Toward Blue Skies: City-Scale Air Pollution Monitoring using UAVs

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***Abstract*—Dangers associated with poor air quality are driving deployments of air quality monitoring technology worldwide. Having a comprehensive understanding of the health effects of pollutants requires understanding both the distribution and dispersion of pollutants in the environments, but currently this information is highly difficult to capture. This article presents a vision for city-scale air pollution monitoring that uses unmanned aerial vehicles (UAVs) to complement current ground and infrastructure-based measurements with a vertical profile of pollutants. We highlight the key requirements and research challenges, demonstrate the benefits UAVs bring through measurements from an industrial and a residential location, and establish a research roadmap for the path forward.**

***Index Terms*—Air Quality, Unmanned Aerial Vehicle, UAV, Sensors, Sensor Networks, Vertical Measurement.**

I. Introduction

Reducing air pollution is one of the grand challenges of our time as poor air quality has significant economic impacts, is linked with a wide range of diseases, and affects millions of people worldwide. Mitigating air pollution and the problems associated with it requires detailed information about pollutant concentrations and their dispersion within the urban environment. Current solutions, such as professional-grade measurement stations [1] and low-cost sensors [2], capture only the pollution distribution close to ground level without being able to capture the *vertical distribution* of pollutants or to explain the dispersion of pollutants in the environment. For example, exhausts from industrial sites form a vertical column of pollutants which wind and weather disperse around the urban environment [3], and urban canyons resulting from buildings can magnify or reduce the dispersion of pollutants depending on wind direction [4]. Having a comprehensive understanding of the health risks and other effects of pollutants thus requires capturing also the vertical distribution of pollutants as accurately as possible.

This article contributes a vision of UAV-assisted city-scale air quality monitoring where UAVs are used to support other measurements by providing information about the vertical distribution and potential dispersion mechanisms of pollutants. In the vision, shown in Figure 1, UAVs carrying air quality sensors work in coordination to collect pollution measurements and connect this information with measurements collected by ground and infrastructure-based sensors. UAVs have significant potential to support air quality monitoring as they can cover large areas rapidly and capture information that is complementary to those captured by existing solutions. UAVs also offer new opportunities for atmospheric studies, e.g., on understanding urban dispersion mechanisms, that can increase the collective understanding of pollutants [5].

Existing works on the use of UAVs for air quality monitoring have demonstrated the technical feasibility of the monitoring [6], [7] or developed solutions for dedicated domains such as forest fires [8] without establishing UAVs as a mechanism that can support city-scale monitoring and work together with existing monitoring solutions. Indeed, existing solutions collect measurements offline without being able to provide real-time information of the changes in pollutant concentrations within the city. Having access to detailed real-time information is essential for understanding the overall pollution situation, for mitigating long-term health effects, and for reacting to sudden changes in pollutant concentrations, e.g., as a result of weather or industrial leaks. Realizing the vision of city-scale monitoring requires addressing several technological and methodological challenges. For example, ensuring the information is useful for city-scale modeling requires support for coordinating the data collection efforts. There are system design challenges in ensuring UAVs can capture high quality air quality information, and there are methodological challenges in ensuring the UAVs can capture information that meets scientific criteria and that is useful for deriving actionable insights. Besides presenting the vision, the paper highlights key research challenges, reflects on the current state-of-the-art, and establishes a research roadmap.

The practical benefits of the vision are demonstrated through benchmark measurements collected from two locations (residential and industrial) using a commercial off-the-shelf UAV and a commercial portable air quality sensing solution. The results highlight the importance of vertical modeling, demonstrating how pollutant distributions differ both vertically and across locations, and how there are significant differences from a background profile provided by a professional-grade measurement station. Capturing these differences is essential for accurate modeling and estimation of dispersion effects and

