

Does the Presence of Vegetation Affect Asthma Hospitalizations Among the Elderly? A Comparison Between Rural, Suburban, and Urban Areas

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Abstract

Climate change and increasing urbanization have intensified scientific interest in understanding the impact of vegetation cover on human health. While the elderly population (persons 65+y.o.) continues to grow, environmental determinants for asthma in this group remain poorly understood. Using spatial and time series analysis we investigated the effect of vegetation cover as measured by the Normalized Difference Vegetation Index (NDVI) on asthma hospitalization rates (AHR)(ICD-9 codes 493.0-9) among Medicare recipients in seven northeastern United States. We considered potential confounders, including income, land cover category, seasonal influenza activity, and population density, classified as urban, suburban, and rural. Time-series analysis identified seasonal patterns in elderly asthma hospitalizations as counter-phase with NDVI: when vegetation vigor increases, AHR decreases ($R^2=0.59$, $p=0.001$). Winter peaks of influenza correlated with an increase in AHR ($R^2=0.43$, $p=0.001$). Spatial multivariate analysis found HRs increased significantly ($RR=1.048$, 95% CI:1.072-1.086, $p=0.001$) as population density increased. Regardless of location, living in poverty increased AHR ($RR=1.014$, 95% CI:1.026-1.018, $p=0.001$). After adjusting for income and percent elderly population, evergreen vegetation in urban areas demonstrated a small, yet protective effect ($RR=0.998$, 95% CI:0.993-0.997, $p=0.02$). These results suggest that urban evergreen vegetation cover could be an important factor for reducing the risk of elderly asthma hospitalizations.

Keywords: *vegetation, elderly, asthma, NDVI, time series, spatial analysis, remote sensing*

Introduction

Asthma is a chronic inflammatory disorder of the airways that affects people of all ages (HEI, 2011). Demographic changes are resulting in a larger elderly population, yet the etiology and environ-

mental determinants of asthma in people 65 and older is poorly understood (Hanania, 2011). Recent studies have linked asthma exacerbations in the elderly to air pollutants, including: particulate

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matter (PM_{2.5} and PM₁₀), nitrogen dioxide (NO₂), nitrogen oxide (NO) and total suspended particles (TSP) (Anderson et al., 2012, Brunekreef et al., 2009, Kloog et al., 2012, and Makra et al., 2012). Acute respiratory infections also exacerbate asthma episodes (Hanania, 2011).

In 2004, the U.S. prevalence of asthma for those 65 or older was 7% (Hanania et al., 2011). Asthma in the elderly is of particular concern: older patients with asthma are more likely to be under-diagnosed, do not respond well to treatment, and asthma exacerbations are more severe than in younger asthmatics (Baiz and Annesi-Maesano, 2012, D'Amato, 2002, Makra, 2012). The reasons for these disparities are thought to be due to age-related decreases in immune cell and lung function, and the presence of airway inflammation (Hanania et al., 2011) as well as chronic comorbidities associated with advancing age increasing the susceptibility to environmental stressors which may exacerbate asthma (Tsai et al., 2013). Environmental changes, including attributes associated with climate change, are linked to increases in asthma prevalence over the past two decades in the general population (Baiz, N., & Annesi-Maesano, 2012).

There is growing scientific interest in the health and environmental benefits of trees and vegetation, including the ability to mitigate environmental pollutants (Baldauf et al., 2010, Brantley et al., 2013, Donovan et al., 2005). Trees and vegetation provide numerous health and environmental benefits including: sequestering carbon and attenuating storm water runoff (Raciti, 2013), improved emotional well-being (Alter, 2013, Khao, 2001, Takano et al., 2002), improved microclimate through reducing wind, noise, and buffering ultraviolet light (Escobedo, 2009), and trapping and absorbing airborne pollutants (Wuyts et al., 2008, Roy et al., 2012). The role that trees play in the mitigation of airborne pollutants is multifaceted: trees can absorb gaseous pollutants through the leaf stomata, and trap particles on leaf and branch surfaces, which may then be resuspended or dropped to the ground (Nowak et al., 2006 and 2012). In theory, such abilities could positively affect population health, particularly where air pollution levels are high. Trees also negatively affect health by releasing volatile organic compounds (VOCs) (Chameides et al.,

1988) and aeroallergens such as pollens and bioaerosols, which contribute to respiratory irritation and asthma (D'Amato, 2002, D'Amato et al., 2000 and 2013, and Kin et al., 2013).

