THESIS

ASSESSING THE TRIPLE BOTTOM LINE CO-BENEFITS AND LIFE CYCLE COST TRADEOFFS OF CLOUDBURST INFRASTRUCTURE IN NEW YORK CITY

Submitted by

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ABSTRACT

ASSESSING THE TRIPLE BOTTOM LINE CO-BENEFITS AND LIFE CYCLE COST TRADEOFFS OF CLOUDBURST INFRASTRUCTURE IN NEW YORK CITY

Urbanization and climate change have increased the risk of urban flooding. Specifically, more frequent cloudburst events are on the rise in cities across the globe. Cloudbursts are characterized by high intensity rainfall over a short duration, causing unpredictable, localized flooding. Effective stormwater management is essential to manage extreme precipitation and runoff induced by cloudbursts. Stormwater control measures have evolved over time shifting from gray infrastructure to nature-based and green solutions. Recently, cloudburst specific infrastructure has emerged as a stormwater intervention strategy designed to handle larger volumes of water by capturing, storing, or conveying excess water in highly impervious areas. Cloudburst infrastructure systems are inextricably linked with land use in cities and thus, their implementation should incorporate life cycle costs, and social and ecological co-benefits. This study assesses the Triple Bottom Line co-benefits and environmental effects of cloudburst systems for flood control in New York City. Specifically, we explore the tradeoffs between the costs and co-benefits of alternative surface vegetation including grass, diverse vegetation, and trees. The study identifies the Pareto optimal set of solutions and quantifies effects of incorporating vegetation into the urban landscape via cloudburst systems. The results indicate that surface vegetation plays a key role in altering the co-benefits and life cycle costs of cloudburst infrastructure. Trees were the most frequent non-dominated solution and were linearly related to Triple Bottom Line score and exponentially related to Life Cycle Cost. The framework and results of this study provide valuable insight to support informed decision-making.

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1. Introduction

1.1 Research Motivation

Runoff quantities in urban environments are affected by the spread of urbanization (J. Chen et al., 2017). Urban development leads to greater impervious surfaces and more densely populated areas. These factors impact the hydrologic response during precipitation events by increasing runoff and decreasing infiltration, thereby, increasing risk of urban flooding (Q. Zhou et al., 2019). Due to the higher density of people and assets in urban environments, more catastrophic consequences are experienced (Jiang et al., 2018). Thus, stormwater management strategies are essential for managing excess runoff that is exacerbated by impervious land use practices in urban environments.

Climate change is another driver that increases urban flood risk (Mahmoud & Gan, 2018). Climate change factors which impact urban flooding include an increase in the frequency and magnitude of extreme precipitation, warmer temperatures, and rising sea levels in coastal regions (Horton et al., 2015; Pörtner et al., 2022). The International Panel on Climate Change (IPCC) predicts that precipitation intensity will increase with every increment of global warming (Pörtner et al., 2022). Additionally, sea level rise paired with extreme rainfall patterns will lead to inundation of coastal regions as early as 2050 with severe disruptions by 2100 (Pörtner et al., 2022).

Climate change is altering the water cycle to include changes in the spatial patterns and amount of precipitation. Storms characterized by their high intensity, short duration, and small spatial scale are sometimes referred to as “cloudbursts” and are becoming a more chronic problem in many cities due to climate change (B. R. Rosenzweig et al., 2018). The term “cloudburst” was originally defined by (Woolley, 1946) as “...a torrential downpour of rain which by its spottiness and relatively high intensity suggests the bursting and discharge of a whole cloud at once.” They are difficult to forecast and can lead to intense localized flooding if not properly managed (Falconer et al., 2009). Many municipalities have begun to account for these extreme, unpredictable cloudburst events in their stormwater management programs.

1.2 Stormwater Management Practices

Urban stormwater management systems are essential for managing runoff and mitigating urban flooding (Kang et al., 2016). Stormwater management has evolved over the centuries from conveyance ditches to underground sewer systems and to the more recent “best management practices” (Burian & Edwards, 2012; B. Rosenzweig et al., 2019). The underground sewer system which exists today consists of conventional gray infrastructure such as conveyance pipes, drains, channels, and pumps which capture and route runoff to a centralized location. Many of these systems were constructed in the 19th century while cities were developing and are now pressured to accommodate greater populations and larger impervious surfaces associated with urban growth. The Clean Water Act of 1972 coined the concept of “best management practices” which aim to reduce pollution entering local waterbodies (Clean Water Act, 1972). Best management practices include structural and nonstructural stormwater strategies which aim to regulate runoff where it originates and preserve water quality downstream (National Pollutant Discharge Elimination System (NPDES) Definitions, 1983; Fletcher et al., 2015). Green stormwater infrastructure (GSI) arose from best management practices in the 1990s (C. Li et al., 2019). GSI aims to retore or mimic natural processes and includes rain gardens, green roofs, permeable pavements, detention ponds, and more, meant to store, infiltrate, evapotranspirate, harvest, and reduce rainwater entering the sewer system or surface waters (Water Infrastructure Improvement Act, 2019; US EPA, 2015).

More recently, China has developed a "sponge city" initiative which incorporates GSI nature-based solutions with the goals of reducing urban flooding, improving stormwater infiltration, and providing ecosystem services (Jiang et al., 2018). The sponge city approach is a holistic approach to stormwater management which incorporates green areas and ecological infrastructure. Studies have shown that sponge cities reduce urban runoff while providing environmental co-benefits such as improved water quality, carbon sequestration, and increased biodiversity (He et al., 2019; Leng et al., 2020; Y. Li et al., 2020). One study assessed the planned sponge city projects in Suzhou, China and determined that runoff volumes could be reduced by 10.1% and by adding additional projects, they could reduce runoff volumes by up to 38.4% (Leng et al., 2020). Another study in Shenzhen, China evaluated pollutants entering the bay and found that the planned sponge city projects could reduce total nitrogen and total phosphorous in the local waterways by 2.4% and 20.2%, respectively (Xiong et al., 2021).

While GSI has provided runoff reductions and ecosystem benefits, it still has its hydrologic limitations. A study in New York City evaluated the performance of GSI and gray infrastructure under extreme rainfall scenarios and found that GSI systems become overwhelmed during extreme events and should be complemented with traditional gray infrastructure systems to increase hydrologic capacity (Ghanbari, 2021). Further, studies by Wang et al. (2023), W. Chen et al. (2021), Xu et al. (2019), and Dong et al. (2017) found that hybrid systems of coupled GSI and gray infrastructure provide improved flood resilience to extreme precipitation as compared to GSI systems alone. These findings suggest that GSI is not individually sufficient to prevent flooding during extreme precipitation events. Additionally, many existing gray stormwater systems no longer meet required performance as they are aging systems designed for smaller populations, more permeable cities, and stationary climate conditions (Bae & Lee, 2020; Price & Vojinovic, 2008). In order to safeguard cities against climate change and extreme cloudburst events, infrastructure improvements and adaptive stormwater solutions are needed.

Some European cities have begun to take adaptive measures to manage cloudbursts. Copenhagen, Denmark and Amsterdam, Netherlands have developed stormwater initiatives specifically targeting cloudburst events (City of Copenhagen, 2012; Naaf & van Eijck, 2014). These initiatives outline adaptive stormwater interventions, or cloudburst systems, designed to mitigate urban flooding caused by cloudbursts. Cloudburst systems incorporate GSI, gray stormwater infrastructure, open space, and natural waterbodies, forming an interconnected system of blue-green infrastructure (BGI) and gray infrastructure. BGI connects water (blue) and land (green) spaces to create a network which restores natural hydrologic functions, manages runoff, and improves water quality (Brears, 2018). The systems are typically large-scale, multipurpose areas designed to manage excess runoff. For example, roadways, pedestrian plazas, and parks are adapted to capture, detain, or convey large volumes of stormwater runoff (Ziersen et al., 2017). Along with surface level interventions, underground cloudburst pipes are implemented to handle even larger quantities of water. Above ground and underground solutions are often paired to complement each other and capture greater volumes of water, allowing for water to be stored underground in cloudburst pipes and at the surface level once the pipes become full. Additionally, the systems can be connected to the existing sewers or disconnected and rely on infiltration or conveyance to local waterways (Ziersen et al., 2017).

Cloudburst infrastructure differs from other stormwater management approaches because it is considered “safe-to-fail” infrastructure. Safe-to-fail infrastructure increases adaptive capacity to climate change and unpredictable risk because it is designed to fail with chosen consequences (Kim, 2018). During extreme precipitation events, cloudburst systems flood within designated areas to prevent flooding in unwanted locations and overwhelming the sewer system. While some studies have begun to analyze flood risk associated with cloudburst events (B. R. Rosenzweig et al., 2018; Knös et al., 2022; Salata et al., 2022), and many have evaluated flood reductions and co-benefits associated with GSI and nature-based solutions (Steis Thorsby et al., 2020; Wang et al., 2023; H. Zhou et al., 2023), few have assessed the impacts of cloudburst-specific infrastructure. A study in Seoul, South Korea evaluated flood adaptive GSI, similar to cloudburst infrastructure. It found that by increasing the spatial area of GSI by 1.7%, 3.4%, and 5.1%, runoff was reduced by 0.625%, 1.25%, and 1.87%, respectively (Lee et al., 2021). Another study analyzed the City of Copenhagen Cloudburst Master Plan and compared it to an expanded cloudburst system under a future 100-year storm (Lerer et al., 2017). It found that the planned cloudburst system reduces water treatment volumes by 8% and the number of surcharging manholes by 28% and that the expanded system can further reduce water treatment volumes and the number of surcharging manholes by 21% and 45%, respectively. B. Rosenzweig et al. (2019) calls for the need to expand quantitative knowledge to support the incorporation of cloudburst infrastructure in urban water management.

1.3 Infrastructure Decision Support Tools

Decision support tools are useful to facilitate quantitative comparisons of infrastructure alternatives. Thorough analyses of the costs and benefits of cloudburst systems should be conducted to support their implementation. The Triple Bottom Line (TBL) assessment and Multi-Criteria Decision Analysis (MCDA) are examples of assessment frameworks that are commonly used to support infrastructure decision-making. The TBL assessment is a conceptual framework which considers the social, economic, and environmental impacts of alternative options. It is a flexible tool which supports sustainable development objectives and measures various indicators with stakeholder input (Taylor et al., 2006). The outcome of a TBL assessment provides transparent results of the social, economic, and environmental pros and cons of the different alternatives. MCDA is an organizational framework that is typically used as part of a TBL assessment as a decision support tool for scoring and ranking alternatives (Taylor et al., 2006). The MCDA process assigns weights to the social, economic, and environmental criteria and scores each of the indicators to determine an alternative's overall weighted score and rank. The MCDA process requires stakeholder input to determine which criteria are most important. Using TBL and MCDA together reaps the benefit of both qualitative and quantitative information to support decision-making while also providing transparency of the goals and objectives of the project.

Further, cost-comparison methods can also be used to support infrastructure investment decisions. Some examples include Benefit-Cost Analysis (BCA), Internal Rate of Return (IRR), Savings to Investment Ratios, Life Cycle Analysis (LCA), and Life Cycle Cost (LCC) (NIST, 1996). Life cycle techniques provides greater accuracy when assessing economic performance by including all costs over time (Ruegg et al., 1980). The LCA method includes costs related to construction and maintenance and also monetizes external costs or benefits related to social and environmental outcomes (Hoogmartens et al., 2014). Conversely, the LCC method only accounts for costs associated with construction and maintenance (Norris, 2001). The LCC method focuses primarily on the costs directly related to budgeting and capital planning and is better fit to be used in combination with other assessment frameworks such as TBL and MCDA previously mentioned. By combining LCC and MCDA frameworks, quantitative information about cost and co-benefits of cloudburst infrastructure can be gained and utilized to support decision-making.

