Improving Landscape Performance Measurements: Using Smart Sensors for Longitudinal Air Quality Data Tracking

Zhongzhe Shen[1], Mintai Kim[2]
[1]Virginia Tech, Virginia/USA · zhongzhes@vt.edu
[2]Virginia Tech, Virginia/USA

Abstract: As addressing climate changes become a pressing issue in landscape architecture, the importance of landscape performance (LAP) became an important topic. An essential part of LAP is accessing data. Some data are easily accessible in the landscape architecture field, but some are not, such as air quality data. When such data are available in the landscape architecture field, they are often not of high enough quality, regarding scale, adequation, and precision. Also, there are sometimes financial barriers to getting the data. The research team explores an alternative way of collecting longitudinal air quality data to improve LAP measurement, using the Arduino-based cheaply made smart sensors installed on-site over time. The research team conducted experiments in nine comparison sites, collected and analyzed air quality data, including temperature, humidity, equivalent carbon dioxide (eCO_2), volatile organic compounds (TVOCs), and fine particulate matter ($PM_{2.5}$). The result shows that compared to publicly available data, longitudinal data collected by smart sensors are more accurate, dense, and frequent. This study investigates the strengths and capacities of using smart sensors for longitudinal air quality data tracking and offers an alternative way of providing data evidence for sustainable design to mitigate some climate changes issues.

Keywords: Smart sensors, air quality data, longitudinal tracking, landscape performance

1 Introduction

This paper considers Arduino-based smart sensors as an alternative method of longitudinal air quality data tracking for improving landscape performance measurements. In this paper, we present our experiments, programming small, cheaply made, conveniently carried, low maintenance and energy request smart sensors. Due to the length limitation, instead of describing the sensors' programming and installation in detail, we focus on presenting the experimental research and discussing the strength and meaning of application of results, with the background of climate change.

1.1 Motivation

There is a need for exploring real-time, real-world LAP data in the landscape architecture discipline. Landscape architectural professionals need quantified LAP data to understand their project sites profoundly and make decisions. Researching these data should primarily consider data accuracy, density, and frequency. Human activities have significantly changed living environments and created various microclimates. The alignment of buildings creates local wind tunnels; particulate emissions from transportation and industrial pollution cause air quality issues; greenhouse gases cause urban heat island effect and intensify the heat. However, limited accessible and reliable quantitative LAP data has prevented landscape architectural professionals from addressing microclimate issues. LAP longitudinal data gathered by smart sensors is becoming an accessible tool for landscape architectural professionals

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to develop and improve solutions to meet specific requirements and objectives. Smart sensors empower them by providing accurate, dense, frequent, and real-time quantitative data evidence. Smart sensors link phenomenological qualitative environmental factors with measurable and reliable quantitative data.

1.2 Background

Climate change has created an unprecedented impact on a global scale. Changes in weather patterns cause more frequent extreme weather events. Several studies have shown that the frequency, intensity, spatial extent, and timing of heavy-to-extreme events have increased worldwide, which can be because of global climate change (STOTT 2016, BOO et al. 2006). The effects of global climate change have accelerated in recent years (SHEFFIELD AND WOOD 2011). The US Fourth National Climate Assessment (WUEBBLES et al. 2017) reports that over the past 50 years, the number and intensity of heavy-to-extreme events, such as hurricanes, floods, droughts, extreme heat/cold waves, have increased in the United States.

The landscape architecture discipline and profession are increasingly recognizing the effects of climate changes on ecosystems and biosystems that it is designing and planning for. Recognizing the importance of accurate measurements of performance, landscape architects are doing more landscape performance research (LANDSCAPE PERFORMANCE SERIES 2020). According to Landscape Performance Series (LPS), “landscape performance can be defined as a measure of the effectiveness with which landscape solutions fulfill their intended purpose and contribute to sustainability” (LANDSCAPE PERFORMANCE SERIES 2020). “Researching and documenting these impacts request quantitative data and tools to distinguish climate impacts in noisy data and understand interactions between climate variability and other drivers of change” (STURROCK et al. 2011). However, not enough performance data is available for the studies of landscape performance regarding climate changes related factors. Some quantitative data are available for landscape architecture discipline while some are not. Furthermore, some of these quantitative data are often in low accuracy, low scale resolution, and especially lack frequency and timeliness.

