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Research Article

Towards a More Granular Picture of the Air We Breathe: Recommendations for Local and Federal Environmental Monitoring Agencies

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Executive Summary

According to the WHO, air pollution is the largest single environmental health risk, estimated to kill 1 in 8 people globally, due to heart disease, stroke, respiratory disease and cancer [1]. More recent research has shown small increase (1 $\mu g/m^3$ increase) in long-term exposure to particulate matter (PM2.5) concentrations leading to a large increase in the COVID-19 death rate [2]. Moreover, blacks and Hispanics are often more exposed to air pollution than whites, despite contributing less towards producing it [3]. Regulatory agencies monitoring air pollution generally use expensive, complex, stationary equipment which limits who collects data, why data are collected, and how data are accessed. Community-based air quality monitoring provides an interesting avenue for research. The widespread diffusion of Internet-of-Things (IoT) connected devices, high-speed telecommunication networks and open data are reconfiguring the way data underpinning policy and science are being produced and consumed. One such recent paradigm in air quality monitoring is the use of low-cost sensor networks for more granular, neighborhood-level air quality assessments. In this memo, a summary of current paradigms in air pollution monitoring are presented along with a discussion on key findings from an experiment deploying 30 low-cost air quality sensors in the City of Santa Monica. Based on findings from our experiment, I provide policy level guidance for federal and local agencies aimed at expanding research and use of community-science based air quality monitoring.

Air Pollution Monitoring – The Current Paradigm

The Clean Air Act (CAA), initially enacted in 1970 (last amended 1990) is the comprehensive federal law that regulates air emissions from stationary and mobile sources [4]. The CAA requires that each state write its own State Implementation Plan containing information on how to monitor air pollution in that state. The extent of atmospheric pollution is measured in terms of 6 levels (ranging from Good to Hazardous), using a scale from 0-500. The index contains five major pollutants: Ozone (O_3), Sulfur and Nitrogen Oxide (Sox/NOx) emissions, Particulate Matter (PM) and Carbon Monoxide (CO) emissions.

Out of the five criteria pollutants, particulate matter pollution (thereafter referred to as 'PM'), holds particular importance due to its high prevalence and known health impacts such as respiratory and cardiovascular diseases, reproductive and central nervous system dysfunctions and (lung) cancer [5]. Vehicle and industrial emissions from fossil fuel combustion, cigarette smoke, and burning organic matter, such as wildfires, all contain PM. Fine particulate matter (2.5 micrometers or less in width), more commonly known as PM 2.5, is 30 times thinner than a human hair and can be inhaled deeply into lung tissue, thus having the potential to contribute to serious health problems. PM 2.5 accounts for most health effects due to air pollution in the U.S [6].

Historically, air quality monitoring has been conducted for legislation surveillance and scientific research by the EPA on a

Federal level and therefore regulatory air quality monitoring sites tend to be sparsely located [7]. Figure 1 shows currently active PM 2.5 sensors from www.epa.maps.arcgis.com and their non-uniform spatial

Figure 1: Currently active PM 2.5 sensors, as of April 30, 2021, across the United States. Source: EPA (https://epa.maps.arcgis.com/apps/webappviewer/index.html?id=5f239fd3e72f424f98ef3d5def547eb5&extent=-146.2334,13.1913,-46.3896,56.5319)

The widespread diffusion of Internet-of-Things (IoT) connected devices, high-speed telecommunication networks and open data are reconfiguring the way data underpinning policy and science are being produced and consumed. This in turn is creating both opportunities and challenges for policymaking and science. One such recent paradigm in air quality monitoring is the use of low-cost sensor networks for more granular, neighborhood-level air quality assessments.

Low-Cost Air Quality Sensors – The New Paradigm?