When considering multi-objectives, tradeoffs often arise between objectives. For example, a lower LCC is typically associated with a lower MCDA score whereas, a higher LCC is typically associated with a higher MCDA score. Evolutionary algorithms can be used to assess these tradeoffs (Deb, 2011). The procedure finds non-dominated solutions where dominance of solution 1 over solution 2 is achieved when “solution 1 is no worse than solution 2 in all objectives, and solution 1 is strictly better than solution 2 in at least one objective” (Miettinen, 1998; Deb, 2011). The set of non-dominated solutions, called Pareto-optimal set, highlight tradeoffs between optimal solutions. These solutions can be plotted on a graph, forming a boundary called the Pareto optimal front. The Pareto-optimal set of solutions can help inform decision-makers so that they can better weigh the tradeoffs among alternatives. A posteriori is usually needed when choosing the final solution to adopt.

1.4 Research Objectives

The goal of this study is to assess tradeoffs of cloudburst infrastructure strategies in New York City (NYC). Specifically, the objectives are to 1) determine the suitability of cloudburst systems under physical, social, and technical factors and 2) conduct a tradeoff analysis of TBL and LCC criteria for alternative vegetation strategies using a non-dominated sorting procedure. This analysis is achieved by conducting case studies of two cities, Copenhagen and Amsterdam, which have planned and constructed cloudburst infrastructure by looking at their design criteria, site selection considerations, and benefits from implementation. It evaluates physical, social, and technical criteria which drive the site selection and feasibility of cloudburst infrastructure. Then, TBL social, economic, and environmental indicators are identified and quantified. An LCC analysis is conducted for alternative cloudburst technologies with varying levels of vegetation. Finally, the Pareto-optimal set of solutions is found and used to assess the tradeoffs of alternative cloudburst infrastructure scenarios. The results of this study will provide insight to support informed decision making for incorporating vegetation into cloudburst infrastructure.

2. Background

Copenhagen, Amsterdam, and New York City are all members of the C40 Cities Climate Leadership Group, which is an organization that brings together mayors around the world who are committed to combating climate change through research and collaboration. These cities are part of the Urban Flooding Network which specifically focuses flood adaptation projects to handle extreme rainfall (C40 Cities, 2023). The following sections discuss their strategies and successes in reducing urban flood impacts, specifically through the use of cloudburst infrastructure.

2.1 Case Study: Copenhagen

Copenhagen has been a global leader in the development of cloudburst infrastructure after experiencing back-to-back extreme cloudburst events in August 2010 and again in July and August 2011 where nearly 6 inches of rain fell within 90 minutes (a 1,000-year event). The single event in July 2011 caused damages over one billion U.S. dollars and led to the swift development of the Copenhagen Cloudburst Management Plan in 2012 as an offshoot of the 2011 Copenhagen Climate Adaptation Plan (City of Copenhagen, 2012). The Cloudburst Management Plan developed new risk dimensioning criteria which considered the acceptable frequency of flooding, damage costs, and operations and maintenance costs. The Plan identified a future 100-year design storm and a risk tolerance which allows for sewer discharge to reach the ground level once every 10-years and 0.4 inches of roadway flooding to occur once every 100-years, not including areas designed for flood storage (City of Copenhagen, 2012).

Copenhagen has a goal of implementing its Cloudburst Management Plan by 2035 by prioritizing areas with high risk of flooding, areas where measures are easy to implement, areas with ongoing projects, and areas where synergistic effects can be gained. The cloudburst systems not only provide flood benefits, but Copenhagen has also seen co-benefits associated with cloudburst infrastructure. These include added recreational value, social resilience, biodiversity, accessibility, improved microclimates, and economic growth (NYC Water, 2021).

2.2 Case Study: Amsterdam

Amsterdam is another city which has led the way for cloudburst infrastructure implementation. After the 2011 cloudburst event in Copenhagen, Amsterdam's water authority conducted cloudburst modeling to determine their own city's vulnerability. The simulation modeled a 4 inch per hour storm and determined there to be considerable risk of severe damage. This led to the development of Amsterdam Rainproof in 2014 which aims to create a rainproof city by 2050 (Naaf & van Eijck, 2014). Amsterdam Rainproof identifies a 3.4 inch per hour design storm for sizing cloudburst infrastructure with a goal of eliminating all damage to homes and critical infrastructure. The existing sewer system is designed to handle a 0.8 inch per hour storm and without the addition of cloudburst infrastructure, the design storm could cause damages upward of 550 million U.S. dollars (Naaf & van Eijck, 2014).

Amsterdam's implementation strategy includes identifying bottleneck areas through flood modeling, rating the locations based on urgency, incorporating cloudburst projects into planned construction where possible, and accelerating cloudburst projects when necessary. So far from cloudburst infrastructure implementation, Amsterdam has seen increased community resilience, public awareness and involvement, rainwater harvesting and reuse, drinking water savings, and pollutant reductions (Naaf & van Eijck, 2014).

2.3 Study Area: New York City

The study area used in this analysis was New York City. NYC is home to 9 million residents who rely on various agencies and utilities services for day-to-day life. Namely, the NYC Department of Environmental Protection (DEP) is responsible for enhancing the environment and protecting public health for residents by providing high quality drinking water, collecting and treating wastewater, and managing stormwater. There are 14 watersheds in the city and each contain its own Wastewater Resource Recovery Facility (WRRF). Altogether, the 14 WRRFs treat 1.3 billion gallons of wastewater each day. Figure 1 shows a map of each sewershed in the city.

Figure 1. New York City Sewersheds

Construction of the existing sewer system took place over a century, beginning in the 1850s. Today, the sewer system consists of over 7,400 miles of sewer pipes, 135,000 catch basins, and 95 wastewater pumping stations. This network is one of the most significant assets in the city (City of New York, 2021a). Approximately 60% of the city is serviced by a combined sewer system where stormwater and wastewater are conveyed together. If flows exceed twice the WRRF design flow during heavy rainstorms, a mixture of stormwater and untreated sewage is discharged directly into the city's waterways, causing a combined sewer overflow (CSO). The remaining 40% of the city is serviced by a Municipal Separate Storm Sewer System (MS4) where wastewater is directed to a WRRF and a separate sewer directs stormwater to waterbodies.

NYC is one of densest cities in the world with an average of 29,300 people per square mile and over 70% impervious land cover (U.S. Census Bureau, 2022; City of New York, 2023a). When it rains, a significant amount of stormwater runoff is generated due to impervious land use practices. When there's excessive runoff and sewers are overwhelmed, urban flooding and CSOs occur, exposing larger populations to flood impacts and degrading local water quality.

Consequently, NYC has regulations and initiatives in place to reduce CSOs and urban flooding. In 2012, a CSO Consent Order was initiated between the New York State Department of Environmental Conservation (DEC) and NYC DEP. This order led to the development of 11 Long-Term Control Plans (LTCPs) which outline long-term solutions to reduce CSOs and improve water quality (City of New York, 2018). The order also leverages the city's Green Infrastructure Program which was launched in 2011 by requiring the utilization of GSI to capture the first inch of rainfall on 10% of impervious surfaces in combined sewer areas by 2030 (City of New York, 2021b). To date, there have been over 11,000 distributed GSI projects constructed within the city to meet this requirement.

NYC also received a State Pollutant Discharge Elimination System (SPDES) MS4 Permit in August 2015, requiring the reduction of pollutants discharging to the MS4. This permit requires agencies to assess the feasibility and incorporate GSI into planned municipal upgrades (City of New York, 2023a). The assessment includes an evaluation of the stormwater generated from the completed upgrades, site conditions and constraints of GSI implementation, hydrogeological analysis, environmental analysis, and cost-effectiveness. Further, the NYC City Council expanded the legal authority of NYC DEP to regulate land development through approval of Local Law 91 in 2020. Local Law 91 revised the Construction and Post-Construction program in the Unified Stormwater Rule in February 2022 and requires new construction and redevelopment that disturbs 20,000 square feet of soil or adds 5,000 square feet of new impervious surfaces to incorporate GSI to control stormwater runoff quantities (City of New York, 2022). These regulations and practices are examples of how NYC has aimed to improve water quality through the implementation of GSI to capture and store runoff, increase infiltration and evapotranspiration, and reduce flows going to the sewers.

Extreme precipitation is a recurring problem in NYC that calls for the need of cloudburst infrastructure to manage urban flooding. Hurricane Sandy in 2012 demonstrated the vulnerability of the city to coastal storm surge and led to inundation of coastal areas, causing $19 billion in damages and taking 44 lives (City of New York, 2023b). However, the torrential downpours caused by Hurricanes Henri and Ida in 2021 and the rainstorm of September 2023 highlighted that inland areas are also vulnerable to stormwater induced flooding. These events quickly overwhelmed the city's drainage system, causing water to back up into streets, basements, and underground transportation systems. Hurricane Ida set a one-hour rainfall record of 3.15 inches, causing hundreds of millions of dollars in damages and taking another 13 lives (City of New York, 2023b). With the threat of climate change and the dense urban environment, NYC has begun to plan and implement cloudburst infrastructure within flood-prone neighborhoods. Cloudburst infrastructure in NYC has the potential to provide supplemental flood control measures to reduce sewer backups and stormwater flooding during extreme cloudburst events.

In September 2015, NYC DEP entered a formal partnership with the City of Copenhagen to collaborate on cloudburst strategies and improve resilience (B. Rosenzweig et al., 2019). While NYC does not have a city-wide cloudburst infrastructure plan, since the formation of the partnership, the city has funded cloudburst projects in three neighborhoods. Additionally, in January 2023, NYC Mayor Adams announced the expansion of the city's cloudburst efforts to four new locations backed with $400 million in capital funds (City of New York, 2023c). The Cloudburst Program in NYC is guided by an interagency task force with representatives from the NYC Mayor's Office of Climate and Environmental Justice (MOCEJ), the Department of Environmental Protection, Department of Parks and Recreation, Department of Transportation, and Department of Design and Construction. These agencies collaborate through planning and implementation to determine cloudburst infrastructure site selection and feasibility.

3. Methodology

This analysis was carried out in three stages, summarized in Figure 2. First, site suitability for cloudburst infrastructure was evaluated. The suitability assessment identified 169 technically feasible cloudburst technologies that were grouped into 31 Cloudburst Hubs based on location. Next, alternative technology options were created within the Cloudburst Hubs by altering the type of vegetation used in vegetated cloudburst technologies. A TBL analysis was conducted utilizing the MCDA weighted-average technique. The LCC was then calculated for each alternative. Finally, a tradeoff analysis was conducted at the sewershed scale and city scale by finding non-dominated solutions of all possible combinations of cloudburst technologies. Equation 1 and Equation 2 outline the multiobjective tradeoff analysis conducted. In Equation 1, M_n is the environmental criteria score, M_s is the social criteria score, and M_c is the economic criteria score. In Equation 2, C_0 is the initial construction cost, MC_t is the annual maintenance cost, RC_t is the rehabilitation cost, i is the discount rate, and t is the years to rehabilitation. The alternatives are subject to a Technical Feasibility Ratio greater than 1, meaning that the cloudburst technology capacity can capture the modeled flood volume without additional infrastructure upgrades.

