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Assessing Variability and Uncertainty in Green Infrastructure Planning Using a High-Resolution Surface-Subsurface Hydrological Model and Site-Monitored Flow Data

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Green infrastructure (GI) is increasingly being used in urban areas to supplement the function of conventional drainage infrastructure. GI relies on the "natural" hydrological processes of infiltration and evapotranspiration to treat surface runoff close to where it is generated, alleviating loading on the conventional infrastructure systems. This research addresses growing interest in identification and quantification of uncertainties with distributed, infiltration-based stormwater control measures, retrofitted on private and public properties and in right-of-ways in existing urban areas. We identify four major sources of variability and uncertainty in cumulative performance of systems that rely on extensive implementation of distributed GI: non-additive effects of individual best management practices (BMPs) at the catchment scale; the spatial configuration of fine-scale land use and land cover changes; performance changes due to climate change; and noise levels present in urban flow monitoring programs. Using a three-dimensional coupled surface-subsurface hydrological model of a residential sewershed in Washington DC, we find that prolonged, large-magnitude rain events affect various spatial configurations of GI networks differently. Runoff peaks and volumes can both be influenced by the spatial permutations of infiltration opportunities in addition to the absolute magnitude of treated area. However, the magnitude of the last source of uncertainty—noise levels in urban flow monitoring programs—may be larger than sources of variability associated with spatial changes in fine-scale land use and land cover. Changes associated with climate change– more frequent and larger rainfall events– will likely intensify performance differences between spatial configurations of GI but also increase noise levels in urban flow monitoring programs.

Keywords: Green infrastructure, variability, uncertainty, fine-scale land cover, climate change, ParFlow

INTRODUCTION

The use of Green Infrastructure (GI) for storm water management has been steadily gaining traction in US cities, where the US Environmental Protection Agency (EPA) has formally recognized its role in supplementing aging conventional sewer and stormwater drainage infrastructure. Instead of channeling stormwater runoff from development into conveyance structures (pipes) away from development as quickly as possible, the purpose of GI is to intercept runoff close to where it is generated. Using amended soils and vegetation to slowly infiltrate water into the subsurface, evapotranspire it through vegetation back into the atmosphere, or at least provide storage and retention enough to mitigate storm hydrograph peaks, GI supplements the designed capacity of the conventional infrastructure to prevent drainage system surcharging and combined sewer overflows (CSOs). GI Best Management Practices (BMPs) are also referred to as Low Impact Development (LID) BMPs or Sustainable Urban Drainage Systems (SUDS). Examples of BMPs include: rain gardens, bioswales, pervious pavement, tree wells/trenches, and rain barrels. Such BMPs are typically engineered or professionally designed to various extents–ranging from engineer-stamped construction documents, to "Do-It-Yourself" residential installations. Below, we review the literature including all Stormwater Control Measures (SCMs) that incorporate functions such as infiltration, detention, and retention, and spatially are either centralized (e.g., one detention pond serving a whole subdivision) or distributed throughout the landscape. We refer to "GI BMPs" as a subset of SCMs that are typically smaller-scale interventions distributed throughout the landscape (e.g., one or multiple installed per property).

Although the concept of GI is well-accepted, both from engineering and community development perspectives, there still exists considerable uncertainty in whether extensive GI plans can achieve the regulatory goals for which they are being deployed in a measurable way. In this study, we develop exploratory and anticipatory scenarios to explore four major areas of uncertainty in widespread GI network planning: network effectiveness, fine-scale land use and land cover changes, climate uncertainty, and signal detection in noisy urban hydrologic datasets. We use a residential sewershed in Washington DC retrofitted extensively with GI to explore the potential non-additive cumulative effects of infiltration and its measurement through two commonly used urban surface runoff metrics: total event runoff volume and peak flow. Non-additive cumulative effects of infiltration within a drainage area could occur when surface conditions interact with subsurface conditions. An example of this would be when pervious areas are saturated and contribute runoff to impervious areas instead of infiltrating runoff. Monitoring data from the study residential sewershed, collected before and after GI construction between 2009 and 2015, were used to calibrate a three dimensional coupled surface-subsurface hydrological model, ParFlow.CLM. In the following section, we review four areas of uncertainty in GI planning. While our review focuses mostly on the US conditions relevant to our study area, the broad areas of uncertainty—network effectiveness, sub-parcel scale land cover change, climate, and monitoring—can be applied to many other geographies of similar climate and density of development.

BACKGROUND: SOURCES OF UNCERTAINTY IN GREEN INFRASTRUCTURE PLANNING

Network Effectiveness

There is extensive research that uses inflow and outflow monitoring and before-after, control-treatment showing that GI is effective at the site scale in reducing peak flows and runoff volumes and improving water quality from rainfall events (Davis, 2007, 2008; Emerson and Traver, 2008; Li et al., 2009; Driscoll et al., 2015; Page et al., 2015). There are several reasons why the sub-catchment-scale may exhibit non-additive cumulative effects of individual SCMs. First, SCMs are usually designed to meet specific criteria, for example, matching a theoretical pre-development peak runoff or volume generated from the site. However, they may not take into consideration other changes to the hydrologic response, such as changes in evapotranspiration, and overall catchment storage (Li et al., 2017). Second, the chosen metric usually corresponds to a prescribed "design storm." For example, Washington DC requires stormwater SCMs to maintain peak discharge from the 2-year storm to pre-development conditions, and therefore SCMs are not designed to mitigate all events equally. Third, SCMs or BMPs are often designed and constructed in a decentralized way, site-by-site, as opportunities arise. Because they are distributed throughout the landscape and implemented incrementally over long periods of time, they may not take into consideration how the timing of runoff hydrographs from multiple sites interact with each other synergistically in a cumulative downstream response (Emerson et al., 2005; Voter and Loheide, 2018). Lastly, individual site interventions can usually be chosen from a palette of acceptable BMPs, which may be intended to perform different kinds of runoff mitigation, for example, infiltration or detention, that will have various effects on the hydrologic regime.

Jefferson et al. (2017) and Li et al. (2017) published thorough reviews and analyses of the literature on the network effectiveness of Stormwater Control Measures (SCMs), which can include more conventional, centralized retention and detention facilities, function at the catchment scale. They reveal that many empirical studies confirm that SCMs increase the minimum rainfall depth required to produce runoff (Hood et al., 2007; Loperfido et al., 2014; Fanelli et al., 2017) and decrease peak flows from urban development (Booth and Jackson, 1997; Meierdiercks et al., 2010; Smith et al., 2015). In addition, although modeling studies have shown that both peak volumetric flow rate and total volumes have been found to decrease with SCMs (e.g., Perez-Pedini et al., 2005; Avellaneda et al., 2017), there is less empirical consensus on the network effect of GI on total runoff volumes. Empirical studies evaluating the capability of SCMs to control total runoff volumes to nearby streams have shown little to no effect (Booth and Jackson, 1997; Dietz and Clausen, 2008; Meierdiercks et al., 2010; Shuster and Rhea, 2013), and that limitations in volume mitigation are particularly apparent during larger rain events (Woznicki et al., 2018).

