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Catchment-Scale Hydrologic Effectiveness of Residential Rain Gardens: A Case Study in Columbia, Maryland, USA

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Abstract: To mitigate the adverse impacts of urban stormwater on streams, watershed managers are increasingly using low-impact development and green infrastructure (LID-GI) stormwater control measures, such as rain gardens—vegetated depressional areas that collect and infiltrate runoff from rooftops and driveways. Their catchment-scale performance, however, can vary widely, and few studies have investigated the cumulative performance of residential rain gardens for event runoff control in intermediate-sized (i.e., 1–10 km^2) suburban catchments. We modeled three years of continuous rainfall-runoff from a 3.1 km^2 catchment in Columbia, MD, USA, using the Storm Water Management Model (SWMM). Various extents of rain garden implementation at residential houses were simulated (i.e., 25%, 50%, 75%, and 100% coverage) to determine the effects on peak flow, runoff volume, and lag time. On average, treating 100% of residential rooftops in the catchment reduced peak flows by 14.3%, reduced runoff volumes by 11.4%, and increased lag times by 3.2% for the 223 rainfall events during the simulation period. Peak flow reductions were greater for smaller storm events ($p < 0.01$). Our results show that residential rain gardens can significantly improve the runoff response of suburban catchments, and that they represent an effective and relatively low-cost option for urban watershed management and restoration.

Keywords: green infrastructure; low-impact development; best management practices; urban stormwater; SWMM; stormwater management; urban hydrology

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1. Introduction

Urban development has numerous adverse impacts on stream health, including alteration of the flow regime, degraded water quality, channel scour and erosion, and reduced biodiversity [1–3]. These changes—termed *urban stream syndrome*—are driven primarily by increased impervious surfaces and soil compaction, as well as reduced vegetation, and the efficiency of engineered drainage systems, which lead to flashier hydrographs, higher peak flows, and greater stormflow volumes [2,4,5]. To better manage urban stormwater and protect aquatic ecosystems, in recent decades, there has been an increase in the use of low-impact development and green infrastructure (LID-GI) practices designed to detain, infiltrate, and/or evapotranspirate stormwater runoff at or near its source [6,7]. One such decentralized stormwater management facility is a bioretention cell or rain garden (RG), i.e., a vegetated depressional area that collects and infiltrates surface runoff [8]. While previous studies have demonstrated the ability of RGs and other LID-GI practices to reduce stormwater runoff from individual lots (e.g., [9–12]), uncertainty remains regarding the effectiveness and optimal implementation of these practices in different physical settings and at larger spatial scales [13–15].

RGs are attractive options for retrofitting residential properties to better manage runoff from rooftops and driveways because of their lower cost, smaller scale, and aesthetic appeal. They are widely promoted to homeowners in suburban areas to help reduce stormwater impacts to receiving streams [16]. Their catchment-scale performance for mitigating event runoff, however, is an ongoing area of research [13,14,17]. Several monitoring studies have demonstrated that distributed, infiltration-based LID-GI practices can, in some cases, reduce runoff volume and peak flow at the catchment scale [18–24], but their performances vary widely. For example, in a before–after control–impact study of two residential streets retrofitted with RGs and rain barrels, Jarden et al. [19] found that peak and total stormflows were reduced by up to 33% and 40%, respectively, on one street, whereas no significant reduction in these indices was observed on the other street. In another study, Woznicki et al. [24] found that, for lower rainfall amounts, a "green" catchment implemented with vegetated swales reduced peak flows and runoff volumes compared to "grey" catchments installed with traditional curb-and-gutter stormwater conveyances; however, as rainfall depths approached 20 mm, runoff characteristics of the green and grey catchments became similar. These results are consistent with those of Hopkins et al. [18], who found that, at non-exceedance probabilities of $\sim$90% and higher, peak flows in two residential catchments implemented with LID-GI practices were similar to those from an urban reference watershed. In general, empirical studies of the catchment-scale effectiveness of LID-GI practices have been challenged by practical limitations, a lack of long-term data, and the difficulty of isolating the effects of LID-GI implementation from the effects of other basin changes [14].

