CitiSense: Adaptive Services for Community-driven Behavioral and Environmental Monitoring to Induce Change

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CitiSense: Improving Geospatial Environmental Assessment of Air Quality Using a Wireless Personal Exposure Monitoring System

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ABSTRACT
Environmental exposures are a critical component in the development of chronic conditions such as asthma and cancer. Yet, medical and public health practitioners typically must depend on sparse regional measurements of the environment that provide macro-scale summaries. Recent projects have begun to measure an individual's exposure to these factors, often utilizing body-worn sensors and mobile phones to visualize the data. Such data, collected from many individuals and analyzed across an entire geographic region, holds the potential to revolutionize the practice of public health.

We present CitiSense, a participatory air quality sensing system that bridges the gap between personal sensing and regional measurement to provide micro-level detail at a regional scale. In a user study of 16 commuters using CitiSense, measurements were found to vary significantly from those provided by official regional pollution monitoring stations. Moreover, applying geostatistical kriging techniques to our data allows CitiSense to infer a regional map that contains considerably greater detail than official regional summaries. These results suggest that the cumulative impact of many individuals using personal sensing devices may have an important role to play in the future of environmental measurement for public health.

Categories and Subject Descriptors
J.3 [**Life and Medical Sciences**]: Health

General Terms
Measurement, Experimentation, Human Factors.

Keywords
Air quality, exposure monitoring, public health.

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1. INTRODUCTION
Understanding the cause of common disorders such as asthma and cancer is necessary in order to lessen the incidence and burden of such diseases. While genotyping techniques have improved drastically in recent years, studying environmental exposures has lagged behind. For many diseases, such as colon and breast cancer, causes are unknown and are likely due to environmental factors [12]. In fact, it is estimated that only about 10-15% of disease etiology can be accounted for by genetic factors, with environmental factors playing a significant role in the pathogenesis of many diseases [13, 14]. Exposure to air pollution is associated with numerous adverse health outcomes including increased cardiopulmonary mortality and hospital admissions, worsening of asthma symptoms and accelerated cognitive decline in older women [10, 19-26]. In 2005, Wild proposed the idea of an "exposome", which encompasses life-style factors as well as environmental exposures during one's life-time [11]. When studied along with the genome, understanding the exposome can yield a more complete picture of disease etiology. However, studying long-term exposure to environmental risks has historically been very difficult. While a large-scale and long term study of a population may help identify locations where individuals experience higher exposure, monitoring the levels of chemicals and other by-products of exposure typically require invasive sampling of blood and tissue [15]. Modeling of exposures can provide a less intrusive method to study large populations, but is highly dependent on the quality of the data used to develop the model.

The most accurate way of tracking an individual's exposure to environmental factors is to directly and continuously monitor the individual's personal space. Thanks to advances in sensor and mobile phone technology, continuous and wireless tracking and reporting is possible for exposure to factors like air pollution. For populations that are particularly concerned with, or sensitive to, an environmental factor, the burden of carrying sensors may be considered acceptable. For most people, however, constantly wearing sensors would not be considered an attractive idea. Therefore, modeling will remain and important tool for studying large populations.

In the case of studying air pollution, air dispersion models for a region typically draw on data from a small number of stationary government monitoring sites and traffic emission models [16]. For example, the San Diego Air Pollution Control District reports pollution measurements from ten locations and use these data to model pollution for the entire county [17], an area of 4000 square miles with a population of over 3 million. Thus, accurately modeling the many, complex microenvironments of a region is extremely challenging with the limited number of inputs currently available.

If the data from existing models and government-maintained monitoring sites were combined with the readings and locations of participating users in the region, more accurate models that capture microenvironment variations become possible. For example, accurately modeling pollution levels at a particular intersection or at a school located near a major highway becomes a possibility. More importantly, these data are captured where people are actually being exposed. The precision yielded from such data may have major implications for the practice of public health surveillance and intervention.

In this paper, we present a user study of CitiSense, a location-aware participatory sensing system for air pollution that collects data from body-worn sensor boards that relay the sensor readings to the wearer's mobile phone both for display to the user and relay to a back-end server for a variety of uses, including the inference of a more detailed regional air quality map. A key result of the study is that CitiSense captures much more detailed information than that provided by the local air quality district. Moreover, the results were surprising to many of the participants, in part perhaps because they were accustomed to the regional-level summaries and the way air pollution is discussed in the media. We conclude that the cumulative impact of many individuals using personal sensing devices may have an important role to play in the future of environmental measurement for public health.

