



STORMWATER GREEN INFRASTRUCTURE CLIMATE RESILIENCE IN  
CHESAPEAKE BAY URBAN WATERSHEDS

by

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## List of Abbreviations

|       |   |
|-------|---|
| GI    | Green infrastructure                          |
| BMP   | Best Management Practice                      |
| SWAT  | Soil and Water Assessment Tool                |
| TMDL  | Total Maximum Daily Load                      |
| N     | Nitrogen                                      |
| P     | Phosphorus                                    |
| CSO   | Combined Sewer Overflow                       |
| CN    | Curve Number                                  |
| GHG   | Greenhouse gas                                |
| RCP   | Representative Concentration Pathway          |
| CMIP5 | Coupled Model Intercomparison Project Phase 5 |
| MACA  | Multivariate Adaptive Constructed Analogs     |
| IPCC  | Intergovernmental Panel on Climate Change     |
| GCM   | Global Climate Model                          |

# Chapter 1: Introduction and Literature Review

## **Urbanization impacts on hydrology and water quality**

Urbanization and the associated creation of impervious surfaces modifies local hydrology. Urban areas have reduced rainfall infiltration, reduced groundwater recharge, increased rate and volume of stormwater runoff, and increased transport of pollutants compared to undeveloped areas (L.B. Leopold, 1968; Shuster et al., 2005). As a result, urban areas have increased risk of flooding, pollution, and the associated risks to human health (U.S. EPA, 1983). Stormwater runoff leads to both fluvial flooding: when streams overflow their banks, and pluvial flooding: when drainage infrastructure reaches capacity and cannot drain the water quickly enough from surfaces. In urban areas with combined storm and sanitary sewers, high runoff volumes cause overflow of the combined stormwater and untreated wastewater to local streams and rivers. The collective effects of urbanization on stream ecology have been defined as “urban stream syndrome” (Walsh et al., 2005). The extent of impact is related to the amount of impervious cover in a watershed (Arnold and Gibbons, 1996). Effects on stream health have been observed at thresholds as low as 0.5% impervious area (King et al., 2011), therefore the impacts extend well beyond large cities to low intensity development areas as well. As a result, stormwater runoff is a concern for all areas with developed land use, regardless of size or population characteristics.

Urban pollutants are susceptible to stormwater scouring and subsequent transport to nearby waterways. Nitrogen (N) and phosphorus (P) from lawn

fertilizers, pet waste, or leaking sanitary sewers, can cause algae blooms and eutrophication in receiving waters (Paul and Meyer, 2001). Toxic contaminants can also be mobilized by stormwater, and delivered to water bodies. Stormwater runoff is a source of mercury in rivers (Lawson et al., 2001). Other metals such as copper, lead, zinc, and cadmium can be washed off of buildings and automobiles and subsequently be transported by stormwater (Davis et al., 2001). Legacy polychlorinated biphenyls (PCBs) remain in the environment and in stormflow (Hwang and Foster, 2008). Coal-tar-based sealcoat, used on pavements and parking lots, is a common source of polycyclic aromatic hydrocarbons (PAHs) in urban lakes (Mahler and Van Metre, 2011). Multiple organochlorine pesticides have also been found in storm flow in rivers (Foster et al., 2000). In urban areas with combined storm and sanitary sewers, high runoff volumes cause overflow of the combined stormwater and untreated wastewater to local streams and rivers. Emerging contaminants such as pharmaceuticals, household and personal care products can be transported via this pathway. Flooding and pollution both have implications for human health and safety. Exposure to pathogens can occur through drinking water or recreation, and intense rainfall has been linked to outbreaks of waterborne illnesses from pathogens such *Cryptosporidium* and *Giardia* (Charron et al., 2004). Elevated nitrates in drinking water can lead to methemoglobinemia in infants (Gaffield et al., 2003). Toxic contaminant bioaccumulation in fish poses risks for consumption. Standing water provides breeding opportunity for mosquitos, with the associated risk of mosquito-borne diseases (Gaffield et al., 2003).

## **Stormwater management approaches and terminology**

Concerns about urban flooding and exposure to pathogens were historically addressed by facilitating quick drainage of stormwater away from urban surfaces. Stormwater infrastructure in most developed areas is primarily concrete (e.g. pipes and culverts) for this reason. Regulations such as the Clean Water Act in the United States, have expanded the goals of stormwater management to include improved water quality (US EPA, 1972). Various methods are employed to reduce the impact of impervious area on hydrology by detaining stormwater and either storing it for reuse or facilitating infiltration or evapotranspiration. Infiltration and evapotranspiration both re-route some of the precipitation that otherwise would become runoff, reducing the total runoff volume moving across the landscape to the stream. There are multiple terms for these stormwater practices, including stormwater control measures (Rhea et al., 2015) or Low Impact Development (LID) (Dietz, 2007). Stormwater Best Management Practices (BMPs) is a generally inclusive term common in US regulations for the traditional centralized practices (e.g. stormwater ponds), the newer decentralized practices (e.g. rain gardens and green roofs), as well as non-structural pollution control measures (e.g. reducing fertilizer application) (Fletcher et al., 2015). I use the term stormwater green infrastructure (GI), to refer specifically to the site-scale, decentralized practices (e.g. rain gardens, green roofs, permeable pavement) that intercept stormwater and often facilitate infiltration or evapotranspiration. I use the term stormwater BMP to refer to both the centralized and decentralized practices. Another approach to categorizing stormwater treatment is by runoff treatment process. Retention type stormwater practices include rain barrels

and green roofs, and function primarily by storing runoff and reducing peak flows. Infiltration type stormwater practices include rain gardens and permeable pavement, and function by using runoff to recharge groundwater (Fletcher et al., 2013). Both infiltration and retention practices can also facilitate evapotranspiration if vegetation is present.

Mechanisms for pollutant removal vary by practice type. N is often treated through biological nitrification and denitrification, such as in bioretention systems (Hunt et al., 2012). Sediment, particulate P, and other particle-bound contaminants such as PAHs can be removed from runoff through filtration processes (Dibiasi et al., 2009; Hunt et al., 2012). Dissolved P and metals can be removed through sorption within soil media (LeFevre et al., 2015). N and P can also be removed through plant uptake in vegetated practices (LeFevre et al., 2015). Pathogen removal from stormwater occurs via filtration, followed by exposure to sunlight or other methods to promote die-off (Hunt et al., 2012).

The state of Maryland requires stormwater GI be used to the “maximum extent practicable” for new development projects to control the 1-year 24-hour storm (MDE, 2009). Stormwater GI and other BMPs are also implemented on new and existing development (e.g. as a retrofit) in order to meet N, P, and sediment pollution reduction targets required by the EPA Chesapeake Bay Total Maximum Daily Load (TMDL) (US EPA, 2010). Maryland’s Phase II Watershed Implementation Plan (Phase II WIP) for the TMDL calls for a 20% decrease in annual N and a 30% decrease in annual P from the urban sector by 2025 compared to 2010 loads (MDE, 2012).

Bioretention (also known as rain gardens) is a stormwater GI practice that has become increasingly popular in recent years. A bioretention cell consists of a ponding surface where water collects prior to infiltration, and a layer of permeable media to support rapid infiltration (MDE, 2009; Prince George's County, Maryland, 2007). The infiltrated water can either be released to surface water via an underdrain, or percolated to surrounding soils. Field and laboratory studies have found that in addition to capturing and slowing stormwater flow, bioretention can remove nutrients, suspended sediments, bacteria, organic compounds, and metals from stormwater (Davis et al., 2003; Diblasi et al., 2009; Hunt et al., 2008). Typically, coarse sediment and particle-bound contaminants such as P are captured near the surface, and finer materials are filtered out within the bioretention media. N removal occurs through biological nitrification and denitrification. N and P are also taken up into plants as a secondary removal mechanism (Hunt et al., 2012). Previous studies have found up to 99% total P removal rates, and up to 240% addition rates, with high dependence on P content of the initial soil media (Davis et al., 2009). Bioretention systems have been found to have total N removal rates between 32-99%, and can vary based on influent water quality (Davis et al., 2009). Denitrification rates vary by temperature, hydraulic retention time, and media depth.

### *Stormwater GI maintenance*

Long term function of stormwater GI depends on design, construction, and maintenance. A Center for Watershed Protection survey of 187 stormwater GI and other BMPs in the James River Watershed in Virginia, found that 46% were in need of maintenance (Hirschman et al., 2009). Common problems with BMPs were

sediment erosion, sediment deposition, clogging, poor vegetation health, trash accumulation and flow bypassing. Their survey also found that 14% of sites lacked maintenance access (i.e. BMP was surrounded by a fence without a gate). They found that some jurisdictions limit their maintenance to BMPs on public property, and there may not be a mechanism to enforce maintenance of private BMPs. One issue compounding the maintenance problem occurs when changes to design occur during construction.

A field survey of 20 rain gardens in Fairfax County, Virginia found that 3 had no infiltration (0 inches/hour) (Rouhi and Schwartz, 2007). 13 of the rain gardens did not have sufficient ponding depth, reducing the total volume of treatment. 3 did not have sufficient planting soil depth, reducing the filtering capacity of the BMP. The rain gardens sampled in this study were between 1 and 7 years old. Those on public sites were better maintained than those on private land. All 20 sites had more clay content in the bioretention mix than is recommended, although the majority still had sufficient infiltration despite this. 15 of the sites' actual conditions differed from their plans. A field survey of 30 rain gardens in Severn River watershed, Maryland found that 13 were in poor condition (The Severn River Association, 2012). 9 had less than 6" of ponding depth, and 11 had soil erosion problems. 20 of the sites had less than 2" of mulch present, reducing the N removal rate at these facilities. It is clear from these evaluations of existing practices that without sufficient maintenance, long-term hydrology and water quality performance GI can decline.

## **Climate change impacts on urban hydrologic cycles**

Climate change is expected to impact global temperature and precipitation patterns in the coming decades (short term) as well as the coming century (long term). According to the Intergovernmental Panel on Climate Change (IPCC), average global surface temperature will continue increasing through the 21<sup>st</sup> century even under the most conservative greenhouse gas (GHG) emissions scenarios (IPCC, 2014a). Most models show continued warming after 2100. Precipitation changes are expected to vary by region with most historically dry regions receiving less precipitation and most historically wet regions receiving more precipitation. The mid-latitude land masses are very likely to experience increased intensity and frequency of extreme events (IPCC, 2014a).

Long term trends for the Northeast US show an observed 8% increase in average annual precipitation and 0.12° C increase in temperature between 1911-1940 and 1970-2000 (Najjar et al., 2008). There is consensus across multiple models that temperature in the Northeast United States will continue to increase (Najjar et al., 2008). Climate change models predict that average annual surface temperatures in the Northeast US will increase between 2.9° and 5.3° C by the end of the 21<sup>st</sup> century compared to late 20<sup>th</sup> century. Models for the Northeast US diverge slightly in their annual precipitation predictions. Precipitation is expected to become more episodic, with increased storm intensities and higher precipitation totals in the winter and spring (Hayhoe et al., 2006; Najjar et al., 2008). Increased precipitation intensity may lead to increased stormwater runoff and flooding in urban areas (Revi et al., 2014).

Changes in temperature and precipitation will also drive changes in urban hydrology. Based upon principles of urban hydrology, increased precipitation intensity should result in higher peak flow rates, and increased risk of pluvial flooding. Increased frequency of intense precipitation will result in more runoff-producing storms, and higher total surface runoff volume. At the same time, increased temperatures will lead to increased evapotranspiration rates. With higher evapotranspiration rates, less rainfall will infiltrate to groundwater, resulting in reduced base flow rates (Hejazi and Moglen, 2008). The total impact to streamflow will be determined by the combined impacts to both surface runoff and base flow. Models for the Mid-Atlantic US vary in their predictions from a 39% decrease to a 37% increase in annual streamflow (Najjar et al., 2008). The reason for this wide variation is likely because temperature will drive a decrease in base flow while precipitation will drive an increase in runoff or quick flow. Given these predictions, there may be an even greater need for stormwater management practices in mid to late century.

## **Role of stormwater GI and other BMPs in climate adaptation and resilience**

Through the process of climate adaptation, urban watersheds can become more resilient to climate change (Folke, 2006; Tyler and Moench, 2012). Stormwater GI may provide climate adaptation to watersheds by infiltrating stormwater from higher intensity storms, which reduces runoff and increases groundwater recharge. These mechanisms could buffer some of the predicted climate change related risks.

Stormwater GI could therefore be expected to increase watershed resilience to climate change by providing these adaptations.

Recent reports for policy makers have emphasized the importance of building resilience to climate change (IPCC, 2014a; Melillo et al., 2014). In the context of climate change, the IPCC defines resilience as “the capacity of social, economic, and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity, and structure, while also maintaining the capacity for adaptation, learning, and transformation” (IPCC, 2014b). This definition of resilience is consistent with the ecological definition, which is based on the concept that a resilient system is able to absorb change and continue to function (Holling, 1973). Urban systems in particular are vulnerable to climate change impacts because of their large populations, and reliance on infrastructure and resources. EPA guidance encourages the use of green infrastructure in building community resilience to climate change impacts such as flooding, drought and urban heat island (US EPA, 2014). I refer to stormwater GI resilience as its capacity absorb shifts in rainfall and temperature and to continue with its desired function. The climate change resilience of the current extent of stormwater GI implementation in Maryland is an open and important management, health, and safety question.

#### *Previous efforts to assess stormwater and climate resilience*

Traditional stormwater management approaches and stormwater GI approaches are based on historic and current climate regimes (Milly et al., 2008). Given the inevitability of climate change, an assumption of climate stationarity may

no longer be reasonable for water management (Milly et al., 2008). Previous studies have evaluated stormwater GI and other BMPs at individual site and watershed scales under climate change conditions. These studies have addressed 1) using stormwater GI as a hypothetical climate adaption measure, 2) how stormwater GI may function under climate change scenarios compared to gray infrastructure, and 3) resilience of existing individual or watershed scale stormwater GI and other BMPs.

### *Stormwater GI and other BMPs as a climate adaptation measure*

Several researchers found evidence of hypothetical BMPs successfully adapting a case study watershed to modeled changes in climate. Pyke et al., (2011) simulated changes to both volume and intensity of precipitation as a proxy for climate change conditions in a watershed near Boston to test whether reducing impervious cover (from 25 to 16%) would reduce the impacts of stormwater runoff on surface water quality under future climate conditions. The low impact (lower impervious cover) future scenario had ~30% reduction in annual runoff volume, N, P and sediment loads compared to the conventional scenario under current climate. Overall, reducing impervious cover offset the increases in runoff simulated for the more extreme climate scenarios in this study. Similarly, Borris et al., (2013) modeled runoff and pollutant loads from a suburban catchment in Sweden under multiple scenarios for the years 2041-2070. Modeling a reduction in directly connected impervious area offset the increase in runoff volume, peak flow, and pollutant loads under future climate. Waters et al., (2003) compared runoff from a current 2-year 1-hour storm in a southern Ontario urban watershed, with simulated runoff from a future storm (modeled as a 15% increase in rainfall intensity). Retrofit measures were

then modeled to keep peak runoff rates at current levels. Scenarios for maintaining both peak runoff rates and total runoff volumes included disconnection of 50% of rooftops, increasing surface storage by an additional 46 m<sup>3</sup> per impervious hectare, or increasing street detention storage by 40 m<sup>3</sup> per impervious hectare.

Some studies investigating specific hypothetical stormwater GI practices have predicted successful adaptation to climate change. Precipitation and runoff for the Bronx River watershed were simulated for the 2-year and 50-year storm for 2030-2059 conditions (Zahmatkesh et al., 2015). A combination of stormwater GI measures (bioretention, porous pavement, rainwater harvesting) reduced annual runoff volume by 41%. Without stormwater GI, annual runoff volume was projected to increase by 48%. Stormwater GI may therefore mitigate the effects of climate change on urban runoff (Zahmatkesh et al., 2015). Kim et al. (2015) modeled precipitation and runoff for a watershed in Seoul for the 2-year and 100-year storm event comparing present (2005) to 2020 and 2050 conditions. They found that with maximum adoption of porous pavement in their study area (~33% of land area), runoff volume and peak flow under future simulated conditions was kept at lower levels than present without porous pavement. This held true for both the 2-year and 100-year storm. Porous pavement thus has the ability to adapt to climate change conditions.

