Socioeconomic Disparities of Low-Cost Air Quality Sensors in California, 2017–2020

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See also Grinesky et al., p. 348.

Objectives. To (1) examine the disparity in availability of PurpleAir low-cost air quality sensors in California based on neighborhood socioeconomic status (SES) and exposure to fine particulate matter smaller than 2.5 micrometers ($PM_{2.5}$), (2) investigate the temporal trend of sensor distribution and operation, and (3) identify priority communities for future sensor distribution.

Methods. We obtained census tract–level SES variables and $PM_{2.5}$ concentrations from the CalEnviroScreen4.0 data set. We obtained real-time PurpleAir sensor data (July 2017–September 2020) to examine sensor distribution and operation. We conducted spatial and temporal analyses at the census tract level to investigate neighborhood SES and $PM_{2.5}$ concentrations in relation to sensor distribution and operation.

Results. The spatial coverage and the number of PurpleAir sensors increased significantly in California. Fewer sensors were distributed in census tracts with lower SES, higher $PM_{2.5}$, and higher proportions of racial/ethnic minority populations. Furthermore, a large proportion of existing sensors were not in operation at a given time, especially in disadvantaged communities.

Conclusions. Disadvantaged communities should be given access to low-cost sensors to fill in spatial gaps of air quality monitoring and address environmental justice concerns. Sensor purchasing and deployment must be paired with regular maintenance to ensure their reliable performance. (*Am J Public Health*. 2022;112(3):434–442. https://doi.org/10.2105/AJPH.2021.306603)

The inequitable distribution of air pollution is one of the most pressing environmental justice issues.[1] Particulate matter with an aerodynamic diameter smaller than 2.5 micrometers ($PM_{2.5}$) is one of the most important pollutants in terms of adverse health impacts, and one that is exacerbating environmental racism.[2] Exposure to $PM_{2.5}$ is known to increase the risk of a wide range of adverse health effects.[3] Disproportionate exposure to $PM_{2.5}$ is particularly concerning among lower socioeconomic status (SES) communities and communities of color[1,4] because these subpopulations are already at greater risk for preventable diseases.[5] Thus, there is growing interest in understanding the inequitable distribution of $PM_{2.5}$ and its impact on vulnerable populations at a fine spatial scale.

Traditional government-operated monitoring stations are usually unevenly and sparsely distributed, which limits their ability to measure $PM_{2.5}$ variability at a local scale.[6] With recent technology advances, low-cost air pollution sensors have been increasingly used to measure air quality at a high spatial and temporal resolution.[7–9] In 2017, low-cost air quality sensors developed by the PurpleAir company began to be deployed to provide real-time $PM_{2.5}$ data globally, with the majority being deployed in the United States. A recent study comparing PurpleAir sensors with regulatory monitoring stations in California showed that PurpleAir data better represented $PM_{2.5}$ spatially, enabling improved detection of air pollution hotspots.[10] Moreover, such low-cost sensors are able to improve the accuracy of air quality index reporting during extreme air pollution episodes such as wildfires.[11] In addition to its high spatial resolution, the PurpleAir sensor network provides real-time particulate matter data at 10-minute intervals, making it suitable for investigating the air quality impacts of short-term pollution events. Through affordable prices, flexibility of deployment, and ease of maintenance, low-cost air pollution sensors can be owned and operated by governments, organizations, or individuals, which can enable broader awareness and finer-scale assessments of air pollution to promote more informed citizens and scientific research. As low-cost air pollution sensors continue to be deployed for various purposes, it is critical to understand sensor availability and operation conditions so as to equitably serve and represent communities of different income brackets and ethnic backgrounds.

A few studies have utilized low-cost air quality sensors to investigate the sufficiency of air quality monitoring and to characterize air pollution at the city or neighborhood scale.[12–14] However, to our knowledge, there have been no prior studies that have examined the geographic distribution and operation of the rapidly expanding PurpleAir sensor network over a large geographic area. A better understanding is needed regarding the sensor distribution across areas of varying SES and disease burdens.

To better understand the spatial distribution and operation of low-cost sensors, we aimed to (1) examine the disparity in the availability of PurpleAir sensors in California based on neighborhood SES and $PM_{2.5}$ exposure, (2) investigate the temporal trend of PurpleAir sensor distribution and operational status, and (3) identify priority communities for future sensor distribution.