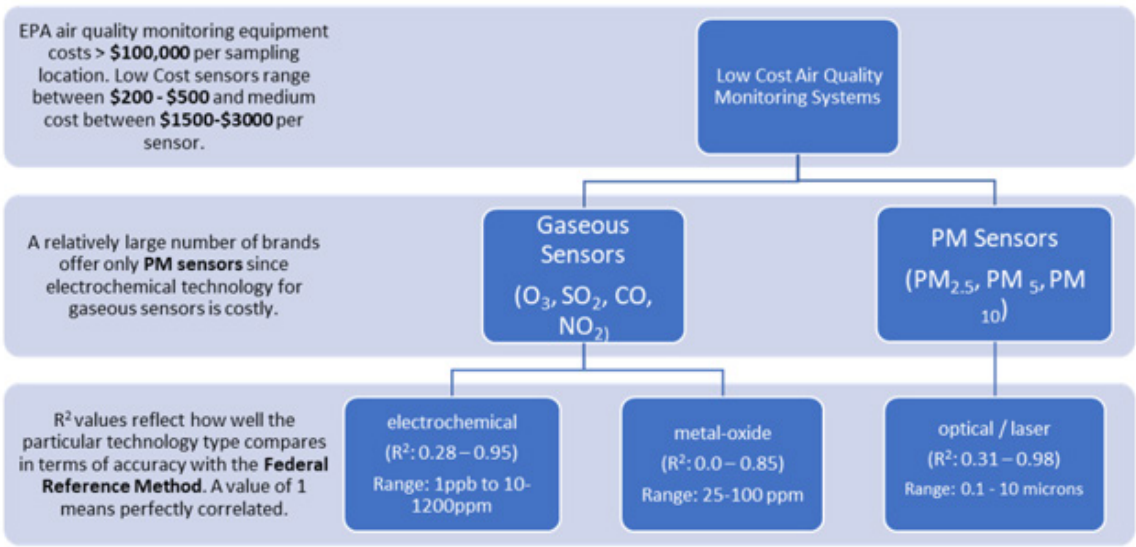

Figure 2: Existing low-cost air monitoring sensor systems and linear correlation coefficients (R^2 values) with Federal Reference Equipment. (Adapted from: https://www.sciencedirect.com/science/article/pii/S1352231019307319).

Low to Medium Cost air quality monitoring devices range in cost from $200 to $3,000 per device. They consist of electronic sensors (optical, UV absorption, electrochemical, etc.) coupled with microprocessors that control the device and convert the sensor

signals to meaningful outputs. These sensors are all at various stages of development. For example, portable ozone monitors employing UV technology recently achieved Federal Equivalence while most brands of sensors for other pollutants (SOx, NOx, PM and CO) are getting close to federal monitoring requirements (Figure 2).

Low cost air quality sensors have been getting more and more attention as citizen science projects gain speed, particularly in Europe. However, legislation around use of data and quality control is incomplete [8]. These sensors, often displayed as a network on a publicly accessible domain, offer air pollution monitoring at a lower cost than conventional methods, in theory making air pollution monitoring possible in many more locations. These sensing technologies and the IoT model for citizen science projects has the potential to be a game changer in monitoring air pollution, traffic management, personal exposure and health assessment.

Given these potential opportunities offered by low-cost air quality sensors, the Tech and Narrative Lab at the Pardee RAND Graduate School conducted a two year experimental study (2018-2019) following a rigorous literature review of available technologies to evaluate, analyze and visualize data from a network of 30 sensors deployed in the City of Santa Monica, California. This policy memo offers recommendations in light of preliminary findings from these sensors.

Santa Monica Air Quality Study

As part of the Cazier Initiative, the RAND team deployed 30 low-cost air-quality sensors throughout the five zip codes in Santa Monica, in a more or less uniform distribution (5-6 sensors in each of the 5 zip codes) using a convenience sampling approach [9]. Based on the sampling approach, it should be noted that results from the study cannot be generalized beyond the sample.

The sensors were selected considering cost, accuracy (lab and field R^2 values), stability, public accessibility of readings and popularity among the citizen science community from an initial list of ~100 low-cost sensors. 2 sensors were co-located to identify reliability and consistency of the specific sensor models. Data analysis and visualization was done using R and Tableau (Figure 3).

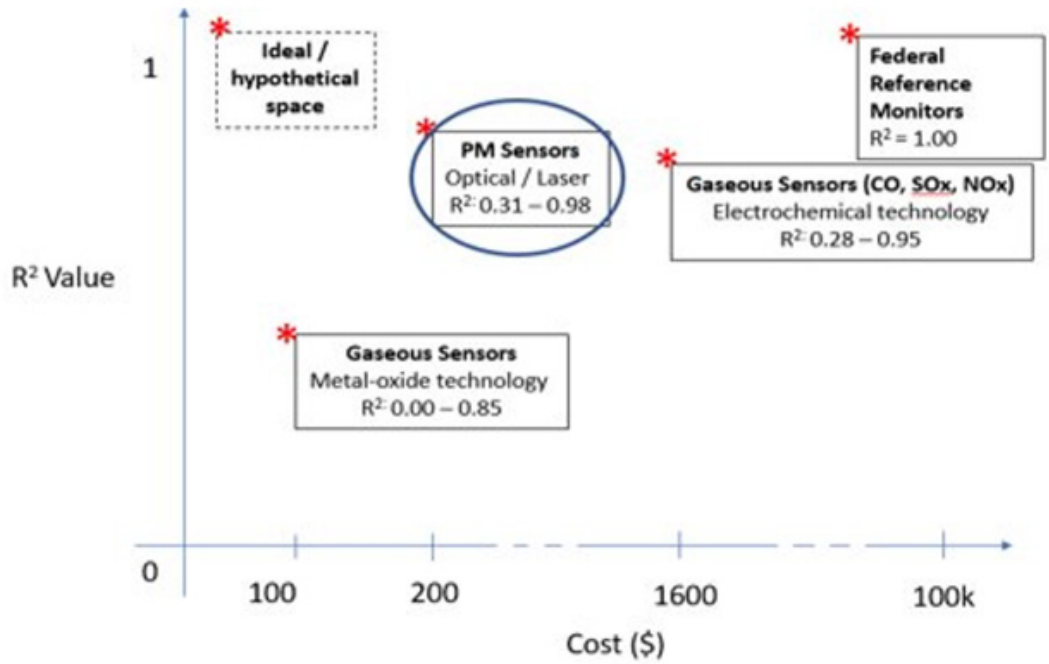

Figure 3: Selection of Purple Air sensors for the pilot study was based on cost, accuracy, public access to data and popularity among the citizen science community. Encircled sensors are used in the experiment.

