

Where to plant urban trees? A spatially explicit methodology to explore ecosystem service tradeoffs



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HIGHLIGHTS

- Tree planting scenarios were developed to meet Baltimore's goal of 40% tree cover.
- Each scenario optimized a single ecosystem service, benefit, or proxy.
- Tradeoffs between scenarios were evident.
- Differences in ecosystem services and benefits between scenarios were quantified.
- Methodology could be expanded into a decision support system for urban forestry.

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ABSTRACT

Urban trees can help mitigate some of the environmental degradation linked to the rapid urbanization of humanity. Many municipalities are implementing ambitious tree planting programs to help remove air pollution, mitigate urban heat island effects, and provide other ecosystem services and benefits but lack quantitative tools to explore priority planting locations and potential tradeoffs between services. This work demonstrates a quantitative method for exploring priority planting and ecosystem service tradeoffs in Baltimore, Maryland using spatially explicit biophysical iTree models. Several planting schemes were created based on the individual optimization of a number of metrics related to services and benefits of air pollution and heat mitigation ecosystem services. The results demonstrate that different tree planting schemes would be pursued based on the ecosystem service or benefit maximized, revealing tradeoffs between services and priority planting locations. With further development including consideration of additional ecosystem services, disservices, user input, and costs of tree planting and maintenance, this approach could provide city planners, urban foresters, and members of the public with a powerful tool to better manage urban forest systems.

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1. Introduction

Urban land cover and the global proportion of urban residents are increasing; by 2050, 86% of people in industrialized countries and 64% in developing countries are predicted to be urban dwellers (DESA, 2010). Urbanization can lead to many negative

environmental effects that adversely impact humans and ecosystems including urban stream degradation (Elmore & Kaushal, 2008; Klockner, Kaushal, Groffman, Mayer, & Morgan, 2009), increased runoff and nutrient export (Duan, Kaushal, Groffman, Band, & Belt, 2012; Morgan, Kline, & Cushman, 2007), elevated species extinctions (Alberti et al., 2003), increased human exposure to air pollutants (Zhang, Shou, & Dickerson, 2009), the urban heat island effect (Imhoff, Zhang, Wolfe, & Bounoua, 2010; US EPA, 2008), and increased material consumption and energy use (Torrey, 2004). At the same time, cities have also advanced human well-being and have great potential for resource efficiency (Alberti et al., 2003; Seto, Sánchez-Rodríguez, & Fragkias, 2010).

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The shifting paradigm recognizing humanity as part of nature has led to a focus on maintaining or enhancing ecosystem services as a means to manage environmental challenges and promote human health and well-being (Halpern et al., 2013; Roy, Byrne, & Pickering, 2012). Changes in land cover, vegetation, and human activities can provide ecosystem services which help alleviate some of the impacts of urbanization. Urban trees remove air pollution, mitigate urban heat island effects, and provide other ecosystem services (Nowak, Hirabayashi, Bodine, & Hoehn, 2013; Thomas & Geller, 2013; Wang et al., 2012). Increased recognition of the multiple ecosystem services and benefits provided by trees has encouraged municipal tree planting programs such as those in Los Angeles, New York City, Baltimore, and elsewhere around the world (Pataki et al., 2011).

Trees can be strategically planted and managed to optimize desired ecosystem services using knowledge of the heterogeneous urban landscape and human demographics. For instance, a location with high levels of air pollutants and high population density could be an optimal location to plant trees to improve health (Cabaran, Kroll, Hirabayashi, & Nowak, 2013; Hirabayashi, Kroll, & Nowak, 2011; Morani, Nowak, Hirabayashi, & Calfapietra, 2011). Incomplete knowledge of the spatial and temporal variation of environmental parameters, ecosystem services, and human demographics and activities poses a challenge to more effective urban forest management (Jenerette, Harlan, Stefanov, & Martin, 2011; Pataki et al., 2011; Thomas & Geller, 2013). Priority planting methodologies have been developed (Locke et al., 2011; Locke, Grove, Galvin, O'Neil-Dunne, & Murphy, 2013; Morani et al., 2011), but have not quantified ecosystem services, benefits, or tradeoffs needed for a comprehensive decision-making context (Haase et al., 2014). The goal of this work is to demonstrate a spatially explicit modeling methodology that can explore priority planting based on multiple ecosystem services, benefits, the potentially complex tradeoffs between them (Carpenter et al., 2009; Rodríguez et al., 2006) and with further development, monetary and resource costs. This work explores optimal planting locations and tradeoffs for the mitigation of two common urban environmental stressors: air pollution and the urban heat island.

Differences in albedo, heat capacity, and thermal emissivity between the natural and built environment as well as reduced tree and vegetative cover (i.e. less shade and evapotranspiration) result in higher urban surface and air temperatures compared to rural surroundings, known as the urban heat island (Grimm et al., 2008; Imhoff et al., 2010; US EPA, 2008). The urban heat island exacerbates regional heat waves and is also of concern in a warming climate (Ye et al., 2011). Pre-existing medical conditions, age, and socioeconomic factors such as low income, poor housing, and lack of access to air conditioning are known to exacerbate risks of heat-related mortality (Hess, Saha, & Luber, 2014; Huang et al., 2011). Exposure to air pollutants and excessive heat in the urban environment are significant causes of hospitalizations and mortality (Harlan, Brazel, Prasad, Stefanov, & Larsen, 2006; Jenerette et al., 2011; Jerrett et al., 2009). Fine particulate matter (PM_{2.5}) and ozone (O₃) can cause asthma, respiratory disease, and premature mortality (Kheirbek et al., 2012). In the urban setting, air pollution is often exacerbated due to industrial and transportation activities as well as the urban heat island (Zhang et al., 2009).

There are several challenges to defining, classifying, and valuing ecosystem services in ways that are useful for decision making (De Groot, Alkemade, Braat, Hein, & Willemen, 2010; Fisher, Turner, & Morling, 2009; Gómez-Baggethun & Barton, 2013). This work distinguishes between ecosystem services and the specific benefits they provide to humans, demonstrating different optimal planting schemes for a service as opposed to the benefit it provides. For instance, air pollutant removal via dry deposition occurs wherever there are trees, but the benefit to humans may be a more

logical focus for decision making (Boyd & Banzhaf, 2007; Fisher et al., 2009; Kumar, 2010). Further, ecosystem services can support other services (Millennium Ecosystem Assessment, 2005) or can directly provide one or several benefits. Tracking benefits can therefore avoid problems of under- or over-counting services (Boyd & Banzhaf, 2007; Fisher et al., 2009; Kumar, 2010).

