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Key Points:

- Warehouse expansion over the last two decades was associated with elevated PM2.5 and elemental carbon concentrations in their ZIP code regions
- Disadvantaged populations living near warehouses are disproportionately exposed to higher levels of air pollution
- Targeted emission control interventions and protective measures are especially needed for vulnerable populations near warehouses

Supporting Information:

Supporting Information may be found in the online version of this article.

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Impact of Warehouse Expansion on Ambient $PM_{2.5}$ and Elemental Carbon Levels in Southern California's Disadvantaged Communities: A Two-Decade Analysis

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Abstract Over the past two decades, the surge in warehouse construction near seaports and in economically lower-cost land areas has intensified product transportation and e-commerce activities, particularly affecting air quality and health in nearby socially disadvantaged communities. This study, spanning from 2000 to 2019 in Southern California, investigated the relationship between ambient concentrations of $PM_{2.5}$ and elemental carbon (EC) and the proliferation of warehouses. Utilizing satellite-driven estimates of annual mean ambient pollution levels at the ZIP code level and linear mixed effect models, positive associations were found between warehouse characteristics such as rentable building area (RBA), number of loading docks (LD), and parking spaces (PS), and increases in $PM_{2.5}$ and EC concentrations. After adjusting for demographic covariates, an Interquartile Range increase of the RBA, LD, and PS were associated with a 0.16 μg/m³ (95% CI = [0.13, 0.19], $p < 0.001$), 0.10 μg/m³ (95% CI = [0.08, 0.12], $p < 0.001$), and 0.21 μg/m³ (95% CI = [0.18, 0.24], $p < 0.001$) increase in $PM_{2.5}$, respectively. For EC concentrations, an IQR increase of RBA, LD, and PS were each associated with a 0.021 μg/m³ (95% CI = [0.019, 0.024], $p < 0.001$), 0.014 μg/m³ (95% CI = [0.012, 0.015], $p < 0.001$), and 0.021 μg/m³ (95% CI = [0.019, 0.024], $p < 0.001$) increase. The study also highlighted that disadvantaged populations, including racial/ethnic minorities, individuals with lower education levels, and lower-income earners, were disproportionately affected by higher pollution levels.

Plain Language Summary Over the past 20 years, more warehouses have been built near ports and in areas where land is cheaper. This has increased truck traffic and goods movement, which has worsened air quality and affected the health of nearby communities that often lack resources and health services. From 2000 to 2019, our study in Southern California examined how this rise in warehouses has impacted air pollution, focusing on very small pollution particles known as PM2.5 and a harmful component of these particles called elemental carbon. Using satellite data to analyze pollution levels across different areas, we discovered that larger warehouses, more loading docks, and increased parking spaces are associated with higher levels of pollution. We also found that this rise in pollution particularly affects disadvantaged groups in these communities, including racial/ethnic minorities, those with less education, and those with lower incomes. This research underscores the long-term trend of warehouse expansion and its effects on air pollution. It highlights the urgent need for careful planning in warehouse construction and better protection for vulnerable communities, particularly those most at risk from increased pollution.

1. Introduction

In the 21st century, the United States has seen a dramatic expansion in manufacturing and e-commerce, leading to a corresponding surge in warehouse construction to meet growing storage demands (Bluffstone & Ouderkirk, 2007). In distribution centers such as the Inland Empire, California, the scale of expansion stood out substantially, as the quantity of mega warehouses—defined as those with a rentable building area (RBA) greater than 100,000 square feet—increased by 166% from 2000 to 2022 (McGhee, 2022). As available land diminishes, communities are gradually being infiltrated by newly built warehouses (Yuan, 2021). A multi-state study reported that an estimated 15 million people in the US live within a mile of warehouse facilities as of 2023 and are facing

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risks associated to daily operation of the warehouses, especially the diesel truck emissions attracted to the facilities (Nowlan, 2023).

Previous literature has established that the proliferation of warehouses has led to a significant amplification of their associated environmental impacts (Fichtinger et al., 2015; Ries et al., 2017), affecting local communities to a greater extent than in previous decades. Additionally, manufacturing industries and e-commerce entities often plan their facility constructions near sea ports and in neighborhoods with less urban development and lower land costs (deSouza et al., 2022). These areas, with their reduced living expenses, have been attracting socio-economical disadvantaged communities (Yuan, 2018, 2021), who now live in close proximity to potential emission sources. The potential environmental impact that disproportionately affects disadvantaged groups highlights warehouse expansion as a pressing issue of environmental injustice.

Among the various environmental challenges that warehouse expansion poses to surrounding communities, air pollution is particularly substantial. The establishment of warehouses contributes to local emissions within the immediate vicinity, encompassing a substantial release of pollutants that include particulate matter with an aerodynamic diameter equal to or less than 2.5 μm ($PM_{2.5}$). Operation of warehouses is directly linked to goods movement via trains and heavy-duty diesel trucks, which leads to increased emissions of elemental carbon (EC) (Shearston et al., 2020). A study conducted before our study period, spanning from 1999 to 2001, observed an increase in EC concentrations at their sites in Southern California, especially in Riverside County with massive warehouse distribution centers, which, in their observation, are gradually becoming bigger in size over time (Salmon et al., 2004). Although the association was not investigated in detail, it suggests that the massive expansion of warehouses could potentially exacerbate the ongoing challenge of efforts to decrease air pollution in urban cities. Recognizing the air pollution impacts associated with the expansion and operation of warehouses, regulatory bodies have begun taking action. For instance, the South Coast Air Quality Management district (South Coast AQMD) recently adopted a rule, known as the Warehouse Indirect Source Rule 2305, to reduce air pollution emissions and impacts associated with warehouses in Southern California. This rule requires warehouses to invest in zero and/or near-zero emission technologies, using solar power, installing onsite charging, or fueling infrastructure, or installing filtration systems in qualified buildings such as schools (AQMD, 2021).

There is extensive literature documenting the detrimental effects of $PM_{2.5}$ and EC on human health. Previously investigated health outcomes associated with $PM_{2.5}$ include but are not limited to chronic pulmonary diseases (Duan et al., 2020; Wang et al., 2022), exacerbated asthma (Orellano et al., 2017), cardiovascular diseases (Vaičiulis et al., 2023), and cancers (Wong et al., 2016). EC, on the other hand, is partially responsible for an increased risk of lung dysfunction among adults with asthma (Huang et al., 2019; McCreanor et al., 2007) and the elderly population, particularly those with chronic obstructive pulmonary disease (Chen et al., 2017; Huang et al., 2019; Pan et al., 2018). Additionally, EC consists of a unique structure with both carcinogenic compounds on its outer layer (Cao et al., 2005) and a highly absorptive core (Oberdörster et al., 2005), enhancing its ability to transport toxic substances into deeper lung tissues. These health outcomes are expressed disproportionately in highly industrialized states such as California (Nunez et al., 2024). The American Lung Association reported that nine out of the top 10 most polluted counties in the United States are located within CA (Smith, 2019), highlighting the necessity of effective interventions within the state. Specifically, the top three most polluted counties —San Bernardino, Riverside, and Los Angeles—fall under the jurisdiction of the SCAQMD, which requires special attention in air quality management (Smith, 2019).

