Deliverable D13 (D2.5)

Description of methodology for mobile monitoring and citizen involvement

RI-URBANS

Research Infrastructures Services Reinforcing Air Quality Monitoring Capacities in European Urban & Industrial AreaS (GA n. 101036245)

By

VITO, UU, CSIC, ISGlobal, UoB, ICL, UHEL & NOA

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Deliverable D13 (D2.5): Description of methodology for mobile monitoring and citizen involvement

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LIST OF ACRONYMS

BC	Black Carbon
CAPTOR	Collective Awareness platform for tropospheric ozone pollution
HOPE	Healthy Outdoor premises for everyone
HRE	High Resolution Exposure
NO_x	Nitrogen Oxides ($NO + NO_2$)
UFP	Ultrafine Particles
AQMNs	Air Quality Monitoring Networks

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1. About this document

1.1 Background

Air quality is measured routinely through fixed air quality monitoring stations (AQMS). These stations include high-quality monitors that fulfil the data quality requirements as set in the European Air Quality Directive (2008/50/EC). Whereas a network of these fixed stations gives information on temporal trends of air quality, the density of the network is not sufficient to give information on air quality at street level. Some pollutants, especially traffic-related ones (e.g. UFP, BC & NOx), can show a very high spatial and temporal variability within a city or neighbourhood. While established urban networks of fixed site monitors have spatial densities on the order of 1-10 km2, concentrations of air pollutants can vary significantly within 10-100 m from roadways (Snyder et al, 2013; Vanden Bossche et al, 2015). It is difficult to extend the density of the network of AQMS due to their high installation and maintenance cost. As an option forward, utilisation of hierarchical air quality observations with super-sites, air quality monitoring sites and complementary sensor networks with indicative capacities have been suggested (e.g., Kuula et al. 2022).

Improved spatiotemporal resolution of multi-component air quality data is critical for improved understanding of the connection between air quality parameters, human exposure and consequent health effects. In practice, to assess the impact of air quality on health it is important to have fine-scale data on air quality exposure; high spatiotemporal resolution is required for the correct interpretation of actual exposure (Baxter et al., 2013; Kumar et al., 2013). Advances in sensor technologies and the availability of portable and sensing devices for indicative measurements give rise to new opportunities for mobile monitoring and denser fixed sensor networks.

This deliverable arises from T2.3 on mobile monitoring of nanoparticles and citizen observatories to improve evaluation of health effects of long-term. More specifically D13 (D2.5) summarizes complementary approaches to traditional AQMS in order to assess AQ exposure for health and epidemiological studies, and to assess policy actions at urban scale. T2.3 will resulted in a proposed methodology, including involving citizens and mechanisms to enrol citizens that can be readily upscaled at European levels.

This is a public document that will be distributed to all RI-URBANS partners for their use and submitted to European Commission as a RI-URBANS deliverable D13 (D2.5). This document can be downloaded at https://riurbans.eu/work-package-2/#deliverables-wp2

1.2 Scope of this deliverable

Different approaches can be used to assess exposure to pollutant concentrations including Ultrafine aerosol particles (UFP), Black carbon (BC), Nitrogen dioxide (NO_2), particle mass concentrations (PM) finer than 2.5 um (PM2.5) at high spatial scale for epidemiological analyses and for better assessing urban policy actions. Mobile sensing platforms and fixed sensor networks can be used as complementary tools to data from fixed regulatory AQMNs (See e.g. Castell et al., 2017; Morawska et al., 2018; Petäjä et al. 2021; Hofman et al. 2022; Kuula et al. 2022), to map pollutant concentrations at a high spatial density. The aim of this deliverable is to propose a methodology, which will be tested in the pilot sites within the RI-URBANS project (WP4).

The collected high-spatial resolution data can, however, be sparse in terms of temporal coverage and, therefore, needs processing in order to obtain **high spatial resolution exposure maps** (i.e., long-term averaged concentration maps) for epidemiological studies and policy assessment. In this deliverable, we focus on approaches that result in concentration maps that can be used for i) exposure assessment in health studies of long-term exposure to air pollution, and ii) advanced policy assessment at urban scale.

The focus of this deliverable is to describe different approaches for generation of outdoor pollution maps. As an option for future applications, these maps can be utilised to assess personal exposure to air pollution. Although personal exposure of individual participants in health studies can also be directly/individually measured by using

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mobile sensors/instruments (Zhao, Sun et al. 2014, Dons, Laeremans et al. 2017, Fan, Pun et al. 2018, Languille, Gros et al. 2022) that the participants carry along during their daily activities (= personal exposure monitoring), the focus of this deliverable is on the variety of approaches to build high resolution pollution maps in the public domain from which exposure estimations can be derived. This, however, does not exclude outdoor personal measurements as input for such maps (Chapter 3).

High-resolution pollution maps can be of interest for local authorities in a variety of applications; i.e., hot spot detection, new AQMS localisation, model validation, evaluation of policy measures, … (See applications in Table 1). For the remainder of this document, however, we will focus on the use of these maps for exposure assessment. Because of the size of epidemiological study populations, personal exposure measurements are not feasible. Epidemiological studies rely on outdoor concentrations as an approximation of personal exposure (ideally at a high spatial resolution). Consistent with these studies, we use the term exposure.

In more detail, this deliverable discusses mobile measurements and sensor networks to generate high resolution exposure (HRE) maps. Such measurements can be collected by citizens or can be collected by research institutes or AQMN. Involving citizens in data collections requires a simple and straightforward monitoring instrument and user-friendly methodology. When using more complex/expensive instruments and/or methods, there is a need for experienced staff to perform the measurements. In this deliverable we make a distinction between **mobile/fixed measurements** and experimental designs **with/without citizens** (see Figure 1).

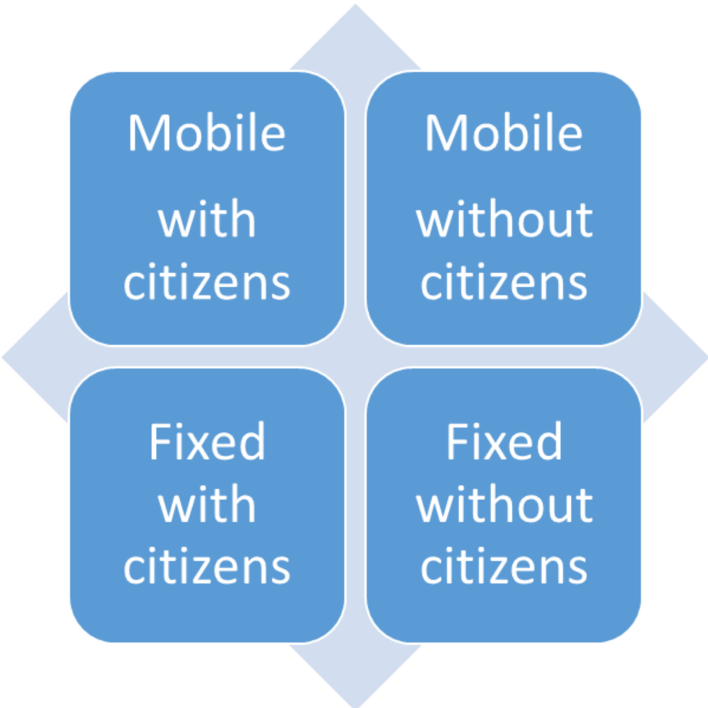

Figure 1: Schematic overview of different approaches for collecting data for high-resolution exposure mapping as discussed in this deliverable.

The collected data can **be processed and analysed** using only measured data or using interpolation /modelling techniques like Land Use Regression (LUR)-based or machine learning models. The selected techniques used for data processing may have an impact on the required data collection approach.

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1.3 Users of the data of these high-resolution maps

Whereas the focus of this deliverable is to describe approaches for better exposure assessments by outdoor concentration maps, mobile mapping and sensor networks can also be used for other applications. In this section, we give an overview of different use cases for high resolution concentration maps, while focusing on exposure assessment in the remainder of the document.

The users of the high-resolution concentration maps/data are:

- Researchers.
- Epidemiologists.
- Local authorities (municipalities/cities).
- Regional authorities (e.g., exploiting AQMN).
- Stakeholders working on navigation (e.g., Garmin, TomTom, Polar): e.g. (healthy) routing applications.
- Stakeholders working on health technology/wearables (e.g., Apple, Fitbit, Garmin, Polar): such as smartwatch, trackers.
- Citizens who are curious of the air pollution in their street.
- Real estate agencies that provide air quality labels for their real estate.
- Other end-users who are interested in the variability of air pollution in high-resolution.

Cities and AQMNs can also be interested in using these high-resolution maps/data for:

- Hot spot detection (e.g., for selection of relevant new AQMS locations or targeted abatement policies).
- Evaluation of policy measures (when comparing data collected before and after introduction of the measures, e.g., traffic measures).
- In support of evidence-based policies: e.g., target areas for policy measures to reduce exposure (e.g., location of facilities for vulnerable groups like schools or hospitals).
- Evaluation/improvement of dispersion models.
- Exposure assessments in health studies.
- Implementation of route-planner apps which can help citizens understand and reduce their exposures to air pollution.
- Gap-filling for certain pollutants not monitored by the networks (e.g., UFP, BC, LDSA), using virtual sensor proxies.

Local authorities (municipalities/cities) are important stakeholders and can also play a role in the recruitment of citizens. The involvement of citizens is discussed in this deliverable (Chapter 2). We will focus here on recommendations on how citizens can be motivated and engaged and how results/feedback can be communicated.

How the information from this D13 (D2.5) has to be taken up by the stakeholders is part of WP5/WP6. Finally, T6.2 will focus on how the developed concept can be integrated in a sustainable way in AQMNs and the engagement strategies that can be used.

1.4 Examples of use cases

Different use cases require highly spatially resolved air quality data in a specific manner. The use of sensor networks or mobile monitoring can give insights that are currently not feasible based on regulatory AQMN alone. However, the required density of the data (moving speed/monitoring resolution), the set-up, potential confounders (noise/turbulence/vibrations), pollutants measured, required data quality will vary from one use case to another. Also, the added value of engaging citizens depends on the use case. Table 1 below gives an overview of possible use cases and highlights the most important requirements.

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In this deliverable, **we focus on the use of high-resolution maps for exposure assessment in health studies**. However, these maps can also be used for other use cases. Note that the data processing, data collection or monitoring set-up might be different depending on the considered use case. Some requirements linked to specific use-cases are listed in Table 1, however, this is not an exhaustive list.

Best practices and tools when deploying mobile or fixed sensor networks (e.g., monitoring setup/calibration/data processing/communication) have also been described in several guidebooks/blueprints:

- Air Sensor Guidebook
- AQMD Sensor Educational Toolkit
- VITO Blueprint for Municipal Air Quality Sensor Networks
- VAQUUMS Air Quality Sensor Roadmap
- Assessing air quality through citizen science, EEAR report 19/2019

These guidelines primarily focus on stationary networks of sensors and do not extensively address mobile approaches. Moreover, in some cases they focus on community-based sensing, including guidelines for citizens on how to use these sensors. The US EPA sensor Guidebook lists applications for sensors like education and information; hot spot monitoring and source characterisation; supplemental monitoring (in addition to fixed AQMN), personal exposure; awareness raising, research. The current version will be updated in 2022 (https://www.epa.gov/air-sensor-toolbox/how-use-air-sensors-air-sensor-guidebook).

Table 1: Overview of different use cases and associated requirements for high-resolution air quality maps.

Use case	User	Requirement
Hot spot detection: in an industrial or in an urban setting	Policy maker Company citizens	Spatial monitoring coverage: entire city or targeted monitoring setup
Evaluation of mobility plans (Low Emission Zone, pedestrian zone, school streets,…)	Policy maker, citizens	Representative sampling (both in time & space)
Evaluation of action plans: e.g., in an industrial area; can be an action to reduce pollution or an action that is thought to deteriorate air quality in the surrounding area.	Policy maker, citizens	Representative sampling (both in time & space); compound specific analysis
Evaluate (the need for) new/alternative AQMS locations	Researcher Policy maker	End result can be compound specific; Interdependency between the new and existing observation sites (network optimisation)
Source identification for secondary pollutants (e.g., ozone in rural areas)	Citizens and policy makers	Need to have sufficient data covering a broad spatial area. Example: CAPTOR project (https://www.captor-project.eu/es/)
Evaluate exposure in specific location, such as school surroundings (both environmental and health related)	Exposure scientist, Policy maker, Concerned citizen	Representative sampling (both in time & space); compound specific analysis

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Evaluate cleanest routes to school	Exposure scientist Policy maker Company, Student / Parent	Representative in terms of sampling platform, routes, means of transportation, air quality compound.
Evaluate exposure in health studies (a.o.. HBM)	Exposure scientist	Representative in terms of locations, people, routes. High accuracy
Impacts of cooking emissions from restaurants in cities	Policy maker	Locations/number of sensors Accuracy: important when focused on absolute values/source attribution, not priority when focused on awareness raising (plume/event detection + impact hours)
Wood burning problems in a neighbourhood: gather evidence and evaluate impact	Researcher Policy maker Citizens in the neighbourhood	Locations/number of sensors Accuracy: important when focused on absolute values/source attribution, not priority when focused on awareness raising (plume/event detection + impact hours)
Alert network during calamities	Researcher Policy maker Company Citizens	High density network, peak detection Accuracy of lesser importance (e.g. forest fires)
Improve air quality modelling by increasing number of validation locations (in addition to regulatory monitoring network)	Researcher	High accuracy! Compound specificity.
Raising awareness of citizens (on air pollution/specific sources)	Citizen awareness	Representative in terms of locations/sources/locations Communication is key Accuracy of lesser importance
School education: first grade (introduction in AQ)	Students	Communication is key Accuracy of lesser importance
School education: High school (evaluations/experiments)	Students	Communication is key Accuracy of lesser importance
Adults (participation in a network)	Citizens	Communication/feedback is key
Wood burning problems in a neighbourhood: raising awareness	Citizens, city officials	Communication/feedback is key Accuracy of lesser importance Need to put the different air quality parameters in perspective against other health hazards
Evaluate exceedances of limit values	Regulatory monitoring	High accuracy Long-term calibration approach
Provide real estate with AQ labels	Company	High accuracy/comparability; Compound specificity
Provide healthy routing services	Company, Citizens	Qualitative (e.g. avoiding peaks/trends) vs Quantitative (Accuracy!)
Provide exposure metrics in health applications/wearables	Company, Citizens	Qualitative (e.g. avoiding peaks/trends) vs Quantitative (Accuracy!)

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2. Citizen involvement and motivation: General recommendations and best practices

A significant part of the EU society is worried about air quality but is unaware of EU air quality regulations and the current air pollution levels in their countries (Perelló et al., 2021 and references therein). The involvement of citizens in air quality monitoring is a growing practice, recommended by the European Environmental Agency (EEA, 2019), that can bring important benefits to both science and society. Some of these benefits are described below.

2.1 Scientific and societal benefits of citizen science for air quality monitoring

From a scientific point of view, citizen science experiments in air quality monitoring can help to obtain reliable, up-to-date, cost-efficient and high-resolution air quality data in a timely manner. High-spatial resolution air quality monitoring is particularly necessary for effective exposure assessment of pollutants of high spatial variability (e.g: NO_2, BC and ultrafine particles) (Perelló et al., 2021 and references therein), and for validation or calibration of urban air quality models. However, the access to traditionally measured high-resolution data is limited by its high costs. Depending on the number of volunteers, citizen science experiments can be used to measure air pollutants in large areas at high spatial resolution (e.g., street level), and complement data from the official urban/traffic air quality stations, which are often insufficient in number. Citizen science may also motivate the development of innovative solutions to air quality problems.

In addition to scientific benefits, experiments involving citizens can promote positive changes in society by, for instance, increasing public awareness to air quality problems, and influencing environmental activism and policymaking (Huyse, Bachus et al. 2019). Citizen science experiments also motivate public learning about science and scientific methods (Perelló et al., 2021), and enhance retention of information in comparison with traditional learning methods (Vohland et al., 2021 and references therein). Through air quality citizen science projects, citizens learn about the current state of air quality in their community and how they can influence it (“seeing is believing”). Dissemination of scientific results (e.g., knowledge) through communities and participants’ social media, further contributes to public environmental awareness and engagement, scientific interest and future public inclusion. An important advantage of citizen science experiments is that they may lead to long-term changes in public environmental perceptions and behavior, which may then contribute to air quality improvements. For instance, participants may opt for environmentally friendly actions such as the use of public transportation, advocate for increasing the number and size of green spaces at the community level, etc.

2.2 Recommendations on how to motivate and engage citizens

Motivating participants is essential for the success of any citizen science project. Below, we list some examples on how to motivate public participation.

Educating participants on the air pollution levels they are exposed to, for instance, during daily commuting routes, and on the effects that this exposure may have on health may motivate citizens to participate in air quality studies and take actions to decrease air pollution.

Educating participants on the complexity of air pollution, like various pollutants, meteorological impacts (e.g., wind, temperature inversions), chemical reactions (e.g., photochemistry) and source contributions (cross-boundary, regional, local) in order to manage citizen expectation.

Public engagement increases when the values of citizens and their community concerns are taken into consideration (Vohland et al., 2021, and references therein). For this reason, whenever possible, citizens should participate in every step of the project and be considered research team members rather than users. Citizens and communities may contribute to the formulation of research questions, search for scientific methods and co-develop project rules. For example, in the xAire project in Barcelona citizens co-designed the study by deciding on which streets the NO_2 Palmes tube passive samplers should be placed (Perelló et al. 2021).

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Diverse entry-points and levels of commitment may increase citizen engagement (Vohland et al., 2021). As an example, the CitieS-Health project developed in Barcelona offered citizens three levels of participation: one in which citizens only answered health-related questionnaires and provided their residential address for air pollution exposure estimation; one in which, in addition to the above mentioned, they shared their geolocalisation (to be able to use spatiotemporal air pollution predictions); and another one in which, in addition to the previous information, they carried a passive tubes to measure NO_2 concentrations (Basagaña et al., 2020).

Citizen science studies should not require from the participants advanced skills or too much preparation as prerequisite. As participants often lack a scientific background, citizen science projects should rely on easy-to-learn tasks, and ready-to-use, easy-to-understand monitoring sensors/sampling/indicators rather than complex ones. One example of this is citizen science contribution in Healthy Outdoor Premises for Everyone (HOPE, Petäjä et al. 2022) project in Helsinki that distributed simple to use multicomponent sensors to the citizens with automatic data collection and upload to cloud service and visualisation. This allowed the citizens to explore air quality in their close vicinity with ease (Rebeiro-Hargrave et al. 2022).

Involving as many actors as possible in the citizen science experiments (e.g., public and private sectors, policy-makers, etc.) improves synergies and supports the development of efficient air quality regulations, which may further motivate future citizen participation.

Communication is key to obtaining realistic expectations from citizens and avoiding disappointment, e.g., on data quality, use of data, own impact. Workshops or other community events can be useful to clarify to citizens the research motivations, to discuss what will be done with the information collected, and to clarify what they will obtain (e.g., a report) and when, and to manage citizens' expectations. In addition, data sharing, communication of project results in a timely manner, and acknowledging citizens participation, particularly in scientific publications, are suggested to increase satisfaction and motivation of participants for future collaborations (de Vries et al., 2019). Sharing preliminary results and/or personal reports (personalised results) with the participants during the project, instead of only at the end of the project, may also increase motivation.

2.3 Ethics for citizen science experiments

Just like with any other research involving humans, ethics is a major issue for citizen science studies, as these studies often collect personal data, geolocation and individual exposure to air pollutants. However, the ethical implications, and therefore the actions needed to implement, may vary depending on the nature of the study. E.g., it is not the same to participate in measuring air quality in a given public location than measuring personal exposure to pollution, which includes addresses and routes that can lead to identifying the participant. When health data are including ethical issues are even more complicated.

In general, before taking part on the study, all the participants should sign an **informed consent form** which contains the purpose of the study, all the potential risks and benefits the participant are exposed to during the study, the type of personal data collected and their freedom to decide how the data will be used. The form should also contain information on who will have access to the data (name and position of the responsible personnel) and contact information of the investigators.

The participants should be aware of their freedom to withdraw their participation from the study at any moment (Kocman et al., 2019) and to request elimination of their personal data from the study or limit the usage of their data for future studies (Basagaña et al., 2020).

Consent forms may be dynamical in nature, being updated whenever the researchers or participant researchers feel that new information should be added (Vohland et al., 2021). "Dynamic consent forms" allow for adaptation of consent forms to issues that may arise throughout the project. The dynamic nature of consent forms may also raise issues; responsible investigators need ensure that they comply with national and/or regional guidelines.

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Regarding data security, citizen science studies should comply with the **General Data Protection Regulation (GDPR)** and any other local or institutional regulations to ensure protection of personal data. For this purpose, all personal data collected by the project (including questionnaires and sensors) should be anonymised before data analysis to avoid identification of the participants. Similarly, project results should be released in an aggregated form to preserve participants identity. Personalised reports sent to individual participants are possible and often an important motivation to participate in a study. Identifiable information should be kept in a password secured environment and accessed only by authorised personnel. All the project personnel should be trained in how to handle confidential personal data, and sign confidentiality agreements (Basagaña et al., 2020). In addition to protecting personal data, project photos that allow identification of participants should not be published without previous consent (Vohland et al., 2021 and references therein).

Other ethical considerations include treating participants as research partners and not just as data providers or "free labour" by involving them in the decisions, and ensure that the study is designed in a way that minimizes the risk that potential biases of the researchers or participating citizens can influence the results.

2.4 Recruitment process

Recruitment of participants can be done for instance through announcements on social media, newspapers and outdoors e.g., in metro stations or similar public places.

Researchers are recommended to investigate motivations and obstacles for participation, and offer tasks that require different levels of engagement based on participants interest, availability, experiences and motivation (Vohland et al., 2021). While the level of participants' experience should be taken into consideration, inclusive communication strategies should be used. For instance, the use of words like "unskilled" may demotivate engaged participants (Vohland et al., 2021).

Simple training should be provided for all the participants explaining project objectives, methodology guidelines, data quality requirements and instrumental usage. A short general introduction to air quality can also help; the level needs to be fine-tuned for the target group.

To avoid frustration, demotivation and participation withdrawals, researchers should be aware of the participants motivations and clearly explain how the project goals align with their expectations. Especially, it should be clear that participating in a research study may not directly lead to changes in environmental policies. One way to improve the level of citizen commitment is to organize an event midway through the citizen science project with a target to discuss initial results, tackle technical challenges and provide an update on the scientific objectives and recent findings. This also underlines to the participating citizens the continuing commitment and progressive insights of the scientific team. To conclude the action, it is important to organize a closing event.

2.5 Representativeness and diversity in citizen science

Diversity in citizen science recruitment improves inclusiveness, and brings varied experiences and perspectives to the project which may result in technological development and innovative solutions. Whenever possible, participants should be selected from different socio-economic backgrounds, cultural status, educational level, location, ethnicity, disabilities and gender. Workshops where successful female scientists talk about their experience in science may be a good way to motivate female participation in citizen science (Vohland et al., 2021). Inclusion of including different ethnic groups may be difficult especially if language problems play a role.

