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Stormwater control impacts on runoff volume and peak flow: A meta-analysis of watershed modelling studies

Colin D. Bell[1] | Jordyn M. Wolfand[1] | Chelsea L. Panos[2] | Aditi S. Bhaskar[3] | Ryan L. Gilliom[2] | Terri S. Hogue[4] | Kristina G. Hopkins[5] | Anne J. Jefferson[6]

[1]Department of Civil and Environmental Engineering, Colorado School of Mines, Golden, Colorado

[2]Hydrologic Science and Engineering Program, Colorado School of Mines, Golden, Colorado

[3]Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, Colorado

[4]Department of Civil and Environmental Engineering, Hydrologic Science and Engineering Program, Colorado School of Mines, Golden, Colorado

[5]U.S. Geological Survey, South Atlantic Water Science Center, Raleigh, North Carolina

[6]Department of Geology, Kent State University, Kent, Ohio

Correspondence
Colin D. Bell, Department of Civil and Environmental Engineering, Colorado School of Mines, 1500 Illinois St., Golden, Colorado 80401, USA.
Email: cdbell01@gmail.com

Present address
Colin D. Bell, Department of Transportation and Infrastructure, City and County of Denver, Denver, Colorado

Jordyn M. Wolfand, Shiley School of Engineering, University of Portland, Portland, Oregon

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Abstract

Decades of research has concluded that the percent of impervious surface cover in a watershed is strongly linked to negative impacts on urban stream health. Recently, there has been a push by municipalities to offset these effects by installing structural stormwater control measures (SCMs), which are landscape features designed to retain and reduce runoff to mitigate the effects of urbanisation on event hydrology. The goal of this study is to build generalisable relationships between the level of SCM implementation in urban watersheds and resulting changes to hydrology. A literature review of 185 peer-reviewed studies of watershed-scale SCM implementation across the globe was used to identify 52 modelling studies suitable for a meta-analysis to build statistical relationships between SCM implementation and hydrologic change. Hydrologic change is quantified as the percent reduction in storm event runoff volume and peak flow between a watershed with SCMs relative to a (near) identical control watershed without SCMs. Results show that for each additional 1% of SCM-mitigated impervious area in a watershed, there is an additional 0.43% reduction in runoff and a 0.60% reduction in peak flow. Values of SCM implementation required to produce a change in water quantity metrics were identified at varying levels of probability. For example, there is a 90% probability (high confidence) of at least a 1% reduction in peak flow with mitigation of 33% of impervious surfaces. However, as the reduction target increases or mitigated impervious surface decreases, the probability of reaching the reduction target also decreases. These relationships can be used by managers to plan SCM implementation at the watershed scale.

KEYWORDS

best management practices, impervious surface, meta-analysis, peak flows, runoff volume, stormwater control measures, stormwater management, urban hydrology

1 | INTRODUCTION

Many municipalities require the installation of stormwater control measures (SCMs) to offset the effects of urbanisation on natural hydrologic processes and nutrient cycling. These effects include increases in stormflow volume, increases in peak stormflow magnitude, changing baseflow, and degraded water quality (e.g., Bhaskar et al., 2016; Panos et al., 2018; Paul & Meyer, 2001; Shuster, Bonta,

Thurston, Warnemuende, & Smith, 2005; Walsh et al., 2005). SCMs combat these effects by collecting, detaining, infiltrating, and/or treating the additional runoff from impervious surface cover (ISC). Decades of research synthesised across studies and locations has identified emergent relationships between the fraction of watershed ISC, as a measure of urbanization, and stream condition, which includes hydrologic, water quality, and ecological metrics (Arnold & Gibbons, 1996; Booth, Hartley, & Jackson, 2002; Center for Watershed Protection, 1998; Schueler, Fraley-McNeal, & Cappiella, 2009). ISC has been used by water managers to set development targets to protect stream health. For example, in 2007, the state of Connecticut wrote the first total maximum daily load (TMDL) regulation based on ISC in the United States for the Eagleville Brook watershed that specified an 11% impervious coverage target for new development to protect stream condition (Arnold, Bellucci, Collins, & Claytor, 2010; Connecticut Department of Environmental Protection, 2007). The State of Maine followed, proposing ISC-based TMDLs for all of their impaired watersheds (Maine Department of Environmental Protection, 2012). In addition to policymakers, planners use ISC to prioritise watersheds for stormwater management actions within municipalities (e.g., City and County of Denver, 2018).

The development of the impervious surface coverage model has impacted the way managers seek to protect urban streams. However, there has not yet been an analogous synthesis of data to build emergent, broadly applicable relationships between the level of watershed mitigation with SCMs and water quantity, water quality, or stream ecological metrics. Li, Fletcher, Duncan, and Burns (2017) synthesised 45 watershed-scale SCM studies and found "that the implementation of SCMs reduced surface runoff and peak discharge." However, the authors did not comment further on the form of these relationships and raised concerns about the lack of support from empirical studies. Jefferson et al. (2017) reviewed 100 published manuscripts and proposed a qualitative, conceptual model of the relationships between impervious surface coverage, mitigation with SCMs, hydrology, and water quality. For example, one of the conceptual relationships outlined by Jefferson et al. (2017) identified a positive correlation between peak discharges with a return period of 2 years and ISC. As shown in Figure 1, when SCMs are first implemented, the fraction of impervious cover mitigated increases, but peak discharges remain unchanged because treating small amounts of ISC with SCMs will not be detectable at the stream outlet above climatic noise. Eventually, with enough mitigation, peak discharge decreases become detectable. Jefferson et al. (2017) posited that even if 100% of ISC is treated by SCMs, the peak discharge will still be higher than that of an undeveloped watershed, because of the limitations of SCM storage (Figure 1). In addition, Jefferson et al. (2017) hypothesised that the form of the response curve will vary depending on the hydrologic metric of interest, but that common elements include a level of treatment required for detectable effects, and a residual effect of urbanization even when 100% of the ISC is mitigated.

Testing the model put forth by Jefferson et al. (2017) in Figure 1 with an integrative, statistical analysis is an important step to validate the conceptual model and its implications for the function of SCMs in urban watersheds. Quantifying the relationships between ISC, area mitigated by SCMs, and event hydrology would also strengthen the conceptualisation of this model by providing numeric descriptions of the curves. With the model validated and quantified, it can better inform management decisions. For example, if there is a level of impervious area mitigated by SCMs that must be crossed before watershed-scale benefits are realized (i.e., the grey arrow in Figure 1), watersheds near this level could be prioritized for future SCM implementation.

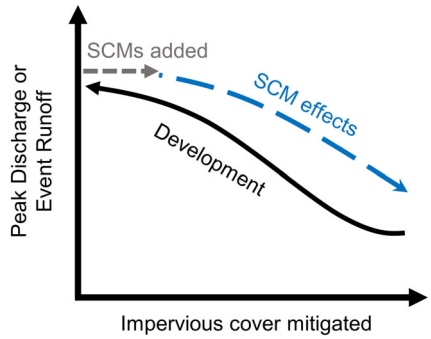


FIGURE 1 Conceptual model of urbanisation and stormwater management (where increasing untreated urban development moves a watershed to the left on the x-axis of impervious cover mitigated) effects on peak discharge or event runoff, modified from Jefferson et al. (2017). Development results in increases in event peak discharge and runoff. SCMs reduce peak discharge and runoff (long-dashed blue line), after enough impervious cover is mitigated that effects can be detected (short-dashed grey line)

This work uses a literature review and meta-analysis of modelling studies on watershed-scale implementation of SCMs to construct quantitative relationships between area mitigated by SCMs and storm event hydrologic variables of peak flow and runoff volume. The studies chosen for the meta-analysis isolate the effects of SCMs from those of development without SCMs, so the results inform the upper part of the hysteresis loop in the Jefferson et al. (2017) conceptual model (i.e., the grey and blue arrows in Figure 1). The objectives of this study were to determine: (a) the shape of the relationship between area mitigated by SCMs and reductions in event runoff and peak flow, (b) the area of SCM mitigation that must be crossed before reductions are observed, and (c) how reductions vary due to other environmental factors such as watershed characteristics and event-based rainfall metrics.

2 | METHODS

2.1 | Study overview

A literature review of 185 papers was completed to conduct a meta-analysis synthesising findings from 52 modelling studies on the watershed-scale effects of SCMs. The studies reported the difference in peak flows and event runoff volumes between a *control* where the

watershed is developed without SCMs, and an *intervention* where the same (or similar) developed watershed has SCMs. Three analyses quantify the general relationships between watershed implementation of SCMs and reductions in runoff volumes and peak flows and identify how other environmental and landscape controls lead to deviations from the general relationships.