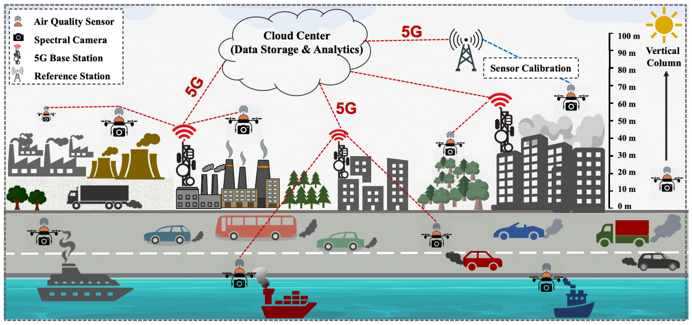

Fig. 1. Vision for air pollution sensing using UAVs at different verticals.

for providing actionable and accurate air quality information.

II. Requirements

Realising the vision of UAV supported city-scale air pollution monitoring requires advances in sensors, algorithms, and hardware to overcome limitations of current technology. The key requirements for realizing this vision are reflected below.

Pollution Detection, Identification and Localization: Having a comprehensive view of the air quality of a city requires information about different types of pollutants. Air quality sensors typically focus on particulate matter and gaseous pollutants (e.g., CO, NO, NO_2, O_3, SO_2), but also other types of pollutants need to be captured to ensure health hazards are reliably monitored. For example, fugitive emissions comprising of undetected and often unintended leaks or chemical or organic compounds are a major health hazard and monitoring their presence is vital. Visualization of these measurements (e.g., 3D maps) is also required to understand the pollutant situation and to derive actionable insights. Visualizations are also helpful for remote operators to coordinate where to sample measurements. The UAVs should also support sealing leaks. At a minimum, this requires coordinating response, e.g., by calling in dedicated personnel to handle the leakage, though optimally the UAVs should be able to localize the origins of the emissions. Emerging 5G and 6G communications are essential for this task as they provide accurate localization with minimal energy consumption [9], [10].

Coordinated Sampling: Capturing air pollution at city-scale requires collecting information at multiple different locations – even if a single area of the city can be covered by a single UAV. Optimally UAVs should supplement measurements produced by (near) ground-level solutions, and hence the sampling locations should depend on where other measurement devices are available. In the near future, air quality sensors are expected to be deployed pervasively into city infrastructure and the citizens may carry sensors with them [1]. This results in a dynamically changing coverage throughout the day. The sampling locations for UAVs should optimally complement the measurements provided by citizens and urban monitoring stations, and hence there is a need for real-time connectivity to adapt and to coordinate the sampling plans of the individual UAVs. Real-time coordination is also essential for reacting to adverse events, e.g., gas leaks from industrial sites or pollutants dispersed by winds. Maximizing data quality may also require the UAVs to switch between horizontal and vertical sampling strategies depending on the (dynamic) availability of other sensors.

Lightweight Sensor and Hardware Designs: Ensuring UAVs can increase the coverage of air quality information requires that they can travel and monitor over a sufficiently large area. Flying and maneuvering UAVs results in high energy drain and thus there is a need for lightweight sensor and hardware designs that have minimal impact on the UAV's operational time. In parallel, the sensor placement needs to be optimized to ensure air flows resulting from the flight operations do not impact the pollution measurements. Existing air quality sensor designs for UAVs, such as the one used in our experiments (see Figure 2), are mostly designed for visualizing emissions or supporting offline analysis of measurements whereas the vision presented in this paper aims at real-time monitoring and sharing of pollutant information which requires additionally integration of computing units that can process the measurements, coordinate flight plans, and support other operations.

III. Challenges and Enablers

Realising the vision of UAV assisted city-scale air pollution sensing is currently difficult due to limitations of existing technology. This section reflects on the state-of-art of existing technologies and highlights key research challenges in enabling the proposed research vision. The challenges and existing solutions are summarized in Table I.

