Development of innovative modelling techniques for improving urban drainage design of high complexities

Lu, Wei

2020

Lu, W. (2020). Development of innovative modelling techniques for improving urban drainage design of high complexities. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/137349>

<https://doi.org/10.32657/10356/137349>

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**DEVELOPMENT OF INNOVATIVE MODELLING
TECHNIQUES FOR IMPROVING URBAN DRAINAGE
DESIGN OF HIGH COMPLEXITIES**

LU WEI
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

2020

**DEVELOPMENT OF INNOVATIVE MODELLING
TECHNIQUES FOR IMPROVING URBAN DRAINAGE
DESIGN OF HIGH COMPLEXITIES**

LU WEI

School of Civil and Environmental Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Qin Xiaosheng

Authorship Attribution Statement

This thesis contains materials from 4 papers (published or in preparation) in the following peer-reviewed journals where I was the first author.

Chapter 3 is published as Lu, W., Qin, X. S. & Jun, C. (2019). A Parsimonious Framework of Evaluating WSUD Features in Urban Flood Mitigation. *Journal of Environmental Informatics*, 33(1). DOI:10.3808/jei.201700373

The contributions of the co-authors are as follows:

- I initiated the research idea, carried out most of the modeling works, designed the computer codes, analyzed the data and prepared the manuscript draft.
- Associate Professor Qin Xiaosheng provided the initial project direction, edited the manuscript structures, provided the original model files, and helped revise the manuscript. Dr. Jun further revised the manuscript and provided suggestions on analyzing the data.

Chapter 4 is published as Lu, W. & Qin, X. S. (2019). An Integrated Fuzzy Simulation-Optimization Model for Supporting Low Impact Development Design under Uncertainty. *Water Resources Management*. DOI: 10.1007/s11269-019-02377-7

The contributions of the co-authors are as follows:

- I initiated the research idea, carried out most of the modelling work, designed the computer codes, analyzed the data and drafted the manuscript.
- Associate Professor Qin Xiaosheng helped revise the manuscript, verify the result and analyze the data.

Chapter 5 is published as Lu, W., Qin, X., & Yu, J. (2019). On Comparison of Two-Level and Global Optimization Schemes for Layout Design of Storage Ponds. *Journal of Hydrology*. DOI: 10.1016/j.jhydrol.2018.10.078.

The contributions of the co-authors are as follows:

- I initiated the research idea, carried out most of the modelling work, designed the computer codes, analyzed the data, and prepared the draft of the manuscript.
- Associate Professor Qin Xiaosheng helped revise the manuscript and verify the result.
- Dr. Yu Jianjun provided suggestions on the coding of modeling platform, and helped further revise the manuscript.

Chapter 6 is published as Lu, W. & Qin, X. S. (2019). Integrated Framework for Assessing Climate Change Impact on Extreme Rainfall and Urban Drainage. *Hydrology Research*. DOI: 10.2166/nh.2019.233

The contributions of the co-authors are as follows:

- I co-initiated the research idea with Associate Professor Qin Xiaosheng, carried out most of the modelling work, designed the computer codes, analyzed the data, and prepared the draft of the manuscript.
- Associate Professor Qin Xiaosheng suggested the steps of modeling works and helped revise the manuscript.

17/03/2020

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17/03/2020

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Lu Wei

ACKNOWLEDGEMENTS

The author wishes to express his heartfelt appreciation to his supervisor, Associate Professor Qin Xiaosheng, for his valuable time, guidance and patience starting from the author's application process and never stopping in the last four years. His invaluable advice, support and enlightenment have led the author to go forward and complete his PhD program, and further establish his career goal in life.

The author also wishes to extend his sincere appreciation to his seniors, Dr. Yu Jianjun, Dr. Changyun Jun, Dr. Huang Ying, Dr. Dai Chao, and Ms. Min Rui for their patience and help in the research works. The author appreciates Elsevier for authorizing him to include the published article in this thesis.

The author is deeply grateful to his parents Mr. Lu Xincan and Ms. Wu Geyang for their unconditional, steadfast and kindly support in the last 26 years since he was born. They always told him to be a broad-minded person, and a striver who will never give up.

Finally, the author would say thanks to his dear wife Chen Siyi (an alumna of NTU), for her selfless love and support.

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SUMMARY

Urban drainage system is one of the most critical urban infrastructures to accommodate extensive rainfall to avoid urban flood damages. However, urbanization and the increasing climatic extremes have challenged the existing drainage systems in many places with sufficient capacity to adapt to escalated frequency and severity of extreme rainfalls. Modelling and optimization techniques have been developed and adopted in urban drainage designs in recent years, in order to achieve a trade-off between infrastructure investment and other conflicting objects such as water quality control, flood resilience and rainwater retention. This PhD research topic will focus on exploring various novel modelling techniques, involving statistical, simulation, optimization, surrogate emulator, climate change impact assessment and uncertainty analysis to help improve the cost-effectiveness of urban drainage designs of high complexities. This thesis summarized the research works done by the author towards the objective of the PhD topic. In Chapter 2, the previous studies conducted by other researchers, which were related to low impact development design, drainage system optimization, uncertainty analysis of urban drainage modelling and optimization, flood damage evaluation and climate change impact assessment on urban drainage systems were reviewed. In the following chapters, four major research works were presented.

In Chapter 3, a parsimonious framework was introduced for evaluating LID features in urban flood mitigation. A hydrological simulation model was established based on a tropical urban catchment. Then, parameters were customized to enable a two-dimensional inundation analysis component of the model. Sensitivity test was carried out to determine the range of variables for three types of LID features. It was found that, the inundation depth and area were both notably affected by the types and layout parameters of LID features; a linear regression model was suitable to describe the relationship between the system cost and the flood damage cost.

As the reliability and precision of urban drainage system and LID designs were affected by a variety of uncertainties, Chapter 4 explored an integrated fuzzy simulation-optimization model (FSOM) for supporting LID design under uncertainty.

Various LID implementation schemes, along with fuzzy model parameters, were embedded into a hydrological simulation model. Fuzzy simulation (FS) and genetic algorithm (GA) were employed to search the optimal schemes of LIDs under various flood control objectives. A comparison of FSOM to two traditional optimization models (e.g. stochastic model and deterministic model) were also given.

The simulation-optimization models were traditionally aided by heuristic methods (like GA), which was time-consuming and also challenging in reaching convergence for large-scale problems with wide decision spaces. Chapter 5 proposed a novel optimization scheme, denoted as two-level optimization (TO) scheme, for supporting rainwater storage pond design in an existing urban drainage system. The TO scheme firstly sought the optimal layout of storage ponds on tributary sub-watersheds, and then proceeded to that of the mainstream one to yield the final solution. Through a case study, the TO scheme was compared with a global optimization (GO) scheme. The results showed that the proposed TO scheme is a prominent alternative to the traditional GO scheme.

Urban areas are becoming increasingly vulnerable to extreme storms and flash floods that are exacerbated by climate change. Chapter 6 presented an integrated framework for assessing climate change impact on extreme rainfall and urban drainage systems. Through a case study in the tropical city, the impact of selection of different general circulation models (GCMs) and Huff distributions on future extreme rainfall and performance of urban drainage were investigated. The proposed framework was flexible and easy-to-implement in generating high temporal-resolution rainfall data under GCM projections, and could offer a summary method of assessing urban flood risks considering the uncertainty arising from climate model projections, downscaling and rainfall design.

Although the above four Chapters adopted different cases and had their own research focuses, these studies and results all contributed to a better understanding of the complexities of urban drainage design (e.g. climate change impact, uncertainties, and novel drainage facilities, etc.), which is the general theme of this thesis. Some

challenging issues are identified in achieving robust design of urban drainage systems and LID features. For large-scale urban catchments, building and calibrating hydrological models with high spatial resolution is normally time-consuming and computationally intensive, and multi-site correlation issues may have to be addressed by using more sophisticated weather generators. In addition, when carrying out simulation-optimization studies for supporting drainage and LID design, uncertainties widely exist in different components such as rainfall, model selection and economic statistics. These uncertainty issues are desired to be tackled in the future research works.

LIST OF PUBLICATIONS

Peer-Reviewed Journal Papers

Lu, W., Qin, X. S., & Jun, C. (2019). A Parsimonious Framework of Evaluating WSUD Features in Urban Flood Mitigation. *Journal of Environmental Informatics*, 33(1). DOI:10.3808/jei.201700373

Lu, W., Qin, X., & Yu, J. (2019). On Comparison of Two-Level and Global Optimization Schemes for Layout Design of Storage Ponds. *Journal of Hydrology*. DOI: 10.1016/j.jhydrol.2018.10.078

Wei Lu and Xiaosheng Qin. (2019). Integrated Framework for Assessing Climate Change Impact on Extreme Rainfall and Urban Drainage. *Hydrology Research*. DOI: 10.2166/nh.2019.233

Wei Lu and Xiaosheng Qin. (2019). An Integrated Fuzzy Simulation-Optimization Model for Supporting Low Impact Development Design under Uncertainty. *Water Resources Management*. DOI: 10.1007/s11269-019-02377-7

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Lu, W., Qin, X.S. and Jun, C.H. (2016). Urban flood damage assessment for water sensitive urban design. In *Proceedings of the 2nd Urban Planning and Property Development (UPPD 2016)*, Singapore, 10-11 October 2016, pp. 90-93. DOI: 10.5176/0000-0000_UPPD.32

Lu, W., Qin, X. and Yu, J. (2017). Emulator-aided optimization of detention tanks for flood reduction. In *Proceedings of the 37th IAHR World Congress*, Kuala Lumpur,

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Lu, W. and Qin, X. (2019). A Generator-Disaggregation Approach for Evaluating Climate Change Impact on Urban Drainage. *In International Conference on Urban Drainage Modelling* (pp. 363-368). Springer, Cham.

Jun, C., Qin, X. and Lu, W. (2019). Temporal Pattern Analysis of Rainstorm Events for Supporting Rainfall Design in a Tropical City. *In International Conference on Urban Drainage Modelling* (pp. 380-384). Springer, Cham

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LIST OF ABBREVIATIONS

2d	Two-dimensional
AAD	Average annual damage
AHP	Analytic hierarchy process
ANN	Artificial neural network
BC	Bio-retention cell
BCD	Bias correction and disaggregation
BMP	Best management practice
CA	Commercial areas
CCP	Chance-constrained programming
CDF	Cumulative distribution function
CFA	Change factor approach
CN	Curve number
CNMS	Constrained nonlinear minimization solver
DEM	Digital elevation model
FCCP	Fuzzy chance-constrained programming
FF	Fitness function
FS	Fuzzy simulation
FSOM	Fuzzy simulation-optimization model
GA	Genetic algorithm
GCM	Global circulation model
GEV	Generalized extreme value
GIS	Geographic information system
GO	Global optimization
GR	Green roof
KNN	K-nearest neighbor
LARS-WG	Long Ashton research station weather generator
IDF	Intensity-duration-frequency
LHS	Latin hypercube sampling
LID	Low impact development
MCS	Monte-Carlo simulation
MF	Membership function

MOO	Multi-objective optimization
PCSWMM	Personal computer storm water management model
PP	Permeable pavement
PSO	Particle swarm optimization
RA	Residential areas
RCM	Regional climate model
RCP	Representative concentration pathways
RSA	Response surface analysis
SA	Simulated annealing
SDSM	Statistical downscaling method
SF	Scaling factor
SP	Start points
SVR	Support vector regression
SWG	Stochastic weather generator
SWMM	Storm water management model
TO	Two-level optimization
UDS	Urban drainage system
WSUD	Water sensitive urban design

CHAPTER 1. INTRODUCTION

1.1 Background

An urban drainage system is an essential infrastructure for the development of urban areas due to the interaction between urban residents and natural water cycle. There are two types of water that need to be drained in urban areas. The first one is wastewater, which may cause pollution if not drained properly; the second one is stormwater, which may bring along inconvenience to urban dwellers, or even flood damage if not drained timely (Butler and Davies, 2004). In a word, urban drainage systems deal with these two types of water for the propose of minimizing the risks to public health and environment.

Thus, urban drainage presents a modern environmental challenge: the need for cost-effective and socially acceptable improvement in an existing system to achieve the tradeoff among investment and other conflicting objects such as water quality control, flood resilience and rainwater retention. Techniques and practices towards urban drainage optimization have been increasingly developed around the world, which include many complexities associated with modern drainage designs, like the new development ideas of water sensitive urban design (WSUD) originated in Australia and low impact development (LID) in North America. These complexities focus on integrating management of water cycle into an urban planning process, and involve many types of features (e.g. permeable pavement, rain garden and bioretention cell), mostly targeting at retaining rainfall, reducing runoff during storm events and improving quality of infiltrated water. As a result, these features play important roles in improving drainage capacity and mitigating urban flood damage.

Over the past years, modelling techniques have emerged as robust tools to aid the planning and design of such features and drainage network. One of the popular methods was to dynamically link a simulation model with an optimization framework that targeted at a specific design of the drainage network or layout (Cibin and Chaubey 2015; Kalcic et al. 2014). Also, from the previous studies, choosing an efficient optimization algorithm was critical for achieving effective convergence of

solutions (Cibin and Chaubey 2015). Evolutionary optimization algorithms such as Genetic Algorithm (GA) (Holland 1992), Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al. 2002) and Simulated Annealing (SA) were popular choices among many optimal designs of storage facilities (Cimorelli et al. 2016; Cunha et al. 2016; Yu et al. 2017). Nevertheless, GA and its peer algorithms still had problems in global convergence and high computational cost if the optimization problem was of a large scale and involved significant number of decision variables.

Moreover, among studies related to urban drainage system and LID designs, the reliability and precision of the design results were challenged by a variety of uncertainties, which could be broadly classified as stochastic (i.e. inherent variation of the systems) and epistemic (i.e. lack of human cognition for the systems) (Fu et al. 2011). In general, uncertainties were intrinsically associated with different components of urban drainage modelling and LID design processes such as rainfall design, model parameters, model structures and economic statistics (Fu et al. 2011; Duan et al. 2016). Therefore, in a comprehensive planning and design framework, the capability of tackling these uncertainty issues was essential. Fuzzy set theory (Zadeh 1965) and stochastic theory based approaches such as Monte Carlo Simulation (MCS) and chance-constrained programming (CCP) (Charnes and Cooper, 1959) were popularly adopted for characterizing and restricting uncertainties.

1.2 Purpose and scope

This thesis is a write up on the research progress of the candidate over the past four years, including literature review, four major studies and an outlook for future works. Based on the literature review, the research gaps are briefly summarized as follows:

- 1) Very limited studies tried to integrate multiple LIDs into a general study framework and investigate their economic effectiveness in mitigating flood risk.
- 2) Uncertainty assessment is important in the field of LID design or urban drainage modeling, whereas the relevant studies are rather limited. Most of previous optimization models are deterministic without enough capability to address how the constraints could be satisfied in a probabilistic manner.

- 3) Genetic Algorithm (GA) has been used widely for identifying ‘optimal’ solutions, but GA has difficulty in obtaining global optimal solutions for large-scale or high-dimensional problems. Thus, there is a need to consider strategies to scale down or simplify the problem.
- 4) Few studies use holistic approaches to tackle downscaling, disaggregation, rainfall design and hydrological simulation for assessing climate change impact on urban drainage systems.

The following block diagram (Figure 1.1) shows the overall structure and connection of the thesis work. The overall research goal is to propose a framework for simulation-optimization-based drainage and LID design of high complexities. The framework integrates various novel modeling techniques, involving statistical analysis, simulation, optimization, surrogate modeling, climate change impact assessment and uncertainty analysis to help improve the cost-effectiveness of urban drainage system designs. The detailed research tasks involve:

- 1) Evaluating the effect of LID features on urban flood mitigation based on a two-dimensional hydrological platform;
- 2) Establishing an integrated simulation-optimization model for supporting LID design under fuzzy environment;
- 3) Proposing novel optimization schemes for layout design of storage ponds;
- 4) Assessing climate change impact on extreme rainfall and urban drainage system under uncertainty;
- 5) Summary of research findings and discussions on potential future works.

Fig. 1.1 Overall structure and connection of the thesis work

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

2.1.1 Principles and practices of urban drainage: concepts and objectives

Urban drainage is a very old field, which can be tracked back to around 3000 BC (Burian & Edwards 2002). The field mainly works on conveying water away from urban areas and controlling flood risk caused by large impervious surfaces (Coutts et al. 2012). While in recent years, the management of urban drainage has become increasingly complicated as it involves many novel concepts such as low impact development (LID) and water sensitive urban design (WSUD). Both concepts involve facilities that focus on detaining water in the urban area through harvesting and infiltration into soils to meet both ecological and financial goals (Coutts et al. 2012), and can be applied across the entire spatial scale (from a catchment-wide regional level to a local building level) (Wong 2006). Representative LIDs can also be categorized into two dominating groups according to their emphasis, with one group focusing on water quality and the other on water quantity (see Table 2.1; adapted from Government of South Australia 2013). As this thesis mainly deals with urban flooding issues, the role of LIDs is emphasized on the water quantity part.

Table 2.1 Overview of common LID (Government of South Australia 2013)

Feature	Focus of LID		Potential benefits	Establishment sites
	Water quality	Water quantity		
Rainwater tanks	Low	High	Reductions in water supply	Proximity to roofs
Rain gardens	Medium	High	Runoff reduction & water quality improvement	Allotment scale
Green roofs	Medium	Medium	Water retention & biodiversity	Flat roofs
Pervious pavements	High	Medium	Runoff detention & sediment export minimization	Allotment areas
Rainwater storage ponds	Medium	High	Reductions in water supply	Areas with a lot of space
Constructed wetlands	Medium	High	Runoff reduction & water quality improvement	Big areas of flat land

2.1.2 Representative LID measures

2.1.2.1 Green roof

Green roofs are capable of retaining rainwater on the roof surface to relieve the stress of urban drainage system, meanwhile lower the thermal loading on buildings by cooling surface layer and inner space under high temperature condition. The design of green roof is usually sophisticated, comprising various abiotic (e.g. dimensions and composition of substrate and drainage layer) and biotic (e.g. substrate chemistry and composition of plant species) variables (Simmons et al. 2008). Figure 2.1 shows a traditional vertical structural component of green roof. Kok et al. (2016) evaluates both qualitative and quantitative effects of an extensive green roof system under tropical climate, and found that the peak discharge of runoff was reduced effectively (up to 26%) compared to a concrete tile roof, whereas the performance of the system was degraded for storms with high intensity. Besides, after installation of the system, there was a slight decrease for the building's indoor temperature.

Fig. 2.1 Structural of a typical green roof platform (Simmons et al. 2008)

2.1.2.2 Rain garden

Rain gardens are shallow depressions which are landscaped with water-tolerant plants, and the soil is processed by soil amendments to increase the water permeability of soil. With stormwater channeled into vegetated basins or trenches with porous filtration media, rain gardens play a role in reducing peak runoff flow rates and volumes, promoting infiltration and evapotranspiration, and improving water quality (DeBusk et al. 2011). Yang et al. (2013) introduced a newly designed biphasic rain garden which consists of a biphasic (water saturated to unsaturated) sequence and a recharge zone (see Figure 2.2), and runoff is first drained into the water saturated

zone followed by the water unsaturated zone.

Fig. 2.2 three-dimensional drainage configuration of the experimental biphasic rain garden (Yang et al. 2013)

2.1.2.3 Rainwater detention tanks/ponds

Rainwater detention tanks or ponds retain runoff during a rainfall event, then release it to the downstream part of drainage system at controlled rates. These detention tanks could be implemented above ground alongside buildings, or underground. Chapman and Horner (2010) observed a detention tank near the street and found that it could achieve 26-52% of runoff retention, as well as most of the incoming pollutants in real-weather conditions of Washington. Huang et al. (2015) adopted rainwater harvesting systems for the spatial design of capacities and quantities of rainwater harvesting tanks (which were implemented on rooftops) for urban flood mitigation, based on a simulation-optimization model and a back-propagation neural network.

2.1.2.4 Permeable pavement

Permeable pavement is suitable for a wide variety of industrial, residential and commercial applications (Scholz and Grabowiecki 2007). Figure 2.3 illustrates a typical vertical structure of a permeable pavement, which usually consists of multiple layers from top to bottom: (1) a surface, (2) a base, (3) a geotextile, (4) a subbase and (5) an impervious membrane. The main objective is to collect, treat and drain any surface runoff for supporting groundwater recharge and removing pollutant like suspended solids.

Fig. 2.3 Typical structure of a permeable pavement (Scholz and Grabowiecki 2007)

2.1.3 Urban flood risks

According to the definitions proposed by Kron (2002), there were three factors determine a risk: hazard, exposure and vulnerability; mathematically, risk is formulated as the product of these three factors. Various research works related to urban flood risk assessment in recent years have been reported. For examples, Oliver and Santoro (2000) put forward an empirical relationship between the urban flood damage and event return period for the city of Palermo. Bouwer et al. (2009) developed a method to simulate inundation and calculate urban flood damage in Netherland. De Moel and Aerts (2011) established a flood risk model combined with uncertainty components estimate urban flood damage. Ward et al. (2011) developed a GIS-based tool for inundation mapping and damage estimation in city of Jakarta, Indonesia. They combined inundation maps (generated by inundation model), land use maps and economic datasets for calculating damage exposure. Recently, Mahmoud and Gan (2018) developed an approach for comprehensive flood susceptibility mapping (shown in Figure 2.4) and applied it to two governorates of Egypt. Compared with past studies related to flood susceptibility mapping, this approach incorporates 11 flood contributing factors (e.g. land use and soil type) and ranked these factors based on their susceptibility levels in relation to flooding.

Fig. 2.4 Flowchart of flood susceptibility mapping (Mahmoud and Gan 2018).

2.1.4 Hydrologic simulation and inundation analysis models

In the research works of this thesis, the EPA Storm Water Management Model (SWMM) is employed as the primary model for urban hydrologic simulations. Other models like MIKE URBAN (DHI 2020) could also be an alternative based on proper calibrations. SWMM is a dynamic rainfall-runoff model for collecting rainfall and generating runoff through the drainage networks (e.g. pipes, channels, storage/treatment units and diversion structures) (Aad et al. 2009). Also, the quality and quantity of runoff generated within each sub-catchment can be tracked. To further investigate the overland urban flood, PCSWMM is adopted to carry out two-dimensional (2D) inundation analysis. The model fully integrates hydrology and hydraulics engine and principles of SWMM, and is capable of addressing various hydrologic processes like rainfall, evaporation, inter-flow between groundwater and drainage system (Lu et al. 2019a). Particularly, PCSWMM is specialized in modeling multifarious flow regimes and 2D flood routing, which can be useful for a reliable assessment of urban flood damage.

2.1.5 Climate change impact on urban drainage

Climate change is projected to pose profound impact on many aspects of water resources systems and the number and severity of extreme storms are expected to

increase over many urban areas around the world (Fischer & Knutti 2016; IPCC 2007; Olsson et al. 2009). As such extreme events would elevate the risk of flash flood problems, it is imperative to address climate change effect when improvement of current drainage systems or design of new systems are needed for long-term usage. Willems (2013) statistically analyzed and downscaled a large ensemble of global circulation model (GCMs) and local regional climate models (RCMs) at Belgium. After identifying climate change impact on the local intensity-duration-frequency (IDF) curves, the study established a conceptual reservoir model to quantify the peak runoff and flood volume under future extreme rainfall events. The study claimed that the intensity of 10-year rainfall can increase up to a half by the end of this century; consequently, the storage capacity needs to be increased by around 50% to keep the future flood frequency at the current level. Neumann et al. (2015) employed three GCMs to project future climate scenarios and established a simplified model to address the excessive runoff volume and adaptation costs for urban drainage systems in 19 cities of US.