The particular processes within urbanized catchments that could lead to differences in cumulative effect have also been a focus of much research. In many of these studies, both conventional drainage infrastructure and green (infiltration-based) infrastructure play a mediating role in determining the dominant hydrological response to rainfall. For example water leakages into and out of urban infrastructures, and changes in evapotranspiration due to vegetation changes, can have major effects on changes in stream baseflows (Bhaskar et al., 2016). Infiltration could impact the function of conventional drainage infrastructure to effectively convey runoff away from development or cause combined sewer overflows of untreated sewage into natural water bodies (Endreny and Collins, 2009; Maimone et al., 2011). The kinds of interactions between conventional infrastructure and surface-subsurface hydrologic dynamics are also dependent on the size of the rainfall event. For example, one study showed how disconnecting storm drains under lower magnitude events results in the expected decrease in peak flow, but that antecedent wetness of soil due to increased infiltration can also result in runoff production in areas not served by storm drains, a counter-intuitive hydrologic response (Tague and Pohl-Costello, 2008).

Modeling of urban runoff has been dominated by the Hortonian concept of runoff generation. In this model framework, runoff is formed when infiltration rates are exceeded by rainfall rates. However, the above examples highlight why a more flexible conceptual model that incorporates surface-subsurface and infrastructure interactions may be necessary. The Urban Variable Source Area (UVSA) and watershed capacitance conceptual model can help organize the conditions when specific properties of the urbanized catchment, including soil permeability, slope, depth to groundwater, land use and land cover, and availability and placement of infiltration opportunities, will influence how runoff is generated under different meteorological and morphological conditions, as is shown in **Figure 1** (Miles and Band, 2015; Lim, 2016). The above examples and the UVSA conceptual model suggests that GI may exhibit a trade-off in cumulative effectiveness during very wet conditions, multiday events, when watershed capacitance is limited, or when infiltration opportunities are clustered together in high flow accumulation areas.

In this research, we take a simulation approach to modeling the complex dynamics that could result in spatially and temporally variable runoff generation in an urbanized catchment. In order to capture times when infiltration of runoff to groundwater could result in runoff onto impervious surfaces, we chose the simulation model ParFlow.CLM, for its capability to represent negative feedbacks and surface-subsurface and lateral subsurface interactions among infiltration opportunities. **Figure 2** conceptually shows how ParFlow.CLM has the capability to model potential surface-subsurface interactions, compared to two other models, the US EPA's Storm Water Management Model, and the Regional Hydro-Ecological Simulation System (RHESSys) model.

Variability Due To Sub-parcel-Scale Land Use Change/Cover Change

The urban landscape is constantly undergoing physical and social change. While many studies investigate the effects of conversion of agricultural or forested land covers to urban land cover, changes in the landscape also occur within the urban boundary. Since the 1990s, US cities show measurable signs of infill and redevelopment (Schneider and Woodcock, 2008; Nowak and Greenfield, 2012). In addition, residential and commercial landowners' landscape preferences may change over time. Research has shown that landscape aesthetics are often mimicked among neighbors. Yard landscaping practices, for example, choice in vegetation types (grass, native plants, xeriscaping, etc.), are expressions of personal preferences as well as functions of historical and social norms. There is evidence that front-yard landscaping is susceptible to social influence among neighbors and has a distinct spatial structure (Zmyslony and Gagnon, 1998). Landscaping decisions have also been correlated with income levels, suggesting that as neighborhood socioeconomic status (or developers' anticipation of socioeconomic status) changes, so too might the landscape (Larsen and Harlan, 2006; Troy et al., 2007). Abandonment and vacancy also provide opportunities for land cover change in urban areas, as more cities consider the co-benefits that could be provided on vacant parcels, including urban green space provision, urban farming, and community revitalization, though sometimes such uses are not permanent (Tzoulas et al., 2007; Schilling and Logan, 2008; Heckert and Mennis, 2012; Drake and Lawson, 2014; Schifman et al., 2017).

Influencing private property owner behavior to promote environmental sustainability is a goal of urban and environmental planners and stormwater infrastructure managers. In contrast to conventional stormwater drainage infrastructure– such as pipes and cisterns– that is located in the public right-of-way (ROW) or on public property, GI can be implemented on both public or private property. Since most land in US cities is privately owned, stormwater infrastructure managers tend to view implementation of green infrastructure on private land as an opportunity to integrate stormwater management goals with landscaping practices, potentially providing environmental amenity and infrastructure improvement goals at lower costs to the city (Montalto et al., 2007; Roy et al., 2008; Keeley et al., 2013).

As a top-down measure, stormwater utility managers use subdivision and land development ordinances (SALDOs) to compel private property owners to adopt BMPs on their properties, or they can encourage adoption through voluntary means. SALDOs can typically only be applied to properties undergoing construction or significant reconstruction. SALDOs stipulate that the owners must implement stormwater control measures on their properties to meet some design standard (for example, store and treat runoff resulting from the properties impervious surfaces for the 1-year, 24-h rain event). However, in order to speed the adoption of green infrastructure practices on private property above the redevelopment rate, some

