Title: Extreme Temperatures, Crop Diversity, and Pesticide Use Behavior: Comprehensive Evidence from California

Short Title: Extreme Temperatures, Crop Diversity, and Pesticide Use Behavior

Authors: Siddharth Kishore and Josue Medellin-Azuara[1]

Author Affiliations:

Siddharth Kishore is postdoctoral scholar in the Department of Civil and Environmental Engineering at UC Merced; and Josue Medellin-Azuara is professor in the Department of Civil and Environmental Engineering at UC Merced. They can be reached at: siddharthkishore@ucmerced.edu and jmedellin@ucmerced.edu.

Abstract

We combine field-level data from California Pesticide Use Reports with high-resolution spatial weather data to investigate how exposure to extreme temperature influences pesticide use behavior for 17 major crops production in California from 1993 to 2022. We find reduced pesticide use in response to extreme temperatures for both perennial and annual crops, but an increased number of pesticide applications per hectare were applied to perennial crops to treat plant diseases and control pests. We demonstrate the impact of temperature on agricultural land-use patterns, leading to a shift towards specialty nut tree crops that reduce overall pesticide use.

Keywords: climate change, crop diversity, pesticide use behavior

JEL classification: O13, Q16, Q54

[1] Acknowledgments: We thank Morgan Malone and the research team members of the Water System Management lab in the Department of Civil and Environmental Engineering at UC Merced for excellent research assistance. This work was funded by a California Natural Resources Agency's 5th Climate Assessment grant, and the grant agreement A21-0557-000-SO, between the California Department of Food and Agriculture and the UC Regents.

Extreme Temperatures, Crop Diversity, and Pesticide Use Behavior: Comprehensive Evidence from California

Abstract

We combine field-level data from California Pesticide Use Reports with high-resolution spatial weather data to investigate how exposure to extreme temperature influences pesticide use behavior for 17 major crops production in California from 1993 to 2022. We find reduced pesticide use in response to extreme temperatures for both perennial and annual crops, but an increased number of pesticide applications per hectare were applied to perennial crops to treat plant diseases and control pests. We demonstrate the impact of temperature on agricultural land-use patterns, leading to a shift towards specialty nut tree crops that reduce overall pesticide use.

Keywords: climate change, crop diversity, pesticide use

JEL classification: O13, Q16, Q54

1. Introduction

Pesticides application is an important strategy for cost-efficient crop production in contemporary agricultural production in controlling pests and treating plant diseases (Epstein and Bassein 2003) and to mitigate uncertainty in crop production (Zilberman et al. 1991). The crop yield-temperature response for major crops in the United States is nonlinear (Hogan and Schlenker 2024) and growers can potentially adopt pesticide application strategies to partially compensate for climate-induced crop yield losses. In addition, warmer temperatures may affect the intensity and frequency of agricultural pesticide use (Yi et al. 2025; Bareille et al. 2024; Luedeling et al. 2011). The impacts of climate change on factors of crop production, including pesticide usage, remain insufficiently understood. Our data, which use pesticide applications at the grower level to estimate the impact of extreme temperatures, allows us to take advantage of field-level temperature-induced changes in pesticide applications, which would otherwise be masked at the national scale and thus not be identified using national data. This paper answers the question of how warming temperature affects factors of crop production, primarily focusing on pesticide applications in California's crops, the largest and most diverse agricultural system in the US, and quantifies the estimates in the context of climate change.

According to data from the UC Davis Cost and Return Studies, California's agricultural pesticide application may only account for between 1.5% and 12% of the total farming operating costs, depending on crop, pest, and location.[1] In spite of that California's pesticide application in intensity and cropland coverage is among the largest in the world. For example, according to the California Department of Pesticide Regulation (CDPR), 82 million kg active ingredients of

[1] For example, corn in California was reported to dedicate approximately 3.9% of its operations costs to the application of pesticides in 2015, while the allocations for pesticide application for strawberries and almonds were 1.7% and 12% respectively in 2024.

pesticides were applied, and 92 million cumulative acres were treated in California for production agriculture in 2022. Most of the pesticides were applied in the Central Valley of California, the state's largest agricultural region, for perennial crops such as almond, pistachio, walnut, grapes, and oranges, as well as annual crops such as cotton, alfalfa, carrots, processing tomatoes, and strawberry (CDPR Pesticide Use Annual Report 2022). Moreover, according to the Food and Agriculture Organization Statistics Database, the national yearly average pesticide usage for the United States ranges from 2.1 kg/ha to 2.9 kg/ha within the 1990-2023 study period, with a total average of 2.4 kg/ha (Pesticides Use and Trade 2025). Meanwhile, in California, the average pesticide use per hectare across crops during the same period was 17 kg/ha.

Extreme temperature can affect growers' pesticide use behavior through three primary pathways. First, pesticide application for major crops follows a calendar-based schedule spray, and an extreme temperature may affect that schedule (Epstein et al. 2000). For example, reduced availability of agricultural labor on hot days to spray pesticides. Secondly, the incidence and severity of pests, pathogens, and weeds are sensitive to extreme temperatures and vary year to year due to temperature changes (Deutsch et al. 2018; Luedeling et al. 2011; Elad and Pertot 2014), which may influence agricultural pesticides application strategies. Thirdly, changes in agricultural land use patterns can also impact pesticide use (Urruty et al. 2016; Wei et al. 2024; Larsen et al. 2023a). We show the nonlinear effects of temperature on agricultural land-use patterns shifts. Specifically, increased land-use shares of annual crops with respect to extreme temperatures. Although pesticides protect crops from pest damage and microbial infections, thus help increase crop yields and farmers' income (Rosenheim et al. 2020; Kawasaki 2023). In the absence of optimal plant disease control strategies, growers may face a potential risk associated with an increase in profit variability due to expenses associated with using more pesticides than recommended, and from disease-induced crop failure associated with undertreatment (Epstein and Bassein 2003; Zhang et al. 2015). Moreover, the active ingredients in pesticides are associated with negative outcomes such as potential risks for human health (Larsen et al. 2017), biodiversity (Larsen et al. 2023b), and broadly, the environment (Larsen et al. 2019). Therefore, the reduction of chemical pesticide use is advised in crop pest management strategies and discussed in regulatory bodies across the country. In California, pesticide use is strictly regulated and reported at the field level.

Climate change impacts both crop yield and the timing of occurrences (or dis-occurrences) of pests and diseases (Rosenheim et al. 2020; Larsen et al. 2019). Growers may increase or decrease the use of pesticides to compensate for climate-induced crop yield losses (Kawasaki 2023). Our study provides useful insights on how growers may potentially adapt their pesticide use to changing climate in water-limited regions. Econometrically, it can be challenging to establish a causal link between temperature, crop diversity, pesticide use, and to isolate the effect between them. We follow agriculture-climate literature to exploit plausibly exogenous variations in temperature to explain the variation in pesticide use rates in our study region. Specifically, we employ two econometric approaches: (1) a non-parametric temperature-bin approach; and (2) a piecewise-linear approach.

We use California's Pesticide Usage Reporting (PUR) database to assess the relationship between pesticide use intensity and frequency and extreme temperatures in the Central Valley during 1993–2022. We find that pesticide use intensity for perennial crops reduces to smaller amounts during extreme temperatures (above 30° C), but in annual crops increases to relatively higher volume. Analysis of heterogeneity among types of pesticides suggests that the use of insecticides in perennial crops decreases on hot days, while the use of insecticides and herbicides increases in annual crops. In addition, pesticide use exhibits an inverse relationship with Herfindahl-Hirschman Index (HHI), a measure of crop diversity. This suggests that a shift toward specialty crops can reduce pesticide use.

Lastly, using our estimated coefficients, we quantify the effects of projected climate change on California's pesticide use intensity. Our estimates, conditional on baseline model, suggest that growers reduce pesticide use intensity with respect to predicted heat degree days for crops such as grapes, citrus, other subtropical fruit trees, cucurbits, leafy and root vegetables, fiber crops, and forage and fodder crops by three to fifty two percent in 2080 under climate projections for the socio-economic pathways of SPP245 and SSP585.

2. Data and Descriptive Statistics

2.1. Pesticide Usage Reporting Data

We utilized pesticide applications from the California Pesticide Usage Reporting (PUR) made available to public through California Pesticide Information Portal (CPIP) by the Department of Pesticide Regulation (DPR).[2] PUR database contains information on all commercial agricultural pesticide use, including information on the chemicals used, application date, crops and acreages for each applications and consistently maintains database since 1993, available at the spatial Public Land Survey (PLS) section (~1.6 x 1.6 km^2 or 640 acres). Our analysis is limited to the spatial grid cells that were associated with the Central Valley region during 1993 and 2022.[3]

---

[2] The data on pesticide usage reporting in California is available at https://calpip.cdpr.ca.gov/main.cfm, which was accessed on August 20th, 2025.

[3] We overlay the boundaries of the Central Valley obtained from the California State Geoportal on the Public Land Survey Section obtained from the California's Pesticide Information Portal to extract grid cells associated with the Central Valley region. There are 17,249 grid cells (or unique PLS sections). Furthermore, from the pesticide usage reporting dataset, we exclude first pesticide use for non-agricultural purposes (i.e., the use record ID equals "C" and "G" and site code below 156 and above 33000). In the online appendix, Table S1, we provide the definition of crop types used in our analysis.

Importantly, using the product database, we categorized pesticides into various pesticide categories, including insecticides, fungicides, herbicides, and other chemicals. Other chemicals include rodenticides and chemicals not directly identified as insecticides, fungicides, or herbicides from their product names and codes, and they are applied as a mixture. Pesticide use data is self-reported by growers, and then DPR public authorities rigorously validate those entries.

For our purposes, we constructed two measures of growers' pesticide use behavior: (1) annual field-level pesticide application intensity and then aggregated to the PLS sections level; and (2) the mean number of pesticide applications per hectare per year at the PLS sections level. To handle outliers in our outcomes of interest, we *winsorize* pesticide use at the PLS sections at the 1st and 99th percentile levels.

Table 1 presents the mean pesticide use intensity and the mean number of pesticide applications per hectare per year for each major crop across PLS sections in our study region. On average, 17.3 kg/ha per year of overall pesticides are applied to the perennial crops during the study period, with the largest pesticide use is applied to other fruit trees (23.4 kg/ha), followed by citrus and other subtropical fruit trees (21.5 kg/ha) and almonds, pistachios, and other nuts (17.5 kg/ha). Herbicide is the most frequently used type of pesticide across crop types. The pesticide use intensity for annual crops is 17.1 kg/ha per year. The largest application is for berries (45.6 kg/ha), followed by root vegetables (30.8 kg/ha). The pesticide type that was applied the most was insecticide, followed by herbicide. The average number of pesticide applications per year for annual and perennial crops was 4, with significant variations among crops ranging from 2 to 14. Figure A1 shows trends in pesticide use across year in our study region. The study period shows a gradual decline in insecticide use across crop types, but an increase in fungicide use. Herbicide usage has been on the rise since 2005. Figures A2a and A2b show the spatial variation in overall pesticide use and by type of pesticide use, respectively, in our study region from 1993 to 2022.

2.2. Climate Data

We obtained climate data from gridMET, a daily surface meteorological dataset with a spatial resolution of approximately 4 km for the years 1993 to 2022 (Abatzoglou 2013).[4] We constructed daily mean temperature bins at 5-degree intervals by utilizing daily minimum and maximum temperatures. We followed climate-agriculture literature to develop degree-days, linear and quadratic functional forms of total precipitation, average solar radiation, and average wind speed during the annual and growing season (April through September) to capture nonlinear effects. Table A1 reports the summary statistics of climate data used in our analysis.

2.3. Agricultural Land-Use Share

We create agricultural land-use shares using the Land IQ database, contracted by the California Department of Water Resources (CDWR), for the years 2014, 2016, and 2018 through 2022. Figure A3 shows the trends in agricultural land-use in California's Central Valley between 2014 and 2022. The vertical axis of Figure A3 represents the average agricultural land-shares ratio by crop type (perennial and annual crops) across the PLS sections and is constructed by dividing the share of each crop type over the base year land-shares (i.e., 2014). The slope of the crop type land-use shares can be interpreted as the rate at which the land-use share of perennial crops within a PLS section increases or the rate at which the share of land-use annual crops within PLS section decreases, compared to the baseline. We observed that the share of perennial crops

[4] The data is accessible at https://www.climatologylab.org/gridmet.html, which was accessed on August, 2025.

substituted annual crops by 15% in 2022 from the baseline acreage in 2014. These increasing trends in specialty crops may generate a relatively lower volume of pesticide sales, which may result in less pesticide application strategies. Figure A4 shows the spatial variation in the share of perennial crops at the PLS section level in 2014 and 2022. It appears that the share of perennial crops increased significantly in 2022 compared to 2014 and is concentrated in the eastern region of the Central Valley.

3. Empirical Approach

The empirical approach of this paper has four parts: (1) First, we will present a simple correlation between pesticide use rate and mean temperature; (2) Then, we will present a crop-specific nonlinear response to overall pesticide use to extreme temperatures in our study region; (3) We will examine the temperature effects on agricultural land-use patterns shifts, as well as the effects of crop diversity on pesticide use; (4) Finally, using the estimated coefficients, we will quantify the effects of projected climate change on California's overall pesticide use. Together, our empirical strategy aims to study the nonlinear effects of temperature on pesticide use behavior and examine whether agricultural land-use and crop diversity can explain the pesticide use behavior in an irrigated agricultural context in water-limited region.

3.1. Correlation between pesticide use rate and mean temperature

We created a standardized measure of total pesticide use rate and mean temperature data that accounts for technological innovations, changes in cultivar practices, and other time varying factors, similar to Troy et al. (2015). We use a seven-year moving window and the estimating equation is

$$Y_t = \frac{y_t - \overline{y_{t-3:t+3}}}{SD(t_{t-3:t+3})} \quad (1)$$

where Y_t is the derived standardized pesticide use rate for each of the 17 major crop groups grown in the Central Valley of California. In equation (1), the numerator is the difference between pesticide use in a year t and a seven-year moving average centered around that year t. And the denominator in equation (1) denotes the standard deviation of pesticide use values for the same seven-year moving window. Similarly, we derive the seven-year moving average of mean annual temperature for perennial crops and mean temperature during the growing season for annual crops. The equation (1) leaves out the first and last 3 years. The years considered are from 1996 to 2019. Figure A5 shows the time series of raw crop-specific pesticide use rate and standardized pesticide use rate using a seven-year moving window.