Findings from Santa Monica Air Quality Study

Key findings from the study are detailed below

- Cazier-project deployed sensors show a more granular picture of air quality, with noticeable spikes during the Woolsey Fire days, when compared with reference readings from nearby federal air quality monitors (Nov 2018). With more granular spatio-temporal resolution, PM 2.5 concentrations along with variables like wind direction and speed, can potentially be used to increase situational awareness and inform better evacuation decisions (Figure 4).

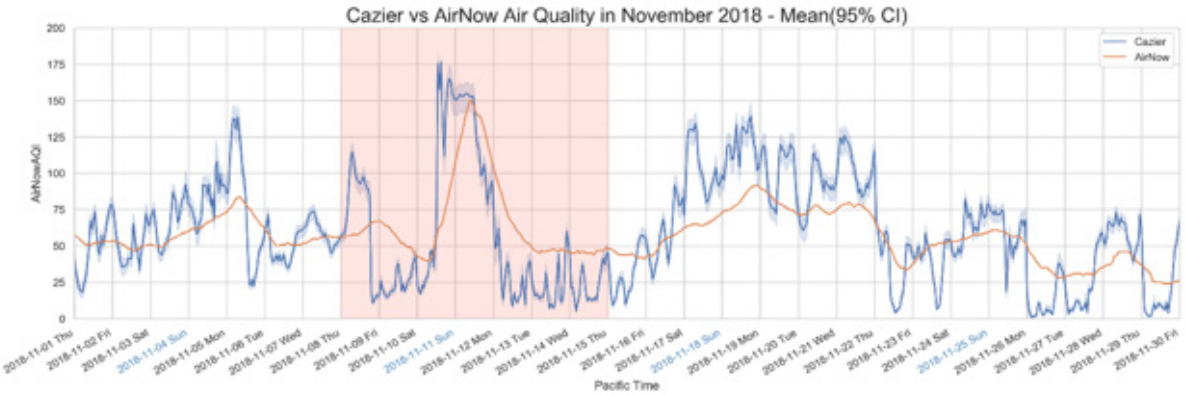

Figure 4: Air Quality Data comparison between EPA's Air Now Monitor (Orange) and Low-Cost Sensors deployed in Santa Monica (Blue). The highlighted region shows the week of Woolsey Fire (11.08.2021 – 11.15.2021).

- Air Quality analysis over the month of Nov 2018 shows marked differences in AQI among the 5 zip codes within SM, reaffirming the hypothesis of high variation in air quality on a neighborhood level. Similarly, significant differences in air quality was observed in communities and schools around a major freeway based on data observed from these sensors (Figure 5).

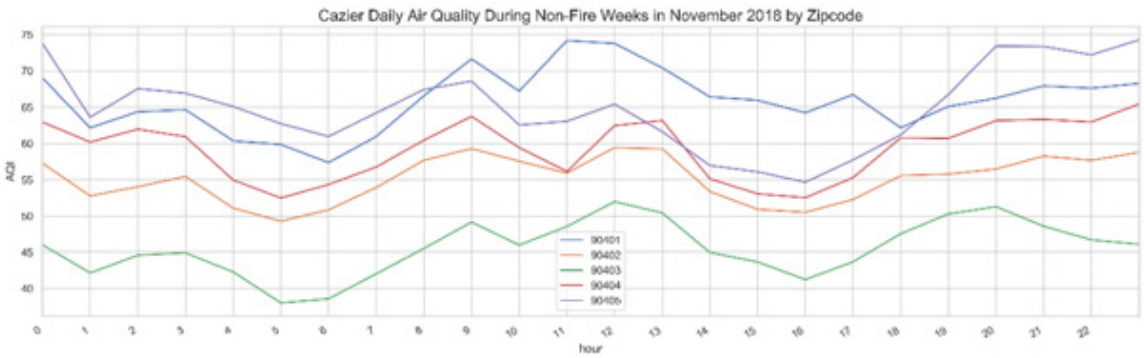

Figure 5: Air Quality variation by zip code across the five zip codes in Santa Monica (AQI Scale: 0-500). Percent difference across zip codes was observed to be as high as 47%.

- In addition to spatial differences, data from the study also revealed temporal differences in air quality by hour of the day, week, month and year as well as differences between PM 2.5 and PM 10 pollutant levels (Figure 6).

