Quantifying and Designing Infrastructure for Nonstationary Flood Risks

Lachlan R. Murphy[1], Simrat S. Saini[1], Noah A. Simsic[1], Petey G. von Ahn[1],
Justin Zheng[1], and Julianne D. Quinn[1,2]

[1] Department of Systems and Information Engineering, University of Virginia, Charlottesville, VA 22904 USA (e-mail: hwf2js@virginia.edu)

[2]Department of Civil and Environmental Engineering, University of Virginia, Charlottesville, VA 22904 USA (e-mail: jdq6nn@virginia.edu)

Abstract— **In recent years, climate change has led to a rise in intense precipitation events, presenting the need for efficient and cost-effective flood management infrastructure. In Charlottesville, VA, one key area identified for improvement is Meadow Creek. This paper examines different infrastructure options for flood management in Meadow Creek under various climate change scenarios. This analysis is carried out by optimizing infrastructure designs with the Environmental Protection Agency's Storm Water Management Model under uncertain future conditions captured by climate projections from the Coupled Model Intercomparison Project 6. The optimization seeks to minimize cost and runoff volume while maximizing cobenefits. Our findings provide a set of non-dominated green infrastructure solutions and provide a methodology for selecting a recommended compromise solution. This analysis contributes to our goal of addressing flood risks and long-term sustainability in the Charlottesville area.**

I. INTRODUCTION

Storm events have grown more intense as time progresses, with nine of the ten costliest hurricanes in United States history occurring in the 21st century [1]. This phenomenon is largely attributed to climate change, and although scientists have observed both increasing CO_2 emissions and larger storms, predicting the future state of climate change remains difficult [2]. As a result, improved infrastructure for flooding is necessary, but how much is needed or how effective it will be under future conditions is uncertain.

In Charlottesville, VA, extreme precipitation events pose challenges exacerbated by local geography. Meadow Creek is a tributary of the Rivanna River, winding through numerous residential areas and beneath major roads. In October 2024, Hurricane Helene caused intense flooding around the Rivanna River closing roads, overwhelming pump stations, and destroying property across Central Virginia [3].

The most recent Federal Emergency Management Agency (FEMA) risk assessments classify roughly 200 properties in Charlottesville as being in a Special Flood Hazard Area (SHFA). These are areas with a 1% probability of being inundated by extreme flooding in any given year, referred to as 100-year flood events. However, FEMA projections fail to account for two-thirds of the mileage of rivers and streams around the United States, and many researchers suggest that they underestimate risk in key areas. The private research entity First Street Technology has tried to improve understanding of flood risk by working with corporations and universities. Their model shows as many as 1,800 properties at risk of major flooding in Charlottesville [4]. By incorporating climate change projections into our study, we aim to discover more resilient infrastructure solutions that will reduce future harm.

Green Infrastructure (GI) is a class of engineered solutions which address flood management issues by restoring an urban area's natural hydrologic processes. GI can be difficult to implement depending on the complexity of existing gray infrastructure solutions, such as stormwater pipes, already built [5]. However, the use of GI in flood resilience engineering has benefits including adaptation to the changing climate, addressing the specific issues of urbanization, flow rate reduction, climate regulation, and local health and habitat support. The use of green infrastructure in effective modeling and research is at the frontier of current flood management studies [6]. GI is the solution type used in this study because of their effectiveness and benefits to the restoration of environmental processes.

II. METHODS

To model the benefits of different flood infrastructure solutions for Meadow Creek in the future, analysis was divided into three main steps: 1) projecting future storm events, 2) modeling precipitation and runoff, and 3) optimizing green infrastructure.

A. Projecting future storm events

To better understand flood risk and how it can be expected to change throughout the coming century, it is vital to consider climate change uncertainty. The Coupled Model Intercomparison Project (CMIP) is a coordinated effort to collate climate research from nations and research institutions around the world [7]. The sixth phase of the project ran from approximately 2016 to 2022, considering historical trends as well as four possible scenarios for the progression of climate change.