This work utilizes spatially explicit biophysical models based on the i-Tree suite of tools (i-Tree, 2014). i-Tree tools have been used by hundreds of researchers, urban foresters, and others around the world to quantify urban forest structure and ecosystem services. Using i-Tree models, we calculate heat mitigation and pollution removal ecosystem services and benefits (or their proxies) for current, increasing, and one decreasing increment of tree cover in Baltimore, Maryland. This allows us to quantify spatially explicit ecosystem service and benefit gradients, the services and benefits obtained from incremental changes in tree cover in different locations across Baltimore. Using the results of this localized gradient approach, we determine priority planting schemes optimized for individual services and benefits constrained to Baltimore's goal of 40% tree cover (Tree Baltimore, 2014). Similarities and differences between optimized tree planting schemes are explored, as well as tradeoffs between the services and benefits provided. The gradient results also provide insight on which trees are most important to protect or maintain particular services or benefits. With further development, this methodology could be used by municipalities and stakeholders around the world to better utilize a growing body of spatial demographic and biophysical data and to improve urban forest management, increase urban forest ecosystem services and benefits, or prioritize specific desired objectives or services.

2. Methods

2.1. Study area: Baltimore, Maryland

Baltimore is the site of a National Science Foundation urban long term social ecological research (LTSER) project aiming to understand the social and ecological trajectories of urban and urbanizing areas (Grove et al., 2013). The city is known to have a pronounced urban heat island effect (Brazel, Selover, Vose, & Heisler, 2000) exacerbated by warm winds carried into the city from suburban sprawl or upstream urbanization (Zhang et al., 2009). The Chesapeake Bay and Baltimore's urban streams are also significantly impacted by urbanization (Elmore & Kaushal, 2008), and the city's pollutant emissions far exceed those of neighboring counties (Boone, Fragkias, Buckley, & Grove, 2014).

The 2010 US Census divides Baltimore into 200 tracts and 653 block groups. High resolution imagery of Baltimore's land cover from the US Forest Service's Urban Tree Canopy (UTC) assessment project reveals that Baltimore has 24% tree cover, 18.9% short vegetation, 1.5% bare soil, 12.2% water, and 43.4% impervious surfaces (Grove & O'Neil-Dunne, 2009) (Fig. 1). The city's Baltimore Sustainability Plan includes a goal of establishing 40% tree cover by 2040 (Tree Baltimore, 2014).

2.2. Potential tree cover and tree cover gradients

Areas with short vegetation and bare soil land cover in Baltimore were identified as areas where tree cover could potentially increase. While cities could convert impervious surfaces to tree cover, the additional complication and expense of such a conversion warranted that such practices not be considered in this initial analysis. The spatial distribution of actual and potential tree cover was quantified using GIS and varied in scale according to the requirements of two spatially explicit models: a) the Pasath air temperature model (Yang, Endreny, & Nowak, 2013) that was run on a 370 m raster

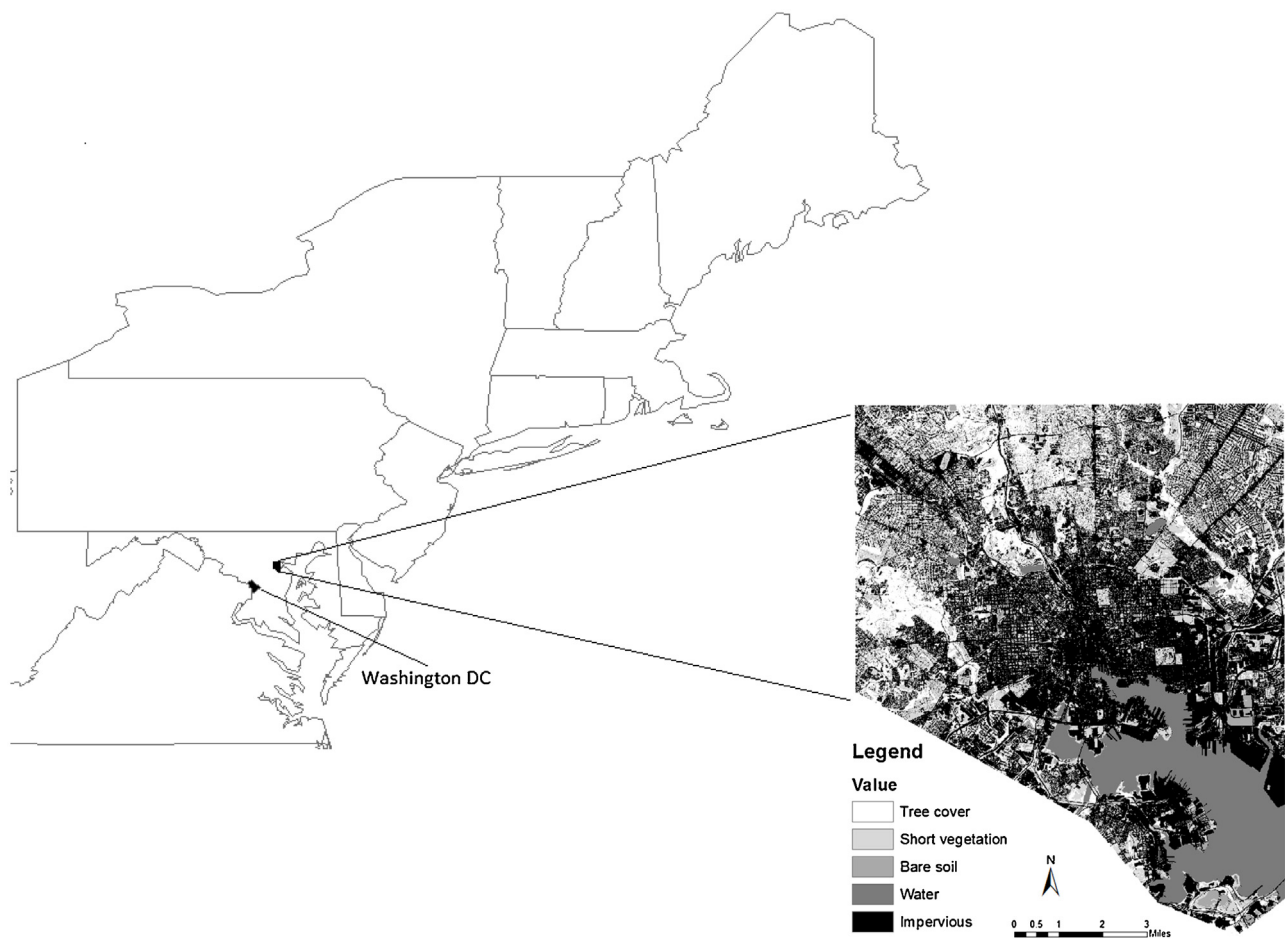


Fig. 1. Location of Baltimore, MD with respect to Washington DC and the United States eastern coast (left). High resolution land cover map of Baltimore, MD from the Urban Tree Canopy (UTC) program (right). Baltimore's urban core with a large proportion of impervious cover is clearly observed as well as less developed, more forested areas in the west and north.

