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2014

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Nowak, David J.; Hirabayashi, Satoshi; Bodine, Allison; and Greenfield, Eric, "Tree and forest effects on air quality and human health in the United States" (2014). *USDA Forest Service / UNL Faculty Publications*. 284.
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Environmental Pollution 193 (2014) 119–129

Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

Tree and forest effects on air quality and human health in the United States

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ARTICLE INFO

Article history:
Received 13 December 2013
Received in revised form
18 May 2014
Accepted 26 May 2014
Available online 10 July 2014

Keywords:
Air pollution removal
Air quality
Ecosystem services
Human mortality
Urban forests

ABSTRACT

Trees remove air pollution by the interception of particulate matter on plant surfaces and the absorption of gaseous pollutants through the leaf stomata. However, the magnitude and value of the effects of trees and forests on air quality and human health across the United States remains unknown. Computer simulations with local environmental data reveal that trees and forests in the conterminous United States removed 17.4 million tonnes (t) of air pollution in 2010 (range: 9.0–23.2 million t), with human health effects valued at 6.8 billion U.S. dollars (range: $1.5–13.0 billion). This pollution removal equated to an average air quality improvement of less than one percent. Most of the pollution removal occurred in rural areas, while most of the health impacts and values were within urban areas. Health impacts included the avoidance of more than 850 incidences of human mortality and 670,000 incidences of acute respiratory symptoms.

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1. Introduction

Air pollution is a significant problem in the United States that affects human health and well-being, ecosystem health, crops, climate, visibility and man-made materials. The Clean Air Act requires the U.S. Environmental Protection Agency (EPA) to set National Ambient Air Quality Standards for six “criteria pollutants” – that are both common throughout the United States and detrimental to human welfare (US EPA, 2013a). These pollutants are: carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), lead (Pb), sulfur dioxide (SO_2), and particulate matter (PM), which includes particulate matter less than 10 microns (PM_{10}) and particulate matter less than 2.5 microns ($PM_{2.5}$) in aerodynamic diameter. Health effects related to air pollution include impacts on pulmonary, cardiac, vascular, and neurological systems (e.g., Pope et al., 2002). In the United States, approximately 130,000 $PM_{2.5}$-related deaths and 4700 O_3-related deaths in 2005 were attributed to air pollution (Fann et al., 2012).

Trees and forests, like air pollution, vary throughout the United States (e.g., percent tree cover, species composition). Trees affect air quality through the direct removal of air pollutants, altering local microclimates and building energy use, and through the emission of volatile organic compounds (VOCs), which can contribute to O_3 and $PM_{2.5}$ formation (e.g., Chameides et al., 1988). However, integrative studies have revealed that trees, particularly low VOC emitting species, can be a viable strategy to help reduce urban O_3 levels (e.g., Taha, 1996; Nowak et al., 2000).

Trees remove gaseous air pollution primarily by uptake via leaf stomata, though some gases are removed by the plant surface. For O_3, SO_2 and NO_2, most of the pollution is removed via leaf stomata. Once inside the leaf, gases diffuse into intercellular spaces and may be absorbed by water films to form acids or react with inner-leaf surfaces. Trees directly affect particulate matter in the atmosphere by intercepting particles, emitting particles (e.g., pollen) and resuspension of particles captured on the plant surface. Some particles can be absorbed into the tree, though most intercepted particles are retained on the plant surface. The intercepted particles often are resuspended to the atmosphere, washed off by rain, or dropped to the ground with leaf and twig fall. During dry periods, particles are constantly intercepted and resuspended, in part, dependent upon wind speed. The accumulation of particles on the leaves can affect photosynthesis (e.g., Darley, 1971) and therefore potentially affect pollution removal by trees. During precipitation, particles can be washed off and either dissolved or transferred to the soil. Consequently, vegetation is only a temporary retention site for many atmospheric particles, where particles are eventually moved back to the atmosphere or moved to the soil. Pollution removal by urban trees in the United States has been estimated at 711,000 tonnes (t) per year (Nowak et al., 2006a).

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http://dx.doi.org/10.1016/j.envpol.2014.05.028
0269-7491/Published by Elsevier Ltd.

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While various studies have estimated pollution removal by trees (e.g., Nowak et al., 2006a; McDonald et al., 2007; Tallis et al., 2011), most studies on pollution removal do not directly link the removal with improved human health effects and associated health values. A few studies that have linked removal and health effects include one in London where a 10 × 10 km grid with 25% tree cover was estimated to remove 90.4 t of PM_{10} annually, which equated to the avoidance of 2 deaths and 2 hospital admissions per year (Tiwary et al., 2009). In addition, Nowak et al. (2013) reported that the total amount of $PM_{2.5}$ removed annually by trees in 10 U.S. cities in 2010 varied from 4.7 t in Syracuse to 64.5 t in Atlanta. Estimates of the annual monetary value of human health effects associated with $PM_{2.5}$ removal in these same cities (e.g., changes in mortality, hospital admissions, respiratory symptoms) ranged from $1.1 million in Syracuse to $60.1 million in New York City. Mortality avoided was typically around 1 person yr^{-1} per city, but was as high as 7.6 people yr^{-1} in New York City.

Tree cover in the United States is estimated at 34.2 percent and varies from 2.6 percent in North Dakota to 88.9 percent in New Hampshire (Nowak and Greenfield, 2012). As people and trees exist throughout a landscape in varying densities, not only will pollution removal and its effects on local pollution concentrations vary, but so will the associated human health impacts and values. The objectives of this paper are to estimate the amount of air pollution (NO_2, O_3, $PM_{2.5}$, SO_2) permanently removed by trees and forests within urban and rural areas of the conterminous United States in 2010, and its associated monetary value and impact on human health.

2. Methods

To estimate avoided health impacts and associated dollar benefits of air pollution removal by trees and forests in the conterminous United States in 2010, four types of analyses were conducted. These analyses were conducted at the county-level for all urban and rural areas to estimate: 1) the total tree cover and leaf area index on a daily basis, 2) the hourly flux of pollutants to and from the leaves, 3) the effects of hourly pollution removal on pollutant concentration in the atmosphere, and 4) the health impacts and monetary value of the change in NO_2, O_3, $PM_{2.5}$ and SO_2 concentration using information from the U.S. EPA Environmental Benefits Mapping and Analysis Program (BenMAP) model (US EPA, 2012a). Urban and rural areas were delimited using 2010 Census data with rural land defined as land not classified as urban (U.S. Census Bureau, 2013).