3.2. Panel estimates

We first regress pesticide usage rates, including insecticides, herbicides, fungicides, and other chemicals on temperature bins, controlling for a set of linear and quadratic terms of other weather conditions, to detect the threshold temperature that potentially results in any change (either increase or decrease) in pesticide use. The estimating equation is

$$y_{i,t} = \sum_m \alpha_m Bin_{i,t}^m + \gamma W_{i,t} + \psi_i + \mu_t + \varepsilon_{i,t} \tag{2}$$

where $y_{i,t}$ denotes pesticide use rates in PLS section i and year t. We transform pesticide use rate using logarithm transformation. $Bin_{i,t}^m$ is a set of temperature variables that measure the number of days with daily temperature falling into specific bin m in year t. We set up 5 degrees bins between 0 degrees and 30 degrees, similar to (Chen and Gong 2021). We chose the reference bin with the highest frequency occurring at [15° C, 20° C). As a robustness check, we also constructed temperature bins with 3-degree and 4-degree intervals.

$W_{i,t}$ is a vector of linear and quadratic terms of other weather variables used in our analysis in year t, including total precipitation and average solar radiation, as well as average wind speed. ψ_{i} and μ_t are PLS section and year-fixed effects to capture time-invariant characteristics of PLS section such as soil attributes and to control for time-varying shocks (e.g., input prices and output prices) that are common to all PLS sections, respectively. Together, the PLS section and year fixed effects help minimize the omitted variable bias. Finally, the expression error terms, $\varepsilon_{i,t}$, represent variations in our outcome variables that are not explained by our model.

Next, to estimate how temperature affects growers' pesticide use behavior, we created crop-specific growing degree days (GDD) and heat degree days (HDD). We follow agronomy literature to calculate degree days, we set a lower threshold value of 8° C and an upper threshold value of 27° C. In our robustness checks, we repeat our main analysis for degree days defined at upper threshold values of 26° C, 28° C, and 29°C. We use a piecewise linear approach to measure the effects of GDD and HDD on pesticide use intensity and frequency. Following existing studies (Yi et al. 2025; Chen and Gong 2021), we estimate the following equation:

$$y_{i,t} = \alpha_0 GDD_{i,t} + \alpha_1 HDD_{i,t} + \gamma W_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \qquad (3)$$

Where $y_{i,t}$ is number of outcomes: (1) log transformed pesticide use in PLS section i and year t; (2) IHS-transformed mean number of pesticide application per hectare per year; and (3) the share of agricultural land-use, including the share of perennial and annual crops. $GDD_{i,t}$ and $HDD_{i,t}$ are growing degree days below critical threshold temperature and heat degree days above threshold temperature in PLS section i in year t. All other variables are defined in equation (2). Because we aggregated field-level pesticide application to the PLS section level and to exploit the variation in the pesticide use within PLS sections, we clustered the standard errors at the PLS section level. As a robustness check, we show estimation results for various spatial combinations of fixed effects including township-range level fixed effects.[5] Importantly, we assumed that pesticide application decisions in each field in the PLS section are independent. As a robustness check, we clustered the standard errors at the township-range level to allow for spatial correlation of error terms at the larger location identifier.[6]

In addition to above panel fixed effects model to estimate the impacts of temperature on agricultural land use share, we also adopt the empirical framework of (Mu et al. 2018; Cho and McCarl 2017), which employs fractional multinomial logit model.[7]

Lastly, to estimate the predicted changes in climate variables in our study region, we use two climate scenarios, SSP245 and SSP585, for the near-medium term (average for 2031–2055) and the long-term (average for 2056–2080) respectively. Using the estimated coefficients from our econometric model, equation (3), we estimated the predicted changes in the projected climate-driven pesticide use intensity with respect to degree days and heat degree days. The estimating expressions are $\left(\frac{\partial E(y_{i,t}|\, W_{i,t})}{\partial GDD_{i,t}} * \Delta\overline{GDD}\right)$ and $\left(\frac{\partial E(y_{i,t}|\, W_{i,t})}{\partial HDD_{i,t}} * \Delta\overline{HDD}\right)$; where $\frac{\partial E(y_{i,t}|\, W_{i,t})}{\partial GDD_{i,t}}$ and $\frac{\partial E(y_{i,t}|\, W_{i,t})}{\partial HDD_{i,t}}$ are marginal effects from panel estimates with respect to degree days and heat degree days, respectively. $\Delta\overline{GDD}$ (and $\Delta\overline{HDD}$) represent the difference between the average projected degree days (and heat degree days) in 2031–2055 (or 2056–2080 for a measure of long-term impact) and the average degree days (and heat degree days) in 1981–2005.

---

[5] The Public Land Survey identifies land use in the following categories: county, municipality, township, range, and section. County is the largest location identifier in our data, while section is the smallest location identifier.
[6] There are 763 unique township ranges in our sample. Quantitatively, panel estimates remain the same as the main specification.
[7] We use a built-in package in Stata, *fmlogit*, to estimate the fractional multinomial logit model (Buis 2008).

Herfindahl-Hirschman Index as a measure of crop diversity

We created a simple yet widely used concentration-specific diversity indicator, the Hirfindahl-Hirschman Index (HHI), based on 22 crops obtained from the Land IQ dataset for the years 2014, 2016, and 2018 through 2022.[8] We define HHI as the sum of the squared crop shares grown within the PLS section level. Our HHI for PLS section i defined as follows:

$$HHI_i = \sum_{k=1}^{K} s_{ik}^2 \quad (4)$$

where $s_{ik} = \frac{c_{ik}}{\sum_{k=1}^{K} c_{ik}}$ is the share of total cropped areas for crops $k = 1, \dots, K$ grown within the PLS section i. K is the total number of crops, which is 22 in our data set (22 cultivated crops and idled/fallowed land). HHI values range between 0 and 1, where 1 indicates the concentration towards one crop. The mean HHI measurement is 0.60, and the standard deviation is 0.27. We observed a gradual increase in HHI, suggesting a decline in crop diversity and shift toward specialty crops in our study region. Figure A6 shows the HHI over Land IQ years across PLS section level.

To examine the relationship between crop diversity and pesticide use, we regressed the log transformed pesticide use on HHI, controlling for weather controls, including mean annual temperature, total precipitation, average solar radiation and wind speed, and their squared terms. We also include PLS section and year fixed effects to minimize omitted variable bias in our econometric specification.

4. Results and Discussion

[8] 22 crop categories are made up of perennial and annual crop types. Perennial crops are almonds, pistachios, walnuts, orchards, grapes, subtropical fruit trees, young perennials. Annual crops consist of field crops, rice, cotton, dry beans, safflower, sunflower, corn, alfalfa, tomatoes, cucurbits, berries, lettuce, onions, garlic, potatoes, and truck crops.

The results are divided into four sections. First, we present a simple correlation between standardized measures of pesticide use rate and mean temperature. Second, we present the panel estimates of nonlinear effects of temperature on pesticide use behavior. Third, we present temperature effects on agricultural land use share, as well as the effects of crop diversity on total pesticide use. Fourth, we quantify the effects of projected climate change on California's pesticide use.

4.1. Relationship between pesticide use rate and mean temperature

Figure A7 shows the correlation coefficient between standardized pesticide use rate and standardized temperature (mean annual temperature for perennial crops and the mean temperature during the growing season for annual crops) in our study region. The positive (or negative) correlation between standardized pesticide use rate and standardized mean temperature can be interpreted as the more sensitivity of pesticide use rate (or less sensitivity) with respect to changes in mean temperature. The pesticide usage rate of almonds, pistachios, and other nuts, citrus and subtropical fruit trees, and other fruit trees have a negative correlation with mean annual temperature. Among annual crops, the pesticide usage rate of root vegetables and other vegetables shows a positive correlation with the mean temperature during the growing season. While grain, grass, forage, and fodder crops, seeds, and oilseeds exhibit a negative relationship with mean temperature during the growing season. In the next section, we empirically estimate the nonlinear effects of temperature on pesticide use rate using fixed effects econometric methods.

4.2. Panel estimates of nonlinear effects of temperature on pesticide use

4.2.1 Impacts of temperature bins on pesticide use rate

Figure 1 shows the impact of temperature bins on overall pesticide use by crop types. Results suggest that days with higher temperatures (above 30° C) are negatively associated with perennial crops, although it is not statistically significant. While the pesticide use in annual crops is positively associated with extreme temperatures days above 30° C, relative to days in the 18° C to 21° C range. Figure A8 shows the effects of temperature bins with 4-degree intervals on pesticide use in perennial and annual crops.

In Figures 2a and 2b, we present the impacts of temperature bins on pesticide use of perennial and annual crops, disaggregated by types of pesticide. It appears that days with extreme temperatures above 30° C are associated with decreased usage of insecticides and herbicide, while increased usage of other chemicals. In contrast, extreme temperatures above 30° C are associated with an increase in usage of insecticides and decreased usage of other chemicals of annual crops.

Figures A9a, A9b, and A9c present crop-specific impacts of temperature bins on all pesticide use, and types of pesticides. It appears that insecticide and herbicide use in grapes is negatively associated with extreme temperatures days above 30° C, relative to days in the 18° C to 21° C range. While positively associated with cucurbits, leafy and root vegetables, legumes, and other vegetables, grain and grass and forage and fodder crops. Citrus and other subtropical fruit trees are negatively associated with extreme temperature days above 30° C. In addition, fungicide use in almonds, pistachios, other nuts, grapes, and cucurbits is positively associated with extreme temperature days above 30° C. While negatively associated with other vegetables, fiber crops, forage and fodder crops.

4.2.2 Panel estimates of nonlinear effects of temperature on pesticide use behavior

Table 2 presents the panel estimates of the impacts of temperature on pesticide use rate across perennial and annual crops. The dependent variable is log transformed pesticide use rates, and the main explanatory variables are degree days below and above threshold temperatures. The critical threshold temperature is set to 27° C. Degree days are accumulated in a year for perennial crops, while they are accumulated during the growing season for annual crops. We run separate regression for insecticides, fungicides, herbicides, other chemicals, and overall pesticide use rates.

Panel A of Table 2 reports the regression results for perennial crops. Results suggest that heat degree days are negatively associated with overall pesticide use in perennial crops, although it is statistically insignificant. However, the use of fungicides in perennial crops has negative and significant association with heat degree days, but positive association with herbicide use. Specifically, for a hundred-unit increase in heat degree days, we expect 10.5% reduction in fungicide use, but 5.1% increase in herbicide use rates. In addition, for a hundred-unit increase in heat degree days, we expect 8.4% reduction in overall pesticide use rate in annual crops, particularly 20.4%, 11.2%, and 3% reduction in insecticides, fungicides, and other chemicals use rates, respectively (Panel B of Table 2). This estimated reduction in overall pesticide use rates across crop types is consistent with decreasing trend of pesticide use in California to promote sustainable agriculture.

Next, we split the sample to present regression results for a selected 17 major crop groups in our study region. (Tables A2a and A2b). It appears that the use of pesticide in almonds, pistachios, and other nuts is negatively associated with degree days. This decline in overall pesticide use rate in almonds, pistachios, and other nuts is primarily driven by a decrease in insecticides, fungicides, and herbicides. Overall pesticide uses rate declines with respect to heat degree days for grapes, citrus, other subtropical fruit trees. In contrast, insecticide and herbicide usage increases for other fruit trees. Overall pesticide use rate in most of the annual crops, including cucurbits, leafy and root vegetables, fiber crops, forage, and fodder crops, is negatively associated with heat degree days, with the largest magnitude for leafy vegetables (a decline of 37.1%) and smallest magnitude for forage and fodder crops (a decline of 10.6%).

4.2.3 Impacts of temperature on intensity of control efforts

Table 3 presents the panel estimates of impacts of temperature on the mean number of pesticide applications. The dependent variable in equation (3) is the IHS-transformed mean of pesticide applications per hectare per year from 1993 to 2022. Results suggest a marginal increase in the mean number of pesticide applications per hectare per year, which captures the intensity of pest and disease control efforts for perennial crops, with heat degree days. The mean number of pesticide applications per hectare per year with respect to heat degree days is positively associated with the use of fungicides, herbicides, and other chemicals, but negatively associated with the use of insecticides.

Tables A3a and A3b present the crop-specific impacts of temperature on pesticide applications. Overall pesticide application marginally decreases with heat degree days for almonds, pistachios, and other nuts, particularly with a decrease in insecticide usage. In contrast, we expect an increase in mean number of pesticide applications with respect to heat degree days for other fruit trees. Overall pesticide applications with respect to heat degree days decrease for leafy vegetables, onions and garlic, but increases for other vegetables.

To sum, we expect marginal decrease in insecticides application but increase in herbicide application across crop types.

4.2.4 Robustness check

First, to show the sensitivity of our results to variations at different spatial level, we utilized various combinations of spatial fixed effects, including PLS range and township, as well as different clustering methods. Table A4 summarizes the regression results. It appears that the estimated coefficient of heat degree days in perennial and annual crops is somewhat sensitive to spatial variation fixed effects at the range and township level, as well as clustering at the township-range level.

Secondly, we repeated the regressions for degree days defined at upper threshold values of 26° C, 28° C, and 29° C. The sensitivity results are quantitatively comparable to the main results (Tables A5a and 5b). However, the statistical significance does not hold for fungicide usage in perennial crops with respect to degree days above the 28° C and 29° C threshold. Moreover, the magnitude of the estimated coefficient becomes larger with an increase in threshold temperature.

Thirdly, we obtained an estimated coefficient that exhibits an inverse U-shape response curve when continuous mean temperature values and their squared term are used in our main specification (Table A6). Specifically, the use of fungicides exhibits an inverse U-shaped relationship between pesticide use and mean temperature for both perennial and annual crops. Mean annual temperature for perennial crops and mean temperature during the growing season for annual crops. In addition, the use of herbicides in perennial crops has an inverse U-shaped relationship with mean annual temperature. The relationship between the use of other chemicals in perennial crops and the mean annual temperature is U-shaped. While in annual crops, the mean temperature during the growing season and the use of other chemicals exhibit an inverse U-shaped pattern.

4.3. Temperature effects on agricultural land-use pattern shifts, as well as the effects of crop diversity on pesticide use

Table 4 presents combined marginal effects obtained from the panel fixed effects model and fractional multinomial logit model to examine changes in agricultural land-use and the probability of switching between crop types (annual and perennial crops). Panel fixed effects model shows a negative association between perennial and heat degree days, but positive association between annual crops and heat degree days. In contrast, the fractional multinomial logit model suggests that perennial crops are more likely to increase in response to heat degree days. Specifically, a hundred-unit increase in heat degree days is associated with very small probability (0.09) to switch to perennial crops, relative to the annual crops in our study region. Figure 3 presents the estimated marginal effects calculated at various levels of the degree days distribution, including the 5th, 10th, 25th, 50th, 74th, 90th, and 95th percentiles.

