Authors' response to minor revisions

2/9/18

Thank you for all your time and care in considering this manuscript for publication. We agree that the paper has been much improved from the beginning. Below, you will find that we have addressed all of the comments.

Associate Editor Decision: Publish subject to minor revisions (review by editor) (30 Jan 2018) by William R. Simpson

Comments to the Author:

Both of the re-reviewers of the manuscript agree that the manuscript is sufficiently improved to be published after minor revisions. I attach the comments of both reviewers so that you can make these minor revisions to the manuscript. Thank you for addressing these minor changes and congratulations.

Referee 1:

"Intra-urban spatial variability of surface ozone in Riverside, CA: viability and validation of low-cost sensors", Sadhighi et al.

2nd version.

This manuscript has been improved dramatically. The decision to remove the CO2 analysis allows more focus and precision on the O3 testing, validation, and interpretation. I have very few mostly wording fixes/comments below.

Specific/technical comments:

P 3, L8: "these sensors" - is this referring to metal oxide sensors specifically, or any low-cost ozone sensor? Just repeat and make clear.

Changed

p3, L13: Seems odd to say "regional air quality body" without naming it. Is it the EPA region or the SCAQMD?

Clarified that this meant SCAQMD.

P3, L16: Also odd to mention funding source here - should this be better located in the acknowledgements at the end of the paper?

Changed, and moved to the acknowledgements

p3, L20, perhaps say "low-cost metal oxide ozone monitors"? Or low-cost ozone monitors at least, to differentiate from pm2.5 which is mentioned right before.

Changed.

P6, prior to the results, I was expecting another short section on "deployment",explaining which sensors were deployed and where. Presumably the three sensors noted in the "validation" section were kept near reference monitors for "validation", but the rest were deployed throughout the region as in Fig.1. A few sentences could explain this and refer to the timeline in Fig.1 .

We have addressed this comment by creating a section 2.3 Field Deployment between the calibration and validation sections in order to make clear the order of events.

p8, L15, this is the first mention of Linear 4, 4T, etc. Perhaps what they are should mentioned here, or prior to Eq 1? (is Eq 1 Linear 4T?). [this was a comment in the first round, which the authors say they addressed, but not sufficiently].

A sentence was added before equation 1 to clarify that the model that we call linear 4T is also equation 1.

p8, L18l should be Masson et al.

The co-authors feel that et al. and co-workers are interchangeable terms and provide some variability to the language.

p9, L18 should have a comma after "contant pressure value"

Thank you, changed.

p9, L16 - P10 L2. This seems odd and a bit arbitrary, to filter the UPod data just based on a maximum value seemed unrealistic. Do you have reason to think the sensors fail for some reason and read higher values than they should? Did this occur during the calibration phase, or for the validation data? Are they discontinuities from a time series (i.e. perhaps the ozone reading jumps suddenly)? At 170 are they correct?

I see the response to my original comments explain this a little more, but the amount of data points affected and final effect could be mentioned in the text as well for the other readers.

We believe we have justified the maximum values. The reason for the filtering was in part due to power interruptions (e.g. during data downloads, power outages) which caused sensor values to abruptly change requiring a warm up period to stabilize. Not all the times of power interruptions are predictable or trackable. In addition, abrupt power changes can last for a short time not captured by the consecutive differences filter method. We mention that table S2 is the place to view data percentage losses.

p10, lines 4-9 - this seems reasonable, so I wonder why the absolute magnitude was needed to be filtered as well. Did the high (> 171 ppb) values occur in the paired sensor in the same location as well? If not, then perhaps some agreement between pairs could be used as a data quality indicator?

We've addressed the first part of this comment in the previous one. This would be an interesting data quality indicator. However, we did not test the concurrent occurrence of high data points between sensors, and believe this level of investigation is outside of our scope.

P14 L5 & L9, should be "Gao et al." in both places.

Previously addressed.

P14 L9 should refer to Fig. 7

Yes, thanks.

Here (Fig 7 and text) and elsewhere you should be clear with the word "concentration". I believe these are mole fractions or mixing ratios (not sure which). A concentration is a mass (or number of moles, if molar) per unit volume and would be in units of moles per liter or grams per liter. At the very least, they should define that they will be using the word concentration to mean moles of ozone per moles of dry air (or whatever is appropriate).

A sentence was added in section 2.2 clarifying that in this paper, concentration refers to the mixing ratio.

p15, L6-10: Although now I am clear that "collocated" = calibration period and spatially distributed = deployment period, this paragraph could be even clearer, for example:

"U-Pod ozone measurements are more correlated to each other during the calibration period (when they were collocated) than during deployment, when they were spatially distributed through the region. The R2 values between collocated pods are very high, with their medians varying from 0.92-0.99 ppbv. Conversely, during the deployment period, the spatially distributed pods were less correlated with each other, leading to R2 distribution medians between 0.52 and 0.86. "

Because we have added the section on deployment near the beginning of the paper (section 2.3), we feel that this distinction has been made clearly.

P16 L23 should be "indicating"

Yes, changed.

Supplement:

Fig S1 typo on y-axis (magnitude)

This typo has been fixed

references:

In the text, often references refer to the authors and then include them again in the citation, that should be fixed. Example p7, line 10, "Barsan and Weimar (Barsan and Weimar, 2001)" should just read Barsan and Weimar (2001) ....

There seem to be some references in the final list that are not referred to in the paper; most seem to be left over from the original manuscript version which included CO2 (Kort, Hutyra, and others). They should be checked thoroughly and removed.

The manuscript has been read through for both of these issues, and addressed them.

Referee 2:

The revised version of the manuscript is significantly improved from the original submission. It seems like the authors have addressed all of the reviewer comments from the first round of comments and significantly revised the manuscript. I have several minor comments below.

(1) The description of the humidity term for Equation 1 is a bit confusing (I do not quite know what a "global absolute humidity" is). It seems like there should be a simpler way to express that all U-Pods, even during deployment, use the AQMS humidity measurement.

We've used global absolute humidity as a definition of this method of calculating the humidity for all U-Pods, at the end of section 2.2. Also in section 2.2, we added a few clarifying words on line 2 of page 6.

(2) Figure 1 should include the year of deployment somewhere near the timeline.

We've added the year to Figure 1

(3) Figure 3 needs a higher resolution image.

We have increased the quality of the text in this image

(4) Last paragraph of section 3.2 - I understand that the authors want to be totally transparent, and therefore describe the situation with the U-Pods that had electrical issues and therefore the data were not used for analysis. However, including these U-Pods throughout the rest of the

manuscript (e.g., in the map in Fig 1) hampers readability. Perhaps it is appropriate to describe the calibration of these units, exclude them from Fig 1, and briefly describe why the data were not used in analysis.

The authors feel it is important to fully describe the measurement campaign as it unfolded. Information regarding the failure of the sensors in addition to showing where these monitors were deployed allows the reader to understand the extent to which the failure occurred and accurately depicts challenges of sensor networks. We also clearly indicate that those sensors are not used in the subsequent analysis.

(5) Figure 6 - Are the red lines in (i) and (ii) a best-fit or 1:1 line? Visually, it would help to rescale the axes so that, at the very least, the axis labels show the same numbers.

This figure was re-done in order to label the line on the (i) and (ii) graphs as 1:1, and also the axes were squared and re-numbered.

(6) The poorer performance on the right of Fig 6 is interpreted purely as time drift, though Eq 1 does include a term for the time drift. Would performance at week 9 be improved by a longer calibration co-location? This could be tested for the U-Pods that remained at an AQMS station for the entire deployment.

This is an interesting area for future research. Many groups are interesting in trying to figure out the exact length and frequency of collocations which work best with low-cost sensors of various types. We wanted to use the same calibration method (including length) for all U-Pods in order to compare them accurately. This deeper investigation is out of our scope.

(7) Figures 10 and 11 focus on differences between D7 and D3. In Figure 1 it looks like D3 is co-located with D4 and DF. Do those U-Pods also see lower O3 than D7? I realize that these two U-Pods have the issue with the electronics board (Section 3.2), but based on Table 2, it seems like the electronics issue introduces a relatively stable bias that can be corrected. Do D4 and DF consistently read lower than D7 even after a bias correction?

Unfortunately, we do not have sufficient information to know if the bias is consistent across pods as D5 was the only pod that suffered the electrical issue yet had collocated reference data with which to compare. The electrical issue occurred between the calibration collocation and the deployment period which would prohibit accurate application of the calibration models.

Intra-urban spatial variability of surface ozone in Riverside, CA: viability and validation of low-cost sensors

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Abstract. Sensor networks are being more widely used to characterize and understand compounds in the atmosphere like ozone (O_3). This study employs a measurement tool, called the U-Pod, constructed at the University of Colorado Boulder, to investigate spatial and temporal variability of O_3 in a 200 km^2 area of Riverside County near Los Angeles, California. This tool contains low-cost sensors to collect ambient data at non-permanent locations. The U-Pods were calibrated using a pre-deployment field calibration technique; all the U-Pods were collocated with regulatory monitors. After collocation, the U-Pods were deployed in the area mentioned. A subset of pods was deployed at two local regulatory air quality monitoring stations providing validation for the collocation calibration method. Field validation of sensor O_3 measurements to minute resolution reference observations resulted in R^2 and root mean squared errors (RMSE) of $0.95 - 0.97$ and $4.4 - 5.9$ ppbv, respectively. Using the deployment data, ozone concentrations were observed to vary on this small spatial scale. In the analysis based on hourly binned data, the median R^2 values between all possible U-Pod pairs varied from 0.52 to 0.86 for ozone during the deployment. The medians of absolute differences were calculated between all possible pod pairs, 21 pairs total. The median values of those median absolute differences for each hour of the day varied between 2.2 and 9.3 ppbv for the ozone deployment. Since median differences between U-Pod concentrations during deployment are larger than the respective root mean square error values, we can conclude that there is spatial variability in this criteria pollutant across the study area. This is important because it means that citizens may be exposed to more, or less, ozone than they would assume based on current regulatory monitoring.

