Title
Applying Low-Cost Air Sensors for Spatiotemporal Variability of Particulate Matter in a Local Community Adjacent to Interstate Highway

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Applying Low-Cost Air Sensors for Spatiotemporal Variability of Particulate Matter in a Local Community Adjacent to Interstate Highway

A thesis submitted in partial satisfaction

of the requirements for the degree Master of Science

in Environmental Health Sciences

by

Yu-Han Chen

2020

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ABSTRACT OF THE THESIS

Applying Low-Cost Air Sensors for Spatiotemporal Variability of Particulate Matter in a Local Community Adjacent to Interstate Highway

by

Yu-Han Chen

Master of Science in Environmental Health Sciences

University of California, Los Angeles, 2020

Professor Yifang Zhu, Chair

A key contributor to urban ambient air pollutants is road traffic. Vehicle emissions are known to be associated with various adverse health effects. Particulate matter (PM), as one of the traffic-related air pollutants (TRAPs), is particularly crucial due to its various chemical composition, morphology, size and numerous adverse health impacts. In this study, we deployed twelve low-cost air sensors to explore the temporal characteristic and the spatial variability of PM in a community adjacent to an interstate highway. In addition, the long-term field performance of the

low-cost air sensors and its potential for identifying the traffic-related PM were also examined. At every sampling site, ambient PM was continuously measured with a 120s resolution from December 1, 2017- November 30, 2018. These data were later converted into hourly data in order to match with the hourly $PM_{2.5}$ and NO_2 data acquired from the EPA stations. The highest $PM_{2.5}$ was observed in the winter (15.7 ± 16.7 μg/m^3) and the lowest was observed in spring (8.8 ± 7.21 μg/m^3). Pairwise sensors were found to be temporally correlated ($r > 0.98$) to each other and spatially (CoD < 0.02) homogeneous within the community. A good correlation ($r > 0.79$) and small CoD (value = 0.17) were also found between the $PM_{2.5}$ at the community and the $PM_{2.5}$ at the EPA monitor site. This suggests that the $PM_{2.5}$ across the community and the EPA monitor site are temporally correlated and spatially homogenous to each other. The temporal patterns of $PM_{2.5}$, $PN_{0.3}$ and NO_2 clearly demonstrated that the traffic is one of the major contributors to the air pollutants at the University Village. In particular, by using pair-wise sensors (downwind sensor and upwind sensor), the highway adjacent to the community, was found to be the main cause of higher concentration of PM.

The thesis of Yu-Han Chen is approved.

Michael Jerrett

Shane Que Hee

Yifang Zhu, Committee Chair

University of California, Los Angeles

2020

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1. INTRODUCTION

Traffic-related air pollutants (TRAPs) has been associated with adverse health effects. For example, in a roadside community, (Fuller et al., 2013) have shown that the biomarker of inflammation, coagulation and blood pressure to be higher in participants lived closer to a interstate highway when compared with those who live farther away. Negative impacts on lung function and associations with asthma were also found on individual who exposed to TRAPs in their early life (Khreis et al., 2017; Schultz et al., 2017). Particulate matter (PM), as one of the TRAPs, is particularly crucial due to its various chemical composition, morphology, size and numerous adverse health impacts. (Smith et al., 2017) estimated that exposing to traffic-related $PM_{2.5}$ higher than 13.8 mg/m^3 during pregnancy has contributed to 3% of low birth weight in London. Children exposing to higher traffic-related $PM_{2.5}$ and PM_{10} were discovered to be more likely to have autism (Volk et al., 2013) In order to propose a comprehensive and effective mitigation strategy, the temporal and spatial characteristics of TRAPs at the study area are of great importance (Patton et al., 2014).

Conventionally, PM concentration is measured at fixed air quality monitoring station using Federal Equivalent Methods (FEMs) or Federal Reference Methods (FRMs) operated by the United States Environment Protection Agency (USEPA). Air quality monitoring stations are the most readily available source for exposure assessment. However, due to the high cost of reference-grade instruments, and regulatory-operational protocols, these monitors are deployed at limited locations. Thus, the insufficient spatial coverage of regulatory monitor hinders its adequacy for exposure and health risk assessment. Advances in technology have prompted the production of various low-cost air sensors, which allows researchers to develop new methods to improved spatiotemporal characterization of PM. Because of their affordable price, relatively small size and flexible use, low-cost air sensors are increasingly becoming more prevalent in air pollution-related studies (Feenstra et al., 2019; Jiao et al., 2016).

Numerous studies have shown various applications of the low-cost air sensors (Ahangar et al., 2019; Gupta et al., 2018; Kaduwela et al., 2019; Mead et al., 2013). (Popoola et al., 2018) demonstrated the use of sensor network to distinguish airport emissions from long-range transport. (Heimann et al., 2015) pointed out that data from low-cost air sensors can be used to obtain the prior knowledge and assumptions about a polluted area of interest, which can be useful for subsequent receptor modeling. However, less is known about using the low-cost air sensors to examine the traffic- related emission, one of the major sources of PM.

In this study, we deployed twelve low-cost air sensors to explore the temporal characteristic and the spatial variability of PM in a community adjacent to an interstate highway. In addition, the long-term field performance of the low-cost air sensors and its potential for identifying the traffic-related PM were also examined.

2. METHOD

2.1 Study Area and Duration

The University of California, Los Angeles (UCLA) university village were selected to be the study area as it is located on the eastern and western sides of the 405 freeway. The sensors were deployed on the roof-top of the apartments, sitting at about the same level as the 405 freeway. Located 60 m to the shoreline, the study area typically experiences steady onshore sea breeze each day beginning in the mid-morning. The sea breeze reaches its maximum in the early to min-afternoon, and recedes in the early evening. A weaker offshore sea breeze prevails during the night. The study was conducted from December 1, 2017 to November 30, 2018. Seasonal data were nominally defined as spring (March-May), summer (June-August), fall (September-November), and winter (December-February).