The development of tools that facilitate the participation of people that would otherwise have difficulties in participating in the study are also recommended. The D-NOSES project (funded by Horizon 2020) for example, complemented the odour pollution data collection method, traditionally done via a smartphone application, with the use of "Odour diaries" aiming at increasing the participation of people that find difficult handling technology (e.g., the elderly). Alternatively, training on the use of mobile applications and participation in different languages

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could be offered to improve inclusiveness (Vohland et al., 2021; and references therein). In general, data collection strategies should adapt to the varying community capabilities (e.g., socio-economic levels) and concerns (Vohland et al., 2021).

2.6 Data collection

2.6.1 General

Air quality citizen science studies often require citizens to measure air pollutants or report on the participants' perception of air quality (e.g., D-NOSES, Vohland et al., 2021). Because citizen science participants often lack scientific background and often the air quality sensors used in these experiments are less accurate than reference methods, data quality is a common concern in citizen science projects. This however, may be less of an issue in co-created citizen science projects, with involvement of researchers and research grade instruments. Citizen science is not synonymous with the use of low-cost sensors (Froeling, 2021).

Data quality has a direct influence on the project impacts (Kocman et al., 2019; and references therein). One should not get the impression that a citizen science study equals a study with low-cost sensors. Citizen science studies can indeed use research-level equipment and, in any case, the data obtained must be as accurate, complete and as relevant as possible. Of course, this needs to be balanced with budgetary constraints, but one should ensure that the project will provide data that is useful, otherwise there is no point in conducting the monitoring campaign.

Other considerations apart from quality of the data come to play when deciding the sensors or instruments to be used, for example that they are light weight and small (if they need to be carried out by citizens for some period of time), and that its instructions of use are easy to understand (Kocman et al., 2019; and references therein).

Researchers and citizens are encouraged to co-create standards for data collection, deciding for instance the location at which sensors should be placed, for example to capture certain sources, to have good geographical variability, or to cover places that are frequently visited by citizens or certain vulnerable populations (e.g., children or the elderly). Other issues such as the time or frequency of measurement can also be decided in collaboration between scientists and citizens. Citizens can also help in making the study protocol or instructions more understandable. In addition, researchers and participants may co-develop strategies to avoid misconduct of research participants. Finally, the project should make all the efforts to generate data under the FAIR (findable, accessible, interoperable, reusable) principles.

2.6.2 Low-cost sensors for air pollution monitoring

Since air quality may be measured at a large number of locations in citizen science studies, common budgetary constraints will point towards the use of low-cost sensors or passive samplers. Nowadays there exists a wide variety of low-cost sensors for measuring a wide range of pollutants, including gaseous (e.g. NO_2, O_3) but also particulate matter (PM).

While low-cost sensors are still unavailable for measurements of ultrafine particles (UFP) (Morawska et al., 2018), PM concentrations can be measured by light scattering low-cost sensors. These sensors however are only capable of measuring particles starting from 0.3 µm in diameter, as smaller particles do not scatter light sufficiently and therefore cannot be detected by the photometer (Rai et al., 2017). It is important to notice that the algorithms used by some sensors to convert signals to particle size are potential sources of error for particle size classification (Rai et al., 2017; and references therein). For this reason, the use of size selective mechanisms, such as impactors and filters, to select particle size (e.g., < 2.5 µm) before entering the instrument are recommended (Rai et al., 2017). It is also very important to note that measuring PM in high relative humidity conditions is very complex since condensation of water interferes with PM measurements, without any possible correction.

In terms of performance, the inter-sensor variability is usually rather small while the comparability with the reference method can be significant. As environmental variables such as temperature and relative humidity may

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affect sensors performance, users are advised to calibrate the instruments under conditions that are similar to those found at the experimental location (Rai et al., 2017). In general, the overall performance of PM sensors is considered reliable when the instrument is properly used and calibrated (Kocman et al., 2019, Hofman et al., 2022; Rai et al., 2017). Monitoring devices are discussed further in Chapter 0 (mobile) and 0 (fixed).

2.7 Data validation

Quality control of the sensors or passive samplers used for citizen science studies should be carried out before, during and after the measurement campaigns. The sensors and/or samplers used in the study should be collocated and compared between themselves and against a reference instrument before the start of the study to ensure their performance is acceptable for data collection. During data collection, it is also advised to perform continuous (e.g. keep 3 sensors co-located next to AQMS) or periodic (e.g. periodic co-locations of used sensors during project) inter-comparisons to assess their performance after some use. Finally, after the measurements are finished all the sensors should be collocated to evaluate their performance at the end of the study and identify potential malfunctioning. This methodology, amongst others, was implemented by Karagulian et al. (2020) and Hofman et al.

Data quality may be validated for instance through the use of testing protocols that aim to estimate the performance of air quality sensors used in the citizen science study in comparison with reference instrumentation. Examples of parameters that can be tested are: linearity between concentrations measured by a reference instrument and those measured by the sensor; accuracy; precision (variation in concentrations from simultaneous measurements); response time to changes in concentrations; lowest detection limit (lowest reliable concentration measured) and detection range; effects of changes in temperature and relative humidity on measured concentrations; and interferences caused by the presence of other air pollutants (Morawska et al., 2018).

2.8 Dissemination of results

Dissemination is an essential step to inform the general public about the study and the importance of the results to society (Arévalo Nieto et al., 2016). Because the project results should be disseminated to different types of audience (e.g. scientific community, general public, policy-makers, etc.) it is recommended that different divulgation and communication strategies are used for each audience group (Arévalo Nieto et al., 2016).

Dissemination of project results and lessons learned is usually done through scientific publications, conferences, social media, newspapers, etc. While these forms of dissemination are efficient to inform the general public, they are “one-way messages” that do not encourage feedbacks from the participants.

Specific activities for dissemination of citizen science project results should be put into practice to allow discussion and questions from all the participants in the study and other audience that could be interested. For instance, it can be done through science cafes, where participants have the opportunity to ask questions, ask for clarifications, or suggest actions. Other options could be online webinars/workshops or informal/festive meetings with time for questions and discussion. Interactive dissemination events are often more inclusive in terms of local participants and stakeholders; hereby facilitating behavior change and local impact in communities more easily than scientific papers or reports.

2.9 Impact Assessment

Citizen science projects may have a number of positive impacts on the scientific community, the citizens, the environment and society as a whole. Kocman et al. (2019) and references therein identified 5 different areas in which the impacts of citizen science projects may be assessed: scientific, individual, environmental, societal and health.

Some examples of impact assessments from the scientific point of view would be the generation of new scientific knowledge, e.g., the number of innovative publications and theses generated by the project as well as number of citations (Kocman et al., 2019; and references therein).

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The impact on individuals may be measured by improved personal skills and the participants satisfaction, evaluating motivation levels and the participants intention to continue participating in citizen science projects in the future (Kocman et al., 2019; and references therein). Phillips et al. (2014) created an evaluation framework for individual learning that takes into consideration changes in behavior and stewardship; increase in interest for scientific topics, activities and careers; confidence on one´s ability to participate in science; and knowledge about scientific processes and research conduct, among others (Kocman et al., 2019; and references therein).

The project impacts can also be measured in terms of environmental improvements, for example enhanced air quality as a consequence of changes in community´s behavior or project influenced changes in air quality policies.

Societal impacts may be an increase in public awareness for environmental issues, or an increase in the number of environmental policies created. Citizen science projects may also be evaluated in terms of improvements in communities' health (Kocman et al., 2019; and references therein).

The above-mentioned outcomes may be evaluated for example through (i) diaries of in-person events; (ii) online and phone interviews; (iii) satisfaction and self-assessment surveys; (iv) group discussions, (v) workshops; (vi) observation of participant behavior (ethnography), and (vii) by questionnaires that assess knowledge about science and understanding scientific methods (Kocman et al., 2019; and references therein). These evaluation tools, when combined, provide both qualitative and quantitative data, and may be used before the project begins, during and after the project is finished.

In addition to the above-mentioned tools, participants are recommended to co-design **impact assessment protocols** with the researchers (Kocman et al., 2019; and references therein). Some projects such as InSPIRES and MICS have developed tools for impact assessment. This bottom-up approach creates assessments based on public interests rather than solely political or scientific aspirations. One way to involve citizens is to create an interactive assessment where the protocol is changed based on participants feedbacks, which may include evaluation questions, anticipated impact outcomes, and the best way to estimate their value (indicators) (Kocman et al., 2019; and references therein). Citizens may also collaborate on the impact assessment data collection, analysis and on the elaboration of the impact assessment report.

3. Mobile monitoring

3.1 Objectives and data needs

A mobile platform provides the possibility to sample spatially diverse environments in a limited time and with a limited number of (costly) monitoring devices. Together with advancements in air monitoring instrumentation, such as higher time resolution and greater portability, these platforms can capture the high variability of air pollutants in space and time in a complex urban terrain. At the same time, mobile measurements usually consist of only a few seconds of data per street segment, needing temporal aggregation in order to be representative for the long-term/average exposure. Fixed sensors/instruments provide high-resolution time series of air quality data, representative for one location, but offering low spatial coverage. So mobile platforms can serve more locations but need more repetitions in time, whereas fixed sensor networks provide temporal profiles but at a limited number of locations.

In this section, we describe the objectives and data needs for mobile mapping in terms of exposure assessment. The approach of mobile measurements and the requirements for the set-up and instruments might be different when one wants to make an air quality map for exposure assessment as compared to a map for hotspot detection. Data collected during mobile measurements can be used (i) directly, (ii) to evaluate dispersion models, (iii) as input for data-driven models (LUR, machine learning or others). Here, we consider mobile measurements when data is

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collected by instruments that are in motion; opposite to data that is collected by portable instruments that are moved from one location to another in order to collect stationary data over short periods.

3.1.1 Monitoring strategy

It is very important to think in advance about the monitoring strategy (**Error! Reference source not found.**related to the use of data before data collection is started. Slight changes in the data collection scheme might result in considerable improved final results. At the same time, the required (personnel) efforts need also be taken into account e.g. opportunistic data collection can result in a wealth of data with limited staff resources.

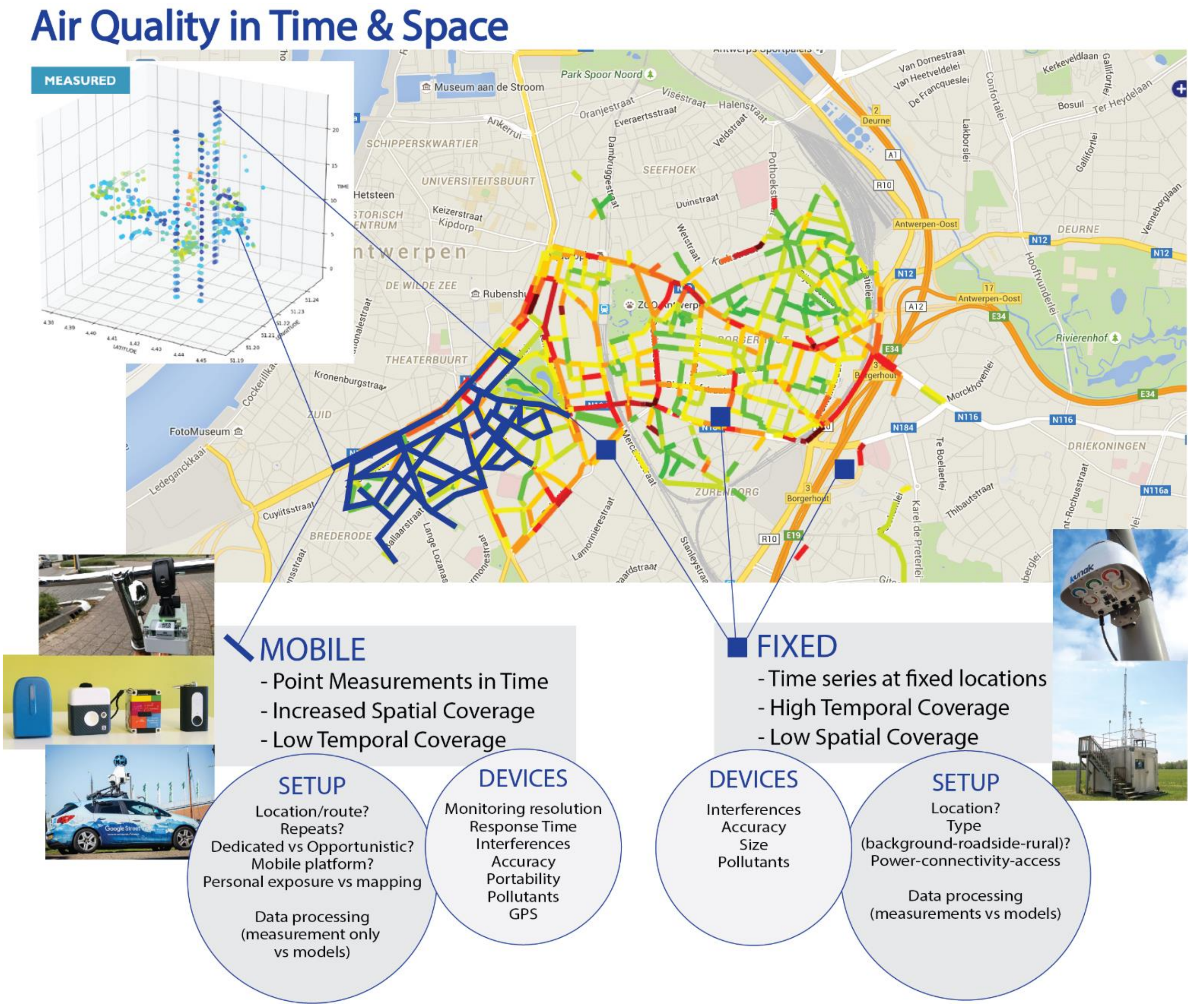

Figure 2: Difference between mobile and fixed air quality measurements in terms of monitoring setup and device requirements.

In this section, we reflect on the data needs on different levels (measurement scheme, monitoring devices, data processing...) as function of how data will be used for and how they will be processed. At the same time, the data processing itself is important for the final result.

The monitoring setup for mobile measurements (**Error! Reference source not found.**), i.e. air quality measurements performed on a mobile platform (walking person, bicycle, car, tram, …), needs careful consideration as the applied mobile platform, measurement timing (e.g. hours of the day), location and routing will determine the

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representativity of the data for the intended application. Thinking about high-resolution exposure maps, it will be important to collect enough monitoring data in both space and time to represent the average air pollution exposure. Moreover, while one can opt for a **dedicated monitoring approach** strictly defined in terms of considered route/number of repeats/hours of the day, an **opportunistic approach** could allow for the collection of more data (in time and space) using existing mobile platforms (eg service fleet vehicles/city servants/…) for data collection. However, design of each approach (e.g. study population) has also an impact. Mobile instruments and IoT sensors are diverse and specific requirements are applicable for mobile monitoring (e.g. high monitoring temporal resolution (depending on the mobile platform used), low response time, relevant pollutants, GPS functionality, portability). In order to obtain time and space representative data, the collected point measurements will need to be processed, either (i) by aggregating /averaging the measurements (ii) by using measured data and statistical techniques to interpolate between time/space instances (IDW/Kriging/…) (Carreras et al., 2020; Hofman et al., 2018; Peters et al., 2014; Qiu et al., 2019; van den Bossche et al., 2016), or (iii) by training models (LUR or machine learning), often in combination with contextual data (e.g. meteo, traffic, spatial) to explain the observed measurements and extrapolate to unknown time/space instances (Boniardi et al., 2019; Do et al., 2020; Hoek et al., 2011; Hofman et al., 2022a; Lim et al., 2019; Qin et al., 2022; Van den Bossche et al., 2020). Data processing is further discussed in one of the next sections.

Compared to mobile measurements, fixed air quality monitoring is more straight forward in terms of setup and instrumentation. As the location is fixed and continuous data is being collected, the approach is by definition representative for that location. However, this representativity of primary importance depends on the considered source environment (urban background, roadside, rural), wind direction, practical requirements (power, connectivity, space)… and is sometimes also a function of practical constraints (power supply, fixing material...). Fixed measurements do not require a high (<1 min) monitoring resolution and are more stable/controlled in terms of turbulence, vibrations, temperature, … Again, data can be reported per location, or inter/extrapolated by mathematical techniques (IDW, Kriging,…) or LUR/machine learning models.

Data needs for mobile monitoring that have to be defined are related to (see also Figure 1):

- Monitoring set-up (route/area, time) = *measurement scheme*; this is a function of use case.
- Parameters/pollutants to be studied; of course, this is function of the data use; when looking at spatial monitoring for exposure mapping it is important to select the parameter that has a strong spatial variability and is of importance in terms of health effects; e.g. it is not relevant to start mobile mapping for a parameter that is expected to have no spatial variability or is not relevant in terms of health effects. It might be useful to map a pollutant that has no direct health effects but is a good proxy for another health-related pollutant.
- Data processing: which data processing models are used – are data extrapolated / interpolated?
- Main distinction between measurement-only maps or maps constructed with models (for example LUR or statistical/machine learning models).
- Data use: two main categories (considered in this report) can be made. Exposure assessment versus hot spot detection: a different data collection approach is used in terms of route/ time.
- For exposure assessment we focus on mobile measurements to construct exposure maps.
- Exposure maps to inform epidemiological studies.
- Exposure maps to inform public and policy.
- For hot spot detection, distinction can be made between known and unknown hot spots-> screening around a known source (or source area) to assess impact on the environment versus screening in a (city-wide) area to find main hot spots.
- Monitoring devices; some specific requirements for mobile mapping are:
    - Response time.
    - Interferences (fast changing conditions in terms of concentrations and interferences).
    - Accuracy.

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- Practical requirements: portability, resilience to shocks and vibrations,...
- Pollutants to be studied.
- (High) monitoring resolution (depending on the mobile platform, typically <1 minute; ~1-10 sec).
- GPS.

- The requirements can be fine-tuned in function of:
  - Data use: (see points above); the accuracy might be different for exposure assessment compared to hot spot detection,
  - Platform of mobile monitoring: with citizens versus without citizens.
- Data processing: The required data processing is a function of data use (at what spatial and time resolution are data needed) and of data collection strategy.

3.1.2 Targeted versus opportunistic approach and involving citizens or not

Mobile monitoring can be performed by **repeating predefined fixed routes** or using a more **opportunistic approach**, using a carrier that performs the measurements during its day-to-day activities without intervening with these activities. Mobile monitoring can be performed with or without the help of citizens.

Another term used in relation to mobile sensing with citizens is Mobile Crowd Sensing (MCS) (Brahem et al., 2021). MCS depends mainly on the use of the people's sensor-enabled mobile devices (e.g. smartphones) carried along during their daily activities, to collect for a particular sensing task. However, currently no mobile devices exist that have good air pollution sensors integrated.

Mobile crowd sensing refers to a broad range of community sensing mainly participatory sensing and opportunistic sensing; Brahem et al. (2021) explain *participatory sensing* as data collection by citizens who measure their own exposure and observe their own environment. When data collection is entirely automatic, the data collection is referred to as *opportunistic* sensing. In the remainder of this deliverable, we refer to opportunistic sensing not strictly to approaches where all data collection is entirely automatic but relate it to the way the data is collected in time and location (not predefined in terms of routing/data coverage).

Van den Bossche et al. (2016) defined opportunistic mobile monitoring as data collection making use of existing carriers to move measurement devices around. The movement of the carriers (the travelled route) is uncontrollable from the point of view of the researcher, as it is not designed and performed with the data collection in mind as primary goal. The data collection takes advantage of **existing mobile infrastructure** or **people's common daily routines**. This contrasts with targeted mobile monitoring, which is a coordinated, goal driven approach in which the mobile measurements are **deliberately planned and carried out with a specific purpose in mind**. The carrier can be citizens, a certain professional group (e.g. city wardens, home nurses, taxi drivers), but also a vehicle (postal van, bus, tram...).

Opportunistic mobile monitoring is a promising approach to collect large data sets that give useful additional information at a reasonable cost compared to classical data collection methods. But, depending on the set-up of the data collection, such new data can lead to new challenges in data processing and interpretation. Campbell et al. (2008) described opportunistic way of data collection already in 2008 as 'opportunistic people-centric sensing' where small computational devices were carried by individuals in their daily activities to collect information related to human activity and to the environment around them (Campbell et al., 2008; Kumar et al., 2015). This approach was utilised in Helsinki in HOPE project, where 100 volunteer citizens carried air quality sensors and made observations during their normal movement within the city (Rebeiro-Hargrave et al. 2022). This provided information on the local air quality but also about urban mobility.

Opportunistic data collection can take different forms (Van den Bossche et al. 2016). Firstly, they can vary according to the degree of human interaction they need. Possible human interactions are related to carrying the

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measurement system, the operation and maintenance of the measurement system and to the data collection and handling. Examples of campaigns that can run independently for long periods without human interaction after initial set-up are those based on sensors mounted on vehicles such as cars, buses or trams. The more human interaction the data collection needs, the more the user-friendliness of the instrument and the motivation of the people involved become important issues. In this deliverable, we make a distinction between data collection **'with' or 'without' citizens**, referring to the carrier. Secondly, the data collection can follow a repeated structure along the same routes and/or within the same time frame or can be rather unstructured. Whereas opportunistic approach is not goal-driven (see above), depending on the involved carrier, the data collection can be rather structured (e.g. commuting to work).

The studies of deSouza et al. (2020), Hasenfratz et al. (2015), Hofman et al. (2022) and Hagemann et al (2014) are examples of opportunistic data collection with a fixed structure, as they performed mobile measurements with sensors installed on the roof of public transport (trams) or service fleet vehicles (postal vans). In these cases, the measurements were restricted to the route of the bus or the tram tracks. Another example of fixed routes are a dedicated monitoring vehicle (Apte, Messier et al. 2017) or commuters performing mobile measurements (e.g. Weichenthal et al., 2008; Moreno et al., 2015; (Carreras et al., 2020; Hofman et al., 2018; Peters et al., 2014; Qiu et al., 2019)), although in this case the route taken is more flexible. Aoki et al. (2009), who built an environmental air quality sensing system and deployed it on street sweeping vehicles, can be situated somewhat in the middle between predefined route or unstructured set-up.

The study of Van den Bossche et al. (2016), involved city wardens carrying measurement devices during their daily surveillance tours resulting in unstructured measurements without distinct patterns in space or time. The studies of Hasenfratz et al. (2015), Hagemann et al. (2014) and Hofman et al. (2022) require limited human interaction as the sensor nodes are supplied with power from the vehicles and data are transmitted automatically (Hasenfratz et al., 2015). When using citizens as mobile carriers (Weichenthal et al., 2008; Van den Bossche et al., 2016), more human interaction is needed.

The choice of targeted versus opportunistic monitoring holds some consequences for the processing and interpretation of the data. The advantage of a targeted approach (fixed route and sampling period) is that all sections along the route are measured 'quasi-simultaneously' during the same days, seasons,... etc. which makes it easier to compare different datapoints in space and also makes it easier to perform background scaling to e.g. yearly average values. A drawback is the workload: when citizens are involved, they have to drive/walk the route in addition to their normal activities and when a vehicle is used, a driver needs to be paid to do the measurements.

