Assessment Of Children’s Personal And Land Use Regression Model-Estimated Exposure To No2 In Springfield, Massachusetts

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Assessment of Children’s Personal and Land Use Regression Model-Estimated Exposure to NO$_2$ in Springfield, Massachusetts

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Secondary Committee: Dr. Brian Leaderer
Abstract:

Personal NO₂ measurements were taken for a cohort of seventh-grade students (n=25) attending a magnet school in Springfield, MA with an elevated prevalence of pediatric asthma (17.2%). These personal measurements were compared with exposures predicted through a land use regression (LUR) model constructed from built environment and land use characteristics across the area to assess personal exposures in NO₂ exposures within the cohort. Springfield, Massachusetts was chosen as the study location because of its elevated prevalence of pediatric asthma (19%) compared to the state average (11%) coupled with the recognized sensitivity of asthmatic children to traffic-related air pollutants. The exposure surface generated will serve as a valuable resource for the analysis health outcomes and risk assessment. Comparison of the different exposure measures suggest that greater variability exists in home than typical individual outdoor exposures, variability which is not captured by the LUR model structure. The findings reaffirm the importance of measuring personal exposures whenever possible to most accurately assess NO₂ as an environmental disease risk factor, though LUR models can provide useful measures of outdoor path exposures and trends in spatial distributions of NO₂.
ACKNOWLEDGEMENT

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1. BACKGROUND:

The severity of the economic and public health burden posed by childhood asthma has brought growing attention to the need to accurately assess exposures to air pollutants associated with adverse respiratory outcomes. Seven million classroom days are missed by school-aged children every year for asthma-associated reasons, increasing missed workdays for each adult family member by 16%. Premature mortality due to childhood asthma alone was responsible for an estimated $211 million in lost productivity in 2013 (Sullivan et al. 2018). While a causal mechanism between pollution exposure and asthma inflammation has not been established (Naidoo 2019), correlation between incidence of childhood asthma and NO$_2$ exposure is well documented (Naidoo 2019, Belanger et al. 2013, Guaderman et al. 2005). Characterizing exposures to these pollutants may provide better understanding of asthma patterns and allow for interventive action to reduce children’s exposures.

The land use regression (LUR) model is an established approach to estimating spatial variability of air pollutants, often used with particulate matter, black carbon, or NO$_x$ compounds (Sanchez et al. 2018, Beelen et al. 2013). The LUR model uses statistical regression to relate spatially distributed field measurements of pollutant concentrations to land use and built environment characteristics at each sample location, yielding a linear equation that can be applied to points at high density across a study area. Interpolation between these high-density points can yield an exposure surface with detailed spatial resolution (Marshall et al. 2008). Most often implemented at the city level, the LUR model design can calculate NO$_2$ or other pollutant exposures in locations without ongoing air quality monitoring, allowing for estimation of exposures of vulnerable populations or those underrepresented by current distributions of ongoing air monitoring initiatives.
However, a key limitation of the LUR model is that exposures represent outdoor NO\textsubscript{2} levels, while people spend ~90\% of their time indoors (Klepeis 2001). Gas stoves and other gas appliances pose the greatest source of NO\textsubscript{2} exposure in most homes, but many factors, including the efficiency of the gas stove, hood usage, and whether the home is in an urban or rural environment contribute to high variability in indoor NO\textsubscript{2} exposures between homes and corresponding differences in asthma symptoms (Belanger 2013). This study therefore seeks to compare home, school, pathway, and time-weighted exposures estimated from an LUR model with personal exposures from wristband samplers deployed to a cohort of students to compare methods for assessing NO\textsubscript{2} exposures and the viability of the different approaches in a cohort with high prevalence of childhood asthma.

2. MATERIALS AND METHODS

2.1 Study Area

Springfield is a medium-sized city in Hampden County, Massachusetts with an estimated population of 155,032 in 2018 (U.S. Census Bureau). The downtown core of the city is outlined by Interstate 90, Interstate 391, and Interstate 291, major arterial roadways that experience heavy traffic flows and traffic emissions from both gasoline and diesel vehicles. High concentrations of traffic pollutants are assumed to comprise the greatest source of NO\textsubscript{2} exposure for city residents and those commuting to work or school in the city (Pioneer Valley Commission), but the manufacturing in the city likely also plays a role in air pollution generation and exposure (U.S. Census Bureau). Springfield has a high pediatric asthma rate of 17.2\%, statistically significantly greater than the state average at a 95\% confidence interval (Bureau of Environmental Health,
2012), suggesting that environmental factors including exposure to roadway emissions play a large role in the elevated prevalence of childhood asthma in the city.