The majority of studies of the pollutant removal abilities of vegetation are model-based and estimate that pollutant reductions by vegetation range from 1.5% up to 30% (Donald, 2007, Tiwary et al., 2009 Bealey et al., 2007, Nowak et al., 2006, and 2012, Tallis et al., 2011, Tiwary et al., 2009) depending on the pollutant measured. Few empirical studies have been completed to support these models (Roy et al., 2011) and those empirical studies measuring the effect of vegetation on pollutant levels have found conflicting and smaller results. One study found insignificant differences in NO₂ and VOCs, PM_{2.5} and PM₁₀ under tree canopies and in adjacent open areas, but larger reductions in particle number count (PNC) by vegetation (Setälä et al., 2013), others have found significant reductions in PM₁₀ (Maher et al., 2013), and black carbon (Brantley et al., 2013). One study in Portugal compared asthma hospital admissions to remotely sensed environmental variables and found a significant relationship in urban areas between NDVI, NO₂ and temperature and asthma hospitalizations in all seasons (Ayes-Sampaio et al., 2014).

Our early investigations had demonstrated the opportunities to conduct epidemiological studies using medical claims data (Morris et al., 1997, Cohen and Naumova 2007, Lofgren et al., 2007, Naumova et al., 2009, Cohen et al., 2009, Castronovo et al., 2009). Compilation of medical records in comprehensive databases is enabling detailed studies in large geographical areas and on a refined spatial scale for distinct populations (Naumova et al., 2009). In the present analysis we investigated the relationship between the presence of trees and vegetation and elderly asthma hospitalizations through time series and spatial analysis of remote sensing data, and 133,648 Medicare hospitalization records in seven north-eastern U.S. states, from January 1, 2005 to December 31, 2006, aggregated to the zip code level. NDVI served as a proxy for vegetation vigor. Centers for Medicaid and Medicare Services (CMS) hospital admission records for the Medicare population 65 years of age and older with a diagnosis containing asthma (Federal Information

Processing standards (FIPS) ICD-9 code 493.0-9) served as the principal health outcome. Population density is a measure of urbanization and was used to classify zip codes as urban, suburban or rural. We hypothesized that mature vegetation might reduce elderly asthma hospitalizations rates and that this effect would be more evident in urban zip codes, after adjusting for influenza-virus activity, land cover classification, and socioeconomic status.

Research Methods

Study Region

The six New England states (Connecticut, Massachusetts, Rhode Island, Vermont, Maine, and New Hampshire) and New York State were selected for their similarities in climate and deciduous vegetation. These states share the same Köppen-Geiger climate classification: “Dfb – moist continental mid-latitude climates”; a temperate climate with snowy winters, warm summers and a boreal forest region with evergreen trees and conifers (Kottek et al., 2006). The Köppen-Geiger classification system is based on the premise that the prevailing type of vegetation in the area can be used to define a climate as the vegetation is based on the temperature and precipitation of the region.

Data Sources and Processing

The sources employed to obtain and process hospitalization cases, NDVI, land cover and demographic data are briefly described.

Hospitalization Data

Two-years of Medicare hospitalization data, from January 1, 2005 to December 31, 2006, were obtained from the Centers for Medicare and Medicare Services (CMS) which provides health coverage for 98% of adults aged 65 and older. Data for the seven states was extracted from the nationwide CMS dataset and included zip code of residence, age, gender, race, date of admission, and discharge diagnosis codes containing asthma (International Classification of Disease (ICD-9) code 493.0-9), and total charges associated with hospital admission and treatment.

NDVI Data

Remote sensing data from the National Aeronautical Space Association (NASA)’s Moderate Resolu-

tion Imaging Spectroradiometer (MODIS) on board of Terra and Aqua satellites was used to compare vegetation phenology spatially and temporally using NDVI majority values. MODIS MYD13Q1 product, a 16-day composite gridded vegetation index at a 250-meter spatial resolution with sinusoidal projection was downloaded from the U.S. Geological Survey website (lpdaac.usgs.gov) containing forty-seven files for each of the “h12v04” and “h13v05” tiles for the years 2005 and 2006. NDVI is a measure of the density of plant growth ranging in value from -1 to 1 with higher values equal to higher vegetation density and vigor. NDVI quantifies vegetation cover and can be used as a proxy for vegetation “greening”, a composite property of leaf chlorophyll content, leaf area, canopy cover, and structure (Glenn et al., 2008, Huete et al., 2002, Hmimina et al., 2013). ArcGIS® was used to extract NDVI majority data from the MODIS tiles and mask it to the study region to obtain zip code level data. The majority value is the most frequently occurring NDVI value in the zip code. The extracted data was examined for outliers and missing data. Where missing data was identified, the zip code’s prior and subsequent values were examined. If more than two of the forty-six periods had missing data that zip code was removed from the data set. Where two or fewer periods had missing data, a value was imputed for the missing data assigning the average of the prior and subsequent period value to the missing point. The dataset was matched by zip code to the hospitalization admission dataset.