The opposite is true for the opportunistic approach. From the perspective of the researcher, there is no control over the specific location and time of the measurements. This could result in sampling bias where certain urban microenvironments are underrepresented or absent in the data. The same holds for the time of sampling. A bias in time can appear in the case of data collection by commuters; the measurements are mainly limited to rush hours and no data will be available during working nor non-working (night time) hours. For the same group, we can also have a sampling bias in locations when e.g. a group of people from one company is selected because all of them commute to the same location and each takes the same route every day (the location bias is than dependent on where they live). Another example is a postman or a parking warden who will not frequently enter green zones such as parks. Also, a time/space bias is possible: this means that data is sampled at the same locations for specific time slots; this can be an additional issue compared to the time or space bias where we just have a lack of data on certain locations or time slots. An example is a postal van or bus driving the same trajectory and always sampling at point A during morning peak hours and at point B during quiet moments (e.g. noon or evening). This might give a wrong idea of the spatial pattern and resulting in an underestimation of concentrations at point B and overestimation at point A. When using an opportunistic approach, the expected sampling time and route needs to

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be evaluated in advance and data processing techniques including scaling for varying background concentrations needs to be considered.

As a consequence, there will be different measurement conditions for different locations, hindering the comparability of the results between these locations. This is a major problem, as it complicates the data interpretation (the comparison of the measured concentrations at the different locations), making it less evident to use the results for air quality mapping. To cope with the time/space bias, data extrapolation can be performed using mathematical (Kriging, IDW,..) or modelling (LUR, machine learning) techniques but for a reliable result, the input data needs to be sufficient. Or use a continuous background monitoring station.

Both targeted and opportunistic approaches can be used with or without involving citizens. A targeted approach (having a fixed monitoring route) without citizens may result in a larger requirement in resources. The advantage of not involving citizens is that (when using a car) more expensive and accurate monitoring equipment can be used and the monitoring is performed in a more standardised way.

The advantage of involving citizens is to raise awareness on AQ. This is also referred to as participatory monitoring.

Finally, the sampling can also be biased by the weather conditions, e.g. when the data collection stops when it rains; 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.

Brahem et al. (2021) defined the core challenges related to MCS as (i) heterogeneity and variety of sensor equipment, measurements, and data analysis, (ii) the end-to-end data quality, (iii) supporting and exploiting mobility of sensors as well as context awareness, or even context inference, and (iv) involving the community in a trusted, fair, and transparent manner into the monitoring activity.

3.1.3 Requirements for monitoring devices

Requirements for monitoring devices need special attention when used for mobile data collection, used for unattended use over several periods, or used by citizens who do not have specialised knowledge on air quality and measurements. Also important for the interpretation of results is to know how the observed effects/gradients are related to the instrument uncertainty (e.g., https://www.mdpi.com/2073-4433/13/6/944).

→ *Pollutants measured*

Care should be taken when selecting monitoring devices in terms of pollutants measured. High-spatial resolution air quality monitoring is particularly important for exposure assessment of:

- Pollutants of high spatial variability (e.g: NO2, BC and UFP) (Perelló et al., 2021 and references therein) (see also chapter 3).
- Pollutants that are known to have adverse health effects or indicators for health-related exposure.
- A match between the anticipated concentration range and available sensitivity of the sensors for this particular air pollutant.

→ *Data quality*

Data quality is important since collecting data with sensors without knowing the data quality is not useful. As miniaturised and/or portable air quality instruments are often condensed/simplified/cheaper versions of regulatory-grade instruments, proper knowledge/understanding on the inherent instrument uncertainty and precision and associated sensitivities of the applied instrumentation (preferably based on local validation campaigns) is needed for an accurate interpretation of the obtained results. For some use cases (e.g. awareness raising, personal measurements, …), the associated data quality is of less importance than for other use cases (e.g.

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sensor networks where sensors are compared to each other, …). However, a certain minimum data quality is also needed for these applications, to avoid misleading interpretations.

In some citizen science studies, data collection of pollution is done as a way of making citizens aware of air pollution, rather than collecting data to be used in scientific studies. The problem is that (in general) these data cannot be used to construct AQ and exposure maps. In addition, there is a risk that the data quality is not good enough to give the citizens the expected feedback; in this case expectation management is very important (see Chapter 2). In this deliverable, we focus on collecting data with sufficient quality to construct exposure maps and try to engage citizens at the same time, rather than only awareness raising.

Snyder et al. (2013) indicate that many commercially available low-cost sensors have not been challenged rigorously under ambient conditions, including both typical concentrations and environmental factors.

Small PM sensors are typically nephelometers or particle counters based on optical measurements. The resulting error of PM sensor measurement devices is dependent on the sensor technology, the calibration algorithm and the calibration aerosol used (Hagan and Kroll, 2020). The error also depends on the environmental conditions and particle size and type.

Most low-cost PM sensors measure particles via light scattering. Sampled particles intercept a beam of light and the scattered light is measured and correlated to a PM concentration. Typically, sensors using the optical measurement principle can be broken down into two main types, nephelometers and Optical Particle Counters (OPC). Nephelometers measure the particles as an ensemble, gathering light scattered by all particles across a wide range of angles, typically 7°-173° to avoid pure forward and backward scattering (Hagan and Kroll, 2020; and references therein). The total scattering amplitude is then correlated to a mass measurement made by a reference instrument (nephelometers that measure scattered light at a single angle are sometimes referred to as photometers; and can be considered as a subclass of nephelometers.) OPCs, by contrast, detect particles individually, providing information on their number and size. Light scattered by each individual particle is measured and each pulse is assigned to a size bin based on its total light intensity, resulting in a histogram which is converted to a mass loading once the entire distribution has been measured. While these technologies have been around for decades, they have recently become available at much lower cost due to the availability of small, inexpensive light sources and electronic components. OPCs can be split into low-cost OPCs and higher-cost OPCs; since higher-cost OPCs use more expensive electronics and optics, they can measure smaller particles; the typical size range is 0.38 – 17 µm for lower cost and 0.1 – 17 µm for higher-cost OPCs (Hagan and Kroll, 2020).

The most important sources of uncertainty for PM sensors are related to (Hagan and Kroll, 2020):

- High relative humidity. Hygroscopic growth of particles at high relative humidity (around >75%) results in overestimation of PM due to growth of particles. All types of OPCs suffer from this interference and the error ranges from 100% to a few hundred %, depending on the hygroscopic properties of the aerosol. This can be solved at least partly by using an in-line dryer or applying a correction algorithm.
- Changes in aerosol optical properties, when the sensor is calibrated using an aerosol with different optical properties. The impact of aerosol optical properties is most important for low-cost OPCs and of medium importance for higher-cost OPCs and nephelometers. The effect is especially relevant (for low-cost OPCs) when the aerosol has strong absorbing properties and when small particles become undetectable with inexpensive optical detectors (due to the small amount of scattered light).
- The particle size distribution. This is very important for low-cost OPCs and nephelometers. In this respect, the ability of a sensor to measure small particles is very important. Since higher-cost OPC are able to measure smaller particles and are typically calibrated for different sizes of aerosol, they can better assess PM mass for different size distributions. In environments where small particles (<300 nm) comprise a large amount of particle mass, low-cost OPCs will be subject to significant error. In environments in which the underlying aerosol

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size distribution is highly variable (e.g. in urban environments), low-cost OPCs and nephelometers will struggle to measure PM mass correctly.

In addition to the sources of uncertainty summed above, some sensors do not estimate the PMcoarse fraction correctly. Some sensors use an algorithm to estimate the PMcoarse (PM10 – PM2.5) based on PM2.5 concentrations. This can be sufficient to estimate PM10 concentrations in urban areas but might result in high uncertainties at locations close to sources characterised by a high amount of coarse dust (Vercauteren, 2020). We will not discuss this further in detail since this is mainly relevant at locations with specific sources with more PM coarse (PM2.5-10) and not related to exposure of UFP (which is our primary focus).

The type of calibrant is very important for the performance of all OPCs.

NO_2 sensors rely on different measurement principles (electrochemical or metal oxide) compared to the chemiluminescence principle of the reference equipment (Hofman, Nikolaou et al. 2022). Electrochemical sensors convert a chemical reaction (reduction at sensing electrode and balancing oxidation at counter electrode) of the pollutant of interest in a quantifiable electrical current, while metal oxide sensors rely on the gas reaction with semiconductor material, resulting in free electrons. Electrochemical sensors are currently most advanced in detecting ambient (parts per billion; ppb) NO_2 concentrations, but suffer from sensor specific activity (nA/ppb response) and have shown to be cross-sensitive to other oxidizing pollutants (e.g. O_3) and environmental conditions (temperature and relative humidity) (Hofman, Nikolaou et al. 2022). Moreover, the sensor's electrolyte (responsible for ion transportation) will age naturally as a result of exhibited temperature and humidity variability; with low humidity (<60%) resulting in drying out of the electrochemical cell affecting sensor response time, and with high humidity (>60%) leading to water absorption and dilution of the electrolyte influencing the sensor characteristics and potentially leading to leakage and resulting corrosion of the sensor pins (Raninec, 2021).

Accurate portable devices are available for components such as O_3, UFP and BC; however, these are so-called mid-range instruments with a cost of approximately 5000 – 10000 euro, complicating wide-scale/large-number deployments. These devices will be further discussed in the detailed description of selected methods. They mostly have a good and acceptable data quality. Recurrent co-location of the instruments used in one campaign and co-location with reference-type (more expensive) instruments is recommended.

→ *Required pollution parameters*

When data is collected to construct air quality maps to be used in health studies, it is important that air pollutants are measured that are relevant for the health endpoint of interest. In addition, pollutants that show a large spatial variability (UFP, BC, NO_x) lend itself most for mobile monitoring. For other health relevant pollutants (such as $PM_{2.5}$, O_3) other approaches may be better.

Particulate matter (PM) in ambient air is a heterogeneous mixture of individual particles of different origin, size, shape and composition. Aerodynamic PM diameters are in the 0.01 – 100 µm range. Coarse particles (PM2.5-10) and PM in the accumulation mode (PM0.1-2.5) contribute the most to the PM mass in the air. Ultrafine particles (UFP, < 0.1 µm aerodynamic diameter) have very small mass but are found in very high numbers in air.

The standard metrics that are actually used in regulation are based on the mass concentration (in µg/m³) of all particles with an aerodynamic diameter lower than 10 µm (PM_{10}) or 2.5 µm ($PM_{2.5}$). However, particle number concentration (PNC, in number per cm³) is used to quantify the smallest particles (UFP) as they hardly contribute to the total mass, but these might have adverse health effects as they are able to migrate deeper inside our organs/bodies and exhibit a larger exposure surface area. Elemental carbon (EC) or Black carbon (BC, soot) measurements relate to unburned carbon particles from incomplete combustion emitted as tiny spherules ranging in size between 0.01 and 0.05 µm, and aggregating to particles of 0.1 - 1 µm, with typical most particles below 300 nm.

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A variety of particle monitors, sensing devices and sensors is available on the market to determine the particle mass concentration in air samples. Different physical principles are used. The reference method is the gravimetric method where particles are actively collected on a filter medium sucking a known volume of air through the filter. Filters are weighed before and after sampling under controlled conditions (EN 12341). Size-selective heads are used to sample a predefined fraction of particles (e.g. PM_{10} or $PM_{2.5}$). Because filter-based methods have a low time resolution (usually 24-hour filters), continuous (automatic) equivalent methods are used in AQMN including instruments using e.g. Beta attenuation, light scattering or oscillating microbalance technology to measure particle concentrations in near-real-time (~1-minute to 1h averages).

It is important to note that in terms of exposure, the spatial variability of each of the PM compounds is different. In addition, they have their specific sources and health effects. So, selecting the right metric is very important for mobile measurements. Even when selecting a PM mass sensing device, the measurement principle can affect the size range. Therefore, care should be taken to use PM sensors, since they might not measure the right metric to assess exposure to UFP or BC.

PM sensors are widely used in studies although they measure undifferentiated PM and might not represent health related parameters and spatial differences. In some cases, they can be used as proxy but we need to be aware that e.g. PNC measured with sensors, might miss the finest fraction (UFP) which may be most health related and in some micro-environment (like airports and traffic sites) can show larger variability compared to undifferentiated PM.

→ *Mobile use*

When using monitoring devices or sensors for mobile use, this sets specific challenges. What needs to be considered is specifications in terms of:

- Fast enough response time.
- High enough time resolution (1-10 seconds).
- Data needs to be associated with geographical information (GPS); this can be integrated in the monitoring device or external GPS data needs to be synchronised with air quality data.
- Portable (function of 'carrier' platform).
- Capacity to adapt to fast changing environments (interferences; vibration, turbulence, housing,…), including movement from indoors to outdoors.
- A fast response time is needed when collecting mobile AQ data. When sensors measure at a time resolution of 1 minute, this means that when driving at a low speed of 15-20 km/h (e.g. by bike), a single measurement point will take 250 - 333 m. When increased to 10 second monitoring resolution, samples will be taken every 42-56 m. At a walking pace (5 km/h), the spatial resolution becomes 14 – 83 m, at respectively, a 10 - 60 second resolution. When using the monitoring equipment on a mobile platform like a tram, bus, car,.. where travelling speeds vary from 30 to 120 km/h the response time and monitoring resolution are even more important.

The requirement for portability depends on the 'carrier'. When involving citizens this is more important, compared to a mobile carrier like a car or truck.

An important issue with mobile monitoring is the fast-changing environment; when sensors used are affected by interferences, this can make more difficult the interpretation of results. Potential interferences need to be co-measured and corrections need to be applied.

→ *Use by citizens*

In general requirements that need to be considered for citizen science use are: Useability, user-friendliness, fool-proof, feedback (good measurements and results) .

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Specific requirements are there when collecting data by citizens. Based on the workshop with local authorities/citizens within the COMPAIR project (VMM 2022) include:

- Data communication: preferential automatic data uploading (NB-IoT, wifi, LTE-M,…) (100%), otherwise 12.5% daily upload, 37.5% weekly upload.
- As autonomous as possible (power on/off, required communication/intervention handling)
- Portability; weight, size, easy to carry/attach, casing/backpack, …
- Noise: as silent as possible.
- Notification: option to mute.
- Optimised battery usage, which is a compromise between sampling time, data upload frequency and individual sensor power requirements.
- Easy charging: daily charging is considered ok.
- Privacy: capacity to anonymize data.

3.1.4 Data processing

→ *Direct mapping versus spatiotemporal interpolation models*

Mobile monitoring data can be used for direct mapping or as input for data driven models. It is important to know in advance which data processing technique will be used to optimize the data collection. Not only whether or not a model is used, but also the type of model used can have impact on the data collection requirements.

When direct mapping is used, it is important to have a good spatial and temporal coverage (representativity). This is also true when data-driven models are used but maybe at a lesser extent as spatiotemporal dependencies are learned from the available dataset.

Completeness of the dataset

In general, data completeness can be defined as ‘the extent to which data are of sufficient breadth, depth and scope for the task at hand’ (Batini et al, 2016).

In a recent paper, 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 facet that captures the extent to which the measurements of a given sensor are complete over a certain sampling period (including also aspects of data transmission and quality of the data). The authors focus on personal exposure measurements but similar concepts can be applied when using mobile measurements for mapping which is the focus of this deliverable. Also, Van den Bossche et al. (2015) discussed temporal and spatial coverage of mobile data. Temporal completeness and temporal coverage (or representability), and spatial completeness and spatial coverage are similar concepts. When both mobile and fixed measurements are plotted on a 3D graph with x/y representing geographical coordinates and z the time (Figure 2) the difference between fixed time series and denser mobile point measurements becomes visible. Ideally, an air quality value for each time and space instance is available (inferred in figure 3)

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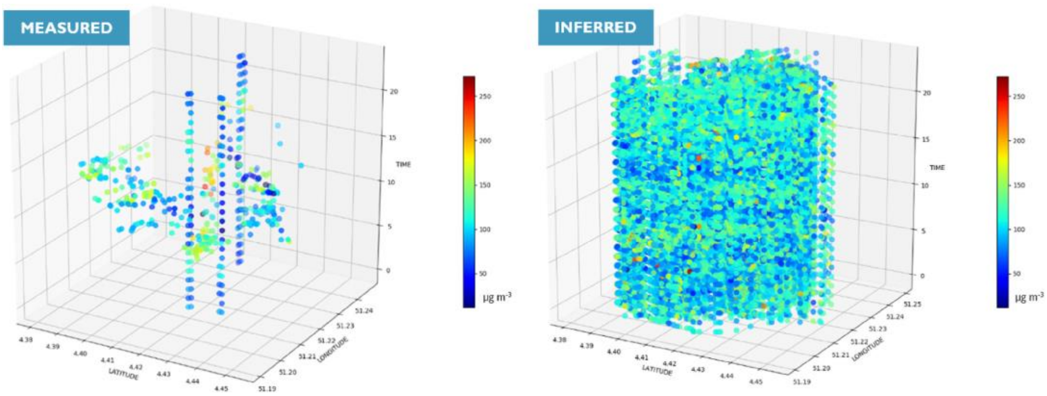

Figure 3: Concept visualisation of fixed and mobile sensor measurements represented as a sparse data matrix in space (x-y plane) and time (z plane). Right: Inferred air quality values by a machine learning model (from Hofman et al. (2022)).

Temporal completeness (according to Mehanna et al., 2022) characterizes the way a given period of time is covered by the collected measurements. Evaluation of the temporal completeness can go with different assumptions; e.g. assuming a uniform distribution over time, versus distributed measurements considering the variation of pollutant levels at different times of the day, month or year.

Spatial completeness is defined by Mehanna et al. (2022) as the extent to which data sufficiently represents a specific spatial area and it characterizes the coverage of this area. In other words, spatial completeness indicates how sufficient and comprehensive the current measurements are for a particular area. Also different assumptions can be made for the spatial coverage; e.g. assuming a uniform distribution of the measurements over the study area or taking into account the variation of pollutant levels in the different cells of the area of study.

In the following, we prefer the last assumption (taking into account variation in concentrations as function of time and location) since we want to use the resulting maps for exposure assessment and try to assess as much as possible the spatial and temporal dynamics. From now on we will use the terms temporal coverage and spatial coverage.

Temporal coverage has different components; for simplicity, we make distinction between a) time of the day, b) day of week, c) season of the year, d) years (see also Vanden Bossche et al., 2015):

The time of day that data are collected affects the final result. In most cases, we want to represent a daily average of the concentrations where a typical diurnal pattern has times with higher and lower concentrations (related to peak hours and/or periods with better and worse dispersion characteristics). In some cases the interest is in a typical hour (e.g. peak hour air pollution when looking at traffic sources) but otherwise the collected data needs to be representative for the exposure time that is considered.

The day of the week can also have an effect on pollutant concentrations with typical lower concentrations during weekend days compared to weekdays. In order to have a good coverage over an entire week, both week and weekend days need to be considered. However, when we want to maximize the observed spatial patterns it might be advisable to collect only data during working days. In some cases (e.g. when applying an opportunistic approach with employees or an opportunistic approach using cars like postal vans) only weekday measurements are achievable due to practical constraints.

The season (or month) in which data are collected also needs to be considered. Concentration differences between seasons can be explained by differences in sources and differences in meteorological conditions (dilution conditions as function of boundary layer height, affecting receptor sites as function of wind direction, washing out pollutants by rain/snow, secondary formation of pollutants as function of sunlight or temperature,...). Typically, data are

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collected at the time when health study is performed. It might be tricky to use data from another year, especially if there is a long time lag between data collected and health study. For example more stringent emission limit values can result in reduced concentrations (e.g. reduction in Pb concentrations of petrol cars, sulfur content in fuel, more stringent EURO norms for cars and HD vehicles), but also local measures (like LEZ in cities) can affect the local AQ.

When looking at annual average exposure, it is recommended to extrapolate the measured average concentration to annual values; this can be done by using data of a fixed AQMS of the network nearby (Van den Bossche et al., 2015).

Spatial coverage means that the study area needs to be mapped and exposure of all participants in the study area needs to be assessed. To generate high-resolution maps large quantities of data are required to include the range of possible meteorological conditions and the range of local air quality conditions (depending on local sources, e.g. traffic intensity), and to counter occasional and exceptional events. It is important to assess whether enough repetitions are made in relation to the goals of the monitoring campaign.

Sensor completeness is related to sensor quality and Mehanna et al. (2022) suggest an approach to improve data completeness by adding information about the quality of the measuring sensors. Whereas this is needed, we do not further discuss their approach here since it is function of instruments used. However, data quality control needs to be considered when collecting data (irrespective of the instrument used). Data quality, sensor uncertainty (comparability against REF) and precision (comparability against other sensor), and data quality control will be addressed when discussing the different tools further in this document.

Data processing for direct mapping

In general, when data is processed for direct mapping, individual data points are averaged over street segments. Details on data processing used in the airQmap approach are given below (see airQmap).

Van den Bossche et al. (2015) investigated how mobile monitoring can be used as an additional tool to acquire air quality data at a high spatial resolution. The study was based on 256 and 96 runs (repetitions) along two fixed routes (2 and 5 km long). They investigated the impact of temporal variability on the representativeness, and developed a methodology to map urban air quality using mobile monitoring. They stated that a limited number of mobile measurements may only represent a snapshot and not be representative and evaluated the number of repetitions needed with and without scaling e.g. for background concentrations. Different data processing methods were compared. They showed that using a trimmed mean and applying background normalisation decreased the required number of repetitions for the same resolution and uncertainty level. They showed that – using a trimmed mean and applying background normalisation – 24-94 repeated measurement runs (depending on location type with a median of 41) are required to map the BC concentrations at a 50 m resolution with an uncertainty of 25%. When relaxing the uncertainty to 50%, these numbers reduce to 5-11 (median of 8) runs. Reducing the length of the street segment (increasing spatial resolution) resulted in an increased number of repetitions required to obtain the same uncertainty level. When performing mobile measurements, it is important to take out extreme events (that influence the average concentrations and are not 'representative'), especially when a low number of repetitions is performed. Event detection algorithms can be used to remove extreme outliers; e.g. Hagler et al. (2012) used the running coefficient of variation (COV) method. In this method, a running 5 s standard deviation of the BC concentrations is calculated and divided by the mean concentration of the entire sampling period. The 99th percentile of the calculated COV is used as a threshold and all data points with a COV above this threshold are removed along with the data points 2 s before and after. This method has the risk that it can mask hotspots where peaks occur systematically.

Spatial aggregation is needed to smooth the data at different spatial levels (routes, streets, segments). Van den Bossche et al. (2015) showed that mapping at a spatial resolution up to 50 m is feasible for BC and a higher spatial resolution of 20 m can be obtained with a slightly increased uncertainty.

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Quality control of GPS data needs some attention when processing mobile measurements (see also Van den Bossche et al., 2016). The processing and filtering of the raw measurements of the GPS device include: filtering for incorrect or unreliable GPS locations, map matching (allocating deviating GPS locations to associated street segment/map) and spatial aggregation. The reason for unreliable GPS data can be indoor periods during the day or outdoor moments with a very bad reception (e;g. travelling by subway, or in street canyons). The filtering of unreliable GPS data can be done based on minimal number of satellites (threshold). The accuracy of GPS data has consistently improved in recent years. When a dedicated route is used it is much easier to filter unreliable data. Map matching is needed when the GPS is slightly off track, which occurs often in urban environments. A way to enhance this is by assuming the measurements are always performed on the streets. This can be done by matching the locations for each individual run and street segment to the shortest distance (max 30 m) of the selected street sections.