2.1.6 Climate downscaling techniques and weather generators

Over the past decades, a fairly large number of research works have been reported to assess climate change impacts on rainfall extremes and urban drainage systems. Most of these studies relied on combinative efforts of GCM projection, climate downscaling, weather generators and hydrological simulations (Alamdari et al. 2017; Bi et al. 2017; Herath et al. 2016; Langeveld et al. 2013; Lu & Qin 2014; Mikovits et al. 2017; Semadeni-Davies et al. 2008a; Semadeni-Davies et al. 2008b; Sharma et al. 2007; Shrestha 2013; Willems et al. 2012). More recently, Shrestha et al. (2017) proposed a spatial downscaling and temporal disaggregation method for developing future IDF curves using the LARS-WG (Semenov & Stratonovitch 2015) and rainfall disaggregation tool HYETOS (Koutsoyiannis & Onof 2001). A correction factor for bias elimination was adopted to mitigate the underestimation problem encountered in calibrating the modelled data by using observed IDF curves. The obtained future IDF curves (from 2011 to 2030) under 5-year return periods and two emission scenarios are picked up for comparison with present IDFs (from 1981 to 2010). Kristvik et al. (2018) applied an integrated spatial-temporal downscaling method which combined

Statistical DownScaling Model-Decision Centric and Generalized Extreme Value (GEV) distribution to predict future rainfall and generate IDF curves in the city of Bergen.

2.1.7 Uncertainty analysis techniques in urban drainage system and LID design

The reliability and precision of urban drainage system and LID designs are often challenged by a variety of uncertainties, given the complexity and extent of uncertainty sources involved. The uncertainty sources can be broadly classified as stochastic (i.e. inherent variation of the systems) and epistemic (i.e. lack of human cognition for the systems) (Fu et al. 2011). Concretely, uncertainties are intrinsically associated with different design components including rainfall design, model parameters, model structures and economic statistics (Duan et al. 2016). Among various countermeasures, it was found that the stochastic theory based approaches, such as probability-distribution-based MCS and CCP (Charnes and Cooper 1959), were popularly adopted for characterizing random information and restricting uncertainties. Besides stochastic approaches, other alternatives such as interval and fuzzy approaches can also be adopted for handling uncertainty based on data availability and quality. For instance, fuzzy set theory is proficient in representing features of imprecision and vagueness and interval theory is good at describing the extreme conditions of uncertain data at the cost of low quality of information (Xu and Qin 2014).

From the previous studies, the probabilistic distributions of model parameters could be challenging to obtain if the related data is limited or at low precision (He et al. 2008); also, certain type of uncertainty may not be suitable to be described as stochastic, like vagueness originated from subjective knowledge (Ross et al. 2009). In contrast, fuzzy set theory is relatively flexible in defining uncertain parameters using membership functions, which can be defined based on public survey or expert experience using limited data. For instance, based on an engineer's experience or available data points, one could simply use the maximum and minimum possible values, plus the most likely value to generate the membership function of a fuzzy parameter (Xu and Qin 2014). Therefore, it has been widely used in many fields

(Combettes 1993; Kruse et al. 1994; Fu et al. 2011). The most common applications of fuzzy set theory include fuzzy chance-constrained programming (FCCP), fuzzy simulation (FS) and fuzzy vertex.

Monte Carlo Simulation (MCS) is a statistical tool that relying on repeating model executions under the whole range of inputs to approximate the distributions of the predictions based on the output samples (Yu et al. 2013). According to Saltelli et al. (2000), it consists of several steps: (1) identification of target variables for analysis; (2) for each target variable, selecting the corresponding PDF with required parameters; (3) generation of outputs based on selected variables and model execution; (4) statistical analysis of outputs to get the cumulative distribution function (CDF).

Chance-constrained programming (CCP) allows the decision makers to evaluate constraints in terms of the probability of their satisfaction, α , which is referred to as the confidence level (Charnes and Cooper 1959; Liu and Iwamura 1998). When CCP comes into a fuzzy environment, it is called a FCCP model, which could be formulated as follows (Huang 1998):

$$\text{Minf}(\bar{x}, \xi) \quad (2.1a)$$

subject to:

$$\text{Poss}\{h_i(\bar{x}, \xi) \leq 0 | \xi\} \geq \alpha_i, i = 1, 2, \dots, m \quad (2.1b)$$

$$g_j(\bar{x}) \leq 0, j = 1, 2, \dots, n \quad (2.1c)$$

where f is the objective function with vector of decision variables $\bar{x}$ and matrix of fuzzy parameters ξ ; h and g are the constraint functions with and without fuzzy parameters, respectively; $\text{Poss}\{\cdot\}$ is the possibility of fuzzy events in $\{\cdot\}$; α_i is the predetermined confidence level in i^{th} fuzzy chance constraints; m and n are the total numbers of i and j , respectively.

However, in the field of LID design or urban drainage modeling, the relevant studies which adopt fuzzy set theory for handling uncertainty are rather limited. One example was given by Yazdi and Neyshabouri (2014), who presented an approach to deal with both hydrological uncertainties and curve number (CN) parameter uncertainties for identifying optimal LID implementation schemes. As the performance of LIDs was affected by CN parameters, these CN parameters were characterized by using fuzzy membership functions (MFs). Fuzzy CNs would consequently lead to uncertain hydrographs (particularly, peak flows for various subcatchments), uncertain water surfaces and fuzzy flood damages. They also established a multi-objective optimization model to minimize both investment cost and expected flood damages, for identifying cost-effective combinations of LIDs. Another study was recently reported by Jato-Espino et al. (2014), who tried to use analytic hierarchy process (AHP) to capture the vagueness of subjective knowledge and convert the judgment of experts into fuzzy sets. These fuzzy sets were combined with MCS to evaluate the aggregate performance (e.g. cost, flexibility and aestheticity) of three types of pervious pavements. However, both the above-mentioned studies lacked a physical simulation model.

2.1.8 Optimization algorithms

Since implementation of hydrological facilities (e.g. LIDs) and rehabilitation of urban drainage systems generally involve significant investment, their designs would need careful consideration on tradeoffs among environmental, social and economic factors (Cunha et al. 2016). Over the past years, optimization techniques have emerged as robust tools for facilitating the cost-effective design, and a number of studies were reported in urban drainage modelling and optimization (Thorndahl and Willems 2008; Freni et al. 2009; Chang et al. 2011; Dotto et al. 2012; Fu and Kapelan 2013). From the previous studies, one of the popular methods was to dynamically link a simulation model (e.g. SWMM) with an optimization framework that targeted at a specific design of the drainage network or layout (Cibin and Chaubey 2015; Kalcic et al. 2014; Tao et al. 2014).

Evolutionary optimization algorithms including SA, GA and NSGA-II are popular choices among many optimal designs of storage facilities (Cimorelli et al. 2016; Cunha et al. 2016; Oxley and Mays 2014; Tao et al. 2014; Yu et al. 2017). These evolutionary algorithms are global optimization algorithms that have the potential to solve multimodal problems and find the global optima, which is difficult to be achieved by exact optimization problems like linear programming and convex nonlinear programming. Nevertheless, GA and its peer algorithms still have problems in global convergence and high computational cost if the optimization problem is of a large scale and involves significant number of decision variables (Andre et al. 2001; Kadaba and Nigard 2014; Lin and Lee 2004).

2.1.9 Surrogate models

Surrogate models (or emulators) are intermediaries for replacing the role of physical simulation model in an optimization framework, for the purpose of breaking down technical barrier of directly linking physical model with optimization algorithm or reducing the high computational burden of tautologically running the simulation-aided optimization models (Lu et al. 2019b). From the previous research, the most popular surrogate models include artificial neural network (ANN) (Sreekanth and Datta 2011), moving least squares (Yu et al. 2015b) and response surface analysis (RSA) (Seo et al. 2012). These surrogate models could be built up with multiple scenarios simulated from hydrological models, and applied to approximate the input-output hydrological relations (Yu et al. 2015a). Particularly, ANN has gained its popularity in recent decades for prediction and forecasting in many areas including environmental science and water resources. ANN has the capability of self-learning and can fit complex nonlinear relationships (Yu et al. 2015a). RSA is a general form of emulators aiming at approximating the relationships between several explanatory variables (e.g. size of LID facilities) and one or more response variables (e.g. performance of these LID measures). This is achieved by fitting the multivariate polynomials using input and output samples obtained from designed parameter sampling space. The common choice of RSA adopts a quadratic polynomial (Lucas 1976):

$$y = b_0 + \sum_{q=1}^s b_q x_q + \sum_{q=1}^s b_{qq} x_q^2 + \sum_{1 \leq q < r \leq s} b_{qr} x_q x_r + e \quad (2.2)$$

where y is the response or dependent variable; x_q is the independent experimental variables; b_0 , b_q , b_{qq} and b_{qr} are the parameters to be estimated using the data from experiment; e is the error term; q , r is the indexes for x and b ; s is the total number of variables x .

2.2 Methodologies of flood risk assessment

2.2.1 Basic framework

For most risk-based methodology, only the monetary damage is considered. The monetary damage can also be divided into direct damage (i.e. damage affecting buildings, furniture, stocks, etc.) and indirect damage (i.e. other economic consequences such as special maintenance works and cleanup costs). In this thesis, we will mainly focus on direct damage in the risk and damage calculations.

Risk map (i.e. frequency-damage map) is a key output in the process of flood risk assessment. It contains information about damage and its frequency, and can be used to calculate the expected Average Annual Damage (AAD) for a given area. As the first step of risk mapping, the hydrologic-hydraulic data, topographic data (e.g. digital elevation model) and economic data need to be collected for the study area (Lu et al. 2019a). Based on these data, an urban hydrological model is established and calibrated to simulate the drainage system, and a 2D model is customized to enable overland inundation analysis. Then, inundation maps can be obtained from the 2D model. Based on different land use categories (e.g. residential, infrastructure and traffic), the maximum damage (the replacement value of goods) can be computed by unit of length or area. Moreover, the relationship between actual damage and water depth is described by a flood damage function. The damage for a flooded area can be calculated in two steps: first, multiply the maximum flood damage of each land use type with the corresponding damage ratio; second, sum up these products for considering damage from all types of land use.

Based on the steps above, we have the basic formula for total direct damages D (Jonkman et al. 2008):

$$D = \sum_i^m \sum_r^n \alpha_i(h_r) \cdot D_{\max,i} \quad (2.3)$$

where i is the land-use category; r is the location in the flooded area; m is the number of land-use categories; n is the number of locations in the flooded area; $\alpha_i(h_r)$ is the relative damage function of inundation depth h_r ; $D_{\max,i}$ is the maximum damage (the replacement value) for land-use category i .

2.2.2 Review of case studies

2.2.2.1 Case study of flood susceptibility mapping in Egypt

Mahmoud and Gan (2018) presented a framework for flood susceptibility mapping in two governorates of Egypt, which had a total area over 10,000 km². The workflow was shown in Figure 2.4. In this work, they considered the impact of both urbanization (through CN method-based surface runoff estimation) and climate change (detected by analysis of long-term climatological data) on urban flood risk. 11 flood contributing factors were identified and mapped for the studied areas, and these factors were ranked by AHP approach. From one of the resulted flood susceptibility maps (Figure 2.5), around 60% of the total area in this zone was assigned moderate, high or very high flood susceptibility. This form of graphical presentation is generally easier for policy makers to understand and take necessary actions to mitigate potential flood damages.

Fig. 2.5 Flood susceptibility map for Beheira governorate in Egypt (Mahmound and Gan 2018).

2.2.2.2 A novel approach for flood risk assessment considering multiple uncertainties

It is noticeable that model uncertainties have a large impact on estimated flood damage (Lu and Qin 2019a). According to a review of previous literatures, the uncertainties of flood inundation modeling, which exist in data inputs (He et al. 2009), hydraulics parameters (Straatsma and Huthoff 2010) and hydraulic model structures, had been explored by stochastic approaches such as MCS, but limited researches showed their applicability in the topic of flood damage assessment. Therefore, a further step had been made by Yu et al. (2013), who used MCS to evaluate uncertainties associated with inundation modeling, meanwhile combining fuzzy

vertex analysis for promulgating human-induced uncertainty (e.g. in the derivation of damage functions). The proposed framework, so-called joint Monte Carlo and Fuzzy Possibilistic Simulation, helps quantify the uncertainty in flood damage estimation arising from the processes of flood modeling, depth-damage function acquisition and damage calculation. A floodplain was used for demonstration and the study results indicated that proposed framework could help analyze the trade-off between investment of flood risk control and allowable flood damage at a certain probability.

2.3 Review of methodologies and case studies about optimal design of urban drainage system and Low Impact Development (LID) under uncertainty

It is imperative for city planners to upgrade the existing urban drainage system for accommodating more runoff under the impact of urbanization and climate change. The optimal design of related facilities (such as detention tanks and LID measures) under the constraints of local flooding control criteria, or the trade-off problems between investment of these facilities and flood control budget, can often be tackled by optimization models (Yu et al. 2017). To tackle this issue, some previous studies on flood risk assessment and optimal design of urban drainage systems and LID have been reported.

2.3.1 Optimal location design of storage ponds for reducing urban inundation

Choi et al. (2016) proposed a novel method named Multi-Dimensional Flood Damage Analysis to calculate flood damage considering flood depth and regional condition, and determine the best layout of storage ponds within an urban drainage system. The study first divided the whole area into five subareas based on the land use condition. For each subarea, a flood volume-damage cost function was obtained by fitting the historical data to exponential regression curves. Then, based on these damage functions, the study enumerated all the candidate scenarios of layout of ponds and acquired damage of each scenario by simulating the total flood volume. Although there was huge computational burden, the proposed MD-FDA method could take advantage of regional information as well as two-dimensional simulation and reliably describe relationships between flood volume and flood damage.

2.3.2 Multi-objective optimization design of detention tanks under local design criteria and model uncertainty

Li et al. (2015) developed a multi-objective optimization (MOO) framework to design the size of rainwater detention tanks and acquired robust solution to minimize both flooding risks and engineering cost. Specifically, the objectives to be minimized include the number of flooding nodes and the total cost of detention tanks. The study tried to apply a modified Particle Swarm Optimization (PSO) combined with NSGA II (Deb et al. 2002) for solving the MOO problem under several constrains. The constraints of optimization model include the maximum area of each tank and the minimum total area of the tank (for contamination control).

As an extension to the work of Li et al. (2015), Duan et al. (2016) investigated the MOO design of detention tanks considering both local constraints and uncertainties. The optimization model was largely remaining unchanged from the previous one, except adding limitations of locations of the tanks (i.e. local design criteria). Another main difference of this study was the incorporation of uncertainties into the former framework. The results included two main parts. First, optimal solutions under several different flooding criteria (e.g. number of flooding nodes) were concluded, and an unambiguous trade-off of the cost-risk relationship was observed, i.e. a larger mean cost of detention tanks could reduce more flooding risk. Besides, uncertainties of these factors can greatly influence the design results compared to a deterministic design. Second, the sensitivity of two design objectives (i.e. total cost and flooding node number) towards the above uncertainty factors was calculated by a linear regression model, for the sake of determining factors which have relatively large impact on design results. Specifically, the study found that three factors (i.e. pipe size, rainfall intensity and catchment permeability) had most important influences towards two design objectives. As a conclusion, it was proposed to take both design criteria and uncertainty analysis into consideration for design and management of a UDS system.

2.3.3 MOO design of detention tank considering climate change

Yu et al. (2015b) applied a similar framework as Li et al. (2015) to optimize the size of detention tank, with the aim of minimizing the construction cost as well as the peak flow at outfall under different climate change scenarios. The nominated locations of detention tank were selected based on a preliminary test of drainage network. Similarly, the flood volume was constrained under a set of thresholds. For each threshold of volume, a relatively sound solution of detention size was searched through GA; meanwhile, the corresponding construction cost was calculated. Future climate change effects were also taken into consideration in the form of three hypothetical designed rainfall events with different intensities. It was demonstrated that the investment of construction would increase drastically for future scenarios to maintain the same threshold of flood volume and a similar peak flow. For example, when the hourly rainfall increases from 76 to 86 mm, the investment would double from 7.93 to 14.8 million \$.

2.3.4 Optimal Positioning and Sizing of In-Line Detention Tanks

Cimorelli et al. (2016) presented a procedure for evaluating the optimal position, configuration and dimension of detention tanks, for the purpose of complying the flow depths and velocities of conduits with the local design criteria. Particularly, the study adapted in-line detentions tank systems in the drainage network. In the first step of the case study, they compared the hydraulic characteristics of the conduit network under two different conditions: the initial condition with low runoff coefficients C^0 , and post-urbanized condition with relatively high runoff coefficients C . It was found that 16 out of 46 conduits did not satisfy at least one criterion under the second condition (i.e. the maximum water depth or flow velocity of the conduit has exceeded the limit), and this could cause surcharging and flooding issues. Next, under such a circumstance, a system of detention tanks was introduced into the drainage network. GA was used to search for the optimal solution, where the fitness function (FF) was set to be the sum of tank system cost and a penalization function. The cost was evaluated in detail under different types of materials (e.g. concrete and reinforcing bars) and excavation depths. After running 16 times of GA procedures, the optimal tank system cost value was obtained, and the corresponding locations and dimensions

of detention tanks were recorded. The study also took into consideration the recipient water bodies, by adding an extra constrain to control the discharge at the downstream end of the drainage network ($Q_{\max}$). Thus, with different preassigned value of $Q_{\max}$, the study obtained the optimal solutions of detention tank system. The results indicated that both tank cost and FF would increase sharply when $Q_{\max}$ decreases.

2.4 Review of case study towards climate change impact assessment and downscaling techniques

Climate change impact is projected to pose profound effect on many aspects of water resources systems, among which the number and severity of extreme storms are expected to increase over many urban areas around the world. As such extreme events would elevate the risk of flash flood problems, it is imperative to address climate change effect when engineers carry out renovation works on current drainage systems or design new drainage systems for the future.

2.4.1 Adopting multiple statistical downscaling approaches for the projection of future rainfall and temperature

Vallam and Qin (2018) proposed three statistical downscaling approaches for future climate prediction, i.e. Statistical downscaling method (SDSM), change factor approach (CFA) and bias correction and disaggregation (BCD). SDSM was a common tool to predict future meteorological (e.g. precipitation and temperature) trends under climate change impact for a single site. The mechanism of SDSM lay in the incorporation of a regression model and a stochastic weather generator (SWG) (Harpham and Wilby 2005). CFA was conducted based on a SWG named LARS-WG (Zamani et al. 2016), which calculated the change between baseline and future climate scenarios (i.e. GCMs) in statistics. The BCD approach aimed at correcting the bias in GCM data by interpolation of GCM outputs, which involved two main steps. Firstly, an inverse interpolation method was used for spatial disaggregating several GCM grid outputs to a target location. Secondly, a second-order Markov chain based SWG was adopted to simulate long-term daily timescale meteorological data.

The above three approaches were applied on five different study sites around the

world. Two GCMs under various emission scenarios (e.g. the latest RCP45 and RCP85) and three prediction periods were combined as future climate scenarios. Generally, the results showed that SDSM would predict a higher increase in temperature and precipitation compared with CFA and BCD, as the latter two were more conservative. This might due to the different algorithms of these weather generators.

2.4.2 Explore the impact of climate change on flooding in peri-urban area in Thailand using an inundation model

Shrestha et al. (2014) assessed the impact of climate change on drainage flow and surface flooding of a peri-urban area in Thailand based on PCSWMM. They compared two approaches for generating future climatic scenarios (e.g. precipitation, temperature, and evaporation). The first approach adopted a dynamic downscaling approach which linked a GCM with a high-resolution RCM for generating hourly data, even though such an approach is computationally intensive, and may not necessarily be better than statistical downscaling methods. The second approach was a simplified statistical approach that followed hypothetical increments of baseline rainfall conditions by percentages. It was shown that, under the dynamic downscaling approach, the annual flood volume of a peri-urban area in Thailand would increase from around 380,000 (baseline) to 485,000 m³ (year of 2091), whereas the second approach suggested a much bigger increment (i.e. up to 670,000 m³ in 2091).

2.4.3 Integrated multisite rainfall downscaling and disaggregation in a tropical urban area

Lu and Qin (2014) proposed an integrated downscaling-disaggregation approach for predicting high spatiotemporal future rainfall data. The approach consisted mainly of two steps. Firstly, the study tested various commonly used methods based on baseline rainfall data, which include: (1) for spatial downscaling: single-site generalized linear model combined with K-nearest neighbor (KNN) (S-G-K) vs. multi-site generalized linear model (M-G); (2) for single-site disaggregation: KNN vs. HYETOS; (3) for multi-site disaggregation: MuDRain (MD) vs. KNN. Secondly, the methods with superior performances in step 1 were selected to form an integrated downscaling-

disaggregation approach for predicting high-resolution (i.e. hourly) future rainfall at multiple sites. KNN was a nonparametric method, which was capable of carrying out both spatial and temporal disaggregation. In the study of Lu and Qin (2014), the author adopted KNN to disaggregate summation of daily rainfall from 8 stations to each single station (i.e. spatial downscaling from the whole watershed to sub-watershed), and to disaggregate daily record to hourly ones (i.e. temporal disaggregation). The mechanism of KNN lay in its selection of the nearest ‘neighbors’ among potential candidates. After step 1, M-G, KNN and MD were selected for constituting the proposed integrated downscaling-disaggregation approach. The results indicated that the fluctuation of annual rainfall depth would be insignificant for future periods, but the wet season rainfall and extreme events would considerably increase.

2.4.4 Climate change impact on IDF curves: a case study in Barcelona, Spain

Rodríguez et al. (2014) analyzed 114 daily rainfall series simulated by applying statistical downscaling methods on the outputs of 5 GCM under 4 emission scenarios, for the propose of investigating the impact of climate change on IDF curves. These 114 series were categorized into two groups: 84 series corresponded to predicted future scenarios, and the rest 30 were baseline scenarios for 5 GCMs. Table 2.2 summarizes the statistics of these series in the form of averaged climate change factors (CF) (i.e. the ratio of future rainfall intensities over the present ones, both under the same return period and duration) under various future, return periods and emission scenarios. From this table, a longer return period would always result in a higher CF, except for A1 and B1 scenarios in the period of 2000 to 2032; also, the highest CF for B2 indicated an over 10% increase in the last third of this century.