The remainder of this paper is organized as follows. In Section 2, we discuss related work in monitoring personal exposure to environmental conditions. Section 3 discusses how air pollution is currently monitored by government agencies and then goes on to describe the CitiSense system. Section 4 presents the findings of our user study, highlighting the potential benefits to public health and exposure modeling from the use of systems like CitiSense. We conclude and discuss future work in Section 5.

2. RELATED WORK

Several recent projects that have utilized mobile phones to provide users with feedback about the environmental factors they are exposed to. Projects like PEIR [2] and iMAP [3] predict exposure to environmental pollution based on a user's mobile phone location history and predicted exposure to weather, traffic conditions and data from regional air quality monitoring sources. Ergo [5] allowed user's to send a SMS text message containing their zip code to receive air quality predictions for their area from the same sources. However, these location-only approaches cannot capture the fine-grained variations in air quality that a user is exposed to or provide feedback to the user in real-time about sudden changes in pollution. The quality of the predictions with such systems is highly dependent on the granularity and accuracy of the pollution model used to generate them.

To provide finer-grained and more accurate exposure information to users, several projects have developed body-worn sensors to track a variety of environmental factors. Sundroid [1] tracks a user's exposure to solar radiation by collecting readings from a wearable UV light sensor. InAir [8] and MAQS [7] assess indoor air quality, the former using a commercial, stationary (non-wearable) particulate matter sensor and the latter a custom, body-worn sensor. In addition, MAQS allowed users without sensors to learn what other users had measured in the particular room they were visiting. A few projects, such as GasMobile [32], AIR [4], and Common Sense [6], have equipped participants with wearable sensors to study outdoor air quality. In our own prior work, we studied how a small group of users responded to having a system like this available to them on a daily basis [33]. In sum, most projects to date have focused on the development of devices for monitoring individual-level exposure and have run short-term, constrained user-studies.

This paper focuses less on the technical details of building exposure monitors or the nature of personal use, and instead explores the implications for public health of deploying several body-worn exposure monitors across a geographic region known to have high levels of traffic-induced pollution. We focus on the actual air quality measurements taken by users during a one-month study throughout the San Diego region, and compare these readings to official air quality measurements and forecasts published by the local Air Quality District. Our purpose was to determine whether personal exposure monitoring could improve users' understanding of their local air quality and overcome the shortcomings of current approaches to monitoring air quality at both the individual and population level.

3. AIR QUALITY MONITORING

This section provides a brief overview of how traditional air quality monitoring works and a description of the CitiSense system, designed to provide fine-grained pollution information that traditional monitoring techniques cannot capture.

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health warnings of emergency conditions. The entire population is more likely to be affected.
Hazardous	301 to 500	Health alert: everyone may experience more serious health effects

Figure 1. The ranges and meanings of each air quality index (AQI) level, as defined by the EPA and presented on the AIRNow website [18].

3.1 Existing Monitoring

If an individual is concerned with the quality of air in their community, they typically would have to look up an air quality forecast online. These forecasts are generated by local government agencies using data collected from air monitoring sites throughout the region. For example, the San Diego Air Pollution Control District (SDAPCD) is the organization responsible for the San Diego region [17]. Each of these local environmental agencies reports its data to the Environmental Protection Agency (EPA), which monitors air quality (along with other environmental factors) across the nation. An individual may find pollution forecasts at either their local agency website or at the EPA maintained AIRNow website, which displays pollution reports for the entire country, including highlighting the five cities with the highest pollution each day [18]. Users can find forecasts for the day's expected high air quality index (AQI), a color-coded map of the region (see Figure 1 for breakdown of colors and AQI levels), and current conditions, much like a typical weather report. In addition, especially interested individuals may browse the hourly updated readings from sensors in the region, though this raw data is often presented in a manner that can be difficult to interpret for an average user.

Figure 2. Map marking the locations of all ten San Diego County ozone-monitoring sites [16].

The specifics of which pollutants are measured, at what frequency and location can be found on the websites of each regional agency. San Diego County, for example, maintains a total of 14 measurement sites. Of these 14, three collect only wind related data, one collects only ambient particulate matter (PM) data, and the remaining 10 collect assorted combinations of other pollution data, such as ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and particulate matter. Most of these sites also collect temperature and wind information, which is used in forecasting. These sensing sites use sensitive, but also large and expensive, equipment that requires regular maintenance to replace filters.

