Green Infrastructure Placement Strategy in Urban Stormwater Network

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Key Points:

- Urban stormwater network structure modulates green infrastructure effectiveness.
- Tradeoff exists between hydrological outcomes, such as managing peak flow rate and inland flooding.
- Effect of green infrastructure saturates at high rainfall intensity.

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Abstract

Green infrastructure are nature-based solutions implemented to improve urban stormwater quality and reduce flooding. Currently, green infrastructure projects are implemented on a case-by-case basis, without considering their spatial configurations relative to each other or placement within the greater watershed. Here, we examine the optimal placement of green infrastructure sites within the urban drainage network – which consist of grey infrastructure and mixed land use and land cover types – to achieve the most flood control benefits. In our approach, we also explore the variabilities in design parameters and address the effects of climate uncertainty on green infrastructure performance.

To do so, we stochastically generate synthetic stormwater drainage networks on a square lattice, whose probability of occurrence follows a Gibbs' distribution with a single parameter describing the sinuosity of the network. Then, different percentages of green infrastructure nodes representing green infrastructure sites are randomly placed across the network. The effects of network structure as well as green infrastructure coverage and placement are investigated using EPA's Storm Water Management Model (SWMM). To account for uncertainty in future precipitation patterns, we force the model with two-hour storms with return periods ranging from two years to 100 years. To account for the variability in the design and site parameters, we simulate our results using multiple parameter combinations based on user-submitted design and field measured data from the International Best Management Practice (BMP) Database.

We find that there is no "one-and-done" solution for green infrastructure planning. The structure of stormwater network alone, without green infrastructure, can modulate the peak flow rate and flood volume by changing the travel time in the network. When rainfall intensity is low, adding green infrastructure and placing them near the drainage outlet can most effectively reduce peak flow at the outlet. However, at higher rainfall intensities, green infrastructure can be overwhelmed and become ineffective at controlling flow. We anticipate that these results will serve as theoretical guidelines for optimal nature-based green infrastructure planning at the watershed scale.

Plain Language Summary

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1 Introduction

The increase of runoff due to the loss of infiltration capacity in urban landscape has been well documented and studied for decades. Underground stormwater drainage networks have been the standard practice to reduce inland flooding for over a century. Runoff from precipitation and snowmelt is quickly transported from upstream urban neighborhoods and discharged to downstream water bodies. These networks transform the stormwater watershed characteristics by shortening the lead and lag time of peak flow in urban streams, and they therefore contribute to higher peak flow during a storm event (Graf, 1977; Jovanovic et al., 2019). The magnitude of this increase in peak flow depends on the travel path configuration within the network (?, ?) and the geographical constraints of the landscape ().

Concerned about peak flow increase and base flow decrease disrupting the receiving streams, engineers and planners have been designing and implementing green infrastructure to reduce runoff at source upstream. Green infrastructure (GI), also known as nature-based solutions and low-impact developments, is both small and large-scaled construction consisting of vegetation and soil (e.g., bio-retention cells, rain gardens, urban greeneries). Green infrastructure decreases the amount of runoff entering the stormwater networks by increasing infiltration and evapotranspiration, and at the same time, it naturally treats stormwater and recharges groundwater ()(United States Environmental Protection Agency, 2020). The existing research focuses on both the technology advancement – in the modeling and measurement of infiltration and pollutant transport phenomena in different porous media (?, ?, ?) – and the feasibility and effectiveness of existing green infrastructure (Avellaneda et al., 2017) at both small, household scale and large, municipal scale. However, the current implementations of green infrastructure are often limited to a parcel scale and primarily driven by stakeholder's interests and convenience, and the design relies on the geographical factors of the project site ()(Center for Watershed Protection; & Maryland Department of the Environment, 2000). When a series of green infrastructure are retrofitted to the existing stormwater network, the spatial distribution of these sites in relation to the existing network becomes nontrivial. But there is very little understanding of the interaction between above-ground green infrastructure and below-ground pipe network. We want to investigate whether the placement of green infrastructure in a stormwater network can maximize hydrological benefits in an urban watershed.

In order to better integrate green infrastructure at a watershed scale, we use tools from graph theory to study and reconstruct the configuration of the urban stormwater networks. These complex infrastructure networks can be stripped down to their most basic components – nodes and edges – which store essential attributes for stormwater modeling. Repeat definitions of nodes and edges. This simplified configurations allow researchers to bypass the acquisition of infrastructure data, and to flexibly manipulate stormwater networks for scenario planning purposes while retaining their essential network structures. Graph theories are sometimes referred to as network theories. The field of network science studies how the components are connected, and how the structures influence the physical phenomena observed in the network (Newman, 2010). Originated from social network studies, networks and network theories have been applied in geosciences (Heckmann et al., 2015) and ecology (Carraro et al., 2020) to provide a perspective on large scale patterns that go unnoticed when focused on the individual parts. When these systems are translated to networks, one can compute the network properties, such as shortest paths between two nodes, or centrality indicators that can indicate the most important nodes within a graph.