grid basis; and b) the i-Tree Eco air pollutant deposition model (Hirabayashi et al., 2011; Nowak et al., 2013; Nowak, Hirabayashi, Bodine, & Greenfield, 2014) that operates at the US Census block group level. To limit the number of inputs and model runs, we estimated tree cover gradients using ten equal intervals of spatially explicit simulated tree cover inputs spanning current to maximum potential tree cover. Each increment represents the conversion of 10% of the total short vegetation and bare soil areas within each modeling unit (i.e. block group or raster grid cell) to tree cover. Additionally, one tree cover map representing a decrease in tree cover was developed by reducing current tree cover by an amount equal to 10% of potential tree cover. In cases where the reduction was greater than actual tree cover, the reduced tree cover was set to 0%. Model results using the decrement of tree cover allow quantification of the change in services and benefits for decreasing tree cover, revealing locations to prioritize protection or maintenance of existing tree cover.

2.3. Quantifying air temperature and humidity: the Pasath model

The physically based analytical spatial air temperature and humidity (Pasath) model (Yang et al., 2013) was used to calculate spatially explicit hourly air temperature and humidity values for Baltimore at a horizontal resolution of 370 m. The model implements a heat balance coupled with a water balance based on i-Tree Hydro (i-Tree, 2014; Wang, Endreny, & Nowak, 2008) and the TOP-MODEL approach (Beven & Kirkby, 1979). Incoming radiation, land cover albedo, evaporation, and evapotranspiration from vegetation

influence heat transfer across three vertical layers: the land surface, the local air layer at canopy height, and the mesoscale climate layer, which is assumed to have uniform temperature and humidity across the study area (Yang et al., 2013).

Spatially explicit inputs of elevation, tree cover, impervious cover and National Land Cover Database (NLCD) land cover class (Fry et al., 2011) are required as well as lumped values for soil parameters, tree leaf area index (LAI), leaf on/off day, and weather (hourly wind, rain, temperature). Elevation data (1/9 arc second) were obtained from the National Elevation Dataset (NED) (Gesch, 2007; Gesch et al., 2002), clipped to the city boundary, and aggregated to a 370 m horizontal resolution using GIS. To create the tree cover inputs of potential tree cover, the short vegetation and bare soil land uses from UTC data were summed and aggregated at a 370 m horizontal resolution. Each map of incremented tree cover was created by adding 10% of each grid cell's total potential tree cover to its actual cover. A layer of reduced tree cover was produced by subtracting 10% of potential tree cover for each grid cell from initial tree cover, setting any resulting negative values of tree cover to zero (see Section 2.2).

Impervious cover was also generated using UTC data aggregated to a 370 m horizontal resolution, and land cover class was obtained from the NLCD dataset (Fry et al., 2011). Hourly weather at the Baltimore Washington Airport was obtained from the National Climate Data Center (National Climate Data Center (NCDC), 2008), and soil parameters were estimated using an i-Tree Hydro calibration routine minimizing differences between modeled and observed (2008) daily flows from the Gwynns Falls gauged watershed outlet in

Baltimore (USGS Gage #01589352). LAI and leaf on/off values were obtained from an i-Tree database (i-Tree, 2014), which are used by the model to simulate seasonal leaf growth and senescence for deciduous trees. The proportion of evergreen trees was set to 9.8% based on US Forest Service plot data.

The Pasath model was run twelve times – once for each tree cover input (current, ten positive increments, and one decrement) – for the period of July 2008, creating hourly outputs of temperature and dew point at a 370 m spatial resolution. July 2008 was chosen since it had high temperatures and humidity.

2.4. Quantifying pollutant removal services and benefits: i-Tree Eco

i-Tree Eco was used to calculate net hourly dry deposition of PM_{2.5} to trees (Nowak et al., 2013) and uptake of O₃ by trees (Hirabayashi et al., 2011; Nowak, Crane, & Stevens, 2006; Nowak et al., 2014) at the US Census block group level for the twelve tree cover inputs. The program calculates pollutant flux per unit leaf area as the product of deposition velocity and pollutant concentration. Deposition velocity for O₃ is based on LAI and a series of atmospheric and plant resistances; deposition velocities for PM_{2.5} are based on LAI, and resuspension of PM_{2.5} is controlled by wind speed. Total deposition at the tree level is the product of deposition velocity, concentration, and total leaf area (canopy area multiplied by LAI). Pollution concentrations are assumed to be uniform within each block group with an air column height equal to the boundary layer height determined from radiosonde data (Hirabayashi et al., 2011; Nowak et al., 2006; Nowak et al., 2013).

The model also incorporates the US Environmental Protection Agency's Benefits Mapping (BenMAP) tool that quantifies and monetizes reductions in morbidity and mortality based on a change in air pollutant concentrations and population characteristics. It uses a database of epidemiological data reflecting age-based sensitivity to air pollutants and assumes that exposure to air pollutants occurs at the location of residence (Abt Associates, Inc., 2010; Nowak et al., 2014). Key outputs from i-Tree Eco include pollutant removal (tonnes/yr) and yearly monetary benefit (\$USD) of pollutant removal for each block group area.

Pollutant concentration data for 2008 was obtained from the EPA Fused Air Quality Surfaces Using Downscaling project (US EPA, 2012a) that provides estimates of daily ozone (8-h max) and PM_{2.5} (24-h average) concentrations at 2010 US Census tract centroid locations. Concentration values were temporally distributed to hourly intervals to meet model input requirements. The temporally distributed 8-h max ozone data was modified by the ratio of daily mean concentration to 8-h max concentration obtained from the EPA Air Quality System Data Mart database for the Furley site in Baltimore (US EPA, 2015) to avoid overestimation of ozone concentrations. Each block group was assigned the same O₃ and PM_{2.5} concentrations as the tract it was located in. Block group population and age demographics were determined using 2010 US Census data (United States Census Bureau, 2010, 2014). The total population within each block group was calculated by summing the population of all blocks within each block group. Block group age distributions were estimated assuming the tract-level age distributions provided by the Census.

