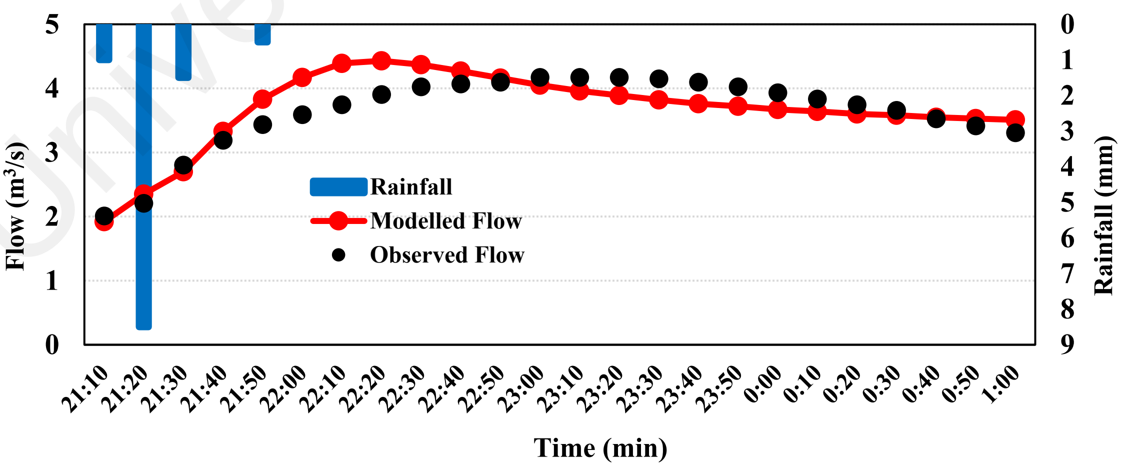

Figure 4.8: Model validation for the 01-08-2017 event.

In order to check the validity of the calibrated model of the 20-09-2018 event, we verified the calibrated model on two other different events to compare the modeled and the observed hydrographs to see whether they match well or not. The rainfall and flow data of the 01-08-2017 and 28-04-2018 events were used for the model validation.

The validation result for the 01-08-2017 event has been illustrated in Figure 4.8. Overall, the modeled and observed hydrographs follow each other throughout the validation process and the result of model evaluation criteria is also satisfactory which means the validation is acceptable. The goodness-of-fit test (Table 4.3) also shows that the validation result is quite acceptable. As can be seen, from Table 4.3, the evaluation parameters, namely D_v, NOF, NSC, and r^2 are 6.68, 0.08, 0.74, and 0.77, respectively, which show an acceptable match between the modeled and observed values.

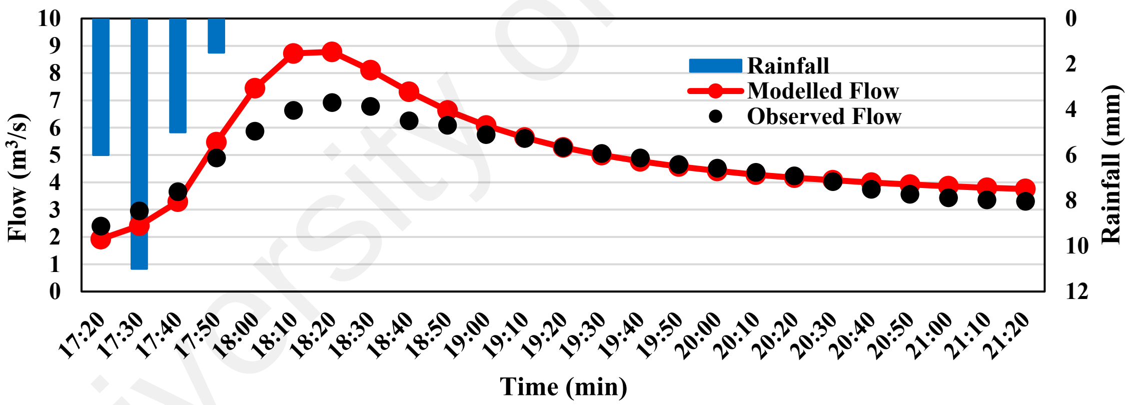

Figure 4.9: Model validation for the 28-04-2018 event.

The validation for the data of the 28-04-2018 event has been depicted in Figure 4.9. As can be seen from the figure, the rising and falling limbs are in good match and the modeled hydrograph well follows the observed one. Although the model overestimates the flow at the peak, overall the two hydrographs follow each other quite well and the result of model evaluation test is satisfactory. The evaluation parameters, namely D_v, NOF, NSC, and r^2 are 10.6, 0.17, 0.61, and 0.93, respectively. This means that the validation is quite acceptable. This could also be confirmed by the results presented in Table 4.3.

4.4 Quality model calibration for the 20-09-2018 event

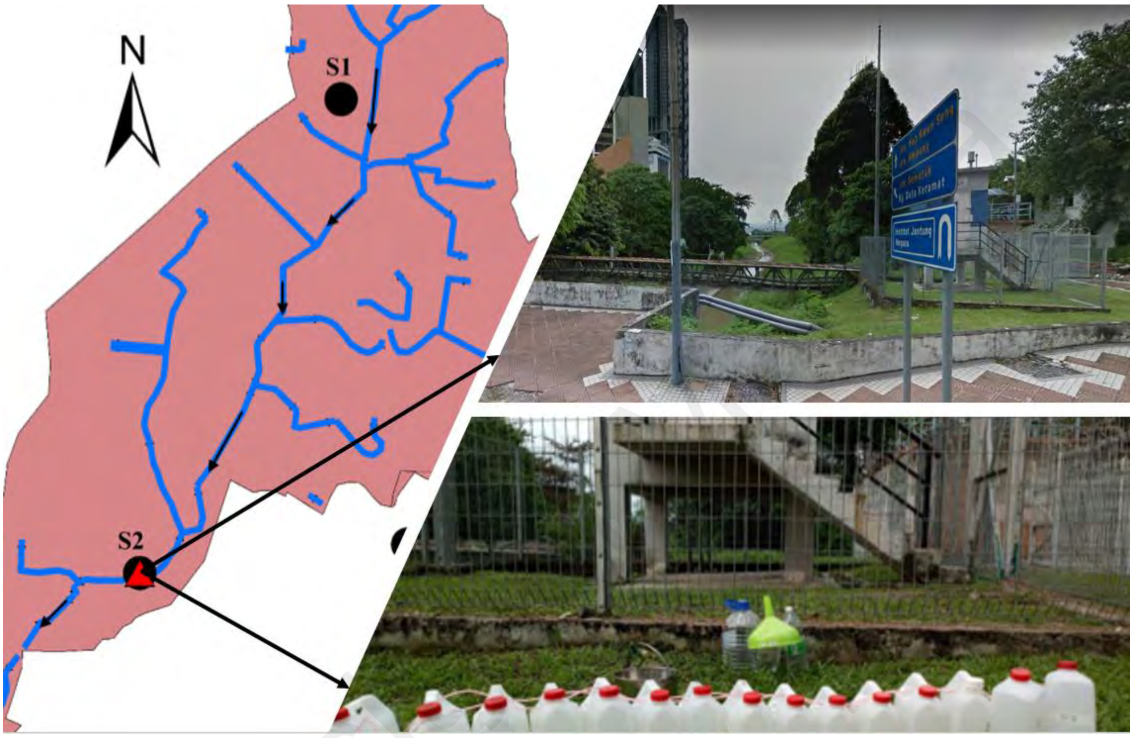

Figure 4.10: location of sampling and the samples collected from the study site on the 20-09-2018 rainfall event.

To conduct the water quality modeling, rainfall samples were collected during the 20-09-2018 event from the hydrological station at Jalan Tun Razak (S2 monitoring point). Totally, seventeen samples were collected and carried to the Environmental laboratory at the University of Malaya to be analyzed. Figure 4.10 illustrates the location of sampling and the samples taken from the study site.

Table 4.1: Quality parameters achieved from rainfall samples analysis.

N	Time	TSS	TDS	Turbid	DO	Con	COD	BOD	NH3	NO3	PO4
1	16:50	44	179	27.26	5.84	247	33.58	2.36	1.01	6.19	0.73
2	17:10	54	167	33.32	6.09	225	140.47	2.67	0.98	4.59	0.63
3	17:30	53	183	32.71	6.66	247	74.24	2.95	0.78	5.67	0.97
4	17:40	43	173	26.44	5.12	233	60.93	2.67	0.84	7.26	0.98
5	17:50	53	161	32.95	6.82	216	104.37	3.12	0.95	6.60	1.04
6	18:00	75	162	46.46	6.25	223	55.34	2.79	0.56	6.72	0.98
7	18:10	74	161	45.87	6.94	219	211.72	3.27	0.64	7.31	1.05
8	18:20	107	142	65.83	6.76	195	60.07	1.35	0.48	8.13	1.89
9	18:30	121	123	74.63	6.48	166	96.76	2.70	0.50	6.47	1.44
10	18:40	118	114	72.68	5.00	156	83.87	2.50	0.36	5.60	0.94
11	18:50	148	104	91.24	6.53	139	87.69	1.85	0.50	4.90	1.46
12	19:00	121	101	74.50	6.47	137	61.89	0.57	0.36	4.27	1.51
13	19:10	104	111	64.02	6.25	152	61.33	2.64	0.5	4.69	1.22
14	19:20	94	127	57.89	6.44	177	338.25	2.94	0.42	4.04	1.73
15	19:30	99	127	61.14	6.17	178	88.8	2.73	0.45	3.45	1.11
16	19:40	87	134	53.64	5.90	189	78.19	2.62	0.34	3.14	1.69
17	19:50	91	132	56.46	7.56	189	75.25	3.10	0.31	3.61	1.59

4.4.1 Rainfall samples analysis for water quality parameters

The water samples were analyzed at the Environmental laboratory at the department of Civil Engineering, University of Malaya. The parameters achieved, using different methods, consisted of Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Suspended Solids (TSS), Total Dissolved Solids (TDS), Turbidity, Conductivity (Con), Dissolved Oxygen (DO), Ammoniacal-Nitrogen (NH3), Nitrate (NO3), Nitrite (NO2) and Phosphate (PO4). Table 4.1 presents the quality parameters achieved from rainfall samples analysis. Few parameters, namely, Turbidity, TSS, Do, TDS and conductivity have also been plotted in Figure 4.11.

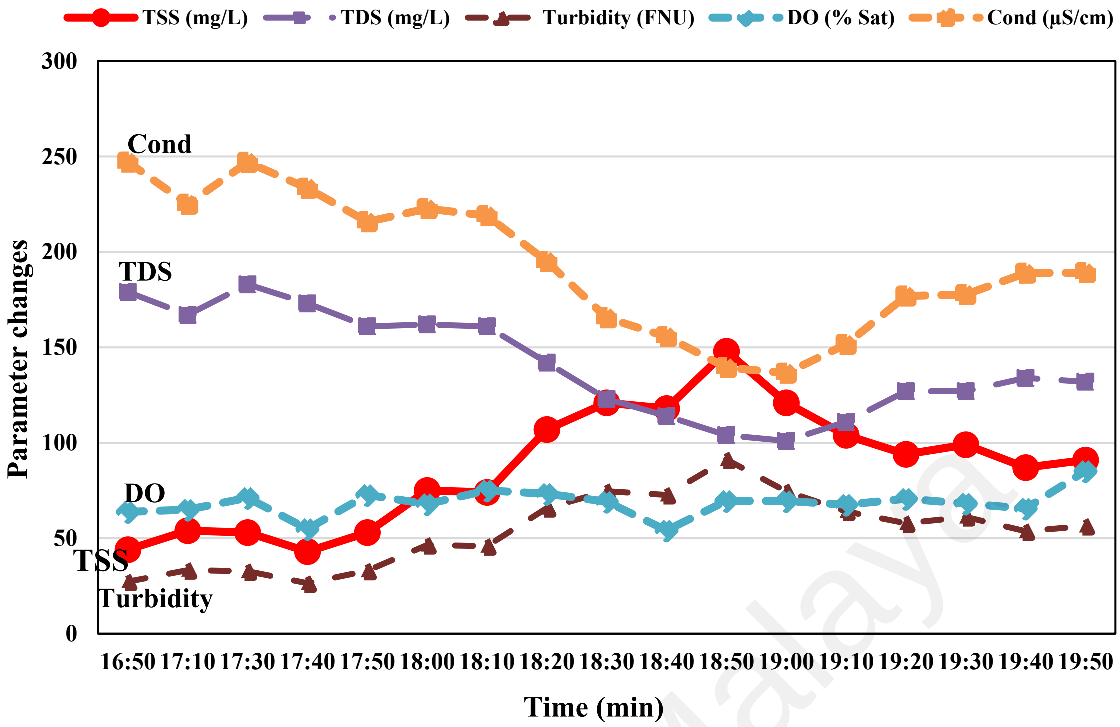

Figure 4.11: Stormwater quality parameters changes during the 20-09-2018 rainfall event.

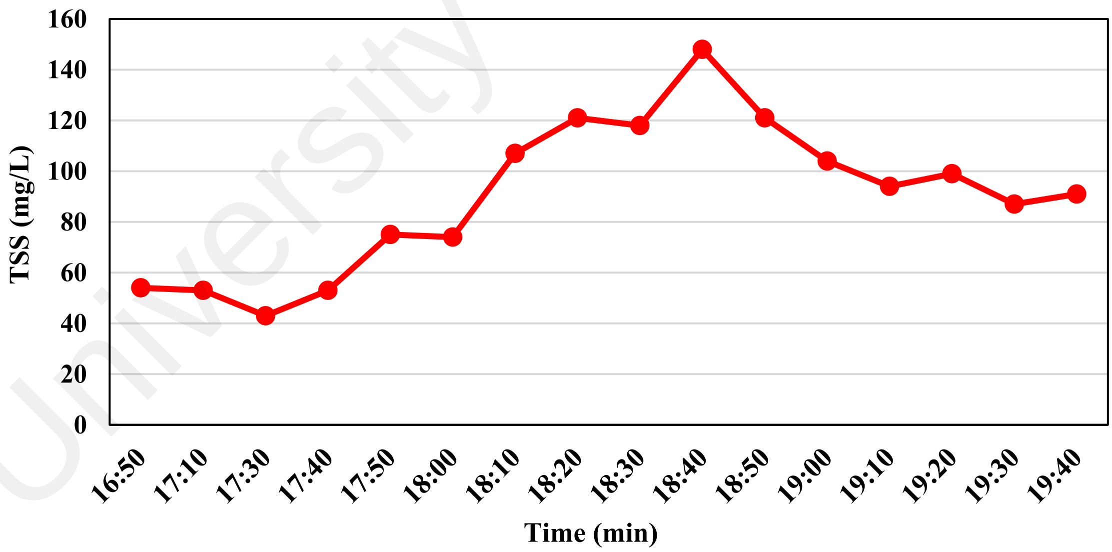

Figure 4.12: TSS parameter for the samples on the 20-09-2018 event.

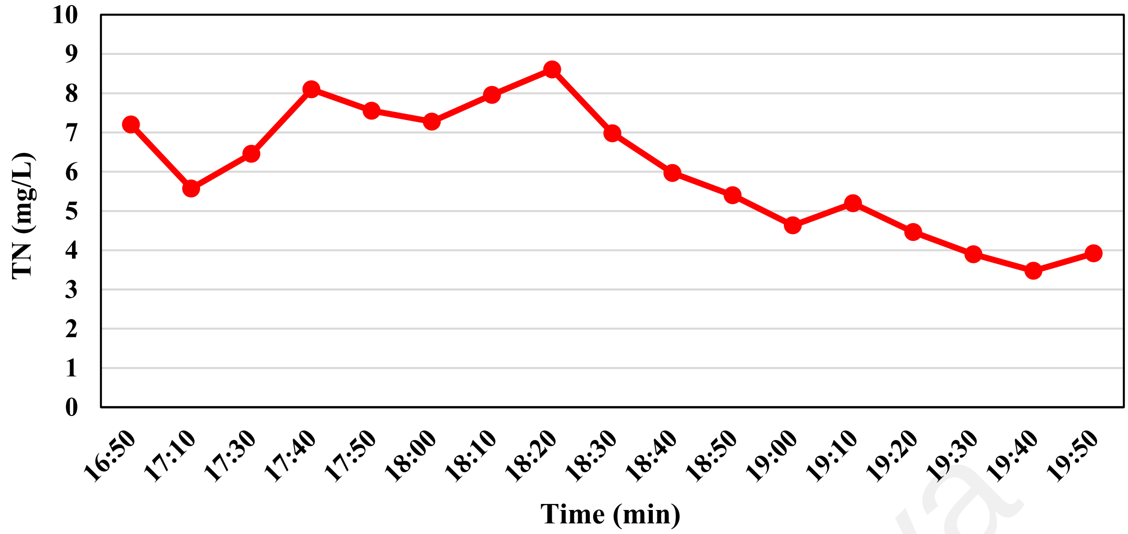

Figure 4.13: TN parameter for the samples on the 20-09-2018 event.

For the quality calibration of the model, Total Suspended Solids (TSS) and (NOx+NH3) (referred to as Total Nitrogen (TN)) were selected. We used Nitrate, Nitrite (NOx) and Ammonia-N (NH3) as the total nitrogen. Dissolved inorganic nitrogen (DIN) includes ammonia (NH3), nitrite (NO2), and nitrate (NO3). The water bodies are greatly affected by these constituents because they are easily available to be up taken by simple organisms (Seitzinger et al., 2002), and may result in eutrophication, hypoxia, and loss of biodiversity and habitat (Galloway et al., 2003). According to Table 3.2, TSS and TN are the most common pollutants in residential areas (Water, 2005). Based on this, they were selected for the model quality calibration to evaluate LIDs quality performance in urban areas. Figure 4.12 and Figure 4.13 present the results of analysis for the parameters used for Quality Modeling, TSS and TN (NOx + Ammonia), respectively.

4.4.2 Quality modeling calibration

In order to calibrate the quality model for TSS and TN parameters derived from the 20 September 2018 event sampling, the catchment was divided into two categories-residential and commercial-consisting of 70% and 30% of the catchment, respectively.

The residential and commercial percentage of the study area were derived through site inspection and google earth.

Similarly, there are influential parameters to be adjusted to calibrate the quality model as well. The most important parameters affecting the model calibration are the buildup and washoff functions and the input parameters (C_1, C_2, C_3, and C_4). Pollutant accumulation can be represented by different types of buildup functions on an urban catchment, including power function, exponential function, or saturation equation, while the washoff is simulated using exponential function, rating curve equation or event mean concentration (EMC). Among various types of pollutant buildup and washoff functions, the exponential function was selected for both buildup and washoff after testing the model for different functions. The exponential functions for buildup and washoff in SWMM are explained as follows.

Buildup follows an exponential growth curve that approaches a maximum limit asymptotically,

$$B = C_1(1 - e^{-C_2 t}) \qquad (4.1)$$

where C_1 = maximum buildup possible (mass per unit of area or curb length), C_2 = buildup rate constant (1/days), and t is the time.

The washoff load (W) in units of mass per hour is proportional to the product of runoff raised to some power and to the amount of buildup remaining, i.e.,

$$W = C_3 q^{C_4} B \qquad (4.2)$$

where C_3 = washoff coefficient, C_4= washoff exponent, q = runoff rate per unit area (inches/hour or mm/hour), and B = pollutant buildup in mass units. The buildup here is the total mass (not per area or per curb length) and both buildup and washoff mass units are the same as used to express the pollutant's concentration. The input parameters (C_1-C_4) for quality modeling are depicted in Table 4.2.

Table 4.2: Buildup and washoff input parameters to calibrate the quality model.

Land use	Pollutant	Build-up		Washoff	
		C_1	C_2	C_3	C_4
Residential	TSS	1.5	0.3	0.4	0.9
	TN	0.002	0.05	12	1.7
Commercial	TSS	12	0.3	1.5	0.6
	TN	0.1	0.7	0.3	3.5

4.4.2.1 Total Suspended Solids (TSS) calibration

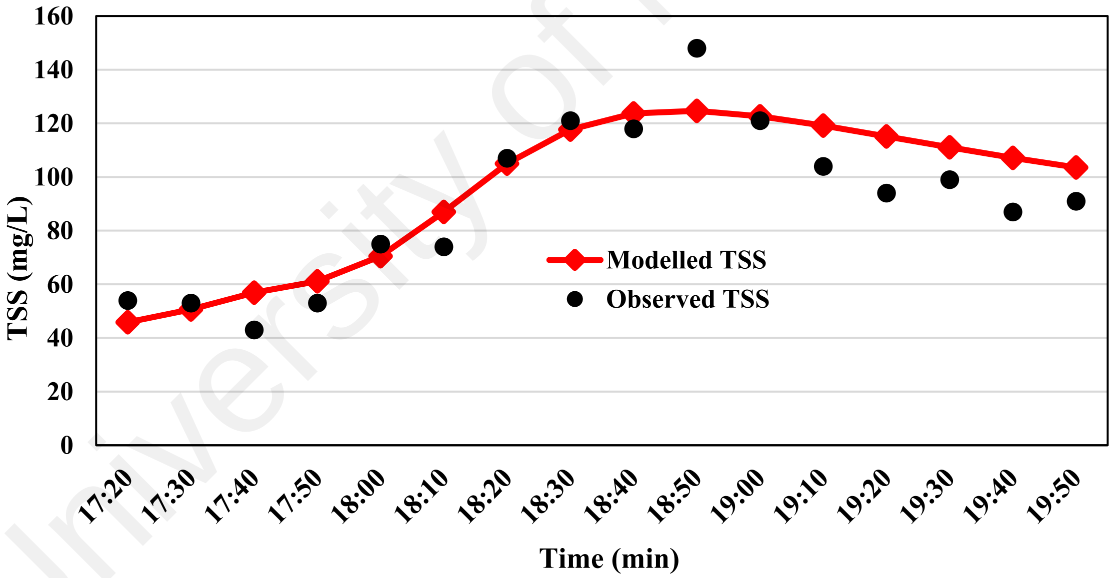

Figure 4.14: Total Suspended Solids (TSS) calibration result for the 20-09-2018 event.

Having adjusted the parameters (C_1–C_4) after many runs, a satisfactory match between the observed and calibrated values for TSS was achieved, as shown in Figure 4.14. As can be seen, there is a good match between the modeled and the observed values with a little difference at the peak. The evaluation parameters in Table 4.3, namely NOF, NSC, and r^2 for TSS, are 0.14, 0.81, and 0.84, respectively, which show a satisfactory match between the modeled and observed values. Overall, it is clear from the calibrated model and the result of test in Table 4.3 that the modeled TSS graph follows the observed TSS graph and the calibration is satisfactory.

4.4.2.2 Total Nitrogen (TN) calibration

The calibration of quality modeling is usually more difficult than quantity modeling. In terms of TN it was even more difficult than TSS to be calibrated and hard effort was made to calibrate TN which can be seen in Figure 4.15. The evaluation parameters in Table 4.3, namely NOF, NSC, and r^2 for TN, are 0.14, 0.74, and 0.74, respectively, which are in the acceptable range and show a good match between the modeled and observed values. Overall, Figure 4.15 and Table 4.3 show that the result of TN calibration was quite satisfactory.

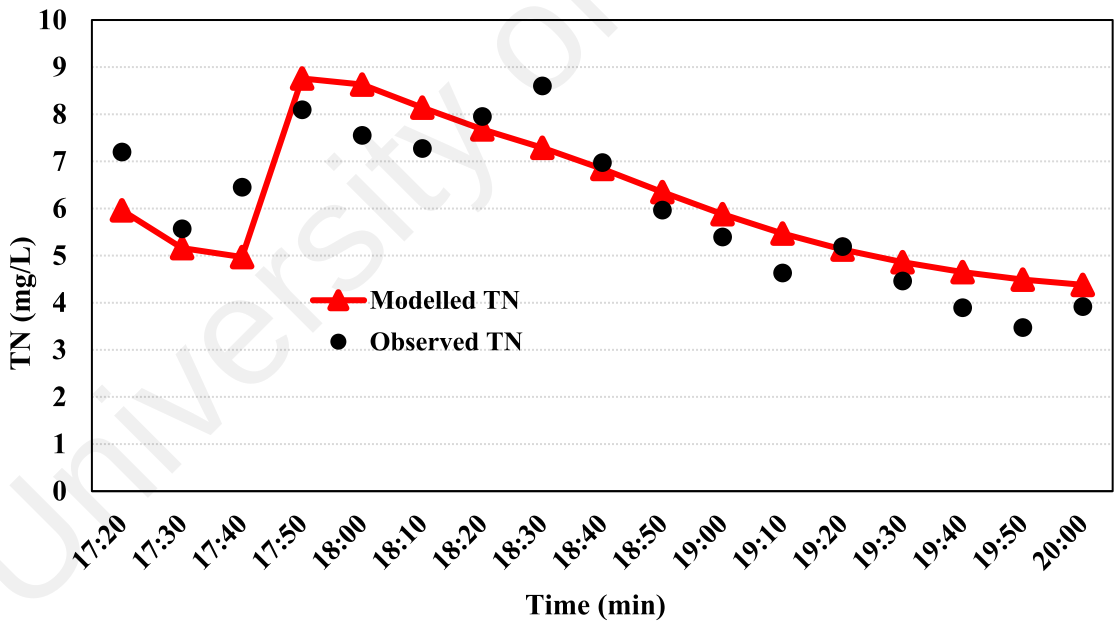

Figure 4.15: Total nitrogen (TN) calibration result for the 20-09-2018 event.

