THE IMPACT OF CLIMATE AND LAND USE ON URBAN STORMWATER RUNOFF, AND IMPLICATION FOR LOW IMPACT DEVELOPMENT AND GREEN INFRASTRUCTURE

A Dissertation

by

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ABSTRACT

Low impact development (LID) and green infrastructure have been increasingly practiced since their emergence in the 1990s. The hydrological benefits of these stormwater management techniques have been extensively studied and documented. However, performance of LID techniques and green infrastructure under increasing climate change and variability with land use conditions of different spatial and temporal scales remains unclear. The major purpose of this study is to expand our current knowledge of the rainfall and runoff process in urban watersheds under varying climate and land use conditions and encourage implementation of sustainable techniques in an effective manner.

This study has two major components: (1) a systematic summary of how performance of site-scale LID techniques responds to climate variability, and (2) an exploration of how land use composition and configuration of green infrastructure contributes to moderating conveyance of stormwater runoff at a regional level. Statistical approaches such as meta-analysis and ordinal logit regression were employed.

The results of weighted meta-analysis revealed a greater sensitivity of runoff volume to changing storm frequency than peak discharge rate, while the retention capacity of LID systems to reduce both volume and peak discharge rate diminished with increasing storm intensity. In addition, the results of an ordinal logit regression showed that the connected pattern of green infrastructure significantly reduced the probability of high-level runoff depth while different spatial forms of urban development expedited

runoff conveyance depending on development intensity. Sprawling patterns of medium- and low-intensity development as well as a connected form of high-intensity development should be avoided to reduce flood risks.

Future explorations of how various LID techniques are sensitive to climate fluctuations will help strategize LID installation for targeted storm patterns and flood mitigation goals at a site scale. In addition, more studies on spatial arrangement of green infrastructure will help develop effective stormwater management policies at a regional level in accordance with land use plan.

DEDICATION

To my beloved husband, Kookjin Sung; my father, Euiyoug Shon; my mother, Gunhee Baek; and my brother, Wonbae Sohn.

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I would like to thank my committee chairs, Dr. Brown and Dr. Li, and my committee members, Dr. Kim and Dr. Jaber, for their guidance and support throughout the course of this research.

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Contributors

This work was supervised by a dissertation committee consisting of Professors Robert Brown, Ming-Han Li, and Jun-Hyun Kim of the Department of Landscape Architecture and Urban Planning and Professor Fouad Jaber of the Department of Biological and Agricultural Engineering. All work for the dissertation was completed independently by the student.

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NOMENCLATURE

ABM	Agent Based Model
AMC	Antecedent Soil Moisture Condition
BMP	Best Management Practice
CA	Cellular Automata
CMA	Comprehensive Meta-Analysis
COHESION	Patch Cohesion Index
CWA	Clean Water Act
DCIA	Directly Connected Impervious Area
ED	Edge Density
EIA	Effective Impervious Area
ET	Evapotranspiration
GCM	Global Circulation Model
GFDL	Geophysical Fluid Dynamic Laboratory
GI	Green Infrastructure
GIS	Geographic Information System
GSSHA	Gridded Surface/Subsurface Hydrologic Analysis
GYRATE	Area-Weighted Radius of Gyration
HEC-RAS	Hydrologic Engineering Left's River Analysis System
HSPF	Hydrological Simulation Program Fortran
ICPR	Interconnected Channel and Pond Routing Model

IPCC	Intergovernmental Panel on Climate Change
LID	Low Impact Development
L-GrID	Landscape Green Infrastructure Design Model
MNN	Mean Nearest Neighbor Distance
MOUSE	Model for Urban Sewers
MPA	Mean Patch Area
MSA	Metropolitan Statistical Areas
MSI	Mean Shape Index
MSE	Mean Squared Error
NAIP	National Agriculture Imagery Program
NHD	National Hydrography Dataset
NPDES	National Pollutant Discharge Elimination System
NRCS	Natural Resources Conservation Service
OLS	Ordinary Least Squares
PD	Patch Density
PRISM	Parameter Elevation Regression on Independent Slopes Model
RCAO	Rossby Center Atmosphere-Ocean Model
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RHW	Rainwater Harvesting System
SG WATER	Smart Growth Water Assessment Tool for Estimating Runoff
SSURGO	Soil Survey Geographic Database

STATA	Software for Statistics and Data Science
SUDS	Sustainable Urban Drainage Systems
SUSTAIN	System for Urban Stormwater Treatment and Analysis Integration
SWAT	Soil and Water Assessment Tool
SWMM	Storm Water Management Model
SWMS2D	Simulating Water Flow and Solute Transport in Two-Dimensional Variably Saturated Media
TIA	Total Impervious Area
TNRIS	Texas Natural Resources Information System
TUFLOW	Two-Dimensional Unsteady Flow
UKCP	United Kingdom Climate Projection
USGS	United States Geological Survey
WinSLAMM	Source Loading and Management Model for Windows
WLS	Weighted Least Squares
WSUD	Water Sensitive Urban Design

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1. INTRODUCTION

1.1. Background

The term low impact development (LID) was first used in a planning report published in Vermont, USA (Barlow et al., 1977). It became more common in practical use after the development of a local design manual by Prince George's County in Maryland, USA (1993). Since then, it has been widely used in North America and New Zealand. While traditional stormwater management systems have emphasized pipe conveyance to drain water away from developed land, LID focused on on-site infiltration near or at pollutant sources (Huber, 2010). Although the performance of LID has often been evaluated at a catchment scale, LID is characterized by site-design and small-scale water treatment facilities such as porous pavement, vegetated swales, green roof, and bioretention systems (Fletcher et al., 2015). It is distinguished from a centralized end-of-pipe detention system.

The Clean Water Act (CWA), enacted in 1972, produced a foundation for regulating stormwater discharges to local surface water bodies in the USA (USEPA, 2017b). Section 402 of the Clean Water Act requires states to obtain National Pollutant Discharge Elimination System (NPDES) permits to ensure that the quality of the nation's water bodies is above the specified standards (e.g., pollutant concentration limits, allowable flow rates, etc.) (USEPA, 2017a). The development of NPDES initially aimed to control point sources such as wastewater treatment plants and industrial sites. However, the regulation scope has been expanded to include non-point sources as urban runoff has been a major cause of water pollution for 40% of the impaired water bodies inspected by USEPA (2004). Since then, any construction sites greater than one acre have been required to obtain the NPDES permit. However, over $20 million in fines had been collected between 2008 and 2010 for not conforming to the permit (StomwaterONE, 2017). Application of LID systems helps local municipalities to meet the permit requirement. The recent guidelines and manuals for local stormwater management have encouraged LID practices for both urban retrofit and new development (Fletcher et al., 2015).

Green infrastructure, often interchangeably used with LID, became known in the 1990s in the USA and the scope of applying green infrastructure stretches beyond stormwater management; the ecological functionality of green space for a regional network system has been emphasized since emergence of green infrastructure (Fletcher et al., 2015). The concept of ecosystem and human health has been the major basis for defining green infrastructure (Tzoulas et al., 2007). Benedict and McMahon defined green infrastructure as “an interconnected network of natural areas and other open spaces that conserves natural ecosystem values and functions, sustains clean air and water, and provides a wide array of benefits to people and wildlife” (Benedict & McMahon, 2012, p.1). They claimed that green infrastructure promotes connections between the existing and future green spaces, thus encouraging an effective land use policy. While LID practices have been typically implemented at a site scale, green infrastructure can be applied across varying spatial scales. It includes small-scale devices such as rainwater harvesting systems, rain gardens, bioswales, and green roofs as well as green spaces at a large scale spanning whole districts, watersheds, or cities (USEPA, 2017c). In this study, the major function of LID systems to store on-site surface runoff is emphasized as stormwater infrastructure, while green infrastructure is defined as any forms of green spaces which provide ecosystem services to human and wildlife beyond the hydrological benefits. They include forests, shrubs, grasslands, agricultural lands, and developed open spaces in urban settings such as lawns and parks.

Since emergence, the performance of LID and green infrastructure to reduce floods has been widely studied across multiple scales. However, effective stormwater management has been challenged by changes in climate and land use patterns over the last decades. Climate characteristics such as storm intensity, duration, and temperature have large variations in both spatial and temporal patterns. Since LID and green infrastructure have a limited capacity to hold and treat stormwater runoff, increasing intensity of extreme events and air temperature as well as extended dry periods affect hydrological performance of stormwater management techniques. While the relationship between impervious surface and runoff is well documented in the literature, the impact of changing climate on the drainage mechanism of LID and green infrastructure still remains unclear. Moreover, interactions of surface flow between different permeabilities can be subject to change when the spatial arrangement of land use alters. Increased and connected impervious surfaces in future cities can speed up the conveyance of urban runoff which can cause severe flooding in downstream low-lying areas. More studies on the performance of LID and green infrastructure will help to optimize their use for varying climate and land use patterns and prepare for future changes in the built and natural environment.

1.2. Research Objectives

This study seeks answers to three overarching questions: 1) How do climate conditions affect the performance of site-scale LID? 2) Does the composition and configuration of land use influence the hydrologic response of urban watersheds under varying climate conditions? 3) What does that imply for application of green infrastructure at a regional scale?

To solve these inquiries, first, this study conducted an extensive and systematic review on the relationship between climatic characteristics and LID effectiveness with selected literature. Second, an empirical study was performed to assess the statistical effect of land use composition and configuration on surface runoff in three Metropolitan Statistical Areas (MSAs) in Texas. The spatial structure of green infrastructure was particularly explored at a regional scale for policy application.

1.3. Dissertation Structure

This dissertation consists of four chapters. Chapter 1 provides an overview of stormwater management techniques in USA and introduces research objectives and inquiries. Chapters 2 and 3 are standalone journal articles which include introductions, methods, results, discussion, and conclusions.

In Chapter 2, the systematic review study provides a structured summary of research on how LID systems are sensitive to climate variability by empirical and hypothetical research approaches. The selected 46 peer-reviewed journal articles published between 2003 and 2017 were analyzed by key variables, including climatic factors, LID types, and hydrologic measures used to quantify LID performance. The methodological approaches were explored by study type. A conceptual framework formulated in this study synthesized the relationship between climate and LID effectiveness. Future directions of research were suggested to enhance existing methods and provide a balance between empirical and hypothetical knowledge.

In Chapter 3, the empirical study measures the quantitative effects of land use composition and configuration on surface runoff under varying climate conditions. Rainfall and runoff depths of watersheds from 2010 to 2017 were monitored on a monthly basis. The spatial arrangement of green infrastructure and urban development was quantified using landscape indices which measure size, edge, shape, isolation, fragmentation, and connectivity. Multiple ordinal logit regression models were then developed by land cover type while controlling for a set of climate and biophysical variables.

Finally, Chapter 4 summarizes key findings in Chapters 2 and 3 and highlights the importance of the research.

1.4. References

Barlow, D., Burrill, G., & Nolfi, J. (1977). Research report on developing a community level natural resource inventory system: Center for Studies in Food Self-Sufficiency, Vermont Institute of Community Involvement.

Fletcher, T. D., Shuster, W., Hunt, W. F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-Davies, A., & Bertrand-Krajewski, J.-L. (2015).

SUDS, LID, BMPs, WSUD and more–The evolution and application of terminology surrounding urban drainage. *Urban Water Journal*, *12*(7), 525-542.

Huber, J. (2010). *Low Impact Development: A design manual for urban areas*. Fayetteville, Arkansas: University of Arkansas Press.

Prince George's County. (1993). *Design manual for use of bioretention in stormwater management*. Landover, MD: Department of Environmental Protection, Water Protection Branch.

StomwaterONE. (2017). The Clean Water Act and the NPDES. Retrieved from https://stormwaterone.com/the-clean-water-act-and-national-pollutant-discharge-elimination-system

Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kaźmierczak, A., Niemela, J., & James, P. (2007). Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review. *Landscape and Urban Planning*, 81(3), 167-178.

USEPA. (2004). *National Pollutant Discharge Elimination System (NPDES) storm water program questions and answers*. United States Environmental Protection Agency, Retrieved from https://www3.epa.gov/npdes/pubs/sw_qanda_entiredocument.pdf.

U USEPA. (2017a). NPDES permit basics. Retrieved from https://www.epa.gov/npdes/npdes-permit-basics

SEPA. (2017b). Summary of the Clean Water Act. Retrieved from https://www.epa.gov/laws-regulations/summary-clean-water-act

USEPA. (2017c). What is green infrastructure? Retrieved from https://www.epa.gov/green-infrastructure/what-green-infrastructure

2. THE INFLUENCE OF CLIMATE ON THE EFFECTIVENESS OF LOW IMPACT DEVELOPMENT: A SYSTEMATIC REVIEW *

2.1. Introduction

Conversion of natural environments to urban land has drastically changed responses of nature to disturbances such as hurricane and flood. The increase in impervious surfaces modifies the hydrological cycle of a watershed and channel morphology (Krug & Goddard, 1986). This leads to a decline in baseflow and groundwater recharge as well as an increase in surface runoff, soil erosion, and pollutant loads on aquifers and local streams (Klein, 1979; Rose & Peters, 2001; Simmons & Reynolds, 1982; Trimble, 1997). Reduced evapotranspiration and cool sinks, and released anthropogenic heat from developed lands cause a positive thermal balance resulting in temperature surges in streams (Nelson & Palmer, 2007; Oke et al., 1991). The ecological degradation of urbanized areas consequently increases social vulnerability to environmental changes such as property damage from flash floods, deficiency of groundwater supply, and increasing heat stress (Brody et al., 2007; Oleson et al., 2015; Xu et al., 2012).

Traditional stormwater management systems emphasize conveyance of stormwater runoff away from point and non-point pollutant sources as promptly as possible (Hood et al., 2007). Storm inlets are placed along urban streets or within

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development sites, allowing the collection of stormwater runoff and its rapid discharge to streams through gutters and closed pipe systems. Drainage pipes are typically designed to handle 1 to 5-year storm events (Butler et al., 2018). On the other hand, centralized best management practices (BMPs) such as detention basins allow storage of a large volume of storm runoff from infrequent storms (e.g., up to 100-year rainfall events) by releasing runoff over an extended period after rainfall events (Clar et al., 2004). However, with continuing urbanization and climate change, waterlogging hazards increase, and aging pipe structures threaten efficient stormwater conveyance (Chughtai & Zayed, 2008). Approximately 30 billion US dollars of local capital have been expended to operate and maintain sewer infrastructure annually in the USA (ASCE, 2017). Rapid discharge of stormwater accelerates channel erosion and pollutant transport downstream (Bledsoe & Watson, 2001). Environmental sustainability is questionable with mechanical approaches because of limited ability to restore the storage and infiltration of natural regimes (Loperfido et al., 2014). Traditional infrastructure for flood control often provides a false sense of security and promotes development in flood-prone areas (Su, 2016).

The low impact development (LID) approach is an adaptation strategy which facilitates on-site infiltration and evapotranspiration by imitating a hydrological regime of pre-development (Dietz, 2007). The adaptive capacity of LID contributes to ecological resiliency to urban floods which cannot be fully achieved by traditional conveyance and storage-based stormwater management systems. It disconnects hydraulic connections between impervious surfaces and stream channels, and thus prevents direct and rapid discharge of polluted runoff (Sohn et al., 2017). Since its emergence in the 1990s in Maryland, the term ‘LID’ has been used most frequently in North America and New Zealand. Other terms, including water sensitive urban design (WSUD) in Australia, sustainable urban drainage systems (SUDS) in the United Kingdom, and green infrastructure (GI) in the United States, share concepts and principles with LID (Fletcher et al., 2015) and are widely explored in the literature.

Hydrologic benefits of LID systems have been well documented in previous review papers (Ahiablame et al., 2012; Dietz, 2007; Lafortezza et al., 2013). Implementation of LIDs reduces runoff volume and peak discharge rate, extends lag time, uptakes nutrients and metals transported in runoff, increases groundwater recharge, and generates cooling effects through evapotranspiration. However, the majority of those previous studies relied on existing climatic assumptions to develop their final estimation models. The climate impacts on LID effectiveness remain unclear when meteorological measures are averaged by or aggregated into large temporal units such as annual precipitation. Climatic factors indeed have large variations in both spatial and temporal scales at an event basis. Greater climate variability has recently been observed all over the world. To illustrate, the strength of hurricanes in coastal cities has been growing as the temperature of sea surface increases (US Global Change Research Program, 2009). The rising air temperature over land also has enhanced evapotranspiration, causing warm and dry extreme events such as heat waves and droughts to be more frequent and severe in tropic and subtropic areas. The global trend of tropospheric humidity has been upward in association with increasing temperature, exacerbating the greenhouse effect in the future (Trenberth et al., 2007). Yet, predicting changes in atmospheric circulation, which is an integral factor accounting for climate variability and changes, is subject to uncertainty when the underlying physics of complex climate systems are numerically approximated (Berliner, 2003). Efficient stormwater management becomes challenged with growing uncertainty in climate predictions.

A better understanding of climate impacts on LIDs is needed to accurately predict their performance under specific storm patterns and formulate an adaptive strategy to deal with uncertain climate variability. Therefore, the main goals of this systemic review are to 1) document evidence of how LID performance is influenced by climate fluctuations; 2) summarize approaches by study type to quantify the relationship between climatic and hydrologic variables; and 3) suggest directions for future research.

2.2. Methods

Documenting the sensitivity of LID performance to climate variability contains two steps of review: 1) a systematic selection and review of 46 peer-reviewed journal articles, and 2) a synthesis of major themes and relationships between climatic and hydrologic factors. A conceptual framework was constructed to characterize these relationships. Future research design was also suggested as a guideline for enhancing construct validity of research.

2.2.1. Search and Selection of Previous Studies

A systematic and extensive literature review was conducted according to guidelines suggested by Xiao and Watson (2017). To allow for a broad examination of the literature, a research question was initially formulated as to what factors determine the effectiveness of LID practices. After screening processes the question was narrowed down to climatic factors. According to the initial question, eight keywords were selected: low impact development, green infrastructure, sustainable urban drainage, best management practice, effectiveness, optimization, runoff, and streamflow. Six search engines, including ScienceDirect, Web of Science, ASCE library, Taylor & Francis, Wiley Online Library, and SpringerLink, were used for searching the selected keywords. The selection criteria of search engines were: 1) they were frequently used in other review papers studying LID, and 2) they were major engines including the most relevant articles when a pilot search was conducted in Google Scholar. Accordingly, 1,973 papers with publication years ranging from 1978 to 2017 were initially extracted from the six search engines. The next step was to screen articles for inclusion. The most relevant peer-reviewed journal articles were identified through title, abstract, and full-text review in consequence (Figure 2.1). At each stage, individual articles were coded based on eligibility and relevance to the research question. Articles which were not written in English or duplicated by search engines or whose full text cannot be found were excluded. Studies on conventional stormwater management practices designed to control infrequent storms in a centralized form or applied for agricultural use only were considered irrelevant. It should be noted that this review only focused on the hydrologic performance of LIDs. Studies on cost effectiveness are beyond the scope of this review. Through the screening process, 93 articles published between January 1997 and April 2017 were selected for final review.

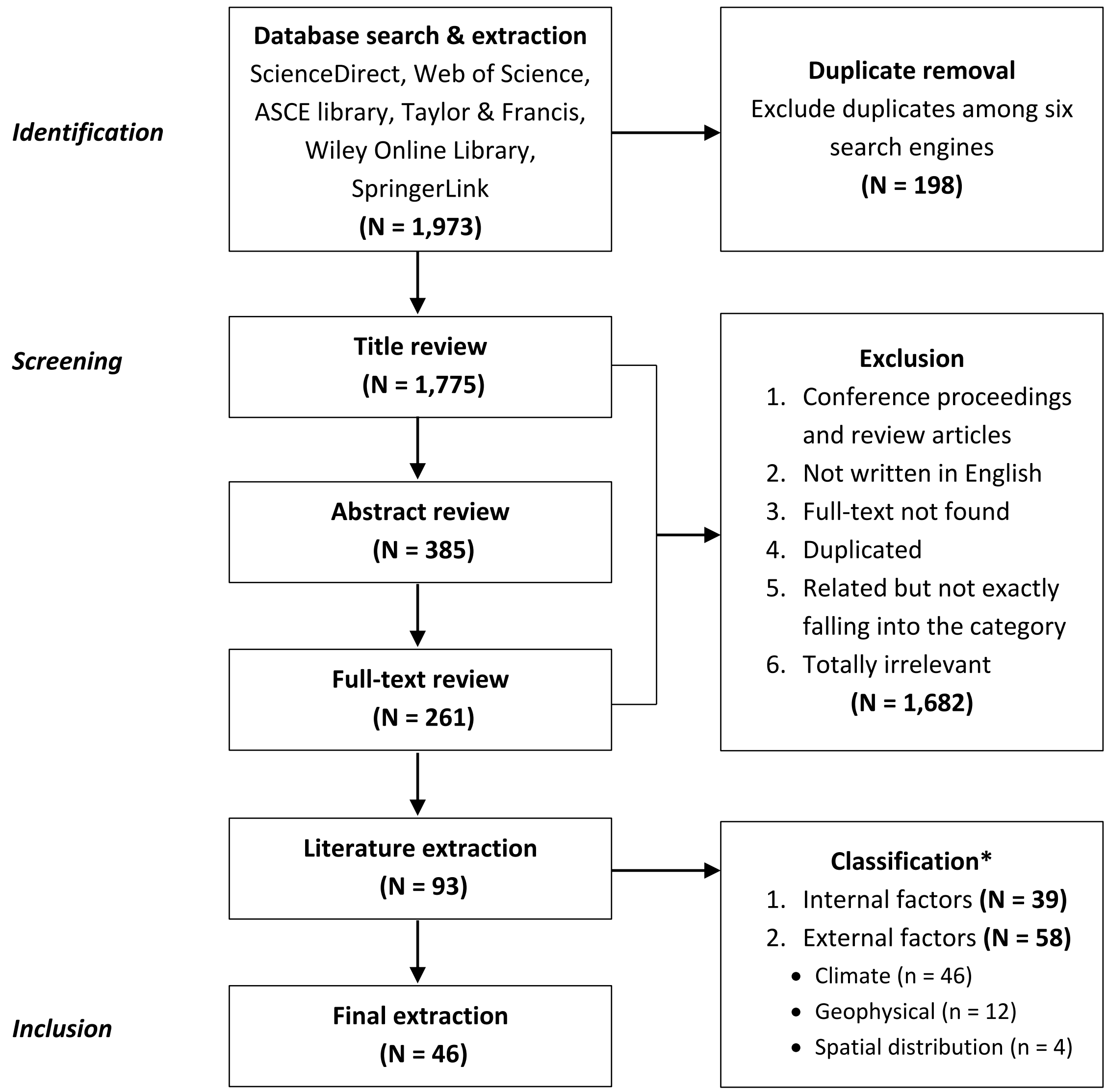


Figure 2.1 Review structure of literature search and selection.
*An article can be categorized into more than one type.

Factors which affect the effectiveness of LID systems were categorized by internal and external factors. The internal factors indicate inner structure of LID systems which determines the capacity of storage units to hold and release water during rainfall events. They include facility size, layer configuration, soil composition, and vegetation type. While the internal factors mainly affect the hydrologic cycle of a site scale, the external factors are influential in a larger geographical unit such as a watershed, city, or state. They contain climate conditions such as storm characteristics and temperature, geophysical components pertaining to nearby land use and streams, and distribution patterns of LID systems. The 93 articles were then classified into the type of internal or external factors. 46 peer-reviewed journal articles published between 2003 and 2017 were finally selected and extracted data were synthesized to document evidence of how climate variability impacts performance of LID systems.

2.2.2. Data Synthesis

The selected 46 peer-reviewed articles were characterized by key variables such as climate characteristics, LID types, and hydrologic measures used to quantify LID performance. For each variable, research trends over time were identified by computing the frequency of articles by year. Furthermore, the methodological approaches and study results were synthesized based on two study types: empirical and hypothetical studies. In this review study, a hypothetical study is classified as research which simulates a hydrologic process of LID systems using a computer model with a set of input parameters such as climate, land use, topography, etc. Conversely, an empirical study is based on observation rather than simulation, which includes experimental and non-experimental studies. An experimental study involves manipulation of rainfall events to monitor hydrologic yields from LID modules in laboratorial settings, while a non-experimental study monitors real-time rainfall and hydrologic performance of LID systems without manipulating rainfall. According to study type, data on research methods including location of study, unit of analysis, timeframe of data analysis, type of statistical or simulation models, climate conditions and LID systems monitored or manipulated were organized for analysis. The reviewed literature revealed multiple relationships between climate and hydrologic variables which demonstrate the varying sensitivity of LID performance to changes in climate conditions. A conceptual framework was constructed based on these relationships.

