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Discussion

Mobile monitoring of air pollution – a position paper on use cases, good practices, challenges, and opportunities

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ABSTRACT

Mobile monitoring has proven to be a very efficient tool to measure and feed into models of air pollution as it complements fixed air quality monitoring networks by adding spatiotemporal resolution. This paper explores best practices, opportunities and challenges related to mobile monitoring of air pollutants, focusing on three key application areas, namely source-, exposure-, and health-related use cases. Use cases are linked to users, ensuring

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mobile monitoring is effectively tailored to diverse research and policy needs. Tailoring mobile monitoring involves experimental design choices (platform, instrumentation, route planning and spatiotemporal coverage) and data processing choices (data-only vs modelling) optimized towards the envisaged use case. This position paper aims to guide researchers and air pollution stakeholders in generating high-quality mobile monitoring datasets. We identify best practices, discuss monitoring strategies, and highlight future research directions. Additionally, mobile monitoring supports public engagement and actionability, allowing communities to advocate for cleaner air and drive behavior change.

1. Introduction

Air pollution (a complex mixture of gases and particles of different sizes and compositions) continues to have significant health impacts worldwide (EEA, 2023; Cohen et al., 2017; WHO, 2021; Brauer et al., 2024); thus, necessitating monitoring, strategies to identify trends and estimate exposures, and inform strategies to reduce pollution and health impacts. Often, air quality is assessed using measurements obtained from stationary Air Quality Monitoring Stations (AQMS). Such networks provide high-quality, standardized information about pollutant concentrations, which is ideal for analyzing spatiotemporal trends across large areas. However, fixed-site monitors and networks of monitors generally cannot capture hyperlocal (street-by-street) variations of air pollution (Apte et al., 2017; HEI, 2010; Boogaard et al., 2022; HEI, 2022; Patton et al., 2024), the scale at which exposures (and, potentially, exceedances of ambient standards) occur.

For pollutants that are spatially relatively homogeneous (e.g., $PM_{2.5}$), a network of a few AQMS (Air Quality Monitoring Stations) might be sufficient to capture the spatiotemporal variability across the urban scale (1–10 km). In contrast, concentrations of ultrafine particles (UFP), black carbon (BC), and oxides of nitrogen (NO/NO_2)) vary significantly over short distances (< 300 m) (Van den Bossche et al., 2015; Fujita et al., 2014; Kaur et al., 2005; Kumar et al., 2018; Morawska et al., 2008; Peters et al., 2014; Pirjola et al., 2012; Simon et al., 2017)), resulting in spatial variability that is often not directly captured by a small number of AQMS. While the new EU air quality Directive (EU), (2024) requires member states to monitor UFP, budgetary and logistic constraints often limit the number of monitors in an AQMS network. However, advances in air quality sensors and Internet of Things (IoT) technologies, participatory science, and the availability of portable monitoring solutions have paved the way for more fine-grained sensor networks and mobile air quality monitoring applications, generating high spatial and temporal resolution data (Gohlke Julia et al., 2023; Hofman et al., 2024). These advances have great potential to improve our understanding of the spatiotemporal dynamics of air pollution.

In this paper, we show the added value of mobile monitoring for increasing the spatiotemporal resolution of air quality data relative to purely fixed-site monitors and networks. We define mobile monitoring as the use of a mobile platform (e.g., a motorized vehicle, bicycle, or a pedestrian) equipped with rapid-response instruments to measure ambient air pollutant concentrations at ground level. An illustrative overview of mobile monitoring studies, including mode of transport, is listed in **Supplementary Table S1**. Personal monitoring and measurements with other mobile platforms including satellites, airplanes, balloons, and drones are out of scope for this article. Of note, low-cost stationary networks of active and passive sensors (typically less than 500 euro) as a third measurement technique can be somewhat in between AQMS and mobile monitoring in terms of spatial and temporal completeness.

Mobile monitoring enables efficient measurement of air pollution in complex and diverse, often urban, built environments. The quick mobilization and inherent advantage of mobility of the monitoring platform allows large spatial coverage, and weaker assumptions related to the number of spatial nodes required to capture relevant concentration patterns compared to a network of monitors at fixed sites. Furthermore, the number of devices needed is limited, enabling the employment of lab-grade instruments (opposed to low-cost sensor networks). Together with advancements in air quality monitoring instrumentation, such as higher time resolution and greater portability, mobile platforms can capture the high variability of air pollutants in space and time. While cost-effective in capturing spatial variability, mobile monitoring lacks temporal continuity, necessitating temporal aggregation of repeated measurements or use of statistical approaches or modelling techniques to estimate long-term averages.

The goal of this paper is to inform researchers and other air pollution stakeholders about successful strategies for generating high quality data sets based on mobile monitoring for specific use cases. We focus on UFP, BC, and NO_2, which are (i) known to exhibit high spatial variability in ambient air and (ii) often considered in mobile monitoring studies, allowing us to derive best practices. Furthermore, we aim to use the consensus among leading researchers in the field of mobile monitoring research as a scientific roadmap for future mobile monitoring campaigns. We do not aim to systematically review all mobile monitoring studies; thus, this work should be seen as a position paper. Specifically, this paper (i) provides an overview of use cases as well as opportunities and associated challenges for mobile air quality monitoring, (ii) reflects on good practices in terms of monitoring design, data processing and modeling, and (iii) highlights potential future research directions.

2. Use cases and users

Mobile monitoring, which has been invaluable in emergency situations, such as accidental pollutant releases (Oladeji et al., 2023) to inform evacuations and other precautions (Shie and Chan, 2013), can be applied to numerous other use cases, from epidemiology and community-wide exposure assessments in a city or larger area to hot spot detection for assessing the impact industrial sources (Galarneau et al., 2023), woodsmoke (Wagstaff et al., 2018), highways (Liggio et al., 2012; Wren et al., 2018), or airports (Hsu et al., 2014; Westerdahl et al., 2008; Austin et al., 2021). Mobile monitoring has also been employed to investigate the effects of various air quality management strategies including industrial emissions controls near fenceline communities (DeLuca et al., 2012) and solid or green barriers along busy roads (Van Ryswyk et al., 2019; Baldauf, 2017). Mobile monitors have been deployed in campaigns using diverse monitoring strategies such as scheduled monitoring on pre-designated monitoring routes, adaptive monitoring to track impacts from individual sources in an area, and non-scheduled opportunistic monitoring.

To effectively tailor best practices, we identified potential use cases and users of mobile monitoring data in Fig. 1. We group the use cases in three categories: source-related, exposure-related, and health-related, and acknowledge that some use cases are broader than the assigned category. We thereby consider use cases as the end points; the platform used, and monitoring design are tools to get there. In the remainder of this section, we match use cases to users and discuss best practices to ensure mobile monitoring is effectively tailored for the user/use case combinations identified in Fig. 1.

Note that there is much overlap in the monitoring strategy of the various use cases, so they are not repeated for every combination of users and use cases. Per design criterion, we first discuss general aspects and then focus on specific use cases. In the following paragraphs, the different use cases for mobile monitoring, outlined in Fig. 1, are presented and delineated in terms of users and application areas.

2.1. Source-related use cases

For effective air quality management, it is essential to know which sources are contributing to air pollution population exposures in an area. To do so, it is important to identify and quantify emissions, the spatial scale of source impacts (hyperlocal, local, neighborhood and regional), and the timescales of impact (peak, diurnal, seasonal and annual). Mobile monitoring can help to identify sources, without relying on *a priori* assumptions on source emissions rates, or on transport and transformation of that source emission within the environment. This allows for a wide range of users to efficiently and accurately quantify impacts and characterize emission plumes. Some applications of this approach include identifying spatial impact of poorly or uncharacterized local sources of air pollution (deSouza et al., 2020), characterizing the range of emission plumes (Hudda et al., 2014), deriving *in situ* emission factors (Kelp et al., 2020), and localization of unknown point sources (e.g., wood burning).

