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A comparison of associations with childhood lung function between air pollution exposure assessment methods with and without accounting for time-activity patterns

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ABSTRACT

Background: To investigate associations between annual average air pollution exposures and health, most epidemiological studies rely on estimated residential exposures because information on actual time-activity patterns can only be collected for small populations and short periods of time due to costs and logistic constraints. In the current study, we aim to compare exposure assessment methodologies that use data on time-activity patterns of children with residence-based exposure assessment. We compare estimated exposures and associations with lung function for residential exposures and exposures accounting for time activity patterns.

Methods: We compared four annual average air pollution exposure assessment methodologies; two rely on residential exposures only, the other two incorporate estimated time activity patterns. The time-activity patterns were based on assumptions about the activity space and make use of available external data sources for the duration of each activity. Mapping of multiple air pollutants (NO2, NOX, PM2.5, PM10, PM10 absorbance, PM10) at a fine resolution as input to exposure assessment was based on land use regression modelling. First, we assessed the correlations between the exposures from the four exposure methods. Second, we compared estimates of the cross-sectional associations between air pollution exposures and lung function at age 8 within the PIAMA birth cohort study for the four exposure assessment methodologies.

Results: The exposures derived from the four exposure assessment methodologies were highly correlated (R > 0.95) for all air pollutants. Similar statistically significant decreases in lung function were found for all four methods. For example, for NO2 the decrease in FEV1 was −1.40% (CI: −2.54, −0.24%) per IQR (9.14 μg/m3) for front door exposure, and −1.50% (CI: −2.68, −0.30%) for the methodology which incorporates time activity pattern and actual school addresses.

Conclusions: Exposure estimates from methods based on the residential location only and methods including time activity patterns were highly correlated and associated with similar decreases in lung function. Our study illustrates that the annual average exposure to air pollution for 8-year-old children in the Netherlands is sufficiently captured by residential exposures.

1. Introduction

Outdoor air pollution is an important determinant of health, and has been estimated to be related to 4.2 million premature deaths annually (World Health Organization, 2018). A large number of studies have demonstrated associations between air pollution and health. The
evidence has been summarized in several review papers (Landrigan et al., 2018; Schlesinger et al., 2006; Thurston et al., 2017). Specifically, outdoor air pollution has been shown to have short- and long-term impacts on the lung function of children (Gotschi et al., 2008; Paulin and Hansel, 2016; Schultz et al., 2017), which is an objective measure of respiratory health and predictor of cardio-respiratory morbidity and mortality (Sin et al., 2005).

A potential limitation of most of the epidemiological studies that have been performed so far is the exposure assessment approach they followed. Actual personal exposure can be described as the time-weighted average air pollution concentration across all activities of a person (Sexton and Barry, 1988). However, most epidemiological studies mainly rely on residential exposures to characterize individual exposure and more specifically on annual average air pollution at typically the front door or at the centre of the parcel of the residence (Clark et al., 2010; Gehring et al., 2013; Kramers et al., 2009; Nordling et al., 2008). This approach assumes that the between person differences in exposures are only due to differences in residential concentrations. Although most people spend most of their time at home (Klepeis et al., 2001), this remains an approximation as people visit various spaces during the day with potentially different air pollution levels (Park and Kwan, 2017).

Most epidemiological studies are based upon residential exposures, because direct personal measurements of air pollution concentrations are not feasible for large study populations (Larkin and Hystad, 2017). Moreover, estimated personal exposure based on actual personal activity patterns are difficult to acquire for extended periods because it is a costly procedure (Larkin and Hystad, 2017; Pekkanen and Pearce, 2001). Furthermore, individual time activity data cannot be obtained for past exposures.