2.1. Tree cover and Leaf Area Index

Tree cover within each county was derived from 2001 National Land Cover Database (NLCD) 30-m resolution tree cover maps (USGS, 2008). These maps were used to determine tree cover within specific geographic locations. However, these maps generally underestimate tree cover (Nowak and Greenfield, 2010). To adjust for potential underestimates, NLCD percent tree cover within each county's NLCD land-cover class was modified according to the Nowak and Greenfield (2010) photo-interpreted values within individual mapping zones (i.e., tree cover estimates were adjusted to match the photo-interpreted estimates for each land cover class within each mapping zone). Adjusted NLCD tree cover estimates were within 0.1 percent of estimates derived from photo-interpretation (PI) of the conterminous United States (PI = 34.2 percent, adjusted NLCD = 34.1 percent), but this difference could be greater at the local scale.

Maximum (mid-summer) leaf area index (LAI: m^2 leaf area per m^2 projected ground area of canopy) values were derived from the level-4 MODIS/Terra global Leaf Area Index product for the 2007 growing season across the conterminous United States (USGS, 2013). In some areas, LAI values per unit of tree cover were missing or abnormally low and were estimated as 4.9 (Nowak et al., 2008) for urban areas (65 percent of urban areas had missing values) and 3.2 (Schlerf et al., 2005) for rural areas (14.5 percent of rural areas had missing values). Many urban areas had missing LAI estimates due to the coarseness of the MODIS data and relatively low amounts of forest cover in urban areas.

Percent tree cover classified as evergreen was determined for each county based on evergreen, deciduous and mixed forest land covers as classified by the NLCD. The proportion of mixed forest cover that was evergreen was estimated as the proportion of evergreen to evergreen plus deciduous forest cover in each county. LAI values were combined with percent evergreen information and local leaf-on and leaf-off (frost) dates (NCDC, 2005) to estimate total daily leaf surface area in each county assuming a four-week transition period centered on leaf-on and leaf-off dates for spring and autumn, respectively.

2.2. Pollution removal by trees

Hourly pollution removal or flux (F in $\mu g\ m^{-2}\ h^{-1}$) was estimated as:

$$F = V_d \times C$$

Where V_d is the deposition velocity of the pollutant to the leaf surface ($m\ h^{-1}$) and C is pollutant concentration ($\mu g\ m^{-3}$) (e.g., Hicks et al., 1989). Hourly concentrations for each pollutant were obtained from the U.S. EPA's Air Quality System national database for the year 2010 (US EPA, 2013b). For PM data, if hourly data did not exist, then daily and 6-day measurements were used to represent the hourly concentration values throughout the day (e.g., the average daily value was applied to each hour of the day). The number of monitors ranged from 399 for NO_2 to 1232 for O_3 (Fig. 1). If no pollutant monitors existed within the rural or urban area of a particular county, the closest data monitor was assigned to represent that area. As there are substantially more counties than monitors, most monitor data were derived from the nearest monitor that existed outside of the county (between 75 percent for O_3 and 92 percent for NO_2). If more than one monitor existed, hourly pollution removal was estimated for each monitor and averaged for the annual results.

To calculate the hourly deposition velocity, local hourly weather data for 2010 from the National Climatic Data Center (NCDC, 2013) were used to obtain hourly meteorological data (910 weather stations) (Fig. 1). If no weather data existed within a rural or urban area of a particular county, the closest monitor data was assigned to represent that area (72 percent of counties used data from outside the county). If more than one monitor existed, the weather data closest to the geographic center of the area was used. Deposition velocities for all pollutants and resuspension rates for particulate matter were calculated based on methods detailed in Nowak et al. (2006a, 2013) and Hirabayashi et al. (2011, 2012). Total removal of a pollutant in a county was calculated as the annual flux value ($\mu g\ m^{-2}\ yr^{-1}$) times total tree cover (m^2). Minimum and maximum estimates of removal were based on the typical range of published in-leaf dry deposition velocities (Lovett, 1994).

2.3. Change in pollutant concentration

To estimate percent air quality improvement due to dry deposition, hourly mixing heights from the nearest radiosonde station (74 stations; NOAA, 2013, Fig. 1) were used in conjunction with local

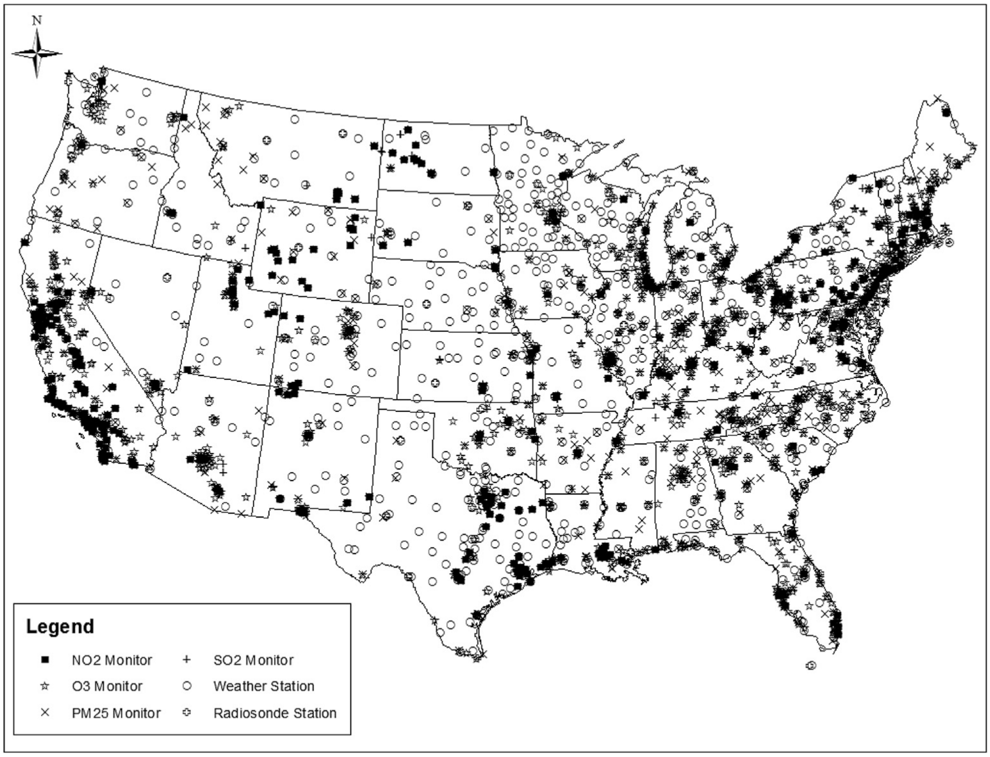

Fig. 1. Location of pollutant, weather and radiosonde stations.

hourly fluxes based on methods detailed in Nowak et al. (2013). As pollution removal by trees affects local measured pollution concentrations, this removal effect is accounted for in the calculation of percent air quality improvement (Nowak et al., 2006a).