To address these challenges, numerous studies in the last decade have used simulation approaches to evaluate the stormwater management performance of different types of LID-GI practices at the catchment scale. For example, Avellaneda et al. [25] used the EPA Storm Water Management Model (SWMM) to model the effects of implementing various infiltration-based practices, including RGs, on a residential street, and found that discharges with 0.5-, 1-, 2-, and 5-year return periods were reduced by an average of 29%. These results are consistent with those of Rezaei et al. [26], who used SWMM to model an 18 km^2 watershed and found that installation of RGs and bioswales reduced peak runoff by up to 27% for rainfall depths less than 70 mm. By contrast, Avellaneda and Jefferson [27], using the Soil and Water Assessment Tool (SWAT) to model a 20.6 km^2 watershed, found that even when most (71%) of the rooftops and pavements in the watershed were connected to RGs, the lowest and highest streamflows of each year were not significantly changed. In a 2020 meta-analysis of 52 modeling studies that underscored the wide range of effects of LID-GI implementation on catchment hydrology, Bell et al. [17] found that even for catchments with most or all imperviousness mitigated by LID-GI practices, runoff reduction varied between 0% and 100%. In other words, depending on factors such as LID-GI type and spatial distribution, catchment physical attributes, and rainfall characteristics, LID-GI can capture all, some, or none of the event runoff from a catchment. A central goal for investigations of cumulative LID-GI effects moving forward is to identify and quantify the factors that impact catchment-scale LID-GI performance [17].

Despite the increasing promotion of residential RGs to homeowners by many states and local governments, and the growing number of studies of catchment-scale LID-GI hydrologic effectiveness, relatively few studies have assessed the effects of residential RG implementation in intermediate-sized suburban catchments, with drainage areas between 1 and 10 km^2 [16,17]. Previous research has primarily focused either on sewersheds and subcatchments < 1 km^2 [19,23–25,28–31], on watersheds larger than 10 km^2 [26,27,32–34], or on highly urbanized or non-residential areas [35–40]. Moreover, previous studies have largely either focused on LID-GI practices other than RGs (such as green roofs, permeable pavement, bioswales, infiltration trenches, or rain barrels), or examined RGs (or bioretention cells) not in isolation, but as part of a suite of LID-GI practices implemented in a study catchment, obscuring the effects of the RGs alone [21,41–44]. This research gap can be attributed, in part, to the substantial level of effort required to explicitly model the engineered drainage system of catchments larger than 1 km^2, while for those larger than 10 km^2, the storm sewer system can, in many cases, be represented implicitly while retaining model accuracy. As such, the hydrologic effects of extensive implementation of residential RGs in suburban catchments with drainage areas at the scale of 1–10 km^2

remain relatively unexplored. Given the increasing suburban population in the United States and globally [45,46], and the compounding challenges faced by watershed managers from urban stormwater and climate change [47], the paucity of studies of catchment-scale RG performance in suburban catchments constitutes a critical research gap.

The aim of this study was to investigate the effects of varying levels of residential RG implementation on event hydrology in intermediate-scale suburban catchments, using a 3.1 km^2 catchment in Columbia, MD, USA, as a case study. Using the EPA Storm Water Management Model (SWMM), we simulated continuous rainfall-runoff in the catchment to assess how treating increasing proportions of detached house rooftops with RGs might affect event runoff indices. This study addresses the research question: What is the capacity of residential RGs to mitigate event runoff in a suburban catchment? We hypothesized that implementation of residential RGs at a majority of detached houses in a suburban catchment would significantly alter catchment hydrologic response by reducing runoff volumes, reducing peak flows, and increasing lag times.

2. Materials and Methods

2.1. Study Area

The study area is a 3.1 km^2 catchment in Columbia, MD, that discharges to a tributary of the Little Patuxent River (Figure 1). The catchment is in the Piedmont physiographic province of central Maryland, and the catchment outlet is located approximately 11.3 km northwest of the Fall Line. Bedrock consists primarily of quartz monzonite (Guilford Granite Formation) and schist (Oella Formation) [48]. Elevations range from 105 to 152 m above sea level. The area has a humid subtropical climate; mean annual precipitation at nearby Baltimore–Washington International Airport is 1.11 m (43.6 in) [49]. A U.S. Geological Survey (USGS) streamflow gaging station (01593370) has been operating at the catchment outlet since 1 October 2012 [50].

