The Impact of Dust Exposure on Farmland Market: Evidence from the California's Central Valley

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Abstract

Exposure to dust particulates can negatively impact plant productivity while also affecting the value of agricultural land. Rising temperatures due to climate change can increase dust particulate concentrations leading to lower crop productivity and resulting in a decline in farmland values. This paper investigates the impact of the concentration of dust particles on farmland transaction values in the Central Valley of California. Using panel data with 11,741 observations representing 5,369 agricultural parcels that were sold between 2001 and 2021, we estimated a hedonic regression equation with parcel and year-of-sale fixed effects. We find an increase in $PM_{2.5}$ (fine particles) is associated with an increase in farmland values, but after a certain threshold point, value decrease, demonstrating an inverse U-shaped relationship. In addition, we find that for every 1% increase in the mean $PM_{10-2.5}$ (coarse particles) over the growing season, the sale price per acre of farmland in the Central Valley decreased by 3%. These findings highlight the damaging effects of anthropogenic airborne pollutants on the farmland market, and thus must be an integral part of any assessment of the impact of climate change on agricultural food security.

Keywords: agriculture, particulate matter, climate change, Central Valley California

JEL Codes: Q12, Q53, Q54

1. Introduction

The exposure of plants to airborne pollutants has been shown to significantly reduce crop yield (Liu and Desai 2021; Lobell, Di Tommaso, and Burney 2022; Hong et al. 2020; Zhou, Chen, and Tian 2018).[1] High concentrations of dust, measured as ambient particulate matter (PM), reduces the photosynthesis and productivity of plants (Hong et al. 2020; Zhou, Chen, and Tian 2018). In particular, dust particles in the atmosphere affect crop growth by reducing solar radiation through absorption and scattering (Cánovas, Lüttge, and Matyssek 2017). Hong et al. (2020), for example, found that high-value perennial crops in California were negatively affected by changes in local temperature and ozone concentrations, with yield losses of 5% to 15%, depending on the varying degree of pollutant exposure and the different crop types. According to that study, yield loss in high-value crops is translated into a loss in production value of roughly US$1 billion per year, suggesting that air pollution combined with the non-linear impact of precipitation and maximum temperature has a significant negative impact on the agricultural economy in California. Achakulwisut et al. (2019) found a relationship between climate change-induced increased aridity and dust levels in the southwestern United States. These papers demonstrate that climate change-induced dust levels can reduce crop productivity. Hence, the income obtained from farmland may be reduced by air pollutants associated with low precipitation and high temperatures during severe drought periods. Dust levels rise with drought, either due to transported dust (windblown dust mobilization) or dust from agricultural operations on less-irrigated farmland that increases as a result of drier soil or dust from poorly managed fallow land. Previous

[1] Particulate matter is a broad term that encompasses any mixture of particles suspended in the air that could impact economic output, including crop losses. We define the concentration of dust as the combination of concentrations of fine particles ($PM_{2.5}$) and coarse particles ($PM_{10-2.5}$). $PM_{10-2.5}$ concentrations were calculated by subtracting $PM_{2.5}$ from PM_{10}.

analytical work from around the world supports the thesis that the rise in levels of air pollution and global climate warming are interconnected. This paper utilizes two strands of literature. First, previous research establishes a relationship between crop yields, climate and air pollution. Second, empirical studies use the Ricardian model to examine the effects of climate-induced multi-pollutant exposure on farmland values.[2] We construct an analytical framework to expand the Ricardian model to incorporate dust particulate exposure (and pollutant-temperature interactions) to quantify the net impact of particulate matter on California agriculture.

While strong evidence of relationship between changes in air pollutants and crop yields, their impact on farmland's value has not been empirically quantified. This paper expands the Ricardian model to include climate-induced windblown dust particulate concentrations and their interaction with variables, such as precipitation and temperature to jointly assess the economic impacts of dust on California's agricultural land value. We use a panel regression analysis of repeated sales of farmland in the Central Valley, and cumulative exposures to dust levels ($PM_{2.5}$, fine particles and $PM_{10\text{-}2.5}$, coarse particles) from 2001 to 2021 to estimate the economic impacts of climate change and dust particulate exposure on land value. Our analysis controls for other pollutants, such as ozone O_3 and nitrogen dioxide NO_2 that could have an impact on crop productivity (Lobell, Di Tommaso, and Burney 2022; Liu and Desai

[2] The relationship between crop yields, climate and air pollution in the United States is well-established (Lobell, Di Tommaso, and Burney 2022; Liu and Desai 2021). In addition, the literature on the Ricardian model is also well-established (Mendelsohn, Nordhaus, and Shaw 1994; Mendelsohn and Dinar 2003; Schlenker, Hanemann, and Fisher 2007; Deschenes and Greenstone 2007).

2021). In doing so, we are able to identify the impact on farmland values from dust particulates only.[3]

The specification includes parcel-by-year-of-sale fixed effects that control for parcel-specific time-varying factors, exposure to other pollutants (ozone O_3 and nitrogen dioxide NO_2 and their squared terms), climate, and non-climate variables. Climate variables include the deviation from the normal (20-year average) precipitation and maximum temperature, wind speed and direction (indicator for southwest and northwest), relative humidity, and soil moisture. All climate and pollution variables are parcel acreage-weighted and averaged during the growing season (April through September) over the sample period (2001–2021). Non-climate variables include an indicator for parcels associated with agricultural types such as orchards and vineyards.

We conduct a series of checks to address the confounding factors between parcel-specific dust particulate exposure and climatic factors. We estimate the interaction effect between PM and climate factors and explore the non-linear impact of PM level and climate factors on the sale price of farmland. Two key findings are: First, we find that $PM_{2.5}$ exhibits an inverse U-shaped relationship with farmland values. The inverse U-shape's increasing portion captures agricultural activities on farmland that also produce dust, but the farmland values decrease after a threshold. This implies that fine dust particulate matter is sufficient to cause pollution-induced crop losses after a threshold point, and, therefore, a decrease in farmland sale price

3 California's agricultural growing areas, such as the Central Valley, are exposed to some of the highest levels of particulate and ozone pollution in the nation, damaging human health and economic output, including revenue from agricultural production (Hong et al. 2020; Huang and London 2012; H. J. Lee, Chatfield, and Strawa 2016). Producers of perennial crops in California are estimated to lose US$1 billion per year because of the negative impacts of climate and pollution (McGrath 2020; Hong et al. 2020). The mechanism of the damaging effect of pollution on crop yield can be understood by the internal reaction of plant tissues to air pollutants (Matyssek et al. 2008). Simply put, the chronic exposure to airborne pollutants causes damage to vegetation through lower stomatal conductance (ability to exchange gases and transpiration through leaf stomata, critical for plant growth).

per acre. Second, for every 1% increase in the mean $PM_{10-2.5}$ over the growing season, the sale price per acre of farmland in the Central Valley decreases by 3%. Analysis of heterogeneous impacts suggests that our main results are driven by winter pollution on farmlands associated with annual crops located in the southern part of San Joaquin Valley of the Central Valley. The Central Valley's agricultural and pollution levels are spatially concentrated. For example, compared to smaller farms in the east side of the Central Valley, larger farms have a greater presence in the west and south. Larger farms invest in perennial trees and vines, and they also grow a variety of field and grain crops (e.g., cotton, wheat, safflower), as well as vegetables (e.g., tomatoes).[4] Air pollution can have varying effects on annual crops (e.g., wheat, rice, maize, and soybean), and perennial crops (e.g., fruits, nuts, and other tree crops). We explore the heterogeneous effects of dust on farmland values by crop types and region. Our results suggest that pollution has a disproportional impact on farmland associated with annual crops. Furthermore, evidence suggests that pollution has a significant negative impact on farmlands in the southern portion of San Joaquin Valley.

This paper presents the first empirical evidence of the impact of parcel-specific dust levels on the sale prices per acre of farmland. Previous research investigating the impact of pollution on agriculture was focused on crop productivity and agricultural labor. Combining these two mechanisms can affect the farmland market through a Ricardian economics model, and the effects are capitalized into farmland sale prices. However, pollution may not affect buyers' expectations of land if they repurpose it for uses other than agriculture, such as solar development, housing development, recharge basins, and upland habitat restoration.

[4] PPIC Blog, August 2023, available at https://www.ppic.org/blog/mapping-farms-by-size-in-the-san-joaquin-valley/?utm_source=rss&utm_medium=rss&utm_campaign=mapping-farms-by-size-in-the-san-joaquin-valley?utm_source=ppic&utm_medium=email&utm_campaign=blog_subscriber

Therefore, it raises the undefined impact of pollution on farmland values, a priori. Our first contribution is to estimate the impact of dust particulate exposure on agricultural land values. Our second contribution is our use of parcel-level data to estimate the effects of windblown dust concentrations on farmland values associated with various crop types, including perennial or annual crops. The results of our study improve the understanding of the impact of pollution, and climate on California's farmland market.

The remainder of the paper is organized as follows: Section 2 provides an analytical framework for quantifying exposure to dust particulates on farmland values in the framework of the Ricardian model. Section 3 provides a description of the study area and data used for this analysis. Sections 4 and 5 discuss identification strategies and present empirical findings. Finally, concluding remarks and policy implications are provided in Section 6.

2. Analytical Framework

2.1. Ricardian model

This section summarizes the analytical framework of a panel Ricardian model as applied to farmland exposed to varying degrees of dust particulate levels. To model the relationship between agricultural production, climate and dust levels, we follow a Ricardian model similar to Mendelsohn, Arellano-Gonzalez, and Christensen (2010), and a partial derivative framework similar to Tai and Val Martin (2017). The Ricardian model is represented by:

$$\pi = \sum P_j^{output} Q_j\left(\boldsymbol{X}_j, PM_j, \boldsymbol{E}_j\right) - \sum P_x^{input} \boldsymbol{X}, j = 1,2,3, \dots, n \tag{1}$$

where Q_j is the output of crop j, $\boldsymbol{X_j}$ is a set of vectors of purchased inputs; PM_j represents exposure to dust particulate matter and $\boldsymbol{E}_j$ is a set of vectors of local environmental conditions, including climate and soil quality, for crop production. P_j^{output} is the market price of crop j, and P_x^{input} is a vector of input prices. Assuming constant exposure of other pollutants to crop productivity, we focus on the effect of particulate matter on crop productivity and thus on the value of farmland. We acknowledge that dust is not always an independent component in crop production and can be partially influenced by weather. We carried out a series of checks to address the confounding factors between dust particulate concentrations and weather variables. Contemporaneous pollution and weather have an interactive effect, and when pollution is included alongside weather variables in the same estimated equation, the estimates will be biased by confounding factors. Because pollution and weather (particularly, maximum temperature) covary, we believe that including contemporaneous measures of pollution ($PM_{2.5}$ and $PM_{10-2.5}$) alongside deviations from the climate normal (20-year averages of precipitation and maximum temperature) may circumvent the issue of pollution-weather covariation.

Furthermore, dust is both a result of dryness of soil due to drought, with a negative impact, but also the result of the production process (e.g., plowing, tillage, pollution from farm machinery, and from vehicle traffic on unpaved roads, etc.) that increases productivity but creates dust and reduces productivity. This raises a concern of simultaneity which could bias our estimates. The empirical section addresses concerns about simultaneity by using the inverse distance weighted interpolation technique to measure parcel-specific pollutants. Particulate matter also has an impact on agricultural productivity by affecting labor force participation, either through productivity loss or absenteeism due to sick days resulting from negative impacts of pollution.

Following Eq. (1), the farmer is expected to choose a set of inputs **X**, such that the rent on the land is maximized. The farmland value is proportional to the net revenue from the land, meaning that $V = \frac{\pi}{r}$ where r is the interest rate.

The reduced form of the Ricardian panel model that examines the relationship between farmland value (V_{it}) of parcel i at time t, dust particulates (PM_{it}), and weather variables (W_{it}) is as follows:

$$ln\, V_{it} = \beta_0 + \beta_1 PM_{it} + \beta_2 PM_{it}^2 + \gamma \boldsymbol{E}_{it} + \alpha_i + \rho_t + \mu_{it} \quad (2)$$

where β is the estimated coefficient and μ_{it} is an error term. PM_{it} represents exposure to the fine ($PM_{2.5}$) and coarse ($PM_{10\text{-}2.5}$) dust particulate concentrations at the parcel level, $i = 1, \ldots, 5396$ in year $t = 2001, \ldots, 2021$. We include quadratic terms of PM in the right-hand side of the model to account for the non-linear relationship between $PM_{2.5}$ and agricultural production. We follow previous literature and include weather variables, such as deviation from the normal precipitation and maximum temperature, wind speed and direction, relative humidity, and soil moisture. We also take into account parcel-specific characteristics, which include crop types (an indicator for orchards and vineyards). We include the parcel's fixed effects, α_i that control for any time-invariant unobserved characteristics with effects on land value (e.g., proximity to urban center). ρ_t is the year of sale fixed effects to capture the time-varying changes on farmland values, such as a common technology trend impacting crop yields. The expression μ_{it} is an error term, representing the variations in farmland values that are not explained by our model. To account for spatial correlation in the error term, we cluster the standard errors at the parcel level. To be able to account for unobserved parcel-level heterogeneity, we focus on parcels that were repeatedly sold during our study period. The marginal effect of pollution on farmland values is given by $\frac{\partial \ln V}{\partial PM} = \bar{V}(\beta_1 + 2\beta_2 \overline{PM})$.

