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Agent-based modelling: A stochastic approach to assessing personal exposure to environmental pollutants – Insights from the URBANOME project

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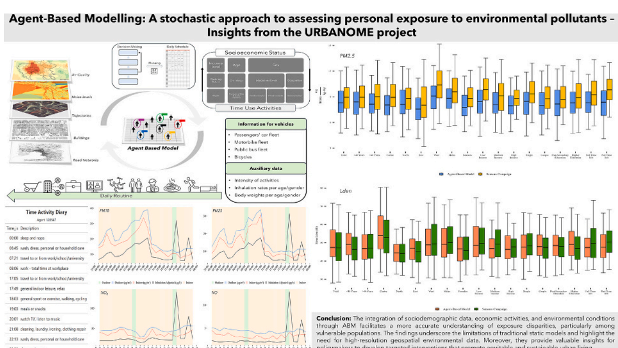
HIGHLIGHTS

- An agent-based model estimated exposure to air pollutants and noise in European cities.
- The model is scalable using data from freely accessible sources.
- Exposure data was gathered via portable sensors, diaries, and smartphone applications.
- Socioeconomic and demographic factors influenced individual exposure patterns significantly.
- Indoor vs. outdoor exposure distinctions were key to assessing inhalation levels accurately.

GRAPHICAL ABSTRACT



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ABSTRACT

In the context of the URBANOME project, aiming to assess European citizens' exposure to air pollutants (PM10, PM2.5, NO2) and noise, an extensive data collection process was undertaken. This involved the distribution of stationary home sensors, portable sensors, and smartphone applications, alongside participants logging their activities while using these devices. By leveraging socioeconomic and socio-demographic statistical data for the residents of Thessaloniki, we developed an agent-based model to estimate exposure levels based on the movement patterns, locations, and data collected from the URBANOME campaign. The model highlights that an individual's exposure is closely linked to the type of activities they perform, their location, age, and gender.

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Whether exposure occurs indoors, or outdoors is important for determining intake levels. Activity selections were found to be strongly influenced by income, age, and social connections, indicating that socio-economic factors significantly shape exposure patterns. The analysis also revealed considerable differences between PM measurements taken from fixed monitoring stations and the sensors used in the campaign. Notably, even agents residing in the same household displayed distinct exposure levels, underscoring the variability within localized environments. Preliminary results from the URBANOME campaign were compared with the ABM outputs, showing differences in median values of up to 20 % of both noise and inhalation intakes. This research emphasizes the importance of using such models for developing future scenarios in large cities aimed at fostering green transitions and enhancing citizens' quality of life. These models provide valuable insights for designing strategies to reduce exposure and improve urban living conditions.

1. Introduction

Before the recent advancements, the exclusive method for determining exposure to air pollutants (PMs, NOx, TVOCs, etc.) involved the spatial estimation of ambient concentration measurements obtained from FMS networks (Ma et al., 2024; Steinle et al., 2013). Residents living in the same neighbourhoods close to monitoring stations were generally considered as homogeneous receptors of similar levels to the ones of the station's location (Buonanno et al., 2014; Dias and Tchepel, 2018; Mijling, 2020; Owoade et al., 2021; Yatkin et al., 2020; Zou et al., 2016). There is a plethora of studies reported that concentrations of air contaminants provided by FMS do not represent the actual concentrations of urban environments (Beckx et al., 2009a, 2009b; Bereitschaft, 2015; Kumar et al., 2018; Setton et al., 2011; Tran et al., 2021). The reason for this is that the stationary FMS approach ignores unique mobility patterns when people are not at home. Ongoing research indicates that most individuals spend the majority of their waking hours indoors, moving between homes, workplaces, and retail establishments rather than remaining in a single location (e.g., home) (Allen and Macomber, 2020; Ochs and Kremer-Sadlik, 2013). Consequently, due to the range of activities they undertake in different microenvironments, even those residing in the same neighbourhood or at the same location may experience different exposure profiles to environmental pollutants and noise (Caplin et al., 2019; Dias and Tchepel, 2018; Kou et al., 2021; Steinle et al., 2015).

Noise pollution, driven by industrial, commercial, transport-related, and recreational activities, is a growing public health concern, particularly in urban environments (Clark et al., 2021; Hemmat et al., 2023). While it is well known that high noise levels can lead to hearing loss and tinnitus due to direct damage to the auditory system, emerging evidence suggests that noise exposure also results in numerous non-auditory health effects (Chen et al., 2023; Münzel et al., 2021). These effects, often triggered by transportation noise, include annoyance, restlessness, disturbances to daily activities, and more severe issues such as metabolic and cardiovascular problems (Mehrotra et al., 2024; WHO, 2011, 2018). There is strong evidence in the available literature that environmental noise is epidemiologically associated with numerous adverse health effects spanning from birth outcomes to metabolic disorders (Münzel et al., 2020, 2021, 2018; Sakhvidi et al., 2018; Smith et al., 2022; Thompson et al., 2022; WHO, 2018). Such impacts can arise even at noise levels that do not directly affect hearing. Strictly speaking, noise exposure activates the autonomic nervous and endocrine systems, leading to stress responses that can disrupt sleep and increase stress hormone production, such as cortisol (Chen et al., 2023; Gabinet, 2024). Long-term sleep disturbances and chronic stress from noise can have serious health implications, including cardiovascular diseases (Halperin, 2014; Münzel et al., 2020, 2018). Interestingly, noise annoyance may serve as a protective mechanism, helping individuals to adapt by reducing exposure and mitigating stress-related health risks.

To this end, it has been emphasized the importance of incorporating behavioural and environmental factors into exposure assessments to accurately capture an individual's varying exposure throughout his/her daily routine, as the static approach of only relying on FMS may inaccurately represent personal exposure to environmental contaminants (Kelly, 2020; Patel et al., 2017) and noise. Given that both individuals and pollutants are constantly in motion in noisy microenvironments, it is imperative to consider the dynamics of environmental pollution in conjunction with the spatiotemporal behaviours of people (Dias and Tchepel, 2018; Peterson et al., 2017; Steinle et al., 2013, 2015; Thessen et al., 2020; Zavala-Yoe et al., 2020). Therefore, modelling exposure necessitates an understanding of daily time-use and multi-routine schedules across numerous ecosystems (Schweizer et al., 2007; Spinazzè et al., 2014). However, exposure also varies according to a population's sociodemographic characteristics. Individuals from different socioeconomic backgrounds may exhibit distinct behavioural and interaction patterns, engaging in a diverse range of activities throughout their daily routines. These differences lead to varying exposure profiles. Consequently, a more refined approach is necessary—one that accurately records exposure for everyone, thereby reducing the risk of potential exposure misclassification by overlooking or failing to account for these variations (Chapizanis et al., 2021; Mueller et al., 2020).

The latest technological advancements have resulted in the development of smart monitoring devices that can be worn by individuals or placed in indoor and outdoor settings. This innovation has enabled the accurate capture of the 'time-geography of exposure', refocusing the current paradigm from the population level to the individual level (Baig and Gholamhosseini, 2013; Sarigiannis et al., 2018). The Arduino microcontroller board, along with multiple small sensors and hardware, enables the collection and integration of data on location, physical activity, and air quality at both community and individual levels (DeLay et al., 2022; Jerrett et al., 2017; Kamel Boulos et al., 2011; Loh et al., 2017; Rai et al., 2017; Sarigiannis and Karakitsios, 2018). People's coordinates can be tracked using GPS devices, which makes it possible to match pollution data with an individual's location (Breen et al., 2014; De Nazelle et al., 2013; Park et al., 2023; Steinle et al., 2013; Wu et al., 2011). Personal activity monitors not only track steps taken, distance traveled, energy expenditure and total time spent in active minutes, but they also assess the intensity of multiple activities, and heart rates which can be linked to the corresponding breathing rates (Bassett, 2012; Bent et al., 2020; Dias and Paulo Silva Cunha, 2018; Donaire-Gonzalez et al., 2013; Wang et al., 2017). To develop individual exposure profiles, portable air quality sensors as well as smartphone technologies for noise monitoring can be of use in determining whether peak exposures and time series data are more relevant than daily average exposure values (Ibekwe et al., 2016; Padilla-Ortiz et al., 2023). In addition to that, TADs can be utilized to gather more details about the activities carried out in each microenvironment (Chatpar et al., 2024; Habib, 2024). There is clear recognition of the advantages of user-friendly and high-time resolution data acquisition facilitated by IoT communication protocols (Abdulkarem et al., 2020; Asghari et al., 2019; H. Li et al., 2022). These technologies enable more convenient monitoring of high-resolution exposure to pollutants and noise over extended periods and across larger scales, making them ideal for population survey. However, measuring direct personal exposure requires individual data collection from a substantial sample of the population, which is practically often impractical due to financial constraints. This is especially true when assessing exposure profiles across the entire sociodemographic spectrum of a region (Sarigiannis et al., 2018). Consequently, the employment of ABM is essential for effectively simulating human movement and interaction behaviour considering the significant ethical and technical challenges of collecting time-use and exposure-related data for entire populations. A similar approach was recently validated using air pollution sensor data collected during a local campaign in Thessaloniki (Chapizanis et al., 2021).

With the employment of a stochastic simulation technique such as ABM, it is possible to investigate and comprehend phenomena in which separate entities interact to form an emergent whole. Organizationally, it is challenging to represent individual behaviour directly; however, ABM streamlines this by structuring data at the level of self-governing decision-makers, referred to as "agents" (Sarigiannis et al., 2018). These software items possess internal states and are designed to respond and behave according to predetermined behavioural guidelines when they encounter their surroundings (Ricci et al., 2011). The diversity among agents can be identified by modelling individual behaviours and interactions, which gives rise to the system's overall behaviour (Dorri et al., 2018; Van Dam et al., 2012).

The growing acceptance of ABMs in recent years can be attributed to the level of interaction that is allowed among the agents of an artificial society (Windridge and Thill, 2018). The high interest in these models stems from the idea that choices made at the individual level are what essentially propel social systems. To investigate human interactions on a social level, such models have already been established primarily within the social sciences, as well as in the domains of finance and gaming (Axtell and Farmer, 2022; Bianchi and Squazzoni, 2015; Conte and Giardini, 2016; Groeneveld et al., 2017; Szczepanska et al., 2022). Concrete examples of ABM applications are stock market behaviour (Llacay and Peffer, 2018; Vasellini, 2023; Wang and Zhang, 2015), epidemic spread prediction, and COVID-19 applications (Lombardo et al., 2022; Makarov et al., 2020; Silva et al., 2020; Wulkow et al., 2021), human immune system modelling (Chiacchio et al., 2014; Shi et al., 2014), human migration simulations (Carmona-Cabrero et al., 2024; Kniveton et al., 2011; Thober et al., 2018), refugee movements (Geiger et al., 2023; Suleimenova et al., 2017), urban evacuation (Barnes et al., 2021; Senanayake et al., 2024; Yang et al., 2023), urban transport systems (Bastarianto et al., 2023; González Cuevas and Suppi, 2022; Li et al., 2021; Wise et al., 2017). It is worth mentioning that very few ABMs have tried to model whole cities regarding human behaviour, exposure to environmental pollutants (Chapizanis et al., 2021), and noise.

The present work provides a novel approach to exposure and noise assessment that is based on agent-based modelling. It generates exposure profiles for both individuals and communities, accounting for numerous microenvironments and sociodemographic traits. The interactions of virtual individuals, who live and work together within an artificial ecosystem that mirrors real-world behaviours, produce the patterns observed among subgroups within the study population. Last but not least, our study serves as a significant paradigm for the green transition in the EU and the Green Deal. It contributes to the reconstruction of exposure profiles for urban citizens and provides a valuable tool for modelling green interventions to achieve the EU's 2050 goals (Karakoltzidis et al., 2024; Leso et al., 2024).

2. Methods

2.1. Software

The ABM was developed in R 4.2.2 (R Developement Core Team, 2009). For geospatial data processing, osmdata (Padgham et al., 2017) enabled the retrieval and processing of spatial data such as buildings, land use, and road networks, while OSRM (Giraud, 2022) facilitated realistic agent movement by calculating optimal routes for all transportation modes. Spatial data handling was supported by libraries including sf (Pebesma, 2018), sp. (Pebesma et al., 2012), rgdal (Bivand et al., 2015), raster (Hijmans et al., 2013), and leaflet (Cheng et al., 2019). Kriging interpolation was performed using gstat (Pebesma, 2023). For data manipulation, dplyr and plyr (Wickham et al., 2020; Yarberry, 2021) R-libraries were employed. Computational efficiency was enhanced through parallel processing using the parallel and foreach libraries (Eugster et al., 2011). Visualization and graphing were achieved with ggplot2 (Wickham, 2011) and ggpmisc (Aphalo, 2016), while deterministic modelling leveraged deSolve (Soetaert et al., 2010). The model also incorporated machine learning using XGBoost (Chen et al., 2019) and caret (Kuhn, 2008) for noise estimates. Additionally, integration with the air-quality-meteo API was implemented via the reticulate library (Ushey et al., 2020), allowing Python-based interactions with the R-based ABM. A detailed description of the software used for the development of the model is provided in the supplementary material.