Not all studies found the ability to fully adapt to climate change. Peak flow rates and runoff volumes from an urbanizing catchment in Sweden were compared across several modeled scenarios of climate change and urban growth through the late 21<sup>st</sup> century (Semadeni-Davies et al., 2008). Simulated implementation of stormwater ponds was able to compensate for changes in runoff and peak flow as a result of

urban growth alone, but not the combined effects of growth and climate change. Accounting for increased impervious surface, especially in areas experiencing urban growth, is an important aspect of climate change adaptation. Similarly, adding 10% green cover, 10% trees, or 100% green roofs to Greater Manchester, UK, provided some modeled runoff volume reduction with climate change, but did not keep the runoff as low as the baseline condition (Gill et al., 2007).

These studies consistently demonstrate 1) increased negative impacts of stormwater in a future without stormwater GI and other BMPs, and 2) some degree of urban watershed adaptation to climate change via stormwater GI implementation. The implications of this are that existing stormwater infrastructure (without any BMPs) is not resilient to changes in climate. This is not surprising given that streamflow is sensitive to changes in precipitation (Sankarasubramanian et al., 2001). Changes to precipitation can cause a disproportionate response in runoff and streamflow characteristics (Najjar et al., 2008). Another implication of these findings is the climate change adaptation potential across a wide range of stormwater management approaches. Most of these studies focused on stormwater GI practices, but some included ponds and detention type practices as well. Unfortunately, none of these studies compared different stormwater management scenarios to assess relative performance by type. A meta-analysis or other cross study comparison would have limited usefulness due to the range in climate conditions, watershed imperviousness, and geographic settings. As a result it is difficult to draw any conclusions about relative effectiveness of different stormwater management approaches as climate adaptation measures from these findings.

### *Stormwater GI compared to gray infrastructure*

A second set of studies explores how stormwater GI may function under climate change scenarios in comparison with to gray infrastructure. For example, Lucas and Sample, (2015) conducted a comparison of combined sewer overflow (CSO) conditions near Richmond, VA. Conditions were simulated based on two past years representing current and intense (future) climate conditions. The effectiveness of four management scenarios were tested for each climate condition: green stormwater infrastructure with and without outlet controls, gray infrastructure (storage tunnel), and existing conditions (no BMPs). Model results of CSOs showed that both of the green infrastructure scenarios were more resilient to changes in hydrologic conditions compared to the gray infrastructure scenario. The authors found that stormwater GI with outlet controls controlled the most overflow volume and was the most resilient to climate change, which they measured by magnitude of change in overflow volume. The system with the smallest shift in overflow was defined as being the most resilient. This study has interesting implications for future work, both in demonstrating that green alternatives may be more resilient to climate impacts than gray approaches, and in direct use of resilience to compare effectiveness of approaches.

### *Resilience of existing stormwater GI and other BMPs*

A final approach to exploring resilience to changing climate conditions is to evaluate a system or site with existing stormwater BMPs, and modeled the site under climate change conditions. For example, precipitation and runoff near Washington D.C. were simulated for the 2-year and 10-year frequency storm comparing present

(1971-2000) to future (2041-2070) conditions (Moglen and Vidal, 2014). They found that a hypothetical detention pond designed to treat runoff under current climate was undersized in most future climate scenarios in terms of peak flow and storage volume. The modeled results relate specifically to detention basins, however they generalize their findings to suggest that all stormwater infrastructure may be undersized with respect to mid-century precipitation and runoff. Although the authors do not advocate for any particular management approach as a result of these findings, they propose progressive adaptation of stormwater infrastructure as one option for managers. Similarly, design standards for detention basins in Las Vegas, Nevada were exceeded in model runs based on a 1.2 factor increase in the 6-hr 100-yr storm (Forsee and Ahmad, 2011). Hathaway et al. (2014) calibrated a hydrology model to runoff, drainage, and overflow data from four field bioretention sites in North Carolina. Climate change scenarios for 2055-2058 showed increased overflow from bioretention systems compared with the baseline 2001-2004 scenario. They found that 9-31cm of additional storage in the bioretention cells would be needed to maintain 2001-2004 overflow rates. Newcomer et al. (2014) also made use of a field scale installation to calibrate a model. Groundwater recharge rates from their field scale infiltration trench were an order of magnitude higher than their control (an irrigated lawn). Recharge efficiency was not affected by simulated climate change. The simulated stormwater GI was able to recharge a higher volume of water to groundwater under the future climate conditions. However, the authors still recommended increasing storage capacity of stormwater GI infiltration practices to further improve recharge rates.

At the watershed scale, modeling scenarios for the Patuxent watershed in Maryland found that most climate and land use change scenarios for 2035-2045 resulted in exceeding the TMDL (US EPA, 2010) for N, P and sediment with current urban stormwater BMPs in place (Fischbach et al., 2015). Fully implementing Maryland's Phase II Watershed Implementation Plan (MDE, 2012) by 2025 reduced the number of scenarios that exceed TMDL loads (however still less than half of them met the TMDL). Scenario discovery indicated that the N TMDL is most often exceeded in scenarios where precipitation increases, impervious area increases, or both increase. The report concluded that it may be difficult to meet the TMDL with existing management options and cost limitations once climate change and land use change are accounted for (Fischbach et al., 2015). Koch et al. (2015) conducted a survey using structured expert judgment with stormwater experts (researcher scientists, practitioners, modelers, and engineers) to assess drivers of variation in BMP performance. Respondents answered a series of questions about site and watershed scale N treatment in two suburban catchments in Maryland. Based on expert opinions summarized in this paper, intensity of rainfall was the primary driver of variability in stormwater BMP N removal efficiency. As a result, BMPs could have higher N losses (lower treatment efficiency) with climate change.

The implications of this set of studies are that adjustment to the sizing (e.g. detention ponds or bioretention), design, or amount of implementation may be needed to maintain current runoff and pollutant conditions, if that is the goal of management. With the detention pond studies, this conclusion is not surprising, as these systems are designed based on historic and current climate. If rainfall intensity increases in the

future, these systems would be expected to overflow or exceed capacity. Bioretention and other stormwater GI practices are often designed to control runoff volume from a specific size storm. If larger events occur more frequently in the future, these systems could be expected to overflow more frequently, posing a threat to climate resilience.

The pollution dynamics of urban watersheds are potentially even more difficult to assess under changed climate. In particular, the complexity of the N cycle makes it difficult to predict how treatment processes will be affected. Increased temperature might be expected to increase biological denitrification rates, which should enhance total N removal in stormwater GI with microbial processes. However, if precipitation becomes more episodic, the pattern of drought followed by inundation in the soil media may favor nitrification processes in soil media, followed by nitrate leaching. Prior bioretention research has shown that ammonium N in the soil media can nitrify during dry periods between storms, and the resulting nitrate is washed out during the next storm event, leading to high nitrate losses (Davis et al., 2006). If climate change increases the length of dry periods between intense storms, bioretention systems and related practices may leach more nitrate. Plant uptake also affects nutrient removal in vegetated stormwater GI, so plant response to climate change is another driver of stormwater GI effectiveness. Ultimately stormwater GI practices may need to be designed differently to counteract these effects.

#### *Literature review conclusions*

The findings from this review of the role of stormwater GI in climate adaptation were that 1) traditional stormwater management (without stormwater GI or other BMPs) may lead to degraded water quality and increased runoff under altered

climate conditions, 2) modeled implementation of hypothetical stormwater GI provided climate adaptation at watershed scales, and 3) increased sizing, design modifications, or expanded implementation of stormwater GI and other BMPs may be needed in order to achieve stormwater and water quality goals under future climate conditions. Assessment of stormwater GI performance with climate change is a relatively new area of research. All studies in this review were published after 2003. There was a focus on modeling hypothetical stormwater GI, and on evaluations of existing stormwater GI at site scale. An opportunity to extend the work that has been done so far is to assess climate resilience of existing stormwater GI at a watershed scale.

### **Context for this study**

Prior research on stormwater GI and climate resilience has focused on 1) simulations of hypothetical stormwater GI at watershed scales, or 2) evaluations of existing site scale stormwater GI practices. Hypothetical simulations are valuable for illustrating the climate adaptation potential of extensive implementation in a watershed. However, the limitation is that stormwater GI implementation may not be possible to the extent simulated in these studies. Site scale evaluations are valuable to understand whether individual stormwater GI practices may need to be sized differently in the future. The limitation of individual stormwater GI practice evaluations is that an individual practice contributes only a small amount to the total runoff reduction at watershed scales.

There have been limited evaluations of existing watershed scale stormwater GI and resilience to climate change. This is partially because stormwater GI is a

relatively new practice (Ahiablame et al., 2012). As a result there are few watersheds with extensive implementation to study. Another challenge to simulating stormwater GI at watershed scales is the lack of implementation data. Because stormwater GI projects are implemented by governments, watershed groups, developers, and individuals, it is challenging to maintain a centralized dataset of all stormwater GI. Working in a watershed within the Chesapeake Bay watershed provides two specific advantages: 1) there is a relatively longer history of implementation in this region. Some of the earliest rain garden implementation was in Prince George's County, Maryland (Liu et al., 2014; Prince George's County, Maryland, 2007); 2) local governments have better records on local BMP implementation (including stormwater GI) because of the Chesapeake Bay TMDL tracking and reporting requirements. Selecting a watershed within the larger Chesapeake Bay watershed therefore provides an opportunity to extend previous research by studying existing stormwater GI at a watershed scale.

## **Research Question**

To build on previous assessments of stormwater GI climate resilience, this research asks, **is current stormwater GI implementation at a watershed scale resilient to climate change?** Specifically, I investigate the following questions:

- Will surface runoff increase in future climate scenarios compared to the present?
- Will the existing stormwater GI provide the same relative reduction in surface runoff in future climate scenarios compared to the present?

- Will hypothetical (expanded) stormwater GI implementation improve watershed resilience to climate change?

## **Hydrologic modeling**

Hydrologic modeling has a wide variety of applications. These include assessing effects of management scenarios, or understanding possible impacts of land use or climate change. The utility of models is in testing a hypothesis where direct observation is not feasible. For example, direct observation may not be feasible if the study is at large spatial and/or temporal scales, or if the research question involves testing a large number of hypothetical scenarios. All mathematical models have uncertainty in them because even the most complex models are a simplification of reality. Interpretation of simulated data should include an understanding of the model itself, including strengths and weaknesses. For this research, a hydrologic model was used to simulate two watersheds under two climate change scenarios, at mid and late 21<sup>st</sup> century time periods, and under multiple management conditions.

Calibration can improve model performance and reduce uncertainty in simulation (Arnold et al., 2012). In general the calibration process involves identifying sensitive model parameters, adjusting those parameters, comparing the model output to measured data, and applying statistics to assess how closely the simulated data fits the measured data (Arnold et al., 2012). Calibration can be completed by manually adjusting parameters, or by using a semi-automated program to adjust parameters within pre-defined ranges. An additional step to improve performance is to validate the model. The process for validation is to use the calibrated model to simulate a time period (different from the calibration period) and

again compare model output to measured data. The same statistics can be used to evaluate how closely the simulated data fits the measured data.

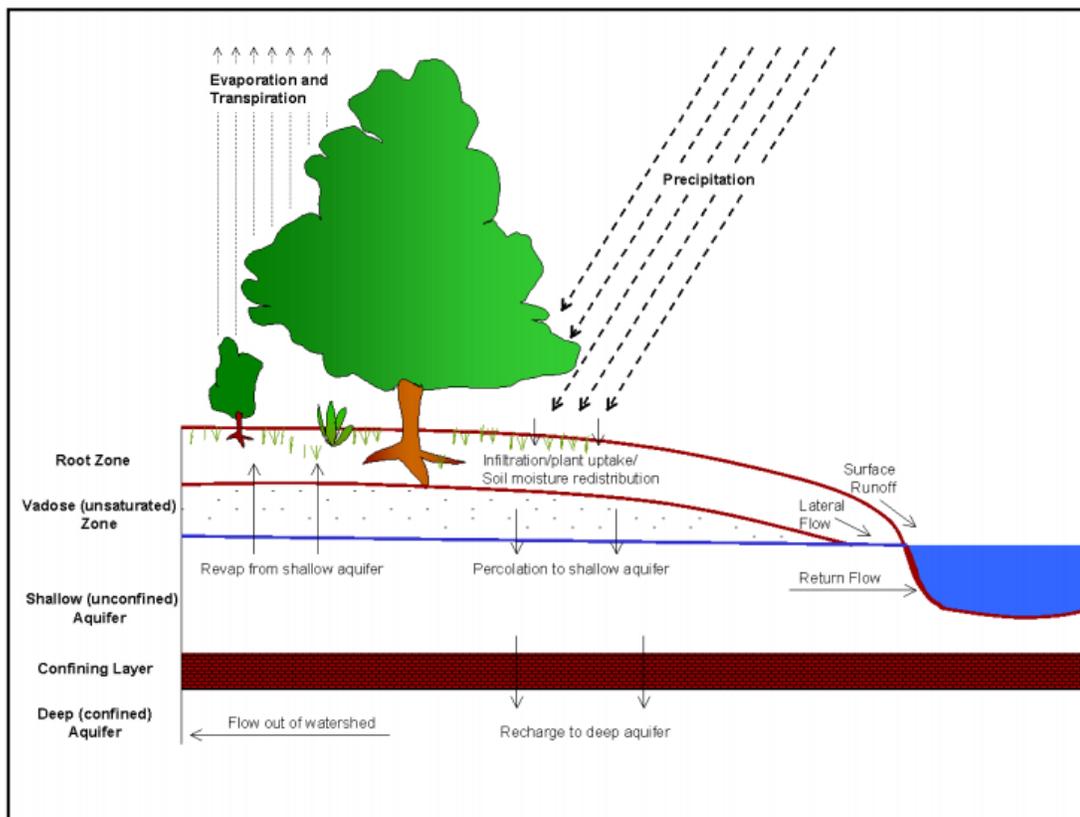
Because even calibrated models are simplifications of the real world, output from models needs to be interpreted with that in mind. For example, a model that has been calibrated to streamflow only is not necessarily sufficient to simulate N loads. For this research, the model was calibrated and validated with measured streamflow data to improve reliability.

### *Soil and Water Assessment Tool (SWAT)*

The USDA Soil and Water Assessment Tool (SWAT) is commonly used to simulate the effects of management, including BMPs, on long-term water quality and quantity at watershed scales (Gassman et al., 2007; Neitsch et al., 2011). SWAT users provide data on weather, soils, topography, and management, which drive the simulation of the hydrologic cycle (Figure 1), as well as pollutant loading and transport. SWAT operates on a daily time-step, and is therefore most appropriate to use for long-term modeling studies, rather than single storm event simulation (Neitsch et al., 2011). Watersheds are divided into subbasins in SWAT based on geographic position. Each subbasin has one or more hydrologic response units (HRUs), which are delineated based on their land cover and soil characteristics. SWAT then uses the curve number (CN) approach (Soil Conservation Service, 1986) to define infiltration and runoff rates for each HRU. CN is adjusted to soil moisture conditions on a daily basis. A higher CN indicates a higher ratio of runoff. Each HRU has a separate hydrologic calculation based on the combination of soil and land cover, which contributes to the totals for the watershed. For an urban watershed with both pervious

and impervious cover, the subbasins and HRUs are a useful approach to represent the diversity of land cover types, each with unique runoff characteristics. To model nonpoint source pollution in urban watersheds, SWAT uses regression equations for total N, total P, and suspended sediment based on watershed area, impervious area, and storm size.

Figure 1. Illustration of SWAT model hydrology from SWAT Theoretical Documentation (2009).



### SWAT simulation in urban watersheds

Although most often applied to agricultural watersheds, SWAT has been used to simulate urban watersheds. Dixon and Earls, (2012) found that SWAT can be used to assess effects of urbanization on streamflow. Qiu and Wang, (2014) applied SWAT in a suburban watershed, where the calibration statistics were satisfactory, however

their model did not capture the flashiness of the monitored data. A challenge when applying SWAT to urban watersheds is simulating stormwater GI. SWAT 2012 includes wet ponds, wetlands, filter strips, and grassed waterways (Neitsch et al., 2011). However, there is a need for better representation of the full range of stormwater GI and other urban BMPs in SWAT (Hunt et al., 2009). Wang, (2015) modeled stormwater GI at the HRU level by adjusting a combination of soil, vegetation, and impervious cover parameters, which were selected to represent stormwater GI mechanisms. The model successfully simulated reductions in runoff, N, P, and sediment that matched literature values for stormwater GI practice reductions.

