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Modeling personal exposure to air pollution with AB²C: Environmental inequality

Evi Dons[a,*], Bruno Kochan[b], Tom Bellemans[b], Geert Wets[b], Luc Int Panis[a,b]

[a]*VITO, Boeretang 200, 2400 Mol, Belgium*
[b]*Transportation Research Institute (IMOB), Hasselt University, Wetenschapspark 5 bus 6, 3590 Diepenbeek*

Abstract

The AB²C model (Activity-Based modeling framework for Black Carbon exposure assessment) was developed to assess personal exposure to air pollution, more specifically black carbon. Currently the model calculates exposure in Flanders, an urbanized region in Western Europe. This model is characterized by the use of time-activity patterns, and air pollution concentrations with a high spatial and temporal resolution, including indoors and in the transport microenvironment. This model can be used for disaggregated exposure assessment or the evaluation of policy scenarios. In this paper, exposure of people from a lower socioeconomic class (SEC) is compared to the exposure of people from a higher SEC. In most North American studies, it is reported that poorer people are exposed to higher concentrations and suffer more from health effects associated with elevated exposure to air pollution. In Europe, fewer studies exist in this field, and results are not always conclusive. In this study, people from a lower SEC were found to be exposed to higher concentrations at home, but 'richer' people travel more, especially in traffic peak hours. This results in an average exposure that is higher for members of a lower SEC, but inhaled doses are similar in both groups. This analysis suggests that differences in health impact between the groups are almost completely explainable by increased susceptibility to air pollution health effects, and not by increased air pollutant intake.

Keywords: Activity-based model; air pollution; black carbon; land use regression; socioeconomic class; income; exposure

* Corresponding author. Tel.: +32-14335190; fax: +32-14582627.
E-mail address: evi.dons@vito.be

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Nomenclature

AB²C	Activity-based modelling framework for black carbon exposure assessment
BC	Black carbon
IQR	Interquartile range
LUR	Land use regression
OD	Origin-Destination
SEC	Socio-economic class

1. Introduction

In 2000, Shiftan et al. [1] proposed to use activity-based transport models to predict traffic emissions and air quality. Later activity-based models were identified to be very well suited for air pollution exposure assessment. There are multiple advantages of using an activity-based model for environmental applications: traffic emissions can be calculated from predicted traffic streams, space-time information for every individual in a population is generated, disaggregated exposure analysis is possible. In 2009, Beckx et al. [2] published a study that incorporated the activity-based model ALBATROSS in a framework that models population exposure to NO_2 in the Netherlands. Several authors around the world developed similar model chains, but still rarely focusing on individuals, exposure during traveling is poorly accounted for, and a proper validation is often missing [3; 4; 5; 6].

Recently, the AB²C model was introduced: an Activity-Based modeling framework for Black Carbon (BC) exposure assessment. The development of this model is described elsewhere [7], but in short it combines individual diaries from an activity-based transportation model with land use regression models, an indoor air model and an in-traffic exposure model to estimate personal exposure to BC. This modeling framework tried to tackle some problems associated with previous models, and it shifted the focus to personal rather than population exposure. The study area is Flanders, an urbanized region in Belgium with approximately 7 million inhabitants. Currently, AB²C predicts exposure to BC: a policy-relevant pollutant because of its health effects and impact on climate change. According to the WHO, sufficient evidence exists for an association of daily variations in BC concentrations with short-term changes in health [8]. Long-term average BC exposure is also associated with all-cause and cardiopulmonary mortality [8]. BC may not be the only/major toxic component of traffic-related particulate matter, but it can be used as an indicator for exposure to traffic-related air pollution. Traffic particles are heterogeneous in time and space, and typically have large decay rates when moving away from emission sources [9]. The latter makes the use of high-resolution air pollution surfaces more valuable; as well as taking into account movement of people.

Environmental equality, the principle that no group of people should bear a disproportionate share of harmful environmental exposure [10], is an important topic, especially in the US [11; 12; 13; 14; 15; 16]. Much less studies are available for Europe, moreover research in Europe is not always conclusive [2; 10; 17]. As an application of the AB²C model, this paper investigates BC exposure in different subgroups of the population: we test the hypothesis that people from a lower socio-economic class (SEC) are exposed to disproportionately high levels of air pollution.