2.4. Health incidence effects and monetary value of NO_2, O_3, $PM_{2.5}$ and SO_2 removal

The U.S. EPA's BenMAP program was used to estimate the incidence of adverse health effects (i.e., mortality and morbidity) and associated monetary value that result from changes in NO_2, O_3, $PM_{2.5}$ and SO_2 concentrations due to pollution removal by trees. BenMAP is a Windows-based computer program that uses Geographic Information System (GIS)-based data to estimate the health impacts and monetary value when populations experience changes in air quality (Davidson et al., 2007; Abt Associates, 2010; US EPA, 2012a). To calculate the health and monetary effects at the county level, the following six steps were conducted. The first four steps were processed using BenMAP (income and currency year of 2010), the last two steps were processed using BenMAP, census and air pollution model outputs for each county.

1) **Air quality grid creation**: Air quality grids were created for a baseline and control year for each pollutant. Years for baseline and control were selected to yield the greatest change in pollution concentration based on national pollution trends (www.epa.gov/airtrends/index.html). Baseline and control years were 2002 and 2004 for O_3, 2000 and 2007 for NO_2 and SO_2, and 2000 and 2006 for $PM_{2.5}$, respectively. The pollution concentration for the grids was interpolated from existing pollution data sets from EPA pollutant monitors using Voronoi neighborhood averaging.

2) **Incidence estimation**: Incidence estimates were calculated using several concentration-response functions (Table 1) that estimate the change in adverse health effects due to change in pollutant concentrations. Health impact functions relate a change in pollutant concentration to a change in the incidence of a health endpoint (i.e., premature mortality). These functions are typically derived from the estimated relationship between the concentration of a pollutant and the adverse health effects suffered by a given population (US EPA, 2012a). The model was run using population statistics from the U.S. Census 2010 county dataset using an economic forecasting model described in the BenMAP user manual (Abt Associates, 2010). BenMAP configures Census block populations into grid cell level data and the calculation is at grid cell level. BenMap data were aggregated to the county level.

3) **Aggregation and pooling**: Incidence estimates were aggregated and pooled. The health effects categories potentially have multiple estimates corresponding to different air quality metrics and age groups. Different age groups are represented because the concentration-response functions are age specific and incidence rate can vary across different age groups. Multiple estimates were pooled by either averaging the estimates using the random/fixed effects method or summing the estimates depending on which process was appropriate. In the end, a final estimate was produced to cover all possible metrics and age groups within a health category. For example, equations for 0–17, 18–64, and 65–99 age groups were summed to produce an estimate for 0–99 age group. More details on the BenMAP model are found in the literature (Davidson et al., 2007; Abt Associates, 2010; U.S. EPA, 2012a).

4) **Valuation estimation**: Valuation estimates were calculated using functions that estimate the health-care expenses (i.e., cost of illness and willingness to pay to avoid illness) and productivity losses associated with specific adverse health events, and on the value of a statistical life in the case of mortality. After running the model, BenMAP reports incidence, monetary value, change in pollution concentration and population results for each county within the conterminous United States.

Table 1
Concentration-response functions used in BenMAP.

Pollutant	Health effect	Metric	Start age	End age	Reference
PM2.5	Acute Bronchitis	D24MeanQ	8	12	Dockery et al., 1996
	Acute Myocardial Infarction				
	Acute Myocardial Infarction, nonfatal	D24Mean	18	99	Peters et al., 2001
		D24Mean	0	99	Pope et al., 2006
		D24Mean	0	99	Sullivan et al., 2005
		D24Mean	0	99	Zanobetti and Schwartz 2006
		D24Mean	0	99	Zanobetti et al., 2009
	Acute Respiratory Symptoms				
	Minor Restricted Activity Days	D24Mean	18	64	Ostro and Rothschild 1989
	Asthma Exacerbation				
	Asthma Exacerbation, Cough	D24Mean	6	18	Mar et al., 2004
	Asthma Exacerbation, Shortness of Breath	D24Mean	6	18	Mar et al., 2004
	Asthma Exacerbation, Wheeze	D24Mean	6	18	Ostro et al., 2001
	Chronic Bronchitis	D24MeanQ	27	99	Abbey et al., 1995
	Emergency Room Visits, Respiratory				
	Emergency Room Visits, Asthma	D24Mean	0	99	Mar et al., 2010
		D24Mean	0	17	Norris et al., 1999
		D24Mean	0	99	Slaughter et al., 2005
	Hospital Admissions, Cardiovascular				
	All Cardiovascular (less Myocardial Infarctions)	D24Mean	65	99	Bell et al., 2008
		D24Mean	18	64	Moolgavkar 2000
		D24Mean	65	99	Moolgavkar 2003
		D24Mean	65	99	Peng et al., 2008
		D24Mean	65	99	Peng et al., 2009
		D24Mean	65	99	Zanobetti et al., 2009
	Hospital Admissions, Respiratory				
	All Respiratory	D24Mean	65	99	Zanobetti et al., 2009
	Lower Respiratory Symptoms	D24Mean	7	14	Schwartz and Neas 2000
	Mortality				
	Mortality, All Cause	D24MeanQ	25	99	Laden et al., 2006
		D24MeanQ	0	1	Woodruff et al., 1997
		D24MeanQ	0	1	Woodruff et al., 2006
	Upper Respiratory Symptoms	D24MeanQ	9	11	Pope et al., 1991
	Work Loss Days	D24Mean	18	64	Ostro 1987
NO_2	Hospital Admissions, Respiratory				
	All Respiratory	D1Max	0	14	Luginaah et al., 2005
		D1Max	15	64	Luginaah et al., 2005
		D24Mean	65	99	Fung et al., 2006
		D24Mean	65	99	Yang et al., 2003
	Emergency Room Visits, Respiratory				
	Emergency Room Visits, Asthma	D1Max	0	99	Peel et al., 2005
		D24Mean	0	99	NYDOH 2006
		D24Mean	0	99	Ito et al., 2007
	Asthma Exacerbation				
	Asthma Exacerbation, Missed school days	D24Mean	4	12	O'Connor et al., 2008
	Asthma Exacerbation, Slow play	D24Mean	4	12	O'Connor et al., 2008
	Asthma Exacerbation, One or More Symptoms	D24Mean	4	12	O'Connor et al., 2008
		D24Mean	4	12	Schildcrout et al., 2006
		D4Mean	4	12	Mortimer et al., 2002
		D8Max	9	17	Delfino et al., 2002
		D8Max	18	18	Delfino et al., 2002
	Acute Respiratory Symptoms				
	Cough	D24Mean	7	14	Schwartz et al., 1994
O_3	Acute Respiratory Symptoms				
	Minor Restricted Activity Days	D1Max	18	64	Ostro and Rothschild 1989
		D8Max	18	64	Ostro and Rothschild 1989
	Emergency Room Visits, Respiratory				
	Emergency Room Visits, Asthma	D8Max	0	99	Peel et al., 2005
		D8Max	0	99	Wilson et al., 2005
	Hospital Admissions, Respiratory				
	All Respiratory	D8Max	0	1	Burnett et al., 2001
		D1Max	0	1	Burnett et al., 2001
		D24Mean	65	99	Schwartz 1995
		D8Max	65	99	Schwartz 1995
	Mortality				
	Mortality, All Cause	D1Max	0	99	Levy et al., 2005
		D24Mean	0	99	Bell et al., 2005
		D8Max	0	99	Bell et al., 2005
		D8Max	0	99	Levy et al., 2005
	School Loss Days				
	School Loss Days, All Cause	D1Max	5	17	Chen et al., 2000
		D8Max	5	17	Chen et al., 2000
		D8Max	5	17	Gilliland et al., 2001
		D8Mean	5	17	Gilliland et al., 2001

