Assessing watershed-scale stormwater green infrastructure response to climate change in
Clarksburg, Maryland, USA

Emma Giese\(^1\), Amanda Rockler\(^2\), Adel Shirmohammadi\(^3\), Mitchell A. Pavao-Zuckerman\(^4\)

1. Department of Environmental Science and Technology, University of Maryland, College Park, MD, United States.
2. University of Maryland Extension, College Park, MD, United States.
3. Department of Environmental Science and Technology, University of Maryland, College Park, MD, United States.
4. Department of Environmental Science and Technology, University of Maryland, College Park, MD, United States.

Abstract

Stormwater green infrastructure (GI) practices are implemented in urban watersheds to control stormwater runoff, reduce pollution, and adapt to climate change. This study evaluated the robustness of a watershed with stormwater GI and a watershed with traditional stormwater controls in Clarksburg, Maryland to future climate change. The USDA Soil and Water Assessment Tool (SWAT) was calibrated to USGS daily streamflow data from 2011-2016 to evaluate watershed-scale daily and seasonal runoff responses to multiple future climate and management scenarios. The stormwater GI watershed had less runoff than the traditional management watershed in climate change scenarios for most days with rainfall (>98% of days). However, the climate change scenarios resulted in increased seasonal fall and winter runoff.
compared to current conditions in both watersheds. Simulated expansion of GI implementation reduced runoff in both watersheds under future climate scenarios. This study assesses climate robustness of existing stormwater GI at a watershed scale, and confirms previous evaluations of hypothetical stormwater GI effectiveness for adapting watersheds to climate change.

Keywords: stormwater management, hydrologic modeling, bioretention, green stormwater management practices
Introduction

Impervious cover in urban watersheds causes increased surface runoff and decreased infiltration to groundwater compared to pre-development conditions (L.B. Leopold, 1968). As a result, urban streams have lower baseflow, higher peak flow, and reduced time to peak compared to streams in non-urban watersheds (L.B. Leopold, 1968; Shuster et al., 2005). The changes in hydrology also lead to increased erosion, increased pollutant transport, and loss of instream habitat and function (Paul and Meyer, 2001; Walsh et al., 2005). In addition to these direct impacts on streams, urban watersheds have increased risk of flooding during storms, and pollutants mobilized by stormwater are transported downstream to receiving water bodies. A variety of stormwater control measures are used to reduce these impacts by treating stormwater volume and water quality.

Stormwater green infrastructure (GI) is employed to mitigate the effects of urbanization on streams and watersheds through design practices that facilitate pre-development processes, including infiltration and evapotranspiration (Dietz, 2007). Examples of infiltration practices include bioretention (rain gardens), swales, and pervious pavement (Bean et al., 2007; Davis et al., 2009, 2012). Many GI practices also reduce nutrient, sediment, and toxic contaminant pollution through biological denitrification, filtration, sorption, or plant uptake (Diblasi et al., 2009; Hunt et al., 2012; LeFevre et al., 2015). Stormwater GI practices are typically small scale and distributed throughout a watershed. This differs from the traditional management approach of centralized treatment, such as retention ponds, or grey infrastructure (Ahiablame et al., 2012).

Climate change will likely place additional pressure on urban watersheds through increasing temperatures (IPCC, 2014a) and increased intensity and frequency of extreme hydrologic events in mid-latitude land masses (IPCC, 2014a). As a result, there may be more
runoff and flooding in urban watersheds under future climate conditions (Praskievicz and Chang 2009). Urban watersheds are vulnerable to climate change, because they have large populations, as well as infrastructure and resource requirements. Stormwater green infrastructure implementation has been recommended as an adaptation tool for climate change impacts that include flooding, drought, and urban heat island (US EPA, 2014). However, GI practices are designed for current climate, and may not be sufficient to achieve these goals under future climate conditions.

Previous assessments of the response of stormwater GI to climate change or as a climate adaptation tool have focused on modeling of hypothetical GI implementation scenarios, and evaluation of existing stormwater GI response to climate change at individual or site scales. Most of these studies found that simulated GI implementation could help adapt an urban watershed to climate change by reductions in the projected increases in runoff (Borris et al., 2013; Gill et al., 2007; Kim et al., 2015; Pyke et al., 2011; Waters et al., 2003; Zahmatkesh et al., 2015, Sarkar et al. 2018). However, evaluations of site scale GI and other stormwater management practices indicated that these practices may be undersized for future climate conditions (Forsee and Ahmad, 2011; Hathaway et al., 2014; Moglen and Vidal, 2014). Evaluating the climate change responses of stormwater GI at watershed scales has been understudied (but see Cheng et al. 2017 focusing on flooding), perhaps due to a lack of data related to implementation and performance at watershed scales. The Chesapeake Bay watershed provides an opportunity to study existing practices at watershed scale, because there is a longer history of implementation (e.g. (Prince George’s County, Maryland, 2007), and there are more complete local government records on GI implementation because of the tracking requirements for the Chesapeake Bay Total Maximum Daily Load (TMDL) (US EPA, 2010).
The response of environmental systems to climate change is often framed as a resilience challenge. Yet, the term resilience has a complex history with disparate meanings and applications across several disciplines. This study adopts an ecological perspective, where resilience refers to the ability of a system to buffer change and persist in the face of environmental pressures, that is to be robust to environmental change (Folke 2006). It should be noted that resilience has other dimensions. For example, the National Academy of Sciences (2012) offers a definition of resilience that is, “the ability to prepare and plan for, absorb, and recover from, and more successfully adapt to adverse effects.” Meerow et al. (2016) define resilience for urban settings (where GI is often situated) as, “the ability of an urban system…to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity.” The ability to maintain desired functions, or system robustness, remains a key component of these definitions of resilience.