Any observed correlations between V, PM, and W could be confounded by the inherent covariation between dust particulate concentrations and weather variables. For example, it is expected that with higher wind speeds more dust is emitted. Also, with an increase in temperature and a decrease in relative humidity, the "stickiness" of the emitting surface might change, making these surfaces prone to more sources of dust. Furthermore, if the pollution and temperature both affect and are affected by current intensive farming in the local area, then this could bias our estimates. One approach to address this concern is to use the predicted value of $PM_{2.5}$ instead of the observed value of $PM_{2.5}$. This is assuming that measurement of $PM_{2.5}$ at the parcel level can be explained by daily maximum temperature, wind speed, and relative humidity, the predicted value of $PM_{2.5}$ can be estimated by regressing daily $PM_{2.5}$ on these predictors. By including the predicted value instead of the observed value in the hedonic regression, this issue could be addressed. The estimated equation is:

$$(3) \qquad ln\, V_{it} = \beta_0 + \beta_1 \widetilde{PM}_{it} + \beta_2 \widetilde{PM}_{it}^2 + \gamma \boldsymbol{E}_{it} + \alpha_i + \rho_t + \mu_{it}$$

where $\widetilde{PM}_{it} = g(tmax, s, h, opt)$, is the predicted $PM_{2.5}$ pollutant, explained by maximum temperature $tmax$, wind speed s, relative humidity h, and atmospheric optical thickness opt. Equation (3) eliminates the confounding effects of covariation between dust particulates and weather variables that are included in the model. This model is similar to two-stage least squares; the first stage can be written as

$$(4) \qquad \widetilde{PM}_{it} = \tau_0 + \tau \boldsymbol{W}_{it} + \alpha_i + \rho_t + \varepsilon_{it}$$

where $\boldsymbol{W}_{it}$ is the contemporaneous weather variables that explain the $PM_{2.5}$ at the parcel level. ε_{it} represents the residual terms $(PM - \widetilde{PM})$. Equation (3) represents the second stage.

Furthermore, to explore the estimate of endogeneity bias, we estimate a correlated coefficient model similar to Bento, Freedman, and Lang (2013), which can be written as

$$(5) \qquad ln\, V_{it} = \beta_0 + \beta_1 PM_{it} + \beta_2 PM_{it}^2 + \psi\widehat{\varepsilon_{it}} + \delta PM_{it} * \widehat{\varepsilon_{it}} + \gamma \boldsymbol{E}_{it} + \alpha_i + \rho_t + \mu_{it}$$

The coefficient on the PM is interpreted as the valuation of exogeneous changes in air quality. The coefficient on the residual term is interpreted as the bias resulting from the endogeneity of $PM_{2.5}$. The coefficient on the interaction term is an indication of the direction of bias.

3. Study Area and Data Sources

This study examines parcels sold repeatedly in 18 counties in the Central Valley of California from 2001 to 2021. The Central Valley is composed of the Sacramento and San Joaquin Valleys (see the study area in Figure 1).[5] The Central Valley grows hundreds of different types of crops due to its Mediterranean-like climate, and supports the food security of the United States (Jessoe, Mérel, and Ortiz 2021). However, it is also vulnerable to future climate change (Lee, De Gryze, and Six 2011), and air pollution (Hong et al. 2020).

The Central Valley's farmland values are primarily determined by its ability to support agricultural production. So, parcel-specific factors, such as pollution, that impact plant

[5] For our analysis, we combine the counties that make up the Sacramento and San Joaquín Valleys. Sacramento Valley comprises the counties of Tehama, Glenn, Butte, Colusa, Yolo, Solano, Sutter, Yuba, Placer, and Sacramento. The northern part of the San Joaquin Valley consists of the counties of San Joaquin, Stanislaus, and Merced. The central part of the San Joaquin Valley includes the counties of Madera, and Fresno. The southern part of the San Joaquin Valley includes the counties of Tulare, Kern, and Kings.

growth are important determinants of land values. The Central Valley was selected to represent the most productive agricultural area in California. The Central Valley has a high concentration of particulate matter that has been well documented to have negative impact on economic outputs—for instance, Huang and London (2012) conducted a study that shows the disproportionate exposure to, and impact of pollution on human health in the San Joaquin valley. This would provide sufficient variation in dust levels for a strong analysis. Finally, it is plausible to assume that the Central Valley area is as homogenous as possible with respect to the variables excluded from the explanatory relationship, such as input prices, prevailing agricultural practices, and sources of air pollution arising from agricultural operations.[6]

3.1. Data sources and sample selection

We obtained farmland sales prices and transactions for the 18 counties in California's Central Valley between 2001 and 2021 from the ATTOM Data Solutions, a private company that aggregates data from county assessor offices. We began with 85,436 unique parcels associated with field-cultivated crops, orchards, and vineyards. We first chose only transacted parcel records, which reduced our sample to 66,476 parcels. Second, we removed transfers without payment for non-arm's-length parcels (3,791 parcels). Typically, these parcels are a quitclaim or other deed file that is similar to a quitclaim. Third, we followed Buck, Auffhammer, and Sunding (2014), and removed parcels with bedrooms (7,333 parcels) to retain only agricultural parcels. Fourth, we removed parcels with lot size of less than 1 acre (1,642 parcels). We consider these parcels either associated with greenhouses that do not necessarily reflect the impacts of climate change or they are sold for non-agricultural purposes. Fifth, we removed records without sales amount information (23,839 parcels).

[6] We acknowledge that input prices, particularly water prices, can differ significantly in Sacramento and the San Joaquin Valley.

Finally, for the purposes of our analysis, we further restricted the sample to parcels repeatedly sold (two or three times) in the Central Valley between 2001 and 2021.[7] Our final sample includes 11,741 observations representing 5,396 parcels (See Appendix Figure 2 for the structure of the repeat-sales sample). In our sample, the average length of time between two sales is 7.5 years.[8]

It is important to mention that our farmland data sales involved multi-parcel transactions. The issue with multi-parcels is that the buyer assigns a lump sum amount to multiple parcels at the time of sale. Using the same document number, property transfer year, and sale price, we identify and collapse multi-parcel sales transactions to the sales level. We use the sale price of the property divided by the acreage of the lot to calculate the variable value per acre. All values are adjusted for inflation. We used the annual Consumer Price Index (CPI) obtained from the Federal Reserve Economic Database to convert nominal values to 2021 US dollars.[9] We winsorize the value per acre variable at the 1 and 99 percentiles to minimize the impact of outliers.

3.2. Air pollutant and meteorological data

3.2.1. $PM_{2.5}$ and PM_{10}

We use seasonal mean (growing season, April through September) $PM_{2.5}$ and PM_{10} on a daily basis to measure fugitive dust at the parcel level for the years 2001 to 2021.[10] The California

[7] Our sample excludes parcels that have been sold more than three times during the study period.
[8] Our sample includes parcels that have been sold twice or three times. The length of sales for parcels that were sold twice is calculated by taking the difference between the first and second year of transactions. For parcels sold three times, the length between the sales is calculated between the first and third year of transactions.
[9] Economic Research, Federal Reserve Bank of St. Louis, available at https://fred.stlouisfed.org/
[10] We obtained daily interpolated data for $PM_{2.5}$ and PM_{10}, but for PM_{10} from 2001, and 2015 to 2021, we obtained the weekly interpolated data due to insufficient daily measures. There are far fewer PM_{10} monitoring sites in the San Joaquin Valley. We used all available sites producing daily observations of $PM_{2.5}$ and PM_{10} in the AQMIS monitoring network. We then performed inverse distance weighted interpolation to a 1 km grid on a daily basis

Air Resources Board (CARB) maintains a wide network of air monitoring stations under the Air Quality and Meteorological Information System (AQMIS), which measures $PM_{2.5}$, PM_{10} and other pollutants in California and can be accessed through the Air Quality Data Portal.[11] The AQMIS monitors more than 80 air quality sites, but not every monitor reports daily measurements, which creates spatial and temporal gaps in the data (Appendix Figure A2 provides information on $PM_{2.5}$ and PM_{10} monitor stations and selected parcels in California). To address this gap, we used the ordinary inverse distance weighted interpolation (IDW) technique to estimate $PM_{2.5}$ and PM_{10} concentrations at the parcel level. The IDW interpolation method takes into account the distance between interpolated points and measuring locations. In each interpolation, the most distant air quality monitoring station from the centroid of the parcel is less weighted. The variation in the fine dust particles ($PM_{2.5}$) and coarse dust particles ($PM_{10-2.5}$, the difference between PM_{10} and $PM_{2.5}$) explains the variation in the farmland sales price in the study area.

3.2.2. Other air pollutants: Ozone and nitrogen dioxide

We obtained daily ozone O_3 and nitrogen dioxide NO_2 concentrations data from the Environmental Protection Agency's (EPA) Air Quality System monitoring site. [12] We also included the monthly mean aerosol optical thickness (AOD) data to predict $PM_{2.5}$ which we obtained from MERRA-2 satellite products.[13]

4.2.3. Meteorological variables

during the study period. For each monitor, we first calculated daily means and then assigned the inverse distance weighted mean of the 1km grid, replacing missing values with the weekly mean.

[11] Data can be downloaded from https://www.arb.ca.gov/aqmis2/aqdselect.php?tab=specialrpt

[12] Data is available at https://aqs.epa.gov/aqsweb/airdata/download_files.html

[13] MODIS Level-3 gridded atmosphere monthly global product with spatial resolution of 1 x 1 degrees, available at https://atmosphere-imager.gsfc.nasa.gov/MOD08_M3

As explained in the theoretical section, we assume that the contemporaneous dust levels ($PM_{2.5}$ and $PM_{10-2.5}$) are independent of the deviation from the climate normal (precipitation and maximum temperature). Using the PRISM daily dataset for precipitation and maximum temperature over the growing season in a year, we constructed parcel-specific deviations from the climate normal. The climate normal is the average of precipitation (mm) and maximum temperature (Celsius) for a parcel over a 20-year period. The PRISM data is a high-resolution dataset suitable for analyzing the heterogeneous landscape of California (Jessoe, Mérel, and Ortiz 2021).

In addition, we obtained parcel-specific daily mean wind speed and the direction of wind and the relative humidity during growing season from the EPA's Air Quality System. We also obtained soil moisture averages for the growing season from GLDAS-2 data products.[14] The influence of these weather variables on pollutant concentrations and farmland values is likely to raise concerns about identification, which we address in the results section.

3.3. Summary statistics

We combine repeated-sale parcels with measures of windblown dust concentrations and meteorological variables on parcels that have been repeatedly sold during our study period (2001–2021) in the Central Valley of California. Table 1 provides the summary statistics of all the variables used in the analysis. All variables used in the analysis are divided by their parcel size. In the Central Valley, the average value per acre for parcels that were sold repeatedly during our study period is $17,587. The annual average fugitive dust particulate

[14]Global Land Data Assimilation System (GLDAS) satellite data products, GLDAS Noah Land Surface Model L4 Monthly 0.25 x 0.25-degree V2.1, available athttps://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_2.1/summary

concentrations, measured as the fine $PM_{2.5}$ and coarse $PM_{10-2.5}$, are 0.67 and 0.56, respectively, for the study periods.

Figure 1 displays the trends in pollution and farmland sale price per acre across the valley from 2001 to 2021. The farmland sale price in the valley increased from \$6,464 per acre in 2001 to \$33,654 per acre in 2021, a 421% increase over two decades. $PM_{2.5}$ and $PM_{10-2.5}$ mean concentrations values (in $\mu g/m^3$) during the growing season are represented in the y-axis on the left of Figure 1. $PM_{2.5}$ concentrations decreased gradually during the study period, from 18 $\mu g/m^3$in 2001 to 11 $\mu g/m^3$ in 2021, with an average decrease of nearly 40%. The number of days during the growing season in a year when $PM_{2.5}$ exceeds a commonly used threshold of 12 $\mu g/m^3$, which is 63. $PM_{10-2.5}$ (obtained by subtracting $PM_{2.5}$ from PM_{10}) was lower than $PM_{2.5}$ between 2003 and 2014, with a range of 4 to 10. From 2015 onwards, we have seen a rise in the concentration of coarse particulate ($PM_{10-2.5}$). The increase in $PM_{10-2.5}$ may come from the increased use of mechanized crop management in drier soil due to prolonged drought.

Our econometric specification takes into account environmental variables. We summarized all control variables at the parcel acreage-weighted level (i.e., all variables are divided by their corresponding lot size). Environmental variables include deviation from the 20-year average precipitation, and maximum temperature, and contemporaneous wind speed and direction, relative humidity, and soil moisture. On average, the selected parcels in the study experienced deficit precipitation (average deviation of -0.19 mm) and increased maximum temperature (average deviation of 0.023 degree Celsius). The mean wind speed was 0.22 miles an hour, and the prevalent wind direction in our study area was from the southwest (80% during growing season), southeast (15% of the time), and northwest (5% of the time). About 2.6% relative humidity was present in our study area.

