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How to select the best tree planting locations to enhance air pollution removal in the MillionTreesNYC initiative

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Carbon and air pollutant uptake by urban forests are highly influenced by mortality rates.

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ABSTRACT

Highest priority zones for tree planting within New York City were selected by using a planting priority index developed combining three main indicators: pollution concentration, population density and low canopy cover. This new tree population was projected through time to estimate potential air quality and carbon benefits. Those trees will likely remove more than 10 000 tons of air pollutants and a maximum of 1500 tons of carbon over the next 100 years given a 4% annual mortality rate. Cumulative carbon storage will be reduced through time as carbon loss through tree mortality outweighs carbon accumulation through tree growth. Model projections are strongly affected by mortality rate whose uncertainties limit estimations accuracy. Increasing mortality rate from 4 to 8% per year produce a significant decrease in the total pollution removal over a 100 year period from 11 000 tons to 3000 tons.

1. Introduction

MillionTreesNYC is a citywide, public-private program with a goal to plant and care for one million new trees across the City's five boroughs (MillionTreesNYC's Official website). Planting one million trees will increase the city's tree population of 5.2 million trees (Nowak et al., 2007) by about 20%, potentially increasing the environmental benefits from the city's urban forest. The environmental benefits from these new trees will vary through space, depending upon where they are planted, and through time as the trees grow in stature and eventually die.

Some of the environmental benefits that can be increased by the new trees are air pollution removal and carbon storage (McPherson et al., 1994). Trees, through their growth process, store carbon within their tissue and reduce concentrations of carbon dioxide – the dominant gas contributing to climate change (Nowak and Crane, 2002; Nowak et al., 2002a,b; IPCC, 2006). Trees also remove air pollutants by absorbing gaseous pollutants via leaf stomata and by intercepting and retaining airborne particles on the plant surface (Beckett et al., 2000; Nowak et al., 2000, 2006). As air pollution affects human health, it is important to target tree planting in areas with relatively high human populations to help reduce air pollution concentrations in populated areas. As numerous environmental benefits are associated with and proximal to tree locations, planting trees near human populations can lead to improved environmental quality and human health and well-being (e.g., Nowak and Dwyer, 2007).

Recommendations of locations for new tree plantings in New York City have been made based on various indicators such as hospitalization and asthma rates (Grove et al., 2006). This paper intends to expand on this work by developing more specific location recommendations for tree planting related to air quality to help guide decisions on planting locations to improve environmental quality and human health. Potential locations to plant trees for air quality are developed based on an index that spatially considers local estimated air pollution levels, human population density, and tree cover.

In addition, the planted trees will annually accumulate carbon and remove air pollution at differing rates as the trees grow through time. Another goal of this paper is to estimate the annual and cumulative amounts of carbon stored and air pollution removed by the one million trees over a 100 year period given varying average annual mortality rates. Finally, this paper will discuss potential limitations of using urban trees to improve air quality and store carbon, and potential limitations of the analysis.

2. Material and methods

To determine the best locations in New York City to enhance pollution removal relative to human populations, three Geographic Information System (GIS) data

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bases were used: 1) human population density, 2) tree cover, and 3) estimated pollution concentration. Population density estimates derived for each census blocks from 2000 U.S. Census data (U.S. Census Bureau's official website http://www.census.gov/).

2.1. Tree cover estimates

Tree cover data were derived from a high-resolution cover map of New York City developed from 2001 color infra-red digital images (0.9 m ground-resolution) based on methods described in Myeong et al. (2001). Each pixel was classified as to either tree, grass, impervious, shadow or water. The accuracy of the map classification was assessed by comparing photo interpretation of randomly located points on the image against the cover type predicted by the cover map for the same point. A total of 1600 points were assessed with an overall user's accuracy of 86%. The user's accuracy for tree cover was 76%. The land cover map was used to determine the amount of tree cover in each census block.

2.2. Pollution concentration estimates

A computer program was developed (Hirabayashi, 2009) to estimate locations with relatively high pollution concentrations by modeling emission dispersion from Gaussian dispersion equations for local point and line (road) source emissions. Air pollutant concentrations were estimated for carbon monoxides (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter with the diameter of 10 micrometers or smaller (PM10).

Pollutants emitted from a point source were modeled to disperse in the three-dimensional field based on a Gaussian dispersion equation (Zannetti, 1990):

$$C = \frac{Q}{2\pi\sigma_y\sigma_z u}\exp\left[-\frac{1}{2}\left(\frac{y_r}{\sigma_y}\right)^2\right]\exp\left[-\frac{1}{2}\left(\frac{h_s+\Delta h - z_r}{\sigma_z}\right)^2\right], \tag{1}$$

where C = air pollutant concentration at a receptor (g/m^3), Q = pollutant emission rate from a source facility (g/s), u = wind speed (m/s), σ_y = Standard deviation of lateral concentration distribution (m), σ_z = standard deviation of vertical concentration distribution (m), y_r = crosswind distance between receptor and source (m), Δh = emission plume rise (m), h_s = height of the source (stack height) (m), and z_r = height of the receptor (=1.5 m).

