

1 **The microenvironmental modelling approach to assess children's exposure to air**  
2 **pollution - a review**

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## 17 **Abstract**

18 Exposures to a wide spectrum of air pollutants were associated to several effects on  
19 children's health. Exposure assessment can be used to establish where and how air  
20 pollutants' exposures occur. However, a realistic estimation of children's exposures to air  
21 pollution is usually a great ethics challenge, especially for young children, because they  
22 cannot intentionally be exposed to contaminants and according to Helsinki declaration,  
23 they are not old enough to make a decision on their participation. Additionally, using  
24 adult surrogates introduces bias, since time-space-activity patterns are different from  
25 those of children. From all the different available approaches for exposure assessment,  
26 the microenvironmental (ME) modelling (indirect approach, where personal exposures  
27 are estimated or predicted from microenvironment measurements combined with time-  
28 activity data) seemed to be the best to assess children's exposure to air pollution as it  
29 takes into account the varying levels of pollution to which an individual is exposed during  
30 the course of the day, it is faster and less expensive. Thus, this review aimed to explore  
31 the use of the ME modelling approach methodology to assess children's exposure to air  
32 pollution. To meet this goal, a total of 152 articles, published since 2002, were identified  
33 and titles and abstracts were scanned for relevance. After exclusions, 26 articles were  
34 fully reviewed and main characteristics were detailed, namely: i) study design and  
35 outcomes, including location, study population, calendar time, pollutants analysed and  
36 purpose; and ii) data collection, including time-activity patterns (methods of collection,  
37 record time and key elements) and pollution measurements (microenvironments, methods  
38 of collection and duration and time resolution). The reviewed studies were from different  
39 parts of the world, confirming the worldwide application, and mostly cross-sectional.  
40 Longitudinal studies were also found enhancing the applicability of this approach. The  
41 application of this methodology on children is different from that on adults because of  
42 data collection, namely the methods used for collecting time-activity patterns must be  
43 different and the time-activity patterns are itself different, which leads to select different  
44 microenvironments to the data collection of pollutants' concentrations. The most used  
45 methods to gather information on time-activity patterns were questionnaires and diaries,  
46 and the main microenvironments considered were home and school (indoors and  
47 outdoors). Although the ME modelling approach in studies to assess children's exposure  
48 to air pollution is highly encouraged, a validation process is needed, due to the  
49 uncertainties associated with the application of this approach.

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51 **Keywords:** Exposure modelling; air pollution; children; microenvironments

52

53 **Conflict of interests**

54 None declared

55

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## 60 **1. Introduction**

### 61 ***1.1. Relevance of the assessment of children's exposure to air pollution***

62 Duan (1982) and Ott (1982) introduced in the early 80's the concept of *human exposure*  
63 (or simply *exposure*), which was defined as “an event that occurs when a person comes  
64 in contact with the pollutant” (Ott, 1982). Thus, exposure to air pollution occurs whenever  
65 a human being breathes air in a location where there are at least trace amounts of airborne  
66 pollutants (Klepeis, 2006). Although the first official efforts to control air pollution have  
67 traditionally focused on outdoor air, it is now apparent that elevated contaminant  
68 concentrations are common inside both private and public buildings (Spengler and  
69 Sexton, 1983). Attention should continue to be paid to outdoor air quality and its influence  
70 on human health, especially in urban and/or industrialized areas of developed countries.  
71 However, people spend up to 90% of their time indoors, making indoor air quality more  
72 important than outdoors (Harrison, 1997). Whilst this does not *per se* mean that indoor  
73 exposures will produce more harmful effects, the evidence is that indoor concentrations  
74 of many pollutants are often higher than those typically encountered outside (Jones, 1999;  
75 Sousa et al., 2012a).

76 Children are highly vulnerable to air environmental hazards, being considered a risk  
77 group (Nieuwenhuijsen et al., 2006; Peled, 2011; Sousa et al., 2009, Sousa et al., 2012b,  
78 Sousa et al., 2013) for several reasons including their relative higher amount of air  
79 inhalation (the air intake per weight unit in a resting infant is twice than in an adult) and  
80 their not fully developed immune system and lungs. As above referred, evidence has been  
81 made that children, as well as adults, spend most of their time in indoor environments and  
82 are therefore more exposed to indoor air pollution. As a consequence, exposures to a wide  
83 spectrum of air pollutants were associated to several effects on children's health, like the  
84 increasing of the occurrence of asthma, other allergies and respiratory diseases (Hulin et  
85 al., 2010; McGwin et al., 2010; Mendell, 2007; Rumchev et al., 2002; Salvi, 2007;  
86 Schwartz, 2004; Sousa et al., 2012a). Evidences of other health outcomes have been  
87 found: i) Brook et al. (2004) and the World Health Organization (WHO, 2006) reported  
88 cardiovascular diseases associated with exposure to air pollutants; and ii) a review from  
89 Beamish et al. (2011) suggested that there is a link between air pollution and intestinal  
90 disease.

91 In their daily routine, children move from one location to another and are exposed to a  
92 large number of air contaminants for different time durations, raising serious questions  
93 about whether such exposures are likely to cause adverse health effects, and what are  
94 pollutants' sources. Thus, a complex multifactorial approach for exposure assessment  
95 seems appropriate aiming to: i) associate exposure with health effects; ii) link health  
96 effects with pollution sources; and iii) determine the exposure value of an individual or  
97 group of individuals relative to the population exposure distribution (Moschandreas and  
98 Saksena, 2002). In this field, epidemiologic studies provide the opportunity to assess the  
99 effects of exposure to air pollution on children's health, i.e., the exposure-response  
100 relationship. Multiple outcomes from this type of studies are of interest (Gilliland et al.,  
101 2005), including the prevalence of asthma and respiratory diseases, as well as the  
102 associated morbidity and mortality. In several countries, as the example of China (Ye et  
103 al., 2007), despite the increasing concern about environmental health, most risk-  
104 assessment activities are conducted focusing on adults, making environmental health  
105 policies inefficient in protecting children's health. Children exposure should be  
106 developed to characterize real-life situations, whereby i) potentially exposed populations  
107 are identified; ii) potential pathways of exposure are identified; and iii) the magnitude,  
108 frequency, duration and time-pattern of contact with a pollutant are quantified (Hubal et  
109 al., 2000). Assessing children's exposure to air pollution cannot be merely reduced to the  
110 measurements of air pollutants concentrations in one or more environments. In fact,  
111 exposure studies can be used to establish where air pollutants exposures occur and the  
112 source of those air pollutants (Weisel, 2002).

113 Hubal et al. (2000) reviewed the factors that strongly influence children's exposure, and  
114 concluded that: i) the physiologic characteristics and behavioural patterns of children  
115 result not only in exposure differences between children and adults, but also in differences  
116 in exposures among children of different developmental stages; ii) significant challenges  
117 are associated with developing and verifying exposure factors for young children, so it is  
118 necessary to develop and improve the methods for monitoring children's exposures and  
119 activities; iii) the data usually available for conducting children's exposure assessments  
120 are highly variable, depending on the route of exposure considered, so it requires the  
121 collection of physical activity data for children (especially young children) to assess  
122 exposure by all routes. Socioeconomic status also greatly influence children's exposure  
123 to air pollution (Chaix et al., 2006).

124

125 ***1.2. Methods to assess children's exposure to air pollution - main advantages and***  
126 ***limitations***

127 The study of exposure assessment has evolved significantly over the past 30 years (Lioy,  
128 2010) through the appearance of a myriad of methods for assessing personal exposure  
129 levels to air pollution. Two different approaches, direct and indirect, described below,  
130 have been taken to assess personal exposure to air pollution (Ott, 1982).

131 There are two available direct methods: i) personal monitoring, which monitors pollution  
132 concentrations using portable equipment worn by the subjects, which can work actively  
133 (pumped) or passively (diffusive); and ii) biomonitoring, which is the use of biomarkers  
134 to assess exposure to air pollution, although its usability on exposure studies to air  
135 pollution is very specific. Simplicity of design and freedom from modelling assumptions  
136 are the advantages of the direct approach (Duan et al., 1991; Wallace and Ott, 1982).  
137 Despite direct measurements clearly reflect individual personal exposure levels best,  
138 measurements of personal exposures are expensive, time consuming and difficult to apply  
139 (Monn, 2001), especially to young children (Jones et al., 2007). It is important to note  
140 that a personal measurement does not *a priori* provide more valid data than a stationary  
141 measurement, i.e. a personal sample in a study investigating effects from a specific place  
142 or source is often influenced by other sources than those on focus of the investigation,  
143 and may thus confound the exposure-effect outcome. Nevertheless, in 1984 EPA  
144 performed two large studies of carbon monoxide (CO) exposure in Washington, DC and  
145 Denver Colorado, where 1987 persons were followed for 24 hours in DC and 1139  
146 persons were followed for two days in Denver. The specific personal monitor used  
147 provided exact times in each microenvironment without having to write them down in a  
148 questionnaire. This was the first and the most complete study to ever include actual ME  
149 measurements, and included many more MEs than in subsequent studies, although being  
150 a personal monitoring study (Akland, 1985). While biomarkers offer clear advantages,  
151 some important criteria must be met when using them for this purpose (Hubal et al.,  
152 2000): i) biomarkers that can accurately quantify the concentration of an environmental  
153 contaminant and/or its metabolite(s) in easily accessible biological media (blood, urine,  
154 and breath) must be available; ii) biomarkers must be specific to the contaminant of  
155 interest; iii) the pharmacokinetics of absorption, metabolism, and excretion must be

156 known; and iv) the time between exposure and biomarkers sample collection must be  
157 known. Although there are a number of biomarkers that meet these criteria, few studies  
158 using biomarkers have collected all of the information required to accurately estimate  
159 exposure. In studies with large sample sizes, long duration and diverse outcomes and  
160 exposures, exposure assessment efforts should rely on modelling to provide estimates for  
161 the entire cohort, supported by subject-derived questionnaire data, although assessment  
162 of some exposures of interest requires individual measurements of exposures using  
163 snapshots of personal and microenvironmental exposures over short periods and/or in  
164 selected microenvironments (Gilliland et al., 2005). In addition, significant challenges are  
165 associated with collecting biomarkers' data from children (Weaver et al., 1998). Although  
166 findings from Sexton et al. (2000) indicated that, with proper care, it could be practicable  
167 to obtain personal volatile organic compounds (VOC) measurements from elementary  
168 school children wearing personal VOC badges samplers, direct methods are unusual on  
169 children studies due to their difficult applicability on their time-space-activity  
170 specifications. For example, personal monitors for suspended particles (PM) may be  
171 particularly impractical for infants or young children due to the requirement of attached  
172 pumps (Jones et al., 2007).