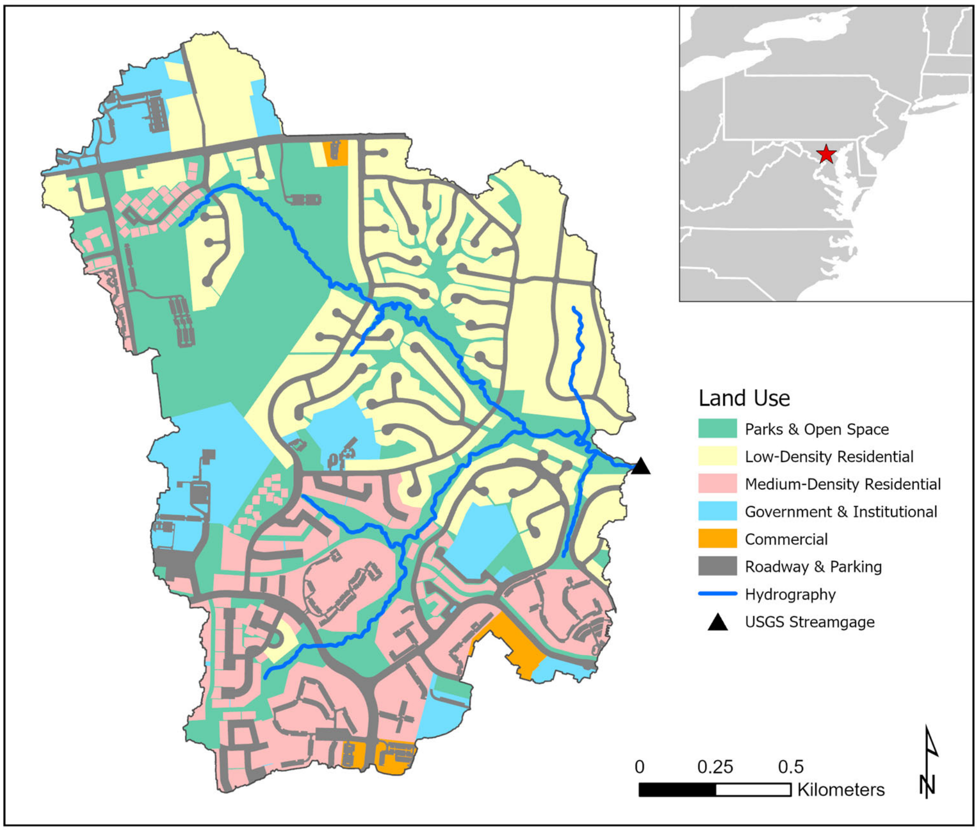

Figure 1. Study area location map and land-use distribution.

This formerly agricultural catchment was developed in the late 1960s with a municipal separate storm sewer that discharges directly to the stream network [51]. Land use within the catchment is predominantly low- to medium-density residential, with some commercial, recreational, and institutional uses (Figure 1). The catchment has 32% total impervious surface cover, and low-density residential land use (i.e., single-family detached housing) accounts for the second largest source of catchment imperviousness after roadways and parking lots. As of 2024, there were 746 detached houses and 819 attached houses (townhomes) in the catchment. Cumulatively, detached house rooftops accounted for 13.1% of imperviousness and 4.0% of total area within the catchment. Based on its topography, land use, surface cover, and drainage characteristics, the study area is considered broadly representative of Mid-Atlantic suburban catchments developed in the 20th century [51].

2.2. Hydrologic Model Development and Calibration

The EPA Storm Water Management Model (SWMM) version 5.2.4 was used to simulate the hydrologic response of the study catchment. SWMM is a semi-distributed hydrology-hydraulic modeling system for single-event or continuous modeling, developed specifically for simulating stormwater runoff in urban environments [52]. To run SWMM, we used the Personal Computer Storm Water Management Model (PCSWMM), proprietary software developed by Computational Hydraulics International (CHI) that integrates the SWMM computational engine with a geographic information system and enhanced analysis capabilities [53]. SWMM simulates infiltration, evaporation, and runoff for user-delineated subcatchments, and then routes the resulting flow through the drainage system to generate an output hydrograph. Pervious and impervious surfaces within a subcatchment are each treated as a nonlinear reservoir whose capacity is the maximum depression storage; runoff occurs when the water depth within the reservoir exceeds the depression storage [25,54].

Watershed delineation and model parameterization were conducted using ArcGIS Pro [55]. The study catchment was discretized into 382 subcatchments based on topography, location of storm drains, and building rooftop pitch and downspout locations. Subcatchment areas ranged from 0.02 ha to 11.44 ha, with a median of 0.48 ha. To parameterize the model, GIS spatial analyses were conducted based on acquired data layers (Table 1) to determine the subcatchment physical characteristics required by SWMM, including area, characteristic width (i.e., width of overland flow), percent imperviousness, surface slope, roughness coefficient and depression storage for pervious and impervious areas, and infiltration parameters (i.e., saturated hydraulic conductivity, suction head, and initial moisture deficit). Storm sewer locations and parameters, including pipe length, slope, cross-section, and roughness, were gleaned from storm drain infrastructure design and as-built drawings (Figure 2). In the case of several inlets and manholes, there were data gaps in the available storm sewer drawings, and field visits were required to measure pipe sizes and storm drain inlet depths. Stream channel geometries were derived from channel topographic cross-sections using PCSWMM's transect creator tool.

Table 1. Data layers and sources used in model construction and parameterization.