4. Identification Strategy

In order to evaluate the impact of changes in dust particulate concentration and climate variables on farmland values, we arranged the parcel-level data in a panel format. Our identification relies on the repeat-Ricardian model. The estimation of fine dust particulate concentrations on farmland values is not straightforward. Fine dust particulate concentrations and climate variables, such as temperature, may have common correlations with the error terms. For example, dust particulate concentrations and farmland values may be correlated with parcel-specific covariates, such as soil types and quality, irrigation and fertilizer applications, elevation, and county-specific covariates, such as traffic density, population density, demographics, and industrial activity including fossil-fuel power plants.

Failing to control for such covariates will lead to biased estimates of β in Eq. (2). Our identification strategy relies on parcel fixed effects, which explicitly address time-invariant omitted variable biases. Furthermore, to test the robustness of our estimates, we include quadratic terms of PM on the right side of the model to account for the non-linear relationship between $PM_{2.5}$ and agricultural production. As previously mentioned, our parcel-level data is in a panel format, and we observe the same parcels that were sold repeatedly during our study period. We assume an independent random variation between the time-varying covariates and the year of sale of the parcels. In addition, the Central Valley data may have measurement errors on observable PM due to the limited number of monitoring stations. We explore remotely sensed particulate data to complement the monitor analysis.

We apply a goodness-of-fit criterion to choose an appropriate form for the hedonic function, as suggested by Rosen (1974). For our purposes, when variables were omitted, we followed Cropper, Deck, and McConnell (1988) to present two main specifications of hedonic regression: linear-linear and log-linear models.[15] The log-linear model has the lowest residual sum of squares, and hence is a better fit. Our preferred hedonic regression model is a log-linear model, with a natural logarithm of farmland value per acre regressed on the vectors of independent variables, such as dust particulate concentrations, controlling for climate and non-climate variables. Refer to Appendix Table A1 for the hedonic model of linear-linear functional forms. The repeated sale of the parcel may cause concern about selection bias. Table 2 presents the comparisons of parcels sold repeatedly to all parcels. We observed that parcels sold repeatedly are cheaper than parcels sold once by $2,000 per acre, on average. Column (3) of Table 2 reports the difference between parcels sold repeatedly and those sold once, with a statistical test to compare the means of the two groups. The results of a statistical test show that parcels sold repeatedly are statistically different from parcels sold once. This may have limited our ability to interpret the effects of dust for all parcels in the Central Valley during the study period.

5. Results

In the following sections, we present results from a series of specifications to estimate the effects of dust particulate concentrations on farmland values and demonstrate the robustness of our estimates.

5.1. Concentration response functions

[15] In general, when variables are omitted, simple forms including linear and log-linear, are preferable for hedonic models.

We begin by presenting a series of checks to demonstrate the independent effect of dust particulate concentrations, precipitation, and temperature on the right-hand side of Equation (1). Figure 2 displays the scatter plot of the relationship between log farmland values and $PM_{2.5}$ particulate concentrations. The y-axis variable represents the mean of farmland values that correspond to $PM_{2.5}$ concentration levels on the x-axis. The plot exhibits an inverse U-shaped relationship between farmland values and $PM_{2.5}$ concentrations. Appendix Figure A3 shows the binned scatterplot of the relationship between $PM_{2.5}$ and the maximum temperature and $PM_{2.5}$ and precipitations, after controlling for county fixed effects. $PM_{2.5}$ has a negative relationship with maximum temperature and a negative relationship with precipitation. Drought and very hot days during the growing season may also affect vegetation, which would typically slow downwind at the surface and reduce dust concentrations. Precipitation, on the other hand, could dampen the surfaces of arid lands and reduce concentrations.

Table 3 presents the correlation matrix between various airborne pollutants, after controlling for the parcel level and year-of-sale fixed effects. The correlation matrix demonstrates how various pollutant concentrations used in the analysis are correlated. $PM_{2.5}$ has a positive correlation with $PM_{10-2.5}$, a negative correlation with both ozone and nitrogen dioxide. $PM_{10-2.5}$ and ozone and NO_2 have a negative correlation. A positive correlation exists between NO_2, which is a precursor to ozone.

Using parcel-level repeat-sales data, we estimated how changes in prices between repeat sales are explained by differences in climate and dust particulate matter. Appendix Figure A4 displays the dust exposure on parcels during the first and second years of sales in our dataset. We observed that the $PM_{2.5}$ exposure on parcels that were sold repeatedly was roughly the same. We observed a higher level of exposure to coarse dust ($PM_{10-2.5}$) on parcels that were sold repeatedly.

5.2. Primary results

The dependent variable is the log of value per acre. The primary explanatory variable is the daily $PM_{2.5}$ concentration at the parcel level. To isolate the impact of fine dust concentrations on farmland values, we included other pollutants, such as ozone (O_3) and nitrogen dioxide (NO_2), and their squared terms in the same estimating equation. Therefore, the impact on farmland values can only be attributed to dust particulates, not other pollutants that also affect crop productivity. All pollutants and climate variables are parcel-acreage weighted averaged during the growing season (April through September) over the sample period (2001–2021). As previously mentioned, agricultural operations are likely one of the primary sources of $PM_{2.5}$ and PM_{10} in the Central Valley of California. First, we find that $PM_{2.5}$ exhibits an inverse U-shaped relationship with farmland values. This result is evident from the coefficient on the quadratic term of fine dust levels, which is statistically significant and negative, suggesting an inverse U-shaped relationship between farmland sale price and fine dust particulate matter. This implies that fine dust particulate matter is sufficient to cause pollution-induced crop losses after a threshold point, and therefore a decrease in farmland sale price per acre. As shown in Figure 3, the slope of $PM_{2.5}$ changes from positive to negative beyond the threshold point of 8.5 $\frac{\mu g}{m^3}$ per acre.[16] Second, for every 1% increase in the mean $PM_{10-2.5}$ over the growing season, the sale price per acre of farmland in the Central Valley decreases by 3%.

[16] The threshold point estimating equation is: $\beta_1 + 2\beta_2 PM = 0$. Plugging in the values of the coefficient estimates into the equation, we obtain $PM = \frac{-\beta_1}{2\beta_2} = \frac{-0.17}{-0.02} = 8.5$.

The first column of Table 4 begins with a simple hedonic panel model. We regressed log of value per acre on $PM_{2.5}$ and the quadratic term, controlling for parcel level and year of sale fixed effects. The next two columns incrementally add other pollutants and climatic and non-climate variables as additional covariates on the right side of the model: column two adds parcel acreage-weighted average ozone O_3 and nitrogen dioxide NO_2; column three adds deviations from the normal precipitation and maximum temperature, wind speed, direction of speed (an indicator for southwest and northwest), relative humidity, soil moisture, and non-climatic variables that include an indicator for orchard and vineyard. In column (3), we decomposed daily maximum temperature and precipitation into deviation from climate normal such that contemporaneous $PM_{2.5}$ concentrations do not covary with climate normal.[17] Thus, it eliminates the confounding effects of covariation between dust particulates and weather variables. All specifications include parcel level and year-of-sale fixed effects to absorb unobserved time-invariant parcel-specific characteristics and time-varying common shocks.

Column (4) of Table 4 displays the regression of the hedonic panel using estimating Equation (1) for coarse particulate matter ($PM_{10\text{-}2.5}$). A 1% increase in coarse dust particulate concentrations at the parcel reduces farmland values in the Central Valley by an average of 3%. Our results suggest that PM_{10} concentrations are statistically significant and have a negative association with agricultural land values. In contrast, $PM_{2.5}$ concentrations have a positive association with agricultural land values. The positive association between $PM_{2.5}$ concentration and farmland values may not be surprising, as agricultural operations (e.g., on-farm work-related soil disturbances), and vehicle traffic on paved and unpaved roads within

[17] Climate normal, defined as a 20-year daily moving average of historical maximum temperature and precipitation.

a parcel also cause the bulk of $PM_{2.5}$. But this could raise concerns about simultaneity, and emissions from the farm itself. We believe that the interpolated measure of fugitive dust particulate concentrations is plausibly exogenous to the parcel and may address the issue of simultaneity. In Column (5), we followed the literature (Cook, Heyes, and Rivers 2023) to include the number of days in a growing season with $PM_{2.5}$ levels >12 and mean $PM_{2.5}$ together on the right-hand side.[18] Our results are comparable in both qualitative and quantitative terms to Column (4).

As mentioned in the data section, we measure parcel-specific dust particulate exposure using the inverse distance weighting interpolation technique. Monitoring stations located far from the parcel are independent of dust particles from agricultural activities in that parcel. Therefore, the interpolated measure of dust particulate is less affected by pollution created by the farm itself.

As previously mentioned, if pollution and temperature both are affected by current intensive farming in the local area, then this may bias our estimates. One approach to address this concern could be to use the predicted value of $PM_{2.5}$ instead of the observed value of $PM_{2.5}$. We assume that the measurement of $PM_{2.5}$ at the parcel level can be adequately explained by aerosol optical thickness, daily maximum temperature, wind speed, and relative humidity. As such, the predicted value of $PM_{2.5}$ can be estimated by regressing annual mean $PM_{2.5}$ on annual mean maximum temperature, wind speed, relative humidity, and soil moisture (See Appendix Table A2). In addition, Appendix Figure A5 shows the scatterplot between the predicted values and the residuals. We observed that, on average, the

[18] The US EPA has set the pollution threshold level to 12 units of as being harmful to human health.

residuals are around zero and tend to grow larger as the fitted values increase. Columns (1) and (2) of Table 5 present the hedonic regression results from Eq. (3) and (4). The results suggest that the association between farmland sale price and predicted fine dust particulate matter is statistically significant. We also find the quadratic behavior of the fine dust particles on farmland sale price significant, with a negative sign for the quadratic term. Column (2) of Table 5 indicates that the endogeneity bias is small and in the upward direction. The finding that the impact of predicted fine dust particulate matter on farmland sale price is inverse U-shaped is helpful in validating the results in our analysis.

5.3. Non-linear effects of $PM_{2.5}$ on farmland values

Estimates of average effects, as shown in the primary results, may mask the non-linear impact of dust on the farmland market. To examine the non-linear effects of $PM_{2.5}$ on farmland values, we estimate the following model:

$$(6) \qquad ln\, V_{it} = \beta_0 + \sum_{n=1}^{4} \beta_n * 1[Bin_n(PM_{2.5})] + \gamma \boldsymbol{E}_{it} + \alpha_i + \rho_t + \mu_{it}$$

where β_n is the estimated coefficients on indicator variables that bin the $PM_{2.5}$ into four bins: [0, 5), [5, 10), [10, 15), and [15, 23]. The first bin (0-5 $\mu g/m^3$) is the reference bin. The remaining terms are the same as Equation (3). Figure 4 presents the non-linear effects of $PM_{2.5}$ on farmland values. The findings indicate that a rise in $PM_{2.5}$ results in a greater decrease in farmland values. The decline in farmland values is 26% with a per acre $PM_{2.5}$ value of 10 $\mu g/m^3$, and rises to 35% with an increase in $PM_{2.5}$ in the range of 15-23 $\mu g/m^3$.

5.4. Heterogeneous effects

This section focuses on the different levels of pollution exposure based on season, crop type, and region. First, we present the heterogeneous effects of pollution across four seasons (winter, spring, summer and fall) in a year.[19] Second, we present the heterogeneous effects by crop type (cultivated field crops and vineyards and orchards). Finally, we present heterogeneity by region within the Central Valley.

5.4.1. Heterogeneity by seasonal pollution

Appendix Figure A6 shows the mean seasonal $PM_{2.5}$ in the Central Valley during the study period (2001-2021). The winter and spring seasons are marked by the highest pollution levels at the lower bound, with the highest levels being found in the central and southern San Joaquin Valley. Table 6 presents the heterogeneous effects across four seasons in a year. Our results suggest an inverse U-shape relationship between $PM_{2.5}$ during the winter season and farmland values. The impact of $PM_{2.5}$ on farmland values during spring, summer, and fall is not statistically significant.

5.4.2. Heterogeneity by crop type

Table 7 presents the heterogeneous effects by crop type (an indicator of annual crops and vineyards). Orchards make up about half of the farmlands in our sample, followed by annual crops and vineyards. A parcel associated with an indicator of orchards is the reference. Our results suggest that pollution has a disproportional impact on farmland associated with annual crops. The annual crops indicator coefficient suggests a negative statistical association with farmland values. The coefficient of the interaction term between $PM_{2.5}$ and an indicator of

[19] Winter pollution corresponds to the average pollution in January, February, and March. Spring pollution corresponds to the average pollution in April, May, and June. Summer pollution corresponds to the average pollution in July, August, and September. Fall pollution corresponds to the average pollution in October, November, and December.

farmland associated with annual crops is positive and statistically significant. Overall, $PM_{2.5}$ has a negative impact on farmland associated with annual crops.

5.4.3. Heterogeneity by region

As mentioned earlier in the data section, the Central Valley has the highest levels of pollution concentration in central and southern San Joaquin Valley. We explored the differential effects of $PM_{2.5}$ on farmland values across region. We categorized the Central Valley counties into indicators for four regions: Sacramento Valley, northern, central, and southern San Joaquin Valley. Farmland sales in the northern San Joaquin Valley were at an average price of $23,113 per acre. The Sacramento Valley had an average sales price per acre of $18,470, while the central and southern San Joaquin Valley had average sales prices of $15,800 and $15,600. Table 8 presents the heterogeneous effects by region. Our results suggest that pollution has a significant negative impact on farmlands in the southern part of San Joaquin Valley. A 1% rise in $PM_{2.5}$ associated with a 13% decrease in farmland value per acre in the northern San Joaquin Valley.