2.2. An outline of the research area

For the Greek metropolis of Thessaloniki (Fig. 1), an agent-based model was developed that specifically considers societal dynamics to assess individual exposure to environmental pollutants. Thessaloniki is the second largest city in Greece as well as a densely populated region. Municipalities included in Thessaloniki are Kalamaria and Pylaia-Chortiatis (east; blue), Thessaloniki (centre; green), and Kordelio-Evosmos, Ampelokipoi-Menemeni, Pavlos Melas (west; red), Neapoli-Sykies (north; grey). These municipalities, which total about 110 km^2, were home to 802,392 people as of the 2021 Greek census. The western industrial zone of the city, along with vehicle emissions and residential heating, is the primary source of air and noise pollution. More information about Thessaloniki morphology is provided in other studies (Chapizanis et al., 2021; Diapouli et al., 2017; Sarigiannis et al., 2017).

2.3. Data acquisition for the agent-based model

The development of a city-scale model reflecting real-world conditions, required the transformation of each entity involved in the system into an agent, thus treated as an individual entity. The system consists, among other components, of road networks, buildings, and human agents as depicted in Fig. 2.

The environment of the system, including the road and building networks of urban Thessaloniki, was defined using shapefiles with high spatial resolution. These shapefiles were incorporated into the model and converted into road and building agents providing information regarding e.g., street capacity or the land use of a structure. Buildings and road networks were retrieved by applying the functionalities of the osmdata library (Padgham et al., 2017). The osmdata library in R is a powerful tool for accessing and processing OSM data, enabling seamless retrieval of geographic information for numerous applications. This library facilitates the extraction of spatial data by providing a user-friendly interface to query OSM's extensive database, allowing for integration with the sf package (Pebesma, 2018). The administrative boundaries of the municipalities within Thessaloniki, along with the region's public transport network obtained from the osmdata library, were also incorporated into the ABM pipeline. Land use data for urban Thessaloniki was compiled by integrating pertinent information from the 2012 Urban Atlas (Cover, 2018) with a land use map obtained from the Thessaloniki Geographical Information Portal.

Population statistics were obtained from the 2021 Greek census conducted by the Hellenic Statistical Authority (ELSTAT), focusing on the municipal level of the urban Thessaloniki area (ELSTAT, 2024). The integration of demographic and socioeconomic status (SES) data has been incorporated into the model to account for the varying time-activity patterns exhibited by different population subgroups. These subgroups utilize diverse modes of transportation and spend differing amounts of time participating in activities across various microenvironments. As a result, the attributes assigned to an agent consist of

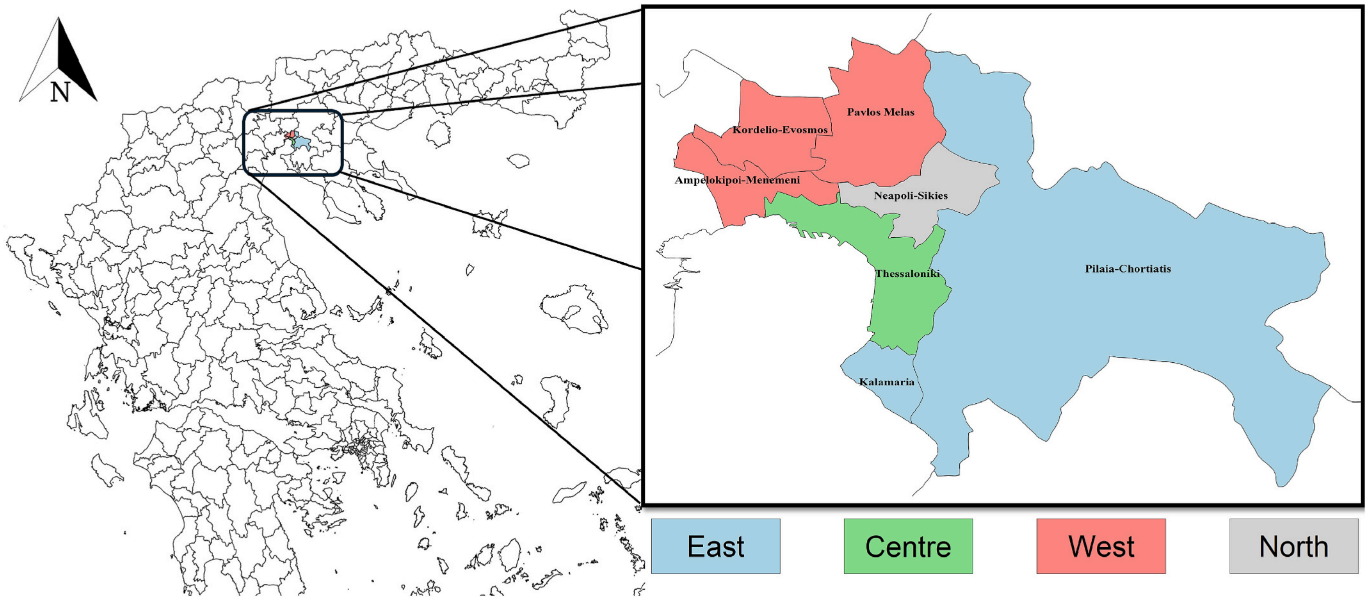

Fig. 1. Map of Metropolitan area of Thessaloniki. The location of the municipalities compared to the map of Greece.

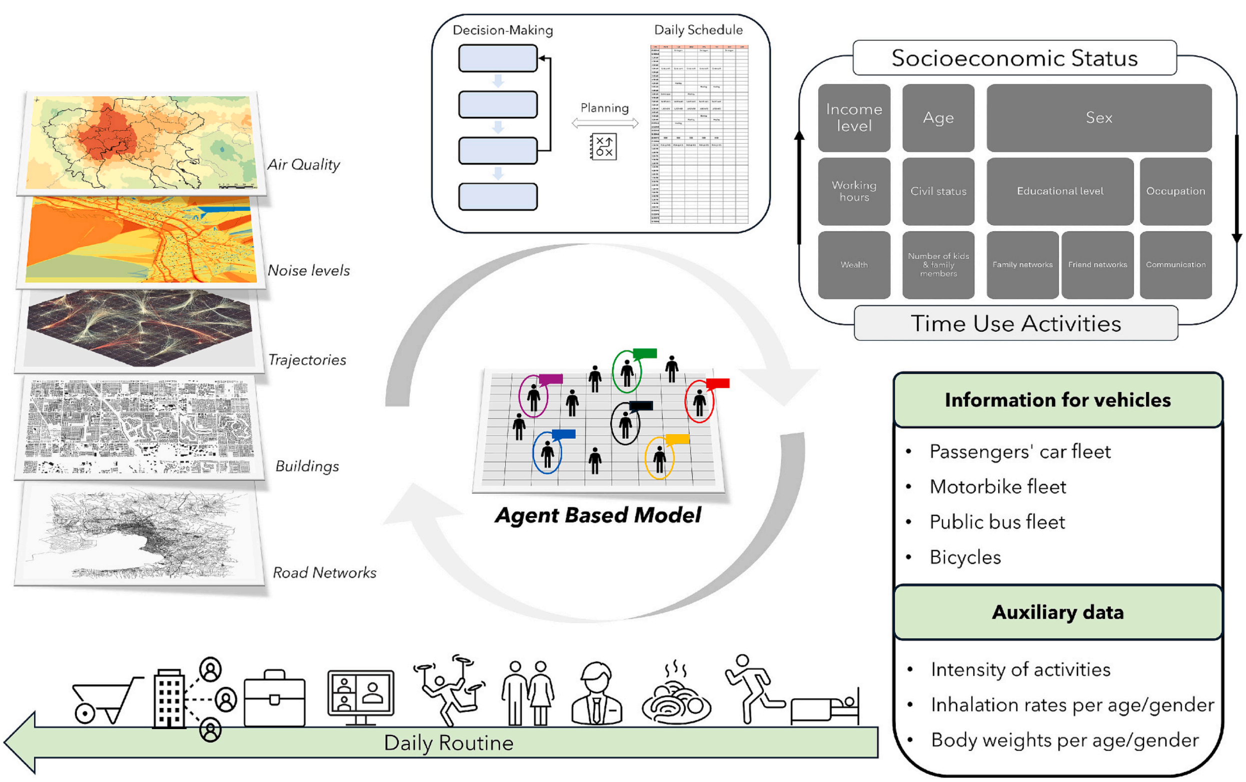

Fig. 2. Input data for the agent-based model.

characteristics such as age, gender, education level, employment status, civil status, and income, which relied on the official population statistics of urban Thessaloniki. This information was collected manually. Physiological characteristics of the agents regarding their weight and height have been obtained from the CDC official website.[1,2,3,4,5] Information regarding breath rate and inhalation rate was sourced from relevant works in the literature (Chapizanis et al., 2021; Hickox and Denton, 2000; Richmond, 1985; Sarigiannis et al., 2012). Data on the composition of the vehicle fleet in Thessaloniki was converted into vehicle agents and incorporated into the model.[6] The attributes of these agents included vehicle type (e.g., car, bus, motorbike) and engine type. Yet, the engine type was included only as a vehicle attribute and did not influence the simulation, contribute to air pollution levels, or accurately represent real-world engine types. Bicycles were also considered in the vehicle dataset as alternative means of transportation. Traffic activity data were derived from simulation runs that modeled agent movements. These simulations did not replicate real-world scenarios in detail, such as higher morning traffic density or bus delays during peak hours. Instead, these factors were indirectly accounted for within the modeled commute times, which were estimated at each timestep using the OSRM library (Giraud, 2022).

The time-activity patterns of the artificial population are derived from the 2013 HETUS conducted in Greece, as no more recent data is available (ELSTAT, 2016). This survey recorded the time individuals spent on 25 activity categories, as presented in Table 1, within a 24-h observation period (Fisher et al., 2015). The dataset output comprises a) a weighted percentage of individuals participating in a specific activity within a subgroup defined by demographic and socioeconomic factors, and b) the weighted average along with standard deviation of the time allocated toon that activity.

Furthermore, it should be noted that the database from the NoiseCapture App (Bocher et al., 2017) was utilized to harmonize noise pollution data within the model. The app provides an efficient and reliable method for incorporating geospatial noise data into the agent-based model due to its ability to capture real-time noise levels with high spatial granularity. The full NoiseCapture dataset was utilized in the subsequent approximations to capture as much noise variability as possible at each point of the grid. The data collected from multiple points were aggregated into seven daily mean values to ensure consistency in the temporal resolution of the noise inputs across the entire model area. The number of daily means was determined based on the simulation time employed for the execution of the model. To further enhance the accuracy of the noise exposure assessments for the agents', kriging interpolation was applied within the simulation grid. This approach allowed the model to seamlessly integrate noise data with varying temporal and spatial resolutions, ensuring that noise exposure was accurately represented throughout the simulation environment. The combination of real-time noise measurements with long-term data, such as seasonal or annual noise maps, enabled to introduce a comprehensive and robust representation of noise pollution in the simulation environment. Last but not least, it is worth noting that the daily mean noise pollution levels remained constant across the grid during the simulation.

The Open-Meteo API was employed to harmonize environmental pollution data within the model, offering an efficient solution for integrating real-time weather and environmental data. More specifically, it provides air quality data by integrating information from multiple authoritative sources, including governmental and scientific monitoring networks. It relies on the Copernicus Atmosphere Monitoring Service (CAMS), a program funded by the European Union and part of the Copernicus Earth Observation initiative. CAMS provides global and regional air quality forecasts using advanced atmospheric models. It delivers data on key pollutants such as e.g., particulate matter (PM10 and PM2.5), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) among others. CAMS is a trusted source because it provides high-resolution, reliable air quality forecasts and analyses on both regional and global scales (Kuenen et al., 2022). Using satellite data, ground-based observations, and numerical models, CAMS delivers accurate real-time insights into air quality, which Open-Meteo leverages to provide its users with valuable information. However, a notable challenge with this tool is its low spatial resolution (11 km), which may lack the localized precision necessary for urban environmental exposure models.

Table 1
Symbolic coding of sociodemographic attributes and activities. Activities in bold represent the major ones, while the non-bold activities indicate free time activities.

Activities	Age	age	Civil status	civstat
cleaning, laundry, ironing, clothing repair	0–9	0	Couple	1
computing, play computer games	10–19	1	Not couple	2
meals or snacks	20–29	2		
adult care	30–39	3	Level of education	**educ**
food preparation, cooking,	40–49	4	Not completed secondary education	1
gardening	50–59	5	Post-secondary/no tertiary education	2
cinema, theatre, restaurant, café, bar, pub	60–69	6	Higher education	3
teach child a skill, help with homework, play	70–79	7	International Standard Classification of Education (ISCED)	
general indoor leisure, relax	80–89	8		
home/vehicle maintenance/collect fuel			**Urban/rural classification**	**urban**
pet care, walk dogs	**Income**	**income**	Urban/suburban	1
read	Lowest 25 %	1	Rural/semi-rural	2
worship and religious activity	Middle 50 %	2		
wash, dress, personal or household care	Highest 25 %	3	**Employment status**	**empst**
purchase goods, personal care services			Full-time hours	1
general sport or exercise, walking, cycling	**Gender**	**gender**	Part-time hours	2
travel	Male	1	Hours of work unknown	3
watch TV, listen to music	Female	2	Student/retired/unemployed	4
voluntary work, civic/organizational activity				
no recorded activity, NA				
sleep and naps				
work - total time at workplace				
school, classes				
travel to or from work/school/university				

[1] https://www.cdc.gov/growthcharts/cdc-growth-charts.htm (Accessed 12/2024).