EPA and state standards dictate requirements for the number of sensing sites and pollutants to be tracked. The actual measurement sites are chosen by the local agencies. The SDAPCD, for example, details in its network plan documents how the topography of San Diego and previous studies of air pollution in the region were used to determine sensing sites. Every few years, additional sensing sites are deployed on a trial basis and old sites are closed or moved if readings are found to not vary significantly from other nearby monitoring sites.

3.2 CitiSense

The CitiSense system consists of three components: a wearable air pollution sensor, mobile phone application, and web interface. The mobile phone and sensor board are to be carried by a user throughout their day, in particular during times when exposure to pollutants would be highest, such as during a rush-hour commute. The phone provides a simple interface that displays the most recent air quality measurements and is to be used for "in the moment" observations. The web interface is designed to allow users to reflect on their overall exposure to pollutants and provides access to maps overlaid with the user's historical data.

3.2.1 Sensor

A mobile sensor board is used to directly measure air quality near the user. Each device includes three electrochemical gas sensors for monitoring exposure to carbon monoxide (CO), nitrogen dioxide (NO2), and ozone (O3). These electrochemical sensors are less sensitive to variations in temperature and require lower power consumption than semiconductor metal oxide sensors, as they do not make use of a heating element for measurements. In addition, sensors are included for monitoring temperature, humidity, and barometric pressure. The sensor board connects to a user's mobile phone wirelessly via Bluetooth.

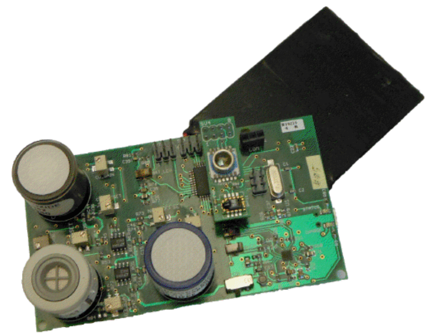

Figure 3. Internals of the CitiSense air quality sensor board.

The board is designed to be light and wearable. To increase durability, a hard plastic shell surrounds the sensor board, with holes and vents throughout the case to allow adequate airflow. Each case includes Velcro straps to allow the device to be easily fastened to a backpack, purse, or bicycle frame. Due to the choice of low-power sensing components, the battery life of the board is approximately five days per charge.

3.2.2 Mobile Phone Application

The phone interface provides a way for users to gain instant access to their current air quality using the data collected from the sensor board. The phone interface is divided into two screens; the home screen supplies glanceable information regarding the current air quality, while the details screen provides the current reading reported by each sensor along with a graph showing the historical readings from that day.

Initial short-term deployments revealed that the AQI color code did not provide sufficient feedback for our curious users. Due to the ranges being relatively large, users reported that they wanted to know when they were in borderline situations (for example a high green, bordering on yellow). To address this user concern we added the color bar to the main screen that indicates where along the color scale the current AQI reading registers using a white arrow and line.

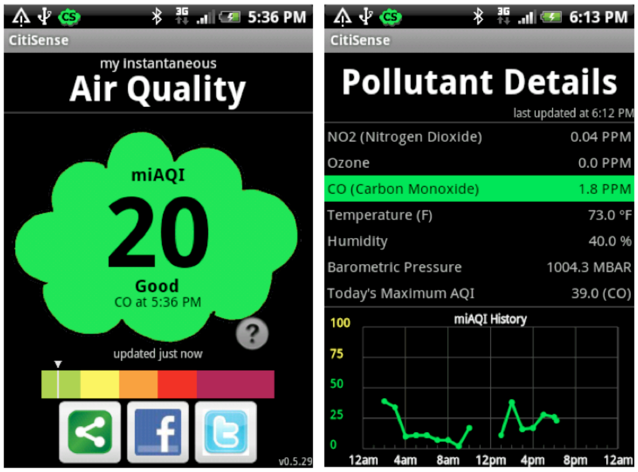

Figure 4. The mobile application interface. The main screen (left) reports the last calculated AQI, along with the worst offending pollutant, within a color-coded cloud. The details screen (right) displays the last reading for all sensor types and a plot of AQI peaks from throughout the day.

