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Full-chain health impact assessment of traffic-related air pollution and childhood asthma

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ABSTRACT

Background: Asthma is the most common chronic disease in children. Traffic-related air pollution (TRAP) may be an important exposure contributing to its development. In the UK, Bradford is a deprived city suffering from childhood asthma rates higher than national and regional averages and TRAP is of particular concern to the local communities.

Aims: We estimated the burden of childhood asthma attributable to air pollution and specifically TRAP in Bradford. Air pollution exposures were estimated using a newly developed full-chain exposure assessment model and an existing land-use regression model (LUR).

Methods: We estimated childhood population exposure to NO_x and, by conversion, NO_2 at the smallest census area level using a newly developed full-chain model knitting together distinct traffic (SATURN), vehicle emission (COPERT) and atmospheric dispersion (ADMS-Urban) models. We compared these estimates with measurements and estimates from ESCAPE's LUR model. Using the UK incidence rate for childhood asthma, meta-analytical exposure-response functions, and estimates from the two exposure models, we estimated annual number of asthma cases attributable to NO_2 and NO_x in Bradford, and annual number of asthma cases *specifically* attributable to traffic.

Results: The annual average census tract levels of NO_2 and NO_x estimated using the full-chain model were 15.41 and 25.68 $\mu g/m^3$, respectively. On average, 2.75 $\mu g/m^3$ NO_2 and 4.59 $\mu g/m^3$ NO_x were specifically contributed by traffic, without minor roads and cold starts. The annual average census tract levels of NO_2 and NO_x estimated using the LUR model were 21.93 and 35.60 $\mu g/m^3$, respectively. The results indicated that up to 687 (or 38% of all) annual childhood asthma cases in Bradford may be attributable to air pollution. Up to 109 cases (6%) and 219 cases (12%) may be specifically attributable to TRAP, with and without minor roads and cold starts, respectively.

Conclusions: This is the first study undertaking full-chain health impact assessment of TRAP and childhood asthma in a disadvantaged population with public concern about TRAP. It further adds to scarce literature exploring the impact of different exposure assessments. In conservative estimates, air pollution and TRAP are estimated to cause a large, but largely preventable, childhood asthma burden. Future progress with childhood asthma requires a move beyond the prevalent disease control-based approach toward asthma prevention.

Abbreviations: AD, atmospheric dispersion; ADMS-Urban, atmospheric dispersion modeling system; COPERT, COmputer Programme to calculate Emissions from Road Transport; E&W, England and Wales; ESCAPE, European Study of Cohorts for Air Pollution Effects; GIS, geographic information systems; HIA, health impact assessment; IMD, Index of Multiple Deprivation; LUR, land-use regression; PAF, population attributable fraction; RR, relative risk; SATURN, simulation and assignment of traffic in urban road networks; TRAP, traffic-related air pollution

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1. Introduction

Asthma is a chronic disease of the air passages leading to and from the lung, and is a condition that is often cited as the most common chronic disease of childhood (Gasana et al., 2012; Fabian et al., 2012; Gaffin and Phipatanakul, 2014). A recent meta-analysis showed statistically significant exposure-response relationships between traffic-related air pollution (TRAP) and development of asthma in children from birth to 18 years of age (Khreis et al., 2017c). The public health relevance of these relationships is largely unknown and the impact of TRAP exposures on the burden of childhood asthma is poorly documented. Due to the ubiquity of TRAP and the number of exposed children, the relatively small individual risks of TRAP-associated asthma could translate into significant public health impact.

Little work has been undertaken to estimate the burden of childhood asthma attributable to TRAP. Only four published studies, coming from the same research group, quantified the number of *prevalent* asthma cases attributable to TRAP (Perez et al., 2009; Perez et al., 2013; Künzli et al., 2008; Perez et al., 2012). Three of these studies were conducted in California, in Long Beach, Riverside and Los Angeles county (Künzli et al., 2008; Perez et al., 2009; Perez et al., 2012). The fourth study was conducted in 10 European cities (Perez et al., 2013). All four studies estimated the impacts of exposure to TRAP, characterized by proximity to major roadways, on asthma prevalence in children between birth and 18 years old. These studies suggested that 6% to 14% of prevalent childhood asthma cases were attributable to TRAP exposures; as characterized by traffic proximity (Table S1).