5.5. *Robustness checks*

5.5.1. *Alternative measures of $PM_{2.5}$ and $PM_{10\text{-}2.5}$*

We replicate our primary analysis by substituting mean levels of $PM_{2.5}$ and $PM_{10\text{-}2.5}$ with median, maximum, and minimum values. We found that the estimated coefficients of log farmland sale price per acre based on maximum $PM_{2.5}$ and $PM_{10\text{-}2.5}$ values are not statistically significant. Our results indicate that the farmland sale price per acre is affected by the lower bound of $PM_{2.5}$ and $PM_{10\text{-}2.5}$ values. The significant negative effect on the quadratic terms of fine dust and the main negative effect of coarse dust are stable, indicating robust results. Appendix Table A4 summarizes these results.

Next, we explore remotely sensed particulate data to complement the monitor analysis. We obtained monthly estimates of fine particulate matter ($PM_{2.5}$) data from Van Donkelaar et al. (2021).[20] We gathere gridded datasets with high spatial resolution (0.01 x 0.01 degrees) during the growing season (April through September) for the years 2001–2021. Appendix Figure A7 displays the comparison of the distribution of the daily mean $PM_{2.5}$ interpolated and the monthly mean $PM_{2.5}$ remotely sensed. The monthly mean $PM_{2.5}$ of remote sensed (10.02 $\mu g/m^3$) is less than the daily mean $PM_{2.5}$ of interpolated (13.63 $\mu g/m^3$). We replicate regression results shown in Table 3 using remote sensed monthly mean $PM_{2.5}$ as the main explanatory variables. For the purposes of our analysis, the monthly averages of $PM_{2.5}$ may be a poor indicator of dust exposure since they do not capture nonlinearities. Appendix Table A5 summarizes the results. We observe that the estimated coefficients for $PM_{2.5}$ are similar to those in column (1) in Table 3. The estimated coefficients in columns (2)-(3) are not statistically significant at the 5% level after controlling for other pollutants and climate and non-climate variables.

5.5.2. *Interaction effects of dust particles*

Appendix Table A6 reports the interaction effects of dust particles with wind speed and the direction of winds. Column (1) of Appendix Table A6 shows that the interaction between $PM_{2.5}$ and mean wind speed over the growing season is significantly negative at the 10% significance level. This result indicates that the lower the wind speed, the smaller the effect

[20] Data is available at: https://sites.wustl.edu/acag/datasets/surface-pm2-5/

of $PM_{2.5}$ on the sale price of farmland. Column (2)-(3) exhibits a statistically insignificant interaction between $PM_{2.5}$ and wind direction, suggesting that the price of farmland sold is not affected by southwest and northwest winds.

5.5.3. Impact of wildfires-induced pollution on farmland values

Studies have attributed recent trends in pollution to sources, such as soil (microbial emissions from soil), and wildfires. For example, ozone levels are enhanced, on average, by 10% in the Central Valley from drought-induced wildfire-burned areas during the study periods (Wang, Faloona, and Houlton 2023). Previous studies have identified fugitive NOx emissions over cropland in the Central Valley. California's Fire and Resource Assessment Program (FRAP) compiles fire perimeters from CAL FIRE, the United States Forest Service Region 5, the Bureau of Land Management, and the National Park Service. Data includes the California fire events that occurred since 1950 and variables include fire alarm dates, containment dates, area burned, and the cause of ignition.[21] For the purposes of our analysis, we focused on the wildfire events that happened in these regions for the years 2001–2021. Appendix Figure A8 shows the trends of wildfire-induced area burned across these years. Trends included an increase in the size and severity of wildfires in last two decades, with wide-ranging impacts to agricultural sector, including the viticulture and wine industry (Zakowski et al. 2023). In addition, an increase in biomass burning activity over past two decades in California is a critical factor contributing to NOx, a precursor for primary pollutants such as ozone and particulate matter.

[21] Data is available at https://data.ca.gov/dataset/california-fire-perimeters-all1

Appendix Table A7 presents the effect of predicted fine dust particles on farmland values after controlling for wildfires. Column (1) of Appendix Table A6 suggests that the results remain unchanged. Column (2) indicates that the coefficient on residuals is statistically significant and negative, suggesting the presence of endogeneity bias, although it is small.

6. Conclusion and Policy Implications

Climate change causes more intense drought cycles, which increase airborne dust, negatively impact agricultural productivity and, therefore, reduce the value of farmland. This paper extends the Ricardian model to include dust particulates (and their interaction with climate variables) to estimate the economic impacts of climate change and dust levels on agricultural land value. We provided causal estimates of the effects of fine and coarse dust particulate on farmland values in the Central Valley from 2001 to 2021. Using an unbalanced panel hedonic regression analysis, our findings indicate that an increase in interpolated fugitive dust particulate concentrations has a negative impact on farmland values. Our results indicate an inverse U-shaped relationship between farmland sale price and fine dust particles ($PM_{2.5}$).

$PM_{2.5}$, among other pollutants that share some common sources, has long been regulated (for example, California has specific regulations on industrial and road-traffic pollution), and rightly so mainly because of its negative impact on human health. Similarly, recent studies highlight the negative impact of pollutants on agricultural productivity and global food security. In this context, our paper attempts to characterize the effects of dust particle exposure on California agriculture and provide policymakers with quantifiable estimates of loss to farmland values. Air pollution control actions have policy implications that reduce greenhouse gas emissions and benefit agricultural production by improving air quality.

Particulate matter is complexly interrelated with climate change through warmer temperatures and changes in agricultural operations, such as the increase in fallow land. Howitt et al. (2015) estimated that 542,000 acres of irrigated land in the Central Valley of California may be out of production due to prolonged drought, leading to more fallow land in the future, which will intensify the problem of dust in agriculture. Therefore, climate mitigation policies in agriculture must incorporate dust suppression (e.g., conservation tillage, mulch cover or surface roughening), and dust avoidance at the local and regional levels, including on-farm dust mitigation measures (e.g., maintenance of stubble and vegetative cover on idle land). Landowners can receive support from the government to manage on-farm dust emissions through incentives and sustained funding. There are a few important caveats to the analysis in this paper: First, an unaddressed issue is of measurement error— interpolated dust concentrations may result in noise and low accuracy, and can potentially bias our results. Second, all pollutants were aggregated at the parcel level, which masks heterogeneity and, therefore, may raise concerns about aggregation bias. Nevertheless, our results add to the impact of air pollution on economic output, by quantifying the economic impact of dust particles on California agriculture.

Tables and Figures

Table 1. Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	Observation
Dependent					
Value per acre	17587	27763	93	200754	11,741
Log (value per acre)	9.029	1.338	4.528	12.210	11,741
Explanatory					
Fine dust ($PM_{2.5}$)					
Mean ($\mu g/m^3$)	0.668	1.276	0.001	19.115	11,741
Median ($\mu g/m^3$)	0.507	0.968	0.001	14.757	11,741
Max ($\mu g/m^3$)	2.864	5.729	0.004	112.924	11,741
Min ($\mu g/m^3$)	0.123	0.247	0.0002	3.878	11,741
Days with $PM_{2.5}$ > 12	63	30	1	144	11,741
Coarse dust ($PM_{10-2.5}$)					
Mean ($\mu g/m^3$)	0.594	1.295	1.22e-06	31.110	11,581
Median ($\mu g/m^3$)	0.514	1.115	0.00005	24.335	11,666
Max ($\mu g/m^3$)	6.528	22.477	0.0002	839.318	9,486
Min ($\mu g/m^3$)	0.245	0.632	0.00004	17.857	11,052
Other pollutants: Ozone O3 and Nitrogen dioxide NO2 concentration					
Ozone (parts per million)	0.002	0.003	3.65e-06	0.047	11,741
Nitrogen dioxide (parts per billion)	0.437	0.871	0.001	13.606	11,741
Climate variables					
Deviation from the normal precipitation	-0.193	3.405	-73.568	54.295	11,741
Deviation from the normal max. temperature	0.024	0.090	-1.368	2.244	11,741
Wind speed (miles per hour)	0.222	0.421	0.001	6.522	11,741
1 (Southeast)	0.147	0.354	0	1	11,741
1 (Southwest)	0.795	0.404	0	1	11,741
1 (Northwest)	0.056	0.230	0	1	11,741
Relative humidity (%)	2.592	4.926	0.004	67.755	11,741

Notes: All variables are summarized during the growing season (April through September) at the parcel level over the sample period (2001-2021). All variables used in the analysis are divided by their parcel size. Land values per acre are *winsorized* at the 1 and 99 percentiles. The climate normal is the average of precipitation (mm) and maximum temperature (degree Celsius) for a parcel over a 20-year period. $PM_{10-2.5}$ is obtained by subtracting $PM_{2.5}$ from PM_{10}. We have dropped the negative differences, which is the reason for the variation in sample size for $PM_{10-2.5}$.

Table 2. Comparison of parcels sold repeatedly to all parcels

	(1) Parcel sold repeatedly	(2) Parcel sold once	Diff. (1)-(2) (t-value)
Value (in thousand dollars)	991	1269	-277***
	(2436)	(3928)	(6.84)
Value per acre (in thousand dollars)	18	20	-2***
	(29)	(33)	(6.10)
Area (acre)	104.36	121.87	17.51***
	(270.20)	(551.66)	(3.27)
Years between two transactions	7.5	-	-
	(4.9)		
Observations	11,741	13,525	
Number of parcels	5,396	13,525	

Note: Mean sale price is reported. The standard deviation is presented in parentheses. Prices are expressed in 2021 real prices. Level of significance: $p < 0.01^{***}$.

Table 3. Correlation matrix between various airborne pollutants

	$PM_{2.5}$	$PM_{10\text{-}2.5}$	Ozone	NO_2
$PM_{2.5}$	1			
$PM_{10\text{-}2.5}$	0.55	1		
Ozone	-0.07	-0.02	1	
NO_2	-0.06	-0.22	0.12	1

Note: Pollution variables are summarized at the parcel level over the sample period (2001–2021). $PM_{10\text{-}2.5}$ is obtained by subtracting $PM_{2.5}$ from PM_{10}. The correlation is obtained by regressing the value per acre on pollutants, controlling for parcel and year-of-sale fixed effects.

Table 4. Impact of dust levels on farmland values

	Dependent variable: Log (value per acre)				
	(1)	(2)	(3)	(4)	(5)
Fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.500***	0.145*	0.145*	0.145*	0.174**
	(0.065)	(0.081)	(0.084)	(0.084)	(0.084)
Fine dust square	-0.020***	-0.006	-0.009*	-0.009*	-0.010**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Coarse dust ($PM_{10\text{-}2.5}$, $\mu g/m^3$)				-0.031**	-0.031**
				(0.014)	(0.014)
Number of days in a growing season with $PM_{2.5}$ > 12					-0.004***
					(0.001)
Observations	11741	11741	11741	11474	11474
Number of parcels	5396	5396	5396	5285	5285
Adjusted R-squared	0.723	0.724	0.724	0.720	0.721
Other pollutants controls	No	No	Yes	Yes	Yes
Climate controls	No	No	Yes	Yes	Yes
Non-climate controls	No	No	Yes	Yes	Yes
Parcel-level FEs	Yes	Yes	Yes	Yes	Yes
Year of sale FEs	Yes	Yes	Yes	Yes	Yes

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. The primary explanatory variable is the interpolated daily $PM_{2.5}$ and $PM_{10\text{-}2.5}$ concentrations at the parcel level. Controls include other pollutants (ozone O_3 and nitrogen dioxide NO_2 and their squared terms), climate and non-climate variables. Climate variables include the deviation from the normal (20-year average) precipitation and maximum temperature, wind speed and direction (indicator for southwest and northwest), relative humidity, and soil moisture. All climate and pollution variables are parcel acreage-weighted averaged during the growing season (April through September) over the sample period (2001–2021). An indicator for the direction of the southeast wind is the reference. Non-climate variables include an indicator for the parcel associated with crop types such as orchards and vineyards.

Table 5. Effect of predicted fine dust particles on farmland values

	Dependent variable: Log (value per acre)	
	(1)	(2)
Predicted fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.767***	
	(0.249)	
Predicted fine dust square	-0.038***	
	(0.011)	
Fine dust ($PM_{2.5}$, $\mu g/m^3$)		0.169
		(0.106)
Fine dust square		-0.010**
		(0.005)
Residual ($PM_{2.5} – PM_{10\text{-}2.5}$)		-0.016
		(0.010)
Fine dust x residual		0.007
		(0.007)
Observations	11,741	11,741
Number of parcels	5396	5396
Adjusted R-squared	0.724	0.724
Other pollutants controls	Yes	Yes
Climate controls	Yes	Yes
Non-climate controls	Yes	Yes
Parcel-level FEs	Yes	Yes
Year of sale FEs	Yes	Yes

Notes: Level of significance: ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. The primary explanatory variable is the predicted $PM_{2.5}$ concentration at the parcel level. Predicted $PM_{2.5}$ is obtained by regressing mean observed $PM_{2.5}$ on regressors such as aerosol optical thickness, mean precipitation, maximum temperature (and their interaction), wind speed, wind direction (indicator for southwest and northwest), relative humidity, and soil moisture during the growing season. Appendix Table A2 reports the results.