1 Introduction

Tropospheric ozone formation and destruction is a complex chemical process involving a series of interdependent chemical reactions of volatile organic compounds (VOCs) and nitrogen oxides (NO_x) in the presence of ultraviolet (UV) radiation (Jacob, 2000). The reactants are produced and consumed both naturally and through anthropogenic activities, as well as through atmospheric chemical reactions. In urban areas, the sources of these emissions and their impact on ozone formation vary in time and space. For example, trucks and cars, acting as mobile sources of primarily NO_x and VOCs, respectively, contribute to the formation and/or destruction of ozone depending on mixing ratios of each and the presence of UV radiation. Due to the health implications of increased ozone exposures, local, regional and national regulatory bodies have the obligation to measure, report and mitigate ambient ozone levels according to the National Ambient Air Quality Standards (NAAQS) (EPA, 2013).

1 The equipment employed at air quality monitoring stations (AQMS) is relatively expensive (>$100k/station) and requires
2 substantial resources to maintain (e.g., technical expertise, shelter, land and power). As such, increasing the spatial resolution of
3 the AQMS network is not readily feasible. Thus, one benefit of low-cost, portable sensing technology is the ability to collect data
4 at more locations, increasing spatial resolution of existing AQMS. These technologies typically range in cost of $1-5k yet often
5 require significant data retrieval and processing resources in addition to extensive characterization of the sensor in a given
6 application. These technologies, in virtually all applications, still depend on reference grade measurements or standards in order
7 to fulfil most research objectives. As such, many view these tools not as replacements of regulatory measurements but rather a
8 supplement to them (Clements et al., 2017). Detecting pollutant variability between the regulatory AQMS supports the idea that
9 more detailed information can be obtained by increased monitoring between existing stations.
10
11 Regulatory monitoring for compliance with the ozone NAAQS is undertaken as dictated by the Code of Federal Regulations, which
12 states, "The goal in locating monitors is to correctly match the spatial scale represented by the sample of monitored air with the
13 spatial scale most appropriate for the monitoring site type, air pollutant to be measured, and the monitoring objective." (EPA,
14 2006). Ozone monitoring site types include: highest concentration, population oriented, source impact, general/background and
15 regional transport, and welfare-related impacts. Siting involves choosing a monitoring objective, selecting a location that best
16 achieves those goals, and determining a spatial scale that fits the monitoring objective.
17
18 The minimum number of ozone monitoring sites required by the US Environmental Protection Agency (EPA) via the Code of
19 Federal Regulations (CFR) in the Riverside and San Bernardino counties is three, given the population is between four and ten
20 million. As of 2013, there were 20 active regulatory sites measuring ozone in Riverside and San Bernardino counties (California
21 Air Resources Board, 2013). While this monitor density is more than sufficient for regulatory requirements, recent studies suggest
22 that the current spacing is not sufficient to capture high spatial resolution of concentration variations (Bart et al., 2014; Moltchanov
23 et al., 2015). This variability could potentially be used to inform exposure assessment for health studies as well as improve our
24 understanding of pollutant sources and fate (Simon et al., 2016; Lin et al., 2015; Blanchard et al., 2014).
25
26 Networks of air quality sensors have been deployed in various settings. Moltchanov et al. (2015) measured O_3, NO_2 and VOCs in
27 Haifa, Israel in the summer of 2013 to test the viability of sensor networks measuring small scale (100s of meters) intra-urban
28 pollution (Moltchanov et al., 2015). Two of the sites used in that study, sites A and B, had correlations between 0.82 and 0.94 with
29 each other, but correlations between A or B and a third site, C, were much lower, between 0.04 and 0.72. Their finding of
30 spatiotemporal variability on a neighbourhood scale means that spatiotemporal variability on the scale of <10km can also be
31 expected. This finding of spatial variability at that temporal and spatial scale was not linked with robust in-field sensor validation
32 that would ensure the result was actual concentration differences instead of measurement artifacts. Sensor validation is an important
33 component of using low-cost sensors because they are subject to drift and confounding species. Drift is the change in measured
34 concentration with time because of factors inherent to the sensor, not necessarily the environment that is being measured. Many
35 metal-oxide sensors have been found to be affected by high temperatures and humidity (Rai et al., 2017). In 2013, Williams et al.
36 (2013) quantified a tungstic oxide ozone sensor in the lab while addressing some of the main drawbacks associated with metal
37 oxide (MO_x) ozone sensors (i.e. drift/long term stability, material degradation and sensitivity fluctuations) (Williams et al., 2013).
38 The ozone sensors in that study were held in a temperature-controlled environment, as the tungsten oxide sensor's conductivity
39 varies strongly with temperature and may affect the concentrations. In the work presented here, temperature was included as a term
40 in the model in an effort to address this issue after, rather than before, data collection. Researchers also deployed these gas

semiconductor sensors in British Columbia over roughly 10,000 km^2 for three months finding low errors (3 ±2 ppbv) between hourly averaged sensor and reference instruments while documenting the challenges of using, in this instance, wireless sensor networks (Bart et al, 2014). Lin et al. (2015) demonstrated high correlations (0.91) between tungsten oxide semiconductor ozone sensors and hourly averaged Federal Reference Method (FRM) chemiluminescence gas analyzer measurements in Edinburgh, UK with similar magnitudes (Lin et al., 2015). While many of these studies show good agreement between metal oxide sensors and reference instruments; there is still a need for uncertainty estimation and framing of the deployment results in light of those uncertainties.

Here we specifically seek to answer the question, are these sensors metal oxide sensors able to detect significant differences on scales that are smaller than current EPA reference stations, given their quantification uncertainty? This study is unique in that the Inland Empire region of the greater Los Angeles frequently experiences high levels of ozone resulting in nonattainment of the NAQQS ozone standard. The combination of abundant sunlight and high VOC concentrations in the presence of NOx is conducive for the formation of ozone. The Pacific inversion layer over southern California and mountains that form a natural basin act together to keep pollutants from dissipating (Littman and Magill, 1953). Moreover, the regional air quality regulatory body, South Coast Air Quality Management District (SCAQMD), has expressed increased interest in low-cost air quality sensor applications and recently installed the nation's first testing center for such technologies. As such, Riverside, CA is an ideal test bed to answer our research question. This research was conducted in part for the CyberSEES project (NSF Award ID: 1442971).

2 Methods

This field study was conducted within a 200 km^2 area of northwestern Riverside county, California, a region frequently designated as nonattainment for failing to meet requirements for ozone and particulate matter designated by the EPA (EPA, 2016). Thirteen low-cost ozone monitors were deployed within aan 8 km radius in Riverside in the summer of 2015 (Fig. 1). These monitors were sited in the cities of Riverside and Jurupa Valley with the aid of the South Coast Air Quality Management District (SCAQMD). Sites were chosen based on availability and power access. Ten locations were identified (Fig. 1) representing a variety of site conditions ranging from university campuses and residential neighborhoodsneighbourhoods to commercial and industrial zones. Within this area, there are two regulatory AQMS that measure O$_3$: Rubidoux and Mira Loma. The transportation authority in California, Caltrans, records traffic volume information for many large highways. Annual average daily traffic (AADT) is recorded at many road intersections. On two major roads in the study area in this region, specifically Hwy 91 and Hwy 60, the averaging of all the milepost traffic count data between junctions shows AADTs of 180,500 and 220,500, respectively ("2015 Traffic Volumes", 2017). Van Buren Avenue does not have AADT data. However, it has two lanes each way, while the other highways have more than four. In general, there is a large number of vehicles traveling around and through this study area daily; these vehicles likely represent the dominant sources of NO$_x$, and VOCs, precursors to ozone formation.

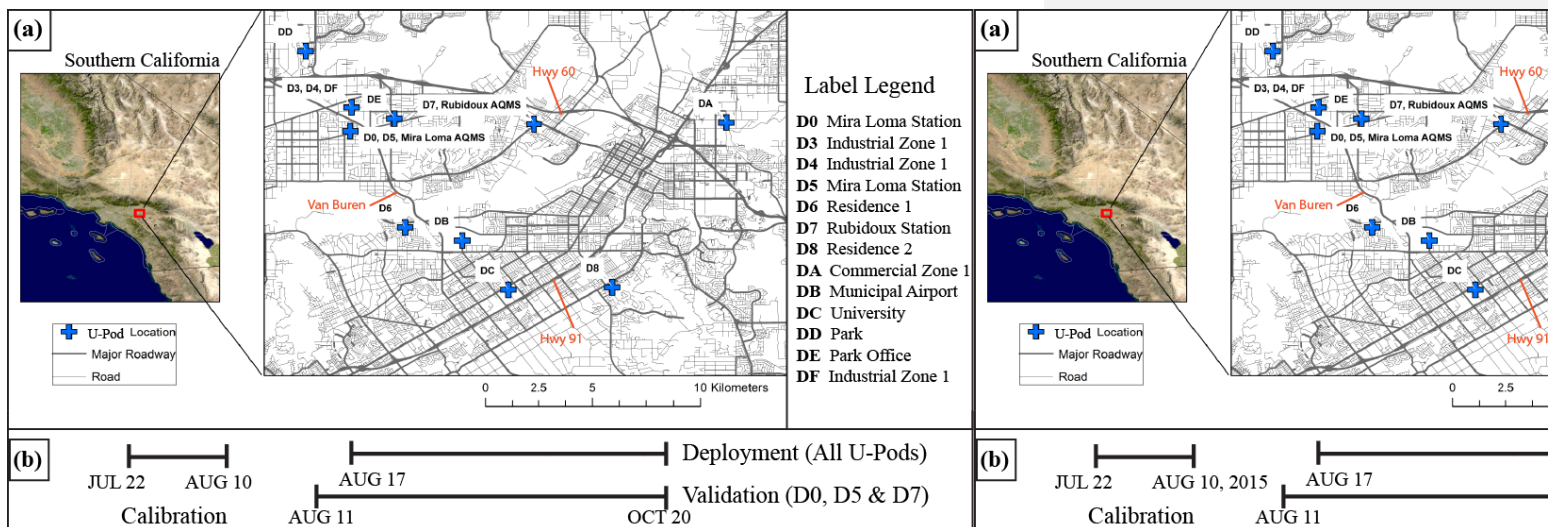



Figure 1. (a) A map of the deployment area. The crosses indicate U-Pod locations, with the AQMS labelled by name and (b) a timeline of project phases, from calibration to deployment. Validation overlapped with the deployment time period.

