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Associations between ambient air pollution and daily mortality in a cohort of congestive heart failure: Case-crossover and nested case-control analyses using a distributed lag nonlinear model

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ABSTRACT

Background: Persons with congestive heart failure may be at higher risk of the acute effects related to daily fluctuations in ambient air pollution. To meet some of the limitations of previous studies using grouped-analysis, we developed a cohort study of persons with congestive heart failure to estimate whether daily non-accidental mortality were associated with spatially-resolved, daily exposures to ambient nitrogen dioxide (NO₂) and ozone (O₃), and whether these associations were modified according to a series of indicators potentially reflecting complications or worsening of health.

Methods: We constructed the cohort from the linkage of administrative health databases. Daily exposure was assigned from different methods we developed previously to predict spatially-resolved, time-dependent concentrations of ambient NO₂ (all year) and O₃ (warm season) at participants' residences. We performed two distinct types of analyses: a case-crossover that contrasts the same person at different times, and a nested case-control that contrasts different persons at similar times. We modelled the effects of air pollution and weather (case-crossover only) on mortality using distributed lag nonlinear models over lags 0 to 3 days. We developed from administrative health data a series of indicators that may reflect the underlying construct of “declining health”, and used interactions between these indicators and the cross-basis function for air pollutant to assess potential effect modification.

Results: The magnitude of the cumulative as well as the lag-specific estimates of association differed in many instances according to the metric of exposure. Using the back-extrapolation method, which is our preferred exposure model, we found for the case-crossover design a cumulative mean percentage changes (MPC) in daily mortality per interquartile increment in NO₂ (8.8 ppb) of 3.0% (95% CI: -0.9, 6.9%) and for O₃ (16.5 ppb) 3.5% (95% CI: -4.5, 12.1). For O₃ there was strong confounding by weather (unadjusted MPC = 7.1%; 95% CI: 1.7, 12.7%). For the nested case-control approach the cumulative MPC for NO₂ in daily mortality was 2.9% (95% CI: -0.9, 6.9%) and for O₃ 7.3% (95% CI: 3.0, 11.9%). We found evidence of effect modification between daily mortality and cumulative NO₂ and O₃ according to the prescribed dose of furosemide in the nested case-control analysis, but not in the case-crossover analysis.

Conclusions: Mortality in congestive heart failure was associated with exposure to daily ambient NO₂ and O₃ predicted from a back-extrapolation method using a land use regression model from dense sampling surveys. The

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methods used to assess exposure can have considerable influence on the estimated acute health effects of the two air pollutants.

1. Introduction

The associations between ambient air pollution and acute health events (e.g., mortality, hospitalisations) have been most often investigated using grouped analyses of parallel time series or grouped case-crossover designs (Goldberg et al., 2003), which estimate marginal changes in risk when the exposure is assumed to be the same across individuals living in a geographically circumscribed area (Lu et al., 2008; Lu and Zeger, 2007; Thomas, 2009). In these types of studies, the objective is to determine whether there are increases in the numbers of hospitalisations or deaths on the day, or the next few days, following an increase in the level of air pollution.

A limitation of these types of studies is that they rely on aggregated data, thus providing limited or no information on individual risk factors and not accounting for individual characteristics or clinical conditions that may vary on short time scales and which may confound the associations or modify the effects of air pollution (Goldberg and Burnett, 2005). An additional issue is that exposure is estimated from routine monitoring systems that are not dense enough to capture small-scale variability, particularly for air pollutants that exhibit greater spatial variability, such as some traffic-related air pollutants (Crouse et al., 2009; Deville Cavellin et al., 2016; Jerrett et al., 2007).

One group of persons that may be at higher risk of adverse health events after exposure to exogenous insults are those with congestive heart failure. In Canada, approximately 600,000 persons are affected by congestive heart failure, with 50,000 new cases diagnosed every year (Heart and stroke foundation of Canada, 2016). Epidemiological time-series and case-crossover studies, including time series of mortality conducted in Montreal (Quebec, Canada) (Goldberg et al., 2001; Goldberg et al., 2013; Goldberg et al., 2003), have reported some of the strongest positive associations between increases in ambient air pollution and daily mortality, hospitalisations and emergency department visits in people having congestive heart failure (Colais et al., 2012; Forastiere et al., 2007; Goldberg et al., 2003; Goldberg et al., 2013; Haley et al., 2009; Hsieh et al., 2013; Koken et al., 2003; Lee et al., 2007a; Lee et al., 2007b; Peel et al., 2007; Pope et al., 2008; Rappold et al., 2011; Stieb et al., 2009; Symons et al., 2006; Ueda et al., 2009; Wellenius et al., 2005; Wellenius et al., 2006; Yang, 2008; Zanobetti et al., 2009). Findings from panel studies also support that air pollution may affect health in persons with heart failure, as indicated by intermediate physiological parameters such as oxygen saturation, pulse rate and diastolic blood pressure (Goldberg et al., 2008; Goldberg et al., 2009; Goldberg et al., 2015a).

To meet some of the limitations of the studies using grouped-analysis, we developed a cohort study of persons with heart failure, with the objectives to estimate whether non-accidental mortality rates among people diagnosed with congestive heart failure were associated with spatially-resolved, daily exposures to ambient nitrogen dioxide (NO₂) and ozone (O₃), and whether these associations were modified according to a series of indicators potentially reflecting a complication or worsening in a person's health. We report herein two distinct types of analyses suitable for estimating the acute effects of air pollution, as well as estimating possible effect modification: a case-crossover design that contrasts the same person at different times, and a nested case-control design that contrasts different persons at similar times (Appendix A).

2. Methods

2.1. The cohort of persons with congestive heart failure

We included persons 65 years of age and older, who were resident of Montreal and having congestive heart failure during the study period of January 01, 1991 to December 31, 2002. We linked administrative health databases as described previously (Goldberg et al., 2013; Goldberg and Burnett, 2005). The databases covered the period 1989–2002, inclusive, and included the registration file from the universal Quebec Medicare system (Régie de l'assurance maladie du Québec, RAMQ), the hospital discharge file, the drug prescription file that included all prescriptions reimbursed during this time period by the Quebec Medicare system for individuals 65 years of age and older, the fee-for medical service file, and the mortality file. These files also include sex and date of birth, as well changes in participants' addresses, according to geographical districts defined by the first three characters of the six-character postal code. These districts represent a block face or a large apartment complex and reflect “natural neighbourhoods” (Ross et al., 2004). There were 98 three-character postal code districts in Montreal in 2001, ranging from 0.3 to 28 km² (average of approximately 6 km²) depending on the population density. Appendix Fig. B1 shows the boundaries of these districts from the 2001 Census Boundary Files (Statistics Canada, 2002).

Appendix B provides a detailed description of the methods used to construct the cohort and shows a schematic of the study design (Fig. B2). Briefly, the date of initiating the cohort was January 1, 1991 and the last date of entry was January 1, 2001, thus leaving a potential of at least two years of follow-up, as the follow-up ended for all non-censored subjects on December 31, 2002. Those entering the cohort were followed until death, migration out of the Montreal area, or termination of follow-up. The cohort was dynamic and because of the information about residential locations was time-varying, it allowed for a person who moved out of Montreal to re-enter the cohort later if they moved back into the study area.

2.2. Definition of congestive heart failure

We defined congestive heart failure using algorithms developed previously (Goldberg et al., 2013): 1) a diagnosis of congestive heart failure in the hospital discharge record or; 2) one or more procedures for congestive heart failure and at least one prescription for a diuretic and digoxin or; 3) one or more procedures for congestive heart failure and at least one prescription for a diuretic and an angiotensin converting enzyme inhibitor. Congestive heart failure diagnoses and procedures were identified using the *International Classification of Diseases* (ICD), 9th Revision codes (see Appendix Table C1 for details).

