Air Pollution and Asthma Burdens in Contra Costa County: An Environmental Justice Case Study

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The purpose of this study is to assess the extent in which air pollution and asthma disproportionately impact low-income, minority communities in Contra Costa County. As one of the nine San Francisco Bay Area counties, Contra Costa is unique in that it has a wide range of pollution sources, including an industrial corridor, major highways, and pesticide-using farmlands. It is also socioeconomically diverse. This environmental justice study, the first to focus on Contra Costa and its varied sources of air pollution, used the Unit Hazard Coincidence (UHC) methodology to assess to what degree populations living near pollution sources are exposed to anthropogenic air pollutants and have higher rates of asthma. It also examined whether these environmental and health burdens are inequitably borne by minority and poorer communities. ArcGIS Online was used to visualize the spatial relationships between variables whereas regression analysis was used to test the statistical significance of these relationships. Results revealed populations living close to environmental hazards, consisting of mostly poorer Latino and African American populations, had statistically significant higher rates of asthma than other populations throughout Contra Costa. High concentrations of air pollutants, including toxic chemical releases, nitrogen oxide (NO2), diesel particular matter, and particular matter 2.5 (PM 2.5), did not have a statistically significant impact on asthma prevalence. More research is recommended to further understand how other air pollutants or non-environmental factors may contribute to the prevalence of asthma throughout the county.

Introduction

Air pollution has long been identified as a major health risk and is often linked with respiratory diseases such as asthma. In urban areas, the burden of air pollution and its adverse health impact is often disproportionately borne by low-income and minority populations. The San Francisco Bay Area, like other major metropolitan areas, is no exception.

Contra Costa County is the third most populous county in the San Francisco Bay Area with a population of 1.1 million[1]. Its name is Spanish for “opposite coast” and refers to its location on the northern part of the East Bay across from San Francisco. The county has a particularly high level of air pollution compared with other Bay Area counties[2] along with a variety of pollution sources, including industrial plants, major highways, and farmlands with heavy pesticide use. It also has a higher concentration of asthma in several communities and diverse socioeconomic populations. This study aims to understand to what extent low-income and minority communities in Contra Costa might have a disproportionate exposure to air pollution and a higher prevalence of asthma.

Existing environmental justice studies

Many environmental justice (EJ) studies have examined the inequitable burden of air pollution and asthma on disadvantaged communities in various municipalities, but just a handful have focused on the Bay Area and even fewer have focused on the East Bay region. The existing studies that include the East Bay where Contra Costa is located produced noteworthy findings.

One of the major pollution sources in Contra Costa County is the refinery corridor, which includes petrochemical plants along the northern part of the county. A couple of studies have focused on this area and found evidence that a disproportionate number of minorities and low-income communities lived near these facilities[3,4]. The study by Menza also examined the relationship between the level of two pollutants (particulate matter 2.5 (PM 2.5) and sulfur dioxide (SO_2)) and emergency room (ER) admission rates for cardiovascular and respiratory events in this refinery corridor. The results were contrary to the researcher’s hypothesis that a stronger relationship between pollutants and ER visits would exist in communities closer to the industrial sites compared to the rest of Contra Costa County[4]. A possible explanation is that the other areas of Contra Costa may also have had elevated levels of pollution and adverse health events that would have accounted for the lack of difference seen between these two areas. This study addresses this possibility by considering other sources of pollution throughout Contra Costa.

Other studies have focused on the highway pollution in the East Bay, but only in Alameda County, the county directly south of Contra Costa. The study by Lee looked at the impact of a truck ban policy along interstate 580 which diverted a significant number of heavy-duty trucks from predominantly white, wealthier neighborhoods to interstate 880 which passes through West Oakland, a community of poor minorities [5]. This study highlights the possibility that in some cases discriminatory policies are the main cause of environmental injustice. The study also noted that higher concentrations of traffic-related air pollutants (TRAP), including black carbon, nitrous oxide, and nitrogen oxide, and a higher prevalence of asthma were found in communities near I-880 versus I-580. Another study by Kim et al. also found correlations between TRAP and asthma cases near Oakland schools surrounded by busy roads [6].

No known study has examined the impact of pesticide use on pollution and asthma in the East Bay or Contra Costa, but other studies have looked at this relationship in California's Central Valley. In the study by Ortiz et al., it was found that low income and minority communities in the Central Valley were exposed to higher levels of PM 2.5 and had higher asthma rates than wealthier, less diverse communities within the valley [7]. The study by Meng et al. showed that populations living in San Joaquin Valley with higher PM 2.5 and ozone (O3) exposure were more likely to have asthmatic events than populations with lower pollutant levels [8].

This paper is the first known study to assess whether air pollution and asthma disproportionately affects minority and low-income communities in Contra Costa County. This study also took a more holistic approach than previous studies by including multiple potential sources of pollution (including polluting facilities, major highways, and farmlands with heavy pesticide use) and air pollutant types that may contribute to higher levels of asthma. This more comprehensive approach better reflects today's more complex urban environments which typically have multiple pollution factors at play.

Asthma prevalence in Contra Costa

Contra Costa has an average crude asthma prevalence rate of 9% [9], similar to the rest of California, but the rate varies significantly depending on the city or community (see Figure 1). Crude asthma rates in 2021, unadjusted for age, represent the percent of people who answered "yes" to the following two questions in the Centers for Disease Control and Prevention (CDC) 2023 Behavioral Risk Factor Surveillance System (BRFSS) survey: "Have you ever been told by a doctor or other health professional that you had asthma?"and "Do you still have asthma?"In the county, asthma rates ranged from 6.5% to 12.7% across all census tracts [10].

Outdoor air pollution and asthma

While the exact causes of asthma are unknown, prior research has indicated there may be multiple causes. In a 2020 comprehensive review, both indoor and outdoor air pollution were mentioned as potential contributors to the development of asthma and triggers of asthma symptoms [11]. Indoor pollutants linked to asthma include cigarette smoke, molds, and wood- and gas-burning heaters. Asthma-related outdoor pollutants most frequently studied include O3, NO2, CO, SO2 and PM [11].

