

# Chapter 13

## Participatory Air Quality Monitoring in Urban Environments: Reconciling Technological Challenges and Participation

Jan Theunis, Jan Peters, and Bart Elen

### 13.1 The Possible Roles of Participatory Air Quality Monitoring in Urban Environments

Whereas emissions of several air pollutants have significantly decreased in the EU and the US in the last decades, the effects of poor air quality are still strongly felt in urban areas (European Environment Agency 2013; U.S. Environmental Protection Agency 2012). In urban environments, exposure to traffic pollution may trigger health effects like cardiovascular diseases and airway inflammation. Understanding local variation in exposure to air pollution is of major importance when trying to assess the health effects of pollutants that are highly variable in time and space, as is the case for traffic-related air pollutants (Setton et al. 2011). Recently, mobile air quality measurements are used in several studies for exposure monitoring, for high resolution mapping of the spatial variability of air pollution and for the characterization of particulate air pollution in urban environments. However, to be representative a lot of data have to be collected in a cost-efficient way.

Participatory monitoring and citizen science are often mentioned as ways to collect large datasets that give useful additional information at a reasonable cost compared to classical data collection methods. There is a growing body of literature on participatory environmental monitoring (also called citizen sensing, citizen science or community-based monitoring) in general and urban sensing more specifically. Often the motivation for voluntary or participatory data collection is rather utilitarian and driven by scientific or policy data needs. Through the efforts of hundreds of volunteers data will be collected with a spatio-temporal granularity that cannot be achieved by regular monitoring campaigns. The challenge then is to

---

J. Theunis (✉) • J. Peters • B. Elen  
VITO Flemish Institute for Technological Research, Mol, Belgium  
e-mail: [jan.theunis@vito.be](mailto:jan.theunis@vito.be); [jan.peters@vito.be](mailto:jan.peters@vito.be); [bart.elen@vito.be](mailto:bart.elen@vito.be)

recruit volunteers who are intrinsically motivated, or to set up incentive strategies to motivate people to participate. Successful examples exist in the field of biodiversity monitoring. Roy et al. (2012), Conrad and Hilchey (2011) and Catlin-Groves (2012) give extensive overviews of cases and lessons learnt in ecology and nature conservation.

Participatory monitoring or citizen science is also believed to raise the awareness and understanding of citizens (e.g. Snyder et al. 2013). Projects can be set up with that specific objective in mind. Citizen science is recognized in many studies as a way to include stakeholders and the general public in the planning and management of local ecosystems (Conrad and Hilchey 2011). Involving organized stakeholders and the general public in environmental assessment can also lead to better and common understanding and awareness of the issues at stake and of the local context, mobilisation of local knowledge, joined problem ownership, and co-creation of solutions. Policy makers, citizens and stakeholders could set up participatory monitoring schemes with the specific intention to create or stimulate dialogue and provide a better basis for decision making. As such, participatory monitoring can have an important role as a part of co-creation and transition processes towards healthier cities. A recent report from the European Commission on Environmental Citizen Science (Science Communication Unit, University of the West of England, Bristol 2013) states however that few studies on public participation in science and environmental education have rigorously assessed changes in attitude towards science and the environment, and in environmental behaviours, and concludes that it is difficult at this point in time to provide evidence for the influence of citizen science on environmental policy making.

When evaluating participatory monitoring approaches we thus have to distinguish clearly between two types of objectives:

1. the *scientific* objective which focuses on the factual results of the monitoring campaign;
2. the *social learning* objective which focuses on processes of creating shared knowledge and visions, awareness and behavioural change, co-creation and transition.

Both objectives cannot be entirely distinguished from each other, and there are clear co-benefits. Whereas participation of people in scientific research programs can be quite instrumental with possibly a beneficial overflow on people's knowledge, awareness and attitude towards the issues at stake, sound monitoring methods are crucial for both objectives.

## 13.2 Challenges for Participatory Air Quality Monitoring

Already in Burke et al. (2006) mentioned the theoretical potential of participatory sensing to investigate relationship between air quality and public health. In Snyder et al. (2013) US-EPA scientists give an overview of possible changes in air

quality monitoring due to the materialization of lower-cost, easy-to-use, portable air pollution monitors (sensors) that provide high-time resolution data in near real-time. Participatory monitoring techniques could be used e.g. to improve the understanding of the relations between urban traffic, air quality and health.

