Prototyping an Affordable and Mobile Sensor Network to Better Understand Hyperlocal Air Quality Patterns for Planning and Design

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Abstract: While there is a growing interest in employing planning and design tactics to improve air quality issues, landscape architects often rely on coarse data that may not reflect hyperlocal conditions. This paper explores how landscape architects might assemble their own sensor network to collect data on hyperlocal air quality patterns, how this data might vary spatially and temporally across a site, and how findings from this exercise might inform the site analysis process. To explore these issues, we prototyped an affordable and mobile sensor network that could be publicly deployed to capture air quality variation at the block scale. We tested the system by building units and collecting data across the University of California, Davis campus for 30 days. By analyzing the resulting data, the sensor system is capable of identifying spatial and temporal hotspots. More generally, when deployed at a larger scale, such a system could be used to improve our understanding of hyperlocal air quality patterns for planning and design.

Keywords: Sensors, landscape architecture, air quality, environmental monitoring, particulate matter

1 Introduction

The field of landscape architecture has a long history of using environmental data to help make informed decisions about planning and design. Oftentimes, though, due to the time and resource intensive nature of site-level data collection, this information tends to be secondary, coarse, and abstract with limited ties to the landscape itself. As a result, assumptions are often made about hyperlocal variations in environmental conditions. Recently, though, there has been a growing desire in the field to find new ways of understanding hyperlocal site conditions through the development and deployment of environmental sensors (CANTRELL & HOLZMAN 2015, LOKMAN 2017, CANTRELL & MEKIES 2018).

In this paper, we explore how landscape architects might assemble their own units to collect data on hyperlocal air quality patterns, how this data might vary spatially and temporally, and how findings might inform the site analysis process. To do this, the paper begins by addressing why landscape architects are increasingly interested in gathering site-level air quality data. The paper then explores how some academics and practitioners are currently experimenting with air quality monitoring in their work. The paper continues by unpacking the methodology of a recent hyperlocal air quality monitoring project with details about the site and general study design. The paper concludes with results from the study, a discussion of preliminary observations as well as potential avenues for future research.

To begin, there are a number of reasons why landscape architects are increasingly interested in gathering site-level air quality data. In a broad sense, the field of landscape architecture has experienced a shift towards evidence-based design and landscape performance metrics (DEMING & SWAFFIELD 2011). Secondly, air pollution is considered a major risk factor for

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adverse health effects and with climate change, air pollution is becoming an increasingly problematic issue (TIBBETTS 2015). Furthermore, in many parts of the world, air pollution is not equally distributed across populations, leading to environmental justice concerns. In addition, recent evidence suggests that tactics employed by landscape architects can improve air quality issues; this can happen at a master-planning scale with the careful siting of programs and site elements to minimize risk and this can also happen at a design scale with the development and incorporation of green infrastructure (BARWISE & KUMAR 2020, HEWITT, ASHWORTH & MACKENZIE 2020). Furthermore, air quality sensors are becoming more affordable and user-friendly due to a changing paradigm in environmental monitoring that is increasing the diversity of available sensor technology (SNYDER et al. 2013). Lastly, these new systems for gathering site-level air quality data are helping to fill gaps in existing knowledge, both spatially and temporally, as landscape architects have traditionally used generalized and averaged air quality information at the local or regional scale.

The potential for employing sensor-based technology in landscape architecture has become a growing topic of discussion in the field (CANTRELL & HOLZMAN 2015, LOKMAN 2017, CANTRELL & MEKIES 2018). At the same time, while some academics and practitioners in the field have experimented with hyperlocal air quality monitoring, the work has been primarily speculative or limited (CHADDERTON 2020, ERVIN 2018). On the speculative end, there are academic projects like Metabolic Forest (COX & DARDEN 2013) and The Digital & The Wild (DUKE 2016), both of which explore the role of air quality sensing in creating responsive feedback loops for design. On the implemented but limited end, there are projects like *Atmosphere InFormed* (SPERANZA et al. 2016) and *Greenscapes to Brownscapes: A Study on Impacts to Contaminant Levels in Landscapes Adjacent to Highways* (HARVEY & ADAMS 2020), both of which are real-world air quality monitoring pilot studies but are not yet scalable.