This research asked: are stormwater GI functions robust to climate change at a watershed scale? Specifically, it evaluated if: 1) surface runoff will increase in future climate scenarios compared to the present; 2) existing stormwater GI will provide the same relative reduction in surface runoff in future climate scenarios compared to the present; and 3) hypothetical (expanded) stormwater GI implementation will improve watershed responses to climate change. To answer these questions the authors modeled two urban watersheds (one with existing stormwater GI and one with traditional stormwater management) using the USDA Soil and Water Assessment Tool (SWAT), calibrated and validated using USGS streamflow records. The calibrated model was used to simulate multiple climate change and stormwater management scenarios to evaluate the robustness of the watershed to climate change.
Methods

Site description

Two watersheds with available USGS observed stream flow data, that are within the same soil type and physiographic region, and within close proximity (within 7 km) of each other were selected for this study: they include a watershed that was developed with centralized, traditional stormwater management and a watershed that was developed using decentralized, low-impact development (LID) green infrastructure practices (Hopkins et al., 2017; Bhaskar et al., 2016; Loperfido et al., 2014). The two watersheds in this study are located in Montgomery County, MD within the Piedmont physiographic region (Figure 1). Both watersheds drain to Little Seneca Creek tributary, and then to the Potomac River. Average annual precipitation at the nearby Damascus 3 SSW MD US station (1980-2010) is 1177.5 mm. Average annual daily maximum temperature is 17°C and average annual daily minimum temperature is 6.9°C at Damascus 3 SSW MD US (1980-2010).

Tributary 104 in Clarksburg, MD is a 1.2 km² watershed, and was primarily farmland and forest until 2004 (Hogan et al., 2014). Between 2004 and 2010 it was developed into a residential area with 30% impervious cover. Tributary 104 is within the Clarksburg Special Protection Area, which requires additional natural resource protection beyond existing environmental regulations for new development, including approval of a water quality plan (Montgomery County Code, 2001). During development, 121 hydrology and water quality stormwater green infrastructure practices were installed in the Tributary 104 watershed to meet these requirements (Loperfido et al., 2014). 68 of the practices were designed for infiltration (e.g. dry swales, stormwater recharge facilities), 12 were designed for hydraulic detention (e.g. dry ponds), 5 were bioretention
facilities designed for both infiltration and detention, and 36 were designed for water quality (e.g. oil and grit separators, sand filters) (Loperfido et al., 2014). Tributary 104 is referred to in this paper as the green infrastructure “GI” watershed. Crystal Rock in Germantown, MD is a 3.1 km² watershed, with 39% impervious cover. Development in Crystal Rock occurred prior to and during the 1990s (Rhea et al., 2015). Crystal Rock has 43 traditional hydrology and water quality stormwater practices. Five of the practices were designed for hydraulic detention (e.g. dry ponds), 7 were designed for detention and water quality (e.g. wet ponds), and 31 were designed for water quality (e.g. oil and grit separators, sand filters) (Loperfido et al., 2014). Unlike Tributary 104, none of the stormwater practices in Crystal Rock were designed for infiltration. Crystal Rock is referred to in this paper as the “traditional” watershed. Together these two watersheds represent differing approaches to stormwater management: a centralized approach with emphasis on hydraulic detention and water quality in the traditional watershed, and a distributed approach with an emphasis on infiltration in the GI watershed. The U.S. Geological Survey (USGS) has continuously monitored both watersheds from 2004-2016. Previous studies in these watersheds have assessed impacts of urbanization on baseflow, elevation changes in the watershed, and impacts of the stormwater management on runoff. (Hopkins et al. 2017; Bhaskar et al., 2016; Hogan et al., 2014; Jones et al., 2014; Loperfido et al., 2014; Rhea et al., 2015).

**SWAT model set up and data sources**

The authors used the USDA SWAT model to simulate each of the two watersheds in this study (Arnold et al., 1998; “SWAT,” 2017). SWAT is a daily timestep, spatially distributed, long-term (i.e., multiple years) continuous simulation model. Thus, SWAT does not handle each storm hydrograph separately, as it is not using breakpoint rainfall data (Arnold et al., 1998; “SWAT,” 2017). This study seeks to simulate and investigate long-term impacts of green
infrastructure practice on urban watershed responses to climate change. Therefore, the SWAT model is suitable for such conditions based on previous studies at watershed scales over long-term simulations (Sexton et al., 2011; Chu et al., 2004a&b). Because SWAT utilizes a daily time-step, this analysis does not consider effects that occur at finer temporal resolutions, rather, it focuses on long-term responses at the watershed scale. Selecting a long-term continuous simulation model over an event-based model (like SWMM, (see Giacomoni and Joseph, 2017, for example)) involves a tradeoff between the increased ability to simulate a long-term continuous period using global climate models and the decreased ability to simulate flooding during individual storms. This study seeks to evaluate long-term watershed responses to climate scenarios, addressing calls in the literature for integrating future conditions into evaluations of GI effectiveness (Brink et al. 2017). The SWAT model has been used at multiple scales, under diverse physiographic regions, and in urban settings (Wang et al. 2015, 2017; Cheng et al. 2017; Franczyk and Chang, 2009). The scale of the watersheds in this study are similar to previous studies conducted by Chu et al. (2004a and 2004b) who simulated hydrologic and water quality responses of a small agricultural watershed with an area of about 3.44 km² located in the piedmont physiographic region of Maryland.