Land Cover Data

The 2006 National Land Cover Dataset (NLCD) was obtained from the U.S. Geological Survey website (mrlc.gov/nlcd2006.php). The Landsat-based data quantifies land cover in the United States from 2001 to 2006 in a 20-class land classification scheme that has been applied across the Conterminous United States at a spatial resolution of 30 meters (Fry et al., 2011). The NLCD dataset was imported into ArcGIS®, and reclassified to five categories per zip code: developed, evergreen forest, deciduous vegetation, water, and other.

Demographic Data

Demographic data was downloaded from the U.S. Census Bureau website (factfinder2.census.gov). Census 2005 and 2006 data was used to identify

population counts per zip code. Both year population estimates were averaged to obtain a single value for the two years in order to adjust for population dynamic in US elderly (Cohen and Naumova, 2007). Census 2010 data, provided at zip code level was used for the percent poverty and social security income variables. The “Estimate of percentage of families and people whose income in the past 12 months is below the poverty level – all people” and “Social Security Income” datasets at the zip code level were obtained and matched to the zip codes for the study area.

Influenza Data

Positive seasonal influenza laboratory test results for 2005 and 2006 for the entire U.S. were obtained from the Centers for Disease Control website (cdc.gov/flu/weekly/weeklyarchives2005-2006). The dataset contained a characterization of percent positive virus samples by week and was aggregated to 46 16-day periods matching Remote Sensing data frequency.

Data Analysis

The analysis aimed to explain the variations in the context of temporal, spatial and demographic differences in elderly asthma occurrence. The data were examined on the spatial and temporal basis using R statistical software version 3.0.2. (R Core team, 2013).

For the temporal analysis, hospital admissions data was aggregated into 46 16-day periods to temporally match the NDVI data. The 46th period that covered only six days at the end of 2006 was subsequently excluded from the temporal analysis. Asthma hospitalization rates (AHR) per 10,000 residents were calculated for each time period, t :

$$\text{AHR}(t) = (\text{count of asthma hospitalization cases per time period}) / (\text{population over 65 in overall area}) * 10,000$$

The temporal format of the NDVI and AHR data allowed comparison of the systematic fluctuations over the two-year period. Time series data were also plotted for zip codes aggregated by income level and the degree of evergreen cover.

Time series regression analysis used AHRs as the dependent variable, and included NDVI majority with one-period lag, and percent positive influenza virus samples aggregated to 16-day periods (FLU_t) as the independent variables. The model also

contained harmonic terms to account for seasonal variability $S1=\sin(2\pi\omega t)$, $C1=\cos(2\pi\omega t)$, $S2=\sin(4\pi\omega t)$, $C2=\cos(4\pi\omega t)$, where $\omega=1/45$ and $t=1,2, \dots, 45$ indicate time period. Thus, the developed model has the following form:

$$\text{AHR}(t) = \beta_0 + \beta_1 \text{NDVI}_{t-1} + \beta_2 S1 + \beta_3 C1 + \beta_4 S2 + \beta_5 C2 + \beta_6 \text{FLU}_t$$

A separate model containing only variables indicating flu activity as percent positive influenza virus samples was explored (Naumova et al, 2009, Cohen et al., 2010, and Wenger and Naumova, 2011).

For spatial analysis, asthma hospitalization rates per 10,000 residents were calculated by zip code, s :

$$\text{AHR}(s) = (\text{count of asthma hospitalization cases per zip code}) / (\text{population over 65 in zip code}) * 10,000$$

To reduce spuriously high rates, zip codes with elderly populations under 100 residents were merged with adjoining zip codes in the same state. Neighboring zip codes with the most similar population size were merged until the joined county elderly population exceeded 100 elderly residents. Merging the counties with neighbors likely to share NDVI values permitted comparison of AHR to NDVI for the newly combined zip codes.

Spatial analysis regressed on a set of zip-code specific explanatory variables: averaged land cover variables (percent developed, deciduous and evergreen), socioeconomic (percent below poverty threshold and social security income), population and elderly population density, and NDVI values against the logged values of $\text{AHR}(s)$. The analysis was performed for each variable separately and also in a combined model. Stepwise backward elimination was used to select variables with significant 95% confidence intervals. Population density was used to divide all zip codes into three groups: urban, semiurban, and rural with population density > 830.7 , $107-830.7$, and < 107 people/mi², respectively. Thus, the models were repeated for each urbanization level (Cohen et al., 2009). The results of the models were expressed as estimates of the relative risk and their 95th confidence intervals.

