Environmental Science & Technology

Article

pubs.acs.org/est

Variability in and Agreement between Modeled and Personal Continuously Measured Black Carbon Levels Using Novel Smartphone and Sensor Technologies

Mark J. Nieuwenhuijsen,*[†,‡,§,∥] David Donaire-Gonzalez,[†,‡,§,∥] Ioar Rivas,[†,‡,§,∥,⊥] Montserrat de Castro,[†,‡,§,∥] Marta Cirach,[†,‡,§,∥] Gerard Hoek,[#] Edmund Seto,[∇] Michael Jerrett,[○,◆] and Jordi Sunyer[†,‡,§,∥]

[†]Centre for Research in Environmental Epidemiology (CREAL), 08003 Barcelona, Catalonia, Spain

[‡]Pompeu Fabra University, 08002 Barcelona, Catalonia, Spain

[§]Biomedical Research Centre Network for Epidemiology and Public Health (CIBERESP), 08036 Barcelona, Catalonia, Spain

[∥]Parc Salut Mar, Institut Hospital del Mar de Investigaciones Médicas (IMIM), 08003 Barcelona, Catalonia, Spain

[⊥]Institute of Environmental Assessment and Water Research (IDAEA), Spanish Council for Scientific Research (CSIC), 08034 Barcelona, Catalonia, Spain

[#]Institute for Risk Assessment Sciences (IRAS), NL-3508 TD Utrecht, Netherlands

[∇]Department of Environmental and Occupational Health Services, University of Washington, Seattle, Washington 98195, United States

[○]Environmental Health Sciences, School of Public Health, University of California, Berkeley, 50 University Hall, Berkeley, California 94720-7360, United States

[◆]Department of Environmental Health, Fielding School of Public Health, University of California, Los Angeles, 650 Charles E. Young Drive South, 56-070 CHS, MC 177220, Los Angeles, California 90095, United States

ABSTRACT: Novel technologies, such as smartphones and small personal continuous air pollution sensors, can now facilitate better personal estimates of air pollution in relation to location. Such information can provide us with a better understanding about whether and how personal exposures relate to residential air pollution estimates, which are normally used in epidemiological studies. The aims of this study were to examine (1) the variability in personal air pollution levels during the day and (2) the relationship between modeled home and school estimates and continuously measured personal air pollution exposure levels in different microenvironments (e.g., home, school, and commute). We focused on black carbon as an indicator of traffic-related air pollution. We recruited 54 school children (aged 7−11) from 29 different schools around Barcelona as part of the BREATHE study, an epidemiological study of the relation between air pollution and brain development. For 2 typical week days during 2012−2013, the children were given a smartphone with CalFit software to obtain information on their location and physical activity level and a small sensor, the micro-aethalometer model AE51, to measure their black carbon levels simultaneously and continuously. We estimated their home and school exposure to $PM_{2.5}$ filter absorbance, which is well-correlated with black carbon, using a temporally adjusted $PM_{2.5}$ absorbance land use regression (LUR) model. We found considerable variation in the black carbon levels during the day, with the highest levels measured during commuting periods (geometric mean = 2.8 $\mu g/m^3$) and the lowest levels at home (geometric mean = 1.3 $\mu g/m^3$). Hourly temporally adjusted LUR model estimates for the home and school showed moderate to good correlation with measured personal black carbon levels at home and school (r = 0.59 and 0.68, respectively) and lower correlation with commuting trips (r = 0.32 and 0.21, respectively). The correlation between modeled home estimates and overall personal black carbon levels was 0.62. Personal black carbon levels vary substantially during the day. The correlation between modeled and measured black carbon levels was generally good, with the exception of commuting times. In conclusion, novel technologies, such as smartphones and sensors, provide insights in personal exposure to air pollution.

Received: November 4, 2014
Revised: January 23, 2015
Accepted: January 26, 2015
Published: January 26, 2015

DOI: 10.1021/es505362x
Environ. Sci. Technol. 2015, 49, 2977−2982

INTRODUCTION

Epidemiological studies of air pollution and adverse health effects often use residential outdoor estimates as the exposure indicator, assuming this to be a good predictor of personal exposure of air pollution.[1,2] Recent quantitative reviews show that the relation between ambient and personal air pollution is variable and may depend upon several factors.[3,4] Empirical studies also suggest heterogeneity in the relation between residential and personal exposure. In Barcelona, for example, we found that the relationship between modeled and measured ambient and measured personal exposure estimates varied by pollutant and were generally low to moderate.[5,6] Possible explanations for this were the limited number of measurements, limited exposure contrast, substantial daily mobility, or some combination of all three factors. With mobility, for instance, people may live in an area with low air pollution but move through roads with high air pollution levels to an area with medium air pollution levels (work and school) or vice versa, thereby reducing the contrast in exposure between people compared to residential outdoor exposures. In this instance, the ambient residential exposure estimates may not be a strong predictor of personal exposure levels. For example, de Nazelle et al.[7] found that, using mobility data and modeled air pollution data, travel activities accounted for only 6% of people's total time budget, but this small portion of the time budget accounted for 24% of the total inhaled daily dose of NO_2 in Barcelona. Dons et al.[8,9] in Belgium and Buonanno et al.[10] in Italy had similar findings for black carbon. The likely explanation is a combination of higher pollution levels near roadways during peak commute hours and higher rates of inhalation, precipitated by walking and bicycling commuting.