2.3. Daily estimates for ambient air pollution and weather

NO₂ and O₃ were two pollutants measured in Montreal routinely by the Canadian National Air Pollution Surveillance network of fixed-site monitors (<https://www.ec.gc.ca/rnspa-naps/>), administered by the City of Montreal. According to previous land use regression surfaces developed from dense sampling surveys in Montreal, NO₂ (Crouse et al., 2009) and O₃ (Deville Cavellin et al., 2016) exhibit substantial intra-urban spatial variability (predicted annual average concentrations ranging from 4.2–35.9 ppb for NO₂ and from 0 to 123 ppb for O₃.)

Errors may result when fixed-site ambient monitoring station data are used to estimate small-scale fluctuations of air pollutants that are

spatially heterogeneous. We thus developed a series of alternative models of O₃ and NO₂ to estimate daily concentrations according to three-character postal code districts (Buteau et al., 2017), and we compared these two models that have been used commonly. Daily estimates of O₃ were restricted to the “warm season” (May–September) whereas estimates of NO₂ were for the whole year. Briefly, we computed, for each day of the study period, 24-hour mean concentrations of NO₂ and daily 8-hour mean concentrations of O₃ and assigned these to our postal code districts (Buteau et al., 2017):

- 1) Inverse-distance weighting interpolation from daily mean values of all fixed-site monitors using a first-order decay;
- 2) A back-extrapolation method (Chen et al., 2010) that used as baseline land-use regression surfaces (LUR) developed from two dense monitoring campaigns (129 monitoring sites for NO₂, Crouse et al., 2009; 76 sites for O₃, Deville Cavellin et al., 2016). These LUR surfaces were multiplied by an inverse-distance weighting surface interpolated for each day of study period from the ratios of concentrations observed at the same fixed-site monitors that were operational at baseline (i.e., year the land use regression surface was developed) and on the day of interest; and
- 3) A Bayesian maximum entropy model (BME) to estimate daily concentrations of O₃ that incorporated daily measurements from fixed-site monitors and spatial predictions from a LUR developed from fixed-site monitors (Adam-Poupard et al., 2014).

In addition, we developed two other exposure metrics that have been used often in the literature, namely:

- 4) The daily mean of concentrations measured at the nearest monitor; and
- 5) The average of concentrations across all monitoring stations. This daily estimate had no spatial variability and was only used in the case-crossover analysis in which comparisons were made across time.

We showed previously that depending on the methods used to predict concentrations there could be substantial differences in the daily mean exposure assigned to a postal code area on a given day (Buteau et al., 2017). In view of these differences, and because we lacked a gold standard to ascertain which model provided the “best” estimates, we thus decided to use, in both designs, the above set of spatially-resolved, daily residential exposures to NO₂ and O₃.

We used hourly weather data from a meteorological station that is operated by Environment Canada (Goldberg et al., 2013; Goldberg et al., 2006; Goldberg et al., 2009). The station is located at the Pierre-Elliott-Trudeau International Airport (Latitude: 45°28'05"N; Longitude: 73°44'29"W), approximately 30 km west of downtown Montreal. From the various metrics of weather available, we retained only daily mean maximum temperature and mean relative humidity for our analyses. With only one site for weather, we could not develop a spatiotemporal model for these variables.

2.4. Statistical analyses

We applied a case-crossover design that contrasts the same person at different times, and an incidence density case-control nested within the cohort that estimates rate ratios across subjects (Maclure, 2007; Maclure and Mittleman, 2000). Both models are suitable for investigating the acute effects of air pollution, as well as estimating possible effect modification. The rationale for using both analyses was that the regression coefficients (or smoothed functions) in each design are estimated consistently with alternative definitions of the risk sets, thus providing two parameters of effect with distinct inferential interpretation. In Appendix A, appealing to the partial likelihood function of the Cox model, we show explicitly how to interpret the estimates in

each of these designs.

In both designs, we used the above set of spatially-resolved, daily residential exposures to NO₂ and O₃ and we used distributed lag non-linear regression models (DLNMs) that account simultaneously for the delayed and possible non-linear effects of air pollution and weather on daily mortality (Armstrong, 2006; Gasparrini et al., 2010; Gasparrini, 2014).

2.4.1. Case-crossover analyses

The case-crossover design was developed originally to investigate acute responses to environmental triggers by using each subject as their own control in a matched analysis, similar to a matched case-control study (Maclure, 1991; Maclure and Mittleman, 2000; Maclure and Mittleman, 2008; Mittleman et al., 1995), and then using a conditional logistic model, or equivalently a stratified Cox model (Prentice and Breslow, 1978), to obtain a population “average”. Therefore, by design, the case-crossover analysis estimates an average within-person risk (Appendix A) and controls for individual time-independent factors throughout each subject’s hazard period and allows for adjustments of causal factors between subjects. The design contrasts exposure of a plausible hazard period immediately preceding the event to that of referent periods assumed to be representative of the exposure distribution in the non-case time periods at risk.

We performed the case-crossover analysis using a time-stratified design (Levy et al., 2001; Lumley and Levy, 2000; Lumley and Sheppard, 2000), but we considered each subject separately rather than as a grouped analysis. Thus, for each subject we matched the day of death to all similar days of the week within the same month. The use of control periods after the event is suitable because the exposures cannot be influenced by the event. In grouped analyses, the time-stratified approach has been shown to minimize bias by controlling for unwanted secular trends in the air pollution and mortality time series (Janes et al., 2005; Mittleman, 2005).

We assigned time-varying exposures to case and control days using the daily mean concentrations across monitoring stations as well as the four spatially-resolved concentrations of O₃ and NO₂ estimated at participants’ residences. We modelled each air pollutant and metric of exposure separately adjusting only for weather conditions, as time trends and time-independent factors were controlled implicitly by design. We modelled weather using maximum temperature and average relative humidity.

Rather than analyzing air pollutants, temperature and relative humidity at separate lags, we made use of the DLNMs (Gasparrini, 2014). We selected a lag period of four days for the effects of air pollution (i.e., lag 0 to lag 3, where lag 0 days corresponds to the case and referent days) as most studies, especially in Montreal (Goldberg et al., 2013), have not found effects for air pollution beyond this period. We used the same lag period for weather variables as for the air pollutants, as we suspected that using a longer lag structure could result in over-adjustment of the effects of air pollution (Goldberg et al., 2013) or possibly a loss of power (Gasparrini et al., 2016). Different smoothing functions were chosen for each predictor and lag spaces. Given our limited lag period, we used an unconstrained lag structure.

We performed the analysis using an extension of the Cox proportional hazards model for time-dependent variables (Fisher and Lin, 1999; Therneau and Grambsch, 2000). We accounted for the matched nature of the selection of cases and controls by defining time intervals that were specific to each individual and not overlapping (this approach is equivalent to conditional logistic regression). Time-independent factors (e.g., gender, socio-economic status) are accounted for by design; thus, our final model was simple, comprising smoothing terms for the air pollutants, maximum temperature, and relative humidity, which were represented by their respective cross-basis functions.

We assessed potential nonlinearity in the response functions for the three covariates (i.e., air pollutants, maximum temperature, relative humidity) by fitting univariate models using natural cubic splines,

using two and three degrees of freedom (knots placed at equally spaced percentiles of the variable's distribution). The “best” fit was assessed through visual inspection of the response function and comparisons of the Akaike information criterion (a measure of goodness-of-fit; AIC; (Akaike, 1974)), with a lower AIC suggesting a better fit to the data, although we excluded smoothers that produced implausible “wiggles” in the response curves. Response functions that were consistent with linearity were replaced by linear functions.

