Mapping Climate Vulnerability and Air Pollution in Contra Costa County:

Identifying Hot Spots and Targeting Interventions

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PSE

Bringing science to energy policy

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About PSE Healthy Energy

PSE Healthy Energy is a nonprofit research institute dedicated to supplying evidence-based scientific and technical information on the public health, environmental, and climate dimensions of energy production and use. We are the only interdisciplinary collaboration focused specifically on health and sustainability at the intersection of energy science and policy. **Visit us at psehealthyenergy.org**.

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Abbreviations

AC	Air conditioning
ACS	American Community Survey
ANOVA	Analysis of Variance
BAAQMD	Bay Area Air Quality Management District
BayREN	Bay Area Regional Energy Network
BC	Black Carbon
CDPH	California Department of Public Health
CES	CalEnviroScreen
FPL	Federal Poverty Level
HAQES	Hazardous Air Quality Ensemble System
HEPA	High-Efficiency Particulate Air
HVAC	Heating, Ventilation and Air-conditioning
IDW	Inverse Distance Weighting
LISA	Local Indicators of Spatial Association
MOMA	Moment-Matching
NAAQS	National Ambient Air Quality Standard
NO_2	Nitrogen Dioxide
NO_x	Nitrogen Oxide
OEHHA	Office of Environmental Health Hazard Assessment
$PM_{2.5}$	Fine particulate matter with diameter < 2.5 micrometers
QA/QC	Quality Assurance/Quality Control
US EPA	United States Environmental Protection Agency
$\mu g/m^3$	Micrograms per cubic meter

Executive Summary

In this report, PSE characterizes the air pollution and extreme heat exposures faced by communities in Contra Costa County and maps the landscape of potential interventions to address these challenges.

To address the monitoring gap in overburdened communities of Contra Costa, PSE, in collaboration with community partners, deployed a low-cost air monitor network of 50 Aeroqual sensors across Contra Costa County from September 2023 through May 2025.We combined these data with data from 700 privately-owned PurpleAir sensors to observe fine particulate matter ($PM_{2.5}$) trends and exposures across different regions, cities, and demographic groups in the county. We pair this with extreme heat data at the census block group level to detail impacts throughout Contra Costa and highlight areas that experience a confluence of these exposures. We then identify climate-vulnerable populations where these exposures overlap with sensitive populations and low adaptive capacity, following the California Department of Public Health's (CDPH) climate vulnerability framework. Additionally, we conducted a literature review of possible air pollution and extreme heat interventions and held a community listening session to understand how interventions may align with community needs and potential barriers to their implementation.

Exposure to air pollution and heat: We estimated average exposure to long-term $PM_{2.5}$ and acute $PM_{2.5}$ episodes by district, city, and demographic groups. Statistically significant differences in exposure to both exposure metrics were found primarily across geography but also by racial groups, age groups, and indoor/outdoor worker types. Using three heat metrics (extreme heat days, extreme warm nights, and extreme heat waves), we identified a strong geographic trend where eastern, more inland parts of the county were hotter on average than western parts of the county adjacent to San Francisco Bay. We similarly estimated average exposures for different populations and observed statistically significant differences between racial groups, age groups, and indoor/outdoor worker types as well. Both heat and air pollution exposures varied more by geography than by demographic. **Our network of low cost sensors, whose deployment was advised by local community members to strategically fill in monitoring gaps, found $PM_{2.5}$ hotspots in Richmond, San Pablo, Antioch, Oakley, and Pittsburg. Long-term $PM_{2.5}$ concentrations in these cities averaged 8-9 micrograms per cubic meter (µg/m³). The insights from our local monitoring network demonstrate the unique value of dense monitoring and can inform mitigation strategies.**

Identification of climate vulnerability patterns: Utilizing population sensitivity measures and adaptive capacity indicators, we identified hot spots where environmental exposures, population sensitivities, and low adaptive capacity overlapped to form specific climate vulnerabilities. These areas may be candidates for priority interventions, as residents are at a high risk of exposure to air pollution, extreme heat, or both, with fewer resources to mitigate exposure. Additionally, these overlaps are important to consider when comparing interventions, as adaptive capacity can present barriers to implementation (e.g., areas with high poverty likely have a harder time implementing household-level interventions without support). Pittsburg, Antioch, and Oakley, and their surrounding suburbs, experienced higher levels of both air pollution and extreme heat exposure. In general, the eastern portion of the county that faced higher extreme heat also had lower canopy coverage. Areas with clusters of higher exposure, sensitive populations, and lower adaptive capacity tended to be smaller and varied. **Communities facing a confluence of exposures, population sensitivities, and low adaptive capacities should be prioritized for interventions that can mitigate their particular combination of vulnerabilities.**

Intervention landscape mapping: Our review and listening session highlighted key factors to consider such as hazards addressed, breadth of benefits, who could execute the intervention, and barriers they may face. In particular, individuals face financial, informational, and bureaucratic barriers when trying to make their homes more resilient to these climate-related exposures. Additionally, stakeholders can account for multiple benefits of an intervention to address multiple vulnerabilities and find alignment with other policy or community goals. We summarized potential interventions with key factors planners and policymakers can consider to support effective intervention design – the hazards addressed, the mechanism of action, potential actors, and potential barriers.

Our data indicate that communities face unique combinations of environmental exposures, population sensitivities, and adaptive capacity. To address these combinations of challenges, policy makers and planners can consider the breadth of potential benefits an intervention can provide and potential barriers residents may face in adopting them. **It is crucial for stakeholders to address a community's unique set of circumstances when planning interventions. Community insights from direct engagement can illuminate their specific needs and barriers to program adoption.** Future studies should expand and include additional climate and environmental hazard exposures, population sensitivities, and adaptive capacities beyond the ones discussed in this report. Characterizing climate vulnerabilities and effective interventions to mitigate them requires multiple types of data, including hyperlocal air monitoring, satellite climate data, census demographic data, scientific literature, and community input.

Introduction and Background

In recent years, California's Contra Costa County has experienced an increase in extreme heat and wildfire smoke (OEHHA, 2022), which both have detrimental impacts on the people and communities living and working in the county. These impacts are projected to worsen as the climate continues to change (OEHHA, 2022). For example, Contra Costa is projected to experience 19 additional extreme heat days (days over 92.8°F) in 2040–2060 and 40 additional days in 2080–2099 (CDPH, 2021). In addition to their public health impacts, wildfires and climate extremes contribute to power outages and economic losses – these losses will increase as the climate changes throughout this century (IPCC, 2007).

These climate-related exposures exacerbate existing air quality and public health challenges in Contra Costa. Wildfire smoke adds to the persistent air pollution from oil refineries, industrial activity, and heavy vehicle traffic. Exposure to this air pollution, specifically to the fine particulate matter known as $PM_{2.5}$, has been linked to respiratory and cardiovascular issues as well as certain cancers and poor birth outcomes (Liu et al., 2022; Liao et al., 2025; EPA, 2025, Kim et al., 2019). The increasingly extreme heat amplifies the urban heat island effect caused by impervious surfaces, low greenspace, and dense buildings. Extreme heat events such as heatwaves and extreme heat days can also have serious health consequences, from acute heat stress to worsening existing health conditions (OEHHA, 2022, WHO, 2024). For example, in July 2006 Contra Costa experienced a fivefold increase in heat-related emergency department visits likely attributable to a ten-day heat wave (Contra Costa Health Services, 2015). Simultaneous exposure to air pollution and extreme heat can compound their health impacts, leading to more severe public health risks (Hu et al., 2022).

What is $PM_{2.5}$?

$PM_{2.5}$ is a mixture of suspended particles that are smaller than 2.5 micrometers in diameter. They are produced from chronic sources like fossil fuel combustion and industrial activity as we as short-term sources like gas-powered cars and wildfire smoke.

High levels of $PM_{2.5}$ exposure have been associated with premature mortality and numerous adverse health outcomes (Guo et al., 2014, EPA, 2025c). To protect public health and welfare, the US Environmental Protection Agency (US EPA) sets regulatory standards for this and other pollutants (EPA, 2025b). As our understanding of the health risks posed by $PM_{2.5}$ pollution have grown, its regulatory standard has been lowered (most recently in 2024) (EPA, 2025).

Low-income communities and communities of color across Contra Costa County are disproportionately impacted by these exposures due to higher existing environmental burdens and greater susceptibility to simultaneous (Shonkoff et al., 2009, Shonkoff et al., 2011, Hajat et al., 2015). Additionally, young children, older adults, and outdoor workers are often more vulnerable to these health risks posed by these hazards.

Effectively mitigating these hazards requires understanding local exposures, which requires neighborhood-level data on air pollution and extreme heat. However, regulatory air monitoring for $PM_{2.5}$ is limited in Contra Costa, with data collected by only three Bay Area Air Quality Management District (BAAQMD) monitors that are spread throughout the county. These three monitors alone cannot capture the local conditions faced by different communities. The northern and eastern portions of Contra Costa County in particular face a monitoring gap despite the presence of industrial sites and overburdened communities.

To address this monitoring gap, we began with community outreach and engagement to understand where there were gaps in air quality monitoring. We then filled those gaps by deploying a network of low-cost Aeroqual sensors at volunteer host sites across the county, in collaboration with community members, community organizations like La Clinica, and the West Contra Costa County Unified School District to identify volunteer air monitor hosts. We then merged this data with measurements from 700 existing privately-owned PurpleAir sensors to generate unprecedented insights into local air quality.

Next, we characterized extreme heat exposures using satellite data. We then contextualized both the $PM_{2.5}$ and extreme heat exposures by considering how they overlap with sensitive populations like older adults and adaptive capacities like existing greenspace, following the climate vulnerability framework of the CDPH (CDPH, 2023). Finally, we conducted a landscape mapping of potential interventions, through literature review and stakeholder outreach, incorporating community perspectives through a community listening session.

There are a number of prior studies examining the relationship between air quality and air pollution exposure, extreme heat, population vulnerability, and adaptive capacity in Contra Costa. The novelty of this analysis is the use of a dense network of low-cost air monitors, particularly in areas with significant pollution but low existing data collection (i.e. inner Richmond and rural areas in eastern Contra Costa), paired with fine-grained heat data to provide air quality and heat exposure data at a high spatial granularity.

Characterizing Exposure to Air Pollution and Extreme Heat in Contra Costa County

Overall Approach

To identify areas of high exposure and characterize local and regional trends, we collected $PM_{2.5}$ and extreme heat data and estimated exposures at the census block group level. We then summarized these exposures using population-weighted averages at the city and supervisorial district levels. When comparing larger spatial areas with one another, we used Contra Costa County's five supervisorial districts (Figure 1). This allowed us to capture regional trends using official administrative borders that are roughly (though not perfectly) divisible into smaller units like census tracts or block groups. Using supervisorial districts offered an advantage over city boundaries as they also account for lightly populated areas and unincorporated territories. For more localized analyses we used city boundaries.

Spatially, District 1 (West) covers the westernmost part of the county, including Richmond, San Pablo, and El Cerrito. District 2 (South) covers southern parts of the county, including wealthier communities such as Danville and Lafayette. To the east, District 3 (East) includes cities like Brentwood, Antioch, and Oakley. District 4 (Central) represents the center of the county (including the cities of Concord, Walnut Creek, and Clayton), and District 5 (North) comprises cities like Pittsburg and Martinez, and census-designated areas such as Bay Point in the north.

We also studied population-weighted $PM_{2.5}$ and extreme temperature exposures for key demographic indicators including race, age, income, and share of outdoor workers using census population data (US Census Bureau, n.d.). We assessed whether the differences in averaged exposure differed by populations using analysis of variance (ANOVA), where groups were weighted according to their population size. We also explored hourly and seasonal patterns of $PM_{2.5}$ given the hourly resolution of the measurements. For detailed data collection and analysis methods, please see the **Methods** section of the **Appendix**.

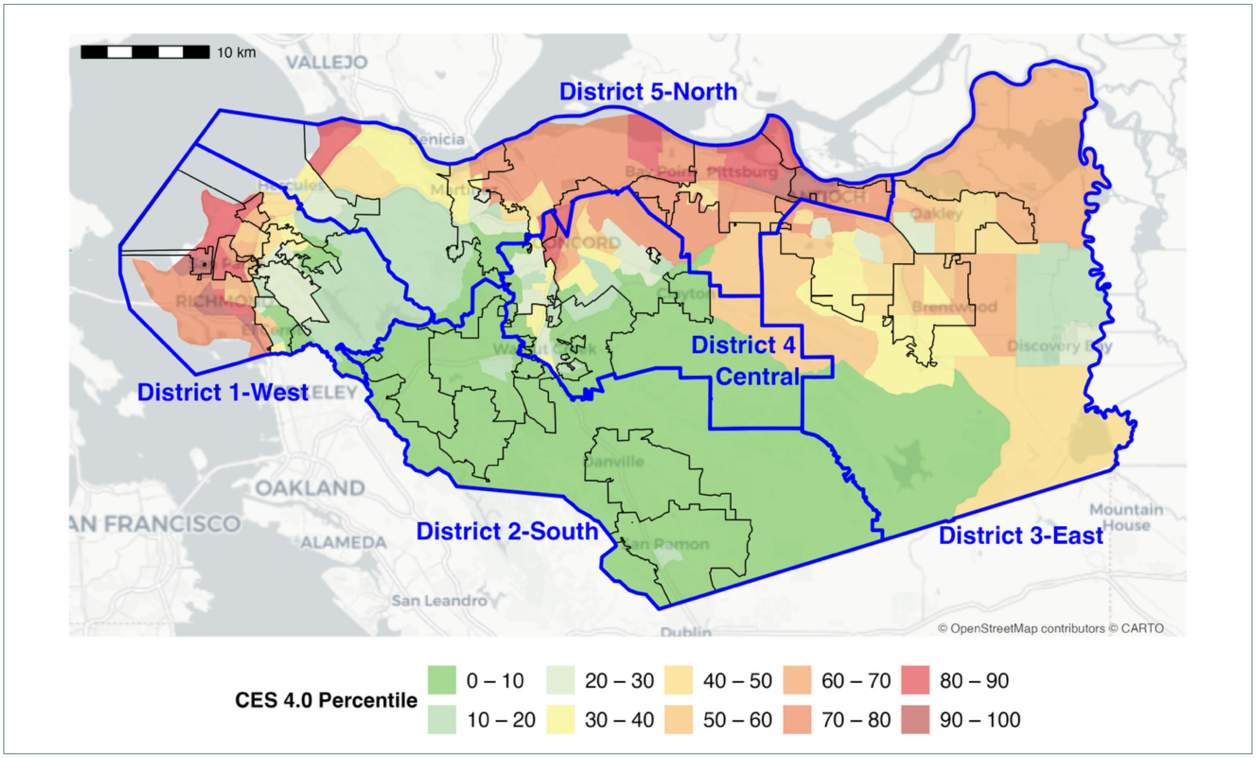

Figure 1. Cumulative exposures and municipal boundaries in Contra Costa County. *Colors indicate CalEnviroScreen (CES) 4.0 scores, which reflect the cumulative environmental, social, and economic burden faced by a community. Boundaries reflect the supervisory districts.*

Air Pollution Approach

We aimed to quantify exposure to $PM_{2.5}$ across the county by aggregating data from multiple air monitoring networks. This included deploying a network of low-cost air monitors in previously under-monitored communities as well as leveraging an existing network of privately-owned PurpleAir sensors.

Contra Costa is home to many PurpleAir monitors that offer insight into local $PM_{2.5}$ concentrations. However, these sensors—which are often purchased by concerned citizens—are concentrated in Whiter, more highly educated, and less polluted areas (Liang et al., 2021, Desouza & Kinney, 2021). For example, in Contra Costa, PurpleAirs are concentrated in areas with lower cumulative burden as measured by CalEnviroScreen (CES), a data-driven metric that combines environmental, social, and economic burdens (**Figure 2**) (OEHHA, 2021). This measurement disparity amplifies the well-documented exposure differences in disadvantaged communities (Tessum et al., 2019) by obscuring true exposures (Chambliss et al., 2021) and hindering environmental protection efforts. To address this disparity, we designed our air monitoring network in partnership with representatives from historically under-monitored communities.

At the start of the project, we met with Contra Costa-based community organizations to identify monitoring and data gaps and solicit volunteers to host monitors. We deployed 50 Aeroqual-brand sensors at volunteer sites (**Figure 2**), which included homes, public schools, a fire department, and a BAAQMD monitoring site. Many of the sensors in Richmond were placed at the same sites as an earlier air quality monitoring project, the Richmond Air Monitoring Network (PSE, 2020), which ended in 2022 (Lukanov et al., 2022). The updated monitoring network collected data from September 2023 – May 2025, with all monitors in-place and active by January 2024.

We also included data from over 700 PurpleAir sensors privately hosted and managed by individuals or organizations not associated with the study. These data were publicly available to download from the PurpleAir site.

We addressed measurement errors through quality control/quality assurance (QA/QC) protocols (see the Methods section and **Table A.M.1** in Appendix A for details) and calibrated the sensor results. For the Aeroqual sensors we applied Aeroqual's recommended Moment-Matching (MOMA) technique (Miskell et al., 2018) and for the PurpleAir sensors we applied the US EPA's calibration equation (Barkjohn, et al., 2022). We estimated the average hourly concentration for each census block group by fusing the measurements via Inverse Distance Weighting (IDW) (Farooqui et al., 2023).

$PM_{2.5}$ Air Quality Standards

The US EPA sets NAAQS for six criteria air pollutants, including $PM_{2.5}$. Primary standards set pollution levels specific to public health, including the protection of more sensitive populations such as children and the elderly. Secondary standards set levels around public welfare, such as protection against decreased visibility from smog and harm to crops and livestock. Both the NAAQS primary and secondary daily (24 hours) maximum level of $PM_{2.5}$ pollution is 35 $\mu g/m^3$ while the NAAQS primary standard for annual (annual mean, averaged over three years) level is 9 $\mu g/m^3$ (EPA, 2025b).

Concentrations above the standards are more likely to pose public health risks such as premature mortality, cardiovascular, respiratory, and pregnancy outcomes (EPA, 2025c). We use these US EPA standards as our benchmark, though $PM_{2.5}$ concentrations below these levels are also associated with health risks (Liu et al., 2019, Peralta et al. 2025).

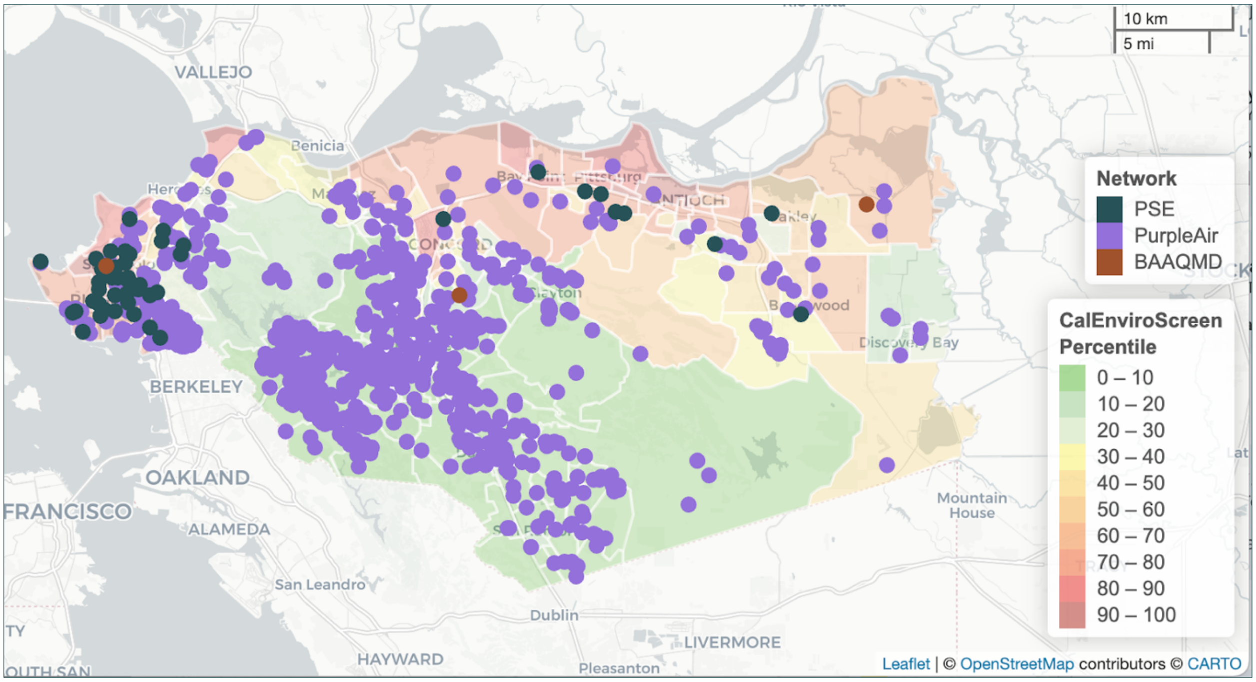

Figure 2. Air Quality Monitoring Network in Contra Costa County. *PSE's Aeroqual monitoring network collected data from September 2023 – May 2025, with monitors hosted by volunteers at homes, public schools, a fire department, and a BAAQMD monitoring site. PurpleAir sites were privately managed by individuals or organizations, independently from this study; these data were available to download from the PurpleAir site. BAAQMD PM2.5 monitoring sites are included for reference, though data from their three regulatory-grade monitors are not included in our analysis.*

We examined both long-term $PM_{2.5}$ levels (average $PM_{2.5}$ concentrations over the 22-month study period) and the number of acute-PM days (the number of days with an average $PM_{2.5}$ over 35 micrograms per cubic meter (µg/m^3)). 35 µg/m^3 is the US EPA's National Ambient Air Quality Standard (NAAQS) level for single-day $PM_{2.5}$ pollution, which is the standard set by the EPA to protect public health and welfare (EPA, 2025b).

We also looked at average $PM_{2.5}$ concentrations during work hours (7:00 am - 6:00 pm) to consider potential outdoor worker exposure and average $PM_{2.5}$ during heavy commuting hours (7:00 am - 9:00 am and 5:00 pm - 7:00 pm) to consider the potential contribution from rush-hour traffic. However, results indicated that these were both highly correlated with average $PM_{2.5}$ concentrations, (**Figure A.S.2**) so we ultimately used average long-term $PM_{2.5}$ for our final analysis.

Air Pollution Findings

Overall, cities in West, North, and East Contra Costa faced the highest levels of air pollution and could be prioritized for air pollution interventions. The local air quality monitoring network of low-cost sensors provided unique, key information including areas of high concentration, short-term peaks in small areas, and local trends, which vary across cities. Monitoring designed to measure regional trends can capture overall trends, but will miss the unique trends of individual cities. While general trends were similar across the county, the expanded monitoring network illustrated local variations that would be missed by only examining regional regulatory air monitoring data. In turn, this localized information can help identify communities prioritize air quality interventions and give insight into potential sources. Given the disparate placement of monitors from private individuals, deliberate interventions can help address the measurement gaps in overburdened communities.

Over the study period, Districts 1 (West) and 3 (East) experienced the highest long-term $PM_{2.5}$ concentrations, especially in the cities of Richmond, San Pablo, Antioch, and Oakley. This was followed by District 5 (North), especially in Pittsburg (Table 1). These higher $PM_{2.5}$ concentrations in cities are likely due to local, urban pollution sources rather than regional ones because the surrounding areas have lower concentrations. Urban pollution sources in these districts include multiple oil refineries (Chevron-Richmond; Martinez; Phillips 66-Rodeo; Golden Eagle-Tesoro), industrial activity like the Levin Coal Terminal in Richmond (Lukanov et al., 2022), transportation activity in the Port of Richmond, dense local vehicle traffic (Kim et al., 2004), natural gas appliances (Zhu et al., 2020), residential wood smoke (BAAQMD, 2017), and power plants like Marsh Landing in Antioch (PSE, 2024).

Cities in the West, North, and East could be prioritized for air pollution interventions because they face especially high levels of $PM_{2.5}$ (Figure 3A, Table 1). The cities with the highest average hourly $PM_{2.5}$ concentrations over the 22-month study period were San Pablo and Richmond, with an average hourly $PM_{2.5}$ concentration of 8.42 µg/m3 and 7.04 µg/m3, respectively. Both cities are in District 1 (West), which had average hourly $PM_{2.5}$ concentrations around 6.52 µg/m3, below the hourly averages for San Pablo and Richmond individually. In District 3 (East), hourly average $PM_{2.5}$ concentrations were 6.8 µg/m3 in Oakley, 6.51 µg/m3 in Antioch, and 6.33 µg/m3 in Brentwood. The average hourly $PM_{2.5}$ concentrations in District 3 (East) was 6.47 µg/m3. In District 5 (North), Pittsburg had an hourly average concentration of 6.83 µg/m3, while the district average was 6.13 µg/m3. These levels are below the NAAQS standard for annual $PM_{2.5}$ concentrations (9 µg/m3), though epidemiological evidence indicates that even very low exposure levels (e.g., below the NAAQS) can still have adverse health effects (Peralta, 2025). However, measurements from low-cost sensors should not be used to determine regulatory exceedances.

Periods of elevated acute $PM_{2.5}$ were most common in neighborhoods in Richmond, Martinez, and Pittsburg. These cities have the highest number of days with $PM_{2.5}$ concentrations at or above the NAAQS daily $PM_{2.5}$ threshold of 35 µg/m3 (Figure 3B, Table 1) (EPA, 2025b). The NAAQS are designed to protect public health, including for sensitive populations, so days with concentrations above this level are more likely to pose health risks for residents. Though as previously mentioned, even lower daily $PM_{2.5}$ concentrations are still associated with negative health outcomes (Liu et al., 2019). These findings align with the US EPA's designation that the Bay Area was in moderate nonattainment of the 24-hour $PM_{2.5}$ standard as of December 2025 (BAAQMD, 2025).