Industrial plants are known to emit several of these pollutants, including SO2, NO2, CO, and PM, as well as toxic chemicals [3, 12]. Highways and roads emit TRAP resulting from motor vehicle exhaust. These pollutants include a mixture of NO2, PM 2.5, PM 10, and black carbon [5, 6]. Similarly, diesel PM emitted by trucks, buses, trains and other vehicles using diesel engines contains pollutants including CO, NO2, SO2 and PM [13]. Farmlands using pesticides have high concentrations of PM 2.5 and O3 [7, 8].

This study focused on four air pollutants related to industrial plants, highways and farmlands, namely: toxic chemical releases to air, NO2, diesel PM, and PM 2.5. Other pollutants were not included due to lack of data availability or data quality issues, as discussed in the data sources section below.

Primary sources of air pollution

Air pollutants logically stem from sources which release pollutants into the air. Pollution sources examined in this study fall into three categories, as defined by the EPA: point, onroad mobile, and nonpoint sources [14]. These pollution sources are described in more detail below.

Point sources of pollution are those that are at a stationary location and have a high emissions capacity. In Contra Costa, the main point sources of pollution include industrial facilities along the north and west coast, an area commonly referred to as the "Refinery Corridor" (see Figure 2). It consists of five petroleum refineries operated by Chevron, Phillips 66, Shell, Tesoro and Valero, seven fossil fuel power plants, chemical plants, manufacturing plants, and other types of pollution emitting facilities [3]. These areas have been historically zoned for heavy industrial use [15].

Onroad mobile sources refer to emissions from light- and heavy-duty vehicles using gasoline, diesel and other fuels. The major onroad mobile sources of pollution in Contra Costa are its major highways. Contra Costa has two major interstates running north and south (I-80 through the western part of the county and I-680 through the central part), as well as two state highways which run east and west (Route 24 through central Contra Costa and Route 4 in northern Contra Costa along the Refinery Corridor). The volume of traffic varies considerably along these highways and is factored into this study.

Nonpoint sources, unlike point sources which are fixed, originate from diffuse sources, such as from atmospheric deposition and land runoff. Pesticides are considered one type of nonpoint solution and are used with varying degrees on farmlands throughout Contra Costa. Most farmlands in Contra

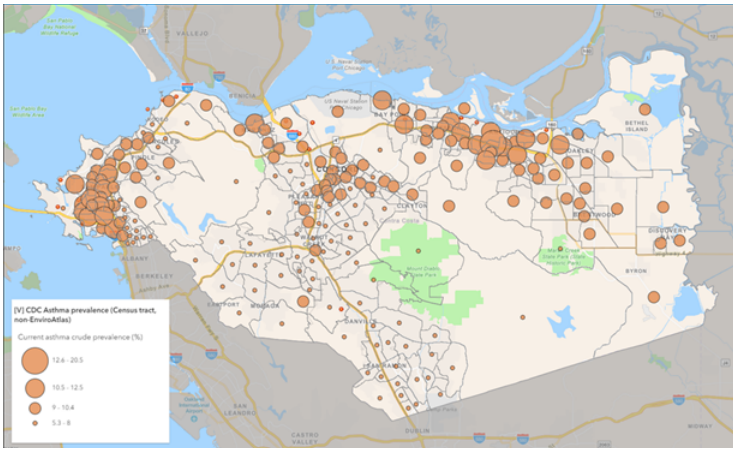


Figure 1. Crude asthma prevalence among adults aged 18 or older in Contra Costa County in 2021 (CDC PLACES: Local Data for Better Health, Census Tract Data, 2023).

Costa are located on the eastern side of the county. The shaded area in Figure 2 represents prime farmland as well as farmland of statewide and local importance[16].

Sociodemographic profile

The geographic scope of this study is Contra Costa County. It is comprised of 717 square miles and encompasses 19 cities as well as numerous unincorporated communities[17]. Contra Costa County was chosen for this study as it has relatively high rates of air pollution and asthma and is socioeconomically diverse[18].

Contra Costa has a mix of races/ethnicities comprised of whites (51%), Hispanics (20%), Asians (16%), African Americans (7%), and other (6%) from 2018-2022[19], but many of its cities are highly segregated (see Figure 3). The cities in central and eastern Contra Costa are predominantly white, whereas cities along the western and northern coasts have a higher concentration of Latinos and African Americans. Asians have the highest concentration in a few cities in the western, northern and southern parts of the county. From an economic perspective, populations in western and northern Contra Costa are generally lower income, whereas populations more inland are wealthier. The county's rising housing costs since the early 2000s have contributed to the higher levels of racial segregation and low-income neighborhoods in recent years[20].

Contra Costa populations are impacted by asthma to varying degrees and live in different proximities to a variety of polluting sources. Given the segregated nature and location of various low-income and minority communities, it is hypothesized that these communities suffer disproportionate burdens of pollution and respiratory health outcomes. The purpose of this study is to uncover to what extent disadvantaged communities might bear a disparate burden of air pollution and asthma in Contra Costa County, taking into account several potential contributing factors.

Methods

The main unit of analysis for this study is the census tract as it is the most granular data available for asthma prevalence, one of the key points of interest in this study. The census tract has also been the standard spatial scale used in EJ studies using GIS[21]. Contra Costa has 242 census tracts total as of 2022[22].

GIS methods

The Unit Hazard Coincidence (UHC) methodology, also referred to as spatial coincidence, was used to assess air pollution exposure and asthma prevalence by low-income, minority communities living near polluting sources. It is a commonly used method in EJ research studies[22, 23]. It involves identifying geographical units (in this case, census tracts) that contain an environmental hazard. Then certain attributes about those tracts (such as pollution exposure, asthma prevalence, and demographics) are compared to these same attributes in tracts that do not contain environmental hazards. This approach allows researchers to assess whether certain populations, by living close to environmental hazards, are more burdened by environmental hazards and their detrimental effects than populations living further away.