Additionally, there are a number of air quality monitoring precedents outside the field of landscape architecture that might be of use for designers interested in collecting site-level data. Two precedents of particular interest for this project come from PurpleAir and Aclima. To start, PurpleAir is a widely used air quality sensor network platform that provides real-time data on an online map. The sensors that are available for purchase through the company are relatively small and affordable – $250 at the low end – and use laser particle counters to detect PM2.5 levels in the air (PURPLEAIR 2020). Due to their stationary design, this network is dependent on a dense and geographically-dispersed series of sensors to provide a holistic overview of hyperlocal conditions. Aclima, on the other hand, has developed an air pollution monitoring platform that pulls data from both stationary and roving sensors. For one project, Aclima affixed air quality sensors onto Google Street View cars and collected data in West Oakland, California. The data from this study showed small-scale variability in air quality, even within individual city blocks, highlighting the potential benefits of a roving sensor system over the interpolation of stationary sensors (APTE et al. 2017). The lab-grade sensors used in this project were expensive and large; thus, the data collection platform cannot be easily configured into a distributed system.

The study outlined in this paper sought to merge principles from both precedent projects outlined above to prototype an affordable and roving sensor network that could be deployed to the public to capture air quality variation at the block scale. The research team was driven by three primary questions: 1) How can we design an air quality unit assembly process to be open and accessible? 2) What general conclusions can be drawn from the spatial and temporal variability in the data? And 3) How might these findings impact the site analysis portion of the design process?

2 Methods

To address these questions, an interdisciplinary team of researchers formed with expertise in landscape architecture, urban design, computer science and electrical engineering. Additionally, experts in atmospheric pollutants and climate science were consulted. Our site for the study was the main campus of the University of California, Davis, located in the Central Valley of California, roughly 24 kilometers west of Sacramento. This region of California – due to its topography, proximity to wildlands and wildfire, and agricultural land use – is a unique landscape for studying particulate matter (PM2.5) levels. Furthermore, the city of Davis has only one regulatory air quality monitor and 21 citizen science monitors; all of these are stationary and only one is located on the main campus of the university.

To study the hyperlocal PM2.5 conditions of campus and to help augment existing air quality data, the team aimed to create a mobile low-cost sensor network called "Aggie Air" to gather hyperlocal and real-time data on PM 2.5 air pollution. The first step towards developing this network was to design hardware for individual units using an Arduino platform. For the sensor itself, the team selected the PMS5003 model by Plantower which "uses laser scattering to radiate suspending particles in the air, then collects scattering light to obtain the curve of scattering light change with time. The microprocessor calculates equivalent particle diameter and the number of particles with different diameter per unit volume" (ADAFRUIT 2020). This specific model was selected because recent studies indicate that it is suitable for studying short-term spatially localized particulate matter concentrations (BULOT et al. 2019).

The alpha version of the unit featured the particulate matter concentration sensor, a GPS module for logging locations, and an SD card module for saving data. After initial testing, the team refined the prototype with a stripped-down beta version; the GPS module and SD card module were removed and replaced with a Bluetooth-enabled mobile app to log locations and transfer data to a cloud-based database (Fig. 1). This shift simplified the construction of the unit while reducing the overall cost to under $100 per unit. Ultimately, a small fleet of twenty units were built that could be affixed onto bikes and used across campus to collect data.