4.5 Model performance evaluation (goodness-of-fit test)

We used four different goodness-of-fit tests to assess the accuracy of the model predicted values against the observed values for quantity modeling. For quality only three evaluation methods were applied. The goodness-of-fit test results for the quantity and quality calibration are depicted in Table 4.3.

Table 4.3: The goodness-of-fit test results to evaluate the reliability of the model.

Parameter	1st Calibration (05-12-2015)	1st *Valid	2nd Valid	2nd Calibration (20-09-2018)	1nd Valid	2nd Valid	TSS Calibration	TN Calibration
D_V (%)	5	-	-	4.70	6.68	10.6	-	-
NOF	0.07	0.21	0.20	0.05	0.08	0.17	0.14	0.14
NSC	0.97	0.85	0.82	0.93	0.74	0.61	0.81	0.74
r^2	0.97	0.88	0.87	0.93	0.77	0.93	0.84	0.74

*Valid=Validation

The table indicates that the results of goodness-of-fit test for quantity calibration is quite satisfactory. As for TSS and TN, although the results are not the same as quantity calibration, the three evaluated parameters still show a good match between the predicted and the observed values in both TSS and TN, based on the criteria for the goodness-of-fit test mentioned in chapter 3 (3.8).

4.6 LID controls designing and assigning to the subcatchments

Having calibrated and validated the model, the selected LIDs (vegetated swale and rain garden) were assigned into the model. The LIDs are assigned to each subcatchment through the LID control editor of the subcatchment. The LID control editor is used to define a low impact development control in each subcatchment which can be placed throughout a catchment to store, infiltrate, and evaporate subcatchment runoff. The design of the LID control is made on a per unit area basis so that it can be placed in any number of subcatchments at different sizes or number of replicates.

To model LID in SWMM, the LID in the model should first be designed. To do so, we need to design the LID parameters based on the characteristics of the catchment such as soil, surface roughness and slope. Having finished the design, the LID should be assigned to each sub-catchment in the model. In this study, the selected LIDs occupy 7% of the catchment. The selected LIDs (swale and rain garden) also treats 40% of the impervious area of each subcatchment. The final model was tested by the calibrated rainfall as well as the TSS and TN to check the model efficiency. after that the model was executed using the selected rainfall scenarios to check efficiency of the developed model for different rainfall intensities.

4.6.1 LID control efficiency results

After assigning LIDs to the model, the performance of LID controls on hydrology and water quality was assessed with the same rainfall event which was used to calibrate the model. The model, with the LID controls, was executed and outputs for both quantity and quality were compared with the model outputs without LID controls. The aim was to check the performance of the model after assigning the LIDs. The results of the model with the applied LIDs are shown in Table 4.4 and Figures 4.16-4.18.

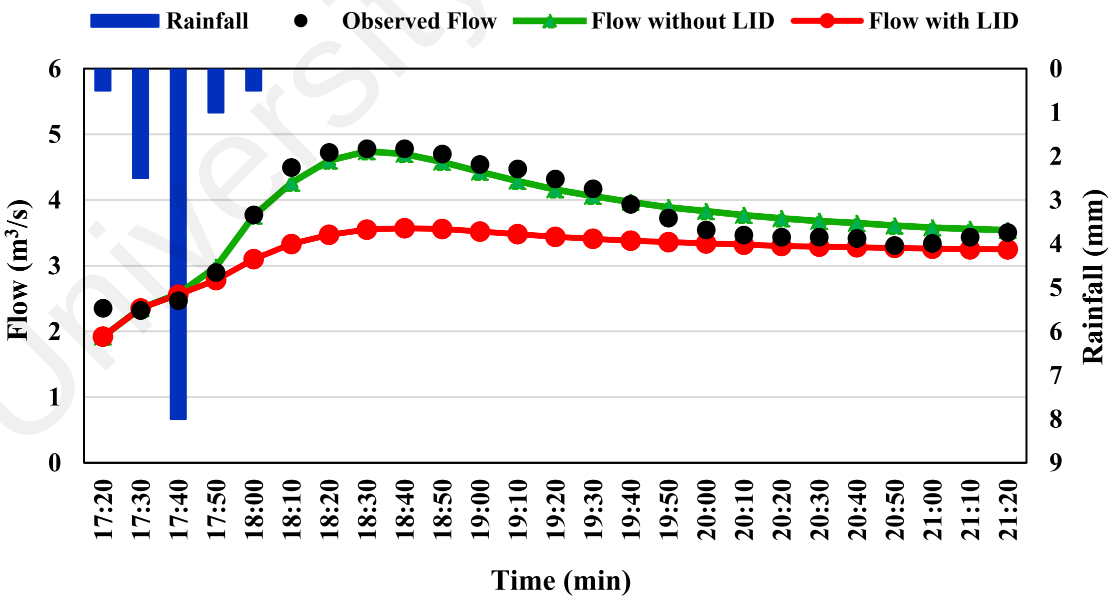

Figure 4.16: Modeled flow with LID controls in the subcatchments for the 20-09-2018 rainfall event.

Table 4.4: Best management practices (BMP) removal and peak runoff reduction after assigning low impact developments (LIDs) to the model.

Rainfall on 20.09.2018 (mm)	LID Removal (%)		Peak runoff reduction (%)
	TN (%)	TSS (%)	
12.50	29	41	23

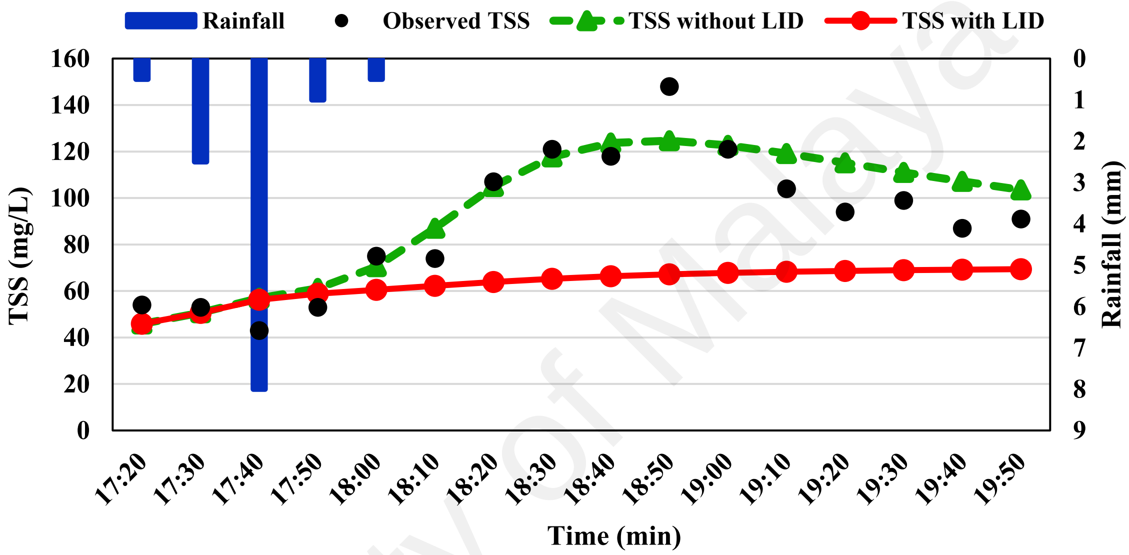

Figure 4.17: Modelled TSS with LID controls in the sub-catchments for the 20-09-2018 event.

The results depicted in Table 4.4 and Figure 4.16 show that the peak runoff reduced by 23% after assigning LIDs to the model. Figures 4.17 and 4.18 and Table 4.4 show that TSS and TN also reduced by 41% and 29%, respectively. The Figures also clearly show that TSS and TN reductions were relatively satisfactory after assigning the LIDs to the model. As can be seen from the table and figures, LIDs have been more efficient to reduce TSS and TN compared to peak runoff.

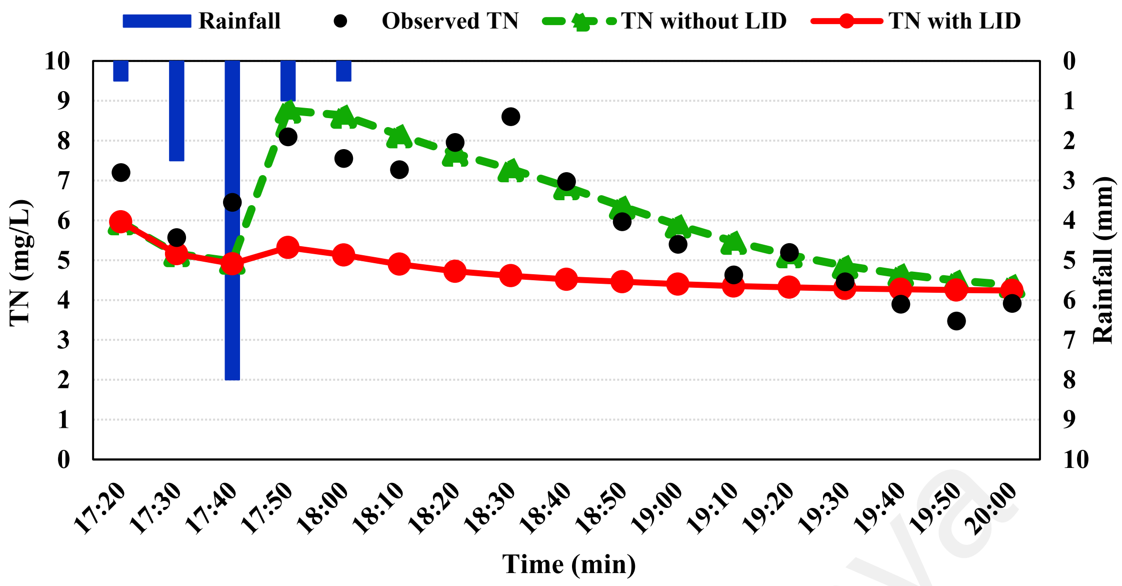

Figure 4.18: Modelled TN with LID controls in the sub-catchments for the 20-09-2018 event.

In this study, both the table and the figures confirm that LID practices are of high importance in all developed urban areas to mitigate the effects of imperviousness on both runoff quantity and quality. Thus, it can be concluded that LID techniques could reduce urban runoff and improve stormwater quality significantly.

4.6.2 Model performance for the selected rainfall scenarios

In order to test the final model with different rainfall scenarios, nine sets of rainfall were selected as follow. The intensity–duration–frequency (IDF) curves for the area had already been prepared by DID and published in the Urban Stormwater Management Manual for Malaysia (MSMA, 2012). These curves have been developed based on 100-year hydrological data for the return periods of 2, 5, 10, 20, 50, and 100 years. They have been particularly developed to be used by researchers working on the respective study areas. In IDF curves, the rainfall durations are depicted on the "X" axis and the intensities are depicted on the "Y" axis. The rainfall frequencies are illustrated in the form of diagonal curves. The return periods of 5 years, 10 years, and 20 years were selected for the three selected durations, namely 1, 1.5, and 2 hours.

Table 4.5: Rainfall scenarios for three return periods and three durations.

Return Period	Duration (hr)	Rainfall (mm)
5	1	72
5	1.5	81
5	2	90
10	1	80
10	1.5	90
10	2	96
20	1	90
20	1.5	99
20	2	110

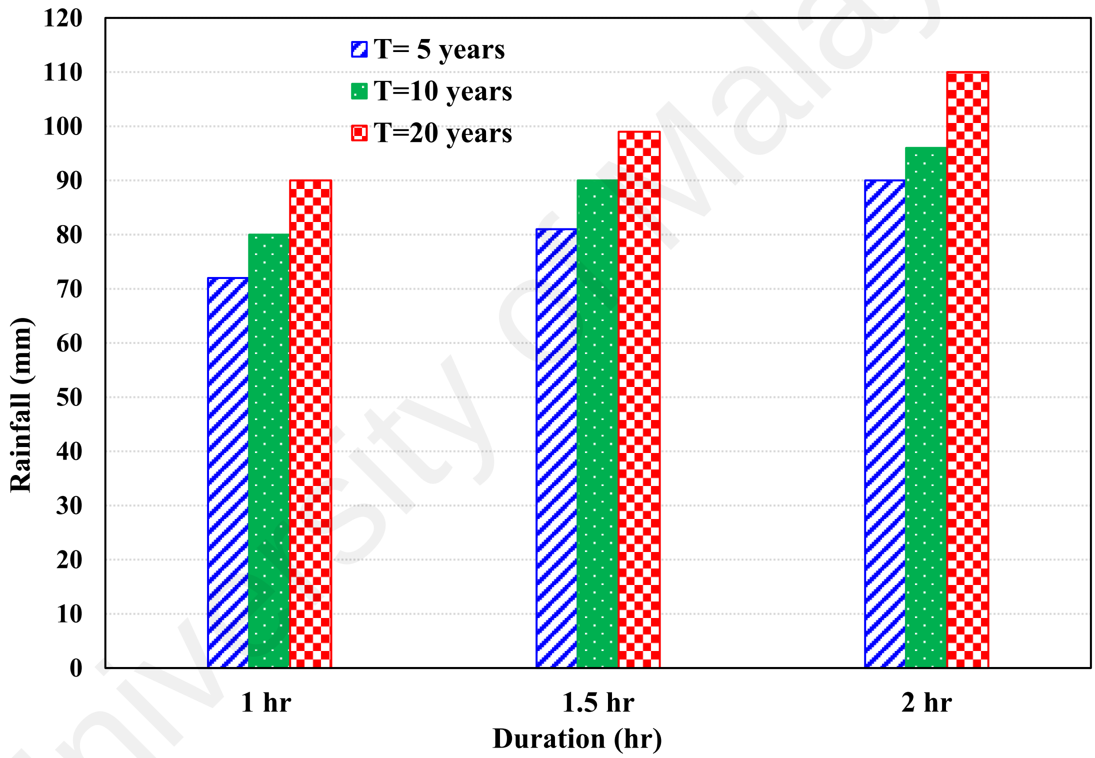

Figure 4.19: Rainfall scenarios for three return periods namely 5, 10 and 20 years.

For instance, to achieve the first rainfall intensity, the 1-hour duration is found on the "X" axis and the intersection of the vertical line with the return period of 5 is found. Then the intersection of the horizontal line with the "Y" axis of this point will be the respective rainfall intensity of that return period and duration. Likewise, the process was repeated for other durations and with other return periods. Therefore, for each return period, three durations were applied to find the corresponding rainfalls. Thus, total nine different rainfalls were achieved. The achieved rainfalls are depicted in Table 4.5 and Figure 4.19.

The final model with LID controls was executed again using the nine rainfall scenarios to check the model performance for the rainfall of different intensities and durations.

Table 4.6: Results of the model performance for the selected rainfall scenarios.

Return Period (T)	Duration (hr)	Rainfall (mm)	LID Removal (%)		Peak runoff reduction (%)
			TN (%)	TSS (%)	
5	1	72	40	61	27
5	1.5	81	40	61	19
5	2	90	40	62	18
10	1	80	40	61	18
10	1.5	90	40	61	9
10	2	96	39	60	0
20	1	90	38	58	0
20	1.5	99	39	59	0
20	2	110	39	60	0

The results of model performance for the selected rainfall scenarios are depicted in Table 4.6 and Figure 4.20. The table shows that the model performance is quite efficient in terms of TSS and TN removal for different rainfall amounts. The LID removal efficiency for TN and TSS is up to 40% and 62%, respectively. Likewise, the peak runoff reduction is also acceptable, based on the type of LIDs and percentage of the catchment they have been applied to. The peak runoff reduction also reached 27% for rainfall of less than 70 mm.

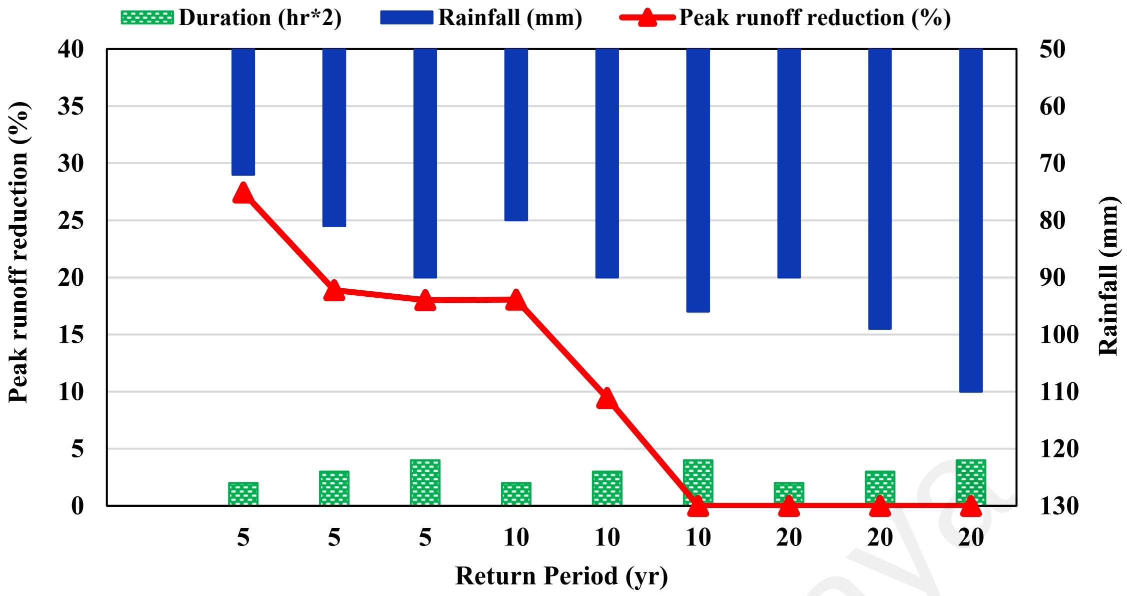

Figure 4.20: Peak runoff reduction for the selected rainfall scenarios.

Figure 4.20 also shows that LID performance for smaller rainfalls of up to 70 mm is much better than higher intensity rainfalls. For the rainfalls of more than 90 mm and for the return period of more than 10 years, the peak runoff reduction will be very poor. The results will be discussed in more details in the discussion chapter (chapter 5).

4.7 Optimization model development and the results

Having prepared the simulation model, the optimization model should also be developed to complete the final simulation-optimization model.

The decision variables for the optimization algorithm and subroutine function should be first defined. According to the number of subcatchments in the simulation model, the decision variables for the MOPSO algorithm were selected 35 for this study. The maximum iterations for the algorithm was 100. The initial size of particle population and repository were also set to 150. These figures were selected based on several times trial and error and figured out that the best results would be achieved when the initial size of the population and repository are set to approximately four to five times of the variables (35). The number of iterations were also achieved by trial and error.

The results of MOPSO algorithm are generated in the form of both Pareto-optimal front curve and matrix. The results give the best options for the best combination of LID controls so that the peak runoff and the mean concentration of both pollutants, namely TSS and TN is optimally reduced. Figure 4.21 illustrates the result of MOPSO pareto-optimal front for peak runoff reduction against different LID combinations generated by the algorithm in MATLAB.

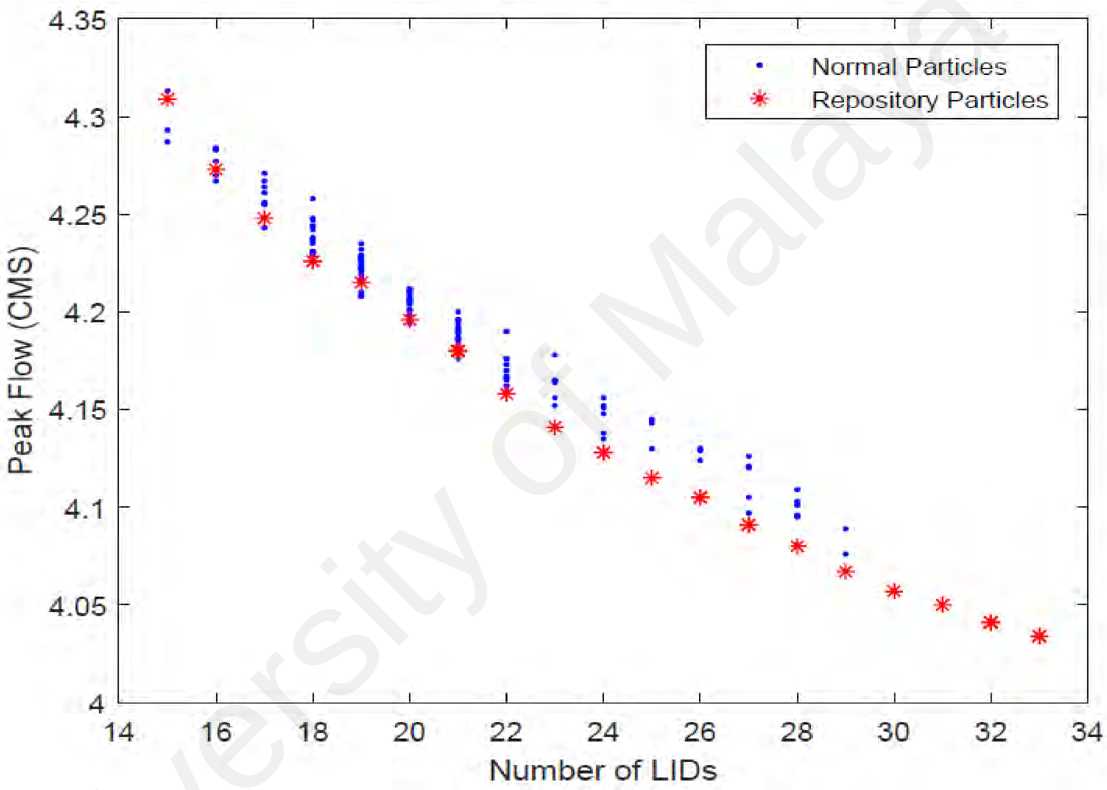

Figure 4.21: MOPSO pareto-optimal front solutions for peak runoff reductions against different LID combinations.

The model parameters were adjusted as such that the model optimize one objective at each run process. Based on the EPA SWMM output file, the parameters were adjusted as 3, 5, and 6 denoting peak runoff, TN, and TSS, respectively. The model needed to be executed for each parameter separately. The result for each parameter is in the form of a matrix as well as a graph, illustrating the Pareto-optimal front. For instance, for the peak runoff, the result achieved was a matrix of 42×37.

Table 4.7: Part of the optimization output for the peak flow with different LID types and combinations.

Sub-catchment	Various LID combinations									
S01	RG	RG	RG	RG	RG	RG	NL	RG	NL	RG
S02	RG	RG	RG	RG	RG	RG	RG	SW	RG	RG
S03	RG	RG	RG	RG	RG	RG	NL	RG	NL	NL
S04	SW	NL	NL	SW	NL	NL	NL	SW	NL	NL
S05	SW	SW	SW	SW	SW	SW	SW	SW	RG	SW
S06	SW	SW	SW	RG	SW	SW	NL	RG	NL	SW
S07	NL	RG	NL	NL	NL	NL	NL	NL	NL	NL
S08	SW	RG	SW	SW	RG	SW	NL	SW	NL	RG
S09	SW	SW	SW	SW	SW	RG	NL	RG	NL	RG
S10	RG	RG	RG	RG	RG	RG	NL	RG	NL	RG
S11	RG	SW	RG	RG	RG	RG	NL	SW	NL	SW
S12	NL	NL	NL	NL	NL	NL	NL	NL	NL	NL
S13	SW	RG	SW	SW	RG	RG	SW	RG	SW	SW
S14	NL	NL	NL	NL	NL	NL	NL	NL	NL	NL
S15	RG	SW	RG	NL	RG	RG	NL	SW	NL	RG
S16	SW	SW	SW	SW	SW	SW	SW	SW	SW	SW
S17	NL	NL	RG	NL	NL	RG	NL	RG	NL	NL
S18	NL	RG	RG	NL	NL	RG	NL	RG	NL	NL
Number of LIDs	26	27	28	24	25	28	10	29	10	21
Peak Flow (m^3/s)	4.108	4.091	4.079	4.139	4.117	4.079	4.385	4.073	4.385	4.176

Table 4.7 presents part of the results for the peak runoff achieved from the optimization model. The two types of LIDs, swale (SW) and rain garden (RG) were both coded in MATLAB as numbers 1 and 3, respectively to be optimized. NL also denotes that no LID has been allocated to the subcatchment. The table shows different types of LIDs and combinations optimized by MOPSO algorithm to achieve the maximum peak runoff reduction. The last two rows of the table present the total number of LIDs for all subcatchments and the respective peak runoff reduction. For instance, in the first column 6 subcatchments have been provided with rain garden, 7 subcatchments receive swale, and 5 subcatchments have got no LIDs in them. The total number of LIDs for all subcatchments (which are not presented in Table 4.7) in this column are 26 as well; in

which case the peak flow runoff will be 4.108 m^3/s, showing 11% reduction compared to the non-LID scenario in the catchment. It should be noted that Table 4.7 only presents part of the results and the whole table is a matrix of 42×37. The same results have also been achieved for TSS and TN.

Likewise, Figures 4.22 to 4.24 depict the non-dominated solutions for the peak runoff, TSS and TN reductions with different types and number of LIDs, respectively. The figures only show the Pareto-optimal front of the model output rather than the whole repository particles.

