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Executive Summary

This document aims to lay out an innovative methodology for accounting for socio-economic status in exposure assessment at the population level in European cities. The ICARUS method relies on the identification of different data sources at variable spatial and administrative levels to inform a database of attributes including age, gender, education level of adults, annual household income, as well as residence location as a minimal cut set of socioeconomic and sociodemographic exposure modifiers. The selection of key socioeconomic and sociodemographic attributes implemented in the ICARUS agent-based model has been made on the basis of a thorough review of recent literature (published since 2011) associating such attributes with the causes of adverse health outcomes associated with urban air pollution and climate change. The probability distributions of the different attributes are used to cluster the urban population constructing clusters of 'agents' that interact with each other and with their environment dynamically pursuing their normal economic activity. The environment is also defined as a collection of physical 'agents', such as the road infrastructure network in cities or the building stock (clustered according to type of land use and physical attributes of buildings).

The different classes of 'agents' are allowed then to interact over extended time periods in a very large number of simulations of city life (in the tens of thousands) until the system converges to a distribution of exposure values characteristic of the population subgroups identified as 'agents' in the agent-based model formulation. Association analysis between the sociodemographic and socioeconomic drivers and modifiers of human exposure to airborne health stressors allows us then to reveal how the variation of specific attributes affects actual population exposure while taking into account the combined contribution of all other influencing factors, be that societal, demographic, economic or environmental.

We have applied the ICARUS approach thoroughly in the case study of Thessaloniki and the project team is geared towards implementing it in the other eight cities participating in ICARUS. Results so far demonstrate the significant importance that socioeconomic and sociodemographic attributes have on population exposure to air pollutants. In fact, differences up to 32% have been found among people living in the same dwelling, whereas variation of exposure up to 77% can be found among people living in the same city neighbourhood/district.

Finally, the limitations of our approach are discussed briefly. These pertain primarily to issues of data collection, effective availability of data and the appropriate spatial scale of analysis on the basis of the available data. Practical solutions to these problems are highlighted succinctly in order to guide the implementation of the developed methodology in the ICARUS participating cities and, indeed, the overall bulk of European cities.

Overall, this report documents the evidence revealing the relevance of socioeconomic and sociodemographic attributes for accurately assessing the human exposure to airborne pollutants in cities. It further develops a novel computational methodology for assessing exposure while taking into account these factors, provides examples of the first case study where the ICARUS method has been used and discusses the salient limitations that would hamper its ready implementation in other urban settings.

1 Introduction

Disentangling the effects of socioeconomic parameters of environmental exposure on populations is of increasing interest to environmental health scientists and urban planners and managers. In fact, at a recent Sustainability Summit organized by the Economist journal in Athens, Greece (September 2018) among the 13 goals of the UN on Sustainable Development, Health was identified as the main driver of sustainable development action at urban settings worldwide.

One of the key innovations of ICARUS is the focus of the project on urban resilience with particular attention paid to the environmental health protection aspects of resilience. In this context, the project is explicitly taking into account the socio-economic dynamics that determine the effective uptake of new technologies, measures and policies that eventually shape the landscape in terms of the plausibility of implementation of specific win-win solutions combatting air pollution and mitigating climate change in cities.

It is often observed that lower socioeconomic (SES) groups of society have a disproportionate share of the burden of social and environmental stressors, due partly to issues of environmental injustice or inappropriate consumer choices and eventually lifestyle. This report provides a critical summary of the literature on socioeconomic status and causes of disease together with new methodological guidelines on how to account for socioeconomic status when modelling and assessing exposure to air pollutants. The document starts by highlighting the associations between sociodemographic characteristics and the causes of health disorders relevant to the exposures examined in the project, i.e. asthma, respiratory and cardiovascular disease, cancer, neurodevelopmental disorders and infant mortality. Exposure, however, is not only determined by the general levels of ambient air quality. It is significantly influenced by details of time activity patterns that characterize different population subgroups. Informed by this evidence, a methodological framework for properly accounting for SES in exposure modeling and assessment is set out.

2 Associations between sociodemographic characteristics and the causes of the health disorders relevant for ICARUS

2.1 Introduction

Socioeconomic status has been found to modify mortality and morbidity predictions (Anderson and Armstead, 1995). It is important to understand and to differentiate the two vectors that relate to socioeconomic disparities. These disparities occur either from behaviors and circumstances that predispose to exposure, or to increased susceptibility and vulnerability to environmental pressures.

One of the major issues to be investigated in Work Package 4 of ICARUS is the link between socioeconomic status, exposure and human disease, especially with regard to the influence of socioeconomic status on personal behaviour, performed activities, consumer choices and selection (e.g. residential area) and formation of the living environment, in relation to demographic characteristics (such as age, gender or ethnicity) which may influence socioeconomic status. Due to the link between demographic characteristics and socioeconomic status it is important to consider sociodemographic characteristics at a higher level of detail rather than just socioeconomic status. Initially it is necessary to establish whether sociodemographic characteristics are associated with the particular health endpoints that are the focus of ICARUS (i.e. for which there is enough scientific evidence that they are related with urban air pollution), so as to define the exposure-related parameters that associate socioeconomic disparities to disease. This part of the literature review has three sections:

1) Description of the search strategies and the diseases and the sociodemographic characteristics on which the ICARUS project focuses
2) Description of the major causes of the diseases associated with urban air pollution
3) Systematic searches of the academic literature to explore
    a. sociodemographic associations with ICARUS-relevant health outcomes (age, gender, ethnicity and socioeconomic status (SES))
    b. mediators and moderator of associations between sociodemographic causes of ICARUS-relevant health outcomes (suggested by points 2 and 3a above)

2.1.1 The search strategies

The systematic searches of the academic literature proceeded as follows:

- Two search engines were used: web of science (title only) and google scholar
- The period covered was 2011-September 2018
- The search terms for 3a (sociodemographic association with ICARUS-relevant health outcomes) were

Review age/ gender/ ethnic*/ socioeconomic*/asthma/ cancer/ neurological/ respiratory/ cardiovascular disease

- The search terms for 3b (modifiers of sociodemographic factors associations with health disorders relevant for ICARUS) were:

Review age/gender/ ethnic*/socioeconomic*[1] smoking prevalence/second hand smoke/ passive smoking/damp/housing conditions /hypertension /noise /cognit*/breakfast/ neck pain/coffee/road traffic accident/falls/IPV/violent crime/alcohol/premature birth/restricted growth/pet/cat/dog/processed food/ sulphites/ poor diet/take away/fast food/ antibiotic/emotion/emotional expression/hazardous workplace exposure

We focused our literature search primarily on reviews rather than original articles for expediency. Reviews could include meta analyses and narrative analyses. If no review could be found two options were taken either (a) include original research – if possible international studies or (b) consider reviews before the specified time period (2011 to 2018). This option was taken particularly where papers that were found within the searches referred to previous earlier reviews.

Only English language studies were included.

2.1.2 The health disorders attributable to urban air pollution

The health disorders that have been defined in ICARUS as attributable (even in part) to urban air pollution are:

- **asthma** (a common long-term condition that can cause coughing, wheezing, chest tightness and breathlessness (NHS, 2014b))
- **Chronic bronchitis**
- **respiratory allergies** (adverse reactions of the body to foods or other substances in the environment which have no effect on people who are not allergic. Allergies develop when the body’s immune system reacts to an allergen as though it is a threat, like an infection and produces an “immune response” (antibodies to fight off the allergen). If a person comes into contact with the allergen again, antibodies are produced which cause the release of chemicals in the body that lead to an allergic reaction such as sneezing, wheezing, itchy eyes, skin rashes and swelling (NHS, 2014a)). In this case we focus on allergies of the respiratory system alone.
- **neurological disorders** (structural disturbances or malfunctions of the central nervous system including stroke, Alzheimer Disease, migraine headaches, epilepsy, Parkinson's disease, sleep disorders, multiple sclerosis, pain, brain and spinal cord injuries, brain tumours, and peripheral nerve disorders (BiologyReference, undated))
- **cancer** (leukemia and lung cancer)
- **cardiovascular disease**

2.1.3 Sociodemographic characteristics

The following characteristics are studied:

- **age** (the length of time a person has lived or a particular stage in life)
- **gender** (by gender we refer to both biological gender (or sex) which includes external genitalia, sex chromosomes, gonads, sex hormones, and internal reproductive structures (Gender Spectrum, undated) and the socially constructed characteristics of women and men

[1] In google scholar also searched for the term “demographic”

– such as norms, roles and relationships of and between groups of women and men (WHO, undated))

- **ethnicity** (common ancestry and elements of culture, identity, religion, language and physical appearance (ONS, undated))
- **socioeconomic status** (access to or control over wealth, prestige and power which provide access to material and social resources and ability to achieve goals such as participating in society; it is often measured through education, income and/or occupation(APA, undated; Australian Bureau of Statistics, 2011; Calixto and Anaya, 2014))

Demographic characteristics (age, gender and ethnicity) are patterned by socioeconomic status. Income is highest in middle age although satisfaction with income continues to grow into older age (Plagnol, 2011). Some ethnic groups tend to have higher socioeconomic status whereas others tend to have lower socioeconomic status. Such differences can be widened by the tendency of ethnic groups to live in segregated communities although there can be wide socioeconomic differences within some ethnic groups (American Psychological Association, undated-b; Barnard and Turner, 2011; Ingleby, 2012). Women are overrepresented among those in poverty and women in the same occupations and with the same education level as men earn less money (American Psychological Association, undated-a). Thus, it is important to consider socioeconomic status in the context of other demographic characteristics.

2.2 Environmental factors associated to health problems attributable to poor air quality in cities

Established causes of the health outcomes relevant for ICARUS are detailed in table 2.1.

Table 2-1| Major causes of the health outcomes relevant for ICARUS

	Major causes
Asthma	Exposure to higher average coarse PM levels is associated with increased asthma prevalence and morbidity (Keet et al., 2018), while PM2.5 exposure is related to the onset of children cough variant asthma (Zhang et al., 2016) *Asthma symptoms can have a range of triggers e.g.:* Short-term effect of PM2.5 on children's hospital admissions and emergency department visits for asthma (Fan et al., 2016a; Lim et al., 2016) In children with asthma, indoor classroom NO_2 levels can be associated with increased airflow obstruction (Gaffin et al., 2018) Significant effects of NO_2 on the airway responsiveness of individuals with asthma (Brown, 2015)

	Major causes
Chronic bronchitis	Living close to a busy road and to a local power plant, heating home by hot air conditioning were associated with chronic bronchitis (Salameh et al., 2012) Exposure to solid fuel smoke is consistently associated with chronic bronchitis (Kurmi et al., 2010) Individual markers of traffic at household level such as reported intensity and outdoor NO_2 were risk factors for chronic bronchitis among females (Sunyer et al., 2006)
Respiratory hospital admissions	Fine PM and several of its constituents, including sulfate, ammonium, and nitrate, are positively associated with respiratory hospitalizations (Jones et al., 2015) Air pollution enhances the effects of influenza in respiratory health (Wong et al., 2010) Coarse PM exposure is critical on first hospitalization for respiratory disease in early childhood (Yang et al., 2004)
Lung cancer	Diesel exhaust and industrial emissions contribute significantly to lung cancer risk, associated with exposure to ambient PAHs (Taghvaee et al., 2018) Biomass burning emitted PAHs induce a high risk of lung cancer (Sarigiannis et al., 2015) Cadmium exposure may increase risk of lung cancer (Chen et al., 2016; Nawrot et al., 2006) Exposure to inorganic arsenic (InAs) has been documented as a risk factor for lung cancer (Fan et al., 2016b; Hsu et al., 2017).
Leukemia	Increased incidence of acute lymphoblastic leukemia associated with heavy-traffic road density near a child's home as a result of exposure to benzene (Filippini et al., 2015; Houot et al., 2015) and other air pollution components (Janitz et al., 2016).
Cardiovascular disease	Fine particulate matter <2.5 µm (PM2.5) air pollution is the most important environmental risk factor contributing to global cardiovascular (CV) mortality and disability (Rajagopalan et al., 2018)

	Major causes
	Oxidative stress (OS) following ambient pollution exposure is implicated in modulating the risk of succumbing to cardiovascular disease and sensitivity to ischemia/reperfusion injury (Kelly and Fussell, 2017) Suggestive evidence of a possible association between road traffic noise and incident ischemic heart disease (Cai et al., 2018)
Neurological disorders	UFP air pollution exposure during periods of rapid neuro- and gliogenesis may be a risk factor not only for ASD, but also for other neurodevelopmental disorders that share features with ASD, such as schizophrenia, attention deficit disorder, and periventricular leukomalacia (Allen et al., 2017) Ambient outdoor air pollution impacts the brain and may affect neurodegenerative diseases, by elevation of cytokines and reactive oxygen species in the brain (Jayaraj et al., 2017) PM have implications in oxidative stress, inflammation, dysfunction of cellular organelles, as well as the disturbance of protein homeostasis, promoting neuron loss and exaggerating the burden of central nervous system (CNS) (Wang et al., 2017)

2.3 Sociodemographic characteristics and the health outcomes relevant for ICARUS

2.3.1 Are sociodemographic characteristics associated with prevalence of the health disorders relevant for ICARUS?

In this section results of the first review of reviews of sociodemographic characteristics and the health outcomes relevant for ICARUS are presented (table 2.2). Where a SES difference was identified, low SES groups mostly tended to be more susceptible.

