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The Influence of Green Space on the Short-term Effects of Particulate Matter on Hospitalization in the U.S. for 2000–2013

Seulkee Heo[1] and **Michelle L. Bell**[1]

[1]School of Forestry and Environmental Studies, Yale University, New Haven, United States

Abstract

Although a few studies have identified positive association between green space and reduced mortality rate, the effect modification of green space for the impact of air pollution on health outcomes is under studied. We quantified whether green space modifies associations between short-term exposure to particulate matter (PM_{10}, $PM_{2.5}$) and hospitalization across 364 urban U.S. counties for 2000–2013. Green space was measured by normalized difference vegetation index (NDVI). Daily number of hospital admissions for cardiovascular or respiratory diseases from Medicare enrollees (>65yrs) and air quality monitoring data for each county were used to assess risks, as percent change in hospitalization related to 10μg/m^3 increase in particulate matter. We computed an absolute change in county-specific relative risks explained by difference in county-level NDVI. The study results found that the association between air pollution and health was less in areas with more green space. We estimated that an interquartile range increase in NDVI corresponds to a 1.68% (95% CI: 0.43, 2.91) decrease in the association between PM_{10} and cardiovascular hospitalization and 10.40% (95% CI: 7.34, 13.34) decrease in the PM_{10}-hospitalization association of acute myocardial infarction. For hospitalization associated with $PM_{2.5}$, a 0.18% (95% CI: −0.39, 0.73) absolute decrease in relative risk was found for cardiovascular hospitalizations. In results stratified by age, younger age groups (65–74, 75–84yrs) had larger reductions for the PM_{10}– hospitalization association with increase in NDVI than older populations (>85yrs) but not for the $PM_{2.5}$–hospitalization association. These findings add evidence for health benefits of green space in diminishing the health impacts of particulate matters on hospitalizations for older populations in the U.S.

Keywords

Air pollution; vegetation; green space; hospitalization; effect modification

*Corresponding author at: School of Forestry and Environmental Studies, Yale University. 195 Prospect Street. New Haven, Connecticut, USA. Tel.: +1 2034467830. seulkee.heo@yale.edu (Seulkee Heo).

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Competing interests

The authors declare they have no actual or potential competing financial interests.

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1. Introduction

The world has experienced growth of urban areas at an unprecedented pace, and more than 50 percent of the population will for the first time live in urban environments by 2020 (Hugo, 2017). While providing some benefits such as access to healthcare, urbanization can contribute to deteriorated environmental conditions, such as increased pollution. Air pollution is widely recognized to contribute to many serious health outcomes including mortality and morbidity (e.g., increased risk of hospital admissions) due to aggravated cardiovascular and respiratory illness on a large scale in developed countries (Schifano et al., 2013). Particulate matter with aerodynamic diameters 10μm or less (PM_{10}) and 2.5μm or less ($PM_{2.5}$) are mixtures of particles varying in size and composition, and both size fractions are known to cause severe health responses (Kampa and Castanas, 2008; Powell et al., 2015). Many epidemiological studies through the past 3 decades have provided evidence of adverse health effects of short-term exposure to particulate matter, particularly due to cardiovascular and respiratory causes (Anderson et al., 2012; Shang et al., 2013).

Human health is simultaneously determined by various biological, environmental, and socioeconomic factors (Marmot et al., 2012). For example, it was suggested that human health is influenced by urban environmental conditions such as green space (Säumel et al., 2015). In our research, we define ‘green space’ as natural vegetation such as grass, bush, plants or trees and the built environment such as urban managed green structures (e.g., parks) and unstructured vegetated areas (Lachowycz and Jones, 2013). The rapid urbanization of the U.S. has changed the population’s exposure to green space. The larger population growth in urban counties (13%) than that in rural counties (3%) since 2000 in the U.S. implies that more persons will live in urban areas and confront health issues derived from deteriorated air quality and decreased green space (Parker et al., 2018). The importance of governance and management in green space to better establish health policies and improve public health is increasingly acknowledged in environmental health studies (Bosch and Nieuwenhuijsen, 2017; Li et al., 2017).

Recent research has explored the effect of green space on human health in cities (Nowak et al., 2006). For example, a small number of recent studies suggested that regional green space reduced mortality risk of residents (Hu et al., 2008; James et al., 2016; Vienneau et al., 2017). Green space may reduce health risks in urban populations by removing air pollution, reducing noise, cooling temperature, enhancing physical activities, reducing psychological stress, and interaction with a clean environment (Markevych et al., 2017). Particularly, diminution in air pollution can be obtained by the roll of vegetation for temperature reduction through evapotranspiration, dry deposition of air pollutants on plant surface, and reducing building energy and emission from power plant (Nowak et al., 2006). Very few studies have investigated effect modifications by green space on the health effects of air pollution. A previous study investigated whether neighbourhood greenness modifies the association between $PM_{2.5}$ and cardiovascular mortality in Massachusetts, USA (Yitshak-sade et al., 2019) and it suggested that the effect of $PM_{2.5}$ on cardiovascular mortality was attenuated by increased greenness in areas with lower socioeconomic status. To our knowledge, no study has been conducted on whether the association between air pollution and hospitalization is modified by green space. Identifying how urban green space affects

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the health impacts of air pollution will provide critical information for reducing vulnerability to health risks of air pollution; some studies have indicated that climate change and the unprecedented increase in urbanization are expected to worsen air quality through changing energy demand and changes in atmospheric conditions in urban regions and to increase air pollution-related health burdens in the future (Abel et al., 2018; Bernard et al., 2001; Orru et al., 2017).

