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Comparison of spatiotemporal prediction models of daily exposure of individuals to ambient nitrogen dioxide and ozone in Montreal, Canada

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ABSTRACT

Background: In previous studies investigating the short-term health effects of ambient air pollution the exposure metric that is often used is the daily average across monitors, thus assuming that all individuals have the same daily exposure. Studies that incorporate space-time exposures of individuals are essential to further our understanding of the short-term health effects of ambient air pollution.

Objectives: As part of a longitudinal cohort study of the acute effects of air pollution that incorporated subject-specific information and medical histories of subjects throughout the follow-up, the purpose of this study was to develop and compare different prediction models using data from fixed-site monitors and other monitoring campaigns to estimate daily, spatially-resolved concentrations of ozone (O_3) and nitrogen dioxide (NO_2) of participants' residences in Montreal, 1991–2002.

Methods: We used the following methods to predict spatially-resolved daily concentrations of O_3 and NO_2 for each geographic region in Montreal (defined by three-character postal code areas): (1) assigning concentrations from the nearest monitor; (2) spatial interpolation using inverse-distance weighting; (3) back-extrapolation from a land-use regression model from a dense monitoring survey, and; (4) a combination of a land-use and Bayesian maximum entropy model. We used a variety of indices of agreement to compare estimates of exposure assigned from the different methods, notably scatterplots of pairwise predictions, distribution of differences and computation of the absolute agreement intraclass correlation (ICC). For each pairwise prediction, we also produced maps of the ICCs by these regions indicating the spatial variability in the degree of agreement.

Results: We found some substantial differences in agreement across pairs of methods in daily mean predicted concentrations of O_3 and NO_2. On a given day and postal code area the difference in the concentration assigned could be as high as 131 ppb for O_3 and 108 ppb for NO_2. For both pollutants, better agreement was found between predictions from the nearest monitor and the inverse-distance weighting interpolation methods, with ICCs of 0.89 (95% confidence interval (CI): 0.89, 0.89) for O_3 and 0.81 (95%CI: 0.80, 0.81) for NO_2, respectively. For this pair of methods the maximum difference on a given day and postal code area was 36 ppb for O_3 and 74 ppb for NO_2. The back-extrapolation method showed a higher degree of disagreement with the nearest monitor approach, inverse-distance weighting interpolation, and the Bayesian maximum entropy model, which were strongly constrained by the sparse monitoring network. The maps showed that the patterns of agreement differed across the postal code areas and the variability depended on the pair of methods compared and the pollutants. For O_3, but not NO_2, postal areas showing greater disagreement were mostly located near the city centre and along highways, especially in maps involving the back-extrapolation method.

Conclusions: In view of the substantial differences in daily concentrations of O_3 and NO_2 predicted by the

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different methods, we suggest that analyses of the health effects from air pollution should make use of multiple exposure assessment methods. Although we cannot make any recommendations as to which is the most valid method, models that make use of higher spatially resolved data, such as from dense exposure surveys or from high spatial resolution satellite data, likely provide the most valid estimates.

1. Introduction

The association between short-term variations in air pollution and health outcomes are most often investigated using grouped analyses of parallel time series or grouped case-crossover designs (Goldberg et al., 2003), but can also be investigated in panel studies (Buteau and Goldberg, 2016) and in longitudinal cohort studies (Goldberg and Burnett, 2005). In time series studies of associations between daily mortality, or other events from routinely collected data, and daily concentrations of pollutants from a fixed-site monitoring network in a circumscribed geographical area, the exposure metric that is often used is the daily average across monitors (Ozkaynak et al., 2013a, 2013b). It is thus assumed that all subjects have the same exposure on a given day. For air pollutants that are relatively spatially homogenous (e.g., fine particulate matter) these metrics can be used to describe changes in exposures over populations and thus more refined exposure assessment methods may not provide any more information on the associations (Baxter et al., 2013; Dionisio et al., 2016). For air pollutants that have greater spatial variability, such as nitrogen dioxide (A: Not applicable,O_2), which is a marker of traffic-related pollution (Health Effects Institute, 2010), the daily mean may provide reasonable estimates of the time varying component if it does not vary dramatically in space. An issue with many time series studies is that exposure is estimated from routine monitoring systems that are not dense enough to capture small-scale variability. Indeed, it has been found that the temporal variability of traffic-related air pollutants may differ spatially in metropolitan area (Dionisio et al., 2013), and stronger associations for respiratory outcomes have been found, for example, when using spatially-resolved estimates of carbon monoxide and nitrogen oxides at the American postal code level (5-digit ZIP codes) as compared to that estimated using fixed-site monitors (Sarnat et al., 2013).

