# Do aerially applied pesticides affect local air quality? Empirical evidence from California's San Joaquin Valley*

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**Abstract**

Many policymakers, public-health advocates, and citizen groups question whether current pesticide regulations properly equate the marginal social costs of pesticide applications to their marginal social benefits—with particular concern for negative health effects stemming from pesticide exposure. Additionally, recent research and policies in public health, epidemiology, and economics emphasize how fine particulate matter (PM2.5) concentrations harm humans through increased mortality, morbidity, mental health issues, and a host of socioeconomic outcomes. This paper presents the first empirical evidence that aerially applied pesticides increase local PM2.5 concentrations. To causally estimate this effect, I combine the universe of aerial pesticide applications in the five southern counties of California's San Joaquin Valley (1.8M reports) with the U.S. EPA's PM2.5 monitoring network—exploiting (**1**) spatiotemporal variation in aerial pesticide applications and (**2**) variation in local wind patterns. I find significant evidence that (upwind) aerial pesticide applications within 1.5km increase local PM2.5 concentrations. The magnitudes of the point estimates suggest that the top decile of aerial applications may sufficiently increase local PM2.5 to warrant concern for human health.

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# 1 Introduction

Recent economic, epidemiological, and public health research strengthens the body of evidence that exposure to high levels of pesticides increases the incidence of a number of negative health outcomes, *e.g.*, low birthweight, gestational length, birth abnormalities (Larsen, Gaines, and Deschênes 2017). In addition, a large body of work demonstrates the effect of exposure to particulate matter (PM) on mortality (Seaton et al. 1995; Pope III et al. 2002; Guaita et al. 2011; Lu et al. 2015), morbidity (Pope III 1989; Currie and Walker 2011; Laumbach and Kipen 2012), mental health (Graff Zivin and Neidell 2013; Volk et al. 2013), and negative social/economic outcomes (Ransom and Pope 1992; Kim, Kabir, and Kabir 2015; Isen, Rossin-Slater, and Walker 2017).

This paper attempts to provide the first empirical evidence on (**1**) the extent to which aerially applied pesticides increase local fine particulate matter (PM2.5)[1] concentrations and (**2**) the degree to which aerial pesticide-induced PM2.5 drifts to neighboring areas. To carry out this test, I use the universe of aerial pesticide applications in the five southern counties of California's San Joaquin Valley from 2000 to 2015, in conjunction with the U.S. Environmental Protection Agency (EPA)'s PM2.5 monitoring network. The empirical tests use (**1**) spatiotemporal variation in aerial pesticide application and (**2**) variation in wind direction to isolate the necessary plausibly exogenous variation to evaluate these questions. I find significant evidence that aerially applied pesticides increase local PM2.5 concentrations (reducing local air quality) within 1.5 kilometers of the application. The magnitude of the effect suggests that the top decile of aerially applied pesticides may increase local PM2.5 concentrations sufficiently to warrant public health concern.

While many issues relating to pesticides—health effects, use, bans—remain hotly debated (Pimentel et al. 1992; Tong 2018), federal (*e.g.*, the EPA) and state (*e.g.*, California's Department of Pesticide Regulation (DPR)) entities regulate, to some degree, the types and amounts of pesticides a farmer may apply to her land—particularly in areas near schools or population centers. Notably, the vast majority of pesticide-use regulations consider the individual farmer as the relevant actor—attempting to limit others' exposures from a farmer's pesticide application. This regulatory strategy may be plausibly efficient/optimal if pesticides do not travel far from their points of application and if neighboring farmers' applications do not correlate positively in time. However, if pesticides drift from their points of application—and if farmers tend to apply pesticides at the same time and in the same area[2]—then regulating individual farmers without concern for local, aggregate behavior may miss important dimensions of exposure. In other words, if each farmer in a highly agricultural area applies pesticides just below an established *safe level*, and if each farmer's pesticides aggregate locally and/or drift slightly downwind onto neighboring areas, then these downwind, neighboring areas may be exposed to levels of pesticide above the established *safe level*. This paper investigates the extent to which statistical evidence supports these hypotheses.

# 2 Data

The empirics in this apply three separate datasets: (**1**) fine particulate matter (PM2.5) monitoring data from the EPA's network of air-quality monitors, (**2**) pesticide-use reports from the

[1]Fine particulate matter, or PM2.5, is defined as any particle with an aerodynamic diameter less than 2.5 $\mu m$ (Volk et al. 2013).

[2]As one might expect if agriculture is correlated in space.

California Department of Pesticide Regulation (DPR), and (**3**) wind data from NASA's North American Land Data Assimilation Systems, version 2 (NLDAS-2).

### 2.1 Air-quality monitors

This paper sets out to measure the effect of aerial pesticide applications on local air quality in California's San Joaquin Valley. The ideal candidate for air-quality measurement would measure air quality throughout the southern San Joaquin Valley with high precision and accuracy—and with high temporal frequency. While many valuable measures of air quality exist, as discussed above, a large literature demonstrates the importance of PM2.5 levels for human health. The EPA's PM2.5 monitoring network therefore provides a sensible candidate for this task: between 2000 and 2015, the EPA monitored PM2.5 levels using 53 unique monitors located throughout the five counties of the southern San Joaquin Valley.[3] Further, in nearly every year, at least one monitor measured PM2.5 concentrations on each day of the year, resulting in approximately 108,000 observations of PM2.5 levels in the southern San Joaquin Valley between 2000 and 2015. Table 1 summarizes the number of monitors and days observed for each year starting in 2000 and ending in 2015 for the five southern San Joaquin Valley counties. In addition, EPA monitors play a central role in implementing the Clean Air Act in the United States and thus supply a policy-relevant candidate for air-quality measurement in this paper (U.S. E.P.A. 2016).

Each of the five counties on the southern end of California's San Joaquin Valley contain multiple EPA monitors.[4] Figure 1 maps out the EPA monitors' locations throughout the five counties. These monitors report hourly PM2.5 local concentrations ($\mu g/m^3$) for a 24-hour period—either each day or every sixth day. Figure 2 plots the daily mean PM2.5 reading at each of the 53 monitors on each day the monitor recorded values.[5] Figure 2 also illustrates (**1**) substantial seasonal variation in PM2.5 concentrations at these monitors—ramping up in the late fall and peaking in January—and (**2**) the tendency for PM2.5 concentrations in these five counties to exceed established air-quality standards (U.S. E.P.A. 2013). Jointly, Figure 1 and 2 suggest the EPA PM2.5 network offers a reasonable solution for measuring air quality in the southern San Joaquin Valley, given its spatial and temporal coverage/variation and its importance to environmental regulation.

### 2.2 Pesticide-use reports

The geographic focus of this paper—the southern counties of California's San Joaquin Valley—stems in part from availability of data on pesticide use. In 1990, the state of California established the United States' first state-level, mandatory full-reporting system for pesticides (California D.P.R. 2000). Today the California DPR's pesticide-use reporting (PUR) system is widely regarded as the world's most comprehensive and high-quality record of pesticide use (California D.P.R. 2000; Wilhoit 2012; Larsen, Gaines, and Deschênes 2017). By law, any individual who applies agricultural pesticides must report the pesticide applications on a monthly basis to the relevant county agricultural commissioner. The county agricultural commissioner then sends the reports to the California DPR, who review, summarize, and publish the PUR data.[6] For application of agricultural pesticides, the user must report (**1**) the

[3] A number of the monitors phased in and out during this time so 22-36 monitors actively observed each year.
[4] By name, the five counties are: Fresno County, Kern County, Kings County, Madera County, and Tulare County.
[5] Figure A1 repeats this exercise but uses the daily *maximum* PM2.5 instead of the *mean*.
[6] The PUR data are publicly available on the California DPR's website.

date of application, (**2**) the location of application (section, township, range), (**3**) the type of pesticide, (**4**) the amount of pesticide, and (**5**) identifiers for the site and user (California D.P.R. 2000).[7] Because the PUR system does not systematically identify PURs below the section-township-range level, the finest spatial resolution is the section, which is a grid of approximately one-square-mile cells. This spatial restriction both limits attribution of pesticide use to PM2.5 concentrations and limits the usefulness of wind-direction data, as I discuss in more detail below.

Figures 3 and 4 depict the number of pesticide use reports and the tons of pesticides applied, respectively, aggregated to the month of sample—across the five study counties from 2000 to 2015. Each figure splits the summaries by (a) aerially applied pesticides and (b) ground-applied pesticides. Figure 5 illustrates the amount (number of tons) of pesticides applied by day of week across the five counties in the same time period.[8] The three sets of figures emphasize suggest several relevant points. First, the five study counties are very active in pesticide application—in the number of applications and in the amount (tons) of pesticides applied. Second, time trends are quite apparent—both in annual cycles and weekly cycles. Third, the time trends differ by the type of pesticide application (aerial versus ground) and by the measure of application (count of PURs versus tonnage of pesticides). Importantly, these time trends—or temporal clustering—exactly describe a situation in which one may be concerned about the build up of particulate matter from pesticide aggregation or drift.

Figures 6 and 7 map the intensities of aerial and ground pesticide use, respectively—summing the total amount of pesticides applied within each section from 2000 to 2015. The color scale of the sections' shading depicts the log[9] intensity of pesticide use within the section over the 16-year period. The white dots denote school locations[10] to visually proxy for human population, and the white lines delineate the five counties' borders. Both maps illustrate the spatial variability of pesticide use in California—and the intensity in many locations. The two maps in Figures 6 and 7 also highlight the proximity of high levels pesticide applications to human populations. While there are holes in density of pesticide applications corresponding to the locations of major cities, many schools—and thus people—are located on the edges of these cities. Many rural schools are located in sections with high levels of pesticide applications.

## 2.3 Wind

The wind data for this project come from NASA's North American Land Data Assimilation Systems, version 2 (NLDAS-2). The NLDAS-2 joins observation-based and model-reanalysis data to generate land-surface models. Part of this process involves generating (forcing) wind-vector data. The resulting wind data are available for each hour since January 1979 at a $1/8^{\text{th}}$-degree grid covering all of North America (Xia et al., NCEP/EMC(2009)). Specifically, the NLDAS-2 generates two wind vectors—a zonal vector $U$ component (the westerly component) and the meridional $V$ component (the southerly component) (Xia et al., NCEP/EMC(2009)). Jointly the two components determine the wind direction (degrees) and speed (meters per second). The data appendix contains more information on these trigonometric calculations.

[7] The PUR also includes crop type, area planted, and area treated when the user applies the pesticide to a crop.

[8] Figure A2 repeats this exercise for the number of pesticide applications by day of week—the trends are quite similar.

[9] Instead of an actual logarithmic transformation, I use the inverse hyperbolic sine so as to include sections with exactly zero pounds of pesticide application.

[10] Using the database of school locations provided by CSCD.

## 3 Empirical strategy

As highlighted above, this paper seeks to answer whether there is significant evidence that aerially applied pesticides aggregate and drift in ways that contribute to the poor air quality observed in the southern counties of California's San Joaquin Vally. In order to detect variation in *air quality*, I specifically consider local PM2.5 concentrations at EPA monitors in the study counties (depicted in Figure 1). Accordingly, one might model the PM2.5 concentration on a given day $t$ at a given monitor $i$ by

$$\text{Concentration}_{i,t}^{\text{PM2.5}} = f(d_{i,t}(\text{Pesticides}_{i,t}), \text{Weather}_{i,t}) + \varepsilon_{i,t} \tag{1}$$

where $d_{i,t}(\text{Pesticides}_{i,t})$ defines an arbitrary distance-based aggregator of the pesticides applied on day $t$,[11] $\text{Weather}_{i,t}$ refers to the weather near monitor $i$ on day $t$, $f$ represents an arbitrary function of the pesticides applied (including their distances) and weather on day $t$ relative to monitor $i$, and $\varepsilon_{i,t}$ catches stochastic variation in PM2.5 concentrations.

### 3.1 Fixed effects

To place some structure on equation 1, I allow quantities of pesticides applied at similar distances from a monitor to similarly affect that PM2.5 concentrations at the monitor. Such an assumption effectively creates buffers—or concentric rings—around each monitor, where each ton of pesticide between rings similarly affects PM2.5 concentrations. This design is sometimes referred to as a *doughnut* design. Figure 8 illustrates this design for three buffers: (**1**) within 1.5km, (**2**) between 1.5km and 3km, and (**3**) between 3km and 25km.

A fixed-effect based estimating equation for this design is

$$\begin{aligned}\text{Concentration}_{i,t}^{\text{PM2.5}} = &\beta_1 \sum_{k(t)} \mathbb{1}\left\{\mathscr{D}_{i,k(t)} < 1.5\text{km}\right\} \times p_{k(t)} + \\ &\beta_2 \sum_{k(t)} \mathbb{1}\left\{1.5\text{km} \leq \mathscr{D}_{i,k(t)} < 3\text{km}\right\} \times p_{k(t)} + \\ &\beta_3 \sum_{k(t)} \mathbb{1}\left\{3\text{km} \leq \mathscr{D}_{i,k(t)} < 25\text{km}\right\} \times p_{k(t)} + \\ &\gamma_i + \delta_t + \varepsilon_{i,t}\end{aligned} \tag{2}$$

where $i$ indexes EPA monitors; $k(t)$ references the $k^{\text{th}}$ pesticide application on day $t$; and $p_{k(t)}$ records the amount of pesticides applied in application $k(t)$. In addition, $\mathscr{D}_{i,k(t)}$ gives the distance (in kilometers) between EPA monitor $i$ and pesticide application $k(t)$ at time $t$; $\mathbb{1}\{\texttt{foo}\}$ denotes an indicator function for whether `foo` is true; and $\gamma_i$ and $\delta_t$ refer to individual-monitor and temporal fixed effects, respectively. I vary the type of temporal fixed effect across several specifications—ranging from day-of-sample to month-of-year, year, and day-of-week.[12]

The temporal fixed-effect specifications vary the identifying variation for the parameters of interest—the $\beta_j$—in equation 2. For instance, month-of-year fixed effects control for the average PM2.5 concentrations and pesticide applications for a day in the given calendar month throughout the sample period (conditional on the individual-monitor fixed effects). Thus, identification of the $\beta_j$ results from (daily) deviations from these observed means. This

[11] While likely goes to zero at some distance, effectively creating a buffer around monitor $i$.

