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A comparison of tree planting prioritization frameworks: i-Tree Landscape versus spatial decision support tool

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ABSTRACT

Different models as well as planting prioritization and optimization schemes based upon diverse ecological, social, and economic goals and preferences have been used to develop more efficient and effective tree planting schemes. We compare tree planting prioritization scenarios identified from i-Tree Landscape's priority planting index to optimal scenarios identified from a spatially explicit multi-objective decision support framework at the census block group level in the Bronx, NY. We explore four scenarios with varying objectives considering populations below the poverty line, avoided runoff, and $PM_{2.5}$ air pollutant removal monetary benefits. Results show that when prioritizing single objectives (e.g., $PM_{2.5}$ air pollutant removal) using the same per area of tree canopy benefits from the spatially distributed modeling of ecosystem services, the two approaches recommend similar block groups for additional tree cover. Scenarios considering multiple objectives, however, result in different optimal solutions, with the decision support framework generally recommending more block groups for increased tree cover than i-Tree Landscape's methodology. When the per area of tree canopy benefits from i-Tree Landscape are used as input in the i-Tree Landscape prioritization scenarios and the spatially distributed benefits used in the decision support framework scenarios, different optimal solutions are identified between the two approaches across all four scenarios, with i-Tree Landscape recommending fewer block groups for increased tree cover. Such a comparison will help inform the development of flexible multi-objective decision support tools to guide future greening initiatives towards prioritizing planting locations that maximize multiple objectives, as well as areas to preserve urban forests.

1. Introduction

As human population densities increase, there is often a spatial mismatch between the places where humans use or need ecosystem services and the location of ecosystems that produce them (Syrbe and Walz, 2012). With numerous tree planting initiatives being undertaken in different cities to provide multiple ecosystem services and benefits to many communities, careful thought needs to be put into considering the placement of trees and their beneficiaries, as well as viable alternatives. According to the Millennium Ecosystem Assessment (2005), ecological management that considers and manages ecosystem service interactions is likely to produce far better outcomes for societies. Increasing tree cover has the potential for significant co-benefits to be realized across a range of human health and environmental arenas (Salmond et al., 2016). Urban forests can help alleviate some of the detrimental environmental and human health impacts of urbanization (Livesley et al., 2016).

To achieve more beneficial outcomes from urban trees, tree planting prioritization schemes employing a variety of approaches and criteria have been explored. In New York City (NYC), Locke et al. (2010) identified and prioritized tree planting sites based on need and suitability, considering air quality, noise pollution, biodiversity, public health, water (flooding), Urban Heat Island (UHI), income and crime. Morani et al. (2011) identified the highest priority planting locations in NYC by combining three main indicators: pollution concentration, population

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density and low canopy cover. Under MillionTreesNYC, the highest priority zones for tree planting within NYC were selected considering air pollutant concentration, population density and low canopy cover (Locke et al., 2010). Zhang et al. (2017) combined remote sensing, Geographic Information Systems (GIS), spatial statistics and spatial optimization to optimize new green spaces that reduce the UHI effect in central Phoenix. Locke et al. (2013) identified where to increase Urban Tree Canopy (UTC) in Baltimore (MD) based upon diverse ecological, social, and economic goals and preferences; they ultimately factored in public health and safety, environmental justice, water quality, air quality, and noise pollution. Bodnaruk et al. (2017) took a more quantitative approach by developing planting schemes based on the optimization of metrics related to ecosystem services and benefits. Their approach was based on gradients of multiple ecosystem services and benefits, specifically optimizing air pollution and heat mitigation ecosystem services by trees in Baltimore (MD). There are a variety of prioritization frameworks for identifying areas to target for tree cover expansion, and there is a need for a more comprehensive framework that integrates diverse value systems to inform decision-making processes, policy options, and management measures in different cities and contexts.

Numerous studies have shown how urban forestry models can help develop more efficient and effective planting schemes to optimize desired ecosystem services, reduce inequities, identify areas where existing forests should be maintained, better quantify the benefits of these forest resources, and improve the overall management of urban forests. However, most of the tools developed to improve science-based decision making in urban forest management often go unused due to highly variable management contexts and changing priorities. 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. With large-scale tree planting activities happening in many cities, there is a need for interdisciplinary research that couples biophysical and social science knowledge to improve the usability and effectiveness of tools for determining future tree planting locations.

The framework of a priority planting index is already part of i-Tree Landscape, i-Tree's spatially explicit modeling platform (https://landscape.itreetools.org/). Among other socio-demographic variables, ecosystem services and benefits derived from running county-based lumped versions of i-Tree tools guide i-Tree Landscape's prioritization scheme. For example, in modeling air pollution removal rates at the national scale, which are used in i-Tree Landscape, the i-Tree Eco model was run at the county scale using local meteorology, Leaf Area Index (LAI), tree cover, human population, and air pollution concentration data to produce an estimate of air pollution removal and associated health effects per square meter of tree cover (Hirabayashi et al., 2012). Lumped models conceptualize and simulate a spatially heterogeneous region as a single unit (e.g., using a mean value from a statistical sample of the trees in a region) to estimate tree effects on carbon sequestration, energy use, pest infestations, air pollution, stormwater volumes, and water quality (Wang et al., 2005). While this lumped approach provides excellent city-scale information for urban planning, it makes assumptions that simplify the relationships between the structure and function of urban forests and the representation of urban landscapes (Nyelele et al., 2019), and does not represent the fine scales that link tree effects to specific local conditions and residential populations and at which local planning occurs (Wang et al., 2005). In addition, unlike objective approaches that obtain weights through mathematical programming, the weighting methodology for identifying priority planting areas in i-Tree Landscape potentially suffers from subjectivity as it requires the decision maker to decide on the contribution of each variable to the goal (Nyelele and Kroll, 2021). Furthermore, prioritization tools such as i-Tree Landscape embrace tree benefits without equivalent attention to their monetary costs (e.g., those related to planting and maintenance) (Escobedo et al., 2011). Current prioritization tools also lack the means to quantify inequities of tree cover and ecosystem service distributions and thus can fail to identify planting schemes that improve areas of greatest need (Nyelele and Kroll, 2020 and 2021).