Afterwards, the study temporally disaggregated these rainfall series to hourly ones based on the scaling invariance of rainfall (Menabde et al. 1999), which derived a simple, yet reliable disaggregation method called simple scaling hypothesis (Bara et al. 2010). The hypothesis pointed out that it was widely observed that the probability distributions of annual maximum daily rainfall intensity at various durations exhibit

scale invariance behavior (Menabde et al. 1999). Such a behavior could be described by a power function as follows (Bara et al. 2010; Rodríguez et al. 2017):

$$I_t^q = \lambda^{K(q)} I_{t=24h}^q \quad (2.4a)$$

$$\frac{1}{48} \leq \lambda = \frac{t}{24h} \leq 1 \quad (2.4b)$$

where I_t and $I_{t=24h}$ are the annual maximum rainfall intensities with duration of t and 24 hours, respectively; q is the moments of order for I_t and $I_{t=24h}$; $K(q)$ is the scale function of q ; λ is the scale parameter of rainfall durations. If the process was assumed to be simple scale, the scaling function $K(q)$ in (2.4a) became a linear function:

$$K(q) = \alpha q \quad (2.4c)$$

where α is the scaling factor. Let $I(t, T)$ and $I(24, T)$ denote the extreme rainfall intensities with durations of t h and 24h, respectively, where T is the return period. Based on (2.4a) to (2.4c), the following equation could be obtained (Rodríguez et al. 2017):

$$I(t, T) = I(24, T) \cdot (t / 24)^\alpha \quad (2.4d)$$

The scaling factor α and the relationship between $I(t, T)$ and $I(24, T)$ for a region could be derived by analyzing baseline rainfall dataset. Once the relationship was established, it could be used to disaggregate future extreme rainfall from daily timescale to sub-daily ones.

Table 2.2 Climate change factors of 114 daily rainfall series (Rodríguez et al. 2014)

Period	Emission scenario	Return period (years)					
		1	5	10	20	50	100
2000-2032	A1B	1.02	1.02	1.03	1.03	1.03	1.03
	A2	1	0.99	0.98	0.98	0.98	0.98
	B1	1.04	1.03	1.03	1.03	1.02	1.02
	B2	0.99	1.02	1.02	1.03	1.04	1.04
2033-2065	A1B	1	1.03	1.04	1.05	1.06	1.06
	A2	1	1	1.01	1.01	1.01	1.01
	B1	1.01	1.02	1.02	1.03	1.03	1.04
	B2	1	1.01	1.01	1.01	1.02	1.02
2066-2099	A1B	1.04	1.05	1.05	1.05	1.05	1.05
	A2	1	1.02	1.03	1.04	1.05	1.06
	B1	0.99	1	1	1	1	1.01
	B2	1	1.05	1.07	1.08	1.1	1.11

2.5 Summary of literature review

From the literature review, the following research gaps are identified:

(1) The previous studies made viable attempts in applying various techniques for urban drainage (including LID) design and flood damage evaluation; but either flood volume or the number of overloaded junctions was used to reflect the flood damage loss; this could result in biased evaluation of flood damage. Besides, very limited studies tried to integrate multiple LIDs into a general study framework to mitigate flood risk. One example work was recently reported by Noordhoek (2014), who tried to examine two kinds of LID features (rainwater tanks and bio-retention basins) for their efficiency of reducing runoff volumes and peak flows.

(2) Uncertainty assessment is an important issue for further exploration. The sources of uncertainty could be from both modeling structure and data acquisition. However, most of the previous optimization models are deterministic without sufficient capability to address how the constraints could be satisfied in a probabilistic manner. The probability theory can help build statistical distribution of uncertain parameters and examine their propagation to modeling results, and the fuzzy set theory is relatively flexible in defining uncertain parameters using membership functions. However, in the field of LID design or urban drainage modeling, the relevant studies are rather limited.

(3) GA has been used widely for searching ‘optimal’ solutions towards various kinds of optimization problems in the field of urban drainage and LID design. But GA has difficulty achieving global optimal solutions for large-scale problems. Thus, there is a need to consider strategies to scale down or simplify the problem. The scale down methods basically focus on each sub-area to obtain the first level preliminary solutions on the first step, and a global model will be constructed for seeking more general solutions to the system on the next step.

(4) From the previous works, it is revealed that statistical downscaling and disaggregation methods are commonly adopted to generate suitable resolutions of climate variables (mainly rainfall) for urban drainage studies. However, due to strict resolution requirement of climate data (both temporally and spatially) and necessity to translate weather variables to flow information for drainage design evaluation, there is still a shortage of studies that use holistic approaches to tackle downscaling, disaggregation, rainfall design and hydrological simulation for climate change impact on urban drainage systems. In addition, there are rare previous works focused on tropical regions, which are normally characterized by monsoons and intense rainfall with short durations (Fong, 2012). It is desired that a more straightforward and flexible approach be proposed for the mentioned purpose.

CHAPTER 3. A PARSIMONIOUS FRAMEWORK FOR EVALUATING LOW IMPACT DEVELOPMENT FEATURES IN URBAN FLOOD MITIGATION¹

3.1 Background

As a consequence of global warming and increasing number and severity of extreme storms, urban floods are observed more frequently all over the world (De Moel and Aerts 2011). Recently, flood damages are responsible for nearly one-third of the economic loss from natural disasters (Re 2005). For instance, the 2013 North India floods resulted in a death toll over 5,000; the 2011 South Asian floods, which affected several countries like Thailand, Cambodia and Vietnam, killed over 500 people and brought a total damage of US\$45 billion (The world bank 2012). In order to mitigate the threat of flooding to industry, traffic, transportation, and human lives, it is crucial to integrate storm water management into long-term urban planning and infrastructure development.

As one of the control strategies for urban floods, the concept of low impact development (LID) involves a series of design features (e.g. pervious pavements, rainwater tanks, green roofs, etc.) and is also synonymous with other stormwater management approaches like low impact urban design and development (LIUDD), best management practices (BMPs) and sustainable drainage systems (SuDS) (Fletcher et al. 2015). LID involves technologies and approaches which aim to retain water in the urban landscape through rainwater harvesting and fit-for-purpose reuse and infiltration into soils to meet social, ecological and financial goals (Coutts et al. 2012). LID features mainly include rainwater tanks, rain gardens, green roofs, pervious pavements, rainwater storage ponds, and constructed wetlands (Government of South Australia 2013), with various focuses on water quality and quantity. Over the past decades, many studies have been conducted regarding the effects of LID features in retaining rainfall, reducing runoff and improving quality of infiltrated water. Wong (2006) found that the bio-retention systems and constructed wetlands

¹ This paper has been published in *Journal of Environmental Informatics*.

only need to take up 2% to 5% of the roof area to effectively treat roof runoff. Chapman and Horner (2010) observed a bio-retention tank near the street and found that it could achieve 26-52% of runoff retention as well as most of the incoming pollutants in real-weather conditions of Washington. Yang et al. (2013) evaluated the ability of a biphasic rain garden for runoff management and pollutant treatment, and found that during a 180 mm/24 h rainfall event, the peak flow and runoff volume were reduced by 67% and 28%, respectively, and meanwhile the rain garden was very effective in removing various pollutant such as nitrate and phosphate. Kok et al. (2016) evaluated both quantitative and qualitative effects of an extensive green roof system under tropical climate, and found that the peak discharge of runoff was reduced effectively (up to 26%) compared to a concrete tile roof. Generally, it is recognized that LID plays an important role in improving drainage capacity and mitigating urban flood damage and is applicable to various catchment scales from building levels to urban areas.

It is also a challenging issue when governments face urgent needs to improve the capacity of their urban drainage systems, and seek tradeoffs between investment of adopting LID features and achievement of flood control goals. To tackle such a problem, many studies on flood risk assessment and tradeoff design of urban drainage systems have been reported. Khastagir and Jayasuriya (2010) presented relationships between size of rainwater tanks with multiple factors (e.g. rainfall, catchment area and water demand). Yazdi et al. (2014) developed a surrogate model, which combined adaptive neural network and GA together, for the design of detention dams for flood control, and achieved superiority in terms of accuracy and efficiency compared with previous simulation model. Li et al. (2015) developed a multi-objective optimization framework to design the size of rainwater detention ponds, and acquired relatively robust solution to minimize both the engineering cost and flooding risks. Yu et al. (2017) used GA to search the most cost-effective size of drainage conduits, taking into consideration several realistic constrains (e.g. acceptable level of flood risk and dimensions of conduits). Huang et al. (2015) established models for seeking solution of spatial quantity and capacity arrangements of rain barrels in an urban area, and also considering economic net benefit (i.e.

subtraction of the investment from the decreased inundation loss). Yazdi et al. (2015) carried out a risk-based optimal design for flood risk mitigation where the uncertainties of flood discharge were considered. These studies generally integrate optimization (e.g. GA and ant-colony optimization) and simulation models to search for optimal solutions to the design of drainage systems or LID layouts under certain constraints. But there are still some research gaps. First, in evaluating the flood damage, the flood volume or the number of overloaded junctions was normally used; such indirect loss information may not be representative of the actual damage in monetary values. Second, very limited studies attempted to integrate multiple LID features into a general study framework to mitigate flood risk. One example work was recently reported by Noordhoek (2014), who tried to examine two kinds of LID features (rainwater tanks and bio-retention basins) in reducing runoff volumes and peak flows. Lu et al. (2016) also made a preliminary test on applying rain gardens and rainwater storage ponds to mitigate urban flood damage under different design rainfall scenarios. Third, most of the previous studies focused on coupled simulation-optimization algorithms, which normally required huge computational burdens (particularly for flood inundation modeling); it is desired to have more efficient ways of carrying out evaluation and future designs.

Thus, this study aims to propose a parsimonious framework to evaluate LID features for mitigating urban flood damage. The flood damages will be simulated and assessed by a 2D inundation model under various design scenarios. Multiple LID features will be integrated into a single modeling framework for easy assessment of their performance in flood mitigation. The relationship between the investment and flood damage, which could be used by local authorities in their decision-making process towards cost-effective flood risk management, is fitted by a linear regression model.

3.2 Methodology

3.2.1 The proposed design framework

Figure 3.1 shows a flow diagram of the proposed design framework. First, different kinds of data sets need to be collected for the study area. They may include (i) hydrologic-hydraulic data such as parameters of sub-catchment and layout of

drainage network; (ii) topographic data, i.e. a high resolution Digital Elevation Model (DEM), which is essential to enable a 2D flood analysis; (iii) rainfall data and on-site water level data during the corresponding rainfall period for the propose of model validation; (iv) economic data which represent economic and social condition of the study area, e.g. land use, value of properties, unit cost of various LID features and the local damage function (which defines the relationship between flood damage and inundation depth). Second, an urban hydrological model is established to simulate the entire drainage system, and a 2D hydraulics model is customized to enable 2D inundation analysis (see Section 2.2). Third, sensitivity test is used to assess the feasibility or practicability of the proposed LID features in mitigating flood damage and identifying the best location for installation (see Section 2.3). Finally, an evaluation framework is formulated to seek the balance between the urban flood damage and LID investment (see Section 2.4). Afterwards, a regression model is applied to for further data analysis.

Fig. 3.1 The flow diagram of the proposed design framework

3.2.2 Urban inundation model

SWMM is a dynamic urban hydrological model for linking rainfall to runoff in the

drainage networks and tracking the water quality of runoff generated within each sub-catchment (Aad et al. 2009). SWMM has been used worldwide for planning, design and analysis related to urban drainage systems (US EPA 2020). This study adopts PCSWMM to simulate both drainage flows and flood inundation. The model fully integrates hydrologic and hydraulics functions and is specialized in modeling multifarious flow regimes and 2D flood routing, which can be useful for a reliable assessment of urban flood damage (James 2005). After model establishment, PCSWMM should be calibrated by using historical rainfall, runoff, and hydrometric records. Normally, overland 2D meshes will be generated at a given resolution. Inundation condition is assessed by evaluating the maximum water depth of 2D meshes during a rainfall event.

3.2.3 Sensitivity analysis of LID features

Many LID features could be applied to the proposed framework for flood mitigation. In this study, the rainwater storage pond, rain garden, and conduit upgrading are selected as concerned features. In order to determine the locations of these measures in the drainage system, sensitivity test is conducted in consideration of the conduits and junctions that are relatively sensitive for reducing urban flood damage in the drainage system. When the 2D inundation model is established and calibrated, the local IDF curve (PUB 2011) and Huff distribution (Huff 1967) are used to design rainfall events for testing the model sensitivity. As multiple drainage units may be reported to suffer from flooding, a set of scaling factors are introduced to evaluate the effect of increasing the rainfall intensity on the flooding extent of the drainage units. The total flood volume and surcharge time are selected as indicators in selecting junctions and conduits that are nominated to be equipped with LID features. A conduit is considered surcharge if its upstream end is full and the hydraulic grade line slope is greater than the conduit slope (Rossman 2015). Storage ponds will be constructed at the site of the selected junctions and the size upgrading will be conducted for the selected conduits.

3.2.4 Formulation of objective function for scenario analysis

The problem under consideration is to find the relationship between investment of

LID (i.e. conduits, rainwater storage ponds and rain gardens) and flood damage. The evaluation model can be written as:

$$I = \sum_{i=1}^{n_c} \left[(A_{C_i}^m - A_{C_i}^o) \cdot l_i \cdot c \right] + \sum_{j=1}^{n_s} A_{S_j} \cdot H_j \cdot d + A_R \cdot g + b \quad (3.1a)$$

$$DC = x \cdot \sum A_{ij} p_{ij} \quad (3.1b)$$

subject to:

$$A_{C_i}^m = F_{C_i} \cdot A_{C_i}^o \quad (3.2a)$$

$$0 \leq A_{S_j} \leq \gamma \quad (3.2b)$$

$$0 \leq A_R \leq A_{OS} \quad (3.2c)$$

where:

On the investment part Eq. (3.1a), I is the gross investment of the whole LID project. A_{C_i} , l_i , n_c , and c are the i^{th} cross section area of conduits, length of conduits, number of conduits, and unit cost of excavation (which includes the cost yielded from evacuation, transportation, disposal and labor for each cubic meter of cut volume), respectively. Superscripts m and o are the candidate and original variables, respectively. A_{S_j} , H_j , n_s , and d are the j^{th} area of storage pond, depth of its original manhole, number of ponds and the unit cost of excavation of ponds by volume, respectively. A_R and g are constructed area of rain gardens and unit cost of building garden by area, respectively. b is the management cost for operating the whole project. On the flood damage part Eq. (3.1b), DC is the total urban flood damage and x is the average property value per unit area, which can be estimated by the total value of properties X divided by surface area A (Oliveri and Santoro 2000). Based on the simulated water depth of each 2D mesh from PCSWMM, we can draw a risk map which uses contour lines to separate the study area into several portions (with each portion area denoted as A_{ij}); each portion contains a group of meshes with maximum water depth falling within the range of (h_i, h_j) . The percentage damage p_{ij} of the portion A_{ij} is related to the range (h_i, h_j) by using a local relative damage function. In addition, a threshold depth is introduced. If the maximum water depth of a 2D mesh is below this threshold, the damage is assumed to be negligible. Eq. (3.2a) to (3.2c) are the constraints for Eq.

(3.1a). F_{Ci} is scaling factors for the i^{th} conduit to increase its cross-section area from A_c^o to A_c^m . The size of ponds A_S is limited by γ which needs to be determined by local requirement. A_{OS} is the total area of open spaces.

3.3 Case Study

3.3.1 Case Background and Setup

Description of the study site

A hypothetical urban catchment adapted from a tropical urban area (i.e. Singapore) was selected for demonstrating the proposed design framework. Some preliminary studies using the similar catchment were recently reported by Le et al. (2014) and Lu et al. (2016). Figure 3.2 shows the general map and layout of the drainage network of the study site. The site is characterized by urban residential area with a typically tropical climate (e.g. sufficient rainfall, high humidity, and hot temperatures throughout the year). The mean annual rain days is 178 and mean annual rainfall total is over 2,300 mm; the mean daily maximum temperature ranges from 30 to 32°C and the minimum one ranges from 23 to 25°C (Meteorological Service Singapore 2020).

Fig. 3.2 Map of the study area

Model setup

An urban hydrological model based on PCSWMM is established for the study area. The model is calibrated and verified by number of storm events occurred in 2012 and 2013. According to Le et al. (2014), the SWMM was calibrated and verified by measured water level data over a number of rainfall events at two downstream gauging stations. As an example, the measured hydrograph of one rainfall event occurred in 2012 (Figure 3.3) showed that the SWMM produced very close flows to the observed data (especially the peak flows), with R-squared value being above 0.90. When the hydrological portion of the model is validated, the parameters and layers of 2D inundation modeling are customized for this study case. The spatial resolution used in generating mesh points is 5 m, considering the relatively small area of the catchment. Finally, a 2D overland mesh network with elevation embedded is established for inundation risk analysis. The related damage computation and data analysis are carried out in the MATLAB platform (Rezaei et al. 2016).

Fig. 3.3 Rainfall hyetograph and Runoff hydrograph of a rainfall event occurred in 2012. Qm and Qp denote measured water level at two downstream gauging stations (TB01 and TB02) and simulated results of SWMM, respectively. (Source: Le et al. 2014)

Design rainfall

Rainfall time series are developed based on intensity-duration-frequency (IDF) curves and Huff distribution. IDF curves reveal the characteristics of the rainfall extremes, which are established based on annual maximum rainfalls with various durations (Arnbjerg-Nielsen 2012). Huff storm distribution (Chow et al. 1988)

includes four types of rainfall patterns, with peak intensity occurring in different quarters of the duration in each pattern. This study considers mitigating urban flood risk under a design rainfall with 25-years return period and 1-hour duration. Referring to Singapore IDF curves (PUB 2011), we obtain the rainfall intensity of 107.5 mm/hr. Le (2014) carried out a historical rainfall analysis of Singapore and discovered that most hourly rainfall events follows the Type-II Huff distribution. The corresponding designed rainfall is then selected to drive the model and generate inundation scenarios. Figure 3.4 shows the corresponding hyetograph with an interval of 3 minutes.

Fig. 3.4 Hyetograph of 1-hour designed rainfall

LID features

Under the designed rainfall, the existing drainage network would suffer from flooding at nodes J16, J18, J19, J38, J43, J46 and J47. Then a scaling factor (SF) of rainfall, ranging from 1.1 to 1.5 and increasing at an interval of 0.1, is adopted to test the sensitivity of rainfall on the flooded nodes (in terms of the total flood volume and the surcharge time). According to the general equation of local IDF, SF on the 25-year return period 1-hour rainfall ranging from 1.1 to 1.5 can equivalently cast as 43, 68, 109, 165 and 243-year return period rainfall events, respectively. It is found that J16, J19, and J47 are more heavily flooded (Figure 3.5(a)), and their linking conduits (C17, C18, and C46) are also notably surcharged (Figure 3.5(b)). Thus, the storage ponds (D1, D2, and D3) are nominated to be constructed at the nodes of J16, J19 and J47, where each pond is assumed to have a fixed cross-section area. Meanwhile, the excavation works are assumed aiming at upgrading conduits C17, C18 and C46. The

control variables for the ponds and conduits are the area and the scaling factor of cross section area, respectively.

Fig. 3.5 Results of (a) flood volume of flooded junctions, (b) surcharge time of overloaded conduits

From statistics of the study area map, the total area of the open spaces which can be converted to rain gardens is 1.18 hectare. Figure 3.6 shows the results of sensitivity test for the areas of rain gardens. The figure demonstrates that the simulated flood depth during the storm event would generally decrease as the greening rate increases from 0 to 100%. In this study, the area of rain garden unit (i.e. the minimum block to form a larger area of rain garden) is set to be 100 m^2 ; thus, by simply changing the number of replicate units implemented in the open space, we can customize the greening rate which is used as a control variable to represent area proportion of the gardens to the open spaces. The detailed properties about LID features are listed in Table 3.1. Some of these values are obtained from the SWMM user manual (Rossman 2015). The ranges of control variables are summarized in Table 3.2, which are based on the sensitivity test results and actual on-site constrains. As shown in Table 3.2, the maximum area of storage pond is set to be 3000 m^2 and the maximum cross section area of conduit is 3 times higher to its original value.

Fig. 3.6 Sensitivity test for greening rate of open spaces

Table 3.1 Properties of the Proposed LID Features

Surface properties				Soil properties			Remark
Rain garden	Berm height (mm)	200	Thickness (mm)	850	Conductivity (mm/hr)	150	Four parts of the vacancy area in this study case can be applied for rain gardens.
	Vegetation fraction	50	Porosity* (volume fraction)	0.45	Suction head* (mm)	1.9	
	Roughness (Manning's n)	0.1	Field capacity* (volume fraction)	0.06	Conductivity slope	3	
	Slope	2.0					
Storage pond			Suction head* (mm)	1.9	Conductivity (mm/hr)	150	The depth of each pond is fixed at its original manhole.
	Not applicable			Initial deficit (fraction)	0.33		

Note: *These values are obtained from the SWMM user manual (Rossman 2015).

Table 3.2 Discrete Sampling Values of Control Variables

Type of measure	Symbol of variable	Implication of variable	Range of variable		
			Min.	Max.	Sampling interval
Storage pond (m ²)	A _S	Area of storage pond	0	3000	500
Conduit upgrading (-)	F _C	Scaling factor of cross section area of conduits	1.0	3.0	1.0
Rain garden (%)	G _R	Greening rate of vacancy area	0	100	25

Setup of evaluation framework

The settings of the evaluation framework include: (i) for simplicity, the unit cost of

evacuation (c and d) and management cost (b) = \$50 per m^3 (the money here is given in terms of Singapore dollar) and 0, respectively; (ii) the unit cost of rain garden building (g) = \$50 per m^2 ; (iii) the maximum area (γ_j) for each conduit = 3000 m^2 , and the threshold depth = 0.15 m; (iv) referring to Singapore Department of Statistics (2019), the total residential property assets of the whole country (X) = \$818.7 billion and the area of the country (A) = 718.3 km^2 ; the property assets per unit area of the country (x) = 1,139.8 \$/ m^2 ; (v) the private flats and flats developed by Housing and Development Board generally have multifamily and multistory residential structures, occupying over 90% of residential dwellings in Singapore; the land use condition of the study area can thus be classified as typical residential area; (vi) the indirect damage (e.g. losses due to suspended commercial and industrial activities) and intangible losses such as human lives (Oliveri and Santoro 2000) have been neglected in this study.

Note that there exist two types of damage functions: (i) relative damage functions, which defines damage as a proportion of the total value of flooded property considering inundation depth and different building types, and (ii) absolute damage functions, which defines damage as an absolute value considering inundation depth and land use conditions. In this study, the relative damage function is adopted to access flood damage, due to its better adaptability when transferred to other regions, better stability with time (Appelbaum 1985) when compared with absolute functions, and the limitation of available data in Singapore. We refer to the damage function obtained by Hydrotec (2001; 2002), which is frequently used for the residential sector in Germany (Merz et al. 2010). For convenience, interpolation is applied for this curve at an interval of 0.3 m. The details are provided in Table 3.3.

