Deliverable D48 (D6.3)

Roadmap for citizen engagement for AQ monitoring

RI-URBANS

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

By

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Deliverable D48 (D6.3): Roadmap for citizen engagement for AQ monitoring

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1. ABOUT THIS DOCUMENT

As outlined in the RI-URBANS Deliverable D13 (D2.5), improved spatiotemporal resolution of multi-component air quality (AQ) data is critical for improved understanding of the connection between AQ parameters, human exposure and consequent health effects. Advances in sensor technologies and the availability of portable and sensing devices give rise to new opportunities for mobile monitoring and denser fixed sensor networks. Different approaches can be used to assess exposure to pollutant concentrations including Ultra Fine Particles (UFP), Black Carbon (BC), nitrogen dioxide (NO_2), particle mass concentrations (PM) smaller than 2.5 µm ($PM_{2.5}$) at high spatial resolution for epidemiological analyses and for better informing urban policy actions. Mobile sensing platforms and fixed sensor networks can be used as complementary tools to data from fixed regulatory Air Quality Monitoring Networks (AQMNs).

D13 (D2.5) summarised complementary approaches to traditional AQMS in order to derive high-resolution exposure maps for health and epidemiological studies, to inform policy actions at urban scale and other applications. Monitoring approaches were classified into four approaches, based upon involvement of citizens (yes/no) and whether monitoring was fixed or mobile. These monitoring approaches were subsequently tested in three RI-URBANS pilot cities as part of WP4. Specifically, pilots were conducted in the cities Birmingham (UK), Rotterdam (The Netherlands) and Bucharest (Romania). The approaches included mobile monitoring with and without involvement of citizens and with and without fixed site measurements or low-cost sensors. The lessons learned from these pilot city initiatives are compiled in Deliverable D14 (D2.6).

The lessons learned in the pilots also resulted in a Service Tool (ST): ST13: Urban mapping and citizen science, available on the website.

This document is the outcome of task 6.2; the aim of this task is the development of a roadmap for citizens participation in AQ monitoring based on best practices from T2.3 and lessons learned in the pilot 4.3. This includes a summary of the technical and scientific issues and will give a guidance on how developed concepts can be integrated in a sustainable way in AQMNs and engagement strategies that can be used by AQMNs.

This document will use the lessons learned in this project and translate them in practical advice for AQMN. D48 (D6.3) will give *guidance on how developed concepts can be integrated in a sustainable way in AQMNs and engagement strategies that can be used by AQMNs* D48 (D6.3)

We will address issues such as:

- Display of data, regular workshops, provision of background information and possibility to ask questions to interpret monitoring results.
- The targeted and opportunistic monitoring approaches, both top-down (initiated from the AQMNs) and bottom-up will be analysed.
- The mobile and the citizen-AQMN approaches will be evaluated, with the local AQMN being responsible for managing the portable devices and running the data processing algorithms on the collected data.
- Guidelines will be provided for QA/QC procedures.

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This is a public document that will be distributed to all RI-URBANS partners for their use and submitted to the European Commission as a RI-URBANS deliverable D48 (D6.3). This document can be downloaded at https://riurbans.eu/work-package-6/#deliverables-wp6.

2. AIMS OF THE DELIVERABLE

In this deliverable, we will translate the lessons learnt reported in deliverable D14 (D2.6) from the application of monitoring methods outlined in Deliverable D13 (D2.5) and tested in RI-URBANS pilot cities (WP4) to strategies that can be used by AQMN.

The aim of this deliverable is to focus on the CS aspect, however, relevant technical and- data processing aspects for CS measurements will be shortly discussed as well.

The aim of this Deliverable D48 (D6.3) is to:

- Summarise added value of mobile monitoring and citizen science to monitoring outdoor air pollution;
- Summarise lessons learned of pilots and translate good practices for AQMN
- Reflections on methodological choices:
  - **Monitoring strategy**: Considerations for study design and impact of design choices;
  - **Data processing**: Reflection on method choices;
  - **Modelling strategy**: Reflection on modelling choices;
  - **Results:** New insights based on pilot studies.

This deliverable D48 (D6.3) focuses on monitoring methods, including direct use of the monitoring results (data-only approach) and modelled extrapolations (model approach). Deterministic modelling is not part of this deliverable. WP3 has evaluated deterministic modelling in detail. The deliverable focuses on the methodological issues and implementation in AQMN, visualization of results, as well as engagement of citizens in AQ data collection. Detailed results of the pilot studies have been reported as part of WP4 reports. Detailed results of the pilots are being combined for a peer-reviewed publication.

3. BACKGROUND ON MONITORING APPROACHES

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 (e.g. UFP, BC & NO_x), can show a very high spatial and temporal variability within a city or neighbourhood. Other sources than traffic such as woodburning may also result in high variability While established urban networks of fixed site monitors have spatial densities on the order of 1-10 km^2, concentrations of air pollutants can vary significantly within 10-100 m from roadways. It is difficult to extend the density of the network of AQMS due to their high installation and maintenance cost.

Improved spatiotemporal resolution of multi-component air quality data is critical for improved understanding of the connection between human exposure to air pollutants and health effects. To assess the impact of air quality on health it is important to have fine-scale data on air quality exposure. Advances in sensor technologies and the

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availability of portable and low-cost sensing devices give rise to new opportunities for mobile monitoring and denser fixed sensor networks.

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 below 2.5 µm ($PM_{2.5}$) at fine spatial scale. Mobile sensing platforms and fixed (low-cost) sensor networks can be used as complementary tools to data from fixed regulatory AQMNs (Morawska et al., 2018; Hofman et al. 2022; WMO, 2024), to map pollutant concentrations at a higher spatial density to provide more localized insight in the state and management of air quality.