The four scenarios, also referred to as Shared Socio-economic Pathways or SSPs, define a potential progression of industry and climate policy around the world and subsequent expectations for climate [8]. These scenarios can be classified by their assumptions on mitigation (reducing emissions at the source) and adaptation (addressing the second-order effects of fossil-fuel use). In CMIP6, four scenarios were deemed to be top priority for consideration to span a range of possible futures:

Table 1. Shared Socio-Economic Pathways and Definitions.

Scenario	Description
SSP1	Sustainability - low challenges to mitigation and adaptation
SSP2	Middle of the road - medium challenges to mitigation and adaptation
SSP3	Regional rivalry - high challenges to mitigation and adaptation
SSP5	Fossil-fueled development - high challenges to mitigation, low challenges to adaptation

For each of these scenarios and the CMIP6 simulated historical data, we obtained data from the Copernicus Climate Change Service (C3S). This service, sponsored by the European Union, provides open-source climate tools and data, including from CMIP6 [9]. To accomplish this goal, daily precipitation simulations from the Community Earth System Model (CESM) were obtained for the years 1984-2014 (historical observations) and 2035-2099 (future projections). The projection data was divided into one time series for mid-century (2035-2065) and another for late-century (2069-2099).

To translate these projected data points of daily precipitation into expectations for how flooding might change, the depth of precipitation for 100-year rainfall events was calculated. First, the maximum precipitation in each year was identified, and the resulting series was fit to a right-hand Gumbel distribution over each period, as this distribution was found to result in the best fit diagnostics. The return value at an interval of 100 years was compared between historical and projected time periods:

$$SSP\_multiplier = \frac{SSP\_100yr\_depth}{Historical\_100yr\_depth}. \tag{1}$$

The data must be in the form of a precipitation event in 15-minute intervals to be used. To generate such a time series, we started with the Soil Conservation Service (SCS, now National Resource Conservation Service) Type-II synthetic rainfall distribution, which approximates the intensity of rainfall over a 24-hour period for the majority of the United States given a depth of total precipitation [10]. NOAA's Atlas 14 estimates the depth of precipitation events with a given probability at locations across the United States [11]. For the region of Charlottesville within which Meadow Creek resides, a 100-year rainfall event was 9.14 inches. Scenario multipliers were calculated using equation (1) and applied to this quantity, resulting in 24-hour storm events for each of the projection scenarios.

B. Modeling Precipitation and Runoff

We model how infrastructure routes precipitation into runoff using the Environmental Protection Agency's (EPA) Storm Water Management Model (SWMM), a free software tool used for runoff simulations of natural water systems worldwide. The Meadow Creek SWMM model input file was obtained from a GitHub repository associated with a study in 2023 [12]. The model divides the watershed into 26 subcatchments with differing amounts of available area that can be converted to green infrastructure. The calculated time series were added to the Meadow Creek input file, from which a specific time series is selected for the optimization.

To optimize infrastructure designs for Meadow Creek, we use Rhodium-SWMM, a recently developed tool which combines the SWMM input file with Rhodium, an open-source Python library used for multi-objective optimization and uncertainty analysis. Our model is similar to a 2023 study by [12] in Meadow Creek, however we use Rhodium-SWMM to address some gaps in that work by taking into account the potential benefits of trading optimal model performance under one climate projection scenario to reduce the sensitivity to the other climate projection scenarios. Rhodium-SWMM enables this in two ways. First, it allows users to manipulate levers (decision variables) in the SWMM input file, such as new GI, and to frame objective values for their multi-objective optimization problem [6]. Second, it evaluates the magnitude of impact that incorrect assumptions about future uncertain factors (e.g. climate change) will have on solution strategies [13].

C. Optimizing Green Infrastructure

The third step of analysis involved setting up the optimization model using the Rhodium-SWMM tool and connecting it to the High Performance Computing (HPC) system at UVA. The base code for the optimization was pulled from the Rhodium-SWMM GitHub repository developed by [6]. Four GI, or low impact development (LID), types are included in Rhodium-SWMM and three more were added for our project. The five used in our study are:

- Bioretention Cells: Ground depressions with soil mixture and vegetation over a gravel drainage layer
- Green Roofs: Soil and vegetation above specially matted roofs for water retention and percolation
- Permeable Pavement: Pavement with immediate drainage to lower gravel layer for natural drainage
- Rain Gardens: Ground depressions with vegetation that collects water for drainage
- Grass Swales: Ground depression channels with vegetated slopes for increased drainage time [14].