Table 1

Descriptive statistics of the CMS Hospitalizations for ICD- 9 (493.0-9) from January 1, 2005-December 31, 2006

CMS dataset	2005	2006
Hospitalizations		
Male / Age*	18,822 (29%) 76.6±7.0	19,525 (29%) 76.8, ±7.8
Female / Average Age	46,694 (71%) / 78.0±8.1	48,105 (71%)/ 78.0, ±8.2
Average Age	77.6, ±8.0	77.9 , ±8.1
Cost of hospitalization	\$22,494	\$24,520
In-hospital death	10,240 (16%)	14,420 (21%)
Male / Average Age	3,413 (33%) / 81.6, ±8.7	4,691 (37%) / 79.6, ±8.4
Female / Average Age	6,827 (67%) / 79.4, ±8.3	9,729 (63%) / 81.0, ±8.9
Race and Ethnicity		
White	52,194 (80%)	53,869 (80%)
Black	7,237 (11%)	7,827 (12%)
Hispanic	1,451 (2%)	1,472 (2%)
Am. Indian	845 (1%)	915 (1%)
Asian	3,498 (5%)	3,279 (5%)
Unknown	108 (0%)	89 (0%)
Hospitalization cases per state		
New York	36,601	37,184
Maine	2,692	2,928
New Hampshire	2,111	2,097
Massachusetts	13,832	14,671
Connecticut	7,425	7,834
Rhode Island	1,745	1,778
Vermont	1,110	1,140
Total	65,516	67,632

* Information on age is given as mean and standard deviation

Results

Descriptive Statistics – CMS dataset

Descriptive statistics of the abstracted dataset of hospitalizations with the discharge diagnosis containing asthma (ICD-9) 493.0-9) from January 1, 2005-December 31, 2006 are summarized in Table 1. The data is comprised of 65,516 cases in 2005 and 67,632 cases in 2006. The majority of patients were white (80%), women (71%), with an average age of 77.6 (s=8.0) years. Nearly three times as many women (71% of the hospitalizations in both years) were hospitalized as men. Averaging the two years, 47,400 (21.7%) of the estimated women and 19,174 (11%) of the estimated men who had asthma, based on US Census popu-

lation statistics, were hospitalized during the study period.

Various comorbid conditions are typical for people admitted to hospitals with ICD-9 (493.0-9). These comorbid diagnoses indicate chronic health issues; heart disease was the most common comorbidity for both men and women (78% and 84%, respectively), followed by hypertension (61% and 62%), lipid metabolism disorders (29% and 33%) and mental disorders (28% and 28%). Table 2 summarizes the top 15 diagnostic categories for 2005 and 2006. The annual charges associated with hospital admission and treatment for our study population were \$1.47 billion in 2005 and \$1.52 billion in 2006.

Table 2

A summary of Comorbid diagnoses of CMS populations in 2005 and 2006

Comorbid diagnoses within CMS data for 2005 and 2006					
2005	Count	Percent	2006	Count	Percent
heart disease	51,229	78%	heart disease	57,276	85%
hypertension	40,163	61%	hypertension	42,000	62%
lipid metabolism	19,181	29%	lipid metabolism	21,282	33%
mental disorder	18,335	28%	mental disorder	19,090	28%
diabetes	13,621	21%	diabetes	14,035	21%
renal	10,014	15%	esophageal reflux	10,619	16%
esophageal reflux	9,888	15%	renal	9,368	14%
lung disease	8,305	13%	lung disease	9,099	13%
pneumonia	7,884	12%	neoplasm	8,080	12%
vascular disease	7,628	12%	pneumonia	7,824	12%
neoplasm	7,433	11%	vascular disease	7,812	12%
hyper thyroidism	7,053	11%	hyper thyroidism	7,393	11%