(a) (b)

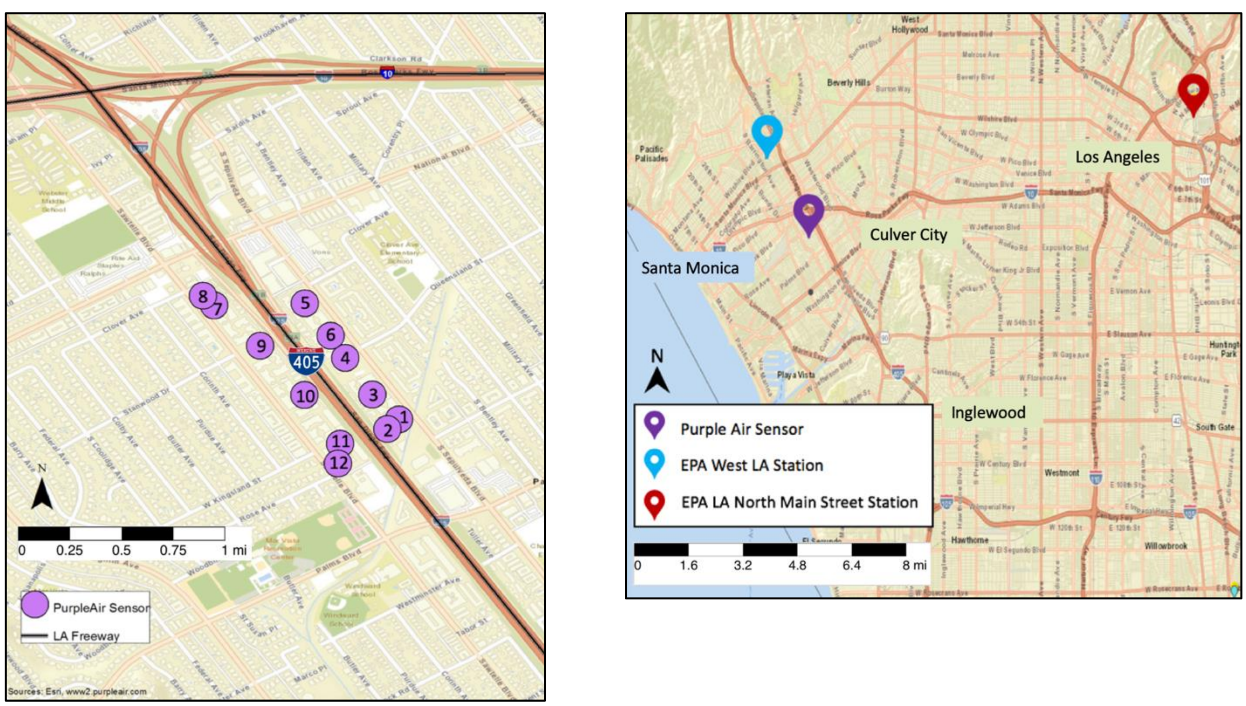

Figure 1. (a) Map of sensors locations at the community. (b) Map of the study location in relation to nearby EPA monitor stations.

2.2 Sampling and Instrumentation

Twelve PurpleAir sensors were deployed at the UCLA university village, with 6 each at the eastside (#1 to #6) and westside (#7 to #12) of I405, respectively. Each PurpleAir sensor has two identical particle counters (Channel A and Channel B) that measure the particle number (PN) concentration (number/cm^3) at cutoff-sizes of 0.3, 0.5, 1, 2.5, 5 and 10 μm with a 120s resolution. The PN data are then used to derive the particle mass concentration (μg/m^3) of PM_1, $PM_{2.5}$ and PM_{10}. Each sensor is also equipped with a meteorological sensor that monitors the ambient temperature, humidity, or barometric pressure. Both laboratory and field evaluation of sensor performance have been carried out by South Coast Air Quality Management District Sensor Performance Evaluation Center (AQ-SPEC, Rubidoux). Channel A and Channel B presented a good correlation ($r > 0.99$), showing a low intra-model variability. Therefore, after reviewing the data coverages of individual sensors, data from Channel A were used in this study. A good correlation ($r > 0.99$) was found between $PM_{2.5}$ of PurpleAir sensors and of Federal Equivalent Method (FEM) instrument GRIMM in the lab evaluation, in which the temperature and humidity were set at 20◦ C and 40%. A field evaluation had been conducted from December 2016 to January 2017 at the South Coast Air Quality Management District Rubidoux Air Monitor Station by collocating the PurpleAir sensors with two FEM instruments: Met One Beta Attenuation Monitor (BEM) and GRIMM. The 24-hour mean of PurpleAir sensors was found to have a good correlation with 24-hour mean of FEM instruments ($r = 0.92$) (Center, 2017a, 2017b)The mass concentration of $PM_{2.5}$ and number concentration of $PN_{0.3}$ from PurpleAir sensors were used to represent the general PM pollution and traffic pollution in the study area, respectively. In specific, $PM_{2.5}$ and $PN_{0.3}$ were converted into hourly data in order to match with the hourly $PM_{2.5}$ and NO_2 data acquired from EPA stations. NO_2, as a marker of traffic pollutant, was used to explore the association between $PM_{2.5}$, $PN_{0.3}$ and traffic. The NO_2 data was acquired from the EPA West Los Angeles monitor site, which is located 2 miles away on the north side of the University Village. EPA Los Angeles- North Main Street monitor site, which is 12 miles away on the east side of the University Village was used to acquire the FEM $PM_{2.5}$ data. A Portable Emission Measurement System (PEMS) vehicle detector station (VDS)-718297 was located on the I-405 section in front of the University Village, and recorded the traffic flow data.