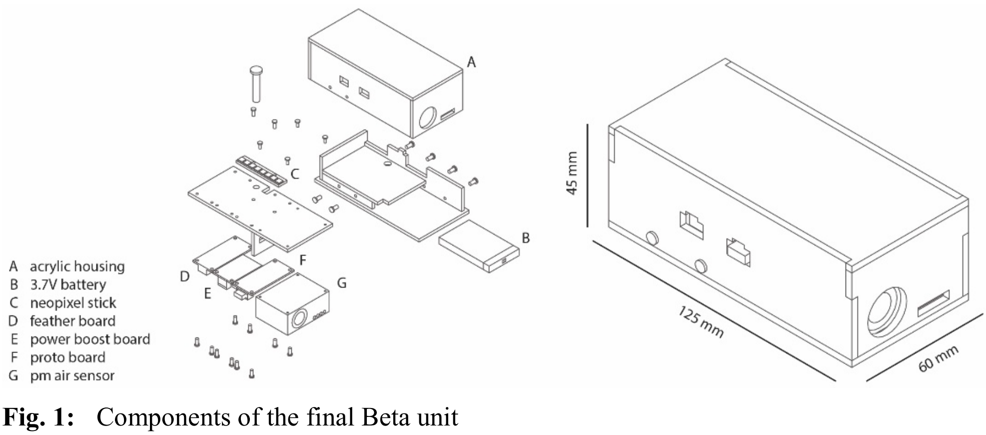

Fig. 1: Components of the final Beta unit

While the research team initially intended to recruit twenty undergraduates to collect data, health and safety concerns associated with COVID-19 precluded this from happening. Thus, one research member from the team collected data for the study. Over the course of 30 days, this research member traced the same route across campus each day following four north-to-south transects, logged air quality data, and mapped surface adjacencies along the route to better understand context (Fig. 2). For the adjacency mapping, the researcher documented the primary surface conditions twenty feet from the route on both sides of the bike. Furthermore, to better understand temporal patterns, the research member alternated the time of day data was collected – 10 days focused on morning hours from 8-11am, 10 days focused on afternoon hours from 1-4pm and 10 days focused on evening hours from 6-9pm.

Fig. 2: The data collection route and the surface adjacency mapping

During the rides, real-time PM2.5 data was expressed through a color-changing LED attached to the unit, which functioned as an actuator, and was displayed on an app displaying a digital map of campus that was searchable by date and time. Both the real-time and batched data used the standard air quality index color code ranging from green (good) to maroon (hazardous).

Lastly, for context, over the course of the 30-day data collection period, the prevailing wind primarily came from the north at an average speed of 8kph, the average temperature was 14 degrees Celsius. Furthermore, while detailed traffic data for the city blocks around campus and along State Route 113 and I-80 was unavailable for the data collection period, it is generally known that weekday mornings and Friday afternoons tend to have higher rates of traffic congestion than other times of the week.

3 Findings

The first question that drove this study focused on how the air quality unit assembly and data collection process might be designed to be open and accessible. To do this, the research team developed a step-by-step instruction manual to lead people through the process in a straightforward manner. While the research team intended to recruit a number of undergraduate students to test the manual, this was not possible due to health and safety concerns associated with COVID-19. That being said, three members of the interdisciplinary team tested the instructions for the Beta design, successfully built fully-functional units, and were able to collect data across campus using the platform.

The second question that drove this study focused on what general conclusions could be drawn from the spatial and temporal variability in the collected data. To unpack the spatial variability in the study, the research team mapped the 90th percentile of PM2.5 levels at each spatial location along the bike route for each of the thirty rides, created a color gradient from purple (fewer instances) to yellow (more instances), and visually analyzed the resulting map. Ultimately, 14 geographically-dispersed hotspots were identified based on areas that contained yellow pixels. Of those 14, three hotspots with the most yellow pixels were selected for further analysis (Fig. 3). These three areas appeared to share four general characteristics. Each areas was located on the edge of campus, close to a vehicular intersection, on a dedicated bike lane along an active road, and were adjacent to surface conditions comprised of hardscape or built-up areas. To unpack the temporal variability in the study, the research team grouped the morning, afternoon, and evening rides and plotted the PM2.5 levels (Fig. 4). The resulting data showed elevated PM2.5 levels in the evening hours followed by elevated levels in the morning hours. Rides done in the afternoon hours showed the lowest PM2.5 levels of the three sets.

