



Assessing personal exposure using Agent Based Modelling informed by sensors technology

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ABSTRACT

Technology innovations create possibilities to capture exposure-related data at a great depth and breadth. Considering, though, the substantial hurdles involved in collecting individual data for whole populations, this study introduces a first approach of simulating human movement and interaction behaviour, using Agent Based Modelling (ABM).

A city scale ABM was developed for urban Thessaloniki, Greece that feeds into population-based exposure assessment without imposing prior bias, basing its estimations onto emerging properties of the behaviour of the computerised autonomous decision makers (agents) that compose the city-system. Population statistics, road and buildings networks data were transformed into human, road and building agents, respectively. Survey outputs with time-use patterns were associated with human agent rules, aiming to model representative to real-world behaviours. Moreover, time-geography of exposure data, derived from a local sensors campaign, was used to inform and enhance the model. As a prevalence of an agent-specific decision-making, virtual individuals of different sociodemographic backgrounds express different spatiotemporal behaviours and their trajectories are coupled with spatially resolved pollution levels.

Personal exposure was evaluated by assigning PM concentrations to human agents based on coordinates, type of location and intensity of encountered activities. Study results indicated that PM_{2.5} inhalation adjusted exposure between housemates can differ by 56.5% whereas exposure between two neighbours can vary by as much as 87%, due to the prevalence of different behaviours.

This study provides details of a new methodology that permits the cost-effective construction of refined time-activity diaries and daily exposure profiles, taking into account different microenvironments and sociodemographic characteristics. The proposed method leads to a refined exposure assessment model, addressing effectively vulnerable subgroups of population. It can be used for evaluating the probable impacts of different public health policies prior to implementation reducing, therefore, the time and expense required to identify efficient measures.

1. Introduction

Until recently, human exposure to air pollutants could be assessed only by performing spatial interpolation of the ambient concentration measurements from networks of Fixed Monitoring Sites (FMS) (Steinle et al., 2013). Typically, people residing in the same neighbourhood near a monitoring station were treated as homogeneous receptors, fixed at

the location of the monitoring station (Buonanno et al., 2014). Several studies have already revealed that air pollutant concentrations, observed at FMS, are not always representative of concentrations sampled in urban settings (Adams et al., 2001; Beckx et al., 2009a, 2009b; Gulliver and Briggs, 2004; Hertel et al., 2001; Kaur et al., 2007; Setton et al., 2011). This is because the static FMS approach assumes people are constantly located at their residential address and fails to consider individual mobility patterns away from home. It is confirmed

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Nomenclature

ABM	Agent Based Modelling
ELSTAT	Hellenic Statistical Authority
ESD	Expected Sleeping Duration
FMS	Fixed Monitoring Stations
GIS	Geographic Information Systems
GPS	Global Positioning System
HETUS:	Harmonised European Time Use Surveys
IoT	Internet of Things
RST	Real Sleeping Time
SES	Socioeconomic Status
SST	Scheduled Sleeping Time
TAD	Time-Activity Diary

that most people spend the greatest portion of any given day in indoor settings – moving between dwellings, offices, and stores, rather than staying in a specific single location (Beckx et al., 2008). Even people residing in the same neighbourhood or even location can have a different exposure profile because of the different activities undertaken in different microenvironments (Dons et al., 2011).

Since the static approach of using FMS might erroneously reflect personal exposure to pollutants, researchers have emphasized the need to integrate environmental and behavioural factors into exposure assessment in order to detect a person's changing exposure throughout the day (Briggs, 2005; Ott, 1982). It is important to take into account people's individual time-space behaviours and the dynamics of air pollution, as both people and pollutants are constantly in motion (Steinle et al., 2015). Understanding, therefore, daily time-use across all microenvironments is essential in order to model exposure to pollutants (Schweizer et al., 2007; Spinazzè et al., 2014).

Exposure though also varies depending on sociodemographic characteristics of a population. Individuals with different socioeconomic characteristics can express different behavioural patterns and perform different activities over the course of the day, reflecting to a different exposure profile. Consequently, there is the need for an enhanced methodology that captures exposure across every single member of a society or groups of its population, rather than potentially misclassifying exposures by disregarding or improperly accounting for differences.

As a result of the latest technological advances, smart monitoring devices have been produced that can be placed in outdoor, indoor environments or worn by a person, allowing for a reliable “time-geography of exposure” to be captured, shifting the current paradigm from a population to an individual level (Sarigiannis et al., 2018). Small sensors and hardware such as the Arduino microcontroller board enable the collection and integration of location, physical activity and air quality data, at a community but also at a personal level (Jerrett et al., 2017; Kamel Boulos et al., 2011; Loh et al., 2017; Rai et al., 2017; Sarigiannis and Gotti, 2014). Global Positioning System (GPS) devices can be used to track people's coordinates, allowing the matching of pollution data with a person's location (de Nazelle et al., 2013; Gerharz et al., 2009). Individual physical activity trackers capture number of steps, distance, energy expenditure, total duration of active minutes or even the intensity of different activities as well as heart rates and can be linked to respective inhalation rates (Bassett, 2012; Donaire-Gonzalez et al., 2013; Mammen et al., 2012; Yang and Hsu, 2010). Portable air quality sensors help to evaluate whether peak exposures and time series of a high granularity are more important than daily average values of exposure and eventually build individual exposure profiles. Moreover, time-activity diaries (TADs) can also be used in order to obtain additional information on the undertaken activities in every microenvironment (Klepeis, 1999; Schweizer et al., 2007). The benefits of the “easy-to-use” and the acquisition of high-time resolution data through

Internet of Things (IoT) communication protocols have been already recognized (Darwish and Hassanien, 2011).

These technologies can facilitate longer-term and wider-scale monitoring of exposure for population surveys. Data from these sensors are indeed advantageous in deriving to conclusions regarding population exposure to pollutants. Measuring, though, personal exposure directly, especially when capturing exposure profiles of the entire sociodemographic spectrum of a region, requires individual measurements from a large sample of population which, practically, is often not feasible due to financial restrictions (Sarigiannis et al., 2018). Considering the significant technical and ethical hurdles related to collecting individual time-use and exposure related data for whole populations, a decision has been made to simulate human movement and interaction behaviour using Agent Based Modelling (ABM), validated against sensor data captured from local campaigns.

1.1. Agent Based Modelling

ABM is a simulation technique that allows us to explore and understand phenomena, where independent entities interact together, forming an emergent whole. While the direct representation of individuals' actions is organisationally difficult, ABM simplifies this process by managing information at the level of the autonomous decision-makers, called “agents” (Sarigiannis et al., 2018). The agents are software objects that have internal states and are programmed to react and act in their environment, while following a set of behavioural rules. By simulating actions and interactions at the individual level, the diversity that exists among agents can be detected, as rise is given to the behaviour of the system as a whole (Macal and North, 2010). Behaviours that were not explicitly programmed into the model's code, arise through the agents' interactions enabling the examination of expected or unexpected emerging behaviours from the bottom-up (De Marchi, 2014).

ABM is based upon an underlying stochastic model and therefore many simulations are required in order to evaluate any particular situation. A detailed account of the system, or even agent – specific history might be essential for an in depth understanding of any model run. As O' Sullivan et al. state (2012) “the difference from the real world target system we seek to understand is that a model allows repeated runs and enables a probabilistic account of the system behaviours and tendencies to be developed”.

The agents-representational approach justifies the increasing popularity of ABMs over the last years. The appeal lies on the fact that individual-level decisions consist a fundamental driver of social systems. ABM techniques have already been established in the fields of finance, gaming but mostly in social sciences, aiming to study human social phenomena. Such studies focus on modelling flows, transmission of culture, propagation of disease as well as interpreting group formation and population dynamics. Notable examples in which ABM was applied, include stock market behaviours (LeBaron, 2002), prediction of epidemics spread (Huang et al., 2004), modelling human immune system (Folcik et al., 2011), simulations of human migration (Klabunde and Willekens, 2016), refugee movements (Suleimenova et al., 2017), urban evacuation (Chen and Zhan, 2008) as well as urban transport systems (Dia, 2002). ABM has also been successfully applied to pedestrian and traffic modelling (Helbing and Balthetti, 2013). There are only few ABMs nowadays that have attempted to model entire cities (Haase et al., 2010). Despite the opportunities provided by ABM on capturing the complex interactions among the various components that form human exposure, only recently this modelling technique has been used in exposure science. More in detail, an ABM that simulates longitudinal patterns in human behaviour has been developed by Brandon et al. (2020) that predicts the longitudinal patterns for sleeping, eating, commuting, and working. The concept was further evolved by Brandon and Price (2020) and parameterized with empirical data aiming at capturing both inter-individual and intra-individual variation in behaviors in different types of individuals, including working and

non-working adults, as well as pre-school and school-age children.

This study provides details of a new exposure assessment methodology, based on ABM, that takes into account different microenvironments as well as sociodemographic characteristics and produces exposure profiles both at the individual and community level. Behaviours of subgroups of population arise through the interaction of virtual individuals that coexist and operate in an artificial, yet representative to real world, society.

2. Methodology

2.1. Overview of the area under study

Using ABM, a city-model was developed for urban Thessaloniki, Greece, where societal dynamics are explicitly taken into account, aiming to assess individual exposure. Urban Thessaloniki is the contiguous densely region built-up around the municipality of Thessaloniki, which is the second largest municipality of Greece. The urban Thessaloniki area covers the municipalities of Thessaloniki (centre), Ampelokipoi-Menemeni, Kordelio – Evosmos, Pavlos Melas (west), Neapoli - Sykies (north), as well as Kalamaria and Pylaia – Chortiatis (east). In the 2011 Greek census, these municipalities had a combined population of 790,824 residents, with a land area of approximately 110 km². The main sources of air pollution include the industrial activity, taking place in the western region of the city, traffic emissions and residential heating. Further details on the Thessaloniki morphology and sources of pollution can be found elsewhere (Diapouli et al., 2017; Kassomenos et al., 2011; Sarigiannis et al., 2017).

2.2. ABM development

After a thorough examination of the available ABM software tools (Abar et al., 2017; Heppenstall et al., 2012; Kravari and Bassiliades, 2015), we decided to use the GAMA platform (Grignard et al., 2013), an open access software platform for developing our original model that allows instantiating agents from various format datasets, and executes large-scale simulations. The choice was made to respect the open

software development paradigm that has been put as a priority for software development and applications, when it comes to products funded by the EU. GAMA is structured on a Java-based rich modelling language, GAML, which allows complex systems to be defined, integrating at the same time geographical vector data and entities of different scales.