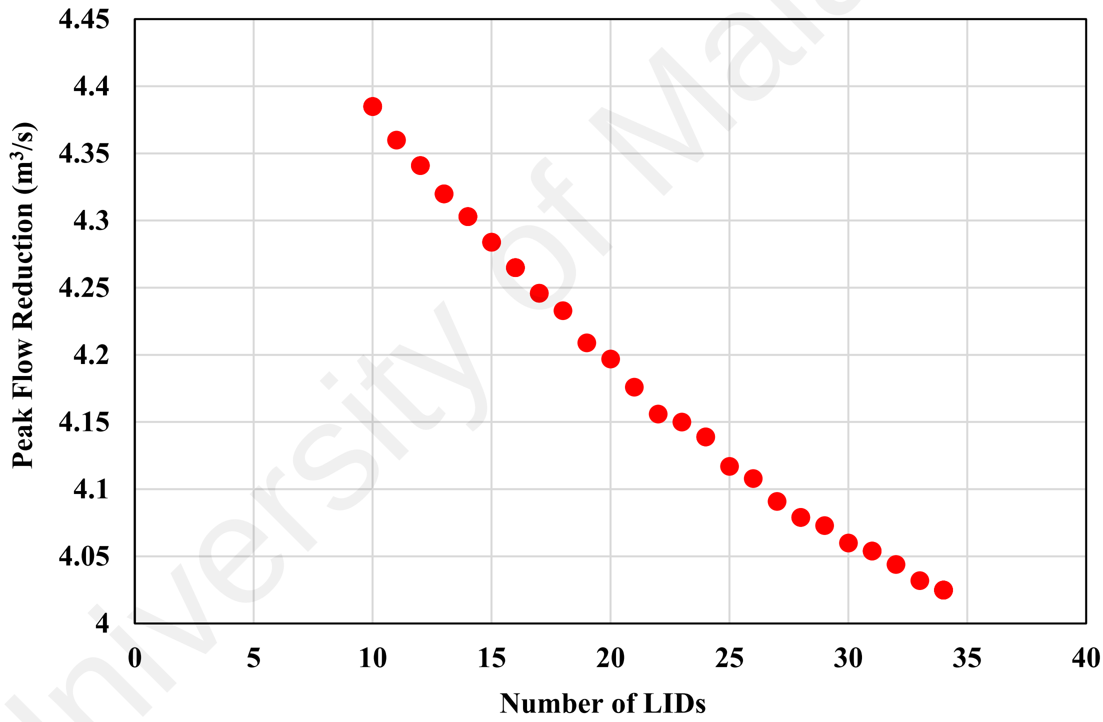

Figure 4.22: The Pareto optimal front for the peak flow reductions with different number of LIDs.

As far as the TSS is concerned, Figure 4.23 and Table 4.8 show that when the number of LIDs is 13, TSS reduction is 38.03%, and it can be seen from the figure and table that the TSS reduction trend is very similar to the peak runoff reduction.

Table 4.8: Peak Runoff, TSS and TN reductions for selected number of LIDs in MOPSO non-dominated solutions.

Number of LIDs	Peak Runoff (m^3/s)	TSS (kg)	TN (kg)	Peak Runoff Reduction (%)	TSS Reduction (%)	TN Reduction (%)
13	4.32	3457.13	245.13	6.70	38.03	22.38
15	4.28	3449.63	243.66	7.47	38.17	22.84
18	4.23	3445.97	241.91	8.57	38.23	23.39
20	4.20	3443.75	240.80	9.35	38.27	23.75
22	4.16	3441.40	240.77	10.24	38.32	23.76
25	4.12	3439.30	240.73	11.08	38.35	23.77
28	4.08	3437.58	240.70	11.90	38.38	23.78
30	4.06	3436.48	240.68	12.31	38.40	23.79
34	4.03	3434.87	240.65	13.07	38.43	23.80

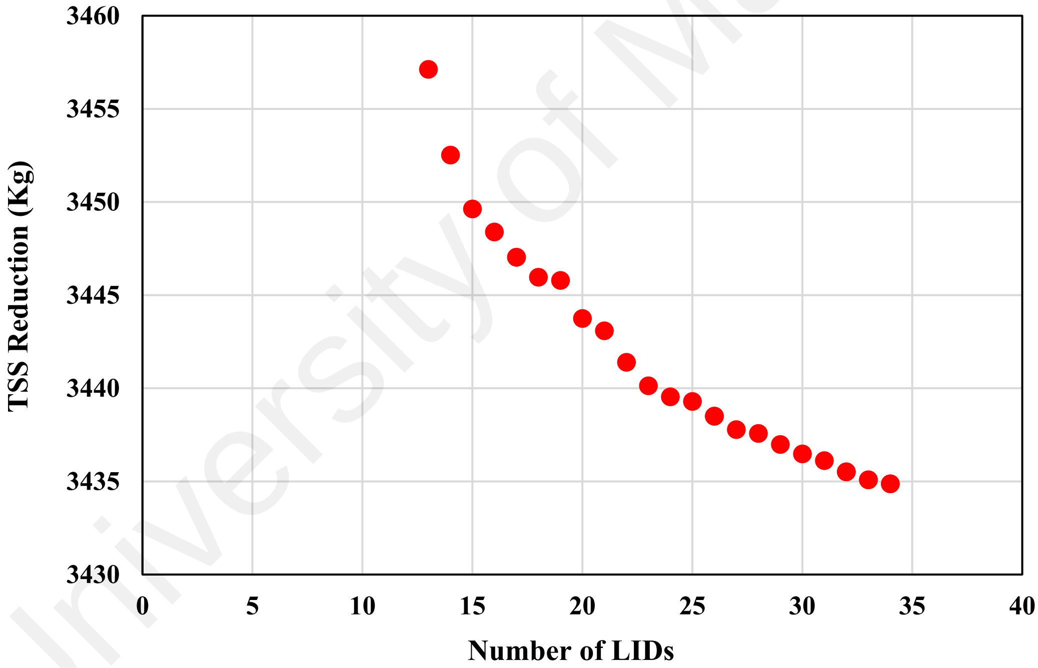

Figure 4.23: The Pareto optimal front for the TSS reduction with different number of LIDs.

Figure 4.24 depicts the non-dominated solutions for the TN reduction with the number of LIDs. Table 4.8 also shows the TN reduction for the selected number of LIDs.

Figures 4.22 to 4.24 show that peak runoff and pollutant loads will reduce more with the greater number of LIDs implemented in the catchment. This is in consistent with other similar studies and will be elaborated more in chapter 5.

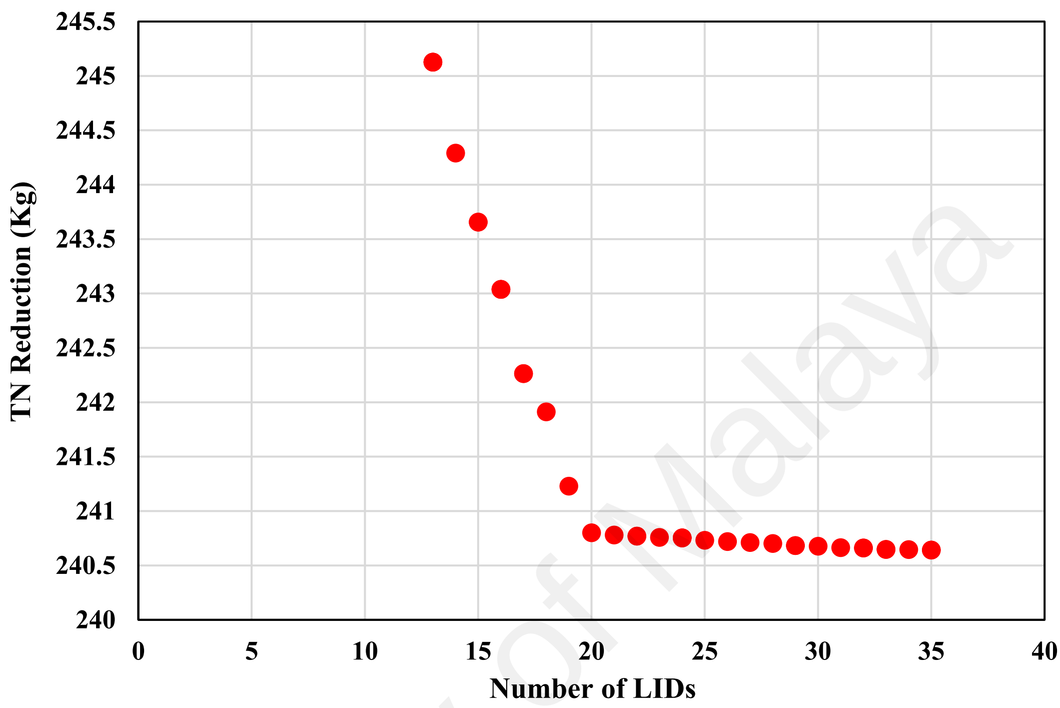

Figure 4.24: The Pareto optimal front for the TN reduction with different number of LIDs.

4.8 LID best combination scenarios

In order to find the best combination of LIDs to achieve minimum runoff and pollutant loads in the catchment, some LID combination scenarios were selected randomly among all non-dominated solutions for peak runoff, TSS, and TN pareto-optimal front and the SWMM was updated by the LID control design. The reason for this was that the scenarios were too complex to be applied to the subroutine function. The LID control scenarios selected were 20, 25 and 30, respectively. For each selected scenario, three different LID combinations were executed namely, runoff, TSS and TN combinations. Also, three different results were recorded by executing the SWMM model which are peak runoff, TSS and TN.

Table 4.9: Results of the selected scenarios to evaluate the optimal number of LID combinations.

Scenarios	Number of LIDs	Peak Runoff (m^3/s)	TSS (kg)	TN (kg)	Peak Runoff Reduction (%)	TSS Reduction (%)	TN Reduction (%)
1	20 for flow	4.20	3446	245	9.35	38.23	22.36
2	20 for TSS	4.24	3444	246	8.42	38.27	22.19
3	20 for TN	4.29	3473	241	7.30	37.75	23.75
4	25 for flow	4.12	3444	242	11.08	38.26	23.51
5	25 for TSS	4.15	3439	243	10.39	38.35	23.13
6	25 for TN	4.18	3456	241	9.65	38.06	23.77
7	30 for flow	4.06	3440	241	12.31	38.34	23.66
8	30 for TSS	4.08	3436	241	11.81	38.40	23.64
9	30 for TN	4.09	3447	241	11.58	38.22	23.79

Totally, 9 different LID combinations were tested using the SWMM simulation model. Based on the selected scenarios results, the best LID combination to get the optimal amount of runoff and pollutant mean concentration was achieved. Table 4.9 and Figure 4.25 depict the results achieved for these scenarios.

According to Table 4.9 and Figure 4.25, the more LIDs are implemented in the catchment, the more the three parameters namely, peak runoff, TSS and TN are reduced. However, to get the optimal reduction with the minimum number of LIDs, an assessment was performed. It is clear from the table and figures that peak runoff is reduced more with the increase of LIDs, compared to TSS and TN. Therefore, the best LID combination will be achieved if the optimal LID combination is selected from the peak runoff scenarios.

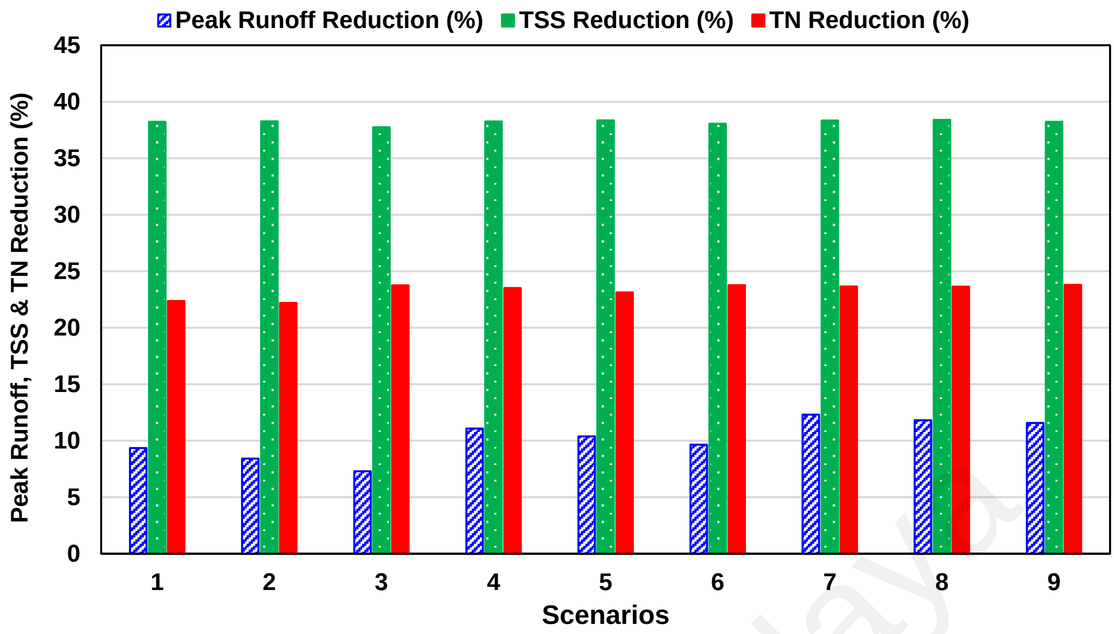

Figure 4.25: Peak Runoff, TSS, and TN Reduction in different selected scenarios.

The table and figures clearly show that the amount of runoff, TSS and TN reductions is not very remarkable after scenario 4 and could easily be ignored. Thus, it could be concluded that the optimal LID combination to achieve the best runoff, TSS and TN reductions would be scenario 4 for the runoff optimization, in which the reduction for peak runoff, TSS and TN is 11.08%, 38.26%, and 23.51%, respectively.

Table 4.10: Number, type and combination of LIDs for the best scenario.

Sub-catchment	LID Type	Sub-catchment	LID Type	Sub-catchment	LID Type
S11	RG	S23	RG	S35	RG
S12	RG	S24	NL	S36	SW
S13	RG	S25	RG	S37	SW
S14	NL	S26	SW	S38	RG
S15	SW	S27	NL	S39	NL
S16	SW	S28	NL	S40	SW
S17	NL	S29	NL	S41	SW
S18	RG	S30	SW	S42	RG
S19	SW	S31	SW	S43	SW
S20	RG	S32	NL	S44	RG
S21	RG	S33	RG	S45	NL
S22	NL	S34	SW		

The details of LID types and combinations for this scenario is presented in Table 4.10 and Figure 4.26. According to Table 4.10 and Figure 4.26, 25 subcatchments are provided with different types of LIDs; among which 13 have been applied with rain garden (RG), 12 have been provided with swale (SW), and 10 subcatchments have no LIDs (NL) in them.

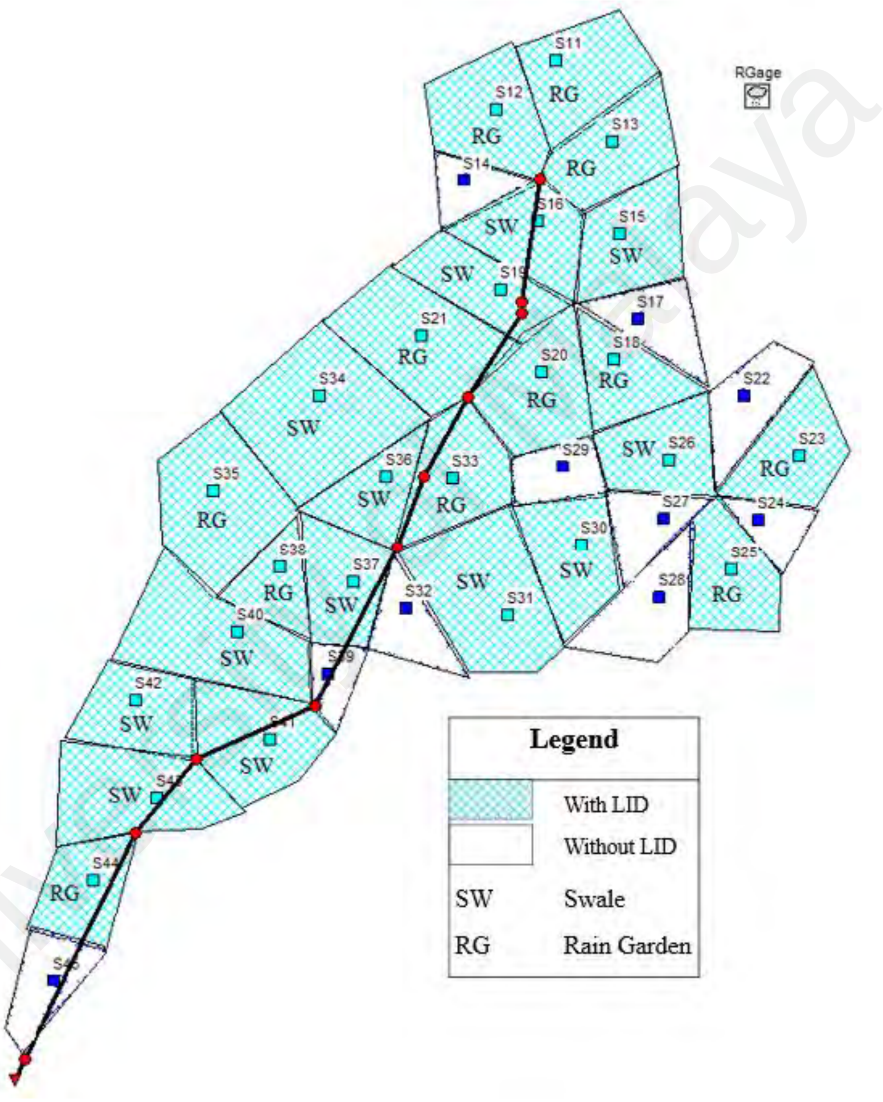

Figure 4.26: Type and combination of LIDs for the best scenario in Bunus catchment.

Figure 4.26 shows that among all types and combinations of LIDs obtained through MOPSO algorithm, the best combination with the maximum peak runoff/pollutant loads reduction will be the one illustrated in Figure 4.26.

4.9 Non-dominated solutions for LID costs

This section presents the results for cost analysis which determines the cost-effective optimization solutions for peak flow, total flow volume, TSS, and TN reduction for bioretention and swale. The discussion on different aspects of costs for LID stormwater control and LID costs for bioretention and swale construction have been presented in chapters 2 and 3. To do the cost analysis for flow, TSS, and TN versus cost, the optimization was carried out for each one separately and the results are presented in the form of graphs and tables. Some scenarios were then selected as well to compare the amount of flow, TSS, and TN reduction for the maximum, average, and minimum cost achieved through optimization.

4.9.1 Non-dominated solutions for peak flow and total runoff volume

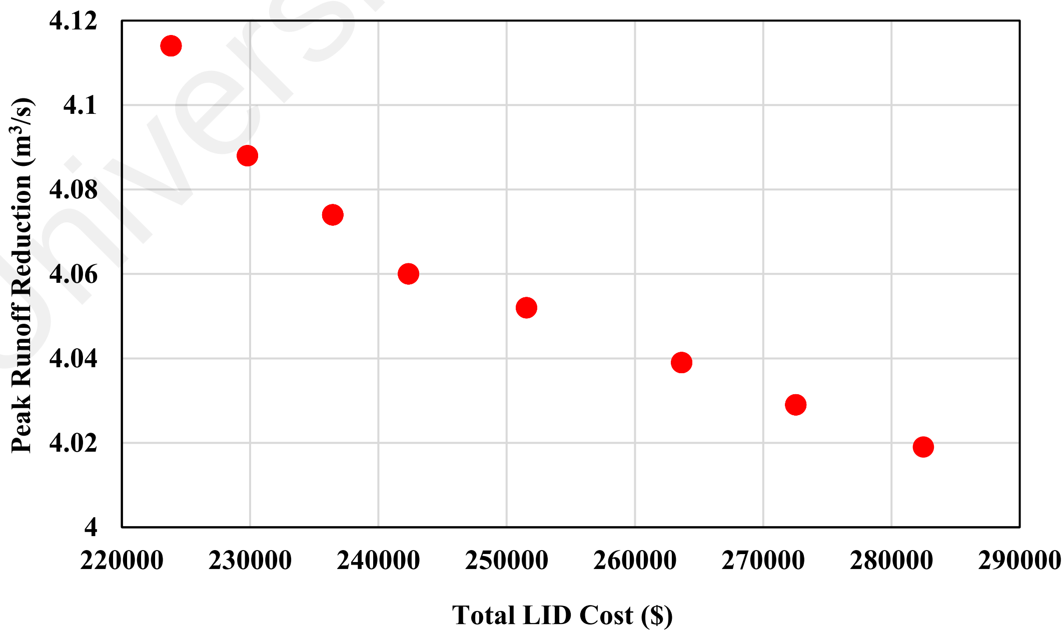

Figure 4.27: Non-dominated solutions for peak flow reduction.

Figures 4.27 and 4.28 depict the non-dominated solutions for the peak runoff and total runoff volume reductions with different costs, respectively. Similar to the case of peak runoff with the number of LIDs, Figure 4.27 shows that the peak runoff remarkably decreases with the increase of total LID cost.

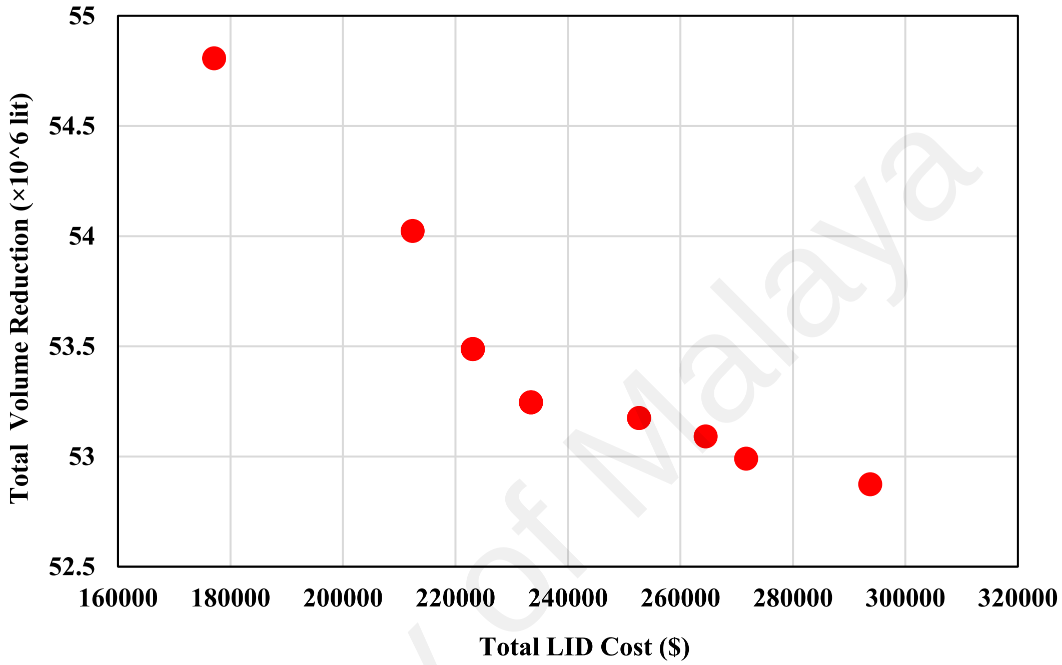

Figure 4.28: Non-dominated solutions for total runoff volume reduction.

Figure 4.28 also illustrates the total runoff volume reduction with the increase of total LID cost. In both cases, the more money is spent, the more the runoff will reduce.

4.9.2 Non-dominated solutions for TSS and TN

Figures 4.29 and 4.30 depict the non-dominated solutions for TSS and TN reduction with the increase of LID cost. As mentioned for runoff, pollutant loads will also reduce more with the increase of cost; however, there is a limit for runoff/pollutant loads reduction, beyond which the reduction will stop with the increase of cost. This will be discussed more in chapter 5.

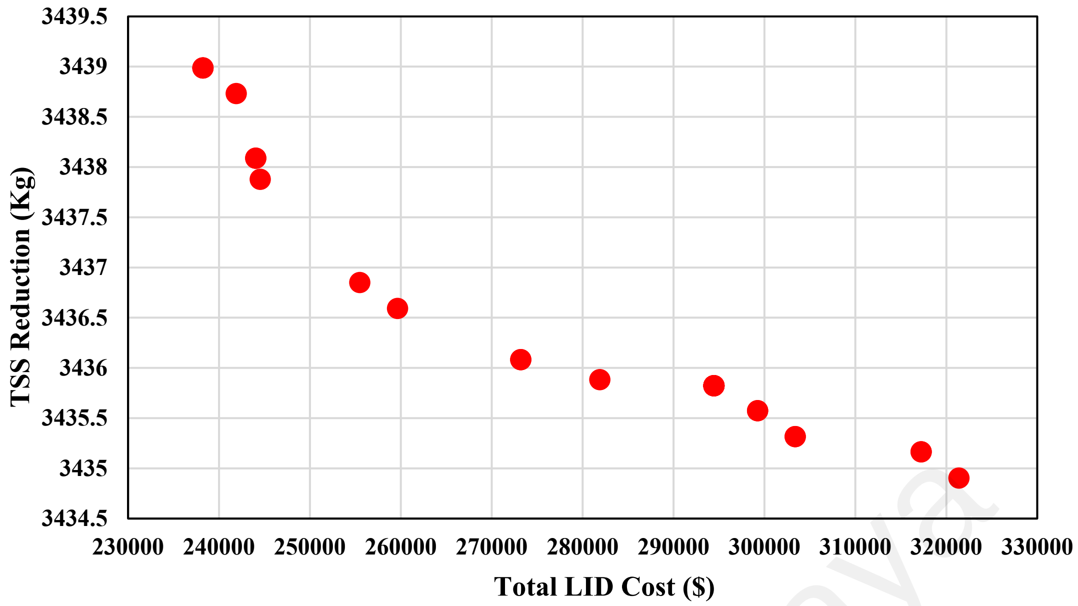

Figure 4.29: Non-dominated solutions for TSS reduction.