The residents of these overburdened counties often face increased exposure to air pollution associated with industrialization and their associated health outcomes. Among these residents, social determinants of health further exacerbate environmental inequities (Jbaily et al., 2022; Liu et al., 2021). Previous studies identified racial/ethnic minorities, communities of lower socioeconomic status, and those with lower levels of education to face a higher risk of air pollution-related health issues (Jbaily et al., 2022; Liu et al., 2021; Lu et al., 2022). While numerous studies have examined the patterns of air pollution in Southern California (Chambliss et al., 2021), less attention has been devoted to investigating the impact of the warehouse expansion, especially on disadvantaged communities.

In this study, we aim to investigate the associations between satellite driven $PM_{2.5}$ and EC concentrations and warehouse presence and characteristics between 2000 and 2019 in Southern California. We identified the regional effect of each warehouse capacity indicator on pollution concentrations and evaluated temporal trends of these relationships. Additionally, we compared average pollution and demographic distributions between ZIP codes

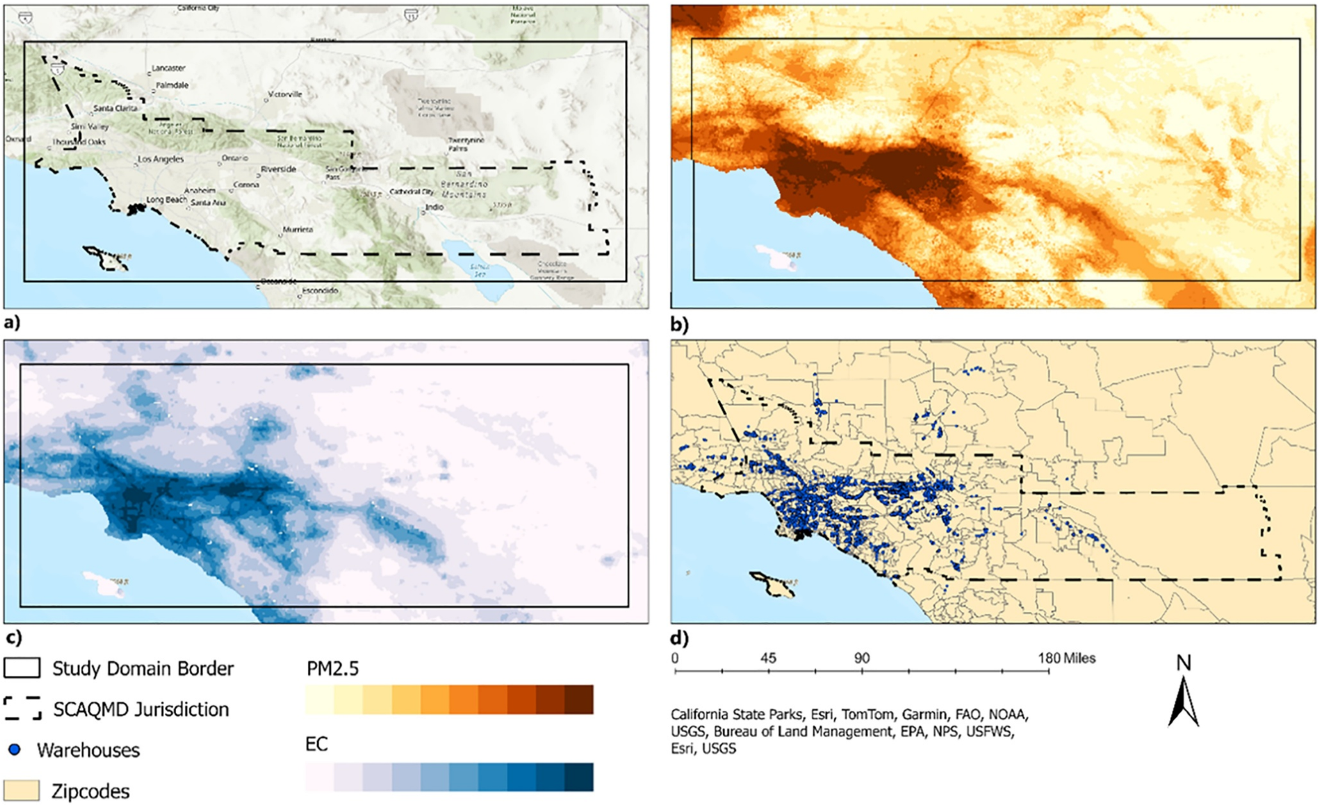

Figure 1. Warehouse and air pollution distribution in the study domain (a) shows the jurisdiction outline of South Coast Air Quality Management District, and the study domain (black outlined rectangle). (b, c) Show the average concentrations of $PM_{2.5}$ during 2000–2018, and elemental carbon during 2000–2019, respectively. (d) Shows the spatial overlay of warehouse distribution over the ZIP codes within the study domain.

with and without warehouse presence. The findings of our study will enhance the understanding of the environmental impact of warehouse expansion in context of the surge in e-commerce, stress the need in developing targeted interventions for vulnerable populations and underscore the importance of addressing environmental justice into future air pollution research.

2. Methods

2.1. Study Domain

Our study domain (Figure 1a) is delineated by the jurisdiction of the South Coast AQMD, encompassing the South Coast Air Basin and the Coachella Valley region, which is part of the Salton Sea Air Basin in Southern California. The area is bordered to the west by the Pacific Ocean, including the major urban areas such as Los Angeles, Riverside, and San Bernardino, and extending south to encompass all of Orange County. The area is predominantly influenced by a Mediterranean and semi-arid steppe climate, with a transition to a desert climate moving toward the Coachella Valley region (EcoAdapt, 2016). We extended 10 km from the most Northern/Southern/Eastern/Western points of the jurisdiction boundary and created a rectangular buffer area in order to capture the impact of regional air pollution transport.

2.2. Warehouse Data

Warehouse coordinates and their associated variables, including rentable building areas (RBA) in square feet, number of loading docks (LD), number of parking spaces (PS), county, and year of construction, were obtained from the database of Costar Realty Information Inc. (Costar) to represent warehouse size, product loading capacity, and vehicle accommodation capacities, which are all potential contributors to the warehouse's emissions to the environment. The data set contained 10,937 observations within the study domain. Any missing values in LD and PS were filled by linear interpolation, using a linear trend between known values for each respective variable.

The RBA values for the same year served as a key reference to ensure better prediction. For missing RBA values, we used the median RBA of the same year across the entire spatial domain, as the median is less affected by outliers and provides a robust estimate for the central tendency.