[2] https://cdn.who.int/media/docs/default-source/child-growth/child-growth-standards/indicators/length-height-for-age/cht-lfa-boys-p-0-2.pdf?sfvrsn=a6488b92_10 (Accessed 12/2024).

[3] https://cdn.who.int/media/docs/default-source/child-growth/child-growth-standards/indicators/length-height-for-age/cht-lfa-girls-p-0-2.pdf?sfvrsn=61b9a4e8_10 (Accessed 12/2024).

[4] https://cdn.who.int/media/docs/default-source/child-growth/child-growth-standards/indicators/weight-for-age/cht-wfa-boys-p-0-2.pdf?sfvrsn=4db44d93_12 (Accessed 12/2024).

[5] https://cdn.who.int/media/docs/default-source/child-growth/child-growth-standards/indicators/weight-for-age/cht-wfa-girls-p-0-2.pdf?sfvrsn=37c200a9_12 (Accessed 12/2024).

[6] https://www.statistics.gr/en/statistics/-/publication/SME18/- (Accessed 12/2024).

To address this limitation, we accessed data measured by the environmental pollution stations spread across the greater Thessaloniki area. The geographic locations of these stations are presented in Fig. 3. Additional information for the air pollution monitoring stations can be retrieved from the Municipality and the Regional Authority. These stations provided us with highly reliable, precise measurements of pollution concentrations at specific locations. Specific information for each station is provided in Table 2. To estimate pollution values for areas without direct measurements, kriging interpolation was applied. This geo-statistical method allowed us to predict pollution levels at unmeasured points by utilizing the spatial relationships between the measured data points. The results of this interpolation (raster layers), which provide continuous estimates of pollution concentrations, are displayed in Fig. 4. Two-year historical data were utilized from both data sources to ensure robust and comprehensive input for the model simulations. Weekly measurement means were aggregated and interpolated to be incorporated into the model. Similarly, all available data, including information on buildings, road networks, aggregated air quality maps, and aggregated noise maps, were converted into layers for integration into the developing ABM. It is important to note that during a simulation day, air pollutant concentrations at a specific point on the grid remained constant.

Finally, significant emphasis should be placed on the methodology for collecting data from APIs, as this facilitates simulations for cities beyond Thessaloniki. All data sources are freely accessible, enabling the model to be reconstructed for application in other cities. The only information that must be collected manually pertains to statistical data from official authorities, which includes details on population composition, time-activity patterns as well as socioeconomic and sociodemographic characteristics.

2.4. Development of the agent-based model

Upon initialization of the agent-based model, human agents are randomly assigned to a residential location within the municipality where they were originally conceptualized. This location serves as their home for the duration of the entire simulation. Additionally, they are allocated to an office, university, or school based on their age, gender, and employment status. Furthermore, they become integrated into family networks by adhering to ELSTAT statistics regarding marital status and the number of children per family at the municipal level. As a result, a network may represent a nuclear family, a single-parent family, a childless family, or an elderly couple (not associated with children). Moreover, during the model initialization, the number of hours each agent will sleep per day is determined based on Table 3. From this, a normal distribution of 100 values is generated for each agent using the minimum and maximum sleeping times, with the mean and standard deviation calculated as follows in Eqs. (1) and (2). The sleeping time for each agent is then randomly sampled from this distribution daily.

$$\textit{mean value} = \frac{hours_{max} + hours_{min}}{2} \tag{1}$$

Table 2
Determination of air pollution monitoring stations employed in the development of the model. Graph column represents the symbol by which the stations are represented in Fig. 3.

Station	PM10	PM2.5	NO	NO2	Graph
Agias Sofias	+	+	+	+	A
AUTh	+	+	+	+	B
Kalamaria	+	+	+	+	C
Kordelio	+		+	+	D
Neohorouda	+	+	+	+	E
Panorama	+	+	+	+	F
Sindos	+		+	+	G
Egnatia	+				H
Eptapirgio	+				I
Lagkada	+				J
25is Martiou	+				K
Stavroupoli	+		+	+	L
Oraiokastro		+			M

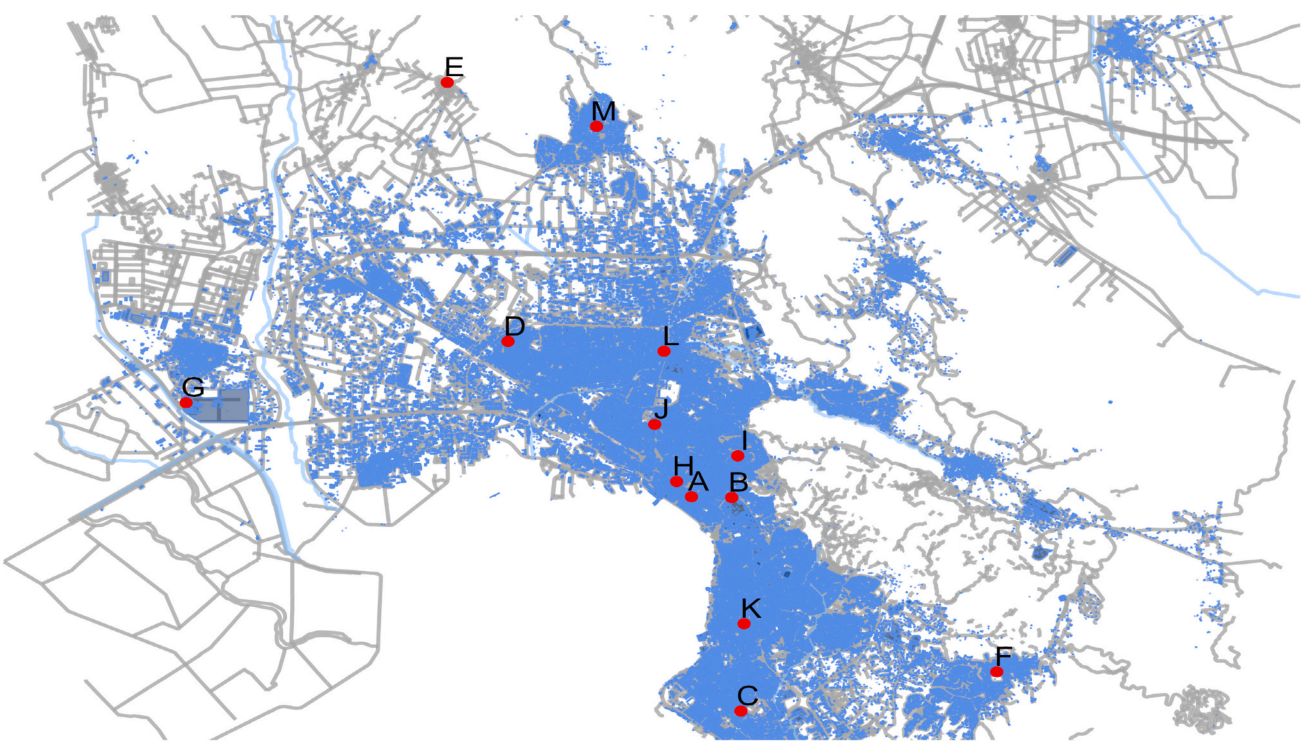

Fig. 3. Location (in red) of the environmental pollution metering stations in the urban area of Thessaloniki. Buildings of the urban area of Thessaloniki are illustrated in blue. The letters correspond to the associations with the station names as outlined in Table 2 and the pollutants that are measured by each station.

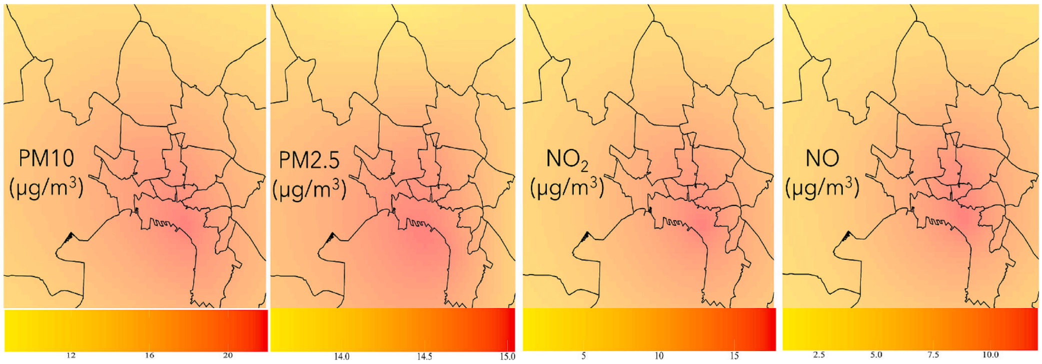

Fig. 4. Kriging interpolation maps of environmental pollutants for Thessaloniki's urban area. Each map includes also a legend in the bottom. From left to right, Map of PM10 (μg/m^3), PM2.5 (μg/m^3), NO_2 (μg/m^3), and NO (μg/m^3). These maps reveal higher pollutant levels in the city's central and southern regions, emphasizing areas with potentially greater environmental health risks.

Table 3
Input information for the generation of sleeping times for each agent.

Age	Minimum hours	Maximum hours
Age $\leq$ 5	9	15
5 < age $\leq$ 13	7	13
13 < age $\leq$ 17	6	12
Age > 17	4	11

$$standard\ deviation = \frac{hours_{max} - hours_{min}}{6} \tag{2}$$

Initially, each agent is assigned an empty tibble with minute-level resolution, consisting of five columns: time, activity name, location of the activity, participating family members (if any), and people from the agent's friend network who are present and can potentially join a free time activity upon accepting an invitation. The number of rows corresponds to the number of minutes in the simulation. The simulation time was set to 7 days. At the beginning of the simulation, each agent's starting point is determined by their age and the time they should wake up in the morning. Every agent receives five mandatory daily activities: (a) sleep, (b) self-care, (c) commute, (d) paid work or education, and (e) commute again. Agents who are unemployed or retired are assigned only the first two activities initially. All agents wake up no later than 09:00 AM. Students wake up at 07:00 AM on weekdays. Agents older than 65 years are registered as pensioners mandatorily. These activities are entirely relied on the individual start/end times assigned to each agent. The subsequent cells of the tibble remain empty until each corresponding activity is completed. Following that, an activity assignment function is triggered, based on each agent's socioeconomic characteristics and the processed HETUS time-use dataset. The probability of selecting a particular activity varies according to the personal characteristics of each agent.

Based on SES attributes and the distance between the point of departure and the intended destination, a rule-based approach is applied at the individual human agent level. In agent-based modelling, rules are typically expressed as 'if-then' statements, similar to real-life decision-making, or as conditions imposing threshold values. For instance, an agent may choose between using a personal car or public transportation for commuting. Given that the car is primarily used by the agent and the job location is over 6 km away, the likelihood of opting for public transportation is minimal. Additionally, when an agent receives invitations to participate in an activity, there is a probability assigned for accepting or declining the invitation, which updates their TAD accordingly. Alternatively, rules may take the form of functions that determine the probability of a human agent performing a specific action. These rules enable emergent phenomena to occur, frequently altering the probabilistic nature of the time-use distributions initially used as input.

In the developing ABM, emergencies are introduced in three key aspects of the human agents' daily routines: a) interactions between human agents, b) decision-making related to transportation and the joining of a free time activity as well as c) adaptive behaviour. The option for agent-based interactions is introduced into the model through invitation sharing among agents within a common family or friend network, allowing them to participate in joint activities. When a human agent initiates a new "free time" activity, an invitation is disseminated to all members of their network, inviting them to participate. Similarly, just prior to the addition of a new activity to a human agent's activity sequence list, is always a check for potential invitations is always performed. The likelihood of a human agent accepting an invitation and joining a group activity is determined using the formula below (Eq. (3)) which was introduced by Chapizanis et al. (2021):

$$Pr_{join} = \frac{w_1 f(var_1) + w_2 f(var_2) + \ldots + w_n f(var_n)}{max(f(var_1))w_1 + max(f(var_2))w_2 + \ldots + max(f(var_n))w_n} \tag{3}$$

where Pr represents the probability of accepting an invitation, var. denotes a SES attribute (such as age, gender, etc.), and w indicates the weight of the corresponding attribute (var). Detailed information about this approach and application examples are also available in the work of Chapizanis et al. (2021). When agents accept an invitation, the joint activity is inserted as the "next" activity in their sequence of activities.

"Commute" activities involve the option for a human agent to either walk, use a car, ride a motorbike, take a bus, or cycle to reach their destination. The artificial population is initially allocated to use a specific transport mode, according to the official statistical authority. Consequently, by utilizing behavioural rules, an adjusted probability is subsequently assigned to human agents based on specific personal attributes, such as e.g., age and income among others. The probability of vehicle selection is finally adjusted during each simulation, considering the distance traveled to the targeted destination (e.g. agents prefer to walk to their job rather than drive if it is located <1 km from their home).