The study school draws students from the surrounding communities of Agawam, Chicopee, East Longmeadow, Hampden, Longmeadow, Ludlow, Springfield, West Springfield, and Wilbraham (in this paper, Greater Springfield, ~187 km²). The communities outside the city proper tend to be more suburban and have more green space. These towns are also farther from the major highways, all of which contribute to expected differences in NO₂ exposures among students commuting to the school from different towns.

Among students at the study school, the total prevalence of asthma was 15.2% in 2008-2009 (Pioneer Valley Commission), also statistically significantly higher than the state average at a 95% confidence interval (Bureau of Environmental Health, 2012). Within the study, 28% of children sampled were asthmatic.

2.2 Sample Collection

Students commute to the study school from Springfield and several surrounding communities. Forty samplers were placed across a 187 km² area encompassing the commute region of the students for a five-day ambient NO₂ measurement in winter 2018 (Figure 1). Personal and ambient exposures were passively sampled using commercially available Ogawa triethanolamine (TEA)-coated polyurethane foams placed in the internal Teflon case assembly from the Fresh Air Wristband (1. Lin 2020). The Fresh Air Wristbands are shown in Figure 2.
**Figure 1:** Location of forty passive NO$_2$ samplers across the greater Springfield area. The study area is shown within the state of Massachusetts in the upper righthand corner.

**Figure 2.** The Fresh Air Wristband. (A) Three faceplates have been designed and fabricated from Teflon. These Teflon chambers were mounted in commercially-available silicone wristbands. (B) Each chamber is 25 mm in diameter and sufficient large to house a PDMS sorbent bar for sampling organic pollutant as well as an Ogawa pad for analysis of NO$_2$.
Ambient samplers were deployed in magnetic silicone holders placed under protective metal caps that allowed open movement of air past the sampler while protecting the assembly from precipitation and decreasing the visibility of the sampler. Samplers locations were chosen to reflect a diversity of downtown curbside, suburban, and rural or green space areas to ensure that as many NO$_2$ conditions across the study area were represented without extrapolation as possible. The sampler assemblies were magnetically attached to the backside of road signs at each sample location (Figure 3).

Figure 3. Sampler deployed on the back of a street sign in Springfield, MA. The sampler is held in a magnetic silicone case within the protective metal cap and placed approximately 8 feet above the ground.
A LandAirSea GPS tracking device was employed during sample deployment to record the coordinates of each sampler and time of each deployment. The path deployment route was retraced during sampler collection and deployment and collection were performed between daily rush hour peaks to minimize differences in deployment time and conditions.

Personal wristband samplers were deployed to a cohort of seventh grade children (n=25) from the study school during the same 5-day period. At the time of wristband distribution on Monday morning, the students were asked to report their address, home type, stove type, whether their stove had a hood and if so the frequency of hood use, whether they lived with a smoker, what type, if any, pets were present in the house, and whether they had asthma. Following wristband collection on Friday afternoon, students were provided with maps of the school and their house and asked to draw their route to school, noting their transportation method, other places they visited during the week, and any times they forgot to wear their wristband.

2.3 Laboratory Analysis

Following collection, the samples were extracted, reacted with sulfanilamide and N-(1-naphthyl)-ethylenediamine dihydrochloride (NEDA) color-producing reagent, and measured through spectrophotometry (545 nm wavelength) following Ogawa protocols (2). A calibration curve relating absorbance to nitrite concentration was used with Ogawa guidelines to compute NO$_2$ exposure from nitrite concentration and average temperature during the deployment period (T =1.1°C). The method to quantify NO$_2$ exposure using the TEA-coated foams was developed and validated during the summer of 2017 (Appendix 1).
2.4 Land Use and Built Environment Characteristics

Land use and built environment predictors were collected to create the land use regression model. All data was obtained in shapefile form and parameters were extracted using ArcMap 10.6.1. To ensure the model found relationships with a theoretical basis, parameters with expected effects on NO₂ (e.g. greater distance to the closest highway would be expected to have a negative effect on NO₂) were assigned when a parameter was only expected to have an effect in one direction. A summary of these parameters is given in Table 1.

