Enhancing Urban Air Quality Mapping through Novel Measurement and Modelling approaches, and Citizen Science: Actionable Insights from the RI-URBANS Project

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Abstract

Air Quality is among the most pressing environmental issues impacting upon urban populations. Traditional air quality networks can assess time trends and assess compliance to air quality regulations, but lack the spatial and temporal resolution to understand individual exposure to air pollution. The RI-URBANS project is a European initiative aiming to develop new strategies and enhance the existing tools to address the air quality challenges and societal needs in European cities. This paper presents an overview of the pilots of the RI-URBANS project associated with air quality mapping and pollution hotspot identification using modelling, novel measurement methodologies and mapping techniques. Special focus is given on the discussion of the novel measurement methodologies introduced with the use of low-cost sensors, mobile measurements and citizen participation in the data collection process. The findings highlight the significance of participatory science, technological advancements in air quality measurement, adoption of novel measurement and modelling strategies and the potential for policy integration. The project's outcomes suggest that integrating stationary sensor networks, mobile monitoring platforms, and citizen engagement can significantly enhance urban air quality management alongside traditional monitoring and modelling approaches. However, harmonisation of data collected using these different methods is essential to ensure comparable outcomes across projects, which was one of the primary aims of RI-URBANS. The project also highlights several practices that improve both data collection and citizen participation. In particular, it emphasises the importance of careful campaign design and clear, direct communication with citizen scientists throughout both the monitoring process and the dissemination of project outcomes. This study highlights the

important work undertaken by the participating cities and the novel approaches used to disentangle the complicated air pollution patterns and improve the air quality for everyone, while making this crucial information easily obtainable.

1. Introduction

Air pollution is one of the most pressing environmental challenges affecting urban populations worldwide (Manisalidis et al., 2020). Poor air quality (AQ) is linked to serious health problems, including respiratory diseases, cardiovascular conditions, neurological disorders, cancers and premature mortality (EEA, 2024). It has been also associated with negatively affecting the cognitive functions of humans (Faherty et al., 2025), thereby likely reducing their productivity and educational outcomes.

To combat urban air pollution, targeted monitoring and data collection are essential. High-resolution AQ data allows for improved air pollution mapping, helping researchers and policymakers to understand AQ dynamics, implement targeted interventions, evaluate policy effectiveness, and empower communities to act. However, Air Quality Monitoring Networks (AQMN), due to their high installation and operation cost, are generally sparsely distributed, failing to provide fine-scale localised AQ data (Idrees and Zheng, 2021). This can be an even greater problem in urban areas where pollution levels can vary significantly over short distances due to factors such as traffic congestion, industrial activity, topography, population spread, the presence of green spaces or hyperlocal sources of air pollution (Sartelet et al., 2025).

Given these limitations, alternative AQ mapping techniques such as novel monitoring and modelling methodologies and citizen science initiatives are increasingly used to complement the current AQMN and atmospheric modelling (San José et al., 2008), the latter being a commonly used alternative when measured AQ data is not available. Novel monitoring methodologies can greatly expand the spatial coverage of the monitored areas, either using technological advancements related with remote sensing or an increase of the number of monitors, using measurement equipment of a lower price, referred to as mid- or low-cost sensors (henceforth LCS) for air pollution monitoring (Kumar et al., 2015; Motlagh et al., 2020). LCS have attracted great interest in the last decade as they can provide an affordable alternative to regulatory monitoring, significantly increasing the monitoring capabilities and allowing for spatially denser air quality mapping (Shabbir et al., 2025). LCS come with specific limitations though, associated with the lack of accuracy and uniformity of their measurements resulting from the more simplified measuring methodologies (Karagulian et al., 2020; Giordano et al., 2021). They also need calibration, typically with colocation with regulatory monitors which take into account local atmospheric and meteorological conditions, including temperature and relative humidity (Hofman et al., 2022; Nalakurthi et al., 2024). However, the portable size, ease of use and low energy demands of LCS make them ideal for deploying in large scale static sensor measurement networks or in mobile set-ups,

LCS can be used in various scenarios greatly increasing the geographical coverage and spatial density of AQ data. On one hand, LCS networks, comprising of great numbers of sensors strategically deployed over large areas can provide detailed information on air pollution's spatial variation in fine detail (Kosmopoulos et al., 2022; Men et al., 2021), allowing for on demand measurements on points of interest without the need for the significant financial burden that comes from AQ monitoring networks (Hofman et al., 2022; Bousiotis et al., 2023). On the other hand, mobile measurement campaigns are not new and have been tested in many studies regarding AQ mapping, traffic emissions or the range of the effect of pollution sources (Deshmukh et al., 2020). Mobile air quality monitoring involves the use of portable LCS and/or regulatory grade instruments mounted on moving platforms (e.g. vehicles, cyclists, pedestrians). As the cost of traditional mobile campaigns is rather high though, the emergence of the low-cost sensors introduced new opportunities for mobile data collection (Singh et al., 2021; Bagkis et al., 2025). There are two types of mobile monitoring strategies, the opportunistic and the targeted. Van den Bossche et al. (2016) defined opportunistic mobile monitoring as data collection making use of existing carriers to move measurement devices around, contrary to the targeted mobile monitoring which is focused on specific pathways and periods.

The participation of citizens in the data collection process is another approach, which has been facilitated by the emergence of the LCS (Oyola et al., 2022). As regulatory instruments come with a great cost and are difficult to operate and maintain, LCS are an affordable solution making data collection more accessible to greater audiences, while medium cost portable devices, which offer better quality data, can be used on campaigns which require simultaneous data collections with fewer participants (Van Poppel et al., 2024). Citizen science offers great value in the data collection process, as it exponentially increases the collection points and amount of data, while increasing awareness and encourages behavioural changes among the public (Relvas, et al., 2025; Ward, et al., 2022). There are specific concerns though with the inclusion of citizens on the quality of the data collected (Fritz, et al., 2022), though these can be overcome with clear instruction and closely follow-up of data, together with a good cooperation of the citizens with specialised personnel.

Modelling of air pollution is also not new in the AQ mapping field. The use of models where measurements are not available is a practice which assisted in the understanding of the air pollution patterns and is harmonised in Europe though FAIRMODE (EPA, 2025; Kushta et al., 2019). The exponential increase of both the computing power and the available AQ data achieved with the use of the LCS, has opened new opportunities on the potential of AQ mapping and understanding.

The present study highlights the outcomes of RI-URBANS

, a project designed and funded by the European Commission (https://riurbans.eu/), to address the limitations of the existing AQMN by incorporating multiple traditional and novel approaches listed above. Among other objectives the project aimed to improve urban AQ mapping by incorporating tested modelling methodologies, novel measuring techniques and data analysis methods and citizen participation to increase data coverage, understanding and public awareness. Apart from the approaches tested, the study discusses the lessons learned from the mobile campaigns undertaken, the added value gained from citizen involvement, and the considerations for their wider and successful application.

2. Methodology

2.1 The RI-URBANS project

RI-URBANS is an EU-funded project aimed at reshaping how urban air quality is measured. It focuses on monitoring emerging hazardous pollutants, including ultrafine particles and black carbon, to better protect public health. The project has developed over 20 innovative measurement protocols, modelling tools, and emission inventories to track previously overlooked, non-regulated pollutants. These methods have been tested in several European pilot cities to demonstrate how complementary data can be integrated into routine monitoring networks. RI-URBANS maps urban exposure and investigates how specific atmospheric nanoparticles affect human morbidity and mortality, directly supporting EU efforts to implement stricter air quality standards. The initiative builds on existing research infrastructures, including ACTRIS, and aligns with World Health Organization guidelines.

While the RI-URBANS project addressed multiple themes (e.g. measurements, modelling and emission inventories of emerging pollutants, source apportionment, health effect assessment; see https://riurbans.eu/project/#service-tools), the present paper focuses on the urban mapping and pollution hotspot identification, discussing the pilots undertaken in RI-URBANS from several European research groups (Fig. 1). In general, there were two main approaches to the AQ mapping and pollution hotspot identification pilots. Firstly, the use of previously tested and novel modelling methodologies was deployed on pre-existing data, for detailed AQ mapping of areas. In several cases, two monitoring and modelling approaches were combined. Secondly, novel measurement approaches were tested, which in some cases involved citizen scientists from the local community. The data collected from these studies were interpreted using AQ mapping and various statistical analyses.

