accepted in Environmental Pollution

Assessing the relationship among urban trees, nitrogen dioxide, and respiratory health

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Abstract

Modelled atmospheric pollution removal by trees based on eddy flux, leaf, and chamber studies of relatively few species may not scale up to adequately assess landscape-level air pollution effects of the urban forest. A land use regression (LUR) model (R^2 = 0.70) based on NO_2 measured at 144 sites in Portland, Oregon (USA), after controlling for roads, railroads, and elevation, estimated every 10 ha (20%) of tree canopy within 400m of a site was associated with a 0.57 ppb decrease in NO_2. Using BenMAP and a 200m resolution NO_2 model, we estimated that the NO_2 reduction associated with trees in Portland could result in significantly fewer incidences of respiratory problems, providing a $7 million USD benefit annually. These in-situ urban measurements predict a significantly higher reduction of NO_2 by urban trees than do existing models. Further studies are needed to maximize the potential of urban trees in improving air quality.

Keywords: NO_2, land use regression, urban forest, health impacts

Capsule

A land use regression model based on in-situ urban measurements of NO_2 shows an association of trees with reduced NO_2 sufficient to provide discernible respiratory health benefits.

Introduction

Epidemiological research has established that urban air pollutants such as NO_2, $PM_{2.5}$ and O_3 can be detrimental to human health. An increase in the average air pollution in a city is correlated with an increase in cardiovascular disease, strokes and cancer (Brunekreef and Holgate, 2002; Dockery et al., 1993; Nyberg et al., 2000; Pope et al., 2002; Samet et al., 2000; Samoli et al., 2005). More recent epidemiological research has shown that the health impacts of air pollution are not uniform across a city. For example, numerous studies show a higher burden of respiratory problems close to major roadways (Brauer et al., 2007; Jerrett et al., 2008; McConnell et al., 2006; Ostro et al., 2001), which is not surprising as primary air pollutants levels are greatest near the source and decay rapidly away from it (Faus-Kessler et al., 2008; Gilbert et al., 2007; Jerrett et al., 2005). A meta-analysis by Karner et al (Karner et al., 2010) shows that air pollutants within cities decay rapidly within 200m of the source, reaching background concentrations between 200m and 1km, creating strong air pollution gradients at short spatial scales within a city.

To address the challenge of reducing human exposure to urban air pollution, then, we need to monitor or model air pollutants at a spatial resolution of 200m or finer. To date, however, institutional observations, monitoring and modelling efforts have primarily focused on the regional and global scales. Active monitoring stations such as those in the US Environmental Protection Agency (US EPA) monitoring network, satellite observations, and atmospheric transport models provide air pollution data at the 10km or coarser spatial scale. Chemical transport models such as CMAQ and WRF-Chem that could be used to model air pollutant levels at the intra-urban scale lack emissions inventories as well as model validation studies at this scale. Land use regression (LUR), a method that has been widely used by epidemiologists, (Hoek et al., 2008; Jerrett et al., 2005; Ryan and LeMasters, 2007) is well-suited to model the intra-urban variability of air. LUR combines measurements of air pollution and statistical modelling using predictor variables obtained through geographic information systems (GIS). The European Union (EU), for example, is currently using LUR in the ESCAPE project , which aims to model the intra-urban variability of several urban air pollutants (Beelen et al., 2013; Cyrys et al., 2012; Eeftens et al., 2012).

Further, we need to understand the factors such as distance from source, terrain, deposition onto the urban forest, photo-chemical environment and local meteorology that affect the dispersion of air pollutants within a city at this highly local scale of 200m. This information is critical for urban dwellers, planners and policy-makers seeking to create healthier cities. However, many of the factors affecting dispersion of air pollutants at these smaller spatial scales are not well understood; specifically, the role of vegetation in urban air pollution is poorly understood. Vegetation pays a complex role in the urban ecosystem, potentially contributing both positively and negatively to urban air pollution. For example, biogenic volatile organic compounds (BVOCs) emitted by trees react with urban NO_x emissions to produce aerosols (a component of $PM_{2.5}$) and ozone, both urban air pollutants regulated by the US EPA, the EU and the

World Health Organization. In addition, several recent studies at the household and neighbourhood scales have found an improvement in human health associated with urban greenery, particularly trees (de Vries et al., 2003; Donovan et al., 2011; Maas et al., 2006), although the explicit relationship between the urban forest, air pollution reduction and human health is not understood. While eddy flux, leaf and chamber studies clearly demonstrate the physiological potential for vegetation to remove air pollutants from the atmosphere (Fujii et al., 2008; Min et al., 2013; Sparks, 2009; Takahashi et al., 2005), landscape level studies show mixed results. For instance, Yin et al found a 1-21% reduction in NO_2 associated with park trees in Shanghai, China (Yin et al., 2011), while Setala et al found no effect associated with NO_2 and trees in Helsinki, Finland (Setälä et al., 2012). However, UFORE (i-Tree, 2011; Hirabayashi et al., 2012) the big-leaf model based on leaf and canopy level deposition studies, scaled to landscape levels, indicates that the urban forest reduces air pollution by < 1% (Nowak et al., 2006).

Our goal for this study is to develop an urban, observation-based, predictive model of NO_2 at the highly spatially resolved scale of 200m and to assess the relative strengths of sources and sinks of NO_2 in the urban environment, focusing especially on vegetation. Further, through application of this high resolution NO_2 model, we can also estimate the economic value of the health benefits provided by trees through the reduction of NO_2. Here, we focus on NO_2, a strong marker for anthropogenic air pollution, as it can be measured accurately and simultaneously at a large number of sampling locations.