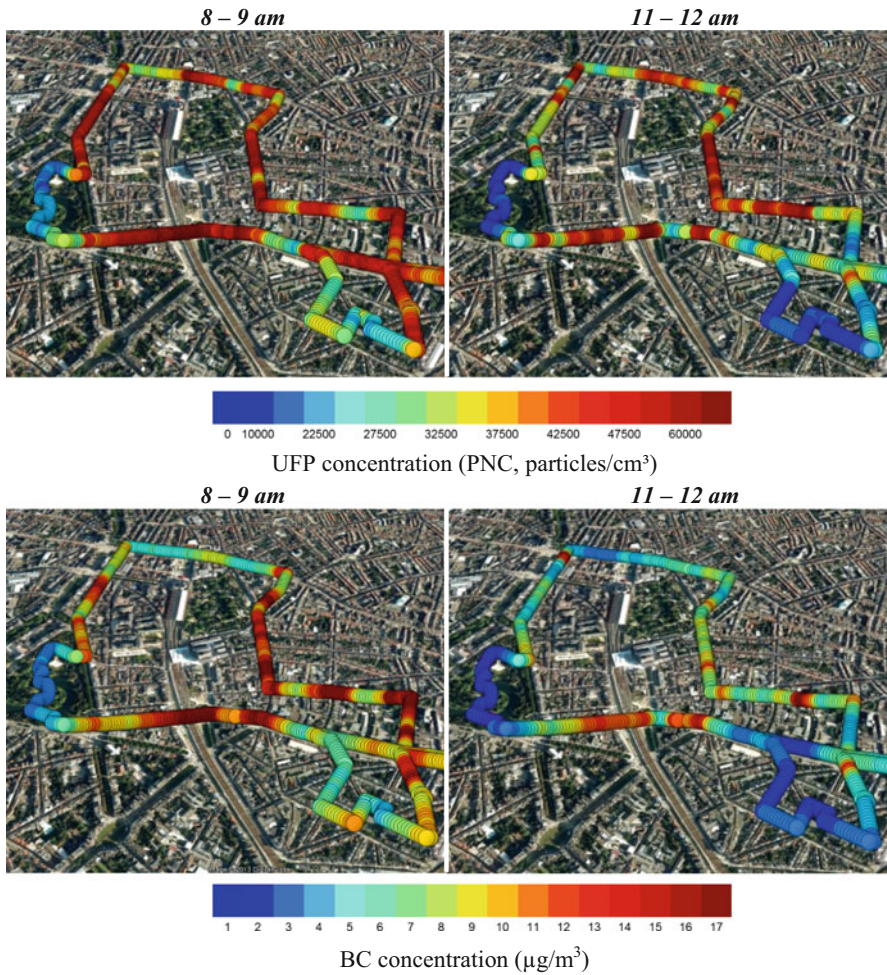
Following successful examples of large scale collaborative efforts such as OpenStreetMap or Wikipedia, bottom-up Do-It-Yourself (DIY) monitoring approaches based on low-cost sensors and smartphone apps are appearing in domains such as noise, air quality or radiation monitoring. Often the idea of pervasive or ubiquitous sensing is put forward, relying on a multitude of sensors with which data are collected in an un-coordinated almost effortless way, and on intelligent data post processing and mining.

In Part 1 of this volume Theunis et al. deal extensively with the availability, cost and quality of environmental sensors and monitors. Although several projects, research groups or companies recently developed light-weight devices, integrating low-cost gas sensors, GPS and mobile phones, the authors conclude that for air quality monitoring—stationary or mobile—no sensors or monitoring devices are available at this point in time that would allow such pervasive effortless data collection either because of inherent quality issues or because of their cost. Proper use of available low-cost sensors still requires important multidisciplinary development efforts.

Air quality monitoring strategies further have to deal with a complex mixture of gases and particles that is highly variable in space and time. Figure 13.1 shows results of an extensive mobile air quality monitoring campaign in Antwerp to assess the exposure of cyclists to ultrafine particles (UFP) and black carbon (BC) (Peters et al. 2014). The same route was measured in repeated continuous measurement runs (up to 258 times) at different times of the day during 11 days with a resolution of 1 s. The measurements were aggregated to fixed points every 10 m using GPS data and a Gaussian weighing function. The hourly averages clearly illustrate the spatial variation and the intraday variation of these components at different locations. Single measurements (or mobile measurement runs) are subject to additional variability, e.g. due to specific events, such as a car passing by, and thus have very limited value in assessing air quality at a specific location.

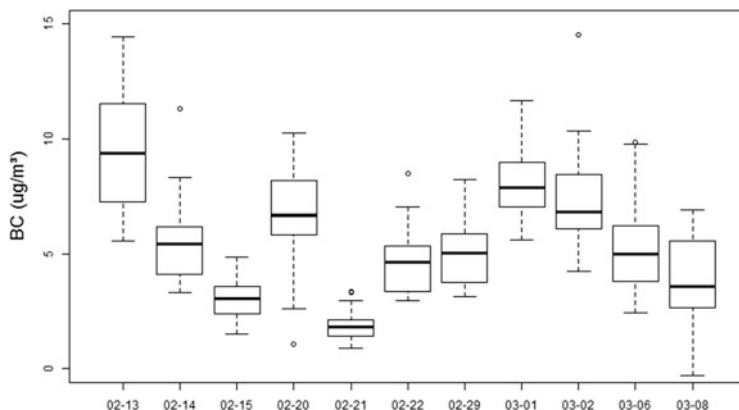
Figure 13.2 shows the daily variation for black carbon during this measurement campaign. It is clear from these data that drawing general conclusions on air quality based on the measurements of just 1 day, or comparing results from two locations that were measured on different days doesn't make sense.

Different air pollutants also show different spatio-temporal patterns. Spatial variability is much higher for ultrafine particles or black carbon, that are directly related to fresh engine exhaust, than for  $PM_{10}$  which is for a large part the result of physico-chemical transformation processes (Peters et al. 2013). Differences in pollution patterns are even more pronounced when comparing e.g. ozone and  $NO_2$  that even show antagonistic behavior, as freshly emitted NO from vehicles reacts with ozone to form  $NO_2$ . As a result, at days with overall high  $O_3$  concentrations,  $O_3$  concentrations tend to be lower in urban areas with a lot of traffic.



**Fig. 13.1** Differences in air pollution at different hours of the day along a cycling route in urban environment. Displayed are hourly averages from 8 to 9 am (*left*) and from 11 to 12 am (*right*) at 10 m resolution of ultrafine particle number counts (PNC) (*on top*) and black carbon (BC) concentrations (*below*) (adapted from Peters et al. 2014)

Monitoring strategies thus have to set clear goals on which components will be monitored, over which area and which time frame. Selection of pollutants to be monitored depends on the issues at stake. Monitoring strategies further have to take into account the spatial and temporal variability of pollution. Finally, the results of monitoring campaigns have to be interpreted in the light of this complexity. All this requires a reasonable level of basic knowledge on air pollution. The role of expertise cannot be underestimated, in assessing the quality of sensing devices, in setting up a monitoring campaign, as well as in the interpretation of the results. Based on



**Fig. 13.2** Differences in air pollution for different days along a cycling route in urban environment. The boxplots show the black carbon (BC) concentrations aggregated at 10 m resolution (adapted from Peters et al. 2014)

a series of qualitative interviews with scientists who participated in the ‘OPAL’ portfolio of citizen science projects that has been running in England since 2007, Riesch and Potter (2014) stress the need for clear goals, careful design of projects and appropriate quality assurance methods. Because of its inherent complexity, this is undoubtedly the case for participatory air quality monitoring.