With a subset of hypothetical studies, meta-analysis was then performed to summarize the overall findings of climate impact on LID effectiveness. The effect size of individual studies, a statistic which measures the magnitude of the LID effects across studies, was computed and aggregated into both non-weighted and weighted mean values with a 95% confidence interval. A random effects model was used for weighted estimates as different treatment effects such as climate settings, LID applications, and population were applied in sample studies. The mean value was inversely weighted by variance within and between populations of individual studies (Borenstein, 2009; Lipsey & Wilson, 2001). Thus, it was hypothesized that the results of studies with a small variance of effect estimate make a greater contribution to the total estimate than others.

In this review, a study's effect size was the mean reduction rate of runoff volume and peak flow by applying LID practices compared to the reference scenario of conventional development. Studies performed at the scale of an LID facility other than a watershed were excluded from selection. Data were collected from text, figures, or tables. Because of limited data availability in published articles, only a subset of hypothetical studies was used for analysis. The weighted average effect size was finally computed by storm frequency of 1, 2, 5, 10, and 100 years using the Comprehensive Meta-Analysis Software (CMA) (Borenstein et al., 2018).

2.3. Results

2.3.1. Overview of LID Research Trends

Although the concept of LIDs emerged in the 1990s, only since the early 2000s have more research publications paid attention to its performance and documented hydrological benefits of LID systems (Dietz, 2007) (Figure 2.2). The majority of articles were published after 2010 (75%). This research trend is in accordance with the increasing focus on sustainable stormwater management as urbanization has accelerated. Since 1993, about 46% of the articles have focused more on external factors than internal ones. Some studies have not addressed either external or internal factors in their research design. Rather, the major goal of these studies was to compare performance of LIDs of different types, or longitudinally monitor a facility before and after construction. The impacts of internal or external factors were not necessarily examined for a particular type of LID practice. Instead, hydrologic benefits were widely documented in comparison with predevelopment or conventional development.

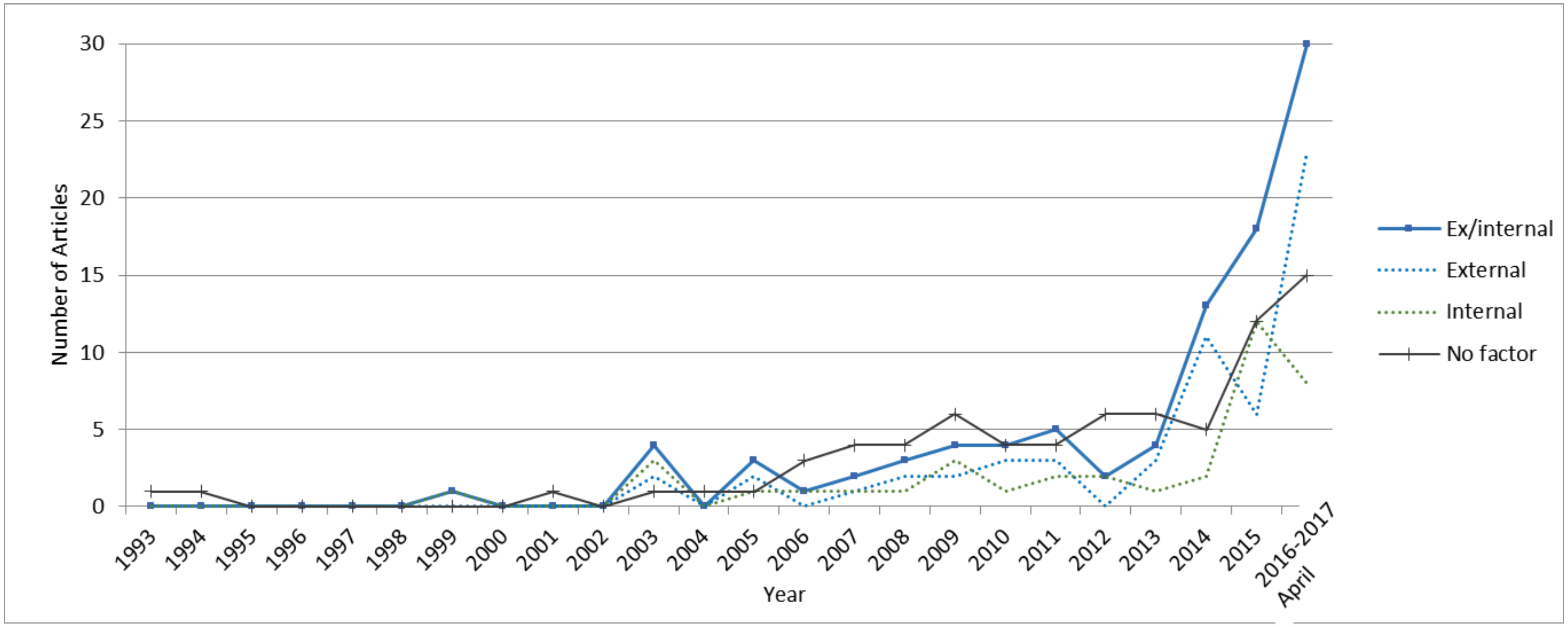


Figure 2.2 Annual number of publications on LIDs from 1993 to 2017.

2.3.1.1. Climatic characteristics

For the selected 46 articles, multiple climatic factors were examined including storm depth, frequency/intensity, duration, timing of peak storm intensity, antecedent soil moisture condition (AMC), temperature and future climate change (Figure 2.3). Storm intensity was the most dominant climatic factor measured since 2003. Conversely, timing of peak storm intensity was seldom studied. The major reason could be the use of synthetic design storms which typically have a symmetric distribution of rainfall (peak ratio ≈ 0.5) (Haan et al., 1994). According to the Natural Resources Conservation Service (NRCS, 2015), legacy rainfall distribution has the highest peak in the middle of storm duration for most geographical areas in the USA except for the west coast and Alaska. It has been widely used to approximate actual patterns of rainfall even though real-time monitoring of rainfall events shows variations in temporal and spatial patterns. Temperature has also been minimally investigated. A limited number of studies investigated seasonal variations in LID performance, or experimentally control temperature in laboratorial settings.

From 2013, the number of studies assessing future climate impacts on LID effectiveness dramatically increased. Integration of global and regional projection tools of climate and hydrologic models enables simulating LID performance under hypothetical future climate conditions. Yet, uncertainty still remains in predictions; depending on hypothetical scenarios, geographical location, and types of models chosen for studies, stormwater runoff volume is expected to grow or abate (Shackley et al., 1998). Inconsistency of results has been found in some selected studies. More details of study results are shown in Section 3.3.

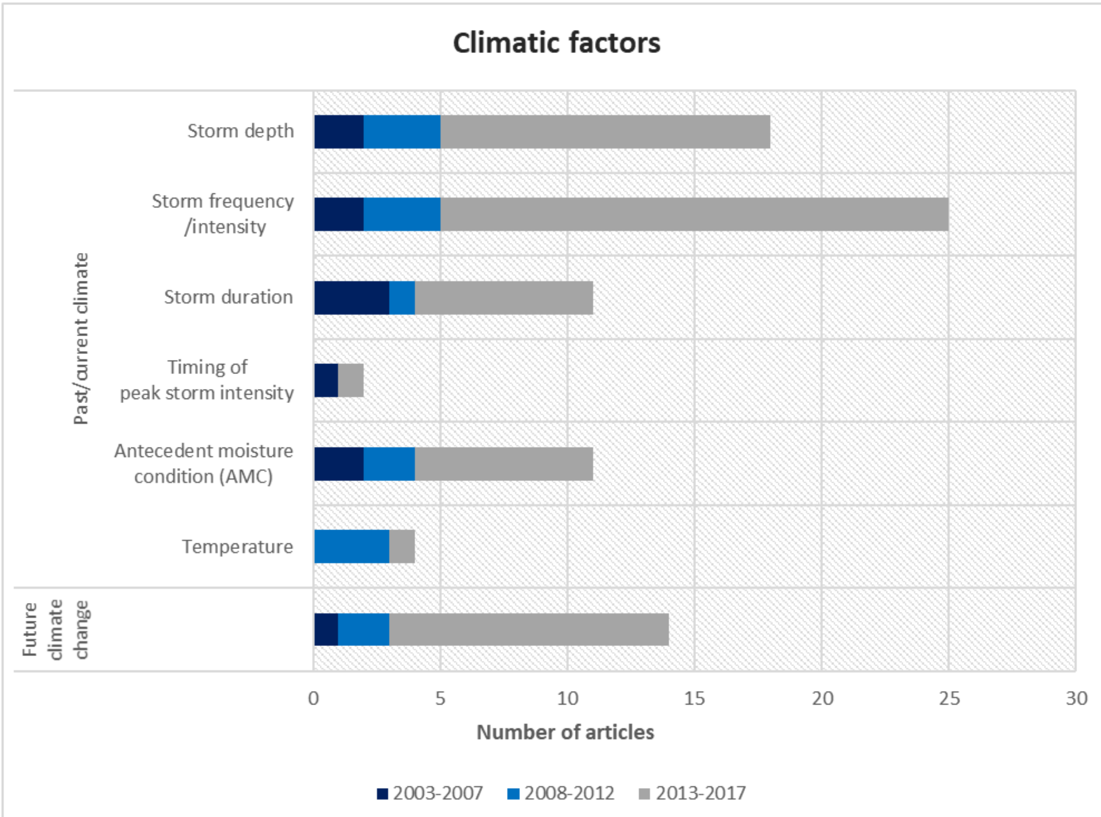


Figure 2.3 Number of publications by climatic factors.

2.3.1.2. Type of LID systems

Extensive green roofs and bioretention systems were the most studied single techniques (Figure 2.4). Both techniques were more actively assessed since 2008 by diverse research methods: empirical monitoring, lab experiments, and computer simulation. Infiltration trenches lack performance data in response to climate variability and have not been studied until recent years (2013-2017). Yet, benefits of infiltration trenches have been more widely documented under a particular climate condition, or overall performance has been investigated under an average climatic condition (Bergman et al., 2011; Emerson et al., 2010; Heilweil & Watt, 2011; Norrström, 2005; Yeon et al., 2014).

In the selected articles, no empirical studies have been conducted on efficiency of rooftop disconnection techniques in response to climate variability. Yet, hypothetical performance of downspout disconnection or rainwater harvesting systems has been simulated often since 2003. Also, seven studies did not specify which type of LIDs was examined in their research.

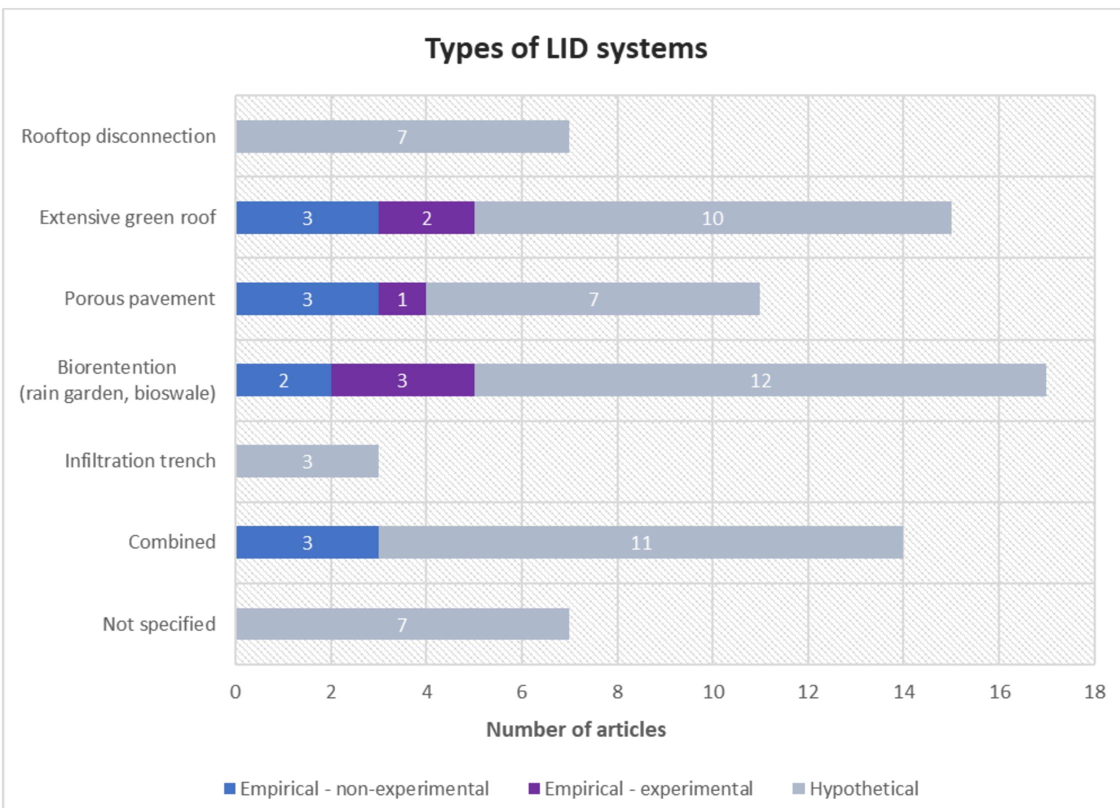


Figure 2.4 Number of publications by LID type.

2.3.1.3. Measures of LID performance

A wide range of direct or indirect measures has been used to quantify hydrologic performance of LID systems (Figure 2.5). A reduction in runoff volume and/or peak discharge rate was most measured or estimated in selected articles. Time delay is typically compared between conventional and low impact developments at a watershed scale or between influent and effluent of an LID system. In the past five years, however, some contributors to hydrologic cycles other than stormwater runoff have been additionally measured to account for the auxiliary benefits of LIDs. They include increasing infiltration, evapotranspiration, groundwater recharge, and baseflow. An indirect measure such as flood damage cost was also used to assess financial impacts of LID implementation for risk management.

While all these measures emphasize the service of LID systems for flood mitigation, a concern has risen as to whether LIDs can be as effective during potential future droughts as global temperature rises. Vegetation water stress is another emerging measure to assess the resiliency of LID systems to drought risks. A few recent studies in the review sample have assessed a trade-off between flood mitigation and plants' drought risks under future climate conditions.

Protecting a watershed from water quality degradation has been one of major purposes of placing LIDs near non-point pollution sources. Yet, only a limited number of studies have examined the dependency of LID systems on temperature or storm characteristics in enhancing pollutant removal efficiency. While 94% of the selected articles directly or indirectly measured water quantity controlled by LIDs and its sensitivity to climate variability, only 17% of them assessed how loads of pollutants transported in urban stormwater runoff can be treated by LIDs at a different level depending on climate conditions.

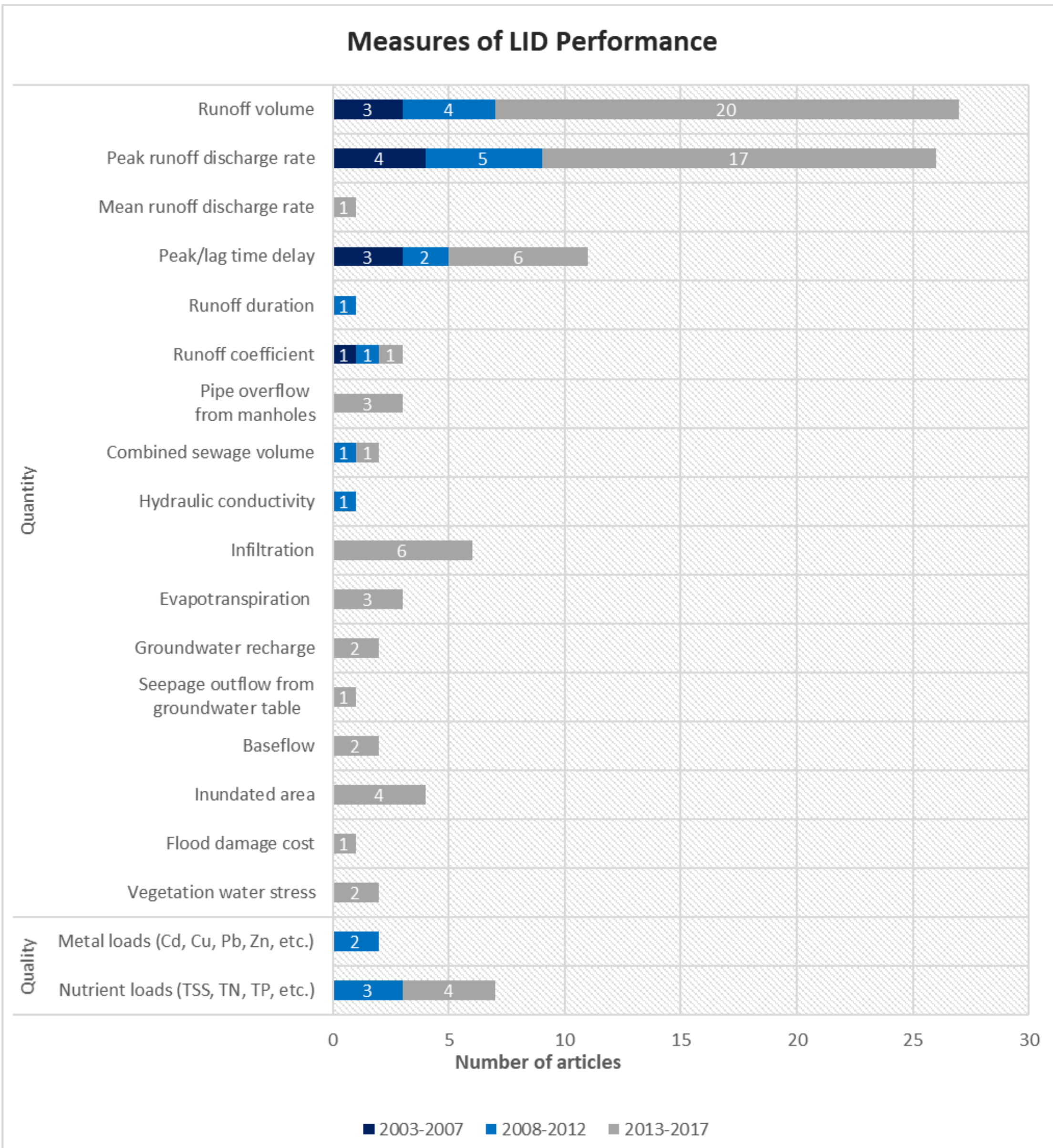


Figure 2.5 Number of publications by measures of LID performance.

2.3.2. Empirical and Non-Experimental Studies

Nine articles are categorized as empirical and non-experimental studies in this review (Table 2.1). These studies measured the impacts of LIDs on hydrologic response of urban watersheds using longitudinal monitoring of LID systems. The sensitivity of LIDs to climate variability was typically examined on a single storm event basis. The monitoring period for articles reviewed ranges from 10 months to 4 years. Statistical analyses were mainly performed to identify the relationship between climate and hydrologic variables by LID type. Depending on the number of storm events recorded, studies often had a limited sample size for a short-term monitoring period. Most reviewed studies examined 100 or fewer storm events.

Based on historically recorded climate data, a typical method to analyze climate impacts is to group individual storm events by climate characteristics and statistically compare hydrologic yields from LID systems among the groups. For example, storm events were classified into multiple groups by relatively large to small storm size (Fassman & Blackbourn, 2010), high to low storm intensity (Jackisch & Weiler, 2017), long to short storm duration, wet to dry initial soil conditions (Hakimdavar et al., 2014; Hood et al., 2007), and hot to cold seasons (Roseen et al., 2009) in the sample of individual studies. The hydrologic performance of LID systems becomes averaged out by the group of storm events.

Table 2.1 Summary of empirical and non-experimental studies.

Authors	Study location	Unit of analysis	LID/BMP feature	Study period	Climate characteristic	Number of storm events monitored	Hydrologic measure*	Statistical analysis**
Emerson and Traver (2008)	Villanova University, Philadelphia, PA, USA	LID Facility	Porous pavement (PP), bioretention system (BS)	PP: 2004 – 2005 BS: 2003 Jan. – 2007 Mar.	Temperature	PP: 15 events BS: 123 events	Hydraulic conductivity	Bivariate & multiple regression
Fassman and Blackbourn (2010)	Auckland, New Zealand	Watershed	Porous pavement	2006 Sep. – 2007 Jan., 2008 July – 2008 Dec.	Storm size, intensity, duration, AMC	81 events	Runoff volume and peak flow, duration, runoff coefficient, lag time	Univariate & bivariate
Hakimdavar et al. (2014)	Columbia University, Manhattan, NY, USA	LID Facility (building)	Extensive green roof (GR)	GR I and II: 2011 Aug. – 2012 July GR III: 2009 Sep. – 2009 Nov.	Storm size, intensity, duration, AMC	GR I: 63 events GR II: 79 events GR III: 6 events	Runoff volume and peak flow, lag time	Univariate
Hood et al. (2007)	Waterford, Southeastern CT, USA	Watershed	Combined (rain garden, porous pavement, retention pond, etc.)	2002 May – 2004 Dec.	Storm size, duration, AMC	104 events	Runoff volume and peak flow, runoff coefficient, lag time	Univariate & bivariate
Jackisch and Weiler (2017)	Vauban district, Freiburg, Germany	Watershed	Combined (green roof, pebble roof, porous pavement, bioretention cell, and other green spaces)	2010 July – 2012 Dec.	Storm size, intensity, duration, AMC	369 events	Runoff volume and peak flow, lag time	Univariate & bivariate
Lewellyn et al. (2016)	Villanova University, southeastern PA, USA	LID Facility	Combined (bioretention systems, infiltration trench)	2012 July – 2014 June	Temperature, storm size, intensity, AMC	101 events	Infiltration rate, runoff volume	Univariate & bivariate
Nawaz et al. (2015)	University of Leeds, Leeds, UK	LID Facility (building)	Extensive green roof	2012 June – Aug., 2013 April – Aug., 2014 Jan. – Feb.	Storm size, intensity, duration, AMC	30 events	Runoff volume	Bivariate & multiple regression
Roseen et al. (2009)	University of New Hampshire, Durham, NH, USA	LID Facility	Surface sand filter, bioretention systems (Type I and II), subsurface gravel wetland, street tree, porous pavement	2004 Aug. – 2006 Aug.	Temperature, storm size	27 events	Runoff peak flow, lag time, metal and nutrient loads	Univariate
Versini et al. (2015)	Trappes, Paris, France	LID facility (building)	Extensive green roof	2011 June – 2012 Aug.	Storm size, intensity, duration, AMC	≈100 events	Runoff volume and peak flow	-

* Hydrologic measure = direct or indirect measure used to assess hydrologic performance of LIDs; ** statistical analysis = major statistical methods used to analyze relationships between climatic and hydrologic measures.

The findings generally revealed that the group of larger storm size, higher intensity, longer duration, and wetter initial conditions diminished the benefits of LID systems in reducing runoff volume and peak flow as well as increasing lag time (Fassman & Blackbourn, 2010; Hood et al., 2007; Jackisch & Weiler, 2017) (Figure 2.6). The water holding capacity of LID systems is subject to extreme climate conditions. It becomes limited when drainage substrates are saturated. However, it remains unclear as to which storm factors contribute more to LID performance than others. For instance, short-duration storms could still yield a larger runoff volume when storm intensity is high (Hakimdavar et al., 2014). Yet, moderate storm intensity could cause higher peak flow of runoff than high storm intensity when the initial level of soil saturation is high (Jackisch & Weiler, 2017). Multiple regression analysis helps to identify climatic factors to which performance of LID systems are most and least sensitive. The literature has shown that mean intensity and duration of storm events better predicted retention capacity of LID systems than the initial level of soil saturation (Nawaz et al., 2015).

Temperature is another critical climatic factor that affects the capacity of LID systems to infiltrate (Figure 2.6). Some empirical studies have evidenced better LID performance in summer than winter (Emerson & Traver, 2008; Lewellyn et al., 2016). Authors argued that increasing temperature reduces water viscosity and thus increases hydraulic conductivity of the soil medium. The dependency on temperature was found to be varied by type of LID systems (Emerson & Traver, 2008) and depth of soil medium (Lewellyn et al., 2016). Yet, a contradicting study found fewer seasonal variations in

LID performance for reducing peak flow and removing contaminants compared to conventional best management practices (BMPs) (Roseen et al., 2009).