Next, we disaggregate perennial and annual crops into 22 major crop categories to examine the impact of temperature on crop-specific land-use shares. Table A7 summarizes the regression results. The land-use shares of almonds, pistachios, other nuts, and tomatoes is negatively associated with heat degree days, but positive for land-use shares of grapes and orchards.

Lastly, Table 5 reports the impact of crop diversity on pesticide use rates. The dependent variable is the log transformed pesticide use rate, and the main explanatory variable is HHI. In the specification, we account for mean annual temperature, and other weather controls, as well as PLS section and year fixed effects. Results suggest a negative and significant association between crop diversity and overall pesticide use rate. Specifically, a unit increase in HHI (i.e., toward more specialized agricultural land use) is associated with a 10% decline in overall pesticide use. In particular, the use of insecticides and fungicides decreases by 13%, while the use of other chemicals decreases by nearly 16%. In summary, extreme temperatures lead to a shift towards specialty crops that potentially reduce overall pesticide use rate.

In the next section, using the marginal effects from Table 2, we will quantify the potential impacts of climate change on pesticide use rates and then utilize the pesticides costs to translate these impacts into dollar terms.

4.4. Projections of impacts under future climate change

Table A8 presents the estimates of predicted heat degree days for the entire year and for the growing season at the PLS section level compared to averages from 1981 to 2005. The mean annual temperature is expected to rise by 1.75° C in the near-medium term, and by 2.01° C over the long term for the SSP245 scenario, compared to the average mean temperature from 1981 to 2005. The predicted increase in the mean annual temperature will result in an increase of nearly 19% of degree days in the near-medium term and 22% in the long-term future compared to the historical mean between 1981 and 2005. Also, the heat degree days over the near-medium term will dramatically increase by 163% (or 66 additional heat degree days) and 187% (or 76 additional heat degree days) in the long term compared to the historical mean heat degree days.

Figure 4 shows the predicted changes in pesticide use rate with respect to degree days and heat degree days under the SSP245 climate scenario. Results suggest that a unit increase in predicted degree days in the near-medium term is expected to increase the pesticide use of grapes, other fruit trees, leafy and root vegetables, and grain and grass crops by approximately 13%, 16%, 46%,19%, and 14%, respectively (Panel A of Table A9). While the pesticide use of almonds, pistachios, and other nuts, seeds and oilseeds are expected to decline by 6% and 24%. In addition, a unit increase in predicted heat degree days in near-medium term is expected to decrease the pesticide use of grapes, citrus, other subtropical fruit trees, cucurbits, leafy and root vegetables, fiber crops, and forage and fodder crops by 3%, 6%, 14%, 24%, 14%, 7%, and 7%, respectively. While the overall pesticide use of seeds and oilseeds and herbs and spices is expected to increase with respect to heat degree days by 9% and 66%, respectively. The net effects of changes in pesticide use rates for some selected crops, such as grapes, leafy and root vegetables, and seeds and oilseeds, appear to be positive with respect to degree days. The long-term potential impacts of climate change have similar projected pesticide use results, but with a greater magnitude (Panel B of Table A9).

Finally, Table 6 presents estimated costs for pesticide use for selected crops potentially affected by degree days in the context of climate change. It appears that the estimated costs for pesticide use in almonds, pistachios, and other nuts and seeds and oilseeds are expected to decrease by $50 per ha and $88 per ha, respectively with respect to degree days in the near-medium term. While it is expected to increase for grapes ($88 per ha), other fruit trees ($210 per ha), leafy vegetables ($840 per ha), root vegetables ($177 per ha), and grain and grass ($46 per ha). The predicted heat degree days are expected to decrease the estimated costs for leafy vegetables ($446 per ha), root vegetables ($130 per ha), cucurbits ($82 per ha), and citrus, other subtropical fruit trees ($67 per ha). In addition, the estimated costs of pesticide for crops such as grapes, fiber crops, forage, and fodder crops also decrease each to less than $50 per ha.

In summary, we could expect a higher cost of pesticide applications for fruit and vegetable crops and a lower cost of pesticide for field and grain crops in response to the expected extreme temperatures in our study region. Our results on estimated pesticide costs must be interpreted considering the cost share of crops. Some crops might see large cost increases, but maybe these are a small share of the total cost of growing that crop.

5. Concluding Remarks

Pest dynamics and agricultural pesticide use are expected to change in areas that have previously not been subject to high levels of pest pressure due to the warming temperatures in California, one of the most productive regions in the world (Luedeling et al. 2011). This paper investigates how extreme temperature affects growers' pesticide use behavior in California. We find marginal decrease in overall pesticide use rates with extreme temperatures, which is consistent with decreasing trends of pesticide applications in California. However, some of the higher-value crops in California, concentrated in the eastern and southern parts of the Central Valley, are expected to increase pesticide applications and therefore growers' dependency on pesticides in the near-medium future. These findings provide useful information for targeted pesticide regulation policy decisions to promote sustainable agriculture. Given that pest pressures for some of the higher value crops are expected to increase and therefore amplify the potential for crop damage alongside regulated pesticide use with fewer licensed products, restricted use rates, and number of applications, and costly pesticide rates. Our study provides useful insights on how growers may potentially adapt their pesticide use to changing climate in water-limited regions.

Figures and Tables

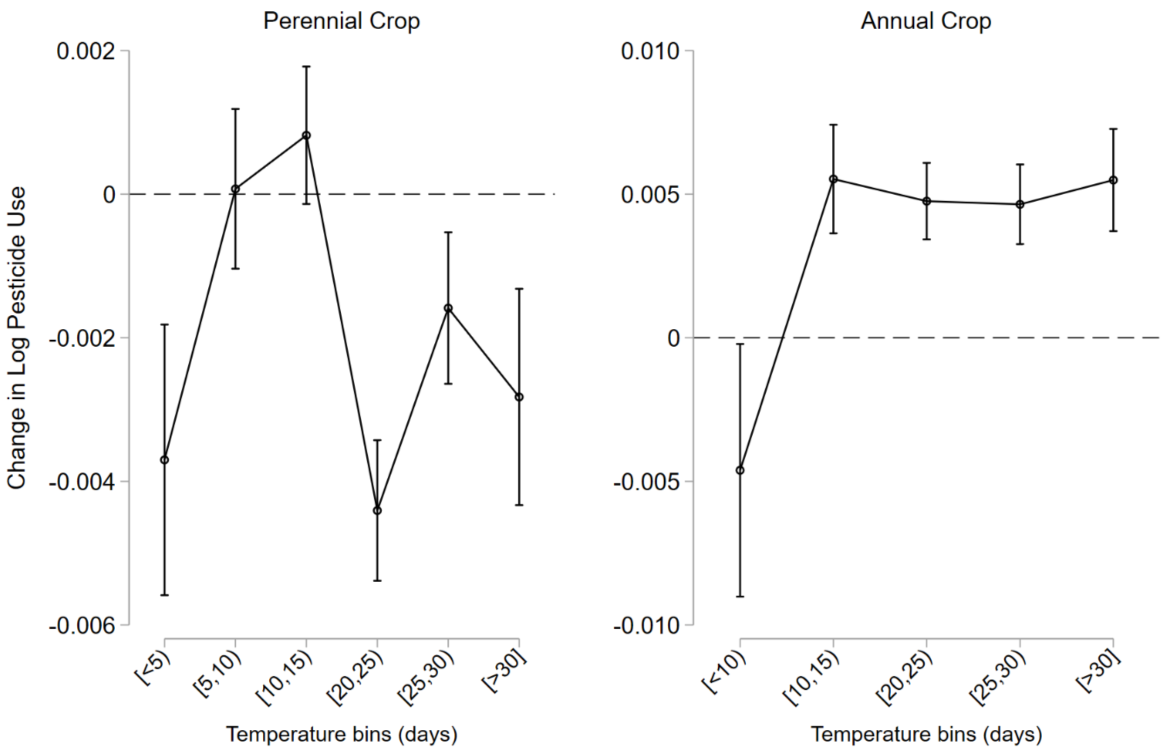

Figure 1. Relationship between temperature and pesticide usage rate in California

Notes: The dependent variable is the log transformed pesticide usage rate from 1993 to 2022. The specification includes second order polynomials for other weather variables, including total precipitation, total solar radiation, and average wind speed, as well as PLS section and year fixed effects. The temperature bin [15 C, 20 C) is the reference category. The figure plots the point estimate and 95% confidence intervals for each crop. The crop pesticide use data is obtained from the California Pesticide Usage Reporting, and temperature bins are derived from gridMET daily data.

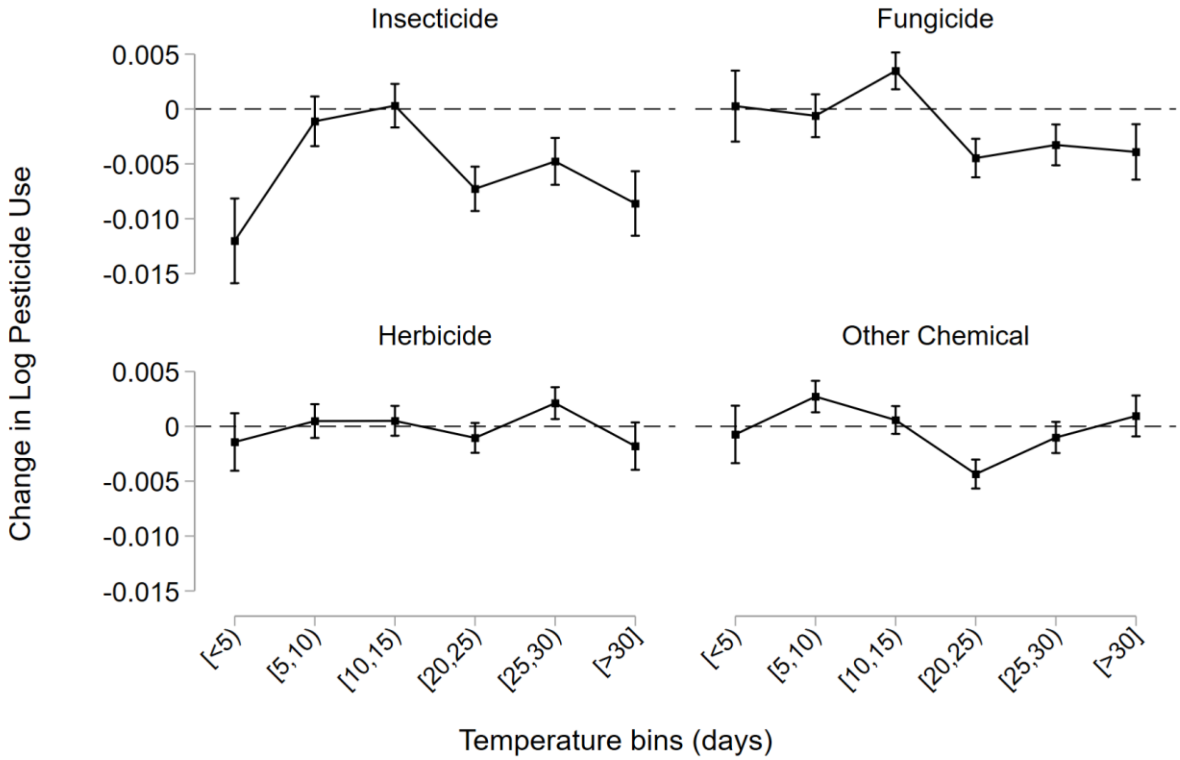

Figure 2a. Impacts of temperature bins on pesticide usage rates of perennial crops

Notes: Temperature bins were created for a whole year.

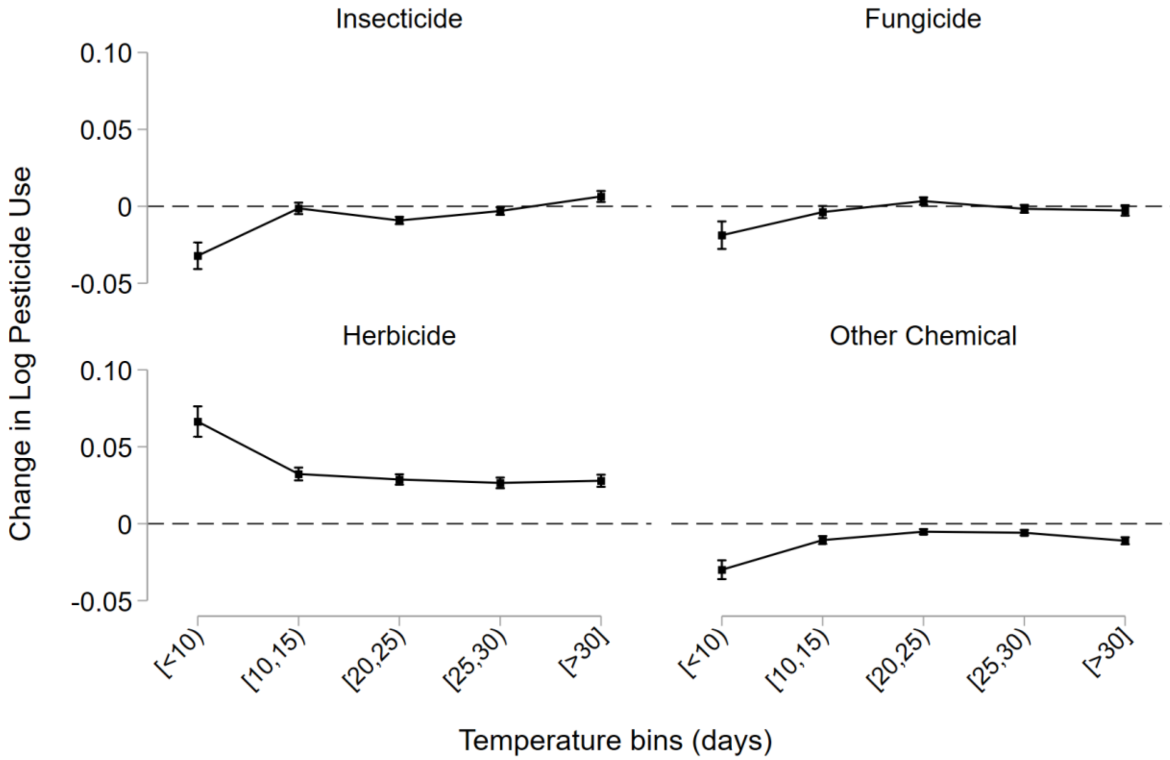

Figure 2b. Impacts of temperature bins on pesticide usage rates of annual crops

Notes: Temperature bins were created during the growing season (April through September).

