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Scalable Multipollutant Exposure Assessment Using Routine Mobile Monitoring Platforms

Apte et al.

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Scalable Multipollutant Exposure Assessment Using Routine Mobile Monitoring Platforms

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with a Commentary by the HEI Review Committee

Research Report 216
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- Integrates HEI's research results with those of other institutions into broader evaluations
- Communicates the results of HEI's research and analyses to public and private decision-makers.

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Research Report 216, *Scalable Multipollutant Exposure Assessment Using Routine Mobile Monitoring Platforms*, J.S. Apte et al.

INTRODUCTION

Accurately estimating people's exposure to various pollutants is essential for evaluating and understanding the health effects associated with the pollutants. Accurate estimates of exposure are also essential for identifying disparities in exposure so that policies can be developed to reduce such disparities if they exist. It is challenging, however, to estimate exposures to outdoor air pollutants that vary highly in space and time. Most air pollution datasets tend to have adequate resolution and accuracy either over space or time, but not both. For example, researchers typically conduct targeted, short-term sampling campaigns used to develop land use regression (LUR*) models or acquire data from fixed-site monitoring networks or chemical transport models with hourly output, but typically resources are not available to obtain both. Fixed-site networks — even those in North America and Western Europe — still have relatively limited spatial coverage in many areas, particularly in suburban and rural locations, and insufficient density to capture small-scale (within-city) variations of pollution.

In recent years, researchers have increasingly used routine mobile monitoring by affixing monitoring devices to vehicles and making measurements while systematically and repeatedly traveling a road network. Such mobile monitoring can provide a very dense map of street-level exposure estimates across a given urban area (Apte et al. 2017; Klompmaker et al. 2015; Messier et al. 2018; Patton et al. 2015; Weichenthal et al. 2016). Although the use of mobile monitoring for mapping local concentrations of traffic-related air pollution is becoming more common, many questions remain. For example, how do on-road measurements compare to data from fixed sites, can the method be scaled up to larger areas, and in which contexts is the approach appropriate and feasible? Also, how much data need to be collected (in terms of spatial coverage and repeated samples) to develop satisfactory, robust maps of long-term patterns of air pollution concentrations?

Dr. Joshua S. Apte's 3-year study, "Scalable Multipollutant Exposure Assessment Using Routine Mobile Monitoring Platforms," began in January 2018. Total expenditures were $426,752. The draft Investigators' Report from Apte and colleagues was received for review in October 2022. A revised report, received in May 2023, was accepted for publication in June 2023. During the review process, the HEI Review Committee and the investigators had the opportunity to exchange comments and clarify issues in both the Investigators' Report and the Review Committee's Commentary.

* A list of abbreviations and other terms appears at the end of this volume.

To investigate and develop further the utility of mobile monitoring, Dr. Joshua Apte of the University of Texas at Austin, submitted an application to HEI titled "Scalable Multipollutant Exposure Assessment using Routine Mobile Monitoring Platforms" in response to HEI's Request for Applications 16-1: Walter A. Rosenblith New Investigator Award. This award was established to provide support for an outstanding new investigator at the assistant professor level to conduct research in the area of air pollution and health; it is unrestricted with respect to the topic of research. Dr. Apte proposed to assess the utility of mobile monitoring data collected previously by fleet vehicles (i.e., Google Street View cars) equipped with instruments to routinely monitor air pollution. His application focused on the utility of the data and the scalability of approaches, and it proposed several related analyses based in two cities: Oakland, California, USA, and Bangalore, India.

HEI's Research Committee recommended funding Dr. Apte's application because it thought that the work proposed was novel and could affect how air pollution health research is done in the future. They appreciated his proposed use of an existing large-scale mobile monitoring dataset along with new measurements to be collected in India that would allow him to evaluate approaches in two very different settings. They also liked the focus on traffic-related air pollutants, especially ultrafine (<0.1 μm) particles (UFPs) for which fixed-site monitoring data are sparse. Additionally, they thought the large amount of data that he would analyze and collect had the potential to contribute significantly to exposure assessment for future epidemiological studies. The study started in 2018 and continued when Dr. Apte moved to the University of California, Berkeley.

This Commentary provides the HEI Review Committee's independent evaluation of the study. It is intended to aid the sponsors of HEI and the public by highlighting both the strengths and limitations of the study and by placing the results presented in the Investigators' Report into a broader scientific and regulatory context.

SCIENTIFIC AND REGULATORY BACKGROUND

Patterns of air pollution around traffic sources are characterized by high spatial and temporal variability related to meteorological conditions, varying emission rates, and other factors (HEI 2022; Park and Kwan 2017; Zhou and Levy 2007). UFPs, compared to some other air pollutants, have especially high spatial and temporal variability. UFPs originate from anthropogenic sources — primarily industrial emissions and combustion of fossil fuels for transportation, energy production, and heating — and from such natural sources as forest fires and marine aerosols, such as sea salt (Moreno-Ríos et al. 2022). They can also form in the atmosphere when combustion processes emit hot, supersaturated vapors that undergo nucleation and condensation while being cooled to ambient temperatures and through chemical reactions in the atmosphere (Sioutas et al. 2005). Their dispersion, transport, and duration of suspension in the atmosphere are affected by environmental and meteorological conditions, including topography, local wind direction and speed, temperature variations, and precipitation, among other factors.

Some of the major challenges in conducting epidemiological studies of air pollution exposure and health include the difficulty of assigning exposures to study participants accurately and quantifying the influence of exposure measurement error on estimated health risks. Those issues are especially challenging for some components of particulate matter (e.g., UFPs) and gaseous outdoor air pollutants, such as nitrogen dioxide (NO_2) and ozone that vary highly in space and time (HEI Review Panel on Ultrafine Particles 2013).