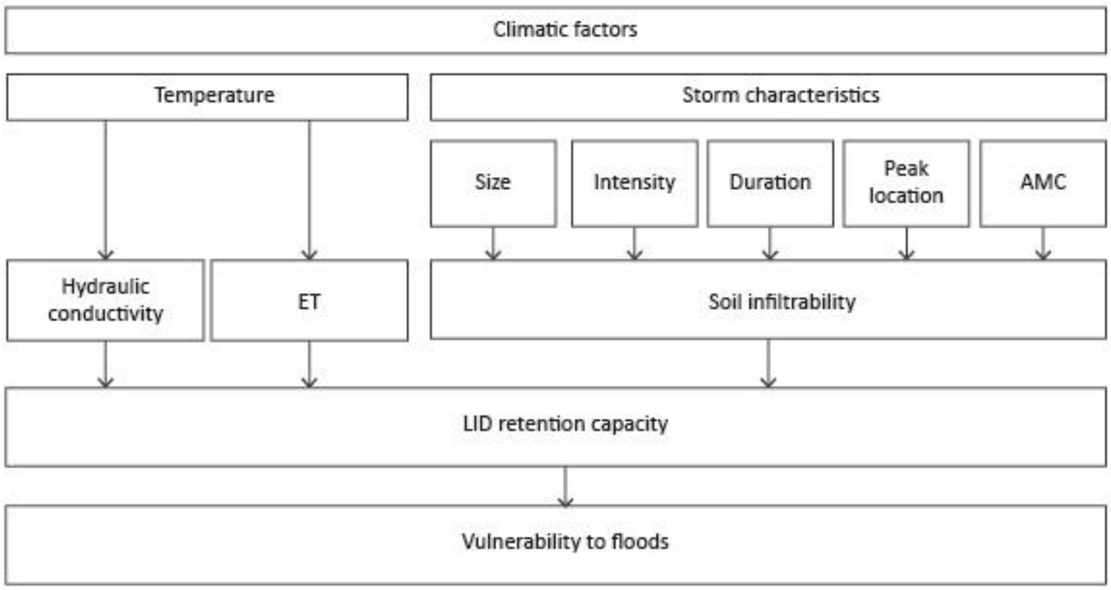


Figure 2.6 Conceptual framework synthesizing relationships between climate and LID performance.
Note. ET = evapotranspiration; AMC = antecedent soil moisture condition.

2.3.3. Empirical and Experimental Studies

For empirical and experimental studies, climate conditions can be controlled by researchers with rainfall simulators and temperature controllers in laboratorial settings (Table 2.2). This allows an unbiased statistical comparison of LID performance among different climate characteristics as well as module types. Hydrologic data of influent and effluent are directly sampled and measured at experiment plots. Similar to non-experimental studies, results from experiments have consistently shown that LIDs perform better with low-intensity and short-duration storms under dry conditions (Alfredo et al., 2010; Barber et al., 2003; Gülbaz & Kazezyılmaz-Alhan, 2017) (Figure 2.6). Yet, it is controversial with regard to peak delay time. When storm duration was controlled for, peak delay time was shortened by increasing storm intensity. However, it remained constant with changing storm duration (Gülbaz & Kazezyılmaz-Alhan, 2017). This result contradicts the simulation results from Palla and Gnecco's study (2015) where peak delay time was independent of storm intensity.

Some studies performed experiments on LID modules to enhance precision of predicting runoff yields in hydrologic modeling. For example, Alfredo et al. (2010) compared the measured value of discharge rates in lab experiments with the predicted value in model simulations to calibrate curve numbers of green roofs with different depths. Similarly, experiment outputs can be used to calibrate LID parameters of paving, soil media, and drainage layers such as field capacity, wilting point, hydraulic conductivity, permeability, etc. (Barber et al., 2003; Palla & Gnecco, 2015).

Table 2.2 Summary of empirical and experimental studies.

Authors	Study location	LID module	Climate characteristic	Experiment		
				Constant	Independent variable	Dependent variable (hydrologic measure*)
Alfredo et al. (2010)	New York, NY, USA	Extensive green roof	Storm intensity, AMC	LID module size (other than storage depth), temperature	Design storms, LID modules with different storage depths	Runoff volume and peak flow
Barber et al. (2003)	Washington State University, Pullman, WA, USA	Ecology ditch (bioretention system)	Storm size, duration, AMC	Experiment I: LID structure, AMC Experiment II: Precipitation, AMC Experiment III: Precipitation, LID structure	Experiment I: design storms Experiment II: LIDs with different side slopes Experiment III: AMC	Experiment I: runoff peak flow, peak time delay Experiment II: wetting front Experiment III: path thickness
Blecken et al. (2011)	Lulea, Sweden	Biofilter (bioretention system)	Temperature	Amount of runoff inflow, LID structure (media depth, soil composition, etc.)	Air temperature	Heavy metal loads
Gülbaz and Kazezyılmaz-Alhan (2017)	Istanbul University, Istanbul, Turkey	Bioretention system	Storm intensity, duration	Amount of runoff inflow, LID structure	Design storms, LID modules with different soil compositions	Ponding depth, runoff peak flow, peak time delay
Palla and Gnecco (2015)	University of Genoa, Genoa, Italy	Green roof, porous pavement	Storm intensity	LID structure	Design storms	Runoff volume and peak flow

* Hydrologic measure = direct or indirect measure used to assess hydrologic performance of LIDs.

2.3.4. Hypothetical Studies

The major purpose of designing hypothetical research is to predict responses of LID systems to changing climate conditions in an experimental setting. Predictions suggest a wide range of options for applying LID to current policies for water resources management. In hypothetical studies, storm events can be either monitored or experimentally designed by researchers. Based on a regional analysis of rainfall patterns, design storms with varying shapes of hyetographs can be developed and their impacts can be compared to one another. Several options for LID practices can be designed such as different facility types, coverages (e.g., implemented in 10% to 50% of a watershed), locations (e.g., upstream and downstream), and structure (e.g., soil depth, slope, size, etc.). They are realized by customizing related parameters in model simulation. Diverse models such as the storm water management model (SWMM), gridded surface/subsurface hydrologic analysis (GSSHA), system for urban stormwater treatment and analysis integration (SUSTAIN), and model for urban sewers (MOUSE) were used in the articles reviewed. Among them, the SWMM model was most popularly utilized (38% of the selected hypothetical studies).

2.3.4.1. Simulation under past or current climate conditions

Using design storms developed based on current and historic climate data, a short-term event-based analysis was conducted in many hypothetical studies. In this review study, a meta-analysis was performed to analyze hydrologic responses of LIDs to storm frequency. The results of computing both non-weighted and weighted average effect sizes revealed an overall declining trend of LID performance in reducing runoff volume and peak flow with more infrequent storms (Figures 2.7). According to the weighted mean values, runoff volume was overall more sensitive to changes in storm intensity than the peak discharge rate; from 1- to 100-year storm events, 32% in reduction rates dropped for runoff volume while 19% dropped for peak flow. The width of 95% confidence interval further declined with an increasing return period, implying a larger variation in predicting LID performance by a sample of watersheds for frequent storms (Table 2.3). The reduction rate of peak flow had a smaller variation in estimating effect size than the rate of runoff volume for every storm frequency. This implies that predictions of runoff volume are more subject to treatment effects such as different climate and watershed settings than those of peak discharge rate.

a)

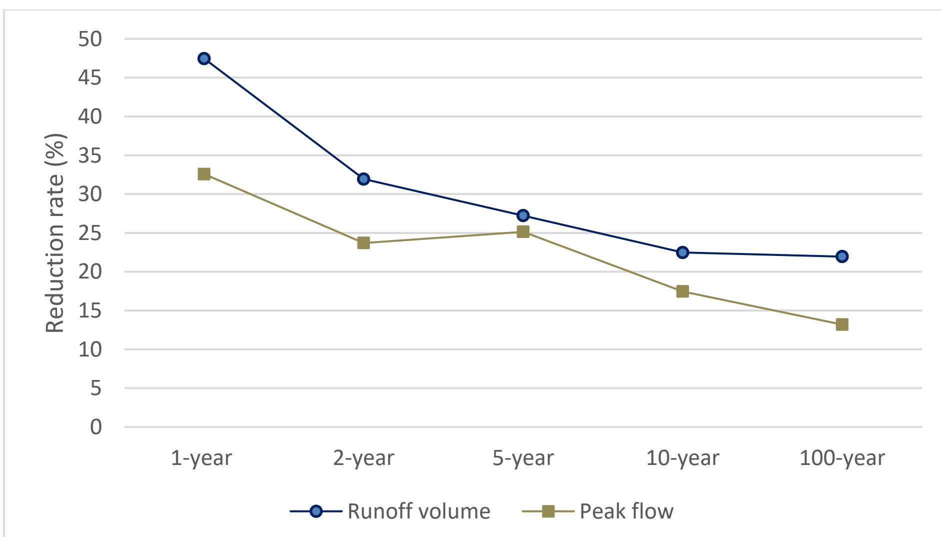


Figure 2.7 a) Non-weighted and b) weighted average effect size of LID performance by storm frequency.

Note. Reduction rates of runoff volume and peak flow rate were measured compared to conventional development (no-LID scenarios). 16 and 10 hypothetical studies were sampled to compute non-weighted and weighted average effect size, respectively. The random effects model was selected when computing weighted values.

b)

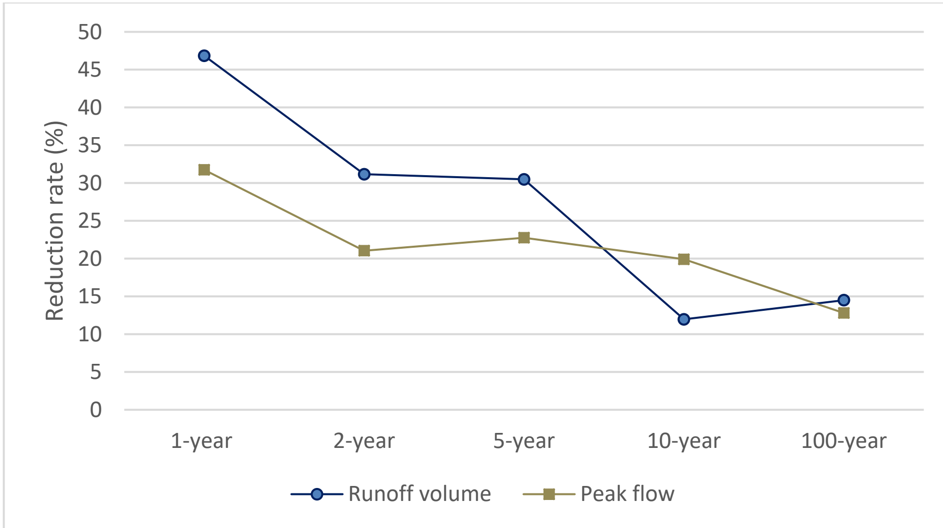


Figure 2.7 Continued.

Table 2.3 Statistics for weighted average effect size and 95% confidence interval.

Storm frequency	Runoff volume reduction rate				Peak flow reduction rate			
	ES	SE	95% CI	Width	ES	SE	95% CI	Width
1-year	46.8	23.4	(0.9, 92.8)	91.9	31.7	8.0	(16.1, 47.4)	31.3
2-year	31.2	20.6	(-9.1, 71.5)	80.6	21.0	4.9	(11.5, 30.6)	19.0
5-year	30.5	7.0	(16.7, 44.2)	27.5	22.8	3.4	(16.2, 29.3)	13.1
10-year	12.0	4.1	(3.9, 20.0)	16.1	19.9	3.0	(13.9, 25.9)	11.9
100-year	14.5	2.5	(9.6, 19.4)	9.9	12.8	0.9	(11.0, 14.6)	3.5

Note. ES = weighted average effect size; SE = standard error; CI = confidence interval; width = width of a 95% confidence interval (2 × margin of errors).

Table 2.4 summarizes twenty-three hypothetical studies selected for this review study. In addition to storm intensity, storm duration was another critical factor which determines soil infiltrability and the load of stormwater runoff on LID systems (Figure 2.6). Studies have found that storm duration is non-linearly and negatively related to flood reduction by LIDs (Barber et al., 2003; Freni & Oliveri, 2005; Liao et al., 2013).

Qin et al. (2013) particularly simulated seven storm events with a same rainfall amount but different storm duration from 1 to 4 hours with a 30-minute increment and explored storm effects on three LID facilities. The result showed a sharp initial reduction of flood volume with increasing storm duration and then a level off over a certain threshold. Barber et al. (2003) also examined the response of a bioretention system to extended duration of rainfall peak intensity and found its negative impact on reducing peak flow. Yet, delay time of peak flow was not affected by the duration of high-intensity rainfall.

Timing of peak storm intensity also played a pivotal role in determining flood risks of a watershed (Figure 2.6). A late peak event generated larger runoff volume and peak flow rate because it lowered permeability of soil by sealing the top layer which induced ponding and diminished overland friction (Dunkerley, 2012; Wang et al., 2016). However, limited hypothetical studies in the review sample have assessed how timing of peak storm intensity affect LID performance. Qin et al. (2013) tested three LID techniques under nine storm scenarios with the same rainfall amount and duration but different time-to-peak ratios (0.1 – 0.9). While conventional drainage systems generated larger flooding risks for a late peak intensity, different types of LID performed better for early, middle, or late peak intensity. Freni and Oliveri (2005) explained that contributions of pervious areas to generating runoff increased with storm events of high intensity, long duration, and late peak locations. Thus, they argued that retention facilities would be needed on pervious areas to intercept and treat stormwater in addition to LIDs on impervious surfaces.

Table 2.4 Summary of hypothetical studies performed under past or current climate conditions.

Authors	Study location	Unit of analysis	LID/BMP feature	Climate characteristic	Simulation			Hydrologic measure*
					Time frame	Model	Hypothetical scenarios	
Alfredo et al. (2010)	New York, NY, USA	LID facility (building)	Extensive green roof	Storm intensity, AMC	-	SWMM	Design storms; LID scenarios (LIDs with different storage depths/ conventional)	Runoff volume and peak flow
Avellaneda et al. (2017)	Parma, OH, USA	Street section	Bioretention system, RHS, combined	Storm frequency (intensity)	2011 April –2016 Oct.	SWMM	LID scenarios (LIDs with different types/ conventional)	Runoff volume and peak flow, infiltration volume, evapotranspiration volume
Barber et al. (2003)	Washington State University, Pullman, WA, USA	LID facility	Ecology ditch (bioretention)	Storm size, intensity, duration, AMC	-	SWMS2D	Design storms; LID scenario	Runoff peak flow, lag time
Chui and Trinh (2016)	Marina catchment, Singapore	Watershed	Bioretention system	Storm size, intensity, AMC	2005	MIKE SHE	LID scenarios (LID/conventional/natural)	Infiltration and groundwater recharge rate/volume
Damodaram et al. (2010)	College station, TX, USA	Watershed	RHS, green roof, porous pavement, combined	Storm size, frequency (intensity)	2009	SWMM, HEC-RAS	Design storms (2, 10, and 100 years); LID scenarios (LIDs with different types and storage depths/BMPs/conventional/ natural)	Runoff peak flow
Ellis and Viavattene (2014)	Birmingham and Coventry, UK	Watershed	Combined (porous pavement and green roof), infiltration basins	Storm size, frequency (intensity)	2007	STORM, FloodArea	LID scenarios (with different types)	Overflow from manholes, flooded area
Freni and Oliveri (2005)	Mondello catchment, Palermo, Italy	Watershed	Not specified	Storm frequency (intensity), duration, peak location	-	SWMM	Design storms; LID scenarios (with different types)	Runoff volume and peak flow
Fry and Maxwell (2017)	Berkley Lake watershed, Denver, CO, USA	Watershed	Bioretention cell	Storm frequency (intensity)	-	GSSHA	Design storms (2-100 years); LID scenarios (LIDs at different locations/ conventional)	Runoff volume and peak flow, infiltration volume, surface storage volume
Gilroy and McCuen (2009)	MD, USA	Residential/ commercial lot	RHS, bioretention system, combined	Storm size, frequency (intensity)	-	Rainfall-runoff model developed by authors	Land use types; Design storms (1& 2 years); LID scenarios (LIDs at different locations and with different amounts)	Runoff volume and peak flow

Table 2.4. Continued.

Authors	Study location	Unit of analysis	LID/BMP feature	Climate characteristic	Simulation			Hydrologic measure*
					Time frame	Model	Hypothetical scenarios	
Hakimdavar et al. (2014)	Columbia University, Manhattan, NY, USA	LID Facility (building)	Extensive green roof	Storm size, intensity, duration, AMC	2009, 2011-2012	HYDRUS	LID scenarios (with different drainage areas)	Runoff volume and peak flow, lag time
Hixon and Dymond (2014)	Blacksburg, VA, USA	Watershed	Not specified	Storm frequency (intensity)	-	SewerGEMS	Design storms (1, 2, 10, 25 years); Stormwater management scenarios (LIDs/conventional/ predevelopment/etc.)	Runoff peak flow, peak time delay (compared to predevelopment)
Hoss et al. (2016)	Upper Patuxent Watershed, Chesapeake Bay, USA	LID facility	Bioretention system, porous pavement, infiltration trench, wet and dry ponds	Storm size, frequency (intensity)	1984-2005	SUSTAIN	LID scenarios (with different types)	Nutrient loads
Jia et al. (2014)	Taohuawu Cultural District, Suzhou, Jiangsu Province, China	Cultural district	Combined (bioretention cell, porous pavement, infiltration pits, buffer strips, wetland)	Storm frequency (intensity)	-	SWMM	Design storms (2, 5, 20 years); LID scenarios (LIDs/ conventional)	Runoff volume, infiltration volume, overflow from manholes, flooded area, nutrient loads
Juan et al. (2016)	White Oak Bayou and The Woodlands watersheds, Houston, TX, USA	Watershed	Green roof, bioretention system	Storm size, frequency (intensity)	-	Vflo	Design storms (<1, 2, 10 years); LID scenarios (LIDs with different types/conventional)	Runoff volume and peak flow
Liao et al. (2013)	Caohejing basin, Xuhui District, Shanghai, China	Watershed	Bioretention system, infiltration trench, porous pavement, RHS	Storm frequency (intensity), duration	-	SWMM	Design storms; LID scenarios (LIDs with different types/ conventional)	Runoff volume and peak flow, runoff coefficient
Liu et al. (2014)	Haidian district, Beijing, China	Community	Bioretention system, porous pavement, retention pond, green space, combined	Storm size, frequency (intensity)	-	Rainfall-runoff model developed by authors	Design storms (1, 2, 5, 10 years); LID scenarios (LIDs with different types/ conventional)	Runoff volume and peak flow
Locatelli et al. (2014)	Denmark	LID facility (building)	Extensive green roof	Storm frequency (intensity)	1989-2010	Rainfall-runoff model developed by authors, MIKE URBAN	LID scenarios (LIDs with different sizes and slopes/ conventional)	Runoff volume and peak flow, peak time delay (compared to conventional development)

Table 2.4. Continued.

Authors	Study location	Unit of analysis	LID/BMP feature	Climate characteristic	Simulation			Hydrologic measure*
					Time frame	Time frame	Time frame	
Palla and Gnecco (2015)	Colle Ometti, genoa, Italy	Watershed	Combined (green roof and porous pavement)	Storm frequency (intensity), AMC	-	SWMM	Design storms (2, 5, 10 years); LID scenarios (LIDs with different amounts and initial saturation levels/conventional)	Runoff volume and peak flow, peak delay time (compared to conventional development)
Qin et al. (2013)	Guang-Ming New District, Shenzhen, China	Watershed	Bioretention system, porous pavement, green roof	Storm size, frequency (intensity), duration, peak location	-	SWMM	Design storms; LID scenarios (LIDs with different types/ conventional)	Overflow from manholes
Versini et al. (2015)	Chatillon basin, Hauts-de-Seine County, Paris, France	LID facility (building), watershed	Extensive green roof	Storm size, intensity, duration, AMC	1993-2011	SWMM	LID scenarios (LIDs with different coverages and depths/ conventional)	Runoff volume and peak flow
Xing et al. (2016)	Northern China	Watershed	Not specified	Storm size	-	SWMM	Design storms; LID scenarios (LIDs at different locations)	Runoff volume and peak flow, nutrient loads
Zellner et al. (2016)	Cook County, IL, USA	Gridded watershed	Not specified	Strom frequency (intensity)	-	L-GrID	Design storms (5 & 100 years); LID scenarios (with different coverages and layouts)	Runoff volume, infiltration volume, flooded area
Zhang et al. (2016)	Nanjing, China	Residential block	Green roof, porous pavement, RHS	Storm size	-	SCS curve number methods and baseflow equations	LID scenarios (with different types and storage depths)	Runoff volume, baseflow volume

* Hydrologic measure = direct or indirect measure used to assess hydrologic performance of LIDs.

Note. RHS = rainwater harvesting system; SWMM = storm water management model; SWMS2D = simulating water flow and solute transport in two-dimensional variably saturated media; HEC-RAS = Hydrologic Engineering Center's river analysis system; GSSHA = gridded surface/subsurface hydrologic analysis; SUSTAIN = system for urban stormwater treatment and analysis integration; L-GrID = landscape green infrastructure design model.

Finally, antecedent soil moisture content (AMC) or dry weather period determined the timing and magnitude of flooding (Figure 2.6). A wet condition lowered infiltration rates of LID soil medium and increased potentials for runoff events (Chui & Trinh, 2016). A result of bivariate analysis has clearly shown that initial saturation levels of LID systems had negative relationships with reduction rates of runoff volume and peak flow as well as hydrograph delay for a 2-year storm event (Palla & Gnecco, 2015). The relationship was linear only for volume reduction, but non-linear for peak flow reduction and hydrograph delay. Dependency of a runoff event on an initial saturation level decreased with increasing storm intensity (Barber et al., 2003). For large storm events (> 4 cm), neither peak reduction nor peak delay time was affected by the level of AMC.

In addition to the short-term event-based analysis, seasonal or yearly variations in LID performance can be assessed with a continuous simulation of hydrologic models based on a long-term record of local climate data. For example, Hoss et al. (2016) simulated 22 years of LID performance and found that its dependency on rainfall size diminished with an aggregation of daily and weekly climate data to a yearly basis. Versini et al. (2015) assessed performance of green roofs for 54 storm events through an 18-year simulation. A multiple regression analysis has shown a stronger relationship of runoff peak reduction with total rainfall depth and initial level of soil saturation than storm duration at both building and watershed scales.

2.3.4.2. Simulation under future climate conditions

The magnitude of hydrological disturbance is expected to grow with increasing air temperature and storm intensity in the near future (Field, 2012; Luber & McGeehin, 2008; Rosenzweig et al., 2001). The growing frequency of extreme events and extended dry periods challenge stormwater management. Concerns have risen as to whether urban drainage systems designed for past and current storm conditions will maintain their functionality under changing climate conditions. Many previous studies still relied on existing climatic assumptions.

Fourteen studies have recently examined how LID systems designed to meet historic performance standards can be resilient to future climate change (Table 2.5). The time span for climate prediction ranges up to the year 2100. Future climate scenarios can be designed based on assumptions such as a 15% increase in rainfall depth (Waters et al., 2003) and a 10% to 45% increase in storm intensity (Pyke et al., 2011) or predicted using climate models such as a general circulation model (GCM) (Dudula & Randhir, 2016; Joyce et al., 2017; Kirshen et al., 2014; Zahmatkesh et al., 2014). By using carbon emission scenarios as climate model inputs, downscaled precipitation changes in volume and intensity can be predicted in a time series. The forecasted climate data then force hydrologic models to simulate LID performance.

Table 2.5 Summary of hypothetical studies performed under future climate conditions.

Authors	Study location	Unit of analysis	LID/BMP feature	Simulation			Hydrologic measure*
				Time period	Model	Hypothetical scenarios	
Borris et al. (2016)	Östersund, Sweden	Watershed	Grassed swale, biofilter (for rooftop disconnection)	2012-2013; middle of the 21st century	WinSLAMM	IPCC emission scenarios (RCP 2.6/4.5/8.5); Socio-economic scenarios (sustainability/intermediate/ security)	Nutrient loads
Dudula and Randhir (2016)	Ipswich River watershed, MA, USA	Watershed	Bioretention system	1960-2006, 2035, 2065	GCM, HSPF	IPCC emission scenarios (baseline/RCP 4.5); LID scenarios (LID/no-LID)	Runoff mean flow, runoff/baseflow/ evapotranspiration volume
Giacomoni et al. (2014)	Village Creek watershed, Dallas/Fort Worth Metropolitan area, TX, USA	Watershed	Combined (RHS, green roof, porous pavement, bioretention system)	2010, 2035	CA, SWAT, HEC-RAS	Land use scenarios (existing/urbanized); LID scenarios (LID/conventional); Design storm events (2, 10, 100 years)	Runoff peak flow, hydrologic footprint residence (inundated area over time)
Jenkins et al. (2017)	London Borough of Camden, London, UK	City	Not specified	1961-1990, 2030s, 2050s	UKCP09, TUFLOW, ABM	Carbon emission scenarios (baseline/high emission); Flood management options (I-XIII)	Flood damage cost
Joyce et al. (2017)	Cross Bayou Watershed in Pinellas County, FL, USA	Watershed	Combined (green roof, porous pavement, bioretention system, retention pond)	2006, 2012, 2030	GCM, TPXO, ICPR	IPCC emission scenarios (baseline/A2); Sea level rise scenarios (SLR/no-SLR); Design storms (convective/frontal storms); LID scenarios (LID/no-LID)	Runoff peak flow, seepage outflow
Tobio et al. (2015)	Goonja watershed, Seoul, South Korea	Watershed	Porous pavement	1961-2011, 2020, 2050	SWMM	Design storm events (2, 100 years); LID scenario	Runoff peak flow
Kirshen et al. (2014)	The Winter Hill and Assembly Square watersheds, Somerville, MA, USA	Watershed	Combined (infiltration trench, porous pavement, RHS, green roof, blue roof, bioretention system)	2011, 2040, 2070	GCM, SWMM	Carbon emission scenarios (baseline/A1B/A2/B1); Design storms (3 months, 10 and 100 years)	Combined sewage volume and peak flow, runoff volume on streets
Newcomer et al. (2014)	San Francisco State University LID research network, San Francisco, CA, USA	LID facility	Infiltration trench	2011-2012, 2099-2100	GFDL, HYDRUS	IPCC scenarios (baseline/A1F1)	Groundwater recharge rate/ volume
Pyke et al. (2011)	South Weymouth Naval Air Station, Boston, MA, USA	Watershed	Not specified	1996-2005, 20 years later, 90 years later	SG WATER	Rainfall scenarios (±20% volume; +10/45% intensity; +10% intensity and +3% volume); LID scenarios (LID/conventional/undeveloped)	Runoff volume, nutrient loads

Table 2.5 Continued.