[12] I use *month of year* to refer to the calendar months (*e.g.*, January) and *month of sample* to reference specific month-year combinations (*e.g.*, January 2010).

*doughnut* empirical design lends an additional source of identifying variation—the concentric circles allow an additional ton of pesticides applied in near proximity to the monitor to have a different effect than an additional ton of pesticides applied farther from the monitor. Put simply: identification in this fixed-effects doughnut design results from the question: On days when pesticide applications near the monitor exceed the monthly norm, do we also see PM2.5 concentrations exceed their monthly norms? Moreover, this design offers a natural check for the plausibility of the results: the estimates for $\beta_1$, $\beta_2$, and $\beta_3$ in equation 2 should be monotonically decreasing, as aerially applied pesticides diffuse through space—far-away applications should have smaller effects. The results are consistent with this plausibility check. Finally, if pesticides negatively affect (local) air quality, then $\beta_1$ should be significantly greater than zero. If $\beta_2 > 0$ or $\beta_3 > 0$, then the estimates imply substantial aerial pesticide drift (movement over space).

Although the fixed-effect identification strategy potentially isolates exogenous variation, it is still susceptible to bias from omitted variables. The concern is that there may be a daily-varying factor excluded from the model that causally affects both PM2.5 concentrations and pesticide applications. If such a variable exists, then the estimates for the $\beta_j$ may be positively or negatively biased, depending upon the relationships between the omitted variable, PM2.5 concentrations, and pesticide applications. The concentric-circles design, in conjunction with day-of-sample fixed effects, may alleviate some omitted-variable bias concerns, as the identifying variation comes both from the amount of pesticide application *and* the distances between the pesticide applications and the sensor. Thus, the omitted variable would need to increase the number of pesticide applications *near the EPA monitor* on the same day it increased the PM2.5 concentration *near the EPA monitor*. Consequently, in addition to demonstrating general robustness, the different fixed-effects specifications that I present in the results—and their different sources of identifying variation—suggest that the results in this paper are not driven by omitted-variable bias.

## 3.2 Wind-angle variation

To further the plausibility of the results, I present a second identification strategy, which extends the fixed-effects *doughnut design* discussed above. This second design further isolates plausibly exogenous identifying variation by incorporating daily deviations from the prevailing wind pattern (angle) at the EPA sensor—separating *upwind*, *downwind*, and *orthogonal wind* pesticide applications.

In order to isolate upwind pesticide applications, I calculate (**a**) the angle between each EPA monitor and each pesticide application[13] and (**b**) the angle of the wind at each EPA monitor.[14] The difference between these two angles gives a measure of whether pesticide application $p_{k(t)}$ occurred upwind of monitor $i$ (in degrees). To integrate this upwind measure into an empirical model, I bin applications into three broad groups: (**1**) **upwind application** where the absolute difference between the wind's angle and the monitor-to-application angle angle is less than 60 degrees; (**2**) **orthogonal application** where the absolute difference between the two angles is between 60 and 120 degrees; and (**3**) **downwind application** where the absolute difference between the two angles is between 120 degrees and 180 degrees.[15] Figure 9a illustrates this wind-angle grouping.

[13]Because the PUR data only identify applications at the section level, I use the geographic coordinates of the section's centroid for each application within the section.

[14]The wind's vector points upwind: the angle between a ray pointing toward the wind's origin and due North.

[15]An alternative way to think about measure is the angle between two vectors: (**1**) the vector between the

Combining this wind-direction information/variation with the fixed-effects doughnut model in equation 2, the estimating equation for this new model is

$$
\begin{aligned}
\text{Concentration}^{\text{PM2.5}}_{i,t} \; = \;& \\
& \alpha_{11} \sum_{k(t)} \mathbb{1}\Big\{\Big(\mathscr{D}_{i,k(t)} < 1.5\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in [0,\ 60]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{12} \sum_{k(t)} \mathbb{1}\Big\{\Big(\mathscr{D}_{i,k(t)} < 1.5\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in (60,\ 120]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{13} \sum_{k(t)} \mathbb{1}\Big\{\Big(\mathscr{D}_{i,k(t)} < 1.5\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in (120,\ 180]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{21} \sum_{k(t)} \mathbb{1}\Big\{\Big(1.5\text{km} \le \mathscr{D}_{i,k(t)} < 3\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in [0,\ 60]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{22} \sum_{k(t)} \mathbb{1}\Big\{\Big(1.5\text{km} \le \mathscr{D}_{i,k(t)} < 3\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in (60,\ 120]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{23} \sum_{k(t)} \mathbb{1}\Big\{\Big(1.5\text{km} \le \mathscr{D}_{i,k(t)} < 3\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in (120,\ 180]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{31} \sum_{k(t)} \mathbb{1}\Big\{\Big(3\text{km} \le \mathscr{D}_{i,k(t)} < 25\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in [0,\ 60]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{32} \sum_{k(t)} \mathbb{1}\Big\{\Big(3\text{km} \le \mathscr{D}_{i,k(t)} < 25\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in (60,\ 120]\Big)\Big\} \times p_{k(t)} + \\
& \alpha_{33} \sum_{k(t)} \mathbb{1}\Big\{\Big(3\text{km} \le \mathscr{D}_{i,k(t)} < 25\text{km}\Big) \wedge \Big(\big|\theta_{i,k(t)}\big| \in (120,\ 180]\Big)\Big\} \times p_{k(t)} + \\
& \gamma_i + \delta_t + \varepsilon_{i,t}
\end{aligned}
\tag{3}
$$

where all quantities maintain the same definitions as in equation 2, and $\theta_{it}$ denotes the difference in the wind angle on day $t$ and monitor $i$ and the pesticide angle between monitor $i$ and pesticide application $k(t)$—as defined and discussed directly above. Put simply, equation 3 allows the effect of a pesticide application on PM2.5 concentration to vary by the application's distance from the monitor *and* by the application's degree of *upwind-ness*—again controlling for a variety of individual ($\gamma_i$) and temporal ($\delta_t$) fixed effects.

By adding wind-induced variation in the (conditional) amount of pesticides applied, equation 3 further relaxes the assumptions required to identify its parameters of interest (the $\alpha_j$). In order for an omitted variable to bias the ordinary least squares (OLS) estimates of the $\alpha_j$, there would need to be an observed variable correlated with both (**1**) PM2.5 concentrations and (**2**) the amount of pesticides applied (**3**) upwind of EPA monitors—and with (**4**) the distances between the pesticide applications and the EPA monitors. In the absence of such a process, OLS will provide causally valid, consistent estimates for the extent to which aerial pesticide applications and their drift affect local PM2.5 concentrations.

The two panels of Figure 9 depict this wind-induced variation design—illustrating how the design estimates a coefficient for each 60-degree segment of the three distance-based radial groups.[16]

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pesticide application and the EPA monitor, and (**2**) the wind vector at the EPA monitor.

[16] I enforce a requirement for symmetry, *e.g.*, pesticide applications within 1.5km have the same effect regardless of whether they occur at -45 degrees or 45 degrees of the wind.

### 3.3 Measurement error

Having outlined this paper's two identification strategies and its datasets, I now discuss an empirically relevant data issue before presenting the results from estimating equations 2 and 3 via OLS.

Measurement error presents problems for both empirical designs in this paper, but it is particularly important for the design using wind-induced variation. One of the main sources of measurement error comes from the lack of spatial precision in the PUR data. As discussed above, the PURs only identify pesticide applications down to the section level. Sections can be as large as 1 mile by 1 mile, meaning geography-based variables are likely to contain substantial noise. The variables of interest in equations 2 and 3 are both based upon the geographic coordinates of the pesticide applications. For the distance-based indicators in the two regressions, this measurement error simply adds noise to the coordinates—akin to rounding, in some sense. Consequently, measurement error for the fixed-effects doughnut design is classical in nature and will simply attenuate OLS parameter estimates (Woolridge 2010).

For the the angle-based measurements, this geographic measurement error induces classical measurement error *for pesticides applications within the same distance of an EPA monitor.* For pesticide applications closer to the monitors, the attenuation bias will be larger. To see this point, consider three cases. First, if a pesticide application occurs in the same section as an EPA monitor, the uncertainty surrounding the application's location prevents one from knowing whether the application is upwind, downwind, or orthogonal to the monitor. Second, if the application occurs in the section next to the monitor's section, it is possible to bound the angle between the EPA monitor and the application between −90 and 90 degrees—potentially ruling out one of the three upwind categories—but we are still left with substantial noise. Finally, for a pesticide application far from the monitor, there is little uncertainty in the angle between the monitor and application. The result of this class of semi-classical measurement error is that estimates for the parameters $\alpha_{1j}$ will be more attenuated than the estimates for $\alpha_{2k}$.[17]

In addition, there are several other pertinent sources of noise in the data and, therefore, in the empirical strategies. First, the reanalysis wind data are not actual historical records—adding noise in addition to identifying variation. Second, the data on pesticide applications come from self-reported pesticide-use reports. Self-reported data often contain a degree of noise—and may contain some bias where incentives lead to dishonest reporting. Third, aggregating pesticide applications into distance- and/or angle-based groups potentially leads to a sort of aggregation bias—averaging across the heterogeneous treatment effects within each group. As a result of these channels of noise and attenuation, the parameter estimates in the next section should be taken as lower bounds of the actual effects of aerial pesticide applications on PM2.5 levels.

## 4 Results

Having described the identification strategies of two models—the fixed-effects doughnut design and the wind-angle design—I now present the OLS estimates for equations 2 and 3.

[17]It is also worth noting that statistical power follows a similar trend due to the close applications covering smaller areas of land than the farther out application—resulting in more observations and greater variation in distance-based groups that are farther from the monitors.

## 4.1 Fixed effects

Table 2 presents the results for estimating equation 2 with OLS. Specifically, Table 2 identifies the effect of an additional ton of aerially applied pesticides—applied in one of three distance-based groups—on the mean PM2.5 concentration at monitor $i$ on day $t$. Each of the five columns of Table 2 represents a different regression from a different fixed-effect specification for equation 2. Each specification includes a monitor fixed effect. Columns (**1**), (**2**), and (**3**) include day-of-sample, week-of-sample, and month-of-sample fixed effects, respectively. Column (**4**) incorporates three sets of time-based fixed effects: week-of-year, day-of-week, and year fixed effects. Column (**5**) uses month-of-sample, day-of-week, and year fixed effects.

Because aerial pesticide applications occur at a specific time during the day, one might expect the daily mean to underestimate the effect of pesticide applications on local air quality—averaging across affected and unaffected times of the day and generating a sort of aggregation or attenuation bias. To potentially remedy this problem, Table 3 replicates Table 2 but uses the daily *maximum* observed PM2.5 concentration rather than the daily *mean*. The problem with this potential remedy is that aerial applications may not move the maximum PM2.5 if they occur at lower points of the PM2.5 diurnal cycle.

In each of the five specifications of Tables 2 and 3, the point estimate for the distance group nearest to the EPA monitor (within 1.5 kilometers) is significantly different from zero. The point estimates range from 0.12 to 0.23 for the daily mean PM2.5 level, and they range from 0.15 to 0.34 for the daily maximum PM2.5 level. The causal interpretation for the first point estimate in column (**1**) of Table 2 is that each additional ton of aerially applied within 1.5 kilometers pesticides increases that day's mean PM2.5 level by approximately 0.23 $\mu g/m^3$ [0.09, 0.37]. For column (**1**) of Table 3, the interpretation is that each additional ton of pesticides applied aerially within 1.5 kilometers of the EPA monitor increases the daily maximum observed PM2.5 concentration by approximately 0.31 $\mu g/m^3$ [0.12, 0.51].

The two panels of Figure 8 illustrate the spatial relationships of the results in conjunction with the fixed-effect doughnut design for the first columns of Tables 2 and 3.

Across the ten regressions of Tables 2 and 3, the results present clear and robust[18] evidence that aerial pesticide applications significantly reduce local air quality (increasing PM2.5 concentrations)—for aerial pesticide applications within 1.5 kilometers of the monitor. None of the results in the two tables present statistically significant evidence that aerial applications affect PM2.5 levels beyond 1.5 kilometers.[19]

## 4.2 Wind-angle variation

Tables 4 and 5 contain the OLS results of estimating the wind-variation based model in equation 3. Each column contains results from a separate fixed-effects specification; all five regressions use daily mean PM2.5 concentration as their dependent variable. Relative to the previously presented results/model in Table 2: the results in Tables 4 and 5 introduce wind-based variation in pesticide exposure.

[18] Appendix tables A1 and A2 demonstrate further robustness by replicating Tables 2 and 3, respectively, with Windsorized PUR application data—diminishing concerns that outliers in the independent variable drive the results. The Data Appendix describes describes this Windsorization in detail.

[19] While the coefficients on the distance groups farther than 1.5 kilometers are not statistically significantly different from zero at conventional levels, the point estimates are consistently positive and also decrease monotonically with distance. Furthermore, I particularly caution the reader from reading too much into null results here, as attenuation bias is clearly present.