Materials and Methods

Field campaign

Our study area is the Portland Metropolitan Area, a mid-size urban area covering 1210 km^2, with a population of ~ 1.5 million, located in the state of Oregon, in north-western USA. It is situated at 45.52^o N, 122.68^o W, and has a temperate climate with relatively dry summers. Portland is home to Forest Park, one of the large forests within urban boundaries in the USA. Portland's urban forest is predominantly deciduous, with big-leaf maple, black cottonwood and Douglas fir constituting > 50% of the urban forest, based on a public tree assessment (Portland Parks & Recreation, 2007). Two rivers flow within the city boundaries – the Willamette and the Columbia, with an active port on the Columbia. The Portland Metro area has some hilly terrain, especially west of the Willamette, with a maximum elevation of 387m.

NOx varies between summer and winter in Portland (summer and winter 2013 NO_2 averages were 7.5 ppb and 11.4 ppb respectively). However, since we were interested in assessing the effect of vegetation on local NOx, we focused our earlier sampling in the summer. NO_2 and NO were measured at 144 sites in the Portland Metro area using passive Ogawa samplers (only the NO_2 results are presented here; NO results will be discussed in a future paper). Sites were chosen using a spatial allocation model coupled with a stratified random approach to encompass the spatial extent of the Portland Metro area and to capture the effect of roads, railroads and vegetation on ambient NO and NO_2. A single passive Ogawa sampler, with an NO_2 pad on one side and a NOx pad on the other, was placed at each site between 2m-3m above ground. Controls were co-located at the Portland State University monitoring station, which actively monitors NO and NO_2 using a calibrated chemiluminescent NOx monitor (Teledyne NOx Analyzer, Model T200). Lab and field blanks were also deployed to detect contamination during assembling the samplers or excess exposure during transportation. Samplers were placed in the field 23rd – 25th Aug 2013, and retrieved 3rd – 5th Sep 2013, for an approximate field exposure of 12 days. Samplers were analysed in the lab on 6th Sep 2013 using the methodology outlined in the Ogawa manual (Ogawa & Co., USA, 2006) and corrected for temperature and relative humidity based on measurements at the Portland State University air quality station. The field and lab blanks readings were all low (with an average reading of ~0.2 ppb NO_2). The NO_2 measured by five co-located Ogawa samplers (average 17.6 +/- 0.5 ppb) was within 5% of the PSU chemiluminescence monitor ambient reading (average 16.9 ppb). (See Fig S1 for map of sites and measured NO_2).

Land-use Regression (LUR)

Briefly, LUR (Briggs et al., 2000; Hoek et al., 2008; Jerrett et al., 2005; Ryan and LeMasters, 2007) is a statistical modelling technique used to predict air pollutant concentrations at high resolution across a landscape based on a limited number of measurements of the pollutant of interest within the study area. Land use and land cover variables are extracted at each measurement site using a spatial analysis program and a regression model developed, with the air pollutant measurements as the dependent variable and the land use parameters as the independent variables.

For this study, we constructed two LUR models. The first model, the sources and sinks model (SSM), was specifically developed to examine the relative strengths of sources and sink of NO_2 in an urban environment. For the SSM model, we considered only those land use and land cover variables that were proxies for known urban sources and sinks of NO_2. Land use and land cover proxies were identified based on a previous LUR model for Portland (Mavko et al., 2008), existing literature on LUR models (Beelen et al., 2013; Henderson et al., 2007; Hoek et al., 2008; Jerrett et al., 2005; Ryan and LeMasters, 2007), and knowledge of sources and sinks of urban NO_2. In all, we identified four classes of roadways, length of railroads, industrial area, population, tree canopy area, and area with grass and shrubs as proxies for urban sources and sinks of NO_2 (Table 1). The second model we developed was a predictive model (PM) to assess the health impacts of NO_2. In this model, we wanted to have the best model fit (R^2), and hence did not constrain the independent variables to be proxies for urban sources or sinks of NO_2. The PM includes all the independent variables identified by the SSM and adds latitude and longitude to the regression variables. While latitude and longitude are neither sources nor sinks of NO_2, these terms capture the spatial variability of the sources and sinks in the Portland Metro area, and hence improve the model fit. All spatial analysis was done using ArcMAP® 10.1 by ESRI.

Table 1 summarizes the land use and land cover variables used in the study and the data source. In addition, elevation, latitude and longitude were associated with each site. Each land use and land cover variable was extracted for each of the 144 sites using spatial analysis in 24 circular buffers ranging from 50m to 1200m in 50m increments. We considered using wind buffers as was done in the previous Portland LUR study (Mavko et al., 2008). However, we found that the average wind direction varied widely across our study area and could not be modelled using a single wind direction, as was done by Mavko et al, due the smaller spatial extent of their study area.

Land use/land cover variable	Data source	Proxy
Freeways (length)	RLIS 2012[a]	traffic emissions
AADT* (traffic volume)	NHPN 2007[b]	traffic emissions
Major Arteries (length)	RLIS 2012[a]	traffic emissions
Arteries (length)	RLIS 2012[a]	traffic emissions
Streets (length)	RLLIS 2012[a]	traffic emissions
Railroads (length)	RLIS 2012[a]	railroad emissions
Industrial Area (area)	RLIS 2012[a]	industrial point sources
Population (number)	RLIS 2012[a] (based on 2010 census)	area sources
Area under tree canopy (area)	City of Portland, 2010	sink through deposition
Area under shrubs/herbaceous cover (area)	City of Portland, 2010	sink through deposition
Elevation (height)	RLIS 2012[a]	potential sink (wind flow)
Latitude	Measured/Google Earth	spatial variability of sources & sinks
Longitude	Measured/Google Earth	spatial variability of sources & sinks

Table 1: Land use/land cover variables used in LUR, data source and NO2 source/sink proxy
*AADT: Annual average daily traffic
[a] Regional Land Information System, Metro Resource Data Center
[b] National Highway Planning Network

In all, we extracted more than 200 land-use and land-cover variables. We did not consider area under grass and shrubs or latitude further in the model as neither showed any correlation with NO_2 at any buffer size between 50m and 1200m. We also did not consider industrial area as it was very highly correlated with both railroads and major arteries. Our approach allowed us to build a parsimonious model for teasing out the relative strengths of primary sources and sinks of NO_2 in the study region. For the land use and land cover variables that showed a correlation with NO_2, we identified the appropriate buffer size for each land use variable based on correlation with NO_2 (Clougherty et al., 2008; Henderson et al., 2007).