2.4.2. Nested case-control analyses

We conducted nested case-control analyses using incidence density sampling with calendar time as the time axis. We generated a risk set at each failure time that was matched on gender, with up to 100 non-censored, matched subjects selected randomly at the failure time to serve as controls. One hundred controls provided a substantial computational benefit, yielding estimates similar to those obtained from an entire cohort analysis (Breslow et al., 1983; Essebag et al., 2003; Kass and Gold, 2005), and without affecting statistical precision (Breslow and Day, 1987; Breslow et al., 1983; Essebag et al., 2005). After the risk sets were created, we incorporated the spatial-temporally resolved daily concentrations of O₃ and NO₂ using each participant's three-character residential postal code at each failure time. In contrast to the case-crossover the daily mean across monitoring stations could not be used because this analysis requires variation in the daily exposure across individuals. This analysis provides an estimate of the between-person hazard ratio for immediate and slightly delayed effects of exposure.

We used the same modeling strategy as in the case-crossover analysis. Use of time intervals in the time-dependent Cox regression model to define each risk set, rather than strata, led to computational times that were approximately 350 times faster (see Appendix F for an example of the R code). Using the DLNM framework, we selected a lag period of 4 days, and we used the same strategy to assess the functional form of the air pollution-daily mortality association. In contrast to the case-crossover analysis, weather was controlled by design as cases and controls were matched by calendar time. We adjusted our models for current age (sex was a matching factor in defining the risk sets) and for the following area-based contextual variables: median household income; unemployment rate; percentage of adults who had not completed high school. These were all continuous variables that were extracted from the 1996 census (Statistics Canada) available for areas defined by the three-first characters of the postal code (thus matching the spatial level of information we had about residential location). Potential non-linearity in the response functions for each air pollutant, age, and contextual variables was assessed using natural cubic splines using a range of degrees of freedom. We inspected the resulting fitted curves and compared the AICs.

2.4.3. Presentation of results

We present results of both analyses by pollutant, recognizing the different parameters being estimated. In both sets of analyses, the effects of NO₂ and O₃ were found to be linear (see Results). To compare pollutant-specific estimates within each type of analysis, we report results as the mean percentage change from the estimated regression coefficient for an increase of the interquartile (IQR) in the daily mean concentration of each air pollutant metric, computed as: $[\exp(\ln(\text{OR}) \times \text{IQR}) - 1] \times 100\%$, where OR is the estimated odds ratio for a unit increase in the pollutant.

2.4.4. Potential effect modification by indicators of “health”

Individuals having congestive heart failure have different natural histories. We presumed that exogenous insults interfere in potential causal pathways linking air pollution and mortality by either “triggering” declines in health or causing exacerbations of concurrent conditions. These changes in health potentially modify a person's risk of experiencing adverse health effects related to daily fluctuation in air pollution. As there is no gold standard by which to define indicators of

“health”, we have developed from the administrative health data the following four indices that may reflect the underlying construct of “declining health”: 1) the number of hospitalisations and emergency room visits in the past three months and 2) in the past six months; 3) the cumulative number of hospitalisations during the whole follow-up; 4) the prescribed dose of furosemide (also referred as *Lasix*, a brand name under which the drug is marketed), which is a loop diuretic commonly used in the treatment of heart failure to prevent the body from absorbing too much salt and thus relieving symptoms of congestion. The first three indicators were treated as ordinal, with all cumulative counts greater than the 99th percentile of the marginal distribution rounded to this value. The fourth indicator based on furosemide was a four-level categorical variable (not taking furosemide, “mild” dose (0–40 mg), “moderate” dose (41–80 mg), “high” dose (> 80 mg, or intravenous or oral solution)). More details about the rationale and assumptions underlying each of these indicators are presented in Appendix D.

In both types of analyses, we considered these four indicators of health separately to determine whether they modified the associations between air pollution and mortality. In the case-crossover analyses, these indicators were time-invariant (we assigned the value at time of death), whereas in the nested case-control study they were time-dependent. We investigated effect modification using an interaction term between the indicator of health and the cross-basis function for the air pollutant (Gasparrini et al., 2015; Gasparrini et al., 2016). We report estimates of association and their 95% confidence intervals for an interquartile increment in the air pollutant. (Appendix E presents the procedure and an example of the R code used to investigate effect modification for both ordinal and categorical indicators of health.)

2.4.5. Other sensitivity analyses

For NO₂, we also conducted the analyses restricted to the warm season (May–September). For both pollutants and designs, we also investigated deviations from a multiplicative model by assessing effect modification by gender. For each metric of exposure, we included in our regression models an interaction term between gender and the distributed lag function for air pollutant, and we reported estimates of association and 95% confidence interval for each gender.

In a previous paper (Buteau et al., 2017), in which we developed spatially-resolved concentrations of O₃ and NO₂ of participants' residences in Montreal, we found that the spatial pattern of agreement differed between pollutants; for O₃, but not NO₂, postal code districts that showed greater disagreement were mostly located near the city centre and along highways. We thus performed case-crossover analyses stratified by postal code area according to the level of absolute agreement in the daily exposure assigned to postal codes across the different metric of exposure. For each pollutant, we created two strata (one for postal code districts showing greater agreement across the different metrics and another for those of higher disagreement) using the median value of the mean absolute agreement intraclass correlation (ICC) across all pairs of metrics as the threshold for determining in which category each postal code was assigned (mean ICC = 0.75 for NO₂; mean ICC = 0.65 for O₃).

3. Results

3.1. Description of the cohort and outcomes

Tables 1 and 2 show a description of the cohort. (Table E1 shows additional details about characteristics of the cases and controls in the nested case-control analysis defined across all failures.) The cohort comprised 63,534 individuals who were residents of Montreal between 1991 and 2003, 65 years of age and older, and identified as having congestive heart failure. Mean age at entry in the cohort was approximately 77 years and with an average follow-up time of approximately four years. At time of entry in the cohort, many subjects had other

Table 1

Description of the cohort of persons 65 years of age and older having congestive heart failure in Montreal, 1991–2003.

	Women	Men	All
Number of persons included in the cohort	37,587	25,947	63,534
Mean (SD) age at entry in the cohort	75.8 (6.9)	78.1 (7.4)	77.2 (7.3)
No. of deaths	14,062	17,645	31,707
Mean (SD) age at death (in years)	79.9 (7.2)	83.2 (7.6)	81.7 (7.6)
Prescribed dose of furosemide at time of death			
Not taking furosemide	6560 (60%)	4394 (40%)	10,954
Mild dose (0–40 mg)	8843 (55%)	7203 (45%)	16,046
Moderate dose (41–80 mg)	2094 (48%)	2274 (52%)	4368
High dose (> 80 mg or intravenous or oral solution)	148 (44%)	191 (56%)	339

	Percentiles					
	5th	25th	50th	75th	95th	99th
Number of selected important health conditions at entry in the cohort ^a	0	1	1	2	4	6
Number of hospitalisations and emergency department visits during follow-up						
No. of hospitalisation and emergency visits in the last 3 months	0	0	1	2	5	8
No. of hospitalisation and emergency visits in the last 6 months	0	0	1	2	6	10
No. of hospitalisation during the whole follow-up	0	0	1	2	6	11

Abbreviation: SD, standard deviation.

^a Refer to Appendix Table C2 for the list of selected important comorbidities and the algorithms used for each condition.