The use of new technologies, such as geographical information systems (GIS), (smartphone-based) geopositioning systems (GPS), and small personal continuous air pollution sensors,[7−12] to track people's location and measure their air pollution levels simultaneously has now made it possible to obtain better personal estimates of air pollution in relation to location, which can provide us with a better understanding of if and how this may be related to residential air pollution estimates allocated to subjects in an epidemiological study.

The aims of this study were to examine (1) the variability in personal air pollution levels during the day and (2) the relationship between modeled residential and school estimates and personal air pollution exposure measurements in different microenvironments (e.g., home, school, and commute). We focused on black carbon as an indicator of traffic-related air pollution

METHODS

We recruited 54 school children (aged 7−11) from 29 different schools around Barcelona of the BREATHE study, an epidemiological study of air pollution and brain development.[13]

For 2 normal week days in 2012−2013, the children were given a smartphone with CalFit software[7,14] to obtain information on their location and physical activity level (the latter was not used here) and a small pollution sensor, the micro-aethalometer model AE51 (AethLabs, San Francisco, CA, 5 min resolution), to measure their black carbon levels simultaneously and continuously. CalFit was developed through collaboration with researchers in Computer Science and Environmental Health Sciences at University of California, Berkeley. It consists of open-source software that runs continuously in the background on Android smartphones. CalFit records the phone's triaxial accelerometry at 10 Hz and a network-assisted global positioning system (aGPS) at 1 Hz. The CalFit application includes an algorithm that adapts to the orientation of the phone, descomposes the triaxial accelerometry into vertical and horizontal forces, and estimates energy expenditure within a sampling period (which for our study was 10 s).[7,14] The aGPS improves the time-to-first-fix (TTFF) and can improve accuracy of the GPS, particularly in dense urban areas, where GPS signals from satellites can often be obstructed. CalFit was installed on Samsung GT-S5360 Android phones.[7,14] CalFit software runs continuously in the background on the Android smartphone and records location continuously.

The micro-aethalometer determines black carbon concentration based on the Beere Lambert law by measuring the light absorbed (attenuation) by optically absorbing particles (i.e., the black carbon particle fraction). In particular, an 880 nm wavelength beam of light is produced by a light-emitting diode (LED) light source aimed at a photodiode detector. During its travel, the light beam passes through the aerosol sample collected on a filter. This sensor is small and portable (250 g) and has a battery life of up to 24 h when logging on a 5 min basis, as was the case in the present study. The pump speed was set at a rate of 100 mL/min. The micro-aethalometers and smartphones were worn together in a waist pouch, which was on a spibelt with a tube to the breathing zone of the children. Generally, we provided the sensor pack to 2 children per week.

At the beginning of each measurement campaign, the children met with a trained research assistant who provided them with details on the study protocol, obtained informed consent, and equipped them with the study instruments. Ethics approval was obtained from the IMIM ethics committee (number 2010/4122/I). After data cleaning, 42 measurements were available for analysis.

In the schools, black carbon levels were also measured with a the same type of micro-aethalometer on the same settings during the days of the personal exposure measurement.[15]

We also estimated the home and school exposure to $PM_{2.5}$ absorbance, which is highly correlated with black carbon, using an ESCAPE $PM_{2.5}$ absorbance land use regression (LUR) model, which has been described elsewhere.[16] Briefly, following the ESCAPE protocol, we selected 20 sites to measure $PM_{2.5}$ absorbance. These sites were a combination of traffic and background locations representing the gradient of various land use, emission sources, and traffic characteristics. Three monitoring campaigns, each 2 weeks long, were conducted in different seasons during 2009 and adjusted for temporal trends to derive annual mean proxy estimates using an ESCAPE protocols and a background monitoring site. European-wide and local GIS data on land uses, traffic indicators, population density, and geographic description of monitoring sites were obtained to create potential predictor variables. A multiple linear regression model was constructed following the ESCAPE supervised forward selection protocol using the annual average concentrations obtained from the sampling campaign as the dependent variable. Predictors for $PM_{2.5}$ absorbance were high-density residential area within a 300 m buffer, inverse distance to the nearest road × traffic intensity in the nearest road, and traffic intensity within a 50 m buffer, and this model had a R^2 of 0.83 and root-mean-square error (RMSE) of 0.38.[16]

Exposure levels to $PM_{2.5}$ absorbance were estimated for each study participant by combining the LUR spatial estimates of pollutants for the geocoded address of residence with a hourly temporal adjusting factor obtained from the routine monitoring data, following ESCAPE guidelines. Specifically, we used the

DOI: 10.1021/es505362x
Environ. Sci. Technol. 2015, 49, 2977−2982

ratio of the concentration of the routine monitor for each hour of the study period to the annual average during the year of the ESCAPE sampling campaign (2009) as the adjustment factor for that hour. Hourly estimates were combined to obtain averages over the whole measurement periods and for periods at home, school, and in commute.