2.3 Data Processing

Quality assurance/quality control (QA/QC) procedure from the manufacture of the laser counter has been applied to the data before analysis. Data points were excluded when the difference between Channel A and Channel B is higher than 10 $\mu g/m^3$ for the $PM_{2.5}$ concentration below 100 $\mu g/m^3$, or when the difference exceeds 10 % for the $PM_{2.5}$ in the range of 100 $\mu g/m^3$ - 500 $\mu g/m^3$. The Openair package in R was used to analyze the data, and R was used for statistical analysis. We applied the slope and intercept from (Feenstra et al., 2019) to the PurpleAir data in order to reduce the discrepancy between PurpleAir sensors and regulatory-grade instruments.

Table A2 shows the data recovery ranges from 1% (sensor 2) to 99.9% (sensor 7) in our sampling period (December 1, 2017- November 30, 2018). WIFI connection is the main reason that causes the incompleteness of the data. After the quality control measure, only 0-2% of data are removed, suggesting that the data quality of PurpleAir sensor is reasonably good. Accordingly, sensors 1, 2, 4 and 11 were excluded in this study due to the incomplete seasonal data throughout the year (Table A1); the main reason for the missing data is due to the instability (loss) of WI-FI connection. Sensor 10 was excluded due to the change of the sampling location in the middle of the sampling period.

2.4 Statistical Methods

The Kolmogorov-Smirnov test with a confidence level set at 95% was used to determine whether parametric or non-parametric statistical methods is appropriate for the collected PM data. Before the Kolmogorov-Smirnov test, our data were log transformed and found not lognormally distributed. Both the raw data and log transformed data failed the Kolmogorov-Smirnov test, therefore, non-parametric statistical methods were used in this study.

Coefficient of divergence (CoD) is a statistical method that can be used to evaluate the degree of uniformity of pollutant measured simultaneously at two sites. It was performed in this study to investigate the similarity of $PM_{2.5}$ collected at every two sites in a relatively short distance in the community. CoD is defined as:

$$\boldsymbol{CoD_{jk}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_{ij}-X_{ik}}{X_{ij}-X_{ik}}\right)^{2}}$$

Where n stands for the number of observations, j and k represent the paired two sites, X_{ij} and X_{ik} mean the i-th concentration measured at site j and site k. CoD lower than 0.2 between two sites are typically seen as spatial homogenous, while a CoD higher than 0.2 shows spatial heterogenous. (Feinberg et al., 2019; Pakbin et al., 2010; Wongphatarakul et al., 1998)

3. RESULTS

3.1 Seasonal Meteorology and $PM_{2.5}$ at University Village

Table A3 shows the ambient temperature in the study period ranged from 18.7 to 26.3°C, with an overall mean of 21.9 ± 5.51°C. RH ranged from 43.3 to 54.4%, with an overall mean of 51.4 ± 16.8% in the sampling period. As shown in Figure A1, for most of our sampling time, the wind predominantly blew from southwest and northwest, with their respective wind speed in the range of 0.1-6 m/s and in the range of 0.1-2 m/s.

As shown in Table A4, with the highest $PM_{2.5}$ were observed in the winter (15.7 ± 16.7 $\mu g/m^3$), followed by autumn (14.6 ± 12.8 $\mu g/m^3$), summer (10.8 ± 6.26 $\mu g/m^3$) and spring (8.8 ± 7.21 $\mu g/m^3$). On average, the mean of $PM_{2.5}$ appeared to exhibit seasonality; though the large variation should be kept in mind.

3.2 Inter-Sensor Variability

The variability between sensors deployed within a short distance throughout the sampling locations (500-600m) were investigated (Figure 1(a)). Spearman correlation coefficient (r) and Coefficient of Divergence (CoD) were used to investigate the temporal trend and spatial variability between pairwise sensors. Table 1 shows that the correlations coefficients among the sensors were all higher than 0.98. This suggests that all the sensors were temporally correlated with each other. Furthermore, the CoD ranged from 0 to 0.02 and this indicating a strong spatial similarity among the sensors (Table 2).

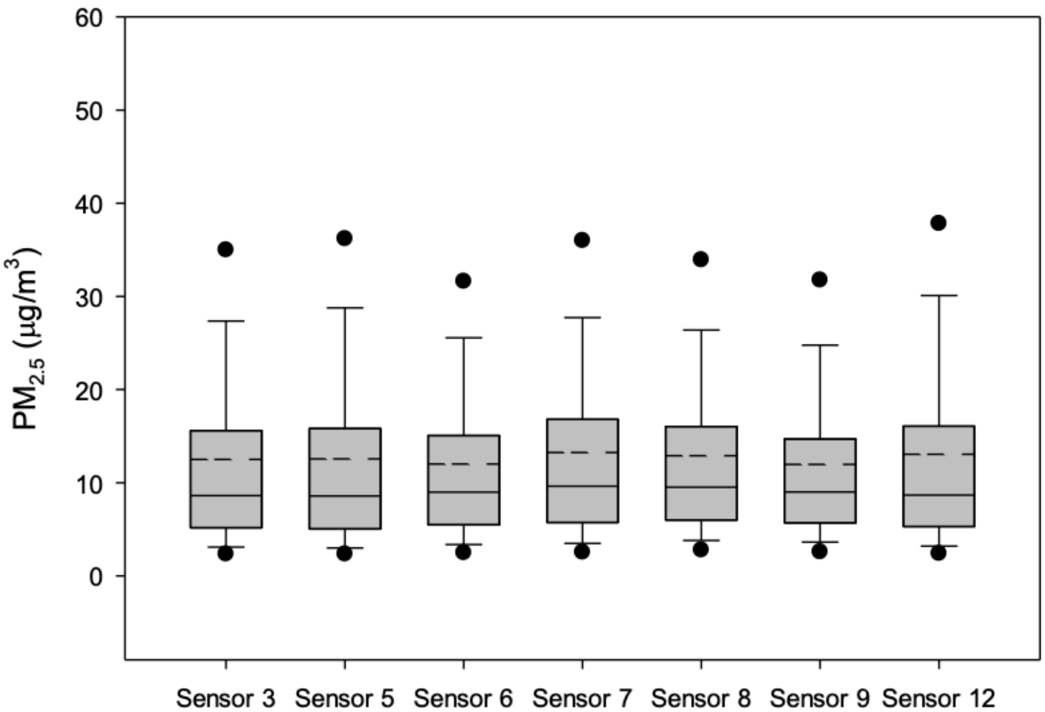

Figure 2. $PM_{2.5}$ distributions across all sensor sites.