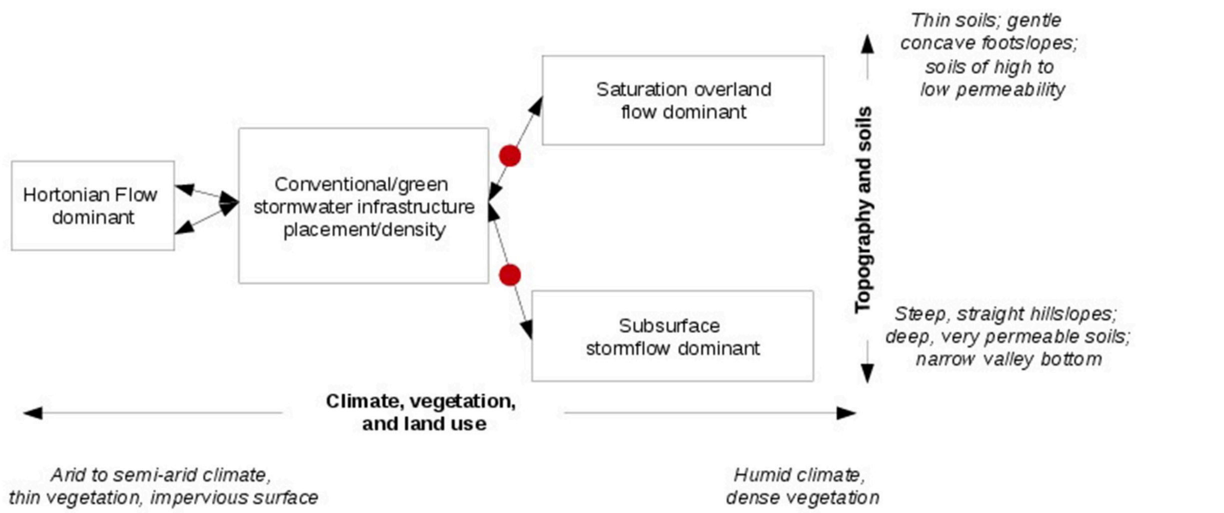
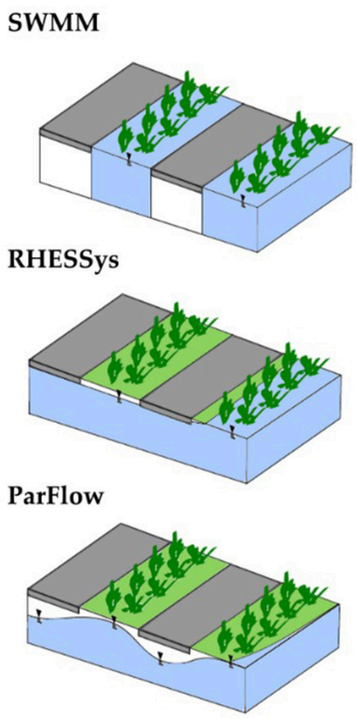


FIGURE 1 | Conceptual model of factors influencing areas contributing runoff in an urbanized catchment area (adapted from Lim, 2016). Conventional and green infrastructure placement and density mediates balance between dominance of Hortonian flow, saturation overland flow, and subsurface stormflow processes at the catchment scale. Red dots indicate processes that are hypothesized to be dependent on antecedent wetness conditions and multiday events.



	Allowed Interaction between Infiltration Areas	Overland Flow Routing	Groundwater Model Specification	Example Testable Hypothesis
SWMM	• If upslope infiltration rate or storage is exceeded, saturation overflow to downslope GI facility	• Lumped within sub-catchment • Hydrological routing: non-linear reservoir method • Less accurate, especially for time< time of concentration	• Moisture in unsaturated zone is averaged, there no shape (lens) • No lateral groundwater flow	• Does implementation of run-on infiltration decrease runoff volumes from impervious areas?
RHESSys	• In addition to above, interactions through shared groundwater table (results in Variable Source Area)	• Distributed within sub-catchment • Hydrological routing: assumes hydraulic gradients follow topography (no hydrographs produced)	• Simple, linear reservoir groundwater model	• How does the position of GI within the watershed (upslope or downslope) affect catchment scale effectiveness?
ParFlow	• In addition to above, lateral groundwater interactions between infiltration areas (mounding)	• Distributed within sub-catchment • Hydraulic routing: kinematic wave (dynamic wave also available) • Most accurate, most computationally intense	• 3-D variably saturated groundwater flow	• How does spatial clustering of multiple run-on infiltration facilities affect catchment scale effectiveness?

FIGURE 2 | Conceptualization of various hydrological models' treatment of overland flow routing and groundwater and example testable hypotheses.

infrastructure managers are trying more innovative means of promoting land use and land cover change. Such examples include the use of stormwater fee systems where residents receive credits to their bills for constructing green infrastructure on their properties, subsidies for GI installation, and partnerships with non-profit groups, education and community development programs (Kertesz et al., 2014; Valderrama and Davis, 2015). Such programs speed the adoption of GI on private properties by providing economic incentives for action, increasing knowledge about environmental impacts, or promoting the flow of information about subsidy programs (Ando and Freitas, 2011; Green et al., 2012; Londoño Cadavid and Ando, 2013; Montalto et al., 2013; Lim, 2017). The intent of distributed BMPs is to change hydraulic and hydrologic properties of landscapes, by improving the permeability and storage capacity of soils, reducing connectivity of impervious surfaces, and increasing evapotranspiration rates from vegetation (Fletcher et al., 2013). The extent to which such changes, based on policy, social and physical change within urban areas, can result in detectable improvements to various hydrologic indicators therefore not only depends on the physical capacitance of the watershed, but also on its social capacitance (Lim, 2017).

Climate Uncertainty

Global climate change impacts are expected to result in both increases in total annual precipitation and intensity of extreme rainfall events in the Northeast United States. In the past century the total amount of precipitation across the continental US has increased by 7%, with the largest 1% of events increasing in frequency by 20% (US Global Change Research Program, 2009). Precipitation has increased particularly in the Northeast US, which has seen a 58% increase in precipitation volume in historical trends (Groisman et al., 2005). Downscaled models' predictions of future changes in precipitation in the Mid-Atlantic US have been shown to vary dramatically between models. Uncertainty in precipitation projections are especially high in summer and fall (Najjar et al., 2009, 2010).

Typically, engineered GI facilities are designed for a particular size or frequency storm, described by a depth of precipitation occurring within a given period of time (e.g., 24 h). If this storm has a 10% probability of occurring in any given year it is called the "10-year" rain event. The design of stormwater management systems according to historical frequencies of extreme events will become less useful under a changing climate regime (Mailhot and Duchesne, 2010). In parts of North America, today's 50-year event will become the 10-year event by the 2090s (Waters et al., 2003). Sometimes, GI design requirements are expressed as a particular depth of rainfall, or "first flush" that BMPs must be able to handle. Acknowledging the non-stationarity of these probabilities under conditions of climate change, engineers apply a percentage based "safety factor" to the required design depth that make their designs more conservative for future conditions (Milly et al., 2008).

However, the concept of design storms, even with safety factors does not include simulation of the continuous meteorological conditions under which GI is intended to perform. In the US, many municipalities/stormwater management districts now recommend hydrological simulation of continuous representative rainfall time series, in order to more realistically represent antecedent wetness conditions between successive events and multiday precipitation events. Incorporating future climate change-influenced continuous precipitation patterns requires a model for constructing what a likely scenario might be.