Watershed delineation

Maryland LiDAR data for Montgomery County from 2013 was the base layer for watershed elevation (Maryland, 2013). The latitude and longitude coordinates of the USGS monitoring stations defined the watershed outlets and the watershed delineation. One-meter resolution land cover data from Chesapeake Conservancy defined land use classes in SWAT (Chesapeake Conservancy, 2016). The detailed land uses were grouped into three categories:
mixed forest, turfgrass, and impervious. Values for the turfgrass and impervious land uses were added to the urban database in SWAT and default values were used for the other classes (Table 1). Parameters for turfgrass were based on curve number (CN) values for open space in good condition and Manning’s n values for bermudagrass (Soil Conservation Service, 1986). Parameters for impervious surfaces were based on CN for impervious cover and Manning’s n values for smooth surfaces (concrete, etc.) (Soil Conservation Service, 1986). USDA Soil Survey Geographic (SSURGO) GIS data defined the soils (NRCS, n.d.). Hydrologic soil group indicates the infiltration capacity and runoff potential of soil based on categories A, B, C, and D. Soils in group A have the lowest runoff potential and soils in group D have the highest runoff potential. Soils were primarily hydrologic soil group B (85% in the GI watershed and 86% in the traditional watershed). The remaining soils were hydrologic soil groups C and D (each between 5-9% of watershed area). LiDAR data defined the slopes in the watersheds. Hydrologic Response Units (HRUs) were defined by the unique combinations of each class of land cover, soil, and slope class. 10% minimum area thresholds for land cover, soil, and slope were used to reduce simulation time. The goals of this project were to analyze streamflow, which is less sensitive to changes in HRU threshold than nutrients and sediment (Her et al., 2015).

Weather data

Daily precipitation data (mm) and daily maximum and daily minimum temperature data (°C) were downloaded for 1/1/2008-12/31/2016 from NOAA’s Climate Data Online tool for the Damascus 3 SSW MD US weather station (NOAA, 2017). The Damascus station is 4.19 km from GI watershed outlet, and 8.23 km from the traditional watershed outlet. Gaps in the precipitation and temperature data were filled with model generated data in SWAT.
Streamflow

Measured daily average streamflow data (m³/s) were downloaded for the traditional watershed for the period of 1/1/2011-12/31/2016 and the GI watershed for the period of 3/1/2011-12/31/2016 from the USGS water data site (https://waterdata.usgs.gov/nwis/uv?01644375 and https://waterdata.usgs.gov/nwis/uv?01644371). The time period for the GI watershed data was selected to begin after construction was completed in the watershed.

Model parameterization, calibration, and validation

The SWAT model was calibrated for both GI and traditional watersheds using a daily time-step. The calibration period was from 1/1/2011-12/31/2014, with a three year warmup period from 2008-2010. The validation period was two years, from 1/1/2015-12/31/2016, with a three year warmup period from 2012-2014 (see figure 2). The authors chose these time periods to represent a range of wet and dry years. Average annual rainfall during the calibration period was 1322.5mm and during the validation period was 1195.3mm.

SWAT Calibration and Uncertainty Programs (SWAT-CUP) public domain software were used for sensitivity analysis and calibration (“SWAT,” 2017). Twenty-five model parameters were selected for calibration based on SWAT hydrology modeling literature (Abbaspour et al., 2015). One-at-a-time sensitivity analyses were conducted in SWAT-CUP for each of the 25 parameters. The sensitive parameters were then used to calibrate the model using the Sequential Uncertainty Fitting Version 2 (SUFI-2) method (Abbaspour et al., 2004). The SUFI-2 method uses Latin hypercube sampling to select parameter values within user-defined ranges (McKay et al.; 1979; Iman et al., 1980; Sohrabi et al. 2003). Latin hypercube sampling is a probability based technique to randomly select parameter combinations, thus it does not have
inherent biases that may arise from user selection of the order of parameters in calibration. The authors ran 500 simulations, each with unique parameter values, per calibration iteration. After each iteration, the simulated daily streamflow data were compared with observed daily streamflow data. Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) and percent bias were used to evaluate how well the model fit the observed data. NSE values range from \(-\infty\) to 1, with values closer to 1 indicating better model fit (Gupta et al., 1999). Percent bias measures the simulated data tendency to be larger or smaller than observed, with values closest to 0 indicating better model fit. NSE > 0.5 and percent bias +/- 25% for streamflow is considered satisfactory (Moriasi et al., 2007). SWAT-CUP provides a narrower parameter range after each iteration, based on the parameter values that achieved the best model fit for NSE. These narrower ranges were used to run each subsequent iteration of 500 simulations. The process was repeated for up to 5 iterations, or until model statistics stopped improving. The final parameter values were then used from the calibration period to run SWAT for the validation time period and again calculated NSE and percent bias to evaluate model fit.

**Calibration and Sensitivity Analysis Results**

Calibration improved the model fit measured by the objective function Nash-Sutcliffe efficiency (NSE) for both the GI and traditional watersheds (Table 2). The traditional watershed had NSE = 0.72 for streamflow at daily time step, indicating good performance (Moriasi et al., 2007). The GI watershed had NSE = 0.84 for streamflow at daily time step, indicating very good performance (Moriasi et al., 2007). Percent bias (%BIAS) was less than +/-10 for both watershed models before and after calibration, indicating very good performance (Moriasi et al., 2007). For the validation period, the traditional watershed had NSE = 0.36, and the GI watershed had NSE = 0.44 (Table 2). These both indicate less than satisfactory performance at daily time step (Moriasi
et al., 2007). The performance of model in both watersheds improved at monthly time step: the
traditional watershed had NSE = 0.71, and the GI watershed had NSE = 0.7. Percent bias was
less than +/- 10 for both watersheds during the validation period, indicating very good
performance.