This study aimed to identify geographical areas that contained three types of environmental hazards linked to air pollution: industrial facilities, high volume traffic areas, and heavy pesticide use. For each type of hazard, buffer zones were created to identify populations that live close to polluting sources. Populations inside these buffers, hypothetically, should have

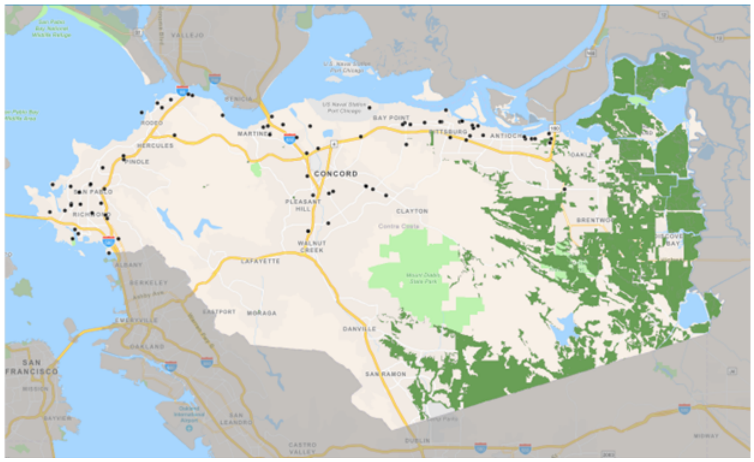


Figure 2. Industrial facilities, major highways, and farmland in Contra Costa County (EPA ICIS-AIR database, California Department of Conservation Farmland Mapping and Monitoring Program).

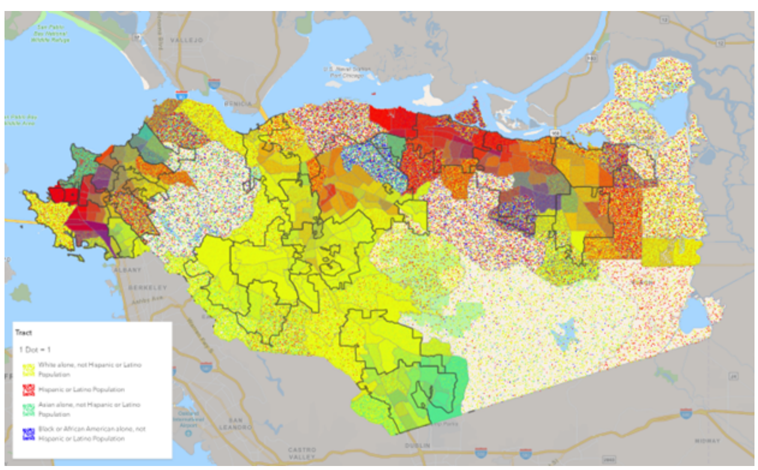


Figure 3. Racial/ethnic communities in Contra Costa County with incorporated cities outlined in black (Census Bureau ACS 2018-2022 5-year Summary, 2023).

greater exposure to pollutants than those outside the buffers. More details on how the buffers were created are given below.

The industrial facility buffer zone was created by identifying census tracts containing air-polluting facilities (see Figure 4a). In most cases, the facilities fell within the census tract boundaries. In some cases, the facility was on the border between two or more census tracts. (Census tract boundaries are sometimes defined by major roads, which happens to be where some facilities are located). For those handful of cases, adjacent census tracts were included in the buffer.

The traffic buffer was created by identifying census tracts that bordered major highways with high daily traffic volumes. The traffic volume and proximity score, explained in more detail below, was the indicator used to define this buffer. As Contra Costa has two highly trafficked interstate highways (I-80 and I-680) and two CA routes (Rte. 24 and Rte. 4), it was important to hone in on just the heaviest trafficked areas that would have the highest amounts of air pollution. While other EJ studies have examined the relationship between TRAP and asthma outcomes, no consistent average annual daily traffic (AADT) and road distance combination was used to define buffers. The U.S. Highway Performance Monitoring System (HPMS), however, uses 75,000 AADT as a threshold for identifying high-volume routes[24]. Since most studies defined buffers ranging from 100 meters to 500 meters from a highway segment, this study selected 750 (daily traffic count/distance to road) as a cutoff to define the traffic buffer (see Figure 4b). It reflects traffic intensities greater than 75,000 AADT within 100 meters and 375,000 AADT within 500 meters.

The pesticides buffer was created by examining tracts with the highest levels of pesticide use. The pesticide data had a natural break in the data around the 50th percentile. Thus, the 50th percentile was chosen as the threshold for creating the pesticides buffer (see Figure 4c). Using a percentile cutoff has been used in at least one other study to define relevant buffer boundaries[3].

Once each individual buffer was created, a buffer combining all three buffer zones was formed (see Figure 4d). For each of the four buffers, statistics on air pollution exposure, asthma prevalence, and socioeconomic characteristics were calculated. The same statistics were calculated for the area outside the buffers. Using this approach, the extent to which populations living within the buffers (e.g., the impacted communities) had a higher environmental and adverse health burden could be determined, along with differences in the socioeconomic makeup of those within and outside of the buffers.

Statistical analyses

To test the statistical significance of the observations from the UHC methodology, a linear regression analysis was conducted. The regression analysis was designed to determine whether the varying levels of asthma prevalence could be explained by environmental, socioeconomic, and demographic factors. The results would be able to show, for example, whether low-income minority communities living close to environmental hazards with higher air pollution exposure suffer higher asthma rates compared with communities with an opposite profile. Asthma prevalence was used as the dependent variable. Independent variables included: proximity to environmental hazards, air pollution concentration, race/ethnicity of impacted communities, and low-income levels. Independent variables were chosen based on their potential impact on asthma prevalence, as described in more detail below.