Across the county, these highest days of $PM_{2.5}$ concentrations only occurred in September 2023 and December 2024. Overall, the data suggest that these instances were due to infrequent, intense sources of pollution such as fireworks (Mousavi et al., 2021), small wood fires for heating, or heightened industrial activity. Wintertime inversions, where cooler ground-level air is trapped by a layer of warm air above, can also increase the likelihood of a high $PM_{2.5}$ day by reducing dilution of emissions (Gramsch et al., 2014). Despite how infrequent they were, these periods of high $PM_{2.5}$are still a cause for concern, as even a single day of high $PM_{2.5}$, exposure can cause adverse cardiovascular outcomes (Hasegawa et al., 2023) and premature mortalities (Liu et al., 2019).

As average $PM_{2.5}$during work and rush hours was highly correlated with long-term $PM_{2.5}$ concentrations, we focused on long-term $PM_{2.5}$ and the number of acute PM days in our analysis (Figure A.S.1; Figure A.S.2).

We did not observe evidence of wildfire smoke in Contra Costa County during our measurement period (September 2023 - May 2025). This is based on a review of our $PM_{2.5}$ data as well as a review of estimated concentrations of Black Carbon (BC), a type of particulate matter produced by wildfire smoke. The BC concentration estimates came from the Hazardous Air Quality Ensemble System (HAQES) (Tong, 2023) which combines multiple models to estimate concentrations from a range of emissions, meteorological, and satellite data (Figure A.S.3.). In previous years, wildfire smoke has significantly increased air pollution exposure in Contra Costa. For example, Richmond's air quality was severely worsened by wildfire smoke in 2020, including a week of concentrations above 100 µg/m3 and multiple hours above 200 µg/m3 (PSE, 2022). These high levels of smoke, while less frequent, are still a serious cause for concern given the consistent epidemiological evidence—including California-based studies—that wildfire smoke contributes to increased risks of mortality, poor respiratory outcomes (Gould et al., 2024), reduced birthweights (Amjad et al., 2021), and instances of preterm birth (Heft-Neal et al., 2022).

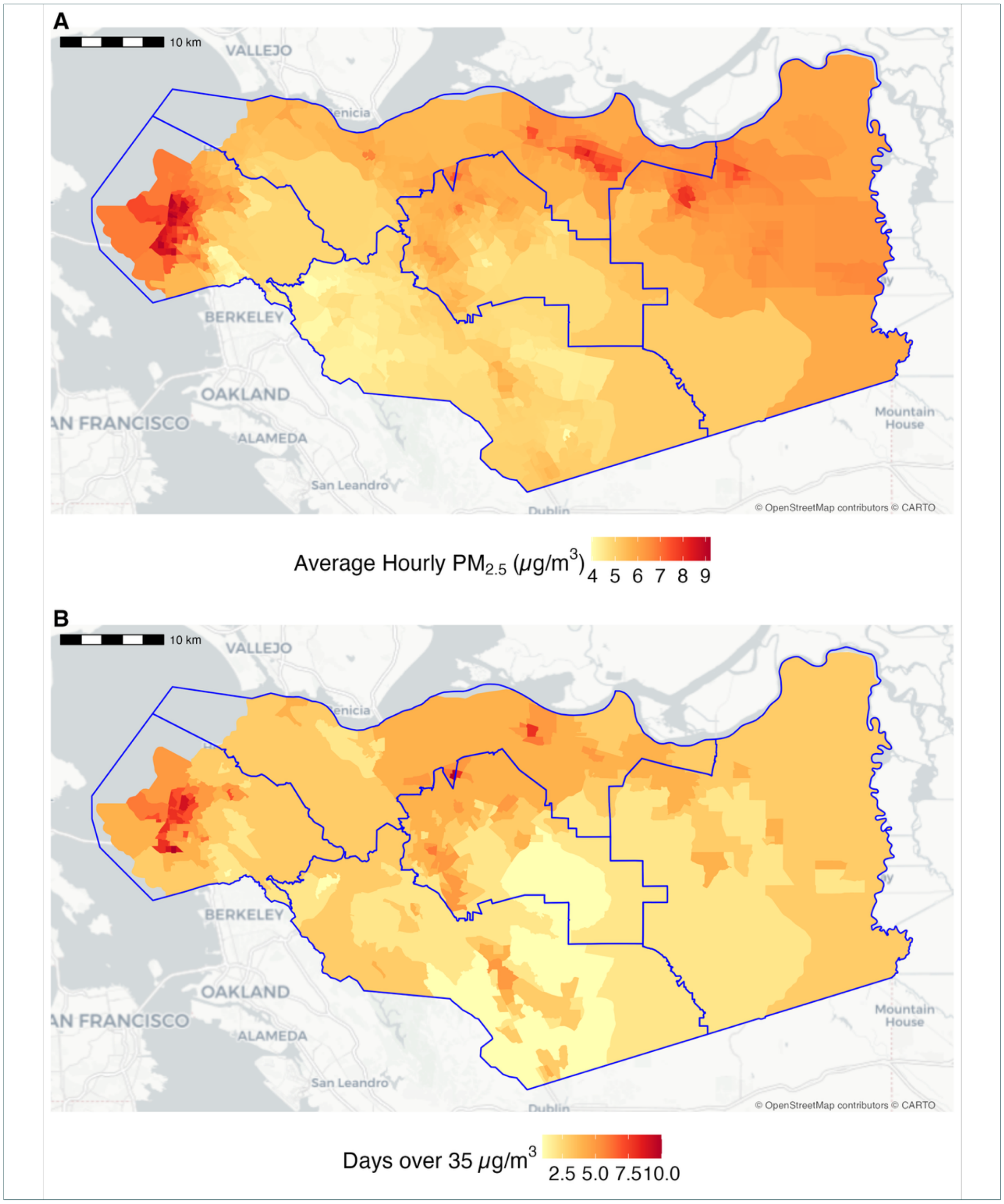

Figure 3. $PM_{2.5}$ concentrations across Contra Costa County, September 2023 – May 2025. *Panel A illustrates the average hourly concentrations across the study period at the census block group, Panel B illustrates the number of days with 24-hour mean $PM_{2.5}$ concentrations above 35 µg/m^3, the US EPA NAAQS for daily $PM_{2.5}$ concentrations, for each block group. Blue lines represent supervisorial district boundaries. It should be noted that while a single day's concentration exceeding the 35 µg/m^3 threshold is a violation of the NAAQS, data from this study were collected via low-cost monitors and cannot be used to determine regulatory compliance.*

Table 1. Summary Statistics of Air Pollution Concentrations by City. Concentrations are population-weighted based on US census block groups.

District	City	Average $PM_{2.5}$ Concentration (bootstrap 95 percent Confidence Interval) [μg/m³]	Interquartile Range (μg/m³)	Number of Days with mean concentration > 35 μg/m³	Average daily minimum concentration (μg/m³)	Average daily maximum concentration (μg/m³)	Average change in concentration over the day μg/m³)
1 (West)	San Pablo	8.42 (8.3, 8.54)	4.22-10.42	7	7.2	9.36	2.16
1 (West)	Richmond	7.04 (6.94, 7.13)	3.53-8.65	5	6.12	7.72	1.6
1 (West)	Pinole	5.28 (5.2, 5.36)	2.64-6.02	3	4.34	6.04	1.7
1 (West)	El Cerrito	4.75 (4.68, 4.83)	2.24-5.63	3	3.89	5.58	1.69
2 (South)	San Ramon	4.97 (4.88, 5.05)	2.43-5.57	1	4.3	5.46	1.16
2 (South)	Orinda	4.35 (4.28, 4.43)	1.94-4.97	3	3.57	5.15	1.58
2 (South)	Moraga	4.43 (4.35, 4.51)	1.93-4.97	2	3.6	5.21	1.61
2 (South)	Lafayette	4.59 (4.51, 4.67)	2.07-5.13	2	3.64	5.38	1.74
2 (South)	Danville	5.05 (4.96, 5.14)	2.41-5.61	4	4.23	5.88	1.65
3 (East)	Oakley	6.8 (6.71, 6.9)	3.46-7.53	3	6.02	7.72	1.7
3 (East)	Brentwood	6.33 (6.24, 6.43)	3.13-6.89	2	5.43	7.23	1.8
3 (East)	Antioch	6.51 (6.42, 6.6)	3.36-7.11	4	5.75	7.25	1.49
4 (Central)	Walnut Creek	5.24 (5.15, 5.33)	2.42-5.67	3	4.23	5.99	1.76
4 (Central)	Pleasant Hill	5.69 (5.6, 5.78)	2.71-6.09	4	4.59	6.75	2.15
4 (Central)	Concord	5.73 (5.64, 5.83)	2.78-6.15	4	4.68	6.72	2.04
4 (Central)	Clayton	4.77 (4.69, 4.85)	2.19-5.45	1	3.78	5.76	1.98
5 (North)	Pittsburg	6.83 (6.73, 6.92)	3.56-7.86	4	6.23	7.29	1.06
5 (North)	Martinez	5.6 (5.5, 5.69)	2.61-6	4	4.73	6.41	1.68
5 (North)	Hercules	5.16 (5.08, 5.25)	2.41-5.92	3	4.28	5.96	1.67

$PM_{2.5}$ levels followed similar time-based trends across all districts, including episodes of very high concentrations in the early winters 2023 and 2024 and lower concentrations in summer 2024 (**Figure 4**). The intensity of these episodes varied by city; for example, San Pablo experienced the highest peak concentration in winter 2024, while cities in Northern and Eastern Contra Costa experienced a longer period of elevated concentrations into 2025 (**Figure 5**). The cities in District 2 (South) experienced similar trends but with generally lower levels, especially for the winter 2024 episode (**Figure A.S.4**). These variations are likely driven by a combination of local pollution sources and geography, which can mitigate or exacerbate regional sources. We observed suggestive evidence of a seasonal trend, with higher concentrations in winter months. While we only observed a few seasonal cycles, BAAQMD has also reported wintertime peaks in the Bay Area, suggesting stagnant weather and residential wood burning as likely sources.

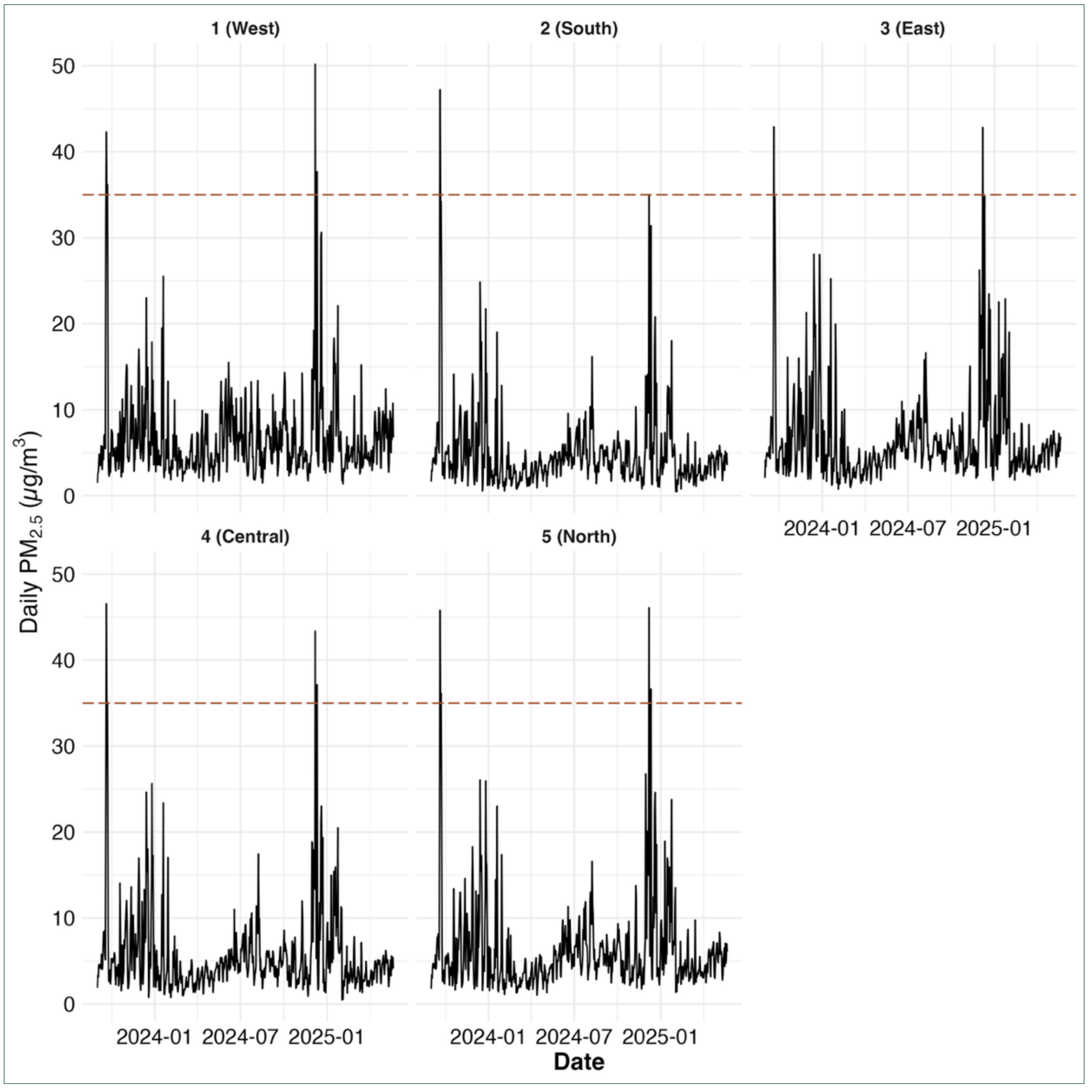

Figure 4. Daily $PM_{2.5}$ concentrations within Supervisorial Districts, September 2023 – May 2025. *Hourly $PM_{2.5}$ concentrations were first averaged for each district, via population weighting, and then averaged for each day. The red horizontal line represents the US EPA Daily NAAQS, 35 ⍰g/m³. Note that a single day above the standard is not considered a violation of the standard, which is evaluated over a period of three years using regulatory-grade monitors.*

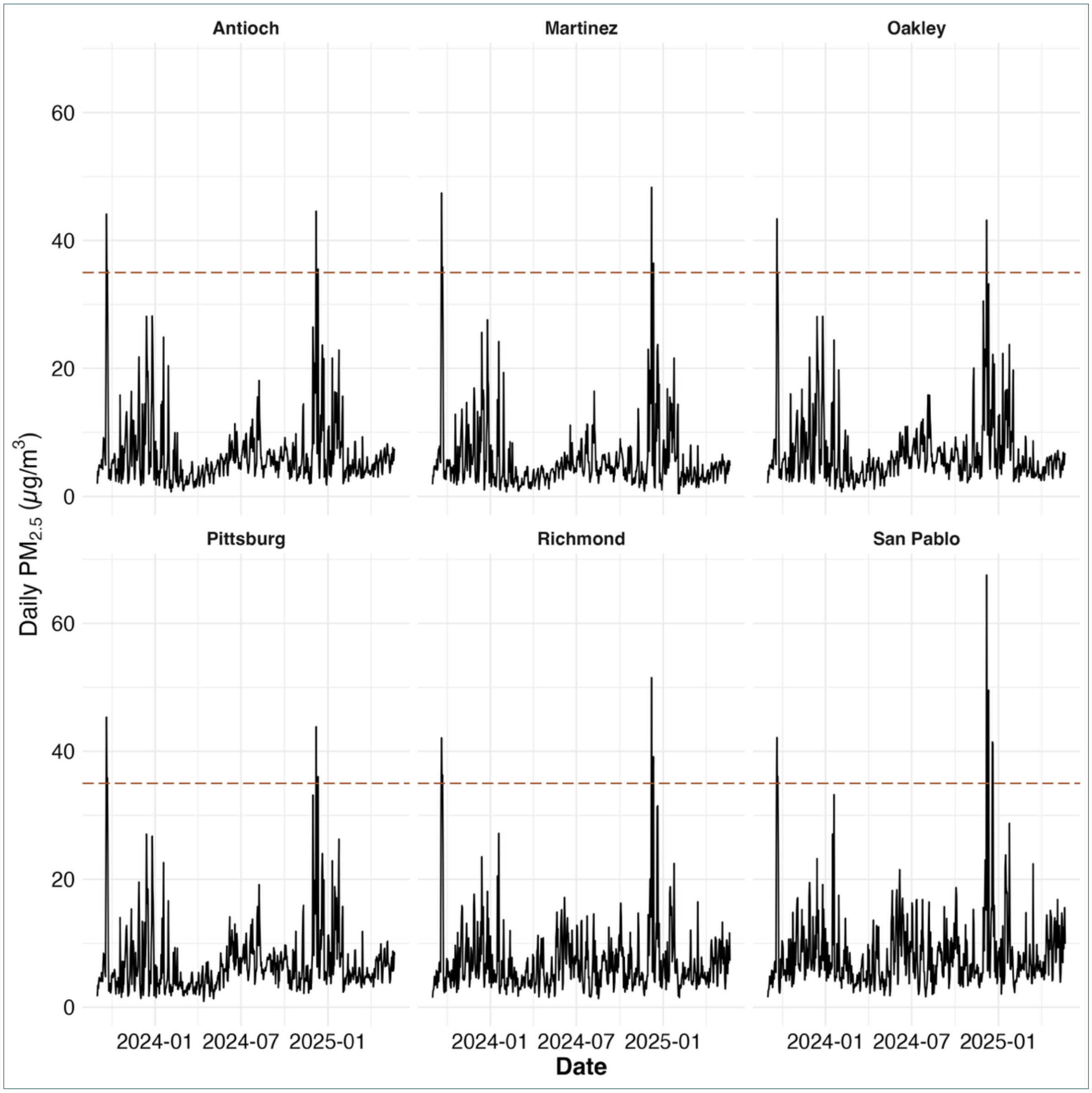

Figure 5. Daily $PM_{2.5}$ concentrations within select cities, September 2023 – May 2025. *Hourly $PM_{2.5}$ concentrations were first averaged for each city, via population weighting, and then averaged for each day. The red horizontal line represents the US EPA Daily NAAQS, 35 µg/m^3. Note that a single day above the standard is not considered a violation of the standard, which is evaluated over a period of three years using regulatory-grade monitors.*

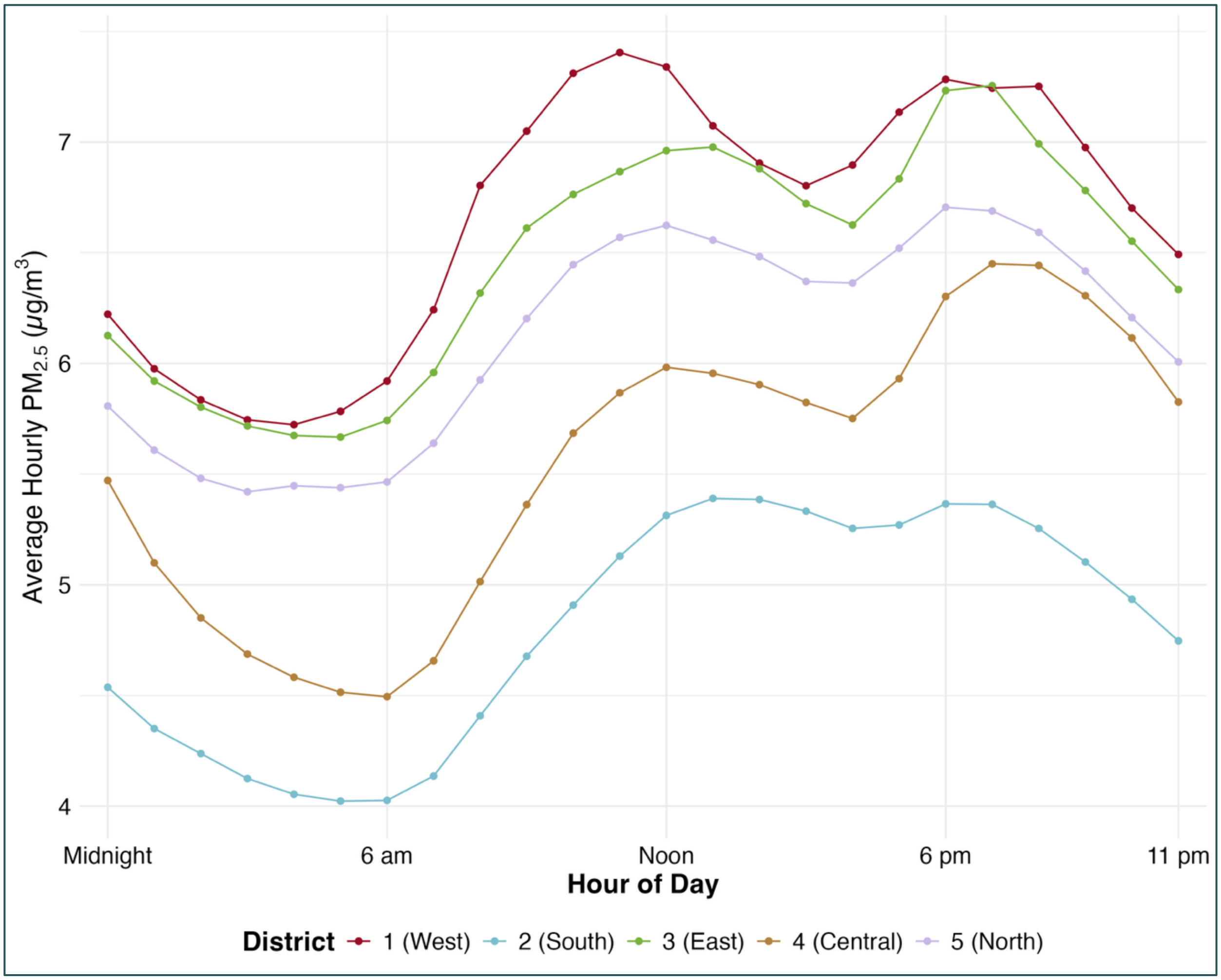

Figure 6. $PM_{2.5}$ concentrations by hour of day and district. *Hourly $PM_{2.5}$ concentrations were first averaged for each district, via population weighting, and then averaged for each hour of the day.*

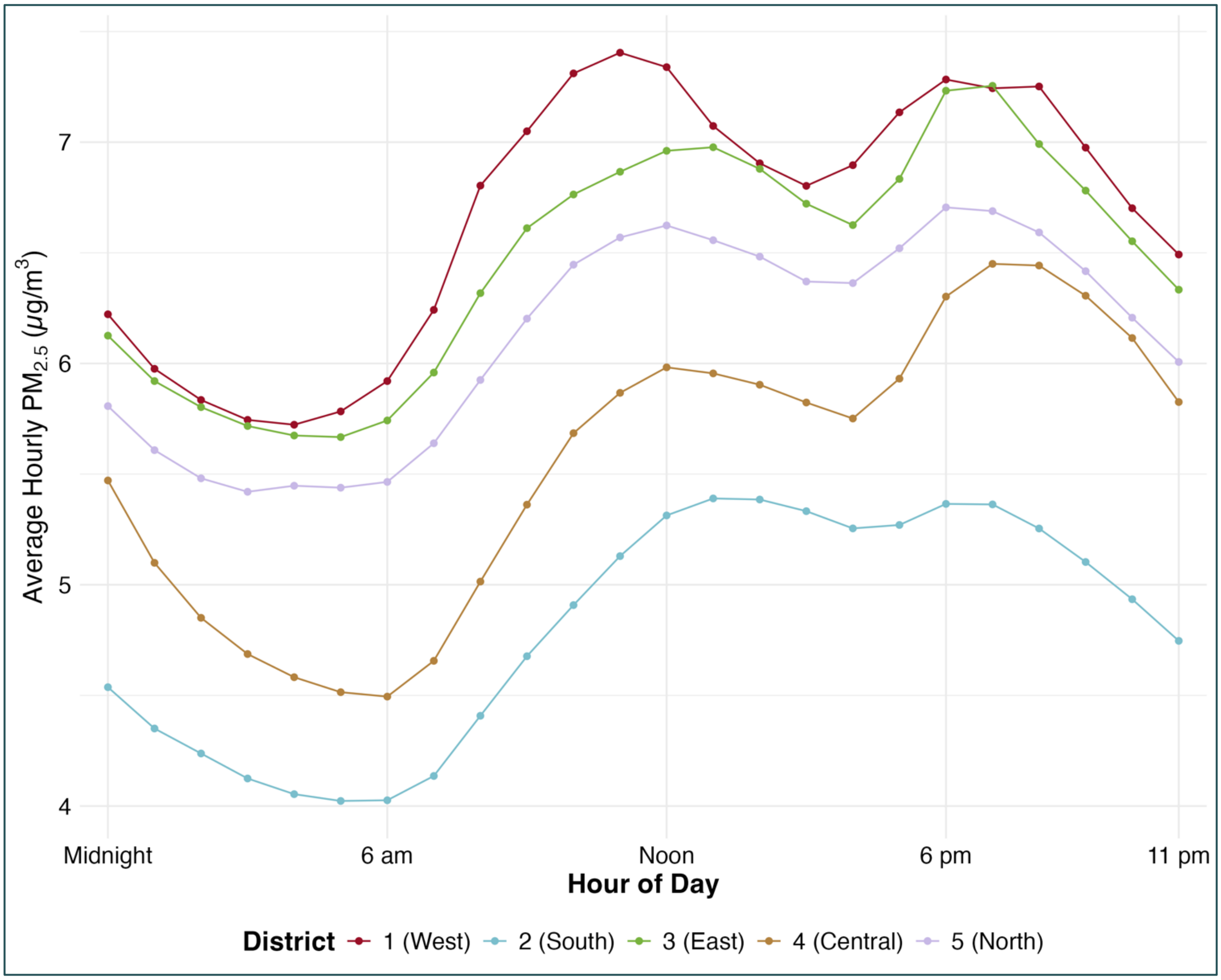

Figure 7. $PM_{2.5}$ concentrations by hour of day for select cities. *Hourly $PM_{2.5}$ concentrations were first averaged for each city, via population weighting, and then averaged for each hour of the day.*

All districts experienced a similar diurnal trend of low pollution at night followed by a steady increase in the morning, a slight drop in midafternoon, and an evening peak (Figure 6). Districts 1 (West) and 4 (Central) experienced the biggest change over the course of the day, of 1.96 µg/m3 and 1.68 µg/m3, respectively, suggesting that human activity (e.g., commuting) and daily weather patterns were more influential at those locations. Regional sources from the rest of the Bay Area may also play a role.