Land cover data was aggregated to the block group level using GIS. LAI was determined for each block group from a 2009 i-Tree Eco field survey of plots in Baltimore reporting tree and leaf area by NLCD land cover class. Leaf on and off dates and % evergreen were also inputs to the model to account for differing seasonal dry deposition rates for deciduous versus evergreen trees. The model was run for current cover, decreased cover, and ten increasing tree cover inputs for the entire 2008 year.

2.5. Calculation of ecosystem service and benefit gradients

Air temperature, humidity, level of exertion, air flow, and exposure to solar radiation are factors that contribute to heat-related illness (OSHA, 2014). The last three factors depend to some degree on individual human behavior and are thus challenging to model for an entire population. The heat index is a quantity derived from both air temperature and humidity and is therefore more relevant to assess the impacts of heat exposure than temperature alone. Relative humidity was calculated from Pasath temperature and dew point outputs (Parish & Putnam, 1977). Heat index values were calculated from temperature and relative humidity (Steadman, 1979). The reduction of urban heat index was considered as an ecosystem service.

The minimum air temperature used in heat index calculations is 26.7 °C (80 °F) (NOAA National Weather Service, 2014); therefore, we restricted our analysis to temperatures above 26.7 °C. Furthermore, the inclusion of lower temperatures would likely skew the heat index reduction gradients since the cooling effects of trees are expected to differ with varying temperatures.

The average heat index in each cell across the 743 hourly time steps was calculated from Pasath model output for each tree cover scenario subject to the 26.7 °C (80 °F) restriction. The average incremental reduction in heat index was calculated by subtracting the average heat index values for each tree cover scenario from the next lowest tree cover scenario's values. Each set of these differences was divided by the change in tree cover area in each cell to obtain the change in heat index per tree cover area ($\Delta^\circ\text{C}/\Delta\text{m}^2$) across the ten positive increments and one decrement of tree cover. For any given cell, the heat index differences across the tree cover scenarios fluctuated around an average value. The final gradient value for each cell was therefore calculated as the average of the heat index differences across all tree cover intervals.

Gradients of pollution removal and monetary benefits were calculated in a similar two-step process. First, the service and benefit values associated with each tree cover scenario were subtracted from those of the subsequent scenario. These marginal values were divided by the change in tree cover area across each tree cover scenario. Values varied between block groups but were found to be constant within any given block group, indicating that the gradient was not a function of tree cover.

2.6. Ecosystem service and benefit indicators/proxies

Two measures related to heat risk were developed as proxies of the human benefit of heat index reduction due to urban trees. The US National Weather Service defines four thresholds of risk based on heat index values: *caution*, *extreme caution*, *danger*, and *extreme danger*, corresponding to heat index values of 26.7, 32.8, 39.4, and 52.2 °C (80, 91, 103, and 126 °Fahrenheit) (NOAA National Weather Service, 2014). The exceedance heat index (EHI) metric was defined as a measure of how much the heat index in a cell exceeds a critical heat threshold over a period of time:

$$EHI_i = \sum_t (H_{i,t} - T_c) \quad (1)$$

where EHI_i is the exceedance heat index value of cell i , $H_{i,t}$ is the heat index at cell i and time t , and T_c is the critical heat index value. The *extreme caution* threshold (32.8 °C) was used as the critical heat index value (T_c) because there were no heat index values in excess of the *extreme danger* value (39.4 °C) in Baltimore for July 2008. The difference $H_{i,t} - T_c$ was set to zero for locations and times in which the heat index was less than the critical value (avoiding negative values). The summation over t is across all 743 hourly time steps in July 2008.

Hess et al. (2014) reports a simple set of relative risk factors for heat exposure across four age groups. Population and age data previously calculated at the block group was converted to a raster grid at a 370 m horizontal resolution using GIS. The population of each block group was multiplied by the ratio of cell area to block group area to estimate the population in each cell. This was used to calculate a population risk EHI metric (P-EHI):

$$P - EHI_i = \sum_p n_{i,p} \cdot r_p \cdot EHI_i \quad (2)$$

where $n_{i,p}$ is the population in cell i in population age class p , r_p is the age-weighted risk factor for population age class p , and EHI_i is the exceedance heat index for cell i . Population age classes employed were 0–17, 18–45, 45–65, and 65+ years, while age-weighted risk factors (r_p) were 1.0, 1.0, 1.39, and 2.35, respectively (Hess et al., 2014). City-wide cumulative EHI and cumulative P-EHI values for the July 2008 period were defined as follows:

$$\text{Cumulative EHI} = \sum_i EHI_i \quad (3)$$

$$\text{Cumulative P - EHI} = \sum_i P - EHI_i \quad (4)$$

These metrics were used as proxies for the benefit of urban temperature moderation because they capture more information about heat-related risk than the heat index value alone. Pollution removal (tonnes/year) and monetary benefits of air pollution (\$USD) outputs from i-Tree Eco directly served as appropriate metrics for air pollution removal services and benefits.

2.7. Ecosystem service metric optimization

Five tree cover scenarios were defined based on five service and benefit metrics to explore differences in spatial patterns and trade-offs. Two scenarios focused on air pollution, while three focused on heat mitigation. Algorithms were written that assigned tree cover to block groups prioritized by pollution removal gradient and monetary benefit gradient values, and to raster grid cells based on gradient values of the EHI metric, the P-EHI metric, and a weighted index (WI) metric, which is the product of P-EHI and the heat index gradient. For example, for pollution removal, all potential plantable area was converted to tree cover first in the block group with the largest gradient, then the block group with the second largest gradient, and so forth until the planting constraint was met. These algorithms optimized the metrics in the sense that the largest or smallest possible values of the metrics were achieved, assuming the gradients stay constant as tree cover changes as indicated by model results. All scenarios were subject to the constraint of Baltimore's goal of 40% tree cover, which equated to 38 km² of simulated tree cover establishment (i.e. planting or natural regeneration).

The pollution removal (PR) optimization scenario maximized the total pollution removal service by planting in locations according to decreasing pollution removal gradient values (highest first), while the monetary benefit (MB) optimization scenario similarly maximized the total monetary benefit of pollution removal by planting according to decreasing benefit gradient values. The exceedance heat index (EHI) scenario prioritized planting based on EHI values where the location with the largest EHI received first priority and the location with the smallest EHI received last priority, resulting in trees first being planted in locations that cumulatively exceed the critical heat threshold by the largest amount. The population exceedance heat index scenario (P-EHI) prioritized planting based on P-EHI values, placing tree cover in locations with a combination of high EHI values and large and/or elderly populations. The

fifth scenario weights the P-EHI metric by the heat index gradient, creating a gradient weighted index (WI) defined as

$$WI_i = P - EHI_i \cdot G_i \quad (5)$$

where P-EHI_{*i*} is the population exceedance heat index in block group i (Eq. (2)) and G_i is the heat index gradient (°C/m² leaf area) in block group i , defined to be positive as the heat index decreases with increasing tree cover. This prioritization metric accounts for extreme heat, population with relative risk by age, and the efficiency of tree cover in reducing the heat index. The location with the largest value of the WI metric was planted first, while the smallest was planted last, subject to total planting constraints. This process created five sets of priority planting scenarios.