Seven hydrology parameters were sensitive and adjusted to calibrate the model for both
watersheds: curve number (CN2), hydraulic conductivity in the main channel (CH_K2), snowfall
temperature (SFTMP), snowmelt base temperature (SMTMP), snow pack lag factor (TIMP),
maximum canopy storage (CANMX), and soil bulk density (SOL_BD). In addition to these
seven, the model was sensitive to groundwater re-evaporation coefficient (GW_REVAP) for GI
watershed, so this parameter was adjusted for GI watershed during calibration. The model was
sensitive to melt factor for snow (SMFMN) in the traditional watershed, so this parameter was
adjusted during the model calibration for the traditional watershed. This SWAT model has
similar sensitive parameters to other SWAT modeling studies in this region (Chu and
Shirmohammadi, 2004; Renkenberger, 2015; Sexton et al., 2011; Wang, 2015; Abbaspour 2007),
giving further confidence that these model simulations were statistically sound and reasonable
for local suburban watershed conditions and their responses to climate drivers.

The model simulated observed streamflow well at a daily time step during the calibration
period both the stormwater GI and the traditional watersheds (Table 2). The model performed
worse during the validation period than the calibration period for both watersheds based on the
NSE metric at daily time step (Table 2). NSE values improved at monthly time step for both
watersheds during the validation period. This improvement in model performance at longer time
intervals has been observed in other SWAT studies (Chu and Shirmohammadi, 2004). The low
percent bias in both watersheds during both calibration and validation periods indicates further confidence that the model is providing reasonable simulation of streamflow.

Scenario analysis

The robustness of the ability of stormwater GI to buffer changes in runoff under projected climate scenarios was assessed by using the calibrated and validated models to test 36 scenario combinations. The scenarios included four climate model forecasts (derived from 2 global climate models (CCSM4 and MRI-CGCM3) and 2 representative concentration pathways (RCP)), and 2 land use management options for 2 time periods (mid (2045-2064), and late-21st century (2075-2094)) for each of the 2 study watersheds. To better inform adaptation management decision making, two additional increments of expanded GI implementation were simulated only for the GI watershed for the one of the climate forecasts at mid and late-21st century (so, 4 additional scenarios). The details of these scenarios are described in the sections below.

Downscaled climate projections

Statistically downscaled climate projections for daily maximum and daily minimum surface air temperature (°C) and daily precipitation (mm) from the Multivariate Adaptive Constructed Analogs (MACA) datasets were used and were downloaded from [http://maca.northwestknowledge.net/index.php](http://maca.northwestknowledge.net/index.php) for the coordinates of the Damascus 3 SSW MD US weather station (39.2647N, -77.2319E). Climate forcings in the MACAv2-METDATA were drawn from a statistical downscaling of global climate model (GCM) data from the Coupled Model Intercomparison Project 5 (CMIP5) (Taylor et al., 2011) utilizing a modification (Hegewisch and Abatzoglou, in prep.) of the Multivariate Adaptive Constructed Analogs
Multiple models are often used in climate evaluations to account for some of the variability between models (e.g. Hayhoe and Stoner, 2015), thus two GCMs were selected from the downscaled data: CCSM4 (National Center for Atmospheric Research, USA) and MRI-CGCM3 (Meteorological Research Institute, Japan). For each GCM, projections from two GHG concentration pathways were used: RCP 4.5 and RCP 8.5, representing moderate and extreme climate futures (Moss et al., 2010). For each GCM and RCP combination, projected climate data for two time periods were used: January 2042-December 2064 (mid-21st century), and January 2072-December 2094 (late 21st century). These time periods allowed for a 3 year warmup period followed by 20 years of output data for analysis for both mid and late 21st century.

Simulating changes in management

Two future management conditions were simulated for each watershed: 1) maintain stormwater infrastructure and 2) expand stormwater green infrastructure. For the “maintain” condition all model parameters were kept at calibrated values, to simulate consistent management over time. This condition could represent either 1) ongoing maintenance to keep current stormwater practices functioning long term, or 2) replacement of failed or expired practices with equivalent functioning practices. For the “expand” condition an increase in infiltration practices were simulated to control an additional 5.08 mm of runoff from a 66.04 mm rainfall event watershed wide. The increase in infiltration was simulated by reducing the CN parameter on the turfgrass portion of each watershed (Table 3). In these simulations, it was assumed that most additional GI implementation would occur as retrofits on existing green space adjacent to roads and buildings, so the implementation was modeled on the turfgrass land use.
To test whether extreme GI implementation could completely buffer changes in runoff under projected climate, and to better inform adaptation management decision making, two additional increments of expanded GI implementation were simulated in the GI watershed for the MRI-CGCM3 RCP8.5 climate scenario. The additional scenarios were: 1) “expand GI 7.62” to control an additional 7.62 mm of runoff from a 66.04 mm rainfall event, and 2) “expand GI 10.16” to control an additional 10.16 mm of runoff from a 66.04 mm rainfall event (Table 3). For the “expand GI 7.62” and “expand GI 10.16” condition an increase in infiltration practices implemented on the turfgrass land use was simulated by reducing the CN parameter, but the “expand GI 10.16” also required a replacement of 40% of the watershed impervious cover with turfgrass.

**SWAT model output data**

SWAT model output for daily streamflow (m³/s) at each watershed outlet was used for analysis. Surface runoff at a daily time step was calculated using the Web based Hydrograph Analysis Tool (WHAT) to separate the baseflow and surface runoff portions of daily streamflow (Lim et al., 2005) using the recursive digital filter method with $BFI_{\text{max}} = 0.80$ for perennial streams with porous aquifers (Eckhardt, 2005). Surface runoff rate (m³/s) was then converted to runoff depth (mm/day). The output data were aggregated to seasonal values as 1) total seasonal surface runoff depth, 2) total seasonal precipitation depth, and 3) average seasonal streamflow rate. Seasons were defined as: Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), and Fall (September, October, November). To find out if existing stormwater GI will provide the same relative reduction in surface runoff in future climate scenarios, the authors compared daily surface runoff depth in the GI watershed with daily surface runoff depth in the traditional watershed for the current condition and for each
climate scenario. To find out if hypothetical expanded stormwater GI implementation will improve watershed responses to climate change, the authors compared differences in surface runoff depth between maintained and expanded implementation for each climate scenario combination and watershed. The data were grouped by amount of daily precipitation into 5 bins based on event analysis by Hopkins et al. (2017) for these watersheds: 1) no rain (0 mm), 2) small (<13mm), 3) medium (13-30mm), 4) large (30-60mm), and 5) largest (>60mm). The daily runoff response from the GI watershed and traditional watersheds for each rain event were compared and this was also compared for each daily precipitation bin.