In light of the above, Nyelele et al. (2019) utilized a spatially distributed implementation of the i-Tree suite of ecosystem service models and mapping tools to estimate the current and future ecosystem services and benefits within each census block group of the Bronx, NY for 2010 and for three 2030 tree cover scenarios. Nyelele and Kroll (2021) went on to use these spatially distributed ecosystem service and benefit estimates to develop a multi-objective decision support framework using a spatially distributed methodology utilizing i-Tree tools to develop improved priority planting locations. The framework is developed with management action and implementation in mind as it can be applied to variable management contexts and changing priorities. Additionally, the framework comprehensively integrates and analyzes multiple objectives focused on maximizing the provision of multiple ecosystem services and benefits, achieving equitable tree cover distributions as well as identifying the best areas to increase urban forest canopy. The multi-objective decision support framework developed by Nyelele and Kroll (2021) could run on any spatial unit, but the case study application of the framework was undertaken at the census block group level, a scale where census demographic data is readily available in the United States (U.S.).

Using the Bronx, NY as a case study at the census block group level, this study explores how optimal locations from Nyelele and Kroll's (2021) decision support framework compare to those from i-Tree Landscape's prioritization scheme. We chose the Bronx to build on ongoing work exploring tree cover distributions and developing tree planting prioritization approaches that identify planting scenarios with improved ecosystem service provisions and have the potential to address existing environmental justice and equity issues in the area. Of interest are the preferred locations where benefits related to stormwater runoff reduction and $PM_{2.5}$ air pollutant removal by trees are maximized. Such a comparison extends the work of Nyelele and Kroll (2021) and we hypothesize that the multi-objective prioritization approach they propose will predict tree planting scenarios that are significantly different to those predicted by i-Tree Landscape. Most importantly, these comparisons will help establish how their proposed decision support framework can be used to improve the methodology in i-Tree Landscape as well as other existing tools to: i) incorporate spatially distributed services and benefit inputs, ii) incorporate objectivity when determining variable weights, iii) embrace tree benefits as well as their monetary costs and, iv) include measures of inequity in identifying optimal and equitable planting schemes. This work is particularly important not only for its direct results, but for the potential of improving tree planting decision support tools so that they have broad and practical applications for a range of agencies and municipalities that work on urban forest management.

2. Research methodology

2.1. Description of the study area

The Bronx, one of NYC's five boroughs, is divided into 1132 census block groups and has an estimated population of approximately 1.4 million people (U.S. Census Bureau, 2010; 2021a). The elevation of the borough ranges from 0 to 97.5m above mean sea level and the area receives mean annual precipitation of 1016 – 1320mm with a frost-free period of 216 – 234 days. The native soils of the area are predominately sandy loam with a parent material of asphalt over human-transported material (U.S. Department of Agriculture Natural Resources Conservation Service, 2017; Nyelele et al., 2019). Fig. 1 shows the location of the Bronx as well as the land cover distribution of the area from a 2010 UTC assessment high resolution dataset processed by MacFaden et al. (2012). Based on these 2010 land cover conditions, the Bronx had 22.7% tree cover, 16.3% short vegetation, 1.1% bare soil, 1.9% water, and 58% impervious surfaces. Most of the tree cover in the Bronx is found in large