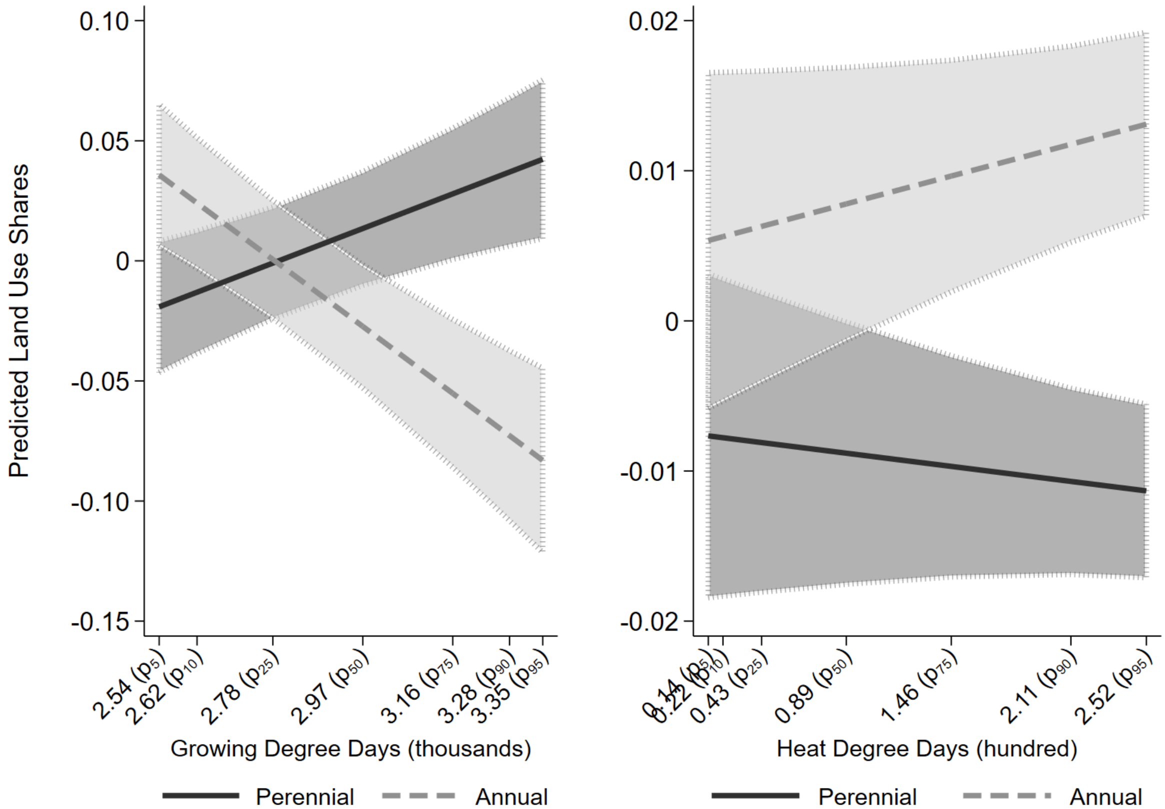

Figure 3. Relationship between predicted agricultural land use shares and degree days

Notes: The graphs are obtained by calculating the average marginal effects from the panel fixed effects model at different intervals of degree days. The gray area represents the 95% confidence intervals. The x-axis has brackets representing the 5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, and 95^{th} percentiles.

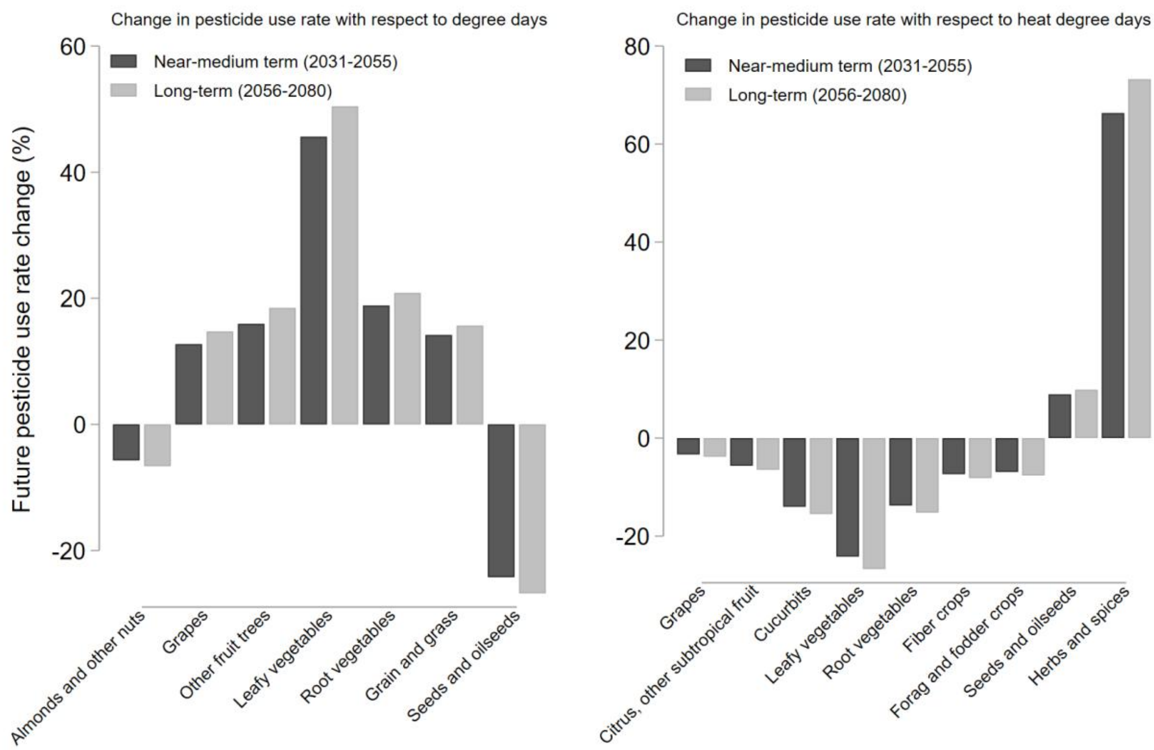

Figure 4. Percentage change in pesticide use rate across Central Valley regions over two periods (2031–2055 and 2056–2080) under SSP245

Notes: The percentage change of projected impacts of climate change on pesticide use rate are reported. These are calculated by multiplying the statistically significant coefficients of average marginal effects (Tables A3a and A3b) and the difference between the average projected climate in 2031–2055 and the average climate in 1981–2005. Similarly, long-term predicted climate impacts are calculated by multiplying the coefficients of average marginal effects and the difference between the average projected climate in 2056–2080 and the average climate in 1981–2005. Table A8 reports full results.

Table 1. Crop-specific and Pesticide Type

	All Pesticide					
	Pesticide Application Intensity (kg/ha)	Mean Number of Pesticide Applications per Year	Insecticide (kg/ha)	Fungicide (kg/ha)	Herbicide (kg/ha)	Other Chemicals (kg/ha)
A. Perennial crops						
Almonds, pistachios, and nuts	17.5	3	12.0	12.7	24.5	18.4
Grapes	10.7	5	9.3	5.3	17.9	10.4
Citrus, other subtropical fruit trees	21.5	5	16.9	9.0	20.0	25.3
Other fruit trees	23.4	5	14.4	12.3	19.0	27.5
Other tree crops	13.3	3	11.8	34.9	15.0	11.8
Total perennial crops	**17.3**	**4**	**12.9**	**14.9**	**19.3**	**18.6**
B. Annual crops						
Cucurbits	10.5	2	10.7	9.1	25.2	9.8
Berries	45.6	2	117.8	5.1	21.6	26.9
Leafy vegetables	8.8	14	7.8	7.4	19.5	8.5
Root vegetables	30.8	3	79.2	7.4	12.3	22.2
Onions and garlic	11.6	2	17.2	10.8	26.0	9.2
Legumes	9.4	2	6.0	16.6	20.7	9.2
Other vegetables	15.2	2	15.6	12.1	14.9	15.7
Fiber crops	14.8	3	7.2	4.1	17.9	16.7
Grain and grasses	12.8	3	6.0	11.1	31.1	9.7
Forage and fodder crops	9.5	2	9.4	16.1	20.8	6.1
Seeds and oilseeds	13.6	3	9.1	4.5	20.5	13.4
Herbs and spices	22.7	10	53.0	2.5	20.3	15.8
Total annual crops	**17.1**	**4**	**28.3**	**8.9**	**20.9**	**13.6**

Notes: Mean values of pesticide types are reported across PLS sections in the Central Valley from 1993 to 2022. Insecticide includes nematicide and miticide. Fungicide includes slimicide, algaecide, bactericide, and molluscicide. Other chemicals include rodenticides and other chemicals not directly identified as insecticides, fungicides, or herbicides from their product names and codes, and they are applied as a mixture in our study region. The mean number of pesticide applications per year is rounded to the next integer.

Table 2. Panel estimates of impacts of temperature on pesticide use

Dependent variable: Log (Pesticide usage rate)	All Pesticide Use	Insecticide Use	Fungicide Use	Herbicide Use	Other Chemical Use
Panel A: Perennial crops					
GDD (8C – 27C; thousands)	-0.014	0.027	0.129^{***}	-0.108^{***}	-0.074^{**}
	(0.029)	(0.056)	(0.048)	(0.041)	(0.035)
HDD (above 27C; hundred)	-0.015	-0.008	-0.105^{***}	0.051^{***}	-0.017
	(0.012)	(0.021)	(0.021)	(0.015)	(0.013)
Mean dependent var.	1.981	1.343	1.530	2.469	2.402
Observations	1,213,775	302,817	239,568	311,096	358,483
Adj. R-squared	0.086	0.164	0.202	0.284	0.137
Panel B: Annual crops					
GDD (8C – 27C; thousands)	-0.062	-0.020	-0.388^{***}	-0.276^{***}	0.259^{***}
	(0.042)	(0.074)	(0.093)	(0.082)	(0.055)
HDD (above 27C; hundred)	-0.084^{***}	-0.204^{***}	-0.112^{***}	-0.003	-0.029^{*}
	(0.012)	(0.023)	(0.027)	(0.025)	(0.016)
Mean dependent var.	1.729	1.321	1.563	2.234	1.759
Observations	1,208,932	309,207	156,538	277,034	462,684
Adj. R-squared	0.071	0.171	0.208	0.157	0.142

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Degree days are accumulated in a year for perennial crops, while they are accumulated during the growing season (April through September) for annual crops. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Panel estimates of impacts of temperature on mean number of pesticide applications

Dependent variable: IHS (mean number of pesticide applications per hectare per year)	All Pesticide Use	Insecticide Use	Fungicide Use	Herbicide Use	Other Chemical Use
Panel A: Perennial crops					
GDD (8C – 27C; thousands)	0.006	0.021^{***}	0.009	-0.008	0.001
	(0.005)	(0.007)	(0.006)	(0.007)	(0.006)
HDD (above 27C; hundred)	0.004^{**}	-0.006^{**}	0.008^{***}	0.009^{***}	0.006^{***}
	(0.002)	(0.003)	(0.02)	(0.03)	(0.002)
Mean dependent var.	0.155	0.139	0.141	0.174	0.162
Observations	1,213,775	302,817	239,568	311,096	358,483
Adj. R-squared	0.321	0.269	0.376	0.355	0.371
Panel B: Annual crops					
GDD (8C – 27C; thousands)	-0.007	-0.009	-0.007	0.005	-0.012
	(0.007)	(0.011)	(0.010)	(0.009)	(0.009)
HDD (above 27C; hundred)	0.001	-0.002	-0.002	0.003	0.001
	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)
Mean dependent var.	0.095	0.106	0.077	0.089	0.098
Observations	1,208,932	309,207	156,538	277,034	462,684
Adj. R-squared	0.457	0.472	0.538	0.530	0.454

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the IHS-transformed mean pesticide applications per hectare per year from 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Degree days are accumulated in a year for perennial crops, while they are accumulated during the growing season (April through September) for annual crops. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Marginal effects evaluated at the mean value of the degree days

	Panel Fixed Effects Model		Fractional Multinomial Logit Model
	Perennial crop [1]	Annual crop [2]	Perennial crop [3]
GDD (8C – 27C; thousands)	0.013	-0.026**	-0.378***
	(0.012)	(0.013)	(0.040)
HDD (above 27C; hundred)	-0.009**	0.008*	0.093***
	(0.04)	(0.004)	(0.015)
Mean dependent var.	0.570	0.413	0.583
Log Likelihood	n.a.	n.a.	-59,143.92
Observations	96,476	96,476	89,141
Clusters	14,882	14,882	14,814

Notes: Standard errors presented in parentheses are derived from the delta method and are clustered at the PLS section level. The dependent variable is the share of perennial and annual crops for the years 2014, 2016, and 2018 through 2022. All regressions include weather controls and dummies for each year. Degree days are accumulated in a year for perennial crops, while they are accumulated during the growing season (April through September) for annual crops. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Crop diversity and pesticide use

Dependent variable: Log (Pesticide usage rate)	All Pesticide Use	Insecticide Use	Fungicide Use	Herbicide Use	Other Chemical Use
	[1]	[2]	[3]	[4]	[5]
HHI	-0.100***	-0.134***	-0.131***	-0.046	-0.157***
	(0.020)	(0.041)	(0.042)	(0.029)	(0.029)
Observations	337,762	85,747	67,087	87,582	95,444
Adj. R-squared	0.138	0.392	0.408	0.356	0.397

Notes: Standard errors presented in parentheses are clustered at the PLS section level. HHI = Herfindahl-Hirschman Index (calculated on cultivated area 22 crops and idled/fallowed land). All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include annual mean temperature, total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: *** $p < 0.01$.