1.3 Existing Urban Sensors

Traditionally, the landscape architecture field relies on existing publicly available meteorological data to experience and evaluate project sites’ environmental factors during design processes. Traditional meteorological sensor monitoring stations are difficult and costly to deploy and maintain, ultimately resulting in sparse environmental data coverage (MULLER et al. 2013). The variability of complex climate or environment across cities and areas should not be only presented by those individual stations. Consequently, environmental data from only a few of these stations does not provide enough details for LAP projects’ decision-making applications (WMO 2008).

With recent advances in technology, miniaturization of electronic equipment, and computing power, environmental sensors are becoming more innovative, reliable, compact, and cheap (GRIMMOND 2006, RUNDEL et al. 2009). More cheaply-made sensors are now able to be more numerous and densely spaced, with vastly improved temporal collection and rapid data transmission (MULLER et al. 2013). Depending on spatial scale areal extent, we divided existing commonly used meteorological sensor networks into five categories: global scale ($> 10^8$ m), country scale ($10^5 - 10^7$ m), regional scale ($10^4 - 10^6$ m), city-scale ($10^4 - 10^5$ m), and local scale ($10^2 - 10^4$ m) (MULLER et al. 2013).

Even the smallest local scale meteorological network covers 10,000 m^2 to 100,000,000 m^2. Environmental data from these local scale sensors is not quality enough (lacking specific LAP data, low scale resolution, low frequency) to understand numerous and complex microclimates. Micro-scale sensors observe environmental changing processes over small areas, such as turbulence within street canyons, air pollution dispersion, micro-climate studies, and infrastructure impacts on local temperature; only micro-scale sensors' data can represent the specific area's microclimate (MULLER et al. 2013). However, few empirical research of micro-scale sensors has been developed. Moreover, none of them are in the landscape architecture discipline.

Sensor Network over Princeton (SNOP) is one of these research, they put seven different types of sensors to simulate heat exchange between the buildings and the atmosphere and estimate energy consumption loads; to be used by the hydrometeorology research group; and for determining surface fluxes of CO_2 and heat (THE TRUSTEES OF PRINCETON UNIVERSITY 2021). Even though it is a micro-climate scale project, their sensors are too big, similar to some meteorological stations, which generally require expensive installation and maintenance costs. And these fixed on-site sensors do not empower landscape architects to move and reuse in a different project site easily. Furthermore, it cannot present microclimate-scale environmental information detailly. Another project is the UScan[FC], Japan. The research team deployed low-cost sensors on experimental sites in Toyko to detect temperatures changes. But only focusing on temperature is not enough to understand complex urban settings' various microclimates.

2 Research Method and Experiment

2.1 Research Hypotheses

Taking cues from previous empirical research and the capacities of Arduino-based sensors themselves (ARDUINO 2021), we post two specific research hypotheses corresponding to the objectives:

- Compared to publicly available data, longitudinal data collected using smart sensors have advantages in responding to the aspects of greenhouse gas and air quality.
- Smart sensors gathered longitudinal data can improve LAP measurement by providing more accurate, dense, and frequent data.

2.2 Research Process

The method of this quantitative study was divided into four sections: selecting experimental sites, building and programming sensors, on-site experiments, and analyses of data results (Figure 1). The collected and analyzed data in this study includes temperature, humidity, equivalent carbon dioxide (eCO_2), volatile organic compounds (TVOCs), and fine particulate matter ($PM_{2.5}$). The following section of this paper describes the preliminary experiment we undertook to program and build the smart device, reports on the current research result at the writing this paper, and discusses the application's strength and meaning.