Table 2

Prevalence of selected important comorbidities at time of entry in the cohort among persons 65 years of age and older having congestive heart failure in Montreal, 1991–2003.^a

Comorbidities	Prevalence (%)
Myocardial infarction	19.0%
Chronic pulmonary disease	18.9%
Diabetes without chronic complication	17.3%
Cerebrovascular disease	13.3%
Peripheral vascular disease	11.4%
Renal disease	10.5%
Any malignancy, including lymphoma and leukemia, except malignant neoplasm of skin	7.3%
Peptic ulcer disease	4.4%
Diabetes with chronic complication	4.1%
Dementia	3.5%
Hemiplegia or paraplegia	3.0%
Mild liver disease	2.2%
Rheumatic disease	1.7%
Metastatic solid tumor	1.5%
Moderate or severe liver disease	0.4%
AIDS/HIV	< 0.1%

^a Comorbidities were identified from primary and secondary diagnoses from hospital discharge data based on the Enhanced ICD-9-CM diagnosis coding algorithms. Please refer to Appendix Table C2 for the coding algorithms used to define each comorbid condition.

important comorbid conditions in addition to congestive heart failure. The most frequent concurrent conditions were myocardial infarction, chronic pulmonary disease, and diabetes (about 20% of prevalence) (Table 2).

Of the 63,534 cohort members, 31,707 (14,062 men and 17,645

women) died during the follow-up period while being resident of Montreal (Fig. 1 shows the spatial distribution of these deaths). Of these deaths, 11,824 (6515 women and 5309 men) occurred during the months of May to September, inclusive. However, 12 individuals (including one during May–September) were excluded from the analysis because of an erroneous postal code at time of death, which prevented us from assigning exposure. Therefore, a total of 31,695 and 11,823 persons who died during the follow-up period were included in our analyses for NO₂ (all year) and O₃ (May–September), respectively.

3.2. Air pollution and weather variables

Appendix Tables E2–E3 show the daily mean concentrations of NO₂ and O₃ that were assigned to individuals included in the case-crossover and in the nested case-control analysis, respectively. For each metric of exposure, the distribution of daily concentrations assigned was similar between the two designs. For NO₂, the back-extrapolation method had the lowest mean daily concentrations (16.6 ppb) whereas the other methods had similar mean estimates ranging from 20.1 to 21.6 ppb. The nearest station approach had the wider distribution of NO₂ (range: 0 to 169.5 ppb; interquartile range (IQR) = 13.6 ppb) as compared to the other metrics (maximum values ranging from 90.6–121.8 ppb; IQR ranging from 8.8 and 10.0 ppb).

For O₃, the daily 8-hour mean concentrations were similar between the nearest station, inverse-distance weighting, and BME methods (ranging from 28.7 to 30.8 ppb), whereas the back-extrapolation (21.1 ppb) and the mean of all stations (used in the case-crossover only; 21.6 ppb) method had a lower mean concentration. However, the back-extrapolation had the widest range of exposures (maximum values of 148.5–174.3 ppb), whereas the mean of all stations yielded to the most constrained one (maximum value of 66.6 ppb).

The distribution of selected weather variables, for the study period 1991–2003, is presented in Appendix Table E4. The average maximum daily temperature was 11.3 °C, varying from –24.0 to 35.4 °C (interquartile range (IQR) of 20.6 °C). For the months of May–September, the average maximum daily temperature was 22.7 °C, varying from –1.2 to 35.4 °C (IQR of 6.8 °C). Maximum temperature was highly correlated with other metrics of temperature (i.e., minimum and mean) as well as with the humidex index (Spearman and Pearson correlation coefficients of about 99%; data not shown).

Appendix Table E5 shows Spearman correlation coefficients for the selected weather variables and same-day air pollutants concentrations for the different metrics. Maximum temperature was positively correlated with both air pollutants, with stronger correlations for O₃. Relative humidity was negatively correlated with both pollutants, but there was no correlation with NO₂.

3.3. Associations between daily non-accidental mortality and ambient NO₂ and O₃

The adjusted response-functions fitted as natural cubic splines with three degrees of freedom between the odds (case-crossover) and hazards (nested case-control) of non-accidental mortality accumulated over the 4-day lag period (referred to as the “cumulative lag”) and the different metrics of NO₂ and O₃ are shown in Appendix Figs. E1–E4. Using two rather than three degrees of freedom removed many of the “wiggles” (data not shown), thus suggesting that these variations were attributable to under-smoothing (i.e., using too many degrees of freedom). In all instances, the 2-df fitted response curves appeared linear and we found a lower AIC, suggesting an improved fit, when using the linear structure in the fully adjusted models (see Appendix Table E6). Therefore, we concluded that for the two types of analyses all response functions for the air pollutants were consistent with linearity.

In the case-crossover analysis, we used a distributed lag non-linear model accumulated over lags 0 to 3 days for maximum temperature

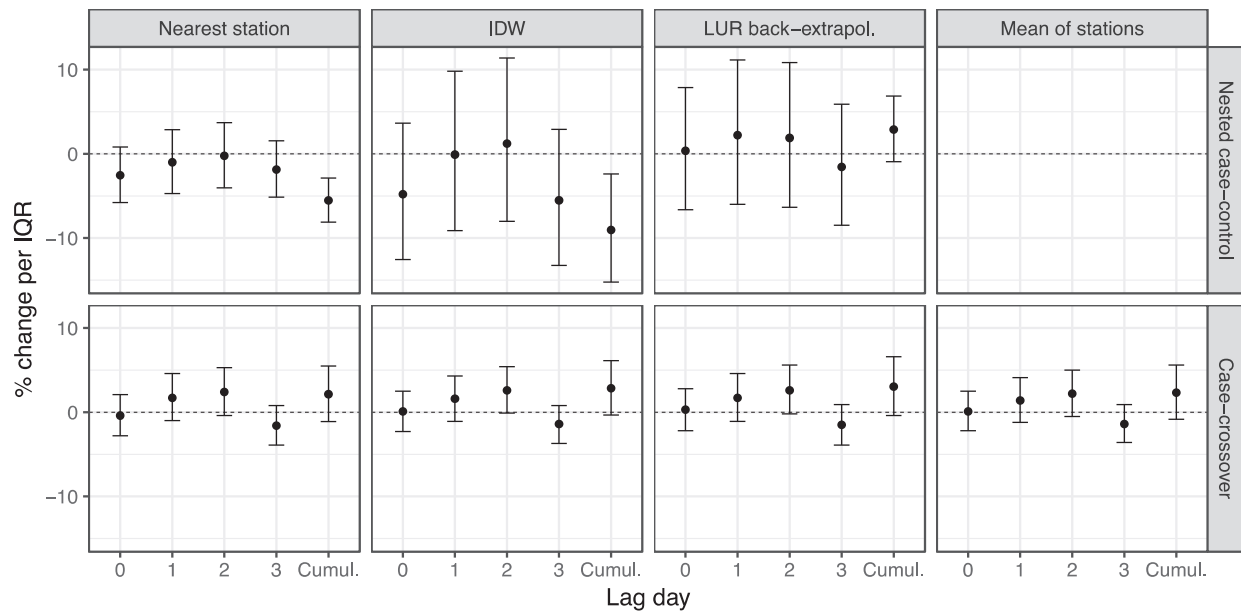


Fig. 1. Estimated percentage change in daily non-accidental mortality among subjects 65 years of age and over with congestive heart failure according to the interquartile range in daily 24-hour mean exposures to ambient NO₂ (all year) from different spatiotemporal methods to predict concentrations and type of analysis, Montreal, 1991–2003. Interquartile ranges (IQRs) were 13.6, 10.0, 8.8 and 9.6 ppb for the nearest station approach (“Nearest station”), inverse-distance weighting (“IDW”), back-extrapolation from a land use regression (“LUR back-extrapol.”), and the daily mean across all stations (“Mean of stations”), respectively. Numbers on the horizontal axis denote single day lags (0 to 3) and the cumulative for these lags (“cumul.”). Dots represent maximum likelihood estimates and bars represent 95% confidence intervals. In both type of analysis NO₂ was fitted from a distributed lag non-linear model accumulated over lags 0 to 3 days using a linear structure for NO₂ and an unconstrained structure for lags. In the case-crossover analyses, time invariant factors and temporal trends were controlled by design and we statistically adjusted for maximum temperature (natural cubic spline with 3 df), and relative humidity (linear), from a distributed lag non-linear model accumulated over lags 0 to 3 days. In the nested case-control analyses, we adjusted for age (natural cubic splines with 3 df), sex, and area-based indicators of socio-economic status including median household income (natural cubic splines with 3 df), unemployment rate among adults (natural cubic splines with 3 df), and percent of adults without high school diploma (linear). We could not in the nested case-control analyses estimate the mean of all stations, as this metric does not have any variability between individuals.