METHODS

We examined population characteristics at the census tract level across the entire state of California. In total, we included 8035 (out of 8057) census tracts in this analysis based on the availability of population data in the CalEnviroScreen database (CES draft 4.0 version, February 2021).[15] Among states in the United States, California is an ideal region to investigate environmental justice issues related to air pollution because it is the most populous (> 39 million people) and most racially/ethnically diverse state, and has diverse air pollution emission sources (e.g., industry, agriculture, and traffic).

PurpleAir Sensor Data

We downloaded 10-minute-interval PurpleAir $PM_{2.5}$ data (July 2017–September 2020) with sensor location coordinates and time stamps using the ThingSpeak's Application Programming Interface provided by the PurpleAir company. The latest PurpleAir sensor model (PA-II-SD) contains 2 PMS5003 instruments, which estimate particle mass concentrations by measuring the amount of light scattered at approximately 680 nm.[16] We first applied a 75% data completeness criterion to daily data. If individual sensors were operating (turned on and reporting data) for less than 75% of a day, we considered these sensors to be "not fully operational" for that day. We calculated the sum of days labeled "fully operational" to define the operational status for a month and a year. Any sensor with readings meeting our completeness criteria (≥ 75%) was labeled "fully operational" for those periods.

Long-Term $PM_{2.5}$ Concentrations

We obtained long-term $PM_{2.5}$ concentration estimates from the CES data set,[15] which was created by the California Environmental Protection Agency (EPA) to inform issues of environmental justice by screening socioeconomic conditions of disadvantaged communities in California. The latest CES includes statewide census tract–level average $PM_{2.5}$ concentrations in 2015 through 2017, which were derived from outputs of a validated high-spatiotemporal resolution (1 km; daily) model that is based on ground-level $PM_{2.5}$ measurements, satellite aerosol optical depth (from the Multi-Angle Implementation of Atmospheric Correction), land use, and meteorology.[17] For $PM_{2.5}$ predictions in 2016, the model showed reasonably high predictive power, with a cross-validation R^2 of 0.73 to 0.81. This continuous surface of high-resolution $PM_{2.5}$ can be used to efficiently capture local and regional $PM_{2.5}$ levels and identify high-risk areas.

Socioeconomic Factors

CES integrates both population characteristics and pollution burdens to produce a composite CES score (Figure A, available as a supplement to the online version of this article at http://www.ajph.org). We included 6 population characteristic indicators, including disease and SES factors (i.e., asthma [2015–2017], cardiovascular disease [2015–2017], educational attainment [2014–2018], poverty [2014–2018], unemployment [2014–2018], and housing burden [2012–2016]), 3 pollution burden indicators (i.e., diesel PM [particle phase of diesel exhaust emitted from diesel engines such as trucks, buses, and heavy-duty equipment, 2016], traffic impacts [2017], and $PM_{2.5}$ concentrations [2015–2017] as described in "Long-Term $PM_{2.5}$ Concentrations"), and 3 summary indicators (population characteristics score, pollution burden score, and overall CES score) at the census tract level. Pursuant to California Senate Bill 535, we defined disadvantaged communities (DACs) as the top 25% CES-scoring census tracts.[18] We used CES to retrieve race/ethnicity and population density (total population/km^2 per census tract) data from the 2018 American Community Survey.

Analysis

We examined the distribution of PurpleAir sensors in relation to $PM_{2.5}$ concentrations, SES, and pollution burden metrics over time and space. We examined the number of deployed sensors within each census tract across the state. Similarly, we examined both deployed and operational sensor count(s) in each census tract separately during each selected period. In the descriptive analysis, we grouped the number of sensors per census tract as "none," "1 or 2," and "3 or more." We further applied the Kruskal–Wallis Wilcoxon rank sum test to assess statistical significance relating to differences in the number of sensors and $PM_{2.5}$ levels and SES factors.

To analyze predictors of the presence or absence (1/0 binary outcome) or the number of sensors (continuous outcome) in a census tract, we performed both a logistic regression and a generalized linear regression (analyses restricted to census tracts with ≥ 1 sensor) on race/ethnicity, socioeconomic factors, and $PM_{2.5}$ concentrations from the CES data set. All models adjusted for population density and rural–urban status. We defined urban areas as those with a rural–urban commuting area code of 1.0, indicating a metropolitan area core with a primary flow of the population within an urbanized area.[19] We conducted all analyses with SAS version 9.4 (SAS Institute, Cary, NC).