Applying downscaling methods to the General Circulation Models (GCMs) is one way to produce a realistic continuous climate-change influenced precipitation record. GCMs produce climate change forecasts given a range of future emissions scenarios; however, they are typically produced at a resolution too coarse to be used at the urban catchment scale. The major methods of producing downscaled rainfall events from climate model simulations for use in local urban drainage system planning include: dynamic downscaling (using physical models), empirical transfer function based methods, historical re-sampling methods, and stochastic rainfall models (Willems et al., 2012; Wilby et al., 2014). Downscaled inputs from different models were shown to generate a wide range of estimates for the local scale. The typical suggested solution to the wide range of estimates is to conduct simulations with multiple downscaled methods to represent the variability of the scenarios. This solution, however, can be computationally costly and complex. Therefore, one approach to mimic future increase in multiday wet periods is to extract pieces of historical records that reflect this condition (Catalano de Sousa et al., 2016). Although this approach may be considered rather simplistic, in this case, it was considered sufficient to explore differences between spatial scenarios, to identify whether additional precipitation scenarios would be necessary. Combining precipitation scenarios that would incorporate the range of uncertainty in projected precipitation for each tested spatial scenario would result in a much larger number of simulations and could result in effects that would be more difficult to tease apart.

Increased intensity and frequency of large rain events would be expected to decrease effectiveness of infiltration-based SCMs, since infiltration is a slow response, and requires to time recover capacity between events (Kristvik et al., 2018). Previous modeling studies have found that GI is typically more effective during smaller events than larger events, and that differences associated with GI are more apparent for peak volumetric flow reduction than for total volume reduction (Palla and Gnecco, 2015; Fry and Maxwell, 2017).

Measurement

Despite the increasing sophistication and accuracy of hydrological models, empirical data collection for calibration and validation of models is still necessary (Maheepala et al., 2001; Silberstein, 2006). However, there is uncertainty associated with monitoring stormwater runoff flows in urban areas. Stormwater runoff monitoring data in urban areas can contain high levels of noise from errors in data logger software and flow monitoring equipment as well as from unexpected disturbances of "experimental conditions" (Liefting and Langeveld, 2008). Before-and-after Control-Intervention (BACI) experimental designs are common in hydrological experiments but can be subject to disruptions (Shuster and Rhea, 2013). Because urban catchments are inherently full of human activities, confounding effects such as lawn watering, car-washing or pipe and fire hydrant leakages may disturb even the most well-planned experiments. For ongoing flow monitoring necessary for permitting purposes (for both separated and combined sewer systems in the US) and demonstrating the effectiveness of GI networks, it is important to show that hydrologic effects in GI interventions can be expected to overcome levels of noise present in urban stormwater flow monitoring data (Lim and Welty, 2017).

Hypotheses

In this study we address the four types of uncertainty described above explicitly through the choice of hydrological model and processes represented, development of scenarios, design of the evaluation criteria, and comparison with empirical monitoring data. **Table 1** summarizes relevant questions that exist in the literature regarding widespread planning of stormwater GI:

In a previous study (Lim and Welty, 2017), data generated from the model applied in the present study showed that, on average, potential infiltration located in areas of high accumulation were more effective at mitigating runoff volume than those located in upslope areas. Lim and Welty also found weaker evidence of a counterintuitive result that infiltration sites in downslope areas were also more effective than those in upslope areas soon after a previous precipitation event. In the present study, we take a closer examination of one continuous series of four rain events of both high magnitude and short inter-event period.

We hypothesize the following:

- Non-additive effects of GI can be observed between scenarios of spatially explicit impervious surface and green infrastructure networks and differences in these non-additive effects will be observable between scenarios, and over multiday rain events.
- Periods of prolonged wetness and large rainfall events will increase the localized saturation of infiltration areas within the study sewershed. This will result in infiltration areas located in high flow accumulation areas having decreased capability to mitigate surface runoff, eventually becoming sources of surface runoff.
- Clearly separable differences between scenarios will be more apparent in the evaluation of peak flow mitigation than they will for total runoff volume mitigation.

TABLE 1 | Sources of planning uncertainty and incorporation in this study.

Source of Planning Uncertainty	Incorporation into This Study
Green infrastructure network effectiveness	Choice of model: 3D coupled surface-subsurface hydrological model, ParFlow.CLM
Relative impacts of spatially explicit fine-scale land use and land cover changes	Development of modeled scenarios
Performance under increased wet conditions (climate change)	Selection of simulation period and design of scenario evaluation/comparison criteria
Role of monitoring	Comparisons and study coordination with empirical monitoring from experimental sites

STUDY SITE DESCRIPTION–RIVERSMART WASHINGTON

In this research we partnered with Washington DC's Department of Energy and the Environment (DOEE) on a project called RiverSmart Washington that evaluated a monitored urban sewershed before and after GI installation. DC's RiverSmart programs were established to help reduce stormwater runoff from entering the District's waterways and the Chesapeake Bay and to restore ecological function to the landscape. In 2015, Washington DC's water and wastewater utility provider, DC Water, revised its Combined Sewer Overflow (CSO) Long Term Control Plan (LTCP) to include GI components that allowed it to dramatically downsize two previously planned underground tunnels (eliminating one, and reducing the planned capacity of the other from 220,000 cubic meters to 114,000 cubic meters). This increased regulatory and institutional support to better understand the physical function of GI configurations and the effects of alternative site development morphologies at the sewershed scale (DC Water, 2015). In particular, city-wide initiatives to promote voluntary residential adoption of subsidized rain gardens and permeable pavement installations motivated a need to better understand how resulting spatial configurations may perform compared to facilities in the right-of-way (ROW), which may be more costly to the city.

Made possible through $4M in joint funding from the U.S. Fish and Wildlife Service, DOEE, and DC Water, DOEE began the RiverSmart Washington monitoring program in 2009. The project first monitored in-pipe flows for the base case, pre-GI condition for 6 months (from July 2010 to December 2010) as well as local precipitation monitoring. This initial monitoring period was followed by extensive construction of GI within several sewersheds in DC. At the Lafayette demonstration site (0.05 km^2, and originally 34% impervious, with 15% building footprint and 19% pavement), the District Department of Transportation (DDOT) oversaw installation of bioretention bump-outs and permeable pavements designed to treat nearly all of the public ROW. In total, a total of 2340.2 m^2 of GI BMPs were installed in the public ROW, treating total contributing area of 2945.4 m^2 (Lim and Welty, 2017). **Figure 3** shows site photographs of BMPs constructed in the public ROW during a rain event.