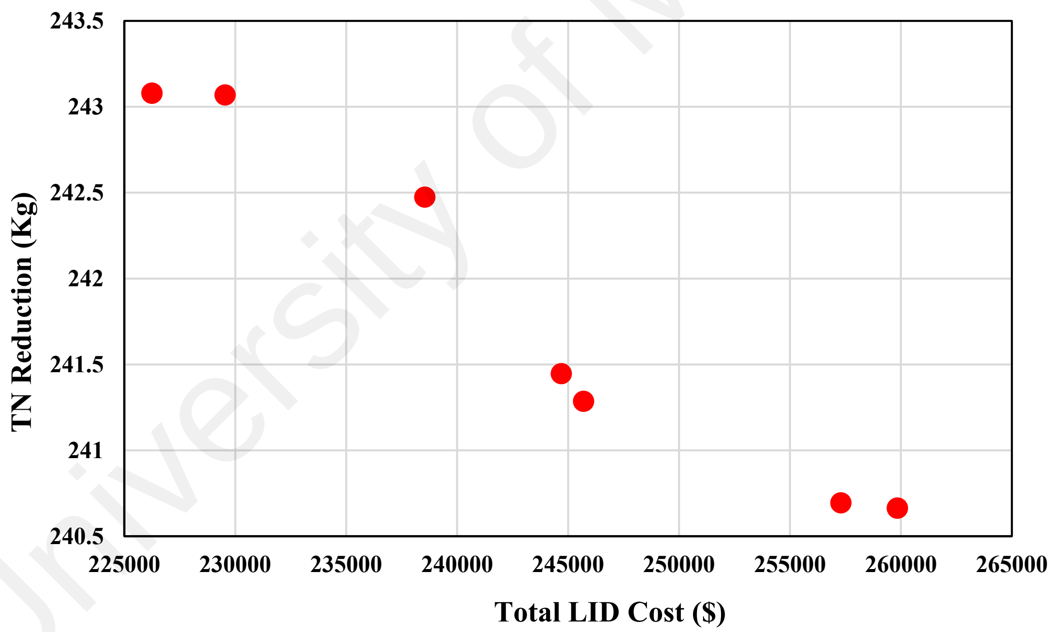

Figure 4.30: Non-dominated solutions for TN reduction.

4.10 Cost non-dominated solutions scenarios for the best LID combinations

The discussion is further supported by the more detailed results presented in Table 4.11 and Figure 4.31. The table gives more detailed information on the percentage of reduction for peak runoff (PR), total runoff volume (TV), TSS, and TN for different LID costs, respectively.

Table 4.11: Peak runoff, total volume, TSS, and TN reduction for selected LID cost scenarios in MOPSO non-dominated solutions.

Cost ($)	PR (m^3/s)	PR Reduction (%)	TV (10^6 lit)	TV Reduction (%)	TSS (kg)	TSS Reduction (%)	TN (kg)	TN Reduction (%)
$177,100	4.30	7	55	4	3467	38	246	22
$203,900	4.17	10	54	6	3449	38	243	23
$223,850	4.12	11	53	6	3591	36	253	23
$233,450	4.10	11	53	6	3440	38	242	24
$238,250	4.13	11	54	6	3439	38	243	23
$242,350	4.06	12	53	7	3437	38	242	23
$244,700	4.11	11	53	6	3443	38	241	24
$259,650	4.07	12	53	7	3437	38	242	23
$282,500	4.02	13	53	7	3435	38	241	24
$293,750	4.04	13	53	7	3436	38	241	24
$351,300	4.02	13	53	7	3435	38	241	24
$397,300	4.02	13	53	7	3435	38	241	24

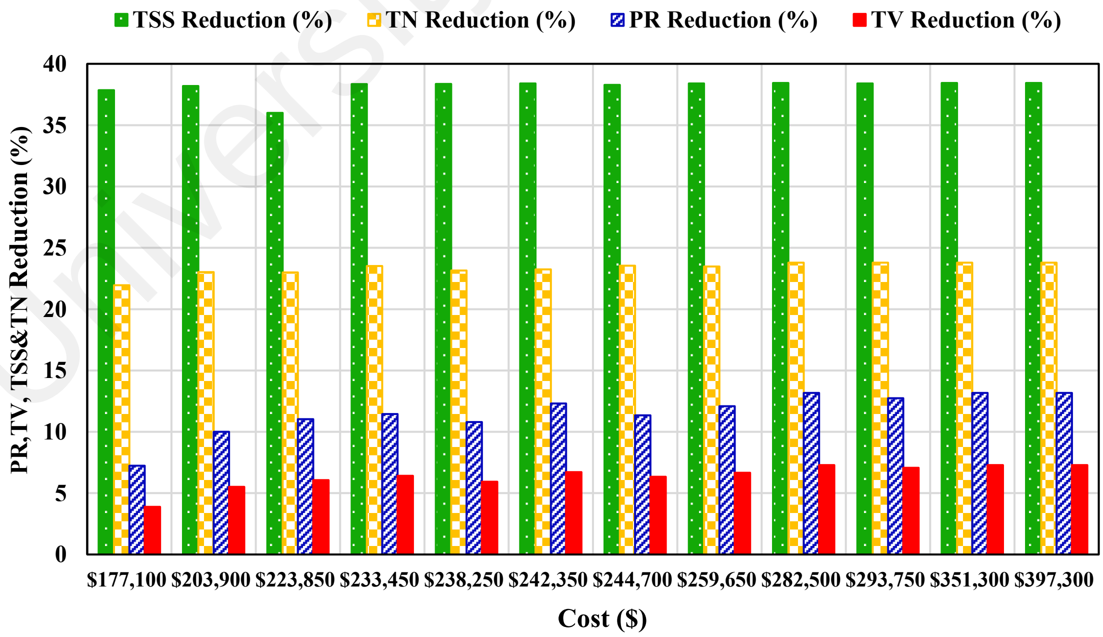

Figure 4.31: Peak Runoff, Total Volume, TSS, and TN reduction for selected LID cost non-dominated solutions scenarios.

The scenario results are depicted in Table 4.11 and Figure 4.31. These results have been achieved by selecting 12 scenarios of minimum, average, and maximum cost for peak flow, total runoff volume, TSS, and TN non-dominated solutions and then run SWMM model to achieve the rest of parameters for the executed one. For instance, the maximum cost for peak flow was run in SWMM and the total runoff volume, TSS, and TN parameters for the same cost was achieved accordingly. Similarly, other parameters were also achieved, and the final results were compared with the results of the simulation model without LID controls.

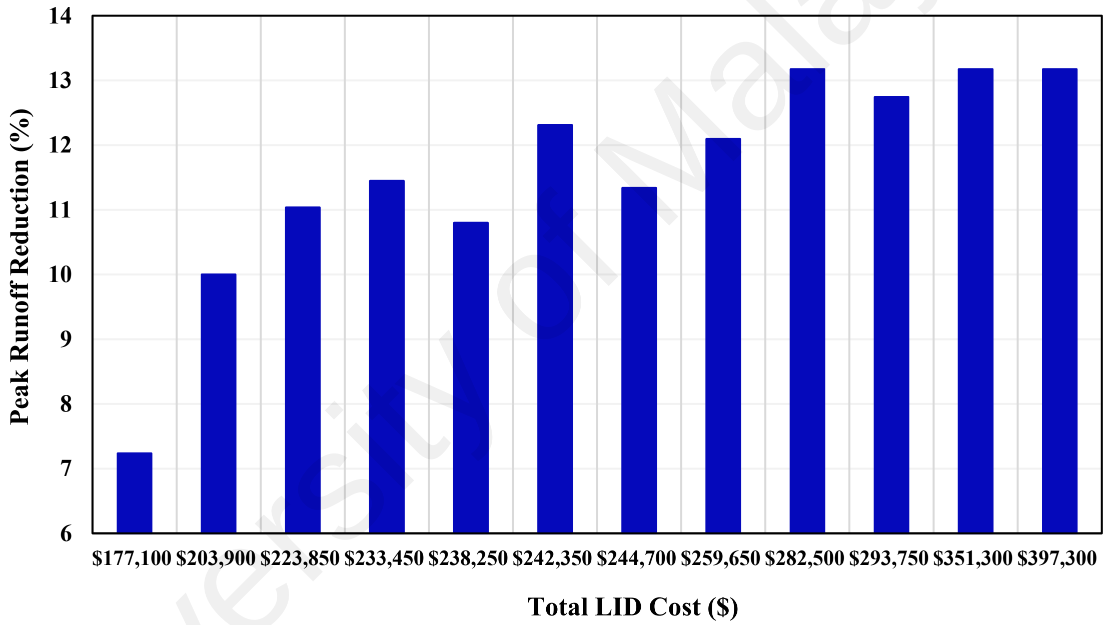

Figure 4.32: Peak runoff reduction with total LID cost.

As can be seen, TSS and TN are almost constant with the increase of cost, but the peak runoff and total runoff volume reduce more with the increase of cost. Figure 4.32 also depicts the changes in peak runoff reduction separately with the increase of cost. It is again clear that the maximum peak runoff reduction is 13%, after which the peak runoff reduction remains constant, too. The reason will be elaborated more in chapter 5.

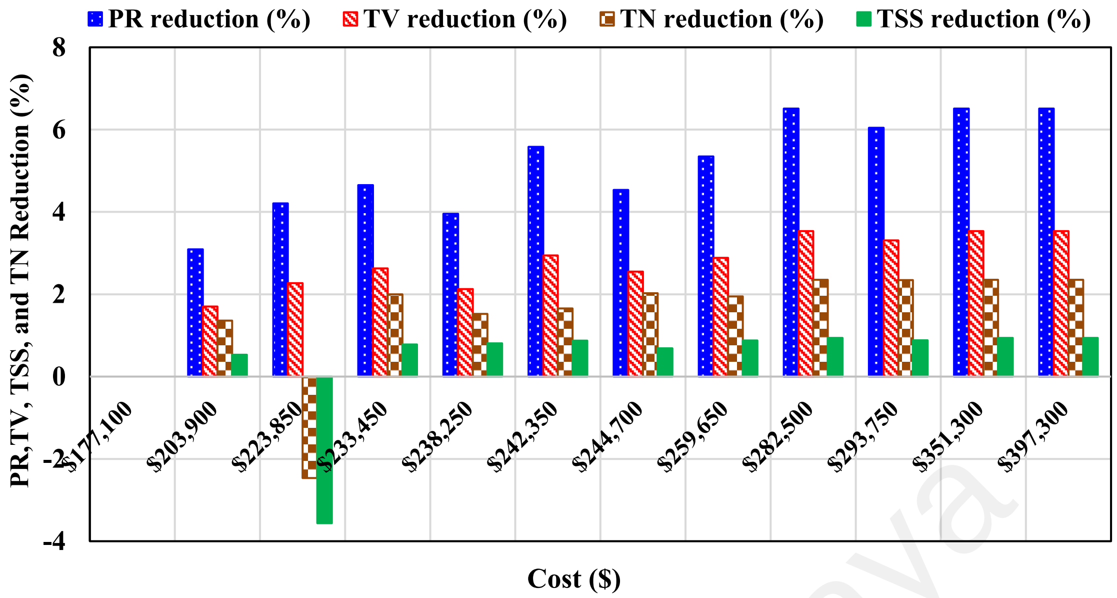

Figure 4.33: Comparison of peak flow, total runoff volume, TSS and TN reduction with the minimum cost scenario.

Finally, all LID cost scenarios were compared with the minimum cost scenario ($177,100) to figure out how much peak runoff, total volume, TSS, and TN will reduce with the increase of cost compared to the minimum cost scenario (Figure 4.33).

As can be seen, the runoff (peak and total volume) have the maximum reduction with the increase of cost, followed by TN, but TSS again remains almost constant. This will also be discussed in chapter 5.

CHAPTER 5: DISCUSSION

Urbanization and alteration of land use/land cover and the increase in the impervious surfaces will adversely affect the urban hydrology, water cycle and water quality, such as increasing the peak runoff and volume (Bell et al., 2016; Chen et al., 2017; Gitau et al., 2016). To manage this excess runoff, resulting from urbanization, new stormwater management strategies should be developed (Kong et al., 2017). In order to control the urban runoff and the adverse impacts, increasing infiltration has always been an important alternative (Yao et al., 2016). The low impact development-best management practices (LID-BMPs) have been proposed as the best management strategies to control stormwater quantity and quality in urban areas (Ahiablame et al., 2012; Liu et al., 2016).

The LIDs have a great potential to solve real life urban runoff quantity and quality problems. The growth of impervious surfaces decreases infiltration capacity, increases runoff generation and direct runoff improves the connectivity of flow and leads to urban flooding. The contaminated stormwater will also deteriorate the water quality in urban areas. The LID techniques are capable of mitigating the impact of imperviousness on both hydrology and water quality of urban stormwater runoff. Particularly, the LID techniques have been developed to mimic the predevelopment hydrologic conditions and promote the storage, infiltration, and evapotranspiration processes. The capability of LID-BMPs in urban runoff reduction and water quality improvement has been well proved in different studies.

5.1 Simulation model and LID assignment

The EPA Stormwater Management Model (SWMM) (Rossman, 2010) was selected to develop the simulation model. SWMM is capable of modeling hydraulic, hydrology and water quality at the catchment scale of mostly urban areas. SWMM has also been provided with the LID control modules (Palla & Gnecco, 2015). In order to develop the simulation model, SWMM needs to be calibrated and validated with the real field data. Before the calibration process, the sensitivity analysis is carried out to minimize the differences between the modelled and observed values (Rosa et al., 2015).

The definition of sensitivity analysis (SA) is understanding how uncertainty in the output can be allocated to various sources of input (Foscarini et al., 2010). There are two classifications for SA methods, local and global (Yang, 2011). In local sensitivity analysis, each parameter is disturbed in turn while all other factors are kept fixed at their nominal values (Baroni & Tarantola, 2014). On the other hand, Global SA (GSA) studies the impacts of input parameters on the outputs within the entire acceptable ranges of input space. GSA methods range from qualitative screening (Campolongo et al., 2011) to quantitative techniques based on variance decomposition (Gamerith et al., 2013; King & Perera, 2013). The significance of sensitivity analysis is that it can reduce the number of parameters for calibration and determine the most influential and most uncertain ones (Dotto et al., 2011; Krebs et al., 2014).

Different parameters have been found sensitive to calibrate SWMM in the previous studies. For example, Barco et al. (2008) and Tsihrintzis and Hamid (1998) found that SWMM is most sensitive to % imperv, Manning's n, N-Perv, DStore-Perv, and DStore-Imperv. In this study, the most sensitive parameters were found to be % imperviousness, % zero imperviousness, Dstore-impervious and Dstore-pervious. However, according to Figure 4.1, the sensitivity of SWMM to these parameters is not the same.

The peak runoff is directly proportional to the changes in the imperviousness and zero imperviousness, whereas it is inversely proportional to the D-Store. This means that the peak runoff will increase with the increase of % imperviousness and % zero imperviousness. Likewise, the peak runoff will decline with the reduction of the two parameters. On the other hand, the peak runoff will decline with the increase of D-Store impervious-pervious, while it will increase with the D-Store impervious-pervious reduction. It should also be noted that the peak runoff is more sensitive to the reduction of the D-Store impervious-pervious than the increase. In other words, the peak runoff will only decrease 5% with the 30% increase in the D-Store impervious-pervious, whereas it will increase 12% with the 30% reduction of D-Store impervious-pervious.

In the model calibration and validation approach, the predicted (modelled) and the observed outflow hydrographs were compared with each other. Particularly, two values, namely the discharge volume and the peak flow rate were assessed for an event. For a good validation result, it is required that the general shape of both hydrographs follow each other, and the results of goodness-of-fit test are satisfactory.

The parameters used in this study for the model calibration and validation evaluation criteria are D_v, NOF, NSC, and r^2. The ideal value for D_v is between 5% to 20% (James, 2003). The lower the D_v value is, the better the match between the predicted and the observed values will be. For the NOF, NSC, and r^2, the acceptable range is values between 0 and 1. For NOF, the closer it is to 0, the better match between the two hydrographs will be achieved. As for NSC and r^2, the closer they are to 1, the better the match between the predicted and the observed values will be. It should also be stated that for the purposes of evaluation, a satisfactory NSC is higher than 0.5 and a good D_v is lower than 20% (Tan et al., 2008). In another study, Yazdi et al. (2019) mentioned that when r^2 and NSC are higher than 0.6 and 0.5, respectively, and D_v is lower than 25%, the model calibration is considered satisfactory.

Appropriate calibration of rainfall–runoff models for urban catchments is necessary to ensure reliable assessment of stormwater modeling results (Mancipe-Munoz et al., 2014). Rainfall–runoff models can be calibrated over a set of single storm events or continuous storm events. Calibrating the model with a single event provides better time to peak and overall hydrograph shape compared to continuous calibration, but continuous event calibration gives more accurate estimation of the total runoff volume (Tan et al., 2008). Single storm event calibration is a rapid process and usually does not require a great deal of observed data (Mancipe-Munoz et al., 2014). A large number of previous studies can be found in the literature that calibrated their models over a single storm event (Fang & Ball, 2007; Palla & Gnecco, 2015; Tan et al., 2008). In the current study, the model was also calibrated using a single storm event since the peak runoff was the target of assessment. Moreover, the model is a quantity–quality one, and calibration was performed for both quantity and quality. There was no continues quality data available to perform continues calibration. Therefore, the quantity–quality calibration was conducted over a single-event, collected individually on 20 September 2018.

For the first calibration, Figure 4.2 illustrates the observed and the modelled hydrographs which closely matched, and the maximum error is less than 9% throughout the whole hydrographs. As it is obvious from Figure 4.2, there is a good match between the modeled and observed values in the rising limb of the hydrograph. At the peak of the hydrograph, the model overestimates the flow a little, immediately followed by underestimation. From the middle of the hydrograph falling limb to the end, the modelled and observed flows show a good consistency. The r^2 is also 0.97 which shows a very good calibration result, whereas in similar studies the r^2 about 0.8 or 0.9 and even lower has been considered as good match between calibrated and observed values; e.g., Rosa et al. (2015).

As for the model validation, it can be seen from Figure 4.4, the model underestimates the flow in the rising limb of the hydrograph and overestimates the flow in falling limb of a little, which is quite normal in the process of calibration and validation. However, as it is obvious from Table 4.3, the evaluation parameters, namely NOF, NSC, and r^2 are 0.21, 0.85, and 0.88, respectively, which show a good match between the modeled and observed values for the validation.

Validation cannot be obtained only by testing the model with some real data because no model is quite perfect. Therefore, validation needs both subjective and objective judgements on various aspects to realize whether adequate information is provided by the results to answer the questions that the decision-makers face in the process of modeling. It should also be noted that any model can be expected to fail at least on some occasions (Xu, 2002).

As for the 2nd validation (Figure 4.5), both the rising and falling limbs of the hydrographs are in good match; however, the model overestimates the peak flow of the modelled hydrograph a little. Nevertheless, the evaluation parameters, namely NOF, NSC, and r^2 are 0.2, 0.82, and 0.87, respectively, which show an acceptable match between the modeled and observed values for the 2nd validation.

Overall, the modelled flow prediction has been plotted against the observed flow in Figures 4.4 and 4.5 for the model validation. As can be seen from the Figures, the modeled hydrographs and the observed flow hydrographs have well matched each other which confirm the validity of the model.

The model was calibrated for the second time for the data collected on the 20-09-2018 rainfall event. As it is obvious from Figure 4.6, there is a discrepancy between the modeled and the observed values at the beginning of the hydrograph which could be due to some uncertainties in modeling. The modeled and observed values are in good match before the hydrograph peak, at which point the model starts underestimating the flow a little. This trend continues up to the middle of the hydrograph falling limb. From this point onward, the model overestimates the flow a little. As it is obvious from Table 4.3, the evaluation parameters, namely D_v, NOF, NSC, and r^2 are 4.70, 0.05, 0.93, and 0.93, respectively, which show a very good match between the modeled and observed values.

Figure 4.8 illustrates the validation result for the second calibration. As can be seen, the modeled and observed values are in good match from the starting point up to the middle of the rising limb. However, the model overestimates the flow at the peak. This might be due to some uncertainties in the observed data. After this, the modeled and observed hydrographs follow each other well, although there is a little underestimation in the falling limb. The evaluation parameters, namely D_v, NOF, NSC, and r^2 are 6.68, 0.08, 0.74, and 0.77, respectively, which show an acceptable match between the modeled and observed values.

Figure 4.9 shows the validation result for the second time for the data on the 28-04-2018. Although the model overestimates the flow at the peak, overall the two hydrographs follow each other quite well and the validation is quite acceptable. The evaluation parameters, namely D_v, NOF, NSC, and r^2 are 10.6, 0.17, 0.61, and 0.93, respectively, which show that there is an acceptable match between the modeled and observed values.

As mentioned earlier, for the purposes of evaluation, r^2 and NSC are higher than 0.6 and 0.5, respectively, and D_v is lower than 25%. In Figure 4.8, the evaluation parameters, namely D_v, NOF, NSC, and r^2 are quite satisfactory and show an acceptable match between the modeled and observed values. In Figure 4.9, although the model overestimates the flow at the peak which could be due to some uncertainties in the input data, overall, the goodness-of-fit test parameters are in the satisfactory range and show that the validation is quite acceptable.

In hydrology and water quality modeling, the four criteria used in this study, namely D_v, NOF, NSC, and r^2, are the most common ones and are widely used to evaluate the model performance and are the best ones. Therefore, these criteria were all used in this study as well to assess the calibration and validation of the quantity-quality model and to make sure the maximum fitting is happening between the modelled and observed hydrographs.

It should be mentioned that there are many uncertainties in modeling urban rainfall-runoff which result in the inaccuracy of modeling. The sources of uncertainties can be classified as input data uncertainties, parameter uncertainties, and model structure uncertainties. Especially, there are always uncertainties in the model input parameters which could be due to the data collection or model structurers. That's the reason calibration and validation are performed to minimize the uncertainties and get the best results possible. However, the hydrological models always show some uncertainties, especially at the hydrograph extremes, e.g., at the peak. That's why most of the time there is a lag time between the observed and the simulated peak timing, but we try to minimize this lag time in the process of calibration and validation.

It is worth mentioning that validation cannot be obtained only by testing the model with some real data because no model is quite perfect. Therefore, validation needs both subjective and objective judgements on various aspects to realize whether adequate information is provided by the results so that we can judge the model is reliable or not. Even if the calibration is perfect and all criteria have been well met, it does not necessarily mean that the validation will also be as perfect as the calibration. Validation does not mean that the simulated and the observed hydrographs should exactly match each other and there are always some discrepancies in some parts due to the mentioned reasons. Besides, for the calibration and validations performed in this study, the evaluation parameters are all in the satisfactory range. The relative errors between the observed and the simulated flow values should be less than 25% for a good calibration result. In this study, the relative errors between the observed and the simulated peak flow values in the first calibration is 4.06% and in the second calibration is 1.69% which are both quite satisfactory.

Several mechanisms determine stormwater quality; the most notably being buildup and washoff. In an urban area, a load of constituents is built up on the impervious surface before a storm, which may or may not be related to time and factors, such as traffic, dry fallout and street sweeping (Chen, 2006). During the storm, this load of constituents is washed off into the drainage system. Washoff is the process of erosion or solution of pollutant constituents from a sub-catchment surface during a period of runoff in urban areas.

For the quality calibration the water samples were analyzed in the laboratory. Figure 4.11 depicts some of these parameters. As can be seen from the figure, conductivity and TDS both have a downward trend, while turbidity, TSS and Do have an upward trend. As the water volume increases, the dissolved solids within the water will decreases (mg/L); this is mainly because the amount of solids dissolved in water is diluted. Likewise, the conductivity will also decline with the decrease of TDS.

On the other hand, TSS and turbidity increase with the increase of runoff. This is mainly because the runoff washes the solids and other surface particles to the water bodies. However, both TSS and turbidity decline at the end as there is no more surface particles to be washed off. DO is mostly fluctuating during the rainfall event.

The calibration of stormwater quality model is normally more difficult than quantity models. As urban runoff quality monitoring needs substantial resources, quality modeling is used to predict, analyze and manage urban water quality and pollution (Zhu et al., 2012). In SWMM, the stormwater quality is modeled using different build-up and washoff equations, such as exponential function, power function, or saturation equation (Rossman & Huber, 2016). There is usually a wide range of variation in urban stormwater quality data between rainfall events. The buildup and washoff equations consist of many parameters which make the stormwater quality difficult to calibrate without on-site data (Tuomela et al., 2019). The spatial and temporal variations of the quality modeling process also make it difficult to use the buildup and washoff equations on a catchment scale (Bonhomme & Petrucci, 2017; Wijesiri et al., 2016). Moreover, the urban stormwater quantity model is usually calibrated first, followed by calibrating the quality module (Chen, 2004).