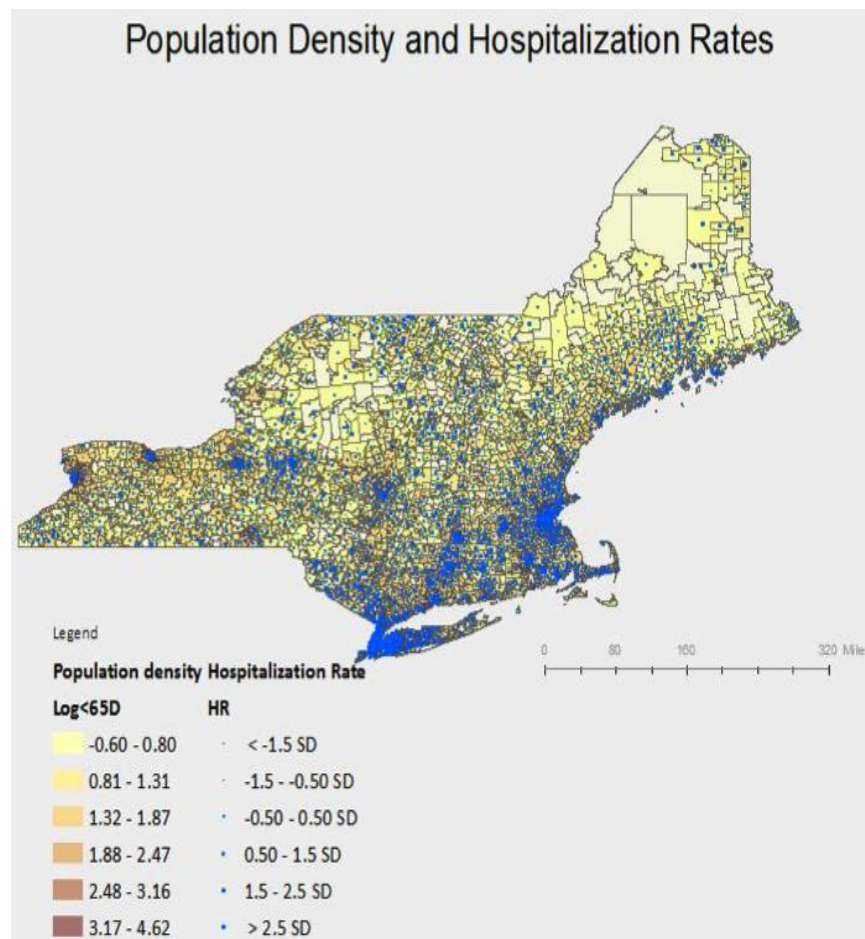


Figure 1: Map of the study region showing population density and standard deviation of hospitalization rates per zip code

Figure 1 maps the study region showing zip-code specific density for elderly population and exceedance of hospitalization rates as compared to its mean based on a standard deviation. In this study area, the elderly population resides in higher proportion in rural (16.35% of total population) than suburban (13.25%) and urban (12.04%) zip codes. An elderly population density variable was added to the regression analysis to examine the effect of this difference. As shown in Figure 2, urban zip codes exhibited the highest AHR (7.51/10,000), followed by rural areas (6.89) then suburban (6.57).

Temporal Analysis

The time series for average NDVI, hospitalization rates, and percent positive influenza test results for New England and New York are shown in Figure 3.

The fitted model describing the temporal fluctuations of AHR, NDVI, and influenza, demonstrated a strong seasonal pattern ($R^2=0.59$, $p=0.001$). Winter peaks of influenza correlated with an increase in AHR ($R^2=0.43$, $p=0.001$). The results indicate the 10% increase in the positive flu tests are associated with 0.448 +/- xx cases of asthma hospitalization per 10,000 elderly. On the other hand an increase in NDVI by 0.1 units may result a decrease of 0.013 +/- xx cases of hospital-

izations. An inverse relationship between one-period lag for NDVI and AHR supports the hypothesis that higher vegetation level has a protective effect on the asthma hospitalization rate.

For exploratory purposes, the time series of hospitalization rate and NDVI majority level were plotted by income categories (Figure 4, panel A and B, respectively). The highest AHRs for the lowest income residents, shown in red and orange; the highest 20% of income, shown in dark blue, have low NDVI values indicating urban residence, suggesting that income might influence spatial associations. AHR also exhibit distinct patterns between the categories of evergreen coverage (Figure 4, panel C) with the urban locations shown in red color.

Spatial Analysis

Table 3 summarizes the univariate spatial analysis results. The average AHRs were highest in urban (7.51/10,000) next highest in rural (6.89/10,000) and lowest in suburban areas (6.51/10,000). For all areas, the percent deciduous land cover ($RR=0.965$, 95% CI: 0.948-0.983) and percent evergreen land cover ($RR=0.897$, 95% CI: 0.870-0.925) had a protective effect on the logged HRs, as did social security income ($RR=0.386$, 95% CI=0.340-0.440) and percent elderly population in zip code ($RR=0.847$, 95% CI: 0.847-0.824).