In the past, many studies relied on data from a few fixed-site monitors to assign exposure to study participants, partly because those were the only data available. To improve exposure assessment resources, researchers have deployed additional fixed-site monitors in specific areas (e.g., busy streets). That approach is particularly needed for measuring UFPs for which fixed-site monitoring networks are lacking. Moreover, in many locations in low- and middle-income countries (LMICs), there are few to no permanent fixed-site regulatory air pollution monitors; thus, creative approaches are needed. More recently, researchers have started to use satellite data to cover regions where no monitors exist and mobile monitoring platforms with real-time instrumentation to measure highly resolved spatial trends in air pollution concentrations (e.g., Apte et al. 2017; Minet et al. 2018; Patton et al. 2014; Riley et al. 2014).

Mobile monitoring strategies can involve on-road mobile measurements made while driving predefined strategic routes, or repeated short-term measurements made while in a parked vehicle at many locations. Data collected through mobile monitoring have been used to develop LUR models and other air pollution maps (Klompmaker et al. 2015; Messier et al. 2018; Patton et al. 2015; Weichenthal et al. 2016). Air pollution maps estimated from such monitoring are being increasingly applied in epidemiological studies (e.g., Alexeeff et al. 2018; Corlin et al. 2018). As noted above, however, questions remain about the scalability of mobile monitoring approaches and their applications in different contexts. The current study was designed to improve on these approaches and to test their applicability in a high-income country and an LMIC.

SUMMARY OF APPROACH AND METHODS

STUDY OBJECTIVES

Dr. Apte and colleagues sought to evaluate and assess the utility of mobile monitoring for a range of air pollution exposure assessment applications. The study builds on previous research by the investigators during which they collected a large amount of mobile monitoring data using Google Street View cars equipped with tools to measure nitric oxide (NO), NO_2, black carbon (BC), UFPs, and fine particulate matter <2.5 μg/m³ in diameter ($PM_{2.5}$) in Oakland, California.

For this study, they specified the following overarching questions: Does large-scale mobile monitoring produce useful results? In what ways and for what exposure assessment applications is mobile monitoring effective? What complementary or additional insights can be revealed by mobile monitoring? What are the potential limitations of mobile monitoring? To address these overarching questions, the investigators proposed the following aims:

1. Validate intensive mobile monitoring as an exposure assessment technique via comparison with observations from a network of fixed-site monitors.
2. Compare insights from mobile air pollution measurement campaigns with those derived from other approaches and data sources, including observations from regulatory networks, dense low-cost sensor networks, and statistical exposure models.
3. Investigate the potential for scaling of mobile monitoring techniques through both direct observation and modeling, to better understand how mobile monitoring could be applied to larger study domains while minimizing the amount of monitoring effort required.
4. Investigate whether mobile monitoring might be a viable option for collecting air pollution data in a low-resource setting that currently lacks robust air pollution monitoring infrastructure.
5. Probe the rich multipollutant dataset with data mining techniques to understand how sources influence population exposures.

Aims 1 through 3 were addressed by working with data collected previously from fixed-site stations and mobile monitoring campaigns for BC, NO, nitrogen oxides (NO_x), NO_2, and UFPs in Oakland, California. Aim 4 was addressed by conducting a new mobile monitoring campaign for BC, UFPs, $PM_{2.5}$, and carbon dioxide (CO_2) in Bangalore, India. Aim 5 was eventually dropped due to time constraints. The investigators organized their study into five interrelated analysis modules (M1–M5) that each contributed to multiple study aims. They are described below and summarized in the **Commentary Table** with key features and findings.

Commentary Table. Key Details of the Five Analysis Modules[a]

Analysis Module	Research Aims Addressed	Pollutants Examined	Period of Measurement	Geographic Location	Key Findings
Analyses That Focus on Comparing Mobile Monitoring with Fixed-Site Monitoring Data					
M1: Intensive comparison of mobile and fixed-site monitoring in Oakland	Validate intensive real-time mobile monitoring as an exposure assessment technique via comparison with fixed observation networks. Compare insights from mobile air pollution measurement campaigns with those derived from other approaches and data sources.	BC	May 2017 – August 2017	West Oakland	Repeated mobile monitoring can reproduce time-averaged, fine-scale spatial patterns of BC with good fidelity, precision, and accuracy relative to a fixed-site sensor network.
M2: Spatiotemporal analysis of traffic-related air pollution dynamics using mobile and fixed sensors in the San Francisco Bay Area	Validate intensive real-time mobile monitoring as an exposure assessment technique via comparison with fixed observation networks. Compare insights from mobile air pollution measurement campaigns with those derived from other approaches and data sources.	BC, CO, NO_x, UFPs	*Mobile measurements*: May 2015 – December 2017 *Regulatory measurements*: Full year, 2015	Mobile measurements: West Oakland and Downtown Oakland Fixed sites: Sebastopol, Livermore, Redwood City, and Laney College	Data from mobile monitoring corroborates a surprising insight from regulatory data: patterns of UFPs and NO_x are coupled in the winter months (indicative of a common primary traffic source), but sharply decoupled in the summer. UFPs in the Bay Area appear to be substantially driven by secondary formation during the summer months.
Analyses that focus on uses and applications of mobile monitoring data					
M3[b]: Assessment of local- and regional-scale air pollution disparities in the San Francisco Bay Area using mobile monitoring	Validate intensive real-time mobile monitoring as an exposure assessment technique.	BC, NO, NO_2, UFPs	May 2015 – December 2017	13 communities across the San Francisco Bay Area	Repeated mobile monitoring can capture exposure heterogeneity across a large urban region. Across the entire Bay Area region, within-neighborhood gradients account for a large to dominant fraction of the overall heterogeneity in the population-concentration distribution. Substantial racial/ethnic disparities are driven mostly by intra-neighborhood segregation.
M4: Scaling air quality mapping of NO and BC through mobile monitoring and spatial modeling in Oakland	Investigate the potential for scaling of mobile monitoring techniques through both direct observation and modeling.	BC, NO	May 2015 – May 2017	West Oakland, Downtown Oakland, East Oakland	With LUR-K modeling, it is possible to drive only a fraction of roads a few times and develop models that are nearly as good as the best models they developed. Data-only maps from repeated driving are superior to LUR-K models in terms of detecting idiosyncratic or unexpected spatial features and hotspots.
M5: Mobile monitoring in Bangalore, India	Investigate whether mobile monitoring might be a viable option for collecting air pollution data in a low-resource setting.	BC, CO_2, UFPs	July 2019 – March 2020	Residential neighborhood in Bangalore (Malleshwaram) and supplemental transects in surrounding areas	Mobile monitoring produced time-stable spatial patterns in Malleshwaram and elsewhere in the study domain. Observed a convergence to time-stable spatial patterns with fewer than 20 repeated mobile monitoring runs over 1 year. Slow traffic speeds in Bangalore present logistical challenges for mobile monitoring.