A major application of these concentration maps is exposure assessment in health studies of long-term exposure to air pollution. High-resolution pollution maps can be of interest for local authorities in a variety of applications; i.e., hot spot detection, new AQMS localization, model validation, evaluation of policy measures. In this text we discuss 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. We make a distinction between mobile/fixed measurements and experimental designs with/without citizens (see Figure 1).**

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

Note that in this deliverable we will focus on methods where citizens are involved. For a broader discussion on mobile mapping and mapping using dense networks we refer to deliverable D13 (D2.5) and D14 (D2.6).

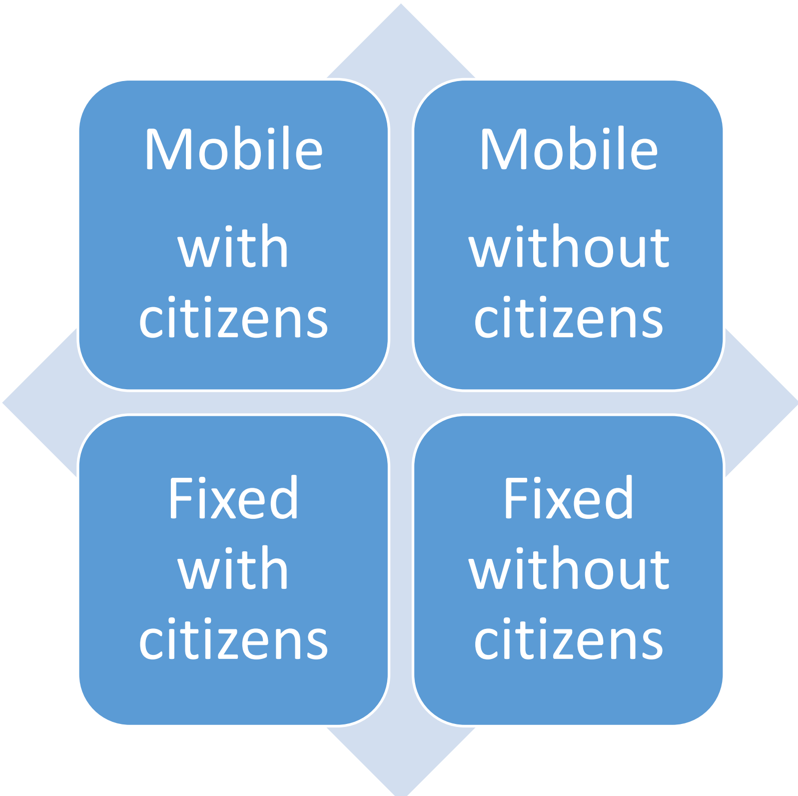

Figure 1. *Schematic overview of different approaches for collecting data for high-resolution exposure mapping.*

4. USE CASES OF HIGH-RESOLUTION CONCENTRATION MAPS

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 environment.
- 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 AQMN 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 (as demonstrated during the Rotterdam pilot). The involvement of citizens is first discussed. We will focus here on recommendations on how citizens can be motivated and engaged and how results/feedback can be communicated.

In the COMPAIR project (wecompair.eu) the use of sensors and citizen science approaches has been explored for policy makers, citizens and researchers. The COMPAIR project has different deliverables that are complementary to this one and will be referred to in a specific section. Also, the SOCIO-BEE project (https://socio-bee.eu) worked on citizen engagement and AQ and some lessons-learned from that project will also be integrated here.

5. CITIZEN INVOLVEMENT AND MOTIVATION: GENERAL RECOMMENDATIONS AND BEST PRACTICES

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. 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. 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

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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 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. 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 behaviour, 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. We also refer to other best practices on citizen science like Citizen science toolkit. https://making-sense.eu/publication_categories/toolkit/

5.1. 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). In GroundTruth 2.0 citizens were involved in defining the measurement requirements and set-up, and execution of the measurements, in close consultation with the scientists and the city council (Van Poppel et al. 2024) 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 geolocalization (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

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citizens with automatic data collection and upload to cloud service and visualization. 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, useability 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 (personalized results) with the participants during the project, instead of only at the end of the project, may also increase motivation. In the pilot Rotterdam of RI-URBANS, a lunch talk (for the participants) was organized to give feedback on the outcome; because not all measurements were collected simultaneously, we also had to explain the differences in personal results related to differences in background concentrations and the need for data processing (background normalization)

The SOCIO-BEE project demonstrated that citizens can be engaged on different level in one project. Their concept is to work according to the beehive metaphor as engagement approach, defining different roles for different participants. The concept is explained in D12 (D2.4) - Target user behaviours & determinants for Citizen Science driven green behaviour, and different engagement profiles are described: e.g. Queen bees (coordination of activities), Worker bees (active participants in activities like data collection), …

5.2. 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. Recruitment can also be done through workplace (if employees are the target group) like in the pilot Rotterdam of RI-URBANS; this makes communication for recruitment, experimental phase and feedback much easier.

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.

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5.3 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. Ethical implications 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.

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 anonymized before data analysis to avoid identification of the participants. Similarly, project results should be released in an aggregated form to preserve participants identity. Personalized 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 authorized 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 (Froeling, 2022).

When participants contribute in a study to collect data for an aggregated map (and not for own personal exposure assessment), and their names are not linked to the collective dataset (concentration and GPS) there are less GDPR issues.

5.4 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.

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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 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).