(non-linear structure fitted as natural cubic splines with three degrees of freedom (df) and relative humidity (linear), and time-invariant characteristics were controlled by design. The unadjusted response-functions between these weather variables and the odds of non-accidental mortality are shown in Appendix Fig. E5.

In the nested case-control analyses, our sampling scheme controlled for gender, weather and time-related factors, and we adjusted explicitly for age (natural cubic splines with 3 df), and time-varying area-based contextual variables (median household income and unemployment rate fitted as natural cubic spline functions with 3 df, and percentage of adults who had not completed high school fitted as linear). Appendix Fig. E6 shows the response-functions of the univariate models between mortality and age and the contextual covariates.

3.3.1. Associations between daily non-accidental mortality and ambient NO₂

Fig. 1 shows the fully-adjusted mean percentage change (and 95% confidence intervals (CI)) in daily non-accidental mortality for single-day lagged effects from lag 0 to lag 3-days, as well as for cumulative effects for an interquartile range increase in the daily 24-hour mean NO₂ exposure (all year), according to each type of analysis and metric of exposure. (Appendix Table E7 shows the numerical values of these figures.)

For the nested case-control analysis, we found negative associations for the nearest station and inverse-distance weighting, with overall cumulative effects of -5.5% (95% CI: $-8.1, -2.9\%$) and -9.0% (95% CI: $-15.2, -2.4\%$), respectively. In contrast, using daily concentrations from the LUR model that was back-extrapolated, the cumulative risk of non-accidental daily mortality over the 4-day lag period was 2.9% (95% CI: $-0.9, 6.9\%$).

For the case-crossover analyses, results were consistent across the different metrics of exposure. All cumulative response-functions were positive and the mean percentage change in the cumulative risk of daily

non-accidental mortality ranged from 2.3% (mean of stations; 95% CI: $-0.8, 5.6\%$) to 3.0% (back-extrapolation from LUR; 95% CI: $-0.3, 6.1\%$). The effects at single day lags were similar across all methods; the estimates were essentially null at lag 0 days and increased in magnitude until lag 2 days, with a negative mean percentage change at lag 3-days. The cumulative effects from the case-crossover were confounded slightly by weather. The unadjusted mean percentage changes were between 0.6% and 0.8% higher than in the fully adjusted estimates (Appendix, Table E8).

3.3.2. Association between daily non-accidental mortality and ambient O₃

Fig. 2 shows the results for the daily 8-hour mean exposure to O₃ (May–September) using the same lags as in the analyses of NO₂. (Numerical values of the estimates are shown in Appendix Table E7.) Note that the scale of the y-axis differs considerably between the two designs. In the case-crossover analysis we were concerned that adjusting for weather may lead to over-adjustments, as ozone formation during the warm season is generally strongly dependent on weather conditions, particularly temperature and relative humidity (Camalier et al., 2007; Jacob and Winner, 2009); therefore, we presented the estimates adjusted and unadjusted for weather.

In the nested case-control analysis, we found a positive cumulative effect for the nearest station (6.7% ; 95% CI: $0.3, 13.5\%$), inverse-distance weighting (18.5% ; 95% CI: $-2.6, 44.1\%$) and back-extrapolation (7.3% ; 95% CI: $3.0, 11.9\%$), whereas the cumulative effect for the BME was close to null (0.8% ; 95% CI: $-7.3\%, 9.5\%$). There were substantial differences in the magnitude of estimated effects at single day lags across the different metrics of exposure, but stronger effects was found at lag 0 and 3 days for the nearest station, inverse-distance weighting and back-extrapolation methods.

For the case-crossover analysis, the adjusted cumulative estimate was negative for the BME (-3.0% ; 95% CI: $-10.0, 4.5\%$) and the nearest station (-2.2% ; 95% CI: $-19.2, 5.2\%$). In contrast, inverse-