Among various types of pollutant buildup functions, the most widely used accumulation form may be the exponential buildup function (Alley & Smith, 1981; Charbeneau & Barrett, 1998; Deletic et al., 1997). In these studies, the form of buildup function was derived based on the assumption that the urban impervious surface was completely washed by the last period of runoff or street sweeping (Alley & Smith, 1981). A pollutant washoff function in an exponential form is widely used in the literature (Alley & Smith, 1981).

For the TSS calibration (Figure 4.14), there is a good match between modelled and observed values in the rising limb. However, there is an inconsistency at the peak, in which one observed point is higher than the modeled peak. This might be due mainly to the uncertainty in sampling, data collection, or the model itself. In contrast, the model overestimates the TSS a little in the falling limb, although the modeled and observed graphs converge at the end. As the quality modeling is always more challenging than quantity one, these discrepancies are quite normal. The r^2 for TSS modeling is also as high as 0.84 which show a good match, too.

For TN, it was even more difficult to calibrate the model as TN is more sensitive to the model parameters. Hard effort was made to adjust the parameters in many runs to get the best result. Figure 4.15 illustrates the result of TN calibration. As it is obvious, there is an incompatibility at the beginning and in the middle of the graphs. For the rest of the calibration, the modeled graph follows the observed one and the two graphs converge very well at the end, although there is an overestimation just before the last point.

The results of goodness-of-fit test in this study have also been compared with the results of some previous studies. Chow et al. (2012) developed a model and presented the results of SWMM calibration and validation for modeling runoff quantity and quality in tropical areas. Mancipe-Munoz et al. (2014) also presented the calibration and validation of a rainfall–runoff SWMM 5 in their study. On the other hand, Rosa et al. (2015) and Chow et al. (2012) carried out calibration for TSS and TN in their water quality modeling. Table 5.1 presents the comparison of flow calibration and validation, as well as TSS and TN calibration with other studies.

Table 5.1: Comparison of the results of goodness-of-fit test with the previous studies.

Parameter	Flow calibration			Flow validation		TSS		TN	
	This study	Chow	Munoz	This study	Munoz	This study	Chow	This study	Rosa
Dv	4.7	5.6	4.32	6.68	0.18	-	-	-	-
NOF	0.05	0.06	-	0.08	-	0.14	0.24	0.14	-
NSC	0.93	0.99	0.6	0.74	0.62	0.81	0.75	0.74	0.71
r^2	0.93	0.99	-	0.77	-	0.84	0.77	0.74	-

According to Table 5.1, the model in this study has outperformed the other two studies in both flow calibration–validation and TSS-TN calibration although the two parameters, namely NSC and r^2, are a little bit lower than Chow et al. (2012) in flow calibration. In terms of TSS and TN, the model in this study has performed much better than Chow et al. (2012) and Rosa et al. (2015) although TSS and TN calibration are more complex than quantity. In other words, the model calibration and validation in this study have been quite satisfactory for both quantity and quality.

Having calibrated and validated the model, the selected LIDs were designed and assigned to the simulation model to prepare the model for the optimization purpose. The common types of LID being defined in SWMM are bioretention cell, rain garden, green roof, infiltration trench, permeable pavement, vegetative swale, and rain barrel. The main purpose of LID controls are to restore the pre-development hydrological conditions in urban areas (Prince George's County, 1999; Zhang & Chui, 2018). According to the literature, the two LIDs have a high capacity of runoff reduction and pollutants removal (Eckart et al., 2017; Jia et al., 2015) and could easily be implemented in urban areas. The two LIDs are also much cheaper compared to other ones (Table 3.3). According to Ahiablame et al. (2012), rain garden efficiency for runoff, TSS, and TN reduction is (48 to 97%), (47 to 99%), and (32 to 99%), respectively. Similarly, the efficiency of swale for TSS and TN is (30 to 98%) and (14 to 61%), respectively. Martin-Mikle et al. (2015) also stated that the rain garden and vegetated swale are able to reduce TSS and TN in urban runoff up to 89% and 58%, respectively.

Low impact development (LID), such as bioretention cells and vegetated swales, are techniques implemented at or near the source of runoff generation to make the ground more permeable and mitigate stormwater runoff and its pollutants (Elliott & Trowsdale, 2007). Particularly, the LID techniques have been developed to mimic the predevelopment hydrologic conditions and promote the storage, infiltration and evapotranspiration processes (Ahiablame et al., 2012). The main roles of LID practices include runoff reduction (peak and volume), infiltration increase, groundwater recharge, stream protection, and water quality enhancement by removing pollutants through mechanics such as filtration, chemical sorption, and biological processes (Hunt et al., 2010b).

Table 4.4 and Figures 4.16 to 4.18 illustrate that TSS, TN, and peak runoff are reduced by 41%, 29%, and 23%, respectively. Rain garden (bioretention) is relatively highly efficient for both runoff and pollutant reduction (Dietz, 2007). Bioretention cells could reduce the average peak flows by at least 45% in Maryland and North Carolina (Hunt et al., 2008). Bioretentions are also capable of reducing sediment and nutrient from 0% to 99% (Dietz, 2007). Swales have also been shown to have an average retention of 14% to 98% for nutrients and TSS, and up to 93% for metals (Ahiablame et al., 2012).

Compared to the literature mentioned, the peak runoff reduction and pollutant removal of LIDs in this study are not compatible with their utmost capabilities. This might be mainly due to the fewer units of LIDs used in this study. In other words, more LIDs are required to be implemented in the study area to improve LID efficiency for both peak runoff reduction and pollutants removal. However, the cost of LID implementation should also be considered. Optimization methods could be applied to find the optimal number and placement of LIDs for the maximum flow and pollutants reduction with the minimum cost.

As for the rainfall scenarios results, depicted in Table 4.6 and Figure 4.20, the LID removal efficiency for TN and TSS reached 40% and 62%, respectively, which show that the LID removal efficiency for TSS and TN is independent of the rainfall amount and the model is highly efficient for TSS and TN removal for both short and long storm events.

As for the peak runoff reduction, it could be concluded from Table 4.5, Table 4.6, and Figure 4.20 that in smaller rainfall amount of up to 70 mm, the model performed well, and the peak runoff reduction reached up to 27%. In rainfall amount of between 70-90 mm, the model performance was moderately good, and the reduction of peak runoff reached up to 19%. In the case of higher intensity rainfalls when the rainfall was higher than 90 mm, the model performance, in terms of runoff reduction, was poor. That is mainly because in high intensity rainfalls the soil is saturated, and the input and output are equal. In this case, no more runoff infiltrates into the soil and the LIDs and the soil beneath act as filters only to remove pollutants. Generally, the model performed satisfactorily for the rainfall of up to 90 mm and for the return period of up to 10 years.

Nevertheless, for the return period of more than 10 years and for the rainfall amount of more than 90 mm, the designed LIDs for the catchment cannot handle the surcharge amount of runoff in urban areas, and either we need more LIDs to be installed or a combination of LIDs and a conventional drainage system is required to tackle the excess runoff in impervious surfaces to avoid any flooding in urban areas during larger storm events. The results obtained in this study for the LID performance are in consistent with the results of other similar studies (Damodaram et al., 2010; Hood et al., 2007; Qin et al., 2013) who found that LIDs perform well in lower intensity rainfalls and cannot handle large storm events alone and should be combined with the traditional drainage systems to avoid flooding during larger storm events. Wang et al. (2018) also stated in their study that LID practices would perform better to control runoff quantity and water quality in shorter return period storms.

Based on the results achieved, the final word on the application of this study could be that LID practices (here swale and rain garden) are vital in all developed urban areas and they can substantially reduce runoff and enhance water quality. They can also replace the conventional stormwater management systems in lower rainfall events (less than 90 mm). However, in higher rainfall events, they need to be coupled with conventional stormwater management systems, such as ponds and constructed wetlands to tackle the runoff, but for pollutant removal, they maintain good efficiency in high intensity rainfall as well. Furthermore, the cost of implementation is also a concern and should be considered in urban planning. It should also be noted that LID-BMP techniques also have treatment capabilities (Liu et al., 2015) and spending more money, and increasing the quantity of LID-BMPs beyond this capability will not reduce runoff/pollutants as significantly (Liu et al., 2016).

5.2 Optimal number, combinations and placement of LIDs

The spatial placement of LID-BMPs is highly important and should be considered seriously in urban planning (Zhang & Chui, 2018). Prior to the implementation of LID-BMPs for the newly developed urban areas, it is vital to find the most cost-beneficial size and location of LID-BMPs to comply with the overall project objectives (Barbosa et al., 2012; Jia et al., 2012). Considering the various physical, social, economic constraints, and interaction between people regarding these strategies, the optimization of their spatial distribution is a major challenge for urban decision-makers (Dhakal & Chevalier, 2017; Kim et al., 2017). Thus, optimal allocation of LID-BMPs in urban areas is critical as their impact may vary from one location to another (Zhang & Chui, 2018). As an example, larger and flatter drainage areas with higher imperviousness are more suitable for LID-BMP practices as more runoff is expected to be generated (Beganskas & Fisher, 2017; Martin-Mikle et al., 2015). The spatial placement will also affect the pollution reduction, depending whether they are implemented in centralized or decentralized positions (Vittorio & Ahiablame, 2015). Therefore, to achieve the maximum benefits with the minimum cost, optimization methods have become popular to optimally place LID-BMP practices at the catchment scale (Lautenbach et al., 2013; Liu et al., 2016). Spatial optimization of LID-BMPs is the most significant multi-objective strategy with the tradeoff results between cost and runoff or pollutants reduction (Liu et al., 2016).

With respect to this, the results achieved in this study for optimization will be discussed here. Table 4.7 and Figures 4.22 to 4.24 show the non-dominated solutions for the peak runoff, TSS, and TN reduction, respectively with various types and number of LIDs optimized by MOPSO. It is worth mentioning that the best results will be achieved when all sub-catchments are provided with both types of LIDs. However, the idea of optimization is to achieve the optimal number and combination of LIDs so that the runoff/peak runoff and pollutants are optimally reduced while the LID implementation is also cost-beneficial.

As for the runoff reduction against type and number of LIDs, Figure 4.22 shows that the runoff remarkably decreases with the increase of LID controls in the subcatchments. However, the minimum number of LIDs should not be fewer than 10. It is clear from the figure that the more LIDs are applied to the catchment, the more runoff reduction will be achieved. However, considering the cost and the amount of runoff reduction with the increase of LIDs, it could be concluded that the optimal number of LIDs to be implemented in the catchment is about 25 to 30. The discussion is further supported by the more detailed results presented in Table 4.8. The table gives more detailed information on the percentage of reduction for peak runoff, TSS, and TN for different selected number of LIDs. The table results have been achieved by comparing the model non-dominated solutions with the results of the simulation model without LID controls. As can be seen, the maximum flow reduction is achieved when the number of LIDs is 34, which is 13%.

Figure 4.23 and Table 4.8 illustrate the TSS reduction with the number of LIDs. However, the TSS reduction is not very remarkable with the increase of the number of LIDs and reaches only to 38.43 when the number of LIDs increases to 34. In other words, it can be inferred that the optimal number of LIDs to achieve the best TSS reduction is about 25 to 30 which is similar to the peak runoff.

Similarly, Figure 4.24 and Table 4.8 indicate that as the number of LIDs increases from 13 to 20, TN reduces from 22.38% to 23.75%. From this point onward, the TN reduction is very little and negligible. It could be concluded that the Pareto-optimal front for TN is totally consistent with the results achieved for peak runoff and TSS. This means that the optimal number of LIDs to achieve the maximum amount of reduction for TN is about 20 to 30 as well. These results are in consistent with the results of other similar studies (Jia et al., 2012; Liu et al., 2016; Maringanti et al., 2009) who also found that to obtain greater runoff/pollutant reduction, the cost of optimally implemented LID-BMPs need to be increased (to increase the number of LIDs, more money should be spent).

To find the best scenario for the LID numbers, combinations, and placement for the maximum runoff/pollutant reduction with the minimum cost, 9 scenarios, namely 20, 25, and 30 for runoff, TSS, and TN were selected. The scenarios were then designed and executed in the simulation model and the results of all scenarios were recorded accordingly. Table 4.9 and Figure 4.25 depict the results achieved from all scenarios and the relevant reductions for peak runoff, TSS, and TN. As can be seen from Table 4.9 and Figure 4.25, the more LIDs are implemented in the catchment, the reductions will be achieved. It is also clear that the peak runoff will reduce more with the increase of LIDs. Therefore, the best LID combination will be achieved if the optimal LID combination is selected from the peak runoff scenarios. However, it is also clear that the amount of reduction is not remarkable after scenario 4.

Hence, it could be concluded that the optimal LID combination to achieve the best runoff, TSS and TN reductions would be scenario 4 for the runoff optimization, in which the reduction for peak runoff, TSS and TN is 11.08%, 38.26%, and 23.51%, respectively.

The details of scenario 4 results are presented in Table 4.10. According to Table 4.10, among the 25 subcatchments which are provided with different types of LIDs, 13 have been applied with rain garden (RG), 12 have been provided with swale (SW), and 10 subcatchments have no LIDs (NL) in them. This is the best scenario for the whole catchment with the maximum peak runoff/pollutant reduction and the minimum cost.

Figure 4.26 also depicts the placement of the final scenario in the real catchment. Figure 2.6 clearly shows the LID numbers, combinations, and placement throughout the whole Bunus catchment. For instance, subcatchment 1 (S1) is provided with rain garden (RG), S5 receives swale (SW), while there is no LID in S4 (NL). In this case, the maximum peak runoff/pollutants reduction will be achieved with the minimum cost.

It should be noted that the LID control techniques are usually able to control stormwater runoff in lower intensity and shorter period rainfalls (Damodaram et al., 2010; Hood et al., 2007); and in extreme rainfalls (based on this study, more than 90 mm), the LID techniques need to be coupled with the traditional stormwater management practices, such as ponds and constructed wetlands to reduce stormwater runoff, whereas they are capable of reducing pollutants in extreme rainfalls as well; However, based on the findings of this study, the LID techniques can significantly reduce urban stormwater runoff and remarkably improve water quality if properly designed and implemented. Nevertheless, the LID-BMPs also have treatment capabilities (Liu et al., 2015) and spending more money beyond this capability will not reduce runoff/pollutants as significantly (Liu et al., 2016).

5.3 Cost-effectiveness of LID combinations and locations

A number of studies have investigated the cost-effectiveness of LIDs; however, there are still some barriers to be addressed in the new developed areas, such as implementation cost and maintenance (Joksimovic & Alam, 2014). The cost-effectiveness of LID-BMP strategies plays an important role in urban planning for decision-makers. Cost analysis of LID-BMPs planning optimization will improve the reliability and truthfulness of these practices in urban areas (Xu et al., 2019). Although LID practices seem to be more cost-effective than conventional stormwater management (Eckart et al., 2017), the number and location of implemented LIDs will affect the cost (Gilroy & McCuen, 2009). The cost of LID-BMPs is a critical factor for flood control to be reliable (Karamouz & Nazif, 2013). Thus, the optimization of stormwater management system can be cost saving (Maharjan et al., 2009).

For the cost analysis, apart from peak runoff, TSS, and TN, total volume runoff was also added to the cost analysis to compare it with the peak runoff reduction against cost. Figures 4.27 and 4.28 illustrate the non-dominated solutions for the peak runoff and total runoff volume reduction, respectively with the increase of cost. It is clear from the figures that the more LIDs are applied to the catchment, the cost will increase, and the more runoff reduction will be achieved. As can be seen, the peak runoff and the total runoff volume both will decrease with the increase of LID cost; however, the reduction in peak runoff is more significant compared to the total runoff volume. It can also be observed that the total cost for peak runoff reduction is less than total runoff volume reduction.

Figures 4.29 and 4.30 depict the results of non-dominated solutions for TSS and TN reduction, respectively with the increase of cost. As discussed earlier for peak runoff and total runoff volume, the TSS will reduce with the increase of cost. However, in the case of TSS, the amount of reduction is not that much remarkable with the increase of cost.

Similar to the TSS discussion, TN will also reduce with the increase of cost, but the reduction is not that much remarkable. Even in the case of TSS and TN, achieving an appropriate pareto front was not that much easy. This was also confirmed by the previous discussion in the literature regarding the calibration of quality modeling. There are various parameters affecting quality modeling which make it difficult for both calibration and pareto front convergence.

Table 4.11 and Figure 4.31 present the results of 12 scenarios of minimum, average, and maximum cost for peak flow, total runoff volume, TSS, and TN. As presented in Table 4.11 and Figure 4.31, the maximum reduction is for TSS coming up to 38%, followed by TN (24%), peak runoff (13%), and total runoff volume (7%). Although, the reduction of peak runoff, total volume, and TN are increasing with the increase of cost, the reduction of TSS has remained almost unchanged for all scenarios, except for the 3rd row of the table. This is in consistent with the results of other similar studies (Jia et al., 2012; Lee J. G. et al., 2012) which found that for initial cost, LID-BMPs can remarkably decrease runoff and pollutants; however, because of treatment limitations of LID-BMPs (Liu et al., 2015), spending more money beyond a certain cost will not reduce runoff and pollutants as remarkably (Liu et al., 2016). The discussion could also be confirmed by Figure 4.29 as well, in which the range of TSS changed for the whole pareto front is between 3435-3439 Kilo grams. Another possible reason for TSS and TN could be that all combinations of LIDs in these scenarios are for 1 pareto front and with these combinations the maximum amount of TSS reduced could not exceed 38%.

Another argument could be that the amount of rainfall for the sampling date was only 12.5 mm and the rainfall continued for few days. In other words, this has been the maximum amount of TSS available to be removed by LIDs. As achieved in the previous section, when the rainfall was increased to 90 mm, the TSS removal was up to 62%. This means that the LIDs have the capacity to remove double than the current amount.

The same argument could be presented for TN reduction amount. As the removal efficiency of LIDs in our case reached 40% in the previous section, the LIDs have the capacity to remove more TN. However, the range of reduction in different combinations here are between 22-24%.

In the case of peak runoff and total runoff volume, both reduce with the increase of total cost; however, the peak runoff reduction is more significant. This could be due to the reason that calculations have been performed in the rising limb of the hydrograph. In this case reduction in peak runoff will be more significant than total volume. If the rain continued for few more hours and the modeling was also carried out for a longer period of time, we would have more reduction in total volume. As can be seen in Figures 4.31 and 4.32, the maximum reduction for the peak runoff is 13%, after which the peak runoff reduction remains constant and spending more money on LID in our case will not be cost-beneficial. Furthermore, LID-BMPs have treatment capabilities, beyond which the runoff/pollutant loads will not decrease as significantly.

As can be seen from Figure 4.33, the comparison of all cost scenarios with the minimum cost again shows that peak flow and total runoff volume decrease with the increase of cost. TN also generally decreases, except for one scenario ($223,850) which has been inversely affected by the increase of cost. This shows that this LID combination is not appropriate for TN in this case study. In the case of TSS, although the figure shows TSS has reduced with the increase of total cost; however, the reduction is not significant. Even in one scenario ($223,850), TSS has been inversely affected by the increase of cost. This means that this combination is definitely not appropriate for TSS removal in the catchment.

In summary, as far as the major findings of the study are concerned, in this study, a simulation-optimization model was developed using SWMM and MOPSO to find the best LID type, combinations, and placement at the catchment scale to minimize peak runoff and pollutants with the minimum number of LIDs and minimum cost and bring the post-development hydrologic conditions to the pre-development hydrologic conditions.

The developed model, is an integrated simulation-optimization and quantity-quality model that concerns the trade-off between total runoff, total cost, and pollutants prevention. Real field data from a real rainfall event was used to calibrate the simulation model. Two types of LIDs were tested for urban stormwater runoff quantity and quality control at the catchment scale in a tropical area with high intensity and long duration rainfalls. It was highly important to check the applicability of LIDs in tropical areas with high intensity and long duration rainfalls. It was the first study of its type in Malaysia at the real catchment sclale. A novel method, using a multi objective optimization model (MOPSO), was used to find the optimal numbers, combinations, and placement of LIDs in a real urban catchment to achieve the maximum runoff/pollutants reduction with the minimum cost. Other similar studies have used different algorithm to optimize LID-BMPs; in this study a new approach was applied using MOPSO to find the optimal numbers, combinations, and placement of LIDs in a real urban catchment.

Overall, the results here reveal that the LID combinations achieved in this study are appropriate for peak runoff, total runoff volume, TSS, and TN. In the previous section, the reduction of peak runoff, TSS, and TN were 23%, 41%, and 29%, respectively, for the same rainfall (12.5 mm). However, the reductions obtained here are for these LID combinations and the minimum cost. If more reduction is targeted, we need to achieve different LID combinations, spend more budget, or change the types of LIDs implemented in the catchment. It should also be noted that only 7% of the whole catchment area (1800 ha) were covered by LIDs (swale and rain garden) and the rainfall amount in our case study was only 12.5 mm. in this case 13% reduction for peak flow, 38% reduction for TSS and 24% for TN are quite satisfactory.

The benefits of stormwater management projects are much greater than the cost imposed by flooding damages, water quality degradation, and natural resources loss (Visitacion et al., 2009). Thus, all these reductions achieved in this study with only very little cost ($300,000) is quite acceptable compared to the budgets spent for the damages caused by flooding, water quality and natural resources loss. Compared with the results of other similar studies in this area of research; e.g., (Eckart et al., 2018; Joksimovic & Alam, 2014) who came up with a high cost of LID implementation, the total cost against the runoff/pollutant loads reduction amount obtained in this study is also quite acceptable.

It should also be restated that to achieve greater reduction of runoff/pollutant loads, the cost of implementation for LID-BMPs should be increased (Jia et al., 2012; Maringanti et al., 2009); however, these techniques also have limitations in terms of treatment capabilities (Liu et al., 2015) and spending more money beyond this capability will not reduce runoff/pollutants as significantly (Liu et al., 2016).

CHAPTER 6: CONCLUSION

6.1 Summary

The vast increase of urbanization has substantially impacted the stormwater runoff and water quality in urban areas. The combination of urbanization and climate change has significantly intensified the process of urban runoff generation. Several studies have investigated the climate change and urbanization to evaluate their effects on different aspects of rainfall-runoff process, and most of them have proved the significant impact of these two factors on the hydrological processes of urban catchments.

The effect of urbanization on the precipitation intensity and patterns as well as the runoff is indispensable. It will change the hydrological response of a catchment to precipitation and this in turn will affect the runoff volume, peak flow and flood risk. Urban land use can also decrease infiltration rates significantly and thus results in higher flow peaks and larger runoff volume.

There are several measures to mitigate and control the excess surface runoff in urban catchments to reduce the resultant adverse effects on both human and ecosystems. Traditionally, urban drainage networks have been used to direct and collect the urban excess runoff to prevent the consequences. However, some newly developed methods have emerged in recent years in this regard. The most known ones are best management practices, shortly known as (BMPs) and low impact development, shortly known as (LID). They are usually denominated as LID-BMPs measures for controlling the urban stormwater runoff quantity and quality. The adverse effects of urbanization need to be controlled by applying the newly developed best management practice, widely known as Low Impact Development (LID) technique instead of traditional stormwater management.

It is also noted that there are various types of LID-BMPs, including retention ponds, rain gardens, vegetated swales, and porous pavements, etc. As there are different types of LID-BMPs, they should be carefully selected based on the urban development planning and quantity or quality control purposes. However, it is vital to optimally design and implement the LID techniques to achieve the maximum runoff and pollutants reduction with the minimum cost. The selection of type and location of LID-BMPs are the most important aspect of implementation that should be considered to achieve more cost-effective results. In any case, the LID-BMPs have been well proved in many studies to be beneficial in mitigating and controlling the urban runoff quantity and quality.

In this study, a simulation-optimization model was developed using the stormwater management model (SWMM) and the multi objective particle swarm optimization (MOPSO). First, the quantity-quality model was developed using the US EPA SWMM to assess the impact of LID on stormwater quantity and quality in a sub-catchment in Kuala Lumpur, Malaysia. The required rainfall-flow data and quality data were collected from a real event on 20-09-2018. The BUNUS sub-catchment was selected as the case study for this research. The LID controls section in SWMM allows the users to design and apply the selected LIDs into the model in order to simulate stormwater quantity and quality. The 18-square-kilometer catchment was divided into 35 sub-catchments using SWMM model to apply LIDs and simulate the runoff and pollutants in the catchment.

The model was calibrated and validated both for quantity and quality using the real data from 20-09-2018 event. A sensitivity analysis was also performed beforehand to find out the most sensitive parameters of the model.

The developed model was to simulate LID techniques at the catchment scale by applying vegetated swale and rain garden as efficient practices for urban areas. The impacts of LID practices on water quantity and water quality were evaluated using both the collected field data and the selected rainfall scenarios derived from the IDF curves for the study area.

In order to satisfy the study objectives, an optimization model was also developed to be coupled with the simulation model to achieve the best combination of LIDs in the catchment. The multi objective particle swarm optimization (MOPSO) was used for the optimization modelling.

To develop the optimization model, the necessary sub-routine functions were coded in MATLAB to be linked with the MOPSO algorithm. The simulation and optimization model were linked to each other using MATLAB. The SWMM output were used as input for the optimization model to generate the optimal number and combinations of LIDs to achieve the best stormwater runoff quantity and quality control in the catchment.