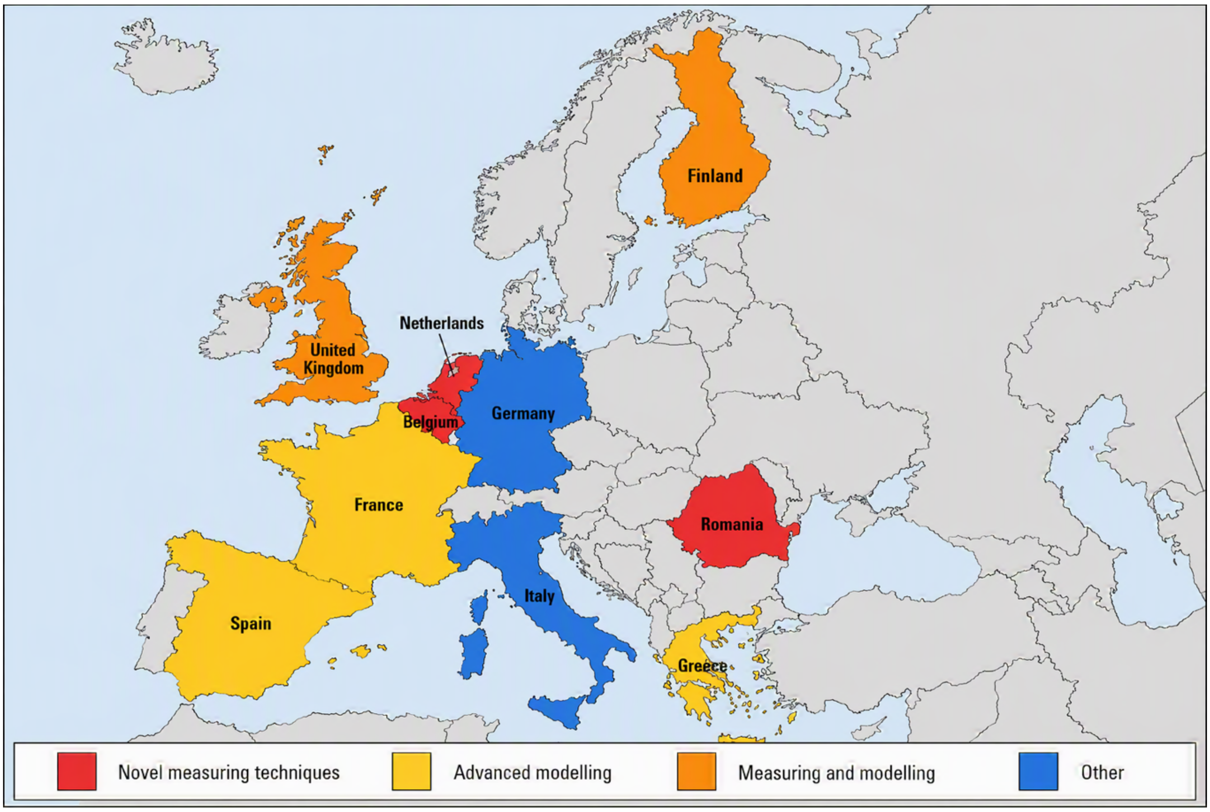


Figure 1: Map of the countries which contributed to the air pollution mapping and hotspot identification pilots (core and partners). Map created by the authors using Microsoft's Copilot (2026)

2.2 Advanced modelling

Different data analysis approaches were used depending on the envisaged research question and/or use case, either data-only or modelling approaches. While the data-only approaches generate AQ maps purely relying on the collected monitoring data, the model approach relies on modelling techniques to extrapolate air quality outside of the spatiotemporal monitoring window. Thus, the modelling techniques can also incorporate data from external sources (remote sensing, traffic intensity, emission factors, etc.) to estimate pollution levels over locations without measurement data, the identification of air pollution sources and the dispersion of their emissions.

Modelling can provide AQ mapping with or without the use of field measurements using information from emission inventories. Dispersion models using emission inventories or Land-Use Regression (LUR) models using emission inventories were developed and were also extensively tested in many studies as part of the RI-URBANS project to predict pollution concentrations across the area studied from the underlying statistical relationships. Data from emission inventories, while offering an alternative when field data are not available, can lead to great discrepancies in areas where localised emission factors or activity data are not available, reducing the reliability of estimated concentrations (Holicki 2011). Regardless, advanced modelling techniques, particularly LUR, source apportionment methodologies, AI-based algorithms and machine learning approaches, which allow meaningful interpretation of heterogenous datasets (Hofman et al., 2022; Yuan et al., 2022) were also tested by the RI-URBANS pilots. Table 1 lists the models used and the pollutants assessed from each pilot country.

The pilots in France mainly used the CHIMERE model, an open-source multi-scale chemistry transport model, which can forecast pollutant concentrations and make long-term simulations for emission control scenarios (LMD, 2025). The pilots in the UK focused on the ADMS (Atmospheric Dispersion Modelling System) model, an advanced dispersion model used to model the air quality impact of existing and proposed industrial installations. Specifically, the ADMS-Urban model can model the dispersion of particulate matter and chemical substances in the urban environment (CERC, 2026). The Environment – High Resolution Limited Area Model (Enviro-HIRLAM), used by the Finnish group, is developed as a fully online integrated numerical weather prediction and atmospheric chemical transport model for research and forecasting of joint meteorological, chemical and biological weather (Baklanov et al., 2017). The pilot cities in Greece used several models. The CAMS (Copernicus Atmosphere Monitoring Service) atmospheric model, an operational global forecasting system that tracks and predicts atmospheric composition, including air quality, greenhouse gases, and aerosols (ECMWF, 2026). Another model used was the Particulate Matter Comprehensive Air Quality Model with Extensions (PMCAMx), which is a state-of-the-art three-dimensional chemical transport model developed to simulate the atmospheric processing, mass concentration, and chemical composition of particulate matter over regional and urban scales (Gaydos et al., 2007). Finally, the group from Patras in Greece developed the SmartAQ system, which incorporates input from models including the PMCAMx, WRF (for meteorological data), MEGAN3 (for biogenic emissions), and outputs concentration forecasts for several gaseous pollutants and PM. The SmartAQ model (1x1 km^2) provides advanced treatment of OA volatility chemistry, and uses an updated emission inventory, including biomass burning emissions and can forecast not only pollutant concentrations but also the source contributions for them (Siouti et al., 2022).

These models can handle large, complex datasets and uncover patterns that may not be evident through traditional statistical techniques, providing high-resolution mapping, exposure assessment, and policy evaluation. Moreover, emission factors from inventories can be optimized based on data assimilation techniques (Nguyen and Soulhac, 2021).

Table 1: Models used from the RI-URBANS pilots

Pilot country	**Pollutants assessed**	**Model**	**Reference**
France	NO_2, BC, PM, O_3	CHIMERE, MUNICH	Park et al., (2025); Di Antonio, et al., (2025a); Vida et al., (2025); Maison et al., (2024)

France	Fungal spores, OA	CHIMERE	Vida et al., (2024)
France	BC, BrC	CHIMERE	Tuccela et al., (2025)
UK	PM, NO_2, BC, UFP	ADMS	Zhong et al., (2023); Zhong et al., (2024);
UK	PM, NO_2, BC	ADMS	Zhong et al., (2025)
Greece	NO_2, $PM_{2.5}$	CAMS/WRF/Episode-City Chem	Myriokefalitakis et al., (2024)
Greece	$PM_{2.5}$, UFP, OA	PMCAMx	Siouti et al., (2023); Patoulias et al., (2025); Siouti et al., (2025)
Greece	$PM_{2.5}$, OA, NOx	SmartAQ	Siouti et al., (2022)
Finland	BC	Enviro-HIRLAM	Savenets et al., (2022)
Spain	BC, PNC, NO_2	Machine learning	Fung et al., (2024)

2.3 Novel data collection techniques and citizen science involvement

Novel measurement techniques involved the setup of stationary networks, mobile measurement approaches or remote sensing to complement the existing regulatory AQMN. Apart from novel setups of research grade instruments (e.g. on vans) low-cost sensors (LCS) were also extensively tested. These LCS can measure a variety of pollutants, including $PM_{2.5}$, PM_{10}, NO_2, CO, O_3, and in some cases black carbon (BC), ultrafine particles (UFP) and organic aerosols (OA). Table 2 lists the campaigns using novel data collection techniques from the RI-URBANS core and partner countries. The Alphasense OPC-N3 was the primary sensor used by the UK group for PM measurements. This is an optical particle counter sensor measuring PM in the range 0.35 to 40 µm, providing PNSD in 24 size bins and using that information to estimate PM_1, $PM_{2.5}$ and PM_{10} concentrations. For UFP measurements the Testo DISCmini, a hand-held ultrafine particle counter measuring the number and average diameter of nanoparticles in the diameter range from 10 to 700 nm, was used. For BC measurements, several sensors were tested, for example the single wavelength microAeth AE51 and Observair and the more advanced MA200, MA350 capable of measuring in multiple wavelengths providing additional information about the carbon content of the samples (Elomaa et al., 2024). Finally, the Kunak Air Mobile, a modular mobile IoT sensor system measuring PM, NO_2 and O_3, was deployed by some of the campaigns.

Remote sensing approaches were also tested for air pollution mapping and hotspot identification in several RI-URBANS sub-projects, in particular the use of satellite and LIDAR data. These approaches are expected to play an increasingly important role in future AQ monitoring, providing data collection with greater spatial coverage.

The combination of all these novel approaches, in combination with the data obtained from the existing AQMN, can deliver valuable insights and help guide urban AQ policies. The combination of different methodologies as well as the use of LCS require robust QA/QC, which within RI-URBANS was achieved through campaign specific AQMN co-location campaigns, data cleaning, calibration, curation and normalisation procedures, assisting in the consistency and accuracy of the data collected. In most cases the data collected were openly available in data banks, such as the ARGOS platform (RI-URBANS, 2025b), further promoting transparency and increasing awareness.

Finally, the involvement of citizen scientists in the monitoring process was used in several pilot cities in the RI-URBANS project. Citizen science projects face several challenges. These, together with the measures adopted to overcome them and the lessons learned from the campaigns, are discussed in this study to inform future citizen science applications.

Table 2: List of the measuring campaigns from the cities of the RI-URBANS project.