Dataset or Layer Name	Description	Source
Digital Elevation Model (DEM)	1 m DEM, dated 2018	USGS 3DEP Program, via USGS National Map Downloader [56]
Orthoimagery	High-resolution (6-inch) aerial photography, dated 2014 and 2020	USGS Earth Explorer [57] and MD iMAP Portal [58]
Impervious Cover	Dated 2020	Howard County Maryland Data Download and Viewer [59]
Land Use	Dated 2024	Howard County Maryland Data Download and Viewer [59]
Forest Cover	"Soft canopy" dated 2018	Howard County Maryland Data Download and Viewer [59]

Table 1. *Cont.*

Dataset or Layer Name	Description	Source
Soil Data	Characteristics for top 2 m of soils	Natural Resources Conservation Service (NRCS) Soil Survey Geographic Database (SSURGO) [60]
Storm Sewer Infrastructure	Geodatabase containing inlet, manhole, pipe, and outfall locations	Howard County Stormwater Management Division [61]
Rainfall	5 min interval rainfall data	Baltimore County Rain Gauge Network [62]
Temperature	Daily maximum and minimum temperature	Observation station operated by a Community Collaborative Rain, Hail, and Snow Network (CoCoRaHS) observer [63]
Discharge	1 min interval discharge at the catchment outlet	USGS streamgage 01593370, via the National Water Information System (NWIS) [50]

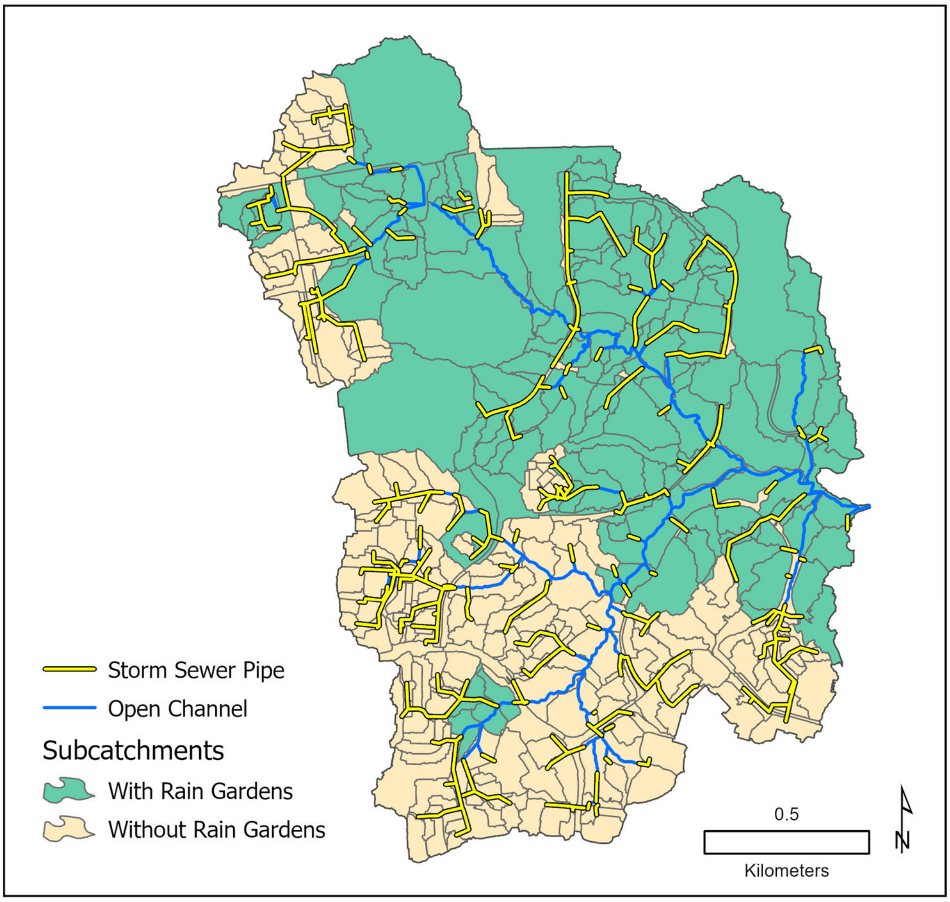

Figure 2. Conduits (storm sewer pipes and open channels) and subcatchments represented in the SWMM model. In the rain garden scenario simulations, subcatchments that contained any number of single-family detached houses (shown in green) were implemented with a proportional number of rain gardens.

Infiltration was simulated using SWMM's Modified Green-Ampt model. The Green-Ampt equation is more physically-based than other infiltration estimation methods, and the Modified Green-Ampt method adjusts the original Green-Ampt procedure by not depleting moisture deficit in the top surface layer of soil during initial periods of low rainfall [52,64]. This method can produce more realistic infiltration behavior for storm events with long initial periods, during which the rainfall intensity is below the soil's saturated hydraulic conductivity [52]. The dynamic wave method was used for hydraulic routing due to its ability to simulate non-uniform, unsteady state flow conditions. SWMM uses the Hargreaves method to simulate evaporation based on a daily minimum and maximum temperature time series and the catchment's latitude [54,65].