Sensor Accuracy: Traditionally air quality is monitored using professional-grade measurement stations that are accurate but bulky and expensive. This limits the density at which they can be deployed [1]. In contrast, city-scale UAV monitoring requires inexpensive and lightweight sensors so that many UAVs can be used to maximize coverage of measurements and the sensors' impact on the UAV's other operations can be minimized. Inexpensive air quality sensors are becoming increasingly available but they tend to suffer from drift and high variability in measurements [2]. Noise can be mitigated by calibrating the sensors in a controlled laboratory environment prior to collecting measurements. This approach does not scale well to city-scale operations and thus there is a need for alternative solutions, e.g., to use opportunistic machine learning-based sensor calibration [1]. Enabling such strategies in practice requires algorithms that can detect model drift, and mechanisms that can coordinate flight schedules to include periods where the sensors are proximate to professional-grade stations to capture reference measurements for calibration. These periods need to be chosen so that differing pollutant and weather conditions are covered to ensure robustness of the calibration models [2]. Weather conditions can also affect the accuracy of the air quality sensors on the UAV. In practice, sampling should be restricted to periods where the UAV is stationary and weather conditions are stable. On-board weather and motion sensors (e.g., accelerometers and gyroscopes) can be used to detect optimal sampling conditions and to validate the quality of collected measurements.

Localization: Maximizing the usefulness of collected information requires following stringent protocols that determine

TABLE I
CURRENT STATE-OF-ART, KEY CHALLENGES AND EMERGING RESEARCH TOPICS FOR CITY-SCALE MONITORING.

	State-of-the-Art	**Key Research Challenges**	**Emerging Challenges**
Sensor accuracy	Accurate but costly static stations and miniaturized low accuracy sensors	Improve accuracy for low accuracy sensors through sensor calibration	Opportunistic calibration that combines high quality sampling and miniaturized sensors
Localization	Traditional localization technologies, such as GPS, and experimental LPWAN localization techniques e.g., LoRA	Accurate and robust 3D localization	Localization using emerging technologies, such as mmWave and Terahertz
Coordination	Coordinating movements of multiple drones, e.g, swarm algorithms	Hybrid planning that considers external information sources too	Advanced coordination to change between vertical and horizontal navigation.
Situational Awareness	Context-aware models for navigation and operational control	Models to analyze reactions of air pollutants in diverse contexts	Advanced models to sample air quality measurements
Power and Operational Time	Battery charging stations and return-to-home protocols	Novel energy management solutions and sampling optimization	Collaborative processing and computing augmentation.
Communications	Short and medium range technologies	Ultra low-latency data transfer, and precise localization	Approaches to integrate UAVs with edge and 5G infrastructure

where to collect measurements as this ensures the measurements can be used for modeling purposes, e.g., for understanding dispersion patterns and how they are affected by weather, buildings, green areas and other factors [11]. This requires precise horizontal and vertical localization. While the accuracy of existing localization solutions, such as GPS, and experimental LPWAN localization techniques, e.g., LoRA [12], is largely sufficient for city-scale purposes, emerging 5G (and particularly 6G) technologies are essential for improving energy-efficiency. Emerging terahertz and mmWave technologies can also further enhance localization accuracy by reaching centimeter level accuracy [9].

Coordination: Rapid changes in air pollutant concentrations at different locations and altitudes combined with obstacles in the environment (e.g., buildings and trees) pose challenges on the UAV coordination and call for real-time navigation and path planning capability. Common UAV coordination mechanisms have been designed for optimizing the movements of multiple UAVs without considering the information other sensors in the city provide [5]. Maximizing the usefulness of air quality data requires hybrid planning solutions that can take into account information captured by existing (ground or near ground level sensors) air quality sensing infrastructure and adapt to changes in the availability of the information [13]. For example, rush hours produce dense measurements around congested junctions but understanding dispersion patterns requires sampling vertically in the downstream wind direction of these junctions. The exact form of the movement depends on the requirements of models integrating the information, but generally they are based on spatial sampling strategies and use static or dynamic transects that are divided according to a pre-defined spatial resolution [14].