Pilot country	Pollutants assessed	Collection method	Citizen involvement	Reference
UK	PM	Static and on foot	Yes	Baruah et al., (2024)
UK	PNC, LDSA, BC	On foot, cycling	No	Damayanti et al., (2026)
UK	PM, LDSA, BC	On foot	Yes	Bousiotis et al., (2024)
UK	PM	Indoor static	Yes	Rathbone et al., (2025)
Netherlands	BC, NO_2, UFP	Car-based	No	Yuan et al., (2024); Fry et al., (2025)
Netherlands	BC	On foot	Yes	Kerchoffs et al., (2022)
Romania	UFP, PM, BC, NO_2	Car-based	No	Talianu et al., (2025)
Romania	BC	Car-based	No	Van Poppel et al., (2023); Nicolae et al., (2025)
Finland	BC	Static	No	Elomaa et al. (2024)
Finland	UFP, $PM_{2.5}$, BC	Cycling	Yes	Kleemola et al. (2024)
Finland	UFP, PNC, PM	Van	No	Järvi et al., (2023); Teinilä et al., (2025)
Finland	Vertical LDSA	Drone	No	Järvi et al., (2023)
Belgium	BC	Cycling	Yes	Van Poppel et al., (2024)
Belgium	PM, NO_2, O_3	Postal service vehicles	Yes	Hofman et al., (2023)

3. Results

3.1 Advanced Modelling

Several models and approaches were tested by different groups within RI-URBANS. For the **Paris** pilot, techniques based on deterministic modelling provided high resolution outdoor exposure city maps. The CHIMERE model (Menut et al., 2024) was used and coupled with the MUNICH street scale model (Sartelet et al., 2020). This model was used to successfully estimate the human exposure to NO_2, BC and PM_1 and $PM_{2.5}$ (exposure scaling factors 1.04 – 1.26) (Park et al., 2025), the variability of O_3 and PM with different meteorological conditions (while ozone was efficiently predicted, $PM_{2.5}$ was overestimated by a factor of 1.5 – 2) (Di Antonio, et al., 2025a), as well as the oxidative potential of atmospheric particles (r = 0.35 – 0.60) (Vida et al., 2025), a metric which can be used for AQ risk assessment. The results from these studies were also evaluated against observations from the local AQMN. Maison et al., (2024) using the CHIMERE-MUNICH model found a mixed effect of the urban trees upon the AQ on the streets of Paris, finding a substantial increase in the organic particle concentrations while an opposing effect on gas and particle concentrations was found from the dry deposition on the leaves. Furthermore, Vida et al., (2024) modelled the fungal spore concentrations (r = 0.60 for the estimation of monthly concentrations), which can make a significant portion of the total PM_{10} in the atmosphere, but are not considered in many air quality models. While the model was successful in estimating the concentrations and seasonal changes in the northern and eastern parts of France, it was not so successful for the southern parts of France, mainly due to the limited dataset availability there. The CHIMERE model was also used for modelling the effect of large-scale events, such as the wildfires in Canada in 2023, for which the dispersion of the BC and Brown Carbon (BrC) emissions were estimated, with the effect reaching up to Eastern Europe, a result which was confirmed when the model estimations were compared against satellite observations (r = 0.65 – 0.79) (Tuccela et al., 2025).

Another commonly used model for the dispersion of the pollutants is the ADMS, which was tested thoroughly in several case studies by the **Birmingham** pilot. The ADMS was used to estimate the dispersion of road and regional emissions for PM, BC and NO_2. For the PM (r = 0.47 – 0.49, for the different size ranges), it was found that while road transport is a major source, the rural background plays a decisive role for ultrafine particle concentrations in the urban environment (Zhong et al., 2023). On a street-scale simulation over Birmingham, UK, it was found that reduction of traffic, while resulting in signficant NO_2 concentration reduction, had a limited effect on $PM_{2.5}$ (r = 0.49 – 0.79, for the different pollutants) (Zhong et al., 2024). Furthermore, the ADMS-Urban model was capable of modelling BC concentrations in different scenarios, though adjustments to emission factors were suggested for improved estimation of the traffic contributions when compared to observations from the AQ monitoring network (r = 0.46 – 0.61, for the different sites) (Zhong et al., 2025).

For the **Athens** pilot, the concentrations of inorganic secondary aerosols was assessed using the multi-scale numerical atmospheric model system CAMS/WRF/EPISODE-CityChem (Myriokefalitakis et al., 2024). The simulated concentrations, within 100 m cells, showed that for the three inorganic secondary aerosols simulated, the mean concentrations compare well with observations satisfying the model performance criteria and goal of Boylan and Russell (2006) in most cases (r = 0.46 – 0.61, for the different aerosols). Another group from the Greek pilot in **Patras** used two models for the prediction and mapping of the air quality. The PMCAMx was the base for the estimation of the concentrations of the gases and aerosols. Using this model the effect of biomass burning on $PM_{2.5}$ (Siouti et al., 2023) as well as that of the different mechanisms of nucleation on the UFP (Patoulias et al., 2025) were estimated throughout Europe. Furthermore, using the Particulate Source Apportionment Technology (PSAT) algorithm (Wagstrom et al., 2008), biomass burning was found to be the most significant contributor to the $PM_{2.5}$ during the winter months (up to 70%). In both cases the results were evaluated against field measurements, which for the first study were derived from measurements from the city's LCS network (Fractional error up to 0.85 for hourly estimations for the first study and normalised mean error up to 61% for the second). The PMCAMx model was also successfully tested to predict the $PM_{2.5}$ concentrations and its sources, as well as exposure in a 1x1 km^2 resolution grid in Athens (Siouti et al., 2025). The performance of the model was good for both $PM_{2.5}$ and OA estimation according to the criteria set by Morris et al., (2005) (Fractional error 0.38 – 0.57, for the different sites). The group from Patras also developed and tested the SmartAQ system for one month for each season in 2021-22 in the city of Patras for $PM_{2.5}$ and NOx. The system performed excellently for $PM_{2.5}$ during the summer and winter times, while its performance was good during autumn for the city centre and average for the suburbs, due to overestimation of long-range transport. Similar was the performance for NOx, with an underestimation of the concentrations during the daytime against the observed values.

Other models were also tested in specific cases. For example, the Enviro-HIRLAM modelling framework was used to estimate the contribution of forest fires on the BC concentrations over Ukraine (Savenets et al., 2022). The model estimated a contribution of 10-20% of BC to the total aerosol mass near the wildfires in the lowest 2 km layer, while BC emissions from the wildfires were found in the accumulation and coarse modes in distances up to 2000 km.

Finally, several machine learning methodologies were tested by Fung et al., (2024) for the mapping of BC concentrations. For this work, the machine learning models were trained in Barcelona and then tested with datasets from urban and traffic sites across Europe. It was found that BC concentrations correlate well with PNC of the accumulation mode and NO_2, which was consistent in other European sites. Overall, the tested ML model gave an acceptable performance (R^2 = 0.75 – 0.83, for the different models), highlighting the transfer possibility of these models across space and time.

3.2 Mobile and citizen science studies

The pilot cities tested novel methods for data collection for air quality mapping. For the **Birmingham** pilot, monitoring included citizen-involved approaches using LCS for static and mobile measurements, including walking and cycling in Selly Oak, a populous neighbourhood next to the University of Birmingham. The main sensor used in all these studies was the Alphansense OPC-N3. The air quality assessment at neighbourhood scale included monitoring at 6 static measuring points (including at the Birmingham Air Quality Supersite, as a background site) which also allowed evaluation of long-term LCS performance vs. research grade instruments for air pollution monitoring. The street level air quality assessment and pollution source apportionment included stationary monitoring and both walking and cycling sessions with the involvement of citizen scientists. For this additional equipment was used, including a Aethlabs microAeth AE51 for BC measurements and a Testo Discmini for PNC and Lung Deposited Surface Area (LDSA), fitted into a backpack for easy transport. This allowed the air quality mapping and identification of PM hotspots (Damayanti et al., 2026) and the estimation of the effect of both regional and local sources at high spatial resolution (100 x 100 m) (Bousiotis et al., 2024), thereby providing valuable information on hyperlocal sources of pollution (Fig. 2). Furthermore, $PM_{2.5}$ concentrations, using a combination of collected data (mobile and static), with additional traffic, topography and demographic data were processed to create a machine learning model to fill data gaps and predict PM concentrations when measured data is not available (Baruah et al., 2024).

Finally, in one of the few indoor air quality studies among the pilots, with the involvement of students at the University, LCS were installed in three student houses, within the same Selly Oak region as the mobile measurements, to assess the differences in PM sources and concentrations within indoor environments (Rathbone et al., 2025).