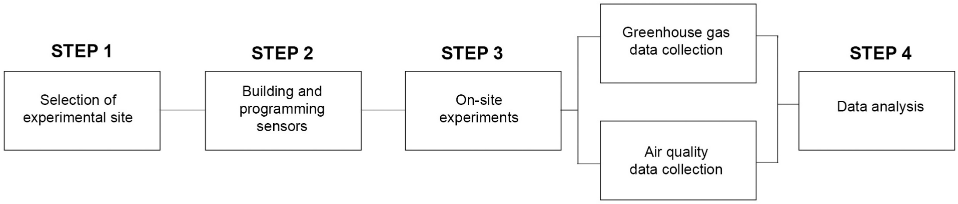

Fig. 1: Research process of this study

2.3 Selection of Experimental Sites

This study selects nine experimental sites (three groups) in urban and suburban settings based on common community surroundings: (1) group one, a community park's green space (Kittredge Park), a commercial area, and a sidewalk near the road in a suburban area of Atlanta, GA; (2) group two, green space of Centennial Olympic Park, a concrete parking lot, and buildings surrounded site in downtown Atlanta, GA; (3) group three, Virginia Tech (VT) Drillfield (green space), an outdoor parking lot area (lot 8 at VT), and a downtown commercial area in Blacksburg, VA, which we consider as the suburban area. Example pictures of experimental sites are below (Figure 2).

Fig. 2: Example images of experimental sites taken by authors: (a) Kittredge Park's green space; (b) a sidewalk area near Kittredge Park; (c) a commercial area near Kittredge Park; (d) Centennial Olympic Park's green space; (e) a concrete parking lot near Centennial Olympic Park; and (f) the buildings surrounded site in downtown Atlanta

2.4 Characteristics of Selected Sensors

Arduino electronic boards are selected by the research team. "Arduino is an open-source electronics platform based on easy-to-use hardware and software" (DUTTA 2021). Our device/sensors meet the needs of a landscape architecture realm on quantitative data collection equipment:

Low price – The cost of each smart sensor node is typically between \$100 and \$200. Micro-scale environmental research often requires dozens to hundreds of sensor nodes. A dense sensor network dramatically increases investment costs. The cost of our sensor node is \$90.

Small size – Micro-scale sensor networks require each sensor node to be portable and be moved and installed easily. The final sensor node of this study is smaller than a 10 cm^3 cube. Currently, because of a breadboard included, the size of the experiment node is 15 cm x 15 cm x 5 cm. This breadboard is only for experimental conveniences and would be removed eventually.

Long lifetime and low energy request – This factor is significant, especially under a large-scale setting background (e. g. A setting requires hundreds to a thousand sensor nodes). It is impossible to replace sensor nodes themselves or the battery frequently for large numbers of sensors, especially where sensor nodes are integrated into other facilities or placed at hardly-reach areas. All of our sensor modules have several years of lifetime, and the overall energy cost of the experimental node is around 1W. Currently, we use a 9V/600 mAh battery to supply power. It can last 5 hours. With the energy storage part, an 15 cm x 15 cm solar panel can provide around 25 W (8 hours average sun time) to enable one sensor node to run 24/7.

Cross-platform –We use the Arduino integrated development environment (IDE), which can run on all commonly used operating systems, such as Windows, Macintosh OSX, and Linux.

Simple and easily learned programming environments – We understand most landscape architectural professionals and researchers have little or no programming knowledge. Arduino IDE is welcome to all users, from beginners to experienced programmers, because of the community of developers and various online libraries.

Community of Developers and Online libraries – Low or no programming experiences landscape architectural professionals and researchers can access thousands of programmed codes through developer communities and online libraries. Most of the codes have detailed instructions with images or video tutorials, which enable users to easily follow and deploy codes without fully understanding the working logic.

Open source and extensible software/hardware – Arduino has an open-sourced software environment, which means it is available for extension for those experienced users. And all Arduino electronic boards use the creative commons license, which means landscape architecture professionals can be able to establish their own modules per research/projects' needs.