Maximize: $$TBL = M_n + M_s + M_c \quad \text{Eq. 1}$$

Minimize: $$LCC = C_0 + \frac{MC_t \cdot [1-(1+i)^{-t}]}{i} + \frac{RC_t}{(1+i)^t} \quad \text{Eq. 2}$$

Subject to: $$TFR > 1$$

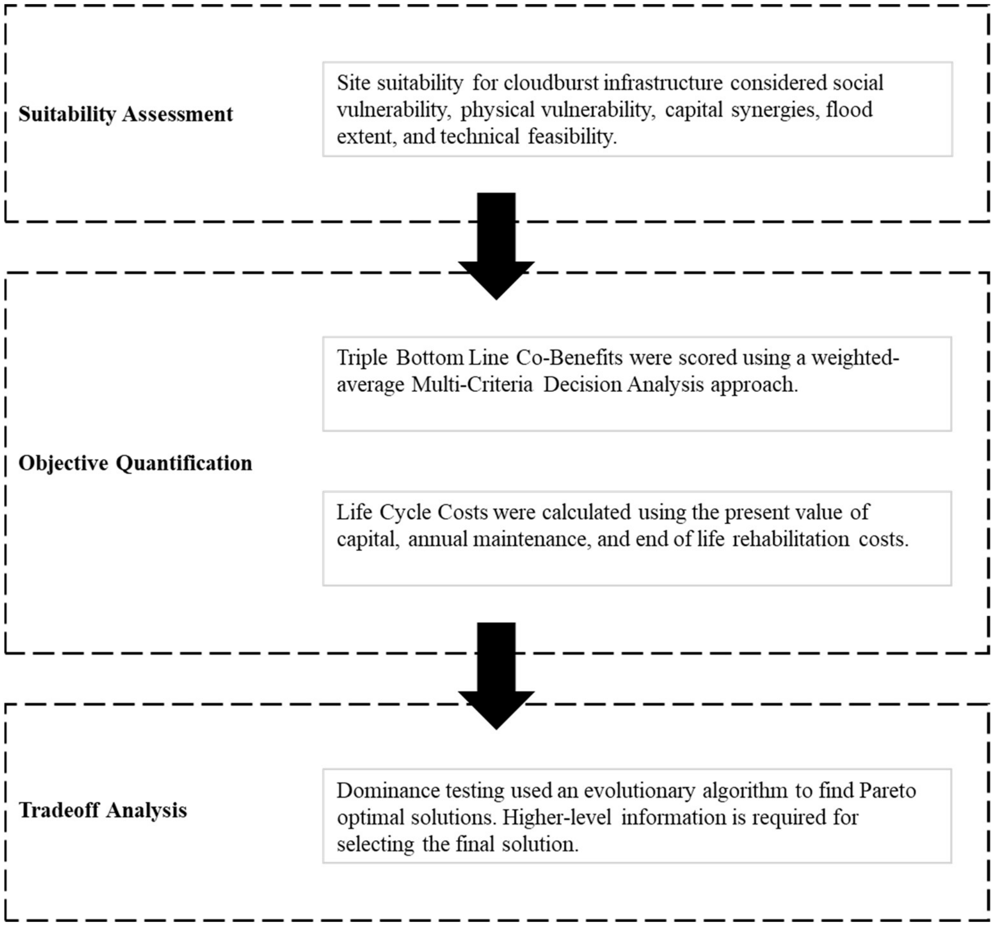

Figure 2. Overall Methodology of the Study

3.1 Suitability Assessment

Site suitability for cloudburst infrastructure was determined by Hazen and Sawyer for the NYC Cloudburst Program. A variety of factors were considered including physical vulnerability, social vulnerability, technical feasibility, agency priorities, and planned capital investments. The Cloudburst Program interagency task force identified 37 priority planning areas at the sub-catchment scale. Within these areas, physical, social, planning, and technical factors were studied. The NYC Stormwater Resiliency Plan developed flood maps under a future 10-year 1-hour storm with 2050 sea level rise which were used to assess physical vulnerability to stormwater flooding (City of New York, 2021a). The flood maps identified 350 flooding hotspots which were categorized into areas of nuisance flooding (at least 4 inches to less than 1 foot) and deep and contiguous flooding (1 foot and greater). Further, areas with historical resident reports of flooding, sewer backups, and structural damage were also considered. These hotspots were grouped into 120 potential Cloudburst Hubs which are similar in size to a typical NYC neighborhood.

For the 120 locations, the Centers for Disease Control (CDC) Social Vulnerability Index (SVI) was used to quantify and assess social vulnerability. The SVI considers 16 variables related to socioeconomic status, household composition and disability, minority status and language, and housing and transportation type (Hallisey et al., n.d.). A high SVI is indicative of greater social vulnerability to stormwater flooding. Population density for each Cloudburst Hub was also retrieved from the U.S. Census Bureau to better understand the number of people impacted by stormwater flooding.

Capital planning and agency priorities were also considerations for site suitability. Cloudburst Hubs within or nearby funded coastal protection projects were not considered suitable locations since infrastructure projects are already underway to protect against coastal storm surge and flooding. Other capital plans were evaluated to determine if cloudburst systems were operationally feasible to incorporate into planned capital projects. If operationally feasible, these capital synergies could allow cloudburst infrastructure to be streamlined into planned projects.

Finally, technical feasibility of cloudburst infrastructure implementation was evaluated through review of existing infrastructure, local topography, and site visits. The causes of flood hotspots were determined and technically feasible cloudburst strategies were identified. Existing drainage infrastructure was assessed to determine any conveyance limitations of sewers. Areas without any planned drainage upgrades and areas where upsizing drainage would not eliminate flooding were sited for cloudburst systems to alleviate the sewer system. Topography was then reviewed using a one-foot resolution digital elevation model (DEM) to determine contributing impervious surfaces to flood hot spots. Cloudburst systems were sited where topography can be leveraged to divert stormwater. Site visits were finally conducted to evaluate onsite storage locations and limitations. Locations with incompatible site grading, utility conflicts, and construction conflicts were determined to be infeasible.

Within the technically feasible locations, cloudburst technologies were studied to determine the best strategy to be implemented. Cloudburst technologies in NYC include porous pavement storage, vegetated and non-vegetated surface retention with subsurface storage, vegetated and non-vegetated right-of-way (sidewalks and medians) storage, and flow diversions. Various siting criteria and clearances based on City regulations were examined to determine the optimal cloudburst strategies for implementation.

The proposed technologies were sized using the Tributary Drainage Area (TDA) and design storm. The TDA to each flood hotspot was calculated considering runoff from streets, sidewalks, and a factor of 10% to account for roofs, backyard drains, and driveways. This method is consistent with TDA and runoff calculations for green infrastructure in NYC. The design storm is the future 10-year 1-hour storm projected for 2040-2069, equivalent to 2.3-inches in 1-hour. The total stormwater volume to the flood hotspot was found by multiplying the TDA and equivalent rainfall depth.

The stormwater volume managed by each cloudburst technology was delineated using the TDA contributing to the system. In some cases, cloudburst technologies capture stormwater flows from outside of the flood hotspot TDA. The percentage of overlap between the cloudburst strategy TDA and flood hotspot TDA was multiplied by the total volume managed by the cloudburst system to estimate the volume managed within the flood hotspot TDA. To compare the benefit provided by cloudburst infrastructure, the Technical Feasibility Ratio (TFR) was calculated using Equation 2 where V_{cb} is the stormwater volume managed by cloudburst infrastructure within the flood hotspot TDA and V_m is the total modeled stormwater volume within the flood hotspot.

$$TFR = \frac{V_{cb}}{V_m} \qquad \text{Eq. 2}$$

A TFR greater than 1 indicates that the capacity of the cloudburst strategy is greater than the modeled flood volume and will likely alleviate flooding. Conversely, areas with TFR less than 1 may require additional upgrades in sewer capacity to alleviate flooding. In total, 31 Cloudburst Hubs had a TFR greater than 1 and can be seen in Table 1. These Hubs are further studied in the following sections. The exact name and location of the Cloudburst Hubs is not released to the public yet, so for the purpose of this study they are numbered items presented by sewershed location.

Table 1. Technical Feasibility Ratio for Cloudburst Hubs

Cloudburst Hub	Sewershed	Technical Feasibility Ratio
1	Tallman Island	3.50
2	Hunts Point	3.10
3	Bowery Bay	3.10
4	Bowery Bay	3.00
5	Bowery Bay	2.40
6	26th Ward	2.20
7	26th Ward	2.10
8	26th Ward	2.10
9	Hunts Point	2.00
10	Hunts Point	1.80
11	Tallman Island	1.80

12	Bowery Bay	1.70
13	26th Ward	1.70
14	Port Richmond	1.70
15	Jamaica	1.60
16	Hunts Point	1.50
17	Newtown Creek	1.50
18	Bowery Bay	1.50
19	Wards Island	1.40
20	26th Ward	1.40
21	26th Ward	1.40
22	Owls Head	1.40
23	Hunts Point	1.30
24	26th Ward	1.20
25	Bowery Bay	1.20
26	Hunts Point	1.20
27	Newtown Creek	1.20
28	Tallman Island	1.10
29	Bowery Bay	1.10
30	Wards Island	1.10
31	Hunts Point	1.10

3.2 Cloudburst Hub Alternative Scenarios

The Suitability Assessment proposed cloudburst technologies to be implemented based on various siting criteria and existing conditions. Within each Hub, between 2 to 12 technologies were proposed including both vegetated and non-vegetated strategies. For vegetated cloudburst systems, alternative options were created by altering the type of vegetation to include grass, diverse plants, or trees while keeping other parameters (i.e., surface area, capacity) the same. For example, a rain garden included an option for grass, diverse vegetation, and trees. By altering the level of vegetation, different co-benefits and life-cycle costs can be expected. Non-vegetated cloudburst technologies (i.e., porous pavement) were not included in the tradeoff analysis since they would remain the same across alternative scenarios and not impact the results.

Alternative scenarios for each Cloudburst Hub were made up of all combinations of technology alternatives. For eadfch Cloudburst Hub, there were 3^n alternative scenarios where n was equal to the number of vegetated technologies proposed. Figure 3 illustrates how alternative scenarios were created.

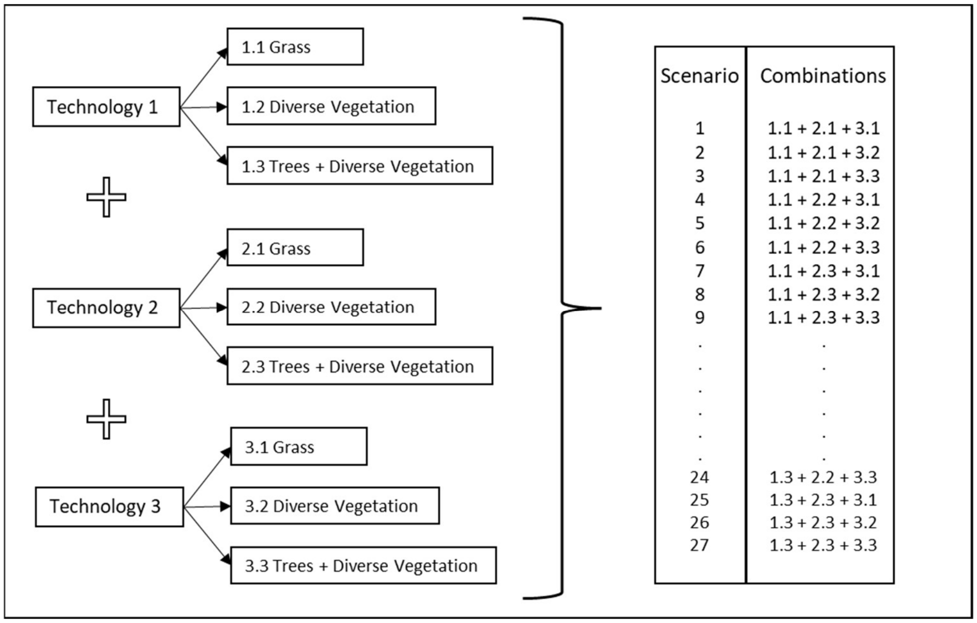

Figure 3. Cloudburst Hub Alternative Scenario Development

Henceforth, the term "technology option" refers to an individual cloudburst technology with different levels of vegetation and the term "alternative scenario" refers to the combination of technology options for a given Cloudburst Hub. In total, 174 alternative scenarios were developed for 20 Hubs. There were 11 Hubs which only sited porous pavement cloudburst systems in roadways, sidewalks, and parking lots. These cloudburst systems would not be feasible to be replaced with vegetated technologies and were not included in the tradeoff analysis.