We used ArcMap 10.7 (ESRI, Redlands, CA) to visualize sensor distribution. We demonstrated the expansion of the sensor network over time by plotting the number of deployed sensors at 4 time periods during the study period: July to December 2017, January to December 2018, January to December 2019, and January to September 2020 (the end of study period). To assess the expansion of the sensor network over time, we examined monthly changes in the percentage of census tracts with deployed sensors and fully operational sensors in DACs (communities with the top 25% CES score) and non-DACs, respectively. To fully capture the differences of sensor development across non-DACs, we further divided census tracts ranked in the 0 to 75th percentile of CES score into 2 subgroups: 0% to 50% versus 50% to 75% CES score. In the temporal analysis, we calculated sensor density, defined as the number of sensors divided by census tract population density. Overall operational status, defined as the number of census tracts with fully operational sensor(s) divided by the total number of census tracts with deployed sensor(s), was also calculated over time.

Furthermore, we identified census tracts without any sensor deployed by September 2020. To identify census tracts that should receive priority in terms of future sensor installation, we considered the following 2 metrics: (1) CES score (DAC: top 25% of score vs non-DAC: 0%–75% of score) and (2) $PM_{2.5}$ concentrations (high: >12 $\mu g/m^3$ vs low: 0–12 $\mu g/m^3$, US EPA's primary annual $PM_{2.5}$ standard).[20] We combined these 2 metrics with an equal weight to create a map identifying future sensor installation priority regions.

RESULTS

Table 1 presents the distribution of PurpleAir sensors by population and pollution characteristics. Overall, 2211 (27.5%) of the 8035 census tracts in California had 1 or more deployed sensors, covering 27.9% of the population (10.9 million of 39.1 million). On average, more deployed and operational PurpleAir sensors were located in census tracts characterized by more affluence, lower disease rates, lower pollution burdens, and lower percentages of Hispanic and African American residents. For instance, the percentage of poverty (35.7%) among census tracts without deployed sensors was nearly double that of census tracts with 3 or more sensors (18.3%). The operational status of sensors showed similar patterns, suggesting that out-of-operation sensors were disproportionately distributed across socioeconomic lines. Results of the Kruskal–Wallis Wilcoxon rank sum test showed that the differences in the number of sensors for all selected CES indicators and race/ethnicity groups were statistically significant, except for the Asian American group.

Table 2 shows results from regression models. After we controlled for population density and urban–rural status, odds ratios were less than 1 for CES score, population characteristics score, SES indicators, proportions of African American or Hispanic residents, and $PM_{2.5}$ concentrations; they were greater than 1 for proportions of non-Hispanic White, Asian American, or other or multiple race/ethnicity populations. The results indicate a significantly lower likelihood of sensor presence in census tracts with higher SES vulnerability, CES scores, $PM_{2.5}$ concentrations, and percentages of African American or Hispanic populations. In generalized

TABLE 1— PurpleAir Sensor Distribution and $PM_{2.5}$ Concentrations by Population and Pollution Characteristics at Census Tract Level as of September 2020: California

Characteristics	Deployed Sensors: None (n = 5824)[a]	Deployed Sensors: 1–2 (n = 1667)	Deployed Sensors: ≥3 (n = 544)	Fully Operational Sensors: None (n = 6763)	Fully Operational Sensors: 1–2 (n = 1171)	Fully Operational Sensors: ≥3 (n = 101)
Total population across the state, millions	28.2	8.2	2.7	32.9	5.7	0.6
CES score, 0–100	30.1	21.6	13.4	28.7	19.4	14.2
Population characteristics in CES, mean						
Asthma rate	54.7	47.6	34.9	53.4	45.1	32.1
Cardiovascular disease rate	14.2	12.1	9.1	13.8	11.5	9.3
Educational attainment, %	20.3	11.9	6.7	19.1	10.1	7.1
Poverty, %	35.7	26.6	18.3	34.2	24.5	21.3
Unemployment, %	7.1	6.0	4.7	6.9	5.8	5.1
Housing burden, %	19.8	16.6	13.6	19.3	15.8	13.1
Population characteristics score, 0–10	5.5	4.4	3.0	5.3	4.0	3.0
Pollution burden indicators in CES, mean						
Diesel PM, tons/year	0.2	0.2	0.2	0.2	0.2	0.1
Traffic impacts, vehicles/hour	1153.7	1010.9	919.1	1135.3	970.1	899.5
$PM_{2.5}$ concentrations, $\mu g/m^3$	10.6	9.2	8.2	10.4	9.1	7.9
Pollution burden score, 0–10	5.3	4.7	4.2	5.2	4.6	4.4
Race/ethnicity, %						
Hispanic	43.2	26.4	15.1	40.7	23.0	15.1
Non-Hispanic White	33.7	49.2	62.3	35.9	53.6	65.9
African American	6.1	4.5	2.9	5.9	4.1	1.9
Native American	0.3	0.6	0.4	0.4	0.7	0.8
Asian American	12.9	15.1	14.5	13.4	14.4	12.0*
Other/multiple	2.9	3.8	4.5	3.1	3.9	4.1