Ecosystem service and benefit values and proxies were subsequently calculated for each of the five priority tree cover configurations. Tree cover maps at the block group scale that were created by air pollutant optimization procedures were converted to 370 m raster grids to calculate heat-related benefit proxies using the heat index gradient. Tree cover maps originally at a 370 m grid resolution were similarly aggregated to block groups to calculate air pollution removal service and benefit values using their respective gradients. Finally, services and benefits were calculated for the maximum tree cover layer in which all short vegetation and bare soil was converted to tree cover (resulting in 44.4% tree cover). These values provide additional context to compare service and benefit values of the tree cover scenarios constrained to 40% tree cover.

3. Results

3.1. Spatially explicit gradient values

Pollution removal service and benefit gradient values varied spatially, but within any given block group were constant per area of additional tree cover (i.e., the effect per m² of tree cover). Heat index gradient values for each cell fluctuated around an average value across the eleven differences in tree cover inputs. The average of the eleven calculated gradients was therefore used as the overall heat index gradient. This assumption simplified the optimization analysis.

The spatial patterns of pollution removal, monetary benefit, and heat index reduction gradients differed from one another. Pollution removal gradients (tonnes yr⁻¹ m⁻²) were greatest in relatively open and forested areas in western and north-northwestern Baltimore as well as some locations in the urban core. The largest monetary benefit gradient values were generally clustered in the urban core and other areas of high population outside the urban core. The heat index gradient was greatest in areas with high proportions of existing tree or short vegetation. Locations with the largest gradient values correspond to priority locations for the protection of existing tree cover, since the loss of tree cover in these areas would result in the greatest loss of services or benefits. This was established by modeling one decrement in tree cover in addition to increments in tree cover (Section 2.2).

3.2. Optimized tree cover

Spatial patterns of optimized tree cover differed among scenarios, indicating the presence of tradeoffs among optimization scenarios. There was a high degree of overlap among scenarios, which is unavoidable because the scenarios each represent the conversion of about 80% of the potential planting area to tree cover. Despite this overlap, scenarios showed differences in locations that would not receive planting as well as differences in the optimal order of planting. Locations with the highest planting priority also correspond to highest priority locations to protect or maintain

Table 1

Ozone and PM_{2.5} pollution removal service (tonnes/yr) and benefit (10⁶ USD/yr) of Baltimore's current and maximum potential tree cover (24% and 44.4%, respectively). Service and benefit values for maximum tree cover are above and beyond current values.

Bounding Scenarios	Removal	Monetary Benefit
	(tonnes/yr)	(Million USD)
Current Tree Cover	211	8.2
Maximum Tree Cover (Incremental Values)	173	6.3

existing tree cover as loss of tree cover in these areas would result in the largest loss of services or benefits.

3.2.1. Optimized tree cover for pollutant removal (service and benefit)

The order of planting for optimized pollution removal and benefit follows the ranking of their respective gradient values from high to low. For pollution removal, high priority areas are concentrated primarily in more open and forested areas in western and north-northwestern Baltimore (Fig. 2). The order of planting for optimized monetary human health benefits is quite different, with priority areas clustered in areas with high populations (Fig. 2). Another way of visualizing the results is as quantiles of established tree cover, which conveys information about both the order of establishment (priority) and the area of tree cover established at each priority level. Fig. 3 shows ten equal quantiles (e.g. 10%, 20%, etc.) of established cover, each representing 3.8 km² of tree cover or one tenth of the additional tree cover needed to achieve Baltimore's 40% goal. These quantiles could be used in planning the timing of plantings; for instance, a 20-year planting program could utilize results displayed by 20 quantiles instead of 10 to help determine where to plant trees each year.

For the monetary benefit (MB) scenario, many locations in the urban core are the first priority for planting, but there is relatively little space for tree planting in these areas. If high priority locations had more available space for planting, fewer locations would have the same shading. For example, if only two block groups shared a particular shading then all 3.8 km² would be established in those two block groups alone.

3.2.2. Optimized tree cover to mitigate heat effects

Optimized planting schemes for the three heat-related metrics show considerable differences from one another (Fig. 4), as well as compared to the air pollutant schemes. Differences between the heat mitigation scenarios demonstrate the dependence of planting schemes on the proxy used to represent heat risk. As expected, plantings for the exceedance heat index metric (EHI) are concentrated in areas with high proportions of impervious surfaces, most notably the urban core. Plantings for the population risk metric (P-EHI) are clustered in high-population areas. Plantings for the weighted index (WI) metric are concentrated in areas with high proportions of existing tree and/or short vegetation cover.

Table 2

Ozone and PM_{2.5} pollution removal service (tonnes/yr) and benefit (10⁶ USD) for the five tree cover optimization scenarios (40% tree cover or 38 km² planted).

Optimization Scenario ^a	PM _{2.5} and O ₃ Removal (tonnes/yr)	% of Value at Max Tree Cover	Monetary Benefit (Million USD)	% of Benefit at Max Tree Cover
EHI	133	77%	5.2	82%
P-EHI	135	78%	6.0	94%
WI	135	78%	5.3	83%
PR	139	80%	4.3	67%
MB	135	78%	6.2	99%

^a EHI = Exceedance heat index, P-EHI = population-risk index, WI = weighted index, PR = pollution removal, MB = monetary benefit.

Table 3

Cumulative exceedance heat index and cumulative population-weighted exceedance heat index values for current and maximum potential tree cover (24% and 44.4%, respectively).

Bounding Scenarios	Cumulative EHI	Cumulative P-EHI
	(10 ⁵ °C)	(10 ⁶ °C person)
Current Tree Cover	5.1	3.8
Maximum Tree Cover	4.9	2.4

3.3. Ecosystem service and benefit values

3.3.1. Pollution removal service and benefit values

Baltimore's current (2007) urban forest provides a particulate matter and ozone pollution removal service of about 211 t/yr and human health benefit valued at \$8.2 million/yr. An additional service of about 173 t/yr pollution removal and \$6.3 million/yr benefit is predicted at maximum potential tree cover (44.4%), representing the conversion of all potential tree cover to actual tree cover. These values provide additional context for the five optimization scenarios since they represent the maximum possible air pollution service or benefit achievable given methodological assumptions (Table 1).