2.2 | Scope

The scope of the meta-analysis included papers published in peer-reviewed journals, pertaining to studies of SCMs at the watershed scale. Watersheds considered could be any size but required multiple SCMs and an outlet where hydrologic metrics were reported. The 100 papers included in the literature review by Jefferson et al. (2017) were used as a starting point for the analysis as the criteria for inclusion were the same in both studies.

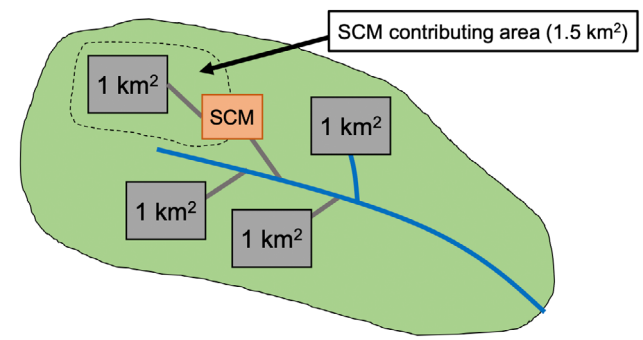
Because the Jefferson et al. study was published in 2017, more recently published studies were added to the list of papers considered. To identify these more recent studies, a series of search strings were developed by first extracting the keywords from the list of 100 papers and determining the 12 most frequently occurring keywords. Keywords were sorted into three categories describing either the scientific field (e.g., urban hydrology and water quality), the intervention (e.g., SCMs), and the scale of analysis (e.g., watershed). Next, search strings were created that included one keyword from each of the three categories (i.e., "any first category word" AND "any second category word" AND "any third category word"). These strings were used to search for papers published on or after January 1, 2016, in the Elsevier ScienceDirect database on September 20, 2018, and the ProQuest database on October 2, 2018. After removing duplicates, the ScienceDirect search produced 903 papers and the ProQuest search garnered 947. The total 1,950 papers were then imported into the Rayyan systematic review software (Ouzzani, Hammady, Fedorowicz, & Elmagarmid, 2017), where they were initially screened for inclusion in this meta-analysis. This initial screen involved reading the title and abstract to determine if the study was generally relevant. If relevant, the full-text article was downloaded and reviewed to determine if it had the proper results and experimental design (described in Section 2.3). Thirty-seven papers from the ScienceDirect search and 48 from the ProQuest search met these criteria, bringing the total number of papers reviewed to 185.

2.3 | Model output collection

The next step in the meta-analysis was to extract relevant information from each study into a database of results. For inclusion in the database, in addition to peak flow and/or runoff volume results, at least one of the following SCM implementation metrics must have been reported directly or be determinable from other information in the study: (a) percentage of impervious surfaces mitigated by SCMs (*ISC mitigated [%]*) or (b) percentage of the total watershed area draining to or treated by SCMs (*watershed area mitigated [%]*). Although we expected that impervious surfaces mitigated by SCMs would be more directly related to hydrologic outcomes, we included studies that reported either metric to increase the number of studies in the meta-analysis, and because urban development in general, not just ISC, can impact hydrologic response (Lim, 2016). Figure 2 contains a graphical description of these metrics and example calculations. Of the 1,950 papers initially screened, 9.5% (n = 185) were reviewed, and 3% (n = 56) were found to have appropriate data for inclusion in the analysis (See Table 1 for included studies). Results for reductions in peak flow and runoff were garnered from 49 and 36 studies, respectively.

Initial screening included both modelling and empirical (field data) studies. However, after preliminary review, it was found that only four empirical studies met the criteria to be included in the meta-analysis (Table 1). To ensure a consistent comparison, we limited our analysis to studies that either compared paired developed watersheds (one with SCM implementation and one without) or monitored a single developed watershed before and after SCM implementation. Given that so few empirical studies met our inclusion criteria, we decided to limit our quantitative analysis to modelling studies only. The quantitative meta-analysis therefore includes 52 modelling studies out of the 56 identified studies. A discussion of this choice and how data from empirical studies compares to quantitative relationships derived from modelling studies is included in Section 4.3.

The data mining process of each publication involved one researcher carefully reading the paper, determining appropriateness for inclusion, and extracting relevant results and information (Table 2) into a database. Once the initial data mining process was completed, a second researcher checked the extracted values for accuracy. Three categories of information were extracted from each study: (a) landscape metrics describing the studied watershed and SCMs,



Watershed Area	$10\ km^2$
Impervious Surface Coverage (ISC)	$4\ km^2 / 10\ km^2 = 40\%$
ISC Mitigated by SCMs	$1\ km^2 / 4\ km^2 = 25\%$
Watershed Area Mitigated by SCMS	$1.5\ km^2 / 10\ km^2 = 15\%$

FIGURE 2 Graphical depiction of example watershed (green), stream (blue), impervious surface cover (grey), SCM area (orange), and SCM implementation metrics. SCM contributing area includes impervious surface pipes draining to SCMs, runoff entering SCMs directly, and pervious surface run-on to impervious areas. Note figure is not to scale

TABLE 1 Studies included in the meta-analysis

	Modelling/ empirical	Model(s) used	Number of scenarios (runoff)	Number of scenarios (peak flow)	SCM(s) studied
Avellaneda, Jefferson, Grieser, and Bush (2017)	M	SWMM	7	4	Bioretention, rain barrel, rain garden
Avila, Avila, and Sisa (2016)	M	PCSWMM	19	19	Cistern
Brander, Owen, and Potter (2004)	M	Infiltration patch (IP) - NRCS runoff	256		Bioretention, EIA reduction, grassed swale
Burns, Fletcher, Hatt, Anthony, and Walsh (2010)	M	RORB - event joint probability		36	Cistern
Carter and Jackson (2007)	M	SCS CN, StormNet builder	60	10	Green roof
Damodaram et al. (2010)	M	*S*-storage CN		85	Dry pond, green roof, porous pavement, rain barrel
Elliott, Trowsdale, and Wadhwa (2009)	M	MUSIC	12	12	Bioretention, cistern, infiltration basin
Emerson, Welty, and Traver (2005)	M	HEC-HMS		30	Dry pond
Faust and Abraham (2016)	M	SWMM	144		Bioretention
Fletcher, Mitchell, Deletic, Ladson, and Séven (2007)	M	MUSIC		12	Wet pond
Gagrani, Diemer, Karl, and Allan (2014)	M	MUSIC		20	Bioretention, dry pond, wet pond
Garcia-Cuerva, Berglund, and Rivers (2018)	M	SWMM	450	330	Bioretention
Giacomoni and Joseph (2017)	M	SWMM	3	3	Green roof, porous pavement
Giacomoni, Gomez, and Berglund (2014)	M	SWAT, HEC-RAS		3	Dry pond
Gilroy and McCuen (2009)	M	Author-created model	39	39	Bioretention, cistern
Guan, Sillanpaa, Koivusalo, Sillanpää, and Koivusalo (2015)	M	SWMM	10	26	Detention vault, green roof, porous pavement, rain barrel
Holman-Dodds, Bradley, and Potter (2003)	M	SCS CN	2	2	Infiltration basin
James and Dymond (2012)	M	Bentley SewerGEMS, NRCS TR-55	12	12	Bioretention, wet pond
Jarden, Jefferson, and Grieser (2016)	E	N/A	3	1	Bioretention, rain barrel, rain garden
Jia et al. (2015)	M	SUSTAIN		2	Bioretention, grassed swale, green roof, porous pavement, rain barrel, wet pond
Kim, Lee, Song, Han, and Joo (2018)	M	SWMM	40		Bioretention, infiltration trench, porous pavement
Kong, Ban, Yin, James, and Dronova (2017)	M	SWMM	2	2	Bioretention, green roof, porous pavement, vegetated filter strip
Lee, Hyun, Choi, Yoon, and Geronimo (2012)	M	SMWM		9	Constructed wetland, grassed swale, infiltration trench
Li Deng, Li, Li, and Song (2017)	M	SWMM	5	5	Bioretention, green roof, porous pavement, rain barrel, vegetated filter strip
Li, Deng, Li, Ma, and Li (2018)	M	SWMM	4	4	Bioretention, green roof, rain barrel

TABLE 1 (Continued)

