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An Analysis of Effects of Woolsey Wildfire on UCLA University Village Air Quality using low-cost sensors

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# UNIVERSITY OF CALIFORNIA

# Los Angeles

An Analysis of Effects of Woolsey Wildfire on UCLA University Village Air Quality using lowcost sensors

A thesis submitted in partial satisfaction of the requirements for the degree Master of Science in Environmental Health Sciences

by

Sitao Jia

#### ABSTRACT OF THE THESIS

An Analysis of Effects of Woolsey Wildfire on UCLA University Village Air Quality using lowcost sensors

by

#### Sitao Jia

Master of Science in Environmental Health Sciences
University of California, Los Angeles, 2019
Professor Yifang Zhu, Chair

The impacts of major gaseous and particulate pollutants emitted by the wildfire of November 2018 on ambient air quality of UCLA University Village which is 20 miles southeast of the fire before, during, and after the fire are analyzed using data available from the PurpleAir Air Quality Monitoring Network and Meteorological Station. It was found that both fine particulate matter (PM smaller than 2.5 µm in diameter [PM2.5]) and inhalable (PM smaller than 10 µm in diameter [PM10]) levels exceeded the federal daily 24-hour average standard during the fire and the elevation of the outdoor PM levels in our target community has a 2-3 days lag. The wind directions as well as the traffic from freeway 405 are two important factors of the outdoor air pollutions. And during the fire, it is found that there was a significant change of the wind direction during the wildfire, while the outdoor air quality has a daily rhythmic change due to the traffic from the freeway as well. The study shows that the use of HVAC system effectively

decreased PM concentration. On the basis of the findings, it is recommended that communities engage in pre-event planning and purification measures that would minimize the indoor impacts as a result of a large wildfire. It is also advised that appropriate agencies engage in the use of all available meteorological forecasting resources, including real-time satellite imaging assets, to accurately forecast air quality and assist firefighting efforts.

The thesis of Sitao Jia is approved.

Michael D. Collins

Shane S. Que Hee

Yifang Zhu, Committee Chair

University of California, Los Angeles

2019

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#### 1. Introduction

## 1.1 Objective and Rationale

The overall objective of this research is to analyze the air pollution introduced by the Woolsey fire during November 2018 to the target community using the data collected by low-cost sensors in order to provide the target community with knowledge about the impacts of wildfires as well as effective mitigations. In a broader and long-term perspective, the implementation of this project will also allow individuals to become more familiar with specific air quality issues affecting their communities and will empower them with the knowledge and experience they need to take action to avoid air pollution exposure during future events including but not limited to wildfires, using low-cost air pollution sensors. Results from this study will also help governmental organizations and other policy deciders to understand air quality issues better at the community level and to make better policy decisions, which will help protect the public from the impacts of wildfire air pollution. These goals will be accomplished by pursuing the following aims: (1) Use data collected by sensors to explore outdoor air quality and weather trends before, during and after the Woolsey fire; (2) Compare the indoor and outdoor air quality and test the influence of self-experiment to give mitigation advice during wildfires; (3) Develop potential new methodologies to educate and engage communities on the use and applications of low-cost sensors.

#### 1.2 Importance and Application

Wildland fires are burning events which occur in natural or semi-natural landscapes such as forests, shrublands, or grazing lands including savannahs. They are one of the major natural hazard (Bowman et al., 2009) and an important source of air pollutants (Langmann, 2009), which

can impact air quality thousands of kilometers downwind (Lee et al., 2005). Wildfires play an important role in some atmospheric chemistry–climate feedback mechanisms as well (Fiore et al., 2012). Wildfire smoke has a distinct composition, containing high levels of fine particles. Since fine particles are generally purified out of the air more slowly than coarse particles, they travel farther than coarse particles from the pollution source (Kinney, 2008). Fine particles as well as ultra-fine particles are also considered important health hazards due to their ability to penetrate into the lung. EPA singled out PM2.5 for special consideration (EPA, 2009). Wildfire smoke exposure impacts millions of people. For example, in 2011 alone, 212 million people were affected by smoke, many of whom live far downwind from the fire sources (Knowlton, 2013).

Throughout the past decades, epidemiology researches have shown a consistent relationship between increases in PM exposures and increases in mortality and morbidity (Q Di et al. 2017; Dockery et al. 1993; Schwartz 1991; Vedal 1997). Wildfires can produce substantial increases in the concentration of gaseous pollutants such as carbon monoxide (CO), nitrogen oxides (NOx), ozone (O<sub>3</sub>), and volatile organic compounds (VOCs) as well as particulate matter (PM) (Briggs, 2016). The Woolsey Fire, which started November 8, 2018, in Los Angeles and Ventura Counties, caused three fatalities and three firefighter injuries. The fire burned 96,949 acres and was 100 percent contained on November 21, 2018. The fire caused the evacuation of more than 295,000 people ("Woolsey Fire", wikipedia).

#### 1.3 Wildfire pollutants and health impacts

Wildfire emit a substantial amount of gaseous pollutants and particulate matter into the environment, which cause people to struggle against respiratory illnesses. Some other consequences include nuisance, ozone (O<sub>3</sub>) generation, and visibility impairment. In recent years, air pollution has been considered an important cause or risk factor for reproductive health. There have been growing concerns about the adverse effects of air pollution on birth outcomes, such as low birth weight (LBW), intrauterine growth retardation, preterm births, and birth defects (Ritz et al. 2002; Bobak, 2000). Coarse PM (PM10) exposure in the second and fourth months has been associated with LBW (Ha, 2013). Particulate air pollution has been associated with both acute and chronic exacerbation of childhood asthma. More chronic symptoms of bronchitis have been observed in previous cross-sectional studies of children with asthma exposed to PM (Heinrich, 2000).

Wildfire smoke is comprised of a complex mixture of particles, gaseous compounds and liquids. These mixtures include PM10, carbon monoxide (CO), and sulfur dioxide (SO2), nitrogen oxides (NOx), oxidants such as O<sub>3</sub>, polycyclic organic material (Liu, 2016), and other toxic pollutants. The emissions of these mixtures may significantly affect local or regional air quality, and even to the global scales. Some events are extremely serious, and the contributions of fires to air pollutant concentrations are readily observable (Bray, 2018). For example, the 1997 Indonesia forest fire caused massive transboundary air pollution, producing large amounts of haze in the region and causing visibility and health problems within Southeast Asia. Furthermore, fires of such magnitude sometimes potentially contribute to climate change like global warming as they emit large amounts of greenhouse gases and pyrogenic products (Li, 2010; Yang, 2013).