## **Research Approach**

**To address my research questions regarding stormwater GI resilience to climate change, I tested existing and hypothetical stormwater GI implementation under current and future climate scenarios using simulations for subwatersheds of the Potomac River watershed calibrated to USGS stream monitoring data. This research advanced prior work on stormwater GI and climate resilience by using monitoring data in a watershed with existing stormwater GI to calibrate watershed models. I then used the calibrated models to evaluate future climate and stormwater GI scenarios.**

## Chapter 2: Stormwater Green Infrastructure Climate Resilience in Clarksburg Maryland Watersheds

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### **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 climate resilience of a watershed with stormwater green infrastructure and a watershed with traditional stormwater controls in Clarksburg, Maryland. We used the USDA Soil and Water Assessment Tool (SWAT) calibrated to USGS daily streamflow data from 2011-2016 to evaluate multiple future climate and management scenarios. We found that the stormwater GI watershed had less runoff than the traditional management watershed under climate change 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. These findings confirm previous evaluations of hypothetical stormwater GI effectiveness for adapting watersheds to climate change.

## **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 increased 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). Green roofs and other vegetated GI practices facilitate evapotranspiration (Oberndorfer et al., 2007; VanWoert et al., 2005). Many GI practices also reduce nutrient, sediment, and toxic contaminant pollution through biological denitrification, filtration, sorption, or plant uptake (Dibiasi 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 (Ahiablame et al., 2012).

Climate change will likely place additional pressure on urban watersheds. Climate change projections indicate increasing temperatures through the mid and late 21<sup>st</sup> century (IPCC, 2014a). Increased intensity and frequency of extreme events is projected for the mid-latitude land masses (IPCC, 2014a). As a result, there may be more runoff and flooding in urban watersheds under future climate conditions (Revi et al., 2014). 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 to improve resilience to climate change impacts including flooding, drought, and urban heat island (US EPA, 2014). However, these practices are designed for current climate, and may not be sufficient to achieve these goals under future climate conditions.

Previous assessments of stormwater GI climate resilience have focused on 1) hypothetical modeling of GI implementation as an adaptation measure, and 2) evaluation of existing stormwater GI climate resilience 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). 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). There have been fewer studies evaluating climate resilience

of existing stormwater GI at watershed scales. This is due, in part, to there being relatively few watersheds with extensive implementation as green infrastructure is a relatively new stormwater practice. Perhaps more importantly is a lack of data related to implementation and performance at watershed scales. Stormwater GI practices are installed by developers, watershed groups, government agencies, and individuals, so it is difficult to obtain complete records of stormwater GI implementation. The Chesapeake Bay watershed provides an opportunity to study existing practices at watershed scale, because 1) there is a longer history of implementation (e.g. (Prince George's County, Maryland, 2007), and 2) 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).

This research asked: is stormwater GI at a watershed scale resilient to climate change? Specifically, we 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 resilience to climate change. To answer these questions we modeled two urban watersheds (one with existing stormwater GI and one with traditional stormwater management) using the USDA Soil and Water Assessment Tool (SWAT). We calibrated and validated both models to USGS streamflow records. We then used the calibrated models to simulate multiple climate change and stormwater management scenarios to evaluate climate resilience.

## Methods

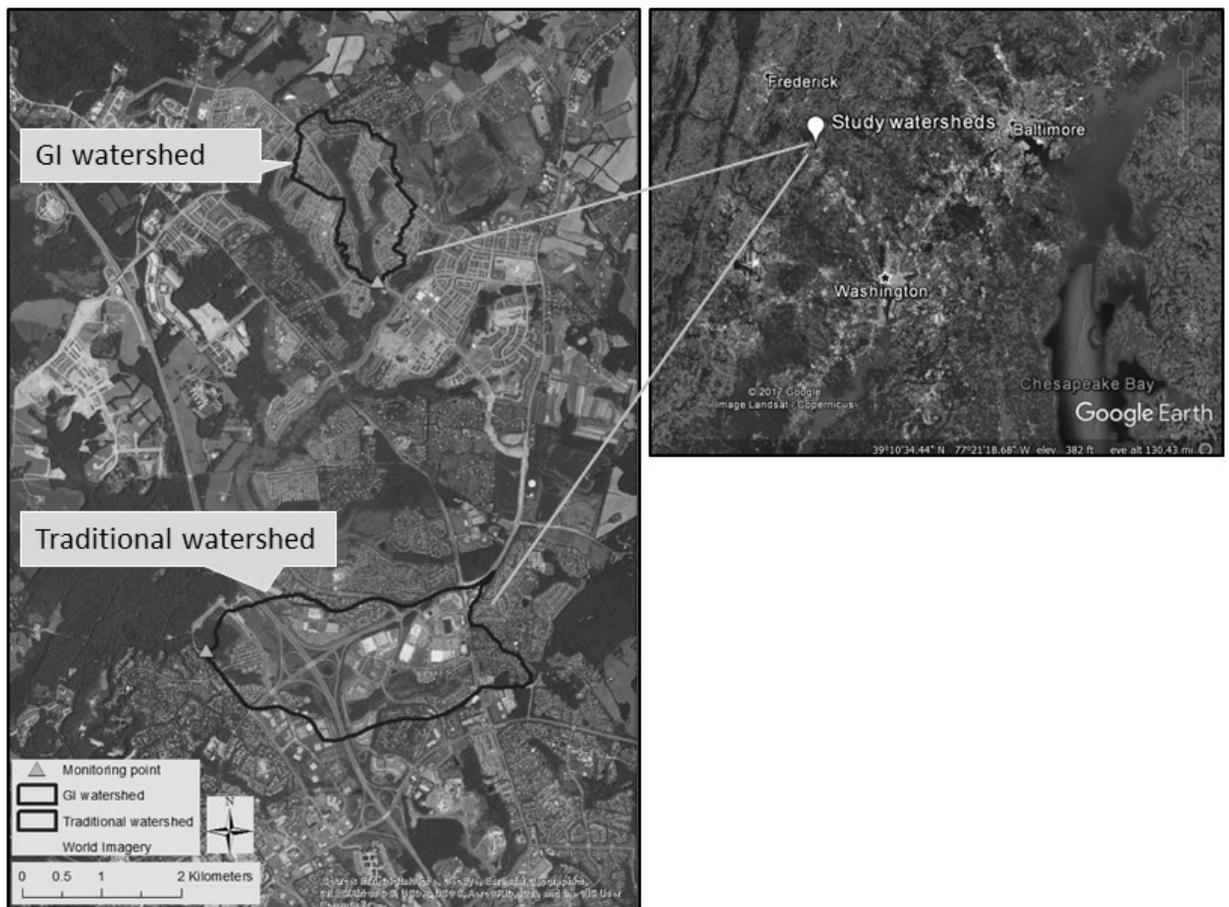
### *Site description*

The two watersheds in this study are located in Montgomery County, MD within the Piedmont physiographic region (Figure 2). 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 km<sup>2</sup> 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). 73 of the practices were designed for infiltration, and 17 for hydraulic detention (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 km<sup>2</sup> 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 (gray infrastructure) hydrology and water quality stormwater practices. None of the stormwater practices in Crystal Rock were designed for infiltration, and

12 were designed for hydraulic detention (Loperfido et al., 2014). Crystal Rock is referred to in this paper as the “*traditional*” 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. (Bhaskar et al., 2016; Hogan et al., 2014; Jones et al., 2014; Loperfido et al., 2014; Rhea et al., 2015).

Figure 2. 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.



### *SWAT model set up and data sources*

We used the USDA SWAT model to simulate each of the two watersheds in this study (Arnold et al., 1998; “SWAT,” 2017). SWAT operates on a daily time step, and simulates the hydrology and water quality impacts of management decisions at watershed scales over long time periods. Users provide data on topography, land cover, soils, weather, and management to model a watershed in SWAT. Users can improve the performance of SWAT by calibrating sensitive model parameters to better match observed streamflow and water quality data.

*Table 1. Datasets used in SWAT modeling of a green infrastructure (GI) and a traditional watershed in Clarksburg, Maryland.*

| <b>Dataset</b>             | <b>Source</b>                     |
|----------------------------|-----------------------------------|
| <b>Topography</b>          | Maryland LiDAR 2013               |
| <b>Land use/land cover</b> | Chesapeake Conservancy 2016       |
| <b>Soils</b>               | USDA-NRCS SSURGO                  |
| <b>Precipitation</b>       | NOAA Damascus 3 SSW MD US station |
| <b>Temperature</b>         | NOAA Damascus 3 SSW MD US station |
| <b>Streamflow</b>          | USGS                              |

### *Watershed delineation*

We used ArcSWAT to combine spatial data layers for SWAT (Table 1). ArcSWAT is a public domain interface that links the SWAT model to ArcGIS (“SWAT,” 2017). We used Maryland LiDAR data for Montgomery County from 2013 as the base layer for watershed elevation (Maryland, 2013). We used the latitude and longitude coordinates of the USGS monitoring stations to define the watershed outlets and the watershed delineation. We used one-meter resolution land cover data from Chesapeake Conservancy to define land use classes in SWAT (Chesapeake Conservancy, 2016). This dataset is higher resolution and has more urban land cover

class divisions than the more common 30-meter resolution land cover datasets (e.g. NLCD 2011 (Homer et al., 2015)). We grouped the detailed land uses into three categories: mixed forest, turfgrass, and impervious (Table 2). ArcSWAT contains default values for mixed forest land uses, but does not have default values for impervious or turfgrass. We added values for the turfgrass and impervious land uses to the urban database in SWAT (Table 3). We defined parameters for turfgrass based on curve number (CN) values for open space in good condition and Manning's n values for bermudagrass (Soil Conservation Service, 1986) . We defined parameters for impervious based on CN for impervious cover and Manning's n values for smooth surfaces (concrete, etc.) (Soil Conservation Service, 1986). We used USDA Soil Survey Geographic (SSURGO) GIS data to define the soils (NRCS, n.d.). Soils were primarily hydrologic group B (85% in the GI watershed and 86% in the traditional watershed). The remaining soils were hydrologic groups C and D (each between 5-9% of watershed area). We used the LiDAR data to define the slopes in the watersheds. 25% of the GI watershed had < 5% slope, 32% had 5-10% slope, and 43% had >10% slope. 51% of the traditional watershed had <5% slope, 26% had 5-10% slope, and 23% had >10% slope. We defined Hydrologic Response Units (HRUs) in SWAT by the unique combinations of each class of land cover, soil, and slope class. We set 10% minimum area thresholds for land cover, soil, and slope 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).

*Table 2. Land use groupings for of a green infrastructure (GI) and a traditional watershed in Clarksburg, Maryland.*

| Chesapeake Conservancy land use      | Grouped land use | Grouped land use code |
|--------------------------------------|------------------|-----------------------|
| Tree Canopy                          | Mixed forest     | FRST                  |
| Shrubland                            | Mixed forest     | FRST                  |
| Low Vegetation                       | Turfgrass        | TURF                  |
| Structures                           | Impervious       | IMPV                  |
| Impervious Surfaces                  | Impervious       | IMPV                  |
| Impervious Roads                     | Impervious       | IMPV                  |
| Tree Canopy over Structures          | Impervious       | IMPV                  |
| Tree Canopy over Impervious Surfaces | Impervious       | IMPV                  |
| Tree Canopy over Impervious Roads    | Impervious       | IMPV                  |

Table 3. Urban land uses and parameter values added to Soil and Water Assessment Tool to represent a green infrastructure (GI) and a traditional watershed in Clarksburg, Maryland. Composite curve numbers (CN) are a weighted average based on fraction of impervious cover (FIMP).

| Land use      | FIMP <sup>1</sup>                            | FCMIP <sup>2</sup> | Composite curve number (CN) <sup>3</sup>           |         |         |         | Manning's n for overland flow  |
|---------------|--|--------------------|--|---------|---------|---------|--|
|               |  |                    | A soils  | B soils | C soils | D soils |  |
| <b>IMPV</b>   | 0.98   | 0.95               | 97   | 97      | 98      | 98      | 0.011  |
| <b>Source</b> | <i>SWAT theory values for transportation</i> |                    | <i>SCS values for impervious</i>                   |         |         |         | <i>TR-55 for smooth surfaces (concrete, asphalt, gravel, or bare soil)</i> |
| <b>TURF</b>   | 0  | 0                  | 39   | 61      | 74      | 80      | 0.41   |
| <b>Source</b> | <i>Land cover data</i>                       |                    | <i>SCS values for open space in good condition</i> |         |         |         | <i>TR-55 for bermudagrass</i>  |

<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 CN = (FIMP\*98) + (1-FIMP)\*CN\_soil

### Weather data

We downloaded daily precipitation data (mm) and daily maximum and daily minimum temperature data (C°) 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. Wind speed, solar radiation, and relative

humidity data were generated within SWAT based on the WGEN\_US\_FirstOrder database (Neitsch et al., 2011).

### *Streamflow*

We downloaded daily average streamflow data (m<sup>3</sup>/s) for the traditional watershed 1/1/2011-12/31/2016 and the GI watershed 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. We replaced provisional data with USGS approved values before final calibration.

### *Model parameterization, calibration, and validation*

We calibrated two models using a daily time-step: one for the GI watershed, and one for the traditional watershed. The calibration period was from 1/1/2011-12/31/2014, with a three year warmup period from 2008-2010. The validation period was from 1/1/2015-12/31/2016, with a three year warmup period from 2012-2014. We chose these time periods to represent a range of wet and dry years. Warmup periods allow the model hydrology to stabilize before output is analyzed. Average annual rainfall during the calibration period was 1322.5mm. Average annual rainfall during the validation period was 1195.3mm.

We used SWAT Calibration and Uncertainty Programs (SWAT-CUP) public domain software for sensitivity analysis and calibration (“SWAT,” 2017). We selected 25 model parameters for calibration based on SWAT hydrology modeling literature (Abbaspour et al., 2015). We conducted one-at-a-time sensitivity analyses in SWAT-CUP for each of the 25 parameters. We then used the sensitive parameters

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. We ran 500 simulations, each with unique parameter values, per calibration iteration. After each iteration, we compared the simulated daily streamflow data with observed daily streamflow data. We used Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) and percent bias 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  $\pm 25\%$  for streamflow is considered satisfactory (Moriiasi 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. We used these narrower ranges to run each subsequent iteration of 500 simulations. We repeated the process for up to 5 iterations, or until model statistics stopped improving. We then used the final parameter values from the calibration period to run SWAT for the validation time period and again calculated NSE and percent bias to evaluate model fit.

### *Scenario analysis*

To address the question of stormwater GI climate resilience, we used the calibrated and validated models to test 36 scenario combinations (Table 4). These scenarios included different climate model forecasts and land use management options for mid and late-21<sup>st</sup> century for each of the two study watersheds. The climate model forecasts included both a moderate greenhouse gas (GHG)

concentration pathway (RCP4.5) and a high concentration pathway (RCP8.5) (Moss et al., 2010). Climate reports for the United States project greater changes to temperature and precipitation with higher GHG concentration pathways (Melillo et al., 2014). The management options included 1) maintaining the existing stormwater infrastructure, and 2) expanding the stormwater GI. We describe the details of these scenarios in the sections below.

*Table 4. Climate scenario and management scenario combinations simulated with calibrated and validated GI watershed and traditional watershed SWAT models. CMIP5 models are two of the global climate models used in the IPCC 5<sup>th</sup> Assessment Report (2014). Representative Concentration Pathways are the greenhouse gas concentration pathways. Management conditions represent 1) maintaining existing stormwater infrastructure through time, and 2) expanding infiltration practices to control an additional 0.2-0.4 inches of runoff from a 2.6 inch rainfall event.*

| <b>Watersheds</b>   | <b>CMIP5 Models</b> | <b>Representative Concentration Pathways (RCP)</b> | <b>Time periods</b> | <b>Management conditions</b>   |
|---------------------|---------------------|--|---------------------|--|
| <b>Traditional.</b> | CCSM4,              | High (8.5),  | 2045-2064,          | <ul style="list-style-type: none"> <li>• Maintain stormwater infrastructure,</li> <li>• Expand GI 0.2</li> <li>• Expand GI 0.3<sup>1</sup></li> <li>• Expand GI 0.4<sup>1</sup></li> </ul> |
| <b>GI</b>           | MRI-CGCM3           | Moderate (4.5)                                     | 2075-2094           |  |

<sup>1</sup> Simulated in the GI watershed with climate scenario MRI-CGCM3 RCP8.5

#### Downscaled climate projections

We used 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, downloaded from <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 (Abatzoglou and Brown, 2012) method with the METDATA (Abatzoglou, 2011) observational dataset as training data.