Urban tree cover optimized for pollution removal (PR) yielded an additional pollution removal of 139 t/yr versus 135 t/yr when optimized for monetary benefits (MB), a tradeoff of 4 t/yr. The tradeoff for monetary benefits was proportionally larger: a \$1.9 million difference between the \$4.3 million and \$6.2 million benefits for the PR and MB scenarios, respectively (Table 2). The EHI, P-EHI, and WI optimization schemes based on heat reduction yielded pollution removal services slightly less than the PR and MB optimization scenarios, and monetary benefits between the PR and MB scenarios, ranging from \$5.2 to \$6.0 million (Table 2).

The five scenarios performed similarly for pollution removal, ranging from 77% to 80% of the removal achieved at maximum tree cover. The results for monetary benefit showed a greater range: 67% to 99% of the maximum achievable. The best performers were the P-EHI scenario (94% of maximum) and the MB scenario (99% of maximum). Both scenarios generally concentrated tree cover in high population areas.

3.3.2. Heat mitigation service and benefits

The cumulative exceedance heat index value (cumulative EHI) for current tree cover is 5.1×10^5 °C and the cumulative population-risk weighted exceedance heat index (cumulative P-EHI) is 3.8×10^6 °C person. At maximum possible tree cover, these values are 4.9×10^5 °C and 2.4×10^6 °C person (Table 3), a reduction of about 4% and 37%, respectively. Reductions in these metric values are desirable to reduce heat stress.

The cumulative EHI values for all scenarios range from 4.9×10^5 °C to 5.1×10^5 °C, with the highest (least desirable) values of 5.1×10^5 °C corresponding to the PR and MB air pollution removal scenarios (Table 4). This result indicates that the heat-related optimization scenarios perform better than the air pollution scenarios for heat reduction, as expected. Reductions in cumulative EHI are approximately 1% to 3% of the initial value while maximum

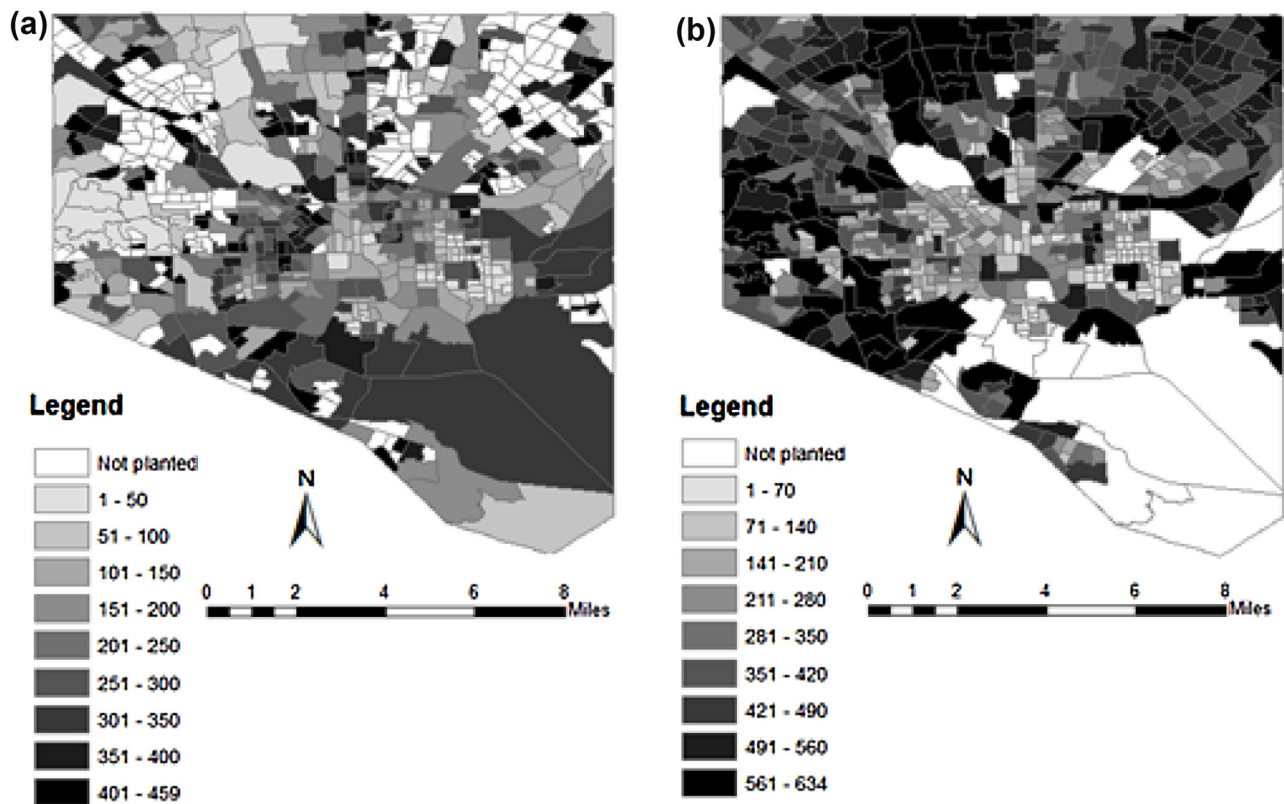


Fig. 2. Optimal order of planting (establishment of tree cover) within US Census block groups to a) maximize total air pollution removal (PR) and b) maximize total monetary benefits (MB) of air pollution removal based on human health. Locations in white are not planted. For the air pollution removal scenario, the lightest shade of gray identifies the 50 highest priority block groups for planting. The next darker shade of gray identifies the next 50 priority block groups. The sum of planted and unplanted block groups is 653, the number of block groups in Baltimore.