Results

Precipitation and runoff changes in climate scenarios

Average winter, spring, and fall precipitation increased and average summer precipitation decreased for most climate scenarios for both mid and late 21st century compared to current conditions (Table 4). The magnitude of decrease for summer precipitation was greater than the increase in precipitation in winter, spring, and fall for most climate scenarios. Average seasonal precipitation increase (in winter, spring, and fall) or decrease (in summer) were sometimes greater for late 21st century compared to mid-century, but this did not differ consistently for all seasons and climate models (Table 4). The CCSM4 model had higher average annual precipitation than the MRI-CGCM3 model. For the RCP 4.5 scenarios, the CCSM4 model was wetter than the MRI-CGCM3 model for winter, spring, and summer at mid-century, and for spring, summer, and fall at late century. In general the RCP8.5 (high emission) scenarios had higher annual precipitation than RCP 4.5 (low emissions) scenarios, and the late century scenarios had higher annual precipitation than the mid-century scenarios.
Change in total seasonal surface runoff depth compared to current conditions varied by season for climate scenarios (Table 5). Winter runoff increased more in the traditional watershed than in the GI watershed. Spring runoff decreased in most climate scenarios, and summer runoff decreased in all scenarios, in both the traditional watershed and the GI watershed. Fall runoff increased less in the traditional watershed than in the GI watershed. Change in runoff ratio (amount of precipitation converted to runoff) for climate scenarios compared to current conditions also varied by season (Table 6). Spring and summer runoff ratio decreased in both the traditional watershed and the GI watershed, and the decrease in the GI watershed was to a slightly larger degree relative to the traditional watershed. Fall runoff ratio increased slightly for most climate scenarios in both the traditional watershed and had a slightly greater increase for the GI watershed. Winter runoff ratio increased for the traditional watershed and remained the same for most scenarios for the GI watershed.

Daily runoff was compared between the GI and traditional watershed for the climate scenarios using a 1:1 line, where more points below the 1:1 line indicates that the traditional watershed produced more daily runoff than the GI watershed (and vice-versa) for each individual rain event (Figure 3). The best fit lines in Figure 3 also facilitate comparison between the responses of the two watersheds to each daily event size class by evaluating their slopes: a slope <1 represents higher runoff from the traditional watershed than from the GI watershed. For the same rain events, the GI watershed produced less daily runoff than the traditional watershed for most days with small (<13mm), medium (13-30mm), and large (30-60mm) rainfall totals (>98% of days with rainfall) (Figure 3a-e). For all climate scenarios there was greater runoff amounts from the traditional watershed than from the GI watershed for small, medium, and large rain events. For days with the largest rainfall total (>60mm) for current climate and CCSM4 model...
climate scenarios, higher runoff from the GI watershed than the traditional watershed was observed (Figure 3a-c).

Watershed response to expanded implementation and climate change

Expanded GI implementation to treat an additional 5.08 mm runoff from the 66.04 mm rainfall event reduced seasonal runoff depth for both watersheds for most climate scenarios (Figure 4). In general, runoff reductions were greater in the GI watershed than the traditional watershed. Runoff reductions were greatest in the winter and fall for both watersheds, but varied by climate model. Expanded implementation reduced runoff depth by twice as much during the spring in the GI watershed than the traditional watershed. Expansion of GI in the GI watershed to treat an additional 7.62 and 10.16 mm of runoff from the 66.04 mm rainfall event for the MRI-CGCM3 RCP8.5 climate scenario further decreased seasonal runoff compared to the “maintain GI” condition (Table 7). Expanded GI (7.62 mm) reduced the increase in late century winter runoff and kept spring runoff the same compared to the 2011-2016 baseline. Expanded GI (10.16 mm) reduced mid-century winter runoff by an additional 11%, and fall runoff by an additional 9% compared to the 2011-2016 baseline. At late-century, winter, spring and fall runoff increased compared to the 2011-2016 baseline, with fall runoff increasing the most (by 30%) (Table 7). Expanded GI (10.16 mm) negated the increase in runoff in winter and spring, and was able to reduce the large increase in runoff in the fall to just a 2% increase over the 2011-2016 baseline.

Discussion

Precipitation and runoff changes in climate scenarios

Projected changes in precipitation differed with season. Winter, spring, and fall precipitation increased, and summer precipitation decreased in most climate projections.
compared to 2011-2016 (Table 4). The increase in winter and spring precipitation is consistent with climate projections for the Northeast US (Najjar et al., 2008). Previous research has shown less model agreement for summer and fall precipitation, with some climate models projecting an increasing trend, and others projecting a decreasing trend (Hayhoe et al., 2006; Najjar et al., 2008). The climate models differed in their projections: the MRI-CGCM3 model projected drier conditions than the CCSM4 model annually and for most seasons. As expected, the higher GHG concentration scenario (RCP 8.5) had more precipitation than the lower GHG concentration scenario (RCP4.5) (Melillo et al., 2014). The daily precipitation projections do not fully capture changes in precipitation intensity because the SWAT model does not include duration of rain events. Other projections for the Washington D.C. region indicate that extreme precipitation events will increase under climate change (Hayhoe and Stoner, 2015). As a result, stormwater GI practices could be overwhelmed more frequently than simulations using SWAT would indicate.