### 13.3 Framework and Guidelines for Participatory Air Quality Monitoring

The potential for participatory environmental monitoring crucially depends on three strongly interdependent factors: the availability, quality and cost of monitoring tools (sensors, apps, . . . ), sound data collection and data processing methods, and finally the participation of volunteers.

In the following paragraphs we will propose a pragmatic framework for participatory air quality monitoring that deals with these three aspects, and illustrate it with practical examples (Fig. 13.3). We will illustrate how participatory air quality monitoring can have an added value in the scientific process—in improving facts and knowledge, and how participatory monitoring campaigns (bottom-up approaches) can be conducted by lay people. Although we acknowledge the possible role of participatory monitoring in processes of awareness creation or decision making, we will not address these issues in detail. However, we do believe that the proposed framework is also applicable in these cases.

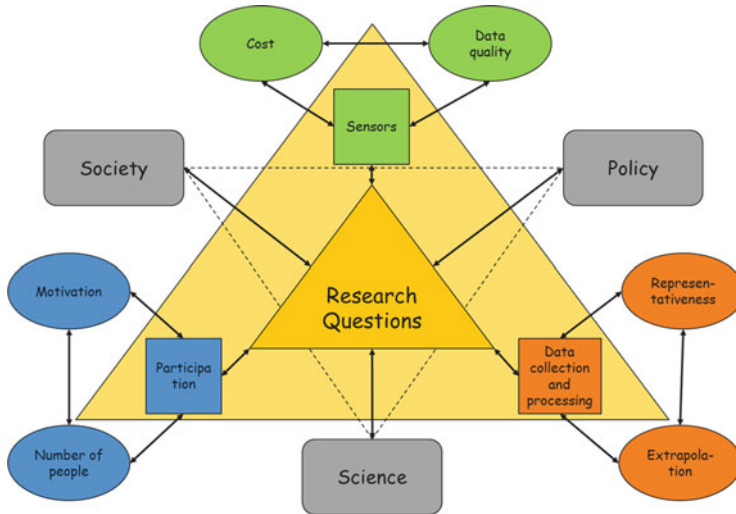


Fig. 13.3 Conceptual framework for participatory air quality monitoring

### 13.3.1 Defining Research Question and Monitoring Objectives

As with all monitoring exercise, the research questions are central to each participatory monitoring exercise. The research questions will determine which components will have to be monitored, over which area and which time frame. For a monitoring campaign to be effective research questions have to be made explicit and specific. Research questions can be defined by policy makers, scientists, stakeholders or the society at large (Fig. 13.3).

A lot of data and information on air quality is already available, some of it in the scientific community, some of it for the general public. The first step is thus to understand what is already known and available. Then research questions can be refined, and efforts can be focused on the possible added value of participatory monitoring campaigns, i.e. compared to official permanent monitoring networks. Spatio-temporal variability might be well covered for some pollutants by the official monitoring networks. E.g. the official monitoring networks will capture day-to-day and intraday variability of  $PM_{10}$  or  $O_3$  quite well, and will be able to provide most answers regarding their spatial variability. The highest added value for participatory monitoring lies in monitoring those components that have a strong micro-level spatial variation, that are health-relevant and/or that are not monitored in official monitoring stations. Therefore, additional monitoring efforts in urban areas are more relevant for black carbon, ultrafine particles or  $NO_x$  than for  $PM_{10}$ ,  $PM_{2.5}$  or ozone (see also Theunis et al. in Part 1 of this volume). We do acknowledge that Do-It-Yourself monitoring can also have an important didactic effect, even if it does not add much to the existing data or knowledge. However, also in those cases learning will be most efficient when these exercises are combined with discussions with

experts. Otherwise the danger of misinterpreting data or re-inventing the wheel is real.

Defining clear research questions, and developing a sound monitoring strategy based on clear objectives, in a clear spatial and temporal framework, is the first step in a successful monitoring campaign. We can broadly distinguish three types of objectives: monitoring *specific events* or *locations*, systematic *mapping of areas* or *personal exposure assessment*.

One can be interested in the effects of *specific events* that are clearly confined in space and time, such as changes in air quality during road works. Events can also be recurrent, e.g. one can be interested in the occurrence of peak concentrations caused by trucks or buses passing by at a certain location. In this case both the magnitude of the peaks as well as the frequency at which they occur can be of interest. It is also possible that the focus is on one *specific location*, e.g. a school or a busy traffic intersection. In most of these cases a stationary monitoring approach will be most suited.

Several objectives can be pursued by systematically *mapping an area*: getting an overview of the air pollution in an area for verification of legal norms or health impact assessment, identifying pollution hot spots and relating them to specific sources, or comparing air pollution on different routes. Representativeness of the maps is a crucial issue, and should be in line with the research questions, e.g. average annual concentrations or average concentration in a holiday period, average pollutant concentration during peak hours or during off peak hours. In this case monitoring strategies can rely on stationary monitoring networks the density of which should be in line with the spatial variability of the pollutant at stake, or on repeated mobile measurements (Peters et al. 2013; Van den Bossche et al. 2015).