Each of these LID types has their own set of parameters pertaining to its surface layer, pavement, soil, storage, and drainage (not all LIDs require every category). The parameters for each of the LIDs were sourced from [10] with some modifications. Each LID also has specific cost and benefit parameters that contribute to the objectives of the optimization. The costs include installation costs, projected lifetime, and operation and maintenance costs, while the benefits include a per tree benefit for smaller areas, a park benefit for larger areas, and the efficacy of the infrastructure, which is a range between 0 and 1 determining the extent to which these benefits are actually realized [11].

After finalizing the input file and LID specifications, some changes were also made to the optimization script. First, we chose our objective functions to minimize the average flow rate , minimize the total cost , and maximize the amount of co-benefits gained from the solutions. The average flow rate is defined as the average flow through the stream at the outlet of the basin. We choose to minimize this since greater flow results in more flooding under the simulated 100-yr event. Cost includes the construction, operation, and maintenance of the infrastructure. Co-benefits refer to the ecosystem benefits provided by green space creation, expressed as a dollar value. Then, the decision variables - the number of each type of 40 ft^2 LID units to build in each subcatchment - were loaded in, as well as a CSV file containing the amount of land in each subcatchment available to be converted into each LID type.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used to optimize infrastructure options across the three competing objectives [15]. The process loops through each subcatchment individually, extracting the amount of available area for each LID and supplying that value as a parameter for each LID lever to ensure that the maximum amount of any LID does not exceed the available area. At each iteration of the optimization, SWMM simulates the set of infrastructure options provided by NSGA-II and returns values for the cost, average flow rate, and co-benefits. After all of the iterations are completed, a set of non-dominated solutions (Pareto set) is returned to provide a final set of potential solutions to choose from. This set is returned in the form of a CSV and contains the counts for each infrastructure type in each subcatchment and the objective values. We ran each optimization for 1,000 iterations.

III. RESULTS

The optimization was run on each of the five different climate projections and periods (mid/late-century) and the historical data. Each scenario resulted in a Pareto set of non-dominated solutions.

Figure 1 displays the solution sets for the two most contrasting scenarios: the historical case and the worst-case (SSP3_late) scenario. Each point on the plots represents a different combination of infrastructure choices that offers its own unique objective values. A recommended compromise solution (as defined later in this section) is circled in red on each plot. The average flow values are closely correlated with the severity of projected storms in the different climate scenarios, with the SSP3_late scenario resulting in much greater runoff than the historical scenario. The other Pareto set plots appear very similar to these, although the exact values on the axes vary.

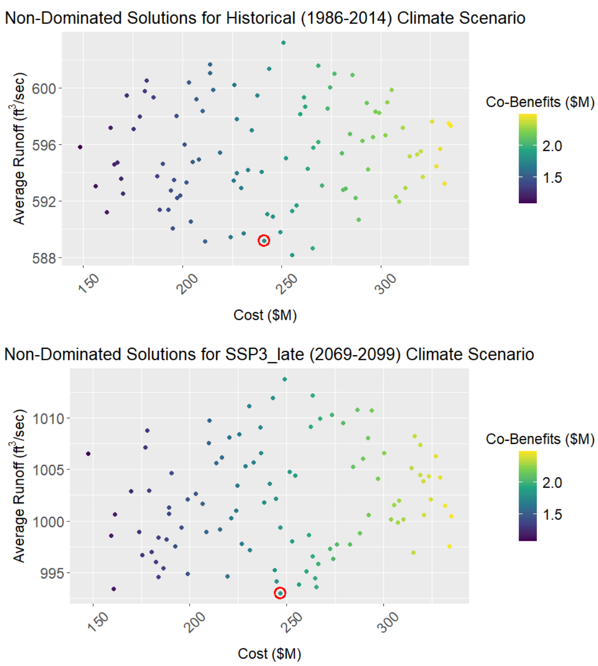

Figure 1. Pareto Set of Optimized Solutions for Historical Scenario and SSP3_late Scenario.