173 Exposure modelling is the indirect method that assesses (estimates or predicts) personal  
174 exposures derived from ambient measurements (i.e., measurements made in locations  
175 frequented by the study participants) combined with time-activity data, which results in  
176 exposure models (MacIntosh and Spengler, 2000; Monn, 2001; Ott, 1982). Some authors  
177 reviewed the existing exposure models and tried to classify them, by dividing them into  
178 different categories, like Klepeis (2006) and Zou et al. (2009), but the most common  
179 classification is into three major groups, as recently reviewed by Milner et al. (2011): i)  
180 Statistical Regression models (not unanimously considered as models), in which linear  
181 and nonlinear regression techniques are used to relate personal exposure to its  
182 determinants based on measurement data (Kollander, 1991); ii) Computational Fluid  
183 Dynamics (CFD), used to model the spatial and temporal variations in pollutants'  
184 concentrations at an extremely fine scale, working on the basic fluid dynamics principles;  
185 and iii) Microenvironmental (ME) modelling, an approach in which weighted average  
186 exposure is calculated using time spent and time-averaged concentrations at various  
187 places where the population under observation is likely to circulate (Duan, 1981; 1975).  
188 There are also examples where different models can be complementary (Mölder et al.,



189 2010a; Mölter et al., 2010b), increasing the amount of available data for assessing  
190 personal exposure to air pollution, or using both indirect and direct approach to compare  
191 the exposure values estimated by the indirect approach with the real personal sampling  
192 measured values, which can also be done to validate the model.. It is feasible to believe  
193 that the indirect methods of exposure assessment can yield estimates closely matching  
194 those of the direct method (Malhotra et al., 2000). However, CFD is not considered  
195 appropriate for generic population exposure modelling, because it is primarily a research  
196 tool used for ventilation, air flow and contaminants' modelling, rather than individual or  
197 population exposure modelling. In the same way, and despite being frequently used in  
198 epidemiologic studies, regression models have major issues that could be constraints to  
199 their applicability, like their transferability to other locations and to other periods of time,  
200 when compared to a mechanistic approach like ME modelling (Ashmore and  
201 Dimitroulopoulou, 2009). In this field, ME modelling can be used to determine exposures  
202 to both individuals and large populations, because it is not often financially practical to  
203 make a sufficient number of exposure measurements to completely characterize the  
204 spatial and temporal range of exposures in large populations, and to predict what changes  
205 in emissions or activities are most effective to obtain reduced exposure (Weisel, 2002).  
206 Furthermore, it has several advantages, mainly the possibility to be rapidly and  
207 inexpensively used to calculate estimates of exposure over a wide range of exposure  
208 scenarios (Klepeis, 1999), and it is also the most appropriate way to examine the potential  
209 outcomes of future environmental and/or building interventions and policies,  
210 safeguarding the importance to consider indoor exposure modelling (Milner et al., 2011).  
211 However, and according to Klepeis (1999), a main disadvantage of this approach  
212 compared to the direct approach is the currently research need for its systematic  
213 validation, i.e., the results of a fully developed indirect exposure assessment must be  
214 compared to an independent set of directly measured exposure levels. The main  
215 advantages and limitations of the methods and approaches available to assess children's  
216 exposure to air pollution, as well as several examples of studies using them, are  
217 summarized in Table 1.

218

### 219 *1.3. Scope and objectives of this review*

220 Exposure studies on children are usually a great ethics challenge especially for young  
221 children, because they cannot intentionally be exposed to contaminants and according to  
222 Helsinki declaration, they are not old enough to make a decision on their participation.  
223 Using adult surrogates for these studies introduce bias, because adults do not behave like  
224 young children, therefore they cannot mimic their contact activities (Hubal et al., 2000).  
225 This is why it is a challenge to develop a realistic estimation of children's exposures to  
226 air pollution.

227 Despite the several available methods within different approaches to assess human  
228 exposure to air pollution, the ME exposure modelling method seemed to have several  
229 advantages and a great application potential to the assessment of children's exposure to  
230 air pollution. With the time children spend in each location (microenvironment) and time-  
231 averaged pollutant concentrations, it is possible to estimate and quantify the exposure  
232 distribution of study subjects. Additionally, it is viable to examine the likely influence of  
233 each location and other exposure factors (Klepeis, 2006). Since children's time-space-  
234 activity patterns are different from those of adults, the performance of this modelling  
235 approach in estimating personal exposures may differ between these two different types  
236 of population (Wu et al., 2005a). Thus, this review aimed to explore the ME modelling  
237 approach methodology to assess children's exposure to air pollution. To meet this goal,  
238 this work reviewed studies from the last decade on the assessment of children's exposure  
239 to air pollution using this approach, focusing on the methodology, challenges and  
240 limitations, to provide a summary of the available scientific findings concerning study  
241 design and data collection (time-activity patterns information, microenvironments'  
242 selection and pollution measurements), and to some extent look at the outcomes and ME  
243 model type.

244

## 245 **2. Methodology of this review**

246 The present review refers to articles published from 2002 to date in the following on-line  
247 databases: *Science Direct*, *Scopus*, *PubMed* and *Google Scholar*. Although no restrictive  
248 criterion was established to limit the language in which the articles were published, all  
249 the citations refer to documents published in English. The search considered only fully  
250 published and in press articles.

251 This review was elaborated to report original research and review studies on the  
252 assessment of exposure in several microenvironments, with children as the main  
253 population study and/or as one of the study sub-groups, and focusing on those using ME  
254 modelling approach to assess children's exposure to air pollution. Thus, the main  
255 keywords used for the search were: "children's exposure", "air pollution", "assessment",  
256 "microenvironment", and "modelling". A total of 152 articles were identified and titles  
257 and abstracts were scanned for relevance. Detailed exposure measurement or estimation  
258 methodologies and models on different approaches are beyond the scope of this review,  
259 and can be found reviewed in other papers (Baxter et al., 2013; Klepeis, 2006; Milner et  
260 al., 2011; Moschandreas et al., 2002; Steinle et al., 2013). The type of article, i.e. being  
261 an original, review, letter or other type, was not used as inclusion or exclusion criteria  
262 due to the limited number of articles that addressed this topic.

263 Exclusions were performed, namely regarding those studies that: i) did not consider  
264 children as the population study or as one of the population sub-groups; ii) studies that  
265 did not used ME modelling approach to assess exposure to air pollution; iii) only  
266 considered a unique microenvironment; and iv) merely focused on the conceptual  
267 framework or only on one of the ME modelling aspects.

268 Studies that relied on both indirect and direct methods for their exposure assessments  
269 were also included. After exclusions, the search performed retrieved 26 articles  
270 containing studies on the assessment of children's exposure to air pollution using a ME  
271 modelling approach.

272

### 273 **3. Results**

#### 274 ***3.1. Conceptual framework***

275 In daily life, people move around and thus are exposed to various levels of pollutants in  
276 various locations. The earlier researchers Fugas (1975), Duan (1981, 1982), and Ott  
277 (1982) introduced the concept of calculating exposure as the sum of the product of time  
278 spent by a person in different microenvironments and the time-averaged air pollution  
279 concentrations occurring in those microenvironments. Equation (1) represents the  
280 standard mathematical formula for integrated exposure.

$$E_i = \sum_{j=1}^m C_{ij} t_{ij} \quad (1)$$

281  $E_i$  is the exposure of the  $i$ th individual,  $C_{ij}$  is the concentration of the pollutant measured  
282 in the  $j$ th microenvironment of the  $i$ th individual,  $t_{ij}$  is the time spent by the  $i$ th individual  
283 in the  $j$ th microenvironment, and  $m$  is the number of different microenvironments, such  
284 that the Equation 2 is satisfied:

$$\sum_{j=1}^m t_{ij} = 24h \quad (2)$$

285 In a review, Milner et al. (2011) distinguished the following types of ME models: i)  
286 measurement-based ME models, based on observational (measured) data, usually long-  
287 term averages, whether from air quality monitoring stations or local outdoor or indoor  
288 measurements; ii) mass-balance ME models, which model the movement of air pollution  
289 throughout a system of one or two ME compartments and from outdoors based on  
290 principles of mass conservation; iii) multizone ME models, based on the same principles  
291 as mass-balance ME models, although in this case a larger number of microenvironments  
292 are modelled, with exceptionally detailed input data requirements; and iv) sub-zonal ME  
293 models, similar to multizone but additional sub-zones are considered to capture within-  
294 room gradients, being useful for buildings/rooms which may have high gradients of  
295 concentration.

296 By using a ME exposure model, the researcher in each case can quantify the exposure  
297 distribution of study subjects and examine the likely influence of each location and other  
298 exposure factors (Klepeis, 2006). When the required input data are available or can be  
299 reliably estimated, the target population exposure distributions can be predicted  
300 accurately enough for the most practical purposes using a ME modelling approach  
301 (Hänninen et al., 2003).