2.5 Measurement

Based on researched LAP factors (i. e. greenhouse gas and air quality), we selected electronic boards and sensors accordingly; programmed and combined them to an experimental smart device (Figure 3). The electronic components are: (1) one Kuman (Arduino-based) UNO R3 board, (2) one carbon dioxide (CO_2) and volatile organic compounds (VOCs) sensor module, (3) one digital particle ($PM_{2.5}$) concentration laser sensor module, (4) one micro SD card read/write module, (5) one temperature and humidity module, (6) one LCD screen module, and (7) one breadboard, which is only for the current experimental stage's convenience.

Research team put sensor nodes on the nine experimental sites. At the current stage, due to cities' regulations and consideration of sensors' safety, we cannot leave sensor nodes on-site without a team member attendee. We implemented experiments in different periods of several days. Each data recording period lasts two hours with five minutes data record intervals. We used this way to simulate sensor nodes automatical working scenarios in the real world. Although one team member needs to be present, sensors collect and store data automatically. That person's responsibility is only to take care of sensor nodes without discarding by others such as park managers or city municipal staff. Deploying a micro SD card is our current method to store sensor collected data. The SD card module writes collected data into a micro SD card in real-time, stores and transfers data to a computer for the following analysis step.

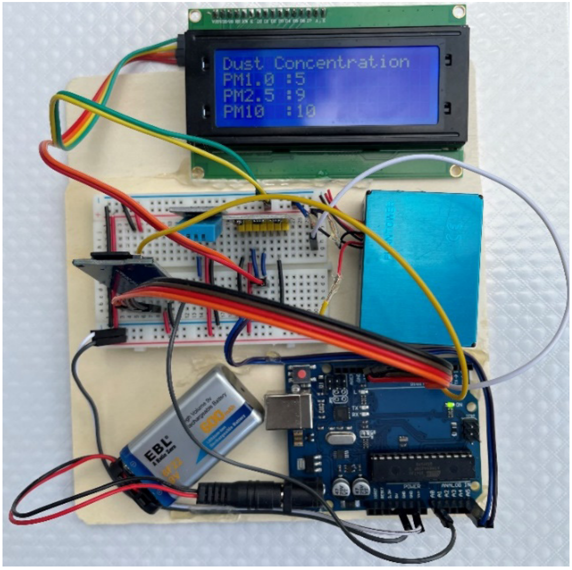

Fig. 3: The example of the experimental sensor nodes. A UNO R3 board is built with an LCD screen, a $PM_{2.5}$ sensor, a temperature and humidity sensor, a CO_2 sensor, and an SD card module. The power supply is a 9V 600mAh battery. A breadboard exists only for quick and convenient experimental assembly and reassembly.

3 Result

The following reported experiment was conducted on January 3, 2022, between 10:00 am to 12:00 pm. The graphs show the differences of CO_2 and $PM_{2.5}$ concentration according to six comparison sites in Atlanta: (1) suburban green space (SG), Kittredge Park; (2) suburban sidewalk area (SS), a sidewalk area near Kittredge Park; (3) suburban commercial area (SC); (4) urban green space (UG), Centennial Olympic Park; (5) urban concrete paving area (UC), a concrete parking lot near Centennial Olympic Park; and (6) urban buildings surrounded area (UB), Atlanta's downtown area.