Table 1 (*continued*)

Pollutant	Health effect	Metric	Start age	End age	Reference
SO_2	Acute Respiratory Symptoms				
	Cough	D24Mean	7	14	Schwartz et al., 1994
	Asthma Exacerbation				
	Asthma Exacerbation, Slow play	D24Mean	4	12	O'Connor et al., 2008
	Asthma Exacerbation, Missed school days	D24Mean	4	12	O'Connor et al., 2008
	Asthma Exacerbation, One or More Symptoms	D24Mean	4	12	O'Connor et al., 2008
		D24Mean	4	12	Schildcrout et al., 2006
		D3Mean	4	12	Mortimer et al., 2002
	Emergency Room Visits, Respiratory				
	Emergency Room Visits, Asthma	D1Max	0	99	Peel et al., 2005
		D24Mean	0	99	Michaud et al., 2004
		D24Mean	0	99	Ito et al., 2007
		D24Mean	0	99	Wilson et al., 2005
		D24Mean	0	14	Wilson et al., 2005
		D24Mean	15	64	Wilson et al., 2005
		D24Mean	65	99	Wilson et al., 2005
		D24Mean	0	99	NYDOH 2006
	Hospital Admissions, Respiratory				
	All Respiratory	D1Max	0	99	Luginaah et al., 2005
		D1Max	0	14	Luginaah et al., 2005
		D1Max	15	64	Luginaah et al., 2005
		D1Max	65	99	Luginaah et al., 2005
		D24Mean	65	99	Schwartz et al., 1996
		D24Mean	65	99	Yang et al., 2003
		D24Mean	65	99	Fung et al., 2006

D24Mean – average of the 365 days of daily means.
D24MeanQ – average of the 4 quarterly means of daily means. The 4 quarters are defined as: Jan–Mar, April–June, Jul–Sep, Oct–Dec.
D4Mean – daily mean of hours 6am-10am.
D1Max – maximum 1 h value in a day.
D8Max – greatest mean for any 8 h window in a day.

5) **County multiplier creation**: Multipliers were created for each county in the conterminous United States using the results reported in BenMAP. Incidence and value results for each pollutant were divided by the county population within age group classes and change in pollution concentration to produce an estimate of number of incidences and monetary value per person per age group per unit concentration (ppb or $\mu g\ m^{-3}$) (U.S. EPA, 2012b).

6) **Tree effect estimates**: To estimate the tree effects on incidence and value for each health category, each county multiplier was multiplied by the 2010 Census county urban and rural population per age group and 2010 estimated change in pollutant concentration due to trees in the urban and rural county areas. The monetary values for all health categories were summed to determine the total value of all pollutant effects from trees in each county.

Dollar value results derived from the health impact of trees in every county were used to determine the relationship between dollar values per tonne of pollution removed and population density using linear robust regression. Errors occurred in BenMAP runs in 0.6 percent of the counties. For these counties, the regression equations and county population data were used to estimate the health values and impacts.

3. Results

The total amount of pollution removal in 2010 by trees and forests in the conterminous United States was 17.4 million t (range: 9.0 million t to 23.2 million t), with a human health value of \$6.8 billion (range: \$1.5 billion to \$13.0 billion) (Table 2). The range in values is based on the typical range of deposition velocities, but other uncertainties based on input data (e.g., tree cover, pollution concentration) and modeling of health benefits would increase the range, but the value of these uncertainties is unknown. Removal was substantially greater in rural areas (16.7 million t) than urban areas (651,000 t), but the pollution removal monetary value (2010) was substantially greater in urban areas (\$4.7 billion) compared with rural areas (\$2.2 billion) (Table 2, Fig. 2). The greatest amount of pollution removal was for O_3 and NO_2, while the greatest value associated with removal was for $PM_{2.5}$ and O_3 (Table 2). States with the greatest pollution removal amounts were California, Texas and Georgia, while states with greatest pollution removal values were

Table 2
Estimated removal of pollution (tonnes × 1000) and associated value (\$ × 1000) due to trees in the conterminous United States. Values in parentheses indicate minimum and maximum range of estimate.