Regulators and urban planners can benefit from hotspot detection and source identification by implementing changes in the urban design or pinpointing the industrial site, evaluate emission limits, discover disparate exposure outcomes, or identify specific source contributors (Yacovitch et al., 2023; deSouza et al., 2020; Robinson et al., 2018; Hudda et al., 2018). This can help provide evidence of, e.g., elevated concentrations near industrial or other point sources and can potentially identify unequal exposures related to location. A better identification of sources can also help to improve models.

2.2. Exposure-related use cases

Mobile monitoring is used by national environmental and health officials to compare with regulatory limit values, especially in areas with no or limited fixed monitoring stations. This can include (i) complementing a stationary monitoring network as can be seen in Dakar, Senegal (WHO, 2023) and (ii) investigating industrial emissions impacts on air quality as can be seen in the Michigan-Ontario region, USA-Canada (Yacovitch et al., 2023). Moreover, dense air pollution measurements are useful for urban planners and local authorities interested in evidence-based air quality management choices. Conducting targeted measurements before and after a policy or program has been implemented can be especially informative when assessing the effectiveness of a policy or action. This is especially true for policies implemented far from fixed-site air quality monitoring stations. For example, when Toronto piloted a car-free street in its financial district, many researchers collaborated to measure the impact of this intervention in the nearby streets and buildings using mobile monitors, which provided crucial information for city managers when evaluating the efficacy of this policy (University of Toronto Engineering News, 2018). This holds as well for using hyper-local data to inform simulations on the impact of a policy, for example in an agent-based model (Sonnenschein et al., 2024). Similarly, the spatial impact of the London ultra-low emission zone was evaluated by a mobile laboratory (Padilla et al., 2022). In addition to policy interventions, mobile monitoring can help define priority areas or population groups for targeted air quality measures. Decades of research have highlighted that racial/ethnic minorities and people of low socioeconomic status in the United States (Jbaily et al., 2022; Bramble et al., 2023), Canada (Giang and Castellani, 2020; Zalzal and Hatzopoulou, 2022) and in some cities in Europe (Fecht et al., 2015), are at higher risk of death from exposure to pollution and are exposed to higher levels of

Fig. 1. Defined users (center) and use cases in source-, exposure- and health-related application domains.

pollution than are other population groups (Johnston and Cushing, 2020), (Marshall et al., 2014). As such, mobile monitoring data can uncover urban-scale and hyper-local exposure disparities (Shah et al., 2020).

Mobile monitoring allows for population-specific exposure studies (e.g. commuters) using portable instruments (Hofman et al., 2024; Moreno et al., 2015; Nwokoro et al., 2012; Int Panis et al., 2010). Although not necessarily representative of long-term exposure, short-term mobile monitoring campaigns can shed light on exposure variability exhibited during activities of interest (e.g., commuting, physical or recreational activity) and for specific population subgroups (Milà et al., 2018). People who live in the areas where monitoring takes place are important stakeholders as neighborhood-scale data and information offers great potential for awareness raising and behavioral change (e.g., on route choice, avoidance of local sources, or making decisions based on understanding how meteorology affects air pollution concentrations and thus exposures).

2.3. Health-related use cases

Mobile monitoring can be conducted to collect fine spatial resolution, population-representative data, which can subsequently be used for epidemiological applications (Blanco et al., 2023b; Apte et al., 2017; Kerckhoffs et al., 2022; Doubleday et al., 2023). Mobile monitoring campaigns have been used to assess the link between air pollution exposures and health outcomes, including cardiovascular (Laeremans et al., 2018b; Provost et al., 2016; Pieters et al., 2015; Cole-Hunter et al., 2016), brain health (Blanco et al., 2024), respiratory (Laeremans et al., 2018a; Laeremans et al., 2018b; Int Panis et al., 2017; Weichenthal et al., 2011) outcomes and mortality (Bouma et al., 2023). Compared to NO_2 or $PM_{2.5}$, UFP and BC have been less frequently measured and assessed in studies of traffic-related air pollution (Patton 2024). The spatial patterns of these pollutants are insufficiently captured by stationary monitoring sites, thus necessitating more extensive spatial coverage to capture their high spatial variability and reduce exposure measurement error. Moreover, research interest has grown in acute health responses from short-term, in-traffic, exposure peaks quantified via mobile monitoring campaigns (Milà et al., 2018; Dons et al., 2018; Jarjour et al., 2013; Jerrett et al., 2005; Cole-Hunter et al., 2016; Int Panis et al., 2017; Laeremans et al., 2018b).

3. Monitoring design

Table 1 shows an overview of the main design options when planning a mobile monitoring campaign, split into the platform, instrumentation and route planning used. Optimal strategies can be different for the different use cases. For example, for exposure-related use cases, high-quality instrumentation is a priority, meaning a platform needs to be considered that can carry such instrumentation. For many epidemiological studies, spatial coverage is most important, meaning a fast (or many) platform(s) should be used. A key message is that the monitoring design needs to be aligned with the research question and subsequent data processing.

Table 1
Design strategies for mobile monitoring campaigns.

Design options	Advantages	Considerations
Platform		
Passenger vehicle (car), cargo van	Large spatial coverage, lab-grade equipment can be used	Inlet system, self-sampling, sensitivity to vibration, power source for vehicle and instrumentation, General Data Protection Regulation (GDPR)
Bicycle	Can access places where cars cannot go, no self-sampling, relevant exposure measurement	Weight (portability) and power source for sampling equipment, GDPR
Public Transport (bus, tram, train, subway)	No need for specific mobile platform	Similar routes, inlet system, permissions, power source for vehicle and instrumentation
Walking	More spatially precise measurements, relevant exposure measurement	Distance that can be covered, weight and power supply of sampling equipment, GDPR
Instrumentation		
Lab-grade instruments	Accurate measurements, source specificity	Expensive, high-power consumption, often not portable
Mid-size (hand-held) instruments	Often portable, most can be used with all platforms	Accuracy, reliability, comparison with reference instruments
Low-cost sensors	More affordable, allowing for more instruments, most can be used with all platforms	Accuracy, reliability, validation comparison with reference instruments
Route planning		
Dedicated	Specific spatial and temporal coverage, platform can also be used for community engagement	Route planning, repeated sampling (Temporal and spatial coverage)
Opportunistic	Add instrumentation on existing mobile platforms	Temporal and spatial coverage
Carried by individuals during daily activities	Relevant exposure measurements, do not require access to motorized or bicycle platforms, not confined to roadways, Community engagement, local experts	Specific routes; limited temporal coverage; logistics
Stop-and-go	Adjustment of measurements to account for movement of the platform not needed, longer measurement averaging time at specific locations	Less spatial coverage for the same amount of driving time
Repeated sampling	More accurate measurements of long-term concentrations at specific locations	Tradeoff with driving on other streets for the same amount of time.

3.1. Mobile platforms

Most mobile monitoring studies have integrated rapid-response instrumentation with either dedicated motorized road vehicles (e.g., cars) to measure air pollutant concentrations (Yuan et al., 2022; Miller et al., 2020; Messier et al., 2018; Apte et al., 2017; Kolb et al., 2004) or service fleet vehicles like taxis, buses, city vehicles, trash trucks and postal vans (deSouza et al., 2020; Wu et al., 2020; Hasenfratz et al., 2015; Tian et al., 2022; Hofman et al., 2023). Other studies have used bicycles (Wesseling et al., 2021a; Elen et al., 2013; Carreras et al., 2020; Hofman et al., 2018; Van den Bossche et al., 2015; Kamińska et al., 2023; Van Poppel et al., 2023), public transport (Kaivonen and Ngai, 2019; Hasenfratz et al., 2015), walking (van den Bossche et al., 2016; Mead et al., 2013), and/or combinations thereof.