To explore the decisions behind the solutions identified in Figure 1, we defined a recommended optimal solution from each optimization that prioritizes balancing all objectives. This solution was identified by calculating the Euclidean distance of each solution to the ideal point and selecting the solution with the smallest distance after scaling all objectives between 0 and 1 to account for their different magnitudes. The optimal normalized values were 0 for cost and runoff and 1 for co-benefits, since cost and runoff should be minimized while co-benefits should be maximized. Table 2 shows the performance of the compromise solution from the historical scenario as well as the most optimistic (SSP1) and pessimistic (SSP3) climate scenarios at mid/late-century.

Table 2. Objective Values for the Selected Solution for Each Scenario.

	Cost ($ millions)	Average Runoff (ft^3/s)	Scenario Average Runoff (ft^3/s)	Co-benefits ($ millions)
Historical	241.18	589.19	595.40	1.77
SSP1_mid	240.87	599.58	605.32	1.78
SSP1_late	236.87	512.19	518.05	1.74
SSP3_mid	246.46	601.20	606.18	1.82
SSP3_late	246.75	993.02	1002.06	1.82

When looking at Table 2, the average runoff values corresponding to each scenario should not be compared directly across scenarios, as each utilizes a different precipitation pattern and therefore has different ranges of values for potential runoff. This is particularly evident for the SSP1_late and SSP3_late scenarios which represent the best and worst case scenarios respectively, explaining why the average runoff value is significantly lower and higher than the other three scenarios. As evidenced by Figure 1, these optimal solutions were one of, if not the best performing solution with regards to runoff in their respective scenario, typically performing between 5 to 10 ft^3/s better than the average proposed solution for each scenario. The costs of these optimal solutions are understandably correlated with the severity of the climate scenario. The historical and short term, best case scenario solutions are almost identical in cost, while the long term, best case scenario is the cheapest since there is less infrastructure needed to deal with the reduction in precipitation levels. In contrast, both the short and long term, worst case solutions are the most expensive options due to increased infrastructure requirements to deal with the worsening storm conditions. Unlike in the best case scenario, the costs for the short and long term solutions are virtually the same for SSP3. The financial returns in the form of co-benefits follow the same trends as costs, mainly just based on the actual number of LIDs implemented in the respective solutions. The SSP3 solutions, while the most expensive, provide the largest cobenefit returns, followed fairly closely by the SSP1 and historical solutions.

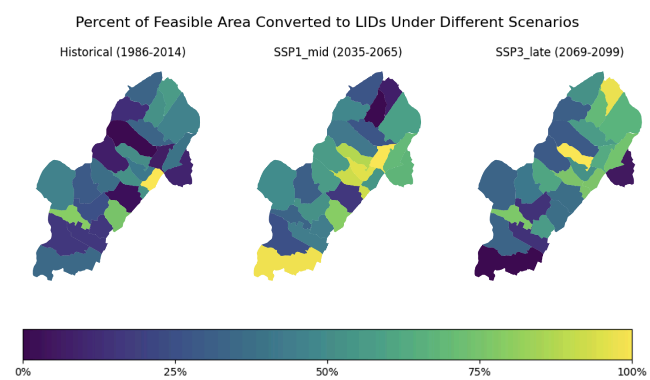

Figure 2. Percent of Feasible Area Converted to LIDs by Subcatchment.

Table 3. Percent of Feasible Area for Each LID That Is Converted.

	Bio-Retention	Green Roof	Grass Swale	Permeable Pavement	Rain Garden
Historical	34.88%	44.31%	44.51%	39.92%	50.91%
SSP1_mid	61.29%	43.71%	48.43%	47.83%	48.53%
SSP1_late	62.91%	41.92%	44.43%	51.01%	50.47%
SSP3_mid	57.70%	41.65%	52.58%	47.15%	56.67%
SSP3_late	63.57%	46.28%	51.87%	41.66%	47.02%
Total Feasible Area (ft^2)	12,271	2,614,327	372,835	260,513	1,062,817