6. DATA COLLECTION AND DATA VALIDATION

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. However, 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). This means that the data obtained must be as accurate, complete and as relevant as possible to ensure that the project will provide data that is useful. Of course, this needs to be balanced with budgetary constraints, but this does not mean that only low-cost sensors can be used in CS projects. A solution to address budgetary constraints is to use mid-range instruments of medium cost that can be loaned by the research institute involved or by the AQMN; By doing so it is also guaranteed that the calibration and/or maintenance is done correctly. Another option is to use diffusive samplers if time resolution is less important; For NO_2, passive samplers are still the method of choice if the interest is in long-term exposure, as they are more reliable than the current state of the art of low-cost NO_2 sensors. A nice example includes the Curieuzeneuzen project, where 20,000 people measured NO_2 concentrations at the façade of their residence (Dons et al. 2020). The same applies to ammonia monitors. In general PM sensor show a better performance than sensors for gases but PM is not always the best parameter to study impact of sources, measures or HI, as PM can be considered a regional pollutant, exhibiting limited spatial variability.

The RI-URBANS pilots in Rotterdam and Barcelona showed the potential of using mid-range portable instruments for BC (microaethalometer) and UFP (Partector) in citizen science.

Other considerations are that selected instruments 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). Instruction manuals were prepared for the participants of the Rotterdam pilot and instrument procedures/handling were kept as little labour intensive as possible.

Researchers and citizens are encouraged to co-create standards for data collection, deciding on measurement set-up or methodology for data collection, in function of the use case. Finally, the project should make all the efforts to generate data under the FAIR (findable, accessible, interoperable, reusable) principles.

Quality control of the instruments used for citizen science studies should be carried out before, during and after the measurement campaigns. A good approach is to do a co-location for between-instrument variability and for comparison to the reference instrument, to ensure the performance is acceptable for data collection (Hofman et al., 2022c, Hofman et al., 2024). A good approach is 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) intercomparisons to assess their performance after some time.

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Monitoring devices are discussed further in Chapter 0 (mobile) and 0 (stationary).

In summary the following points are relevant for a successful CS project (related to data collection and validation):

- Need for easy to understand and operate equipment.
- Need for equipment that is easy to carry along (light weight & small).
- Need for acceptable data quality (to be used and trusted).
- Right instruments to measure the relevant pollutants.
- Correct measurement protocol and set-up.
- Use of proper data validation approach including co-location and/or calibration.

A guide for AQ monitoring by citizens was developed in the COMPAIR project with input from RI-URBANS (see COMPAIR | Wecompair.eu)

Also, the SOCIO-BEE Project discussed the challenges related to monitoring devices for CS Project; determining the accuracy and general reliability was identified as a main general challenge. Specific challenges for wearable equipment (mobile mapping) were identified as i) strong humidity transients affecting gas measurements (indoor/outdoor), ii) user dependent handling and storage (related to clear instructions and unified procedures), iii) short measurement times that do not allow for proper validation, iv) battery management. Challenges for stationary were identified related to i) selecting (suitable/relevant) locations, ii) continuous power and connectivity, iii) higher band width for data transfer.

7. 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 feedback 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 or lunch talks, where participants can 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 behaviour change and local impact in communities more easily than scientific papers or reports. In the RI-URBANS Rotterdam pilot, we had an interactive DCMR lunch talk to disseminate results and collect feedback from participants on ease of use of instrumentation and their experiences with regard to monitoring, awareness raising and/or behavioural change.

The COMPAIR project showed that citizen science can be a powerful catalyst for behavioural change; participants who were actively involved in data collection demonstrated a greater awareness of environmental issues and were likely to alter their behaviours (such as reducing car use and supporting local environmental policies). (source: D6.2 pathways to behavioural change report COMPAIR (in prep)). COMPAIR concludes that empowering citizens through science not only enhances their understanding of environmental issues but also motivates them to adopt more sustainable practices. The project recommends that future initiatives continue to focus on community-driven

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approaches, ensuring that participants have a strong sense of ownership over the data and outcomes. Additionally, the findings suggest that integrating citizen science into broader environmental strategies can significantly amplify the impact of such efforts.

8. LESSONS LEARNED FROM THE PILOTS

The approach of involving citizens in mobile monitoring of air pollution worked well, both in Birmingham and Rotterdam. In Rotterdam, these were employees of the DCMR and municipality of Rotterdam. These were more knowledgeable in terms of air quality than the average citizen. In addition, it made it easy to have a local coordinator from DCMR organizing and supervising the campaign. In Birmingham citizens were invited from the population, sometimes with a reward for participation added. The latter increased the response rate, but also resulted in students primarily interested in the reward.

The Birmingham pilot obtained useful experiences for interacting with citizens for LCS monitoring in or near their home. Building trust between citizens and researchers is an important issue. Respecting anonymity is another requirement for both citizens and schools and other organizations. Providing relevant feedback is important as citizens often participate because they are interested in the topic.

The Birmingham indoor AQ showed that people were interested in the AQ of the spaces they spend most of their time in, and the factors that affect their quality of life. Simultaneous collection of data from as many indoor environments as possible. In Birmingham, houses as well as the three classrooms had significant differences between them, even though they were located very close to each other.

Amount of collected data, awareness raising, identification of hotspot locations, more representative personal exposure assessments in urban environments/during specific activities (e.g., commuting) were identified as added value of involving citizens in the Rotterdam pilot.

The Rotterdam pilots also showed the need to explain difference in (individual) results when data were not collected simultaneously (e.g. due to differences in background concentrations) and the need to rescale data that is collected at a different moment in time (background normalization).

9. MOBILE MONITORING

Good practices on monitoring approaches and strategies are extensively discussed in D13 (D2.5) and D14 (D2.6).

Below, we give a brief summary of methods and requirements when citizens are involved.

9.1. Monitoring strategy

It is very important to think in advance about the monitoring strategy in function of the use of data before data collection is started. Slight changes in the data collection scheme might result in considerable improvement of the results. At the same time, the required efforts and number of volunteers need also be considered.

Figure 2 shows different approaches (mobile and fixed); it illustrates the considerations in terms of set-up and devices that can be used, and also lists the pros and cons of the two approaches. For more details on the set-up and devices we refer to D14 (D2.6) and the ST13.