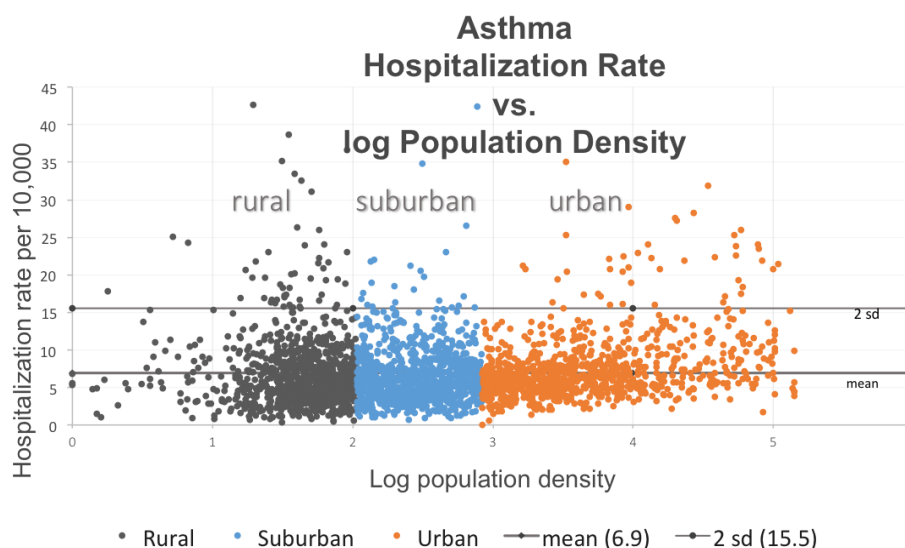


Figure 2: Zip-code specific Hospitalization rates as a function of population density for rural, suburban and urban zip codes

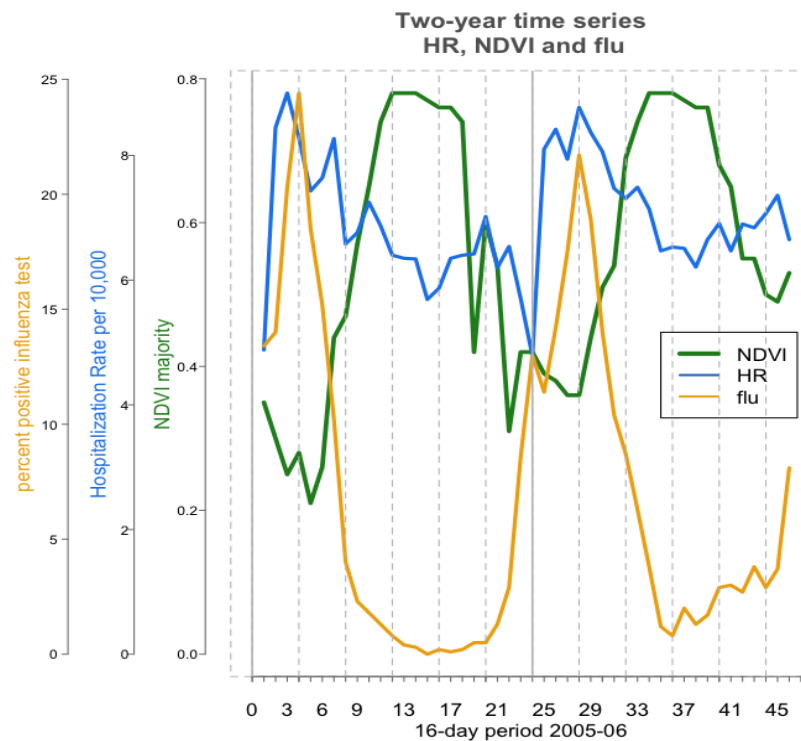


Figure 3: Time series of average NDVI values and average hospitalization rate and percent positive influenza test results per period

Table 3

The result of univariate spatial regression models for All, Rural, Suburban, and Urban Areas

Spatial Modeling	ALL mean	RR	LCL	UCL	RURAL mean	RR	LCL	UCL	SUBURBAN mean	RR	LCL	UCL	URBAN mean	RR	LCL	UCL
Hospitalization Rate per 10,000	6.99				6.89				6.57				7.51			
Environmental Factors																
NDVI majority	0.550	0.956	0.862	1.061	0.580	1.056	0.803	1.389	0.550	0.961	0.802	1.151	0.510	1.123	0.988	1.275
% deciduous cover in zip code	8.290	0.965	0.948	0.983	13.330	0.964	0.912	1.020	9.630	0.964	0.912	1.020	1.920	0.983	0.965	1.001
% evergreen cover in zip code	34.500	0.897	0.870	0.925	50.900	0.900	0.799	1.014	40.740	0.900	0.799	1.014	11.840	0.918	0.893	0.943
% of developed are in zip code	33.160	1.183	1.140	1.228	5.000	1.019	0.983	1.056	17.620	1.022	0.971	1.075	76.880	1.458	1.312	1.619
Socio-economic Factors																
% of residents in zip code living in poverty	10.701	1.177	1.147	1.208	11.783	1.049	0.978	1.124	7.886	1.049	1.005	1.095	12.417	1.324	1.284	1.365
% elderly population in zip code	13.870	0.847	0.824	0.870	16.350	0.904	0.836	0.979	13.250	0.878	0.823	0.937	12.040	0.740	0.692	0.792
social security income (\$ in thousand)	16,796	0.386	0.340	0.440	16,347	0.476	0.357	0.635	17,480	0.551	0.431	0.704	16,574	0.271	0.233	0.314
Log (elderly population density)	1.710	1.166	1.120	1.214	0.810	0.859	0.775	0.953	1.570	1.005	0.999	1.011	2.750	2.053	1.748	2.411
Log (population density)	5.950	1.316	1.243	1.394	3.710	0.500	0.312	0.801	5.670	1.019	0.997	1.041	8.460	9.140	5.574	14.989