Note. CES = CalEnviroScreen 4.0 version; n = the number of census tracts; $PM_{2.5}$ = particulate matter with a diameter smaller than 2.5 μm; diesel PM = particle phase of diesel exhaust emitted from diesel engines. The total number of census tracts was n = 8035. Deployed sensors: sensors located within a census tract as of September 2020; fully operational sensors: sensors with readings meeting our completeness criteria (≥ 75%) between January 2020 and September 2020; asthma rate: age-adjusted rate of emergency department visits for asthma per 10 000; cardiovascular disease rate: age-adjusted rate of emergency department visits for heart attacks per 10 000; educational attainment: percentage of population older than 25 years with less than a high school education; poverty: percentage of population living below 2 times the federal poverty level; unemployment: percentage of the population aged > 16 years that is unemployed and eligible for the labor force; housing burden: percentage of low-income households and households severely burdened by housing costs.

linear regressions, the number of sensors in census tracts with deployed sensor(s) was significantly negatively ($B < 0$) associated with all selected SES indicators, African American or Hispanic residents, and $PM_{2.5}$ concentrations, suggesting a smaller number of sensor deployment in census tracts with lower SES, higher $PM_{2.5}$ concentrations, and higher proportions of African American or Hispanic residents in California.

The spatiotemporal development of the PurpleAir sensor network is presented in Figure B (available as a supplement to the online version of this article at http://www.ajph.org). Both the spatial coverage and number of sensors increased substantially from 2017 to 2020, as shown by the increased number of census tracts with deployed sensors (although not necessarily fully operational) as well as the increased number of sensors within certain census tracts over time. Statewide, the number of outdoor PurpleAir sensors grew roughly 20-fold, from 251 in December 2017 to 5180 in September 2020. Furthermore, only 238 census tracts had more than 1 sensor as of December 2018, compared with 1025 as of September 2020. However, 91% of the total number of outdoor sensors were deployed in non-DACs. Specifically, 12% of DACs (242 of 1983) and 33% of non-DACs (1981 of 6052) had

TABLE 2— Associations Between Population and Pollution Characteristics and Number of PurpleAir Sensors per Census Tract for Tracts With PurpleAir Sensors and Presence or Absence of a PurpleAir Sensor in a Census Tract as of September 2020: California

Characteristics	Association With No. of Sensors in Census Tracts With ≥1 Sensor Deployed, B (95% CI)	Presence or Absence of a Sensor in a Census Tract, OR (95% CI)
CES score	−0.03 (−0.04, −0.03)	0.96 (0.95, 0.96)
Educational attainment, %	−0.04 (−0.05, −0.03)	0.94 (0.94, 0.95)
Poverty, %	−0.02 (−0.03, −0.02)	0.96 (0.96, 0.97)
Unemployment, %	−0.06 (−0.07, −0.04)	0.91 (0.89, 0.92)
Housing burden, %	−0.02 (−0.03, −0.02)	0.95 (0.94, 0.96)
Population characteristics score	−0.21 (−0.24, −0.18)	0.72 (0.70, 0.74)
Race/ethnicity, %		
Hispanic	−0.02 (−0.03, −0.02)	0.97 (0.96, 0.97)
Non-Hispanic White	0.01 (0.01, 0.01)	1.03 (1.03, 1.03)
African American	−0.03 (−0.04, −0.01)	0.97 (0.97, 0.98)
Native American	−0.04 (−0.10, 0.03)	1.02 (0.997, 1.05)
Asian American	0.00 (−0.003, 0.003)	1.02 (1.01, 1.02)
Other/multiple	0.04 (0.03, 0.06)	1.18 (1.16, 1.21)
$PM_{2.5}$ concentrations	−0.09 (−0.12, −0.07)	0.70 (0.68, 0.72)

Note. CES = CalEnviroScreen 4.0 version; CI = confidence interval; OR = odds ratio; $PM_{2.5}$ = particulate matter with a diameter smaller than 2.5 μm. All models were adjusted for population density and urban–rural status.