We therefore developed a method to estimate individual time activity patterns of children that can be applied to large populations (Ntarladima et al., 2019). This approach is based on buffers, which represent typical activity spaces around the residential addresses. The exposures derived from each buffer were weighted with the estimated time spent on specific activities from an external database (Ntarladima et al., 2019). Enriching residential exposures with estimated activity pattern gives the potential to capture the spatial variation in air pollution exposure amongst several microenvironments that children visit daily (home, school, playing ground and street network).

We developed our approach in a population of children aged 5 years living in a fairly small quarter of the city of Utrecht with limited spatial variation in outdoor air pollution (Ntarladima et al., 2019). The current paper extends our approach and evaluates the methodology in the Dutch prospective PIAMA (Prevention and Incidence of Asthma and Mite Allergy) birth cohort study. Participants of the PIAMA cohort live spread in exposures are only due to differences in residential concentrations. Although most people spend most of their time at home (Klepeis et al., 2001), this remains an approximation as people visit various spaces during the day with potentially different air pollution levels (Park and Kwan, 2017).

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Data were obtained by questionnaires which were completed by parents. Parents reported home and school addresses at each round of follow up (Wijga et al., 2013).

The lung function measurements were performed by obtaining at least three acceptable maneuvers by trained personnel when children were 8 years as described previously (Gehring et al., 2013). The lung function measurement used in this study are the commonly used measures: forced expiratory volume in 1 s (FEV1) and forced vital capacity (FVC).

2.2. Study population

This study uses data from the Dutch prospective Prevention and Incidence of Asthma and Mite Allergy (PIAMA) birth cohort study (Wijga et al., 2013). The PIAMA study has been selected for this study for several reasons. First, this cohort has already examined the associations between air pollution and lung function (Gehring et al., 2013). Second, the PIAMA cohort recruited participants from three different regions of the Netherlands (North, Southwest and Central) including urban and rural areas which ensures contrasts in air pollution exposure. Third, information on the school location was available to be used in one of the exposure assessment methodologies. Participants were born in 1996/97 in the Netherlands.

The current analysis included participants with successful lung function measurements at 8 years of age, complete information on sex, age, height, and weight at the time of lung function measurement as in a previous study (Gehring et al., 2013) and for whom in addition a valid school address was available (n = 668). We have compared the population included in the analysis with the full PIAMA population and the population of all participants with successful measurements of lung function (Table S1). Children with allergic mothers were overrepresented by design among the participants with lung function data and the current sample. Apart from that, the characteristics of the different populations were very similar. Due to missing values on potential confounders, 638 participants were included in the models.

2.3. Air pollution exposure assessment

To assess air pollution levels at home, at school and at other locations we used land use regression (LUR) models. LUR models are used in many epidemiological studies for estimating annual average outdoor air pollution concentrations at the home addresses of cohort subjects as the performance of the method in urban areas is typically better or equivalent to geo-statistical methods, such as kriging, and dispersion models (Hoek et al., 2008). The models were originally developed in the European Study of Cohorts for Air Pollution Effects (ESCAPE) project and described elsewhere (Beelen et al., 2013; Eeftens et al., 2012). Following the original paper on air pollution and lung function (Gehring et al., 2013), we used the annual average concentrations of the same year (2009) as in the original analysis. Air pollution levels were calculated at any location (5*5 m grids) in the study area for several air pollutants including nitrogen oxides (NOx, NO2) and particulate matter (PM10, PM2.5, and PM2.5sabsorbance) (Schmitz et al., 2018).

To calculate air pollution exposures, we followed four methodologies. Two of the methodologies were based on the residential location only and the two other methods included both home and school location and integrated activity patterns. The activity patterns have been estimated for weekdays only. An overview of the methodologies that have been applied in the current analysis is presented in Table 1 and an example of how the exposures were calculated using GIS is illustrated in Fig. 1. Information about the specific datasets used for the calculation can be found in Table S2.

The first methodology applied is the conventional residential
Table 1: Overview of the exposure assessment methodologies.