Table 6. Estimated costs for pesticide use

Crop	Projected Impact (1)	Mean Pesticide Use Rate (kg/ha) (2)	Marginal Effect (kg/ha) (3) = (2)*(1)/100	Total Pesticide Costs ($/ha) (4)	Estimated costs for pesticide use ($/ha) (5) = (4)*(1)/100
Panel A: Projected impact of temperature on pesticide use rate with respect to degree days					
Almonds, pistachios, and other nuts	-5.7	17.5	-1.0	879	-50
Grapes	12.7	10.7	1.4	692	88
Other fruit trees	15.9	23.4	3.7	1,319	210
Leafy vegetables	45.6	8.8	4.0	1,843	840
Root vegetables	18.9	30.8	5.8	939	177
Grain and grass	14.2	12.8	1.8	321.1	46
Seeds and oilseeds	-24.2	13.6	-3.3	366	-88
Panel B: Projected impact of temperature on pesticide use rate with respect to heat degree days					
Grapes	-3.3	10.5	-0.3	692	-23
Citrus, other subtropical fruit trees	-5.6	21.5	-1.2	1,203	-67
Cucurbits	-14.0	10.5	-1.5	583	-82
Leafy vegetables	-24.2	8.8	-2.1	1,843	-446
Root vegetables	-13.8	30.8	-4.3	939	-130
Fiber crops	-7.4	14.8	-1.1	338	-25
Forage and fodder crops	-6.9	9.5	-0.7	235	-16
Seeds and oilseeds	8.9	13.6	1.2	321	29
Herbs and spice	66.3	22.7	15.1	338	224

Notes: The projected impact was obtained from Table A8. The mean pesticide use rate was obtained from Table 1. Total pesticide costs in column 4 were obtained from the cost and returns studies, University of California Cooperative Extension and agricultural issues center. All dollar values are inflation-adjusted in 2017.

References

Abatzoglou, John T. 2013. "Development of Gridded Surface Meteorological Data for Ecological Applications and Modelling." *International Journal of Climatology* 33 (1): 121–31. https://doi.org/10.1002/joc.3413.

Bareille, François, Raja Chakir, and Derya Keles. 2024. "Weather Shocks and Pesticide Purchases." *European Review of Agricultural Economics* 51 (2): 309–53. https://doi.org/10.1093/erae/jbae008.

Buis, Maarten L. 2008. "FMLOGIT: Stata Module Fitting a Fractional Multinomial Logit Model by Quasi Maximum Likelihood." June. https://ideas.repec.org/c/boc/bocode/s456976.html.

Chen, Shuai, and Binlei Gong. 2021. "Response and Adaptation of Agriculture to Climate Change: Evidence from China." *Journal of Development Economics* 148 (January): 102557. https://doi.org/10.1016/j.jdeveco.2020.102557.

Cho, Sung Ju, and Bruce A. McCarl. 2017. "Climate Change Influences on Crop Mix Shifts in the United States." *Scientific Reports* 7 (1): 40845. https://doi.org/10.1038/srep40845.

Deutsch, Curtis A., Joshua J. Tewksbury, Michelle Tigchelaar, et al. 2018. "Increase in Crop Losses to Insect Pests in a Warming Climate." *Science* 361 (6405): 916–19. https://doi.org/10.1126/science.aat3466.

Elad, Yigal, and Ilaria Pertot. 2014. "Climate Change Impacts on Plant Pathogens and Plant Diseases." *Journal of Crop Improvement* 28 (1): 99–139. https://doi.org/10.1080/15427528.2014.865412.

Epstein, Lynn, and Susan Bassein. 2003. "Patterns of Pesticide Use in California and the Implications for Strategies for Reduction of Pesticides." *Annual Review of Phytopathology* 41 (1): 351–75. https://doi.org/10.1146/annurev.phyto.41.052002.095612.

Epstein, Lynn, Susan Bassein, and Frank G. Zalom. 2000. "Almond and Stone Fruit Growers Reduce OP, Increase Pyrethroid Use in Dormant Sprays." *California Agriculture* 54 (6): 14–19. https://doi.org/10.3733/ca.v054n06p14.

Hogan, Dylan, and Wolfram Schlenker. 2024. "Non-Linear Relationships between Daily Temperature Extremes and US Agricultural Yields Uncovered by Global Gridded Meteorological Datasets." *Nature Communications* 15 (1): 4638. https://doi.org/10.1038/s41467-024-48388-w.

Kawasaki, Kentaro. 2023. "Impact of Climate Change on Crop Pests and Diseases: Ensemble Modeling of Time-Varying Weather Effects." *Journal of the Association of Environmental and Resource Economists* 10 (6): 1515–43. https://doi.org/10.1086/725323.

Larsen, Ashley E., Steven D. Gaines, and Olivier Deschênes. 2017. “Agricultural Pesticide Use and Adverse Birth Outcomes in the San Joaquin Valley of California.” *Nature Communications* 8 (1): 302. https://doi.org/10.1038/s41467-017-00349-2.

Larsen, Ashley E., Michael Patton, and Emily A. Martin. 2019. “High Highs and Low Lows: Elucidating Striking Seasonal Variability in Pesticide Use and Its Environmental Implications.” *Science of The Total Environment* 651 (February): 828–37. https://doi.org/10.1016/j.scitotenv.2018.09.206.

Larsen, Ashley E., Amy Quandt, Iris Foxfoot, Nicol Parker, and Daniel Sousa. 2023a. “The Effect of Agricultural Land Retirement on Pesticide Use.” *Science of The Total Environment* 896 (October): 165224. https://doi.org/10.1016/j.scitotenv.2023.165224.

Larsen, Ashley E., Amy Quandt, Iris Foxfoot, Nicol Parker, and Daniel Sousa. 2023b. “The Effect of Agricultural Land Retirement on Pesticide Use.” *Science of The Total Environment* 896 (October): 165224. https://doi.org/10.1016/j.scitotenv.2023.165224.

Luedeling, Eike, Kimberly P. Steinmann, Minghua Zhang, Patrick H. Brown, Joseph Grant, and Evan H. Girvetz. 2011. “Climate Change Effects on Walnut Pests in California: CLIMATE CHANGE EFFECTS ON WALNUT PESTS.” *Global Change Biology* 17 (1): 228–38. https://doi.org/10.1111/j.1365-2486.2010.02227.x.

Mu, Jianhong E., Bruce A. McCarl, Benjamin Sleeter, John T. Abatzoglou, and Hongliang Zhang. 2018. “Adaptation with Climate Uncertainty: An Examination of Agricultural Land Use in the United States.” *Land Use Policy* 77 (September): 392–401. https://doi.org/10.1016/j.landusepol.2018.05.057.

Pesticides Use and Trade. 2025. FAO. https://doi.org/10.4060/cd5968en.

Rosenheim, Jay A., Bodil N. Cass, Hanna Kahl, and Kimberly P. Steinmann. 2020. “Variation in Pesticide Use across Crops in California Agriculture: Economic and Ecological Drivers.” *Science of The Total Environment* 733 (September): 138683. https://doi.org/10.1016/j.scitotenv.2020.138683.

Troy, T J, C Kipgen, and I Pal. 2015. “The Impact of Climate Extremes and Irrigation on US Crop Yields.” *Environmental Research Letters* 10 (5): 054013. https://doi.org/10.1088/1748-9326/10/5/054013.

Urruty, Nicolas, Tanguy Deveaud, Hervé Guyomard, and Jean Boiffin. 2016. “Impacts of Agricultural Land Use Changes on Pesticide Use in French Agriculture.” *European Journal of Agronomy* 80 (October): 113–23. https://doi.org/10.1016/j.eja.2016.07.004.

Wei, Hanlin, Rachael Goodhue, and Minghua Zhang. 2024. “Pesticide Use and Cropland Consolidation in California Organic Agriculture.” *Ecological Economics* 218 (April): 108121. https://doi.org/10.1016/j.ecolecon.2024.108121.

Yi, Fujin, Huilin Liu, and Quan Quan. 2025. “Impacts of Climate Change on Agricultural Chemical Inputs: Evidence from Pesticide Usage in China.” *Agricultural Economics*, August 3, agec.70057. https://doi.org/10.1111/agec.70057.

Zhang, Chao, Ruifa Hu, Guanming Shi, Yanhong Jin, Mark G. Robson, and Xusheng Huang. 2015. “Overuse or Underuse? An Observation of Pesticide Use in China.” *Science of The Total Environment* 538 (December): 1–6. https://doi.org/10.1016/j.scitotenv.2015.08.031.

Zilberman, David, Andrew Schmitz, Gary Casterline, Erik Lichtenberg, and Jerome B. Siebert. 1991. “The Economics of Pesticide Use and Regulation.” *Science* 253 (5019): 518–22. https://doi.org/10.1126/science.253.5019.518.

Appendix Figures and Tables

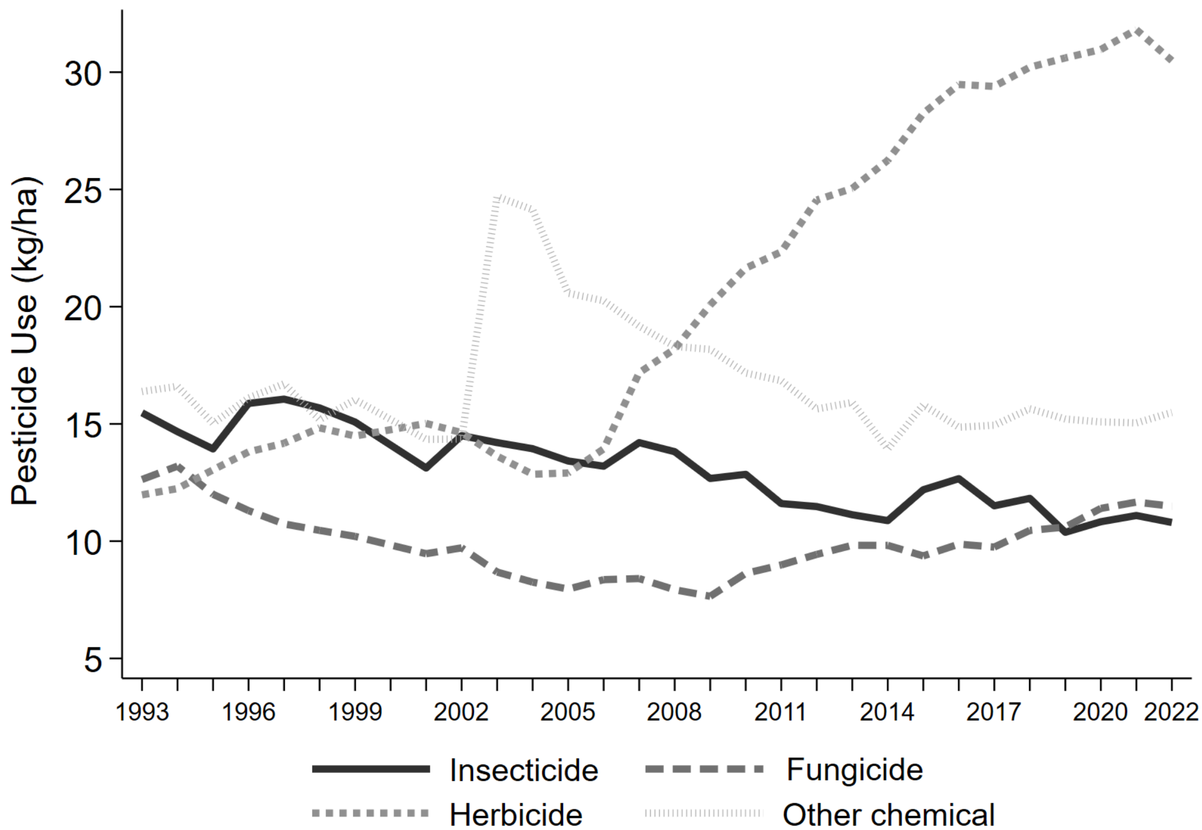

Figure A1. Pesticide use trends across Public Land Survey Sections in the Central Valley

Notes: The mean pesticide use time series data for various types of pesticides is derived from the California Pesticide Usage Reporting Program.

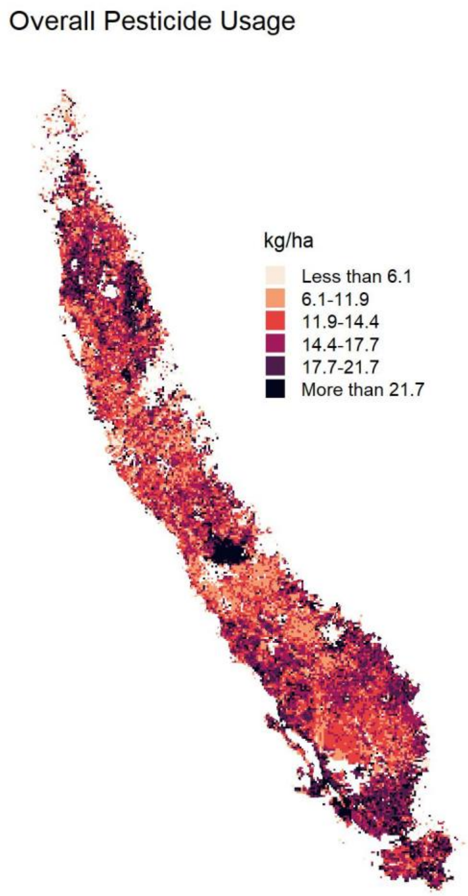

Figure A2a. Spatial variation in overall pesticide use at the PLS section level in Central Valley from 1993 to 2022