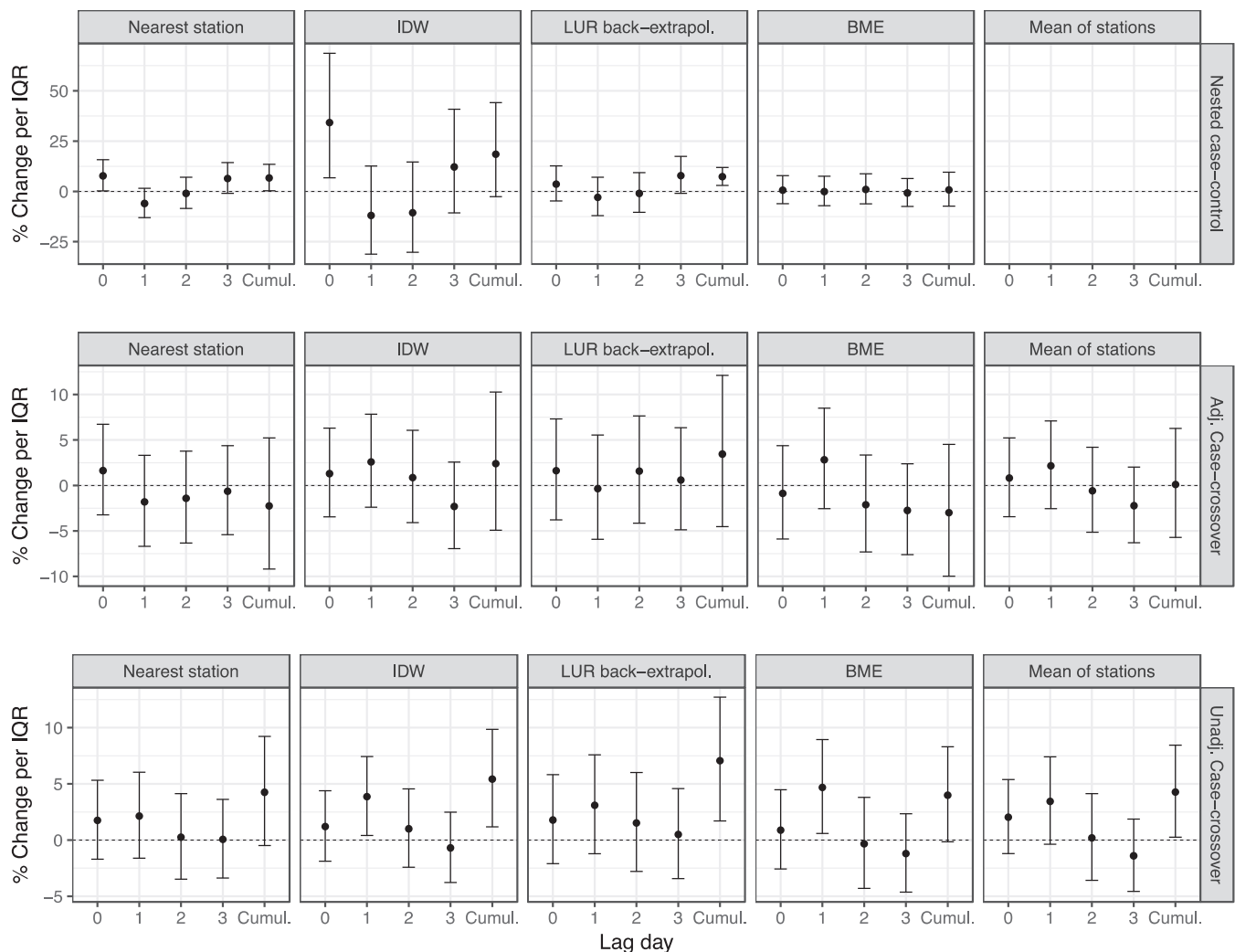


Fig. 2. Estimated percentage change in daily non-accidental mortality among subjects 65 years of age and over with congestive heart failure according to the interquartile range in daily 8-hour mean exposures to ambient O_3 (May–September) from different spatiotemporal methods to predict concentrations and type of analysis, Montreal, 1991–2003. Interquartile ranges (IQRs) were 19.6, 16.6, 16.4, 11.6 and 11.8 ppb for the nearest station approach (“Nearest station”), inverse-distance weighting (“IDW”), back-extrapolation from a land use regression (“LUR back-extrapol.”), Bayesian maximum entropy model (“BME”) and the daily mean across all stations (“Mean of stations”), respectively. We present results for the case-crossover adjusting (“Adj. Case-crossover”) and not adjusting for weather (“Unadj. Case-crossover”). Numbers on the horizontal axis denote single day lags (0 to 3) and the cumulative for these lags (“cumul.”). Dots represent maximum likelihood estimates and bars represent 95% confidence intervals. In both types of analyses, O_3 was fitted from a distributed lag non-linear model accumulated over lags 0 to 3 days using a linear function for O_3 and an unconstrained structure for lags. In the nested case-control analysis, we adjusted for age (natural cubic splines with 3 df), sex, and area-based indicators of socio-economic status including: median household income (natural cubic splines with 3 df); unemployment rate among adults (natural cubic splines with 3 df); and percent of adults without high school diploma (linear). The case-crossover controlled for time invariant factors and temporal trend by design and in the adjusted model (“Adj. Case-crossover”) we statistically adjusted for maximum temperature (natural cubic spline with 3 df), and relative humidity (linear), from a distributed lag non-linear model accumulated over lags 0 to 3 days. We could not in the nested case-control analyses estimate the mean of all stations, as this metric does not have any variability between individuals.

distance weighting (2.4%; 95% CI: $-4.9, 10.3\%$) and back-extrapolation (3.5%; 95% CI: $-4.5, 12.1\%$) yielded positive associations, whereas the cumulative association was essentially null for the mean of all stations (0.1%; 95% CI: $-5.7, 6.3\%$). The 95% confidence intervals for all adjusted estimates substantially overlapped across metrics of exposure and included the null. Single lag day effects were stronger at lag 0 days for the nearest station and the back-extrapolation analyses, both showed a mean increase of 1.6% in the risk of non-accidental daily mortality per interquartile increase in daily mean 8-hour O_3 exposure. For the other metrics of exposure, the larger increase in the risk of mortality was observed at lag 1-day, with magnitude of the effect ranging between 2.2% (95% CI: $-2.5, 7.1\%$) and 2.8% (95% CI: $-2.6, 8.5\%$).

Adjusting for weather in the case-crossover analysis did not yield a meaningful improvement in the fit of the model (Appendix Table E8); however, there was strong confounding by weather on O_3 during the warm season, particularly for the BME (from 4.3% to -2.2%) and for

the nearest station (from 4.0% to -3.0%). The unadjusted results were fairly consistent across the different metrics, with cumulative percentage changes ranging from 4.0% (95% CI: $-0.1, 8.3\%$) to 7.0% (95% CI: 1.7, 12.7%). For all metrics, the effects at lag 0 days were positive and stronger effects were observed at lag-1 day, ranging from 2.1% (nearest station; 95% CI: $-1.6, 6.0\%$) to 4.7% (BME; 95% CI: 0.6, 8.9%).

3.3.3. Potential heterogeneity in the associations between non-accidental mortality and air pollution

Appendix Fig. E7 shows the response-functions of the univariate models between daily mortality and each of the four indicators of health. Appendix Table E9 shows the effects of adjustments for each indicator of health on the model fit and hazard of non-accidental mortality in the nested case-control analyses (in the case-crossover analysis, these were controlled by design). In general, the influence on the estimates was modest but adjustment for the indicator of