We selected two GCMs: CCSM4 (National Center for Atmospheric Research, USA) and MRI-CGCM3 (Meteorological Research Institute, Japan), from the downscaled data. Multiple models are often used in climate evaluations to account for some of the variability between models (e.g. Hayhoe and Stoner, 2015). For each GCM, we used projections from two GHG concentration pathways: RCP 4.5 and RCP 8.5, representing moderate and extreme climate futures. For each GCM and RCP combination, we used projected climate data for two time periods: January 2042-December 2064 (mid-21<sup>st</sup> century), and January 2072-December 2094 (late 21<sup>st</sup> century). These time periods allowed for a 3 year warmup period in the SWAT model followed by 20 years of output data for analysis for both mid and late 21<sup>st</sup> century.

#### *Simulating changes in management*

We simulated two future management conditions for each watershed: 1) maintain stormwater infrastructure and 2) expand stormwater green infrastructure. For the “maintain” condition we kept all model parameters 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 we simulated an increase in infiltration practices to control an additional 0.2 inches of runoff from a 2.6 inch rainfall event watershed

wide. 2.6 inches is equivalent to the 1-year 24-hour storm for Montgomery County. We simulated the increase in infiltration by reducing the CN parameter on the turfgrass portion of each watershed (Table 5 and Table 6). We assumed that most additional GI implementation would occur as retrofits on existing green space adjacent to roads and buildings, so we modeled the implementation 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, we also simulated two additional increments of expanded GI implementation in the GI watershed for the MRI-CGCM3 RCP8.5 climate scenario. The additional scenarios were: 1) “expand GI 0.3” to control an additional 0.3 inches of runoff from a 2.6 inch rainfall event, and 2) “expand GI 0.4” to control an additional 0.4 inches of runoff from a 2.6 inch rainfall event. For the “expand GI 0.3” condition we simulated an increase in infiltration practices implemented on the turfgrass land use. For the “expand GI 0.4” condition we simulated 1) the same increase in infiltration practices implemented on the turfgrass land use as for the “expand GI 0.3” condition, and 2) replacement of 40% of the watershed impervious cover with turfgrass. Here we also simulated the increase in infiltration by reducing the CN parameter on the turfgrass portion of each watershed (Table 6).

*Table 5. Adjustments to curve number (CN) values used to simulate expanded implementation in the traditional watershed.*

| Traditional watershed |                  |               |
|-----------------------|------------------|---------------|
|                       | Calibrated model | Expand GI 0.2 |
| IMPV CN               | 97               | 97            |

|                                  |           |           |
|----------------------------------|-----------|-----------|
| FRST CN                          | 71        | 71        |
| TURF CN                          | 70        | 54        |
| <b>Weighted CN for watershed</b> | <b>80</b> | <b>76</b> |

Table 6. Adjustments to curve number (CN) values used to simulate expanded implementation in the GI watershed.

| GI watershed                     |                  |            |                        |                        |
|----------------------------------|------------------|------------|------------------------|------------------------|
|                                  | Calibrated model | Expand 0.2 | Expand0.3 <sup>1</sup> | Expand0.4 <sup>1</sup> |
| IMPV CN                          | 97               | 97         | 97                     | 81                     |
| FRST CN                          | 66               | 66         | 66                     | 66                     |
| TURF CN                          | 64               | 51         | 43                     | 43                     |
| <b>Weighted CN for watershed</b> | <b>73</b>        | <b>68</b>  | <b>65</b>              | <b>61</b>              |

<sup>1</sup> Simulated with climate scenario MRI-CGCM3 RCP8.5

#### SWAT model output data

We used SWAT model output for daily streamflow ( $\text{m}^3/\text{s}$ ) at each watershed outlet for analysis. We calculated surface runoff at a daily time step 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  $\text{BFI}_{\text{max}} = 0.80$  for perennial streams with porous aquifers (Eckhardt, 2005). We then converted surface runoff rate ( $\text{m}^3/\text{s}$ ) to runoff depth (mm/day). We aggregated the output data to seasonal values as 1) total seasonal surface runoff depth, 2) total seasonal precipitation depth, and 3) average seasonal streamflow rate. We defined seasons as: Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), and Fall (September, October, November). For each future climate scenario, we calculated the percent change in each parameter

compared to the watershed's current climate (2011-2016) scenario output. We calculated percent change in surface runoff depth between maintained and expanded implementation for each climate scenario combination and watershed.

We 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. We grouped the data by amount of daily precipitation into 5 bins: 1) no rain (0 mm), 2) small (<13mm), 3) medium (13-30mm), 4) large (30-60mm), and 5) largest (>60mm). We calculated a linear regression between GI watershed and traditional watershed runoff for each daily precipitation bin to compare the watersheds' runoff response.

## **Results**

### *Calibration and Sensitivity Analysis*

Calibration improved the model fit measured by the objective function Nash-Sutcliffe efficiency (NSE) for both the GI and traditional watershed models (Table 1). The traditional watershed had NSE = 0.72 for streamflow at daily time step, indicating good performance (Moriassi et al., 2007). The GI watershed had NSE= 0.84 for streamflow at daily time step, indicating very good performance (Moriassi et al., 2007). Percent bias (%BIAS) was less than +/-10 for both watershed models before and after calibration, indicating very good performance (Moriassi 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 (Moriassi et al., 2007). The performance of both watershed models

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 watershed models during the validation period, indicating very good performance.

*Table 7. Green infrastructure (GI) watershed and traditional watershed model performance statistics for the calibration period (2011-2014) for streamflow at daily and monthly time step.*

| Model       | Uncalibrated model – daily |       | Calibrated model - daily |       | Calibrated model - monthly |       |
|-------------|----------------------------|-------|--------------------------|-------|----------------------------|-------|
|             | NSE                        | %BIAS | NSE                      | %BIAS | NSE                        | %BIAS |
| Traditional | 0.53                       | -6.4  | 0.72                     | 4     | 0.8                        | -3.6  |
| GI          | 0.64                       | -6.8  | 0.84                     | 9.9   | 0.84                       | 9.8   |
| Goal        | >0.5                       | +/-20 | >0.5                     | +/-20 | >0.5                       | +/-20 |

*Table 8. Green infrastructure (GI) watershed and traditional watershed model performance statistics for the validation period (2015-2016) for streamflow at daily and monthly time step.*

| Model       | Validation - daily |       | Validation – monthly |       |
|-------------|--------------------|-------|----------------------|-------|
|             | NSE                | %BIAS | NSE                  | %BIAS |
| Traditional | 0.36               | -9.2  | 0.71                 | -9    |
| GI          | 0.44               | -3.3  | 0.7                  | -3.1  |
| Goal        | >0.5               | +/-20 | >0.5                 | +/-20 |

Seven hydrology parameters were sensitive in both the GI watershed model and the traditional watershed model and were adjusted to calibrate both models: 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 GI watershed model was sensitive to groundwater re-evaporation coefficient (GW\_REVAP), so this parameter was adjusted for GI watershed model calibration. The traditional watershed model was sensitive to melt factor for snow (SMFMN), so this parameter was adjusted for the traditional watershed model calibration.

### *Climate Simulations*

Average winter, spring, and fall precipitation increased and average summer precipitation decreased for most climate scenarios for both mid and late 21<sup>st</sup> century compared to current conditions (Figure 3). Change in winter precipitation was between -6% and +9% at mid-century and between -1% and +8% at late century. Change in spring precipitation was between +2% and +7% at mid-century and between 0% and +17% at late century. Change in summer precipitation was between -11% and -27% at mid-century and between -3% and -29% at late century. Change in fall precipitation was between +2% and +12% at both mid and late century. Precipitation projections varied by climate model (Figure 3). 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. For the RCP 8.5 (high emission) scenarios, the CCSM4 model was wetter than the MRI-CGCM3 model for spring and summer at mid-century, and for summer at late century. In general the RCP8.5 (high emission) scenarios had higher precipitation than RCP 4.5 (low emissions) scenarios, and the late century scenarios had higher precipitation than the mid-century scenarios.

Change in total seasonal surface runoff depth compared to current conditions varied by season for climate scenarios (Figure 4). Winter runoff increased more in the traditional watershed (+5% to +35% range) than in the GI watershed (-11% to +7% range). Spring runoff decreased in most climate scenarios in both the traditional watershed (-21% to +1% range) and the GI watershed (-19% to +6% range). Summer

runoff decreased in all climate scenarios in both the traditional watershed (-65% to -31% range) and the GI watershed (-71% to -36% range). Fall runoff increased less in the traditional watershed (-6% to +23% range) than in the GI watershed (-4% to +31% range).

Change in runoff ratio (amount of precipitation converted to runoff) for climate scenarios compared to current conditions also varied by season. Spring runoff ratio decreased in both the traditional watershed (-21% to -10% range) and the GI watershed (-17% to -6% range). Summer runoff ratio decreased in both the traditional watershed (-53% to -33%) and the GI watershed (-61% to -39%). Fall runoff ratio increased for most climate scenarios in both the traditional watershed (-6% to +15% range) and the GI watershed (-4% to +25% range). Winter runoff ratio increased for the traditional watershed (+10% to +22% range) and decreased for the GI watershed (-6% to -2% range).

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 5a-e). Linear regressions of GI watershed runoff compared to traditional watershed runoff for days with small, medium, and large rainfall totals had slope <1 for all climate scenarios, representing higher runoff from the traditional watershed than from the GI watershed. Linear regressions for days with the largest rainfall total (>60mm) had slope > 1 for current climate and CCSM4 model climate scenarios, representing higher runoff from the GI watershed than the traditional watershed (Figure 5a-c). Slope of regression lines for medium, large, and largest precipitation amounts did not increase between current climate and

future climate scenarios (Table 9). In general, slope of regression lines increased with increasing daily rainfall amount for most climate scenarios (Table 9).

*Table 9. Linear regression equations and R<sup>2</sup> values for comparison of modeled runoff depth in the GI watershed compared to the traditional watershed for current and projected climate conditions on days with small (<13mm), medium (13-30mm), large (30-60mm), and largest (>60mm) rainfall totals.*

| Simulated date range | Climate scenario | Rainfall amount  | Equation            | R <sup>2</sup> |
|----------------------|------------------|------------------|---------------------|----------------|
| 2011-2016            | Observed         | small (0-13mm)   | $y = 0.46x + 0.17$  | 0.17           |
|                      |                  | medium (13-30mm) | $y = 0.62x + 0.49$  | 0.71           |
|                      |                  | large (30-60mm)  | $y = 0.72x + 1.8$   | 0.61           |
|                      |                  | largest (>60mm)  | $y = 1.18x + -4.68$ | 0.92           |
| 2045-2064            | CCSM4 RCP8.5     | small (0-13mm)   | $y = 0.48x + 0.1$   | 0.4            |
|                      |                  | medium (13-30mm) | $y = 0.67x + 0.44$  | 0.72           |
|                      |                  | large (30-60mm)  | $y = 0.45x + 5.54$  | 0.35           |
|                      |                  | largest (>60mm)  | $y = 1.11x + -2.43$ | 0.94           |
|                      | MRI-CGCM3 RCP8.5 | small (0-13mm)   | $y = 0.59x + 0.07$  | 0.52           |
|                      |                  | medium (13-30mm) | $y = 0.71x + 0.24$  | 0.82           |
|                      |                  | large (30-60mm)  | $y = 0.83x + 1.58$  | 0.6            |
|                      |                  | largest (>60mm)  | $y = 0.91x + 2.26$  | 0.81           |
| 2075-2094            | CCSM4 RCP8.5     | small (0-13mm)   | $y = 0.68x + 0.05$  | 0.83           |
|                      |                  | medium (13-30mm) | $y = 0.76x + 0.04$  | 0.86           |
|                      |                  | large (30-60mm)  | $y = 0.56x + 4.49$  | 0.51           |
|                      |                  | largest (>60mm)  | $y = 1.28x + -6.64$ | 0.89           |
|                      | MRI-CGCM3 RCP8.5 | small (0-13mm)   | $y = 0.64x + 0.06$  | 0.68           |
|                      |                  | medium (13-30mm) | $y = 0.7x + 0.26$   | 0.8            |
|                      |                  | large (30-60mm)  | $y = 0.65x + 3.46$  | 0.54           |
|                      |                  | largest (>60mm)  | $y = 0.93x + 1.82$  | 0.78           |

Expanded implementation to treat an additional 0.2 inches of runoff from the 2.6 inch rainfall event reduced seasonal runoff depth for both watersheds for most climate scenarios (Figure 6). Winter runoff reductions were between 2-3% in the traditional watershed and 3-5% in the GI watershed. Spring runoff reductions were between 0-1% in the traditional watershed and 3-4% in the GI watershed. Summer runoff reductions were between 0-1% in the traditional watershed and 0-3% in the GI

watershed. Fall runoff reductions were between 1-2% in the traditional watershed and 4-6% in the GI watershed.

Expansion of GI in the GI watershed to treat an additional 0.3 and 0.4 inches of runoff from the 2.6 inches rainfall event for the MRI-CGCM3 RCP8.5 climate scenario decreased seasonal runoff compared to the “maintain GI” condition (Table 10, Table 11). This effect was greater as GI implementation increased. For the seasons where runoff increased under the “maintain GI” condition, additional expansion of GI buffered that increase. At mid-century, winter runoff increased 5%, and fall runoff increased 17% under the “maintain GI” condition compared to the 2011-2016 baseline (Table 10). Expanded GI (0.3 inches) reduced mid-century winter runoff by 1% and reduced the increase in fall runoff to 9% compared to the 2011-2016 baseline. Expanded GI (0.4 inches) reduced mid-century winter runoff by 11%, and fall runoff by 9% compared the 2011-2016 baseline. At late-century, winter runoff increased 7%, spring runoff increased 6% and fall runoff increased 30% compared to the 2011-2016 baseline (Table 11). Expanded GI (0.3 inches) reduced the increase in late century winter runoff to 1%, and kept spring runoff the same compared to the 2011-2016 baseline. Expanded GI (0.4 inches) reduced late century winter runoff by 9% and spring runoff by 15%, and reduced the increase in fall runoff to 2% compared to the 2011-2016 baseline.

Table 10. Scenarios of incremental GI expansion in the GI watershed. Change in mid-century (2045-2064) seasonal surface runoff with MRI-CGCM3 RCP8.5 climate scenario for each GI expansion scenario relative to 2011-2016 baseline. Values near or below 0 indicate the expanded GI can buffer the change and keep runoff at or below current levels.

| <b>Season</b> | <b>Maintain GI</b> | <b>Expand GI (0.2inches)</b> | <b>Expand GI (0.3inches)</b> | <b>Expand GI (0.4inches)</b> |
|---------------|--------------------|------------------------------|------------------------------|------------------------------|
| Winter        | 5%                 | 1%                           | -1%                          | -11%                         |
| Spring        | -7%                | -11%                         | -12%                         | -26%                         |
| Summer        | -61%               | -63%                         | -63%                         | -72%                         |
| Fall          | 17%                | 9%                           | 8%                           | -9%                          |

Table 11. Scenarios of incremental GI expansion in the GI watershed. Change in late-century (2075-2094) seasonal surface runoff with MRI-CGCM3 RCP8.5 climate scenario for each GI expansion scenario relative to 2011-2016 baseline. Values near or below 0 indicate the expanded GI can buffer the change and keep runoff at or below current levels.

| <b>Season</b> | <b>Maintain GI</b> | <b>Expand GI (0.2inches)</b> | <b>Expand GI (0.3inches)</b> | <b>Expand GI (0.4inches)</b> |
|---------------|--------------------|------------------------------|------------------------------|------------------------------|
| Winter        | 7%                 | 2%                           | 1%                           | -9%                          |
| Spring        | 6%                 | 1%                           | 0%                           | -15%                         |
| Summer        | -58%               | -59%                         | -59%                         | -70%                         |
| Fall          | 30%                | 22%                          | 20%                          | 2%                           |

Figure 3. Change in seasonal precipitation projected for 2045-2064 (a) and 2075-2094 (b) relative to current (2011-2016) conditions for both a green infrastructure (GI) watershed and traditional watershed. Graphs show 4 different climate scenarios (combinations of global climate model (CCSM4 and MRI-CGCM3) and representative concentration pathway (RCP4.5 and RCP8.5)).