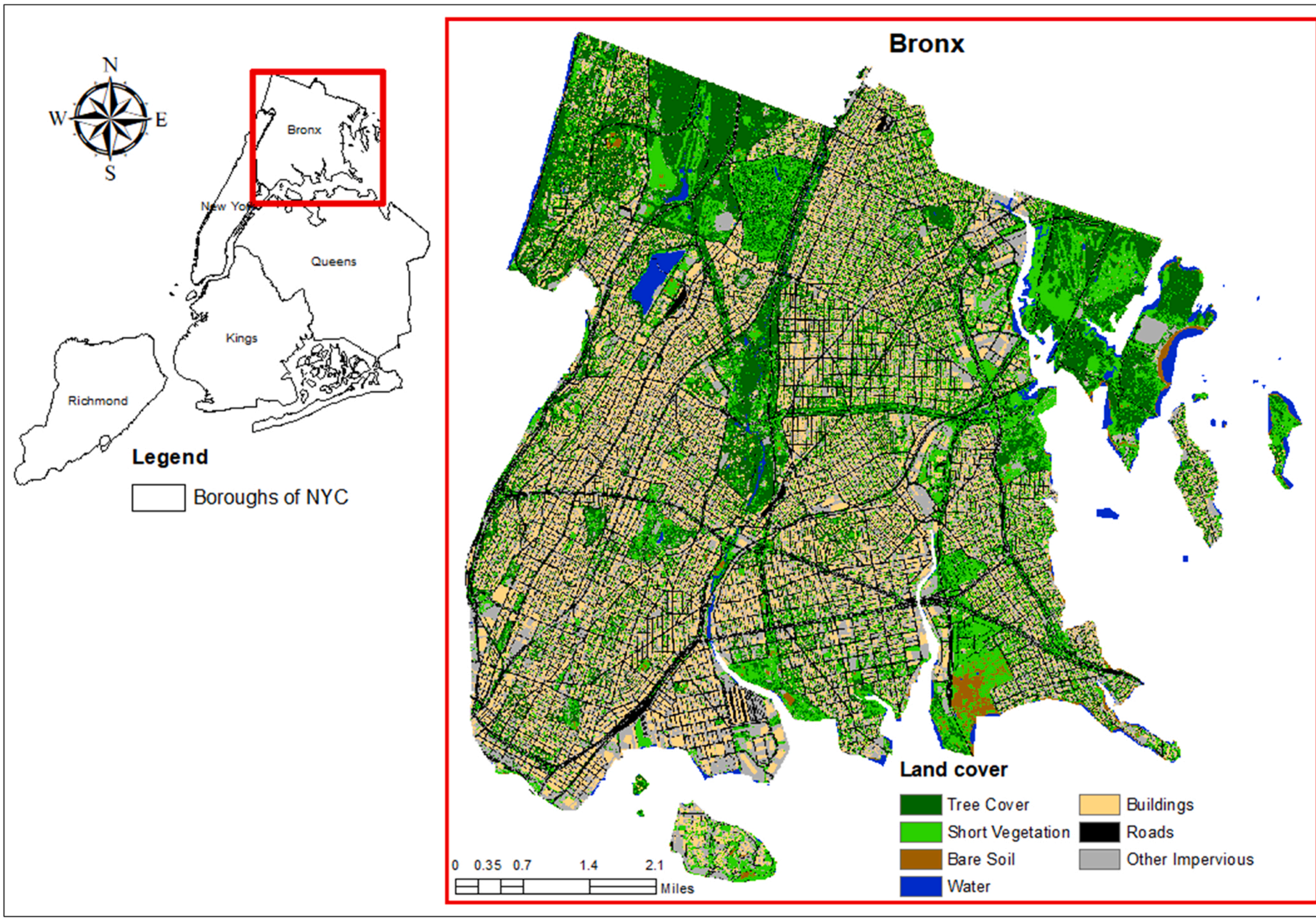

Fig. 1. Land cover of Bronx, NY from 2010 UTC assessments
(Source: Nyelele et al. (2019)).

groups of trees, primarily urban parks and natural areas owned and managed by the Department of Parks and Recreation.

2.2. Estimation of ecosystem services and benefits

2.2.1. Spatially distributed ecosystem services and benefits

Spatially distributed ecosystem service and benefit estimates used in the analysis were derived from Nyelele et al. (2019) who estimated ecosystem services and benefits for the 2010 tree cover conditions shown in Fig. 1 using spatially distributed versions of i-Tree models at the census block group level in the Bronx. Specifically, $PM_{2.5}$ air pollutant reductions (g/m^2 tree cover/person) and the monetary benefits (\$/m^2 tree cover/person) of those reductions (based on estimates of incidences of adverse health effects and associated monetary values resulting from changes in pollutant concentrations) were modeled using i-Tree Eco (Nowak et al., 2008). Avoided runoff was modeled using i-Tree Hydro (Wang et al., 2008) and the monetary benefits of the avoided runoff was calculated at the national average of \$2.36/m^3 based on the USFS' Community Tree Guide series (Hirabayashi, 2013). Carbon storage and sequestration were calculated using the latest per area of tree canopy cover carbon removal rates for NYC (Nowak et al., 2018) while the monetary benefits of carbon storage (\$) and sequestration (\$/yr) were estimated at \$129.8 per ton of carbon based on the social costs of carbon for 2015 (Nowak and Greenfield, 2018). The methodology related to the estimates presented above is detailed in Nyelele et al. (2019).

2.2.2. i-Tree Landscape ecosystem services and benefits from lumped i-Tree models

In the Bronx, i-Tree Landscape utilizes tree, impervious and land cover data from the UTC assessment, U.S. census data and ecosystem service output for each county in the U.S. from the i-Tree Eco model. In the lumped county model, local tree cover, LAI, percent evergreen, meteorological, pollution, and population data are used to estimate pollution removal (g/m^2 tree cover/person) and values (\$/m^2 tree cover/person) in urban and rural areas for each county of the U.S (Nowak et al., 2014). Monetary estimates of air pollutant removal are based on local health impacts estimated using the U.S. EPA BenMAP model for each county. These values are applied to the local block group population total and tree cover to estimate pollution removal values for each census block group. Similarly, estimates of the avoided runoff for each county in the conterminous U.S. in 2010 were developed using the lumped county i-Tree Eco model and local LAI and meteorologic data (Hirabayashi, 2015; Hirabayashi and Endreny, 2015; Hirabayashi and Nowak, 2015). These values are then scaled to per unit area (m^2) of tree cover to determine removal and monetary values related to increases (or decreases) in tree cover. To derive ecosystem service and benefit estimates from the lumped i-Tree Eco county model used in i-Tree Landscape, we ran i-Tree Landscape at the census block group level using the 2010 UTC land cover assessment (Fig. 1).

2.3. Comparison of tree planting prioritization schemes

2.3.1. i-Tree Landscape's planting priority index

To determine priority locations to plant or protect trees in i-Tree

Landscape, tree, and impervious cover data in conjunction with the U.S. census data are used to create an index that highlights priority areas among the selected geographic units. The index is developed by weights for user selected layers (ranging between 0 and 100 such that the sum of the layer weights equal 100). The higher the index value, the higher the priority of the area for tree planting or protection. Multiple layers can be used in the prioritization, and these can be selected from future climate, land cover, tree canopy benefits, health risk, forest risk, and U.S. census-derived data including population density, minority population density, percent population below poverty line, tree cover per capita, and tree stocking level (percent of pervious land occupied by tree cover). To account for differences in geographic areas, all index inputs are either in percentages or standardized per unit area or person. Each non-percentage layer is standardized on a scale of 0–1 with 1 representing the geographic area with the highest value in relation to the priority (e.g., areas with highest population density, lowest stocking density or lowest tree cover per capita are standardized to 1). The following is an example of an index from the i-Tree Landscape website which combines individual scores from population density (PD), tree stocking level (TS) and tree cover per capita (TPC) layers to produce an overall priority index (PI) value. Default weights of 40, 30 and 30 are used to illustrate how the sum of weights should be equal to 100.

$$PI = (PD * 40) + (TS * 30) + (TPC * 30) \tag{1}$$

PD, TS and TPC are standardized values (0−1) calculated as follows:

$$PD = (n_1 - m_1) / r_1 \tag{2}$$

$$TPC = 1 - [(n_2 - m_2) / r_2] \tag{3}$$

$$TS = [1 - (t / (t + g)] \tag{4}$$

Where:

n_1 = population density for the census block group in question (population/km^2).
m_1 = the minimum population density for all census block groups (population/km^2).
r_1 = the range of population density across all census block groups (population/km^2).
n_2 = the tree cover per capita for the census block in question (m^2/capita).
m_2 = the minimum tree cover per capita for all census block groups (m^2/capita).
r_2 = the range of tree cover per capita across all census block groups (m^2/capita).
t = percent tree cover for the census block group in question.
g = percent grass cover for the census block group in question.