The existing network theory applications to hydrology include municipal and river networks generation (?, ?; Poulter et al., 2008; Troutman & Karlinger, 1985; ?, ?, ?, ?), network structural or scale-depent effects on hydrological responses (Riasi & Yeghiazarian, 2017; Rodríguez-Iturbe & Valdés, 1979), and optimization to improve hydrological network efficiency (). Tools from network theory are particularly helpful in understanding these hydrological pathways. They can generalize spatial layouts, demonstrate network properties without relying on the exact layouts, and still preserve the instantaneous unit hydrographs from observed stream flow data (?, ?). In particular, the exact configurations of municipal stormwater networks exist as as-builts and shapefiles in municipal databases, and they are difficult to access due to geospatial data sharing restrictions. To overcome this challenge, we stochastically generate synthetic drainage networks, which probability of occurrence follows a Gibbs' distribution, to imitate a drainage network in a small urban catchment.

This should be an overview of the workflow. May flow better as a beginning paragraph for Methods section. We want to establish a green infrastructure placement strategy at a watershed level and to upscale green infrastructure's effect on stormwater. To do so, we stochastically generate stormwater networks and model their hydrological responses with different numbers and locations of green infrastructure under a range of light to heavy rainfall scenarios. We hypothesize that green infrastructure performance depends on rainfall intensity, and implementing more green infrastructure near outlet may reduce peak flow and inland flooding.

2 Methodology

In order to develop the optimal distribution of green infrastructure nodes in different configurations of stormwater networks and to understand the role of network spatial structure in peak flow attenuation and inland flooding prevention, we performed rainfall-runoff simulation on random stormwater networks. We investigated the performance of green infrastructure under more intense rainfall, and examined whether the optimal green infrastructure allocation changes as climate conditions change. Come up with question and hypothesis we are investigating. Watershed-level green infrastructure planning.

Add something workflow. The network structure, green infrastructure percentage and green infrastructure location are the three key design variables considered for this study, and the corresponding responses are provided as in Figure 2.

Below, we will discuss our method to generate urban stormwater network, the design parameters for the experiment set-up, and the specific implementation in SWMM.

2.1 Generating urban stormwater networks

Stormwater sewer networks can be represented in abstraction using "directed tree graphs". Define graphs (nodes + edges and can be connected different ways. Contains information), introduce concepts of vertices, edges, and paths. Be more fundamental. By definition, tree graphs are acyclic. Tree graphs are graphs where any two vertices are connected by exactly one path, and all the edges are directed. Tree graphs are acyclic, like many stormwater networks. Move the definition up front to nodes. The nodes in the graph represent access points to the drainage networks and directed edges represent stormwater pipes and their flow directions. Define a graph and a subgraph. Consider defining spanning trees in first paragraph.

We will generate spanning trees on G to represent stormwater networks. From a graph G, one way to generate tree graphs is to generate spanning trees, which are subgraphs of G, include all of the vertices of G, and are tree graphs. Our choice of generating the spanning trees is on an n by n lattice grid graph G to reduce the dimensionality of synthetic network. Although all spanning trees of G share the same vertices with graph G, the path between two vertices can change in different spanning trees. This variation in network paths among an array of realized spanning trees is used as a network structure parameter. And the difference between the sum of the realized paths in a spanning tree s and the sum of the shortest paths in G is called $H(s)$, and it will be used as a design variable for network structure in our study.

One way to sample spanning trees from a given graph G is to use a stochastic model, where the probability of a spanning tree's occurrence follows a probability distribution of choice. In this case, a Gibbs distribution based stochastic model used in Troutman and Karlinger ? (?) is used to generate tree graphs. More commonly seen in statistical mechanics, Gibbs distribution gives the probability that a system will be in a certain state as a function of that state's energy and the temperature of the system (). We use a single parameter β, which measures the sinuosity of a network (the energy at a certain state). When $\beta = 0$, the sampling distribution is uniform, and the resulting samples are more likely to have higher $H(s)$. When β is large, the resulting samples are more likely to have lower $H(s)$ and are more efficient graphs. A Gibbs distribution has the following probability density function:

$$P_\beta\{s\} = [C(\beta)]^{-1} e^{-\beta H(s)}$$

As described in above, β is a distribution parameter that measures the sinuosity of probability distribution, $H(s)$ is the network path difference calculated for each graph generated. $C(\beta)$ is a normalization coefficient. The spanning tree networks are generated