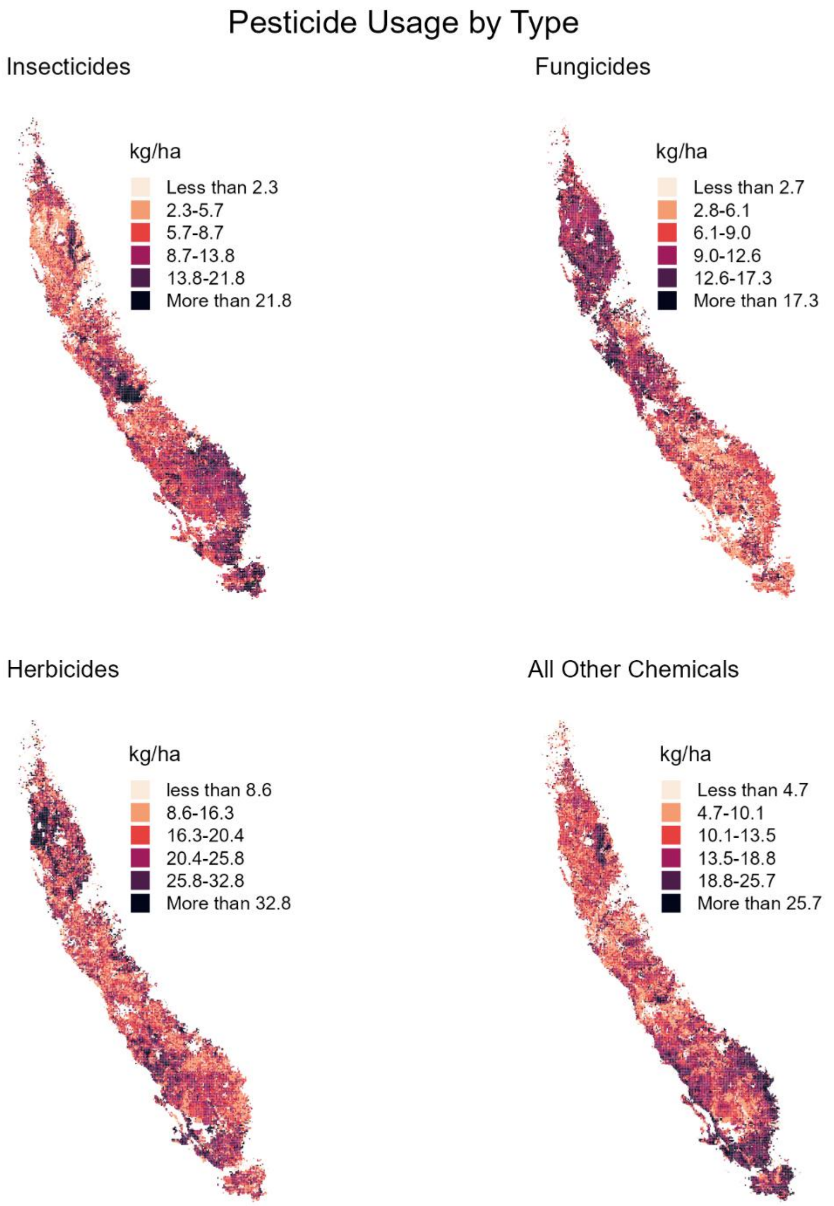

Figure 2b. Spatial variation in type of pesticide use at the PLS section level in Central Valley from 1993 to 2022

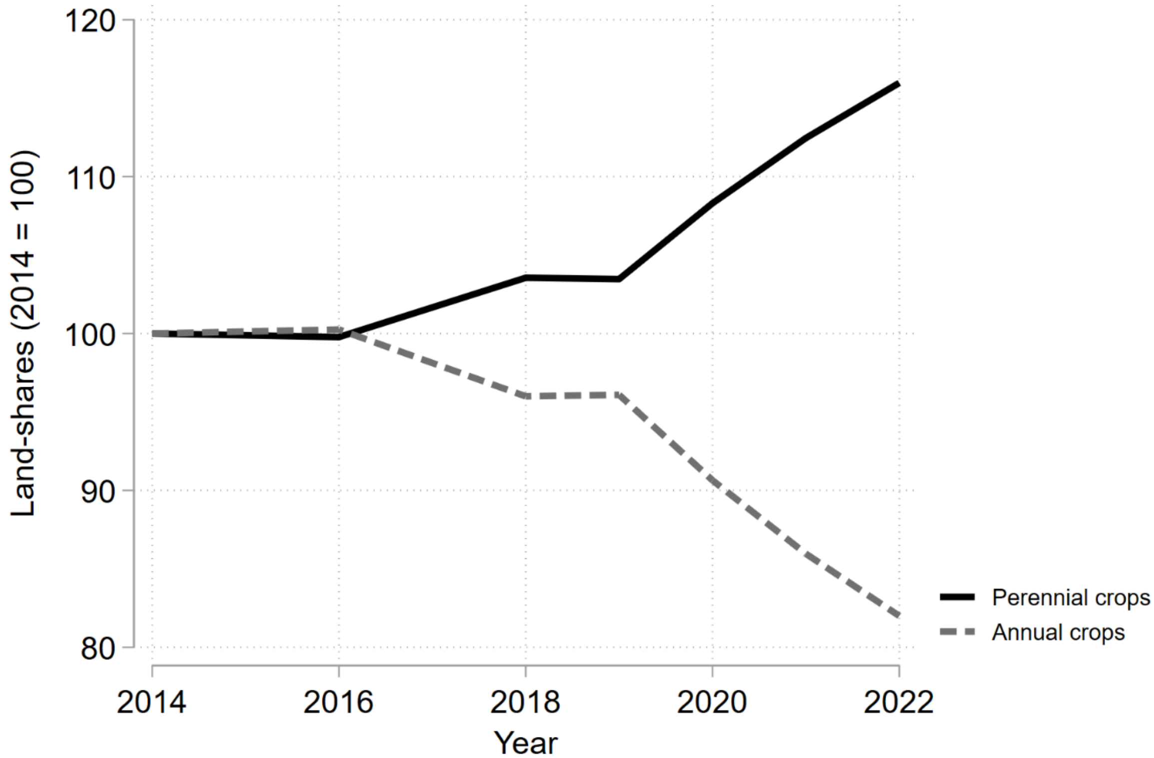

Figure A3. Trends in the land-use shares of perennial and annual crops in California's Central Valley between 2014 and 2022.

Source: Authors' calculations are based on data from Land IQ, which was contracted by the California Department of Water Resources.

Note: The upward and downward trends can be interpreted as an increase in perennial acreage and a decrease in annual crop acreage.

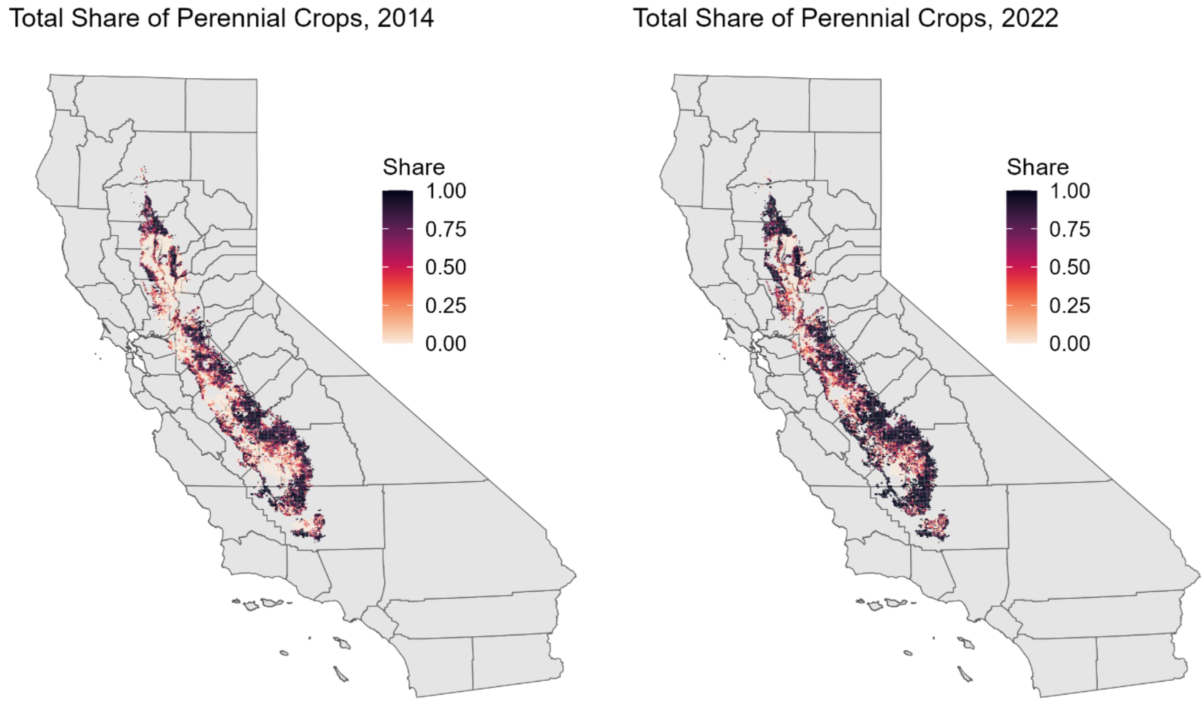

Figure A4. Perennial crops share at the PLS section level in 2014 (left panel) and 2022 (right panel)

Notes: The share of perennial crops is calculated by taking the ratio of perennial crops to total cultivated crops, including both perennial and annual crops. The perennial crops include almonds, pistachios, walnuts, grapes, orchards, subtropical fruit trees, and young perennial trees. The cropland data is obtained from the Land IQ for the years 2014 and 2022.

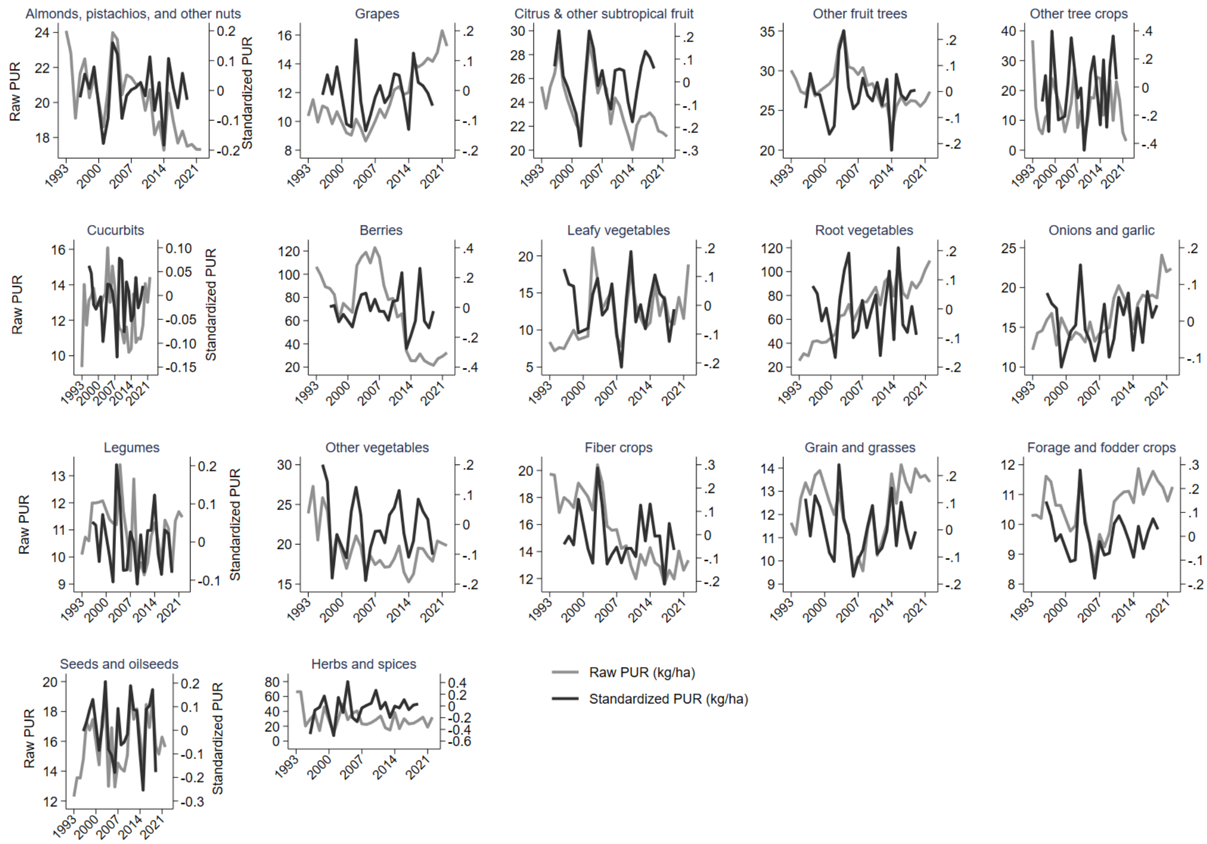

Figure A5. Crop-group trends in reported and standardized moving average pesticide use rates.

Notes: The gray line represents the pesticide use rates reported in kg/ha, while the dark line represents the standardized pesticide use rates based on a seven-year moving average window. The pesticide use rates time series data is obtained from the California Department of Pesticide Regulation (CDPR) Program.

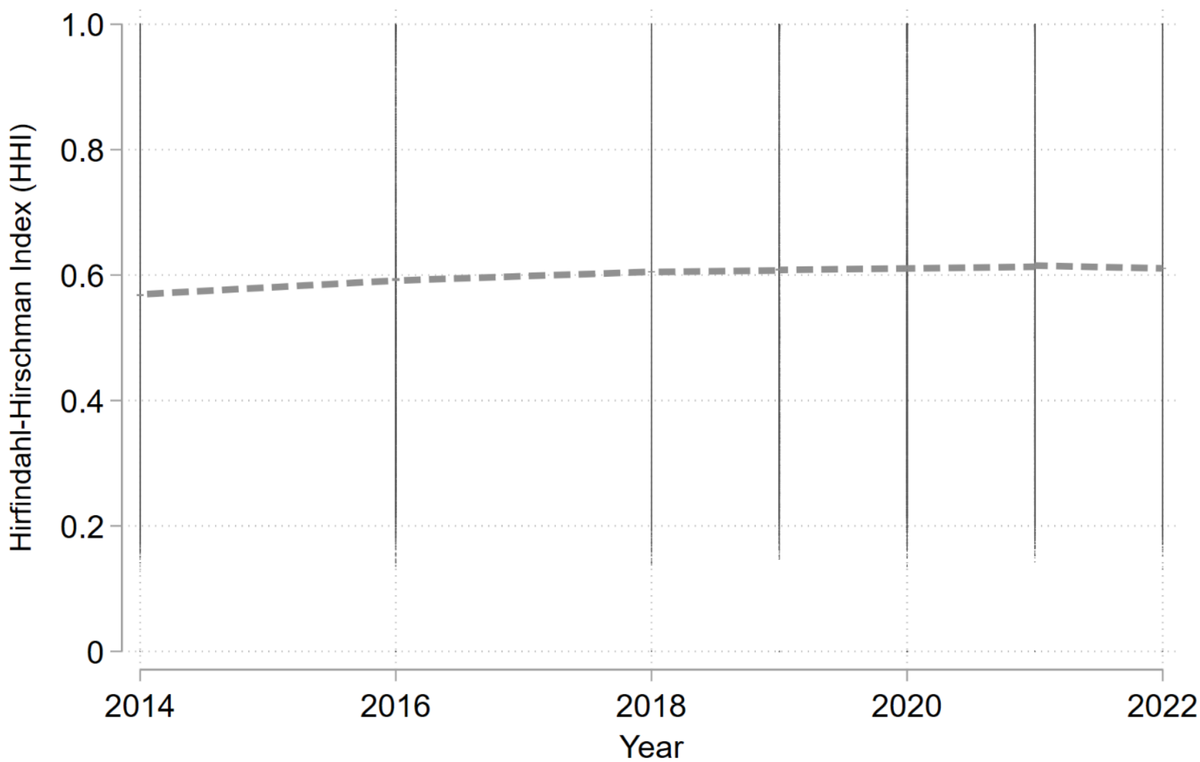

Figure A6. Crop diversity index across all PLS sections. HHI = Herfindahl-Hirschman Index (calculated on cultivated area of 22 crops and idled/fallowed land obtained from the Land IQ for the years 2014 to 2022).