	Modelling/ empirical	Model(s) used	Number of scenarios (runoff)	Number of scenarios (peak flow)	SCM(s) studied
Li, Zhang, Li, and Li (2018)	M	MIKE FLOOD	6	6	Bioretention
Li, Zhang, Mu, and Chen (2018)	M	MIKE FLOOD	7	7	Bioretention, green roof, porous pavement
Liu, Chen, and Peng (2015)	M	Author-created model	1		Bioretention
Lucas and Coombes (2009)	M	Water urban flow simulator (WUFS)	2	2	Infiltration trench
Lucas and Sample (2015)	M	SWMM	6	6	Bioretention, green roof, porous pavement
Mallin, Turner, McIver, Toothman, and Freeman (2016)	E	N/A	2		Bioretention, grassed swale, infiltration basin
Mao, Jia, and Yu (2017)	M	SUSTAIN		4	Bioretention, grassed swale, green roof, porous pavement, rain barrel, wet pond
McCuen (1974)	M	Author-created model		2	Dry pond
McCuen (1979)	M	SCS TR-20	12	12	Wet pond
Mei et al. (2018)	M	SWMM	6	6	Bioretention, green roof, porous pavement, grassed swale
Page, Winston, Mayes, Perrin, and Hunt (2014)	E	N/A	1	1	Bioretention, porous pavement
Palla and Gnecco (2015)	M	SWMM		12	Green roof, porous pavement
Palla, Gnecco, and La Barbera (2018)	M	SWMM	1	1	Green roof
Pappalardo, La Rosa, Campisano, and La Greca (2017)	M	SWMM	6	12	Green roof, porous pavement
Perez-Pedini et al. (2015)	M	SCS CN		9	Infiltration basin
Pomeroy, Roesner, Coleman, and Rankin (2008)	M	SWMM		6	Dry pond
Rosa, Clausen, and Dietz (2015)	M	SWMM	4	1	Bioretention, EIA reduction, grassed swale, porous pavement, rain barrel
Shannak (2017)	M	SWAT	12	12	Bioretention, porous pavement
Smith, Smith, Baeck, and Miller (2015)	M	GSSHA		12	Dry pond
Tao, Li, Peng, and Ying (2017)	M	SWMM	12	12	Bioretention, infiltration trench
Trinh and Chui (2013)	M	MIKE SHE		6	Bioretention, green roof
Versini, Gires, and Tchinguirinskaia (2016)	M	SWMM		8	Green roof
Versini, Jouve, Ramier, Berthier, and de Gouvello (2016)	M	Multi-hydro	48	48	Green roof
Walsh, Pomeroy, and Burian (2014)	M	SWMM		25	Cistern, rain barrel
Wilson, Hunt, Winston, and Smith (2015)	E	N/A	1	2	Bioretention, cistern, detention vault, grassed swale
Xie, Chen, Liao, Gu, and Zhu (2017)	M	MIKE URBAN	51		Bioretention, green roof, porous pavement, rain barrel, vegetated filter strip
Xing et al. (2016)	M	SWMM	2	3	Infiltration basin

(Continues)

TABLE 1 (Continued)

	Modelling/ empirical	Model(s) used	Number of scenarios (runoff)	Number of scenarios (peak flow)	SCM(s) studied
Yang and Chui (2018)	M	SWMM		36	Bioretention
Yau, Radhakrishnan, Liong, Zevenbergen, and Pathirana (2017)	M	SWMM	8	8	Bioretention, grassed swale, vegetated filter strip
Zahmatkesh, Burian, Karamouz, Tavakol-Davani, and Goharian (2015)	M	SWMM		56	Bioretention, cistern, porous pavement, rain barrel
Zanandrea and da Silveira (2018)	M	SWMM	4	4	Porous pavement, vegetated filter strip

Note: The number of scenarios refers to the number of model runs completed in a particular study.
Abbreviations: E, empirical study; HEC-HMS, Hydrologic Engineering Center Hydrologic Modelling System; HEC-RAS, Hydrologic Engineering Center River Analysis System; M, modelling study; MUSIC, Model for Urban Stormwater Improvement Conceptualisation; NRCS, Natural Resources Conservation Service; PCSWMM, Personal Computer Stormwater Management Model; SCS CN, Soil Conservation Service Curve Number; SUSTAIN, System for Urban Stormwater Treatment and Analysis IntegratioN; SWAT, Soil & Water Assessment Tool; SWMM, Stormwater Management Model.

(b) a description of the storm event scenario, and (c) the event-scale results for peak flow and/or runoff volume reduction (Table 2). Individual studies often included runoff and peak flow results from multiple scenarios (Table 1) (i.e., multiple watersheds, multiple storm events, and/or multiple SCM configurations), which was accounted for in the statistical analyses using a weighting scheme as described further in Section 2.4.1. Studies that reported an average percent reduction over a period of time or several events were included in the database as a single scenario. If information on SCM metrics (i.e., watershed area, watershed mitigated area, etc.) and precipitation data (i.e., return interval or rainfall depth) was not provided in the publication, the study's corresponding author was contacted via email to try to obtain this additional information. Thirty-eight authors of the original 185 studies reviewed were contacted; of those 38 authors contacted, 50% (19) responded and 32% (12) were able to provide model output sufficient to include the study in the database. The information requested from the authors is provided in the Supporting Information.

Model output extracted documented runoff volumes (mm) and/or peak flow ($m^3\ s^{-1}\ km^{-2}$) from the *control* and *intervention* watersheds, and/or the percent change between the two for each scenario. Changes in runoff volume or peak flow with SCM implementation depend on the watershed condition that is used for reference. For example, SCM implementation has been reported to reduce peak flow compared to an urban watershed without SCMs, but still have a greater peak flow than a forested watershed (Hopkins, Bhaskar, Woznicki, & Fanelli, 2019). For the most direct comparison across studies, the database includes the one experimental design that allows for the quantification of the difference between a developed watershed without SCMs (the *control*) and the same or very similar (developed) watershed with SCMs (the *intervention*).

Percent change of hydrologic variables was calculated as 100 * (*intervention-control*)/*control*. Percent reductions, which are equal to the percent change reported in the database multiplied by −1 (Table 2), were used in the analysis. For example, a decrease in peak flow in the intervention watershed relative to the control would have a negative percent change, but a positive percent reduction. The extracted values were further reviewed by the entire team to consolidate outstanding comments, reformat, and check that only studies meeting the inclusion criteria were in the final database.

Each study provided a number of individual runoff and/or peak flow results, ranging from 1 to 450 scenarios per study with a median of six for runoff and eight for peak flow results. Studies reported differing metrics of impervious area (e.g., Total Impervious Area or Effective Impervious Area). When *ISC mitigated* was not reported by studies, these other metrics were used to calculate the *ISC mitigated* metric used in statistical analyses.

2.4 | Analysis

Three separate analyses were performed on the database of extracted results to (a) identify the shape of the relationship between area mitigated by SCMs and reductions in event runoff and peak flow, (b) identify values of mitigation at which targeted reductions are observed, and (c) test what other environmental factors function as controls that lead to deviations from the general relationship. All analyses were performed in R (R Core Team, 2019).

2.4.1 | Relationship between SCM implementation and hydrologic impacts

A series of weighted linear regression analyses were applied to the database of results extracted from the 52 papers to determine the statistical significance and shape of the relationship between the magnitude of hydrologic change and SCM implementation. Models were

TABLE 2 Information extracted from each study and scenario used in data analysis

Variable	Units	Description
Landscape metrics		
Watershed area	km^2	Area draining to the monitoring location
Impervious surface coverage (ISC)	%	Impervious surface area/total watershed area
ISC mitigated	%	impervious surface are mitigates/total impervious surface area
Watershed area mitigated	%	SCM contributing area (pervious and impervious)/Total watershed area
SCM types	Code	SCM types include: Bioretention (BR), cistern (C), constructed wetland (CW), detention vault (DV), dry pond (DP), effective impervious area reduction (EIA), grassed swale (GS), green roof (GR), infiltration basin (IB), infiltration trench (IT), porous pavement (PP), rain barrel (RB), vegetated filter strip (VS), and wet pond (WP)
Primary land use	Code	Primary land use in the studied watershed. Land use codes include: Single family residential (SFR), multi-family residential (MFR), mixed residential (MR), mixed urban (MU), commercial (COM), industrial (IND), and other (OTH)
Storm event scenario description		
Storm event description	Code	Brief description of the storm event
Return interval	Yr	Return interval of the storm event
Duration	Hr	Length of the precipitation event for the scenario
Depth	Mm	Precipitation depth for the scenario
Average intensity	$mm\ hr^{-1}$	Average precipitation intensity for the scenario
Scenario peak flow or runoff results		
Scenario peak flow scenario runoff	$m^3\ s^{-1}\ km^{-2}\ mm^{-1}$	Peak flow or runoff in the intervention (developed, with SCMs) watershed for the scenario
Control peak flow control runoff	$m^3\ s^{-1}\ km^{-2}\ mm^{-1}$	Peak flow or runoff flow in the control (developed, no SCMs) watershed for the scenario
Percent change in peak flow or runoff	%	Percent change in peak flow or runoff calculated as 100 * (intervention - control)/control

constructed using one of the two SCM implementation metrics (watershed or impervious area mitigated by SCMs) as the independent variable and percent reductions in runoff or peak flow as the dependent variable, for a total of four variable combinations. Both area mitigated metrics were included in the analysis to determine which was more predictive.

