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A multi-objective decision support framework to prioritize tree planting locations in urban areas

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HIGHLIGHTS

- The placement of trees needs careful thought and consideration of beneficiaries.
- Strategic placement of trees in landscapes is required to maximize benefits.
- Multi-objective prioritization identifies locations for greater greening benefits.
- Optimization frameworks help cities address diverse urban greening goals.

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ABSTRACT

With tree planting initiatives being undertaken in different cities, careful thought needs to be put into the placement of trees, the beneficiaries of ecosystem services from these trees, and the potential impacts of alternative tree planting schemes. Using a spatially explicit methodology within biophysical ecosystem service models, this research develops a multi-objective decision support framework to guide future greening initiatives towards prioritizing planting locations that maximize multiple objectives. In a case study application of the framework in the Bronx, NY, the analysis utilizes spatially distributed census block group data and linear programming, a mathematical optimization technique, to identify optimal and equitable planting locations considering increases in tree cover, monetary benefits from avoided runoff, $PM_{2.5}$ air pollutant removal and heat index reduction as well as tree planting costs and the equality and equity of urban tree ecosystem services. Using different optimization scenarios, the framework identifies optimal planting schemes by minimizing planting costs, maximizing increases in tree cover and ecosystem service benefits, and the equity of canopy cover and ecosystem services, arriving at a wide range of different planting recommendations. We conclude that multi-objective prioritization frameworks can identify optimal locations for greater total benefits from urban greening and that the proposed framework has the potential to inform decision making in different cities.

1. Introduction

Increased urbanization can exacerbate adverse environmental impacts such as elevated temperatures, increases in air pollution and stormwater quantity, and decreases in stormwater quality, posing environmental and public health problems in cities. There is growing interest in the ecosystem services and benefits provided by urban ecosystems (Eigenbrod et al., 2011; Seto & Shepherd, 2009). Forested ecosystems are a particularly important resource, providing multiple services and benefits to urban inhabitants, including the regulation of environmental conditions and other social and human health benefits linked to improved human health and well-being (Venter, Shackleton, Van Staden, Selomane, & Masterson, 2020). With numerous tree planting initiatives being undertaken in different cities for various economic, environmental, social and human health benefits, careful thought needs to be put into considering the placement of trees and their beneficiaries (Salmond et al., 2016). However, constrained resources and lack of adequate space necessary to generate ecosystem services

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challenge the design of environmental solutions that meet multiple objectives (Almeter et al., 2018).

Studies have shown that greater returns on greening investments occur when considering multiple human health and environmental benefits (Chazdon & Guariguata, 2018; Salmond et al., 2016). Prioritization tools are increasingly being used to highlight important synergies and trade-offs that help determine how and where to achieve the most desirable and feasible outcomes from urban trees, including the mitigation of environmental hazards and the provision of ecosystem services to vulnerable and underserved populations (Almeter et al., 2018; Grêt-Regamey, Altwegg, Sirén, van Strien, & Weibel, 2017; Locke et al., 2010; Meerow & Newell, 2017; Yoon, Kim, & Lee, 2019). Systematic approaches to both afforestation and reforestation activities are increasingly being adopted to identify priority areas which identify land use conflicts, evaluate trade-offs among ecosystem benefits and assess divergent stakeholder needs across a wide range of social, political, economic, and ecological dimensions (Almeter et al., 2018; Chazdon & Guariguata, 2018).

For instance, new tree plantings for the MillionTrees New York City (NYC) initiative were based on prioritizing neighborhoods with fewer trees to improve local air quality and help prevent respiratory illnesses, particularly high incidence of asthma among young people (Campbell, Monaco, Falxa-Raymond, Lu, Newman, Rae, & Svendsen, 2014; Garrison, 2019; Grove, O'Neil-Dunne, Pelletier, Nowak, & Walton, 2006). The second half of the NYC initiative was also guided by an Urban Tree Canopy assessment (UTC) spatial prioritization framework to identify tree planting priorities by weighting different biophysical and socio-economic criteria. Using the UTC framework, priority planting areas were identified by ranking variables representing need (whether trees can help address specific issues in the community (e.g., air quality, biodiversity, public health, urban heat) and suitability (e.g., biophysical constraints, local goals) (Campbell et al., 2014; Grove et al., 2006; Locke et al., 2010). Ultimately, MillionTreesNYC did not follow this prioritization to a measurable degree and planted more trees in areas with greater existing tree canopy including parks, playgrounds, and natural areas due to the availability of plantable space, particularly in areas owned and managed by the NYC Department of Parks and Recreation (Garrison, 2019; Nyelele, Kroll, & Nowak, 2019). Emphasis was also placed on six "Trees for Public Health" neighborhoods with fewer than average street trees, higher than average juvenile asthma rates, and poor air quality identified across all five boroughs of the city. Other cities have used a Priority Planting Index which combines weights of population density, canopy green space and tree canopy cover per capita to identify potential tree planting areas (Nowak & Greenfield, 2008). A similar weighting methodology is utilized in i-Tree Landscape (https://landscape.itreetools.org/), i-Tree's spatially distributed modeling system, to prioritize tree planting locations based on land cover, demographics, risk, and ecosystem service and benefit data derived from running county-level lumped versions of i-Tree tools. However, lumped models and coarse scale prioritization tools simplify the relationships between the structure and function of urban forests and the representation of urban landscapes. Furthermore, the ranking or weighted approach used in frameworks such as the UTC spatial prioritization framework that was developed for MillionTreesNYC and the Priority Planting Index is subjective as it requires the decision maker to decide on the contribution of each variable to the goal.

Despite the multiple benefits that can be generated by urban forests, there is limited scientific literature on decision making and tree planting prioritization based on ecosystem benefits. According to Chazdon and Guariguata (2018), few studies incorporate economic analyses to generate planting scenarios based on cost-effectiveness and the total costs of specific restoration interventions. Furthermore, most studies supporting the planning of green spaces with a quantitative basis focus on a single benefit of greening, such as to improve cooling benefits or runoff regulation (Bodnaruk et al., 2017; Meerow & Newell, 2017; Wu & Chen, 2017; Yoon et al., 2019; Zhang, Murray, & Turner, 2017). In the process of maximizing a specific benefit by changing the location and the composition of green spaces, other benefits can be enhanced or diminished because of trade-offs or synergies (Bodnaruk et al., 2017). However, the failure to provide a comprehensive treatment of multiple benefits from urban green spaces has resulted in the failure to meet some stakeholder preferences and achieve regional sustainability (Raum et al., 2019).

Most urban forest priority planting frameworks also lack a means to quantify the inequity of tree cover distribution and green infrastructure (Almeter et al., 2018; Nyelele & Kroll, 2020). Given the competition for resources and space in urban settings, strategic investments in green infrastructure require not only accounting for the multiple services potentially generated, but also the intensity of need for those services. In a study of 108 United States (U.S.) urban areas, Hoffman, Shandas, and Pendleton (2020), like many other studies before them, found consistent patterns between the lack of tree canopy and historically underserved urban areas at both national and regional scales. Vulnerable communities are disproportionately exposed to public health threats such as extreme heat, that would have otherwise been lessened by improved access to green spaces and the many benefits they provide. Without considering environmental equity, it is possible that the establishment of tree cover to promote certain goals could exacerbate inequity, making susceptible populations more vulnerable to the adverse impacts associated with low canopy cover. Schwarz et al. (2015) highlight that with many studies reporting an uneven distribution of environmental amenities that disfavor racial and ethnic minority and low-income neighborhoods, fairness of public investment in the distribution, delivery, and maintenance of services derived from urban tree canopies is a basic environmental justice concern. There is need for additional equity and equality studies that provide a more comprehensive framework to inform decision-making processes, policy options, management measures and equity tradeoffs between different planting scenarios.

This study evaluates the relative benefits provided by increasing tree cover on either plantable pervious areas (currently short vegetation or bare soil areas) or plantable impervious areas (impervious areas such as asphalt or concrete surfaces, excluding roads and buildings, that are theoretically available for the establishment of tree canopy). We expect that establishing tree canopy on plantable impervious areas will have a greater impact on net improvements in avoided stormwater runoff, water quality and summer temperatures (O'Neil-Dunne, 2012), but should incur higher planting and maintenance costs. Also, while other studies assume that tree planting resources are unlimited, the framework presented here ensures that objectives are met under varying real-world resource constraints.

In this study, we first develop a flexible framework for multi-objective optimization within the context of maximizing the services, benefits, and equity of urban forest planting initiatives. We then address common resource and implementation constraints that are encountered in practice. We then show how this framework could be implemented using a case study where a spatially explicit modelling methodology at the census block level is used to develop and implement a multi-objective decision support framework. This case study is used to identify priority planting locations in the Bronx, NY by optimizing ecosystem service and benefit provisions related to heat index and storm water runoff reductions, air pollutant removal, tree cover increases and the equity of urban forest cover.