<table>
<thead>
<tr>
<th>Activity areas</th>
<th>Method 1: Residential exposure (point estimate)</th>
<th>Method 2: Residential exposure (20 m buffer)</th>
<th>Method 3: Time-activity weighted exposure using estimated school address</th>
<th>Method 4: Time-activity weighted exposure using actual school address</th>
</tr>
</thead>
<tbody>
<tr>
<td>Staying at home</td>
<td>Air pollution level at front door of home address (point estimate)</td>
<td>Average air pollution level within a 20 m buffer around front door of home address</td>
<td>Average air pollution level within a 20 m buffer around front door of home address</td>
<td>Average air pollution level within a 20 m buffer around front door of home address</td>
</tr>
<tr>
<td>Playing in the neighborhood</td>
<td>–</td>
<td>–</td>
<td>Average air pollution level for open public and private spaces within a 500 m buffer around home address</td>
<td>Average air pollution levels for open public and private spaces within a 500 m buffer around home address</td>
</tr>
<tr>
<td>Travelling to school</td>
<td>–</td>
<td>–</td>
<td>Average air pollution level on the road network within a 2000 m buffer around home address</td>
<td>Average air pollution level on the road network between actual home location and actual school location (based on shortest route). For passive commuters we used the car road network and for active commuters the cycling network. Average air pollution level within a 20 m buffer around the actual school address</td>
</tr>
<tr>
<td>Being at school</td>
<td>–</td>
<td>–</td>
<td>Average air pollution level for all schools within a 2000 m buffer around home address. The number of school addresses within a 2000 m buffer can be found in Table S2.</td>
<td>–</td>
</tr>
</tbody>
</table>

Fig. 1: Representation of the four methodologies, depicted for a single (arbitrarily chosen) residential address (red square) within the area of interest. Blue indicates the land use related to each activity space (dark blue: actual activity area). 1, first methodology: concentration at the residential address (front door coordinate); 2, second approach: 20 m buffer around residential address; 3, third approach: 3a, same as 2; 3b, 500 m buffer including open public and private space around residential address to represent playing in the neighborhood activity; 3c, 2000 m buffer including road network to represent travelling; 3d 20 m around all schools included within a 2000 m buffer around the residential address; 4a, same as 2; 4b, same as 3b; 4c, travelling from residential address to school address for children where dark blue represents passive travelling and bright blue active travelling; 4d, 20 m buffer around the actual school address to represent the activity being at school. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
exposure (Fig. 1, panel 1). This methodology is applied in most air pollution epidemiological studies and makes use of the air pollution level at the home address only. More specifically, the exposure estimate relies on estimated air pollution level within the 5*5 raster cell around the front door coordinate. For the second methodology we applied a 20 m buffer around the front door coordinate and averaged the concentrations within this buffer (Fig. 1, panel 2). This approach aims to cover the complete home footprint and not only the front door as in the previous methodology. The third and fourth methodologies aim to estimate the children’s exposure over the course of a day. These methodologies were also based on the residential addresses, but in addition they incorporate simulated children’s activity patterns for schooldays. The activities we assumed as major daily activities were being at home, playing in the neighborhood, travelling to/from school, and being at school. The activity spaces are based on assumptions of how far the activities would take place from home and on which land uses. To estimate the average time spent at each activity we used an external dataset which includes data on mobility in the Netherlands for the year 2010 (CBS, 2015). The assumptions and the calculations for each activity are presented in Table 1.