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

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 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.

When considering mobile monitoring it is important to consider the type of mobile platform (walking person, bicycle, car, tram, …), the measurement timing (e.g. hours of the day), and monitoring locations/route. To construct high-resolution exposure maps, it is important to collect enough monitoring data in both space and time to represent the average air pollution exposure.

Mobile monitoring can be performed by **repeating predefined fixed routes (dedicated approach)** or using a more **opportunistic approach**, using a carrier that performs the measurements during its day-to-day activities without

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intervening with these activities. When using the opportunistic approach, constraints are needed in the post-processing (e.g. map matching, number of repeats) to obtain robust exposure data.

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 document, 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). It can also be a vehicle (postal van, bus, tram...) but this is not with involvement of citizens and thus not the focus of this deliverable. However, dedicated versus opportunistic approach is not a black or white story and there are situations where data can be collected in an opportunistic way, but still having some control on the number of repetitions and the trajectories. A good example is the organization of a campaign in a company/institute/government entity/university asking employees to measure their exposure during commuting; In the Rotterdam pilot, we explored the approach of employees collecting data during daily commuting from and to work. The routes can be selected (by selecting employees with most relevant commuting routes) and participants can be asked to measure the same route (excluding other activities) multiple times and aligning this monitoring protocol along the participants. This approach has additional advantages: the campaign can be more easily coordinated by one responsible person and the communication can also be easily organized e.g. through a lunch talk.

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 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 utilized in Helsinki in the 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. A similar exercise was performed for PM2.5 by cyclists in the province of Utrecht, The Netherlands (Wesseling et al., 2021).

A prior careful consideration of spatial and temporal variation is needed as measurements are only representative for the space and time they have been collected. Temporal variation tends to be higher than the spatial variation so at least you must consider sufficient replications of the temporal component in each relevant spatial location to obtain representative exposure assessments.

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 makes it easier to perform background scaling to e.g. yearly average values. A drawback is the workload: when citizens are involved, they must drive/walk the route in addition

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to their normal activities and when a vehicle is used, a driver needs to be paid to do the measurements. Note that data collection during commuting can reduce the workload but reduces the synchronization of the measurements (e.g. Rotterdam pilot). The Rotterdam pilot showed that commutes are not only performed during rush hours!

The opportunistic approach can 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. 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.

Consider that mobile measurements are representative for the time and space they have been collected. As such, (i) the monitoring strategy will determine the applicability of the results and (ii) repeated sampling and temporal corrections are needed to obtain location-representative results and (iii) model extrapolation might be needed to predict air quality at other time and space instances.

9.2. Requirements for monitoring devices

Requirements for monitoring devices need special attention when used for mobile data collection or used for unattended use over several periods, and used by citizens who do not have specialized knowledge on air quality and measurements. Also important for the interpretation of results is to know whether the observed concentration gradients are within the instrument uncertainty or not. More details on monitoring devices are given in ST13 and D13 (D2.5). Below we give a condensed summary of the different topics.

Data quality

Data quality is important since collecting data with sensors without knowing the data quality is not useful. As miniaturized 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. 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.

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.

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

- High relative humidities. Hygroscopic growth of particles at high relative humidity (around >75%) results in overestimation of particle mass due to growth of particles. 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 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. In environments where small particles (<300 nm) comprise a large amount of particle mass, low-cost OPCs will be subject to significant error.

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In addition to the sources of uncertainty summed above, some sensors do not estimate the PM_{coarse} fraction correctly. Some sensors use an algorithm to estimate the PM_{coarse} (PM_{10} – $PM_{2.5}$) based on $PM_{2.5}$ concentrations. This might result in high uncertainties at locations close to sources characterized by a high amount of coarse dust (Vercauteren, 2020).

NO_2 sensors rely on different measurement principles (electrochemical or metal oxide) (Hofman et al., 2022b). 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 et al., 2022b). Moreover, the sensor's electrolyte (responsible for ion transportation) will age naturally as a result of exhibited temperature and humidity variability (Raninec, 2021).

Accurate portable devices are available for pollutants such as 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.

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).
- 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 driving at a low speed of 15 km/h (e.g. by bike), a single measurement point will take respectively 250 m and 42 m at a time resolution of respectively 1 minute and 10 seconds. At a walking pace (5 km/h), the spatial resolution becomes 14 m, at a 10 second resolution.

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. It is recommended that sensors/instruments are co-located/evaluated prior to use at a stationary location.

Use by citizens

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

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.

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- Notification: option to mute.
- Optimized 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.

9.3. Data processing: direct and model-based mapping

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

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

More details on data processing methods are given in ST13. ST13 gives more details on the following topics (which are very short explained in the paragraph below):

- Completeness of datasets.
- Data processing for direct mapping.
- Models based on monitoring.

Completeness of the dataset

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 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. In the remaining of the text, we use temporal coverage and spatial coverage.

When both mobile and fixed measurements are plotted on a 3D graph with x/y representing geographical coordinates and z the time, 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)