The number of studies and results in each regression varied with data availability because not all studies in the database reported all four variables included in the regresion models. To prevent studies with many scenarios dominating the outcome (e.g., Garcia-Cuerva et al., 2018 in Table 1), the regression weighted each of the results by the number of scenarios from each study raised to the negative one-half power. Studies that reported the average percent reduction over multiple events received a weight of 1, if the average was the only result from the study. This weighting scheme caused each of the studies to impact the regression more evenly, whereas each scenario has equal leverage when the regression is unweighted.

For each combination of independent and dependent variables, we evaluated the regression of a linear form and a power form. The power relationship coefficient was determined by performing a simple linear regression on log-transformed datasets (i.e., $\log(y) = m * \log(x)$). In all cases, the y-intercept was fixed at zero in the real and

transformed spaces because this point is known; if there is no SCM implementation, there is no change from the control. Both regression forms were included to determine if the shape of the curve was linear or non-linear. A non-linear response could indicate that there are certain watershed conditions that could result in greater (or smaller) hydrological changes with incremental SCM implementation.

Models were deemed significant at $p < .1$. Root mean square error (RMSE) quantified goodness-of-fit of each regression.

2.4.2 | Analysis of area mitigated by SCMs

A series of weighted logistic regression models were used to identify levels of area mitigated by SCMs that must be met before a targeted change in hydrology is likely. This analysis used the same four combinations of independent and dependent variables, input values, and weighting scheme as the linear regression analysis.

Percent reductions in runoff and peak flows were converted to a binary variable, based on whether they exceeded a specified reduction target. For example, a result of 15% reduction in peak flow would receive a value of one when evaluated against a 10% reduction target, but it would receive a value of 0 when evaluated against a 20% reduction target. The reduction targets considered ranged from 1 to 30%, by increments of 1%, because the reduction results found in most of the modelling studies were below 30% reductions in peak flow or runoff. Weighted logistic regression models were constructed for all 30 reduction targets for each of the four combinations of variables, making a total of 120 models. Each model was tested for significance ($p < .1$) and goodness-of-fit was quantified by four metrics recommended by Dougherty (2011): the percent of results predicted on the correct side of .5 probability (i.e., >.5 for observations of one, and <.5 for observations of zero), the sum of the squared residuals, the correlation coefficient, and a pseudo-R^2 quantified as $1 - L_{full}/L_{intercept}$ where L_{full} is the log-likelihood of the model using both coefficients and $L_{intercept}$ is the log-likelihood of the model using only the *y*-intercept.

2.4.3 | Environmental controls

The linear regression models and their coefficients relate a watershed's SCM implementation to potential reductions in event hydrologic metrics. However, these models do not include any other landscape features that are known to affect hydrology, such as ISC. They also do not account for any within-site variability due to storm characteristics. To understand how other environmental controls such as watershed and rain event metrics modulate the hydrologic impacts of SCMs, a weighted Pearson correlation analysis was performed between the residuals of four linear regression models (one for each independent and dependent variable combination) and four other environmental factors in the database: (a) watershed area, (b) ISC, (c) storm event rainfall depth, and (d) storm event rainfall average intensity. The weighted correlation analysis was performed using the `weights` package in R (Pasek, 2018), following the same weighting method outlined above. The analysis was performed on model residuals, rather than the raw percent reductions, to remove the effects of SCM implementation and focus on the environmental factors that would cause deviations from the general trends. As with the linear regression models, the actual number of observations and studies varied for each correlation analysis depending on availability. Significant correlations are quantitively defined when $p \leq .1$, and further qualitatively defined as *weak* when $|r| \leq 0.1$, as *slight* when $0.1 < |r| \leq 0.4$, as *moderate* when $0.4 < |r| \leq 0.7$, and as *strong* when $0.7 < |r| \leq 1.0$.

3 | RESULTS

3.1 | Study characteristics

Table 1 provides information on each of the 52 modelling studies included in the final database as well as the four empirical studies used for comparison. The 56 total studies were conducted across the globe in 46 locations (Figure 3). A variety of models were used in the modelling studies, most commonly SWMM/PCSWMM (50%) and the curve number method (8%). Other models used included MIKE FLOOD/MIKE SHE/MIKE URBAN (DHI Group) and MUSIC (eWater Ltd.). Bioretention was the most commonly investigated SCM type (48% of modelling studies), then green roof (32%), porous pavement (30%), and rain barrels (18%).

Of the studies included in this meta-analysis, 87% (n = 45), 75% (n = 39), and 46% (n = 24) include SCMs with detention, retention, or infiltration, respectively, as the primary hydrologic function (as defined by Bell et al., 2019). It was common for the studies to include multiple SCM types to target multiple hydrologic functions. Forty-two percent of the 52 studies (n = 22) investigated a single SCM type while the other 58% (n = 30) modelled two or more SCM types. Forty percent of studies (n = 21) included SCM types to target both detention and retention and 29% (n = 15) included SCM types to target detention, retention, and infiltration.

The studied values of *watershed area mitigated* and *ISC mitigated* are unevenly distributed, with more scenarios focused on low levels of mitigation; 69% of studies examined 0–25% of watershed area mitigated, and 45% of studies focused on 0–25% of ISC mitigated (Figure 4). Seven percent of the studies included scenarios with 100% *watershed mitigated area* and 18% included scenarios with 100% *ISC mitigated*.

3.2 | Relationship between SCM implementation and hydrologic impacts

All eight regression models constructed to characterise the form of the relationship between hydrologic impact (i.e., percent reductions) and SCM implementation had *p*-values <.001, and all eight demonstrated a positive relationship between area mitigated by SCMs and reductions in runoff and peak flow (Table 3). For runoff volume, the

FIGURE 3 Map showing the locations of the 56 studies included in the meta-analysis