In methodology 3 all activity spaces were calculated using buffers around the residential address and all activity durations were based on the external mobility dataset (CBS, 2015). The choice of the buffer-sizes was based on educated guesses of the children’s activities considering the age of the children, the average degree of urbanization and the average time needed to reach a place. Specifically, we observed that within 500 m of most homes, playgrounds exist. 500 m correspond to a 5 min ‘walk’ which is a reasonable time to reach an activity space. Therefore, we used a 500 m buffer for the playing activity in the neighborhood. We used a 2000m buffer for travelling to school and being at school activity as (within our datasets) this was the maximum distance between the participants’ homes and the nearest school. In methodology 4, the exact school addresses available from the PIAMA questionnaire have been utilized for the activity being at school and for the travelling from/to school activity instead of estimated school addresses (Fig. 1). For the activity travelling from/to school we used the shortest-path algorithm between the home and actual school address on the car road network for the children who travel passively (i.e. by bus or by car, Figs. 1 and 4c) and on the cycling road network for the children travelling actively (i.e. on foot or by bike, Figs. 1 and 4c). The duration of travelling was calculated based on the shortest road network distance between home and school, the average biking speed for children (Hummer et al., 2006) and the car average speed in urban streets with moderate congestion levels (Svyk, 2020). The information about active or passive travel of a child was derived from parental-completed questionnaires included in PIAMA. The estimated exposure for child i for methodologies 3 and 4 has been calculated as:

\[ E_i = \frac{T_{h(i)}C_{h(i)} + T_{p(i)}C_{p(i)} + T_{s(i)}C_{s(i)} + T_{t(i)}C_{t(i)}}{1440} \]  

(1)

where \( E_i \) is the personal exposure for child i (\( \mu g/m^3 \)), \( C_{h(i)} \) the air pollution concentration (\( \mu g/m^3 \)) representative for home activity, and \( T_{h(i)} \) the time (minutes) spent at home; \( C_{p(i)} \) the air pollution concentration for playing in the neighborhood, \( T_{p(i)} \) the time spent playing in the neighborhood, \( C_{s(i)} \) the air pollution concentration at school network, \( T_{t(i)} \) the time spent travelling. The denominator represents the total number of minutes per day.

All spatial computations based on vector files were performed using ArcGIS Pro and the raster calculations were performed in PCRaster environment (Karssenberg et al., 2010).

2.4. Covariates

The participants’ height and weight were measured by trained researchers during the medical examination at age 8 years. Also, information on recent respiratory infections (during the 3 weeks prior to the lung function measurement, yes/no) was collected during the medical examination. Information on other important covariates such as sex, Dutch nationality (defined as both parents being born in the Netherlands, yes/ no), paternal and maternal education (defined as the maximum educational level attained by the mother or father; low: primary school, lower vocational, or lower secondary education; medium: intermediate vocational education or intermediate/higher secondary education; high: higher vocational education and university), maternal and paternal allergies (asthma, hay fever allergies to house dust mites or pets, yes/no), breastfeading at age 12 weeks (yes/no), maternal smoking during pregnancy (defined as maternal smoking in at least the first 4 weeks of pregnancy, yes/no), smoking in the child’s home (yes/no), mold/damp spots in the living room and/or child’s bedroom (yes/no), and furry pets in the child’s home (cats, dogs, and/or rodents, yes/no) was obtained from the parent-completed questionnaires. For time-varying covariates, we used information from the questionnaire that coincided best with the air pollution exposure.

2.5. Data analyses

To assess the correlations between the four exposure assessment methodologies we used Pearson’s correlation coefficients. As the correlation for the full cohort is affected by regional variation and within-region variation, we also assessed the correlations for the Northern region and the remaining regions (Central, Southwest) of the Netherlands separately. The Northern region has lower air pollution levels than the other parts of the country (Schmitz et al., 2019). We also performed stratified analysis to study whether urban and rural areas showed different correlations between methodologies. The distinction between urban and rural was based on the CBS categorization (Centraal Bureau voor de Statistiek, 2015), that defines 5 categories based on the number of addresses per km², ranging from <500 addresses/km² to >2500 addresses/km². Urban areas were classified as areas with >1000 addresses per km², rural areas as areas with <1000 addresses per km². Finally, we assessed correlations between the exposures at the simulated school location and actual school location, to test how well we estimated school-based exposures, an important micro-environment.