Statistical Analyses. We conducted descriptive statistical analyses and Pearson correlation analyses to assess the correlation between average measured and modeled data for the whole measuring period and home, school, and commuting.

Table 1. Duration of Time (h) Overall and in Each Microenvironment (Using Different Buffers)

		tertiles of home outdoor ESCAPE $PM_{2.5}$ absorbance estimates (μg m^3)		
	all	(1.01, 2.26)	(2.26, 2.68)	(2.68, 4.56)
	mean (SD)[a]	mean (SD)	mean (SD)	mean (SD)
	2.5 (0.7)	1.8 (0.4)	2.5 (0.1)	3.3 (0.6)
time home (100 m) (h)	13 (4)	12 (4)	13 (4)	13 (4)
time home (300 m) (h)	15 (3)	15 (3)	15 (3)	15 (2)
time home (500 m) (h)	17 (4)	17 (4)	18 (5)	17 (4)
time home (1000 m) (h)	20 (5)	18 (5)	21 (4)	20 (5)
time school (100 m) (h)	7 (2)	6 (2)	7 (2)	7 (2)
time school (300 m) (h)	8 (2)	8 (2)	8 (2)	8 (2)
time school (500 m) (h)	13 (7)	13 (7)	14 (8)	13 (7)
time school (1000 m) (h)	19 (7)	16 (7)	21 (5)	19 (8)
commute (h)	0.7 (1)	0.9 (0.7)	0.5 (0.7)	0.8 (1.3)
distance between home and school (m)	1057 (1005)	1194 (946)	912 (973)	1066 (1140)
accuracy of location (m)	446 (558)	745 (691)	300 (429)	293 (419)
missing minutes per day	20 (62)	24 (64)	31 (87)	4 (11)

[a]SD = standard deviation.

We produced Bland–Altman plots to evaluate the agreement over the exposure range. We used analyses of variance with trend analyses to assess the relationship between the mean of modeled and measured black carbon data.

■ RESULTS

The children spent the largest part of their day at home, followed by school, and on average less than 1 h commuting (Table 1). The school was on average around 1 km from the home. The commuting trips were spread all over Barcelona (Figure 1).

Personal black carbon levels varied during the day, with the highest average levels occurring between 8 and 9 during rush hour in the morning and the lowest levels from 5 to 6 in the morning (Figure 2). Two lower peaks around 17.00 and 21.00 are likely due to the school and work rush hours back home. The lowest levels of black carbon were measured at home [geometric mean (GM) = 1.3 μg/m^3], followed by higher levels at school (GM = 1.6 μg/m^3), with the highest levels observed during commute (GM = 2.8 μg/m^3) (Table 2). The correlation between school and home personal black carbon measurements was 0.47 ($p = 0.002$). The correlation between the background station and personal black carbon measurements was 0.57. The contribution of home, school, commute, and other to the total personal exposure (estimated as percentage of duration × concentration) over the sampling period was 46, 32, 13, and 8%, respectively.

The correlation between modeled temporally adjusted ESCAPE LUR home $PM_{2.5}$ absorbance and the personal black carbon measurements was moderate over the whole day ($r = 0.62$) and for time spent at home ($r = 0.59$), lower for when at school ($r = 0.49$), and considerably lower when commuting ($r = 0.32$) (Table 2). The GM of the personal black carbon measurements increased with tertiles of temporally adjusted