Proximity to environmental hazards: Living close to a pollution source has been the focus of other studies examining the links between pollution and asthma[4, 12]. Census tracts that fall within the three buffers defined above are considered the areas close to environmental hazards.

Air pollution concentration: This variable was included due to its established link with respiratory conditions, including asthma. Multiple studies have shown that higher levels of air pollutants, including toxic chemical releases, NO2, diesel PM, and PM 2.5, are associated with increased asthma risks[3, 6, 7, 11].

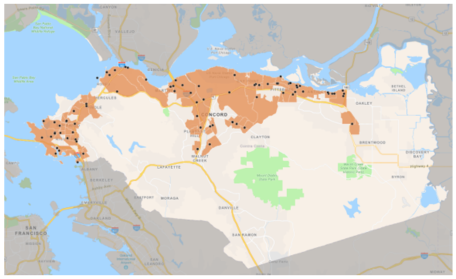
Low-income levels: This variable was selected as it represents potentially multiple factors that could make populations more susceptible to asthma, including poorer housing conditions that may expose residents to mold and pest infestations as well as less access to quality healthcare for managing respiratory symptoms. Lower-income populations are often concentrated in areas close to pollution sources due to lower housing costs in these areas[25].

Race/Ethnicity: This is another variable that captures several underlying factors that may contribute to asthma. Structural racism has been shown to impact socioeconomic status, access to quality healthcare, and the physical environment where people live, factors which have been linked to asthma prevalence[25].

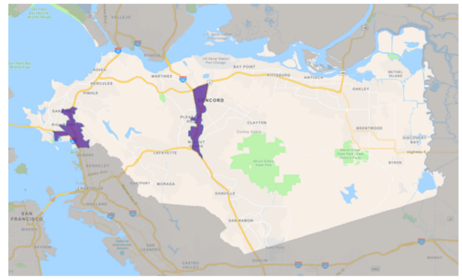
Since this study leveraged the most recent data available centered around the year 2020, which coincided with the COVID-19 pandemic when highway traffic and TRAP were lower, it was important to investigate whether the results were stable and applicable under normal conditions. To test the model's stability, an analysis of covariance (ANCOVA) test was conducted to compare two regressions anchored on the years 2020 and 2019. The results would show whether the two regression results are significantly different in terms of intercept and slope. The methodology used to create the 2020-based regression model was used for the 2019-based model.

Visualization and analytical tools

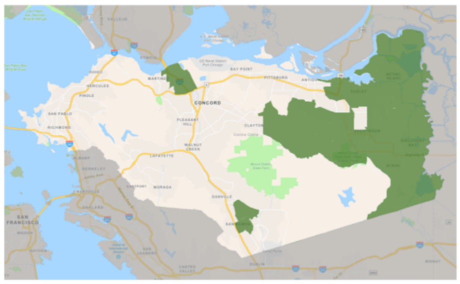
ArcGIS Online was used to visualize the data, create the buffers, and run the statistics for both inside and outside of the buffers. It was also used to create the graphics for this study. Microsoft Excel was used to conduct the regression analysis and XLSTAT



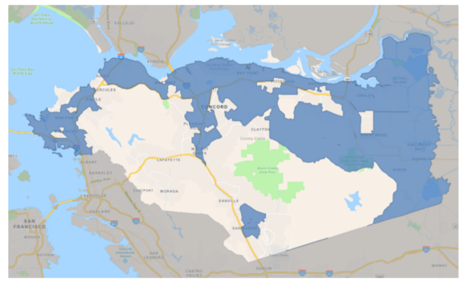
a. Facilities buffer



b. Traffic volume and proximity buffer



c. Pesticide use buffer



d. Combined buffer

Figure 4. Buffer zones created around a) facilities, b) traffic and c) pesticides, plus the d) combined buffer zone.

was used to conduct the ANCOVA test.

Data sources

Once the relevant buffers were created, statistics characterizing the pollution levels, demographics, and health outcomes from inside and outside the buffers were compared. This study leveraged data primarily from three sources: the US Environmental Protection Agency (EPA), the US Census Bureau (USCB), and the US Center for Disease Control and Prevention (CDC). The most recent data available was used and anchored on the year 2020, and in some cases represented a year or two earlier or later. In all cases, data was pulled for the closest possible dates to 2020. Environmental data were retrieved via the EJ Screen tool 2.3 (released in July 2024) rather than CalEnviroScreen 4.0 (released in Oct 2021) unless otherwise noted. Original data sources are described in the sections below.

As briefly mentioned earlier, the start of the COVID-19 pandemic occurred in early 2020 and traffic and TRAP-related data were lower than usual in 2020. An ANCOVA test was conducted to determine if the variables influenced by traffic volume and TRAP-related air pollution had a significant impact on the results compared with the preceding year. EJ Screen 2.2 was used as the primary source for 2019 data. Relevant 2019 data were also retrieved from the USCB and CDC to support the ANCOVA test.

Environmental hazard locations

Three data sources were used to identify the location of point, onroad mobile, and nonpoint pollution sources. These are described in more detail below.

The locations of point sources of air pollution (including refineries, industrial plants, etc.) were identified using the EPA Integrated Compliance Information System AIR database (ICIS-AIR)[26]. These facilities are regulated by the EPA, state, and local air pollution agencies and are monitored for compliance with various regulations under the Clean Air Act. Eighty-one facilities in Contra Costa were being monitored for air pollution in 2019 and were included in this study.

Mobile sources of pollution are the traffic on major highways throughout Contra Costa; areas closest to highways with higher traffic volume are most impacted by air pollution. The traffic volume and proximity score is one of the indicators in the EPA EJ Screen tool and is derived from the 2020 HPMS. It was included in this study since residential proximity to traffic has been associated with adverse health impacts, including asthma exacerbation and possibly asthma onset. The score is calculated by taking the count of motor vehicles (e.g., AADT) at major roads within 500 meters, divided by distance in meters from the census block centers.