2.1 Low-Cost Monitor

Measurements were taken using the University of Colorado U-Pod air quality monitoring platform (mobilesensingtechnology.com) described in previous work (Piedrahita et al. 2011). Briefly, the U-Pod consists of an Arduino data acquisition system and a suite of environmental sensors enclosed in a small, ventilated, portable case (Fig. 2). Specifically, O_3 is measured using a metal oxide (MO_x) sensor, (MiCS 2611, SGX Tech. formerly e2v ~ $11). Enclosure air temperature and relative humidity were also measured. U-Pod locations were verified using an on-board GPS chip and all data were saved to a micro SD card. Logged data were collected into minute medians to match the highest temporal resolution of nearby regulatory air quality stations. Median values were used to reduce the influence of outliers within each minute. Duplicate O_3 sensors were included in most U-Pods to investigate sensor variability and model performance.

MO_x sensors operate through reduction/oxidation processes at the gas-semiconductor surface resulting in changes in electrical resistance (Barsan and Weimar, 2001; Korotcenkov et al. 2007). This change in resistance is in part a function of the concentration of the target gas (i.e., ozone) in the surrounding air, as well as temperature and humidity. Comprehensive reviews of MO_x gas sensors (Korotcenkov et al., 2007) and experimental tests (Masson et al., 2015; Rai et al., 2017) document potential concerns of using sensors in long term ambient monitoring campaigns and other sensing applications. A variety of environmental factors such as long-term exposure to water causing hydration of the oxide surface layer can lead to drift in the sensing chemistry, as well as cross sensitivity to other oxidizing species like NO_x. This poses special concern for conditions amenable to condensation. The MiCS 2611 datasheet warns specifically of overheating, a cause of sensor degradation or possibly permanent damage. Heating power supplied to the sensing resistor at 80mW is recommended to keep this element at 430°C (e2v MiCS-2611). Lower sensor resistor temperatures can result in decreased sensitivity and longer response times making measurements of heater element voltage and/or well-regulated circuits valuable in regards to long term sensor integrity (Masson et al., 2015). The magnitude and sources of sensor variability from this study are discussed further in Section 3.1.

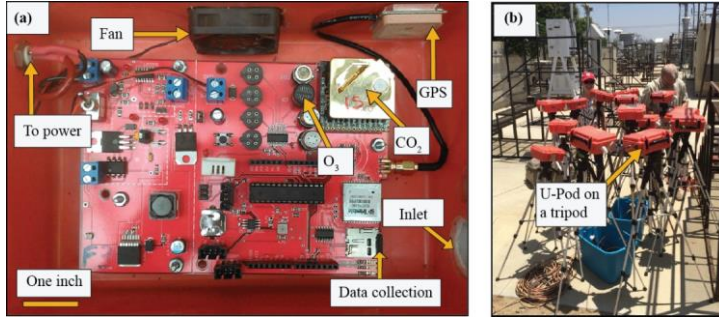



Figure 2. Demonstration of the U-Pod layout (a), including sensor locations and other features. (b) A photo of the field calibration collocation at Rubidoux AQMS.

2.2 Field Calibration

Sensors were calibrated using a field calibration technique commonly employed with low-cost sensor networks which involves collocating sensors with a reference grade monitor for an extended period of time prior to and/or directly following a field deployment (Piedrahita et al, 2011). The concept of field calibration is straightforward: develop regressions between the reference measurement and gas sensor signal using combinations of concurrently collected environmental data. All U-Pods were calibrated at the SCAQMD Rubidoux AQMS (elev. 248m above sea level) for three weeks, July 22 – Aug 10, prior to the field deployment. The Rubidoux station sampling scale is classified as "urban" for ozone and is located 119 m from Hwy. 60 (SCAQMD, 2015). Reference ozone is measured using a designated Federal Equivalent Method (FEM) Thermo 49i dual cell UV photometric monitor. This monitor is equipped with temperature and pressure compensation, which adjusts for changes in sensor signal due to changes in the sample gas. Numerous field calibration relationships were developed using a suite of custom MATLAB codes. This process involves performing linear and nonlinear regressions using sensor signal, measured U-Pod enclosure temperature, absolute humidity and time (to account for sensor drift) against the reference gas concentrations. MO_x sensor signals are the ratio of instantaneous resistance to a reference resistance defined during the field calibration. To evaluate the resulting regression fit, we used coefficient of determination (R^2), root mean square error (RMSE) and explored residuals with relation to each input variable, specifically looking for normal distributions. An interaction term between temperature and ozone concentration improved the model fit at higher mixing ratios leading to overall higher correlations, lower error, and improved residual distributions (see Table 1 in Section 3). The best performing model for ozone during calibration incorporates temperature, absolute humidity, and ~~time~~ time, and is also referred to as the linear 4T model (Eq. 1).

$$S = p_1 + Cp_6(T + p_2) + Tp_3 + Ap_4 + (t - t_o)p_5 \qquad (1)$$

In Equation 1, S is the sensor signal in R/R_o, where R is the sensor resistance and R_o is a specific normalizing resistance value. C is the pollutant concentration in ppbv, T is the temperature in Kelvin, A is absolute humidity in mole fraction, $t-t_0$ is the duration since the start of the calibration and the p variables are coefficients determined by the regression minimising least squares. Throughout this paper, concentration refers to the ozone mixing ratio. In this model, a global absolute humidity term was employed;

1   this absolute humidity was calculated using Rubidoux reference station temperature and relative humidity, and a constant pressure,

2   and was used in all U-Pods throughout the measurement campaign. The values of these coefficients are described in section 3.1.

4   **2.3 Field Deployment**

5   Following the field calibration, the U-Pods were relocated throughout the study area to the sites shown in Fig. 1. Sites were chosen

6   based on availability and zoning. A mix of industrial, residential and commercial areas were selected including a university campus

7   and public parks. U-Pod D7 remained at Rubidoux station while D0 and D5 were relocated to Mira Loma Reference station for

8   the purpose of validation.

9   **2.43 Field Validation of Model Performance**

10   To quantify the performance of the calibration model coefficients, a nearly three month long validation dataset was collected

11   comparing reference grade gas concentration measurements to sensor data after applying the model coefficients to the raw sensor

12   data. Previous air quality sensor campaigns have either had mixed results when performing validation in the field or no validation

13   was included. Moreover, no study, to our knowledge, has validated ozone sensor measurements to reference grade monitors at one-

14   minute resolution. Two validation approaches were investigated. First, we compared sensor measurements to reference grade

15   observations in the *same* location as was used for the field calibration. Second, we compared sensor measurements to reference

16   grade observations in a *different* location from the field calibration site. The second approach can be used to address error associated

17   with site specific confounders, such as NO_x or transient temperature effects present away from the initial collocation site. U-Pod

18   D7 was validated using the first approach, as it remained at Rubidoux AQMS for the duration of the deployment. U-Pods D0 and

19   D5 were moved from Rubidoux AQMS, after the calibration, to Mira Loma AQMS and validated using the second approach. The

20   outcome of the field validation is presented in the results.

21   **3 Results**

22   **3.1 Field Calibration Results**

23   Calibration results for various models showing correlation and RMSE of the calibrated ozone data against the reference monitor

24   data are provided in Table S1. For the sake of simplicity, results from the overall best performing model, see Eq. 1, are shown in

25   Table 1. R^2 values and errors (RMSE) range from 0.97 – 0.99 and 1.8 – 3.9 ppbv, respectively.

27   **Table 1: Field calibration results of the model, see Eq. 1, for ozone sensors showing R^2 and RMSE with the reference monitor data.**

28   **Two O_3 entries means there are two different sensors in the same U-Pod.**

U-Pod ID	D0	D3	D4	D5	D6	D7	D8	DA	DB	DC	DD	DE	DF
Sensor 1 R2, RMSE	0.98, 3.1	0.98, 3.0	0.98, 2.6	0.99, 2.7	0.98, 3.5	0.98, 2.8	0.98, 3.0	0.97, 3.9	0.98, 2.8	0.99, 2.6	0.99, 1.8	0.97, 3.4	0.98, 3.1
Sensor 2 R2, RMSE	0.98, 3.2	0.98, 3.0	0.98, 2.7	0.98, 3.0	0.99, 2.4	0.98, 3.0		0.97, 3.9		0.98, 2.7	0.99, 1.8	0.98, 2.9	0.98, 3.0