PI is then standardized to yield values between 0 (lowest priority) and 100 (highest priority). This approach selects weights based on preferential information given by the decision maker and may reflect the subjective experience and judgment of the decision maker or expert.

2.3.2. Multi-objective optimization from the decision support framework

Nyelele and Kroll (2021) developed a general optimization framework which can be applied to inform urban greening and restoration interventions in any city if spatially specific data including ecosystem services and benefits per unit area of tree cover can be derived. Such a framework is useful in identifying Pareto optimal locations, where one can assess the tradeoffs and synergies between different objectives. Although the framework can incorporate ecosystem service and benefit data from any model, the case study application in the Bronx utilized a spatially specific implementation of various i-Tree tools (i-Tree Eco, i-Tree Hydro, and i-Tree Cool) at the census block group level to characterize urban forest ecosystem services and benefits.

The multi-objective decision support framework could run on any spatial unit (depending on data availability) and is set up as a general optimization problem which maximizes (or minimizes) some objective function subject to a series of constraints by changing a set of decision variables. 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:

$$Max \quad \sum_{i=1}^{N} \sum_{j=1}^{M} \left[\left(CI_{i,j} * \Delta TCI_i \right) + \left(CP_{i,j} * \Delta TCP_i \right) \right] \tag{5}$$

Subject to: $g_i(\Delta TCI_i, \Delta TCP_i) \geq, \leq \ or \ = b_i$ where:

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

The decision variables in the above formulation are the increases (or in some instances decreases) in tree canopy cover (m^2) on either plantable pervious or impervious areas in each block group. This is another key difference between the decision support framework proposed by Nyelele and Kroll (2021) and i-Tree Landscape's prioritization. i-Tree Landscape has the option of prioritizing planting areas in "plantable spaces" whose estimates are derived from National Land Cover Database (NLCD) data and calculated as land area minus the sum of canopy and impervious area. To identify areas better suited to meet planting goals, in each block group the decision support framework evaluates available plantable pervious (short vegetation or bare soil) and plantable impervious (impervious surfaces that are not buildings or roads) areas defined from 2010 high-resolution UTC land cover imagery (MacFaden et al., 2012). Coefficients in the objective function (CI and CP), indicate the contribution of one m^2 of the corresponding change in tree cover (Chinneck and Ramadan, 2000; Kim et al., 2018) for each ecosystem service being considered. There is no limit on the number of services or benefits to include; this will depend on the problem being addressed and the availability of the data.

Such a framework can handle multiple objectives either in a single objective function (if they can be expressed in commensurate terms, for example monetary units), with one selected objective reflected in the objective function and the other objectives treated as constraints, or similarly to i-Tree Landscape by developing the overall objective as the weighted sum of the individual objectives (Brisset and Gillon, 2015; El-Sobky and Abo-Elnaga, 2018; Wurbs, 1991). Additionally, the multi-objective framework allows for the incorporation of restrictions or limitations on the decision variables or other resources. These 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, the problem can be solved using a variety of optimization techniques that include linear programming, dynamic programming, and nonlinear programming.

2.3.3. Prioritizing tree planting locations

In Nyelele and Kroll (2021) 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%. Three ecosystem benefits from trees were considered (air quality improvements, urban heat index and storm water runoff reductions) as well as the inequality and inequity in the distribution of tree cover across census block groups. Planting costs were assumed to be $430/m^2 on plantable impervious areas while the planting costs for increasing tree cover on plantable pervious surfaces were estimated at $100/m^2. Here, we show how this spatial optimization technique and i-Tree Landscape differ in how they identify priority or optimal planting locations using four scenarios that consider monetary benefits related to air quality and avoided runoff. Each scenario described below is undertaken in the decision support framework and following the i-Tree Landscape prioritization scheme by equally weighting the relevant data layers to see which census block groups are given priority and then increasing tree cover in order of priority. Table 1 describes input variables used in the optimization scenarios considered here.

Since i-Tree Landscape does not plant on impervious areas, to be consistent we assumed that we cannot plant on impervious areas. Thus, following the i-Tree Landscape methodology, in each block group the potential planting area (*MTCP*) was calculated as the total land area minus the sum of tree canopy and impervious area. Following is a general description of the four different optimization scenarios considered in this analysis. Each of these scenarios is explored in a case study in the Bronx.

2.3.3.1. Scenario 1 and 2: Prioritizing individual ecosystem services. The first two scenarios illustrate how the monetary benefits associated with $PM_{2.5}$ air pollutant removal and avoided runoff can be prioritized during tree planting. Assuming a $100/m^2 planting cost, we include a $100 million budget to limit increasing tree cover in all block groups and to enable comparison of optimal solutions to those obtained from the i-Tree Landscape prioritization scheme. In the decision support framework this was achieved using the spatially distributed per area of canopy benefits from Nyelele et al. (2019) as follows:

$$\text{Scenario 1}: Max \sum_{i=1}^{N=1132} \left[\left(CP_{i,PM} * \Delta TCP_i\right)\right] \tag{6}$$

$$\text{Scenario 2}: \ Max \sum_{i=1}^{N=1132} \left[\left(CP_{i,SW} * \Delta TCP_i\right)\right] \tag{7}$$

Subject to:

$1: \quad \Delta TPI_i \le MTCP_i \ i = 1, \ldots., 1132$ Available Plantable Areaa

$2: \quad \sum_{i=1}^{N=1132} (100 * \Delta TCP_i) \le TB$ Total Budget

Note that the limit on how much we plant can either be expressed as a budgetary constraint ($100 million) as shown in constraint 2 above or as a canopy goal (CG) constraint illustrated below, where the total canopy goal is 1 million m^2 based on the planting budget and $100/m^2 planting costs.