Nonpoint pollution sources (in this case, pesticide use) came from the California Department of Pesticide Regulation (DPR) and were retrieved through CalEnviroScreen 4.0[27]. The pesticide indicator reflects the average amount of 132 pesticide ingredients (in pounds) used in agricultural production per square mile, from 2017 to 2019. Census tracts with high usage of pesticides were used to identify concentrations of nonpoint pollution sources.

Air pollutant data

For air emission data, this study examined four types of pollutants: toxic releases to air from stationary facilities, diesel PM, NO2, and PM 2.5. Prior research has shown that exposure to these air pollutants is correlated with asthma prevalence and events, as noted earlier.

The toxic releases to air indicator captures the concentration and toxicities of certain chemicals emitted from facilities in the EPA's Toxic Release Inventory (TRI) program in 2021. These facilities are a subset of the ICIS-AIR facilities and are the largest polluters. The air dispersion of these chemicals is estimated using the EPA's Risk-Scoring Environmental Indicators (RSEI) model which considers factors such as weather patterns, facilities' stack height, and pollutant decay rate to estimate the travel path of these pollutants[28].

Diesel PM data is from the EPA Office of Air Quality Planning and Standards' (OAQPS) AirToxScreen tool. Block group-level source data from 2020 was aggregated into census tracts. This indicator is the estimated concentration of diesel PM in the air, measured in micrograms per cubic meter ($\mu g/m3$).

NO2 data is from NASA's Health and Air Quality Applied Sciences Team (HAQAST). Similar to diesel PM data, block group-level source data from 2020 was aggregated to census tracts. This indicator represents average annual NO2 levels expressed as part per billion.

PM 2.5 is from the EPA OAQPS. The tract-level data is from 2020. This indicator measures the potential exposure to inhalable particles that are 2.5 micrometers or smaller and reflects the annual average PM 2.5 levels, measured in micrograms per cubic meter. PM 2.5 is known to originate from anthropogenic emissions, such as fuel combustion, vehicle exhaust emissions, and pesticides, as well as natural sources, such as pollen, fires, and volcanic eruptions.

For this study, the percentiles for each emission were used, rather than the raw values, as a way to normalize and more easily compare data across all emission types.

While O3 is another air pollutant linked to asthma, it was not included in the study as only a few monitors throughout Contra Costa are used to collect that data and are not granular enough to capture accurate data at the census tract level[29]. Data on SO2, another known pollutant linked to asthma, was not available on a census tract basis and therefore was not included in this study.

Asthma prevalence

Similar to other studies, the health outcome selected for this study was asthma prevalence in order to capture the magnitude of the asthma problem[25,30]. While asthma hospitalization and emergency room visits were also options, those measures generally only correspond to the most severe cases. The prevalence of asthma came from the 2023 CDC PLACES health database for small areas across the US. It shows asthma prevalence among adults aged 18 or older in 2021 and is available at the census tract level.

Socioeconomic data

All socioeconomic data used in this study were from the Census Bureau's American Community Survey (ACS) 2018-2022 5-year Summary[9]. Three core measures were used: people of color, low income, and a demographic index. Definitions of these measures are consistent with those used by EPA EJScreen. All data was available at the census block level but aggregated to the census tract level.

People of color represent individuals who list their racial status as non-white and/or list their ethnicity as Hispanic or Latino. Non-white races include Blacks or African Americans, Asians, Native Hawaiians or other Pacific Islanders, or American Indians or Native Alaskans. People of any race can identify as Hispanic. In addition to the aggregate people of color metric, major race/ethnic groups by census tract were analyzed.

Low-income represents households with income less than or equal to twice the federal poverty level. In 2022, the low-income threshold was $59,000, which was two times the $29,950 poverty level defined by the Census Bureau for that year[22]. Any household below this threshold would be categorized as low income in this study.

The demographic index is used by the EPA in its EJ Screen tool and is intended to reflect the vulnerability of certain communities based on income level and people of color. It is derived by taking the average of the percent of low income and percent of people of color for a census tract. A high demographic index score represents a census tract with a high percentage of poor minorities and is generally considered a disadvantaged community. A low demographic score represents census tracts with predominantly wealthy, white residents.

Results

The buffers created by the methodology highlighted several noteworthy insights about the population densities in Contra Costa. First, the consolidated inside buffer accounted for nearly half of the square mileage of Contra Costa and nearly half of the total population (see Table 1). However, the population per square mile across the various buffers varied greatly. The traffic buffer, which accounts for just 2% of the total square miles in the county is home to 10% of the population, producing an average population per square mile of 6,923. Contrast that segment with the pesticides buffer which claims 30% of the county in square miles, yet just accounts for 15% of the population. The facilities buffer also has a relatively dense population, with around 31% of the population living in 17% of the square mile area. As a way of comparison, the outside buffer includes roughly half of the population and area. These results underscore the fact that impacted communities tend to have more high-density populations, except for rural communities (such as those within the pesticides buffer) which are lower density.

Data visualization

Overlaying the pollution data layers uncovered several additional insights. The heaviest concentrations of air pollutants generally fell within the inside buffer but were concentrated in areas close to their primary pollution source (see Figure 5). Toxic releases to air, for example, were most concentrated in areas surrounding air-polluting facilities in the western and the northern parts of the county (Figure 5a). Diesel PM was heavily concentrated in the census tracts within the traffic buffer, but also stretched further north along I-80 in western Contra Costa (Figure 5b). Lower concentrations of diesel PM appeared along Rte. 4, Rte. 24 and southern parts of I-680 as well. NO2, which is emitted by both industrial facilities and road traffic, was highly concentrated in both the facility and traffic buffers (Figure 5c). While more dispersed throughout the county than other pollutants, PM 2.5 was most heavily concentrated inside the pesticides buffer in the eastern side of Contra Costa (Figure 5d). PM 2.5 was less present in the western region where industrial plants and major highways are located. This was surprising since PM 2.5 is known to originate from the fuel combustion of plants and vehicle exhaust. Based on these observed PM 2.5 concentrations, however, it is plausible that agricultural activity emits greater PM 2.5 emissions than the other sources in this study, and that these PM 2.5 emissions can result from not only from heavy pesticide use, but other agricultural practices, including soil tillage, fertilizer and manure distribution, harvesting, and burning of crop residues[31]. This correlation between heavy PM 2.5 emissions and agricultural activity is also supported by the extremely high concentrations of PM 2.5 seen in California's agricultural-focused Central Valley.