To investigate the associations between lung function and air pollution, we fitted separate linear regression models for the two lung function variables (FEV₁ and FVC) and all pollutants (NO₂, NOₓ, PM₁₀, PM₂.₅, and PM₄.₅absorbance) derived from the four exposure-assessment methodologies. As in previous analyses (Gehring et al., 2013), we applied natural-log transformation to the lung function variables. We adjusted for the potential confounders described above. Age, height and weight were natural-log transformed and entered as continuous variables. All other potential confounders were entered as binary variables apart from age, weight and height which were entered as continuous variables. As recent respiratory infections we included participants which have symptoms three weeks prior to the lung-function measurement.

The exposures were entered as continuous variables without transformation assuming linear exposure-response relationships. The associations are presented as the percent-change in each lung function parameter and expressed per interquartile range (IQR) increase in exposure, to facilitate comparison of effect estimates between air pollutants and methodologies.

The statistical analysis was performed using R version 3.5.1.

3. Results

3.1. Characteristics of the study population

Data on 668 children (mean age, 8.1 years) were used in the analyses. Characteristics of the study population and lung function parameters are presented in Table 2.
Table 1
Population characteristics and lung function measurements (N = 668).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>n (%) or mean (SD)</th>
<th>missings (count)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>8.08 (0.29)</td>
<td>0</td>
</tr>
<tr>
<td>Female sex</td>
<td>339 (50.7)</td>
<td>0</td>
</tr>
<tr>
<td>Weight (kg)</td>
<td>28.85 (4.72)</td>
<td>0</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>132.96 (5.55)</td>
<td>0</td>
</tr>
<tr>
<td>Recent respiratory infectionsa</td>
<td>159 (24.1)</td>
<td>9</td>
</tr>
<tr>
<td>Dutch nationality</td>
<td>632 (96.0)</td>
<td>10</td>
</tr>
<tr>
<td>High maternal SES</td>
<td>266 (39.8)</td>
<td>0</td>
</tr>
<tr>
<td>High paternal SES</td>
<td>299 (45.2)</td>
<td>0</td>
</tr>
<tr>
<td>Allergic mother</td>
<td>409 (61.2)</td>
<td>0</td>
</tr>
<tr>
<td>Allergic father</td>
<td>214 (32.1)</td>
<td>1</td>
</tr>
<tr>
<td>Breast-feeding (≥12 weeks)</td>
<td>357 (53.4)</td>
<td>0</td>
</tr>
<tr>
<td>Mother smoking during pregnancy</td>
<td>96 (14.5)</td>
<td>6</td>
</tr>
<tr>
<td>Smoking at home</td>
<td>158 (23.7)</td>
<td>1</td>
</tr>
<tr>
<td>Mold/dampness at home</td>
<td>181 (27.3)</td>
<td>6</td>
</tr>
<tr>
<td>Furry pets at home</td>
<td>267 (40.0)</td>
<td>0</td>
</tr>
<tr>
<td>Living in urban areas</td>
<td>481 (72.0)</td>
<td>0</td>
</tr>
<tr>
<td>Living in the North</td>
<td>167 (25.0)</td>
<td>0</td>
</tr>
</tbody>
</table>

Lung function measurements

- FEV1 (L) = 1.78 (0.25) (0)
- FVC (L) = 1.97 (0.29) (0)

Table 2

3.2. Exposure to air pollution

The distributions of the estimated annual average air pollution concentrations for the four different exposure assessment methodologies are presented in Table 3. In Method 3, we assumed that children spent on average 964 min per day at home, 399 min at school, 28 min playing in the neighborhood, and 49 min travelling to school. In method 4 we used estimated time activity and travelling time based on the distance between home and school. In method 4 we used the same durations for all activities, except for travelling. For travelling we calculated the child’s travelling time based on the distance between home and school and on average was 5 min.