2. AB²C modeling framework

2.1. Activity-based transportation model

Time-space modeling of activities and trips is nowadays preferably done using activity-based transportation models. These models predict diaries for each synthetic agent in a predefined population. Single parameters that are predicted are start and end time of an activity, day of week, type of activity, transport mode, location, household members involved, etc.. The FEATHERS activity-based model was developed for Flanders [18]; this model is largely based on the earlier developed ALBATROSS, an activity-based model for the Netherlands [19]. These activity-based models lean on rules derived from decision trees (based on revealed preference data) and are stochastic in nature. Weeklong diaries for all adult agents (older than 18) in the population are generated and hourly OD-matrices are constructed. The trips are assigned to the road network resulting in traffic flows. In traffic assignment, capacity of the roads and congestion effects are taken into account (equilibrium assignment using TransCAD software). Dynamic population density is also calculated: not based on static addresses, but based on the locations that agents actually visit during each hour. Individual diaries of agents with specific characteristics (i.e. low or high SEC) are produced to calculate their exposure to BC in the AB²C model.

2.2. Air pollution modelling

To model the minute-to-minute exposure of individuals to BC, three (groups of) submodels were implemented, each to model a specific part of the exposure.

- Hourly land use regression (LUR) models for ambient concentrations;
- In-traffic personal exposure models for exposure during trips;
- Indoor air model for exposure in indoor micro-environments.

The LUR technique uses concentrations measured on approximately 40-60 locations to predict concentrations for other locations in the study area [20; 21]. Rather than using few fixed monitors or simple interpolation, LUR includes geographical data (traffic streams, total road length in buffers, truck traffic, population density, land use) in a linear regression model producing air pollution surfaces. In Flanders, dedicated monitoring of BC on 63 locations took place in 2010 and 2011, on 13 street sites, 25 urban traffic sites, 11 urban background sites and 14 rural sites [22]. Because the spatial concentration pattern varies during a day, hourly LUR models were developed (24 models for weekday-hours, and 24 models for weekend-hours) [22]. Weekday hourly models performed well during the day and on traffic peak hours, explaining 60 to 80% of variability [22]. At night and in the weekend, concentrations were lower and more homogeneous resulting in less predictive models when considering R^2, on the other hand the mean squared error was also low. Traffic and population variables from the activity-based model were only sporadically included, e.g. traffic intensity on the nearest road was significant only on traffic peak hours. Hourly models were developed independently of neighboring hours, but still similar variables return in consecutive models demonstrating the robustness of the models. Seasonal trends are not taken into account because also the FEATHERS activity-based model does not predict seasonal differences in activity pattern and traffic streams. The LUR models are used in the AB²C model to predict ambient BC concentrations on 10 random addresses in 2386 subzones in the study area; the median concentration is assumed to be representative for the concentration on all addresses in that subzone.

Because exposure to BC while traveling might deviate significantly from ambient concentrations, a separate model was developed for exposure in transport microenvironments [23]. Mobile monitoring data was collected in the study area: approximately 1500 trips using different modes (motorized modes, active modes, public transport) were registered by volunteers. 5-min exposure and 1-sec GPS during these trips was linked to traffic and road characteristics, degree of urbanization, travel speed, transport mode and timing of the trip. Concentrations were highest in motorized modes (car, bus, light rail / metro), and lowest for active modes and trains. In-vehicle BC concentrations were elevated on highways and on urban roads, during rush hour and on weekdays. With these data models were fit to predict exposure to BC in different transport modes.

As people spend 80 to 90% of their time in indoor environments [24], it is important to take into account differences between ambient and indoor concentrations. Indoor sources of BC are relatively rare, but candles and some cooking activities can contribute to elevated indoor concentrations [25; 26]. These sources were implicitly included in the indoor/outdoor-ratio that was calculated from in-the-field measurements in 24 houses in Flanders. Outdoor concentrations were found to be higher than indoor concentrations: a ratio of 0.76 will be applied for activities in indoor micro-environments.

2.3. Integration of models and validation

Four data sources are used to predict personal exposure to BC: individual whereabouts from FEATHERS, hourly LUR models, an in-traffic personal exposure model, and an indoor air model (Fig. 1). Minute-to-minute personal exposure is then modeled as a combination of two interacting geographies: the lifeline of an individual and a constantly changing air quality. When agents are traveling, the in-traffic exposure model is applied taking into account transport mode, timing, location and duration of the trip. For touring activities, the in-traffic exposure model for active modes is used (these are activities where people are in transport but without a specific destination and with the same start and end point). The activity-based model is not specifically built for air pollution exposure assessment: for example there is no formal distinction between indoor and outdoor activities and trips by public transport are grouped in one category (although concentrations inside buses are a factor 2-3 higher than exposure in trains). As a simplification, all activities are assumed to be indoors except for travel.