Finally, one can be mainly interested in the level of pollution people are personally exposed to during (part of) their daily activities. People can be interested in their individual exposure. But, one can also be interested in the personal exposure of subgroups of people, such as children or cyclists, possibly during specific activities, e.g. while going to school or work. In this case people can be carrying personal air pollution monitors and simultaneously record their whereabouts and activities (Dons et al. 2011). When repeated, these personal exposure data can give rise to more generalized personal exposure patterns which can be used for optimising personal choices or policy measures.

### 13.3.2 Sensors

The quality of the sensing devices is a clear, but often overlooked aspect in participatory air quality monitoring. Several research groups have developed portable devices, integrating commercially available low-cost gas sensors, GPS and mobile phones (Dutta et al. 2009; Zappi et al. 2012), but according to our knowledge and experience virtually none of these sensors can be used as such to measure outdoor air quality. Snyder et al. (2013) indicate that many commercially available sensors have

not been challenged rigorously under ambient conditions, including both typical concentrations and environmental factors. An important deal of the complexity, and associated high cost, of air quality monitoring devices is exactly related to the fact that they have to be highly sensitive, component-specific and independent from external environmental conditions (i.e. weather effects). An overview of the state of the art is given by Theunis et al. in Part 1 of this volume.

Accurate portable instruments are now available for components such as ultrafine particles and black carbon. They can be used by non-specialist users (Buonocore et al. 2009; Dons et al. 2011), but they are expensive which limits their widespread use. Approaches based on these kind of instruments will thus rely on the availability of these instruments at some kind of central repository (at a government agency, a scientific institute or a non-governmental organization). Further below we will illustrate examples of such an approach.

Efforts to use low-cost sensing devices result in additional technical complexity (and cost) at device level or in complex calibration or data processing algorithms, which again bring them into the realm of technical and scientific expertise which is not readily available for the general public but which could be made available for use through some kind of central repository.

### ***13.3.3 Data Collection and Processing***

Monitoring strategies depend both on the available monitoring devices and the defined research questions. At this point in time the availability and cost of monitoring devices does not yet allow large-scale effortless data collection. Clear research questions are therefore essential to focus efforts, and monitoring strategies have to be adapted accordingly. In this context we can roughly distinguish between *stationary monitoring* and *mobile monitoring*.

*Stationary monitoring* refers to measurements at one specific location over a well-defined time window with a fixed measurement instrument. The spatial coverage may range from one specific location to the coverage of a spatial grid. Stationary measurements are well suited for monitoring specific events or locations, or for following up large scale temporal trends, i.e. for pollutants with limited spatial variability. Spatial representativeness depends on the number of deployed measurement devices (which is related to the cost of the devices, and to practical considerations such as safety, permanent power supply or available space, i.e. in busy streets or at intersections) in comparison to the extent of the area that is monitored and the spatial variability of the pollutant.

*Mobile monitoring* has gained attention with the onset of portable monitoring devices. Mobile monitoring refers to the collection of data along a route. For example, a volunteer performing measurements while commuting to and from his work is performing a mobile data collection. As such systematic spatio-temporal datasets from a route (e.g. a number of streets) over a well-defined time frame (e.g. during the morning peak hours) are acquired. Mobile monitoring allows to



increase the spatial coverage of measurements, but at the expense of temporal representativeness (see below).

Mobile data collection can be performed in a *targeted* or an *opportunistic* way. In a *targeted* data collection scheme, volunteers deliberately plan and carry out measurements with a specific purpose in mind. They concentrate efforts in a well-defined area (e.g. a number of streets) over a specific time frame (e.g. during the morning peak hours) in an attempt to get a representative picture of reality. Literature examples of targeted data collection approaches using fixed routes are Hagler et al. (2010), Hsu et al. (2014), Pattinson et al. (2014) and Peters et al. (2014). These examples did not involve volunteers in conducting the measurements but results from these studies concerning the targeted monitoring approach can be extrapolated to participatory monitoring actions with limited numbers of participants. Obviously, with increasing numbers of participants the argument for using a targeted approach to guarantee a good coverage becomes less stringent.

In an *opportunistic* data collection scheme, on the contrary, measurements are collected by volunteers in their normal daily routines. This can be city wardens, parking wardens, street cleaners, bike couriers or postman, but as well commuters that cycle every day to work. The participant does not decide on measurement location and time from his/her interest to monitor a given event. They do not envisage to cover a specific period of time, nor a specific location or route. Opportunistic data collection (ideally) requires measurement devices that measure continuously without any intervention of the user. The planning, efforts and commitment for opportunistic data collection can be relatively low, but it will result in a (possibly) sparse and biased dataset, and entails additional challenges in data quality control, data processing and interpretation. Usefulness of the data will depend very much on the fact whether or not the volunteers cover the same routes and places regularly, and whether all locations and time periods of interest are sufficiently covered.

Data processing of the collected data is needed for various reasons: (1) data cleaning and validation with screening algorithms to remove erroneous measurements, (2) data processing to reshape, rescale, filter, smooth or aggregate the mobile data into meaningful, research question-specific data, and (3) data analysis. For mobile measurements the data validation should be performed on both the air quality as the GPS data. In case of GPS failure for short periods, which is sometimes observed in cities due to shading effects, interpolation algorithms may be used to estimate GPS locations based on previous and following measurements. Errors in air quality data may have different causes ranging from sensor failure to inappropriate use of the sensing device. The selection of data processing strategies depends on the experimental design and research questions driving the analysis.

Van den Bossche et al. (2015) used the same dataset described in 2 (Peters et al. 2014) to develop data processing methods, and draw conclusions on the results that can be expected from limited sets of repeated mobile measurement runs. After allocating all data to street segments of a specific length (i.e. 50 m), they apply a trimmed mean for each segment to reduce the effect of extreme events. Background normalization is applied to account for the day-to-day variability in air pollution.