Time-series and panel studies have shown acute increases in ambient PM to be associated with increases in emergency room visits (Norris, 1999), hospital admissions for asthma (Clark, 2009; Janssen, 2011), acute symptoms (Brozek, 2010; Ciencewicki, 2008; Weinmayr, 2009), medication use (Brozek, 2010; Weinmayr, 2009), and a decline in peak expiratory flow rates (Ciencewicki, 2008; Chung, 2009). There was a 91% increase in asthma and chronic bronchitis incidences during a fire in central Florida in 1998, putting a heavy burden on clinics and hospitals. The main health impact is from the exposure to PM. It is a major component of souces of smoke and is comprised of a complex mixture of tars, soot, thus, is harmful to human health (Liu, 2016). In many cases, pollutant gases, such as SOx, NOx, and VOCs, interact with other compounds in the air to form fine particles. Their physical and physical compositions may vary depending on the location, time in the year, and the weather (EPA, 2009). Fine PM (PM2.5) is becoming more and more commonly measured during fire-related events and disasters because the fine fraction predominates in the smoke and haze, and it is thought to be more responsible than larger particles for many observed health effects (Huang, 2014; Watson, 2002).

# 1.4 Vulnerability of UCLA University Village

UCLA University Village, 20 miles away from the Woolsey fire, was built to offer housing designed to meet the needs of undergraduate and graduate families, married students, and single-parent students, making it a community with a high-proportion of young kids and pregnant women. Children and pregnant women are vulnerable populations to most of the air pollutants (Makri et al. 2008).

#### 1.5 Low-cost sensor as a potential household inspection tool

Because of recent technological advancements in the areas of electrical engineering and wireless networking, manufacturers have recently begun marketing "low-cost" air monitoring sensors to measure air pollution in real-time (Snyder et al., 2013). Considering how fast this type of technology is evolving, it is likely that the type and numbers of these sensors will substantially increase in the future. These devices, assuming they produce reliable data, can significantly augment and improve current ambient air monitoring capabilities that predominantly rely on the more sophisticated and expensive federal-reference (or federal-equivalent) monitoring instruments and methods operating at fixed sites. Given their low cost, these sensors are becoming an attractive means for local environmental groups and individuals to independently evaluate air quality. This new approach is receiving acknowledgement from the U.S. EPA and may shift air monitoring towards a different paradigm in which traditional monitoring by air quality agencies is supplemented by community-based monitoring using "low-cost" sensors ("Roadmap for Next Generation Air Monitoring"; US EPA, 2013).

As individuals learn more about sensor technology, they become more educated and informed about specific air quality issues in their community. This knowledge has the potential to empower them to develop community-based strategies to reduce air pollution exposures to protect their health (Snyder et al., 2013). The concept of engaging the public in making observations and collecting / recording data is typically referred to as "citizen science" (Cornwall and Jewkes, 1995). In this context, citizen science activities can take advantage of community-based participatory monitoring and "crowd sourcing" where many individuals voluntarily collect large amounts of data using hand-held devices, cell-phones, and other portable devices that are

then compiled and analyzed (White et al., 2012). Widespread data collection and data sharing using new sensors is already occurring in the U.S. and in Europe. In most cases such air quality data is freely available on the web along with interactive maps showing spatial distributions of pollutant levels.

While the quality of current sensor data collected by citizen scientists is usually uncertain, these activities demonstrate the interest and potential for individuals and communities to increase the amount and spatial coverage of air monitoring data collected. However, despite these new potential applications, there are often no independent or systematic means by which these devices are evaluated, and data from these monitors are usually accepted at face value. Preliminary tests performed in the U.S. and Europe seem to suggest that many of the commercially available sensors have poor reliability, do not perform well in the field under "actual" ambient conditions, and do not typically correlate well with data obtained using "standard" measurement methods employed by regulatory agencies (Vallano et al., 2012). Poor quality data obtained from unreliable sensors (especially when in conflict with data obtained from traditional, more sophisticated monitoring networks) may not only lead to confusion but also jeopardize the successful evolution of "low-cost" sensor technology. Therefore, there is an urgent need to better characterize the actual performance of air monitoring sensors and their long-term reliability, as well as educate the public and users who lack specific technical training on the potential applications and limitations of these devices.

#### 2. Methods

#### 2.1 Location

The study was conducted at the UCLA University Village. It's around 20 miles distance from the Woolsey wildfire source as shown in Figure 1.



Figure 1 Maps of UCLA University Village and the Woolsey fire.

The community is located closely alongside the I-405 as shown in Figure 2, with the closest distance of 15 meters to the freeway sound barrier. As this freeway is found to be a significant PM source, the residents near freeway maybe exposed to a high PM level in both outdoor and indoor environments. As the Village has a large proportion of sensitive people including babies, kids and pregnant women, air quality is of more significant importance to the community. The unique location, population structure, and interest of residents in air quality at UCLA university village make it an ideal location to conduct this community engaged air quality study.

#### 2.2 Sensor selection

Several factors were taken into account before selecting one or more air monitoring sensor types for this project. Factors with high importance include targeted pollutant, detection range, redundant and detection limit, accuracy and precision, calibration requirements, data collection, storage and retrieval, energy consumption, durability and the ease of use. Other factors include time resolution, response time, price and known performance of the sensors.

The sensors adopted in this study, PurpleAir II, was selected out of 8 commercially available low-cost sensors as Table 1 shows. 30 PurpleAir II sensors were installed in the UCLA



**Figure 2 a)** All 30 sensors including 18 indoor and 12 outdoor, which are distributed along two sides of the 405 freeway. **b)** 12 outdoor sensors with 6 on the west side and 6 on the east side.

University Village. Among them 12 are outdoor sensors, 6 on Sawtelle side and 6 on Sepulveda side. 18 are indoor sensors, 8 on Sawtelle side and 10 on Sepulveda side. All the sensors deployed in this study were calibrated by running DustTrak for 15 minutes shortly after installation. Each sensor monitors specific PM levels borne by sources pertaining to the location.