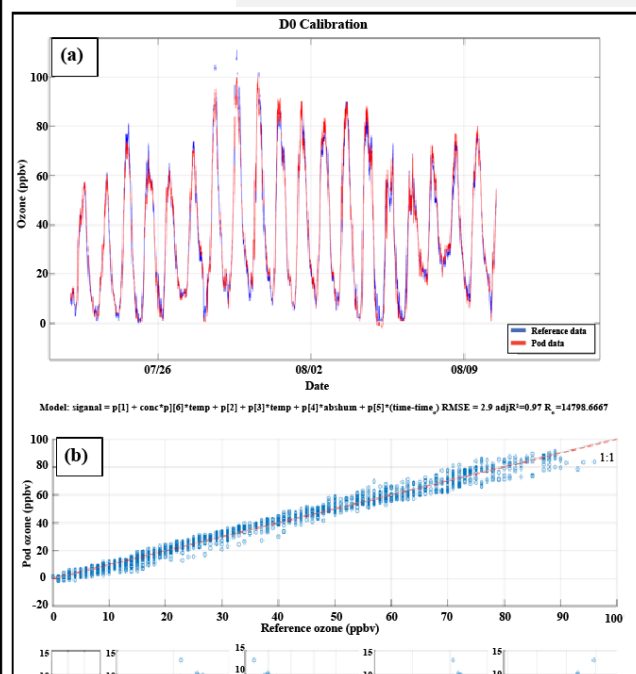
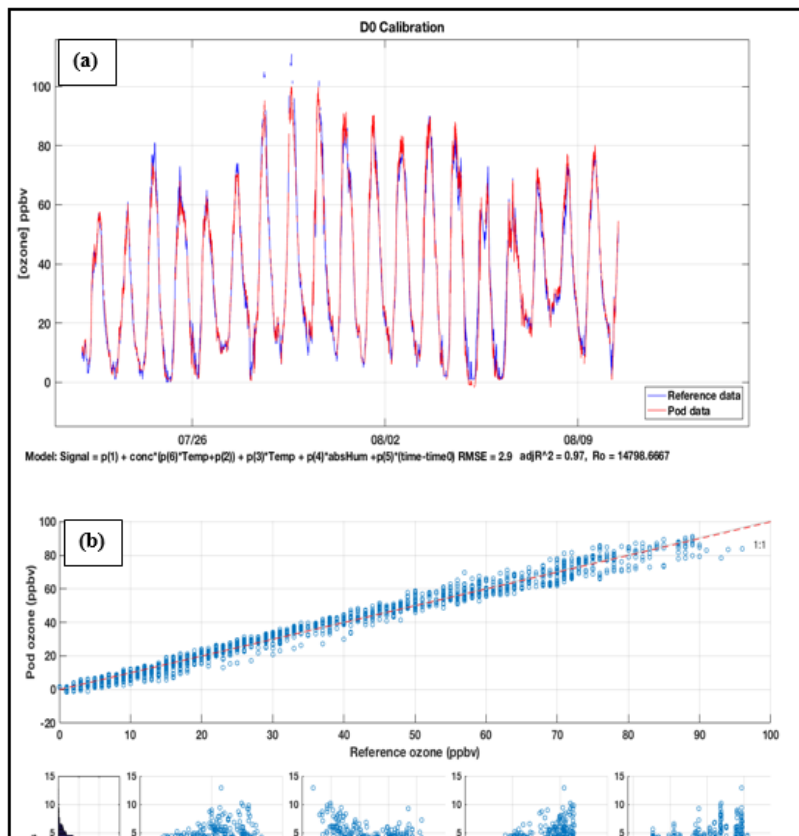
1 Figure 3 illustrates the calibration results for U-Pod D0. Residuals were calculated as modeled minus reference instrument

2 concentrations. The normally distributed residuals shown in panel c were indicative of an unbiased model. Residuals were plotted

3 versus various model parameters to assess bias in the model performance as a function of the predictors. The slightly negative

4 slope of the trend line in panel e indicated under predicting at increasing absolute humidity whereas positive slopes in panels d and

5 f shows the opposite trend, slight over-prediction at higher values of concentration and temperature. The R^2 and RMSE values for

6 the calibration of this sample U-Pod were 0.97 and 2.9 ppbv respectively.

8 **Figure 3. Example calibration results for one ozone sensor in U-Pod D0. Panel (a) shows the modeled ozone sensor time series (red)**

9 **with the reference measurements (blue) along with the model expression below and (b) shows a scatterplot of the minute**

10 **measurements, (c) the distribution of residuals and the relationship between residuals and model variables: (d) concentration, (e)**

11 **absolute humidity, (f) temperature, and (g) time.**

13 The quickly expanding sensor community has been convening to discuss practical and theoretical considerations of low-cost sensor

14 applications in the modern landscape identifying a need for increased understanding of inter-sensor variability (Clements el al.,

15 2017). Few groups have thoroughly investigated the physiochemical relationships governing MOx (and more specifically tin oxide)

16 sensor operating principles. Yet, Barsan and Weimar (~~Barsan and Weimar,~~ 2001) and subsequently Masson et al. (~~Masson et al.,~~

17 2015) lay forward an in-depth discussion on MOx conduction models and how those models incorporate chemical kinetics and

1 semiconductor electrical properties in explaining sensor signals. Masson et al. focused particular attention to temperature effects

2 finding ambient temperature to be one of the most significant confounders in ambient air monitoring using CO sensors (MiCS-

3 5525). Petersen et al. explored the experimental effects of power supply fluctuations on O_3 (MiCS-2614) and NO_2 (MiCS-5914)

4 sensors as it relates to acute sensor response and long term sensor stability finding different responses from sensors exposed to the

5 same environment – crediting these differences to mainly manufactural discrepancies (Petersen et al., 2017).

6 Additional insight into this effort can be gleamed by exploring the results of sensor-specific model parameters from the nearly

7 three-week calibration period of this study. To directly compare model parameters (i.e., coefficients), standardized regression

8 coefficients were generated by rescaling model input variables from 0 to 1. Rescaling was achieved by dividing the difference

9 between each variable data point from its respective distribution minimum by the maximum difference measured (e.g., [v_i-

10 v_{min}]/[v_{max}-v_{min}]). This process allows one to directly compare the magnitude of one predictor variable to any other; an advantage

11 of dimensionless analysis. Figure 4 shows the fractional contribution of each model parameter during the calibration period towards

12 estimating the sensor signal (R/R_o). Concentration (reference, ppbv) and the concentration temperature interaction term combined

13 explain 86% of the predictive capability of Eq.1 for the average sensor used in this campaign. The temporal drift coefficient (p5)

14 contributes less than one percent to the overall regression indicating minimal signal drift during the 19 days of calibration and also

15 explaining the minimal improvements in the descriptive statistics from the "Linear 3" and "3T" models to the calibration models

16 including a temporal drift term (e.g., "Linear 4" and "4T", see Table S1). Absolute humidity, temperature and the intercept,

17 combined, are less than 15% of the total predictive contribution. Figure 4 acts as visual evidence as to the significance of the

18 concentration-temperature interaction feature in this sensor model and perhaps other gas-specific MOx sensor models. This

19 interaction term could be capturing what Masson ~~and colleagues~~et al. discovered when performing MOx sensor signal regressions

20 with temperature and CO reference gases; namely, "this improvement of fit with concentration coincides with the observation that

21 the response data [R/R_o] becomes more linear with temperature as concentration is increased" (Masson et al., 2015). Figure S1

22 illustrates the inter-sensor standardized regression coefficient variability.

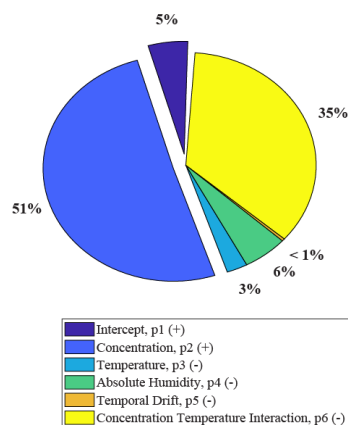



Figure 4: Average relative effect size of model parameters predicting sensor signal (R/R_o) from standardized regression coefficients.

The direction of the parameter effect is shown in the legend (+ or -).

28 It is important to note that the reference resistance, R_o, which is the resistance in clean air, had moderately high inter sensor

29 variability; a coefficient of variance (standard deviation divided by the mean) of 0.92. This reference resistance corresponds to the

1 minimum resistance at 25 °C, and each sensor has a different R_o. Differences in R_o could possibly be explained by sensor age or

2 even MO_x nanostructure as posed by some research (Sun et al., 2012). Manufacturer heterogeneity, sensor age and lifetime

3 exposure to oxidants are posed as potentially contributing to this variation but more investigation is recommended in future

4 sampling (Rai et al., 2017).

6 **3.2 Deployment Data Filtering and Processing**

7 Some temperature and humidity values were experienced by the U-Pods during the deployment that were not experienced during

8 the calibration time period. This means that the environmental parameter space sampled during the calibration time did not cover

9 the parameter space experienced during the deployment. Deployment data were filtered for conditions that would require

10 extrapolation, an example of which is shown in Fig. 5. Because ozone measurements are dependent on temperature and humidity,

11 one way to reduce error in the deployment data is to only use ozone data points whose temperature and humidity were in range of

12 that of the calibration data. All U-pod data from the deployment period were filtered to eliminate points that had temperature and

13 relative humidity values out of the ranges recorded during calibration. The global absolute humidity in Fig. 5a is the same for all

14 U-Pods. Normally, the absolute humidity would be calculated for each U-Pod using its individual recorded temperature, relative

15 humidity, and pressure. However, during the deployment, the relative humidity sensors failed in several U-Pods. The relatively

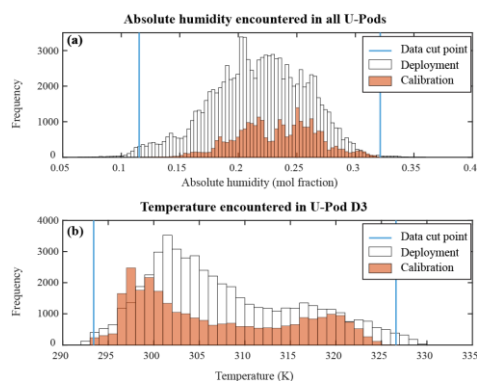
16 high chance of sensor failure in the field is one of the limitations of low cost sensor networks. Four of the U-Pods experienced RH

17 values below zero. However, the RH sensor sets these values to zero. Therefore, there was no way to recover any data below zero.

18 All of the U-Pods experienced, at some point, at least one week of missing data. Because of this, temperature and relative humidity

19 data from Rubidoux AQMS, along with a constant pressure value, were used to calculate the global absolute humidity for the

20 Riverside area for each minute. During calibration, the same values of absolute humidity were used for each U-Pod, but

21 temperatures were U-Pod specific.