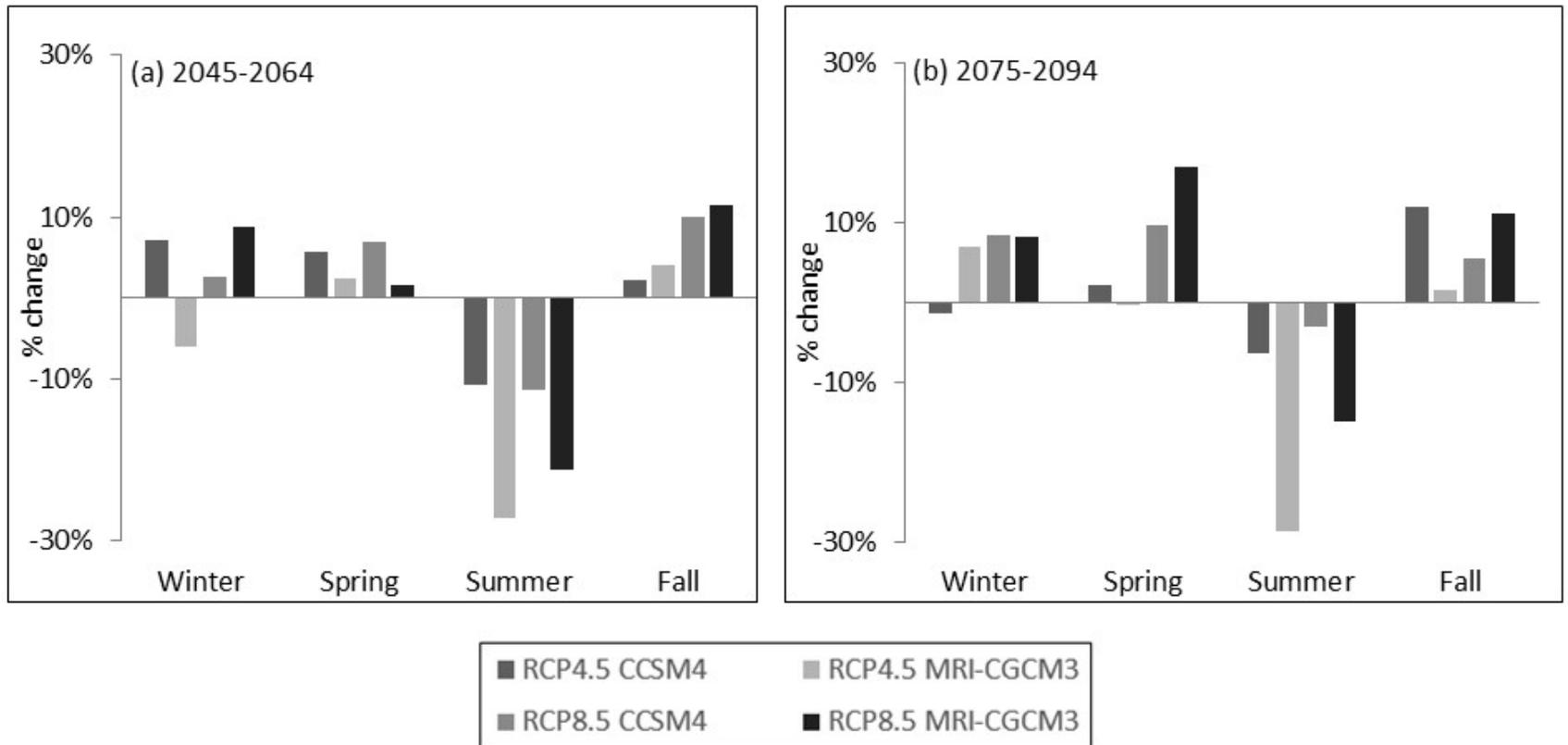


Figure 4. Change in seasonal runoff depth for 2045-2064 (a, c) and 2075-2094 (b, d) relative to current (2011-2016) conditions for GI watershed (a, b) and traditional watershed (c, d). Graphs show 4 different climate scenarios (combinations of global climate model (CCSM4 and MRI-CGCM3) and representative concentration pathway (RCP4.5 and RCP8.5)).

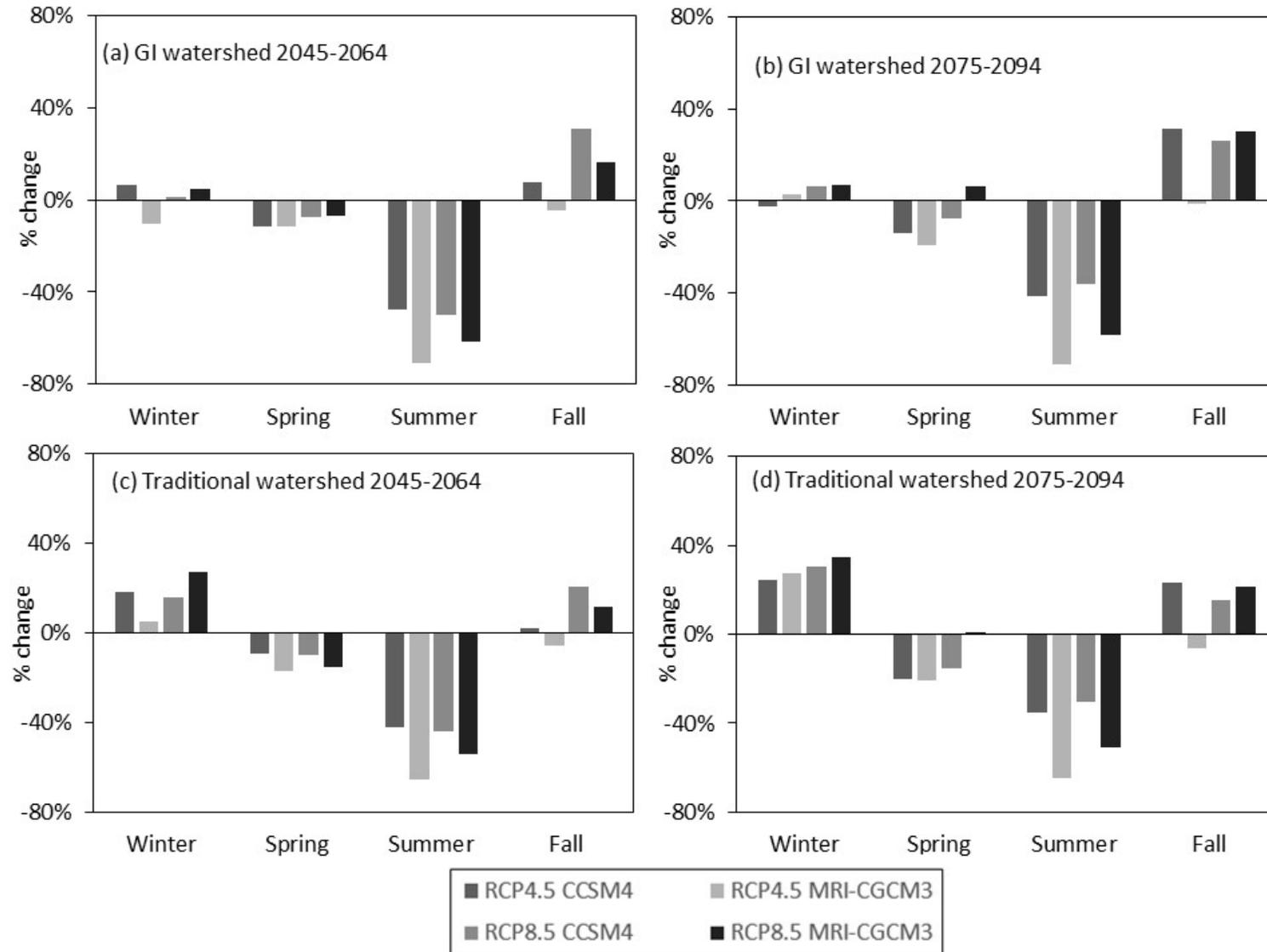
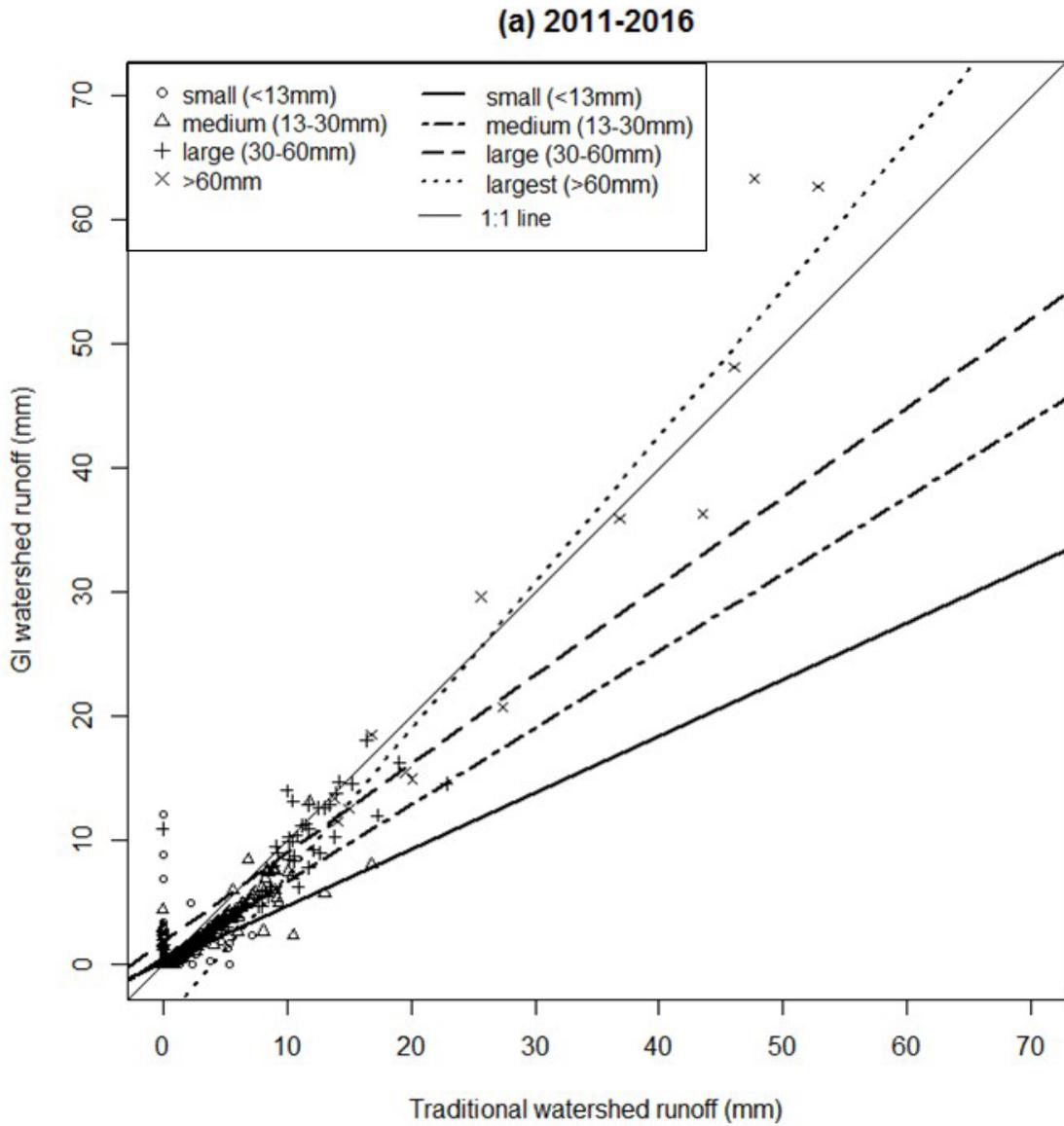
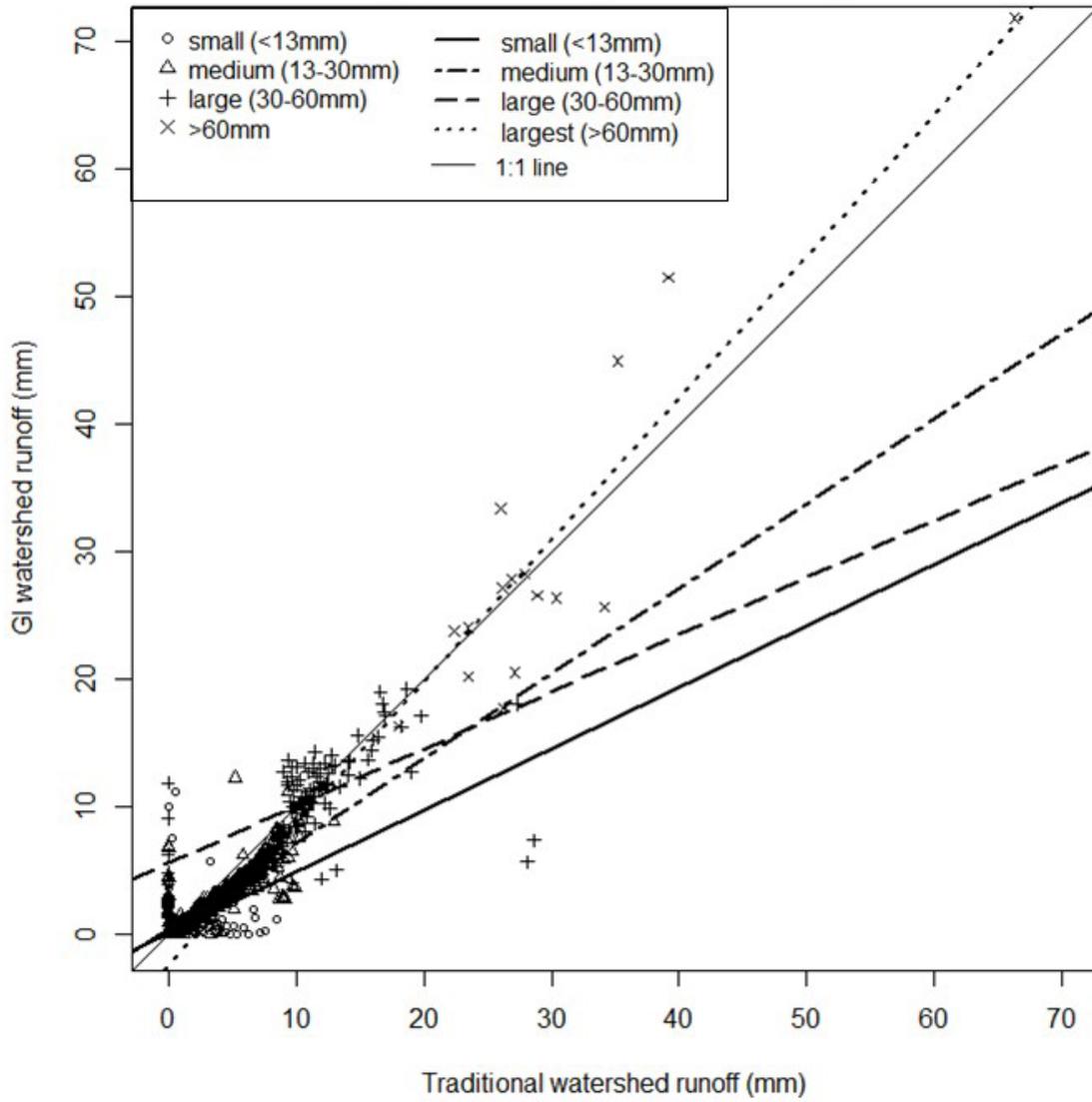