[a] Source: Investigators' Report Table 2

[b] As described below, this analysis was not part of the original study plan.

METHODS

Analysis M1: Intensive comparison of mobile and fixed-site monitoring of black carbon in Oakland, California

The purpose of analysis module M1 was to evaluate the capabilities of mobile monitoring for representing long-term spatial patterns of black carbon by comparing repeated mobile air pollution measurements with data from a large set of continuous fixed-site monitors. For this analysis, the investigators leveraged mobile-monitoring data that they had collected and described previously (see Apte et al. 2017 and sidebar) along with data from a dense network of low-cost, fixed-site BC monitors custom-built and deployed by colleagues at the University of California, Berkeley (Caubel et al. 2019).

The BC monitors deployed by Caubel and colleagues were installed at 100 sites in residential, industrial, and high-traffic microenvironments at an average density of 6.7 sites per km^2 in West Oakland. The instruments were mounted at a height of 1.5 m on fences, porches, or street poles at a median distance of 15 m from the nearest road. Of these 100 sites, 97 were located within 30 m of the road network covered by the mobile monitoring described in the sidebar, and three were located at upwind background sites along the San Francisco Bay. This network was in operation during a 100-day period between May and August 2017. Apte and colleagues computed the median daytime concentration at each site. They then calculated the ordinary Pearson R^2 coefficient of determination between the median concentration of BC of all drive pass means within 95 meters of the 97 custom-built BC detectors with valid data. They chose a distance of 95 meters because the precision of the fixed-site detectors to estimate on-road concentrations decreased notably at distances greater than 95 meters. In total, the mobile monitoring vehicles sampled roads within 95 meters of these fixed-site detectors for nearly 56 hours, with a median of 73 drives past each site. Each visit of a mobile monitoring vehicle to a fixed site lasted about 17 seconds for a median total time of 29.3 minutes at each site.

Analysis M2: Spatiotemporal analysis of traffic-related air pollution dynamics using mobile and fixed sensors in the San Francisco Bay Area

The purpose of this analysis module was to evaluate how the spatiotemporal patterns of UFPs compared with other traffic-related air pollutants that are monitored routinely. For this module, the investigators made use of the mobile monitoring data collected in 10 neighborhoods across the San Francisco Bay area, as described in the sidebar. For this analysis, the investigators compared particle number concentrations (as their proxy for UFPs) obtained through the mobile monitoring with concentrations of NO_x obtained at four regulatory fixed-site monitoring stations operated by the Bay Area Air Quality Management District. Specifically, they used hourly data from 2011 to 2018 from regulatory sites representative of a gradient in traffic influence, namely, near-highway, urban, suburban, and rural.

Analysis M3: Assessment of local- and regional-scale air pollution disparities in the San Francisco Bay Area using mobile monitoring

This analysis was not part of the original application and study plan but was included in the investigators' final report to present the totality of analyses that the investigators conducted with mobile monitoring datasets. The purpose of this analysis was to describe how variability in concentrations of air pollution affected estimates of population exposure and environmental disparities in the San Francisco Bay Area. This analysis module also made use of the mobile monitoring datasets described earlier. Here, the investigators estimated long-term pollution concentrations of BC, NO, NO_2, and UFPs for 6,362 census blocks in 13 communities around the San Francisco Bay Area. The communities ranged in size from 95 to 930 census blocks (median: 447 blocks). The mean census block had an area of about 14,000 m^2 (equivalent to 120 meters × 120 meters) with a mean population of 70 people. The investigators estimated pollution concentrations for each block as the median of observations from roads within about 100 meters of the block center point.

They used U.S. Census Bureau block-level population data for the year 2010, the most recent year for which block-level data were available, to describe the populations in the 13 communities. Specifically, they used the racial and ethnic designations provided by the U.S. census to summarize proportions of populations described as Latino or Hispanic in one group ("Hispanic") and then categorized non-Hispanic populations by race: Asian, Black, White, and "Other," including those of Native American, Pacific Islander, multiracial, or other racial identity. In 2010, about 450,000 people lived in these areas.

The investigators used the pollution and population datasets together to describe distributions of the various pollutants within each community and to describe the exposure distributions according to the racial and ethnic compositions of the population.