Table 6. Heterogeneity by season

	Coef.	SE
Winter $PM_{2.5}$	0.493^{***}	(0.152)
Winter $PM_{2.5}$ square	-0.022^{***}	(0.008)
Spring $PM_{2.5}$	0.101	(0.096)
Spring $PM_{2.5}$ square	-0.004	(0.004)
Summer $PM_{2.5}$	0.019	(0.048)
Summer $PM_{2.5}$ square	-0.001	(0.001)
Fall $PM_{2.5}$	-0.010	(0.040)
Fall $PM_{2.5}$ square	-0.0003	(0.002)
Parcel-level & year of sale FEs	Yes	
Observations	11,226	
Adjusted R-squared	0.720	

Notes: Level of significance: *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. Winter pollution corresponds to the average pollution in January, February, and March. Spring pollution corresponds to the average pollution in April, May, and June. Summer pollution corresponds to the average pollution in July, August, and September. Fall pollution corresponds to the average pollution in October, November, and December. See notes to Table 3 for other details.

Table 7. Heterogeneity by crop type

	Coef.	SE
Fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.068	(0.081)
Fine dust square	-0.008^{*}	(0.004)
1 (Annual crops)	-0.239^{**}	(0.122)
$PM_{2.5}$ x 1 (Annual crops)	0.123^{***}	(0.056)
1 (Vineyard)	0.193	(0.137)
$PM_{2.5}$ x 1 (Vineyard)	0.106	(0.117)
All Controls & FEs	Yes	
Observations	11,741	
Adjusted R-squared	0.726	

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. A parcel associated with an indicator of orchards is the reference. See notes to Table 3 for other details.

Table 8. Heterogeneity by region

	Coef.	SE
Fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.187^{***}	(0.077)
Fine dust square	-0.007^{*}	(0.004)
$PM_{2.5}$ x 1 (northern San Joaquin Valley)	0.132	(0.115)
$PM_{2.5}$ x 1 (central San Joaquin Valley)	-0.074	(0.071)
$PM_{2.5}$ x 1 (southern San Joaquin Valley)	-0.126^{***}	(0.056)
All Controls & FEs	Yes	
Observations	11,741	
Adjusted R-squared	0.724	

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. The Central Valley counties were categorized into indicators for four regions: Sacramento Valley, northern, central, and southern San Joaquin Valley. The reference is an indicator for the Sacramento Valley. See notes to Table 3 for other details.

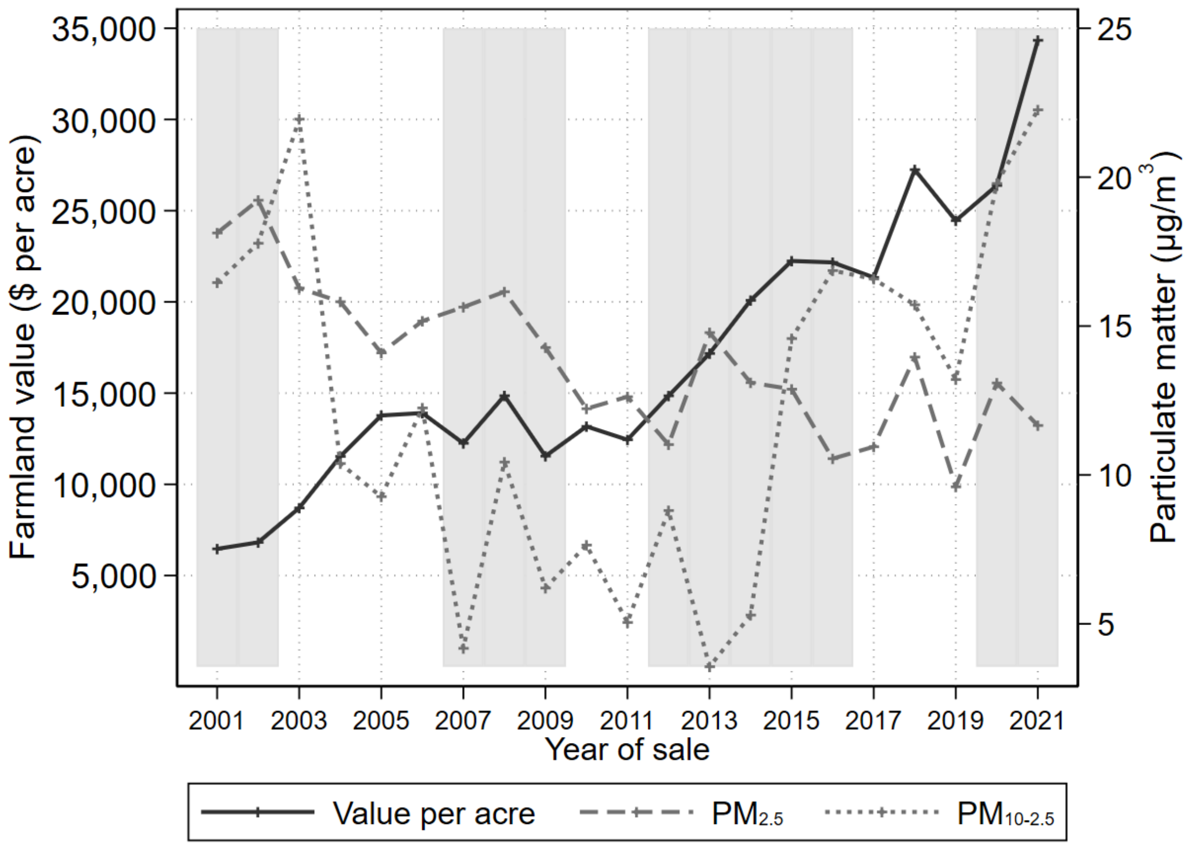

Figure 1. Trends of pollution and land values in the Central Valley for the years 2001–2021

Notes: Pollution and farmland sale prices per acre are summarized at the parcel level. Farmland values per acre are adjusted for inflation (in 2021 $). In the background of the graphs, we highlight the major droughts in California, which included droughts between 2001–2002, 2007–2009, 2012–2016, and 2020–2021.

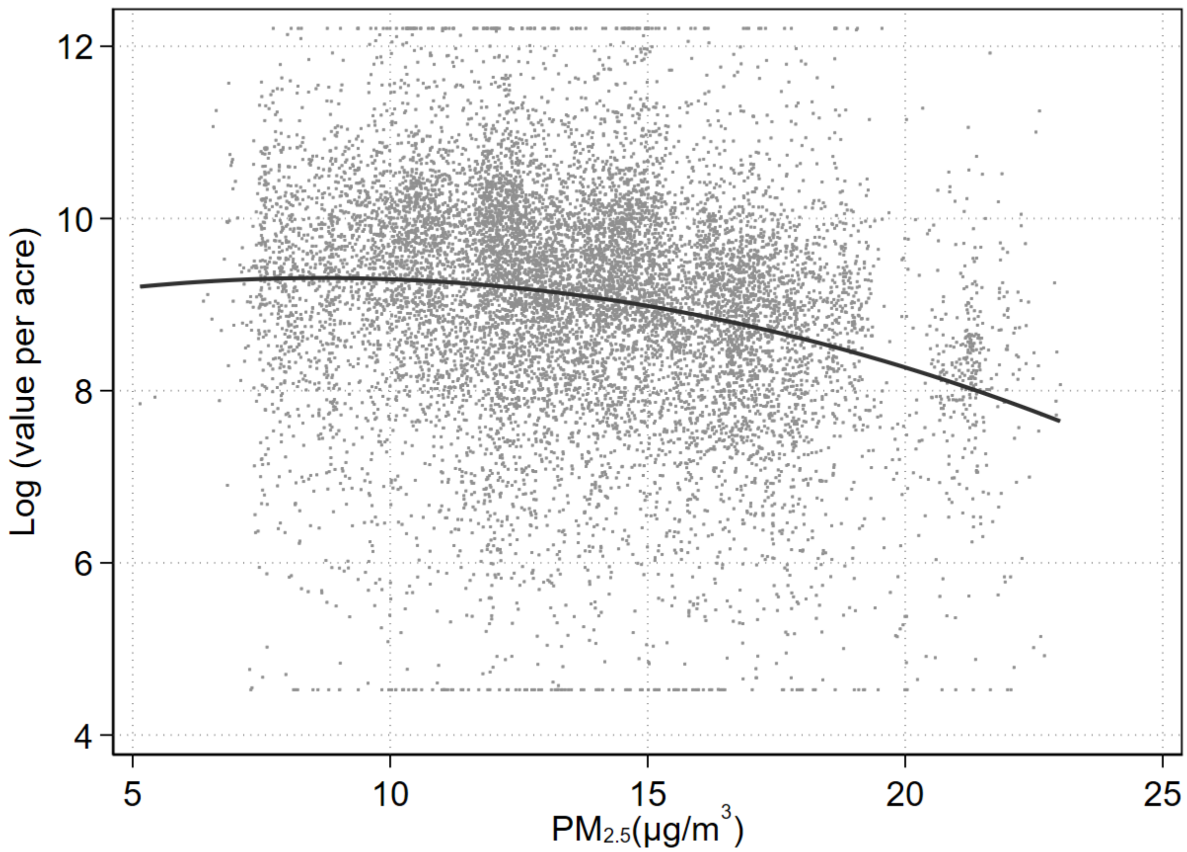

Figure 2. Scatter plot for the correlation between the log farmland values and $PM_{2.5}$ particulate concentrations

Notes: The x-axis represents the log values per acre, while the y-axis represents the $PM_{2.5}$ particulate concentrations. The dots represent the log farmland values per acre, and the dark line represents the quadratic fit values. The properties (farmland) are in the Central Valley.

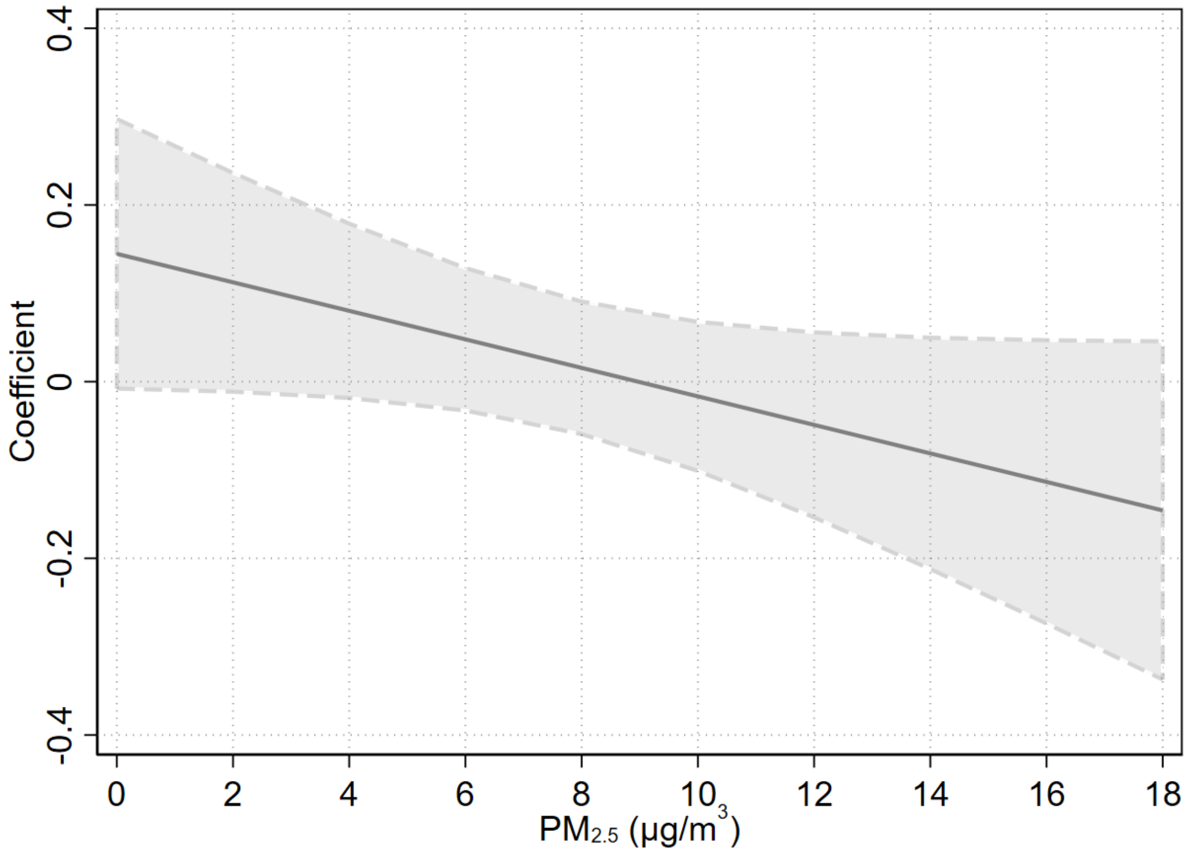

Figure 3. Average marginal effect of $PM_{2.5}$ on farmland values

Note: The slope of $PM_{2.5}$ changes from positive to negative beyond the threshold point of 8.5 $\frac{\mu g}{m^3}$ per acre. The shaded area represents the 95% confidence interval.