$3: \quad \dfrac{\sum_{i=1}^{N=1132} (TC_i + \Delta TCP_i)}{\sum_{i=1}^{N=1132} (Area_i)} \ge CG$ Total Canopy Goal

Table 1
Description of variables.

Variable	Description
ΔTCP_i	Change in tree cover in block group i (m^2)
CG	Total canopy goal for entire borough (m^2)
$CP_{i,PM}$	The $PM_{2.5}$ air pollutant removal monetary benefit per unit area increase in tree cover for block group i ($/m^2)
$CP_{i,SW}$	The avoided runoff monetary benefit per unit area increase in tree cover for block group i ($/m^2)
$MTCP_i$	Maximum increase of plantable area in block group i (m^2)
N	The number of block groups (1132 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

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. Note that with our $100 million budget and the assumed $100/m^2 planting costs, a total canopy of CG = 23.5% would be obtained in the Bronx.

Scenarios 1 and 2 were also implemented following i-Tree Landscape's prioritization scheme by filling in the block groups with the highest priority for each ecosystem service first until the 1 million m^2 additional tree cover requirement was met. Here, the priority ranking was based on the $PM_{2.5}$ air pollutant removal or avoided runoff monetary benefit per unit area increase in tree cover for each block group, with higher priority given to block groups with the highest benefits per unit area for each ecosystem service. Both the spatially distributed and default i-Tree Landscape per area of tree cover benefits were explored in the i-Tree Landscape methodology to establish whether the different benefit estimates lead to different optimal solutions.

2.3.3.2. Scenario 3: Maximizing monetary benefits of air pollutant removal and avoided runoff. Scenario 3 was developed to illustrate how the $PM_{2.5}$ air pollutant removal and avoided runoff monetary benefits can be maximized simultaneously. Like the previous scenarios, we use the spatially distributed benefit estimates and include a $100 million budget limitation (or canopy goal constraint) to constrain tree cover increases for easy comparisons.

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

Subject to:

$1: \quad \Delta TPI_i \le MTCP_i \quad i = 1, \ldots., 1132$ Available Plantable Area

$2: \quad \sum_{i=1}^{N=1132} (100 * \Delta TCP_i) \le TB$ Total Budget

OR

$3: \quad \dfrac{\sum_{i=1}^{N=1132} (TC_i + \Delta TCP_i)}{\sum_{i=1}^{N=1132} (Area_i)} \ge CG$ Total Canopy Goal

For the i-Tree Landscape prioritization scheme, this scenario was created by prioritizing equal weights of the monetary benefits associated with $PM_{2.5}$ air pollutant removal and avoided runoff. Again, both the spatially distributed and i-Tree Landscape default benefit estimates were used, and we filled in the block groups with the highest priority first until the 1 million m^2 canopy goal was met. Following the i-Tree Landscape example presented in Section 2.3.1, the priority index (PI) used in this scenario was developed as follows:

$$\mathrm{PI} = (CPS_{i,PM} * 50) + (CPS_{i,SW} * 50) \tag{9}$$

$CPS_{i,PM}$ and $CPS_{i,SW}$ are standardized values (0−1) $CP_{i,PM}$ and $CP_{i,SW}$ calculated as:

$$(\mathrm{n{-}m})/\mathrm{r} \tag{10}$$

Where:

n = the monetary benefit per unit area increase in tree cover for block group i ($/m^2).

m = the minimum monetary benefit value across all block groups.

r = the range of monetary benefit values across all block groups (maximum - minimum).

To better align the i-Tree Landscape prioritization scenario to the decision support framework, we also formulated Eq. 9 as:

$$\mathrm{PI} = (CP_{i,PM} * \mathrm{w1}) + (CP_{i,SW} * \mathrm{w2}) \tag{11}$$

where:

$$\mathrm{w1} = 100 * [\overline{CP}_{PM} / (\overline{CP}_{PM} + \overline{CP}_{SW})]$$

$$\mathrm{w2} = 100 * [\overline{CP}_{SW} / (\overline{CP}_{PM} + \overline{CP}_{SW})]$$

where $\overline{CP}_{PM}$ and $\overline{CP}_{SW}$ are the average values of $CP_{i,PM}$ and $CP_{i,SW}$ across all block groups, respectively. In this situation, the weights used in the i-Tree Landscape scheme are derived from the average monetary benefits from $PM_{2.5}$ and avoided runoff.

2.3.3.3. Scenario 4: Maximizing the monetary benefits of air pollutant removal to meet equity goals. To identify optimal and equitable planting areas that ensure tree cover and resultant ecosystem services reach those that most rely on these services, Nyelele and Kroll (2021) included populations advocated by environmental justice and equity communities. Similarly, in this scenario, the spatially distributed estimates of $PM_{2.5}$ air pollutant removal monetary benefits were maximized while incorporating the population with income below the poverty level in 2010 (U.S. Census Bureau, 2018) in the ith the block group (PPI_i) into the objective function. The U.S Census Bureau uses a set of income thresholds that vary by family size and composition to determine who is in poverty. For example, the weighted average poverty thresholds for a family of three, four and five in 2010 were $ 17,374, $22,314, and $26, 439, respectively (U.S. Census Bureau, 2021b). Again, to limit the amount of tree cover increases and for easy comparisons with the i-Tree Landscape priority locations, the $100 million planting budget or 1 million m^2 canopy goal are included as constraints.

$$Max \quad \frac{\sum_{i=1}^{N=1132} PPI_i (CP_{i,PM} * \Delta \mathrm{TCP}_i)}{\sum_{i=1}^{N=1132} PPI_i} \tag{12}$$