When considering the type of mobile platform, the representativeness of the data for the intended use case will be determined by the measurement duration or period (e.g., hours of the day, days of the week, seasons), sampling location and its geographical extent, required spatial resolution and route. Depending on the area (small/large) and the resolution (per 5 m, street segment) you can select another platform (function of speed). Bicycle measurements might be more appropriate to quantify cyclist exposure or map car-free streets/areas when compared to on-road car measurements. Public transport operates outside daily business hours, while postal or garbage trucks cover all postal addresses of a city but are often not operational on Sundays; however, such campaigns necessitate that measurements can be carried out unattended (by the research team) and quality checks can be performed before and after campaigns. Next, a dedicated monitoring design, delineated in terms of spatial area, specific routes, and time of sampling, can be optimized for a specific research question or use case, while opportunistic data collection on existing platforms can provide more data at a lower cost.

Some aspects to consider when designing a mobile platform for air pollution monitoring include having sufficient electricity to operate all instruments and pumps (often supplied by rechargeable batteries and an inverter), adequate manifolds, tubing that is as short as possible and made of conductive material (to prevent particle losses) or nonreactive material (to prevent chemical consumption of gases), and for non-electric cars the sampling inlet system (preferably isokinetic) is as far away from the exhaust as possible to minimize self-sampling. Additionally, some instruments need proper anchoring and stabilization as they use optics that can be disturbed by vibrations. For instrumentation in backpacks or attached to bikes, weather-proof housing, and portability (size and weight) are vital. Lastly, in some cases when instruments are placed on buses or street sweepers self-pollution is not trivial and needs to be accounted for. Though, this is not the case if commuter (bus riders) or occupational (street sweepers) exposure is of interest and the measurement is made within the rider's cabin.

For use cases requiring large geographical areas be monitored, it is advised to adjust the speed based on the size of the study area and the strength of near-road sources. For example, a use fast-moving vehicle (> 15 km/h) or multiple platforms are often used by health scientists and epidemiologists wanting to measure exposures for people living in a large region or country (Gkatzelis et al., 2021; Kerckhoffs et al., 2021). For this setup, measuring all different topologies and characteristics of an area is often prioritized over full coverage or the number of repeats. On the other hand, a slow-moving vehicle (< 15 km/h) would be more appropriate when assessing variations in air pollution exposures in neighborhoods close to a busy road (Patton et al., 2014). For intra-urban mapping, evaluation of interventions, fenceline monitoring, and hotspot detection, walking or biking might also suffice. Here, the spatial resolution of the measurements themselves and number of repeats is more important. Though, cars (or buses, trams, etc.) can still significantly decrease the duration of the campaign by covering many more streets over the same time duration. The advantage of walking is that measurements made on residential streets are generally more representative of (home) outdoor pollution levels (which is often used in epidemiological studies) because they are further away from busy commercial streets. This holds for citizen engagement as well, as the impact increases when citizens can perform and reflect on their own measurements.

3.2. Instruments

The selection of monitoring instruments depends on the pollutants that are most in line with the use case, for example pollutants that are expected to have a larger spatial variability to identify sources or to be a proxy for the health effects studies. The technical specifications of the instruments, such as measurement technique (e.g., chemiluminescence, light-scattering), time-resolution, size, and weight are implicitly linked to study design criteria. The most important requirement for instruments mounted on or inside a mobile platform is their ability to accurately measure pollutant concentrations at a high temporal resolution: a resolution of 1 s (bicycle, car) to 10 s (pedestrian) is important to achieve a spatial monitoring resolution of ~5–15 m. A list of instruments frequently used in mobile monitoring studies can be found in **Supplementary Table S2**. One division is based on the quality of the instruments; high-grade (reference and lab-grade instruments; 20,000 euros plus), mid-grade (portable and precise instruments in the range of 5,000–10,000 euros) and low-grade (low-cost sensors; 10 to 500 euros).

Some instruments need signal-to-noise correction to cope with the high temporal resolution as signals fluctuate too much on a 1-second timescale. For example, BC aethalometers (AE51, MA200) often need to be post-processed to remove impacts of noise and mechanical vibrations from uneven road surfaces and travel speeds. An optimized noise-reduction algorithm (ONA; a flexible moving average) is commonly applied to achieve this (Hagler, 2011). A moving average of a couple of seconds is another way of dealing with this issue (thereby decreasing the spatiotemporal resolution). Similarly, some instruments, such as particle-size classifiers, which are designed to count particles in one size bin at a time, need up to tens of seconds to measure all different size bins. For these instruments, each measurement reflects a larger distance, decreasing spatial resolution of measurements. One solution is to implement a stop-and-go strategy if particle size distribution is important to the use case.

Another aspect that needs to be considered is the response time of the instrument, which depends on the length of the sampling line (the time it takes to sample air from the inlet to an instrument) and the intrinsic response time of the instrument. For example, most optical devices allow for faster internal response times compared to electrochemical instruments. It is therefore important to correct for any differences in instrument response times, otherwise measurements will not be correctly joined with locations and inter-pollutant correlations will be artificially low, e.g., concentration peaks of different pollutants may not coincide.

Precision and accuracy of the instruments is also important to consider. For hotspot detection and health-effects use cases, instruments that have high precision are often prioritized over instruments with high accuracy. This is also true for campaigns where multiple devices are combined to distinguish measured pollution gradients from instrument uncertainty. For comparisons with regulatory limit values, instrument accuracy is more important than precision, although precision becomes important when concentrations are close to the regulatory limits. For citizens and urban planners interested in a general idea of air pollution in an area, there is less need for the most precise and accurate equipment. Also, for hotspot detection, concentration peaks can be captured adequately by low- to mid-grade devices.

Technological advances have allowed for quantification of some pollutants (e.g., PM, NO_2) with low-cost sensors (LCS) at a high spatiotemporal resolution, while for other pollutants mid- or high-grade instruments are required to accurately measure concentrations (i.e., UFP, BC). A large disadvantage of LCS is the low to moderate agreement of measurements of individual sensors with measurements from reference monitors. In stationary settings this can be solved by averaging over longer times or using multiple sensors but in mobile settings the sensor uncertainties are combined with the short sampling time per location. Some research has evaluated LCS in mobile settings (Russell et al., 2024; Santana et al., 2021; Hofman et al., 2023; deSouza et al., 2023; Mui et al., 2021, Hofman et al., 2024) and determined that factors such as the choice of calibration model, the positioning of the LCS on the vehicle, air velocity, sensor age, and pollution gradients can impact LCS performance. Despite the uncertainties in using LCS for mobile measurements some campaigns have found these instruments effective for use in community engagement campaigns (Mijling et al., 2017; Hofman et al., 2022b; Hofman et al., 2022c; Wesseling et al., 2021a).

For all instrumentation (especially for LCS), it is advised to follow manufacturer guidance and to evaluate accuracy and precision with available reference equipment, preferably under similar environmental conditions (meteorology, concentration range, etc.). Data quality can be optimized by applying calibration algorithms (trained in representative environmental conditions), often achieved through co-location campaigns at reference urban Air Quality Monitoring Stations (AQMS).

3.3. Route planning

Mobile monitoring or mapping can be performed in a very 'controlled' way or a more 'opportunistic' way. We define opportunistic monitoring as data collection in which the route is uncontrolled from the point of view of the researcher, for example, by using public service vehicles as the mobile monitoring platform or asking independent citizen scientists to carry the monitors as they go about their days (Wesseling et al., 2021b; Van den Bossche, 2016; Hofman et al., 2023).

Dedicated routes, on the other hand, are deliberately planned with specific spatial coverage in mind (Van Poppel et al., 2024; Kamińska et al., 2023). Somewhat in between is when a researcher controls the spatial coverage that needs to be covered in a time window by the monitoring platform without a specific route plan (Kerckhoffs et al., 2022). We consider this a dedicated approach because the researcher is still in control, for example by making sure enough randomization is applied in terms of street topologies, geographic domain, and temporal coverage.

A big advantage of opportunistic monitoring is that it uses existing mobile infrastructure or people's common daily routines. Examples of campaigns that can run independently for long periods without human interaction after initial setup are those based on sensors mounted on vehicles such as cars, buses, postal vans, street sweeping vehicles or trams (deSouza et al., 2020; Hasenfratz et al., 2015; Hofman et al., 2023). In these cases, the measurements are restricted to the route followed and/or schedule of the driver.