## 2.3. Validation and Data cleaning

The meteorological data were from the nearest monitoring station which has almost the same distance to the Pacific Ocean as University Village.

**Table 1** Sensor Comparisons

Manufacturer (Model)	Pollutant(s)	Approx. Cost (USD)	*Field R <sup>2</sup>	Lab R <sup>2</sup>
TSI (AirAssure)	PM2.5	~\$1,500	$R^2 \sim 0.82$	$R^2 \sim 0.99$
Air Quality Egg (Version   )	PM	~\$240	$PM_{2.5}$ : $R^2 \sim 0.79$ to 0.85 $PM_{10}$ : $R^2 \sim 0.31$ to 0.40	
DC1100 PRO	PM(0.5-2.5)	~\$300	$R^2 \sim 0.65 \text{ to } 0.85$	$R^2 \sim 0.89$
Foobot	PM2.5	~\$200	$R^2 \sim 0.55$	
Hanvon N1	PM2.5	~\$200	$R^2 \sim 0.52$ to 0.79	
Laser Egg	PM <sub>2.5</sub> & PM <sub>10</sub>	~\$200	$PM_{2.5}$ : $R^2 \sim 0.58$ $PM_{10}$ : $R^2 \sim 0.0$	
PurpleAir (PA   )	$PM_{1.0}, PM_{2.5}\& PM_{10}$	~\$200	PM <sub>1.0</sub> : $R^2 \sim 0.96$ to 0.98 PM <sub>2.5</sub> : $R^2 \sim 0.93$ to 0.97 PM <sub>10</sub> : $R^2 \sim 0.66$ to 0.70	$PM_{1.0}$ : $R^2 \sim 0.99$ $PM_{2.5}$ : $R^2 \sim 0.99$ $PM_{10}$ : $R^2 \sim 0.95$
Shinyei (PM Evaluation Kit)	PM2.5	~\$1,000	$R^2 \sim 0.80$ to 0.90	$R^2 \sim 0.93$

<sup>\*</sup>The correlation coefficient (R2) is a statistical parameter indicating how well the performance of each sensor compares to that of a Federal Reference Method (FRM), Federal Equivalent Method (FEM), or Best Available Technology (BAT)

Sensor data was validated periodically through a rigorous QA/QC process to evaluate sensor performance and reliability. Once validated, this data was analyzed using statistical software R 'openair' package. The raw data was originally from sensor deployment in University Village, meteorological data from the nearest monitoring station North Main (Downtown LA, ~ 10 miles), and from the questionnaires and pre-/post-study surveys. All collected data were carefully evaluated and validated. After passing the validation processes, data was qualified for further uses to draw plots and figures.

The PM levels were collected around every 80 seconds. When analyzed, it was calculated into average hourly values or 5-minute values due to different uses. For hourly data, only those hours

with less than 25% missing values are used for analysis. For 5-minute data, all duration are calculated into 5-minute average levels. The whole rows of those missing values are deleted for one plot.

#### 2.4 Statistical Analysis

- I. Test the statistical distribution of PM concentrations. The PM2.5 concentration data collected by sensor Scuv\_01 was chosen to test the statistical distribution of concentration data, the result of which could be a reference for our statistical analysis.
- II. Summary data collected by 12 outdoor sensors. Use daily average data and 5-minute interval data to show overall PM levels before, during and after the fire, then compare the concentration with federal standards for PM2.5 and PM10. Also narrow down to look into outdoor air quality during the 3 days when PM levels sharply increased in order to find out the specific hours that PM levels reach the highest.
- III. Evaluate time trends and spatial trends of the outdoor air quality. Calculate the PM level of the same time for every day in November 2018 to determine daily PM2.5 level trends.Conduct spatial trend analysis across all the outdoor sensors before and during the Woolsey fire, in particular the first weekend after the fire began to find out the main pollution source direction.
- IV. Statistical test of difference between outdoor and indoor air quality. First the O/I difference for each interval was calculated by:

O/I difference =  $PM(Outdoor)_t$  -  $PM(Indoor)_t$ 

Then use two-sample t-test to find out whether there is any significant difference between concentration O/I difference values before and during the event. Also conduct another two-

sample t test for ln(O/I difference). The hypothesis is the O/I as well as ln(O/I difference) difference is greater during the event than before the event. If the P-value is lower than 0.001, we could draw conclusion, that the wildfire brought more fine particles in the air than normal.

- V. Statistical test of wind condition changes before and during the wildfire event. Use twosample t test to find out whether there is any significant difference between wind direction and wind speed before and during the event, which may be influenced by the wildfire.
- VI. Effect of individual behavior intervention. In this study our participant with the indoor sensor SCUV\_21 did some experimenting with the HVAC during the wildfire. The effects of such intervention would be tested.

#### 3. Results

Smoke from the large Woolsey fire of Los Angeles and Ventura Counties began to drift over the Los Angeles area on November 8th and blanketed the entire region. This resulted in abrupt and dramatic, but short-lived, concentration increases in both PM2.5 and PM10 on those days.

#### 3.1 Overall PM levels before, during and after the fire

#### 3.1.1. Outdoor versus indoor before, during and after the event

According to the calendar plots (Figure 3), the indoor particles increased as with outdoor's but was more slightly. Although both indoor and outdoor PM2.5 levels were increased heavily, the outdoor levels of PM2.5 were twice the concentration of the indoor level. A week after the maximum level of PM, the air pollution once again increased above federal limit and lasted for a week.