Figure 2 shows the amount of feasible area converted to any LID in the compromise solution across various scenarios, while Table 3 shows the portion of feasible area for each LID that the compromise solutions convert to GI. The figure shows substantial variance in the amount of area converted to GI across the different subcatchments. The fact that the distribution of the selected LIDs varies dramatically depending on the amount of precipitation suggests one of two things: the optimal arrangement of LIDs is highly sensitive to the climate projections, or there are several different distributions of LIDs that could yield similar performance on the objectives. The first highlights the importance of considering uncertainty, while the latter suggests it could be important to add an equity objective, as two solutions could achieve similar benefits at the outlet, but those benefits might be unevenly distributed across the watershed.

While Figure 2 highlights differences in the spatial distribution of LIDs, Table 3 shows bioretention cells are prevalent across the climate scenario projections due to their high performance at relatively low costs (while providing less co-benefits due to their greater size). This allows the SSP3_late solution to be comparable in cost and co-benefits to the SSP1 solutions (though the average runoff in this case is much higher due to the elevated precipitation levels). The table also indicates a significant reduction in the usage of permeable pavement in the SSP3_late solution for this reason, as those LIDs are less effective for runoff reduction but provide more co-benefits. This strategy is not employed as extensively in the other solutions since the lower precipitation levels allow for other LIDs that provide more co-benefits to be used while maintaining similar performance levels. The LID usage between the SSP1_mid and SSP1_late solutions are virtually identical, which contrasts with the more stark differences between the SSP3 solutions. Finally, despite Table 2 showing that the historical solution yielded similar objective values to the SSP1_mid solution, the LID implementation is fairly different, with fewer bioretention cells. This may be because of the increased emphasis on co-benefits in this scenario, as the precipitation levels are not as high as in the projection scenarios.

Based on these findings, we can make different recommendations for implementing flood infrastructure depending on what stakeholders prioritize. If preparation for the most severe storms is valued (SSP3_late), then a long-term solution that focuses on bioretention cells and green roof conversions would be the most cost-effective option (but offer minimal co-benefits). For stakeholders who prioritize ecosystem improvements (measured in co-benefits) at a greater expense, a solution that uses more permeable pavement and grass swales (like the SSP3_mid compromise) would be the better option. Across all scenarios, bioretention cells most efficiently reduce runoff for the area they take up, though they provide less co-benefits. Expanding the amount of potential area for bioretention cells would likely be a worthwhile investment regardless of what the future holds.

IV. DISCUSSION

Table 2 provides interesting insights about how to best balance our three objectives under different possible climate futures. However, these represent the optimal solutions for only one possible set of preferences that may not capture stakeholders' true values. One region missing from our Pareto sets in particular is ultra-low cost solutions that make minimal impact on the average flow rate. While these omitted solutions may not substantially reduce flooding, ignoring them from consideration puts unintended constraints on the cost of proposed solutions that may be harmful if minimizing cost is the sole priority.

There are also limitations in the estimated objective values. The LID performance parameters were pulled from previous flood studies in the region, but these parameters could be changed to describe alterations to the LIDs, which would also give different results. Furthermore, different LID types were not included in this model, such as rain barrels and infiltration trenches. Another area of concern is that the calculated values for the objectives are entirely dependent on the accuracy of the cost/benefit parameters for different LIDs and the climate projections. While the cost/benefit parameters were all pulled from different studies, many of these values were given as ranges that were then distilled to a single value. This is especially true for the co-benefits values, as calculating the expected ecosystem benefits from new infrastructure as a dollar value is an ambiguous process and yields wide ranges of values. The GI efficacy value enables some fluctuations in the efficiency of each infrastructure type, but still results in a few static values across the entire model. Future work could explore the effects of changing some of these assumed values to create a more robust optimization.

There is also uncertainty in the climate projections, both in which scenario(s) will occur and in the simulated values under those scenarios. While these projections are the best predictions we could utilize, there is still substantial uncertainty surrounding the exact precipitation levels Charlottesville will experience. Future work could consider a wider range of climate scenarios (e.g., from different climate models) and infrastructure options to equip city leadership to make more informed decisions about flood mitigation. Combining consideration of climate projections with social vulnerability modeling could also serve to improve the impact of this work.