Situational Awareness: Autonomous UAV operations require high degree of situational-awareness from the participating UAVs. Firstly, UAVs need to be able to avoid collisions with urban infrastructure or other UAVs. Existing mechanisms for collision avoidance, e.g., computer vision or sound-based, are mostly designed for horizontal movements without accounting for potential obstacles in vertical directions. Another challenge for situational awareness results from navigating in dense urban environments as the urban structures may result in blind spots that prevent UAVs of having a line of vision with nearby obstacles. Situational awareness is also challenged by weather conditions. Even if UAVs are capable of navigating in challenging conditions, including in rain and in the presence of strong wind gusts, the weather has an effect on pollutants and causes problems in ensuring accurate pollutant measurements. For example, reactive gaseous compounds such as SO_2 and H_2 react with water, making it difficult to collect measurements in rainy or highly humid conditions. Similarly, $PM_{2.5}$ may absorb water which causes the particles to become heavier and fall to the ground. This requires UAVs to integrate models that can account for the current weather conditions and adapt sampling patterns to maximize quality of collected information.

Power and Operational Time: Power is a bottleneck as consumer-grade UAVs tend to have short operational time, only supporting flying times between half an hour to one hour. City-scale operations would require flying times of several hours – or a mechanism that transports the UAVs to different locations while also charging them. For example, we could envision UAVs to be transported by public transport infrastructure or cars (e.g., taxis or delivery trucks) and only fly briefly at the destination location while charging their batteries during the transit periods. Overcoming the energy bottleneck thus requires both novel energy management solutions, e.g., energy harvesting or wireless charging techniques that can support charging the UAVs during transit, and novel data collection models that can maximize the benefits of UAVs while reducing their use outside of measurement collection. These measures can also help compliance with regulations. For example, many countries restrict operations that go beyond line-of-sight. Limiting the UAV operations to vertical column sampling or spot samples from horizontal locations that have partial coverage helps to ensure the UAVs remain close to the entity that is coordinating their operations. Note that operating air quality sensors and processing the data tends to have a low power consumption and can be supported by a separate power source that is integrated directly with the sensor carried as payload. For example, the sensor considered in our experiments is powered by $1-4$ rechargeable batteries that are integrated directly onto the sensor.

Communications: Efficient and robust communications provide the foundation for city-scale operations. UAVs sampling air quality data at different locations within the city need to connect to different networks that may support different technologies and have different characteristics, e.g., how far the stations are. Delay-tolerant networking is needed to ensure UAVs can cope with the heterogeneity of the networking infrastructure and operate robustly against disruptions caused by connectivity black spots or interference. City-scale monitoring is also foreseen to benefit from emerging 5G and 6G communications infrastructure as emerging communication standards integrate localization support which allows UAVs to couple localization with connectivity [9], [10]. This reduces energy drain from localization and helps to increase both flight times and the coverage of information. Indeed, existing UAV solutions for air quality have highlighted energy drain as a major factor in limiting data availability [5]. As noted, operating the drone and coordinating the operations of multiple drones across the entire city are the main sources of power drain, not the sampling or processing of measurements. Offloading computations to edge nodes can reduce the power draw of these operations, thus improving the operational time of the UAVs [15] without increasing the latency of the operations. Another benefit from emerging communication standards is that they target low-latency and high bandwidth communications. Low-latency is essential for coordination, ensuring the sampling strategies of the UAVs can adapt to changes in the availability of sensors throughout the city and react to adverse events such as leaks, whereas high bandwidth is essential for supporting collecting data from additional sensor modalities, such as hyperspectral imaging.

IV. Experiments

Professional-grade measurement stations and sensors deployed in the urban infrastructure are likely to be the main source of information and the main benefits from UAVs come from providing information about the vertical distribution of pollutants and covering locations that have poor sensor coverage. This section demonstrates these benefits using benchmark experiments that consider measurements collected at different altitudes (every 10 meters from 0 to 100 meter altitude) from two locations: an industrial site and a residential urban area. The measurements were collected using a commercial off-the-shelf UAV and a commercial emission measuring device.