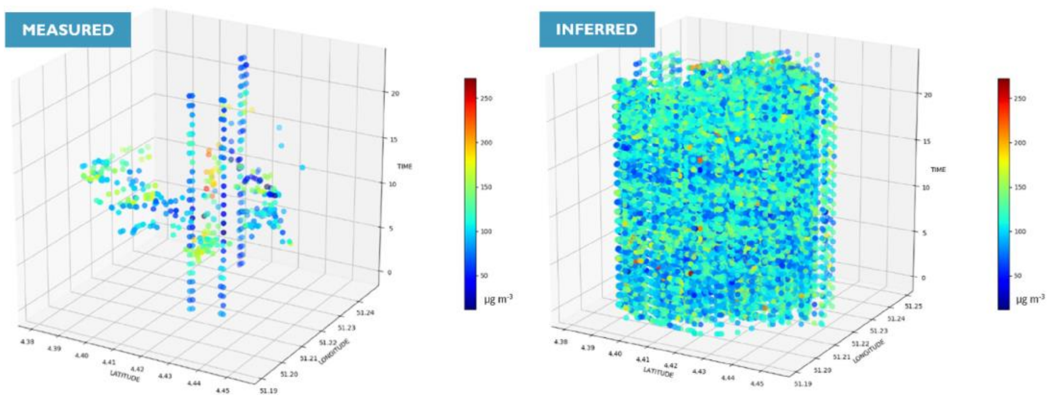

Figure 3. *Concept visualisation of fixed and mobile sensor measurements represented as a sparse data matrix in space (x-y plane) and time (z plane). Right: Inferred air quality values by a machine learning model (from Hofman et al. (2022a)).*

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Temporal coverage (completeness according to Mehanna et al., 2022 or "segment" coverage in Hofman et al. (2023)) characterizes the way a given period of time is covered by the collected measurements. Evaluation of the temporal completeness can go with different assumptions. 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 outcome. 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 influence pollutant concentrations with typical lower concentrations during weekend days compared to weekdays. When we want to maximize the observed spatial patterns, it might be advisable to collect only data during working days (e.g; with highest traffic load). 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. To assess the air quality in a city, it is recommended that measurements be taken in different seasons. However, this is not always possible due to constraints, such as the budget or availability of volunteers (Van Poppel et al., 2024).

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). In the Rotterdam pilot, data processing techniques (winsorizing + additive or relative background normalization) were tested to rescale the data to representative seasonal exposure estimates. We refer to Deliverable D14 (D2.6) for further information.

Spatial coverage means that the entire study area needs to be mapped. This is referred to as "Area Coverage" in Hofman et al. (2023).To generate high-resolution maps large quantities of data are required to include day-to-day changes 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.

Data processing for direct mapping

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 (model approach).

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). The applied data processing flow in the Rotterdam pilot is shown in Figure 4, with successively synchronization of GPS and pollutant data at 1 sec resolution, noise/background correction of pollutant data, map matching of measurements to followed monitoring trajectory, aggregation within point buffers (subsequently for every passage and for all passages).

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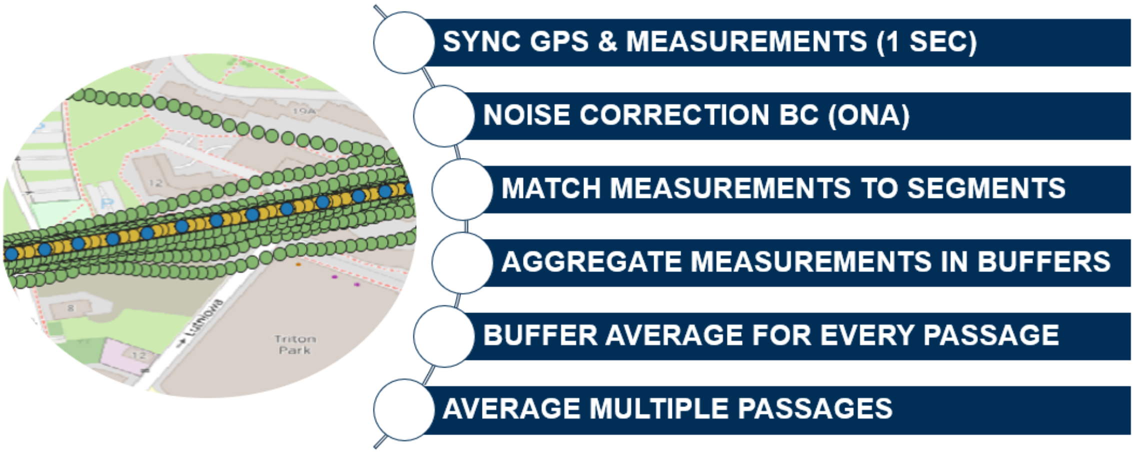

***Figure 4**. Data processing flow of mobile data (multiple repeated sampling runs denoted by green trajectories) collected in the Rotterdam pilot, matched to designated study trajectory (yellow) and averaged into point buffers (blue dots).*

Details on previous studies are given in ST13. 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

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.

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. 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.

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.

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), Mechelen (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 has shown to reduce the number of required repetitions). It also depends on the targeted representativity of the map (e.g. daily average or peak exposure).

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

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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 NO_2 in urban environments and mobile measurements might need more repeats to achieve a stable average. Mobile air quality data on PM, UFP and BC was collected in 2024 in Warsaw to evaluate this (analysis ongoing). Areas where non-traffic sources are dominant, with a stronger dependence on wind direction may require a different amount of mobile data.

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.

Models based on monitoring

In the review papers of Jerrett et al. (2005) and Hoek (2017), different classes of models to derive intra-urban exposure assessment were identified and also Xie et al. (2017) described different data modelling techniques ranging from geostatistical techniques, Gaussian models, linear regression, artificial intelligence to compressed sensing, to assess pollutant concentrations and personal exposure. An overview of these models is summarized in ST13. These models are not only applicable to CS data. For CS we need to take into account the representativity of the dataset (as discussed in section above). Some modelling techniques require a dense network of sampling sites, or need data that are collected at different type of sites representing the predictor data (LUR models). Some models can handle spatio-temperal resolved data.

For monitoring campaigns that intend to create **LUR models**, 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. 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, if 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).

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 resulting dataset can also be used to validate and improve **dispersion models**. Van Poppel et al, 2024 showed how mobile data can be used for model validation. The study showed that that dispersion models can underestimate concentrations at (some) traffic locations, related to absence of good traffic data. On the other hand, using mobile data for dispersion model validation also has some concern like synchronisation of modelled and

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measured data; in the study of Van Poppel et al., 2024, dedicated model runs were performed to map modelled with measured data; Another concern is the occurrence of specific events during the mobile measurements, which can be accommodated by repeated measurements.