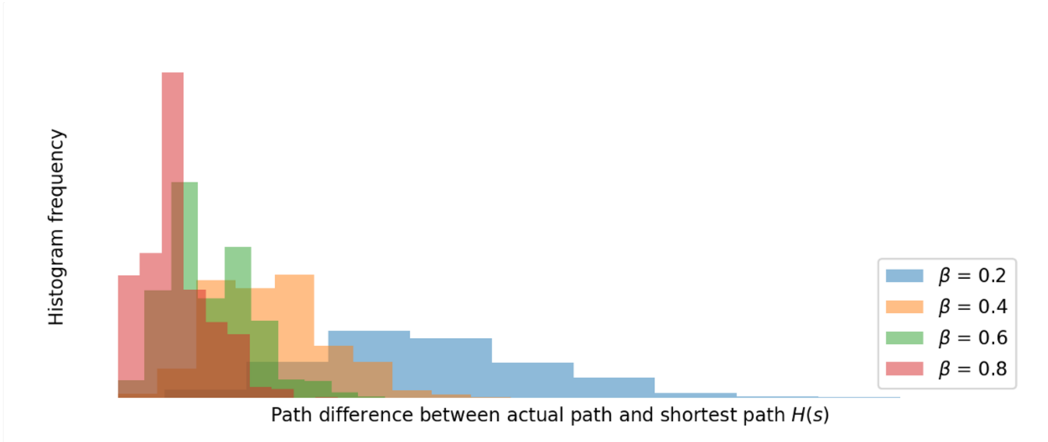


Figure 1. Gibbs distribution with different parameter β

following the simulated annealing methods on the basis of a stochastic Markov chain (?, ?, ?, ?). Supporting information: describing the process and transition matrix etc.

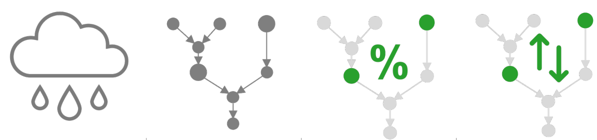
The motivation for generating networks with different degrees of sinuosity is so that we can differentiate the response of stormwater networks that share the same footprint but have different flow pathways/lengths. These different flow pathways can be encapsulated in a scenario of urban sprawl (i.e. low-density), assuming low and high density follows... High (sinuosity), low (more spreadout, direct pathways). translate above-ground development patterns (e.g. urban sprawl versus high-density clusters) to underground infrastructure. Given the same acreage of land (i.e. the node size of the network), some communities are more tightly clustered and others are more spread out. The more clustered communities have lower degrees of sinuosity, because they take the nearly shortest paths to the network outlet. The actual flow paths existing in the communities with higher degrees of urban sprawl have higher degrees of sinuosity.

We generate networks from a n-by-n grid graph to reduce the dimensionality.

Once the structure of the network is determined, we can place green infrastructure on the nodes of the network. The green infrastructure can be placed in the network by random assignment or by mean distance to the stormwater network outlet.

2.2 Green infrastructure and stormwater network design variable

Talk about theory, save implementation for later In this study, we generated graphs on an n-by-n grid. For each simulated network, the network path difference $H(s)$ is calculated to represent the network structure, because we are comparing networks with fixed grids, and $H(s)$ is a more direct calculation of a graph's sinuosity than the normalized parameter β for Gibbs distribution. Green infrastructure percentage ranges from 0 to 50% at an increment of 10%. The location of green infrastructure is calculated based on the nodes' distance to the network outlet. To study this effect, we created clusters of 10 green infrastructure nodes (10 %) to reduce the large-variance effects arisen from a wide range of distances, and averaged the distances to outlet for each node in a cluster. (Why we do this cluster)