3.3 CLASIC Tool Triple Bottom Line and Life Cycle Cost Procedures

To assess alternatives, Community-enabled Lifecycle Analysis of Stormwater Infrastructure Costs (CLASIC) methodologies were utilized for TBL and LCC quantification. CLASIC is a web-based tool that is meant to be a simplified version of the Stormwater Management Model (SWMM) to aid in stormwater planning and decision-making (Catena Analytics, 2021). The tool is hosted on the Environmental Resource Assessment and Management System (eRAMS) platform, allowing for a geographical information system (GIS) interface and interaction with national databases for data pulling. CLASIC assesses 10 stormwater technologies including rain gardens, sand filters, infiltration trenches, detention basins, wet ponds, stormwater harvesting, storage vaults, permeable pavement, stormwater disconnection, and green roofs (Catena Analytics, 2021). The tool outputs social, environmental, and economic co-benefits, life-cycle costs, hydrologic performance, and pollutant load reductions. The subsequent sections discuss the methods used for quantifying TBL and LCC for the tradeoff analysis.

3.3.1 Triple Bottom Line Quantification

CLASIC quantifies TBL co-benefits using a weighted average Multi-Criteria Decision Analysis (MCDA) to score alternative scenarios under environmental, social, and economic criteria (Catena Analytics, 2021). The developers conducted an extensive literature review to develop a methodology for estimating performance scores. In total, CLASIC quantifies and scores 16 indicators. For this study, the indicators which compared size or capacity were not included since size and capacity were consistent between alternative scenarios. Overall, 7 indicators were included and are listed in Table

2 with brief descriptions on their estimation. The TBL score is the sum of the environmental (M_n), social (M_s), and economic (M_c) criteria score. Each criterion has a maximum score of 5 points, making the maximum possible TBL score 15. The scores for the environmental, social, and economic criteria are the weighted average of the applicable indicators shown in Table *2* where w_n represents the applied weight and m_n represents the indicator. The subsequent sections further discuss how each indicator was scored. This methodology was used outside of CLASIC to estimate the TBL indicators for each technology option.

Table 2. TBL Criteria and Indicators

	Criteria	**Indicator**	**Description**
Triple Bottom Line Score $TBL = M_n + M_s + M_c$	**Environmental** $M_n = w_1 m_1 + w_2 m_2$	(m_1) Ecosystem Services	Assigns a score from 0 to 5 based on the percentage of flowering species and number of species.
		(m_2) Carbon Sequestration	Calculates the pounds of CO_2 removed per year and interpolates a score from 0 to 5 based on ascending order.
	Social $M_s = w_3 m_3 + w_4 m_4 + w_5 m_5$	(m_3) Health Impacts from Air Quality	Calculates the pounds of pollutants removed per year and interpolates a score from 0 to 5 based on ascending order.
		(m_4) Mental Health	Assigns a score from 0 to 5 based on replacement of impervious surfaces with green space.
		(m_5) Thermal Comfort	Calculates the reduction in urban heat from vegetation and interpolates a score from 0 to 5 based on ascending order.
	Economic $M_c = w_6 m_6 + w_7 m_7$	(m_6) Costs from Illness	Calculates the cost savings per year based on pollutant removal and interpolates a score from 0 to 5 based on ascending order.
		(m_7) Employment Opportunity	Calculates the annual maintenance costs and interpolates a score from 0 to 5 based on ascending order.

3.3.1.1 Environmental Co-Benefits Estimation

The indicators for environmental co-benefits included ecosystem services and carbon sequestration. These indicators depend on the vegetation used and placement of the technology. Ecosystem services included two sub-criteria for scoring: pollinator support and biodiversity

(Jones et al., 2017). The pollinator support indicator assigned a score from 0 to 2 based on the percentage of flowering species. A score of 0 was given for no vegetation or flowering species, a score of 1 was given for vegetation with 0% to 50% flowering species, and a score of 2 was given for vegetation with greater than 50% flowering species. The biodiversity indicator assigned a score from 0 to 3 based on plant coverage and number of species. A score of 0 was assigned for no vegetation, a score of 1 was assigned for 1 to 2 diverse species, a score of 2 was assigned for 3 to 9 diverse species, and a score of 3 was assigned for 10 or more diverse species. The score for ecosystem services was found by summing the pollinator support and biodiversity scores. The indicator for carbon sequestration calculated the pounds of CO_2 sequestered per year based on the addition of herbaceous vegetation and trees and the placement of the technology (Getter et al., 2009; Jo & McPherson, 1995). For diverse vegetation placed in a captured impervious area, Equation 3 was used, where L_{CO2} is the pounds of CO_2 sequestered per year, A is the technology area in square feet, and n_t is the number of trees.

$$L_{CO2} = [(0.0818 \cdot A) + (0.14 \cdot A) + (\, n_t \cdot 8)] \cdot 3.67 \qquad \text{Eq. 3}$$

For diverse vegetation placed in a surrounding pervious area, the Equation 4 was used.

$$L_{CO2} = [(0.0818 \cdot A) + (\, n_t \cdot 8)] \cdot 3.67 \qquad \text{Eq. 4}$$

In this analysis, technology options with diverse vegetation were assumed to have 10 or more different species with less than 50% being flowering vegetation. This assumption was determined from the NYC Housing Authority South Jamaica Houses Cloudburst Master Plan which plans to implement 17 herbaceous species with about 50% flowering species in the vegetated cloudburst systems (NYCHA, 2018). Trees were implemented with diverse vegetation cloudburst systems and the number of trees incorporated was determined using a 2020 tree inventory completed by the NYC Housing Authority (NYCHA, 2021). The tree inventory was completed for 18 housing developments which averaged 24 trees per acre. Since vegetated cloudburst systems are generally placed in parks or housing areas, this tree density was applied to the cloudburst technology area to find the number of trees implemented for the technology option.

3.3.1.2 Social Co-Benefits Estimation

The indicators for social co-benefits included health impacts from air quality, mental health, and thermal comfort. Reduced health impacts are associated with the removal of ozone, PM_{10}, NO_2, SO_2, and CO (Nowak et al., 2002). For each pollutant, the pounds removed per year was calculated using Equation 5, where $L_{pollutant}$ is the pounds of pollutant removed per year, A is the technology area in square feet, f_{dv} is the diverse vegetation removal factor, n_t is the number of trees, and f_t is the tree removal factor.

Table *3* lists the removal factors for each pollutant.

$$L_{pollutant} = (A \cdot f_{dv}) + (\, n_t \cdot f_t) \qquad \text{Eq. 5}$$

Table 3. Removal Factor for Diverse Vegetation and Trees (Nowak et al., 2002)

Pollutant	**Diverse Vegetation Removal Factor**	**Tree Removal Factor**
Ozone	0.000486	0.12355
PM_{10}	0.000434	0.08155
NO_2	0.000393	0.08365
SO_2	0.000231	0.04585
CO	0.000119	0.0154

The mental health indicator was scored based on the replacement of impervious surfaces with green space (Jones et al., 2017). Technologies with no vegetation or technologies placed in surrounding pervious areas were given a score of 0. For technologies with vegetation placed in captured impervious areas were, the score was based on the technology area in acres. The thermal comfort indicator was estimated using a 25% reduction in urban heat island effect (UHIE) based on the addition of vegetation in captured impervious areas (H. Li, 2016; Oke, 1987).

3.3.1.3 Economic Co-Benefits Estimation

The indicators for economic co-benefits include reduced costs from illness and employment opportunities. Costs associated with illness are reduced specifically through the removal of ozone, NO_2, and SO_2 (Nowak et al., 2014). For each pollutant, the cost reduction (CR) was found using Equation 6 by multiplying the pounds of pollutant removed per year ($L_{pollutant}$) by a cost saving factor (C_{sf}). Table 4 lists the cost factors for ozone, NO_2, and SO_2.

$$CR = L_{pollutant} \cdot C_{sf} \qquad \text{Eq. 6}$$

Table 4. Cost Savings Associated with Pollutant Removal (Nowak et al., 2014)

Pollutant	**Cost Saving Factor ($ per ton)**
Ozone	286
NO_2	436
SO_2	148

Finally, the employment opportunity indicator was based on the annual maintenance cost per year. The following section discusses how costs were calculated.

3.3.2 Life Cycle Cost Estimation

CLASIC utilizes the LCC method to assess the total cost of an asset over its lifetime by using a defined study period, initial and periodic capital costs, operations and maintenance costs, discount rates, and inflation factors (Catena Analytics, 2021). Costs are converted to present value for comparison of alternatives. The developers collected comprehensive data on green infrastructure costs and assigned an associated capital, maintenance, and rehabilitation cost for each technology type. The University of Utah conducted a review of cost estimating tools used for the development of the CLASIC tool (Geosyntec Consultants & Wright Water Engineers, n.d.). The methodology developed was used outside of CLASIC for calculating LCC for each technology option.

Capital, maintenance, and rehabilitation costs are based on the size of technology, storage depth, landscaping, and materials such as underdrains, liners, and pavement type. The standard design for each cloudburst technology was provided by NYC DEP (shown in Figure 4) and was used for determining cost parameters. Each cloudburst system in this analysis has an underdrain, no liner, and varies by vegetation type. Grass is installed through seeding and the mowing and irrigation season is from April through November, based on information from the Institute for Urban Parks Central Park Conservancy (Central Park Conservancy, 2016). Diverse vegetation and trees are planted and were assumed to be native species that do not require irrigation.

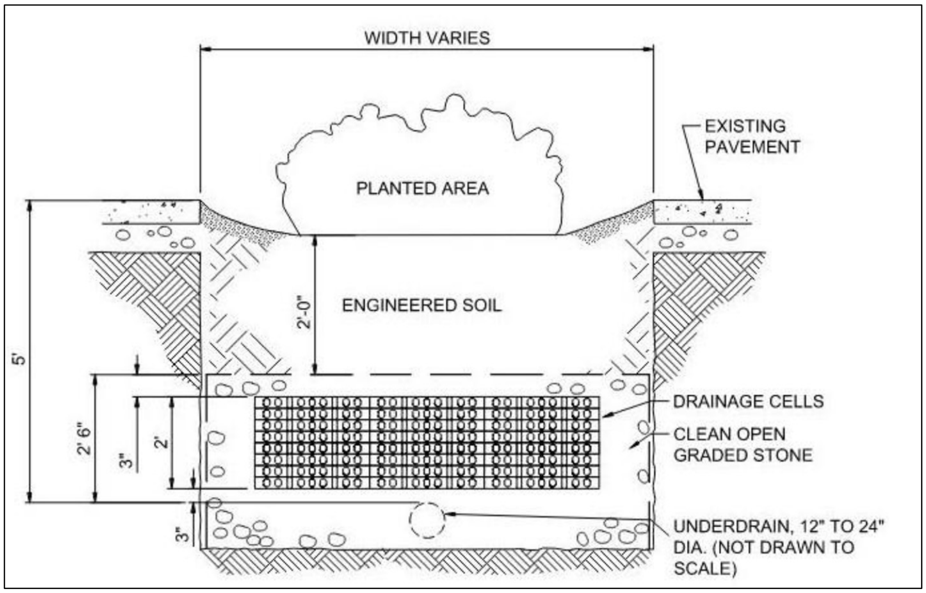

Figure 4. Standard Vegetated Cloudburst System Design

Using these construction and vegetation parameters, the capital, maintenance, and rehabilitation costs were determined from the CLASIC estimation tool. Because the CLASIC tool assumes default values for technology area and number of trees, size and tree adjustment factors were applied to accommodate for the differences in CLASIC technologies versus cloudburst technologies. The size adjustment factor was found by dividing the cloudburst technology area by the default CLASIC value. The tree adjustment factor was based on the average cost of incorporating one tree when multiple trees are planted. The CLASIC tool costs were multiplied by the adjustment factors to obtain an accurate estimation of capital, maintenance, and rehabilitation costs for each unique technology option.