We investigated whether green space modifies the association between short-term exposure to particulate matter (PM_{10} and $PM_{2.5}$) and risk of hospital admissions at the county level in the U.S. for 2000–2013. We quantified how the association between air pollution and health differs by the amount of healthy vegetation in the counties. We considered hospitalization due to cause-specific cardiovascular and respiratory diseases in the elderly (age ≥ 65 years), and examined modification for risks stratified by age, sex, and geographical regions. To our knowledge, this study is the first large-scale analysis of the effect modification of green space for the hospitalization risks of air pollution in the U.S.

2. Materials and Methods

2.1. Data

Our analysis included 364 U.S. counties with populations larger than 200,000 based on the 2010 Census. The area of a study county averaged 4002 km^2, and ranged 23.93 km^2 to 52,080 km^2.

Daily counts of hospital admissions at the county level for 2000–2013 were obtained for persons ≥ 65 years from billing claims of Medicare enrollees (fee-for-service beneficiaries). Disease types were based on the primary discharge diagnosis code of each patient. The following outcomes [International Classification of Diseases, Ninth Revision (ICD–9 codes)], which were indicated as significantly associated with short-term exposure to particulate matter in numerous epidemiologic studies (Franklin et al., 2015; Khafaie et al., 2016; Kim et al., 2015), were considered: all cardiovascular diseases [390–459], acute myocardial infarction (AMI) [410], ischemic heart disease [410–414, 429], heart failure [428], and stroke [430–438], all respiratory diseases [460–519], and respiratory tract infections [464–466, 480–487]. Data include the sex and age of each study participant, and the number of participants at risk of hospitalization for each county and day. This study obtained appropriate Institutional Review Board approvals.

Daily $PM_{2.5}$ and PM_{10} measurements were obtained from the EPA's Air Quality System. Similar approaches have been used to assess exposure to air pollution at the county level in numerous previous epidemiological studies (Geer et al., 2012). When multiple monitors for a given pollutant existed in a county for a given day, we averaged concentrations across those monitors to calculate the daily average concentration value for that day and county. Monitors with data for less than 10% of study days were omitted from the analysis. Our study counties contained 1444 air monitoring sites. A map of the study counties and the air monitoring sites is shown in Supplementary Figure 3. Daily county-specific mean temperature and dew-point temperature data were collected from the National Climatic Data Center.

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Green space was measured using the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) NASA's Earth Observing System. The MODIS product MOD13Q1 is a 16–day composite image at 250–meter resolution. The index uses instrumentation for quantifying intensity of light reflected by the Earth and determines the photosynthetic capacity of the vegetation for a given pixel (NASA, 2018). NDVI is calculated as near-infrared radiation minus visible radiation divided by near-infrared radiation plus visible radiation. The index ranges from −1 to +1 with higher NDVI values indicating more dense vegetation and −1 indicating waterbody features.

The steps for obtaining county-specific NDVI values included downloading satellite imageries (tiles), mosaicking the imageries, re-projecting the mosaicked raster, and extracting raster average values to county polygon. The mosaicking and re-projecting process were specifically needed in our study in order to have coherence of geo-processed NDVI values, particularly at the borders stitching tiles across the U.S. Mosaicking and re-projection were conducted at 1–km resolution by the NASA Reprojection Tool called MRT, and we obtained geo-processed NDVI raster for each 16–day date composite in the study period.

The county-specific NDVI value was obtained by applying a population-weighted averaging approach, which sought to increase representativeness of spatial coverage of NDVI for the geographical distribution of population and population's exposure level to green space in a given study county (Ivy et al., 2012). Population-weighting takes into account the different population densities throughout a county and assigns higher weight of exposure to NDVI categories in regions with higher population density. Using an extreme case as an example, a given NDVI category may be only a small part of a county, but if the majority of the county's population lives in that area, that NDVI category represents the population's exposure to greenness better than an area-wide average of NDVI for the county. We calculated the average NDVI for every census tract in each study county using the NDVI pixel values within and surrounding the census tract boundary. Then, we calculated population-weighted average NDVI for each county for each time granule of the MODIS images through the study period as $NDVI_{i,t} = \sum_1^i \left(NDVI_{ci,t} \times POP_c\right)/POP_i$ Here, $NDVI_{i,t}$ is the NDVI value of county i on time granule t, $NDVI_{ci,t}$ is the NDVI value of census tract c of county i on time t, POP_c is the population of census tract c (average of 2000 and 2010), and POP_i is the population of county i. We averaged the calculated population-weighted NDVI values throughout the study period between the start and end dates of the county's available air quality monitoring data, which subsequently determine the study period of the times-series analysis for each study county. We calculated area-weighted average NDVI for each county by averaging the pixel values within and surrounding the county boundary and compared the estimated effect modification by area-weighted average NDVI to the effect modification estimates by population-weighted average NDVI. We present the main results based on population-weighted average NDVI, as the area-weighted average NDVI overestimated population exposure to NDVI, thereby indicating that the densely populated areas had lower density of vegetation. The NDVI calculation was conducted using ArcGIS software and the R statistical program.