2. Research methodology

2.1. A theoretical optimization framework

The multi-objective decision support framework could run on any spatial unit; here we propose the census block group level, a scale where census demographic data is readily available in the U.S. The framework is set up as a general optimization problem which maximizes (or in some instances minimizes) some objective function subject to a series of constraints by changing a set of decision variables. We developed the framework in the R statistical computing software (R Core Team, 2013), but the framework can easily be implemented in any programming language. In a general application of this framework, the objective function is to maximize multiple ecosystem services or benefits from increased (or decreased) tree cover as follows:

$$Max \sum_{i=1}^{N} \sum_{j=1}^{M} \left[\left(CI_{i,j} {}^{*} \Delta TCI_i \right) + \left(CP_{i,j} {}^{*} \Delta TCP_i \right) \right] \tag{1}$$

$Subject\ to:\ g_i(\Delta TCI_i, \Delta TCP_i) \geqslant, \leqslant or = b_i$
$where:\ M$ = $number\ of\ services\ or\ benefits\ considered$
N = $number\ of\ block\ groups$
$CI_{i,j}$ = $benefit\ per\ unit\ area\ increase\ in\ tree\ cover\ over\ impervious\ surfaces\ for\ service\ or\ benefit\ j\ in\ block\ group\ i$
$CP_{i,j}$ = $benefit\ per\ unit\ area\ increase\ in\ tree\ cover\ over\ pervious\ surfaces\ for\ service\ or\ benefit\ j\ in\ block\ group\ i$
ΔTCI_i = $change\ in\ tree\ cover\ over\ impervious\ surfaces\ in\ block\ group\ i$
ΔTCP_i = $change\ in\ tree\ cover\ over\ pervious\ surfaces\ in\ block\ group\ i$
g_i = $some\ function\ of\ the\ decision\ variables\ (\Delta TCI_i\ and\ \Delta TCP_i)$
b_i = $limit\ of\ the\ available\ resources\ or\ a\ minimum\ goal\ of\ a\ specific\ objective$

Decision variables in this case are the increases (or decreases) in tree canopy cover (m^2) on either plantable pervious or impervious areas in each block group. Coefficients in the objective function (CI and CP) indicate the contribution of one m^2 of the corresponding change in tree cover for each ecosystem service being considered. CI and CP could be constants (assuming a linear response which is plausible over small changes in canopy cover) or a function of the decision variables or other environmental conditions, making the objective function nonlinear. In addition, ΔTCI_i and ΔTCP_i could be disaggregated into species specific plantings (thus facilitating biodiversity and other species-specific objectives); here it is assumed all species are aggregated into these variables. The number of services and benefits depends on specific city goals.

Multiple objectives can be combined in a single objective function if they can be expressed in commensurate terms, for example monetary units. Considering that some human health and aesthetic benefits from trees cannot be adequately captured by monetary terms or quantified in commensurate units, non-commensurate objectives can be accommodated in our framework to handle trade-offs between objectives. For non-commensurate objectives, the optimization can be executed with one selected objective reflected in the objective function and the other objectives treated as constraints or by treating each objective as a weighted component of the objective function (El-Sobky & Abo-Elnaga, 2018). In the weighting option, the non-commensurate objectives are weighted to reflect their relative importance; such a method suffers from the same subjective bias as the UTC prioritization framework and the Priority Planting Index. Here, we implement a constraint method for non-commensurate objectives to develop Pareto fronts, a set of non-dominated solutions where no objective can be improved without adversely impacting another objective.

Constraints can be incorporated as restrictions or limitations on the decision variables or other resources. Constraints can be functions of contractual obligations, planting or implementation costs, budget allocations, available and feasible planting spaces or any resource constraints defined by the user to guide the decision-making process. Depending on the form of the objective function and constraints (whether linear or non-linear), optimal solutions can be identified using a variety of mathematical optimization techniques including linear programming (Nash & Sofer, 1996), dynamic programming (Réveillac, 2015) and nonlinear programming (Sun & Yuan, 2006).

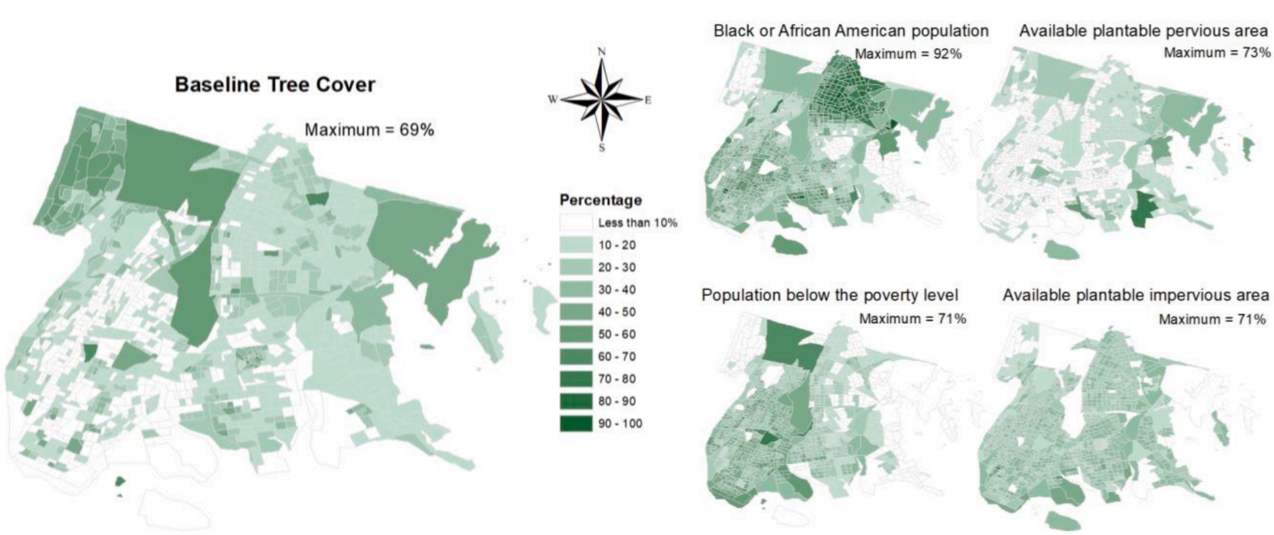

Fig. 1. 2010 tree cover distribution and proportions of Black or African American populations, available plantable pervious and impervious area and population with income below poverty level in each block group of the Bronx. "Maximum" refers to the largest value across all block groups. Note that most of the larger block groups contain parks and playgrounds.

Table 1
Description of variables.

Variable	Description
ΔTCI_i	Change in tree cover over impervious surfaces in block group i (m^2)
ΔTCP_i	Change in tree cover over pervious surfaces in block group i (m^2)
$Area_i$	Total area of block group i (m^2)
CG	Total canopy goal for entire borough (m^2)
$CI_{i,HI}$	Heat index reduction benefit per unit area of tree cover over impervious surfaces in block group i (K/m^2)
$CI_{i,PM}$	$PM_{2.5}$ air pollutant removal monetary benefit per unit area increase in tree cover over impervious surfaces for block group i ($\$/m^2$)
$CI_{i,SW}$	Avoided runoff monetary benefit per unit area increase in tree cover over impervious surfaces for block group i ($\$/m^2$)
$CP_{i,HI}$	Heat index reduction benefit per unit area of tree cover over pervious surfaces in block group i (K/m^2)
$CP_{i,PM}$	$PM_{2.5}$ air pollutant removal monetary benefit per unit area increase in tree cover over pervious surfaces for block group i ($\$/m^2$)
$CP_{i,SW}$	Avoided runoff monetary benefit per unit area increase in tree cover over pervious surfaces for block group i ($\$/m^2$)
G	Gini coefficient
HI	Total heat index reduction target for the Bronx (K)
MC_i	Minimum canopy threshold across all block groups
$MTCI_i$	Maximum increase of plantable impervious area in block group i (m^2)
B_AA_i	Number of people who identify as Black or African American in block group i
$MTCP_i$	Maximum increase of plantable pervious area in block group i (m^2)
N	Number of block groups (1,132 in the Bronx)
PPI_i	Number of people with income below the poverty level in block group i
TB	Total budget available for new plantings ($)
TC_i	Current tree cover in block group i (m^2)

2.2. Case Study: Bronx, NY

Optimal and equitable tree cover scenarios were explored to expand tree canopy in the Bronx from the baseline 2010 tree canopy cover of 22.7%. The Bronx was chosen as the case study location to test this framework because of a) air quality, storm water and urban heat island issues in this borough, b) its diverse demographics, and c) the lack of ecosystem services and benefits to some communities (Nyelele et al., 2019). Here, three ecosystem benefits are considered, improving air quality and reducing the urban heat index and storm water runoff, as well as the inequality in the tree cover percentage across block groups and inequity in the distribution of tree cover between more and less advantaged block groups, for example along socio-demographic and socio-economic parameters including wealth, class and race. These were all primary goals of MillionTreesNYC (Campbell et al., 2014; Locke et al., 2010). In each census block group plantable pervious and plantable impervious areas were defined from 2010 high-resolution UTC land cover imagery (MacFaden, O'Neil-Dunne, Royar, Lu, & Rundle, 2012). Across the 1,132 census block groups in the Bronx, there were a total of 2,264 decision variables, the increase in tree cover on plantable pervious and impervious surfaces in each block group. Fig. 1 illustrates the distribution of tree cover across census block groups in the 2010 baseline scenario, as well as the distribution of available plantable pervious and impervious areas, and percentages of Black or African American and population below the poverty level.