24 **Figure 5. Example filtering for a U-Pod (D3) showing lower absolute humidity (a) and higher temperatures (b) occurred during the**

25 **deployment than during the calibration. The data cut point shows where minimum and maximum values of the variables included in**

26 **the data were excluded.**

28 In addition, deployment data were filtered for maximum values of O_3. In some instances, the ozone data spikes to unrealistically

29 high levels. The 95th percentile of the absolute differences between the two reference stations during the calibration period was 11

1 ppbv. The maximum one-minute value recorded by either station during this time was 160 ppbv. As such, we employed 171 ppbv
2 as a realistic maximum level of ozone to expect across the study area. Concentrations that were over this threshold were removed.
3 No minimum filtering was needed for O_3.
4
5 Lastly, data were filtered using consecutive differences. Data were omitted when they fell more than eight standard deviations
6 away from the mean consecutive difference in values. This is a standardized way to cut out spikes in data caused by power control
7 issues. The results of the deployment data filtering, including percent of data lost, are shown in Table S2. Most U-Pods (except D8
8 and DB) have two ozone sensors. For U-Pods with two ozone sensors, only one was used for the analysis. The data from the
9 calibration time period for each sensor was compared to the reference data at Rubidoux. Whichever sensor had the highest
10 correlation and lowest RMSE with the reference was chosen for subsequent analysis.
11
12 U-Pod DD was omitted from this analysis due to a lack of data. This pod lost almost 46% of its data after the filtering process and
13 collected significantly less data than the others due to site security issues. U-Pods D4, D5, D6, D8 and DF required a modification
14 be made to their electronics boards. This modification to the U-Pod system appeared to have shifted ozone baseline signal values
15 resulting in biased values for D5 (see section 3.3 below). In a conservative effort, all U-Pods that were modified as described above
16 were removed from the subsequent ozone analysis. Since some U-Pods were at the same location, the removal of these U-Pods
17 resulted in the loss of three sites from the study. All the remaining sites were left with one U-Pod each.

18 **3.3 Validation of Field Calibration**

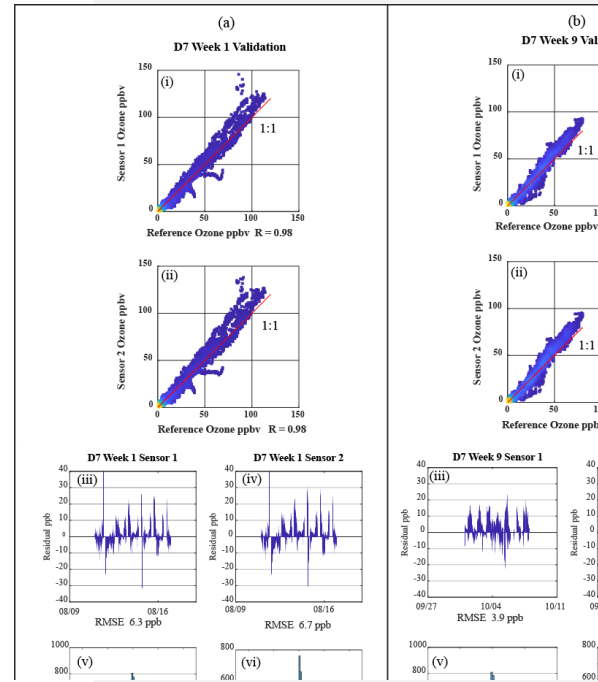
19 Validation of the field calibration models was achieved by deploying U-Pods next to reference instruments during times when the
20 others were spread out over the study area. The validation time period (Aug 11 – Oct 25) overlapped with the deployment time
21 period (Aug 17 – Oct 20). Coefficients generated from the regression models (Table S1) were applied to the filtered data from D7,
22 D0 and D5. The best performing model was selected based on R^2, RMSE and residual distributions. Ozone concentrations were
23 best modeled over the entire validation time period using the model shown in Eq. 1, similar to what was observed for the calibration.
24 The purpose of this comparison was to verify that the model that resulted in the best statistics for the calibration, also did so for
25 the deployment time period. In order to gain a better understanding of the dependency of model performance on the selection of
26 the validation data, we randomly selected 10% of the validation data and calculated validation statistics for this subset of the
27 validation period and repeated this process 200 times. This iterative method allows us to assess the sensitivity of the validation
28 statistics to the data randomly selected. The resulting distributions for the performance metrics are shown in Table 2. Tight
29 distributions show little dependence on the data selected. Detailed results from the entire validation period are presented in Figs.
30 S2, S3 and S4 for pods D0, D5 and D7, respectively.
31
32 **Table 2. Overall validation sensitivity results showing mean residuals, median residuals, R^2 and RMSE of sensor measurements against**
33 **Rubidoux or Mira Loma AQMS O_3 (ppbv) observations. Two-hundred iterations of 10% randomly selected minute-data were used for**
34 **validation statistics (± 1 SD).**

U-Pod ID	mean residual	median residual	mean R^2	mean RMSE	validation method
D7 O_3 Sensor 1	2.4 ±0.1	1.2 ±0.1	0.965 ±0.001	5.6 ±0.1	Same location
D7 O_3 Sensor 2	2.8 ±0.1	1.5 ±0.1	0.963 ±0.001	5.9 ±0.1	Same location
D0 O_3 Sensor 1	0.7 ±0.1	0.8 ±0.1	0.974 ±0.001	4.4 ±0.1	Different location

D0 O$_3$ Sensor 2	1.1 ±0.1	1.0 ±0.1	0.971 ±0.001	4.9 ±0.1	Different location
*D5 O$_3$ Sensor 1	5.5 ±0.1	5.1 ±0.1	0.971 ±0.001	5.0 ±0.1	Different location
*D5 O$_3$ Sensor 2	6.4 ±0.1	3.9 ±0.1	0.953 ±0.001	7.2 ±0.1	Different location

1   *D5 experienced an electrical issue resulting in data omission from analysis

3   The first validation method (U-Pod in the same location as the reference station, D7) would be expected to have better validation
4   statistics than U-Pods validated using the second method (U-Pod relocated to a different location, D0 and D5) because the
5   environmental conditions (e.g., temp, humidity, distance to roadway and other site-specific conditions) encountered by the pods
6   were the same as the reference for the first validation method. However, in viewing the statistics, this is not the case as both O$_3$
7   sensors in D0 show better or similar performance to the Mira Loma station reference data than the two sensors in D7 compared to
8   the Rubidoux station reference concentrations. For transparency, validation results from D5 were presented in Table 2 to show the
9   effect of the electrical modification; the mean residuals for D5 are biased at 5.5 and 6.4 ppbv and much higher than those from D7
10   and D0. The mean RMSE from D0 and D7 sensors in Table 2 can be equated to the overall U-Pod uncertainty for the deployment.

12   Organizations using or planning to use sensors to monitor ambient air quality are interested in how frequently sensors require
13   calibration as to keep them within a specified "tolerance" of reference-grade measurements. As a precautionary note, durations
14   between suggested calibrations are highly dependent on the environment, quality and robustness of the calibration, and gas species
15   of interest. The validation statistics presented so far have been aggregated over the entire deployment period (or have been selected
16   at random) in the case of the iterative validation described above. However, to further inform the sensor community on how robust
17   calibration models can be through time and environmental space (e.g., humidity and temperature), validation was performed
18   independently for the first week and last full week of the deployment and the results for each week are shown below in Figure 6.

2 **Figure 6: Validation results from the (a) first week and (b) ninth week of the deployment period for D7 ozone sensors separated by the**
3 **red line. Subpanels (i) show a scatterplot of sensor 1 and reference measurements with warmer shading showing a higher density of**
4 **points, (ii) show a scatterplot of sensor 2 and reference measurements with warmer shading showing a higher density of points. (iii)**
5 **Ddepict residuals over time for sensor 1 with RMSE, (iv) depict residuals over time for sensor 2 with RMSE, (v) is a histogram of**
6 **residuals with mean and median residual for sensor 1, (vi) is a histogram of residuals with mean and median residual for sensor 2.**
1

8 Within the first week of the validation (panel a), the range of reference ozone concentrations (~0 to 115 ppbv) is much larger than
9 those found in week nine (panel b, ~0 to 80 ppbv) although the Pearson's correlation coefficients (R) are remarkably high (≥0.98)
10 for both sensors in both weeks (i, ii). The red lines are 1:1 lines, not lines of best fit. The residuals plotted as a function of time
11 over each week (iii, iv) are similar in magnitude but by week nine (b; v-vi) there is a slight bias (mean = 2.7-3.0 ppbv) towards
12 higher sensor measurements even though the RMSEs are lower in week nine (3.9 and 4.2 ppbv) than in week one (6.3 and 6.7
13 ppbv). Calibrations performed more frequently than every 9 weeks may reduce slight shifts in mean residuals. Monthly calibrations
14 could balance monitoring resources and quality of ozone sensor data for a region like Riverside, but should be done on a case-by-
15 case basis.

1 Figure 6 has two identifiable deviations from the 1:1 line. These two events, identifiable as the "claws" in week one (shown in

2 panel (a (i-ii)), demonstrate higher reference measurements than both D7 sensors leading to large residuals. These claws are

3 separated in time but each claw is a single event (consecutive measurements) lasting one and eight hours in duration. To explore

4 these claws further, a scatterplot for each sensor colored by temperature and humidity at each time point were created (Fig. S5).

5 They show that the two events visible for D7 occur at drastically different temperatures and humidity. The first (lower) claw has

6 low temperature and high humidity, and the second has the reverse conditions. This finding provides evidence for a separate

7 confounding variable, as it is not the same condition in temperature or humidity that causes these under predictions in ozone

8 measurements. In future studies, the U-Pod could be outfitted with sensors to detect other possibly confounding gasses, such as

9 NO_x or VOCs.

11 SCAQMD performed nightly precision checks (PC) consisting of measuring the ozone concentration of a known gas standard that

12 typically ranges between 90-100 ppbv for one hour. When PC measurements deviated more than 5% from expected values

13 (corresponding to approximately 5 ppbv), subsequent data would be flagged and a work order would be generated for service or

14 calibration. Values that are within 5% of the standard would not be flagged. This serves as a reference point for the quality of the

15 reference ozone measurements. During validation, O_3 sensors had measurement error (RMSE), median residual and mean residual

16 ranges of $4.3 – 7.3$, $1.7 – 5.2$, and $0.6 – 6.5$ respectively. Both median and mean of the residuals were calculated to assess bias. As

17 discussed earlier, D5 experienced an electrical issue during the calibration period which resulted in a clear bias throughout the

18 validation dataset. This particular electrical issue points to the challenges of using such sensor platforms in an ambient monitoring

19 context, a topic widely discussed in the air sensor community (Kumar et al. 2015). Median bias for the other U-Pods was relatively

20 small and on the order of 1-2 ppbv.