We followed a cross-validation design in developing both regression models. The monitored data was divided into 5 sets. Four sets were combined at a time to create 5 sets of training data, with the excluded set kept aside for validation. A hierarchical nested regression analysis (Cohen et al., 2003) was also done on the SSM to estimate the direct and indirect contributions of each land use category to urban NO_2. All statistical analyses were done in SPSS 19.

We developed five spatial distributions of NO_2 to estimate the effect of scale and tree canopy on respiratory health:

(i) A “rural background” NO_2 spatial distribution, assuming a uniform NO_2 distribution of 0.1 ppb (estimated level in rural areas upwind of Portland) (Lamsal et al., 2013) across the Portland Metro area.

(ii) A “regional” NO_2 spatial distribution, based on the average Oregon DEQ NO_2 measurement for the period of the study (7.5 ppb).

(iii) A 200m predictive NO_2 spatial distribution across Portland Metro, generated by applying the predictive LUR model to points on a 200m grid (the PM model)

(iv) A 200m sources-and sinks spatial distribution of NO_2 across Portland Metro, generated by applying the sources-and-sinks model to points on a 200m grid (the SSM model)

(v) A 200m resolution “no trees” map of NO_2 in the Portland area modelling the NO_2 levels in the absence of trees, generated by applying the sources-and-sinks model without the sink term associated with tree canopy, to points on a 200m grid (the SSM model without trees).

Respiratory Health Impact Analysis

Analysis of several asthma-related endpoints – including asthma exacerbation resulting in missed school among children aged 4-12; asthma exacerbation resulting in one or more symptoms among children 4-12; emergency room visits for asthma at any age; and hospital admissions (HA) for any respiratory condition among elderly persons aged 65 and over – to estimate incidence and economic valuation was done in The Environmental Benefits Mapping and Analysis Program version 4.0.35 (BenMAP) (U.S. Environmental Protection Agency, 2010). BenMAP is a Windows-based computer program developed by the US EPA that uses a Geographic Information System (GIS)-based approach to estimate the health impacts and economic benefits (or dis-benefits) occurring when populations experience changes in air quality. BenMAP comes with multiple built-in regional and national datasets, including health impact functions and baseline incidences, to facilitate health benefits modeling. It has been used to estimate the health impacts of urban air pollutants at the regional and national scales (Davidson et al., 2007; Fann et al., 2009; Hubbell et al., 2009, 2004).

For this study, we estimated the incidence and valuation for four respiratory endpoints of NO_2, using the health impact and valuation functions built into BenMAP (Table S1). We used Popgrid, a population allocation tool that comes with BenMAP to allocate the census population into age bins required by BenMAP (Abt Associates Inc., 2010). We estimated the respiratory health impacts of NO_2 on the Portland population at two different spatial scales of assessment. At the city-scale, we used the "regional" NO_2 distribution based on the Oregon DEQ NO_2 measurements. For the highly spatially resolved scale, we used our 200m predictive NO_2 LUR model (PM model). Incidences of respiratory outcomes for both scales were assessed against an estimated rural background of 0.1 ppb NO_2 (Lamsal et al., 2013). The respiratory health outcomes under these two different scale scenarios were compared to evaluate the role of scale in health impact assessments.

Respiratory health benefits of trees due to reduction in NO_2 associated with tree canopy were assessed by comparing the respiratory outcomes based on the 200m NO_2 distribution generated using the SSM LUR model with and without the sink term for tree canopy.

Results and Discussion

LUR Models

Two LUR models were developed based on the NO_2 measured at 144 sites (Fig S1) and the adjoining land use. The SSM fit estimated NO_2 using only land-use proxies for urban sources and sinks of NO_2. The PM added longitude (as X_DIST) to the SSM to account for the spatial variability of land use within the Portland Metro area (Fig 1).