PurpleAir sensors as of September 2020.

Figure 1a shows the temporal trend of sensor density for DACs and non-DACs from 2017 to mid-2020. All communities exhibited a steady increase in sensor density, followed by a decrease for DACs in mid-2020 but a sharp increase for non-DACs, especially within more advantaged non-DACs (0%–50% CES score). Interestingly, the sensor density for less advantaged non-DACs (50%–75% CES score) was even lower than for DACs. Figure 1b shows the operational status of sensors. On average, the proportion of operating sensors among non-DACs was higher than among DACs. The operational status of sensors fluctuated substantially during the initial period of the PurpleAir sensor network, from 2017 to 2018. Afterward, the average proportion of census tracts with fully operational sensors increased from approximately 36% in 2018 to 88% in early 2020. Subsequently, as of March 2020, we observed extensive missing data (i.e., not fully operational). We observed a considerable decline in the proportion of operating sensors for both DACs and non-DACs until the end of the study period.

Figure 2 shows future deployment priority areas based on CES scores and $PM_{2.5}$ concentrations. Among census tracts without any sensors, we considered those with top 25% CES scores and high $PM_{2.5}$ levels to be in greatest need of sensor deployment to close the gap of environmental inequity. The high-risk regions (red), characterized by both a high socioeconomic disadvantage and high air pollution, were mainly located in the San Joaquin Valley and southern Los Angeles County and downwind areas.

DISCUSSION

To the best of our knowledge, this is the first study that examined the distribution and operation of low-cost sensors in relation to sociodemographic factors over multiple years across a large geographic region, and that identified priority areas for future sensor deployment. Our findings suggest that SES and race/ethnicity are related to sensor distribution, operation, and $PM_{2.5}$ concentrations in California; specifically, census tracts with higher estimated $PM_{2.5}$ concentrations, lower SES, and higher proportions of racial/ethnic minority populations had lower sensor availability. The gap between DACs and non-DACs tends to widen over time. This pattern runs counter to necessity since air pollution sensors are in the greatest need where air pollution is highest and where residents are more vulnerable to adverse health impacts from air pollution. These results underscore the need to prioritize such communities for future sensor distribution. In addition, although many PurpleAir sensors were deployed, concerns exist about the operational condition of the sensors, especially in DACs.

Understanding how SES and race/ethnicity are correlated with air pollution is crucial to addressing environmental injustice. Enhancing community-based air quality monitoring—and, in turn, promoting the use and sharing of air pollution data—could help to strengthen awareness, education, and action to reduce environmental injustice.[21] A recent study (February