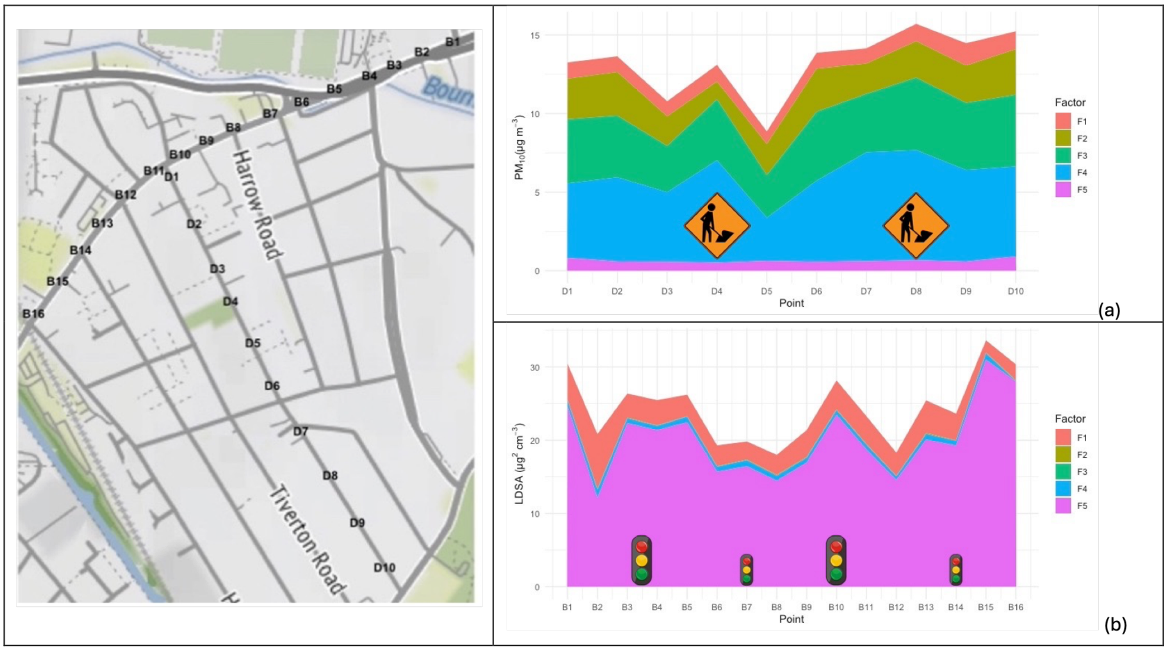


Figure 2: (a) Variation of the sources of PM_{10} for a transect across Dawlish Road, a relatively small residential road in Selly Oak, Birmingham. The location of construction sites is highlighted. (c) Variation of the sources of the LDSA for a transect across Bristol Road, a road with significant traffic activity. The location of major (on a junction) and minor (no junction) traffic light points are marked. In both cases, F1 represents the Urban Background source, F3 the Marine source, F5 the traffic source and F2, F4 local sources (Bousiotis et al., 2024).

In the **Rotterdam** pilot, citizen-based mobile monitoring and car-based measurements were performed. The citizen science mobile monitoring was performed following methods developed by van den Bossche (2015). In total, 38 participants collected data whilst commuting (to/from work) with portable instruments for BC. The data was used to map exposure and derive representative long-term average AQ maps during commuting hours in winter and summer. Like the Birmingham pilot, the microAeth AE51 was used for data collection, after confirming the comparability against the reference (AE33) by means of an initial co-location. The variability reported by the mobile sensors was similar to that of the reference monitor, and representative spatial maps of BC exposure were derived. Moreover, a sensitivity (subsampling) analysis revealed that up to 15 and 29 sampling repeats were needed to obtain within-season and multi-season representative AQ results, after post-processing the mobile data by means of winsorizing (process of limiting the extreme pollution measurements so they do not disproportionally affect the analysis) and background normalization (Fig. 3).

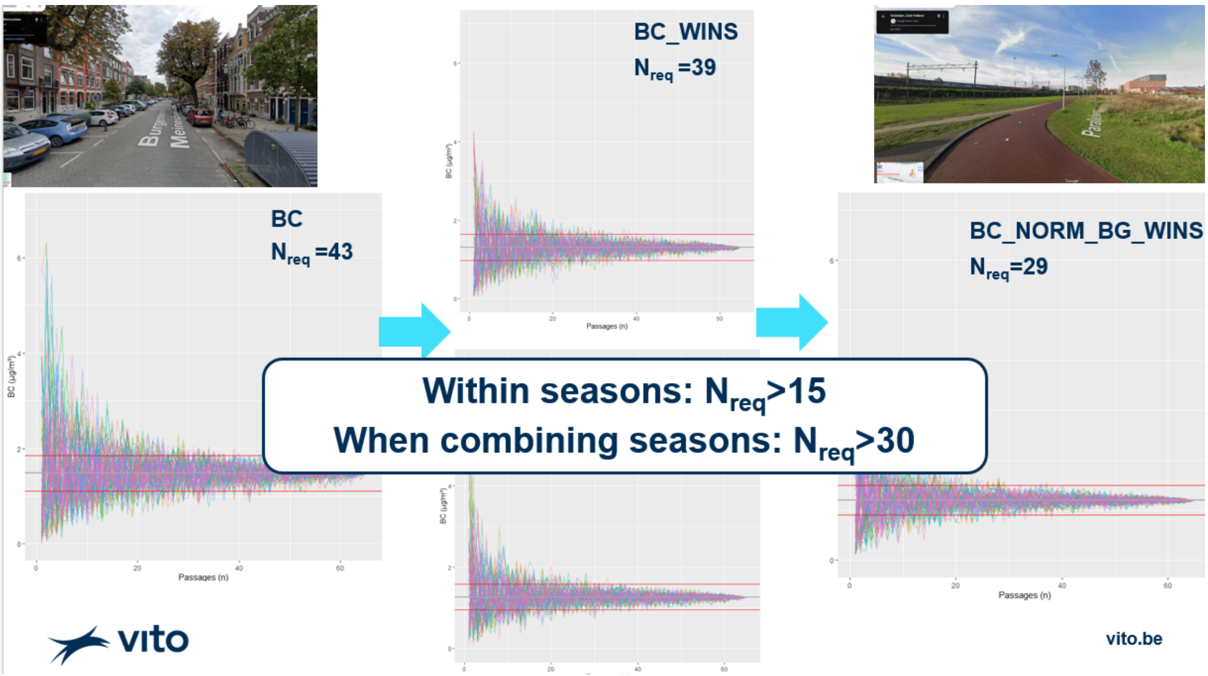


Figure 3: Subsampling analysis to derive the number of required repeats (N_{req}) in order to be within 25% of the long-term mean. The number of required repeats was derived from the raw BC data (BC), winsorized BC data (BC_wins), background normalized BC data (BC_norm_bg) and fully post-processed (winsorizing + background normalization), for each of the considered seasons (winter/summer) or considering multiple seasons. The choice of the number of repeats should depend

on the considered pollutant (variability expected) and reevaluated during the campaign.

Car-based mobile monitoring was also implemented In Rotterdam, measuring the ambient concentrations of NO_2 (CAPS, Aerodyne Research Inc., USA), BC (Magee Scientific AE33) and UFP (TSi EPC 3783). The collected measurements were used to develop a mixed-effect model following methods described in Kerckhoffs et al (2022). Predictions represent long-term average air pollution concentration maps, and where possible, to investigate the impact of industrial sources (mainly port activities) on the total concentration values. The pilot was successful in producing maps of the individual pollutants, but less successful in the interpretation based upon monitoring data directly. The ratios between the pollutants offered new insights into the source contribution of the pollutants. UFP was often elevated near airports, whereas BC and NO_2 were more confined to road traffic sources. This dataset was also used to elucidate the effect of street trees on the pollutants measured (Fry et al., 2025). Concentration of NO_2 and BC were higher during the summertime (when trees had more leaves) in areas with many trees due to pollutant trapping (Vos et al., 2013), while $PM_{2.5}$ was lower, highlighting that this pollutant is usually transported from other areas into street canyons. Finally, these data were combined with data from mobile campaigns from Copenhagen and were used to develop LUR models for Amsterdam, for which mobile data was also available for evaluation (Yuan et al., 2024). Testing of the models highlighted the ability for successful hyperlocal air pollution mapping for a city even without any pollution measurements, with Pearson correlations reaching up to 0.92 for NO_2 and 0.90 for UFP.