Costs were converted to present value and summed to find the total LCC using Equation 2 below where C_0 was the initial construction cost, MC_t was the annual maintenance cost, RC_t was the rehabilitation cost, t was the years to rehabilitation, and i was the discount rate.

$$LCC = C_0 + \frac{MC_t \cdot [1 - (1 + i)^{-t}]}{i} + \frac{RC_t}{(1 + i)^t} \qquad \text{Eq. 2}$$

The present value formula accounts for the "time value of money" which is the concept that a dollar today is worth more now than compared to in the future due to potential earning capacity and inflation. A study period of 25 years was used which is the CLASIC default number of years to rehabilitation for rain gardens. The discount rate was set to 0% which assumes that the inflation rate is equal to the discount rate. This is a valid simplification which presents a higher present value and accounts for potential increase in labor and material costs (Catena Analytics, 2021). By converting all costs to present value, the monetary value of all alternative scenarios could be compared.

3.3.3 Aggregation of Triple Bottom Line Scores and Life Cycle Costs for Alternative Scenarios

For each alternative scenario, TBL scores and LCC were aggregated for the combinations of technology options. The individual TBL indicators were determined for each technology option. The indicators were then combined for the correlating alternative scenarios for finding the overall TBL score. The indicators were either assigned a score from 0 to 5 or were calculated and assigned a score from 0 to 5 based on linear interpolation. A score of 5 was for the best-case scenario and a score of 0 was for the worst-case scenario. The scores for the environmental, social, and economic categories were calculated through a weighted average MCDA approach. For this analysis, each indicator used equal weights. The overall TBL score for each alternative scenario was found by summing the scores for the environmental, social, and economic categories as shown in Equation 1, where M_n is the environmental score, M_s is the social score, and M_c is the economic score. A score of 15 was the maximum possible score for the Cloudburst

Hub scenarios. The present value LCC for each alternative scenario was found simply by summing the LCC for the applicable technology options.

$$TBL = M_n + M_s + M_c \qquad \text{Eq. 1}$$

3.4 Tradeoff Analysis of Alternative Scenarios at the Sewershed Scale

Using the results from section 3.3 CLASIC Tool Triple Bottom Line and Life Cycle Cost Procedures, a tradeoff analysis was conducted at the sewershed scale. First, alternative scenarios were developed at the sewershed scale for all possible combinations of cloudburst technology options. Next, a non-dominated sorting algorithm was applied to find the Pareto optimal set of technology combinations. Finally, the non-dominated solutions were evaluated against the proposed cloudburst systems in NYC to determine the tradeoffs between TBL co-benefits and LCC.

3.4.1 Sewershed Alternative Scenarios

A Python algorithm was used for the development of alternative sewershed scenarios. The sewershed scenarios were based on the number of Cloudburst Hubs within the sewershed and number of alternative scenarios within the Hubs. There were 7 sewersheds assessed and each had a different number of Cloudburst Hubs and sited technologies. Figure 5 displays the general process for the development of alternative sewershed scenarios. Henceforth, “Hub scenarios” refers to scenarios at the Cloudburst Hub scale and “sewershed scenarios” refers to scenarios at the sewershed scale. For each sewershed scenario, the algorithm summed the TBL score and LCC for the respective technology options. Table *5* lists the number of Cloudburst Hubs, sited technologies, Hub scenarios, and sewershed scenarios for the 7 sewersheds evaluated.

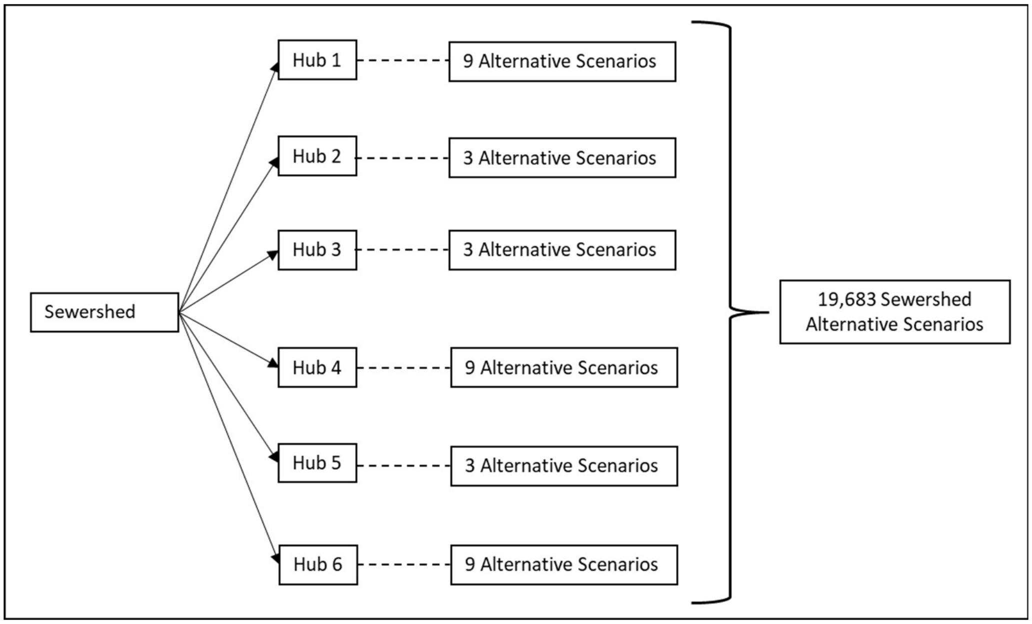

Figure 5. Sewershed Scenario Development

Table 5. Number of Alternative Scenarios Assessed per Sewershed

Sewershed	Number of Cloudburst Hubs	Number of Technologies	Number of Hub Alternative Scenarios	Number of Sewershed Alternative Scenarios
26th Ward	6	9	36	19,683
Bowery Bay	4	9	66	19,683
Hunts Point	5	6	21	729
Jamaica Bay	1	1	3	3
Newton Creek	1	3	27	27
Port Richmond	1	2	9	9
Tallman Island	2	2	12	27
Total	**20**	**33**	**174**	**40,161**

3.4.2 Dominance Testing of Sewershed Scenarios

A second Python algorithm carried out dominance testing of all sewershed scenarios to find the non-dominated scenarios. The dominance test compared TBL score and LCC of the sewershed scenarios where a higher TBL score and lower LCC dominate. For a scenario to be non-dominated, it must meet two dominance criteria where Scenario 1 dominates Scenario 2 if

Scenario 1 is no worse than Scenario 2 in all objectives and Scenario 1 is strictly better than Scenario 2 in at least one objective. The set of non-dominated solutions were plotted on a graph of LCC vs. TBL score, forming the Pareto optimal front.

Sewershed scenarios not contained in the Pareto optimal set are dominated by other sewershed scenarios and should not be considered unless higher-level information is driving the decision. The proposed scenarios from the suitability assessment were plotted as a highlighted point and compared to the Pareto optimal front. When the proposed scenario was not included in the Pareto optimal front, the distance between the point and Pareto optimal front was calculated to find the closest Pareto solution. The closest Pareto solution is the most feasible non-dominated solution that could be adopted by NYC. Additionally, the point with the nearest TBL score and the point with the nearest LCC were determined. The solution with the nearest TBL score could offer cost-savings opportunities while achieving the same co-benefits and the solution with the nearest LCC could provide greater co-benefits for the same cost.

3.5 Tradeoff Analysis at the City Scale

Using the Pareto optimal set from each sewershed, the dominance test was repeated at the city scale. In order to make the analysis computationally possible, the Pareto optimal set from each sewershed was discretized using a binning method to reduce the number of distinct data points (Han et al., 2011). For each sewershed with greater than 6 Pareto optimal solutions, the Pareto optimal set was split into 6 bins using LCC values and the solution closest to the median LCC value was kept as a representative point. The planned solution or nearest Pareto solution to the proposed scenario were also included in the dataset.

City-wide scenarios were developed using the discretized Pareto optimal solutions from each sewershed using the same procedure as the sewershed scenarios. A total of 24,000 combinations were created and used to find the Pareto optimal solution. Dominance testing utilized the same criteria where a higher TBL score and lower LCC dominates, and Scenario 1 dominates if it is strictly better in one objective and no worse in the second objective. The Pareto optimal front was plotted and compared to the City's proposed cloudburst strategy.

4. Results

The results of this study determined the Pareto optimal set of solutions at the sewershed and city-scale to assess the tradeoffs of different infrastructure selections. The proposed cloudburst scenarios from the suitability assessment are contained within the Pareto optimal set of solutions in 5 of 7 sewersheds. The results highlight that surface vegetation strategies have a significant effect on the TBL co-benefits and LCC tradeoffs of cloudburst infrastructure. Specifically, trees are a great driver of increased TBL score and, although trees add an additional cost to cloudburst infrastructure, the implementation of diverse vegetation was the greatest driver of cost increase. Therefore, within the Pareto optimal set of solutions, trees were the most frequent vegetated strategy, followed by grass then diverse vegetation.

4.1 Triple Bottom Line and Life Cycle Cost Tradeoffs of Pareto Optimal Solutions

The Pareto optimal set was found for 7 sewersheds in NYC. Only 7 of the 14 sewersheds were included in the analysis based on the location of proposed vegetated cloudburst infrastructure. The proposed scenario from the suitability assessment was a non-dominated solution for 5 out of the 7 sewersheds. Table 6 provides a summary of the total number of sewershed scenarios assessed and the total number of Pareto optimal solutions found by sewershed. The 26th Ward, Bowery Bay, and Hunts Point Sewersheds had the greatest number of Pareto optimal solutions and will be discussed in more detail in the following subsections. The 4 remaining sewersheds did not have enough alternative scenarios to produce a Pareto optimal set solution outside of the Hub scenarios. The graphs for these sewersheds can be found in the Appendix.

Table 6. Summary of Sewershed Alternative Scenarios and Pareto Optimal Solutions

Sewershed	**Number of Alternatives Assessed**	**Number of Pareto Optimal Solutions**
26th Ward	19,683	256
Bowery Bay	19,683	170
Hunts Point	729	57
Jamaica Bay	3	3
Newton Creek	27	24
Port Richmond	9	6
Tallman Island	27	16
Total	**40,161**	**532**

4.1.1 26th Ward Sewershed Tradeoffs

The 26th Ward Sewershed consisted of 6 Cloudburst Hubs with a total of 9 vegetated cloudburst technologies. Figure *6* shows a plot of the Pareto optimal front with all sewershed scenarios and the proposed scenario highlighted. In total, 19,683 scenarios were evaluated and 256 scenarios were contained within the Pareto optimal front. The maximum possible TBL score was 90 based on the 6 Hubs within the sewershed with each Hub having a maximum TBL score of 15.