Analysis M4: Scaling air quality mapping of NO and BC through mobile monitoring and land use regression in Oakland, California

The purpose of analysis module M4 was to evaluate the advantages and tradeoffs of coupling mobile monitoring with LUR and Kriging approaches to estimate intraurban variation in air pollution in a data-efficient manner. This analysis module made use of the mobile monitoring datasets described earlier. Here, Apte and colleagues investigated approaches to reduce the intensity of field data collection required for producing high-resolution pollution maps of NO and BC from mobile monitoring data. For this analysis, they focused on West Oakland, Downtown Oakland, and East Oakland. They considered two broad approaches to data reduction for developing reliable estimates of spatial patterns, namely a "data only" approach and a "land use regression-Kriging model (LUR-K)" approach.

SIDEBAR

Prior to applying to this RFA, Apte and colleagues had already collected a large amount of mobile-monitoring data in the San Francisco Bay Area. Briefly, the investigators had equipped two Google Street View cars with instruments for measuring BC, NO_x, and particle number concentrations (a strong proxy for UFPs). Drivers of the vehicles conducted 6–8-hour long shifts between 8 a.m. and 6 p.m. between May 2015 and December 2017. They were assigned 1–5-km^2 areas to cover each day within which they were asked to drive each road in that area at least once, in any order. They conducted intensive monitoring in West Oakland, Downtown Oakland, and East Oakland (totaling over 1,300 hours of monitoring) and added an additional 300 hours in West Oakland alone. They also sampled 1,000 hours in 10 other neighborhoods in the greater San Francisco Bay Area to cover locations with various land uses (e.g., industrial, commercial, dense residential, and light residential), atmospheric and climate conditions, share of open or green space, traffic density, and demographic composition.

The investigators used the air pollution measurements to estimate long-term, average concentrations of the pollutants along roadways that represented the weekday, daytime conditions of the period sampled in these locations. For this task, they divided the measurement domains into 30-meter road segments (equivalent to about 3–10 seconds of observation). For the core Oakland domain, this network included about 20,000 such segments. First, they calculated the mean of all measurements in each 30-meter road segment for each individual drive pass (i.e., the mean of all observations taken during that single 3–10-second period of a drive pass). Then, they computed the median of all repeated drive pass mean concentrations to use as their core metric for analysis. These datasets were used in the various analysis modules described in the investigators' report.

For the data-only approach, they mapped concentrations of pollutants based exclusively on data from the mobile observations, with no support from spatial modeling techniques. Here, they attempted to minimize the number of repeated visits to each road at the cost of reducing the precision and accuracy of the resulting estimated concentrations.

For the LUR-K approach, they applied their mobile-measured observations in a statistical model that combined LUR and Kriging. Briefly, LUR is a spatial modeling technique that uses observations of pollutant concentrations at given locations as the dependent variable and data describing such characteristics as road density and land use as the independent variables, in a multivariate regression model to estimate pollutant concentrations at unsampled locations. Kriging, on the other hand, is a method of spatial interpolation whereby values are predicted at unsampled locations based on measurements taken at nearby locations. As such, for the LUR-K approach, pollution concentrations can be estimated at unsampled locations and mobile observations are not needed from every road in the study domain.

The investigators simulated several variations of approaches to reducing data requirements for mobile sampling:

- Data-only mapping based on mobile monitoring data from a reduced subset of drive days (i.e., sampling on all highway and nonhighway roads, but only 4 days of sampling on each segment).
- Data-only mapping based on mobile monitoring data from a reduced subset of roads sampled (i.e., sampling on all highways and on a random selection of 30% of the nonhighway roads, including all days of sampling).
- LUR-K modeling based on mobile monitoring data from the reduced subset of drive days.
- LUR-K modeling based on mobile monitoring data from the reduced subset of roads sampled.
- Joint scenario with LUR-K modeling where drive days and roads sampled were reduced simultaneously.

Ultimately, they used visual inspection and analyzed model residuals, coefficients of determination (R^2), and normalized root mean square errors (NRMSEs) to compare and evaluate the various approaches.

Analysis M5: Mobile monitoring in Bangalore, India

The purpose of analysis M5 was to investigate their mobile monitoring approach in a low-resource setting. This analysis was set in Bangalore, India, which is located in the southern state of Karnataka, and has a population greater than 12 million people. For this analysis module, Apte and colleagues combined instruments for measuring BC, UFPs, $PM_{2.5}$, CO_2, meteorological parameters, and GPS into a mobile monitoring platform mounted in a compressed-natural gas-powered hatchback car. They used CO_2 concentrations as an indicator of the degree to which their measurements were influenced by the fresh exhaust of traffic emissions.

The investigators conducted mobile monitoring in four regions, including streets in urban residential areas (Malleshwaram), the central business district, and in peri-urban areas. Drivers conducted shifts of about 4 hours long between 9 a.m. and 1 p.m. between July 2019 and March 2020, which covered all seasons except the hottest summer months. As such, results generally represent late morning conditions on weekdays.

Similar to the analysis process described in analysis M1, the investigators used the mobile air measurements to estimate long-term, average pollutant concentrations representative of the period sampled. As was done in Oakland, they divided the measurement domains into 30-meter-long road segments, which in this case was about 5,000 segments. Again, they computed the median of the repeated drive pass mean concentrations to use as their core metric for analysis.

All modules described above were conducted at various times between May 2015 and March 2020. The key findings from the analyses are presented below.