Roads

The total length of highways (class 1 - 3), the length of major roads (class 1 - 4), and the length of all roads (class 1 – 6) were calculated for 50m, 100m, 200m, 300m, 500m, 750m, and 1000m buffers. The distance to the nearest highway, major road, or road of any type was also calculated. Data for all calculations was sourced from the Massachusetts Department of Transportation (MassGIS Data: Massachusetts Department of Transportation (MassDOT) Roads). Length of roads within buffers was assigned a positive effect while distance to nearest road was assigned a negative effect and all values were calculated in m.

Rail Lines

Rail length in m within 50m, 100m, 200m, 300m, 500m, 750m, and 1000m buffers and distance to the nearest rail line in m were computed, with distance to nearest rail line assigned a negative effect and total rail line lengths within each buffer assigned a positive effect. Data was obtained from the Federal Railroad Authority GIS Web Application (FRA GIS Web Application).
**Population**

Population data from US Census, provided spatially by MassGIS Data (MassGIS Data: Datalayers from the 2010 U.S. Census) was used to calculated population count within 500m, 750m, and 1000m buffers.

**Land Use**

The area of land with commercial, governmental/institutional, resource/industrial, open area, parks, residential, and waterbody designations was calculated within 50m, 100m, 200m, 300m, 500m, 750m, and 1000m buffers. All data was obtained from MassGIS Data and all areas were calculated in m²; waterbody area was found using Hydrography data (MassGIS Data: Hydrography (1:100,000)) and all anthropogenic land uses were found using 2005 land use data (MassGIS Data: Land Use (2005)).

**Buildings**

Building footprint within 50m, 100m, 200m, 300m, 500m, 750m, and 1000m buffers was calculated in m² using data obtained from MassGIS (MassGIS Structures).

**Airports**

Distance to the nearest airport in m was calculated using data from the MassDOT Aeronautics Division (Airports). Airport distance was assigned a negative effect on NO₂ level.
Distance of each point from the nearest shoreline was calculated in m from data obtained from the Massachusetts Data Repository (MassGIS Data: Hydrography (1:100,000)). No effect direction was assigned to the parameter.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Variable Name</th>
<th>Direction of Effect</th>
<th>Data Source</th>
</tr>
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<tbody>
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<tr>
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<td>rd_maj_(buffer)</td>
<td>+</td>
<td>MassGIS Data: Massachusetts Department of Transportation (MassDOT) Roads</td>
</tr>
<tr>
<td>Length of roads (class 1 - 6)</td>
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<td>rd_all_(buffer)</td>
<td>+</td>
<td>MassGIS Data: Massachusetts Department of Transportation (MassDOT) Roads</td>
</tr>
<tr>
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<td>d_rd</td>
<td>-</td>
<td>MassGIS Data: Massachusetts Department of Transportation (MassDOT) Roads</td>
</tr>
<tr>
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<td>d_majrd</td>
<td>-</td>
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<tr>
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<tr>
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<td>FRA GIS Web Application</td>
</tr>
<tr>
<td>Distance from the closest rail line</td>
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<td>d_railline</td>
<td>-</td>
<td>FRA GIS Web Application</td>
</tr>
<tr>
<td>Population</td>
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<td>MassGIS Data: Land Use (2005)</td>
</tr>
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<td></td>
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<tr>
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<td></td>
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<td>------</td>
<td>------------------------------</td>
<td>---------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Area of open area land use</td>
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<td>open_(buffer)</td>
<td>MassGIS Data: Land Use (2005)</td>
<td></td>
</tr>
<tr>
<td>Area of parks land</td>
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<td>forest_(buffer)</td>
<td>MassGIS Data: Land Use (2005)</td>
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</tr>
<tr>
<td>Area of residential land use</td>
<td>m²</td>
<td>res_(buffer)</td>
<td>MassGIS Data: Land Use (2005)</td>
<td></td>
</tr>
<tr>
<td>Area of waterbody land use</td>
<td>m²</td>
<td>water_(buffer)</td>
<td>MassGIS Data: Hydrography (1:100,000)</td>
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</tr>
<tr>
<td>Area of buildings</td>
<td>m²</td>
<td>build_(buffer)</td>
<td>MassGIS Structures</td>
<td></td>
</tr>
<tr>
<td>Distance from the closest airport</td>
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<td>d_airport</td>
<td>Airports</td>
<td></td>
</tr>
<tr>
<td>Distance from the shore</td>
<td>m</td>
<td>d_shore</td>
<td>MassGIS Data: Hydrography (1:100,000)</td>
<td></td>
</tr>
</tbody>
</table>

**Table 1.** Summary of predictors compiled for land use regression model

### 2.5 Land Use Regression Model

An LUR model based on Laura Minet’s work was developed in R version 3.5.1 in collaboration with Marianne Hatzopoulou’s group at the University of Toronto (Minet et al. 2017). Variables with an assumed direction of influence on NO₂ levels (e.g. proximity to nearest road is expected to increase NO₂ exposure) were checked to ensure that they aligned with theoretical expectations. The parameters were initially ranked by their $R^2$ correlations with NO₂ and agreement of predicted directional effects using the NO₂ values measured at the 40 ambient sampler locations. When variables were correlated with a Spearman correlation coefficient > 0.8, only the parameter with the highest $R^2$ was included.