2.2.1. Input data - system agentification

Aiming to develop a representative to real-world conditions city-scale model, every entity taking part in the system is being agentified, it is therefore considered as an individual agent. The system is composed, among else, of road, building and human agents (Fig. 1).

2.2.1.1. City data. In order to define the system's environment, road and buildings networks of urban Thessaloniki, formed as high spatial resolution shapefiles, were included into the model and transformed to road and building agents respectively. These agents carry attributes, such as the capacity of each street or land use information of a structure. Specifically, the buildings network was based on a polygons shapefile retrieved by the Hellenic Statistical Authority (ELSTAT). Land use information for the entire region was captured by merging relevant information from the 2012 Urban Atlas (EEA, 2017) and a land use map retrieved from the Thessaloniki Geographical Information Portal (Topography Department of the Municipality of Thessaloniki, 2017). The road network, clustered in smaller road segments was based on a relevant file published by the Prefecture of Central Macedonia and was fused with information retrieved from the URGENCHE study (Sarigiannis et al., 2017). Administrative boundaries of the municipalities of urban Thessaloniki as well as the region's public transport network were also included as shapefiles.

2.2.1.2. Population data - incorporation of socioeconomic status (SES) data. In order to extract information for the societal system under study, the 2011 Greek census population statistics were used, retrieved by the Hellenic Statistical Authority at the municipality level of the urban Thessaloniki area. Based on the population data of each municipality, a number of human agents that corresponds to ca. 45% of actual

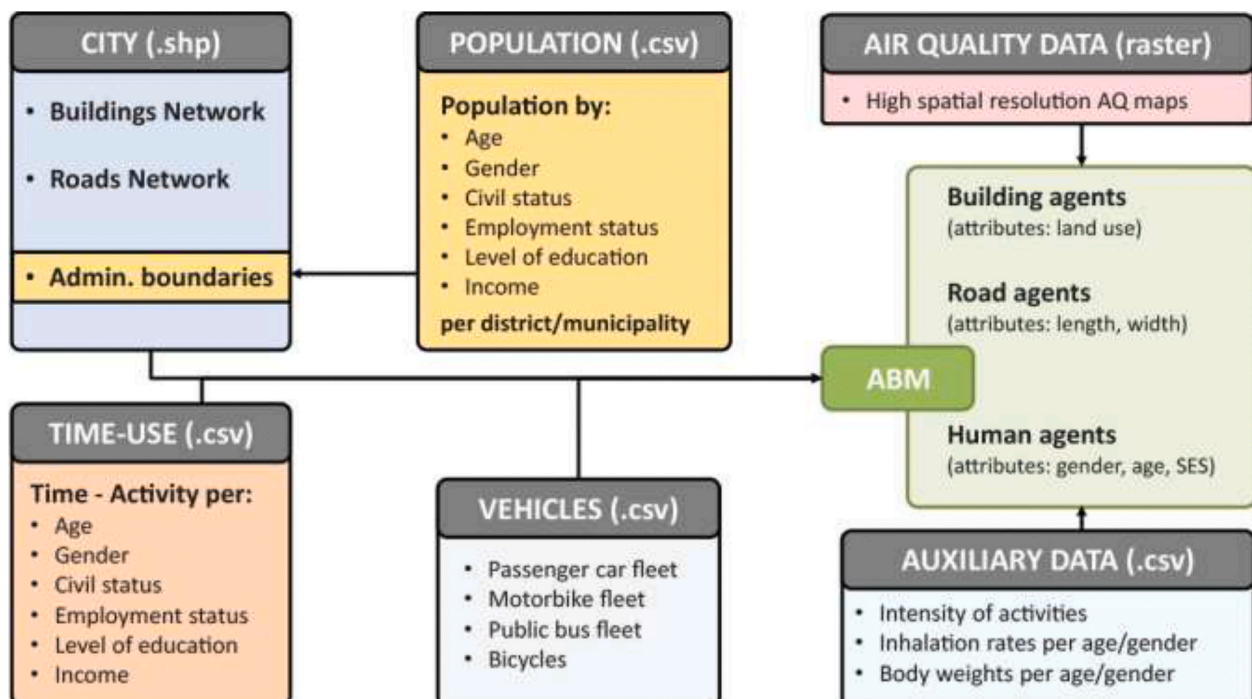


Fig. 1. ABM input data.

population is being generated at the scale for which spatial information is available. Emphasis is given in the case of in-model incorporation of demographic and SES data, since subgroups of population have different time-activity patterns, travel by different modes, and spend different amounts of time doing activities within different microenvironments. The virtual population acquires attributes such as age, gender, level of education, employment status, civil status and income, by following the official population statistics of the region where they were first conceptualised.

2.2.1.3. Time - use data. Time-activity patterns of the under-examination population were retrieved from a 2013 Harmonised European Time Use Survey (HETUS) that took place in Greece (ELSTAT, 2016), recording the time a diarist spends on 25 activity categories (Table 1) within 24 h' observation time (Fisher et al., 2015). The output of the dataset includes: a) a weighted percentage of people engaged in a certain activity in a subgroup defined by demographic and socioeconomic status and b) a weighted average and standard deviation of the time spent on a certain activity (Table 2).

2.2.1.4. Vehicles. Existing data regarding the Thessaloniki vehicles fleet composition, was transformed to vehicle agents, containing attributes, such as the type of vehicle and the type of engine. A number of bicycles was also included in the vehicles dataset.

2.2.2. Model description

2.2.2.1. Model initialisation. When the model is initialized, human agents are randomly allocated to a residential place, within the municipality where they were first conceptualised. This will serve as their home for the entire simulation. They are also arbitrarily assigned to an office, university or school depending on their age, gender and occupational status. Moreover, they become part of family networks, by following ELSTAT statistics on marital status and number of children per family, at the municipality level. A network, therefore, could be a nuclear family, a single-parent family, a no-children family or an elderly couple (not attached to children).

2.2.2.2. Human agent activities. There is an ArrayList (initially blank)

that corresponds to every human agent, containing the sequence of his/her chosen activities within a simulated day. During the model's initialisation, each human agent is located inside his/her household and the first 4 cells of his/her ArrayList are filled with 4 fixed, in terms of sequence, activities: a) sleep, b) commute, c) paid work or education, d) commute. These activities are fully dependent on start/end times that are assigned at the individual level. The next cells of the ArrayList remain blank until the current activity that takes place is the last one of the current list. An *event-triggering function* is always used to assign the next activity based on the HETUS time-use processed dataset (according to which the probability of choosing a particular activity varies based on the human agents' personal attributes).

2.2.2.3. Emerging behaviour and influence of SES. Depending on socio-demographic attributes and distance between point of departure and the targeted destination, a series of rules is being established at the personal - human agents level. Rules in ABM are expressed as "if-then" statements, as statements that impose threshold values or as functions that define the probability of a human agent to proceed to a certain action. These rules allow for emergent phenomena to take place, often shifting the probabilistic nature of the time-use distributions that were used as input. Emergency in the developed ABM, is introduced in three major expressions of the human agents routine: a) interaction between human agents, b) decision making with regard to transportation and c) adaptive behaviour.

a. Human agents' interaction

Human agents have the option of interacting with each other by evaluating invitations to participate in joint activities (e.g. invitation to watch TV, eat etc.) within their network. Members of the same family network can share the same activity when it takes place at the same location. When a human agent starts a new "free-time" activity, an invitation is being sent to all of his/her network members, asking them to join in. In a parallel way, right before a new activity is being added to a human agent's activities sequence list, there is always a check for potential invitations. The probability of a human agent to accept an invitation and participate in a joint activity is calculated using the following formula (Equation (1)):

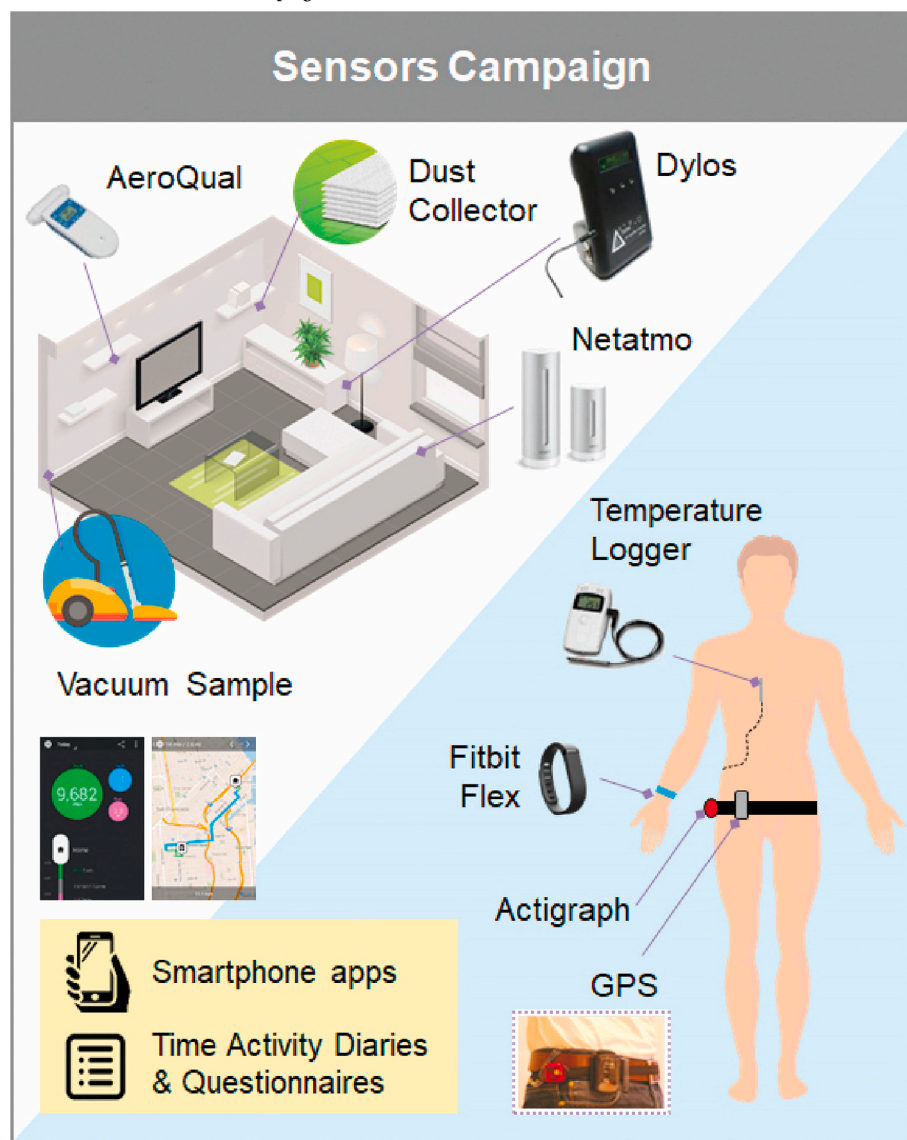
Table 1
Sociodemographic attributes and activities coding format.