Table 2-2| Associations between sociodemographic characteristics and the health endpoints related to ICARUS

	Age	**Gender**	**Ethnicity**	**SES**
Asthma	Mostly under 7 (Jenkins et al., 1994)* # (Ballardini et al., 2012)*	Females higher (Kynyk et al., 2011) (Clough, 2011)	Second generation immigrants> 1st generation suggestions: air pollution, heavy traffic, urban	Higher among low SES groups (Uphoff et al., 2015) suggestions: obesity, tobacco smoking indoor and outdoor pollution

	Age	**Gender**	**Ethnicity**	**SES**
			areas, and damp and mould at home, exposure to violence (Cabieses et al., 2014; Corlin and Brugge, 2014), Non-Hispanic blacks increased sensitivity of asthma outcomes from PM2.5 exposure (Nachman and Parker, 2012)	More severe symptoms (Goulden et al., 2015), lower socioeconomic groups have a higher prevalence and incidence of asthma (Ellison-Loschmann et al., 2007)
Chronic bronchitis	Increasing risk by age after 45 years old (Ferré et al., 2012)	Higher prevalence of women compared to men (Ferré et al., 2012; Karunanayake et al., 2013)	Higher prevalence of white against ethnic minorities (Karunanayake et al., 2013) compared to men	Higher risk associated with low educational level and occupational class (Ellison-Loschmann et al., 2007)
Respiratory hospital admissions	Prenatal or perinatal exposure to air pollutants results in in respiratory diseases in children and adults (Kim et al., 2018)	Higher rate of respiratory admissions of adult males related to PM10 and for women related to coefficient of haze (Luginaah et al., 2005)		Lower SES results in higher hospitalization rates (Gwynn and Thurston, 2001)
Lung cancer	Squamous cell carcinoma predominates in the ≥ 72-year age group (Franceschini et al., 2017)	Higher incidence rate of non-small cell lung cancer for men, while adenocarcinoma predominates in women	Asians present a better prognosis compared to non-Asians and Whites over African	Lower SES results in higher lung cancer OR (Hovanec et al., 2018), Area-Level Socioeconomic Status and Industrial Exposure result in higher lung cancer

	Age	**Gender**	**Ethnicity**	**SES**
		(Franceschini et al., 2017)	Americans (Liu, 2017)	incidence (Hagedoorn et al., 2016)
Leukemia	incidence of leukemia increases with age (Schoch et al., 2001)	Boys present 4 times higher-risk of B-precursor acute lymphocytic leukemia than girls (Forsythe et al., 2010), male gender is associated with higher risk of acute myeloid leukemia (Acharya et al., 2018)	Hispanic and non-Hispanic black patients increased risk of leukemia mortality compared with non-Hispanic white patients (Acharya et al., 2016), increased risk of leukaemia in South Asians immigrants in UK (Sayeed et al., 2017)	Economic-educational disadvantages, housing-instability and immigration-related features result in higher leukemia risk (Knoble et al., 2016), neighborhood-level poverty rate result in higher leukemia risk (Acharya et al., 2016)
Cardiovascular disease	Increasing age enhances cardiovascular effects of ozone (Day et al., 2018)	Mens are more prone to CVD than women (Puddu et al., 2012),	Blacks and Hispanics may have greater mortality risk compared with whites and Asians after adjusting for atherosclerosis burden (Orimoloye et al., 2018), whites with type 2 diabetes, are in lower CVD risk compared to Pakistani ethnicity, whereas Chinese were at lower risk (Malik et al., 2015)	Low SES at ages older than 45 years is associated with an increased 10-year CVD incidence (Kollia et al., 2016), inverse association between SES and CVD (de Mestral and Stringhini, 2017), (Backholer et al., 2017), women with lower neighborhood-level SES may be more susceptible to air pollution-related CVD (Chi et al., 2016)

	Age	**Gender**	**Ethnicity**	**SES**
Neurological disorders	Redox homeostasis that triggers oxidative damages to biomolecules compromising neuronal function is age dependent (Paladino et al., 2018)	Men reported higher rates of functional neurological disorders (Matin et al., 2017)	Adult neurogenic communication disorders relate to ethnicity (Ellis, 2009)	Lower SES is important risk factor for many neurological disorders and neurodevelopmental disabilities (Durkin and Yeargin-Allsopp, 2018)

2.3.2 Modifiers of the association between sociodemographic characteristics and the health outcomes relevant for ICARUS

In this section sociodemographic differences in the causes of diseases linked to air quality in cities as outlined in ICARUS are described (table 2.3). The characteristics in the table are those associated with higher levels of each mediator. The risks are divided into three groups: external conditions, health behaviours and internal defects. For most health impact modifiers where a difference was found, those at the extremes of the age range were more at risk (older people and children/young adults). Women were often at more risk than men – sometimes this was to do with gender patterning of socioeconomic status. Exceptions were smoking, violence, premature birth and high blood pressure which were more common among men.

Generally, less socioeconomically advantaged ethnicities and low SES groups were more likely to display characteristics which might increase the risk of the adverse health outcomes associated with urban air pollution and climate change. However, there were more dust mites in high SES housing, there were no SES differences in cat ownership and there were more complex relationships between SES and coffee drinking and toxicants. Some occupational groups were more exposed to risk: for example computer users could be more exposed to neck pain (Hoy et al., 2010) and agricultural workers could be more exposed to pesticides (Parliament of Canada, 2000).

For some modifiers prevalence was not higher in sociodemographically disadvantaged groups but these groups were more at risk of harm when these risks were present. For example low SES groups experience harm from alcohol (World Health Organization, 2014) and women experience more harm from pesticides (Parliament of Canada, 2000).

Table 2-3| Associations between sociodemographic characteristics and possible mediators and moderators of the health outcomes relevant for ICARUS

	Age	*Gender*	*Ethnicity*	*SES*
External conditions				
Air pollution	No clear pattern (Hiscock et al., 2015)	Women (Hiscock et al., 2015)	Less advantaged ethnicities (Hiscock et al., 2015)	Low SES (Hajat et al., 2015) (Hiscock et al., 2015) Indoor air –also low SES (Kolokotsa and Santamouris, 2015) (Adamkiewicz et al., 2011)
Poor housing (damp, mould, poor repair)	Children more likely to live in poor housing than older people (Barnes et al., 2013)*		Less advantaged ethnicity (poorer housing generally)(Barnes et al., 2013)*(Jacobs, 2011)*	Low SES (Sharpe et al., 2014) (Kolokotsa and Santamouris, 2015) (Adamkiewicz et al., 2011)
Noise			Less advantaged (Hiscock et al., 2015)	Low SES (Laußmann et al., 2013)* (Kolokotsa and Santamouris, 2015) (Hiscock et al., 2015)
Road traffic accidents	15 to 44 (World Health Organization, 2013)			Low SES (Roberts, 2012)
Second hand smoke exposure	More children exposed than adults (Öberg et al., 2011)	Little gender difference (Öberg et al., 2011)	Varies between countries (Orton et al., 2014)	Low SES (Orton et al., 2014)
Toxicants				DDE/DDT low SES, PCB high SES (Hiscock et al., 2015)

	Age	*Gender*	*Ethnicity*	*SES*
Workplace exposures		Men more exposed but women more affected (one study only) (Campos-Serna et al., 2013)	Ethnic minorities more exposed (Stanbury and Rosenman, 2014)*	Technicians, operators, agricultural workers, workers in elementary occupations (Montano, 2014)

* Not review
** commercial literature
#Pre 2011

2.4 Conclusions

Risks for asthma, cardiovascular disease (CVD), lung cancer, leukemia, chronic bronchitis and respiratory hospital admissions, were described in this chapter. Sociodemographic characteristics were associated with these risks. In general, those most socioeconomically disadvantaged had higher risks of poorer external conditions and health-averse behaviours. These relationships might explain sociodemographic associations with these diseases and they have to be analysed further on the basis of rigorous exposure assessment considering the relevant sociodemographic factors.

3 Space-Time Geography of Exposure

3.1 Introduction

Population movement affects the distribution of disease through alteration of exposure opportunities. The literature review (section 2) suggested that individual exposure to environmental risk factors may result in one of the adverse health outcomes that can be attributed to poor urban air quality and the related health burden could be further compounded by climate change. Thus, the geography of commuting, socialising, travel, migration; of places of residence, vacation and work and of the time spent in each may have relevance for exposure and eventually on disease occurrence. Note that population movement also can lead to spreading of communicable diseases; however, infectious diseases are not considered as direct effects of air pollution, thus they will not be further considered in this report. Population movement may also mean a complete change of living environment (for example migration from Syria to Germany). This gives rise to what Schærström (1997) has called Space-Time lag. From a geographical point of view, this means that the place or environment where the case is discovered and diagnosed is not necessarily the same place or environment where the exposure occurred or started (Picheral, 1982). In this context, retrospective exposure assessment is a major concept of the urban exposome and is incorporated in our methodology. Beyond the straight forward approach of questionnaires and environmental pollution maps, this could be greatly supported by exposure reconstruction starting from biomonitoring data.

Clearly, mapping of this exposure is a challenging task. There are considerable conceptual and computational difficulties involved in intersecting, often to a considerable degree of spatial and temporal resolution, data on the distributions of pollutants, and/or the patterns of movements of recipient individuals or groups (Briggs, 1992).

In the absence of any one general theory or methodology for handling mobility and exposure, and to address the problems of obtaining spatially and temporally accurate case histories, the starting point for accounting for SES in exposure modelling in ICARUS is to use the concept of time geography, an approach originally suggested by Hägerstraand (1970)).

3.2 Time Activity Patterns

Human exposure to a pollutant has been defined as when "a person comes into contact with a pollutant" Ott (1982), p.186). It is often assumed each person in society has the same exposure level, which is obtainable from static monitors reflecting the mean concentrations at a given location (Buonanno et al., 2014). This can however lead to estimation errors in exposure of an individual because, as already discussed, exposure is strongly related to space-time geography and an individual's distance to the pollutant source. Drawing upon this definition and the concept of time-geography, we are aware that people move through space and time and in doing so their contact with a pollutant varies both spatially and temporally. More awareness of spatial and temporal variation and technological advances in recent years has led to the development of personal exposure monitoring which overcomes some of these fundamental issues; personal sampling enables the monitoring of pollutant concentrations to which people are exposed to in every locality they visit during a typical day (Steinle et al., 2013). In addition to the pollutant concentration in a given space and time point, time-activity patterns of a person's movements are required to estimate exposure. These are usually measured by GPS receivers and time activity diaries.

In ICARUS we are not only interested in individuals' movements, but how these movements vary between different sociodemographic sub-groups. In recent years, studies have emerged regarding time-activity patterns for personal exposure; yet, only a few examine sociodemographic differences in detail. Data from ground based air quality monitors can be linked to demographic, socio-economic, and other personal attributes. Differences in exposure profiles between people can be explained by time-activity patterns of individuals, as well as the environments they spend their time (Spinazzè et al., 2014). In fact, even people living in the same neighbourhood can experience different exposure profiles because of different activities undertaken and different locations visited (Dons et al., 2011). These locations are also known as microenvironments.

3.2.1 Microenvironments

The concept of microenvironments is used in exposure studies to connect exposures to a specific space, and is defined as "a chunk of air space with homogeneous pollutant concentration" (Duan, 1982, p.305). According to Meade (1977)), people spend most of their time in relatively few microenvironments. The most common microenvironments considered in exposure studies are: *indoor home*, *outdoor home*, *other indoor* (work, school), *other outdoor*, and *transport*. In the home, individuals might be exposed to a range of temperatures, humidity and ventilation. They might receive magnetic radiation from watching television, or radon from underlying geologic structures. At work, noise, psychological and social stress and exposure to crowds might be important. People also travel, directly receiving pollutants by driving along a motorway for example. Time use activity studies discussed in this section draw upon literature where similar methods to the FP7 project HEALS (GPS and/or time use diaries) have been used.

There are fairly consistent results between studies regarding time-activity patterns in different microenvironments. The ICARUS project is a European wide study and therefore our search of the time activity literature has focused on Europe so there is greater argument that findings can be extrapolated to our study population. Many studies, and the World Health Organisation (WHO), have noted that people tend to spend most of their time indoors whether it is the home environment or another indoor environment (Sarigiannis, 2014). This is particularly true for Europe where it has been found that on average people spend 80-90% of their time indoors (Simoni et al., 2003; World Health Organization, 1999), and a study conducted in the late 1990s found that preschool children and pregnant mothers in the UK spent over 85% of their time at the home (Farrow, et al., 1997). However, in recent years this proportion may have declined as mothers continue to work and young children receive out of home childcare. The WHO estimate 20% of people's time is spent at work, school, or other locations away from the home, with 4% of time being spent in transit (World Health Organization, 2005).