Pollutant	Conterminous US		Urban areas		Rural areas	
	Removal (t × 1000)	Value (\$ × 1000)	Removal (t × 1000)	Value (\$ × 1000)	Removal (t × 1000)	Value (\$ × 1000)
NO_2	1439 (999–1750)	38,470 (23,390–48,830)	68 (41–85)	29,500 (17,650–37,930)	1371 (958–1661)	8939 (5736–10,900)
O_3	14,330 (7330–18,520)	2,219,000 (864,400–2,917,000)	523 (201–691)	1,497,000 (550,000–1,988,000)	13,810 (7130–17,830)	721,600 (314,400–929,800)
$PM_{2.5}$	696 (95–1560)	4,579,000 (607,600–10,070,000)	27 (4–58)	3,127,000 (414,700–6,928,000)	669 (91–1503)	1,452,000 (193,000–3,141,000)
SO_2	907 (583–1390)	7457 (4391–11,680)	33 (20–52)	4923 (2864–7793)	873 (564–1339)	2534 (1527–3891)
Total	17,370 (9010–23,220)	6,844,000 (1,500,000–13,050,000)	651 (266–887)	4,659,000 (985,000–8,960,000)	16,720 (8740–22,330)	2,185,000 (515,000–4,090,000)

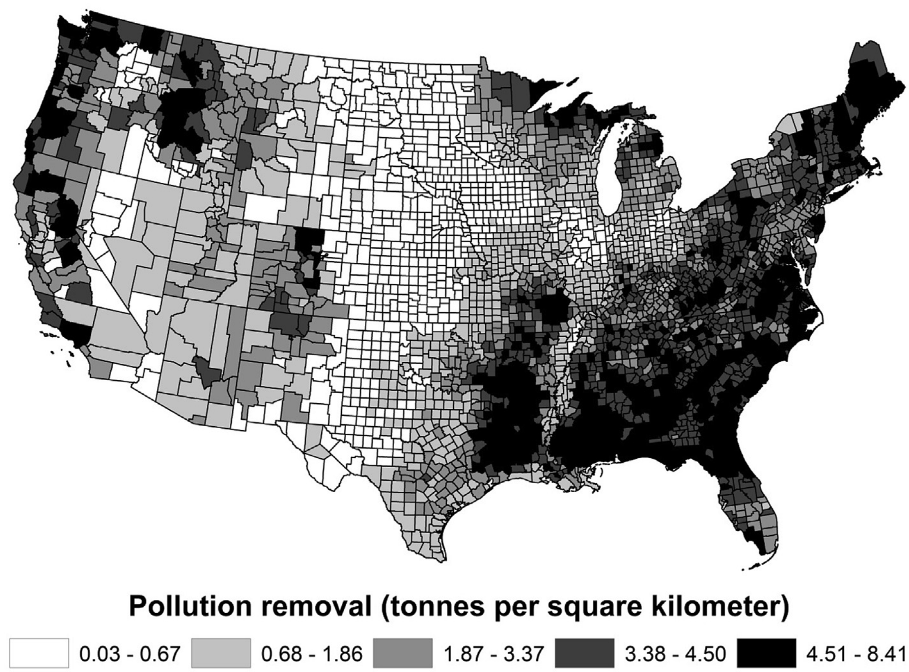

Fig. 2. Estimated removal per square kilometer of land (tonnes km^{-2}) of all pollutants (NO_2, O_3, $PM_{2.5}$, SO_2) by trees per county in 2010.

Florida, Pennsylvania and California (Table 3). Most of these benefits were dominated by the effects of reducing human mortality, with a national reduction of more than 850 incidences of human mortality (range: 184–1634) (Table 4). Other substantial health benefits include the reduction of more than 670,000 incidences of acute respiratory symptoms (range: 221,000–1,035,000), 430,000 incidences of asthma exacerbation (range: 198,000–688,000) and 200,000 school loss days (range: 78,000–266,000).

The monetary values associated with reduced adverse health effects increased with county population density. Dollar values per tonne removed were highest in New York County, New York (Manhattan): NO_2 = \$7200 t^{-1}; O_3 = \$63,800 t^{-1}; $PM_{2.5}$ = \$3,852,400 t^{-1}; SO_2 = \$2600 t^{-1}. Average pollution removal values per t in urban areas were: NO_2 = \$436 t^{-1}; O_3 = \$2864 t^{-1}; $PM_{2.5}$ = \$117,106 t^{-1}; SO_2 = \$148 t^{-1} (Table 5). These values were substantially higher than in rural areas.

The regression equations estimating dollars per tonne (y) based on population density (people per km^2, x) were:

NO_2: $y = 0.7298 + 0.6264x$ ($r^2 = 0.91$)

O_3: $y = 9.4667 + 3.5089x$ ($r^2 = 0.86$)

$PM_{2.5}$: $y = 428.0011 + 121.7864x$ ($r^2 = 0.83$)

SO_2: $y = 0.1442 + 0.1493x$ ($r^2 = 0.86$)

These equations will produce average values based on population density, not specific population parameters (e.g., age class distribution) and can give rough estimates of values in areas where BenMAP cannot be applied.

Average removal per square meter of canopy cover for all pollutants varied from 6.65 g m^{-2} yr^{-1} in rural areas to 6.73 g m^{-2} yr^{-1} in urban areas, with a national average of 6.66 g m^{-2} yr^{-1} (Table 5). The national average value per hectare of tree cover was about \$26, but varied from \$9 in rural areas to \$481 in urban areas. The average annual percent air quality improvement due to trees varied among pollutants and ranged from a low of 0.13% in urban areas for $PM_{2.5}$ to a high of 0.51% in rural areas for O_3 (Table 5).

4. Discussion

Pollution removal by trees and forests in the United States is substantial at more than 17 million t removed in 2010. As 96.4 percent of the conterminous United States is rural land and percent tree cover is comparable between urban and rural land (Nowak and Greenfield, 2012), 96.3 percent of pollution removal from trees occurred on rural land. However, as human populations are concentrated in urban areas, the health effects and values derived from pollution removal are concentrated in urban areas with 68.1 percent of the \$6.8 billion value occurring with urban lands. Thus, in terms of impacts on human health, trees in urban areas are substantially more important than rural trees due to their proximity to people. The greatest monetary values are derived in areas with the greatest population density (e.g., Manhattan).

The reason urban areas have substantially greater values than rural areas is that the BenMAP values and effects analyzed are based upon human health, which is related to US EPA air primary quality standards. Primary standards are designed to provide public health protection, while secondary standards provide public welfare protection, including protection against decreased visibility and damage to animals, crops, vegetation, and buildings (US EPA, 2013a). If the analysis shifted more toward secondary standard issues, particularly protection from damage to animals, crops and vegetation, the valuation in urban and rural areas would change. The valuation provided in this study is conservative as it predominantly addresses only human health values. It also only addresses four of the six criteria pollutants.

BenMAP values are relatively low compared to other valuation approaches. Using median air pollution cost factors from Europe that include health costs, building and material damage, and crop losses (Van Essen et al., 2011), the value of pollution removal by U.S. trees would jump to \$86 billion, a 13 fold increase in value. Externality values and pollution costs are constant values per tonne that

Table 3
Estimated removal of pollution and associated value (total and per hectare of land area) due to trees in the conterminous United States by state and District of Columbia.