302 Time-activity patterns are an important determinant of personal exposure to air pollution  
303 and crucial in ME modelling exposure, not only because of the time spent on those  
304 microenvironments but also because: i) personal exposure to environmental toxics is  
305 largely dependent on the movement across locations or microenvironments; and ii) of the  
306 different contributions of microenvironments on specific population groups (Dons et al.,  
307 2011). Therefore, time spent in different microenvironments makes a significant  
308 contribution to the total exposure. Regarding children, differences in their behaviour,  
309 particularly the way in which children interact with their environment, may have a

310 profound effect on the magnitude of exposures to contaminants. In fact, the manner in  
311 which children, and in special infants and toddlers, move is significantly different from  
312 the manner in which adults move and can significantly impact their exposure to  
313 contaminants in the air (Hubal et al., 2000). Plus, socio-demographic and environmental  
314 factors define time-activity patterns and also define quantifiable differences in personal  
315 exposures to different sources and individual compounds (Edwards et al., 2006). These  
316 and other determinants of time-microenvironmental-activity patterns need to be taken into  
317 account in exposure assessment, epidemiological analyses, and exposure simulations, as  
318 well as in the development of preventive strategies that focus on time-microenvironment-  
319 activity patterns that ultimately determine exposures (Schweizer et al., 2007).

320 The main characteristics of the ME modelling approach to assess children's exposure to  
321 air pollution in the 26 reviewed studies are listed in: i) Table 2, regarding study design  
322 and outcomes, namely location, study population, calendar time, pollutants analysed,  
323 purpose and type of study; and ii) Table 3, regarding data collection, namely time-activity  
324 patterns (including methods of collection, record time and key elements included), and  
325 pollution measurements (including microenvironments, methods of collection and  
326 duration and time resolution).

327

### 328 ***3.2. Study design and outcomes***

329 Any exposure research should start by planning the design: purpose and objective, study  
330 population, pollutants analysed, temporal and spatial resolution, type of study as well as  
331 outcomes. It is possible to observe from Table 2 that eleven of the reviewed studies were  
332 performed in the USA, but there were also studies performed in Europe, Australia, Latin  
333 America, India and Asia.

334 The majority of the selected studies had the assessment of children's exposure to air  
335 pollution as main purpose, and in some cases relating it with adverse health effects. Some  
336 of those studies also aimed to compare children's exposure between different areas of the  
337 same city or region like urban vs. suburban; influence from streets with different degrees  
338 of traffic intensity, or between cities from different countries (Ballesta et al., 2006;  
339 Shimada and Matsuoka, 2011; Mestl et al., 2006; Van Roosbroeck et al., 2007; Van  
340 Roosbroeck et al., 2006).

341 In the majority of the reviewed studies the calendar time was described, although in some  
342 it was not reported (Harrison et al., 2002; Rojas-Bracho et al., 2002; Shimada and  
343 Matsuoka, 2011; Mestl et al., 2006; Van Roosbroeck et al., 2007; Wu et al., 2005b; Zhang  
344 and Batterman, 2009). The reviewed studies were published since 2002 and in some cases  
345 there was a gap between the period when the study took part and its publication date, as  
346 for example in Crist et al. (2008) where this gap was more than 8 years.

347 The overwhelming majority of the reviewed studies were cross-sectional, and only 3 were  
348 longitudinal: i) a cohort study where children's exposure was estimated and health  
349 outcomes were evaluated every year from age one until the age three (Ryan et al., 2008);  
350 ii) a panel study involving repeated measurements of outcomes and exposures in  
351 individuals (Wu et al., 2005a); and iii) a panel study conducted in several different  
352 monitoring sessions in each one of the two consecutive years (Liu et al., 2003).

353 The reviewed studies considered children from birth (Hänninen et al., 2009; Ryan et al.,  
354 2008; Shimada and Matsuoka, 2011; Mestl et al., 2006; Wang et al., 2008), to  
355 schoolchildren with ages comprised between 5 and 14 years old (Briggs et al., 2003;  
356 Mölter et al., 2012; Zhao et al., 2007), although, in some of them children were a subgroup  
357 of the entire study population (Ballesta et al., 2006; Briggs et al., 2003; Chau et al., 2002;  
358 Harrison et al., 2002; Liu et al., 2003; Shimada and Matsuoka, 2011; Mestl et al., 2006;  
359 Wheeler et al., 2011; Zhang and Batterman, 2009). In the latter studies, a stratified  
360 sampling was used, despite the study population selection was normally done by a  
361 probability sample – children were normally selected on a school-based strategy, thus  
362 recruited from schools. Nevertheless, Wu et al. (2005b), Adgate et al. (2004b) and  
363 Saksena et al. (2003) recruited children based on a probability sample of households, and  
364 Wheeler et al. (2011) recruited study participants from a previous study. In the particular  
365 cases of Liu et al. (2003) and Yip et al. (2004), only children aged 7-11 with known or  
366 probable asthma were selected from the general population, thus not using a probability  
367 sampling.

368 Exposures to a wide spectrum of environmental pollutants were considered for  
369 investigation in the studies selected, including air pollutants of indoor and outdoor origin,  
370 gaseous compounds and/or particles. Nevertheless, in all studies reviewed and presented  
371 in Table 2, the pollutants analysed were mainly combustion-related, with the exceptions  
372 of ozone in Lee et al. (2004), and radon in Briggs et al. (2003). Additionally, no examples

373 were found of the application of ME modelling approach to study children's exposure to  
374 biological compounds, like aeropathogens, moulds and allergens.

375 Regarding the outcomes which are deeply related with the purpose and objectives of the  
376 study, the reviewed studies were mostly in the field of the characterization of children's  
377 personal exposures and their relation with outdoor and indoor concentrations (Table 2).  
378 A common conclusion in the reviewed studies was the significant importance of air  
379 quality in indoor microenvironments to children's exposure to air pollution.

380

### 381 **3.3. Data collection**

#### 382 *3.3.1. Time-activity patterns information*

383 The reviewed studies mainly used a time-activity diary as method for collecting time-  
384 activity patterns (Table 3). A questionnaire or information from previous studies or  
385 existing databases were also used in some cases (Shimada and Matsuoka, 2011; Mestl et  
386 al., 2006; Zhang and Batterman, 2009) to collect time-activity patterns information. Crist  
387 et al. (2008) and Zhao et al. (2007) did not report the methods of collection used. Chau et  
388 al. (2002) and Lee et al. (2004) used diaries and questionnaires done by telephone surveys  
389 to the parents. To support survey's information in a study from Italy (Hänninen et al.,  
390 2009), time-activity patterns information was also derived from school administration and  
391 using typical daily timetables of schoolchildren. In the study of Wu et al. (2005a)  
392 participants used an electronic time-activity diary.

393 Time-activity patterns information were usually recorded in a daily basis (24-h  
394 recordings), although Ryan et al. (2008) reported one complete year (12 months) and  
395 Chau et al. (2002) and Wang et al. (2008) a 7-day period. On the other hand, a shorter  
396 period was also found in Lee et al. (2004), with a specific period of the day (from 8:00  
397 a.m. to 9:00 p.m.). The most common time-interval found was 15-min, but different time-  
398 intervals were also found. Wheeler et al. (2011) and Briggs et al. (2003) used 30-min  
399 intervals to record time-activity patterns information for children.

400 Additional information on microenvironments' characteristics (Lazenby et al., 2012;  
401 Mölter et al., 2012), possible indoor sources (Liu et al., 2003; Van Roosbroeck et al.,  
402 2007; Van Roosbroeck et al., 2006), data on exposure to tobacco smoke and other

403 potential modifiers (Adgate et al., 2004a; Adgate et al., 2004b; Rojas-Bracho et al., 2002;  
404 Wheeler et al., 2011), basic socio-demographic and/or socioeconomic data (Chau et al.,  
405 2002; Zhang and Batterman, 2009), and health information (Ryan et al., 2008) were also  
406 often collected.

407

### 408 *3.3.2. Pollution measurements*

409 All the reviewed studies chose the specific microenvironments for pollution  
410 measurements according to the time-activity information collected (Table 3). They  
411 considered mostly both outdoor and indoor (home and school) microenvironments,  
412 although some studies also considered in traffic (Adgate et al., 2004b; Hänninen et al.,  
413 2009; Mölter et al., 2012; Rojas-Bracho et al., 2002; Wang et al., 2008; Wheeler et al.,  
414 2011; Wu et al., 2005a; Wu et al., 2005b; Zhang and Batterman, 2009). Crist et al. (2008),  
415 Zhao et al. (2007), Van Roosbroeck et al. (2007) and Lee et al. (2004) had only school  
416 indoor and outdoor as the unique studied microenvironments, and Briggs et al. (2003) did  
417 the same but for home. Mölter et al. (2012), Shimada and Matsuoka (2011), and Wang et  
418 al. (2008) went further in the analysis and divided home indoors into different  
419 microenvironments, like kitchen, living room and children's bedroom. Also Crist et al.  
420 (2008) and Adgate et al. (2004a) have considered different microenvironments in school  
421 indoors (different classrooms). Chau et al. (2002) and Harrison et al. (2002) sub-divided  
422 the main microenvironments according to time-activity patterns information collected.  
423 Ryan et al. (2008) considered home and non-home (including daycare, babysitter,  
424 relative's home and other locations). Chau et al. (2002) considered a higher number of  
425 microenvironments (20), but grouped them into indoor at home, indoor away from home,  
426 enclosed traffic and outdoor. Some regular activities were also considered as  
427 microenvironments in some cases, as the example of cooking and sleeping sessions  
428 (Saksena et al., 2003) and leisure activities (Harrison et al., 2002).