2.3. Air Pollution Data

We defined our study period as two decades before the COVID-19 pandemic, which led to massive changes in socioeconomic patterns and human activities. Annual and monthly mean $PM_{2.5}$ concentrations at 1 km resolution in California from 2000 to 2018 were estimated by a satellite-driven ensemble machine learning model incorporating multiple predictor variables including satellite and meteorological factors, land-use, chemical transport, and elevation (Di et al., 2019). The 1 km resolution is sufficient to estimate air pollution concentrations at the ZIP code level. This model, specifically for the Pacific region including the study domain, has a cross-validation R^2 value of 0.80, indicating good model performance. Annual mean EC concentrations at 1 km spatial resolution from 2000 to 2019 were obtained from a separate satellite driven $PM_{2.5}$ component model (Amini et al., 2023). The model performance varies across urban and non-urban areas but consistently demonstrates high performance, with R^2 values above 0.9. All pollution data were spatially aggregated to the ZIP code levels for our modeling analysis. There are 576 ZIP codes included in the study domain.

2.4. Demographic Data

Demographic variables were obtained from the 2000 and 2010 U.S. Census, and the American Community Survey for 2005–2012. Selected variables included ZIP code level percentage of the populations who were racial/ethnic minorities (residents other than Caucasians), percentage of residents aged over 65, percentage of the population with education less than high school, population, and median annual household income. The original method for interpolating demographic data from various sources was performed by Ma et al., for their Medicare study. The detailed method of data set assignment could be found at the GitHub repository: https://github.com/schwartzgroup/ses-imputation, where the authors adopted several methods involves several stages, including crosswalks and interpolation techniques, to ensure accurate and consistent demographic data across different years. The final step involved linear interpolation of missing years using weighted least-squares regression models, with the year as the predictor and the geographic characteristic as the response variable (Ma et al., 2022).

2.5. Statistical Analysis and Data Visualization

We developed linear mixed effect models to test the association between air pollution concentrations, demographic variables, and warehouse characteristics. Warehouse characteristics variables included total RBA, total number of LD and total number of PS, each analyzed independently. We built two models for each pollutant mapping to each warehouse characteristic variable. Model 1 only considered the effect of a single warehouse characteristic variable as the fixed effect and year as the random effect. Model 2 further controlled selected demographic variables, as shown below.

$$Y_{ij} = \beta_0 + u_{0j} + \beta_1 \text{warehouse variable}_{ij} + \beta_2 \text{race}_{ij} + \beta_3 \text{income}_{ij} + \beta_4 \text{age}_{ij} + \beta_5 \text{education}_{ij} + \beta_6 \text{population}_{ij} \quad (1)$$

where Y represents EC or $PM_{2.5}$ concentration, i and j indicate grouping of the data. β_0 is the overall intercept, β_1 is the regression coefficient of the individual warehouse variables, β_2 to β_6 are the regression coefficients of the demographic covariates, and u_{0j} represents the random intercept across the years. The covariates included in Model 2 were tested for multicollinearity using the Variance Inflation Factor (VIF), and all variables showed VIF values below 5, indicating low to moderate correlation that does not significantly affect the model.

Additionally, we stratified the data into 5-year rolling intervals and used multiple linear regression models to test the periodic change in the association between $PM_{2.5}$ and EC concentrations and warehouse characteristics within our study period. Each pollutant was mapped to a single warehouse capacity variable while controlling for demographic variables, as shown below.

$$Y = \beta_0 + \beta_1 \text{warehouse variable} + \beta_2 \text{race} + \beta_3 \text{income} + \beta_4 \text{age} + \beta_5 \text{education} + \beta_6 \text{ population} \quad (2)$$

Similar to Equation 1, Y represents each pollutant, β_0 is the overall intercept, β_1 represents the intercept of the individual warehouse variables, and β_2 to β_6 are the slopes of the controlled demographic covariates. The model was fitted for each 5-year period and the beta coefficients were compared across the periods for interpretation.

We used another linear mixed effect model to investigate the relationship between demographic distribution and presence of warehouse in ZIP codes. Presence of warehouses (0 or 1) was mapped to percent of racial minority, percent of residents with education under high school, percent of residents with age above 65, and median household income independently, with population served as an adjustor variable in the model. The equation of this mixed-effect model is shown below.

$$Y_{ij} = \beta_0 + \beta_1 \text{warehouse presence}_{ij} + \beta_2 \text{population}_{ij} + \left(1 \middle| \text{Zip}_j\right) \tag{3}$$

where Y represents each demographic variable, i and j indicate grouping of the data. β_0 is the overall intercept, β_1 and β_2 is the regression coefficient of the binary warehouse presence variable and population variable, respectively. $(1|\text{Zip}_j)$ represents the random intercept across the different Zip codes.

We further employed the Welch Two-Sample t-test to evaluate variations in pollution concentrations between the ZIP codes containing warehouses ($n = 331$) and control ZIP codes without warehouses ($n = 34$) within the study domain. The control ZIP codes were chosen based on similar median populations to the ZIP codes with warehouses. ZIP codes with a median population within the range of ±20% of the average median population of ZIP codes with warehouses were included as control groups (Figure S1 in Supporting Information S1). Additionally, we evaluated the monthly average concentration of $PM_{2.5}$ and their mean difference across the ZIP codes with and without warehouse presence. All statistical analyses were conducted using R version 4.3.0.

Additionally, we generated maps using satellite driven data for $PM_{2.5}$ and EC at a 1 km resolution in ArcGIS Pro 3.1.0 to show the average levels of $PM_{2.5}$ and EC across the study period. We also showed the locations of warehouses within the study domain, identified any warehouse clusters, and compared their spatial relationships to areas with higher air pollution.

3. Results

3.1. Warehouse Summary Statistics

Among the 10,937 warehouses included in the study domain, 2,038 were constructed during our study period (2000–2019), constituting 18.64% of the total number and 27.64% of the total RBA of the entire data set (Table 1). Of the warehouses built within the study period, the majority were constructed between 2000 and 2010. The year with the most significant increase in warehouse count and RBA in the last two decades was 2000, with a count of 221 (2.02%) and an RBA of 20.6 million ft^2 (2.87%) The temporal trends in warehouse characteristics by five major counties were displayed in Figure 2. Between 2001 and 2010, the annual number of newly constructed warehouses showed a trend of gradual decrease over time, except from 2005 to 2008 (Table 1). After 2010, the number of newly constructed warehouses started to increase again, with a few years of exception, such as 2016 and 2019 (Table 1, Figure 2a). Similar trends were observed in the annual increase in RBA as well (Table 1). While the annual trends of warehouse count and sum of RBA varied, the annual average of RBA demonstrated substantial growth after 2010, especially in the San Bernardino and Riverside counties, which are part of the Inland Empire (Figure 2c), the area characterized by a massive increase in product demands for outbound distribution (McGhee, 2022). We observed an increase in warehouse capacity, with the median and IQR of RBA, LD, and PS showing a significant rise in 2012, followed by a gradual decline before reaching another peak in 2019 (Table 2). Additionally, Figure 1 also demonstrates dense clusters of warehouses in the Inland Empire region, supporting the results displayed by Figure 2.