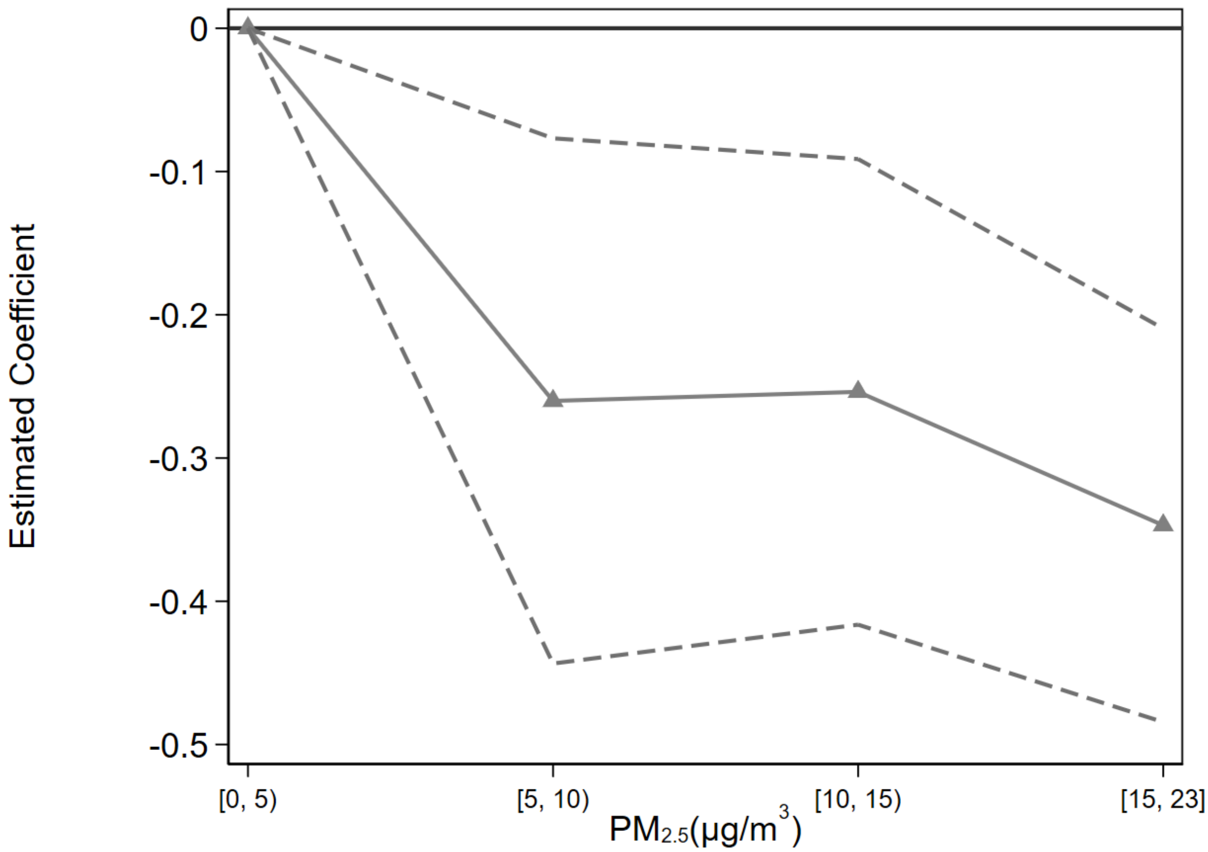

Figure 4. Non-linear effects of $PM_{2.5}$ on farmland values

Note: The first bin (0-5 $\mu g/m^3$) is the reference bin. The solid line represents the point estimate, and the dashed line represents the 95% confidence level. Appendix Table A3 reports the full results.

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Appendix Tables and Figures

Appendix Table A1: Hedonic regression results using linear-linear function forms

Dependent var.: Value per acre	(1) Linear-Linear	(2) Linear-Linear
Fine dust ($PM_{2.5}$, $\mu g/m^3$)	5884.242*	
	(3119.768)	
Fine dust square	-343.996**	
	(171.662)	
Coarse dust ($PM_{10\text{-}2.5}$, $\mu g/m^3$)		-946.371
		(612.847)
O_3 (ppm)	1958415.384	2184462.800
	(1533121.671)	(1673362.271)
NO_2 (ppb)	-2784.005	-2780.443
	(2107.226)	(2069.197)
Climate variable		
Deviation from the normal precipitation	-36.596	73.167
	(135.260)	(137.234)
Deviation from the normal max. temp.	676.724	6943.145
	(8768.773)	(10479.756)
Wind speed (mph)	8872.836	9478.610
	(6970.412)	(7178.468)
1 (Southwest)	476.032	760.508
	(793.695)	(829.540)
1 (Northwest)	-292.482	-8.388
	(1375.683)	(1399.404)
Relative humidity	740.172	1271.512*
	(734.748)	(726.468)
Parcel-level FEs	Yes	Yes
Year of sale FEs	Yes	Yes
Mean dependent variable	17587.225	17553.394
SD dependent variable	27763.482	27426.672
Number of parcels	5396	5286
Observations	11741	11474
Adjusted R-squared	0.709	0.700

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$. Robust standard errors in parentheses are clustered at the parcel level. See notes to Table 3 for other details.

Appendix Table A2: Predicted fine dust particulate matter ($PM_{2.5}$)

	$PM_{2.5}$
Optical thickness	-0.878***
	(0.194)
Precipitation (mm)	0.016*
	(0.010)
Max. temperature (degree C)	0.119***
	(0.053)
Precipitation x max. temperature	-0.0005
	(.0003)
Windspeed (mph)	0.252***
	(0.042)
1 (Southwest)	-0.350***
	(0.109)
1 (Northwest)	-0.259***
	(0.118)
Relative humidity (%)	-0.030***
	(0.011)
Soil moisture (kg/m^2)	-0.071***
	(0.019)
Parcel-level FEs	Yes
Year of sale FEs	Yes
Observations	11,741
Adjusted R-squared	0.889

Notes: Level of significance: *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the interpolated daily $PM_{2.5}$ concentration at the parcel level. All climate and pollution variables are parcel acreage-weighted averaged during the growing season (April through September) over the sample period (2001–2021).

Appendix Table A3. Non-linear effects of $PM_{2.5}$ on farmland values

	Dependent variable: Log (value per acre)
$PM_{2.5} \in [0, 5)$	Baseline
$PM_{2.5} \in [5, 10)$	-0.260***
	(0.094)
$PM_{2.5} \in [10, 15)$	-0.254***
	(0.083)
$PM_{2.5} \in [15, 23]$	-0.347***
	(0.070)
All Controls & FEs	Yes
Observations	11,741
Adjusted R-squared	0.725

Notes: Level of significance: *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. See notes to Table 3 for other details.

Table A4. Alternative measures of $PM_{2.5}$ and $PM_{10-2.5}$

Dependent var.: Log (value per acre)	Baseline	Median	Max.	Min.
Fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.145*	-0.011	0.009	0.797***
	(0.084)	(0.119)	(0.013)	(0.254)
Fine dust square	-0.009*	-0.003	-0.0001	-0.183*
	(0.005)	(0.007)	(0.0001)	(0.068)
Coarse dust ($PM_{10-2.5}$, $\mu g/m^3$)	-0.031**	-0.050***	0.0001	-0.065***
	(0.014)	(0.018)	(0.001)	(0.025)

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. Land values per acre are *winsorized* at the 1 and 99 percentiles. See notes to Table 3 for other details.

Appendix Table A5. Remotely sensed monthly mean $PM_{2.5}$ and farmland sale price per acre

	Dependent variable: Log (value per acre)		
	(1)	(2)	(3)
Remote sensed $PM_{2.5}$ ($\mu g/m^3$)	0.306***	0.021	-0.013
	(0.053)	(0.045)	(0.020)
$PM_{2.5}$ square	-0.009***	-0.001	0.0001
	(0.002)	(0.001)	(0.001)
Observations	11,741	11,741	11,741
Adjusted R-squared	0.719	0.723	0.724
Other pollutants controls	No	Yes	Yes
Climate controls	No	No	Yes
Non-climate controls	No	No	Yes
Parcel-level FEs	Yes	Yes	Yes
Year of sale FEs	Yes	Yes	Yes

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. Land values per acre are *winsorized* at the 1 and 99 percentiles. The primary explanatory variable is the remote sensed monthly mean $PM_{2.5}$ concentration at the parcel level. See notes to Table 3 for other details.

Appendix Table A6. Interaction effects of dust particle concentrations

	Dependent variable: Log (value per acre)		
	(1)	(2)	(3)
Fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.126	0.143*	0.142*
	(0.077)	(0.080)	(0.078)
Fine dust square	0.004	-0.008*	-0.008*
	(0.006)	(0.004)	(0.004)
$PM_{2.5}$ x wind speed	-0.062**		
	(0.024)		
$PM_{2.5}$ x 1 (Southwest)		0.003	
		(0.021)	
$PM_{2.5}$ x 1 (Northwest)			0.007
			(0.032)
All controls & FEs	Yes	Yes	Yes
Observations	11,741	11,741	11,741
Adjusted R-squared	0.724	0.724	0.724

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. Land values per acre are *winsorized* at the 1 and 99 percentiles. An indicator for the direction of the southeast wind is the reference. See notes to Table 3 for other details.

Appendix Table A7. Effect of predicted fine dust particles on farmland values after controlling for wildfires

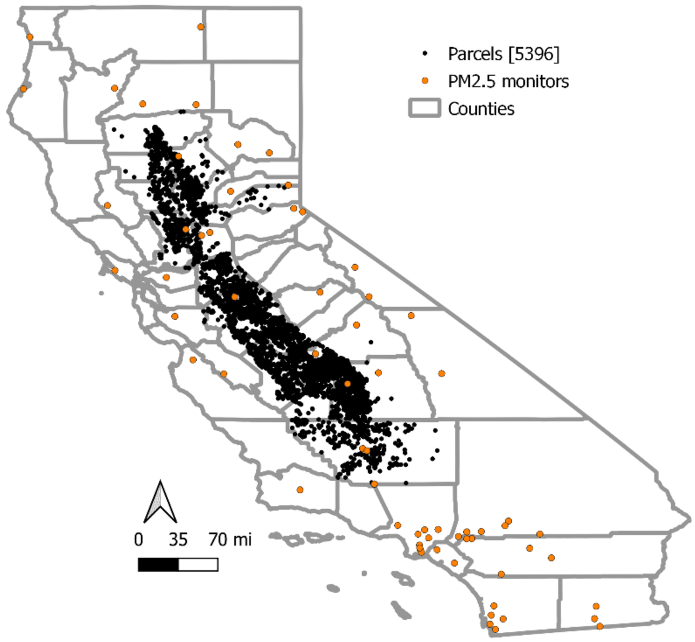
	Dependent variable: Log (value per acre)	
	(1)	(2)
Predicted fine dust ($PM_{2.5}$, $\mu g/m^3$)	0.476**	
	(0.214)	
Predicted fine dust square	-0.032***	
	(0.010)	
Fine dust ($PM_{2.5}$, $\mu g/m^3$)		0.141
		(0.106)
Fine dust square		-0.010*
		(0.005)
Residual ($PM_{2.5}$ – $PM_{10\text{-}2.5}$)		-0.020*
		(0.011)
Fine dust x residual		0.014
		(0.009)
Observations	11,741	11,741
Adjusted R-squared	0.724	0.724
Other pollutants controls	Yes	Yes
Climate controls	Yes	Yes
Non-climate controls	Yes	Yes
Parcel-level FEs	Yes	Yes
Year of sale FEs	Yes	Yes

Notes: Level of significance: ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log value per acre. Land values per acre are *winsorized* at the 1 and 99 percentiles. The primary explanatory variable is the predicted $PM_{2.5}$ concentration at the parcel level. Predicted $PM_{2.5}$ is obtained by regressing mean observed $PM_{2.5}$ on regressors such as aerosol optical thickness, mean precipitation, maximum temperature (and their interaction), wind speed, wind direction (indicator for southwest and northwest), relative humidity, and soil moisture during the growing season. Appendix Table A8 reports the results.