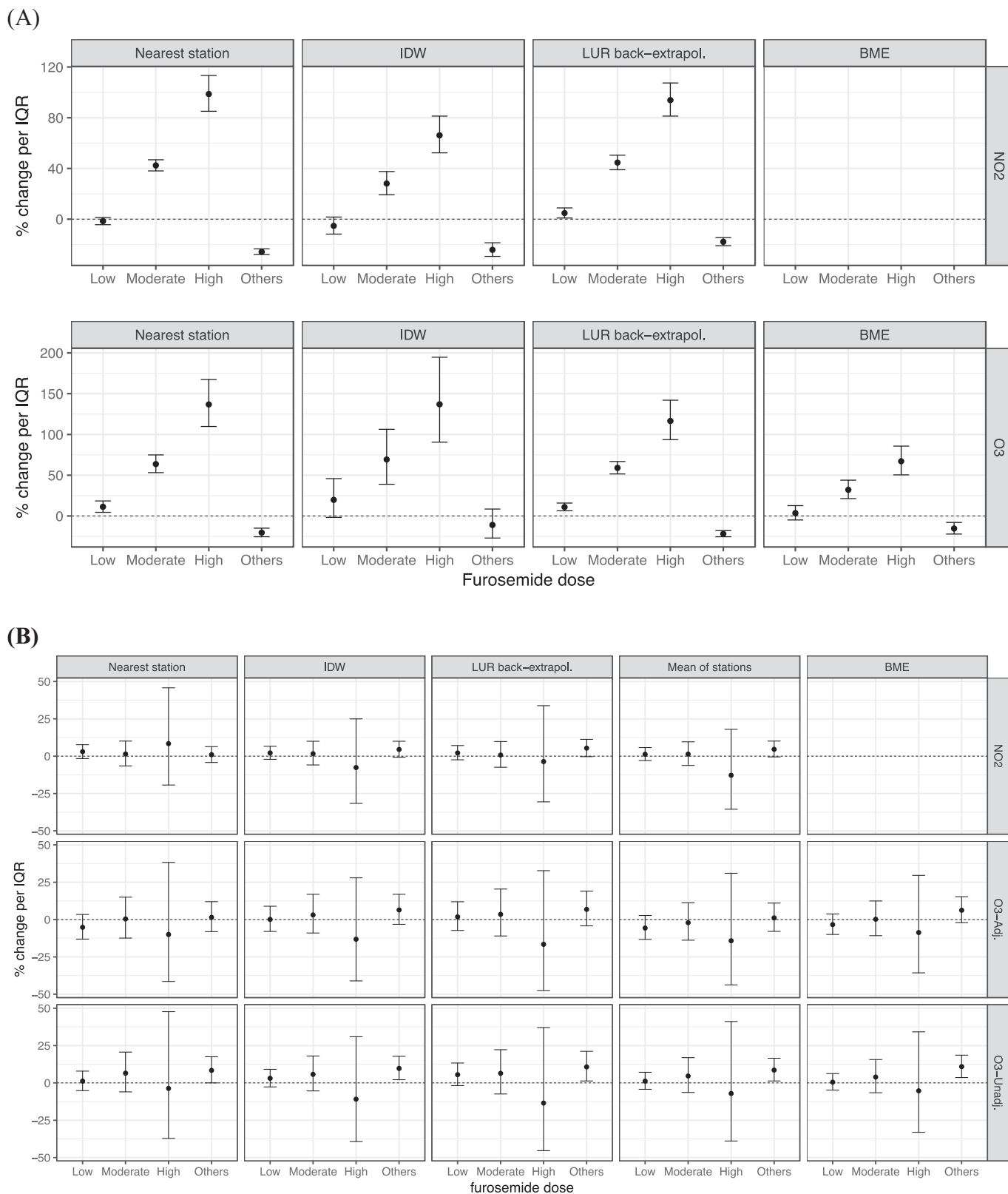


Fig. 3. Estimated cumulative percentage change in the (A) nested case-control and, (B) case-crossover analysis on the risks of non-accidental mortality per interquartile range increase in daily 24-hour mean exposures to ambient NO_2 (all year) and, daily 8-hour mean exposures to ambient O_3 (May-September), according to the prescribed dose of furosemide. Dots represent maximum likelihood estimates and bars represent 95% confidence intervals. For O_3 , we present results adjusting (“O3-Adj.”) and not adjusting for weather (“O3-Unadj.”). The horizontal axis indicates the different categories based on the dose of furosemide, with “Others” defining people who were not taking furosemide. We did not develop the BME model for NO_2 . For NO_2 , interquartile ranges (IQRs) were 13.6, 10.0, 8.8 and 9.6 ppb for the nearest station approach (“Nearest station”), inverse-distance weighting (“IDW”), back-extrapolation from a land use regression (“LUR back-extrapol.”), and the daily mean across all stations (“Mean of stations”), respectively. For O_3 , IQRs were 19.6, 16.6, 16.4, 11.6 and 11.8 ppb for the nearest station, IDW, LUR back-extrapol., BME and mean of stations, respectively.

hospitalisations and emergency department visits yielded lower AICs.

Fig. 3 shows the cumulative risk of non-accidental mortality over the entire lag period per interquartile increase in each air pollutant, according to the prescribed dose of furosemide. In the nested case-control analyses, we found evidence of effect modification for both air pollutants. However, in the case-crossover analyses, the confidence intervals were wide, particularly for the high dose category arising from a limited number of subjects, and there was no evidence of heterogeneity.

The results of the assessment of effect modification according to the number of hospitalisations and emergency room in the past three months, six months and the number of hospitalisations since the beginning of follow-up, are presented in Appendix Figs. E8–E10. There were some positive trends in the estimated mean effect according to values of these indicators, particularly for O₃ during the warm season. However, for all three indicators, the confidence intervals of the estimated effects were wide, particularly for the higher values of the indicators, and there was substantial overlap between the different values of the indicators.

Cumulative estimates of associations by gender are presented in Appendix Fig. E11. For NO₂, there was no evidence of heterogeneity by gender. For O₃, in the nested case-control study, men were found to be at greater risk when exposure was estimated from the nearest station (women: -1.4% (95% CI: $-8.7, 6.6\%$); men: 46.2% (95% CI: $13.6, 88.3\%$) and inverse-distance weighting (women: -2.2% (95% CI: $-23.5, 24.9\%$); men: 46.2% (95% CI: $13.6, 88.3\%$)), whereas there was no evidence of heterogeneity by gender for the other metric of exposure as well as in the case-crossover analysis.

For NO₂, restricting the analyses to the “warm” season generally lead to attenuated estimates, but confidence intervals were broad and substantially overlapped, thus we concluded that there was no evidence of effect modification (Appendix Table E10). For both pollutants, we also found no evidence of heterogeneity for three-character postal code districts that showed higher agreement between the different metrics as compared to postal code districts that showed lower agreement (Appendix Table E11).

4. Discussion

In these individual-level analyses of the associations between daily mortality and short-term exposures to NO₂ and O₃, we estimated the acute effect of air pollution on mortality using case-crossover and nested case-control designs, as both designs are suitable for investigating the acute effects of air pollution, as well as estimating effect modification. Although from a statistical point of view, the case-crossover and nested case-control designs can be viewed as two similar conditional models using different risk sets, we emphasize that the inferential questions addressed by each design are distinctly different. The case-crossover design, which contrasts the same persons at different times, addresses the question “Why this person dies now rather than one or a few weeks ago?”, whereas the nested case-control, which contrasts different persons at the similar time, addresses the question “Why this persons dies now whereas others did not?” (Maclure, 2007; Maclure and Mittleman, 2000). Moreover, another conceptual difference between the nested case-control and the case-crossover designs resides in their study base, as persons who did not die were excluded from the case-crossover analysis. Both designs are valid and can be used to assess the hypothesis that increases in daily ambient air pollution increases the risk of daily mortality.

In the case-crossover analyses, we made use of five alternative exposure metrics and found similar positive associations between daily mortality and daily ambient NO₂. These metrics were the same as the ones we published previously (Buteau et al., 2017), and in that paper we concluded that, in view of the substantial differences in daily concentrations of NO₂ and O₃ predicted at participants' residences by these different metrics, health effects should be analyzed using multiple

exposure assessment methods.

For O₃, the direction of the associations varied, although statistical variability was substantial. However, we were concerned with potential over-adjustments by weather. In the eastern United-States, for example, daily maximum 8-hour concentrations of O₃ were found to be explained (R² as high as 80%) by weather, with temperature and relative humidity being the most important factors (Camalier et al., 2007). Because of this strong dependence, we suggest that weather acts to some extent as a surrogate for O₃, particularly during episodes of high O₃ concentrations, and thus it seems plausible to assume that the true effects of O₃ maybe in between the adjusted and unadjusted values. In the nested case-control analyses, results for NO₂ varied among the four alternative exposure metrics, but suggested a positive association for O₃.

We found that the estimates of risk depended on which exposure method was used. This influence was more pronounced in the nested case-control design for which the contrast in exposures was essentially driven by the spatial component, as the analysis contrasted same day exposures between persons living at different location in Montreal. In contrast, the case-crossover contrasted exposures from the same individual, thus living at the same spatial location, on different days; thus, the contrast in exposures was essentially temporal.

Although we cannot state which exposure method is the most valid, our preference in exposure models is the back-extrapolation from a land use regression model because it made use of measurements from dense sampling surveys that captured the influence of very local sources such as roadways, whereas the other methods relied solely on measurements from the sparse, fixed-site monitoring network. Using this exposure metric, in the case-crossover the cumulative mean percentage changes in daily mortality were 3.0% (95% CI: $-0.9, 6.9\%$) and 3.5% (95% CI: $-4.5, 12.1$) per interquartile increment in NO₂ (8.8 ppb) and O₃ (16.5 ppb), respectively. For O₃, the increases in daily mortality unadjusted for weather was 7.1% (95% CI: $1.7, 12.7\%$). In the nested case-control approach, the cumulative increases in daily mortality was 2.9% (95% CI: $-0.9, 6.9\%$) for NO₂ and 7.3% (95% CI: $3.0, 11.9\%$) for O₃. These positive associations were consistent with the findings of the latest time-series study conducted in Montreal (Goldberg et al., 2013); for similar increments in ambient NO₂ and O₃, the cumulative increases in non-accidental mortality among the elderly with heart failure were approximately 3.3% (95% CI: $1.2, 5.4\%$) and 3.4% (95% CI: $-2.1, 9.0\%$), respectively.