We assumed that all trees planted would grow to maturity and that current tree cover would be maintained. We also assumed planting costs on plantable impervious areas of $\$430/m^2$ (NYC Parks and Recreation, 2020), or $2,150 per tree assuming a $5\,m^2$ canopy area (McPherson, Simpson, Xiao, & Wu, 2011), while the planting costs for increasing tree cover on plantable pervious surfaces were estimated at $\$100/m^2$ (Central Park Conservancy, 2020), or $500 per tree. By including this as a budgetary constraint, the user could vary the cost of tree plantings throughout a city, which is a more accurate description of actual costs in most cities where land value and maintenance costs vary. Fourteen scenarios with varying objectives were explored to examine how different objectives lead to alternative preferred planting schemes. Table 1 describes input variables used in the optimization scenarios considered here.

2.2.1. Scenarios 1 to 3: Maximize individual ecosystem services and meet total canopy goal

To illustrate how single ecosystem service benefits can be maximized, three scenarios were analyzed, each maximizing a single benefit related to either $PM_{2.5}$ air pollutant removal monetary benefits, avoided runoff monetary benefits or heat index reduction benefits while meeting a 26% canopy goal. The 26% canopy goal is a midpoint between the current canopy and the 30% ultimate tree canopy goal of the MillionTreesNYC (Grove et al., 2006; Nyelele et al., 2019). The $400 million initial budget of the MillionTreesNYC initiative was also adopted (MillionTreesNYC, 2020).

$$\text{Scenario 1}: Max\sum_{i=1}^{N=1132}\left[\left(CI_{i,PM}*\Delta TCI_i\right)+\left(CP_{i,PM}*\Delta TCP_i\right)\right] \tag{2}$$

$$\text{Scenario 2}: Max\sum_{i=1}^{N=1132}\left[\left(CI_{i,SW}*\Delta TCI_i\right)+\left(CP_{i,SW}*\Delta TCP_i\right)\right] \tag{3}$$

$$\text{Scenario 3}: Max\sum_{i=1}^{N=1132}\left[\left(CI_{i,HI}*\Delta TCI_i\right)+\left(CP_{i,HI}*\Delta TCP_i\right)\right] \tag{4}$$

Subject to :

$$1:\ \sum_{i=1}^{N=1132}(430*\Delta TCI_i)+(100*\Delta TCP_i)\leqslant TB \quad \textit{Total Budget}$$

$$2:\ \Delta TCI_i\leqslant MTCI_i\ \ i=1,\ldots,\ 1132 \quad \textit{Available Plantable Impervious Area}$$

$$3:\ \Delta TPI_i\leqslant MTCP_i\ \ i=1,\ldots,\ 1132 \quad \textit{Available Plantable Pervious Area}$$

$$4:\ \frac{\sum_{i=1}^{N=1132}(TC_i+\Delta TCI_i+\Delta TCP_i)}{\sum_{i=1}^{N=1132}(Area_i)}\geqslant CG \quad \textit{Total Canopy Goal}$$

2.2.2. Scenario 4: Maximize tree cover, maintain budget and meet equality target

In this study we used the Gini coefficient as our inequality metric (Gini, 1909; Nyelele & Kroll, 2020). The Gini coefficient allows us to better assess current inequalities and work to achieve greater equity in the distribution of tree cover. Here we set the threshold for the maximum Gini for overall tree canopy distribution at 0.25 representing the midpoint between the current Gini = 0.35 and Gini = 0.16, the target Gini index from a Green Equity scenario in Boston, MA (Danford, Cheng, Strohbach, Ryan, Nicolson, & Warren, 2014). Scenario 4 maximizes canopy cover while keeping the Gini index below a specific target. Again the $400 million MillionTreesNYC budget was used.

$$Max \sum_{i=1}^{N=1132} [(\Delta TCI_i) + (\Delta TCP_i)] \tag{5}$$

Subject to :

$$1: \sum_{i=1}^{N=1132} (430*\Delta TCI_i) + (100*\Delta TCP_i) \leqslant TB \quad \textit{Total Budget}$$

$$2: \Delta TCI_i \leqslant MTCI_i \ i = 1, \ldots, 1132 \quad \textit{Available Plantable Impervious Area}$$

$$3: \Delta TPI_i \leqslant MTCP_i \ i = 1, \ldots, 1132 \quad \textit{Available Plantable Pervious Area}$$

$$4a: \frac{2*\sum_{i=1}^{N=1132}\left(i*\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)/Area_{(i)}\right)}{N*\sum_{i=1}^{N=1132}\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)/Area_{(i)}} - \frac{N+1}{N} \leqslant G \quad \textit{Equality Target}$$

The fourth constraint, the Equality Target, is nonlinear, but can be linearized as:

$$4b: \sum_{i=1}^{N=1132} [(2*i) - N*G - N - 1] * \frac{\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)}{Area_{(i)}} \leqslant 0$$

where $\frac{\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)}{Area_{(i)}}$ represents the percent tree cover for the block group with the i^{th} smallest percent tree cover. To maintain this ranking throughout the simulation, an additional constraint is needed:

$$5: \frac{\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)}{Area_{(i)}} \leqslant \frac{\left(TC_{(i+1)} + \Delta TCI_{(i+1)} + \Delta TCP_{(i+1)}\right)}{Area_{(i+1)}} \ i = 1, \ldots, 1131 \quad \textit{Tree Cover Ranking}$$

Without this constraint, a multi-step optimization would be needed, where after tree cover is added to block groups, the block groups would be reranked based on percent tree cover, and the optimization would be rerun based on these new rankings until convergence.

2.2.3. Scenarios 5 and 6: Maximize poverty- or race-weighted tree cover at specific budget

To fully address the issue of equity, i.e., the fair distribution of resources, especially the absence of systematic disparities between more and less advantaged social groups, we weighted new tree canopy by the number of people with income below the poverty level in 2010 (U.S. Census Bureau, 2018) in the i^{th} the block group (PPI_i) (Scenario 5), and the number of people in each block group identified as Black or African American (B_AA) in the 2010 census (U.S. Census Bureau, 2018; Scenario 6):

$$\text{Scenario 5}: Max \frac{\sum_{i=1}^{N=1132} PPI_{i*}(\Delta TCP_{i+}\Delta TCI_i)}{\sum_{i=1}^{N=1132} PPI_i} \tag{6}$$

Subject to :

$$1: \sum_{i=1}^{N=1132} (430*\Delta TCI_i) + (100*\Delta TCP_i) \leqslant TB \quad \textit{Total Budget}$$

$$2: \Delta TCI_i \leqslant MTCI_i \ i = 1, \ldots, 1132 \quad \textit{Available Plantable Impervious Area}$$

$$3: \Delta TPI_i \leqslant MTCP_i \ i = 1, \ldots, 1132 \quad \textit{Available Plantable Pervious Area}$$

Subject to :

$$1: \sum_{i=1}^{N=1132}(430^*\Delta TCI_i) + (100^*\Delta TCP_i) \leqslant TB \quad \textit{Total Budget}$$

$$2: \Delta TCI_i \leqslant MTCI_i \; i = 1, \ldots, 1132 \quad \textit{Available Plantable Impervious Area}$$

$$3: \Delta TPI_i \leqslant MTCP_i \; i = 1, \ldots, 1132 \quad \textit{Available Plantable Pervious Area}$$

$$4: \frac{2^*\sum_{i=1}^{N=1132}\left(i^*\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)/Area_{(i)}\right)}{N^*\sum_{i=1}^{N=1132}\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)/Area_{(i)}} - \frac{N+1}{N} \leqslant G \quad \textit{Equality Target}$$

$$5: \frac{\left(TC_{(i)} + \Delta TCI_{(i)} + \Delta TCP_{(i)}\right)}{Area_{(i)}} \leqslant \frac{\left(TC_{(i+1)} + \Delta TCI_{(i+1)} + \Delta TCP_{(i+1)}\right)}{Area_{(i+1)}} \; i = 1, \ldots, 1131 \quad \textit{Tree Cover Ranking}$$

$$\text{Scenario 6}: Max \frac{\sum_{i=1}^{N=1132} B\_AA_{i^*}(\Delta TCP_{i+}\Delta TCI_i)}{\sum_{i=1}^{N=1132} B\_AA_i} \tag{7}$$