Pollutant emission rate and stack height were derived from the US EPA's National Emission Inventory (NEI) database for 2002 – the latest year available (NEI, 2008), with annual emissions converted to average emissions per second. Wind speed and other meteorological variables were derived from the National Oceanic and Atmospheric Administration (NOAA)'s National Climate Data Center (NCDC) for 2005 (NCDC, 2008).

σ_y and σ_z in Equation (1) were calculated as (Green et al., 1980):

$$\sigma_y = \frac{k_1 x_r}{\left(1+\frac{x_r}{k_2}\right)^{k_3}} \tag{2}$$

$$\sigma_z = \frac{k_4 x_r}{\left(1+\frac{x_r}{k_2}\right)^{k_5}}, \tag{3}$$

where k_i = constants defined for the Pasquill stability categories, and x_r = downwind distance between receptor and source (m).

The effective stack height is the sum of the actual stack height h_s and the plume rise Δh. The buoyancy flux was calculated (Seinfeld and Pandis, 2006) to determine emission plume rise for each hour based on equations from Briggs (1969, 1971, 1974). The downwind and crosswind distances between the source and the receptor, x_r, y_r, respectively can be calculated as:

$$x_r = \text{easting} \times \sin\theta + \text{northing} \times \cos\theta \tag{4}$$

$$y_r = \text{northing} \times \sin\theta - \text{easting} \times \cos\theta \tag{5}$$

where θ = wind direction with respect to North. Equation (1) was applied for receptors whose downwind distance $x_r > 0$. The grid size used for New York City was 30 m with a 2000 m buffer around points sources to estimate dispersion.

2.2.1. Air pollutant estimation for line sources

Air pollutant dispersion from roads was estimated based on a) emissions from automobiles, which were based on traffic volume and emission factors, and b) pollutant dispersion, which was estimated with the Gaussian dispersion equation. Topologically Integrated Geographic Encoding and Referencing (TIGER, 2008) road network data were used to calculate length of road segments within each cell. Four road types, interstate highway (A1), other freeway and expressway (A2), other principal arterial (A3), and local road (A4) from these data were used to estimate air pollutant dispersion. U.S. Department of Transportation (2008) were used to determine the total length and daily vehicle-miles of travel (VMT) for the four road types in New York City.

The source emission rate per unit length of road was calculated for each of the four road types. First, the daily VMT was converted to VMT per second. This VMT was then divided by total length of the road type to derive VMT per unit length. Finally, this VMT was converted to the source emission rate per unit length by multiplying emission factors.

$$Q_i = \frac{\text{VMT}_i}{L_i} f_i \tag{6}$$

where Q_i = emission rate per unit length for the road type i (g/s/mile), VMT$_i$ = total vehicle-miles of travel for the road type i (mile/s), L_i = total length for the road type i (mile), and f_i = emission factor for the road type i (g/mile).

Emission factors were obtained from emission sensitivity tables issued by U.S. Environmental Protection Agency (US EPA, 1998) for CO and NO_x, and from modeled results by PART5 (US EPA, 2009a) for PM10 and SO_2. Based on the combination of altitude, calendar year, ambient temperature, cold/hot start VMT weighting, and average vehicle speed (Table 1), an emission factor for all mobile sources combined for CO and NOx can be retrieved from the emission sensitivity tables. A combination of the low altitude, the year of 2005, 20.6% cold start, 52.1% stabilized, and 27.3% hot start, and 75 F were used for both CO and NO_x emission factors. For the road type A1, A2 and A3, and A4, 55.0, 35.0, and 19.6 mph are chosen, respectively. Similar conditions are defined to run PART5 to obtain emission factors for PM10 and SO_2 (Table 2).

Air pollutant dispersions are separately estimated for each road type based on a modified General Finite Line Source Model (GFLSM) (Luhar and Patil, 1989; McHugh and Thomson, 2003)

$$C_i = \frac{Q_i}{2\sqrt{2\pi}\sigma_z u}\exp\left[-\frac{1}{2}\left(\frac{z_r - z_s}{\sigma_z}\right)^2\right]\left[erf\left(\frac{y_r + L_i/2}{\sqrt{2}\sigma_y}\right) - erf\left(\frac{y_r - L_i/2}{\sqrt{2}\sigma_z}\right)\right] \tag{7}$$

where C_i = air pollutant concentration for the road type i (g/m^3), Q_i = pollutant emission rate per unit length for the road type i (g/s/m), u = wind speed (m/s), σ_y = standard deviation of lateral concentration distribution (m), σ_z = standard deviation of vertical concentration distribution (m), y_r = crosswind distance between receptor and source (m), L_i = in-cell road length for the road type i (m), Z_s = height of the source (=0.5 m), and Z_r = height of the receptor (=1.5 m).

The GFLSM employs a single straight road segment and estimates air pollutant concentration at a neighboring receptor with the Gaussian dispersion equation. To estimate the spatial distribution of the concentration, this process is often repeated for multiple receptor locations. As the model domain in this study contained thousands of straight road segments, it was impractical to apply the GFLSM for each of these road segments. To handle this situation more efficiently with the raster-based GIS analysis, an approximation was made. The whole urban area of interest was represented with 30-meter grid cells and each cell may have contained road segments of the four road types. For a given cell, the road length of each road type included in that cell was calculated and the GFLSM was applied to that cell assuming that road segments were a single straight road that ran perpendicular to the wind direction. The dispersion from roads in each cell was limited with a 40 m buffer around the cell.