Authors	Study location	Unit of analysis	LID/BMP feature	Simulation			Hydrologic measure*
				Time period	Model	Hypothetical scenarios	
Semadeni-Davies et al. (2008)	Helsingborg, Sweden	City	Not specified	1994-2003, 2081-2090	RCAO, MOUSE	IPCC scenarios (baseline/A2/B2); Urbanization scenarios (storyline 1-4)	Combined sewage volume, nutrient loads
Stovin et al. (2013)	Four cities, UK - NW Scotland - Sheffield - Cornwall - East Midlands	LID facility (building)	Extensive green roof	Baseline, 2050s	UKCP09, rainfall-runoff model developed by authors	Carbon emission scenarios (baseline/medium emission); LID scenario	Runoff volume, evapotranspiration rate, drought stress
Vanuytrecht et al. (2014)	Flemish region, Belgium	LID facility (building)	Extensive green roof	1981-2010, 2031-2065	GCM, RCM, GreenRoof	IPCC scenarios (baseline/A1B); LID scenarios (LID with grass-herb or sedum-moss vegetation/no-LID)	Runoff volume, drought stress
Waters et al. (2003)	Malvern subdivision in Burlington, Ontario, Canada	Watershed	Rooftop disconnection, dry/wet ponds	1970s, 100 years later	SWMM	Rainfall scenario (+15% volume); LID scenarios with different types	Runoff volume and peak flow, lag time
Zahmatkesh et al. (2014)	Bronx River watershed, NY, USA	Watershed	Combined (RHS, porous pavement, bioretention system)	1950-1979, 2030-2059	GCM, SWMM	IPCC scenarios (baseline/RCP 2.6/RCP 6.0/RCP 8.5); LID scenarios (LID/no-LID)	Runoff volume and peak flow

* Hydrologic measure = direct or indirect measure used to assess hydrologic performance of LIDs.
Note. RHS = rainwater harvesting system; WinSLAMM = source loading and management model for Windows; GCM = global circulation model; HSPF = hydrological simulation program Fortran; CA = cellular automata; SWAT = soil and water assessment tool; HEC-RAS = Hydrologic Engineering Center's river analysis system; UKCP = UK climate projections; TUFLOW = two-dimensional unsteady flow; ABM = agent based model; ICPR = interconnected channel and pond routing model; GFDL = geophysical fluid dynamic laboratory; SG WATER = smart growth water assessment tool for estimating runoff; RCAO = Rossby Center atmosphere-ocean model; MOUSE = model for urban sewers; RCM = regional climate model; IPCC = intergovernmental panel on climate change; RCP = representative concentration pathway.

Many studies have suggested positive future prospects of using LID systems even with increasing frequency of high-intensity storms. Compared to a present baseline scenario where no flood mitigation measures are implemented, LID techniques were found to reduce runoff yields in the future below the level of the baseline scenario offsetting the adverse impact of climate change (Pyke et al., 2011; Semadeni-Davies et al., 2008; Tobio et al., 2015; Waters et al., 2003). LIDs were even predicted to outperform conventional BMPs such as detention ponds for small storms (Giacomoni et al., 2014). Although detention ponds could reduce peak flow more than LIDs, the release of runoff from detention ponds over an extended period after rainfall events would cause higher flow for a longer duration, resulting in a larger inundated area over time. Zahmatkesh et al. (2014) conducted a flow frequency analysis of annual peak flow predicted over 30 years (2030 – 2059) to evidence future benefits of LIDs. With mean precipitation of four carbon emission scenarios, the results revealed that future runoff of a 25-year return period from existing development would agree with that of a 50-year return period from LID systems. However, particular attention is needed in respect of sea level rise for vulnerable places such as coastal cities. A rising groundwater table in the future can cause increasing peak flow with installation of infiltration-based LIDs (Joyce et al., 2017). In addition, the benefits of LIDs compensating for the negative climate impact can be offset when there are remarkable socio-economic changes such as rapid population growth and urban sprawl (Borris et al., 2016).

Although LIDs can generally be effective in response to climate change in the near future, some research has shown concerns about its sustainability for the distant future. Dudula and Randhir (2016) predicted increasing peak flow by 15 – 25% by 2065 even with LID implementation. Similarly, Kirshen et al. (2014) found that LIDs alone could not compensate for the adverse impacts of climate change by 2070 for both 10 and 100-year storms. A combination of LIDs and flood mitigation measures at property level still showed an increase of the flood vulnerability of houses by 33% for 2050 (Jenkins et al., 2017). Increasing temperatures under future climate conditions could also threaten longevity of LIDs. Studies have shown that vegetation would suffer from drought stress in summer due to increasing evapotranspiration (Stovin et al., 2013; Vanuytrecht et al., 2014). However, increasing evapotranspiration helps to retain/reduce more stormwater by LID systems resulting in a larger volume of runoff reduction in summer (Figure 2.6). Thus, these studies have accentuated the need for a deep substrate and a mixture of vegetation with diverse stress levels to balance a trade-off between runoff reduction and drought risks in the future.

2.4. Discussion

The focus of this review study is to document evidence of contributing climatic factors to determine the hydrologic performance of LIDs. A meta-analysis was conducted with a subset of hypothetical studies, and a declining trend of LID performance was observed with increasing storm intensity. However, only a limited number of articles was explored in this meta-analysis. Information about storm frequency, observed or simulated, was often constrained in some studies. The measurement variations in runoff volume and/or peak discharge rate were also limited for each article when a single treatment effect (e.g., watershed setting, LID type, etc.)

was applied. More studies on LID performance under varying treatment conditions will enhance validity in estimating average effect sizes. Further meta-analysis with different climate characteristics such as short and long storm duration, antecedent dry and wet conditions, as well as early and late peak storm events will provide salient evidence to synthesize climate impacts on stormwater management and efficiently meet the needs of LIDs in response to local climate variability.

This systematic review also explored methodological approaches adopted in studies to monitor or manipulate climate conditions by study type. A short- or long-term event-based analysis has been most performed in identified articles. Based on synthesized findings, suggestions are made to expand existing methods and guide directions for future research. They include 1) exploration of both extreme and non-extreme storm events; 2) scenario design for policy implementation; 3) control of other contributing factors; and 4) integration of empirical and hypothetical research.

2.4.1. Exploration of Both Extreme and Non-Extreme Storm Events

For empirical and non-experimental studies, sufficient monitoring periods are essential to include both wet and dry years. For single events, factors such as precipitation patterns, temperature, humidity, and antecedent soil moisture levels holistically determine the hydrologic cycle of LID systems. An observation of only frequent storm events can generate a bias in predicting LID performance under varying storm conditions (Nawaz et al., 2015). The sample of individual storm events often lacks infrequent storms due to short monitoring periods in empirical studies. A regression model developed based on biased sampling may not accurately predict the retention capacity of LIDs in response to climate variability.

Similarly, hydrologic models of high performance allow simulation of diverse storm patterns with minimized prediction errors. For hypothetical studies, calibrating and validating models with both frequent and infrequent storm events enhance predictions of LID performance in response to climate fluctuations (Fry & Maxwell, 2017; Juan et al., 2016). In the selected articles, frequent storms with less than a 2-hour or equal to a 24-hour duration have been most studied (Figure 2.8). Lack of simulations with moderate or high storm intensity and duration increases uncertainty of LID performance under unpredictable climate conditions. Further analysis of diverse climate patterns would enhance the efficiency of LID systems to adapt to climate variability.

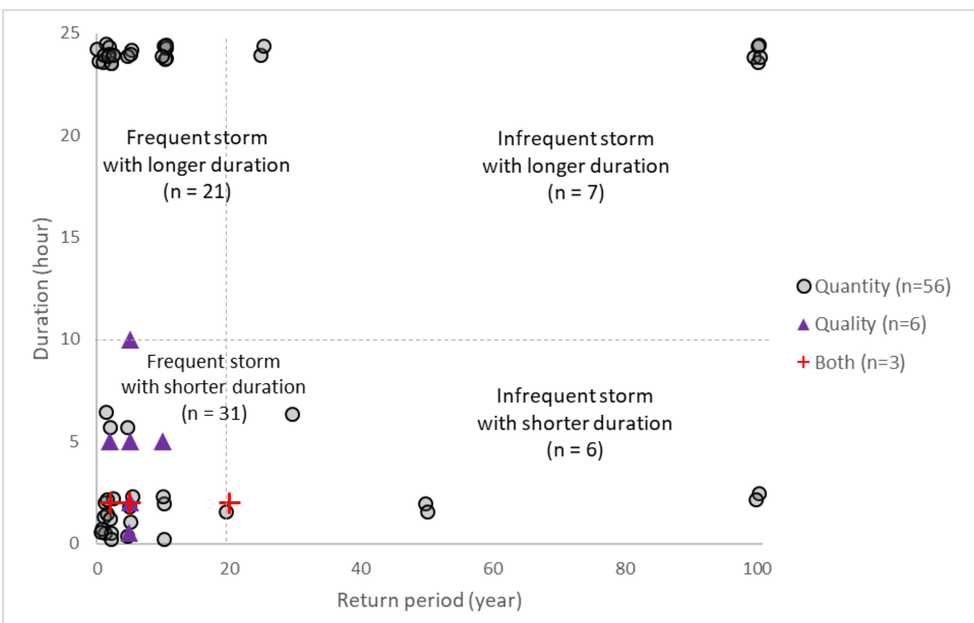


Figure 2.8 Return period and duration of design storm events simulated in hypothetical studies (Data derived from 19 studies).

2.4.2. Diverse Options of LIDs for Policy Development

The design of LID scenarios is particularly significant for hypothetical studies to suggest a wide range of plausible options for policy development. The most typical method adopted in the selected articles is by type of LID systems: single or combined LID techniques in a comparison with no-LID or pre-development scenarios. The percent coverage of LID systems at a watershed level varied by studies depending on available space by land use type, topography, depth of groundwater table, etc. Different storage depths of LIDs can also be applied to optimize the size of facilities which adapt to climate variability (Alfredo et al., 2010; Damodaram et al., 2010; Zhang et al., 2016). Simulating LIDs at multiple geographical locations helps to strategize placement of LIDs at the most optimal place for targeted storm events (Fry & Maxwell, 2017; Xing et al., 2016; Zellner et al., 2016).

However, many studies have developed LID scenarios based on an assumption that facilities are widely and immediately implemented within a watershed at the beginning stage of the study period. This assumption often causes overstated foresight towards LID policy. A temporal scale of policy development needs to be considered for practical use. Kirshen et al. (2014) emphasized the importance of considering triggering points when climate change urges actions for LID implementation. According to the concept of adaptive management, new policies to reorganize societies are likely to be adopted when a system crosses over a threshold triggered by an external disturbance (Olsson et al., 2006; Walker & Salt, 2006). Thus, further experimentation will be needed on the temporal effects of policy adoption in respect of potential flooding threats and how it helps to prepare for climate variability.

2.4.3. Control of Other Contributing Factors

Many interacting factors other than climatic features affect the hydrologic cycle of LID systems. They include soil composition, efficient storage depth, plant species, number of facilities, drainage area, distance to channel streams, etc. When these parameters contribute more than climatic factors to retaining and treating stormwater runoff, interpretations about climate impacts can be misleading. For this reason, providing detailed information about other internal and external variables affecting LID performance is essential to factor out their contributions. More caution is required when comparing hydrologic efficiency of LIDs by design type. For example, individual LID systems have different drainage or coverage areas depending on practical purposes and environmental settings. Rainwater harvesting systems have limited rooftop areas to apply, while bioretention systems are able to collect water from larger drainage areas such as backyards and parking lots. The retention rate of runoff by unit area will then be a better measure than the total reduction of hydrologic yields. A careful selection of hydrologic parameters to represent LID performance is significant particularly for non-experimental studies where a strict control of treatment effects is often unavailable.

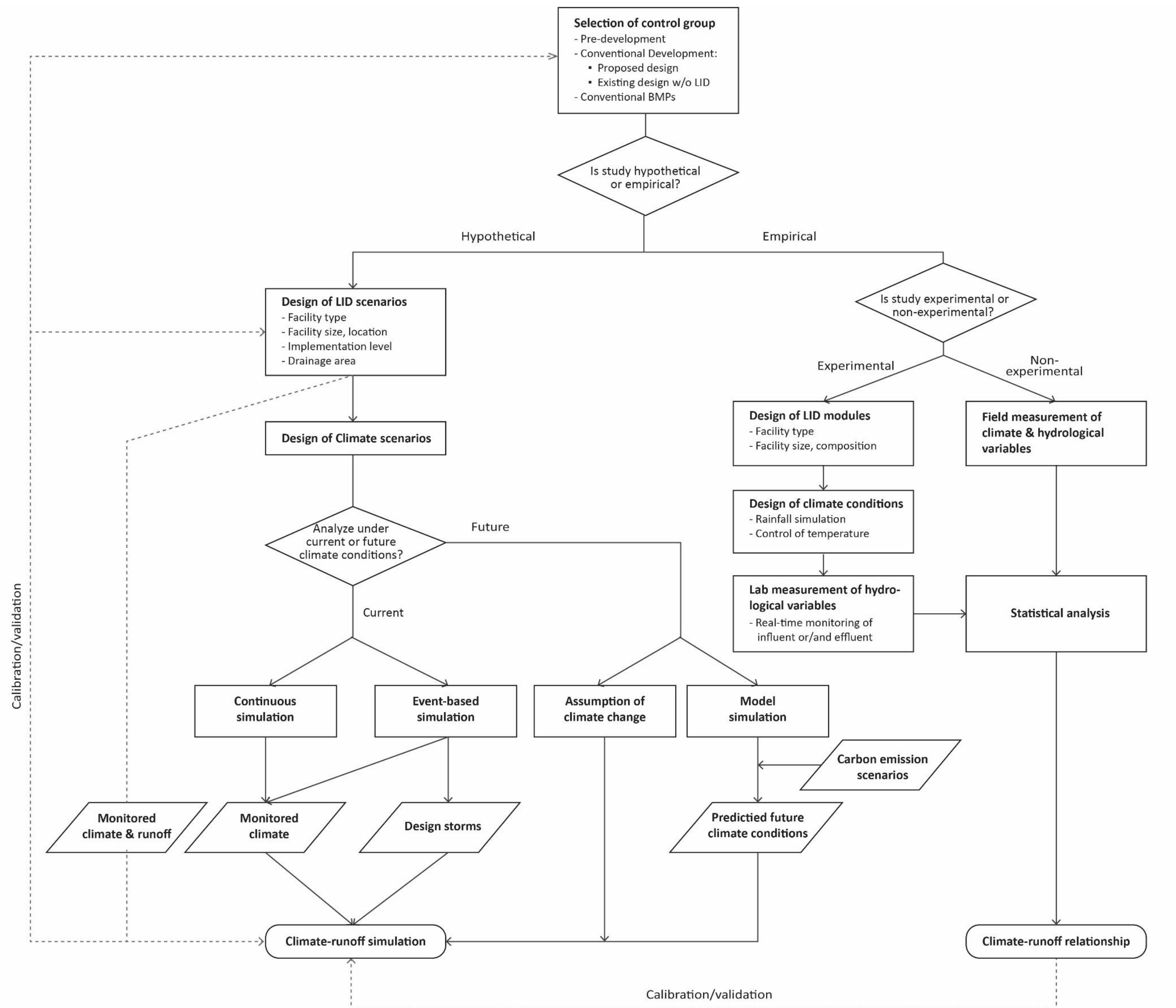


Figure 2.9 Linkage between hypothetical and empirical studies.

2.4.4. Integration of Empirical and Hypothetical Research

Empirical and hypothetical research reviewed in this study have used different approaches to design or measure treatment effects and environmental settings for identical research aims. Empirical and non-experimental studies provide evidence based on real-time monitoring, while experimental studies manipulate environmental settings of LID modules to control interacting factors other than climate conditions, removing alternative explanations. Hypothetical studies allow for testing diverse hypotheses at more flexible settings of an LID module or a watershed. By linking these methodological approaches, research designs can supplement one another (Figure 2.9).

Hypothetical studies typically calibrate and/or validate hydrologic models under an environmental setting of a control group such as pre-development, no-LID scenario, or conventional BMP design. With the short academic history of LID systems which started in the early 1990s, LID policy is in the evolving stage of adoption for watershed management. More regulations and funding policies have been developed in recent decades, although facilities are still minimally implemented in urban watersheds where space for new development is limited. The ability to calibrate models with watershed-scale LIDs implemented is confined accordingly. Given challenges, empirically measured performance of LID systems under various climate conditions provides data to calibrate models at a scale of LID module or sub-watershed. This process enhances the validity of model predictions and allows a wider range of LID hypotheses to be tested. For example, a few recent studies simultaneously calibrated topographic and channel parameters of a watershed based on an observation of existing conditions with no LIDs implemented as well as hydrologic parameters of LID systems based on monitored data of experimental plots (Palla & Gnecco, 2015; Versini et al., 2015). Further approaches of integrating empirical and hypothetical research design will provide a better insight into framing salient foundations to support effective LID policy and cope with climate variability.

2.5. Conclusion

Future climate change makes flood prediction more difficulty. The resulting climate variation by spatial and temporal scale challenges effective stormwater management. This study reviewed research trends in exploring climate impacts on LID performance and synthesized methodological approaches and findings by study type. The meta-analysis with a subset of hypothetical studies suggests a diminishing and less variable retention capacity of LIDs with increasing storm intensity. Runoff volume shows to be more sensitive to changes in storm frequency than peak discharge rate according to analysis of weighted effect size. More studies with diverse treatment effects of LID applications will expand current evidence supported by meta-analysis.

A conceptual framework formulated in this review study summarizes the relationship between climate characteristics and stormwater management (Figure 2.6). Consistent results from studies have shown that LIDs perform better in a warmer season with a smaller storm event of low intensity, duration, and antecedent moisture level. Different types of LIDs were found to be efficient to control early and late peak storms. This relationship suggests strategizing LID implementation by regional climate conditions or for specific storm patterns to achieve flood mitigation goals effectively.

Yet, studies are seldom found to measure dependency of LID performance to treat stormwater pollutants on climate conditions. The effects of temperature and some storm factors such as timing of peak storm intensity were also rarely studied. Rather, studies on future climate change impacts are growing with development of climate prediction models.

Current research can be further developed by 1) exploring more diverse extreme and non-extreme climate events; 2) testing hypotheses of LID design with multiple treatment effects; 3) controlling for other possible causes to affect LID performance; and 4) integrating methodological approaches of empirical and hypothetical studies. More research on LID performance will expand the current knowledge of stormwater control in response to increasing climate variability and encourage policy development to prepare for future uncertainty driven by climate change.

2.6. References

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

Alfredo, K., Montalto, F., & Goldstein, A. (2010). Observed and modeled performances of prototype green roof test plots subjected to simulated low-and high-intensity precipitations in a laboratory experiment. *Journal of Hydrologic Engineering, 15*(6), 444-457.

ASCE. (2017). *Infrastructure report card: A comprehensive assessment of America's infrastructure* (2221-3783). Retrieved from https://www.infrastructurereportcard.org/wp-content/uploads/2016/10/2017-Infrastructure-Report-Card.pdf

Avellaneda, P. M., Jefferson, A. J., Grieser, J. M., & Bush, S. A. (2017). Simulation of the cumulative hydrological response to green infrastructure. *Water Resources Research*, doi:10.1002/2016WR019836

Barber, M. E., King, S. G., Yonge, D. R., & Hathhorn, W. E. (2003). Ecology ditch: A best management practice for storm water runoff mitigation. *Journal of Hydrologic Engineering, 8*(3), 111-122.

Bergman, M., Hedegaard, M. R., Petersen, M. F., Binning, P., Mark, O., & Mikkelsen, P. S. (2011). Evaluation of two stormwater infiltration trenches in central Copenhagen after 15 years of operation. *Water Science and Technology*, *63*(10), 2279-2286.

Berliner, L. M. (2003). Uncertainty and climate change. *Statistical Science*, 430-435.

Blecken, G. T., Marsalek, J., & Viklander, M. (2011). Laboratory study of stormwater biofiltration in low temperatures: Total and dissolved metal removals and fates. *Water Air and Soil Pollution*, *219*(1-4), 303-317. doi:10.1007/s11270-010-0708-2

Bledsoe, B. P., & Watson, C. C. (2001). Effects of urbanization on channel instability. *Journal of the American Water Resources Association*, *37*(2), 255-270.

Borenstein, M. (2009). *Introduction to meta-Analysis*. Chichester, U.K.: Wiley.

Borenstein, M., Hedges, L., Higgins, J., & Rothstein, H. (2018). Comprehensive meta-analysis version 3. Englewood, NJ: Biostat.

Borris, M., Leonhardt, G., Marsalek, J., Österlund, H., & Viklander, M. (2016). Source-based modeling of urban stormwater quality response to the selected scenarios combining future changes in climate and socio-economic factors. *Environmental management, 58*(2), 223-237.

Brody, S. D., Zahran, S., Maghelal, P., Grover, H., & Highfield, W. E. (2007). The rising costs of floods: Examining the impact of planning and development decisions on property damage in Florida. *Journal of the American Planning Association, 73*(3), 330-345.

Butler, D., Digman, C. J., Makropoulos, C., & Davies, J. W. (2018). *Urban drainage*: Crc Press.

Chughtai, F., & Zayed, T. (2008). Infrastructure condition prediction models for sustainable sewer pipelines. *Journal of Performance of Constructed Facilities, 22*(5), 333-341.

Chui, T. F. M., & Trinh, D. H. (2016). Modelling infiltration enhancement in a tropical urban catchment for improved stormwater management. *Hydrological Processes, 30*(23), 4405-4419. doi:10.1002/hyp.10926

Clar, M. L., Barfield, B. J., & O'Connor, T. P. (2004). Stormwater best management practice design guide volume 3 basin best management practices. *Environmental Protection Agency*.

Damodaram, C., Giacomoni, M. H., Prakash Khedun, C., Holmes, H., Ryan, A., Saour, W., & Zechman, E. M. (2010). Simulation of combined best management practices and low impact development for sustainable stormwater management.

JAWRA Journal of the American Water Resources Association, 46(5), 907-918. doi:10.1111/j.1752-1688.2010.00462.x

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

Dudula, J., & Randhir, T. O. (2016). Modeling the influence of climate change on watershed systems: Adaptation through targeted practices. *Journal of Hydrology*, *541*, 703-713. doi:10.1016/j.jhydrol.2016.07.020

Dunkerley, D. (2012). Effects of rainfall intensity fluctuations on infiltration and runoff: Rainfall simulation on dryland soils, Fowlers Gap, Australia. *Hydrological Processes, 26*(15), 2211-2224.

Ellis, J. B., & Viavattene, C. (2014). Sustainable urban drainage system modeling for managing urban surface water flood risk. *Clean-Soil Air Water, 42*(2), 153-159. doi:10.1002/clen.201300225

Emerson, C. H., & Traver, R. G. (2008). Multiyear and seasonal variation of infiltration from storm-water best management practices. *Journal of Irrigation and Drainage Engineering*, *134*(5), 598-605.

Emerson, C. H., Wadzuk, B. M., & Traver, R. G. (2010). Hydraulic evolution and total suspended solids capture of an infiltration trench. *Hydrological Processes*, *24*(8), 1008-1014.

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

Field, C. B. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*: Cambridge University Press.

Fletcher, T. D., Shuster, W., Hunt, W. F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-Davies, A., & Bertrand-Krajewski, J.-L. (2015). SUDS, LID, BMPs, WSUD and more–The evolution and application of terminology surrounding urban drainage. *Urban Water Journal*, *12*(7), 525-542.