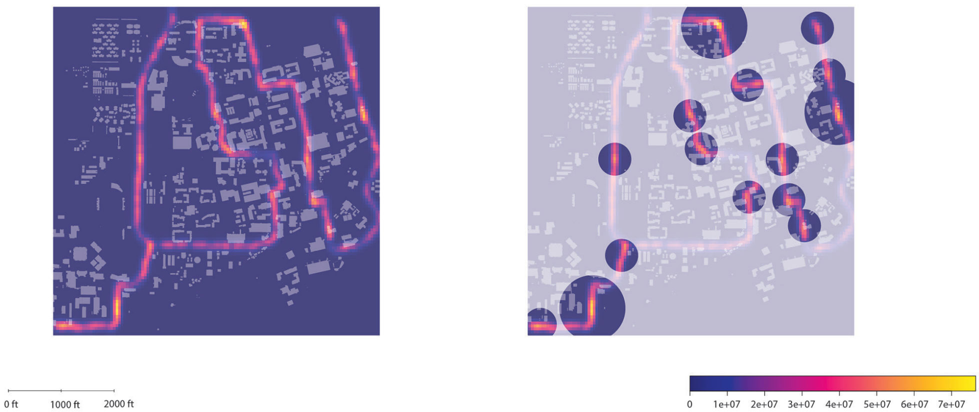

Fig. 3: Heat map showing 90th percentile PM2.5 areas for the 30 rides and the 14 hotspots

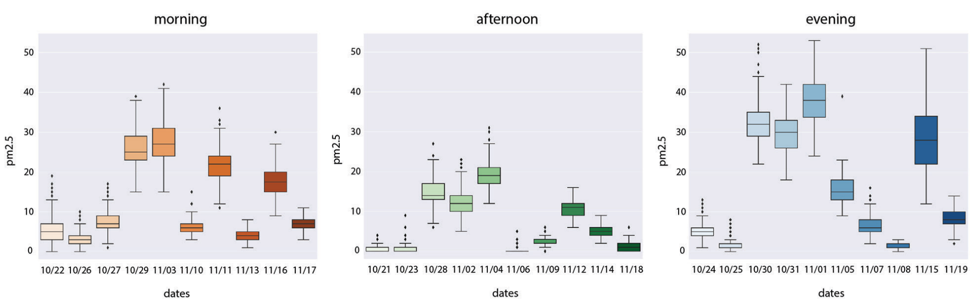

Fig. 4: PM2.5 levels grouped by morning, afternoon, and evening rides

The final question that drove this study considered how the spatial and temporal patterns observed in the data might inform the site analysis process. For this, the research team speculated about how design and planning professionals might use this data in their work and how the general conclusions from the study might raise questions about potential site interventions in the future. Based on the spatial findings from the study, two questions were developed for potential development sites located on the edge of campus, near active roads and intersections, and next to significant hardscape or built-up zones: 1) Should areas like these be reserved for certain types of campus programming to reduce long-term exposure to elevated PM2.5 levels? And 2) Might these areas benefit from increased green infrastructural interventions to reduce hyperlocal air quality issues? Based on the temporal findings from the study, one question for future research was developed: Could responsive landscape systems be designed to offer sites more protection in the evening hours?

4 Discussion and Conclusion

The potential for using an affordable and mobile sensor network, like the one outlined in this study, to better understand hyperlocal air quality patterns for planning and design is significant. This kind of system could be employed by landscape architects for site analysis to understand hyperlocal environmental risks and could also be helpful post-construction for designers to monitor the impact of built work on air quality levels in an effort to guide future management protocols and site design. The individual units developed for the project are significantly more affordable than off-the-shelf units and are easy enough to assemble with the step-by-step manual. Furthermore, the research team was able to draw general spatial and temporal conclusions from the pilot project data that might be helpful for designers.

Currently, though, the data collection process put forth in this study should only serve as a tool that can be used to generate hypotheses for further testing and exploration. To move the project forward towards specific design and planning recommendations, a number of study limitations must be addressed. To begin, more people should be recruited to test the unit assembly process to better understand the ease of construction. Secondly, more PM2.5 data should be gathered. Multiple units should collect data simultaneously to cross-validate levels, the route should be expanded to include more areas of campus, and the data collection process should extend beyond 30 days to capture multiple seasons and conditions. Furthermore, more time should be spent on analyzing site conditions to better understand potential correlations. Lastly, the following technical issues with the system should be addressed. The campus-wide WiFi network was often too weak and unreliable to use for data collection so the research team resorted to using mobile phone hotspots. The mobile app had to be physically open for the data to be logged and the app only functioned on Android devices. The mobile phone and the unit had to be charged before every ride for a reliable power supply. Lastly, while this was not an issue for the short-term study outlined in this paper, future longer-term studies should consider the potential for data drift and should plan for sensor re-calibration.

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