At the end of a simulation, each human agent's activity patterns and space-time trajectories are recorded, capturing the influence of agent-specific decision-making dynamics throughout the experimental period. This data reflects the emergent behavioural patterns unique to each agent, shaped by individual preferences and responses to the simulated environment. The trajectories of human agents, derived from the coded routines, were recorded as points at each simulation step, encompassing information such as coordinates, types of microenvironments, and the activities undertaken in both space and time.

One of the key challenges in introducing activity tables for each agent lies in managing PC memory efficiently. Although simulating seven days may not seem excessive, it still generates 10,800 records per agent (minute-based resolution of a week). This quickly adds up, leading to significant memory consumption, which can degrade the simulation's performance. In fact, when the present simulation was scaled to 100,000 agents, memory management failures made it impossible to run. To address this issue, local activity log tables were created for each agent at the beginning of the simulation. When the simulation required an agent's activity table, it accessed it locally rather than storing all data in memory. These tables included not only the agent's activities but also sensor readings for air and noise pollution, as well as the agent's location (latitude and longitude) for each minute. For efficient data storage and quick retrieval, the RDS format was chosen (Giorgi et al., 2022). This format compresses and stores data efficiently, preserving the structure and attributes of R objects, making it well-suited for dynamic simulations. It allows large datasets to be handled without excessive disk space consumption while enabling rapid access to simulation states when needed. Its native support in R ensures compatibility across projects, offering a practical solution for saving and restoring simulation data seamlessly. Given the availability of population statistics from the relevant authorities and simulation data from freely accessible APIs, as previously described, the primary consideration for scaling the model up or down lies in the selection of the number of agents at the start of the simulation. Additionally, the simulation duration must be carefully determined, bearing in mind that computation time and resource requirements increase significantly with larger-scale simulations. It is important to consider that the discussion takes place only for urban information that is included in the documentations of OSM library.

Agent trajectories data can subsequently be overlaid onto high spatial resolution maps of the area. In the current superimposed onto high-resolution atmospheric pollutant concentration maps. In this study, minute-based variation with high spatial resolution PM25, PM10, NO_2, and maps of urban Thessaloniki were employed, based on dispersion modelling results, applying both traffic and non-traffic sources, fused with ground monitoring measurements (Sarigiannis et al., 2017). Exposure for each agent was estimated as each agent had a personal sensor by using its location (indoor/outdoor) and TADs. Exposure concentrations were captured by utilizing the coordinates of each agent at every timestep of the simulation and mapping them onto raster layers for each pollutant.

Indoor air concentrations were estimated by using the functionalities of INTEGRA platform (Sarigiannis et al., 2014), i.e., Eq. (4) which takes into consideration primary processes influencing PM and NOx concentrations such as potential emissions, indoor/outdoor exchange rate, etc.

$$V\frac{dC}{dt} = Q(inf_{Rate}C_{out} - C_{ind}) + E - k_{dep}C_{ind}V \tag{4}$$

V: volume of indoor location, Q: indoor/outdoor air exchange rate, inf: infiltration rate, C_{out}: outdoor concentration, C_{ind}: indoor concentration, E: emission source (mass/time), and k_{dep}: deposition rate. More details about this model and other potential applications could be retrieved from other works (Sarigiannis et al., 2014, 2012, 2015).

Another important aspect to highlight is the difference in environmental noise exposure between indoor and outdoor settings. The building materials and the state of the windows—whether they are open or closed—are important factors in the transmission of external sounds into indoor spaces. To address this, the conversion equations provided by Andargie et al. (2023) were utilized, specifically those with $R^2 >$ 0.40. Given that specific information about the construction materials and precise measurements for each building in the urban area of Thessaloniki were lacking, we relied on these linear regression equations. These equations, as detailed in the work of Andargie et al. (2023) work, are given in Table 4.

Since each regression model can make different predictions for indoor sound levels, all three predicted values are used to construct a normal distribution of 100 values. The smallest and largest values are derived from the predictions of the equations, forming the boundaries of the distribution, i.e., minimum and maximum. A value is then randomly selected from this distribution to estimate the internal value of noise.

Table 4
Linear regression equations for the conversion of outdoor noise to indoor noise (Andargie et al., 2023). Buildings A and B are sample buildings from the study derived from.

Building	Equation	R^2
Building A	Indoor L = 36.90 + 0.15 * Outdoor L	0.54
Building B – 2nd floor	Indoor L = 10.87 + 0.37 * Outdoor L	0.45
Building B – 6th floor	Indoor L = 2.79 + 0.52 * Outdoor L	0.58

Additionally, the time of day is of significant importance in measuring environmental noise, as day and night exhibit significant differences in noise levels at numerous measurement points. It was assumed that the data included in the ABM only consisted of daytime measurements. To account for nighttime variations, a study conducted by the Hellenic Ministry of Environment and Energy (2024), which includes both day and night noise measurements for Thessaloniki, was utilized. The measurements of the present study were taken in specific points around the city, resulting in a dataset of 4,992,373 observations with corresponding latitude and longitude coordinates, as well as day and night noise values. This dataset was randomly separated into a training set (80 %) and a test set (20 %) to train a XGboost model capable of converting daytime noise levels into nighttime equivalents by using as input values coordinates and daytime measurements. The parameters obtained from the model optimization are shown in Table 5 together with the metrics achieved by the model on the test dataset. The model obtained an R-squared value of 0.84 on the test set. Its performance on the test set is illustrated in Fig. 5, while the kriging interpolation results for both daytime and nighttime values are shown in Fig. 6.

For kriging interpolation, the spherical variogram model was used and integrated within the methodological pipeline of the ABM. This model is advantageous because it effectively captures spatial dependencies over defined ranges, a significant aspect for modelling pollutant dispersion. The spherical model accounts for the fact that pollutants such as PMs, NOx, and noise levels have localized impacts that diminish with distance, reflecting real-world patterns of environmental diffusion. By incorporating this method into the ABM, where agents move based on activities and transport modes, the spherical model ensures that pollution exposure accurately mirrors spatial correlation up to a certain distance, beyond which agents are no longer affected. This enhances the realism of the model, helping predict how pollution from sources such as traffic and industry affects different parts of the city, ultimately providing valuable insights into the development of a robust model (ABM).

Each agent spent a certain amount of time in an indoor or outdoor location exposed to a pollutant concentration (Cn). Given his/her activity an inhalation rate was introduced in minute-based resolution for each agent. The inhalation rate highly depends on individuals' age, gender, and the intensity of the activity. Daily intakes for an agent were then estimated by multiplying the concentration of an environmental contaminant with the corresponding inhalation rate and correcting with his/her the bodyweight leading to the introduction of a well-established exposure assessment. Detailed information regarding the derivation of inhalation rates given a specific type of activity is provided in the work of Sarigiannis et al. (2012). The proper simulation time was found to be higher than four days. In addition to that, agents sleeping time duration on a daily basis converges to the Expected Sleeping Duration. As a result, the model was tested on a virtual week-simulation time. Human agents allocate personal time for sleeping to take place in an activity and vice versa. It highly depends on their age and their social network. The number of agents generated within a simulation affects the decision and the time allocation of an agent. To this end, a virtual population similar to the real one of Thessaloniki was generated with a simulation step of 1 min.

Finally, the integration of a Lden (Day-Evening-Night Level) indicator into the agent-based model enhances the precision of the daily

Table 5
Parameters employed to train the XGboost model and performance metrics on the test set.

Parameters						
nrounds	max_depth	eta	gamma	colsample_bytree	min_child_weight	subsample
1000 I	16	0.99	0	0.99	10	1

Model performance							
R^2	0.84	RMSE	3.17	MAE	2.45	$Coef_{Pearson}$	0.91

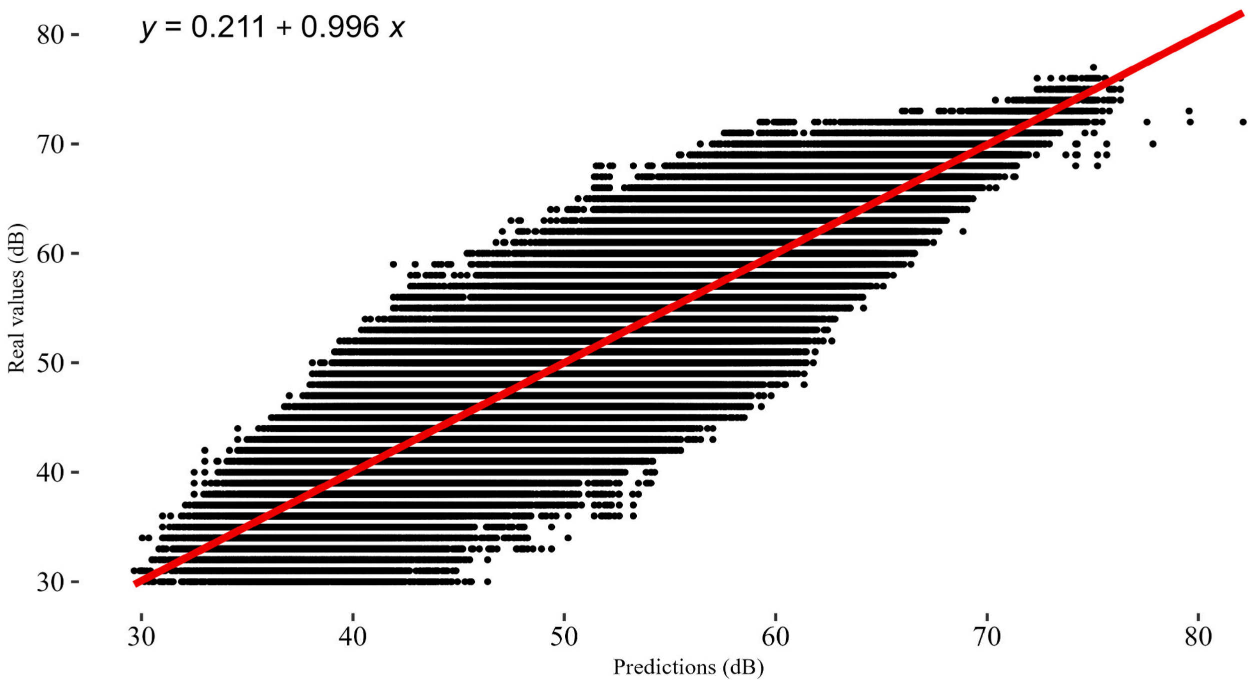

Fig. 5. Model predictions against the real values measured in the study of the Ministry of Environment.

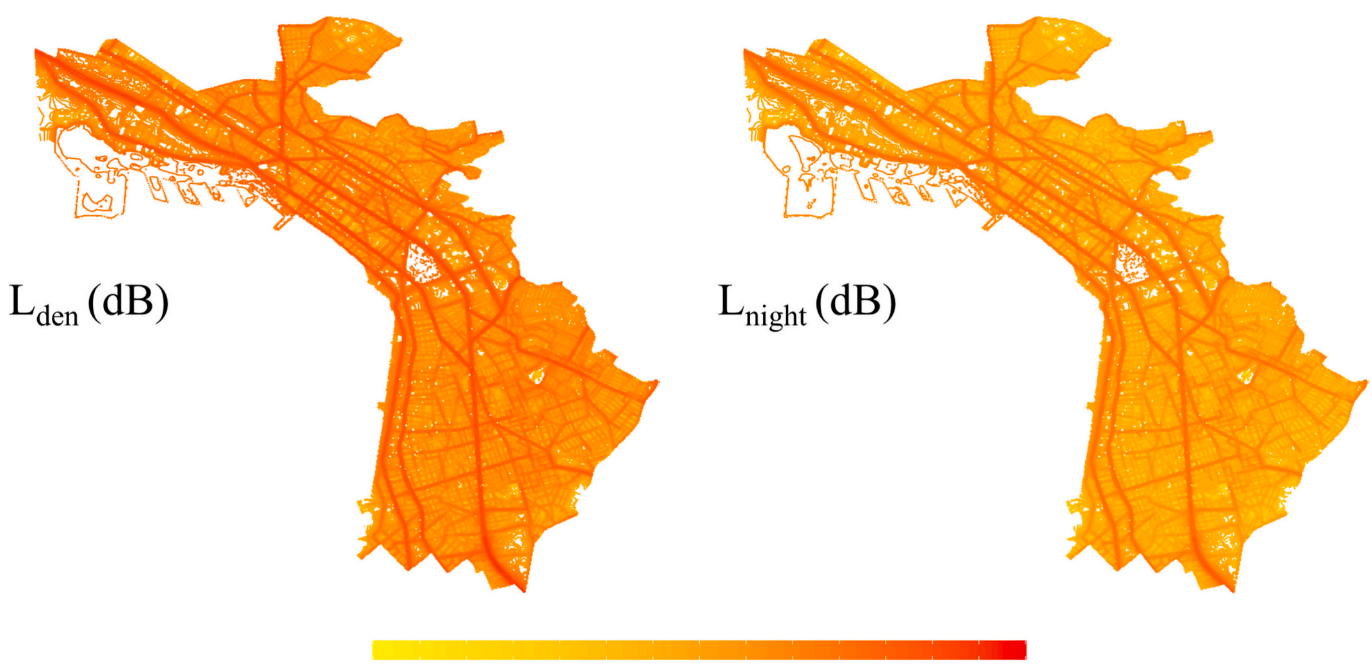

Fig. 6. Daytime (left) and night (right) noise levels in the urban area of Thessaloniki. Data was retrieved from a study of the Hellenic Ministry of Environment and Energy (2024).

noise exposure assessment by accounting for variations in noise levels throughout different periods of the day. Lden is a standardized metric that reflects cumulative noise exposure by giving additional weight to evening and night-time noise, periods typically associated with greater sensitivity to disturbance. The incorporation of the Lden into the ABM allows for robust simulations of how individuals, based on their locations and movement patterns, experience noise exposure over time (Brink et al., 2018). The estimation of the Lden was performed with Eq. (5).

$$L_{den} = 10log_{10}\left(\frac{1}{24}\left(12*10^{\frac{L_d}{10}} + 4*10^{\frac{L_e+5}{10}} + 8*10^{\frac{L_n+10}{10}}\right)\right) \quad (5)$$

L_d is the daytime noise level (from 07:00 to 19:00); L_e is the evening noise level (from 19:00 to 23:00) with a + 5 dB penalty to account for increased sensitivity during this period; L_n is the nighttime noise level (from 23:00 to 07:00) with a + 10 dB penalty due to the higher sensitivity to noise during night hours.