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Socio-economic and demographic data were obtained from the U.S. Census Bureau: population density (2000), average of annual percent of the population that was age ≥ 65 years (%) (Census data for 2000–2013), annual median household income (2000–2013), and percent of people > 65 years in poverty based on the Census Bureau's criteria (2000–2013). The fraction of the population 65 years and older was obtained from the Census Bureau's Population Estimates Program, which estimates demography by calculating a time series of population based on the recent decennial census data. Median annual household income and percent of people > 65 years in poverty were obtained from the SAIPE data, which were produced on a yearly basis based on the American Community Survey and the Annual Social and Economic Supplement of the Current Population Survey by the U.S. Census Bureau.

2.2. Statistical Analysis

A two-stage statistical model, which was applied in previous multi-sites time-series studies (Bell et al., 2012; Benmarhnia et al., 2015), was used to first estimate the impact of short-term exposure to particulate matter on risk of hospitalization for each county, and then estimate whether a county's NDVI modified county-specific PM-hospitalization associations.

In the first stage, a generalized additive model (GAM) with a link function and a Quasi-Poisson distribution was separately applied for each pollutant (PM_{10}, $PM_{2.5}$), each county and each health outcome to estimate county-specific relative risks of hospital admission with level of air pollution on the same day (lag 0). The models were fitted separately for sex or age group (all ages within the study population as ≤65 years, or age groups: 65 to 74, 75 to 84, >85 years). The GAMs were as follows:

$$\ln\left[\mathrm{E}\left(Y^{c}{}_{t}\right)\right] = \beta_0{}^{i} + \beta_1{}^{i} PM^{i}{}_{t} + B_2{}^{i} DOW_t + s\left(Time_t, 8\right) + s\left(T^{i}{}_{t}, 6\right) + s\left(D^{i}{}_{t}, 3\right) + \mathrm{off}\left(P^{i}{}_{t}\right),$$

where $\mathrm{E}\left(Y^{c}{}_{t}\right)$ = the expected number of cause-specific hospital admissions for county i on day t; $\beta_0{}^{i}$ = the model intercept, $PM^{i}{}_{t}$= concentration of PM_{10} (or $PM_{2.5}$) on day t, DOW_t = indicator variables for day of the week, $s(Time_t,8)$ = the smooth function of calendar time with 8 degrees of freedom per year, $s\left(T^{i}{}_{t}, 6\right)$= the smooth function of daily mean temperature on day t with 6 degrees of freedom, $s\left(D^{i}{}_{t}, 3\right)$ = the smooth function of daily mean dew point temperature on day t with 3 degrees of freedom, $\beta_1{}^{i}$ = log relative risk relating particulate matter to risk of hospital admissions, and $\mathrm{off}\left(P^{i}{}_{t}\right)$ = the offset term of Medicare beneficiaries in the study population who could be hospitalized on day t for county i (i.e., population at risk). Smooth functions using natural cubic splines were applied to a variable representing calendar time to adjust for long-term trends and seasonality. The degrees of freedom for temperature and dew point on the same day were selected based on a previous study (Dominici et al., 2006). The results of risk estimation were represented as the percent change of daily number of hospital admissions per 10– g/m^3 increase in concentration of particulate matter $\left(\left[\exp\left(10\beta_1{}^{i}\right) - 1\right] * 100\right)$. The datasets of each study county yielded 1,206 data points

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(days) on average with 545 data points for the interquartile range (IQR) (Q1=641, Q3=1186) for PM_{10} in 267 counties. For $PM_{2.5}$, the average number of data points was 440 days with 2,176 days of IQR (Q1=1474, Q3=3650) in 235 counties.

In the second stage, a mixed-effect meta-regression model with DerSimonian-Laired estimation method was applied to quantify the effect of NDVI for explaining heterogeneity in county-specific risk estimates of particulate matter on hospitalizations while adjusting for county-level socio-economic and demographic characteristics. The meta-regression model extends the basic meta-analysis by allowing the risk of mortality to differ by effect modifiers as follows;

$$Y_i = \beta' x_i + \theta_i + e_i, \theta_i \sim N\left(0, \tau^2\right), e_i \sim N\left(0, V_i\right),$$

where Y_i= the log relative risk in county i for a given pollutant (PM_{10} or $PM_{2.5}$), $_i$= county-level covariates, θ_i= the corresponding true risk, e_i = the sampling error, τ^2 = the amount of residual heterogeneity among the true risks, and V_i= the sampling variances (Viechtbauer, 2010). A one unit increase in a covariate (β') indicates a corresponding change of the average log relative risk.