Notes: HHI values range between 0 and 1, where 1 indicates the concentration towards one crop.

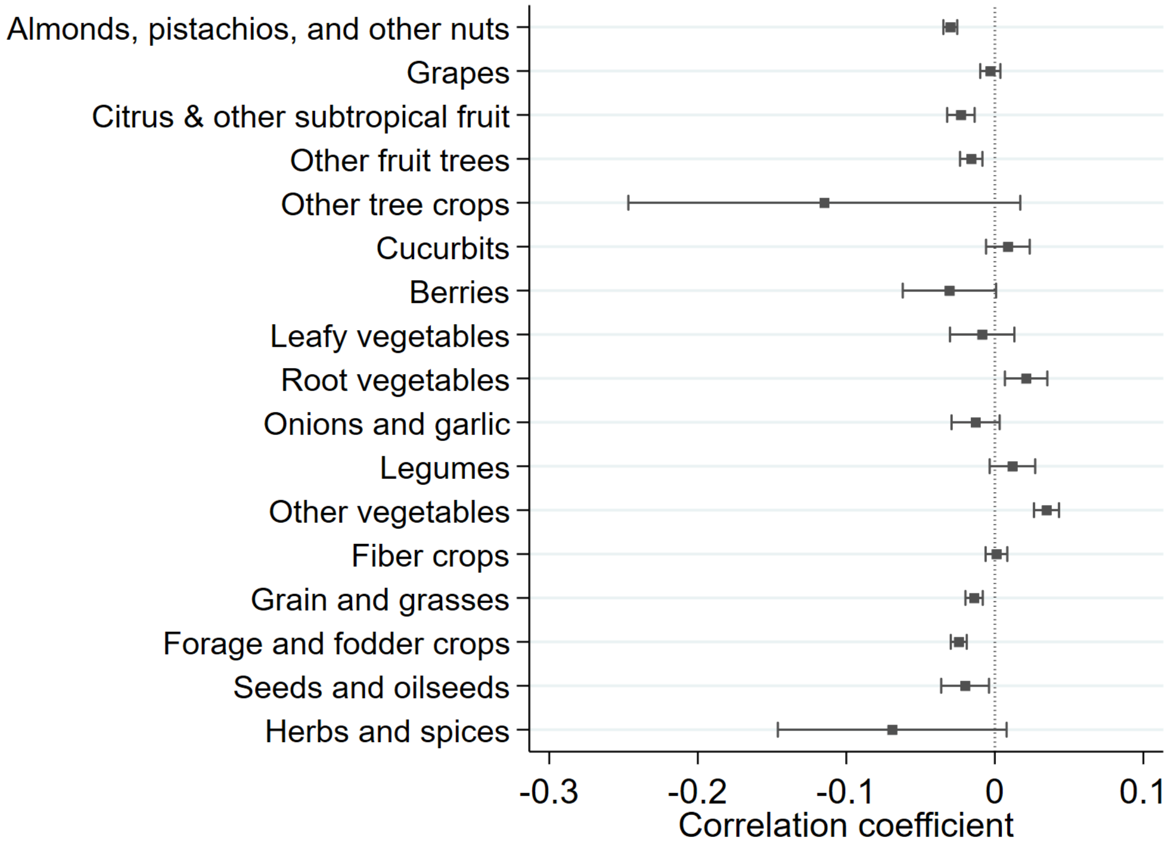

Figure A7. Relationship between pesticide use rate and mean temperature

Notes: The x-axis represents the estimated correlation coefficient. The Pearson correlation is estimated between the standardized pesticide use rate and the standardized mean temperature (mean annual temperature for perennial crops and the mean temperature during the growing season for annual crops). The 95% confidence interval is obtained from 1,000 bootstraps.

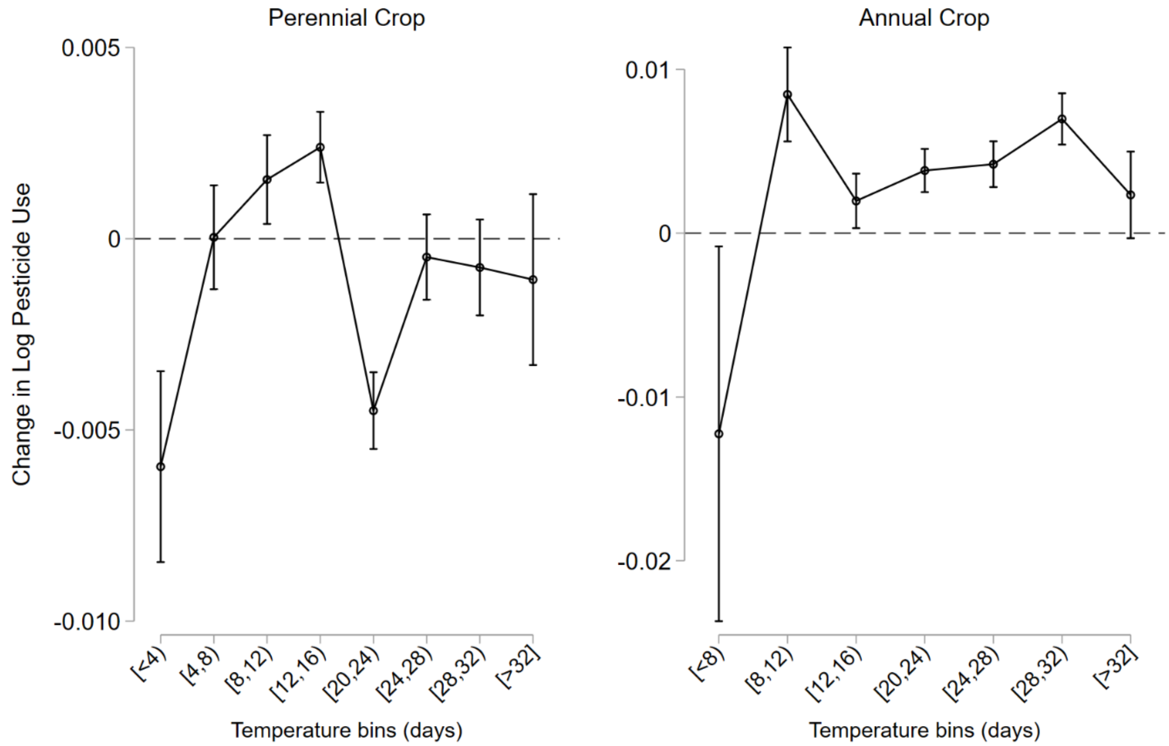

Figure A8. Impacts of temperature bins with 4-degree interval on pesticide use

Notes: The temperature bin [16,20) is the omitted category.

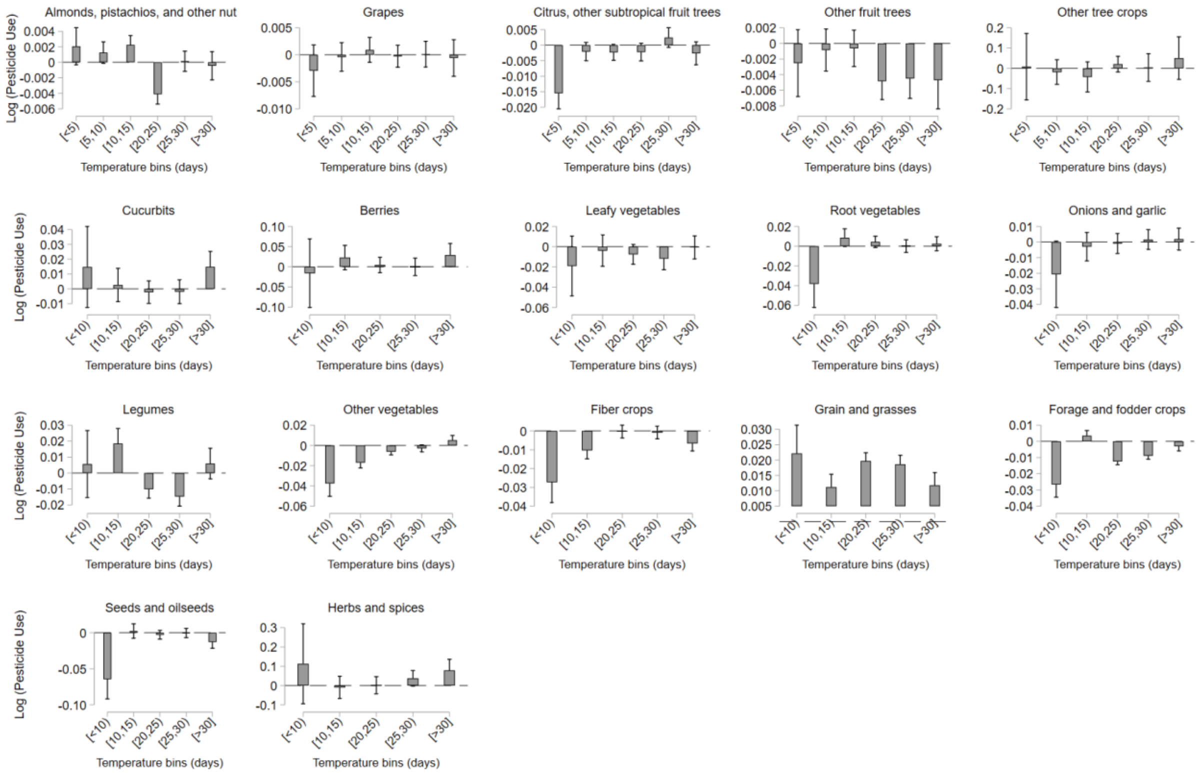

Figure A9a. Crop group-wise impacts of temperature bins on overall pesticide use

Notes: The dependent variable is the log transformed pesticide usage rate from 1993 to 2022. The specification includes second order polynomials for other weather variables, including total precipitation, total solar radiation, and average wind speed, as well as PLS section and year fixed effects. The temperature bin [15 C, 20 C) is the reference category. The figure plots the point estimate and 95% confidence intervals for each crop. The crop pesticide use data is obtained from the California Pesticide Usage Reporting, and temperature bins are derived from gridMET daily data.

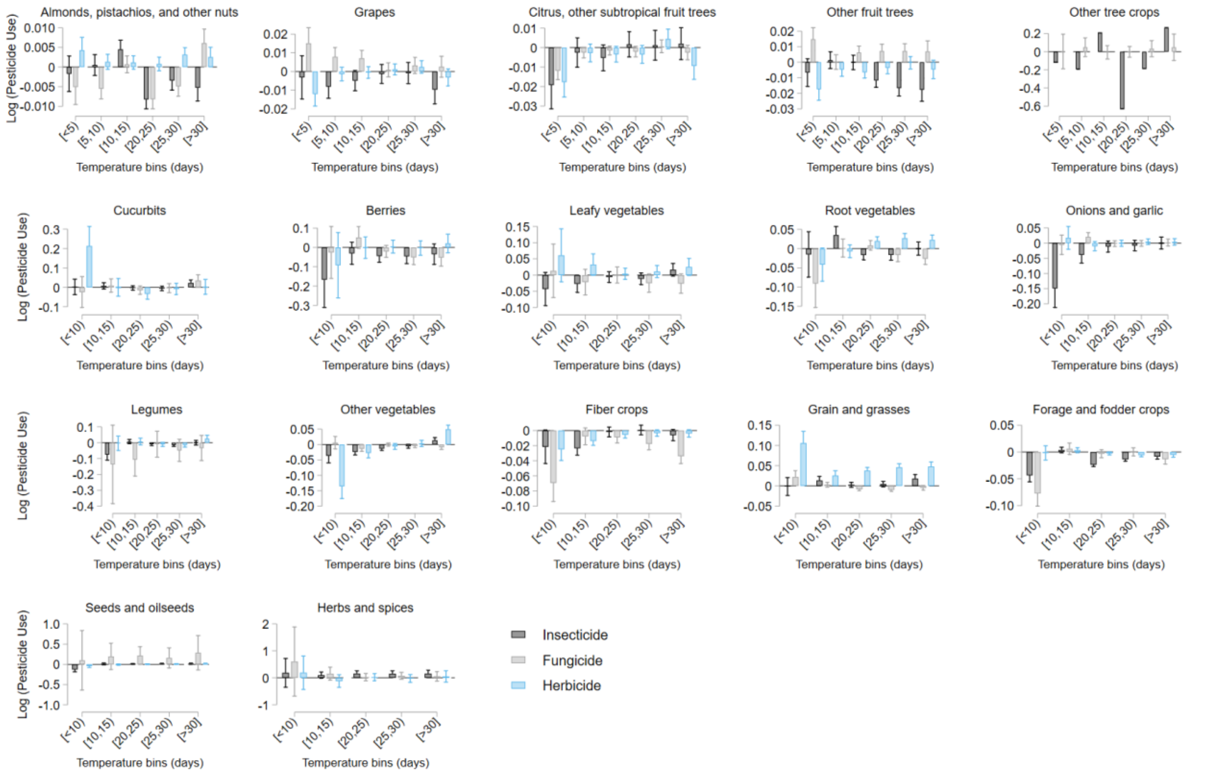

Figure A9b. Crop group-wise impacts of temperature bins on insecticide, fungicide, and herbicides

Notes: The dependent variable is the log transformed pesticide usage rate from 1993 to 2022. The specification includes second order polynomials for other weather variables, including total precipitation, total solar radiation, and average wind speed, as well as PLS section and year fixed effects. The temperature bin [15 C, 20 C) is the reference category. The figure plots the point estimate and 95% confidence intervals for each crop. The crop pesticide use data is obtained from the California Pesticide Usage Reporting, and temperature bins are derived from gridMET daily data.