One main advantage of the case-crossover design is that the self-matching accounts for within-person, time-invariant confounding (Maclure and Mittleman, 2000; Mittleman and Mostofsky, 2014; Weinberg, 2017). Therefore, risk factors, such as smoking history, obesity, physical activity, were eliminated by design. These are risk factors for which information at the individual level is typically lacking in cohorts constructed from administrative health data, like ours. In the nested case-control analyses, we adjusted for these factors by using some area-based indicators of socioeconomic status, but it is possible that some residual confounding remained. We could not perform indirect adjustments (Shin et al., 2014; Steenland and Greenland, 2004; Villeneuve et al., 2011) for smoking behaviour and obesity due to unavailability of data at the geographical level that we used. In some previous cohort studies of air pollution conducted in Canada, indirect adjustments for smoking and obesity have had limited impact, generally in the range of ± 1 –2% in the hazard ratios for non-accidental mortality (Chen et al., 2013; Crouse et al., 2015; Villeneuve et al., 2013).

Historical exposures as well as disease severity and comorbidity are among risk factors that were controlled by self-matching in the case-crossover design but may have varied considerably in the nested case-control analysis between persons in a given risk set. While we consider that these factors may play an important role in the development of congestive heart failure and contribute in putting individuals at different risks for exogenous exposures, these are not a common cause of both acute mortality and daily exposures. Therefore, under our

hypothetical model, not controlling or matching for factors such as disease severity, comorbidities and historical air pollution exposures should not be expected to bias the results, as these may act not as confounders but rather as potential effect modifiers. This is the same implicit assumption made in grouped time series and case-crossover studies. Specifically, we could not assess potential effect modification by historical exposures to air pollution as we lacked information about residential locations of participants prior to our study period, we did not have exposure data prior to the study, and we had no reason to believe that their exposure at entry into the cohort or during the follow-up period was representative of their exposure decades ago.

In the present study, we estimated whether a worsening in one's health, as reflected by our indicators of health, modified the risk of mortality associated with daily exposures to ambient air pollution. In the nested case-control analyses, we found evidence of effect modification according to the prescribed dose of furosemide, but not in the case-crossover analysis. The differences in the two designs of the results of effect modification may be explained by the study bases, which differed between the two designs, as the case-crossover is restricted to persons who died. In addition, in the case-crossover analyses, the indicators of health did not vary substantially over the one month time period that included the case and referent time periods. The definition of "health" is complex and multidimensional (Goldberg et al., 2015b), and definitions of our indicators of health were limited by the information that was available in the administrative data. To the best of our knowledge, similar indicators have not been used in previous studies of acute air pollution. The modeling framework used here can form the basis of future investigations to elucidate factors, such as physiological conditions, disease processes and concurrent comorbidity, that may modify the underlying risk profile of persons. Such investigations may contribute important insights both for clinical management and public health in the current context of aging populations and increasing rates of age-related diseases, notably cardiovascular diseases.

A main strength of this study was its population-based design conducted over a 12 year follow-up period and to nearly capturing the entire population of persons 65 years and older residing in Montreal. To our knowledge, cohort studies have been used only twice (Beverland et al., 2012; Lepeule et al., 2006) to investigate the associations between acute exposures to ambient air pollution and daily mortality. In these two cohort studies (Beverland et al., 2012; Lepeule et al., 2006), age rather than calendar time was used to generate risk sets and thus daily means of fixed-monitors were used in principle to distinguish spatial exposures. Although this is a clever way to solve the problem of resolving exposures spatially, secular trends need to be adequately accounted for. A strength of our study was the ability to conduct individual-level analysis by incorporating spatially-resolved time-dependent concentrations of ambient NO₂ and O₃.

Although we had tens of thousands of deaths and we used a large number of referents, the confidence intervals were in some instances relatively wide, and this is likely due to lower than optimal spatial and/or temporal variability. Notably, the inverse-distance weighting method yielded wider confidence intervals likely because it generated a smoother surface of concentrations, thus constraining between-person exposure variability. In general, confidence intervals from our nested case-control analysis were wider as compared to the time-stratified case-crossover analysis despite using a greater number of referents (100 controls per risk set in the nested case-control design versus 3–4 control days in the case-crossover design), and this was probably due to reduced spatial variability in exposure at each failure time as compared to the case-crossover design which had greater temporal variation at a given location.

Another key strength of this study was the application of DLNMs to individual level data (Gasparrini, 2014). The application of these flexible statistical models can substantially improve the characterization of relationships between mortality and air pollution and weather. We consider that these models are the most appropriate for time series

analyses and are clearly an essential method for characterizing delayed effects in cohort studies.

The present study also adds to the limited literature comparing the influence of different methods to predict daily exposures on the magnitude of the acute mortality or morbidity of air pollution (Sarnat et al., 2013). Because NO₂ and O₃ exhibit a substantial degree of spatial variability within Montreal (Crouse et al., 2009; Deville Cavellin et al., 2016), the expectation is that enhancing the spatial resolution of our ambient air concentration data should contribute in reducing exposure measurement errors as compared to assuming that the daily mean concentration of air pollutant is spatially homogeneous over the study area. However, the spatiotemporal methods used to predict exposures have limitations (Buteau et al., 2017) and these may in part explain the observed differences in the estimated associations. In particular, in the back-extrapolation method it is assumed that the surface derived from a land use regression model would change from day to day in proportion to what was observed at fixed-site monitoring stations in the study area. Therefore, the accuracy of the predictions from this method depends first on the land use regression model, but also on the number and spatial distribution of available historical monitors. The nearest station and inverse-distance weighting interpolation both depended entirely on the density of the monitoring network and ignored sources (e.g., road traffic) and other factors (e.g., meteorological, built environment, topography) that potentially influence daily concentrations. Of note is that the monitors are situated in areas to assess compliance to regulations (many monitors in high air pollution areas) as well as some are placed in residential areas, thus providing an over representation of high or low concentrations relative to that of population exposure (Sheppard et al., 2012). The Bayesian maximum entropy model developed for O₃ (Adam-Poupart et al., 2014) was also highly depended on the monitoring network, as the model used measurements at fixed-site monitors and incorporated a land use regression model developed from only the fixed-site monitors. The predictive ability of a LUR derived from a fixed-site network will be constrained by the number of monitoring stations and the variability in the land use characteristics surrounding the monitoring sites (Jerrett et al., 2005).

Another limitation was that residential postal codes of subjects, although time-varying, were not updated on a daily basis. Daily mobility or activity patterns were also not available, but because of the age and compromised health conditions of participants, it is plausible that many spent a greater amount of time near their homes.

Potential misclassification of congestive heart failure due to inaccurate diagnostic or coding on the medical records is another potential limitation. Our definitions of congestive heart failure were based on knowledge of clinical practice in Quebec but have not been validated against patient charts and other clinical data. Also, before August 1996 prescriptions for persons age 65 years and over were covered entirely by the Quebec Health Insurance Plan; however, this has changed through time and the public drug insurance program was estimated to cover 96.6% of persons aged 65 and over in 1998 and 89.6% in 2003 (Goldberg et al., 2013). Thus, it is unlikely that there were large errors in characterizing these subjects as having heart failure.

5. Conclusions

In this population-based cohort study of persons having congestive heart failure in Montreal, 1991–2003, non-accidental mortality was found to be associated with spatially-resolved exposures to daily ambient concentrations of NO₂ and O₃ predicted from a back-extrapolation method using a land use regression model from dense sampling surveys. We showed that the method used to assess daily exposures of individuals influenced the estimates of risk. Notably, this study suggests that more effort is needed to improve exposure models for estimating daily exposures at the individual level. Additional cohort studies making use of subject-specific information (including residential history) and of refined spatiotemporal exposure models are needed to

further elucidate how air pollution exposures (both daily and historical) and individual factors, notably physiological conditions, disease processes (e.g., heart failure severity) and changes in a person's health, contribute to the underlying personal risk profile.

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Conflict of interest

None declared.

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Appendix A–F. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envint.2018.01.003>.

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