2.2.2. Model adjustment

For a given hour, hourly air pollutant concentration maps separately created for facility stacks and the four road types were merged into one map by taking summation of values in each of corresponding cells. Due to many factors, including background concentrations, the cell value and measured value at a monitor site may not have exhibited a good agreement. To ensure that the estimated concentration was identical to the measured value at a monitor site, an adjustment was performed using measured air pollution concentration data obtained from U.S. Environmental Protection Agency (EPA)'s Air Quality System (AQS) (US EPA, 2009b).

If multiple monitor sites existed in the area of interest, the area was divided into Thiessen (Voronoi) polygons that define individual areas of influence around each of

Table 1
Possible values for Parameters determining emission factors used in the pollutant dispersion model.

Parameter	Values
Altitude	High, low
Calendar year	1990, 1995, 2000, 2005, 2010, and 2020
Ambient temperature	0, 25, 50, 75 and 100 F
Cold/hot start VMT weighting	100% stabilized
	100% hot start
	100% cold start
	50% cold start, 50% stabilized
	50% hot start, 50% stabilized
	50% cold start, 50% hot start
	20.6% cold start, 52.1% stabilized, and 27.3% hot start
Average vehicle speed	2.5, 5.0, 10.0, 19.6, 35.0, 55.0, and 65.0 mph

Table 2
Emission factors employed in the pollutant dispersion model from line sources.

Road type	Emission factor (g/mile)			
	CO	NO_x	SO_2	PM10
A1	7.4	2.58	0.113	0.096
A2	10.58	2.02	0.113	0.096
A3	10.58	2.02	0.113	0.096
A4	20.52	2.02	0.113	0.095

monitor sites. Thiessen polygons are mathematically defined by the perpendicular bisectors of the lines between all points. Within each Thiessen polygon, the background concentration was determined as a difference between the measured concentration and the value of the cell on which the monitor points resides:

$$BC = MC - C_{i,j} \quad (8)$$

where BC = air pollutant background concentration (g/m^3), MC = measured air pollutant concentration (g/m^3), and $C_{i,j}$ = estimated air pollutant concentration at (i, j) where monitor site resides (g/m^3). Values of all cells in that Thiessen polygon were then adjusted with this background concentration:

$$CC_{i,j} = BC + C_{i,j} \quad (9)$$

where $CC_{i,j}$ = adjusted air pollutant at (i, j) (g/m^3) and $C_{i,j}$ = estimated air pollutant concentration at (i, j) (g/m^3). If only one monitor site existed in the area, the same procedure was applied to the whole area.

2.3. Planting index values

Three indicators (population density, % tree cover, and pollution concentration) were used to develop an index (modified from Nowak and Greenfield, 2008) that prioritizes tree planting locations with larger index values indicating higher priority for planting. The index assumes higher priority areas for planting are in areas with higher population densities, higher pollution concentration, and lower percent tree cover values. The final index value integrates all three factors in determining the index value for the highest priority for tree planting. Thus the index value integrates factors related to risk (pollution concentration and population density exposed to pollutants) and areas under-served with tree cover (low tree cover and high population density).

To combine these three indicators, each indicator was standardized on a scale of 0 to 1 and combined the indicators for the final index value based on a weighting of:

$$I = (PD \times 30) + (POLL \times 40) + (LTC \times 30)$$

where I is the combined index score, PD is the standardized value for population density, POLL is the standardized value for air pollutants, and LTC is the standardized value for low tree cover.

The combined index score (I) was standardized again and multiplied by 100 to produce a planting priority index (PPI) that ranges between 0 and 100. Air pollution concentration was weighted slightly more than population density and low canopy cover because it is the dominant indicator in relation to human health.

The standardized value for population density (PD) was calculated (Nowak and Greenfield, 2008) as PD = ((n − min)/r), where PD is the value between 0 and 1, n is the value for population density (population km^{-2}) in each census block, min is the minimum among all population density values and r is the range of density values. To prevent a limited number of small census tracts with abnormally high population densities from dominating the density part of the index, all tracts with a population density of 100 000 were considered to be the maximum value. This adjustment prevented outliers from skewing the range of index values.

As there were four different pollution concentrations estimated for each census tract, a combined base air pollutant concentration value was calculated by weighting the estimated concentration of each of the four pollutants by the California Ambient Air Quality Standards for the pollutant 2005 (Table 3) (Nowak et al., 2008).

The base pollution value (BPV) was calculated as:

Table 3
California Ambient Air Quality Standards. Weight was based on referencing against the 24-hour PM10 standard.

Standards	Particulate Matter (PM_{10})	Nitrogen Dioxide (NO_2)	Sulfur Dioxide (SO_2)	Carbon Monoxide (CO)
1-hour		470 μg/m^3	655 μg/m^3	23 000 μg/m^3
24-hour	50 μg/m^3		105 μg/m^3	
Weight*	1	0.66	0.47	0.02

$$BPV = \left(PM_{10}\mu gm^{-3}1.00\right) + \left(NO_2\ \mu gm^{-3}0.66\right) + \left(SO_2\ \mu gm^{-3}0.47\right) + \left(CO\ \mu gm^{-3}0.02\right)$$

The standardized value for air pollution concentration (POLL) was then calculated as POLL = ((n − min)/r), where n is the BPV for each census block, min is the minimum among all base pollution concentration values and r is the range of pollution concentration.