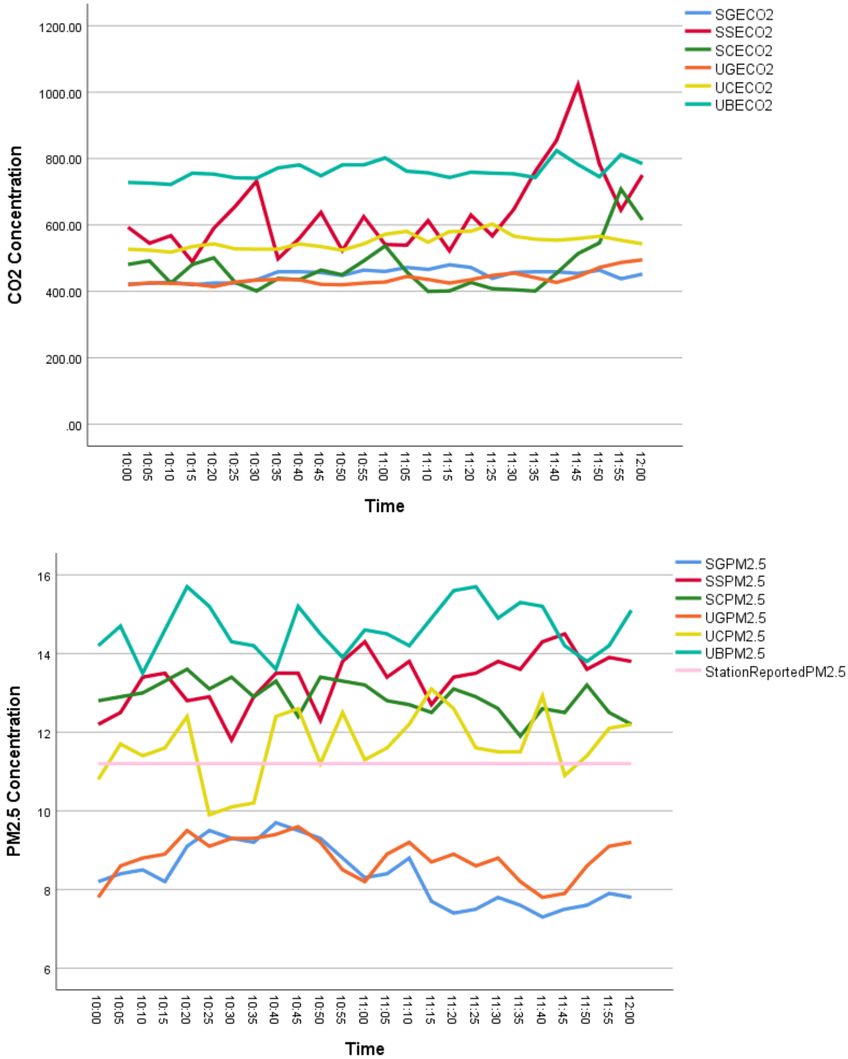

Fig. 4: eCO_2 and $PM_{2.5}$ changes (January 4, 2022)

The left image from figure 4 shows the CO_2 concentration changes of six settings during the experiment period. The SS and UB settings present higher CO_2 concentration fluctuation than the other four settings. The right image shows six settings' $PM_{2.5}$ concentration changes compared with a static publicly available $PM_{2.5}$ data the US IQAir Clean Air Facility (IQAir) program.

The mean comparison result of experimental sites' eCO_2 concentration is as follows (Table 1). Compared with the mean and standard deviation between the six groups, the UG had the lowest eCO_2 concentration level. In contrast, the UB showed the highest concentration level. SS rated the highest standard deviation while SG had the lowest number.

Table 1: Six sites' eCO_2 results of the mean comparison

	SGECO₂	SSECO₂	SCECO₂	UGECO₂	UCECO₂	UBECO₂
Mean	449.5200	635.6800	470.5600	437.7600	549.5200	762.2000
N	25	25	25	25	25	25
Std. Deviation	17.84218	124.15572	73.02287	20.52494	22.24882	26.14543
Minimum	420.00	489.00	400.00	414.00	518.00	722.00
Maximum	480.00	1022.00	708.00	495.00	603.00	824.00
Range	60.00	533.00	308.00	81.00	85.00	102.00
Variance	318.343	15414.643	5332.340	421.273	495.010	683.583

For the $PM_{2.5}$ section, we included the IQAir's $PM_{2.5}$ data in the mean comparison. (Table 2). Compared with the static IQAir data, the other six groups presented dynamic $PM_{2.5}$ concentration data. On average, the urban group (UG, UC, and UB) showed a higher $PM_{2.5}$ concentration level than SG, SS, and SC in the suburban group.