If one visually combines the darkest shaded regions in each of the maps in 5a through 5d, a certain geographic pattern emerges. This pattern largely corresponds to the combined buffer defined above and suggests that populations inside the buffer are exposed to the heaviest concentration of pollution within the county.

The socioeconomic and asthma data overlays had a more striking correlation than the pollution overlays. Both the low-income and people of color overlays mostly fell within the combined inner buffer (see Figures 6a and 6b). The socioeconomic buffer overlay confirmed that poorer minority populations were within the defined combined buffer (see Figure 6c). The asthma overlay was primarily within the combined buffer but had a few false positives and false negatives (see Figure 6d). A few false positives occurred where a high asthma prevalence did not exist inside the buffer (such as in San Ramon and Danville in southern Contra Costa) and false negatives where high asthma prevalence was not captured in a handful of census tracts throughout the outside buffer. Most of the false negatives occurred in census districts surrounded by other census districts of high asthma prevalence, suggesting that the impact of borderline sources of pollution had a more far-reaching impact than just within its census borders.

The above visualization exercise provided an initial understanding of the underlying prevalence of air pollution and asthma within socioeconomically disadvantaged communities. The spatial coincidence analysis below aimed to estimate the magnitude of the differences between inside and outside of the buffers.

UHC/Spatial coincidence results

The statistical comparison of average pollution and socioeconomic values inside and outside of the buffer confirmed some of the earlier observations (see Table 2). For example, populations within the inner buffer, which were closest to the polluting sources, in general had a higher exposure to air pollutants than populations outside the buffer. These differences, however, were most pronounced in areas where a certain air pollutant was near its primary polluting source. Toxic chemical releases to air, for instance, were the highest in areas closest to air polluting facilities in both the facilities and traffic buffers. (Note: 6 of the 8 of the polluting facilities that happen to fall in the traffic buffer were in western Contra Costa where concentrations of air toxic releases were the heaviest.) Similar observations can be drawn between other pollutants and their primary pollution source in each of the three buffers.

What the statistical comparison does not reflect well is the variation of pollutants throughout the buffers. As seen through the data visualization above, air pollution concentrations vary substantially through each inside buffer and often spill into the outside buffer, especially in the case of toxic chemical releases and PM2.5. Only the heaviest concentrations of air pollutants were consistently within the inside buffer.

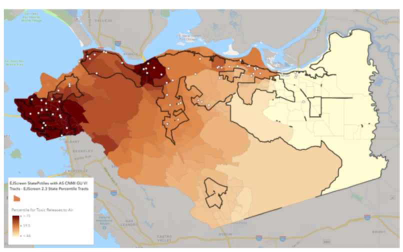
In terms of health outcomes, the inside buffer had an average asthma prevalence of 9.24%, roughly a half percent higher than outside the buffer at 8.69% (Table 3). In percentile terms, the difference in asthma prevalence between inside and outside the buffer is more pronounced at the 38th percentile vs. 19th percentile, respectively.

Socioeconomic indicators showed a similar contrast (see

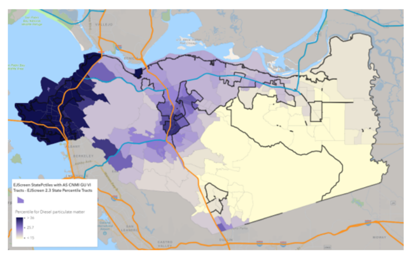
Table 1. Buffer geographical and population characteristics.

	Geography		Population		
Buffer type	**Area (square miles)**	**Area (%)***	**Total population (count)**	**Total population (%)**	**Population per square mile**
Inside	338	46	547,567	48	1,621
Facilities	126	17	346,706	31	2,748
Traffic	16	2	108,306	10	6,923
Pesticides	219	30	173,625	15	791
Outside	400	54	585,212	52	1,462

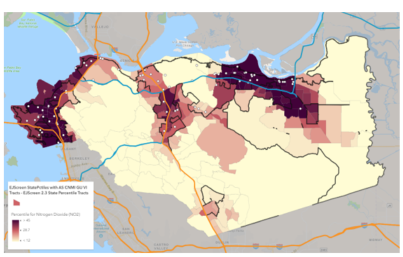
*Note: The sum of percentages for the three inside buffers is slightly higher than the inside buffer percent due to a slight overlap of territories among the inside buffers.



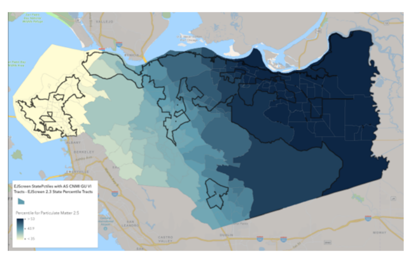
a. Toxic Release to Air shown with Industrial Facilities (white dots)



b. Diesel PM shown with Major Highways (colored lines)

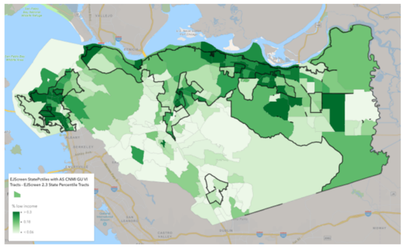


c. NO2 shown with Industrial Facilities (white dots) & Highways (colored lines)

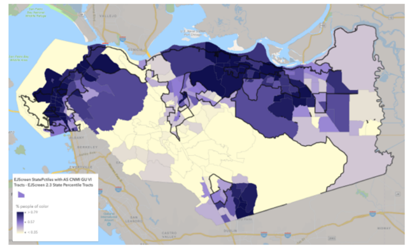


d. PM 2.5

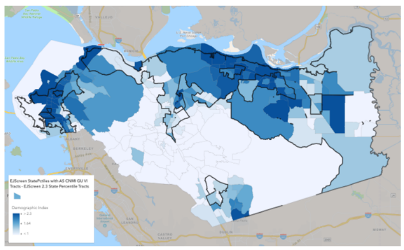
Figure 5. Air pollution concentrations in 2020/2021 overlayed by the combined buffer boundary (EPA EJScreen 2.3 State Percentile Tracts, 2024).