This is also true when citizens or commuters are performing the measurements (Moreno et al., 2015; Carreras et al., 2020; Hofman et al., 2018; Peters et al., 2014; Qiu et al., 2019; Weichenthal et al., 2011). The more human interaction the data collection needs, the more user-friendliness of the instrument and the motivation of the people involved become important requirements. The disadvantage of opportunistic monitoring by citizens is that it could result in sampling bias in which certain urban microenvironments or timeslots are underrepresented or absent in the data. This complicates the data interpretation (the comparison of the measured concentrations at the distinct locations) as well as the applications of the data.

The advantage of a dedicated approach (Kerckhoffs et al., 2022) (Van Poppel et al.; 2024; Blanco et al., 2023a; Kamińska et al., 2023) is that the campaign can be tuned to ensure it is well suited to the ultimate use case and includes appropriate comparison (background) areas. Balancing temporal coverage (time of day, days of the week, and seasons) makes it easier to compare measurements made at distinct locations and to ensure good estimates of the target quantities of interest (i. e., long-term location-specific average concentrations). However, the monitoring team will need to be able to improvise in cases of construction or unplanned road closures. In the absence of advanced navigation systems as in many Low- to Middle Income Countries (LMIC) settings, additional staff might also be required for manual navigation when driving every street segment in a specific area. Lastly, targeted monitoring reduces bias due to weather conditions, as a commuter might take their personal car instead of walking/biking with the monitoring device on rainy or cold days.

The involvement of citizens in data collection is an important part of community engagement and assessing personal exposures. When citizens are part of the route planning it can benefit hotspot detection and representativeness of sampling, as they often know their neighborhood very well. Likewise, they can provide valuable input when interpreting mobile measurements. For epidemiology, it is important to cover the entire population of interest by unbiased measurements, so the design of the mobile monitoring route can additionally benefit from maps of the study area and other resources. This requires adherence to an appropriate study design; however, not all streets need to be measured to create an accurate exposure map.

3.4. Spatial and temporal coverage

3.4.1. Number of repeats

The number of repeated measurements at distinct locations or at different times will depend on the location and the use case. It is evident that with just a few drives on a street segment (1–4 drives) it is not possible to characterize long-term average concentrations with measurements only. However, a Land Use Regression (LUR) model based on mobile data with only a few repeats per street segment may predict relative differences between street segments within the measured area (Kerckhoffs et al., 2021). Therefore, how many times a street segment needs to be measured depends on processing method (data-only vs model), the use case and temporal variability of local sources of air pollution. For identification of intermittent hotspots and comparisons with regulatory limit values, repeated measurements on street segments are crucial because regulatory limits are usually based on long-term averages. However, for its use in epidemiology, it might be less important to know the exact absolute air pollution values on every single street segment because measuring a lot of street segments with similar characteristics can be seen as pseudo repeats when it comes to developing LUR models. In other words, the associations between street (and land-use) characteristics and its measured concentration are captured due to the many combinations of features and measurements. Though this only holds if the relative spatial differences in exposure values at different locations are captured accurately (Kerckhoffs et al., 2021). When comparing different situations (before and after measures or comparing different seasons) repeated measurements are needed to take into account background variations and can be complemented with rescaling based on concentrations at fixed AQMS location(s).

To evaluate the representativeness of short-term mobile measurements for estimating long-term exposure, subsampling analysis can be performed on the mobile data to derive a minimal number of required repeats at a location or street segment of interest (Van den Bossche et al., 2015; Apte et al., 2017; Hofman et al., 2023). Doing so, Van den Bossche et al. (2015) found that the required number of repeats to be within 25 % of the long-term average concentration varied widely when considering measured BC concentrations in different 50 m street segments along a cycling route, with 33–141 repeats to obtain convergence (95 % probability and 25 % deviation). Additional postprocessing via the use of trimmed mean and background normalization (Van den Bossche et al., 2015; Peters et al., 2014; Apte et al., 2017), reduced the number of required passages to 24–94 (10 and 90 percentiles of 50 m segments) (Van den Bossche et al., 2015). Similarly, another study found that about 45 repeats (31 after postprocessing) were required to derive representative long-term NO_2 exposure data from an opportunistic mobile air quality dataset collected on postal vans (Hofman et al., 2023).

Blanco et al (2023b) showed that about 28 stationary off-road measurements per site were needed to approximate long-term average NOx concentrations within 25 % error for that site (average of 10.000 random samples at 69 sites). The same sampling error was found for street segments in London (Padilla et al., 2022). In a study by Messier et al. (2018), they assumed that 50 unique drive days on a road segment would represent a stable long-term average concentration. They then created subsets of the data with varying numbers of drive days per road segment and compared the average concentration of the subset with the average concentration of the full measurement campaign. The authors found that the correlation between having about 20–25 drive days per street segment and the full dataset was still very high ($R^2 > 0.9$).

Comparing data-only to model approaches, Messier et al. (2018) found that 4 to 8 repeats were already sufficient to create an exposure map at measured locations for BC and NO better or at par with a LUR model based on the same data. Fig. 2 shows the correlation pattern between data-only/LUR models and long-term average concentrations related to the number of drive days per street segment. So, all street segment averages based on the subsets of the mobile data (x-axis) were correlated with the same street segment averages based on the full dataset (50 drive days). The figure also shows that repeated measurements per street segment do not help in creating a better LUR model. A LUR model based on one measurement per street segment already provides enough information to create a stable LUR model (Kerckhoffs et al., 2024), though Clark et al. (2024) found that beta coefficients for individual features were not stable with limited repeats per segment. Future research should verify if this holds in other geographical areas and for other pollutants. For example, UFP concentrations vary more than NO_2 in urban environments.

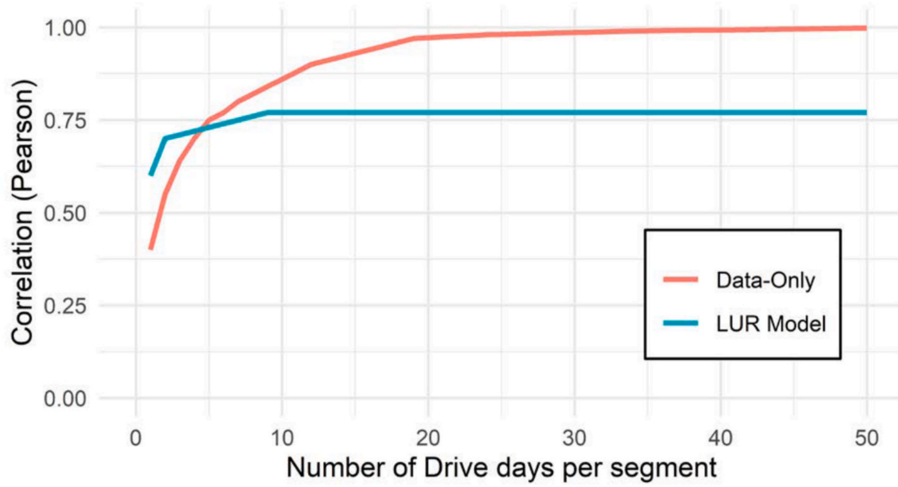

Fig. 2. Performance of data-only mapping and LUR models for NO related to the number of drive days per segment where the reference is 50 drive days per segment (reproduced from Messier et al (2018)).

3.4.2. Temporal coverage

Unlike continuous stationary monitoring networks that can characterize long-term trends at a few sites, mobile monitoring campaigns inherently achieve the opposite – increased spatial coverage at the expense of limited temporal coverage. In this regard, a distinction can be made between area coverage (percentage of street segments or fraction of area covered; i.e., spatial coverage) and street segment coverage (repeated measurements per street segment; i.e. temporal coverage) (Hofman et al., 2023). Blanco et al. (2023a) reported that the most relevant factor for good predictions of the annual average exposure surface in Seattle was the total number of stops (# locations/segments * repeats).