Table 1. Pairwise correlation of $PM_{2.5}$ among the PurpleAir sensors.

Sensor ID	3	5	6	7	8	9	12
3	0						
5	0.98	0					
6	0.99	0.98	0				
7	0.99	0.98	0.99	0			
8	0.99	0.98	0.99	1	0		
9	0.98	0.98	0.99	0.99	0.99	0	
12	0.99	0.98	0.99	0.99	0.99	0.99	0

Table 2. Pairwise coefficient of divergence (CoD) among the PurpleAir sensors.

Sensor ID	3	5	6	7	8	9	12
3	0						
5	0.02	0					
6	0.01	0.004	0				
7	0.02	0.01	0.01	0			
8	0.01	0.01	0.01	0.01	0		
9	0.01	0.01	0.004	0.01	0.01	0	
12	0.02	0.01	0.01	0.01	0.01	0.01	0

3.3 PurpleAir and Reference Instrument

The $PM_{2.5}$ from 7 sensors (#3, #5, #6, #7, #8, #9, #12) were averaged and compared with the $PM_{2.5}$ from the EPA monitor station shown in Figure 3. Data were aggregated to annual means to be more representative of the long-term relationship. Strong positive correlations (weekday: $r = 0.79$, weekend: $r = 0.82$) were found between the sensor derived $PM_{2.5}$ at the university village and the $PM_{2.5}$ at the EPA monitor site. The value of CoD is 0.17, suggesting a relatively homogenous distribution of $PM_{2.5}$ across the university village and the EPA North Main Street monitor site.

(a) (b)

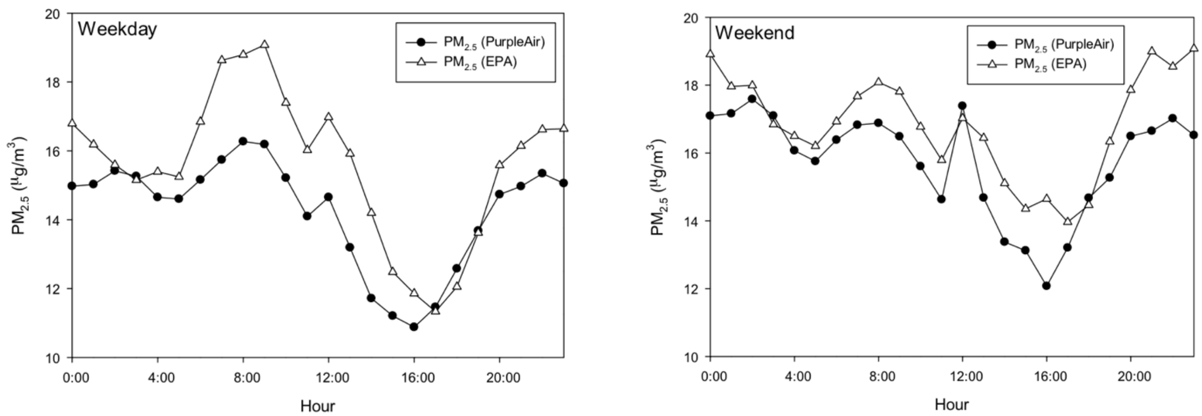

Figure 3. Hourly variation of EPA $PM_{2.5}$ and measured $PM_{2.5}$ during (a) weekdays (b) weekends.

3.4 Temporally-resolved Traffic Impact

Figure 4 illustrates the temporal variability of hourly traffic flow, $PM_{2.5}$, $PN_{0.3}$ and NO_2, averaged over the study period, for weekdays and weekends. As shown, the traffic flow on I405 had a maximum (6000 #/hour) at 10:00 LT and another small peak (5000 #/ hour) at about 19:00-20:00 LT during both weekdays and weekends. Though, the rise of morning traffic flow occurred more sharply during weekdays than weekends. The NO_2 reached a maximum shortly after the rise of morning traffic flow, and 2 hours later followed by $PM_{2.5}$ and $PN_{0.3}$ also reaching their maxima. The morning peaks of $PM_{2.5}$ and $PN_{0.3}$ lagged few hours behind the morning NO_2 peak, suggesting that they were not only emitted from vehicles but also coming from other sources. In addition, the lag may also in part due to the fact that gaseous pollutants transport and disperse more efficiently than particle pollutants (Cai et al., 2009). These are clear indication that elevated NO_2, $PM_{2.5}$ and $PN_{0.3}$ in the morning at University Village were associated with traffic emissions from I405. Unlike NO_2, both $PM_{2.5}$ and $PN_{0.3}$ show elevated concentration at noon time, suggesting potential contributions from secondary formation under strong solar intensity

(Kuprov et al., 2014). NO_2, $PM_{2.5}$ and $PN_{0.3}$ all reached a minimum between 15:00-16:00 LT, likely due to the well-mixed atmosphere condition in the late afternoon. In the evening around 20:00 LT, there are another rise and drop of traffic flow. In the meantime, NO_2, $PM_{2.5}$ and $PN_{0.3}$ began to rise and, unlike the traffic flow drop, continue on late into the midnight. This agrees with the result in the previous study that NO_2 has a better correlation in the morning than in the evening (Kendrick et al., 2015) Regardless of weekdays or weekends, NO_2, $PM_{2.5}$ and $PN_{0.3}$ showed strong positive correlations with each other ($r > 0.64$).