Less rainfall was converted to runoff in the GI watershed than in the traditional watershed under current and projected climate conditions for most days with <60mm of rainfall (Figure 3a-e). This is consistent with previous assessments of GI for reducing stormwater runoff compared to traditional stormwater management (Dietz, 2007; Hood et al., 2007). The GI watershed controlled less runoff than the traditional for some of the days with the highest rainfall (>60mm). However, it should be noted that the SWAT model performed relatively poorly with the daily time step. The reduced control of runoff for days with the highest rainfall could be due to the SWAT model’s underestimation of peak events (e.g. Qiu and Wang, 2014). This is due to the fact that the model uses daily precipitation as input rather than the breakpoint rain events, thus missing the impact of high intensity storms. Observation and modeling studied have both shown that stormwater GI is effective for all sizes of storm events, but that effectiveness decreases for
the larger events (Guan et al., 2015; Hood et al., 2007). The relative difference in runoff production between the GI and traditional watershed for the same size rain events did not differ between current and future climate scenarios (Figure 3). However, the existing GI was not able to buffer the full increase in fall and winter runoff simulated with some climate change scenarios. Taken together, this suggests that the stormwater GI watershed will be more robust than the traditional watershed to the projected changes in climate for some seasons, but additional GI implementation would be needed to improve watershed scale robustness.

Climate induced changes in watershed surface runoff were seasonal and, with the exception of spring, were mostly consistent with the seasonal changes in precipitation (Table 5). This pattern is expected because the SWAT model is sensitive to changes in precipitation (Arnold et al., 2012). While the runoff ratio in spring and summer decreased in both watersheds under climate scenarios, this occurred to a larger degree in the GI watershed. This is likely due to the role of vegetation enhancing ecohydrologic flows (e.g., transpiration, infiltration) during the growing season in the GI features (Bhaskar et al. 2016). The increased runoff ratio observed for fall in both watersheds and winter in the traditional watershed is consistent with the disproportionate increase in runoff expected as a result of increased precipitation (Najjar et al., 2008). The relatively smaller increase in GI watershed’s winter runoff compared to the traditional watershed in most climate scenarios may indicate greater robustness in the GI watershed for this season. Both watershed models were sensitive to multiple snow parameters during calibration, so different calibrated parameter values between watersheds may explain some of the difference in winter runoff response. Increased fall and winter runoff under climate change scenarios suggests greater risk for both watersheds at these times of year for flooding and pollutant transport. Previous assessments found that individual stormwater GI and traditional
management practices may be undersized to control future storm events (Forsee and Ahmad, 2011; Hathaway et al., 2014; Moglen and Vidal, 2014) or that the extent of implementation may need to increase to meet future goals (Fischbach et al., 2015). The results of this study support these findings: watershed-wide implementation may need to increase to buffer the increases in fall and winter runoff. However, the relatively smaller increase in winter runoff in the GI watershed suggests that the GI is still providing a benefit compared to traditional management. This benefit from the GI is estimated to come at a substantial (15-80%) savings in capital costs relative to traditional stormwater approaches (EPA 2007), despite the GI watershed having an order of magnitude more stormwater control measures per area of impervious cover treated than the traditional watershed (366.7 features per km² of impervious cover versus 31.5 features per km² of impervious cover, (Hopkins et al. 2017).

The modeling approach used in this study assumes that the effectiveness of stormwater GI is consistent through time. It is implicitly assumed that all GI practices were maintained or replaced when their lifespan was exceeded to keep performance consistent. Long term performance of stormwater GI has yet to be studied in detail (Davis et al., 2009); however, a survey of 187 stormwater GI and other stormwater practices in the James River Watershed in Virginia, found that 46% were in need of maintenance (Hirschman et al., 2009) and 3 out of 20 rain gardens surveyed in Fairfax County, Virginia had no infiltration (0 mm /hour) (Rouhi and Schwartz, 2007). The assumption of GI maintenance or replacement therefore may artificially inflate the runoff reductions projected during the future timeframes that were simulated.

Watershed response to expanded implementation and climate change

Expanded GI implementation to treat an additional 5.08 mm of runoff from the 66.04 mm rainfall event reduced surface runoff under future climate conditions for most climate scenarios
(Figure 4). Expanding GI implementation in the GI watershed to treat an additional 7.62 and 10.16 mm of runoff from the 66.04 mm rainfall event further reduced surface runoff. These results are consistent with the models’ sensitivity to the CN parameter (Abbaspour, 2007). These findings indicate that increased implementation of infiltration practices can improve watershed robustness to climate change by compensating for some of the projected increases in runoff depth in fall and winter. Previous climate adaptation studies showed that hypothetical GI implementation resulted in less runoff under projected climate change than scenarios without GI (Borris et al., 2013; Gill et al., 2007; Kim et al., 2015; Pyke et al., 2011; Waters et al., 2003; Zahmatkesh et al., 2015, Sarkar et al. 2018). The results of this study build on those findings by demonstrating similar climate adaptation capacity in a calibrated model of a watershed with existing GI.