Collecting temporally balanced measurements is necessary to estimate unbiased longer-term averages that capture the exposure period of interest. Sampling across two or more seasons during both weekdays and weekends and during most hours of the day (5 AM – 11 PM), for example, is necessary to estimate unbiased annual averages of both fine particulate matter ($PM_{2.5}$) as well as more spatially variable pollutants like UFP, BC, NO_2, NOx, and CO_2 (Blanco et al., 2023a; Blanco et al., 2023b). The extent of bias likely varies in different settings related to the degree of diurnal and seasonal variation and the stability of spatial contrast across hours, days and seasons (Upadhya et al., 2023). So, when annual average concentrations are of interest, it is important that the repeated measurements cover different seasons, days of week, and times of day which can affect pollution levels significantly.

Notably, most campaigns typically sample during typical business hours because a technician is required to operate the monitoring platform, thereby allowing some bias related to characterizing the long-term average (Blanco et al., 2023a; Blanco et al., 2023b; Downward et al., 2018). Opportunistic mobile monitoring applications on service fleet vehicles (deSouza et al., 2020; Hofman et al., 2023) or public transport (Hasenfratz et al., 2015; Kaivonen and Ngai, 2019; Wu et al., 2020) can extend this time window to weekend days, holidays, or night hours.

3.4.3. Spatial coverage

For most use cases it is clear where the measurements should be taken. However, when considering a large cohort study, it is impossible to measure every street segment enough times in an area where the cohort participants reside. At least 5–10 % of the street segments within the domain need to be measured (once) to develop a detailed prediction map of the area long-term average pollution (Hatzopoulou et al., 2017; Kerckhoffs et al., 2017; Messier et al., 2018), with the prerequisite that all different topologies (major and minor roads, industrial areas, airports, etc.) within the area have been sampled. Ideally, balanced sampling has been done to capture all times of day, days of week and seasons. In general, more repeated measurements per location will result in better performance scores of the training model (Blanco et al, 2023), though when looking at external (independent) validation data, more repeated measurements do not necessarily improve performance scores.

While there is no ground truth for deriving spatial patterns from mobile monitoring, Messier et al. (2018) produced robust weekday daytime exposure prediction models for NO and BC with samples from approximately 30 % of the roads within a 30 km^2 domain in Oakland, CA, and with 4–8 repeat visits per road segment (Messier et al., 2018). Hofman et al (2023) showed that opportunistic data collection using service fleet vehicles (e.g., postal vans) was an efficient approach to rapidly cover a 6 km^2 domain in Antwerp, Belgium, with $>$ 50 % of total street length (709 km) covered after deploying 17 sensor units for 1 month. (Hatzopoulou et al., 2017) found that different subsets of ~150–200 road segments and 10–12 visits per segment across three seasons produced stable PNC and NO_2 prediction models in Montreal, Canada (470 km^2 domain). Even LUR models based on 100 (out of 480) segments predicted on average 73 % variation (opposed to 74 % for the full dataset), albeit with a wider range (55–85 % opposed to 70–78 % for the full dataset).

3.4.4. On-road measurements versus off-road concentrations

Most mobile campaigns explicitly collect on-road measurements on a moving platform, meaning there are considerations when using predictions from these data for epidemiologic applications. Because measurements are done on or in the vicinity of roads (different for car, cyclists and pedestrians), predictions from mobile monitoring models are typically higher than those from roadside stationary monitoring, especially for high concentration areas (Kerckhoffs et al., 2016); Doubleday et al., 2023). Studies have found differences in the range of 20–30 % between on-road and off-road (roadside or facade) measurements (Sabaliauskas et al., 2015; Kaur et al., 2005; Simon et al., 2017), but the difference depends on the setting and pollutant. Differential exposure misclassification could thus be a concern when these predictions are applied to cohort locations. Several approaches have been taken to adjust on-road measurements to better approximate off-road (e.g., residential) locations (Brantley et al., 2014; Doubleday et al., 2023; Kerckhoffs et al., 2016). These include plume detection approaches (Kerckhoffs et al., 2016), transfer learning (Yuan et al., 2022, Yuan et al., 2023) and those that leverage both stationary and multi-pollutant measurements to detect and remove estimated on-road sources from the long-term averages (Doubleday et al., 2023).

4. Data processing

4.1. Quality control

Like all data collection campaigns, air pollution measurements from mobile monitoring campaigns need to be processed to remove faulty measurements. Note however that mobile measurements are typically collected at a high temporal resolution (1–10 sec) and are taken on the road itself, so extremely high values are more plausible than observed in hourly average values at fixed measurement stations and outlier tests need to be applied with care. Erroneous outlier measurements are rarer than short-term increases (or spikes) in air pollutant concentrations that might coincide with local activity such as a truck passing by. Whether such spikes should be removed or not depends on the use case and whether long-term baseline or average concentration is more relevant.

Because extreme concentration measurements can significantly affect mean values for a road segment, options to decrease (but not remove) the impact is to calculate a median value instead of the mean (more on this in section 4.3) or by applying winsorizing. Winsorizing means that values below and above a certain threshold (e.g., 5^{th} and 95^{th} percentile) are set to the 5^{th} and 95^{th} percentile, respectively. After winsorizing, the measurement is still very high but does not dominate the average value for a road segment. Winsorizing at the site level is preferable to doing so at the dataset level to avoid shifting entire sets of observations from extremely low or high concentration sites, thus distorting the exposure surface (Doubleday et al. 2023). Another approach to dealing with extreme observations is to remove them (Van den Bossche et al., 2015), although this assumes that those observations are rare and unrepresentative of general trends and that selectively removing data based on its value is appropriate in the context of the specific use case. They can also be included in analyses if the data are normalized, for example by a log-transform and the location of the extreme values is predictable (Patton et al. 2014).

In addition, ambient air measurements should not be influenced by the emissions generated by the measuring vehicle. Measurements taken when the vehicle is stationary with the engine or power generators running can lead to increased measured values and should be tested for and filtered out if needed before further analysis.

4.2. Localization of measurements

Mobile measurements depend on geographical localization using GPS with a high (e.g., 1 sec) temporal resolution; without GPS, mobile measurements are often useless for understanding spatial patterns. However, GPS signals are not always accurate in urban settings and might not align perfectly with a street (e.g. Hofman et al. (2024)). Since we know the mobile platform (especially if it is a car) was on the road, all measurements sampled with this platform can be snapped to the nearest road segment if the nearest road segment was the most likely measurement location or manually adjusted to road segments based on knowledge of the route. Additionally, for mobile monitoring not restricted to roadways, e.g., data collected by pedestrians or bicyclists, automatic snapping based on roadways could be incorrect, and instead snapping to manually drawn trajectories could be preferred.

Subsequent aggregation along the trajectories depends on the use case and can be done by aggregating (i) on street segments, (ii) in predefined (point) buffers along street segments (e.g. (Van Poppel et al., 2024; Peters et al., 2014), or (iii) in grids. The speed and mode of the mobile platform will affect the spatial aggregation that can be used. Most LUR models based on mobile data use the street segments as spatial aggregation for their models, defined as a line segment from one intersection to the next, or as predefined distances of e.g., 20–200 m (Hofman et al., 2018; Van den Bossche, 2016; Hankey and Marshall, 2015; Kerckhoffs et al., 2017; Kerckhoffs et al., 2016; Chambliss et al., 2020; Doubleday et al., 2023; Patton et al., 2014). Hankey and Marshall (2015) analyzed the impact of spatial resolution in a mobile monitoring campaign and found very little difference between the performance of LUR models that were based on segments where concentrations were averaged over 50, 100 and 200 m. Similar conclusions were obtained in Amsterdam (Tian et al., 2025). However, for hotspot detection it can be crucial to keep the length of road segments (or size of grids) as small as possible, preferably within 50 m. The impact of diverse spatial units (i.e., segments and grids) on model accuracy when shifting scales (from 50 to 500 m) remains unclear. In addition to the discrete aggregation, continuous use of measurements has been applied as well, e.g. via Gaussian Kernels (Wilde et al., 2024).