Age	age	Gender	gender	Civil status	civstat	Activities	Description
0–9	0	Male	1	Couple	1	Cleanetc*	cleaning, laundry, ironing, clothing repair
10–19	1	Female	2	Not couple	2	Commute†	travel to or from work/school/university
20–29	2					Compint*	computing, play computer games
30–39	3					Eatdrink*	meals or snacks
40–49	4	Employment status			empst	Education†	school, classes
50–59	5	Full-time hours			1	Eldcare*	adult care
60–69	6	Part-time hours			2	Foodprep*	food preparation, cooking,
70–79	7	Hours of work unknown			3	Garden*	gardening
80–89	8	Student/retired/unemployed			4	Goout*	cinema, theatre, restaurant, café, bar, pub
						Ikidcare*	teach child a skill, help with homework, play
						Leisure*	general indoor leisure, relax
						Maintain*	home/vehicle maintenance/collect fuel
Income	income	Level of education+			educ	Paidwork†	work - total time at workplace
Lowest 25%	1	Not completed secondary education			1	Petcare*	pet care, walk dogs
Middle 50%	2	Post-secondary/non-tertiary education			2	Pkidcare*	physical or medical child care, supervise
Highest 25%	3	Higher education			3	Read*	read
		Urban/rural classification			urban	Religion*	worship and religious activity
		Urban/suburban			1	Selfcare*	wash, dress, personal or household care
		Rural/semi-rural			2	Shopserv*	purchase goods, personal care services
						Sleep†	sleep and naps
						Sportex*	general sport or exercise, walking, cycling
						Travel*	travel
						Tvradio*	watch TV, listen to music
						Volorgwk*	voluntary work, civic/organisational activity
						Missing	no recorded activity

† major activities

* free-time activities

Table 2
Sensors used at the HEALS campaign.



Item	Measured variables
Personal – wearable sensors	
Elitech logger	Temperature, humidity
QStarz BT1000 GPS	Coordinates, speed
Fitbit Flex	Steps, distance, sleeping patterns
Actigraph	Steps, distance, active minutes
Smartphone applications (Android, iPhone)	
Moves	Coordinates, activities
WideNoise Plus	Noise
Static sensors (participants' households)	
Dylos DC1700	PM2.5
Aeroqual Series 500	NO ₂ , O ₃
Netatmo	CO ₂ , noise, temperature, humidity
Additional data	
Time Activity Diaries	Type of location, activities
Questionnaires	SES, household information
Dust Collector	
Vacuum sample	

$$Pr_{join} = \frac{w_1 f(var_1) + w_2 f(var_2) + \dots + w_i f(var_i)}{\max(f(var_1))w_1 + \max(f(var_2))w_2 + \dots + \max(f(var_i))w_i} \quad \text{Equation 1}$$

Where:

- Pr [0,1]: the probability of a human agent to accept an activity invitation by a network member
- var_i: a sociodemographic attribute (age, gender, level of education etc.)
- f (var_i): utility function of attribute var_i

For example:

$$f(\text{age}) = \begin{cases} 2, & \text{if } 20 < \text{age} < 29 \\ 1, & \text{if } 50 < \text{age} < 59 \\ 0, & \text{if } \text{age} < 19 \text{ or } \text{age} > 60 \end{cases} \quad f(\text{educ}) = \begin{cases} 1, & \text{low education} \\ 2, & \text{medium education} \\ 3, & \text{high education} \end{cases} \quad f(\text{gender}) = \begin{cases} 1, & \text{male} \\ 2, & \text{female} \end{cases}$$

- W_i [>0]: weight, based on the strong/weak influence of attribute var_i

When human agents accept an invitation, the joint activity is added as the “next” one in their activities sequence list.

b. Human agents' transportation

“Commute” activities entail that a human agent can either walk, take a car, a motorbike, a bus or a bicycle, in order to reach his/her destination. The human agents population is initially distributed to use a certain transport mode, according to the official modal share statistics. Through the use of behavioural rules, an adjusted probability is then being assigned to virtual individuals, depending on agent-specific personal attributes, such age, educational status and income. As a last step, the probability of choosing a certain vehicle is finally re-adjusted, at each simulation cycle, taking into account the travelled distance to the targeted destination. For example, child agents will express a much higher preference to walk to school, if it is located in a less than 1.3 km distance.

c. Adaptive behaviour

Working/education start times (t_{start}), as well as an *Expected Sleeping Duration* (ESD), are arbitrarily assigned to individual human agents at the time of the model's initialisation. Based on these values, human agents can program their *Scheduled Sleeping Time* ($SST_{day N}$) at a daily basis (Equation (2)). When $SST_{day N}$ is reached, “sleeping” is added to the individuals' sequence list, right below their current activity. This, though, does not mean that present actions will be interrupted; it's only when the current activity's duration times out that the agent will go to sleep. This time is registered as the human agent's *Real Sleeping Time for day N* ($RST_{day N}$). Before next day ($N+1$) begins, human agents can estimate the amount of sleeping hours lost (Equation (3)) and plan a *new Scheduled Sleeping Time* ($SST_{day N+1}$), taking into account the previous days' error/loss (Equation (4)).

$$(SST_{day N})_x = (t_{start})_x - (ESD)_x \quad \text{Equation 2}$$

$$(Error_{day N})_x = (SST_{day N})_x - (RST_{day N})_x \quad \text{Equation 3}$$

$$(SST_{day N+1})_x = (SST_{day N})_x + (Error_{day N})_x \quad \text{Equation 4}$$

While next day begins and the first 4 cells of the ArrayList are filled, human agent X understands the need to gain sleeping hours. Similarly, though, this new day will not necessarily flow without a loss of sleeping time so there might still be a difference between scheduled and real times. The human agent will take this into account and will, same ways, re-schedule for next day and so on and so forth. Human agents learn from the past and adapt to future (Fig. 2). and eventually after a number of simulated days, the average sleeping duration (sum of sleeping duration/number of days) will converge to a certain value (Fig. 3).

2.2.2.4. Human agent trajectories and exposure assessment. At the end of a model run, activity patterns and space-time trajectories are captured for every human agent, as an outcome of the prevalence of a human

agent-specific emergent decision-making throughout the simulated time of experiment. Trajectories of human agents, retrieved by the coded routine were captured as points per simulation step, carrying information such as coordinates, type of microenvironment and enrolled activities in space and time.

2.2.2.4.1. Air quality data - outdoor concentration per human agent point. Trajectories data can then be superposed onto atmospheric pollutants concentration maps of a high spatial resolution. In this study, hourly variation high spatial resolution PM2.5 and PM10 maps of urban Thessaloniki were used, based on dispersion modelling results, using both traffic and non-traffic sources, fused with ground monitoring measurements (Sarigiannis et al., 2017). Exposure was calculated at the level of building block (30–40 m).

This study goes beyond the approach of classic epidemiology where outdoor PM concentration is the main proxy for assessing exposure. For the cases where human agents are located in indoor environments, such as residential buildings, offices or schools, indoor concentrations were estimated using the INTERA computational platform (INTERA, 2011). Calculations were based on a mass balance model, described by the following equation (Equation (5)), that takes major processes governing particle concentration into consideration i.e. emissions, indoor/outdoor exchange rate, deposition, and outdoor infiltration:

$$V \cdot \frac{dC}{dt} = Q \cdot (inf \cdot C_{out} - C_{ind}) + E - k_{dep} \cdot C_{ind} \cdot V \quad \text{Equation 5}$$

V represents the volume of indoor location, Q the indoor/outdoor air exchange rate, inf is the infiltration rate, C_{out} is the outdoor concentration, C_{ind} the indoor concentration, E the strength of the emission sources (mass/time) and k_{dep} the deposition rate. Further details on the usage of the aforementioned equation can be found elsewhere (Sarigiannis et al., 2014, 2015).

Personal exposure, inhalation adjusted exposure and intake dose calculation.

Based on the ABM-derived trajectories of a human agent, personal exposure over a given period of time, E_T , was calculated (Equation (6)) knowing that he/she spent a fraction of time, f_n , in n locations where the concentration of the under-consideration pollutant was C_n .

$$E_T = \sum_n f_n \cdot C_n \quad \text{Equation 6}$$

Inhalation-adjusted exposure, E_{inh} , was then calculated (Equation (7)), taking into account an adjustment factor, inh_{acts} related to the intensity of every activity the human agent followed during the simulated period. Different activities (e.g. leisure or sports) demand different

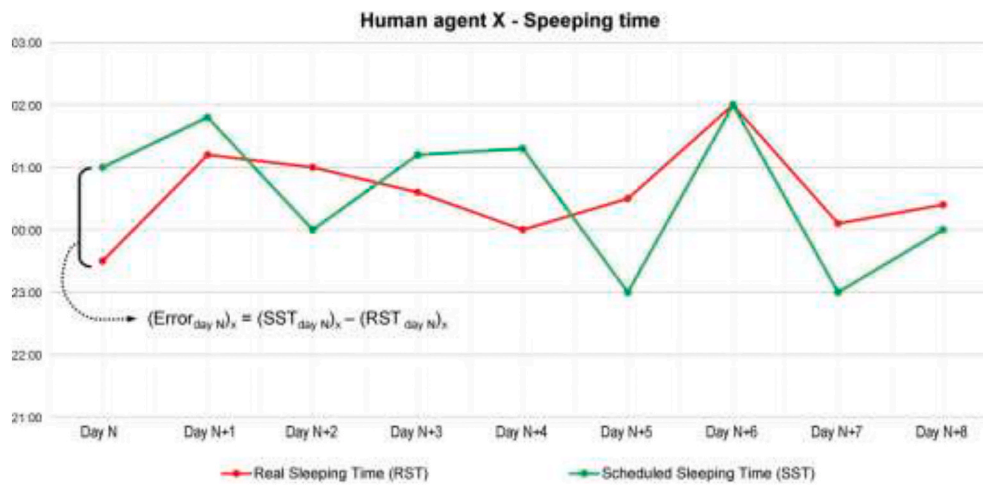


Fig. 2. Sleeping pattern of a human agent.