The standardized values for low tree cover were calculated using a reverse index of tree canopy cover where the lower the tree cover, the higher the standardized value. The standardized value for low tree cover (LTC) was calculated as LTC = ((max − n)/r) where n is the percentage of canopy cover in each block, max is the maximum among all values for tree canopy cover and r is the range of canopy cover values.

As the pollution concentration layer does not overlay the census blocks layer perfectly, blocks on the edge of water bodies do not have pollution concentration data and therefore do not have PPI value assigned.

2.4. Projecting future pollution and carbon removal

A population projector model was used to analyze future dynamics of the new trees that are to be planted in New York City. This model uses modeled field data from New York City (Nowak et al., 2007) to annually project the number of trees, percent canopy cover, annual carbon sequestration, and air pollution (O_3, PM_{10}, SO_2, NO_2, CO) removal based on growth rates and user inputs of annual tree planting and annual mortality rates (Nowak et al., 2004). In this study, the annual growth rate in tree diameter was set at 0.61 cm yr^{-1}. This default value is based on length of growing season, an estimated crown competition and tree conditions for New York City trees (Nowak et al., 2007, 2008). The projection model was run just for the new million tree population with 100 000 trees being planted annually for 10 years. Of these 100 000 trees, 62 000 were assumed to have a diameter at breast height (1.37 m) of 2.54 cm. The remaining 38 000 trees per year were planted as seedlings in parks (http://www.milliontreesnyc.org). These seedlings were assumed to take 5 years to reach 2.54 cm in diameter (minimum model diameter) and that 20% of the seedlings would die by year 5.

Trees were entered in the model in the year of planting (year 1 to 10) and tree growth was simulated using the average growth rate. As the population will not only grow through time, but also a certain percentage of the population will die each year, a mortality rate is used in the model to remove trees annually based on tree mortality. In Baltimore, the average annual mortality of the tree population was 6.6% between 1999 and 2001. As the mortality rate for the tree planting in New York City is unknown, average annual mortality rates of 4, 6 and 8% were used. As mortality rates vary by diameter class, the overall average annual mortality rate for the population was based on the existing tree population in New York City. That is, mortality rates for each diameter class varied such that the overall population mortality rate was the assigned mortality value (4, 6, or 8%). The assignment of the diameter class specific mortality rates were based on diameter mortality distribution from street trees in Syracuse (Nowak, 1986): 2.9% for trees 0 to 7 cm in diameter; 8 to 15 cm = 2.2%; 16 to 46 cm = 2.1%; 47 to 61 cm = 2.9%; 62 to 76 cm = 3.0%; and 77+ cm = 5.4%. The proportional change among these classes was held constant as the overall mortality rate varied (Fig. 1). As trees grow within the model between years,

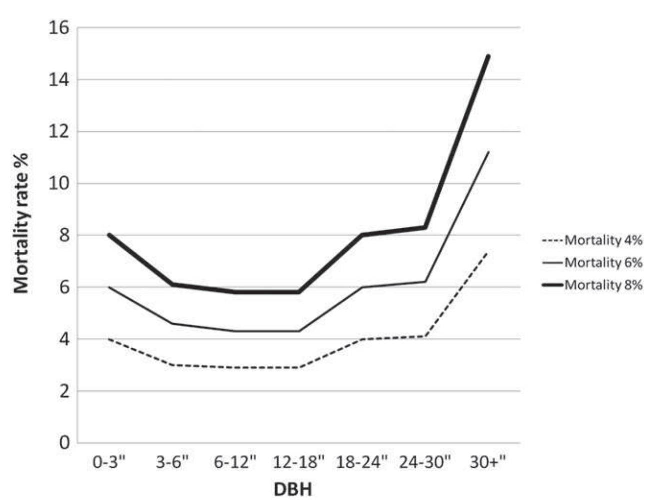

Fig. 1. Variations of the mortality rates of 4, 6 and 8% per year used for the different DBH classes.

the mortality rate of the tree population class would change as trees grow into a new diameter class.

The tree population was run for a 100 year period by entering the trees at time of planting and simulating growth, mortality and air pollution removal and carbon storage for each year of the simulation period. For each year, the number of trees surviving and the tree size were passed to the next simulation year for calculations of benefits. Air pollution removal was calculated each year using average pollutant flux rates per unit of canopy derived from the i-Tree Eco (formerly UFORE) model (USDA Forest Service, i-Tree Eco manual) for New York City (Nowak et al., 2006, 2007, 2008), and projection model estimates of canopy cover based on crown width – dbh relations for the million trees (Frelich, 1992; Nowak et al., 2004). Annual benefits were summed to estimate the cumulative effects over the 100 year period. Carbon storage estimates were based on tree dbh using formulas from Jenkins et al. (2003). The formula for spruce was used to estimate urban tree biomass for New York City as this formula produced a carbon estimate closest to the original estimate for the i-Tree Eco model (Nowak et al., 2007). The spruce formula estimates were multiplied by 1.03 to adjust for the differences between the model estimates for New York.