Appendix Table A8. Predicted fine dust particulate matter ($PM_{2.5}$) after controlling for wildfires

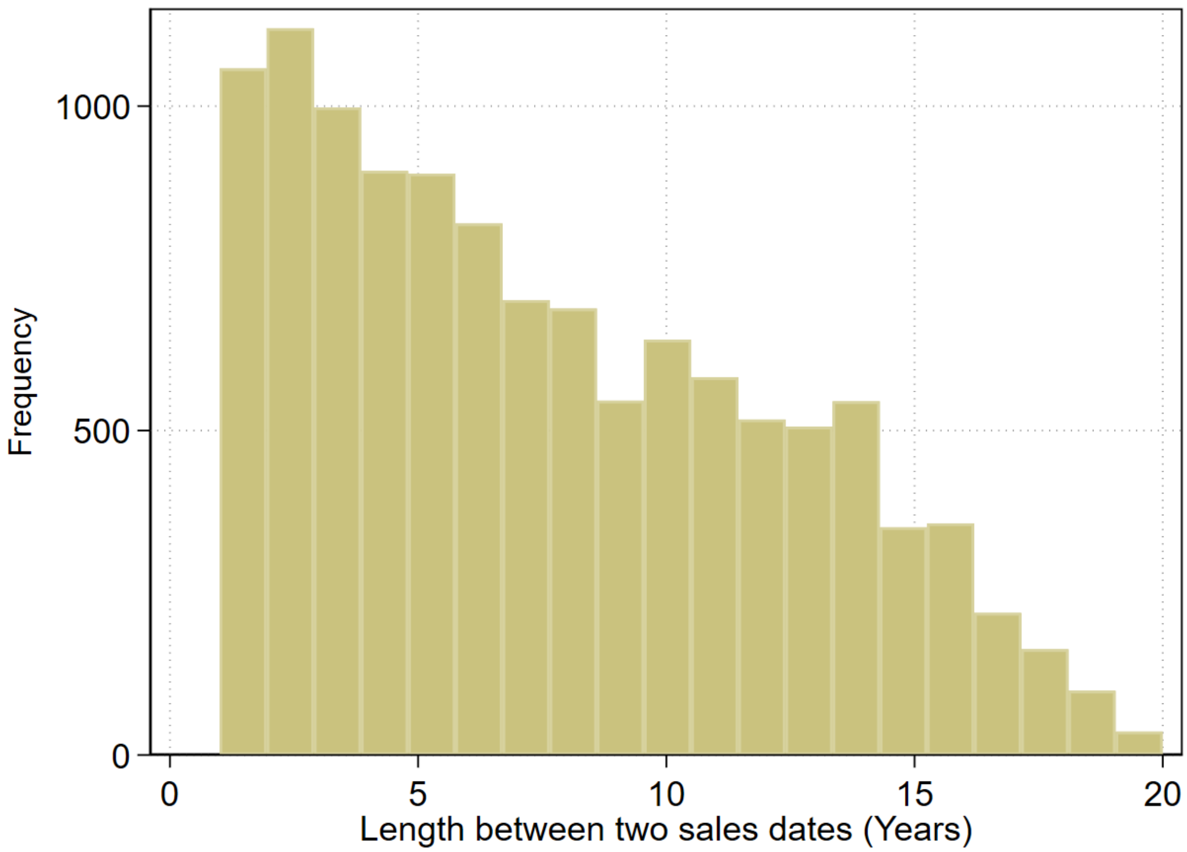
	$PM_{2.5}$
Optical thickness	-0.201
	(0.179)
Precipitation (mm)	0.026^{***}
	(0.007)
Max. temperature (degree C)	0.132^{***}
	(0.050)
Precipitation x max. temperature	-0.0007^{***}
	(.0002)
Windspeed (mph)	0.229^{***}
	(0.040)
1 (Southwest)	-0.342^{***}
	(0.103)
1 (Northwest)	-0.309^{***}
	(0.112)
Relative humidity (%)	-0.025^{***}
	(0.011)
Soil moisture (kg/m^2)	-0.049^{***}
	(0.019)
Area burned (acres)	$4.12e\text{-}06^{***}$
	(2.02e-07)
Parcel-level FEs	Yes
Year of sale FEs	Yes
Observations	11,741
Adjusted R-squared	0.899

Notes: Level of significance: *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the interpolated daily $PM_{2.5}$ concentration at the parcel level. All climate and pollution variables are parcel acreage-weighted averaged during the growing season (April through September) over the sample period (2001–2021).



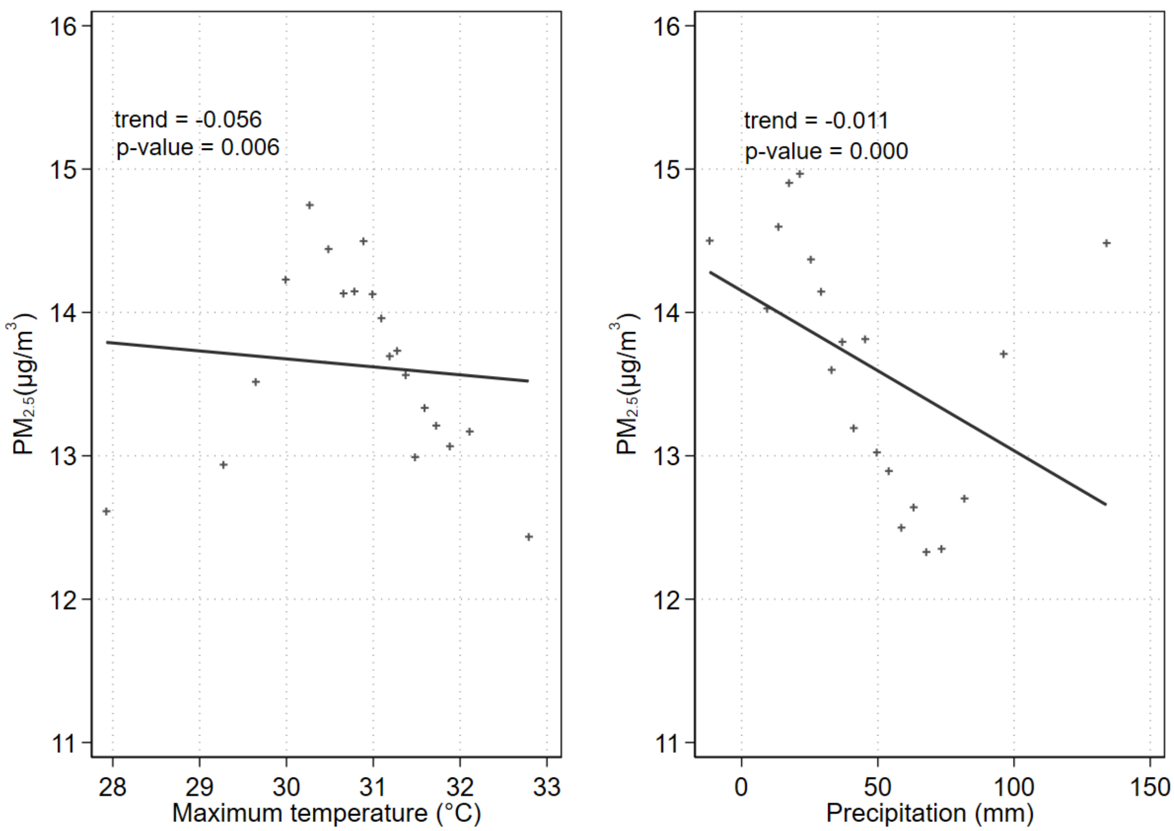
Appendix Figure A1: Selected parcels repeatedly sold from 2001 to 2021 in the Central Valley of California.

Notes: The figure shows the selected parcels as dots. PM2.5 monitor stations are in orange dots (85). The county boundaries are shown in gray.



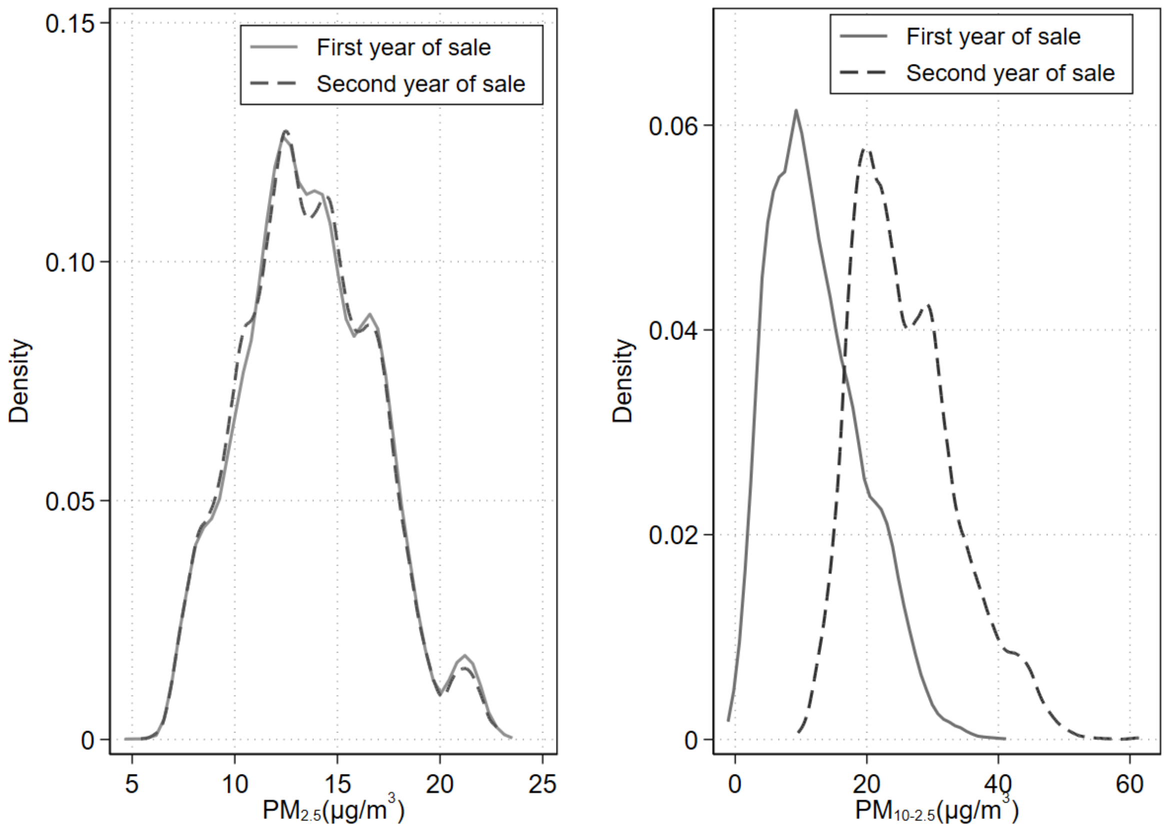
Appendix Figure A2: Structure of the repeat-sales sample

Notes: The figure shows the frequency of the period between two transactions in our repeat-sales sample. Our sample includes parcels that have been sold twice or three times. The length of sales for parcels that were sold twice is calculated by taking the difference between the first and second year of transactions. For parcels sold three times, the length between the sales is calculated between the first and third year of transactions.



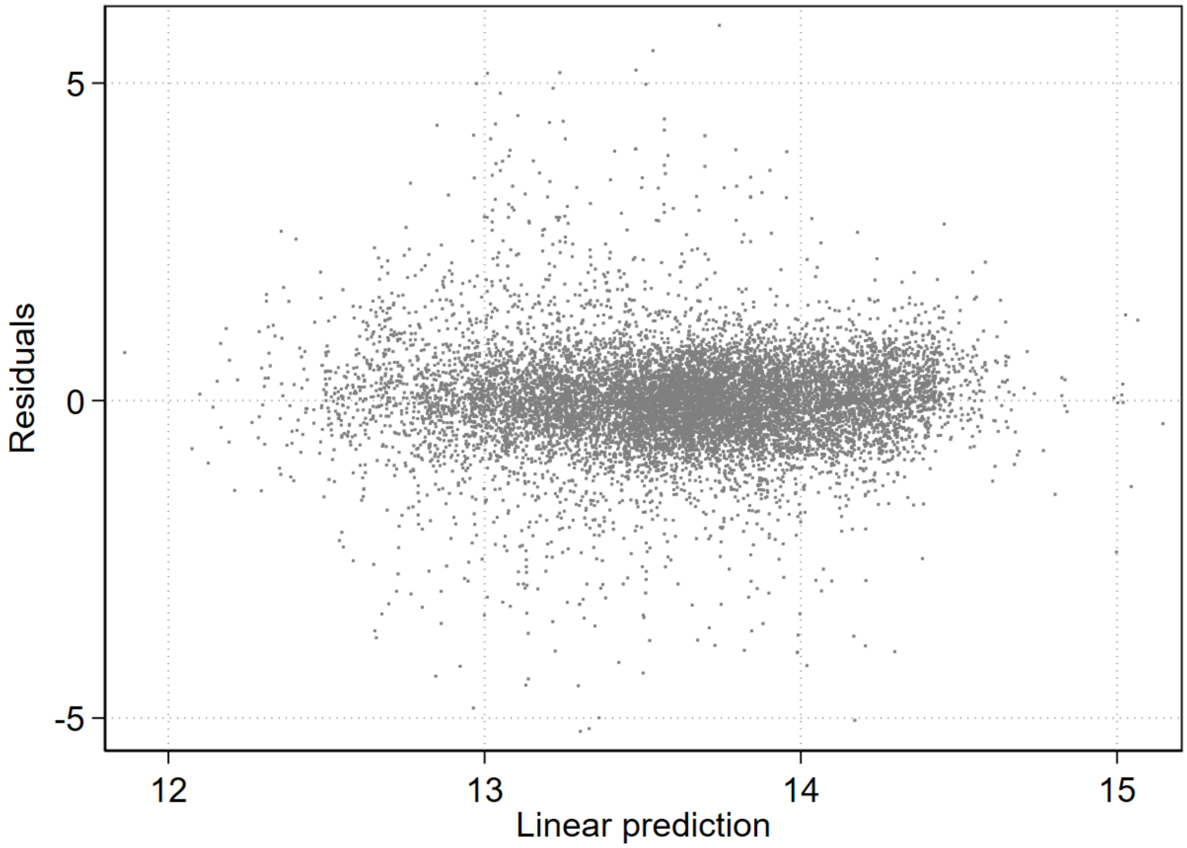
Appendix Figure A3: Binned scatterplot and linear fit line, conditional on county fixed effects.