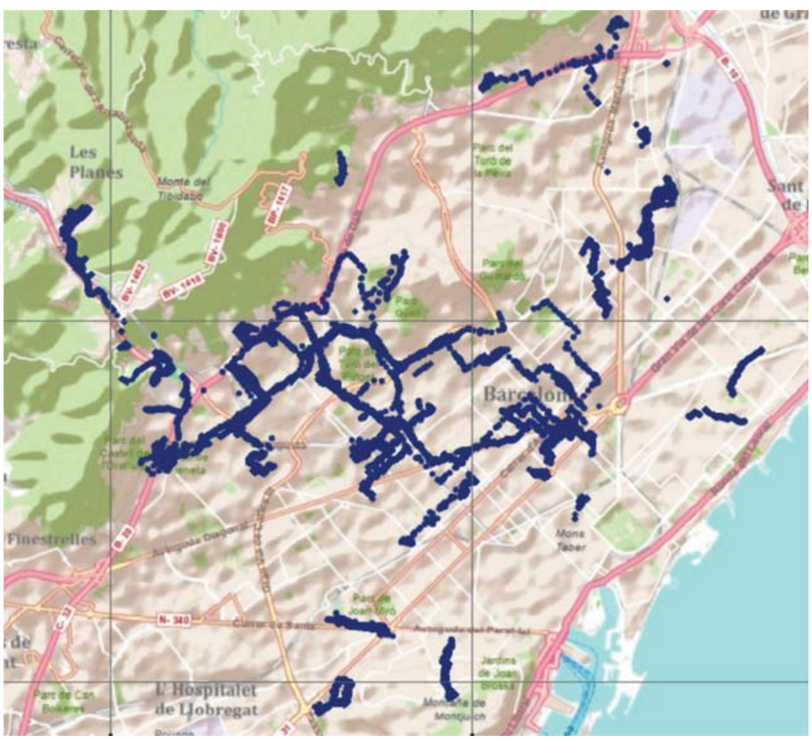

Figure 1. Map of all of the trips in Barcelona overlaid on major roads. The center of the city is indicated with "Barcelona". The green area (west of the city) is Collsera park with a major road called Rhonda de Dalt running alongside, and the blue area is the sea with a major road called Rhonda Literal running alongside.

DOI: 10.1021/es505362x
Environ. Sci. Technol. 2015, 49, 2977–2982

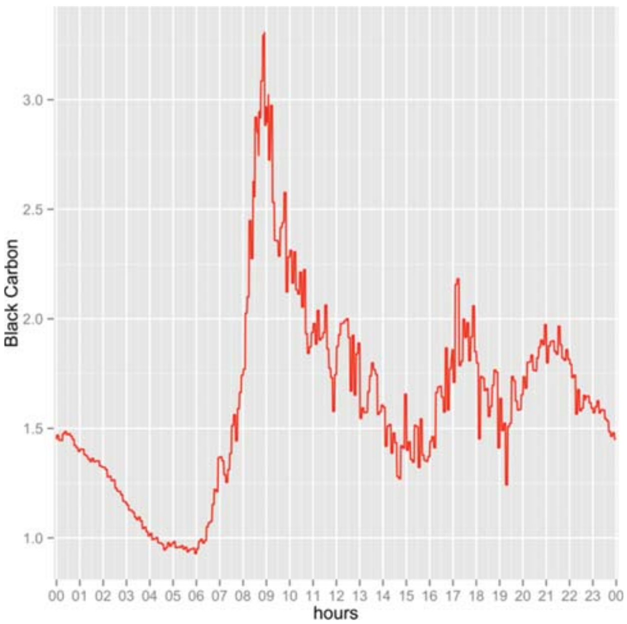

Figure 2. Average black carbon levels (μg/m^3) over the day (all personal measurements combined).

ESCAPE LUR home $PM_{2.5}$ absorbance, overall, for home, school, and commuting.

The correlation between modeled temporally adjusted ESCAPE LUR school $PM_{2.5}$ absorbance and the personal black carbon measurements was moderate over the whole day ($r = 0.44$), considerably higher for time spent at school ($r = 0.68$), and lower for when at home ($r = 0.31$) and commuting ($r = 0.21$) (Table 3). The correlation between modeled temporally adjusted ESCAPE LUR school $PM_{2.5}$ absorbance and the static black carbon measurements in the schools was good ($r = 0.70$). The mean (GM) of the personal black carbon measurements generally showed an increasing trend with tertiles of temporally adjusted ESCAPE LUR school $PM_{2.5}$ absorbance, overall, for home, school, and commuting. Bland–Altman agreement plots showed some tendency for under- and overestimation of the models at the extremes of the exposure range, but the tendency was not statistically significant (panels a and b of Figure 3).

■ DISCUSSION

In this study, we measured personal black carbon levels of children and found considerable variation in the levels during the day. The highest levels were measured during commuting, and the lowest levels were measured at home. Temporally adjusted LUR models for the home and school showed moderate to good correlation with personal levels at home and school, respectively, but only low to moderate correlation with commuting. The results demonstrate that novel technologies, such as smartphones and sensors, together with GIS can provide new insights in personal exposure to air pollution.

Our average personal black carbon levels were similar to those reported in adults in Belgium (1.59 μg/m^3)[9] but lower than those reported in children in Italy (5.1 μg/m^3).[10] As in other studies of black carbon in children[8] and adults,[8,9] levels in the road/commuting environment were higher compared to the home or other environments. As with many other studies and the studies