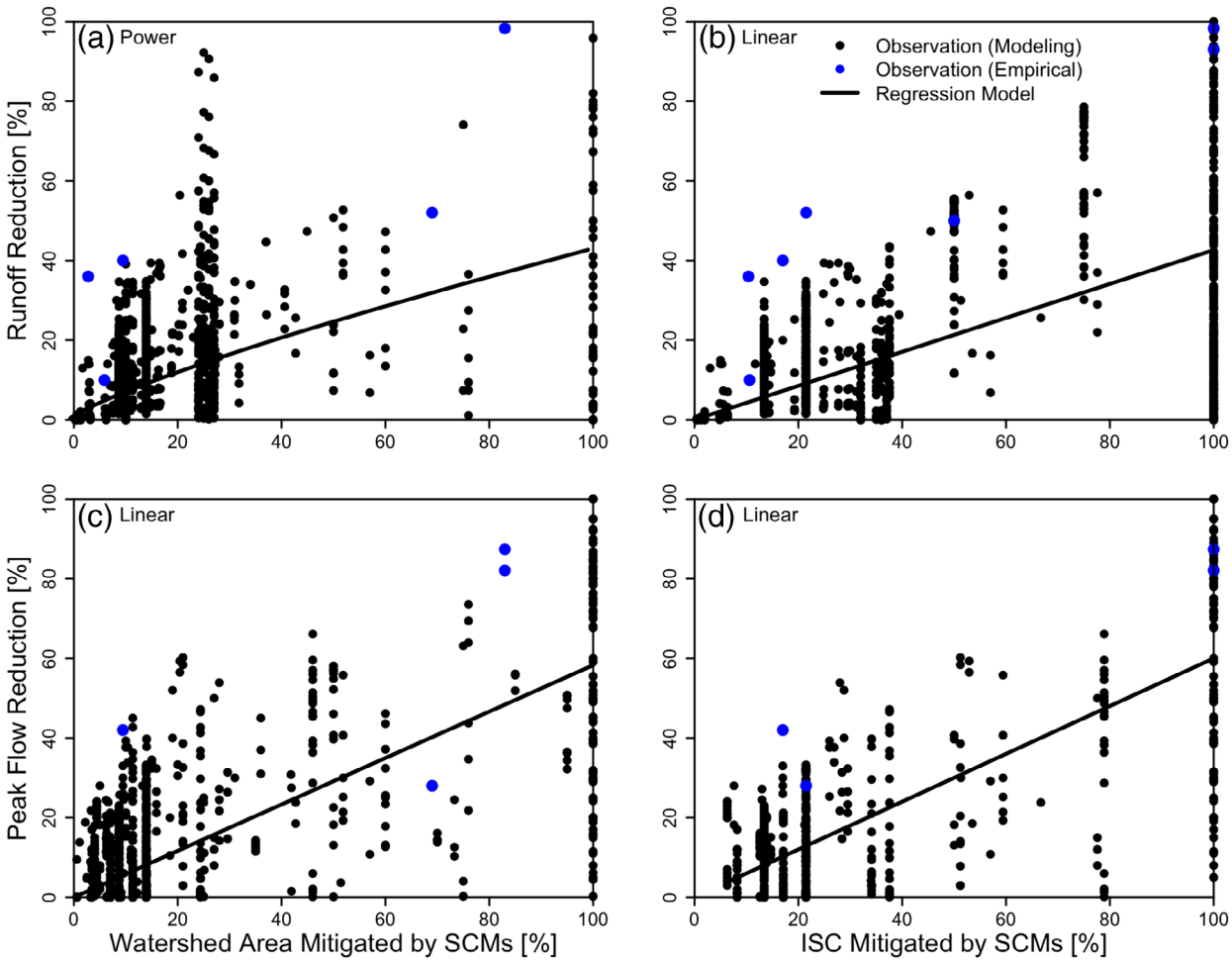


FIGURE 4 Reductions in runoff and peak flow in the meta-analysis database plotted vs. two SCM implementation metrics. The regression models shown on the plot are the best fitting of two relationships tested (linear vs. power) as indicated in the panel label

TABLE 3 Summary of the 8 regression models, their goodness-of-fit metrics, and the number of results included

Model equation	RMSE (%)	R^2	# of observations	# of studies
Runoff percent reduction = 0.441 * watershed area mitigated	16.1	0.53	1,027	22
Runoff percent reduction = watershed area Mitigated$^{0.815}$	15.0	0.85	1,027	22
Runoff percent reduction = 0.427 * ISC mitigated	20.1	0.62	993	16
Runoff percent reduction = ISC Mitigated$^{0.756}$	20.8	0.87	993	16
Peak flow percent reduction = 0.583 * watershed area mitigated	16.4	0.72	861	35
Peak flow percent reduction = watershed area Mitigated$^{0.845}$	16.5	0.85	861	35
Peak flow percent reduction = 0.600 * ISC mitigated	15.7	0.80	645	23
Peak flow percent reduction = ISC Mitigated$^{0.804}$	17.7	0.88	645	23

Note: All models had *p*-values <.001.

TABLE 4 Summary of logistic regression models between two SCM implementation metrics (independent variable) and percent reduction in two hydrologic metrics (dependent variable)

Hydrologic metric percent reduction (%)	SCM implementation metric (%)	Number significant (p < .1)	Percent predicted correctly	*Sum squared residuals	*Outcome correlation	*Pseudo-R^2	# of observations	# of studies
Event runoff	Watershed area mitigated	21/30	72.3%	189	0.265	0.056	1,027	22
	ISC mitigated	29/30	71.2%	182	0.373	0.089	993	16
Event peak flow	Watershed area mitigated	30/30	74.3%	148	0.446	0.170	861	35
	ISC mitigated	30/30	74.2%	110	0.469	0.230	645	23

Note: Each row summarizes models for all 30 reduction targets analysed (i.e., 1–30% reduction). *Goodness-of-fit metrics are averaged across the 30 models constructed for the 30 reduction targets.

power relationship using *watershed mitigated area* as the predictor variable produced the lowest RMSE (15.0%) (Figure 4a). The coefficient for this relationship was 0.815, which means that the slope of the relationship decreases as the *watershed mitigated area* increases. For peak flow, the linear relationship using the *ISC mitigated* metric produced the lowest RMSE (15.7%) (Figure 4d). While these two models performed best based on RMSE, all eight models performed comparably, having RMSEs within 5.8%. Using a different evaluation metric (e.g., R^2) could result in identification of a different best model. All but one of the percent reductions observed in empirical studies fall above the regression lines (blue points in Figure 4). There is considerable variation in percent reduction observations of both runoff volume and peak flow across both SCM implementation metrics. This is especially true for the scenarios with 100% *watershed area mitigated* and *ISC mitigated* because many of the studies include scenarios with full watershed mitigation.

The coefficients for the linear models in Table 3 can be interpreted explicitly: an increase in 1% of the mitigation metric will lead to an increase in percent reduction equal to the value of the coefficient. For example, the linear model shown in Figure 4b has a coefficient of 0.441. Therefore, for every additional 1% of ISC that is mitigated by SCMs, a 0.441% reduction in runoff can be expected. The coefficients for the linear regression models for peak flow as a function of *watershed area mitigated* and *ISC mitigated* were 0.583 and 0.600, respectively, which are higher than the respective coefficients for runoff (0.441 and 0.427), meaning SCMs have a slightly greater impact on peak flow reduction versus runoff reduction. The statistical model coefficients can be useful for interpreting potential mitigation effects; however, there is also substantial variability in hydrologic performance across all levels of mitigation. This variability is analysed in the Section 3.4 below.

3.3 | Area mitigated by SCM analysis

Generally, logistic regression relationships between SCM implementation metrics and the probability that a reduction target will be exceeded were significant (p < .1; Table 4). Detailed descriptions of all 120 models, including model coefficients, are provided in the Table S1. Ten of the 60 models for runoff were not statistically

significant, nine of which were for SCM reduction targets of <10% mitigated impervious area. All models had positive coefficients, which indicate that as SCM implementation increases, the probability of exceeding a reduction target also increases. Models constructed with *ISC mitigated* as the independent variable outperformed those with *watershed area mitigated* for both runoff and peak flow, as measured by all goodness-of-fit metrics except the percent of observations predicted correctly.

Figure 5 shows logistic regression curves for six selected reduction targets (5, 10, 15, 20, 25, 30%) for each of the four independent and dependent variables. As the reduction target increases, the curves shift down the y-axis, indicating that the probability of meeting that reduction target decreases. There is a positive probability of meeting a low reduction target with close to no area mitigated by SCMs, which reflects the noisy nature of the study output informing these models (Figure 4). The curves for runoff, shown in Figure 5a,b, are relatively linear, so increases in area mitigated by SCMs result in proportional increases in the probability of meeting a target. The slope of the curves with runoff reduction targets <15% are typically flatter than those ≥15%, and the relationship between *watershed area mitigated* and runoff at a reduction target of 5% is non-significant and not shown in Figure 5a. The curves for peak flow, shown in Figure 5c,d, are non-linear. Specifically, they all demonstrate a decline in slope at higher levels of mitigation, which could indicate diminishing returns at higher levels of mitigation (i.e., less peak flow reduction per increase in area mitigated).

Another way to evaluate these curves is by identifying the level of mitigation (*x*-axis) at which each curve crosses through a particular probability (*y*-axis). At a probability of .5, this quantifies the level of mitigation where reaching a reduction target becomes equally as likely as not. For example, Figure 5c shows that a reduction in peak flow of 10, 20, and 30% have a .5 probability when 0.6%, 37.7%, and 62.2% of the watershed area are mitigated, respectively. Larger reduction targets or a greater probability of achieving a desired reduction require more mitigation. Figure 6 reports these implementation values at probabilities of .5, .75, and .9 for all 30 reduction targets and all four combinations of independent and dependent variables (also in Table S2).