We quantified the estimated effect of NDVI in the form of percent change in hospitalizations by calculating exponential values of the coefficients (β') of NDVI. The exponentiation of the beta represents an absolute difference in the risk estimates of the study counties primarily calculated in the form of percent changes in hospitalizations within the given county. As an example, a 20% difference in the hospitalization risks associated with a unit change in NDVI corresponds to a NDVI beta of 0.18 in a meta-regression model. We present the estimation of the effect modification according to an interquartile range (IQR) change in NDVI. The same approach of meta-regression was applied to sex- and age-group-specific risks for the first-stage. The significance of interaction effects of sex and age on the modification of hospitalization risks by NDVI was tested by calculating the ratio of relative risks (RRR) as suggested by Altman and Bland and as used in previous studies (Altman, 2003; Bell et al., 2015).

We built several different meta-regression models by adding potential covariates one at a time and selected the model with the highest R squared value for cardiovascular and respiratory hospitalizations. Then, we applied the same set of variables to the other study diseases. The finally selected model in the main results were the fully adjusted model included variables for NDVI, median household income, percent of the population ≥ 65 years, percent of persons >65 years in poverty, an offset term for population density (persons/mile^2), mean of annual level of PM_{10} (or $PM_{2.5}$) (μg/m^3), and latitude of the county. Among the models, estimated coefficients of NDVI were robust. The first-stage and the second-stage models were conducted using R (version 3.3.1) ‘mgcv’ and ‘metafor’ packages, respectively.

We performed sensitivity analyses by separately conducting the meta-regression analyses by geographic regions (Midwest, Northeast, South, and West) based on regions defined by the U.S. Census Bureau (U.S. Census Bureau, 2018). Also, estimation of county-specific NDVI

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through the study period was compared to a different aggregation of NDVI approach: aggregation through the period in which air monitoring data are available, which varied by county and aggregation based on data through the study period (2000–2013). The main results were based on the NDVI aggregated through the period of available air monitoring data for each county. Other sensitivity analyses considered distributed lags (Bell et al., 2004) for particulate matter.

3. Results

The descriptive statistics for air quality, hospitalizations, and county-level covariates are shown in Table 1. The mean of county-specific NDVI levels was 0.45 with a range of 0.14 – 0.67 for the study period.

Figure 1 shows the estimated county-specific relative risks of particulate matter with hospital admissions by NDVI level. The PM-related hospitalization risk for all cardiovascular diseases decreased as the NDVI level increases for the study counties (Fig. 1.1). The red dashed line represents linear prediction for the relative risks as a function of the county-level NDVI (Fig. 1.1). Estimated effect modification of NDVI obtained from the meta-regression analysis is shown in Table 2. The estimates represent the absolute difference in the hospitalization risks (i.e., % change in hospitalizations associated with exposure to particulate matter) (for those ≥ 65 years) attributable to an IQR increment in county-level NDVI. The effect modification was significant for the risks of all cardiovascular diseases, ischemic heart disease, and acute myocardial infarction associated with PM_{10} exposure. For example, risk difference driven by an IQR increase in NDVI for the PM_{10}-related risk for all cardiovascular disease was −1.68% (95% CI: −2.91, −0.43%) indicating reduction in the hospitalization risk associated with exposure to PM_{10}. The range of the risk differences for an IQR increase in NDVI for the estimated $PM_{2.5}$-hosplitaization association showed a reduction of cause-specific hospitalizations ranging from 0.01% (all respiratory) to 0.85% (acute myocardial infarction), but the results were not statistically significant. The estimated risk differences associated with an IQR increase in NDVI for the risks related to PM_{10} was larger than those of the risks due to $PM_{2.5}$ although the results for $PM_{2.5}$ were not significant. Supplemental Table 1 shows results analogous to Table 2, but for cumulative lags (0–1, 0–2, and 0–3 days) of particulate matter. The absolute changes related to an IQR increase in NDVI were robust among different lag exposures of $PM_{2.5}$, whereas the direction of effect modification of NDVI (i.e., increasing vs. reducing) was inconsistent among different lag structures for the risks of PM_{10}.

We analyzed effect modification of NDVI for the PM-hospitalization risks stratified by sex and age. The effect modification of NDVI for the PM_{10}-related risks of all cardiovascular diseases by sex and age is shown in Figure 1.2 and Figure 1.3. The risks declined with increase in the NDVI, and the decrease was larger for the 65–74 and the 75–84 year age groups compared to those >85 years. The effect modification of an IQR increase in NDVI, measured as risks difference (%), for the study diseases related to PM_{10} and $PM_{2.5}$ are shown in Table 3. Except for all respiratory diseases, younger age groups (65–74 or 75–84 years) tended to have the largest decrease for hospitalization risks related with PM_{10}. For the hospitalization risks related to $PM_{2.5}$, no particular pattern for larger reduction in risks in

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relation to age was found. The estimated risk differences by sex for PM_{10} and $PM_{2.5}$ were inconsistent among the diseases. Although several sex and age sub-groups showed statistically significant changes in hospitalization risk by NDVI increase, there was no evidence to support a significant interaction effect of sex or age for the risk of PM_{10} and $PM_{2.5}$ according to the results of calculated Ratio of relative risk.