SUMMARY OF KEY RESULTS

ANALYSIS M1: INTENSIVE COMPARISON OF MOBILE AND FIXED-SITE MONITORING OF BLACK CARBON IN OAKLAND, CALIFORNIA

The investigators found that the spatial patterns of BC produced with their mobile monitoring data were similar to the daytime medians calculated with observations from the 97 fixed-site detectors. The correlation (R^2) between the measurements at the fixed sites and the mobile measurements sampled within 95 meters was 0.51. The correlations varied but were approximately 0.5 for measurements within distances of 50–90 meters and were in the range of 0.4 to 0.3 for measurements within distances of 100 to 150 meters (Investigators' Report [IR], Figure 5d). Although their results were influenced somewhat by the choice of days and seasons in which they sampled pollutants, they ultimately concluded that their mobile monitoring design was sufficiently robust for the purpose of characterizing spatial patterns of air pollution.

Overall, the median concentration of BC measured along all nonhighway road segments within 95 meters (i.e., 0.44 µg/m^3) matched closely the median concentration among the fixed sites of 0.48 µg/m^3, suggesting that the data collected on-road were broadly representative of the near-road concentrations based on data from fixed sites. The mobile measurements had the advantage of detecting road-level variability not available from the fixed-site monitors, as well as estimates on highways, where placement of fixed-site monitors would likely be infeasible.

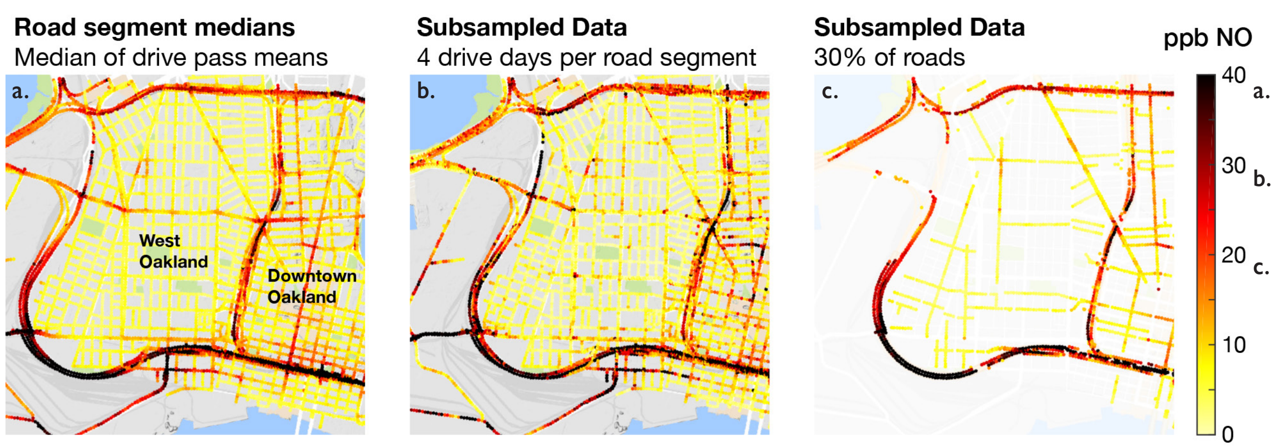
ANALYSIS M2: SPATIOTEMPORAL ANALYSIS OF TRAFFIC-RELATED AIR POLLUTION DYNAMICS USING MOBILE AND FIXED-SITE MONITORS IN THE SAN FRANCISCO BAY AREA

The investigators compared diurnal profiles of UFPs and NO_x stratified by season and weekday or weekend at the four regulatory fixed-site locations. During winter conditions, they observed generally consistent diurnal (hour-of-day) patterns for UFPs and NO_x (IR, Figure 6a). The summertime diurnal patterns for each pollutant, however, notably differed; observations for NO_x were generally lower than those for UFPs. For example, there were daytime peaks in UFP concentrations at multiple sites during the warmer months that were not observed with NO_x. Observations of NO_x were also notably lower in summer than in winter and lowest on weekend days.

Overall, the investigators concluded that daytime UFP concentrations in this area, especially during summer, appeared to be influenced strongly by nontraffic sources of UFPs, including secondary new particle formation events. Given the differences in spatiotemporal patterns of NO_x concentrations compared to those of UFPs, they suggested that using NO_x (or other traffic-related air pollutants) as a proxy for UFPs could result in inaccuracies in estimating UFP exposure.

ANALYSIS M3: ASSESSMENT OF LOCAL- AND REGIONAL-SCALE AIR POLLUTION DISPARITIES IN THE SAN FRANCISCO BAY AREA USING MOBILE MONITORING

The population-weighted means of the measured pollutants among the 13 communities were: 0.31 µg/m^3 for BC, 4.6 ppb for NO, 8.2 ppb for NO_2, and 19,100 cm^3 for UFPs. Generally, correlations between block-level concentrations of the



Commentary Figure 1. Maps showing results of data reduction schemes for estimating daytime median concentrations of NO in Oakland, California, during 2015–2017 using a data-only approach. (**a**) Median of drive-pass mean concentrations using all available data (all roads, all drive passes). (**b**) Four randomly selected drive days per road segment (all roads, fewer drive passes). (**c**) All drive days but subsampled to represent 30% of the arterial and residential roads (fewer roads, all drive passes). Source: IR Figure 3.

individual pollutants were variable, and they observed the lowest correlations between UFPs and the other pollutants (interquartile range Pearson's *r* ranged from 0.4 to 0.7).

In this study area, based on data from the 2010 U.S. Census, 33% of the population was Non-Hispanic White, 31% was Asian, 21% was Hispanic, and 14% was Black. The investigators found that Non-Hispanic White populations were exposed to lower concentrations of NO, NO_2, and UFPs than other groups, with median exposures 16% to 27% below the total population median, while Black and Hispanic populations were exposed to concentrations 8% to 30% higher than the total population medians (IR, Figure 8a).