They conclude that mapping at a high spatial resolution is possible, but a lot of repeated measurements are required: depending on the location 24–94 repeated measurement runs (median of 41) are required to map black carbon concentrations at a 50 m resolution with an uncertainty of 25 %.

Brantley et al. (2014) provide a framework to determine spatial trends of near source air pollution. To minimize the impact of sporadic proximate exhaust, local exhaust plumes are isolated using time-series analysis techniques. Then background estimations are made to isolate local from background components. Including background areas in the sampling routes is one way to obtain background values. Baseline estimations from time series statistics is another approach (Van Poppel et al. 2013; Brantley et al. 2014). Finally, temporal or spatial smoothing is often applied to reduce variation. Temporal smoothing (e.g. 15-s moving average) leads to spatial blurring of the mobile measurements, whereas spatial smoothing is used to aggregate measurements from different times, potentially made under different conditions, to a spatial entity (e.g. a street section or a city block).

### ***13.3.4 Participation***

The success of the monitoring strategies will depend highly on the participation of volunteers, i.e. the number of people that can be involved, their (intrinsic or extrinsic) motivation, and the level to which the latter is in line with the objectives and needed data collection efforts. Some monitoring strategies are clearly more demanding than others. Targeted mobile monitoring campaigns will require highly committed participants who are prepared to spend time and efforts to repeatedly cover the targeted monitoring area on the appropriate moments. The planning, efforts and commitment for opportunistic data collection on the other hand can be relatively low, but depend on the user-friendliness of the devices, i.e. the capability for continuous measurements with minimal intervention of the user. In practice monitoring campaigns can be a mix of both with targeted monitoring efforts complementing opportunistic data where needed.

## **13.4 Participatory Mobile Air Quality Monitoring**

### ***13.4.1 Mobile Air Quality Monitoring***

Air pollution monitoring on mobile platforms is increasingly applied for exposure monitoring. Mobile measurements are frequently applied as a complementary tool to the stationary air quality measurements at fixed locations, because fixed stations are not capable to depict the full spatial distribution of air pollution over the extent of an urban area. Monitoring instruments have already been installed on all kinds of

mobile platforms, such as trams, buses, cars, bicycles or backpacks. Two tracks in using mobile measurements for exposure assessment are encountered in the literature. The larger number of exposure studies applies personal monitoring by directly equipping the study subjects with portable integrated sampling equipment or real-time monitors (see e.g. Dons et al. 2011). A second group of studies addresses the potential of using mobile measurements to construct air pollution maps at a high spatial (and temporal) resolution and to derive exposure to pollutants from these maps (see Pattinson et al. 2014; Van den Bossche et al. 2015).

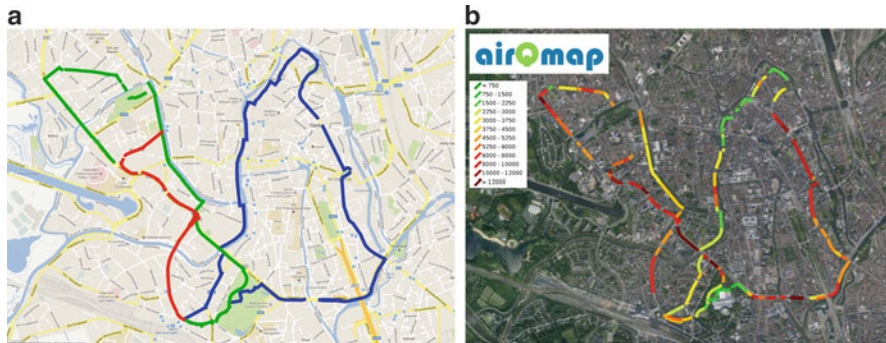
Deriving high-resolution maps from mobile data requires large quantities of data to represent the range of possible meteorological and traffic conditions (Padró-Martínez et al. 2012) and to aggregate very localized spatio-temporal snap-shots into broader-scale pollution maps. Peters et al. (2014) showed that mobile monitoring can give additional insights in spatial variability and exposure assessment, at a resolution of street level and even within-street level. To be representative and useful for personal or community decision making, mobile measurements have to be repeated regularly, data have to be aggregated over relevant time frames and locations, and carefully interpreted using data handling and expert knowledge to filter out inaccuracies. To increase comparability and reduce the number of repeated runs, measurements can be normalized with air quality data at background locations. These methodological issues are thoroughly addressed in Brantley et al. (2014), Peters et al. (2013), Van Poppel et al. (2013) and Van den Bossche et al. (2015). Both targeted and opportunistic participatory monitoring schemes can have an important role in collecting these large datasets as we will illustrate in the following paragraphs.

### 13.4.2 Case Study: Exploring Healthy Cycling Routes

In Ghent, a local environmental organization called the Gents Milieufrent (GMF), wanted to investigate traffic-related air pollution on some important cycling routes. They set up a *targeted monitoring* campaign during 2 weeks on a selection of urban roads with a total length of roughly 18 km split up in three routes (Fig. 13.4a). On each of these routes a total of 15 repeated continuous measurement runs was carried out.

To collect the data they used airQmap ([www.airqmap.com](http://www.airqmap.com)). airQmap is a platform to collect mobile black carbon measurements and to process them into street-level black carbon (BC) exposure maps. airQmap has been designed with usability, autonomy and continuity in mind. It causes minimal nuisance for the person conducting the measurements. This is required to allow unskilled volunteers to collect mobile BC measurements.

airQmap contains a data acquisition part and a data transmission part. The first part consists of a small bag with a GPS (Locosys Genie GT-31) and a portable black carbon monitor (AethLabs microAeth model AE51). The second part is a home station with a netbook and custom-made, easy to use software to read out the



**Fig. 13.4** (a) Overview of the monitoring routes: routes were sampled between 8 and 9 AM (green), between 14 and 15 PM (blue), and between 17 and 17.30 PM (red) and (b) BC concentration map: street-level average BC concentrations (in  $\text{ng}/\text{m}^3$ ) (available at <http://www.airqmap.com/ghent.html>)

measurement devices, keep their clocks synchronized and transmit the data over the Internet.