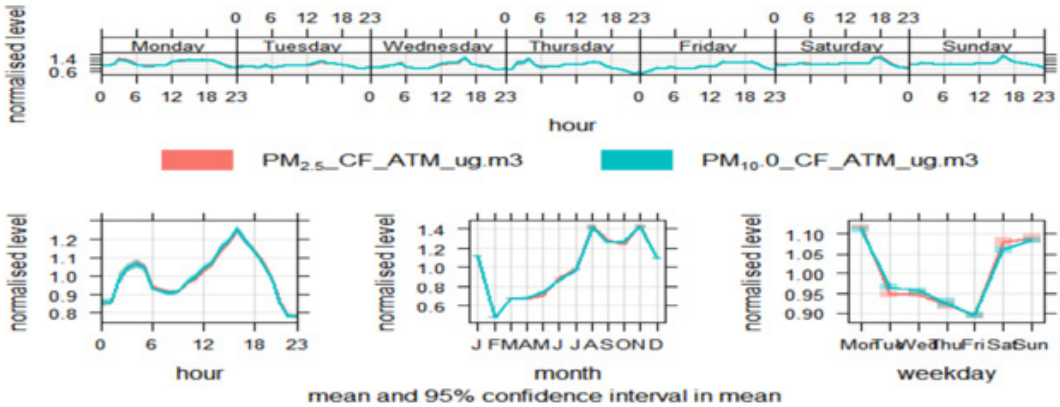

Figure 6: Air Quality variation by hour of the day, week vs weekday and month.

Various visual representations of air quality using data from low-cost sensors allows the opportunity for research on the most effective ways to communicate air quality data for personal decision-making (Figures 7a & 7b).

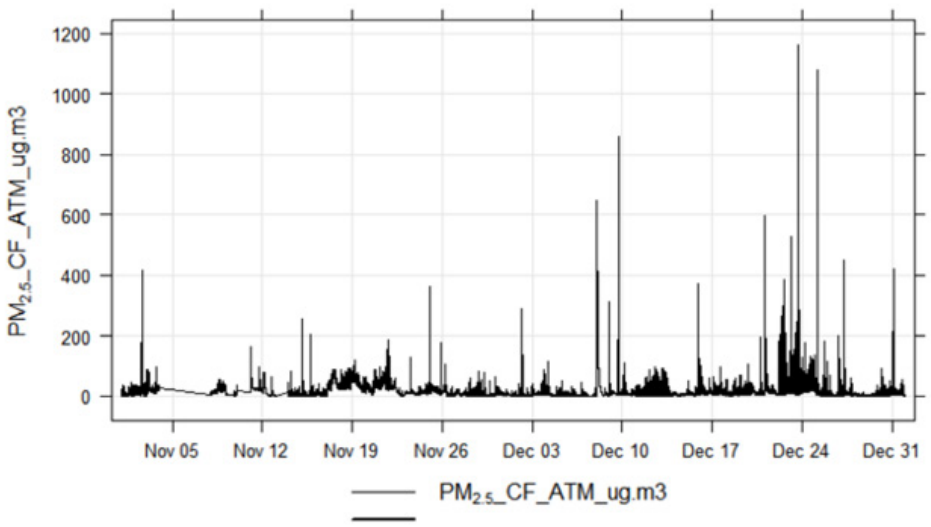

Figure 7a: Simple Time Series Chart for air quality.

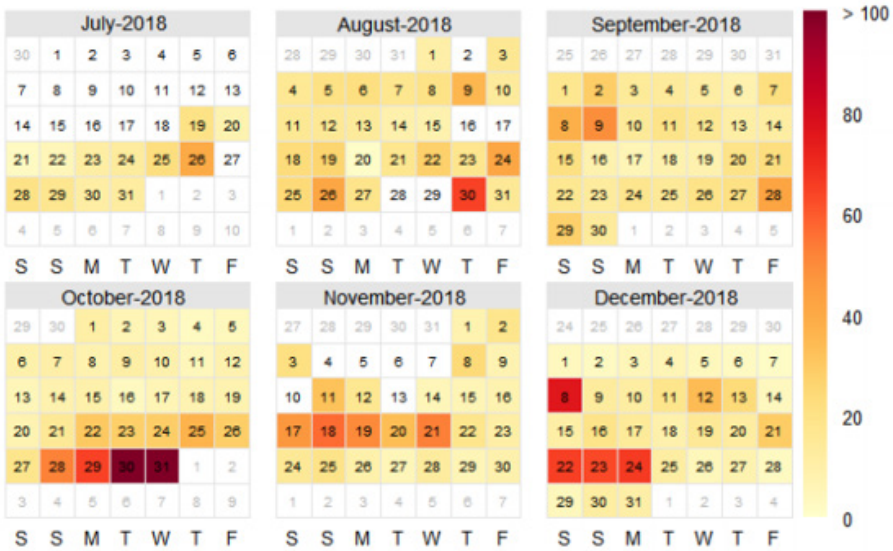

Figure 7b: 'Calendar Plot' of air quality data.