3.2. Demographic Variations

When the population variable was adjusted, the distribution between ZIP codes with warehouse presence and those with no warehouse presence revealed significant differences across all selected variables (Table 3). Specifically, ZIP codes with the presence of a warehouse are associated with a 3.29% increase in the racial minority percentage (95% CI = [1.91%, 4.67%], $p < 0.001$), a 1.90% increase in the percentage of individuals with education under high school (95% CI = [0.69%, 3.12%], $p = 0.002$), a 2.29% decrease in the percentage of

Table 1
Annual Summary Statistics of Warehouses (2000–2019)

Year	Warehouses constructed (*n*)	% Of total warehouses	Rentable building area constructed (ft^2)	% Of total rentable building area
<2000	8,899	81.36%	515,530,557	71.93%
2000	221	2.02%	20,572,296	2.87%
2001	189	1.73%	16,041,421	2.24%
2002	170	1.55%	13,847,628	1.93%
2003	144	1.32%	10,485,707	1.46%
2004	144	1.32%	9,277,036	1.29%
2005	181	1.65%	14,031,346	1.96%
2006	150	1.37%	12,323,717	1.72%
2007	131	1.20%	9,477,016	1.32%
2008	142	1.30%	14,425,018	2.01%
2009	75	0.69%	5,283,899	0.74%
2010	16	0.15%	1,241,113	0.17%
2011	10	0.09%	1,292,578	0.18%
2012	16	0.15%	3,303,345	0.46%
2013	23	0.21%	4,775,833	0.67%
2014	43	0.39%	9,153,043	1.28%
2015	57	0.52%	11,211,134	1.56%
2016	51	0.47%	5,850,261	0.82%
2017	94	0.86%	11,113,155	1.55%
2018	117	1.07%	14,722,564	2.05%
2019	64	0.59%	12,761,454	1.78%
All	10,937	–	716,720,121	–

individuals aged above 65 (95% CI = [3.33%, 1.25%], $p < 0.001$), and a \$2,975 decrease in median household income (95% CI = [\$5,835, \$133], $p = 0.036$).

3.3. Changes in $PM_{2.5}$ and EC Levels

We identified notable trends when comparing changes in the annual average concentrations of $PM_{2.5}$ and EC across warehouse-concentrated regions and the control region (Table 4). Overall, the annual concentrations of $PM_{2.5}$ and EC have been decreasing in warehouse-concentrated areas and the control from 2000 to 2019 with a few exceptions (Figures 3e and 3f). Notably, both pollution concentrations started to show a slight increase after 2016 across the regions (Figures 3e and 3f). Additionally, ZIP codes containing warehouses consistently exhibited higher $PM_{2.5}$ and EC concentrations (Figure 3, Table 4).

In the last two decades, the annual mean concentrations of $PM_{2.5}$ and EC near warehouses ($\text{mean}_{PM} = 13.37 \pm 4.57$ μg/m³, $\text{mean}_{EC} = 0.96 \pm 0.37$ μg/m³) were higher by 0.60 μg/m³ ($p < 0.05$) and 0.11 μg/m³ ($p < 0.001$), respectively, compared to the control average ($\text{mean}_{PM} = 12.77 \pm 4.15$ μg/m³, $\text{mean}_{EC} = 0.85 \pm 0.31$ μg/m³). The maximum and minimum values for annual concentrations of $PM_{2.5}$ were observed in 2001 and 2016, respectively, for both warehouse areas (max = 20.02 μg/m³, min = 8.90 μg/m³) and the control (max = 18.73 μg/m³, min = 8.53 μg/m³) (Table 4). For EC in the comparable regions, maximum concentrations were both observed in 2000 ($EC_{ware} = 1.33$ μg/m³, $EC_{control} = 1.17$ μg/m³), and the minimum concentrations were both observed in 2016 ($EC_{ware} = 0.68$ μg/m³, $EC_{control} = 0.60$ μg/m³). Additionally, we found that the concentration for $PM_{2.5}$ in the study domain peaked in October. The differences in the monthly averages of $PM_{2.5}$ concentration between regional groups, however, were highest from November to January from 2000 to 2016 (Figure 4). We observed dense clusters of warehouses in the Inland Empire region aligning with areas exhibiting higher concentrations of $PM_{2.5}$ and EC from 2000 to 2019, which was consistent with the results of the comparative analysis (Figure 1).