4. Discussions

While effect modification by demographic and socioeconomic factors has been studied, far less is known about effect modification by environmental factors. Previous studies have examined if more access to urban green space reduces the mortality risks in populations for disease causes that were plausibly related to green space (i.e., cardiovascular and respiratory diseases) (Ayres-Sampaio et al., 2014; Kioumourtzoglou et al., 2016; Richardson and Mitchell, 2010; Vienneau et al., 2017) and birth outcomes (Dadvand, 2012; Dadvand et al., 2012; Ebisu et al., 2016; Hystad et al., 2014). However, the effect of green space on reducing the risks of health outcomes, particularly caused by short-term exposure to air pollution (i.e., effect modification), has been rarely reported. Using data of hospitalization of Medicare enrollees, this study found evidence for health benefits of green space for diminishing the health impacts of particulate matter on hospitalizations of older persons in the U.S. population.

Development in available data on greenness has enabled the study of the effect of greenness on human health. We used the Normalized Vegetation Index, a commonly applied dataset that is available from NASA satellite imagery data. As the imagery taken from the satellite covers the whole planet with high temporal resolution, the data have been widely used by many environmental and health studies (Beck et al., 2000). As a high NDVI level indicates dense vegetation (e.g., forest) and lower NDVI level indicates grassland or desert (NASA, 2018), NDVI is suitable to explore exposure to greenness and its health benefits in urban regions. This method is particularly meaningful as tress may have more capability for reducing the concentrations of particulate matter than does grass, although potentially different effects on human health has been rarely studied (Jeanjean et al., 2016).

Potential pathways through which urban green space could reduce health impacts of air pollution are reduction of air pollution levels, and general health enhancement through physical activities (Markevych et al., 2017; Nieuwenhuijsen et al., 2017). Dense vegetation and wide canopy cover are relevant to reducing ambient particulate matter concentrations (Irga et al., 2015). Another pathway through which vegetation can impact air pollution is through changes in pollution's chemical composition and/or concentration. In addition to reduced air pollutants and various mechanisms related to vegetation (e.g., deposition to leaf surfaces, reduced ambient temperature) (Nowak et al., 2006), changes in the chemical composition of particles could alter the association between particulate matter and health, such as through the removal of polycyclic aromatic hydrocarbons (PAHs) and heavy metals (Sæbø et al., 2012).

The ability of trees to reduce air pollution, thereby changing the chemical mixture of air pollution, is complex as vegetation can increase pollution in some cases. As one example, in

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regions with lower wind speed and pollutant sources below the canopy (e.g., vehicles), trees can trap pollutions at ground level (Nowak et al., 2006). Biogenic emissions from vegetation include precursors to tropospheric ozone (Bryan and Steiner, 2013) and $PM_{2.5}$ (Nowak et al., 2018; Yang et al., 2015). Furthermore, characteristics of leaves (e.g., thickness and hairiness) and particle size affect the deposition rate of particulate matter (Janhäll, 2015; Sæbø et al., 2012). Despite the limited literature, some evidence suggests that the removal of air pollutants by trees is smaller for fine particulate matter ($PM_{2.5}$) than coarser particles (Selmi et al., 2016). A previous study reported that the estimated annual removal of $PM_{2.5}$ by urban trees is substantially lower than for PM_{10} in selected U.S. cities (Nowak et al., 2013). The difference in urban trees' correlation with PM_{10} and $PM_{2.5}$ may relate to urban forms (e.g., open road, street canyon) that may affect the form of urban green space and the physical interaction between particulate matter and vegetation such as leaves (Abhijith et al., 2017; Janhäll, 2015). In our study, NDVI was positively correlated with $PM_{2.5}$ and negatively correlated with PM_{10} (Supplementary Table 4), and the difference in correlation may suggestdifferent behaviour of particles within the two size ranges (i.e., $PM_{2.5}$ vs. PM_{10}) and corresponding diverse relationships with vegetation. Most previous studies focused on PM_{10} and $PM_{2.5}$ without considering type of vegetation (Nowak et al., 2013), so future work is warranted comparing removal efficiency by particle size in relation to vegetation types.

Individuals' air pollution exposure may be affected by micro-urban environmental forms (Yang et al., 2015). Urban design with small spatial green areas (e.g., tree barrier in street canon) could affect short-term and long-term exposure patterns to air pollution for local residents and workers. Such exposure to air pollutants varies by daily activities and lifestyle (Makri and Stilianakis, 2008), and exposure to green space can also vary by these characteristics. While most studies have assumed a high likelihood of more frequent park use in regions with more green space and hypothesized beneficial effects of green space, concerns have been raised regarding the potential for increased intake of air pollution due to promoted physical activities in urban green spaces (Markevych et al., 2017; Wolch et al., 2014). This issue may be more significant for exposure to air pollution near parks located in areas with heavy traffic (Makri and Stilianakis, 2008) and near streets lined with trees to which persons are highly allergenic (Nieuwenhuijsen et al., 2017). Thus, time-activity patterns and urbanicity are important factors for future studies for more accurate estimation of the influence of green space on health, including in relation to air quality.