The phone application is also responsible for recording the geographical location of each sensor reading. To prolong battery life we only use the phone's Global Positioning Service (GPS) when the user is moving. The remainder of the time a user's location is determined at the network level using cell towers, a procedure that has a much smaller impact on battery life.

3.2.3 Web Interface

The web interface is designed for reflection and review of collected data over time. The central aspect is the interactive map screen where users can view their personal data overlaid on a Google map [9]. Each bubble on the map screen is numbered so that users can tell by glancing when each sample was collected. This allows for users to quickly identify samples from different trips that occupied the same physical location, such as driving to work, and driving back home; a process that will likely utilize the same roads but at different times. If users are interested in a specific sample point they can click on the bubble to gain additional information about the exact time the sample was taken, the pollutant which the AQI calculation was based on, and the raw sensor readings. Each bubble's color corresponds to the associate AQI reading to allow users to quickly scan for problem regions.

In addition to the interactive pollutant map, we also provide a timeline that tracks pollutant exposure throughout the day. This timeline show a more fine grain exposure than the graph on the phone as the additional space allows us to plot each sample collected rather than just the maximum sample per hour as we do on the phone.

4. STUDY

4.1 Study Setup

We conducted a month-long user study to better understand the microenvironment variations of air quality within the San Diego region, while also exploring the perceived value of this information to users. Using an on-campus mailing list, 16 participants, in two groups of eight, were recruited from the UCSD community. Participants included students, faculty, and staff that worked or attended classes on campus each day. Commuting methods included car, bus, bicycle, motorized scooter, trolley, and train. The only recruitment criteria was that each participant have a commute to and from campus of at least 20 minutes each direction and that they be a regular user of an online social network.

Figure 5. Users are able to view an interactive map of their exposure history for each day. Each color-coded marker represents the computed AQI value at that location.

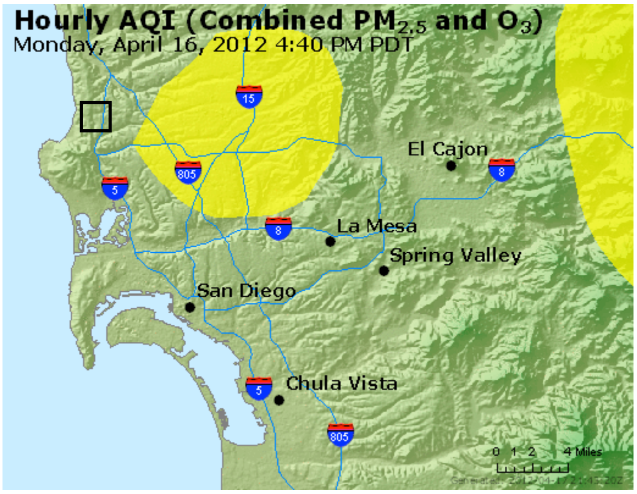

Figure 6. EPA provided AQI map of the San Diego County region April 16th, 2012 at 4:40 PM PDT, with a box added to mark the location of the UCSD campus.

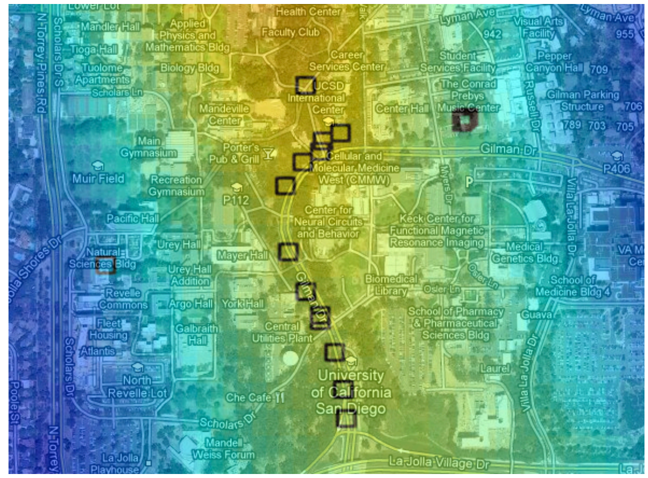

Figure 7. AQI map generated using data collected by CitiSense for the UCSD campus area during a five-minute window on April 16th, 2012 at 4:27 PM PST. The boxes represent pollution reading locations during that window.