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 measurements, as evidenced by a validation exercise of 2 machine learning models trained on 3 different mobile datasets (Hofman et al., 2022a). Accurate and representative data in both space and time is, therefore, needed to properly train the models and provide reliable results (Hofman et al., 2022a). The total number of repeats (#locations x #repeats) is in this regard decisive (Blanco et al., 2023). 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). Note that the examples given do not include citizens but use another platform.

10. STATIONARY SENSOR NETWORKS

10.1 Monitoring strategy

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 or LUR/machine learning models.

A complementary network of stationary (low-cost) sensors can give a better spatial and 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 described for mobile monitoring. As already mentioned in the previous chapter, care should be taken to assure a good data quality of the sensors. In Deliverable 2.6 an overview of different projects where fixed monitoring tools are used is given in table 4.

10.2 Monitoring equipment

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 NO_2 diffusion tubes in particular. Also in Flanders (BE) an extensive CS project was performed using diffusion tubes: Curieuzeneuzen (Dons et al., 2020). 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 are better able to provide highly time resolved measurements but lack the accuracy of the substantially more expensive regulatory grade instruments, and are greatly affected by meteorological conditions (principally temperature and high relative humidity), and particle physical and chemical properties. Thus, 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 rarely reported. Regardless of that, they offer opportunities of measurements that were not feasible before due to their portability and low cost.

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Using a spatially dense network can help measure and understand the impact of local sources that arenot adequately spatially resolved, 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. However, it is important to consider the larger uncertainty associated with these sensors; the advantages in spatial resolution will be limited by the uncertainty.

Co-location of small 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 1000 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.

11. COMBINED APPROACHES

While stationary monitoring offers high time resolution air quality data (time series), mobile data captures the spatial heterogeneity which better reflects changes in emissions and exposure. 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.(2022b)), or can be used to construct maps correcting for variability in background concentrations (Van den Bossche et al., 2015).

Mobile data collection can be combined with 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 study area 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
- 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.
- To evaluate sensor drift over time (during mobile campaign), evaluated in Hofman et al. (2023)

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.

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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.

Stationary measurements are often used for calibration and validation, model development, background normalisation. 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. 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.

12. LESSONS LEARNED FROM THE PILOTS RELATED TO THE METHODOLOGY

One overall message from the three pilot studies is that substantial new information can be learned by campaigns of mobile monitoring or low-cost sensor (LCS) fixed site indoor and outdoor monitoring of a limited duration (weeks to months) with a proper design. This makes these methods useful as an addition to routine monitoring with reference grade instruments at a small number of fixed sites. Obviously, in a specific domain, the longer the additional campaign, the more precise estimates of air pollution patterns can be obtained. We note that these campaigns are intended to provide complementary information to the fixed site monitoring, not replace such measurements, as they provide excellent temporal resolution (at a limited number of locations).

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

In the paragraphs below, we summarize the lessons learned from the pilots related to the methodology. Lessons learned related to the engagement of citizens are summarized in (Chapter 5).

The following methodological aspects are discussed:

- Monitoring strategy: Considerations for study design and impact design choices;
- Data processing: Reflection on method choices;
- Modelling strategy: Reflection on modelling choices;
- Results: New insights based on pilot studies.

12.1 Monitoring strategy

The pilots showed that **different monitoring strategies** can result in new (spatial) information on AQ, complementary to AQMN. The pilot in Rotterdam (with citizens) also showed that approaches between dedicated and opportunistic campaigns can have success in terms of execution of the data collection and involvement of citizens. The pilot in Rotterdam with the car showed that different pollutants result in different hot spot locations.

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Below we give a summary (checklist) related to data needs as preparation of the monitoring set-up.

Data needs for mobile monitoring that must be defined are summarized below (see also Figure 1 above); For more information on specific topics, we refer to the specific chapters /paragraphs in the text.

- Monitoring set-up (route/area, time) = *measurement scheme*; this is a function of use case:
  - The measurement scheme is function of the info that we want to take out the campaign.
  - For mobile mapping and sensor networks it is important to also include background areas (with typical background concentrations); if possible, an AQMS along the route (or nearby) is also interesting, or a co-location of one of the sensors at an AQMS.
  - Route for mobile measurements:
    - Dedicated approach: this means that the route is defined.
    - An organized and controlled opportunistic approach:
      - The route is defined by specific activities (eg commuting) but participants are selected, and same routes are repeated.
      - Different areas are defined in which data collection will take place.
    - Opportunistic approach: no intervention in terms of route.
    - Important to note here is that whereas opportunistic seems to be the most favourable in terms of collecting data, data will be not necessary collected at locations of interest.
- 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. Also, the relation between expected variability and measurement resolution of the measurement device needs to be considered.
- 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). Especially when measurement-only maps will be constructed, data need to be rescaled when collected at different moments in time and need to be compared to data at fixed stations to understand the representability of background concentrations.
- Data use: Exposure assessment versus hot spot detection: a different data collection approach is used in terms of route/ time (see also monitoring set-up):
  - For exposure assessment we focus on mobile measurements to construct exposure maps (this means we do not focus on personal exposure measurements, since this requires a different approach).
  - 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.
  - Practical requirements: portability, resilience to shocks and vibrations, ...
  - (High) monitoring resolution (depending on the mobile platform, typically <1 minute; ~1-10 sec).
  - GPS (for mobile mapping); also taking care of synchronization of monitoring instrument and GPS.
  - In addition, it is recommended to do a side-by-side intercomparison with reference instruments through collaboration with AQ peers (see also quality control below)
- 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.

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- 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.