levels of effort and are therefore associated to different inhalation rates, also dependent on age and gender. A detailed description of activity-based inhalation rates is given elsewhere (Sarigiannis et al., 2012).

$$E_{inh} = \sum_n f_{loc} \cdot C_{loc} \cdot inh_{act} \quad \text{Equation 7}$$

As a final step, exposure assessment was extended to the calculation of daily intake dose (Equation (8)) by integrating daily exposure data. Representative values for breathing rate (OEHH, 2012; Richmond, 1985) and body weight (Cole, 2012), per gender and age, were retrieved from literature.

$$\text{daily intake dose (mg/kg-day)} = \frac{\text{total exposure} \left(\frac{\mu\text{g}}{\text{m}^3} \right) * \text{daily breathing rate} \left(\frac{\text{m}^3}{\text{day}} \right)}{\text{body weight (kg)} * 1000 \left(\frac{\mu\text{g}}{\text{mg}} \right)} \quad \text{Equation 8}$$

2.2.2.5. Model robustness and computer implementation. Indicative ABM results, as presented in the following section, capture exposure differences between different sociodemographic groups of urban Thessaloniki. Virtual trajectories and exposure-related information starts being recorded right after human agent-specific goals are properly defined; that is after we reach model convergence. According to our observations, it takes 4 simulated days so that time-dependent, human agent-specific goals, converge to a certain duration value. With progressive iteration, simulation reaches an equilibrium state where the human agent's average sleeping duration converges to the *Expected Sleeping Duration (ESD)*. Over this period, human agents practically attempt to combine personal activities by making sacrifices regarding their time spent sleeping which, in turn, has an impact on the time spent in all daily activities. For example, they exchange sleep time over free time or sleep for much longer periods than what they actually need.

It should also be noted that human agents emerging behaviour and communication is clearly affected by the total number of virtual population taken into account. Based on repeated experiments, a conclusion was made that a virtual population of at least 300,000 human agents is needed over a simulation run. This threshold reassures that a sufficient number of human agents will be conceptualised in each municipality so

that human agents interaction takes place, including virtual persons of the complete range of the under-examination SES spectrum.

The aforementioned observations are based on extensive attempts to investigate and specify the modelling conditions that yield robust results. Simulating an insufficient number of days or virtual population would have a negative impact to the quality of ABM output data, leading to results that do not represent real-world conditions. Findings presented in this study are based on ABM simulations ran on an i7 CPU @ 3.20 GHz with 16 GB RAM. Detailed activity and exposure profiles were assessed, based on an ABM run for a population of 400,000 human agents for an overall duration of 16 consecutive days, with a simulation step of 10 min. Increasing the number of virtual agents to, say, 500,000

has had no significant effects on the output of the model; thus, our results are robust against significant differences in computational capacity or reasonable variations in the number of agents used for each urban simulation.

2.3. Compatibility control

The ABM derived time-use and exposure results can be parametrised and validated against real "time-geography" of exposure data, retrieved from personal monitoring of individuals and groups of population with a similar sociodemographic background. This information can be retrieved from personal sensors campaigns.

As part of the HEALS research project, a sensor campaign was designed and established, using location tracking, physical activity and air quality monitoring sensors in order to capture individuals' spatio-temporal behaviour as well as residential exposure. Having obtained the necessary ethical approvals, the HEALS sensors campaign took place in 5 EU cities within 2016–2017. 50 participants in each city wore devices such as a) a temperature logger, to identify changes between indoor and outdoor conditions, b) two fitness tracking devices, Fitbit Flex and Actigraph, to capture number of steps and distance covered, c) a GPS device, QStarz BT1000XT, to detect location and speed along with d) Moves, a smartphone application that enables tracking of location and

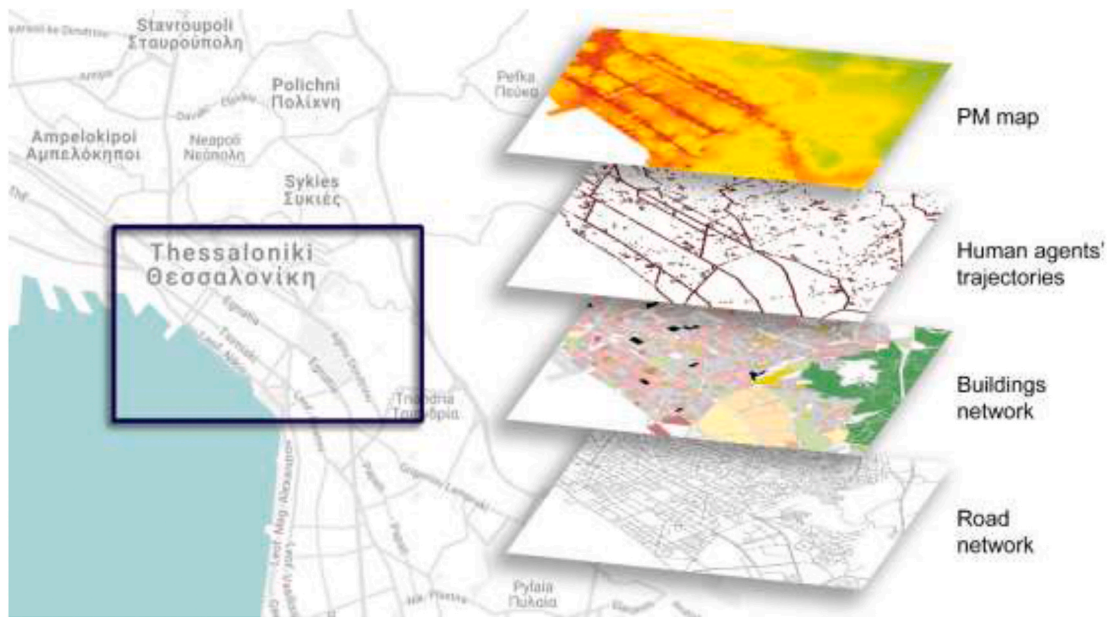


Fig. 3. GIS layers - Exposure assessment at personal/community level, using ABM. Indoor concentration per human agent point.

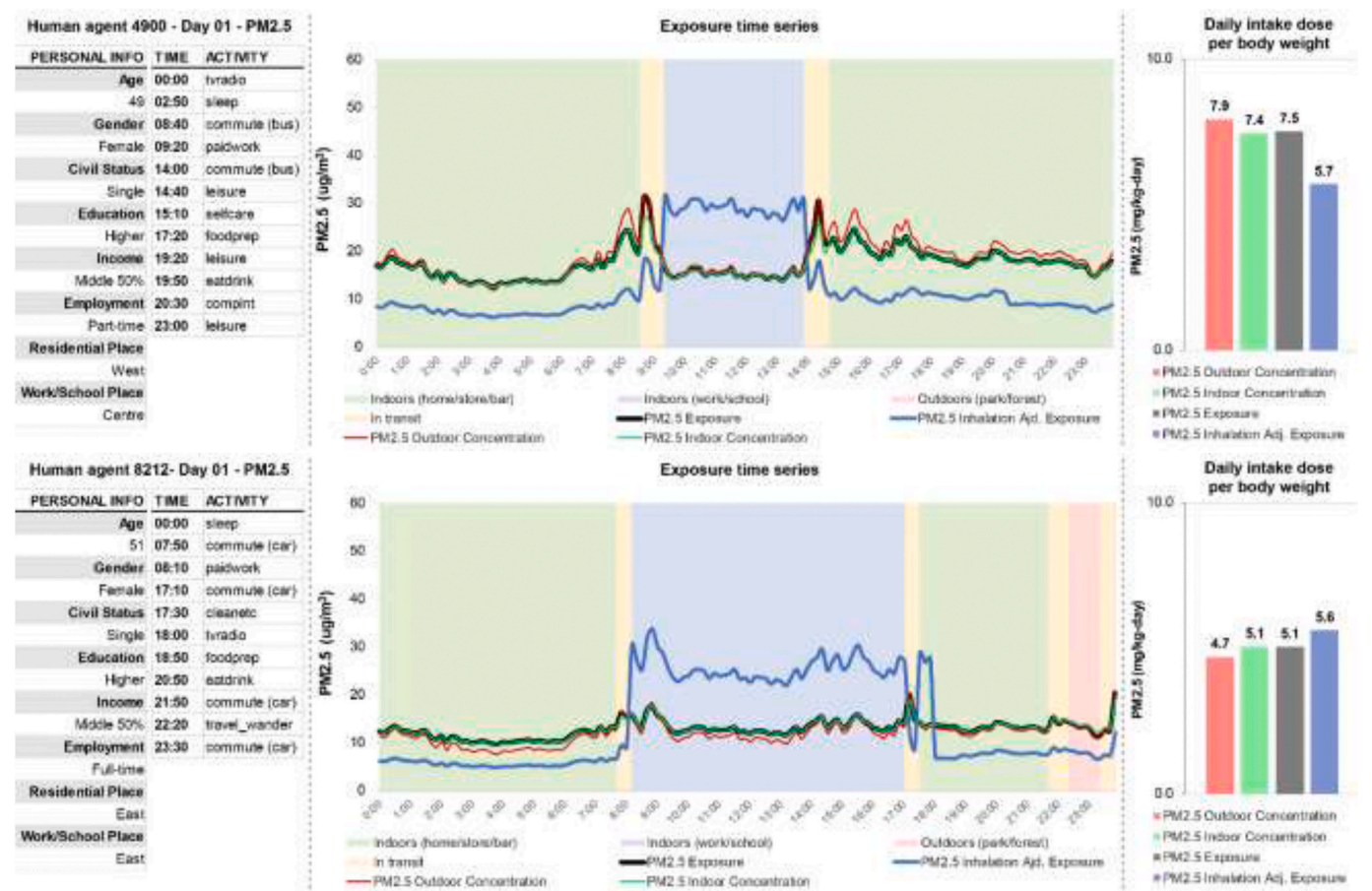


Fig. 4. Activity and PM2.5 exposure profiles for two randomly picked human agents.

activity. At the participant's residential place, a series of additional devices was placed such as a) the Dylos, a small static PM sensor that captures PM concentration in 2 size ranges $>0.5 \mu\text{m}$ and $>2.5 \mu\text{m}$ diameter, b) two Aeroqual Series 500 sensors measuring NO_2 and O_3 respectively and c) the Netatmo station, which measures indoor air

temperature, humidity, CO_2 and noise. Moreover, a dust sample was collected from dust settled onto an electrostatic sheet and a sample from the household's vacuum cleaner's bag was retrieved. Participants were also asked to fill in a TAD and to answer to a questionnaire, aiming at capturing potential sources of pollution, household conditions, and

personal socio-demographic information. The Thessaloniki HEALS campaign lasted from October to March 2016 and provided useful insight on the utility of several devices as modular add-ons to exposure studies. Campaign's data analysis results and ABM compatibility tests are presented in detail at the Results section.