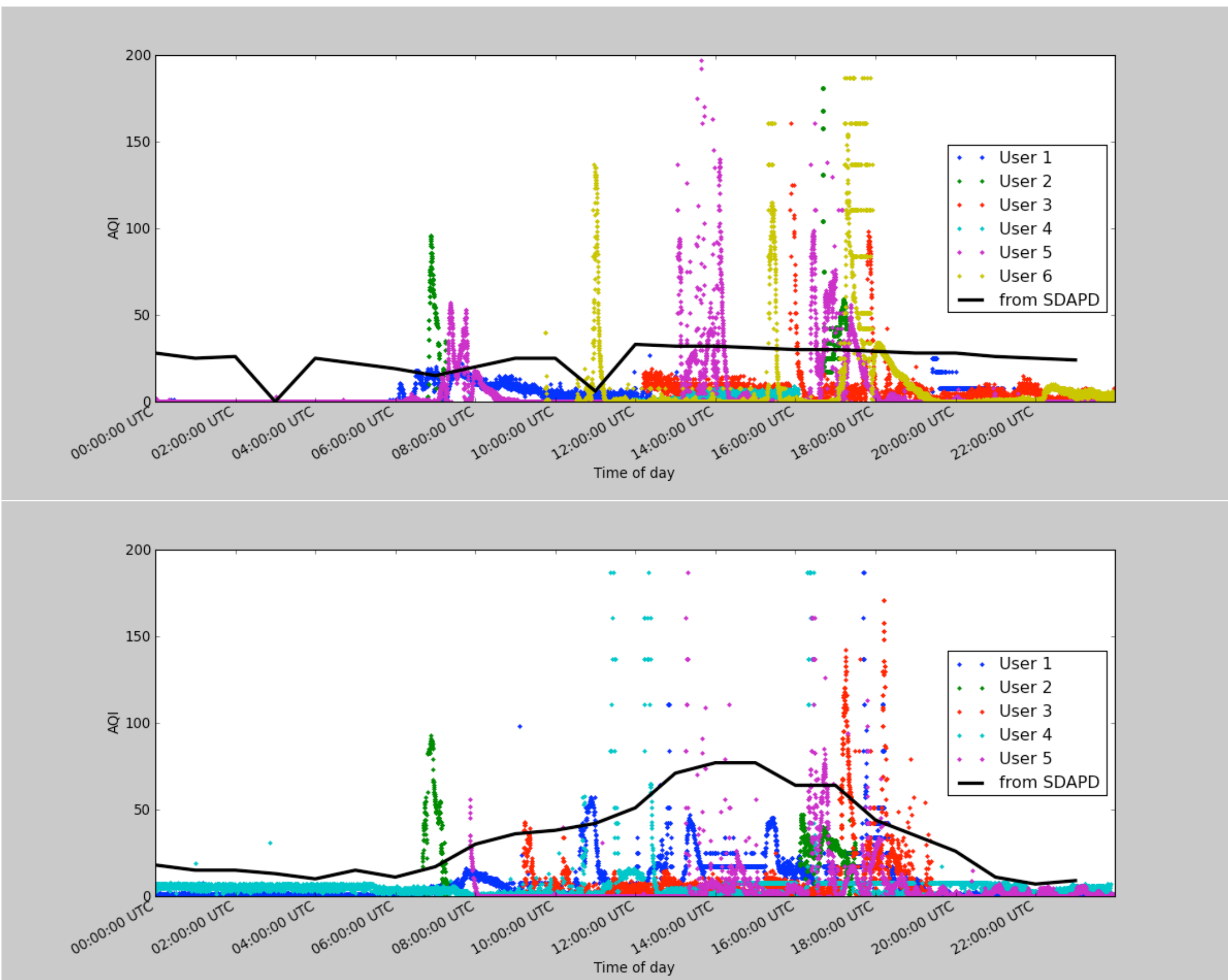

Figure 8. Plots of AQI readings during March 15th, 2012 (top) and April 16th, 2012 (bottom) for a subset of CitiSense user study participants. The colored points represent actual AQI measurements taken by users, while the solid line represents the EPA reported AQI during the course of the day.

Each participant agreed to carry a provided CitiSense sensor and smartphone each day for four weeks. The mean round trip commute for our users was 40 miles. Each participant completed an online questionnaire before commencing the study, at mid-study, and at the conclusion of the study. $75 was provided to each participant as compensation for time and travel costs.