Detailed frequent **quality control** is essential, both in studies employing LCS and in studies using reference grade instruments. Comparisons with routine monitoring stations prior to and after fixed or mobile monitoring studies are important. Results need to be evaluated immediately such that potential errors can be detected before embarking on the campaign.

The pilots also delivered a large number of practical considerations to make low-cost monitoring near homes possible, including the observation that connection to the main electricity network was a limitation and therefore (car) batteries were a viable solution.

When involving citizens, it is important that instruments are easy to use and robust. Experiences with specific **instruments** suitable for mobile monitoring and citizen monitoring were obtained:

- The AE51 portable BC monitor provided useful information in both Birmingham (UK) and Rotterdam (The Netherlands). Though this device only works well when the moving speed is low and/or pollution levels are high. To reduce the noise of the instrument, concentrations often need to be averaged over about a minute, meaning you should not cover too much space in this time frame. In the pilot studies, the device was used while walking or cycling. In Rotterdam, the device was used at 1 s resolution and applying ONA corrections.
- In a car-based platform, experiences with the AE33 were very good as well. However, this cannot be used in CS context and only be used by trained people.
- The frequent required maintenance of the DiSCmini instrument was burdensome for citizens and schools, rendering the instrument less useful for longer-term monitoring.
- Preliminary results of experiments conducted (after the initial pilots) in Warsaw (as multiplicator city), showed that the Partector 2.0 is more user-friendly and can be used as an instrument to measure PNC and OpenSeneca sensor is easy to use and applicable for PM.
- The PM sensor needed much less attention. Comparability of different LCS sensors is an issue when comparing data.

In the three pilots, mobile campaigns were performed with cars, bicycles, and pedestrians. All these options resulted in informative campaigns. It depends on the research question and the size of the study area which platform is most suitable. However, cars cannot be used on a large scale in CS projects whereas they lend themselves more easily to include non-portable reference grade instruments such as the AE33 aethalometer instead of the cheaper and portable AE51. With cars, also a larger study area can be covered, such as in Rotterdam where measurements were conducted in the wider Rijnmond area. When aiming to engage citizens in data collection and understanding air pollution, typically mid-range instruments or LCS are a better option, with restriction of area covered and data quality of the instruments.

The time of data collection (hour, day and season) is important as well as the **number of repetitions**. As there is well-documented seasonal variability, and the aim is to create long-term average estimates, conducting monitoring in at least two seasons is crucial. If the interest is in specific sources e.g. wood burning than a season-specific campaign could be sufficient. In the summer season, optical low-cost PM sensors tend to perform better than in the winter, because of less days with high relative humidity. For the same reason, indoor measurements are less problematic with low-cost PM sensors than outdoor measurements.

In most cases, interest is in daily concentrations (because of exposure and practical concerns related to data collection). It was not feasible to perform mobile monitoring at night in any of the pilots, hence the measured concentrations primarily reflect daytime averages. In the Rotterdam car pilot, a limited number of monitoring days

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were performed during the weekend, but as in the other pilots monitoring was mostly performed in weekdays. Night-time monitoring raises safety concerns when performed by cycling or walking.

12.2 Data processing

For **calibration** of the LCS, a simple linear relationship between sensor and reference grade instrument may not be optimal as the influence of temperature, relative humidity, and cross interferences between gases is well known. In the Breathe London Network (https://www.breathelondon.org/), $PM_{2.5}$ and NO_2 are measured using the Clarity Node-S LCS at 2 minute resolution. All sensors are initially calibrated at an urban background AQMS before being deployed. A set of reference LCS are collocated at representative urban background and roadside AQMS in London. These provide a dynamic (hourly), site type (background / roadside) correction factor for both $PM_{2.5}$ and NO_2 which is applied every hour before dissemination.

As mobile measurements consisted of point measurements in time and are affected by fluctuating **background** concentrations, in the cycling Rotterdam pilot we applied a rescaling method to remove some of the temporal variation, using data from a continuous reference site. Whether this is needed, depends on using the measured data directly or using the data as input for further empirical models. In the latter case, rescaling contributes less. More details on data processing tests (winsorizing and additive and relative background normalization) is given in section 4.2 of D2.6; in addition section 4.3 of that deliverable discusses the number of repetitions needed -> or add it here in Annex)

Mobile measurements include a synchronization of data (GPS and measurement devices) and assigning the **measured concentration to a certain location**. Mobile measurements were assigned to the nearest road segment using GIS tools. This added a limited amount of uncertainty. Careful graphical evaluation of the original GPS readings is needed in addition to scripted procedures to avoid potential large errors, as we observed on a single day in the Rotterdam car pilot. GPS devices are becoming more accurate, and some devices (like sport watches phones) include already an accurate GPS; as a result, watches can also be used for proper allocation of concentrations. Repeated measurements mean that concentrations measured during different runs will be allocated to a street segment. This also needs proper data processing considering uncertainty of measurement devices.

12.3 Modelling strategy

The monitoring is useful to document variability in space, e.g. between different homes (eg in Birmingham) using longer-term monitoring with LCS or along routes frequently driven by DCMR employees in Rotterdam. In addition, the monitoring served as data to derive empirical models. This was done in Birmingham using machine-learning, and in Rotterdam using a manually guided stepwise linear regression, based on a variety of land use predictors.

Machine-leaning models in Birmingham performed better when predicting $PM_{2.5}$ than PM_{10} data, which were a lot harder to model, possibly related to the lower quality of PM_{10} data from the specific sensor used, but also to greater spatial variability.

In the Rotterdam pilot, we compared the map based on mobile monitoring with results from dispersion modelling from our partner DCMR. Both types of models were moderately correlated. Integration of the two approaches may be optimal. Evaluating locations, where the two types of models disagree, may give useful hints at modelling issues in both approaches.