Subject to:

$$1: \quad \Delta TPI_i \leq MTCP_i \quad i = 1, \ldots, 1132 \quad \text{Available Plantable Area}$$

$$2: \quad \sum_{i=1}^{N=1132} (100 * \Delta TCP_i) \leq TB \qquad \text{Total Budget}$$

OR

$$3: \quad \frac{\sum_{i=1}^{N=1132} (TC_i + \Delta TCP_i)}{\sum_{i=1}^{N=1132} (Area_i)} \geq CG \quad \text{Total Canopy Goal}$$

To prioritize similar objectives in the i-Tree Landscape scheme, the priority planting index (PI) was created from equal weights of the layers representing the monetary benefits of $PM_{2.5}$ air pollutant removal (one scenario used spatially distributed benefits while the other utilized i-Tree Landscape default estimates) as well as the proportion of the population below the poverty level. Block groups were filled in with tree cover based on their priority ranking until 1 million m^2 of additional canopy was met. PI corresponding to this scenario was calculated as:

$$\mathrm{PI} = (CPS_{i,PM} * 50) + (PPIS_i * 50) \tag{13}$$

$CPS_{i,PM}$ was standardized as described in Scenario 3 above while the block group population below the poverty level ($PPIS_i$) was calculated as the percent population below the poverty level in that block group divided by 100 (following the methodology used in i-Tree Landscape).

2.3.4. Comparison of scenarios

Comparisons of the planting solutions derived from implementing i-Tree Landscape's prioritization scheme and those obtained from the decision support framework were made to establish whether similar block groups were identified for future tree cover increases in each of the four scenarios explored in this analysis. Graphical and statistical methods in the R statistical computing software (R Core Team, 2013) were used to summarize the number of optimal block groups identified for tree cover increases and the additional tree cover increases in the recommended block groups in each scenario. The differences between additional tree cover increases in the block groups recommended for tree cover increases by either the decision support framework or i-Tree Landscape's prioritization framework in any of the scenarios explored are non-normally distributed (based on the Shapiro-Wilk normality test (Shapiro and Wilk, 1965). As such the Wilcoxon paired signed rank test, a non-parametric statistical hypothesis test (McCrum-Gardner, 2008; Rosner et al., 2006) was used to test the null hypothesis that the medians of the canopy cover increase in each block group from the decision support framework and those from i-Tree Landscape's prioritization framework are equal. The Wilcoxon paired signed rank test was selected based on its ability to compute the difference between each set of matched pairs as well as its appropriateness for a repeated measure design where the same subjects (in this case block groups) are evaluated under two different conditions (decision support framework versus the i-Tree Landscape prioritization) (Marino, 2018; Scheff, 2016).

3. Results

Results of the analysis show that the number of block groups identified for increased tree cover in each of the four scenarios modeled will be different depending on the formulation of the optimization problem. Fig. 2 illustrates the spatial distribution of the optimal block groups recommended for tree cover increases in each of the scenarios explored. When the spatially distributed benefits estimates from Nyelele et al. (2019) are used for both the decision support framework and i-Tree Landscape's methodology, Scenario 1 and 2 have similar spatial patterns and prioritize the same block groups for increased tree cover in both prioritization techniques, while the optimal solutions from the decision support framework target more block groups than i-Tree Landscape's prioritization scheme in Scenarios 3 and 4. However, when the weights used in i-Tree Landscape's Scenario 3 are changed as shown in Eq. 11, both the decision support framework and i-Tree Landscape identify similar solutions. Additionally, due to higher $PM_{2.5}$ air pollutant removal monetary benefits per unit area increase in tree cover in each block group when compared to the avoided runoff benefits, Scenario 3 of the decision support framework identifies optimal block groups similar to those recommended for additional tree cover in Scenario 1. As depicted in Fig. 2, by incorporating the population below the poverty level into the objective function (Scenario 4, Eq. 12 and 13), the decision support framework does not recommend tree cover increases in large block groups that typically contain parks and playgrounds and have few people living in them, contrary to recommendations from i-Tree Landscape's prioritization approach (regardless of the weights and benefit estimates used). When using the default i-Tree Landscape benefit estimates obtained from the lumped county modeling of i-Tree tools (Fig. 2b and c), the i-Tree Landscape prioritization results in much fewer block groups being identified for tree cover increases when compared to the decision support framework. When spatially distributed benefit estimates are used in i-Tree Landscape's methodology (Fig. 2a), many more block groups are identified for tree planting, though still slightly fewer than the decision support framework for Scenarios 3 and 4.

Additionally, when spatially distributed benefit estimates are used in both modelling approaches for Scenario 4, the Wilcoxon paired signed rank test shows that the median tree cover increases obtained from i-Tree Landscape's prioritization scheme are statistically different at $\alpha = 0.05$ from those derived from the decision support framework. No statistically significant differences are observed in the median tree cover increases for Scenarios 1, 2 and 3 obtained from implementing i-Tree Landscape's prioritization scheme and the decision support framework using the same spatially distributed data as input. When the i-Tree Landscape benefit estimates are used in the i-Tree Landscape scenarios (as compared to the spatially distributed benefits used above), the