2.5. Compatibility control and URBANOME study presentation

The output obtained from the ABM can be evaluated with real-time exposure data collected from a campaign monitoring clusters of people with comparable socioeconomic backgrounds. For this purpose, personal sensors were employed for each individual participating in the campaign. Sensors were calibrated using measurements from fixed monitoring sites and the Grimm aerosol spectrometer Model 11-R. A detailed evaluation of the campaign sensors, however, lies beyond the scope of this work.

In the framework of the URBANOME project, a sensor-based campaign was designed and implemented employing physical activity, location tracking, air quality sensors, and noise capture to retrieve an individual's behaviour in a multidimensional context. Securing ethical approvals enabled the launch of the URBANOME sensor campaign in six EU cities, including Thessaloniki, Athens, Stuttgart, Aarhus, Milan, and Madrid in 2023–2024. Participants of each sub-campaign used multiple devices to monitor multiple environmental conditions such as (i) temperature (indoor-outdoor), (ii) a GPS device, namely QStarz BT1000XT, for location detection and movement speed identification, (iii) one physical activity monitoring device (Xiaomi Band 7) for number of steps and distance measuring, (iv) smartphone applications for location and activities tracking, and noise capturing, (v) smartwatch applications for sleep quality measuring. Moreover, all participants' residencies were equipped with (i) small stationary sensors able to measure PM concentrations. The participants filled out a TAD, a questionnaire targeting the identification of prospective sources of pollution as well as SES information. The campaign officially started back in March 2023, and these are the results from phase (a).

3. Results

3.1. Agentified exposure profiles

Initially, a picture of three students is presented, all 15 years old, with similar body masses. Student 094133 is a female living in the city centre, weighing 58 kg. Student 583,117, a male residing on the east side of town, weighs 62 kg, while 746,135, another male from the west side, weighs 65 kg. These students follow a similar daily activity schedule, as shown in Fig. 6. They wake up around 07:00, engage in morning routines such as all agents, and then commute to school. After returning home, each follows their routine until bedtime. Notably, the varying intensity of the activities performed throughout the day will significantly shape their exposure time series, as illustrated in the analysis below.

The analysis of the overall results for the three agents (Figs. 8, 9, and 10) across all days indicates that the agent residing on the west side of the city (746135) experiences higher PM and NOx intake than the agents living in the city center and the east side. Namely, information for PM10, PM25, NO_2, NO, and Lden is provided for the three agents across the following figures. This intake is also bodyweight-dependent, which is why agents with similar body weights were selected. The elevated pollution levels on the west side are attributed to intense industrial and anthropogenic activity in that area, which is typical for urban Thessaloniki (Sarigiannis et al., 2015). Despite this, the agents live far enough from these pollution sources so that their noise exposure remains relatively low. However, air pollution is significantly worse on the west side, exacerbated by wind patterns carrying pollutants across the area. In contrast, the agent living in the city center (094133) faces higher noise exposure, likely due to the heavy traffic flow, especially during peak hours. The west-side agent follows in terms of noise exposure, while the east-side agent (583117) experiences the lowest exposure levels overall, both in terms of air pollution and noise, due to the lower density of human activity in that zone of the city.

A more detailed analysis of exposure patterns is warranted daily; therefore, the fifth day of the simulation was selected for closer examination, with activities illustrated in Fig. 7. The exposure levels experienced by each agent fluctuate by both their inhalation rates and the intensity of the activities performed are presented in Figs. 11 (094133), 12 (583117), and 13 (746135). As a result, the exact inhalation intake with minute-based resolution is provided for each agent in the left y-axis while noise levels are presented in the right y-axis. The applied methodology emphasizes inhalation-adjusted exposure, in alignment with the practices outlined by Chapizanis et al. (2021), providing a comprehensive and robust assessment of air pollution exposure. This approach facilitates personalized data monitoring for each individual, making it an ideal tool for measuring exposure to air pollution and noise. Specifically, the agents residing in the west and East both engage in outdoor physical activities. Notably, the agent living in the east experiences lower exposure compared to the one residing in the West. This difference highlights the significant impact of inhalation rates on the overall exposure levels. Performing strenuous outdoor activities in a polluted environment markedly increases the rate of exposure. Furthermore, as previously demonstrated in the intake figures, the agent living in the city centre is subject to substantially higher levels of noise pollution than the other two agents, highlighting the amplified exposure risks associated with densely populated urban areas.

An important factor to consider is the high variability of noise levels in an agent's exposure intake. This variability stems from the significant fluctuations in the data provided by the Noise Capture App and is not related to the methodological pipeline used by the ABM.

The development of an analytical Agent-Based Model enables the exploration of how socio-economic status and demographic factors influence decision-making related to engaging in specific activities. As in real life, agents with different SES backgrounds follow distinct activity patterns and select activities based on varied criteria. Understanding not only which activities agents undertake but also where they are located during exposure and the nature of the activity performed is critical. In Fig. 14, we present the exposure levels for PM10, PM2.5, NO2, and NO, for an agent residing in the western part of the city, highlighting how exposure fluctuates based on the different activities recorded in their time-activity diary. For better clarity, these results are displayed on an hourly basis, allowing for a clearer view of the exposure levels across different activities and times of the day. The discussion is focused on agent 128,547, a 39-year-old male who is married and has one child. Analyzing the figure, it is evident that the inhalation rate significantly influences the intake. Factors such as age and gender, which are directly linked to breathing rate, also are instrumental in determining exposure levels.

The present work also highlights those individuals living in the same location (e.g., the same home) do not necessarily experience similar exposure levels to environmental noise and air pollution. The model's outputs reveal that differences in time-activity diaries can lead to

Time Activity Diary
Agent 094133

Time_is	Description
00:00	Sleep and Naps
07:01	Wash, Dress, Personal or Household Care
07:23	Commute
08:09	School, Classes
14:46	Commute
15:35	General Indoor Leisure, Relax
16:48	Watch TV, Listen to Music
19:58	Commute
20:23	Meals or Snacks
20:45	Commute
21:17	Watch TV, Listen to Music
23:43	Sleep and Naps

Time Activity Diary
Agent 583117

Time_is	Description
00:00	Sleep and Naps
07:01	Wash, Dress, Personal or Household Care
07:34	Commute
08:27	School, Classes
15:04	Commute
15:39	Meals or Snacks
16:15	Computing, Play Computer Games
18:28	Wash, Dress, Personal or Household Care
19:00	Commute
19:17	General Sport or Exercise, Walking, Cycling
20:56	Commute
21:22	Sleep and Naps

Time Activity Diary
Agent 746135

Time_is	Description
00:00	Sleep and Naps
07:01	Wash, Dress, Personal or Household Care
07:30	Commute
08:20	School, Classes
14:45	Commute
15:09	Meals or Snacks
16:07	Wash, Dress, Personal or Household Care
16:46	Watch TV, Listen to Music
18:42	General Sport or Exercise, Walking, Cycling
19:48	Watch TV, Listen to Music
22:24	Sleep and Naps

Fig. 7. Time activity diaries of the student-agents.

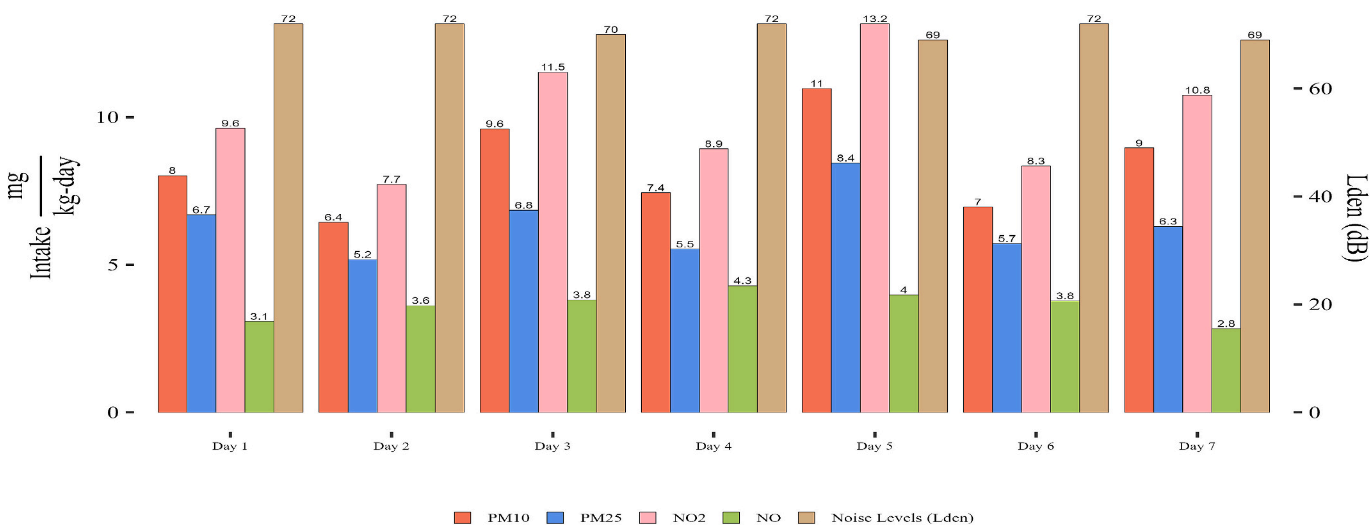

Fig. 8. Exposure profile of the agent 094133 for all the days of the simulation.

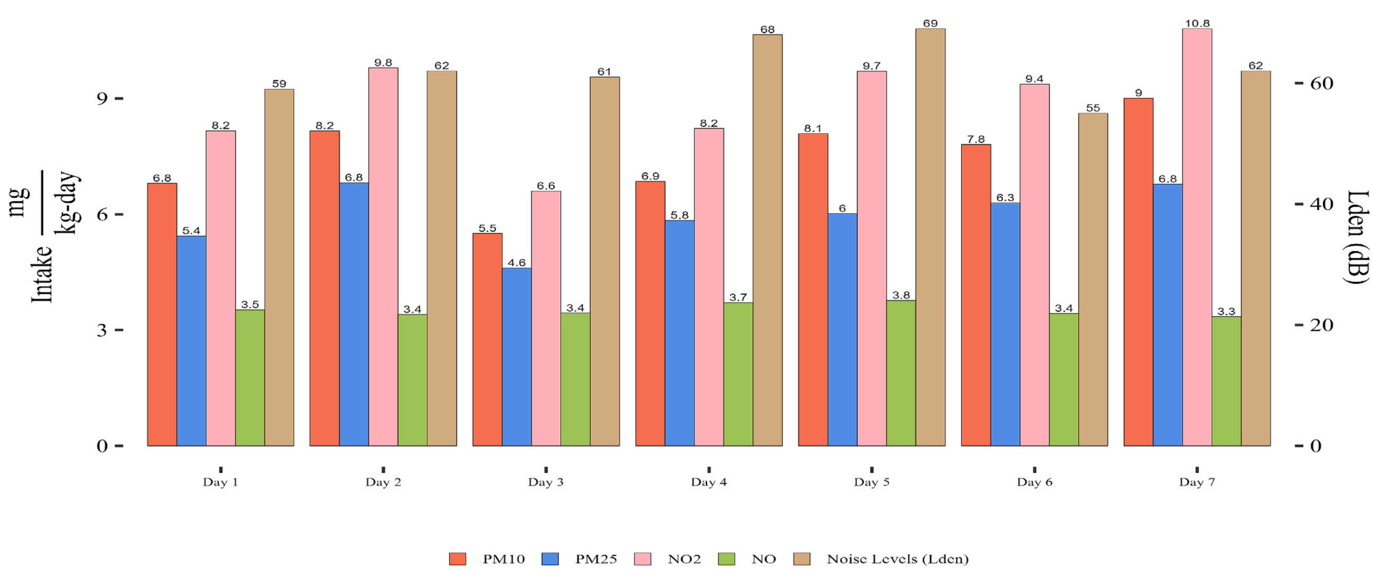

Fig. 9. Exposure profile of the agent 583,117 for all the days of the simulation.