3. Results

3.1. The planting priority index map

The planting priority index map (Fig. 2) indicates that the areas of highest priority for planting based on the index are generally in Middle and Lower Manhattan and few blocks in Brooklyn and Queens. The middle and lower areas of Manhattan are characterized by blocks with high population density, high base pollution values (BPVs) and low canopy cover. Some of the blocks with the highest PPI values (colored in dark red on Fig. 2) have a population density of about 80 000 people per km^2, a BPV of about 68 and a canopy cover of 2%. Staten Island is characterized by medium low (21–40) and medium (41–60) PPI values. The Bronx is defined mostly by low (0–20), medium low (21–40) and medium (41–60) PPI values.

Lower and Middle Manhattan and part of Brooklyn and west Queens have many areas considered with the highest priority for the planting campaign. They have high population density, high pollution values and low canopy cover. Nevertheless, those blocks are mostly characterized by impervious surfaces where there is not much suitable space for trees, but where there are many people living. Parks and cemeteries scattered among the five boroughs tend to have low (0–20) and medium low (21–40) PPI values (colored in yellow and light orange on Fig. 2). These low values are a consequence of low population density values and high canopy cover percentage. The BPV varies among boroughs, with higher values in Staten Island, Manhattan and most of Brooklyn and relatively low values in Queens and the Bronx. Central Park, situated in the core of Manhattan, is characterized by PPI values in the range 21–40, even with low population density values. In this case, the medium low PPI values are due to the high base pollution values (BPV) in the park. Staten Island is the borough with the lowest population density in the city of New York with PPI values in the range 21–40 and 41–60. These relatively low values are mostly driven by population density values, despite relatively high pollution values and medium-high percentage of canopy cover.

3.2. The population projector model

The million tree population will vary in the future depending upon mortality rate with the new tree population peaking at 714 000, 598 000 and 518 000 trees for the 4, 6 and 8 % mortality rates, respectively (Fig. 3). After 100 years, the tree population would be 46 000, 9200, ad 1900 trees for the 4, 6 and 8 % mortality rates, respectively.

The amount of additional tree cover added due to the new tree population also varies with peak increases in city tree cover of 6.5%, 3.9% and 2.4% for the 4, 6 and 8 % mortality rates, respectively occurring between 30 and 50 years after planting (Fig. 4). After 100 years, the percent tree cover from the new trees would drop to about 3.3%, 0.8% and 0.2% for the 4, 6 and 8 % mortality rates, respectively.

Annual pollution removal peaks at 153, 93 and 58 tons, with removal at year 100 at 79, 18 and 4 tons for the 4, 6 and 8 % mortality rates, respectively (Fig. 5). Total pollution removal over a 100 year period is estimated at 11 000 tons, 6000 tons, and 3000 tons with mortality rates of 4, 6 and 8%, respectively.

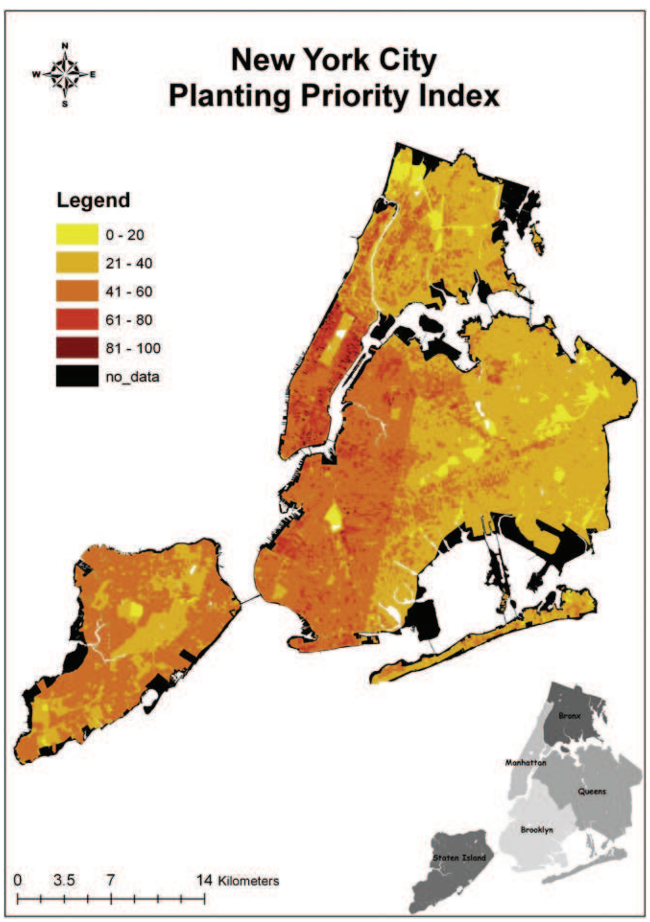

Fig. 2. Planting Priority Index (PPI) map for block subdivisions. The blocks with higher values indicate higher priority for planting.