State	All land						Urban land				Rural land			
	Removal		Value				Removal		Value		Removal		Value	
	t × 1000	kg ha^{-1}	$ × M[a]	$ ha^{-1}	%Urban[b]	%Tree[c]	t × 1000	kg ha^{-1}	$ × M[a]	$ ha^{-1}	t × 1000	kg ha^{-1}	$ × M[a]	$ ha^{-1}
Alabama	639.8	48.8	227.1	17.3	4.4	70.0	18.8	32.9	104.2	182.0	621.0	49.6	122.9	9.8
Arizona	446.6	15.2	24.9	0.8	1.9	19.2	6.0	10.6	20.9	36.9	440.5	15.3	4.0	0.1
Arkansas	548.6	40.8	95.8	7.1	2.1	57.2	7.0	24.8	37.7	132.7	541.6	41.2	58.2	4.4
California	1035.3	25.6	446.2	11.0	5.3	36.1	36.4	17.0	404.3	189.4	999.0	26.1	41.9	1.1
Colorado	534.3	19.9	15.7	0.6	1.5	23.6	2.0	5.0	5.0	12.8	532.4	20.1	10.6	0.4
Connecticut	49.0	39.0	120.3	95.7	37.7	72.6	15.6	32.9	102.3	216.0	33.4	42.6	18.0	23.0
Delaware	15.7	31.0	21.1	41.7	20.9	33.3	2.7	25.4	15.8	150.0	13.0	32.5	5.3	13.2
District of Columbia	0.3	18.5	7.7	483.3	100.0	28.6[d]	0.3	18.5	7.7	483.3	na	na	na	na
Florida	638.9	44.6	569.2	39.8	13.7	54.9	61.5	31.4	465.5	237.8	577.5	46.7	103.7	8.4
Georgia	731.7	48.7	352.3	23.5	8.3	66.4	50.0	40.1	226.2	181.7	681.7	49.5	126.1	9.2
Idaho	565.7	26.4	42.8	2.0	0.6	37.9	1.4	10.5	18.7	144.0	564.4	26.5	24.1	1.1
Illinois	140.3	9.8	149.4	10.4	7.1	15.6	11.2	10.9	133.0	130.4	129.2	9.7	16.4	1.2
Indiana	164.0	17.7	96.2	10.4	7.0	25.7	8.4	12.9	63.1	96.9	155.5	18.1	33.0	3.8
Iowa	86.5	6.0	28.2	2.0	1.7	10.4	2.1	8.4	18.5	75.3	84.4	5.9	9.7	0.7
Kansas	85.8	4.1	16.7	0.8	1.2	8.0	2.1	8.2	11.7	46.5	83.8	4.0	5.0	0.2
Kentucky	334.9	32.6	99.9	9.7	3.6	58.0	6.9	18.8	42.1	115.0	328.0	33.1	57.7	5.8
Louisiana	447.7	40.3	142.6	12.8	4.6	51.5	15.7	31.0	85.5	168.4	431.9	40.7	57.0	5.4
Maine	401.0	49.9	78.3	9.7	1.2	83.1	3.6	38.3	23.2	248.1	397.4	50.0	55.1	6.9
Maryland	95.2	37.6	134.9	53.3	20.6	42.8	16.8	32.1	111.8	214.4	78.5	39.0	23.1	11.5
Massachusetts	89.7	43.8	250.1	122.2	38.0	70.8	30.2	38.9	222.8	286.3	59.4	46.8	27.3	21.5
Michigan	496.3	33.7	177.4	12.0	6.4	59.5	21.8	23.2	107.1	113.9	474.5	34.4	70.3	5.1
Minnesota	335.5	16.3	46.9	2.3	2.2	34.8	4.6	10.5	26.7	60.3	330.9	16.4	20.1	1.0
Mississippi	564.2	46.8	156.8	13.0	2.4	64.0	10.5	36.6	60.4	210.9	553.7	47.0	96.4	8.2
Missouri	502.7	28.2	127.7	7.2	3.0	40.3	10.4	19.5	70.2	132.1	492.4	28.5	57.5	3.3
Montana	727.7	19.3	28.1	0.7	0.2	27.5	0.5	6.6	5.6	72.4	727.2	19.3	22.5	0.6
Nebraska	44.0	2.2	5.4	0.3	0.7	3.6	0.5	3.9	3.9	28.6	43.5	2.2	1.5	0.1
Nevada	210.1	7.4	9.0	0.3	0.7	11.6	1.7	8.6	8.1	41.0	208.4	7.4	0.9	0.0
New Hampshire	115.5	49.6	44.1	18.9	7.2	88.9	5.9	35.2	17.3	103.7	109.6	50.7	26.7	12.4
New Jersey	69.1	36.0	181.3	94.3	39.7	57.0	21.9	28.7	165.5	216.9	47.2	40.8	15.7	13.6
New Mexico	452.7	14.4	8.5	0.3	0.7	19.1	2.1	9.9	4.3	20.0	450.6	14.4	4.2	0.1
New York	422.5	34.6	433.4	35.5	8.7	65.0	31.9	30.0	345.9	325.5	390.6	35.1	87.5	7.9
North Carolina	564.7	44.8	315.4	25.0	9.5	62.6	42.0	35.1	176.5	147.5	522.7	45.8	138.9	12.2
North Dakota	21.2	1.2	1.4	0.1	0.3	2.6	0.1	2.1	0.8	16.1	21.1	1.2	0.6	0.0
Ohio	233.3	22.1	268.0	25.3	10.8	39.9	24.5	21.5	205.3	179.7	208.8	22.1	62.6	6.6
Oklahoma	302.9	17.1	58.6	3.3	1.9	25.9	3.9	11.5	26.9	79.6	299.0	17.2	31.6	1.8
Oregon	676.1	27.1	159.9	6.4	1.2	40.8	5.0	17.5	102.8	358.4	671.1	27.3	57.1	2.3
Pennsylvania	437.0	37.7	543.5	46.9	10.5	65.8	30.8	25.2	368.8	302.3	406.2	39.2	174.7	16.8
Rhode Island	10.5	38.7	33.6	123.3	38.7	70.3	2.9	27.8	27.9	264.6	7.6	45.6	5.7	34.3
South Carolina	371.2	47.6	204.3	26.2	7.9	64.6	23.6	38.4	118.5	192.3	347.6	48.4	85.8	11.9
South Dakota	45.7	2.3	3.7	0.2	0.3	5.7	0.2	4.2	1.9	33.2	45.4	2.3	1.8	0.1
Tennessee	402.5	37.7	183.2	17.2	7.0	57.1	19.9	26.5	103.1	137.2	382.6	38.6	80.1	8.1
Texas	1011.9	14.9	317.2	4.7	3.3	23.4	36.5	16.1	222.0	97.8	975.4	14.8	95.2	1.4
Utah	331.4	15.6	15.0	0.7	1.1	17.8	2.4	10.0	11.5	48.6	329.0	15.6	3.5	0.2
Vermont	96.4	40.3	22.2	9.3	1.7	81.5	1.0	25.5	6.1	150.9	95.4	40.5	16.1	6.8
Virginia	446.1	43.5	171.6	16.7	6.8	66.7	21.4	30.8	103.9	149.7	424.7	44.4	67.7	7.1
Washington	535.5	31.0	241.1	13.9	3.6	47.2	13.9	22.5	168.6	272.6	521.5	31.3	72.5	4.3
West Virginia	262.8	42.2	77.7	12.5	2.7	81.4	4.5	27.5	28.9	174.5	258.2	42.6	48.8	8.1
Wisconsin	333.1	23.7	84.8	6.0	3.5	47.7	7.0	14.4	47.7	98.0	326.1	24.1	37.1	2.7
Wyoming	296.6	11.8	4.3	0.2	0.2	14.5	0.4	7.0	1.9	36.8	296.2	11.8	2.4	0.1
Conterminous U.S.	17,370.3	22.7	6843.2	8.9	3.6	34.2	650.5	23.7	4658.4	169.6	16,719.8	22.6	2184.9	3.0