Apparatus: Measurements were collected using an UAV model X4S (see Figure 2). The weight of the UAV frame is $2\,\mathrm{kg}$ and the maximum take-off weight (MTOW) is $6.4\,\mathrm{kg}$. The size of the UAV is $58\,\mathrm{cm}\times 58\,\mathrm{cm}\times 37\,\mathrm{cm}$ without propellers. The X4S-UAV was equipped with a battery with an output of $22.2\,\mathrm{V}$ and capacity of $16\,\mathrm{A\,h}$, allowing for a maximum flight time of $74\,\mathrm{minutes}$. During the experiments the UAV was controlled manually using the UAV's command and control radio while having line-of-sight with the UAV as this permits better control over the vertical sampling. The UAV was stabilized before taking measurements, and it was kept stationary during the sampling to minimize potential effects of turbulence. Measurements were taken for a continuous period (up to 5 minutes), after which the drone was moved to the next altitude and the process was repeated. All measurements were taken outside the drone downwash using a $80\,\mathrm{cm}$ rigid probe that pointed forward (see Figure 2).

Sensors: Emissions were measured using an Aeromon BH-12 sensor (see the right-hand side of Figure 2) which is a portable piece of equipment to detect, measure and map airborne gaseous compounds and particulate matter (PM). The PM sensors in the current module are based on light-scattering particle sensor (LSP) technology, which uses a laser beam on air passing through an inlet to estimate the concentration and size of particles [2]. Note that modern sensors regulate the airflow through the inlet to ensure a stable and consistent flow rate, thus making the measurements robust to varying wind and other flow conditions. The PM sensor can detect concentrations from $0.01\,\mathrm{\mu g/m^3}$ to $1500\,\mathrm{mg/m^3}$. The PM sensors are factory calibrated by the manufacturer, whereas the gas sensors are field calibrated in actual measurement conditions with certified gases to ensure maximal accuracy and traceability. The sensors have been validated against reference sensors that fulfill requirements of air quality monitoring standards (ISO 21501-04, EN481, and US EPA guidelines for PM monitoring) and the sensors have been validated as part of a prior study [4]. These comparisons have shown the sensors to have high internal consistency and good correspondence with reference sensors that are co-located. The frame of the device is also equipped with a CPU, GPS, four rechargeable batteries supporting up to 8 hours of measurements, a modem, a sample pump, and environmental sensors measuring the relative humidity (RH%), temperature (T) and pressure (P).

Experiment Sites: The measurements were carried out in the city of Kotka in Southern Finland. The industries in the site of Kotka are mostly pulp and paper, and consumer board industries where bio-materials from wood are manufactured. These industrial processes produce a large amount of steam and aerosols formed from steam. The urban area of Kotka generally has good air quality index, resulting in small concentrations of gaseous pollutants and hence the experiments focus exclusive on measuring the three main particle sizes: $PM_{1.0}$, $PM_{2.5}$, PM_{10}, referring to particles whose diameter is at most $1.0\,\mathrm{\mu m}$, $2.5\,\mathrm{\mu m}$ and $10.0\,\mathrm{\mu m}$, respectively.

Environmental Conditions: The measurements at the industrial area were collected in November, 2020. The environmental conditions were: air temperature $6\,^{\circ}\mathrm{C}$, wind speed $2\,\mathrm{m/s}$

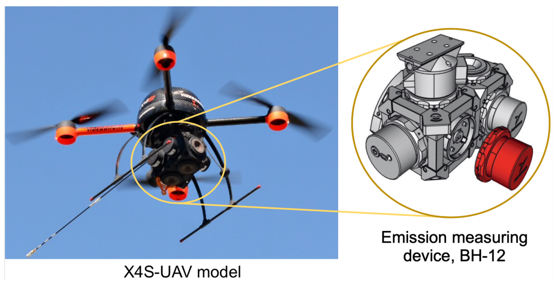

Fig. 2. UAV and the emission measuring device used in the experiments.

TABLE II
MEAN AND RANGE OF POLLUTANT CONCENTRATIONS FOR THE RESIDENTIAL (RES) AND INDUSTRIAL (IND) DISTRICTS.