2.2.4. Scenario 7: Maximize monetary benefits of air pollutant removal and avoided runoff and meet total canopy goal

Subject to :

$$1: \sum_{i=1}^{N=1132}(430^*\Delta TCI_i) + (100^*\Delta TCP_i) \leqslant TB \quad \textit{Total Budget}$$

$$2: \Delta TCI_i \leqslant MTCIi \; i = 1, \ldots, 1132 \quad \textit{Available Plantable Impervious Area}$$

$$3: \Delta TPI_i \leqslant MTCP_i \; i = 1, \ldots, 1132 \quad \textit{Available Plantable Pervious Area}$$

$$4: \frac{\sum_{i=1}^{N=1132}(TC_i + \Delta TCI_i + \Delta TCP_i)}{\sum_{i=1}^{N=1132} Area_i} \quad \textit{Total Canopy Goal}$$

Here we maximized the $PM_{2.5}$ air pollutant removal monetary benefits and avoided runoff monetary benefits to meet the 26% canopy goal. The $400 million planting budget from MillionTreesNYC was again employed.

$$Max \sum_{i=1}^{N=1132}\left[\left(CI_{i,SW} + CI_{i,PM}\right)^*\Delta \mathrm{TCI_i} + \left(CP_{i,SW} + CP_{i,PM}\right)^*\Delta \mathrm{TCP_i}\right] \tag{8}$$

2.2.5. Scenario 8: Maximize monetary benefits of air pollutant removal and meet equality goals under specified budget

This scenario maximized the $PM_{2.5}$ air pollutant removal monetary benefits while not exceeding the $400 million planting budget for MillionTreesNYC while adding an equality constraint to obtain a tree cover distribution with a specific Gini. To explore trade-offs between these non-commensurate objectives, we varied the right-hand side of the equality constraint (Gini) from 0.22 to 0.31 and plotted the Pareto front to illustrate how the equality constraint influences $PM_{2.5}$ air pollutant removal monetary benefits.

$$Max \sum_{i=1}^{N=1132}\left[\left(CI_{i,PM}^*\Delta TCI_i\right) + \left(CP_{i,PM}^*\Delta TCP_i\right)\right] \tag{9}$$

2.2.6. Scenarios 9 and 10: Maximize poverty- or race-weighted monetary benefits of air pollutant removal and meet equity goals under specified budget

To more fully address equity in Scenario 8, we incorporated the population with income below the poverty level into the objective function in Scenario 9 and added the population classified as Black or African American in Scenario 10:

$$\text{Scenario 12}: Max \frac{\sum_{i=1}^{N=1132} PPI_i\left[\left(CI_{i,SW}+CI_{i,PM}\right)^*\Delta \mathrm{TCI_i}+\left(CP_{i,SW}+CP_{i,PM}\right)^*\Delta \mathrm{TCP_i}\right]}{\sum_{i=1}^{N=1132} PPI_i} \tag{13}$$

$$\text{Scenario 13}: Max \frac{\sum_{i=1}^{N=1132} B\_AA_i\left[\left(CI_{i,SW}+CI_{i,PM}\right)^*\Delta \mathrm{TCI_i}+\left(CP_{i,SW}+CP_{i,PM}\right)^*\Delta \mathrm{TCP_i}\right]}{\sum_{i=1}^{N=1132} B\_AA_i} \tag{14}$$

$$\text{Scenario 9}: Max \frac{\sum_{i=1}^{N=1132} PPI_i\left[\left(CI_{i,PM}{}^*\Delta \mathrm{TCI_i}\right)+\left(CP_{i,PM}{}^*\Delta \mathrm{TCP_i}\right)\right]}{\sum_{i=1}^{N=1132} PPI_i} \tag{10}$$

$$\text{Scenario 10}: Max \frac{\sum_{i=1}^{N=1132} B\_AA_i\left[\left(CI_{i,PM}{}^*\Delta \mathrm{TCI_i}\right)+\left(CP_{i,PM}{}^*\Delta \mathrm{TCP_i}\right)\right]}{\sum_{i=1}^{N=1132} B\_AA_i} \tag{11}$$

Subject to :

$1: \sum_{i=1}^{N=1132}(430^*\Delta TCI_i)+(100^*\Delta TCP_i)\leqslant TB$ *Total Budget*

$2: \Delta TCI_i \leqslant MTCI_i \; i=1,\ldots, 1132$ *Available Plantable Impervious Area*

$3: \Delta TPI_i \leqslant MTCP_i \; i=1,\ldots, 1132$ *Available Plantable Pervious Area*

$4: \dfrac{2^*\sum_{i=1}^{N=1132}\left(i^*\left(TC_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)/Area_{(i)}\right)}{N^*\sum_{i=1}^{N=1132}\left(TC_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)/Area_{(i)}}-\dfrac{N+1}{N}\leqslant G$ *Equality Target*

$5: \dfrac{\left(TC_{(i)}+\Delta TCI_{(i)}+\Delta TCP_{(i)}\right)}{Area_{(i)}}\leqslant\dfrac{\left(TC_{(i+1)}+\Delta TCI_{(i+1)}+\Delta TCP_{(i+1)}\right)}{Area_{(i+1)}} \; i=1,\ \ldots,\ 1131$ *Tree Cover Ranking*

$6: \dfrac{(TC_i+\Delta TCI_i+\Delta TCP_i)}{Area_i}\geqslant MC_i \; i=1,\ldots, 1132$ *Minimum Canopy Threshold*

Subject to :

$1: \sum_{i=1}^{N=1132}(430^*\Delta TCI_i)+(100^*\Delta TCP_i)\leqslant TB$ *Total Budget*

$2: \Delta TCI_i \leqslant MTCI_i \; i=1,\ldots,1132$ *Available Plantable Impervious Area*

$3: \Delta TPI_i \leqslant MTCP_i \; i=1,\ldots,1132$ *Available Plantable Pervious Area*

2.2.7. Scenario 11: Maximize monetary benefits of air pollutant removal and avoided runoff and meet equality and minimum canopy goals under specified budget

We also explored how adding the equality, minimum canopy threshold and budget constraints together influence the maximization of the monetary benefits of $PM_{2.5}$ air pollutant removal and avoided runoff. The \$400 million planting budget for MillionTreesNYC was again used. The 10% minimum tree canopy threshold in each census block group was adopted from canopy cover goals from the City of Tallahassee (2018).

$$Max \sum_{i=1}^{N=1132}\left[\left(CI_{i,SW}+CI_{i,PM}\right)^*\Delta TCI_i+\left(CP_{i,SW}+CP_{i,PM}\right)^*\Delta TCP_i\right] \tag{12}$$

2.2.8. Scenarios 12 and 13: Maximize poverty- or race-weighted monetary benefits of air pollutant removal and avoided runoff to meet equity and minimum canopy goals under specified budget

To address the issue of equity in Scenario 11, we modified the objective function and incorporated the population with income below poverty levels (Scenario 12) and number of Black or African American people (Scenario 13) to obtain a more equitable solution where resultant

$$\begin{array}{lll} \textit{Subject to}: & & \\ 1: & \sum_{i=1}^{N=1132}(430^{*}\Delta TCI_i)+(100^{*}\Delta TCP_i)\leqslant TB & \textit{Total Budget} \\ 2: & \Delta TCI_i\leqslant MTCI_i \;\; i=1,\ldots,\; 1132 & \textit{Available Plantable Impervious Area} \\ 3: & \Delta TPI_i\leqslant MTCP_i \;\; i=1,\ldots,\; 1132 & \textit{Available Plantable Pervious Area} \\ 4: & \frac{(TC_i+\Delta TCI_i+\Delta TCP_i)}{Area_i}\geqslant MC_i \;\; i=1,\ldots,\; 1132 & \textit{Minimum Canopy Threshold} \end{array}$$

$$\begin{array}{lll} \textit{Subject to}: & & \\ 1: & \sum_{i=1}^{N=1132}(430^{*}\Delta TCI_i)+(100^{*}\Delta TCP_i)\leqslant TB & \textit{Total Budget} \\ 2: & \Delta TCI_i\leqslant MTCI_i \;\; i=1,\ldots,\; 1132 & \textit{Available Plantable Impervious Area} \\ 3: & \Delta TPI_i\leqslant MTCP_i \;\; i=1,\ldots,\; 1132 & \textit{Available Plantable Pervious Area} \\ 4: & \sum_{i=1}^{N=1132}\left(CI_{i,HI}^{*}\Delta TCI_i\right)+\left(CP_{i,HI}^{*}\Delta TCP_i\right)\geqslant HI & \textit{Heat Index Target} \end{array}$$

ecosystem services reach those that most rely on these services. The MillionTreesNYC planting budget ($400 million) was used.