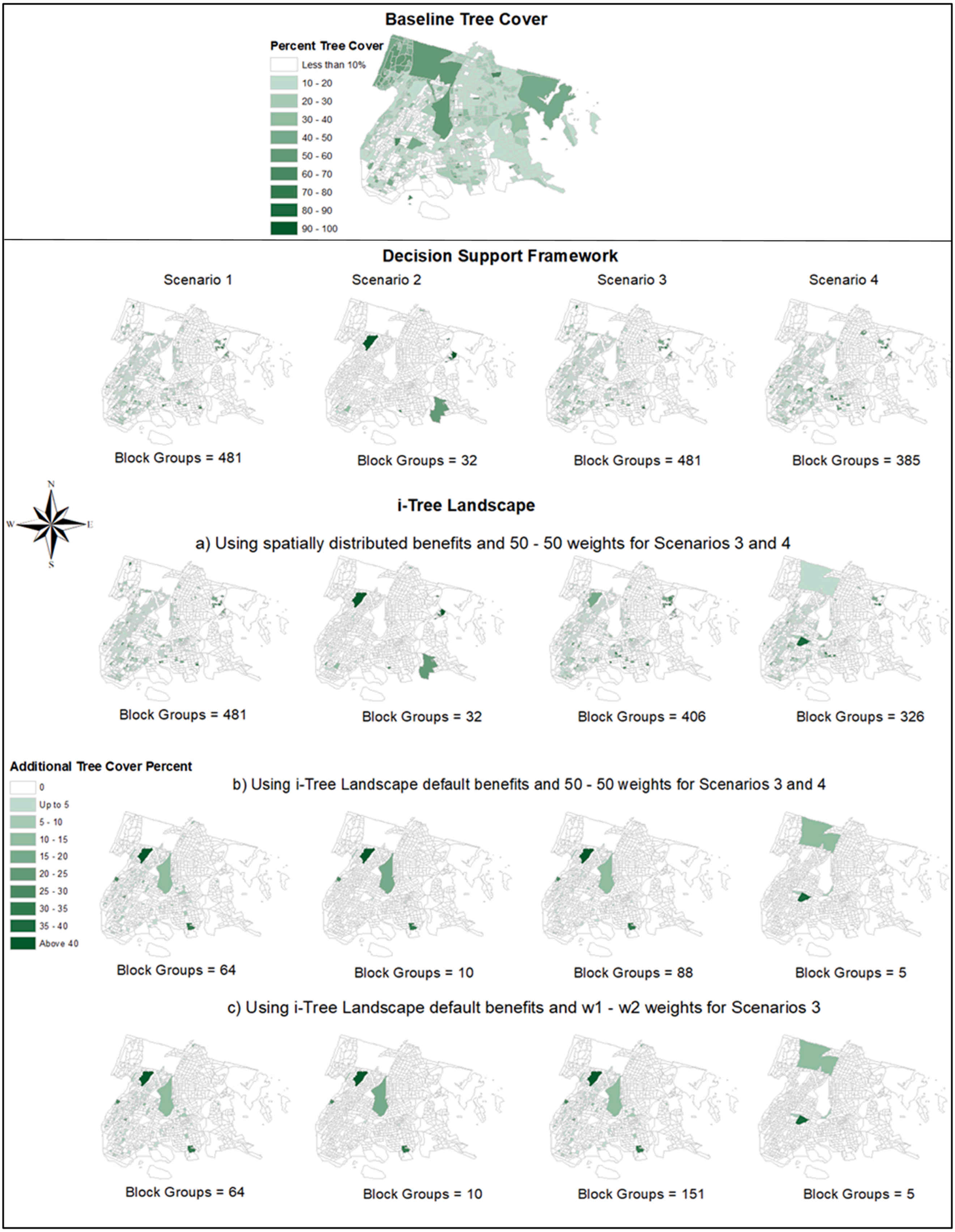

Fig. 2. 2010 tree cover distribution in the Bronx (top), number of optimal block groups with increased tree cover and amount of tree cover increases for each scenario from the decision support framework and i-Tree Landscape's planting prioritization. Scenario 1 prioritizes $PM_{2.5}$ air pollutant removal benefits, Scenario 2 prioritizes the benefits of avoided runoff, Scenario 3 maximizes the benefits of air pollutant removal and avoided runoff simultaneously, and Scenario 4 maximizes the benefits of air pollutant removal to meet equity goals.

median tree cover increases obtained from i-Tree Landscape's prioritization scheme are statistically different at $\alpha = 0.05$ from those derived from the decision support framework across all four scenarios.

4. Discussion

This study presents a comparison between i-Tree Landscape's prioritization scheme and the decision support framework developed by Nyelele and Kroll (2021) to determine optimal locations for tree cover increases considering multiple objectives. We hypothesized that the multi-objective prioritization approach proposed by Nyelele and Kroll (2021) will predict tree planting scenarios that are significantly different to those predicted by i-Tree Landscape. Results of the four scenarios explored support this hypothesis and highlight how these two approaches identify different optimal and priority planting locations. The results of these comparisons could be used to answer critically important restoration questions on how to improve prioritization techniques and the identification of locations to increase canopy or preserve urban forests. For example, the methodology used in prioritizing areas to increase tree cover can be improved to comprehensively considering multiple ecosystem services and benefits from increased tree cover, particularly in areas of greatest need. Additionally, the ranking or weighted scoring 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). While the approach used in the decision support framework is not entirely free from subjectivity, it obtains weight modeled benefits per unit canopy cover increase and appears less subjective than user identified weights employed in common priority planting scenarios.

Scenarios 1 and 2 maximize an individual ecosystem service benefit, resulting in similar optimal solutions between i-Tree Landscape and the decision support framework. This is expected considering that the same input data is used for both approaches, and both prioritize block groups that have higher benefits and result in similar solutions. However, when considering multiple objectives (Scenario 3) or incorporating equity (Scenario 4), the decision support framework produces different optimal solutions than i-Tree Landscape. For example, the results shown in Fig. 2 illustrate how in general the number of block groups identified for tree cover increases with the decision support framework are greater than those obtained from using the prioritization scheme in i-Tree Landscape. While i-Tree Landscape directs resources into fewer and bigger block groups that are typically parks and playgrounds with already higher amounts of existing tree cover, the decision support framework recommends increased tree cover in more smaller block groups that have limited tree cover and have more people living in them. Fisher et al. (2009) highlight that an ecosystem service is only a service if there is a beneficiary, an important feature of the decision support framework. i-Tree Landscape and other prioritization schemes often focus on planting more trees in parks and natural areas with greater existing tree canopy, which can exasperate the inequitable distribution of tree cover. Additionally, statistically significant differences are observed between the decision support framework and i-Tree Landscape's recommended tree cover increases when the i-Tree Landscape benefit estimates are used for the i-Tree Landscape scenarios. These differences highlight how areas prioritized for tree cover expansion depend on the prioritization or optimization method used. Below we provide insights into how the methodology used in the decision framework can be used to improve i-Tree Landscape as well as other existing tools for decision making.