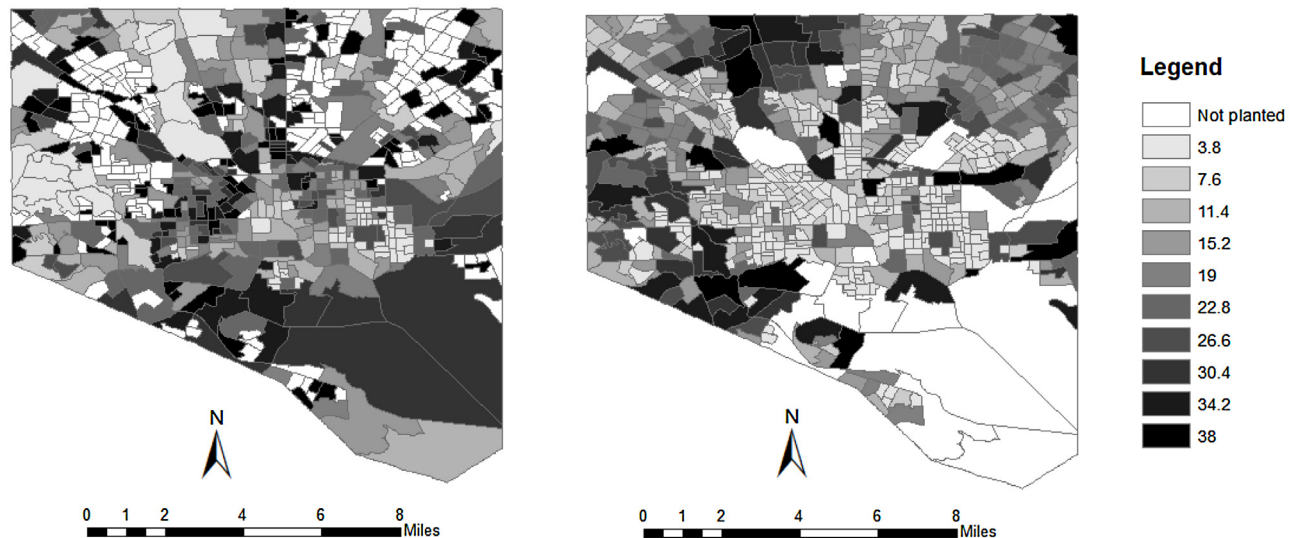


Fig. 3. Ten quantiles of planting priority for block groups with each value representing 3.8 km² of established tree cover to a) maximize total air pollution removal (PR) and b) maximize total monetary benefits (MB) of air pollution removal. Locations in white ("Not planted") would have no additional tree cover established. Locations with a value of 3.8 represent the first 3.8 km² to be planted. Locations with a value of 7.6 represent the second priority for planting an additional 3.8 km², bringing the total planted to 7.6 km².

potential tree cover achieved a reduction of about 4%. The values of the cumulative P-EHI metric range between 2.4×10^6 °C person to 2.5×10^6 °C person from an initial value of 3.8×10^6 °C person, a reduction of 34% – 37%. The highest values again correspond to the PR and MB scenarios, as they did for the cumulative EHI metric.

3.4. Evaluation of optimization scenarios

Comparing normalized scores for each service and benefit across scenarios is one way to evaluate scenario performance. Normalized scores were calculated for each service or benefit value y_i as

$$\frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \quad (6)$$

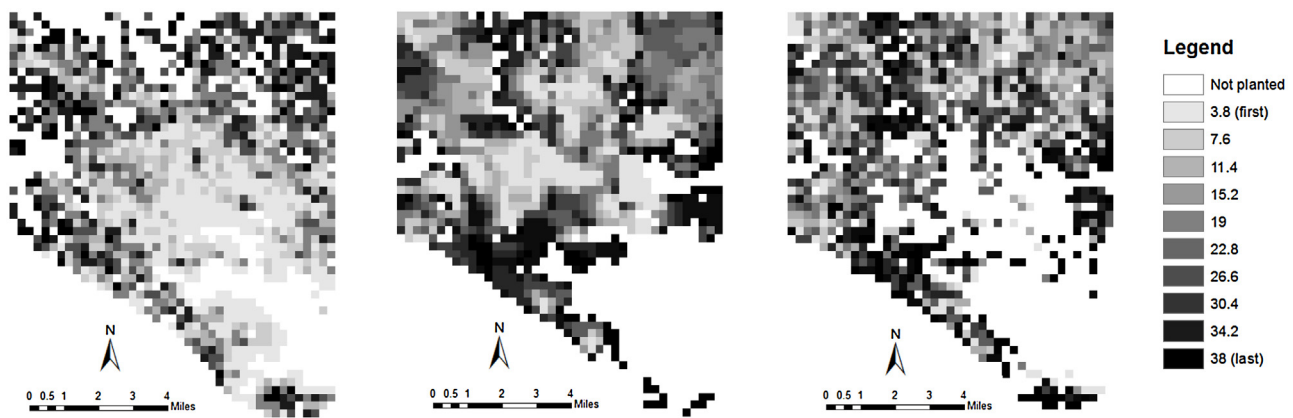


Fig. 4. Quantiles of tree cover establishment in 3.8 km² groupings for planting by EHI metric (left), P-EHI (middle), and WI (right). Locations in white are not planted.

Table 4

Cumulative and population weighted exceedance heat index values for the five optimized tree cover scenarios.

Optimization Scenario ^a	Cumulative EHI (10 ⁵ °C)	% Reduction from initial value	% of Maximum Reduction ^b	Cumulative P-EHI (10 ⁶ °C person)	% Reduction from initial value	% of Maximum Reduction ^c
EHI	4.9	3.0%	70%	2.4	35%	96%
P-EHI	5.0	2.4%	56%	2.4	35%	96%
WI	4.9	3.0%	70%	2.4	37%	100%
PR	5.1	0.9%	21%	2.5	34%	92%
MB	5.1	0.9%	21%	2.5	34%	92%

^a EHI = Exceedance heat index, P-EHI = population-risk index, WI = weighted index, PR = pollution removal, MB = monetary benefit.

^b Maximum tree cover yields a 4.3% reduction in cumulative EHI.

^c Maximum tree cover yields a 37% reduction in P-EHI.

for metrics for which large values are desirable, producing a value of 1 for the maximum value and 0 for the minimum value of a service or benefit. Normalized scores for cumulative EHI and cumulative P-EHI were calculated as

$$\frac{|y_i - y_{\max}|}{y_{\max} - y_{\min}} \quad (7)$$

such that the lowest score received a value of 1 (most desirable) while the largest received a score of 0 since decreases in these metrics reflect decreased heat stress. For example, the maximum pollution removal was 139 t/yr and the minimum was 133 t/yr, yielding a range of 6 t/yr for the denominator of Eq. (5). The relative pollution removal score for the P-EHI scenario with a removal value of 135 t/yr is $(135 - 133)/6 = 0.33$ (Table 5).

Final scores could reflect a stakeholder's preference of desired services or benefits by weighting the normalized scores and summing them. Three possible combinations are calculated (Table 5): an equal weighting score consisting of the sum of all relative scores, an effects-based score summing the relative score of metrics that are ecosystem services (pollution removal and temperature reduction), and a people-based score consisting of the sum of benefit or benefit proxy scores (monetary value of pollution removal and cumulative P-EHI reduction). Although in all three cases the WI scenario has the best score, the choice of weightings or alternative performance indicators can influence conclusions about optimal scenarios.