3. Results

3.1. ABM results - personal exposure profiles and time-activity behaviour

Fig. 4 shows the activity and exposure profiles of two randomly picked human agents, as derived by the ABM. Exposure time series are based on outdoor (red line) as well as indoor (green line) concentrations. Exposure to PM₁₀ (black line) as well as inhalation adjusted exposure (blue line) were also calculated. The integration of daily exposure data, taking into account representative values for individual weight and breathing rate, lead to the estimation of daily intake dose for all of these four exposure proxies (Equation (8)).

In practice, the one that describes better the actual intake of the individual is the inhalation adjusted exposure (blue line), which accounts for both the spatiotemporal variability of each individual time-space line, as well as the actual intake rate defined by the inhalation rate. In contrast, ambient air concentration (red line) is a commonly used proxy for exposure, capturing only partially the space-time course. Indoor concentration (green line) captures better the actual exposure than ambient air concentration, since it represents a higher fraction of the overall daily activity, however it misses the contribution of exposure from outdoor activities. Exposure (black line) captures the complete time-space trajectory of the individual, however, does not reflect the actual intake rate, since it does not count for the differences in

inhalation rate based on the respective activities (and the intensity thereof). Overall, this allows us to further differentiate the actual intake among individuals with phenomenally similar exposure levels, if the calculation was based on exposure proxies such as ambient or indoor air. This is better illustrated in the following two examples.

Human agent 4900 (up) is a 49-year-old female virtual person, single, with a part-time job, a medium income and a higher education. She lives in the western Thessaloniki region and works at the centre of Thessaloniki. *Human agent 8212 (down)* is a 51-year-old female virtual person, single, with a full-time job, a medium income and a higher education. She lives and works in the eastern Thessaloniki region. It is interesting to observe how the value of intake dose changes depending on what we use as a proxy. Inhalation adjusted exposure is clearly affected by the intensity of the encountered activities and the human agents age and gender.

ABM allows us to explore how the sociodemographic background of a virtual person impacts his or her decision making. Human agents of a different age, gender and socioeconomic status follow a different type, sequence and duration of activities. Fig. 5 showcases the activity and exposure profiles during a simulated day of two human agents that reside in the same neighbourhood (Fig. 6).

Human agent 60 is a 20-year-old female virtual person, a university student, single, with a low income. She lives in the central Thessaloniki region the same region where her university is located. *Human agent 85* is a 38-year-old male virtual person, in a couple, with a full-time job, higher education and a high income. He also lives and works in the central Thessaloniki region. These two human agents reside in the same neighbourhood (region of the same postal code). Their trajectories - including all spots visited over their diurnal activities - cover a spatial range located within the same region of central Thessaloniki. Even

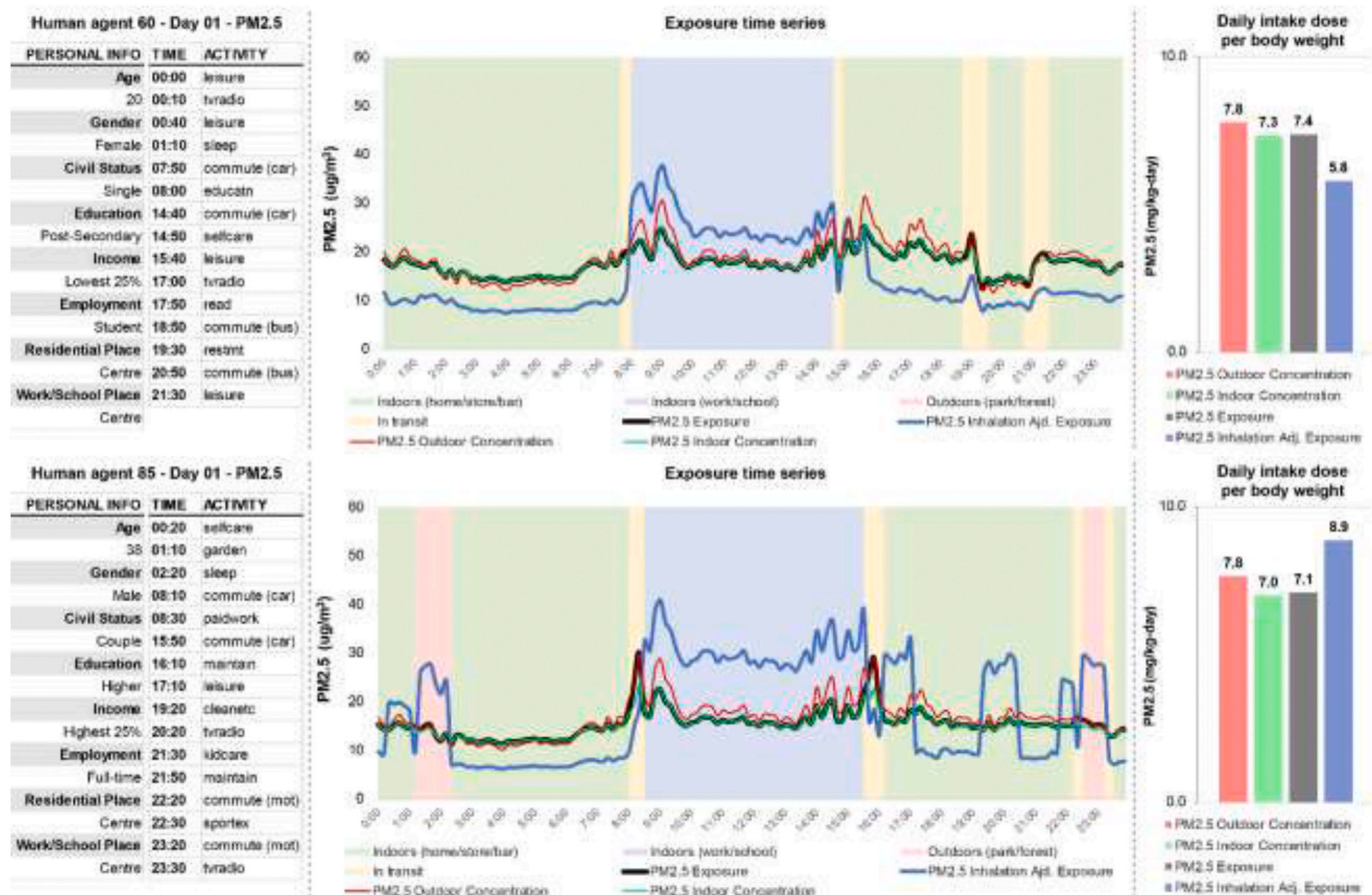


Fig. 5. Activity and PM2.5 exposure profiles for 2 human agents living in the same neighbourhood.

though they are both phenomenally exposed to similar outdoor air pollution levels (PM_{2.5} outdoor concentration daily intake dose of 7.8 mg/kg-day), their actual exposure, taking into account the intensity of their activities, changes by 53% (intake dose of 5.8 and 8.9 mg/kg-day respectively), due to the prevalence of different behaviours. If we would only use outdoor concentration as a proxy, we would not be able identify this major difference.

ABM runs confirm that virtual people that reside in the same location or even in the same dwelling might not necessarily be exposed to similar levels of pollution. Several cases of entirely different exposure profiles, mainly justified by differences in time-activity patterns, have been observed. Findings indicated that exposure to outdoor PM concentrations between two flatmates (e.g. family members living in the same house) can differ by 32.2% for PM_{2.5} and 35% for PM₁₀. If inhalation adjusted exposure is used as a proxy, the change rate is remarkably increased; up to 56.5% for PM_{2.5} and 61% for PM₁₀. This is due to the different intensity of the enrolled activities and the differences in breathing and inhalation rate values, explained by the different age and gender of the examined virtual persons. Inhalation adjusted exposure differences between 2 individuals living in the same neighbourhood can vary by as much as 87%, due to different spatiotemporal behaviours. This major difference was observed for cases where one human agent has a full-time job and exercises in outdoor courts whereas his/her neighbour is a retired homemaker.

Grouping individual exposure profiles based on criteria such as age, gender, SES indicators or even based on the area of residence/work/study, enables the extraction of representative exposure profiles for subgroups of population. Indicative ABM results, as seen below, capture exposure differences between different sociodemographic groups of urban Thessaloniki.

Findings indicate that the four most vulnerable (highly exposed) groups are: child agents, adult male agents with a full-time job, low-income male agents residing in western Thessaloniki region and human agents of a lower educational level. Inhalation adjusted exposure median difference between children and the elderly reaches approx. 50%, justified by the radically more intense activity patterns that

younger agents follow. Virtual population subgroups with low income as well as groups that reside in western, highly polluted, municipalities of urban Thessaloniki appear to be exposed to higher levels of PM. Based on population statistics, western municipalities population has a higher share of people with low income and low education. Moreover, higher concentration levels are indeed observed in the western side of the Thessaloniki region, due to the extended industrial complex. Major industrial activities involve petrochemical, oil refining, acid and fertilizer production (Sarigiannis et al., 2017).

Human agents with a higher income appear to be less exposed, often spending the majority of their time in less polluted sections of the urban agglomeration. PM_{2.5} intake dose median values comparison between male agents with a low income living in the western region of the city to the high-income male agents residing in the eastern, less polluted region shows that the change rate for outdoor PM reaches 32% whereas inhalation adjusted exposure differences is at 15%. An important difference was observed between female agents with a part-time job and male agents with a full-time job, with a change of PM_{2.5} inhalation adjusted exposure intake dose median values at 34%. As confirmed by the time-use retrieved information, male human agents tend to perform energy demanding activities at a higher frequency compared to female virtual persons.

It is also possible to extract time-use data for any group of the population, even for groups for which information does not exist in current traditional datasets, and observe the average time spent on major activities. This allows us to extract a better insight of the group's behavioural patterns, as demonstrated in Fig. 7. This bar chart showcases the differences, with regard to average daily time spent in main activities, between 40 and 49-year-old female agents, with a child aged 10–18-year-old, a full-time job and a medium income (pink) and same age male agents, also with a full-time job and medium income (blue). On average, female agents tend to spend less time in work compared to male agents. Male agents spend remarkably more time in commute, eating and watching TV whereas female agents spend more time in shopping, food preparation and cleaning.