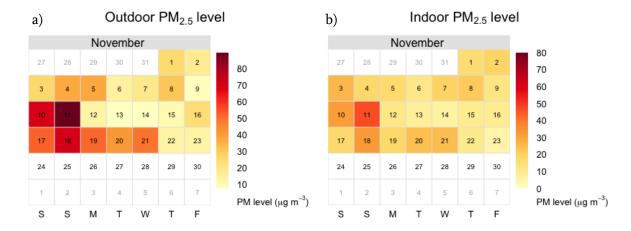
**Table 2** The average of PM concentrations for outdoor sensors  $(mg/m^3)^{-1}$ 

Sensor number	Particles	Min	Max	Mean
scuv_1	PM2.5	0.91	468.43	27.37
scuv_1	PM10.0	0.91	539.62	29.59
conv. 2	PM2.5	0.4475	314.3600	30.8071
scuv_3	PM10.0	0.9433	334.7650	35.4638
conv. 4	PM2.5	0.5733	400.8850	29.3133
scuv_4	PM10.0	1.247	469.770	35.710
	PM2.5	0.19	231.22	30.39
scuv_5	PM10.0	0.83	255.18	37.24
	PM2.5	0.5767	385.5600	34.3056
scuv_6	PM10.0	1.252	464.640	40.020
7	PM2.5	0.8475	389.7400	32.3064
scuv_7	PM10.0	1.062	459.062	36.199
0	PM2.5	0.5225	172.0000	31.3067
scuv_8	PM10.0	0.78	184.17	35.06
0.000	PM2.5	0.45	409.64	32.01
scuv_9	PM10.0	0.6767	467.9575	35.3002

	PM2.5	0.9525	512.4150	34.4831
scuv_11	PM10.0	1.115	557.933	37.429
scuv_12	PM2.5	0.8225	422.6900	34.8755
seuv_12	PM10.0	1.19	511.89	39.26

# 3.1.2. PM levels compared with federal standards

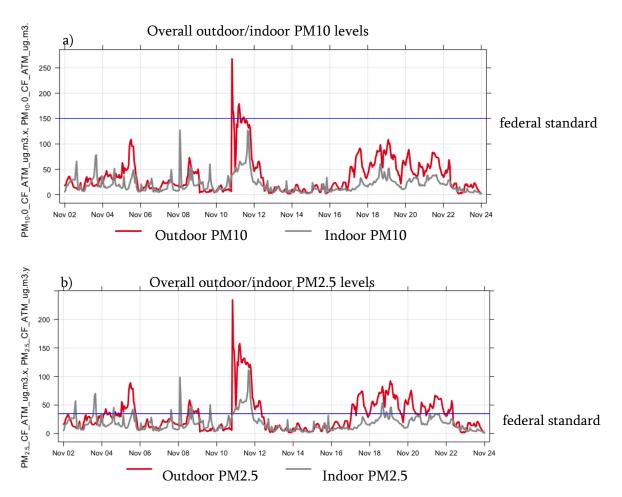
The PM levels were calculated and compared with the federal standard by EPA. Summary data for each sensor is on Table 2. The samples collected by the sensors over a period of 24 hours were averaged and compared against the federal air quality standards (maximum 24-hr standard: 150g/m3). The results indicate that only on the day with the top PM10 level, the outdoor PM level exceeded the federal limit (Figure 4a). Indoor PM10 levels were under the standard. On the



**Figure 3** Daily average outdoor and indoor PM2.5 levels before, during and after the events and the comparison.

**a)** Outdoor: on 10th Nov the outdoor concentration had a sharp increase and reached peak on 11s Nov. **b)** Indoor: the overall concentration wasn't influenced so much but 11s Nov had the highest PM2.5 concentration.

other hand, PM2.5 levels for both indoor and outdoor exceeded the federal limit (average 24-hr standard: 35g/m³) some days before, during or after the event (Figure 4b).



**Figure 4** Overall outdoor and indoor PM levels before, during and after the events and the comparison with Federal standards.

a) PM10: on Nov.11 with the top PM10 level, the outdoor PM level exceeded the standard. b) PM2.5: both indoor and outdoor exceeded the federal standard (average 24-hr federal standard  $35g/m^3$ ) some days before, during or after the event.

# 3.1.3. The 72 hours following the fire ignition

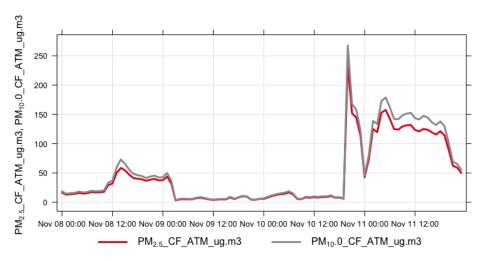
A closer look to the 72 hours following the fire ignition shows an abrupt peak of pollutant concentration (Figure 5). The PM2.5 and PM10 were 234 and 268 ug/m³, respectively, on Nov.10 20:00 - 21:00 PST time. The dramatic increase in PM concentrations lasted for 4 to 5

hours. 24-hour average concentrations of PM2.5 and PM10 were 35 and 39 ug/m<sup>3</sup>, respectively, on Nov.10 and 112 and 127 ug/m<sup>3</sup>, respectively, on Nov.11. The sharp decrease after the hour with the highest concentration was because of the high wind speed.

Between Nov.10 and Nov.12 during which the PM levels increased, the sharp increase of the PM levels came from the North direction for both PM2.5 and PM10 (Figure 6), which is corresponded to the wildfire direction.

## 3.2 Further assessment of spatiotemporal trends of the outdoor air quality.

The daily PM2.5 level plot shows the average PM2.5 level during 24 hours of a day for November 2018. The figure shows that the PM level is relatively high during 00:00 - 09:00 am at around 30 - 35 ug/m<sup>3</sup>. There is a short elevation at around 00:00. And the PM level started to

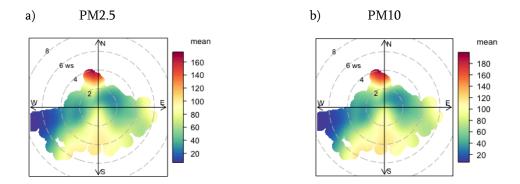


**Figure 5** Hourly PM 2.5 level during 11.8 - 11.12.

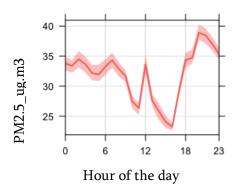
Peak 1-hour concentrations of PM2.5 and PM10 were 234 and 268 ug/m³, respectively, on November 10th 20:00 - 21:00 PST time. 24-hour average concentrations of PM2.5 and PM10 were 35 and 39 ug/m³, respectively, on November 10th and 112 and 127 ug/m³, respectively, on November 11st.

increase sharply from 17:00 and reaches up to 39 - 40 ug/m<sup>3</sup>. Generally elevated PM2.5 at night (after 17:00) and in the early morning (06:00-09:00) as Figure 7 shows.