- In general, AQI positively correlates with humidity but less clear (slightly negatively correlated) with temperature. These parameters are useful for sensor calibration over time.
- The cost of sensing devices can be reduced by encouraging more Do-It-Yourself projects. In our demonstration, we achieved results which correlated well with commercial sensors at almost half the cost (Figure 8).

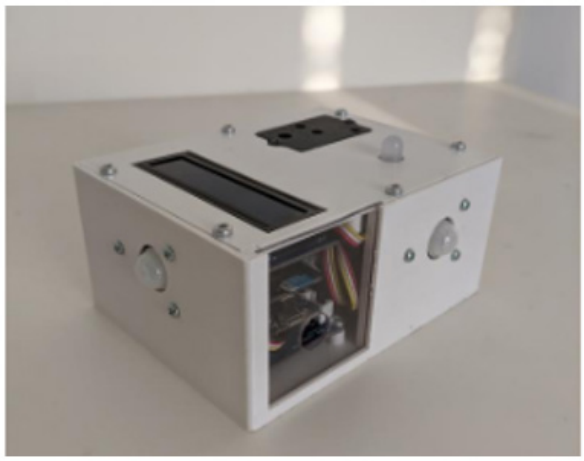

Figure 8: Particulate Matter, Temperature, Humidity sensor with 3D printed housing.

Pittsburgh Air Quality Assessment

The plot below shows the respective locations of air quality sensors installed in Pittsburgh. As seen in the density plot, the sensors are concentrated in the west, where air quality has historically been poor due to power plants upwind of Pittsburgh, and heavy industry, like US Steel's Clairton Coke Works in the Mon Valley. The 27 sensors installed were based on a convenience sample of RAND researchers, similar to the sensors in Santa Monica (Figures 9&10).

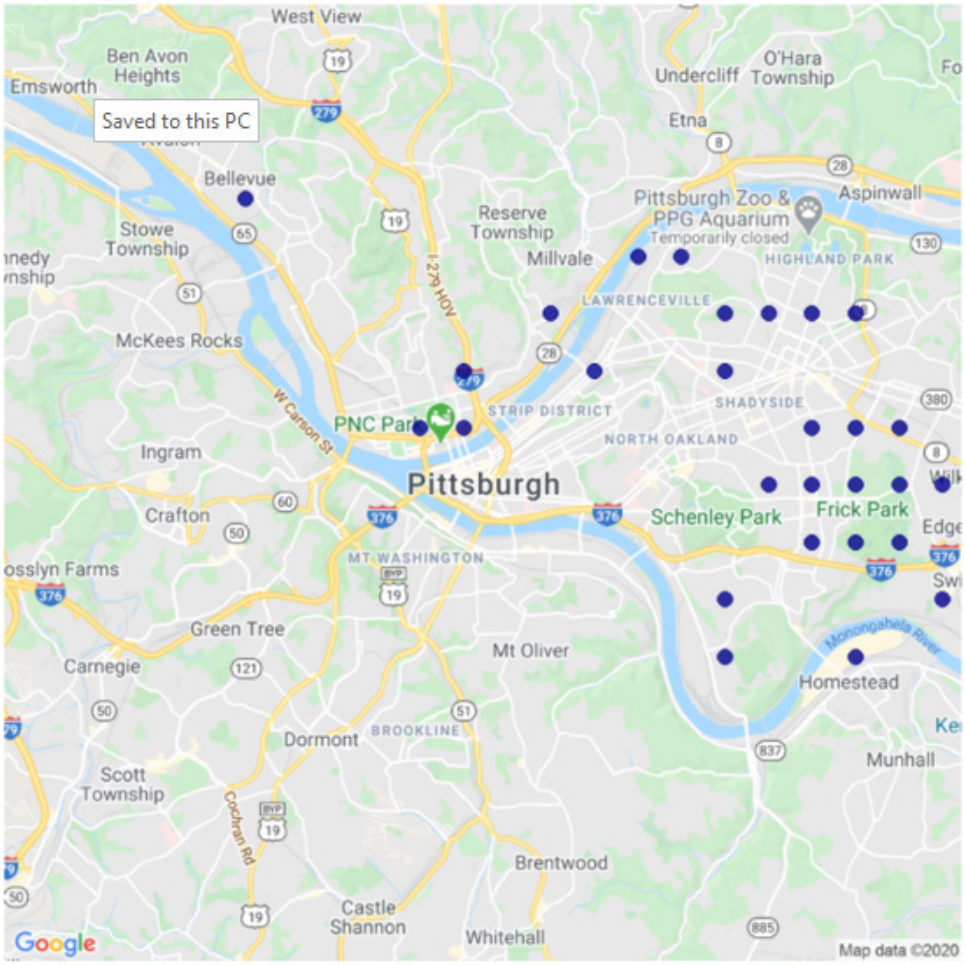

Figure 9: Sensor Locations in Pittsburgh.