Figure 9a illustrates the spatial relationship and implications of the coefficients estimated in Tables 4 and 5—specifically depicting the results of column (**1**) of Table 4. The results portrayed in Figure 9a—and across all the columns Tables 4 and 5—again suggest that aerially applied pesticides within 1.5km increase local PM2.5 concentrations. Further, the wind-angle results suggest—as one would expect from a more physics-based model—that this increase in PM2.5 levels induced by aerial pesticides particularly stems from upwind pesticide applications. Across the five specifications in Tables 4 and 5, the point estimates for *Upwind* applications within 1.5 kilometers range from 0.24 to 0.29—slightly larger than the non-wind results from Table 2. The causal interpretation for these results—using column (**1**) of Table 4—is that each additional ton of aerial pesticides applied upwind within 1.5 kilometers increases the daily mean PM2.5 concentration by 0.29 $\mu g/m^3$ [0.05, 0.55].

The point estimates for the effect of upwind aerial pesticide applications within 1.5 kilometers are statistically significant and notably large across all five specifications in Tables 4 and 5. The point estimates for downwind applications 3–25 kilometers away are also significant across all five specifications, though the magnitude of the point estimates is quite small. No other estimated effect is consistently significant across all five specifications.

Tables 6 and 7 replicate Tables 4 and 5 but with daily *maximum* PM2.5 rather than daily *mean* PM2.5 . Figure 9b depicts the spatial effects of aerial-pesticide applications, as estimated in column (**1**) of Table 6.

Overall, the results for the daily maximum PM2.5 concentration are fairly similar to the results that use the daily mean. The estimated effect of upwind pesticide applications within 1.5 kilometers is highly statistically significant, and the point estimates for this effect are larger than the estimates for the mean, ranging from 0.29 to 0.49 $\mu g/m^3$. The causal interpretation of this effect (for column (**1**) of Table 6) is that each additional ton of pesticides aerially applied upwind within 1.5 kilometers increases the daily local maximum PM2.5 concentration by 0.49 $\mu g/m^3$ [0.19, 0.78]. One surprising outcome is the large (in magnitude) and negative coefficient for pesticides applied within 1.5 kilometers orthogonally to the wind. This effect is statistically significant at the 5-percent level in three of the five specifications.

Finally, while this empirical design offers greater potential for isolating exogenous variation by using changes in wind patterns, one should bear in mind that this design is also more prone to bias from measurement error. This susceptibility to measurement-error induced bias originates in the lack of precise spatial information in the PUR data and potential noise in the reanalysis wind data.[20]

# 5 Discussion and conclusion

Across two empirical designs and a many specifications, this paper finds significant evidence that aerially applied pesticides reduce local air quality—increasing PM2.5 concentrations at EPA monitoring sites. Whether the results use distance-based variation or wind-and-distance variation, I find evidence consistent with aerial pesticide applications increasing both daily mean and daily maximum PM2.5 levels. The point estimates suggest that each additional ton of aerial pesticides applied within 1.5 kilometers increases local PM2.5 concentrations by approximately 0.2 to 0.3 $\mu g/m^3$. To put this coefficient in perspective: for days on which at least one aerial pesticide application occurred in a section[21], the $90^{\text{th}}$ ($99^{\text{th}}$) percentile

[20] See the *Measurement error* subsection of the Empirical strategy section for a detailed description of these measurement-error issues.

[21] Fifteen percent of section-days have at least one aerial pesticide application.

of the amount of aerial pesticides is 3 tons (18.4 tons).[22] Thus I estimate that applications at the 90$^{\text{th}}$ percentile increase local PM2.5 concentrations by approximately one $\mu g/m^3$, and applications at the 99$^{\text{th}}$ percentile increase PM2.5 levels by approximatley 5 $\mu g/m^3$—nearly half of the national standard for annual PM2.5 concentrations[23]. Accordingly, while most aerial applications do not appear to substantially increase local PM2.5 concentrations, a small percentage of large applications present cases for concern with regards to degraded air quality. This result is consistent with recent work tying large, local applications of pesticides to adverse health effect: Larsen, Gaines, and Deschênes only find evidence the top five percentiles of pesticide exposure increased adverse birth outcomes.

The results of this paper present some good news and some bad news for public-health advocates. The good news: The results suggest that *most* aerial pesticide applications do not meaningfully increase PM2.5 exposure—and the PM2.5 drift may stay within a radius of approximately 1.5 kilometers. The bad news: The top five-to-ten percent of applications substantially increase local PM2.5 concentrations in a region that already suffers from high levels of exposure to PM2.5 and other pollutants.

That said: attenuation matters. As discussed in the empirical strategy and results sections, there are many reasons to believe that measurement error attenuates the results in this paper. Thus, while this paper finds statistically significant evidence of PM2.5 increases due to aerial pesticide applications, the point estimates are most likely lower bounds for the true effect of aerial pesticide applications on local PM2.5 levels. Therefore, much of the "good news" discussed above should be taken with some caution. In addition, many of the results in this paper rely upon daily mean PM2.5 , which averages across the 24 hourly PM2.5 readings. While the daily mean PM2.5 level is relevant for regulation and—to some degree—health, contemporaneous exposure to PM2.5 also matters. The results of this paper likely substantially underestimate the effect of aerial pesticides on contemporaneous air quality. For instance, if a user applies pesticides at 8:00 AM—as many of the PURs report—the daily mean will include eight *unaffected* hours preceding the application, followed by 16 *affected* hours—suggesting the true effect may be 50 percent larger that the estimated effect.[24]

A final *caveat*: PM2.5 is only one measure of local air conditions. For many emissions—and particularly for pesticides—exposures to specific chemicals are of great importance.

Overall, the results in this paper suggest that large aerial pesticide applications substantially increase local PM2.5 exposure—particularly downwind of the application. While policies that target individual pesticide applications or individual users may assist in limiting harmful levels of PM2.5 exposure, they likely miss important effects from the spatiotemporal aggregation of pesticides. This outcome is particularly important for instances where users apply pesticides in close spatial and temporal proximities—especially when these applications are near sensitive/vulnerable individuals. Such areas (conceivably illustrated in Figure 6) provide particularly fruitful settings for attention from both policymakers and researchers—offering the potential for investigating the degree to which these observed PM2.5 increases affect health and/or considering efficient spatiotemporal regulations that internalize the costs of pesticide agglomeration and drift.

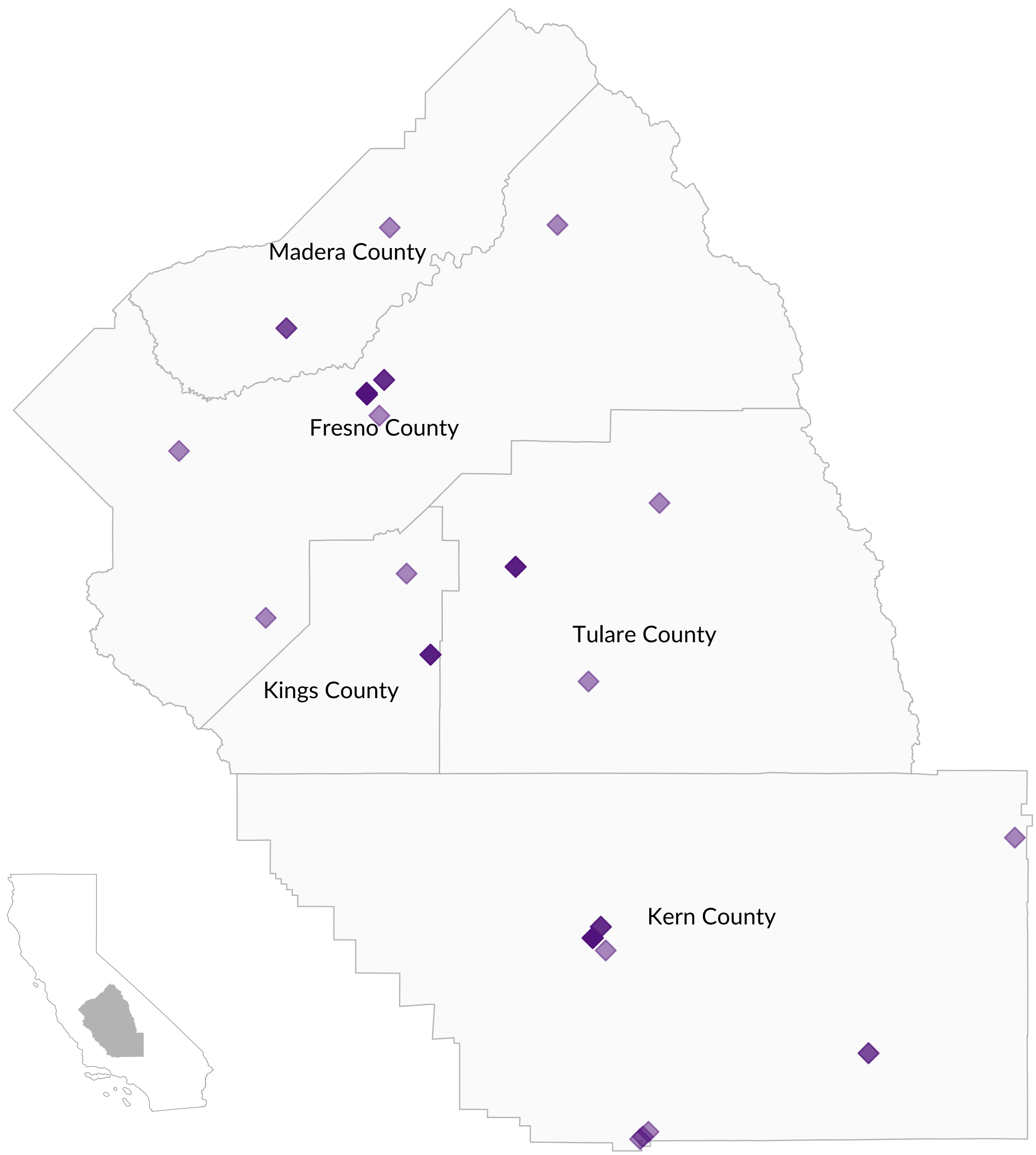
[22]Between 2000 and 2015, in the average year, the agricultural sector in the five study counties aerially applied over 40,000 tons of pesticides.

[23]The EPA reduced the standard for PM2.5 in late 2012 from 15 $\mu g/m^3$ to 12 $\mu g/m^3$. The (U.S. E.P.A. 2013).

[24]This calculation assumes a homogeneous effect on the 16 hours following the application. If only a few of the 16 hours are actually affected, the true contemporaneous effect of aerial pesticides applications on local air quality will be many times larger than the point estimates in this paper, *e.g.*, twelve times that of the mean effect if only two hours are *affected*.

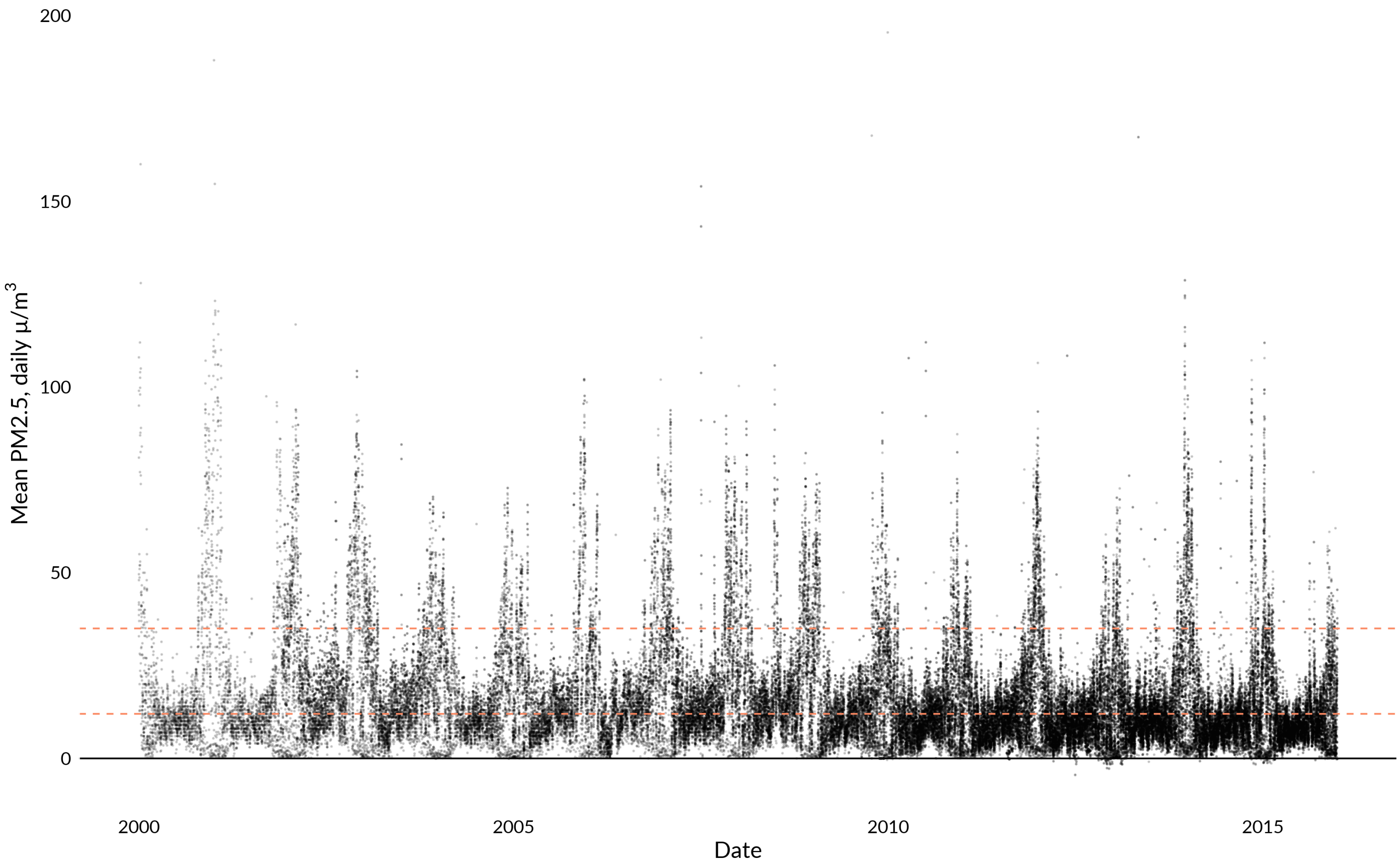
# 6 Figures

Figure 1: **EPA PM2.5 monitor locations:** Unique monitors, 2000–2015




**Notes:** This figure maps the locations of the EPA's PM2.5 monitors (shaded diamonds) in the five counties of the southern San Joaquin Valley. Darker shading denotes the presence of multiple monitors at/near the same site.