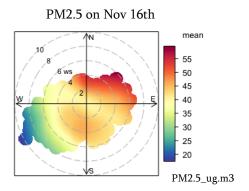
Enhancements occurred across all the outdoor sensors again a week after the Woolsey fire was active, in particular the weekend of Nov.17-18th. Interestingly, the direction of the pollution was carried by winds blowing from around 45° northeast direction, corresponding to about 90° away from the Woolsey fire sites, which can be seen in the polar plot of PM2.5 levels on Nov 16th (Figure 8).



**Figure 6** Enhancements of the community come from sources to the north, which is corresponded to the wildfire direction.



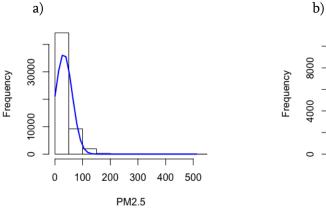
**Figure 7** Daily PM2.5 level plot: Generally seeing elevated PM2.5 at night and in the early morning

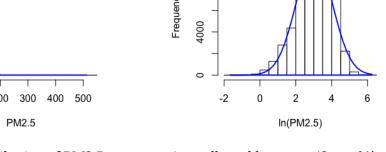


**Figure 7** Enhancements of the pollution come from sources to the east on Nov 16th.

#### 3.3 Statistical distribution of PM levels data

According to the test, the data distribution of the same monitoring point within one month accords with the lognormal distribution (Figure 9). Therefore, the proper value should be geometric mean. But considering the EPA US standards and California State standard of PM levels use arithmetic means, the following evaluations are still dominated by the arithmetic means.





**Figure 8** The distribution of PM2.5 concentration collected by sensor 'Scuv\_01'. **a)** Histogram of concentration is skewed to the right. **b)** Histogram of logarithmic concentration is normal distributed

## 3.4 Statistical test of difference between outdoor and indoor air quality

From the complete sensor data time plot during November, most of the time, outdoor PM levels were higher than indoor (Figure 5). Nevertheless, there were time points when the indoor PM levels were sharply higher than the outdoor levels in the late afternoons, which should correspond to cooking times. To test if there's significant difference between such O/I differences before and during the event, a two-sample t-test was conducted. O/I difference were calculated by the formula:

$$O/I$$
 difference =  $PM(Outdoor)_t$  -  $PM(Indoor)_t$ 

The two-sample t-test between the O/I concentration difference before and during the event was conducted to test the mean of the O/I difference values and log O/I difference values. The test gives a p-value of 2.2e-16 (<0.001) and indicates that there is significant difference between the means of before and during event periods. The test for ln(O/I difference) gives p-value of 1.229e-08 (<0.001) and indicates significant difference as well.

**Table 3** Two-sample t test for O/I difference before and during the fire

37.1	Concentration difference	In concentration difference	
Value	(outdoor - indoor)	(outdoor - indoor)	
t	-12.259	-5.7163	
df	3696.4	2309.3	
P	< 2.2E-16	1.229E-08	

	Confidence	(-10.105110, -7.318612)	(-0.3255403 -0.1592363)
<b></b>	Before event	7.786746	2.365497
mean	During event	16.498607	2.607886

# 3.5 Statistical test of wind condition changes before and during the wildfire event

From the results of the two-sample t test of meteorological data during November (Table 4), The test gives a p-value of 2.2e-16 (<0.001) and indicates that there is significant difference between average wind directions before and during the fire, while there is no significant difference between the average wind speed as the p-value is 0.2939. The directions on the map (Figure 10) shows the average wind direction during the fire is more paralleled with the direction between fire sources and the target community.



Figure 9 Maps of wind direction change before and during Woolsey fire.

Yellow arrows show the average wind direction before Woolsey while there's a significant difference with the wind direction during Woolsey as red arrows.

Table 4 Two-sample t test for average wind conditions before and during the fire

Value		Wind direction	Wind speed
	t	-10.637	1.0501
	df	13821	28366
	P	< 2.2E-16	0.2937
	Confidence Interval	(-17.65327, -12.15959)	(-0.06457311, 0.21360548)
maan	Before event	218.6297	2.05164
mean	During event	233.5361	1.977128

#### 3.6 Mitigation effects of individual behavior intervention.

The participants who have our sensors in their apartments also realized the sharp increase of the PM levels during the event. The one with the indoor sensor SCUV\_21 did some experimenting with the HVAC during the wildfire. The time series of the PM data during the fire in that unit

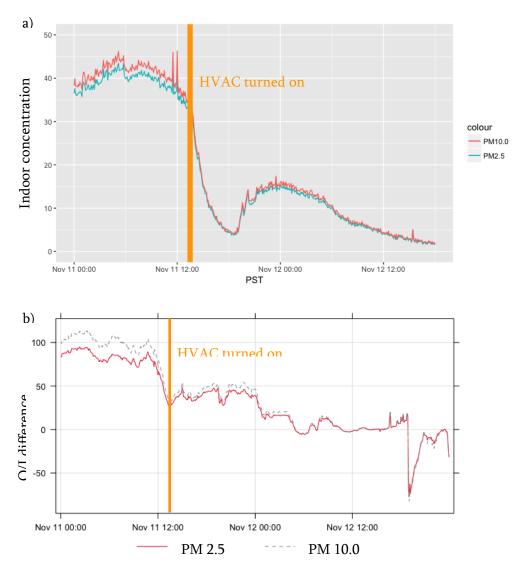


Figure 10 Time plots of PM2.5 in Scuv\_21 and O/I difference.

**a)** The participant turned on HVAC on 1:30 pm and there was a sharp improvement in indoor air at the same time. **b)** The O/I difference increased at the same time which indicates the indoor air quality improvement was not because of the outdoor but the HVAC activity.

came out with very obvious outcomes. According to the participant, on November 11, 2018 he noticed high indoor PM levels, so around 1:30 pm, he turned on the HVAC unit to see if this

would help reduce indoor PM, the sharp improvement in indoor air with HVAC (Figure 11) use suggests that using HVAC may provide good mitigation of the air pollution. The O/I difference also increased at the same time which indicates this indoor air quality improvement was not a result of the outdoor air quality improvement but the HVAC activity.