RR= relative risk; LCL= lower confidence limit; UCL= upper confidence limit

Variables increasing the AHR were: percent developed land cover (RR=1.183, 95% CI: 1.140-1.228) log population density (RR=1.316, 95% CI: 1.243-1.394) and percent of all residents living in poverty (RR=1.177, 95% CI: 1.147-1.208).

In urban areas percent evergreen coverage has shown a protective effect (RR=0.918, 95% CI: 0.893-0.943) as was percent elderly population in

the zip code (RR=0.740, 95% CI: 0.692-0.792) and social security income (RR=0.271, 95% CI: 0.233-0.314). An increase in log-population density is strongly associated with an increase in the AHR (RR=9.140, 95% CI: 5.57-14.99) similarly to elderly population density (RR=2.053, 95% CI: 1.748-2.411) and percent of residents in the zip code living in poverty (RR=1.324, 95% CI: 1.284-

1.365). Elderly income was higher in urban areas with lower NDVI, and despite the protective effect of wealthier residents in urban locations, urban zip codes had the highest AHR.

While many environmental variables lost statistical significance when added to multiple regression models, percent evergreen coverage remained significant (RR=0.998, 95% CI: 0.993-0.997, $p=0.02$) after adjusting for zip code specific income and elderly population percentage.

Discussion

This study explored the relationship between vegetation level and land cover and elderly asthma hospitalizations in a seven state region, and was motivated by the larger questions “how does vegetation impact human health?” Results showed that while the seasonal pattern in elderly asthma hospitalizations is likely to be driven by the seasonal effect of influenza (ref 8), the differential presence of trees and vegetation is likely to contribute to spatio-temporal distribution of asthma. Although NDVI has been shown to have a protective effect on health (Ayres-Sampaio et al., 2014) we believe this is the first study to identify a relationship between urban evergreen vegetation cover and asthma hospitalizations in elderly.

The analysis provided insight into the characteristics of elderly asthma-related hospitalizations and associated charges. Comorbid diagnoses show that a population in poor health may be vulnerable to environmental triggers for asthma exacerbations. Heart disease, nearly ubiquitous in this age group, may play a role in disguising symptoms of asthma exacerbation. Episodic morning wheezing is a sign of congestive heart failure, and those with both heart disease and asthma may present in ways that make it difficult to distinguish between the two (Hanania, 2011). It also may be that heart disease renders a person less likely to recover from an asthma exacerbation or respiratory infections that leads to seasonal exacerbation (Wenger and Naumova, 2010). In our earlier work we demonstrated that management of influenza in communities could reduce the severity of exacerbations and subsequent hospitalizations for the vulnerable elderly population (Cohen et al., 2011 and Cohen et al., 2010). One means to do so would be broad vaccination strategies for all ages.

We demonstrated that reduced vegetation vigor results in increased asthma hospitalizations. The percent of evergreen cover had a small but significant impact on the urban elderly asthma AHR. For each one percent increase in urban evergreen vegetative cover, which averaged 11.84% in this study area, the asthma hospitalization rate would decrease by 0.2%. Considering an average cost of over \$23,000 per hospitalization and high readmittance rates with 82% of patients who survive the hospitalization, one percent increase in urban evergreen coverage might result in 444 fewer hospitalizations, which would save \$10,437,000 annually in our study region.

Multivariate spatial analysis illustrated the relationship between urban HRs and population density (RR=1.06, $p<0.001$) and poverty (RR=1.02, $p<0.001$), indicating the most densely populated and lowest income neighborhoods are at highest risk for asthma hospitalizations. These results are similar to findings on respiratory diseases in the elderly (Cohen et al., 2009). On the other hand, AHRs increased in elderly residing in rural zip codes with very low population density, potentially indicating the diminishing access to specialized health care services, as observed for other respiratory problems (Naumova et al., 2009).