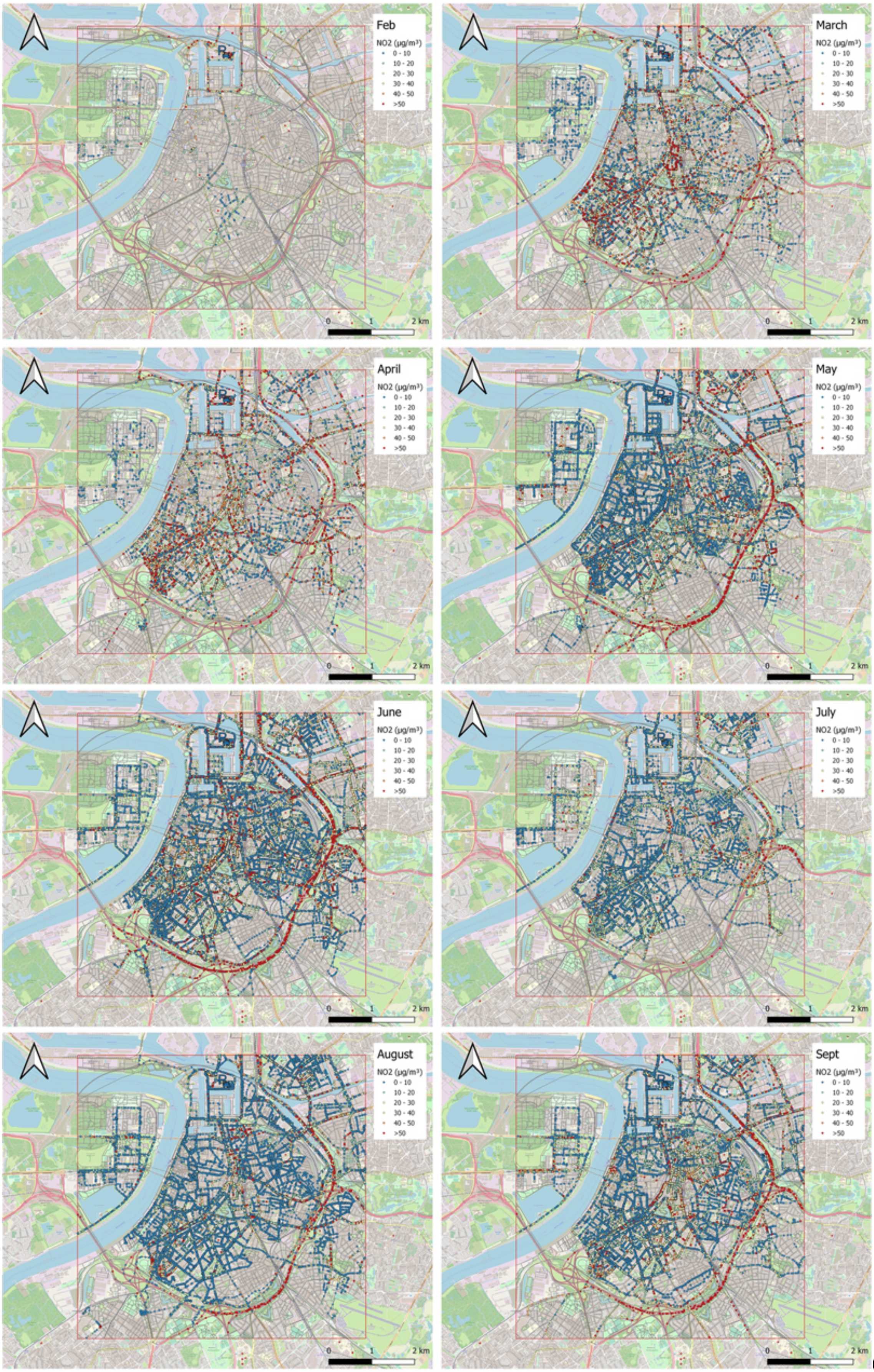
For the **Bucharest** pilot, mobile measurements campaigns without citizens' involvement were carried out for UFP, particulate matter fractions (PM_1, $PM_{2.5}$, and PM_{10}), BC and NO_2 using LCS on specified routes (including heavy traffic roads, inside the city, residential, industrial, commercial, sub-urban areas), along with the ESCAPE LUR model, the PyLUR tool and QGIS. Maps based on car measurements showed that the UFP sources seem to be widely distributed during summer, while winter is characterized by more homogeneous sources (Talianu et al., 2025). Significantly elevated concentrations were found mainly in the industrial area and urban agglomerations, but also on some important traffic routes. Overall, while the model performed better during the cold season, NO_2 values were overestimated, and PM_{10} levels were slightly underestimated during the warm season, resulting from the assumptions made and the uncertainty of the data used for training the models. Similar was the variance found for BC, using mobile data collected by a car in the city of Cluj-Napoca during periods within and out of the COVID-19 lockdown periods (Van Poppel et al., 2023). The BC concentrations on roads with high traffic intensities were found to be up to four times greater compared to those with reduced traffic. Furthermore, about halved BC concentrations were found during the lockdown periods highlighting the effect of limiting the traffic activity during these periods.

Additionally, using mobile measurements and the LUR model developed from the Rotterdam pilot for pollutant concentration prediction, the effect of power plants on the nearby residential areas in the city of Bucharest was assessed (Nicolae et al., 2025). It was found that despite the initial estimations, the power plant in the western side of the city was not the main source of pollutants for the nearby residential area. Such studies provide crucial information on the assessment of the environmental impact of industrial activities, which in many cases can be misinterpreted, thus leading to erroneous actions which may increase the environmental action cost without providing the anticipated impact.

Helsinki measurements includes the Kumpula campus campaign measurements of BC (Elomaa et al. 2024) and a mobile bike-based measurement campaign (Kleemola et al. 2024). In the urban area, on the Kumpula campus the measurements were conducted at the SMEAR-III station as an urban background environment (Järvi et al., 2009) and at the Mäkelänkatu supersite as the urban street canyon (Barreira et al., 2021). A network of four types of small-scale filter-based BC sensors (AE51, MA200, MA350, Observair) was deployed with the objective to evaluate these sensors for monitoring ambient BC concentrations and to study variations in high resolution data. Sporadic and transient high values were observed both with sensors and with the reference instruments indicating spatially and temporally varying BC sources in the area. For this campaign the sensor data correlated relatively well against the reference (Pearson corelation 0.78-0.84). Mobile bike-based UFP, $PM_{2.5}$, BC measurements were also performed in Helsinki, where instrumentation was constructed on a bike and connected to cloud-services for data access. Sampling was done on a route that connected areas with high variability in aerosol number concentration and two AQ supersites, namely SMEAR-III and the Mäkelänkatu supersite. However, results showed that the correlation was modest. As expected, the highest concentrations were observed near traffic and considerably lower concentrations were observed in the park areas. Apart from bike campaigns, mobile measurements were also collected using the ATMo-Lab (Aerosol and Trace Gas Mobile Laboratory), a van carrying instruments targeted on the assessment of traffic derived UFP. Measurements collected using the van were combined with measurements from the Traffic and UB AQ stations in Helsinki for a source apportionment study to identify organic factors connected to different particulate sources (Teinilä et al., 2025). It was found that local traffic emissions increased the PNC, especially for particle sizes <10 nm, while long range transport increased the PM mass concentration and particle size. A different van, the “Sniffer”, was used to identify pollution hotspots in the city centre of Helsinki (Järvi et al., 2023). In this campaign, with the use of the mobile data along with data from the local monitoring station, both the horizontal and vertical pollutant variation was studied. For the vertical measurements a drone collecting LDSA data (Naneos Partector) was used. Using this data the mechanisms causing pollution hotspots in street canyons were explored, pointing to different drivers for the warm and cold periods of the year, highlighting the role of thermal processes within the street canyon as an important factor during the winter.

Finally, analysis of mobile measurements was also implemented in **Belgium** as part of the RI-URBANS, though the datasets were collected in other studies. Two approaches were tested, involving citizens in the collection of BC data using bicycle rides in a targeted approach, and the use of postal service vehicles for PM, NO_2 and O_3 data in an opportunistic approach. For the first project, the measurements were collected by citizen volunteers in Mechelen, Belgium who participated in a local citizen observatory, as part of the GroundTruth2.0 project (Van Poppel et al., 2024). For this campaign the citizen scientists, under the guidance from members of the research partner VITO and the city council, collected BC data using the AE51 in repeated rides on four predefined routes within the city in periods from all seasons. As repeated measurements are needed for adequate assessment of the BC concentrations, for each route and campaign 25 repetitions were done. Strong seasonality of the BC concentrations was observed, with the highest concentrations found in the late autumn campaign and the lowest in the summer campaign, while the diurnal variability was more complex and was found to depend on the proximity to sources, dilution and dispersal dynamics. The mobile measurements were also used to evaluate modelled results from the ATMO-Street model (using multiple data sources including the AQ network). The mobile measurements presented a fair correlation with the modelled data. Higher correlations were found in the measurements collected in the suburban areas, where the cyclists were not exposed to traffic emissions. The model underestimated the peak concentrations observed in areas with heavier traffic. For the second study, the Kunak Air Mobile was used (Hofman et al., 2023). Twenty of these systems were installed on postal vehicles operating in Antwerp. A total of 945 km of road was covered by the vehicles in the 7-month campaign, providing about 8 million datapoints scattered throughout the city. NO_2 measurements properly reflected the observed exposure range as measured by the AQMN in the city and pollution hotspots were mapped throughout the city (Fig. 4). This opportunistic data collection method was proven to be a valid approach for pollution exposure assessments and a valuable source of air quality data for cities with a limited monitoring network. The same mobile mapping approach was also used in a project in Cluj-Napoca, Romania, with the the participation of citizens, where the impact of traffic on BC concentrations during the COVID-19 lockdown was assessed highlighting that background corrections are needed for better assessment of the traffic impact (Van Poppel et al., 2023).

(a)


Feb
NO2 (µg/m³)
0 - 10
10 - 20
20 - 30
30 - 40
40 - 50
>50
0
1
2 km
March
April
May
June
July
August
Sept

(b)

Figure 4: (a) Kunak® Air Mobile sensor systems co-located at the R817 AQMS; three in fixed shields, 17 in mobile enclosure (upper), details of the Kunak® Air Mobile sensor system (lower left), and rooftop deployment on a postal van in Antwerp (lower right). (b) maps of monthly collected mobile NO_2 measurements (µg m^{-3}) in the city of Antwerp between February and September 2021. (Hofman et al., 2023)

3.3 Other approaches

A number of alternative approaches were also tested in the RI-URBANS project from both the pilot and partner cities. An interesting approach for air mapping data was used by a group from **Barcelona**. In this study, sand and soil was collected from 23 playgrounds and parks around Barcelona (González-Romero et al., 2025). The mineral content and trace element content of the samples were determined offline at the laboratory using two types of spectrometry. The sand samples from several parks exhibited significant enrichment factors for elements associated with road emissions (brake or tyre wear), while others exhibited elevated content of Pb and Sb which are most likely associated with industrial and port activities. Using this methodology improves the understanding of the urban PM dynamics while pollution hotspots can be identified. However, caution is necessary in data interpretation due to the long residence time of many trace elements in soil and associated legacy effects.