Table 3.3 Depth-percent damage table with interpolated values

Inundation Depth h (m)	0.15	0.3	0.6	0.9	1.2	1.5	1.8	2.1	2.4
Percent Damage p (%)	0	14.8	20.9	25.6	29.6	33.1	36.2	39.1	41.8

Note: Information source: Merz et al. (2010)

3.3.2 Result analysis

Figure 3.7 shows the simulated results under all scenarios (which are generated by combining all possible points which are shown in Table 3.2) using a scatter diagram. Each scatter point corresponds to one simulated scenario of LID features, and the x, y coordinates of that point give the gross investment and flood damage cost, respectively. It shows that the damage cost would decrease with the increase of the investment of LID features (i.e. cost of building storage ponds, rain gardens and conduit enhancement). When the gross investment increases from 0 to 1.19 million \$, the damage cost would decrease from 4.61 to 3.41 million \$. When we consider the total cost, which is the sum of investment and damage cost, as the criteria of design, Table 3.4 gives the obtained top five cost-effective layouts of LID features for this case. It is noted that the top ‘optimal’ layout would suggest a combination of medium area of ponds, large area of rain gardens and unchanged size of conduits. The following linear regression equation can be used to describe the relationship between the investment and the damage:

$$\mathbf{DC} = -1.069 \cdot \mathbf{I} + 4.706 \times 10^6 \quad R^2 = 0.93 \quad (3.3a)$$

This regression curve achieves a satisfactory goodness of fitting, with R^2 at 0.9. Also, the linear relationship turns to be more stable as we increase the investment of LID features. Such information is useful for decision makers to foresee the trade-off between investment of LID and flood damage. Khan and Valeo (2015) also used a linear model to predict daily peak flow rates for the Bow and Elbow Rivers in southern Albert.

Fig. 3.7 The scatter diagram and the linear regression curve of the simulated results

Table 3.4 Top five cost-effective layout of LID features

Solution No.	Total cost (10 ³ S\$)	Damage (10 ³ S\$)	Investment (10 ³ S\$)	Details about LID		
				Storage ponds (As, m ²)	Rain gardens (Gr, %)	Conduits upgrading (Fc)
1	4444.20	3727.72	716.49	1500	75	1.0
2	4461.94	3597.70	864.24	1500	100	1.0
3	4527.66	3981.21	546.45	3000	0	1.0
4	4542.18	3882.39	659.81	2000	50	1.0
5	4555.05	3811.86	743.19	1500	75	2.0

In addition to the overall design of LID features, the effect of mitigating flood damage by an individual type can be investigated by using the control variable method. When each variable LID feature (which can adjust within its range) is considered, the other two become controlled LID features (which only adopt fixed values). In total, three scenarios are established for each variable LID feature (with details being provided in Table 3.5). Scenario I only uses the variable LID feature for mitigating flood damage; Scenario II takes into consideration the usage of a moderate level of the controlled LID features; Scenario III accounts for a full usage of the controlled LID features. Figure 3.8 shows the related results when using (a) storage ponds, (b) rain gardens, and (c) conduit upgrading as the objective feature. Three linear regression curves (denoted as i, ii, and iii) are generated for the three groups of scenarios, correspondingly. From Figure 3.8(a), it can be found that the storage ponds are efficient in mitigating flood damage, especially when they are combined with other LID features. For example, the slope of regression curve would increase from 1.07 (i)

to 1.44 (iii) when the number of LID features increases from one to three. Figure 3.8(b) demonstrates that the rain gardens can also achieve a satisfactory effect (i.e. a slope near or above 1) when there exist other LID features. However, an extended use of other features would be challenging to further improve the performance of rain gardens. This can be explained by the relatively small change of slopes of between line (ii) and line (iii). Figure 3.8(c) shows that the conduit upgrading alone would make a relatively small contribution to flood mitigation and may not be economical (i.e. slopes all below 1).

Table 3.5 Details about selected scenario sets in Figure 3.8

Variable LID	Parameter of Variable LID		Controlled LID	Parameters of Controlled LID	Line Type ¹	Remark ²
Storage ponds (As, m ²)	Min.	Max.	Sampling Interval	Conduit upgrading & Rain garden	Fc=1, Gr=0	i I
	0	3000	500		Fc=2, Gr=50%	ii II
					Fc=3, Gr=100%	iii III
Rain gardens (Gr, %)	Min.	Max.	Sampling Interval	Storage ponds & Conduit upgrading	As=0, Fc=1	i I
	0	100	25		As=1500, Fc=2	ii II
					As=3000, Fc=3	iii III
Conduit upgrading (Fc)	Min.	Max.	Sampling Interval	Rain garden & Storage ponds	As=0, Gr=0	i I
	1.0	3.0	0.5		As=1500, Gr=50%	ii II
					As=3000, Gr=100%	iii III

Note: 1. Line type: i: Solid line with dots; ii: Dotted line with triangles; iii: Chain line with rhombus. 2. Remarks: I: No Controlled LID (use objective LID only); II: Moderate use of Controlled LID; III: Full use of Controlled LID.

Fig. 3.8 Performance analysis of (a) storage ponds, (b) rain gardens and (c) conduit upgrading

A multi-linear regression model (Cerdà et al. 1993) is introduced to conclude the results of above control variable method, which can be mathematically expressed as:

$$\mathbf{DC} = k_0 + \sum_{i=1}^n \mathbf{k}_i \cdot \mathbf{c}_i \quad (3.3b)$$

where $\mathbf{DC}$ is damage cost vector, $\mathbf{k}$ and $\mathbf{c}$ are vectors of investment of each LID features and the corresponding coefficient of features, respectively. k_0 is an independent term required to account for a non-zero intercept in the regression. n account for the total types of adopted features. By applying the curve-fitting tool, the following equation can be acquired:

$$\mathbf{DC} = 4.697 \times 10^6 - 1.215 \cdot \mathbf{s} - 0.683 \cdot \mathbf{c} - 1.002 \cdot \mathbf{r} \quad R^2 = 0.944 \quad (3.3c)$$

where $\mathbf{s}$, $\mathbf{c}$, and $\mathbf{r}$ are investment of storage ponds, conduit augment and rain gardens, respectively, and both sides of equation are consistent in unit. The coefficients of Eq. (3.3c) reflect the sensitivity and performance of various LID features, where the largest absolute value (1.215) for the storage ponds means they are relatively more effective in mitigating damage cost. To verify Eq. (3.3c) by using the original inundation model, n stochastic scenarios of LID features are generated based on uniform distributions of variables listed in Table 3.2. Then the simulated results of damage cost are compared with those derived from Eq. (3.3c). Table 3.6 gives the relative errors of damage estimation. Overall, the relative errors are below 3.0% for stochastic scenarios.

Table 3.6 Details about Variables and Simulated Results of the Stochastic Scenarios

No. of scenario	Variable set				Damage from modeling results (10 ³ S\$)	Damage from Eq. (3.3c) (10 ³ S\$)	Relative Error of damage (%)
	Type of LID	Storage pond (As, m ²)	Conduit upgrading (Fc)	Rain garden (Gr, %)			
1	Random value of variable	2337.60	1.24	52.85	3799.62	3862.34	1.62
2		2802.00	1.67	16.56	3931.32	3966.52	0.89
3		389.70	1.32	60.20	4246.28	4248.33	0.05
4		1706.40	2.59	26.30	4236.18	4134.63	2.46
5		1408.20	1.62	65.41	4087.86	3986.64	2.54
Overall correlation coefficient of damages for five stochastic scenarios							0.87

Figure 3.9 shows the inundation maps under four scenarios. Figure 3.9(a) represents the original inundation scenario without any LID features; Figure 3.9(b) shows the scenario with fully upgraded conduits; Figure 3.9(c) represents the scenario with maximum upgrading of conduits and maximum area of storage ponds; Figure 3.9(d) shows the scenario with a full usage of all LID features. The northeastern part of study area (i.e. the downstream portion close to the outlet) has been scaled up in these sub-figures in order to show the inundation area more clearly. The color blocks represent several flooded area (A_{ij}) with different water depths, and the numbers (p_{ij})

within these blocks indicate the intervals of water depth. From Figure 3.9, the storage ponds and rain gardens are much more efficient than conduit upgrading in mitigating flood inundation level and reducing the size of the impact area.

Fig. 3.9 Partial enlarged inundation map for scenario with (a) original inundation scenario, (b) max. augment of conduits only, (c) max. augment of conduits and max. area of storage ponds and (d) max. usage of three types of LID feature.

3.4 Discussion

This study attempts to integrate various techniques into an overall evaluation framework for planning LID features. These techniques involve urban hydrological modeling, 2D inundation modeling, regression curve fitting, and flood damage assessment. There are a few advantages of the proposed framework. First, the urban flood damage assessment is based on PCSWMM platform, which is efficient in

conducting both hydrological and hydraulic analysis. Second, the relationship between two main objective variables (i.e. investment and damage cost) are useful in helping decision makers better understand the potential of different kinds of LID features for mitigating flood damage. Third, the proposed framework is flexible in integrating various LID features, by customizing the simulation and evaluation models and incorporating local climatic and hydrometric conditions. It is possible for other types of LIDs (e.g. green roof and pervious pavement) to achieve a super-linear performance for flood damage mitigation. This may happen when the unit cost of LID is relatively low, and the layout (i.e. unit size and number of units in each subcatchment) of LIDs can be optimized by sophisticated algorithms to maximize their performance. For example, aiming at retaining rainwater on the roof surface and decreasing the thermal loading on buildings (Simmons et al. 2008), green roofs can be combined into the simulation model by applying customized green roofs to several residences and sub-catchment, and the cost evaluation process of green roofs can be formulated as:

$$I_g = r \cdot \sum_{i=1}^n S_{ri} + b \quad (3.4)$$

where I_g is investment of green roof, r is unit cost of green roof by area, and b is design and management cost of all roofs. The area of green roof (S_{ri}) is limited by the actual area of roof. In return, the economic benefits of green roof include cooling effect which saves energy especially for hot climates, and thermal comfort improvements in outdoor spaces. The assessment of economic benefits of green roof can be carried out in multiple ways (Alexandri and Jones 2008).

There are also limitations of the proposed framework and the case study. First, uncertainty is an important factor that may influence the modeling outputs. The sources of uncertainty could be from both modeling structure and data acquisition. Due to the lack of economic data for the case study, some parameters were based on estimation or references. A detailed field survey about socio-economic data (e.g. persons per household, living styles and common indoor furniture) is needed if a local

damage curve is intended to be built for flood damage assessment (Kang et al. 2005). In addition, the probability theory could help build statistical distributions of uncertain parameters and examine their propagation to modeling results. Example works could be found in Ahmadi et al. (2015). Besides, as rainfall is the essential driving force for SWMM, uncertainties arising from rainfall should be addressed in a future extension of this study by adopting design rainfalls with various depth (i.e. return period), duration and temporal pattern. Second, it should be noted that the proposed optimization scheme in this study relies on searching for the best combination of control variables from a discrete decision space; strictly speaking, this is not a “continuous” optimization process. However, the process is significantly more efficient and could save computational efforts for many large-scale practical applications. For continuous optimization solutions, heuristic approaches (like GA) could be considered.

3.5 Summary

A parsimonious framework of evaluating water sensitive urban design (LID) for mitigating urban flood damage was proposed in this study. The framework was effective in finding the relationship between investment of LID features and reduction of flood damages. A hypothetical case adapted from a tropical urban community was selected for demonstration. The results showed that the flood damage would linearly decrease from 4.61 to 3.41 million \$ as the investment of LID increased from 0 to 1.19 million \$. A satisfactory goodness of fit was achieved when a regression curve was introduced to describe the relationship between damage and investment. The inundation maps under different LID scenarios were also drawn for a direct comparison. The proposed framework is so-called “parsimonious” as it does not involve complex algorithm in linking simulation and optimization models and can provide relatively rich and practical information regarding the tradeoff between investment and flood damage for LID designs. Uncertainty may significantly affect the evaluation process and shall be addressed in our future works.

CHAPTER 4. AN INTEGRATED FUZZY SIMULATION- OPTIMIZATION MODEL FOR DESIGNING LOW IMPACT DEVELOPMENT WITH UNCERTAINTIES¹

4.1 Background

Urbanization has been taking place worldwide since the 1950s, leading to rapid change of city landuse, increasing runoff discharges, and high risk of flooding. As one of the strategies for controlling urban floods, the concept of low impact development (LID) became popular in North America (Dhalla and Zimmer 2010). It involves a series of decentralized stormwater management practices, such as green roof (GR), pervious pavement (PP) and bio-retention cell (BC), with focuses on water quality and quantity control (Noordhoek 2014). The term LID is also synonymous with other management approaches of urban stormwater like water sensitive urban design (WSUD) and best management practices (BMPs) (Fletcher et al. 2015).

In recent years, with the aid of hydrological modeling tools such as Storm Water Management Model (SWMM) (Rossman 2015) and Flo-2D model (Hu et al. 2017), LIDs are proven effective on retaining rainwater and mitigating urban flood (Noordhoek 2014; Chui et al. 2016). However, the reliability of LID design is affected by a variety of uncertainties (Duan et al. 2016). Many previous studies have investigated various kinds of uncertainties associated with different components of LID design, such as rainfall design and economic statistics. In 2013, Qin et al. (2013) discussed the effects of LIDs on urban flooding under different rainfall characteristics; later, Chui et al. (2016) discussed the cost-effectiveness of specific LIDs among different regions; most recently, Lu et al. (2019a) discussed the tradeoff between investment of LIDs and mitigation of urban flood damage.

Nevertheless, few studies in urban drainage and LID design attempted to address uncertainties associated with model parameters. One example work was reported by Fu et al. (2011), who tried to investigate uncertainties arising from model parameters

¹ This paper has been published in *Water Resources Management*.

of roughness coefficient for conduits and runoff coefficient, and their influence on modeling output of sewer flooding; Fu and Kapelan (2013) combined probabilistic rainfall and fuzzy model parameters to calculate the lower and upper exceedance probabilities of flood depths. However, in these two studies, the concerned model parameters were both predetermined and short of a selection process. A framework that is capable of sorting out key model parameters and tackling uncertainties arising from these parameters is desired for more feasible LID designs.

Besides uncertainty analysis, optimization technique is also imperative for facilitating cost-effective design of UDS and LIDs. Previously, a number of studies were reported in dealing with uncertainties arising from urban drainage modelling and optimization. In earlier years, Chang et al. (2011) discussed the optimization of GRs for water conservation and energy savings under uncertainties originated from rainfall and economic statistics; Dotto et al. (2012) discussed four different techniques dealing with uncertainty issues in UDS modeling; Yazdi et al. (2014) presented an optimization approach for drainage rehabilitation by integrating copula function, MCS, hydrological modelling and optimization algorithm. More recently, Duan et al. (2016) established different types of distribution functions to address various uncertainties in UDS (e.g. rainfall intensity and conduit roughness), and adopted MCS for stochastic analysis. Yu et al. (2017) proposed a CCP model to optimize drainage design and used MCS to deal with the violation risk of constraints containing stochastic variables (Charnes and Cooper 1959). Ronalds and Zhang (2019) discussed impact of rainfall pattern uncertainty on regional hydrographs by carrying out MCS on a runoff-routing model.

Among the above-mentioned studies, it was found that the stochastic-theory-based approaches such as MCS and CCP were popularly adopted for characterizing uncertainties. One drawback of traditional stochastic theory is that the probabilistic distributions of stochastic model parameters are difficult to obtain if the related data is limited or unreliable (He et al. 2008). Moreover, some types of uncertainty may not be suitable to be described as stochastic, such as the vagueness originated from subjective knowledge (Ross et al. 2009). Fuzzy set theory is an alternative tool in

handling uncertainty. It can be used to capture expert knowledge and imprecise data, and is relatively flexible in defining uncertain parameters using the concept of fuzzy membership function (MF) (Zadeh 1965).

Fuzzy set theory has been widely used in applications of hydraulic structure design and water resources management (e.g. Mooselu et al. 2019). However, in the field of LID design or UDS modeling, the relevant studies are rather limited. Yazdi and Neyshabouri (2014) presented an approach to deal with both hydrological uncertainties and curve number (CN) parameter uncertainties in search of optimal implementation plans of LIDs. The performance of LIDs was affected by CN parameters, which were characterized by using fuzzy MF. Another study tried to use AHP to capture the vagueness of subjective knowledge and convert the judgment of experts into fuzzy sets (Jato-Espino et al. 2014). These fuzzy sets were combined with MCS to evaluate the aggregate performance (e.g. cost, flexibility and aesthetic) of three types of PPs. Nevertheless, both of the mentioned studies were in absence of a physical simulation model and did not consider the selection of LID parameters during evaluation or optimization processes.

To fill the above-mentioned research gaps, this study aims to propose a fuzzy-based, simulation-aided optimization model, namely fuzzy simulation-optimization model (FSOM), for supporting optimal design of LIDs and addressing uncertainties arising from hydrological model parameters. The model integrates hydrological simulation, fuzzy sets, fuzzy simulation (FS), CCP and evolutionary algorithm into a general modeling framework. The main novelty of FSOM is that it could offer cost-effective schemes of LIDs for controlling the flood risks at various confidence levels, which reflect the degree of system uncertainty handled by fuzzy sets. Through a case study of a small urban catchment, the applicability and efficiency of the proposed FSOM will be compared with two traditional models (i.e. deterministic and stochastic models) under various scenarios.

4.2 Methodology

4.2.1 System Framework

Figure 4.1 illustrates the overall flow of the proposed model and its individual components. In general, physical model is established first, followed by the formulation of the optimization problem. Then, the simulation-optimization model needs to run under predefined parameters (e.g. confidence levels) to yield the optimal solutions under various scenarios.

To be more specific, firstly, necessary data should be collected for the study area, which may include specifications of drainage network (e.g. layout of conduits), configuration of land use, the potential types and locations of LIDs in each subcatchment and long-term meteorological data (e.g. rainfall and evaporation). Secondly, initial LID schemes are generated by random sampling and simulated by the hydrological model. Uncertain model parameters are sorted out and described by fuzzy sets. Thirdly, a design rainfall is used to reflect extreme rainfall condition and drive the model. Finally, the objective function, FS process and constraints are formulated for building the FSOM, where the output of hydrological model provides runoff and flood information for checking the violation of constraints. A few parameters need to be predefined, including (1) total acceptable flood volume of the system and allowable flood volumes for sensitive junctions (e.g. commercial areas and heavy traffic roads), (2) confidence levels of constraint satisfaction, and (3) configuration parameters of optimization algorithm.

GA is employed to solve the FSOM. It is a widely adopted algorithm based on the evolutionary idea of natural selection (Xu and Qin, 2013). During GA operation, the candidate children (i.e. solutions) are generated by applying three major rules to their parent generation, including: (i) selection, which selects parents for the next generation based on suitable fitness values; (ii) crossover, which combines two parents to form a new child for the next generation; (iii) mutation, which triggers small random changes to parents to increase genetic diversity in searching (MATLAB 2015). These candidate children are then evaluated by FS process to check the probability of constraint satisfaction. Generally, a penalty (i.e. a large real number) is

sensitivity analysis, and adopts fuzzification to tackle the uncertainties arising from these key parameters.

A general FSOM embedded with CCP can be formulated as a FCCP model (see Section 2.1.7, model (2.1)). Specifically, the FSOM for LID design and optimization subjected to uncertainty could be formulated as follows (Dai et al. 2018; Yu et al. 2017):

$$MinC = \sum (c_p^c + \varphi \cdot c_p^m) + \pi_1 + \pi_2, p = 1, 2, \dots, v \quad (4.1a)$$

subject to:

$$c_p^c = \sum x_{p,q} \cdot u_q, q = 1, 2, \dots, w, \forall p \quad (4.1b)$$

$$c_p^m = \lambda \cdot c_p^c, \forall p \quad (4.1c)$$

$$Poss \{Q = SWMM(\vec{x}, r, \xi) \leq \gamma | r, \xi\} \geq \alpha \quad (4.1d)$$

$$s_i \leq \omega_i, i = 1, 2, \dots, n \quad (4.1e)$$

$$0 \leq \vec{x} \leq x_{\max} \quad (4.1f)$$

where C is total cost of LID design, which consists of construction cost, maintenance cost and penalty factors; p is index of subcatchment; v is number of subcatchment; c_p^c and c_p^m are construction and maintenance costs of LIDs for p^{th} subcatchment, respectively. c_p^m is defined as a certain ratio λ to c_p^c ; φ is the discount factor; π_1 is penalty factor for violation of fuzzy constraints (4.1d); π_2 is penalty factor for violation of deterministic constraints (4.1e) or (4.1f); $x_{p,q}$ is decision variable which represents the implementation level (e.g. unit size) of the q^{th} type of LID for the p^{th} subcatchment (as it is assumed that the number of each type of LID facilities for each subcatchment is predefined, and these facilities would share the same $x_{p,q}$); u_q is unit cost of the q^{th} type of LID; Q is total flood volume with a threshold of γ ; the threshold volume γ is used in the fuzzy simulation (FS) process as the maximum acceptable total flood volume of the whole drainage system, which is elaborated later in this section; Q is the output of *SWMM*, which is driven by its input rainfall (r) and vector of decision variables ($\vec{x}$); ξ is matrix of fuzzy parameters (e.g. roughness

coefficients); confidence level α is used to compare with the possibility of fuzzy events in $\{\cdot\}$, i.e. $Poss\{\cdot\}$, which is calculated through FS process. α could be interpreted as ‘although the model parameters have uncertainty, α is the lowest confidence we have for satisfying the flood constraint goal under this particular implementation scheme of LID’. After FS process, if $Poss\{\cdot\}$ is smaller than the given α (i.e. fuzzy constraint (4.1d) is not satisfied), a penalty π_l will be added into fitness to reject the candidate LID scheme; i denotes index of junctions which locate in important areas (e.g. subway entrance, school and hospital) and have special requests of preventing flood risks; n is the total number of i ; s_i is surcharge volume at the i^{th} junction; ω_i is threshold level of s_i ; x_{max} is vector confines the maximum value of $\vec{x}$.

Generally, to solve model (4.1), the fuzzy constraint (4.1d) needs to be converted to its crisp equivalent. This is particularly efficient when the fuzzy constraint is linear, and the fuzzy MF $\mu(\xi)$ have specific shapes like triangular or trapezoidal (Liu and Iwamura 1998). In this study, as the fuzzy constraint is interweaved with simulation model, which is highly non-linear, it is infeasible to convert the constraint to its crisp equivalent (i.e. deterministic). To solve this problem, a fuzzy simulation (FS) approach proposed by Liu and Iwamura (1998) is introduced to compute the possibility under fuzziness ($Poss$). Taking constraint (4.1d) as an example, the steps of FS are briefly summarized as follows:

Step 1: Set $Poss = 0$;

Step 2: Generate a vector ξ^0 uniformly from the α -cut of ξ ;

Step 3: Compute the total flood volume Q^0 under the realization of ξ^0 . If $Q^0 \leq \gamma$ then set $\mu = \min(\xi^0)$, otherwise, set $\mu = 0$;

Step 4: If $Poss < \mu$, then set $Poss = \mu$, otherwise, $Poss$ remains unchanged;

Step 5: Repeat *Step 2* to *Step 4* for a given number of cycle n . Finally, $Poss$ will be compared with pre-determined confidence level α for checking violation of fuzzy constraint.

For numerical examples of FS, readers can refer to He et al. (2008) and Xu and Qin (2013). The computational time of FS is mainly determined by a predetermined number of cycle c .