Table 2. Characteristics of the Black Carbon Levels (Geometric Means and Geometric Standard Deviations) Overall and by Tertiles of Temporally Adjusted Modeled Home ESCAPE $PM_{2.5}$ Absorbance

	all	tertiles of home outdoor ESCAPE $PM_{2.5}$ absorbance estimates (adjusted) (μg m^3)						
		(0.20, 1.08)	(1.08, 2.08)	(2.08, 3.97)				
	GM^a (GSD)^b	GM (GSD)	GM (GSD)	GM (GSD)	ANOVA p value	p trend	correlation estimate	Pearson p value
overall micro-aethalometer estimation	1.4 (1.6)	1.1 (1.4)	1.4 (1.6)	1.9 (1.5)	<0.001	<0.001	0.62	<0.001
micro-aethalometer estimation for school (GPS)	1.6 (1.7)	1.2 (1.7)	1.6 (1.6)	2.1 (1.6)	0.008	0.002	0.49	0.001
micro-aethalometer estimation for home (GPS)	1.3 (1.8)	0.9 (1.5)	1.3 (1.8)	1.9 (1.8)	0.001	<0.001	0.59	<0.001
micro-aethalometer estimation for commute (GPS)	2.8 (2.2)	2.3 (2.4)	2.5 (1.9)	3.8 (2.3)	0.216	0.116	0.32	0.087
ESCAPE exposure for home	2.4 (1.4)	2.1 (1.4)	2.4 (1.2)	2.9 (1.2)				
ESCAPE exposure for home (adjusted by ratio)	1.4 (2.1)	0.6 (1.7)	1.6 (1.2)	2.8 (1.2)				

^{a}GM = geometric mean. ^{b}GSD = geometric standard deviation.

Table 3. Characteristics of the Black Carbon Levels (Geometric Means and Geometric Standard Deviations) Overall and by Tertiles of Temporally Adjusted Modeled School ESCAPE $PM_{2.5}$ Absorbance

	all	tertiles of school outdoor ESCAPE $PM_{2.5}$ absorbance estimates (adjusted) (μg m^3)						
		(0.13, 0.98)	(0.98, 1.5)	(1.5, 4.0)				
	GM^a (GSD)^b	GM (GSD)	GM (GSD)	GM (GSD)	ANOVA p value	p trend	correlation estimate	Spearman p value
overall micro-aethalometer estimation	1.4 (1.6)	1.2 (1.6)	1.2 (1.6)	2.0 (1.4)	0.003	0.006	0.44	0.004
micro-aethalometer estimation for school (GPS)	1.6 (1.7)	1.2 (1.7)	1.5 (1.5)	2.5 (1.3)	<0.001	<0.001	0.68	<0.001
micro-aethalometer estimation for home (GPS)	1.3 (1.8)	1.2 (1.7)	1.0 (1.8)	1.8 (1.7)	0.039	0.077	0.31	0.044
micro-aethalometer estimation for commute (GPS)	2.8 (2.2)	2.4 (2.5)	1.9 (1.5)	4.17(1.9)	0.046	0.093	0.21	0.271
school monitoring	1.2 (1.7)	0.8 (1.7)	1.1 (1.5)	1.8 (1.4)	<0.001	<0.001	0.70	<0.001
ESCAPE exposure for school	2.0 (1.6)	1.3 (1.4)	2.1 (1.5)	2.8 (1.1)				
ESCAPE exposure for school (adjusted by ratio)	1.2 (2)	0.6 (1.8)	1.2 (1.1)	2.4 (1.4)				

^{a}GM = geometric mean. ^{b}GSD = geometric standard deviation.