Variation in exposures was much larger for NOx than for PM2.5 and PM10 for which the variation was limited in all four approaches. The mean levels and variation did not differ much between the residential exposure approaches (M1, M2) and the time-weighted activity pattern methodologies (M3, M4). Correlations between the four methodologies are presented in Fig. 2 for NOx and Figure S1 for the remaining pollutants. Air pollution exposures derived from the four methodologies were highly correlated (r between 0.95 and 1) and correlations between the two residence-only methods (M1 and M2) were generally highest (0.99 for all the pollutants).

We explored several causes for the high correlation between exposures estimated with the four methodologies (M1-M4). One possible explanation is that variation in exposure between children is mainly caused by large contrasts in air pollution levels between regions of the country or between urban and rural areas. In this case, the differences in exposures assessed by different methodologies would be overshadowed by contrasts occurring at the larger scale. However, stratified analyses revealed high correlations between the four exposures also within the urban areas and rural areas and within the northern and central/southwestern parts of the Netherlands (Fig. S3). A second possible explanation for the high correlation between exposures calculated with different methodologies is a high correlation between exposures during different activities, which are the components of our exposure assessment calculations for the different methods. We found strong correlations between air pollution exposures at home and in the different activity spaces that we used in the four methodologies (home –front door estimate-, home –20 m buffer-, travelling in the neighborhood, travelling –simulated-,school –simulated-, travelling by bike –based on shortest path-, travelling by car –based on shortest path-, school –actual location-) as shown in Table 4.

3.3. Associations between air pollution and lung function

Most associations between air pollution exposures and lung function were negative, indicating a decrease in lung function with increasing exposures. The associations were significant for FVC for all exposures and for FEV1 for NOx, PM2.5, and PM10 whereas for NOy a significant association was observed only when using methodology 3 (Table 5). Associations between air pollution exposures and lung function were very similar for all exposure assessment methodologies. The association estimates were slightly higher for the two methodologies which incorporated the time activity patterns.

Estimates are adjusted for ln (age), sex, ln (height), ln (weight), recent respiratory infections, ethnicity/nationality, parental education, allergic mother, allergic father, breastfeeding, mother smoking during pregnancy, smoking at home, mold/dampness at home, furry pets at home. In bold are the significant associations. The effect estimates are presented per IQR increase in exposure: 9.14 μg/m3 for NOx, 12.37 μg/m3 for NOy, 1.15 μg/m3 for PM2.5, 0.32 10^-3/m for PM2.5 absorbance, 0.99 μg/m3 for PM10.

4. Discussion

Our study among 8-year-old children, living spread over the Netherlands, showed small differences in estimated exposure between the four air pollution assessment methodologies. Exposures from all four methods were highly correlated. Consistently, associations with lung function were very similar for the four exposure assessment methods.

4.1. Interpretation of the high correlation between exposures

First, the exposure estimates for all activity-spaces were highly correlated with the exposure at home. This is probably because all major activities of young children were assumed to take place around the home address. Second, children undergo activities with different, exposures from those at home for limited time. For example, children commute for limited time, which is usually the activity with the highest exposure (Chaney et al., 2017), while they spend 16 h at home based on our calculations.

The correlations between activity spaces indicate that the correlations between the exposures at school and at home were lower than the
Fig. 2. Scatterplot matrix and correlations for NO\textsubscript{2} exposures for the four exposure assessment methodologies.

Fig. 3. Scatterplot matrix for NO\textsubscript{2} of correlations between the four exposure assessment methodologies by region (left panel: Central/Southwest, right panel: North).
correlations between the exposure at home and during other activities (i.e., commuting and playing). Specifically, the correlations were between 0.68 and 0.89 for the exposures between at home and at school. As a result, home exposures contain the least information about school exposure, which is the second most important activity in terms of time spent after staying at home. Furthermore, the high correlation between the exposure at the estimated school and the actual school locations (0.81 < R < 0.94) suggests that the simulated school exposures are good estimates of “true” school exposures. Importantly, the correlation was higher for the estimated school exposure than with the residential

Table 4
Correlation between exposure estimates for different activity spaces for all air pollutants.