#### 4. Discussions

#### 4.1 Key findings

In this study, the air quality data collected by low-cost sensors proved that the Woolsey wildfire brought higher concentration than the federal limit of fine particles to UCLA University Village area. The quick increase of outdoor PM levels happened around 2 and a half days after the fire started, which was due to the 20-mile distance and the wind conditions, while the indoor air was not influenced as much as outdoor. In addition, there was another source of air pollution a week after the fire started that prolongated for 5 days. We proved that the wind direction was significantly different before and during the wildfire which is an important cause of the PMs distribution. Within the community, on daily trends, the concentrations tend to be higher during night and early morning hours. Finally, the self-experiment proved that HVAC is a quick and efficient method to mitigate the indoor air pollution brought by the fire.

#### 4.2 Air quality and weather effects from Woolsey and the use of low-cost sensors

To my knowledge, this is an innovative study to estimate daily PM levels of wildfire-specific particles at the community level and to enroll in the participation of the community members under the Woolsey fire.

Wildfire-specific PM can impose burdens by impacting medical care, tourism, and properties, and costs of forest recovery. It can cause ecological damage and also impacts visibility, which can impact transportation, aesthetics, and tourism (Hystad and Keller 2008).

A review paper has summarized previous studies on wildfire-related air pollution and health and found that PM2.5 levels exceeded the NAAQ standard during or after wildfires in 12 out of 14 studies that reported PM2.5 levels before, during, or after wildfires (Liu et al. 2015). Our findings are in line with previous literature and indicated potential human health concerns in the community scale. In addition, our findings indicate that more fire suppression will be required in the future in order to mitigate air pollution and reduce potential health concerns.

Fire smoke is likely to be especially deleterious to human health (Delfino et al. 2002; Moore et al. 2006; Hänninen et al. 2009) due to the emission of very high PM2.5 level. It's also estimated that substantial populations of elderly, children, pregnant women, poor people may be the most vulnerable to the health risks related to exposure to PM from wildfires. Our research's target community, full of populations of high risk, requires decision makers in wildfire management, public health, emergency department, and self-awareness to mitigate the negative effects associated to wildfires.

Our use of PurpleAir sensors produces real-time total PM level data with better accessibility, lower cost and easier operability than other monitoring methods. Previous studies linking air pollution and wildfire activity in the western US mostly focused on trends in monthly or seasonal mean area burned or carbonaceous aerosol and were focused on the hospital admission and elevated emergency rate associated to the fires. In contrast, our study focused on daily and even

hourly PM levels, which is a metric relevant to human health demonstrated by plenty of epidemiology studies and reviews (e.g. Dominici et al. 2006; Liu et al. 2015). Compared with the maps analysis which most of precious studies did, we conducted statistical tests to find out the difference before and during the wildfire and combine it with polar plots to show the additional pollution the Woolsey Fire brought.

#### 4.3 Recommendations for future catastrophic events

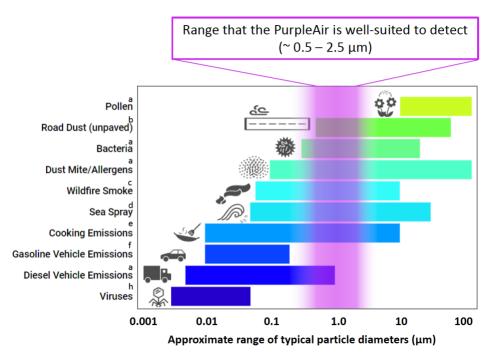
The following recommendations are made when a similar catastrophe occurs in the future:

- I. Improve the capability of accurate real-time PM level monitoring activities, because PMs are one of the concerns that has an immediate impact on the health of community residents; real-time low-cost sensor capability is an added resource, because individuals most care about the specific air quality level in their rooms and outside, promotion of the use of low-cost sensors give them a chance to better assess the actual condition independently and take actions immediately;
- II. Encourage local hospitals and emergency departments to engage in prevention planning and trainings that would ensure a rapid and effective response to the effects on the healthcare system as a result of large wildfires;
- III. Use all available meteorological forecasting resources, including real-time satellite imaging assets to accurately forecast air quality, assist firefighting efforts, and mobilize emergency service providers.

#### 4.4 Limitations and Next steps

There are several limitations in this study. Our results may underestimate specific PMs, as PurpleAir Sensors perform well for PM2.5 (PM diameters < 2.5 µm), however, detection drops

off for smaller particles (Figure 12). From the PurpleAir data sheet, 98% counting efficiency at 0.5 µm, while only 50% counting efficiency at 0.3 µm, which means PM from gasoline vehicles is likely not detected. The data used in this study is from a single community within a single wildfire event. Future studies may include more wildfires with the research to more sites instead of only one community. The meteorological data is not exactly the weather in our target community, instead it was from a closest meteorological station. There might be some difference between the two sites. In order to improve the accuracy, future studies could be conducted in sites with their own meteorological station. In addition, future researches should include more mitigation measurements and involve more participants.



**Figure 11** Approximate range of typical particle diameters  $(\mu m)$  and range that the PurpleAir is well-suited to detect.

\*Particle Size Sources: a(Owen & Ensor, 1992), b(Zhao et. al., 2017), c(Saarnioet. al., 2010), d(O'Dowd et. al., 1997), e(Buonannoet. al., 2009), f(Karjalainenet al., 2014), g(Biswas et. al., 2008), h(Hinds, 1982)

Future investigations are needed to estimate the health, ecologic, as well as economic consequences of wildfires using community scale air pollutant data, and to develop policy decisions and better healthcare administration frameworks in response to these consequences.

Wildfires are considered to be an increasingly important source of PM in the California. While other sources of PMs, such as from vehicles or power plants, can be more easily regulated, PMs from wildfire events cannot be fully controlled. Therefore, PMs brought by wildfires may not only enhance acute exposure, but also play an important role in local people's chronic exposure. Therefore, both acute and chronic impacts of air pollution from wildfires should be considered when making future decisions and doing wildfire management. The community in this study and other communities with similar population as at risk of more vulnerability would benefit from the establishment or modification of public health programs and evacuation plans in response to such disasters. Our results will advance understanding of the impacts of wildfires, and aid in the education and popularization of home use low-cost sensors to monitor real-time air quality in order to mitigate indoor air quality elevating as early as possible and help the design of early warning systems, fire suppression policies, and public health programs.