Despite pioneering in studying asthma as an outcome in the burden of disease assessment of TRAP, these studies relied on residential proximity to major roadways as the TRAP exposure metric. Proximity to major roadways is a crude exposure metric (Beevers et al., 2013; Jerrett et al., 2005) and alternative improved approaches are now more readily available (Khreis and Nieuwenhuijsen, 2017). Individual measurements are the preferred exposure assessment method, but since it is often not possible to measure air pollution exposures for the large populations included in health impact assessment and most epidemiological studies, many rely on less costly and more practical modeling approaches. Land-use regression (LUR) (Eeftens et al., 2012; Beelen et al., 2013; De Hoogh et al., 2014) and atmospheric dispersion (AD) modeling (Rancière et al., 2017; Yamazaki et al., 2014; De Hoogh et al., 2014) are two common modeling methods used to obtain air pollution exposure estimates for relatively large areas and number of people.

These two exposure modeling methods are fundamentally different and vary in their spatial and temporal resolution, specificity to traffic and advantages and disadvantages (Khreis and Nieuwenhuijsen (2017). AD models rely on mathematical formula and an understanding of underlying emission and dispersion processes to estimate air pollution exposures (Nieuwenhuijsen, 2015). On the other hand, LUR is an empirical method that uses least squares regression to combine air pollution measurements with geographic information system (GIS)-based predictor variables which reflect pollutant sources (for example, road, traffic and buildings density, green space etc.). The practical and policy advantage of AD modeling is that it allows for easier estimation of the contribution of different sources, such as traffic, to air pollution exposure estimates. On the other hand, the true contribution of traffic to the regression in LUR models is not always known or reported (Health Effects Institute, 2010).

In this study, we aimed to construct a full-chain health impact assessment model (Nieuwenhuijsen et al., 2017), to estimate the annual number of childhood asthma cases in Bradford, UK, attributable to air pollution, and specifically to TRAP. In the full-chain health impact assessment model, we combined four distinct models of traffic, emission, AD and health impact assessment (HIA), which covered the full-chain from the source of air pollution to the health impacts (Fig. 1). We then compared the burden of disease estimates obtained using the full-chain model with those obtained using exposure estimates from a LUR model, instead.

2. Methods

2.1. Setting

The study was set in Bradford, a city in the North of England, with an estimated 534,300 inhabitants (City of Bradford Metropolitan District Council, 2017). Bradford's population has a notably different structure from other cities in England and Wales (E&W) with more people under the age of 16 (Bradford has 22.6% whilst E&W have 18.7%) (Fielding, 2012). Based on the British government's residential area Index of Multiple Deprivation (IMD) (ESRI, 2017) and considering factors like income, employment, education and health deprivation, crime, barriers to housing and services and living environment deprivation, Bradford is one of the 10% most deprived local authorities in the UK, with significant deprivation discrepancy between the different neighborhoods (Fielding, 2012; Wright et al., 2013). The major sources of air pollution in the district have been identified as regional rural concentrations, traffic, industry, and domestic, institutional and commercial space heating. Less important sources include point sources, rail, and aircrafts (Department for Environment Food and Rural Affairs, 2010).

The work presented in this paper is part of ongoing work in Bradford assessing the emissions and air quality profile in the district and the associated childhood health effects and population-based impacts. The analysis year was 2009; when the LUR model and the traffic model used to construct the AD model were available.

2.2. Health impacts assessment framework

The HIA followed classical HIA methodology combining information on exposure estimates, baseline incidence rates of the outcome of interest and meta-analytical exposure-response functions (Mueller et al., 2017).

NO_x and NO_2 were the exposures studied and were estimated using:

- an existing LUR model and
- a newly developed AD model.

To validate and enhance the AD model's estimates, we used information gained from measured NO_x data from the ESCAPE project (Cyrys et al., 2012), as will be described next.

2.3. Land-use regression model

The first set of exposure estimates were derived using NO_2 and NO_x LUR models which were developed in Bradford as part of the ESCAPE project (European Study of Cohorts for Air Pollution Effects, 2014). These models were based on NO_2 and NO_x measurements at 41 sites across Bradford, using Ogawa passive samplers (www.ogawausa.com). The passive samplers were administered between *1 June 2009* and *15 December 2009* and contained two collection filters, one for sampling NO_2 and the other for NO_x (Cyrys et al., 2012).

The measurement sites were classified into regional background (n = 2), urban background (n = 24) and traffic sites (n = 15) (Table 1 and Fig. 2). At each site, measurements were made for three 14-day periods, with each period representing a different season namely the warm, cold and intermediate seasons. The measurements were adjusted for temporal variability using measurements obtained from a reference fixed-site monitoring station which was operated all year around (Cyrys et al., 2012; Beelen et al., 2013).

The summary statistics of the adjusted measurements made at the 41 sites are shown in Table 1. The cross-validation R^2s of the NO_x and NO_2 LUR models were 0.88 and 0.80, respectively, and a full validation description has been reported elsewhere (Beelen et al., 2013). The final