Sex and age differences in the effect of greenness on health outcomes including cardiovascular and respiratory diseases have been reported by a few studies with inconsistent results (Richardson and Mitchell, 2010; Vienneau et al., 2017). We focused on health outcomes associated with short-term exposure to PM. The younger age groups within our older population (65–74 or 75–84 years) tended to have the largest decrease for hospitalization risks related to PM_{10} compared to those >85 years, although the differences were not statistically significant. One possible explanation for sex or age differences in the health risks from air pollution is larger vulnerability in women than men in terms of biological differences (e.g., smaller airways and higher flow rates in women) (Oiamo and Luginaah, 2013) and pre-existing health conditions in the elderly. In relation to the effect of green space, the finding for less physical activity of women and older age groups in the elderly (Keadle et al., 2016) suggests possible less use of outdoor green space by U.S.

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women, while these issues can be complicated by social and socioeconomic status in communities (Lee and Maheswaran, 2011). Occupational outdoor exposures may also lead to more interaction with green space for men (Vienneau et al., 2017).

The effect modification by NDVI across the 4 sub-regions was examined for each cause of hospitalization and form of particulate matter (Supplementary Table 2 and 3). Results for the West region generally showed the largest uncertainty. County size, distribution of population, main air pollution sources and corresponding chemical size and composition, and socioeconomic development were decisive factors of county-specific hospitalization risk and effect modification by NDVI. The average health benefits of NDVI may differ by vegetation, which can relate to the seasonality of leaves. In our data, the West region showed relatively consistent NDVI levels between the warm and the cold seasons, whereas other regions showed a larger seasonal difference in NDVI (higher in the warm season). Further studies with more spatially-resolved regions and seasonality of vegetation would aid understanding of the health benefits of green space by region and vegetation type.

Another important question for effect modification of green space on the impact of air pollution is whether and how the amount of effect modification of green space changes in relation to socioeconomic level. In the U.S., people of color and/or with lower income level typically live in regions where green space is scarce (Wolch et al., 2014). Although our study estimated effect modification of county-level socio-economic status (shown in Table 1), the health benefit of green space might also vary by individual-level socio-economic status(Painter and Waters, 2013), which warrants future study.

A strength of this study was the large number of study areas on a nationwide scale using Medicare data, which provided heterogeneity for demographical factors. To the best of our knowledge, our study is the first study to address the effect of green space on reducing risks of hospitalizations caused by short-term exposure to air pollution. We considered various socio-economic and demographic factors, which enabled identification of their relationship with vegetation level and effect modification of those factors on health risks of air pollution.

We also have several limitations. First, exposure to air pollution was assessed using aggregated data for the county level. Some studies suggested that using area average air pollution exposures in time-series analysis attenuated statistical power (Butland et al., 2013). Thus, our results of the association between particulate matter and hospitalization may represent conservative estimates. Nevertheless, using aggregated exposure data from multiple monitors may exclude populations distant from monitors and limit comprehensive characterization of health effects of air pollution for the general population (Bravo et al., 2012), and our ability to explore effect modification. Also, our results of the association between particulate matter and hospitalization based on the county unit might be subject to the Modifiable Areal Unit Problem (Parenteau and Sawada, 2011; Soobader et al., 2006). County-level aggregation of green space might not reflect the actual level of greenness for an individual's exposure throughout their daily interactions (e.g., proximity to greenness, frequency of interaction with greenness). Information on time-activity patterns of individuals was not available in our study, which relates to interaction with green space related to time at work versus home, and indoors versus outdoors (Helbich, 2018). Also, lack of information

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on individual-level exposure to noise, walkability, and socio-economic status limits investigation of health effects of green space mediated by urban environment and individual-level health determinants. On the other hands, NDVI indicates overall vegetation level regardless of vegetation species, although patterns of effect modification could vary by type of vegetation. We were not able to remove the potential health effects of blue surface (i.e., water) on health risks (Völker et al., 2016) from the NDVI imagery data as the values indicating blue surface of raw NDVI satellite imagery were removed in averaging raster values at the specified new resolution for geo-processing (e.g., mosaicking and re-projection). However, we assumed that the impact of blue surface on the calculated NDVI values was small as the obtained county-specific NDVI values were obtained by averaging grid values at a 1-km resolution to county polygons.

In conclusion, remaining questions include effects by vegetation type, which could interact differently by particle size, tree species, micro-urban structure, and time-activity patterns. Given the rapid loss of green space and redistribution of tree species in the U.S. driven by climate change, further efforts are needed to investigate these issues to inform urban design and environmental health policies to support public health.