This analysis found that differences in population exposures to NO and BC were driven mostly by variability in concentrations within individual neighborhoods (i.e., very local-scale variability; within 1 km), whereas differences in exposures to NO_2 and UFPs across the area were driven principally by differences in larger-scale, neighborhood-level mean concentrations.

ANALYSIS M4: SCALING AIR QUALITY MAPPING OF NO AND BC THROUGH MOBILE MONITORING AND LAND USE REGRESSION IN OAKLAND, CALIFORNIA

Apte and colleagues produced maps of pollutant concentrations on sampled road segments using the various approaches described earlier. Visual inspection suggested that each approach had generally good face validity and captured key features of the long-term concentrations of NO and BC. For example, in all cases, concentrations appeared lowest on residential streets, and highest on highways and in the downtown area of Oakland. **Commentary Figure 1** presents maps of NO patterns created with the data-only approach using all available data (left panel) and reduced datasets (middle and right panel).

The map produced using the data-only approach with the full dataset (i.e., many dozen drive passes on all roads, with a total drive time of about 1,300 hours) contained many localized pollution hotspots at intersections and locations with industries or other emissions sources that were not apparent in the maps created with the reduced datasets. The data-only map produced with a dataset restricted to only four drive days of observation, but coverage of all streets (i.e., 6% of the full dataset; about 80 hours in total; middle panel of Commentary Figure 1), resulted in only a slight decrease in performance, but with a substantial drop in mobile-monitoring data requirements. The panel on the right of Commentary Figure 1 shows the estimated NO concentrations based on all available days of observation but limited to only 30% of the arterial and residential roads.

The LUR-K approaches developed using either a sampling of all roads, but from a reduced subset of drive days, or a subset of roads, but sampled many times, both resulted in only negligible decreases in model predictions and performance.

Finally, the LUR-K model based on a highly restricted dataset (i.e., 30% road coverage and only four days of observation) also reflected only a moderate reduction in model performance despite the substantial reduction in data requirements. More details can be found in IR Figures 3 and 10 for maps created using the various alternative approaches.

Ultimately, the overarching conclusion from this analysis was that viable LUR-K models could be developed even with little mobile monitoring data. Although the data-only approach outperformed the LUR-K in precision with only a modest number of repeated samples (i.e., <10 repeated days), this was at the cost of having to sample every road for which exposure measurements are desired.

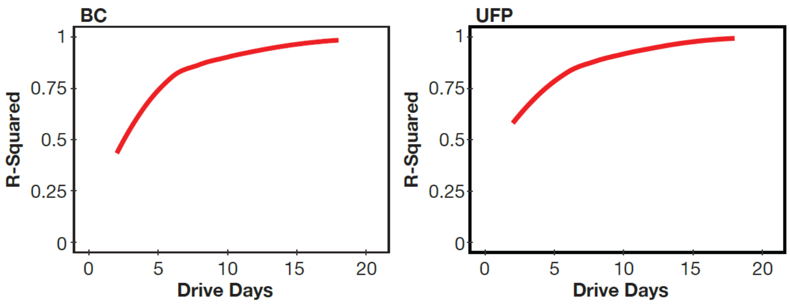
ANALYSIS M5: MOBILE MONITORING IN BANGALORE, INDIA

Due to various logistical issues, the work in India was not as extensive as originally planned, and so the investigators focused on the results from Malleshwaram, a large, urban neighborhood of Bangalore. This area was the only one for which they were able to conduct complete block-by-block repeated monitoring comparable to that of their San Francisco Bay Area campaign. Their study design involved collecting one weekly sample of the entire Malleshwaram area over two consecutive days, resulting in 44 days of data collection and 22 repeated drive days for each road segment. In total, they sampled about 150 km of roads across Bangalore, about 62 km of which were in Malleshwaram.

The spatial means (and medians) representing morning-time concentrations on the nonsummer weekdays for the road segments in the Malleshwaram study domain were about 26 $\mu g/m^3$ (15 $\mu g/m^3$) for BC and about 81,000 cm^3 (62,000 cm^3) for UFPs. Similar to the maps for the San Francisco Bay Area, the maps produced here again had strong face validity with the highest observations observed along highways, lower observations on major arterial roads, and the lowest observations on smaller, residential streets (with similar patterns for all three pollutants). The observed concentrations of BC and UFPs in Malleshwaram were both much higher than those observed in the San Francisco Bay Area, with the observations for UFPs about four times higher in Malleshwaram than in the Bay Area and those for BC about 100 times higher. The investigators suggested that this finding is likely due to the high proportion of older diesel engines operating in India.

As was done in analysis M4, the investigators examined how many repeated samples would be needed to capture the spatial patterns observed with the full dataset of 22 repeated drives. Here, they observed that including information from each additional drive pass increased rapidly until about 7 sampling days, and then only minimally thereafter (**Commentary Figure 2**).

As such, despite the differences in terms of fleet composition, population density, and mean pollutant concentrations between the two settings of Malleshwaram and the San Francisco Bay Area, the reduced sampling results in both locations suggested that mobile monitoring produced relatively stable



Commentary Figure 2. Subsampling analysis for the Malleshwaram neighborhood in Bangalore. Source: IR Figure 13.

maps after about 10 drive days, with diminishing returns to precision with additional sampling beyond that. The finding from this analysis module, therefore, is consistent with those presented earlier for analysis M4 and from previous work by these investigators (Apte et al. 2017).

HEI REVIEW COMMITTEE'S EVALUATION

STUDY DESIGN, DATASETS, AND ANALYTICAL APPROACHES

In its independent evaluation of the study, the Review Committee noted that at the time of funding, in June 2017, this study proposed the largest, most extensive campaign to examine the potential applications, strengths, and limitations of mobile monitoring. Overall, the HEI Review Committee was impressed with the extent to which the investigators described, compared, and analyzed the data.