Whereas some studies collect data during a limited period resulting in an aggregated map, collecting data using opportunistic approach or platforms (like trams, postal vans,...) can result in continuous update of input data. Real-time dynamic pollution maps can provide personalised exposure information.

Van den Bossche et al. (2020) showed that spatio-temporal models (see below) can also provide a dynamic pollution map. When data are collected continuously using an opportunistic approach, a model can be constructed that is continuously updated with these new data. The R^2 and Explained Variance (EV) of the different Cross Validation (CV) schemes can then be regarded as the predictive ability of the model under different circumstances.

→ *Models for intra-urban exposure assessment*

In the review paper of Jerrett et al. (2005), different classes of models to derive intra-urban exposure assessment were identified and also Xie et al. (2017) described different data processing techniques ranging from geostatistical techniques, Gaussian models, linear regression, artificial intelligence to compressed sensing, to assess pollutant concentrations and personal exposure. Not all models are based on measurements but we sum them up here for completeness. The model and data-processing techniques used can be generally distinguished as:

- The simplest models are <u>proximity-based assessments</u>: in these models proximity to a pollution source is measured; most commonly used to assess exposure to traffic-related air pollution, where distance to road and traffic counts are the main indicators for exposure estimates; these models do not use measured data but use proximity data to explain variability in pollution levels, and are *out of scope for this study.*
- <u>Spatial interpolation methods</u> (sometimes referred to ‘geostatistical models’, Jerret et al., 2005) estimate concentrations at unmeasured locations by measured concentrations at neighbouring locations. They can be based on deterministic and stochastic geo-statistical techniques. Four interpolation methods are commonly used in air pollution estimation and assessment: spatial averaging, nearest neighbour, inverse distance weighting and krigging approach (Xie et al., 2017).
  Spatial averaging calculates the mean of pollutant measurements from the nearby monitoring stations (located within a predefined grid, a country, or even a city). *Nearest neighbor* assigns the pollutant measurements of the closest monitoring station to the unmeasured location, regardless of the actual distance between them. The first two do not consider spatial variability of the concentrations as they only take into account one monitoring station or do not consider distance to neighbouring monitoring stations to calculate the unknown concentration. Therefore, they are no longer commonly used. *Inverse Distance Weighting (IDW)* is a deterministic method for spatial interpolation and calculates the value at the unknown locations as the weighted average of the measurements at the monitoring stations, using inverse distance as weighing factor. IDW approaches are applied at different spatial levels. *Kriging* is also a weighted combination of measurements at surrounding monitoring stations. Kriging is the most common geostatistical technique used in the air pollution field. Kriging assigns weights at each concentration by exploiting the spatial correlation among the observed measurements. It generates the estimate and standard deviation. Kriging models exploit spatial

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dependence in the data to develop continuous surfaces of pollution. IDW takes into account the distance and more stations but is not suitable to be used on e.g. an urban scale where very high spatial gradients may exist (e.g. street canyons). Also Kriging assumes a homogeneous terrain where concentrations are only determined by the distance to the nearest AQMS, while this is not the case in real-life. Geostatistical modelling requires a dense network of sampling sites.

- Land-Use Regression (LUR) models use measured pollution concentrations at locations in the study areas to predict concentrations at unmonitored locations based on land use types within buffers around the locations. They are based on the principle that the pollutant concentrations at any location depend on the environmental characteristics of the surrounding area. The models are developed through construction of multiple regression equations describing the relationship between the pollutant measurements at the monitoring stations and the predictor variables usually obtained through Geographic Information Systems (GIS), such as traffic intensity, road length, distance to the major road, road type, population density, land cover, wind speed, etc. A dense monitoring network is required to cover the different land-use parameters. LUR is a *common technique* to assess spatial variation in air pollution to estimate exposure to air pollution in epidemiological studies (Jerrett et al., 2005; Hoek et al., 2008; Brauer et al., 2008; Beelen et al., 2014) or health studies (e.g. Dons et al. 2014; Hoek et al., 2011). Therefore, the basic principles are explained here in more detail.

Input data. LUR models require AQM data at multiple locations across the study area. Typically, stationary monitoring is used at 20-100 locations (Hoek et al., 2008). However, Basagana et al. (2012) proposed that LUR models for complex urban settings should be based on a much larger number of measurement sites (> 80 in their study). Mobile monitoring can be a way to improve the spatial resolution of the measurements. In addition to AQM data collected, the LUR model uses predictor variables including traffic, population and land-use variables in buffers with variable sizes. **Spatio-temporal resolution.** In most cases, the LUR models focus on the spatial variation in (annual) average concentration and do not include a temporal dimension. However, in many applications, temporal variability is an important factor for exposure. To incorporate the temporal dimension in LUR models, different approaches are used in literature. One approach is temporal adjustment of annual average model output (Brauer et al., 2008; Wu et al., 2011; de Nazelle et al., 2013), in which the annual average exposure at each location is adjusted to temporal variations in air pollution concentrations. Another approach is to develop separate models for each typical hour (Dons et al., 2013) or for each time period (Hasenfratz et al., 2015; Mueller et al., 2016). A third approach is to include time-dependent data that are related to the temporal variability of the air quality in the model (e.g. Maynard et al., 2007; Ragettli et al., 2014 and references in Van den Bossche et al., 2020). In Van den Bossche et al. (2020) opportunistic measurements by city wardens are used to build a real-time pollution map. Possible time-dependent variables include meteorological variables (wind speed and direction, temperature) and air pollution measurements at fixed site monitoring stations.

- Machine Learning (ML) Models: Due to the observed correlation over both space and time, data matrices of air quality data are in some cases considered 'low rank' and thus explainable by statistical/numerical techniques (Asif et al., 2016; Udell and Townsend, 2019). The underlying low rank and slowly time-varying structure of the air quality data can be leveraged to create numerical models that facilitate an effective spatiotemporal extrapolation, enabling the prediction of air quality at unmonitored locations (Paliwal, Biyani et al. 2020). Machine learning (ML) approaches allow for training of underlying dependencies based on large air quality datasets and supplied context information (traffic, meteorology, street type, speed limit), hereby enabling data inference or matrix completion (Figure 2) in both space and time (Hofman, Do et al. 2022). These statistical approaches are *data driven* and include models based on copula functions and neural network models. The term 'data-driven spatial prediction methods' is to distinguish them from the dispersion models; data driven models do not rely on underlying physical processes. Examples of machine learning models to predict air quality include Do et al. (2019; 2020), Lim et al. (2019), Qin et al. (2022; 2021). Models of Do et al. and Qin et al. were recently applied and validated based on diverse mobile (bicycle, Google car, postal van) datasets resulting in

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comparable model performances, ultimately depending on the applied instrumentation (sensor performance) and acquired spatiotemporal data coverage (Hofman, Do et al. 2022).

- Dispersion models simulate the physical and chemical processes of the dispersion and transformation of atmospheric pollutants to predict the pollutant concentrations, based on emissions sources (strength, temporal profile, locations,...), meteorological data, buildings, ... Dispersion models vary depending on the mathematics used to develop the model. Gaussian-based dispersion models are the most commonly used models for pollutant dispersion analysis. In these models, the dispersion in downwind direction is a function of the mean wind speed blowing across the Gaussian plume under steady state conditions. They often use monitored data (e.g. from the AQMN) as input for 'background concentration' (e.g. the RIO-IFDM model: Lefevre et al., 2013) and/or for model validation. They might suffer from a lack of input data (e.g. traffic data). Dispersion models have the potential advantage of incorporating both spatial and temporal variation of air pollution within a study area without the need of a dense AQ network. However dense AQ data are needed for model validation. More recently a combination of dispersion models with more dense measured AQ data is used by data fusion or assimilation.
- Integrated meteorological-emission models combine meteorological and chemical modules to simulate dynamics of atmospheric pollutants. They require high-end computational facilities. These are not further discussed here.
- Hybrid models combine personal or regional exposure monitoring with other air pollution exposure models. Two classes of combining one of the preceding methods were identified: with personal/household exposure monitoring or regional monitoring.

Furthermore, a relative new method is data-assimilation in which dispersion models use data of sensor networks to improve the model output.

When data are collected continuously, data aggregation (direct mapping) or data prediction (modelling) needs to be updated. The data aggregation to build 'measured maps' (can be specific for certain time of day, day of week, ...).

3.1.5 Mobile monitoring projects and large trials

In this section we give an overview of projects and large trials where mobile monitoring has been used to generate air quality maps. Details of the approach, set-up, instruments, data processing will be given in the next paragraphs.

Table 2 shows an overview of different projects where mobile mapping tools are used.

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Table 2: Overview of projects where mobile monitoring tools are used and of which selected methods will be further described in this deliverable.

Name project	Short description of monitoring device	Partner involved	reference
airQmap projects	BC measurements (AE51) Portable unit (AE51, GPS) Dedicated route Data processing to construct aggregated maps	VITO	www.airQmap.com Van den Bossche, J., 2015. Atmos. Environ. 105: 148-161.
Opportunistic BC measurements	BC measurements (AE51) Portable unit (AE51, GPS) Opportunistic route Data processing to construct aggregated maps	VITO	Van den Bossche J., 2016. Atmos.Environ., 141, 408 – 421 Van den Bossche J., 2018. Environmental modelling and Software, 99, 58-67. Van den Bossche J., 2020. Environmental Modelling and Software, 133, 104837
AirView	Normal car with BC (AE33), UFP (EPC 3783) NO2 (CAPS Aerodyne). Aim: create hyper-local map of city.	UU	https://pubs.acs.org/doi/10.1021/acs.est.1c05806
MACE	BC measurements following a predefined route	TROPOS	Alas et al., 2018, Aerosol Air Qual. Res. 18(9), 2301-2317 https://www.tropos.de/aktuelles/messkampagnen/blogs-und-berichte/mace-2015
SMURBS	Fixed and mobile; a compilation of urban air quality mapping solutions	NOA	Grivas et al., 2019. Air Qual Atmos Health 12, 1405–1417
BelAir project	Kunak sensor boxes, mounted on 17 postal vans in Antwerp 10 sec resolution/6 months of data PM, NO_2 and O_3 Opportunistic routing Data processing via: - Machine learning models - Aggregated maps	VITO/IMEC	https://www.imeccityofthings.be/en/projecten/bel-air Hofman et al., 2020. IEEE Sensors, doi: 10.1109/SENSORS47125.2020.9278941 Hofman et al., 2022. Environmental modelling & Software, 149, 105306, doi: 10.1016/j.envsoft.2022.105306 Do T. H. et al., 2020. IEEE Internet of Things, 7 (9), 8943 – 8955, doi: 10.1109/JIOT.2020.2999446

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			Qin X. et al., 2022. Remote Sensing, 14, 2613, doi:10.3390/rs14112613
Snuffelfiets	Bicycle mounted SODAQ Air sensors Opportunistic routing in Utrecht (NL) $PM_{2.5}$ and PM_{10} Data processing via machine learning models	VITO/IMEC	https://snuffelfiets.nl/ Hofman et al., 2021. Pattern Recognition, ICPR International Workshops and Challenges Proceedings, 12666, 139–47, doi:10.1007/978-3-030-68780-9_14 Hofman et al., 2022. Environmental modelling & Software, 149, 105306, doi: 10.1016/j.envsoft.2022.105306
Google Air	Two Google Street View vehicles with Aclima instruments Dedicated routes in Oakland (US), Utrecht (NL) Data processing via aggregation (Apte et al) LUR models (UU) or machine learning models (Hofman et al)	UU VITO/IMEC	https://www.google.com/earth/outreach/special-projects/air-quality/ Apte et al. 2017. Environmental Science & Technology, 51 (12), 6999-7008, doi: 10.1021/acs.est.7b00891 Hofman et al., 2022. Environmental modelling & Software, 149, 105306, doi: 10.1016/j.envsoft.2022.105306
City Scanner	OPC-N2 sensors deployed on two garbage trucks April 21 - August 14, 2017 Cambridge, Massachusetts (US)	MIT	http://senseable.mit.edu/cityscanner/ DeSousa et al. 2020. Sustainable Cities and Society, 60, 102239, doi: 10.1016/j.scs.2020.102239
OpenSense	Sensors CO, NO2, CO2, O3 deployed on busses and trams in Lausanne and Zurich Switserland Dedicated repeated routes Data processing via interpolation/dispersion models		http://opensense.epfl.ch/ Hasenfratz, D. et al. 2015. Deriving high-resolution urban air pollution maps using mobile sensor nodes. Pervasive Mob Comput 16, 268-285, doi: 10.1016/j.pmcj.2014.11.008

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			Mueller et al 2016. Atmospheric Environment, 126, 171-181, doi: 10.1016/j.atmosenv.2015.11.033
HOPE, with citizens	Low-cost PM2.5, O3 and NO2 sensors; opportunistic monitoring with 100 volunteer citizens	UHEL, FMI, HSY, City of Helsinki	Rebeiro-Hargrave, A., Fung, P.L., Varjonen, S., Huertas, A., Sillanpää, S., Luoma, K., Hussein, T., Petäjä, T., Timonen, H., Limo, J., Nousiainen, V. and Tarkoma, S. (2021) City wide participatory sensing of air quality, Front. Environ. Sci. doi: 10.3389/fenvs.2021.773778.
Megasense*	Wearable PM2.5 sensors; opportunistic monitoring in urban transit system; personal exposure analysis; connecting the citizen observations to air quality monitoring network data for quality control	UHEL, HSY	Motlagh, N. et al. 2021 Transit pollution exposure monitoring using low-cost wearable sensors, Transport. Res. D: Transport & Environ. 98, 102981. Kortoçi, P. et al. (2022) Air pollution exposure monitoring using portable low-cost air quality sensors, Smart Health 23, 100241, doi.org/10.1016/j.smhl.2021.100241. Zaidan, M. et al. Intelligent calibration and virtual sensing for integrated low-cost air quality sensors, IEEE Sensors, 20, 13638-13652, doi:10.1109/JSEN.2020.3010316.
ASAP East AFrica ** www.asap.uk.com	Low-cost PM sensors used in static locations and mobile measurements	UoB	https://iopscience.iop.org/article/10.1088/2515-7620/ac0e0a https://acp.copernicus.org/articles/18/15403/2018/acp-18-15403-2018.html https://www.researchsquare.com/article/rs-1953022/v1 https://acp.copernicus.org/articles/22/10677/2022/
POLLUSCOPE*	Participative observatory for the surveillance of individual exposure to air pollution relating to health		http://polluscope.uvsq.fr/
Expanse	Creating several European-wide external exposure surfaces including air pollution, using GWR among others. New mobile measurement campaigns are being carried out in the 'Urban Labs'; Basel, Barcelona, Athens, Munich and Lodz.	UU	https://expanseproject.eu/

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HOUSE	High ozone and secondary organic aerosols episodes in Spain. Very precise O_3 mobile measurements using balloons by means of a PO3M analyser using the ultraviolet spectrometry. Cost is around 9000 Euros Done in different cities, Barcelona, Vic, Madrid and Sevilla.	CSIC	Querol et al., 2018. https://doi.org/10.5194/acp-18-6511-2018 Querol et al., 2017. https://doi.org/10.5194/acp-17-2817-2017 In't Veld et al., 2021. https://doi.org/10.1016/j.scitotenv.2020.144579

* more focused on personal exposure monitoring and therefore not further discussed in this deliverable

** The ASAP project is not discussed in detail below. The ASAP project used PM sensors (Alphasense OPC-N2) to enhance local decision-making abilities in the capital cities of Ethiopia (Addis Ababa), Kenya (Nairobi), and Uganda (Kampala) to improve urban air quality, reduce the effects of air pollution upon human health, and allow for sustainable development to proceed without further deterioration in air quality. Low cost sensors were used in both static locations (indoor and outdoor) and mobile (outside of vehicles to measure spatio-temporal information and within vehicles to estimate transport related exposure). The data from the low cost sensors were also used to calibrate a chemistry transport model (WRF combined with CHIMERE) to be able to model regional and local air quality data.

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In response to the need for higher monitoring granularity, recent mobile sensing networks have been collecting mobile data in cities around the globe. Examples of sensor applications on service fleet vehicles include postal vans in Antwerp (BE) (Qin et al., 2021), garbage trucks in Cambridge, Massachusetts (US) (deSouza et al., 2020) and trams and buses in Lausanne and Zurich (CH) (Mueller et al., 2016). Other applications include personal monitors on cars (Apte et al., 2017; Chen et al., 2022) or bicycles (Franco et al., 2016; Hofman et al., 2018; N Genikomsakis et al., 2018; Peters et al., 2014; Qiu et al., 2019) and city wardens (van den Bossche, Theunis et al. 2016). These networks provide valuable in situ data on experienced exposure levels throughout the city. Nevertheless, the collected mobile data are still sparse in time and space and need proper processing in order to derive exposure maps (Hofman, Do et al. 2022).

Some projects listed in the table below do not generate air quality maps but contain important insight that can be used in this deliverable. As an example, *The Polluscope project* aims at evaluating the capacities and the limitations of sensors in fine-grained understanding of personal exposure to air pollutants; the project focusses on personal exposure measurements and also relates to health impact (notably for asthmatic and COPD subjects). The purpose of *Polluscope* is to design, develop and test a platform for collection, management and analysis of data from individual lightweight environmental sensors; it covers gaseous pollutants (O_3, NO_2), particulates and Volatile Organic Compounds. The project does not focus on mapping but on individual exposure in indoor and outdoor environments. However, some results reported in papers are included in this deliverable.

3.2 Detailed description of selected methods

3.2.1 airQmap

AirQmap is a platform that allows people with limited or no air pollution expertise, such as citizen scientists or municipal officials, to carry out air quality measurements and to get a detailed view on the air quality at street level. This approach allows to compile air quality maps at a feasible cost for citizens, cities and municipalities. More info on airQmap can be found here https://vito.be/en/airqmap and is summarised below.

→ *Data collection*

- Pollutant: BC
- Instrumentation:
  - BC measurements with AE51 (https://aethlabs.com/microaeth/ae51/overview) which is a battery-powered pocket-size instrument that measures changes in light absorption of 880 nm light by aerosol deposition.
  - GPS.
  - Netbook ("home station") for data integration from AE51 and GPS and data transmission.
- Data collection by mobile monitoring.
  - BC monitor and GPS sensor are placed in portable bag.
  - Carried around on foot or by bicycle.
  - Following predefined routes that are repeated (+25 times) at predefined timeslots over a period of days to weeks.
  - Sometimes repeated campaigns in different seasons or year.
- Possibility to use several measurement sets in one campaign to increase action radius, number of streets or neighbourhoods covered.
- QA/QC
  - Regular comparison of AE51 instruments (inter-comparison of portable instruments).
  - Regular comparison with reference BC monitor used in AQMS (MAAP or AE33).
  - All the equipment is provided to users with a short training on their use and instructions on how to collect the data to get a reliable result.

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The number of repetitions needed to get a representative result was studied by Van den Bossche et al. (2015) by performing subsampling analysis of a large dataset (256 repeated runs); for a few well-covered street segments, they evaluated how many repetitions were needed to obtain a representative idea of the average pollutant concentration (minimizing error when compared to overall average/median, see Figure 4). Data experiments showed that when 13 repetitions are performed, BC concentrations can be assessed with a deviation of less than 50% at 90% of the 20 m road segments. Increasing the number of repetitions will reduce the deviation. In airQmap studies we aim at approximately 25 repetitions (runs) for each route and campaign.

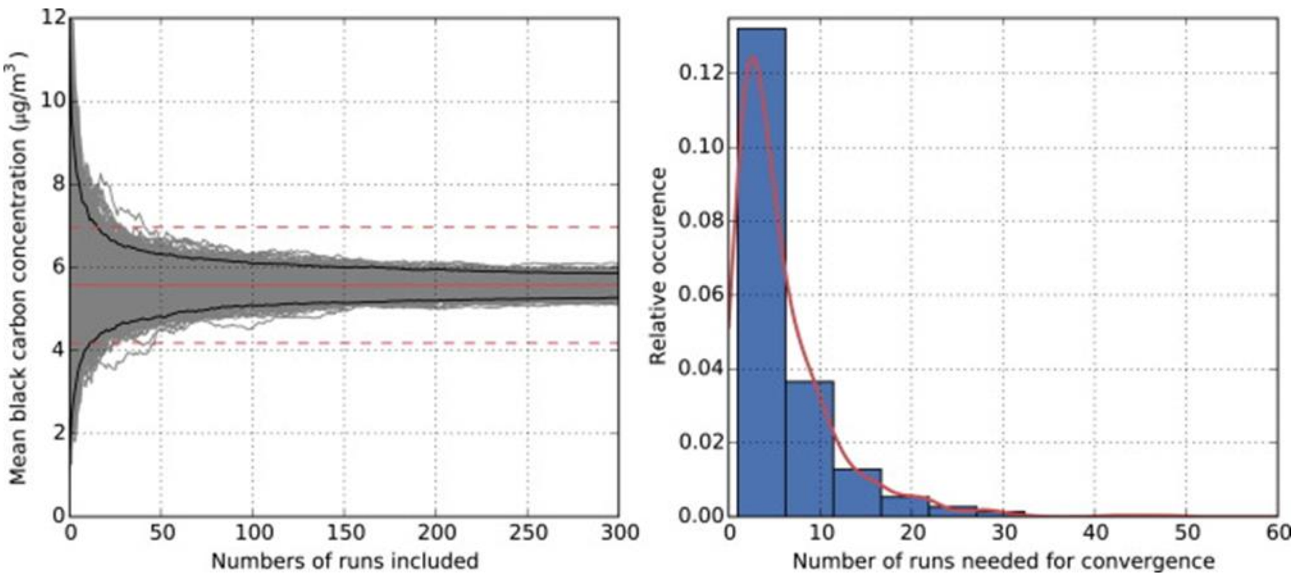

Figure 4: Example of a data experiment for all data (total of 256 runs). Left: evolution of the mean value in function of the number of repetitions for 1000 iterations with the overall mean (red line), the deviation of 25% around this mean (red dotted line) and the 2.5% and 97.5% percentiles of the mean value (black line). Right: density plot of the required number of runs to obtain convergence for these iterations.

→ *Data transmission and processing*

- The user receives a netbook ("home station") for data upload from BC and GPS devices. Data are synchronised and merged. Data is sent to VITO server.
- Further data processing is done at VITO, and includes:
  - Reduction of noise in BC measurements.
  - Reduction of noise in GPS measurements.
  - Creation of a mapping layer (equidistant points on streets, user defined distance between point, e.g. 30 m).
  - Attribution of measurements to the mapping layer points (user-defined distance criterion).
  - Aggregation of measurements per mapping layer point (trimmed mean, additional user-defined parameters such as minimum number of passages for inclusion).
  - Export map (fixed format: openstreetmap base layer, BC concentration overlay, fixed scaling and colour coding).

→ *Result*

The result is a map with BC concentrations. The map is a high-resolution representation of the ambient BC concentration that citizens are exposed to. A colour scale from green over yellow and orange to red is used to represent the data (Figure 5). The scale is adjustable, but generally provides enough contrast for interpretation.