	Rainfall Scenarios	Network Structure	% GI Nodes	GI Distance to Outlet	Takeaway
Figure 2: Effect of Network Structure	2, 5, 25, & 100-Year 2-Hour Storms	Continuously increase H(s) from 0 to 1600	No GI	No GI	Higher H(s) reduces downstream peak flow at the expense of increasing inland flooding
Figure 3: Effect of GI Percentage	2, 5, 25, & 100-Year 2-Hour Storms	Fixed on one graph H(s) = 28	0% to 50%, incrementally increases at 10%	Randomly assigned	Increasing green infrastructure nodes can reduce peak flow and inland flooding at low rainfall intensity (i.e. 2-year, 10-year), but becomes ineffective in intense storms.
Figure 4: Interaction between GI & Network Structure	5 & 25-Year 2-Hour Storms	H(s) = 28 vs H(s) = 74	0% to 50%, incrementally increases at 10%	Randomly assigned	At low intensity rainfall, adding green infrastructure more effectively reduces peak flow in networks with lower H(s). At high rainfall intensity, green infrastructure is ineffective; the effect of network structure dominates.
Figure 5: Effect of GI Location	2, 5, 25, & 100-Year 2-Hour Storms	Many graphs, all have H(s) = 28	0% to 50%, incrementally increases at 10%	Assigned closed to each other, at a distance from the outlet	The locations of green infrastructure nodes do not affect total inland flooding volume. But when the green infrastructure nodes are clustered around the outlet, they can reduce peak flow rate at low rainfall intensity (i.e. 2-year).

Figure 2. Pending caption

Table 1. Network Design Attributes (SWMM Input)

Asset type	Attributes	Initial values	Exceptions
Nodes	Relative elevation (ft)	90 - 100	85 (outlet node)
	Subcatchment drainage area (acre)	2	5×10^8 (outlet node)
	Manhole area (sqft)	50	5×10^8 (outlet node)
	Subcatchment impervious area (%)	60	–
	Subcatchment slope (%)	0.5	–
	Initial level (ft)	0	1 (outlet node)
	Flood level (ft)	10	0 (outlet node)
	GI/LID type	Bioretential Cell	–
	Berm height (in)	9	–
	Surface roughness (–)	0.1	–
	Surface slope (%)	1.0	–
	Berm height (in)	9	–
	Soil thickness (ft)	2	–
	Soil porosity (-)	0.43	–
	Soil field capacity (-)	0.4	–
	Soil wilting point (-)	0.18	–
	Soil conductivity (in/hr)	1.5	–
	Soil conductivity slope (%)	40	–
	Soil suction head (in)	3.5	–
	Storage thickness (in	0	–
	Storage void ratio (–)	0.25	–
	Storage seepage (in/hr)	1.3	–
	Potential ET loss (ft/day)	0.005	–
	Rooting depth (ft)	1	–
Pipes	Design storm	10-year 24-hour	–
	Slope	0.008	–
	Manning's n	0.01	–
	Length (ft)	400	(outlet pipe)
	Shape	Circular	–
	Hydrographs		

Table 2. Rainfall Intensities of a Two-Hour Storm

Return period	Total rainfall (inch)	15-minute simulation (inch)
2-Year	1.69	0.211
5-Year	2.15	0.269
10-Year	2.59	0.324
25-Year	3.29	0.411
100-Year	4.55	0.569

2.3 SWMM implementation

We evaluated the performance of the green infrastructure network under two objectives: lowering peak flow rate at the stormwater network outlet, and reducing inland flooding volume upstream. The hydrological modeling was conducted using the Stormwater Management Model from Environmental Protection Agency (EPA-SWMM). The peak flow rate and inland flooding volume from SWMM output files were parsed and recorded. (Supporting Information) The fixed design attributes for the stormwater network itself and for the green infrastructure within the network are listed in Table 1.

We hypothesized that certain environmental variables may reduce green infrastructure's effectiveness. As a result, the SWMM model was run under five different two-hour rainfall scenarios, with return periods ranging from two years to 100 years. The two-hour storm was uniformly distributed to 15-minute intervals in the hyetographs as listed in Table 2.

Directed edges in the network represent the stormwater pipes and their flow directions. Notably, the pipes in the network are sized using rational method with a 10-year 24-hour design storm. Talk about sizing

Nodes in the network represent access points in the stormwater network. How do we determine the percentage of land cover distribution?

Green infrastructure nodes. Parameters for green infrastructure International Best Management Practice (BMP) Database

3 Results

Based on the simulated stormwater network and SWMM results, we investigate three design variables that may affect green infrastructure's ability in reducing inland flooding and downstream peak flow under different rainfall intensities, ranging from two-year to 100-year storms. In general, we see that tradeoff exists between managing the two hydrological outcomes, and the effects of green infrastructure saturate at high rainfall intensity. In the sections below, we will present the results on the specific design parameters.