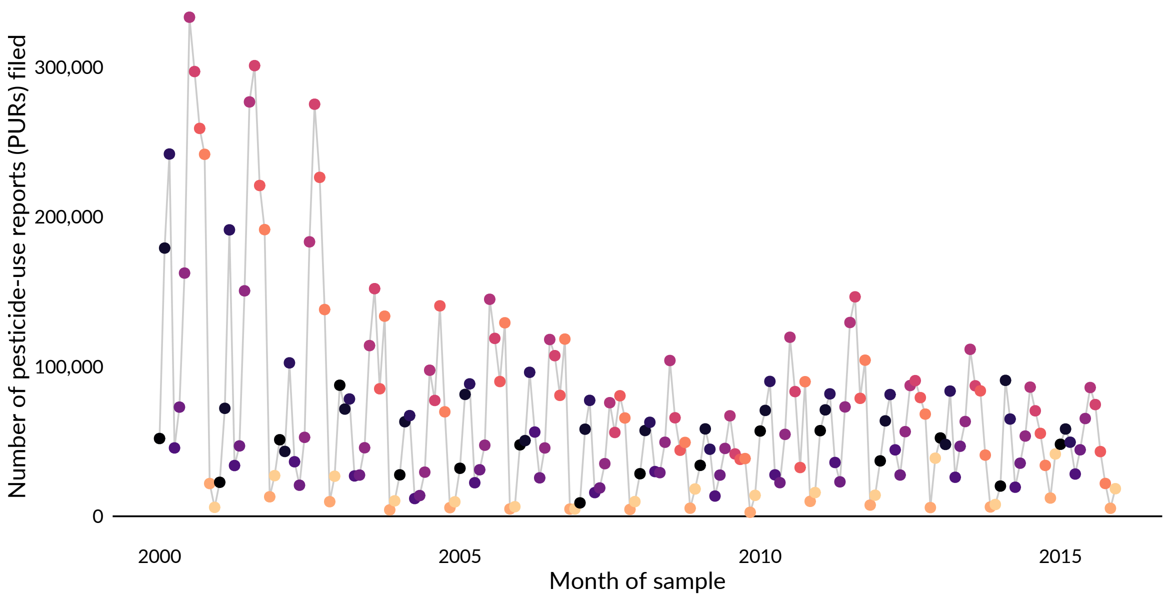
Figure 2: **EPA PM2.5 records:** Daily mean PM2.5 concentration at each monitor, 2000–2015



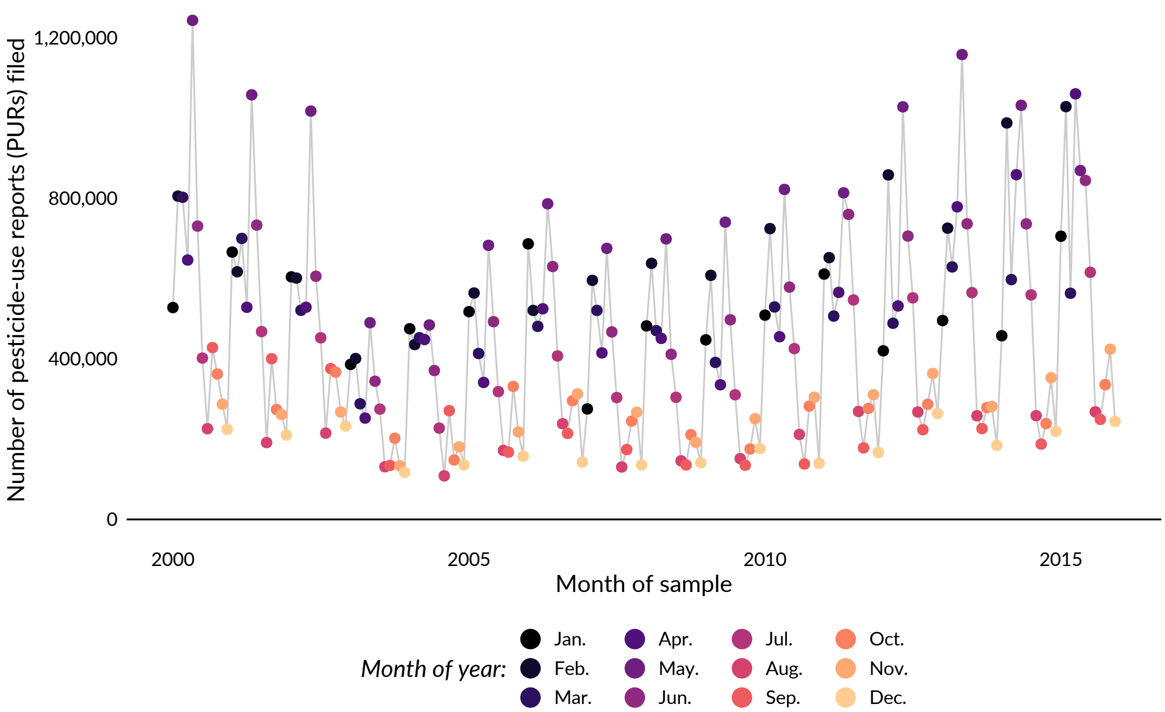

**Notes:** Each point in this figure represents the mean PM2.5 on the given day ($x$ axis) for a specific monitor. The two dashed horizontal lines denote two different primary National Ambient Air Quality Standards (NAAQS), established January 15, 2013. The lower line establishes the standard (12.0 $\mu g/m^3$) for the the 3-year arithmetic mean. The higher line marks the standard (35 $\mu g/m^3$) for the 3-year mean of the 98$^{th}$ percentile (U.S. E.P.A. 2013).

Figure 3: **Number of pesticide applications:** 2000–2015, by month

(a) **Aerially applied pesticides**




(b) **Ground-applied pesticides**

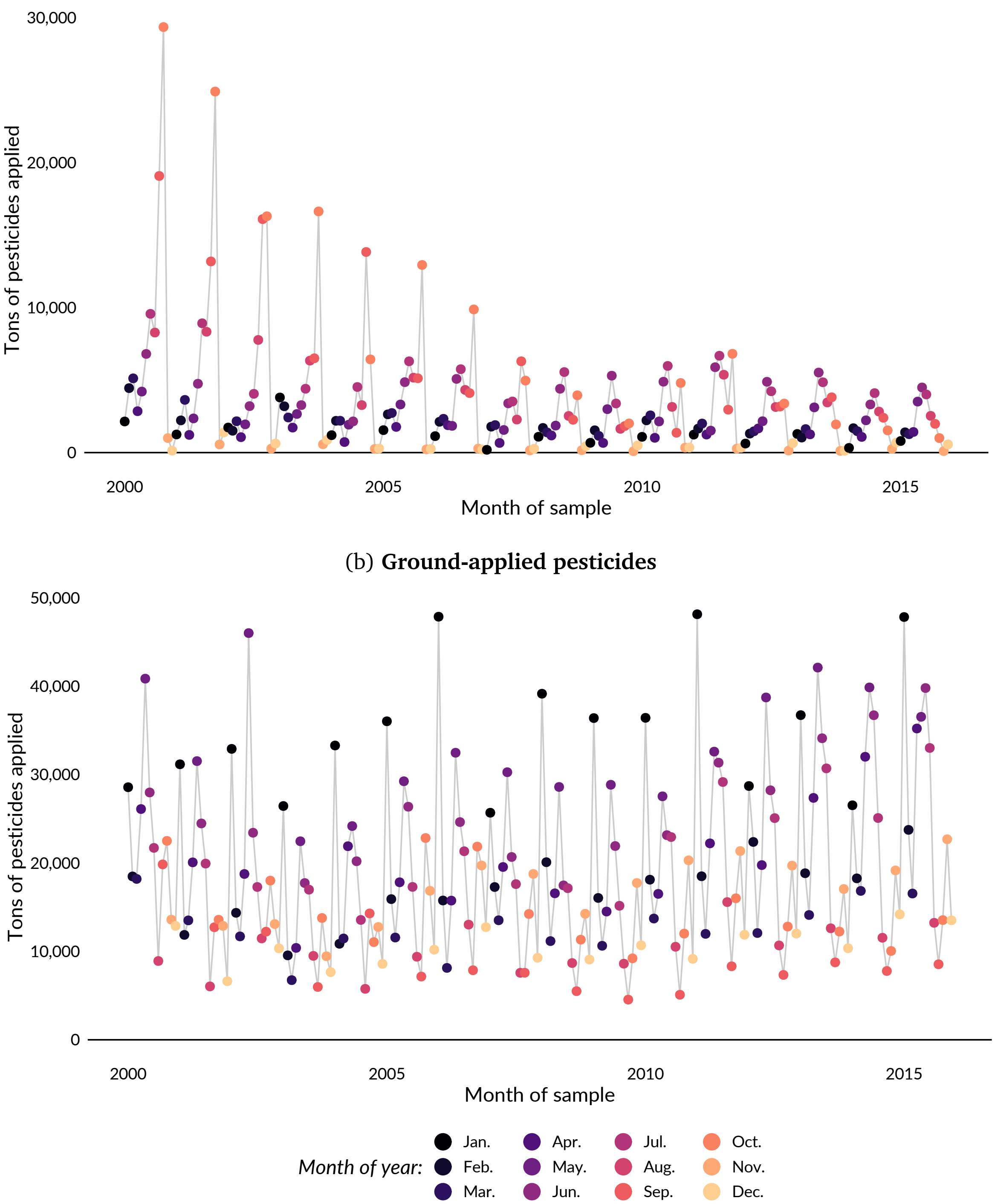



**Notes:** These figures depict the number of PURs file each month for aerial applications (top) and ground applications (bottom). The counts only include the PURs from the five counties of southern San Joaquin Valley that this paper studies. *Source:* Author using data from California D.P.R. 2013.