Data are stored in a central database. Data processing algorithms and visualization tools are linked to the database. The data processing is a cascade of different steps to reduce the noise in the data (using the ONA algorithm, Hagler et al. 2011), to carry out background normalization to account for day-to-day differences in background concentrations, to validate GPS and BC data, to project the data on a street map, and to aggregate the data to street average concentrations (spatial smoothing by averaging measurements per street). The processed data are plotted on an interactive map showing the street average BC concentrations for streets with sufficient numbers of observations. Street statistics can be viewed by clicking on the streets. In addition, a coverage map is build showing the number of repetitions, i.e. the number of distinct measurement series, per street. The maps are shown in a web application (<http://www.airqmap.com/ghent.html>) and are accessible from most current GIS software through the open OGC WMS service standard.

The selection of volunteers to do the mobile monitoring was organized by GMF. GMF also proposed the measurement routes and a final time schedule was made up in a coordinated and targeted way, taking into account the need for repetitions. A total of approximately 75,000 validated individual measurement points was obtained in a period of one month and a half (26/09/2012–12/11/2012). The measurements were assigned to 181 unique streets, but to a significant number of these streets only few measurements were allocated. This happens, for example, at cross-roads where adjoining streets are crossed and few measurements may get attributed to these streets. Therefore the data analysis and visualization makes use of a threshold for the number of measurements per street as a criterion for inclusion in the assessment. The BC concentrations at these streets were compared and allowed for the identification and ranking of streets and zones according to the measured pollution levels. By comparing street averaged BC values with the BC values

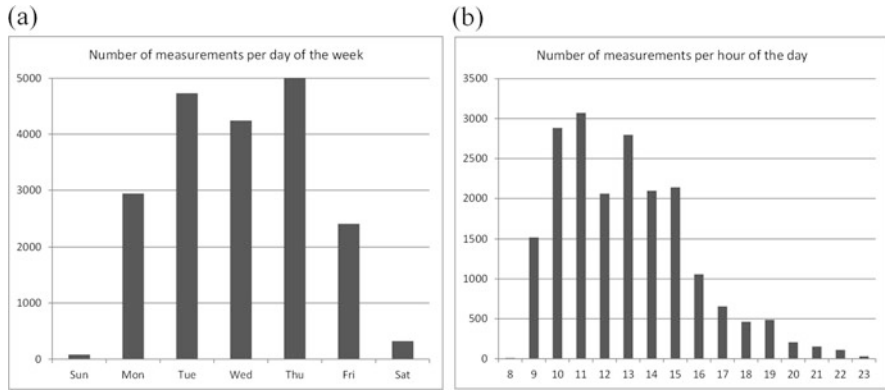
obtained at urban background locations, i.e. urban green or park, the impact of local traffic contributions can be estimated. Results were explained by looking at the street topology (openness, presence/absence of separate biking lanes) and traffic volumes. Healthier alternative commuting routes with lower exposure to BC were recommended based on this research. In conclusion, the targeted approach with fixed sampling routes and timings resulted in a high number of repeated measurements in a selection of streets with limited resources (i.e. 1 sampling system, brief monitoring period). Knowledge about the monitoring routes and the way the sampling is performed directly results in lower data rejection in the data validation step.

### ***13.4.3 Case Study: Opportunistic Air Quality Monitoring by City Wardens in Antwerp***

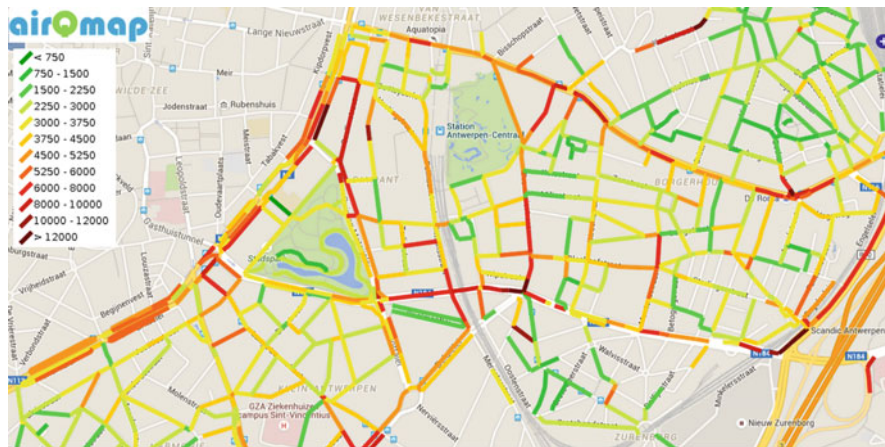
In Antwerp a case study was set up in collaboration with the city authorities to explore the possibility to map urban air quality based on an *opportunistic monitoring campaign*. Three teams of city wardens patrolling through the city during a 12 month period used airQmap (2012-07-02 until 2013-06-28). The air quality was monitored on 110 days. The city wardens did not follow predefined routes, they just carried out measurements during their daily tasks. They have a delineated area in which they operate, so in that sense their monitoring efforts were confined to a specific neighbourhood. The monitoring efforts were confined in time predominantly to working hours and weekdays. So, although monitoring did not follow predefined routes, space and time coverage was restricted and far from random.