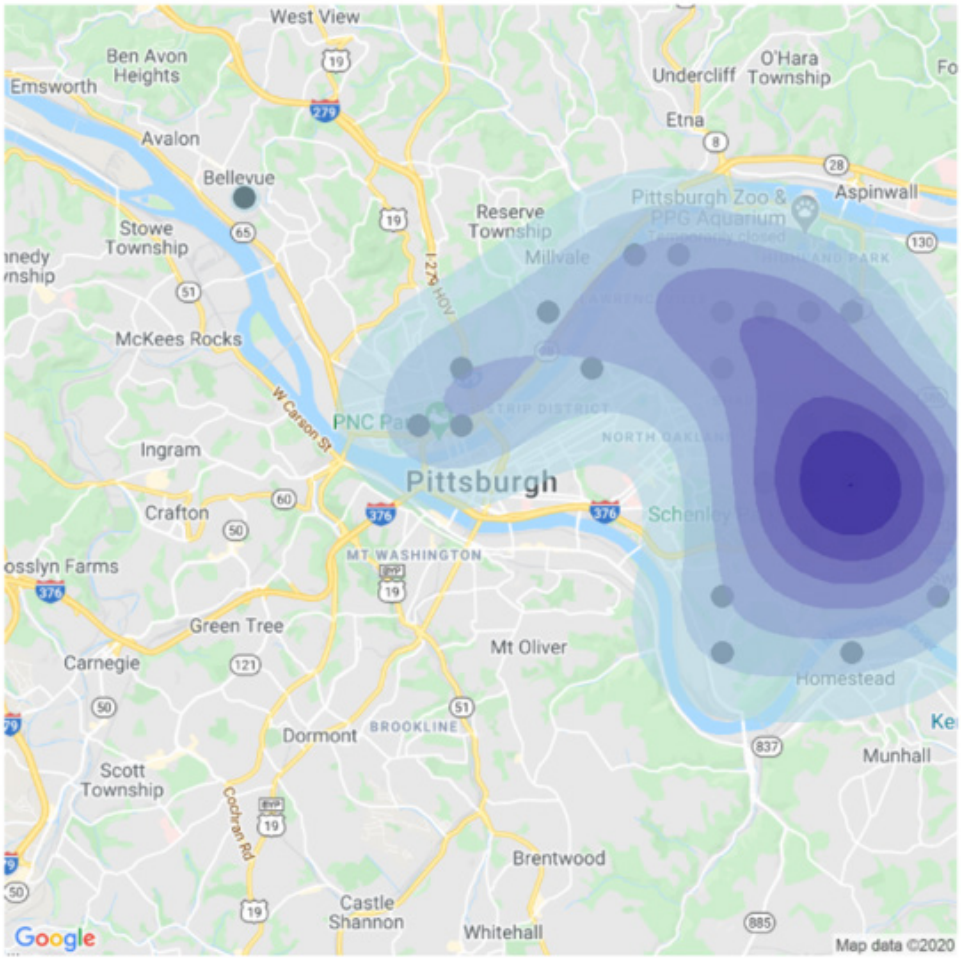

Figure 10: Sensor density plot in Pittsburgh.

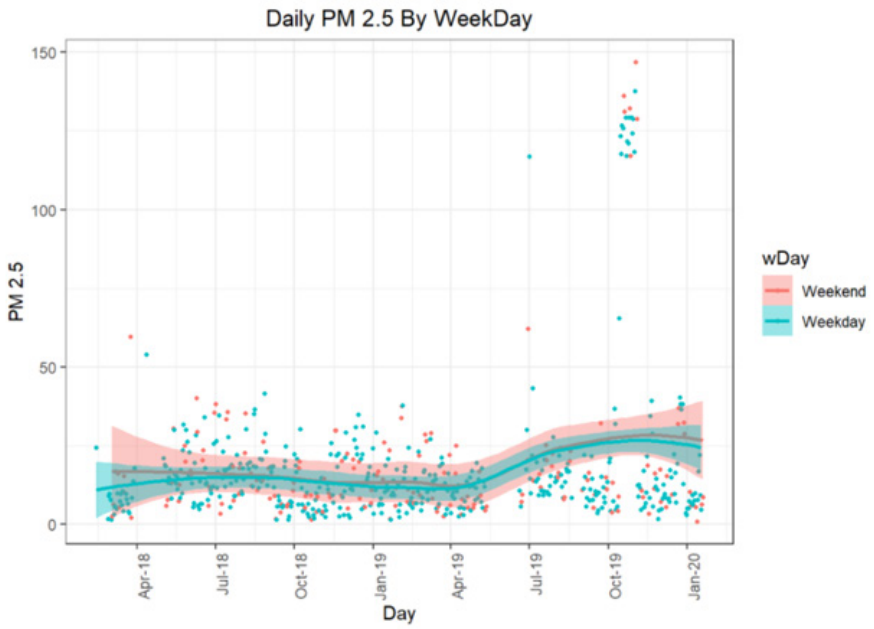

Figure 11: Weekend- vs Weekday air quality trends.