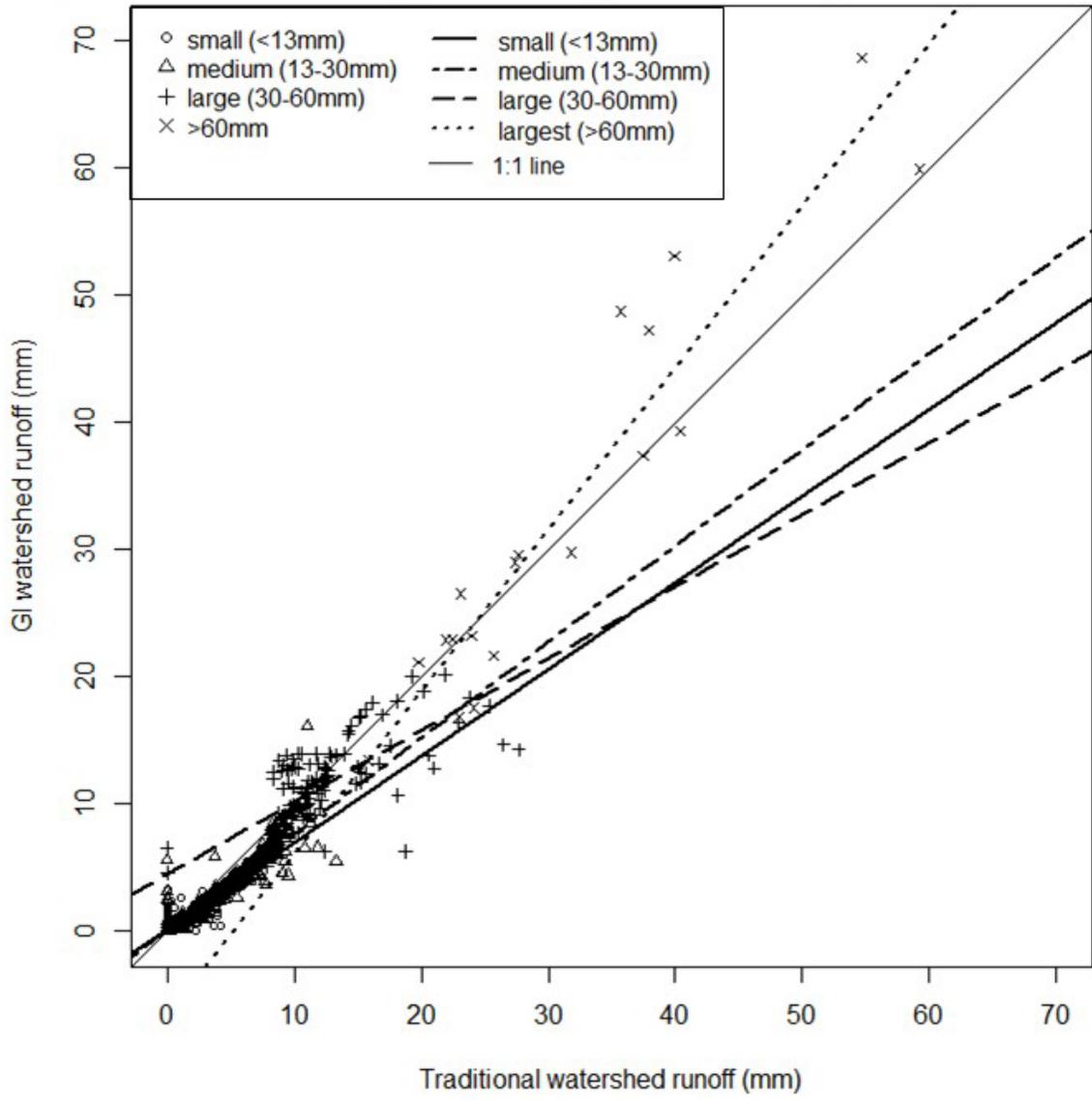
Figure 5. Comparison of modeled runoff depth in the GI watershed and in the traditional watershed for current conditions(2011-2016) (a), and projected climate conditions (b-e) compared to a reference line with slope=1. Regression lines fit to runoff depth values on days with small (<13mm), medium (13-30mm), large (30-60mm), and largest (>60mm) rainfall totals. Graphs b-e show 2 different climate scenarios (CCSM4 and MRI-CGCM3) with RCP8.5).



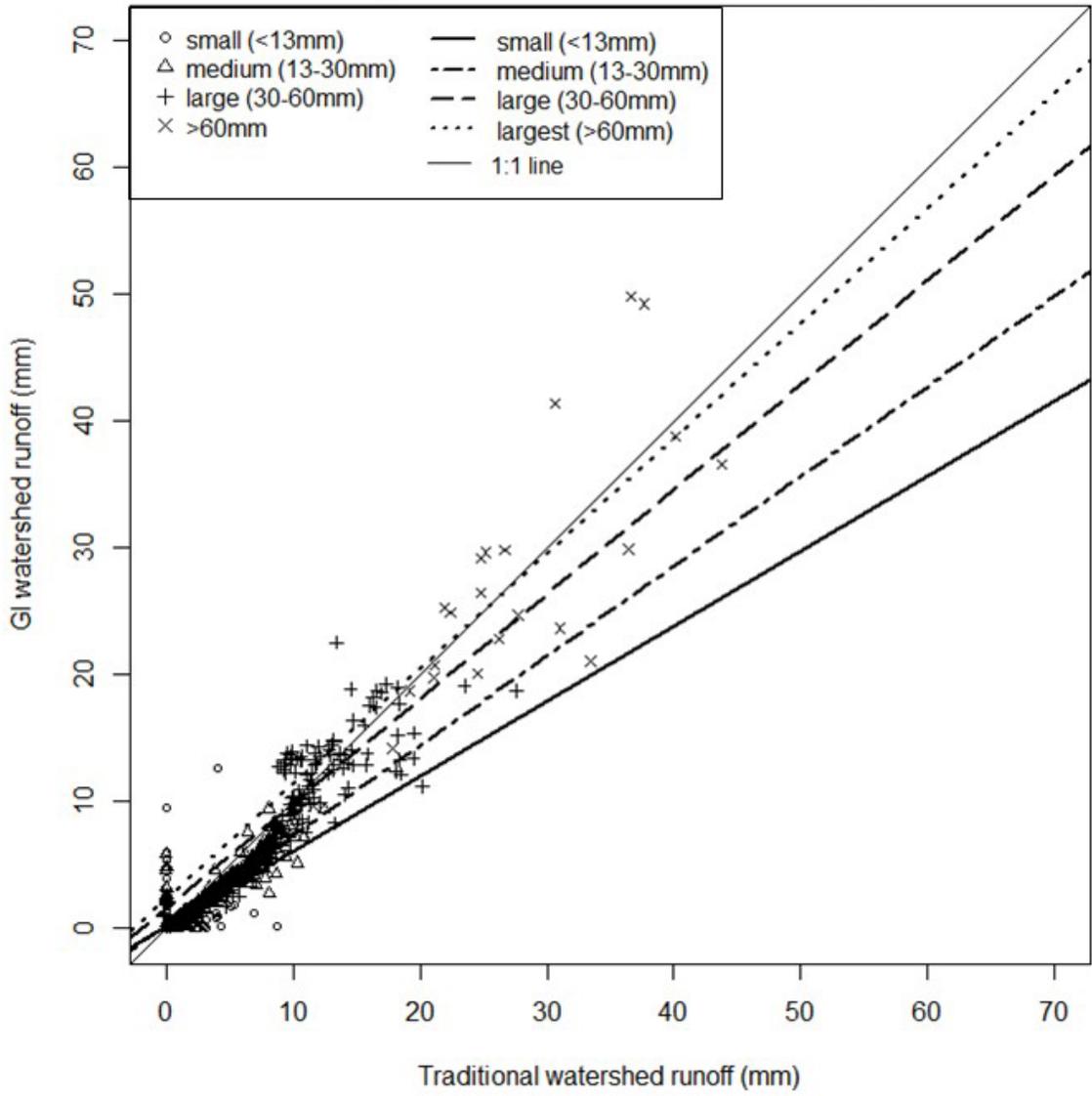
(b) 2045-2064 (CCSM4 RCP8.5)



(c) 2075-2094 (CCSM4 RCP8.5)



(d) 2045-2064 (MRI-CGCM3 RCP8.5)



(e) 2075-2094 (MRI-CGCM3 RCP8.5)

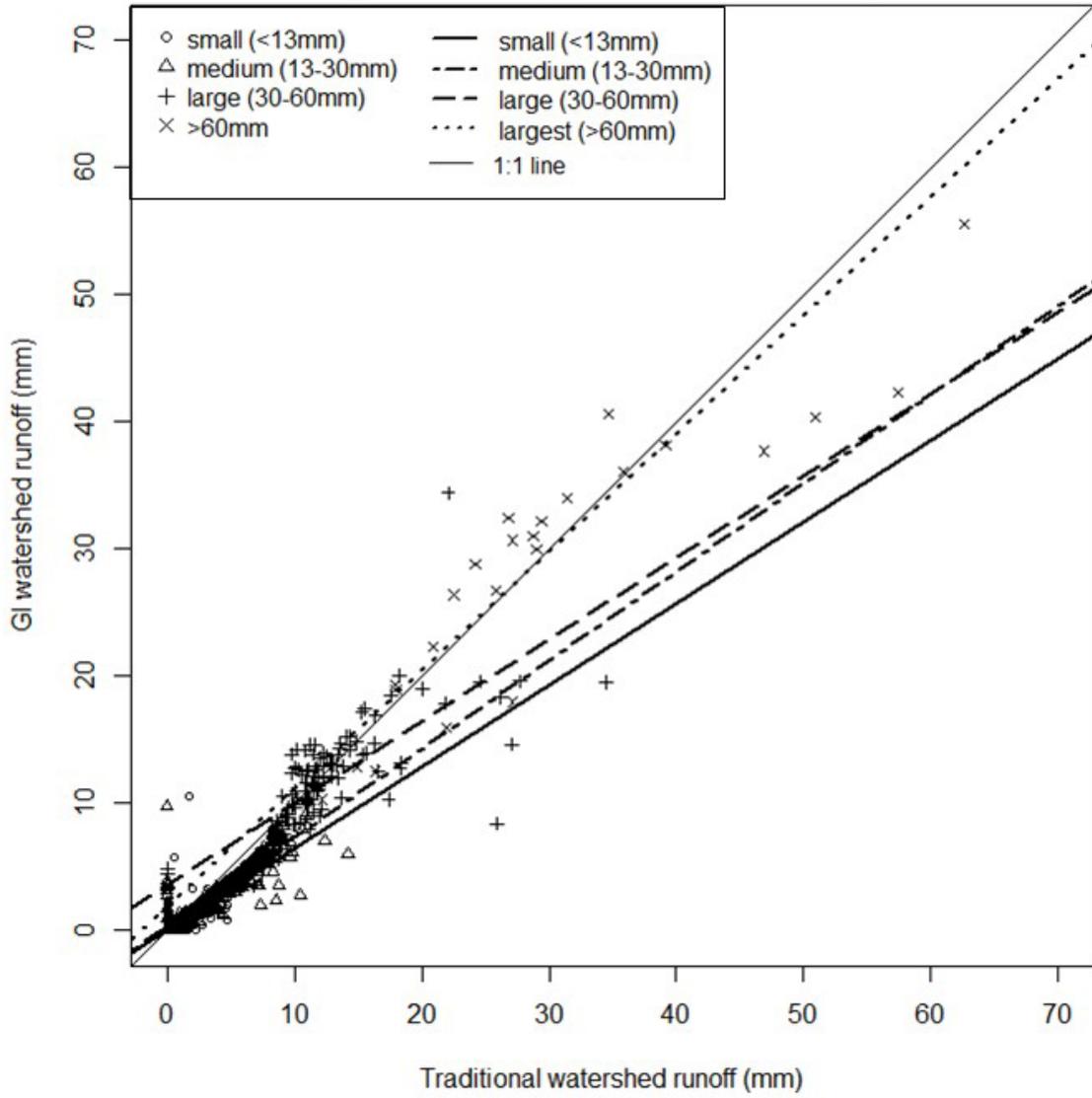
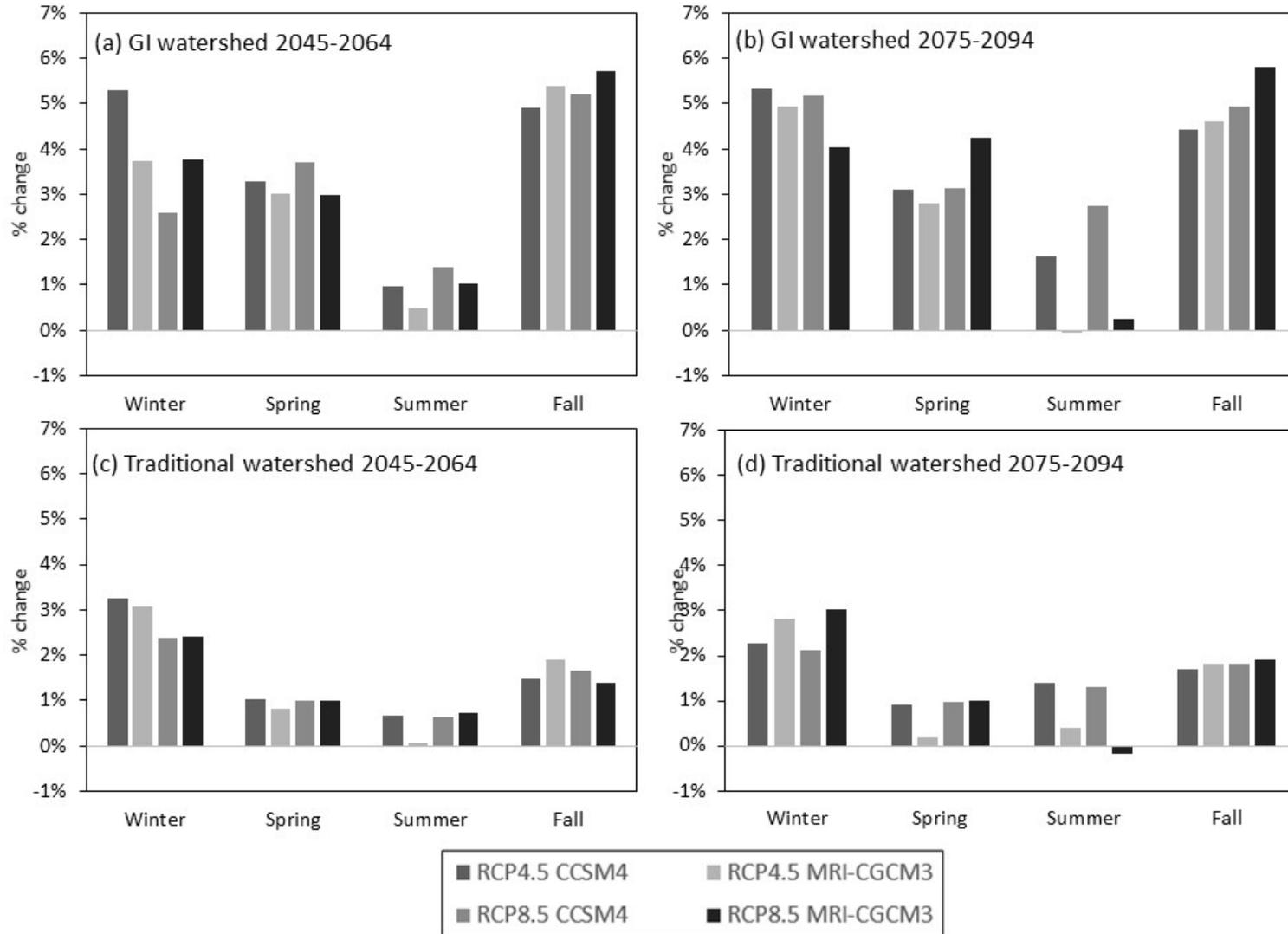


Figure 6. Seasonal runoff depth reduction with expanded GI implementation scenarios for 2045-2064 (a, c) and 2075-2094 (b, d) for green infrastructure (GI) watershed (a, b) and traditional watershed (c, d). Data show the percent change between expanded GI implementation compared to maintained GI implementation 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)).