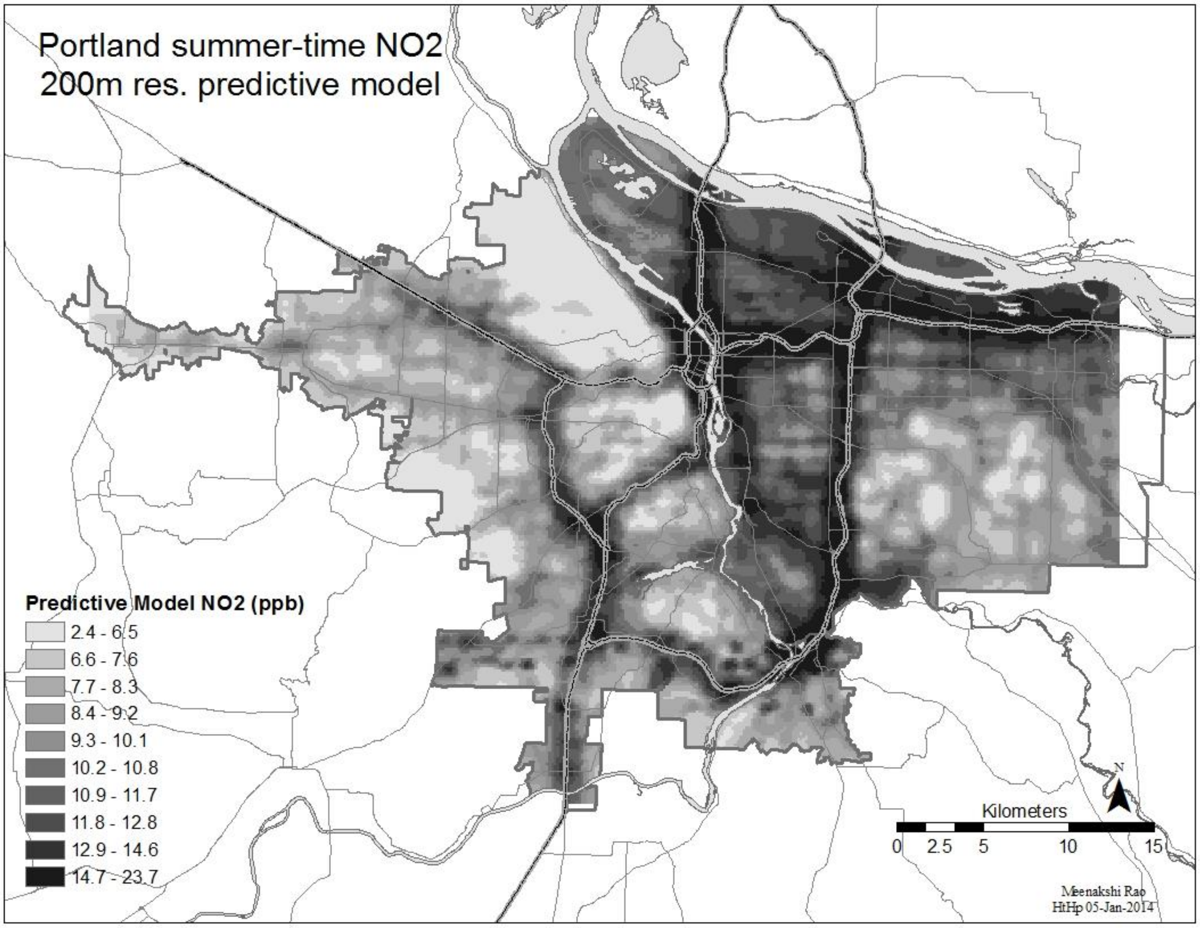

Fig 1: NO_2 quantiles, based on the predictive NO_2 LUR model (PM) applied at a 200m spatial resolution

The average adjusted R^2 (across 5 training models) and average RMSE (across 5 validation models) was 0.70 (2.6 ppb) and 0.80 (2.2 ppb) for the sources and sinks (SSM) and predictive models (PM), respectively. The R^2 for the models is consistent with published R^2 values, ranging from 0.50 to 0.90, while the RMSE is on par with the lowest measured RMSE values (1.4 – 34 ppb) (Hoek et al., 2008).

The coefficients of the two LUR models are similar for roadways and area sources, but differ for railroads, tree canopy and elevation. This is an indication that roadways and population are relatively evenly distributed across the Metro area, while railroads, trees and elevation show a strong spatial gradient across the city, consistent with the local geography.

Based on the regression equation (Eq 2) ambient NO_2 in Portland in the absence of considered land use sources and sinks is 7.7 ppb. Ambient NO_2 levels increase by 1.1 ppb for every 100 000 vehicle kilometers traveled (annually) on freeways within a 1.2 km buffer of the site. NO_2 levels increase by an additional 0.65 ppb for each kilometer of major arteries within 500m of the site, and 1.7 ppb NO_2 for each kilometer of arteries within 350m. However, ambient NO_2 levels decrease by 0.57 ppb for every 10 ha of trees (20% tree cover) within 400m of a site. (See S2 for descriptive statistics of model predictor variables).

Sources and sinks model (SSM)

$$NO_2(i) = 9.4 + 1.2x10^{-8}*FWY\_AADT_{1200,i} + 5.0x10^{-4}*MAJ\_ART_{500,i} + 1.8x10^{-3}*ARTERIES_{350,i} + 1.7x10^{-8}*STREETS(POP)_{800,i} + 1.5x10^{-3}*RAILS_{250,i} - 3.5x10^{-3}*ELEVATION_i - 8.4x10^{-6}*TREES_{400,i} \quad \text{(.Eq 1)}$$

Adj R^2 = 0.70, validation RMSE = 2.6

Predictive model (PM)

$$NO_2(i) = 7.7 + 1.1x10^{-8}*FWY\_AADT_{1200,i} + 6.5x10^{-4}*MAJ\_ART_{500,i} + 1.7x10^{-3}*ARTERIES_{350,i} + 1.8x10^{-8}*STREETS(POP)_{800,i} + 1.0x10^{-3}*RAILS_{250,i} - 1.0x10^{-2}*ELEVATION_i + 1.4x10^{-5}*(ELEVATION_i)^2 - 5.73x10^{-6}*TREES_{400,i} + 1.1x10^{-4}*X\_DIST_i \quad \text{(Eq 2)}$$

Adj R^2 = 0.80, validation RMSE = 2.2

Where:

NO_2(i) …………………………………….NO_2 ppb, at site (i)
$FWY\_AADT_{1200,i}$ ………………………………freeway (m) in 1200m, weighted with AADT
$MAJ\_ART_{500,i}$ ……………………………..…..major arteries (m) in 500m
$ARTERIES_{350,i}$ ……………………………… arteries (m) in 350m
$STREETS(POP)_{800,i}$ …………………………..…streets (m) in 800m, weighted by the population
$RAILS_{250,i}$ ………………………………..…railroads (m) in 250m
$ELEVATION_i$ ……………………………….…elevation (ft)
$TREES_{400,i}$ ……………………………….….tree cover (m^2) in 400m
X_DIST_i …………………………………distance from center of city (in m), along E-W axis

Scale & health impact assessment

Based on the 200m predictive NO_2 spatial distribution in BenMAP (on an annualized basis, i.e., assuming comparable levels of NO_2 over the year, and assuming the same association of reduced NO_2 with trees across all seasons), we estimate 140 370 excess cases annually of asthma exacerbation in 4-12 year-olds, valued at $30 million (2013 USD), over a rural background NO_2 background of 0.1 ppb. Further, we estimate 384 incidents (annually) of ER visits due to NO_2-triggered asthma and 423 incidents of hospitalization in the elderly due to respiratory problems triggered by NO_2**.** Altogether, the four NO_2 triggered end-points considered here result in an economic cost to society of roughly $46 million (2013 USD). Assessing the same respiratory health impacts, using the same population distribution, but using the regional NO_2 level for Portland for the summer sampling period instead, we estimate 105 819 excess cases of asthma exacerbation in 4-12 year-olds annually, 280 excess ER visits and 296 excess hospitalizations among the elderly attributable to urban NO_2. Altogether the four endpoints considered at this scale result in an estimated $34 million (2103 USD) cost to society (Table 2).