2.2.9. Scenario 14: Maximize monetary benefits of air pollutant removal and avoided runoff and non-commensurate heat index reduction and meet total canopy goal

To show how non-commensurate objectives can be included in the same optimization, in this scenario we maximized the monetary benefits of air pollutant removal and avoided runoff in the same objective function and included the heat index reduction benefits as a constraint. Thus, the objective was to maximize the $PM_{2.5}$ air pollutant removal and avoided runoff monetary benefits subject to meeting the heat index reduction constraint. We used the $400 million MillionTreesNYC planting budget.

$$Max \sum_{i=1}^{N=1132}\left[\left(CI_{i,SW}+CI_{i,PM}\right)^{*}\Delta \mathrm{TCI_i}+\left(CP_{i,SW}+CP_{i,PM}\right)^{*}\Delta \mathrm{TCP_i}\right] \tag{15}$$

While the right-hand side of the heat index reduction constraint (*HI*) can be defined as the desired heat index reduction in each block group,

Table 2
Summary of scenarios explored.

Scenario	Tree cover increases	$PM_{2.5}$ air pollutant removal monetary benefit	Avoided runoff monetary benefit	Heat index reduction target	$400 million total budget	Available plantable area	26% canopy goal	0.25 Gini goal	Minimum 10% canopy threshold	Population below poverty weight	Black or African American population
1		OF			C	C	C				
2			OF		C	C	C				
3				OF	C	C	C				
4	OF				C	C		C			
5	OF				C	C				OF	
6	OF				C	C					OF
7		OF	OF		C	C	C				
8		OF			C	C		[a]C/ OF			
9		OF			C	C				OF	
10		OF			C	C					OF
11		OF	OF		C	C		C	C		
12		OF	OF		C	C			C	OF	
13		OF	OF		C	C			C		OF
14		OF	OF	C	C	C					

OF = Added to objective function.
C = Included as constraint.
[a] The right-hand side of this constraint is varied from 0.22 to 0.31 to develop a Pareto front; thus, this constraint is used as part of the objective function.

Table 3
Costs and benefits associated with increasing tree cover in each optimization scenario. Dollars ($) and area ($m^2$) are expressed in millions. Note that in all scenarios the number of block groups with heat index reductions is the same as the number of block groups with new tree cover.

Scenario	Block groups with new tree cover	Gini equality index	Potential percent tree canopy	$PM_{2.5}$ monetary benefits ($/yr.)	Avoided runoff monetary benefits ($/yr.)	Plantable pervious costs ($) (tree cover increases (m^2))	Plantable impervious costs ($) (tree cover increases (m^2))
1	873	0.35	26.0%	4.92	0.26	359 (3.59)	41 (0.10)
2	181	0.36	26.0%	1.25	0.46	359 (3.59)	41 (0.10)
3	554	0.31	26.0%	2.21	0.30	359 (3.59)	41 (0.10)
4	820	0.25	25.6%	1.82	0.36	295 (2.95)	105 (0.25)
5	552	0.35	25.9%	2.79	0.24	349 (3.49)	51 (0.12)
6	82	0.37	24.5%	1.79	0.55	152 (1.52)	248 (0.58)
7	873	0.35	26.0%	4.92	0.26	359 (3.59)	41 (0.10)
8	1077	0.25	25.2%	2.66	0.45	249 (2.49)	151 (0.35)
9	490	0.36	24.2%	4.48	0.59	131 (1.31)	269 (0.63)
10	453	0.37	25.0%	4.25	0.44	223 (2.23)	177 (0.41)
11	1077	0.25	25.1%	2.25	0.46	231 (2.31)	169 (0.39)
12	581	0.31	24.7%	3.62	0.52	173 (1.73)	227 (0.53)
13	464	0.31	24.7%	2.70	0.52	176 (1.76)	224 (0.52)
14	395	0.36	24.0%	3.94	0.74	66 (0.66)	334 (0.78)

the estimated heat index reduction benefits due to a change in tree cover in this analysis were small in each block group. As such we set *HI* as the total heat index reductions in Kelvins (K) across all block groups (0.2 K**N*), where *N* is the number of block groups and 0.2 K is the average per block group heat index reduction goal. Such a constraint allows us to maximize heat index reductions where possible to compensate for block groups that cannot achieve the 0.2 K reduction on their own.

2.3. Estimation of ecosystem service benefits

While the optimization framework presented can utilize data from any ecosystem service and benefit model, per unit area of tree cover services and benefits for this study were estimated for each census block group using spatially distributed i-Tree tools for 2010 tree cover conditions following Nyelele et al. (2019) methodology. Supplementary File 1 details an improvement over Nyelele et al.'s estimation of block group $PM_{2.5}$ air pollutant concentrations. To estimate air pollutant removal

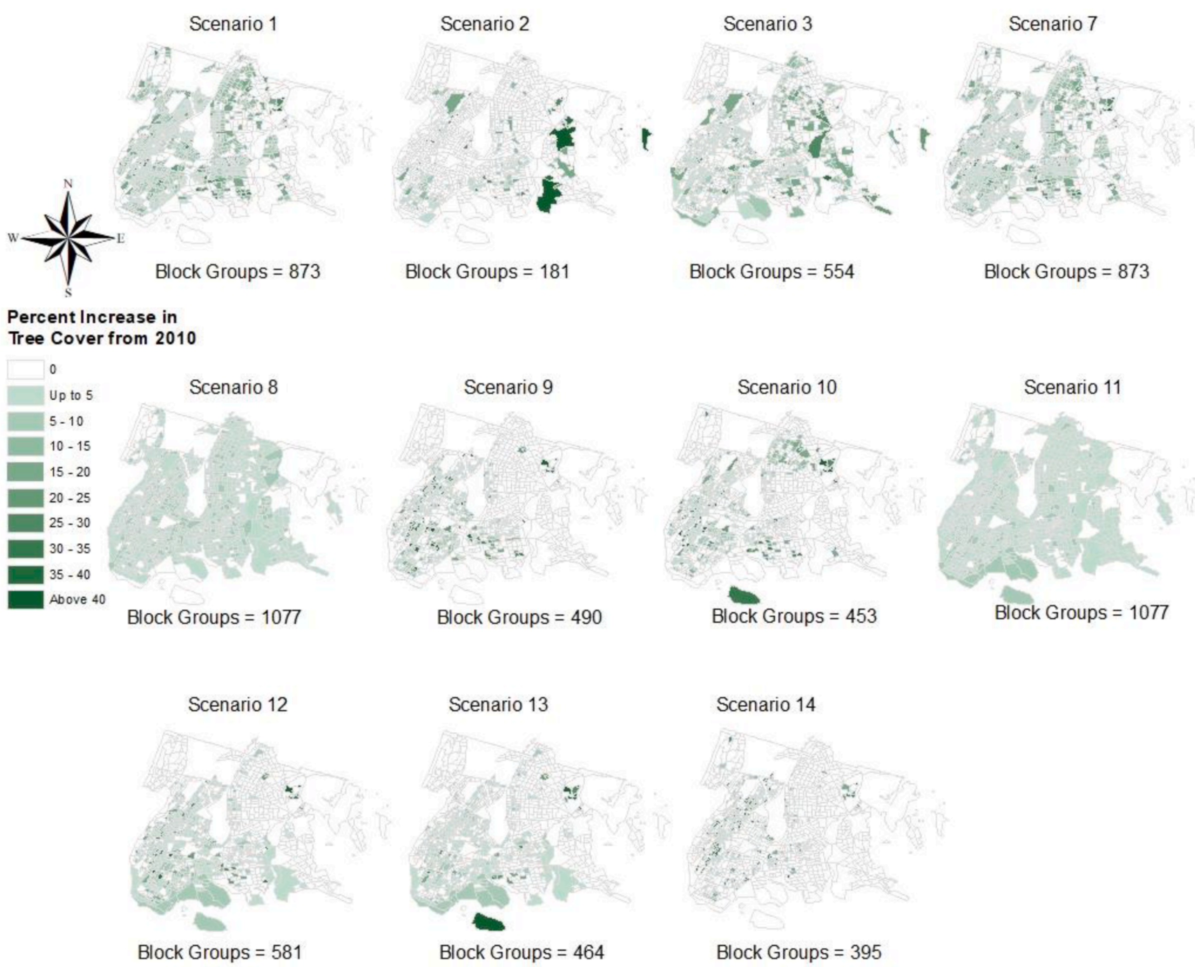

Fig. 2. Number of optimal block groups and percent tree cover increase from 2010.