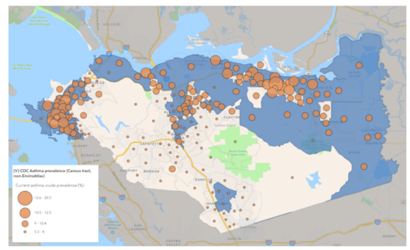
a. Low income percent



b. People of color percent



c. Demographic index percent



d. Asthma prevalence percent

Figure 6. Socioeconomic indicators (2018 - 2022) and asthma prevalence (2021) in Contra Costa, overlayed by the combined buffer (EPA EJScreen 2.3 State Percentile Tracts, 2024; CDC PLACES: Local Data for Better Health, Census Tract Data, 2023).

Table 2. Air pollution sources and emission percentiles for Contra Costa County.

	Pollution sources			**Air pollutants**			
Buffer type	**Facilities (count)**	**Traffic proximity (percentile)**	**Pesticide use (percentile)**	**Toxic releases to air (percentile)**	**Diesel PM (percentile)**	**NO2 (percentile)**	**PM 2.5 (percentile)**
Inside	81	20	47	46	18	17	50
Facilities	81	35	12	57	24	26	39
Traffic	8	68	14	76	36	46	37
Pesticides	14	11	68	39	15	11	56
Outside	0	28	19	55	18	10	45

Table 3). The percent of low-income individuals was nearly twice as high inside the combined buffer as outside (18% vs. 10%). A higher concentration of minorities lived inside the buffer than outside (58% vs. 42%). It is also worth noting the more detailed ethnic/racial differences between the buffers. Both Hispanics and African Americans had a much higher concentration inside the buffer, whereas both whites and Asians had higher concentrations outside the buffer. These results implied that primarily Hispanics and African Americans bore most of the pollution and asthma burdens, given their closer proximity to pollution sources. Based on these results, the impact on Hispanic and African American populations were modeled in the regression analysis.

The regression coefficients produced some interesting observations. The intercept value can be interpreted as the baseline asthma prevalence rate of 7.96% that would result if a census tract was not near any environmental hazard, had no Hispanic, African, or low-income populations, and had no air pollution exposure. Living near an environmental hazard alone would boost the predicted asthma rate value by 0.31% to 8.27%. This percentage increase implies that approximately 1,300 more people, or 0.31% of the adult population living within the inside buffer, would suffer from asthma as a result of living near pollution sources. If the census tract had a 10% Hispanic and African American population and a 10% low-income population, the predicted asthma rate would increase by approximately 0.20% and 0.30%, respectively, due to these factors. Given these input value assumptions, the predicted asthma value would be 8.76%, or 0.8% higher than the baseline value.

Applying the regression results to two census tracts in different regions of Contra Costa illustrates some of the disparities throughout the county. The first tract in Walnut Creek is in the central part of the county, and the second tract is in Richmond in the western region. See Figure 2 for a more precise location of these two cites.

Census tract 6013355302 in Walnut Creek is not located near any specified environmental hazard and is not exposed to heavy levels of air pollution. Six percent of its population is either Hispanic or African American, and 6% are considered low income. After applying the coefficients above, the predicted asthma prevalence for the tract resulted in 8.25% (vs. an 8.30% actual value).

Census tract 6013376000 in Richmond is near an environmental hazard and is exposed to poor air quality. Eighty-six percent of its population is either Hispanic or African American, and 48% qualify as low-income. Its predicted asthma prevalence is 11.41% (vs. 11.30% actual value).

The notable contrast above illustrates the degree to which poorer, Hispanic and African American communities in Contra Costa County are exposed to environmental hazards and air pollution and suffer from higher asthma rates compared with communities with an opposite profile. In general, communities along the western, northern and eastern sides of Contra Costa, all of which have higher concentrations of less wealthy Hispanics and African Americans, suffer a greater burden of air pollution and asthma than in the rest of the county.

ANCOVA results

To test whether the regression results above were stable between COVID and pre-COVID times, an ANCOVA test was conducted to see if the regression results centered on 2020 data were statistically different than regression results centered around 2019. Table 5 shows the result of that test. In short, the ANCOVA results showed that that the intercept and slope coefficients were stable between 2019 and 2020; specifically, the intercept and slope coefficients for all variables (except the air pollution concentration variable) were found to be statistically significant, while the coefficient for the categorical 2019 base year variable was insignificant, meaning the regression results based on 2019 were not statistically different than those based on 2020.

Discussion

The above analyses produced several insights about the asthma and pollution burdens borne by populations living near polluting sources in Contra Costa. First, populations within the inner buffer, who lived closer to environmental hazards, in general had higher levels of asthma than populations outside the buffer. The regression analysis results indicated that proximity to these environmental hazards alone increased the predicted asthma rate by 0.30% from a baseline rate of 7.96%.

Second, populations living near environmental hazards had higher concentrations of minorities and were socioeconomically disadvantaged. Latinos and African Americans made up 39% of the population within the inside buffer, compared with 16% outside of the buffer. Low-income households made up 18% of the population within the inside buffer, compared with 10% outside the buffer. The percent of Hispanic and African Americans and the percent of low-income households were both found to have a positive and statistically significant relationship with the asthma prevalence rate across all census tracts. These results potentially reflect several underlying factors that may make low-income and minority populations more susceptible to asthma, including older housing conditions, indoor air pollutants, and less access to healthcare.