Network structure can regulate hydrological outcomes, but tradeoff exists between managing different flow control objectives; a network cannot lower peak flow and flooding at the same time. Networks with higher $H(s)$ increase the total flow path and travel time of the network, hence they can effectively reduce the peak flow rate at stormwater network outlet as shown in Figure 3. However, networks with higher $H(s)$ also increase inland flooding. Also due to the increasing travel time, these networks are less efficient in mitigating stormwater from upstream to downstream, especially when the event storm intensities exceed that of the design storm.

The marginal hydrological benefits achieved by adding green infrastructure depend on the rainfall intensities and network structure. In a fixed network, increasing number or percentage of green infrastructure can reduce peak flow and inland flooding at low rainfall intensity (i.e. 2-year, 10-year), as shown in Figure 4. However, at high rainfall intensity (i.e. 25-year, 100-year), the effect of additional green infrastructure saturated and the network structure $H(s)$ dominates the outcomes; although increasing percentage of green infrastructure can still reduce inland flooding volume, it can no longer reduce peak flow rate. The green infrastructure in the network transitions from a flood control measure to a flooding contributor (Run this again and see why 25-year is like that? and combine the interaction with network structure). Comparing different network structures, the network with lower $H(s)$ benefit $H(s)$ benefit more from additional green infrastructure in the network at lower rainfall intensity.

Table 3. Summary of Simulation Set-up and Results

Figure	Rainfall Scenarios	Network Structure	% GI Nodes	GI Distance to Outlet	Takeaway
Fig 1: Effect of network structure	2, 10, 25 & 100-Year 2-Hour Storms	$H(s)$ **from 0 to 1600**	No GI	No GI	Higher $H(s)$ reduces downstream peak flow at the expense of increasing inland flooding
Fig 2: Effect of GI Percentage	2, 10, 25 & 100-Year 2-Hour Storms	Fixed on one graph $H(s) = 28$	**0% to 50%, incrementally increases at 10%**	Randomly assigned	Increasing green infrastructure nodes can reduce peak flow and inland flooding at low rainfall intensity (i.e. 2-year, 10-year), but becomes ineffective in intense storms.
Fig 3: Interaction between GI & Network Structure	5 & 25-Year 2-Hour Storms	$H(s) = 28$ **vs** $H(s) = 74$	**0% to 50%, incrementally increases at 10%**	Randomly assigned	At low intensity rainfall, adding green infrastructure more effectively reduces peak flow in networks with lower H(s). At high rainfall intensity, green infrastructure is ineffective; the effect of network structure dominates.
Fig 4: Effect of GI Location	2, 10, 25 & 100-Year 2-Hour Storms	Many graphs, all have $H(s) = 28$	0% to 50%, incrementally increases at 10%	**Assigned closed to each other, at a distance from the outlet**	The locations of green infrastructure nodes do not affect total inland flooding volume. But when the green infrastructure nodes are clustered around the outlet, they can reduce peak flow rate at low rainfall intensity (i.e. 2-year).