From this analysis, it is clear that the spatial resolution of the NO_2 estimates used to assess the health impacts makes a significant difference in the magnitude of predicted health outcome. Specifically for Portland, the 200m scale predictive NO_2 model results in an estimate 30-45% higher than the number of incidences and economic cost as the uniform regional value. Even keeping in mind that different health impact and valuation functions will result in different health and economic cost estimates, the critical point – that the incidence and valuation increase significantly for Portland when using the 200m map of NO_2 – holds.

Health Impact	Incidence estimate 200m LUR NO_2	Economic Valuation (in $1,000,000) 200m LUR NO_2	Incidence estimate Regional NO_2	Economic Valuation (in $1,000,000) Regional NO_2
Asthma Exacerbation, Missed school days (4-12 years)	47 918	5.55	36 239	4.20
Asthma Exacerbation, One or More Symptoms (4-12 years)	140 370	29.70	105 819	22.39
Emergency Room Visits, Asthma (all ages)	384	0.16	280	0.12
HA, All Respiratory (65 and older)	423	10.58	296	7.43
Estimated cost		*$45.99 million*		*$34.14 million*

Table 2: Comparison of incidence and valuation of respiratory problems attributable to NO2 at the 200m and regional scale. All valuations are in 2013 USD.

For a mid-size city like Portland with relatively clean air and US criteria pollutants below US standards, for an urban air pollutant like NO_2, which is related to relatively mild respiratory health outcomes, the single regional value for NO_2 underestimates the annual respiratory health impacts on the order of $10 million (2013 USD). The majority of EPA monitors are focused on assessing area-wide air quality, and are required to be sited *to minimize near-road influences* (Ambient Air Quality Surveillance, 2007). Thus, we can expect underestimation of air pollutants to hold for other air pollutants such as $PM_{2.5}$ whose health impacts include mortality, neurological, pulmonary, and cardiovascular diseases, particularly in larger cities that show greater variation in intra-urban distribution of urban air pollutants. This disparity between the highly resolved spatial scale and a single regional representative value is likely to grow even more when the cumulative health impacts of all urban air pollutants are taken into account. Thus, this analysis emphasizes the need for spatially (and temporally) resolved air pollutant data to more accurately assess the health, social, and economic costs of urban air pollution.

Relative strength of sources and sinks

LUR models have been extensively used to capture the intra-urban variability of urban air pollutants in epidemiological studies that focus on establishing health impact functions for urban air pollutants (Cyrys et al., 2012; Eeftens et al., 2012; Henderson et al., 2007; Jerrett et al., 2005). To our knowledge, LUR models have not been used to examine the relative strength of sources and sinks of urban air pollutants within cities. To examine the relative strengths of sources and sinks of NO_2, we look at the SSM from several different perspectives (Table 3).

The standardized regression coefficients (betas) in the SSM show that the freeway traffic volume within 1.2km of a site has the strongest association with local NO_2. One standard deviation increase in freeway traffic volume corresponds to a 0.4 standard deviation increase in NO_2 levels at a site. Roadways, taken together, have a strong association with NO_2 – a combined beta of 0.7. The association of trees and elevation with NO_2 is much weaker, corresponding to a reduction in local NO_2 levels by 0.2 and 0.15 standard deviations for each standard deviation increase in tree canopy and elevation respectively.

Another way to examine the relative strengths of NO_2 sources and sinks is to see how much each source (sink) increases (decreases) the background NO_2. The modelled urban NO_2 background, that is the NO_2 level in the absence of LUR sources and sinks, is 9.4 ppb. The average traffic volume value across the 144 sites of 120 x 10^3 vehicle-km increases the ambient NO_2 by16% (1.5 ppb) over background. Roadways, considered together, on average across the 144 sites, increase NO_2 levels by 25% (2.4 ppb) over background. Trees, on average, reduce the NO_2 by about 15% of background (1.4 ppb).

From a planning perspective, it is also important to know the range of change in NO_2 levels associated with a specific source or sink that can be encountered in the city. Based on the SSM and the range of values observed for the land use variables in the Portland Metro area (Table 3), we find that freeway traffic can increase NO_2 from 0-7.9 ppb above the 9.4 ppb background. Roadways taken together can increase NO_2 from 0-11.8 ppb; railroads can increase NO_2 from 0 to 3.3 ppb; while tree canopy can decrease NO_2 from 0 - 4.2 ppb from the urban background.

We further used hierarchical nested regression analysis (Cohen et al., 2003) to address the question of whether the reduction in NO_2 seen with elevation and tree canopy could be attributed simply to the absence of sources, as sites at high elevation and with dense tree cover are less likely to have high traffic volume roads, railroads and area sources in the vicinity. The hierarchical analysis shows that about 30% of the total reduction in NO_2 associated with elevation is directly due to elevation, while 38% is related to increased tree canopy at higher elevation, 12% due to fewer railroads, 14% due to fewer area sources and 6% due to lower road traffic. Similarly, 56% of the reduction in NO_2 associated with trees is directly associated with tree canopy, while 14% is due to fewer area sources and 30% due to fewer roadways and lower traffic volume. LUR analyses using ordinary linear regression are not able to disentangle these effects.