Freni, G., & Oliveri, E. (2005). Mitigation of urban flooding: A simplified approach for distributed stormwater management practices selection and planning. *Urban Water Journal*, *2*(4), 215-226. doi:10.1080/15730620500386461

Fry, T. J., & Maxwell, R. (2017). Evaluation of distributed BMPs in an Urban Watershed – High resolution modeling for Stormwater Management. *Hydrological Processes*, n/a-n/a. doi:10.1002/hyp.11177

Giacomoni, M. H., Gomez, R., & Berglund, E. Z. (2014). Hydrologic impact assessment of land cover change and stormwater management using the hydrologic footprint residence. *JAWRA Journal of the American Water Resources Association, 50*(5), 1242-1256. doi:10.1111/jawr.12187

Gilroy, K. L., & McCuen, R. H. (2009). Spatio-temporal effects of low impact development practices. *Journal of Hydrology, 367*(3-4), 228-236. doi:10.1016/j.jhydrol.2009.01.008

Gülbaz, S., & Kazezyılmaz-Alhan, C. M. (2017). Experimental investigation on hydrologic performance of LID with rainfall-watershed-bioretention system. *Journal of Hydrologic Engineering, 22*(1), D4016003.

Haan, C. T., Barfield, B. J., & Hayes, J. C. (1994). *Design hydrology and sedimentology for small catchments*: Elsevier.

Hakimdavar, R., Culligan, P. J., Finazzi, M., Barontini, S., & Ranzi, R. (2014). Scale dynamics of extensive green roofs: Quantifying the effect of drainage area and rainfall characteristics on observed and modeled green roof hydrologic performance. *Ecological Engineering, 73*, 494-508. doi:https://doi.org/10.1016/j.ecoleng.2014.09.080

Heilweil, V. M., & Watt, D. E. (2011). Trench infiltration for managed aquifer recharge to permeable bedrock. *Hydrological Processes, 25*(1), 141-151.

Hixon, L. F., & Dymond, R. L. (2014). Comparison of stormwater management strategies with an urban watershed model. *Journal of Hydrologic Engineering, 20*(9), 04014091.

Hood, M. J., Clausen, J. C., & Warner, G. S. (2007). Comparison of stormwater lag times for low impact and traditional residential development. *JAWRA Journal of the American Water Resources Association, 43*(4), 1036-1046. doi:10.1111/j.1752-1688.2007.00085.x

Hoss, F., Fischbach, J., & Molina-Perez, E. (2016). Effectiveness of best management practices for stormwater treatment as a function of runoff volume. *Journal of Water Resources Planning and Management, 142*(11). doi:10.1061/(asce)wr.1943-5452.0000684

Jackisch, N., & Weiler, M. (2017). The hydrologic outcome of a Low Impact Development (LID) site including superposition with streamflow peaks. *Urban Water Journal, 14*(2), 143-159. doi:10.1080/1573062X.2015.1080735

Jenkins, K., Surminski, S., Hall, J., & Crick, F. (2017). Assessing surface water flood risk and management strategies under future climate change: Insights from an Agent-Based Model. *Science of The Total Environment, 595*, 159-168. doi:https://doi.org/10.1016/j.scitotenv.2017.03.242

Jia, H., Ma, H., Sun, Z., Yu, S., Ding, Y., & Liang, Y. (2014). A closed urban scenic river system using stormwater treated with LID-BMP technology in a revitalized historical district in China. *Ecological Engineering, 71*, 448-457. doi:https://doi.org/10.1016/j.ecoleng.2014.07.049

Joyce, J., Chang, N. B., Harji, R., Ruppert, T., & Imen, S. (2017). Developing a multi-scale modeling system for resilience assessment of green-grey drainage infrastructures under climate change and sea level rise impact. *Environmental Modelling & Software, 90*, 1-26. doi:10.1016/j.envsoft.2016.11.026

Juan, A., Hughes, C., Fang, Z., & Bedient, P. (2016). Hydrologic performance of watershed-ccale low-impact development in a high-intensity rainfall region. *Journal of Irrigation and Drainage Engineering*, 04016083.

Kirshen, P., Caputo, L., Vogel, R. M., Mathisen, P., Rosner, A., & Renaud, T. (2014). Adapting urban infrastructure to climate change: a drainage case study. *Journal of Water Resources Planning and Management, 141*(4), 04014064.

Klein, R. D. (1979). Urbanization and stream quality impairment. *Journal of the American Water Resources Association, 15*(4), 948-963.

Krug, W. R., & Goddard, G. L. (1986). *Effects of urbanization on streamflow, sediment loads, and channel morphology in Pheasant Branch Basin near Middleton, Wisconsin*. Retrieved from https://pubs.er.usgs.gov/publication/wri854068

Lafortezza, R., Davies, C., Sanesi, G., & Konijnendijk, C. C. (2013). Green Infrastructure as a tool to support spatial planning in European urban regions. *iForest-Biogeosciences and Forestry, 6*(3), 102.

Lewellyn, C., Lyons, C. E., Traver, R. G., & Wadzuk, B. M. (2016). Evaluation of seasonal and large storm runoff volume capture of an infiltration green infrastructure system. *Journal of Hydrologic Engineering, 21*(1), 04015047.

Liao, Z. L., He, Y., Huang, F., Wang, S., & Li, H. Z. (2013). Analysis on LID for highly urbanized areas' waterlogging control: demonstrated on the example of Caohejing in Shanghai. *Water Science and Technology*, *68*(12), 2559-2567. doi:10.2166/wst.2013.523

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Thousand Oaks, Calif: SAGE Publications, Inc.

Liu, W., Chen, W. P., & Peng, C. (2014). Assessing the effectiveness of green infrastructures on urban flooding reduction: A community scale study. *Ecological Modelling, 291*, 6-14. doi:10.1016/j.ecolmodel.2014.07.012

Locatelli, L., Mark, O., Mikkelsen, P. S., Arnbjerg-Nielsen, K., Bergen Jensen, M., & Binning, P. J. (2014). Modelling of green roof hydrological performance for urban drainage applications. *Journal of Hydrology, 519, Part D*, 3237-3248. doi:https://doi.org/10.1016/j.jhydrol.2014.10.030

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

Luber, G., & McGeehin, M. (2008). Climate change and extreme heat events. *American Journal of Preventive Medicine, 35*(5), 429-435.

Nawaz, R., McDonald, A., & Postoyko, S. (2015). Hydrological performance of a full-scale extensive green roof located in a temperate climate. *Ecological Engineering, 82*, 66-80. doi:https://doi.org/10.1016/j.ecoleng.2014.11.061

Nelson, K. C., & Palmer, M. A. (2007). Stream temperature surges under urbanization and climate change: data, models, and responses. *Journal of the American Water Resources Association, 43*(2), 440-452.

Newcomer, M. E., Gurdak, J. J., Sklar, L. S., & Nanus, L. (2014). Urban recharge beneath low impact development and effects of climate variability and change. *Water Resources Research, 50*(2), 1716-1734. doi:10.1002/2013WR014282

Norrström, A. C. (2005). Metal mobility by de-icing salt from an infiltration trench for highway runoff. *Applied Geochemistry, 20*(10), 1907-1919.

NRCS. (2015). Information on Rainfall, Frequency, & Distributions. Retrieved from https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/water/?cid=stelprdb1044959

Oke, T., Johnson, G., Steyn, D., & Watson, I. (1991). Simulation of surface urban heat islands under 'ideal' conditions at night Part 2: Diagnosis of causation. *Boundary-Layer Meteorology, 56*(4), 339-358.

Oleson, K., Monaghan, A., Wilhelmi, O., Barlage, M., Brunsell, N., Feddema, J., . . . Steinhoff, D. (2015). Interactions between urbanization, heat stress, and climate change. *Climatic Change, 129*(3-4), 525-541.

Olsson, P., Gunderson, L. H., Carpenter, S. R., Ryan, P., Lebel, L., Folke, C., & Holling, C. S. (2006). Shooting the rapids: navigating transitions to adaptive governance of social-ecological systems. *Ecology and Society, 11*(1).

Palla, A., & Gnecco, I. (2015). Hydrologic modeling of Low Impact Development systems at the urban catchment scale. *Journal of Hydrology, 528*, 361-368. doi:10.1016/j.jhydrol.2015.06.050

Pyke, C., Warren, M. P., Johnson, T., LaGro Jr, J., Scharfenberg, J., Groth, P., Freed, R., Schroeer, W., & Main, E. (2011). Assessment of low impact development for managing stormwater with changing precipitation due to climate change. *Landscape and Urban Planning, 103*(2), 166-173. doi:https://doi.org/10.1016/j.landurbplan.2011.07.006

Qin, H.-p., Li, Z.-x., & Fu, G. (2013). The effects of low impact development on urban flooding under different rainfall characteristics. *Journal of Environmental Management, 129*, 577-585. doi:https://doi.org/10.1016/j.jenvman.2013.08.026

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

Roseen, R. M., Ballestero, T. P., Houle, J. J., Avellaneda, P., Briggs, J., Fowler, G., & Wildey, R. (2009). Seasonal performance variations for storm-water management systems in cold climate conditions. *Journal of Environmental Engineering, 135*(3), 128-137.

Rosenzweig, C., Iglesias, A., Yang, X., Epstein, P. R., & Chivian, E. (2001). Climate change and extreme weather events; implications for food production, plant diseases, and pests. *Global Change & Human Health, 2*(2), 90-104.

Semadeni-Davies, A., Hernebring, C., Svensson, G., & Gustafsson, L.-G. (2008). The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Combined sewer system. *Journal of Hydrology, 350*(1–2), 100-113. doi:https://doi.org/10.1016/j.jhydrol.2007.05.028

Shackley, S., Young, P., Parkinson, S., & Wynne, B. (1998). Uncertainty, complexity and concepts of good science in climate change modelling: Are GCMs the best tools? *Climatic Change, 38*(2), 159-205.

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

Sohn, W., Kim, J.-H., & Li, M.-H. (2017). Low-impact development for impervious surface connectivity mitigation: assessment of directly connected impervious areas (DCIAs). *Journal of Environmental Planning and Management, 60*(10), 1871-1889.

Stovin, V., Poë, S., & Berretta, C. (2013). A modelling study of long term green roof retention performance. *Journal of Environmental Management, 131*, 206-215. doi:https://doi.org/10.1016/j.jenvman.2013.09.026

Su, Y.-S. (2016). Discourse, strategy, and practice of urban resilience against flooding. *Business and Management Studies, 2*(1), 73-87.

Tobio, J. A. S., Maniquiz-Redillas, M. C., & Kim, L.-H. (2015). Optimization of the design of an urban runoff treatment system using stormwater management model (SWMM). *Desalination and Water Treatment, 53*(11), 3134-3141. doi:10.1080/19443994.2014.922288

Trenberth, K., Jones, P., Ambenje, P., Bojariu, R., Easterling, D., Klein Tank, A., . . . Rusticucci, M. (2007). Observations: surface and atmospheric climate change. Chapter 3. *Climate Change*, 235-336.

Trimble, S. W. (1997). Contribution of stream channel erosion to sediment yield from an urbanizing watershed. *Science, 278*(5342), 1442-1444.

US Global Change Research Program. (2009). *Global climate change impacts in the United States*: Cambridge University Press.

Vanuytrecht, E., Van Mechelen, C., Van Meerbeek, K., Willems, P., Hermy, M., & Raes, D. (2014). Runoff and vegetation stress of green roofs under different climate change scenarios. *Landscape and Urban Planning, 122*, 68-77. doi:https://doi.org/10.1016/j.landurbplan.2013.11.001

Versini, P. A., Ramier, D., Berthier, E., & de Gouvello, B. (2015). Assessment of the hydrological impacts of green roof: From building scale to basin scale. *Journal of Hydrology, 524*, 562-575. doi:https://doi.org/10.1016/j.jhydrol.2015.03.020

Walker, B., & Salt, D. (2006). *Resilience thinking: sustaining ecosystems and people in a changing world*: Island Press.

Wang, W., Yin, S., Xie, Y., Liu, B., & Liu, Y. (2016). Effects of four storm patterns on soil loss from five soils under natural rainfall. *CATENA, 141*(Supplement C), 56-65. doi:https://doi.org/10.1016/j.catena.2016.02.019

Waters, D., Watt, W. E., Marsalek, J., & Anderson, B. C. (2003). Adaptation of a storm drainage system to accommodate increased rainfall resulting from climate change. *Journal of Environmental Planning and Management, 46*(5), 755-770. doi:10.1080/0964056032000138472

Xiao, Y., & Watson, M. (2017). Guidance on Conducting a Systematic Literature Review. *Journal of Planning Education and Research*, 0739456X17723971.

Xing, W., Li, P., Cao, S. B., Gan, L. L., Liu, F. L., & Zuo, J. E. (2016). Layout effects and optimization of runoff storage and filtration facilities based on SWMM simulation in a demonstration area. *Water Science and Engineering*, *9*(2), 115-124. doi:10.1016/j.wse.2016.06.007

Xu, Y.-S., Ma, L., Du, Y.-J., & Shen, S.-L. (2012). Analysis of urbanisation-induced land subsidence in Shanghai. *Natural Hazards*, *63*(2), 1255-1267.

Yeon, J. S., Jang, Y. S., Shin, H. S., & Kim, E. S. (2014). Analysis of infiltration trench facility for runoff reduction effect. *Journal of the Korea Academia-Industrial cooperation Society*, *15*(9), 5813-5819.

Zahmatkesh, Z., Burian, S. J., Karamouz, M., Tavakol-Davani, H., & Goharian, E. (2014). Low-impact development practices to mitigate climate change effects on urban stormwater runoff: Case study of New York City. *Journal of Irrigation and Drainage Engineering, 141*(1), 04014043.

Zellner, M., Massey, D., Minor, E., & Gonzalez-Meler, M. (2016). Exploring the effects of green infrastructure placement on neighborhood-level flooding via spatially explicit simulations. *Computers, Environment and Urban Systems, 59*, 116-128. doi:https://doi.org/10.1016/j.compenvurbsys.2016.04.008

Zhang, X. Q., Guo, X. Y., & Hu, M. C. (2016). Hydrological effect of typical low impact development approaches in a residential district. *Natural Hazards, 80*(1), 389-400. doi:10.1007/s11069-015-1974-5

3. THE EFFECT OF LAND USE COMPOSITION AND CONFIGURATION ON SURFACE RUNOFF UNDER VARYING CLIMATE CONDITIONS

3.1. Introduction

3.1.1. Composition of Development

The amount of impervious surface is a typical land use measure which indirectly quantifies the urbanization impacts on local flooding and health of streams. It serves as an integrative and practical indicator for land use and water resource managers to diagnose and plan for urban expansion although it approximates the complexity of the urban hydrology system (Arnold Jr & Gibbons, 1996). Limiting the maximum coverage of impervious surface for a development lot has commonly been used for regulating local flooding.

Increasing impervious surface dramatically changes the hydrological cycle of a city. While natural ground cover generates approximately 10% of runoff, 40% of evapotranspiration, and 50% of infiltration, 75% to 100% of urbanized areas increase runoff by 45% and reduced evapotranspiration and infiltration by 10% and 35%, respectively (Livingston & McCarron, 1992; USEPA, 1993). A substantial body of literature has consistently supported the devastating impacts of urban expansion on flooding. It is found that urbanization can contribute to increasing annual runoff volume and peak flows by 146% and 159%, respectively (Olivera & DeFee, 2007). Every 1% increase in low-density development with a sprawling pattern can lead an increase of $161,800 of damage costs per year, per watershed (Brody et al., 2015).

Expansion of impervious surface also causes stream degradation. It is found that a stream becomes ‘impacted’ and no longer sustains its initial capacity to recover from disturbance when a watershed is urbanized more than 10%. When the imperviousness level goes beyond 30%, a stream becomes ‘degraded’ (Arnold Jr & Gibbons, 1996; Olivera & DeFee, 2007). Based on these findings, local governments have adopted a threshold-based land use policy which employs imperviousness as a regulatory tool for stream protection. The policy limits a certain amount of the imperviousness level for current and future development in the form of a zoning code or planning guideline (Moglen & Kim, 2007; Sung et al., 2013). Such simplicity and practicability of measuring impervious surface facilitate applications in a wide range of hydrological studies and land use policy.

While the total amount of impervious surface (TIA) has been one of the most useful and applicable indicators to quantify urbanization impacts, directly connected impervious area (DCIA), also referred to as effective impervious area (EIA), is another emerging measure which emphasizes hydraulic connectivity between impervious surface and stream network (Brabec et al., 2002). DCIA is a subset of TIA, where surface runoff directly drains into stream outlets through closed pipe systems (Shuster et al., 2005). For example, if runoff from a rooftop in a single-family housing drains to a backyard, the rooftop is considered to be disconnected and excluded from DCIA measurement (Sohn et al., 2017).

There have been debates as to which measure, TIA versus DCIA, is a better predictor to assess the impact of development on urban hydrology (Ebrahimian et al., 2016a). Some previous studies have shown that using DCIA instead of TIA helps to prevent overestimation of runoff volumes, peak discharge, and infiltration rates, and oversizing of drainage pipe systems (Alley & Veenhuis, 1983; Brabec et al., 2002). As the need for specifying DCIA values grows to improve accuracy of runoff predictions, some recent efforts have attempted to correct runoff estimates which were traditionally derived from TIA values. For instance, the weighted average curve number of impervious surface was adjusted by treating non-DCIA as pervious area (Pandit & Regan, 1998). A DCIA value can also substitute for the multiplied value of runoff coefficient and drainage area in the conventional Rational Method for correcting overestimated peak discharge rates (Lee & Heaney, 2003). With the upgraded version 5 of Storm Water Management Model (SWMM), DCIA and non-DCIA were partitioned and the internal flow between pervious and impervious areas could be routed by inputting new parameters (Chen et al., 2008).

A better understanding of DCIA mechanisms helps to effectively control stormwater runoff in urban settings where regulating TIA is challenging due to ongoing population growth and urbanization. Green infrastructure has a great potential to mitigate the level of DCIA as either an urban retrofit, new development, or a conservation easement. Rerouting runoff generated from impervious surfaces to green infrastructure can lead to increased flood storage of landscapes. Sohn et al. (2017) found that the combination of three site-level green infrastructures (rainwater harvesting system, porous pavement, and vegetated swale) helped to disconnect DCIA by 21% in single-family housing and by 51% in commercial areas compared to conventional development, while TIA reduction was minimal. Aulenbach et al. (2017) statistically examined the relationship between DCIA reduction by detention ponds and runoff yields over 8 years of monitoring and found that 2.7% of stormwater yields per year can be reduced for every 1% increase in DCIA reduction by detention ponds.

However, the hydrologic performance of DCIA has not yet been fully investigated because estimation of DCIA has been challenging. For small study areas, field assessment allows collection of a high quality of data in return for investment of extra time and cost (Lee & Heaney, 2003; Roy & Shuster, 2009). For study areas where field reconnaissance is restricted, a dataset of impervious cover, drainage network system, and/or digital elevation model is often used to estimate DCIA (Sahoo & Sreeja, 2011; Yang et al., 2011). Yet, the validity of measurement highly depends on the spatial resolution of data and accuracy of image classification (Han & Burian, 2009). For this reason, many studies have relied on assumptions or a simple formula to approximate DCIA (Endreny & Thomas, 2009; Yang et al., 2011). Further examination of DCIA is necessary to understand the drainage mechanisms of urban watersheds and effectively mitigate flooding impacts by promoting hydraulic connectivity between development and green infrastructure.

3.1.2. Configuration of Development and Green Infrastructure

The spatial pattern of land use is another factor which affects the internal flow routes of surface runoff between impervious and pervious areas. When a city grows beyond the capacity of a watershed to urbanize, the connectivity of impervious surfaces functions as an important factor to increase runoff conveyance (Olivera & DeFee, 2007).

In contrast, a connected form of landscapes serves as green infrastructure at a regional level moderating peak runoff (Kim & Park, 2016). Some recent studies have quantified the spatial pattern of development and landscape to identify its relationship and/or correlation with runoff yields using various methods. Automated algorithms allow generation of random hypothetical land use patterns to simulate runoff yields at a watershed scale (Mejía & Moglen, 2009; Zhang et al., 2013; Zhang & Shuster, 2014). Statistical relationships with empirical land use patterns have also been explored using measurable indices such as a compactness index, Shannon's diversity index, and landscape indices (Brody et al., 2013; Kim & Park, 2016; Lee et al., 2009; Olivera & DeFee, 2007).

Landscape indices, developed based on the theory of landscape ecology, were originally designed to understand spatial heterogeneity of landscape and ecological interactions among patches (Gustafson, 1998). Quantification of landscape structures provides a theoretical foundation to comprehend landscape function, process, and change (Forman & Godron, 1986). The spatial type of indices includes area, edge, shape, core area, contrast, aggregation, and diversity (McGarigal, 2014). Since development in 1980s, they have been widely applied in the field of forestry, soil science, agricultural management, geography, and land use planning, etc.

A few recent studies in urban hydrology have emphasized the significance of using spatial indices for understanding hydrological interactions among development and landscape patches. In a longitudinal study, Olivera and DeFee (2007) found that the number of development patches in the White Oak watershed located in Houston, USA, decreased since 1972 after it reached the maximum value. The result implied that continuing urbanization caused saturation of existing development patches in 1972 and connectivity among those patches in limited urban space contributed to increasing runoff volume. Similarly, another cross-sectional study showed that large and highly connected development patches in irregular shapes statistically increased annual peak runoff in major metropolitan areas, while less fragmented and more connected forms of landscape contributed to reducing flooding impacts (Kim & Park, 2016). Some inconsistent study results were also found; hypothetically fragmented urban forests reduced runoff volume, while fragmented urban areas increased peak flow (Zhang et al., 2013). Brody and his colleagues (2013) studied development patterns of different intensity and their association with flooding damage cost. They found that clusters of low-intensity development increased flood loss while clusters of medium-intensity development lowered flood risk.

Hydrologic responses of a watershed to changing patterns of development and landscape imply the edge effects between pervious and impervious surface. The internal flow routes between different surface permeabilities would be susceptible to changes in shapes and sizes of land patches. Although benefits of regulating the amount of development and expanding green spaces have been well documented, the hydrologic impact of land use configuration still remains unclear. Facing increasing flooding threats, understanding the relationship between land use configuration and runoff yields is critical to plan regional-scale green infrastructure and wisely manage urban expansion.

Urban resilience to floods can be enhanced with an integrative and holistic approach which considers both composition and configuration of land use.

3.2. Methods

3.2.1. Research Hypotheses

The major purpose of this study is to empirically examine how composition and configuration of development and green infrastructure affect surface runoff under varying climate conditions. Highly urbanized areas were monitored from 2010 to 2017 as a case study. Multiple statistical models were developed to identify the relationship between composition and configuration variables of land use as independent variables and the probability of runoff yields as a dependent variable. In terms of composition, this study focuses on revealing how TIA and DCIA behave differently in response to rainfall events. Based on the research question, three hypotheses were formulated.

Hypothesis 1. The high level of TIA and DCIA is likely to increase the probability of high-level runoff depths.

Hypothesis 2. DCIA will contribute more than TIA to increasing flood risks.

Hypothesis 3. Contributions of DCIA will be subject to changes in precipitation depths.

The spatial configuration of development and landscape was also explored focusing on size, edge, shape, isolation, fragmentation, and connectivity at a watershed scale. Findings in previous studies support the following hypotheses.

Hypothesis 4. Larger and connected patterns of development are likely to increase the probability of high-level runoff depths.

Hypothesis 5. Less fragmented, more connected, and more irregular-shaped patterns of green infrastructure tend to reduce the probability of high-level runoff depths.

3.2.2. Study Area

The study area includes 92 watersheds located within three metropolitan statistical areas (MSAs) in Texas, including Houston-The Woodlands-Sugar Land (Greater Houston), San Antonio-New Braunfels (Greater San Antonio), and Austin-Round Rock MSAs (Greater Austin) (Figure 3.1). The populations in 2017 were 6.9 million, 2.5 million, and 2.1 million, respectively and from 2010 to 2017, the three MSAs were ranked 14th, 18th, and 2nd in population growth out of 388 MSAs in the USA (United States Census Bureau, 2017). With increasing population density and impervious surfaces, urban floods have become one of the major concerns for watershed protection (Olivera & DeFee, 2007; Sung et al., 2013). Some local regulations, such as restricting impervious coverage by land use type (City of Austin, 2019) and charging stormwater fees by property lots (City of Houston, 2019a; City of San Antonio, 2019), have been designed to decrease risks of flooding and water pollution.

The watersheds were delineated based on streamflow data obtained from USGS gauge stations and national elevation dataset (30-meter resolution) by using Arc Hydro, a hydrologic model performing in ArcGIS (Maidment, 2002). The simulated stream network was visually verified in a comparison with the observed channel network obtained from the National Hydrography Dataset (NHD Plus). Watersheds were manually edited where needed. The monitoring period for rainfall and runoff depths ranges from January 2010 to December 2017 on a monthly basis.