Two difficult stretches of road to deal with in mobile monitoring studies are tunnels and overpasses. Tunnels because the GPS signal goes missing or deviates from the actual route and overpasses because the GPS cannot distinguish on which segment the measurement was taken. When the measurement cannot be pinpointed to a specific location it is difficult to use. Depending on the use case, those data can either be deleted or assigned to locations along the known trajectory by assuming uniform vehicle speed from when the signal is lost to when it is reacquired (Perkins et al., 2013). For population health-related use cases the tunnel data can often be deleted because there are no residences in a tunnel. One reason to keep the measurements is when you are specifically interested in the generally higher (Martin et al., 2016; Pant and Harrison, 2013) pollutant concentrations in the tunnel from a commuter exposure perspective or are using mobile monitoring to assess emissions (e.g., Perkins et al 2013). Telematics data can sometimes be used to extrapolate such dark spots in the GPS measurements (Ghaffarpasand et al., 2022).

4.3. Temporal adjustments of data aggregated to the segment level

A fundamental challenge with mobile monitoring is that it is difficult to separate temporal and spatial variation, as the platform is moving in time and space. To better compare mobile measurements sampled on different hours, days and seasons, a temporal correction is often applied. The reason for doing this is to separate the impact of spatial features from the temporal conditions since extensive spatial and temporal coverage is ideal but not possible. Pollutant concentrations will namely fluctuate across multiple time-scales due to meteorological (e.g., temperature inversions, wind conditions), seasonal and anthropogenic (e.g., rush hours, wood burning) factors. However, temporal corrections are not a panacea since they also introduce noise into the data; more work is needed to understand when temporal corrections improve understanding for various use cases.

A method that is often used to address temporal unbalanced sampling schemes is background normalization, using the temporal pollutant dynamics at a central fixed site (van de Beek et al., 2020; Dons et al., 2017; Kerckhoffs et al., 2021; Van Poppel et al., 2024). With this method you match the time of the mobile measurement with a reference site and adjust the mobile measurements based on the fixed measurement on the same time relative to the average of the reference site for the full campaign, either by calculating the absolute (additive) or relative (multiplicative) difference (Dons et al., 2017). For the assessment of individual locations or personal exposure this can be very important, as it makes the comparison between road segments or subjects easier. However, it strongly assumes that all monitoring sites share the same temporal pattern. This assumption is underlying epidemiological time series studies based on a central monitoring site but may not apply universally. Further, not only do temporal adjustments rely on estimates which introduce additional noise in the measurements, but disparities in the time trends across locations have been observed in specific locations making it difficult to identify a reference site that is suitable to apply to all locations (Blanco et al., 2023b, Blanco et al., 2022). Documenting the trade-offs between potential bias reduction and increased noise from different temporal adjustment approaches is an important topic for future research.

A transformation method that can be helpful to distinguish between regional, urban, and local influences is deconvolution. This approach was developed by Brantley et al. (2014) and applied by Shairsingh et al (2019) in which measurements were averaged over different timescales ranging from 60 to 2000 s. Then, the optimal timescale for each geographical level is determined based on a spline of minimums. In the end the total concentrations measured are divided into a regional background contribution, an urban background contribution and a local contribution. This can be helpful for use cases such as hotspot detection and source identification.

4.4. Quality control of mobile monitoring

Especially when mobile measurements are based on mid-grade instruments or low-cost sensors, information about the instrument uncertainty is crucial. Focus should be on comparability with a reference station (accuracy) and between-sensor uncertainty (precision). Instruments are typically co-located near a regulatory Air Quality Monitoring Station (AQMS) to evaluate uncertainty and apply local calibration of the applied monitoring equipment (Hofman et al., 2022c; van Zoest et al., 2019; Petäjä et al., 2021; Elomaa et al., 2024; Hofman et al., 2023). One co-location station near or along the route (similar urban environment and pollutant composition) may suffice. However, also with high-grade instruments, co-location with reference stations is recommended to document performance, especially if frequent calibration common in routine fixed site monitoring is not performed.

5. Modelling

Although mobile monitoring data can be used on itself to answer certain research questions (data-only approach), mobile measurements are often used to develop models, leveraging their inherent spatio-temporal nature, mainly for use cases that need to cover a large area or consider long-term exposure. A data-only approach might not capture enough spatiotemporal repeats to create a robust long-term average exposure map or lack measurements at certain locations that need to be predicted. Common approaches for air pollution modelling include deterministic modelling such as dispersion and chemical transport modeling, and statistical modelling, such as Land-Use Regression (LUR). Modelling approaches can be combined in so-called hybrid models which combines various modelling approaches (Jerrett et al., 2005; Hoek, 2017). For instance, a hybrid model might combine a chemical transport model, which simulates the physical and chemical processes of air pollution dispersion, with a machine learning model, which can capture complex, non-linear relationships in the data (Feldman et al., 2024; Mathew et al., 2023).

In terms of data input, fine resolution traffic (Shen et al., 2024) and emission (Paunu et al., 2024) data provide helpful information about pollution sources, particularly industrial emissions, etc. (Borge et al., 2014). Furthermore, the influence of meteorological parameters, such as wind speed and direction, temperature, and humidity, on air pollution dispersion and short- and long-range transport is well documented. Besides high-resolution traffic and meteorological information, urban topology (e.g. height/width ratio) and the presence of urban green will affect local natural ventilation and pollutant dispersion (Voordeckers et al., 2021; Hofman et al., 2020; Morakinyo et al., 2016; Gallagher et al., 2015; Vranckx et al., 2015; Gromke and Ruck, 2007; Vos et al., 2013). Thus, when possible, it is worthwhile to include these predictors to develop more accurate air pollution models (Hofman et al., 2022a; Qin et al., 2022; Qin et al., 2021; Do et al., 2020).

Other data sources, such as satellite-derived air quality products, can also be integrated with models or mobile measurements. Satellite-derived air quality data provide information on columnar abundance of air pollutants over large geographical areas during daylight hours (Knibbs et al., (2014)). However, satellite retrievals from polar-orbiting satellites tend to have low temporal resolution (daily at best). New geostationary satellites like GEMS over Asia and TEMPO over North America provide higher spatial and temporal resolution than was previously available with about 1-km spatial resolution hourly satellite retrievals. For higher spatial or temporal resolution, other sources of air quality data – like those from mobile monitoring – are still needed (Holloway et al., 2021). Additionally, satellite data needs to be adjusted for most use cases that use mobile monitoring or other ground-based measurements in order to predict ground-level concentrations instead of columnar abundance (Holloway et al., 2021; Verhoelst et al., 2021; Bechle et al., 2013; Wei et al., 2022) To date, air quality and health applications have primarily utilized satellite observations and satellite-derived products relevant to near-surface $PM_{2.5}$ and NO_2 (Holloway et al., 2021).

Mobile monitoring records air pollution under specific multi-variable spatiotemporal conditions, such as meteorology, traffic patterns, and land use. Therefore, models built from mobile monitoring data can adapt to spatiotemporal changes in these variables to estimate pollution levels at a higher temporal resolution. Though, it is important to note that a model is always bound to assumptions, smooths local information over a larger domain and can only implement known sources of air pollution. The use of a model in hotspot detection, interventions and source identification is therefore only helpful if one knows what one is looking for. Also, for regulatory comparisons, it is common practice to only use fixed-site routine monitor measurements. Various interested parties might have more trust in measurements (compared to models), advocating for the model applications combined with or derived from (mobile) measurements.

Performance of models derived from mobile monitoring measurements should be evaluated by comparison against independent reference data (when available), often measurements from AQMS (Hofman et al., 2022a) or long-term home-outdoor concentrations, though, such measurements are rarely available for UFP and BC. The FAIRMODE guidance document on modelling quality objectives and benchmarking published by JRC (Janssen and Thunis, 2022), can serve as methodological guidance. A recent study applied this framework to temporally validate two machine learning models trained on mobile monitoring data from different cities and pollutants (PM, NO_2 and BC) showing that the data-driven models approached physicochemical dispersion models in terms of performance (Hofman et al., 2022a). Other evidence exists that models derived from mobile monitoring can have comparable performance to other types of near-road air quality models.