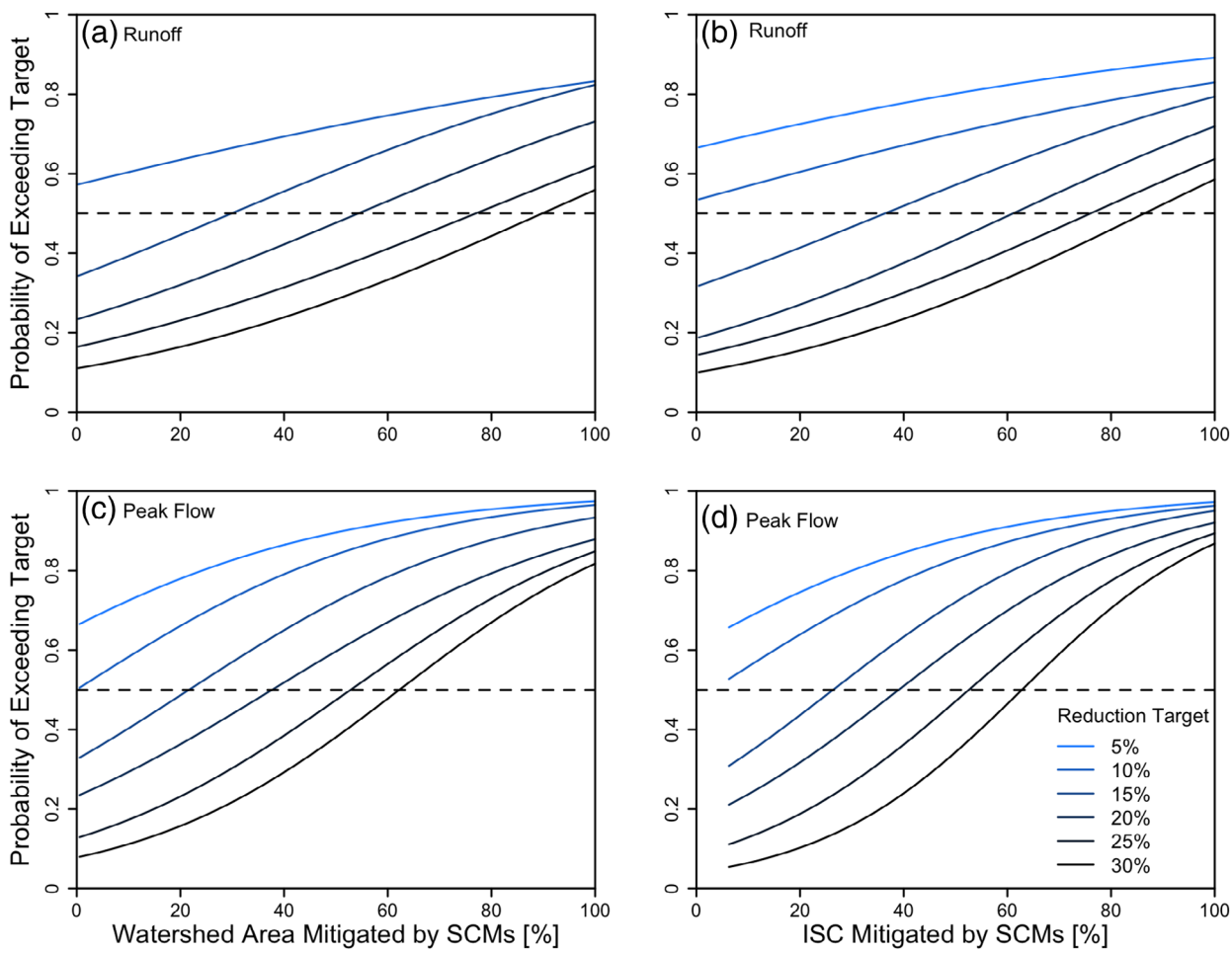


FIGURE 5 Logistic regression models predicting the probability of exceeding 6 reduction targets for runoff and peak flow as a function of the two SCM implementation metrics. The labels indicate that panels (a) and (b) are for event runoff and that (c) and (d) are for event peak flow. The reduction targets are labelled in the legend in panel (d). The dashed horizontal line represents .50 probability. Model synthesis outputs are not plotted because the data varies for each reduction target. No 5% reduction target line is drawn for (a), because the model was not significant at $p < .1$

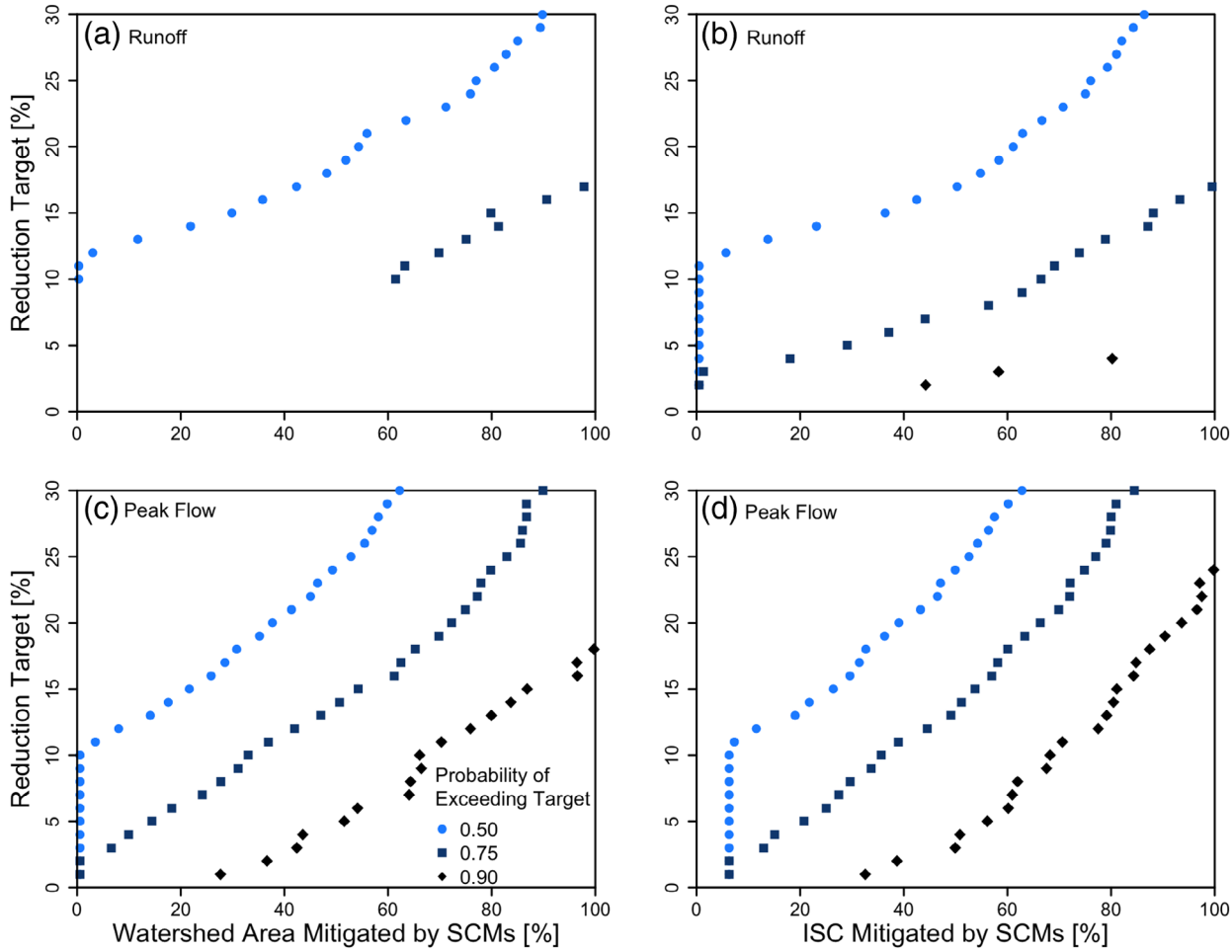


FIGURE 6 SCM implementation values (x-axis) required to meet a given reduction target (y-axis) at probabilities of .50, .75, and .90 (colour code). For example, for runoff in Figure 6a, for a reduction target of 20%, about 50% of the watershed area would need to be mitigated by SCMs to achieve this runoff reduction at a probability of 0.50. The panels show all four combinations of dependent variables [i.e., Runoff (a, b) and Peak Flow (c, d)] and independent variables [i.e., *Watershed Area Mitigated* (a, c) and *ISC Mitigated* (b, d)]. Note that this figure only shows points for which the logistic regression was significant ($p < .10$), and that models for which the reduction target was across the range of *Watershed Area Mitigated* and *ISC Mitigated* values are plotted at the lowest implementation metric on the *x*-axis

TABLE 5 Weighted Pearson correlation coefficients between model residuals and four landscape and rain event metrics

Residual of model	SCM implementation metric	Area (km^2)	Impervious area (%)	Rainfall depth (mm)	Rainfall intensity (mm hr^{-1})
Runoff (power)	Watershed area mitigated	NA	−0.139	−0.437	NA
Runoff (linear)	ISC mitigated	NA	0.182	−0.332	−0.236
Peak (linear)	Watershed area mitigated	0.091	NA	−0.168	−0.154
Peak (linear)	ISC mitigated	0.163	0.126	−0.259	NA

Note: Non-significant correlations ($p > .1$) are reported as "NA."