429 Data availability and its quality for model input are critically important, so distinct  
430 methods of collection were found in the 26 reviewed studies (Table 3), mainly depending  
431 on the microenvironments analysed. Outdoor concentrations were often obtained through  
432 continuous measurements from the nearest urban monitoring air quality station (Hänninen  
433 et al., 2009; Mölter et al., 2012; Wang et al., 2008; Wu et al., 2005a), or with the support  
434 of dispersion models (Ryan et al., 2008; Mestl et al., 2006; Wu et al., 2005b). In some



435 studies, indoor concentrations were obtained from continuous measurements in the indoor  
436 microenvironments (Adgate et al., 2004a; Briggs et al., 2003; Harrison et al., 2002;  
437 Wheeler et al., 2011). In other cases, personal individual monitoring was performed in  
438 indoor microenvironments instead of indoor ME measurements (Van Roosbroeck et al.,  
439 2007; Van Roosbroeck et al., 2006). Indoor concentrations were also estimated i) through  
440 the use of modelling, mainly mass-balance or infiltration models (Hänninen et al., 2009;  
441 Wu et al., 2005b); or ii) from the fuel consumption and room characteristics (Shimada  
442 and Matsuoka, 2011); or iii) estimated based on data from databases or previous studies  
443 in the literature (Chau et al., 2002; Mestl et al., 2006; Zhang and Batterman, 2009).  
444 Passive or diffusive sampling was also found as a method to collect pollution  
445 measurements in the reviewed studies, mainly to obtain indoor ME concentrations  
446 (Adgate et al., 2004b; Ballesta et al., 2006; Lazenby et al., 2012; Rojas-Bracho et al.,  
447 2002). Lazenby et al. (2012), Mölter et al. (2012), Van Roosbroeck et al. (2006) and Wu  
448 et al. (2005b) also collected general meteorological data. A different method to measure  
449 the pollutants concentrations was performed by Lee et al. (2004), in which each  
450 participating child and family had a set of personal (wearable) / indoor / outdoor passive  
451 O<sub>3</sub> samplers. Other cases exist in which a personal individual sampler was also used,  
452 particularly to compare with the ME concentrations measured indoor and/or outdoor  
453 (Crist et al., 2008; Liu et al., 2003; Mölter et al., 2012; Yip et al., 2004). In fact, Mölter  
454 et al. (2012) proposed a simple validation process in their ME model, by comparing the  
455 modelled with the measured personal exposure results, which allowed to understand if,  
456 by using a ME exposure modelling approach, the modelled values estimated the  
457 children's personal exposure to air pollution with efficiency. Besides pollutants'  
458 concentrations, the ME model proposed by Adgate et al. (2004a) also included singular  
459 characteristics of the microenvironments as covariates, like for example the "design"  
460 (season, English or non-English-speaking home, race/ethnicity, and level of education),  
461 source variables (e.g., presence of a smoker in household), and ventilation.

462 The duration and time resolution of pollution measurements were found to be variable  
463 within the reviewed studies (Table 3). In fact, it varied from periods of 24 and/or 48 hours  
464 of measurements (Crist et al., 2008; Lazenby et al., 2012; Rojas-Bracho et al., 2002;  
465 Saxena et al., 2003; Van Roosbroeck et al., 2007; Wang et al., 2008; Zhao et al., 2007)  
466 to periods of several weeks (Briggs et al., 2003; Lee et al., 2004; Wheeler et al., 2011) or  
467 even an entire school year of measurements (Hänninen et al., 2009). In some cases,

468 different measurement periods or campaigns were considered (Ballesta et al., 2006; Liu  
469 et al., 2003; Van Roosbroeck et al., 2006), and in some of them measurement campaigns  
470 were made in different seasons to study seasonal variability (Adgate et al., 2004a; Mölter  
471 et al., 2012; Wheeler et al., 2011; Yip et al., 2004).

472

#### 473 **4. Discussion**

474 There is no universal methodology to use a ME modelling approach to assess children's  
475 exposure to air pollution. In addition, there is evidence that usually a methodology  
476 developed for a certain exposure study is very specific for that particular purpose,  
477 objectives, and mainly for that study group or population, and for that spatial and temporal  
478 context. This makes the studies' methodology harder to extrapolate to other contexts, and  
479 consequently makes the studies' comparison tricky. Unfortunately, most of the studies in  
480 the literature are focused on adult subjects. Since children's time-space-activity patterns  
481 are different from those of adults, the performance of this modelling approach in  
482 estimating personal exposures may differ between these two different types of population  
483 (Wu et al., 2005a). Nevertheless, 26 studies were reviewed using a ME modelling  
484 approach to assess children's exposure to air pollution, from different countries, which  
485 enhances the possibility of a worldwide application of this approach.

486 In the majority of the studies reviewed, children were selected through a probability  
487 sample, and in some cases a stratified sampling was also used. This does not imply any  
488 escape from probability selection but a better precision, because it ensures that subgroups  
489 of the population will be included in the sample to maximize the accuracy of the study  
490 (Kollander, 1991). One potentially successful design strategy is to maximize the number  
491 of contrasting pollution profiles among study subjects by using a quasi-factorial approach  
492 to select populations distributed over geographic regions with different pollution profiles  
493 (Gauderman et al., 2000). However, steps such as identifying, contacting, recruiting, and  
494 monitoring a children population are difficult, especially in economically disadvantaged  
495 areas. A school-based strategy (Sexton et al., 2000) is relevant to select the study  
496 population to assess air exposures of schoolchildren and related health effects, but it is  
497 also important to improve the understanding of other factors (e.g. cultural, economic,  
498 psychological, social) affecting the willingness of families/children to participate in such  
499 studies.

500 Although the majority of the reviewed studies were cross-sectional, thus involving  
501 measurements at one specific point in time, ME modelling approach to assess children's  
502 exposure to air pollution was also reported in longitudinal (panel and cohort) studies. As  
503 far as known, the ME modelling approach was not used to study children's exposure to  
504 other compounds than combustion-related, ozone and radon, like for example biological  
505 compounds (aeropathogens, moulds and allergens) which have been proven to have  
506 negative effects on children's health, namely associated with respiratory symptoms,  
507 allergies, asthma and immunological reactions (Spengler and Sexton, 1983; WHO, 2009).  
508 However, nothing seemed to indicate the impossibility of its applicability to study  
509 exposures to that kind of pollutants. Although outcomes from the studies reviewed were  
510 mainly focusing on the characterization of children's personal exposures, other outcomes,  
511 like health ones were also reported.

512 There are several methods to obtain reliable data on time-activity patterns to use in a study  
513 on children's exposure assessment through a ME modelling approach, such as the recent  
514 geopositioning (GPS), accelerometer and photodiary methods. However, the main three  
515 methods found in the reviewed studies were time-activity diaries, questionnaires and  
516 surveys. In fact, the standard research tool is still the structured, self-reported and  
517 longitudinal diary (Decastro et al., 2007). Obtaining these diary data usually represents  
518 considerable effort in an exposure assessment study, due to the development of the diary  
519 structure, checks on subjects' reporting compliance and clarification of subjects' diary  
520 entries. Nowadays, new versions are being developed and used also on children's  
521 exposure studies like electronic time-activity diaries (Wu et al., 2005a). Another example  
522 is a broad time-activity patterns database, such as that of the National Human Activity  
523 Pattern Survey (NHAPS) in the United States, which is a 2-year probability-based  
524 telephone survey of exposure-related human activities, that has a primary purpose to  
525 provide comprehensive and current exposure information over broad geographical and  
526 temporal scales, particularly to use in probabilistic population exposure models (Klepeis  
527 et al., 2001). Questionnaires are also important tools as they are low cost and can be used  
528 to identify and quantify contacts with potential sources which is especially important to  
529 identify indoor sources that do not reflect the same mixtures than outdoor sources (Monn,  
530 2001). Questionnaires can also provide other important information, like children's health  
531 symptoms, household characteristics and presence of environmental tobacco smoke. It is  
532 easily understandable that in the case of infants, toddlers and children, questionnaires

533 should be filled by parents/guardians or with their support. Although seldom used on  
534 children studies, diaries and questionnaires can also be done as telephone surveys to the  
535 parents, as in the cases of Chau et al. (2002) and Lee et al. (2004), because in those cases  
536 they were found less expensive than paper ones. Freeman and Saenz de Tejada (2002)  
537 also reported direct observation and videography as useful methods to obtain time-  
538 activity information about small children. Daily basis time-activity patterns recordings  
539 were usual, but longer and shorter periods were also found, although rare. The longer the  
540 periods considered, the more reliable the information is. Although several time-intervals  
541 were used, 15-min intervals were the most common to record time-activity patterns  
542 information. However, to obtain children's time-activity patterns data longer periods (30-  
543 min) were also used, due to their lower mobility along the day when comparing to adults.