Notes: Figure shows the correlation between $PM_{2.5}$ and maximum temperature (left) and precipitation (right). Each point represents the mean of $PM_{2.5}$ in a given maximum temperature and precipitation bin. $PM_{2.5}$ is derived from daily pollution concentrations in a parcel over the growing season (April through September). The maximum temperature is the average temperature for a given year during the growing season, which is based on the daily maximum temperature. Based on daily precipitation, the total precipitation for a given year during the growing season is calculated.



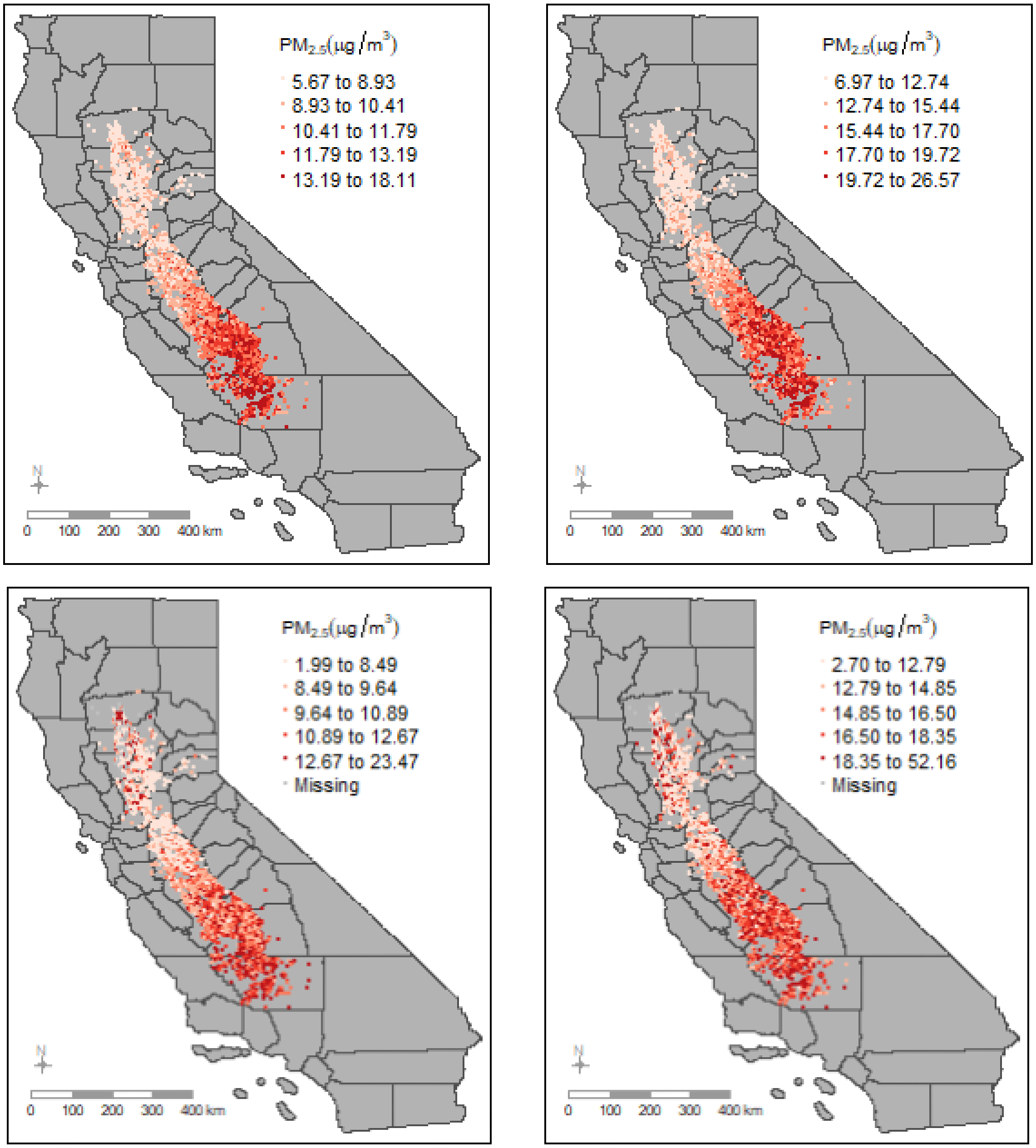
Appendix Figure A4: Kernel density estimate of $PM_{2.5}$ (left) and $PM_{10-2.5}$ (right) exposure on parcels that were repeatedly sold

Notes: Our sample includes parcels that have been sold twice or three times. The length of sales for parcels that were sold twice is calculated by taking the difference between the first and second year of transactions. For parcels sold three times, the length between the sales is calculated between the first and third year of transactions.



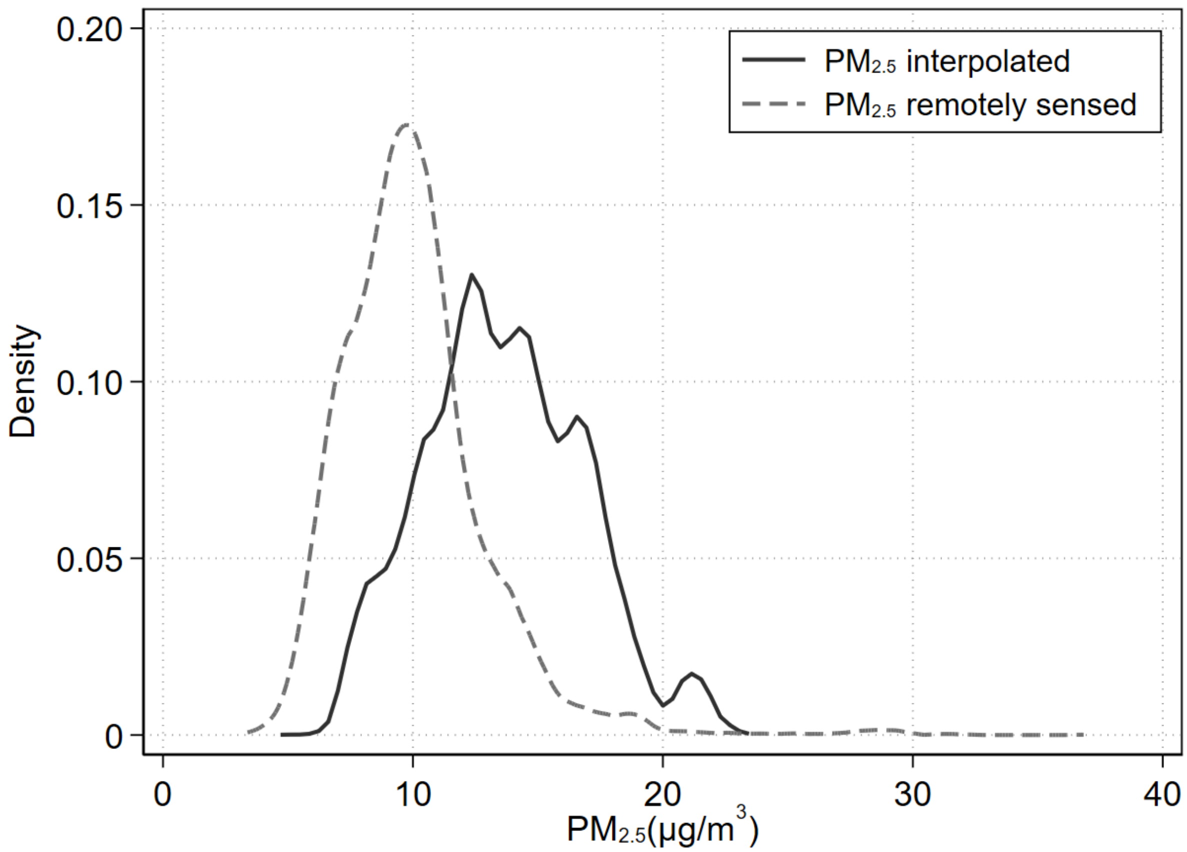
Appendix Figure A5. The scatter plot shows the relationship between the predicted values and the residuals

Note: This figure shows that the residuals are around zero and tend to grow larger as the fitted values increase.



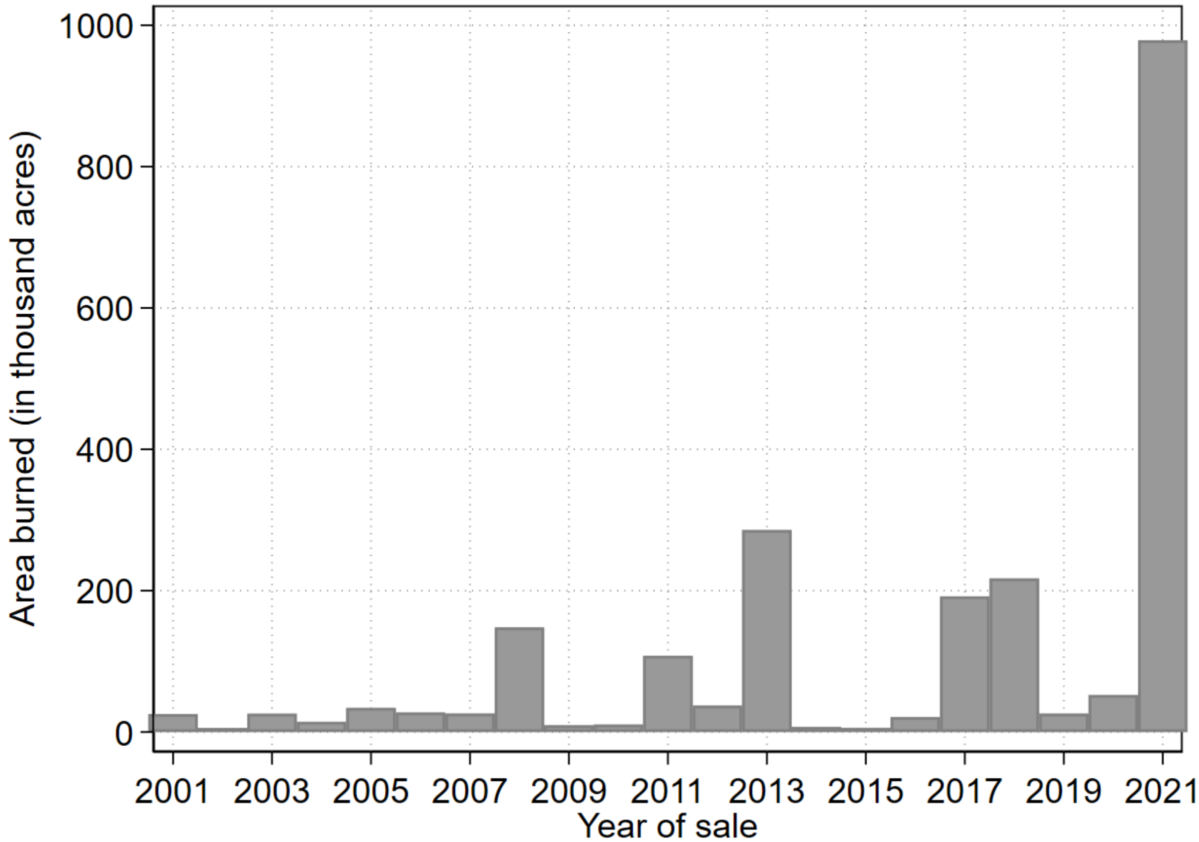
Appendix Figure A6. The mean seasonal $PM_{2.5}$ in the Central Valley during the study period (2001–2021)

Note: The clockwise presentation of $PM_{2.5}$ shows winter at the top left, spring at the top right, summer at the bottom left, and Fall at the bottom right. The winter and spring seasons are marked by the highest pollution levels at the lower bound, with the highest levels being found in the central and southern San Joaquin Valley.



Appendix Figure A7. Kernel density estimate of $PM_{2.5}$ interpolated and $PM_{2.5}$ remotely sensed

Note: The monthly mean $PM_{2.5}$ of remotely sensed (10.02) is less than the daily mean $PM_{2.5}$ of interpolated (13.63).



Appendix Figure A8. The wildfire-induced area burned around the Central Valley

Source: Author’s calculations based on the fire perimeters from CAL FIRE.

Notes: We select wildfires that affect the Central Valley during the growing season (fire months from April to September) each year. We assign wildfires to the four regions of the Central Valley (Sacramento Valley, northern, central, and southern San Joaquin Valley). To the region of Sacramento Valley, we assign wildfire unit IDs: Tehama-Glenn CAL FIRE TGU, Butte CAL FIRE BTU, and Sacramento National Wildfire Refuge SWR. To the northern San Joaquin Valley region, we assign San Joaquin River National Wildfire Refuge (SJR), Stanislaus National Forest STF, and Merced National Wildfire Refuge (MCR). To the region of central San Joaquin Valley, we assign Madera – Mariposa CAL FIRE MMU, and Fresno – Kings CAL FIRE FKU. We assign Tulare CAL FIRE TUU, Kern County KRN, and Kern National Wildlife Refuge KRR to the southern San Joaquin Valley.