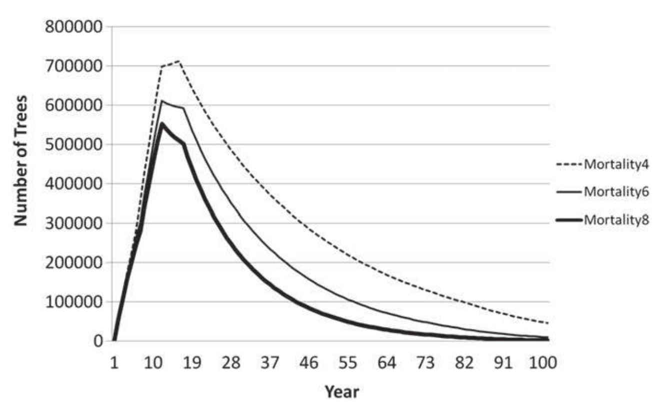

Fig. 3. Projected tree population totals over the next 100 years with varying mortality rates. Mortality4 = 4% average annual mortality rate, Mortality6 = 6% average annual mortality rate, Mortality8 = 8% average annual mortality rate.

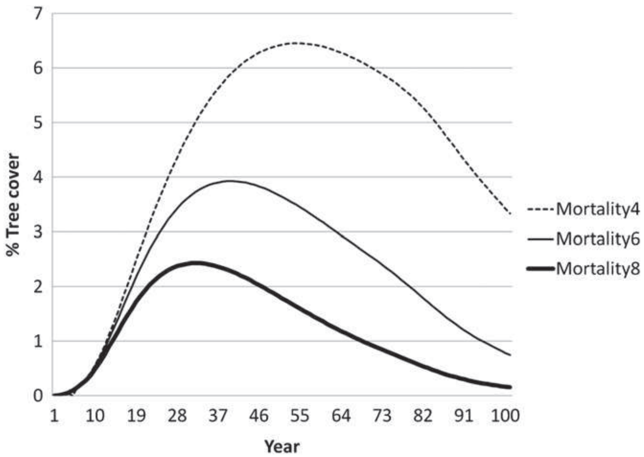

Fig. 4. Projected tree canopy cover of three different mortality rates. Mortality4 = 4% average annual mortality rate, Mortality6 = 6% average annual mortality rate, Mortality8 = 8% average annual mortality rate.

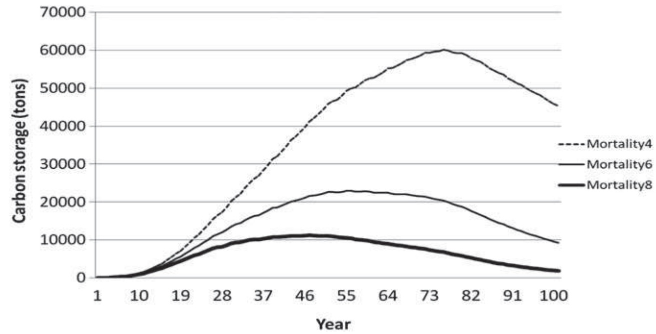

Fig. 6. Projected total carbon storage for three different mortality rates. Mortality4 = 4% average annual mortality rate, Mortality6 = 6% average annual mortality rate, Mortality8 = 8% average annual mortality rate.

Cumulative carbon storage in the planted trees will increase through time and then start to decline as loss of carbon from trees dying exceeds the carbon gained through the growth of existing trees. Peak carbon storage is estimated at 60 000, 23 000 and 11 000 tons for the 4, 6 and 8% mortality rates, respectively (Fig. 6).

4. Discussion

The planting priority index map is an attempt to illustrate potential areas to target to remove air pollution relative to areas with relatively high human populations and low tree cover. It is just one of several types of decisions that can be used to guide the determination of tree planting locations (e.g., Grove et al., 2006) and has uncertainties and limitations that need to be discussed. One is related to the estimation of pollutant concentration which is one of the factors driving the PPI.

Ozone and $PM_{2.5}$ were not taken into account among air pollutants even though they are of major concerns for human health and despite several cities like New York City are not in compliance with the EPA standards for those pollutants (US EPA http://www.epa.gov/airquality/greenbk.). Ozone is not directly emitted from facilities or automobiles but formed through chemical reactions with volatile organic compounds (VOC) and NOx under sunlight. For this reason the dispersion model should have been coupled with a chemical-atmospheric model which was not available for this study. Additionally, when the dispersion model was developed it accounted only for PM_{10} which at that time was considered a proxy for particulate.

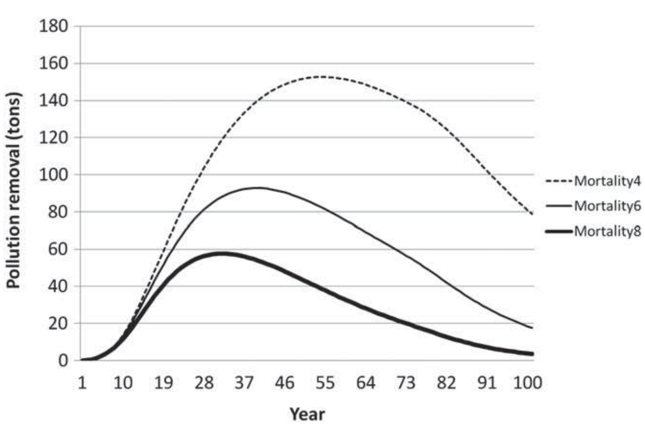

Fig. 5. Projected annual pollution removal graph for three different mortality rates. Mortality4 = 4% average annual mortality rate, Mortality6 = 6% average annual mortality rate, Mortality8 = 8% average annual mortality rate.