i-Tree Landscape utilizes pre-loaded maps that cover a wide range of social, demographic, economic and environmental indicators and guides the user towards selecting layers of interest in the prioritization. On the other hand, the decision support framework requires that the user prepare spatially distributed inputs for the optimization problem they are addressing. Thus i-Tree Landscape has the advantage of being easily implemented by decision makers without extensive domain knowledge, resulting in priority planting scenarios that can be displayed as a map output for easy interpretation and communication. However, there are also limitations with the input data used in i-Tree Landscape which utilizes a lumped county approach to model ecosystem services and the weighted approach that depends on user specified weights. For cities where UTC data are not available, i-Tree Landscape uses NLCD data which is coarser and has been shown to underestimate tree canopy cover (Nowak and Greenfield, 2010). Due to preprocessing of block group results, i-Tree Landscape further restricts the user from using locally derived and improved datasets in their analysis. Although the lumped model ecosystem service estimates from i-Tree Eco are redistributed to the block group in i-Tree Landscape based on local tree cover and population data, studies using lumped models or lumped input data in their decision making should consider the impact of coarse scale data and underlying assumptions regarding spatial homogeneity. Such concerns have been raised by Smith and Crowder (2011) who highlight that extending models to account for heterogeneity would be an interesting direction for future research. In this analysis, we have shown how i-Tree Landscape's methodology could be implemented outside of the tool with improved spatially distributed input data.

Although similar objectives were prioritized for tree cover increases both with the decision support framework and i-Tree Landscape, implementing the same analysis within the i-Tree Landscape tool would not have allowed us to put a cap on the amount of additional tree cover. While the priority ranking produced in i-Tree Landscape is useful in showing which block groups should get priority, this decision is not based on availability of resources. This availability could be implemented in i-Tree Landscape to allow users to incorporate limits on available resources in the analysis. This feature is one key advantage of the decision support framework, which is developed to meet a defined objective while meeting specified resource constraints, which is more synonymous with real world planning. According to Saaty (2007), in addition to knowing which areas to prioritize, costs and benefits are important considerations for decision makers. Without the flexibility to add real world resource constraints, priority planting indices may fail to identify plausible planting scenarios. Additionally, without a way to constrain resources, using i-Tree Landscape's prioritization scheme will allocate additional tree cover to fewer block groups that have both a high priority and a lot of plantable space, as we have shown particularly in Scenario 4 where one of the highly ranked block groups had more than 2 million m^2 potential plantable area resulting in us exhausting the available planting resources in that block group.

A key advantage of the decision support system is its flexibility to handle a wide array of scenarios and data depending on the optimization problem. For example, the decision support framework can assess tree cover increases on both plantable pervious and plantable impervious areas whereas i-Tree Landscape currently only considers tree canopy expansion on areas that are bare soil or short vegetation. While decision makers are likely to use i-Tree Landscape's approach and typically convert areas that are bare soil or short vegetation to tree cover due to the obvious low cost of implementation, increased benefits can be found by incorporating plantable impervious areas into urban greening plans. For example, despite the higher cost of planting and maintenance, establishing tree canopy on plantable impervious areas will have a greater impact on net improvements in water quality and summer temperatures (O'Neil-Dunne, 2012).

Kim et al. (2015) found city totals for carbon storage and sequestration on urban vacant land in the City of Roanoke (VA) to be high relative to other land uses. Consideration of both plantable pervious and impervious areas in decision making is also important considering that most of the bare soil and short vegetation areas are likely to be in parks and playgrounds whereas in most urban areas the people that rely on the tree cover and resultant ecosystem services are found in areas that are predominantly impervious surface. Additionally, in i-Tree Landscape the prioritization is only based on the baseline conditions selected in the definition of the study area and available data layers without the flexibility to choose from different cover types and scenarios to explore the impact of increasing tree cover on one surface over the other (e.g., impervious vs. pervious land).

Although the existing methods in i-Tree Landscape contribute greatly to the science and practice of urban tree planning and management, this case study has shown how the methodology in i-Tree Landscape could benefit from the improvements recommended by Nyelele et al. (2019) and Nyelele and Kroll (2021). For example, i-Tree Landscape developers should recommend weights used to develop the priority index (PI) based on the value of the pollutant or benefit under consideration to eliminate biases associated with user selected weights. An important future direction of this research is to work with responsible municipal agencies in different cities on actual management plans and priorities. This will address the research implementation gap and prepare for actual implementation of the decision support framework while working towards its integration into existing planning tools such as i-Tree Landscape. This also promotes the transparency in decision making models, since it is important for communities as well as other stakeholders to understand what factors go into models that inform decision making and how forest management issues are prioritized.

5. Conclusions

While many cities are implementing large-scale tree planting initiatives, most have limited guidance on how to optimize plantings to achieve desired benefits and to evaluate the tradeoffs and synergies between competing objectives. This study explores how two tree planting prioritization approaches identify different optimal areas for increased tree cover, which impacts how tree planting resources are allocated. The differences presented in the analysis have implications regarding which block groups decision makers ultimately target for future tree plantings and protecting existing trees. Although the study is based on the Bronx, these results can be used to improve on tools that guide the maintenance and management of urban forests in different cities. While the specific goals of tree planting may vary across cities, improvements to decision support tools and prioritization models using the decision support framework will help planners and decision makers systematically consider a range of scenarios, objectives, constraints, and stakeholder and societal preferences to gain insight into the full spectrum of feasible solutions. Additionally, the study has shown how spatially distributed modeling approaches are useful to refine service and benefit estimates and to illuminate the spatial differences and potential environmental justice concerns needed to guide more local scale decision making and to allocate resources in a more equitable and just manner.

Author statement

Charity Nyelele, Charles N. Kroll, and David J. Nowak 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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