Third, air pollution concentration was not a significant determinant of asthma prevalence. This result potentially reflects the greater dispersion of air pollution from pollution sources as observed earlier; the pollutant indicators, while concentrated within the inside buffer, spilled outside the buffer to a greater degree than the socioeconomic and race/ethnicity factors and appeared to be less correlated with asthma rates. It is also

Table 3. Asthma prevalence and demographic profiles inside and outside the buffers.

	Health		Sociodemographics					
Buffer type	**Asthma prevalence (percent)**	**Asthma prevalence (percentile)**	**Low income (percent)**	**People of color (percent)**	**White (percent)**	**Hispanic (percent)**	**Asian (percent)**	**African American (percent)**
Inside	9.24	38	18	58	42	29	13	10
Facilities	8.74	21	19	66	34	31	17	12
Traffic	9.08	34	22	60	40	26	17	11
Pesticides	9.48	48	17	53	47	29	10	9
Outside	8.69	19	10	42	58	12	19	4

Table 4. Regression analysis results: association between asthma prevalence and proximity to environmental hazards, socioeconomic factors, and air pollutants.

Variable	Coefficient	P-value
Intercept	7.958445	< .001
Hazard proximity	0.30719	< .001
Hispanic & black (%)	1.988553	< .001
Low income (%)	2.940347	< .001
Air pollution concentration	0.023196	0.778

Regression statistics	
Multiple R	0.889808
R square	0.791758
Adjusted R square	0.786859
Standard error	0.461348

Table 5. Analysis of Covariance (ANCOVA) XLSTAT results: comparing two regression results centered around 2020 and 2019. Dependent variable is crude asthma prevalence.

Variable	Coefficient	Pr > |t|	p-values signification codes*
Intercept	7.966	**<0.0001**	***
Hazard proximity	0.266	**<0.0001**	***
Hispanic & black (%)	1.978	**<0.0001**	***
Low income (%)	2.988	**<0.0001**	***
Air pollution concentration	-0.002	0.784	°
Base year 2019	-0.046	0.409	°
Base year 2020	0.000		

*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1

Regression statistics	
DF	5
F	17773.554
Pr>F	**<.0001**
p-values significant*	***

plausible that other pollutants not included in this study due to data limitations (including O3 and SO2) may have added more explanatory power, or that different air pollution specifications would have produced a significant impact.

Fourth, the results of this study were consistent with, and slightly differed from, those of other EJ studies focused on California. The study by Greenfield et al., for example, also showed that socioeconomic indicators, such as race and income, were stronger determinants of disease outcomes than pollution levels[32]. Another study by Lombardi et al., however, showed that air pollution exposure exacerbated asthma outcomes, and that low-income and minority communities experienced even greater adverse asthma outcomes for similar levels of air pollution exposure[33]. Further investigation is warranted to see if the model specification used in the Lomardi et al. study would produce similar results for Contra Costa County specifically.

Overall, the results of this study show that poorer, Latino and African American communities living near pollution sources in Contra Costa County bear a disproportionate burden of asthma outcomes. While these communities were also exposed to a higher level of air pollution emitted by these sources, namely toxic chemical releases, NO2, diesel PM, and PM 2.5, this exposure was not a significant determinant of asthma prevalence. These results were stable between 2019 and 2020. This study's key finding supports the notion that a community's living conditions, impacted by social, racial, and economic inequities, were stronger indicators of asthma prevalence than air pollution exposure.

Conclusion

This is the first known study to examine the relationship between air pollution and asthma in Contra Costa County and how it impacts low income, minority communities. It is also the first to factor in pollution from a variety of sources, including industrial sites, major highways and pesticide-heavy farmlands. The results of this study show a strong correlation between the proximity to air pollution sources and the prevalence of asthma throughout the county, as well as how communities with higher concentrations of poorer Hispanics and African Americans bear a disproportionate amount of these burdens. Exposure to higher levels of air pollution was not found to be a significant determinant of asthma prevalence.

The findings from this study can be used to help identify and prioritize communities most impacted by pollution and higher asthma rates in Contra Costa and to funnel resources and programs to help address these inequities. Some programs to consider include those that would improve the living environment where low-income, minority communities reside. These could entail providing resources to purchase air purifying equipment or providing better access to foods that reduce asthma risk, including fruits, vegetables, and whole grains, and education on foods that increase risks, including high-fat meats and dairy products[34].

These results may also be useful in shaping the county's EJ policies in the future. More research should be done to further understand how other air pollutants or non-environmental factors may contribute to the prevalence of asthma throughout the county. Further investigation into what policies have helped alleviate the air pollution and asthma levels in other jurisdictions with industrial areas, major highways, and/or pesticide-using farmlands, would also be worthwhile.

Limitations

This study has some limitations. Since asthma prevalence data was not available at the census block level, the study was designed around census tract-level data. While the census tract is a common spatial unit used in these types of studies, more granular data would have provided the ability to conduct a more precise analysis. Other studies have acknowledged that using the smallest unit of analysis generally yields the most realistic and accurate results[12].

Another drawback of using census tracts is that they have artificial boundaries that assume a uniform distribution of air pollution and populations within the tract which is known not to be true. The census tracts are also of varying size and shape. Proximity analysis, where fixed distances around pollutant sources are used, is sometimes employed to address this limitation (e.g., drawing a half mile radius around a polluting facility rather than using the census tract boundary to create a buffer). This method, too, has its flaws as radial distances around pollution sources are often subjective and do not consider air dispersion of pollutants.

Lastly, not all outdoor air pollutants linked to asthma, including O3 and SO2, were included in this study due to data unavailability or data collection limitations, as discussed in the air pollutant data section. Further studies should assess the impact of these pollutants once the data becomes available or limitations have been addressed. Indoor air pollution was also not included in this study but should be considered for future studies.

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