4.2 Observations

Figure 6 is an example of an AQI pollution map that is taken directly from the EPA-maintained AIRNow website.[1] This snapshot of the map represents the predicted air quality for the entire San Diego County region on April 16^{th}, 2012 at 4:40PM PDT. Maps are provided for every 20-minute interval using data from the local agency-maintained sensor sites. The map is color coded in the same manner as presented in Figure 1. Most of the map is colored green to represent "Good" air quality (an AQI of less than 50), with two pockets of yellow, or "Moderate", air quality. A black box has been placed on the map to represent the location of the UC San Diego campus, which will be helpful when examining Figure 7.

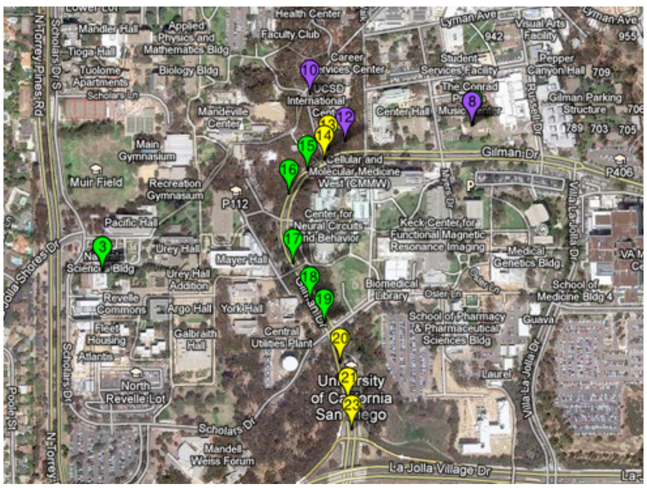

Figure 9. User reported AQI measurements during a 5-minute window starting at 4:27PM PST on April 16^{th}, 2012. Each marker is color coded to match the corresponding AQI levels, as defined by the EPA.

In contrast to the uniform presentation of data in Figure 6, a more detailed map generated using CitiSense user-collected sensor readings is presented in Figure 7. This map was generated using a five minute window of sensor readings starting on April 16^{th}, 2012 at 4:27 PM PST, approximately the same time as the EPA map in Figure 6. Darker blue locations represent lower (better) AQI values (anywhere from 0 to 5 AQI on average), while orange and red locations represent higher (worse) readings (35 - 40 AQI on average). It should be noted that since the data over the five-minute window is averaged, sudden spikes from events like passing buses are suppressed. During this five-minute snapshot, AQI peaked as high as 203, or "Very Unhealthy". Figure 9 shows the color-coded AQI readings for the same location and time frame, before being processed to generate the map in Figure 7. The interpolation of user data for this map was done using standard geostatistical kriging techniques, which are often used in the environmental sciences [27].

[1] This figure and those in the remainder of this paper are best comprehended when seen in color.

There are many observations that can be made with this new map that were not previously possible. The band of higher readings that runs up the center of the image follows along a road that hosts most of UCSD's bus traffic, as well as much road traffic. In addition, the road lies in a sort of 'urban valley' between several tall buildings and walls, apparently trapping air pollution. Users of our system that frequently took the bus noted that they observed large spikes in AQI between 100 and 200 (up to "Unhealthy") while waiting for their bus along this road. One user noted that *"...just by walking through a high bus area exposes you to unhealthy air (more than I would have thought)"*. Another user noted, in reference to observed AQI readings on their phone, that they were *"... surprised how it spikes to yellow, red, or purple anytime I go near a busy street"*. These spikes are captured in the time series plots of AQI measurements versus EPA expected exposure, as seen in Figure 8. On the other hand, many of our users' readings during the day fall below the EPA estimates because they are spending a majority of their time indoors at work. Spikes in the readings were noted by users primarily during their commutes or when leaving work to get lunch, which put them on or near roads. Another interesting observation was that participants who used their own car as their primary method of transportation were exposed to lower levels of air pollution than those that took the bus, likely due to cabin filters that can be found in most new cars that absorb pollutants such as ozone and nitrogen dioxide.