5. Conclusion

Our findings suggest that areas with less green space generally have higher particulate matter-hospitalization associations for cardiovascular and respiratory diseases. The risk reduction was generally higher in younger age groups (65–74, 75–84 years) compared to those ≥85 years, while no particular pattern was observed for reduction in the association by sex. The changes in the particle-hospitalization association in relation to NDVI varied by particle size (PM_{10}, $PM_{2.5}$). Our study adds evidence for health benefits of green space for reducing the health impacts of particulate matter on hospitalizations in the U.S. older population, with those benefits differing among subpopulations.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviation

NDVI	Normalized Difference Vegetation Index

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Highlight

- The effect modification of green space on the hospitalization risk of air pollution was assessed.
- Amount of green space was measured by the Normalized Difference Vegetation Index.
- The hospitalization risk of air pollution was less in areas with more green space.
- The benefit for decreased health risk was larger for the younger age groups.

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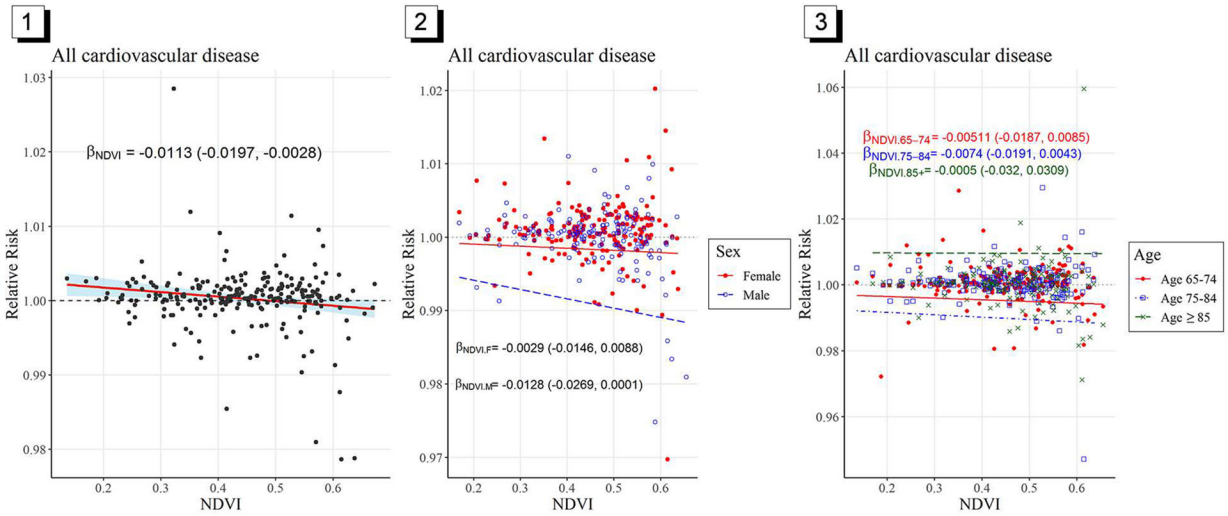

Figure 1.

Effect modification by NDVI for the hospitalization risk of all cardiovascular diseases associated with a 10-μg/m^3 increase in PM_{10} in the same day in urban counties in the U.S. (00–13). The x-axis is the county-level NDVI and the y-axis is the estimate of county-specific relative risk and for (1) whole study population (≥ 65 years), (2) subgroups of sex, and (3) subgroups of age.

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Table 1.

Descriptive statistics of county-level variables of urban counties in the U.S. (n=364).

Variable	Mean	IQR	Range (Min-Max)
PM_{10} (μg/m^3)	23.7	16.7	0.3 – 396.0
PM_{25} (μg/m^3)	11.7	8.4	0.1 – 160.0
Daily Temperature (°F)	56.1	11.2	17.8 – 76.3
Daily dew point (°F)	42.7	9.2	12.8 – 66.8
Medicare enrollees ≥ 65y (10^5)	1,901	1,969.80	15.50 – 10,950
Sum of daily hospital admissions (2000 – 2013)			
All cardiovascular	51,008	47,394	176 – 803,041
Acute myocardial infarction	4,950	4,643	17 – 69,561
Ischemic heart disease	12,301	10,620	37 – 175,137
Heart failure	10,735	10,768	33 – 188,121
Stroke	9,335	8,755	41 – 140,185
All respiratory	14,838	13,787	26 – 214,089
Respiratory tract infection	9,646	8,623	19 – 146,888
NDVI	0.45	0.15	0.14 – 0.67
Median household income (US$)	49,484	13,619	29,404 – 106,068
Percent of the population ≥65y) (%)	6.39	1.84	2.58 – 15.34
Percent of persons ≥65 in poverty (%)	13.63	5.94	3.38 – 33.96
Population density (persons/mile^2)	1189.90	895.1	1.8 – 66940.10

Notes: The range of PM_{10}, $PM_{2.5}$, and temperature variables show the smallest and the largest values of any study county.

NDVI was calculated based on the aggregation of 16-day NDVI data for each study county between the start and the end dates of the county's available air quality monitoring data.

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Table 2.

Absolute difference in the percent change in PM_{10}- and $PM_{2.5}$-related hospitalizations attributable to an IQR increase in NDVI in urban U.S. counties (00–13).