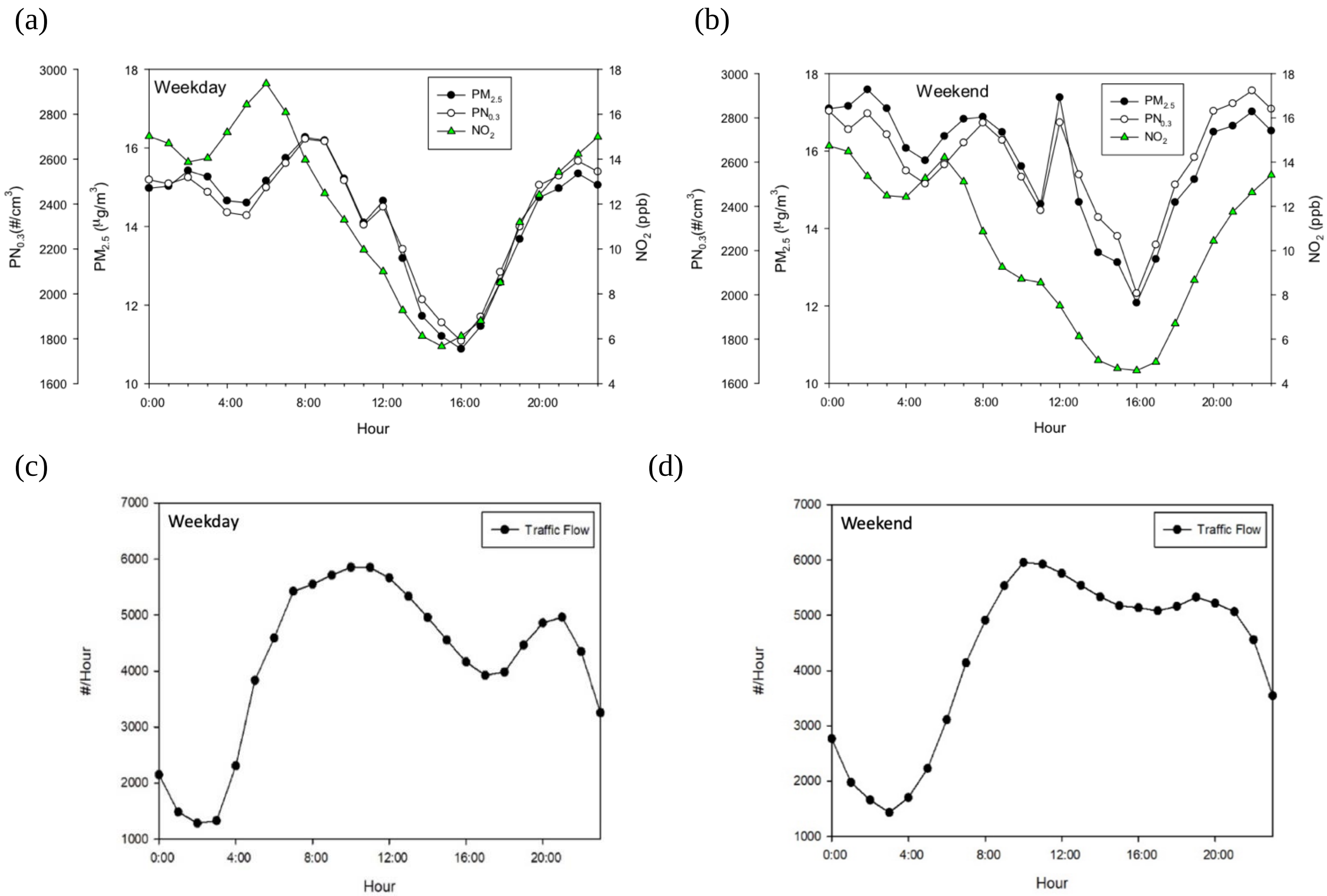

Figure 4. Hourly variation of $PM_{2.5}$, $PN_{0.3}$, NO_2 and traffic flow. (a) $PM_{2.5}$, $PN_{0.3}$ and NO_2 pattern during weekdays. (b) $PM_{2.5}$, $PN_{0.3}$ and NO_2 pattern during weekends. (c) Traffic pattern during weekdays. (d) Traffic Pattern during weekends.

3.5 Spatially-resolved Traffic Impact

I405 is a major north-south auxiliary Interstate Highway in Southern California. The average traffic flow acquired from PEMS reached 4203 (vehicle/ hour) during the study period. To investigate whether traffic emissions from I405 has a major impact on $PM_{2.5}$ and $PN_{0.3}$ at the University Village, sensors on both sides of I405 were analyzed. In specific, sensors 3, 5, 6 were located at the east side, whereas sensors 7, 8, 9 and 12 were located at the west side of I405. Depending on wind directions, either side could be upwind and downwind of I405.

In order to see the impact of I405 under high traffic flow (> 5000 #/hour), polar plots of the $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ between the eastside and the westside were examined. Figure 5 shows the $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ between the eastside and the westside of I405. Interestingly, regardless of which side, $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ were predominantly red in the direction of I405 in the polar plots. This shows that $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ were typically higher downwind of I405, and thus implies the impact of traffic emissions from I405 on the pollutant level at the University Village. This illustrates that polar plots can be used to spatially resolve nearby traffic emissions.

Although using the average concentration of the eastside and the westside sensors suggests that $PN_{0.3}$ can be used to detect the traffic signal, a closer examination is shown in Figure A2. Instead of using the averaged data of sensors, polar plots of pairwise sensors (each eastside sensor in combination with each westside sensor) were created to show the origin of higher concentration; The higher concentration (red area) is expected to be at the east (right) side of the polar plots (I405 is located at the east side). However, the results are not consistent in these polar plots, some of them showed that the higher concentration comes from the north side or the east side, whereas some of them showed the higher concentration comes from the direction of I405, this suggests that using $PN_{0.3}$ to pick up the traffic signal stays equivocal. In contrast, relative consistent results were found when the same technique was applied using $PM_{2.5}$, except for the plot of sensor 8 and sensor 3, other plots of pairwise sensors indicated that the higher concentration comes from the direction of I405 (Figure A3).