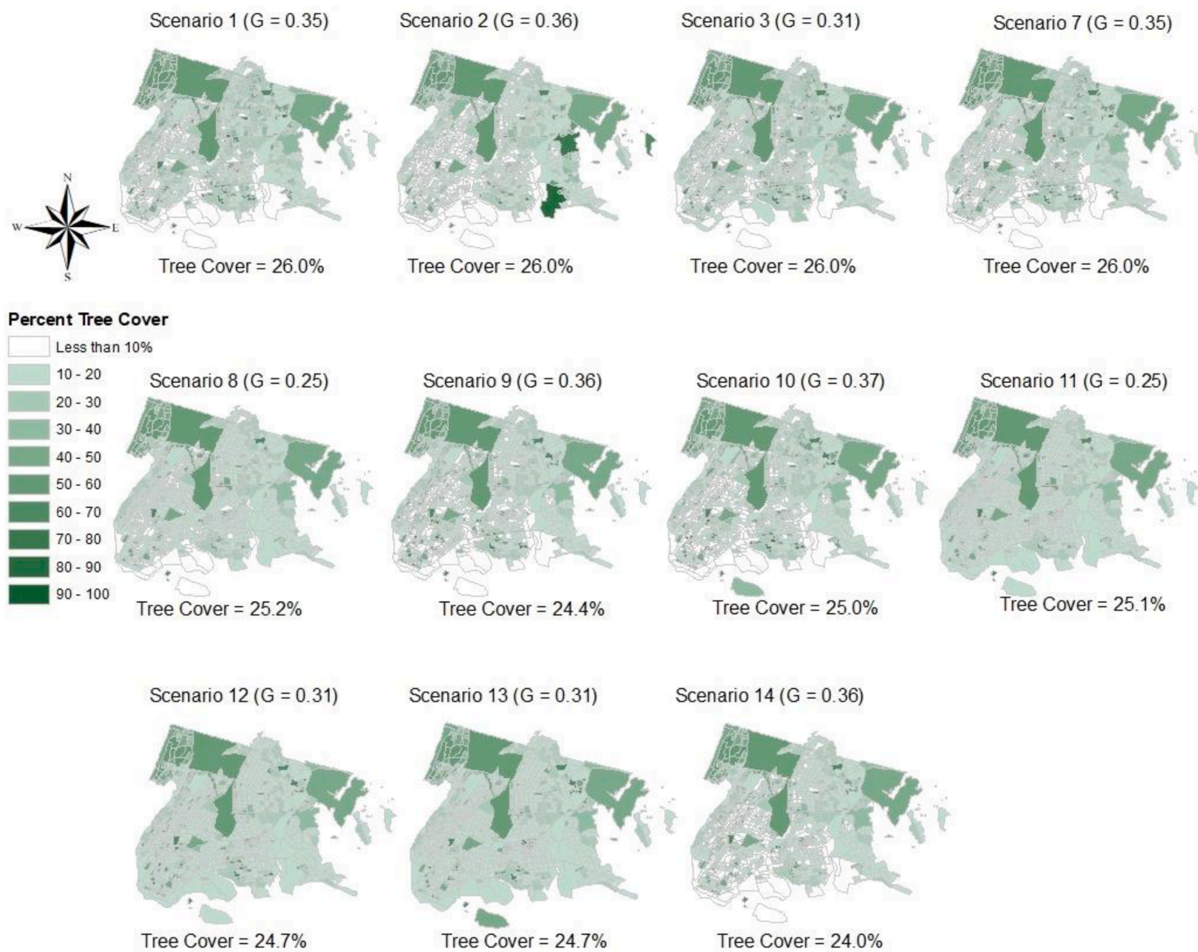

Fig. 3. Resulting tree cover distributions from maximizing multiple ecosystem service benefits.

services, i-Tree Eco does not distinguish between different land cover types; thus, in each block group the same per area of tree canopy monetary benefits were used in this analysis to estimate $PM_{2.5}$ air pollutant removal benefits from potential increases over both plantable pervious and impervious areas (CI and CP). To estimate CI and CP associated with 2010 avoided runoff and July 2010 heat index reductions in each block group, ecosystem services and benefits were first estimated for the 2010 tree cover conditions using i-Tree Hydro and i-Tree Cool following the methodology from Nyelele et al. (2019). Supplementary File 2 highlights how the models were run for plantable pervious and impervious scenarios.

2.4. Solution methodology

In this case study, the objective functions and all constraints except for the equality constraint were linear (Scenario 4 shows how to linearize the equality constraint). As such, linear programming using the package lpSolve in the R statistical computing software (R Core Team, 2013) was employed as the solution methodology to examine the optimal planting scheme obtained from the above multi-objective

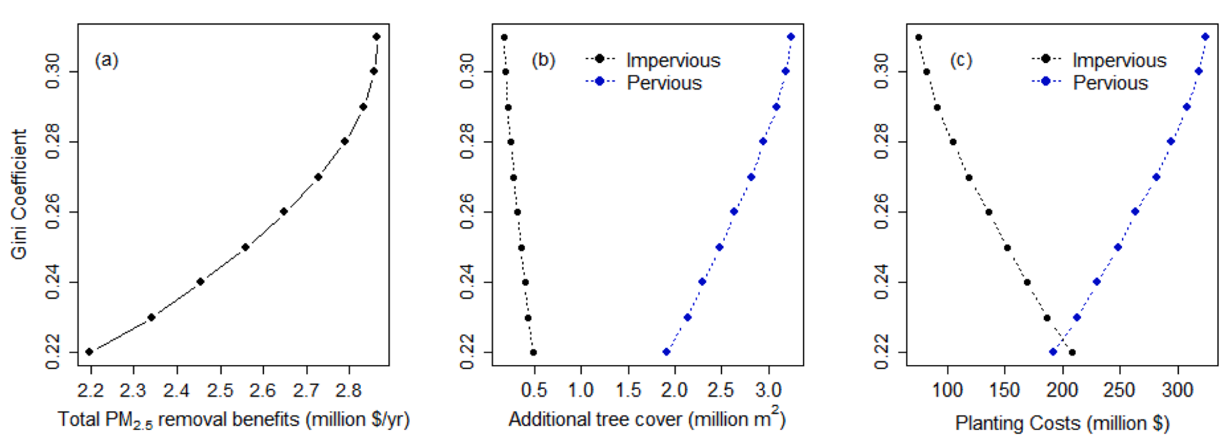

Fig. 4. Influence of the equity target on: a) $PM_{2.5}$ monetary benefits, b) additional tree cover increases over plantable pervious and impervious surfaces and c) planting costs associated with plantable pervious and impervious areas.

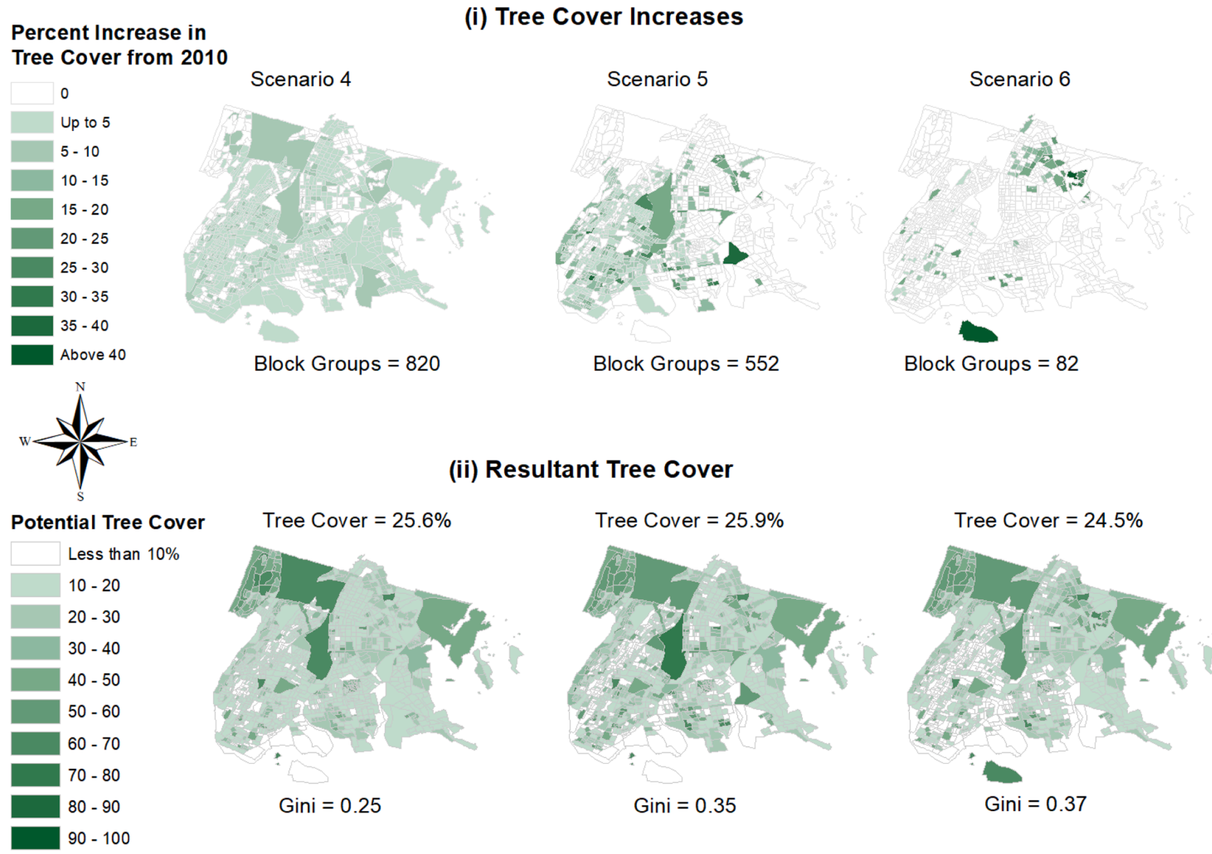

Fig. 5. (i) Percent tree cover increases and number of block groups identified for increased tree cover, and (ii) resultant tree cover distribution and Gini coefficient for Scenarios 4, 5 and 6.

optimization problem. If the coefficients in the objective function (CI and CP) were not assumed constant, a nonlinear optimization algorithm would be needed to solve this problem. Linear programming is generally a preferred solution algorithm over nonlinear optimization, as a global optimal should be obtained assuming a convex solution space (Griva, Nash, & Sofer, 2009). Linear programming also lends itself to easily interpretable sensitivity analyses due to changes in the right-hand side of constraints, which could be beneficial in some applications of this methodology.