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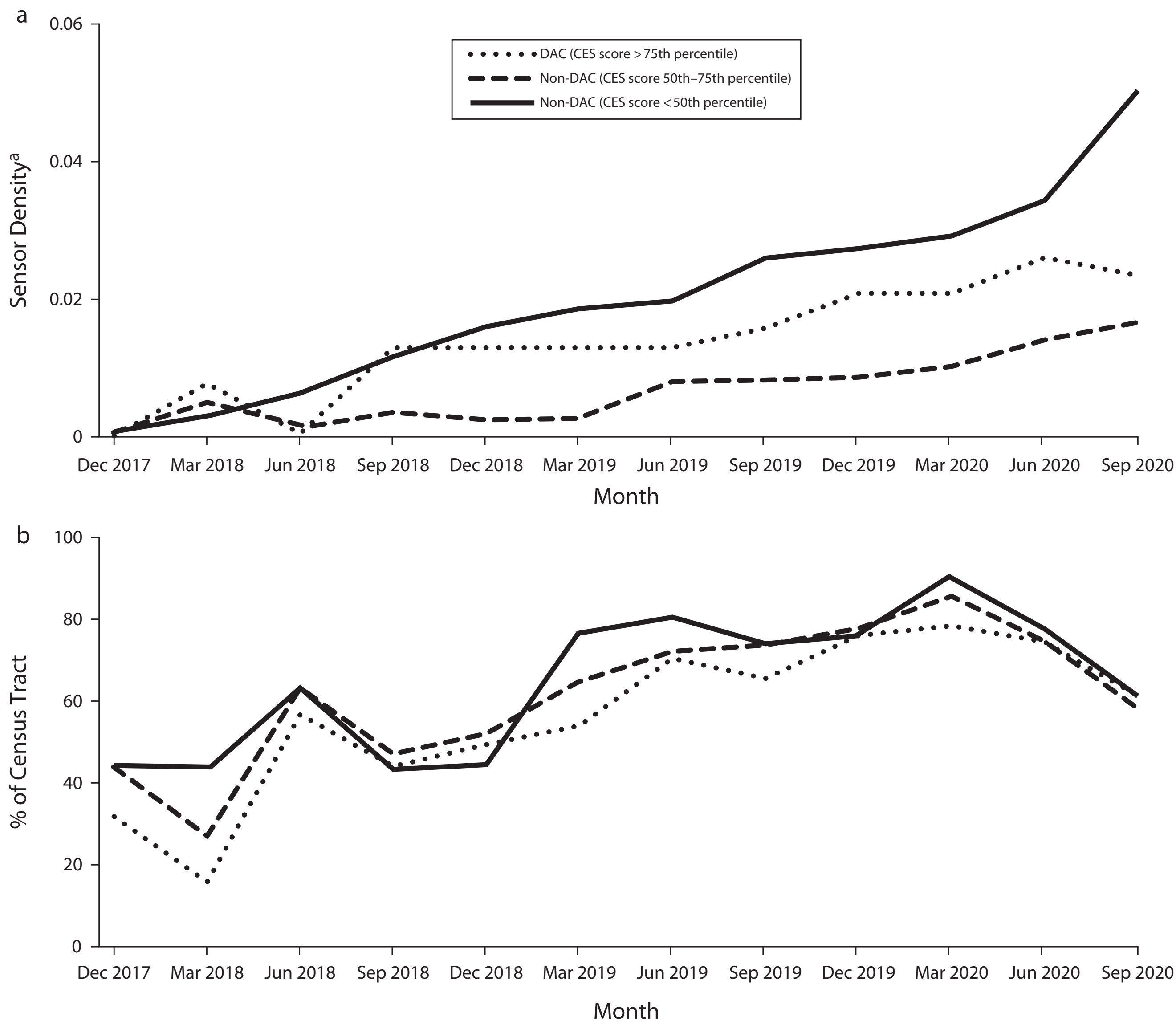

FIGURE 1— PurpleAir Sensor Network (a) Sensor Density and (b) Operational Status: California, 2017–2020

Note. CES = CalEnviroScreen 4.0 version; DAC = disadvantaged communities; $PM_{2.5}$ = particulate matter with a diameter smaller than 2.5 µm.

[a]Defined as the number of sensors per census tract divided by census tract population density.

2020)[22] examined patterns of PurpleAir sensor distribution as a snapshot in the United States as a whole as well as in California; it found a higher number of sensors in census tracts with higher income, higher education, and a greater proportion of White residents. Nationwide, more PurpleAir sensors were deployed in census tracts with higher $PM_{2.5}$ concentrations, whereas the trend was opposite in California. We observed similar patterns between PurpleAir sensor distribution and SES, race/ethnicity, and $PM_{2.5}$ concentrations in California. Furthermore, we included more comprehensive socioeconomic factors, analyzed the sensor distribution longitudinally over time, and examined the operational status of sensors to develop a more comprehensive understanding of sensor distribution and operation.

We found it encouraging that PurpleAir sensors expanded rapidly in California. Of note, "deployment" in this analysis indicates sensors purchased and installed by both residents and government. In addition to sensors purchased and installed by communities or citizens, several government programs have promoted and contributed to the development of low-cost sensor networks. For example, 15 community-scale