21 **3.4 Deployment Data**

22 As mentioned above, U-Pods were deployed, spread out across 200 km² area² area in Riverside, CA; as such, the aim of our data

23 analysis is to present spatial differences of U-Pod measurements that include measurement uncertainty, and thus allow us to

24 understand the ability of the sensors to detect variability. To examine this spatial variability, we computed the R^2 values and median

25 absolute differences for all possible U-Pod pairs. Unless otherwise stated, median minute time resolution data recorded during the

26 approximately 10 week deployment were used in the following analysis. The model coefficients obtained during the calibration

27 time period (collocation with the reference monitor) were applied to all data during both the calibration and deployment time

28 periods. Applying the model to the data collected during the collocation yields the best possible accuracy of the U-Pod sensors, as

29 the model is being applied to the data from which it was derived. As such, comparisons of deployment data to collocation data are

30 useful to assess the variability observed when the U-Pods are deployed vs. when they are collocated. This allows us to observe

31 actual spatial and temporal differences. In all following figures, hours of the day are given in local time.

32

33 The U-Pods sampled for approximately 2900 hours total, 58% of which consisted of the deployment period data. The medians of

34 ozone value distributions during the calibration range from 29-30 ppbv. During calibration, the 5th and 95th percentiles ranged from

35 2-5 ppbv and 70-83 ppbv, respectively. During deployment, the median ozone values were between 14 and 31 ppbv while the 5th

36 and 95th percentile ranges were 0-6 ppbv and 67-99 ppbv, respectively.

37

38 Ozone concentrations experience a diurnal cycle. This cycle usually incorporates low ozone at night and during the early morning,

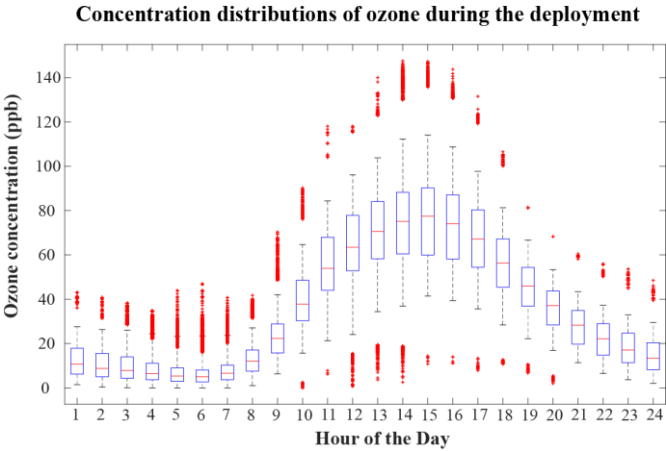
39 and a peak in concentration sometime during the day. Gao (2007) and co-workers used hourly ozone measurements recorded over

1   southern California from June 16th to October 15th, 1997 and found that ozone began to increase in the region around 8:00, peak

2   between noon and 15:00, and then undergo reduction until about 21:00. The precursors to forming ozone: sunlight, VOCs and

3   NO_x also have daily cycles, that in turn affect the ozone cycle profile (Gao, 2007). Figure 78 shows the diurnal cycle for ozone

4   based on concentrations collected during this study.

Concentration distributions of ozone during the deployment

6   **Figure 7. The diurnal cycle of ozone during the deployment. Distributions are concentrations from all U-Pods during each hour.**

7   **Whiskers indicate the 5th and 95th percentile, with + marks falling outside of this range. The box boundaries span the 25th to 75th**

8   **percentiles.**

10   Figure 7 offers context of what the temporal variability in ozone concentrations in this study looks like. There are trends in ozone

11   concentrations across Southern California that would be expected. Ozone is lowest from midnight to 6:00. Then the accumulation

12   period takes place between 6:00 and 14:00. Peak concentrations occur between 14:00 and 16:00, and for the remaining hours,

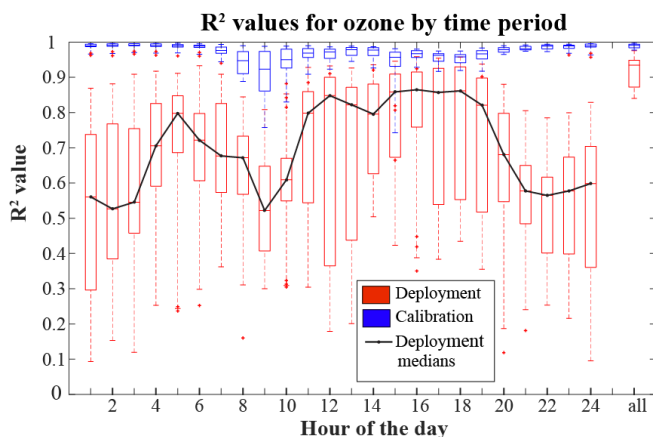
13   concentrations decrease again.

15   In order to assess spatial variability, we examined the R^2 values for all possible U-Pod pairs for each hour of the day. The larger

16   the spread and smaller the magnitude of the R^2 values, the more spatial variability was likely present in that hour across the study

17   region. Figure 8 shows correlation information between U-Pods for each hour of the day for ozone. For this plot, all data were

18   binned by hour. Then within those bins, correlations were performed for every possible U-Pod pair. As such, each boxplot consists

19   of 21 points.

2 **Figure 8. Each boxplot is a collection of the R^2 values between every pair of U-Pods for each hour of the day. There are 21 points in**

3 **each boxplot. Medians of distributions are marked by horizontal lines. Whiskers indicate the 5th and 95th percentile, with + marks**

4 **falling outside of this range. The box boundaries span the 25th to 75th percentiles. The "all" category includes all hours of the day.**

6 U-Pod ozone measurements are more correlated to each other during calibration than deployment. The R^2 values between

7 collocated pods are very high, with their medians varying from 0.92-0.99 ppbv. Conversely, spatially distributed pods were less

8 correlated with each other, leading to R^2 distribution medians between 0.52 and 0.86. The "all" category in Fig. 8 represents the

9 R^2 values between U-Pods, without binning by hour. The medians for the calibration and deployment in this column, respectively,

10 are 0.99 and 0.93 ppbv, with slightly more skewness towards lower R^2 in the deployment distribution. It is only when binning by

11 hour that greater differences are seen. U-Pods are most different from each other during the hours from 21:00 to 3:00, and at 9:00.

12 U-Pods are most similar around 5:00 and between 11:00 and 19:00. Relationships in R^2 values between pods are changing most

13 quickly through time between 3:00 and 11:00, and again between 19:00 and 21:00.

15 Absolute O_3 concentration differences between pairs of U-Pods were also examined to understand temporal and spatial variability.

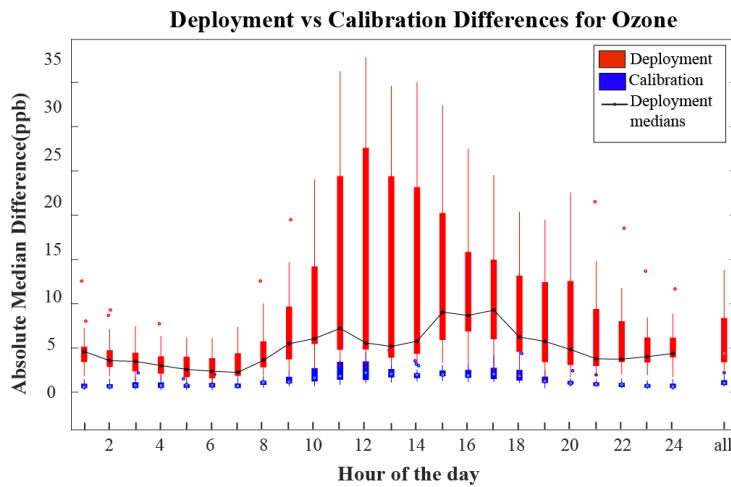
16 Figure 9 shows distributions of median absolute differences. All the minute median data were time-matched and binned by hour.

17 Hourly datasets were paired to include every possible U-Pod pair. Within the time matched pairs, the median absolute difference

18 between the two U-Pods was calculated. The distributions in Fig. 9 consist of those 21 points for each hour. The median values of

19 these boxplots increase during the middle of the day, with two major increases observed at hours 10:00 and 15:00, and were lower

20 during the night and early morning.

Deployment vs Calibration Differences for Ozone

2 **Figure 9. Distributions of medians of absolute differences between all pairs of pods for each hour of the day. Whiskers show 95%**

3 **intervals. The black line connects the medians of the deployment. The "all" category includes all hours of the day.**

5 We expected that times of day where the spatial variability was the lowest (R^2 highest) the smallest values of absolute differences

6 would be observed. In other words, the deployment medians in Figs. 8 and 9 were expected to have an inverse relationship. There

7 is an increase in R^2 while there is a decrease in absolute median differences around 4:00 to 5:00. There is also an increase in the

8 differences that correspond to increasing R^2 with a peak around 9:00. The absolute median differences reach their minimums and

9 maximums later than the R^2 values reach theirs by a few hours. Sometimes however, this inverse relationship between large R^2 and

10 smaller differences does not appear. The second jump in median absolute differences between 15:00 and 17:00 was not reflected

11 in reduced R^2 values during those same hours. From 6:00 to 10:00, the slope for the deployment medians in Fig. 9 is steep,

12 indicating that pod differences were increasing quickly across the region, and over that same time period the spatial correlation

13 was lower. The slope between 13:00 and 15:00 looks similar, but the R^2 values were roughly stable and relatively high. In other

14 words, we observed spatial concentration differences and low correlation during the morning commute times, but in the afternoon

15 when we observed the maximum concentration differences, we also observed relatively high spatial correlation. Absolute

16 differences are growing during the morning period and into the afternoon, but since the whole area is experiencing accumulation,

17 there is an increase in correlation as well. Furthermore, although Fig. 7 shows high concentrations during the day, Fig. S6

18 demonstrates that percent differences at these times are lower.