DOI: 10.1021/es505362x
Environ. Sci. Technol. 2015, 49, 2977–2982

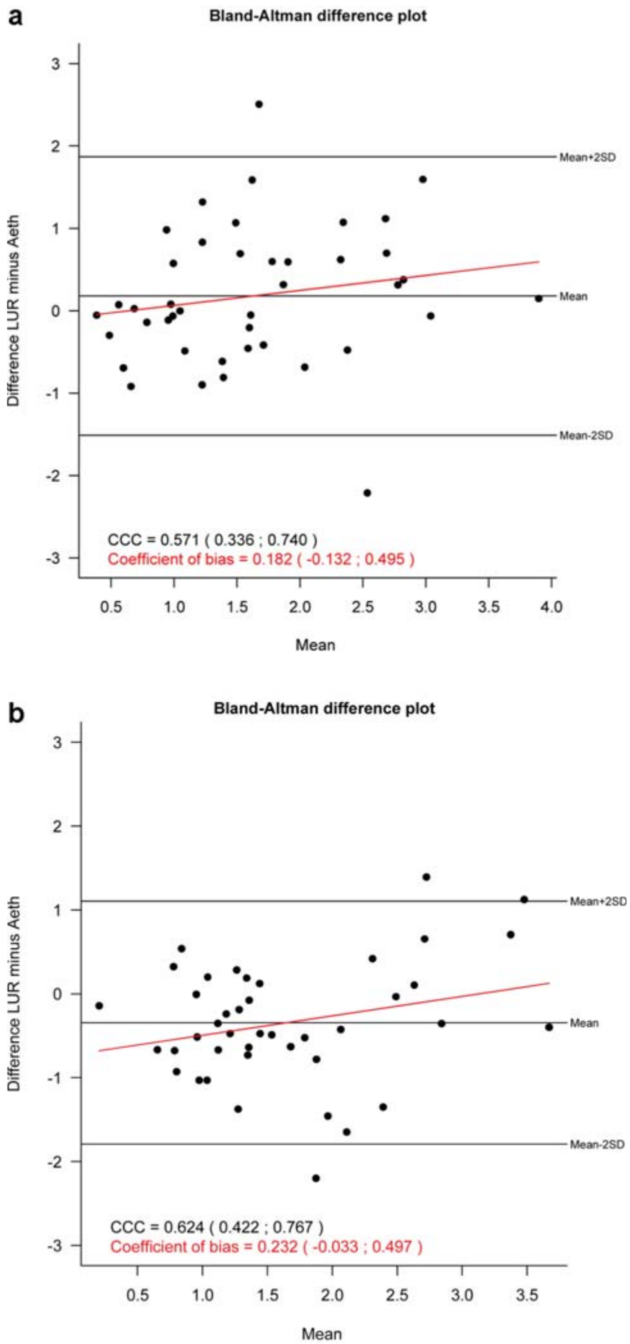

Figure 3. Bland−Altman plots of (a) home LUR−personal home and (b) school LUR−personal school.

from Italy[10] and Belgium,[8,9] we found that children spent the majority of their time at home and only a small proportion (around 3% in our study) commuting. As others studies have shown, even though the commuting time is short, it may contribute to a larger proportion (25% or so) of the total inhaled dose during the day.[7−10] We did not attempt to estimate the inhaled dose in our study, but the contribution to total exposure was 13%.

Previously, in Barcelona, we found a similar moderate correlation (R^2 = 0.45) between annual LUR models for $PM_{2.5}$ absorbance and personal measurements of $PM_{2.5}$ absorbance in 15 adults measured over three 14 day periods.[5] Dons et al.[17] found a lower correlation (r = 0.45) between temporally adjusted black carbon LUR models and personal black carbon exposure measurements in 62 adult volunteers. There are differences between their analyses and ours, as they included corrections for indoor/outdoor ratios, while we did not apply such adjustments.

As may be expected, the home temporally adjusted LUR model estimates for $PM_{2.5}$ absorbance were better correlated with black carbon measurements at home than at school and the school temporally adjusted LUR model estimates were better correlated with the black carbon measurements at school than at home; however, the differences was not that large (r = 0.59 versus 0.68). For both modeled estimates, the correlation was weakest with commuting black carbon exposures. Also, putting the temporally adjusted home and school LUR model estimates into tertiles showed that, for all measurements (overall, home, school, and commute), there was an increasing trend in average measured personal black carbon exposure with the modeled estimates. This may be partly due to the relatively small distance between home and school, the short commuting time, and possibly the larger day-to-day variability in black carbon levels. The recent VE3SPA study reported that the temporal correlation between $PM_{2.5}$ absorbance from a background station and personal $PM_{2.5}$ absorbance levels was larger (R^2 = 0.64)[18] than the spatial correlation between LUR model estimates for $PM_{2.5}$ absorbance and personal $PM_{2.5}$ absorbance measurements (R^2 = 0.45).[5] Here, we found a correlation of 0.57 between the background station and personal black carbon measurements, which was only slightly lower than the correlation between the LUR model estimates for $PM_{2.5}$ absorbance and personal black carbon levels (r = 0.62), suggesting that the temporal variability is the most important determinant of short-term personal black carbon levels but that still there is marginal benefit when including spatial variability.

We did not try to model commuting levels and assess the agreement with personal black carbon measurements or the street characteristics determining the exposure, as did Dons et al.,[19] because commute estimates are not often used in epidemiological studies, which is the main focus of this work. In general, in epidemiological studies, home estimates are used as an index of exposure and these are sometimes combined with school estimates.

The strength of the study was the use of novel technologies, such as smartphone tracking software and sensor measurements, to assess objectively the location and the black carbon concentrations during the day. These new technologies can provide insights for air pollution and other exposures, such as noise, temperature, and green space; however, these technologies are in their infant state, which limits their use, and further improvements need to be made.[20] Moreover, we developed good LUR models as part of an European project using standard methodology.

The weakness of the study is the relatively small sample size and the limited number of days of measurements. These types of studies are labor-intensive and can also be burdensome for the subjects, particularly children. Fortunately, we had good compliance from the children, but we still had a considerable number of recordings (12 of 54) that were too short for inclusion in the daily analyses. Furthermore, for the LUR models, we used $PM_{2.5}$ absorbance as a surrogate for black carbon, and even though it is highly correlated with black carbon, it may have led to lower correlations because the two measures have some differences. Also, for this reason, we focused more on correlations rather than absolute values of the exposure levels. We did not correct for differences in indoor/outdoor ratios, because we previously found a large variability between homes and seasons[5] and we did not have the indoor/outdoor measurements for houses in our study. Finally, we choose black carbon as a marker for traffic-related air pollution

DOI: 10.1021/es505362x
Environ. Sci. Technol. 2015, 49, 2977−2982

because can be well-measured on a person as a result of the availability of the micro-aethalometer. Black carbon, though, is only one component of personal traffic-related air pollution, and there are many other constituents that may be important.[5,17,21,22]

This study provides further understanding of the personal black carbon levels among children during the day and the relationship with modeled estimates. It also demonstrates the utility of a novel smartphone sensor. Further studies are required, particularly also for when the distance between the home and the school or work environment are larger.