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A large campaign was set up in Mechelen as part of the GroundThruth project; the citizen platform was named "MeetMeeMechelen" (translated as Measures with us Mechelen) (see also https://mechelen.meetmee.be/kaart)

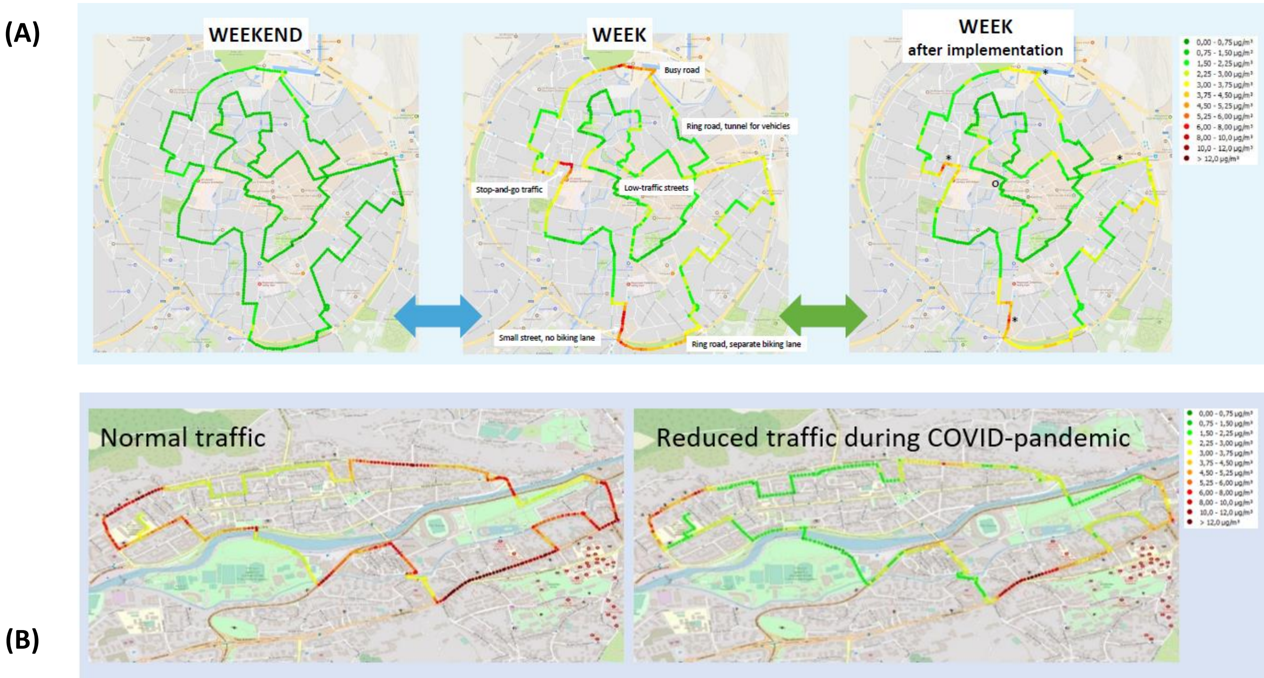

Figure 5: Two examples of high-resolution BC maps generated by airQmap. Example (A) shows the difference in concentrations between weekend and work week days and between work days before and after the implementation of a new traffic circulation plan. Example (B) shows the effect of reduced motor transport due to COVID restrictions on the BC concentration.

Another example where a predefined route is followed and BC is measured is the MACE project (TROPOS), following a similar set-up but slightly different data processing as the airQmap approach (Alas et al., 2018). In this study two fixed routes were measured, which covered different micro-environments and exposure scenarios. The aerosol was dried using silica based diffusion dryer. Data processing included 10 sec median averaging but no ONA correction was applied and moving averages (on 50m resolution) were used to plot the data. Filter tickets were changed every day to prevent overloading of the filter. Background was corrected based on lowest percentiles as described by Van Poppel et al.,)

→ *Citizen involvement*

- Implementation: airQmap is relatively easy to use, but user instructions are needed. A manual is available to get started.
- Organisation: repeated measurements are needed and more routes to map a city or larger area. This means that significant efforts are needed from participants and need for participant organisation to work together for data collection.
- Data protection: no sensitive data because BC data is not linked to the person who performed the measurement and route is independent from the address of the participants.

→ *Strong and weak points*

- Strong points
  - Dedicated route, so no sampling bias.
  - Flexible system: possibilities for implementation that deviate from the standard airQmap set-up in terms of coordination, data collection, data-processing and reporting of results.

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- Extensive experience in at least 12 campaigns in Flanders and 4 international campaigns.
- Useful data to identify hot-spots of bad air quality from motor transport.

- Weak points
  - Data processing not fully integrated.
  - Intensive campaigning: large effort from participants.
  - Hard to cover a wide area: many participants needed.
  - Temporal coverage restricted to participants (e.g. night time/weekend data).

3.2.2 Opportunistic measurements with city wardens in Antwerp

The potential of opportunistic mobile monitoring to map the exposure to air pollution in the urban environment at a high spatial resolution was investigated in a case study in Antwerp, Belgium. Opportunistic mobile monitoring makes use of existing mobile infrastructure or people's common daily routines to move measurement devices around. Opportunistic mobile monitoring can also play a crucial role in participatory monitoring campaigns as a typical way to gather data.

A case study to measure BC was set up in Antwerp, Belgium, with the collaboration of city employees (city wardens, Figure 6). The Antwerp city wardens are outdoors for a large part of the day on surveillance tours by bicycle or on foot. In the case study they gathered a total of 393 h of measurements. The data collection is unstructured both in space and time, leading to bias. A temporal adjustment can only partly counteract this bias. Although a high spatial coverage was obtained, there is still a rather large uncertainty on the average concentration levels at a spatial resolution of 50 m due to a limited number of measurements and sampling bias. Despite of this uncertainty, large spatial patterns within the city are clearly captured.

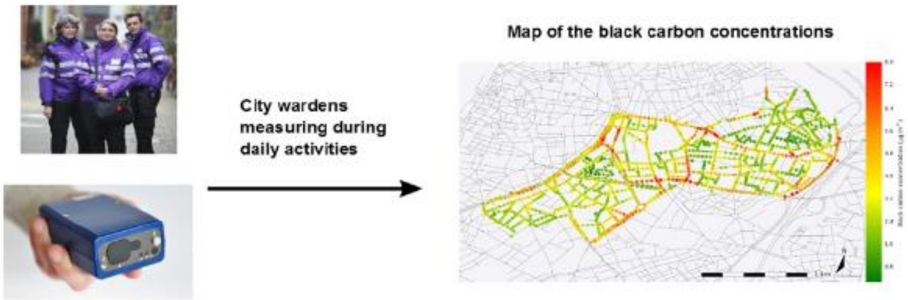

Figure 6. Case study of mobile BC measurement set up in Antwerp, Belgium, with the collaboration of city employees (city wardens).

→ *Data collection*

The instrumentation of airQmap (see 0) was used by city wardens in Antwerp. They are city employees with a surveillance task, and are outdoors for a large part of the day carrying out surveillance tours by bicycle or on foot. These surveillance tours do not follow fixed routes or times. Three teams of 2 city wardens each were equipped with a measurement unit. During the measurement campaign, 393 h of raw 1 s measurements were recorded for the three teams combined (459 h of measurements before filtering for GPS quality), spread over 110 days. Most of the measurements were done between 10h and 16h. during working days.

A considerable amount (14%) of raw data was rejected based on the GPS data. Firstly, the GPS data are filtered by quality. Of all available GPS data, 71% had a fix (i.e. a minimum of three satellite signals to calculate the position); the remaining data probably consist of indoor periods during the day or outdoor moments with a very bad reception. Starting from these data, some filtering criteria were adopted to remove incorrect or unreliable GPS locations: 1) assuming all data were gathered by bike or on foot, the speed may not be above 25 km/h and 2) to

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ensure the GPS quality, the 30 s centred moving mean of the number of satellites should be above 4. After these filtering steps, 86% of the data with a fix remained, corresponding to 393 h of measurements.

→ *Data processing*

The airQmap data processing chain was adopted (see 0).

→ *Citizen involvement*

The ‘citizens’ were limited to city wardens and not general public. They were collecting data as part of their work and were not specifically interested in air quality.

→ *Strong and weak points*

- Strong points: Working with the city wardens offered some benefits compared to volunteers or other professionals. Because they are city personnel, all instruments were always connected and recharged at their office and the follow-up could be centralised. Further, the city wardens went to varying places in the city as indicated by the high spatial coverage, e.g. also visited traffic-free and green areas. Other examples of carriers such as postmen or parking wardens can partly have the same advantages (involved through their job), but can have a more limited temporal or spatial coverage. For example, postmen or parking wardens will typically less likely visit traffic-free or green areas.
- Weak points:
    - A lot of variability was introduced due to several factors such as varying modes of transport, sampling during different hours of the day and of the year. A stronger follow-up of the wardens could have kept the level of measurements more constant during the year. The mixed mode of transport of the wardens is an additional complication and it should be avoided if possible because results are now averaged out over both modes of transport, while in reality differences in exposure of cyclists and walkers could be substantial, for example, by the difference in distance to the traffic.
    - Another problem is the low GPS quality in urban environments, and consequently an intensive processing of these data is needed. No a priori knowledge on the tracks that are monitored is available. Combined with the low GPS quality, this complicated the detailed mapping of the air quality. Due to a possibly large deviation from the true position, some measurements may not have been assigned to the correct street.
    - Mixing of outdoor and indoor measurements. It turned out to be hard to detect, in a reliable way, when a city warden was entering a building. We have tried to tackle this by filtering the data on the number of satellites, but this may have led to some excessive data cleaning of good measurements on the one hand or the incorrect use of indoor measurements on the other hand.
    - A next issue is the instrument used to measure the air quality. The micro-aethalometer signals may sometimes be noisy or show instabilities. This will be an extra factor contributing to the uncertainty on the results.
    - The bag does not protect the micro-aethalometer from the rain, so no measurements are made under rainy conditions.
    - Collecting data consistently during a one-year period by the city wardens is quite a challenge (as illustrated by the weak points above) and turned out to be less evident than expected.

3.2.3 Project Airview

The ambient concentrations of NO_2, BC and UFP, were measured in Amsterdam and Copenhagen during October 2018 – March 2020. The measurements were carried out by three Google Street View (GSV) cars. In Amsterdam, two GSV cars measured concentrations from 25 May 2019 to 15 March 2020, whereas, in Copenhagen, the third

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GSV car measured pollution levels from 15 October 2018 to 15 March 2020. Both campaigns were stopped on 15 March 2020 due to Covid-19 lockdown restrictions. All streets in the two cities have been monitored.

The GSV cars were equipped with 1 Hz NO_2 (CAPS, Aerodyne Research Inc., USA), 1 Hz BC (AE33, Magee Scientific), and 1 Hz UFP (EPC 3783, TSI) monitors. A Global Positioning System (GPS) (G-Star IV, GlobalSat, Taiwan) was used to record the location of the car, which was linked to the measuring equipment via date and time. The measurements were mainly carried out between 08:00 to 22:00 hours (excluding weekends) and in different parts of both cities. The aim was to reduce possible space and time autocorrelation. This was particularly relevant for Amsterdam, where two GSV cars were used.

The measured 1-second NO_2 values > 500 µg/m^3 and < 0 were discarded. For BC, we removed values higher than 30 µg/m^3, and for UFP, we removed values higher than 500,000 particles/cm^3 from the data as such values are not physically possible in the measured environments. As measurements were carried out at different times of the day and week, the measured data were temporally corrected using nearby routine monitoring stations. The corrected data was subsequently winsorised to the 2.5th and the 97.5th percentile. That is, measured concentration levels below the 2.5th percentile and above the 97.5th percentile were “replaced” by the respective percentile values. This procedure is done to limit the unduly influence of more extreme values. Then, the data was assigned to the nearest street, and aggregated over each 30 -60m street segment per individual drive day. Then, we calculated a “mean of means”, reflecting the mean of all the drive days.

→ *Strong and weak points*

The biggest limitation of the measurement set-up used in this work is the amount of time, energy, and significant initial investment it takes to collect such enormous amounts of data. Though, the number of vehicles could be reduced if data is combined with LUR models. A few drives are needed to develop a LUR model, while adding more and more drives increases the accuracy of data-only mapping. So, when more and more data is collected, actual measurements could explain more and more local variation.

3.2.4 MUSIC, EXPOsOMICS and RUN

The goal of these studies was to compare mobile measurements versus short-term LUR models, both by correlating exposure estimates and comparing predictions to home outdoor measurements (3 times 24 hours) allowing an unbiased comparison of the validity of both approaches.

→ *Data collection*

These campaigns consist of both mobile and short-term stationary measurements, covering in total about 20.000 street segments and 800 short-term stationary sites (3x30 minutes) to develop fine resolution UFP and BC maps. Short-term stationary and on-road measurements were made using an electric vehicle (REVA, Mahindra Reva Electric Vehicles Pvt. Ltd., Bangalore, India). A condensation particle counter (TSI, CPC 3007) and a micro Aethalometer (Aethlabs, CA, USA) were used to monitor UFP and BC concentrations respectively. The CPC had a measurement every second, whereas the Aethalometer averaged measurements over one minute. Data was collected between 9:00 and 16:00 to avoid rush hour traffic, in order to better compare concentration levels between sites/segments. About 8 short-term sites were sampled each day over 8-10 routes per city and per season. This way, the within-day, day-to-day and seasonal variability of UFP and BC concentration levels was captured

→ *Data processing*

UFP values of 500 particles/cm^3 or less were removed from the data set, as these reflect malfunctioning of the instrument. If the UFP data increased or decreased in one second by a factor 10 or more, the data was removed as well. Both criteria were used in other studies and resulted in less than 1% removal of UFP data.

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For temporal correction, a reference site with the same equipment as the electric vehicle was set up near Utrecht. A difference method was used to correct the spatial data following previous studies (Klompmaker et al., 2015). This method first calculates the overall mean concentration at the reference site over the entire campaign. Next, using the data at the reference site, the average reference concentration of 30 minutes around the time of sampling was subtracted from the overall mean. This difference was used to adjust the measured concentration at the sampling locations.

→ *Model Development*

Like multiple mobile monitoring studies, the middle of each road segment was identified and this coordinate was used to acquire GIS predictors for LUR modelling. Variable selection was done using a supervised forward stepwise selection procedure.

→ *Citizen involvement*

Measurements were done solely by employees of the institute, so no citizen involvement.

→ *Strong and weak points*

Mobile monitoring is a cost-effective method to generate LUR models, as a wide range of conditions can be captured in a limited amount of time and with a limited number of instruments. A high spatial density of measurements can be obtained, sampling more sites which are more representative for people's exposures such as near-intersections and close proximity to traffic lights.

The mobile UFP LUR models generated higher predicted concentrations than short-term stationary models for the same locations.

For developing a national model, separate modelling of background and local scale exposures should be considered. For larger countries, characterisation of the regional background is likely best by a combination of fixed site monitoring and deconvolution of the mobile monitoring signal. To assess the potential overestimation by mobile monitoring models, longer-term measurements at a limited number of residential sites spread over the study domain should be part of the study design. Models used in this study included regional, urban background and local information on UFP concentrations, making them applicable to large nation-wide cohorts in the Netherlands.

3.2.5 BELAIR project in Antwerp

Kunak Air Mobile (Kunak Technologies SL, Spain) sensor systems equipped with Alphasense series sensors for PM, NO_2, O_3 and a dedicated LABAQUA housing to avoid turbulence over the sensors, mounted on the roof of 17 vans of the Belgian postal service (BPost) in Antwerp (Figure 7). Sensor systems are factory-calibrated and include a property algorithm to compensate for environmental effects. Sensor boxes were co-located in advance at an urban background air quality monitoring station in Antwerp (R817) to perform validation and additional local calibration in order to improve accuracy further. Calibration (slope calibration for PM and baseline calibration for NO_2) was performed in batches of 5 sensors, followed by consecutive deployment on the postal vans. Three sensor boxes remained next to the R817 station to evaluate the performance over time, 17 were deployed on postal vans. The sensor units are deployed in front of the roof, at the opposite side of the car exhaust to avoid self-sampling (Figure 2). Postal routes can be considered opportunistic. Vans were mobile from Monday-Saturday between ~6-18h. Monitoring resolution was configured to 10 seconds during the day (when mobile) and 5 min during night time in order to avoid battery drainage (powered via car battery).

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Figure 7: Kunak Air Mobile sensor unit in its dedicated LABAQUA housing, deployed on the roof of a postal van.

→ *Data processing*

From January onwards, the sensor systems were co-located at the R817 AQMS in Antwerp. Batches of 5 sensors were consecutively locally calibrated based on 1 week of co-location data and validated based on the following week, and subsequently deployed on the postal vans during February and March. Mobile data was collected between March and September, 2021. Full capacity (17 monitoring vans) was reached from May onwards, resulting in ~1.6-2.1 million monthly datapoints with a fairly comparable monthly spatial coverage. In total, we collected 10 380 831 datapoints between January and September over the city of Antwerp (figure 8).

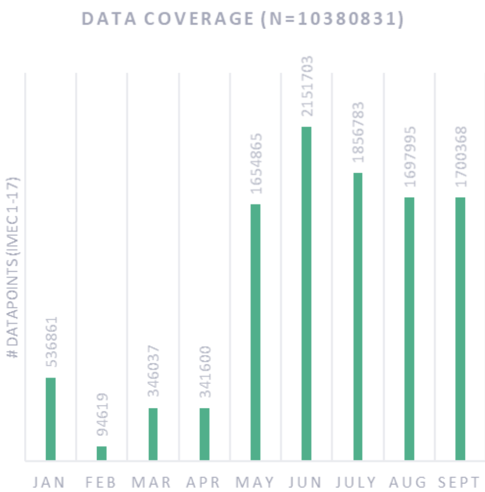

Figure 8: Monthly data collection of the 17 sensor boxes (January-September 2021) during the Belair project.

Processing option 1: Data aggregation

With a predefined target area of the city of Antwerp, data was aggregated in street segment buffers (10m radius), and pollutant and data coverage summary statistics were calculated for every month and for the entire dataset (Jan-Sept), as can be seen from Figure 8. Between January and September, 20572 street segments were sampled (>0 datapoints) and highest data coverage was obtained at the postal depot (n=1806556) and garage (n=304007). The street segment with highest mobile coverage was the Quellinstraat (n=16377), located in the city centre of Antwerp, for which we explored the required monitoring coverage (#repeated runs) to reach acceptable

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mean/error statistics. Moreover, an evaluation was made on the number of street segments samples within the target area (city centre, Figure 9).

Figure 9: Street segment aggregation of mobile datapoints.

Average/median pollutant maps for NO_2 and $PM_{2.5}$ were calculated based on the mobile measurements and provided for the period January-September and pollutant NO_2 in Figure 10.

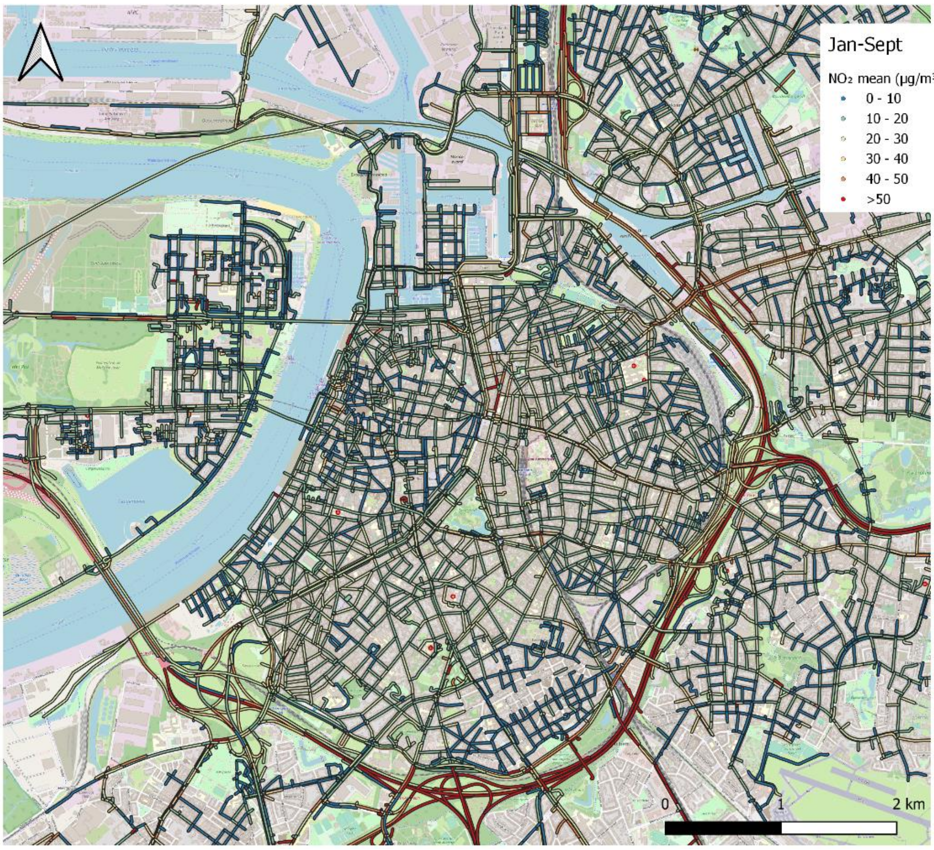

Figure 10: Street segment-aggregated exposure map of the mean NO_2 concentration between January and September, 20 2021.

As the mobile monitoring coverage (number of datapoints per street segment) varied considerably over the Antwerp area, we evaluated data representativity by performing subsampling analysis. For a few well-covered street segments, we evaluated how many repetitions were needed to obtain a representative idea of the average pollutant concentration (minimizing error when compared to overall average/median). This methodology was previously applied on mobile datasets from car- (Apte et al., 2017; Chen et al., 2022) and bicycle-mounted (Van den Bossche, Peters et al. 2015) sensors/instruments.

Processing option 2: Machine learning models

When representing mobile data along geographical (x-y) and temporal (z) axes, it becomes clear that the collected mobile data is still sparse in both space and time. Due to the observed correlation in space and time (e.g. diurnal variability of pollutant concentration at multiple reference stations in a city), data quality matrices can be considered low rank and thus explainable by statistical/numerical techniques (Asif et al., 2016; Udell and Townsend, 2019). We, therefore, trained two machine learning models (AVGAE (Do et al., 2019; Do et al., 2020) and GRF (Qin, Huu Do et al. 2021)) on the collected mobile dataset from March, 2021, together with time- and space-variant context features, in order to infer the measured concentrations in both space and time (~matrix completion as shown in Figure 10. Doing so, the models generate pollutant concentrations for every time/space instance. Both machine learning models were temporally validated at 5 available AQMS stations (R801, R802, R803, R804, R805) in Antwerp. For each validation exercise, one reference station was excluded from the model training/testing and only used for validation.

Temporal validation statistics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Index of Agreement (IA), Accuracy (Acc), Normalized Mean Bias (NMB), Normalized Mean Standard Deviation (NMSD) and the FAIRMODE defined Model Quality Indicator (MQI) (Janssen et al., 2017; Kushta et al., 2019). Results are presented in Table 3.