544 Time-activity patterns information allows identifying the optimum number of  
545 microenvironments that should be monitored. This is a crucial step to assess children's  
546 exposure to air pollution using a ME modelling approach. The most common  
547 microenvironments considered are merely reduced to outdoor and indoor (home and  
548 school). Children spend most of their time indoors and consequently, according to  
549 Ashmore and Dimitroulopoulou (2009), their personal exposure is dominated by air  
550 pollution in three microenvironments: home, school and transport. However, other  
551 authors considered multiple microenvironments in each one of these. In fact, home  
552 microenvironment is one of the major important contributors to children's personal  
553 exposure to air pollution. Sometimes it is possible to distinguish different patterns in the  
554 house characteristics in specific areas (e.g., inner-city, suburban), and relate it to  
555 predisposition to cause a particular health effect (Simons et al., 2007). A study in  
556 Bangladesh, from the World Bank (Dasgupta et al., 2006), suggested that young  
557 children's exposures vary considerably with households' conditions, which depends on  
558 the incoming and education of the families. For instance, indoor O<sub>3</sub> concentrations were  
559 associated with influences from the outdoor air and several housing characteristics (i.e.,  
560 central air conditioning, fan use, and window opening) (Lee et al., 2004). Due to  
561 differences in exposures inside homes, particular microenvironments were usually  
562 considered to refine the study, as the example of kitchen, bedrooms, living rooms, garage,  
563 and home outdoor. Zipprich et al. (2002) found that close to 70% of the variation in adults  
564 and children's personal exposure to NO<sub>2</sub> and NO<sub>x</sub> was due to exposure in the bedroom  
565 and other indoor locations, especially the kitchen. Also bedroom concentrations were

566 found to explain 90% of the variation of the personal exposure to formaldehyde  
567 (Gustafson et al., 2005). Although not necessarily considered as microenvironments,  
568 there are some aspects related to home that significantly influence children's exposure to  
569 air pollution in this microenvironment, and should be taken into account, otherwise results  
570 could be deceivers. Tobacco smoking, gas-stove usage, outdoor temperature and wind  
571 speed, as well as the presence of wooden material, heating, and location in a suburb area,  
572 are determinants of indoor air quality in homes, and consequently influence exposures  
573 (Lai et al., 2006). Exposure in nurseries and schools, including children day care centres,  
574 has been somehow ignored, despite the fact that is a major contributor for children  
575 exposure to indoor air pollutants (Ashmore and Dimitroulopoulou, 2009), because  
576 children usually spend large amounts of time in there. A study from the United States  
577 Environmental Protection Agency (Ligman et al., 1999) concluded that particulate matter  
578 concentrations were higher in schools than in office buildings, as it was also higher  
579 indoors than outdoors (Stranger et al., 2008), although outdoor influence cannot be  
580 neglected. Inside the school, sometimes it is important to consider distinct  
581 microenvironments (e.g., kitchen, playground, different classrooms, and teacher's  
582 lounge), as stated by Mejía et al. (2011) in a recent review, in which the methodologies  
583 employed to assess the exposure of children to air pollutants at school were explored,  
584 namely how these methodologies influenced the assessment of the impact of this exposure  
585 on children's health, in particular related with traffic emissions. Outdoor environment is  
586 usually considered as a whole microenvironment. However, several differences were  
587 reported when assessing children's exposure to outdoor air in the school than in transit,  
588 for example. Thus, some studies divided the outdoor environment into several  
589 microenvironments, for example school outdoor, home outdoor and, the most common  
590 and important, in transit. Exposure in transit was also often ignored as an important  
591 contributor to children exposure to air pollution (Janssen et al., 2001). Although low when  
592 compared to the time spent in other microenvironments like home or school, children tend  
593 to spend some time commuting from home to school and vice-versa, by car, by bus, by  
594 bike or walking, and it is expected to have a significant influence to their exposure to air  
595 pollution, especially concerning combustion-related pollutants (Janssen et al., 2001; Van  
596 Roosbroeck et al., 2006). This was also stated by some studies that specifically showed  
597 influence of bus-commuting on children's exposure to air pollution, in particular to  
598 traffic-related air pollutants (Behrentz et al., 2005; Sabin et al., 2005).

599 After choosing the microenvironments for the study, it is necessary to obtain data from  
600 the pollutants' concentrations in those microenvironments. Data availability and its  
601 quality for model input are critically important. These data can be obtained by  
602 measurements in-situ (fixed or personal samplers) or by predictive models, and both cases  
603 were found in the reviewed studies. Predictive models included mass-balance or  
604 infiltration models, modelling from the fuel consumption and room characteristics. To  
605 estimate concentrations based on data from databases or previous studies in the literature  
606 was also found in the reviewed studies. ME monitoring is a special case of environmental  
607 monitoring in which the location where measurements are made is considered to be  
608 homogenous with respect to concentrations of the targeted pollutants over the averaging  
609 time of interest, and it should be consistent with the microenvironments considered to  
610 study. As a different example from the reviewed studies, Diapouli et al. (2007) developed  
611 experimental procedures to measure ultrafine particles' concentrations in different  
612 microenvironments (school, home and in-traffic), including: i) continuous monitoring  
613 outdoor and indoor schools (in different rooms) during school hours; ii) 24-hour indoor  
614 measurements in residences (in a bedroom, at breathing height); and iii) a counter placed  
615 on a co-driver's seat of a private car moving along selected routes. In the absence of data,  
616 indoor concentrations can be obtained by some existing predictive models as a function  
617 of ambient concentrations, effective penetration rates and contribution of indoor sources,  
618 as also exemplified by Chaloulakou and Mavroidis (2002) who predicted indoor air  
619 concentrations of CO at a public school, or by Kruize et al. (2003) in a Dutch population  
620 study (including children as a subpopulation group). Sensitivity analyses can be  
621 performed to determine the most significant factors of exposure. Furthermore, if the  
622 measurements are not conducted in collaboration with concurrent health studies, it could  
623 result in a low participant rate. The duration and time resolution of pollution  
624 measurements can vary from short to long periods and from single to multiple  
625 measurements' periods or campaigns. Multiple periods or campaigns seem to be useful  
626 to study seasonal variability of exposure (mainly in longitudinal studies). In fact, some  
627 authors found that personal exposure was significantly different by season, like Lee et al.  
628 (2013) found for NO<sub>2</sub>.

629 Considering the ME modelling classification proposed by Milner et al. (2011),  
630 measurement-based was the ME model type found in almost all of the 26 reviewed  
631 studies, with exception of Hänninen et al. (2009), Shimada and Matsuoka (2011), and Wu

632 et al. (2005b) which were found to be mass-balance ME models. Thus, the ME modelling  
633 approach in exposure assessment studies has several advantages for it takes into account  
634 the varying levels of pollution to which an individual is exposed during the course of the  
635 day (Malhotra et al., 2000). The key advantage of these models is that they are relatively  
636 straightforward to apply and produce results which may be easily compared with  
637 exposure observations (Milner et al., 2011). However, there are problems with both the  
638 limited temporal and spatial resolutions of these techniques. Nerriere et al. (2005)  
639 identified some of the main sources of error when applying a ME approach to assess  
640 children's exposure: i) method of recall, because frequently the data collected is based on  
641 the ability of the respondents to recall; ii) ability of respondent, for example sometimes  
642 the study can be hindered by the low literacy level of the study subjects; iii) nature of  
643 study, in itself contributes to a source of error, because it is difficult for any respondent,  
644 irrespective of the intellectual ability or memory, to account for every half an hour or  
645 even an hour in the daily schedule; and iv) difference between ideal and real situations,  
646 because in real social situations it is not possible to manipulate all the variables.

647 As reviewed by Milner et al. (2011), there are uncertainties associated with the application  
648 of exposure models, mostly due to the lack of detailed time-activity information or due  
649 to the assumptions and simplifications that are usually necessary along the assessment  
650 process. Thus, according to the same review, it is crucial for studies with exposure models  
651 to have a validation process. Sometimes this can be performed comparing ME  
652 concentrations of pollutants with direct personal exposure measurements in the entire or  
653 in a selected small group of the study population, so as to examine variations in results  
654 (Moschandreas and Saksena, 2002). In fact, only 5 of the 26 reviewed studies have not  
655 done any kind of validation process (Briggs et al., 2003; Saksena et al., 2003; Wang et  
656 al., 2008; Wu et al., 2005b).

657 Besides being a powerful tool to assess children exposure to air pollution, ME models  
658 can also have a potential opportunity to extrapolate data to an entire children population.  
659 Although not specific for children exposure assessment, there are examples of some  
660 models that were developed with the ability to predict personal exposure. Those models  
661 rely on the characterization of activity patterns of the population at risk as human  
662 activities impact the timing, location and level of personal pollutant's exposure, which is  
663 especially important for the evaluation of public policies and urban planning that may

664 change the behaviour of individuals, resulting in a concurrent shift in the patterns of  
665 exposure experienced by the population (Schweizer et al., 2007).

666

## 667 **5. Conclusions**

668 From all the different available approaches and methods for determining exposure, the  
669 ME modelling approach (indirect approach) seemed to be the best to assess children's  
670 exposure to air pollution as it is faster and less expensive, and takes into consideration  
671 several levels of pollution to which a child is exposed during the course of the day. By  
672 considering the pollutants' concentrations in different locations attended by the study  
673 participants (microenvironments), and the time they spend in those locations (time-  
674 activity patterns information), it is possible to determine the children's exposure to air  
675 pollution, both in individuals and/or extend it to populations' groups.

676 There are a limited number of children's exposure assessment studies using the ME  
677 modelling approach. Since 2002, it was only possible to find and review 26 studies.  
678 Almost half of them were performed in the USA, but there were studies also performed  
679 in Europe, Australia, Latin America, India and Asia, which confirms the possibility of a  
680 worldwide application of the ME modelling approach to assess children's exposure to air  
681 pollution. Although the majority of the reviewed studies were cross-sectional, thus  
682 involving measurements at one specific point in time, ME modelling approach to assess  
683 children's exposure to air pollution was also found in longitudinal (panel and cohort)  
684 studies, which enhances the applicability of this approach to that kind of studies.

