Environment International 113 (2018) 100–108

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Integrating travel behavior with land use regression to estimate dynamic air pollution exposure in Hong Kong

Robert Tang[a], Linwei Tian[a], Thuan-Quoc Thach[a], Tsz Him Tsui[a], Michael Brauer[b], Martha Lee[b], Ryan Allen[c], Weiran Yuchi[c], Poh-Chin Lai[d], Paulina Wong[f], Benjamin Barratt[e,*]

[a] The University of Hong Kong, School of Public Health, Hong Kong Special Administrative Region
[b] University of British Columbia, School of Population and Public Health, Canada
[c] Simon Fraser University, Faculty of Health Sciences, Canada
[d] The University of Hong Kong, Department of Geography, Hong Kong Special Administrative Region
[e] King's College London, MRC-PHE Centre for Environment & Health and NIHR HPRU Health Impact of Environmental Hazards, UK
[f] Lingnan University, Science Unit, Hong Kong Special Administrative Region

A R T I C L E I N F O

Handling Editor: Guan Zhu

Keywords:
Air pollution
Dynamic exposure
Land use regression
Exposure assessment
Travel behavior
Time-activity

A B S T R A C T

Background: Epidemiological studies typically use subjects' residential address to estimate individuals' air pollution exposure. However, in reality this exposure is rarely static as people move from home to work/study locations and commute during the day. Integrating mobility and time-activity data may reduce errors and biases, thereby improving estimates of health risks.
Objectives: To incorporate land use regression with movement and building infiltration data to estimate time-weighted air pollution exposures stratified by age, sex, and employment status for population subgroups in Hong Kong.
Methods: A large population-representative survey (N = 89,385) was used to characterize travel behavior, and derive time-activity pattern for each subject. Infiltration factors calculated from indoor/outdoor monitoring campaigns were used to estimate micro-environmental concentrations. We evaluated dynamic and static (residential location-only) exposures in a staged modeling approach to quantify effects of each component.
Results: Higher levels of exposures were found for working adults and students due to increased mobility. Compared to subjects aged 65 or older, exposures to $PM_{2.5}$, BC, and NO_2 were 13%, 39% and 14% higher, respectively for subjects aged below 18, and 3%, 18% and 11% higher, respectively for working adults. Exposures of females were approximately 4% lower than those of males. Dynamic exposures were around 20% lower than ambient exposures at residential addresses.
Conclusions: The incorporation of infiltration and mobility increased heterogeneity in population exposure and allowed identification of highly exposed groups. The use of ambient concentrations may lead to exposure misclassification which introduces bias, resulting in lower effect estimates than 'true' exposures.

1. Introduction

Epidemiological studies assessing the health impacts of air pollution typically use ambient concentrations of subjects' residential address as individual exposure estimates (Künzli et al., 2000; Hoek et al., 2007, 2008; Brauer et al., 2008). However, the exposure to air pollutants is unlikely to be static in reality, as people may be exposed to air pollution at work, study and other locations and during commute. The pollutant levels in microenvironments are influenced by the spatial and temporal changes in ambient pollution, as well as infiltration rates of different buildings (Allen et al., 2012). In addition, population studies rarely account for subject's movement (Wilson et al., 2005). Since time-activity patterns may differ significantly between population groups, this may lead to variability in exposure within the population that is not considered in estimates based on residential address. The inclusion of mobility data allow dynamic exposure to air pollution to be assessed which may help to avoid exposure misclassifications, and reduce errors and biases in health analyses (Jerrett et al., 2005; Setton et al., 2011).

In studies assessing the long-term health effects of air pollution, surrogates of personal exposure including fixed-site monitoring stations (Oglesby et al., 2000; Monn, 2001) or modeled concentrations (Jerrett et al., 2004) are often used to assign exposure estimates for large

* Corresponding author at: MRC-PHE Centre for Environment & Health, King's College London, 150 Stamford Street, London SE1 9NH, UK.
E-mail address: benjamin.barratt@kcl.ac.uk (B. Barratt).

https://doi.org/10.1016/j.envint.2018.01.009
Received 11 September 2017; Received in revised form 24 December 2017; Accepted 15 January 2018

populations. Recently, land use regression (LUR) has been used extensively to model intra-urban pollutant spatial variability (Hoek et al., 2008; Eeftens et al., 2012). However, the use of ambient concentrations, even at the residential address, is unlikely to fully represent the 'true' exposure to air pollution. Evaluation studies have shown that ambient concentrations at home locations were significantly different than personal exposures of subjects (Oglesby et al., 2000; Wilson et al., 2000; Payne-Sturges et al., 2003). The effects of mobility on air pollution exposure are rarely accounted for in epidemiologic studies, as LUR are static models which do not incorporate travel patterns.

The use of ambient concentrations as exposure estimates assume subjects do not leave home, where in reality people may spend 8–10 h per day at work or school locations with pollutant levels higher or lower than at their home addresses. This difference becomes significant where there is high pollutant spatial variability in the study area, with a substantial proportion of the population (e.g. working adults) commute from lower pollution outlying areas to highly polluted city centre. In this case, the residence-based exposure estimate will be biased low, directly affecting the strength and significance of relative risk estimates with health outcomes.