Table 3: Validation results of the AVGAE and GRF models in Antwerp (from Hofman et al., 2022)-

Model	Station	MAE	RMSE	IA	Acc	r	NMB	NMSD	MQI
AVGAE	R801	4.52	9.09	0.94	0.85	0.90	0.01	−0.17	0.34
AVGAE	R802	4.84	9.10	0.93	0.84	0.90	−0.11	−0.09	0.34
AVGAE	R803	9.91	14.08	0.80	0.63	0.71	0.02	−0.33	0.54
AVGAE	R804	16.79	21.23	0.72	0.63	0.68	−0.31	−0.28	0.69
AVGAE	R805	7.98	11.52	0.89	0.75	0.81	−0.07	−0.13	0.44
GRF	R801	6.03	8.42	0.96	0.81	0.94	0.06	−0.16	0.32
GRF	R802	7	9.5	0.94	0.78	0.89	−0.03	−0.1	0.37
GRF	R803	11.6	13.85	0.88	0.58	0.86	0.31	−0.12	0.51
GRF	R804	15.47	19.27	0.74	0.67	0.59	−0.13	−0.22	0.68
GRF	R805	9.03	11.8	0.89	0.73	0.83	−0.02	−0.26	0.46
AVGAE	**Avg**	**8.81**	**13.00**	**0.86**	**0.74**	**0.80**	**−0.09**	**−0.20**	**0.47**
GRF	**Avg**	**9.83**	**12.57**	**0.88**	**0.71**	**0.82**	**0.04**	**−0.17**	**0.47**

→ *Strong and weak points*

- Automatic data collection on service fleet does not require additional traffic/people for sampling.
- Postal service vehicles deliver at "every doorstep" resulting in a good coverage (when selecting vehicles covering all districts).
- Routine calibration/maintenance is needed (~every 6 months) to guarantee data quality.
- All sensors are co-located every day (when vans are parked at depot), which allows for calibration/maintenance/evaluation precision at one location.
- Data processing is needed to cope with over/under sampling at specific locations and generate exposure maps.
- Monitoring locations are restricted to delivery addresses of postal vans.

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- Low cost sensors were used with lower data quality compared to research grade instruments used in previous mobile monitoring campaigns.

3.2.6 MAPLE

Here sampling was done with a mobile platform over a seven-day period. Mobile Analysis of ParticuLate in the Environment (MAPLE), was deployed on weekdays outside of peak traffic time (10:00 a.m.–4:00 p.m.) so as to minimize differences in traffic conditions such as stop-and-go traffic during peak hours, and maximize sampling of a wider geographic range Sampling with a mobile monitoring platform was conducted across the Greater Toronto Area over a seven-day period during summer 2015. This mobile monitoring platform (small truck) was equipped with instruments for measuring a wide range of pollutants at time resolutions of 1 s (ultrafine particles, black carbon) to 20 s (nitric oxide, nitrogen oxides). The monitored neighbourhoods were carefully selected based on their contrasting and diverse land use sources (industrial, traffic) and land use categories (commercial, park or residential areas). Each neighbourhood was sampled on one day with the sampling route being repeated 2–3 times on that given day

The high time-resolution data allowed pollutant concentrations to be separated into signals representing background and local concentrations (Figure 11). A method that we refer to as deconvolution.

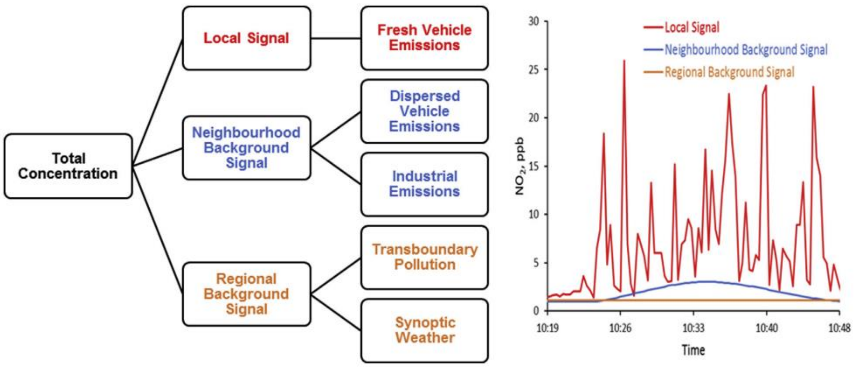

Figure 11: Separation between background and local signals.

Strong point of this method is that it is not needed to use costly fixed monitoring stations to assess background concentrations levels. Furthermore, by isolating the local from the background signals it is easier to understand what the impact is of different emission sources on neighbourhood concentrations. This will help source apportionment in urban environments.

3.2.7 Hankey and Marshall. Bike measurements spatial aggregation

In this study bicycles were equipped with air pollution instruments: particle number (PN) concentration (CPC 3007, TSI, Inc., Shoreview, MN), black carbon (BC) mass concentration (AE51, AethLabs, San Francisco, CA), fine particulate ($PM_{2.5}$) mass concentration (DustTrak 8320, TSI, Inc.), and particle size distributions (NanoScan, TSI Inc.). Mobile measurements were collected with the goal of LUR-development in mind; three sampling routes were selected to span various levels of traffic, types of land use, and cover a large number of neighbourhoods. The routes were sampled repeatedly (thereby mitigating the effect of singular events during anyone sampling run) during morning (7–9 am) and afternoon (4–6 pm) rush-hour; reference measurements were collected at a central site before and after each sampling run to control for day-to-day variability in background concentrations among sampling days.

For this document, we want to highlight the sensitivity analyses the authors did on spatial and temporal aggregation of mobile measurements. In total, the authors developed and examined 1224 separate LUR models and discuss

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trends in model performance. They found very little difference between the performance of LUR models that were based on segments and designs where concentrations were averaged over 50, 100 and 200m grids. Regarding the temporal aspect, they also developed models without temporal adjustment of the measurements and found that the model performance in terms of R2 only decreased by 0.02.(Hankey and Marshall, 2015).

3.2.8 SMURBS

SMURBS (H2020) aimed to increase urban resilience targeting challenges with respect to air quality, and also to urban growth, natural/manmade disasters and more complex municipal issues such as the migrant crisis and the health implications of environmental pressures. A portfolio of diverse Earth Observation (EO) solutions brought in by the wide consortium, was implemented at an expansive ensemble of European cities with different problems, by a horizontal refocusing of effort under the smart city banner to produce new data, information, tools and services, tailored to the needs of the citizens and decision makers and enabling informed decision making.

→ *Data collection*

Within the framework of the project, the spatial variability of ambient BC concentrations in the Greater Area of Athens (GAA) was studied during an intensive wintertime campaign (Figure 12). Short-term daytime BC measurements were conducted at 50 sites (traffic and urban/suburban/regional background) and on-road along 12 routes, using a portable micro-aethalometer (AE51, microAETH®). The coordinates and speed were recorded using a GPS receiver, synchronised to the micro-aethalometer's clock, to facilitate the geospatial representation of results.

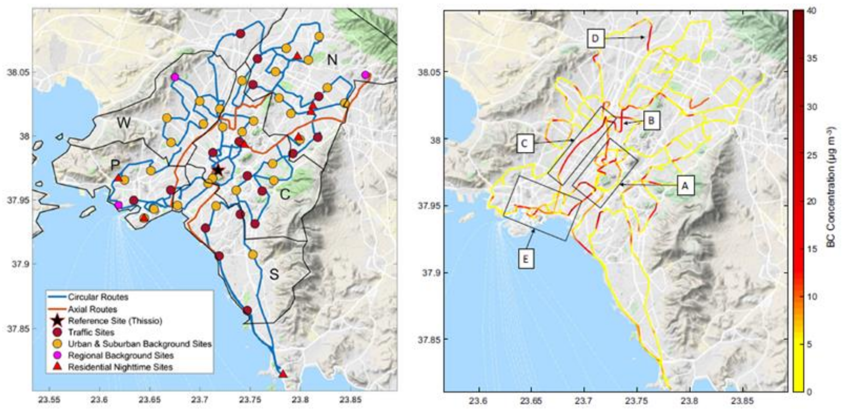

Figure 12: Overview of the GAA indicating the stationary points and routes of mobile monitoring (left) and mapping of BC levels during the on-road measurements (right).

→ *Data processing*

An inter-comparison was performed between AE51 and AE33 7-λ aethalometers (Magee Scientific, Berkeley, CA), situated at the urban background NOA measurement station of Thissio, indicating the ability of the portable instrument to precisely track the temporal variability of BC. Consequently, mean AE51 concentrations were corrected for the intra-day background variability (effects of non-local emissions and meteorology), based on data from continuous BC measurements at Thissio. For on-road measurements, the Optimised Noise-Reduction Algorithm (ONA), a data cleaning method that performs adaptive time-averaging of BC based on incremental attenuation, was implemented to reduce the impact of noise in short-term concentrations due to vibration-motion artefacts. Values corresponding to periods when the vehicle was not moving were screened out to reduce the possibility of interference from its own or other highly localised emissions. One-minute averages were calculated for on-road data and midpoints of the corresponding road segments were used for visualisation of results.

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→ *Citizen involvement*

Citizens were involved in the deployment of the micro-aethalometers for stationary measurements, where the instruments were placed in residential locations covering the GAA and different sectors/neighbourhoods. Also citizens performed the on-road measurements, using their own passenger cars, following the measurement protocol.

→ *Strong and weak points*

- Strong points:
  - The first spatial variability study of BC concentrations in the GAA.
  - Revealed in-city exposure "hotspots", due to traffic and residential heating emissions.
  - Demonstrated the potential of portable BC measurements to be used for the development of land use regression models.
- Weak points:
  - Limited number of repetitions of each route, due to the expansive targeted GAA area.
  - Time constrains and limited number of available instruments.

3.2.9 City Scanner

City Scanner (http://senseable.mit.edu/cityscanner/), a project by MIT, proposes a drive-by solution to capture the spatiotemporal environmental variation in urban areas such as air quality or thermal flux. Instead of deploying a dedicated fleet, they deployed various types of environmental sensors in garbage trucks in the city of Cambridge.

→ *Data collection*

They collected air quality data with Alphasense OPC-N2 sensors deployed on two trash-trucks in the City of Cambridge for a total of 27 days between April and August 2019, to gain qualitative insights into potential sources of PM in this urban environment. The Alphasense OPC-N2 sensor measures particle counts in 16 size bins ranging from 0.38 to 17.5 µm. After initial benchmarking of the sensor performance, they decided to focus on particle number concentration instead of mass concentrations.

→ *Data processing*

- Authors presented three techniques to:
  - Identify and characterize PM2.5 hotspots
  - Estimate the averaged air pollution over the sampled routes
  - Analyse aerosol size distribution from the OPC-N2s, yielding estimates of PM source signatures in different parts of the sampling route. Hotspots were characterised using hierarchical clustering of peak measurements (>100 µg/m³) in the same spatial area using a distance cut off of 100 m (Figure 13), and selected hotspot clusters as >30 individual measurements or >1 unique measurement day.

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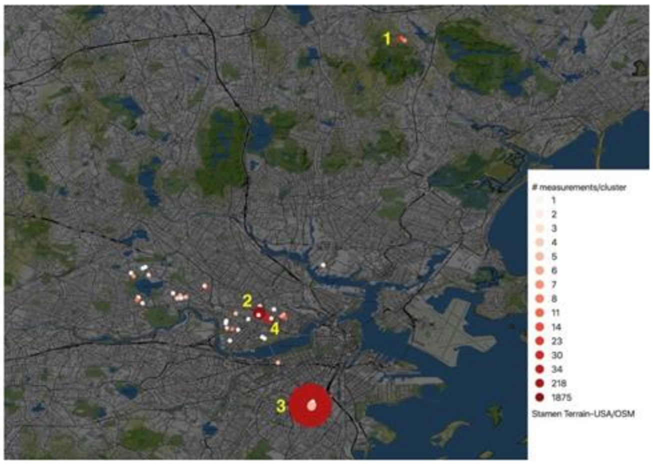

Figure 13: Hotspot identification with the number of identified peak measurements (>100µg/m³) per cluster (from de Souza et al., 2020).

The averaged air pollution was calculated by testing three different background correction approaches (hourly concentration from reference AQMS, lowest 10% during route, splines-of-minimums; (Brantley, Hagler et al. 2014). The considered correction approaches seemed to result in very similar background concentrations (<5%). Authors applied a time-of-day correction as well to normalise for the temporal variability. Point measurements were aggregated to 30m street segments and selected the median as an outlier-resistant metric of concentration central tendency (Figure 14). They applied a set of bootstrap resampling procedures to quantify the effect of sample-to-sample variability and of sampling error on the median concentrations.

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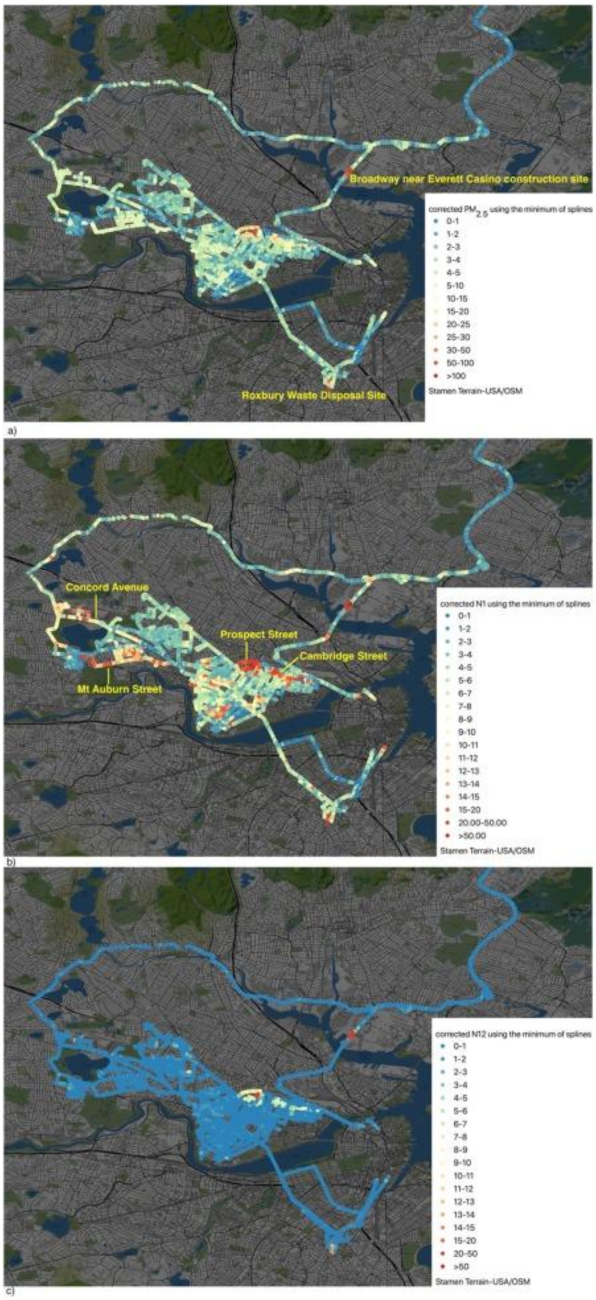

Figure 14: Upper: Map of median background-corrected PM2.5 (µg/m^3) for each 30-meter road segment that the trash-trucks travelled, Middle: Map of the median background-corrected number concentration (#/mL) of particles with diameters between 0.38-1µm (N1), Lower: Map of the median background-corrected number concentration (#/mL) of particles with diameters between 1-12 µm (N12) (from de Souza et al., 2020).

Authors evaluated OPC size distributions by clustering the size-bin observations (without background-correction) using the k-means technique. This technique allows to identify a small number (5) of typical aerosol size distributions that can be compared across space and time, which can give us insights into the kinds of sources responsible for measurements within a cluster (de Souza, Anjomshoaa et al., 2020) (Figure 15).

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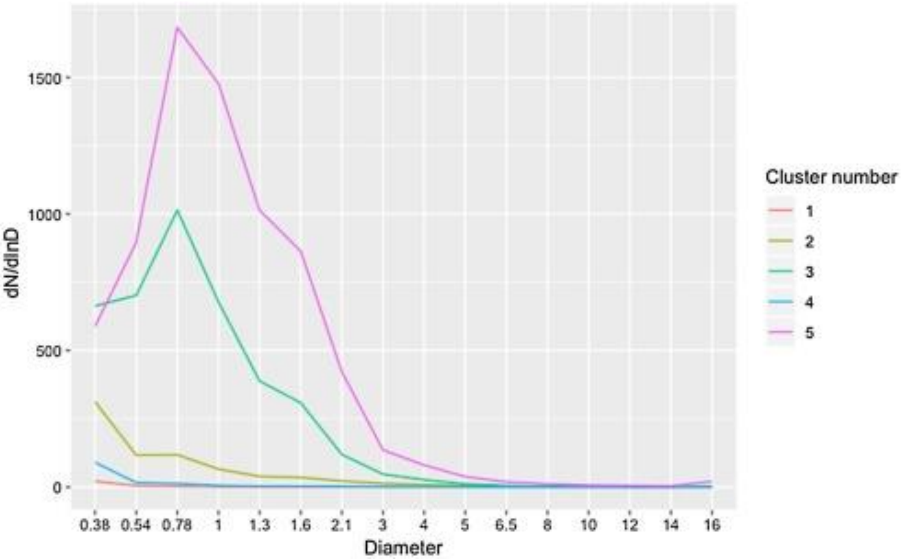

Figure 15: Average size distribution of each identified cluster (from de Souza et al., 2020).

→ *Citizen involvement*

No citizens were involved in this project, but opportunistic measurements on fleet vehicles (garbage trucks).

→ *Strong and weak points*

- Insights into the spatial and temporal nature of sources and their impact in the urban environment can be obtained via low-cost monitors. Combining the deployment and analytical tools, we believe that mobile air quality monitoring using existing urban vehicles can be done more extensively and relatively inexpensively.
- Background: As background pollution appears to comprise a major fraction of the aerosol concentrations measured by the trash-trucks, in future deployments it is important to ensure that background pollution concentration is well characterised, probably using measurements from nearby fixed monitors located in areas away from local sources.
- Representativity: Our insights result from the deployment of low-cost monitors on trash-trucks, which run from 07:00 to 14:00 on weekdays. Thus, in future studies these measurements need to be supplemented by other scheduled or non-scheduled vehicles that operate at different hours to obtain truly representative pollution values over the region
- Service fleet vehicles: Scheduled vehicles, such as buses, have the advantage of traversing the same street segments several times per day, whereas with unscheduled vehicles, such as taxis, we can still use a relatively small fleet (if compared with the total fleet of the city) to collect data in more randomly distributed street segments not covered by buses.

3.2.10 Opensense

The Nano-Terra Opensense I and II project (http://opensense.epfl.ch/wiki/index.php/OpenSense_2.html) deployed low-cost sensors (CO, CO_2, UFP, NO_2, NO, temp, RH) on trams in Zurich and buses in Lausanne (Switzerland) and collected mobile data. This mobile data was leveraged to build a spatio-temporal model (LUR) that provided real-time air quality data on a map consultable via an app or online dashboard (Figure).

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Figure 16: The Opensense sensor node (upper; from Hasenfratz et al., 2015) and data pipeline (lower) with mobile air quality data collected by the Global Sensor Networks (GSN), visualisation dashboard of the measurements and trained spatiotemporal model and visualisation.

→ *Data processing*

After calibration and data cleaning, the spatial coverage was evaluated. Measurements covered a large set of diverse location characteristics. For example, the data included measurement locations at terrain elevations from 400–610 m and diverse traffic densities ranging from vehicle-free zones to 90,000 vehicles per day (Hasenfratz, Saukh et al. 2015). Authors proposed a three-fold validation approach to assess the quality of the measurements; (i) analyse the statistical distribution of the monitored particle concentrations, (ii) evaluate the baseline signal of each device, and (iii) compare our measurements to data from two high-quality stations collected during the same time period but at different locations in Switzerland (Hasenfratz, Saukh et al., 2015) (Figure 17).

Next, mobile data was used to construct a LUR model via Generalized Additive Models (GAMs) with 12 explanatory variables, which were evaluated for inter-correlations.

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Variable [unit]	Variable [unit]
Population [inhabitants/ha]	Industry [industry buildings/ha]
Building height [floor levels/ha]	Heating [oil and gas heatings/ha]
Terrain elevation [average m/ha]	Road type [busiest road type/ha]*
Distance to next road [m]	Distance to next large road [m]†
Terrain slope [average degree/ha]	Terrain aspect [average degree/ha]
Traffic volume [vehicles per day/ha]	Distance to next traffic signal [m]

*Five road types: residential, tertiary, secondary, primary, and freeway.

†Road types classified as large: secondary, primary, and freeway.

Figure 17: Upper: Ten mobile sensor nodes deployed on top of buses achieve a good coverage of the city of Zurich (Switzerland). The black dots denote locations with at least 50 measurements over the course of two years. Lower: explanatory variables used to construct the LUR (GAMs) models (Hasenfratz et al., 2015).

→ *Citizen involvement*

No citizens were involved in this project, as measurements were performed on service fleets of public transportation (trams and buses).

→ *Strong and weak points*

- This application used a small number of sensor nodes deployed on top of public transport vehicles to automatically obtain a constant coverage in the area of interest (Hasenfratz, Saukh et al. 2015)
- In this work, authors developed LUR models since they have, compared to other models, a relatively low computational overhead, which is beneficial when deriving many hundreds of models (Hasenfratz, Saukh et al. 2015).
- Authors revealed that the accuracy of pollution maps with sub-weekly temporal resolution suffers from the limited number of measurements available to model the pollution concentrations. This problem could be solved by proposing a novel modelling approach, which is able to make use of past measurements to increase the available data volume (Hasenfratz, Saukh et al. 2015).
- The tram-based OpenSense mobile sensor network does not provide equally distributed measurements in terms of the employed predictor variables. Some location types within the city are not captured by measurements at all. Consequently, the data set is representative for a limited area only. An extension of the

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network by static sensor nodes at selected locations such as heavily congested or background locations could remove these limitations. However, this study leaves open the impact of an optimised network on the accuracy of the results (Mueller, Hasenfratz et al. 2016).

3.2.11 HOPE mobile measurements

HOPE stands for Healthy Outdoor Premises for Everyone which was funded by Urban Initiative Action (UIA) (https://ilmanlaatu.eu/). Within HOPE project the mobile sensors (which are low-cost and portable) were given to citizens to carry and measure their level of exposure to the air pollutants in cities. The HOPE project is an excellent example of how the collaboration between different actors from businesses to scientist and to citizens can be built. At the same time, it showcases the possibilities of data utilization to create higher quality services that meet the individual needs of the users.

→ *Data collection*

For mobile measurements with citizens, the HOPE sensors (as shown in Figure 18) were given to the citizens of Helsinki living in the Pakila district in the city. Then, the data collection campaign took place during the time period from October 30, 2019, to January 15, 2020. A total of 40 devices were given out to citizens to carry around and measure air quality. Citizens were instructed to use the devices in Pakila but were not necessarily limited to the area. The analysis of the measurements was considered inside an area of circa 6 km2. The purpose of the experiment was to test the accuracy of the low-cost devices and investigate their behavior in the given area.