	Std beta (avg of 5 training models)	% of background NO2 on average	NO2 contrib (ppb) based on avg land-use values for 144 sites	NO2 contrib (ppb) based on max land-use values for 144 sites
FWY_AADT_{1200}	0.414	15.8 %	1.5 ppb	7.9 ppb

MAJ_ART_{500}	0.121	4.3 %	0.4 ppb	2.0 ppb
$ARTERIES_{350}$	0.189	5.6 %	0.5 ppb	1.9 ppb
$STREETS(POP)_{800}$	0.222	6.6 %	0.6 ppb	2.7 ppb
$RAIL_{250}$	0.164	5.6 %	0.5 ppb	3.3 ppb
ELEVATION	-0.148	-10.8 %	-1.0 ppb	-4.0 ppb
$TREES_{400}$	-0.179	-14.7 %	-1.4 ppb	-4.2 ppb

Table 3: Comparison of relative strengths of sources and sinks of urban NO2 based on land use proxies

An assessment of the relative strengths of sources and sinks of air pollutants within a city is important and relevant data for determining optimum air pollution strategies. Chemical transport models, which are used extensively to evaluate mitigation policies at the regional scale, do not encode local dispersion phenomenon such as the urban canyon effect, the role of trees in changing wind flow, or deposition of air pollutants to the urban forest. Another shortcoming is the lack of emissions inventories and validation at the intra-urban scale. LUR is a technique that can be readily used to both inform policy and chemical transport model adaptation to the intra-urban scale. Of course, it is necessary to develop LUR models for diverse cities, collecting and analysing the data using a standard methodology, along the lines the ESCAPE project has undertaken for determining health impact functions for the European population.

Role of vegetation

Based on the SSM LUR model for NO_2 in the Portland Metro area, every 10ha of trees within 400m of a site is associated with a 0.57 ppb reduction in NO_2 at the site in summer. Of this reduction, 56% is directly associated with trees, while 14% is due to the absence of area sources and 30% due to fewer roads and lower traffic volumes associated with treed area. Fig. 2 maps the reduction in NO2 associated with the presence of trees (as % of the background) in the Portland Metro area. The reduction in NO_2 ranges from < 1% of background (< 0.1 ppb) to a maximum of 45% of background (~4 ppb). Not surprisingly, the greatest reduction in NO_2 is in Forest Park, a 2092 ha forest within the Portland Metro area, while the least reduction is in the industrial areas in North Portland, which have very little tree cover.

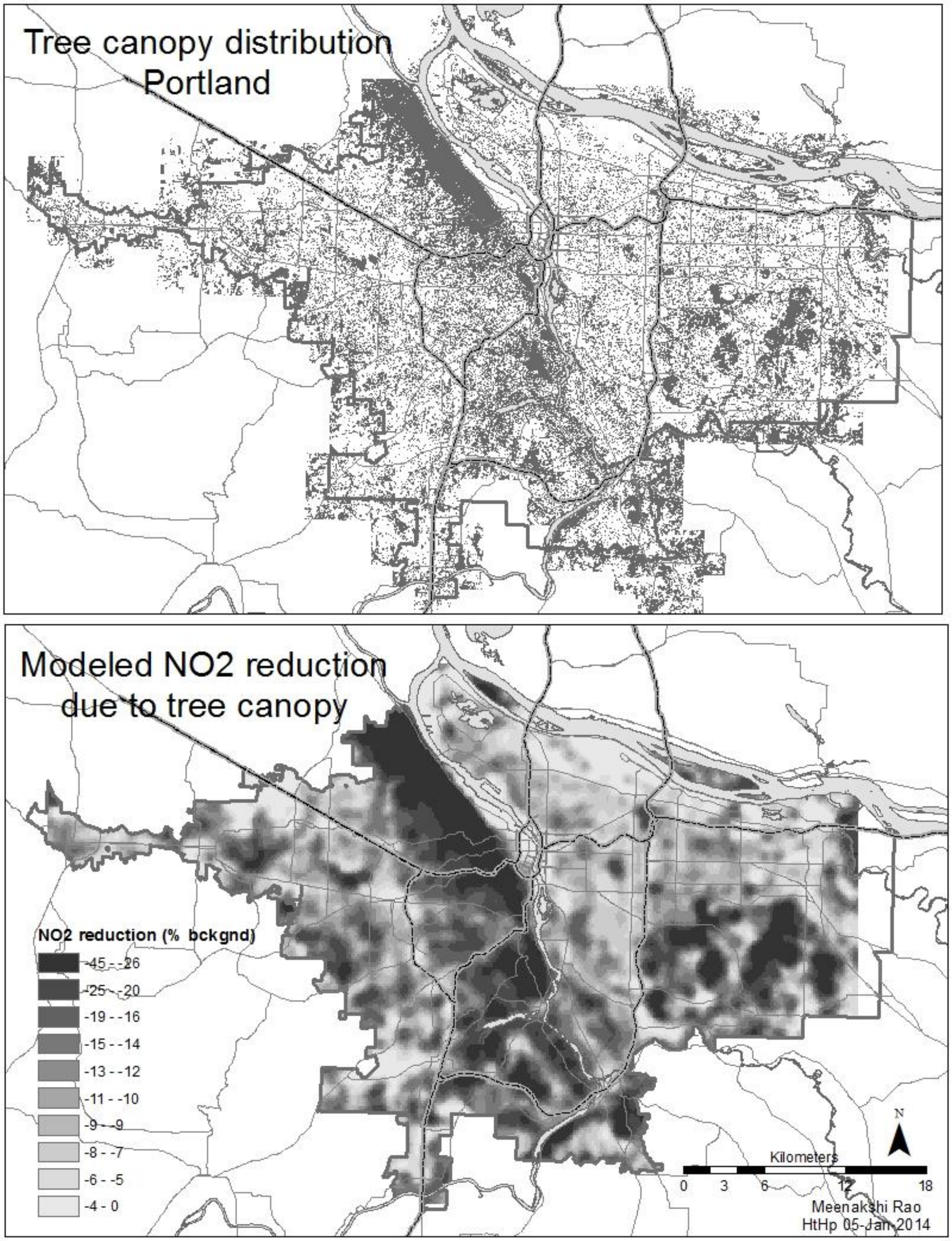

Fig 2 Quantile map showing the modelled reduction of NO_2 (as percentage of background) attributable to tree canopy, based on the NO_2 SSM LUR model, with map of tree canopy above for comparison.