GI retrofits were also constructed on private properties by willing residents. Residential GI BMPS included: permeable pavers, rain gardens, native landscaping, and rain barrels. Native landscaping and rain garden installations included amended soils, adjusted site grading and planted native vegetation. Permeable pavements increased permeability of impervious surfaces and provided storage in an underlying gravel layer. Of the 74 households within the sewershed, 25 agreed to install subsidized GI on their properties. Private installations disconnected over 1,400 m^2 of residential rooftop and over 550 m^2 of private paths and driveways from the stormwater drainage system. Prior to rooftop disconnection, all rooftops were directly connected to the pipe system in the ROW via buried PVC pipes that drained either into the street of the adjacent sidewalk (Lim and Welty, 2017). Additional detail on the hydraulic properties of both the local geology (which was measured in geotechnical reports as part of the RiverSmart

FIGURE 3 | Site Photographs of BMPs treating the sewershed's public ROWs. **(A)** Permeable asphalt: surface runoff is visible, indicating lower than expected infiltration performance. **(B)** Bioswale with a flush curb cut extending beyond the ROW into adjacent grass strip. **(C)** Permeable concrete installed in the center of a reverse crowned alley. **(D)** Permeable concrete spanning the full width of the ROW. **(E)** Foreground shows permeable rubber sidewalk adjacent to bioswale. Permeable pavers in parking lane are visible in the background.

Washington monitoring project), and the GI retrofits can be found in Lim and Welty (2017).

After the construction of all public ROW and voluntary residential GI retrofits, in-pipe flows and precipitation were monitored for the site for 6 months. Like the Base case (pre-GI construction) monitoring, in-pipe flows were measured using an ADS Flowshard meter that used four ultrasonic level sensors to record stage data, a low-profile Doppler velocity monitor and a pressure sensor. The monitoring equipment transmitted data via a cellular communications-enabled data logger. **Figure 4** shows the land cover types present within the sewershed boundary after the GI construction. The sewershed is defined as the area draining to the point where the in-pipe flow monitoring both before and after GI construction was located.

METHODS

Model Selection

The ParFlow.CLM model was chosen for its capability to model potential hypothesized feedbacks between locally saturated groundwater conditions and overland flow that is key to the UVSA model (Miles and Band, 2015). Unlike other ecohydrological models that include feedbacks between groundwater and surface runoff generation (e.g., RHESSys), ParFlow.CLM is three-dimensional, and therefore can capture spatially explicit effects of event-based local saturation. Unlike lumped-parameter models such as the US EPA's SWMM model, which requires the total modeled area to be represented as a series of subcatchments, ParFlow.CLM solves the Richards equation via finite differences over a regular gridded discretization. The numerical solution of Richards equation allows the user to apply ParFlow.CLM over grids as fine as $<1\,\text{m} \times 1\,\text{m}$, to much larger grids (e.g., $500 \times 500\,\text{m}$ in regional models). Further, ParFlow.CLM is optimized to perform on massively parallelized high performance computers, which makes it very efficient (Ashby and Falgout, 1996; Jones and Woodward, 2001; Kollet and Maxwell, 2006; Maxwell, 2013). It has also been dynamically linked to a land-atmosphere model CLM that allows for coupled simulation between the land surface and groundwater models (Maxwell and Miller, 2005; Kollet and Maxwell, 2008).

FIGURE 4 | Domain of the study sewershed with public and private installations of GI and monitoring locations. Building footprints and sidewalks are in brown; streets are in gray; pervious areas are indicated by pale green; dark blue indicates public GI projects; dark green indicates private GI projects; the red arrow points to the monitoring location.

The model was calibrated by adjusting Manning's n for several events during the monitored pre-GI period (2009), comparing the modeled output with in-pipe monitored flows from the site. More detail on calibration and model spinup and parameterization of the ParFlow model application is provided in Lim and Welty (2017).

Scenario Development

Scenario analyses can be divided into two major types: exploratory scenarios, and anticipatory scenarios. Exploratory scenarios are used to test known processes of change and past extrapolations to define future scenarios. Anticipatory scenarios start with desired or feared visions of the future. Anticipatory scenarios may incorporate potential policy responses, and expert and stakeholder-defined assumptions to frame the subjectivity of anticipated future states (Mahmoud et al., 2009). Neither exploratory nor anticipatory scenarios are meant to be predictions of future states. Rather, they are meant in this study to represent physical sensitivity of the site to realistic parameters (in the case of the exploratory scenarios), and the physical sensitivity of the site to potential policy and social-process driven change. In addition to a Base scenario, eight additional scenarios were tested, organized below into the exploratory and anticipatory types of scenario development:

Exploratory

- GI_DRY: Treat runoff from rooftops on low flow accumulation properties with GI
- GI_WET: Treat runoff from rooftops on high flow accumulation properties with GI
- IS_DRY:Remove impervious surface areas on low flow accumulation properties
- IS_WET: Remove impervious surface areas on high flow accumulation properties

Anticipatory

- GI_ROOF: Treat runoff from all rooftops on private property
- GI_ROW: Treat the public ROW surface (equal treated area to GI_ROOF)
- IS_DISC: Disconnect all roofs from the storm drain (drain onto grass)
- IS_MAX: Allow maximum impervious surface area per property according to zoning regulations

More detail and maps of scenarios can be found in Lim and Welty (2017).

Selection of Simulation Period

After model spinup, all scenarios were initialized using a common pressure boundary layer and simulated using a 6-month period of meteorologic input data from 1 March 2015–1

September 2015. From this 6-month period, one 10-day window was chosen for further analysis for this study. Although the 10-day window is not derived from any downscaled GCM scenario, it was chosen as a period of rainfall that could become more characteristic with future climate change. This window represented the wettest 10-day period (total cumulative rainfall) during the summer of 2015 and contained the single largest rain event in the modeled period (**Figure 5**). The total rainfall accumulated during the four distinct rainfall events during this period was 110 mm (34.0, 21.6, 7.6, and 47.0 mm).

Regional climate change scenarios indicate that the Mid-Atlantic US will likely experience both increases in total rainfall and increases in rainfall intensity (Easterling, 2000; Najjar et al., 2009). The use of an especially wet period is similar to the approach of used in the historical re-sampling method of testing how future climate change scenarios might affect local hydrology (Willems et al., 2012). In addition, Global Climate Change models indicate that prolonged increase wetness in the Mid-Atlantic US is likely to occur in winter months. Here, we have chosen a wet interval from summer months hypothesizing that summer-months infiltration capacity will be optimally recovered between events due to increased evapotranspiration from the site. This is meant to represent "the best" that distributed stormwater management practices on the site can do.