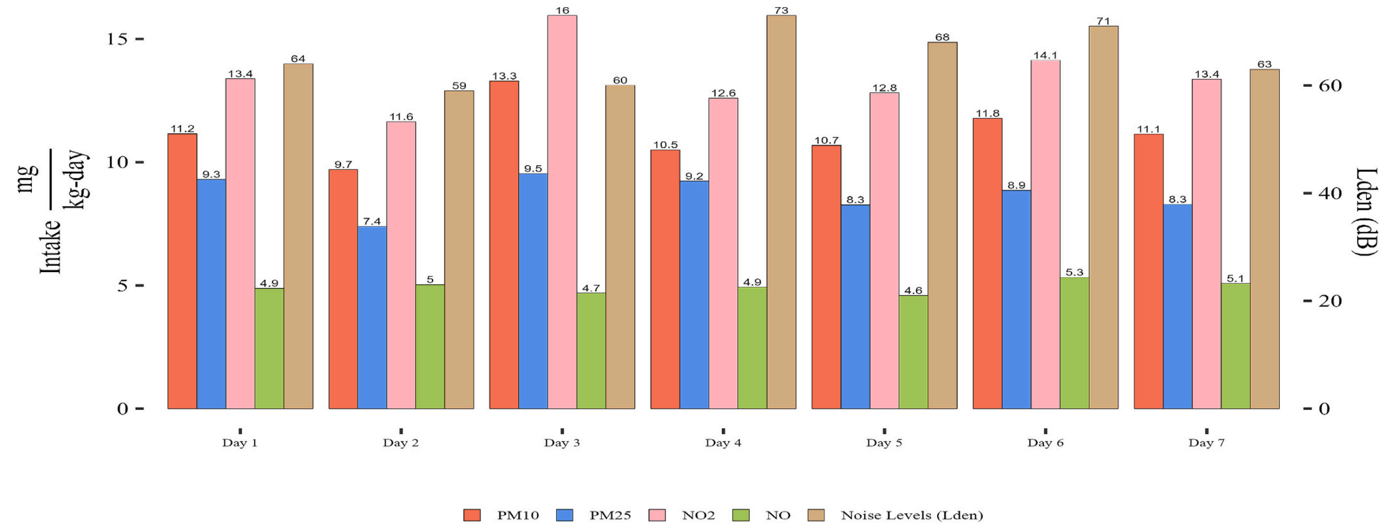

Fig. 10. Exposure profile of the agent 746,135 for all the days of the simulation.

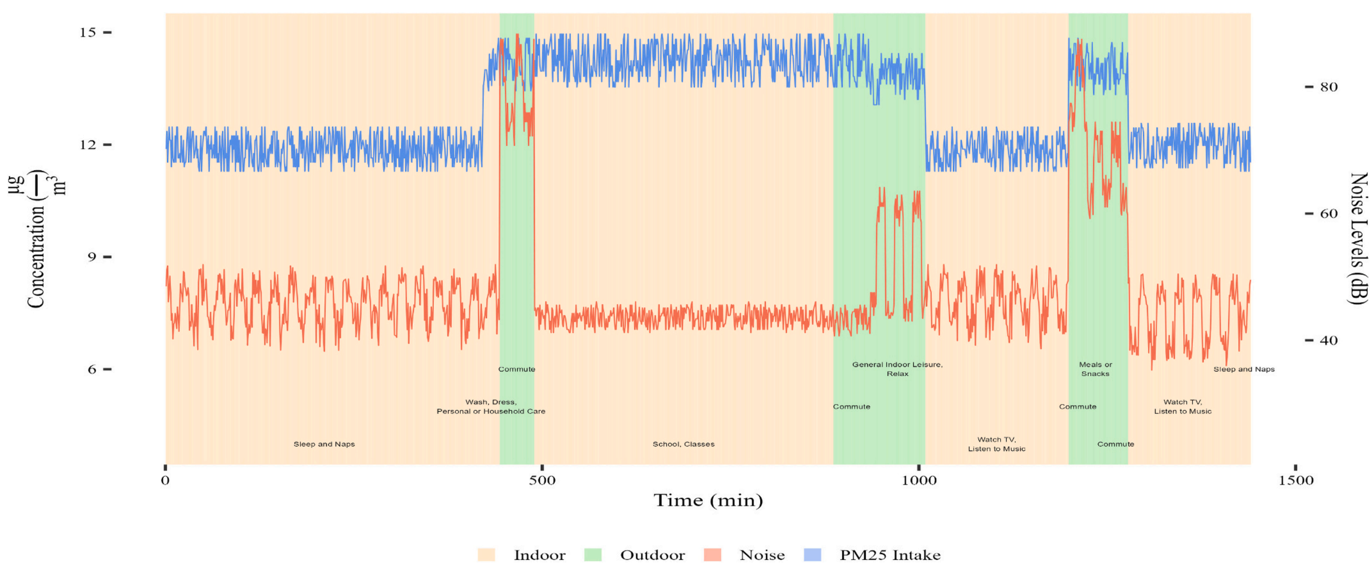

Fig. 11. Exposure profile of the agent 094133. Indoor and outdoor locations are illustrated in the background.

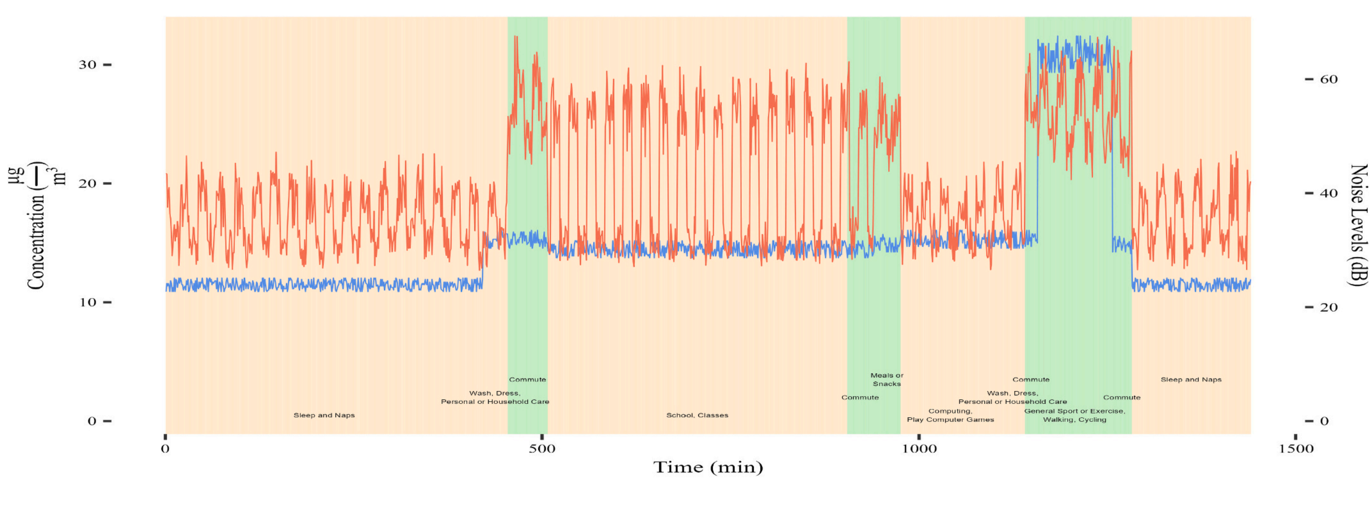

Fig. 12. Exposure profile of the agent 583117. Indoor and outdoor locations are illustrated in the background.

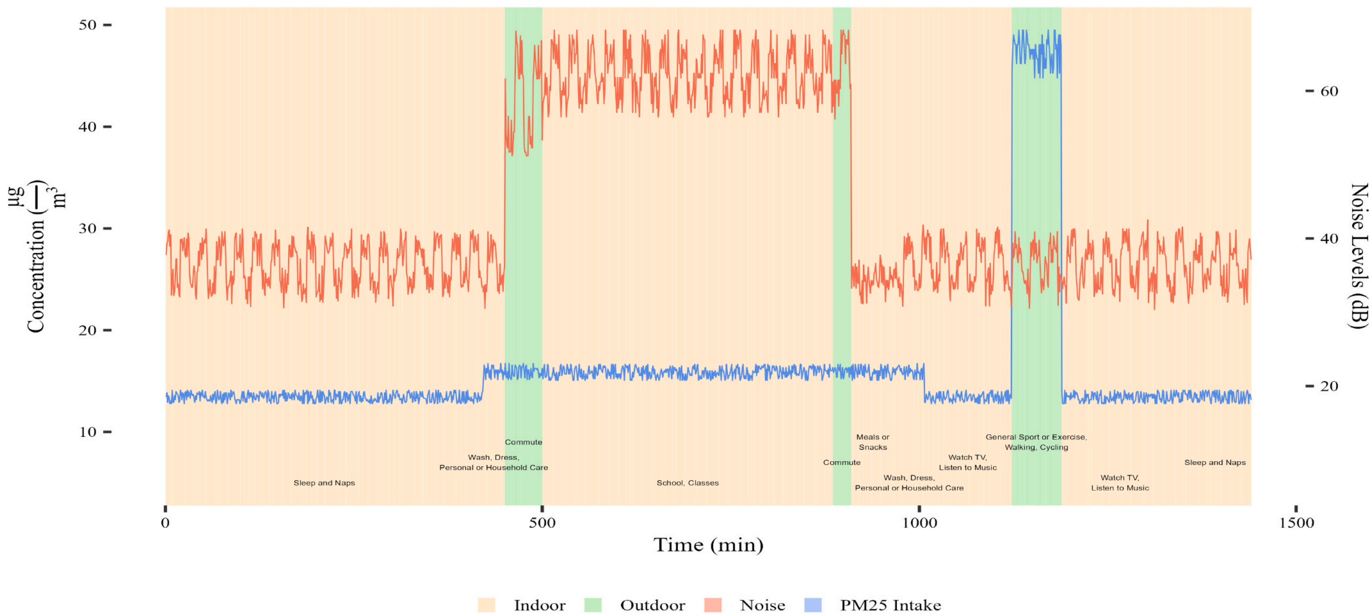

Fig. 13. Exposure profile of the agent 746135. Indoor and outdoor locations are illustrated in the background.

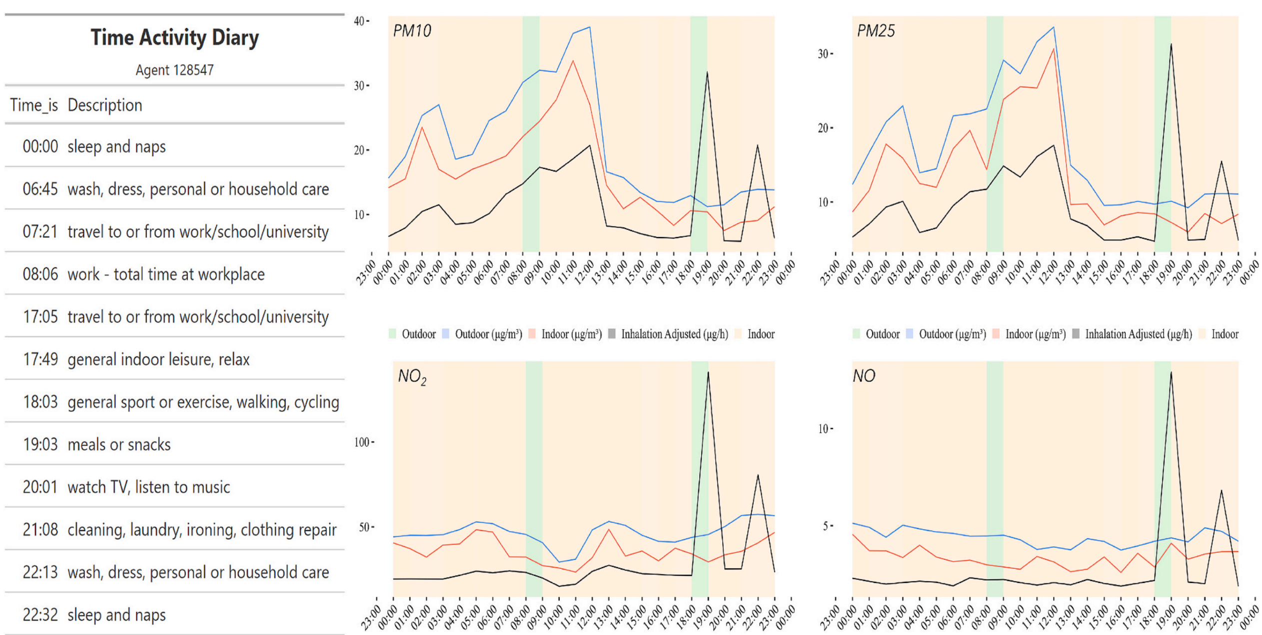

Fig. 14. Indoor concentration, outdoor concentration, and inhalation-adjusted exposure profiles for agent 128547 reveal that the type of activity the agent engages in is of significant importance in shaping the exposomic profile. Intense activities, which increase inhalation rates, directly contribute to higher pollutant intake levels.

varying exposure levels. When adjusting for inhalation-exposure, the disparities grow even larger, reaching up to 56.5 % for PM2.5 and 61 % for PM10. Notably, the inhalation adjusted agent exposure profiles within the same neighbourhood can differ by over 75 % on average, with some extreme cases showing differences close to 90 %. These significant discrepancies often arise when for example one individual holds a full-time job and exercises outdoors on the west side of Thessaloniki, while their roommate is a retired agent who spends most of their time at home. This confirms the importance of considering individual behaviour, occupation, and daily routines when assessing personal exposure to environmental stressors.