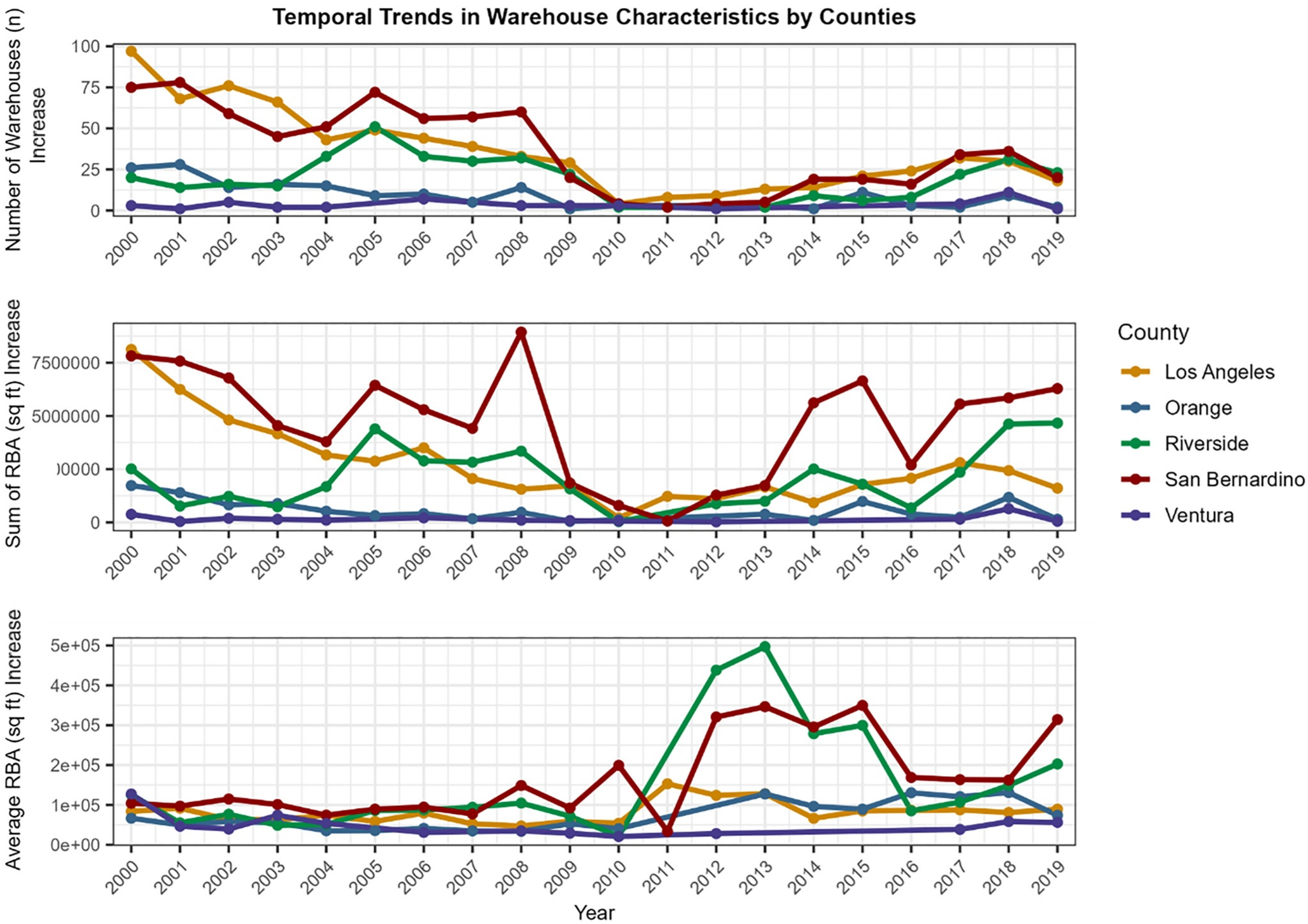

Figure 2. Temporal trends of warehouse characteristics from 2000 to 2019. The temporal change in warehouse characteristics by five major counties, specifically the number of construction and rentable building area (RBA), are demonstrated in this figure. (a, b) Show the annual increase in the number of newly constructed warehouses and their sum of RBA in ft^2, while (c) displays the annual average of RBA increase.

3.4. Warehouse Characteristics and Pollutant Concentration

Our mixed-effects models revealed statistically significant associations between warehouse capacity variables and both $PM_{2.5}$ and EC concentrations. Specifically, an interquartile range (IQR) increase in RBA was found to be associated with a 0.27 μg/m³ increase in $PM_{2.5}$ concentrations (95% CI = [0.24, 0.30], $p < 0.001$, IQR = 5,027,268) and a 0.035 μg/m³ increase in EC concentrations (95% CI = [0.032, 0.038], $p < 0.001$, IQR = 5,055,969) in Model 1. After adjusting for demographic covariates, the beta coefficient decreased to 0.16 for $PM_{2.5}$ μg/m³ (95% CI = [0.13, 0.19], $p < 0.001$) and to 0.021 μg/m³ for EC (95% CI = [0.019, 0.024], $p < 0.001$) (Table 5).

An IQR increase in LD was associated with a 0.15 μg/m³ increase in $PM_{2.5}$ concentrations (95% CI = [0.13, 0.17], $p < 0.001$. IQR = 414) and a 0.017 μg/m³ increase in EC concentrations (95% CI = [0.016, 0.019], $p < 0.001$, IQR = 417) before controlling for demographic covariates (Model 1). After the addition of demographic variables in the model, an increase of 0.10 μg/m³ and 0.014 μg/m³ were associated with a IQR increase in the number of LD for $PM_{2.5}$ (95% CI = [0.08, 0.12], $p < 0.001$) and EC (95% CI = [0.012, 0.015], $p < 0.001$), respectively.

In Model 1, an IQR increase in the number of PS was linked to a 0.26 μg/m³ rise in $PM_{2.5}$ concentrations (95% CI = [0.23, 0.30], $p < 0.001$, IQR = 5,692) and a 0.031 μg/m³ increase in EC concentrations (95% CI = [0.027. 0.034], $p < 0.001$, IQR = 5,790). After adjusting for demographic covariates, the beta coefficient changed to 0.21 for $PM_{2.5}$ (95% CI = [0.18, 0.24], $p < 0.001$) and 0.021 for EC (95% CI = [0.019, 0.024], $p < 0.001$). Overall, adjusting for covariates lowered the coefficient estimates for all models (population variable only lowered the

Table 2
Annual Summary of Newly Constructed Warehouses, 2000–2019

	Rentable building area (RBA) in ft^2		Number of loading docks		Number of parking spaces	
Year	Median	IQR	Median	IQR	Median	IQR
<2000	35,791	35,358	4.00	6.00	48.00	54.00
2000	54,493	81,014	6.00	15.00	81.00	96.00
2001	46,663	70,450	5.00	14.50	63.50	74.75
2002	41,461	44,702	4.00	13.00	60.00	58.00
2003	39,587	43,463	5.00	6.00	60.00	45.50
2004	32,313	31,866	4.00	4.75	56.00	60.00
2005	34,840	39,277	5.00	10.00	53.00	45.25
2006	41,819	69,851	4.00	17.00	68.00	82.00
2007	31,914	40,221	4.00	19.00	50.50	56.25
2008	45,867	73,641	14.00	20.00	60.00	74.00
2009	42,040	43,213	4.00	6.00	48.00	43.00
2010	31,767	32,748	6.00	9.00	50.00	65.50
2011	33,921	81,059	2.50	17.50	45.50	46.00
2012	162,564	270,290	51.00	58.00	112.00	127.50
2013	142,053	166,733	37.50	35.00	116.50	187.00
2014	96,408	161,447	16.00	28.00	76.00	78.00
2015	99,998	130,585	12.00	21.00	121.00	125.50
2016	85,042	90,914	14.00	13.00	66.00	78.00
2017	63,284	92,358	7.00	19.00	84.00	93.00
2018	63,654	78,951	6.00	11.00	86.00	80.00
2019	94,706	159,468	9.00	14.00	111.00	120.00
All	37,424	41,515	4.00	8.00	50.00	59.00

models for PS and not the others), yet the significant association between warehouse capacity and pollutant concentrations persisted.

The linear regression models for 5-year rolling intervals established significant associations between an increase in all warehouse capacity variables and elevated $PM_{2.5}$ and EC concentrations for all time periods (Figure S2 in Supporting Information S1). Specifically, we observed a consistent decreasing trend in beta coefficients between warehouse variables and $PM_{2.5}$ concentrations over time. The beta coefficient for the association between EC and warehouses increased from 2003 to 2008, peaked at the 2004–2008 period, and began to decrease in the 2005–2009 period. The association between $PM_{2.5}$ and EC and warehouses increased subtly during the 2011–2015 period for all characteristic variables.

4. Discussion

In this study, we explored the relationship between air pollution, warehouse capacity, and their disparate impact on disadvantaged groups in Southern California from 2000 to 2019. Our results revealed that increases in warehouse capacity were associated with higher concentrations of $PM_{2.5}$ and EC in local communities, leading to elevated exposure for socially disadvantaged groups residing near these facilities. First, our results supported the significant contribution of warehouses to elevating pollution concentrations within the ZIP codes in which they were located. Previous literature has identified a positive relationship between the accumulation of the warehouse facility and the increase in local air pollutant emissions (Shearston et al., 2020), primarily attributed to the heavy-duty diesel trucks and train emissions essential to warehouse operations (deSouza et al., 2022; Grondys, 2019). With the ongoing expansion of warehouse facilities, especially the disproportionate increase in the Inland Empire region, major pollutants such as $PM_{2.5}$ and EC, a prominent byproduct of heavy-duty diesel vehicles (Ji et al., 2019), are anticipated to continue to adversely impact nearby environments. The results of our mixed-effect models were consistent with previous findings (deSouza et al., 2022; Yuan, 2021) and indicated a positive relationship between increases in all selected warehouse variables and elevations in both $PM_{2.5}$ and EC across the study domain. Specifically, increases in RBA, the number of LD, and the number of PS would each individually lead to an increase in the average $PM_{2.5}$ and EC concentration within the study domain.