In a previous study, it was observed that ultrafine particle has an 80-90 % decline in peak/edge-of-road number concentration by 300-400 m of the road, and fine particle (0.3 μm) was found to have no trend regards to the distance to the edge-of-road while $PM_{2.5}$ has a less rapid decay(Karner et al., 2010). A similar pattern of number concentration was found in (Zhu et al., 2002) study, demonstrating that smaller particle (6-25 nm) decay rapidly by 100 m and larger particle (100-220 nm) has no trend in regard to the distance to the edge-of-road.

As a result, based on our findings, the capability of the PurpleAir sensor to pick up the traffic signal by using $PN_{0.3}$ remains ambiguous at best, and this might be due to the distance of our sensors to I405 and the 50% collecting efficiency of $PN_{0.3}$ of PurpleAir.

(a) (b)

Figure 5. Polar plots of $\Delta PM_{2.5}$ and $\Delta PN_{0.3}$ between the eastside and the westside of I405 for (a) $PM_{2.5}$ (b) $PN_{0.3}$.

4. CONCLUSIONS

Our results show that the mean of the $PM_{2.5}$ appeared to exhibit seasonality, with large variations at the University Village; Highest concentration in the winter, and lowest in the spring. Strong correlations were found between the $PM_{2.5}$ of pairwise sensors deployed within a short distance within the community. This suggests that these sensors are all temporally correlated with each other. In addition, CoD with values in the range of 0-0.02 reveals that the sensors spatially shared a great similarity. A positive correlation was also found between the $PM_{2.5}$ at the University Village and the $PM_{2.5}$ at the EPA monitor sites, indicating that sensors at the University Village are temporally correlated with the closest EPA monitor site. Furthermore, a CoD of 0.17 was found between the $PM_{2.5}$ at the University Village and the EPA monitor site, suggesting that these two sites are not only temporally correlated but also spatially correlated to each other.

The strong correlations of the temporal patterns of $PM_{2.5}$, $PN_{0.3}$ and NO_2 clearly demonstrated that the traffic is one of the major contributors to the air pollutants at the University Village. Using two sensors set at each side of the highway could be used to visualize the hotspots for source locations. In specific, for PurpleAir, $PM_{2.5}$ might be a more reliable parameter to trace the traffic emission instead of $PN_{0.3}$, because the $PN_{0.3}$ concentration decays more quickly with increasing distance.

Generally, PurpleAir shows a good long-term stability in measuring $PM_{2.5}$ and $PN_{0.3}$ in the field; however, we found that the WIFI connection is the main issue that might reduce the number of collected data in this community study. In addition to the accuracy of the sensors, the strategical deployment of the sensors is also critical since it might cause different interpretations of the pollutants and affect the decision of which parameter is most effective to a specific question in a study.

APPENDICES

Table A1. Summary of the sensors performance in different seasons.

Sensor 3 (N=7101)	Sensor 4 (N=2608)	Sensor 5 (N=6780)	Sensor 6 (N=6249)	Sensor 7 (N=8709)	Sensor 8 (N=7800)	Sensor 9 (N=7408)	Sensor 10 (N=6022)	Sensor11 (N=2553)	Sensor 12 (N=6156)
1694 (23.9%)	0 (0%)	2198 (32.4%)	1928 (30.9%)	2196 (25.2%)	2042 (26.2%)	2186 (29.5%)	1683 (27.9%)	0 (0%)	1926 (31.3%)
1143 (16.1%)	0 (0%)	1035 (15.3%)	1650 (26.4%)	2196 (25.2%)	2194 (28.1%)	2190 (29.6%)	2133 (35.4%)	0 (0%)	1012 (16.4%)
2149 (30.3%)	1552 (59.5%)	1475 (21.8%)	1566 (25.1%)	2181 (25.0%)	2155 (27.6%)	2182 (29.5%)	678 (11.3%)	1543 (60.4%)	1379 (22.4%)
2115 (29.8%)	1056 (40.5%)	2072 (30.6%)	1105 (17.7%)	2136 (24.5%)	1409 (18.1%)	850 (11.5%)	1528 (25.4%)	1010 (39.6%)	1839 (29.9%)

	Sensor 1 (N=2507)	Sensor 2 (N=54)
Spring (MAM)	544 (21.7%)	0 (0%)
Summer (JJA)	900 (35.9%)	0 (0%)
Autumn (SON)	0 (0%)	54 (100%)
Winter (DJF)	1063 (42.4%)	0 (0%)

Table A2. Summary of yearly performance and data recovery of the sensors.

	Raw Data	After QAQC
Sensor 1	2654 (30%)	2512 (29%)
Sensor 2	54 (1%)	54 (1%)
Sensor 3	7153 (82%)	7103 (81%)
Sensor 4	2625 (30%)	2606 (30%)
Sensor 5	6837 (78%)	6781 (77%)
Sensor 6	6310 (72%)	6252 (71%)
Sensor 7	8750 (99.9%)	8715 (99%)
Sensor 8	7828 (89%)	7808 (89%)
Sensor 9	7439 (85%)	7415 (84%)
Sensor 10	6218 (71%)	6029 (69%)
Sensor 11	2578 (29%)	2551 (29%)
Sensor 12	6255 (71%)	6161 (70%)

Table A3. Summary of meteorology at the sampling sites.