Scenario Evaluation Criteria

Two convenient measures of stormwater runoff response commonly used in land development standards are total runoff volume and peak flow. Both these measures are derived from event-based overland flow time series output from the ParFlow simulations for each scenario. The method for calculating overland flow at any point within the domain is based on Manning's equation:

$$Q = VA = \left(\frac{1.00}{n}\right) AR^{\frac{2}{3}} S^{\frac{1}{2}}) \tag{1}$$

where Q is volumetric flowrate (L^3T^{-1}), V is flow velocity (LT^{-1}), A is cross-sectional area (L^2), n is Manning's roughness coefficient ($TL^{-1/3}$), R is the hydraulic radius (L), and S is bed slope. Within ParFlow, Manning's equation (above) is adapted to use pressure head calculated at any surface grid cell, so that the equation for overland flow at that point is:

$$Q = \left(\frac{dx}{n}\right) P^{\frac{5}{3}} S^{\frac{1}{2}} \tag{2}$$

where dx (L) is the horizontal resolution of the domain, and P is the pressure head (L) output from the three dimensional array at the time t at the location of the grid cell. The ParFlow application of Manning's equation assumes that for wide channels, the hydraulic radius can be replaced by depth, which is equivalent to pressure head (Maxwell et al., 2016). The grid cell that was chosen to calculate overland flow was the outlet of the sewershed, where flow monitoring was carried out, pre- and post-installation of GI, also referred to the sewershed's "pour point" (red arrow in **Figure 4**). All overland flow from the sewershed flows past this point, therefore overland flow at this point is an integrated measure of flow heterogeneity within the sewershed. Overland flow was calculated for the entire simulation period for all nine scenarios.

Two measures of effect of GI configuration on surface runoff were chosen to compare the scenarios: the total volume of runoff resulting from an event, and peak volumetric flow rate of the event. From an infrastructure management perspective, lower overall volumes and lower peak flows are both desirable outcomes. This may differ from urban stream restoration goals that may seek to restore pre-development baseflows while mitigating flashiness (storm runoff peaks). From an infrastructure-centric perspective, infrastructure managers are typically trying to reduce loading on centralized drainage infrastructures, especially those that are shared with domestic wastewater conveyance.

Contextualizing Site Sensitivity to Noise Levels in Monitoring Data

In order to contextualize the variation in site runoff (total runoff volume) between each of the four events in the 10-day period, we compared the differences in runoff volumes between pairs of modeled scenarios to the monitored data. Because the monitored data was taken from a period different from the modeled scenarios, we captured the variation of the runoff volume conditional on total event depth by calculating the absolute width of the confidence percentile intervals estimated from the regression of the total event volume on the total event precipitation from the monitored precipitation and flow data from the summer months of the pre-GI period (March–August 2010). We also included two important controls to capture the effects of antecendent wetness on local saturation: the interevent period (length of time between each rain event and the previous rain event), and the interaction between the event precipitation depth and the interevent period. **Equation 3** shows the regression specification:

$$\begin{aligned} \textit{runoff volume}_{b,t} = \; & \beta_{0,b} + \beta_{1,b} prcp_t + \beta_{2,b} intertime_t \\ & + \beta_{3,b} prcp_t * intertime_t + e_{t,b} \end{aligned} \tag{3}$$

where *runoff volume*$_{\{b,t\}}$ is the runoff volume calculated from the empiricall monitoring data from the pre-GI conditions (Base case) during time t (m3)$prcp_t$ is the total depth of precipitation during event t (mm), $intertime_t$ is the inter-event period in hours between the start of event t and the end of previous event *t-1*, $beta_b$ are the coefficients estimated through linear regression and $e_{\{t,b\}}$ is the error. After obtaining the coefficients through regression, the estimated model was used to predict the linear relationship between precipitation depth and runoff volume, given four different interevent periods: 23, 42, 47, and 69 h (the mean interevent period in the empirical data was 57.3 h). These four interevent periods correspond the interevent periods for Events 1, 4, 2, and 3 in the 10-day simulation window, respectively.

The confidence interval of these predicted runoff volumes represents the area in which the "true" mean runoff volume is likely to reside, taking into account the amount of variation and

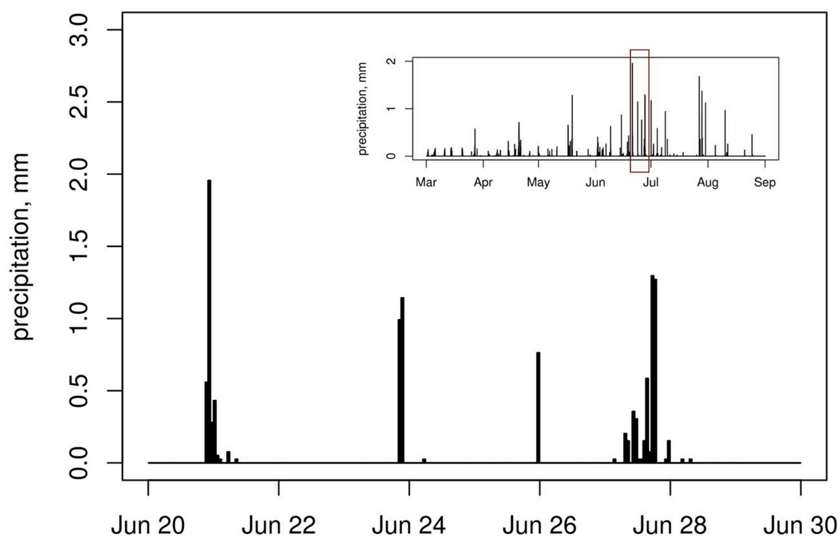


FIGURE 5 | June 20, 2015–June 30, 2015. Inset shows the selected window for overland flow examination in the context of the entire simulation period, from March 1, 2015–September 1, 2015. This window includes the highest-intensity rainfall event as well as the wettest 10-day period.

number of observations in the empirical data. The width of the confidence interval was calculated by differencing the upper and lower confidence interval limits for the 90% confidence level. Each of the scenarios' runoff volumes, were then subtracted from to runoff volumes of the base case simulation for in each event during the 10-day period. If the event-based differences exceeded the width of the confidence interval, then the effect of that scenario (compared to the Base case) exceeds the boundaries of confidence present in the monitored data, and may be noticeable over the ordinary levels of noise in the data.

RESULTS AND DISCUSSION

Event-Based Comparisons of Peak Runoff and Total Volume

A comparison of the overall 10-day rankings shows that IMP2 (maximum allowable imperviousness per-parcel for every parcel) had the highest magnitude values for both max peak flow over the 10-day period and for total volume of runoff over the 10-day period. The max peak flow for IS_MAX (0.070 cms) is 19% greater than the max peak flows for Base (0.059 cms) and 23% greater than the IS_DISC, the scenario where all roofs are disconnected from the ROW. During the 10-day period, disconnecting roofs from the ROW decreased the max peak flow by 3%, compared to Base. In the first two rain events, IS_DISC mitigated peak flows compared to Base. However, by the third rain event, the peak flow from IS_DISC marginally exceeded the peak flow from Base. This suggests that the mere disconnection of rooftop imperviousness with no provision of additional storage in the receiving lawn area may do little to mitigate flow peaks during multiday events, after the initial soil storage is exhausted. A comparison between total runoff volumes between Base and IS_DISC even show that disconnected roofs resulted in about 4% *more* total runoff volume than Base, suggesting that additional volume capture is necessary (for example through rain barrels or rain gardens) in order for downspout disconnection to have the desired effect on flow mitigation and illustrating how trends for peak flow reduction do not necessarily translate into trends for total volume reduction. The measures and rankings for each scenario were calculated (**Table 2**). A visualization of changes in ranking between events is shown in **Figure 6**.