Most studies explore gender differences and exposure for couples that have a clearly defined household structure with a homemaker and full-time worker. In all studies women spent more time in the home than men (Aguilera et al., 2009; Brasche and Bischof, 2005; Schweizer et al., 2006). For example Buonanno et al. (2014) showed that in Italy the average total time spent at home was approximately 72%, with women (homemakers) spending more time at home (84%) than their male counterparts (59%). In addition to gender differences some studies have found differences for different age groups. Elderly people (> 64 years) have been shown to spend a higher proportion indoors on average (19.5 hours) than other age groups, children < 7 years of age are second group to spend more time indoors (17.6 hours). Across all age groups females spent more time indoors than their male counterparts, with the most pronounced difference being between the 25-34 age group (Brasche and Bischof, 2005). This could be due to this age group being the most common for women to become give birth to their first child.

The EXPOLIS study (Schweizer et al., 2006) analysed and compared time activity patterns for adults in indoor microenvironments for seven EU cities. Unlike other studies that focused on gender differences EXPOLIS computed statistics on different sociodemographic characteristics that may affect time spent in different microenvironments or doing activities within them. The average mean time spent in each microenvironment for all cities was 13.95 hours at the home, 6.71 at work, and 1.67 at other locations. Overall men spent less time in the home than women, with the largest gender difference in Athens. Families with children tended to spend more time at the home whereas participants who lived alone tended to spend less time at home. Men and people with high education levels were more likely to work and thus spent more time away from the home.

Time-activity patterns have been recorded for pregnant women (reported in the 32nd week of pregnancy) in the INMA Sadabell Cohort, Bracelona, Spain. The study observed differences between weekdays and weekends, with those women who did not work during pregnancy spending more time at home and non-residential outdoor environments, they also spent less time in the transport microenvironment compared with women who worked during pregnancy. However overall time spent in indoor microenvironments did not vary between the two groups, rather women who worked spent less time in non-residential outdoor microenvironments (Aguilera et al.). Nethery et al. (2008) also found changes in time-activity patterns for pregnant women with the time spend in the home increasing by an hour a day for each trimester of pregnancy. Accounting for demographic and person factors they also noted that those in the lowest income group spent 2.6 hours a day more at home, and those not in employment spent 3.5 hours more at home.

Literature regarding ethnicity and religion differences in Europe is sparse. An Australian study found fewer Muslim women were in employment than non-Muslim women (30.7%, 63.2%) and occupation levels varied with more Muslim women in low status occupations (20.7%, 12.5%) compared to non-Muslim women. The proportion of Muslim and non-Muslim women with middle status occupations was a similar pattern to low status occupations but the proportion of Muslim women with high status occupations was more similar to non-Muslim women (30.1%, 38.8%) (Foroutan, 2008). Although not a European example this study provides an insight to the possible differences in work patterns for different sub groups and therefore may be useful to help inform time activity patterns. This information is of highly importance for ICARUS, where differences in ethnic or other minorities are to be explored in the urban development scenarios considered.

For incorporating data in the frame of the methodology set out in section 4, databases of time use surveys will also be used. Due to the complexity of these databases they are not discussed in detail here; rather a summary of data availability is provided.

European time use surveys are available for at least 15 EU countries; among them they cover all the 9 cities where the ICARUS methodology is applied. One source of available data is the Multinational Time Use Study (MTUS) (Fisher, 2013). MTUS offers harmonised episodes of time-activity patterns including the activities being carried out within the microenvironments. It is possibly the most comprehensive database available to researchers covering 60 datasets from 25 countries (globally) including data from various projects. Data is also available from the Harmonised European Time Use Survey (HETUS) which allows users to put together a database with comparable data representing the European countries included (2007). HETUS provides data from surveys carried out in 2000 for 20-74 year olds, and the given statistic is mean time spent on the activities in hours and minutes per day. There are 49 primary activities, and 10 secondary activities as well as 5 modes of transport. In addition, the database provides information on 'with whom' the activity is carried out. Although the database only provides mean values for each country, the addition of information on the population subgroups associated with the specific activity may be helpful in ICARUS to differentiate exposure profiles in relation to specific sociodemographic and socioeconomic aspects.

Moreover, access to original time use data appears to be available through national Government statistics departments. Most of these databases have been interrogated to assess data quality and availability so that the data can be readily used in support of exposure modeling and assessment (see next chapter).

3.2.2 Transport mode choice

The *transport* microenvironment has received considerable attention in exposure literature (Adams et al., 2001; Dons et al., 2011; Hertel et al., 2001; Kaur and Nieuwenhuijsen, 2009; Krzyżanowski et al., 2005). WHO estimates that people spend approximately 1-1.5 hr/day in this microenvironment (World Health Organization, 2005), and various studies show that the time spent in transit varies from 3-8%, with males tending to spend longer in transit than females (Buonanno et al., 2014; Dons et al., 2011). The young, elderly and women make fewer and shorter trips compared by employed males (Giuliano and Dargay, 2006). Exploring this specific microenvironment in more detail, studies suggest that car use is the primary means for transit accounting for around 60% of use across society (Buehler, 2011; Giuliano and Dargay, 2006). The high proportion of car use could be linked to increasing incomes that make car ownership feasible. Income and car ownership have been good predictors of mode choice internationally (Buehler, 2011). However, it has also been noted that in industrialised countries most households can afford a car (Lipps and Kunert, 2005). This implies that demographic variables may be more important than SES in determining car use in wealthy countries. When investigating gender and age group differences studies have found that males, and individuals in a high-income group, are more likely to use a car than other means of transport (Table 3-1). Employed adults in households with children are most likely to drive.

A German study found that public transport usage was twice as high for those living near (within 400m) of a bus stop, and when public transport is used it is predominately for work trips rather than social (Buehler, 2011). Population density also plays a role in mode choice, with people living in more densely populated areas less inclined to use the car, preferring to walk or use public transport. The same study has shown that 42% of retired people use other modes of transport other than the car.

Table 3-1. Example of mode choice in the transport microenvironment to be applied to the ABM

Author	Country	SES attribute/ destination	Car	Bike	Foot	Public Transport
Buehler, R. (2011)	Germany	Male	65%	9%	No data	No data
		Female	57%	9%	No data	No data
		Low income	52%	10%	29%	9%
		Mid income	62%	9%	23%	6%
		High income	66%	8%	19%	6%
		Work	73%	9%	7%	10%
		Shopping	59%	9%	27%	5%
		Recreation	54%	11%	30%	5%
Giuliano & Dargay (2006)	UK	All persons	61.8% (driver (47.4%), passenger (14.4%))	1.5%	27.9%	8.4%

4 The ICARUS framework for accounting for sociodemographic characteristics in exposure assessment

4.1 Introduction

Exposure to environmental stressors in general varies depending on sociodemographic characteristics as well as in space and time. Thus, there is the need for a methodology that accounts for this complex nexus of interactive exposure determinants, rather than potentially misclassifying exposures by ignoring or improperly accounting for differences. Taking into account the theoretical discussion in sections two and three, we will now provide details of a framework that can be used in exposure assessment to take account of sociodemographic characteristics at the individual and population level. We draw upon conceptual models of exposure assessments to describe and create a new methodology appropriate for accounting for SES in exposure modeling and assessment.

4.2 The conceptual model

To analyse external exposure in ICARUS we have developed a conceptual model to account for sociodemographic characteristics in exposure assessment. Based on this model we aim to understand how external exposure varies across different societal sub-groups. The model builds upon traditional approaches for assessing personal exposure to air pollutants and the more recent conceptual model developed by Steinle et al. (2013)) but goes further to integrate the wider context of sociodemographic differences and account for total external exposures considering the complex space-time geography of exposure across different settings. The conceptual model in Figure 4-1 depicts the methodology to account for sociodemographic characteristics in exposure modelling in ICARUS.

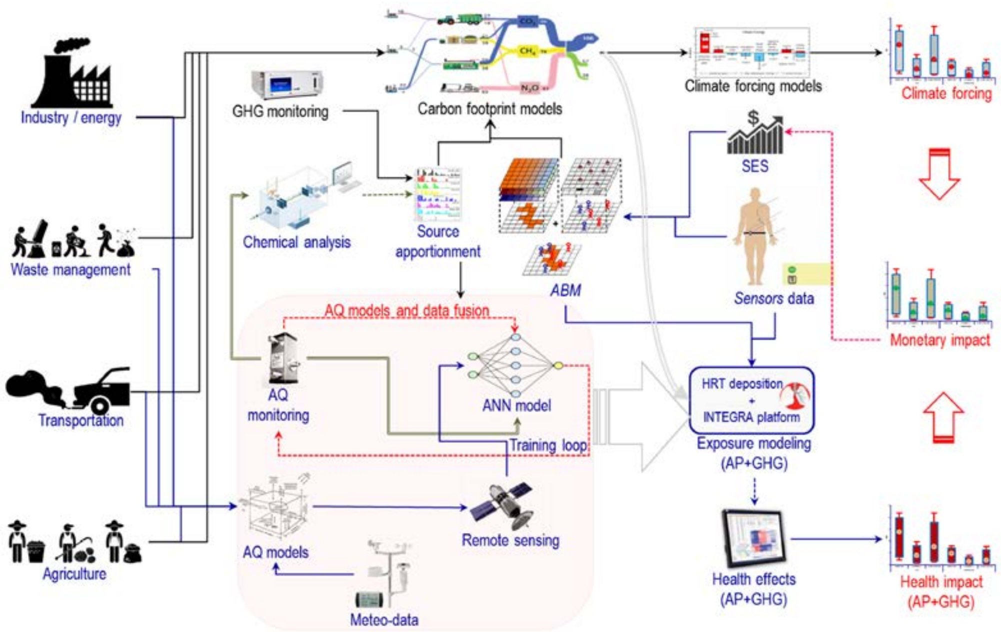

Figure 4-1. Conceptual model for accounting for sociodemographic characteristics in exposure assessments and linking them to sources of pollution and urban form

The model integrates several technologies including personal and remote sensors, as well as more conventional fixed ground monitors that are used for regulatory monitoring and compliance checking. In addition, exposure modeling and assessment methods are used with the final part using Agent Based Models to apply the approach to the wider population.

The model begins with an individual exposure assessment. This is estimated using three components; the sociodemographic context, time activity patterns, and the pollutant(s). *Sociodemographic characteristics* (education, occupation, and income) are included in the model because literature indicates subgroups have different time activity patterns, travel by different modes, and spend different amounts of time doing activities within the microenvironments, such as physical activity, sleeping, and eating. In order to understand and incorporate SES differences, questionnaires are used with the aim to find out household structure, family background, and occupation in the studied population. Given the literature review in section 2, ICARUS is taking into account demographic characteristics. For this reason, when considering SES in the model there are two strands; *demographic* and *SES data*. *Demographic* data include information such as age, gender, ethnicity, religion, while *SES data* comprise education, occupation, and income. The parameters included under the umbrella of sociodemographic characteristics, will affect both (a) time-activity and behavioural patterns and (b) contamination of the media coming into contact with the studied individuals, including all pathways and routes related to air and settled dust.

The combined use of portable GPS receivers and time activity diaries provide information regarding individuals' daily movements during a day in all microenvironments. The exposure aspect of the model relates to the exposure(s) being assessed in ICARUS in particular. These include air pollution and noise as well as the use of cleaning products (as part of the source bundle of indoor air pollution). Data are collected through static monitors in the home in addition to satellite data to account for exposure when individuals move through the city.

Assessing exposure for the wider population is done through the combination of methods similarly to the individual exposure. Population data are required and are available from census data or European data. Census data are more detailed and at a finer resolution, whereas European data (Eurostat) are distributed within NUTS regions (Nomenclature of Territorial Units for Statistics). There are three types of NUTS regions; they range from major socio-economic regions (NUTS1) where there are 98 regions across Europe to small regions for specific diagnoses (NUTS3) where there are 1342 regions. Population data including demographics and SES data are used to model the studied population as accurately as possible. Individual data are obtained from the ICARUS time activity diaries (TADs), existing literature, and databases. Using data from the three sources allows triangular validation of how different sociodemographic sub-groups move through space and time, how long they spend in each microenvironment, and what activities they do within the microenvironments. Informed by these data, educated assumptions need to be made for societal sub-groups in order to cluster people with similar attributes.

State-of-the-art simulation models allow us to capture and mathematically describe time-space interactions that affect time use and activity patterns on a daily basis. Individuals are not only allocated time to various microenvironments within a 24-hour day, but behaviour is determined by sociodemographic characteristics in addition. Understanding daily time use and activity across all microenvironments rather than within a specific single microenvironment is increasingly being recognised as prerequisite to model exposure across all societal strata. Beckx et al. (2008) suggest that activity-based models can be advantageous to assess exposure to pollutants because they provide more accurate information on the location of the pollution and the exposed individuals. They have shown that a significant fraction of air pollution exposure can be attributed to people moving in and out of the city centre for different activities (Beckx et al., 2008).

- Socioeconomic status affects exposure to environmental pollutants, which can be encountered by the studied population in variable ways, such as:

- Living close to an industrially contaminated area or close to a municipal waste incinerator might result in higher exposure to several compounds (organics and heavy metals) through multiple exposure pathways
- Living in the proximity of a heavily trafficked street canyon or a gasoline station (Karakitsios et al., 2007) will result in higher exposure levels to all traffic related compounds
- Living in a house with deprived air quality due to use of bad building materials and furnishing
- Energy poverty might result in use of biomass burning in open fireplaces, which in turn will result in poor indoor air quality (Sarigiannis et al., 2014) and eventually higher exposure to toxic compounds such as PAHs (Sarigiannis et al., 2015)

Additional elements that have to be taken into account when assessing the effect of sociodemographic characteristics pertain to exposure conditions beyond the ones that affect exposure to air pollution, such as the following:

- different age groups, are exposed to different compounds, that relate to the consumer products that are used, e.g. children are exposed to higher amounts of BPA, since they are consuming infant formula within polycarbonate bottles.