We generally observed the same diurnal pattern in individual cities, though the magnitude of the mid-day increase varied by city. San Pablo, Pleasant Hill, Concord, and Clayton had the biggest difference between nighttime and peak concentrations (2.16 µg/m3, 2.15 µg/m3, 2.04 µg/m3, and 1.98 µg/m3, respectively) (Table 1; Figure 7). Notably, concentrations in San Pablo were higher than Richmond throughout the day, especially in the middle of the day, with a 1.64 µg/m3 and a 1.08 µg/m3 difference in average maximum and minimum concentration, respectively (Table 1). This suggests that daytime sources such as vehicle traffic on freeways like I-580 and I-80 may be especially influential for local $PM_{2.5}$ concentrations. Similar diurnal trends were observed in the Richmond-San Pablo area during our earlier 2020 – 2022 air monitoring study. This study also demonstrated comparable nitrogen dioxide (NO2) and BC patterns in these areas, pointing to the influence of vehicle traffic emissions, particularly heavy-duty diesel trucks, in the region (Lukanov et al., 2022).

These diurnal patterns are also present when looking at concentrations during the weekends, indicating that they cannot be explained just by daily commuter traffic (**Figure A.S.5; Figure A.S.6; Figure A.S.7**).

These air pollution peaks may be particularly concerning for public health given the growing evidence that even elevated hourly concentrations are associated with worse cardiovascular functioning (Park et al., 2025), and higher daily peaks have been associated with premature mortality (Lin et al., 2017a, Lin et al., 2017b).

Air Pollution Exposure by Demographics and Geography

On average, Hispanic and Black populations lived in areas with higher $PM_{2.5}$ exposures than their White or Asian counterparts. This was true for both acute (days over 35 µg/m^3) and long-term average (over the 22-month monitoring period) $PM_{2.5}$ exposures (**Table 2**). These differences in exposure across racial groups were statistically significant (p-value for population-weighted ANOVA < 0.05). While the long-term $PM_{2.5}$ exposure concentrations all fell under the annual NAAQS standard of 9 µg/m^3, they are still a concern as they still contribute to health risks (Peralta et al., 2025). **Table 2** shows the average long-term concentrations and average number of acute $PM_{2.5}$ days experienced by selected racial, age, and other demographic groups in Contra Costa County.

Table 2. Average $PM_{2.5}$ exposures by demographic group for Contra Costa County. Average values are calculated by estimating exposure for members of the population based on averages for each census block group and then averaging across all members of the population.

Demographic	County Population	Average Acute PM Days	Average Long-Term PM Concentration (µg/m^3)
Hispanic	306,895	4.17	7.34
Black	97,612	3.89	7.41
White	471,751	3.01	6.12
Asian	209,562	3.04	6.30
Outdoor Workers	43,248	3.95	7.25
Non-outdoor Workers	1,119,400	3.4	6.59
Under 200 percent FPL	50,386	3.85	6.96
Over 200 percent FPL	1,112,262	3.41	6.60

Age – Under 5	62,829	3.52	6.70
Age – Over 65	190,307	3.24	6.36

Census data indicates that outdoor workers tended to live in areas with higher acute $PM_{2.5}$ exposures than non-outdoor workers. This was a statistically significant difference, driven by the high concentration of outdoor workers in east-county cities. It is important to note that outdoor workers do not necessarily work in the same areas where they live, however, high $PM_{2.5}$ exposure at home can compound high exposure at work. Other observed differences between sensitive and other populations were not statistically significant for either acute or long-term $PM_{2.5}$.

Differences between other demographic groups were not statistically significant, though, with a weighted one-way ANOVA, $p > 0.05$. For example, populations living under 200 percent of the Federal Poverty Level (FPL) experienced slightly higher PM exposures than those over 200 percent FPL. With regard to age, children under 5 faced higher exposures than adults over 65, but the differences in exposure between age groups were less pronounced than between racial groups. Exposures for children are likely higher than for other groups because there are more children in cities, where $PM_{2.5}$ exposures are higher (**Figure 10C)**.

Overall, differences between racial groups were the most pronounced among demographic comparisons. This builds on findings from other studies on racial disparities in air pollution exposure in the San Francisco Bay Area, that have found that Black and Hispanic populations experience between 8-30 percent higher concentrations of ultrafine particulate matter and nitrogen oxides (NOx) (Chambliss et al., 2021). Between metrics, differences in exposure to acute $PM_{2.5}$ days were more pronounced than for average $PM_{2.5}$ exposure. For example, the Hispanic population experienced a roughly 30 percent higher frequency of acute $PM_{2.5}$ days than the White population, but only about 16 percent higher long-term $PM_{2.5}$. This indicates that only looking at long-term average concentrations does not capture the full picture of how air pollution exposure and its associated health impacts differs between populations.

Table 3. Population-weighted $PM_{2.5}$ exposure metrics by supervisorial districts in Contra Costa County.

Supervisor District	District Population	Average Acute $PM_{2.5}$ Days	Average Long Term $PM_{2.5}$ Concentration (µg/m³)
District 1 (West)	232,559	4.77	7.90
District 2 (South)	245,016	2.02	4.83
District 3 (East)	221,067	2.99	7.51
District 4 (Central)	244,588	3.56	5.96

District 5 (North)	219,418	3.86	7.06

That said, $PM_{2.5}$ exposure differences are more prominent across geographical space than between demographic groups, as shown in **Table 3.** Districts 1 (West) and 5 (North), representing areas with significant industrial and highway activity, have more than 2 μg/m^3 higher average long-term $PM_{2.5}$ concentrations than District 2 (South), and roughly twice the average number of acute $PM_{2.5}$ days. A resident of Richmond in District 1 (West), for instance, experienced nearly five acute $PM_{2.5}$ days—more than twice that of a Lafayette resident in District 2 (South). People within Districts 1 (West) and District 3 (East) experienced the highest average long-term $PM_{2.5}$ exposures, suggesting that long-term $PM_{2.5}$ exposures and acute $PM_{2.5}$ exposures do not trend perfectly with one another.

Acute $PM_{2.5}$ exposures were also more variable than long-term $PM_{2.5}$ exposures. One possible explanation is statistical—annual averages are calculated using the mean of the data, while acute $PM_{2.5}$ days are calculated by intentionally sampling the tail end of the distribution, which adds inherent variability. Additionally, acute $PM_{2.5}$ days may be more affected by localized or brief emissions spikes (e.g., industrial events), while long-term $PM_{2.5}$ concentrations are influenced more by regional background PM levels (i.e. regular industrial activity, traffic).

Air Pollution Data Limitations

Limitations to the air quality data include the limited scope of the data. We only collected data on $PM_{2.5}$, and not on other health-damaging pollutants that impact the county such as ozone. Furthermore, these data only represent general outdoor concentrations, and do not represent hyperlocal conditions (e.g., exposures at a bus stop or busy intersection) or indoor air quality. Our analysis of air quality trends did not include wildfire smoke exposure because such exposure did not occur during the study period; nevertheless wildfire smoke is a critical issue for the Bay Area and should be considered as part of air quality management. The measurements from individual low-cost sensors have lower precision than regulatory-grade monitors, and thus individual measurements should be interpreted with caution. Still, from careful QA/QC and validated calibration, and by combining measurements from multiple instruments, we expect that the block group estimates capture key air quality trends. Finally, our approach for averaging measurements across monitors assumed that all monitors were equally accurate.

Extreme Heat

Data Collection - Extreme Heat

We measured extreme heat trends across Contra Costa County using satellite-derived data for 2019 - 2023 from DayMet Version 4 (Thornton et al., 2020). We estimated extreme heat exposures by calculating population-weighted, averaged daily minimum and maximum temperatures for each census block group (See **Extreme Heat Data and Metrics** in the **Methods** section of **Appendix A** for further detail on these data and calculations). We measured extreme heat using three distinct but related metrics: extreme heat days, extreme warm nights, and extreme heat waves. In particular, extreme warm nights do not allow people to cool down at night and interfere with sleep (Obradovich et al., 2017). We followed California's Office of Environmental Health Hazard Assessment's (OEHHA) definitions for extreme heat (OEHHA, 2022), which state:

- **An extreme heat day** is one where the maximum daily temperature exceeds the 95th percentile of historical maximum temperatures,
- **An extreme warm night** is one with a minimum temperature above the 95th percentile of historical minimum temperatures, and
- **A heat wave** is two or more consecutive days with daily minimum and maximum temperatures above the 95th percentile of historical minimum and maximum temperatures.

Extreme Heat Geospatial Trends

There were strong geographic trends across all heat metrics, with eastern parts of the county hotter on average than western regions (**Figure 8**). This is likely driven by topography and proximity to the ocean—western parts of the county are adjacent to the San Francisco Bay and divided from the eastern half of the county by a line of hills. This keeps temperatures milder in the western portions of Contra Costa, while inland areas of the county face more extreme heat events. This finding aligns with the trends observed in Contra Costa Health Services' 2015 report on climate vulnerability (Contra Costa Health Services, 2015) as well as California OEHHA's report on climate change indicators (OEHHA, 2022).

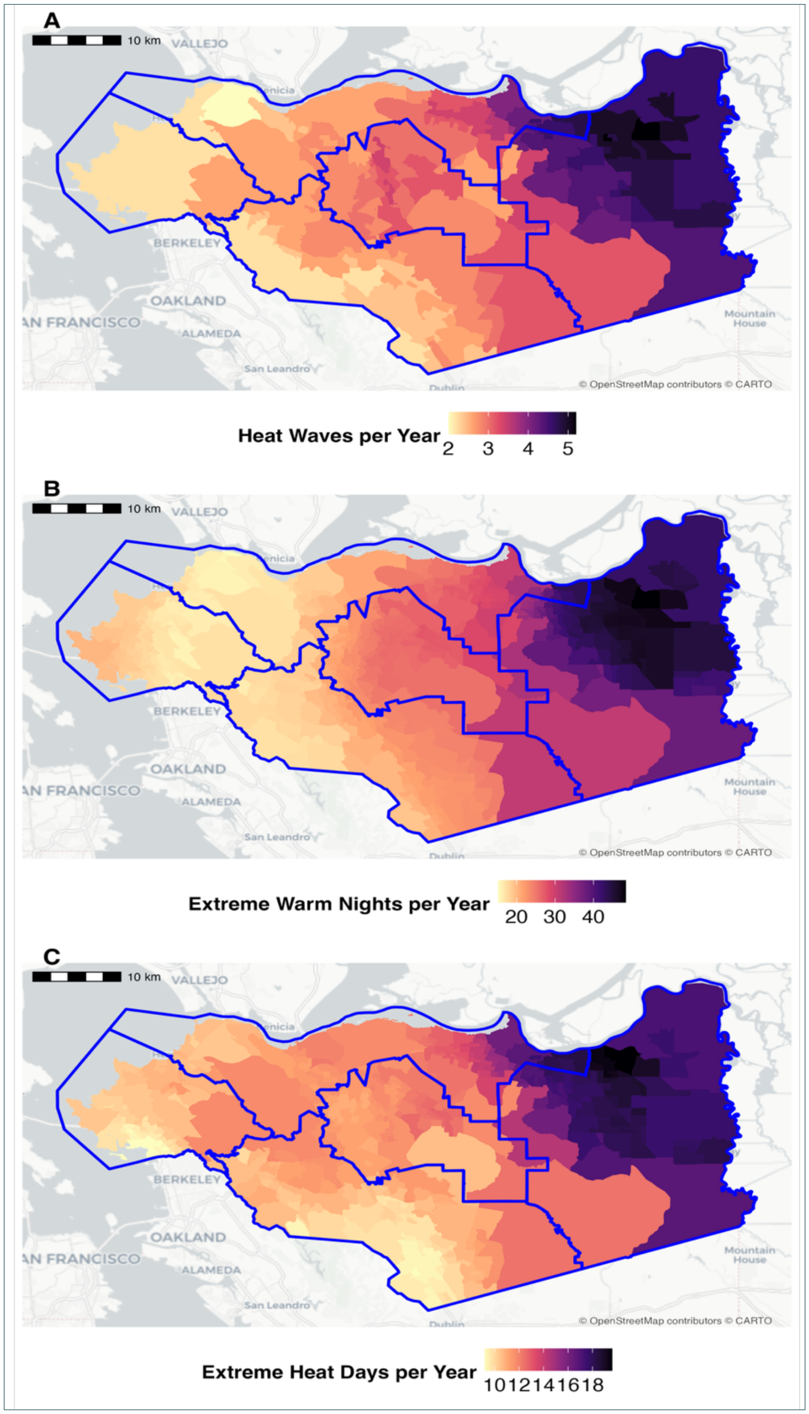

Figure 8. Annual frequency of heat waves (A), extreme warm days (B), and extreme warm nights (C) across Contra Costa County from 2019–2023. *A strong spatial trend indicates eastern parts of the county experience more heat events than western areas.*

Additionally, much of the county has gotten hotter in the past twenty years, with much of the increase in heat events occurring in the eastern portions of the county (Contra Costa Health Services, 2015) (**Figure 9**). The evidence suggests that eastern portions of Contra Costa are not only hotter but are getting hotter faster than western portions of the county. This raises concerns about the health and well-being of residents in these areas, particularly as this trend is likely to worsen over time, based on projections of future extreme heat (California Natural Resources Agency, n.d.).

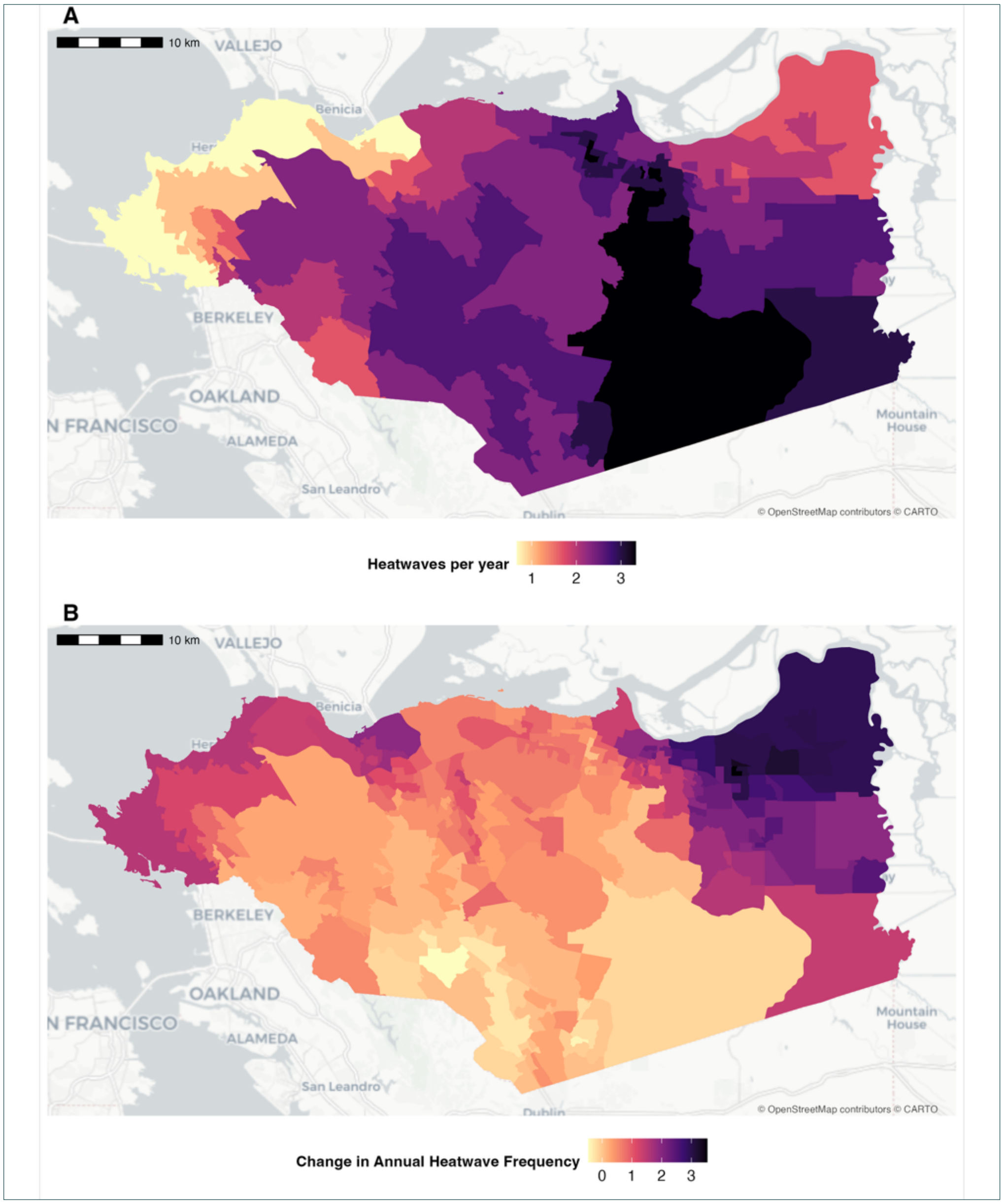

Figure 9. Change in extreme heat waves in Contra Costa County. *Panel A illustrates the heatwave frequency in 2000-2002. Panel B illustrates the change in frequency from 2000-2002 to 2019-2023. The frequency of heat events in the county has increased over the past two decades, with eastern parts of the county facing the brunt of the increase.*

Extreme Heat Exposure

We calculated the average extreme heat exposure for different populations using demographic data from the US Census (US Census Bureau, n.d.).

Across demographics, we observed small differences in exposures to extreme heat days, extreme warm nights, and heat waves (**Table 4**). On average, Black and Hispanic people lived in areas with higher heat exposures than White and Asian people. Likewise, children under the age of five lived in areas with more heat exposures than adults over 65 and outdoor workers lived in areas with more extreme heat exposures than indoor workers, on average. Differences between racial groups, age groups, and worker type were statistically significant (weighted one-way ANOVA, $p < 0.05$) for all three metrics. However, differences in residential outdoor heat exposure between those under 200 percent FPL and those over 200 percent FPL were small and not statistically significant.

Table 4. Heat exposure averages by demographic group for Contra Costa County.

Demographic	County Population	Average Extreme Heat Days Experienced	Average Extreme Warm Nights Experienced	Average Extreme Heat Waves Experienced
Hispanic	306,895	12.89	26.68	3.13
Black	97,612	13.29	27.68	3.21
White	471,751	12.40	25.79	3.07
Asian	209,562	11.88	24.49	2.89
Outdoor Workers	43,248	13.09	27.36	3.20
Non-outdoor Workers	1,119,400	12.49	25.88	3.06
Under 200 percent FPL	50,386	12.53	25.76	3.05
Over 200 percent FPL	1,112,262	12.51	25.95	3.06
Age – Under 5	62,829	12.65	26.33	3.12
Age – Over 65	190,307	12.27	25.01	2.99

Table 5. Heat exposure averages by supervisorial district for Contra Costa County.

Supervisor District	District Population	Average Extreme Heat Days Experienced	Average Extreme Warm Nights Experienced	Average Extreme Heat Waves Experienced
District 1 (West)	232,559	10.19	17.98	2.20
District 2 (South)	245,016	10.50	21.37	2.59
District 3 (East)	221,067	17.81	42.32	4.57

District 4 (Central)	244,588	11.53	24.31	2.98
District 5 (North)	219,418	12.99	24.79	3.10

Exposures to residential outdoor extreme heat metrics varied mostly by geography. Residents in eastern regions of Contra Costa County (District 3 (East)) on average experienced almost double the number of extreme heat days, extreme warm nights, and heat waves than residents in more western or southern parts of the county (District 1 (West) and 2 (South)) (**Table 5**). As observed with air pollution exposures, heat exposures varied more by district (e.g., geographic location) than by demographic, indicating strong regional trends in heat exposures. Given these regional trends, a key step in assessing the impact of these exposures is characterizing the populations in Eastern Contra Costa.

Extreme Heat Data Limitations

Limitations to the heat data include the focus on outdoor conditions and only temperature. The heat data only reports outdoor weather, which does not exactly capture what people experience inside their homes and other buildings. Additionally, while higher humidity can amplify the health impacts of high temperatures, the heat exposure metrics in this study only consider temperature and thus do not capture all the health risks.

Characterizing Sensitive Populations in Contra Costa County

Sensitive populations are those that may be more impacted by climate and environmental hazards than average due to their physiological traits, professions, or other factors (CDPH, 2023). Given the higher likelihood of adverse health outcomes for these populations, it is important that planners and policymakers identify and prioritize them for climate interventions, as well as intentionally develop interventions to address their needs. For this analysis, we focused on outdoor workers, people living in poverty, children, and older adults, as these are well-established populations with high sensitivity. Given the nature of their work, outdoor workers are more exposed to extreme temperatures and poor air quality compared to indoor workers (EPA, 2025e). This increased exposure to extreme temperatures and poor air quality increases the risk of heat or respiratory illnesses (Heinzerling et al., 2020). People living in poverty are more likely to live in more polluted areas and thus have an increased risk of pollution exposure. Moreover, they have fewer resources to respond or adapt to environmental hazards, such as installing air conditioning (AC) to mitigate extreme heat exposure, or having access to health care (EPA, 2025f). Children tend to spend more time outdoors, increasing their exposure to extreme temperatures and poor air quality (Brumberg et al., 2021). Additionally, children are more vulnerable to the adverse effects of environmental hazards due to their physiology and metabolism (EPA, 2025g). Older adults are more likely to have pre-existing health conditions that can be exacerbated by air pollution and climate hazards, and their bodies are less able to compensate for the effects of environmental hazards (EPA, 2025h). Populations that already face cumulative exposures to various environmental and socioeconomic stressors might also be more susceptible to climate hazards (Li et al., 2023). These data were collected from the 2020 American Community Survey (ACS), and poverty was defined as the proportion of households with income under two times the FPL. For our analysis we also use the CES score, which is a measure of cumulative impact that combines pollution burden and population characteristics (OEHHA, 2021), as a proxy to identify populations that are already overburdened by environmental and socioeconomic stressors and thus might be more sensitive to climate hazards.

Overall, census block groups with a high percentage of sensitive populations relative to the rest of the county were more likely to be in District 1 (West) (in the Richmond San Pablo area), and in Districts 3 (East) and 5 (North). District 2 (South) tended to have populations that were less sensitive to climate hazards. Climate interventions focused on sensitive populations may better target those populations by focusing on Districts 1 (West), 3 (East), and 5 (North).

In most census block groups in Contra Costa County, the median percentage of outdoor workers was 5.5 percent (Table 6). However, there were some block groups where almost half of residents over the age of 16 were outdoor workers (Table 6). It is important to note that outdoor workers may work in a different area than where they live, but their residential exposure can still compound their occupational exposure. Census block groups in the Richmond-San Pablo area (District 1 (West)) and the eastern part of the county, including Martinez, Pittsburg, Antioch, Oakley, Brentwood, and

Discovery Bay (i.e. Districts 5 (North) and 3 (East)), tended to have higher proportions of outdoor workers relative to District 2 (South) in the southwestern part of the county (Figure 10A). Richmond-San Pablo and Bay Point had more block groups with a higher percentage of people living in poverty compared to areas like Orinda, Lafayette, Walnut Creek, and Moraga (Figure 10B). Most block groups had a relatively low percentage (<5 percent) of the population living below two times the FPL, but there were a few census block groups in Richmond and Concord where the percentage of people living in poverty was almost 10 times higher than the county average (Table 6). There was a slight trend of more children under 5 years of age living in urban areas, though some rural and suburban areas also had high portions of young children (Figure 10C). There were a few block groups in Richmond, San Pablo, Concord, Antioch, and Oakley where over 10 percent of the total population were children under 5 (Table 6, Figure 10C). There tended to be a higher percentage of older adults on the west side (parts of Districts 1 (West) and 2 (South)) of the county compared to the east side (parts of District 3 (East)) (Figure 10D). Understanding where in the county residents may be more sensitive to air pollution and extreme heat—and the nature of that sensitivity—can help planners target the most appropriate interventions.

Table 6. Summary Statistics of Population Sensitivity Variables in Contra Costa County.