The Committee noted several strengths of the study design. For example, Apte and colleagues compiled a large amount of data from several sources, including mobile monitoring data in several locations (in two countries) and data from several fixed-site networks. In addition, the richness of the data allowed the investigators to explore many issues, including the comparability of long-term observations from fixed-site monitors with observations collected through mobile monitoring and the utility of mobile monitoring data for describing spatial gradients in pollution. Their application of these measurements to estimate potential population-level exposures was also appreciated as an enhancement to our understanding of environmental inequities within the population. The datasets also allowed the investigators to evaluate the feasibility of applying these approaches in different settings. The wide spatial and temporal extent of data used here also allowed the investigators to conduct simulation studies to evaluate various logistical and study design considerations that can affect the potential benefits and costs associated with mobile monitoring. Another strength of the study is the examination of the performance of air quality models that integrate mobile monitoring data into LUR-K modeling.

The rich datasets used by the investigators also allowed them to explore and identify the relative trade-offs between intensive repeated sampling and several alternative approaches to data reduction, including reducing the number of roads sampled and the number of repeated passes on given roads. The Committee agreed with the investigators that in both the San Francisco Bay Area and in Malleshwaram, mobile monitoring produced relatively reproducible maps for several traffic-related pollutants with data from relatively few repeated drive passes.

The Committee also noted some limitations to the approach. For example, one issue with the mobile monitoring is that the drivers drove some routes and areas always in the same order and at the same time of day. This pattern of data collection makes it difficult to disentangle whether the pollution concentrations in a given location are indeed representative of the daytime typical average conditions, or if the concentrations for that location in fact represent temporal trends much higher than average levels occurring during rush hour or lower than average values during a low-traffic time of day.

The Committee also wondered whether the results are generalizable to other pollutants, longer periods, or to other locations (including to wider areas within the San Francisco Bay and Bangalore areas, as well as to other locations in the United States or elsewhere). For example, all the comparisons between mobile and fixed-site measurements from analysis M1 pertain to only one pollutant (BC), one study area (West Oakland), and cover a relatively short period (May-August 2017). Similar analyses of other pollutants would be useful in the future. It is also difficult to know the extent to which the observed correspondences between UFPs and NO_x described in analysis M2 would apply to other locations with different geographies, mixes of vehicles, or kinds of point sources of air pollution. Finally, the monitored area in Bangalore (i.e., Malleshwaram) comprised only a few square kilometers so might not accurately capture variations that might have been observed elsewhere in the very large city or in the surrounding regions.

It is important to acknowledge that the limitations above, along with a few other issues, might affect the suitability of mobile measured air pollution data for use in epidemiological analyses when used as the only data source. For example, we would expect on-road measurements to be different from those observed at fixed-site stations because they are collected in the middle of the road rather than at roadsides or other locations that might be closer to where people live. This is in contrast to measurements from fixed-site monitors, and even satellite-based measurements, that can be collected in a variety of locations, including away from busy roads. The mobile monitoring was also performed only during daytime hours on weekdays and does not reflect concentrations during the times of day when people might be more likely to be at home (i.e., in the evenings, at night, and on weekends). Moreover, most cohort studies have information on the residential addresses of individuals for the purpose of estimating air pollution exposures. Given the intensiveness of mobile monitoring, there will often be a mismatch between the period captured by the mobile measurements and the window of exposure most relevant for epidemiological purposes, especially if the focus is on the health impacts of long-term exposures.

Nonetheless, these measurements did provide additional spatial resolution that might not be captured by the limited fixed-site monitoring network or area-based satellite measurements. Additionally, mobile measurements might be especially useful for estimating exposures for commuters, especially cyclists and pedestrians. Overall, the Committee agrees with the investigators that there are further opportunities to explore these kinds of rich datasets, especially for combining the mobile measured data with fixed-site data to develop exposure models for use in epidemiological analyses and for identifying disparities in population exposures.

FINDINGS AND INTERPRETATION

Generally, the Committee found that the report presented a comprehensive and thoughtful discussion of the findings from the numerous research modules and analyses. Results from this study answered important questions and contributed interesting insights about collecting and working with mobile-measured air pollution data.

The descriptive analyses of BC, NO_x, and UFPs provide valuable new insights about their spatial and temporal patterns, and particularly, how they compare with those of other traffic-related pollutants in different contexts. For example, the investigators were able to identify that patterns of UFPs and NO_x shared similar spatial and hourly patterns during winter months in the San Francisco Bay Area, a result indicating a common primary traffic source during this season. However, during summer months the patterns were dissimilar, with the suggestion that summer concentrations of UFPs in this area were more strongly influenced by new secondary particle formation rather than primary emissions. The Committee agreed with this conclusion and felt that these data highlight nicely the value of combining detailed mobile mapping with at least a few fixed-site monitors that can provide long-term data.

The Committee also agreed with the investigators that some pollutants appear to be better suited for mobile monitoring than others. Generally, pollutants with a high degree of spatial variation and a low degree of temporal variation, such as NO_x, should be among the best suited to this kind of approach. In contrast, $PM_{2.5}$ is likely less suited for this approach because it tends to have relatively low spatial variability within an urban area. Similar conclusions could be made about the kinds of locations that would benefit most from mobile monitoring. Specifically, locations with greater heterogeneity in local sources will benefit from the richer spatial information of a mobile monitoring campaign.