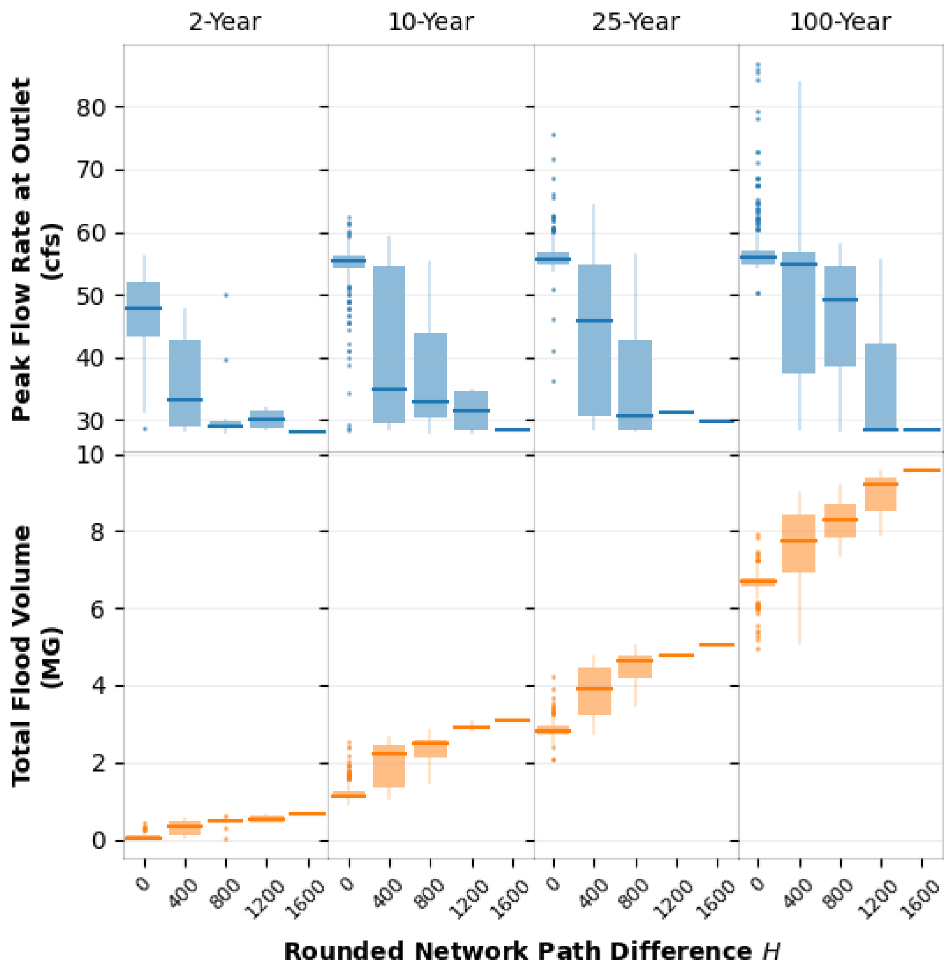


Figure 3. Effect of network structure: peak flow and inland flooding in networks with varying degrees of network path difference $H(s)$, under 2-year to 100-year two-hour storms. Generally, increasing $H(s)$ lowers peak flow rate, but it does so at the expense of increasing inland flooding. Network structure's effect on increasing inland flooding is more obvious in high-intensity storm.

The placement strategy of green infrastructure also depends on the targeted rainfall intensity and desired hydrological outcome. When placed closer to the outlet, green infrastructure can typically lower peak flow, but at the expense of slightly increasing inland flooding. The results, as shown in Figure 6, also demonstrate that the peak flow reduction effects are more prominent under lower-rainfall intensity. The peak flow reduction of green infrastructure saturates at high rainfall intensity.

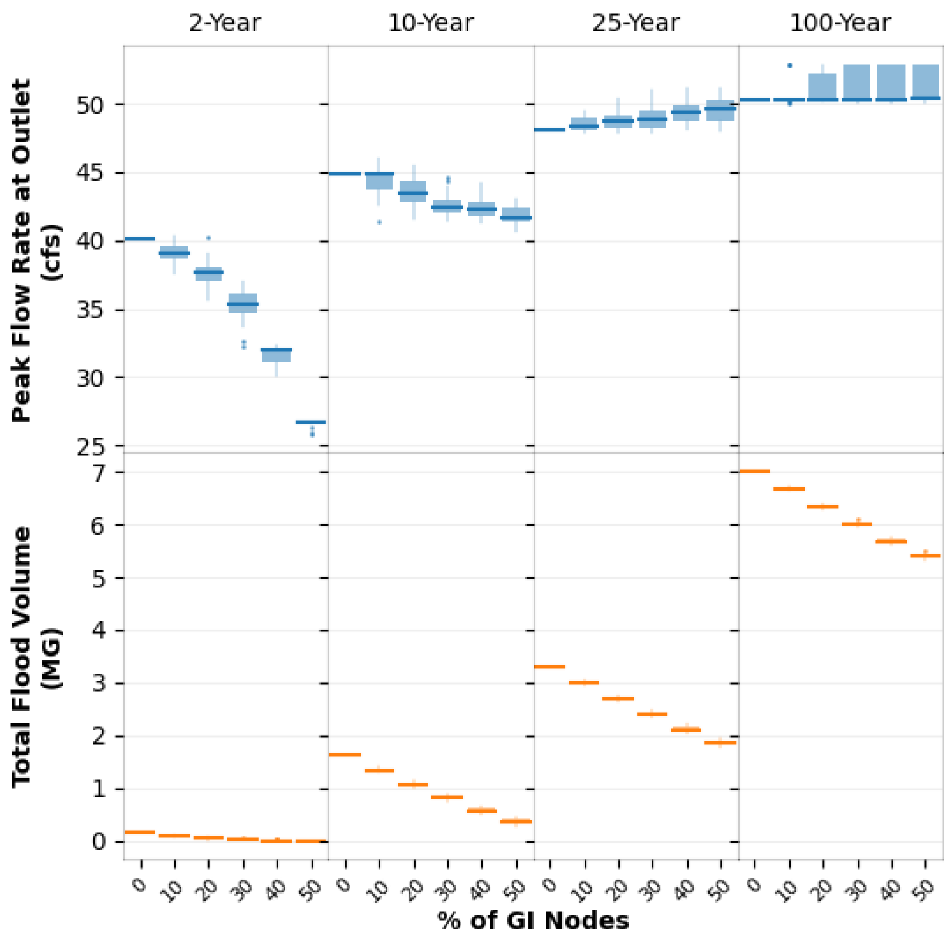


Figure 4. Effect of green infrastructure percentage: peak flow and inland flooding in networks with a fixed network and varying percentages of green infrastructure nodes, under 2-year to 100-year 2-hour storms.