5.1. Deterministic modelling

Deterministic modelling, also known as dispersion and chemical transport modelling, is a fundamental approach in air quality assessment. These models (spatial resolution: address- or street-scale) such as the Danish AirGIS system (Khan et al., 2019) are based on atmospheric physical, chemical reaction, and emission data to simulate the emission, accumulation, dispersion, and transfer of pollutants in the air (Shiva Nagendra et al., 2021). Because pollutant levels are simulated based on scientific understanding rather than measured, for many use cases it can be very useful to leverage deterministic model outputs with mobile measurements to improve (e.g. through data assimilation (Nguyen and Soulhac, 2021; Wang et al., 2000)) or validate deterministic models.

Researchers have combined mobile monitoring and deterministic modelling to assess air pollution levels and compare measurements against model predictions. For instance, Fattoruso et al. (2022) assessed NO_2 and CO concentrations in Portici, Naples, using mobile monitoring and the SIRANE dispersion model (Soulhac et al., 2011), finding recorded concentrations three times higher for CO and twice as high for NO_2 compared to simulations. They suggest that while SIRANE is useful for preliminary evaluations, an integrated approach with pervasive monitoring is needed to understand discrepancies, noting significant uncertainty in average concentration levels from unstructured campaigns. Similarly, Zwack et al. (2011) combined mobile monitoring and dispersion modeling (QUIC) to analyze UFP concentrations in Brooklyn, New York, finding that this combination provides a richer characterization of spatial concentration patterns, though it requires robust emission factors and background concentration characterization. Another study (Zalzal et al. 2024) showed that mobile monitoring can also be used to downscale chemistry-transport models, enhancing their resolution. Mobile monitoring can leverage deterministic models as well by e.g., refining emission factors for urban pollutants. In this regard, a study by Wilde et al., (Wilde et al., 2024) showed through mobile monitoring that road emission intensity in London was clearly linked to traffic behavior (congestion).

5.2. Statistical and stochastic modelling

With mobile monitoring it is customary to produce aggregated air pollution levels. This, among others, is significantly useful for analyzing the relationship between average air pollution levels and land use features at many distinct locations. While the sampling time for each road segment is small, typically ~1–15 s per segment, different road segments with similar characteristics can be seen as pseudo repeats (Kerckhoffs et al., 2019). For example, there are many road segments with a certain number of cars and specific road width. By averaging all the relationships between pollution and traffic intensity on all similar road segments, the model can learn the correct correlation for that domain.

Many statistical models applied to mobile monitoring data are land use regression (LUR) models, which use a variety of predictors in a multiple linear regression model (Yuan et al., 2023; Van den Bossche et al., 2020; Shairsingh et al., 2019; Messier et al., 2018). Some groups extend the LUR approach to characterize the residual spatial structure using a universal kriging (UK) geostatistical model (Blanco et al., 2023a; Blanco et al., 2022). The relationship between land use covariates and pollutant measurements can be characterized in a wide variety of ways, including partial least squares and machine learning (Blanco et al., 2023a; Blanco et al., 2023b; Blanco et al., 2022).

Machine learning models can integrate the same predictors as LUR and find underlying relationships with air quality, accounting for non-linear relationships and interactions between predictors (De Vito et al., 2020; Lim et al., 2019; Qin et al., 2021; Do et al., 2020; Yuan et al., 2022). Applying those algorithms, such as Support Vector Machines, Artificial Neural Networks, and Random Forest to mobile monitoring data can facilitate identifying patterns and (non-linear) relationships that would be difficult to discern using traditional statistical regression-based methods (Kerckhoffs et al., 2019; Rybarczyk and Zalakeviciute, 2018; Qin et al., 2022; Hofman et al., 2021). Once machine learning models predict outside of their training conditions, however, model performance has shown to quickly deteriorate for sensor calibration and air quality mapping applications (Hofman et al., 2022a, Hofman et al., 2022b).

A disadvantage of stochastic models is that they learn the relationship between measurements and predictor variables at the location of the measurements (often on-road). However, in most use cases off-road exposure is more relevant. As an alternative to correcting the on-road data before modeling, an approach to narrow the gap between the training (on-road) and prediction (off-road) domain is to use transfer learning (Yuan et al., 2022; Yuan et al., 2023). This method reweighs the mobile input data to the desired long-term off-road domain with more appropriate parameters.

5.3. Hybrid modelling

Hybrid modeling aims to combine the best information from two or more modeling types. For example, physical and chemical interdependencies from deterministic modelling and data patterns from machine learning can be combined to build hybrid model variants that estimate pollutant concentrations more accurately. (Jerrett et al., 2005; Simon et al., 2017). For example, Adams and Kanaroglou (2016) combined mobile monitoring with fixed-site monitors and neural networks to map NO_2 health risks for conventional environmental management in Hamilton, Ontario, Canada. A study by Kushwah and Agrawal (2024) introduced a hybrid model for air quality prediction that combines empirical mode decomposition (EMD), long short-term memory (LSTM) networks, and optimization techniques such as random search and Bayesian optimization. This hybrid approach significantly improved prediction accuracy, demonstrating the potential of integrating multiple methodologies to enhance air quality forecasts (Kushwah and Agrawal, 2024). Similarly, Huang et al. (Huang et al.) proposed a novel hybrid model using dimension reduction and error correction techniques to predict air quality indices (AQI). Their model, which incorporates empirical mode decomposition, K-means clustering, and LSTM networks, showed superior performance in predicting AQI across multiple urban centers (Huang et al., 2024).

5.4. Performance evaluation of air quality models

Mobile measurements consist of a few seconds per road segment and are therefore very variable, while most studies aim to predict a long-term average exposure. The performance of models based on mobile data can therefore be poor. However, poor performance of mobile models does not mean a poor performance when evaluated with robust long-term average concentrations. This means that when evaluating mobile models, it is crucial to assess their performance on a long-term hyperlocal average concentration domain, focusing on spatial validation. For example, Hatzopoulou et al. (2017) compared LUR models developed on road segments with at least 3 visits to segments with at least 16 visits and found that road segments with at least 16 observations achieved a higher adjusted model R^2 with fewer explanatory variables compared to the model developed with segments having 3 + visits. This higher performance is mainly due to increased accuracy of the test set, not of the training set. However, it can be challenging to achieve such good model performance for the case of UFP and BC due to the high spatial and temporal variability of these pollutants, as well as the influence of numerous local sources and meteorological conditions.

Hofman et al. (2022a) temporally validated two machine learning models (Qin et al., 2021; Do et al., 2019) trained on different mobile monitoring data (NO_2, $PM_{2.5}$ and BC) at multiple fixed AQMS, following the JRC FAIRMODE protocol (Janssen and Thunis, 2022) They demonstrated that good model performance is achievable, depending on the amount and representativity of the training data. Performance metrics approached state-of-the-art chemical transport models while requiring fewer resources, computational power, infrastructure, and processing time. However, model performance relies on the spatiotemporal monitoring coverage of the mobile measurements. Accurate and representative data in both space and time are essential to train the models and provide reliable results.

Of note, mobile data can also be used as validation for prediction models based on fixed data, although careful consideration is needed on the boundary conditions of both approaches (Van Poppel et al., 2024). Global or continental deterministic models are adequate in mapping regional differences but often lack high-resolution data to scale models to map local differences. Mobile monitoring data can potentially leverage these models, enhancing their spatial accuracy.

5.5. Strengths and limitations

The biggest advantage of mobile monitoring is that many locations can be measured in a short amount of time. For source-related use cases this means that identification of sources can be done very locally, and expected and unexpected hotspots can be detected much more efficiently. From an exposure perspective, mobile monitoring sheds light on exposure disparities while quantifying impacts from air quality management choices. For health-related use cases, this means that exposure estimates to participants can be assigned with more accuracy due to more precise spatial resolution.