Conclusion

While there are gaps in the understanding of types and configuration of vegetation to reduce air pollution exposures, to our knowledge this is the first study which evaluates the relationship between elderly asthma hospitalizations and remotely sensed environmental variables, illustrating potential protective effects of evergreen on respiratory health. Our findings suggest that the selective use of trees and vegetation, particularly evergreen vegetation in urban areas, may be employed to reduce the rate of asthma hospitalizations among elderly residents. Multivariate spatial analysis found socioeconomic and environmental risk factors for elderly asthma hospitalization were the most significant in urban zip codes. Possible refinements to this ecological study would include the addition of air pollution data and extending the length of study period beyond two years so that seasonality may be more effectively accounted for.

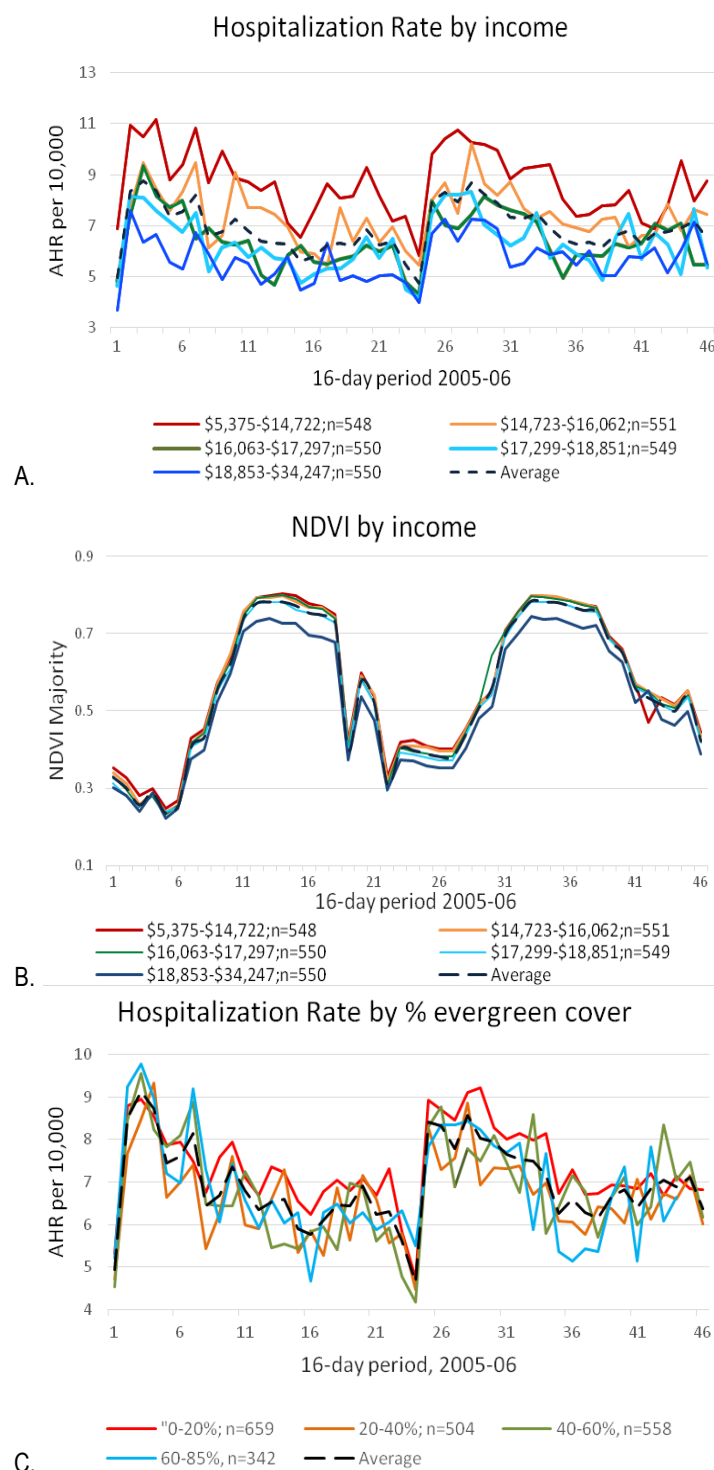


Figure 4: Time series of average hospitalization rate (Panel A) and average NDVI values by income (Panel B) and by percent evergreen coverage (Panel C).

With continuing urbanization these factors will need to be considered by urban planners and health care providers. The access and availability of

remotely sensed data combined with health outcomes will continue to benefit future research on the environmental determinants of health.

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