## **Discussion**

The purpose of this study was to assess whether a case study watershed with stormwater GI is resilient to climate change. To answer this question, we calibrated SWAT to observed streamflow data in two watersheds: one with stormwater GI, and one with traditional management. We used these models to evaluate 1) whether surface runoff would increase in future climate scenarios compared to the present, 2) if the existing stormwater GI would provide the same relative reduction in surface runoff in future climate scenarios compared to the present, and 3) whether expanded stormwater GI implementation would improve watershed resilience to climate change.

### *Calibration and Sensitivity Analysis*

Both the stormwater GI and the traditional watershed SWAT models simulated observed streamflow well at a daily time step during the calibration period (Table 7). Both watershed models performed worse during the validation period than the calibration period based on the NSE metric at daily time step (Table 8). This could be due to differing rainfall conditions in each time period. Average annual rainfall was 1323 mm during the calibration period and 1195 mm during the validation period. The difference in model performance could also be due to the relatively shorter time period simulated for the validation period. A longer time period with both wet and dry years is recommended for calibration and validation (Arnold et al., 2012). However, a longer time period was not possible for this study because of the land use change and construction in stormwater GI watershed prior to 2011. NSE values improved at monthly time step for both watersheds during the validation period. This improvement in model performance at

longer term intervals has been observed in other SWAT studies (Chu and Shirmohammadi, 2004). The low percent bias in both watersheds during both calibration and validation time periods indicates further confidence that our models are not consistently over or underestimating streamflow.

The GI and traditional watershed models were sensitive to similar parameters used in other SWAT modeling studies, including parameters controlling surface runoff, groundwater, snow, and soil bulk density. CN, which controls surface runoff, is commonly a sensitive parameter for streamflow in SWAT (Abbaspour, 2007). Other SWAT studies calibrated CN in their simulations of watersheds in Maryland (Chu and Shirmohammadi, 2004; Renkenberger, 2015; Sexton et al., 2011; Wang, 2015). Hydraulic conductivity (CH-K2) was calibrated in another study in Maryland (Wang, 2015). Snow parameters (SFTMP, SMTMP, SMFMN, TIMP) have been found to be sensitive for hydrology in SWAT studies (Abbaspour, 2007). SMFMN was calibrated in one other Maryland study (Wang, 2015). The groundwater re-evaporation parameter (GW\_REVAP) controls the amount of water moving from bank storage to adjacent unsaturated zones in the soil. This parameter was calibrated in three other Maryland studies (Renkenberger, 2015; Sexton et al., 2011; Wang, 2015). Maximum canopy storage (CANMX) controls the amount of water intercepted by vegetation, and was calibrated in two other Maryland studies (Renkenberger, 2015; Wang, 2015). Soil bulk density (SOL\_BD), has been sensitive for hydrology in other SWAT studies (Abbaspour, 2007). The similarity in sensitive parameters used for calibration in our models compared to other local SWAT modeling studies gives further confidence that our models are able to simulate local conditions and responses to climate drivers.

## *Climate Simulations*

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 (Figure 3). 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 we used differed in their projections: the MRI-CGCM3 model projected drier conditions than the CCSM4 model annually and for most seasons, so our results include more variability than if we had used only one climate model. 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 include duration of rainfall events. Therefore these results may not fully capture changes in precipitation intensity. 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 would likely be overwhelmed more frequently.

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 5a-e). This is consistent with previous assessments of GI for reducing stormwater runoff compared to traditional stormwater management (Dietz, 2007; Hood et al., 2007). We found that the GI watershed controlled less runoff than the traditional for some of the days with the highest rainfall (>60mm). This could be due to the SWAT

model's underestimation of peak events (e.g. Qiu and Wang, 2014). A previous monitoring study of these two watersheds found that the GI watershed controlled more runoff than the traditional watershed for a 248 mm, 4 day storm event (Loperfido et al., 2014). A possible reason for this difference is that the previous study covered the period 3/1/2011-9/30/2012, while the baseline for this study was 3/1/2011-12/31/2016 and included more high rainfall days (14 days with >60mm). Others have found 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). Within most climate scenarios the slopes of regression lines increased with larger daily precipitation amounts, suggesting that the GI provided more relative runoff reduction for smaller precipitation amounts (Table 9). The slopes of regression lines for rainfall amounts >13mm did not increase between current and future climate scenarios, indicating continued function of GI under future climate (Table 9). This suggests that the stormwater GI watershed will be resilient to the projected changes in climate, and will continue to respond to most rainfall events with less surface runoff than the traditional watershed.

Changes in watershed surface runoff were seasonal and were mostly consistent with the seasonal changes in precipitation (Figure 4). This fits our expectations because the SWAT model is sensitive to changes in precipitation (Arnold et al., 2012). 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 winter runoff compared to the traditional watershed in most climate scenarios may indicate greater resilience 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). Our results support these findings to some extent: 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.

Our modeling approach 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 timeframe we simulated.

Expanded GI implementation to treat an additional 0.2 inches of runoff from the 2.6 inch rainfall event reduced surface runoff under future climate conditions for most climate scenarios (Figure 6). Expanding GI implementation in the GI watershed to treat an additional 0.3 and 0.4 inches of runoff from the 2.6 inch 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 resilience by compensating for some of the projected increases in runoff depth in fall and winter. Findings from previous climate adaptation studies showed that watersheds with hypothetical GI implementation had 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). Our results build on those findings by demonstrating similar climate adaptation capacity in a calibrated model of a watershed with existing GI.

Expanding GI to treat 0.2 inches of runoff from the 2.6 inch 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 (Figure 6, Table 10, Table 11).

Expanding GI to treat 0.4 inches of runoff from the 2.6 inch 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 10, Table 11). Treating 0.4 inches of runoff reduction in the GI watershed required both an increase in infiltration practices (e.g. rain gardens, swales) and replacement of impervious cover.

A key implication for management from this research is the importance of planning for future climate conditions rather than for historic climate conditions (Milly et

al. 2008). For the Northeast US, this should include planning for increased intensity storms and increased winter precipitation. Our modeling results showed seasonal increases in surface runoff under projected climate conditions when management remained at current levels (Figure 4). Watershed management options to prepare for future climate conditions include: 1) sizing individual practices larger so that they have higher capacity to treat greater intensity storms, 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.

## **Conclusion**

We simulated 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. These results indicate that the stormwater GI is resilient to climate change. However, there were seasonal increases in fall and winter runoff for both watersheds under most climate scenarios compared to current conditions. Simulated expansion of stormwater GI implementation to treat an additional 0.2 inches of runoff from the 1-yr 24-hr storm reduced runoff in both watersheds for all seasons. Our study assesses climate resilience of existing stormwater GI at a watershed scale, and confirms previous studies of hypothetical GI 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 watersheds to buffer some of the projected seasonal increases in runoff expected with climate change.

## Chapter 3: Conclusions

To assess stormwater GI resilience to climate change, I completed 1) a formal literature review of previous assessments of stormwater GI climate resilience and 2) a SWAT modeling study of two urban watersheds in Clarksburg, Maryland. The literature review included evaluations of stormwater GI and other stormwater BMPs in urban watersheds published before 2015. Results from the literature review were that 1) hypothetical implementation of stormwater GI at watershed scales can help buffer increases in runoff projected for climate change, 2) existing individual stormwater GI and other stormwater BMPs may be undersized for future climate, and 3) a green infrastructure stormwater management approach was more resilient to climate change than a traditional stormwater management.

The modeling study bridged a gap in the literature by modeling existing GI implementation at a watershed scale. I calibrated the SWAT model to 6 years of measured streamflow conditions for two watersheds: one with existing watershed-wide stormwater GI implementation, and one with traditional management. The research questions for this study were:

- 1) Will surface runoff increase in future climate scenarios compared to the present?
- 2) Will the existing stormwater GI provide the same relative reduction in surface runoff in future climate scenarios compared to the present?
- 3) Will hypothetical (expanded) stormwater GI implementation improve watershed resilience to climate change?

Results from the modeling study confirmed the findings from the literature review that expanded implementation can buffer some of the seasonal increases in runoff. The stormwater GI was resilient to modeled changes in climate: demonstrated by the GI watershed's continued ability to reduce runoff compared to the traditional watershed under climate change conditions. However, there were seasonal increases in fall and winter runoff under climate change scenarios for both watersheds, indicating there may still be a need for expanded implementation to meet future hydrology goals under climate change conditions.

## References

- Abatzoglou, J.T., 2011. Development of gridded surface meteorological data for ecological applications and modelling. *Int. J. Climatol.* 33, 121–131.  
doi:10.1002/joc.3413
- Abatzoglou, J.T., Brown, T.J., 2012. A comparison of statistical downscaling methods suited for wildfire applications. *Int. J. Climatol.* 32, 772–780.  
doi:10.1002/joc.2312
- Abbaspour, K., 2007. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT.
- Abbaspour, K.C., Johnson, C.A., van Genuchten, M.T., 2004. Estimating Uncertain Flow and Transport Parameters Using a Sequential Uncertainty Fitting Procedure. *Vadose Zone J.* 3, 1340. doi:10.2136/vzj2004.1340
- Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *J. Hydrol.* 524, 733–752. doi:10.1016/j.jhydrol.2015.03.027
- Ahiablame, L.M., Engel, B.A., Chaubey, I., 2012. Effectiveness of Low Impact Development Practices: Literature Review and Suggestions for Future Research. *Water, Air, Soil Pollut.* 223, 4253–4273. doi:http://dx.doi.org/10.1007/s11270-012-1189-2
- Arnold, C.L., Gibbons, C.J., 1996. Impervious Surface Coverage: The Emergence of a Key Environmental Indicator. *J. Am. Plann. Assoc.* 62, 243–258.  
doi:10.1080/01944369608975688

- Arnold, J.G., D. N. Moriasi, P. W. Gassman, K. C. Abbaspour, M. J. White, R. Srinivasan, C. Santhi, R. D. Harmel, A. van Griensven, M. W. Van Liew, N. Kannan, M. K. Jha, 2012. SWAT: Model Use, Calibration, and Validation. *Trans. ASABE* 55, 1491–1508. doi:10.13031/2013.42256
- Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large Area Hydrologic Modeling and Assessment Part I: Model Development1. *JAWRA J. Am. Water Resour. Assoc.* 34, 73–89. doi:10.1111/j.1752-1688.1998.tb05961.x
- Bean, E.Z., Hunt, W.F., Bidelspach, D.A., 2007. Field Survey of Permeable Pavement Surface Infiltration Rates. *J. Irrig. Drain. Eng.* 133, 249–255. doi:10.1061/(ASCE)0733-9437(2007)133:3(249)
- Bhaskar, A.S., Hogan, D.M., Archfield, S.A., 2016. Urban base flow with low impact development. *Hydrol. Process.* 30, 3156–3171. doi:10.1002/hyp.10808
- Borris, M., Viklander, M., Gustafsson, A.-M., Marsalek, J., 2013. Simulating future trends in urban stormwater quality for changing climate, urban land use and environmental controls. *Water Sci. Technol.* 68, 2082–2089. doi:10.2166/wst.2013.465
- Charron, D.F., Thomas, M.K., Waltner-Toews, D., Aramini, J.J., Edge, T., Kent, R.A., Maarouf, A.R., Wilson, J., 2004. VULNERABILITY OF WATERBORNE DISEASES TO CLIMATE CHANGE IN CANADA: A REVIEW. *J. Toxicol. Environ. Health A* 67, 1667–1677. doi:10.1080/15287390490492313
- Chesapeake Conservancy, 2016. Land Cover Data Project [WWW Document]. Chesap. Conserv. URL <http://chesapeakeconservancy.org/conservation-innovation-center/high-resolution-data/land-cover-data-project/> (accessed 6.24.17).

- Chu, T.W., Shirmohammadi, A., 2004. Evaluation of the SWAT model's hydrology component in the Piedmont physiographic region of Maryland. *Trans. ASAE*.
- Davis, A.P., Hunt, W.F., Traver, R.G., Clar, M., 2009. Bioretention Technology: Overview of Current Practice and Future Needs. *J. Environ. Eng.-Asce* 135, 109–117. doi:10.1061/(ASCE)0733-9372(2009)135:3(109)
- Davis, A.P., Shokouhian, M., Ni, S., 2001. Loading estimates of lead, copper, cadmium, and zinc in urban runoff from specific sources. *Chemosphere* 44, 997–1009. doi:10.1016/S0045-6535(00)00561-0
- Davis, A.P., Shokouhian, M., Sharma, H., Minami, C., 2006. Water Quality Improvement through Bioretention Media: Nitrogen and Phosphorus Removal. *Water Environ. Res.* 78, 284–293. doi:10.2175/106143005X94376
- Davis, A.P., Shokouhian, M., Sharma, H., Minami, C., Winogradoff, D., 2003. Water quality improvement through bioretention: Lead, copper, and zinc removal. *Water Environ. Res.* 75, 73–82. doi:10.2175/106143003X140854
- Davis, A.P., Stagge, J.H., Jamil, E., Kim, H., 2012. Hydraulic performance of grass swales for managing highway runoff. *Water Res., Special Issue on Stormwater in urban areas* 46, 6775–6786. doi:10.1016/j.watres.2011.10.017
- Dibiasi, C.J., Li, H., Davis, A.P., Ghosh, U., 2009. Removal and Fate of Polycyclic Aromatic Hydrocarbon Pollutants in an Urban Stormwater Bioretention Facility. *Environ. Sci. Technol.* 43, 494–502. doi:10.1021/es802090g
- Dietz, M.E., 2007. Low Impact Development Practices: A Review of Current Research and Recommendations for Future Directions. *Water. Air. Soil Pollut.* 186, 351–363. doi:http://dx.doi.org/10.1007/s11270-007-9484-z

- Dixon, B., Earls, J., 2012. Effects of urbanization on streamflow using SWAT with real and simulated meteorological data. *Appl. Geogr.* 35, 174–190.  
doi:10.1016/j.apgeog.2012.06.010
- Eckhardt, K., 2005. How to construct recursive digital filters for baseflow separation. *Hydrol. Process.* 19, 507–515. doi:10.1002/hyp.5675
- Fischbach, J.R., Lempert, R.J., Molina-Perez, E., Tariq, A.A., Finucane, M.L., Hoss, F., 2015. Managing Water Quality in the Face of Uncertainty [WWW Document].  
URL [http://www.rand.org/pubs/research\\_reports/RR720.html](http://www.rand.org/pubs/research_reports/RR720.html) (accessed 1.16.16).
- Fletcher, T.D., Andrieu, H., Hamel, P., 2013. Understanding, management and modelling of urban hydrology and its consequences for receiving waters: A state of the art. *Adv. Water Resour.*, 35th Year Anniversary Issue 51, 261–279.  
doi:10.1016/j.advwatres.2012.09.001
- Fletcher, T.D., Shuster, W., Hunt, W.F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-Davies, A., Bertrand-Krajewski, J.-L., Mikkelsen, P.S., Rivard, G., Uhl, M., Dagenais, D., Viklander, M., 2015. SUDS, LID, BMPs, WSUD and more – The evolution and application of terminology surrounding urban drainage. *Urban Water J.* 12, 525–542.  
doi:10.1080/1573062X.2014.916314
- Folke, C., 2006. Resilience: The emergence of a perspective for social–ecological systems analyses. *Glob. Environ. Change* 16, 253–267.  
doi:10.1016/j.gloenvcha.2006.04.002

- Forsee, W.J., Ahmad, S., 2011. Evaluating Urban Storm-Water Infrastructure Design in Response to Projected Climate Change. *J. Hydrol. Eng.* 16, 865–873.  
doi:10.1061/(ASCE)HE.1943-5584.0000383
- Foster, G.D., Roberts, E.C., Gruessner, B., Velinsky, J., 2000. Hydrogeochemistry and transport of organic contaminants in an urban watershed of Chesapeake Bay (USA). *Appl. Geochem.* 15, 901–915. doi:10.1016/S0883-2927(99)00107-9
- Gaffield, S.J., Goo, R.L., Richards, L.A., Jackson, R.J., 2003. Public health effects of inadequately managed stormwater runoff. *Am. J. Public Health* 93, 1527–1533.  
doi:10.2105/AJPH.93.9.1527
- Gassman, P.W., Reyes, M., Green, C.H., Arnold, J.G., 2007. The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. *Trans. ASABE* 50, 1211–1250.
- Gill, S., Handley, J., Ennos, A., Pauleit, S., 2007. Adapting Cities for Climate Change: The Role of the Green Infrastructure. *Built Environ.* 33, 115–133.  
doi:10.2148/benv.33.1.115
- Guan, M., Sillanpää, N., Koivusalo, H., 2015. Assessment of LID practices for restoring pre-development runoff regime in an urbanized catchment in southern Finland. *Water Sci. Technol.* 71, 1485–1491. doi:10.2166/wst.2015.129
- Gupta, H.V., Sorooshian, S., Yapo, P.O., 1999. Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. *J. Hydrol. Eng.* 4, 135–143. doi:10.1061/(ASCE)1084-0699(1999)4:2(135)