Air quality mapping with the use of the Aerosol Optical Depth (AOD) to monitor the aerosol load and distribution in the atmosphere is a tested approach which was also used by some pilot groups. The group for the **Paris** pilot studied the variation in Paris and its surrounding area Using the variations of the different wavelengths between the urban and sub-urban environments (Di Antonio et al., 2025b). In this study, the organic aerosols contributed up to 50% of the aerosol mass with variations observed between urban and forested areas. Similarly, the AOD was used from the pilot in **Athens** for the estimation of the impact of the wildfires in Athens, Greece in August 2021 on local AQ (Kaskaoutis et al., 2024). The biomass burning tracers used in this study, like nss-K^+ (from $PM_{2.5}$ filter samples) presented high correlations with BC, OC and EC, as well as with specific scattering and absorption coefficients, highlighting the ability of this approach to provide AQ data without the need for traditional monitoring instruments. Using the same methodology, a group of institutions in Italy formed a network of automated lidar ceilometers in 2015, the ALICENET. The ALICENET, comprising of 22 stations throughout Italy (in urban, industrial, coastal and mountainous sites), allows the monitoring of vertical aerosol profiles over a wide range of environmental and atmospheric conditions (Bellini et al., 2024). Apart from routine monitoring the network monitors all kinds of events, such as Saharan dust events, short and long range transport of biomass burning emissions, and the emissions from the volcanic activity in the South of the country. The data provided by the ALICENET network were tested as part of the RI-URBANS project against the ERA5 dataset and CAMS model with good agreement on variables such as the Boundary Layer Height and PM_{10} (Bellini et al., 2025), providing an alternative and cost-effective way for fine spatiotemporal air quality data collection. In a similar manner but using satellite lidar data instead, the pilot group from **Helsinki** collaborated with the University of Jordan in one of the first tests of simultaneous use of ground based and satellite observations for air quality mapping in the city of Amman, Jordan (Panahifar et al., 2023). Analysing the data from the space-borne Cloud-Aerosol Lidar with Orthogonal Polarisation (CALIOP) three main groups of aerosols were found over Amman, the coarse mode dust, the fine mode dust (polluted dust) and non-dust aerosols (pollution). The vertical aerosol profile over Amman was mapped and using the trajectory analysis, the sources of the incoming pollutants were distinguished (Fig. 5).

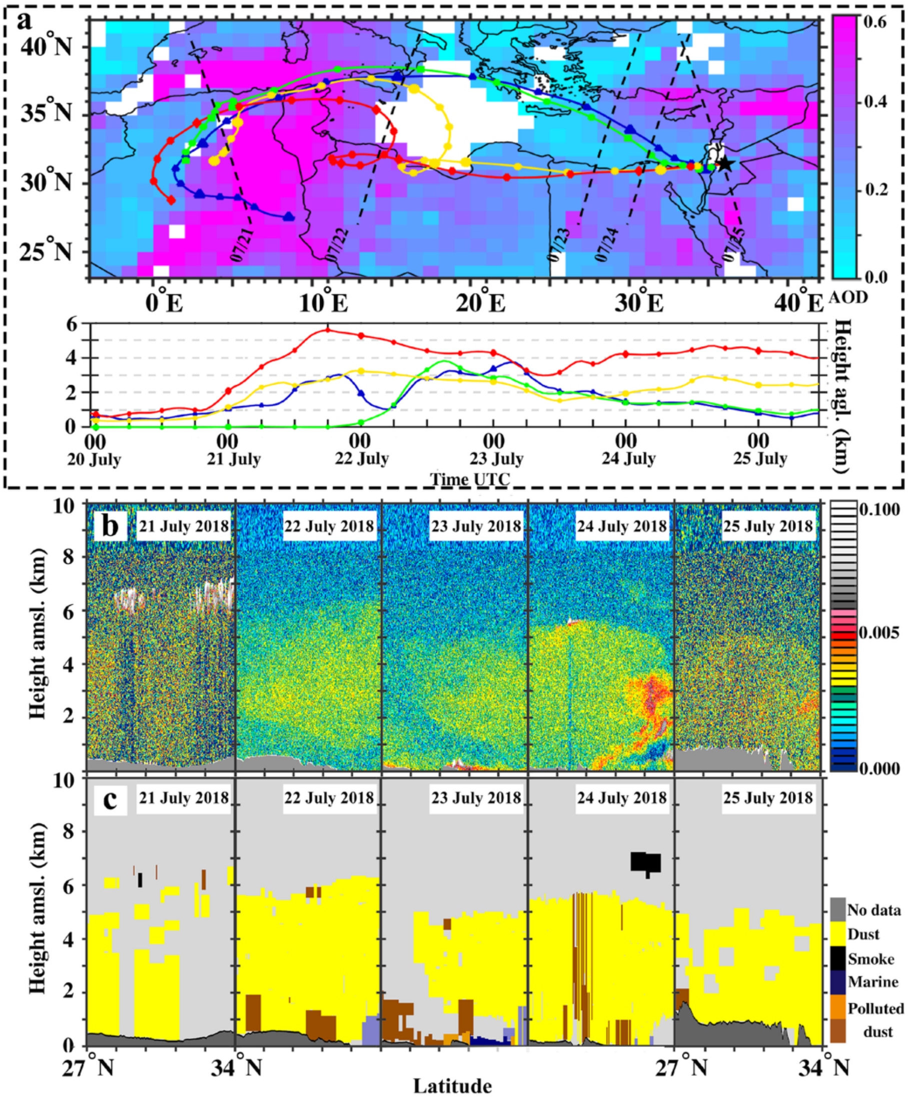


Figure 5: (a) Backward trajectories during the past 132 h by the HYSPLIT model on 25 July 2018 calculated at different heights, overlaid by MODIS Deep Blue AOD (on 21 July 2018) and corresponding CALIPSO ground track during transport path. (b) The attenuated backscatter coefficient in arbitrary units (AU). (c) The CALIPSO aerosol subtype classification. The horizontal axis for all panels of (b) and (c). This axis shows latitude from 27∘ N to 34∘ N. (Panahifar et al., 2023)

Finally, a novel approach on air quality mapping using street images was tested as part of the RI-URBANS. For this, 2800 high resolution street images were captured in 4 locations in Germany (Augsburg, Neubiberg, Warnemünde) and the Czech Republic (Zelezna Ruda). Using three ML methodologies on the luminance of the red, blue and green colours found in each pixel of the images the PM concentrations was assessed. To assist the model construction, sampling campaigns were conducted in the study areas. These sampling campaigns included walks around the study areas in sunny and cloudy days, for the collection of PM_1, $PM_{2.5}$, PM_{10}, BC, BrC, PNC and LDSA data. The models tested demonstrated adequate performance and satisfactory generalisation capabilities in both temporal and spatial dimensions, indicating that with proper calibration this approach can be used in different areas and seasons (Liu et al., 2024) (Fig. 6).

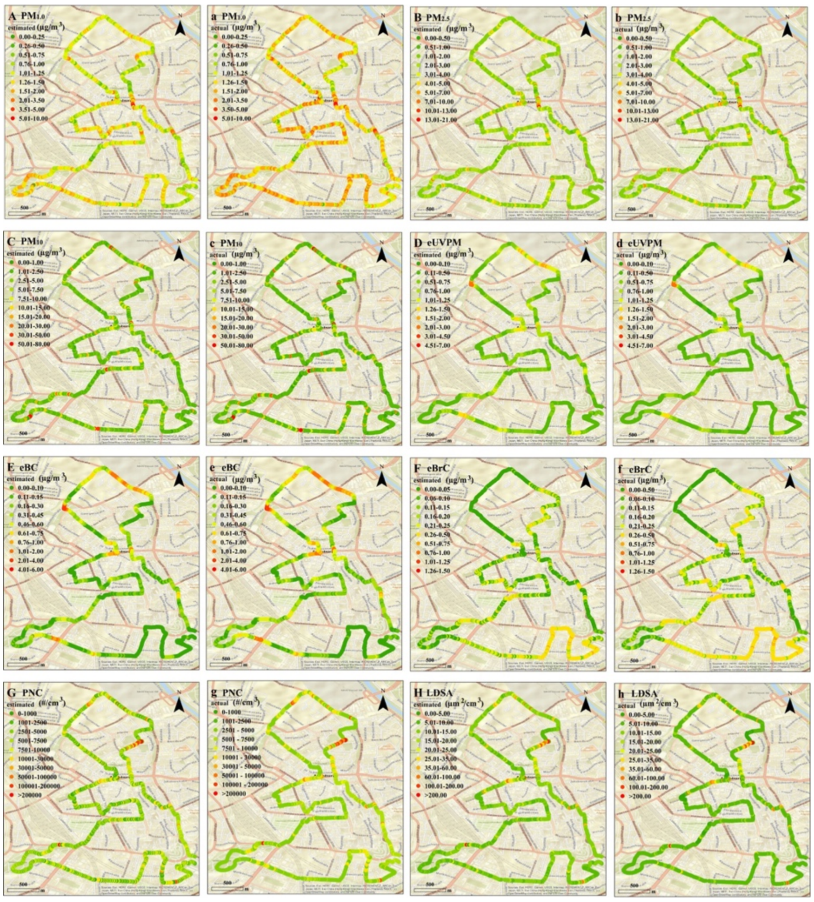


Figure 6. Spatial distribution estimates of eight air PM metrics using the LSTM-HSV model (A–H, capital letters) compared with actual monitoring (a–h, lowercase) in the downtown of Augsburg (Liu et al., 2024)

4. Discussion

4.1 Combining modelling and novel measurement techniques to complement the information from existing AQMN. The RI-URBANS promise.