The model was calibrated using two years of observed discharge at a one-minute time-step at the catchment outlet, 5 min rainfall data from a rain gage 0.75 km (0.47 mi) from the catchment boundary, and temperature data (daily minima and maxima) from an observation station 0.98 km (0.61 mi) from the catchment boundary. A sensitivity analysis was performed using PCSWMM's Sensitivity-based Radio Tuning Calibration (SRTC) tool, which runs the model repeatedly, varying the values of selected parameters based on user-defined uncertainty ranges, and displays the ranked sensitivity of an objective function (e.g., peak flow) to the parameters. The selected calibration parameters were the seven most sensitive subcatchment attributes: characteristic width (a proxy for subcatchment shape), percent imperviousness, saturated hydraulic conductivity, depression storage for pervious areas, Manning's roughness for pervious areas, suction head, and surface slope. Although SWMM can simulate groundwater flow based on aquifer parameters, calibration results were improved when the groundwater process model was turned off, so groundwater flow was not simulated. The calibration period was water years 2019–2020, and the Nash–Sutcliffe Efficiency (NSE, a commonly used statistic for assessing the goodness-of-fit of hydrologic models) after calibration was 0.766 [66]. Values of the NSE closer to 1 indicate a model with more predictive power; models with values of NSE between 0.7 and 0.8 are commonly classified as "satisfactory" [67,68]. The calibrated model was validated against one year of observed discharge (water year 2021), for which the NSE was 0.711. Based on evaluations of model performance criteria in the literature, the model was considered satisfactory [68].

2.3. Rain Garden Scenario Simulations

To test the effects of varying extents of residential rain garden (RG) implementation on event runoff, multiple scenarios were created in SWMM to represent the treatment of detached house rooftops by RGs. SWMM allows the user to explicitly simulate the performance of low-impact development and green infrastructure (LID-GI) practices, including RGs. An RG is defined by SWMM as a bioretention cell without a storage layer (i.e., a gravel bed) or underdrain, and thus has only a vegetated surface layer and a soil layer. Runoff from RGs is estimated by a mass balance equation consisting of inputs (run-on and direct precipitation) and outputs (infiltration, evapotranspiration, and overflow). To test the effects on event hydrology of retrofitting of residential houses with RGs in the study catchment, four RG implementation scenarios were modeled. These included 25%, 50%, 75%, and 100% implementation scenarios, which correspond to one quarter, one half, three quarters, and the entirety of the rooftop area of all detached single-family houses in the catchment draining to RGs, respectively.

A generic RG was parameterized and duplicated for use in the RG scenario simulations. RG attributes were based on both reference values and previous RGs installed in Columbia, MD [69]. The following values were used for the surface layer in a RG: a berm height of 102 mm, a vegetation volume fraction of 0.1, a Manning's roughness coefficient of 0.3, and a surface slope of 0.25%. The following values were used for the soil layer: thickness of 889 mm, porosity of 0.44, field capacity of 0.11, wilting point of 0.05, hydraulic conductivity of 25 mm/h, conductivity slope (average slope of log of conductivity versus soil moisture deficit curve) of 7.5, and a suction head of 89 mm. These values are consistent with those given in Rossman and Huber [69] and Avellaneda et al. [25]. RG area was set to 20.9 m^2, which can treat approximately 43.3 m^2 of rooftop, or one quarter of the average detached house rooftop area in the study catchment. Thus, the average detached house in the study catchment would be treated by exactly four RGs. In the 100% RG implementation scenario, 2985 RGs covering an area of 6.2 ha were installed to treat 746 houses in 137 subcatchments (Figure 2).

A three-year simulation period was used in the scenario simulations (water years 2016–2018). A three-year simulation period was selected to capture seasonal variability and a range of annual rainfall (i.e., relatively wet, dry, and average years), and to include enough runoff events for robust statistical analyses. There were 365 rainfall events in the simulation period, identified using a minimum inter-event time of 6 h (rainfall occurring more than 6 h after the previous rainfall constituted a new event). These events were filtered to 224 events that generated significant runoff in the baseline scenario, i.e., those producing peak flows greater than 0.057 cubic meters per second (2 cubic feet per second). One of these events was removed as an outlier because it produced a double hydrograph peak that led to erroneous peak flow reduction and lag time increase calculations, leaving a sample of 223 runoff events for analysis. For each of these events, peak flow, event runoff volume, and time of peak flow were calculated from the simulated hydrographs. From these data, peak flow reductions, runoff volume reductions, and lag time increases were calculated for all events in each experimental scenario, relative to the baseline scenario. Lag time was calculated as the time from rainfall centroid to peak discharge (centroid lag-to-peak). To evaluate the difference between the sets of paired hydrologic metrics (before and after RG implementation), one-sided Wilcoxon Signed Rank Tests for paired samples were performed in R. The non-parametric paired difference hypothesis test was employed because it could not be assumed that the populations of variable values were normally distributed. The tests were one-sided because it was expected that the median differences in peak flows, event runoff volumes, and times of peak flow between the baseline and RG implementation scenarios were, respectively, a decrease, a decrease, and an increase. The null hypothesis was that the median difference between the two populations was zero, with an alpha value threshold for significance of 0.05. Additionally, linear regression was used to test whether rainfall depth had a relationship with each of the runoff parameters of peak flow, event runoff volume, and lag time.