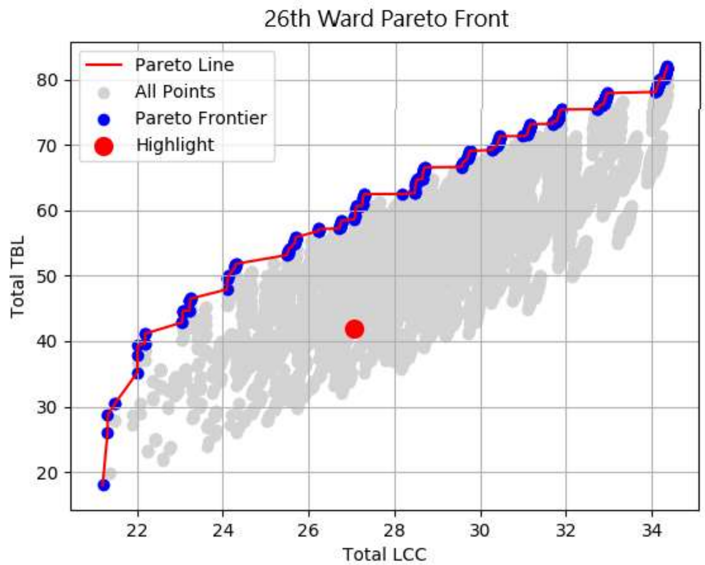

Figure 6. Pareto Optimal Front for 26th Ward

The proposed scenario in the 26th Ward Sewershed was a dominated solution located below the Pareto optimal front. NYC could change some of their cloudburst technologies to reach a non-dominated solution and achieve optimal TBL co-benefits and LCC. Table *7* lists the nearest Pareto optimal solutions to the proposed scenario based on closest LCC, closest TBL score, and closest overall. It shows the total LCC, TBL score, and the percent area and count of vegetation types. These nearest solutions are the most feasible alternatives compared to the proposed solution.

The nearest overall Pareto optimal solution is the closest in both LCC and TBL score. In the 26th Ward sewershed, the nearest Pareto solution is \$3.99M less in LCC and 1.02 points greater in TBL score. The nearest Pareto solution incorporates 1 more grass and tree technology and 2 fewer diverse vegetation technologies. The Pareto optimal solution with the closest LCC, achieves a TBL score 16.76 points greater and incorporates 2 more tree technologies and 1 less grass and diverse vegetation technology. The Pareto optimal solution with the closest TBL score, saves \$4.85M in LCC and incorporates 1 more grass technology, 3 more tree technologies, and 4 less diverse vegetation technologies.

Table 7. Pareto Optimal Solutions Near the 26th Ward Proposed Solution

Scenario	**LCC ($M)**	**TBL Score**	**Grass Techs**		**Diverse Veg Techs**		**Trees Techs**	
			% Area	**Count**	**% Area**	**Count**	**% Area**	**Count**
Proposed Solution	27.04	41.85	55.4%	5	44.6%	4	0	0
Nearest Pareto Solution	23.05	42.87	86.4%	6	13.5%	2	0.1%	1
Pareto Solution with the Closest LCC	27.06	58.61	55.4%	4	39.2%	3	5.5%	2
Pareto Solution with the Closest TBL	22.19	41.16	93.2%	6	0	0	6.8%	3

4.1.2 Bowery Bay Sewershed Tradeoffs

The Bowery Bay Sewershed consisted of 4 Cloudburst Hubs with a total of 9 vegetated cloudburst technologies. Figure 7 shows a plot of the Pareto optimal front with all sewershed scenarios and the proposed scenario highlighted. In total, 19,683 scenarios were evaluated and 170 scenarios were contained within the Pareto optimal front. The maximum possible TBL score was 60 based on the 4 Hubs within the sewershed.

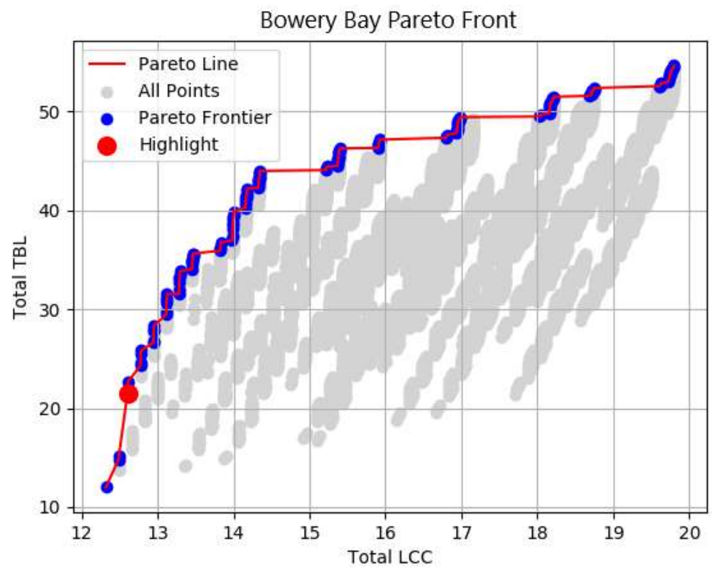

Figure 7. Pareto Optimal Front for Bowery Bay

The proposed scenario in the Bowery Bay Sewershed is located on the Pareto optimal front. It is a non-dominated solution that offers an optimal LCC and TBL score. Table *8* displays the LCC, TBL score, and vegetation type details for the proposed solution. There are still tradeoffs in the Bowery Bay Sewershed. For example, NYC could choose to invest more and increase its TBL score. Alternatively, they could decide to lower their monetary investments and in-turn reduce the TBL score. The Pareto optimal front offers a guideline to inform their investment decisions.

Table 8. Proposed Solution Contained in the Pareto Optimal Set for Bowery Bay

Scenario	**LCC ($M)**	**TBL Score**	**Grass Techs**		**Diverse Veg Techs**		**Trees Techs**	
			% Area	**Count**	**% Area**	**Count**	**% Area**	**Count**
Proposed (Pareto) Solution	12.60	21.50	95.9%	8	4.1%	1	0	0

4.1.3 Hunts Point Sewershed Tradeoffs

The Hunts Point Sewershed consisted of 5 Cloudburst Hubs with a total of 6 vegetated cloudburst technologies. Figure *8* shows a plot of the Pareto optimal front with all sewershed scenarios and the proposed scenario highlighted. In total, 729 scenarios were evaluated and 57 scenarios were contained within the Pareto optimal front. The maximum possible TBL score was 75 based on the 5 Hubs within the sewershed.

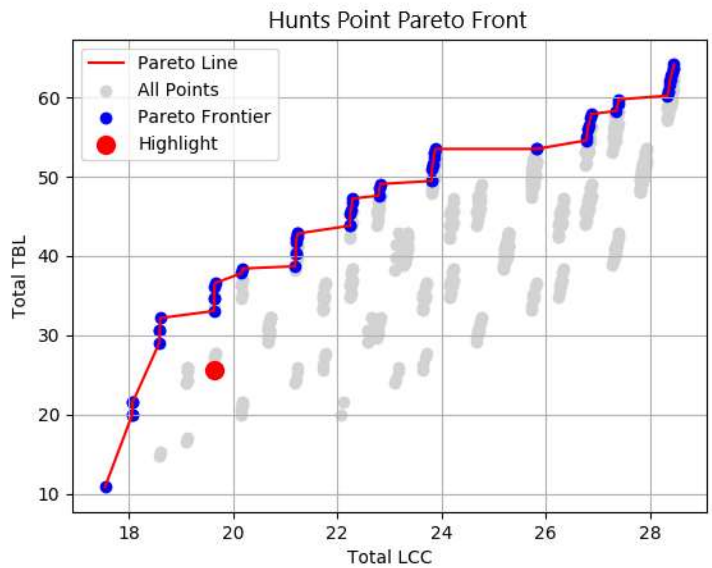

Figure 8. Pareto Optimal Front for Hunts Point

The proposed scenario for the Hunts Point sewershed is a dominated solution located below the Pareto optimal front. Table 9 lists the nearest Pareto optimal solutions to the proposed scenario based on closest LCC, closest TBL score, and closest overall. The nearest Pareto solution is $1.04M less in LCC and 3.45 points greater in TBL score. Compared to the proposed scenario, this scenario has the same number of grass, diverse vegetation, and tree technologies, however, in different locations. The percent area of grass is 9.7% greater in the nearest Pareto solution. The Pareto optimal solution with the closest LCC, achieves a TBL score 7.47 points greater by reducing the number of grass technologies by 1 and increasing the number of diverse vegetation technologies by 1. The Pareto optimal solution with the closest TBL score is the same as the closest overall Pareto optimal solution.

Table 9. Pareto Optimal Solutions Near the Hunts Point Proposed Solution

Scenario	LCC ($M)	TBL Score	Grass Techs		Diverse Veg Techs		Trees Techs	
			% Area	Count	% Area	Count	% Area	Count
Proposed Solution	19.63	25.58	80.6%	4	19.4%	2	0	0
Nearest Pareto Solution	18.59	29.03	90.3%	4	9.7%	2	0	0
Pareto Solution with the Closest LCC	19.63	33.05	80.6%	3	19.4%	3	0	0
Pareto Solution with the Closest TBL	18.59	29.03	90.3%	4	9.7%	2	0	0

4.1.4 Citywide Tradeoffs

At the city-scale, all 20 Cloudburst Hubs were included. Using the discretized data, a total of 24,000 scenarios were evaluated and 210 scenarios were contained within the Pareto optimal front. The maximum possible TBL score was 300 based on all 20 Hubs. Figure 9 shows a plot of the Pareto optimal front with the 24,000 scenarios developed and the proposed citywide solution. The graph does not show all possible citywide combinations since the data was discretized to make the analysis computationally possible.

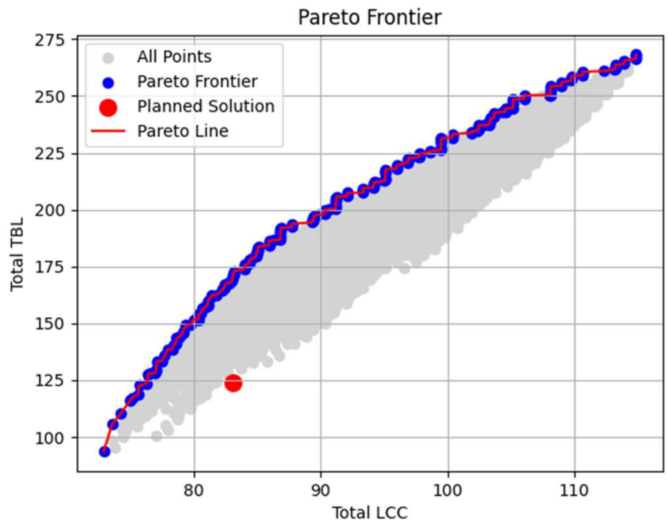

Figure 9. Citywide Pareto Front

The citywide solution is a dominated solution located below the Pareto optimal front. Table 10 lists the nearest Pareto optimal solution from the discretized data to the proposed solution based on closest LCC, closest TBL score, and closest overall. These solutions represent possible optimal solutions, however, since the full set of data was not used, other nearest solutions may exist.