■ AUTHOR INFORMATION

Corresponding Author

*Telephone: ++34-93-2147337. Fax: ++34-93-2147302. E-mail: mnieuwenhuijsen@creal.cat.

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

The authors thank the Air Quality Department from the Government of Catalonia for providing the routine air pollution data. The research leading to these results has received funding from the European Research Council (ERC) under the ERC Grant Agreement 268479, the BREATHE project and NIH NIEHS Grant R01-ES020409. The authors acknowledge all of the families participating in the study for their altruism and particularly to the schools Antoni Brusi, Baloo, Betània–Patmos, Centre d'estudis Montseny, Col·legi Shalom, Costa i Llobera, El sagrer, Els Llorers, Escola Pia de Sarrià, Escola Pia Balmes, Escola concertada Ramon Llull, Escola Lourdes, Escola Tècnica Professional del Clot, Ferran i Clua, Francesc Macià, Frederic Mistral, Infant Jesús, Joan Maragall, Jovellanos, La Llacuna del Poblenou, Lloret, Menéndez Pidal, Nuestra Señora del Rosario, Miralletes, Ramon Llull, Rius i Taulet, Pau Vila, Pere Vila, Pid'en Xandri, Projecte, Prosperitat, Sant Ramon Nonat–Sagrat Cor, Santa Anna, Sant Gregori, Sagrat Cor Diputació, Tres Pins, Tomàs Moro, Torrentd'en Melis, and Virolai. The authors also acknowledge the ESCAPE project for the design and supervision for modeling of air pollution.

■ REFERENCES

(1) Beelen, R.; Raaschou-Nielsen, O.; Stafoggia, M.; Andersen, Z. J.; Weinmayr, G.; Hoffmann, B.; Wolf, K.; Samoli, E.; Fischer, P.; Nieuwenhuijsen, M.; et al. Effects of long-term exposure to air pollution on natural-cause mortality: An analysis of 22 European cohorts within the multicentre ESCAPE project. *Lancet* **2014**, *383*, 785–795.

(2) Raaschou-Nielsen, O.; Andersen, Z. J.; Beelen, R.; Samoli, E.; Stafoggia, M.; Weinmayr, G.; Hoffmann, B.; Fischer, P.; Nieuwenhuijsen, M. J.; Brunekreef, B.; Xun, W. W.; et al. Air pollution and lung cancer incidence in 17 European cohorts: Prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). *Lancet Oncol.* **2013**, *14* (9), 813–822.

(3) Avery, C. L.; Mills, K. T.; Williams, R.; McGraw, K. A.; Poole, C.; Smith, R. L.; et al. Estimating error in using Ambient $PM_{2.5}$ concentrations as proxies for personal exposures: A review. *Epidemiology* **2010**, *21* (2), 215–223.

(4) Meng, Q. Y.; Svendsgaard, D.; Kotchmar, D. J.; Pinto, J. P. Associations between personal exposures and ambient concentrations of nitrogen dioxide: A quantitative research synthesis. *Atmos. Environ.* **2012**, *57*, 322–329.

(5) Montagne, D.; Hoek, G.; Nieuwenhuijsen, M.; Lanki, T.; Pennanen, A.; Portella, M.; Meliefste, K.; Eeftens, M.; Yli-Tuomi, T.; Cirach, M.; et al. Agreement of land use regression models with personal exposure measurements of particulate matter and nitrogen oxides air pollution. *Environ. Sci. Technol.* **2013**, *47* (15), 8523–8531.

(6) Schembari, A.; Triguero, M.; de Nazelle, A.; Dadvand, P.; Vrijheid, M.; Cirach, M.; Martinez, D.; Figueras, F.; Querol, X.; Basagaña, X.; et al. Personal, indoor and outdoor air pollution levels among pregnant women in a high diesel environment. *Atmos. Environ.* **2012**, *64*, 287–295.

(7) de Nazelle, A.; Seto, E.; Donaire-Gonzalez, D.; Mendez, M.; Matamala, J.; Rodriguez, D.; Nieuwenhuijsen, M.; Jerrett, M. Improving estimates of air pollution exposure through ubiquitous sensing technologies. *Environ. Pollut.* **2013**, *176*, 92–99.

(8) Dons, E.; Int Panis, L.; Van Poppel, M.; Theunis, J.; Willems, H.; Torfs, R.; Wets, G. Impact of time–activity patterns on personal exposure to black carbon. *Atmos. Environ.* **2011**, *45*, 3594–3602.