In addition to the effects of individual warehouse capacity, our comparative analysis further revealed that ZIP codes with the presence of warehouses consistently exhibited higher levels of both $PM_{2.5}$ and EC despite the interannual variations. We also observed that from November to January, the difference of $PM_{2.5}$ concentrations between warehouse-concentrated areas and ZIP codes with no warehouses increased significantly. Although the regional average $PM_{2.5}$ concentrations during these months are lower compared to October, the differences across regional groups remained the highest. These results highlighted the effect of warehouses on local pollution, as the months with elevated differences in pollution concentration coincided with major shopping seasons such as Thanksgiving, Christmas, and New Year. These holidays corresponded to peak sales in e-commerce and heavy demands for product storage and shipping. Our results also recognized the effectiveness of previous efforts in regulating diesel emissions, as the association between warehouse capacity and $PM_{2.5}$ concentrations in 5-year rolling intervals has reduced over time. More specifically, the association between warehouse capacity and EC started to decrease after the 2004–2008 period, which coincided with the EC regulation implemented in California in 2007 (Mousavi et al., 2018). The observed uptick in the 2011–2015 period across the association between $PM_{2.5}$, EC, and warehouse variables could be

Table 3
Mixed-Effect Models for Demographic Distribution and Warehouse Presence

	Warehouse presence		
	β	95% CI	*P* value
% Racial/ethnic minority	3.29	[1.91, 4.67]	<0.001*
% Education under high school	1.90	[0.69, 3.12]	0.002*
% Population over age 65	−2.29	[−3.33, −1.25]	<0.001*
Median household income	2,975	[5,835, 133]	0.036*

Note. This table used presence of warehouse in ZIP codes (0 or 1) to compare the demographic distribution between regions. (*) Indicates p value < 0.05.

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Table 4
Annual Average of $PM_{2.5}$ and Elemental Carbon (EC) Concentrations

	$PM_{2.5}$		EC	
Year	Warehouse concentrated	Control	Warehouse concentrated	Control
2000	18.79	17.31	1.33	1.17
2001	20.02	18.73	1.16	1.02
2002	18.75	17.48	1.00	0.89
2003	17.77	16.58	1.06	0.93
2004	16.27	15.80	1.05	0.93
2005	14.41	13.49	1.14	1.01
2006	13.33	12.35	1.14	1.00
2007	13.88	13.66	1.21	1.08
2008	12.71	12.27	1.12	0.97
2009	12.51	11.86	0.92	0.80
2010	10.23	10.09	0.93	0.81
2011	10.85	10.46	1.02	0.90
2012	11.03	10.82	0.83	0.74
2013	10.16	9.91	0.71	0.64
2014	10.03	9.48	0.74	0.65
2015	9.75	8.98	0.87	0.75
2016	8.90	8.53	0.68	0.60
2017	12.28	12.11	0.81	0.72
2018	12.96	12.77	0.68	0.62
2019	N/A	N/A	0.82	0.73
Total mean	13.37 ± 4.57	12.77 ± 4.15	0.96 ± 0.37	0.85 ± 0.31

Note. The concentrations of $PM_{2.5}$ and EC are both reported in μg/m³. $PM_{2.5}$ and EC concentrations were compared between ZIP codes with and without warehouse presence. The mean differences for both $PM_{2.5}$ and EC during 2000–2018 were statistically significant ($p < 0.05$ for $PM_{2.5}$ and $p < 0.001$ for EC).

attributed to a complex interplay of factors. This observation aligns with previous studies conducted at the Ports of Los Angeles and Oakland, which also reported unexpectedly higher emissions in 2015 (Haugen & Bishop, 2018; Preble et al., 2018). Both studies suggested that the significant deterioration of Diesel Particulate Filters in older trucks, which were subsequently repaired or replaced in later years, could be a major factor influencing the overall emission rates measured in the study area, given the overlap of the study domain and period (Haugen & Bishop, 2018; Preble et al., 2018). Collectively, our findings suggest that expansion in warehouse capacity was responsible for the increase in $PM_{2.5}$ and EC levels regionally, especially during times of higher product demands. Meanwhile, continuous efforts in diesel control programs have had potential mitigating effects on warehouse-associated emissions over the long term.

Furthermore, our linear mixed-effect models for demographic variables and warehouse presence showed that ZIP codes with warehouses had higher percentages of socially disadvantaged populations, which subjected them to elevated air pollution. The issue of health inequity was identified as a critical concern in environmental health, as social determinants of health pose exacerbating effects on the exposure levels for disadvantaged populations and increase susceptibility to various health outcomes (Jbaily et al., 2022). Previous studies have demonstrated existing disparities in air pollution exposure among socially disadvantaged populations (Bell & Ebisu, 2012; Chambliss et al., 2021; Liu et al., 2021; Rosofsky et al., 2018). Our results aligned with previous findings and identified that racial/ethnic minorities, those with lower levels of education, and those with lower median household incomes were found to live in proximity to warehouses at higher percentages compared to others. Many factors could potentially lead these socially disadvantaged groups to reside close to warehouse facilities. On the one hand, the expansion of warehouses leads to an influx of job opportunities, attracting younger age groups and lower-income individuals to reside in proximity for better work access. On the other hand, racial, and ethnic