685 Those studies usually aimed to determine or characterize children's exposure to air  
686 pollution, but other outcomes were also reported. The methodology looks similar when  
687 using this approach on children or on adults' studies, however children's singularities  
688 lead to considerable differences in the application of this approach, like those related to  
689 the data collection: i) the methods for collecting time-activities patterns must be different;  
690 and ii) the time-activity patterns are itself different, which leads to choose different  
691 microenvironments to pollutants' concentrations data collection. In fact, to gather  
692 information on time-activity patterns, the most used methods were questionnaires and  
693 diaries, although different methods were also found to be feasible for children studies.  
694 Time-activity information led to the choice of the study microenvironments. The main



695 microenvironments used were home and school (indoors and outdoors) and in traffic.  
696 Some of the studies reviewed divided home and/or school in different sub-  
697 microenvironments as kitchen, bedroom and different classrooms, but others can be  
698 considered. Data on pollutants' concentrations can be obtained by in-situ measurements  
699 (fixed or personal samplers) or by predictive models, respectively measurement-based  
700 and mass-balance models, and both cases were found in the reviewed studies. Some  
701 studies also reported this type of data estimated from databases or in the literature.

702 The use of the ME modelling approach in studies to assess children's exposure to air  
703 pollution is highly encouraged, as it has several advantages for it takes into account the  
704 varying levels of pollution to which an individual is exposed during the course of the day,  
705 being relatively straight forward to apply and produce results which may be easily  
706 compared with exposure observations. However, there are uncertainties associated with  
707 the application of this approach, mostly due to the lack of detailed time-activity  
708 information (particularly difficult in children studies), or due to the assumptions and  
709 simplifications that are usually necessary along the assessment process (existing in  
710 children's studies). Thus, a validation process is needed, which can be performed by  
711 comparing ME concentrations of pollutants with direct personal exposure measurements  
712 in the entire or in a selected small group of the study population.

713

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1001 **Table 1 – Methods and approaches to assess children’s exposure to air pollution: main advantages and limitations, and examples of children’s studies.**

Approach and method		Main advantages	Main limitations	Examples
Direct	Personal monitoring	<ul style="list-style-type: none"> <li>- Simplicity of design</li> <li>- Freedom from modelling assumptions</li> </ul>	<ul style="list-style-type: none"> <li>- Expensive and time-consuming</li> <li>- Limited for large population studies (e.g. cohort/panel studies) and for young children</li> </ul>	Gonzalez-Flesca et al. (2007); Thiriart et al. (2009); Buonanno et al. (2013); Both et al. (2013)
	Biomonitoring	<ul style="list-style-type: none"> <li>- Useful measure of direct exposure</li> <li>- Aggregate over all sources and pathways</li> </ul>	<ul style="list-style-type: none"> <li>- Expensive and time-consuming</li> <li>- Complex methodologies</li> <li>- Hard to collect all of the info required to accurately estimate exposure</li> </ul>	Delfino et al. (2006); Neri et al. (2006a); Neri et al. (2006b); Ruchirawat et al. (2007)
Indirect	Statistical regression models	<ul style="list-style-type: none"> <li>- Frequently used in epidemiologic studies</li> </ul>	<ul style="list-style-type: none"> <li>- Limited to extrapolate to other locations and to other periods of time</li> </ul>	Gauvin et al. (2002); Chaloulakou and Mavroidis (2002); Delfino et al. (2004); Zhou and Zhao (2012)
	CFD <sup>a</sup>	<ul style="list-style-type: none"> <li>- Enables modelling at an extremely fine scale</li> <li>- Good as a research tool for ventilation, air flow and contaminants modelling</li> </ul>	<ul style="list-style-type: none"> <li>- Not considered appropriate for generic population exposure modelling</li> <li>- High technical and very specific knowledge and software are required</li> </ul>	Huang et al. (2004); Valente et al. (2012)
	ME <sup>b</sup> modelling	<ul style="list-style-type: none"> <li>- Conceptually easy to apply</li> <li>- Can be used to determine exposure to both individuals and large populations</li> <li>- Rapidly and inexpensively calculates exposures over various scenarios</li> <li>- The best way to predict the potential outcomes of future interventions and policies to reduce exposure</li> </ul>	<ul style="list-style-type: none"> <li>- There is a research need for its systematic validation</li> </ul>	Mölter et al. (2012); Wang et al. (2008); Ballesta et al. (2006); Briggs et al. (2003)

1002 <sup>a</sup>CFD – Computer Fluid Dynamics; <sup>b</sup>ME - Microenvironmental

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1005 **Table 2 – Summary of the study design characteristics and outcomes of the reviewed studies using ME modelling approach to assess children’s exposure to air pollution since 2002.**

Reference	Study design						Outcomes
	Location	Study population	Calendar time	Pollutants analysed	Purpose	Type of study	
Lazenby et al. (2012)	2 suburbs of Perth, Western Australia	41 children aged 9-12 years	November 2006 to August 2007	Formaldehyde	To investigate seasonal variations in exposure.	Cross-sectional	Only a little variation detected between the seasonal monitoring periods, slightly higher in winter samples.
Möller et al., (2012)	Secondary school in Greater Manchester, England	Children aged 12-13 years	30 <sup>th</sup> April 2008 until 23 <sup>rd</sup> January 2009	NO <sub>2</sub>	To develop a new ME exposure model.	Cross-sectional	A ME model provides better exposure estimates than the nearest urban monitor or an outdoor pollution model.
Shimada and Matsouka (2011)	16 Asian countries	Population divided into sub-groups by age, of which children (0, 1-4 and 5-14) were considered	NR <sup>a</sup>	PM <sub>2.5</sub>	To estimate exposure concentrations emitted through the consumption of fuel inside residences in individual countries in Asia, in order to assess associated health risks.	Cross-sectional	Individual exposure was greatly affected by people’s use of time indoors. In each studied country, PM <sub>2.5</sub> exposure was higher for children and unemployed women aged 35-64.
Wheeler et al. (2011)	Windsor, Ontario, Canada	48 adults + 47 asthmatic children	2005 to 2006	Ultrafine particles (UFP), black carbon (BC) and PM <sub>2.5</sub>	To examine the relationships between indoor and outdoor concentrations and personal exposures.	Cross-sectional	Mean outdoor concentrations were significantly higher than either indoor or personal ones. This exposure modelling estimation method performs well during different seasons when activity patterns and aerosols can vary.
Hänninen et al. (2009)	Turin and Bologna, Italy	333 school children (6-10 years) from Bologna + 101,563 children (0-14 years) from Turin	1 <sup>st</sup> June 2004 to 31 <sup>st</sup> May 2005 in Bologna and 14 <sup>th</sup> January 2003 in Turin	PM <sub>10</sub>	To present a ME and time-activity-based approach for exposure model to provide quantitative health-based tools for air quality-related policy refinement and evaluation.	Cross-sectional	Majority of the children were exposed to levels of health concerns in the case of an episode. Especially highest exposures experienced while in traffic may affect children spending substantial periods of time in or close to traffic environments.
Zhang and Batterman (2009)	USA	8297 people, of which 5.8% were 0-4 years old and 14.5% were 5-17 years old	NR <sup>a</sup>	Benzene and PM <sub>2.5</sub>	To investigate changes in time allocation patterns and pollutant exposures that result from traffic congestion.	Cross-sectional	Changes in exposures depended on the duration of the congestion and the pollutant. Time allocation shifts and the dynamic approach to time-activity patterns improve estimates of exposure impacts from congestion and other recurring events.

Crist et al. (2008)	Columbus and Athens in Ohio, USA	30 Children, students from 4 <sup>th</sup> and 5 <sup>th</sup> grade elementary school	January 1999 to August 2000	PM <sub>2.5</sub>	To characterize indoor, outdoor and personal PM exposures of school children.	Cross-sectional	At all the studied sites, personal PM <sub>2.5</sub> exposures were significantly affected by indoor PM <sub>2.5</sub> , presumably the result of re-suspension by human activity.
Ryan et al. (2008)	Ohio, USA	642 children (age 0-36 months)	2001 to 2005	Diesel Exhaust Particles (DEP)	To estimate exposure to DEP, and to determine if exposure to high values of DEP during childhood increases the risk for developing allergic diseases.	Longitudinal	Using birth addresses to estimate a child's exposure may result in exposure misclassification for some children who spend a significant amount of time at a location with high exposure to DEP.
Wang et al. (2008)	Chongqing, China	Children (0-14), adults (15-64) and elders (>65)	2004 to 2006	PM <sub>10</sub>	To determine population exposure to particulate matter.	Cross-sectional	Home was the largest contributor to personal exposure, especially on the rural areas, due to solid fuels burning. Elder people had higher exposure, due to more time spent in indoor microenvironments.
Zhao et al. (2007)	Denver, Colorado, USA	56 asthmatic children aged 6-13 years enrolled in the Kunsberg School	Two winters (October 2002-March 2003 and October 2003-March 2004)	PM <sub>2.5</sub>	To identify and apportion the PM <sub>2.5</sub> sources that were common resulting in exposure to asthmatic children, and consequently interferes with regular school attendance and progress.	Cross-sectional	Secondary nitrate and motor vehicle emissions were the largest external sources of particulate matter. Cooking was the largest internal source. Also a significant influence of indoor smoking and high traffic flow outside the school in indoor air quality.
Van Roosbroeck et al. (2007)	Utrecht, Netherlands	54 children attending four different schools	NR <sup>a</sup>	PM <sub>2.5</sub> , soot, NO <sub>x</sub> and NO <sub>2</sub>	To validate exposure classification based on school location.	Cross-sectional	The school's proximity to a freeway can be used as a valid estimate of exposure in epidemiological studies on the effects of the traffic-related air pollutants, soot and NO <sub>x</sub> in children.
Van Roosbroeck et al. (2006)	Amsterdam, Netherlands	14 children aged 9-12 years	March to June 2003	NO, NO <sub>2</sub> and soot	To assess personal exposure to air pollution in children living in homes on streets with different degree of traffic intensity.	Cross-sectional	Children living near busy roads were found to have a 35% higher personal exposure to "soot", but smaller contrasts for NO and NO <sub>2</sub> .
Ballesta et al. (2006)	Six European cities: Brussels, Lisbon, Bucharest, Ljubljana, Madrid and Dublin.	150 people, 25 of them school children, in each studied city.	22 October 2002, 27 May, 3 December 2003 and 28 April 2004.	Benzene	To assess population exposure to air pollutants in Europe, using one day cross-sectional campaigns.	Cross-sectional	Evident linear relationship between ambient levels and human exposure, although this was higher. Highest indoor concentrations were measured in bars and inside motor vehicles, due to tobacco and traffic influence.
Staff Mestl et al. (2006)	Shanxi province, China	Population from rural area of Shanxi and urban area of Taiyuan, divided in age	NR <sup>a</sup>	PM <sub>10</sub>	To estimate daily average exposure for different population groups: rural coal users, urban coal users, and urban gas users.	Cross-sectional	Young children and elderly spend most the time indoors and had the highest daily exposure in the coal using population. The rural population experienced higher exposure than the urban ones, even though the outdoor air is significantly cleaner in rural areas.