4.3 Discussion

As seen in the study, CitiSense enables identifying pollution hot spots in the microenvironment that have developed due to, for example, busy roads, buildings, and natural topology. These hot spots not only contribute to increasing one's average exposure. It has been shown that exposure to high levels of pollution can trigger cardiac arrest [28]. The detailed maps produced by a system like CitiSense would allow at-risk individuals to take steps to minimize their risk of a deadly reaction to poor air quality.

4.3.1 Implications for Public Health

More broadly, the study highlights the important role individuals can play in environmental monitoring for public health: individuals are able to provide hyper-local measurements where people actually spend their time, enabling the production and sharing of detailed AQI maps like those in figure 10. As one user stated during an interview, *"One of the things that was surprising was how sort of local the pollution is."*

Much like how dedicated hobbyists today run their own weather stations and contribute their data to the national weather service [29], citizens may now do the same for air quality. Who might these users be? We see three possible classes of users: dedicated hobbyists (as with weather stations); those with respiratory issues; and athletes with an interest in understanding the relationships between air quality and their performance and health. The latter two groups share a common interest – their possible sensitivity to air pollution. Thus, while these individuals are personally motivated, the cost of sharing that data with others would be essentially free (since the data is already downloaded to a server for personal use; see Section 3.2.3). Motivated individuals, collecting data during their commutes or at home, may identify hot spots of pollution that local government agencies are not aware of. Government agencies could then move more quickly to address sources of unhealthy air and provide guidance to places like schools and parks to minimize exposure.

CitiSense has the potential to advance population-level understanding of the influences of air quality on health outcomes. Purposeful deployment of CitiSense in a representative sample of a region's population could provide a measure of overall population exposure to air pollution. This could provide public health practitioners a new way to estimate not just pollution levels in a region, but also cumulative impact of this exposure on regional health outcomes.

If successfully deployed with more individuals over longer periods of time, CitiSense has the potential to advance our understanding of the exposome and its contribution to premature morbidity and mortality. Deployed across an entire region, CitiSense users can provide information to augment traditional measures of air quality for everyone. Moreover, as the quotes from users suggest, CitiSense can provide individual users with new and actionable information about their personal air space. Given the increasing prevalence and costs—and the reduced quality of life—associated with asthma and other lung diseases, further research on systems like CitiSense is warranted.

4.3.2 *Opportunities and Challenges*

Going forward with the development of CitiSense, we see several opportunities for improving the system. When collecting sensor readings, contextual information about the user would be beneficial, allowing us to label data we believe to have been collected while indoors versus data collected while outdoors. This would allow us to generate more accurate models for outdoor pollution that leave out especially low readings gathered while indoors, while allowing us to generate an indoor quality rating for buildings, similar to that done by [7]. In addition, more advanced modeling that takes advantage of advanced machine learning techniques is currently in development [30], allowing us to take better advantage of historical pollution data collected by our users and the EPA to generate air quality forecasts based. Both of these additions to our system in the near future will enable us to create even better fine-grained pollution maps.

There are also challenges that need to be overcome. One is that public health practitioners need high confidence in their data, requiring that sensors be calibrated regularly. This currently requires technical skill and special equipment, leading some researchers to propose "online" alternatives [31]. Similarly, we anticipate that the machine learning techniques that we are applying to generate region-scale maps can be adapted to "soft" calibration of sensors, dramatically extending the time between required calibrations at a service center. A very different challenge is privacy and security. While encryption and anonymization can provide a level of privacy, a remaining problem is manipulation of sensor readings, say by covering the sensor holes. Again, machine learning could be useful, as it is capable of detecting and correcting outlier values. Finally, an on-going challenge is power management. While we have developed techniques for saving energy on both the board and the phone [34] (See Section 3.2.2), the phone remains an open challenge, as the GPS technology currently available on phones is a major power consumer, requiring users to plug their phones in at work to get through a long day.

5. CONCLUSION

In this paper we presented CitiSense, a participatory air quality sensing system that bridges the gap between personal sensing and regional measurement to provide micro-level detail at a regional scale. In a study of 16 commuters using CitiSense, measurements were found to vary significantly from those provided by official regional pollution monitoring stations, enabling the identification of pollution hot spots and microenvironments that would otherwise be difficult using typical monitoring. Moreover, applying geostatistical kriging techniques to our data allows CitiSense to infer a regional map that contains considerably greater detail than official regional summaries. These results suggest that the cumulative impact of many individuals using personal sensing devices may have an important role to play in the future of environmental measurement for public health.

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