Variable	Minimum	25th Percentile	Median	Mean	75th Percentile	Maximum
Outdoor Workers	<0.01 percent	1.5 percent	5.5 percent	7.5 percent	10.8 percent	47.1 percent
Children under 5	<0.01 percent	2.4 percent	4.7 percent	5.2 percent	7.2 percent	29.32 percent
Adults over 65	<0.01 percent	10.1 percent	15.5 percent	18 percent	23.3 percent	97.4 percent
Poverty	<0.01 percent	0.6 percent	2.6 percent	4.4 percent	5.8 percent	39.8 percent

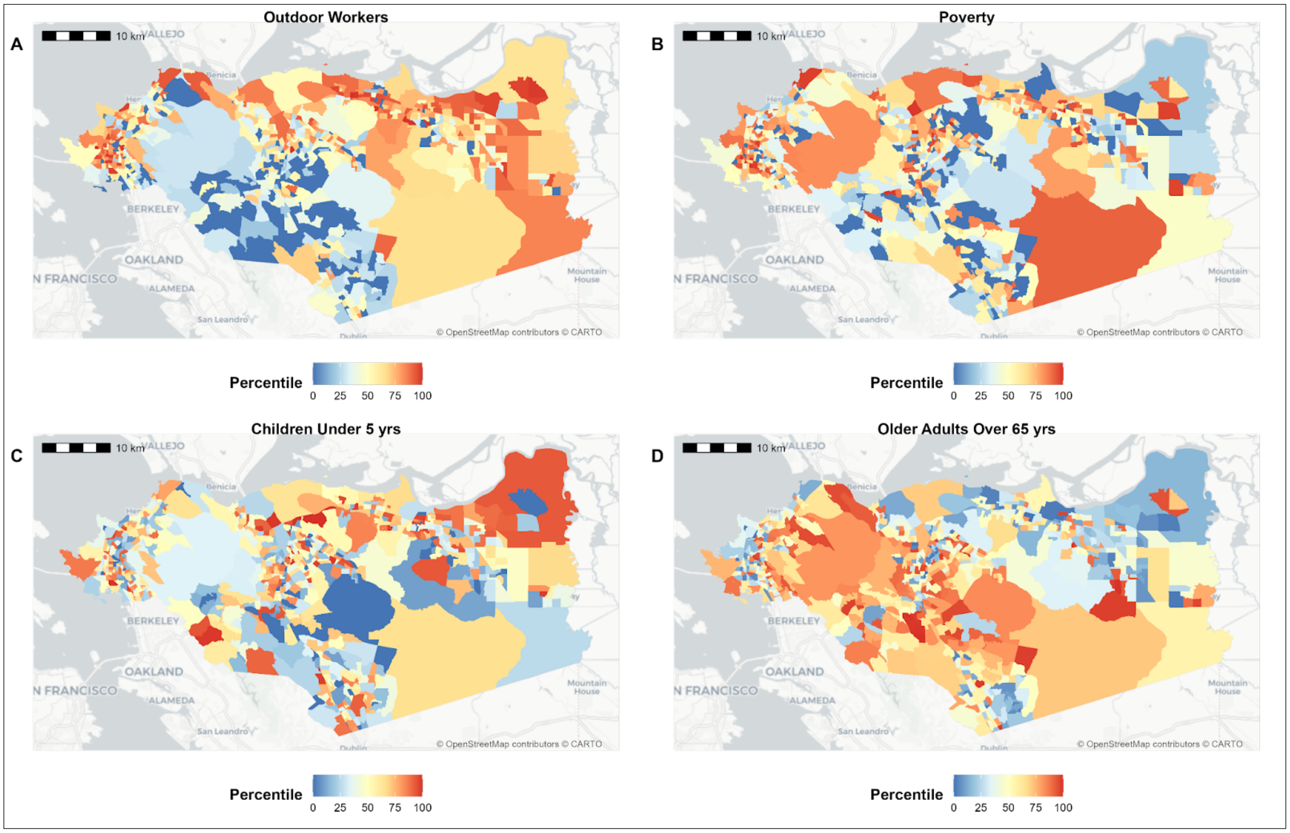

Figure 10. Population sensitivity in Contra Costa County at the census block group level. *Panel A illustrates the relative proportion of outdoor workers in each census block group, by percentile of all block groups in Contra Costa. Panel B illustrates poverty, based on household income below 200% of the Federal Poverty Line; Panel C illustrates the proportion of children under five years of age, and Panel D illustrates the proportion of older adults over 65 years of age.*

Populations with high environmental and socioeconomic burdens according to CES were in the Richmond-San Pablo area (District 1 (West)) and in Martinez, Pittsburg, Antioch, and Brentwood (Districts 5 (North) and 3 (East)) (**Figure 11**). District 2 (South), including Orinda, Lafayette, Moraga, Walnut Creek, Danville, and San Ramon tended to have the lowest vulnerability compared to the rest of the county.

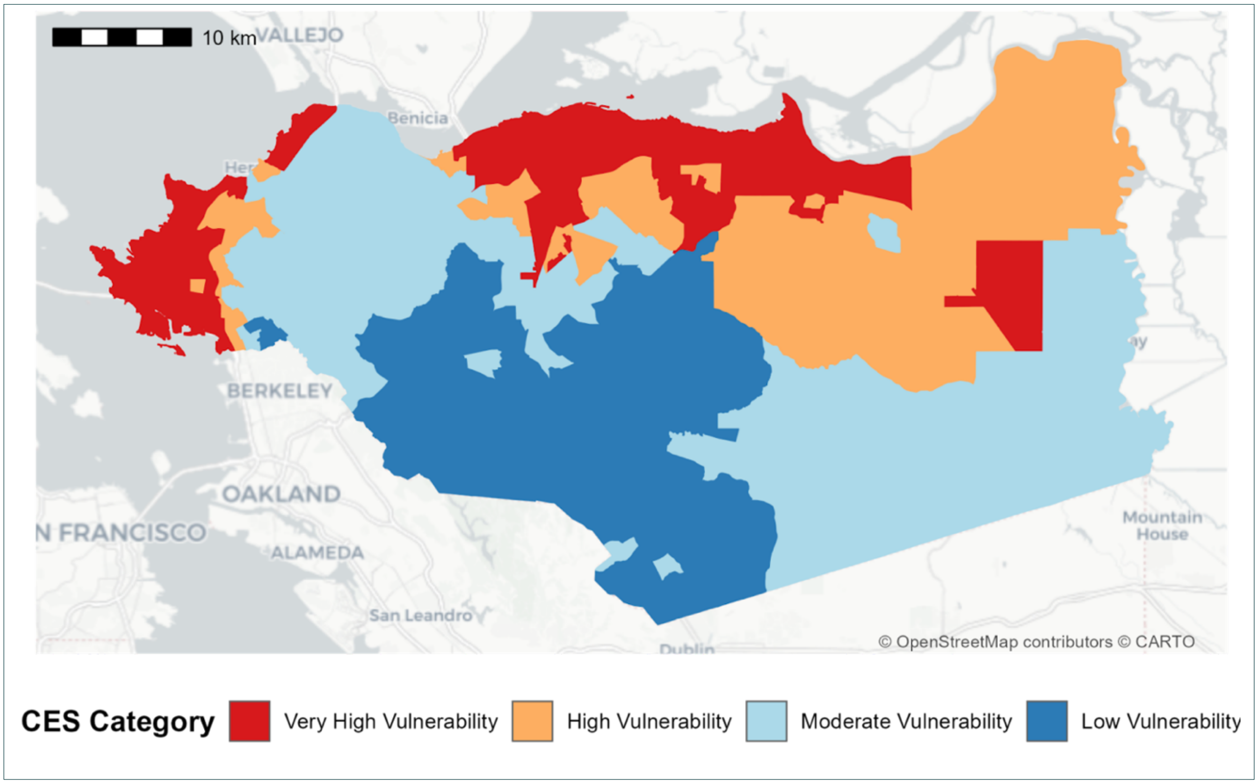

Figure 11. Map of Cumulative Vulnerability in Contra Costa County at the census tract level. *Cumulative vulnerability measured by CES 4.0 Category. We used the raw CES score to categorize cumulative vulnerability, where low vulnerability is defined as the raw CES score ≤ 8.5, moderate vulnerability is 8.5 < raw CES score ≤ 19, high vulnerability is 19 < raw CES score ≤ 33, and very high vulnerability is raw CES score > 33.*

Characterizing Adaptive Capacities in Contra Costa County

Adaptive capacity is the ability to respond and adjust to environmental and climate impacts (CDPH, 2023). Mapping adaptive capacity across Contra Costa can tell us which interventions are more or less relevant (e.g., tree-planting would yield lower marginal benefit in an area that already has high canopy cover) and which barriers could hinder an intervention if not addressed (e.g., poorer areas are likely unable to build a resilience hub without financial support). While data on indicators for adaptive capacity at the census block group is limited, we identified two indicators at the census tract or finer level that could speak to potential interventions: 1) Canopy coverage, which can provide shade to shield people from extreme heat as well as reduce the urban heat island effect (EPA, 2025d), and 2) AC prevalence, which can help to reduce the temperature in homes that have an AC. Later in the report, we describe the climate vulnerability analysis where we examine the overlap of exposures, population sensitivities, and adaptive capacity, and we also consider poverty as an indicator of adaptive capacity because it directly shapes access to resources and how people are able to respond to climate hazards.

Canopy coverage varied across and within supervisorial districts. Many census block groups in Districts 2 (South) and 4 (Central), as well as parts of District 1 (West), had a higher percentage of canopy cover compared to block groups in other parts of the county (**Figure 12A**). However, the percentage of canopy cover in any given block group was relatively low, with most block groups having less than 15 percent canopy coverage (**Table 7**), whereas 40 percent coverage is associated with significant reduction of the urban heat island effect (Ziter et al., 2019). The Richmond-San Pablo area (much of District 1 (West)) and the northern and eastern parts of the county (Districts 3 (East) and 5 (North) covering Martinez, Pittsburg, Antioch, Brentwood, Oakley, Bethel Island, and Discovery Bay) had the lowest percentages of canopy coverage, with most block groups in those areas having less than 10 percent of canopy cover. Within Contra Costa, areas with higher percentages of canopy coverage tend to be more suburban or less densely populated, while areas with less canopy coverage tend to be urban and more densely populated (**Figure 12A**).

Over 50 percent of houses in Contra Costa County had AC (**Table 7**). There was not a consistent spatial pattern of houses with AC, though some rural areas and western Richmond had much lower rates (**Figure 12B**). However, data on AC coverage is modeled rather than collected via survey, and so may not perfectly represent unique areas. For example, Rossmoor is a planned retirement community in District 2 (South) that likely has higher AC rates than the model suggests (Rossmoor Walnut Creek, n.d.).

Table 7. Summary Statistics of Adaptive Capacity Variables for Contra Costa County.

Variable	Minimum	25th Percentile	Median	Mean	75th Percentile	Maximum
Canopy Coverage	0.05 percent	3.5 percent	6.8 percent	9.1 percent	13.4 percent	45 percent
Houses with AC	54.1 percent	83.02 percent	89.3 percent	87.3 percent	93.9 percent	100 percent

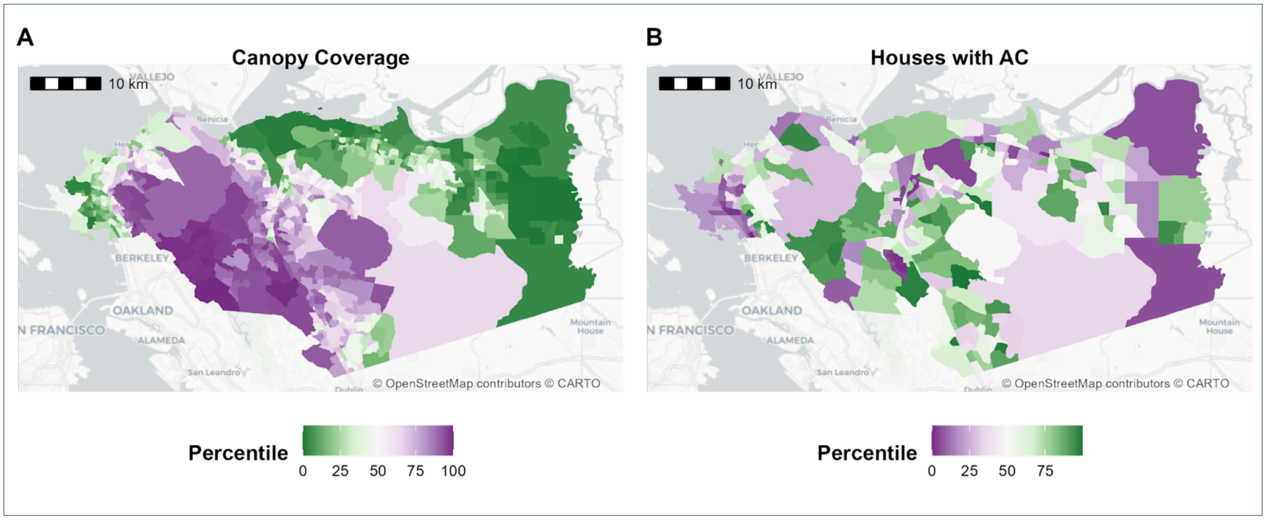

Figure 12. Map of adaptive capacity in Contra Costa County. *Panel A illustrates the relative degree of canopy coverage in each census block group, by percentile of all block groups in Contra Costa. Panel B illustrates percentiles of the proportion of Households with AC at the census tract.*

See appendix in "Energy Affordability in Maryland" report (Krieger et al., 2023) for more detail regarding estimated downscaling of AC adoption methodology.

Identifying Climate Vulnerability Hot Spots

To better understand spatial patterns of climate vulnerability across Contra Costa County, we identified statistically significant clusters—or "hot spots"—of high climate sensitivity, low adaptive capacity, and elevated exposure to extreme heat and/or $PM_{2.5}$. Mapping these clusters allows us to pinpoint areas where multiple census tracts exhibit overlapping stressors, providing valuable insights for targeted resilience planning and climate adaptation interventions. For example, a cooling center may confer greater benefit in a neighborhood whose surrounding area also experiences frequent extreme events than a neighborhood surrounded by cooler areas. These hot spots do not necessarily overlap with municipal boundaries such as cities, and their size can vary from a few census block groups to a wide swath of the county.

The climate vulnerability hot spots are not the only locations where climate sensitivity, limited adaptive capacity, and elevated exposure risks occur. These conditions are present throughout the county. However, hot spots represent spatial concentrations of these factors—areas where multiple factors combine in multiple neighboring census tracts. They are not synonymous with "priority areas," as there may be individual block groups outside of these clusters that score just as high on one or more vulnerability dimensions but remain spatially isolated. Rather, hot spots represent clusters of vulnerable block groups that offer strategic opportunities for targeted interventions.

In this analysis we identify hot spots as clusters as groups of neighboring census block groups with high values for the variable of interest (e.g., $PM_{2.5}$ concentrations), relative to the rest of the county. These clusters do not necessarily follow municipal borders and can include any number of census block groups; the clusters are based on the data itself. We identified these clusters through also known as Local Indicators of Spatial Association (LISA) that uses local Moran's I, a measure of spatial autocorrelation, to identify statistically relevant clusters (Anselin, 1995). Identifying these clusters through spatial analysis, such as Moran's I, enhances our understanding of spatial relationships and highlights areas that may not be as apparent through simple indicator mapping, as presented in the sections above.

Individual Vulnerability Hot Spots

This cluster analysis identified hot spots of high air pollution, extreme heat, and both in combination – these areas are potential strategic targets for interventions that impact a neighborhood or larger area. These clusters can supplement the maps above by highlighting discrete areas where these factors are concentrated.

The cluster analysis identified hot spots of elevated long-term $PM_{2.5}$ and acute $PM_{2.5}$ days in Richmond (**Figure 13A, 13B**). A second hot spot of elevated long-term $PM_{2.5}$ is present along the northeast edge of the county, spanning from Pittsburg to Oakley, and a second hot spot of acute $PM_{2.5}$ days is present in Clyde and Bay Point (**Figure 13A, 13B**). Our cluster analysis identified hot spots of elevated heat waves on the eastern side of the county, aligning with the strong west-to-east geospatial distribution of extreme heat (**Figure 13C**). Air pollution and heatwave hot spots overlapped in the northeast side of Contra Costa (District 3), including Antioch, Brentwood, Bethel Island, and surrounding unincorporated areas (**Figure 13D**). These locations are of particular concern for public health because air pollution can amplify the health effects of extreme heat and vice versa (Chen et al., 2018, Hu et al., 2022, Zhang et al., 2024).

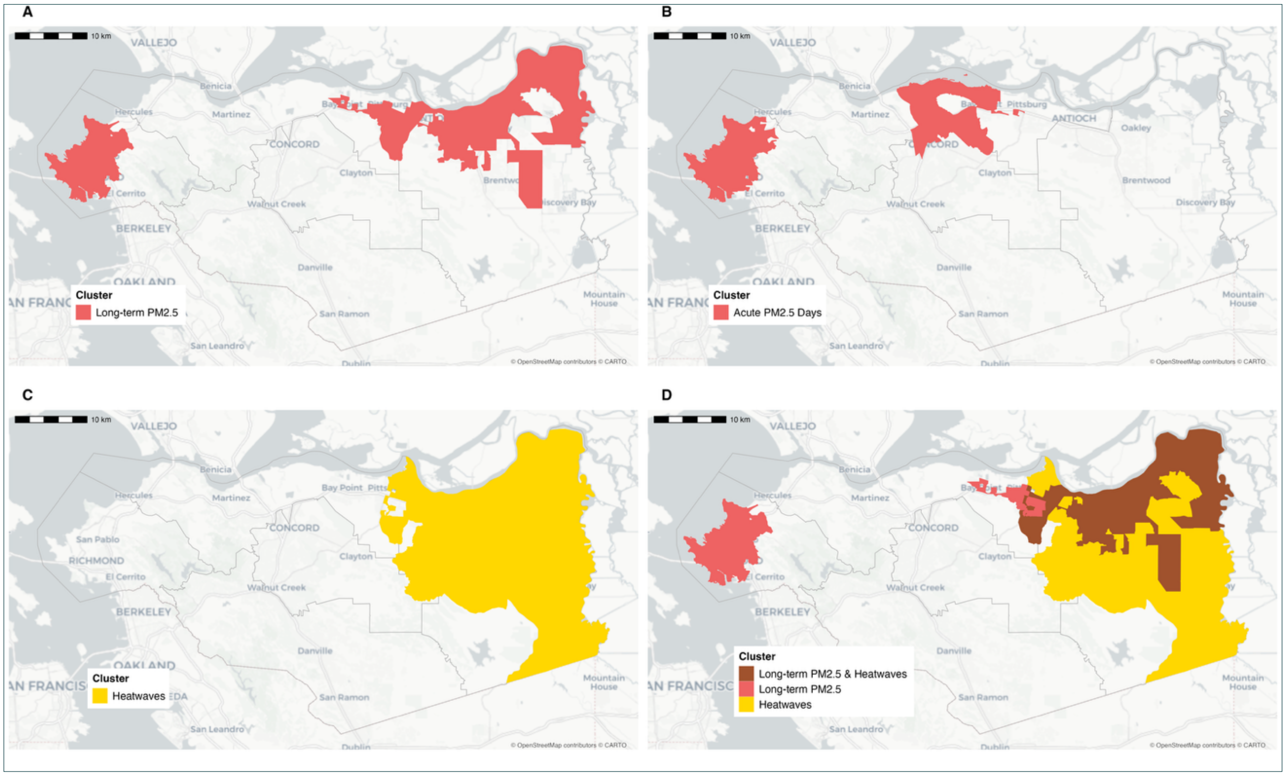

Figure 13. Clusters of Air Pollution and Extreme Heat Exposures. *Hot spots identified from clusters of neighboring census block groups of relatively high values via LISA. Panel A illustrates hot spots of long-term $PM_{2.5}$; Panel B illustrates hot spots of acute $PM_{2.5}$ days; Panel C illustrates clusters of heatwave frequency, and Panel D illustrates the overlap of long-term $PM_{2.5}$ and heatwave clusters.*

Our cluster analysis identified sensitive population hot spots where interventions could be targeted to prioritize a particular population (**Figure 14**). Many of these hot spots did not overlap, again indicating that prioritizing a specific sensitivity will not always lead to the same priorities as prioritizing overall vulnerability. Our cluster analysis identified two main hot spots where high percentages of outdoor workers live: a) San Pablo and Richmond in District 1 (North) and b) Bay Point and sections of Antioch in District 3 (East). There were clear hot spots of poverty within four cities, specifically Richmond, Concord, Martinez, and Antioch. The clusters of older adults were in the suburbs of Richmond and Walnut Creek, whereas clusters of children under 5 years old were more spread out but still tended to be in cities.

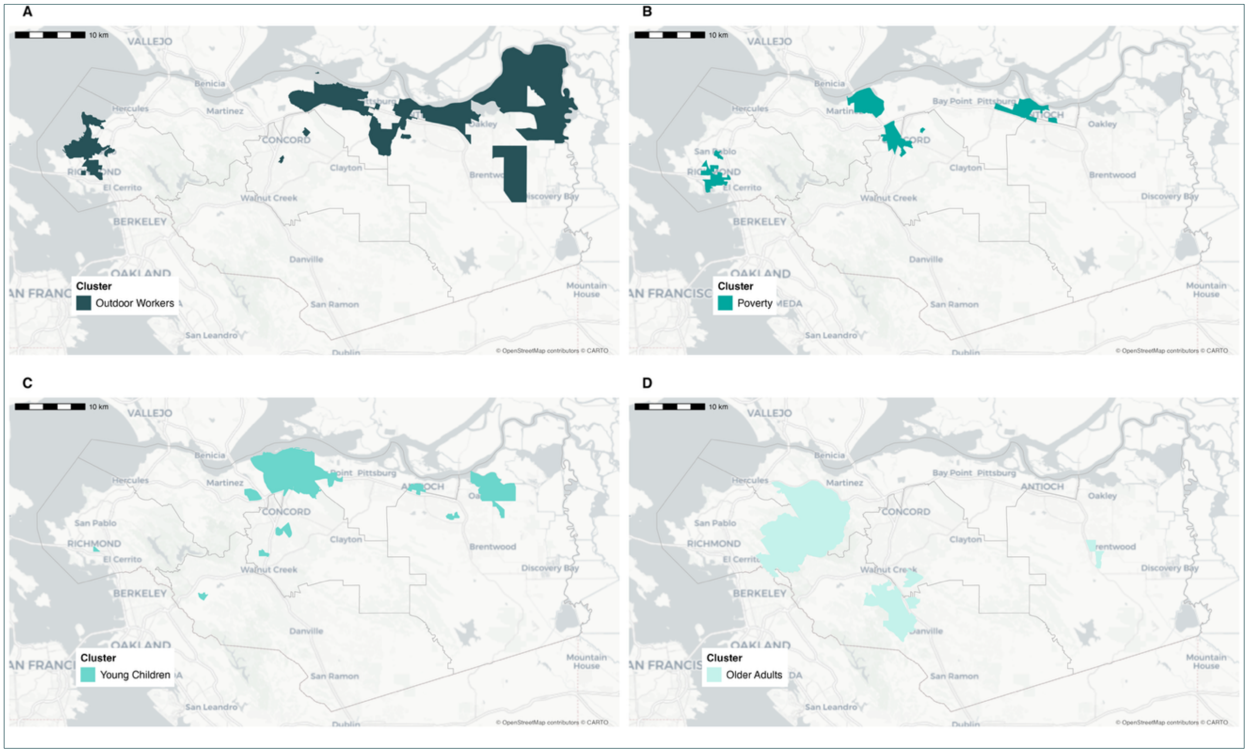

Figure 14. Univariate Clusters of Population Sensitivity. *Hot spots identified from clusters of neighboring census block groups of relatively high values via LISA. Panel A illustrates hot spots of outdoor worker residence; Panel B illustrates hot spots of poverty based on household income; Panel C illustrates clusters of heatwave frequency, and Panel D illustrates the overlap of long-term $PM_{2.5}$ and heatwave clusters.*

Our cluster analysis identified hot spots of low adaptive capacity which could especially benefit from community-scale interventions to supplement the limited capacity (**Figure 15)**. For example, the areas with low canopy cover could especially benefit from greening efforts or other interventions to mitigate heat exposure. Of note, the western side of Richmond has particularly low canopy and AC prevalence, suggesting that while climatic conditions here tend to be cooler due to proximity to the Bay, residents have less relief indoors and outdoors from heat events. It is noteworthy that the hottest region of the county, District 3, also has low canopy coverage. Greening in these regions can help mitigate the effects of extreme heat events experienced in the area. We identified low-canopy clusters in Richmond and throughout the eastern and northern portions of the county. Hot spots in Contra Costa with a low prevalence of household AC include the coastal areas of Richmond and San Pablo in District 1 (West), Concord in District 4 (Central), Rossmoor in District 2 (South), and in the Antioch area in District 5 (North). The hot spot in Rossmoor should be interpreted with caution as a review of buildings suggests that at least some buildings have AC (Rossmoor Walnut Creek, n.d.).

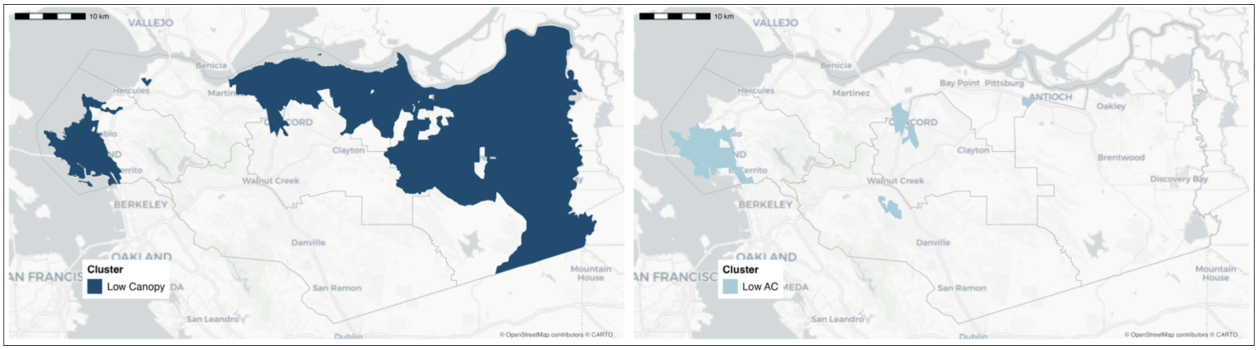

Figure 15. Univariate Clusters of Adaptive Capacity. *Hot spots identified from clusters of neighboring census block groups of relatively high values via LISA. The left panel illustrates hot spots of low canopy coverage; the right panel illustrates hot spots of low households with AC.*

Combined Climate Vulnerability Hot Spots

We identified several hot spots that experienced different combinations of climate vulnerability (**Figure 16**). These clusters may be candidates for priority interventions, as residents are at a higher risk of $PM_{2.5}$ and extreme heat and higher risk of negative health outcomes but have fewer resources to contend with their exposures. For example, in Antioch the higher levels of poverty can limit resident's ability to reduce exposure to air pollution (**Figure 16A, 16B**). The eastern portion of the county that faced higher extreme heat also had lower canopy coverage (**Figure 16D**); in these areas the urban heat island effect will be stronger, and residents will have less outdoor shade to get relief from the heat. Overlap in these clusters can also indicate which intervention strategies may be more relevant; for instance, the northeastern edge of Contra Costa experiences high levels of air pollution and frequent extreme heat (**Figure 13D**) and thus would benefit more from interventions that simultaneously address both exposures. Additionally, these overlapping factors can inform intervention design because lower adaptive capacity can hinder implementation or adoption, and stakeholders may want to prioritize relevant sensitive populations. For example, areas of high poverty will likely have a harder time adopting an at-home intervention like installing an AC unit without financial support. In particular, in Richmond, San Pablo, and Concord there are hot spots of low AC and high poverty where financial barriers could limit AC installation and usage without corresponding policy (**Figure 16D**). Analyzing specific climate vulnerabilities tells a more complete story than just overall vulnerability because different hot spots were in different locations – meaning that different communities face different, unique challenges. For example, portions of Richmond and Antioch had high $PM_{2.5}$, poverty, and outdoor workers, whereas clusters of extreme heat, poverty, and outdoor workers were scattered across Antioch, Oakley, and Brentwood (**Figure 16**).