The objectives of the study were to minimize the peak runoff, total suspended solids (TSS) and total nitrogen (TN) with the minimum number of LIDs. The sizing, selection and placement of LIDs are the most challenging issues in the LID implementation process. The simulation-optimization models are tools to successfully solve the issue. The developed simulation-optimization model was impressively successful in generating the best combinations of LIDs in the catchment to satisfy the defined objectives.

In order to achieve the maximum runoff and pollutant reduction with the lowest cost, it is vital to find the optimal number and combination of LID controls implemented on impervious surfaces. LID techniques are usually more cost-effective than traditional stormwater management systems. The most important benefits of stormwater management are related to reducing flooding and improving drainage. If LID implementation can reduce flooding damage and pollutants in urban areas, then the cost savings would be significant.

6.2 Conclusion and Appraisal

The following conclusions could be made from both the simulation and the optimization models:

As far as the simulation modeling is concerned, the most sensitive parameters of the model are % imperviousness, % zero imperviousness and D-Store impervious-pervious. In other words, a slight change in the imperviousness, the depression storage or the depth of depression storage will significantly change the simulated runoff and the peak flow. However, the model is more sensitive to D-Store impervious-pervious rather than the other two parameters. It was also noted that the peak runoff will be more affected when D-Store impervious-pervious decreased rather than increased. It means that a slight reduction in the depth of depression storage will substantially increase the peak runoff.

In terms of water quality, the developed model performed well. The LID removal efficiency reached up to 40% for TN and up to 62% for TSS, respectively. The LID removal efficiency of the model was independent of the rainfall intensity and duration, taking into account the current research rainfall scenarios.

As for the peak runoff reduction, in smaller rainfall of up to 70 mm the model performed well, and the peak runoff reduction reached up to 27.44%. In rainfall amount between 70-90 mm, the model performance was moderately good, and the reduction of peak runoff reached up to 19%. In the case of higher intensity rainfalls when the rainfall was higher than 90 mm, the model performance in terms of runoff reduction was poor which was due mainly to the soil inundation. In this case, the LIDs and the soil beneath performed as filters for the pollutant removal.

Overall, the model performed satisfactorily for rainfall of up to 90 mm and for the return period of up to 10 years. Nevertheless, for the return period of more than 10 years and for the rainfall amount of more than 90 mm, the designed LIDs for the catchment cannot handle the surcharge amount of runoff in urban areas.

The LIDs applied for the catchment in this study are more effective in peak runoff reduction during lower intensity rainfall events. Therefore, it would be more efficient to combine the LID techniques with other conventional stormwater management practices to control urban flooding in case of longer storm events. However, the LID removal efficiency for TSS and TN were quite satisfactory in all selected rainfall scenarios. The LIDs applied in this study performed well in improving water quality in both low and high intensity rainfall events. Thus, the simulation model confirms the significant role of LIDs in reducing peak runoff and improving water quality in urban stormwater events.

As for the simulation-optimization model, the results are in the forms of graphs, known as Pareto optimal front solutions. For the peak runoff, the number of LIDs plays an important role. The more LIDs applied to the catchment, the more the runoff will be reduced. For TSS and TN, the reduction is almost the same as peak runoff; however, the reduction of TN approximately levels off after a certain number of LIDs implemented. Adding more LID units might not help for further reduction after this certain number of LIDs. The simulation-optimization model was able to reduce the peak runoff, TSS and TN up to 13%, 38% and 24%, respectively which can be considered as an acceptable achievement.

In order to find the best combination of LIDs for maximum runoff, TSS and TN reduction, 9 different scenarios selected from the simulation-optimization model were tested using SWMM. The final conclusion was that the optimal number of LIDs for the best stormwater control and minimum cost is 25 with different types of LIDs and combinations. The optimal number achieved consisted of 13 sub-catchments with rain gardens, 12 with swales and 10 sub-catchments received no LIDs; in which case the peak runoff, TSS and TN were reduced by 11.08%, 38.26% and 23.51%, respectively.

In the case of cost non-dominated solutions, the MOPSO was able to find the pareto optimal front for the best non-dominated solutions for peak runoff, total runoff volume, TSS, and TN. Likewise, to find the best combination of LIDs for maximum runoff, total runoff volume, TSS, and TN reduction with the minimum cost, 12 different scenarios selected from the simulation-optimization model were tested using SWMM. The combinations were quite acceptable for flow and TN, but in the case of TSS, the LID combination could only reduce TSS up to a certain amount. Overall, the maximum reduction for peak runoff, total runoff volume, TSS, and TN were 13%, 7%, 38%, and 24%, respectively. This amount of reductions with the minimum cost applied are quite satisfactory, compared to similar studies.

For the initial reduction of runoff/pollutant loads, spending more money and increasing the number of LIDs will lead to greater reduction in the runoff volume, peak runoff, and pollutant loads. However, as LID-BMPs have treatment capabilities, increasing the number of LIDs beyond this limit will not reduce runoff/Pollutants as significant. Moreover, regarding the combination of LIDs optimized by MOPSO, various combination of LIDs from the same Pareto-optimal front will have similar result of reduction for both runoff and pollutant loads.

The LID controls are not generally designed for extreme rainfall cases and could be more successful in lower intensities and shorter duration precipitations. LID-BMP techniques can reduce greater amount of runoff/pollutant loads with the increase of cost and implementing more of these techniques in urban areas. Nevertheless, they also have limitations in terms of treatment capabilities, beyond which spending more money will not be cost-beneficial and LID-BMPs cannot reduce runoff/pollutant loads as significantly. However, the study broadly approved that the LID techniques can be remarkably successful in reducing runoff/pollutant loads if properly designed and optimally implemented. They are even more successful in improving water quality in urban areas. It could also be concluded that MOPSO is able to identify the optimal number, size, location, and combinations of LID-BMPs for the best stormwater quantity and quality control with minimum cost.

6.3 Future Works and Recommendations

It seems that urbanization can significantly affect the precipitation intensity and the spatial–temporal distribution of rainfall in urban catchments. However, it is suggested that more research needs to be carried out to study the possible impacts of urbanization on precipitation patterns more accurately in urban areas.

Since several studies have proved that urbanization and climate change have strong effects on surface runoff generation, it is advisable to investigate these two factors more carefully in further research. Whenever possible, climate change and urbanization can be coupled together to investigate the impacts of both on the rainfall-runoff behaviors. As some studies found the climate change effect on hydrological processes more significant than urbanization, it would also be a good idea to put more effort to investigate climate change impacts on urban hydrology more comprehensively.

Climate change significantly affects the hydrologic cycle in urban water systems. It changes rainfall patterns in urban areas and consequently the runoff volume and peak flow are increased. Yet, in general, the climate change-induced uncertainty is still a challenge for those who are involved with planning and designing urban water engineering systems. Thus, it is vital to determine appropriate and cost-effective measures that can mitigate the climate change effects and address multiple objectives. A better understanding of LID applications in the context of climate change adaptations can help urban management decision-makers to reduce the adverse effects of climate change in the future.

Spatial variability is of high importance in urban catchments. The land cover is heterogeneous, and the topography is complex. These characteristics affect the physical processes in urban catchments. However, the spatial-temporal distribution of precipitation has not been addressed enough in the pertinent studies. Therefore, there should be research directed towards this issue to figure out the spatial-temporal distribution of precipitation in urban catchments more accurately.

The data used in urban hydrological modeling are usually derived from hydrological stations or collected manually which both cases are certainly bound to uncertainty and inaccuracy in modeling. Remote sensing is a major and more accurate source of special data in hydrological modeling. Nevertheless, this source of information has not been well practiced in urban modeling. Thus, the future studies can probably couple the remote sensing information and site inspection data to come up with better and more accurate results in urban rainfall-runoff modeling.

Although depression storage and land slope both have great effects on urban runoff, they have not been well considered in urban modeling. It is suggested that future studies consider these two variables in urban hydrological modeling to achieve more accurate results of surface runoff.

Another issue to be considered is that there are many other pollutants in urban areas, such as heavy metals and pathogens. These pollutants could be investigated in further research to study the removal efficiency of LIDs more accurately.

The LIDs selected for this study were swale and rain garden which are the cheapest ones among all LIDs. Thus, other researchers could test different types of LIDs with different combinations in tropical areas to achieve higher runoff and pollutants reduction in urban areas.

Vulnerability to flooding is the major concern in urban areas to be considered in other related studies. The depth of water in flooded areas plays a significant role in calculating the vulnerability of urban areas to flooding. Therefore, if water depth in flooded areas could be calculated, the vulnerability index for each particular urban area could also be achieved. By calculating the vulnerability index, the appropriate measures could be suggested to mitigate flood damages in urban areas.

Finally, reducing uncertainty plays an important role in the development of complex integrated models. There are many uncertainties in modeling urban rainfall-runoff which result in the inaccuracy of research in this field. The sources of uncertainties can be classified as input uncertainties, parameter uncertainties, and model structure uncertainties. To obtain a more sustainable modeling and achieve precise results, these uncertainties should be addressed in future studies. Thus, urban hydrology is steel the most significant variable in the urban water system management, but when the climate, land use, ecosystems and society interactions are combined and investigated together, the best results will be attained.

REFERENCES

Abustan, I., & Ball, J. (2000). Modelling the export of phosphorous from urban catchments. *Australian Journal of Water Resources, 4*, 33.

Ahiablame, L., & Shakya, R. (2016). Modeling flood reduction effects of low impact development at a watershed scale. *Journal of Environmental Management, 171*, 81-91.

Ahiablame, L. M., Engel, B. A., & Chaubey, I. (2012). Effectiveness of low impact development practices: literature review and suggestions for future research. *Water, Air, & Soil Pollution, 223*(7), 4253-4273.

Ahn, K.-H., & Merwade, V. (2014). Quantifying the relative impact of climate and human activities on streamflow. *Journal of Hydrology, 515*, 257-266.

Albrecht, J. C. (1974). *Alterations in the hydrologic cycle induced by urbanization in Northern New Castle county, Delaware: magnitudes and projections*. Delware, USA: University of Delaware.

Algeet-Abarquero, N., Marchamalo, M., Bonatti, J., Fernández-Moya, J., & Moussa, R. (2015). Implications of land use change on runoff generation at the plot scale in the humid tropics of Costa Rica. *Catena, 135*, 263-270.

Alley, W. M., & Smith, P. E. (1981). Estimation of accumulation parameters for urban runoff quality modeling. *Water Resources Research, 17*(6), 1657-1664.

Arnfield, A. J. (2003). Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. *International journal of climatology, 23*(1), 1-26.

Arnold Jr, C. L., & Gibbons, C. J. (1996). Impervious surface coverage: the emergence of a key environmental indicator. *Journal of the American Planning Association, 62*(2), 243-258.

Aronica, G., & Lanza, L. (2005). Drainage efficiency in urban areas: a case study. *Hydrological processes, 19*(5), 1105-1119.

Autixier, L., Mailhot, A., Bolduc, S., Madoux-Humery, A.-S., Galarneau, M., Prévost, M., & Dorner, S. (2014). Evaluating rain gardens as a method to reduce the impact of sewer overflows in sources of drinking water. *Science of the Total Environment, 499*, 238-247.

Baek, S.-S., Choi, D.-H., Jung, J.-W., Lee, H.-J., Lee, H., Yoon, K.-S., & Cho, K. H. (2015). Optimizing low impact development (LID) for stormwater runoff treatment in urban area, Korea: experimental and modeling approach. *Water Research, 86*, 122-131.

Barbosa, A., Fernandes, J., & David, L. (2012). Key issues for sustainable urban stormwater management. *Water Research, 46*(20), 6787-6798.

Barco, J., Wong, K. M., & Stenstrom, M. K. (2008). Automatic calibration of the US EPA SWMM model for a large urban catchment. *Journal of Hydraulic Engineering, 134*(4), 466-474.

Baroni, G., & Tarantola, S. (2014). A general probabilistic framework for uncertainty and global sensitivity analysis of deterministic models: a hydrological case study. *Environmental Modelling & Software, 51*, 26-34.

Bedan, E. S., & Clausen, J. C. (2009). Stormwater runoff quality and quantity from traditional and low impact development watersheds. *Journal of the American Water Resources Association, 45*(4), 998-1008.

Beganskas, S., & Fisher, A. T. (2017). Coupling distributed stormwater collection and managed aquifer recharge: field application and implications. *Journal of Environmental Management, 200*, 366-379.

Beighley, R. E., Kargar, M., & He, Y. (2009). Effects of impervious area estimation methods on simulated peak discharges. *Journal of Hydrologic Engineering, 14*(4), 388-398.

Bell, C. D., McMillan, S. K., Clinton, S. M., & Jefferson, A. J. (2016). Hydrologic response to stormwater control measures in urban watersheds. *Journal of Hydrology, 541*, 1488-1500.

Berezowski, T., Chormański, J., Batelaan, O., Canters, F., & Van de Voorde, T. (2012). Impact of remotely sensed land-cover proportions on urban runoff prediction. *International Journal of Applied Earth Observation and Geoinformation, 16*, 54-65.

Berndtsson, J. C. (2010). Green roof performance towards management of runoff water quantity and quality: a review. *Ecological Engineering, 36*(4), 351-360.

Berthier, E., Dupont, S., Mestayer, P., & Andrieu, H. (2006). Comparison of two evapotranspiration schemes on a sub-urban site. *Journal of Hydrology, 328*(3), 635-646.

Björklund, K. (2011). *Sources and fluxes of organic contaminants in urban runoff*: Chalmers University of Technology.

Blöschl, G., & Sivapalan, M. (1995). Scale issues in hydrological modelling: a review. *Hydrological processes, 9*(3-4), 251-290.

Bonhomme, C., & Petrucci, G. (2017). Should we trust build-up/wash-off water quality models at the scale of urban catchments? *Water Research, 108*, 422-431.

Booth, D. B. (1991). Urbanization and the natural drainage system-impacts, solutions, and prognoses. *The North West Environmental Journal, 7*(1), 93-118.

Booth, D. B. (2000). *Forest cover, impervious-surface area, and the mitigation of urbanization impacts in King County, Washington*. Retrieved from https://digital.lib.washington.edu/researchworks/handle/1773/19552:

Booth, D. B., & Jackson, C. R. (1997). Urbanization of aquatic systems: degradation thresholds, stormwater detection, and the limits of mitigation. *Journal of the American Water Resources Association, 33*(5), 1077-1090.

Brabec, E., Schulte, S., & Richards, P. L. (2002). Impervious surfaces and water quality: a review of current literature and its implications for watershed planning. *Journal of planning literature, 16*(4), 499-514.

Brath, A., Montanari, A., & Moretti, G. (2006). Assessing the effect on flood frequency of land use change via hydrological simulation (with uncertainty). *Journal of Hydrology, 324*(1), 141-153.

Brilly, M., Rusjan, S., & Vidmar, A. (2006). Monitoring the impact of urbanisation on the Glinscica stream. *Physics and Chemistry of the Earth, Parts A/B/C, 31*(17), 1089-1096.

Burns, D., Vitvar, T., McDonnell, J., Hassett, J., Duncan, J., & Kendall, C. (2005). Effects of suburban development on runoff generation in the Croton river basin, New York, USA. *Journal of Hydrology, 311*(1), 266-281.

Burns, M. J., Fletcher, T. D., Walsh, C. J., Ladson, A. R., & Hatt, B. E. (2012). Hydrologic shortcomings of conventional urban stormwater management and opportunities for reform. *Landscape and Urban Planning, 105*(3), 230-240.

Burns, M. J., Walsh, C. J., Fletcher, T. D., Ladson, A. R., & Hatt, B. E. (2015). A landscape measure of urban stormwater runoff effects is a better predictor of stream condition than a suite of hydrologic factors. *Ecohydrology, 8*(1), 160-171.

Cairns Jr, J. (1995). Urban runoff in an integrated landscape context. In E. E. Herricks (Ed.), *Stormwater runoff and receiving systems: impact, monitoring, and assessment* (pp. 9-20). Florida, United States: CRC Press, Lewis.

Campana, N. A., & Tucci, C. E. (2001). Predicting floods from urban development scenarios: case study of the Dilúvio basin, Porto Alegre, Brazil. *Urban Water, 3*(1), 113-124.

Campolongo, F., Saltelli, A., & Cariboni, J. (2011). From screening to quantitative sensitivity analysis. a unified approach. *Computer Physics Communications, 182*(4), 978-988.

Cantone, J., & Schmidt, A. (2011). Improved understanding and prediction of the hydrologic response of highly urbanized catchments through development of the Illinois urban hydrologic model. *Water Resources Research, 47*(8).

Carle, M. V., Halpin, P. N., & Stow, C. A. (2005). Patterns of watershed urbanization and impacts on water quality. *Journal of the American Water Resources Association, 41*(3), 693-708.

Carlson, T. N., & Arthur, S. T. (2000). The impact of land use-land cover changes due to urbanization on surface microclimate and hydrology: a satellite perspective. *Global and Planetary Change, 25*(1), 49-65.

Chang, N.-B. (2010). Hydrological connections between low-impact development, watershed best management practices, and sustainable development. *Journal of Hydrologic Engineering, 15*(6), 384-385.

Changming, L., Jingjie, Y., & Kendy, E. (2001). Groundwater exploitation and its impact on the environment in the North China plain. *Water International, 26*(2), 265-272.

Characklis, G. W., & Wiesner, M. R. (1997). Particles, metals, and water quality in runoff from large urban watershed. *Journal of Environmental Engineering, 123*(8), 753-759.

Charbeneau, R. J., & Barrett, M. E. (1998). Evaluation of methods for estimating stormwater pollutant loads. *Water Environment Research, 70*(7), 1295-1302.

Chen, C., Scanlin, J., & Feng, A. (2002). *Simulating the fate of diazinon in Castro Valley watershed by SWMM*. Paper presented at the Global Solutions for Urban Drainage: Ninth International Conference on Urban Drainage (9ICUD), Portland, Oregon, United States.

Chen, J. (2004). *Integrated urban stormwater management modeling.* (Doctoral thesis, University of Toronto), Retrieved from https://www.researchgate.net/publication/34005676.

Chen, J., Hill, A. A., & Urbano, L. D. (2009). A GIS-based model for urban flood inundation. *Journal of Hydrology, 373*(1), 184-192.

Chen, J., Theller, L., Gitau, M. W., Engel, B. A., & Harbor, J. M. (2017). Urbanization impacts on surface runoff of the contiguous United States. *Journal of Environmental Management, 100*(187), 470-481.

Chen, W.-B. B. (2006). *Optimal allocation of stormwater pollution control technologies in a watershed.* (Doctoral thesis, The Ohio State University), Retrieved from https://www.researchgate.net/publication/272505086.

Chen, Y., Samuelson, H. W., & Tong, Z. (2016). Integrated design workflow and a new tool for urban rainwater management. *Journal of Environmental Management, 180*, 45-51.

Cheng, C.-T., Ou, C., & Chau, K. (2002). Combining a fuzzy optimal model with a genetic algorithm to solve multi-objective rainfall–runoff model calibration. *Journal of Hydrology, 268*(1), 72-86.

Cheng, L., Xu, Z., Wang, D., & Cai, X. (2011). Assessing interannual variability of evapotranspiration at the catchment scale using satellite-based evapotranspiration data sets. *Water Resources Research, 47*(9).

Chin, D. A., Mazumdar, A., & Roy, P. K. (2000). *Water resources engineering* (Vol. 12). Englewood Cliffs, New Jersey: Prentice Hall.

Choi, W. (2008). Catchment-scale hydrological response to climate-land-use combined scenarios: a case study for the Kishwaukee river basin, Illinois. *Physical Geography, 29*(1), 79-99.

Chow, M., Yusop, Z., & Toriman, M. E. (2012). Modelling runoff quantity and quality in tropical urban catchments using storm water management model. *International Journal of Environmental Science and Technology, 9*(4), 737-748.

Chow, V. T., Maidment, D. R., & Mays, L. W. (1988). *Applied hydrology*.

Chung, E. S., Park, K., & Lee, K. S. (2011). The relative impacts of climate change and urbanization on the hydrological response of a Korean urban watershed. *Hydrological processes, 25*(4), 544-560.

Coello, C. A. C., Pulido, G. T., & Lechuga, M. S. (2004). Handling multiple objectives with particle swarm optimization. *IEEE Transactions on evolutionary computation, 8*(3), 256-279.

Cohen, J. E. (2003). Human population: the next half century. *Science, 302*(5648), 1172-1175.

Collins, K. A., Hunt, W. F., & Hathaway, J. M. (2008). Hydrologic comparison of four types of permeable pavement and standard asphalt in Eastern North Carolina. *Journal of Hydrologic Engineering, 13*(12), 1146-1157.

Cook, D., & Dickinson, W. (1985). *The impact of urbanization on the hydrologic response of the Speedvale experimental basin, Ontario-a case study.* Paper presented at the International Symposium on Urban Hydrology, Hydraulic Infrastructures and Water Quality Control.

Costa, M. H., Botta, A., & Cardille, J. A. (2003). Effects of large-scale changes in land cover on the discharge of the Tocantins river, Southeastern Amazonia. *Journal of Hydrology, 283*(1), 206-217.

Dabberdt, W. F., Crook, A., Mueller, C., Hales, J., Zubrick, S., Krajewski, W., . . . Bornstein, R. (2000). Forecast issues in the urban zone: report of the 10th prospectus development team of the US weather research program. *Bulletin of the American Meteorological Society, 81*(9), 2047-2064.

Dale, V. H., Brown, S., Haeuber, R., Hobbs, N., Huntly, N., Naiman, R., . . . Valone, T. (2000). Ecological principles and guidelines for managing the use of land. *Ecological Applications, 10*(3), 639-670.

Damodaram, C., Giacomoni, M. H., Prakash Khedun, C., Holmes, H., Ryan, A., Saour, W., & Zechman, E. M. (2010). Simulation of combined best management practices and low impact development for sustainable stormwater management. *Journal of the American Water Resources Association, 46*(5), 907-918.

Davis, A. P. (2005). Green engineering principles promote low-impact development. *Environmental Science & Technology, 39*(16), 338A-344A.

Davis, A. P., Hunt, W. F., Traver, R. G., & Clar, M. (2009). Bioretention technology: overview of current practice and future needs. *Journal of Environmental Engineering, 135*(3), 109-117.

Dayaratne, S. T., & Perera, B. (2004). Calibration of urban stormwater drainage models using hydrograph modelling. *Urban Water Journal, 1*(4), 283-297.

Debo, T., & Reese, A. (2003). Stormwater management programs. *Municipal Stormwater Management*.

DeFries, R., & Eshleman, K. N. (2004). Land-use change and hydrologic processes: a major focus for the future. *Hydrological processes, 18*(11), 2183-2186.

Deletic, A., Maksimovic, e., & Ivetic, M. (1997). Modelling of storm wash-off of suspended solids from impervious surfaces. *Journal of hydraulic research, 35*(1), 99-118.

Dhakal, K. P., & Chevalier, L. R. (2017). Managing urban stormwater for urban sustainability: barriers and policy solutions for green infrastructure application. *Journal of Environmental Management, 203*, 171-181.

Dietz, M. E. (2007). Low impact development practices: A review of current research and recommendations for future directions. *Water, Air, and Soil Pollution, 186*(1-4), 351-363.

Dietz, M. E., & Clausen, J. C. (2008). Stormwater runoff and export changes with development in a traditional and low impact subdivision. *Journal of Environmental Management, 87*(4), 560-566.

Dixon, P. G., & Mote, T. L. (2003). Patterns and causes of Atlanta's urban heat island-initiated precipitation. *Journal of Applied Meteorology, 42*(9), 1273-1284.

Dotto, C. B., Kleidorfer, M., Deletic, A., Rauch, W., McCarthy, D. T., & Fletcher, T. D. (2011). Performance and sensitivity analysis of stormwater models using a bayesian approach and long-term high resolution data. *Environmental Modelling & Software, 26*(10), 1225-1239.

Doyle, M. W., Harbor, J. M., Rich, C. F., & Spacie, A. (2000). Examining the effects of urbanization on streams using indicators of geomorphic stability. *Physical Geography, 21*(2), 155-181.

Duan, H.-F., Li, F., & Yan, H. (2016). Multi-objective optimal design of detention tanks in the urban stormwater drainage system: LID implementation and analysis. *Water Resources Management, 30*(13), 4635-4648.

Dubé, S., Plamondon, A. P., & Rothwell, R. L. (1995). Watering up after clear-cutting on forested wetlands of the St. Lawrence lowland. *Water Resources Research, 31*(7), 1741-1750.

Dunne, T., & Leopold, L. B. (1978). *Water in environmental planning*. New York: Macmillan.

Easterling, D. R., Karl, T. R., Gallo, K. P., Robinson, D. A., Trenberth, K. E., & Dai, A. (2000). Observed climate variability and change of relevance to the biosphere. *Journal of Geophysical Research: Atmospheres (1984–2012), 105*(D15), 20101-20114.

Eberhart, R., & Kennedy, J. (1995). *A new optimizer using particle swarm theory*. Paper presented at the the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan.

Ebrahimian, A., Gulliver, J. S., & Wilson, B. N. (2018). Estimating effective impervious area in urban watersheds using land cover, soil character and asymptotic curve number. *Hydrological Sciences Journal, 63*(4), 513-526.

Eckart, K., McPhee, Z., & Bolisetti, T. (2017). Performance and implementation of low impact development–a review. *Journal of Hydrology, 607*, 413-432.

Eckart, K., McPhee, Z., & Bolisetti, T. (2018). Multiobjective optimization of low impact development stormwater controls. *Journal of Hydrology, 562*, 564-576.