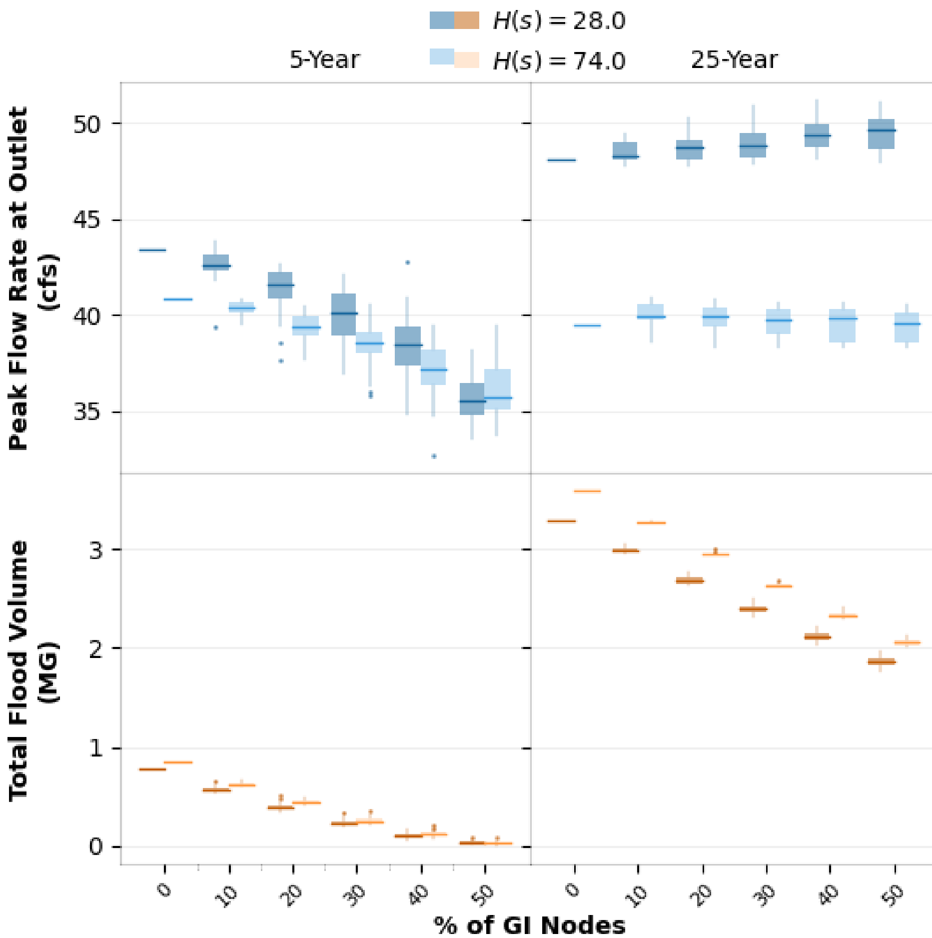


Figure 5. Interaction between green infrastructure and network structure: peak flow and inland flooding in networks with two fixed networks – $H(s) = 28$ and $H(s) = 74$ – and varying percentages of green infrastructure nodes, under 5-year and 25-year 2-hour storms.