The Committee thought this report highlighted what we can learn about spatial patterns of traffic-related air pollution and population exposures when mobile monitoring data are leveraged. Importantly, mobile monitoring can provide measurements directly on highways where fixed-site monitoring is infeasible. This has value for better capture of emissions from the vehicle fleet and for reflecting exposures to drivers on the road. Apte and colleagues also demonstrated clearly that mobile monitoring is able to detect localized pollution hot spots, such as at specific intersections and along designated truck routes, which would not be captured by measurements from fixed-site stations alone.

The investigators estimated potential population exposures by averaging observations collected on surrounding streets to the centers of city blocks. Here, they found that across the San Francisco Bay Area, Non-Hispanic White populations were exposed to lower concentrations of NO, NO_2, and UFPs than other groups, and Black and Hispanic populations were exposed to higher-than-average concentrations of those pollutants. The Committee saw the value in using these data for characterizing environmental disparities and was generally satisfied with this approach though they acknowledge the potential challenge of disentangling differences in concentration due to time and space as discussed above.

An especially important aspect of this study was a detailed analysis to determine how much mobile monitoring data are needed to get relatively accurate maps of long-term patterns of traffic-related air pollution along roadways. The Committee noted that the investigators demonstrated that adequate pollution maps were produced by models supported by LUR-K approaches that used relatively limited data from mobile monitoring. Importantly, this study showed that sampling on every road is not needed for the model output to be effective. The investigators also showed that maps produced with only mobile monitoring data (i.e., without support from the spatial modeling approaches) outperformed the LUR-K in precision with only a modest number of repeated samples (i.e., fewer than 10 repeated days), but at the cost of having to sample every road. Researchers using these methods for epidemiological studies will need to evaluate the extent to which the added cost of mobile monitoring yields sufficient improvements to exposure modeling and prediction.

A novel aim of this study was the investigators' efforts to implement mobile monitoring in a low-resource setting, namely Bangalore, India, with traffic patterns and pollution concentrations that are very different from those in the San Francisco Bay Area. The investigators demonstrated that with sufficient funding and expertise, mobile monitoring was a viable technique for estimating fine-scale concentrations of traffic-related air pollution in that area. They noted that key challenges of conducting mobile monitoring in this setting included the low traffic speeds (typically 10-15 km/h), which limited the area that could be covered in a given sampling session, and that the instruments used required study personnel to accompany the drivers at all times to ensure the instruments were operating properly. Both of those issues limited the efficiency of the process, as compared to that undertaken in Oakland. The Review Committee perceived the work in India as a feasibility study given the small sampling area that was ultimately sampled. Therefore, although the Review Committee commends the investigators for undertaking this analysis, they note that more work is needed to know if this is a feasible approach in other LMICs, and perhaps in India more broadly.

Another aim of this study was to investigate the potential for scaling mobile monitoring techniques to larger study domains (i.e., not just neighborhoods, but across entire cities and regions). The analyses with LUR-K modeling demonstrated how the mobile monitoring data could be leveraged for creating spatial models to cover areas where not all roads are sampled. The leveraging of measurements collected previously using Google Street View cars was a unique opportunity that the investigators benefited from in their study. However, a potential limiting factor for scaling or replicating these analyses is that Google Street View cars are not available on demand to other researchers or in other locations. Other fleet vehicles that regularly drive around cities, such as taxis or delivery trucks, are an alternate possibility but might be less suitable options for this purpose because they are driven less systematically through communities and researchers would have no control over the routes covered.

It is worth noting that mobile monitoring, in addition to being time-consuming and laborious, can be costly, especially in areas that do not have sufficient resources dedicated to air quality monitoring and research. The investigators estimated a cost of about $1 million per year (which would include vehicles, equipment, and salaries for drivers and analysts) to conduct mobile monitoring equivalent to what was done in Oakland in a large urban area in the United States. The investigators noted that costs to do this might be lower in LMICs settings where labor costs are generally lower, but personnel with the required training and expertise might not be readily available. Ultimately, these estimated costs are much higher than what might be expected for establishing or expanding a network of low-cost, fixed-site monitors to capture more detailed data on pollutant concentrations for epidemiological or regulatory purposes. A related question, therefore, is whether mobile monitoring is really needed in some locations, such as in LMICs, or would time and resources be better spent in building the basic air quality monitoring infrastructure first? Certainly, the answer will depend on the pollutant, location, and question of interest.

CONCLUSIONS

In this pioneering study, Apte and colleagues conducted very thorough analyses of the various strengths, limitations, and potential uses of mobile monitored air pollution data. They showed that mobile monitoring data (which provide dense spatial coverage) coupled with observations from fixed-site stations (which provide long-term temporal coverage) and spatial modeling approaches can produce robust maps of spatiotemporal patterns of traffic-related pollution that can capture highly localized hotspots of pollution. On their own, however, data from mobile monitoring can have important limitations and therefore careful consideration is needed before using them in exposure assessment or epidemiological analyses.

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ABBREVIATIONS AND OTHER ITEMS

ABCD	aerosol black carbon detector
BC	black carbon
CACES	Center for Air, Climate and Energy Solutions
CO	carbon monoxide
CO_2	carbon dioxide
GPS	global positioning system
ICC	intra-class correlation
IEG	integrated empirical geographic
LMIC	low-middle income country
LOD	limit of detection
LUR	land use regression
LUR-K	land use regression-kriging
MAE	mean average error
NO	nitric oxide
NO_2	nitrogen dioxide
NO_x	nitrogen oxides
NRMSE	normalized root-mean-square error
PAX	photoacoustic extinctiometer
PM	particulate matter
$PM_{2.5}$	fine PM, particulate matter with aerodynamic diameter ≤2.5 µm
ppb	parts per billion
RMSE	root-mean-square error
SSD	sum-of-square deviation
UFPs	ultrafine particles

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