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Characterizing the spatial distribution of ambient ultrafine particles in Toronto, Canada: A land use regression model

Scott Weichenthal^{a,*}, Keith Van Ryswyk^a, Alon Goldstein^b, Maryam Shekarrizfard^c,
Marianne Hatzopoulou^c

^a Air Health Science Division, Health Canada, Ottawa, Canada

^b School of Urban Planning, McGill University, Montreal, Canada

^c Department of Civil Engineering, McGill University, Montreal, Canada

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ABSTRACT

Exposure models are needed to evaluate the chronic health effects of ambient ultrafine particles ($<0.1 \mu\text{m}$) (UFPs). We developed a land use regression model for ambient UFPs in Toronto, Canada using mobile monitoring data collected during summer/winter 2010–2011. In total, 405 road segments were included in the analysis. The final model explained 67% of the spatial variation in mean UFPs and included terms for the logarithm of distances to highways, major roads, the central business district, Pearson airport, and bus routes as well as variables for the number of on-street trees, parks, open space, and the length of bus routes within a 100 m buffer. There was no systematic difference between measured and predicted values when the model was evaluated in an external dataset, although the R^2 value decreased ($R^2 = 50\%$). This model will be used to evaluate the chronic health effects of UFPs using population-based cohorts in the Toronto area.

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1. Introduction

Traffic-related air pollution is known to contribute to cardiovascular morbidity including both acute and chronic health effects (Hoek et al., 2013; Mehta et al., 2013; Shah et al., 2013; Sun et al., 2010; Weichenthal, 2012). To date, population-based studies interested in the potential health effects of traffic-related air pollution have generally relied on NO_2 as a surrogate measure of exposure owing to the availability of existing land use regression models (Crouse et al., 2009, 2010; Jerrett et al., 2009). However, other air pollutants such as ultrafine particles (UFPs) ($<0.1 \mu\text{m}$) may also contribute to adverse health effects. In particular, a number of studies have examined the acute health effects of UFPs and existing evidence suggests that these pollutants may contribute to acute changes in vascular function and cardiac autonomic modulation (Weichenthal, 2012) likely through pathways involving oxidative stress (Miller et al., 2012; Miller, 2014). Nevertheless, few studies have evaluated the chronic health effects of UFPs largely owing to the absence of exposure models

suitable for use in large population-based studies. However, one recent study used a chemical transport model to estimate residential exposure to ambient UFPs and the findings suggest that UFP exposures may contribute to ischemic heart disease mortality (Ostro et al., 2015). To date, land use regression models have been developed for UFPs in Vancouver, Canada (Abernethy et al., 2013), Girona, Spain (Rivera et al., 2012), and Amsterdam, Netherlands (Hoek et al., 2011) but studies have yet to apply these models to examine associations between long-term exposure to UFPs and cardiovascular morbidity/mortality. In this study, we developed a land use regression model for UFPs in Toronto, Canada in order to characterize the spatial distribution of these pollutants in Canada's largest city. Sabaliauskas et al. (2015) recently described a land use regression model for Toronto based on afternoon monitoring data collected during summer 2008. Here we expand on this previous campaign by including more recent data collected during morning and afternoon periods in both the summer and winter months over a broader geographic region using mobile monitoring. Mobile monitoring has many advantages in conducting such studies as it offers a cost-effective means of characterizing spatial variations in ambient UFPs over large geographic areas that may otherwise be infeasible to capture given practical constraints.

* Corresponding author. 269 Laurier Ave West, Ottawa, Ontario, K1A 0K9, Canada.
E-mail address: scott.weichenthal@hc-sc.gc.ca (S. Weichenthal).

2. Methods

2.1. Mobile monitoring of ultrafine particles

Ambient UFP data were collected during a mobile monitoring campaign conducted in Toronto, Canada for two weeks in September 2010 (summer) and one week in March 2011 (winter). These months were selected to capture the wide range of temperatures typical of Toronto, Canada. Details of this campaign have been described previously (Weichenthal et al., 2015). Briefly, each day three separate vehicles (Chevrolet Grand Caravans) equipped with roof-top monitoring devices (TSI Model 3007) monitored real-time ambient UFPs ($<0.1 \mu\text{m}$) at 1-second resolution. Each vehicle collected UFP data for six hours each day: once in the morning (7:00–10:00) and once in the afternoon (15:00–18:00). All samples were collected on weekdays and ambient temperatures ranged from -9.2 – 24°C (mean = 10.3°C). Each vehicle focussed on specific portions of the city including downtown areas, major highways, and suburban areas. Dedicated routes were not assigned; instead, drivers focused on maximizing coverage of these regions during each sampling period with a different route taken each day. All vehicles carried a GlobalSat DG-100 monitor to log geographic coordinates which were subsequently matched to real-time UFP data at 1-second resolution.