It should be considered that estimating pollutant concentrations at the local scale is technically difficult because it requires knowledge of spatial and temporal variability of pollutant concentrations at a small area (Jerrett et al., 2007). Methods for estimating urban pollution concentration patterns involve the interpolation of concentration taken from existing monitoring networks (Wong et al., 2004), statistical regressions of observed concentrations with surrounding land-use, traffic characteristics (Brauer et al., 2003; Briggs et al., 1997; Ollinger et al., 1993; Ross et al., 2006), and meteorological processes (Jerrett et al., 2007; Ainslie et al., 2008). However, due to the insufficient density of the monitoring network, small scale concentration variability cannot be resolved with these methods. In this study, therefore, dispersion modeling techniques were employed. One major drawback of this technique is its reliance on detailed spatial and temporal emissions inventories that are known to have large uncertainties (Hanna et al., 2001). In this study, the temporal resolutions of the road and facility emission data employed were originally annual and downscaled to per-second values to be incorporated in the dispersion equations. Since weekly or diurnal variations of emissions due to driving and facility operational patterns were not taken into consideration in the downscaling process, the air pollutant concentrations may have larger uncertainties. In addition, street canyon effects (Wang et al., 2008) were ignored and background concentrations (Jensen et al., 2001) were not fully addressed in the model, which could imply that air pollutant concentrations could be underestimated.

Besides to pollutant concentration the planting priority index considers areas with low canopy cover as underserved so in need for planting, while impervious surfaces are not taken into account because of the great difficulties in distinguishing buildings from streets, street sidewalks, parking lots and school playgrounds, although they can be considered locations for tree planting. It occurs often, such as in the MillionTreesNYC initiative, that many trees are being planted on sidewalks, parking lots and school playgrounds that are currently impervious cover. Whereas the final prioritization map is an important product of analysis and tool for guiding the planting campaign, field validation of the results cannot be avoided. Moreover, the PPI developed in this study is limited by the fact that in several cities, the areas where trees are more needed are the ones with few space available for trees to live as often the areas with the highest priority are heavily populated areas with large amounts of impervious surfaces. Halverson and Rowntree (1986) showed an inverse relationship between tree crown cover percentage and population density in eight U.S. cities, whereas trees would be more needed where people live, not only for health but also for psychological issues. Ulrich (1986) presented a study showing how natural landscapes have positive influence on emotional and psychological states and how those benefits produced by trees and vegetation increased in case of individuals experiencing anxiety and stress. O'Brien and Murray in 2007 showed how forest school had positive impacts on children in terms of confidence, social skills, language and communication, motivation and concentration, physical skills and knowledge and understanding. Moreover, as showed by Mitchell and Popham in 2008, green space has effects on health and health-related behaviors.

Though this map mainly targeted pollution levels, there are numerous other aspects that need to be considered in making planting decisions (Wu et al., 2008). The indicators taken into account to develop the planting priority index, i.e. pollution concentration, population density and low canopy cover could be used with other indicators such as the social acceptability of new tree plantings, community preferences, aesthetic values, runoff reduction, water remediation and so on. Thus, it is necessary to choose the most suitable indicators according to planning targets and urban manager goals. A Possible Urban Tree Canopy (PUTC) index was developed by Grove et al. (2006) that considers asthma and hospitalization rates as the main indicators to prioritize planting locations. The highest PUTC values were in an area of the Bronx due to high asthma rates whereas the main goal of the PPI was improving air quality and that is why we focused on those areas that were highly polluted and populated.

If planting trees for air quality improvement is a goal of the tree planting program, the negative attributes of trees in relation to air quality also need to be considered. Pollution removal and reduction in air temperatures, which can consequently reduce pollutant concentrations and emissions, are positive benefits from trees that should most likely be concentrated near human populations to enhance human health. However, on the negative side, design of trees near human populations need to be considered. As many urban emissions come from automobiles with emissions at the ground level, increasing canopy cover in populated areas with automobile emissions could potentially trap these emissions near the ground and increase pollutant concentrations. The dispersion of pollutants is an important process in reducing concentrations, and although increased canopy cover would enhance removal of pollution from the atmosphere, it could potentially increase local pollutant concentrations in some instances. Gross (1987) and Ries and Eichhorn (2001) found that tree planting in street canyons reduces wind flow velocity, thus increasing pollutants concentration.