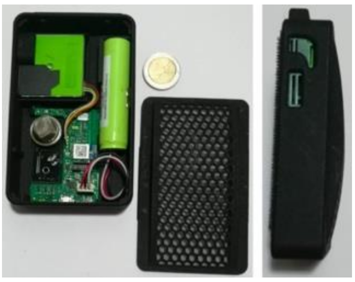

Figure 18: HOPE mobile sensor used for collecting air quality data.

The HOPE sensors are based on a BMD340 System on a module and mobile phone app called HOPE. The platform connects to COTS Android smartphones over Bluetooth Low Energy, and the smartphones report their readings further to a collecting server. The sensor model for measuring the PM is a Sensirion SPS30. The platform is powered with a 3500mAh battery and enclosed in a 3D-printed case made of ESD-PETG filament. HOPE sensor is capable of measuring temperature, humidity, pressure, battery level, UV, particulate matter PM1, PM2.5, PM4, PM10 carbon monoxide (CO), nitrous dioxide NO2, ozone O3, and positioning information and a timestamp. HOPE sensors transmit their data using Wi-Fi and cellular systems to the Megasense backend system. Wi-Fi-based HOPE sensors send their measurements every 60 seconds; and the mobile sensors transmit their measurements every 30 seconds (Motlagh, N.H. et al. 2021a).

→ *Sensor validations*

HOPE sensors were validated by deploying them at the bottom of SMEAR III scientific measurement station (Kulmala, M., 2018), as shown in Figure 19 (a).

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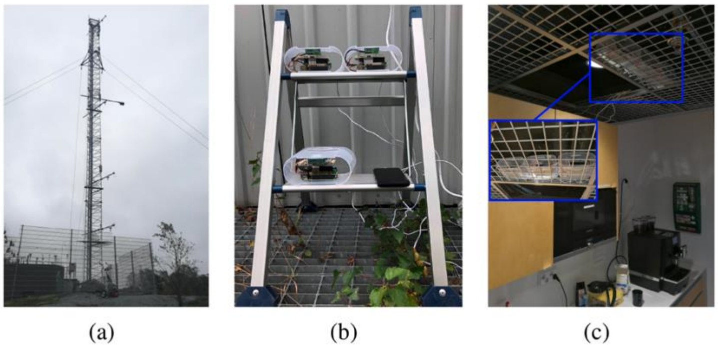

Figure 19 (a): Smear III reference station, (b): Consistency experiment of portable sensors outdoors at the base of Smear III, (c): Consistency experiment indoors.

Measurements were collected for one week, sampling the devices once per minute. To protect the devices from rain and wind, the sensors were wrapped inside a weatherproof casing (see Figure 19 (b)). While encasing the devices, the air-intake of the PM sensors were ensured to remain unobstructed. In addition, indoor functionality was tested by deploying the devices close to the ceiling inside a break room for staff at the University of Helsinki (see Figure 19 (c)). The validation results were in line with regulatory criteria on evaluation (Motlagh, N.H. et al. 2021b).

→ *Data processing*

For mobile measurements with citizens, the hope sensors transmitted their measurements to the Megasense server system for further processing and analytics (Rebeiro-Hargrave, A. et al. 2020). Megasense is a system (https://megasense-server.cs.helsinki.fi/) that is developed to provide real-time massive scale air quality sensing in urban areas by integrating a large number of air quality sensors at the scale of for example tens of thousands or even millions of air quality sensors (Motlagh, N.H. et al. 2020). Megasense system consists of three main parts, the Sensing System, Edge Layer and Cloud Layer as shown in Figure 20.

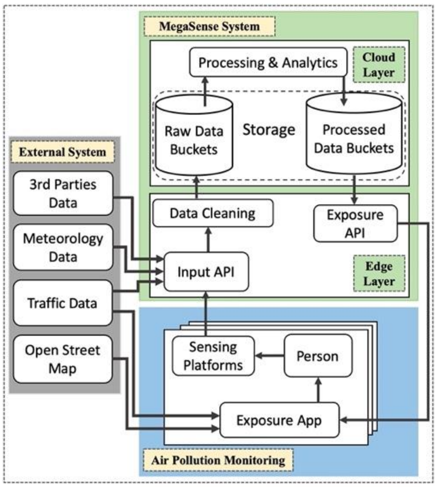

Figure 20. Megasense data system architecture and its components.

The Sensing system includes the sensing sources deployed in urban areas as well as the radio communication interfaces. The sensing sources include data received from any type of air quality sensor devices, open street map data, city air pollution monitoring stations, crowd-sourced data, and many other sources. The Cloud layer offers a long-term and scalable storage system as well as processing and analytics services. This layer aggregates data received from different sensing sources and stores the cleaned data. The processed data is further used by decision

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makers for clean urban planning as well as the research communities for obtaining insights about the air pollution sources and suggesting solutions for mitigating the pollution. The Edge layer is responsible for reactively receiving air quality data from the deployed sensors within Megasense as well as the external sensors owned by third parties. The edge layer is also responsible for data preprocessing, data cleaning and aggregating, calibrating and providing in real-time (seconds) air quality information at the edge using pre-trained machine learning models (Zaidan, M.A. et al. 2020). Both processed and raw data is further relayed to the cloud for long-term storage for further sensor calibration and open data access based on request.

→ *Strong and weak points*

- Strong points.
    - The HOPE pilot project is feasible to be scaled up.
    - The Megasense backend system is efficient in managing air quality data streamed from the HOPE sensors.
    - The HOPE sensors proved to be useful for reporting personal health exposure.
    - The HOPE sensors support complementing air quality maps in cities.
    - The HOPE sensors provided a good avenue to involve interested citizen scientists in air quality project.
- Weak points.
    - The HOPE sensors need to be improved further, due to some technical issues including battery discharge in short time and stability of sensor calibration.
    - Megasense platform is at prototype stage. The Megasense platform needs to be improved to be more user friendly, e.g., Graphical User Interface (GUI) needs to be further developed.

3.3 Conclusions on mobile measurements

Mobile monitoring can be applied to generate a hyperlocal exposure air pollution map in a city or region. The map can be generated based on measured data only (data-only approach) or by combining measured data with models often incorporating geographical predictor variables. Given the large temporal and spatial variability of air quality concentrations, mobile monitoring has some challenges because of the spatio-temporal nature of the collected dataset. Care should be taken during data collection and/or data processing for a good data interpretation.

Deriving the map from only measurements can be achieved by measuring every single street segment a lot of times, . This is possible in a small area, like a couple of streets or a neighbourhood (for example to measure pollution before and after an intervention policy), and can also be interesting to study specific trajectories (e.g. to compare commuting traffic or routes to school). However, for a regular (European) city, this takes a large amount of time and effort. Nevertheless, examples exist in Antwerp (BE), Oakland (US), Amsterdam (NL) and Copenhagen (DK). For large (national) cohorts, it takes too much time to measure. A limited number of repetitions to overcome this huge workload can create uncertainty in average concentration levels. Therefore, in most studies that use mobile monitoring, the measurements are supplemented with a model. The numbers of repetitions required for data-only mapping depends on the study area (variability of sources) and on the data processing (e.g. background correction can reduce the number of required repetitions). It also depends on the targeted representativity of the map (e.g. daily average or peak exposure).

One more potential disadvantage of the data-only approach is the fact that the resulting map consists of only segments and not the locations where people live. Depending on the use case, there may be a need to translate on-road measurements to residential addresses. Work in the Netherlands has documented that UFP and BC models derived from mobile monitoring represented contrast in residential concentrations well without further procedures. Furthermore, only a modest overestimation was found. On-road measurement translation could be done for example by transfer learning, a machine learning method that uses long-term/residential concentration distributions to better estimate residential exposure. The biggest advantage is the small-scale variation (<50m) and

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hotspots of air pollution it can detect, whereas LUR models generally have more difficulty characterising small-scale variation.

Data-only mapping seems viable from a policy standpoint, where small-scale variation can be detected and acted upon with interventions. From an epidemiological standpoint, especially regarding large multi area cohorts, it makes more sense to use models. It is evident that with just a few drives on a road segment (1-4 drives) we are not able to characterise long-term average concentrations, but a LUR model can easily achieve a good correlation with only 1 or 2 drives. However, some studies found that the ability of data-only mapping surpasses the LUR model at about 5 drives when it comes to predicting long-term average (on-road) concentrations (Messier et al., 2018). Future research should verify if this holds in other geographical areas and for other pollutants. For example, UFP is more variable than NO2 in urban environments and mobile measurements might need more repeats to achieve a stable average.

The balance between data-only and model maps also depends on how extensive and detailed predictor variables are available. More and better predictors are likely to increase the performance of LUR models. Mobile monitoring complements traditional air quality data with more variation in contextual information (traffic, urban topology, road types, …), when compared to stationary AQMS, which is important information to train spatiotemporal models.

For monitoring campaigns that intend to create **LUR models**, the number of repeats is less of an issue, as only a few repeats on a large number of road segments are needed for model development. It is important that there is enough spatial coverage by including all different spatial characteristics (road type variation) of the domain. Similar considerations apply to representing other relevant sources in the neighbourhood, e.g. airports, harbours. Next, one needs to consider the time of day (daytime, night-time, rush hour), day of the week and season the road segments are measured. Multiple studies found that with a limited number of repeats and limited amount of street segments robust external predictions can be made. In a mobile setup, street segments with similar characteristics serve as pseudo repeats, meaning LUR models can be developed based on street segments with mobile measurements only measured once, as long as coverage and distribution of all predictor variables is similar to the prediction sites. It is important that the situation during the measurements is representative (e.g. no road closure/deviation, or very polluting vehicles that passes).

Most LUR models based on mobile data use the road segments as spatial aggregation for their models, defined as stretch of road from one intersection to the next. Length is mostly between 100 and 300m in urban environments. A few studies evaluated the impact of spatial resolution in a mobile monitoring campaign and found very little difference between the performance of LUR models that were based on segments where concentrations were averaged over 50, 100 and 200m. As the goal of mobile monitoring is often to find fine-scale variation of air pollution it is best to keep the spatial resolution as low (< 200m) as possible. It is important to aggregate homogeneous points, possibly favouring street segments over regular grids.

Data-only mapping can also be combined with LUR models in a **mixed-model framework**. Here, a LUR model is used to create a base map, and with more and more measurements more local variation can be added to the map. Since models will never perfectly predict concentration levels there will always be a moment where measurements are more precise than models when measuring long enough. By creating a mixed model with a LUR model as the fixed effects and all road segments as random effects, both LUR model and all measurements influence the predicted concentration per road segment. The more precise the on-road measurements are (i.e., less variation in measurements), the more this influences the output. This approach requires repeated measurements on all roads of interest.

The performance of **machine learning models** is very sensitive to the representativity of the air quality dataset. model performance still relies on the spatial representativity (spatial monitoring coverage) of the mobile

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measurements. Accurate and representative data in both space and time is, therefore, needed to properly train the models and provide reliable results (Hofman, Do et al. 2022). As a result, machine learning models will only be useful when a vast amount of mobile data is collected (e.g. opportunistic/automated sampling on service fleet vehicles).

Data collection can be done in a **dedicated** (pre-defined route) or **opportunistic** (monitoring devices go around with platforms on day-to-day activities) way. The first requires less data processing since data during one run is collected (more or less) simultaneously, whereas the latter will need to consider that data at different locations is not collected simultaneously and may have different background.

It is clear that there are not many monitoring campaigns that include citizens for data collections. An advantage of including citizens is the benefit of their involvement, awareness raising, … A disadvantage is the difficulty in controlling the data collection and its quality.

4. Stationary sensor networks

4.1 Stationary sensor networks

4.2 Objectives and data needs

A complementary network of stationary (low-cost) sensors can give a better spatial resolution and also temporal resolution than the regulatory monitoring networks. Dense sensor networks can also be combined with models to extrapolate data and/or to improve the data quality of the sensors. Dense sensor networks can also be used to evaluate dispersion models. In general, similar data processing techniques can be used as describe for mobile monitoring. As already mentioned in the previous chapter, care should be taken to assure a good data quality of the sensors.

4.3 Overview of projects and large trials

In this section we give an overview of projects and large trials where fixed low-cost sensor networks have been used to generate air quality maps. Details of the approach, set-up, instruments, data processing will be given in the next paragraphs. Table 4 shows an overview of different projects where fixed monitoring tools are used.

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Table 4: Overview of projects where sensor networks are used and of which selected methods will be further described in this deliverable.

Name project	Short description	Partner involved	Reference/link
CAPTOR	Low-cost ozone sensors for fixed deployment	CSIC	https://www.captor-project.eu/en/ Ripoll et al., 2019. STOTEN, 651, 1166-1179 https://cordis.europa.eu/project/id/688110/es;
Breathe London		UU, ICL	https://www.breathelondon.org
PANACEA	Low-cost PM2.5 sensors for monitoring air quality	NOA	https://www.iqair.com/greece/attica/athens/panacea-national-observatory-of-athens
HOPE Healthy Outdoor premises for everyone	AQT530 mid-cost sensor network supporting the regulatory air quality monitoring and air quality modeling	UHEL	https://ilmanlaatu.eu/briefly-in-english Petäjä, T. et al. (2021) Added value of supporting air quality observations with the use of Vaisala AQT530 sensor as a part of a sensor network, Frontiers in Env. Sci., https://doi.org/10.3389/fenvs.2021.719567.
RI-URBANS*	Virtual sensor for BC	CSIC, UHEL	J. Rovira, J.A. Paredes-Ahumada, J.M. Barceló-Ordinas, J. García Vidal, C. Reche, Y. Sola, P.L. Fung, T. Petäjä, T. Hussein, M. Viana (under review) Non-linear models for black carbon exposure modelling using air pollution datasets. Environmental Research, *submitted*.
Curieuzeneuzen	Network with diffusive tubes and citizen involvement	VITO	De Craemer et al., 2020. https://viewer.curieuzeneuzen.be/
Samen Meten	Network with low cost sensors of especially NO_2 and $PM_{2.5}$ / PM_{10}.	RIVM/UU	Wesseling J, de Ruiter H, Blokhuis C, Drukker D, Weijers E, Volten H, Vonk J, Gast L, Voogt M, Zandveld M, van Ratingen S, Tielemans E. Development and Implementation of a Platform for Public Information on Air Quality, Sensor Measurements, and Citizen Science. Atmosphere 2019, 10, 445.

* This approach uses only stationary reference instruments and is not further discussed in this document

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4.4 Detailed description of selected methods

4.4.1 CAPTOR in Catalonia (Spain)

→ *Data collection*

Tropospheric O_3 monitoring with custom-built O_3 sensors. Fixed monitoring at volunteer homes, in rural areas within a 60 km radius downwind of the Barcelona conurbation.

→ *Data processing*

Two-step calibration process: initial calibration against reference data at a reference station in Barcelona, and subsequent calibration at a second reference station in the vicinity of the monitoring locations. Data processing using multilinear regression and machine learning algorithms (SVR)

→ *Strong and weak points*

- Strong points:
  - Broad spatial coverage of the data, and high citizen engagement.
  - High data quality achieved.
- Weak points:
  - Large area covered, implying long travel times when instruments required maintenance or replacement.

4.4.2 BreatheLondon

Breathe London is a community-based air pollution monitoring network. A core network is funded by the Greater London Authority, targeting sensitive receptors (hospitals, schools) and areas of high public exposure. Additional sensors are funded by local government, industry, philanthropic organisations or community groups and sited to address their specific air pollution concerns (heavily trafficked roads, sensitive receptors etc). All site location information (e.g. height, distance to road or other nearby emission sources) is held in the central database. All sensors are deployed according to the manufacturer's instructions [Deploying your Clarity Node-S (cellular) devices.]

→ *Data collection*

PM2.5 and NO_2 are measured using the Clarity Node-S providing a 2-minute mean concentration.

Each node has a GSM sim and transmits data to the Clarity data server and echoed to the Imperial College data collection system every hour.

→ *Data processing*

All sensors are initially calibrated against reference sensors at the London urban background supersite in Honor Oak Park before being deployed.

A set of reference sensors are collocated with reference instruments at representative urban background and roadside stations in London in the London Air Quality Network. These provide a dynamic (hourly), site type (background / roadside) correction factor (slope and intercept) for both PM2.5 and NO_2 which is applied every hour before dissemination. Uncertainty is calculated at the hourly limit value (200 µg/m^3) for NO_2 and the daily limit value of 35 µg/m^3 for PM2.5. This approach results in all the PM2.5 sensors achieving the 50% indicative threshold with a mean uncertainty of 19%. 90% of the NO_2 sensors achieve the indicative threshold of 25% and have a mean uncertainty of 9%. Data is processed through a set of algorithms to prevent erroneous data being disseminated immediately. Data is reviewed daily to ensure consistency.

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→ *Citizen involvement*

Community groups can apply for a sensor to deploy in their area from a pool of centrally funded units or seek independent funding to fund one. They are deployed to address their specific air pollution concerns (heavily trafficked roads, sensitive receptors etc).

→ *Strong and weak points*

- Centralised real-time quality assurance linked to reference network.
- Limited number of pollutants measured.

4.4.3 PANACEA

The PANhellenic infrastructure for Atmospheric Composition and climatE chAnge (PANACEA) is envisioned to become the high-class, integrated Research Infrastructure (RI) for atmospheric composition and climate change not only for Greece, but also for southern Europe and eastern Mediterranean, an area that is acknowledged as a hot spot for climate change. The RI is designed to be in full compliance with EU Regulation 651/26.6.2014 and act as the Greek component of ACTRIS/ESFRI (Aerosols, Clouds and Trace gases Research Infrastructure) and ICOS/ESFRI (Integrated CO_2 Observation System). On the other hand, PANACEA is investing on a complementary low-cost PM2.5 monitoring network throughout Greece, aiming at increasing the spatial resolution of PM2.5 measurements in both cities and remote areas.

→ *Data collection*

$PM_{2.5}$ are measured using the Purple Air PA-II devices which provide data at a 2 min temporal resolution, through a cloud-based service provided by the device manufacturer. Data are collected in real-time through an API, and stored in the PANACEA database, before being averaged, corrected and visualised in the developed web portal https://air-quality.gr/en" \h

→ *Data processing*

All sensors, before deployment, are initially co-located with reference instrumentation (beta-attenuation monitor and reference-grade optical monitor (Stavroulas, Grivas et al. 2020) at the Thissio urban background monitoring station operated by the National Observatory of Athens (NOA). Their performance is evaluated in terms of correlation to reference measurements, while assessing the regression coefficients (slope and intercept), as well as in terms of MBE (mean bias error) and nRMSE (normalised root mean squared error). A linear correction factor is then assigned which is applied to the hourly average concentrations before dissemination. After field deployment, sensors are brought back periodically for performance re-evaluation. During deployment an algorithm based “health check” is implemented to all sensor PM2.5 measurements in real time.

→ *Citizen involvement*

Different academic and research groups have already and are encouraged to contribute with sensors and data to the network, once sensors are calibrated and evaluated by NOA. PANACEA is also in close collaboration to Greek local authorities (e.g. regional authorities and municipalities) having installed sensors at authority buildings and schools in different parts of the country.

→ *Strong and weak points*

- Strong points:
  - Centralised real-time quality assurance and online air quality information to the public, especially during pollution events (e.g. wildfires).

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- Weak points:
  - Limited number of pollutants measured significant bias in the presence of coarse particles.

4.4.4 HOPE

European Innovation Action “Healthy Outdoor Premises for Everyone (HOPE, Petäjä et al. 2021)” in Helsinki combined efforts from University of Helsinki (atmospheric sciences, computer sciences), Finnish Meteorological Institute, Helsinki metropolitan quality authority, Helsinki city government and private company, Vaisala. The work included mobile measurements with citizens (described in earlier section) and deployment of an additional fixed sensor network that expanded the air quality monitoring capacity of the local air quality authority. In total, 25 Vaisala AQT 530 air quality sensors were placed around Helsinki. Three areas were targeted specifically (Figure 18):

- Jätkäsaari area, with a large harbour and on-going construction of new housing. The air quality issues at this location included shipping emissions, heavy duty traffic and construction dust.
- Vallila district mainly influenced by emissions from busy main streets and street canyons with high exhaust gas and seasonal street dust concentrations.
- Pakila residential area where local small-scale wood combustion is an air quality issue together with vehicular traffic.

The sensor locations were optimised with ENFUSER (Johansson, Epitropou et al. 2014) regional air quality model that indicated key measurement locations, where additional data would be needed. Technical aspects as well as expert evaluation on the relevance was included in the decision making regarding the sensor placement.

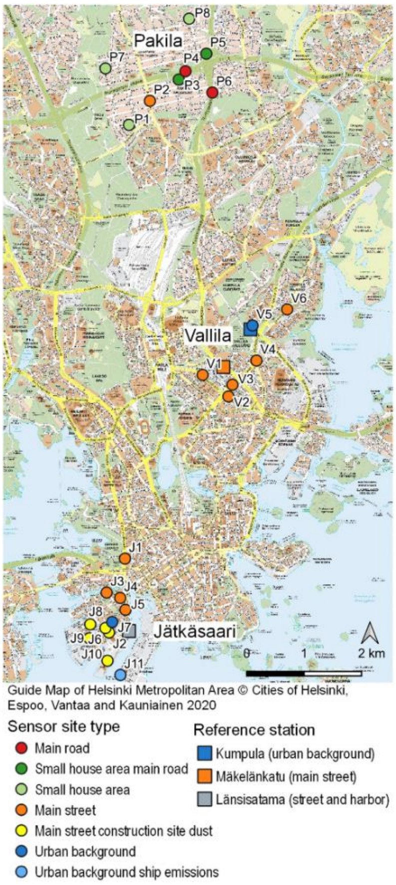

Figure 21: Map of Vaisala AQT 530 sensor placement around the city of Helsinki during HOPE project. For more information, see Petäjä et al. (2021).

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→ *Data collection*

Vaisala AQT 530 sensors monitor measures both gas phase (NO, NO_2, O_3 and CO) and aerosol phase components. (PM2.5 mass concentration with an optical particle counter). The sensor measurement campaign lasted for 1.5 years. The data was collected to Vaisala developed data platform with a pipeline to ENFUSER air quality model.

→ *Data processing*

At the beginning of the measurements, all sensors were first co-located at Mäkelänkatu supersite for quality control against the high-quality instrumentation for few weeks. This provided us with sensor and compound specific correction factors. Five sensors were located at the supersite for extended half-year period to explore sensor stability in more detail. At the end of the deployment the sensor performance was again verified against the supersite instrumentation.

→ *Citizen involvement*

Some of the sensor locations were in the property of Helsinki citizens, e.g. in their balcony (Jätkäsaari) or back yard (Pakila). The citizens were eager to host the instruments and wanted to follow the concentrations that were measured with "their" instrument. For the citizens, we prepared an information package that included a summary of air quality parameters and their typical sources in that specific location. At the end of the campaign, we prepared a sensor specific data sheet that included a typical diurnal cycle from the individual sensor. In contrast we plotted data from the closest official air quality location.

→ *Strong and weak points*

- A network of sensors provided additional spatial information on the distribution of air quality around the city.
- Co-location improved the quality of sensor data.
- Data flow was compatible with ENFUSER air quality modelling framework.
- Only a limited number of air quality parameters were measured.
- PM2.5 was based on optical measurements.