(9) Dons, E.; Int Panis, L.; Van Poppel, M.; Theunis, J.; Wets, G. Personal exposure to black carbon in transport microenvironments. *Atmos. Environ.* **2012**, *55*, 392–398.

(10) Buonanno, L.; Stabile, L.; Morawska, A.; Russi. Children exposure assessment to ultrafine particles and black carbon: The role of transport and cooking activities. *Atmos. Environ.* **2013**, *79*, 53–58.

(11) Berghmans, P.; Bleux, N.; Int Panis, L.; Mishra, V. K.; Torfs, R.; Van Poppel, M. Exposure assessment of a cyclist to PM_{10} and ultrafine particles. *Sci. Total Environ.* **2009**, *407* (4), 1286–1298.

(12) de Nazelle, A.; Fruin, S.; Westerdahl, D.; Martinez, D.; Ripoll, A.; Kubesch, N.; Nieuwenhuijsen, M. A travel mode comparison of commuters' exposures to air pollutants in Barcelona. *Atmos. Environ.* **2012**, *59*, 151–159.

(13) Sunyer, J.; Esnaola, M.; Alvarez-Pedrerol, M.; Rivas, I.; Forns, J.; Foraster, M.; Garcia-Esteban, R.; Basagaña, X.; Viana, M.; Cirac, M.; Moreno, T.; Alastuey, A.; Sebastian, N.; Nieuwenhuijsen, M.; Quero, X. The negative effects of traffic related air pollution in school on cognitive function growth. *N. Engl. J. Med.* **2014**, manuscript submitted.

(14) Donaire-Gonzalez, D.; de Nazelle, A.; Seto, E.; Mendez, M.; Rodriguez, D.; Mark Nieuwenhuijsen, M.; Jerrett, M. Comparison of physical activity measures using smartphone based CalFit and Actigraph. *J. Med. Internet Res.* **2013**, *15* (6), No. e111.

(15) Moreno, T.; Rivas, I.; Bouso, L.; Viana, M.; Jones, T.; Àlvarez-Pedrerol, M.; Alastuey, A.; Sunyer, J.; Querol, X. Variations in school playground and classroom atmospheric particulate chemistry. *Atmos. Environ.* **2014**, *91*, 162–171.

(16) Eeftens, M.; Beelen, R.; Bellander, T.; Cesaroni, G.; Cirach, M.; Declerq, C.; Dèdelè, A.; Dons, E.; de Hoogh, K.; De Nazelle, A.; et al. Development of land use regression models for $PM_{2.5}$, $PM_{2.5}$ absorbance, PM_{10} and PM_{coarse} in 20 European study areas; results of the ESCAPE project. *Environ. Sci. Technol.* **2012**, *46* (20), 11195–11205.

(17) Dons, E.; Van Poppel, M.; Int Panis, L.; De Prins, S.; Berghmans, P.; Koppen, G.; Matheeussen, C. Land use regression models as a tool for short, medium and long term exposure to traffic related air pollution. *Sci. Total Environ.* **2014**, *476–477*, 378–386.

(18) Montagne, D.; Hoek, G.; Nieuwenhuijsen, M.; Lanki, T.; Siponen, T.; Portella, M.; Meliefste, K.; Brunekreef, B. Temporal associations of ambient $PM_{2.5}$ elemental concentrations with indoor and personal concentrations. *Atmos. Environ.* **2014**, *86*, 203–211.

(19) Dons, E.; Temmerman, P.; Van Poppel, M.; Bellemans, T.; Wets, G.; Int Panis, L. Street characteristics and traffic factors determining road users' exposure to black carbon. *Sci. Total Environ.* **2013**, *447*, 72–79.

(20) Nieuwenhuijsen, M. J.; Donaire-Gonzalez, D.; Foraster, M.; Martinez, D.; Cisneros, A. Using personal sensors to assess the exposome and acute health effect. *Int. J. Environ. Res. Public Health* **2014**, *11*, 7805–7819.

(21) Minguillón, M. C.; Cirach, M.; Hoek, G.; Brunekreef, B.; Tsai, M.; de Hoogh, K.; Jedynska, A.; Kooter, I. M.; Nieuwenhuijsen, M.; Querol, X. Spatial variability of trace elements and sources for improved exposure assessment in Barcelona. *Atmos. Environ.* **2014**, *89*, 268–281.

(22) Minguillón, M. C.; Schembari, A.; Triguero-Mas, M.; de Nazelle, A.; Dadvand, P.; Figueras, F.; Salvado, J. A.; Grimalt, J. O.; Nieuwenhuijsen, M.; Querol, X. Source apportionment of indoor, outdoor and personal $PM_{2.5}$ exposure of pregnant women in Barcelona, Spain. *Atmos. Environ.* **2012**, *59*, 426–436.

DOI: 10.1021/es505362x
Environ. Sci. Technol. 2015, 49, 2977–2982