4.3 Case study

4.3.1 Case Background and Model Setup

Description of the study site

A hypothetical urban catchment adapted from a real tropical urban area is selected to demonstrate the proposed framework. Figure 4.2 shows a land use map and layout of the drainage network of the study site. The site is of an area of about 98 hectare and mainly characterized by urban commercial and residential areas under a tropical climate, where the average rainy days is about 167 days of the year, and the long-term mean annual rainfall is 2166 mm (Meteorological Service Singapore, 2020). An urban hydrological model is setup on SWMM based on drainage map and land use map, which consists of 10 subcatchments, 21 junctions, 21 conduits and 1 outfall. The cross-section type of all conduits is closed rectangle.

Fig. 4.2 Drainage system and land use of study area

Design rainfall

The designed rainfall is based on local intensity-duration-frequency (IDF) curve and Huff storm distribution. The IDF curves reveal the characteristics of the rainfall

extremes, which are established based on annual maximum rainfalls with various durations (Arnbjerg-Nielsen 2012). The Huff storm distribution (Huff 1967) includes four types of rainfall patterns, where the peak intensity of each pattern would occur in different quarters of the rainfall duration. For this study, we assume a 1-hour design rainfall with a total depth at 92 mm (i.e. 10-year return) and a Type-II Huff distribution (Jun et al. 2019). The design rainfall is used to set up the model and generate flood scenarios. The 10-year rainfall is chosen based on test runs to ensure that under such a magnitude of design rainfall, the maximum implementation level of LID could largely reduce the flood damage in the studied case. Whilst under a more severe design rainfall (e.g. 25-year rainfall, as used in Chapter 3), the effect of LID could be rather limited.

Sensitivity test

Sensitivity tests are needed to identify key model parameters that may cause notable impact on flooding results and are necessary to be addressed as uncertainty factors (i.e. fuzzy parameters). Based on the pervious works (Krebs et al. 2013; Yu et al. 2017) and local hydrological conditions, six candidate parameters are selected for sensitivity test. They include: (i) subcatchment properties: slope, impervious depression storage and overland flow width, which are highly diverse even within single subcatchment; (ii) hydraulic roughness for conduits and overland flows, which may change with time and difficult to estimate. Based on their default values, these parameters are allowed to vary within their corresponding sampling range following a fixed sampling step. Based on the test results, the conduit roughness n_c , the Manning's n for pervious overland flow n_p and the width of overland flow path W_f are determined to be the most sensitive parameters in SWMM. For detailed information about candidate parameters and their test results, please refer to Table 4.1 and Figure 4.3, respectively.

Table 4.1 Potential model parameters for sensitivity analysis

Parameter	Description	Original value	Sampling range	Sampling step
S (%)	Slope of subcatchments	1.0	0.5-2.0	0.1
D_i (mm)	Depression storage for impervious surfaces	1.5	1.0-2.0	0.1
W_f (m)	Width of overland flow path	500	200-800	50
n_i (s/m ^{1/3})	Manning's n for impervious overland flow	0.01	0.005-0.02	0.001
n_p (s/m ^{1/3})	Manning's n for pervious overland flow	0.1	0.05-0.4	0.05
n_c (s/m ^{1/3})	Conduit roughness	0.015	0.005-0.03	0.005

Fig. 4.3 Sensitivity test of 6 model parameters

Properties and Layouts of LIDs

Three types of LIDs are proposed in this study, namely green roof (GR), bio-retention cell (BC) and permeable pavement (PP). As shown in Figure 4.2, areas within subcatchment $S3$, $S5$, $S6$ and $S8$ are classified as commercial areas (CA) with busy roads, while the remaining 6 subcatchments are residential areas (RA). GR and BC are applicable on both of CA and RA, as they can reduce the overall peak and have aesthetic benefits for the city landscape. PP is assumed only applicable on RA as it is considered not suitable for roads with large traffic volume (Hu et al. 2017).

The detailed properties about LIDs are listed in Table 4.2 and Table 4.3. Some of these values are referred to the Rossman (2015) and Chui et al. (2016). Note that the

soil layer properties of BC and PP are the same as GR, except that the thicknesses of soil layers are 700 mm and 200 mm for BC and PP, respectively. Considering the fact that the area of each subcatchment is significantly larger than the unit size of each LID facility, there will be multiple facilities (with the same unit size) of the same type of LID deployed in one catchment. The detailed allocation of the LID numbers in each subcatchments can be obtained from Table 4.4. The decision variables are areas of each facility for GR, BC and PP in different subcatchment. Thus, there are in total 26 (i.e. $4 \text{ CA} \times 2 \text{ types of LIDs} + 6 \text{ RA} \times 3 \text{ types of LIDs}$) continuous decision variables.

Table 4.2 Properties of green roof

Surface layer		Soil layer		Drainage layer			
Berm height (mm)	200	Thickness (mm)	100	Conductivity (mm/hr)	3.3	Thickness (mm)	40
Vegetation fraction	0.5	Porosity (volume fraction)	0.46	Suction head (mm)	88.9	Void fraction	0.3
Roughness	0.1	Field capacity	0.23	Conductivity	5	Roughness	0.1
Slope (%)	2.0	(volume fraction)		slope (%)			

Table 4.3 Properties of bio-retention cell and permeable pavement

Type	Surface layer		Drainage layer		Storage layer	
Bio-retention cell (BC)	Berm height (mm)	250	Flow coefficient	0.5	Thickness (mm)	600
	Vegetation fraction	0.3	Flow exponent	0.5	Void fraction	0.5
	Roughness	0.1	Offset Height (mm)	200	Seepage Rate (mm/hr)	50
	Slope (%)	1.0				
Permeable pavement (PP)	Berm height (mm)	30	Flow coefficient	0.5	Thickness (mm)	300
	Vegetation fraction	0.5	Flow exponent	0.5	Void fraction	0.5
	Roughness	0.01	Offset Height (mm)	150	Seepage Rate (mm/hr)	50
	Slope (%)	1.0				

Table 4.4 Number of LID facilities and land use of each subcatchment

LID	<i>S1</i>	<i>S2</i>	<i>S3</i>	<i>S4</i>	<i>S5</i>	<i>S6</i>	<i>S7</i>	<i>S8</i>	<i>S9</i>	<i>S10</i>
GR	20	50	60	50	20	80	180	100	70	80
BC	20	60	70	50	20	100	120	150	70	60
PP	20	50	/	60	/	/	200	/	50	60
Land use	RA	RA	CA	RA	CA	CA	RA	CA	RA	RA

Note: GR, BC and PP denote green roof, bio-retention cell and permeable pavement, respectively; RA and CA denote residential areas and commercial areas, respectively.

Setup of FSO framework

Configuration of the optimization framework is: (i) according to Chui et al. (2016), the unit construction costs (u_q) of GR, BC and PP = 152, 153 and 61 US\$/m²; (ii) the discount factor (φ) = 11.1, which is a function of design life and interest rate; (iii) the ratio of maintenance to construction cost (λ) = 0.03; (iv) the threshold of total flood volume (γ) = [35000, 40000, 45000, 50000] m³, and each junction is equally important in the case area (i.e. $n = 0$ for Eq. 2e); (v) confidence level (α) = [0.55, 0.75, 0.95]; (vi) the maximum unit size (x_{max}) for GR, BC and PP are all set to 500 m². From sensitivity test, n_c , n_p and W_f are assumed as fuzzy sets. For simplicity of calculation, these fuzzy sets are denoted as triangle or trapezoid-shaped MF (as shown in Figure 4.4. Generally, the shapes of fuzzy sets could be more specific (e.g. exponential or Gaussian) based on actual survey or data analysis, as the FS process is applicable to any kinds of MF (Xu and Qin 2013).

Fig. 4.4 Membership functions for fuzzy model parameters

The SWMM is directly linked with MATLAB GA toolbox (version of 2015b). Processes of candidate generation, file reading, model calling, fuzzy simulation, and fitness calculation are all coded and executed under the MATLAB platform. Several main parameters are set as follows: (i) maximum number of generation = 30 (selected according to the convergence speed of minimum fitness value); (ii) population size = 50 (chosen to have an affordable computational cost of FSOM while maintaining the diversity of population in each generation); (iii) crossover fraction = 0.8 (adopted the default value in MATLAB); (v) penalty factor $\pi_1 = 1 \times 10^8$ and $\pi_2 = 1 \times 10^8$ (selected to be notably larger than the maximum fitness value to ensure rejection of unqualified solutions); (vi) the cycle number $c = 500$ for FS process (selected to have reliable results with affordable computational cost). The GA operation is carried out on a 32-core AMD Opteron 2.6 GHz workstation and it takes approximately 30 hours to solve FSOM in a single run. In comparison, a deterministic model with all parameters fixed at their intermediate values takes about 1.5 hours on the same machine.

4.3.2 Result analysis

Figure 4.5 shows the optimized total costs of LIDs (C , unit in million US\$) from the FSOM and the deterministic model under various confidence levels (α) and thresholds of system flood volume (γ) (unit in 10^3 m^3 , the same hereinafter). It implies that for the FSOM, α and γ determine the strictness of LID implementation: a higher α or a lower γ normally leads to a higher C and vice versa. Particularly, when α increases from 0.75 to 0.95, C would increase from 83.47 to 96.08 with $\gamma = 35$ and from 50.27 to 58.58 with $\gamma = 50$. For deterministic model, C would fall between the FSOM results with confidence levels of 0.75 and 0.95 under most γ levels (except for $\gamma = 45$). In general, FSOM and deterministic models achieve comparable costs under various conditions. The advantage of FSOM lies in that, with various confidence levels being considered, it could offer a spectrum of solutions for decision makers who could eventually determine a suitable tradeoff between risk and cost.

Since a higher confidence level generally corresponds to a more reliable system, the result from the confidence level of 0.95 will be focused on. Figure 4.6 shows the maps with optimal coverage areas of LIDs and the percentages of vacant areas (i.e. area

free of LIDs) marked in different subcatchments under different γ levels. Subplots (a) to (d) represent the scenarios with $\gamma = 35, 40, 45$ and 50 , respectively. Generally, Figure 4.6 shows that, for most subcatchments, the percentage of vacant area would increase with the increase of γ , and this leads to a lower C . The only exception is subcatchment $S7$, where the LID coverage percentages are 53.95% and 59.08% under $\gamma = 35$ and 50 , respectively. Besides, in some subcatchments, some specific types of LID tend to be dominant (e.g. GR for $S5$, BC for $S3$ and $S8$, and PP for $S2$ and $S7$), while some prefer a more balanced implementation among three types of LIDs (e.g. $S1$ and $S10$).

Under the four optimal layouts of LIDs illustrated in Figure 4.6, SWMM (embedded with fuzzy parameters) has run another 1,000 times for each layout. Figure 4.7 uses box plots to show the variation of flood volume at individual junctions (with a threshold of $1,000 \text{ m}^3$ for extreme flood volume) based on the simulation results. The purpose is to investigate the impact of parameter uncertainties on model performance after the implementation of LIDs. It is indicated from Figure 4.7 that the uncertainty associated with SWMM parameters may lead to spatial variations of flooding. In terms of extreme flood conditions, the outliers of some junctions are well outside their normal ranges. For instance, the median flood volume of J13 is $2,110 \text{ m}^3$ ($\gamma = 35$), but the outliers may reach up to $4,437 \text{ m}^3$ (210.3% of median); whereas one outlier of J6 (483 m^3 , $\gamma = 35$) is only 31.8% of its median ($1,521 \text{ m}^3$, $\gamma = 35$). In terms of heavily flooded junctions whose maximum flood volumes are over $4,000 \text{ m}^3$, some are subjected to higher uncertainties (e.g. J13 and J17, but only when γ is relatively small), and some are much more stable (e.g. J14 and J19) under all γ levels. The less flooded junctions (e.g. J12 and J21) witness a variety of degree of uncertainties, but the measures to match their maximum outliers are affordable. For these junctions, the absolute increases of flood volumes are limited and thus manageable by extra LID implementations nearby. These results may help decision makers understand the potential extreme flood risks in specific areas after adopting the optimal solutions, and take necessary actions by adjusting local settings (Yu et al. 2017).

Fig. 4.5 Optimized total cost of LIDs from deterministic model and FSOM with different confidence levels (alpha) and thresholds of system flood volume

Fig. 4.6 Maps with coverage area of GR (vertical line), BC (horizontal line), PP (cross line) and percentage of the vacant area marked in different subcatchments. Optimized by FSOM under confidence level of 0.95 and system flood volume threshold of (a) 35,000 (b) 40,000 (c) 45,000 and (d) 50,000 m^3

Fig. 4.7 Boxplot of flood volume at individual junctions (with a threshold of 1,000 m^3). LIDs are optimized by FSOM under confidence level of 0.95 and system flood volume threshold of (a) 35,000 (b) 40,000 (c) 45,000 and (d) 50,000 m^3

4.3.3 Comparison with a traditional stochastic model

In order to demonstrate the applicability of FSOM, a traditional MCS-based stochastic model (e.g. Duan et al. 2016) is also applied to solve the problem under similar setup (i.e. $\alpha = 0.95$ and the same options of GA). Instead of defining uncertainty parameters (i.e. W_f , n_p and n_c) as fuzzy sets, they are assumed as stochastic variables with normal distributions, which are summarized in Table 4.5. Figure 4.8 shows a comparison of the iteration processes between FSOM (denoted as F) and stochastic model (denoted as S). Subplots (a) to (d) represent the processes with $\gamma = 35, 40, 45$ and 50 (unit in 10^3 m^3 , the same hereinafter), respectively. In each subplot, solid lines and dash lines are used to represent the minimum and mean fitness value in each generation of GA, respectively.

Figure 4.8 shows that the stochastic model outperforms FSOM with respect to mean fitness value under various γ ; in other words, the gap between the mean and the

minimum values for stochastic model is usually narrower than that of FSOM. Taking $\gamma = 45$ as an example, the mean values of FSOM would fluctuate between 125.7 and 158.8 million \$, which are much larger than the corresponding minimum values (63.1 to 75.9 million \$). This may be because the FS process is sensitive to not only the simulation model, but also the number of fuzzy parameters. When there is more than one fuzzy parameter (e.g. three in this case study), FS adopts the minimum α -cut of these parameters as the possibility (i.e. $Poss$) under fuzziness. Therefore, under a high confidence level (i.e. $\alpha = 0.95$), FS is relatively difficult to acquire a $Poss$ that is larger than α when the cycle number is reached, which would bring penalties (π_1 , 100.0 million \$) into fitness values of candidates. As a result, the mean values of FSOM would increase in each generation. On the other hand, there is no concept of α -cut for stochastic model, and $Poss$ is calculated by the proportion of candidates that satisfy the flood constraint, which reduces the risk of constraint violation.

In terms of minimum value, which is deemed as a practical criterion for optimization models, FSOM and stochastic model achieve very close results in their final generations in subplots (b) ($\gamma = 40$) and (d) ($\gamma = 50$), and the relative differences are 2.5% and 2.8%, respectively. For the remaining two subplots, in subplot (a) ($\gamma = 35$), FSOM is defeated with a relative difference of 7.3%, whereas in subplot (c) ($\gamma = 45$), FSOM surpasses stochastic model with a relative difference of 9.0%. It is worth noting that both models have drawbacks regarding the iterative processes. Stochastic model has the risk of deviation in the last few generations in subplot (c); FSOM gains no feasible candidate (i.e. candidate without penalty) in both 9th and 20th generations in subplot (d), which endangers the feasibility of the following generations. In general, the two models achieve comparable performances based on minimum fitness values and both models could be considered as feasible alternatives to deal with uncertainty issues addressed in the study case. However, by adopting MF and FS, it is believed that FSOM could address the imprecision and vagueness arising from the modeling process and expert knowledge in a more flexible way.

Table 4.5 The coefficients of normal distributions for uncertain parameters

Parameter	Description	Mean (μ)	Standard deviation (δ)	Minimum value
W_f (m)	Width of overland flow path	500	100	100
n_p (s/m ^{1/3})	Manning's n for pervious overland flow	0.1	0.05	0.01
n_c (s/m ^{1/3})	Conduit roughness	0.015	0.005	0.001

Note: The purpose of setting minimum values is to prevent the generation of negative values, which could lead to an error in SWMM and interrupt GA iteration process.

Fig. 4.8 Comparisons between iteration processes (solid line: min fitness value; dash line: mean fitness value) of FSOM (denoted as F) and stochastic model (denoted as S). Both under confidence level of 0.95 and system flood volume threshold of (a) 35,000 (b) 40,000 (c) 45,000 and (d) 50,000 m³

4.3.4 Further Discussions

This work attempts to integrate various techniques into FSOM for supporting LID design under uncertainty. These techniques involve urban hydrological modeling, chance-constrained programming, fuzzy simulation and an evolutionary algorithm. The model allows generation of robust optimal solutions that could achieve tradeoffs between the flood risks (e.g. thresholds of system flood volume and corresponding confidence levels) and the total cost of LIDs. More importantly, the framework of

FSOM is flexible for various practical problems, such as hydrological model for other locations and additional types of LIDs (e.g. rain garden and vegetative swale). The performance of the proposed FSOM is justified by comparing it to the traditional deterministic and stochastic models, and it is a feasible alternative to the traditional optimization models.

As the first attempt in proposing FSOM, we also encountered some limitations. Firstly, the decision variables (i.e. implementation levels of LIDs) are set as the unit area of each LID facility in each subcatchment, and the numbers of these facilities are fixed in all subcatchments. In this way, the coverage of LIDs could be adjusted, and the number of decision variables could be limited to the product of subcatchment number and number of LID types. In practical design, the number of LID facilities in each subcatchment may also be considered as decision variables. Secondly, the computational burden for FSOM is much higher than the traditional deterministic model, as FS requires repetitive execution of hydrological model for a cycle number of times. Surrogate approaches such as ANN (He et al. 2008; Lu et al. 2017) may be a promising solution to help alleviate computational cost by explicitly mimicking the relationships between decision variables and system responses. Thirdly, we only address uncertainties related to model parameters. Other types of uncertainties (e.g. rainfall pattern, climate change impact, and setup of optimization algorithm) are desired to be tackled in future works. Moreover, the flood risk is controlled by the system flood volume. It is believed that, with the support of further geographical data and social economic input, a two-dimensional inundation model could further improve the accuracy of flood risk assessment.

4.4 Summary

An integrated fuzzy simulation-optimization model (FSOM) for supporting low impact development (LID) design was proposed. FSOM integrated techniques of fuzzy simulation, chance-constrained programming, hydrological modeling and evolutionary algorithm to achieve trade-offs between investments of LIDs and flood risks. The performance of the proposed FSOM were tested through a case study of a hypothetical urban catchment. FSOM applied a simulation-based iteration process,

which could effectively address the uncertainty associated with hydrological model. Meanwhile, the constraints with fuzzy variables were allowed to be satisfied at specified confidence levels. It was shown that a higher confidence level and a lower threshold of flood volume would bring a more reliable system but a less economically attractive plan. The applicability of FSOM was also demonstrated through comparison to an MCS-based traditional stochastic model. The heavy computational burden of FS process is a major limitation of this work. In addition, the absence of surficial inundation modeling may limit the precision of flood risk assessment. Both issues are desired to be tackled in future works.

CHAPTER 5. ON COMPARISON OF TWO-LEVEL AND GLOBAL OPTIMIZATION SCHEMES FOR LAYOUT DESIGN OF STORAGE PONDS¹

5.1 Background

Urbanization has been taking place worldwide since the 1950s, resulting in rapid change of city geography and increasing runoff discharges (Wang et al. 2017; Cimorelli et al. 2016). Climate change is also believed to have resulted in escalated frequency and severity of extreme rainfalls around the world (Chen et al. 2016; Kirshen et al. 2014). Both effects are threatening the existing urban drainage systems by posing higher flooding risks and bringing severe damages to property assets, transportation systems, industrial manufacturers, and human lives (Lu et al. 2019a). As one of the efficient solutions to reduce peak flows and cope with flood impact, hydraulic structures such as storage tanks, floodplain storages and stormwater capture tanks are widely adopted (Chapman and Horner 2010; De Martino et al. 2012; De Paola and Ranucci 2012; De Paola et al. 2013; Tao et al. 2014; Huang et al. 2015; Li et al. 2015; Topa et al. 2015; Bellu et al. 2016). Since implementation of these facilities generally involves significant investment, their designs would need careful consideration on tradeoffs among environmental, social and economic factors (Cunha et al. 2016). Over the past years, optimization techniques have emerged as robust tools to aid the planning and design of such facilities.

From the previous studies, one of the popular methods was to dynamically link a simulation model with an optimization framework that targeted at a specific design of the drainage network or layout (Cibin and Chaubey 2015; Kalcic et al. 2014; Tao et al. 2014). Hydrological simulation models such as storm water management model (SWMM) (Rossman 2015) and PCSWMM (Lu et al 2017b) could be utilized for describing the relationship between control measures and hydrological responses. It is also found from previous studies that choosing efficient optimization algorithm is

¹ This paper has been published in *Journal of Hydrology*.

critical for achieving effective convergence of solutions (Cibin and Chaubey 2015). Evolutionary optimization algorithms such as SA, GA and NSGA-II are popular choices among many optimal designs of storage facilities (Tao et al. 2014; Oxley and Mays 2014; Li et al. 2015; Cunha et al. 2016; Yu et al. 2017).

Nevertheless, GA and its peer algorithms still have problems in global convergence and high computational cost if the optimization problem is of a large scale and involves significant number of decision variables (Andre et al. 2001; Lin and Lee 2004; Kadaba and Nigard 2014). To tackle such an issue, several multi-level optimization approaches were proposed for splitting massive and complex problems into smaller ones. For example, James and Dovit (1985) proposed a method for decomposing an optimization problem into several sub-problems, and introduced a coordination mechanism that preserved coupling between sub-problems. The method was tested for an assembled structural optimization problem where a shorter design time was achieved. Cibin and Chaubey (2015) developed a multi-level spatial optimization approach (MLSOPT) for dealing with watershed-scale spatial optimization problems by disaggregating the watershed into sub-watersheds and identifying optimum layout for each one. The study demonstrated that MLSOPT achieved robust convergence and high-efficiency in computation compared with the single-level option. Wang et al. (2017) presented a two-stage multi-objective optimization scheme for designing storage tanks. The scheme included an analytical module (stage I, to obtain a preliminary scheme) and an iteration module (stage II, to search for optimal scheme based on the preliminary scheme). Generally, few of these studies took into account the hydrological characteristics of an urban watershed in dividing sub-watersheds, and carried out optimization in consideration of tributary and mainstream interactions.

Moreover, building and calibrating a large-scale hydrological model is normally time-consuming (Krebs et al. 2013), and the high computational burden of tautologically running the simulation-aided optimization models may restrict the applicability of the method. One possible solution is to use surrogate models like artificial neural network (Sreekanth and Datta 2011), moving least squares (Yu et al.

2015b) and response surface models (Seo et al. 2012), to replace the physical models, instead of linking them directly into the optimization modules. These surrogate models could be built up with multiple scenarios simulated from hydrological models, and applied to approximate the input-output hydrological relations for achieving computationally more efficient predictions (Yu et al. 2015a). In general, there were rarely reported studies that adopted surrogate models in multi-level optimization frameworks in the field of drainage infrastructure design.