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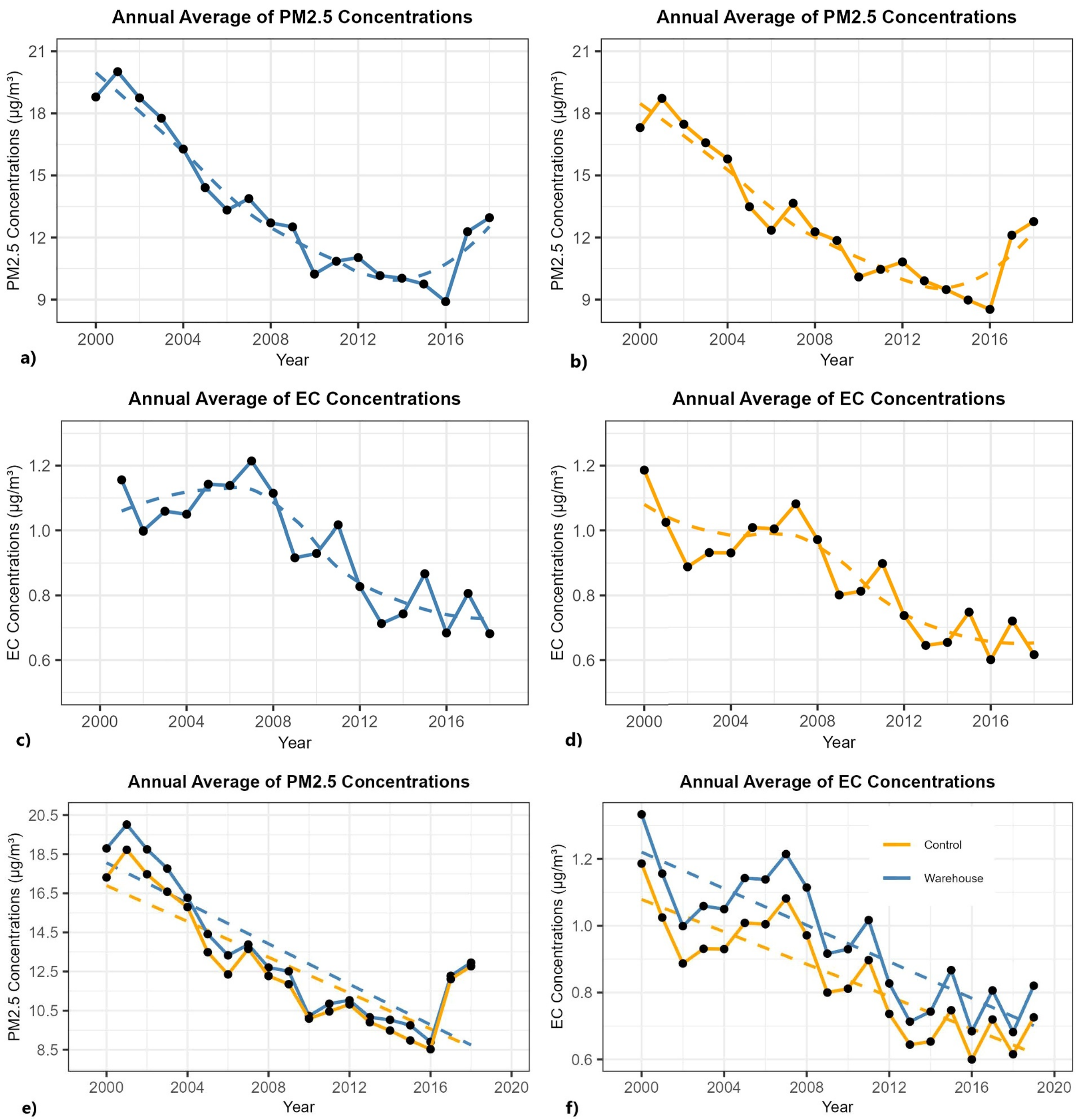

Figure 3. Changes in annual average $PM_{2.5}$ and elemental carbon concentrations from 2000 to 2019. $PM_{2.5}$ concentrations were available through 2000–2018. Blue shows the annual average for warehouse concentrated regions while orange shows which of the control regions. Blue and orange dash lines indicate trend lines for warehouse group and control group, respectively. Panels (a, b) present annual trends for $PM_{2.5}$, while (c, d) display annual trends for EC. Panel (e) compares $PM_{2.5}$ trends between zip codes with and without warehouses, and panel (f) compares EC trends between these zip codes.

minorities, who are more likely to face marginalization, often have limited choices in residential locations due to factors such as housing prices, living expenses, and the presence of established communities that share their similar social vulnerabilities in the regions. While our analysis revealed that warehouse-concentrated areas have higher percentages of vulnerable groups than other regions, we did not find a higher representation of individuals aged over 65 in these areas. A possible explanation is that the elderly, who are typically retired and often prefer serene living environments, are likely to choose residential locations away from highly industrialized areas (Duncombe et al., 2003). Although fewer elderly people reside near warehouse-concentrated areas, this population should not be ignored given their increased susceptibility to urban air pollution-associated diseases (Delgado-Saborit et al., 2021; Gong et al., 2005) and the effect of intersectionality, which becomes significant

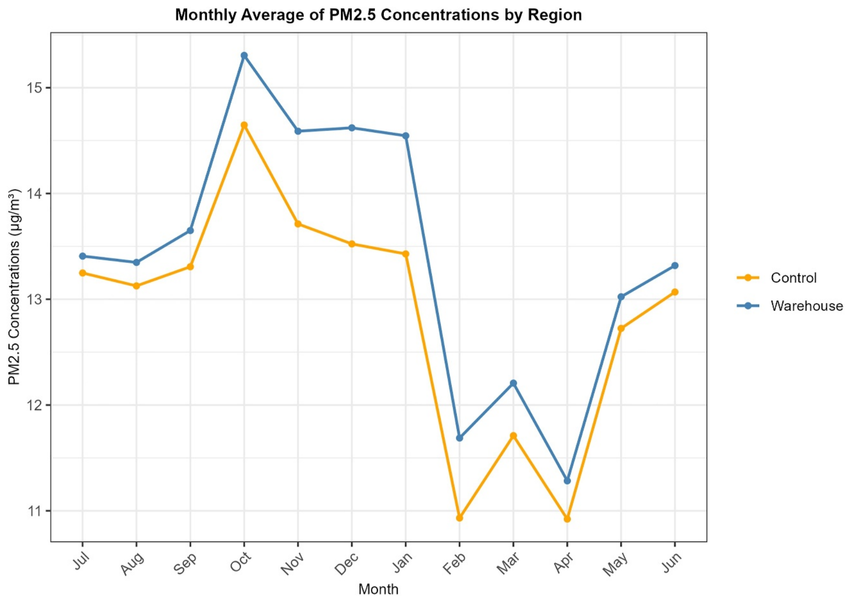

Figure 4. Monthly average of $PM_{2.5}$ concentrations for ZIP code with and without warehouse presence were compared.

when elderly populations also possess one of more other identified vulnerable characteristics (Alvarez et al., 2022). Despite the emerging environmental injustice concerns associated with the warehouse boom, the specific health impacts of warehouse-induced air pollution remain understudied, particularly among vulnerable populations. Further epidemiological studies are warranted to assess the susceptibility of socially disadvantaged groups to health issues directly linked to air pollution from warehouses. Addressing this knowledge gap is critical for developing targeted interventions and policies that protect the most vulnerable communities.

There are several strengths in our study. Previous studies exploring urban air pollution have identified many limitations among current air quality monitoring systems in highly industrialized regions. For example, Shearston et al. suggested the incapability of their ground monitors to provide sufficient spatial and temporal coverage of air pollutant concentrations near warehouses, as their data were limited to a few sites and to the period when the monitors were in operation (Shearston et al., 2020). A similar study by deSouza et al. addressed this limitation by utilizing satellite driven data and investigated effects of mega-warehouses (>100,000 ft^2) on local $PM_{2.5}$ concentrations, but only covered a relatively short study period (2015–2017) and in much broader perspective (deSouza et al., 2022). Our study went further by utilizing long term satellite-driven pollution data to capture spatial trends for $PM_{2.5}$ and EC, an important tracer of diesel emissions, within the study domain for two decades, while incorporating warehouses of all sizes. The consistent data sources and their broad coverage in space and time allowed us to address the association between warehouse activities and elevated local air pollution from a chronic perspective. By including 20 years of data, we identified populations that have historically been and continues to be more affected by warehouse associated air pollution.