3. Results

For each of the four rain garden (RG) scenarios (25%, 50%, 75%, and 100%), differences in peak flow, stormflow volume, and time of peak flow between the 223 matched events were found to be statistically significant ($p < 0.01$) for all RG implementation scenarios. Mean peak flow reductions (PFRs) for the 25%, 50%, 75%, and 100% RG implementation scenarios were 3.6%, 7.2%, 10.8%, and 14.3%, respectively (Figure 3). For the 100% RG implementation scenario, PFRs ranged from 4.0% to 22.2% (Figure 4). For only the 18 events with rainfall depths > 38.1 mm (1.5 in), mean PFR in the 100% RG implementation scenario was reduced to 9.3%, while for the 131 events with rainfall depths < 12.7 mm (0.5 in), mean PFR increased to 15.4%. Peak flow reduction (PFR) was inversely correlated with rainfall depth ($p < 0.01$) (Figure 5).

Mean event runoff volume reductions (RVRs) for the 25%, 50%, 75%, and 100% RG implementation scenarios were 2.9%, 5.8%, 8.6%, and 11.4%, respectively (Figure 6). For the 100% RG implementation scenario, RVRs ranged from 4.2% to 14.5% (Figure 7). For events with rainfall depths > 38.1 mm (1.5 in), mean RVR in the 100% RG implementation scenario was 10.5%, while for events with rainfall depths < 12.7 mm (0.5 in), mean RVR was 11.1%. A regression analysis did not find a significant linear relationship between runoff volume reduction and rainfall depth.

The mean lag time (centroid lag-to-peak) for the 223 events in the baseline scenario was 1 h and 16 min. This lag time was increased in the 25%, 50%, 75%, and 100% RG implementation scenarios by <1 min, 1.4 min, 1.9 min, and 2.4 min, respectively.

Overall, for the smallest level of RG implementation at 25%, corresponding to 3.3% of total impervious area (TIA) treated in this 3.1 km^2 catchment, we found that event runoff improved by a mean reduction of peak flow of 3.6%, and a mean reduction in runoff volume of 2.9%. For full implementation of residential RGs at the 100% level (or 13.1% of TIA), we found that, on average, peak flows were reduced by 14.3%, runoff volumes were reduced by 11.4%, and times of peak flow were delayed by 3.2%.

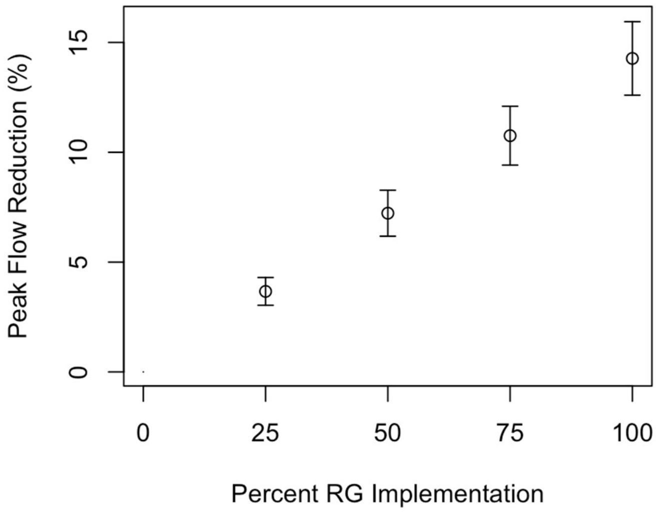

Figure 3. Mean peak flow reductions for the four rain garden (RG) scenario simulations. Error bars are one standard deviation.

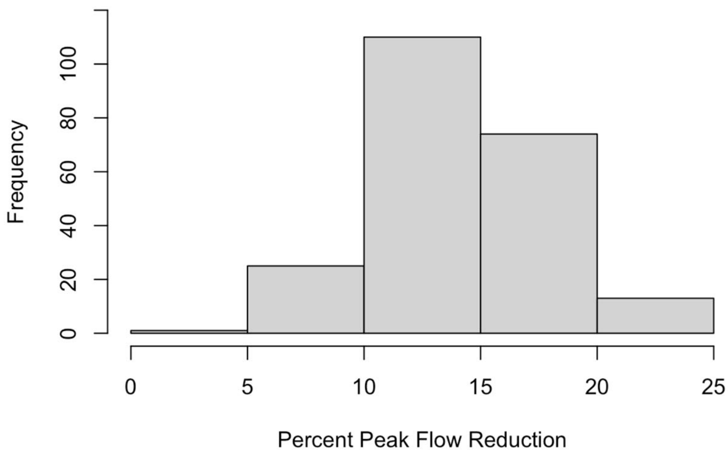

Figure 4. Histogram of percent peak flow reduction for the 100% rain garden implementation scenario (223 total events).