20 Towards the end of daylight hours, between 16:00 and 20:00, the medians of absolute concentration differences have a decreasing

21 trend in time of day, which should be indicating that the U-Pods are becoming more similar because their differences are smaller.

22 However, in the same hours and later, the R^2 values between all U-Pods decrease over time and remain low during the night,

23 indicat~~inged~~ that U-Pods are more different from each other than during the afternoon. Some studies have assumed negligible

24 ozone precursor spatial differences in the first hours of the day and therefore spatial ozone homogeneity during the early morning

25 hours (Moltchanov et al., 2005; Jiao et al., 2016). Figure 9 shows that the range of spatial absolute differences in O_3 is smallest at

26 night. However, Fig. 8 suggests that spatial correlation at night is relatively low, causing concern for assumptions about the

27 homogeneity of ozone concentrations at night for this location, although this assumption could be valid for other areas (Moltchanov

1   et al., 2015). Furthermore, the discrepancy between low absolute differences, but also low R^2 values may show that correlations

2   alone are not enough to determine how similar two sites are. The actual differences in concentrations can reveal elements of spatial

3   variability not captured by correlations, especially since correlations can be influenced by leveraging fewer high data points.

5   To further understand the factors impacting the observed spatial variability, we examined U-Pods individually in more detail. We

6   undertook this investigation by comparing each U-Pod to a common reference U-Pod, to illuminate differences between locations

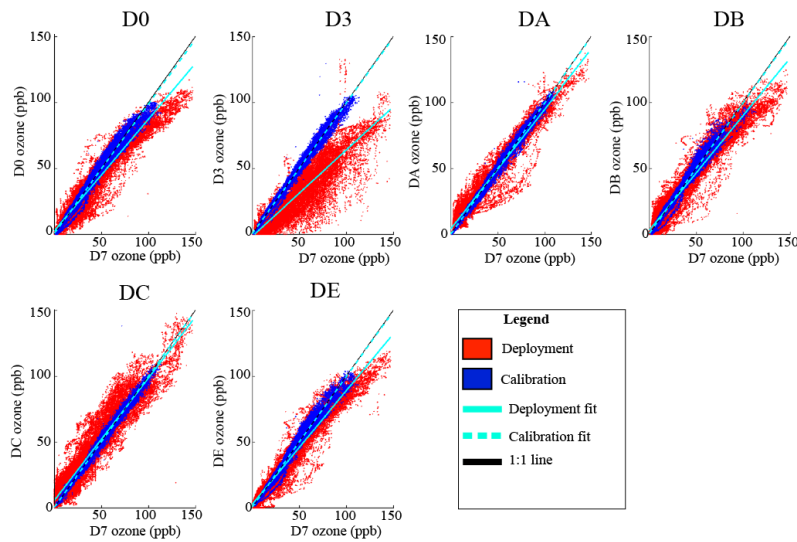
7   in a normalized way. If no spatial variability was observed, then comparing two U-Pods' ozone measurements would show a 1:1

8   relationship with spread near the RMSE values determined in the validation (4.4-5.9 ppbv). To explore this analysis, D7 was used

9   for normalization. U-Pod D7 was never moved from Rubidoux station throughout the project and as such was employed in the

10   validation effort mentioned previously. This U-Pod was used as the normalization instead of an AQMS reference monitor in order

11   to compare two similar types of measurement. The U-Pod to U-Pod comparisons are shown with the differences between

12   calibration period trends and deployment trends in Figure 10 as well as hourly patterns in Figure 11.

14   **Figure 10. U-Pod D7 ozone concentrations are plotted on the x-axis and other U-Pod ozone concentrations recorded at the same times**

15   **are on the y-axis. The sets are color coded according to time period their data were taken, and each color is fit with a linear line.**

17   In Fig. 10, the calibration data points, representing collocated O_3 measurements, are consistently more densely grouped than the

18   red data points which show the spatial deployment data. This further demonstrates that individual U-Pods were observing spatial

19   differences in O_3. Also, D0, DA, DB, and DE have interesting deviations of O_3 concentrations away from the central cloud of

20   deployment points, in the form of curved areas away from the center line. The deployment trend line slopes (solid line) are lower

21   than the calibration slopes (dotted line). As such, D7 at the Rubidoux site typically measured higher O_3 than the other U-Pods that

22   were spatially deployed (excluding DC and DA).

1 Examining the data in this way allows for detailed comparison of U-Pods at different sites. For example, sites D0, D3 and DE were

2 not more than 1.8 km away from each other, near Van Buren Blvd. in the north west of the project area, and all were less than 1.2

3 km from the road. Therefore, one might expect data from these U-Pods to be very similar. Indeed, D0 and DE have similar data

4 cloud shapes in Fig. 10. However, data from D3 looks to be rather different. This could indicate that a localized source is affecting

5 the ozone concentrations at that site. Perhaps a local emission of NO was scavenging ozone at Industrial Zone 1 as a result of

6 industrial operations. Alternatively, this difference could be caused by unique meteorological conditions at this site. However,

7 when investigated further, the lower ozone values of D3 compared to D7 also appears more pronounced on weekdays (Fig. S7)

8 reinforcing the hypothesis of industrial activities causing such differences.

10 U-Pod DA was the farthest away from the other monitors (~7.5km from any other U-Pod, in the north east), while DC and DB

11 were closer together (3 km). However, it was DA and DB that have a similar spread of data around the 1:1 line, and a similar curve

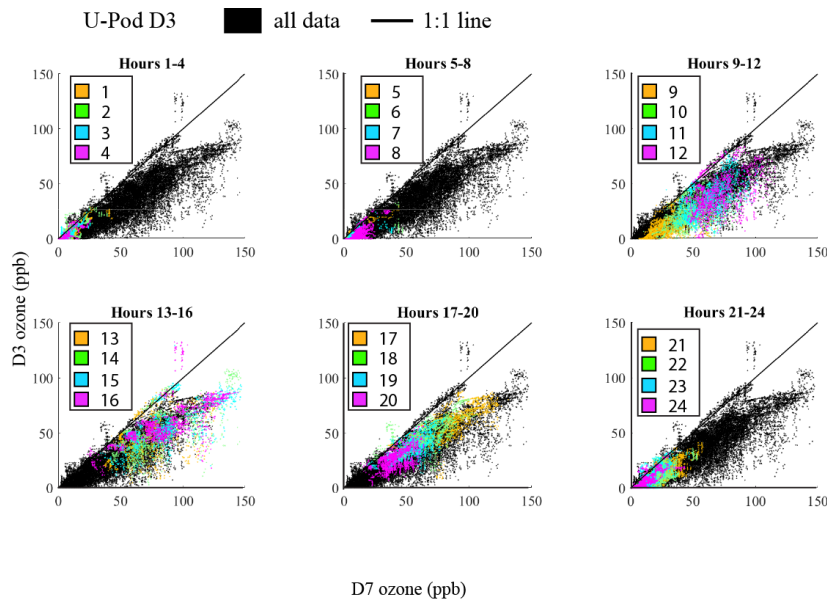
12 of data points below the main data cloud. In other words, DA and DB were more similar than DC and DB even though these two

13 U-Pods were closer together. A possible explanation for this may be proximity to roads; DC is closest (0.6 km) to highway 91, a

14 major freeway. Another explanation could be the environment these pods are in. DB and DA are in areas with industrial activity,

15 whereas DC is in a more residential location.

17 Temporal variation in ozone values can be visually examined in more detail by singling out certain hours of data, compared to the

18 full set. Figures 11 and 12 demonstrate this concept.

21 **Figure 11. Data from D3, at Industrial Zone 1, plotted against D7 (at Rubidoux). In each scatterplot, colored data in the legend**

22 **represents four hours of the day, and the black data represents the complete deployment dataset (all hours). The black line is a 1:1 line,**

23 **not a line of best fit.**

1 Figure 10 and 11 show that the deployment data for D3 is consistently lower when compared to D7 than the other U-Pods. D3 is

2 7 km from D7, in the north of the project area. U-Pod D3 was sited at a company in an industrial area where there are potentially

3 more VOCs in the air. This site was half a kilometer from the Van Buren roadway and as such there is also the potential for elevated

4 levels of NO_x. The NO_x reduction hypothesis posits that depending on the ratio of NO_x to VOCs in an area, increasing NO_x can

5 increase or decrease the concentration of ozone. The titration of ozone with NO_x can deplete concentrations of ozone. The proximity

6 of D3 to Van Buren and the potential for increased local industrial sources of VOCs affecting the ratio, may cause ozone at D3 to

7 appear lower when compared to that of D7. Beginning in hour 9:00 and extending through hour 12:00, there were general increases

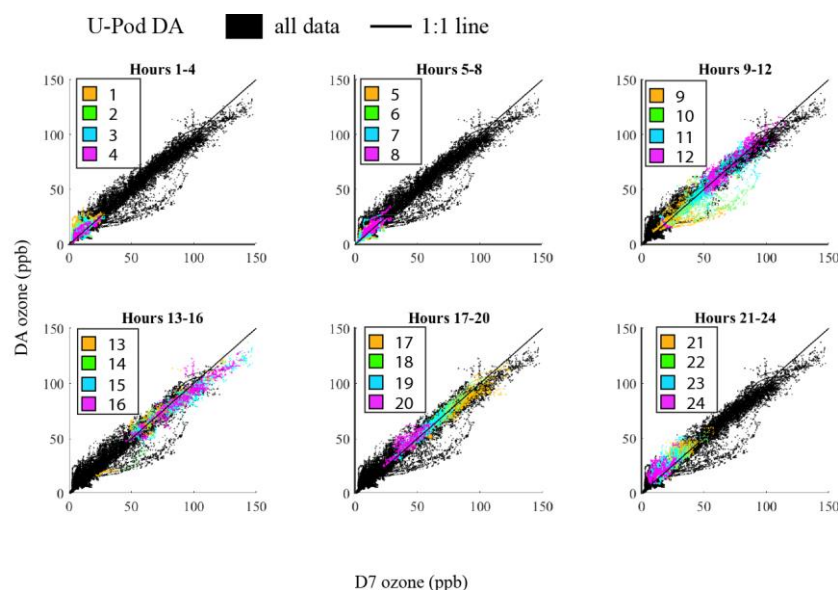
8 in the ozone concentrations recorded, and the points start to spread out, demonstrating significant spatial variations that are

9 temporally relevant. From hours 13:00 to 16:00, there was less of a trend in terms of generally increasing or decreasing, and values

10 cover a large range of ozone. From 17:00 – 20:00, we observed a reversal of the trend in the 9:00 – 12:00 hour block as ozone

11 starts to decrease again and becomes more densely clustered. The reversed color trend from left to right in these two subplots is

12 very clear. Lastly, for the remaining hours of the day, the measurements become very dense and values decrease again, completing

13 a daily cycle.