	Pollutant	Mean	Range (min - max)
RES	$PM_{1.0}$	2.04 ± 1.59 µg/m^3	0.71 µg/m^3 - 6.25 µg/m^3
	$PM_{2.5}$	2.07 ± 1.66 µg/m^3	0.72 µg/m^3 - 6.42 µg/m^3
	PM_{10}	2.13 ± 1.63 µg/m^3	0.72 µg/m^3 - 6.42 µg/m^3
IND	$PM_{1.0}$	31.45 ± 22.83 µg/m^3	2.50 µg/m^3 - 71.19 µg/m^3
	$PM_{2.5}$	1136.77 ± 1404.99 µg/m^3	2.55 µg/m^3 - 3798.15 µg/m^3
	PM_{10}	20633.55 ± 28378.82 µg/m^3	2.55 µg/m^3 - 75 391.60 µg/m^3

and wind direction from 5° to 48° north-east. Samples at residential area were taken in February 2021 in the following conditions: air temperature -9 °C, wind speed 5 m/s and wind direction from 5° to 10° north.

Procedure: We use X4S-UAV and BH-12 sensor to collect air pollutant samples at 11 different heights, every 10 meters, starting from ground level, i.e., 0 meters to 100 meters height. Due to small concentrations of other pollutants, we focus exclusively on particular matter measurements in our analysis.

V. Results and Analysis

Vertical Distribution: The vertical distributions of particulate matter for the two measurement locations and for the three different particle sizes are shown in Figure 3, and the mean concentrations and the range of values for the two districts are summarized in Table II. For the residential environment, the higher concentrations are (as expected) at the ground level, though significant concentrations can be observed even at 70 meter height. Note that the overall concentrations in the residential area are very small, indicating clean overall air. Particle counter technology, including the sensor used in the experiments, has limited resolution in capturing small particle counts. Thus the vertical column at 1.0 µg/m^3 in the figure is mostly indicative of negligible concentrations and only the higher concentrations are meaningful.

Significantly higher concentrations can be observed for the industrial location. On the ground level, the concentrations are largely similar to those in the residential environment, whereas at higher altitudes the plume from the industrial processes increases particle concentrations significantly. The variations in the particle distribution depend on the particle size and altitude with the largest particles having the highest concentration at the highest altitudes. This is explained by hygroscopic growth as the pollution mostly consists of water vapor which absorbs smaller particles and increases their particle size. Note that while water vapour is the main source of high particle concentrations, it also captures and binds other pollutants. At higher altitudes, the pollutants either fall to the ground or are dispersed in the environment, depending on whether the pollutants are released below or above the so-called inversion layer. The altitude at which inversion occurs varies as a function of temperature, shape of the landscape, and other factors [16]. Thus, monitoring the vertical column and capturing pollutants at different altitudes is essential for capturing the dispersion patterns of pollutants and understanding the factors that affect it. Indeed, monitoring the vertical column also increases the coverage of pollutant information and enables a detailed view of the pollutant distribution and the mechanisms governing its dispersion in an urban environment.

Correlation and Significance Testing: For the residential site, Spearman's ρ between PM concentration and altitude shows a strong negative and statistically significant correlation for all three particle sizes: $PM_{1.0}$, $\rho = -0.7$, $p < .05$; $PM_{2.5}$, $\rho = -0.6$, $p < .05$; and PM_{10}, $\rho = -0.7$, $p < .05$. For the industrial site the direction of the correlations is reversed as the ρ values are positive and statistically highly significant: $PM_{1.0}$, $\rho = 0.8$, $p < .01$; $PM_{2.5}$, $\rho = 0.9$, $p < .01$; PM_{10}, $\rho = 0.9$, $p < .01$. These results thus further demonstrate the differences in vertical distribution are both significant and dependent on the sampling location. Understanding the full extent of health risks and the processes that govern the dispersion of pollutants requires capturing these variations.