## 5. Conclusions and perspective

On the second to third day during the Woolsey Wildfire on November 8, 2018, the UCLA University Village sensors recorded the highest PMs concentration level, about four times the average concentration of the period before the fire. The meteorological condition during this phase of the fire progression was such that the heavy smoke produced by the fire was allowed to rise and spread by wind. The wind direction changed significantly during the fire which also contributes to the PM resolution. Our study proved that the air quality in UCLA University

Village were negatively affected by both the PMs created by wildfire and the significantly changed wind direction. Under this condition, low-cost sensors are an efficient and easy method to be used by individuals to monitor and take action to mitigate the negative effect of indoor air quality. HVAC was shown by our study to be an effective mitigation measurement but need further confirmation. The findings of this study contribute to the overall understanding of air quality impacts by wildfires and provide insight to the meteorological impacts of the Woolsey wildfire and potential mitigation measurements. Furthermore, this research gave us an understanding of how and how long it takes for a fire to effect a specific community, and how the use of low-cost sensors encourage the communities to improve awareness of monitoring as well as taking actions to protect themselves from wildfires and other events.

#### **REFERENCES**

- Bobak, M. Outdoor Air Pollution, Low Birth Weight, and Prematurity; Environ. Health Perspect. 2000, 108, 173-176.
- Bowman, D. M. J. S., Balch, J. K., Artaxo, P., Bond, W. J., Carlson, J. M., Cochrane, M. A., D'Antonio, C. M., DeFries, R. S., Doyle, J. C., Harrison, S. P., Johnston, F. H., Keeley, J. E., Krawchuk, M. A., Kull, C. A., Marston, J. B., Moritz, M. A., Prentice, I. C., Roos, C. I., Scott, A. C., Swetnam, T. W., van der Werf, G. R., and Pyne, S. J.: Fire in the earth system, Science, 324, 481–484, 2009.
- Bray, C. D., Battye, W., Aneja, V. P., Tong, D. Q., Lee, P., & Tang, Y. (2018). Ammonia emissions from biomass burning in the continental United States. Atmospheric Environment, 187, 50-61.
- Briggs, Nicole L., Jaffe, Daniel A., Gao, Honglian, Hee, Jonathan R., Baylon, Pao M., Zhang,
  Qi, Zhou, Shan, Collier, Sonya C., Sampson, Paul D., & Cary, Robert A. Particulate Matter,
  Ozone, and Nitrogen Species in Aged Wildfire Plumes Observed at the Mount Bachelor
  Observatory. United States. doi:10.4209/aaqr.2016.03.0120.
- Brook, R. D., Rajagopalan, S., Pope III, C. A., Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., ...
  & Peters, A. (2010). Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. Circulation, 121(21), 2331-2378.

- Brożek, J. L., Bousquet, J., Baena-Cagnani, C. E., Bonini, S., Canonica, G. W., Casale, T. B., ... & Schünemann, H. J. (2010). Allergic Rhinitis and its Impact on Asthma (ARIA) guidelines: 2010 revision. Journal of Allergy and Clinical Immunology, 126(3), 466-476.
- Chung, K. F., & Pavord, I. D. (2008). Prevalence, pathogenesis, and causes of chronic cough. The Lancet, 371(9621), 1364-1374.
- Ciencewicki, J., Trivedi, S., & Kleeberger, S. R. (2008). Oxidants and the pathogenesis of lung diseases. Journal of Allergy and Clinical Immunology, 122(3), 456-468.
- Clark, N. A., Demers, P. A., Karr, C. J., Koehoorn, M., Lencar, C., Tamburic, L., & Brauer, M. (2009). Effect of early life exposure to air pollution on development of childhood asthma. Environmental health perspectives, 118(2), 284-290.
- Cornwall, A. and Jewkes, J. (1995) "What is Participatory Action Research?" Social Science & Medicine; 41:1667-76
- Delfino RJ, Zeiger RS, Seltzer JM, Street DH, McLaren CE (2002) Association of asthma symptoms with peak particulate air pollution and effect modification by anti-inflammatory medication use. Environ Health Perspect 110:A607–A617
- Di, Q., Wang, Y., Zanobetti, A., Wang, Y., Koutrakis, P., Choirat, C., ... & Schwartz, J. D.(2017). Air pollution and mortality in the Medicare population. New England Journal of Medicine, 376(26), 2513-2522.
- Dockery, D.W., Pope, A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., Ferris, B. G., and Speizer, F. E. (1993). An Association Between Air Pollution and Mortality in Six U.S. Cities, N. Engl. J. Med. 329:1753–1759.

- Dombeck MP, Williams JE, Wood CA (2004) Wildfire policy and public lands: integrating scientific understanding with social concerns across landscapes. Conserv Biol 18:883–889 Dominici F, Peng RD, Bell ML, Pham L, McDermott A, Zeger SL, Samet JM (2006) Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. JAMA-J Am Med Assoc 295:1127–1134
- Du, Y., Xu, X., Chu, M., Guo, Y., & Wang, J. (2016). Air particulate matter and cardiovascular disease: the epidemiological, biomedical and clinical evidence. Journal of thoracic disease, 8(1), E8.
- EPA U.S, 2009. Integrated Science Assessment for Particulate Matter (Final Report). US

  Environmental Protection Agency Washington, DC, Washington, DC. U. S. Environmental

  Protection Agency, Washington.
- Fiore, A. M., Naik, V., Spracklen, D. V., Steiner, A., Unger, N., Prather, M., Bergmann, D., Cameron-Smith, P. J., Cionni, I., and Collins, W. J.: Global air quality and climate, Chem. Soc. Rev., 41, 6663–6683, 2012.
- Flannigan M, Stocks B, Turetsky M, Wotton M (2009) Impacts of climate change on fire activity and fire management in the circumboreal forest. Glob Chang Biol 15:549–560
- Franklin, B. A., Brook, R., & Pope III, C. A. (2015). Air pollution and cardiovascular disease. Current problems in cardiology, 40(5), 207-238.
- Ghio, A. J., Kim, C., & Devlin, R. B. (2000). Concentrated ambient air particles induce mild pulmonary inflammation in healthy human volunteers. American journal of respiratory and critical care medicine, 162(3), 981-988.