Edmonton, C. (2011). *City of Edmonton low impact dvelopment – best management practices design guide* (1 Ed.). Edmonton, Alberta: City of Edmonton.

Edwards, E. C., Harter, T., Fogg, G. E., Washburn, B., & Hamad, H. (2016). Assessing the effectiveness of drywells as tools for stormwater management and aquifer recharge and their groundwater contamination potential. *Journal of Hydrology, 539*, 539-553.

Elliott, A., & Trowsdale, S. (2007). A review of models for low impact urban stormwater drainage. *Environmental Modelling & Software, 22*(3), 394-405.

Fang, T., & Ball, J. E. (2007). Evaluation of spatially variable control parameters in a complex catchment modelling system: a genetic algorithm application. *Journal of Hydroinformatics, 9*(3), 163-173.

Fassman, E. A., & Blackbourn, S. (2010). Urban runoff mitigation by a permeable pavement system over impermeable soils. *Journal of Hydrologic Engineering, 15*(6), 475-485.

Field, R., & Sullivan, D. (2002). *Wet-weather flow in the urban watershed: technology and management* (1 ed.). Florida: CRC Press, Lewis.

FISRWG, U. (1998). *Stream corridor restoration: principles, processes, and practices*. United States: Federal Interagency Stream Resoration Working Group, USDA-NRCS.

Fletcher, T., Andrieu, H., & Hamel, P. (2013). Understanding, management and modelling of urban hydrology and its consequences for receiving waters: a state of the art. *Advances in Water Resources, 51*, 261-279.

Forman, R. T. (2000). Estimate of the area affected ecologically by the road system in the United States. *Conservation Biology, 14*(1), 31-35.

Foscarini, F., Bellocchi, G., Confalonieri, R., Savini, C., & Van den Eede, G. (2010). Sensitivity analysis in fuzzy systems: integration of SimLab and DANA. *Environmental Modelling & Software, 25*(10), 1256-1260.

Foster, I., Gurnell, A. M., & Webb, B. (1995). *Sediment and water quality in river catchments*. Chichester, UK: John Wiley & Sons.

Foster, S. S. (1990a). Impacts of urbanization on groundwater. *Hydrological processes and water management in urban areas. Wallingford, UK, International Association of Hydrological Sciences–Association Internationale des Sciences Hydrologiques (IAHS–AISH Pub. No. 198)*.

Foster, S. S. (1990b). Impacts of urbanization on groundwater. *Hydrological Processes and Water Management in Urban Areas. IAHS Press, Wallingford, UK, 198,* 187-208.

Fu, G., Barber, M. E., & Chen, S. (2007a). Impacts of climate change on regional hydrological regimes in the Spokane river watershed. *Journal of Hydrologic Engineering, 12*(5), 452-461.

Fu, G., Barber, M. E., & Chen, S. (2007b). Impacts of climate change on regional hydrological regimes in the Spokane River Watershed. *Journal of Hydrologic Engineering*.

Fu, G., Butler, D., Khu, S. T., & Sun, S. A. (2011). Imprecise probabilistic evaluation of sewer flooding in urban drainage systems using random set theory. *Water Resources Research, 47*(2).

Galloway, J. N., Aber, J. D., Erisman, J. W., Seitzinger, S. P., Howarth, R. W., Cowling, E. B., & Cosby, B. J. (2003). The nitrogen cascade. *Bioscience, 53*(4), 341-356. doi: https://doi.org/10.1641/0006-3568(2003)053[0341:TNC]2.0.CO;2

Gamerith, V., Neumann, M. B., & Muschalla, D. (2013). Applying global sensitivity analysis to the modelling of flow and water quality in sewers. *Water Research, 47*(13), 4600-4611.

Garcia-Fresca, B., & Sharp, J. M. (2005). Hydrogeologic considerations of urban development: urban-induced recharge. *Reviews in Engineering Geology, 16*, 123-136.

Geiger, W., Marsalek, J., Rawls, W., & Zuidema, F. (1987). *Manual on drainage in urban areas. Volume I–Planning and design of drainage systems*. Paris: UNESCO.

German, J., Vikstrom, M., Svensson, G., & Gustafsson, L. (2005a). *Integrated stormwater strategies to reduce impact on receiving waters.* Paper presented at the Proceedings of the 10th International Conference on Urban Drainage, Copenhagen/Denmark.

German, J., Vikstrom, M., Svensson, G., & Gustafsson, L. (2005b). *Integrated stormwater strategies to reduce impact on receiving waters.* Paper presented at the 10th International Conference on Urban Drainage, Copenhagen, Denmark.

Gilroy, K. L., & McCuen, R. H. (2009). Spatio-temporal effects of low impact development practices. *Journal of Hydrology, 367*(3), 228-236.

Gitau, M. W., Chen, J., & Ma, Z. (2016). Water quality indices as tools for decision making and management. *Water Resources Management, 30*(8), 2591-2610.

Goodchild, M. F. (1993). The state of GIS for environmental problem-solving. In M. F. Goodchild, L. T. Steyaert, & B. O. Parks (Eds.), *Environmental modeling with GIS* (pp. 8-15). New York, United States: Oxford University Press Inc.

Gregoire, B. G., & Clausen, J. C. (2011). Effect of a modular extensive green roof on stormwater runoff and water quality. *Ecological Engineering, 37*(6), 963-969.

Gregory, J. H., Dukes, M. D., Jones, P. H., & Miller, G. L. (2006). Effect of urban soil compaction on infiltration rate. *Journal of Soil and Water Conservation, 61*(3), 117-124.

Guo, J. C. (2008). Volume-based imperviousness for storm water designs. *Journal of Irrigation and Drainage Engineering, 134*(2), 193-196.

Guo, J. C., & Urbonas, B. (1996). Maximized detention volume determined by runoff capture ratio. *Journal of Water Resources Planning and Management, 122*(1), 33-39.

Hamel, P., & Fletcher, T. D. (2014). Modelling the impact of stormwater source control infiltration techniques on catchment baseflow. *Hydrological processes, 28*(24), 5817-5831.

Han, L., Zhou, W., Li, W., & Li, L. (2014). Impact of urbanization level on urban air quality: a case of fine particles (PM 2.5) in Chinese cities. *Environmental Pollution, 194*, 163-170.

Heier, T., & Starrett, S. K. (2005). *SWMM and SMADA model predictions vs. field data.* Paper presented at the Impacts of Global Climate Change, Alaska, United States.

Hicks, A., & Larson, J. (1997a). Impervious surface area and benthic macroinvertebrate response as an indicator of impact from urbanization of freshwater wetlands. *US Environmental Protection Agency Library Report Number: EPA-R-822916-01-0; EPA/600/R-97/075*.

Hicks, A., & Larson, J. (1997b). *Impervious surface area and benthic macroinvertebrate response as an indicator of impact from urbanization of freshwater wetlands. US Environmental Protection Agency, Washington, D.C.* (EPA/600/R-95/074). Retrieved from https://cfpub.epa.gov/si/si_public_record_Report.cfm?Lab=NHEERL&dirEntryId=40948&CFID=18178852&CFTOKEN=62302400&jsessionid=cc30ca8a68963824a51d17401975804d4652:

Hollis, G. (1975). The effect of urbanization on floods of different recurrence interval. *Water Resources Research, 11*(3), 431-435.

Hood, M. J., Clausen, J. C., & Warner, G. S. (2007). Comparison of stormwater lag times for low impact and traditional residential development. *Journal of the American Water Resources Association, 43*(4), 1036-1046.

Hosseini, S. S., Hamidi, S. A., Mansuri, M., & Ghoddosian, A. (2015). Multi objective particle swarm optimization (MOPSO) for size and shape optimization of 2D truss structures. *Periodica Polytechnica Civil Engineering, 59*(1), 9-14. doi: https://doi.org/10.3311/PPci.7341

Hsu, M.-H., Chen, S. H., & Chang, T.-J. (2000). Inundation simulation for urban drainage basin with storm sewer system. *Journal of Hydrology, 234*(1), 21-37.

Huang, H. j., Cheng, S. j., Wen, J. c., & Lee, J. h. (2008a). Effect of growing watershed imperviousness on hydrograph parameters and peak discharge. *Hydrological processes, 22*(13), 2075-2085.

Huang, S.-y., Cheng, S.-j., Wen, J.-c., & Lee, J.-h. (2008b). Identifying peak-imperviousness-recurrence relationships on a growing-impervious watershed, Taiwan. *Journal of Hydrology, 362*(3), 320-336.

Huang, S.-Y., Cheng, S.-J., Wen, J.-C., & Lee, J.-H. (2012). Identifying hydrograph parameters and their relationships to urbanization variables. *Hydrological Sciences Journal, 57*(1), 144-161.

Huber, W. C., Dickinson, R. E., Barnwell Jr, T. O., & Branch, A. (1988). *Storm water management model, version 4*. Washington, D.C., United States: Environmental Protection Agency.

Hunt, W., Smith, J., Jadlocki, S., Hathaway, J., & Eubanks, P. (2008). Pollutant removal and peak flow mitigation by a bioretention cell in urban Charlotte, NC. *Journal of Environmental Engineering, 134*(5), 403-408.

Hunt, W. F., Traver, R. G., Davis, A. P., Emerson, C. H., Collins, K. A., & Stagge, J. H. (2010a). Low impact development practices: designing to infiltrate in urban environments. In N.-B. Chang (Ed.), *Effects of urbanization on groundwater* (pp. 308-343). Reston, USA: ASCE.

Hunt, W. F., Traver, R. G., Davis, A. P., Emerson, C. H., Collins, K. A., & Stagge, J. H. (2010b). Low impact development practices: designing to infiltrate in urban environments. *Effects of urbanization on groundwater: an engineering case-based approach for sustainable development*, 308-343.

Hvitved-Jacobsen, T., Vollertsen, J., & Nielsen, A. H. (2011). *Urban and highway stormwater pollution: concepts and engineering*. Florida: CRC Press.

Iroumé, A., Huber, A., & Schulz, K. (2005). Summer flows in experimental catchments with different forest covers, Chile. *Journal of Hydrology, 300*(1), 300-313.

Jacobson, C. R. (2011). Identification and quantification of the hydrological impacts of imperviousness in urban catchments: A review. *Journal of Environmental Management, 92*(6), 1438-1448.

Jakeman, A. J., Letcher, R. A., & Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. *Environmental Modelling & Software, 21*(5), 602-614.

James, W. (2003). *Rules for responsible modeling*. Guelph, Ontario, Canada: CHI.

Jang, S., Cho, M., Yoon, J., Yoon, Y., Kim, S., Kim, G., . . . Aksoy, H. (2007). Using SWMM as a tool for hydrologic impact assessment. *Desalination, 212*(1), 344-356.

Jia, H., Lu, Y., Shaw, L. Y., & Chen, Y. (2012). Planning of LID–BMPs for urban runoff control: the case of Beijing Olympic Village. *Separation and Purification Technology, 84*, 112-119.

Jia, H., Wang, X., Ti, C., Zhai, Y., Field, R., Tafuri, A. N., . . . Shaw, L. Y. (2015). Field monitoring of a LID-BMP treatment train system in China. *Environmental Monitoring and Assessment, 187*(6), 373.

Jia, H., Yao, H., Tang, Y., Shaw, L. Y., Zhen, J. X., & Lu, Y. (2013). Development of a multi-criteria index ranking system for urban runoff best management practices (BMPs) selection. *Environmental Monitoring and Assessment, 185*(9), 7915-7933.

Jiang, Y., Liu, C., Huang, C., & Wu, X. (2010). Improved particle swarm algorithm for hydrological parameter optimization. *Applied Mathematics and Computation, 217*(7), 3207-3215.

Joksimovic, D., & Alam, Z. (2014). Cost efficiency of low impact development (LID) stormwater management practices. *Procedia Engineering, 89*, 734-741.

Jones, J. A., Swanson, F. J., Wemple, B. C., & Snyder, K. U. (2000). Effects of roads on hydrology, geomorphology, and disturbance patches in stream networks. *Conservation Biology, 14*(1), 76-85.

Jung, Y.-w., Han, S.-i., & Jo, D. (2016). Optimal design of permeable pavement using harmony search algorithm with SWMM. In J. H. Kim & Z. W. Geem (Eds.), *Harmony search algorithm. Advances in intelligent systems and computing* (Vol. 382, pp. 385-394). Berlin/Heidelberg, Germany: Springer.

Kalyanmoy, D. (2001). *Multi objective optimization using evolutionary algorithms*. New York, NY, USA: John Wiley and Sons.

Karamouz, M., & Nazif, S. (2013). Reliability-based flood management in urban watersheds considering climate change impacts. *Journal of Water Resources Planning and Management, 139*(5), 520-533.

Kim, J.-H., Kim, H. Y., & Demarie, F. (2017). Facilitators and barriers of applying low impact development practices in urban development. *Water Resources Management, 31*(12), 3795-3808.

King, D., & Perera, B. (2013). Morris method of sensitivity analysis applied to assess the importance of input variables on urban water supply yield–a case study. *Journal of Hydrology, 477*, 17-32.

Kliment, Z., & Matoušková, M. (2009). Runoff changes in the Šumava mountains (Black Forest) and the foothill regions: extent of influence by human impact and climate change. *Water Resources Management, 23*(9), 1813-1834.

Knox, J. C. (2001). Agricultural influence on landscape sensitivity in the Upper Mississippi river valley. *Catena, 42*(2), 193-224.

Kok, K. H., Sidek, L. M., Abidin, M., Basri, H., Muda, Z., & Beddu, S. (2013). *Evaluation of green roof as green technology for urban stormwater quantity and quality controls.* Paper presented at the IOP Conference Series: Earth and Environmental Science, Putrajaya, Malaysia.

Kong, F. H., Ban, Y. L., Yin, H. W., James, P., & Dronova, I. (2017). Modeling stormwater management at the city district level in response to changes in land use and low impact development. *Environmental Modelling & Software, 95*, 132-142.

Kornecki, T. S., Sabbagh, G. J., & Storm, D. E. (1999). Evaluation of runoff, erosion, and phosphorus modeling system-simple. *Journal of the American Water Resources Association, 35*(4), 807-820.

Krauße, T., Cullmann, J., Saile, P., & Schmitz, G. (2011). Robust multi-objective calibration strategies-chances for improving flood forecasting. *Hydrology & Earth System Sciences Discussions, 8*(2), 3693-3741.

Krebs, G., Kokkonen, T., Valtanen, M., Setälä, H., & Koivusalo, H. (2014). Spatial resolution considerations for urban hydrological modelling. *Journal of Hydrology, 512*, 482-497.

Kuchment, L. S. (2004). The hydrological cycle and human impact on it. *Water Resources Management*.

Kuok, K., Harun, S., & Shamsuddin, S. (2010). Particle swarm optimization feedforward neural network for modeling runoff. *International Journal of Environmental Science and Technology, 7*(1), 67-78.

Lai, F.-h., Fan, C.-Y., Shoemaker, L., & Field, R. (2003). Development of a decision-support framework for placement of BMPs in urban watersheds. *Proceedings of the Water Environment Federation, 2003*(4), 837-857.

Lautenbach, S., Volk, M., Strauch, M., Whittaker, G., & Seppelt, R. (2013). Optimization-based trade-off analysis of biodiesel crop production for managing an agricultural catchment. *Environmental Modelling & Software, 48*, 98-112.

Lee, J.-m., Hyun, K.-h., Choi, J.-s., Yoon, Y.-j., & Geronimo, F. K. F. (2012). Flood reduction analysis on watershed of LID design demonstration district using SWMM5. *Desalination and Water Treatment, 38*(1-3), 255-261.

Lee, J. G. (2003). *Process analyses and optimization of distributed urban stormwater management strategies.* (Doctoral thesis, University of Colorado at Boulder Adviser), Retrieved from https://elibrary.ru/item.asp?id=5920645.

Lee, J. G., & Heaney, J. P. (2003). Estimation of urban imperviousness and its impacts on storm water systems. *Journal of Water Resources Planning and Management, 129*(5), 419-426.

Lee, J. G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J. X., Shoemaker, L., & Lai, F.-h. (2012). A watershed-scale design optimization model for stormwater best management practices. *Environmental Modelling & Software, 37*, 6-18.

Leigh, D. S. (2008). Late quaternary climates and river channels of the Atlantic Coastal Plain, Southeastern USA. *Geomorphology, 101*(1), 90-108.

Leitão, J., Carbajal, J., Rieckermann, J., Simões, N., Marques, A. S., & de Sousa, L. (2018). Identifying the best locations to install flow control devices in sewer networks to enable in-sewer storage. *Journal of Hydrology, 556*, 371-383.

Leopold, L. B. (1968). *Hydrology for urban land planning: a guidebook on the hydrologic effects of urban land use*. Washington: US Government Printing Office.

Lerner, D. N. (2002). Identifying and quantifying urban recharge: a review. *Hydrogeology Journal, 10*(1), 143-152.

Li, L., Hao, Z.-C., Wang, J.-H., Wang, Z.-H., & Yu, Z.-B. (2008). Impact of future climate change on runoff in the head region of the Yellow river. *Journal of Hydrologic Engineering, 13*(5), 347-354.

Li, Q., Cai, T., Yu, M., Lu, G., Xie, W., & Bai, X. (2011). Investigation into the impacts of land-use change on runoff generation characteristics in the Upper Huaihe river basin, China. *Journal of Hydrologic Engineering, 18*(11), 1464-1470.

Liong, S., Chan, W., & Lum, L. (1991). Knowledge-based system for SWMM runoff component calibration. *Journal of Water Resources Planning and Management, 117*(5), 507-524.

Liu, G., Chen, L., Shen, Z., Xiao, Y., & Wei, G. (2019). A fast and robust simulation-optimization methodology for stormwater quality management. *Journal of Hydrology, 576*, 520-527.

Liu, R., Zhang, P., Wang, X., Wang, J., Yu, W., & Shen, Z. (2014). Cost-effectiveness and cost-benefit analysis of BMPs in controlling agricultural nonpoint source pollution in China based on the SWAT model. *Environmental Monitoring and Assessment, 186*(12), 9011-9022.

Liu, Y. (2009). Automatic calibration of a rainfall–runoff model using a fast and elitist multi-objective particle swarm algorithm. *Expert Systems with Applications, 36*(5), 9533-9538.

Liu, Y., Bralts, V. F., & Engel, B. A. (2015). Evaluating the effectiveness of management practices on hydrology and water quality at watershed scale with a rainfall-runoff model. *Science of the Total Environment, 511*, 298-308.

Liu, Y., Cibin, R., Bralts, V. F., Chaubey, I., Bowling, L. C., & Engel, B. A. (2016). Optimal selection and placement of BMPs and LID practices with a rainfall-runoff model. *Environmental Modelling & Software, 80*, 281-296.

Liu, Y., Gebremeskel, S., De Smedt, F., Hoffmann, L., & Pfister, L. (2006). Predicting storm runoff from different land-use classes using a geographical information system-based distributed model. *Hydrological processes, 20*(3), 533-548.

Liu, Y., Zhang, X., Xia, D., You, J., Rong, Y., & Bakir, M. (2011). Impacts of land-use and climate changes on hydrologic processes in the Qingyi river watershed, China. *Journal of Hydrologic Engineering, 18*(11), 1495-1512.

Liuzzo, L., Noto, L. V., Vivoni, E. R., & La Loggia, G. (2009). Basin-scale water resources assessment in Oklahoma under synthetic climate change scenarios using a fully distributed hydrologic model. *Journal of Hydrologic Engineering*.

Long, H., Liu, Y., Hou, X., Li, T., & Li, Y. (2014). Effects of land use transitions due to rapid urbanization on ecosystem services: implications for urban planning in the new developing area of China. *Habitat International, 44*, 536-544.

Loperfido, J. V., Noe, G. B., Jarnagin, S. T., & Hogan, D. M. (2014). Effects of distributed and centralized stormwater best management practices and land cover on urban stream hydrology at the catchment scale. *Journal of Hydrology, 519*, 2584-2595.

Lucas, W. C., & Sample, D. J. (2015). Reducing combined sewer overflows by using outlet controls for green stormwater infrastructure: case study in Richmond, Virginia. *Journal of Hydrology, 520*, 473-488.

Ma, Z., Kang, S., Zhang, L., Tong, L., & Su, X. (2008). Analysis of impacts of climate variability and human activity on streamflow for a river basin in arid region of northwest China. *Journal of Hydrology, 352*(3), 239-249.

Mackay, R., & Last, E. (2010). SWITCH city water balance: a scoping model for integrated urban water management. *Reviews in Environmental Science and Bio/Technology, 9*(4), 291-296.

Maharjan, M., Pathirana, A., Gersonius, B., & Vairavamoorthy, K. (2009). Staged cost optimization of urban storm drainage systems based on hydraulic performance in a changing environment. *Hydrology and Earth System Sciences, 13*(4), 481–489.

Maksimovic, C., & Tucci, C. E. (2001). Urban drainage in specific climates. Volume I: Urban drainage in humid tropics. In *IHP-V technical documents in hydrology* (Vol. 1). Paris: Unesco.

Mancipe-Munoz, N. A., Buchberger, S. G., Suidan, M. T., & Lu, T. (2014). Calibration of rainfall-runoff model in urban watersheds for stormwater management assessment. *Journal of Water Resources Planning and Management, 140*(6), 05014001.

Mansell, M., & Rollet, F. (2009). The effect of surface texture on evaporation, infiltration and storage properties of paved surfaces. *Water Science and Technology, 60*(1), 71.

Maringanti, C., Chaubey, I., & Popp, J. (2009). Development of a multiobjective optimization tool for the selection and placement of best management practices for nonpoint source pollution control. *Water Resources Research, 45*(6).

Mark, D. M., & Gould, M. D. (1991). Interacting with geographic information: a commentary. *Photogrammetric Engineering and Remote Sensing, 57*(11), 1427-1430.

Marques, G. F., de Souza, V. B., & Moraes, N. V. (2017). The economic value of the flow regulation environmental service in a Brazilian urban watershed. *Journal of Hydrology, 554*, 406-419.

Marsalek, J., Cisneros, B. J., Karamouz, M., Malmquist, P.-A., Goldenfum, J. A., & Chocat, B. (2008). *Urban Water Cycle Processes and Interactions: Urban Water Series-UNESCO-IHP* (Vol. 2): CRC Press.

Marsalek, J., & Schreier, H. (2009). *Innovation in stormwater management in Canada: The way forward*: Citeseer.

Martin-Mikle, C. J., de Beurs, K. M., Julian, J. P., & Mayer, P. M. (2015). Identifying priority sites for low impact development (LID) in a mixed-use watershed. *Landscape and Urban Planning, 140*, 29-41.

Martin, C., Ruperd, Y., & Legret, M. (2007). Urban stormwater drainage management: the development of a multicriteria decision aid approach for best management practices. *European Journal of Operational Research, 181*(1), 338-349.

Mejía, A. I., & Moglen, G. E. (2010). Impact of the spatial distribution of imperviousness on the hydrologic response of an urbanizing basin. *Hydrological processes, 24*(23), 3359-3373.

Meyer, S. C. (2005). Analysis of base flow trends in urban streams, Northeastern Illinois, USA. *Hydrogeology Journal, 13*(5-6), 871-885.

Miller, J. D., Kim, H., Kjeldsen, T. R., Packman, J., Grebby, S., & Dearden, R. (2014). Assessing the impact of urbanization on storm runoff in a peri-urban catchment using historical change in impervious cover. *Journal of Hydrology, 515*, 59-70.

Milliman, J. D., Farnsworth, K., Jones, P., Xu, K., & Smith, L. (2008). Climatic and anthropogenic factors affecting river discharge to the global ocean, 1951–2000. *Global and Planetary Change, 62*(3), 187-194.

Mitchell, V., Duncan, H., Inma, R. M., Stewart, J., Vieritz, A., Holt, P., . . . Maheepala, S. (2007). *State of the art review of integrated urban water models*. Paper presented at the NOVATECH 2007–Sixth International Conference on Sustainable Techniques and Strategies in Urban Water Management, Lyon, France.

Moglen, G. E. (2009). Hydrology and impervious areas. *Journal of Hydrologic Engineering, 14*(4), 303-304.

Montalvo, I., Izquierdo, J., Schwarze, S., & Pérez-García, R. (2010). Multi-objective particle swarm optimization applied to water distribution systems design: an approach with human interaction. *Mathematical and Computer Modelling, 52*(7-8), 1219-1227.

Moramarco, T., Melone, F., & Singh, V. (2005). Assessment of flooding in urbanized ungauged basins: a case study in the Upper Tiber area, Italy. *Hydrological processes, 19*(10), 1909-1924.

MSMA. (2012). *Urban stormwater management manual for Malaysia (MSMA 2nd edition)*. Kuala Lumpur, Malaysia: Government of Malaysia, Department of Irrigation and Drainage. Retrieved from https://www.water.gov.my/jps/resources/PDF/MSMA2ndEdition_august_2012.pdf

Myers, B., Beecham, S., & van Leeuwen, J. A. (2011). *Water quality with storage in permeable pavement basecourse.* Paper presented at the Proceedings of the Institution of Civil Engineers-Water Management, London.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I-a discussion of principles. *Journal of Hydrology, 10*(3), 282-290.

Newcomer, M. E., Gurdak, J. J., Sklar, L. S., & Nanus, L. (2014). Urban recharge beneath low impact development and effects of climate variability and change. *Water Resources Research, 50*(2), 1716-1734.

Niemczynowicz, J. (1999). Urban hydrology and water management–present and future challenges. *Urban Water, 1*(1), 1-14.