Figure 6 illustrates all changes in rankings in flow peak and total volume magnitudes that occur over the 10-day analysis period. Examining rank crossovers (RCs) between paired scenarios across the four events in the 10-day period allows us to explore potential thresholds for changes in hydrological response, and to anticipate outcomes of potential policy responses. For the exploratory scenarios (GI_DRY/WET, IS_DRY/WET), RCs highlight when and how previous events begin to affect the performance of the site. For the anticipatory scenarios (GI_ROOF/ GI_ROW, IS_DISC, and IS_MAX), RCs highlight how an intended policy compares to an alternative under a multiday scenario.

Peak Flow RCs and Magnitude Comparisons

Comparing paired scenario peak flow rankings (**Figure 6A**), the only RC between paired scenarios occurs between Base and IMP_DISC (discussed above). Other paired scenarios GI_ROW and GI_ROOF, GI_DRY and GI_WET, and IS_DRY and IS_WET all maintain consistent relative rankings: GI_ROW has lower flow peaks than GI_ROOFS in all four events; GI_WET has lower flow peaks than GI_DRY in all four events, and IS_DRY has lower flow peaks than IS_WET in all four events. The RC exhibited by IS_DISC and Base on the third event may reflect that the subsurface storage difference between the two scenarios has been exhausted and that delayed runoff response from previous events in the IS_DISC scenario may also have contributed to raising the third event peak flow.

TABLE 2 | Scenario rankings for peak flows and total event volumes for four consecutive events in 10-day window.

	Event 1: 6/21/2015		Event 2: 6/24/2015		Event 3: 6/25/2015		Event 4: 6/28/2015		10-day max	
	cms	**rank**	**cms**	**rank**	**cms**	**rank**	**cms**	**rank**	**cms**	**rank**
PEAK FLOWS										
Base	0.059	2	0.034	2	0.019	3	0.056	2	0.059	2
GI_DRY	0.054	4	0.028	4	0.017	4	0.050	4	0.054	4
GI_WET	0.050	6	0.026	5	0.016	5	0.048	7	0.050	6
IS_DRY	0.050	7	0.026	7	0.015	7	0.048	6	0.050	7
IS_WET	0.050	5	0.026	6	0.015	6	0.048	5	0.050	5
GI_ROOF	0.048	8	0.025	8	0.015	8	0.045	8	0.048	8
GI_ROW	0.030	9	0.016	9	0.009	9	0.030	9	0.030	9
IS_DISC	0.057	3	0.032	3	0.019	2	0.056	3	0.057	3
IS_MAX	0.070	1	0.039	1	0.022	1	0.066	1	0.070	1
TOTAL RUNOFF VOLUMES										
	m3	**rank**	**m3**	**rank**	**m3**	**rank**	**m3**	**rank**	**m3**	**rank**
Base	603	3	376	3	105	3	1,043	3	2,127	3
GI_DRY	478	5	256	6	70	5	884	5	1,688	4
GI_WET	469	6	253	7	66	7	869	6	1,657	6
IS_DRY	478	4	243	8	66	6	893	4	1,680	5
IS_WET	460	7	257	5	65	8	857	7	1,639	7
GI_ROOF	437	8	227	9	58	9	822	8	1,543	8
GI_ROW	354	9	272	4	72	4	728	9	1,425	9
IS_DISC	641	2	386	2	112	2	1,085	2	2,225	2
IS_MAX	749	1	441	1	136	1	1,209	1	2,534	1

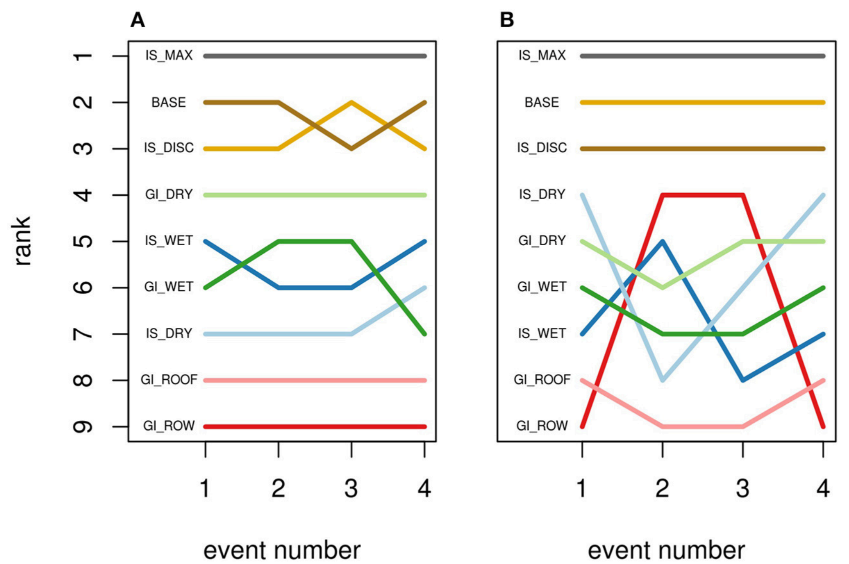


FIGURE 6 | Comparisons of magnitude rankings for **(A)** peak volumetric flow rates, and **(B)** event runoff volumes, between nine simulated scenarios, over four rainfall events in a 10-day window.

The differences in magnitude between peaks between IS_DRY and IS_WET were negligible (about 1% in all four events), indicating that spatial configuration of imperviousness when no additional storage volume is provided has limited effect on peak flow mitigation. In contrast, differences in spatial configuration in placement of GI treatment areas (GI_ROW vs. GI_ROOF and GI_DRY vs. GI_WET) were as high as 66%. Larger differences in attributed to spatial configuration were observed between the GI_ROW and GI_ROOF scenarios, which had 14.2 and 15.6% of the area within the sewershed treated with GI, respectively. GI_DRY and GI_WET had smaller proportions of their total contributing area retrofit with GI (7.3 and 8.2%, respectively), about half of the total treated area in the GI_ROW and GI_ROOF scenarios. This result implies that differences in peak flow mitigation associated with spatial configuration and placement of GI become more apparent as the total area treated with GI increases. In Miles (2014), no differences in streamflow were found when upslope vs. downslope roofs in a low-medium density neighborhood were treated with GI. In that study, residential rooftops comprised only about 7% of the total watershed area.