Combined Effect of Altitude and Location: The full potential of UAVs comes their use to capture the three dimensional distribution of pollutants. Next, we assess the joint effect that location and altitude have on the measurements by considering each 10 meter increase in altitude as a separate interval and simultaneously comparing the differences in pollution distributions across the two locations and the different intervals. In line with earlier analysis, a repeated measures ANOVA shows significant main effects for location and altitude interval, but no interaction effect (location: $F = 10.048$, $p < .01$, $\eta^2 = 0.167$; altitude interval: $F = 10.059$, $p < .01$, $\eta^2 = 0.167$; interaction: $F = 1.788$, $p = 0.094$, $\eta^2 = 0.243$). Here F refers to the F-statistic of the ANOVA and η^2 is the proportion of variance that is explained). Post-hoc comparisons (Bonferroni correction) indicate statistically significant differences from 70 meters onward. Differences in emissions can thus be at highly different altitudes and monitoring both horizontal and vertical dimensions is required to capture the full extent of pollutants.

Comparison to Reference Station Baseline: The final part of the experiments contrasts the UAV measurements with those provided by reference stations. The reference sensors are particle matter measurements provided by the Environmental Services Unit of the City of Kotka. The city has three measurement stations and we matched our measurements with those of the closest station. The reference stations are located close to ground level, but the altitude of the sensing units varies from approximately 4 meters to 8 meters depending on the reference station. The comparison uses the altitude of the corresponding station and is limited to $PM_{2.5}$ as other particle

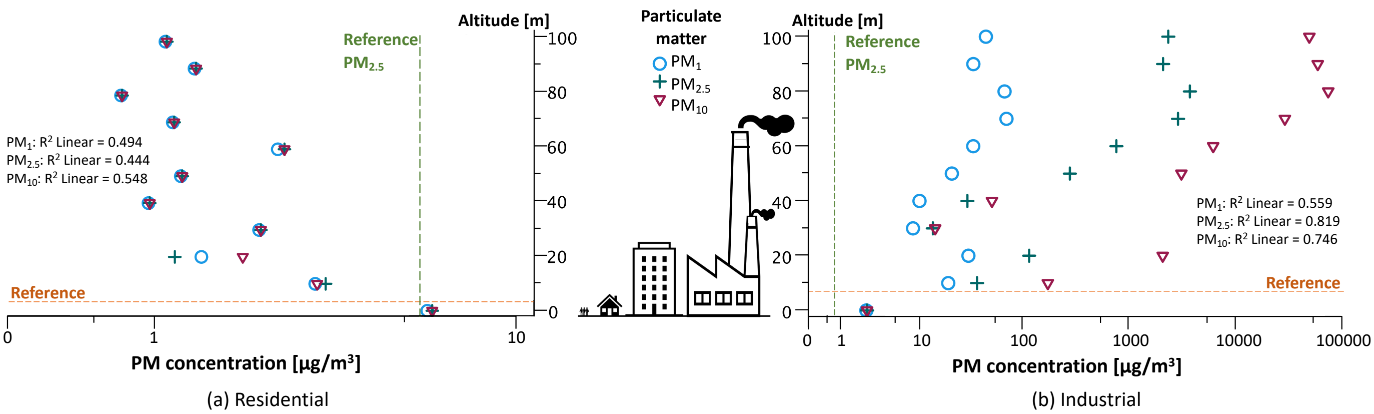

Fig. 3. Concentration of particulate matters (PMs) at different air column altitude within different environmental profiles.

sizes were only intermittently available from the ground truth stations during the days that the samples were collected.

The mean $PM_{2.5}$ values, as given by the reference stations, are 5.58 ± 2.25 $\mu g/m^3$ for the residential site and 6.34 ± 1.26 $\mu g/m^3$ for the industrial site. The differences between the reference stations mostly result from differences in the deployment location, with the reference station closest to the industrial site being located in a more densely populated area than the reference station closest to the residential area. In both cases the mean values are small and correspond to normal levels of background pollution. For the residential location, the reference lines in Figure 3 show that the reference measurements closely match the values in the experiments. In contrast, the measurements from the industrial site deviate and contain higher concentrations than those from the reference station. The higher concentrations are in line with the higher degree of pollutants, as also shown by the statistics of the pollutant concentrations. The difference to reference values indicates that the high pollutant concentrations are heavily localized, and the pollutants get dispersed over a larger area, thus resulting in only a small increase within a single location.