[a] Millions of dollars.
[b] Percent of state land classified as urban (2010).
[c] Percent tree cover in state (from Nowak and Greenfield, 2012).
[d] From Nowak et al. (2006b).

estimate more than human health impacts, while BenMAP's health valuation is dependent on human population density. Health values vary with human populations as humans are the recipients of the health benefits.

The greatest impact of trees on air pollution in terms of both magnitude and value were for O_3 and particulate matter. Pollution removal amounts were highest for O_3 due to the combination of relatively high concentrations and removal rates by trees for these pollutants (e.g., Lovett, 1994). Pollution removal monetary values were greatest for O_3 and $PM_{2.5}$ due to the estimated impact of changes in these pollutant concentrations on human mortality. BenMAP assigns the greatest value per incidence for human mortality, averaging $7.8 million per incidence.

The amount and pattern of pollution removal in this study is comparable to those found for U.S. urban areas circa 1994 (Nowak et al., 2006a), which used 1990 census data and 1994 pollution data to estimate pollution removal in U.S. urban areas at 711,000 t ($3.8 billion). This amount compares to the current study's 2010 estimate for U.S. urban areas of 651,000 t ($4.7 billion). These numbers are not directly comparable as the 1990 values included estimates for CO and PM_{10} removal, but did not directly include $PM_{2.5}$ removal. In addition, the valuation process has changed, shifting from externality-based estimates to human-health (BenMAP) estimates of dollar values. The total amount of urban land and thus urban tree cover has also increased between 1990 and 2010. Percent urban land in the conterminous United States increased

Table 4
Reduction in number of incidences and associated monetary value ($) for various health effects due to pollutant reduction from trees.

		Conterminous US		Urban areas		Rural areas	
Pollutant	Adverse health Effect	No. Inc[a]	Value	No. Inc[a]	Value	No. Inc[a]	Value
NO_2	Asthma Exacerbation	271,402	21,772,000	214,236	17,178,000	57,166	4,594,000
	Hospital Admissions	640	16,037,000	470	11,823,000	170	4,214,000
	Acute Respiratory Symptoms	18,179	565,000	14,666	455,000	3513	110,000
	Emergency Room Visits	238	100,000	185	78,000	53	22,000
	Total		38,473,000		29,534,000		8,939,000
O_3	Mortality	275	2,137,630,000	185	1,439,586,000	90	698,044,000
	Acute Respiratory Symptoms	481,275	41,143,000	345,581	29,543,000	135,695	11,600,000
	Hospital Admissions	1977	20,326,000	1776	13,852,000	201	6,474,000
	School Loss Days	202,399	19,874,000	146,939	14,428,000	55,460	5,446,000
	Emergency Room Visits	231	97,000	167	70,000	63	26,000
	Total		2,219,069,000		1,497,479,000		721,590,000
$PM_{2.5}$	Mortality	577	4,488,013,000	394	3,062,289,000	183	1,425,724,000
	Chronic Bronchitis	149	41,706,000	106	29,720,000	43	11,987,000
	Acute Respiratory Symptoms	169,701	16,634,000	122,484	12,006,000	47,216	4,628,000
	Acute Myocardial Infarction	125	11,219,000	85	7,629,000	40	3,590,000
	Asthma Exacerbation	137,298	11,161,000	98,467	8,005,000	38,831	3,157,000
	Work Loss Days	28,815	4,758,000	20,836	3,602,000	7979	1,157,000
	Hospital Admissions, Cardiovascular	71	2,705,000	49	1,876,000	22	829,000
	Hospital Admissions, Respiratory	58	1,850,000	39	1,246,000	19	604,000
	Lower Respiratory Symptoms	3900	202,000	2809	146,000	1091	57,000
	Upper Respiratory Symptoms	3168	142,000	2284	103,000	883	40,000
	Emergency Room Visits	203	84,000	150	62,000	53	22,000
	Acute Bronchitis	320	28,000	231	20,000	89	8000
	Total		4,578,503,000		3,126,703,000		1,451,800,000
SO_2	Acute Respiratory Symptoms	2865	90,000	2042	64,000	823	26,000
	Asthma Exacerbation	25,334	1,998,000	17,680	1,393,000	7654	605,000
	Emergency Room Visits	111	46,000	81	34,000	30	12,000
	Hospital Admissions	174	5,322,000	112	3,432,000	62	1,891,000
	Total		7,457,000		4,923,000		2,534,000

[a] reduction in number of incidences.

Table 5
Average annual values per tonne ($ t^{-1}) of removal and per hectare of tree cover ($ ha^{-1}), average grams of removal per square meter of tree cover ($g\ m^{-2}$) and average absolute and percent reduction in pollutant concentration in the conterminous United States (2010).