The preceding sections outlined the multi-faceted strategy adopted by the RI-URBANS project to advance urban AQ monitoring and pollution hotspot identification. The need for spatially dense datasets and on demand campaigns led to the considerations of more flexible monitoring methodologies. The LCS can provide on demand air quality measurements for a wide range of atmospheric variables with an affordable cost and great flexibility. Stationary sensor networks offer cost-effective means of expanding long-term monitoring coverage, especially in underrepresented or vulnerable communities (Shabbir et al., 2025), while mobile measurements can substantially expand the spatial coverage. Standardized QA/QC protocols across municipalities would enhance trust and enable cross-comparative analyses (Bousiotis et al., 2025). The integration of stationary and mobile measurements allows for real-time assessment of pollution hotspots and population exposure across diverse urban environments. These platforms are especially valuable for identifying local sources of pollution, validating traffic-related emission controls, and assessing the effectiveness of urban interventions. For example, Hofman et al., (2022) showed the significant air quality impacts of temporary traffic restrictions in a school street using a stationary sensor network.

The pilot studies focused on modelling, and mobile monitoring with reference grade monitors or portable LCS which have been shown to compare well with reference grade monitors. Dispersion modelling was useful and agreed well with measurement data from the often-few regulatory monitoring stations. The mobile approaches also worked well to develop maps across the city, useful for studies which could benefit from finer resolution, for example epidemiological studies. Figure 7 illustrates the difference between mobile and stationary monitoring approaches and associated considerations in terms of monitoring set-up and device requirements. For the identification of specific hotspots, more focus on data-only approaches is needed, as was the case on the approach adopted in Rotterdam. Monitoring data are useful to identify locations where current models under- or overestimate concentrations. Furthermore, citizen involvement increases the awareness and enriched interpretation as citizens were able to provide feedback on observed spikes and hotspot locations in their commuting environment. Identification of hotspot locations, and assessment of personal exposure during commuting are additional merits of mobile monitoring.

In general, modelling is easier to implement since it requires a fewer number of repeat measurements, and can provide sufficient air pollution mapping, if prior expertise already exists and input data on emissions are available. However, contrary to data-only approaches, models only provide AQ predictions and the robustness of these model predictions relies on underlying model assumptions. Challenges may be raised by the requirements of regulatory modelling, limiting the flexibility of model choice. This applies less to unregulated pollutants such as UFP. Novel measurement techniques though, can assist in expanding current AQ mapping capabilities. LCS monitoring, stationary or mobile, is promising to refine spatial resolution, assist in hotspot identification and evaluate models' output. As one of the main targets of the RI-URBANS project was to expand the adoption of both mobile measurements and citizen involvement, the lessons learnt from these applications will be discussed on the next sections.

Figure 7: Main differences between mobile and stationary air quality measurements in terms of associated monitoring setup and device requirements (RI-URBANS, 2022)

4.2 Mobile measurements and citizen involvement

4.2.1 Design of mobile and citizen campaigns

It is important to choose the monitoring strategy that best targets a specific research question or use case. Slight changes in the data collection protocol can significantly alter the results. At the same time, the required efforts and number of volunteers need to be considered. Involving citizens has obvious merits but can entail significant workload amongst the project support team, for example in recruiting, communication, engagement and feedback to the citizen scientists.

Several opportunistic mobile campaigns were attempted in RI-URBANS using common daily routines of people or service fleet vehicles. While the data collection process is automated, the travelled route is uncontrollable from the point of view of the researcher, as it is not designed and performed with data collection from a specified route in mind. This approach was utilized on cyclists in the RI-URBANS pilot in Rotterdam, cyclists in the province of Utrecht, the Netherlands (Wesseling et al., 2021), on trams and buses in Zurich (Mueller et al., 2016) and Birmingham (Damayanti et al., 2026), postal vans in Antwerp (Hofman et al., 2023) and in the HOPE project in Helsinki (Rebeiro-Hargrave et al. 2022). These studies provide information on the local AQ but also about urban mobility.

The opportunistic approach contrasts with targeted mobile monitoring, which is a coordinated approach in which the mobile measurements are deliberately planned in terms of sampling route and monitoring period. The carriers, which are not expected to make any changes in their usual habits, can be citizens, a certain professional group (e.g. city wardens, home nurses, taxi drivers), or vehicles equipped with AQ instruments (Kerckhoffs et al., 2022).

Choosing between a targeted and an opportunistic approach is not a simple binary decision. In practice, data can be collected opportunistically while still maintaining some control over the number of repetitions and the trajectories followed. For example, a campaign could be organized within a company, institute, government entity, or university that invites employees to measure their exposure during their daily commute. This approach was adopted in the Rotterdam pilot, in which employees collected data during daily commuting from and to work. In such case, the routes can be selected (by selecting employees with most relevant commuting routes) and participants can be asked to measure the same route multiple times and aligning this monitoring protocol among the participants.

Careful consideration of the required spatial and temporal monitoring coverage is essential, as measurements are only representative of the locations and time periods in which they are collected. Temporal variability often exceeds spatial variability; therefore, sufficient temporal repetitions should be ensured at each relevant spatial location. Variations across times of day, weekdays, and seasons can strongly influence pollutant concentrations and should be taken into account when designing the monitoring campaign and when processing the collected mobile measurements (e.g., through background normalization) to obtain data that are representative for exposure assessments.

The choice of targeted versus opportunistic monitoring holds some consequences for the processing and interpretation of the data as well. The advantage of a targeted approach is that all sections along the route can be optimized in terms of monitoring repeats and are measured ‘quasi-simultaneously’ during the same days, seasons, etc. which makes it easier to directly compare different datapoints in space and perform background scaling to e.g. yearly average values. A drawback is the workload; when citizens are involved, they must drive/walk the route in addition to their normal activities. Furthermore, compensation might be required for such additional work. It should be noted that data collection during commuting can reduce the workload but also reduces the synchronization of the measurements. Thus, the opportunistic approach can result in spatial and temporal sampling bias. Certain urban microenvironments might be underrepresented or absent in the data. Furthermore, temporal bias can appear in the case of data collection by commuters, as the measurements are mainly limited to rush hours, and no data will be available during working nor non-working (night-time) hours.

Finally, the sampling can also be biased by the weather conditions, e.g. when the data collection stops when it rains. However, this is not only true for opportunistic approaches (e.g. when the commuter takes the car instead of the bicycle on rainy days) but is also true when the monitoring equipment is not fully protected from rain.

4.2.2. Mobile measurements – strategies and lessons

Kerckhoffs et al. (2025) extensively discussed the design choices and strategies of true mobile monitoring studies. For example, mobile monitoring data can be used for direct mapping or as input for models. It is important to consider the type of mobile platform (walking person, bicycle, car, tram, etc.), the measurement timing (e.g. hours of the day), and monitoring locations/route. It is also crucial to know in advance which data processing technique will be used to optimize the data collection. Not only whether a model is used, but also the type of model used can have impact on the data collection requirements. Furthermore, the data from mobile campaigns can also be used for model evaluation and improvement. When direct mapping is used, it is important to optimize monitoring repeats to obtain a representative spatial and temporal coverage. This is also true but to a lesser extent when models are developed, as spatiotemporal dependencies are learned from the available dataset. Additionally, the sampled concentrations of specific pollutants on a vehicle or bicycle on the road will likely exceed those of a pedestrian on the sidewalk and may not compare well with model outputs which estimate exposure of residents at their homes. Concentrations may also differ substantially between sides of a street canyon if influenced by a wind-driven vortex.

Mehanna et al. (2022) defined three parameters for completeness of datasets: sensor completeness, temporal completeness, and spatial completeness. Sensor completeness is defined as a quality factor that captures the extent to which the measurements of a given sensor are complete over a certain sampling period. Similarly, Hofman et al. (2023) considered area coverage (% of covered street segments) and segment coverage (#measurements/segment) in the Antwerp campaign. To assure the completeness of data collected from a mobile campaign several aspects should be considered when designing and implementing the monitoring strategy.

Monitoring devices need special attention when used for mobile data collection or by citizens who do not have specialised knowledge on AQ and measurements. Additionally, a high temporal monitoring resolution and fast response time is needed when collecting mobile AQ data. For example, when driving at a low speed of 15 km/h, a single measurement point will take 42 m at a time resolution of 10 seconds. At a walking pace (5 km/h), this spatial resolution becomes 14 m. Another important issue associated with the sensors' measurement resolution and response time is the fast-changing environment, especially in urban setups. The sensors chosen should effectively adapt and collect reliable measurements in changing environments, including moving from indoors to outdoors. Additionally, a precise geolocation sensor is also very important when collecting mobile measurements. Such information is vital for mobile campaigns, and the price of GPS sensors is quite low nowadays, while retaining their high precision. Finally, the sensors need to be portable but sturdy. Especially in bicycle or walking campaigns, the size and weight of the sensors can be a limiting factor for their time and distance covered. Also, as mobile sensors are subjects to vibrations, turbulence or even drops, they should be sturdy enough to withstand certain abuse, while having sufficient sampling flow to collect data under variable and changing wind conditions.

The pilot studies underscored the importance of repeated measurements for data reliability. For example, the model tested from the Bucharest pilot was trained with mobile on-road data, and it was found that it constantly overestimated NO_2 exposures, pointing the need for multiple campaigns on multiple periods. Thus, in Rotterdam, at least 15 and 30 repeated bicycle runs per route were needed to derive representative within-season and cross-seasonal pollution estimates when implementing data-only approach. Similarly, a study on cycling data collected with a targeted approach in Warsaw showed comparable results with 12 and 17 required repeats for the winter and summer season respectively. Without sufficient repetitions, there is a risk of over/underestimating pollution levels due to temporal anomalies. The latter was also pointed by the Birmingham pilot, in which specific activities (eg. construction works) were captured only on specific days and hours in the day, a factor which should be considered on the data analyses. As mobile measurements are representative for the time and space they have been collected, it should be considered that (i) the monitoring strategy will determine the applicability of the results and (ii) repeated sampling and temporal corrections are needed to obtain location-representative results and (iii) model extrapolation might be needed to predict air quality at other time and space instances (Kerckhoffs et al., 2025).