The results highlight both that UAV measurements are sufficiently accurate for pollution monitoring and that they offer additional information that environmental stations or other existing solutions are likely to miss. First, the results for the residential area where pollution levels generally are small, indicate that the UAV measurements are largely in line with those obtained from the fixed environmental stations. The accuracy of the sensors has been separately verified in laboratory conditions and thus the result merely confirms that the measurements produce meaningful insights also when deployed in the wild. Second, the emissions from the industrial site were not observable in the reference station measurements due to the reference station being distant from the site and the wind-patterns prevailing at the time (low wind speed and in the opposite direction as the reference station). Reference stations are likely to capture only parts of the emissions when the wind and weather conditions align with the dispersion direction. City-scale UAV monitoring increases the scale of monitoring and fills in the gaps in the measurements to help understand dispersion and potential health effects associated with it regardless of the weather conditions.

VI. Discussion

Benefits to Stakeholders and Applications: Municipal authorities and public transportation providers can assess the dispersion and distribution of pollutants in detail, offering insights into the health effects of pollutants and a way to monitor the effectiveness of clean air initiatives. Industry can use vertical air pollution profiles to assess their own pollution levels, e.g., compliance with environmental regulations or the potential of emission offsetting operations. Similarly, vertical profiles captured at ports or airports help to understand how pollutants resulting from passenger and freight transport are dispersed within the city. Finally, city-scale 3D pollution monitoring supports scientific studies and innovative applications, e.g., UAVs are useful in modeling pollutant dispersion caused by wildfires and other events.

City-Scale UAV Deployment: Ensuring adequate coverage of pollutant information requires multiple UAVs to operate simultaneously at different parts of the city. UAV intercommunication using short range communications can improve cooperation and better localization can reduce collisions, whereas state-of-the-art mission planning solutions can be extended to consider the vertical column of air quality when sampling data. However, massive city-scale deployments also require connectivity to centralized stations where operators can interpret and schedule simultaneous explorations. Emerging 5G/6G networks provide the backbone to achieve the vision.

Regulations and Other Challenges: UAV operations have potential to be disruptive and cause damage to transport and other urban functions. This is resulting in UAV operations becoming increasingly regulated. For example, in Finland most UAV operations need to be registered, the UAVs must always remain within the line of sight of the operator, and the maximum flight altitude is $150\,\mathrm{m}$ unless special permission is obtained. Many countries also restrict UAV operations in specific areas, such as residential areas or near ports, airports or other strategically important locations. This implies that any large-scale operations need to be carried out in cooperation with local and national authorities, and that the flying distance of the UAVs needs to be restricted. Potential solutions would be to carry the UAVs on top of vehicles – such as public transit vehicles or even autonomous cars – and to sample the air column at predetermined locations only, or to crowdsource the measurements by taking advantage of existing flight operations, e.g., using commercial aircrafts or taking advantage of emerging UAV package delivery services.

VII. Summary and Conclusion

We developed a vision of city-scale air pollution monitoring where UAVs collaborate with existing city infrastructure. UAVs capture the vertical distribution of pollutants and increase the spatial coverage of other sensor technology, helping to scale up air quality information and to model and understand pollution dispersion patterns. By contrasting the vision against current solutions, key requirements and research challenges were identified. These include improvements in sensor designs, hybrid positioning mechanisms, low latency energy-efficient communications, situational awareness, and novel mechanisms for improving energy-efficiency, including models of how to operate together with other infrastructure. Finally, benchmark experiments were presented to highlight how both location and altitude are essential for capturing the extent of pollutants and understanding their dispersion into the environment.

Acknowledgments

This research is supported by the European Social Fund via the IT Academy Programme, by Nokia Center for Advanced Research (NCAR), by the Technology Industries of Finland Centennial Foundation to Urban Air Quality 2.0 project, and by the Academy of Finland projects grant number 324576, 335934 and 339614.

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