Dynamic exposure is calculated making full use of the AB²C model, i.e. by including population mobility. The FEATHERS model simulates one diary for every agent in the population, for every day of the week, and the AB²C model can calculate exposures from these data.

The final outcome of the AB²C model, i.e. personal exposure to BC, was validated using weeklong personal monitoring in 62 subjects (Fig. 1) [7]. All volunteers were living in Flanders, some in urban areas and some in more rural areas. Participants were asked to carry a micro-aethalometer measuring BC, an electronic diary to register their time-activity pattern, and a GPS logger. Personal measurements were done in 2010-2011, and were rescaled to account for changing background concentrations. For each participant in the monitoring campaign, a synthetic population of 100 model-agents per day was made up with all agents having the same characteristics (age, work situation, household composition, home location subzone, etc.) as each real-life agent. When these model-agents pass through AB²C, it results in a distribution of potential exposures for each individual. The AB²C model estimates average personal exposure more accurately compared to ambient concentrations as predicted for the home subzone; however the added value of a dynamic model lies in the potential for detecting short term patterns and peak exposures, e.g. while traveling, rather than modeling average exposures [7].

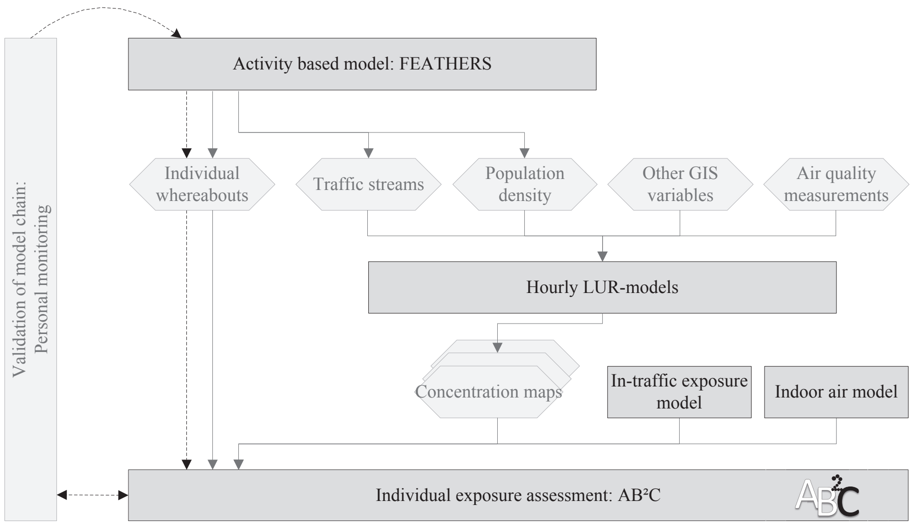

Fig. 1. Integration of submodels to predict personal exposure to black carbon: the Activity-Based modelling framework for Black Carbon exposure assessment (AB²C).

3. Application of AB²C: Environmental inequality

To investigate the impact of individual or household characteristics on personal exposure to air pollution in Flanders, the AB²C model was applied to perform a disaggregated exposure analyses. The activity-based model FEATHERS distinguishes between 'agents' or 'modeled citizens' of a high SEC and people from lower SECs. This categorization in 4 groups is made according to the net income of the household where the individual belongs to. For each agent belonging to either the highest or the lowest SEC, a one-week diary was sampled. Since the activity-based model does not take seasonal effects into account, a 7-day diary is assumed to be representative for an average week over the year. The lowest SEC consists of 272,311 adults; the highest SEC of 734,310 agents.

3.1. Time use

A major difference between both SEC, is that people of a higher SEC spend more time at work and less time at home (Table 2). Also the time spent for utilitarian travel is larger for members of a higher SEC (51 minutes compared to 33 minutes): these extra minutes are almost exclusively done by car, as a driver, and on traffic peak hours. Time in public transport or by active modes is only slightly higher. Also the number of trips is remarkably higher for people of a high SEC: 2.59 trips/day versus 1.55 trips/day.

3.2. Exposure

The average exposure to BC of an agent of the lowest SEC is 1523 ng/m³ (IQR = 652 ng/m³): this number takes into account exposure at different locations, while traveling, and in indoor microenvironments. This is in contrast with static exposure assessment that assumes individuals being indoors at home for 24h; in this case the exposure would be estimated as 1438 ng/m³. Agents from the highest SEC are exposed, on average, to 1409 ng BC/m³ (IQR = 512 ng/m³) using the dynamic exposure estimation. Static exposure is also lower: 1219 ng/m³.