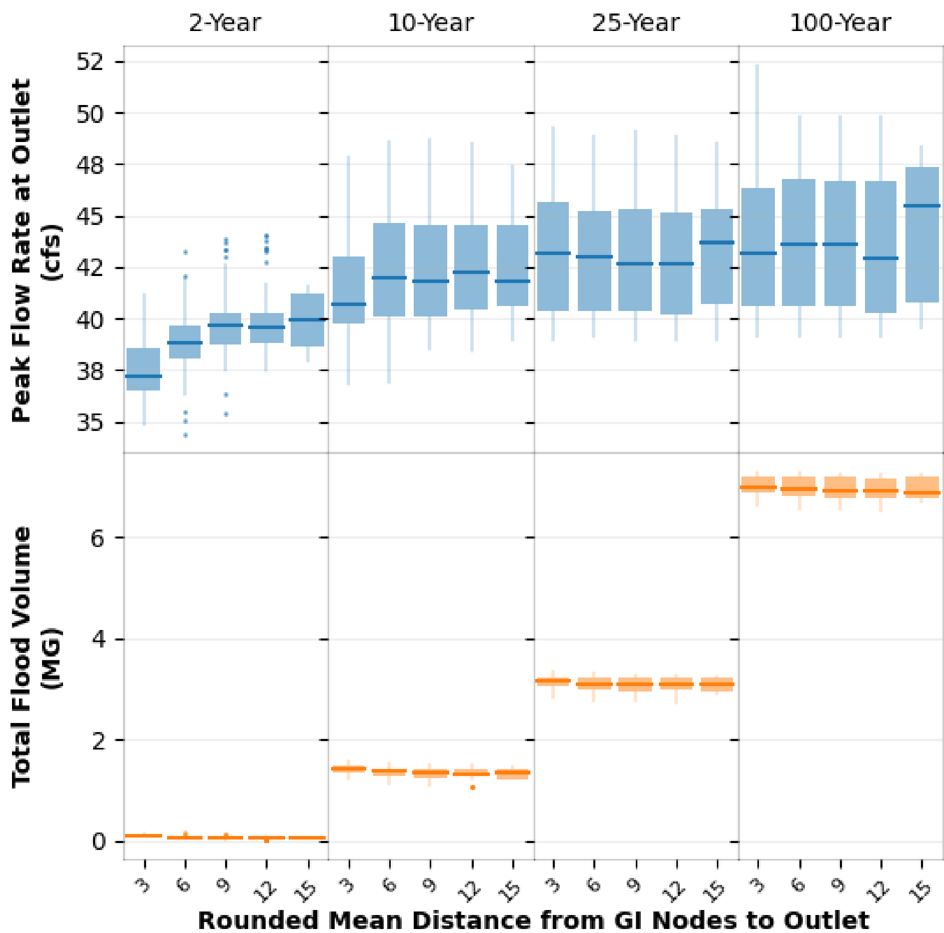


Figure 6. Effect of green infrastructure placement shown as the distance to the network outlet: peak flow and inland flooding in multiple networks with $H(s) = 28$ and varying placement of green infrastructure nodes, under 2-year to 100-year 2-hour storms.

4 Discussion

(Summarize then open up to the introductory questions again) What does this mean for the design of network structure?

What questions would need to be answered for this to be a useful tool for infrastructure planners?

Does this line of work suggest that decentralized stormwater management is likely to be more effective at reducing flooding, as opposed to more centralized stormwater detention? Have other studies address the spatial placement problem using SWMM? Are these surprising results (e.g. 5-10 references with GI performance under high rainfall intensity? City-wide rain garden adoption?) Network structures (e.g. maybe natural systems?) How novel is the finding or how well it fits into other studies? What are the limitations of the study (e.g. uncertainty related to parameter values, different types of green infrastructure)? What kind of new questions do we want to do in a new study?

Appears to be the first study to combine the network structure with green infrastructure placement, where the network is quantified by its flow path instead of its topology.

In this paper, we have shown that urban stormwater network and green infrastructure design can only effectively control water quantity under certain rainfall scenario. Tradeoff exists between managing different hydrological outcomes, and green infrastructure become ineffective under high rainfall intensity. Although there is no one-size-fits-all solution for green infrastructure implementation, refining the hydrological control objectives and understanding the network structure of the urban stormwater network will contribute to green infrastructure site selections at a watershed scale.

The 100-node networks in this study were generated on a 10-by-10 grid. At this scale, our networks are large enough to capture the nuances in the competing hydrological outcomes and allow reasonably flexible re-configuration for scenario testing purposes, but these graphs are small comparing to any actual stormwater networks. More realistic reconstructions of stormwater networks require expansion of the network size and in-depth analyses of the real municipal stormwater network structure. However, these are non-trivial hurdles. Increasing the grid size will significantly increase the computational time to generate a graph. And spatial data for municipal stormwater networks have proven to be hard to access.

Current literature on the effectiveness of green infrastructure focuses on either local-scale benefits, or specific configurations within a real-world stormwater network. As green infrastructure gets more attention as a valuable asset for climate adaption at a municipal level, the effectiveness of green infrastructure needs to be upscaled accordingly, and the underlying stormwater conveyance networks green infrastructure belongs to also needs to be evaluated.

What is the missing gap for the next steps?

(How does this fit in the larger research context? How does it contribute to the larger research?)

Acronyms

GI Green Infrastructure

SWMM Stormwater Management Model

Open Research

Acknowledgments

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