<table>
<thead>
<tr>
<th></th>
<th>Home (20 m average)</th>
<th>Playing</th>
<th>Travelling (estimated)</th>
<th>School (estimated)</th>
<th>Travelling by bike (shortest path)</th>
<th>Travelling by car (shortest path)</th>
<th>School (actual location)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO₂</td>
<td>0.99</td>
<td>0.96</td>
<td>0.92</td>
<td>0.92</td>
<td>0.93</td>
<td>0.91</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Corr: 0.989***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NO₂</td>
<td>0.99</td>
<td>0.95</td>
<td>0.77</td>
<td>0.76</td>
<td>0.83</td>
<td>0.75</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>Corr: 0.989***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PM₂.5</td>
<td>0.99</td>
<td>0.91</td>
<td>0.88</td>
<td>0.90</td>
<td>0.84</td>
<td>0.76</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>Corr: 0.989***</td>
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<td>PM₂.₅₅</td>
<td>0.99</td>
<td>0.94</td>
<td>0.86</td>
<td>0.88</td>
<td>0.87</td>
<td>0.82</td>
<td>0.84</td>
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<td></td>
<td>Corr: 0.989***</td>
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<td>PM₁₀</td>
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<td>0.95</td>
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<td>0.79</td>
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<td>Corr: 0.989***</td>
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Fig. 4. Scatterplot matrix for NO₂ and correlations between the four exposure assessment methodologies for urban (left panel) and rural area (right panel).

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mates (around 0.5 which integrate activities (Blanchard et al., 2018; Dhondt et al., 2012; Setton et al., 2011). The same bias estimation method was used in another study (Ragettli et al., 2015) where they used daily activity patterns, which may deviate from actual time activity patterns for individuals.

### 4.2. Comparison with previous studies

Several studies have compared static exposures with exposures which integrate activities (Blanchard et al., 2018; Dhondt et al., 2012; Ragettli et al., 2015; Setton et al., 2011; Strand et al., 2006). Only one of them was carried out in children (Strand et al., 2006) while the remaining studies included either adults (Blanchard et al., 2018; Setton et al., 2011) or a mixed population of adults and children (Dhondt et al., 2012; Ragettli et al., 2015).

Blanchard et al. (2018) compared the static approach with an approach which also includes commuting of pregnant women and concluded that air pollution exposure can be underestimated when mobility and commuting mode are not integrated in the exposure estimates (around 0.5–1.5 g/m³ for NO₂) (Blanchard et al., 2018). Similarly, in our study the underestimation was also very small in absolute terms (between 0.6 and 0.8 g/m³).

Setton et al. (2011) used paired individual residence and mobility exposure estimates and calculated bias in epidemiological analyses when mobility is not included. They concluded that ignoring daily mobility patterns can contribute to bias towards the null (bias range: 0.63–0.77; SD: 0.02) in exposure-health analyses (Setton et al., 2011). They additionally found that the bias was dependent on the amount of time spent away from home and the distance between the home and work address (Setton et al., 2011). The same bias estimation method used in another study (Ragettli et al., 2015) where they used both activity data, including travel data in Basel. Despite the relative small contributions of travelling exposure to the total exposure they found significant (12%) underestimation of health effects. Similarly, Dhondt et al. (2012) developed an exposure modelling framework to assess population-based air pollution exposure and the relation with health. They found a significant 1.2% increase in respiratory mortality for NO₂ by incorporating time-activity patterns compared to a static exposure (Dhondt et al., 2012). Our analyses did not reveal significant increase in lung function by incorporating time-activity patterns as in the aforementioned studies. This could be a result of the young age (8 years) of our cohort participants. Young children usually spent more time at home or around home location compared to adults.