2.2. Assigning ultrafine particle concentrations to road segments

The mid-point of each road segment (mean length: 162 m; interquartile range: 74–201 m) was assigned a mean UFP concentration based on data collected throughout the monitoring campaign over both seasons (Supplemental Material Fig. S1). The number of data points available for each road segment varied depending on the number of times it was traversed throughout the monitoring period. Our model is based on road segments with at least 250 UFP data points (mean: 595 points/segment; interquartile range: 312–690) as this threshold provided the best balance of spatial coverage and points per segment for model development. In preliminary analysis, we also examined models based on road segments with at least 400–600 data points (6.7–10 min per segment) to increase the duration of measurement data available for each segment; however, this resulted in decreased spatial coverage and points primarily reflected major highways (data not shown). Similarly, models based on road segments with at least 100–200 data points were examined but only small gains in spatial coverage were apparent and model RMSE (root mean square error) values increased owing to a decreased number of points per segment. Therefore, the final criteria of at least 250 points per segment was selected as this threshold provided the best balance of spatial coverage and air pollution data available for model development.

2.3. Derivation of land use and built environment data for model development

The midpoint of each road segment was geocoded in a geographic information systems (GIS) environment using Arc-MAP10.2 and spatially intersected with a number of GIS layers describing land-use and built environment. We associated each point with a set of variables either by generating buffers around the point and calculating means or sums within the buffer or by computing distances between each point and potential sources. We generated several buffer sizes (50–300 m) and intersected these buffers with the following GIS layers: road network, bus network, restaurants, on-street trees, and land-use classes. We also generated five distance variables by computing the straight-line distance

between every segment midpoint and the nearest highway, nearest major road, nearest bus route, the central business district, and Pearson International Airport. Air pollution maps were generated by first dividing the city of Toronto into $100 \times 100 \text{ m}$ grid cells. Buffers were drawn around the centroids of each grid cell and were intersected with land-use layers in order to derive predictors for each cell; final model coefficients were applied to each cell to generate a surface for UFPs at a resolution of $100 \times 100 \text{ m}$.

2.4. Statistical analysis

Land use regression models were developed for mean UFP concentrations as well as \ln -transformed UFP concentrations. Single-predictor linear regression models were first examined to evaluate the impact of each candidate predictor on ambient UFPs; in total, 44 predictors were evaluated. Candidate predictors included distances to potentially important sources including highways/major roads, bus routes, Pearson International airport (the major international airport in Toronto), and the central business district along with other factors integrated within circular buffers (100–300 m) including total road length, land use variables (e.g. residential, commercial, industrial, parks, open space), total restaurants/bars, total number of on-street trees, total bus stops, and total length of bus routes. Open space reflects undeveloped land not including parks or recreational areas. A 50 m buffer was also examined for total restaurants/bars. Variables for the natural logarithms of distance variables were also evaluated to account for non-linear decreases in UFPs with distance from traffic sources (Zhu et al., 2002). We did not place any *a priori* restrictions on the direction of coefficients for inclusion in multivariable models as the primary purpose of modeling was prediction.

Variables that were associated with ambient UFP concentrations in single-predictor models (i.e. 95% confidence intervals excluded the null) were retained for evaluation in multivariable models. If more than one buffer size was examined for a given variable, the buffer size with the strongest association (i.e. largest R^2 value and lowest RMSE) was retained for analysis. Spearman correlations were also examined between candidate predictors; if two variables were highly correlated ($r > 0.80$) the variable with the strongest association with UFP was retained for analysis. The remaining variables were included in multi-variable linear regression models. Variables that were not statistically significant in multivariable models were only removed if doing so decreased (or did not substantially change (i.e. $<1\%$)) the RMSE of the model.

Although monitoring was conducted during the same portion of each day (i.e. morning and evening rush hour), individual road segments were monitored at different times on different days throughout the monitoring period and as a result temporal variations might have contributed to differences in UFP concentrations between road segments. Previous studies have used correction factors derived from fixed site monitoring data for UFPs (Abernethy et al., 2013; Hoek et al., 2011) or NO_x (Rivera et al., 2012) to adjust for temporal variations between samples collected at different times. Since fixed-site UFP data were not available in Toronto, we used ambient temperature to adjust for temporal variability between sampling periods as temperature is known to be an important determinant of day-to-day fluctuations in ambient UFPs (Alm et al., 1999; Kaur and Nieuwenhuijsen, 2009; Weichenthal et al., 2008, 2014; 2015). Specifically, each road segment was assigned a value for mean ambient temperature using real-time data (1-second resolution) collected from vehicle rooftop monitors (HOBO Datalogger) at the same time as UFP measurements. Both linear and quadratic terms for ambient temperature were included in all regression models to account for potential non-linearity in the relationship between temperature and UFPs. Wind speed was also

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