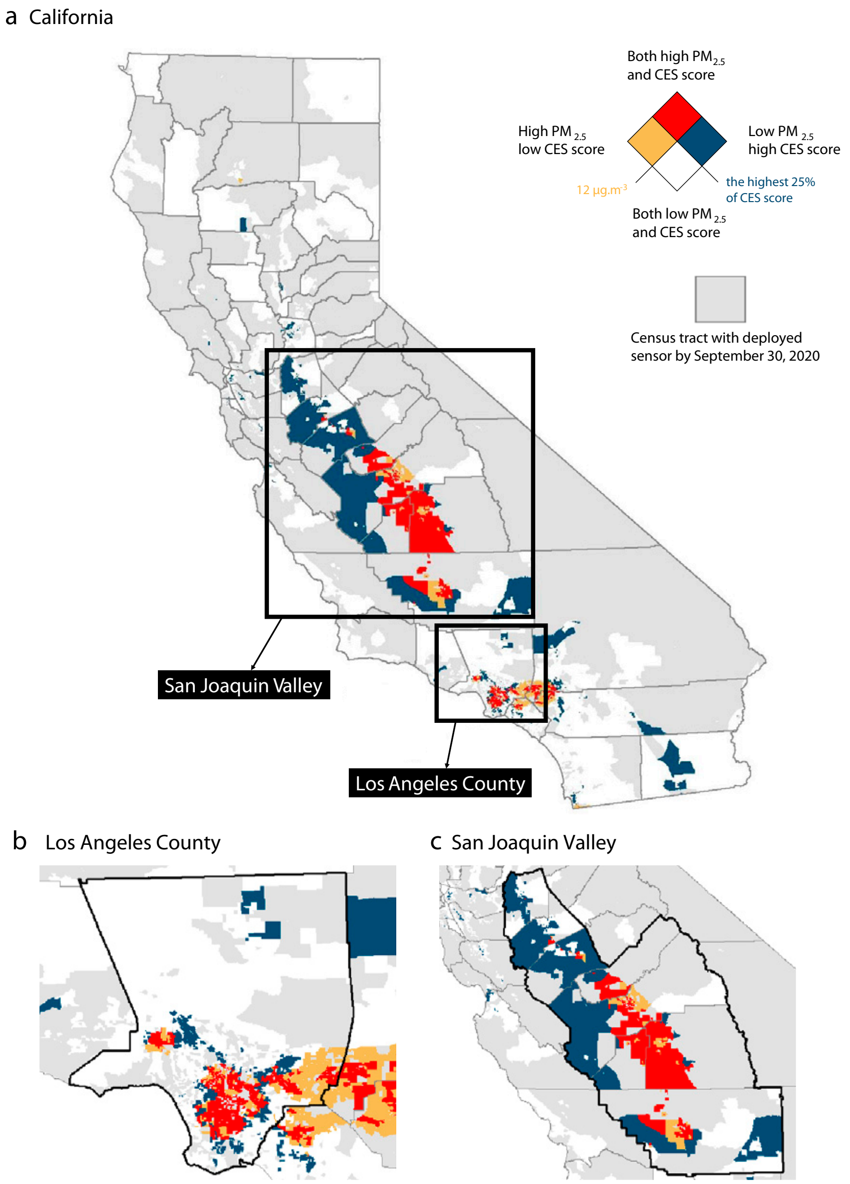

FIGURE 2— Future Sensor Deployment Priority Based on CalEnviroScreen (CES) Score and $PM_{2.5}$ Concentrations Across (a) California, (b) Los Angeles County, and (c) San Joaquin Valley

Note. $PM_{2.5}$ = particulate matter with a diameter smaller than 2.5 μm. The maps were based on data from September 2020.

low-cost sensor networks have been deployed around the state as of 2020 under the California Air Protection Program, developed in response to Assembly Bill 617 and founded by the California Air Resources Board.[23] Approximately 400 PurpleAir sensors have been deployed in 14 California communities as of 2019 by the South Coast Air Quality Management District through a US EPA Science to Achieve Results (STAR) grant.[24] Previous studies also indicated that disadvantaged communities were given priority for sensor deployment through government programs.[25,26] Nonetheless, disparities were still evident for PurpleAir sensor monitoring. We also observed that many new sensors were installed in mid-2020, mostly among more advantaged communities (0%–50% CES score), which coincided with the widespread smoke that engulfed much of California during the record-breaking wildfire season in 2020. Future sensor deployment needs to give attention to the top 25% of DACs,[18] as well as other communities that, although not fitting this definition, are still characterized by low SES, heavy pollution burdens, and high proportions of minority populations. We found that the PurpleAir sensor density among less advantaged non-DACs (50%–75% CES score) was consistently the lowest among all census tracts, which may partially be caused by a lack of both government support that usually focuses on DACs and investment of individual citizens who are unaware of air pollution and sensor technology because of lower education levels (or simply do not want to spend limited resources on sensor purchase). For example, the percentage of the population older than 25 years with less than a high school education in communities with a 50% to 75% CES score was much higher than that of communities with a 0% to 50% CES score (20% vs 8%), as well as the percentage of the population living below two times the federal poverty level (37% vs 21%).