Expanding GI to treat an additional 5.08 mm of runoff from the 66.04 mm 24-hour rainfall event in this study reduced runoff but was not enough to completely buffer the increase in fall and winter runoff simulated with climate change, indicating that additional implementation would be needed to completely buffer the increase in runoff (Figure 4, Table 7). Expanding GI in the GI watershed to treat an additional 10.16 mm of runoff from the 66.04 mm 24-hour rainfall event completely buffered the increase in seasonal runoff at mid-century, and limited the increase in fall runoff to 2% at late century (Table 7). Treating 10.16 mm of runoff in the GI watershed required both an increase in infiltration practices (e.g. rain gardens, swales) and replacement of impervious cover. This is because there was not enough non-impervious area in the watershed to achieve 10.16 mm of runoff reduction through a modeled increase in infiltration practices alone.
The key implications for management from this research are 1) the importance of planning for future climate conditions rather than for historic climate conditions (Milly et al. 2008, Yang 2010), and 2) the ability of GI to buffer increases in runoff at the watershed scale. For the Northeast US, planning for future climate should include planning for increased intensity storms and increased winter precipitation. Modeling results showed seasonal increases in surface runoff under projected climate conditions when management remained at current levels (Table 5). Watershed management options to prepare for future climate conditions include: 1) re-design and sizing individual practices larger so that they have higher capacity to treat greater intensity storms (Renkenberger et al. 2017), and 2) increasing extent of implementation across urban watersheds so that treatment capacity is increased at a watershed scale. The type of GI implemented to achieve these goals could include infiltration practices, such as those simulated in this study (e.g. rain gardens and swales) as well as replacement of impervious cover. It is important to note that the use of GI as an adaptive tool to enhance robustness and resilience to climate change is not just dependent upon increasing treatment capacity at the watershed scale. Several additional factors can affect the implementation of GI, including socio-economic factors and barriers to adoption related to policy, equity, and financial constraints (Staddon et al. 2018). Importantly, in selecting specific GI approaches to implement, the installation and operation costs can vary greatly (Center for Watershed Protection, 2017).

Conclusion

This research used simulations of two urban watersheds (one with stormwater GI implementation, one with traditional stormwater controls) in Clarksburg, MD using SWAT models calibrated to USGS streamflow monitoring data to assess climate change resilience. For most days with precipitation (>98% of days), the GI watershed continued to produce less surface...
runoff than the traditional watershed under projected future climate conditions. However, fall
and winter runoff increased for both watersheds under most climate scenarios compared to
current conditions. These results indicate that the existing stormwater GI is robust to climate
change, but the response varies seasonally. Simulated expansion of stormwater GI
implementation to treat an additional 5.08 mm of runoff from the 1-yr 24-hr storm reduced
runoff in both watersheds for all seasons. This study assesses the response of existing stormwater
GI to climate change at watershed scales, and confirms previous studies of hypothetical GI
implementation effectiveness for adapting watersheds to climate change by reducing surface
runoff and increasing groundwater infiltration or evapotranspiration. There is potential therefore
for expanded GI in urban/suburban watersheds to buffer some of the projected seasonal increases
in runoff expected with climate change.

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### Table 1. Urban land uses and parameter values.

<table>
<thead>
<tr>
<th>Land use</th>
<th>FIMP&lt;sup&gt;1&lt;/sup&gt;</th>
<th>FCMIP&lt;sup&gt;2&lt;/sup&gt;</th>
<th>Composite curve number (CN)&lt;sup&gt;3&lt;/sup&gt;</th>
<th>Manning’s n for overland flow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>A soils</td>
<td>B soils</td>
</tr>
<tr>
<td>Impervious</td>
<td>0.98</td>
<td>0.95</td>
<td>97</td>
<td>97</td>
</tr>
<tr>
<td>Source</td>
<td>SWAT theory values for transportation</td>
<td>SCS values for impervious</td>
<td>TR-55 for smooth surfaces (concrete, asphalt, gravel, or bare soil)</td>
<td></td>
</tr>
<tr>
<td>Turfgrass</td>
<td>0</td>
<td>0</td>
<td>39</td>
<td>61</td>
</tr>
<tr>
<td>Source</td>
<td>Land cover data</td>
<td>SCS values for open space in good condition</td>
<td>TR-55 for bermudagrass</td>
<td></td>
</tr>
</tbody>
</table>

<sup>1</sup>Fraction of impervious cover in land use  
<sup>2</sup>Fraction of directly connected impervious cover in land use  
<sup>3</sup>Composite curve numbers (CN) are a weighted average based on fraction of impervious cover (FIMP).  

Composite CN = (FIMP*98) + (1-FIMP)*CN_soil

### Table 2. Green infrastructure (GI) watershed and traditional watershed model performance statistics.

<table>
<thead>
<tr>
<th></th>
<th>Uncalibrated model – daily</th>
<th>Calibrated model – daily</th>
<th>Calibrated model - monthly</th>
<th>Validation - daily</th>
<th>Validation – monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>NSE</td>
<td>%BIAS</td>
<td>NSE</td>
<td>%BIAS</td>
<td>NSE</td>
</tr>
<tr>
<td>Traditional</td>
<td>0.53</td>
<td>-6.4</td>
<td>0.72</td>
<td>4</td>
<td>0.8</td>
</tr>
<tr>
<td>GI</td>
<td>0.64</td>
<td>-6.8</td>
<td>0.84</td>
<td>9.9</td>
<td>0.84</td>
</tr>
<tr>
<td>Goal</td>
<td>≥0.5</td>
<td>+/-20</td>
<td>≥0.5</td>
<td>+/-20</td>
<td>≥0.5</td>
</tr>
</tbody>
</table>

### Table 3. Adjustments to curve number (CN) values used to simulate expanded GI implementation.

<table>
<thead>
<tr>
<th></th>
<th>Traditional Watershed</th>
<th>GI Watershed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calibrated Model</td>
<td>Expand GI 5.08 mm</td>
</tr>
<tr>
<td>IMPV CN</td>
<td>97</td>
<td>97</td>
</tr>
<tr>
<td>FRST CN</td>
<td>71</td>
<td>71</td>
</tr>
<tr>
<td>TURF CN</td>
<td>70</td>
<td>54</td>
</tr>
<tr>
<td>Weighted CN for watershed</td>
<td>80</td>
<td>76</td>
</tr>
</tbody>
</table>

<sup>1</sup>Simulated with climate scenario MRI-CGCM3 RCP8.5  
Note: Expanded implementation scenarios are to treat additional runoff from a 66.04 mm rainfall event.