		groups (0-1; 2-6; 7-14; 15-64; >65)					
Wu et al. (2005a)	Alpine, California, USA	20 asthmatic children aged 9-17 years attending 5 different schools	September-October 1999, April-June 2000	PM <sub>2.5</sub>	To characterize children's short-term personal exposures and separate them into ambient and non-ambient components. 2 different model approaches were used.	Longitudinal (panel study)	Study subjects only received 45% of their exposure indoors at home, even though they spent more than 60% of their time there. 29.2% of their exposure was received at school, where they spent only 16.4% of their time.
Wu et al. (2005b)	Southern California, USA	5000 children aged 9-18 years from Southern California Children's Health Study (CHS)	NR <sup>a</sup>	CO, NO <sub>2</sub> , PM <sub>10</sub> , PM <sub>2.5</sub> and elemental carbon	To investigate the relationship between air pollution and children's chronic respiratory health outcomes.	Cross-sectional	Local traffic significantly increased within-community variability for exposures. Inter-community exposure differences were affected by location, traffic density, locations of residences and schools, and time activity patterns of the children.
Adgate et al. (2004a)	Minneapolis, Minnesota, USA	153 children (from 2 <sup>nd</sup> to 5 <sup>th</sup> grade) attending two different schools.	November 1999 to May 2000	VOC (15 compounds)	To characterize air pollution exposures in inner-city children predominantly from low-income households for providing benchmarks.	Cross-sectional	Media and upper-bound home and personal exposures were well above health benchmarks for several compounds, so outdoor measurements likely underestimate long-term health risks from children's exposure to these compounds.
Adgate et al. (2004b)	Minneapolis, Minnesota, USA	Probability sample of children (3-12 years) from 284 households.	May to September 1997	VOC (10 compounds)	To determine and compare personal, indoor and outdoor exposure, and statistical associations with common sources and modifiers of exposure.	Cross-sectional	A consistent pattern of personal > indoor > outdoor exposure was observed for 9 of 10 VOC. For most children, the indoor at-home microenvironment was strongly associated with personal exposure.
Lee et al. (2004)	Nashville, Tennessee, USA	36 elementary school children (10 to 12 years). 99 children provided additional time-activity info.	June and July 1994	O <sub>3</sub>	To determine weekly outdoor, indoor and personal exposure estimates of school children. To determine if systematic exposure differences among children exist.	Cross-sectional	Personal O <sub>3</sub> exposures reflected the proportional amount of time spent in indoor and outdoor environments (higher out). Centrally air-conditioned indoor environments confer a substantial protect from ambient O <sub>3</sub> levels.
Yip et al. (2004)	Detroit, Michigan, USA	20 children, aged 7-11 years with asthma	2000 to 2001	PM <sub>10</sub>	To characterize the children's personal exposures with respect to the measured values at the ambient sites, in the classrooms, and in the homes.	Cross-sectional	Children's personal exposure strongly correlated with their home environment and weak correlations with the ambient (outdoor) and classroom environments.
Briggs et al. (2003)	Northampton and Kingsthorpe, UK	567 adult residents + 247 college students +	1998 to 1999	Radon	To model potential exposures to radon in domestic environment for different population sub-groups	Cross-sectional	Students and schoolchildren were found to have the lowest home occupancy, consequently they were found to have the lowest home radon exposure.

		447 schoolchildren (9-13 years old)					
Liu et al. (2003)	Seattle, USA	89 elderly people + 19 children with asthma (6-13 years old)	1999 to 2001	PM <sub>2.5</sub> and PM <sub>10</sub>	To examine the particulate matter exposures and health effects in individuals.	Longitudinal	When personal exposures were directly measured, asthmatic children had the highest exposures. However, this model based on the three MEs did not well correlated with the measured values for PM personal exposure of asthmatic children.
Saksena et al. (2003)	Delhi, India	Infants and women from two slums	December 1994 to February 1995	Respirable Suspended Particles (RSP) and carbon monoxide	To assess the daily exposure of infants (and their mothers) and to determine the factors that influence exposure.	Cross-sectional	Indoor background levels during the day and at night-time exceedingly high, due to re-suspension of dust and infiltration. Outdoor levels measured poorly correlate with integrated exposure.
Chau et al. (2002)	Hong Kong	396 Hong Kong inhabitants, of which 14 were children (<14 years old)	April to August 1998	CO <sub>2</sub> , CO, NO <sub>2</sub> and PM <sub>10</sub>	To estimate the total exposure to air pollutants for different population age groups, and to compare their exposure profiles with respect to different commuting and behaviour patterns.	Cross-sectional	Homes were shown to be one of the major exposure sites for all age groups. 24h NO <sub>2</sub> exposures for individuals spending more than 2h in commuting daily exceeded the 24h NO <sub>2</sub> exposure standards.
Harrison et al. (2002)	Birmingham, UK	11 healthy adult subjects and 18 members of groups more susceptible to adverse health changes (including 6 schoolchildren ~10 years old)	NR. <sup>a</sup>	PM <sub>10</sub> , NO <sub>2</sub> and CO	To investigate the relation between personal exposure and exposures estimated from static concentrations measured within the same microenvironments, for healthy individuals and susceptible groups.	Cross-sectional	ME measurements of CO and NO <sub>2</sub> can well represent the personal exposures of individuals within that ME. Elderly subjects and those with pre-existing disease received generally lower PM <sub>10</sub> exposures than the healthy adults and schoolchildren, due to their less active lifestyles.
Rojas-Bracho et al. (2002)	Santiago, Chile	20 children (age 10-12 years), living in non smoking households	NR. <sup>a</sup>	PM <sub>2.5</sub> , PM <sub>10</sub> and NO <sub>2</sub>	To characterize particle and gaseous exposures of children (aged 10-12 years), living in Santiago, Chile	Cross-sectional	Outdoor particles contributed significantly to indoor concentrations. The presence of gas cooking stoves in the homes results in NO <sub>2</sub> weak associations for indoor-outdoor and personal-outdoor relationships.

1006 a) N.R. - Not reported

1007



1008 Table 3 – Summary of data collection characteristics of the reviewed studies using ME modelling approach to assess children’s exposure to air pollution since 2002.

Reference	Time-activity patterns			Pollution measurements		
	Methods of collection	Record time	Key elements included	Microenvironments	Methods of collection	Duration and time resolution
Lazenby et al. (2012)	Daily activity diary and a questionnaire.	15-min intervals of each 24-h record period.	Information about the indoor and outdoor environment, children’s lifestyle and activities.	Indoor domestic, outdoor domestic, school indoors	Microenvironment concentrations were passively collected using a badge sampler. Also personal badge samples were made to compare the results.	24-h periods: one weekday and one weekend.
Mölter et al. (2012)	Time activity diary, filled in by the participants.	15-min time intervals.	ME, period of time, additional information on home characteristics.	Home, school and journey (all indoor and outdoor). Home indoor divided into kitchen, living room, and child’s bedroom.	Home indoor calculated through an indoor exposure model. School indoor also estimated. Outdoors from the nearest urban monitoring system. Also use of a personal sampler.	2 days in each one of the four seasons (Spring, Summer, Autumn and Winter), for both stationary and personal.
Shimada and Matsouka (2011)	Several time-use surveys data in Asia region.	NR <sup>b</sup>	The daily life children activities were adapted from the adult surveys.	Home indoors: kitchen and living room; heating; illumination.	Estimated from the fuel consumption and room characteristics.	NR <sup>b</sup>
Wheeler et al. (2011)	Time activity diary (TAD).	15-min and 30-min, intervals for adults and children respectively.	Information on activities and presence in various locations and on whether the participants were close proximity to smokers, and for how long.	According to TAD: indoors (at home, away and at school), and outdoors (at home, away and in vehicles).	Integrated and continuous monitors were employed to measure indoor and outdoor particles and BC (only at home). Personal sampling was also conducted.	5 sampling days each in the winter (January-March) and summer (July-August) of each year for stationary, and only in 2006 for personal.
Hänninen et al. (2009)	Information derived from school administration, from a survey on two children samples, and using typical daily timetables of schoolchildren in Italy.	NR <sup>b</sup>	Estimation on time spent travelling between home and school.	Residential indoors, school indoors, in traffic and residential outdoors	Indoor concentrations were modelled using either a mass-balance model or infiltration model. Outdoor and in-traffic concentrations were estimated using fixed site monitoring stations (the last one multiplied by coefficients observed in a number of studies reviewed by WHO).	1 school year in Bologna and 1 day in Turin
Zhang and Batterman (2009)	From the National Human Activity Pattern Survey (NAHPS),	Variable, depending on the answers.	Locations and activities in a diary for a 24-h period, along with	Indoor: Home, workplace, shopping, bar/restaurant, school/public building,	Concentrations were based on recent literature, and Monte Carlo analyses were used to address both the variation and uncertainty in the available data.	NR <sup>b</sup>