- women are exposed to significantly higher amounts of personal care products

- consumer choices such as use of domestic heating fuel, cosmetics, house detergents and space deodorants. All of the above determine the overall indoor air quality and consequently the total exposure profile of the population and they are conditioned by sociodemographic factors that include also cultural elements.

4.3 Agent Based Modelling

4.3.1 Background

A model that advances our understanding is one that represents what are considered, in a particular context, to be the key features of a system and thus enables us to improve our understanding of how that system works. Any gain in understanding of the system resulting from the modelling process derives from our ability to analyse the model and experiment with it. Complex phenomena are best understood through consideration of the behaviour of all interacting parts since macroscopic events emerge through microscopic actions and interactions. Agent-Based Modelling (ABM) helps to understand and explore this kind of phenomena, such as nonlinear systems, where typically independent and autonomous entities interact together to form a new emergent whole. While direct representation of the behaviours of individuals is organisationally difficult, ABM simplifies this process by managing information at the individual level. An example of such a system is the flocking behaviour of birds (Levy, 1993). Although each bird is independent, somehow they interact together to form a flock, and seemingly without any leading entity, manage to stay in tight formations. With this in mind, simulations using ABM attempt to discover the rules embedded in these individual entities that could lead to the emergent behaviour and eventually attempt to make interpretations about future states of these systems. It is, therefore, a simulation technique, capable of representing the kinds of systems where one level of abstraction (individual agents) can generate a new level of abstraction through the interactions that occur in the system, such as how individual birds form a flock.

By simulating the actions and interactions of autonomous software objects, the “agents”, at an individual level, the full effects of the diversity that exists among agents in their attributes and behaviours can be observed as rise is given to the behaviour of the system as a whole. Patterns, structures, and behaviours that were not explicitly programmed into the model, arise through the agent interactions enabling therefore the prediction and examination of expected and unexpected emerged behaviours.

The agents (which can be people, vehicles, roads, cities, animals, products, etc.) are programmed as autonomous decision-makers to react and act in their environment and to have goals that they aim to satisfy, according to a set of rules. In practice, agent actions in models revolve around exercising choice among available options in order to achieve defined goals. The outcome of an agent making a particular choice is translated as a difference in either the location of the agent (i.e. the agent moves) or in the environment. Depending on the model context, this may involve: (a) the agent exploiting resources at its current location (there will be therefore a shift regarding the supply of those resources at that location), (b) altering the state of the location (e.g. changing the land use), (c) acquiring the land at its present location; or, perhaps simply updating its current ‘map’ of the environment. In each case, there may be an accompanying change in the state of the agent itself, such as when resource exploitation increases the agent’s wealth or energy resources.

In most cases ABMs are a relatively late arrival in a field where there is considerable previous experience with styles of model that adopt a more aggregated approach, and these aggregated models continue to be widely used. The increasing ease with which ABMs can be developed, coupled with their representational approach, in which each software agent represents an “actor” (whether an individual or a group of individuals), is the main reason why this modelling approach became more popular during the recent years. The appeal lies on the fact that individual-level decision making is the fundamental driver of social systems.

The process of building an agent-based model begins with a conceptual model, where basic questions or goals, elements of the system (e.g. agent attributes, rules of agent interaction and behaviour, the model environment, etc.), and the measurable outcomes of interest are identified (Brown, 2006). According to (Couclelis, 2001), agents and their environment can either be (a) designed (i.e. explanatory) or (b) analysed (i.e. predictive – empirically grounded). Designed agents are endowed with attributes and behaviours that represent (often simplified) conditions for testing specific hypotheses about general cases. Analysed agents are intended to accurately mimic real-world entities, based on empirical data or ad hoc values that are realistic substitutes for observed processes. Similarly, the environment that agents are situated within can be (a) designed (i.e. provided with characteristics that are simplified to focus on specific agent attributes), or (b) analysed (i.e. represent a real-world location). Once a model has been conceptualised, it must be formalised into a specification which can be developed into a computer programme. The process of formalisation involves being precise about what an identified theory relating to a phenomenon of interest means.

In general, two types of simulation/modelling systems are available to develop ABMs: toolkits or software. Toolkits are simulation systems that provide a conceptual framework for organising and designing ABMs. They provide appropriate libraries of software functionality that include pre-defined routines/functions specifically designed for ABM. However, the object-oriented paradigm allows the integration of additional functionality from libraries not provided by the simulation toolkit, extending the capabilities of these toolkits. The idea of object-oriented programming (OOP) is crucial to ABM, which is why almost all related software packages are built using an OOP language, such as Java, C++, or Visual Basic. A program developed in an OOP language typically consists of a collection of objects. An object is able to store data in its own attributes, and has methods that determine how it processes these data and interacts with other objects. When using OOP to design an ABM, one creates a class for each type of agent, provides attributes that retain the agents' past current state (memory), and adds suitable methods that observe the agents' environment (perception) and carry out agent actions (performance) according to some rules (policy). In addition, one needs to program a scheduler that instantiates the required number of agents at the beginning of the simulation and gives each of them a turn to act.

During the last years, of particular interest is the integration of functionality from geographic information systems (GIS) software libraries (e.g. ESRI's ArcGIS), which provide ABM toolkits with greater data management and spatial analytical capabilities required for geospatial modelling

In a spatial ABM:

- Agents may be mobile, it is however important that each agent has a different relationship with the spatial environment, most simply in terms of a location in the environment. If all agents have the same spatial relationship with the environment (if, for example, every agent sees and responds to an aggregate 'average' of the environment), then it makes little sense to formulate the model as an agent model;
- Agents may change their spatial relationship with the environment over time, which may be by moving, or it may be by alteration, acquisition or disposal of locations; and
- Agents are able to evaluate spatial configurations. This ability may be as simple as determining that the availability of some resource at the current location is sufficient for some purpose, or is greater than at neighbouring locations. Alternatively, it may involve a complicated evaluation of the spatial distribution of resources with respect to the current location, relative to a number of alternative locations.

This framework for thinking about agents in a spatial ABM, may be illuminated by considering the example (see also Figure 4-2) of pedestrians or other mobile agents in a model of an urban streetscape. The primary choice made by such agents is to determine, with respect to their intended destinations, which - among the possible next locations - they should move to. In most models of this kind, the location of other agents is an important element in the choice, but the decision will also be affected by the agents' local physical environments (e.g. building geometries, road capacity). Decisions are usually made by agents over some timeframe of interest, which may in turn imply a relevant spatial grain. In the pedestrian model this timeframe might be minute-by-minute, as pedestrians adjust their course to avoid obstacles (including other agents). In this specific example, each pedestrian agent is a significant element in the local environment of many other agents, and decisions made by one agent immediately alter the local decision-making environment of nearby agents. Generally, mobile agents (whether human or some other animal) will be making decisions at time scales dictated by their mobility on the one hand and their perception of the nature of the spatial distribution of resources on the other. The decision-making timeframe combined with the speed of movement of the agents then effectively frames a sensible spatial grain for a model of this type.

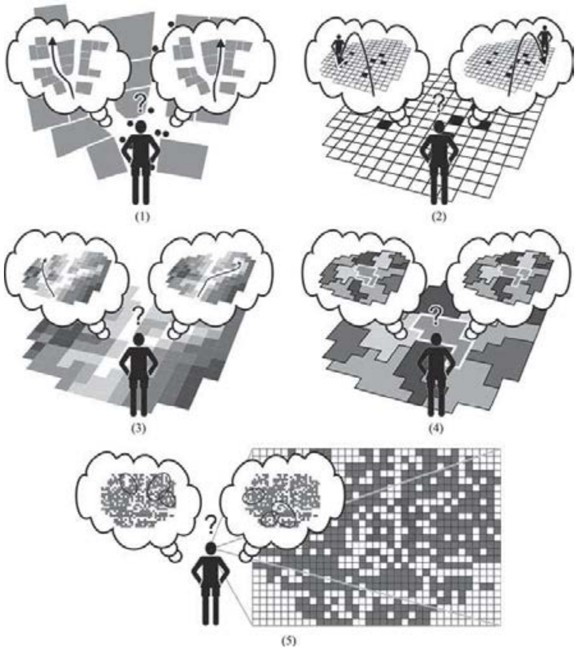

Figure 4-2. Schematic illustration of possible choices facing agents in different types of models.

Decision making is the engine of many ABMs, particularly those involving human actors, and in turn it has many ties to complexity. It has long been a core concern of many fields, including geography, economics, management, and psychology. ABMs have helped draw out the similarities and differences among different decision-making theories by emphasizing the importance of **developing basic rules for agents to follow**, leading to research focused on how such rules embody their decision-making strategies. Agents in an ABM usually pursue certain goals set by the modeller with given resources and constraints. For example, commuters want to minimize their commuting time. The ability of ABMs to describe the behaviour and interactions of a system allows for system dynamics to be directly incorporated into the model. This represents a movement away from the static nature of earlier styles of urban and regional modelling.

It should be noted that an ABM requires many simulations to evaluate any particular situation as it is based upon an underlying stochastic model. Randomness is applied to many involved processes; accordingly two model runs will not result in exactly the same result.

It is also worth noting that the resulting model is often one where a full explanation of the model behaviour calls for a chronological interpretation of the events in the model. Describing and understanding the model specific agent-agent interactions will matter, and a detailed account of the model "history" may be necessary for a complete understanding of any particular model run. The difference from the real world target system we seek to understand, is that a **model allows repeated runs and enables a probabilistic or general account of the system behaviours and tendencies to be developed.**

Overall, ABM simulations should be viewed as a research tool capable of providing insight into the real system and identifying what needs to be understood about the real system in order to develop a theory of the system itself (Bankes, 2002). When agents' preferences and (spatial) situations differ widely, and when agents' decisions substantially alter the decision-making contexts for other agents, then this is most probably a good case for exploring the usefulness of an ABM approach. This argument focuses attention on three model features: (a) ***heterogeneity* of the decision-making context of agents, (b) the importance of *interaction effects*, and (c) the overall *size* and *organization* of the system**. All these criteria favouring the adoption of ABM, call for considerable prior knowledge and insight about system characteristics on the part of those developing models.

4.3.2 Using ABM in the ICARUS framework, incorporating SES data

4.3.2.1 Approach

Assessing the total exposure of individuals and population subgroups to multiple airborne health stressors via different pathways is a key objective of ICARUS, since, as already discussed in the Introduction chapter, health protection is one of the most important (if not **the** most important) among the UN sustainable development goals, of particular relevance to the development of sustainable and resilient cities. Towards this aim, as already mentioned in previous sections, an extensive data collection / data mining scheme is being employed. Using data fusion techniques, traditional health and exposure data derived from fixed monitoring networks are being supplemented by a range of emerging techniques and technologies such as mobile phone apps, environmental sensor-webs, micro-sensors, satellite remote sensing and ABM. In this case, the use of ABM enables us to better understand the behaviour of individuals and populations in social and evolutionary settings, and to 'fill-in' the gaps in the exposome currently not available from real-world monitoring and sensor data.

Innovations in sensor technology create possibilities to collect environmental data at unprecedented depth and breadth. With the advent of GIS, GPS to track individuals, and personal environmental monitoring, undertaking such analyses throughout an individual's routine, or even lifetime, is now possible. Finding the right balance between limited amounts of high quality data from standardized environmental monitoring campaigns and large amounts of moderate quality data by sensor networks can transform the way we understand and interact with our environment. Due to the substantial technical and ethical hurdles involved in collecting real individual space-time movement data for whole populations, a decision has been made to **simulate movement and interaction behaviour using ABM,**

informed by sensor technologies. Measuring personal exposure directly requires a large number of people and therefore is often not feasible due to time and financial constraints, thus we take advantage of ABM to **allow us to extrapolate the sample data from our selected cities to the larger populations of these regions and from a limited number of individual citizens to population subgroups and whole populations**.

There are at least three challenges in the efforts to model human behaviour in agent based systems: (a) understanding humans, (b) data, and (c) validation and verification. Research communities develop data on how people behave under certain circumstances and this is replacing the poor default of assuming that human behaviour is random and unknown. In ICARUS observations and distributions derived from the sensors campaign are transformed into computer code that defines and shapes the agents world. Moreover **data on lifestyle/behaviour patterns** (e.g.: timetables for various activities per gender and age group) **and SES data** (e.g.: information on educational level, income, occupational status) **derived from EU scale or regional studies and surveys are also implemented** in a human agents population. **Survey outputs are associated with human agent behavioural rules, with the aim to model representative to real world conditions.**

Particular emphasis is given in the case of in-model incorporation of SES data. SES variables can explain differences in external exposure because of different prevalence of specific preferences and decision-making (behaviours) in some groups, e.g. differences in diet between SES groups. **Different human agents based on different age, sex or income will follow different rules, will express different behaviours (for example they will choose different means of transportation to reach their destination, they will purchase different consumer products, follow different diet patterns) and this would lead to a different exposure profile.** Moreover, knowledge of human agent characteristics by other human agents provide a signal that acts to enable or prevent interaction from occurring.