Finally, there is currently no measure of how these infrastructure options will affect nearby residents. A social equity objective could help ensure that the costs/benefits of building infrastructure is evenly distributed across the subcatchments, a concern highlighted by the variability seen in the spatial distribution of LIDs from selected solutions in Figure 2. This metric could be paired with (or replace) the co-benefits objective, given that both metrics are more fluid than the runoff/cost ones.

V. CONCLUSION

This project uses optimization to recommend infrastructure to combat a variety of climate scenarios in Charlottesville, VA. Though the city is not located near any large bodies of water, many households are at risk of flooding during major storms, particularly those along streams like Meadow Creek. With climate change becoming a more pressing concern every year, more robust and sustainable means of reducing stormwater runoff will be required. The implementation of green infrastructure in the region surrounding Meadow Creek will reduce flood risks in the region while promoting ecosystem health.

REFERENCES

[1] "Most Extreme Tropical Cyclones." Accessed: Apr. 07, 2025. [Online]. Available: https://www.nhc.noaa.gov/dcmi.shtml

[2] O. US EPA, "Causes of Climate Change." Accessed: Apr. 07, 2025. [Online]. Available: https://www.epa.gov/climatechange-science/causes-climate-change

[3] J. Armesto, "Central Virginia braces for Helene, floodwaters already pouring in," The Daily Progress. Accessed: Apr. 07, 2025. [Online]. Available: https://dailyprogress.com/news/local/weather/article_67fdc480-7c38-11ef-b29c-536e556c1669.html

[4] "Charlottesville, VA Flood Map and Climate Risk Report," firststreet.org. Accessed: Apr. 07, 2025. [Online]. Available: https://firststreet.org/

[5] D. Green *et al.*, "Green infrastructure: The future of urban flood risk management?," *WIREs Water*, vol. 8, no. 6, p. e1560, 2021, doi: 10.1002/wat2.1560.

[6] N. Tebyanian *et al.*, "Rhodium-SWMM: An open-source tool for green infrastructure placement under deep uncertainty," *Environ. Model. Softw.*, vol. 163, p. 105671, May 2023, doi: 10.1016/j.envsoft.2023.105671.

[7] "CMIP6 Homepage." Accessed: Nov. 13, 2024. [Online]. Available: https://pcmdi.llnl.gov/CMIP6/

[8] K. Riahi *et al.*, "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview," *Glob. Environ. Change*, vol. 42, pp. 153–168, Jan. 2017, doi: 10.1016/j.gloenvcha.2016.05.009.

[9] "About us | Copernicus." Accessed: Apr. 07, 2025. [Online]. Available: https://climate.copernicus.eu/about-us

[10] mpt@nationalstormwater.com, "Urban Hydrology for Small Watersheds - TR-55," National Stormwater Trust. Accessed: Apr. 07, 2025. [Online]. Available: https://nationalstormwater.com/urban-hydrology-for-small-watersheds-tr-55/

[11] "NOAA Atlas 14 Precipitation Frequency Data Server." Accessed: Apr. 07, 2025. [Online]. Available: https://hdsc.nws.noaa.gov/pfds/

[12] R. S. Herbst, T. B. Culver, L. E. Band, B. Wilson, and J. D. Quinn, "Integrating Social Equity into Multiobjective Optimization of Urban Stormwater Low-Impact Development," *J. Water Resour. Plan. Manag.*, vol. 149, no. 8, p. 04023038, Aug. 2023, doi: 10.1061/JWRMD5.WRENG-5981.

[13] A. Hadjimichael, D. Gold, D. Hadka, and P. Reed, "Rhodium: Python Library for Many-Objective Robust Decision Making and Exploratory Modeling," *J. Open Res. Softw.*, vol. 8, no. 1, Jun. 2020, doi: 10.5334/jors.293.

[14] O. US EPA, "Storm Water Management Model (SWMM)." Accessed: Apr. 14, 2025. [Online]. Available: https://www.epa.gov/water-research/storm-water-management-model-swmm

[15] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002, doi: 10.1109/4235.996017.