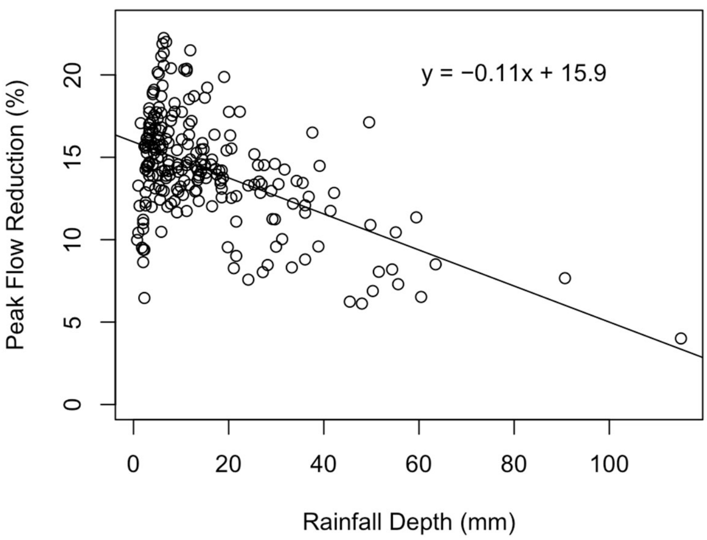

Figure 5. Relationship between peak flow reduction and rainfall depth for the 223 rainfall events, with linear regression line ($p < 0.01$).

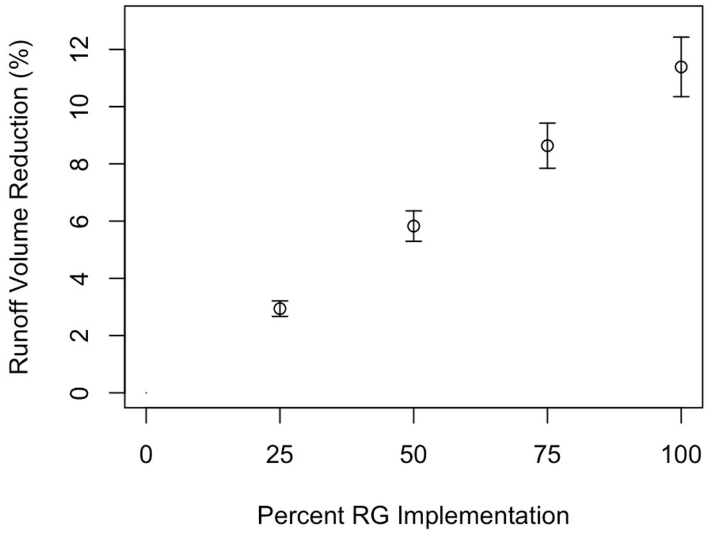

Figure 6. Mean runoff volume reductions for the four rain garden (RG) scenario simulations. Error bars are one standard deviation.

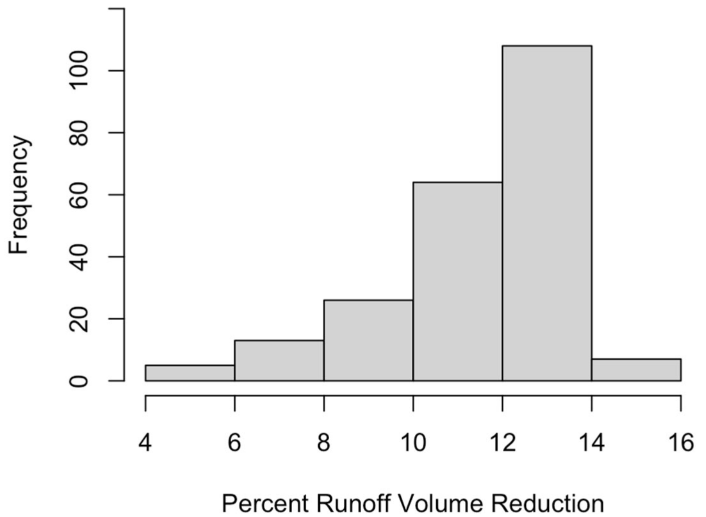

Figure 7. Histogram of percent runoff volume reduction for the 100% rain garden implementation scenario (223 total events).