The classification of agentified exposure profiles relies on principles such as age, gender, socioeconomic status indicators, and geospatial factors such as area of residence, work, or study. The exposome of each individual can be effectively represented by taking into consideration specific population subgroups. This stratification facilitates a more focused and robust analysis, offering valuable insights into how different demographic or socioeconomic groups are distinctly affected by environmental noise and air pollution. Such approaches can effectively support the development of equitable public health interventions and policies. To this end, the outputs of the agent-based model can perfectly capture multiple socio-economic ensembles in the urban area of Thessaloniki. As a result, five population groups were found to be exposed most, namely adult males working on a full-time basis, adult females working on a full-time basis, agents living on the west side of Thessaloniki, and human agents with low educational levels and income.

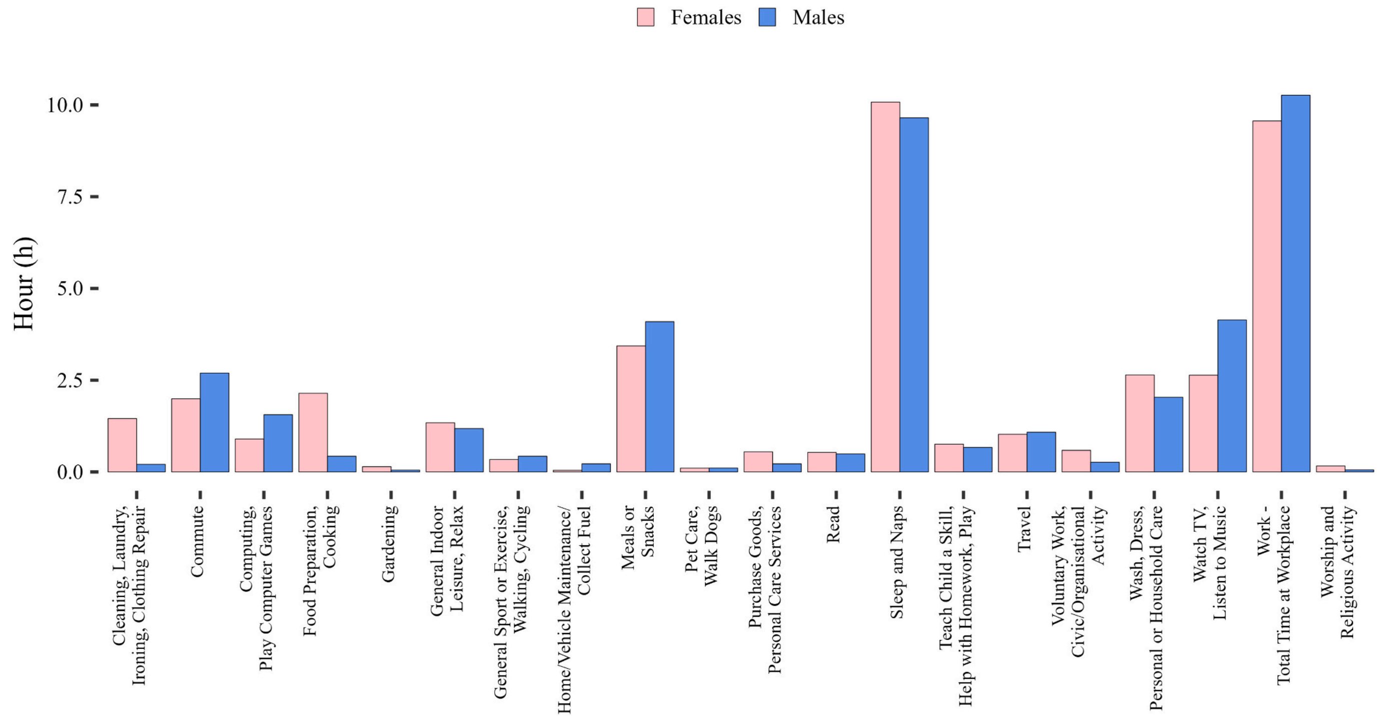

Fig. 15. Mean time allocation among coupled agents aged between 40 and 49 years, each with at least one child aged 10–18.

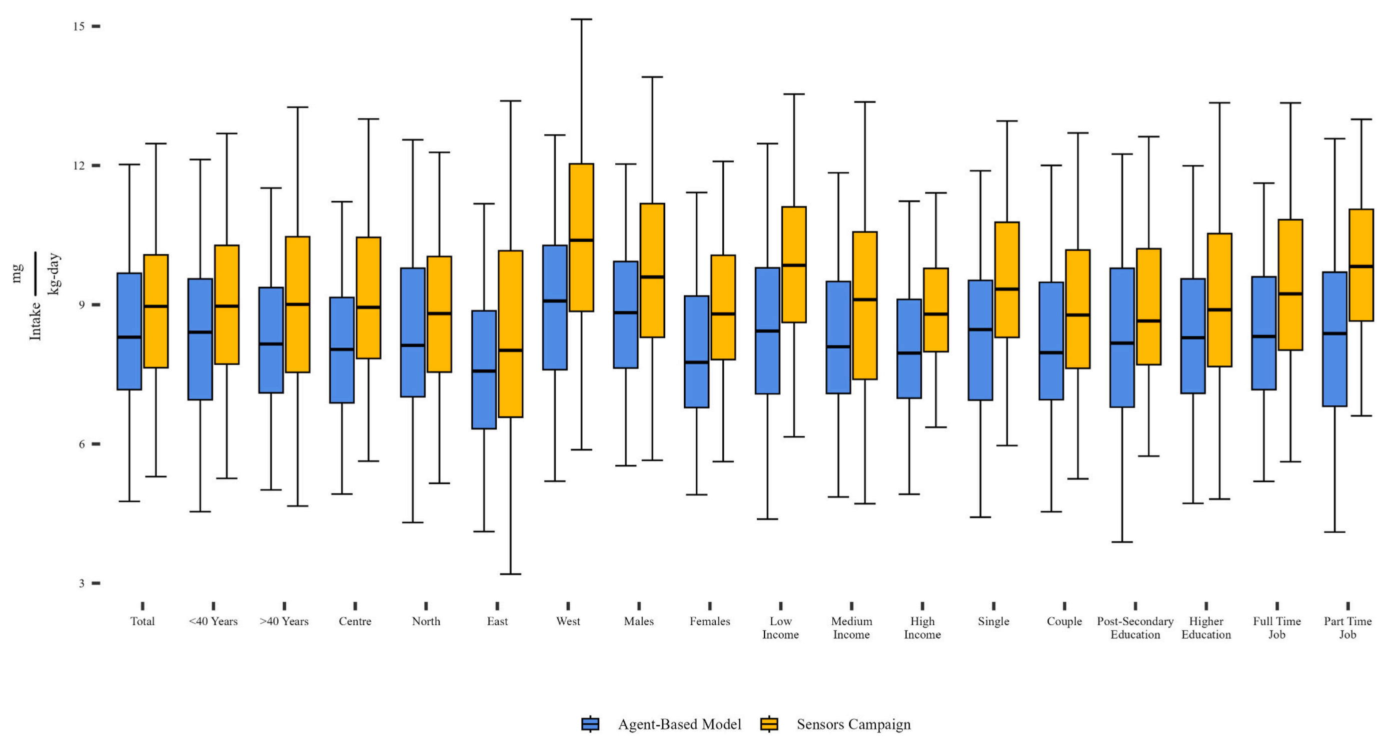

Fig. 16. Agent-based model outputs vs outputs from sensor campaign utilizing multiple SES criteria for PM25 intake.

Population statistics revealed that the western municipalities of the city have a higher potential for exposure to both pollutants and noise. This is largely due to the presence of an extensive industrial complex in this area such as petrochemical processes and oil refining (Sarigiannis et al., 2017). Additionally, the socio-economic profile of these municipalities shows a concentration of lower-income residents and individuals with lower educational levels, which further exacerbates their exposure risks. As a result, the critical intersection of environmental and socio-economic factors is highlighted, indicating that vulnerable populations in the western part of the city are disproportionately affected by environmental stressors. It is worth mentioning that highly intense activities significantly drive exposure to air contaminants, particularly in terms of pollutant intake. More specifically, they can increase the actual intake of an individual (as shown in Fig. 14) or decrease it. Last but not least, the location where these activities occur is significant for exposure to noise.

Income is also a driving force regarding the selection of activities by

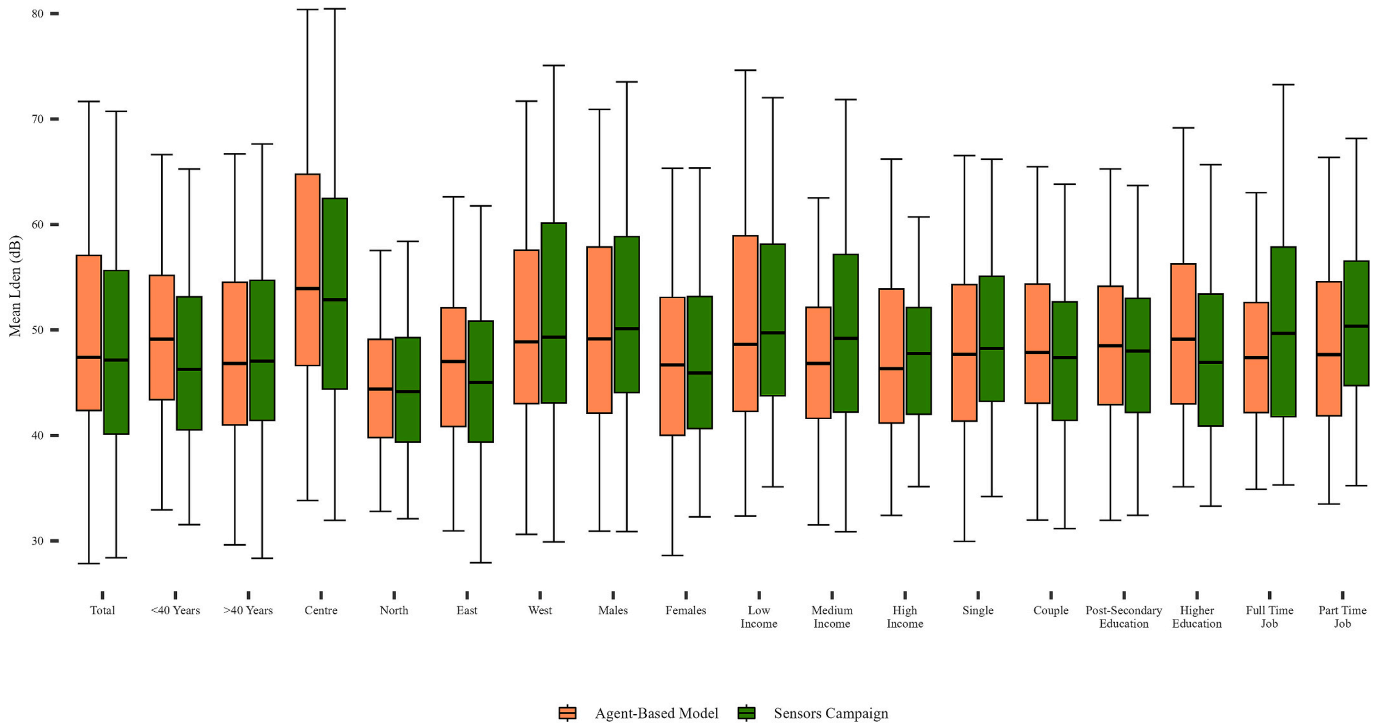

Fig. 17. Agent-based model outputs vs outputs from sensor campaign utilizing multiple SES criteria for Lden values.

the agents which corresponds to lower exposure levels and the allocation of their time in less polluted places. Intake of PM2.5 varies between low-income agents who live on the western side of the city and high-income agents located in the less polluted eastern region revealing significant differences in exposure. Specifically, outdoor PM2.5 exposure levels exhibit a 30 % difference (data not shown), emphasizing that individuals in the more polluted western region are exposed to significantly higher levels of outdoor pollution. However, when considering inhalation-adjusted exposure, which accounts for activity intensity and the respective inhalation rates, the difference between the two groups decreases to 10 %. To this end, individuals who live or work near crowded avenues such as Egnatia and Tsimiski in Thessaloniki face a significantly higher risk of noise exposure compared to those in less active areas. The increased concentration of human activities in these high-traffic zones drives noise levels up. The difference in noise exposure between people in these areas and those in quieter zones is nearly 28 % (data is not shown). This highlights the strong influence of urban activity patterns on environmental noise exposure. While this analysis primarily focuses on the outputs of the ABM, it is important to note that noise exposure is strongly associated with adverse effects on mental health and BMI (Hahad et al., 2024; Kheirandish et al., 2021; A. Li et al., 2022; Pyko et al., 2015). Given these associations, the importance of accurately modelling noise exposure becomes clear, as it is essential for assessing its broader health implications in urban populations.