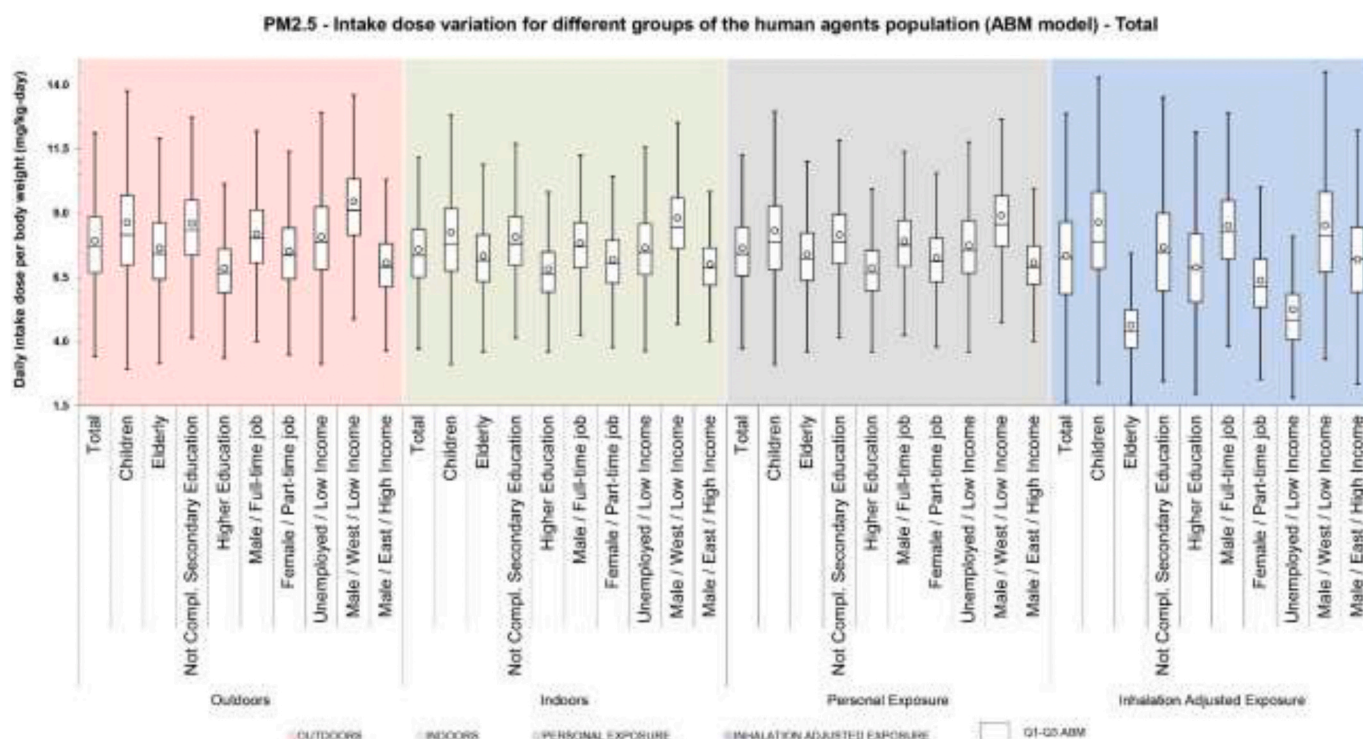


Fig. 6. Intake dose variation for different groups of the human agents population.

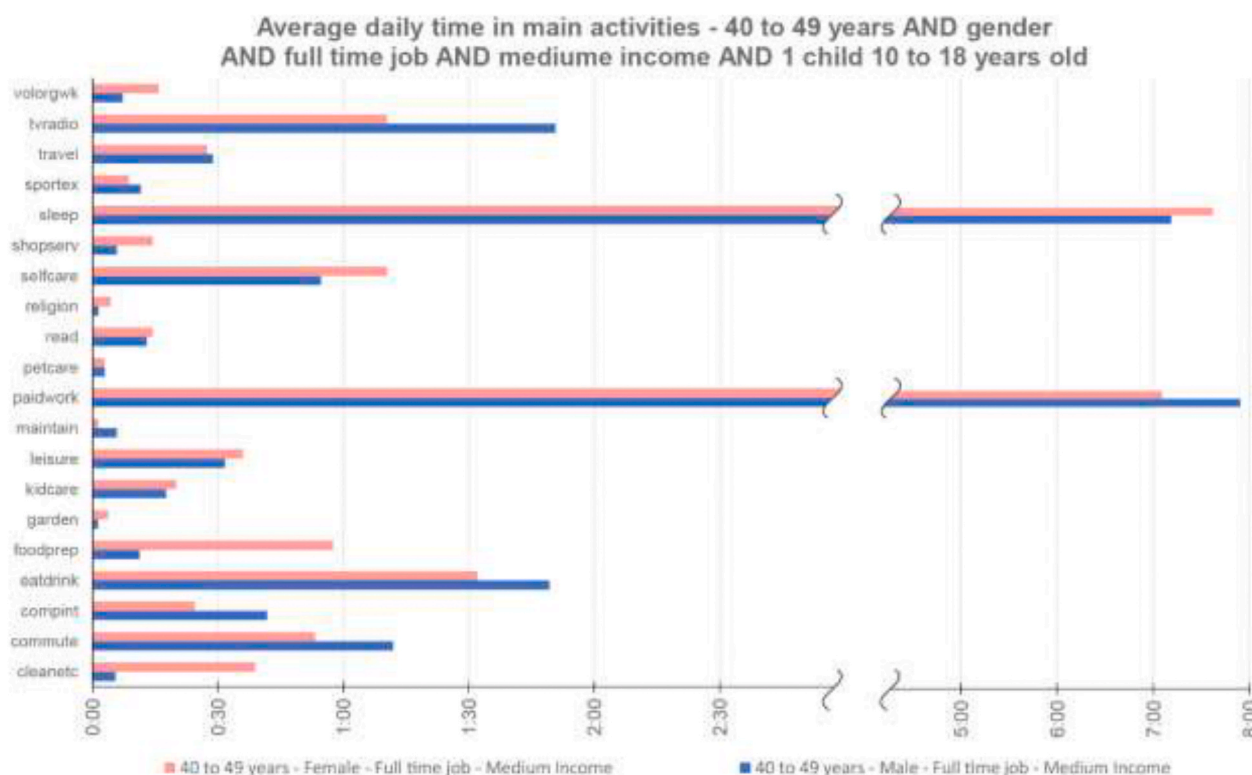


Fig. 7. Average daily time in main activities for male and female human agents aged 40–49 years with a child aged 10–18-year-old, a full-time job and a medium income.

3.2. Sensors campaign results and ABM model compatibility test

The HEALS campaigns have investigated methods for assessing external exposure using sensors and smartphone technologies. Data analysis showed that the Moves smartphone application tends to capture participants' trajectory with reasonable accuracy compared to the dedicated GPS device, while it underestimates the daily encountered steps compared to Fitbit Flex and Actigraph, respectively. Sensors data was further analysed using statistical learning methods. Specifically, an Artificial Neural Network (ANN) model was developed with the aim to identify the type of location-based solely on sensors data, hence, overcoming the major drawback of the GPS-type sensors that fail to capture whether a person is indoors, outdoors or in transit. Further details on sensors analysis have been published by [Stamatelopoulou et al. \(2018\)](#).

Processing of the Thessaloniki campaign data led to the creation of a big dataset containing personal trajectories for 50 individuals. Participants' spatiotemporal behaviour data was combined with air quality data (PM_{2.5} concentrations), retrieved by atmospheric dispersion modelling for a representative day of the 2016 in urban Thessaloniki, fused with the participants' in-house PM measurements. The extraction of real exposure information enabled the parametrization and validation of the ABM methodology. This was achieved by applying a compatibility check, as demonstrated below ([Fig. 8](#)) comparing exposure data of real population groups to the ABM-derived simulated exposure information of human agent groups with similar age, gender or SES.

Findings from this personal exposure comparison indicate that the difference between the median values in box plots of the same population group does not exceed the range of 5–12%. This demonstrates that the ABM-derived emergent trajectories are compatible to real spatio-temporal, which is of crucial importance since space-time and activity information is a key determinant of personal exposure.

Within 2019, wider-scale sensors campaign will take place, also using a custom-built wearable PM sensor, aiming to capture personal exposure of a representative sample of the urban Thessaloniki

population, including a larger sample of participants from all major sociodemographic groups. Campaigns' data will further enhance the developed ABM.

4. Discussion

Personal exposure is linked to the every-day activity patterns of an individual and the spatial distribution of air pollution across the urban agglomeration, which is also strongly affected by the city economic activities. Thus, a key outcome of the applied methodology is that it allows us to incorporate multiple sociodemographic attributes directly in exposure assessment.

The established modelling approach indicates the way with which exposure to environmental stressors is affected by individual preferences. Virtual individuals communicate within networks and, according to their sociodemographic background, design their path through the city by following different types and sequence of activities and using different means of transportation. For example, a 40-year old male agent with a full-time job and a higher income will have a higher probability of using the car to reach his office, than a 28-year old woman agent with a part-time job and a low income. Human agents' decisions during different simulation cycles, often alter the probabilistic nature of the time-use distributions that are used as input. Simulated days are filled with activities not in a pre-scheduled way but rather in a dynamic one. The very same human agent might follow a different sequence or even a different set of activities day by day. Model data can be collected at different spatial and time scales, providing insight on how different mobility behaviours might eventually affect personal exposure.