4. Discussion

The simulation results indicated that rain garden (RG) implementation can significantly reduce peak flows and runoff volumes, and increase lag times, even when implemented at only 25% of detached house rooftops. Treating 100% of residential rooftops in the catchment (4.1% of the catchment area and 13.1% of total impervious area [TIA]) could reduce peak flows by up to 22.2%, and runoff volumes by up to 14.5%. Mean reductions in peak flow and runoff volume were greater for smaller storm events, and peak flow reduction was linearly related to rainfall depth ($p < 0.01$). These results are consistent with those of Samouei and Özger [37], who found in a simulation study that treating 10% of TIA with various LID-GI practices, including bioretention cells in a 1.05 km^2 catchment, reduced peak flows and runoff volumes from the 2-year storm by 12% and 8%, respectively. In another modeling study, Hoghooghi et al. [70] found that implementing a 0.94 km^2 mixed suburban, agricultural, and forested watershed with RGs and other LID-GI practices reduced peak flow and surface runoff of 8.5% and 8.0%, respectively. Based on a statistical relationship between percentage of TIA treated and catchment-scale LID-GI hydrologic performance developed in a meta-analysis by Bell et al. [17], if 13.1% of TIA was redirected to RGs (as in the 100% RG implementation scenario), peak flows and event runoff would be expected to be reduced by 7.9% and 5.6%, respectively. The RG performances simulated in this study were generally consistent with those observed in previous, similar investigations, and bear out the findings that percent peak flow reductions typically exceed runoff volume reductions, and that performance diminishes with increasing storm depth. This study is distinguished by its scale, level of detail (382 subcatchments), its use of continuous rather than event-based simulations, and its focus on residential RGs in suburban areas.

Simulated lag time increases (2.4 min on average for the 100% implementation scenario) were consistent with those of Palla and Gnecco [71], who developed a SWMM model of a 5.5 ha catchment and found that treating up to 36% of the effective impervious area (EIA) with green roofs and permeable pavement increased lag times from the 2-year storm by ~3 min. The lag time increases in the present study were smaller than those observed by Li et al. [72], who used SWMM to model the effects of RG implementation in a 16.5 km^2 highly urbanized catchment, and found that treating 4% of the catchment delayed peak flows from the 2-year storm by up to 7 min. In general, the results of the present study support the prior body of evidence that implementation of LID-GI such as RGs can result in modest but statistically significant increases in lag time. Few, if any, previous studies, however, have specifically examined the catchment-scale performance of residential RGs in suburban basins of this size.

The present study, like other modeling investigations of LID-GI hydrologic performance, is subject to several assumptions and limitations. For example, as a lumped (semi-distributed) hydrologic model, SWMM is based on the assumption that physical characteristics within each subcatchment (e.g., soil type and surface slope) are uniform [52]. We addressed this limitation to some extent by our fine-scaled delineation of subcatchments, with each selected to group together similar topographic and land-use characteristics within the hydrologic network of the study area. Further assumptions are associated with process representation in SWMM, such as the Green-Ampt method for modeling infiltration, which assumes that a sharp wetting front exists within the soil column, and rainfall, which is assumed to be uniform over the catchment [52]. Nonetheless, Green-Ampt is a physically-based model that has shown satisfactory agreement with observation [64], and rainfall spatial variability over an area the size of the study catchment can be considered negligible, as verified by model calibration.

For this study specifically, the SWMM model did not explicitly represent floodplain storage, snowmelt, or groundwater contributions to stream discharge, although as in many small, urban watersheds, these contributions were deemed to have minimal impacts on event flow indices [73]. The extensive calibration and validation periods showed that the model, as implemented, satisfactorily matched observed streamflow at the outlet USGS streamgage. Additionally, a single, generic RG was parameterized and duplicated for use in this study's RG scenarios, whereas real-world RG implementations can vary widely in composition and construction. Temporal variations in RG functioning were also ignored, such as deterioration in performance due to clogging, vegetation change, or lack of maintenance, which could lead to over-estimation of long-term catchment-scale effectiveness [15].

This study addressed an important research gap in the literature by investigating the catchment-scale effectiveness of residential RGs in an intermediate-sized suburban catchment. Moreover, the present study was notable for its fine scale and level of detail, with the model containing 382 subcatchments, and explicitly representing 473 storm sewer inlets and manholes in a catchment area of only 3.1 km^2. Future research should examine the effects of varying the spatial distribution of RGs on their cumulative performance, as well as temporal factors, such as seasonal variation in antecedent moisture conditions, soil distributions and disruptions in urban settings, and non-stationarity of climate variables. As watershed managers increasingly look to LID-GI approaches to address the compounding effects of urbanization and climate change on water quality and quantity, the results of this study indicate that residential rain gardens can significantly improve the runoff response of suburban catchments, and that rain gardens can be an effective tool for improving stormwater management in residential areas.

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