Therefore, this study aims to propose a new optimization scheme for supporting optimal design of storage ponds by embedding surrogate models into a two-level optimization framework. The level-I optimization will focus on upstream area, mainly involving tributary sub-watersheds. Upon receiving the outputs from the level-I, the level-II optimization will embark on downstream area comprising the mainstream sub-watershed. Quadratic regression models (i.e. the surrogate models) are introduced to describe the hydraulic relationships between the layout (i.e. location and sizes) of storage ponds and the overloaded flood volume in the drainage system. The proposed scheme will be compared with traditional single-level optimization scheme in terms of applicability, reliability and computational efficiency. A hypothetical urban watershed is introduced as the study case and discussed on comparing the two schemes.

5.2 Methodology

Figure 5.1 shows a flowchart of the overall methodology. Two optimization schemes for layout design of storage ponds are introduced, including (i) a two-level optimization (TO) scheme with quadratic regression and gradient-based solution algorithm; (ii) a global optimization (GO) scheme with GA aided solution. Details of the two schemes are given below.

Fig. 5.1 Flow diagram of the proposed design framework

5.2.1 TO scheme

Establishment of the physical model

A physical model is normally utilized to demonstrate the hydraulic or hydrologic relations in an urban drainage system. SWMM is a dynamic model for linking rainfall to runoff in the drainage networks and tracking the water quality of runoff generated within each sub-watershed (Aad et al. 2009), and it has been used worldwide for planning, design and analysis related to urban drainage systems (US EPA 2020). Generally, mainstream and tributaries can be identified according to the hydraulic structure of a drainage system. In this study, sub-watersheds contributing to tributaries will be grouped into tributary sub-watersheds, whereas those contributing to the mainstream will be categorized as mainstream sub-watersheds. In TO scheme, the tributary sub-watersheds are the target areas for level-I optimization, and the mainstream sub-watershed will be tackled at level-II.

Establishment and validation of surrogate models

Polynomial surrogate models are adopted to explore the relationships between several explanatory variables (e.g. locations and size of interested hydraulic units) and one or more response variables (e.g. performance and construction cost of these hydraulic units). Polynomial models are essential intermediaries for replacing the physical models during the optimization process in TO scheme. The main reason lies on the avoidance of using simulation model under an optimization framework, which may bring along technical difficulty and high computational burden. Also, comparing with other surrogate models like ANN, polynomial models have explicit mathematical expressions which are more favourable for optimization model expression and solution. Taking a quadratic model as an example, the formulation is given by Eq. (2.2).

For model establishment, all the junctions over the study area are assumed potential locations to install storage ponds. Random samples of storage pond layout (i.e. locations and surface area of ponds) can be generated by using Latin Hypercube Sampling (LHS) (McKay et al. 1979). For each sample of layout, SWMM will run under a specific design rainfall to compute the total surcharged runoff (i.e. flood volume) from all nodes (i.e. junctions and ponds) within sub-watersheds. Then a polynomial surrogate model is introduced to mimic the relationship between the layout of storage ponds and the corresponding flood volume. For model validation, the samples can be split into training and testing groups. The testing group does not contribute to the model construction, but only be used to test the predicted values from the training group.

Formulation of optimization models

In this study, the total number of implemented storage ponds within each sub-watershed is firstly determined. The criteria could be set by the decision makers considering budget availability, land susceptibility, or flood control balance. Here we use the evenness of flood distribution over sub-watersheds under the design rainfall. After the number of storage ponds are determined, the optimal layout (including

location and size) of ponds within each sub-watershed can be identified through the following two-level optimization process. In level-I optimization, the model will generate the optimal layout of storage ponds in each tributary sub-watershed. By controlling the total flood volume in the tributary area, it lays a foundation for the level-II optimization, which focuses on the mainstream area. Let i denote the i^{th} sub-watershed (S_i), the corresponding optimization model can be formulated as (Tao et al. 2014):

$$\text{Min}TC_i = \sum_{k=1}^{j_i} [a \cdot (A_k \cdot H_k)^e + b \cdot A_k + g(A_k)] \quad (5.1a)$$

subject to

$$j_i \leq p_i \quad (5.1b)$$

$$F_i = f_i(A_k) \leq c_i, \forall k \quad (5.1c)$$

$$a, b, g(\cdot) = \begin{cases} \text{const}, & A_k \geq A_{\min} \\ 0, & A_k < A_{\min} \end{cases}, \forall k \quad (5.1d)$$

$$A_{\min} \leq A_k \leq A_{\max} \quad (5.1e)$$

where TC_i is total cost of building the storage ponds in S_i ; j_i is number of storage ponds in S_i ; p_i is maximum number of storage ponds in S_i ; k is index of j_i ($k = 1, 2, \dots, j_i$); A_k is surface area of the k^{th} storage pond, varying within the range of $(A_{\min}, A_{\max})$; H_k is depth of the k^{th} storage pond; a and e are coefficients pertaining to the dimension of storage pond and b = a coefficient reflecting the unit land cost in the area; $g(\cdot)$ is launching cost of each storage pond (Li et al. 2015; Huang et al. 2015), which can also be considered as an additional cost for initializing the storage pond construction. Eq. (5.1d) denotes that a , b and $g(\cdot)$ will automatically turn to 0 for leaving out the construction cost of a specific storage pond when the iterated input of A_k is less than $A_{\min}$; otherwise, they will be set constant, regardless of the exact size of the storage pond. F_i is total flood volume from all junctions (or ponds) in S_i , which is equal to the excessive runoff that beyond the capacity of junctions and storage ponds in S_i . F_i is calculated based on the corresponding variables A_k of the regression model (here

denoted as function f_i) for S_i ; c_i is total flood volume threshold from all junctions (or ponds) in S_i .

The mainstream sub-watershed is distinguished from the remaining sub-watersheds located in tributaries, as the hydraulic-hydrological performance of the mainstream drainage is significantly influenced by the runoff from tributaries. Thus, level-II optimization will adopt the optimization results from level-I (i.e. layout of storage ponds in all the tributary sub-watersheds) as its inputs. The corresponding regression model will be established for the mainstream sub-watershed, keeping all tributary watersheds fixed at A_k ($k = 1, 2, \dots, j_i$; $i = 1, 2, \dots$) from level-I. The objective of level-II optimization is the optimal layout of storage pond in mainstream sub-watershed. The optimization formulation at level-II is formulated as:

$$MinTC_M = \sum_{m=1}^{j_M} [a \cdot (A_m \cdot H_m)^e + b \cdot A_m + g(A_m)] \quad (5.2a)$$

subject to

$$j_M \leq p_M \quad (5.2b)$$

$$F_M = f_M(A_m) \leq c_M, \forall m \quad (5.2c)$$

$$a, b, g(\cdot) = \begin{cases} const, A_m \geq A_{\min} \\ 0, A_m < A_{\min} \end{cases}, \forall m \quad (5.2d)$$

$$A_{\min} \leq A_m \leq A_{\max} \quad (5.2e)$$

$$A_k = const, \forall k, \forall i \quad (5.2f)$$

where TC_M is total cost of building the storage ponds in mainstream; j_M is number of storage ponds in mainstream; p_M is maximum number of storage ponds in mainstream; m is index of j_M ($m = 1, 2, \dots, j_M$); A_m denotes the surface area of the m^{th} storage pond; H_m is depth of the m^{th} storage pond; a, e, b and $g(\cdot)$ are similar coefficients from level-I. F_M is total flood volume from all junctions (or ponds) in mainstream, which is calculated based on the corresponding regression model (here denoted as function f_M); c_M is total flood volume threshold from all junctions (or ponds) in mainstream. In

addition, Eq. (5.2f) emphasizes that the areas and locations of storage ponds outside the mainstream sub-watershed are kept unchanged in the level-II optimization process.

5.2.2 GO scheme

The GO scheme searches optimal solutions at a global scale. Compared with TO scheme, the GO one does not need division of sub-watersheds, and the number of storage ponds is unconstrained in the study area. GA is adopted for searching solutions that could minimize the construction cost and satisfy local constraints (e.g. total flood volume, area limit of storage ponds, etc.). As the problem involves much more decision variables when compared with TO scheme, the sampling space in GA has been largely expanded. The optimization formulation is shown as:

$$MinTC_N = \sum_{n=1}^N \left[a \cdot (A_n \cdot H_n)^e + b \cdot A_n + g(A_n) \right] \quad (5.3a)$$

subject to

$$F_N = s(A_n) \leq c_N, \forall n \quad (5.3b)$$

$$a, b, g(\cdot) = \begin{cases} const, A_n \geq A_{\min}, \forall n \\ 0, A_n < A_{\min} \end{cases} \quad (5.3c)$$

$$A_{\min} \leq A_n \leq A_{\max} \quad (5.3d)$$

where TC_N and N are total cost of building the storage ponds and total number of storage ponds in the entire study area, respectively; n is index of N ; F_N is total flood volume from all the overloaded junctions and ponds, which is calculated based on the output of SWMM (s) under different scenarios of A_n ; c_N is total flood volume threshold in the study area. Definitions and principles of the remaining variables and constants remain the same as in the TO scheme.

5.3 Case study

5.3.1 Case Background and Model Setup

Description of the study site

A hypothetical urban catchment adapted from a real tropical urban area is selected for demonstrating the proposed design framework. Figure 5.2 shows the general map and layout of the existing drainage network of the study site. The site is characterized by urban commercial and residential areas under a tropical climate, where the average rainy days is about 167 days of the year and the maximum hourly rainfalls could reach up to 147 mm (Meteorological Service Singapore 2020).

Fig. 5.2 Layout of the studied drainage network and model setting.

Design rainfall

Rainfall are designed based on IDF curves and Huff distribution. IDF curves reveal the characteristics of the rainfall extremes, which are established based on annual maximum rainfalls with various durations (Arnbjerg-Nielsen 2012). Huff storm distribution includes four types of rainfall patterns, with peak intensity occurring in different quarters of the duration in each pattern (Chow et al. 1988). This study assumes a design rainfall (with total depth at 107.5 mm) with 1-hour duration, Type-

II Huff distribution and 25-years return period (PUB 2011). The design rainfall is established to set up the model and generate flood scenarios.

SWMM and division of sub-watersheds

An urban drainage model based on SWMM is established for the study case with an area of 25.14 km². In this study, the routing model of SWMM is the dynamic wave, which solves the complete one-dimensional Saint-Venant flow equations and therefore produces the most theoretically accurate results. Dynamic wave routing can account for problems including channel storage, backwater, flow reversal and pressurized flow, and it is the method of choice for systems subjected to significant backwater effects due to downstream flow restrictions (e.g. the effect of downstream pond design on flooding of upstream areas), at a price of much higher computational cost (Rossman 2015). Originally, the model consists of 44 subcatchments, 81 junctions, 81 conduits and 1 outfall. These subcatchments are basic hydrological units in SWMM, and they are grouped into several sub-watersheds. Depending on the criteria of division, the drainage system will be aggregated into 1 mainstream sub-watershed and 3-6 tributary sub-watersheds. Based on this structure, 34 subcatchments are considered as in tributary areas, and the remaining 10 subcatchments contribute their runoff directly to the mainstream. The 34 subcatchments in tributary areas are disaggregated into three sub-watersheds (*S1*, *S2* and *S3*), which have 11, 12 and 11 subcatchments (20, 21 and 20 junctions), respectively. The remaining subcatchments form the mainstream sub-watershed *S4*, which has 10 subcatchment (20 junctions). Figure 5.3 shows the result of sub-watershed division. The criteria of division are based on considerations of (i) computational efficiency (i.e. no excessive number of sub-watersheds) and (ii) local hydrological and topographical condition of the study case (i.e. runoff from each sub-watershed independently flows into the mainstream sub-watershed). As the criteria is quite universal, other areas can also be subjected to this method of division. In practical, the division of urban watershed is usually made by decision maker or stake holders.

Setup of optimization framework

In TO scheme, the Constrained Nonlinear Minimization Solver (CNMS) (Coleman et al. 1999; MATLAB 2015) is adopted as the iterative algorithm for searching the optimal layout in TO scheme, and the CNMS is embedded with the regression model as one of model constraints (see Eq. (5.1c) and (5.2c)). In GO scheme, the SWMM is directly linked with MATLAB platform. Therefore, the execution results of SWMM can be automatically extracted into MATLAB for the iteration process of GA. Also, a penalty-based algorithm is adopted in GA process for model solution.

To test the TO scheme, the following parameter settings are adopted (as Scenario I). The coefficients of a , b and e are set as: $a = \$500$, $b = \$100$, and $e = 0.69$. As the launching cost for each storage pond, the value of $g(\cdot)$ is assumed to be \$5000 if the pond is actually implemented. The minimum and maximum areas for each storage pond are set as $A_{\min} = 500$ and $A_{\max} = 10000 \text{ m}^2$, respectively. The depth of each storage pond is set to be equal to its original junction for ease of construction. If the iterated input of A_k and A_m in TO is less than 500 m^2 , it will not be implemented and there is no construction cost calculated for that pond. For the TO scheme, the total flood volume threshold for all nodes in each sub-watershed (c_i and c_M) is set to $20,000 \text{ m}^3$. For consistency, the c_N is set at $80,000 \text{ m}^3$ for the four sub-watersheds in GO.

For the TO scheme under Scenario I, the maximum number of storage ponds is set to 42. In practical applications, this number could be determined based on financial capability, available land area for pond installation, and policy requirement. Then, the number of implemented storage ponds p_i within sub-watershed S_i can be determined either by decision-makers' preference or local condition. In this study, we use design rainfall to test the flooding condition for all sub-watersheds and then apply the percentage of flood volume at each sub-watershed to estimate the maximum number of ponds that should be deployed into each sub-watershed. The detailed results are shown in Table 5.1.

Table 5.1 Flooding information and allocated storage ponds for sub-watersheds in Scenario I.

Sub-watershed No. (S_i)	Flood volume (10^3 m^3)	Flood percentage (%)	Number of allocated ponds (p_i)	Number of original junctions
S_1	192.5	27.6	11	20
S_2	155.3	22.2	10	21
S_3	181.1	26.0	11	20
S_4	169.0	24.2	10	20
Sum	697.9	100	42	81

Fig. 5.3 Division of sub-watersheds over the study domain

Setup of surrogate models

The quadratic regression models are adopted and established in TO scheme. The sampling number for each sub-watershed is customized to 1000. To verify the accuracy of quadratic models, among the 1000 samples and their outputs (i.e. total flood volume), 90% of them (i.e. 900 sample sets) are divided into the training group which is used to fit the quadratic model, while the rest 10% are divided into the testing group. The testing results for three tributary sub-watersheds S_1 , S_2 and S_3 are shown

in Figure 5.4 (sub-figures (a), (b) and (c) correspond to *S1*, *S2* and *S3*, respectively). In Figure 5.4, each scatter represents a sample, plotted by using the predicted value of total flood volume from quadratic model on the x axis and simulated results from testing group on the y axis. The straight line in each sub-figure represents the line ' $y=x$ '. From Figure 5.4, most of the regressions achieved a decent fitness with R^2 above 0.95, except for sub-watershed *S2* which has a R^2 of 0.89. This is mainly because of the over-estimation of the flood condition in a small portion of samples by the regression model. After verifying the accuracy of quadratic models, the optimal layout of sub-watersheds *S1* to *S3* is identified by running level-I of TO optimization (details are provided in the Result Analysis and Discussion). Afterwards, the quadratic regression model is built for the mainstream sub-watershed *S4* (subfigure d) and the R^2 level of regression performance is 0.977.

Fig. 5.4 Regression performance of quadratic surrogate model for tributary sub-watersheds *S1* to *S4*

5.3.2 Result Analysis and Discussion

Results of TO and GO scheme

Table 5.2 shows the optimal layouts of storage ponds for all sub-watersheds and the overall performance of TO scheme under Scenario I. Generally, for the TO scheme, the solution with a layout of 42 storage ponds could be obtained, with an overall cost around 42.41 million \$ and overall flood volume at 78,418 m³. For the GO scheme, after a 50-generation iteration (with a population size of 200 for each generation) in the GA-SWMM interaction process (Figure 5.5), the solution with a layout of 71 storage ponds among 81 potential locations is found (see Figure 5.6, the corresponding overall cost is 48.09 million \$ and the overall flood volume is 79,934 m³). The cost of GO scheme is about 13.4% higher than that of TO scheme, while the simulated flood volume under both schemes are both close to the sum of thresholds for all sub-watersheds (i.e. 80,000 m³).

Table 5.2 Optimal layout of storage ponds in each sub-watersheds and overall performance of TO scheme under Scenario I

Sub-watershed	Optimal layout of storage pond												Cost (\$)
S1	Pond	J09	J36	J61	J51	J60	J50	J48	J25	J17	J37	J10	10,293,580
	Area (m ²)	9800	6298	5554	9604	6954	3435	5713	7464	2115	500	2468	
S2	Pond	J47	J23	J21	J32	J44	J42	J57	J41	J40	J31	9,316,161	
	Area (m ²)	3655	7221	3457	9193	6241	3274	6068	6491	5549	2298		
S3	Pond	J68	J78	J82	J72	J65	J80	J69	J63	J74	J77	J67	10,855,816
	Area (m ²)	4088	7058	4768	7471	8509	4297	4758	5820	5391	5521	4446	
S4	Pond	J04	J05	J06	J11	J12	J13	J19	J28	J38	J54	11,945,893	
	Area (m ²)	6969	7604	6680	6478	6942	6219	7567	5867	5911	6244		
Overall flood volume (m ³)					78,418			Overall Cost				42,411,450

Fig. 5.5 Iterative process under GO Scheme

Fig. 5.6 Final generation under GO Scheme

To investigate the two optimization schemes under different settings of constraints, two more scenarios, namely Scenarios II and III, are examined in addition to Scenario I. Scenario II assumed a lower maximum number of storage ponds (i.e. 38), and a higher threshold of flood volume for each sub-watershed (i.e. 30,000 m³). The maximum storage pond area is limited to 8,000 m². Scenario III allows more storage ponds to be constructed (maximum number set to 50) but their maximum storage area is reduced to 6,000 m². The threshold of flood volume for this scenario is set to 15,000 m³. There are no strict rules to set these parameters, as the main purpose is to test the consistency of TO performance under different conditions. Since the maximum number of ponds has changed, the allocation patterns are also adjusted. Under Scenario III, the number of ponds is still allocated based on the same percentage of flooding used under Scenario I. The allocation pattern for Scenario II has some adjustment assuming decision-makers prefer to add more storage ponds in the mainstream sub-watershed. Scenario IA is added to test the effect of changing the maximum number of ponds for the TO scheme under Scenario I. For a fair comparison between TO and GO schemes, Scenario IA adopts the same settings as Scenario I, except that the maximum number of storage ponds is fixed at 71 which is the same as the optimal number of ponds obtained from GO scheme, Scenario I.

Table 5.3 summarizes the results of the two optimization schemes under Scenarios I, IA, II and III. Generally, both schemes would lead to similar flood levels, and the TO

scheme would achieve a lower cost under Scenario I, II and III (reduction of cost varied from 8.7% to 11.8%) due to reduced number of storage ponds while satisfying local criteria of flood reduction. Whereas, the Scenario IA for TO scheme achieved a final layout of 49 ponds and the overall cost would be somewhat higher than that with TO scheme in Scenario I due to the heavy investment in mainstream sub-watershed (which has a layout of 17 storage ponds at a cost of 23.21 million \$ based on its level-II optimization). That means in Scenario IA, the ponds in mainstream area undertakes more runoff and demands a higher cost of construction, which explain the increase of total cost for this scenario compared with Scenario I. It is noted that the cost from TO scheme under Scenario IA is slightly higher than that from GO scheme, possibly due to the fact that GO's searching is more global, and the achieved average area of ponds (i.e. 3282 m²) from GO is much lower than the Scenario IA (i.e. 5905 m²). The above results demonstrate that, in terms of optimization performance, TO scheme could lead to solutions with superior or at least comparable results than GO scheme.

Table 5.3 Results of two optimization schemes under Scenarios I, IA, IB, II and III

Scenarios	Optimized number of ponds: TO					Optimized number of ponds: GO	Overall cost (\$)		Total flood volume (m ³)		Total run time (hour)	
	S1	S2	S3	S4	Sum		TO	GO	TO	GO	TO	GO
I	11	10	11	10	42	71	42,411,450	48,090,220	78,418	79,934		
IA	12	10	10	17	49		50,335,665		79,483			
IB	11	8	15	9	43		43,456,687		79,366		3.3	6.5
II	9	9	9	11	38	66	38,866,884	43,252,806	117,866	111,278		
III	13	11	13	12	49	74	48,108,047	52,684,022	59,283	58,422		

In terms of efficiency of model runs, the total run times for the TO and GO schemes are approximately 3.3 and 6.5 hours, based on a desktop computer (Xeon™ W3550 CPU @3.07 GHz, 12G RAM). The run time for the TO scheme is estimated based on the following considerations: (1) each SWMM run is about 3s and the time required to run all 1000 samples for 4 sub-watersheds is about $3s \times 4 \times 1000 / 3600 = 3.3$ hours; (2) the optimization process generally takes less than 1 minutes to complete. For GO scheme, the simulation model is called within the optimization framework multiple times depending on the population size for each generation and the total number of generations. It is worth mentioning that the workload of the sampling process to set up the regression surrogate model could be easily alleviated by using

parallel computing (e.g. multiple computers, multiple CPU cores, or cloud computing). It is technically more challenging to reduce computational time for the GO scheme.

Impact of selecting different start points on optimization results

Based on model test, the start points (SP) (i.e. initial value of variables, which refer to the areas of ponds) were found to have a noticeable effect on the optimization results. For TO scheme, the solutions of optimization models show a strong dependence on SP; some sets of SPs cannot even support a feasible solution (i.e. they cannot satisfy the constraints before reaching the stopping criteria). Figures 5.7(a) shows the solutions of storage pond layout and their corresponding objective function values (i.e. construction costs) of 5 runs for sub-watersheds *S1* to *S4* under Scenario I, and each sub-watershed adopted 5 random sets of SPs generated by LHS. It is found that the majority of storage ponds have quite stable areas among five runs (e.g. pond number 1 to 10). However, some solutions are not feasible as they would lead to exceedance of the maximum number of storage ponds. From the figure on the upper right, the objective function values (i.e. construction cost) of 5 runs for 4 sub-watersheds all show indistinct fluctuations, which indicates a stable performance of the TO scheme towards different SPs. The infeasibility issue of solutions may be due to the inherent error associated with the quadratic regression model and the limitation of solution algorithm (i.e. CNMS) that is affected by the selection of SPs and local optima.

For the GO scheme, taking Scenario III as an example, Figure 5.7(b) show that GA performance (i.e. final fitness values) would range from 49.8 to 55.6 million, which is comparable with the 48.1 million achieved by TO scheme under the same scenario. Moreover, Figure 5.7(b) demonstrates that the optimized layout from GO is generally highly diversified among various runs; while the final solutions in the TO scheme are much more stable (as shown in Figure 5.7(a)). Apparently, when the scale of the problem is large (like the studied case), GA may not perform satisfactorily in seeking global optimal solutions.