Correct allocation of the data to their spatial position on the maps proved to be much more challenging than in the targeted monitoring case (4.2). No a priori knowledge on the tracks that are monitored is available. Also, data are not only taken outdoors. The occurrence of indoor measurements led to increased missing GPS values and GPS errors. This resulted in considerable loss of data compared to the targeted approach. In the data validation, approximately 2/3rd of the data is rejected based on uncertain geographical information. Still a large amount of data is still available (222 h) from 540 different streets. Measurements were mostly made on weekdays between 9 am and 4 pm (Fig. 13.5). Distributions were quite inhomogeneous. On Monday and Friday, the amount of data was approximately half the amount of the other weekdays. Important differences are also observed between the different hours of the day.

The BC concentration map that is obtained after data processing and by using a minimum of 10 monitoring episodes on 10 different days per street is shown in Fig. 13.6. Background rescaling was performed based on reference BC data to rescale the measurements over time, i.e. to account for variations in the background BC concentration. Data analysis also took into account the variations in BC



**Fig. 13.5** Distribution of the measurements over the days of the week (a) and the hours of the day (b)



**Fig. 13.6** Overview of street-averaged BC concentrations (in  $\text{ng}/\text{m}^3$ ) in Antwerp based on opportunistic data collection by city wardens (available at <http://www.airqmap.com/cityGuards.html>)

concentration per street by using quartile statistics (first and third quartile for low and peak concentrations respectively). Given the opportunistic nature of this case study a quite homogeneous coverage of the area was obtained. Of course, the city wardens operated in well-confined areas in the city mostly during working hours on weekdays resulting in repeated measurements on several locations. Still, further analysis of these data is needed to investigate the impact of spatial and temporal biases in the measurements on the resulting street-level averages.

This experiment was set up with minimal involvement of research staff during the data collection. Having a consistent data set over the long period of time of 12 months turned out to be less evident. A lot of measurements were collected in

the first few weeks after which the number of measurement gradually dropped. It increased again in the last 2 months of the campaign after some reminders to the city wardens by the research staff. Good *usability* of the monitoring equipment is crucial. Tasks which look simple at first such as making sure the battery of the measurement device is recharged, changing a filter, or turning of measurement devices after completion of the measurement day seem to go wrong regularly. A little to our surprise, most problems didn't arise in the beginning of the project but after some time, maybe due to decreased motivation. The volunteers in this case study did seem to conceive the monitoring as an extra task to their daily job. When monitoring actions grow from community concerns, decreased motivation may be less of an issue. An additional challenge is the *privacy* of the volunteers. For each second of the measurement days the precise location of the persons is recorded, but this level of detail about their location cannot be made public. A certain level of data anonymization is needed before the results can be made public.

### 13.5 Conclusions

A conceptual model is provided to frame participatory monitoring initiatives in regard of the sensor availability, the methodology followed to do the monitoring and the form and degree of participation. The interplay between sensors, methodology and participation is determined by well-defined research questions that need to be addressed.

For air quality monitoring, it is possible to set-up sensor networks or mobile monitoring campaigns to investigate the urban air quality at a high spatial resolution. However, measurement equipment is expensive, and the integration into a mobile platform with GPS tracking and data communication facilities is not readily available. Also the advanced data processing currently forms a barrier for its widespread use in participatory science. Nevertheless, literature and the case studies highlighted in this chapter indicate the potential for (mobile) participatory air quality monitoring. Tools exist that allow to get a detailed view on the street level exposure to traffic-related pollution (BC) of cyclists and pedestrians in urban environments based on targeted or opportunistic measurements. Systematic differences in exposure in streets of interest can be detected with a relatively short targeted measurement approach.

At this point in time it seems difficult to rely on a strategy with only low-cost sensors for air quality monitoring in which data are collected, processed and interpreted almost effortlessly. Proper combination of sensors and additional contextual data, and careful interpretation of the resulting data require expert knowledge. However, community participation and citizen science can play an important role in large scale data collection with low cost sensors, in more targeted data collection with sophisticated portable sensors, and in providing relevant contextual information and interpretation. The complexity of air quality research asks for a community science

approach in which citizen scientists and regular scientists work closely together to answer specific research questions.