Table 10. Pareto Optimal Solutions Near the Citywide Proposed Solution

Scenario	**LCC ($M)**	**TBL Score**	**Grass Techs**		**Diverse Veg Techs**		**Trees Techs**	
			% Area	**Count**	**% Area**	**Count**	**% Area**	**Count**
Proposed Solution	83.10	123.9	75.1%	21	24.9%	12	0	0
Nearest Pareto Solution	76.33	123.6	66.7%	22	21.2%	7	12.1%	4
Pareto Solution with the Closest LCC	83.07	170.6	45.5%	15	15.2%	5	39.4%	13
Pareto Solution with the Closest TBL	76.33	123.6	66.7%	22	21.2%	7	12.1%	4

4.2 Frequency of Vegetation Strategies in the Pareto Optimal Front

4.2.1 Sewershed Results

Within the Pareto optimal set of solutions, tree cloudburst technologies were the most frequent. Figure 10 displays the count of vegetation type in the Pareto optimal set at the sewershed scale. In all three sewersheds, trees make up nearly half or more of the technologies in the Pareto optimal set. Grass is the second most frequent vegetation type, followed by diverse vegetation.

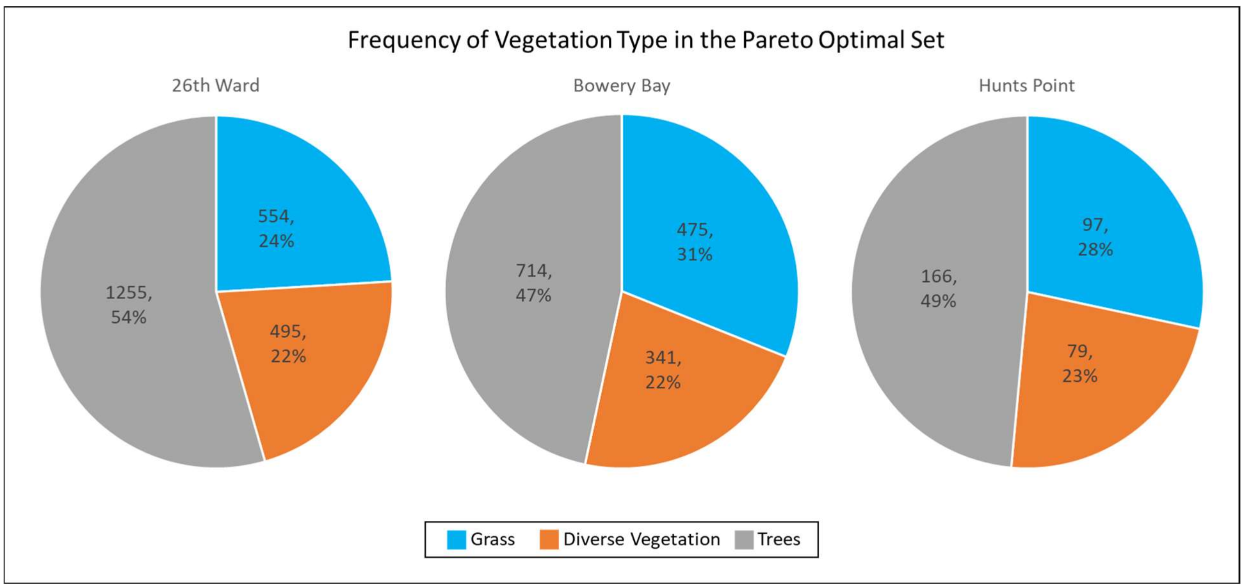

Figure 10. Pie Charts of Vegetation Strategies by Sewershed

Figure *11* shows the Pareto optimal front with the percent area color-coded for all three vegetation types for the 26th Ward, Bower Bay, and Hunts Point sewersheds. The graphs illustrate that at a lower LCC, grass is the dominant vegetation type which also correlates with a lower TBL score. As LCC increases, the TBL score rises and so does the percentage of diverse vegetation and tree technologies.

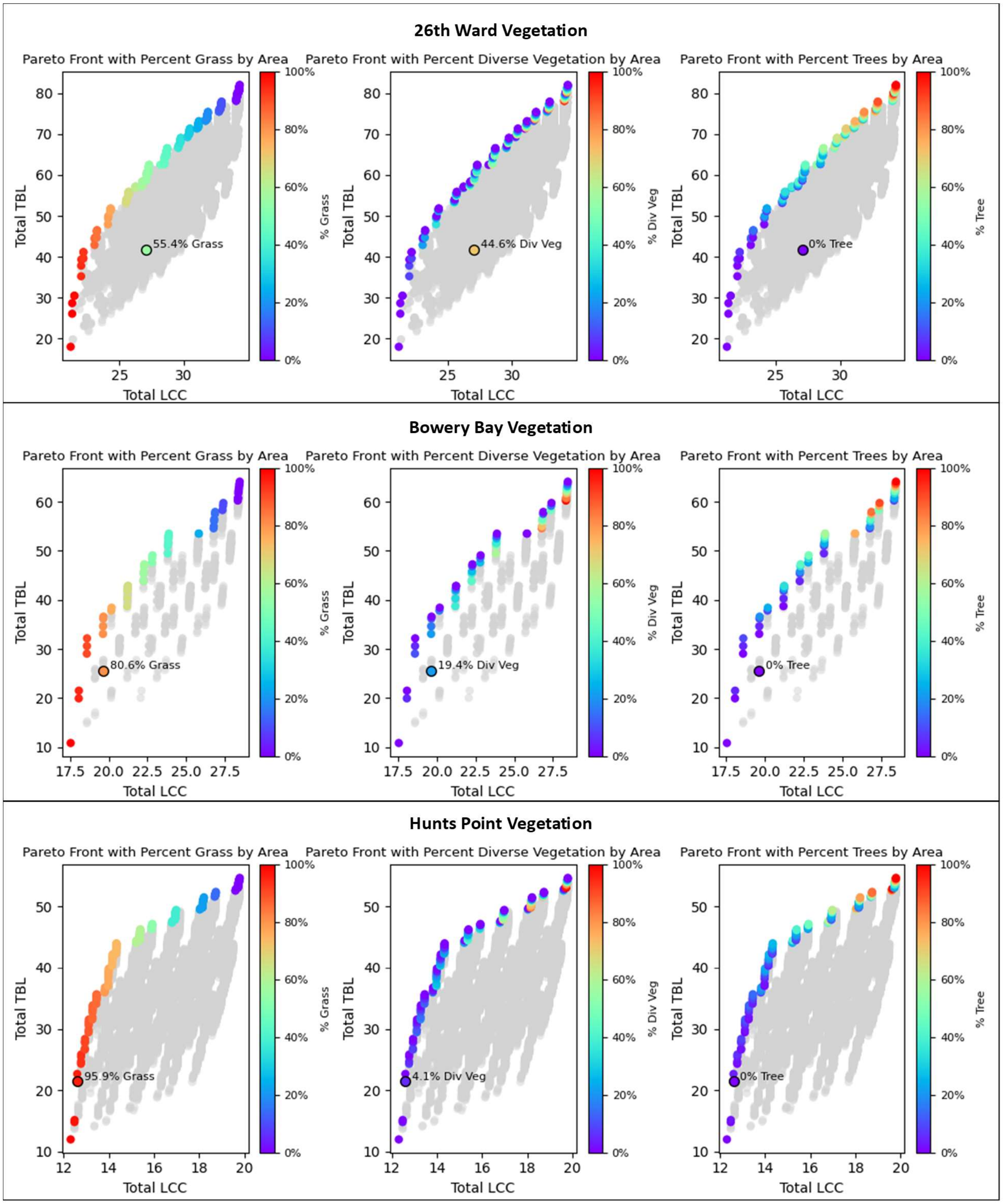

Figure 11. Sewershed Vegetation in the Pareto Front

4.2.2 Citywide Results

At the city-scale, trees were the most frequent vegetation strategy contained within the Pareto optimal set. Like the sewershed results, trees make up nearly half of the technologies in the city-wide optimal solutions. Figure 12 displays the count and percentage of vegetation type contained within the Pareto optimal solutions.

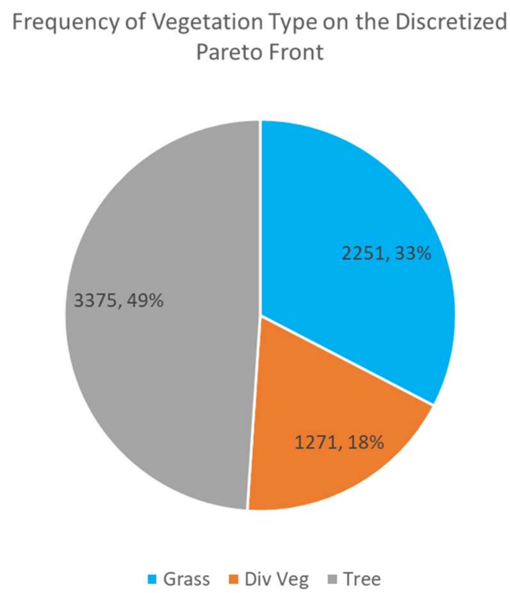

Figure 12. Pie Chart of Citywide Vegetation Strategies

Figure 13 shows the citywide Pareto optimal front with the percent area of all three vegetation types color-coded. The results at the city-scale show that at a lower LCC, grass is the dominant vegetation type and TBL score is lower. At a higher LCC, trees are the dominant vegetation type and the TBL score is higher. Diverse vegetation only makes up 30% or less of the area on the entire Pareto optimal front.

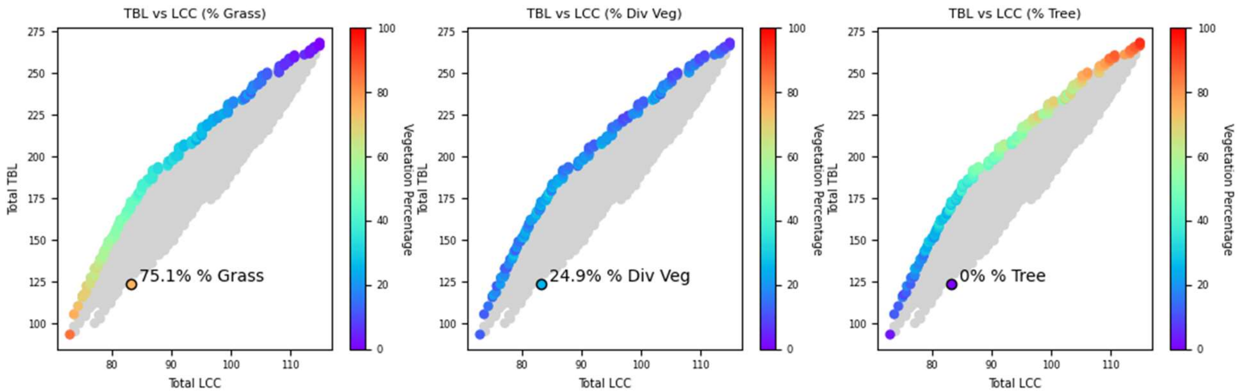

Figure 13. Citywide Vegetation in the Pareto Front

4.3 Impact of Trees on Triple Bottom Line Score and Life Cycle Cost

By incorporating trees in cloudburst technology, there is an increase in TBL score and an increase in LCC. Figure 14 shows the relationship between the percentage of trees by area compared to the TBL score and LCC of alternative scenarios at the city-scale. The results show that trees are linearly related to TBL score and exponentially related to LCC. Figure *13*