- Ha, E.H.; Lee, B.E.; Park, H.S.; Kim, Y.J.; Hong, Y.C.; Kim, H.; Lee, J.T. Exposure to Air Pollution during Different Gestational Phases Contributes to Risks of the Low Birth Weight; Hum. Reprod. 2003, 18, 638-643.
- Hänninen OO, Salonen RO, Koistinen K, Lanki T, Barregard L, Jantunen M (2009) Population exposure to fine particles and estimated excess mortality in Finland from an East European wildfire episode. J Expo Sci Environ Epidemiol 19:414–422
- Heinrich, J.; Hoelscher, B.; Wichmann, H.E. Decline of Ambient Pollution and Respiratory Symptoms in Children; Am. J. Respir. Crit. Care Med. 2000, 161, 1930-1936.
- Huang, Y., Shen, H., Chen, H., Wang, R., Zhang, Y., Su, S., ... & Wang, X. (2014).Quantification of global primary emissions of PM2. 5, PM10, and TSP from combustion and industrial process sources. Environmental science & technology, 48(23), 13834-13843.
- Hystad, P. W., & Keller, P. C. (2008). Towards a destination tourism disaster management framework: Long-term lessons from a forest fire disaster. Tourism management, 29(1), 151-162.
- Janssen, N. A., Hoek, G., Simic-Lawson, M., Fischer, P., Van Bree, L., Ten Brink, H., ... & Cassee, F. R. (2011). Black carbon as an additional indicator of the adverse health effects of airborne particles compared with PM10 and PM2. 5. Environmental health perspectives, 119(12), 1691-1699.
- Kim, K. H., Kabir, E., & Kabir, S. (2015). A review on the human health impact of airborne particulate matter. Environment international, 74, 136-143.
- Kinney, P.L., 2008. Climate change, air quality, and human health. Am. J. Prev. Med. 35, 459–467.

- Knowlton, K., 2013. Where there's fire, there's smoke: wildfire smoke affects communities distant from deadly flames. NRDC Issue Brief.
- Langmann, B., Duncan, B., Textor, C., Trentmann, J., and van der Werf, G. R.: Vegetation fire emissions and their impact on air pollution and climate, Atmos. Environ., 43, 107–116, 2009.
- Le Tertre, A., Medina, S., Samoli, E., Forsberg, B., Michelozzi, P., Boumghar, A., ... & Sunyer, J. (2002). Short-term effects of particulate air pollution on cardiovascular diseases in eight European cities. Journal of Epidemiology & Community Health, 56(10), 773-779.
- Lee, K. H., Kim, J. E., Kim, Y. J., Kim, J., and von Hoyningen- Huene, W.: Impact of the smoke aerosol from Russian forest fires on the atmospheric environment over Korea during May 2003, Atmos. Environ., 39, 85–99, 2005.
- Li, W. J., Shao, L. Y., & Buseck, P. R. (2010). Haze types in Beijing and the influence of agricultural biomass burning. Atmospheric Chemistry and Physics, 10(17), 8119-8130.
- Liu JC, Mickley LJ, Sulprizio MP, Yue X, Dominici F, Bell ML (2016) Exposure to wildfire-specific fine particulate matter and risk of Hospital Admissions in urban and rural Counties in the Western US 2004–2009 Epidemiology (Cambridge, Mass.) (accepted)
- Liu, Z., Murphy, J. P., Maghirang, R., & Devlin, D. (2016). Health and environmental impacts of smoke from vegetation fires: a review. Journal of Environmental Protection, 7, 1860-1885.
- Makri, A., & Stilianakis, N. I. (2008). Vulnerability to air pollution health effects. International journal of hygiene and environmental health, 211(3-4), 326-336.
- Moore D, Copes R, Fisk R, Joy R, Chan K, Brauer M (2006) Population health effects of air quality changes due to forest fires in British Columbia in 2003: estimates from physician-

- visit billing data. Canadian J Public Health = Revue canadienne de sante publique 97:105–108
- Norris, G., YoungPong, S. N., Koenig, J. Q., Larson, T. V., Sheppard, L., & Stout, J. W. (1999).

  An association between fine particles and asthma emergency department visits for children in Seattle. Environmental Health Perspectives, 107(6), 489-493.
- Pope III, C. A., & Dockery, D. W. (2006). Health effects of fine particulate air pollution: lines that connect. Journal of the air & waste management association, 56(6), 709-742.
- Ritz, B.; Yu, F.; Fruin, S.; Chapa, G.; Shaw, G.M.; Harris, J.A. Ambient Air Pollution and Risk of Birth Defects in Southern California; Am. J. Epidemiol. 2002, 155, 17-25.
- Schwartz, J. (1991). Air Pollution and Daily Mortality in Philadelphia. Presented at the 1991 Meeting of the American Lung Association, Anaheim, CA.
- Snyder, E., Watkins, T., Thoma, E., Williams, R., Solomon, P., Hagler, G., Shelow, D., Hindin,
  D., Kilaru, V., Preuss, P. (2013) "Changing the paradigm for air pollution monitoring"
  Environmental Science and Technology; 47: 11369-11377
- Vallano, D., Snyder, E., Kilaru, V., Thoma, E., Williams, R., Hagler, G., Watkins, T. Air Pollution Sensors (2012) "Highlights from an EPA workshop on the evolution and revolution in low cost participatory air monitoring" Environmental Manager; Issue, 28-33
- Vedal, S. (1997). Ambient Particles and Health: Lines That Divide, J. Air Waste Manag. Assoc. 47:551–581.
- Watson, J. G., Zhu, T., Chow, J. C., Engelbrecht, J., Fujita, E. M., & Wilson, W. E. (2002).

  Receptor modeling application framework for particle source
  apportionment. Chemosphere, 49(9), 1093-1136.

- Weinmayr, G., Romeo, E., De Sario, M., Weiland, S. K., & Forastiere, F. (2009). Short-term effects of PM10 and NO2 on respiratory health among children with asthma or asthma-like symptoms: a systematic review and meta-analysis. Environmental health perspectives, 118(4), 449-457.
- White, R., Paprotny, I., Doering, F., Cascio, W., Solomon, P., Gundel, L. (2012) "Sensors and Apps for Community-Based Atmospheric Monitoring" Environmental Manager; Issue, 36-46
- Yang, Y., Liu, X., Qu, Y., Wang, J., An, J., Zhang, Y., & Zhang, F. (2015). Formation mechanism of continuous extreme haze episodes in the megacity Beijing, China, in January 2013. Atmospheric Research, 155, 192-203.