16 **Figure 12. Data from DA, located at Commercial Zone 1, plotted against D7 (Rubidoux). Each scatterplot is four hours of the day, with**

17 **the black data representing the complete deployment dataset (all hours) and data points recorded within each hour bin are marked by**

18 **the colors and times in the legend. The black line is a 1:1 line, not a line of best fit.**

20 Figure 12 shows the relationship between DA and D7 at varying hours during the day, highlighting some interesting observations.

21 First, there was far less spread around the 1:1 for DA (compared to D3) indicating that ozone measurements from D7 and DA were

22 more similar than D7 and D3. DA is similarly distanced from D7 as D3, about 7.5 km away, but still in the northern area of the

23 study. These plots show concentrations from DA are more similar to D7 than those of D3, because there is much less deviation

24 from the 1:1 line in data points. Also of interest is the strange claw shape on the underside of the black data cloud. The analysis in

1   Fig. 12 was conducted for all pods, but not all are shown here. It appears that many of these points occur mostly in hours 9:00

2   through 11:00 for all affected U-Pods. The data points from the claws in DA occur in a few consecutive hours on three different

3   days, similar to D7. The claw in D7 is not causing this effect in DA, because they occur at different times. One possible explanation

4   for this may be the presence of one or more gas species that is not captured by the model which affects either the sensor directly,

5   or the concentration of ozone in the vicinity for a short time. These gases could be localized ozone precursor emissions such as

6   NOx or reactive organic gases (ROGs) which happen to correlate with morning rush hour. This claw-shape occurs at the D0, DB,

7   and DE sites as well, all of which are closest to Van Buren Blvd. Also, the data within this claw shape appear to happen more often

8   on the weekend than on weekdays (Fig. S7). We do not have sufficient data on NO_x concentrations or high-resolution traffic

9   information to draw specific conclusions about how these may be affecting ozone at different sites. This could be an area for future

10   research.

11   **4 Conclusions**

12   In the region of Riverside, CA, we were able to observe spatial and temporal variability of ozone across an area of roughly 200

13   km^2. Field validation of sensor O_3 measurements to minute resolution reference observations resulted in R^2 and RMSE of 0.95-

14   0.97 and 4.4-7.2 ppbv. The Thermo Scientific Model 49i Ozone Analyzer that SCAQMD uses for FRM has an acceptable

15   measurement noise of 5% of the precision gas input, or around 5 ppbv for ozone. The measurements from the MiCS 2611 ozone

16   sensor should not be thought of as a way to replace regulatory AQMS or prevent future stations from being built, but rather

17   supplement that information. After all, these sensors not only depend on reference grade measurements but also the quality control

18   and assurance carried out at those stations. These low-cost sensors can help in deciding where future AQMS be erected as well as

19   inform the existing gaps between stations.

21   Technological difficulties of obtaining sensor data through environmental extremes, increased sensor variability with high ozone

22   values, electrical issues and data retrieval are all issues encountered when using a U-Pod sensor network. Although the sensors

23   themselves are low-cost, the data retrieval, validation and analysis are not. Data were retrieved on a biweekly basis which required

24   a field visit to each site. Sensor platforms that wirelessly transmit data (or stream data) require additional hardware and may limit

25   sensor placement yet are promising for many applications. The U-Pod has since evolved to incorporate wireless data transmission

26   in some units. Processing (e.g., QAQC, filtering) and analysis of these data (~2 MB/pod/day) constitutes the majority of time for

27   such campaigns. Future projects may involve very large numbers of sensors, therefore time expenditure for this network method

28   needs to be reduced.

30   The highest amount of variability between U-Pods based on the R^2 values of all their possible pairs to occur between 21:00 and

31   3:00, as well as at 9:00. U-Pods are more correlated around 5:00 and the period between 11:00 and 19:00. Based on the median

32   absolute differences between all possible U-Pod pairs, the U-Pods are most similar at 6:00, and peaks in differences (least similar)

33   occur at 10:00 and 15:00-6:00. The uncertainty of these measurements, as determined by the validation results of D0 and D7 is 4.4

34   – 5.9 ppbv.

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36   For future sensor research, an analysis of the amount of time spent collocating (calibrating) to the amount of time deployed

37   (applying calibration) would be very beneficial for the sensor community. This information can inform how long sensors can be

38   deployed in given region under given environmental conditions before recalibration is warranted. In this study, for nearly three

weeks of collocation time, sensors were deployed for more than nine weeks with only slightly variation of performance from week one to week nine. It is important to collocate the sensors as frequently as possible while balancing other resources. Sensor quantification using different mathematical approaches to linear regression could improve the performance. Since higher values of ozone are of the greatest interest to regulators and the public from a human health standpoint, and the sensor variability increases at those higher values, perhaps the regression could be fit differently to suit those needs. An example could be to fit a piecewise function, to better capture the low-ozone and high-ozone regimes separately, or other non-linear models.

Additionally, including measurements of other compounds in the study could help to explain causes for spatial and temporal variability in both ozone. For example, including information on nitrogen oxides could help inform the effects on traffic on these compounds, while land use data could reveal the effect of vegetation or industrial operations on measurements. Furthermore, this study was conducted in an area with relatively high levels of ozone, which can be simpler to detect. Many people live in areas that have ozone levels closer to EPA required levels, though they still experience some periods of non-attainment. To make this research more relevant to all people, the next step could be to try and detect the same spatial and temporal variability in these places as well.

Code and Data availability

The final, filtered dataset and the codes used to make the plots in this manuscript are available on Mendeley at DOI: 10.17632/j36zwxy8v4.1. All codes used to perform the linear regression are not included. Raw data are not included because they cannot be interpreted in concentrations without the regression model codes, and results from raw voltages could be misleading. Reference data provided by SCAQMD did not undergo usual procedures of quality assurance and quality control before they were provided to us.

Author Contributions

K. Sadighi helped conduct the field experiment and analyze deployment data, and prepared the manuscript with contribution from all authors. E. Coffey was the lead field scientist, performed the calibrations and validation analysis, and conducted the literature review. A. Polidori and B. Feenstra facilitated collaboration between the Hannigan group and the South Coast Air Quality Management District and provided useful information on air quality conditions in Riverside County. Q. Lv, D. K. Henze, and M. Hannigan provided guidance and academic support for the project.

Competing Interests

The authors declare that they have no conflict of interest.

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Tables

Table 1: Field calibration results of the Linear 4T model for ozone sensors showing R2 and RMSE with the reference monitor data.
Two O3 entries means there are two different sensors in the same U-Pod.

U-Pod ID	D0	D3	D4	D5	D6	D7	D8	DA	DB	DC	DD	DE	DF
R^2, RMSE	0.98, 3.1	0.98, 3.0	0.98, 2.6	0.99, 2.7	0.98, 3.5	0.98, 2.8	0.98, 3.0	0.97, 3.9	0.98, 2.8	0.99, 2.6	0.99, 1.8	0.97, 3.4	0.98, 3.1
	0.98, 3.2	0.98, 3.0	0.98, 2.7	0.98, 3.0	0.99, 2.4	0.98, 3.0		0.97, 3.9		0.98, 2.7	0.99, 1.8	0.98, 2.9	0.98, 3.0

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28 **Table 2. Overall validation sensitivity results showing mean residuals, median residuals, R^2 and RMSE of sensor measurements against**
29 **Rubidoux or Mira Loma AQMS O_3 (ppbv) observations. Two-hundred iterations of 10% randomly selected minute-data were used for**
30 **validation statistics (± 1 SD).**

U-Pod ID	mean residual	median residual	mean R^2	mean RMSE	validation method
D7 O_3 Sensor 1	2.4 ±0.1	1.2 ±0.1	0.965 ±0.001	5.6 ±0.1	Same location
D7 O_3 Sensor 2	2.8 ±0.1	1.5 ±0.1	0.963 ±0.001	5.9 ±0.1	Same location
D0 O_3 Sensor 1	0.7 ±0.1	0.8 ±0.1	0.974 ±0.001	4.4 ±0.1	Different location
D0 O_3 Sensor 2	1.1 ±0.1	1.0 ±0.1	0.971 ±0.001	4.9 ±0.1	Different location
*D5 O_3 Sensor 1	5.5 ±0.1	5.1 ±0.1	0.971 ±0.001	5.0 ±0.1	Different location
*D5 O_3 Sensor 2	6.4 ±0.1	3.9 ±0.1	0.953 ±0.001	7.2 ±0.1	Different location

31 *D5 experienced an electrical issue resulting in data omission from analysis

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