Figure 4: **Tons of pesticides applied:** 2000–2015, by month

(a) **Aerially applied pesticides**

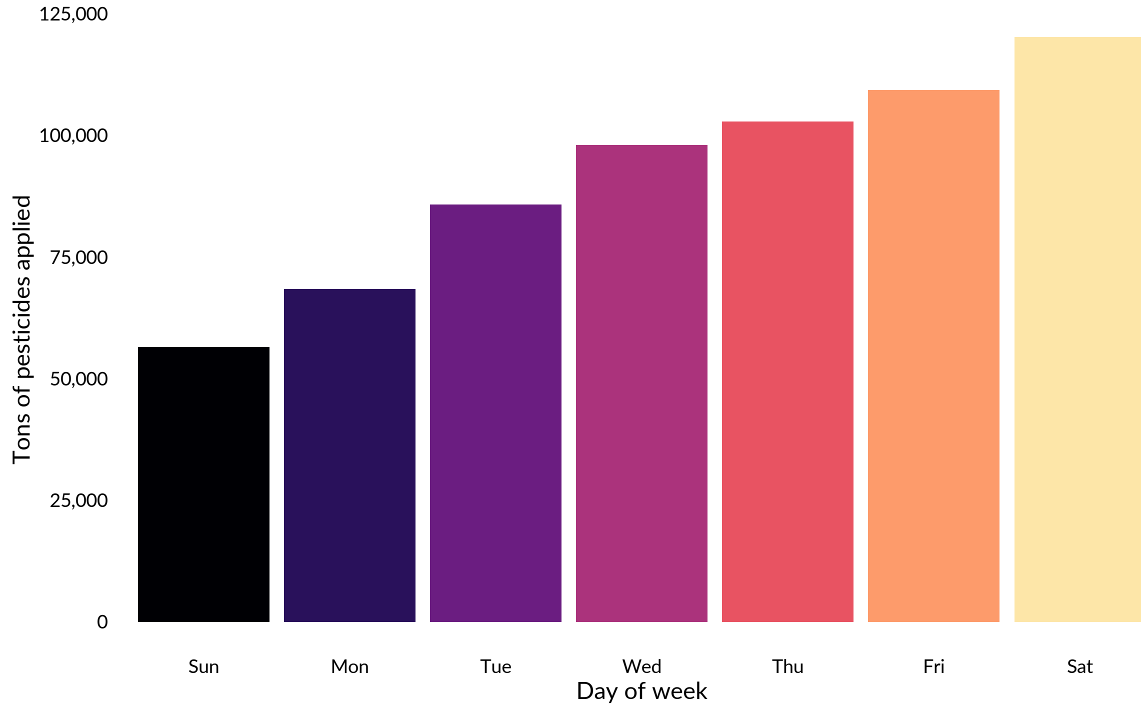
(b) **Ground-applied pesticides**



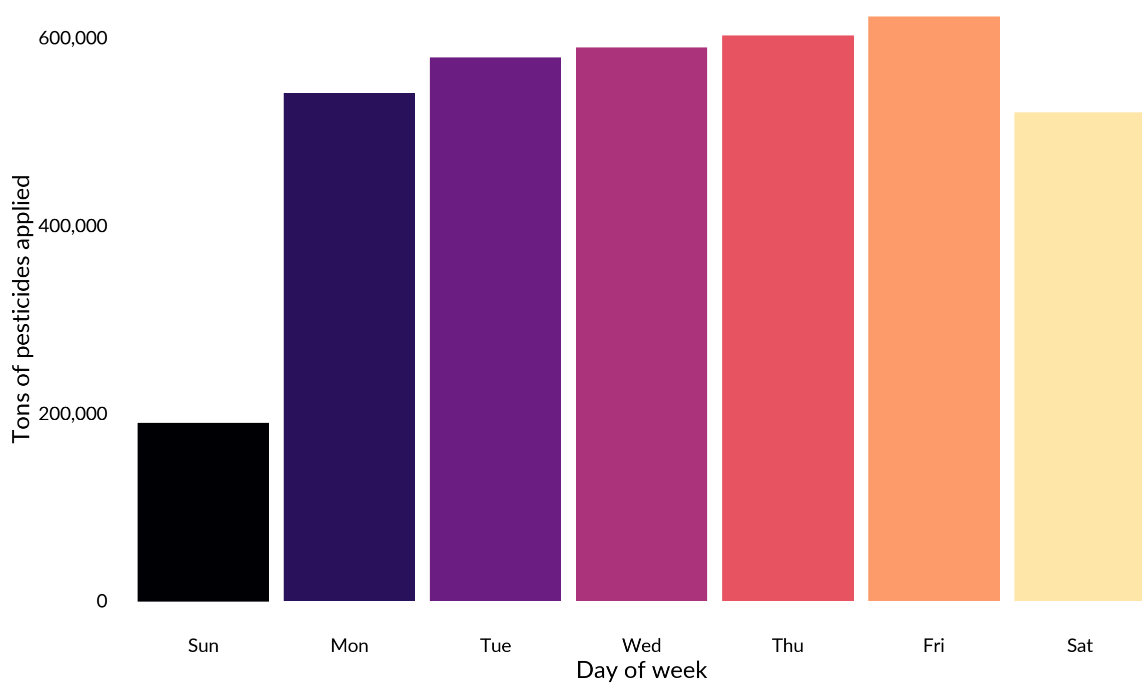

**Notes:** These figures depict the amount of pesticides (tons) applied each month in the five study counties between 2000 and 2015, separating the pesticide applications by aerial applications (top) and ground applications (bottom). *Source:* Author using data from California D.P.R. 2013.

Figure 5: **Tons of pesticides applied:** 2000–2015, by day of week

(a) **Aerially applied pesticides**

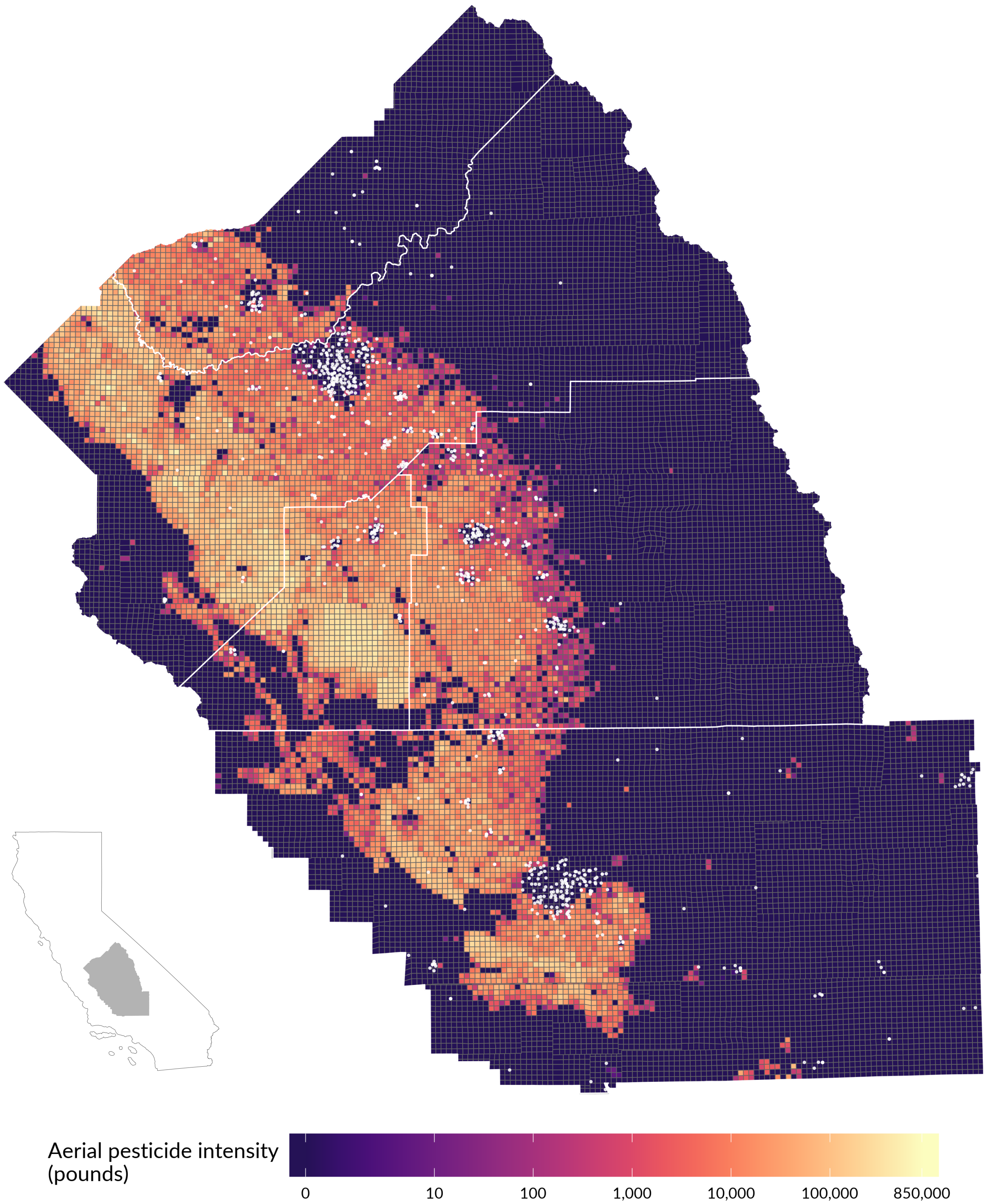



(b) **Ground-applied pesticides**



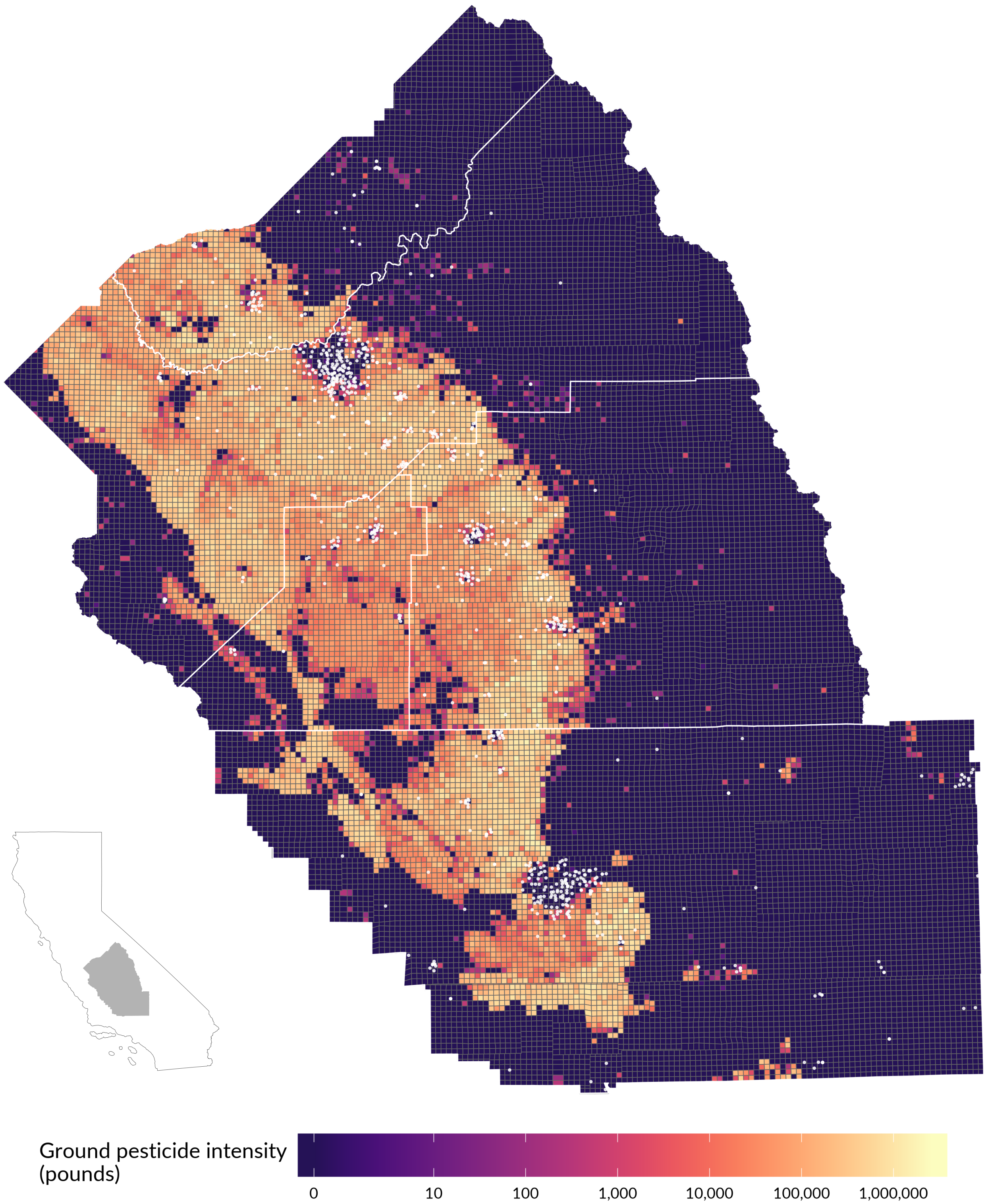

**Notes:** These figures depict the amount of pesticides (tons) applied by day of week in the five study counties between 2000 and 2015, separating the pesticide applications by aerial applications (top) and ground applications (bottom).*Source:* Author using data from California D.P.R. 2013.

Figure 6: **Spatial intensity of aerial pesticide use:** Total pounds of aerial pesticide applications in study counties, 2000–2015




**Notes:** The shading on the map shows the intensity of aerial pesticide applications within each section from 2000–2015. The shading uses an inverse hyperbolic sine scale (approximately log). White dots denote schools, which I provide as a visual proxy for population. White lines reference county borders.

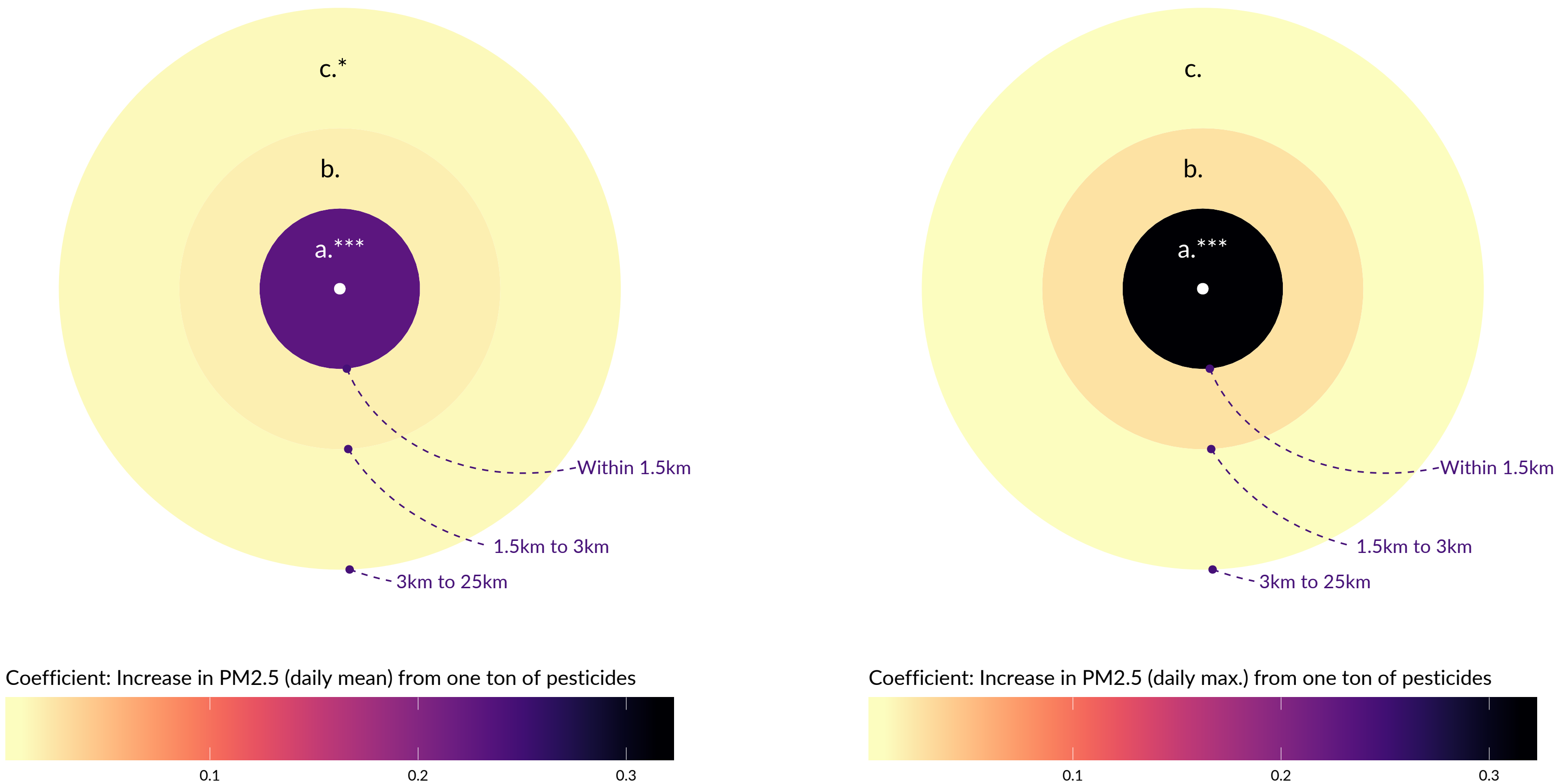
Figure 7: **Spatial intensity of ground pesticide use:** Total pounds of ground pesticide applications in study counties, 2000–2015




**Notes:** The shading on the map shows the intensity of ground pesticide applications within each section from 2000–2015. The shading uses an inverse hyperbolic sine scale (approximately log). White dots denote schools, which I provide as a visual proxy for population. White lines reference county borders.