4.4.5 Curieuzeneuzen

The Curieuzeneuzen Project was a citizen science Project in Flanders where 20,000 participants measured NO_2 concentrations using diffusive tubes. At the same time a communication campaign was set-up to teach people about air Quality and impacts from air quality. The data were used to get better insight on spatial variability of NO_2 concentrations and to validate and improve dispersion models.

https://2018.curieuzeneuzen.be/vlaanderen-2018/in-english/

→ *Data collection*

The data set includes NO_2 concentrations that were obtained via Palmes diffusion tubes over consecutive 2-week sampling periods. Passive samplers were collocated at a subset of 24 reference stations of the AQMN of Flanders.

→ *Data processing*

To reduce sampler bias, NO_2 concentrations from passive samplers were calibrated by orthogonal regression against the data from the reference stations at which they were co-located. The data for the two-week period was also normalised to get "annual average" concentrations. Resulting data were plotted on a map (Figure 22).

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Figure 22: NO_2 concentrations collected during Curieuzeneuzen project.

→ *Citizen involvement*

Citizens were recruited via a large media campaign (television, newspapers) and the project was partly funded by the newspaper. About 50,000 people registered to participate and 20,000 were selected. The results were also extensively communicated to the broad public.

→ *Strong and weak points*

- Strong points:
  - Citizen participation, education on AQ.
  - Dense network.
- Weak points:
  - No time resolution (integrated 2-week value).

4.5 Conclusions on fixed sensor networks

The most established low-cost sensors are diffusion tubes or badges. In various countries, including the UK and the Netherlands, cities have set up networks of especially NO_2 diffusion tubes. Extensive calibration procedures have been developed, involving co-location with regulatory grade monitors. These diffusion tubes have good performance but can only provide integrated measurements (weekly to monthly averages). Depending on the use case, this may however be sufficient (e.g. epidemiological studies of long-term air pollution exposure). Low-cost real-time sensors have several limitations due to their nature. In their current state while they are able to provide very frequent measurements, they lack the accuracy of the substantially more expensive regulatory grade instruments and are greatly affected by extreme meteorological conditions (mainly high relative humidity). Thus,

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constant calibration and data evaluation is needed. Low-cost sensors (OEMs) have typical lifetimes of 1-2 years and long-term performance evaluations are still scarcely reported. Regardless of that, they can open opportunities of measurements that were not feasible before due to their portability and low cost.

Using a spatially dense network can help in measuring and understanding the effect of sources that are usually "lost in the big picture", such as the effect of hyper-local sources of pollution (e.g. a restaurant, a fire or very local combustion source). Additionally, this very dense measuring network can also help in understanding the evolution of the emissions in short ranges within the urban topography and their importance in local conditions. This cannot be achieved using the existing network of expensive regulatory grade instruments, as the measuring points are rather limited and in most cases in a great distance between them.

Co-location of sensors with reference-grade analysers (at AQMS) can improve the data quality. Due to their low cost, sensors can also be used in citizen science projects. However, a good calibration and follow-up of their performance and a good expectation management are important.

Not all sensors are available at low cost; some sensor systems cost a few 1,000 euros per unit, include a yearly data/cloud platform subscription and also the set-up, follow-up, maintenance and interpretation of the results needs to be considered.

5. Combined approaches

5.1 General

While stationary monitoring offers high-resolution temporal air quality data (time series), mobile data captures the spatial heterogeneity while the point measurements are not very representative over longer time periods. Combining both approaches (fixed + mobile) yields valuable high-resolution data across both time and space that can serve as input for spatiotemporal models (e.g. Hofman et al., 2022) or can be used to construct maps correcting for variability in background concentrations (Van den Bossche et al., 2015).

5.2 Origin and use of stationary data

Mobile data collection can be combined with stationary data, using stationary data of different origin. These stationary data can come from:

- Reference data (from stationary AQMN) along the mobile route or in its surroundings.
- Sensor networks (using stationary sensors) with different locations in the same area as where mobile monitoring is performed.
- Measurements with stationary sensors where the mobile instruments are used to collect data (stationary) when people are e.g. at home, at work,... A disadvantage of this approach is that there are no continuous time series available since stationary data are lacking during the mobile data collection.

Each of these approaches has its own advantages and disadvantages and requires a different way of combining the data.

The stationary data can be used to supplement info for the mobile data in different ways:

- To give additional information on the representativity of the mobile data in terms of concentrations; to give info on variation during one run (between start and stop) or over different repetitions.
- To scale the mobile collected data (for background variations); this can be done within different runs, between different runs or to compare data sets that are collected in different time periods/seasons.

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- To calibrate sensors when co-located (for a short time).
- To adapt calibration algorithms over time (when sensor is co-located with reference site during the mobile campaign), correcting for sensor behaviour over time.

We have to note that scaling or correcting data for varying background concentrations has some limitations and cannot correct for e.g. seasonal local sources.

5.3 Conclusions

A combined approach using stationary and mobile measurements can provide insight in air quality dynamics and contributing sources at neighbourhood level. While stationary measurements provide data of proven value (in the case of AQMN), mobile measurements (using low-cost sensors) can provide street level exposure information and be used by non-scientific personnel. Many shortcomings are expected to come with such an approach. Mobile measurements are very sensitive to very local emissions (such as cars passing by, activities with a very local footprint etc.), which while being a significant factor in personal exposure can still bias the long-term (community) exposure maps. This should be explained to the involved participants and considered in the monitoring strategy (enough repeated measurements), data processing, and dissemination.

In the previous chapters some examples of combined approaches are shown, where stationary measurements are used for calibration and validation (e.g. BelAIR), model development (e.g. OpenSense), background normalisation (e.g. City Scanner),… Many mobile use cases can, therefore, be regarded as combined approaches. Stationary data can be derived from existing data sources (e.g. AQMS), but can also be collected using a dedicated (temporary) network or fixed sensor site.

An example of a combined approach with dedicated fixed sensor network is the Birmingham pilot (see Annex for a full description). This study will help in better understanding not only the strengths and weaknesses in using low-cost sensors (as their performance will be evaluated using the nearby BAQS, as well as against each other), but for more demanding applications as the one presented here and the real-life challenges arising with citizen involvement as well.

6. Conclusions

Different approaches can be used to assess exposure to pollutant concentrations including ultrafine aerosol particles (UFP), black carbon (BC), nitrogen dioxide (NO_2), particulate mass below 2.5 µm ($PM_{2.5}$) at high spatial resolution for epidemiological studies and other applications. Mobile sensing platforms and fixed (low-cost) sensor networks can be used as complementary tools to data from fixed regulatory AQMN to map pollutant concentrations at a higher spatial density. These data are needed to obtain a better estimate of exposure and related health outcomes.

In this deliverable, an overview of mobile and stationary approaches to increase the spatial resolution of AQ data is given. We summarised general approaches and showed examples of previous projects. Best practices will be tested in the pilot sites within the RI-URBANS project (WP4).

In this deliverable we make a distinction between **mobile/fixed measurements** and experimental designs **with/without citizens**. The collected data can **be processed and analysed** using only measured data or using interpolation/modelling techniques like Land Use Regression (LUR)-based or machine learning models. The selected techniques used for data processing may have an impact on the required data collection approach.

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Each of the approaches has strengths and weaknesses. When selecting a method, the user needs to define the aim of the data collection (research question) and other considerations e.g. one may prefer to engage citizens as part of awareness training on AQ. This is schematically represented in Figure 23.

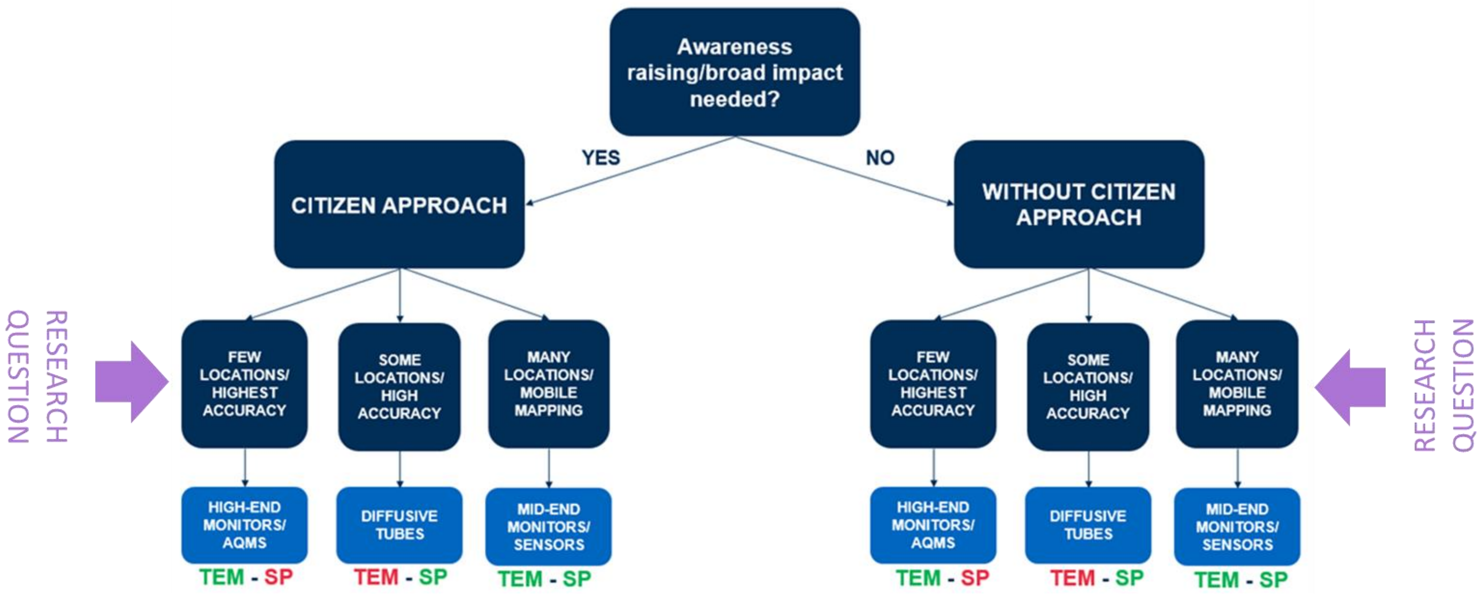

Figure 23: Flow chart with key decision to be taken when implementing mobile and fixed measurements for detailed characterisation of urban variability of atmospheric pollutants, with or without citizen approaches and function of the research question addressed; The colours green and red indicate that the temporal (TEM) or spatial (SP) resolution is good (green) or bad (red)

Mobile monitoring can be used to map pollutants at a high spatial resolution with a limited number of instruments (in contrast to stationary monitoring) and can also use high-end or mid-end instruments exhibiting higher data quality than sensors. Mobile monitoring has some challenges because of the spatiotemporal nature of the collected dataset. Care should be taken during data collection and/or data processing in order to obtain representative results.

Low-cost fixed sensor networks have several limitations, especially for the real-time sensors which have shown varying performances. Good performance has been documented for low-cost diffusive samplers. Diffusive samplers only provide weekly to monthly averages, but this may be sufficient for specific use cases. If so, diffusive samplers are the method of choice. While real-time sensors are able to provide very frequent measurements, they lack the accuracy of the substantially more expensive regulatory grade instruments and are greatly affected by extreme meteorological conditions (mainly high relative humidity). Therefore, a proper calibration and validation approach is needed. We can recommend co-location performance evaluation to evaluate intra- and inter-sensor uncertainty and continuous calibration/validation to compensate for seasonal effects from e.g. temperature and relative humidity. Regardless of that, they provide sensing opportunities that were not feasible before due to their portability and low cost. Using a spatially dense network can help in measuring and understanding the effect of sources that are usually "lost in the big picture", such as the effect of hyper-local sources of pollution.

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Some high-level conclusions are:

- Mobile monitoring can collect more datapoints but give a snap-shot (no time trends). Repeated measurements, and associated sensitivity analysis, are needed to obtain representative results.
- Targeted mobile monitoring makes it easier to compare different locations (collected at the same time). compared to opportunistic approaches (but are often more constrained in space and time coverage).
- Opportunistic approaches mostly require less effort in data collection, result in large datasets but need proper processing to obtain representative results.
- Involving citizens can significantly contribute to awareness raising and obtained impact from the collected results, but will require more time and effort for communication, logistics and dissemination.
- Sensors can be deployed at a lower cost compared to mid- and high-end instruments but suffer from lower data quality. If a high temporal resolution is no requirement, diffusion samplers may be the preferred low-cost approach.
- Sensor calibration and compensation can significantly improve data quality.
- Different approaches for sensor calibration are used, varying from co-location calibrations next to AQMS or reference sensors, real-time network calibrations based on sensor-AQMS comparisons, or purely data-driven models including known covariates (e.g. temperature, RH, O_3).

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8. Annex 1: Description of approaches used in pilots

8.1 General

This annex describes approaches that will be used in pilot cities in RI-URBANs. Whereas the main part of this document describes lessons learned from previous studies, this annex describes the set-up from pilots in RI-URBANs. The results from these pilots will be described in WP4 and the lessons learned from these pilots will be included in D14 (D2.6).

8.1.1 Combined approach used in Birmingham

→ *Data collection*

The area to be studied is in Selly Oak, Birmingham (Figure 21). The area covered will be about 1 km^2, located south of the University of Birmingham. This is a very densely populated area (about 10,000 residents are estimated) consisting mainly of students at the University of Birmingham. Several significant sources of pollution are found in the area, including train stations, construction sites, traffic from nearby roads, local activities (e.g., residential activities, restaurants etc.), greatly affecting the air quality in the area.

A combination of mobile and stationary measurements will be conducted in this area in the period between October – December 2022. For the data collection the Alphasense OPC-N3 (http://www.aqmd.gov/aq-spec/product/alphasense) will be used in both applications (Figure 22). This is a low-cost sensor (~£250) which collects particle number size distribution data and PM mass concentrations in the range between 0.4 to 40 µm in a up to 1 second resolution. The set-up for mobile measurements is shown in Figure 23 and Figure 24.

The **stationary measurements** will be done using the sensor as is, set in several locations within the measuring area. The sensors will be set in buildings within the measuring area. Public buildings such as schools, churches, council buildings etc. (further information in the citizen involvement section) will be used for this. Several buildings will be used to ensure sufficient spatial coverage. In case of limited access to mains a camp battery will be used to provide the electricity needed. Stationary measurements will run for a continuous period of 1 to 2 months (depending on the location). 5 sensors will be initially placed in the measuring area.

The **mobile measurements** will be done using the same sensor attached in a backpack. Along with it will be a geolocalisation device which will provide positioning data. 5 sensors will be given to students at the University of Birmingham (further information in the citizen involvement section) living within the measuring area. These 5 sensors will collect data for 1 month. Data will be collected when subjects will commute from and to the University. The possibility of measuring within the University grounds is still in consideration.

Both methods will run simultaneously for 1 month. The possibility of a second month of stationary-only measurements but in a denser spatial coverage (using all sensors available) will be considered depending on site availability. Data will be stored locally in the sensors' attached SD card, as well as sent on a secure University's online storage using the GSM network. This will also ensure the continuous monitoring of the network of sensors.

http://www.aqmd.gov/aq-spec/product/alphasense

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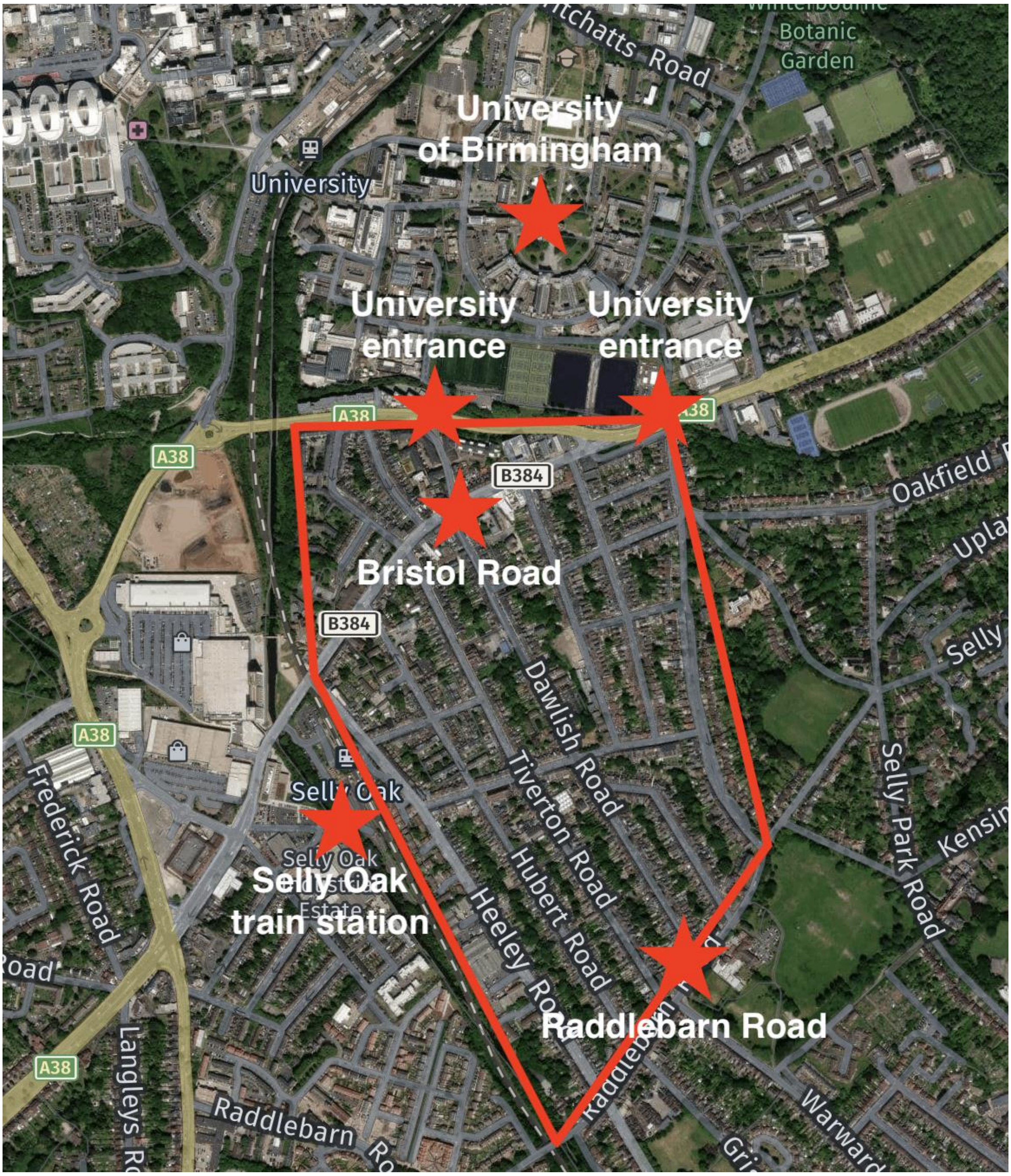

Figure 24: Map of the measuring area and points of interest.

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Figure 25: The Alphasense OPC-N3 sensor.

Figure 26: Current setup of the sensor which will be used for mobile measurements.

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Figure 27: An opened case of the mobile measurement setup. The current iteration can collect and upload to the cloud PNSD, PM mass measurements, and geolocalisation data for about 2.5 days. Weighs about 500 grams with the battery installed.

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→ *Data processing*

The sensors will be collocated and calibrated using the regulatory grade instruments at the Birmingham Air Quality Supersite (BAQS) both at the start and the end of the campaign to ensure the integrity of the measurements. As the sensors have certain limitations when measuring in high relative humidity conditions, the correction factor proposed by Crilley et al., 2018 will be used when necessary. Additionally, there will be a measuring point at one of the gates of the University. This will be used for a daily colocation of the mobile sensors as they will pass from it.

Using the data collected by both methods detailed air quality maps will be generated and the effect of several pollution sources will be checked. Additionally, the spatial evolution of the pollution from these sources will be studied applying statistical methodologies on both the stationary and mobile measuring points spread within the studied area. Finally, pollution source apportionment will be attempted using methodologies which have been tested with low-cost sensors in previous studies (Bousiotis et al., 2021, 2022). Using these, the range of the effect of the sources of pollution in the area will be quantified and reported for possible actions to limit them.

→ *Citizen involvement*

For stationary measurements, several community buildings will be used. Among others, the sensors will be set in buildings such as schools or nurseries. The researchers will have the chance (if permitted) to explain the importance of such campaigns in tackling with air quality problems, explaining to the subjects the sources and problems caused by air pollution in simple words (such as air quality deterioration and the health effects resulting from it). Additionally, the actions that can be taken by the subjects to assist in air pollution reduction will be discussed.

For mobile measurements, students at the University will be engaged. The importance of such measurements in understanding the level of air quality in their living area, their contribution to it and the ways they can help in tackling air quality problems will be explained. By doing so, the subjects are expected to be more willing to help, cooperate, carry out their 'mission' and spread the word of the importance of such campaigns. This may also ensure their future cooperation in similar campaigns of the subjects and others who will be informed by them. To achieve that, a part of the results should be shared with them in a simple and comprehensive way, ensuring their engagement to the 'goal'.

→ *Strong and weak points*

- Strong points:
    - Increase of spatial coverage.
    - Measurements on neighbourhood level.
    - Help people understand the importance of such measurements and their cooperation for the greater good.
    - By sharing the results in a simple way, we can ensure that the air pollution problem is understood and it is not "a thing only scientists care about".
    - Wider public engagement. This can be achieved by understanding the air quality in their area and what affects it, as well as the benefits from their cooperation.
    - Increase awareness and willingness for citizens to engage in future campaigns and plans for air quality improvement.
- Weak points:
    - Time is needed to clarify the importance of such campaigns. People need to be educated and understand the benefits of such campaigns in the problem of air pollution.
    - Subjects of mobile measurements will be paid to carry out their part. They can consider this as a "job" rather than being a contribution to common benefits and thus not completely follow the instructions.

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- People are not educated enough to understand the importance of their engagement. For many “we are just spending government money”. The question “what do I get for this?” was heard when looking for sites.
- The biggest limitation on mobile measurements is to ensure subjects’ commitment. Regardless, the kit provided should need minimum input from the subjects to ensure reliability of the measurements.
- Battery limitations (size versus capacity) should be considered to make the kit as compact as possible. The frequency of battery maintenance should be as limited as possible.
- The route cannot be fixed. Routing will be decided according to the participants’ residence. The longest possible routes will be chosen from the pool of the participants, though this will be limited by the latter.
- For stationary measurements we experience great willingness for cooperation from the community. Some areas though lack public buildings and this makes it harder to get measuring sites in them.
- For long measurement periods electricity is needed. Since the sensors will be put outdoors, access to mains electricity is not always possible without modifications or compromises on the buildings. In many cases there was a willingness to participate but not for such modifications on the subjects’ residence. The use of large batteries becomes mandatory in such cases, increasing the cost of the installation.
- Only a fraction of the day will be covered using the mobile data. Mobile data will mainly be used to evaluate the ability of the sensors in collecting sensible data on the move and less for the characterisation of the air quality (hopefully this can be achieved as well). For mobile measurements a more dedicated plan should be carried out, using fixed routes, longer measuring periods and variability on the time of the day.

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