	Conterminous US			Urban areas					Rural areas				
Pollutant	$ t^{-1}	$ ha^{-1}	$g\ m^{-2}$	$ t^{-1}	$ ha^{-1}	$g\ m^{-2}$	ΔC[a]	% ΔC[b]	$ t^{-1}	$ ha^{-1}	$g\ m^{-2}$	ΔC[a]	% ΔC[b]
NO_2	27	0.15	0.55	436	3.05	0.70	0.018	0.229	7	0.04	0.55	0.021	0.296
O_3	155	8.50	5.49	2864	154.76	5.40	0.107	0.359	52	2.87	5.49	0.156	0.514
$PM_{2.5}$	6587	17.54	0.27	117,106	323.14	0.28	0.013	0.127	2169	5.78	0.27	0.019	0.199
SO_2	8	0.03	0.35	148	0.51	0.34	0.006	0.340	3	0.01	0.35	0.009	0.483
Total		26.22	6.66		481.47	6.73				8.69	6.65		

[a] Average annual reduction in hourly concentration in ppb, except for $PM_{2.5}$ ($\mu g\ m^{-3}$).
[b] Average percent annual reduction in hourly concentration.

from 2.5 percent in 1990 to 3.1 in 2000 (Nowak et al., 2005) and to 3.6 in 2010. The amount of urban tree cover has increased from around 6.7 million hectares in 1990 to 9.6 million hectares in 2010. Thus, as urban land and population continue to expand, the amount and value of pollution removal by urban trees will continue to increase.

Typical annual air quality improvement due to pollution removal by trees was less than one percent, which is comparable to values in Nowak et al. (2006a). Maximum annual air quality improvement in some areas reached between 2 and 4.5 percent depending upon meteorological conditions. In heavily forested areas, peak one hour improvements could reach as high as 16 percent (Nowak et al., 2006a).

In general, the greater the tree cover, the greater the pollution removal; and the greater the removal and population density, the greater the value. However, trees also affect air quality in ways not analyzed in this paper. Trees reduce air temperatures, which can lead to reduced emissions from various anthropogenic sources (e.g., Cardelino and Chameides, 1990). Trees around buildings alter building energy use (e.g., Heisler, 1986) and consequent emissions from power plants. Trees reduce wind speeds, lowering mixing heights and can therefore increase pollution concentrations (e.g., Nowak et al., 2006a). Trees also emit varying levels of volatile organic compounds (VOCs) that are precursor chemicals to O_3 and $PM_{2.5}$ formation (e.g., Chameides et al., 1988; Hodan and Barnard, 2004). More research is needed on how these factors combine to affect air pollution concentrations.

The issue of fine-scale effects on pollution concentrations also needs to be addressed – how do tree configurations alter local pollutant concentrations? Local-scale effects will differ depending upon vegetation designs. This county-wide modeling focused on broad-scale estimates of pollution removal by trees on air quality. At the local scale, pollution concentrations can be increased if trees: a) trap the pollutants beneath tree canopies near emission sources (e.g., along road ways, Gromke and Ruck, 2009; Wania et al., 2012; Salmond et al., 2013; Vos et al., 2013), b) limit dispersion by reducing wind speeds, and/or c) lower mixing heights by reducing wind speeds (Nowak et al., 2006a). Under stable atmospheric conditions (limited mixing), tree removal could lead to greater reductions in pollution concentrations at the ground level by limiting mixing with air pollutants above the canopy. Large stands of trees can also reduce pollutant concentrations in the interior of the stand due to increased distance from emission sources and increased dry deposition (e.g., Dasch, 1987; Cavanagh et al., 2009). Thus, local-scale design of trees and forests can affect local-scale pollutant concentrations. More research is needed that accounts for vegetation configuration and source-sink relationships in order to maximize beneficial tree effects on pollutant concentrations and human exposure to air pollution.

Removal rates by trees will vary locally based on several additional factors, including: a) amount of tree cover – increased cover increases removal; b) pollution concentration – increased concentration generally increases removal; c) length of growing season – longer growing seasons increase removal; d) percent evergreen leaf area – increased evergreen leaf area increases pollution removal during leaf-off seasons; and e) meteorological conditions – these affect dry deposition pollution removal rates. In addition, various factors that affect tree health and transpiration (e.g., drought or other environmental stressors) can affect the removal of gaseous pollutants by trees by limiting gas exchange at the leaf surface.

This study does not address the issue of advection, where pollution removal in rural areas surrounding urban areas could lower the pollution concentrations arriving into urban areas (or vice versa). As many pollutants are generated locally, this may not be a major factor, but for some pollutants, particularly secondary pollutants such as O_3 that are formed from chemical reactions, the reduction of pollutants in rural areas could have an impact on urban pollutant concentrations. The magnitude of this potential impact is unknown.

Though there are various limitations to these estimates, the results give a first-order approximation of the magnitude of pollution removal by trees and their effect on human health. Limitations of the analysis include: a) limitations associated with modeling particulate matter removal and resuspension (see Nowak et al., 2013), b) limited number of weather and pollutant monitors nationally, i.e., use of closest weather and pollution data might not represent the true average for the county and rural concentrations may be overestimated if using urban monitors to represent rural areas, c) uncertainties associated with estimating tree cover and leaf area indices in each county, d) the boundary layer is assumed to be well-mixed (unstable), which will likely lead to conservative estimates of concentration reductions during stable conditions, e) limitations associated with estimating human health effects and values using BenMAP, and f) results focus only on pollution removal and do not include other generally positive (i.e., air temperature reduction, building energy use conservation) and negative (VOC emissions, reduced wind speeds) effects of trees on air quality.

Despite the limitations, there are several advantages to the modeling estimates, which include: a) use of best available measured tree, weather, population and pollution data for each county, b) incorporating hourly interactions between deposition velocities and pollution concentrations ($F = V_d \times C$), c) hourly resuspension of $PM_{2.5}$ based on wind speeds, d) estimates of pollution removal effects on pollution concentration changes, and e) linking pollution effects with human health effects through BenMAP. The methodological approach used in this paper can also be applied in other countries to help assess the broad-scale impacts of pollution removal by trees on air quality. If BenMAP analyses are not run to determine health impacts, the generalized regression equations could give a broad indication of health values provided by improved air quality based on population density. Though future research and modeling are needed to help overcome current limitations, these estimates provide the best available and most comprehensive estimates of pollution removal effects by U.S. trees on human health.

5. Conclusion

Modeling broad-scale effects of pollution removal by trees on air pollution concentrations and human health reveals that while the percent reduction in pollution concentration averages less than one percent, trees remove substantial amounts of pollution and can produce substantial health benefits and monetary values across the nation, with most of the health values derived from urban trees.

Acknowledgments

Funding for this project was provided in part by the U.S. Forest Service's RPA Assessment Staff and State & Private Forestry's Urban and Community Forestry Program. We thank Laura Jackson and Shawn Landry for comments on previous versions of this manuscript and John Stanovick for statistical assistance and review.

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