Figure 8: **The effect of pesticides on PM:** Estimated increase in PM2.5 from one ton of aerially applied pesticides using fixed-effects *doughnut* design

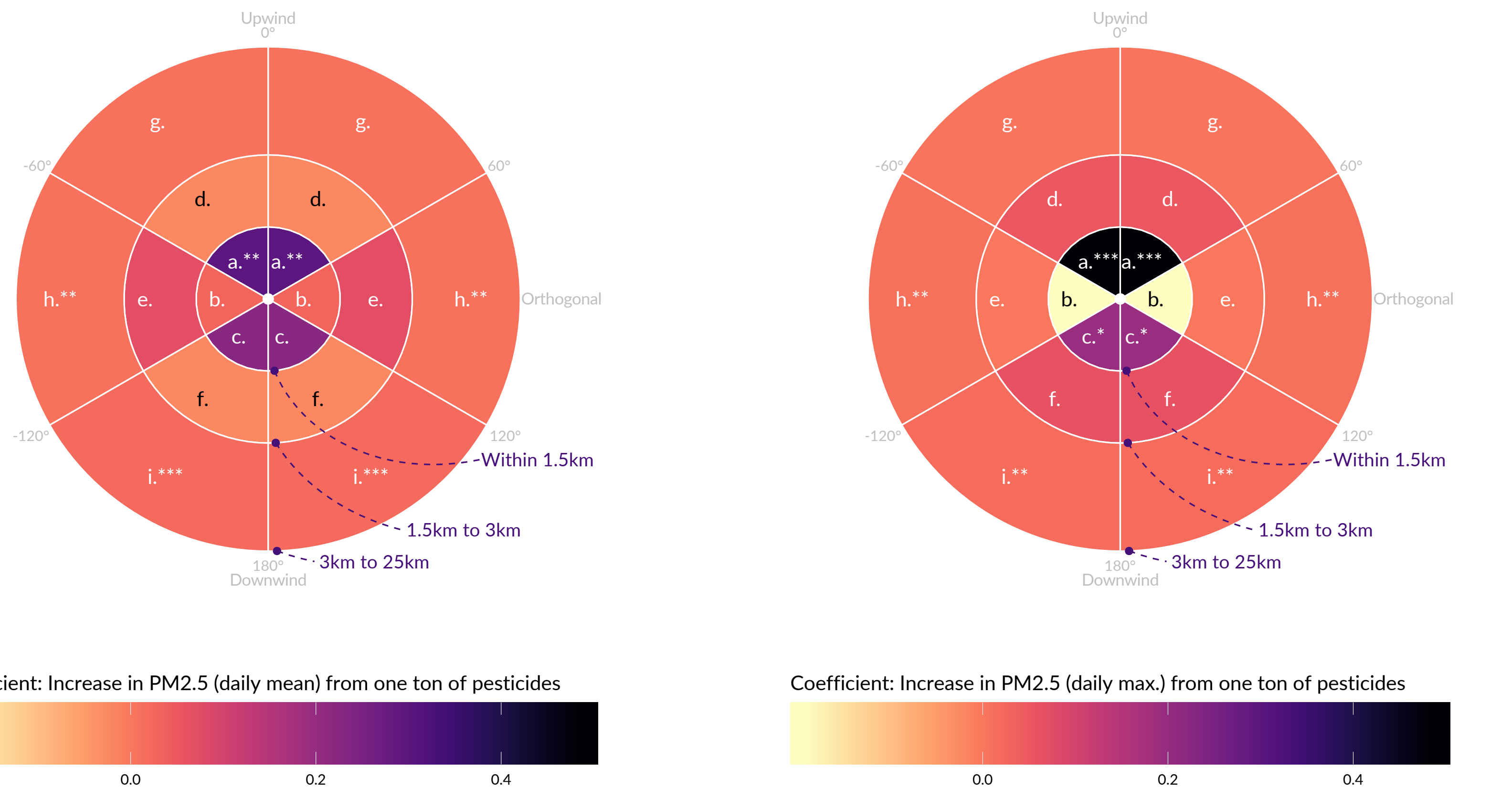
(a) **Daily mean PM2.5** (b) **Daily max. PM2.5**




**Notes:** This figure illustrates the fixed-effect *doughnut* design of equation 2 and the resulting OLS coefficient estimates—as given in column (**1**) of Table 2 (a) and column (**1**) Table 3 (b).

Figure 9: **The effect of pesticides and wind on PM:** Estimated increase in PM2.5 from one ton of aerially applied pesticides using wind variation

(a) **Daily mean PM2.5** (b) **Daily max. PM2.5**




**Notes:** This figure illustrates the wind-variation design of equation 3 and the resulting OLS coefficient estimates—as given in column (**1**) of Table 4 (a) and column (**1**) Table 6 (b).

# 7 Tables

Table 1: **Number of monitors and observations** US EPA PM2.5 monitoring network in study counties

| Year | N. unique days | N. unique monitors | N. observations |
|---|---|---|---|
| 2000 | 353 | 23 | 1,978 |
| 2001 | 361 | 23 | 2,261 |
| 2002 | 365 | 22 | 4,068 |
| 2003 | 365 | 22 | 4,310 |
| 2004 | 366 | 23 | 3,596 |
| 2005 | 365 | 23 | 4,276 |
| 2006 | 365 | 23 | 4,391 |
| 2007 | 365 | 26 | 6,483 |
| 2008 | 366 | 28 | 6,312 |
| 2009 | 365 | 30 | 6,926 |
| 2010 | 365 | 29 | 8,916 |
| 2011 | 365 | 31 | 10,174 |
| 2012 | 366 | 36 | 11,165 |
| 2013 | 365 | 33 | 11,337 |
| 2014 | 365 | 32 | 10,842 |
| 2015 | 365 | 30 | 11,150 |
| **All** | 5,827 | 53 | 108,185 |

**Notes:** The total number of observations in a year does not equal $N_{\text{days}} \times N_{\text{monitors}}$ because some monitors run every sixth day, rather than every day. For that same reason—and if one or more daily monitors or out of operation—the EPA will observe fewer than 365 days in the year.

Table 2: **Increases in mean PM2.5**: Same-day, aerially applied pesticides

**Dependent variable:** Mean daily PM2.5 level

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Tons of pesticide (**a**) | 0.2298*** | 0.1167** | 0.1952** | 0.1765** | 0.2173** |
| within 1.5km | (0.07384) | (0.04824) | (0.09388) | (0.07626) | (0.09743) |
| Tons of pesticide (**b**) | 0.0187 | 0.0290 | 0.0491 | 0.0471 | 0.0428 |
| between 1.5km and 3km | (0.08380) | (0.05007) | (0.05252) | (0.06065) | (0.06687) |
| Tons of pesticide (**c**) | 0.0124* | 0.0173** | 0.0087 | 0.0088 | 0.0055 |
| between 3km and 25km | (0.00734) | (0.00679) | (0.00722) | (0.00733) | (0.00787) |
| Monitor FE | T | T | T | T | T |
| Day-of-sample FE | T | F | F | F | F |
| Week-of-sample FE | F | T | F | F | F |
| Month-of-sample FE | F | F | T | F | F |
| Week-of-year FE | F | F | F | T | F |
| Month-of-year FE | F | F | F | F | T |
| Day-of-week FE | F | F | F | T | T |
| Year FE | F | F | F | T | T |
| *N* | 26,242 | 26,242 | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table 3: **Increases in max. PM2.5**: Same-day, aerially applied pesticides

**Dependent variable:** Maximum daily PM2.5 level

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Tons of pesticide (**a**) | 0.3149*** | 0.1321*** | 0.2104** | 0.1607** | 0.2036** |
| within 1.5km | (0.09769) | (0.04612) | (0.08501) | (0.06697) | (0.08453) |
| Tons of pesticide (**b**) | 0.0277 | 0.0454 | 0.0713 | 0.0740 | 0.0675 |
| between 1.5km and 3km | (0.09168) | (0.05163) | (0.05048) | (0.05977) | (0.06364) |
| Tons of pesticide (**c**) | 0.0099 | 0.0142* | 0.0040 | 0.0020 | −0.0020 |
| between 3km and 25km | (0.00809) | (0.00759) | (0.00851) | (0.00809) | (0.00895) |
| Monitor FE | T | T | T | T | T |
| Day-of-sample FE | T | F | F | F | F |
| Week-of-sample FE | F | T | F | F | F |
| Month-of-sample FE | F | F | T | F | F |
| Week-of-year FE | F | F | F | T | F |
| Month-of-year FE | F | F | F | F | T |
| Day-of-week FE | F | F | F | T | T |
| Year FE | F | F | F | T | T |
| *N* | 26,242 | 26,242 | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table 4: **Increases in mean PM2.5 from aerial pesticides**: Wind-variation results

**Dependent variable:** Mean daily PM2.5 level

| | (1) | (2) | (3) |
|---|---|---|---|
| Tons of pesticide (**a**) | 0.2983** | 0.2380*** | 0.2781*** |
| within 1.5km; Upwind | (0.12671) | (0.07876) | (0.09443) |
| Tons of pesticide (**b**) | 0.0306 | −0.4253*** | −0.0473 |
| within 1.5km; Orthogonal | (0.12767) | (0.05577) | (0.11644) |
| Tons of pesticide (**c**) | 0.2227 | 0.1212* | 0.1606 |
| within 1.5km; Downwind | (0.14474) | (0.07032) | (0.19808) |
| Tons of pesticide (**d**) | −0.0216 | 0.0349 | 0.0783 |
| between 1.5km and 3km; Upwind | (0.10813) | (0.10567) | (0.09928) |
| Tons of pesticide (**e**) | 0.0691 | 0.0202 | 0.0462 |
| between 1.5km and 3km; Orthogonal | (0.04851) | (0.04303) | (0.03805) |
| Tons of pesticide (**f**) | −0.0210 | 0.0464 | −0.0059 |
| between 1.5km and 3km; Downwind | (0.25762) | (0.14887) | (0.11126) |
| Tons of pesticide (**g**) | 0.0107 | 0.0122 | 0.0018 |
| between 3km and 25km; Upwind | (0.01057) | (0.00839) | (0.01026) |
| Tons of pesticide (**g**) | 0.0105** | 0.0200*** | 0.0136 |
| between 3km and 25km; Orthogonal | (0.00500) | (0.00650) | (0.00846) |
| Tons of pesticide (**i**) | 0.0216*** | 0.0310*** | 0.0248*** |
| between 3km and 25km; Downwind | (0.00753) | (0.00889) | (0.00828) |
| Monitor FE | T | T | T |
| Day-of-sample FE | T | F | F |
| Week-of-sample FE | F | T | F |
| Month-of-sample FE | F | F | T |
| *N* | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* ‘(**a**)’) reference labeled areas in the figures associated with these results.