3.4 | Environmental controls

Table 5 contains the Pearson correlation coefficients between the regression model residuals and four other landscape and rain event metrics. A positive correlation coefficient means that as the given environmental control increases, the percent reductions increase relative to the general pattern. Watershed area was only weakly correlated to the residuals of two of the four models, and only slightly positively correlated to the peak flow residuals predicted by the model using *ISC mitigated* as the independent variable. The residuals of the runoff and peak flow models using *ISC mitigated* as the independent variable were slightly positively correlated to ISC, which would indicate that the SCM percent reduction increases at greater ISC. All four model residuals were slightly or moderately negatively

correlated to total rainfall depth, which indicates that as the size of the rainfall event increases, the percent reductions in hydrologic metrics attributable to SCMs decrease. The correlations between model residuals and average rainfall intensity demonstrate similar directional patterns as for rainfall depth, but the correlations were only slightly negative for two of the four models, and not correlated for the other two.

4 | DISCUSSION

4.1 | Event hydrologic response to mitigation

A synthesis of results from 52 modelling studies showed that watershed-scale implementation of SCMs was significantly, positively related ($p < .1$) to reductions of runoff volumes and peak flows. While this finding is consistent with individual studies, it is the first time that many studies have been quantitatively analysed to demonstrate this conclusion across multiple locations and types of SCMs. The shape of the significant relationships between reductions in runoff and peak flow and measures of SCM implementation is generally linear. The linear relationship implies that, regardless of the current level of area mitigated by SCMs, additional area mitigated will lead to proportional reductions in event peak flows and runoff volumes. There is much variation about this general pattern due to other factors, including environmental controls, discussed below, as well as modelling choices, SCM spatial arrangement, SCM design, and drainage networks such as pipes.

At equal levels of implementation, SCMs can reduce peak flows by a greater percentage than corresponding reductions in runoff. This could be due to differences in the mechanisms for reductions of peak flow versus runoff. One explanation is that detention, which reduces peak flows by slowing the release of captured runoff and altering flow timing, is easier to achieve than retention, which reduces runoff volumes through on-site infiltration. Detention can occur if there is available storage in the SCM, which means that simply designing an SCM to be deeper will lead to more detention. For retention and infiltration to occur, SCMs must promote two processes: first storing the runoff (retention) and then transmitting it into the subsurface (infiltration). The second process, transmission into the subsurface, is limited by the SCM's design percolation rate. The percolation rate is influenced by subsurface conditions (e.g., soil properties or groundwater contamination) and footprint area. Expanding the footprint of an SCM is often more difficult to achieve in practice than increasing its depth, due to land availability and cost, especially in heavily urbanised environments. Additionally, the drainage rate and structure of the urban soils beneath the SCMs may limit actual infiltration rates below the design rates (Shuster, Darner, Schifman, & Herrmann, 2017). Other SCMs, such as green roofs and rain barrels, focus on harvest (evapotranspiration or water reuse) rather than infiltration as the primary stormwater reduction process (Eger, Chandler, & Driscoll, 2017; Askarizadeh et al., 2015) and can be easier to implement in space-limited urban environments.

These results provide mathematical form and support for some components of the Jefferson et al. (2017) conceptual model (Figure 1) about the nature of the response to impervious surface mitigation by SCMs, while also adding caveats. As posited by Jefferson et al. (2017), peak discharge and runoff volume decrease as *ISC mitigated* increases, although the model outputs analysed here identify a linear or near-linear relationship rather than the hypothesised non-linear one (Figure 7). A power relationship between runoff reduction and *watershed area mitigated* was found to marginally outperform the linear model; however, raising the range of *watershed area mitigated* in a particular study (0–100%) to the model coefficient (0.815) produces a nearly linear shape. Jefferson et al. (2017) also posited that there was a residual in which 100% ISC was treated in a developed watershed, but hydrologic metrics remained changed relative to undeveloped conditions. Given the choice of control watersheds (urbanized without SCMs) in this analysis, this portion of the Jefferson et al. (2017) conceptual model remains untested.

Finally, the Jefferson et al. (2017) model also included a region of "no detectable SCM effect" when only a small fraction of a watershed's impervious area was treated by SCMs. The weighted linear regression in this study fixed the y-intercept at zero, which does not allow for this component of the model to be tested. However, the logistic regression analysis allows examination of values for detection. Results show that the detectability of an effect depends on both the probability that the effect will occur and the magnitude of the effect. For example, a 5% reduction in runoff volume can be detected when only 0.49% of ISC is mitigated for 50% of cases. But to achieve that detectability in 75% of cases, about 29% of ISC must be treated, and there is no level of ISC mitigation that will ensure a 5% reduction in 90% of cases. The importance of probability is also shown for peak flows: to achieve a 5% reduction in peak flow in 50, 75 and 90% of cases, 6.3, 20, and 56% ISC must be treated, respectively. This shows that while a detectable effect may become likely (i.e., >50%

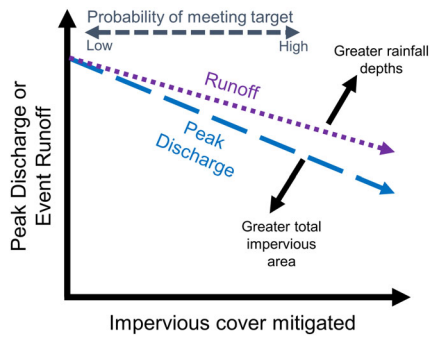


FIGURE 7 Conceptual model of urbanization and stormwater management revisited. Regression analysis shows when SCMs are added, event peak discharge and runoff decrease (blue and purple lines). Mitigating more impervious cover increases the probability that a detectible or desired target reduction is achieved (grey line). For equal fractions of impervious cover mitigated, residual analysis shows that less reduction is likely for events with greater rainfall depths. More reduction is likely in watersheds with greater total impervious area

probability) at low levels of mitigation, confidence in that effect occurring (i.e., >90% probability) requires more mitigation. Also, larger effect magnitudes (i.e., reduction targets) require greater mitigation, shown by the curves moving up and to the right in Figure 6.

For comparison to the Jefferson et al. (2017) conceptual model, we define the minimum detectable effect as one having a 90% probability and producing a reduction >1% in magnitude. For a 90% probability of >1% reductions in peak flow, at least 28% of total watershed area and 32% of impervious area need to be mitigated (Figure 6). A similar analysis was not performed for runoff volume due to lack of model significance at low target reduction.

4.2 | Environmental controls

SCM performance at reducing peak flows and runoff volumes is also dependent on environmental factors. The residual analysis showed that the ability of SCMs to reduce runoff volumes and peak flows is inhibited during larger rain events. Many individual modelling studies have shown similar results (e.g., Carter & Jackson, 2007; Damodaram et al., 2010), and the findings are corroborated by empirical studies (e.g., Winston, Dorsey, & Hunt, 2016). This idea is included in the Jefferson et al. (2017) conceptual model, as SCMs are unable to fully return peak flows to pre-development conditions because SCMs have a finite capacity. The same relationship was not true for rainfall intensity, which could be because greater intensity does not necessarily result in a greater volume of water falling on the watershed. The interaction of rainfall intensity and depth (i.e., rain events with large total depths and high intensities) may show a higher correlation with the residuals, but this tertiary effect was not explored here.

Watersheds with the same rates of *ISC mitigated* will see greater reductions in runoff and peak flow, on average, when the total ISC of the watershed is greater. In other words, SCM implementation in more urbanised watersheds may be more effective than the same rates of implementation in less urbanised watersheds. This could be because in more urbanised watersheds, a greater portion of the total runoff hydrograph is from impervious surface runoff, and therefore SCMs have the potential to provide greater percent reductions. The secondary effect of *watershed area* on the ability of SCMs to reduce runoff and peak flows, however, was weak and inconsistent. Combining the regression results with the analysis of environmental controls suggests that targeting watersheds with greater ISC, regardless of size or existing SCM infrastructure, may realise the greatest percent reductions.

The generally weak or non-significant correlations between the residuals and the environmental controls explored here suggest that the univariate approach taken in this meta-analysis is sufficient to broadly explain watershed hydrologic response to SCMs. Multivariate approaches with other continuous watershed or event attributes would decrease the sample size for analysis because of incomplete reporting in published papers, without adding much insight. While the relationship between residuals and categorical values (e.g., SCM type, primary land use) was not analysed, splitting the primary analysis by category would similarly limit sample size and the broad applicability of the models presented here.