In the forwards stepwise model, parameters were added from the ranked list to the model if they improved the total adjusted $R^2$ of the model by at least 1% and maintained an overall model p-value of below 0.05. At each step, the previously included values were retested to ensure that they remained significant. In the backwards stepwise model, parameters with a p-value > 0.05 from a simple linear regression with NO₂ and a sign in agreement with the predicted directional effect were ranked and all initially included. The lowest ranking predictor was
removed if the model RMSE decreased or did not increase by >1%, repeating the process until no more variables were removed. The forwards and backwards models were cross-validated by calculating coefficients based on a randomly selected 90% of the samples and then estimating NO$_2$ values for the 10% of sample sites reserved. After 100 repetitions, the median correlation between estimated and measured NO$_2$ at the reserve sites was 0.88 and 0.89 for forwards and backwards models, respectively.

The adjusted R$^2$ of the final forwards and backwards models were 0.63 and 0.73, respectively, so the backwards model was selected to construct the exposure surface. The parameters and coefficients selected by the backwards model are given in Table 2.

<table>
<thead>
<tr>
<th>Land Use Regression Model Parameter</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of roads within 1km (m)</td>
<td>0.000759</td>
</tr>
<tr>
<td>Distance to nearest rail line (m)</td>
<td>-0.00123</td>
</tr>
<tr>
<td>Building footprint within 1km (m$^2$)</td>
<td>-3.03E-05</td>
</tr>
<tr>
<td>Area of institutional land within 1km (m$^2$)</td>
<td>9.24E-06</td>
</tr>
</tbody>
</table>

*Table 2. Selected parameters and coefficients selected by the backwards stepwise model. The intercept of the model was 15.57 and the adjusted R$^2$ was 0.73.*

Once the most significant model for estimating NO$_2$ from the samples was selected, a 100m x 100m fishnet grid was applied over the study area and the intersections of the grid were converted to points. The value of each predictor was calculated for each point and the LUR
model intercept and coefficients were applied to estimate NO\textsubscript{2} at each grid location. Kriging interpolation was then used to create a raster exposure surface over the study area.

### 2.6 Personal Exposure Assessment

Personal exposures were estimated by time weighting NO\textsubscript{2} exposure values at home, school, and along transportation pathways. A total of 25 wristbands were received from students.

*Home and School Exposures:*

As the LUR estimates outdoor exposures, indoor exposures at school and at the children’s home were estimated by extracting the NO\textsubscript{2} value at each location from the LUR and adjusting by indoor infiltration rate. An infiltration rate of 0.71 was used for the school exposure and 0.79 was used for the home infiltration rates (Tang et al. 2018). The resulting school exposure was 30.8 ppb NO\textsubscript{2} and the home exposures average 28.2 ppb, ranging from 16.8 ppm to 36.2 ppb NO\textsubscript{2}.

*Path Exposures*

The commute paths the students drew on maps in their initial surveys were used to create shapefiles of their commutes. When students left their commute path blank or their drawing was otherwise unusable, the commutes were approximated using Google Maps directions to arrive at the school at 7:25 am. These paths were then converted to points every 10 m and NO\textsubscript{2} values were extracted from the exposure surface for each point. These point exposures were then averaged to obtain the average exposure along the commute. Point exposure values along the children’s commutes are shown in Figure 4.
Figure 4. Point NO₂ exposures along the children’s commute paths. The study school is indicated with a school icon.

Time-Weighted Exposures:

A time-weighted average of each exposure was used to estimate 5-day average exposure. Each student was assumed to be at school between 7:25am and 2:25pm. Commute times reported by students were used or estimated from Google Maps travel times along the indicated commute route (arriving at school at 7:25am) when commute time was left blank.
2.7 Statistical Analysis:

As the data was not normally distributed and simple transformations did not produce normally distributions, a Kruskal-Wallis test was run between home, path, time-weighted, and personal exposures. As this test produced significant results (p < 0.00001), pairwise Wilcoxon tests were then performed to find the significance of the correlations between each exposure measure. The p-values were adjusted with a conservative Bonferroni p-value adjustment. Differences in exposure by home type, stove type, smoking in the home, pet in the home, and asthma were investigated using Dunn’s test with the Holm procedure correction. All statistical analyses were completed in R version 3.5.1.