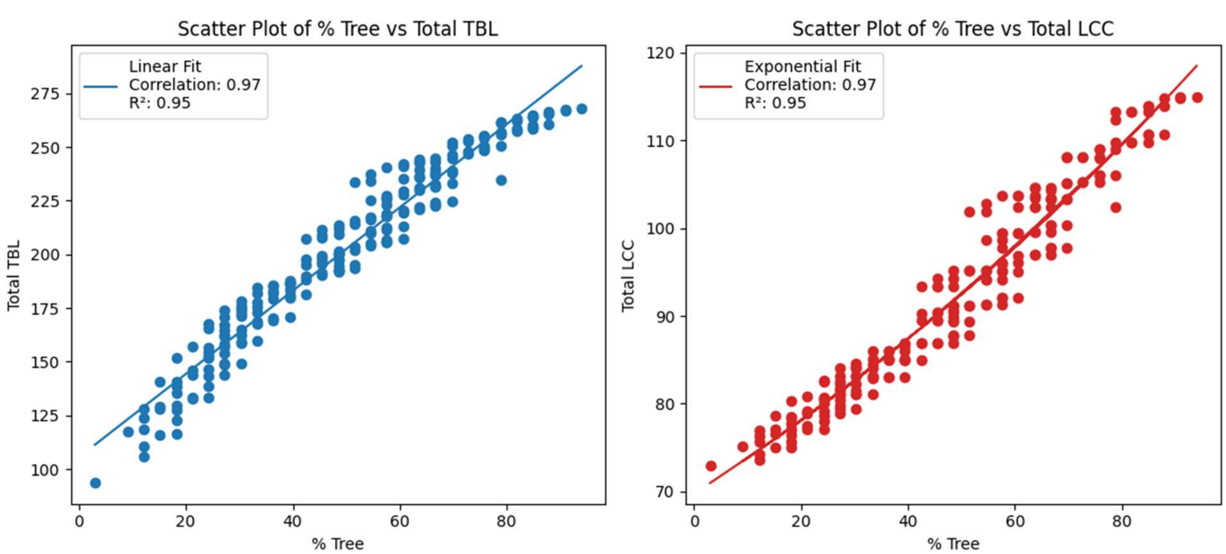

Figure 14. Plot of Tree Percentage vs. TBL Score and LCC for the Citywide Pareto Optimal Set

To better understand the effects of trees on the TBL metrics, the total carbon sequestered and ozone, PM_{10}, NO_2, SO_2, and CO removed was found for each Pareto optimal solution. Figure 15 displays the relationship between the percentage of trees with carbon sequestration and total pollutant removal in tons per year. Like TBL score, the amount of carbon sequestered and total pollutant removed is linearly related to an increase in area of trees.

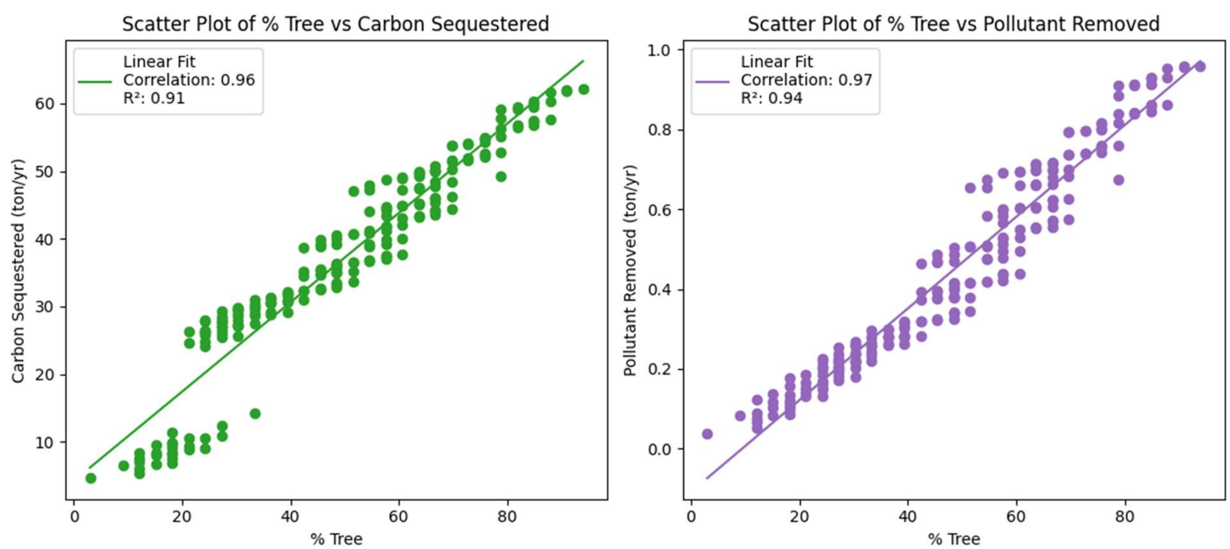

Figure 15. Plot of Tree Percentage vs. Carbon Sequestration and Pollutant Removal for the Citywide Pareto Optimal Set

4.4 Impacts of Life Cycle Cost on the Pareto Optimal Set

The LCC for the different vegetation types impacts the frequency in which they appear in the Pareto optimal set. The LCC was quantified for each vegetation alternative at the Hub scale. These costs were summed for each vegetation type for comparison. Figure *16* shows the breakdown of present value capital cost, rehabilitation cost, and annual maintenance costs for each vegetation type. The results show that capital costs make up nearly 50% or more of the total

LCC and rehabilitation and annual maintenance costs each account for approximately 25% of the total LCC.

Incorporating trees into cloudburst technologies cost $2.44M more than including diverse vegetation alone. Whereas, by incorporating diverse vegetation was $77.5M more expensive than incorporating grass. This large cost disparity between grass and diverse vegetation can explain why trees are more frequent in the Pareto optimal set than diverse vegetation.

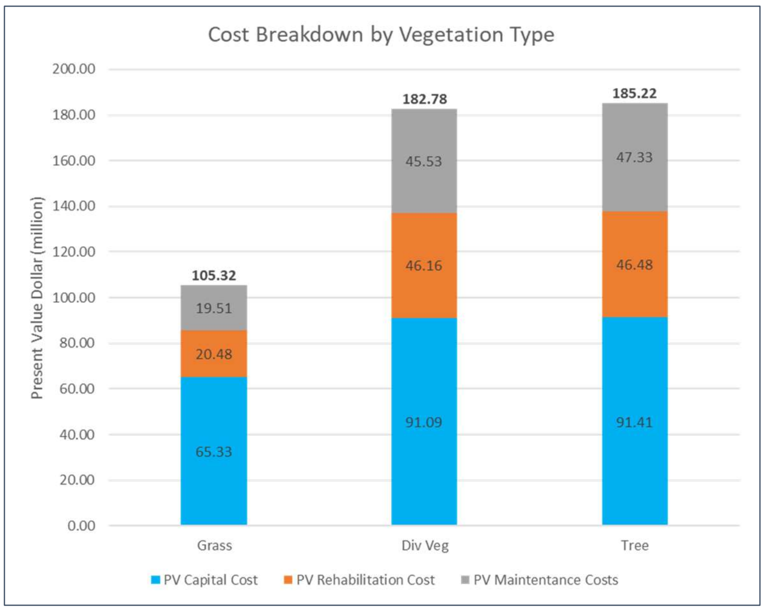

Figure 16. Present Value Costs for Each Vegetation Strategy

5. Discussion

This study leveraged the Triple Bottom Line (TBL) and Life Cycle Cost (LCC) assessment frameworks to evaluate the tradeoffs of cloudburst technology alternatives. It highlights clear tradeoffs between TBL score and LCC when different surface vegetation is incorporated. The results showed that alternatives with higher TBL scores have a higher LCC. The findings underscore the importance for policy- and decision-makers to balance financial constraints with environmental goals.

5.1 Role of Vegetation in Cloudburst Infrastructure

The results of this study indicate that grass, diverse vegetation, and trees vary in their costs and co-benefits. Grass had the lowest TBL score and LCC while trees showed the highest values in both categories. Diverse vegetation was observed to have a mid-range TBL score while having a significantly greater LCC than grass and slightly less LCC than trees. This discovery explains why trees are the most frequent vegetation strategy within the Pareto optimal set. They offer the greatest co-benefits while costing only marginally more than diverse vegetation. These findings are key to understanding how different vegetation types contribute to the LCC and co-benefits of cloudburst infrastructure.

5.2 Implications for Urban Flood Management

The findings from this study suggest that by incorporating different vegetation types into cloudburst management, NYC could achieve more optimized outcomes in terms of TBL co-benefits and LCC. Understanding the effects of the different vegetation strategies provides a foundation for developing more sustainable urban landscapes. By integrating the results into urban stormwater management, cities can enhance their capacity to manage extreme precipitation events while also achieving environmental and social benefits.

5.3 Limitations and Future Research

While this study provides insight into the TBL and LCC trade-offs of vegetated cloudburst infrastructure, it does have limitations. This study excluded the existing drainage infrastructure due to lack of data and, therefore, flood volume reductions were not considered. Future research should incorporate the existing drainage infrastructure to assess the urban flood reductions associated with cloudburst infrastructure. These studies could provide a more holistic understanding of the hydrological impacts of cloudburst infrastructure in addition to their co-benefits and costs. Moreover, these studies could further influence decision-making in urban flood management.

The CLASIC tool methodologies were used and are backed by extensive research, however, the software still has its limitations. Because the tool is designed to evaluate green infrastructure, certain parameters are not editable to the user. This drove the analysis to be conducted outside of the web-based tool. The CLASIC tool is continually being improved to conduct additional analyses and should consider allowing the user to test different infrastructure designs, such as cloudburst infrastructure.

6. Conclusions

Urban flooding is exacerbated by the dense development of impervious surfaces and is a concern for cities across the globe that. Climate change has led to more frequent cloudburst events which have potential to cause significant damage (Falconer et al., 2009). Cloudburst infrastructure is a promising solution to combat intense rainfall, however, few studies have been conducted to support their implementation (B. R. Rosenzweig et al., 2018). This study has aimed to enhance the understanding of cloudburst infrastructure in the context of climate change and urbanization.

Decision support frameworks were utilized to determine optimal cloudburst infrastructure strategies in New York City (NYC). Specifically, Triple Bottom Line (TBL) and Life Cycle Cost (LCC) assessments were conducted for alternative vegetation strategies in cloudburst infrastructure using CLASIC methodologies. The co-benefit metrics considered in the TBL assessment included ecosystem services, carbon sequestration, health impacts from air quality, mental health, thermal comfort, costs from illness, and employment opportunity. The TBL score was quantified using an MCDA method with 15 being the highest possible score within a Cloudburst Hub. The LCC assessment utilized capital, rehabilitation, and maintenance cost data from the CLASIC tool and converted them to present value for comparison. The TBL scores and LCC were utilized for evaluating different combinations of strategies at the sewershed and city scale. Through non-dominated solution testing, clear tradeoffs were identified between grass, diverse vegetation, and tree technologies. The Pareto optimal set of solutions was determined for different combinations of vegetation strategies.

The key findings of this study indicate that vegetation plays a clear role in enhancing the TBL co-benefits of cloudburst infrastructure but not without an associated increase in LCC.

Within the Pareto optimal set, trees were the most frequent vegetation strategy, followed by grass, then diverse vegetation. Trees had the highest TBL score and highest associated LCC, however, the LCC was only marginally greater than that of diverse vegetation, making trees a more frequent optimal solution. The effect of trees was further studied to determine the relationship with co-benefits and costs. The results showed that the percentage of trees is linearly related to TBL score but exponentially related to LCC.

Overall, this research offers a broader understanding of cloudburst infrastructure in terms of the potential co-benefits and costs associated with implementation. It highlights the critical role vegetation plays in enhancing the co-benefits of cloudburst infrastructure while combatting urban flooding. Decision-makers interested in environmental, social, and economic co-benefits may face budgetary tradeoffs and constraints. The results can be utilized to support informed decision making. In conclusion, this study contributes to the growing body of knowledge on sustainable urban planning, emphasizing the need for resilience in infrastructure design to cope with extreme weather events.

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Appendix

Pareto Optimal Front with planned solution for Jamaica Bay, Newton Creek, Port Richmond, and Tallman Island Sewersheds.