4.3 | Empirical vs. modelling studies

Empirical studies appear to show better SCM performance than would be predicted by modelling studies only (Figure 4). In contrast, a previous review of watershed-scale SCMs found that modelling studies overestimate SCM effectiveness compared to empirical studies (Li, Fletcher, et al. 2017). Only four empirical studies were included in the comparison analysis with seven results for runoff volume and four results for peak flow (Table 1). Three of the four empirical studies included were located in North Carolina, providing limited geographic context for watershed-scale SCM implementation. This small sample was likely a result of the strict criteria for including a control watershed without any SCMs, which can only be met by empirical studies employing a before-after-control-impact and some paired catchment experiments.

The empirical studies that were included report average percent change from storms occurring during the monitoring period. The average reduction of observed events includes a great number of high-probability events that have lower precipitation depths. In contrast, modelling studies often focused on design storms with a return period of 1 year or greater, so even the smallest design storms in modelling studies have a longer return period and correspondingly greater precipitation amounts than the events in the empirical studies. As shown in Table 5, larger rainfall events are associated with smaller reductions in peak flow and runoff and may explain why empirical results outperformed modelling studies in this meta-analysis.

Although it would have been ideal to have enough empirical studies with the appropriate criteria of a control and intervention watershed to perform a meta-analysis on empirical studies alone, this does not represent the reality of published work in this field. Empirical studies of watershed-scale impacts of SCMs in general are limited by the constraints and impracticality of conducting field studies of observed data at the watershed scale (Ahiablame, Engel, & Chaubey, 2012). Modelling studies are useful to demonstrate the effectiveness of SCMs at different spatial and temporal scales and in response to infrequent events (Ahiablame et al., 2012; Liu, Ahiablame, Bralts, & Engel, 2015). A meta-analysis of modelling studies provides benefits compared to either relying on a limited number of empirical studies or needing to undertake modelling for each watershed of interest.

The results presented here reflect and integrate across the process representations embedded within various hydrologic model structures (Wagener & Gupta, 2005). Tradeoffs between complexity and realism are ubiquitous in hydrological models. In addition to the structural uncertainty inherent in numerical models of complex systems, the availability and uncertainty of data required to construct and calibrate models influence their ability to represent hydrological reality as measured in empirical studies (Deletic et al., 2012). However, some of the studies included in the meta-analysis were

calibrated to observed data, indicating a reasonable ability to represent observed hydrological phenomena. Further, the meta-analysis offers an aggregate assessment of stormwater management modelling results that includes different sites, assumptions, and biases from many studies using over 20 different models. Convergence of results through multiple models and methodologies is a strength of this meta-analysis process.

Our meta-analysis also builds in regional variability absent from the small number of available empirical studies or from individual modelling efforts. Studies included in the meta-analysis are informed in their SCM selection based on contextual decision-making with regional, real-world knowledge from the authors. In addition, the meta-analysis revealed information about which SCMs are commonly modelled, which watershed and storm event metrics are reported, and which control targets are common across studies (e.g., 25% mitigated area).

4.4 | Study limitations

Limitations to the meta-analysis method include the authors' interpretations of results from the reviewed studies. This was addressed by at least two authors reviewing each study to confirm the results in the database. An additional drawback is that the meta-analysis prevents the investigation of variables that were not commonly reported in the reviewed studies, such as slope, soils, or watershed shape. SCM study authors can facilitate future meta-analyses by reporting all key metrics and tables of all results in Supporting Information. Trends towards journal publishers requiring greater data availability support this need.

The types of SCMs investigated across the included studies are potential limitations of this meta-analysis. Nearly half of the studies in the meta-analysis included scenarios with bioretention, potentially overrepresenting one type of SCM that is often designed for volume rather than peak flow control. In many studies (22/52) included in this meta-analysis, only a single type of SCM was assessed in the modelling scenario, which may not represent a reality in which typically many SCMs are implemented within a watershed. Metrics describing SCM design such as footprint, depth, and outlet design have a significant effect on the performance of an individual SCM and the response downstream at the watershed outlet. However, this information was not frequently reported in the studies reviewed and therefore could not be included as a metric in this meta-analysis. We hypothesise these and other factors such as climate, topography, and drainage density also contribute to the variability in the observed behaviour not accounted for by the models presented. Future work should incorporate these environmental factors, and other important decision criteria such as cost, as more studies are published, and more data becomes available.

Most studies in this analysis were conducted in watersheds in developed countries, specifically in the northeast United States and China, with a handful in Europe, Australia, and South America (Figure 3). Because of the limited geography represented in available studies, approaches to stormwater control that are more popular outside the United States and China may be underrepresented in this analysis. Also, any effects of seasonal or annual climate on our results cannot be distinguished, beyond the effect of event size being studied. Future work could consider climate and other spatially varied factors that may impact SCM performance.

There was no qualitative evaluation of the studies during the literature review for this meta-analysis. For example, studies were not evaluated based on study design, study period, modelling approach or performance, or statistical significance of results. While study quality is a common method of weighting studies in meta-analyses, Ahn and Becker (2011) recommend against using qualitative weights in meta-analyses. We note that the quality of the studies included in this meta-analysis were variable. Here, weighting was solely based on the number of scenarios per study raised to the negative one-half power. This weighting spreads influence on the meta-analysis across the studies more evenly, but still follows the convention of giving studies with a greater number of samples greater weights (Pai et al., 2004). Weighting schemes which raise the number of scenarios per study to a different power were explored during preliminary analysis (not shown), and the results were generally consistent with those presented here. However, different weighting powers did lead to slight variations in regression coefficients, model performance, and p-values.

4.5 | Suggestions for future work

One component of the Jefferson et al. (2017) conceptual model remains untested: that an urban watershed with 100% treated impervious area would have higher peak flows and greater runoff volumes than its undeveloped counterpart. Although this has been documented in individual watersheds (Hopkins et al., 2019), a future meta-analysis could compare studies with undeveloped watersheds as controls to assess this part of the conceptual model.

The constraint of this meta-analysis to the most common scenarios found in the literature also limits the scope of watershed response metrics. Results on metrics other than peak flow and runoff volume (e.g., annual water yield) were not reported frequently enough to support regression, so longer-term mitigation impacts have not been examined. Water quality response to SCM implementation should also be studied further; these studies are most often empirical and present different challenges for database consistency in the meta-analysis approach.

5 | CONCLUSIONS

A recent literature synthesis by Jefferson et al. (2017) posited a conceptual model between the effects of SCM implementation at the watershed scale and resulting urban runoff and water quality patterns. This work uses a literature review of 185 studies from across the globe, and a meta-analysis of modelling results from 52 of those studies to validate and to quantify components of the Jefferson et al. (2017) conceptual model. Findings from the analysis confirm that

as SCM implementation (quantified by both watershed area and ISC mitigated) increases, event runoff volumes, and peak flows decrease. This work also quantifies the rate of decline in runoff volumes and peak flows with increased mitigation, and the values of mitigation required to meet reduction targets for runoff and peak flow. Quantifying these general relationships is a valuable tool for stormwater managers prioritizing watersheds for SCM intervention or using watershed-based metrics to measure program success. Additionally, results show that the ability of SCMs to reduce runoff volumes and peak flows is diminished during larger rain events, and that watersheds that are more impervious are likely to see greater percent reductions in runoff and peak flow for each percent of imperviousness that is managed. The meta-analysis approach offers a conglomerate assessment of stormwater management that includes different sites, locations, assumptions, and biases from many studies and researchers.

DISCLAIMER

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. The manuscript has not been formally reviewed by the U.S. Environmental Protection Agency. The views expressed in this document are solely those of the authors and do not necessarily reflect those of the U.S. Environmental Protection Agency.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the HydroShare repository at https://doi.org/10.4211/hs.63f44659faee4d859c59992784f4b27c (Bell et al., 2019).

ORCID

Colin D. Bell https://orcid.org/0000-0001-8712-9859
Jordyn M. Wolfand https://orcid.org/0000-0003-2650-4373
Chelsea L. Panos https://orcid.org/0000-0002-2171-9570
Aditi S. Bhaskar https://orcid.org/0000-0001-9803-4003
Ryan L. Gilliom https://orcid.org/0000-0002-8706-6525
Terri S. Hogue https://orcid.org/0000-0003-1524-8896
Kristina G. Hopkins https://orcid.org/0000-0003-1699-9384
Anne J. Jefferson https://orcid.org/0000-0002-0585-9602

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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