Our model shows a correlation between reduction in the urban air pollutant NO2 and trees. However, without being able to relate this reduction to known mechanisms through which trees affect NO2, i.e., through wet and dry deposition, changing airflow, accelerating chemical transformation, we cannot discount unknown factors associated with trees themselves. Nevertheless, it is instructive to estimate the potential health benefits associated with trees due do this statistical reduction of NO2 as a way to assess the viability of trees as a mitigation strategy. We used a BenMAP simulation to estimate both the incidence and economic valuation of the decrease in respiratory problems attributable to reduction in NO_2 by trees (Table 4). The potential annual respiratory health benefit associated with trees in Portland due to reduction in NO_2 is approximately 21 000 fewer incidences and 7000 fewer days of missed school due to asthma exacerbation for 4-12 year-olds; 54 fewer ER visits across people of all ages; and 46 fewer cases of hospitalization due to respiratory problems triggered by NO_2 in the elderly. The economic value of these health benefits is approximately $7 million (2013 USD).

Health Impact (Annualized)	Reduced Incidence due to Trees	Valuation of Reduced Incidence (in $1,000,000 USD)
Asthma Exacerbation, Missed school days (4-12 years)	7 380	0.85
Asthma Exacerbation, One or More Symptoms (4-12 years)	21 466	4.55
Emergency Room Visits, Asthma (all ages)	54	0.03
HA, All Respiratory (65 and older)	46	1.16
Potential estimated respiratory health benefit due to trees		*$ 6.59 million*

Table 4 Incidence and valuation of potential respiratory health benefits due to reduction in NO_2 attributable to tree canopy. Valuations are in 2013 USD.

Our findings that trees are associated with a significant reduction in NO_2 is not unique: previous epidemiological LUR models include a term for trees or green spaces with a negative sign (Dijkema et al., 2011; Gilbert et al., 2005; Kashima et al., 2009; Mavko et al., 2008; Novotny et al., 2011). Here, however, we show for the first time – in our understanding – that this landscape-level reduction in NO_2 associated with trees in Portland is large enough to make a discernible contribution to improved human respiratory health. Estimates using the big-leaf model UFORE indicate, however, that the urban forest in Portland removes only approximately 0.6% of atmospheric NO_2 through deposition and foliar uptake (Nowak et al., 2006), which suggests that refinement of these deposition and uptake values are required or that other mechanisms may be the dominant mechanisms for landscape-level NO_2 removal by trees in our study. In general, UFORE models of air pollution removal for US cities show < 2% air pollutant removal by trees, leading urban ecologists (Pataki et al., 2011) to question the efficacy of urban tree plantings in mitigating air pollution. Our observations of the large reduction in NO_2 associated with trees at the landscape level and the magnitude of the associated health impacts serve to highlight the need to understand, quantify and model the mechanisms through which trees impact urban air pollution at the landscape level, so we can effectively incorporate trees into the urban environment, balancing their benefits and dis-benefits.

One avenue to explore in understanding the role of the urban forest in air pollution mitigation is to determine whether the current generation of UFORE significantly underestimates the potential for tree-associated reduction of NO_2 in urban areas. If the big-leaf model is indeed correct, then possibly other, less seasonal, mechanisms may dominate landscape level NO_2 reduction, and we may find landscape-level winter reduction of NO_2 to be roughly on par with our observed summer reduction. Eventually, species-specific measures of NO_2 removal by intact urban canopies would provide the necessary foundation for a metabolically informed rational design of urban forest canopies, where key tree species are planted intentionally to maximize local NO_2 removal, while taking into consideration the complex role of the urban trees in ozone production, allergen production, effect on local wind dispersion. Trees are an integral part of many urban environments, and hence, in an era of increasing global urbanization, it becomes even more important to understand the various mechanisms through which trees, of diverse forms and functions, are associated with reduced NO_2, and potentially other more harmful urban air pollutants such as $PM_{2.5}$.

Summary and conclusions

We live in a rapidly urbanizing world – more than half of the world's population lives in cities today, and more than two-thirds will live in urban areas by 2050 (United Nations, 2011). An unintended consequence of increasing urbanization is an increase in anthropogenic emissions due to increased human activity, which in turn means more people are exposed to air pollution, potentially leading to reduced life expectancy, reduced productivity and a decrease in quality of life for urban dwellers (Straf et al., 2013). Due to the geographic variation in the distribution of air pollutants in a city, the health impacts are not uniform and tend to be increasingly borne by susceptible and socially disadvantaged urban populations (Clougherty and Kubzansky, 2009; Clougherty et al., 2007). Our study demonstrates the need to monitor or model air pollutants at a highly local scale in order to correctly assess the health impacts of urban air pollutants and to address social equity issues.

Our study is further suggestive of the potential of an urban forest to reduce the air pollutant NO_2 and hence provide health benefits on the order of millions of dollars (on an annualized basis) due to reduced incidence of respiratory problems. It emphasizes the need to resolve the NO_2 conundrum so urban planners and urban foresters can better understand if and how trees may be more effectively incorporated into urban designs for healthier cities.