Furthermore, real time data increases the value and usability of the data. In this manner, the Helsinki pilot data were connected to operational air quality modelling (e.g. ENFUSER, Johansson et al. 2022) which allowed novel insights into the spatial variability of emerging air pollutants. Similarly, the Birmingham pilot used a cloud service for instant monitoring and reporting (the data was reported every 10 seconds). This has multiple benefits for the campaigns, as apart from the ability to instantly see the effect of anticipated sources, it allows for identifying sensor downtimes or lack of internet or GPS connection. Sensor downtime is one of the most common reasons for data loss from LCS, thus any means to reduce that should be considered.

The Helsinki pilot group also pointed the need for minimum exposure of the participants' while collecting data. Since most of the campaigns are done within urban environments, the participants are often subject to high concentrations of pollutants, a factor which may reduce their will to participate.

4.2.3 Citizen Engagement Strategies and lessons learned

Effective citizen engagement is essential for the success and sustainability of citizen science initiatives in AQ monitoring. These strategies aim to recruit, educate, and retain participants, ensuring meaningful contributions and long-term involvement in environmental monitoring. A well-designed engagement approach empowers individuals to take ownership of the data they collect and recognize their role in shaping healthier communities. Citizen science has proven to be a powerful mechanism for data collection, public awareness, and civic engagement. By empowering individuals with tools and knowledge, RI-URBANS has facilitated local advocacy and enriched datasets with otherwise inaccessible micro-scale information. However, challenges remain in sustaining long-term participation, ensuring data validity, and addressing inclusivity so that all communities can benefit from and contribute to such efforts.

One of the most common methods of engagement involves training workshops and community events that introduce participants to the goals of the project, the functionality of air quality sensors, and the broader significance of air quality. These sessions help demystify scientific tools and build confidence in handling equipment and interpreting data. Overall, great interest was expressed by non-researchers in participating in AQ campaigns. Citizens were interested in the AQ of their areas and homes and were keen to participate in the initiatives presented. The Rotterdam pilots though pointed the need to explain the results and the difference in individual measurements when data were not collected simultaneously, to increase awareness and understanding.

In Birmingham, community engagement was central to success. Students and staff at the University contributed to the placement of stationary LCS and participated in indoor AQ monitoring, providing valuable insights into personal exposure and the influence of local sources. The student invitation process sometimes included rewards for the participation, increasing the response and participation rates, though this resulted in the reward being the primary interest for some participants. Apart from students and staff, citizens and local companies were also invited to participate in the data collection process. The Birmingham pilot also obtained useful experiences from the interaction with citizens for LCS monitoring in or near their home. Building trust between citizens and researchers is probably the most important issue. Respecting anonymity is a requirement for citizens, schools and other organizations. Providing relevant feedback is also important as citizens often participate because they are interested in the topic. The Birmingham indoor AQ further showed that people were interested in the AQ of the spaces they spend most of their time in, and the factors that affect their quality of life.

For the Belgium project in Mechelen (mobile BC mapping with citizens) less data was collected during summer season because the lack of volunteers (Van Poppel et al., 2024). This pointed the need for a good preparation, clear explanation of the expectations and outputs to the participants and meaningful reasons for people to participate (either by giving “rewards” or increase awareness on the benefits of these campaigns). Furthermore, all pilots pointed the difficulty in finding participants for weekend and evening monitoring. Thus, projects may also partner with local schools, NGOs, and municipal governments to broaden outreach and encourage participation from diverse groups. For example, in one of the Rotterdam campaigns, employees of DCMR and the municipality of Rotterdam were deployed for the data collection. These were more knowledgeable in terms of AQ than the average citizen, hence it was easier for the local coordinator to organise and supervise the campaign. The Birmingham pilot also included schools as data collection points, which provided an excellent opportunity for an introduction of the air pollution concepts to children.

Providing recognition, such as certificates, public displays of contribution, or inclusion in project reports, can further motivate continued involvement and create a sense of community ownership over the initiative. Mobile applications and interactive dashboards play a crucial role in sustaining engagement. These platforms allow citizens to upload sensor data, access pollution maps, and receive personalized air quality updates in real time. Some apps also offer gamification features, encouraging users to collect data in new locations or participate in group challenges. For one of the Birmingham campaigns the participants had access to the air quality data as collected increasing both their interest and understanding on what affects the air they breathe.

There were also some interesting inputs from the deployment and the maintenance of the sensors from the RI-URBANS initiatives. Some instruments needed extra steps in providing sensible data. For example, filter changing or regular maintenance was sometimes needed. Citizens were happy to cooperate in this, though reluctant to carry on the work themselves. As maintenance though had to take place regularly, mild complains about the repeated nuisance were expressed, without though affecting their will to participate and willingness to do so in future campaigns. Specifically for one of the Birmingham pilots, the need for electricity to run the sensors was the main setback for citizens' involvement. In many cases, while people were happy to cooperate the lack of specific infrastructure to operate the sensors (e.g. access to power sockets, safe location) led to their exclusion from the campaigns. This was the most significant difficulty in finding people to work with for outdoor campaigns. For this, specific solutions were considered (e.g. car batteries), though this partially jeopardised the safety of the equipment, as in some cases the sensors were left in relatively easily accessible locations.

Furthermore, in the COMPAIR project (wecompair.eu) the use of sensors and citizen science approaches has been explored and lessons learned are summarised in course material (see https://www.wecompair.eu/post/new-online-course-for-citizen-science-practitioners). Specific requirements were defined for the equipment used when collecting data by citizens: preferred automatic data uploading, as autonomous measurements as possible (power on/off, required communication/intervention handling), good portability (weight, size, easy to carry/attach, casing/backpack, etc), low noise, long battery time, easy charging, capacity to anonymize data.

Ultimately, the goal of these strategies is to ensure that citizen participation is not only productive but also empowering and repetitive. By fostering transparency and providing meaningful feedback, citizen engagement becomes a cornerstone of sustainable urban air quality monitoring. While citizen science may seem like an easy approach to extend the amount of data collected, dedicated communication and engagement strategies are required to ensure proper data collection, reliability and usefulness of the collected data, and ultimate impact of the research outcomes.

5. Conclusions and future directions

The RI-URBANS project has demonstrated that urban air quality mapping can be significantly enhanced through the integration of traditional methodologies, innovative technologies and citizen participation. By combining modelling, mobile monitoring, stationary sensor networks, and citizen science, hybrid approaches offer a more detailed, adaptive, and inclusive system for assessing pollution levels across urban environments. Improved AQ monitoring technologies provide the necessary tools to understand pollution sources, model future trends, and design mitigation strategies that create healthier, more sustainable cities.

On the one hand, the pilot studies which used modelling approaches highlighted the diverse information obtained even without the need for field measurements, though they rely heavily on expert work, proprietary data, model assumptions and methods which are not affordable and may carry great uncertainties for areas without local information. On the other hand, insights from several pilot studies underscore the value of diversified monitoring approaches, including both static and mobile measurements using either regulatory grade instruments or low-cost sensors, to generate AQ maps from data-only or hybrid modelling techniques. Furthermore, citizen science proved especially effective in increasing public engagement and spatial coverage, particularly in Birmingham and Rotterdam

A proper monitoring and data processing strategy, calibration and QA/QC emerged as critical pillars of data integrity. Data harmonization techniques—including collocation, additive rescaling, and machine learning algorithms—enabled more accurate and comparable datasets. Our findings suggest that hybrid monitoring strategies not only improve exposure mapping and policy responsiveness but also contribute significantly to public engagement and scientific innovation. From a policy perspective, high-resolution exposure mapping supports localized interventions, hotspot identification, and health risk assessments.

However, several challenges remain, such as the development of standardized calibration protocols across Europe, long-term citizen engagement, and the integration of multi-source data into policy mechanisms. Addressing these areas through coordinated research and shared best practices will be vital for replicating RI-URBANS's success at scale. For this purpose, RI-URBANS developed a dedicated service tool for mobile mapping and citizen science (RI-URBANS, 2024).

Looking ahead, future research should prioritize:

- Development of harmonized calibration and QA/QC standards for sensor networks.
- Exploration of long-term health impacts using more spatially granular hybrid monitoring datasets.
- Studies quantifying behavioural change and policy responsiveness stemming from citizen-led data.
- Expansion of real-time, AI-driven forecasting tools for public and policy use.
- Inclusive governance models that embed citizen science into urban decision-making frameworks.

In summary, RI-URBANS illustrates that with the right blend of participatory science, emerging technologies, and cross-sector collaboration, cities can move toward more responsive, equitable, and effective air quality management. RI-URBANS lays a robust foundation for the future of urban air quality monitoring which future projects should build upon. Continued investment in interdisciplinary research, policy integration, and public engagement will be critical for scaling these innovations and delivering cleaner, healthier cities.

CRediT authorship contribution statement

DB: Methodology, investigation, writing – original draft, **FDP**: Conceptualisation, project administration, funding acquisition, supervision, **JH**: Investigation, writing –

review & editing, **MVP**: investigation, funding acquisition, writing – review & editing, **JK**: Investigation, writing – review & editing, **RMH**: Conceptualisation, funding acquisition, supervision.

Declaration of competing interest

FDP is a member of the editorial board of Atmospheric Measurement Techniques. The other 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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Data availability

This review paper generates no primary data. All data can be aquired via the referenced papers.

6. References

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