Total Runoff Volume RCs and Magnitude Comparisons

Total runoff volumes for each event exhibited several RCs between paired spatial configuration scenarios (**Figure 6B**). During the first rainfall event (34 mm) GI_ROW reduced total runoff volumes more than GI_ROOF (by 23%), and IMP_WET reduced total runoff volumes more than IMP_DRY (by 4%). Both these comparisons provide evidence that spatial configuration of GI and imperviousness matter: when run-on opportunities and storage areas are located in more downslope areas, more runoff volume is intercepted. However, after the first event, during the second (21 mm) and third (7.6 mm) events, the scenarios that provide upslope infiltration and storage opportunities mitigate more total volumes than the scenarios that provide downslope infiltration and storage opportunities. For GI_ROW/GI_ROOF these differences are by 17 and 19% for events 2 and 3, respectively. For IS_DRY/IS_WET, these differences are much smaller: 5 and 0.4% for events 2 and 3, respectively. After these two events, capacity is "recovered" in downslope areas, and maximum infiltration opportunities in the downslope configurations again realizes its advantage in intercepting more subsurface flow during the fourth event (1.85 mm).

While peak flows were lower for the disconnected roof scenario (IS_DISC) compared to Base in three out of four rain events, Base had lower total volumes of runoff compared to IS_DISC in all four rain events. The increased volume of total runoff in each event for IS_DISC ranged between 2.7 and 6.5% higher than the volume of total runoff for the Base scenario. No RCs were observed for GI_DRY and GI_WET: the total runoff volume from GI_DRY was slightly higher than the total runoff volume from GI_WET in each rainfall event during the multiday period (ranging between 1.6 and 6.3% larger volumes).

Event-Based Comparisons to Noise Levels in Monitoring Data

The 90% confidence levels of estimated runoff volumes, given total precipitation depth and length of interevent period (according to Equation 3), are shown as lines in **Figure 7**. The figure shows that for shorter interevent periods (e.g., 23 h), the amount of noise in the monitored data was greater, requiring a greater difference between scenarios before we would be able to confidently effectiveness of the scenario attributable to sub-parcel-scale land use changes.

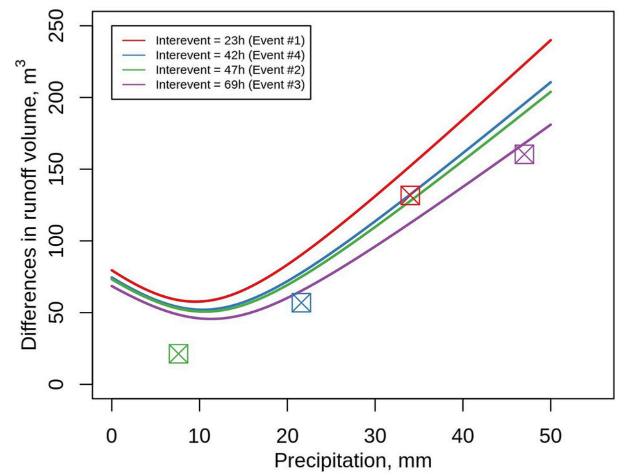


FIGURE 7 | Differences in runoff volume required to overcome noise in monitoring data, given depth of rainfall event and interevent period (colored lines) compared to runoff volume differences between two scenarios for each event (colored boxes). Colored Boxes represent differences in runoff volume simulated between two most different micro land use scenarios in this study: IS_MAX and GI_ROW. None of the colored boxes exceed the predicted magnitude of noise associated with that event.

None of the scenarios exhibit large enough differences from the Base case to surpass the level of noise at the 90% confidence level, in any of the four events during the 10-day simulation period. Of all the combinations of scenarios in this study, the maximum differences in total event runoff volume were between IS_MAX (the maximum allowable impervious surface per property as per zoning regulations) and GI_ROW (all of the public ROW treated with GI). The differences in event-based runoff volume for these two scenarios during the four events is shown in **Figure 7.** Even between the most and least optimal scenarios tested in this study, during a multi-day wet period however, **Figure 3** indicates that we would not be able to confidently distinguish the effects of micro land cover changes from the noise in the monitoring data. This is a different result from what was found in Lim and Welty (2017), where the differences between these two scenarios were expected to be distinguishable from the noise, when relationships between all rainfall events were analyzed together (not just the events during a particularly wet period).

CONCLUSIONS

This study used a three-dimensional surface-subsurface coupled model, ParFlow.CLM to examine four main areas of uncertainty relevant to GI Planning: network effects, sub-parcel-scale land use and land cover changes, climate, and urban pipeflow monitoring noise. Isolating a 10-day simulation window containing four rain events, we showed evidence of non-additive effects of GI networks. Non-additive effects become apparent during multi-day events when subsurface storage capacity, especially in watershed capacitance-constrained scenarios, had not yet been recovered. While in general, downslope network spatial configurations intercept more runoff volume than upslope configurations, the opposite is true during multiday events. This implies that GI in downslope locations may be more susceptible to obsolescence (given equal design storm specifications) than GI in upslope locations under changing climate conditions.

Previous studies have found that GI networks have empirically decreased peak flows, but there is less evidence that GI networks reduce runoff volumes associated with urbanization (Jefferson et al., 2017). The results of this study in a medium-density residential neighborhood retrofit with GI show that peak flows behave in a more consistent way, and peak flow mitigation is not sensitive GI in differently configured spatial networks, even under multi-day conditions. Total runoff volume, however does exhibit evidence of being more responsive to spatial configuration. In empirical studies, the difficulty of quantifying spatial configurations, and therefore not controlling for them, may be one reason why the effects of GI networks on total runoff generation have been weaker. Other reasons may be that design standards either do not specify a particular GI facility to meet a total runoff-based performance standard, or that GI designs typically do not consider the performance of upslope/downslope contributions of other infiltration opportunities that could affect a particular BMP or be affected by a particular BMP.

Lastly, the problem of detectable change (Lim and Welty, 2017) has implications for municipalities to be able to adapt their infrastructure under changing conditions. In this study, we demonstrated that an increase in noise/variability associated with rain events happening quickly following a previous rain event makes it more difficult to confidently attribute changes attributable to GI or micro land cover implementation. Non-stationary climate conditions, when rain events in many areas are expected to increase in severity or frequency, will likely make it more difficult to detect unaddressed needs and adapt the management of the infrastructure.

AUTHOR CONTRIBUTIONS

TL contributed the project concept, research design, collaboration with partners, ParFlow simulations, analysis, and manuscript preparation. CW contributed to simulations and manuscript preparation.

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