A preliminary assessment of data from Pittsburgh over 7 months of monitoring period shows that our sensors consistently report lower values of PM 2.5 (shown in blue in Figure 11) compared to EPA's air now sensors (shown in red). Reasons for under-estimation of air quality data include, but are not limited to, sensor physical location, orientation, calibration requirements, effect of humidity / temperature and effect of dust and moisture on sensor output. Further investigation (including land-use regressions, comparison of R-squared values using linear model comparing EPA vs low-cost sensors) is needed to systematically assess causes of under-estimation of air quality by our sensors. Note that this behavior is contrary to findings from Santa Monica, which can be attributed to some of the factors mentioned above, in particular, different temperature and humidity profiles between Santa Monica and Pittsburgh.

Similar to findings from Santa Monica, weekends report worse air quality than weekdays.

Similarly, air quality (PM 2.5) seems to be positively correlated with humidity as shown below (Figure 12):

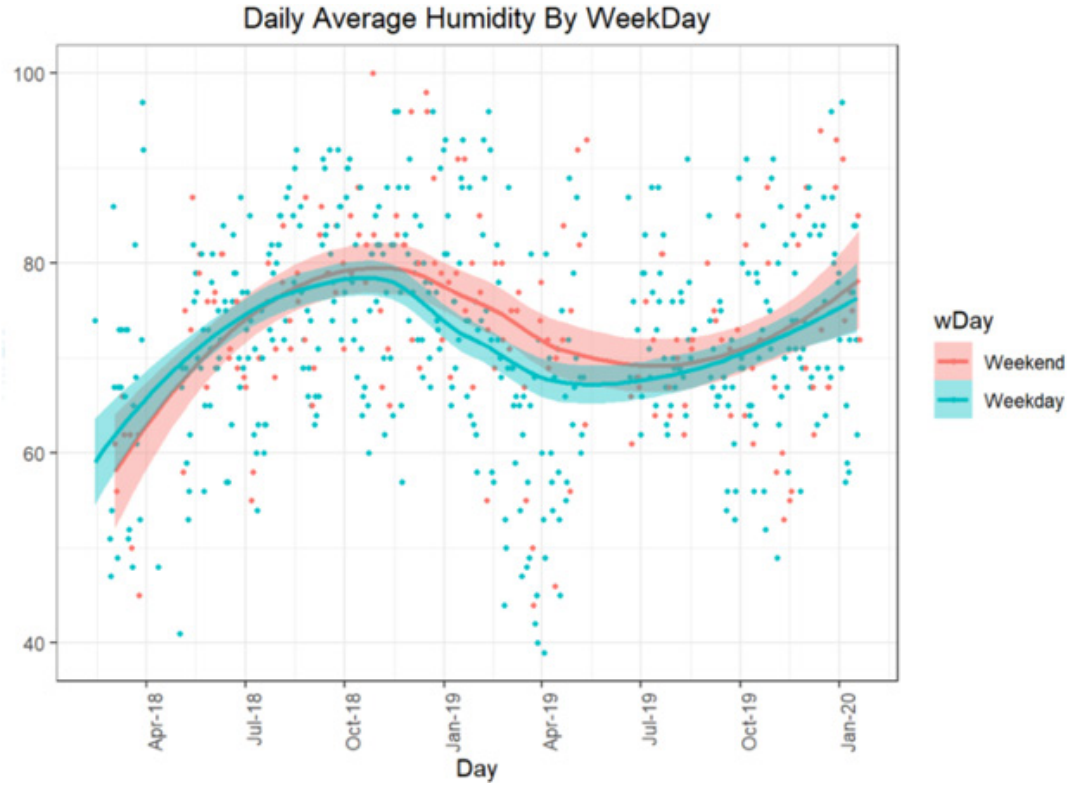

Figure 12: Daily average Humidity profile from April 2019 to Jan 2020.

However, the correlation plot below shows weak positive and negative correlations between PM 2.5 and environmental variables like wind, temperature, humidity and precipitation. Further investigation, and longer assessment durations) can help identify correlations between PM2.5 trends and weather variables (Figure 13).

Policy Recommendations

Currently air pollution monitoring is largely the jurisdiction of state and local environmental agencies (i.e., government authorities, scientists, health experts) using static monitoring stations equipped with federal reference instruments. As such, there is little to no community involvement in an issue that has remarkable community-wide health impacts. Based on results from our pilot, we believe that the availability of low-cost air pollution sensors provides an opportunity for more robust, community-based monitoring networks.