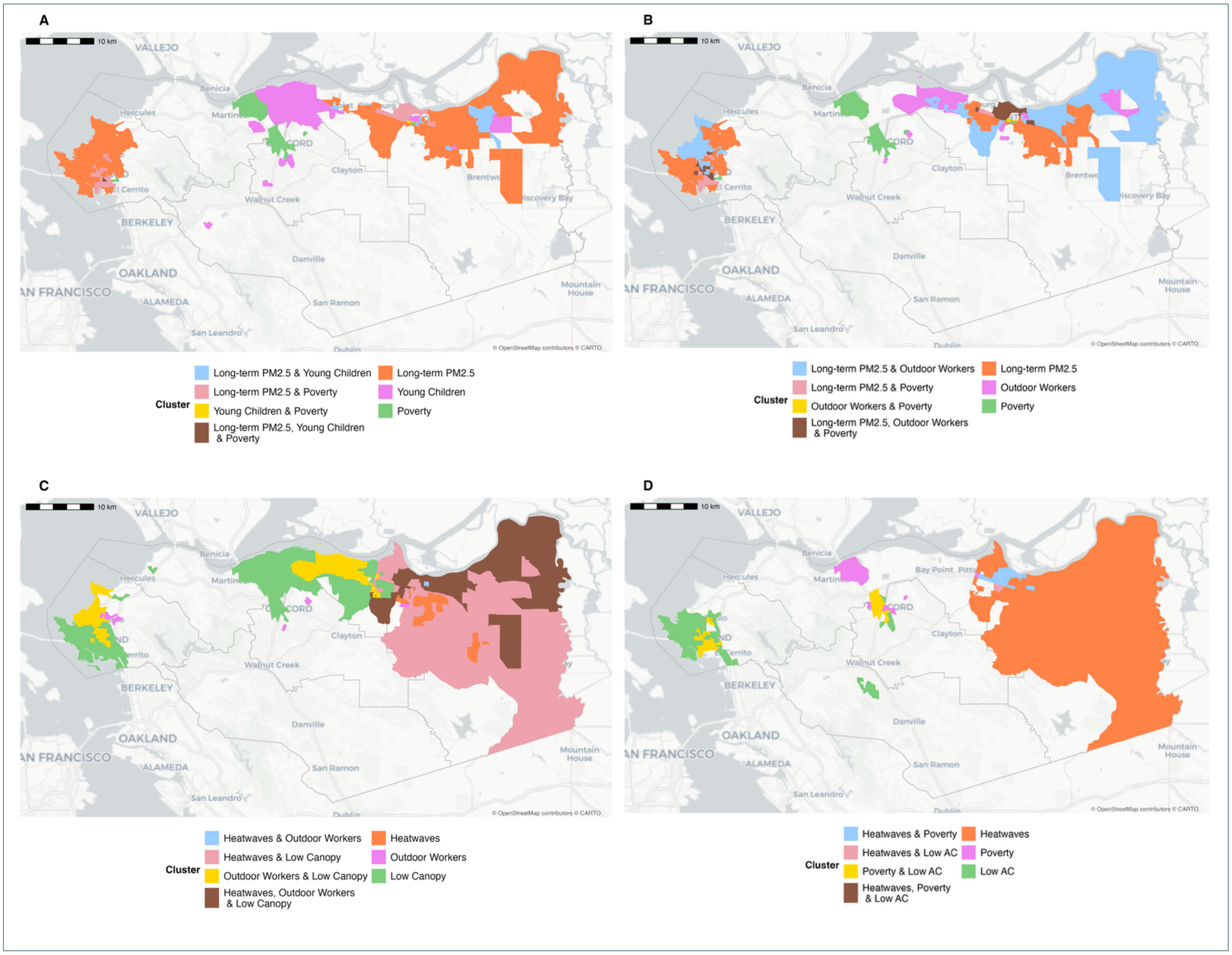

Figure 16. Overlap of Exposure, Sensitivity, and Adaptive Capacity Clusters. *Figures illustrate overlapping clusters of neighboring census block groups with relative high vulnerability. Figure A illustrates the overlap of relatively high long-term PM2.5, young children, and poverty; Figure B illustrates the overlap of relatively high long-term PM2.5, outdoor workers, and poverty; Figure C illustrates the overlap of relatively high heatwave frequency, outdoor workers, and low canopy cover; Figure D illustrates the overlap of relatively high heatwave frequency, low air conditioning, and poverty.*

Limitations of the Climate Vulnerability Analysis

Limitations to the sensitive population and adaptive capacity analysis include the limited set of variables and spatial resolution. There are other sensitivities and capacities that were not included in our analysis, partly due to the limited availability of such data at a neighborhood scale. In addition, among the variables we did measure, there may be hyperlocal hot spots (e.g., a block with zero trees) that are not captured by a census block group.

Landscape Mapping of Interventions to Address Intersections of Exposure Risk, Population Sensitivity, and Low Adaptive Capacity

The overlaps of exposures, sensitive populations, and low adaptive capacity demonstrate that effective interventions need to address the intersections of these challenges. The most appropriate interventions for an individual or community will depend on their particular combination of hazards and vulnerabilities, as well as additional social, cultural, and financial factors. Thus, prioritizing interventions for a particular community requires characterizing potential interventions and understanding how they may work within a given community context (including potential accessibility barriers.)

To map out the landscape of potential interventions, presented in **Table 8**, we first identified and characterized interventions through a review of materials from earlier community outreach and advisory committee meetings as well as academic literature, policy documents, and news articles. We then held a community listening session to hear more of the lived experiences of community members in Contra Costa. This allowed us to ground-truth our initial literature review and supplement it with additional community context—including ways in which certain existing (or possible future) intervention programs were not accessible to the communities they were intended to serve. Informed by the literature review and the community outreach, we identified a set of key factors to consider when designing interventions:

- Intervention locations and actors
- Barriers faced by actors
- Mechanisms
- Breadth of intervention applicability
- Intervention co-benefits and alignment with other goals and priorities.

This landscape mapping presents an overview of potential interventions and considerations, and can serve as a starting point for further intervention analysis. Next steps could include community engagement activities such as localized listening sessions to understand a specific community's context. Such activities could provide key information like community members' lived experience with climate and environmental exposures, their history with interventions and adaptation, barriers they've faced in adopting interventions, where they see opportunities for progress, and other adaptive capacity measures or sensitive populations in their communities that are not captured in our data.

Interventions Literature Review

Using the sources outlined above, we conducted a literature review **(Appendix B)** focused on interventions with the potential to address extreme heat and/or air pollution exposure. We categorized these interventions into a handful of descriptive, narrative categories defined, in part, by their implementation methods. (See **Appendix B** and the **Interventions Literature Review section** of **Appendix A** for a summary of the full literature review.)

Narrative intervention categories included:

- Behavior Modifications
- Educational Programming/Outreach
- Limiting Utility-Triggered Wildfires & Their Energy System Impacts
- Physical/Permanent Home Upgrades
- Portable/Temporary Home Interventions
- Public Space/Built Environment Modifications
- Reducing Underlying Risk Factors
- System-Level Support for Behavior Modifications

After compiling interventions, we characterized them according to key factors to consider: hazard(s) targeted, mechanism of action, who can implement (actor/level), and potential barriers (**Table 8**). This helped us to understand the breadth of benefits offered by different interventions as well as how accessible (or not) they might be to different communities. We note that this is an incomplete list of interventions, illustrating interventions most commonly described in the literature or a representative subset of interventions from a narrative category. The potential barriers list is also incomplete, serving as a representative sampling rather than an exhaustive list.

Table 8. Examples of Air Pollution and Extreme Heat Interventions.

	Factors to Consider			
	Breadth of Benefits		Accessibility	
Intervention Description	Exposures Addressed	Mechanisms	Location & Actors	Barriers & Gaps *(key examples)*
Behavior Modifications				
Limit outdoor activities when air quality is poor	Air Pollution	Reduce Exposure	Individual	Timely air quality data; job constraints
Seek out places with filtered air and/or AC like malls, movie theatres, and community centers	Air Pollution	Reduce Exposure	Individual	Information on protective sites; transportation access

Avoid activities that increase indoor air pollution (like burning candles, using a gas stove or fireplace, vacuuming, etc)	Air Pollution	Reduce Sources	Individual	Awareness gaps; availability of alternatives; housing constraints
Wear facemasks (respirators)	Air Pollution	Reduce Exposure	Individual	Financial resources
Commute changes	Air Pollution & Heat	Reduce Exposure	Individual, Municipal	Timely air quality data; available routes; transit limitations
Close windows / vents	Air Pollution & Heat	Reduce Exposure	Individual/Household	Timely air quality data; housing quality
Water cooling (self-dousing/foot immersion, wet clothing, evaporative coolers, misting fans, ice towels, cold water ingestions)	Heat	Reduce Exposure	Individual	Education; short term relief; limited water access
Educational Programming / Outreach				
Air quality monitoring / maps / indices	Air Pollution	Reduce Exposure	Community/Municipal	Local, timely air quality data; language access; technological literacy gaps
Poor air quality related educational programming / outreach	Air Pollution	Reduce Exposure	Community/Municipal	Community usage; trust barriers
Wildfire smoke emergency plans	Air Pollution	Reduce Exposure	Community/Municipal	Education; language barriers
Wildfire smoke related educational programming / outreach	Air Pollution	Reduce Exposure	Community/Municipal	Community usage; language barriers
Extreme heat maps	Heat	Reduce Exposure	Community/Municipal	Community usage; language barriers
Heat vulnerability maps / indices / assessments	Heat	Reduce Exposure	Community/Municipal	Community usage; language barriers
Extreme heat related educational programing / outreach	Heat	Reduce Exposure	Community/Municipal	Community usage; language barriers
Extreme heat emergency plans	Heat	Reduce Exposure	Community/Municipal	Education; language barriers
Heat wave early warning systems	Heat	Reduce Exposure	Community/Municipal	Community usage; language barriers
Limiting Utility-Triggered Wildfires & Their Energy System Impacts				

Increasing distributed energy resources (DER) - Solar and/or energy storage	Wildfires	Reduce Sources	Utility/Municipal	Financial resources; renter-owner conflict
Clean microgrids	Wildfires	Reduce Sources	City Planning	Must work with the utility; financial resources
Undergrounding power lines	Wildfires	Reduce Sources	Utility/Municipal	Only available to utilities
Vegetation management around power lines	Wildfires	Reduce Sources	Utility/Municipal	Only available to utilities
Updating aging electric distribution infrastructure	Wildfires	Reduce Sources	City Planning	Only available to utilities
Public Safety Power Shutoffs (PSPS events)	Wildfires	Reduce Sources	Utility/Municipal	Only available to utilities
Enhanced Power System Safety Setting (EPSS) on power lines	Wildfires	Reduce Sources	Utility/Municipal	Only available to utilities
Physical / Permanent Home Upgrades				
Weatherization (sealing windows, improving insulation, improving the building envelope)	Air Pollution and Heat	Reducing Exposure	Household	Financial resources; renter-owner conflict
Cool roofs / Green roofs	Heat	Reduce Sources & Exposure	Household	Financial resources; renter-owner conflict; maintenance
Heat pumps (AC)	Heat	Reduce Exposures	Household	Financial resources; renter-owner conflict; electrical capacity
HVAC systems (AC and/or air filters like MERV 13+ and HEPA filters)	Heat, potentially Air Pollution	Reduce Exposures	Household	Financial resources; renter-owner conflict; maintenance
Portable / Temporary Home Interventions				
Air purifiers (HEPA)	Air Pollution	Reduce Exposures	Household	Financial resources; timely exposure information
Window or free-standing AC units	Heat	Reduce Exposures	Household	Financial resources; housing restrictions
Fans	Heat	Reduce Exposures	Household	Financial resources; smoke infiltration
Designated cool home areas (e.g., basements)	Heat	Reduce Exposures	Household	Financial resources; housing design limits;

				multiple families per household (overcrowding)
Create a 'clean room' in your home (close windows and doors; run your HVAC continuously with the outdoor air intake closed and using the highest MERV your system allows; use an air purifier / HEPA filter fan)	Air Pollution	Reduce Exposures	Household	Financial resources; timely exposure information; multiple families per household (overcrowding)
Public Space / Built Environment Modifications				
Tree planting	Heat	Reduce Sources & Exposure	Community/Municipal	Land use conflict; maintenance
Greening / greenspaces	Heat	Reduce Sources & Exposure	Community/Municipal	Land use conflict; maintenance; gentrification risk
Resilience hubs	Wildfires, Heat, and Air Pollution	Multiple	Community/Municipal	Community awareness; travel distance; financial resources; limited capacity
Cooling and/or wildfire smoke clean air centers	Heat and/or Air Pollution	Reducing Exposure	Community/Municipal	Community awareness; travel distance; transportation barriers; limited capacity
Water cooling - public water parks	Heat	Reducing Exposure	Community/Municipal	Community awareness; travel distance; transportation barriers
Sidewalk and street materials (e.g., cool pavement, etc)	Heat	Reduce Sources & Exposure	Community/Municipal	Resources; coordination; maintenance
Reducing Underlying Risk Factors				
Poverty reduction	Heat and Air Pollution	Multiple	Community, Municipal, Policy	Financial resources; cross-sector coordination
Food/nutrition assistance	Heat and Air Pollution	Multiple	Community, Municipal, Policy	Financial resources; enrollment barriers; cross-sector coordination
Increasing health care access	Heat and Air Pollution	Multiple	Community, Municipal, Policy	Financial resources; education; trust barriers; cross-sector coordination

System-Level Support for Behavior Modifications for Workers				
Safety regulations & enforcement around extreme heat and air pollution (e.g., temperature or air quality thresholds for allowing outdoor work or other activities)	Heat and/or Air Pollution	Reducing Exposure	Occupational Policy	Structural barriers; enforcement capacity; worker retaliation fears
Slower work / more breaks in response to extreme weather	Heat	Reducing Exposure	Occupational Policy, Private Business	Structural barriers; wage impacts; employer resistance
Postponing work in response to extreme weather	Heat	Reducing Exposure	Occupational Policy, Private Business	Structural barriers; income loss; job insecurity; job constraints
Shifted work schedules	Heat and/or Air Pollution	Reducing Exposure	Occupational Policy, Private Business	Structural barriers; wage impacts; job constraints

Brief Overview of Interventions Efforts in Contra Costa

Contra Costa is already working towards many of the interventions identified in **Table 8**. The county's climate action and adaptation plans include some of these interventions, and both governmental and non-governmental organizations across Contra Costa and the state have programs in place to support interventions that can address air pollution and/or extreme heat.

Although centered on achieving state-mandated greenhouse gas emissions reduction targets, the County's 2015 Climate Action Plan notably identifies co-benefits of proposed emission reduction measures that can simultaneously improve air quality, improve public health, or improve community resiliency to climate change. (Contra Costa County Department of Conservation and Development, 2015). For example, one of their policies is to "reduce urban heat islands through vegetation management and cool surfaces" and calls out cool roofs and new shade trees as performance targets. As we describe below, the breadth of benefits an intervention can provide can increase alignment with different policies and objectives. The Plan also identified healthy community strategies—for instance, identifying areas with disproportionate health burdens and prioritizing projects eligible for cap-and-trade funding—to help guide County staff in coordinating and educating the public on health impacts from climate change and to ensure climate-related public health measures were incorporated into future planning efforts. Our mapping of individual and combined climate vulnerabilities could support such targeting.

The County's Climate Action and Adaptation Plan 2024 updates its 2015 plan with additional emissions reduction and climate adaptation strategies, with a particular focus on strategies for unincorporated areas of the county (PlaceWorks, 2024). Interventions in this plan include minimizing heat island effects using cool roofs, green infrastructure, tree canopy, and cool pavement as well as establishing and maintaining community resilience hubs, increasing the amount of electricity generated from renewable sources, and building energy efficiency measures. Similarly, our vulnerability mapping identified that while the whole county faces increasing extreme heat, there are more frequent extreme heat events and far lower canopy cover to provide shade in eastern Contra Costa, including across unincorporated communities in District 3 (East).
Beyond the emissions-focused measures of the County's Climate Action and Climate Action and Adaptation Plans, a few examples of programs or initiatives active in Contra Costa include:

- Richmond's Heat Safety & Air Quality program, which includes a Heat and Poor Air Quality Emergency Operations Plan, provides education around extreme heat safety and preparedness, and hosts a local cooling map and other resources (City of Richmond, 2025).
- The Contra Costa County Asthma Initiative, which works to reduce asthma-related emergency room visits by conducting asthma education and providing energy efficiency services (Hardman-Saldana, 2025).
- Marin Clean Energy's Home Energy Savings program, which provides home-energy assessments and home energy updates to qualifying homeowners and renters (Marin Clean Energy, n.d.).

- Numerous residential energy programs and rebates offered by Bay Area Regional Energy Network (BayREN), including their Efficiency and Sustainable Energy (EASE) home program, which supports income-eligible residents with home energy upgrades. (BayREN, n.d.-1, BayREN, n.d.-2).
- BAAQMD's 2017 Clean Air Plan, which includes energy efficiency and electrification initiatives designed to reduce air pollution (BAAQMD, 2023).

The state also supports interventions that are relevant to Contra Costa. For example, the Governor's Office of Land Use and Climate Innovation's Extreme Heat and Community Resilience Program supports local and regional efforts to reduce the impacts of extreme heat (CA Governor's Office of Land Use and Climate Innovation, n.d.).
The above list of programs, initiatives, and plans is only a representative sample, but demonstrates critical work being done in Contra Costa to address the impacts of air pollution and extreme heat on residents. As we found in our literature review and community engagement efforts, many of the interventions require governmental or other support due to financial constraints, land-use constraints, and/or other barriers. However, existing efforts may not effectively address the disparities in exposure to these hazards if they do not consider recent data on local exposures. In particular, top-down programs that do not sufficiently take the context of an impacted community into account risk offering resources that the community cannot take advantage of without further support.

Community Feedback on Interventions

We asked community members across Contra Costa County to provide feedback on their lived experiences with climate vulnerability interventions. By including community knowledge and experience, we can better understand the practical limitations and additional opportunities to support communities with these interventions (CDPH, 2023). Over 30 community groups were contacted to participate in the Collecting Community Feedback on Health Risks & Solutions - Listening Session to capture their lived experiences, and ultimately six community members participated in a community listening session. Organizations contacted for outreach represented a broad range of sectors, including environmental justice and climate advocacy, grassroots community organizing, health and social services, youth leadership and education, environmental stewardship and food systems, and regional energy and air quality entities.

The community feedback focused on eight intervention themes organized by climate exposure (heat or air pollution) and where the intervention takes place (home/personal vs community/city/state/other). Intervention themes were AC, home improvements, home greening, leveraging existing home resources, greening & green spaces, community infrastructure, home equipment, and outdoor mitigations & structural support (see **Table 8**). Rather than using the delineated categories above, these themes sought to match community feedback materials with how people experience interventions. For example, using AC to mitigate extreme heat impacts could cause a household's electricity bill to skyrocket, making electric bill assistance programs necessary for a household to access this intervention. Community feedback highlights a concept we detail below—that barriers to independent action exist for some individuals, households, and communities, and that these actors may need support from higher level actors (e.g., planners and policymakers at the city, county, and state levels) in order to overcome those barriers.

Table 9. Summary of Interventions and Themes Presented at Community Listening Session. An intervention's location (e.g., in a home, in a neighborhood, etc) and who is required to take action to facilitate that intervention (e.g., an individual, a city government, etc) are closely tied and thus referred to as "Actor/Location."

Climate Exposure & Actor/Location	Intervention Theme	Intervention Examples
Heat Exposure - Personal/Home	Air Conditioning	Updating AC units, rebates for homes without AC, electricity bill assistance, etc.
Heat Exposure - Personal/Home	Home Improvements	Home repairs, weatherization, solar panels, installing ac for homes without it, etc.
Heat Exposure - Personal/Home	Home Greening	Cool roofs, green roofs, etc.
Heat Exposure - Personal/Home	Leveraging Existing Home Resources	Designated cool home areas, water cooling, etc.
Heat Exposure - Community/City	Greening & Green Spaces	Updating sidewalk & street materials, building shade structures along sidewalks or outdoor work areas, expanding trees and shade in parks, schools, and bus stops, etc.
Heat Exposure - Community/City	Community Infrastructure	Resilience hubs, cooling centers, public water parks.
Air Pollution - Personal/Home	Home Equipment	Face masks, air purifiers, creating a "clean" room, portable air cleaners for wildfire smoke days, subsidizing HVAC upgrades with filtration, etc.
Air Pollution - Community/City	Outdoor Mitigations & Structural Support	Face masks, air quality monitoring/maps/notifications, workplace accommodations, wildfire smoke clean air centers, wildfire smoke emergency plans, etc.

For all intervention categories except Greening & Green Spaces, the majority of community members reported that very few to none of them (either them or their community) knew about existing interventions in that category (**Figure 17**). For AC, we can assume that community members were familiar with AC itself, but not policies to facilitate AC access or usage as an intervention against extreme heat. Half of the community members reported that they and/or most of their community knew about Greening & Green Spaces interventions.

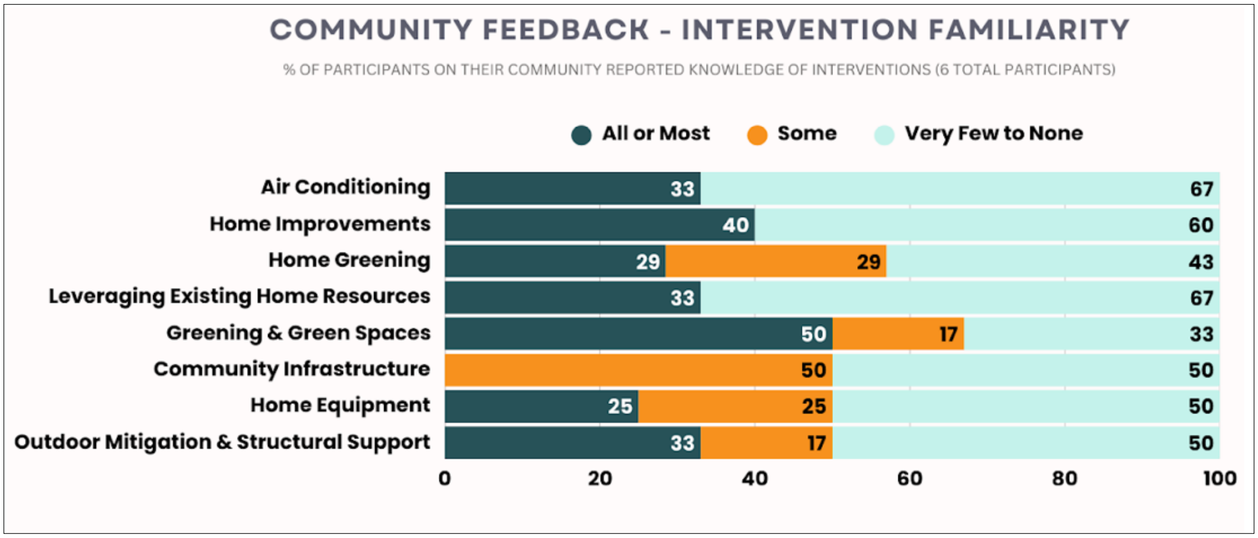

Figure 17. Community listening session results regarding community members' familiarity with different types of interventions.

Additionally, when asked "is this type of intervention being implemented," the majority of community members reported that few to none of the interventions in the intervention categories were being implemented in their communities (**Figure 18**). Greening & Green Spaces was again the only exception, with only 50 percent of community members reporting that few to none of these interventions were being implemented.