Recent studies have used travel surveys (Saraswat et al., 2016), activity-based simulations (Setton et al., 2008; Dhondt et al., 2012), GPS or mobile-based tracking (Dons et al., 2011; de Nazelle et al., 2013), travel smartcard (Smith et al., 2016) or cellular network data (Dewulf et al., 2016) to derive dynamic exposure estimates. These approaches have facilitated detailed spatio-temporal analysis of individual travel behaviors. A number of studies found static estimates underestimated exposure levels (Dhondt et al., 2012; de Nazelle et al., 2013; Dewulf et al., 2016; Nyhan et al., 2016; Saraswat et al., 2016). Simulations based on travel survey and air pollution modeling data found integrating mobility can affect exposure estimates by as much as 30% (Marshall et al., 2006). When these were applied to epidemiologic effect estimates, results indicated bias of effect estimates towards the null when mobility is not considered (Setton et al., 2008). In addition, epidemiological studies also assume subjects of different demographic groups to have the same exposure. This may not be accurate as the time-activity of population groups (e.g. between children/elderly and adults) can be considerably different. The impact of mobility on exposure is likely to be dependent on spatial heterogeneity of pollutant (Steinle et al., 2013). The development of dynamic exposure models also allow for scenario analysis to assess the impact of changes in transportation patterns and land use on exposure.

To date, none of these approaches have been integrated with LUR to assess dynamic air pollution exposure which can be applied to investigate of long-term health impacts of air pollution. The aim of this work is to assimilate, characterize and integrate population movement to create a dynamic LUR model layer for the population of Hong Kong (HK). HK is a densely-populated city with significant air quality issues. Using a population-representative travel survey, we incorporated population mobility in LUR models to estimate dynamic time-weighted air pollution exposure for different age, sex and employment groups. This study evaluates the use of static ambient concentrations as exposure estimates, and the effects of stratification of exposure to different population groups of particulate matter ($PM_{2.5}$), black carbon (BC), and nitrogen dioxide (NO_2).

2. Materials and methods

The method can be divided into three steps: (i) mobility data (i.e. time, location, transport, purpose and duration of trips) were extracted from a territory-wide travel characteristics survey for each subject; then (ii) the microenvironment and time spent were classified and calculated based on the extracted information; finally (iii) the time-activity information were matched with corresponding micro-environmental concentrations to calculate time-weighted dynamic exposure. The modeled outputs (i.e. time-weighted dynamic exposure) account for crossing multiple locations, and can accurately determine the spatial contrast in pollutant concentrations along the travel route. Detailed maps of the study area are shown in Figs. S1 and S2, with the overall process summarized in Fig. S3 (Supporting Information).

2.1. Population mobility data

We used a large population-representative survey to characterize travel behavior and derive population movement patterns in HK. The Travel Characteristics Survey (TCS) 2011 Survey (To et al., 2005; Transport Department, 2014), published by the HK Transport Department, polled 50,000 randomly chosen households, with each household member providing detailed trip information, including: start & end locations; form of transport used; number of trips made; time and duration of journeys to place of work or study. In the main survey, trip information and subject characteristics were collected on a weekday (24 h; not a public holiday). The number of subjects totaled 101,385, with self-reported mode, route and frequency of travel recorded during the sample day. Individual data on age, sex and occupation were available for each subject. In addition, we also used the HK 2011 Census to validate results (Census and Statistics Department, 2012). The use of a travel smartcard is widespread in HK, however these data were not accessible for this study due to privacy and data protection concerns.

From the original number of subjects (N = 101,385), we excluded subjects who may not represent the general population travel patterns or those who were not representative of study population of health effect studies. We excluded subjects who: (1) were professional drivers; (2) were mobile residents and domestic helpers; (3) had cross-boundary trips and trips to airports during the period of the travel survey, as they were assumed to travel outside the study area. After these exclusion criteria were applied, the total number of subjects included in model development was 89,385 (Table S1 in Supporting Information).

Next, we constructed time-activity patterns for each survey subject, based on travel time, location and purpose of the trips made during the day. We assembled population mobility information from the survey data in detail, including movements between tertiary planning units (TPUs) per hour of the day. TPUs are the smallest spatial administrative units in HK (N = 289, Fig. S2 in Supporting Information), devised for population census and town planning purposes. The median population size of a TPU was 21,450. Data from the 2011 Census was also available at TPU level.

2.2. Air pollution data

Details of the $PM_{2.5}$, BC, and NO_2 LUR models have been described in Lee et al. (2017). The models were developed from a comprehensive monitoring campaign and predictor variables representing traffic, land use and population. We ran a zonal statistics analysis to compute the average pollutant concentrations for each TPU using ArcGIS (ESRI; Version 9.0). There were four components to the air pollution exposure estimates: (1) ambient concentrations for each TPU; (2) indoor microenvironments; (3) transport microenvironments; and (4) diurnal profile factors. We estimated pollutant concentrations in indoor microenvironments with the use of infiltration efficiencies (F_{inf}) derived from seasonal field campaigns monitoring paired indoor/outdoor $PM_{2.5}$ and BC continuously over a seven-day period at 24 naturally ventilated residences during 2016 and 2017. F_{inf} is a unitless quantity defined as the equilibrium concentration of outdoor pollution that penetrates indoors and remains suspended, and was calculated following Allen et al. (2012). Indoor/outdoor (IO) relationships obtained from local studies were used for NO_2 (Lee et al., 1999; Lee and Chang, 2000). Air-conditioning systems are used extensively in non-residential buildings in HK, therefore different infiltration efficiencies were used for indoor microenvironments with natural ventilation or with the use of mechanical ventilation and air conditioning (MVAC) systems. For transport microenvironments, we re-classified modes of travel in the travel