4. Discussion

Air pollution ecosystem service and benefit values for Baltimore's current tree cover were comparable to other studies of urban systems using i-Tree (Nowak et al., 2013, 2014). Many high priority locations for the establishment of tree cover were in the urban core which has limited available area for planting. Exploring alternative definitions of potential planting area that include

impervious area would increase the plantable area. The current definition of potential planting area may also underestimate the area of tree cover that could be established since tree canopy can extend over impervious areas.

The heat index gradient was largest for locations mostly outside of the city core, an unexpected result since the urban heat island is associated with impervious cover. For instance, tree canopy would shade more impervious cover in the urban core than in areas outside of the city core with less impervious cover and more tree cover. Heat index values across cells for the WI scenario decreased compared to the initial tree cover scenario with a median decrease of 0.06 °C and a maximum decrease of 0.64 °C. These values are on the low end of values reported in the literature (Simpson, 2002). These results are explained by model assumptions within Pasath and our assumption that only pervious areas could be replaced by tree cover. Evapotranspiration was limited in areas with high proportions of impervious area, stunting the cooling effects of trees. Furthermore, Pasath does not account for shading, transfer of heat between cells, or effects of potential irrigation, which can all impact the heat balance and local air temperature (Jenerette et al., 2011; Pataki et al., 2011; Zhang et al., 2009). Larger heat index gradients and higher priority of planting in the urban core would be expected if impervious area was considered as potential plantable area since this would restore hydrologic functioning and evapotranspiration modeled by Pasath.

The largest pollution removal gradients are expected in locations with the highest pollutant concentrations such as highly developed areas with industry and/or heavy traffic since modeled removal is proportional to air pollutant concentration. Our results, however, show the largest removal gradients in less developed and forested land cover classes. These results are explained by the minimal spatial variability (1–2%) of the EPA fused pollutant data due to the single air quality monitor in Baltimore and the large modeling resolution (12 km) used in creating the data set (USEPA, 2012b). The use of improved pollutant emission data with a more advanced air

Table 5

Performance indicators of the five tree cover scenarios.

Optimization Scenario	Pollution Removal Relative Score "Effect"	Monetary Benefit Relative Score "People"	Cum. EHI Relative Score "Effect"	Cum. P-EHI Relative Score "People"	Equal weighting score	Effect-based Score	People-based score
EHI	0.00	0.47	1.00	0.50	1.97	1.00	0.97
P-EHI	0.33	0.89	0.50	0.50	2.23	0.83	1.39
WI	0.33	0.53	1.00	1.00	2.86	1.33	1.53
PR	1.00	0.00	0.00	0.00	1.00	1.00	0.00
MB	0.33	1.00	0.00	0.00	1.33	0.44	1.00

pollutant transport model could create a more realistic spatial distribution of air pollutant concentrations reflecting larger expected variations (Boone et al., 2014). Given the minimal spatial variability, our results are explained by larger LAI values associated with forested and less developed land cover, since trees with a greater LAI will remove more pollutants.

Our current modeling approach also does not allow for the selection of specific tree species based on LAI values or affinity for trapping particles. Sæbø et al. (2012), for instance, found particle trapping rates varied over an order of magnitude for different tree and shrub species. On the other hand, dense tree cover surrounding pollutant sources such as roads has the potential to trap pollutants in those areas, raising the concentration people are exposed to (Pugh, MacKenzie, Whyatt, & Hewitt, 2012; Thomas & Geller, 2013).

A comprehensive systems approach to analyzing urban forest ecosystem services, benefits, costs (e.g. maintenance, water use), and disservices (e.g. allergen production, volatile organic compound emission) is needed to better inform decision making (Dobbs, Escobedo, & Zipperer, 2011; Escobedo, Kroeger, & Wagner, 2011; Roy et al., 2012). Comparisons with other methods of reaching sustainability and human health goals such as pollutant source reduction would further inform city-wide planning (Pataki et al., 2011; Whitlow et al., 2014). Modeling of a typical and proposed multi-pollutant risk-based approach to air quality source control in Detroit, for instance, indicated a respective \$1.1 billion and \$2.4 billion benefit of avoided mortality and morbidity (Wesson, Fann, Morris, Fox, & Hubbel, 2010). The concept of optimal planting should also include other factors such as the extent of rooting space and quality of urban soils for supporting trees (Mullaney, Lucke, & Trueman, 2015; Pauleit, 2003). Finally, the accuracy of predictions from this methodology depend both on the accuracy of data inputs and of the models used. Future work could expand services analyzed, address environmental justice, utilize improved data sources as they become available, allow user choice and preference among services, provide means to incorporate local knowledge/expertise, account for tree grow-out, and explicitly consider monetary and resource costs as constraints and tradeoffs. It is also hoped that this methodology will spur improvements in the data sources and models required to better support ecosystem service studies.

5. Conclusion

This work presents an initial framework and methodology that utilizes spatially explicit biophysical models to explore strategies for tree planting based on ecosystem service and benefit gradients. Gradients of pollution removal, monetary benefit of pollution removal defined by human health impacts, and heat index with respect to tree cover were found to be spatially varying and different from one another. Five planting scenarios were calculated to maximize pollution removal, removal benefit, and reduce the heat index and heat-related risk proxies; each scenario was constrained to achieve Baltimore's goal of 40% tree cover. Tradeoffs

were evident through differences in the order of planting and locations that did not receive plantings across scenarios. Planting order is important because municipal tree planting programs are usually implemented over many years.

Ecosystem services and benefits were quantified for the five planting scenarios and compared to services and benefits provided by Baltimore's current tree cover (24%) and potential maximum tree cover (44.4%). Pollution removal across scenarios ranged from 133 to 139 t/yr and monetary benefits ranged from \$4.3 M to \$6.2 M. Metrics or proxies of heat stress decreased across all scenarios, but a clearer link to human health is needed to compare benefits. Developed locations were generally high priority areas for plantings, but these areas had limited planting space due to high proportions of impervious cover. Additional services such as stormwater infiltration or carbon sequestration as well as costs (e.g. budgetary, water resources) could be considered, and the approach adapted for use as a decision support system. Consideration of the feasibility, costs, and benefits of impervious surface removal to increase plantable area should also be explored. With further expansion and continued advancement of relevant spatial data and models, this methodology could aid municipalities and stakeholders around the world in urban forest management and help increase desired ecosystem services and benefits.

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