Fig. 5.7 Results based on Scenario III with different SPs for (a) optimized pond areas and costs of each sub-watershed from TO scheme and (b) optimized pond areas and final costs from GO scheme

Effect of mainstream pond design on sub-watershed flooding

During the sampling stage for building up the quadratic regression model, the physical model (i.e. SWMM) would have to run based on each sample input. The physical model takes the entire watershed into consideration, including the interactions between the mainstream and tributary sub-watersheds. It is found that the layout of storage ponds in the mainstream sub-watershed would also cause flood conditions in the tributary sub-watersheds, mainly through the connecting junctions. To control or alleviate such an effect, if desired, we could consider modify the level-

II optimization model structure. For example, we could add additional constraints of limiting the flood volume at the junctions of concern (e.g. sensitive areas like residential buildings, main roads, and commercial centers) within a certain range. For demonstration purpose in this study, if the refluent of excessive runoff from the mainstream junctions to the adjacent tributary junctions (defined as the “backflow effect”) is of the major concern to decision makers, three extra constraints (denoted as Extra-con) could be added into the level-II optimization framework to limit the gap between the flood volume of the adjacent junctions in mainstream model and tributary model within an allowable level (i.e. 500 m³). Examples of adjacent tributary junctions are J09, J21, and J63, as shown in Figure 5.2. Specifically, from ordinary condition of node flooding under Scenario I, the flood volume for J09, J21 and J63 is 6348, 0 and 2400 m³, respectively. Thus, the extra constraints limits the maximum flood volume of J09, J21 and J63 at 6848, 500 and 2900 m³, respectively. The way to limit the flood volumes of these junctions is adopting regression models to estimate the relationship between flood volumes of junctions and area of mainstream ponds.

Figure 5.8 shows the 1000 sample scenarios of total flood volumes at three tributary sub-watersheds (i.e. *S1*, *S2* and *S3*) and the mainstream sub-watershed *S4*, where the *x* axis denotes the flood volume in the mainstream sub-watershed in an ascending order. It is indicated that the flood volumes from the sampled layouts of storage ponds would vary in both the mainstream sub-watershed and three tributary sub-watersheds. The relationship between these two sets of data is investigated, and the correlation coefficient between them is 0.765, which shows a loose but positive correlation between flood volume in mainstream and tributary sub-watersheds, which indicates that the backflow effect may cause the excessive flood volumes in the tributary sub-watersheds. Figure 5.9 shows the flooded volumes at various junctions (with a threshold of 500 m³) from the two types of models under the TO scheme, which consist of the original model (Scenario I) and the model with Extra-con on controlling backflow effect. It can be found that the junctions of J38 and J63 was heavily flooded in the original model; with the Extra-con, the flooding in J38 and J63 would be significantly eliminated, while the flood conditions at other junctions would fluctuate

around the original level. The details of pond layout in mainstream with Extra-con can be referred to Table 5.4. The results demonstrated that, for TO scheme, more specific constrains at sensitive junctions could be adopted to mitigate the effect of mainstream pond design on flooding conditions of the sub-watersheds. Under original model (Scenario I) and model with Extra-con, the total flood volume would decrease notably from 78,418 to 68,977 m³, and the overall cost would decrease slightly from 42.41 to 41.97 million \$.

Fig. 5.8 Sample scenarios of total flood volumes at tributary sub-watersheds (S1, S2 and S3) and mainstream sub-watershed S4

Fig. 5.9 Flood volume at various junctions (with a threshold of 500 m³) from two optimal solutions (i.e. original Scenario I model and the model with Extra-con on controlling backflow effect) under the TO scheme

Table 5.4 Optimal layout of storage pond in mainstream with Extra-con

Optimal layout of storage pond in mainstream sub-watershed										Cost (\$\$)
Pond	J04	J06	J11	J12	J19	J28	J38	J54		11,506,203
Area (m ²)	10000	10000	8905	10000	5558	6113	8084	7821		
Overall flood volume (m ³)					68,977	Overall Cost				41,971,760

Effect of different division of sub-watersheds on optimized results

In this study, the urban watershed is divided into sub-watersheds according to computational efficiency and local hydrological and topographical condition, but these criteria are still a little bit vague now. In order to test the sensitivity of division of sub-watersheds, we conduct another division (see Figure 5.10), which have 11, 8, 16 and 9 subcatchments for *S1*, *S2*, *S3* and *S4*, respectively; this division is similar to Scenario I, which has 11, 12, 11 and 10 subcatchments for *S1*, *S2*, *S3* and *S4*, respectively. Extra scenario simulations which are denoted as Scenario IB are carried out based on the new division. The Scenario IB adopts similar settings as Scenario I (e.g. maximum number of total storage ponds and maximum area for each ponds). The results of Scenario IB are compared with Scenario I in Table 5.3, which shows a similar overall cost and system flooding between Scenario I and IB.

Effect of different GA options on optimized results of GO scheme

In GO scheme, besides start points, options of GA (e.g. elite count, crossover fraction and mutation function) may also affect the algorithm's efficiency for searching global optimal solutions and satisfy local constraints. In this study, the GA adopt default rates (i.e. 10, twentieth of the Population Size) for 'elite count' which specifies the number of individuals that are guaranteed to survive to the next generation. The 'crossover fraction' which specifies the fraction of the next generation that crossover produces is set to be default rates (i.e. 0.8). The 'adaptive feasible' is chosen as the mutation function, which is the recommended function for constraint-dependent optimization problems (MATLAB, 2015).

Fig. 5.10 The new division of sub-watersheds over the study site for Scenario IB

To further investigate the sensitivity of GO scheme towards options of GA, taking Scenario I as an example, three extra GO scheme runs (with different settings on crossover fraction and elite count rate) has been carried, and the results are summarized in Table 5.5. It is shown that the overall cost ranges from 46.6 to 49.8 million \$, and run No. 2 and No. 4 achieve a lower overall cost than original scenario No. 3, but the total flood volume is slightly closer to the threshold (i.e. 80000 m³). In general, the reliability and convergence of solutions of GO scheme under different options has been verified.

Table 5.5 Results of GO scheme under different GA options

No. of run	Options of GA		Results of GO	
	Elite count	Crossover fraction	Overall cost (\$)	Total flood volume (m ³)
1	3	0.6	49,763,148	79,392
2	6	0.7	46,628,648	79,991
3	10	0.8	48,090,220	79,934
4	15	0.85	46,795,460	79,984

Further discussion

This study attempts to integrate various techniques into a TO scheme for storage pond planning and design. These techniques involve urban drainage modeling, sub-watersheds division, surrogate model construction and CNMS iterative algorithm. The performance of the proposed TO scheme is compared with traditional GO scheme. It is revealed that the TO scheme has the following advantages:

(1) Applicability

Applicability indicates the scope of the proposed scheme to be used in applications (Yu et al, 2015a). The TO scheme could be applied to optimize a large-scale catchment which involves a significant number of decision variables. With the aid of the two-level (or even multi-level) optimization structure, the number of variables in each level would significantly decrease; furthermore, within each level, the regression models are combined with an iterative algorithm for more efficient searching of the optimized results. As for GO scheme, it is proven to be difficult or time-consuming in reaching a global optimal solution if the problem involves a large number of decision variables. Also, under various modelling scenarios in this study, it is found that the TO scheme managed to converge to better or comparable results in terms of overall cost compared with GO scheme (see Table 5.3).

(2) Reliability

Reliability is an indicator showing logical coherence of the scheme and the feasibility of the optimized results under uncertainty. In TO scheme, the regression models are verified (see Figure 5.4) for carrying on the optimization framework. Uncertainty issues, including setup of start points and mainstream effect, and their impact on optimized results were also investigated. Figure 5.7 proves a more stable performance of TO scheme over GO scheme.

(3) Computational efficiency

In this study, TO scheme showed a relatively more efficient computational effort than GO scheme. However, TO is deemed potentially more advantages in undertaking a

parallel computing using multiple cores or computers, as its main time-consuming part is the running of samples to build up the surrogate models and it needs almost negligible time to run the optimization model. GO scheme requires both physical model and optimization run at the same time, which is more challenging to be parallelized.

As the first attempt in proposing TO scheme, we also encountered some limitations. Firstly, the scale control of each tributary sub-watershed is an important issue. For TO scheme in this study, the decision variables (i.e. number of junctions) for each sub-watershed is controlled around 20, ensuring sufficient accuracy of regression models (e.g. in Figure 5.4, all the regression models achieved a decent fitness with R^2 around 0.9 or above). However, when the number of decision variables increases significantly (e.g. each sub-watershed has over 100 junctions), it is likely that the regression models could not achieve an acceptable level of fitness. By simply increasing the number of sub-watersheds may bring extra run time and may not be applicable for optimizing large-scale watersheds. Multi-level optimization may be a good solution, but it needs further investigations. Secondly, as indicated in Scenario I and IA, the performance (i.e. overall cost) of TO scheme is subjected to the user-defined settings (e.g. patterns and maximum number of storage ponds), which may bring along uncertainty issues for the optimization results. Users are recommended to set a relatively lower limit of the number of ponds for saving cost, if the constraints of flood volume can be satisfied. Moreover, the performance of TO is comparable but not necessarily better than the GO scheme, as the main advantages of TO scheme lies in that it saves much computational efforts when the physical model is large and complex and the dynamic linking of GA and model becomes impractical. Thirdly, In the real application, the following considerations are needed: if the number of storage ponds exceeds the capacity of constructing of local construction team, sequence of construction needs to be considered based on sensitivity of flood of each sub-watershed towards storage ponds implementation. Taking the results of this study for example, if there is no storage ponds in the system, the flood volume for the whole system will be 693,200 m³; under the solution which is obtained in Scenario I, if storage ponds are only constructed for one sub-watershed, the flood volume for the

whole system will drop to 537,400, 572,200, 537,700 and 509,800 m³ in *S1* to *S4*, respectively. Therefore, it is recommended that the storage ponds are implemented in an order of *S4*, *S1*, *S3* and *S2*.

5.4 Summary

A two-level optimization (TO) scheme was proposed for supporting optimal design of storage ponds in urban drainage systems. The scheme focused on optimization of storage pond layout in tributary sub-watersheds (level-I optimization) first, and then proceeded to optimization for the mainstream sub-watershed (level-II optimization). The performances of the proposed TO scheme and the traditional global optimization (GO) scheme were tested and compared in terms of applicability, reliability and computational efficiency. A hypothetical case adapted from a tropical urban community was selected for demonstrating the applicability of methodology. The results showed that both schemes could achieve convergences under different settings of optimization constraints. Compared with the GO scheme, the TO one could achieve a comparable or lower system cost, save almost half of the run time and obtain a more stable solution with different setups of start points. It is a good alternative of GO scheme for tackling large-scale problems, although there is still much room for improvement in the future. Also, for both schemes, the effect of backflow from mainstream to tributary areas and their propagation to optimization results need to be further investigated.

CHAPTER 6. INTEGRATED FRAMEWORK FOR ASSESSING CLIMATE CHANGE IMPACT ON EXTREME RAINFALL AND URBAN DRAINAGE SYSTEM¹

6.1 Introduction

Climate change impact is projected to pose profound effect on many aspects of water resources systems (Kerkhoven and Gan 2011; Kuo and Gan 2015), and the number and severity of extreme storms are expected to increase over many urban areas around the world (Olsson et al. 2009; IPCC 2007; Fischer and Knutti 2016; Lu and Qin 2019b). As such extreme events would elevate the risk of flash flood problems, it is imperative to address climate change effect when improvement of current drainage systems or design of new systems are needed for long-term usage. Over the past decades, a large number of research works have been reported to assess climate change impacts on urban rainfall extremes and drainage systems (Willems et al. 2012; Langeveld et al. 2013; Lu & Qin 2014; Bi et al. 2017). Most of these studies relied on combinative efforts of general circulation model (GCM) projection, downscaling and hydrological modelling (Sharma et al. 2007; Semadeni-Davies et al. 2008a, 2008b; Shrestha 2013; Herath et al. 2016; Alamdari et al. 2017).

Specifically, Willems (2013) statistically analysed and downscaled a large ensemble of GCMs and local regional climate models (RCMs) in Belgium. After deriving changes in intensity-duration-frequency (IDF) curves, the study established a conceptual reservoir model to quantify the discharge rate under future extreme scenarios and found that up to 50% increase in storage capacity would be needed to keep the future overflow frequency at the current level. Le et al. (2014) assessed the impact of climate change on urban drainage flow through automated statistical downscaling and K-nearest neighbour (KNN) based disaggregation. Shrestha et al. (2014) assessed the impact of climate change on urban drainage flow by comparing two approaches for generating future climatic scenarios. The first one adopted dynamic downscaling which linked GCM with RCM and the second one followed

¹ This paper has been published in *Hydrology Research*.

hypothetical increments of baseline rainfall conditions by percentages. Zahmatkesh et al. (2015) studied the climate change effect on urban runoff in a river watershed, where downscaling and disaggregation methods were used to obtain hourly rainfall time series. Neumann et al. (2015) employed three GCMs to project future climate scenarios and established a simplified model to address the excessive runoff volume and adaptation costs for urban drainage systems in 19 cities of US.

More recently, Shrestha et al. (2017) proposed a spatial downscaling and temporal disaggregation method for developing future IDF curves using the Long Ashton Research Station Weather Generator (LARS-WG) (Semenov and Barrow 2002; Semenov & Stratonovitch 2015) and rainfall disaggregation tool, HYETOS (Koutsoyiannis & Onof 2001). Kristvik et al. (2018) applied an integrated spatial-temporal downscaling method, which combined Statistical DownScaling Model-Decision Centric and Generalized Extreme Value (GEV) distribution to project future rainfall and generate IDF curves in the city of Bergen. The study also investigated the effect of rain gardens as an adaptation measure to climate change.

From the previous works, it is revealed that statistical downscaling and disaggregation methods are commonly used to generate climate variables (mainly rainfall) for urban hydrological studies. However, due to fine resolution requirement of climate data both temporally and spatially at an urban scale (even at minutes level), it is still a challenging task to carry out climate change impact study for urban drainage systems using individual statistical or modelling methods. Although very limited attempts were made using holistic approaches involving downscaling, disaggregation, rainfall design and hydrological simulation (e.g. Shrestha et al. 2017), the connection of various modules was rather complex. In addition, there are few previous works focused on tropical regions, which are normally characterized by monsoons and intense rainfall with short durations (Fong 2012). It is desired that a more straightforward and flexible approach be proposed for the mentioned purpose.

Therefore, the objective of this study is to propose an integrated framework for assessing climate change impact on extreme rainfall and urban drainage systems. The

framework follows a top-down strategy, covering downscaling and disaggregation techniques for generating high-resolution, on-site rainfall data under climate model projections and hydrological simulations for evaluating performance of the drainage systems. The framework is able to address multiple types of uncertainties arising from climate-change scenarios, model randomness and rainfall design types, and is straightforward to apply. A small urban catchment in the tropical region is used as the study catchment for demonstration.

Study area and data

A small urban catchment located at a tropical city is selected to demonstrate the proposed framework (Le et al. 2014). Figure 6.1 shows its general map and layout of the existing drainage network of the study site. The site is of an area of about 36.4 ha and characterized by urban commercial and residential areas under a tropical climate, where the average rainy days (a rainy day refers to the day with a total rainfall of 0.2 mm or more) is about 167 days in a year and the maximum 1-hour rainfall depth could reach up to 147 mm (Meteorological Service Singapore 2020). The observed rainfall data used for this site includes hourly time series for the baseline period from 1980 to 2010. Other observed weather data including maximum temperature, minimum temperature and solar radiation over the same period for the study site are obtained from Climate Forecast System Reanalysis (NCEP 2020).

Fig. 6.1 Map of land use and drainage system for the study site

6.2 Methodology

6.2.1 System framework

Figure 6.2 shows a flowchart of the overall methodology. There are five major components in the integrated framework, including generator setup, future scenario generation, rainfall disaggregation, rainfall design and hydrologic simulation. Firstly, a stochastic weather generator (SWG) will be used to conduct site analysis based on long-term observed weather records (i.e. temperature, precipitation and solar radiation) for the study site. Secondly, future climate scenarios under various combinations (e.g. GCM, emission scenario and period of prediction) are executed by the generator, and the results are used to generate daily rainfall intensities under various return periods based on Gumbel distribution. Thirdly, the simple scaling method is applied to disaggregate rainfall from daily timescale to hourly one. Then, Huff distributions are adopted to generate minute-level designed rainfalls. Finally, the designed rainfall events are used to drive hydrologic simulations to obtain runoff

information. The detailed description for individual component is given in the followed sections.

Fig. 6.2 Flowchart of the overall methodology

6.2.2 Stochastic weather generator

SWGs are algorithmic models for generating time series of climate variables exhibiting analogous statistical properties as observed data (Semenov and Barrow 2002). They usually work for downscaling an ensemble of climate model outputs and offer probabilistic inferences about future climate impacts. The LARS-WG is one of the SWGs that has been widely used for projecting future daily weather data (including precipitation, temperature and solar radiation) at a single site (Racsko et al, 1991; Semenov et al, 1998; Semenov and Barrow 2002). The latest version of this generator is LARS-WG v6, which comprises a subset of 18 GCMs with 2 Representative Concentration Pathways (RCPs) scenarios (Semenov & Stratonovitch, 2015). The two RCPs (i.e. RCP 4.5 and RCP 8.5) are categorized from Intergovernmental Panel on Climate Change (IPCC) Assessment Report V (IPCC, 2014). For more detailed introduction of LARS-WG, readers are referred to Semenov

and Stratonovitch (2015).

6.2.3 Gumbel distribution

In hydrology, the Gumbel distribution (Cheng et al. 2014; Gumbel, 2012) is popularly used to analyze variables such as monthly and annual maximum values of daily rainfall. When adopting Gumbel distribution for calculating daily rainfall intensities under various return periods, the input is a vector based on statistical analysis of the output of SWGs, and the values of vector represent the annual maximum daily rainfall depth for a length of record of years (e.g. 100 years of record will contribute to a vector with 100 values). Then, a bar plot is created accordingly, and a Gumbel distribution curve is fitted on the plot. Key parameters of the fitted curve include μ (location) and β (scale). In hydrology, given a return period T , the exceedance probability (P) is the reciprocal of T . Thus, in the quantile function (inverse cumulative distribution function), the variable (y) is calculated as:

$$y = 1 - P = 1 - \frac{1}{T} \quad (6.1)$$

According to the quantile function of Gumbel distribution, the corresponding rainfall depth ($Q(y)$) is given by (Gumbel, 1941):

$$Q(y) = \mu - \beta \ln(-\ln(y)) \quad (6.2)$$

Thus, by adopting Gumbel distribution, we can specify a series of return periods and get the corresponding maximum daily rainfall intensities.

6.2.4 Simple scaling method

A simple scaling method has been proved as a simple yet reliable disaggregation method (Bara et al. 2010; Herath et al. 2016; Rodríguez et al. 2017) since the scaling hypothesis has been verified by Menabde et al. (1999). The hypothesis points out that it was widely observed that the probability distributions of annual maximum daily rainfall intensity at various durations exhibit scale invariance behavior (Menabde et

al. 1999). The mechanism of simple scaling has been described in Section 2.4.4 and Eq. (2.8).

6.2.5 Huff storm distributions

Knowledge of the temporal distribution of rainfall storms is of vital importance in dealing with hydrologic problems, such as the design of urban drainage system (Huff, 1967). The 1-hour rainfall remains relatively coarse in temporal resolution and is unable to describe accurately the rainfall-runoff process at the fine scales of urban drainage systems. Referring to the related previous studies, Le et al. (2014) chose one type of Huff storm distribution (Huff, 1967) to develop design rainfall from IDF curves; Yu et al. (2017) considered all four types of Huff distributions for addressing uncertainty arising from the selection of types of Huff design and further explored the impact of temporal distribution of extreme storms on the hydraulic performance. Recently, Jun et al. (2019) divided historical rainstorm events in Singapore into four quartile types based on Huff's method and indicated that four types are all possible but type II is relatively more dominant. Therefore, in this study, Huff storm distributions are adopted in the form of tabular data (Huff 1990). Based on time interval of 5% of the total rainfall duration, 3-minute level hyetographs from 1-hour rainfall are derived with all four types of rainfall patterns being considered.

6.2.6 Establishment of the physical model

A physical model is normally utilized to demonstrate the hydraulic or hydrologic relations in an urban drainage system. SWMM is a dynamic program for linking rainfall to runoff in urban drainage networks, meanwhile tracking the water quality of runoff generated within each sub-watershed (Aad et al. 2009). It has been used worldwide for helping design and management of urban drainage systems (US EPA, 2020). SWMM is a complex ensemble consisting of several hydraulic-hydrological modules (e.g. subcatchments, aquifers, conduits and junctions). In order to improve the reliability of the model before carrying out any simulations, it is important to calibrate the model by comparing the model outputs with the observed record. More technical details of SWMM can be referred to Rossman (2015).

6.3 Case study

6.3.1 Prediction by the stochastic weather generator and Gumbel distribution

LARS-WG v6 is adopted to synthesize baseline climate condition and simulate future climate scenarios. There are other alternative weather generators like Downscaling-Disaggregation Weather GENERator (Mezghania and Hingray, 2009). The observed weather data are arranged into daily time series, serving as benchmark data to LARS-WG for calibration purpose. It is important to have a good fit of a specific distribution to historical data before we use it for synthetic data. Then, Gumbel distribution is fitted on the historical annual maximum daily rainfall record, and the result is shown in Figure 6.3. The coefficient of determination (R-squared) is 0.861, which shows a decent performance of Gumbel distribution. Afterwards, synthetic baseline scenarios are generated by LARS-WG under different random seeds which are linked to the stochastic component of the generator. There are two steps of calibration. Firstly, in the process of site analysis, basic statistics from the generated test file are carefully checked, such as p-values and correlation coefficient between synthetic and baseline datasets in 'RAIN daily maxima' section. It should be noted that the selection of section for check is subject to the purpose of study. We choose 'RAIN daily maxima' section as the intended output of generator will be daily rainfall intensities. If these results are not satisfactory, the site analysis would need to be redone until the criteria are satisfied. Secondly, the matrix of extreme value feature (i.e. synthetic and baseline daily rainfall intensities over various return periods) should be calculated to further identify the best random seed for calibrating the generator (Semenov and Barrow 2002). For each synthetic scenario, the Gumbel distribution is adopted to generate daily rainfall intensities under various return periods. In this study, we set the threshold of p-values at 0.95, and the correlation coefficient between synthetic and baseline daily maximum rain datasets (i.e. the median, 95 percentile and maximum values in 12 months of a year) all at a threshold of 0.8. The results indicate that the best seed could achieve an average relative error (defined as the sum of percentage differences between the corresponding elements of two sets divided by the common length of these two sets) around 0.36% based on the comparison of the synthetic daily rainfall intensities and the baseline intensities over various return periods.

Fig. 6.3 Gumbel distribution fits on annual maximum daily rainfalls of the baseline dataset

In this study, 5 GCMs under a rising radiative forcing pathway of emission (i.e. RCP 8.5) (Riahi et al. 2011) are adopted in LARS-WG to estimate changes in future climate for the time periods of 2061-2080. Detailed information of the adopted GCMs are provided in Table 6.1. The record length of each generated climate scenario is set to be 100 years. These climate scenarios are also fitted into Gumbel distribution, and the rainfall intensities are predicted by fitted curves and Equations 1 and 2 under various return periods. Figure 6.4 shows the prediction results, indicating that 4 out of 5 GCMs suggest higher rainfall intensities than the baseline scenario. The GCM model HadGEM2-ES suggests a decrease of intensity ranging from -2.9 ($T = 5$ years) to -6.3% ($T = 100$ years) under various return periods, and it is also found that a longer return period would lead to a larger decrease.