- Hathaway, J.M., Brown, R.A., Fu, J.S., Hunt, W.F., 2014. Bioretention function under climate change scenarios in North Carolina, USA. *J. Hydrol.* 519, Part A, 503–511. doi:10.1016/j.jhydrol.2014.07.037
- Hayhoe, K., Stoner, A., 2015. Climate Change Projections for the District of Columbia. ATMOS Research and Consulting.
- Hayhoe, K., Wake, C.P., Huntington, T.G., Luo, L., Schwartz, M.D., Sheffield, J., Wood, E., Anderson, B., Bradbury, J., DeGaetano, A., Troy, T.J., Wolfe, D., 2006. Past and future changes in climate and hydrological indicators in the US Northeast. *Clim. Dyn.* 28, 381–407. doi:10.1007/s00382-006-0187-8
- Hegewisch, K.C., Abatzoglou, J.T., in prep. An improved Multivariate Adaptive Constructed Analogs(MACA) Statistical Downscaling Method. Prep.
- Hejazi, M.I., Moglen, G.E., 2008. The effect of climate and land use change on flow duration in the Maryland Piedmont region. *Hydrol. Process.* 22, 4710–4722. doi:10.1002/hyp.7080
- Hirschman, D., Woodworth, L., Drescher, S., 2009. Stormwater BMPs in Virginia’s James River Basin: An Assessment of Field Conditions & Programs (Part of the Extreme BMP Makeover Project). Center for Watershed Protection.
- Hogan, D.M., Jarnagin, S.T., Loperfido, J.V., Van Ness, K., 2014. Mitigating the Effects of Landscape Development on Streams in Urbanizing Watersheds. *J. Am. Water Resour. Assoc.* 50, 163–178. doi:10.1111/jawr.12123
- Holling, C.S., 1973. Resilience and Stability of Ecological Systems. *Annu. Rev. Ecol. Syst.* 4, 1–23. doi:10.1146/annurev.es.04.110173.000245

- Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.D., Wickham, J.D., Megown, K., 2015. Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. *Photogramm. Eng. Remote Sens.*
- Hood, M.J., Clausen, J.C., Warner, G.S., 2007. Comparison of Stormwater Lag Times for Low Impact and Traditional Residential Development1. *JAWRA J. Am. Water Resour. Assoc.* 43, 1036–1046. doi:10.1111/j.1752-1688.2007.00085.x
- Hunt, W.F., Davis, A.P., Traver, R.G., 2012. Meeting Hydrologic and Water Quality Goals through Targeted Bioretention Design. *J. Environ. Eng.-Asce* 138, 698–707. doi:10.1061/(ASCE)EE.1943-7870.0000504
- Hunt, W.F., Kannan, N., Jeong, J., Gassman, P.W., 2009. STORMWATER BEST MANAGEMENT PRACTICES: REVIEW OF CURRENT PRACTICES AND POTENTIAL INCORPORATION IN SWAT. *Int. Agric. Engi Neering J.*
- Hunt, W.F., Smith, J.T., Jadlocki, S.J., Hathaway, J.M., Eubanks, P.R., 2008. Pollutant Removal and Peak Flow Mitigation by a Bioretention Cell in Urban Charlotte, N.C. *J. Environ. Eng.* 134, 403–408.
- Hwang, H.-M., Foster, G.D., 2008. Polychlorinated biphenyls in stormwater runoff entering the tidal Anacostia River, Washington, DC, through small urban catchments and combined sewer outfalls. *J. Environ. Sci. Health Part - ToxicHazardous Subst. Environ. Eng.* 43, 567–575. doi:10.1080/10934520801893527
- IPCC, 2014a. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on

Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)].  
Geneva, Switzerland.

IPCC, 2014b. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A:  
Global and Sectoral Aspects. Contribution of Working Group II to the Fifth  
Assessment Report of the Intergovernmental Panel on Climate Change.  
Cambridge University Press, Cambridge, United Kingdom and New York, NY,  
USA.

Jones, D.K., Baker, M.E., Miller, A.J., Jarnagin, S.T., Hogan, D.M., 2014. Tracking  
geomorphic signatures of watershed suburbanization with multitemporal LiDAR.  
*Geomorphology* 219, 42–52. doi:10.1016/j.geomorph.2014.04.038

Kim, H., Jung, M., Mallari, K.J.B., Pak, G., Kim, S., Kim, S., Kim, L., Yoon, J., 2015.  
Assessment of porous pavement effectiveness on runoff reduction under climate  
change scenarios. *Desalination Water Treat.* 53, 3142–3147.  
doi:10.1080/19443994.2014.922286

King, R.S., Baker, M.E., Kazyak, P.F., Weller, D.E., 2011. How novel is too novel?  
Stream community thresholds at exceptionally low levels of catchment  
urbanization. *Ecol. Appl.* 21, 1659–1678. doi:10.1890/10-1357.1

Koch, B.J., Febria, C.M., Cooke, R.M., Hosen, J.D., Baker, M.E., Colson, A.R., Filoso,  
S., Hayhoe, K., Loperfido, J.V., Stoner, A.M.K., Palmer, M.A., 2015. Suburban  
watershed nitrogen retention: Estimating the effectiveness of stormwater  
management structures. *Elem. Sci. Anthr.* 3, 000063.  
doi:10.12952/journal.elementa.000063

- Lawson, N.M., Mason, R.P., Laporte, J.-M., 2001. The fate and transport of mercury, methylmercury, and other trace metals in Chesapeake Bay tributaries. *Water Res.* 35, 501–515. doi:10.1016/S0043-1354(00)00267-0
- L.B. Leopold, 1968. *Hydrology for Urban Land Planning-A Guidebook on the Hydrologic Effects of Urban Land Use*. U.S. Geologic Survey.
- LeFevre, G.H., Paus, K.H., Natarajan, P., Gulliver, J.S., Novak, P.J., Hozalski, R.M., 2015. Review of Dissolved Pollutants in Urban Storm Water and Their Removal and Fate in Bioretention Cells. *J. Environ. Eng.* 141, 04014050. doi:10.1061/(ASCE)EE.1943-7870.0000876
- Lim, K.J., Engel, B.A., Tang, Z., Choi, J., Kim, K.-S., Muthukrishnan, S., Tripathy, D., 2005. Automated Web GIS Based Hydrograph Analysis Tool, WHAT. *JAWRA*.
- Liu, J., Sample, D.J., Bell, C., Guan, Y., 2014. Review and Research Needs of Bioretention Used for the Treatment of Urban Stormwater. *Water* 6, 1069–1099. doi:10.3390/w6041069
- Loperfido, J.V., Noe, G.B., Jarnagin, S.T., Hogan, D.M., 2014. Effects of distributed and centralized stormwater best management practices and land cover on urban stream hydrology at the catchment scale. *J. Hydrol.* 519, 2584–2595. doi:10.1016/j.jhydrol.2014.07.007
- Lucas, W.C., Sample, D.J., 2015. Reducing combined sewer overflows by using outlet controls for Green Stormwater Infrastructure: Case study in Richmond, Virginia. *J. Hydrol.* 520, 473–488. doi:10.1016/j.jhydrol.2014.10.029

- Mahler, B.J., Van Metre, P.C., 2011. Coal-tar-based pavement sealcoat, polycyclic aromatic Hydrocarbons (PAHs), and environmental health (USGS Numbered Series No. 2011–3010), Fact Sheet. U.S. Geological Survey, Reston, Virginia.
- Maryland, 2013. MD iMAP | LiDAR Download [WWW Document]. URL <file:///C:/Users/AE/AppData/Roaming/Mozilla/Firefox/Profiles/xhhvtuz0.default/zotero/storage/3X2JRPB3/lidar-download.html> (accessed 6.24.17).
- MDE, 2012. Maryland’s Phase II Watershed Implementation Plan for the Chesapeake Bay TMDL. Maryland Department of Environment (MDE).
- MDE, 2009. Maryland Stormwater Design Manual. Maryland Department of Environment (MDE).
- Melillo, J.M., Richmond, T.C., Yohe, G.W., 2014. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program.
- Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., Stouffer, R.J., 2008. Stationarity Is Dead: Whither Water Management? *Science* 319, 573–574. doi:10.1126/science.1151915
- Moglen, G.E., Vidal, G.E.R., 2014. Climate Change and Storm Water Infrastructure in the Mid-Atlantic Region: Design Mismatch Coming? *J. Hydrol. Eng.* 19, 04014026. doi:10.1061/(ASCE)HE.1943-5584.0000967
- Montgomery County Code, 2001. , Section 2, Chapter 19, Article 5: Water Quality Review in Special Protection Areas.

- Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L.,  
2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in  
Watershed Simulations. *Trans. ASABE* 50, 885–900.
- Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren,  
D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell,  
J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M.,  
Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate  
change research and assessment. *Nature* 463, 747–756. doi:10.1038/nature08823
- Najjar, R., Patterson, L., Graham, S., 2008. Climate simulations of major estuarine  
watersheds in the Mid-Atlantic region of the US. *Clim. Change* 95, 139–168.  
doi:10.1007/s10584-008-9521-y
- Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I  
— A discussion of principles. *J. Hydrol.* 10, 282–290. doi:10.1016/0022-  
1694(70)90255-6
- Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and Water  
Assessment Tool Theoretical Documentation Version 2009. Texas Water  
Resources Institute.
- Newcomer, M.E., Gurdak, J.J., Sklar, L.S., Nanus, L., 2014. Urban recharge beneath low  
impact development and effects of climate variability and change. *Water Resour.*  
*Res.* 50, 1716–1734. doi:10.1002/2013WR014282
- NOAA, 2017. National Centers of Environmental Information. Climate Data Online  
[WWW Document]. URL <https://www.ncdc.noaa.gov/cdo-web/search> (accessed  
6.24.17).

- NRCS, n.d. Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Soil Survey Geographic (SSURGO) Database [WWW Document]. URL <https://sdmdataaccess.sc.egov.usda.gov> (accessed 6.24.17).
- Oberndorfer, E., Lundholm, J., Bass, B., Coffman, R.R., Doshi, H., Dunnett, N., Gaffin, S., Köhler, M., Liu, K.K.Y., Rowe, B., 2007. Green Roofs as Urban Ecosystems: Ecological Structures, Functions, and Services. *Biosci. Oxf.* 57, 823–833.
- Paul, M.J., Meyer, J.L., 2001. Streams in the Urban Landscape. *Annu. Rev. Ecol. Syst.* 32, 333–365.
- Prince George’s County, Maryland, 2007. The Bioretention Manual. Dept. of Environmental Resources, Prince George’s County, Md.
- Pyke, C., Warren, M.P., Johnson, T., LaGro Jr., J., Scharfenberg, J., Groth, P., Freed, R., Schroerer, W., Main, E., 2011. Assessment of low impact development for managing stormwater with changing precipitation due to climate change. *Landsc. Urban Plan.* 103, 166–173. doi:10.1016/j.landurbplan.2011.07.006
- Qiu, Z., Wang, L., 2014. Hydrological and Water Quality Assessment in a Suburban Watershed with Mixed Land Uses Using the SWAT Model. *J. Hydrol. Eng.* 19. doi:10.1061/(ASCE)HE.1943-5584.0000858
- Renkenberger, J., 2015. THE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL CRITICAL SOURCE AREAS (CSAS) AND BEST MANAGEMENT PRACTICES (BMPS) IN EASTERN MARYLAND.
- Revi, A., Satterthwaite, D.E., Aragón-Durand, F., Corfee-Morlot, J., Kiunsi, R.B., Pelling, M., Roberts, D., Solecki, W., 2014. Urban areas. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral*

Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Rhea, L., Jarnagin, T., Hogan, D., Loperfido, J.V., Shuster, W., 2015. Effects of urbanization and stormwater control measures on streamflows in the vicinity of Clarksburg, Maryland, USA. *Hydrol. Process.* 29, 4413–4426.  
doi:10.1002/hyp.10505

Rouhi, A., Schwartz, D., 2007. Physical Assessment of Selected Rain Gardens in Fairfax County, Virginia - raingardenstudy.pdf. Northern Virginia Soil and Water Conservation District.

Sankarasubramanian, A., Vogel, R.M., Limbrunner, J.F., 2001. Climate elasticity of streamflow in the United States. *Water Resour. Res.* 37, 1771–1781.  
doi:10.1029/2000WR900330

Semadeni-Davies, A., Hernebring, C., Svensson, G., Gustafsson, L.-G., 2008. The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Suburban stormwater. *J. Hydrol.* 350, 114–125.  
doi:10.1016/j.jhydrol.2007.11.006

Sexton, A.M., Shirmohammadi, A., Sadeghi, A.M., Montas, H.J., 2011. Impact of Parameter Uncertainty on Critical SWAT Output Simulations. *Trans. ASABE.*

- Shuster, W.D., Bonta, J., Thurston, H., Warnemuende, E., Smith, D.R., 2005. Impacts of impervious surface on watershed hydrology: A review. *Urban Water J.* 2, 263–275. doi:10.1080/15730620500386529
- Soil Conservation Service, 1986. *Urban hydrology for small watersheds*. U.S. Department of Agriculture, Technical Release 55.
- SWAT: Soil and Water Assessment Tool [WWW Document], 2017. URL <http://swat.tamu.edu/> (accessed 6.24.17).
- Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2011. An Overview of CMIP5 and the Experiment Design. *Bull. Am. Meteorol. Soc.* 93, 485–498. doi:10.1175/BAMS-D-11-00094.1
- The Severn River Association, 2012. *RainGardenSurveyResults*.
- Tyler, S., Moench, M., 2012. A framework for urban climate resilience. *Clim. Dev.* 4, 311–326. doi:10.1080/17565529.2012.745389
- US EPA, 2014. *Green Infrastructure for Climate Resiliency* [WWW Document]. URL [https://www.epa.gov/sites/production/files/2015-10/documents/climate\\_res\\_fs.pdf](https://www.epa.gov/sites/production/files/2015-10/documents/climate_res_fs.pdf) (accessed 4.8.16).
- US EPA, 2010. *Chesapeake Bay Total Maximum Daily Load for Nitrogen, Phosphorus and Sediment (Reports and Assessments)*. US EPA.
- U.S. EPA, 1983. *Results of the Nationwide Urban Runoff Program*.
- US EPA, 1972. *Clean Water Act (1972)*.
- VanWoert, N.D., Rowe, D.B., Andresen, J.A., Rugh, C.L., Fernandez, R.T., Xiao, L., 2005. Green roof stormwater retention: effects of roof surface, slope, and media depth. *J. Environ. Qual.* 34, 1036–1044. doi:10.2134/jeq2004.0364

- Walsh, C.J., Roy, A.H., Feminella, J.W., Cottingham, P.D., Groffman, P.M., Morgan, R.P., 2005. The urban stream syndrome: current knowledge and the search for a cure. *J. North Am. Benthol. Soc.* 24, 706. doi:10.1899/0887-3593(2005)024\{0706:TUSSCK\}2.0.CO;2
- Wang, Y., 2015. A DIAGNOSTIC DECISION SUPPORT SYSTEM FOR SELECTING BEST MANAGEMENT PRACTICES IN URBAN/SUBURBAN WATERSHEDS. University of Maryland.
- Waters, D., Watt, W.E., Marsalek, J., Anderson, B.C., 2003. Adaptation of a Storm Drainage System to Accommodate Increased Rainfall Resulting from Climate Change. *J. Environ. Plan. Manag.* 46, 755–770. doi:10.1080/0964056032000138472
- Zahmatkesh, Z., Burian, S.J., Karamouz, M., Tavakol-Davani, H., Goharian, E., 2015. Low-Impact Development Practices to Mitigate Climate Change Effects on Urban Stormwater Runoff: Case Study of New York City. *J. Irrig. Drain. Eng.* 141, 04014043. doi:10.1061/(ASCE)IR.1943-4774.0000770