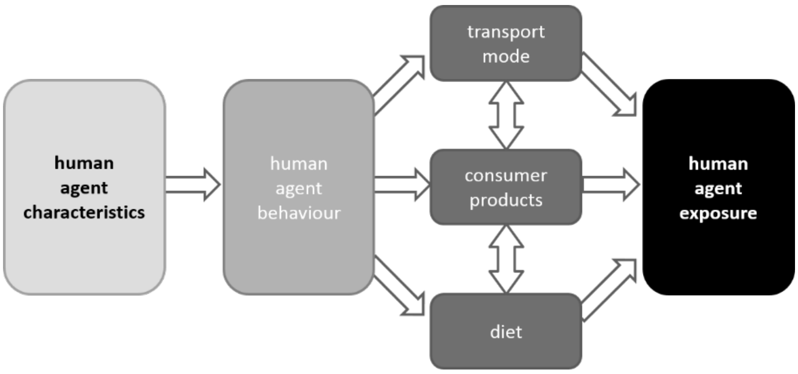

Figure 4-3.Human agents' behaviour impact on their personal exposure

4.3.2.2 Methodology

For the purposes of this project, the GAMA agent-based simulation platform (Grignard et al., 2013) is being used. This platform offers a complete modelling and simulation development environment for building spatially explicit multi-agent simulations. GAMA provides a rich modelling language based on Java, GAML, which allows to define complex models integrating at the same time, entities of different scales and geographical vector data. It provides a true geometry to all situated agents. This geometry, which is based on vector representation, can be simple (point, polyline or polygon) or complex (composed of several sub-geometries). The agents' geometry can be defined by the modeller (a list of points) or directly loaded from a shapefile. In the context of simulation, the advantage of geographical data agentification is to give the possibility to manage geographical objects (buildings, roads) exactly like other agents (people) in the simulation: you can give them an internal state and a behaviour. It is possible to initialize the virtual work to a present arrangement and then let the model run and observe its behaviour. Agent states of various sub-populations can be measured and aggregated across many simulation runs at each point in time in the simulation.

The developed ABM model is being informed by data related to:

a) an individual's behaviour within his/her environment (such as movement data within specific micro-environments, food consumption, use of consumer products, etc.), derived by sensor campaigns data that were then analysed and extrapolated to a representative population
b) the interaction between individuals, exploring associated behaviours based on literature, and
c) risk determinants, such as socio-economic status (SES) data. Using existing national population censuses and surveys, we apply geospatial analysis methods to distribute estimates across all sectors of society at a local neighbourhood scale.

Using these parameters and taking into account the evolution of agents, our simulations can produce detailed information relating to the emulated system, producing data that can be used to fill in the gaps that exist in traditional datasets.

By importing a series of GIS files in the GAMA platform, we are able to project a city's map with its road and buildings network as well as information on land use. Every entity taking part in this system is agentified, it is therefore considered as an individual agent (the system is composed of road, building, vehicle and human agents).

Road and building shapefiles of a building block resolution are imported in GAMA containing spatial information such as the capacity of a street and land use characteristics respectively. Tables with population data with information on sex, gender coming from surveys and censuses are transformed into moving human agents inside the ABM platform. Moreover, national or regional studies usually provide SES information such as occupational status, educational level and ethnicity per postal code (e.g. education level per postal code). In cases where this kind of data is available, human agents will acquire these characteristics, following a distribution among the population of the smaller region for which specific information exists.

When the model is initialized, human agents are clustered in age groups, depending on their age and are randomly allocated to a residential place which will serve as their house for the whole simulation. **Human agents' characteristics provide capabilities or constraints on the agents' behavioural rules** (the reference point could be, for example, age or income that influence their preferences and decision-making). Based on their age and SES characteristics, and of course based on the distance between point of departure and their targeted destination, human agents will choose different means of transportation. In the same way different human agents will follow a different sequence and types of activities. For example, children and adults are programmed to move from a household to an assigned school or office whereas human agents that belong to the elderly will follow a different sequence of activities.

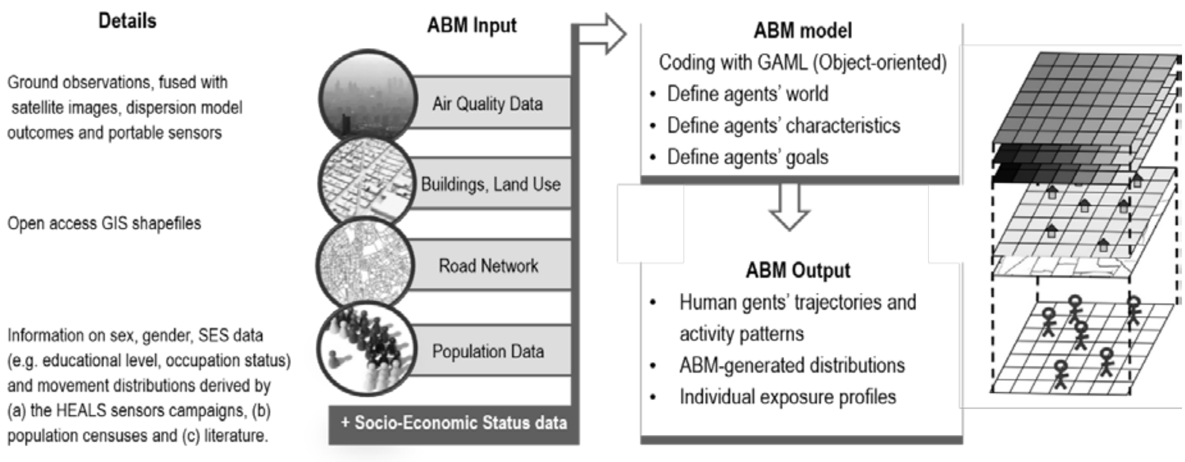

Figure 4-4. ABM model overview

At the end of a run (a single run corresponds to a typical day), human agents' trajectories, derived by the coded routine, are captured as points (1 point captured per simulation step) and are exported as a GIS shapefile together with a database that contains their coordinates and activities in time through different locations/microenvironments.

The ABM exported GIS layer containing human agents' trajectories can then be superposed onto high spatial resolution urban air quality modelled maps (for the same region) of hourly concentration of pollutants (such as PM10, PM2.5, PM1, NOx). Personal exposure, expressed as inhalation-adjusted exposure to air pollutants can then be evaluated by assigning pollutant concentrations to a human agent based on his/her coordinates, activities and the corresponding inhalation rate.

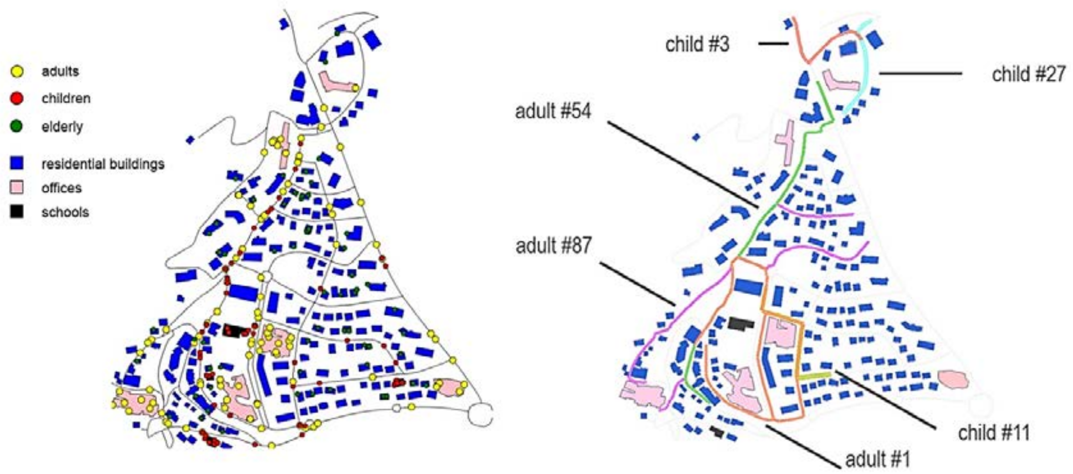

Figure 4-5. Right: ABM model running over a neighbourhood with building, roads and moving people being agentified. Left: At the end of the ABM run, trajectories of specific human agents over the period of a typical day (together with information on their activities over this period of time) can be exported.

Such a model can be useful for assessing exposure of specific vulnerable subgroups, such as children, the elderly and people with low socioeconomic status, taking into account their different activity patterns, consumer behaviours and other lifestyles.

The city of Thessaloniki has been chosen as case study to test the aforementioned methodology for the purposes of this report. Due to the complexity and availability of input data the simulation of the two cities are slightly different but provide examples of two ways to extrapolate individual data to population wide data using the conceptual framework described in section 4. In Thessaloniki SES details are only provided at municipality level (an area with a population ranging from 6000 to 360,000). On average each designated area in the ABM will have a population of 1000. This is a useful analysis because population data available to us for other cities may be at different resolutions. Thus, the Thessaloniki example provides an insight as to what is possible with the data we may be able to access for other cities.

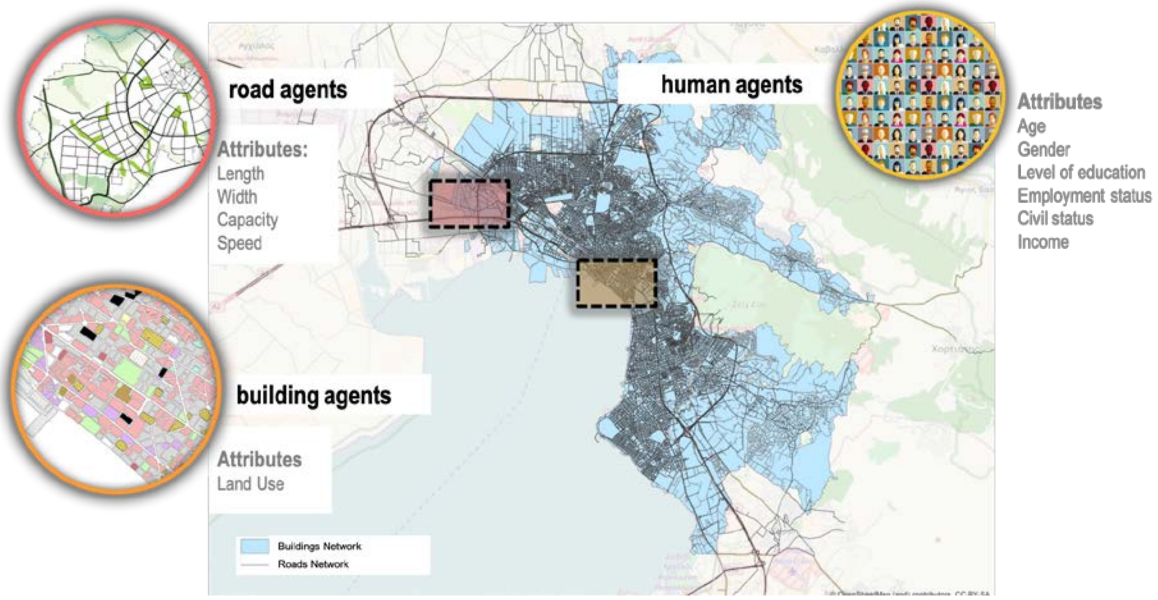

Figure 4-6. Agent Based Model of the city of Thessaloniki – the main components.

Figure 4-6 summarises the different types of agents employed in the Thessaloniki agent-based model. These include both population subgroups clustered according to sociodemographic features such as age, gender, education level, employment status, civil status and annual income level; and physical agents such as buildings (clustered according to type of land use) and roads (clustered according to length, width, capacity and operational speed of traffic). This formulation allows us not only to estimate population exposure at a very high level of granularity but also to use the resulting information as a means to experiment (and thus evaluate) with different alternatives in urban planning (mostly related to building construction and retrofitting, including energy efficiency measures and transport infrastructure (road network, but also the effect of intermodal transport and the introduction of disruptive technologies such as underground rail).