Table 6.1 Global climate models used in the study

Model no.	GCM	Country/Region	Grid resolution	Reference
1	MIROC5	Japan	$1.39^{\circ} \times 1.41^{\circ}$	Watanabe et al. (2011)
2	EC-EARTH	Europe	$1.125^{\circ} \times 1.125^{\circ}$	Hazeleger et al. (2012)
3	HadGEM2-ES	UK	$1.25^{\circ} \times 1.88^{\circ}$	Jones et al. (2011)
4	GFDL-CM3	USA	$2.0^{\circ} \times 2.5^{\circ}$	Donner et al. (2011)
5	MPI-ESM-MR	Germany	$1.85^{\circ} \times 1.88^{\circ}$	Brovkin et al. (2013)

Fig. 6.4 Prediction of future daily rainfall intensities (i.e. $I_t=24h$) under various return periods from different GCMs under RCP 8.5 and baseline scenario

6.3.2 Disaggregation by simple scaling

The series of I_t , which denote the annual maximum mean rainfall over the time duration t (i.e. 1h, 2h, 3h, 4h, 5h, 6h, 8h, 10h, 12h, 16h, 20h and 24h in this study), are derived from baseline dataset (i.e. 1980 to 2010). Figure 6.5 shows the process of acquiring scaling factor of simple scaling. Subfigure (a) shows the logarithmic plot of the corresponding q -order (increases from 0.5 to 3.0 at an increment of 0.5) moments I_t^q versus t . Straight lines indicate that the scale invariance has been fitted by linear regressions over a temporal range from 1 hour to 24 hours (with an average R^2 at 0.99); similar patterns of regression have been reported previously (Bara et al. 2010; Rodríguez et al. 2014; Rodríguez et al. 2017). Subfigure (b) also demonstrates a decent linear relationship between the scale function $K(q)$ (i.e. the slopes of lines in Subfigure (a)) and the order q with a scaling factor α being -0.801.

The simple-scaling method is based on the assumption that the data of I_t exhibits a simple mono-scaling behavior (i.e. as stated by Eq. (2.8c), $K(q)$ is assumed to be a linear function of q). Fig 6.5 well supports the assumption for this basin. But if the assumption is proved invalid for other areas, the simple scaling may have to be adjusted. In addition, the reliability of the assumption is rather sensitive to the statistics of original rainfall dataset. Even for a nearby location, the same linear-scaling assumption may not hold. This limitation may complicate the selection and

development of the disaggregation model, as specific assumption of scaling needs to be selected for individual basin or rain gauge station. Afterwards, baseline and future daily rainfall intensities (Figure 6.4) are disaggregated into 1-hour rainfall intensities by using Eq. (2.8d). The results are shown in Table 6.2. The model MIROC5 is picked up as an example to derive IDF curves with durations from 0.5h to 3h (see Figure 6.6).

Fig. 6.5 (a) A logarithmic plot of statistical q -moments of the rainfall intensity (in mm/hr) versus duration t (from 1 h to 24 h); (b) Linear relationship between the scale function $K(q)$ and the order q of the moments in the scaling range

Table 6.2 1-hour rainfall intensities under various scenarios from simple scaling

GCMs	Return Period T (year)			
	5	10	20	50
MIROC5	118.3	140.5	161.7	189.2
EC-EARTH	88.2	101.3	113.9	130.2
HadGEM2-ES	76.2	87.1	97.7	111.3
GFDL-CM3	90.0	103.2	115.9	132.4
MPI-ESM-MR	98.5	112.0	125.0	141.8
Baseline	78.5	90.9	102.8	118.2

Note: unit in mm/hr.

Fig. 6.6 IDF curves derived from output of MIROC5 by using simple scaling

Validating the results of simple scaling by baseline dataset is essential for further design or disaggregation of rainfall. The validation procedure involves several steps. Firstly, the series of annual maximum 1-hour rainfall is extracted from baseline dataset, and the corresponding CDF curve is generated. Secondly, GEV distribution is used to fit the CDF curve (see Figure 6.7), as it is found to be able to achieve the best fit among various types of distributions. Thirdly, according to the formulation of the fitted GEV distribution, the 1-hour rainfall intensities under various return periods are calculated. By comparing the results of rainfall intensities between simple scaling and GEV fitting, it is found that the relative errors for all the return periods are lower than 10%. The detailed results are summarized in Table 6.3. The performance of simple scaling is considered acceptable for our study purpose.

Table 6.3 Comparison between the results of rainfall intensities based on simple scaling and GEV fitting of baseline

Source	Return Period T (year)			
	5	10	20	50
GEV fitting (mm)	85.5	92.8	99.3	107.0
Simple scaling (mm)	78.5	90.9	102.8	118.2
Relative error (%)	8.9	2.1	-3.4	-9.5

Fig. 6.7 GEV distribution fits on the annual maximum 1-hour rainfalls of baseline dataset

6.3.3 Rainfall design by Huff distribution

Huff distributions are adopted to design rainfall at temporal resolution of minutes. The suitability of Huff design also needs to be verified by the baseline dataset. We have collected 1-minute interval rainfall data with 1-year duration (i.e. Jul. 2010 to Jun. 2011) from the study area. The threshold of rainfall depth is set to 30 mm for identifying individual large storm events with durations being around 1 hours (i.e. 0.5 to 2 hours). As a result, 18 events are identified, and these events are divided into four quartile groups depending on the location where the peak rainfall intensity occurs (Figure 6.8). It is shown that the number of events categorized into quartile group I, II, III and IV are 4, 8, 5 and 1, respectively. For a clear view of rainfall patterns, T/T_d (i.e. the ratio of time T over total rainfall duration T_d) versus P/P_d (i.e. the ratio of rainfall record depth P over total depth P_d) is plotted for each identified event and four types of Huff distributions. It is found from Figure 6.8 that the shapes of actual rainfall events are much more complex than the idealized Huff curves, and many real events are even multimodal instead of the Huff curves' sole peak point. However, a general qualitative comparison indicates that each quartile group shares somewhat similarities with the corresponding type of Huff distribution regarding the overall shape and the location of peak point.

Fig. 6.8 Quartile group classifications and rainfall patterns of 18 large storm events (all with 1-minute interval of record) happened from July 2010 to June 2011.

6.3.4 Hydrologic simulation and post-simulation analysis

An urban drainage model based on SWMM is established for the study site. The physical model consists of 55 subcatchments, 50 junctions, 50 conduits and 1 outfall. To improve the reliability of the model before carrying out any simulations, it is important to calibrate the model by comparing the model outputs with the observed record. It is shown that the SWMM produced very close flows to the observed data (especially the peak flows) (please refer to Figure 3.3). It should be noted that rainfall is the most important weather information for calibrating and driving the hydrological model in this study. Other weather variables like temperature and radiation are considered negligible in calibration due to short-term simulations.

Figure 6.9 summarizes various SWMM outputs driven by the designed 3-minute level rainfall time series under Huff type I distribution and various GCM. Subfigures (a) and (b) denote the maximum flow and time to peak at the outfall, respectively; subfigures (c) and (d) show the total outflow from the system (i.e. sum of discharge volume at the outfall and system flood volume) and the system flood volume, respectively. It appears that the maximum flow (Figure 6.9(a)), system outflow (Figure 6.9(c)) and system flood volume (Figure 6.9(d)) are all dependent on rainfall

intensity, however, among these outputs, the degrees of sensitivity vary notably. The maximum flow at outfall is relatively insensitive to the rainfall intensity, especially for intensive rainfall events: for $T = 50$ years, the 1-hour rainfall ranges from 111.3 mm (GCM model HadGEM2-ES) to 189.2 mm (GCM model MIROC5, 1.70 times of HadGEM2-ES), and this would lead to maximum flow ranging from 26.6 m³/s (HadGEM2-ES) to 28.7 m³/s (MIROC5, 1.08 times of HadGEM2-ES), whereas both of system outflow and system flooding are highly sensitive to rainfall, and the volume of flash flood could reach up to 18,789 m³ (GCM model MIROC5, $T = 50$ yr). In comparison, the baseline scenarios ($I_t = 118.2$ mm/hr, $T = 50$ yr) would lead to flood volume of 4,727 m³. The time to peak under most scenarios fluctuates within the range of 13 to 15 minutes, implying low sensitivity of this output towards rainfall intensity.

Based on the SWMM settings, if the small fraction of loss of rainfall (e.g. evaporation and infiltration) is ignored, the runoff would all be drained to the drainage system. Hence, they could either be the discharge leaving the system from outfall or the flooding coming out of junctions and getting lost from the system. Therefore, the system outflow (i.e. discharge plus flooding, Figure 6.9(c)) could be directly compared with the input rainfall depth, and the system flooding (Figure 6.9(d)) reflects the deficiency of drainage capacity towards the rainfall input. From Figure 6.9(d), under Huff type I distribution, the existing drainage system in this study case could only accommodate the rainfall up to 10-year return period under current climate or ‘weak’ GCMs model like HadGEM2-ES, but fail on the rainfall under ‘strong’ GCM models like MIROC5. Generally speaking, when the amount of rainfall increases above a certain threshold (e.g. 90 mm/hr), the conveyance capacity of the drainage network would be exhausted and a further increase in rainfall would only result in more flooding, while the maximum flow at outfall (Figure 6.9(a)) remains somewhat stable.

Comparison of model results among rainfall events with different types of Huff distributions is useful to further understand the temporal distribution of extreme storms on urban drainage system. Figure 6.10 shows the outfall loading, system

outflow and system flood volume driven by the GCM model GFDL-CM3 (which suggests a moderate rainfall intensity) under different types of Huff distributions and return periods. From Figure 6.10, rainfall with Huff type IV distribution would lead to the highest maximum flow at outfall (up to $27.9 \text{ m}^3/\text{s}$) and the worst flood condition (up to a total flood volume of $8,262 \text{ m}^3$), whereas rainfall with Huff type II would give the most optimistic output. From subfigures (a) and (d), under a fixed rainfall intensity (i.e. the same GCM and return period), a larger maximum flow at outfall may indicate a more severe flooding, as some patterns of rainfall distribution could result in a concentrated runoff over a short time period that challenge the drainage capacity. The system outflow (Figure 6.10(c)) is directly influenced by the input rainfall depth. For instance, the rainfall depth is 90.0 mm under $T = 5\text{yr}$, which will result in a volume of 327.4 (unit in 10^3 m^3 , hereinafter the same) within the area of study catchment. This volume is very close to the system outflows (ranging from 325.8 to $326.1 \times 10^3 \text{ m}^3$) under four Huff types. The maximum hydrograph value (Figure 6.10(a)) is more sensitive to Huff types from rainfalls with lower intensity. For instance, under $T = 5\text{yr}$, the peak values are 19.4 , 25.2 , 25.7 and $26.6 \text{ m}^3/\text{s}$ for Type II, III, I and IV, respectively (i.e. the ratio of peak value is $1.00: 1.30: 1.32: 1.37$ for Type II: III: I: IV, respectively); whereas under $T = 50 \text{ yr}$, the corresponding ratio would be $1.00: 1.05: 1.06: 1.08$. The time to peak (Figure 6.10(b)) is mainly influenced by the type of Huff distribution, as it does not vary significantly over different return periods. The magnitude of flooding (Figure 6.10(d)) is the most sensitive SWMM output to the types of Huff distributions. Taking T of 50 years as an example, the volumes of system flood are 2451 , 5550 , 7136 and 8262 m^3 (with ratios at $1.00: 2.26: 2.91: 3.37$) under Type II, III, I and IV design rainfall patterns, respectively. This indicates the impact of temporal distribution of extreme storms on the hydraulic performance of the drainage system. Under $T = 50 \text{ yr}$, Figure 6.11 shows the hyetograph and hydrograph at outfall for rainfalls with four types of Huff distributions. Subfigure (a) shows a sharp increase of runoff at about 15 minutes , and the peak runoff stabilizes at around $27 \text{ m}^3/\text{s}$ for about 10 minutes ; subfigure (b) demonstrates that the maximum flow of $25.9 \text{ m}^3/\text{s}$ would occur after the peak of rainfall at about 24 minutes ; subfigure (c) indicates a fluctuation of runoff in the first half hour before it reaches its peak at about 41 minutes ; subfigure (d) illustrates that

the highest peak flow of $27.9 \text{ m}^3/\text{s}$ would occur at about 51 minutes. The change of Huff types could also have a great effect on spatial distribution of flooding (please refer to Figure 6.12).

Fig. 6.9 SWMM output under Huff type I distribution: (a) maximum flow at outfall, (b) time to peak on outfall, (c) total outflow from the system, and (d) system flooding caused by extreme rainfall events from different GCM outputs and baseline condition.

Fig. 6.10 SWMM output based on GCM model GFDL-CM3: (a) maximum flow at outfall, (b) time to peak at outfall, (c) total outflow from the system, and (d) system flooding caused by extreme rainfall events from different Huff types of distribution and return periods.

Fig. 6.11 Hyetograph and hydrograph at outfall based on the GFDL-CM3 model for rainfall events with 50-year return period and Huff distribution: (a) type I; (b) type II; (c) type III; (d) type IV.

Fig. 6.12 Fluctuation of junction flood under the four hydrographs of Figure 6.11. These six junctions are selected for demonstration based on the criterion that the highest flood volume of that junction under four types of Huff distributions should exceed 500 m^3 .

6.4 Discussion

This study attempts to integrate various techniques into a holistic framework for assessing climate change impact on extreme rainfall and urban drainage system.

These techniques involve stochastic weather generator (SWG), Gumbel distribution, simple scaling method, Huff distribution and urban drainage modelling. The outputs of 5 global circulation models (GCMs) are disaggregated to 1-hour rainfall and further converted to 3-minute level designed rainfall, which are used to drive an urban drainage model. Statistical validations of each component of the framework are also provided to form a rigorous framework. It is revealed that under the emission scenario of RCP 8.5, the selection of different GCMs has a remarkable impact on the future daily rainfall intensities under various return periods when compared to the baseline condition (Figure 6.4). Both GCMs and the type of Huff distributions play important roles in the outfall runoff and flooding condition of the drainage system (Figures 6.9 to 6.12).

The proposed framework is proved to have a number of advantages. Firstly, the proposed framework is simple-to-use, rigorous and comprehensive in climate change impact assessment and urban drainage studies. By adopting a simple yet efficient disaggregation method (i.e. simple scaling), it allows estimation of future design rainfall at hourly resolution with selected return periods by using only a power-law relationship along with rainfall information from GCMs. By tracking outputs from hydrologic model, the impact from climate change could directly project to drainage flow which is particularly useful for evaluating performance and design of the drainage system under various conditions. Secondly, the proposed framework addresses multiple types of uncertainties. The uncertainty arising from selection of climate-change scenarios is addressed by incorporating five representative GCM models for future rainfall projections as the first step. The model randomness of weather generator is addressed and restrained by a two-step calibration procedure to make sure that the generator adopts appropriate parameters (e.g. random seed) and produces feasible outputs. Also, four types of Huff distribution are considered for rainfall design. The capability of addressing these uncertainties could help evaluate a holistic impact from future climate change, downscaling and disaggregation in comparison to baseline scenario obtained from historical record. Obviously, more scenarios could be easily added if a more comprehensive evaluation is of interest.

It is worth noting that addressing the issue of GCM independence is crucial in explaining why agreement among GCM models should boost confidence that their results have based on reality (Pirtle et al. 2010). Nevertheless, it is hard to provide a definitive answer to the question that ‘whether different GCMs are independent to each other or not’, as the related literature is rare, and such an answer will take the combined efforts climate scientists, and perhaps scholars in other fields as well. However, we could identify major similarities and differences among GCMs from the perspective of their structures, key characteristics and model forcing agents. It is found that most of GCMs share a similar or dependent model structure (e.g. coupled atmosphere-ocean models) (Leduc et al. 2014), but may vary greatly in detailed model characteristics (e.g. originating institution, oceanic and atmospheric resolution and number of layers, and grid type) as well as model forcing agents (e.g. various types of greenhouse gases and aerosols are included or not). Based on that, one could believe that different GCMs may hold their dependence to some extent, but also may predict different results for a particular study area (e.g. Fig. 6.4 in Chapter 6).

To implement the proposed framework, we also encountered some limitations. The hydrologic simulations for future climate scenarios are based on current catchment without considering changes over time such as urban development, land use changes and local implementation of low impact development (LID) (Willems et al. 2012). In addition, the study catchment adopted in this study was relatively small. But we believe this size is sufficient for applying single site rainfall disaggregation. However, if a large size catchment is considered, multi-site correlation issues may have to be addressed using more sophisticated weather generators. For instance, Mezghani and Hingray (2009) presented a weather generator developed for multisite generation of hourly precipitation time series over complex terrain, and the generator could reproduce spatial and temporal correlation between weather variables (e.g. precipitation) at different scales. Lastly, under the same return period T , the maximum rainfall intensity at one point is always larger than the maximum areal average intensities (Fowler et al. 2005). Thus, for further application at larger scales (e.g. a city scale), the concept of areal reduction factors (ARFs) (Allen and DeGaetano 2005) could be adopted as a bridge to relate the maximum areal average rainfall rate to the

maximum rate estimated at a point (e.g. observations from rain gauges and downscaled results of simple scaling).

6.5 Summary

An integrated framework was proposed for supporting climate change impact assessment on extreme rainfall and urban drainage. The framework adopts the stochastic weather generator for future climate scenario acquisition, the simple scaling method and Huff distributions for rainfall disaggregation and design, and hydrologic model for rainfall-runoff simulation. An urban catchment located in the tropical rainforest climate region was selected for demonstrating the detailed procedures, applicability and rigor of methodology. The results showed that the selection of different GCMs has a noticeable impact on the future daily rainfall intensities. Meanwhile, temporal distribution of rainfall plays important roles in the outfall runoffs and system flooding. The simple scaling method is proved to be a good alternative for tackling daily rainfall disaggregation. Conventional methods may lack the capability of coalescing various modules (e.g. downscaling, disaggregation and hydrological simulation) into a rigorous framework while considering uncertainties arising from different sources (e.g. selection of GCMs and rainfall patterns). The proposed framework is easy to implement and a promising alternative to conventional methods for evaluating performance and design of the drainage system under various types of uncertainties. The overall methodology is general, and the adopted models/tools are mostly open source and easily accessible. Therefore, it is believed that this work could be generalized to many urban areas around the world to address the climate change impact on drainage flow and urban flooding problems.

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

This thesis focused on exploring innovative modeling and optimization techniques for the design of modern urban drainage and Low Impact Development (LID), which involved statistical analysis, simulation, optimization, regression and surrogate emulating, downscaling, uncertainty analysis by stochastic and fuzzy theories, etc. These techniques have been reported in four main chapters of case studies (i.e. Chapters 3 to 6) for validating their applicability, reliability and computational efficiency.

In Chapter 3, a parsimonious framework of evaluating LIDs for mitigating urban flood damage was proposed. The framework was effective in finding the relationship between investment of LIDs and reduction of flood damages. Through a case study, a satisfactory goodness of fit was achieved when a regression curve was introduced to describe the relationship between damage and investment, which showed that the flood damage would linearly decrease from 4.61 to 3.41 million \$ as the investment of LIDs increased from 0 to 1.19 million \$. The inundation maps under different LID scenarios were also drawn for a direct comparison.

In Chapter 4, an integrated fuzzy simulation-optimization (FSO) model for supporting LID design was proposed to achieve the trade-off between investment of LIDs and flood risks. The performances of FSO model and a traditional deterministic model were tested through a case study. The results showed that the fuzzy-simulation-based iteration process, as applied in FSO model, could effectively address the uncertainty associated with hydrological model and allowing the fuzzy constraints to be satisfied at predetermined confidence levels. A higher confidence level and a lower threshold of flood volume would bring a more reliable system but result in a less economically attractive design plan. The applicability of FSO model was also demonstrated through comparison with traditional stochastic model.

In Chapter 5, a two-level optimization (TO) scheme was proposed for supporting optimal design of storage ponds in urban drainage systems. TO scheme focused on optimization of storage pond layout in tributary sub-watersheds first, and then proceeded to optimization for the mainstream sub-watershed. The performances of TO scheme and the traditional global optimization (GO) scheme were tested and compared through a hypothetical case study. The results showed that both schemes could achieve convergences under different settings of optimization constraints, whereas TO could achieve a comparable or lower system cost, save almost half of the run time and obtain a more stable solution with different setups of start points. TO was a good alternative of GO for tackling large-scale problems.

In Chapter 6, an integrated framework was proposed for supporting climate change impact assessment on extreme rainfall and urban drainage. The framework adopted the stochastic weather generator for future climate scenario acquisition, the simple scaling method and Huff distributions for rainfall disaggregation and design, and hydrologic model for rainfall-runoff simulation. The results of case study showed that the selection of different GCMs had a noticeable impact on the future daily rainfall intensities. Meanwhile, temporal distribution of rainfall played important roles in the outfall runoffs and system flooding. The simple scaling method was proved to be a good alternative for tackling daily rainfall disaggregation. The proposed framework was easy to implement and a promising alternative to conventional methods for evaluating performance and design of the drainage system under various types of uncertainties.

It is worth mentioning that, among the above four Chapters, although the methodology and adopted cases are different, they could be re-interpreted across the Chapters for better addressing the general topic of this thesis, i.e., achieving a more realistic and robust urban drainage design under various complexities.

7.2 Recommendations on future works

Based on the above fundamental works, some challenging issues are identified for further studies:

For large-scale urban catchments, building and calibrating hydrological models with high spatial resolutions is normally time-consuming and computationally intensive, and multi-site spatial correlation of climate variables (e.g. precipitation and temperature) are desired be addressed using more sophisticated weather generators at a finer temporal resolution (e.g. hourly scale). Moreover, a two-level optimization (TO) scheme may be insufficient as the number of decision variables in each tributary sub-watershed increases significantly, and it is likely that the regression models could not achieve an acceptable level of fitness. Multi-level optimization (MO) may be a good solution which needs further investigations.

In Chapter 4, the fuzzy simulation (FS) is a computational expensive method which requires repetitive execution of hydrological model for a cycle of times (usually over 500 times) for calculating each of the possibility of fuzzy event *Poss*. Surrogate approach such as artificial neural network (ANN) (He et al. 2008) may be a promising technique to be incorporated into FSO model for alleviating computational cost, whereas the outcomes should be compared and verified by the traditional FS method.

For climate change impact studies, the hydrologic simulations for future climate scenarios are based on current catchment without considering changes over time such as urban development, land use changes and local implementation of LIDs (Willems et al. 2012). Also, in Chapter 6, it is assumed that the rainfall patterns from Huff distributions remain unchanged under the effect of climate change. Future works are desired to take the impact of urbanization on hydrologic characteristics of catchment and the trend of future minute-level rainfall patterns into consideration.

For a comprehensive planning and design of LIDs, benefits of LIDs except for flood risk management and runoff volume reduction should be taken into consideration, which include domestic water supply, infiltrated stormwater quality improvement, visual amenity and urban heat island mitigation. Limited previous works have provided methods to quantify (i.e. monetize) multiple benefits of LIDs and establish

a more sophisticated optimization framework, which leaves a question worth probing in the future.

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