Despite many PurpleAir sensors being installed, a substantial proportion did not continuously collect data, likely because of several external factors related to real-world conditions such as weather changes, poor Internet connections, and human behavior. Outdoor PurpleAir sensors are usually installed on the outside walls of buildings, powered by an outdoor electricity outlet, and require a local Wi-Fi network for data uploading. It is noteworthy that a vast number of sensors are purchased and deployed by individuals or volunteers instead of professionals (i.e., government authorities, scientists), which may result in inappropriate sensor maintenance (e.g., disrupted Wi-Fi connection or power supply), improper cleaning, or lack of regular checking on operational status.[27] In addition, many sensors were a result of project-based deployment and were not maintained after the termination of projects.[28] Furthermore, adverse events related to personal health and economics may affect human behavior (e.g., relocation, power or Wi-Fi being off) and sensor operation. The number of non-operational sensors has increased substantially since March 2020, likely because of the COVID-19 lockdowns and related hardship. People might also have voluntarily turned off devices if they were not concerned about air quality during the lockdown. To optimize sensor operation and data collection, targeted interventions from the PurpleAir company or relevant agencies can be developed in the future, such as sending messages to the sensor owners that encourage them to continuously monitor and conduct proper maintenance checks.

A primary strength of this study is the evaluation of the spatiotemporal distribution and operating status of PurpleAir sensors across sociodemographic factors as well as disease and pollution burdens. This is in contrast with other low-cost sensor studies focusing on technical feasibility and measurement accuracy[26,29,30] but not considering SES contexts and operational status.[31] Our findings help to facilitate further development of low-cost sensor networks to maximize their social and environmental health benefits.

The second strength is the focus on California, which has a diverse population, high air pollution levels, and dense PurpleAir sensor network. As of September 2020, the number of PurpleAir sensors in California accounted for approximately 60% of the global total, allowing us to characterize the air quality monitoring network at a fine spatial scale in a state where air pollution is a top concern. The third strength is that we examined multiple years of data to quantify the expansion of the PurpleAir sensor network and to identify potential factors that affect the operational status of the sensor network.

Several limitations should be noted when interpreting these study findings. First, there is a potential temporal mismatch given that the majority of population and pollution indicators, including $PM_{2.5}$ estimates from the CES data set, were before 2018, whereas the PurpleAir distribution spanned 2017 to 2020. Second, our analysis was limited to the census tract level because of a lack of finer-scale data (e.g., block group or block). Additionally, although sensors on the edges of census tract boundaries may contribute to monitoring of surrounding areas, we did not take into account sensors in adjacent tracts. Furthermore, we solely used $PM_{2.5}$ estimates from a spatial model. Despite the increasing coverage of the PurpleAir sensor network, 72% of census tracts in California still had no single sensor as of September 2020; the direct use of sensor data might introduce bias in exposure estimates in areas and time periods with varying number of sensors.

That being said, future studies may use sensor-based measurements through statistical and machine learning models to improve $PM_{2.5}$ estimates at a higher spatiotemporal resolution; these sensor data need to go through quality assurance and calibration to ensure that they are comparable to the measurements from federal reference or equivalent methods.[32] Because aging may affect the performance of sensors over time, future work is needed to track the long-term distribution and performance of sensors, understand other factors that may influence sensor operation, and provide guidance for long-term data collection. Lastly, only the PurpleAir sensor network was examined in this analysis. To explore common assumptions about general sensor distribution and provide guidance for future sensor installation and maintenance, we selected the PurpleAir sensor network—the predominant low-cost sensor network currently in use—because of its wide use in government programs,[24] scientific research, and individual air monitoring as well as its robust performance,[33] high sensor density, and rapid and continued expansion. With the development of various low-cost air quality sensors, it would be valuable for future studies to investigate and compare other air pollutants from other low-cost sensor networks. AJPH

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CONTRIBUTORS

Y. Sun participated in methodology, software, data curation, formal analysis, and writing of the original draft. A. Mousavi participated in software, data curation, and writing, reviewing, and editing the article. S. Masri participated in methodology and writing, reviewing, and editing the article. J. Wu participated through conceptualization, supervision, project administration, funding acquisition, methodology, data curation, and writing, reviewing, and editing the article.

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CONFLICTS OF INTEREST

The authors declare that they have no known conflict of interest that could have appeared to influence the work reported in this article.

HUMAN PARTICIPANT PROTECTION

This research involved only secondary data analysis using publicly available data and so was not subject to protocol approval.

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