On the other hand, for panel studies and longitudinal analyses of cohort studies that incorporate time-dependent exposure of individuals, capturing not only temporal changes but also spatial variability in exposure is critical (Baxter et al., 2013). In some panel studies, personal monitoring has been carried out (e.g., Maikawa et al., 2016) so that spatial-temporal patterns for many pollutants were estimated. In large longitudinal studies, personal monitoring or dense monitoring networks that capture small-area variations may not be practical, so that it is often necessary to use data from existing fixed-site monitoring stations to predict statistically concentrations at times and places in which measurements were not made. Methods used in epidemiological studies to predict spatiotemporal exposure to air pollution include time-varying indicators of residential proximity to important sources (e.g., distance to high traffic-density roads (Brauer et al., 2008) or industries (Labelle et al., 2015; Lewin et al., 2013)), assigning the measurements from the nearest fixed-site monitor to participants' residences (e.g., Basu et al., 2004; Brauer et al., 2008), and spatial interpolation using inverse-distance weighting (e.g., Brauer et al., 2008; Lin et al., 2015) or kriging (Beelen et al., 2009). Multivariate land-use regression modelling is another method of spatial interpolation that is usually derived from spatially dense monitoring campaigns (Crouse et al., 2009; Hoek et al., 2008; Jerrett et al., 2005), but unless multiple measurements are made through time these methods do not have a temporal component.

Advances in developing space-time models at refined scales include use of remote sensing data from satellites (Kloog et al., 2011), dispersion and atmospheric chemical models (Hennig et al., 2016), kriging with external drift (Ramos et al., 2016), and sophisticated hierarchical or hybrid models that can accommodate the unbalanced nature of monitoring data from different campaigns (Keller et al., 2015), or combine data from different sources (e.g., measurements from fixed-monitors and predictions from a land use regression model) in a Bayesian framework (e.g., Adam-Poupart et al., 2014; de A: Not applicable,azelle et al., 2010; Reyes and Serre, 2014; Vicedo-Cabrera et al., 2013; Xu et al., 2016; Yu et al., 2009).

The present analysis is part of a longitudinal study of the acute effects of air pollution that incorporates subject-specific information, including location of residences and medical histories of subjects throughout the follow-up. The purpose of this study was to develop and compare different prediction models using data from fixed-site monitors and other monitoring campaigns to spatiotemporally estimate concentrations of daily concentrations of ozone (O_3) and A: Not applicable,O_2 to subjects in our cohort. Specifically, we used a variety of indices of agreement to compare estimates of exposure assigned from the following four methods: (1) assigning concentrations from the nearest monitor; (2) spatial interpolation using inverse-distance weighting; (3) back-extrapolation from a land-use regression model; and (4) a combination of a land-use and Bayesian maximum entropy model (Adam-Poupart et al., 2014).

2. Materials and methods

2.1. Study population, period and geographic unit for exposure estimation

The cohort of subjects for whom we had health data and information about their residence was limited to residents of Montreal for the period from January 1, 1991 to December 31, 2002. Because of confidentiality restrictions, we were only provided the first three characters of the six-character postal codes of participants' residential addresses during the follow-up. The first three characters of the Canadian postal code represent what is called a forward sortation area, and allows mail to be delivered to local post offices. There were 98 three-character postal code districts on the Island of Montreal in 2001 and these had an average area of approximately 6 km^2, ranging from 0.3 to 28 km^2 for area with lower population density. Fig. 1 shows for Montreal the boundaries of these three-character postal code units (from the 2001 Census Boundary Files (Statistics Canada, 2002)).

2.2. Air pollution data and fixed monitoring sites

We used data from the Canadian A: Not applicable,ational Air Pollution Surveillance network of fixed-site monitors in the Montreal region (https://www.ec.gc.ca/rnspa-naps/). The main purpose of the network is for surveillance of population-based ambient concentrations of selected air pollutants. For each day of the study period, we computed daily mean concentrations at each fixed-site monitor from hourly measurements. For A: Not applicable,O_2, we used the daily 24-h average and for O_3 we used the daily 8-h average, from 9 a.m. to 5 p.m. These averaging times correspond to models that were developed previously for O_3 (Deville Cavellin et al., 2016) and for A: Not applicable,O_2 (Crouse et al., 2009; Deville Cavellin et al., 2016). Daily station-specific means were computed using a criterion of 75% data completeness, representing at least 6 h (between 9 and 5 p.m.) of data for O_3 and 18 h (during the whole day) of data for NO_2.

Location of the fixed-site monitors is presented in Fig. 1 and a brief description of the monitoring sites is provided in Appendix (Table A1).