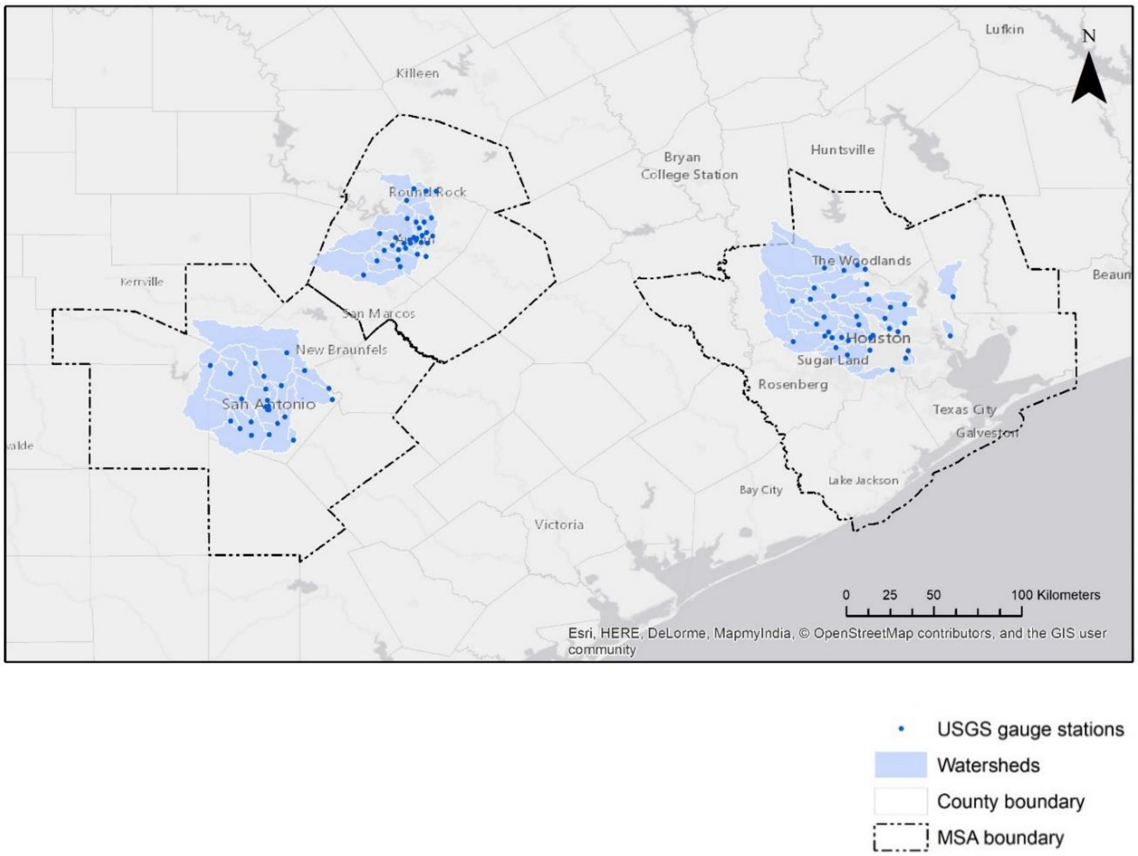


Figure 3.1 Locations of three MSAs, watersheds, and USGS gauge stations.

According to the spatial statistics of the selected watersheds (Table 3.1), Greater Houston has the highest ratio of TIA and DCIA but the flattest slope and low hydraulic conductivity on average. In contrast, Greater San Antonio has the lowest mean value of TIA and DCIA as well as the lowest mean hydraulic conductivity. None of flood-control reservoirs were designed in the selected watersheds in Greater Austin.

Table 3.1 Spatial characteristics of watersheds by MSA.

	Houston-The Woodlands-Sugar Land (n = 36)		Austin-Round Rock (n = 33)		San Antonio-New Braunfels (n = 23)	
	Mean	Std	Mean	Std	Mean	Std
TIA (%)	31.90	19.20	27.35	17.82	21.97	19.41
DCIA (%)	20.33	14.70	11.49	14.20	6.56	12.74
Flood-control reservoirs (binary)	0.06	0.23	0	0	0.04	0.21
Slope (%)	0.54	0.40	4.79	2.90	4.45	3.25
Hydraulic conductivity (mm/hr)	13.18	9.90	20.71	14.16	8.30	4.09

3.2.3. Data Construct and Analysis

3.2.3.1. Measurement of Hydrologic Variable

To compute the dependent variable, monthly runoff depth per unit watershed area was estimated using streamflow data gauged at each watershed outlet from January 2010 to December 2017. The hydrologic effect of upper to downstream watersheds was factored out by subtracting the influx of streamflow from outflow at each watershed. Four quantiles of monthly runoff depth where monthly precipitation is above 1 mm were then computed for each MSA (Table 3.2). Some potential outliers such as observations where runoff depth is higher than precipitation depth were excluded from the sampling. The possible reasons for such outliers include sea level rise along the Gulf of Mexico and/or overflow from bordering watersheds during heavy storm events. Based on the quantiles, an ordinal level of runoff yields from 1 to 4 was assigned to each observation (Table 3.3). The level of 1 was given if a monthly runoff depth of a watershed is below the 10th percentile and categorized as a far below average depth. Similarly, the levels of

2, 3, and 4 were assigned if the runoff depth is at or above the 10th percentile and below the 50th percentile, at or above the 50th percentile and below the 90th percentile, and at or above the 90th percentile categorized as a below average, above average, and far above average runoff yield, respectively. Accordingly, the mean runoff depths of the four categories are 0.93, 10.58, 44.71, and 116.85 mm in order.

Table 3.2 Percentiles of monthly runoff depth for each MSA.

MSA	Observation	Percentile of runoff depth (mm)		
		10th	50th	90th
Houston-The Woodlands-Sugar Land	2,613	4.12	29.23	115.60
Austin-Round Rock	1,811	0.23	12.15	62.66
San Antonio-New Braunfels	355	0.02	6.14	45.92
	4,779			

Table 3.3 Mean precipitation and runoff depths by runoff depth level.

Level	Ordered category	Percent frequency	Observation	Precipitation (mm)		Runoff depth (mm)	
				Mean	Std	Mean	Std
1	Far below average	10%	477	40.20	38.11	0.93	1.26
2	Below average	40%	1,914	59.92	44.07	10.58	8.18
3	Above average	40%	1,911	118.22	60.88	44.71	24.67
4	Far above average	10%	477	286.27	166.61	116.85	128.84
		100%	4,779				

3.2.3.2. Measurement of Composition and Configuration Variables

3.2.3.2.1. Composition of Development

The geospatial data of 30-m resolution impervious cover were obtained from the USGS national land cover dataset produced in 2011 using a regression tree algorithm (Yang et al., 2003). It was assumed that land development had been saturated during the study period even with growing city populations. Thus, land use changes were assumed to have had minimal impacts on development amounts and were neglected in this study. Using the impervious map, the watershed-level TIAs were computed using the Python programming language in ArcGIS version 10.4 and inputted to statistical models as independent variables.

To estimate DCIA, the method developed in a previous study (Boyd et al., 1993) and further developed by Ebrahimian et al. (2016b) was applied in this study. DCIA has been estimated using diverse methods such as rainfall-runoff analysis, field survey, remote sensing and GIS analysis, and development of empirical formulas. Among them, DCIA estimates derived from rainfall-runoff data appear to be most valid because the hydrologic and hydraulic processes of runoff production and losses from impervious surfaces are well accounted for (Ebrahimian et al., 2015). According to Boyd et al. (1993), the slope of the first segment in Figure 3.2 represents percent DCIA when event-based runoff depth is plotted against rainfall depth. If a rainfall exceeds a certain threshold, disconnected impervious and pervious surfaces begin to produce runoff. However, when the size of a rainfall event is small, DCIA is the only contributing factor to generating runoff. Thus, runoff depth can be defined as:

$$\mathrm{Q} = (P - I_a) f_{DCIA} \tag{1}$$

where Q is runoff depth, P is rainfall depth, $I_a$is initial loss, and f_{DCIA} is the fraction of DCIA. Depending on the level of antecedent soil moisture, initial loss of runoff can be varied. Based on this theory, Boyd and his colleagues developed multiple regression models to find the consistent slope of *Segment I*. Yet, small events with high storm intensity, long storm duration, or antecedently wet soil can still produce runoff from pervious areas. To exclude such events from analysis, a deviation of 1 mm above the regression line was used as a criterion to drop outlier events while developing successive regression models. This simple linear regression model can be expressed in matrix form as:

$$Y = X\beta + \varepsilon \qquad if\ \varepsilon \leq 1 \tag{2}$$

where Y is a $(n \times 1)$ vector of runoff depths, X is a $(n \times 2)$ matrix with ones in the first column and rainfall depths in the second column, β is a (2×1) vector of population parameters, and ε is a $(n \times 1)$ vector of the random error.

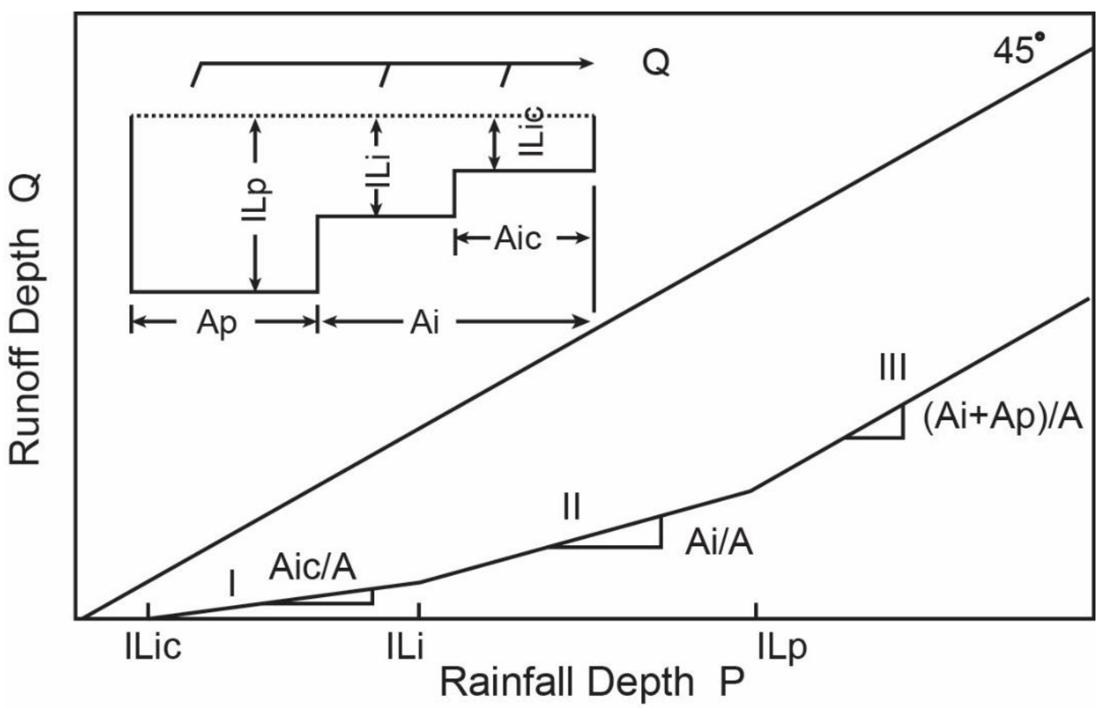


Figure 3.2 Schematic rainfall-runoff relationship (Reprinted from Boyd et al., 1993).

Note. *Ai* = total impervious area; *Aic* = directly connected impervious area; *Ap* = pervious or semi-pervious area; *A* = total watershed area (*A* = *Ai* + *Ap*); *IL* = initial loss; *P* = rainfall depth; *Q* = runoff depth.

However, DCIA estimates using this successive ordinary least squares (OLS) method with the 1 mm criterion is subject to bias when residuals are heteroscedastic. To remove this potential problem and subjectivity involved in the original method, Ebrahimian et al. (2016b) developed the successive weighted least squares (WLS) method with a new criterion to omit runoff events attributed to pervious area. Observations with large variances in residuals are inversely weighted in the WLS method, and runoff events where residuals are greater than 2 times standard error or 1 mm above the regression line become omitted. The WLS model is then recursively developed until the slope becomes consistent and no observations are identified meeting the criterion. The vector of population parameters for the final WLS model is thus:

$$\beta_{WLS} = \begin{bmatrix} -I_a f_{DCIA} \\ f_{DCIA} \end{bmatrix} = (X^T W X)^{-1} X^T W Y \quad if\ \varepsilon_i \leq \max[2\sigma_\varepsilon, 1] \tag{3}$$

where ε_i is the i^{th} residual $(i = 1, \ldots, n)$, σ_ε is the standard error of regression whose value squared equals to the mean squared error (MSE), and W is a $(n \times n)$ weight matrix where diagonal elements have weights for observation i and the off-diagonal elements are zeros as follows:

$$W = \frac{1}{Var(\varepsilon_i)} = \begin{bmatrix} 1/\sigma_1{}^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/\sigma_n{}^2 \end{bmatrix} \tag{4}$$

where σ_i is the constant variance of the i^{th} residual. The OLS model has $W = \mathbf{I}$ where I is an identity matrix.

In this study, the successive WLS method was adopted if heteroscedasticity was found in residual variances, or the OLS method if not. The monthly rainfall and runoff depths were individually plotted by watershed and similar trends to Figure 3.2 were identified. In the study sample, the precipitation threshold where disconnected impervious or pervious surfaces contribute to generating runoff (IL_i in Figure 3.2) was found to be close to 100 mm. The estimated fraction of DCIA was finally converted to percentage and compared with percent TIA to confirm that DCIA is smaller than TIA.

3.2.3.2.2. Configuration of Development and Green Infrastructure

To quantify spatial patterns of land use, the 30-m resolution land cover map for 2011 obtained from the USGS national land cover dataset was reclassified into development and green infrastructure in ArcGIS (Overall accuracy = 82%). The classification codes of low- (22), medium- (23), and high-intensity development (24) were grouped into urban development, while developed open space (21), deciduous forest (41), evergreen forest (42), mixed forest (43), shrub/scrub (52), grassland (71), pasture (81), and agricultural land (82) were combined into green infrastructure. The reclassified map was then masked by individual watersheds.

Based on previous research exploring the impacts of land use configuration on urban floods (Brody et al., 2013; Kim & Park, 2016; Olivera & DeFee, 2007; Zhang et al., 2013), the most relevant seven landscape indices were selected in this study to measure the spatial structure of development and green infrastructure: mean patch area (MPA), edge density (ED), mean shape index (MSI), mean nearest neighbor distance (MNN), patch density (PD), patch cohesion index (COHESION), and area-weighted radius of gyration (GYRATE). Each landscape index quantifies various components of configurations such as size, edge, shape, isolation, fragmentation, and connectivity

(Table 3.4). MPA and ED literally measure the mean size of individual patches and the density of patch perimeters for a particular land use class. MSI is a perimeter to area ratio standardized for a square form, and the value increases when a patch shape becomes more irregular. MNN and PD measure the shortest edge-to-edge distance and the number of patches per unit area, together quantifying the level of isolation and fragmentation of a corresponding land use type. COHESION and GYRATE represent the physical connectedness of a patch. COHESION increases when patches are connected in a clumped or aggregated pattern, while GYRATE represents a correlation length which increases when the average distance that one can traverse within a patch increases (McGarigal, 2014).

Using FRAGSTATS version 4.2.1, a spatial pattern analysis software program developed by McGarigal and Marks (1995), the landscape indices were individually computed for two major land use types including urban development and green infrastructure as well as three sub-classes of development including low-, medium-, and high-intensity development. According to the metadata of the USGS national land cover dataset, low-, medium-, and high-intensity development is defined to be covered by impervious surfaces by 20 – 49%, 50 – 79%, and 80 – 100%, respectively.

Table 3.4 Construct variables, data source, and analytical tools.

Construct	Variables (Acronym)	Formula[*]	Units (Range)	Source; Analytical tools
Dependent variable				
	Level of runoff depth		None (1 – 4)	USGS
Independent variables				
Composition of development				
	Total impervious area (TIA)		%	USGS; ArcGIS
	Directly connected impervious area (DCIA)		%	PRISM & USGS; STATA

Table 3.4 Continued.

Construct	Variables (Acronym)	Formula*	Units (Range)	Source; Analytical tools
Configuration of development and green infrastructure				
Size & Edge	Mean patch area (MPA)	$\sum_{j=1}^{n} a_{ij} \Big/ [n_i \cdot (10{,}000)]$	ha	USGS; FRAGSTATS
	Edge density (ED)	$\left[\sum_{j=1}^{n} e_{ij} \big/ A\right] \cdot (10{,}000)$	m/ha	USGS; FRAGSTATS
Shape	Mean shape index (MSI)	$\sum_{j=1}^{n} \frac{.25\, p_{ij}}{\sqrt{a_{ij}}} \Big/ n_i$	None (MSI≥1, without limit)	USGS; FRAGSTATS
Isolation	Mean nearest neighbor distance (MNN)	$\sum_{j=1}^{n} h_{ij} \Big/ n_i$	m	USGS; FRAGSTATS
Fragmentation	Patch density (PD)	$\frac{n_i}{A} \cdot (10{,}000) \cdot (100)$	Count/100ha	USGS; FRAGSTATS
Connectivity	Patch cohesion index (COHESION)	$\left[1 - \frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij} \cdot \sqrt{a_{ij}}}\right] \cdot \left[1 - \frac{1}{\sqrt{Z}}\right] \cdot (100)$	None (0 < COHESION<100)	USGS; FRAGSTATS
	Area-weighted radius of gyration (GYRATE)	$\sum_{j=1}^{n} \left[\left(\sum_{r=1}^{z} \frac{h_{ijr}}{z}\right)\left(\frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}}\right)\right]$	m	USGS; FRAGSTATS
Control Variables				
Climate/biophysical variables				
	Precipitation		mm	PRISM; ArcGIS
	Antecedent wetness		mm	PRISM; ArcGIS
	Flood-control reservoir		binary (0/1)	TNRIS; ArcGIS
	Slope		%	USGS; ArcGIS
	Hydraulics conductivity (K_{sat})		mm/hour	NRCS – SSURGO; ArcGIS
Location and time variables				
	MSA		Houston (0/1), Austin (0/1), San Antonio (0/1)	-
	Year		2010-2017 (0/1)	-
	Month		January – December (0/1)	-

Note. n_i = number of patches in the landscape of patch type (class) i; a_{ij} = area (m^2) of patch ij; e_{ij} = total length (m) of edge in p_{ij} = perimeter of patch ij; h_{ij} = distance (m) from patch ij to nearest neighboring patch of the same type, based on edge-to-edge distance; h_{ijr} = distance (m) between cell ijr placed in patch ij and the centroid of patch ij based on cell center-to-center distance; A = total landscape area (watershed area in this study) (m^2); Z = total number of cells in the landscape.

USGS = United States Geological Survey; PRISM = Parameter Elevation Regression on Independent Slopes Model; TNRIS = Texas Natural Resources Information System; NRCS – SSURGO = Natural Resources Conservation Service - Soil Survey Geographic Database; GIS = Geographic Information System; STATA = Software for Statistics and Data Science.

* See McGarigal and Marks (1995) for more details.

3.2.3.3. Measurement of Climate and Biophysical Variables

For control variables, multiple climate and biophysical variables were measured. Monthly precipitation maps from 2010 to 2017 were retrieved from the Parameter Elevation Regressions on the Independent Slopes Model (PRISM) Climate Group. PRISM interpolated the spatial patterns of precipitation using the climate-elevation regression method at a 4-km resolution (Daly et al., 2008). As an antecedent wetness factor, one-month prior precipitation was computed which would affect runoff yields on pervious surfaces. The existence of flood-control reservoirs was also examined by observing the National Agriculture Imagery Program (NAIP) imagery obtained from the Texas Natural Resources Information System (TNRIS). The small-scale reservoirs for agricultural or recreational purposes were excluded from analysis. The average slope was computed in ArcGIS by using the USGS national elevation dataset (30-m resolution). Finally, the saturated hydraulic conductivity of soils, K_{sat}, was derived from the Natural Resources Conservation Service's (NRCS) Soil Survey Geographic Database (SSURGO).

3.2.3.4. Statistical Analysis

When the dependent variable is an ordinal response, simple linear regression models can be problematic as the assumption of normal distribution and homoscedasticity is violated. The predicted value can be even out of range (Agresti, 1997). To avoid these potential issues, this research adopted ordinal logit regression models to statistically explain the relationship between the ordered level of runoff yields and the composition and configuration variables of land use.

In this study, the ordinal response variable denoted as Z is the ordered level of runoff depths, having four categories (Table 3.3). The cumulative probability that the response on Y falls in category j $(1 \leq j \leq 3)$ or below are thus as follows:

$$P(Z \leq j) = p(Z = 1) + \cdots + P(Z = j) \tag{5}$$

Accordingly, the odds of response in category j or below in ordinal logit regression models are:

$$\frac{P(Z \leq j)}{P(Z > j)} \tag{6}$$

In this study, the logged odds or logits were assumed to have a linear relationship with the four group of independent variables:

$$Y = \alpha - \beta_1 CP - \beta_2 CF - \beta_3 CB - \beta_4 LT \tag{7}$$

$$y_j = log\left[\frac{P(Z \leq j)}{P(Z > j)}\right] \in Y \tag{8}$$

where Y is a (3×1) vector of logits, α is a (3×1) vector of intercepts, CP is a $(m \times 1)$ vector of configuration variables, CF is a $(n \times 1)$ vector of configuration variables, CB is a $(k \times 1)$ vector of climate/biophysical variables, LT is a $(l \times 1)$ vector of location/time variables, and β_1, β_2, β_3, and β_4 are $(3 \times m)$, $(3 \times n)$, $(3 \times k)$, and $(3 \times l)$ matrixes of estimated parameters, respectively. The ordinal logit model assumes that the effect of independent variables is identical for each cumulative probability.

To identify a model of a better fit for each logit in Eq. 8, the likelihood-ratio test was performed. The test measures the difference in the log-likelihood functions for the unrestricted and restricted models through a stepwise selection procedure (Wooldridge, 2009). This iterative process ends when no more inclusion of variables results in model improvement, and at the same time the chi-squared statistic for log likelihood difference reaches the maximum value. The null hypothesis ($\beta = 0$) was then tested at a 0.05 significance level.

Five ordinal logit regression models were developed in this study. To avoid multicollinearity issues among land use patterns, the models were separately developed by five land cover types – low-, medium-, and high-intensity development, urban development, and green infrastructure, and some interrelated landscape indices were omitted from analysis. In addition, average marginal effects of changes in regressors were further assessed to identify how the probability of runoff yields responds to an increase in independent variables. The coefficient of the average marginal effect is similar to that of an OLS model allowing interpretation of the practical significance of the results, and the sum of coefficients is zero for each variable (Williams, 2012).

3.3. Results

3.3.1. The Effects of Development Composition on Urban Runoff

The results of ordinal logit regression models in Table 3.5 show the positive association of TIA and DCIA with the cumulative logit of runoff depths. The level of runoff depth increases with TIA or DCIA, holding all other variables constant. DCIA was a more dominant factor than TIA. According to the standardized coefficient, DCIA was the second most powerful predictor to estimate the cumulative logit of runoff depth in all five models following precipitation depth (b = 4.1 – 4.8; p<0.01). With a 1% increase in DCIA, the probability of either runoff level 1 or 2 decreased by 0.58 – 0.66%, while that of runoff level 3 increased by 0.83 – 0.93 % on average (Table 3.6). In contrast, TIA lost significance in Models 1, 3, and 5 when the spatial patterns of green infrastructure and high-intensity and medium-intensity development were added. Otherwise, every 1% increase in TIA resulted in decreasing the probability of either runoff level 1 or 2 by 0.10 – 0.13% while increasing that of runoff level 3 by 0.14 – 0.18% on average. The probability of runoff level 4 was yet less affected by TIA and DCIA than that of runoff level 3.

The standardized coefficients in Table 3.5 also reveal the higher contribution of DCIA than that of COHESION or GYRATE. This implies that the hydraulic connectivity between development and sewer drainage systems in urban settings outperforms the spatial connectivity of land use in determining the level of runoff depths.

Table 3.5 Five ordinal logit regression models for cumulative probabilities of runoff yields.