Another advantage is that monitoring equipment can be deployed by individuals on their day-to-day commutes, or on service fleet vehicles. Real-time pollutant exposure feedback for participants and behavioral impacts (e.g., considered transport modes or cycling routes) are useful for raising awareness, potentially driving behavior change and creating impact. Furthermore, mobile platforms can measure locations which are out of reach for stationary regulatory monitoring, such as intersections or near traffic lights. Mobile campaigns are also well suited to measurement of highly spatially heterogeneous pollutants with high quality instruments that might be expensive or otherwise difficult to locate at many sites throughout a study area. Lastly, mobile monitoring only requires limited instruments to measure at many different places, which makes it an interesting tool for low- and middle-income countries.

The inherent disadvantage of mobile monitoring is the sparse temporal coverage. By increasing the spatial coverage, the temporal coverage per location measured is very limited. While there are both design and modelling solutions to address the lack of temporal coverage that will vary depending upon the use case, mobile monitoring is not intended to replace stationary monitoring. Stationary monitoring sites use reference-grade instruments and adhere to certain protocols that make them suitable for air pollution trend analyses and air quality limit value compliance.

Mainly for health-related use cases, when assigning long-term average exposure estimates, the on-road versus off-road difference can be important as well, depending on the platform (e.g., pedestrian or cyclist routes might be better than motorized vehicles at sampling off-road) and monitoring approach (e.g., measurements at the roadside versus while driving). Measurement locations are in the middle of the road lane for mobile monitoring and are per definition not the same as home addresses of study participants. Because the on– versus off-road differences can reach 20–30 %, it is important to adjust mobile monitoring data for on-road sources. Further, it is important to consider the on– versus off-road difference when absolute levels are of interest.

Due to the low spatial variability of PM within cities, mobile monitoring does not contribute much to insights in local to urban scale concentration maps beyond existing stationary air quality stations. Though, for areas with no or limited fixed stations, mobile PM measurements can still contribute useful information.

The potential of low-cost sensors in mobile monitoring studies has been shown for PM and NO_2 but requires careful validation (accuracy and precision) and calibration work. Low-cost NO_2 sensors are still hampered in terms of data quality and calibration protocol. Nevertheless, studies have shown their potential in stationary applications mainly for citizen engagement use cases. Of note, other pollutants require mid- or high-grade instruments to accurately measure concentration levels (UFP, BC).

5.6. Future directions and actionability

Mobile monitoring data enables the development of fine-scale spatiotemporal air quality maps. These maps can highlight the spatiotemporal exposure variability in urban areas, revealing pollution exposure dynamics in complex urban terrain or during certain time-activity patterns (e.g., commuting exposure). Moreover, when including multiple pollutants in future mobile monitoring studies, more insights about e.g., source attribution can be obtained. When combining spatiotemporal maps with daily activity data of cohort participants collected by diaries, GPS trackers, or mobility models personal exposure estimates can be developed for use in health effect association studies. Local monitoring data, which is often collected with mobile (or stationary) platforms, can be used to engage citizens and advocacy groups to build capacity and advocate for change in their community. Mobile monitoring also provides the ability to assess short-term peak exposure and associated acute health responses (e.g., lung function, oxidative potential).

We hope that this paper can contribute to regulatory recognition of mobile monitoring. Despite its demonstrated value in capturing fine-scale spatial variability it remains absent in major regulatory frameworks such as the EU Directive on Ambient Air Quality and comparable international acts. Future policy efforts should consider integrating mobile monitoring as a complementary tool into official air quality management strategies, especially in areas where fixed-site coverage is limited.

Since many mobile monitoring studies collect data on multiple pollutants at the same time, this greatly expands the opportunities for multi-pollutant insights. Ratios between pollutants can facilitate source identification, source apportionment, and disentangle the health effects of different pollutants in epidemiological studies. This could even be extended to other components (next to air pollution as well. Multi-component (noise, air quality, health, safety, stress, etc.) exposure assessments (exposome) are the way forward as stressors can have a synergistic effect and will impact the resilience of community groups or individuals.

One of the aspects that is still unclear is how to best translate on-road measurements to residential exposure estimates. Therefore, it makes sense to combine mobile measurements with other data sources and modelling techniques in a data fusion approach. This can be done with land use regression, transfer learning, or other means of blending different models and measurement strategies to maximize the individual strengths of each source. For example, using mobile monitoring as the primary source for the spatial variation (with its limited and random temporal scale) and fusing with temporally rich measurements (AQMS and stationary LCS) in an empirical or deterministic modelling framework. Some data sources that are marginally used, such as street view images, street topology and greenery can help in resolving this issue as well. With the rise of artificial intelligence frameworks, mobile data can be integrated with real-time data and virtual sensors for next level exposure assessment.

Lastly, as most of the mobile monitoring studies have been conducted in high income countries (HIC), authors would like to encourage mobile monitoring applications in highly polluted and LMIC countries, which often have limited stationary monitoring stations.

6. Conclusions

Today, mobile monitoring applications complement stationary monitoring networks to obtain high spatiotemporal information on spatially variable pollutants (e.g., UFP, BC and NO_2) and improve contemporary exposure assessments. This paper presents opportunities and challenges related to mobile monitoring. We identified relevant source-, exposure- & health-related use cases for mobile monitoring and relevant pollutants (UFP, BC and NO_2). The monitoring strategy will depend on the envisioned use case (research question) and involve careful consideration of the used mobile platform, air quality instruments and route planning. Design choices will determine temporal (number of repeats) and spatial (number of road segments) monitoring coverage which should be balanced when aiming at long-term average air quality assessments. The data collection strategy can vary from dedicated to opportunistic in terms of routing and number of repeats.

When aiming at specific urban areas, population subgroups or time windows (e.g., rush hour exposure), data-only approaches can generate representative and meaningful data when appropriately designed (balanced in terms of spatial and temporal coverage). When aiming at air quality assessments over very large areas, high spatial and temporal monitoring coverage becomes challenging for data-only approaches, requiring modelling approaches to extrapolate mobile measurements to other time and space instances. Validation of mobile measurements or model predictions is crucial and should include (i) comparability against a reference (e.g., AQMS), ideally in similar conditions as the mobile monitoring use case or application, and (ii) between-sensor comparability (precision) when using multiple instruments.

CRediT authorship contribution statement

Jules Kerckhoffs: Writing – original draft, Resources, Formal analysis, Data curation, Conceptualization. **Jelle Hofman:** Writing – original draft, Data curation, Conceptualization. **Jibran Khan:** Writing – original draft, Data curation, Conceptualization. **Matthew D. Adams:** Writing – review & editing. **Magali N. Blanco:** Writing – review & editing. **Priyanka deSouza:** Writing – review & editing. **John L. Durant:** Writing – review & editing. **Sasan Faridi:** Writing – review & editing. **Scott Fruin:** Writing – review & editing. **Steve Hankey:** Writing – review & editing. **Mohammad Sadegh Hassanvand:** Writing – review & editing. **Marianne Hatzopoulou:** Writing – review & editing. **Gerard Hoek:** Writing – review & editing. **Kees de Hoogh:** Writing – review & editing. **Neelakshi Hudda:** Writing – review & editing. **Meenakshi Kushwaha:** Writing – review & editing. **Julian D. Marshall:** Writing – review & editing, Conceptualization. **Laura Minet:** Writing – review & editing. **Allison P. Patton:** Writing – review & editing. **Tuukka Petäjä:** Writing – review & editing. **Jan Peters:** Writing – review & editing. **Albert A. Presto:** Writing – review & editing. **Kerolyn Shairsingh:** Writing – review & editing. **Lianne Sheppard:** Writing – review & editing, Conceptualization. **Matthew C. Simon:** Writing – review & editing. **Sreekanth Vakacherla:** Writing – review & editing. **Keith Van Ryswyk:** Writing – review & editing. **Martine Van Poppel:** Writing – review & editing. **Roel C.H. Vermeulen:** Conceptualization. **Robert Wegener:** Writing – review & editing. **Zhendong Yuan:** Writing – review & editing. **Heresh Amini:** Writing – original draft, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2025.109582.

Data availability

No data was used for the research described in the article.

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