### Table 4. Seasonal projected precipitation (in mm).
<table>
<thead>
<tr>
<th>Time Period</th>
<th>Concentration Pathway</th>
<th>Climate Model</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>NA</td>
<td>NA</td>
<td>282.1</td>
<td>318.0</td>
<td>365.0</td>
<td>316.0</td>
</tr>
<tr>
<td>Mid-century</td>
<td>RCP4.5</td>
<td>CCSM4</td>
<td>302.2</td>
<td>336.0</td>
<td>325.7</td>
<td>322.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>265.3</td>
<td>325.6</td>
<td>265.8</td>
<td>328.8</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>CCSM4</td>
<td>289.7</td>
<td>340.2</td>
<td>323.5</td>
<td>347.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>306.6</td>
<td>322.9</td>
<td>287.7</td>
<td>352.3</td>
</tr>
<tr>
<td>Late-century</td>
<td>RCP4.5</td>
<td>CCSM4</td>
<td>278.5</td>
<td>325.2</td>
<td>341.5</td>
<td>354.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>301.7</td>
<td>317.0</td>
<td>260.3</td>
<td>321.2</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>CCSM4</td>
<td>306.1</td>
<td>348.8</td>
<td>354.2</td>
<td>333.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>305.4</td>
<td>372.0</td>
<td>310.4</td>
<td>351.2</td>
</tr>
</tbody>
</table>

Table 5. Projected seasonal runoff depth (in mm).
Table 6. Projected seasonal runoff ratio (fraction).

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Concentration Pathway</th>
<th>Climate Model</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>NA</td>
<td>NA</td>
<td>0.20</td>
<td>0.25</td>
<td>0.17</td>
<td>0.21</td>
</tr>
<tr>
<td>Mid-century</td>
<td>RCP4.5</td>
<td>CCSM4</td>
<td>0.22</td>
<td>0.22</td>
<td>0.10</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.22</td>
<td>0.21</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>CCSM4</td>
<td>0.22</td>
<td>0.21</td>
<td>0.10</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.23</td>
<td>0.21</td>
<td>0.09</td>
<td>0.22</td>
</tr>
<tr>
<td>Late-century</td>
<td>RCP4.5</td>
<td>CCSM4</td>
<td>0.25</td>
<td>0.20</td>
<td>0.11</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.24</td>
<td>0.20</td>
<td>0.08</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>CCSM4</td>
<td>0.24</td>
<td>0.20</td>
<td>0.12</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.25</td>
<td>0.23</td>
<td>0.10</td>
<td>0.23</td>
</tr>
<tr>
<td>GI watershed</td>
<td>Current</td>
<td>NA</td>
<td>0.22</td>
<td>0.20</td>
<td>0.15</td>
<td>0.18</td>
</tr>
<tr>
<td>Mid-century</td>
<td>RCP4.5</td>
<td>CCSM4</td>
<td>0.22</td>
<td>0.17</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.21</td>
<td>0.18</td>
<td>0.06</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>CCSM4</td>
<td>0.22</td>
<td>0.17</td>
<td>0.08</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.21</td>
<td>0.18</td>
<td>0.07</td>
<td>0.19</td>
</tr>
<tr>
<td>Late-century</td>
<td>RCP4.5</td>
<td>CCSM4</td>
<td>0.22</td>
<td>0.17</td>
<td>0.09</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.22</td>
<td>0.17</td>
<td>0.06</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>CCSM4</td>
<td>0.22</td>
<td>0.17</td>
<td>0.09</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MRI-CGCM3</td>
<td>0.22</td>
<td>0.19</td>
<td>0.07</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Table 7. Effect of incremental GI expansion scenarios in the GI watershed on surface runoff.

<table>
<thead>
<tr>
<th>Season</th>
<th>Mid-Century (2045-2064)</th>
<th>Late-Century (2075-2094)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maintain GI</td>
<td>Expand GI (5.08 mm)</td>
</tr>
<tr>
<td>Winter</td>
<td>5%</td>
<td>1%</td>
</tr>
<tr>
<td>Spring</td>
<td>-7%</td>
<td>-11%</td>
</tr>
<tr>
<td>Summer</td>
<td>-61%</td>
<td>-63%</td>
</tr>
<tr>
<td>Fall</td>
<td>17%</td>
<td>9%</td>
</tr>
</tbody>
</table>
Figure 1. Map of study watersheds in Clarksburg, Maryland with USGS streamflow monitoring station locations. Tributary 104 is the GI watershed, and Crystal Rock is the traditional watershed. Maps created in ESRI ArcGIS and Google Earth.
Figure 2. SWAT modeling hydrograph for Tributary 104 watershed in Clarksburg, Maryland for monthly time step for calibration (2011-2014) and validation (2015-2016) periods. Precipitation and observed and simulated stream flow are shown. Two calibration and validation metrics indicate model performance: Nash-Sutcliffe model efficiency coefficient (NSE) and percent bias (PBIAS).
Figure 3. Comparison of modeled runoff depth in the GI watershed and in the traditional watershed for current conditions (2011-2016) (a), and projected climate conditions (b-e) compared to a reference line with slope=1. Regression lines fit to runoff depth values on days with small (<13mm), medium (13-30mm), large (30-60mm), and largest (>60mm) rainfall totals. Graphs b-e show 2 different climate scenarios (CCSM4 and MRI-CGCM3) with RCP8.5).
Figure 4. Seasonal runoff depth reduction with expanded GI implementation scenarios for 2045-2064 (a, c) and 2075-2094 (b, d) for green infrastructure (GI) watershed (a, b) and traditional watershed (c, d). Data show the percent change between expanded GI implementation (and additional 5.08 mm from a 66.04 mm rainfall event) compared to maintained GI implementation scenarios. Graphs show 4 different climate scenarios (combinations of global climate model (CCSM4 and MRI-CGCM3) and representative concentration pathway (RCP4.5 and RCP8.5)).