3. Results

The optimization framework was able to identify the optimal block groups and amount of tree cover increases in plantable pervious and impervious areas in each of those block groups for the different optimization scenarios in the Bronx. The following sections present results for the various optimization scenarios explored. For each scenario we show the optimal block groups, tree cover increases, resultant tree cover distributions, as well as the costs incurred, and benefits obtained.

3.1. Maximizing ecosystem benefits

This section presents results from scenarios that maximized individual ecosystem service benefits (Scenarios 1, 2, 3, 8, 9 and 10), maximized the monetary benefits from $PM_{2.5}$ air pollutant removal and avoided runoff (Scenarios 7, 11, 12 and 13) and maximized $PM_{2.5}$ air pollutant removal, avoided runoff and heat index reduction benefits simultaneously (Scenario 14) under differing constraints. For ease of reference, we summarize these 14 scenarios in Table 2.

All scenarios resulted in tree cover increases over both plantable pervious and impervious areas. Results indicate that with the same budget of $400 million, different multi-objective approaches can be used to achieve varying tree cover distributions with different amounts of additional $PM_{2.5}$ air pollutant removal, avoided runoff and heat index reduction benefits (Table 3). We found the greatest increase in the number of block groups with additional tree cover in Scenarios 8 and 11 (Fig. 2), both of which address issues of equality via the inclusion of the Gini coefficient.

Scenario 14, which does not have a tree canopy goal constraint, results in the smallest amount of resultant canopy cover (24%) across all scenarios (Fig. 3). As depicted by the Gini coefficient (G) associated with each scenario, some scenarios (Scenarios 3, 8, 11, 12 and 13) result in a reduction in the inequality associated with their resultant tree cover distribution when compared to the 2010 baseline (Gini = 0.35).

In Scenario 8 we varied the Gini between 0.22 and 0.31 to illustrate potential tradeoffs between optimal solutions. Fig. 4a shows the Pareto front when the equality goal is relaxed (i.e., Gini increases) and there is an increase in the air pollutant benefits. Relaxing the equality constraint results in less tree cover increases over plantable impervious areas (Fig. 4b) and less money spent for impervious area plantings (Fig. 4c).

3.2. Maximizing tree canopy increases

Here we examine Scenarios 4, 5 and 6 that maximized tree canopy increases using equity or population weighted objectives. Scenario 4, which maximizes canopy cover while keeping the Gini index below 0.25, has the greatest number of block groups with optimal tree cover. Adding a measure targeting populations below the poverty level (Scenario 5) results in the highest amount of resultant canopy cover (25.9%) across these three scenarios (Fig. 5). Additionally, when compared to tree cover increases observed in Scenario 4, Scenarios 5 and 6 which targets block groups with Black or African American populations limit tree cover increases in large block groups that we know to typically contain parks and playgrounds and have few people living in them, as shown in Fig. 1. These results highlight how varying the optimization problem leads to different optimal solutions, and how tree cover goals can target specific populations.

3.3. Costs and benefits associated with increased tree cover

The various optimization scenarios also result in different ecosystem service and benefit spatial distributions. Table 3 summarizes the total benefits from increased tree cover for each scenario based on aggregating the canopy over plantable pervious and impervious benefits across block groups as well as the planting costs associated with achieving each scenario. Ecosystem service benefits from the resultant tree cover scenarios illustrate that the resultant tree cover increases will simultaneously lead to increases of different ecosystem services and benefits with potentially improved levels of equality and equity. Results show that while additional tree cover increases on both pervious and impervious surfaces result in increased benefits, there is a lower cost of implementation for trees planted in plantable pervious areas, and thus most of the tree cover increases occur over these areas. As a result, all scenarios, except for Scenarios 6, 9, 12, 13 and 14, identify solutions where most of the planting budget is in pervious areas (Table 3). Scenarios 9, 10, 12 and 13, which target populations below the poverty level and Black or African American populations, result in increased amounts of additional tree cover in plantable impervious areas and reduced amounts of additional tree cover over plantable pervious areas when compared to Scenarios 8 and 11 that address equality without any weighting of populations below the poverty level.

Scenario 1, which maximizes the monetary benefits from $PM_{2.5}$ removal and Scenario 7, which maximizes $PM_{2.5}$ removal and avoided runoff monetary benefits, result in the largest benefit for $PM_{2.5}$ removal. Scenario 14, which maximizes the monetary benefits of both air pollutant removal and avoided runoff and includes the heat index reduction benefits as a constraint, achieves the largest avoided runoff reduction monetary benefits. In general, scenarios that consider all three ecosystem benefits (Scenario 14) or target populations below the poverty level or with more Black or African American populations (Scenarios 9 and 10), perform well across all ecosystem service benefits.

4. Discussion

This analysis was motivated by the lack of studies that recommend areas to increase tree cover by comprehensively considering multiple ecosystem services and benefits from increased tree cover, particularly in areas of greatest need. Current frameworks may fail to fully inform decision-making processes of more equitable tree cover distributions, potentially exacerbating environmental injustice concerns. The weighted approach used in most studies to prioritize planting locations is subjective and often cannot determine optimal options beyond the existing expert's knowledge (Yoon et al., 2019). As such, where and how to increase tree canopy, particularly at fine scales such as the census block group, remains a problem for decision makers. This study sought to fill this informational gap and improve the decision-making process by creating a framework that could be used to answer critically important restoration questions on where to increase canopy or preserve urban forests.

To demonstrate the utility of the framework as a planning tool, we explored fourteen optimization scenarios at the census block group level in the Bronx, NY. Spatial optimization tools that systematically consider a range of scenarios, objectives, constraints, and stakeholder or societal preferences can help decision-makers gain insight into the full spectrum of feasible solutions (Weeks, Mason, Ausseil, & Herzig, 2014). In the scenarios explored, we focused on issues of concern to the Bronx: air quality, storm water, urban heat island and the inequality and inequity of tree cover (Campbell et al., 2014; Locke et al., 2010; Nyelele & Kroll, 2020; Nyelele et al., 2019). In general, results from these different scenarios illustrate how a multi-objective prioritization approach can be used to identify optimal locations for greater total benefits from urban greening. Knight et al. (2008) highlight that most tools and models in the literature do not result in management action, primarily because researchers never plan for implementation. Understanding that there are other underlying causes to this science-policy action gap (e.g., issues related to institutional capacity and capability, governance and resource availability), to illustrate how our framework can be used in the real world, we have shown different scenarios whose results indicate potential greening opportunities in relation to the imposed constraints. Our framework is flexible to handle a range of urban greening scenarios that can satisfy different environmental, economic, and social requirements of tree planting initiatives in different cities, potentially reducing the gap between scientific assessment and its application. For example, in Fig. 4a, we have shown how a manager interested in reducing inequities among block groups by lowering the Gini coefficient must be willing to trade-off on the potential $PM_{2.5}$ benefits to be realized from tree planting. The summary presented in Table 3 is useful for decision makers to assess how their urban planning goals compare to other scenarios in terms of costs, benefits, equality, and areas to target for tree cover increases. For example, one can focus on a scenario that considers all three ecosystem benefits (Scenario 14) or targets populations below the poverty level or with more Black or African American populations (Scenarios 9 and 10).