	Temperature (°C)		Humidity (%)		Windspeed (m/s)	
	Mean (SD)	Median	Mean (SD)	Median	Mean (SD)	Median
Spring (MAM)	20.0 (4.13)	19.2	54.3 (15.1)	57.3	0.98 (0.67)	0.82
Summer (JJA)	26.3 (4.79)	25.6	54.4 (12.0)	56.7	1.09 (0.75)	0.93
Autumn (SON)	23.1 (4.67)	22.4	52.8 (17.6)	57.0	0.93 (0.64)	0.72
Winter (DJF)	18.7 (5.34)	17.8	43.3 (19.3)	43.0	0.94 (0.68)	0.72
Overall	21.9 (5.51)	21.4	51.4 (16.8)	54.3	0.96 (0.68)	0.78

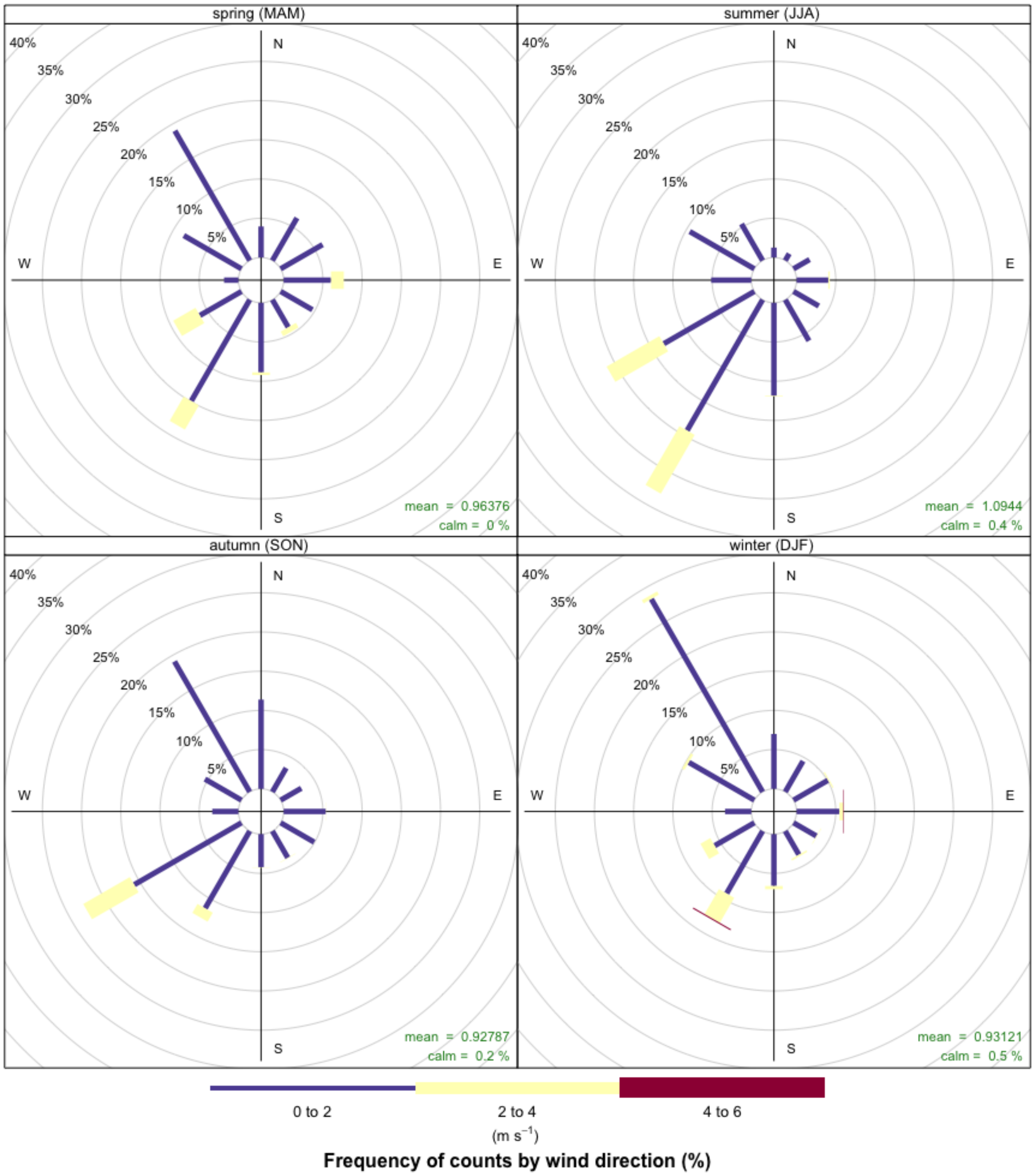

Figure A1. Wind direction and wind speed nearby the sampling sites.

Table A4. Summary of $PM_{2.5}$ in different seasons.

	Spring (MAM) (n=16217)	Summer (JJA) (n=14482)	Autumn (SON) (n=16753)	Winter (DJF) (n=16098)
$PM_{2.5}$ ($\mu g/m^3$)				
Mean (SD)	8.8 (7.21)	10.8 (6.26)	14.6 (12.8)	15.7 (16.7)
Median	6.71	8.83	10.6	10.1
[Min, Max]	[1.66, 150]	[1.74, 42.1]	[1.67, 226]	[1.65, 628]