By estimating the daily time-activity patterns of subgroups of population, we were able to estimate exposure and intake dose per body weight at the individual and community level based on 4 exposure proxies (outdoor, indoor, personal and inhalation adjusted exposure). The established methodology confirms that if calculations were only based on outdoor PM concentration levels, as commonly established in

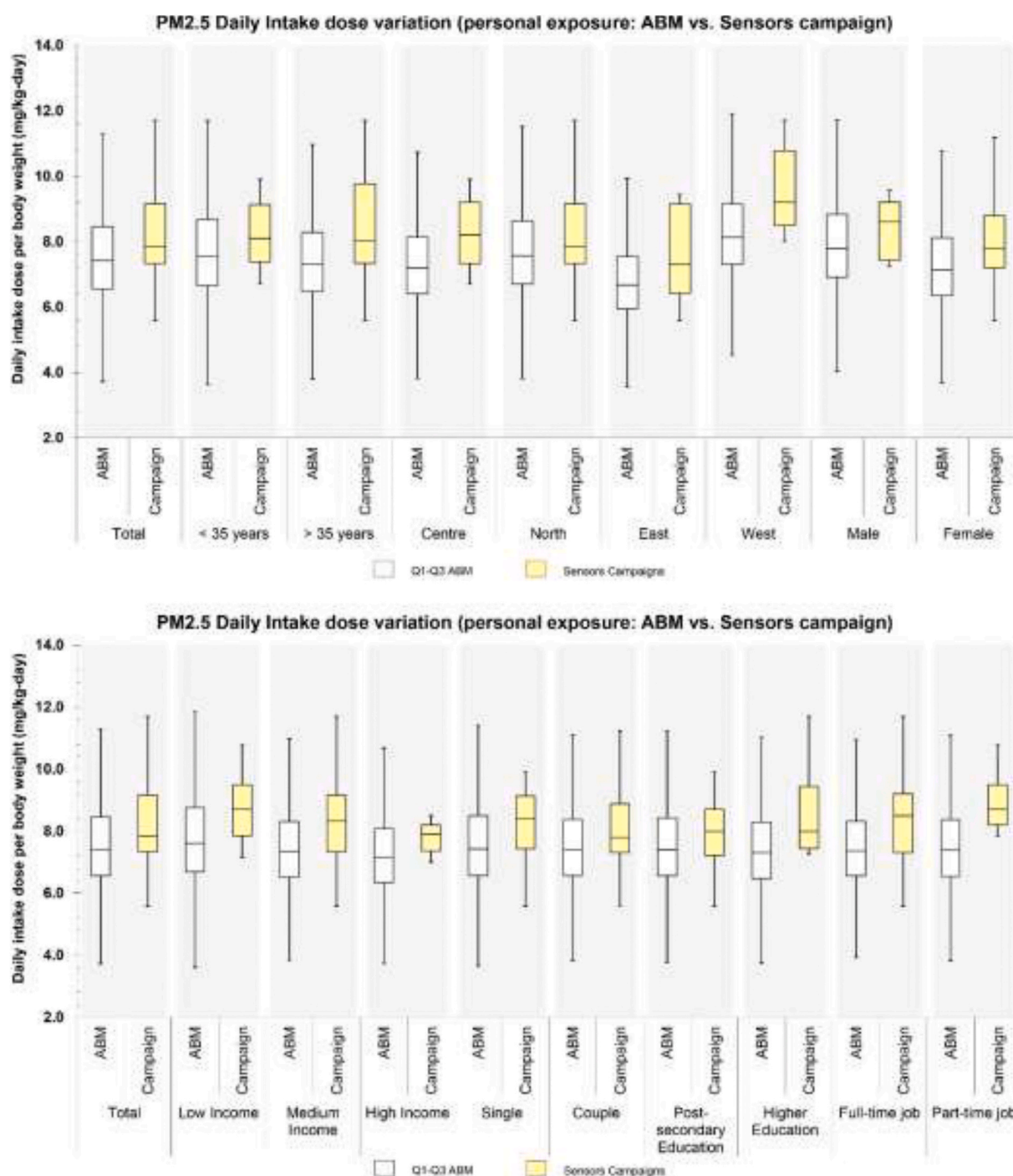


Fig. 8. PM2.5 personal exposure daily intake dose variation for virtual population groups (ABM) and sensors campaign participants groups (Sensors Campaign).

current exposure studies, we might have an underestimation or overestimation of personal exposure. If we had disregarded the time one spends in different microenvironments and the intensity of enrolled activities, we would not be able to identify crucial exposure differences.

The identification of exposure peaks and troughs throughout the day in exposure time series leads to useful conclusions regarding capping exposure to high levels of pollution. The dynamic nature of intake dose assessment at the individual and population level allows for the derivation of guidance regarding behaviours that are linked with exposure to high levels of pollution. ABM results indicate that exposure varies between different individuals and population subgroups with different sociodemographic characteristics.

This study demonstrates that ABM can indeed be used for personal exposure assessment, giving access to an unprecedented amount of “individualized exposure data”, which can improve our understanding of exposure and health associations, but which are worthless without interpretation. Since the strength of ABM results is depended on the quality of input data and programmed rules, valid data on the geography of the under-study city-system and accurate population statistics are essential. Moreover, lifestyle patterns are needed to understand individual and population-based geospatial lifelines. Rules and functions can be informed by first principal argument or calibrated against data retrieved from empirical surveys or, ideally, from personal monitoring campaigns.

The developed ABM was validated against data retrieved by a sensors campaign, where exposure was assessed for 50 individuals in the urban Thessaloniki area. Findings demonstrate that the ABM-derived emergent trajectories are compatible to real spatiotemporal behaviours. The wider scale campaigns that are scheduled to take place will be used to further inform and enhance the ABM model. These campaigns provide valuable information on the utility of several wearable devices as modular additions to exposure studies. Sensors investigations offer valuable evidence on personal habits and societal dynamics that are often not officially documented.

5. Conclusions

Our approach takes exposure in every microenvironment a virtual individual has stayed/passed through during the day, taking into account sociodemographic differences. This leads to the estimation of personal level of exposure, where exposure can be viewed as the summation of an individual's travel through "hazard fields" in space over time. By modelling the heterogeneous routine of human agents, our ABM can produce detailed information related to the societal system examined and can generate data that could be used to fill in the gaps that exist in traditional datasets. This method signifies a step forward, away from the earlier static nature approaches of urban modelling, where total population is divided into homogeneous subpopulations. The extracted evidence from the combined use of ABM and sensors networks improves exposure modelling using deterministic or probabilistic approaches and supports the establishment of new epidemiological methods that attempt to connect modelled exposure to health outcomes.

The establishment of an ABM approach that integrates SES indicators with the capacity for aggregation and analysis at various levels of population size, leads to an exposure assessment model especially useful for vulnerable groups of population, such as children, low SES groups and people living in hot spot areas. This is an opportunity to capture evidence for cases where specific subgroups of population are disproportionately exposed to higher levels of environmental risk than other parts of the same society. This study already shows how low-SES populations might be at a particularly higher risk for PM exposure. This is, therefore, a method where cases that exhibit environmental injustice can be detected and interpreted through an artificial society type model.

It should also be mentioned that this approach can be established for different cities, by changing the input data, without the need of altering the basic programming architecture. Such a model can be further used to examine hypothetical scenarios and study the effects of different actions to reduce pollution levels in urban areas. The realistic representation of the surrounding geography makes the developed model a valuable tool for estimating or even predicting the effects of new measures on a local and regional area. It can be used as a means for evaluating and comparing the probable impacts of different public health policies prior to implementation, or conversely, the impact of non-health-related policies on public health status. Policy makers could evaluate several policy measures by changing the key parameters influencing the behavioral elements of human exposure, e.g. the improvement of public transport or the development of new bicycle lanes is something that would result in a shift of transportation mode for a significant number of residents. The same occurs for other changes on a wider scale, for example changes in financial status of the population could influence their means of space heating or use of transportation means, thus, influencing their exposure to indoor and/or outdoor air pollution. These simulations can, therefore, lead to better initial choices and can reduce the time and expense required to identify effective strategies.

Declaration of competing interest

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

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References

- Abar, S., K Theodoropoulos, G., Lemarinier, P., O'Hare, G., 2017. Agent Based Modelling and Simulation Tools: A Review of the State-Of-Art Software.
- Adams, H.S., Nieuwenhuijsen, M.J., Colville, R.N., McMullen, M.A.S., Khandelwal, P., 2001. Fine particle (PM_{2.5}) personal exposure levels in transport microenvironments. London, UK. *Science of The Total Environment* 279, 29–44.
- Bassett, D.R., 2012. Device-based monitoring in physical activity and public health research. *Physiol. Meas.* 33, 1769–1783.
- Beckx, C., Int Panis, L., Arentze, T., Janssens, D., Torfs, R., Broekx, S., Wets, G., 2009a. A dynamic activity-based population modelling approach to evaluate exposure to air pollution: methods and application to a Dutch urban area. *Environ. Impact Assess. Rev.* 29, 179–185.
- Beckx, C., Int Panis, L., Uljee, I., Arentze, T., Janssens, D., Wets, G., 2009b. Disaggregation of nation-wide dynamic population exposure estimates in The Netherlands: applications of activity-based transport models. *Atmos. Environ.* 43, 5454–5462.
- 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.
- Brandon, N., Dionisio, K.L., Isaacs, K., Tornero-Velez, R., Kapraun, D., Setzer, R.W., Price, P.S., 2020. Simulating exposure-related behaviors using agent-based models embedded with needs-based artificial intelligence. *J. Expo. Sci. Environ. Epidemiol.* 30, 184–193.
- Brandon, N., Price, P.S., 2020. Calibrating an agent-based model of longitudinal human activity patterns using the Consolidated Human Activity Database. *J. Expo. Sci. Environ. Epidemiol.* 30, 194–204.
- Briggs, D., 2005. The role of GIS: coping with space (and time) in air pollution exposure assessment. *J. Toxicol. Environ. Health, Part A* 68, 1243–1261.
- Buonanno, G., Stabile, L., Morawska, L., 2014. Personal exposure to ultrafine particles: the influence of time-activity patterns. *Sci. Total Environ.* 468, 903–907.
- Chen, X., Zhan, F.B., 2008. Agent-based modelling and simulation of urban evacuation: relative effectiveness of simultaneous and staged evacuation strategies. *J. Oper. Res. Soc.* 59, 25–33.
- Cole, T.J., 2012. The development of growth references and growth charts. *Ann. Hum. Biol.* 39, 382–394.
- Darwish, A., Hassanien, A.E., 2011. Wearable and implantable wireless sensor network solutions for healthcare monitoring. *Sensors* 11, 5561.
- De Marchi, S., 2014. Agent-based models. *Annu. Rev. Polit. Sci.* 17, 1–20.
- de Nazelle, A., Seto, E., Donaire-Gonzalez, D., Mendez, M., Matamala, J., Nieuwenhuijsen, M.J., Jerrett, M., 2013. Improving estimates of air pollution exposure through ubiquitous sensing technologies. *Environ. Pollut.* 176, 92–99.
- Dia, H., 2002. An agent-based approach to modelling driver route choice behaviour under the influence of real-time information. *Transport. Res. C Emerg. Technol.* 10, 331–349.
- Diapoulis, E., Manousakas, M., Vratolis, S., Vasilatou, V., Maggos, T., Saraga, D., Grigoratos, T., Argyropoulos, G., Voutsas, D., Samara, C., Eleftheriadis, K., 2017. Evolution of air pollution source contributions over one decade, derived by PM₁₀ and PM_{2.5} source apportionment in two metropolitan urban areas in Greece. *Atmos. Environ.* 164, 416–430.
- Donaire-Gonzalez, D., de Nazelle, A., Seto, E., Mendez, M., Nieuwenhuijsen, M.J., Jerrett, M., 2013. Comparison of physical activity measures using mobile phone-based CalFit and Actigraph. *J. Med. Internet Res.* 15, e111.
- 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. *Atmos. Environ.* 45, 3594–3602.
- EEA, 2017. Copernicus Land Monitoring Service - Urban Atlas 2012. European Environment Agency.
- ELSTAT, 2016. Time - Use Survey 2013 - 2014. Hellenic Statistical Authority.
- Fisher, K., Gershun, J., Mullan, K., Sullivan, O., Morris, S., 2015. Innovations and lessons from the UK 2014-2015 everyday life survey. *Electronic international journal of time use research* 12, 163–169.
- Folcik, V.A., Broderick, G., Mohan, S., Block, B., Ekbote, C., Doolittle, J., Khoury, M., Davis, L., Marsh, C.B., 2011. Using an agent-based model to analyze the dynamic communication network of the immune response. *Theor. Biol. Med. Model.* 8, 1-1.