People with a lower socioeconomic status are exposed to higher BC concentrations while being at home (1348 ng/m³ compared to 1160 ng/m³). This is in line with previous research stating that poorer people tend to live in areas with higher air pollution, e.g. near major roads or in densely populated urban areas [6; 10; 12; 15; 27; 28]. Also on other locations that these people visit, their exposure tends to be higher than that of people of a high SEC. The AB²C model does not account for differences in ventilation conditions, which may lead to even higher exposures at home for people of a lower SEC [6; 13]. Only while traveling, the exposure of people of a high SEC is higher: this can be explained by the larger number of trips in cars and trips on traffic peak hours; this was also observed by Beckx et al. [2] in the Netherlands.

3.3. Inhaled dose

With the exposure estimates of the AB²C model and assumptions on inhalation during different activities, dose or ‘internal exposure’ can be calculated. Minute volumes for adults per activity type and in different transport modes were derived from Allan & Richardson [29] (Table 1).

Inhaled dose is larger for people of lower SECs, but the difference with the other group becomes very small (22,761 ng/day compared to 22,296 ng/day). The exact numbers depend on the assumptions made on inhalation per activity, and on the gender distribution within the groups. The analysis nevertheless reveals an important trend: people from higher SECs inhale more BC particles during shorter time spans, namely while traveling (which assumes increased physical activity). Lower SECs travel less, but are exposed to higher concentrations at home, their 24h average breathing rate is assumed to be lower at home, resulting in an almost equal amount of inhaled BC particles as compared to the higher SEC.

Table 1. Summary of minute volume assumptions (L/min). Numbers based on Allen & Richardson (1998).

Activity	Male adults	Female adults
Being at home / Car passenger	8.3	7.5
Work / Services / Car driver	10.5	12.5
Bring/get / Shopping / Social visits / Leisure / Other / Public Transport	16.1	13.0
Touring / On foot / Bike	49.2	39.8

3.4. Discussion

Analyzing the time-activity pattern, exposure to BC, and inhaled doses of BC reveals interesting patterns. Due to the high BC concentrations in transport, this pollutant contributes disproportionally to exposure. Exposure at home becomes less important, partly because this includes night hours with lower BC concentrations. The contribution of non-home based activities to inhaled BC dose is approximately 50%, with one third of the dose coming from 4% of time traveling. People with a high socioeconomic status generally work more and travel more, especially in traffic peak hours; lower SECs spend more time at home (Table 2). Taking into account population mobility and travel behavior is very important when studying social inequality from air pollution: the difference in time-activity pattern between low SEC and high SEC results in an almost equal inhaled dose of BC. Nevertheless many studies do not account for this and only consider concentrations at homes [12; 13; 14]. A general pattern, however, is that, irrespective of exposure, subjects of low socioeconomic status experience greater health effects of air pollution [10; 14; 27]. According to our analysis, the differences in health impact between these groups may probably be explained by increased susceptibility to air pollution health effects (health care access, nutrition, fitness, drug and alcohol use) and by some health conditions and traits that cause vulnerability to air pollution (e.g. diabetes, asthma) [27], and not by increased air pollution exposure.

Table 2. Time-activity patterns, contribution of different activities to exposure to BC, and contribution of different activities to inhaled dose: comparison between lowest SEC and highest SEC quartiles.

	Low SEC			High SEC		
Activity	Time use	Contribution to exposure	Contribution to dose	Time use	Contribution to exposure	Contribution to dose
Home	85.6%	76.9%	57.1%	75.4%	62.0%	44.5%
Transport (including traveling for leisure)	3.8%	12.8%	30.0%	4.8%	19.0%	34.2%
Work	3.9%	3.9%	4.5%	13.0%	12.7%	13.1%
Social	3.4%	3.2%	4.4%	3.3%	3.1%	4.2%
Shopping	2.2%	2.1%	2.6%	2.0%	1.8%	2.2%
Other	1.1%	1.1%	1.4%	1.5%	1.4%	1.8%

4. Conclusions

The AB²C modeling framework proved to be a useful tool to assess personal exposure of different groups in society. The shift from population exposure to personal exposure is important when considering health effects associated with exposure. In the future, other disaggregated exposure evaluations can be conducted with the AB²C model, e.g. workers versus non-workers, younger versus older people, urban versus rural dwellers, households with versus households without children. Policy-relevant scenarios can be calculated as well: e.g. what is the impact of better public transport on exposure, what are the effects of an ageing society, or stimulation of teleworking?

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