Variable	Model 1 (Green infrastructure pattern)	Model 2 (Urban development pattern)	Model 3 (High-intensity development pattern)	Model 4 (Medium-intensity development pattern)	Model 5 (Low-intensity development pattern)
Composition Variables					
TIA	0.007	0.018**	0.007	0.002	0.025**
	(1.126)	(1.380)	(1.134)	(1.027)	(1.538)
DCIA	0.121**	0.121**	0.125**	0.125**	0.112**
	(4.601)	(4.600)	(4.812)	(4.833)	(4.089)
Configuration Variables					
MPA	-0.001	-0.002	(omitted)	0.394**	(omitted)
	(0.942)	(0.875)		(1.398)	
ED	-0.012**	-0.005˙	(omitted)	(omitted)	(omitted)
	(0.676)	(0.840)			
MSI	(omitted)	-0.576	-3.264**	(omitted)	-2.106*
		(0.850)	(0.746)		(0.863)
MNN	0.004**	-0.004*	-0.003**	-0.009**	-0.059**
	(1.133)	(0.885)	(0.824)	(0.775)	(0.552)
PD	0.078**	-0.011	0.005	0.009	-0.038**
	(1.691)	(0.966)	(1.025)	(1.096)	(0.680)
COHESION	0.102**	0.053*	0.001	-0.019˙	-0.056**
	(1.936)	(1.144)	(1.015)	(0.864)	(0.661)

Table 3.5 Continued.

Variable	Model 1 (Green infrastructure pattern)	Model 2 (Urban development pattern)	Model 3 (High-intensity development pattern)	Model 4 (Medium-intensity development pattern)	Model 5 (Low-intensity development pattern)
GYRATE	-0.0002**	0.00008	0.001**	-0.0003	0.001**
	(0.692)	(1.119)	(1.263)	(0.931)	(1.159)
Climate/Biophysical Variables					
Precipitation	0.038**	0.037**	0.037**	0.037**	0.038**
	(40.650)	(40.146)	(39.620)	(39.744)	(40.788)
Antecedent wetness	0.006**	0.006**	0.006**	0.006**	0.006**
	(1.744)	(1.743)	(1.742)	(1.741)	(1.746)
Flood-control reservoir	-0.132	-0.264	-0.222	-0.470˙	-0.316
	(0.980)	(0.960)	(0.966)	(0.930)	(0.952)
Slope	0.112**	0.127**	0.071**	0.125**	0.054*
	(1.330)	(1.383)	(1.198)	(1.375)	(1.149)
K_{sat}	-0.002	-0.009*	-0.018**	-0.013**	-0.018**
	(0.977)	(0.900)	(0.815)	(0.859)	(0.821)
Location/Time Variables					
Houston, baseline	0	0	0	0	0
Austin	1.448**	1.801**	2.066**	1.620**	1.674**
	(2.019)	(2.395)	(2.725)	(2.195)	(2.252)
San Antonio	2.142**	2.324**	2.559**	2.457**	2.517**
	(1.754)	(1.840)	(1.956)	(1.905)	(1.935)
2010, baseline	0	0	0	0	0
2011.Year	-0.765**	-0.755**	-0.762**	-0.748**	-0.780**
	(0.789)	(0.791)	(0.789)	(0.793)	(0.785)
2012.Year	-0.308*	-0.315*	-0.321*	-0.300*	-0.321*
	(0.905)	(0.903)	(0.901)	(0.907)	(0.901)
2013.Year	-0.631**	-0.631**	-0.625**	-0.611**	-0.624**
	(0.812)	(0.812)	(0.813)	(0.817)	(0.814)
2014.Year	-0.549**	-0.555**	-0.535**	-0.526**	-0.555**
	(0.829)	(0.828)	(0.833)	(0.836)	(0.828)
2015.Year	0.090	0.061	0.086	0.101	0.091
	(1.031)	(1.021)	(1.030)	(1.036)	(1.032)
2016.Year	0.265˙	0.254˙	0.258˙	0.275˙	0.252˙
	(1.094)	(1.090)	(1.091)	(1.097)	(1.089)
2017.Year	-0.017	-0.033	-0.030	-0.002	-0.024
	(0.994)	(0.989)	(0.990)	(0.999)	(0.992)
1 (January), baseline	0	0	0	0	0
2.Month	-0.457**	-0.457**	-0.455**	-0.454**	-0.456**
	(0.881)	(0.881)	(0.881)	(0.882)	(0.881)
3.Month	-0.0001	-0.009	-0.014	-0.004	-0.017
	(1.000)	(0.997)	(0.996)	(0.999)	(0.995)
4.Month	-0.845**	-0.828**	-0.824**	-0.830**	-0.828**
	(0.795)	(0.799)	(0.800)	(0.799)	(0.799)
5.Month	-1.291**	-1.279**	-1.279**	-1.276**	-1.298**
	(0.694)	(0.696)	(0.696)	(0.697)	(0.692)
6.Month	-1.496**	-1.490**	-1.498**	-1.492**	-1.518**
	(0.657)	(0.658)	(0.656)	(0.658)	(0.653)
7.Month	-1.905**	-1.902**	-1.908**	-1.895**	-1.925**
	(0.592)	(0.592)	(0.591)	(0.593)	(0.589)

Table 3.5 Continued.

Variable	Model 1 (Green infrastructure pattern)	Model 2 (Urban development pattern)	Model 3 (High-intensity development pattern)	Model 4 (Medium-intensity development pattern)	Model 5 (Low-intensity development pattern)
8.Month	-2.292**	-2.281**	-2.283**	-2.278**	-2.313**
	(0.538)	(0.540)	(0.540)	(0.540)	(0.535)
9.Month	-1.721**	-1.721**	-1.718**	-1.715**	-1.731**
	(0.616)	(0.617)	(0.617)	(0.618)	(0.615)
10.Month	-1.467**	-1.458**	-1.461**	-1.449**	-1.479**
	(0.682)	(0.684)	(0.683)	(0.685)	(0.680)
11.Month	-1.222**	-1.221**	-1.231**	-1.214**	-1.240**
	(0.714)	(0.714)	(0.712)	(0.716)	(0.711)
12.Month	-0.859**	-0.862**	-0.863**	-0.859**	-0.868**
	(0.784)	(0.783)	(0.783)	(0.784)	(0.782)
cut 1	10.714**	5.470*	-2.686**	-0.720	-11.419**
cut 2	15.235**	9.949**	1.785*	3.753**	-6.900**
cut 3	20.959**	15.679**	7.511**	9.467**	-1.168
Observations	4,779	4,779	4,779	4,779	4,779
LR chi2(37)	5580.26	5542.89	5542.73	5533.76	5583.25
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.4894	0.4861	0.4861	0.4853	0.4896

Note: Standardized coefficient in the parenthesis.
˙$p<0.1$; * $p<0.05$; ** $p<0.01$.

Table 3.6 Average marginal effects of changes in regressors on the probability of runoff yields.

Variable	Model 1 (Green infrastructure pattern)		Model 2 (Urban development pattern)		Model 3 (High-intensity development pattern)		Model 4 (Medium-intensity development pattern)		Model 5 (Low-intensity development pattern)	
	Level	dy/dx	Level	dy/dx	Level	dy/dx	Level	dy/dx	Level	dy/dx
Composition Variables										
TIA	1	-0.0004	1	-0.0010**	1	-0.0004	1	-0.00008	1	-0.0013**
	2	-0.0004	2	-0.0010**	2	-0.0004	2	-0.00008	2	-0.0013**
	3	0.0005	3	0.0014**	3	0.0005	3	0.0001	3	0.0018**
	4	0.0002	4	0.0006**	4	0.0002	4	0.00004	4	0.0008**
DCIA	1	-0.0064**	1	-0.0065**	1	-0.0066**	1	-0.0066**	1	-0.0058**
	2	-0.0064**	2	-0.0063**	2	-0.0066**	2	-0.0066**	2	-0.0060**
	3	0.0089**	3	0.0090**	3	0.0093**	3	0.0093**	3	0.0083**
	4	0.0038**	4	0.0038**	4	0.0039**	4	0.0040**	4	0.0035**
Configuration Variables										
MPA	1	0.00004	1	0.0001	1	-	1	-0.0209**	1	-
	2	0.00004	2	0.0001	2	-	2	-0.0208**	2	-
	3	-0.00006	3	-0.0002	3	-	3	0.0292**	3	-
	4	-0.00003	4	-0.00007	4	-	4	0.0125**	4	-

Table 3.6 Continued.

Variable	Model 1 (Green infrastructure pattern)		Model 2 (Urban development pattern)		Model 3 (High-intensity development pattern)		Model 4 (Medium-intensity development pattern)		Model 5 (Low-intensity development pattern)	
	Level	dy/dx	Level	dy/dx	Level	dy/dx	Level	dy/dx	Level	dy/dx
ED	1	0.0006**	1	0.0003·	1	-	1	-	1	-
	2	0.0006**	2	0.0002·	2	-	2	-	2	-
	3	-0.0009**	3	-0.0003·	3	-	3	-	3	-
	4	-0.0004**	4	-0.0001·	4	-	4	-	4	-
MSI	1	-	1	0.0309	1	0.1732**	1	-	1	0.1090*
	2	-	2	0.0297	2	0.1721**	2	-	2	0.1135*
	3	-	3	-0.0424	3	-0.2425**	3	-	3	-0.1563*
	4	-	4	-0.0182	4	-0.1029**	4	-	4	-0.0663*
MNN	1	-0.0002**	1	0.0002*	1	0.0001**	1	0.0005**	1	0.0031**
	2	-0.0002**	2	0.0002*	2	0.0001**	2	0.0005**	2	0.0032**
	3	0.0003**	3	-0.0003**	3	-0.0002**	3	-0.0007**	3	-0.0044**
	4	0.0001**	4	-0.0001*	4	-0.00009**	4	-0.0003**	4	-0.0019**
PD	1	-0.0041**	1	0.0006	1	-0.0003	1	-0.0005	1	0.0020**
	2	-0.0041**	2	0.0006	2	-0.0003	2	-0.0005	2	0.0021**
	3	0.0057**	3	-0.0008	3	0.0004	3	0.0007	3	-0.0028**
	4	0.0025**	4	-0.0004	4	0.0002	4	0.0003	4	-0.0012**
COHESION	1	-0.0053**	1	-0.0029*	1	-0.00006	1	0.0010·	1	0.0029**
	2	-0.0054**	2	-0.0027*	2	-0.00006	2	0.0010·	2	0.0030**
	3	0.0075**	3	0.0039*	3	0.00009	3	-0.0014·	3	-0.0042**
	4	0.0032**	4	0.0017*	4	0.00004	4	-0.0006·	4	-0.0018**
GYRATE	1	0.00001**	1	-0.000004	1	-0.00004**	1	0.00002	1	-0.00004**
	2	0.00001**	2	-0.000004	2	-0.00004**	2	0.00002	2	-0.00004**
	3	-0.00001**	3	0.000006	3	0.00006**	3	-0.00002	3	0.00006**
	4	-0.00001**	4	0.000002	4	0.00003**	4	-0.00001	4	0.00003**
Climate/Biophysical Variables										
Precipitation	1	-0.0020**	1	-0.0020**	1	-0.0020**	1	-0.0020**	1	-0.0019**
	2	-0.0020**	2	-0.0019**	2	-0.0020**	2	-0.0020**	2	-0.0020**
	3	0.0028**	3	0.0028**	3	0.0028**	3	0.0028**	3	0.0028**
	4	0.0012**	4	0.0012**	4	0.0012**	4	0.0012**	4	0.0012**
Antecedent wetness	1	-0.0003**	1	-0.0003**	1	-0.0003**	1	-0.0003**	1	-0.0003**
	2	-0.0003**	2	-0.0003**	2	-0.0003**	2	-0.0003**	2	-0.0003**
	3	0.0004**	3	0.0004**	3	0.0004**	3	0.0004**	3	0.0004**
	4	0.0002**	4	0.0002**	4	0.0002**	4	0.0002**	4	0.0002**
Flood-control reservoir	1	0.0071	1	0.0148	1	0.0122	1	0.0270·	1	0.0173
	2	0.0067	2	0.0128	2	0.0111	2	0.0221*	2	0.0159
	3	-0.0097	3	-0.0196	3	-0.0166	3	-0.0351·	3	-0.0237
	4	-0.0041	4	-0.0080	4	-0.0068	4	-0.0139*	4	-0.00953
Slope	1	-0.0059**	1	-0.0068**	1	-0.0038**	1	-0.0066**	1	-0.0028*
	2	-0.0059**	2	-0.0066**	2	-0.0037**	2	-0.0066**	2	-0.0029*
	3	0.0082**	3	0.0094**	3	0.0053**	3	0.0093**	3	0.0040*
	4	0.0035**	4	0.0040**	4	0.0022**	4	0.0040**	4	0.0017*
K_{sat}	1	0.0001	1	0.0005*	1	0.0010*	1	0.0007**	1	0.0009**
	2	0.0001	2	0.0005*	2	0.0010*	2	0.0007**	2	0.0009**
	3	-0.0001	3	-0.0007*	3	-0.0014*	3	-0.0010**	3	-0.0013**
	4	-0.00006	4	-0.0003*	4	-0.0006*	4	-0.0004**	4	-0.0006**

Note: The location and time variables are not reported in this table as a brief.
·$p<0.1$; * $p<0.05$; ** $p<0.01$.

3.3.2. The Effects of Land Use Configuration on Urban Runoff

Although composition variables are more powerful to predict each probability of runoff level than configuration variables, the spatial pattern of land use is still a significant factor to be considered in land use policy. In Model 1, while the ***size*** of green infrastructure lost significance, the ***edge*** measured by ED had a negative relationship to the cumulative logit of runoff yields at a 0.01 significance level (Table 3.5). In contrast, the ***isolation*** and ***fragmentation*** measures including MNN and PD were positively related to the probability of high-level runoff depths (p<0.01) (Table 3.6). For ***connectivity***, COHESION and GYRATE showed reserve impacts; the probability had a positive association with COHESION but a negative one with GYRATE (p<0.01). The findings imply that more connected, less clumped, less fragmented, less isolated, and higher edge-density green infrastructure is more likely to reduce the probability of high-level runoff depths. The standardized impacts of some landscape indices such as COHESION and PD were particularly greater than those of antecedent wetness or slope.

In Model 2, the result reveals the positive impacts of COHESION (p<0.05) and the negative impacts of MNN and ED (p<0.05 and p<0.1 respectively) on the cumulative logit of runoff yields. This implies that urban development with a more clumped, less isolated, and lower edge-density pattern is more likely to yield a higher level of runoff depths. Yet, this result was not consistent when the configuration of sub-classes of urban development was separately assessed.

In Model 3, MNN and MSI were negatively related to the yield of high-level runoff, while GYRATE was positively associated (p<0.01). Thus, the more connected, less isolated, and more regularly-shaped patterns of high-intensity development contributed to increasing the probability of high-level runoff depths when holding all the other variables constant. This relationship also applied to low-intensity development. However, COHESION was found to be negatively related to the probability in both Models 4 and 5 (p<0.1 and p<0.01, respectively). In other words, the dispersed patterns of low- and medium-intensity development increased the probability of high-level runoff yields (Figure 3.3).

In addition, the standardized impact of landscape indices differed by development intensity. While the spatial connectivity was found the most powerful predictor for both low- and high-intensity development, the size of patches was more influential than other landscape indices for medium-intensity development.

(a) **(b)**

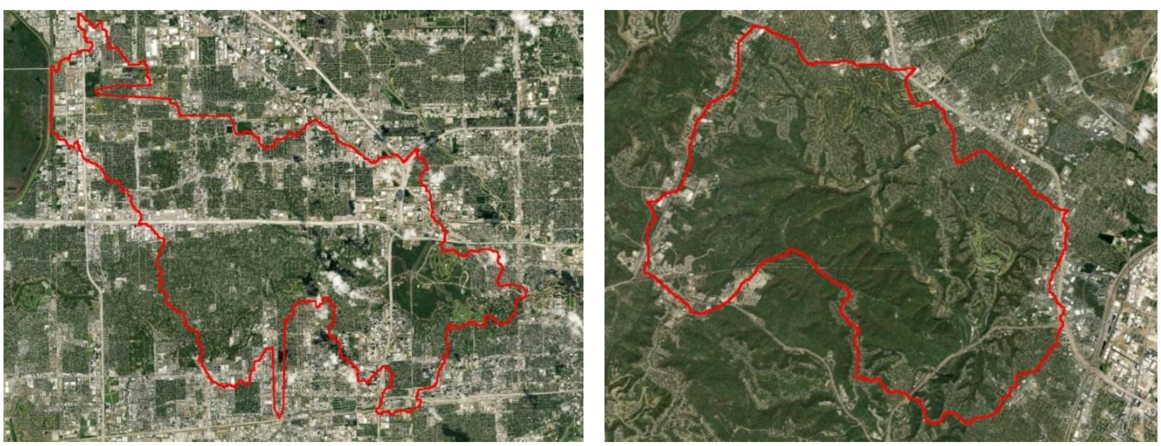


Figure 3.3 a) Clumped and b) dispersed patterns of low-intensity development in the study area.

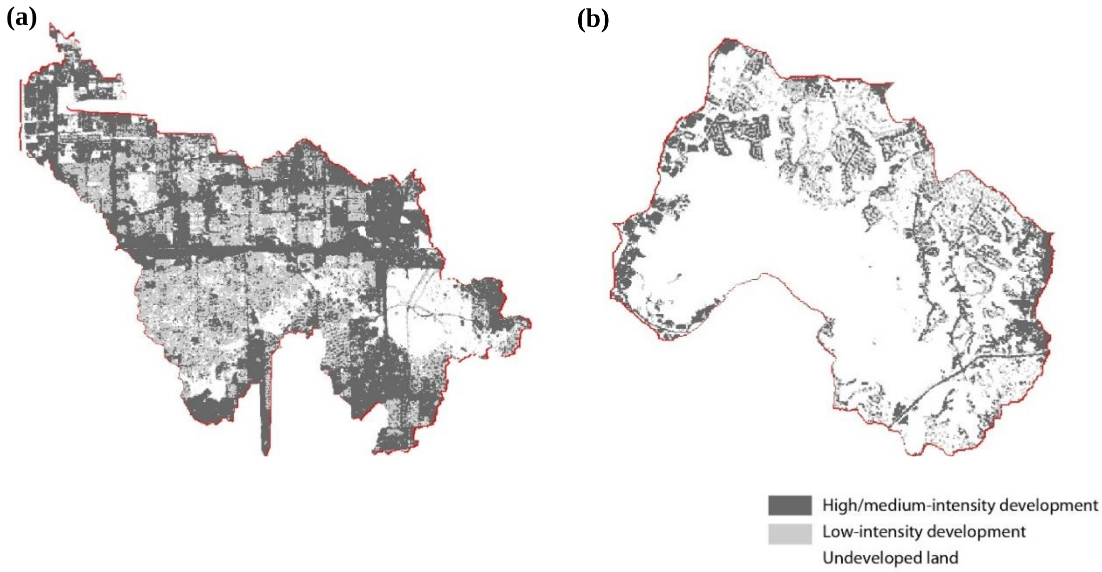


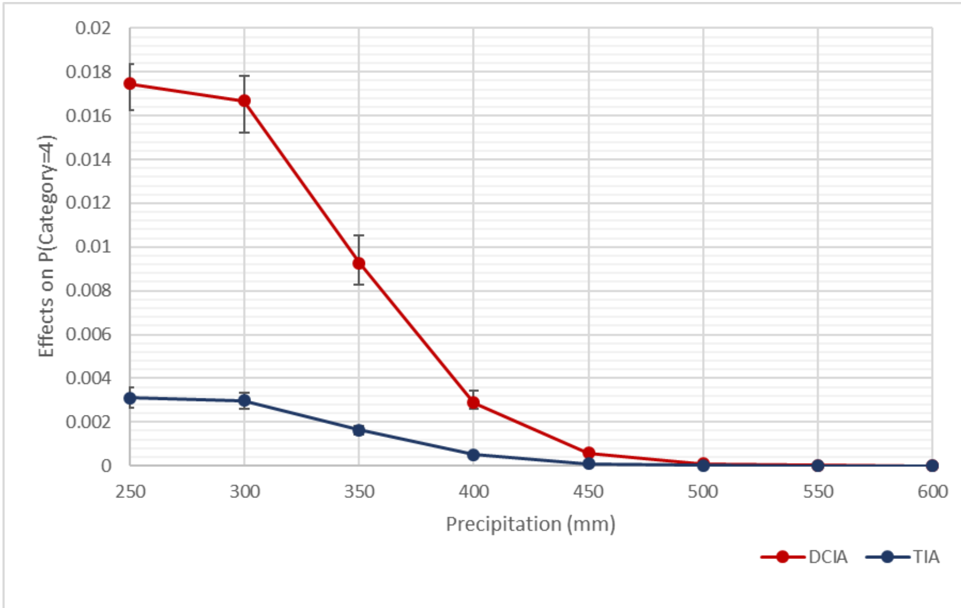
Figure 3.3 Continued.

3.3.3. Climate Effects on TIA and DCIA Performance

As shown in Figure 3.4, the average marginal effects of changes in TIA and DCIA were further assessed for changing precipitation depths. The probability of runoff level to be 4 was particularly studied as level 4 poses the greatest flood risks among the possible categories. Across the five ordinal logit regression models, the effect of TIA and DCIA on increasing flood risk decreased in association with rainfall depth. When the monthly precipitation depth was 250 mm, the probability of runoff depth to be far above average increased by 0.15 – 0.17% with a 1% increase in DCIA. Yet, the probability became nearly independent from TIA and DCIA when rainfall was above 450 mm and 500 mm, respectively in Greater Houston and 400 mm and 450 mm in Greater Austin and San Antonio. This finding corresponds with the third hypothesis implying the fluctuating effect of TIA and DCIA in response to climate variability.

When rainfall exceeds a certain threshold, changes in either TIA or DCIA no longer contributes to increasing the probability of high-level runoff.

a)



b)

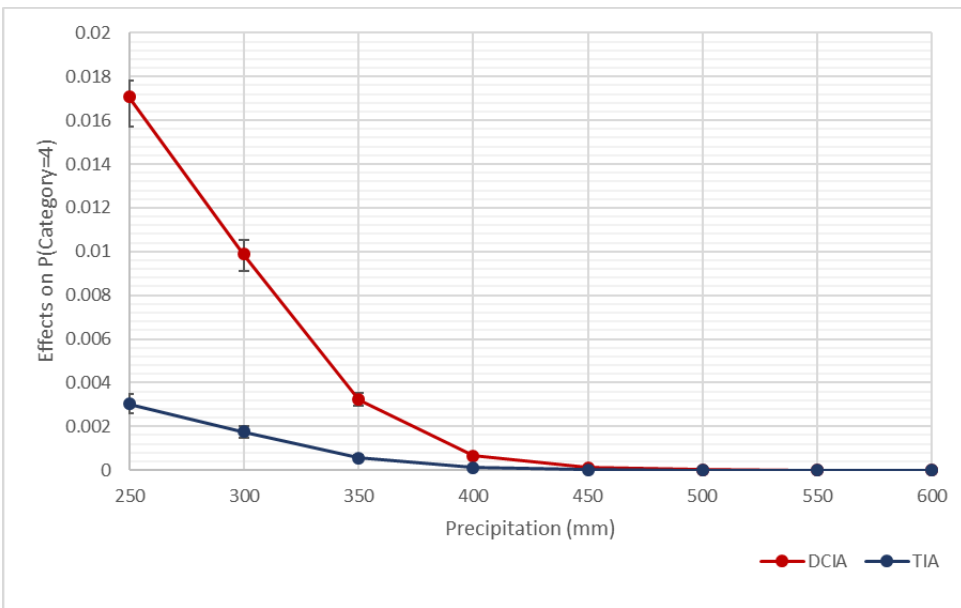


Figure 3.4 Marginal effects of changes in TIA and DCIA on the probability of runoff level 4 across Models 1 to 5 in a) Greater Houston; b) Greater Austin; and c) Greater San Antonio.

c)

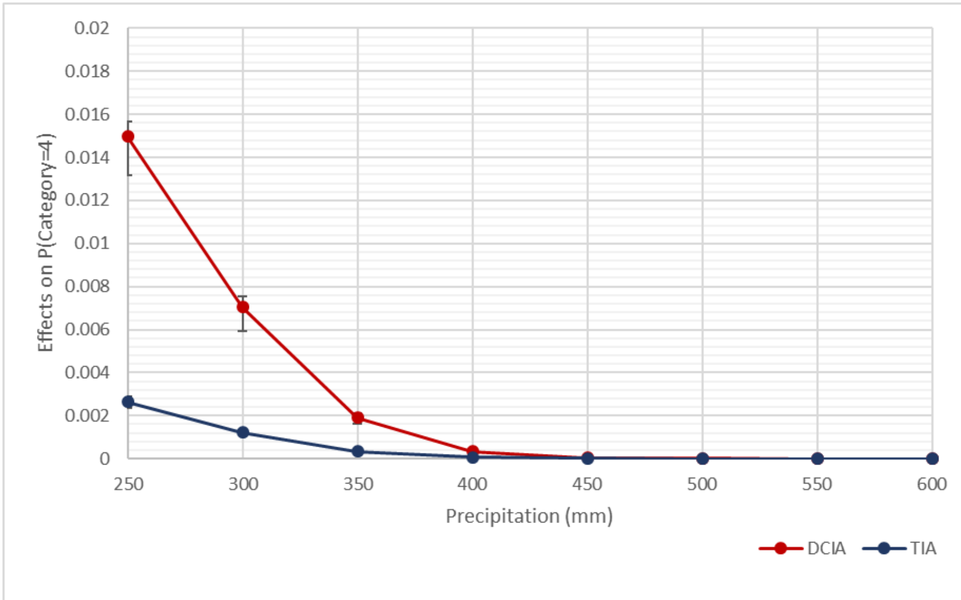


Figure 3.4 Continued.