12.4 Results

Mobile monitoring was an effective tool for characterizing spatial variation in the three pilot cities Rotterdam, Birmingham and Bucharest. Replication actions of the Rotterdam citizen-based approach were conducted in Barcelona and Warsaw. Bucharest is further excluded in this report since it did not include citizens or volunteers to perform the measurements.

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As mobile monitoring involves on-road monitoring (especially for car and cycling-based campaigns), using the data directly to map air pollution concentrations across the city will overestimate the concentrations experienced at the façade of homes and other buildings. However, the cycling-based data represents the real exposure of the cyclist. The overestimation likely depends on the distance of homes from the road. The overestimation is less for models based upon model monitoring, as the predictors of these models (e.g., traffic load in a 50 m buffer) have lower values when homes are located at a larger distance from roads. In Dutch studies (using a car), an overestimation of about 30% of UFP was found for mobile monitoring models (Kerckhoffs, 2016; Kerckhoffs, 2017). The daytime monitoring also plays a role here.

In the Rotterdam pilot, we identified the impact of motorised traffic as in many previous mobile monitoring studies. In addition, by linking wind direction data, source locations and the individual measurements (that is, not averages across measurement days), we also found influences of the harbour, industrial area, and airport on the measured air pollution variables. This was done based on mobile data from car measurements.

Indoor measurements were usually very consistent without significant discrepancies from the research grade instruments' measurements. A simple linear regression between the OPC-N3 sensor in Birmingham and the research grade instrument used was enough to greatly improve the data.

Opportunistic data collection in the Rotterdam citizen pilot, resulted in an inadequate number of repeated runs on most of the trajectories to derive representative long-term average maps based on measurements alone. The minimal number of required repeats for long-term average representativity, based on the subsampling analysis, varied between 24 and 54 (depending on the road segment) to be within 25% of the mean when considering the raw BC values, or between 22 and 39 when applying additional post-processing (winsorising and/or background normalization). This number is consistent with values found in other studies.

Special care needs to be taken concerning the visualization of data since no 'reference framework' exists for these measurements. This is due to:

- Limited time of data collection, not fulfilling the guidelines for reference monitoring set by the AQD. This is the case for short stationary networks of sensors (e.g. during a few weeks or months), temporary networks of passive samplers (e.g. during one week or 1 or a few months), and is also relevant for mobile measurements, where typically day-time measurements are performed or even focus is on peak hours (when concentrations or high, relevant for source apportionment and exposure of commuters).
- Absence of limit values (e.g. for UFP or BC).

This gives some difficulties in selection of colours, especially when the citizens are involved and expect 'easy to understand' data.

13. HOW CAN RESULTS OF CS PROJECTS BE INTEGRATED IN AQMN?

One of the questions that needs to be addressed in this deliverable is how developed concepts can be **integrated in a sustainable way in AQMNs and engagement strategies that can be used by AQMNs**.

Whereas in this project the focus was on methodological aspects and lessons learned; we acknowledge that the pilots were limited and therefore we cannot draw conclusion of potential other applications and approaches.

Involving citizens in AQ monitoring can help AQMN by:

- Making citizens more aware of their actions and behaviours.
- By supporting city decisions and policy makers to be able to act on real evidence (based on local data).

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- Providing new data sources for researchers.
- Stimulate knowledge sharing and action in related domains like climate change.
- Evaluate priority areas for model improvements.

(These examples are taken from the COMPARE website https://www.wecompair.eu/what-we-are-doing)

AQMN can play an active role in **the logistics** of AQM campaigns involving citizens; they have the instrumental and domain knowledge and can organise the logistics related to CS projects (in terms of instrumentation, calibration or co-location, …). Moreover, they have the reference data at first hand. The Rotterdam pilot was a good example of how logistics can be organised; however the pilot was restricted to the participation of employees of DCMR (the Environmental Protection Agency of the Rijnmond region) so participants (employees) had easy access to the venue where instruments had to be collected. AQMN could expand their instrumentation to mid-range and sensors to organise CS projects and to promote and improve the integration of CS initiatives in their data.

The results do not necessarily need to be integrated in the data platform of the AQMN in order to be useful. Other ways of **integrating/using these results** are:

- Using the data for model optimalisation or understanding short-comings of dispersion models. This was explored with the Rotterdam data (discrepancies between mobile exposure map and modelled map explored by DCMR) and also in citizen science projects (Dons et al., 2020, Van Poppel et al., 2024).
- Understanding the impact of measures where no data of the AQMN is available. This was also not tested but examples of fixed networks (Hofman et al., 2022c) and mobile measurements (Van Poppel et al., 2023) exist

Other ways how these additional maps: information and engaging citizens can be useful (for AQMN) are:

- Evaluation of additional location for (more permanent) AQMS or studies.
- Identification of unknown sources.
- Trying to initiate behavioural change of citizen by involving them in data collection and interpretation.

An effective integration in data platforms was not part of this project. We refer to other projects where citizen science data are integrated in the AQMN data platforms. Some examples (outside this project):

- RIVM: https://samenmeten.rivm.nl/dataportaal/
- Samen meten voor zuivere Lucht: https://samenvoorzuiverelucht.eu/

Or where separate platform was set up to share data:

- Curieuzeneuzen: https://viewer.curieuzeneuzen.be/

This website is in Dutch, so we give a short summary: the projects aim was to measure and present NO_2 concentrations at citizens home address. Concentrations are measured using diffusive samplers (during one month) and citizens collected the measurements at their home; locations were characterized by different traffic exposure and at different distances from the street. The results are presented using a color code on the map and results are also used to evaluate and improve AQ models. The project is also aiming to raise awareness on air pollution and showing how citizens can contribute to reduce air pollution (e.g. impact of how we commute). The project was supported by a local newspaper and reached a broad audience.

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