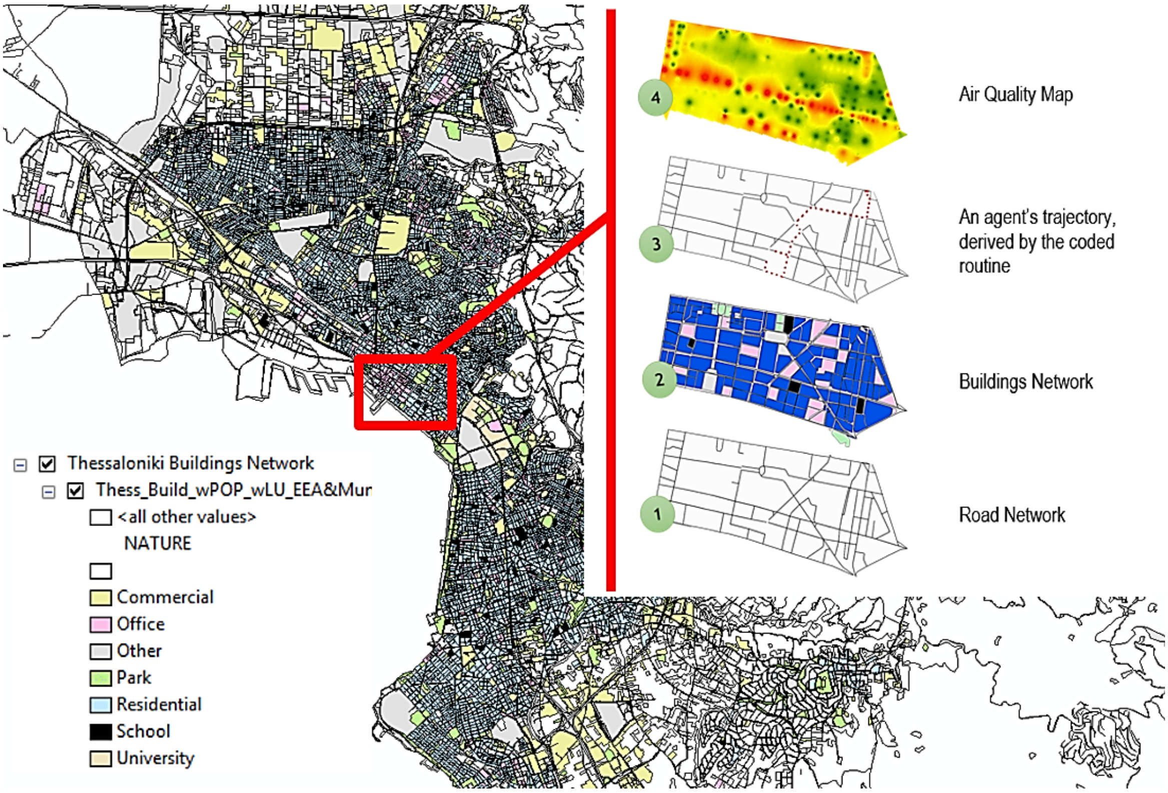

Figure 4-7. GIS layers - exposure assessment using Agent Based Modelling.

Figure 4-7 demonstrates the different information layers used in population exposure assessment using the ABM formulation in Thessaloniki. The conceptual model to account for SES in exposure modelling forms a suitable methodology for what we want to achieve in ICARUS and can be applied to real city examples. Thus, the method is easy to implement even in other settings beyond the ones covered in the project. The detailed outcomes of the models for Thessaloniki are expected to be published this year (2018). An example of the input for the model can be understood easily if we look at means of transportation. In this case, the overall population would originally be distributed to use a certain transport mode; for example, 60% will use the car, 25% will walk, 10% cycle, and 5% will use public transport. However, this will change with each agent depending on sociodemographic characteristics and distance to their destination and infrastructure. This leads to many 'rules' which are applied and thus alter the distribution; if, for example, an agent is male, employed, and belongs to a high-income group, the agent will have a higher probability of using the car to travel to work and be in the car for longer, than a woman, who is a homemaker, with children. The output provides us with information regarding the distribution of transport mode choice throughout the day and we can focus on certain time windows within a day for more detail. This is an example where we can achieve a deeper and more precise understanding of the underlying phenomena and how they affect overall human exposure. ABM-generated distributions can also work as input into a probabilistic exposure assessment model.

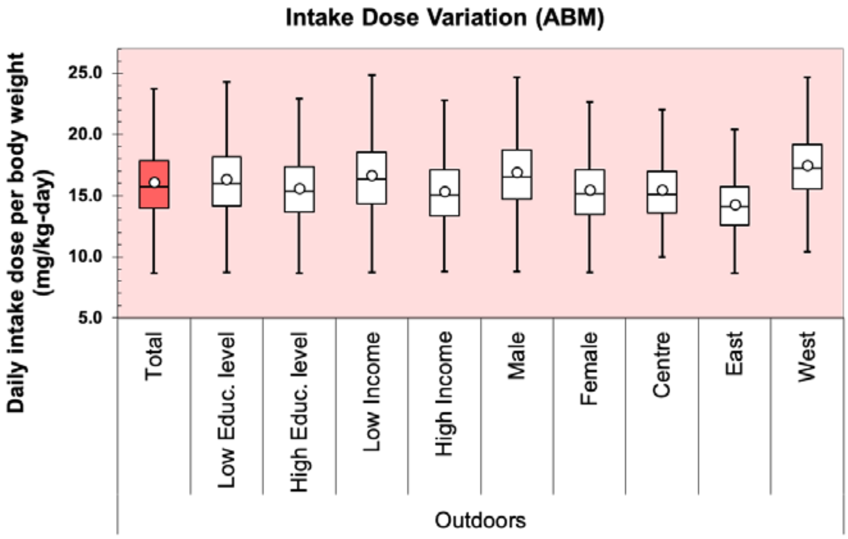

Figure 4-8. Results of the application of the ABM for exposure assessment: effect of sociodemographic attributes on population exposure.

Figure 4-8 provides a synthesis of a large number of ABM simulations for the Thessaloniki case study isolating the effect of socioeconomic and sociodemographic features on population exposure to airborne pollutants. The exposure metric used is daily intake dose expressed in quantity of pollutant inhaled per body weight over 24 hours. This is useful for consideration of the interactions among different chemicals in urban air that may have beyond additive effects on human health, especially after chronic exposure. The results indicate the significant role of specific socio-economic attributes such as education level of the individuals and annual income of the household in terms of affecting the actual exposure levels. Additional sociodemographic features of high importance include gender and, very importantly, the residence location of the population within the urban fabric. Exposure differs up to 32% for people living under the same roof, while exposure variation rise up to 77% for people in the same neighbourhood as a function of specific differences in socio-economic and cultural elements.

4.4 Limitations

4.4.1 Data collection

To understand variations in exposure across all groups in society large population samples are needed, representing both different time periods (weekends, weekdays, and seasons) and subgroups, see (Burke et al., 2001; Freijer et al., 1998; Gulliver and Briggs, 2005). Collecting a large enough sample is costly both financially and timewise, and requires a lot of personal information from participants. This can be overcome through the use of ABM where observed data from different groups either through the ICARUS campaigns or existing databases can be used to make predictions about the behaviour of subgroups throughout the entire population.

4.4.2 Data availability

Population data at a detailed level (e.g. census) are not available for many countries. However, Eurostat data is available which, although a much coarse resolution, it is available for all EU countries at the Nomenclature of Territorial Units for Statistics 3 region (NUTS3), which is the finest NUTS region of this data (http://ec.europa.eu/eurostat/web/nuts/overview). SES data is also difficult to access for some countries, and where it is available, due to privacy restrictions matrixes of data can be difficult to manipulate.

4.4.3 Spatial scale

Spatial distribution of pollution sources or emission concentrations are often linked to aggregated socio-demographic characteristics of neighbourhoods or other spatial areas. Although this provides some information, the overall usefulness may be limited because group level associations between exposure and social determinants may not reflect the true exposure of individuals within the aggregated areas. This is not ideal, however in some of the ICARUS cities this will have to be done due to the available population data, or rather the paucity thereof. In cities where population data are available, this will be avoided by using individual SES attributes from census data and grouping on characteristics rather than areas. For example, people with similar characteristics can live in any area within a city rather than all people in one area having similar characteristics.

5 Conclusions

We have shown that there are links between the health disorders relevant for ICARUS and sociodemographic characteristics. As links have been established, we moved on to explore how time exposure modifiers such as activity patterns and consumer behaviours vary between people with different socio-demographic characteristics. Limited European literature exists on *sociodemographic* exposure modifiers, particularly socioeconomic status patterns, and thus these are poorly understood. Recognising this lack of data, additional data that relate the various sociodemographic parameters to exposure modifiers, will be collected from (a) the sensors campaign in the 9 cities of ICARUS and from (b) city and regional/national statistics. Our conceptual model provides a methodology to estimate exposure at the individual level and uses these data to support population-wide exposure assessment. An important aspect of this model is accounting for demographic attributes in addition to several SES measures, as demographic characteristics influence socioeconomic status. One SES measure alone is not sufficient to account for cultural and demographic difference within and between countries. Through the use of agent-based modelling (ABM) we are able to simulate time activity patterns and thus exposure estimates for whole populations and show how this can be done even when the quality of input data varies.

6 References

Harmonised European Time Use Survey, HETUS. In: S. F. a. S. Sweden, (Ed.), 2007.

Acharya, S., Hsieh, S., Shinohara, E. T., DeWees, T., Frangoul, H., Perkins, S. M., 2016. Effects of Race/Ethnicity and Socioeconomic Status on Outcome in Childhood Acute Lymphoblastic Leukemia. J Pediatr Hematol Oncol. 38**,** 350-4.

Acharya, U. H., Halpern, A. B., Wu, Q. V., Voutsinas, J. M., Walter, R. B., Yun, S., Kanaan, M., Estey, E. H., 2018. Impact of region of diagnosis, ethnicity, age, and gender on survival in acute myeloid leukemia (AML). J Drug Assess. 7**,** 51-53.

Adamkiewicz, G., Zota, A. R., Fabian, M. P., Chahine, T., Julien, R., Spengler, J. D., Levy, J. I., 2011. Moving Environmental Justice Indoors: Understanding Structural Influences on Residential Exposure Patterns in Low-Income Communities. American Journal of Public Health. 101**,** S238-S245.

Adams, H. S., Nieuwenhuijsen, M. J., Colvile, R. N., McMullen, M. A. S., Khandelwal, P., 2001. Fine particle (PM2.5) personal exposure levels in transport microenvironments, London, UK. Science of The Total Environment. 279**,** 29-44.

Aguilera, I., Guxens, M., Garcia-Esteban, R., Corbella, T., Nieuwenhuijsen, M. J., Foradada, C. M., Sunyer, J., 2009. Association between GIS-Based Exposure to Urban Air Pollution during Pregnancy and Birth Weight in the INMA Sabadell Cohort. Environmental Health Perspectives. 117**,** 1322-1327.

Allen, J. L., Oberdorster, G., Morris-Schaffer, K., Wong, C., Klocke, C., Sobolewski, M., Conrad, K., Mayer-Proschel, M., Cory-Slechta, D. A., 2017. Developmental neurotoxicity of inhaled ambient ultrafine particle air pollution: Parallels with neuropathological and behavioral features of autism and other neurodevelopmental disorders. Neurotoxicology. 59**,** 140-154.

American Psychological Association, Fact sheet: Women and socioeconomic status. undated-a.

American Psychological Association, Factsheet: Ethnic and Racial Minorities & Socioeconomic Status. undated-b.

Anderson, N. B., Armstead, C. A., 1995. TOWARD UNDERSTANDING THE ASSOCIATION OF SOCIOECONOMIC-STATUS AND HEALTH - A NEW CHALLENGE FOR THE BIOPSYCHOSOCIAL APPROACH. Psychosomatic Medicine. 57**,** 213-225.

APA, Socioeconomic status. undated.

Australian Bureau of Statistics, Socioeconomic status. 2011.

Backholer, K., Peters, S. A. E., Bots, S. H., Peeters, A., Huxley, R. R., Woodward, M., 2017. Sex differences in the relationship between socioeconomic status and cardiovascular disease: a systematic review and meta-analysis. J Epidemiol Community Health. 71**,** 550-557.

Ballardini, N., Kull, I., Lind, T., Hallner, E., Almqvist, C., Östblom, E., Melén, E., Pershagen, G., Lilja, G., Bergström, A., Wickman, M., 2012. Development and comorbidity of eczema, asthma and rhinitis to age 12 – data from the BAMSE birth cohort. Allergy. 67**,** 537-544.

Bankes, S. C., Agent-based modeling: A revolution? , Proceedings of the National Academy of Sciences of the United States of America, 2002.

Barnard, H., Turner, C., 2011. Poverty and ethnicity: A review of evidence. Joseph Rowntree Foundation.

Barnes, M., Cullinane, C., Scott, S., Silvester, H., People living in bad housing–numbers and health impacts. London: NatCen Social Research. http://england. shelter. org. uk/__data/assets/pdf_file/0010/726166/People_ living_in_bad_housing. pdf, 2013.

Beckx, C., Torfs, R., Arentze, T., Janssens, D., Wets, G., 2008. Establishing a dynamic exposure assessment with an activity-based modeling approach: methodology and results for the Dutch case study. Epidemiology. 19**,** S378-S379.

BiologyReference, Neurological diseases. undated.

Brasche, S., Bischof, W., 2005. Daily time spent indoors in German homes – Baseline data for the assessment of indoor exposure of German occupants. International Journal of Hygiene and Environmental Health. 208**,** 247-253.

Briggs, D. J., Mapping environmental exposure. In: C. J. Elliott P, English D and Stern R, (Ed.), Geographical and Environmental Epidemiology: Methods for small-area studies. OUP, Oxford, 1992, pp. 158-176.

Brown, D. G., The Earth's changing land: An encyclopaedia of land-use and land-cover change. Agent-based models. In H. Geist (Ed.). Greenwood Publishing Group, 2006, pp. 7-13.

Brown, J. S., 2015. Nitrogen dioxide exposure and airway responsiveness in individuals with asthma. Inhal Toxicol. 27**,** 1-14.