In addition to design, species and site issues also need to be considered. Tree species emit in varying amounts biogenic volatile organic compounds (BVOC) (Owen et al., 2003), which play an important role in the formation of photochemical smog in the troposphere, leading to the formation of ozone (O_3) and other secondary pollutants (Fehsenfeld et al., 1992; Fuentes et al., 2000). Therefore, species selection in cities with ozone air quality problems should consider species composition relative to BVOC emissions to potentially reduce ozone concentrations. Though urban trees can contribute to ozone formation due to BVOC emissions (e.g., Taha, 1996), in a study that included the New York City region, changes in urban tree species composition had no detectable effect on ozone concentrations (Nowak et al., 1998). In this region urban tree VOC emissions were relatively small compared with anthropogenic and non-urban hydrocarbon emissions, that high or low VOC emitting species in urban areas had no effect on model estimates. Rather it was the physical processes associated with increased urban tree cover that tended to lead to lower ozone concentrations in the urban areas. Changes in pollution removal rates and meteorology, particularly air temperatures, wind fields, and mixing-layer heights, affected ozone concentrations. Tree effects were both positive in terms of pollutant uptake and negative in terms of biogenic emission and lead to an overall reduction in model estimates of ozone concentrations. As an example of negative effects, *Liquidambar styraciflua* and *Quercus coccinea* are high-BVOC emitting species that are among the species to be planted in the MillionTreesNYC initiative (Benjamin and Winer, 1998). Another factor which should be taken into account when choosing tree species is pollen production since it can have quite severe health effects as hay-fever and it is also a source of particles. Species and site selection can also be important in term of enhancing survival rates of newly planted trees. Matching tree species to sites where they can survive and thrive is important for reducing tree mortality rates whose uncertainty however is the main limit for the population projector. Though the actual mortality rates for trees in New York are not known, model projections of tree population and benefits clearly indicate how tree mortality affects long tree population benefits. Due to the limitations of model projections, the model estimates should only be considered gross estimates of potential effects as mortality and growth rates are estimated and can significantly influence model outputs. However, the projection results give a general indication of the magnitude and trends of effects through time. They also show how benefits from trees go far beyond the length of the MillionTreesNYC initiative being maximized many years later the end of the initiative. As expected from the projections, the tree population declines through time, but the tree cover and benefits increase for a period of time, and then decrease as the addition of canopy cover associated with tree growth is more than offset by canopy losses due to tree mortality. Thus, even though tree population can decrease in numbers, benefits can still increase depending upon the growth of the surviving tree population. Urban tree populations are dynamic. The key to sustaining or enhancing the ecosystem services from urban trees is understand the local population structure through field measurements and developing management plans that enhance tree population through planting or natural regeneration while reducing tree mortality. Numerous factors will affect planting, regeneration and mortality through time, so management plans and urban forests need to be monitored to adjust plans as needed to ensure local management goals are met. Monitoring of urban forests will also provide critical base line data needed to make better urban forest projections in the future (e.g., mortality rates).

Results of the population projector reveal the magnitude that canopy cover, and consequently uptake of pollutants and carbon, can increase due to the tree growth, but also the magnitude of the decrease over time due to mortality. Comparing different mortality rates, it is clear how projected tree cover and the air pollution removal curves have similar patterns and how mortality affects the magnitude of tree cover and benefits. Reducing mortality rates increases both total and peak benefits and shifts the peak effects to later time periods.

The new tree population planted in New York City will sequester an average of 7000 metric tons of carbon per year and remove around 10 grams of air pollutants (O_3, PM_{10}, SO_2, NO_2, CO) per square meter of canopy cover ($g\ m^{-2}$) per year with a mortality rate of 4%.

The benefits and canopy cover produced by the newly planted trees can be maximized by ensuring long-term survival (reducing mortality rates), enhancing growth rates, and utilizing species that produce maximum size and benefits. Reducing mortality can also be accomplished by choosing tree species that are well adapted to the urban environment. Tree adapted to local sites may also reduce long-term maintenance needs and costs. Trees remove pollutants but can also be affected by high levels of pollution. Normal pollution level does not adversely affect most trees, but for areas with high pollutant levels, tree species should be selected that are resistant to acute and chronic exposure to pollutants. Trees should be also resistant to pathogens and insects attacks. Healthy trees with high leaf surface areas and transpiration rates can enhance pollution removal (Nowak et al., 2002a,b), unless water limitation becomes an issue.

Planting campaigns, thus decisions on species selection and planting design, are more likely to be successful if they have a well defined goal, such as maximizing one or several of the benefits produced by trees. Management plans should focus on optimizing, in a certain area, those benefits that are considered having the highest priority to optimize benefits for society (Nowak et al., 2007).

5. Conclusions

Trees in urban environment improve air quality and consequently human health through pollution removal. In massive tree planting campaigns, as the MillionTreesNYC initiative, planting site selection is crucial to maximize tree benefits. Planting design, site and species selection, tree protection and maintenance are fundamental to ensure survival and tree benefits. The planting priority index developed in this paper is unique because it considers pollution concentration as the main indicator for driving decisions on planting sites. However, spatially distributed pollutant concentrations are still hard to obtain through dispersion model, especially for pollutants such as ozone that are highly reactive and not directly emitted. Moreover, more accurate data on $PM_{2.5}$ concentration are needed because of its extreme hazard for human health. The planting priority index is also innovative but could be integrated by other indicators that should be taken into account to make decisions on planting locations. Selecting one indicator instead of another is strictly related to stakeholders and planners needs.

In our study it emerged that the population projector is a valuable tool to quantify pollution and carbon uptake by trees over time, estimating future tree dynamics and proving how the benefits produced by trees last much longer than planting campaigns. However, those estimates are strongly dependent on mortality rate whose information is still scarce enabling accuracy of the estimates. Besides, social acceptance of the new tree population should be investigated and communities involved in order to reduce the dramatic phenomenon of vandalism that is often the first cause of mortality for trees in urban environment.

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