The functionalities of the ABM provide an opportunity to retrieve time-activity diaries for all agents, enabling the extraction of personalized activity patterns based on each agent's SES profile and physiological data. For instance, in the bar chart (Fig. 15), the meantime allocation among agents who are couples aged between 40 and 49 years, with at least one child aged 10–18 is illustrated. Both males and females in this group have full-time jobs and a medium income. Remarkably, male agents tend to spend more time working and sleep less compared to their female counterparts. Additionally, male agents prefer to spend their leisure time watching TV and eating, whereas female agents allocate more time to shopping, cleaning, and food preparation.

3.2. Results from the sensors' campaign vs ABM model

The URBANOME campaign conducted an in-depth investigation into methodologies for assessing exposure to air pollutants and noise based on individuals' daily routines. Data collected from the sensor campaign will be presented in detail in a dedicated manuscript, as the campaign is still ongoing, and the results discussed here are preliminary. The final analysis will utilize advanced statistical methods, machine learning techniques, and time series approaches to examine the association between the exposome and human health and well-being.

The overall dataset comprises 246 participants, making it the largest dataset of its kind for the urban area of Thessaloniki, to our knowledge. Each participant's movement data was integrated into the original dataset, alongside air pollution and noise data obtained from sensors and smartphone applications. The participants also filled out a time activity diary which was also harmonized with the rest of the data. Residential concentrations of air contaminants were also captured using respective sensors and combined with the indoor air quality model from the INTEGRA platform (Sarigiannis et al., 2014). Data from the sensors were additionally used to validate the ABM outputs. A detailed comparison between participants from the Thessaloniki campaign and the ABM simulation results was conducted based on multiple SES criteria, focusing on exposure to PM2.5 (Fig. 16) and noise (Fig. 17).

Notably, the comparison between the exposomic profiles of the agents and the participants from the sensors' campaign revealed differences in the median values of no >20 %. Consequently, the ABM outputs can be utilized to characterize the exposome of individuals living in urban areas with high incidents of air pollution and noise. Furthermore, these outputs can inform targeted strategies and interventions aimed at promoting sustainable urban environments such as green cities. For example, mandating the use of electric vehicles in city centres could significantly reduce noise levels. As more data becomes available from the ongoing URBANOME campaigns in cities such as Athens, Milan, Madrid, Montpellier, Aarhus, Aberdeen, Stuttgart, and Ljubljana, the model can be further refined, expanding its applicability and providing valuable insights.

4. Discussion

The individual exposome is intricately associated with daily activity patterns and the spatial distribution of air pollution and noise across numerous urban microenvironments. These exposures are further shaped by the economic activities within a city, which can vary significantly across neighbourhoods and regions. Consequently, a key outcome of the employed methodology lies in its ability to integrate multiple socio-economic status attributes into a comprehensive and robust assessment of environmental exposures. By doing so, this approach allows for a more accurate and robust understanding of how SES influences the individual exposome, providing valuable insights for policy-making and urban planning.

The ABM framework presented here illustrates how exposure to environmental stressors and noise is shaped by individual preferences and behaviours. Artificial populations interact within dynamic networks, where their movements and activities are influenced by their sociodemographic characteristics. Each agent follows a stochastically constructed agenda, engaging in multiple activities and utilizing different modes of transportation based on their unique backgrounds. For instance, a 35-year-old male agent with a full-time job and higher income is more likely to commute by car to his work, while a 20-year-old female agent with a part-time job and lower income may rely on public transportation or active modes such as walking. Human agents make decisions during each simulation that adjust the probabilistic nature of time allocation, allowing them to dynamically fill their days with a varying sequence of activities. As a result, the same agent may engage in different activities or follow a different order of tasks from one day or simulation to the next. This dynamic nature of the ABM allows for a detailed representation of personal mobility, behaviour and how it impacts exposure to environmental stressors and noise. Model data can be captured at multiple spatial and temporal scales, providing valuable insights into how distinct mobility behaviours affect individual exposure in an urban setting.

The analysis of daily time-activity patterns for population subgroups enabled assessment of exposure and intake dose per body weight at both individual and community levels, utilizing three exposure proxies: outdoor, indoor, and inhalation-adjusted exposure. Through the integration of functionalities provided by the NoiseCapture App, the noise exposure for each agent was also approximated. This methodology highlights the potential pitfalls of relying solely on outdoor PM concentration levels, as commonly seen in current exposure studies. Such an approach can result in either underestimation or overestimation of personal exposure. Without accounting for the time spent in different microenvironments and the varying intensity of activities, critical differences in exposure levels would have remained undetected. This underlines the importance of considering personal activity patterns and environmental contexts for a more accurate assessment of exposure to pollutants and noise.

Identifying exposure peaks throughout the day in a time series analysis offers constructive perceptions for managing exposure to elevated pollution and noise levels. The dynamic assessment of intake doses at both individual and population levels enables the development of guidance on behaviours associated with high pollution exposure. Findings from the ABM reveal that exposure levels vary significantly among individuals and population subgroups with different socio-demographic characteristics. These variations underscore the need for targeted strategies that address the specific exposure risks faced by diverse demographic groups. By understanding how sociodemographic factors influence exposure patterns, stakeholders—including policy-makers, urban planners, public health officials, community organizations, and environmental agencies can implement more effective interventions and policies to mitigate health risks associated with environmental stressors and noise.

The present study demonstrates that agent-based modelling can effectively be utilized for personal exposure assessment, providing availability to an unparalleled amount of "individualized exposure data". This data can significantly enhance our understanding of the associations between exposure and health; however, its value is contingent upon proper interpretation. The strength of agent-based models lies in the quality of input data and the programmed rules, making valid data on the geospatial characteristics of the modeled city and accurate population statistics essential. Furthermore, a deep understanding of lifestyle patterns is imperative for comprehending individual and population-based geospatial lifelines. The rules and functions within the model can be informed by fundamental principles or calibrated against data obtained from empirical surveys. Ideally, these calibrations would be based on personal monitoring campaigns, which provide rich, real-world insights into exposure dynamics. This integrated approach not only strengthens the model's reliability but also enhances its applicability for informing public health strategies and the transition to green urban settings.

The ABM was validated against preliminary data obtained from a sensor campaign in Thessaloniki conducted in the framework of the URBANOME project, which assessed exposure for 250 individuals in the urban area. The findings indicate that the emergent trajectories derived from the ABM align well with real spatiotemporal behaviours. Upcoming data collection from other campaigns in the framework of the URBANOME project will be utilized to further inform and improve the agent-based model. These campaigns will provide valuable insights into the effectiveness of numerous wearable devices as modular additions to exposure studies, thereby enhancing the generalization of the model application. Sensor investigations offer significant evidence regarding personal habits and societal dynamics that are often not officially documented. The incorporation of these insights into the model can more effectively capture the complexities of human behaviour and environmental interactions, resulting in more accurate assessments of exposure to air pollution and noise. This continuous refinement enhances the model's robustness and relevance in addressing the challenges of urban environmental exposures, ultimately supporting improved public health outcomes and informed decision-making.

Last but not least, it is important to mention that the proposed ABM approach offers significant advancements over traditional exposure assessment methods. Conventional approaches, such as deterministic models, FMS and GIS-based techniques, typically rely on aggregated data and static assumptions, limiting their ability to capture individual-level variability and temporal dynamics. It is worth noting that our approach enables integration with deterministic models that capture physiological variations within the population, while also dynamically informing the model's parameterization. Additionally, our ABM can simulate the behaviours and movements of individual agents, enabling the identification of fine-scale exposure patterns. For instance, by modelling daily routines and socio-economic disparities, the ABM reveals exposure hotspots and time-specific risks that are obscured in aggregate analyses. Additionally, the ABM facilitates scenario testing, such as evaluating the impact of urban planning or policy changes, providing predictive insights that FMS or traditional models cannot. The integration of socio-economic data uncovers the differential exposure burdens faced by vulnerable populations, offering a more comprehensive understanding of urban environmental inequalities. It is also fundamentally important to note that agent-based models can be valuable tools for generating data in scenario testing, which can subsequently inform deterministic models.

5. Study limitations

The present study provides an in-depth framework for socio-economic analyses and scenario modelling at the level of entire artificial cities, enabling the exploration of numerous types of intervention scenarios. However, there are some limitations in the current analysis that fall beyond the scope of this work. First, while FMS data collected from air pollution stations and the Open-Meteo API provided valuable insights, they only cover a limited number of points in the spatial resolution of the ABM. Specifically, the Open-Meteo API offers geospatial data with a resolution of 11 km. Despite applying kriging interpolation, there is still a high risk of introducing bias into the model estimates due to the coarse resolution of the initial data. In contrast, integrating high-resolution air pollution data, including real-time measurements, would significantly enhance the reliability and accuracy of the model predictions. Another limitation concerning environmental pollution, which affects the indoor exposure estimates, stems from two assumptions made in Eq. (4). The first assumption is that agents' indoor activities are always considered to be in a room of 25 m^3. The volume of indoor spaces is a significant factor in estimating pollutant concentrations indoors. The second assumption is related to the ventilation rate of indoor spaces, which is highly dependent on factors such as window status and building insulation. More precise information on the building structure, usage, and the number of occupants could considerably improve the accuracy of the pollutant exposure estimates. These limitations highlight areas for potential future improvement, particularly by integrating higher-resolution data and more detailed assumptions about indoor environments. Last but not least, it is important to note that no real-world traffic data was used in order to simulate agents' movement.

Regarding noise pollution estimates, we assumed that all values obtained from the NoiseCapture application and not from the data stored by participants were daily measurements. Since we do not have the exact time of day for each measurement, this could introduce another layer of inaccuracy in the model's estimations. At this point, it is worth noting that noise levels recorded by the app used by campaign participants were organized in a time-dependent format. Additionally, to convert daytime measurements to nighttime equivalents, we relied on a study from the Ministry of Environment. Although the model showed strong performance, the values used were estimates rather than actual observations, which could potentially affect the accuracy and robustness of the noise pollution estimates. Moreover, whether the windows in each indoor space are open or closed plays a crucial role in determining the extent to which noise pollution penetrates the interior. This factor is heavily influenced by the building materials used in construction, such as insulation, which can significantly alter the internal noise levels. The absence of precise information regarding these building-specific characteristics further contributes to uncertainties in the indoor noise pollution estimates.

Last but not least, it is important to note that ABMs are inherently stochastic due to their reliance on simulating individual agents with unique behaviours and interactions. This stochastic nature introduces uncertainty, as the outcomes of the model may vary across multiple simulations due to random elements in agent decision-making, personal characteristics or movement. For instance, agents may have probabilistic rules for choosing specific activities or routes, which can lead to divergent trajectories and outcomes. To this end, in each simulation, the agents may reside and work in different locations compared to the previous one, which also affects the composition of their family and friend networks. Additionally, the assumptions used to model agent behaviour—such as preferences, mobility patterns, or response to external stimuli—may not fully capture real-world variability. This discrepancy can impact the robustness of predictions, particularly in scenarios where agent heterogeneity is significantly important in determining system-level dynamics. Another significant source of uncertainty in ABMs arises from the environmental data used as input, such as spatial distributions of pollutants, noise levels, or traffic patterns, as previously described. Temporal variability in environmental conditions—such as changes in weather, traffic flow, or pollutant emissions—may further complicate model reliability. This is because the very strong correlation between the concentration of pollutants with weather conditions (Asimakopoulos et al., 2012). Integrating such changes often necessitates additional assumptions, which not only introduce varying levels of uncertainty but also significantly increase the model's complexity.

6. Conclusions

This work models daily personal exposure to environmental hazards by integrating individual movements through "hazard fields" over time, considering sociodemographic factors. The ABM generates granular data on exposure dynamics, surpassing traditional static approaches that grouped populations into homogeneous subgroups. The combination of the agent-based model with sensor networks enhances exposure estimation and can be linked to health outcomes and informing targeted interventions to address environmental stressors, particularly for vulnerable populations. The present model reveals disparities in exposure, such as higher PM exposure risks for low-SES groups, enabling the detection of environmental injustices. Policymakers can use these insights to implement equitable measures, such as improving public transport or building bike lanes, reducing pollution exposure and fostering healthier, sustainable urban environments. This flexible approach is capable of being applied across multiple cities by only adjusting input data, allowing exploration of hypothetical scenarios and policy impacts. The only matter of concern regards the number of agents that will be generated which something that significantly increases the computational time. The simulation of multiple intervention scenarios facilitates cost-effective and informed decision-making, thereby supporting the development of improved public health and urban planning strategies.

Abbreviations

ABM	Agent-based model
FMS	Fixed monitoring sites
GPS	Global positioning system
HETUS	Harmonized European Time Use Survey
IoT	Internet of Things
NO	Nitrogen oxide
NO_2	Nitrogen dioxide
OSM	OpenStreetMap
OSRM	Open-Source Routing Machine
PM	Particulate matter
SES	Socioeconomic status
TADs	Time-activity diaries

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.178804.

Data availability

The data utilized in this framework is freely accessible through the Greek Statistical Authority and open source APIs. Campaign data will be made available upon request.

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