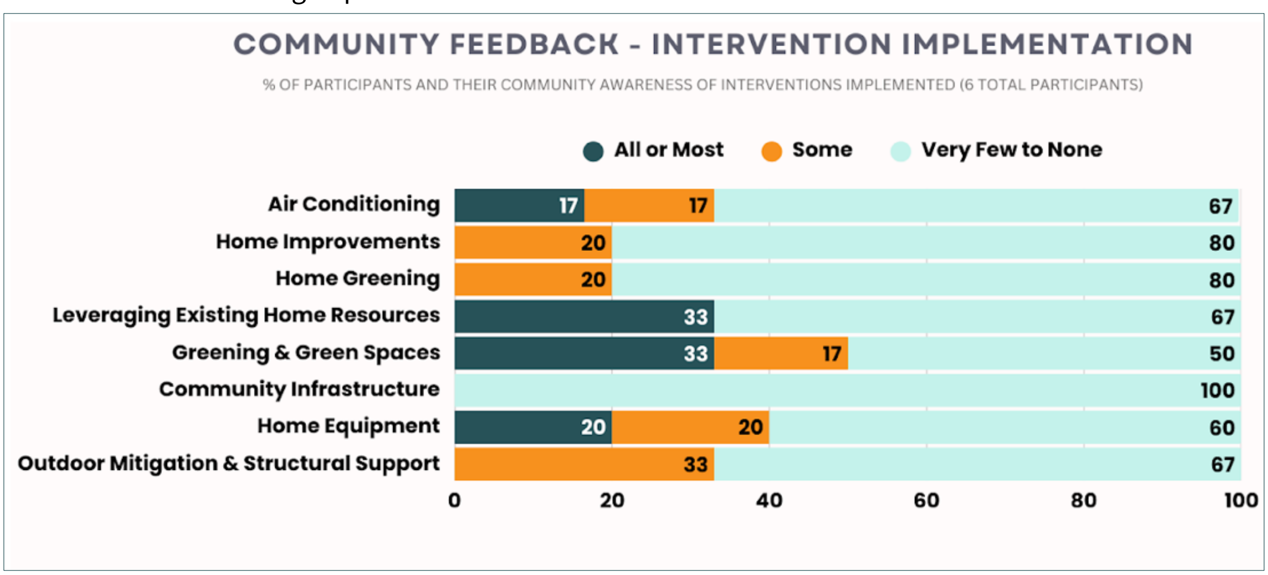

Figure 18. Community listening session results regarding community members' awareness of whether interventions are implemented in their communities.

Similarly, when asked if they had seen or tried any of these interventions, most community members reported that they had seen or implemented few to none of the interventions (**Figure 19**). But the Greening & Green Spaces and Home Equipment categories had only 50 percent of community members reporting they had seen or tried few to none of the interventions.

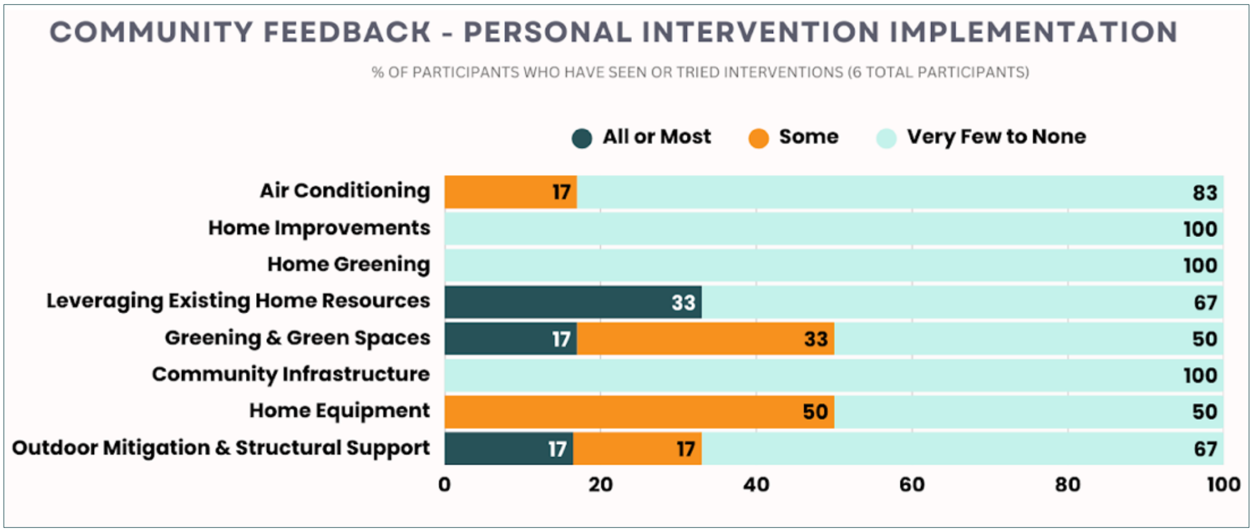

Figure 19. **Community listening session results reporting whether community members personally had implemented interventions.**

Community participants further expanded on the successes, challenges, and areas for improvement for each of the intervention categories. A common theme for all categories is that communities do not have or know where to access information on intervention resources in their communities. In other words, lack of information was a barrier to implementing or supporting interventions.

More specifically, for AC, there were concerns about many homes not having AC units or AC units that cannot handle long durations of heat exposure, both because the household cannot afford the increased energy bills and because the equipment cannot handle prolonged use. The financial burden of energy bills was another concern for many participants, with several noting that bill assistance is limited to certain income brackets. Additionally, participants flagged that unhoused populations, who have greater sensitivity to heat but fewer resources to adapt, are left out of this intervention but are still vulnerable to heat exposure. These comments illuminate barriers to individuals protecting themselves from extreme heat.

Feedback around Home Improvements highlighted that the difference in intervention adoption is largely dependent on homeowner versus renter status—the tension between actors with different costs and benefits from home improvement. Renters are often unable to implement these improvements, or if these types of interventions are implemented, there are often negative impacts including rent increases, additional scrutiny or surveillance from landlords, or even eviction from their rental homes. Participants noted that concern for these negative consequences could discourage renters from advocating for home improvements. For homeowners, community participants said their priority is home maintenance and upkeep, before implementing home improvement interventions.

When asked about Home Greening, 100 percent of participants said they had tried few to none of these interventions. The majority of community participant examples centered on community or business structures, recognizing the actors that may have more readily accessible resources for implementation. Participants said these types of interventions are dependent on city building codes and require more specific maintenance. Suggestions for improvement included working with the city to improve the process to build and install home greening solutions, as well as to implement these interventions in low-income areas and apartment complexes. Overall community feedback reflected the need for municipal support to implement greening, both in public spaces and in homes.

Community members reported that some of the Leveraging Existing Home Resources interventions were well known, for instance keeping curtains or blinds closed, increasing air flow, or "trapping" cool outside air inside during the morning. However, most participants also mentioned that many of these intervention strategies were not very effective for long periods of time.

Greening & Green Spaces were the most familiar interventions. However, several participants described issues with the planting and upkeep of trees in their communities. According to one community member, if trees are not properly maintained it "becomes a burden on the community instead of a benefit." This feedback highlights the importance of incorporating community knowledge to ground which interventions are successful in practice. Several participants suggested that these types of interventions should be implemented at a more local level and in coordination with local groups who are already doing environmental resilience in their communities (e.g. a mix of actors). This also highlights that actors often need structural support in their endeavors. Additionally, other actors may not need to reinvent the wheel when it comes to implementing interventions but instead can leverage preexisting groups, networks, and efforts. Some participants expressed that additional greening and green spaces would also yield co-benefits to commuters, especially youth who walk to school or take the bus.

All participants reported that few to none of the Community Infrastructure interventions were implemented or seen in their communities, with many saying there should be more outreach to the communities about these resources. Participants highlighted vulnerable populations (e.g. people experiencing homelessness, people without transportation, low-income populations, etc.) that would benefit from greater outreach and access to these interventions. These populations both have lower adaptive capacity to protect themselves from climate exposures and less ability to access these resources.

When asked about Home Equipment interventions, participants reported that the biggest barriers to implementing some of these interventions were funding and knowledge of the interventions. Participants suggested implementing programs for at-risk individuals that could provide assistance and financial support. Relatedly, for areas that already have these types of assistance programs or financial supports, further outreach could help more community members to become aware of these interventions and programs. Additionally, participants suggested that utility companies responsible for wildfires and the resulting air pollution should provide more information to communities on these types of interventions.

Community members highlighted a variety of challenges when it came to implementing Outdoor Mitigation & Structural Support interventions, predominantly when it came to outdoor workers. Participants described that outdoor workers were dependent on employers to monitor and provide the outdoor interventions, which many employers are not incentivized to implement. Enacting these interventions involves multiple actors, including the workers and employers, who face tensions between conflicting costs and benefits. Additionally, outdoor workers may not be able to advocate for themselves to receive interventions as doing so could impact their financial security and employment status, which in turn may impact immigration status. Participants highlighted that emergency plans, air monitoring, and air quality maps have been a great resource in tracking air pollution, extreme heat, and the health risk, but more can be done to partner with local organizations to promote outreach and accessibility. One community member said, “air quality maps are useful to plan out activities and work, when you are able to make that decision, but it isn't always your choice.”

Finally, community members were asked to prioritize all heat exposure and air pollution intervention categories. For exposure to both heat and air pollution, Home Improvements, Home Equipment, and Outdoor Mitigations were the highest priorities. Moderate priorities were Greening & Green Spaces, Community Infrastructure, and Leveraging Existing Home Resources. Home Greening and AC were the lowest priority interventions.

Limitations to the community outreach and feedback data include the limited time to engage with communities about their lived experiences. The community feedback data are based on community members’ personal knowledge and may not be representative of their entire areas of work and living. We did not apply methods to verify community member observations of effective or ineffective implementation of interventions.

Factors to Consider When Designing Interventions

Designing effective and appropriate interventions requires not just an in-depth understanding of the problems (e.g., what overlapping hazards, population sensitivities, and adaptive capacity gaps are driving the need for these interventions), but also an understanding of which interventions are feasible, who can implement them, what barriers they face, how they align with other goals, and the distribution of their costs and benefits. In the literature review and community engagement and feedback session, we identified commonly reported interventions as well as a set of factors that helped informed feasibility and community fit.

Understanding how these factors interact with local community context can offer practical insight into which interventions may be most successful and how to design effective programs to implement them. Community engagement and feedback—including lived experiences of barriers and co-benefits, social contexts, and opportunities for community engagement—are critical for assessing the potential success of interventions.

Intervention Locations and Actors

When designing an intervention program, we recommend accounting for where the intervention takes place (e.g., within someone's home or in a public space) and who has the power to undertake that intervention or jurisdiction to make changes in that location. In this context, actors can be individuals, city or county governments, policymakers, utilities, and any other person, group of people, or institution that could implement an air pollution and/or extreme heat intervention.

Some interventions can only be implemented by certain actors, or by actors in combination due to the location. For instance, interventions that alter public spaces—such as using green infrastructure and cool pavement to mitigate heat island effects—must be done at the community or city/county/state planning level. The location of a given intervention can also constrain who must be involved in its implementation. For example, a community-based organization seeking funding for a clean-energy microgrid under California's Microgrid Incentive Program must either partner with their local government or provide a letter of support from whichever authority has jurisdiction in the area (PG&E, 2025). For those in unincorporated communities, this might mean working with the county government. At-home interventions in particular can be limited by whether or not you own or rent your home.

In some cases, there is also a tension between who pays for an intervention and who benefits most from it. The classic example is between landlords and tenants. Installing building upgrades like heat pumps, insulation, efficient windows, and the like is most often done by and paid for by the property owner. The primary beneficiary, though, is the tenant, in the form of reduced energy bills, greater comfort in the home, and reduced exposure to and negative health outcomes from poor air quality and extreme heat. Resolving these tensions can be challenging—for example, if a landlord does upgrade a building, they may increase rents, which in turn may force out the tenants who were going to benefit from the upgrade. These tensions were highlighted by participants in our community listening session.

Barriers Faced by Actors

Understanding constraints on different actors—who can take action directly, who *could* take action if given opportunity, and who lacks the adaptive capacity to take action without stronger support—can help determine optimal interventions. Some interventions that require an individual to take a specific action may also require system-level support and/or educational programming and outreach. For example, when air pollution is particularly bad, a person could reduce their own exposure by seeking out places with filtered air. However, this requires the city, county, or a higher-level agency to provide air quality monitoring, maps, and education. And in some cases, further support—on the level of workplace safety regulations and enforcement—may be required, for instance to reduce exposure among outdoor workers (as highlighted by participants in our community listening session).

Additionally, widespread implementation of some interventions will require support in the form of monetary incentives and/or policy changes. This is particularly true for interventions that also provide greenhouse gas emission reduction benefits in line with state goals. For example, installing heat pumps can protect households from extreme heat while reducing their air pollution and greenhouse gas emissions, for many households it is only viable when supported by multiple actors. For a home facing extreme heat exposure, installing a heat pump can provide the same cooling benefits while using less energy than a traditional AC unit. That same heat pump could also be used for heating and would be a more efficient heating unit than either electric baseboard heaters or a gas furnace. In that way, this heat pump intervention not only provides extreme heat exposure benefits but can also reduce a household's greenhouse gas emissions by using less energy for the same tasks. However, heat pumps are expensive to install, not accessible to all demographics (e.g., renters), and do not function during power outages (unless they are connected to a backup power source). Thus installing heat pumps becomes a viable intervention for many households only when multiple actors across multiple levels and locations support it, including, potentially: federal and/or state authorities implementing heat pump subsidies; federal and state authorities providing resilient energy subsidies; energy state and city authorities providing rent protection to prevent upgrades from causing gentrification; state utility regulators ensuring circuits are upgraded to enable electrification; and landlords or homeowners installing heat pumps (Brockway et al., 2021, Joseph et al., 2025).

Intervention Mechanisms

Different interventions use different mechanisms to improve health outcomes. These mechanisms can be broken down into three broad categories:

1. Reducing sources of air pollution and/or extreme heat (e.g., reducing harmful emissions).
2. Reducing exposure to air pollution and/or extreme heat (e.g. avoiding pollution).
3. Mitigating the potential health impacts of these hazards (e.g. reducing vulnerability by improving baseline health).

Reducing sources of air pollution and/or extreme heat works by eliminating the hazard itself, thereby reducing the need for interventions that reduce exposure. While some interventions can reduce sources of air pollution and/or extreme heat—for example, undergrounding power lines to reduce the number of utility-sparked wildfires, thereby reducing the amount of wildfire smoke in the air—it is not feasible to eliminate all sources of all hazards. It is more attainable to reduce exposure to hazards, for instance by providing the opportunity and ability for people to avoid hazards. Reducing exposure works by lowering the hazard dose—e.g., breathing in less smoke by wearing a respirator facemask during wildfire season or beating the heat by going to a cooling center during a heat wave. Finally, reducing people's underlying vulnerability, for instance by improving their baseline health, can mitigate the potential health impacts of hazards. Further examples of interventions that use each of these mechanisms are shown in **Table 8 above**.

While it is helpful to understand the broad mechanisms, some interventions blur these lines. For example, a solar-and-storage powered resilience hub—a community facility designed to support local residents, particularly before, during, and after hazard events (Baja, 2018)—can help reduce individuals' exposures to extreme heat and air pollution during a power outage while also reducing sources of air pollution by allowing nearby residents to avoid using diesel generators during the outage.

Breadth of Intervention Applicability

Policymakers may use benefit-cost calculations to help determine which interventions or intervention programs to implement. These calculations should take into account the multiple benefits of some interventions as well as how these benefits are distributed. Given the range of exposures, sensitivities, and adaptive capacities of different Contra Costa communities, interventions that can address multiple challenges faced by a community may better meet community needs. At the same time, broadly applicable interventions may require less targeting because they address a wider set of problems. We capture a slice of breadth of applicability by identifying which hazards each intervention addressed in **Table 8**.

From the literature review, we found that there is no single intervention that addresses all sensitivities, exposures, or adaptive capacities (**Appendix B**). Poverty reduction, though, may be an intervention that can mitigate across all population sensitivities and hazards, and increase adaptive capacity where it is most lacking. Poverty reduction alleviates harms associated with poverty itself (e.g., food insecurity, housing insecurity, energy insecurity, lack of access to healthcare, lack of access to education, and more), and also reduces numerous health problems that can be exacerbated by poverty (e.g., depression, heart disease, diabetes, stroke, high blood pressure, respiratory illness, childhood development issues) (Khullar & Chokshi, 2018). Poverty reduction addresses the underlying challenge that poorer households have lower adaptive capacity than wealthier households given little or no savings, little or no insurance, and very little ability to invest in household resilience prior to an event, and so are hit harder by and take longer to recover from hazard exposures or disasters (Sengupta & Costella, 2023, Lankes et al., 2024). Poverty reduction specifically addresses community feedback that cites a lack of funds as a major barrier to household-level interventions.

Some interventions address multiple climate hazard exposures and vulnerabilities while also providing additional benefits. For instance, weatherizing a home by sealing windows and improving insulation offers energy efficiency and affordability benefits alongside reducing exposure to extreme heat and outdoor air pollution (Stenger et al., 2023, RAMP, 2018). Similarly, tree planting or other greening can address extreme heat exposure for sensitive populations if targeted to relevant locations (e.g., on school campuses for young children or in retirement communities for older adults). If broadly applied with long-term maintenance for tree survival, increasing canopy covers can reduce broader urban heat island effects (EPA, 2025d), yielding benefits across the community. This, in turn, could potentially (given widespread, effective, well-maintained adoption) reduce extreme heat exposure for outdoor workers even if their tasks do not allow them to seek shade (Sousa-Silva et al., 2024).

Such multi-hazard interventions are especially relevant in Contra Costa County where northeastern cities experience higher levels of extreme heat and air pollution. For example, a modern heating, ventilation and air-conditioning (HVAC) system installed in a home or school to provide cooling during extreme heat events can also be designed to accommodate a Minimum Efficiency Reporting Value (MERV) 13+ or High-Efficiency Particulate Air (HEPA) filter to reduce occupants' air pollution exposure, and so mitigate exposures to both air pollution and extreme heat in young, old, and other sensitive populations. However mechanical cooling and air filtration both increase energy use and energy bills, and may be challenging solutions for households that are already energy cost burdened. Thus, ongoing support for high energy bills may be required for this solution to be adopted. While ongoing financial support may increase the costs of this intervention, the benefits are broad (e.g., addressing both extreme heat and air pollution) and the additional financial support may allow the benefits to be distributed to populations that would otherwise be unable to adopt this intervention.

Certain interventions are designed to target particular or singular hazards, including supplementing gaps in adaptive capacity. In our review, interventions that only target heat exposure were more common than those only targeting air pollution. It should be noted that interventions that can reduce personal exposure to air pollution (e.g., face masks) are generally also effective against wildfire smoke.

Intervention Co-Benefits & Alignment with Other Goals & Priorities

Detailed, local benefit-cost analyses should attempt to include the value of multiple co-benefits that can be achieved from individual investments, and consider who is receiving these benefits, when making cost-effectiveness determinations. When these co-benefits align with the other goals of a relevant actor, for instance by reducing emissions as well as air pollution, it facilitates cross-actor support. The *Contra Costa County Climate Action and Adaptation Plan 2024 Update* similarly recognizes that interventions to safeguard communities against climate hazards can have various co-benefits (PlaceWorks, 2024). In fact, co-benefits are listed as part of each of the Plan's climate adaptation strategies. For example, the plan includes a general strategy to "Minimize heat island effects through the use of cool roofs, green infrastructure, tree canopy, cool paint and pavement, and other emerging strategies" and listed co-benefits include "improved air quality, improved community equity, improved public health, increased economic opportunities, reduced disaster impacts, and reduced resource use." (PlaceWorks, 2024) Similarly, Contra Costa developed its Climate Action and Adaptation Plan as a companion to its 2045 General Plan, rather than developing plans in isolation.

For example, when implemented at scale, interventions that increase household energy efficiency or promote the use of clean energy can lower greenhouse gas emissions in line with California's emission reduction goals as well as reduce harmful $PM_{2.5}$ emissions. A more specific example is a household replacing an older AC unit with a more efficient heat pump. This not only reduces the household's energy usage, furthering a household's budgetary goals, it does so especially during the late-afternoon and early-evening hours when fossil fuel peaker plants are being turned out to meet high energy demands–furthering California's emissions goals.

Limitations to the Interventions Analysis

Limitations to this intervention analysis include limited community engagement feedback, and that intervention cost-benefit analysis is highly localized. Because community outreach was limited, community comments on the history and effectiveness of interventions locally is anecdotal and cannot be considered comprehensive. The available cost-benefit analyses reviewed tended to focus on regions with extremely high pollution, and results may not apply to moderately high pollution regions. Thus, this analysis focused on factors to consider when designing extreme heat or air quality interventions rather than modeling the distributional costs and benefits for different interventions.

Conclusions

In this study we aimed to identify opportunities for interventions to protect vulnerable populations from climate- and pollution-related exposures in Contra Costa County. This included characterizing climate-related exposures and mapping the landscape of potential interventions.

By integrating data from an existing network of low-cost air monitors and strategically deploying additional monitors to fill gaps identified by local community members, we found air pollution hot spots in Richmond, San Pablo, Antioch, Oakley, and Pittsburg, including long-term $PM_{2.5}$ concentrations around 8-9 µg/m^3. While these concentrations were just below the US EPA standard of 9 µg/m^3, this pollution may still pose a health risk based on epidemiologic evidence of the harmful effects of low-level $PM_{2.5}$. Richmond, Martinez, and Pittsburg experienced more frequent episodes of acute air pollution. Average $PM_{2.5}$ concentrations overall were higher in Districts 1 (West), and 5 (North) that have a number of polluters (oil refineries, power plants, industrial activity) and heavy vehicle traffic, as well as District 3 (East) which experiences high temperatures which could trap and amplify air pollution in the area.

Extreme heat exposures followed an east-west gradient, with the most frequent extreme heat events in District 3 (East). Over the past 20 years, the frequency of extreme heat has increased over time, especially in east Contra Costa. From this, we saw Contra Costa's northeastern communities faced the greatest dual exposure to air pollution and extreme heat. Evidence also suggested that Black and Hispanic populations, as well as outdoor workers and children under the age of five, experienced higher air pollution levels and extreme heat events than other demographic groups. People living under 200 percent of the Federal Poverty Limit experienced slightly higher air pollution levels as well. Overall, this work illustrates that **dense local monitoring with low-cost sensors can illuminate the unique hazard exposures and exposure trends within a community, offering a more detailed picture than dispersed regulatory monitors. These local insights can then support more targeted intervention planning and community engagement around intervention implementation.**

Every community faces unique challenges. Local data is critical for characterizing their specific climate vulnerabilities—where their environmental exposures, population sensitivities, and low adaptive capacities overlap. While cumulative vulnerability, as measured by CES 4.0, was concentrated in Richmond, San Pablo, and cities in Districts 5 (North) and 3 (East), the specific measures of population sensitivities and adaptive capacity followed varying spatial patterns. We found hot spots of specific climate vulnerabilities throughout the county, such as the portions of District 3 (East) that faced more frequent extreme heat days, low canopy coverage, and high proportion of outdoor workers as residents. **These clusters of overlapping exposures, population sensitivities, and low adaptive capacity are potential priority areas for interventions that target**

their unique combination of vulnerabilities – and account for barriers faced by community members.

The landscape mapping of potential interventions included a literature review to identify interventions that can address residents' exposure to air pollution and extreme heat. We characterized interventions by key factors that inform applicability and community fit—the hazard(s) they can address, the actors required for successful implementation, and their mechanism of action. This framework helps clarify the potential breadth of benefits offered and possible accessibility challenges posed by different interventions. In turn, the community listening session gave community members a platform to illustrate some of their lived experience and explain barriers they face, such as financial limitations that prevent them from adopting certain interventions and a lack of information about existing programs or resources. **This landscape mapping suggests that it is critical for stakeholders to account for a community's specific context when designing intervention programs, directly engaging with community members to understand their unique needs and possible barriers.**

Overall, this study provides building blocks for designing effective, appropriate interventions to protect climate-vulnerable populations from climate- and pollution-related exposures in Contra Costa County. In future steps, we recommend stakeholders, planners, and policymakers consider additional exposures, population sensitivities, and adaptive capacities. This could include additional pollutant exposures and hyper-local impacts of other extreme weather events; populations with pre-existing health conditions, pregnant people, or language barriers; and the existence and local knowledge of emergency response plans, among others. Furthermore, given the increasing frequency and intensity of extreme heat events across the county and clusters of overlapping exposures, we encourage planners and policymakers to continue considering how interventions can be designed to mitigate multiple exposures. Critically, we recommend targeted, localized community engagement to understand what interventions would best fit a community's needs and what lines of communication and support are necessary to ensure residents are both aware of and can access these targeted interventions.

Ultimately, multiple types of information—from on-the-ground, local monitoring to satellite and demographic data, scientific literature, and community feedback—are essential to fully characterize climate vulnerabilities and design effective interventions.

Appendix A – Methods and Supplemental Information

Methods

Air Quality Data

Aeroqual Data Collection and QA/QC

Through stakeholder engagements, PSE identified priority areas for monitoring and identified monitor hosts. $PM_{2.5}$ measurements were collected in part by fifty Aeroqual sensors (25 older AQY model sensors previously used in Richmond and 25 newer model AQY-R sensors) sited at volunteer homes, schools, restaurants, and local institutions (e.g. fire departments). Monitor sites were chosen based on:

1. Volunteer interest
2. High census tract CES scores for environmental and socioeconomic burdens
3. Areas with minimal existing air monitor coverage

Volunteer monitor hosts were corresponded with over email and phone call to coordinate monitor installation and maintenance (if needed). Sensor and network diagnostics were performed weekly using the provided Aeroqual diagnostics software to check for offline sensors or sensor errors. If a sensor was offline for at least two days, the monitor host was contacted to ensure the monitor was still plugged in and connected to WiFi. If so, a site visit would be scheduled to troubleshoot the monitor.

Aeroqual monitor data was uploaded to the cloud at minutely intervals. Raw monitor data was downloaded from the cloud quarterly, and averaged at the hour level. For each monitor, hours that had less than 75 percent data completeness (less than 45 minutes of data out of 60) were removed. Additionally, raw data was screened for data quality issues and data that met the below criteria were removed before calibration (see table S.M.AP.X).