Table 5
Mixed Effect Models for Pollution Concentration and Warehouse Characteristics

	$PM_{2.5}$			EC		
	β	95% CI	*P* value	β	95% CI	*P* value
Rentable building area						
Model 1	0.27	0.24, 0.30	<0.001*	0.035	0.032, 0.038	<0.001*
Model 2	0.16	0.13, 0.19	<0.001*	0.021	0.019, 0.024	<0.001*
Loading docks						
Model 1	0.15	0.13, 0.17	<0.001*	0.017	0.016, 0.019	<0.001*
Model 2	0.10	0.08, 0.12	<0.001*	0.014	0.012, 0.015	<0.001*
Parking spaces						
Model 1	0.26	0.23, 0.30	<0.001*	0.031	0.027, 0.034	<0.001*
Model 2	0.21	0.18, 0.24	<0.001*	0.021	0.019, 0.024	<0.001*

Note. This table used warehouse variables as exposures and $PM_{2.5}$/EC as outcomes. The β coefficients and 95% confidence intervals are reported in 1 IQR increase. (*) Indicates p value < 0.05. For $PM_{2.5}$, IQR (RBA) = 5,027,268, IQR (LD) = 414, IQR (PS) = 5,692; For EC, IQR (RBA) = 5,055,969, IQR (LD) = 417, IQR (PS) = 5,790.

Our study also has a few limitations. First, we assumed that all reported warehouse capacities were accurately recorded and that their operational statuses and air pollution emissions remained constant throughout our study period. The Costar data set. although being the most extensive real estate database recording warehouse information in the US, it does not provide any quality assurance on the completeness of the data (Kerr et al., 2024). However, some warehouses constructed in earlier years might have closed or altered their operations, potentially introducing biases into our analysis. Additionally, our study lacks a comprehensive sensitivity analysis regarding the sources of $PM_{2.5}$ and EC emissions. The data sets used, specifically from Di et al. (2019) and Amini et al. (2023), include $PM_{2.5}$ and EC emissions from all sources, not exclusively those associated with warehouse activities. During the two-decade study period, emissions from various source sectors, such as electricity generation and non-warehouse related traffic emissions, have substantially reduced, while other sources, such as wildfire related air pollution, remained in higher levels. Given the lack of specific data on the contributions from these other sources over space and time, we were unable to evaluate the sensitivity of our mixed-effect models to changes in these sectors. To address this limitation to some extent, we compared $PM_{2.5}$ and EC concentrations in ZIP codes with warehouses to nearby ZIP codes without warehouses. While this comparison is not perfect, it provides a current method for considering the impact of warehouses on air pollution. As a result, our conclusion on the significance of warehouse emission on local air pollution should be interpreted with caution. It is possible that other factors, such as seasonal variations (e.g., wildfires) and reductions in emissions from other sectors, could have influenced the observed changes in air pollution levels. Additionally, the presence of strong positive spatial autocorrelation in $PM_{2.5}$ concentrations (Moran's Index = 0.93, $p < 0.001$), indicating significant clustering that we were unable to fully account for in our models. This may lead to potential bias in our regression estimates and affect the robustness of our regional analysis. Future research should aim to incorporate more granular data on the contributions of various emission sources, as well as temporal and spatial variations, to provide a more robust analysis. Despite these limitations, our findings contribute valuable insights into the association between warehouse expansion and air pollution exposure, highlighting the need for further investigation into this important issue. Incorporating epidemiological analysis, such as exploring the susceptibility of socially disadvantaged populations to diseases associated with air pollution near warehouses, would further contribute to understanding the effects of warehouse expansion from a population perspective.

This study's timeframe concludes prior to the onset of the COVID-19 pandemic, which brought unprecedented changes to many sectors, including e-commerce and logistics. During the pandemic, quarantine measures and social distancing mandates led to a significant surge in online shopping (Szász et al., 2022), thereby increasing the demand for warehouse space and related activities. This heightened demand likely accelerated the expansion of warehouse facilities to accommodate the increased volume of goods being stored and distributed. However, the pandemic also posed challenges to warehouse operations. Lockdowns and health restrictions meant that workforce availability was reduced, impacting the ability to maintain normal operational levels. This dual effect—an increased demand for warehouse services but a constrained ability to operate fully—introduces complexities in understanding the overall impact on air pollution during this period. Given these factors, it is essential to conduct further research to explore how the COVID-19 pandemic has influenced the relationship between warehouse expansion and air pollution, thus develop a clearer understanding of the long-term implications of the pandemic on warehouse operations and associated environmental impacts.

5. Conclusion

In the present study, we used satellite driven data sets to investigate the association between warehouse capacity, ambient $PM_{2.5}$ and EC concentrations, and demographic characteristics in Southern California from 2000 to 2019. Our results revealed that the presence of a warehouse is associated with a higher level of $PM_{2.5}$ and EC concentrations in their proximity, especially from November to January. Vulnerable population groups living in proximity to the warehouses, such as racial/ethnic minorities, those living under poverty, and those with lower levels of education, were disproportionately exposed under higher air pollution. The evident association between warehouse capacity and air pollution, along with its disproportionate impact on socially disadvantaged communities, suggests the need for further interventions in emission managements, specifically in areas with a high density of warehouses and near communities of vulnerable populations. Our research contributes to the ongoing efforts to understand air pollution distribution in urban environments, provides evidence to support future interventions for vulnerable populations, and promotes environmental justice in the context of urban air pollution studies.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data supporting the findings of this study are available from several sources under different access conditions. Satellite-driven estimates of annual and monthly mean $PM_{2.5}$ concentrations at 1 km resolution in California from 2000 to 2016 are openly accessible as described by Di et al. (2019, 2021) at NASA Socioeconomic Data and Applications Center (SEDAC) (https://sedac.ciesin.columbia.edu/data/set/aqdh-pm2-5-concentrations-contiguous-us-1-km-2000-2016). The annual mean elemental carbon (EC) concentrations at 1 km spatial resolution from 2000 to 2019 described by Amini et al. (2023) are also available at SEDAC (https://sedac.ciesin.columbia.edu/data/set/aqdh-pm2-5-component-ec-nh4-no3-oc-so4-50m-1km-contiguous-us-2000-2019). Warehouse data are available for purchase from the Costar Realty Information, Inc. (https://www.costar.com). The demographic dataset was processed originally by Ma et al. (2022) and the directions are available at the repository (https://github.com/schwartzgroup/census-ses-covariates). The data for $PM_{2.5}$ concentrations on the ZIP code level from 2017 to 2018 and the code employed in this research is openly available at the Zenodo repository (Yang, 2024) under an open-source license.

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