3. RESULTS

3.1 Map of Estimated NO₂

A map of NO₂ estimated by the land use regression model is shown in Figure 5.
**Figure 5.** NO$_2$ exposure surface modeled over the Greater Springfield area using the parameters selected by the backwards stepwise model. The school icon indicates the location of the study school.

### 3.2 Student Exposures

In the comparison between the wristband exposures and estimated exposures (home, path, and time-weighted), personal exposures only correlated significantly with path exposures (Table 3). Path exposures also correlated significantly with home exposures and time-weighted exposures.

<table>
<thead>
<tr>
<th></th>
<th>Home</th>
<th>Path</th>
<th>Personal</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Path</strong></td>
<td>&lt;0.00001</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Personal</strong></td>
<td>1</td>
<td>0.022</td>
<td>-</td>
</tr>
<tr>
<td><strong>Weighted</strong></td>
<td>1</td>
<td>&lt;0.00001</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 3.** While home and path exposures and time-weighted and path exposures were significantly correlated, personal exposures only correlated significantly with path exposures.

Boxplot comparisons of the different exposures indicate that more variability existed in personal wristband measurements than in LUR model estimates of exposures (Figure 5). Time-weighted and path exposures displayed the least variability, likely because all students experienced the same NO$_2$ levels during the seven hours they spent at school per day and all students commute to the same location.
No significant differences were found between any NO₂ exposure (personal, home, path, or time-weighted) by type of home, type of stove, smoking in the home, pet in the home, or self-reported asthma (all p values > 0.1). All statistical analyses were completed in R version 3.5.1.

4. CONCLUSIONS

The LUR model explained a large portion (73%) of the variability of NO₂ across the study area and performed consistently with city-level LUR models of NO₂ constructed in other cities (Hoek et al. 2008). The model, robust during the validation process, also identified characteristics associated with the transportation network (length of roads within 1 km² and
distance to nearest rail line) and the downtown core (building footprint area within 1 km² and area of institutional land within 1 km²), two subjects of focus expected to experience elevated NO₂ in a mixed urban/suburban study area.

The correlation between personal and path exposures indicates that the LUR model is useful for representing exposures, but the lack of correlation between home and time-weighted exposures implies that even after adjustment for indoor infiltration the LUR model does not reflect indoor exposure conditions well. Home exposures predicted by the LUR model suggested relatively little variability between homes (Figure 5), while the presence of a gas stove, hood usage, and differing home cooking practices can produce great variation in levels of indoor NO₂ and result in indoor NO₂ levels higher than outdoor levels (Belanger 2013). Poor characterization of home exposures was also likely the reason that the time-weighted exposure was not associated with personal exposures. Uncertainties associated with home exposures may have contributed to the lack of correlation seen between home and time-weighted exposures and any home environment characteristics or asthma outcomes, but as personal exposures also did not see any significant associations, the low sample size (n=25 total students surveyed) or inaccurate survey reporting by the seventh-grade cohort were likely greater factors.

As many of the health conditions resulting from exposure to NO₂, including asthma, can be controlled with medical intervention through management programs and the reduction of environmental exposure (Bureau of Environmental Health 2012), personal NO₂ exposure assessment will likely become an important method of monitoring environmental factors for respiratory and cardiovascular outcomes. LUR models can provide helpful assessments of spatial trends in NO₂ concentrations across cities, an important goal for environmental and regulatory standpoints, but they are limited in their ability to reflect major disparities in indoor exposures.
When personal sampling is not feasible, these limitations of LUR models must be remembered to most apply LUR models most appropriately to public health research and interventions.
5. REFERENCES


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6. APPENDIX 1

Calibration curve for calculation of nitrite concentration from absorbance. The absorbance of two sets of stock nitrite solutions at 0, 0.1, 0.2, 0.4, 0.6, 0.8, and 1 µg/ml measured through spectrophotometry at 545 nm. Limit of detection and inter- and intra-test variability tests performed in summer 2017 ascertained accuracy to 0.003 µg/ml nitrite concentration and precision to 0.007 µg/ml nitrite.