	developed by the USEPA.		basic socio-demographic data.	other; outdoor: near road and other; transport: in-vehicle		
Crist et al. (2008)	NR <sup>b</sup>	NR <sup>b</sup>	NR <sup>b</sup>	School indoors (selected classroom away from the kitchen) and school outdoors	Indoor monitors during the classroom's usage time. Continuous ambient monitor to measure outdoor concentrations. Also personal samplers (pumped) – one student per classroom.	Daily (24-h) both for indoor and ambient. Also school day period (8 a.m. to 3 p.m.) for ambient, indoor and personal.
Ryan et al. (2008)	Annual complete parental report of the locations where child spent eight or more hours per week, in the last 12 months.	1 complete year (12 months)	Locations where children spent eight or more hours per week. Additional health information in the questionnaire.	Home and non-home environments (includes daycare, babysitter, relative's home or other locations)	A land-use regression (LUR) model was developed using geographic data as independent variables and sampled levels of a marker of DEP as the dependent variable.	Daily levels obtained of each sampling site, averaged to minimize the effect of seasonal and temporal variations as health outcomes were measured annually.
Wang et al. (2008)	Recall questionnaire sent to families.	A full 7-day period report, between January and March 2006	Time spent in the different MEs considered.	Kitchen, bedroom, living room, school/work, other indoors away from home, transit, and outdoors	Outdoor concentrations from air quality monitoring stations. Indoor concentrations measured at 21 sites containing major indoor MEs. In transit levels were estimated based on data from literature.	Indoor measurements conducted continuously for at least 24 h. Outdoor data for each month of 2004 available at 10 ambient air quality monitoring stations.
Zhao et al. (2007)	NR <sup>b</sup>	NR <sup>b</sup>	NR <sup>b</sup>	Indoor (inside school) and outdoor (outside school)	Fixed monitors were located in the main corridor of the school (indoor) and outdoors on the roof of the school. Use of personal samplers (pumped) to personal monitoring (for comparison).	Continuous measurements (24 h), both for indoor, outdoor and personal.
Van Roosbroeck et al. (2007)	Questionnaire on time-activity patterns.	N.R. <sup>b</sup>	Daily activity patterns, school travel mode and additional data on housing conditions and possible indoor sources.	Outdoor and indoor at school (and personal for comparison)	Personal monitoring was performed in 48-h periods, by a personal wearable bag sampler. Indoor and outdoor measurements were done using the same equipment as for personal sampling, but with a shelter.	48-h measurements periods, from Monday to Wednesday and from Wednesday to Friday.
Van Roosbroeck et al. (2006)	Questionnaire on time-activity patterns.	N.R. <sup>b</sup>	Additional information on possible indoor sources.	Outdoor and indoor (school and home).	Personal monitoring was performed by a personal wearable bag sampler. Outdoor measurements were done using the same equipment.	Measurements took place from Monday to Wednesday or from Wednesday to Friday, in a total of 8 measurement periods of 48 h.

Ballesta et al. (2006)	Time-micro-environment-activity diary.	Data entered into a database file that recorded intervals of 15-min	Movements and activities of the sampled population.	Outdoor: city background and hot spots. Indoor: homes and specific locations (schools, offices, shops and bars)	Simultaneous diffusive measurements of outdoor, indoor and human exposure benzene concentrations.	Measurements were made during one day campaigns, on six groups.
Staff Mestl et al. (2006)	Based on earlier publications: urban from a Hong Kong study and rural from a Bangladesh study.	Depending on the earlier publications	Information about the variability of the number of hours spent in the different MEs.	Indoor: kitchen, bedroom, living areas, school/work; and outdoors	Indoor concentrations were estimated based on data from previous studies. Outdoor concentration levels were estimated by an air dispersion model (AERMOD).	Depending on the previous studies.
Wu et al. (2005a)	Electronic time-activity diary used by the subjects.	24-h recordings, with 15-min resolution	Time, locations and activities.	Indoor (home, school and other places), and outdoor (home, other places, and on road or in transit).	To measure outdoor concentrations central-site fixed stations were used. Personal nepholemeters to measure indoor concentrations and personal exposure to compare with the modelling results.	Two 14-day runs in 1999 and five runs in 2000, where 1-min PM concentrations were determined continuously.
Wu et al. (2005b)	Using information from a time-activity survey administered twice a year to each child, and from the Consolidated Human Activity Database developed by the USEPA.	24-h time-activity series (15-min intervals) for each child	How much time (by 5 categories) they spent outdoors, and also if they spent more than 15 min daily travelling between school and home and by what means.	Residential (indoor and outdoor), school (indoor and outdoor), and in vehicle.	Combine of central-site ambient observations with 2 dispersion models to estimate outdoor concentrations: CALINE4, to traffic emissions; and SMOG airshed model, to transported pollutants and non-mobile sources. A single-compartment steady-state mass balance equation to estimate indoor concentrations.	N.R. <sup>b</sup>
Adgate et al. (2004a)	Each subject kept a time-activity diary.	24-h recordings	Time spent in 7 primary MEs as well as data on exposure to tobacco smoke and other potential modifiers.	Indoors: child's home, five randomly selected classrooms in each school; outdoor at each school.	Personal and home measurements were collected continuously for 2 days; school measurements after school hours; and outdoor measurements continuously from Monday to Friday	Winter (24 January – 18 February) and Spring (9 April – 12 May) 2000
Adgate et al. (2004b)	Each subject kept a time-activity diary.	24-h recordings	Time spent in 7 primary MEs as well as data on exposure to tobacco smoke and other potential modifiers.	Indoor (at home, school and other); outdoor (home, school and other); and in transit.	VOCs were collected by passive diffusion, indoor and outdoor urban and nonurban residences. Also personal sampling was carried to compare the results.	Screening-phase, followed by an intensive-phase. 6-day average concentrations on fixed monitors (indoor and outdoor) and in personal samplers.
Lee et al. (2004)	Activity diaries collected during	Daily activities from 8:00 a.m. to 9:00 p.m.	Times, location and activities.	School and home, both indoors and outdoors.	Continuous outdoor and passive indoor and outdoor home measurements were	6 week monitoring period during the school's

	sampling period. 99 children provided additional info on time-activity by telephone interview.	for a sample of 15 non-consecutive days			done. Each participating child and family had a set of personal (wearable) passive O <sub>3</sub> samplers to personal sampling (compare the results).	summer vacations, in June and July of 1994.
Yip et al. (2004)	Children recorded their activity in logs.	24-h recordings	Time, location and activities.	School and home, both indoors and outdoors.	Daily ambient and indoor measurements at two elementary schools, as well as concurrent measurements inside the children homes. Personal samplings also made.	Daily 24-h measurements were made in 8 seasonal sampling campaigns.
Briggs et al. (2003)	Survey of home occupancy rates, and surveys of time activity and journey patterns.	Over a 24-h weekday period, for half-hourly intervals.	Daily time spent indoors home, other time-activity and journey patterns.	Home outdoors, home downstairs, home upstairs.	Radon levels obtained for a representative occupied house, by continuous monitoring.	Continuous monitoring over an 18 day period.
Liu et al. (2003)	Individual diary.	Daily, with a 15-min time intervals.	Time, activity and location. Additionally, technicians recorded occurrence of events that potentially affect PM concentrations at homes.	Indoor (including home and other places), outdoor near home, and outdoor away from home.	Indoor and outdoor PM concentrations were measured with single-stage inertial monitors. Personal monitoring was also measured using a personal monitor device for comparison with the modelled values.	26 monitoring sessions, each one with 10 consecutive monitoring days, starting on Tuesdays and ending on Fridays.
Saksena et al. (2003)	Estimated through recall-based questionnaires.	NR <sup>b</sup>	Time spent in the six MEs.	The three cooking sessions, the session between meals which could be spent indoors or outdoors, and the sleeping session.	Concentration levels were measured using portable samplers, for two consecutive days in each house.	Continuously (24-h) for two consecutive days.
Chau et al. (2002)	Time diaries obtained from recall questionnaires by telephone.	7-day, with 15-min time intervals.	Both socioeconomic characteristics of the respondents, locations and activities on weekdays and weekends.	20 grouped in: Indoor at home, Indoor away from home, enclosed traffic and outdoor.	Directly measured in the major MEs, and obtained by the data reported in various open literature for the remaining MEs.	NR <sup>b</sup>
Harrison et al. (2002)	Activity diaries.	N.R. <sup>b</sup>	The periods of time spent by the subject in the different MEs.	Outdoor and indoor (home and workplace/school). Additional MEs: leisure activities (social clubs, pubs and cafes), transport (cars,	Static measurements were performed in the indoor and outdoor microenvironments. Additionally, direct personal measurements were performed in healthy subjects. In susceptible subjects, a shadowing approach was performed for the	Continuously. Duration not reported.

				buses and trains), shops and park area (dog walking).	additional direct personal sampling to compare the results.	
Rojas-Bracho et al. (2002)	Time-activity diary. A recall diary was also used to report activities and conditions that could affect indoor concentrations or personal exposures.	N.R. <sup>b</sup>	Time intervals spent in different MEs, time spent near smokers, and specific info on buildings.	Indoors, outdoors, and in transportation (motor vehicle, walking or bicycle).	Indoor and outdoor samples were done by passive badges. Personal samples were done by a pumped wearable device to compare the results.	Personal, indoor and outdoor 24-h samples were collected for five consecutive days.
1009	a) according to Milner et al. (2011); b) NR – not reported					
1010						
1011						
1012						