Buehler, R., 2011. Determinants of transport mode choice: a comparison of Germany and the USA. Journal of Transport Geography. 19**,** 644-657.

Buonanno, G., Stabile, L., Morawska, L., 2014. Personal exposure to ultrafine particles: the influence of time-activity patterns. Science of the Total Environment. 468**,** 903-907.

Burke, J. M., Zufall, M. J., Ozkaynak, H., 2001. A population exposure model for particulate matter: case study results for PM2. 5 in Philadelphia, PA. Journal of exposure analysis and environmental epidemiology. 11**,** 470-489.

Cabieses, B., Uphoff, E., Pinart, M., Antó, J. M., Wright, J., 2014. A systematic review on the development of asthma and allergic diseases in relation to international immigration: the leading role of the environment confirmed.

Cai, Y., Hodgson, S., Blangiardo, M., Gulliver, J., Morley, D., Fecht, D., Vienneau, D., de Hoogh, K., Key, T., Hveem, K., Elliott, P., Hansell, A. L., 2018. Road traffic noise, air pollution and incident cardiovascular disease: A joint analysis of the HUNT, EPIC-Oxford and UK Biobank cohorts. Environ Int. 114**,** 191-201.

Calixto, O.-J., Anaya, J.-M., 2014. Socioeconomic status. The relationship with health and autoimmune diseases. Autoimmunity Reviews. 13**,** 641-654.

Campos-Serna, J., Ronda-Pérez, E., Artazcoz, L., Moen, B. E., Benavides, F. G., 2013. Gender inequalities in occupational health related to the unequal distribution of working and employment conditions: a systematic review. Int J Equity Health. 12**,** 12-57.

Chen, C., Xun, P., Nishijo, M., He, K., 2016. Cadmium exposure and risk of lung cancer: a meta-analysis of cohort and case-control studies among general and occupational populations. J Expo Sci Environ Epidemiol. 26**,** 437-44.

Chi, G. C., Hajat, A., Bird, C. E., Cullen, M. R., Griffin, B. A., Miller, K. A., Shih, R. A., Stefanick, M. L., Vedal, S., Whitsel, E. A., Kaufman, J. D., 2016. Individual and Neighborhood Socioeconomic Status and the Association between Air Pollution and Cardiovascular Disease. Environ Health Perspect. 124**,** 1840-1847.

Clough, S., 2011. Gender and the hygiene hypothesis. Social Science & Medicine. 72**,** 486-493.

Corlin, L., Brugge, D., 2014. The Hidden Asthma Epidemic in Immigrant Subpopulations. Environment: Science and Policy for Sustainable Development. 56**,** 18-27.

Couclelis, H., Why I no longer work with agents: A challenge for ABMs of human-environment interactions. Proceeding of Special Workshop on Land-Use/Land-Cover Change, 2001, pp. 14–16.

Day, D. B., Clyde, M. A., Xiang, J., Li, F., Cui, X., Mo, J., Gong, J., Weschler, C. J., Zhang, Y., Zhang, J. J., 2018. Age modification of ozone associations with cardiovascular disease risk in adults: a potential role for soluble P-selectin and blood pressure. J Thorac Dis. 10**,** 4643-4652.

de Mestral, C., Stringhini, S., 2017. Socioeconomic Status and Cardiovascular Disease: an Update. Curr Cardiol Rep. 19**,** 115.

Dons, E., Int Panis, L., Van Poppel, M., Theunis, J., Willems, H., Torfs, R., Wets, G., 2011. Impact of time–activity patterns on personal exposure to black carbon. Atmospheric Environment. 45**,** 3594-3602.

Duan, N., 1982. Indoor Air Pollution Models for human exposure to air pollution. Environment International. 8**,** 305-309.

Durkin, M. S., Yeargin-Allsopp, M., 2018. Socioeconomic Status and Pediatric Neurologic Disorders: Current Evidence. Semin Pediatr Neurol. 27**,** 16-25.

Ellis, C., 2009. Does race/ethnicity really matter in adult neurogenics? Am J Speech Lang Pathol. 18**,** 310-4.

Ellison-Loschmann, L., Sunyer, J., Plana, E., Pearce, N., Zock, J. P., Jarvis, D., Janson, C., Anto, J. M., Kogevinas, M., 2007. Socioeconomic status, asthma and chronic bronchitis in a large community-based study. Eur Respir J. 29**,** 897-905.

Fan, J., Li, S., Fan, C., Bai, Z., Yang, K., 2016a. The impact of PM2.5 on asthma emergency department visits: a systematic review and meta-analysis. Environ Sci Pollut Res Int. 23**,** 843-50.

Fan, Y., Jiang, Y., Hu, P., Chang, R., Yao, S., Wang, B., Li, X., Zhou, Q., Qiao, Y., 2016b. Modification of association between prior lung disease and lung cancer by inhaled arsenic: A prospective occupational-based cohort study in Yunnan, China. J Expo Sci Environ Epidemiol. 26**,** 464-70.

Ferré, A., Fuhrman, C., Zureik, M., Chouaid, C., Vergnenègre, A., Huchon, G., Delmas, M.-C., Roche, N., 2012. Chronic bronchitis in the general population: Influence of age, gender and socio-economic conditions. Respiratory Medicine. 106**,** 467-471.

Filippini, T., Heck, J. E., Malagoli, C., Del Giovane, C., Vinceti, M., 2015. A review and meta-analysis of outdoor air pollution and risk of childhood leukemia. J Environ Sci Health C Environ Carcinog Ecotoxicol Rev. 33**,** 36-66.

Fisher, J. G. a. K., Multinational Time Use Study. In: U. o. O. Centre for Time Use Research, (Ed.), 2013.

Foroutan, Y., 2008. Women's employment, religion and multiculturalism: Socio-demographic emphasis. Journal of Population Research. 25**,** 63-90.

Forsythe, A., Breland, T., Majumdar, S., Elkin, T. D., Johnson, D., Megason, G., 2010. Gender differences in incidence rates of childhood B-precursor acute lymphocytic leukemia in Mississippi. J Pediatr Oncol Nurs. 27**,** 164-7.

Franceschini, J. P., Jamnik, S., Santoro, I. L., 2017. Survival in a cohort of patients with lung cancer: the role of age and gender in prognosis. J Bras Pneumol. 43**,** 431-436.

Freijer, J. I., Bloemen, H. J. T., de Loos, S., Marra, M., Rombout, P. J. A., Steentjes, G. M., van Veen, M. P., 1998. Modelling exposure of the Dutch population to air pollution. Journal of Hazardous Materials. 61**,** 107-114.

Gaffin, J. M., Hauptman, M., Petty, C. R., Sheehan, W. J., Lai, P. S., Wolfson, J. M., Gold, D. R., Coull, B. A., Koutrakis, P., Phipatanakul, W., 2018. Nitrogen dioxide exposure in school classrooms of inner-city children with asthma. J Allergy Clin Immunol. 141**,** 2249-2255.e2.

Gender Spectrum, Understanding gender. undated.

Giuliano, G., Dargay, J., 2006. Car ownership, travel and land use: a comparison of the US and Great Britain. Transportation Research Part A: Policy and Practice. 40**,** 106-124.

Goulden, R., Ibrahim, T., Wolfson, C., 2015. Is high socioeconomic status a risk factor for multiple sclerosis? A systematic review. European Journal of Neurology. 22**,** 899-911.

Grignard, A., Taillandier, P., Gaudou, B., Vo, D., Huynh, N., Drogoul, A., GAMA 1.6: Advancing the Art of Complex Agent-Based Modeling and Simulation. In: G. Boella, et al., Eds.), PRIMA 2013: Principles and Practice of Multi-Agent Systems. Springer, Berlin Heidelberg, 2013, pp. 117-131.

Gulliver, J., Briggs, D. J., 2005. Time–space modeling of journey-time exposure to traffic-related air pollution using GIS. Environmental Research. 97**,** 10-25.

Gwynn, R. C., Thurston, G. D., 2001. The burden of air pollution: impacts among racial minorities. Environmental health perspectives. 109 Suppl 4**,** 501-506.

Hagedoorn, P., Vandenheede, H., Willaert, D., Vanthomme, K., Gadeyne, S., 2016. Regional Inequalities in Lung Cancer Mortality in Belgium at the Beginning of the 21st Century: The Contribution of Individual and Area-Level Socioeconomic Status and Industrial Exposure. PLoS One. 11**,** e0147099.

Hägerstraand, T., 1970. WHAT ABOUT PEOPLE IN REGIONAL SCIENCE? Papers in Regional Science. 24**,** 7-24.

Hajat, A., Hsia, C., O'Neill, M., 2015. Socioeconomic Disparities and Air Pollution Exposure: a Global Review. Current Environmental Health Reports. 2**,** 440-450.

Hertel, O., Jensen, S. S., Andersen, H. V., Palmgren, F., Wåhlin, P., Skov, H., Nielsen, I. V., Sørensen, M., Loft, S., Raaschou-Nielsen, O., 2001. Human exposure to traffic pollution. Experience from Danish studies. Pure and Applied Chemistry. 73**,** 137-145.

Hiscock, R., Schieberle, C., Li, N., Gari, M., Grimalt, J., Deliverable 1.3 A critical review of how much of the difference in disease betsween socioeconomic and other social groups can be explained by differences in the "group" exposome. HEALS (Health and Environment-wide Associations based on Large population Surveys, 2015.

Houot, J., Marquant, F., Goujon, S., Faure, L., Honore, C., Roth, M. H., Hemon, D., Clavel, J., 2015. Residential Proximity to Heavy-Traffic Roads, Benzene Exposure, and Childhood Leukemia-The GEOCAP Study, 2002-2007. Am J Epidemiol. 182**,** 685-93.

Hovanec, J., Siemiatycki, J., Conway, D. I., Olsson, A., Stucker, I., Guida, F., Jockel, K. H., Pohlabeln, H., Ahrens, W., Bruske, I., Wichmann, H. E., Gustavsson, P., Consonni, D., Merletti, F., Richiardi, L., Simonato, L., Fortes, C., Parent, M. E., McLaughlin, J., Demers, P., Landi, M. T., Caporaso, N., Tardon, A., Zaridze, D., Szeszenia-Dabrowska, N., Rudnai, P., Lissowska, J., Fabianova, E., Field, J., Dumitru, R. S., Bencko, V., Foretova, L., Janout, V., Kromhout, H., Vermeulen, R., Boffetta, P., Straif, K., Schuz, J., Kendzia, B., Pesch, B., Bruning, T., Behrens, T., 2018. Lung cancer and socioeconomic status in a pooled analysis of case-control studies. PLoS One. 13**,** e0192999.

Hoy, D. G., Protani, M., De, R., Buchbinder, R., 2010. The epidemiology of neck pain. Best Practice & Research Clinical Rheumatology. 24**,** 783-792.

Hsu, K. H., Tsui, K. H., Hsu, L. I., Chiou, H. Y., Chen, C. J., 2017. Dose-Response Relationship between Inorganic Arsenic Exposure and Lung Cancer among Arseniasis Residents with Low Methylation Capacity. Cancer Epidemiol Biomarkers Prev. 26**,** 756-761.

Ingleby, D., 2012. Ethnicity, Migration and the 'Social Determinants of Health'Agenda Etnicidad, Migración y la Agenda de los "Determinantes Sociales de la Salud".

Jacobs, D. E., 2011. Environmental health disparities in housing. American journal of public health. 101, S115-S122.

Janitz, A. E., Campbell, J. E., Magzamen, S., Pate, A., Stoner, J. A., Peck, J. D., 2016. Traffic-related air pollution and childhood acute leukemia in Oklahoma. Environ Res. 148, 102-111.

Jayaraj, R. L., Rodriguez, E. A., Wang, Y., Block, M. L., 2017. Outdoor Ambient Air Pollution and Neurodegenerative Diseases: the Neuroinflammation Hypothesis. Curr Environ Health Rep. 4, 166-179.

Jenkins, M. A., Hopper, J. L., Bowes, G., Carlin, J. B., Flander, L. B., Giles, G. G., 1994. Factors in childhood as predictors of asthma in adult life. Bmj. 309, 90-93.

Jones, R. R., Hogrefe, C., Fitzgerald, E. F., Hwang, S. A., Ozkaynak, H., Garcia, V. C., Lin, S., 2015. Respiratory hospitalizations in association with fine PM and its components in New York State. J Air Waste Manag Assoc. 65, 559-69.

Karakitsios, S. P., Delis, V. K., Kassomenos, P. A., Pilidis, G. A., 2007. Contribution to ambient benzene concentrations in the vicinity of petrol stations: Estimation of the associated health risk. Atmospheric Environment. 41, 1889-1902.

Karunanayake, C. P., Hagen, B., Dosman, J. A., Pahwa, P., 2013. Prevalence of and risk factors for chronic bronchitis in a Canadian population: the Canadian Community Health Survey, 2007 to 2008. Can Respir J. 20, 231-6.

Kaur, S., Nieuwenhuijsen, M. J., 2009. Determinants of Personal Exposure to PM2.5, Ultrafine Particle Counts, and CO in a Transport Microenvironment. Environmental Science & Technology. 43, 4737-4743.