Notter, B., MacMillan, L., Viviroli, D., Weingartner, R., & Liniger, H.-P. (2007). Impacts of environmental change on water resources in the Mt. Kenya region. *Journal of Hydrology, 343*(3), 266-278.

Novotny, V., & Olem, H. (1994). *Water quality: prevention, identification, and management of diffuse pollution*. New York: Van Nostrand Reinhold.

O'Loughlin, G., Huber, W., & Chocat, B. (1996). Rainfall-runoff processes and modelling. *Journal of hydraulic research, 34*(6), 733-751.

Obropta, C., & Del Monaco, N. (2018). Reducing directly connected impervious areas with green stormwater infrastructure. *Journal of Sustainable Water in the Built Environment, 4*(1), 05017004.

Ogden, F. L., Raj Pradhan, N., Downer, C. W., & Zahner, J. A. (2011). Relative importance of impervious area, drainage density, width function, and subsurface storm drainage on flood runoff from an urbanized catchment. *Water Resources Research, 47*(12).

Ozdemir, H., & Elbaşı, E. (2014). Benchmarking land use change impacts on direct runoff in ungauged urban watersheds. *Physics and Chemistry of the Earth, Parts A/B/C, 79-82*, 100-107.

Palla, A., & Gnecco, I. (2015). Hydrologic modeling of low impact development systems at the urban catchment scale. *Journal of Hydrology, 528*, 361-368.

Palmer, M. A., Bernhardt, E. S., Chornesky, E. A., Collins, S. L., Dobson, A. P., Duke, C. S., . . . Kranz, R. (2004). Ecology for a crowded planet. *Science, 304*(5675), 1251-1252.

Pan, A., Hou, A., Tian, F., Ni, G., & Hu, H. (2011). Hydrologically enhanced distributed urban drainage model and its application in Beijing city. *Journal of Hydrologic Engineering, 17*(6), 667-678.

Paul, M. J., & Meyer, J. L. (2001). Streams in the urban landscape. *Annual Review of Ecology and Systematics, 32*, 333-365.

Paule-Mercado, M., Lee, B., Memon, S., Umer, S., Salim, I., & Lee, C.-H. (2017). Influence of land development on stormwater runoff from a mixed land use and land cover catchment. *Science of the Total Environment, 599*, 2142-2155.

Petrucci, G., & Bonhomme, C. (2014). The dilemma of spatial representation for urban hydrology semi-distributed modelling: trade-offs among complexity, calibration and geographical data. *Journal of Hydrology, 517*, 997-1007.

Pitt, R. (1999). Small storm hydrology and why it is important for the design of stormwater control practices. *Journal of Water Management Modeling, 7*, 61-91. doi:10.14796/JWMM.R204-04.

Poelmans, L., Rompaey, A. V., Ntegeka, V., & Willems, P. (2011). The relative impact of climate change and urban expansion on peak flows: a case study in central Belgium. *Hydrological processes, 25*(18), 2846-2858.

Price, K. (2011). Effects of watershed topography, soils, land use, and climate on baseflow hydrology in humid regions: a review. *Progress in Physical Geography, 35*(4), 465-492.

Price, R. K., & Vojinovic, Z. (2011). *Urban hydroinformatics: data, models, and decision support for integrated urban water management*. London, UK: IWA publishing.

Prince George's County, M. (1999). *Low-impact development hydrologic analysis*. Prince George's County, Maryland, USA: Department of Environmental Resources, Programs and Planning Division.

Pringle, C. M. (2001). Hydrologic connectivity and the management of biological reserves: a global perspective. *Ecological Applications, 11*(4), 981-998.

Qin, H.-P., Li, Z.-X., & Fu, G. (2013). The effects of low impact development on urban flooding under different rainfall characteristics. *Journal of Environmental Management, 129*, 577-585.

Ragab, R., Bromley, J., Rosier, P., Cooper, J., & Gash, J. (2003a). Experimental study of water fluxes in a residential area: 1. rainfall, roof runoff and evaporation: the effect of slope and aspect. *Hydrological processes, 17*(12), 2409-2422.

Ragab, R., Rosier, P., Dixon, A., Bromley, J., & Cooper, J. (2003b). Experimental study of water fluxes in a residential area: 2. road infiltration, runoff and evaporation. *Hydrological processes, 17*(12), 2423-2437.

Ramier, D., Berthier, E., & Andrieu, H. (2011). The hydrological behaviour of urban streets: long-term observations and modelling of runoff losses and rainfall–runoff transformation. *Hydrological processes, 25*(14), 2161-2178.

Read, L. K., Hogue, T. S., Edgley, R., Mika, K., & Gold, M. (2019). Evaluating the Impacts of Stormwater Management on Streamflow Regimes in the Los Angeles River. *Journal of Water Resources Planning and Management, 145*(10), 05019016.

Rhoads, B. L. (1995). *Stream power: a unifying theme for urban fluvial geomorphology*. Boca Raton, Florida: Lewis Publishers.

Rodriguez, F., Andrieu, H., & Morena, F. (2008). A distributed hydrological model for urbanized areas–model development and application to case studies. *Journal of Hydrology, 351*(3), 268-287.

Rosa, D. J., Clausen, J. C., & Dietz, M. E. (2015). Calibration and verification of SWMM for low impact development. *Journal of the American Water Resources Association, 51*(3), 746-757.

Rose, S., & Peters, N. E. (2001). Effects of urbanization on streamflow in the Atlanta area (Georgia, USA): a comparative hydrological approach. *Hydrological processes, 15*(8), 1441-1457.

Rossman, L. (2004). *SWMM (stormwater management model), version 5, user's manual. EPA/600/R-05/040*. Washington, D.C.: US Environmental Protection Agency.

Rossman, L., & Huber, W. (2016). *Storm water management model reference manual, volume II–Hydraulics. US Environmental Protection Agency* (EPA/600/R-17/111). Retrieved from https://cfpub.epa.gov/si/si_public_record_report.cfm?Lab=NRMRL&dirEntryId=337162:

Rossman, L. A. (2010). *Storm water management model user's manual, version 5.0. EPA/600/R-05/040*. Washington, D.C.: U.S. Environmental Protection Agency, Office of Research and Development.

Rowe, D. B. (2011). Green roofs as a means of pollution abatement. *Environmental Pollution, 159*(8), 2100-2110.

Roy-Poirier, A., Champagne, P., & Filion, Y. (2010). Review of bioretention system research and design: past, present, and future. *Journal of Environmental Engineering, 136*(9), 878-889.

Roy, A. H., & Shuster, W. D. (2009). Assessing impervious surface connectivity and applications for watershed management. *Journal of the American Water Resources Association, 45*(1), 198-209.

Roy, A. H., Wenger, S. J., Fletcher, T. D., Walsh, C. J., Ladson, A. R., Shuster, W. D., . . . Brown, R. R. (2008). Impediments and solutions to sustainable, watershed-scale urban stormwater management: lessons from Australia and the United States. *Environmental Management, 42*(2), 344-359.

Rumman, N., Lin, G., & Li, J. (2005). Investigation of GIS-based surface hydrological modelling for identifying infiltration zones in an urban watershed. *Environmental Informatics Archives, 3*, 315-322.

Sajikumar, N., & Remya, R. (2015). Impact of land cover and land use change on runoff characteristics. *Journal of Environmental Management, 161*, 460-468.

Salvador, R., Bautista-Capetillo, C., & Playán, E. (2011). Irrigation performance in private urban landscapes: a study case in Zaragoza (Spain). *Landscape and Urban Planning, 100*(3), 302-311.

Salvadore, E., Bronders, J., & Batelaan, O. (2015). Hydrological modelling of urbanized catchments: a review and future directions. *Journal of Hydrology, 529*, 62-81.

Sample, D. J., Heaney, J. P., Wright, L. T., Fan, C.-Y., Lai, F.-H., & Field, R. (2003). Costs of best management practices and associated land for urban stormwater control. *Journal of Water Resources Planning and Management, 129*(1), 59-68.

Schirmer, M., Leschik, S., & Musolff, A. (2013). Current research in urban hydrogeology–a review. *Advances in Water Resources, 51*, 280-291.

Scholz, M., & Grabowiecki, P. (2007). Review of permeable pavement systems. *Building and Environment, 42*(11), 3830-3836.

Schueler, T. R., Fraley-McNeal, L., & Cappiella, K. (2009). Is impervious cover still important? review of recent research. *Journal of Hydrologic Engineering, 14*(4), 309-315.

Seitzinger, S. P., Sanders, R., & Styles, R. (2002). Bioavailability of DON from natural and anthropogenic sources to estuarine plankton. *Limnology and Oceanography, 47*(2), 353-366.

Sheeder, S. A., Ross, J. D., & Carlson, T. N. (2002). Dual urban and rural hydrograph signals in three small watersheds. *Journal of the American Water Resources Association, 38*(4), 1027-1040.

Shepherd, J. M. (2006). Evidence of urban-induced precipitation variability in arid climate regimes. *Journal of Arid Environments, 67*(4), 607-628.

Shepherd, J. M., Pierce, H., & Negri, A. J. (2002). Rainfall modification by major urban areas: observations from spaceborne rain radar on the TRMM satellite. *Journal of Applied Meteorology, 41*(7), 689-701.

Shi, P.-J., Yuan, Y., Zheng, J., Wang, J.-A., Ge, Y., & Qiu, G.-Y. (2007). The effect of land use/cover change on surface runoff in Shenzhen region, China. *Catena, 69*(1), 31-35.

Shoemaker, L., Lahlou, M., Doll, A., & Cazenas, P. (2000). *Stormwater best management practices in an ultra-urban setting : selection and monitoring* (FHWA-EP-00-002). Retrieved from https://rosap.ntl.bts.gov/view/dot/25727:

Shuster, W., Bonta, J., Thurston, H., Warnemuende, E., & Smith, D. (2005). Impacts of impervious surface on watershed hydrology: A review. *Urban Water Journal, 2*(4), 263-275.

Shuster, W., & Pappas, E. (2010). Laboratory simulation of urban runoff and estimation of runoff hydrographs with experimental curve numbers implemented in USEPA SWMM. *Journal of Irrigation and Drainage Engineering*.

Sillanpää, N., & Koivusalo, H. (2015). Impacts of urban development on runoff event characteristics and unit hydrographs across warm and cold seasons in high latitudes. *Journal of Hydrology, 521*, 328-340.

Simmons, D. L., & Reynolds, R. J. (1982). Effects of urbanization on base flow of selected south-shore streams, Long island, New York. *Journal of the American Water Resources Association, 18*(5), 797-805.

Singh, V., & Fiorentino, M. (2013). *Geographical information systems in hydrology* (Vol. 26). Berlin/Heidelberg, Germany: Springer Science & Business Media.

Skotnicki, M., & Sowiński, M. (2015). The influence of depression storage on runoff from impervious surface of urban catchment. *Urban Water Journal, 12*(3), 207-218.

Slonecker, E. T., Jennings, D. B., & Garofalo, D. (2001). Remote sensing of impervious surfaces: a review. *Remote Sensing Reviews, 20*(3), 227-255.

Smakhtin, V. (2001). Low flow hydrology: a review. *Journal of Hydrology, 240*(3), 147-186.

Smith, R., & Wheater, H. S. (2004). Multiple objective evaluation of a simple phosphorus transfer model. *Hydrological processes, 18*(9), 1703-1720.

Sun, N. (2012). *Development of a stormwater model for testing the hydrological effectiveness of green infrastructure implementation scenarios in urban sewersheds*. New York: State University of New York, College of Environmental Science and Forestry.

Taha, H. (1997). Urban climates and heat islands: albedo, evapotranspiration, and anthropogenic heat. *Energy and buildings, 25*(2), 99-103.

Tan, S. B., Chua, L. H., Shuy, E. B., Lo, E. Y.-M., & Lim, L. W. (2008). Performances of rainfall-runoff models calibrated over single and continuous storm flow events. *Journal of Hydrologic Engineering, 13*(7), 597-607.

Tomer, M. D., & Schilling, K. E. (2009). A simple approach to distinguish land-use and climate-change effects on watershed hydrology. *Journal of Hydrology, 376*(1), 24-33.

Tsihrintzis, V. A., & Hamid, R. (1998). Runoff quality prediction from small urban catchments using SWMM. *Hydrological processes, 12*(2), 311-329.

Tuomela, C., Sillanpää, N., & Koivusalo, H. (2019). Assessment of stormwater pollutant loads and source area contributions with storm water management model (SWMM). *Journal of Environmental Management, 233*, 719-727.

UnitedNations. (2010). World Population Prospects: The 2009 Revision, New York, sn.

USEPA. (2000a). *Low impact development (LID): a literature summary. EPA-841-B-00-005*. Washington, D.C.: US Environmental Protection Agency, Office of Water.

USEPA. (2004a). *The use of best management practices in urban watersheds. EPA-R-04-184*. Washington, D.C.: US Environmental Protection Agency, Office of Water.

USEPA. (2004b). *Stormwater best management practice design guide: volume 1. general considerations. EPA-600-R-04-121*. Washington, D.C.: US Environmental Protection Agency, Office of Water.

USEPA. (2006). *Methods for optimizing urban wet-weather control system. EPA-600-R-06-034*. Washington, D.C.: US Environmental Protection Agency, Office of Research and Development.

USEPA. (2007). *Reducing stormwater costs through low impact development (LID) strategies and practices. EPA 841-F-07–006*. Washington, D.C.: US Environmental Protection Agency, Nonpoint Source Control.

van Roon, M. R. (2011). Water sensitive residential developments: application of LIUDD principles and methods in the Netherlands, Australia and New Zealand. *Urban Water Journal, 8*(6), 325-335.

Vezzaro, L., Eriksson, E., Ledin, A., & Mikkelsen, P. S. (2011). Modelling the fate of organic micropollutants in stormwater ponds. *Science of the Total Environment, 409*(13), 2597-2606.

Visitacion, B. J., Booth, D. B., & Steinemann, A. C. (2009). Costs and benefits of storm-water management: case study of the Puget Sound region. *Journal of Urban Planning and Development, 135*(4), 150-158.

Vittorio, D. D., & Ahiablame, L. (2015). Spatial translation and scaling up of low impact development designs in an urban watershed. *Journal of Water Management Modeling*, 1-9. doi:https://doi.org/10.14796/JWMM.C388.

Vrebos, D., Vansteenkiste, T., Staes, J., Willems, P., & Meire, P. (2014). Water displacement by sewer infrastructure in the Grote Nete catchment, Belgium, and its hydrological regime effects. *Hydrology and Earth System Sciences, 18*(3), 1119-1136.

Vrugt, J. A., Gupta, H. V., Bouten, W., & Sorooshian, S. (2003). A shuffled complex evolution metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resources Research, 39*(8).

Wagesho, N., Jain, M., & Goel, N. (2012). Effect of climate change on runoff generation: application to rift valley lakes basin of Ethiopia. *Journal of Hydrologic Engineering, 18*(8), 1048-1063.

Walesh, S. G. (1989). *Urban surface water management*. New York: John Wiley & Sons.

Walsh, C. J., Roy, A. H., Feminella, J. W., Cottingham, P. D., Groffman, P. M., & Morgan, R. P. (2005). The urban stream syndrome: current knowledge and the search for a cure. *Journal of the North American Benthological Society, 24*(3), 706-723.

Wang, D., & Cai, X. (2010). Comparative study of climate and human impacts on seasonal baseflow in urban and agricultural watersheds. *Geophysical Research Letters, 37*(6).

Wang, G., Liu, J., Kubota, J., & Chen, L. (2007). Effects of land-use changes on hydrological processes in the middle basin of the Heihe river, Northwest China. *Hydrological processes, 21*(10), 1370-1382.

Wang, G., Yang, H., Wang, L., Xu, Z., & Xue, B. (2014). Using the SWAT model to assess impacts of land use changes on runoff generation in headwaters. *Hydrological processes, 28*(3), 1032-1042.

Wang, G., Zhang, J., Pagano, T., Lin, J., & Liu, C. (2011). Identifying contributions of climate change and human activity to changes in runoff using epoch detection and hydrologic simulation. *Journal of Hydrologic Engineering, 18*(11), 1385-1392.

Wang, J., Zhang, S., & Guo, Y. (2019). Analyzing the impact of impervious area disconnection on urban runoff control using an analytical probabilistic model. *Water Resources Management, 33*(5), 1753-1768.

Wang, M., Zhang, D. Q., Su, J., Dong, J. W., & Tan, S. K. (2018). Assessing hydrological effects and performance of low impact development practices based on future scenarios modeling. *Journal of cleaner production, 179*, 12-23.

Wang, S., Wang, Y., Ran, L., & Su, T. (2015). Climatic and anthropogenic impacts on runoff changes in the Songhua River basin over the last 56years (1955–2010), Northeastern China. *Catena, 127*, 258-269.

Wang, Y.-m., Li, Y.-j., Cheng, S.-j., Yang, F.-t., & Chen, Y.-t. (2015). Effects of spatial-temporal imperviousness on hydrological responses of various areas in an urbanized watershed. *Water Resources Management, 29*(10), 3551–3567.

Warwick, J., & Tadepalli, P. (1991). Efficacy of SWMM application. *Journal of Water Resources Planning and Management, 117*(3), 352-366.

Water, M. (2005). *WSUD engineering procedures: stormwater*. Clayton, Victoria, Australia: CSIRO PUBLISHING.

Weng, Q. (2001). Modeling urban growth effects on surface runoff with the integration of remote sensing and GIS. *Environmental Management, 28*(6), 737-748.

Wijesiri, B., Egodawatta, P., McGree, J., & Goonetilleke, A. (2016). Understanding the uncertainty associated with particle-bound pollutant build-up and wash-off: a critical review. *Water Research, 101*, 582-596.

Willmott, C. J. (1984). On the evaluation of model performance in physical geography. In G. L. Gaile & C. J. Willmott (Eds.), *Spatial statistics and models* (Vol. 40, pp. 443-460). Berlin/Heidelberg, Germany: Springer.

Worqlul, A. W., Ayana, E. K., Maathuis, B. H., MacAlister, C., Philpot, W. D., Leyton, J. M. O., & Steenhuis, T. S. (2018). Performance of bias corrected MPEG rainfall estimate for rainfall-runoff simulation in the upper Blue Nile Basin, Ethiopia. *Journal of Hydrology, 556*, 1182-1191.

Wright, T. J., Liu, Y., Carroll, N. J., Ahiablame, L. M., & Engel, B. A. (2016). Retrofitting LID practices into existing neighborhoods: is it worth it? *Environmental Management, 57*(4), 856-867.

Xu, C.-y. (2002). *Hydrologic models*. Uppsala, Sweden: Uppsala University, Department of Earth Sciences Hydrology.

Xu, C., Jia, M., Xu, M., Long, Y., & Jia, H. (2019). Progress on environmental and economic evaluation of low-impact development type of best management practices through a life cycle perspective. *Journal of cleaner production, 213*, 1103-1114.

Xu, Y.-P., Zhang, X., Ran, Q., & Tian, Y. (2013). Impact of climate change on hydrology of upper reaches of Qiantang river basin, East China. *Journal of Hydrology, 483*, 51-60.

Yang, G., Bowling, L. C., Cherkauer, K. A., & Pijanowski, B. C. (2011). The impact of urban development on hydrologic regime from catchment to basin scales. *Landscape and Urban Planning, 103*(2), 237-247.

Yang, G., Bowling, L. C., Cherkauer, K. A., Pijanowski, B. C., & Niyogi, D. (2010). Hydroclimatic response of watersheds to urban intensity: an observational and modeling-based analysis for the White river basin, Indiana. *Journal of Hydrometeorology, 11*(1), 122-138.

Yang, J.-j., ZHOU, J.-z., Wu, W., & Liu, F. (2005). Application of improved particle swarm optimization in economic dispatching. *Power System Technology, 2*, 29.

Yang, J. (2011). Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis. *Environmental Modelling & Software, 26*(4), 444-457.

Yang, J., Entekhabi, D., Castelli, F., & Chua, L. (2014). Hydrologic response of a tropical watershed to urbanization. *Journal of Hydrology, 517*, 538-546.

Yang, J., Zhou, J., Liu, L., & Li, Y. (2009). A novel strategy of pareto-optimal solution searching in multi-objective particle swarm optimization (MOPSO). *Computers & Mathematics with Applications, 57*(11-12), 1995-2000.

Yang, L., Tian, F., & Niyogi, D. (2015). A need to revisit hydrologic responses to urbanization by incorporating the feedback on spatial rainfall patterns. *Urban Climate, 12*, 128-140.

Yang, T., Zhang, Q., Chen, Y. D., Tao, X., Xu, C. y., & Chen, X. (2008). A spatial assessment of hydrologic alteration caused by dam construction in the middle and lower Yellow River, China. *Hydrological processes, 22*(18), 3829-3843.

Yang, Y., & Chui, T. F. M. (2018). Optimizing surface and contributing areas of bioretention cells for stormwater runoff quality and quantity management. *Journal of Environmental Management, 206*, 1090-1103.

Yao, L., Wei, W., & Chen, L. (2016). How does imperviousness impact the urban rainfall-runoff process under various storm cases? *Ecological Indicators, 60*, 893-905.

Yazdi, M. N., Sample, D. J., Scott, D., Owen, J. S., Ketabchy, M., & Alamdari, N. (2019). Water quality characterization of storm and irrigation runoff from a container nursery. *Science of the Total Environment, 667*, 166-178.

Yen, B. C. (1993). Criteria for evaluation of watershed models. *Journal of Irrigation and Drainage Engineering, 119*(3), 429-442.

You, L., Xu, T., Mao, X., & Jia, H. (2019). Site-Scale LID-BMPs Planning and Optimization in Residential Areas. *Journal of Sustainable Water in the Built Environment, 5*(1), 05018004.

Zartman, R., Ramsey, R., & Huang, A. (2001). Variability of total and dissolved elements in stormwater runoff. *Journal of Soil and Water Conservation, 56*(3), 263-266.

Zhang, G. (2009). *Development of a multi-objective optimization framework for implementing low impact development scenarios in an urbanizing watershed.* (Doctoral thesis, The Pennsylvania State University), Retrieved from https://etda.libraries.psu.edu/catalog/10187.

Zhang, J., & Wang, G. (2007). Impacts of climate change on hydrology and water resources. *Science and Technology Press*, 138-181.

Zhang, J., Wang, G., He, R., & Liu, C. (2009a). Variation trends of runoffs in the middle Yellow river basin and its response to climate change. *Advances in Water Science, 20*(2), 153-158.

Zhang, J., Wang, G., He, R., & Liu, C. (2009b). Variation trends of runoffs in the Middle Yellow River basin and its response to climate change. *Adv Water Sci, 20*(2), 153-158.

Zhang, J., Wang, G., Pagano, T., Jin, J., Liu, C., He, R., & Liu, Y. (2012). Using hydrologic simulation to explore the impacts of climate change on runoff in the Huaihe river basin of China. *Journal of Hydrologic Engineering, 18*(11), 1393-1399.

Zhang, K., & Chui, T. F. M. (2018). A comprehensive review of spatial allocation of LID-BMP-GI practices: strategies and optimization tools. *Science of the Total Environment, 621*, 915-929.

Zhou, Y., Wang, Y., Gold, A. J., & August, P. V. (2010). Modeling watershed rainfall–runoff relations using impervious surface-area data with high spatial resolution. *Hydrogeology Journal, 18*(6), 1413-1423.

Zhu, H., Xu, Y., Yan, B., & Guan, J. (2012). Snowmelt runoff: a new focus of urban nonpoint source pollution. *International Journal of Environmental Research and Public Health, 9*(12), 4333-4345.

Zhu, Z., Chen, Z., Chen, X., & Yu, G. (2019). An assessment of the hydrologic effectiveness of low impact development (LID) practices for managing runoff with different objectives. *Journal of Environmental Management, 231*, 504-514.

Zitzler, E., & Thiele, L. (1998). *Multiobjective optimization using evolutionary algorithms-a comparative case study.* Paper presented at the 5th International Conference on Parallel Problem Solving from Nature-PPSN V, Amsterdam, The Netherlands.

LIST OF PUBLICATIONS AND PAPERS PRESENTED

1- **Rezaei A. R.,** Ismail Z., Niksokhan M. H., Dayarian M. A., Ramli A. H., & Shirazi S. M. (2019). A quantity–quality model to assess the effects of source control stormwater management on hydrology and water quality at the catchment scale. *Water*, 11(7), 1415 (ISI-Indexed).

2- **Rezaei A. R.,** Ismail Z., Niksokhan M. H., Ramli A. H., Mohh Sidek L., & Dayarian M. A. (2019). Investigating the effective factors influencing surface runoff generation in urban catchments – A review. *Desalination and Water Treatment*, 1-17 (ISI-Indexed).

3- **Rezaei A. R.,** Ismail Z., Niksokhan M. H., Dayarian M. A., Ramli A. H., & Yusoff S. (2019). Optimal implementation of low impact development for urban stormwater quantity and quality control using multi-objective optimization. E*nvironmental Monitoring and Assessment* (Under review).

4- **Abdul Razaq REZAEI**, Mohamed Roseli ZAINAL ABIDIN, Shatirah MOHAMED AKIB, Devi PEECHMANI (2014). Benefits and Site Storage Requirement Design Concept of Porous and Permeable Pavements in Tropical Areas. 13th International Conference on Urban Drainage, Sarawak, Malaysia, 7-12 September 2014 (Conference proceedings).