Many high priority locations identified for the establishment of tree cover from our analysis were in block groups that initially had limited amounts of tree cover. Interestingly, these are low-income neighborhoods, including most of the southern and western neighborhoods of the Bronx. These optimal schemes are different from the plantings undertaken under MillionTreesNYC where most of the new trees were planted in large block groups that mostly consist of parks and playgrounds due to the availability of plantable space (Garrison, 2019; Nyelele et al., 2019). Increasing tree cover in natural areas, parks and playgrounds makes sense if the goal is to maximize tree cover without consideration of the ecosystem benefits to be realized and the beneficiaries of those services and benefits. However, considering that block groups in the urban core have relatively few existing trees and limited opportunities to expand tree canopy (O'Neil-Dunne, 2012), communities most in need of additional tree cover might not receive it. By defining potential planting areas to include plantable impervious areas, we have increased the potential plantable area and shown how different optimal planting schemes may be identified. While some differences in scenarios do not appear particularly large, the difference between 24% and 26% canopy tree cover is approximately 2.1 million m^2 of tree cover. Thus, even a 0.5% tree canopy difference between the scenarios represents a large amount of tree cover. Similarly, to achieve a small change in the Gini coefficient requires a lot of resources to be invested in improving block groups with lower tree cover, especially considering that half the block groups with the lowest amount of tree cover account for less than 30% of the total tree cover in the Bronx.

Our results have shown that when there is a budgetary constraint and planting costs vary between plantable pervious and impervious areas, more tree cover increases will occur in plantable pervious areas due to the lower implementation cost. Schemes that consider only pervious areas such as bare soil and short vegetation as possible plantable areas will likely identify optimal areas that are typically parks and other natural areas with limited ecosystem service beneficiaries since these areas often have lower population densities. It is imperative to plant on both plantable impervious and pervious areas, especially for services such as heat island and stormwater abatement where reduction in impervious areas generally increase ecosystem benefits (O'Neil-Dunne, 2012). Our results show that to generate tree cover scenarios with greater overall benefits in the Bronx, we have to maximize multiple benefits simultaneously and plant on both plantable pervious and impervious areas (e.g., Scenarios 9, 10 and 14). While cities might focus on a single ecosystem service, we have shown that considering improving benefits across multiple ecosystem services (e.g., Scenario 14) can result in greater improvements in specific benefits without major decreases in other benefits. Assessment and evaluation of the goals, costs, and benefits of alternative tree planting initiatives such as those shown in Table 3 should be part of any urban forest management plan. While the specific goals of tree planting may vary across cities, planners and decision makers should systematically consider a range of scenarios, objectives, constraints, and stakeholder and societal preferences to gain insight into the full spectrum of feasible solutions. This will help identify the potential tradeoffs between different goals and allow policy makers to better understand the consequences of specific tree planting actions. For a manager, results from the different scenarios illustrate how a multi-objective prioritization approach can be used to explore different tree plantings scenarios that strategically target areas to plant and manage trees to optimize desired ecosystem services and realize greater total benefits while improving the distributional equity of tree cover and resultant ecosystem services and benefits. These results support an assertion by Almeter et al. (2018) that multi-objective designs that consider several benefits simultaneously will generate greater total benefits than single objective designs. Campbell (2014) also indicated that planting plans that quantify, monetize, and promote the urban forest for its multiple benefits are likely to be more successful.

Some of the outcomes that communities care most about (e.g., social cohesion, quality of place, and health) do not lend themselves to monetization (Almeter et al., 2018). We have shown how non-monetary objectives can be incorporated in our methodology to propose tree cover increases which provide non-commensurate ecosystem services. Our results have illustrated how the framework can be used to explore the tradeoffs in tree plantings schemes that promote equality and distributional equity of tree cover. Although most scenarios led to reductions in the Gini coefficient, distributions with improved equality targeted census block groups previously identified as underserved, particularly those in the south Bronx with disadvantaged socio-demographic and socio-economic neighborhoods with disproportionately low tree cover (Nyelele & Kroll, 2020). These areas have lower vegetation cover and associated ecosystem services relative to more affluent areas, yet these areas tend to be populated by those who rely more heavily upon these services (Escobedo, Clerici, Staudhammer, & Corzo, 2015; Flocks, Escobedo, Wade, Varela, & Wald, 2011; Hoffman et al., 2020; Jenerette, Harlan, Stefanov, & Martin, 2011; Nyelele & Kroll, 2020; Schwarz et al., 2015; Soto, Escobedo, Adams, & Blanco, 2016). To fully incorporate equity, studies should address both the production and the intended beneficiaries of ecosystem services. By including the number of people with income below the poverty level and those that identify as Black or African American, we have shown how tree planting prioritization can be carried out to ensure that resources reach the intended beneficiaries or communities that need them most. This component of the decision support framework improves on current prioritization schemes that often focus on planting more trees in areas with greater existing tree canopy, which can exasperate tree cover inequity (Garrison, 2019). Results from this study (e.g., Scenarios 9 and 10) have shown the potential for incorporating environmental justice within a decision making framework to achieve more beneficial outcomes from trees, especially for disadvantaged socio-economic and socio-demographic groups as well as marginalized communities that lack tree cover and the important ecosystem services and benefits they provide. This is important considering the history of environmental racism potentially mitigated by increased tree cover in communities of color and low-income communities in the U.S. (Bullard, 1993).

In our case study we implemented a constraint method for non-commensurate objectives to develop Pareto fronts by changing the right-hand side of the Gini coefficient equality constraint (Scenario 8). This allowed us to assess potential tradeoffs between different objectives. Howe, Suich, Vira, and Mace (2014) and Halpern et al. (2011) highlight that there are inherent trade-offs between ecosystem services or benefits and equity as well as equality. Identification of potential tradeoffs allows policy makers to better understand the hidden consequences of preferring one objective to another. For example, with $PM_{2.5}$, the greater the tree cover the greater the pollutant removal, and the greater the pollutant removal and population density, the greater the monetary value of this benefit (Nowak, Hirabayashi, Bodine, & Greenfield, 2014; Nyelele et al., 2019). However, due to the minimal spatial variation in the weather and pollutant concentration data used in this study, the primary driver of PM_{25} removal rates was canopy cover, which resulted in increases in canopy cover in pervious areas that are typically parks and natural areas. On the other hand, achieving a more equitable tree cover distribution will result in some tradeoff with $PM_{2.5}$ air pollutant removal benefits since achieving equality requires planting be undertaken in block groups that have limited plantable pervious area. Such an analysis can help planners explore the sensitivity of their tree planting plans to the constraints on their system. Since linear programming was used in this analysis, for each scenario one can easily calculate the marginal change in the objective function due to a change in the right-hand-side of each constraint. For example, if the budget is increased or decreased between a certain range of values, one can explore what services and benefits are impacted by the resulting solution.

While the optimization framework was successful in identifying optimal and equitable planting locations in the Bronx and can be used to improve decision-making for comprehensive urban greening plans satisfying multiple objectives, there are limitations of this work. For example, in this analysis we did not consider the full range of benefits that trees provide, focusing here on the three primary benefits of interest in the Bronx. We also did not consider time elapsed for the full benefits from newly planted trees to be realized. Chazdon and Guariguata (2018) highlight that modeling the potential supply of ecosystem services at a given location does not provide information on the temporal trajectory required to reach this potential, which can be critically important for restoration planning. We assumed that benefits are immediate, that current cover will be maintained, and that newly planted trees will reach maturity with no mortality. Future studies can build on this work and explore ecosystem benefit curves under various growth and mortality scenarios as well as how to incorporate differing stakeholder social values and preferences, facilitating the use of more accurate and spatially varying input data (Weeks et al., 2014). Additionally, future studies could also consider the differences in synergies and tradeoffs associated with prioritizing specific tree species or increasing the diversity of vegetation across an urban area. While this study uses the i-Tree modeling framework, there are other modeling tools available to quantify and commodify the value of urban forests. This study focuses on an optimization framework which could be used in different cities where spatially varying data can be obtained. The successful application of the framework will depend on the mathematical and computational skills necessary to implement this multi-objective prioritization model as well as the complexity of the optimization problem being addressed, including the number of ecosystem services and benefits considered, their spatial interaction and the degree of linearity or non-linearity of the services and benefits considered (Weeks et al., 2014).

5. Conclusion

This study developed a framework to facilitate decision-making for comprehensive urban greening plans satisfying multiple objectives and applied this framework to a case study in the Bronx, NY to identify optimal planting locations for potential tree cover increases. Results of this study have shown the utility of the decision support framework in identifying optimal locations for tree cover increases based on different objectives and resource constraints, as well as how multi-objective prioritization can be used to identify optimal locations that generate greater total benefits from urban greening. While the direct results of this study are important, the significance of this study is in its potential to improve decision making for a range of decision makers that work on urban forest management, as well as individuals and community-based organizations who are advancing tree planting efforts from alternative priorities and objectives such as climate resilience, ecological and environmental health, human health, as well as social and health equity priorities in different cities. With numerous tree planting initiatives being undertaken in different cities and with limited space for greening in most urban areas, it is crucial for decision makers to know how to optimize the spatial configuration of greenspaces to get the maximum benefit from increased tree cover. Beyond identifying the best locations to plant trees, this framework can also help cities systematically reach other social, economic, and ecological goals.

6. Author statement

Charity Nyelele and Charles N. Kroll contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2021.104172.

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