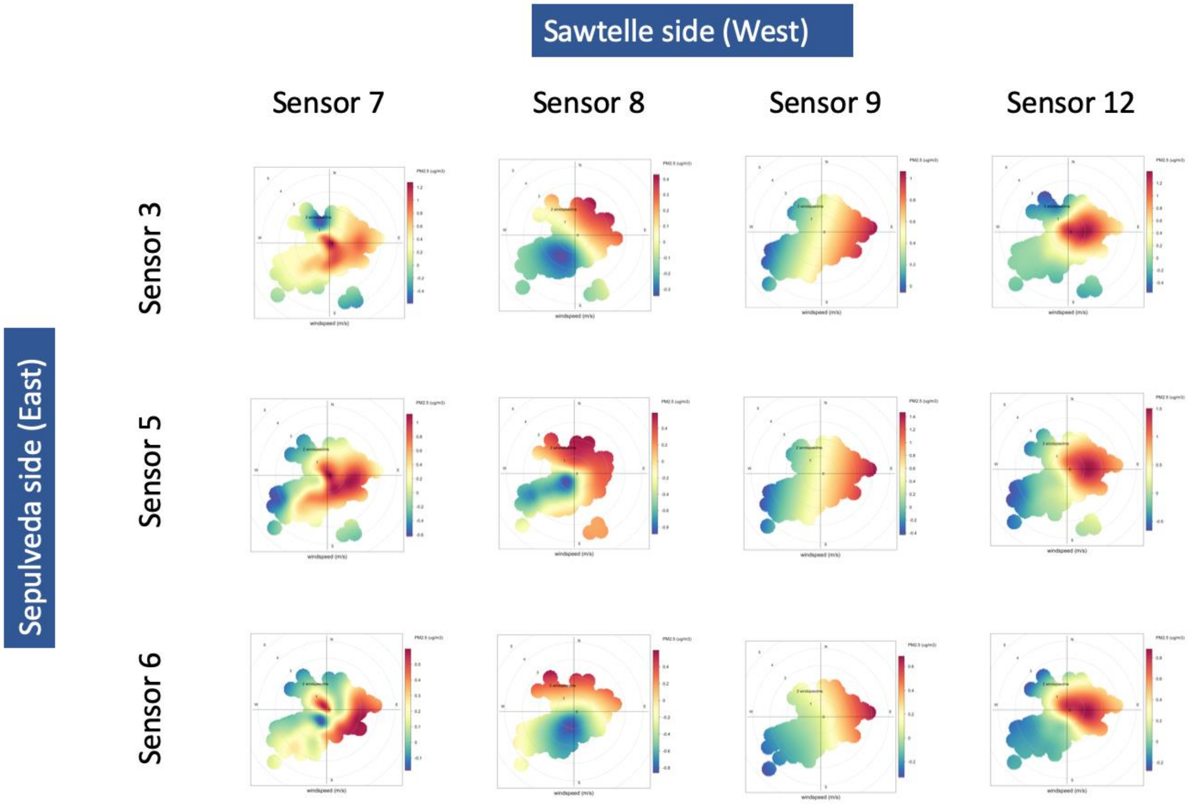

Figure A2. Pairwise polar plots of $\Delta PM_{2.5}$ between the eastside and the westside of I405.

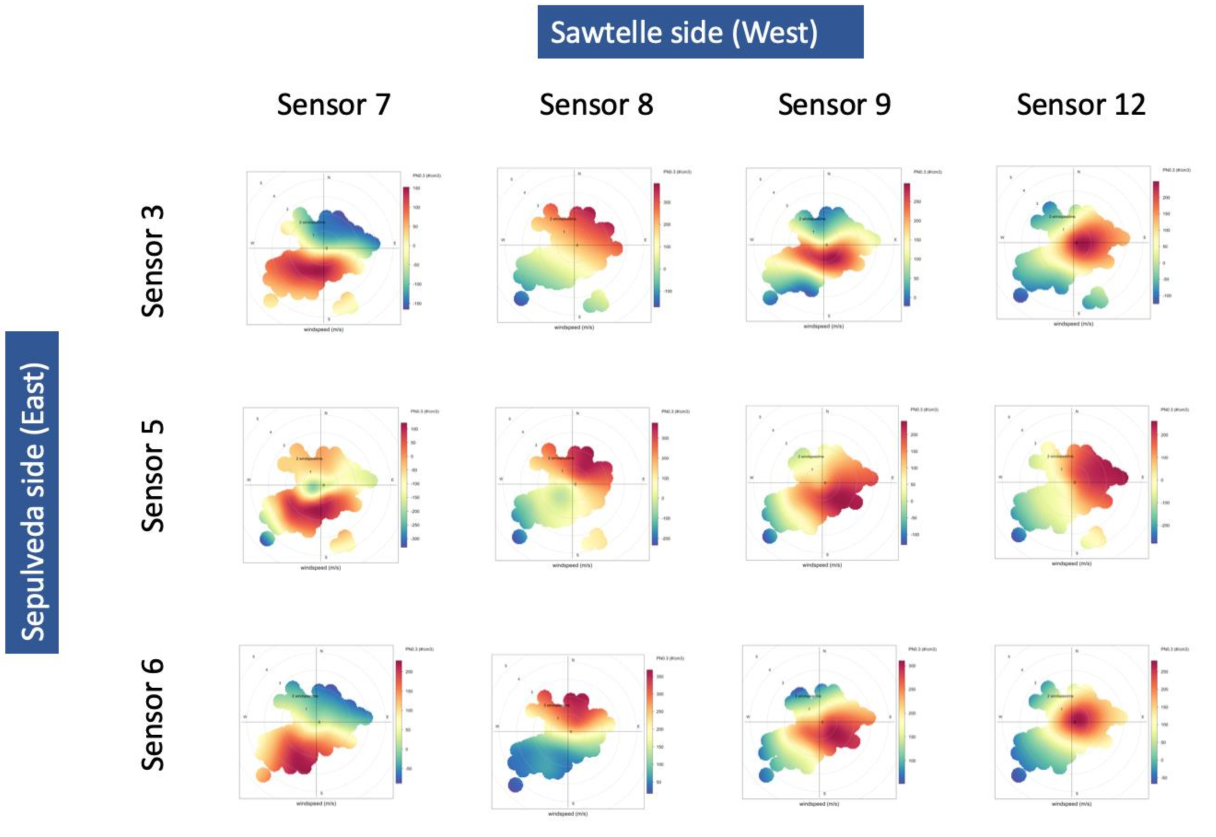

Figure A3. Pairwise polar plots of $\Delta PN_{0.3}$ between the eastside and the westside of I405.

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