- Gerharz, L.E., Krüger, A., Klemm, O., 2009. Applying indoor and outdoor modeling techniques to estimate individual exposure to PM_{2.5} from personal GPS profiles and diaries: a pilot study. *Sci. Total Environ.* 407, 5184–5193.
- Grignard, A., Taillandier, P., Gaudou, B., Vo, D., Huynh, N., Drogoul, A., 2013. GAMA 1.6: advancing the art of complex agent-based modeling and simulation. In: Boella, G., et al. (Eds.), *PRIMA 2013: Principles and Practice of Multi-Agent Systems*. Springer, Berlin Heidelberg, pp. 117–131.
- Gulliver, J., Briggs, D.J., 2004. Personal exposure to particulate air pollution in transport microenvironments. *Atmos. Environ.* 38, 1–8.
- Haase, D., Lautenbach, S., Seppelt, R., 2010. Modeling and simulating residential mobility in a shrinking city using an agent-based approach. *Environ. Model. Software* 25, 1225–1240.
- Helbing, D., Balthé, S., 2013. How to do agent-based simulations in the future: from modeling social mechanisms to emergent phenomena and interactive systems design. In: Helbing, D. (Ed.), *Social Self-Organization*, pp. 25–70.
- Heppenstall, A.J., Crooks, A.T., See, L.M., Batty, M., 2012. *Agent-Based Models of Geographical Systems*. Springer Netherlands, Dordrecht.
- Hertel, O., De Leeuw Frank, A.A.M., Oleraaschou, N., Jensen Steen, S., Gee, D., Herbarth, O., Pryor, S., Palmgren, F., Olsen, E., 2001. Human exposure to outdoor air pollution (IUPAC Technical Report). *Pure Appl. Chem.* 73, 933.
- Huang, C.Y., Sun, C.T., Hsieh, J.L., Lin, H., 2004. Simulating SARS: small-world epidemiological modeling and public health policy assessments. *JASSS* 7.
- INTERA, 2011. The INTERA platform, 2012. (Accessed 2 January 2013).
- Jerrett, M., Donaire-Gonzalez, D., Popoola, O., Jones, R., Cohen, R.C., Almanza, E., de Nazelle, A., Mead, I., Carrasco-Turigas, G., Cole-Hunter, T., Triguero-Mas, M., Seto, E., Nieuwenhuijsen, M., 2017. Validating novel air pollution sensors to improve exposure estimates for epidemiological analyses and citizen science. *Environ. Res.* 158, 286–294.
- Kamel Boulos, M.N., Resch, B., Crowley, D.N., Breslin, J.G., Sohn, G., Burtner, R., Pike, W.A., Jezierski, E., Chuang, K.-Y.S., 2011. Crowdsourcing, citizen sensing and sensor web technologies for public and environmental health surveillance and crisis management: trends, OGC standards and application examples. *Int. J. Health Geogr.* 10, 67.
- Kassomenos, P.A., Kelessis, A., Paschalidou, A.K., Petrakakis, M., 2011. Identification of sources and processes affecting particulate pollution in Thessaloniki, Greece. *Atmos. Environ.* 45, 7293–7300.
- Kaur, S., Nieuwenhuijsen, J., Colville, R.M.N., 2007. Fine Particulate Matter and Carbon Monoxide Exposure Concentrations in Urban Street Transport Microenvironments.
- Klabunde, A., Willekens, F., 2016. Decision-making in agent-based models of migration: state of the art and challenges. *Eur. J. Popul.* 32, 73–97.
- Klepeis, N.E., 1999. An introduction to the indirect exposure assessment approach: modeling human exposure using microenvironmental measurements and the recent National Human Activity Pattern Survey. *Environ. Health Perspect.* 107, 365–374.
- Kravari, K., Bassiliades, N., 2015. A survey of agent platforms. *J. Artif. Soc. Soc. Simulat.* 18, 11.
- LeBaron, B., 2002. Short-memory traders and their impact on group learning in financial markets. *Proc. Natl. Acad. Sci. Unit. States Am.* 99, 7201–7206.
- Loh, M., Sarigiannis, D., Gotti, A., Karakitsios, S., Pronk, A., Kuijpers, E., Annesi-Maeso, I., Baiz, N., Madureira, J., Oliveira Fernandes, E., Jerrett, M., Cherrie, J.W., 2017. How sensors might help define the external exposome. *Int. J. Environ. Res. Publ. Health* 14, 434.
- Macal, C., North, M., 2010. Tutorial on agent-based modelling and simulation. *J. Simulat.* 4, 151–162.
- Mammen, G., Gardiner, S., Senthinathan, A., McClellmont, L., Stone, M., Faulkner, G., 2012. Is this bit fit? Measuring the Quality of the Fitbit Step-Counter 5, 10.
- O'Sullivan, D., Millington, J., Perry, G., Wainwright, J., 2012. Agent-based models – because they're worth it? In: Heppenstall, A.J., et al. (Eds.), *Agent-Based Models of Geographical Systems*. Springer Netherlands, Dordrecht, pp. 109–123.
- OEHA, 2012. Technical Support Document for Exposure Assessment and Stochastic Analysis - Office of Environmental Health Hazard Assessment - California EPA.
- Ott, W.R., 1982. Concepts of human exposure to air pollution. *Environ. Int.* 7, 179–196.
- Rai, A.C., Kumar, P., Pilla, F., Skouloudis, A.N., Di Sabatino, S., Ratti, C., Yasar, A., Rickerby, D., 2017. End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Sci. Total Environ.* 607–608, 691–705.
- Richmond, C.R., 1985. ICRP publication on reference man. *Br. J. Radiol.* 58, 576–577.
- Sarigiannis, D., Gotti, A., 2014. New methods for personal monitoring of air pollution through the use of passive sensors during childhood. *Pneumologia Pediatrica* 54, 37–43.
- Sarigiannis, D., Karakitsios, S., Handakas, E., Papadaki, K., Chapizanis, D., Gotti, A., 2018. Informatics and data analytics to support exposome-based discovery: Part 1 - assessment of external and internal exposure. In: Miltiadis, D.L., Paraskevi, P. (Eds.), *Applying Big Data Analytics in Bioinformatics and Medicine*. IGI Global, Hershey, PA, USA, pp. 115–144.
- Sarigiannis, D.A., Karakitsios, S.P., Antonakopoulou, M.P., Gotti, A., 2012. Exposure analysis of accidental release of mercury from compact fluorescent lamps (CFLs). *Sci. Total Environ.* 435–436, 306–315.
- Sarigiannis, D.A., Kontoroupi, P., Nikolaki, S., Gotti, A., Chapizanis, D., Karakitsios, S., 2017. Benefits on public health from transport-related greenhouse gas mitigation policies in Southeastern European cities. *Sci. Total Environ.* 579, 1427–1438.
- Sarigiannis, D.A., 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., Karakitsios, S.P., Kermenidou, M.V., 2015. Health impact and monetary cost of exposure to particulate matter emitted from biomass burning in large cities. *Sci. Total Environ.* 524–525, 319–330.
- Schweizer, C., Edwards, R.D., Bayer-Oglesby, L., Gauderman, W.J., Ilacqua, V., Jantunen, M.J., Lai, H.K., Nieuwenhuijsen, M., Kunzli, N., 2007. Indoor time-microenvironment-activity patterns in seven regions of Europe. *J. Expo. Sci. Environ. Epidemiol.* 17, 170–181.
- Setton, E., Marshall, J.D., Brauer, M., Lundquist, K.R., Hystad, P., Keller, P., Cloutier-Fisher, D., 2011. The impact of daily mobility on exposure to traffic-related air pollution and health effect estimates. *J. Expo. Sci. Environ. Epidemiol.* 21, 42–48.
- Spinazzè, A., Cattaneo, A., Peruzzo, C., Cavallo, D.M., 2014. Modeling population exposure to ultrafine particles in a major Italian urban area. *Int. J. Environ. Res. Publ. Health* 11, 10641–10662.
- Stamatelopoulou, A., Chapizanis, D., Karakitsios, S., Kontoroupi, P., Asimakopoulos, D. N., Maggos, T., Sarigiannis, D., 2018. Assessing and enhancing the utility of low-cost activity and location sensors for exposure studies. *Environ. Monit. Assess.* 190, 155.
- 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. *Sci. Total Environ.* 443, 184–193.
- Steinle, S., Reis, S., Sabel, C.E., Semple, S., Twigg, M.M., Braban, C.F., Leeson, S.R., Heal, M.R., Harrison, D., Lin, C., Wu, H., 2015. Personal exposure monitoring of PM_{2.5} in indoor and outdoor microenvironments. *Sci. Total Environ.* 508, 383–394.
- Suleimenova, D., Bell, D., Groen, D., 2017. A generalized simulation development approach for predicting refugee destinations. *Sci. Rep.* 7, 13377.
- Topography Department of the Municipality of Thessaloniki, 2017. Thessaloniki Spatial Data Infrastructure. Municipality of Thessaloniki.
- Yang, C.-C., Hsu, Y.-L., 2010. A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors* 10, 7772–7788.