Raw data was calibrated using Aeroqual's calibrator app, which applies Aeroqual's MOMA (Miskell et al., 2018) calibration methodology to the raw sensor data. The calibrator app assigns BAAQMD regulatory air monitors to each Aeroqual monitor to act as a proxy site, and seeks 5-day windows to generate calibration parameters for each monitor based on the proxy site data. These calibration parameters, a gain and offset, are used to calibrate raw data with the following equation:

$$PM_{2.5calibrated} = PM_{2.5gain} * (PM_{2.5raw} - PM_{2.5offset})$$

Calibration parameters are downloaded for each monitor at monthly intervals. However, the calibrator was often unable to calculate gains and offsets for monitors, for reasons including: 1) The proxy monitor was offline for a substantial period of the month, 2) the Aeroqual monitor was offline for a substantial period of the month, or 3) Raw $PM_{2.5}$ concentrations read by the Aeroqual monitors were too low for the calibrator to properly generate gains and offsets. Any of these three factors could cause a monitor to be missing gains and offsets for the months in question. In this case, based on Aeroqual feedback, the missing calibration parameters for a given month were backfilled using the previous or subsequent month's parameters (whichever one had parameters more suitable to the missing month, based on raw data trends). This reduces calibration precision for backfilled months, but provides improved data completeness. However, there are times this method can cause calibrated $PM_{2.5}$ values to be negative, due to a combination of low raw $PM_{2.5}$ values and a high backfilled offset. In these instances, negative $PM_{2.5}$ values were set to zero to maintain some data completeness, rather than removing negative values entirely or keeping them and lowering network averages.

Calibrated data was then assessed for a number of data quality issues, and data that was determined to be problematic was flagged and removed from analysis. Data exclusion criteria for Aeroqual and PurpleAir sensors are listed in **Table S.M.1** below

Purple Air Data Collection and QA/QC

To supplement our monitoring network, we also collected outdoor $PM_{2.5}$ concentration data from PurpleAir monitors. These monitors are managed by individuals and organizations independently from this project. Past research has shown that PurpleAirs tend to be disproportionately located in wealthier areas (Sun et al., 2022), which can lead to a more precise picture in those areas, but not necessarily bias the data. We first collected data from any PurpleAir monitor that had been active in Contra Costa County sometime between January 2015 and October 2023 and were labeled as outdoor monitors. We then corrected the estimates via the calibration approach developed by the US EPA (Barkjohn et al., 2022). We excluded observations based on our exclusion criteria (see Table A.M.1).

Black Carbon Data

As a supplemental assessment of wildfire smoke exposure, we reviewed estimates of BC concentrations from HAQES (Tong, 2023). HAQES estimates pollutant concentrations by combining multiple pollutant models from different research teams and giving more weight to more accurate estimates. For BC, these estimates are available for three-hour averages at 12 km/ 12 km scale; we estimated daily (24-hour) averages, identified the maximum concentration in the county for each day, and reviewed their time trends for evidence of wildfire smoke. Since our review did not indicate any evidence of wildfire smoke exposure during the study period, we did not further analyze these data.
Aeroqual & Purple Air Data Integration

When we combined the monitoring data, we excluded any locally extreme observations (defined as any observation more 75ug/m3 higher than any of the contemporaneous observations of the ten nearest monitors) (see Table A.M.1). We then estimated hourly concentrations across the county using

IDW (Farooqui et al., 2023), allowing the weights to vary each hour (see Figure A.M.1 for example). IDW leverages the strength of low cost sensors by averaging nearby measurements, whereby closer measurements are given higher weight. This approach will not capture all local spatial variability, but also overcomes the limitations of individual low-cost sensors.

Table A.M.1 Exclusion Criteria for Air Quality Data. Observations or instruments that met any of these criteria were excluded from the final dataset.

Applicable Sensors	Which data to apply the flag to?	Exclusion Criteria	Description	Comment
Aeroqual	uncalibrated data	Uneven temporal coverage	< 75 percent of data available for the averaging window (1hr)	Data averaged to 1 hour if 75 percent of data is available for a given hour. The flag for this criterion is not added as a flag; instead, the hours with less than 75 percent of data aren't averaged. The column "mins measure" provides insight into which hours didn't have enough data and, thus, were averaged.
Aeroqual	calibrated	Other Error	Incorrect calibration or aberrant trends	Based on implausible values identified from review of the data and not borne out by neighboring monitors or proxy sites.
PurpleAir	uncalibrated data	Missing data	Missing $PM_{2.5}$ from channel A or B, or missing humidity	Barkjohn, K. K., Holder, A. L., Frederick, S. G., & Clements, A. L. (2022). Correction and Accuracy of PurpleAir PM2. 5 Measurements for Extreme Wildfire Smoke. Sensors, 22(24), 9669.
		Mislabeled as "outdoor location"	> 50 percent of diurnal temperature ranges are < 5 C	A cut off of 10 degrees included an unrealistic number of monitors, but 50 percent below 5C nicely identified the consistently low-TR monitors. Kramer, A. L., Liu, J., Li, L., Connolly, R., Barbato, M., & Zhu, Y. (2023). Environmental justice analysis of wildfire-related $PM_{2.5}$ exposure using low-cost sensors in California. Science of The Total Environment, 856, 159218. https://doi.org/10.1016/j.scitotenv.2022.159218
		$PM_{2.5}$ channel disagreement	channel A - Channel B > 5 ug/m3 and percent difference > 70 percent	Barkjohn, K. K., Holder, A. L., Frederick, S. G., & Clements, A. L. (2022). Correction and Accuracy of PurpleAir PM2. 5 Measurements for Extreme Wildfire Smoke. Sensors, 22(24), 9669.
	data with all other flags removed	Short measurement period	Data < four weeks	Insufficient data

Both	uncalibrated data	Impossible temperature value	Temperatures outside the PurpleAir acceptable range of −40 °F < Temperature < 200 °F (−40–93C°)	Kramer, A. L., Liu, J., Li, L., Connolly, R., Barbato, M., & Zhu, Y. (2023). Environmental justice analysis of wildfire-related PM2.5 exposure using low-cost sensors in California. Science of The Total Environment, 856, 159218. https://doi.org/10.1016/j.scitotenv.2022.159218
		Impossible relative humidity	0 percent < relative humidity (RH) < 100 percent	
		Flatline for relative humidity	24 rolling hours with same relative humidity value	
	calibrated	$PM_{2.5}$ anomalous values	Remove calibrated $PM_{2.5}$ values > 800 ug/m3	Liang, Y., Sengupta, D., Campmier, M. J., Lunderberg, D. M., Apte, J. S., & Goldstein, A. H. (2021). Wildfire smoke impacts on indoor air quality assessed using crowdsourced data in California. Proceedings of the National Academy of Sciences, 118(36), e2106478118.
		Flatline for $PM_{2.5}$	24 rolling hours with same $PM_{2.5}$ value	
Both - Combined	calibrated merged monitors	$PM_{2.5}$ outliers & spikes	measurement is at least +/- 50 ug/m3 above or below measurements from the ten nearest sensors.	Based on review of distribution of disagreement among nearby monitors

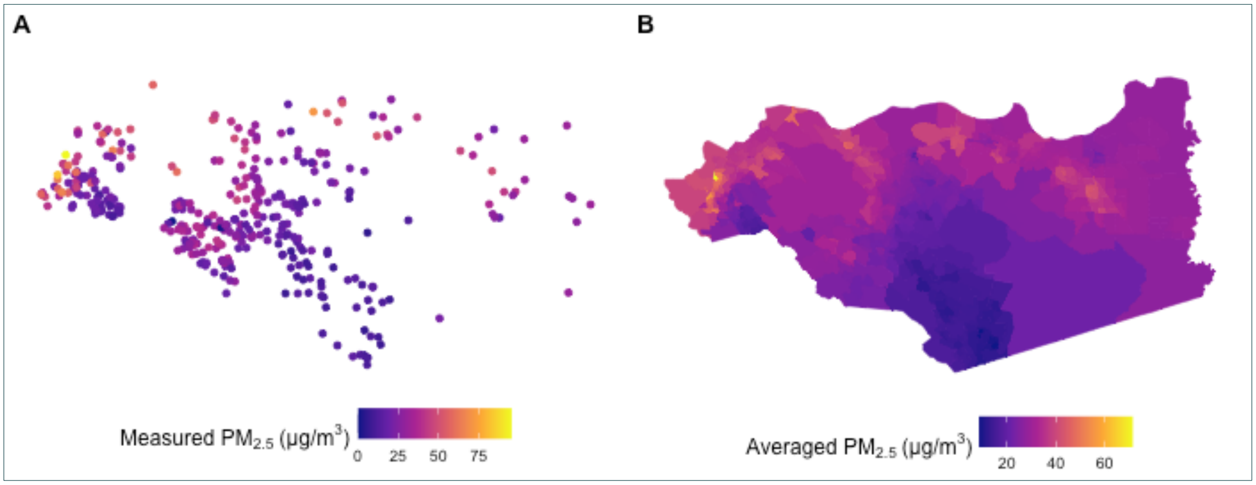

Figure A.M.1. Illustration of spatial smoothing of Hourly $PM_{2.5}$ data, 8 AM on December 12, 2024. *Panel A illustrates the hourly concentrations at each instrument for 8 AM of December 12, 2024. Panel B illustrates the census block group average concentrations after averaging over space via IDW.*

Air Quality Metrics and Trends Analysis

We considered four air quality metrics: (a) mean $PM_{2.5}$ (representing typical exposure), (b) mean $PM_{2.5}$ during work hours (7 am – 6 pm), (c) mean $PM_{2.5}$ during rush hour (7-9 am; 5-7 pm) and (d) number of days with average $PM_{2.5}$ over 35 ug/m3 (estimating exceedance of US EPA's daily NAAQS) (EPA, 2025b). It should be noted that a single day's concentration exceeding the 35 µg/m^3 threshold is a violation of the NAAQS, because the US EPA looks at multi-year data from regulatory-grade monitors when determining compliance with 24-hour standards. We found that the three metrics of mean $PM_{2.5}$ were highly correlated (Figure A.S.2), so we only analyzed mean $PM_{2.5}$ and number of days with 24-hour mean $PM_{2.5}$ over 35. We note that these metrics do not capture all aspects of exposure, including indoor exposure and other pollutants like ozone.

We mapped the air quality metrics at the census block group level based on the 2020 ACS (US Census Bureau, n.d.) to visually assess trends and identify hot spots. We examined long-term and diurnal weekly temporal trends for cities and supervisorial districts, and then assessed whether trends differed for select cities.

Extreme Heat Data and Metrics

Data for these four metrics was sourced from satellite Daymet V4 and GRIDMET. Daymet V4 provides gridded estimates of daily weather for North America, Hawaii, and Puerto Rico (Thornton et al., 2022). GRIDMET provides daily surface temperature, precipitation, wind, humidity, and solar radiation at a high spatial resolution (4 km) across the contiguous United States, from 1979 to 2025 (Abatzoglou, 2013). Daily max/min summer temperature (May–September) from 2019–2023 was first collected at the block group level. We calculated historical values using 1980-1999 and contemporary exposure using data from 2019-2023.

We initially assessed four metrics of extreme heat, following OEHHA's definitions: Extreme heat days, extreme warm nights, heat waves, and the heat index. We calculated the number of extreme heat events for each year, and then averaged across years. Ultimately, we dropped the heat index as a metric, as it correlated closely with the other three metrics. The three metrics are defined as:

1. **Extreme heat day:** Days with a maximum temperature above the 95th percentile of the historical maximum temperature (1980-1999).
2. **Extreme warm night:** Days with a minimum temperature above the 95th percentile of the historical minimum temperature (1980-1999).
3. **Heat wave:** two or more consecutive days whose daily maximum temperature was above the 95th percentile of maximum temperatures and whose daily minimum temperature was above the 95th percentile of minimum daily temperatures.
4. **Heat Index:** average value of the daily heat index, a measurement of the combined experience of temperature and humidity.

The Heat Index is calculated with temperature and relative humidity; we collected relative humidity at 4km x 4km resolution from GRIDMET. Given the crude resolution, we validated these data against the weather stations measurements (May 2019–Sept 2023) and found satisfactory performance (mean absolute error: 8.6%; mean bias: 6.2%; correlation: 0.84). We then estimated the Heat Index using the approximation approach from the National Weather Service (Ahn et al., 2024).

We aggregated extreme heat exposure at the supervisorial district via population weighting and examined correlations of the exposure metrics as well as spatial and historical trends via visualization.

Estimating Exposures

Air pollution

We estimated the average $PM_{2.5}$ exposure for different demographic groups (racial groups, age groups, income classes, outdoor worker residence) across the county as well as population-weighted average exposure for each supervisorial district. We calculated these for long-term and acute exposure as follows:

1. **Average acute PM days**: Population of a demographic in a census block group multiplied by the number of acute $PM_{2.5}$ days (24-hour $PM_{2.5}$ average > 35 μg/m^3) for that block group. Sum for all census block groups in the county and divide by the county population for that demographic. This provides an average estimate of how many acute $PM_{2.5}$ days each demographic group experienced. In other words, a weighted average where each census block group is weighted by the proportion of the county's population in that block group. Equation below:

$$person \cdot \ acute\ PM\ days_{demographic} = \frac{sum(block\ group\ population_{demographic} \times block\ group\ acute\ PM\ days)}{county\ population_{demographic}}$$

2. **Average long term PM exposure**: Population of a demographic in a census block group multiplied by the mean $PM_{2.5}$ for that block group. Sum for all census block groups in the county and divide by the county population for that demographic. This provides an estimate of the average long-term PM2.5 exposure each demographic group experienced. Equation below:

$$person \cdot \ long\ term\ exposure_{demographic} \ = \frac{sum(block\ group\ population_{demographic} \times block\ group\ long\ term\ PM)}{county\ population_{demographic}}$$

At the supervisorial district level, populations and exposures are summed by supervisorial district rather than by demographic, to compare results between districts rather than between demographic groups.

We compare significance of differences between demographic groups using a one-way ANOVA test with the demographic factor as the independent variable and block group extreme PM days and person-mean PM exposure as the dependent variables. We weighted by the block group population fraction for each demographic relative to the county population for the demographic.

Extreme Heat

We estimated extreme heat exposure using three metrics: person-extreme heat days, person-extreme warm nights, and person-heat waves.

1. **Average extreme heat days**: Population of a demographic in a census block group multiplied by the number of extreme heat days for that block group. Sum for all census block groups in the county and divide by county population for that demographic.

$$person \cdot extreme\ heat\ days_{demographic} = \frac{sum(block\ group\ population_{demographic}\ \times\ block\ group\ extreme\ heat\ days)}{county\ population_{demographic}}$$

2. **Average extreme warm nights**: Similar to above but using extreme warm nights.
3. **Average heat waves**: Similar to above but using heat waves.

Population Sensitivity

We analyzed five population sensitivity indicators: percentage of outdoor workers, percentage of children under the age of 5, percentage of older adults over the age of 65, percentage of people living in poverty, and CES scores of cumulative population environmental, socioeconomic, and health burdens.

We downloaded block group level data on each indicator, except CES, from the 2018-2022 ACS (US Census Bureau, n.d.). The percentage of outdoor workers was defined as the percentage of employed individuals over the age of 16 employed in outdoor occupations. Following the CDPH's CalBRACE project definition of outdoor workers, we defined outdoor occupations as occupations in farming, fishing, forestry, construction, and extraction (CDPH, 2020). The percentage of people living in poverty was defined as the percentage of individuals living below 200 percent of the FFPL. The percentage of children under the age of 5 was the percentage of people out of the total population under the age of 5. The percentage of older adults over the age of 65 was the percentage of people out of the total population over the age of 65.

We downloaded census tract level CES scores from the California OEHHA's CES 4.0 (OEHHA, 2021). The CES score combines indicators of pollution burden and population characteristics to get a cumulative impact score for each census tract. We then categorized the scores by quartile, in which the 25th percentile and below was low vulnerability, the 25th to 50th percentile was moderate vulnerability, 50th to 75th percentile was high vulnerability, and 75th percentile and higher was very high vulnerability.

Adaptive Capacity

We analyzed two adaptive capacity variables: canopy coverage and houses with AC. We chose these two variables due to available data and interventions.

Canopy coverage refers to the percentage of the census block group with overhead tree canopy. We estimated the average percentage of canopy coverage per census block group using Google Earth Engine and data from United States Department of Agriculture, Forest Service (USDA Forest Service, 2023). Canopy coverage can provide shade to shield people from extreme heat as well as reduce the urban heat island effect.

Houses with AC was the percentage of houses in the census tract with AC. To estimate adoption rates of home AC, we developed a custom probabilistic model that estimates the likelihood of households to adopt AC based on several demographic variables including race, income, renter status, heating fuel type, cooling degree days and home type. Specifically, combinatorial optimization methods were used to identify correlations between these demographic and home attribute variables found in ACS microdata at the Public Use Microdata Areas scale. This approach then builds a household level dataset that matches the tallies found in ACS census tract (2018-2022) survey data. A random forest regression model was then used to estimate the likelihood for each household of AC adoption using Residential Energy Consumption Survey microdata from California. Lastly, these likelihoods were merged with total AC adoption data from the American Housing Survey across California. The results of our survey-based model likely differed from Contra Costa's climate change vulnerability report (Contra Costa Health Services, 2015) due to different modeling assumptions and input data.

Clustering Analysis

Since many interventions can benefit a broader area than individual census block groups, we identified hot spots, or areas with neighboring block groups with relatively high values. these spatial clusters could be used in intervention design to target neighborhoods with a particular sensitivity and limited adaptive capacity. We identified the clusters using LISA (Anselin, 1995, Anselin, 2020). LISA identifies areas with consistently high or low values by computing the similarity of neighboring block groups (i.e., calculating the local Moran's i). It is important to note that if an area lacks a cluster, that does not mean that the area does not face any challenges, but that the area is not high relative to the rest of the county. For example, the entire county experienced heat waves, but the heave-wave clusters are only found in the eastern portion, where the heat exposure was most intense.

computing local spatial autocorrelation

Interventions Literature Review

We built on the statistically significant clusters—or "hot spots"—identified in clustering analysis. Without focusing on any specific geographies identified, we target interventions with potential to mitigate the heightened risks in hot spots and review the potential effectiveness of interventions toward mitigating various risks within these areas. To identify potential interventions for reducing air-quality and heat-exposure risks, we conducted a structured review of peer-reviewed articles, gray literature, and relevant reports (Appendix B). We identified each intervention discussed in the literature and compiled them into a tracking spreadsheet. Interventions were categorized by level/actor: individual home, community-level, city-planning-level, and other, as well as by mechanism and by applicability. We then documented the primary goal or intended outcome of each. Using this approach created a clear and evidence-driven set of potential interventions that we brought to the community listening sessions (detailed in the following section).

Community Listening Session Outreach & Feedback

Over 30 community groups were contacted to participate in the Collecting Community Feedback on Health Risks & Solutions - Listening Session to capture their lived experiences. Community groups were invited based on their work in Contra Costa County focusing on community health and climate risks. This selection process included identifying organizations that work directly with residents who may be impacted by climate-related risks within the scope of the study, such as air pollution and extreme heat. A broad set of criteria was used, including organizations engaged in on the groundwork with impacted communities and those addressing issues such as outdoor worker health, energy equity, and environmental justice. Community groups were compensated with a $100 e-gift card for their participation in the listening session. Only one listening session was held with six community members in attendance, but additional sessions were offered to groups that may need Spanish language accommodations.

The Collecting Community Feedback on Health Risks & Solutions - Listening Session was structured to provide a brief overview of climate vulnerability, interventions, extreme heat exposure and air pollution, followed by reviewing key intervention categories. Interventions were based off of a literature review and organized into categories based on the type of climate exposure (heat vs air pollution) and actor/level (home/personal, vs community/city/state/other): This resulted in eight categories: AC, home improvements, home greening, leveraging existing home resources, greening & green spaces, community infrastructure, home equipment, and outdoor mitigations & structural support (see Table A.M.2).

Table A.M.2. Summary of Interventions and Themes Presented at Community Listening Session. An intervention's location (e.g., in a home, in a neighborhood, etc.) and who is required to take action to facilitate that intervention (e.g., an individual, a city government, etc.) are closely tied and thus referred to as "Actor/Location"

Climate Exposure & Actor/Level	Intervention Category	Intervention Examples
Heat Exposure - Personal/Home	Air Conditioning	Updating AC units, rebates for homes without AC, electricity bill assistance, etc.
Heat Exposure - Personal/Home	Home Improvements	Home repairs, weatherization, solar panels, installing ac for homes without it, etc.
Heat Exposure - Personal/Home	Home Greening	Cool roofs, green roofs, etc.
Heat Exposure - Personal/Home	Leveraging Existing Home Resources	Designated cool home areas, water cooling, etc.
Heat Exposure - Community/City	Greening & Green Spaces	Updating sidewalk & street materials, building shade structures along sidewalks or outdoor work areas, expanding trees and shade in parks, schools, and bus stops, etc.
Heat Exposure - Community/City	Community Infrastructure	Resilience hubs, cooling centers, public water parks
Air Pollution - Personal/Home	Home Equipment	Face masks, air purifiers, creating a "clean" room, portable air cleaners for wildfire smoke days, subsidizing HVAC upgrades with filtration, etc.
Air Pollution - Community/City	Outdoor Mitigations & Structural Support	Face masks, air quality monitoring/maps/notifications, workplace accommodations, wildfire smoke clean air centers, wildfire smoke emergency plans, etc.

For each intervention category, examples were provided for what that type of intervention could look like in application. Additionally, guiding questions were provided to prompt discussion and provide nuance when it comes to the potential effectiveness, challenges, etc. for each intervention category. For each intervention category, participants were prompted to complete a zoom poll with a set of standard questions (see **Table A.M.3**). Participants were also encouraged to unmute and verbally share any personal knowledge or experience, which was recorded and transcribed for reporting purposes.

Table A.M.3. Survey Questions of Community Listening Session. The set of questions were posed for each intervention category.

Survey Question	Answer Options
Do you or your community know about this intervention?	• Myself and my community know about this intervention. • Most of us (you and your community) know about this intervention. • Some of us (you and your community) know about this intervention. • Very few of us (you and your community) know about this intervention. • None of us (you and your community) know about this intervention.
Optional: Please elaborate. Are you or your community more knowledgeable about some intervention examples than others?	Open Text
Is this type of intervention being implemented?	• All interventions are being implemented. • Most of the interventions are being implemented. • Some of the interventions are being implemented. • A few of the interventions are being implemented. • None of the interventions are being implemented.
Have you seen or tried any of these interventions?	• All • Most • Some • Few • None
If you have seen or tried any of these interventions, what were the challenges?	Open Text
How can these interventions be improved?	Open Text
If you haven't seen these interventions, what can be done to make these interventions possible?	Open Text

The Community Outreach and Feedback data consisted of the responses of six community member participants. Survey questions were divided into quantitative and qualitative data responses.

Additionally, for the qualitative analysis, verbal discussions that took place during the listening session were also transcribed and analyzed.

Quantitative survey responses were originally captured in a 5-point Likert scale that was later converted into a 3-point Likert scale (combining all and most, and few and none, resulting in a all to most, some, and few to none answer options). Due to the small sample size, quantitative data was analyzed via descriptive statistics, with no additional statistical analyses performed. Descriptive statistics were compiled for each question, for each intervention category.

Qualitative analysis consisted of reviewing community member responses by intervention category. Due to the nature of the study, and the limited short answer responses, larger themes were not compiled. However, key takeaways from the responses were compiled for each intervention, including from the verbal discussion.