## References

- Brantley, H.L., Hagler, G.S.W., Kimbrough, E.S., et al.: Mobile air monitoring data-processing strategies and effects on spatial air pollution trends. *Atmos. Meas. Tech.* **7**, 2169–2183 (2014). doi:[10.5194/amt-7-2169-2014](https://doi.org/10.5194/amt-7-2169-2014)
- Buonocore, J.J., Lee, H.J., Levy, J.I.: The influence of traffic on air quality in an urban neighborhood: a community-university partnership. *Am. J. Public Health* **99**, S629–S635 (2009)
- Burke J, Estrin D, Hansen M, et al.: Participatory Sensing. SenSys ‘06 – WSW’06 (2006)
- Catlin-Groves, C.L.: The citizen science landscape: from volunteers to citizen sensors and beyond. *Int. J. Zool.* **2012**, 1–14 (2012). doi:[10.1155/2012/349630](https://doi.org/10.1155/2012/349630)
- Conrad, C.C., Hilchey, K.G.: A review of citizen science and community-based environmental monitoring: issues and opportunities. *Environ. Monit. Assess.* **176**, 273–291 (2011). doi:[10.1007/s10661-010-1582-5](https://doi.org/10.1007/s10661-010-1582-5)
- Dons, E., Int Panis, L., Van Poppel, M., et al.: Impact of time-activity patterns on personal exposure to black carbon. *Atmos. Environ.* **45**, 3594–3602 (2011). doi:[10.1016/j.atmosenv.2011.03.064](https://doi.org/10.1016/j.atmosenv.2011.03.064)
- Dutta, P., Aoki, P., Kumar, A., et al.: Common sense: participatory urban sensing using a network of handheld air quality monitors. In: Proceedings of the 7th International Conference on Embedded Networked Sensor Systems (SenSys 2009), Berkeley, 4–6 November 2009, pp. 349–350. ACM, New York (2009) [ISBN 978-1-60558-519-2]
- European Environment Agency: Air quality in Europe—2013. Report (2013)
- Hagler, G.S.W., Thoma, E.D., Baldauf, R.W.: High-resolution mobile monitoring of carbon monoxide and ultrafine particle concentrations in a near-road environment. *J. Air Waste Manag. Assoc.* **60**, 328–336 (2010). doi:[10.3155/1047-3289.60.3.328](https://doi.org/10.3155/1047-3289.60.3.328)
- Hagler, G.S.W., Yelverton, T.L.B., Vedantham, R., et al.: Post-processing method to reduce noise while preserving high time resolution in aethalometer real-time black carbon data. *Aerosol Air Qual. Res.* **11**, 539–546 (2011). doi:[10.4209/aaqr.2011.05.0055](https://doi.org/10.4209/aaqr.2011.05.0055)
- Hsu, H.-H., Adamkiewicz, G., Houseman, E.A., et al.: Using mobile monitoring to characterize roadway and aircraft contributions to ultrafine particle concentrations near a mid-sized airport. *Atmos. Environ.* **89**, 688–695 (2014). doi:[10.1016/j.atmosenv.2014.02.023](https://doi.org/10.1016/j.atmosenv.2014.02.023)
- Padró-Martínez, L.T., Patton, A.P., Trull, J.B., et al.: Mobile monitoring of particle number concentration and other traffic-related air pollutants in a near-highway neighborhood over the course of a year. *Atmos. Environ.* **61**, 253–264 (2012). doi:[10.1016/j.atmosenv.2012.06.088](https://doi.org/10.1016/j.atmosenv.2012.06.088)
- Pattinson, W., Longley, I., Kingham, S.: Using mobile monitoring to visualise diurnal variation of traffic pollutants across two near-highway neighbourhoods. *Atmos. Environ.* **94**, 782–792 (2014). doi:[10.1016/j.atmosenv.2014.06.007](https://doi.org/10.1016/j.atmosenv.2014.06.007)
- Peters, J., Theunis, J., Van Poppel, M., Berghmans, P.: Monitoring PM10 and ultrafine particles in urban environments using mobile measurements. *Aerosol Air Qual. Res.* **13**, 509–522 (2013). doi:[10.4209/aaqr.2012.06.0152](https://doi.org/10.4209/aaqr.2012.06.0152)
- Peters, J., Van den Bossche, J., Reggente, M., et al.: Cyclist exposure to UFP and BC on urban routes in Antwerp, Belgium. *Atmos. Environ.* **92**, 31–43 (2014). doi:[10.1016/j.atmosenv.2014.03.039](https://doi.org/10.1016/j.atmosenv.2014.03.039)
- Riesch, H., Potter, C.: Citizen science as seen by scientists: methodological, epistemological and ethical dimensions. *Public Underst. Sci.* **23**, 107–120 (2014). doi:[10.1177/0963662513497324](https://doi.org/10.1177/0963662513497324)
- Roy, H.E., Pocock, M.J.O., Preston, C.D., Roy, D.B., Savage, J., Tweddle, J.C., Robinson, L.D.: Understanding citizen science & environmental monitoring. Final Report on behalf of UK-EOF. NERC Centre for Ecology & Hydrology and Natural History Museum, London (2012)



- Science Communication Unit, University of the West of England, Bristol: Science for Environment Policy In-depth Report: Environmental Citizen Science. Report produced for the European Commission DG Environment (December 2013)
- Setton, E., Marshall, J.D., Brauer, M., et al.: The impact of daily mobility on exposure to traffic-related air pollution and health effect estimates. *J. Expo. Sci. Environ. Epidemiol.* **21**, 42–8 (2011). doi:[10.1038/jes.2010.14](https://doi.org/10.1038/jes.2010.14)
- Snyder, E.G., Watkins, T.H., Solomon, P.A., et al.: The changing paradigm of air pollution monitoring. *Environ. Sci. Technol.* **47**, 11369–11377 (2013). doi: [10.1021/es4022602](https://doi.org/10.1021/es4022602)
- U.S. Environmental Protection Agency: Our Nation’s Air—Status and Trends through 2010. Report (2012)
- Van den Bossche, J., Peters, J., Verwaeren, J., et al.: Mobile monitoring for mapping spatial variation in urban air quality: development and validation of a methodology based on an extensive dataset. *Atmos. Environ.* **105**, 148–161 (2015). doi:[10.1016/j.atmosenv.2015.01.017](https://doi.org/10.1016/j.atmosenv.2015.01.017)
- Van Poppel, M., Peters, J., Bleux, N.: Methodology for setup and data processing of mobile air quality measurements to assess the spatial variability of concentrations in urban environments. *Environ. Pollut.* **183**, 224–233 (2013). doi: <http://dx.doi.org/10.1016/j.envpol.2013.02.020>
- Zappi, P., Bales, E., Park, J.-H., et al.: Mobile sensing: From smartphones and wearables to big data. In: 2nd International Workshop on Mobile Sensing Workshop co-located with IPSN '12 and CPSWEEK (IPSN 2012), Beijing, 16 April 2012; The 11th ACM/IEEE Conference on Information Processing in Sensor Networks, Beijing, 16–19 April 2012. [http://research.microsoft.com/en-us/um/beijing/events/ms\\_ipsn12/papers/msipnsn-park.pdf](http://research.microsoft.com/en-us/um/beijing/events/ms_ipsn12/papers/msipnsn-park.pdf)