Table 5: **Increases in mean PM2.5 from aerial pesticides**: Wind-variation results

**Dependent variable:** Mean daily PM2.5 level

| | (1) | (2) |
|---|---|---|
| Tons of pesticide (**a**) within 1.5km; Upwind | 0.2465** (0.11788) | 0.2819** (0.12110) |
| Tons of pesticide (**b**) within 1.5km; Orthogonal | −0.0721 (0.09426) | −0.0578 (0.10508) |
| Tons of pesticide (**c**) within 1.5km; Downwind | 0.1883 (0.14685) | 0.2392 (0.18599) |
| Tons of pesticide (**d**) between 1.5km and 3km; Upwind | 0.0981 (0.10155) | 0.0963 (0.11903) |
| Tons of pesticide (**e**) between 1.5km and 3km; Orthogonal | 0.0891* (0.05109) | 0.0755 (0.05202) |
| Tons of pesticide (**f**) between 1.5km and 3km; Downwind | −0.1957 (0.17549) | −0.1793 (0.16402) |
| Tons of pesticide (**g**) between 3km and 25km; Upwind | 0.0019 (0.01037) | −0.0005 (0.01166) |
| Tons of pesticide (**g**) between 3km and 25km; Orthogonal | 0.0135 (0.00896) | 0.0091 (0.00952) |
| Tons of pesticide (**i**) between 3km and 25km; Downwind | 0.0249** (0.01032) | 0.0198** (0.00978) |
| Monitor FE | T | T |
| Week-of-year FE | T | F |
| Month-of-year FE | F | T |
| Day-of-week FE | T | T |
| Year FE | T | T |
| *N* | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table 6: **Increases in max. PM2.5 from aerial pesticides**: Wind-variation results

**Dependent variable:** Maximum daily PM2.5 level

| | (1) | (2) | (3) |
|---|---|---|---|
| Tons of pesticide (**a**) | 0.4869*** | 0.3073*** | 0.3458*** |
| within 1.5km; Upwind | (0.15024) | (0.08086) | (0.10892) |
| Tons of pesticide (**b**) | −0.1899 | −0.6967*** | −0.2682* |
| within 1.5km; Orthogonal | (0.25160) | (0.10545) | (0.13782) |
| Tons of pesticide (**c**) | 0.1961* | 0.1174 | 0.1401 |
| within 1.5km; Downwind | (0.11802) | (0.08083) | (0.19523) |
| Tons of pesticide (**d**) | 0.0508 | 0.1402 | 0.1958 |
| between 1.5km and 3km; Upwind | (0.14342) | (0.12992) | (0.12136) |
| Tons of pesticide (**e**) | 0.0024 | −0.0324 | 0.0116 |
| between 1.5km and 3km; Orthogonal | (0.07906) | (0.04590) | (0.04432) |
| Tons of pesticide (**f**) | 0.0627 | 0.0449 | −0.0498 |
| between 1.5km and 3km; Downwind | (0.30296) | (0.28186) | (0.18293) |
| Tons of pesticide (**g**) | 0.0068 | 0.0060 | −0.0055 |
| between 3km and 25km; Upwind | (0.01207) | (0.00989) | (0.01270) |
| Tons of pesticide (**g**) | 0.0122** | 0.0224*** | 0.0133 |
| between 3km and 25km; Orthogonal | (0.00566) | (0.00749) | (0.00973) |
| Tons of pesticide (**i**) | 0.0171** | 0.0303*** | 0.0220** |
| between 3km and 25km; Downwind | (0.00803) | (0.00997) | (0.00977) |
| Monitor FE | T | T | T |
| Day-of-sample FE | T | F | F |
| Week-of-sample FE | F | T | F |
| Month-of-sample FE | F | F | T |
| *N* | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table 7: **Increases in max. PM2.5 from aerial pesticides**: Wind-variation results

| **Dependent variable:** Maximum daily PM2.5 level | | |
|---|---|---|
| | (1) | (2) |
| Tons of pesticide (**a**) within 1.5km; Upwind | 0.2856*** (0.10680) | 0.3221*** (0.11132) |
| Tons of pesticide (**b**) within 1.5km; Orthogonal | −0.3417*** (0.10677) | −0.2873** (0.12585) |
| Tons of pesticide (**c**) within 1.5km; Downwind | 0.1484 (0.13873) | 0.1934 (0.17877) |
| Tons of pesticide (**d**) between 1.5km and 3km; Upwind | 0.2173* (0.12125) | 0.2081 (0.13675) |
| Tons of pesticide (**e**) between 1.5km and 3km; Orthogonal | 0.0603 (0.06407) | 0.0554 (0.06387) |
| Tons of pesticide (**f**) between 1.5km and 3km; Downwind | −0.2374 (0.28403) | −0.2399 (0.25004) |
| Tons of pesticide (**g**) between 3km and 25km; Upwind | −0.0086 (0.01273) | −0.0114 (0.01450) |
| Tons of pesticide (**g**) between 3km and 25km; Orthogonal | 0.0130 (0.00953) | 0.0075 (0.00994) |
| Tons of pesticide (**i**) between 3km and 25km; Downwind | 0.0208** (0.01057) | 0.0149 (0.01019) |
| Monitor FE | T | T |
| Week-of-year FE | T | F |
| Month-of-year FE | F | T |
| Day-of-week FE | T | T |
| Year FE | T | T |
| *N* | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

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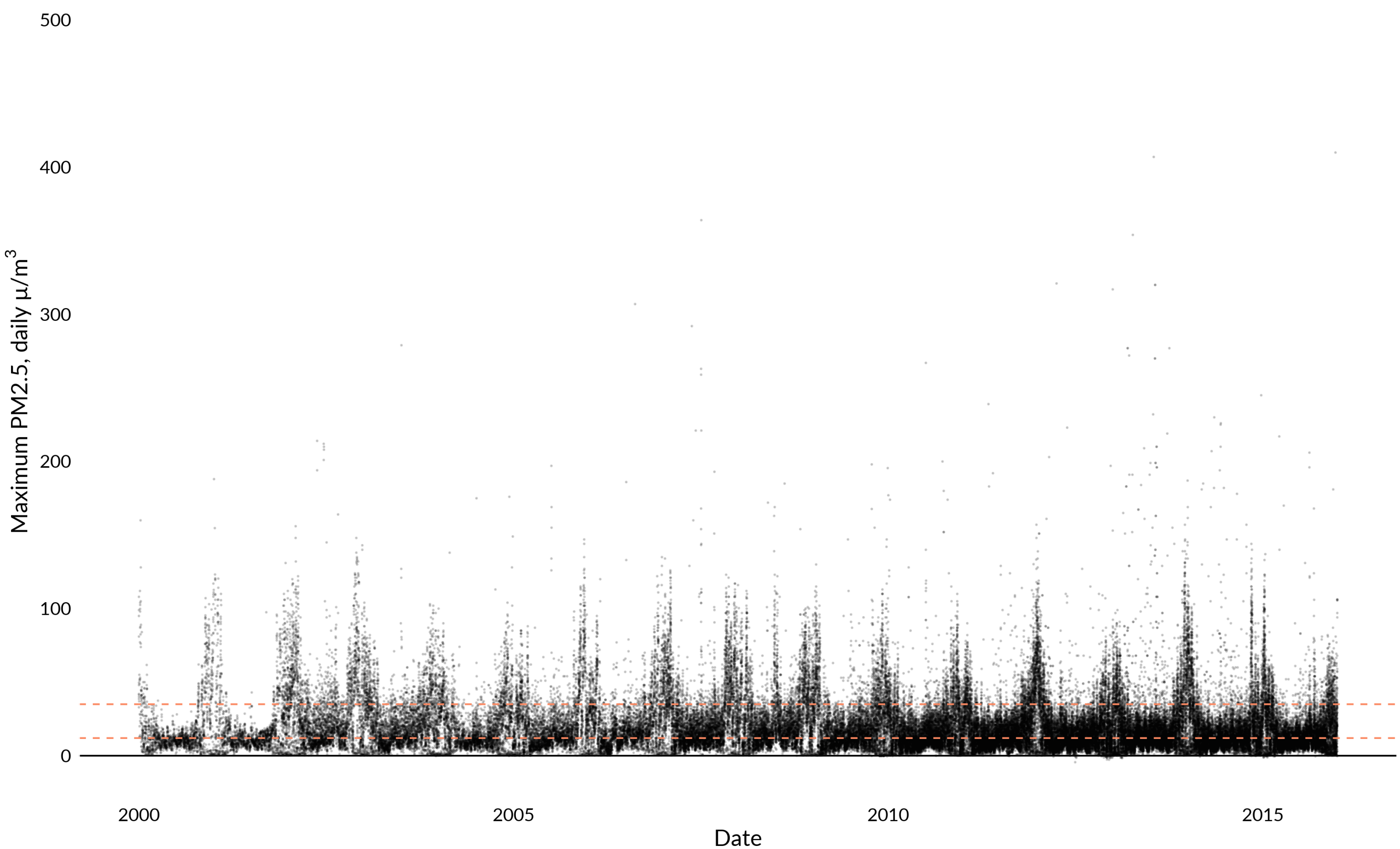
# A Appendix

## A.1 Appendix figures

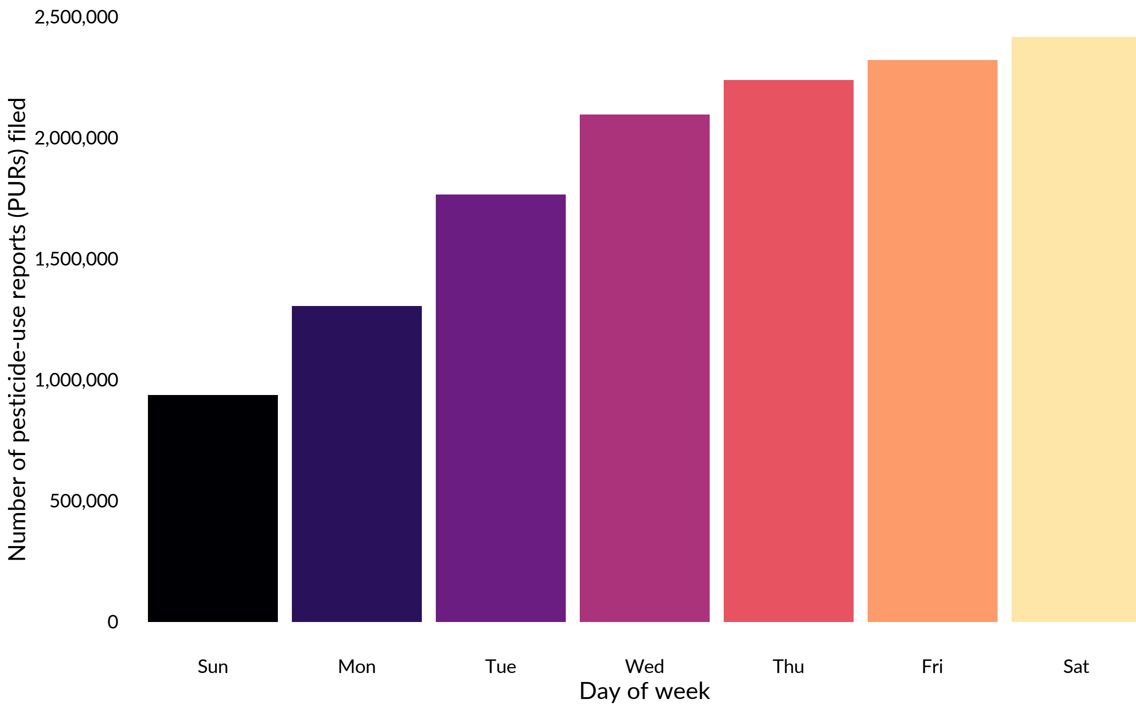
Figure A1: **EPA PM2.5 records:** Daily maximum PM2.5 concentration at each monitor, 2000–2015



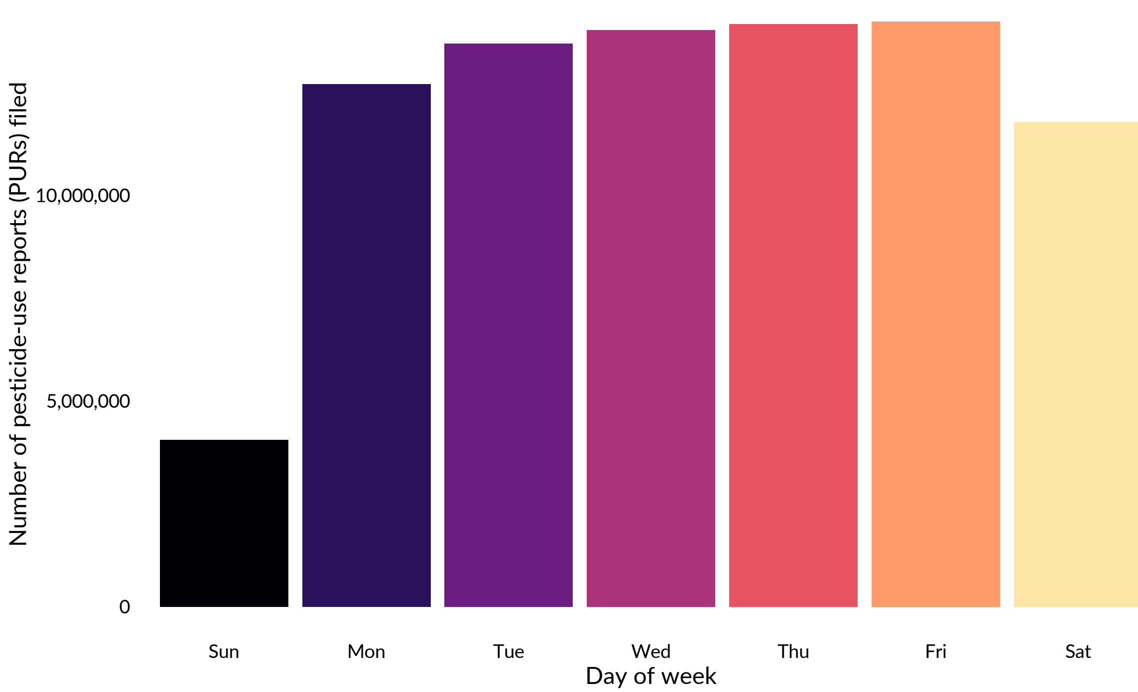

**Notes:** Each point in this figure represents the maximum PM2.5 on the given day ($x$ axis) for a specific monitor. The two dashed horizontal lines denote two different primary National Ambient Air Quality Standards (NAAQS), established January 15, 2013. The lower line establishes the standard (12.0 $\mu g/m^3$) for the the 3-year arithmetic mean. The higher line marks the standard (35 $\mu g/m^3$) for the 3-year mean of the 98$^{th}$ percentile (U.S. E.P.A. 2013).

Figure A2: **Number of pesticide applications:** 2000–2015, by day of week

(a) **Aerially applied pesticides**




(b) **Ground-applied pesticides**




**Notes:** These figures depict the number PURs filed by day of week in the five study counties between 2000 and 2015, separating the pesticide applications by aerial applications (top) and ground applications (bottom).*Source:* Author using data from California D.P.R. 2013.