3.4. Discussion

3.4.1. Hydrologic Significance of DCIA for Flood Control

The probability of high-level runoff yields was found to be positively associated with both TIA and DCIA, while DCIA was a better predictor in this study. The findings support the first two hypotheses suggesting that DCIA mitigation should be the primary goal to TIA reduction for effective flood control. DCIA was also found to be more influential than spatial patterns of land use. In other words, in urban settings hydraulic disconnection of development from existing sewer systems more powerfully contributes to reducing flood potential than disconnection of spatial patterns of land use to reroute surface flow. To our knowledge, this is one of the first empirical studies comparing hydraulic and spatial connectivity of development in assessing flood impacts.

Many recent studies have emphasized the importance of DCIA over TIA (Chen et al., 2008; Ebrahimian et al., 2016a; Han & Burian, 2009; Lee & Heaney, 2002; Roy & Shuster, 2009; Sahoo & Sreeja, 2011, 2016). However, current land use or flood mitigation policy has rarely reflected this tendency. In the selected three MSAs, TIA has served as a common quantitative tool to regulate urban development and flooding. For example, the City of Austin has developed local ordinances which limit the level of TIA by land use type and lot size: a single-family house with a minimum size of 534 m^2, a duplex or single-family house smaller than 534 m^2, a multi-family house, and a commercial area are not allowed to exceed TIA over 45%, 55%, 60%, and 65%, respectively (City of Austin, 2019). The City of Houston has begun to charge stormwater fees on property owners based on TIA (City of Houston, 2019a). The base rate per square meter of impervious surfaces is $ 0.344 annually, and a 20% discount is given if an open ditch is implemented in single-family housing (City of Houston, 2019b). Similarly, a stormwater fee is calculated based on the amount of impervious surfaces in San Antonio regardless of drainage types (City of San Antonio, 2019). This pricing method cannot account for the hydrologic benefits of green infrastructure. While maintaining the total amount of impervious cover, different types of green infrastructure can disconnect development from existing drainage patterns at a varying level, reducing the load of stormwater discharge at downstream outlets (Sohn et al., 2017). As a surrogate for TIA, DCIA reflects such diversity of drainage patterns into the pricing of stormwater fees and prevents overestimation of development impacts. Moreover, methodologies adopted in this study provide an efficient tool to make a quick estimate of runoff probabilities over a large geographical area in response to changes in DCIA and precipitation depth. This approach helps to proactively achieve a target goal of DCIA reduction for certain climate conditions. Immediate action of preserving and creating green infrastructure is particularly needed for the watersheds with the high-level DCIA to avoid frequent floods.

In this study, DCIA is found to be responsive to climate variability. With an increasing precipitation depth, the effect of DCIA and TIA on increasing the probability of the highest level of runoff depth decreased. Yao et al. (2016) found the similar trend of decreasing DCIA effect on increasing runoff volume with a growing storm intensity while contributions of TIA increased. For a far-above-average runoff depth, the runoff volume probably far exceeds the design capacity of water volume to be delivered through connected drainage systems, and thus an additional increase in DCIA may not be as effective. Moreover, when a rainfall depth exceeds a certain threshold, the pervious area that is saturated no longer absorbs runoff but rather acts as an impervious surface (Guan et al., 2016). Thus, while DCIA is controlled for, decreasing TIA may not have significant impacts on reducing runoff probabilities as the effect of having less disconnected impervious area will be compensated by having more pervious area which also generates runoff. This study result indicates the challenges of flood mitigation plans for an increasing storm size. Similarly, many studies have supported the decreased performance of green infrastructure for large and high-intensity storm events (Avellaneda et al., 2017; Barber et al., 2003; Fry & Maxwell, 2017; Hoss et al., 2016; Palla & Gnecco, 2015; Sohn et al., 2019; Zhang et al., 2016). If monthly precipitation is above 500 mm in Greater Houston and 450 mm in Greater Austin and San Antonio, DCIA reduction will no longer assure safety from floods.

3.4.2. Spatial Patterns of Land Use and Implications for Green Infrastructure

The statistical performance of configuration variables in this study indicates the significant role of land use forms in moderating flood risks. This provides an insight for water resource managers and local planners into enhancing land use regulations over spatial forms and developing a related guideline for long-term resilience. According to the study result, more connected, less fragmented, and higher edge-density green infrastructure in a dispersed pattern contributed to reducing the probability of high-level runoff depths, supporting the fifth hypothesis. The mean patch size still lost significance in this study. The connected landscapes possibly increase the infiltration capacity of land, intercepting a larger volume of surface flow. The increasing edge density would facilitate the interaction of lateral flow between impervious and pervious surfaces. Also, green infrastructure dispersed throughout a watershed rather than aggregated in a certain location may contribute to shortening the travel time of runoff and collecting runoff from multiple development sources. In contrast, more clumped and less isolated development patterns increase the probability of high-level runoff depths. The fourth hypothesis cannot be fully supported since multiple landscape indices measuring spatial patterns of urban development did not show significance in this study. However, clumped patches of development in a closer distance are likely to increase conveyance capacity of a watershed, leading to high flood potential.

When the structure of urban development was more closely examined by development intensity, the study results supported a disconnected and irregular shape of high-intensity development rather than the sprawling pattern of medium- and low-intensity development for flood mitigation. Urban sprawl is characterized by a low-density development with a large developed area per capita (Davis & McCuen, 2005). Auto-dependency is high as transportation facilities are the major impervious cover, and the leapfrogging pattern features longer travel miles. From hydrologic perspectives, the findings in this study imply that urban sprawl is undesirable for the same amount of development. Large dwelling units tend to limit the capacity of land to store water and increase surface runoff (USEPA, 2006). Likewise, a connected form of high-intensity development appears not to be desirable for urban resilience to floods. The connected impervious cover possibly acts as a conveyance to rapidly transport runoff to downstream outlets with little loss. This finding indicates the significance of integrating green infrastructure into high-intensity development in a way to disconnect the spatial continuity of impervious surfaces and increase the edge density to facilitate interactions of surface flows between pervious and impervious surfaces. In summary, the study results suggest that the current stormwater burden can be abated in a more efficient manner by strategically managing spatial patterns of development and green infrastructure. In many cases, local municipalities have planned for the configuration of green spaces in comprehensive plans for the major purpose of conserving biodiversity and promoting walkability (DEP, 2019; Stosur & Pugh, 2018; Walsh, 2019). The spatial connectivity of green spaces is often mapped and schemed for future networks. Yet, more dimensional approaches of understanding the full structure of land use such as size, edge, shape, isolation, and fragmentation in addition to connectivity, can expand the current understanding of landscape functions and enhance the capacity of cities to absorb hydrologic disturbances from floods. Non-structural approaches such as zoning, land acquisition, clustering standards, conservation easement, and transfer of development rights can also assist the decision-making process by taking the spatial form of development and green infrastructure into consideration.

Nevertheless, this study includes four limitations. First, land use change from 2010 to 2017 was assumed to be minimal. The high temporal-resolution of land use map can be further developed to explain longitudinal effects of urbanization. Second, different types of green infrastructure may have varying effects to capture surface runoff and disconnect hydraulic flows. More studies on specified types of green infrastructure will complement our findings and elaborate favored landscape patterns to maximize flood mitigation. Third, the statistical models developed in this study rely on an assumption that the effect of composition, configuration, and climate/biophysical variables is the same for each cumulative probability of runoff depth. Yet, the changing marginal effects of TIA and DCIA in response to precipitation depths imply that the linear relationship between multiple regressors and the runoff probability can be subject to change by climate variability. Advanced models can be additionally developed by different storm conditions to fully explore climate impacts and prepare for future changes in rainfall patterns. Finally, forthcoming research could expand the current methodology on the event basis. Individual storm events have distinctive characteristics such as storm intensity, duration, peak ratio, and lengths of dry periods, which are aggregated in monthly-based analyses. The event-based approach would allow for water resource managers to predict impacts of alternative urbanization models for a specific storm pattern.

3.5. Conclusion

This study assessed the effect of land use composition and configuration on the probability of four-leveled runoff yields under varying climate conditions over the three MSAs in Texas. Although TIA has been the major indicator of urbanization and has been extensively studied, hydraulic connectivity of impervious surfaces and their physical patterns have seldom been examined through years-long monitoring. The study results revealed the significant roles of DCIA and specific land use forms in reducing flood potential. While both TIA and DCIA showed a positive association with the probability of high-level runoff depths, the contributions of DCIA outweighed those of TIA corresponding to the first and second hypotheses. The DCIA impacts was reduced for heavy storms supporting the third hypotheses. The fourth hypothesis that larger and connected patterns of development are likely to increase a runoff level was not fully supported in this study because the impact of MPA and GYRATE of urban development was found to be insignificant. However, spatial patterns of urban development still expedited runoff conveyance at a varying level depending on development intensity. Sprawling patterns of medium- and low-intensity development as well as a connected form of high-intensity development should be avoided to minimize flood risks. Finally, the fifth hypothesis was supported by the finding that the more connected and less fragmented form of green infrastructure reduced the probability of high-level runoff yields although the shape index was omitted in analysis due to multicollinearity.

The process of urban drainage examined in this study could be translated into two hydrologic/hydraulic systems: 1) the interaction among heterogeneous land use patches that regulate the pattern of overland flow, and 2) the connectivity of impervious surfaces to piped systems which determines hydraulic flow. The findings in this study expand the current knowledge of the rainfall and runoff process in urban hydrology in an integrated manner. The configurational role of green infrastructure also provides an insight into how urban resilience can be managed by structuring landscapes strategically.

The unreliable estimation of runoff yields by neglecting important variables can result in over-budget appropriations for constructing hydraulic structure and flood prevention devices (Sahoo & Sreeja, 2016). The predicted model in this study will allow policy makers to easily assess the impact of multiple development and landscape variables other than TIA on urban runoff and prevent overspending on flood mitigation measures. Further studies on spatial arrangement of development and green infrastructure under varying climate conditions at a finer temporal and spatial scale will enhance results in this study and lead to integrated flood management.

3.6. Reference

Agresti, A. (1997). Logistic regression: Modeling categorical responses *Statistical methods for the social sciences* (3rd edition ed., pp. 575-619). Upper Saddle River, New Jersey: Prentice Hall.

Alley, W. M., & Veenhuis, J. E. (1983). Effective impervious area in urban runoff modeling. *Journal of Hydraulic Engineering, 109*(2), 313-319.

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

Aulenbach, B. T., Landers, M. N., Musser, J. W., & Painter, J. A. (2017). Effects of impervious area and BMP implementation and design on storm runoff and water quality in eight small watersheds. *Journal of the American Water Resources Association, 53*(2), 382-399.

Avellaneda, P. M., Jefferson, A. J., Grieser, J. M., & Bush, S. A. (2017). Simulation of the cumulative hydrological response to green infrastructure. *Water Resources Research, 53*(4), 3087-3101. doi:10.1002/2016WR019836

Barber, M. E., King, S. G., Yonge, D. R., & Hathhorn, W. E. (2003). Ecology ditch: A best management practice for storm water runoff mitigation. *Journal of Hydrologic Engineering, 8*(3), 111-122.

Boyd, M., Bufill, M., & Knee, R. (1993). Pervious and impervious runoff in urban catchments. *Hydrological Sciences Journal, 38*(6), 463-478.

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

Brody, S. D., Highfield, W. E., & Blessing, R. (2015). An analysis of the effects of land use and land cover on flood losses along the Gulf of Mexico Coast from 1999 to

2009. *Journal of the American Water Resources Association, 51*(6), 1556-1567. doi:10.1111/1752-1688.12331

Brody, S. D., Kim, H., & Gunn, J. (2013). Examining the impact of development patterns on flooding on the Gulf of Mexico Coast. *Urban Studies, 50*(4), 789-806. doi:10.1177/0042098012448551

Chen, M., Shyamprasad, S., Heineman, M., & Carter, C. S. (2008). Representation of non-directly connected impervious area in SWMM runoff modeling. *Journal of Water Management Modeling*.

City of Austin. (2019). Code of ordinances: 25-8-392 - uplands zone. Retrieved from https://library.municode.com/tx/austin/codes/code_of_ordinances?nodeId=TIT25LADE_CH25-8EN_SUBCHAPTER_AWAQU_ART9SUWARE_S25-8-391APCO

City of Houston. (2019a). Code of ordinance: Sec. 47-822. Retrieved from https://library.municode.com/tx/houston/codes/code_of_ordinances?nodeId=COOR_CH47WASE_ARTXIVMUDRUTSY_DIV2FU_S47-822DRCHESEX

City of Houston. (2019b). Drainage utility charge. Retrieved from https://www.rebuildhouston.org/drainage-utility-charge-faqs

City of San Antonio. (2019). Learn about the storm water utility fee. Retrieved from http://www.sanantonio.gov/TCI/Projects/Storm-Water-Fee/Learn-About-the-Storm-Water-Utility-Fee

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., & Pasteris, P. P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology: a Journal of the Royal Meteorological Society, 28*(15), 2031-2064.

Davis, A. P., & McCuen, R. H. (2005). *Stormwater management for smart growth*. New York, NY: Springer Science & Business Media.

DEP. (2019). *Florida greenways and trails: System plan 2019-2023*. Florida Department of Envrionmental Protection. Retrieved from https://floridadep.gov/sites/default/files/FL-Greenway%2BTrails-System-Plan-2019%2C%202023.pdf.

Ebrahimian, A., Gulliver, J. S., & Wilson, B. N. (2015). *Determination of effective impervious area in urban watersheds.* (Ph.D.), University of Minnesota

Ebrahimian, A., Gulliver, J. S., & Wilson, B. N. (2016a). Effective impervious area for runoff in urban watersheds. *Hydrological Processes, 30*(20), 3717-3729. doi:10.1002/hyp.10839

Ebrahimian, A., Wilson, B. N., & Gulliver, J. S. (2016b). Improved methods to estimate the effective impervious area in urban catchments using rainfall-runoff data. *Journal of Hydrology, 536*, 109-118.

Endreny, T. A., & Thomas, K. E. (2009). Improving estimates of simulated runoff quality and quantity using road-enhanced land cover data. *Journal of Hydrologic Engineering, 14*(4), 346-351.

Forman, R., & Godron, M. (1986). *Landscape ecology* (Vol. 4). New York, NY: John Wiley & Sons.

Fry, T. J., & Maxwell, R. (2017). Evaluation of distributed BMPs in an urban watershed – high resolution modeling for stormwater management. *Hydrological Processes, 31*(15), 2700-2712. doi:10.1002/hyp.11177

Guan, M., Sillanpää, N., & Koivusalo, H. (2016). Storm runoff response to rainfall pattern, magnitude and urbanization in a developing urban catchment. *Hydrological Processes, 30*(4), 543-557. doi:10.1002/hyp.10624

Gustafson, E. J. (1998). Quantifying landscape spatial pattern: what is the state of the art? *Ecosystems, 1*(2), 143-156.

Han, W. S., & Burian, S. J. (2009). Determining effective impervious area for urban hydrologic modeling. *Journal of Hydrologic Engineering*, *14*(2), 111-120.

Hoss, F., Fischbach, J., & Molina-Perez, E. (2016). Effectiveness of best management practices for stormwater treatment as a function of runoff volume. *Journal of Water Resources Planning and Management, 142*(11). doi:10.1061/(asce)wr.1943-5452.0000684

Kim, H. W., & Park, Y. (2016). Urban green infrastructure and local flooding: The impact of landscape patterns on peak runoff in four Texas MSAs. *Applied Geography*, *77*, 72-81.

Lee, J. G., & Heaney, J. P. (2002). *Directly connected impervious areas as major sources of urban stormwater quality problems—Evidence from South Florida.* Paper presented at the 7th Biennial stormwater research and watershed management conference.

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

Lee, S.-W., Hwang, S.-J., Lee, S.-B., Hwang, H.-S., & Sung, H.-C. (2009). Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. *Landscape and Urban Planning, 92*(2), 80-89. doi:https://doi.org/10.1016/j.landurbplan.2009.02.008

Livingston, E. H., & McCarron, E. (1992). Stormwater management: A guide for Floridians. *Tallahassee, FL: Florida Department of Environmental Regulation*.

Maidment, D. R. (2002). *Arc Hydro: GIS for water resources* (Vol. 1). Redlands, CA: ESRI, Inc.

McGarigal, K. (2014). FRAGSTATS help. *Documentation for FRAGSTATS, 4*.

McGarigal, K., & Marks, B. J. (1995). *Spatial pattern analysis program for quantifying landscape structure*. (PNW-GTR-351). Gen. Tech.

Mejía, A. I., & Moglen, G. E. (2009). Spatial patterns of urban development from optimization of flood peaks and imperviousness-based measures. *Journal of Hydrologic Engineering, 14*(4), 416-424. doi:10.1061/(ASCE)1084-0699(2009)14:4(416)

Moglen, G. E., & Kim, S. (2007). Limiting imperviousness: Are threshold-based policies a good idea? *Journal of the American Planning Association, 73*(2), 161-171.

Olivera, F., & DeFee, B. B. (2007). Urbanization and its effect on runoff in the Whiteoak Bayou Watershed, Texas. *Journal of the American Water Resources Association, 43*(1), 170-182.

Palla, A., & Gnecco, I. (2015). Hydrologic modeling of Low Impact Development systems at the urban catchment scale. *Journal of Hydrology, 528,* 361-368. doi:10.1016/j.jhydrol.2015.06.050

Pandit, A., & Regan, J. (1998). What is the impervious area curve number. *Journal of Water Management Modeling*.

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

Sahoo, S. N., & Sreeja, P. (2011). *Indirect determination of effective impervious area (EIA) of an urban city of North East India.* Paper presented at the World Environmental and Water Resources Congress 2011: Bearing Knowledge for Sustainability.

Sahoo, S. N., & Sreeja, P. (2016). Determination of effective impervious area for an urban Indian catchment. *Journal of Hydrologic Engineering, 21*(4), 1-10.

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

Sohn, W., Kim, J.-H., & Li, M.-H. (2017). Low-impact development for impervious surface connectivity mitigation: Assessment of directly connected impervious areas (DCIAs). *Journal of Environmental Planning and Management*, 1-19.

Sohn, W., Kim, J.-H., Li, M.-H., & Brown, R. (2019). The influence of climate on the effectiveness of low impact development: A systematic review. *Journal of Environmental Management, 236*, 365-379.

Stosur, T., & Pugh, C. (2018). *Baltimore green network: A plan for a green and connected city*. Baltimore, MD Retrieved from https://www.dropbox.com/s/szs9d0elvotosp1/GreenNetworkPlan_FullDocument_Reduced_2018_0926.pdf?dl=0.

Sung, C. Y., Yi, Y.-j., & Li, M.-H. (2013). Impervious surface regulation and urban sprawl as its unintended consequence. *Land Use Policy, 32*, 317-323.

United States Census Bureau. (2017). *Metropolitan and micropolitan statistical areas population totals: 2010-2017*. Retrieved from: https://www.census.gov/data/tables/2017/demo/popest/total-metro-and-micro-statistical-areas.html

USEPA. (1993). *Guidance specifying management measures for sources of nonpoint pollution in coastal water*. (EPA 840-B-92-002). Washington D.C.: United States of Environmental Protection Agency, Retrieved from https://www.epa.gov/sites/production/files/2015-09/documents/czara_chapter4_urban.pdf.

USEPA. (2006). *Protecting water resources with higher-density development*. (EPA 231-R-06-001). United States of Environmental Protection Agency, Retrieved from https://www.epa.gov/sites/production/files/2014-03/documents/protect_water_higher_density1.pdf.

Walsh, M. (2019). Boston green links. Retrieved from https://www.boston.gov/departments/transportation/boston-green-links

Williams, R. (2012). Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal, 12*(2), 308-331.

Wooldridge, J. M. (2009). Introductory Econometrics: A Modern Approach, 4th. *CENGAGE Learning, Canada*.

Yang, G., Bowling, L. C., Cherkauer, K. A., & Pijanowski, B. C. (2011). The impact of urban development on hydrologic regime from catchment to basin scales. *Landscape and Urban Planning, 103*(2), 237-247. doi:http://dx.doi.org/10.1016/j.landurbplan.2011.08.003

Yang, L., Huang, C., Homer, C. G., Wylie, B. K., & Coan, M. J. (2003). An approach for mapping large-area impervious surfaces: Synergistic use of Landsat-7 ETM+ and high spatial resolution imagery. *Canadian Journal of Remote Sensing, 29*(2), 230-240.

Yao, L., Wei, W., & Chen, L. (2016). How does imperviousness impact the urban rainfall-runoff process under various storm cases? *Ecological Indicators, 60*, 893-905.

Zhang, G., Guhathakurta, S., Dai, G., Wu, L., & Yan, L. (2013). The control of land-use patterns for stormwater management at multiple spatial scales. *Environmental management*, *51*(3), 555-570.

Zhang, X. Q., Guo, X. Y., & Hu, M. C. (2016). Hydrological effect of typical low impact development approaches in a residential district. *Natural Hazards, 80*(1), 389-400. doi:10.1007/s11069-015-1974-5

Zhang, Y., & Shuster, W. (2014). Impacts of spatial distribution of impervious areas on runoff response of hillslope catchments: Simulation study. *Journal of Hydrologic Engineering*, *19*(6), 1089-1100.

4. CONCLUSION

Many studies have supported the applications of LID and green infrastructure in urban watersheds to mitigate adverse impacts of urbanization. Limited studies have yet emphasized how to prioritize their use and/or maximize effectiveness under varying climate and land use conditions. A better understanding of the climate and land use impacts on urban drainage system helps to strategically and effectively implement stormwater management techniques in limited urban areas and prepare for future changes in climate and urbanization patterns. To build up current knowledge, Chapter 2 summarizes the climate impact on the performance of LID systems designed at a site scale through a systematic review. The research trends and methodologies were identified by key variables and study types. Meta-analysis was performed with selected hypothetical studies to measure sensitivity of runoff yields to storm frequency. Chapter 3 expands applications of green infrastructure to a regional level and empirically assesses the effect of land use composition and configuration on the level of runoff depth in three MSAs in Texas. TIA and DCIA were used to measure composition of urban development while multiple landscape indices were employed to quantify size, edge, shape, isolation, fragmentation, and connectivity of development as well as green infrastructure. Five ordinal logit regression models were developed by land cover type, and changing contributions of TIA and DCIA to runoff reduction were further analyzed by rainfall depth in each MSA.

Findings in this study suggest a strategic use of LID and green infrastructure in accordance with local climate and land use patterns. In Chapter 2, the high performance of LID systems for a small storm event of low intensity, duration, and antecedent moisture level as well as a high temperature was consistently found from the selected studies. The meta-analysis also showed a decreasing trend of LID performance in reducing both runoff volume and peak discharge rate for infrequent storm events. The analysis of weighted effect size revealed higher sensitivity of runoff volume than peak discharge rate to changes in storm frequency. Furthermore, different types of LIDs performed at an optimal level for varying peak locations. Thus, LID systems cannot be expected to operate at the same level when climate patterns temporally and spatially vary. Future performance of LIDs may decrease if storm intensity and duration increase. Instead of adopting one standard for designing LID systems across states and counties, climate variations in temporal and spatial scales should be considered as key variables to predict LID performance and be reflected in flood mitigation policy.

Similarly, results in Chapter 3 support applications of green infrastructure as an effective tool to reduce DCIA. Increasing hydraulic connectivity between development and landscapes was found to be more effective than reducing the total amount of impervious cover to mitigate high-level runoff depth. However, the result showed that the retention capacity of landscapes became limited for large storms. Further reductions of DCIA could no longer efficiently prevent floods when rainfall exceeded a certain threshold. The spatial patterns of green infrastructure still served as an important factor to mitigate flood impacts. More connected, less fragmented, and higher edge-density green infrastructure in a dispersed pattern was found to be more efficient in reducing high-level runoff depth. In contrast, a connected and regular shape of high-intensity development as well as a sprawling pattern of low- and medium-intensity development should be avoided for flood mitigation. Green infrastructure can be judiciously integrated into development in a way to disconnect spatial continuity of high-intensity development and cluster low- and medium-intensity development. The study results indicate the importance of considering land use structure in a flood mitigation policy. While recent land use policies have emphasized networks of green infrastructure, more dimensional approaches to examine land use forms including size, edge, shape, isolation, and fragmentation in addition to connectivity will provide policy makers and planners with a structural framework of urban design which leads to long-term resilience for cities. Future studies can expand the methodology adopted in this study and measure the impact of climate change and land use on the performance of LID and green infrastructure at a diverse temporal and spatial scale.