Acknowledgements

The authors gratefully acknowledge support from the US Forest Service Award #2011-DG-11062765-016. We would also like to thank the numerous volunteers that helped with the field campaign.

Supplementary Data

Fig S1: Map of Portland showing the 144 sites, and measured NO_2

Table S1: BenMAP NO_2 health impact endpoints and valuation methods considered in this study

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Supporting Information

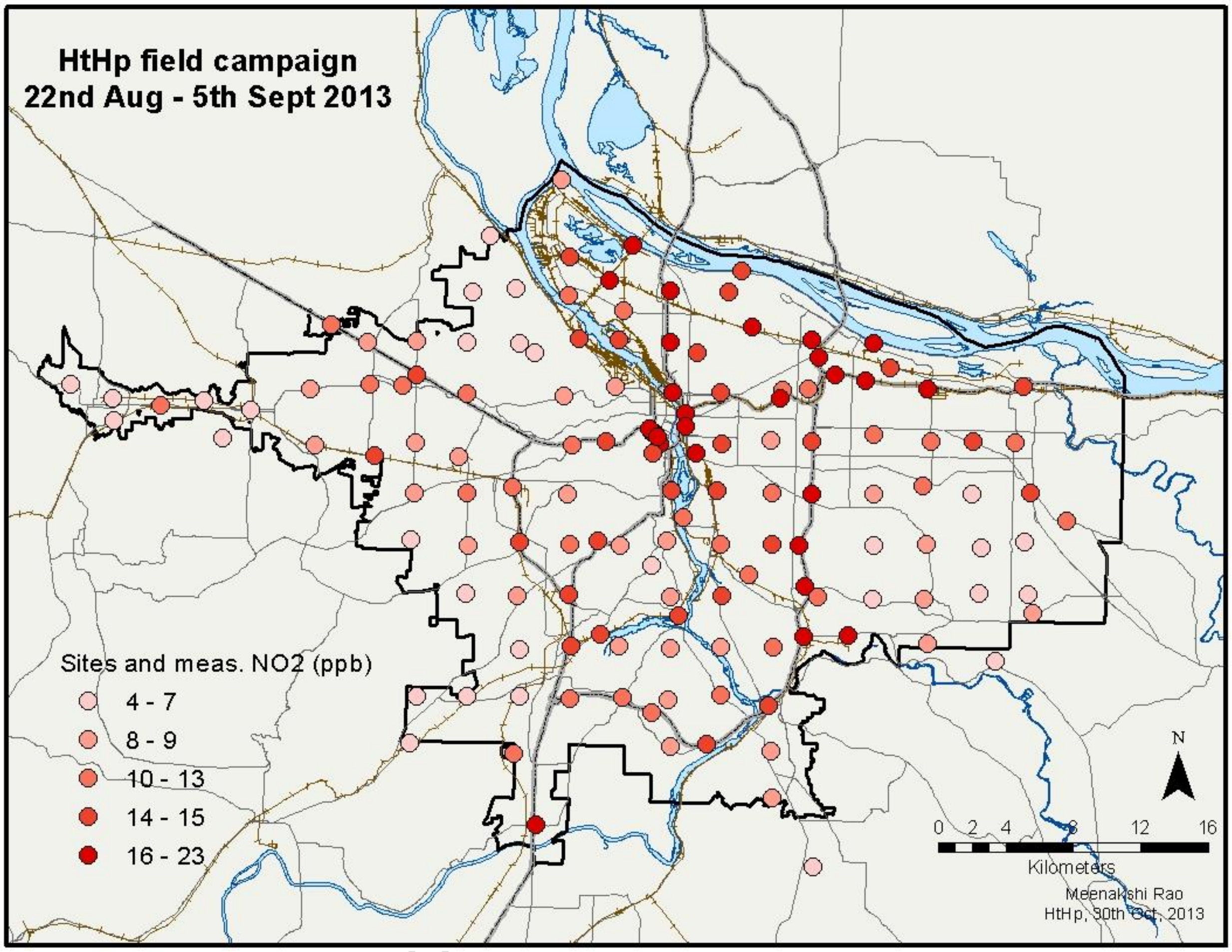

Fig S1: Map of Portland showing the 144 sites, and measured NO_2.

NO_2 Health Impact Endpoints	Study	Location	Valuation Method
Asthma Exacerbation, Missed school days (4-12 years)	O'Connor et al (2008)	7 inner cities	WTP: 2 x bad asthma day, Rowe and Chestnut (1986)
Asthma Exacerbation, One or More Symptoms (4-12 years)	O'Connor et al (2008)	7 inner cities	WTP: Dickie and Ulery (2002)
Emergency Room Visits, Asthma (all ages)	Ito et al (2007)	New York City	COI: Smith et al. (1997)
Hospital Admissions, All Respiratory (65 and older)	Yang et al (2003)	Vancouver, Canada	COI: med costs + wage loss
Hospital Admissions, Chronic Lung Disease (less Asthma) (65 and older)	Yang et al (2005)	Vancouver, Canada	COI: med costs + wage loss

Table S1: BenMAP NO2 health impact endpoints and valuation methods considered in this study.

Descriptive Statistics

	Unit	Minimum	Maximum	Mean	Std. Deviation
NO_2	ppb	4	23	11	5
FWY_AADT_{1200}	number.m	0	638035958	131756480	160745541
MAJ_ART_{500}	m	0	6508	976	1162
$ARTERIES_{350}$	m	0	3022	417	516
$STREETS(POP)_{800}$	m.number	8601	278594583	48044826	61987551
$RAILS_{250}$	m	0	2210	253	524
ELEVATION (centered)	ft	-251	869	0	203
$(ELEVATION)^2$	ft^2	1	754968	41095	94816
$TREES_{400}$	m^2	5120	500487	149304	101814
X_DIST	m	-34529	24337	0	12289

Table S2: Descriptive statistics of LUR model predictor variables.