Cause of ho spitalization	PM_{10}		$PM_{2.5}$	
	Percent change in hospital admissions (95% CI)	I^2(%)	Percent change in hospital admissions (95% CI)	I^2(%)
All cardiovascular disease	−1.68 (−2.91,−0.43)	28.67	−0.18 (−0.73, 0.39)	34.14
Stroke	−7.71 (−17.84, 3.67)	99.83	−0.39 (−1.65, 0.89)	9.71
Ischemic heart disease	−3.63 (−7.00,−0.15)	96.03	−0.39 (−1.46, 0.68)	0.00
Acute myocardial infarction	−10.40 (−13.34,−7.34)	12.50	−0.85 (−2.50, 0.83)	0.00
Heart failure	−0.67 (−5.96, 4.90)	99.51	−0.50 (−1.71, 0.72)	8.69
All respiratory disease	−1.29 (−3.36, 0.83)	3.15	−0.01 (−1.03, 1.01)	8.18
Respiratory tract infection	−6.64 (−13.59, 0.87)	99.85	−0.70 (−1.93, 0.55)	12.00

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Table 3.

Absolute difference in the percent change in sex- and age-specific hospitalizations among the study counties attributable to an IQR increase in NDVI (00–13).

Cause of hospitalization	PM_{10}	$PM_{2.5}$
	change in hospital admissions (95% CI)	change in hospital admissions (95% CI)
All cardiovascular disease		
Male	−1.90 (−3.95, 0.19)	−0.32 (−1.21, 0.57)
Female	−0.43 (−2.17, 1.33)	−0.33 (−1.21, 0.55)
65≤Age<75	−0.76 (−2.76, 1.28)	−0.11 (−1.13, 0.91)
75≤Age<85	−1.11 (−2.83,0.64)	−0.47 (−1.37, 0.44)
85≤Age	−0.08 (−4.68, 4.74)	−0.13 (−1.25, 0.99)
Stroke		
Male	−1.80 (−13.05, 10.90)	−1.43 (−3.37, 0.56)
Female	−4.57 (−11.01, 2.33)	0.55 (−1.17, 2.29)
65≤Age<75	−3.56 (−7.35,0.40)	−0.04 (−2.30, 2.27)
75≤Age<85	0.64 (−2.72,4.12)	−1.04 (−2.94, 0.90)
85≤Age	1.31 (−2.35,5.10)	2.84 (0.00, 5.75)
Ischemic heart disease		
Male	−13.25 (−18.93,−7.16)	−1.25 (−3.06, 0.59)
Female	−9.93 (−17.49,−1.67)	−2.54 (−4.23, −0.83)
65≤Age<75	−0.15 (−1.54, 1.26)	−0.17 (−1.78, 1.47)
75≤Age<85	−0.01 (−1.44,1.45)	−0.05 (−1.78, 1.71)
85≤Age	−0.15 (−1.73, 1.45)	−1.58 (−4.14, 1.04)
Acute myocardial infarction		
Male	16.02 (−29.76, 91.65)	−1.55 (−3.82, 0.77)
Female	−24.12 (−62.66, 54.19)	0.63 (−1.77, 3.09)
65≤Age<75	−4.84 (−17.21, 9.39)	−0.2 (−2.89, 2.57)
75≤Age<85	2.30 (−1.05, 5.75)	−0.85 (−3.46, 1.83)
85≤Age	0.32 (−2.39, 3.10)	−0.97 (−3.98, 2.13)
Heart failure		
Male	4.32 (−34.10, 65.13)	−0.72 (−2.50, 1.10)
Female	3.52 (−16.53, 28.39)	−0.29 (−1.93, 1.38)
65≤Age<75	−0.03 (−1.43, 1.40)	0.87 (−1.28, 3.08)
75≤Age<85	−0.16 (−1.61, 1.30)	−1.74 (−3.54, 0.30)
85≤Age	0.08 (−1.50, 1.69)	−3.38 (−5.47, −1.24)
All respiratory disease		
Male	12.55 (−8.85, 38.96)	−0.44 (−1.94, 1.08)
Female	−9.36 (−24.30, 8.52)	0.49 (−0.95, 1.94)
65≤Age<75	0.22 (−3.77, 4.37)	0.51 (−1.70, 2.78)
75≤Age<85	−1.98 (−6.01, 2.22)	0.54 (−1.11, 2.23)

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Cause of hospitalization	PM_{10}	$PM_{2.5}$
	change in hospital admissions (95% CI)	change in hospital admissions (95% CI)
85≤Age	1.87 (−1.13, 4.96)	−0.42 (−2.38, 1.59)
Respiratory tract infection		
Male	−43.31 (−60.57,−18.50)	−0.54 (−2.31, 1.26)
Female	−1.62 (−40.08, 61.54)	−0.53 (−2.23, 1.20)
65≤Age<75	−0.12 (−1.51, 1.30)	−0.81 (−3.08, 1.51)
75≤Age<85	0.05 (−1.39, 1.52)	0.19 (−1.83, 2.25)
85≤Age	−0.19 (−1.75, 1.40)	−1.13 (−3.28, 1.06)