### A.2 Appendix tables

Table A1: **Increases in mean PM2.5**: Same-day, aerially applied pesticides, Windsorized

**Dependent variable:** Mean daily PM2.5 level

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Tons of pesticide (**a**) | 0.2575*** | 0.1455** | 0.2066* | 0.2139** | 0.2545** |
| within 1.5km | (0.0915) | (0.0588) | (0.1094) | (0.0984) | (0.1180) |
| Tons of pesticide (**b**) | 0.0613 | 0.0295 | 0.0588 | 0.0482 | 0.0660 |
| between 1.5km and 3km | (0.1421) | (0.0787) | (0.0868) | (0.1047) | (0.1160) |
| Tons of pesticide (**c**) | 0.0413 | 0.1047 | 0.0625 | 0.0413 | 0.0124 |
| between 3km and 25km | (0.0788) | (0.0664) | (0.0645) | (0.0790) | (0.0767) |
| Monitor FE | T | T | T | T | T |
| Day-of-sample FE | T | F | F | F | F |
| Week-of-sample FE | F | T | F | F | F |
| Month-of-sample FE | F | F | T | F | F |
| Week-of-year FE | F | F | F | T | F |
| Month-of-year FE | F | F | F | F | T |
| Day-of-week FE | F | F | F | T | T |
| Year FE | F | F | F | T | T |
| *N* | 26,242 | 26,242 | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Windsorization* replaces any value *above* the 97.5$^{\text{th}}$ percentile of a variable with the 97.5$^{\text{th}}$ percentile. Windsorization attempts to limit the influence of extreme values within the independent variables(s). I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table A2: **Increases in max. PM2.5**: Same-day, aerially applied pesticides, Windsorized

**Dependent variable:** Maximum daily PM2.5 level

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Tons of pesticide (**a**) | 0.3400*** | 0.1466*** | 0.2006** | 0.1730** | 0.2140** |
| within 1.5km | (0.1026) | (0.0484) | (0.0975) | (0.0841) | (0.0994) |
| Tons of pesticide (**b**) | 0.1140 | 0.0949 | 0.1327 | 0.1188 | 0.1384 |
| between 1.5km and 3km | (0.1792) | (0.0968) | (0.0997) | (0.1223) | (0.1346) |
| Tons of pesticide (**c**) | 0.0218 | 0.0845 | 0.0349 | 0.0030 | −0.0321 |
| between 3km and 25km | (0.0862) | (0.0740) | (0.0752) | (0.0804) | (0.0802) |
| Monitor FE | T | T | T | T | T |
| Day-of-sample FE | T | F | F | F | F |
| Week-of-sample FE | F | T | F | F | F |
| Month-of-sample FE | F | F | T | F | F |
| Week-of-year FE | F | F | F | T | F |
| Month-of-year FE | F | F | F | F | T |
| Day-of-week FE | F | F | F | T | T |
| Year FE | F | F | F | T | T |
| *N* | 26,242 | 26,242 | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Windsorization* replaces any value *above* the 97.5$^{th}$ percentile of a variable with the 97.5$^{th}$ percentile. Windsorization attempts to limit the influence of extreme values within the independent variables(s). I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table A3: **Increases in mean PM2.5 from aerial pesticides**: Wind-variation results, Windsorized

**Dependent variable:** Mean daily PM2.5 level

| | (1) | (2) | (3) |
|---|---|---|---|
| Tons of pesticide (**a**) | 0.2954** | 0.2557*** | 0.2607** |
| within 1.5km; Upwind | (0.1504) | (0.0856) | (0.1094) |
| Tons of pesticide (**b**) | −0.0080 | −0.4481*** | −0.0936 |
| within 1.5km; Orthogonal | (0.1395) | (0.0482) | (0.1039) |
| Tons of pesticide (**c**) | 0.3131** | 0.2040** | 0.2123 |
| within 1.5km; Downwind | (0.1549) | (0.0835) | (0.2183) |
| Tons of pesticide (**d**) | 0.0772 | 0.0704 | 0.1267 |
| between 1.5km and 3km; Upwind | (0.1327) | (0.1029) | (0.1018) |
| Tons of pesticide (**e**) | 0.0582 | −0.0267 | −0.0055 |
| between 1.5km and 3km; Orthogonal | (0.2065) | (0.1400) | (0.1100) |
| Tons of pesticide (**f**) | 0.0302 | −0.0092 | −0.0489 |
| between 1.5km and 3km; Downwind | (0.2739) | (0.1801) | (0.1392) |
| Tons of pesticide (**g**) | −0.0270 | −0.0210 | −0.0966 |
| between 3km and 25km; Upwind | (0.1593) | (0.1218) | (0.1246) |
| Tons of pesticide (**g**) | 0.0445 | 0.1522** | 0.1454** |
| between 3km and 25km; Orthogonal | (0.0625) | (0.0592) | (0.0654) |
| Tons of pesticide (**i**) | 0.1280** | 0.2272*** | 0.1982*** |
| between 3km and 25km; Downwind | (0.0527) | (0.0519) | (0.0609) |
| Monitor FE | T | T | T |
| Day-of-sample FE | T | F | F |
| Week-of-sample FE | F | T | F |
| Month-of-sample FE | F | F | T |
| *N* | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Windsorization* replaces any value *above* the 97.5$^{th}$ percentile of a variable with the 97.5$^{th}$ percentile. Windsorization attempts to limit the influence of extreme values within the independent variables(s). *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table A4: **Increases in mean PM2.5 from aerial pesticides**: Wind-variation results, Windsorized

**Dependent variable:** Mean daily PM2.5 level

| | (1) | (2) |
|---|---|---|
| Tons of pesticide (**a**) | 0.2604* | 0.2961** |
| within 1.5km; Upwind | (0.1377) | (0.1393) |
| Tons of pesticide (**b**) | –0.1157 | –0.1079 |
| within 1.5km; Orthogonal | (0.0997) | (0.1018) |
| Tons of pesticide (**c**) | 0.2294 | 0.2871 |
| within 1.5km; Downwind | (0.1617) | (0.1962) |
| Tons of pesticide (**d**) | 0.1421 | 0.1659 |
| between 1.5km and 3km; Upwind | (0.1117) | (0.1306) |
| Tons of pesticide (**e**) | 0.1427 | 0.1242 |
| between 1.5km and 3km; Orthogonal | (0.1537) | (0.1557) |
| Tons of pesticide (**f**) | –0.2580 | –0.2195 |
| between 1.5km and 3km; Downwind | (0.2255) | (0.2159) |
| Tons of pesticide (**g**) | –0.1045 | –0.1484 |
| between 3km and 25km; Upwind | (0.1421) | (0.1421) |
| Tons of pesticide (**g**) | 0.1078 | 0.0917 |
| between 3km and 25km; Orthogonal | (0.0741) | (0.0750) |
| Tons of pesticide (**i**) | 0.1746* | 0.1545* |
| between 3km and 25km; Downwind | (0.0927) | (0.0843) |
| Monitor FE | T | T |
| Week-of-year FE | T | F |
| Month-of-year FE | F | T |
| Day-of-week FE | T | T |
| Year FE | T | T |
| *N* | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Windsorization* replaces any value *above* the 97.5$^{th}$ percentile of a variable with the 97.5$^{th}$ percentile. Windsorization attempts to limit the influence of extreme values within the independent variables(s). *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table A5: **Increases in max. PM2.5 from aerial pesticides**: Wind-variation results, Windsorized

**Dependent variable:** Maximum daily PM2.5 level

| | (1) | (2) | (3) |
|---|---|---|---|
| Tons of pesticide (**a**) | 0.5264*** | 0.3499*** | 0.3399** |
| within 1.5km; Upwind | (0.1745) | (0.0799) | (0.1334) |
| Tons of pesticide (**b**) | –0.2352 | –0.7615*** | –0.3614*** |
| within 1.5km; Orthogonal | (0.2582) | (0.1061) | (0.1333) |
| Tons of pesticide (**c**) | 0.2621** | 0.1662** | 0.1430 |
| within 1.5km; Downwind | (0.1273) | (0.0724) | (0.2130) |
| Tons of pesticide (**d**) | 0.1283 | 0.1610 | 0.2410* |
| between 1.5km and 3km; Upwind | (0.1817) | (0.1314) | (0.1264) |
| Tons of pesticide (**e**) | 0.0328 | 0.0672 | 0.1092 |
| between 1.5km and 3km; Orthogonal | (0.3910) | (0.2236) | (0.1692) |
| Tons of pesticide (**f**) | 0.1200 | –0.0378 | –0.1210 |
| between 1.5km and 3km; Downwind | (0.3151) | (0.3269) | (0.2205) |
| Tons of pesticide (**g**) | –0.0838 | –0.1033 | –0.1820 |
| between 3km and 25km; Upwind | (0.1787) | (0.1373) | (0.1428) |
| Tons of pesticide (**g**) | 0.0583 | 0.1649** | 0.1571* |
| between 3km and 25km; Orthogonal | (0.0748) | (0.0712) | (0.0808) |
| Tons of pesticide (**i**) | 0.1262*** | 0.2586*** | 0.2113*** |
| between 3km and 25km; Downwind | (0.0467) | (0.0611) | (0.0665) |
| Monitor FE | T | T | T |
| Day-of-sample FE | T | F | F |
| Week-of-sample FE | F | T | F |
| Month-of-sample FE | F | F | T |
| *N* | 26,242 | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Windsorization* replaces any value *above* the 97.5$^{th}$ percentile of a variable with the 97.5$^{th}$ percentile. Windsorization attempts to limit the influence of extreme values within the independent variables(s). *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* '(**a**)') reference labeled areas in the figures associated with these results.

Table A6: **Increases in max. PM2.5 from aerial pesticides**: Wind-variation results, Windsorized

**Dependent variable:** Maximum daily PM2.5 level

| | (1) | (2) |
|---|---|---|
| Tons of pesticide (**a**) within 1.5km; Upwind | 0.3085** | 0.3422** |
| | (0.1301) | (0.1343) |
| Tons of pesticide (**b**) within 1.5km; Orthogonal | –0.4266*** | –0.3842*** |
| | (0.1188) | (0.1312) |
| Tons of pesticide (**c**) within 1.5km; Downwind | 0.1274 | 0.1756 |
| | (0.1493) | (0.1828) |
| Tons of pesticide (**d**) between 1.5km and 3km; Upwind | 0.2430* | 0.2657* |
| | (0.1372) | (0.1584) |
| Tons of pesticide (**e**) between 1.5km and 3km; Orthogonal | 0.2582 | 0.2714 |
| | (0.2262) | (0.2353) |
| Tons of pesticide (**f**) between 1.5km and 3km; Downwind | –0.3153 | –0.2958 |
| | (0.3397) | (0.3098) |
| Tons of pesticide (**g**) between 3km and 25km; Upwind | –0.1947 | –0.2469 |
| | (0.1530) | (0.1559) |
| Tons of pesticide (**g**) between 3km and 25km; Orthogonal | 0.1032 | 0.0822 |
| | (0.0853) | (0.0852) |
| Tons of pesticide (**i**) between 3km and 25km; Downwind | 0.1744** | 0.1500* |
| | (0.0883) | (0.0798) |
| Monitor FE | T | T |
| Week-of-year FE | T | F |
| Month-of-year FE | F | T |
| Day-of-week FE | T | T |
| Year FE | T | T |
| *N* | 26,242 | 26,242 |

**Notes:** Each column denotes a separate regression. Errors are two-way clustered within (1) EPA sensor and (2) day of sample. *FE* refers to *fixed effect*. *Windsorization* replaces any value *above* the 97.5$^{th}$ percentile of a variable with the 97.5$^{th}$ percentile. Windsorization attempts to limit the influence of extreme values within the independent variables(s). *Upwind* refers to the degree to which pesticide applications occured upwind of the EPA monitor—0 and 60 degrees (in absolute value). Similarly, I label angles between 60 and 120 degrees as *Orthogonal* and angles between 120 and 180 degrees as *Downwind*. See the Empirical Strategy section for a detailed explanation. I two-way cluster the errors by (1) monitor and (2) day of sample. *Significance levels:* *10%, **5%, ***1%. The letters in parentheses (*e.g.,* ‘(**a**)’) reference labeled areas in the figures associated with these results.

## A.3 Data appendix

### A.3.1 EPA monitoring data

I downloaded the EPA PM2.5 monitoring data from the EPA's I use daily data from both FRM/FEM mass systems and non-FRM/FEM mass systems.[25]

### A.3.2 PUR data

I only use PUR data related to agricultural production (`record_id` of `2` or `C`) and for pesticides that were applied aerially (`type = A`). Because both empirical strategies rely on geography and timing, I drop use reports missing dates or coordinates (*i.e.*, no `NA`s).

With regards to the California DPR's map of sections, I drop 42 sections (approximately 0.03% of sections) that map to multiple polygons—again because both empirical strategies rely on confidently locating pesticide applications in space. The dropped sections account for approximately 0.2% of the pounds of pesticide reported in the PUR system.

Tables A1 and A2 use Windsorized values of the PUR data. Specifically, I Windsorize the variable that represents the total pounds of pesticide applied, replacing any value that exceeds the 97.5$^{\text{th}}$ percentile with the 97.5$^{\text{th}}$ percentile.

### A.3.3 Wind data

The NLDAS-2 data come from the Goddard Earth Sciences Data and Information Services Center (GES DISC). While the NLDAS-2 generates hourly data, the paper uses wind estimated at noon at 10 meters above the ground.[26] I calculate wind speed and direction using the $U$ and $V$ wind vectors and trigonometry:

$$\text{Wind}_{\text{Speed}} = \sqrt{u^2 + v^2} \tag{4}$$

$$\text{Wind}_{\text{Angle}} = \tan^{-1}\left(\frac{u}{v}\right) \times \frac{180}{\pi} \tag{5}$$

In addition, geographic resolution is not the only source of noise in the wind-based measurements. While the NLDAS-2 provides NASA's best attempts to recreate historical wind outcomes at a high spatiotemporal level, the the NLDAS-2 wind data likely introduce additional noise and, consequently, attenuation.

[25]*FRM* is the acronym for Federal Reference Method; *FEM* abbreviates Federal Equivalent Methods.
[26]The time-of-day data in the PURs do not appear to meet data-quality standards.

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