Keet, C. A., Keller, J. P., Peng, R. D., 2018. Long-Term Coarse Particulate Matter Exposure Is Associated with Asthma among Children in Medicaid. Am J Respir Crit Care Med. 197, 737-746.

Kelly, F. J., Fussell, J. C., 2017. Role of oxidative stress in cardiovascular disease outcomes following exposure to ambient air pollution. Free Radic Biol Med. 110, 345-367.

Kim, D., Chen, Z., Zhou, L.-F., Huang, S.-X., 2018. Air pollutants and early origins of respiratory diseases. Chronic diseases and translational medicine. 4, 75-94.

Knoble, N. B., Alderfer, M. A., Hossain, M. J., 2016. Socioeconomic status (SES) and childhood acute myeloid leukemia (AML) mortality risk: Analysis of SEER data. Cancer Epidemiol. 44, 101-108.

Kollia, N., Panagiotakos, D. B., Georgousopoulou, E., Chrysohoou, C., Tousoulis, D., Stefanadis, C., Papageorgiou, C., Pitsavos, C., 2016. Exploring the association between low socioeconomic status and cardiovascular disease risk in healthy Greeks, in the years of financial crisis (2002-2012): The ATTICA study. Int J Cardiol. 223, 758-763.

Kolokotsa, D., Santamouris, M., 2015. Review of the indoor environmental quality and energy consumption studies for low income households in Europe. Science of The Total Environment. 536, 316-330.

Krzyżanowski, M., Kuna-Dibbert, B., Schneider, J., 2005. Health effects of transport-related air pollution. WHO Regional Office Europe.

Kurmi, O. P., Semple, S., Simkhada, P., Smith, W. C., Ayres, J. G., 2010. COPD and chronic bronchitis risk of indoor air pollution from solid fuel: a systematic review and meta-analysis. Thorax. 65, 221-8.

Kynyk, J. A., Mastronarde, J. G., McCallister, J. W., 2011. Asthma, the sex difference. Current opinion in pulmonary medicine. 17, 6-11.

Laußmann, D., Haftenberger, M., Lampert, T., Scheidt-Nave, C., Social inequities regarding annoyance to noise and road traffic intensity - Results of the German Health Interview and Examination Survey for Adults (DEGS1). Epidemiologie und Gesundheitsberichterstattung, 2013.

Levy, S., 1993. Artificial Life: A Report from the Frontier Where Computers Meet Biology. Random House Inc.

Lim, H., Kwon, H. J., Lim, J. A., Choi, J. H., Ha, M., Hwang, S. S., Choi, W. J., 2016. Short-term Effect of Fine Particulate Matter on Children's Hospital Admissions and Emergency Department Visits for Asthma: A Systematic Review and Meta-analysis. J Prev Med Public Health. 49**,** 205-19.

Lipps, O., Kunert, U., Measuring and Explaining the Increase of Travel Distance: A Multilevel Analysis Using Repeated Cross Sectional Travel Surveys. DIW-Diskussionspapiere, 2005.

Liu, M., 2017. Dr. Viola Zhu: is ethnicity a prognostic factor in lung cancer? Translational lung cancer research. 6**,** S99-S100.

Luginaah, I. N., Fung, K. Y., Gorey, K. M., Webster, G., Wills, C., 2005. Association of ambient air pollution with respiratory hospitalization in a government-designated "area of concern": the case of Windsor, Ontario. Environmental health perspectives. 113**,** 290-296.

Malik, M. O., Govan, L., Petrie, J. R., Ghouri, N., Leese, G., Fischbacher, C., Colhoun, H., Philip, S., Wild, S., McCrimmon, R., Sattar, N., Lindsay, R. S., 2015. Ethnicity and risk of cardiovascular disease (CVD): 4.8 year follow-up of patients with type 2 diabetes living in Scotland. Diabetologia. 58**,** 716-25.

Matin, N., Young, S. S., Williams, B., LaFrance, W. C., Jr., King, J. N., Caplan, D., Chemali, Z., Weilburg, J. B., Dickerson, B. C., Perez, D. L., 2017. Neuropsychiatric Associations With Gender, Illness Duration, Work Disability, and Motor Subtype in a U.S. Functional Neurological Disorders Clinic Population. J Neuropsychiatry Clin Neurosci. 29**,** 375-382.

Meade, M. S., 1977. Medical geography as human ecology: the dimension of population movement. Geographical Review. 379-393.

Montano, D., 2014. Chemical and biological work-related risks across occupations in Europe: a review. J Occup Med Toxicol. 9**,** 28.

Nachman, K. E., Parker, J. D., 2012. Exposures to fine particulate air pollution and respiratory outcomes in adults using two national datasets: a cross-sectional study. Environmental health : a global access science source. 11**,** 25-25.

Nawrot, T., Plusquin, M., Hogervorst, J., Roels, H. A., Celis, H., Thijs, L., Vangronsveld, J., Van Hecke, E., Staessen, J. A., 2006. Environmental exposure to cadmium and risk of cancer: a prospective population-based study. The Lancet Oncology. 7**,** 119-126.

Nethery, E., Brauer, M., Janssen, P., 2008. Time-activity patterns of pregnant women and changes during the course of pregnancy. J Expos Sci Environ Epidemiol. 19**,** 317-324.

NHS, Allergies. 2014a.

NHS, Asthma. 2014b.

Öberg, M., Jaakkola, M. S., Woodward, A., Peruga, A., Prüss-Ustün, A., 2011. Worldwide burden of disease from exposure to second-hand smoke: a retrospective analysis of data from 192 countries. The Lancet. 377**,** 139-146.

ONS, Ethnic group. undated.

Orimoloye, O. A., Budoff, M. J., Dardari, Z. A., Mirbolouk, M., Uddin, S. M. I., Berman, D. S., Rozanski, A., Shaw, L. J., Rumberger, J. A., Nasir, K., Miedema, M. D., Blumenthal, R. S., Blaha, M. J., 2018. Race/Ethnicity and the Prognostic Implications of Coronary Artery Calcium for All-Cause and

Cardiovascular Disease Mortality: The Coronary Artery Calcium Consortium. J Am Heart Assoc. 7**,** e010471.

Orton, S., Jones, L. L., Cooper, S., Lewis, S., Coleman, T., 2014. Predictors of Children's Secondhand Smoke Exposure at Home: A Systematic Review and Narrative Synthesis of the Evidence.

Ott, W. R., 1982. Concepts of human exposure to air pollution. Environment International. 7**,** 179-196.

Paladino, S., Conte, A., Caggiano, R., Pierantoni, G. M., Faraonio, R., 2018. Nrf2 Pathway in Age-Related Neurological Disorders: Insights into MicroRNAs. Cell Physiol Biochem. 47**,** 1951-1976.

Parliament of Canada, Pesticides: making the right choice for the protection of health and the environment. 2000.

Picheral, H., 1982. Géographie médicale, géographie des maladies, géographie de lu santé. Espace géographique. 11**,** 161-175.

Plagnol, A. C., 2011. Financial satisfaction over the life course: The influence of assets and liabilities. Journal of Economic Psychology. 32**,** 45-64.

Puddu, P. E., Iannetta, L., Schiariti, M., 2012. Age- and Gender-Normalized Coronary Incidence and Mortality Risks in Primary and Secondary Prevention. Cardiology research. 3**,** 193-204.

Rajagopalan, S., Al-Kindi, S. G., Brook, R. D., 2018. Air Pollution and Cardiovascular Disease: JACC State-of-the-Art Review. J Am Coll Cardiol. 72**,** 2054-2070.

Roberts, I., 2012. The truth about road traffic accidents. British Journal of Surgery. 99**,** 8-9.

Salameh, P., Salame, J., Khayat, G., Akhdar, A., Ziadeh, C., Azizi, S., Khoury, F., Akiki, Z., Nasser, Z., Abou Abbass, L., Saadeh, D., Waked, M., 2012. Exposure to outdoor air pollution and chronic bronchitis in adults: a case-control study. Int J Occup Environ Med. 3**,** 165-77.

Sarigiannis, D., Karakitsios, S. P., Kermenidou, M., Nikolaki, S., Zikopoulos, D., Semelidis, S., Papagiannakis, A., Tzimou, R., 2014. Total exposure to airborne particulate matter in cities: the effect of biomass combustion. Sci Total Environ. 493**,** 795-805.

Sarigiannis, D. A., Combined or multiple exposure to health stressors in indoor built environments: An evidence-based review prepared for the WHO training workshop " Multiple environmental exposures and risks " 16-18 October 2013 Bonn, Germany. Copenhagen, Denmark, 2014.

Sarigiannis, D. A., Karakitsios, S. P., Zikopoulos, D., Nikolaki, S., Kermenidou, M., 2015. Lung cancer risk from PAHs emitted from biomass combustion. Environmental Research. 137**,** 147-156.

Sayeed, S., Barnes, I., Ali, R., 2017. Childhood cancer incidence by ethnic group in England, 2001-2007: a descriptive epidemiological study. 17**,** 570.

Schærström, A., 1997. Pathogenic paths? A time geographical approach in medical geography. Geografiska Annaler: Series B, Human Geography. 79**,** 57-59.

Schoch, C., Kern, W., Krawitz, P., Dugas, M., Schnittger, S., Haferlach, T., Hiddemann, W., 2001. Dependence of age-specific incidence of acute myeloid leukemia on karyotype. Blood. 98**,** 3500.

Schweizer, C., Edwards, R. D., Bayer-Oglesby, L., Gauderman, W. J., Ilacqua, V., Juhani Jantunen, M., Lai, H. K., Nieuwenhuijsen, M., Kunzli, N., 2006. Indoor time-microenvironment-activity patterns in seven regions of Europe. J Expos Sci Environ Epidemiol. 17**,** 170-181.

Sharpe, R., Thornton, C., Osborne, N., 2014. Modifiable factors governing indoor fungal diversity and risk of asthma. Clinical & Experimental Allergy. 44**,** 631-641.

Simoni, M., Jaakkola, M. S., Carrozzi, L., Baldacci, S., Di Pede, F., Viegi, G., 2003. Indoor air pollution and respiratory health in the elderly. European Respiratory Journal. 21**,** 15s-20s.

Spinazzè, A., Cattaneo, A., Peruzzo, C., Cavallo, D. M., 2014. Modeling Population Exposure to Ultrafine Particles in a Major Italian Urban Area. International Journal of Environmental Research and Public Health. 11**,** 10641-10662.

Stanbury, M., Rosenman, K. D., 2014. Occupational health disparities: A state public health-based approach. American Journal of Industrial Medicine. 57**,** 596-604.

Steinle, S., Reis, S., Sabel, C. E., 2013. Quantifying human exposure to air pollution—Moving from static monitoring to spatio-temporally resolved personal exposure assessment. Science of The Total Environment. 443**,** 184-193.

Sunyer, J., Jarvis, D., Gotschi, T., Garcia-Esteban, R., Jacquemin, B., Aguilera, I., Ackerman, U., de Marco, R., Forsberg, B., Gislason, T., Heinrich, J., Norback, D., Villani, S., Kunzli, N., 2006. Chronic bronchitis and urban air pollution in an international study. Occup Environ Med. 63**,** 836-43.

Taghvaee, S., Sowlat, M. H., Hassanvand, M. S., Yunesian, M., Naddafi, K., Sioutas, C., 2018. Source-specific lung cancer risk assessment of ambient PM2.5-bound polycyclic aromatic hydrocarbons (PAHs) in central Tehran. Environ Int. 120**,** 321-332.

Uphoff, E., Cabieses, B., Pinart, M., Valdés, M., Antó, J. M., Wright, J., 2015. A systematic review of socioeconomic position in relation to asthma and allergic diseases. European Respiratory Journal. 46**,** 364-374.

Wang, Y., Xiong, L., Tang, M., 2017. Toxicity of inhaled particulate matter on the central nervous system: neuroinflammation, neuropsychological effects and neurodegenerative disease. J Appl Toxicol. 37**,** 644-667.

WHO, Gender. undated.

Wong, C. M., Thach, T. Q., Chau, P. Y., Chan, E. K., Chung, R. Y., Ou, C. Q., Yang, L., Peiris, J. S., Thomas, G. N., Lam, T. H., Wong, T. W., Hedley, A. J., 2010. Part 4. Interaction between air pollution and respiratory viruses: time-series study of daily mortality and hospital admissions in Hong Kong. Res Rep Health Eff Inst. 283-362.

World Health Organization, 1999. Monitoring ambient air quality for health impact assessment.

World Health Organization, 2005. Principles of characterizing and applying human exposure models. World health organization.

World Health Organization, 2013. WHO global status report on road safety 2013: supporting a decade of action. World Health Organization.

World Health Organization, 2014. Global status report on alcohol and health-2014. World Health Organization.

Yang, Q., Chen, Y., Krewski, D., Shi, Y., Burnett, R. T., McGrail, K. M., 2004. Association between particulate air pollution and first hospital admission for childhood respiratory illness in Vancouver, Canada. Arch Environ Health. 59**,** 14-21.

Zhang, Y. X., Liu, Y., Xue, Y., Yang, L. Y., Song, G. D., Zhao, L., 2016. Correlational study on atmospheric concentrations of fine particulate matter and children cough variant asthma. Eur Rev Med Pharmacol Sci. 20**,** 2650-4.