Table 2: The mean comparison of $PM_{2.5}$ concentration included the data collected from six experimental sites' sensor nodes and the publicly available data from IQAir

	$SGPM_{2.5}$	$SSPM_{2.5}$	$SCPM_{2.5}$	$UGPM_{2.5}$	$UCPM_{2.5}$	$UBPM_{2.5}$	Station Reported$PM_{2.5}$
Mean	8.3720	13.3480	12.8840	8.8040	11.6688	14.6320	11.200
N	25	25	25	25	25	25	25
Std. Deviation	.75912	.68137	.41801	.51759	.85450	.63424	.0000
Minimum	7.30	11.80	11.90	7.80	9.90	13.50	11.2
Maximum	9.70	14.50	13.60	9.60	13.10	15.70	11.2
Range	2.40	2.70	1.70	1.80	3.20	2.20	.0
Variance	0.576	0.464	.175	.268	.730	.402	.000

4 Discussion

This study indicates the feasibility of the landscape architecture discipline can have its own real-time, dense, accurate, and frequent quantified LAP data longitudinally. This study explores cheaply made smart sensors' capacities for longitudinally tracking environmental data and improving the LAP measurements. We analyzed and quantified the relationship between various urban/suburban settings and microclimate performances (eCO_2 and $PM_{2.5}$ changes).

The mean comparison of both eCO_2 and $PM_{2.5}$ concentrations shows the quantified impacts of site settings on micro-scale environments be collected by smart sensors longitudinally. Especially for the $PM_{2.5}$ part, compared with the static IQAir public data, our sensors recorded dynamic data clearly present $PM_{2.5}$ level changes in short time intervals in all six experimental sites.

Two research hypotheses have been supported. The statistical result supports our smart sensors' strengths and capacities in responding to the aspects of greenhouse gas and air quality data monitoring and analyses. The existing publicly available meteorological data limits landscape architectural professionals from accessing desired environmental data for specific conceptual or evaluating purposes in LAP projects. Compared to limited numbers of meteorological stations, smart sensors empower landscape architectural professionals to create a dense sensor network to achieve dense and accurate data and better understand project sites' micro-scale environments. Also, self-built sensors allow users to collect desired environmental data accordingly for projects' specific purposes. Furthermore, smart sensors support improving LAP measurements not only on data's density and accuracy but also on providing frequent LAP data. Landscape architectural professionals can adjust data collection frequency based on project scale, size, and type. Compared to hourly meteorological data, smart sensors allow data resolution to jump into minutes, even seconds.

Due to the objectives of this study and various variables in experimental sites that would weaken the statistical meaning, we did not conduct the ANOVA test.

When we analyzed the result, some unconsidered factors attracted the research team's awareness. The wind is an essential variable. We assume some eCO_2 and $PM_{2.5}$ data's fluctuations in results were impacted by wind. Also, unpredictable factors such as traffic flow and vehicles' types and conditions could cause data fluctuations as well. These factors need to be covered in further study's scope. However, from a different perspective, these valuable potential research variables support the necessity and importance of using smart sensors to track micro-scale environmental data longitudinally.

In addition, when we shared our study and results with some landscape architects, we realized sensor nodes' location should be reported in more detail. It will help them to deeper understand various microclimates in their project sites. Moreover, once we plant dense sensor networks on future experimental sites, we have to know each node's exact location for data analyses.

More sensor types should be included in future studies to quantify more. We need to consider other setting types (e. g. industrial and residential sites) and the regional setting. The rural area is a considerable setting as there is much less available environmental data in rural areas than in urban and suburban regions. In addition, experimental settings should be divided more specifically (e. g. tree dominated green space, green space with some trees and shrubs, open green space, etc.).

5 Conclusion

In this paper, we have described our experiments of using Arduino-based smart sensors to collect CO_2 and $PM_{2.5}$ concentration data on six experimental sites. Our finding indicates the strengths of smart sensors in collecting and quantifying greenhouse gas and air quality data longitudinally. This study introduces an alternative way to collect the landsdcape architecture discipline's own longitudinal environmental data and help to improve the LAP measurements. It enables landscape architectural professionals to access dense, accurate, and frequent environmental data to understand their sites' microclimate conditions better and make decisions accordingly. Although there are some limitations in this research, the insights gained from our findings provide an alternative approach to study microclimates and to improve the LAP measurement.

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