Supplemental Information

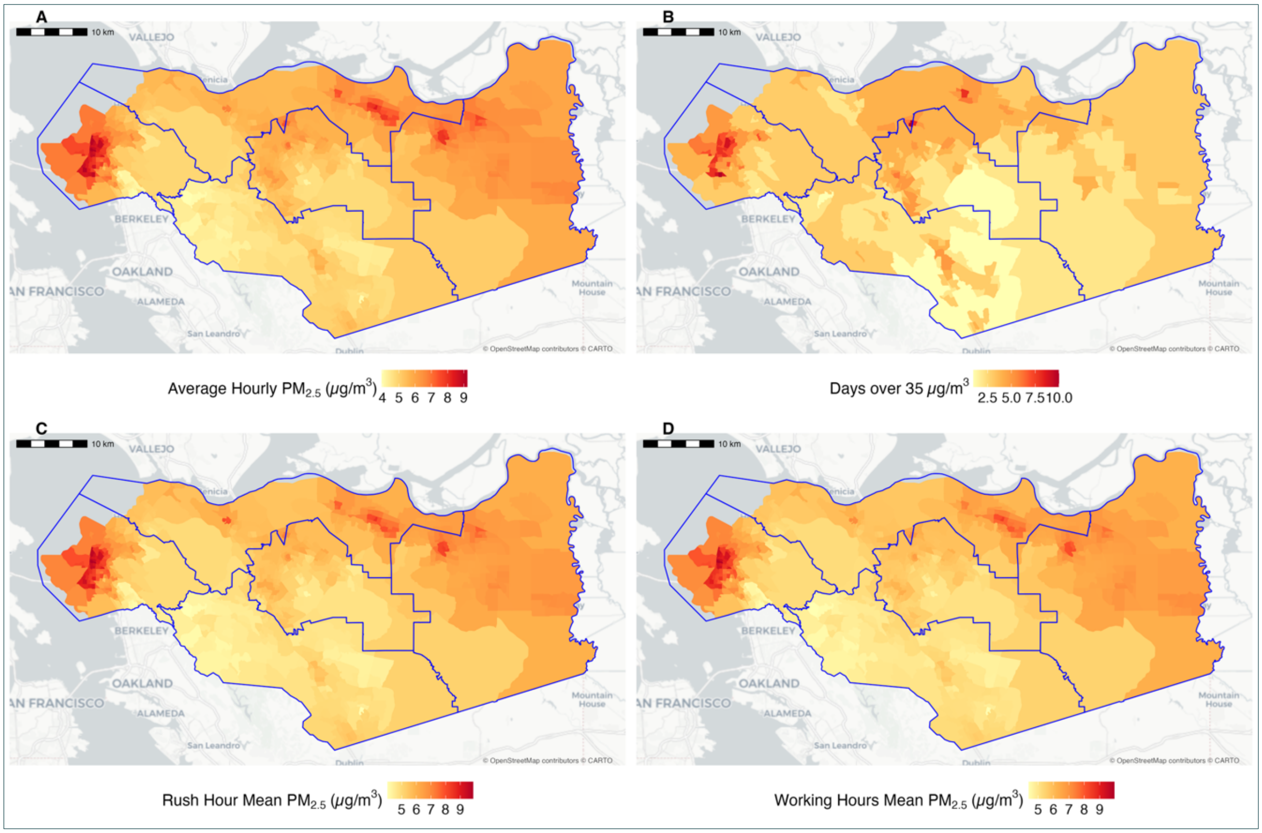

Figure A.S.1. $PM_{2.5}$ exposures across Contra Costa County, September 2023 – May 2025. *Panel A illustrates average hourly concentrations across the study period at the block group and Panel B illustrates the number of days with 24-hour mean $PM_{2.5}$ concentrations above 35 ug/m3, the US EPA NAAQ for daily PM2.5 concentrations, for each block group. Panel C illustrates the average concentration during rush hours (7-9 am and 5-7 pm Monday- Friday) and panel D illustrates the average concentration during working hours (7 am – 7 pm Monday- Friday).*

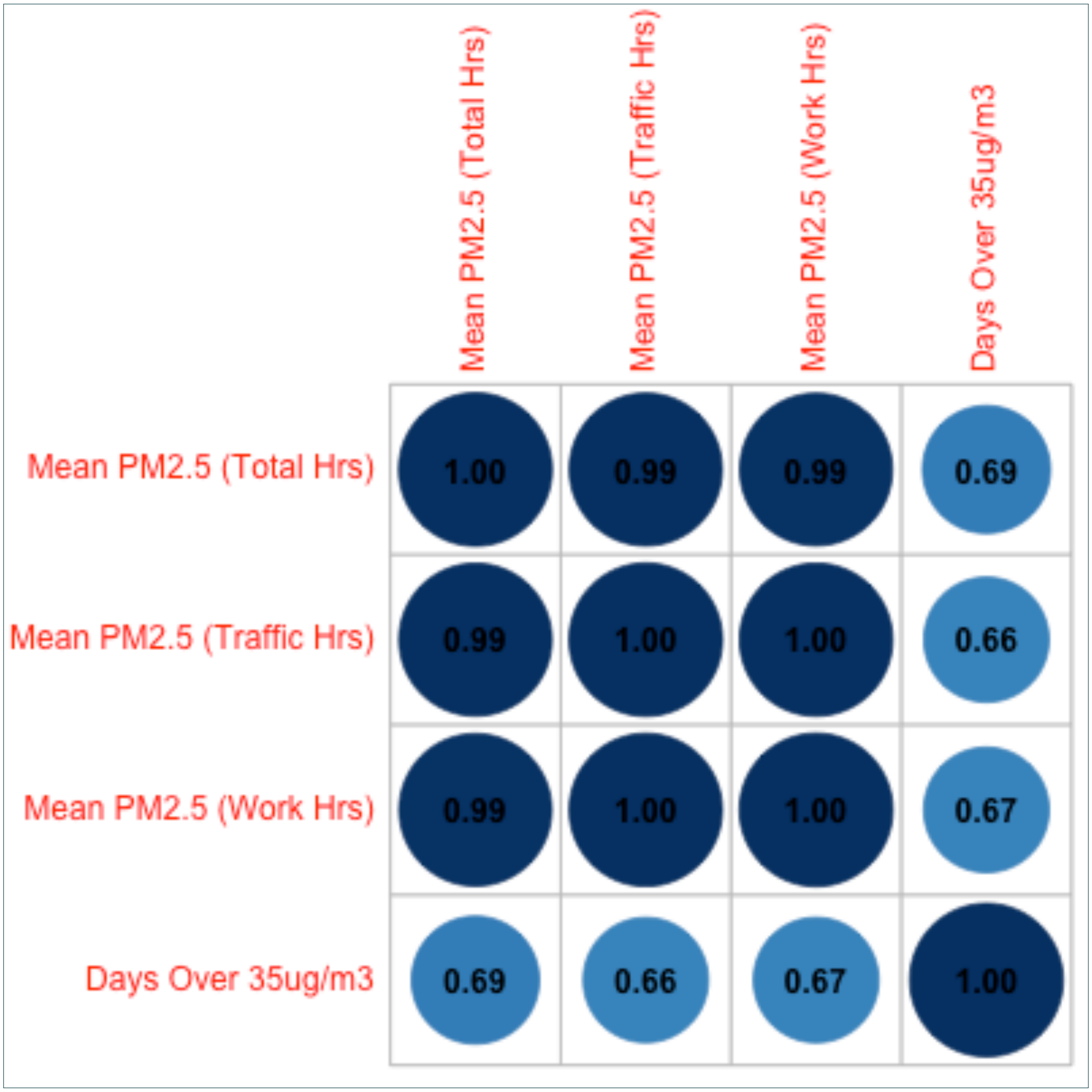

Figure A.S.2. Spearman Rank Correlations of air quality metrics.

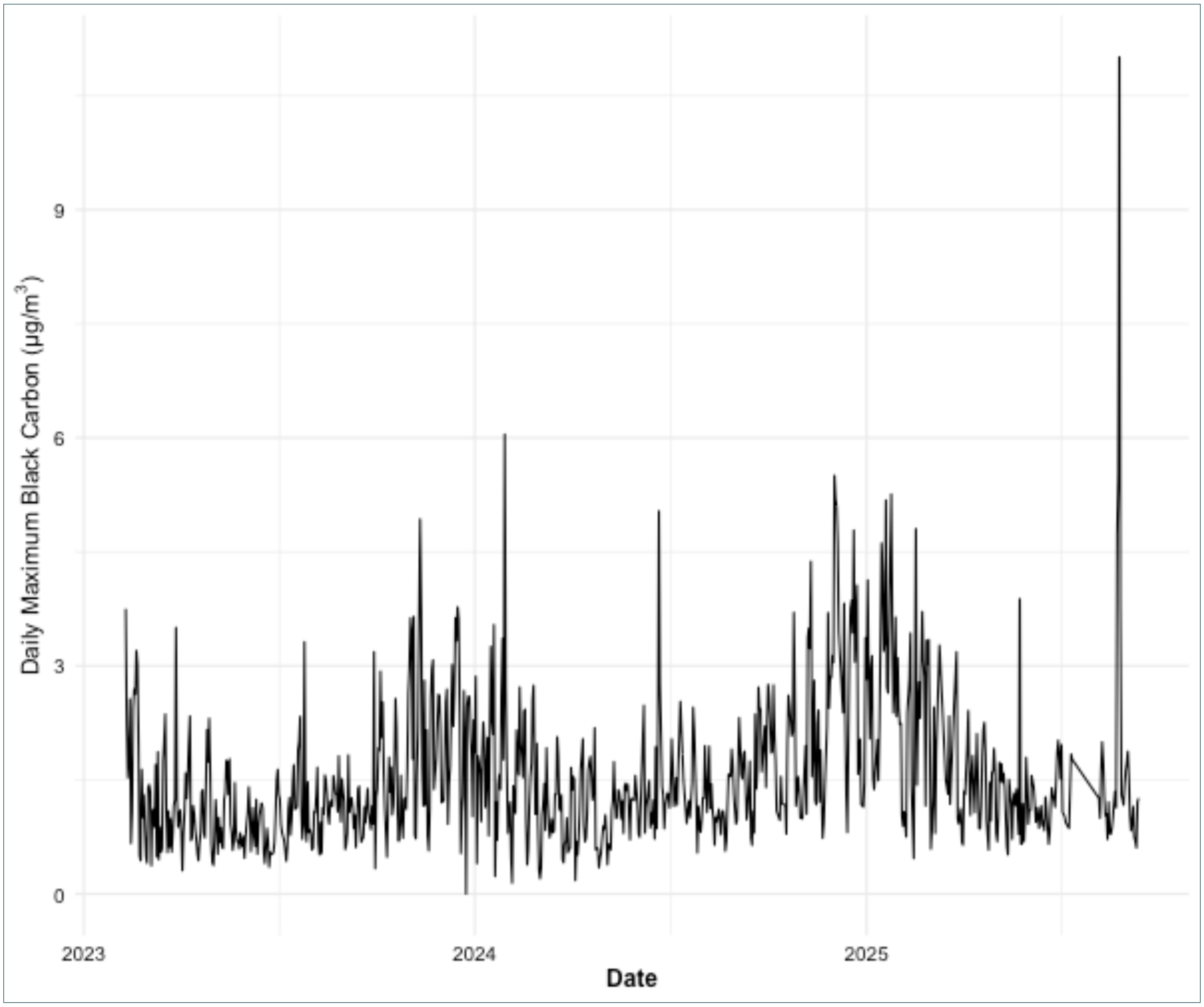

Figure A.S.3. **Maximum black carbon estimates across Contra Costa County.** *BC estimates from the HAQES–Version 1.0 model Makkaroon 2023)*

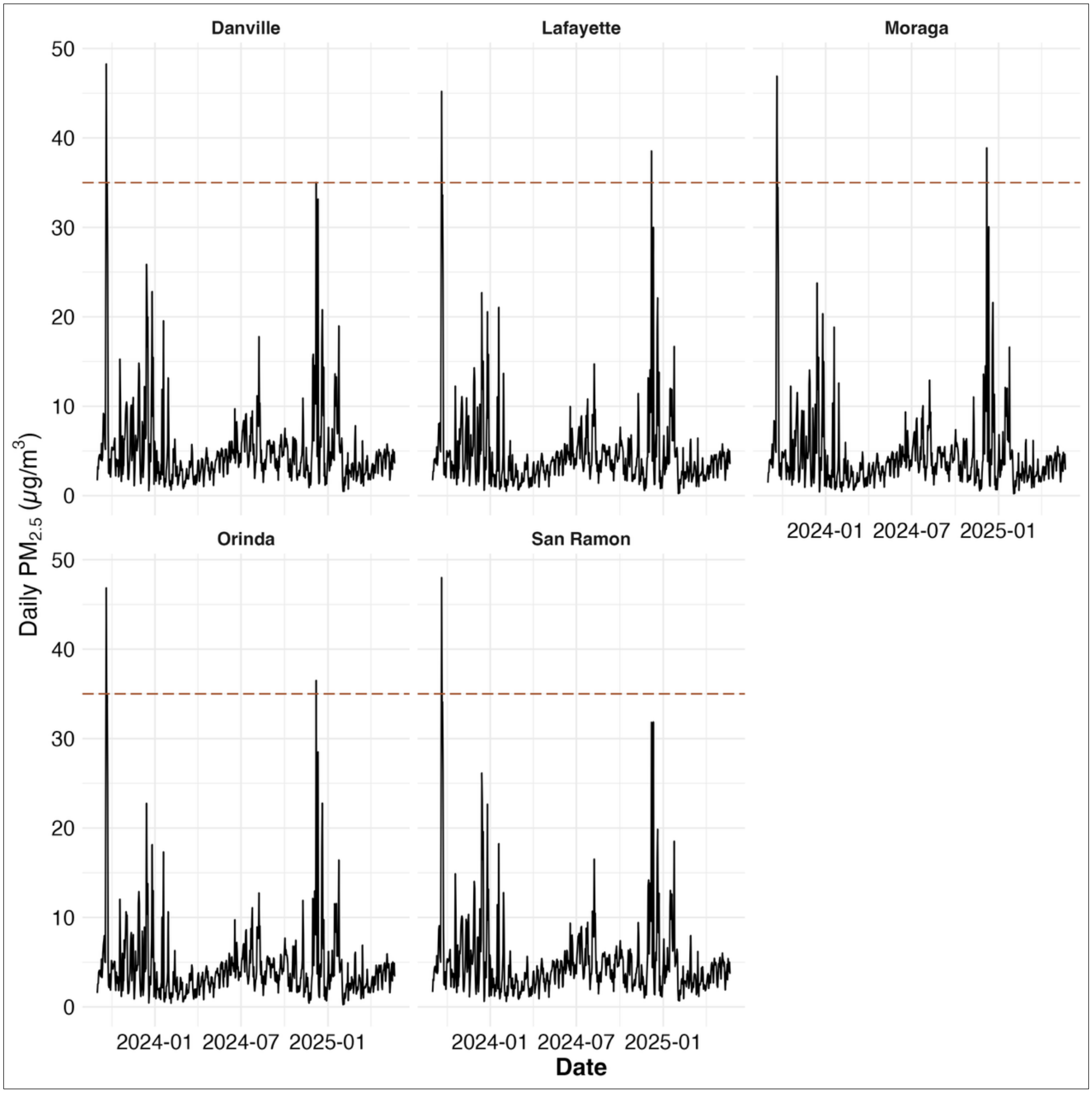

Figure A.S.4 Daily $PM_{2.5}$ exposures within select cities, September 2023 – May 2025. *Hourly $PM_{2.5}$ concentrations were first averaged for each city, via population weighting, and then averaged for each day.*

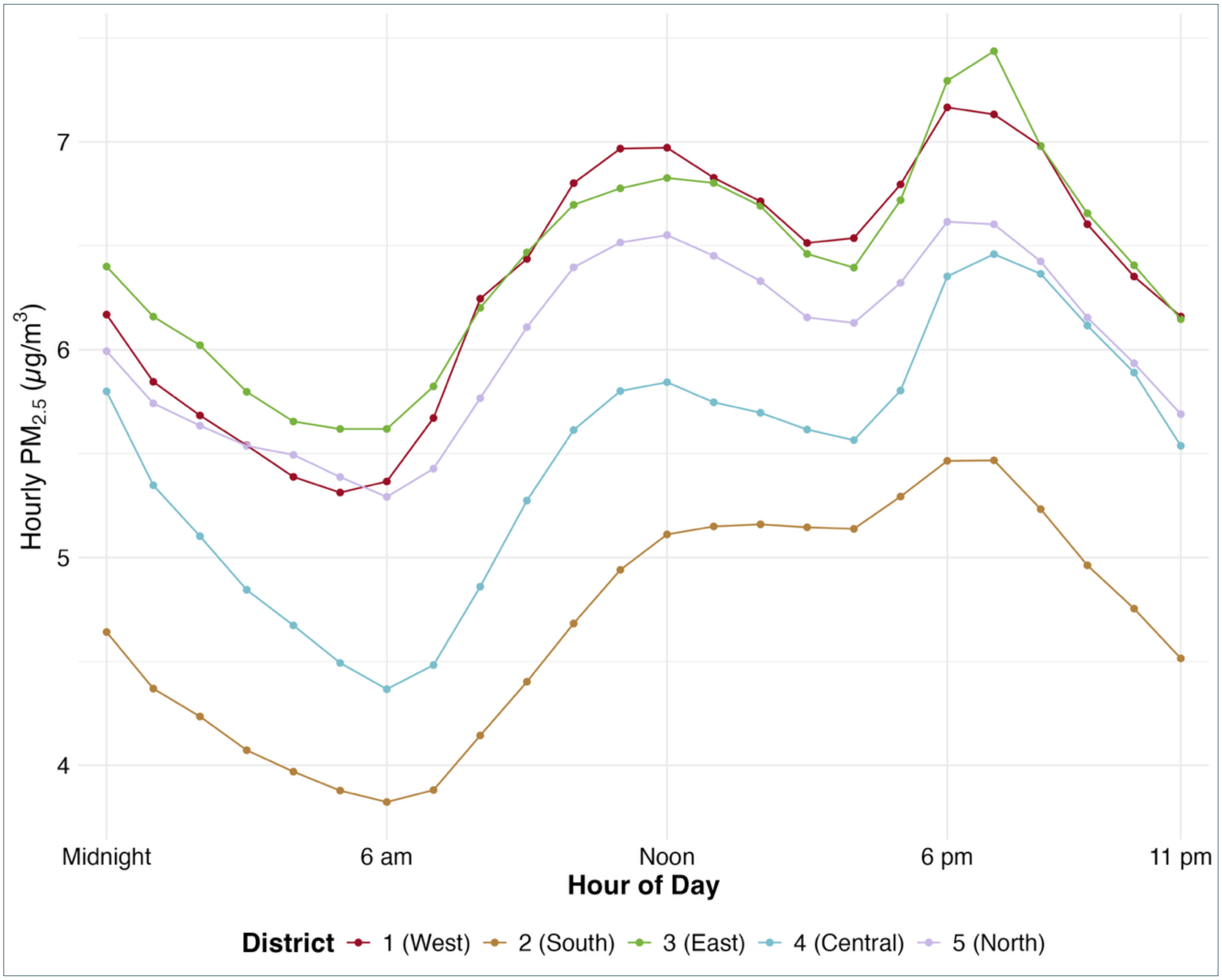

Figure A.S.5. Hourly $PM_{2.5}$ exposures by hour of day and district over the Weekend. *Hourly $PM_{2.5}$ concentrations were first averaged for each district, via population weighting, and then averaged for each hour of the day, for only Saturday and Sunday.*

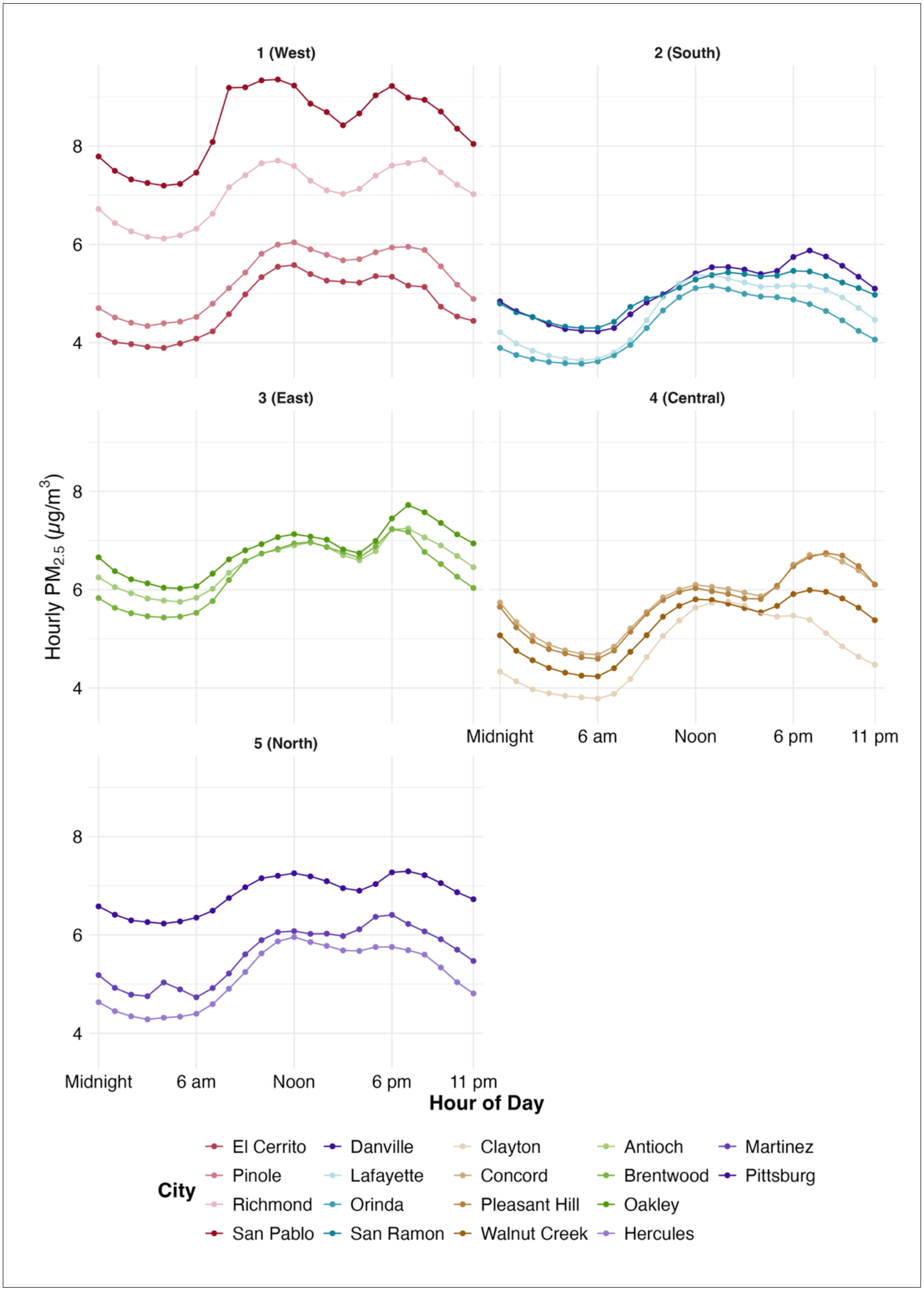

Figure A.S.6. HourlyPM$_{2.5}$ exposures by hour of day and city over the Week. *Hourly PM$_{2.5}$ concentrations were first averaged for each city, via population weighting, and then averaged for each hour of the day.*

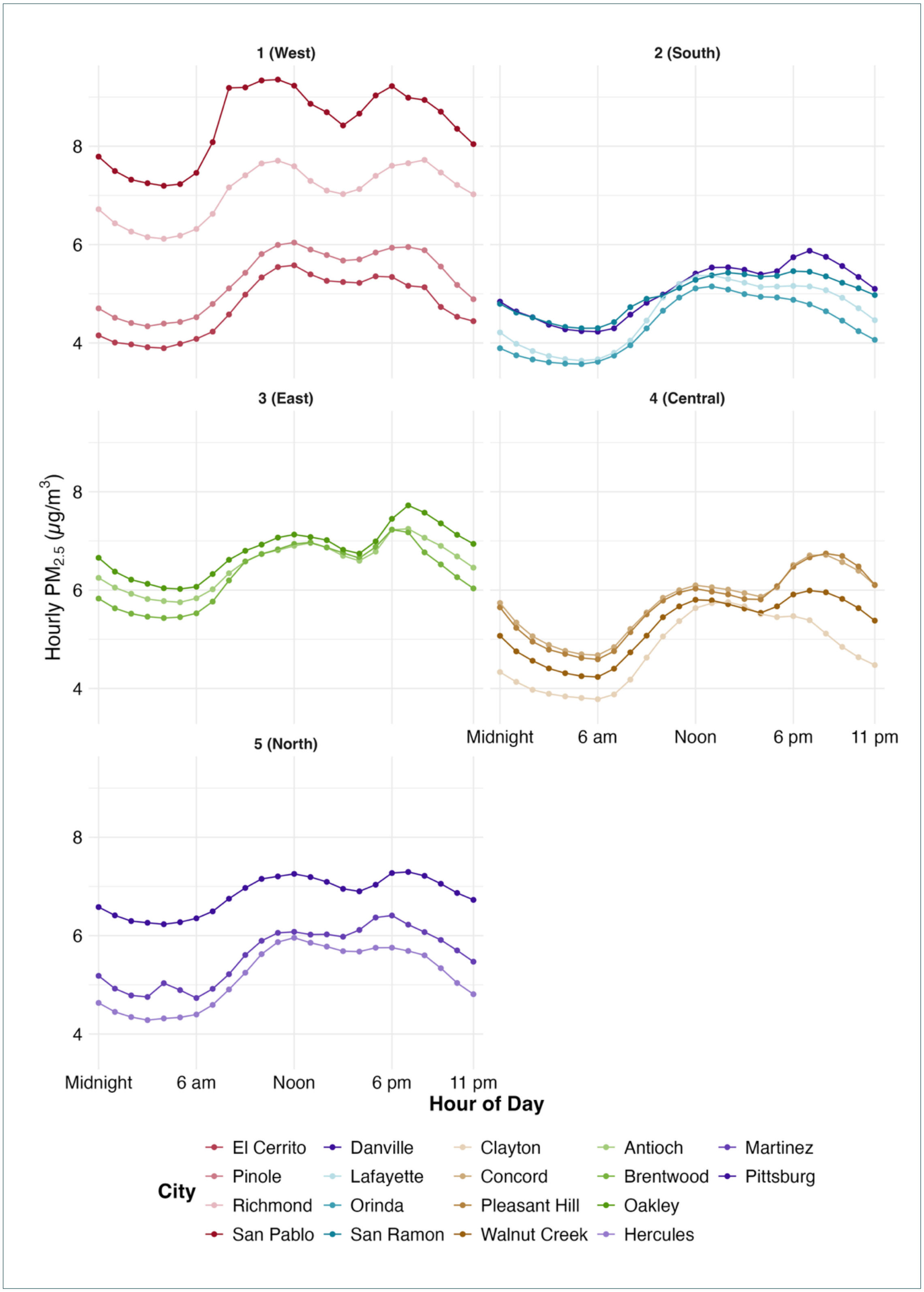

Figure A.S.7 Hourly $PM_{2.5}$ exposures by hour of day and city over the Weekend. *Hourly $PM_{2.5}$ concentrations were first averaged for each city, via population weighting, and then averaged for each hour of the day.*

Table A.S.1. Summary Statistics of Air Pollution Concentrations by District. Concentrations are population-weighted based on census block groups.

District	Average $PM_{2.5}$ Concentration (bootstrap 95 percent Confidence Interval) [µg/m³]	Interquartile Range (µg/m³)	Number of Days with mean concentration > 35 µg/m³	Average daily minimum concentration (µg/m³)	Average daily maximum concentration (µg/m³)	Average change in concentration over the day (µg/m³)
1 (West)	6.67 (6.58, 6.77)	3.38–8.09	5	5.72	7.4	1.68
2 (South)	4.8 (4.72, 4.89)	2.27–5.39	2	4.02	5.39	1.37
3 (East)	6.47 (6.38, 6.56)	3.3–7.04	3	5.67	7.25	1.59
4 (Central)	5.54 (5.45, 5.64)	2.65–5.97	4	4.49	6.45	1.96
5 (North)	6.12 (6.03, 6.22)	3.12–6.81	4	5.42	6.71	1.29

Appendix B - Interventions Literature Review Summary

[Appendix B Interventions Literature Review Summary.pdf]

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