Federal Level: These policy recommendations pertain to federal authorities, chiefly the EPA, and including but not limited to, the US Department of Agriculture Air Quality Task Force and the US Department of Transportation.

- **Data Quality Standards:** One of the biggest challenges to better utilization of data from low cost sensors in the United States is lack of data quality standards. This is due to a lack of research on short and long-term reliability, EPA-defined performance metrics and region-specific calibration guidelines [10]. Even though the EPA already has robust programs to facilitate, communicate and promote the responsible use of air pollution sensor data, a dedicated approach to create standards for sensor manufacturers (e.g. along the lines of the European Directive for Air Quality) is missing.

- **Data Interoperability Standards:** In addition to data quality, access to sensor networks is another concern due to the lack of incentive for sensor manufacturers to share metadata and services across industry and community. Various sensor manufacturers provide their own IoT infrastructure, devices, APIs, and data formats leading to interoperability issues [11]. Similarly, proprietary protocols for logging sensor measurements and lack of interoperability between components (e.g. measurement devices and protocols) create information silos, thus impeding widespread comparison and analysis of sensor data by researchers [12].

Local Level: These policy recommendations pertain to regional environmental monitoring authorities at the state, local, tribal and territorial levels.

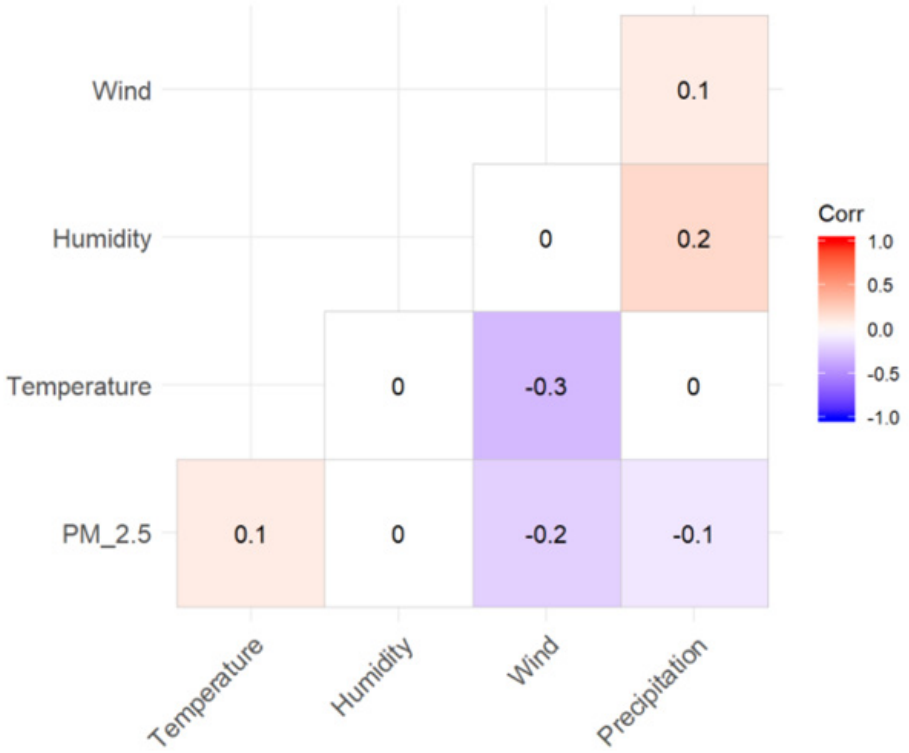

Figure 13: Correlation Matrix showing PM2.5 and Environmental Variables.

Community-Based Participatory Monitoring

Low-cost and easy-to-use air pollution sensors provide citizens and communities with opportunities to monitor the local air quality that has direct personal health-related consequences. This not only allows members of the community to become more conversant on potential air quality issues, but also better positions them to develop community-based strategies to reduce air pollution exposures in their communities. Citizen science activities that take advantage of community-based participatory monitoring and "crowd sourcing" have been successfully implemented under Assembly Bill 617 in various counties in California. The Community Air Protection Program, established under the Bill, provides opportunities to other States to target communities with disproportionate climate-related health impacts under a similar, participatory framework.

Engaging Students and Researchers in Air Quality Research

Local agencies can incentivize researchers, students, and hobbyists to participate in air quality research by funding targeted research areas specific to their region. Research has shown high degrees of variation in low-cost sensor performance by region, geography, and climate. Better data sharing and quality control practices can allow researchers, students and hobbyists to use data from these devices to supplement existing in-situ and satellite-based dispersion models [13]. Data analysis that spans a wider geographic area allows better global calibration models and therefore helps improve data quality from these devices. Machine learning techniques like artificial neural networks have shown promise in forecasting air quality and hardware research on these sensors indicates potential for reducing cost of these devices even further, thereby making them more accessible to tribal and territorial public health agencies.

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Conflict of Interest

No conflict of interest.

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