An epidemiological study which studied the association between FEV₁ and personal exposure to sulphate in children aged 6–12 years with asthma, indicated that the use of personal exposure estimates enhance sensitivity for detecting associations with health outcomes (Strand et al., 2006). Specifically, they found that a 10 mg/m³ increase in PM₂.₅ was associated with a 2.2% decrease in FEV₁ at a 1-day lag of the pollutant (95% CI: 0.0–4.3% decrease) compared to a 1.0% (95% CI: 0.0–2.0% decrease by using a fixed monitor. The same study showed that personal exposure to sulphate was highly correlated with home exposure (R = 0.94) and school exposure (R = 0.92) (Strand et al., 2006), those high correlations are in agreement with our very high correlations between the exposures.

### 4.3. Strengths and limitations

The major strength is that we systematically compared methods of exposure assessments that can be scaled to large populations. One of the strengths of the present study is the spatial distribution of the PIAMA home addresses that are well dispersed geographically both in urban and rural areas ensuring variability in exposure. Additionally, the maps of the air pollutants and especially of NO₂ NOₓ and PM₂.₅ absorbance exhibit substantial small-scale spatial variation. Furthermore, we were able to investigate the associations between air pollution exposures and lung function with exposure assessment methodologies applicable to large populations. We were able to incorporate within the daily activity pattern of one of our methodologies the actual school addresses; while such information is not often available in cohort studies.

A limitation is that our method is based upon estimated time activity patterns, which may deviate from actual time activity patterns for individual children. We only had individual information about the location of the home and school locations. We note however that for a scalable solution to the problem of including time activity data in epidemiological studies, estimation of time activity patterns is inevitable. Additionally, we were not able to validate our exposure assessment methodologies against “true” exposures from personal monitoring. We did observe that the estimated school exposures calculated as the average exposure at all schools within 2 km of a participant’s home were highly correlated with exposures at the actual school location. The number of hours spent at school does not differ between children, because this is regulated in the Netherlands and therefore it is easier to account for it when no information on the duration of activities is available. Another limitation is that we did not take into account weekends and (school) holidays. For weekend days and holidays, time activity patterns likely differ more between children and are less predictable. We note that we covered five of seven days, the majority of time. Furthermore, we assigned estimated annual average concentrations to all activities, we expect that the error will differ among the activities which are related to lifestyle and weather conditions such as playing in the neighborhood.
4.4. Generalizability of findings

The added value of including exposure at non-residential locations in the air pollution exposure assessment was rather limited for this specific age-group and setting. Hence, for this age group, residential exposures may be sufficient to capture the air pollution exposures. This is an important finding for air pollution epidemiology studies on children in the Netherlands and possibly for other European countries. However, the findings of this study may not be generalizable to other countries which have different urban structure as the assumptions about distances of activity spaces from home were designed using Dutch datasets. Furthermore, the findings may differ in an adult population whose activities would take place for longer durations and further away from the home addresses (e.g., working activity and related commute trips).

5. Conclusions

Air pollution exposure estimates for 8-year-old children in the Netherlands, from methods based on the residential location only and methods including time activity patterns, were highly correlated and associated with similar decreases in lung function. Our study illustrates that the contrast in annual average exposure to air pollution for school children across the Netherlands was sufficiently captured by residential exposures.

Credit author statement

Anna-Maria Ntarladima, conceived the manuscript. Anna-Maria Ntarladima, Oliver Schmitz, Meng Lu, prepared and checked the geo data. Anna-Maria Ntarladima, wrote the initial draft and had the responsibility for submitting for publication. Ulrike Gehring, Derek Karsenberg, Ilonca Vaartjes, Gerard Hoek, Diedrick E. Grobbee, Jolanda Boer, Gerard Koppelman, Judith Vonk, Roel Vermeulen, contributed with offering the PIAMA data. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2021.111710.

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