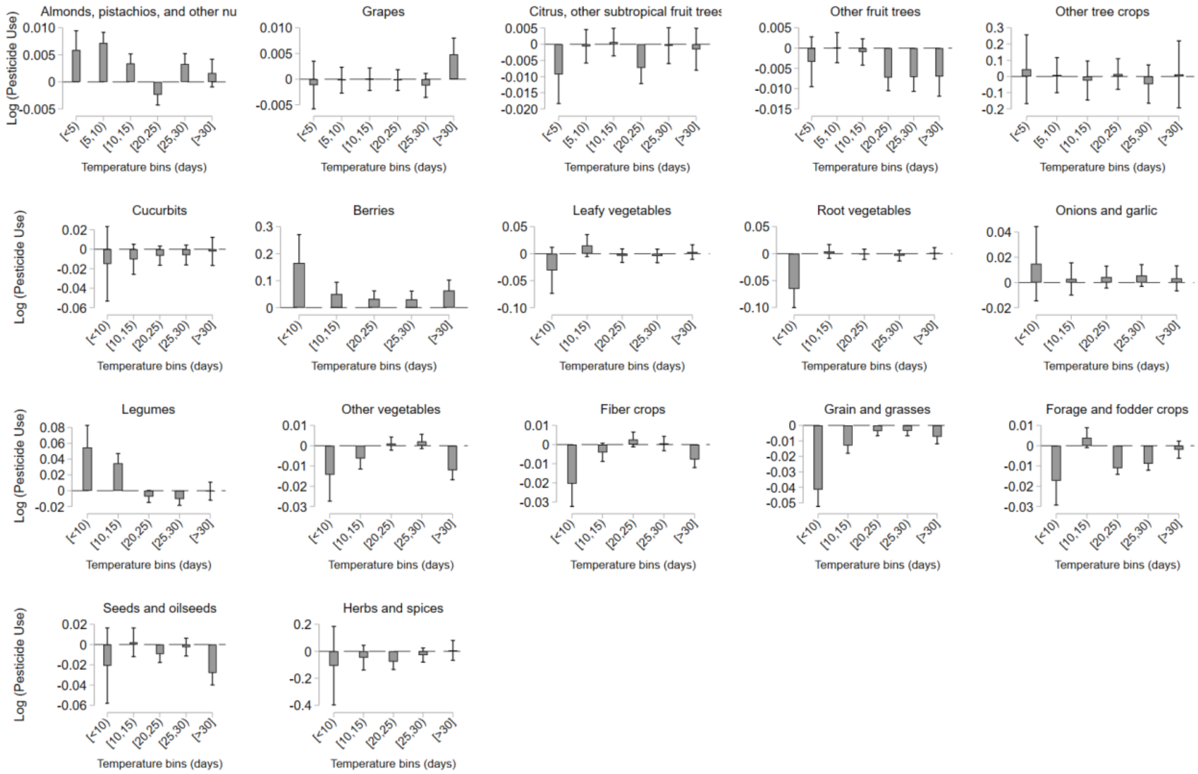

Figure A9c. Crop group-wise impacts of temperature bins on other chemicals

Notes: The dependent variable is the log transformed pesticide usage rate from 1993 to 2022. The specification includes second order polynomials for other weather variables, including total precipitation, total solar radiation, and average wind speed, as well as PLS section and year fixed effects. The temperature bin [15 C, 20 C) is the reference category. The figure plots the point estimate and 95% confidence intervals for each crop. The crop pesticide use data is obtained from the California Pesticide Usage Reporting, and temperature bins are derived from gridMET daily data.

Table A1. Summary statistics of the weather variables used in the analysis

Variable	Mean
Temperature Bin:	
[0,3)	1.7
[3,6)	11.1
[6,9)	36.0
[9,12)	53.7
	(4.1)
[12,15)	48.0
	(10.2)
[15,18)	43.7
	(19.0)
[18,21)	40.4
	(26.9)
[21,24)	43.7
	(38.0)
[24,27)	46.0
	(44.2)
[27,30)	29.6
	(29.1)
[>30]	11.0
	(11.0)
Mean annual temperature (C)	17.5
Mean seasonal temperature (C)	22.9
Total precipitation (mm)	322.0
Solar radiation (watts/m2)	224.2
Wind speed (m/s)	3.0

Notes: Mean values are reported across PLS sections in the Central Valley between 1993 and 2022. Mean values in parentheses are reported for the growing season across PLS sections from 1993 to 2022.

Table A2a. Panel estimates of the impact of temperature on pesticide usage in perennial crops

Dependent variable: Log (Pesticide usage rate)	Almonds, pistachios, and other nuts	Grapes	Citrus, other subtropical fruit trees	Other fruit trees	Other tree crops
Panel A1: All Pesticide Usage					
GDD (8C – 27C;	-0.087**	0.194***	0.020	0.243***	1.401
thousands)	(0.036)	(0.058)	(0.075)	(0.063)	(2.589)
HDD (above 27C;	-0.021	-0.050**	-0.085**	0.035	0.168
hundred)	(0.014)	(0.022)	(0.035)	(0.026)	(0.834)
Observations	582,008	274,304	141,259	215,328	369
R-squared	0.126	0.130	0.167	0.125	0.539
Panel A2: Insecticide Usage					
GDD (8C – 27C;	-0.021	0.610***	0.257*	0.589***	n.a.
thousands)	(0.067)	(0.136)	(0.153)	(0.117)	
HDD (above 27C;	-0.131***	0.0001	-0.305**	0.104**	n.a.
hundred)	(0.026)	(0.046)	(0.064)	(0.042)	
Observations	152,432	62,640	30,876	55,902	
R-squared	0.271	0.328	0.327	0.338	
Panel A3: Fungicide Usage					
GDD (8C – 27C;	-0.185***	0.087	-0.101	0.362***	n.a.
thousands)	(0.067)	(0.101)	(0.065)	(0.112)	
HDD (above 27C;	-0.083***	-0.043	0.001	-0.031	n.a.
hundred)	(0.024)	(0.041)	(0.026)	(0.051)	
Observations	100,352	62,544	30,554	45,125	
R-squared	0.285	0.308	0.300	0.402	
Panel A4: Herbicide Usage					
GDD (8C – 27C;	-0.105**	-0.135*	0.014	0.147	-1.692
thousands)	(0.049)	(0.078)	(0.121)	(0.103)	(2.324)
HDD (above 27C;	-0.029*	0.009	-0.089	0.143***	0.460
hundred)	(0.018)	(0.029)	(0.063)	(0.042)	(0.971)
Observations	154,643	68,205	37,837	49,260	179
R-squared	0.383	0.416	0.386	0.371	0.725
Panel A5: Other Chemical Usage					
GDD (8C – 27C;	-0.087*	0.178***	0.008	-0.059	6.287*
thousands)	(0.051)	(0.053)	(0.125)	(0.079)	(3.207)
HDD (above 27C;	0.015	-0.054***	-0.065	0.001	-0.903
hundred)	(0.020)	(0.020)	(0.056)	(0.030)	(1.578)
Observations	172,547	79,988	41,028	63,786	122
R-squared	0.247	0.280	0.378	0.282	0.746

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3b. Panel estimates of the impact of temperature on pesticide usage in annual crops

Dependent variable: Log (Pesticide usage rate)	Cucurbits	Berries	Leafy vegetables	Root vegetables	Onions and garlic	Legumes	Other vegetables	Fiber crops	Grain and grasses	Forage and fodder crops	Seeds and oilseeds	Herbs and spices
Panel A1: All Pesticide Usage												
GDD (8C – 27C; thousands)	-0.064	0.714	1.149***	0.475**	-0.207	0.029	-0.079	-0.073	0.357***	-0.053	-0.610***	-0.707
	(0.236)	(0.645)	(0.328)	(0.213)	(0.191)	(0.223)	(0.107)	(0.081)	(0.091)	(0.065)	(0.208)	(1.456)
HDD (above 27C; hundred)	-0.215***	-0.362	-0.371***	-0.211***	0.026	-0.012	-0.048	-0.113***	-0.005	-0.106***	0.137***	1.017*
	(0.068)	(0.239)	(0.122)	(0.066)	(0.062)	(0.073)	(0.030)	(0.029)	(0.027)	(0.019)	(0.057)	(0.551)
Observations	45,460	7,898	21,565	50,872	41,331	40,456	171,808	226,507	221,843	342,690	31,641	1,535
R-squared	0.244	0.328	0.283	0.262	0.195	0.235	0.132	0.127	0.155	0.123	0.222	0.297
Panel A2: Insecticide Usage												
GDD (8C – 27C; thousands)	0.410	-0.734	1.319**	1.898***	-0.734	-0.362	-0.266	-0.002	0.316*	-0.002	-1.077***	-4.885
	(0.317)	(1.188)	(0.579)	(0.459)	(0.538)	(0.328)	(0.184)	(0.159)	(0.175)	(0.104)	(0.387)	(3.173)
HDD (above 27C; hundred)	-0.462***	0.736	-0.631***	-0.562***	-0.029	0.038	-0.185***	-0.065	-0.199***	-0.207***	0.157	2.300*
	(0.094)	(0.471)	(0.198)	(0.157)	(0.191)	(0.095)	(0.054)	(0.058)	(0.055)	(0.032)	(0.107)	(1.372)
Observations	16,988	2,331	6,321	13,279	6,880	13,377	43,258	58,753	28,759	101,454	7,135	367
R-squared	0.398	0.554	0.462	0.557	0.408	0.358	0.296	0.323	0.483	0.330	0.395	0.683
Panel A3: Fungicide Usage												
GDD (8C – 27C; thousands)	1.483**	0.189	1.216	0.299	-0.085	-1.212	-0.085	-0.532***	-0.065	-0.497**	7.204	-1.666
	(0.634)	(1.157)	(1.045)	(0.463)	(0.279)	(1.652)	(0.163)	(0.192)	(0.121)	(0.218)	(4.337)	(3.399)
HDD (above 27C; hundred)	-0.860***	-0.103	-0.697**	0.102	0.052	-0.013	-0.130***	-0.210***	-0.026	-0.044	0.866	1.193
	(0.198)	(0.295)	(0.340)	(0.120)	(0.087)	(0.573)	(0.045)	(0.068)	(0.033)	(0.077)	(1.520)	(0.824)
Observations	4,235	873	2,018	6,301	9,281	434	36,858	38,169	29,453	21,944	145	163
R-squared	0.659	0.683	0.595	0.451	0.451	0.687	0.299	0.353	0.416	0.446	0.458	0.766
Panel A4: Herbicide Usage												
GDD (8C – 27C; thousands)	1.087	1.141	-0.339	-1.080***	0.032	0.389	0.066	0.052	-0.111	-0.154	-0.266	3.949
	(0.910)	(1.202)	(0.568)	(0.353)	(0.277)	(0.437)	(0.310)	(0.106)	(0.229)	(0.100)	(0.343)	(4.553)
HDD (above 27C; hundred)	-0.013	-0.654	0.013	0.089	0.032	-0.337**	-0.316***	-0.117***	-0.139**	-0.043*	-0.059	0.080
	(0.261)	(0.406)	(0.215)	(0.102)	(0.083)	(0.171)	(0.085)	(0.037)	(0.062)	(0.025)	(0.093)	(1.018)
Observations	2,867	1,406	3,133	9,515	7,212	6,219	33,951	58,018	48,879	89,566	6,463	78
R-squared	0.596	0.642	0.581	0.449	0.460	0.483	0.351	0.303	0.564	0.291	0.522	0.810

Panel A5: Other Chemical Usage												
GDD (8C – 27C; thousands)	-0.503	1.196	0.994**	0.399	0.113	-0.032	0.243**	0.002	0.833***	0.207**	-0.490*	2.713
	(0.337)	(0.831)	(0.387)	(0.297)	(0.262)	(0.302)	(0.102)	(0.087)	(0.116)	(0.098)	(0.290)	(1.811)
HDD (above 27C; hundred)	0.017	-0.660**	-0.100	-0246***	-0.025	0.157**	0.101***	-0.092***	-0.049	-0.092***	0.196**	0.494
	(0.090)	(0.328)	(0.165)	(0.086)	(0.078)	(0.080)	(0.028)	(0.033)	(0.034)	(0.027)	(0.078)	(0.535)
Observations	17,294	2,884	8,076	17,946	14,489	16,408	54,183	68,980	109,047	125,933	15,539	621
R-squared	0.340	0.433	0.411	0.335	0.305	0.362	0.355	0.246	0.357	0.229	0.321	0.530

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3a. Panel estimates of the impact of temperature on number of pesticide applications for perennial crops

Dependent variable: IHS (Mean Number of Pesticide applications Per Hectare Per Year)	Almonds, pistachios, and other nuts	Grapes	Citrus, other subtropical fruit trees	Other fruit trees	Other tree crops
Panel A1: All Pesticide Usage					
GDD (8C – 27C;	0.009	-0.0017**	0.042***	0.009	-1.139**
thousands)	(0.006)	(0.007)	(0.014)	(0.012)	(0.495)
HDD (above 27C;	-0.006**	0.002	0.003	0.013**	-0.002
hundred)	(0.002)	(0.002)	(0.006)	(0.005)	(0.143)
Observations	582,008	274,304	141,259	215,328	369
R-squared	0.372	0.642	0.568	0.573	0.623
Panel A2: Insecticide Usage					
GDD (8C – 27C;	0.019	-0.007	0.028	0.010	n.a.
thousands)	(0.012)	(0.008)	(0.021)	(0.014)	
HDD (above 27C;	-0.021***	0.001	0.016*	0.005	n.a.
hundred)	(0.005)	(0.002)	(0.009)	(0.005)	
Observations	152,432	62,640	30,876	55,902	
R-squared	0.306	0.577	0.446	0.551	
Panel A3: Fungicide Usage					
GDD (8C – 27C;	0.002	-0.001	0.007	-0.003	n.a.
thousands)	(0.007)	(0.008)	(0.014)	(0.017)	
HDD (above 27C;	0.002	0.002	0.017***	0.023***	n.a.
hundred)	(0.003)	(0.003)	(0.006)	(0.007)	
Observations	100,352	62,544	30,554	45,125	
R-squared	0.500	0.678	0.542	0.642	
Panel A4: Herbicide Usage					
GDD (8C – 27C;	0.001	-0.033***	0.060***	-0.002	-0.868
thousands)	(0.07)	(0.010)	(0.020)	(0.018)	(0.571)
HDD (above 27C;	0.003	-0.003	-0.003	0.013*	-0.049
hundred)	(0.003)	(0.004)	(0.010)	(0.008)	(0.124)
Observations	154,643	68,205	37,837	49,260	179
R-squared	0.516	0.634	0.676	0.584	0.717
Panel A5: Other Chemical Usage					
GDD (8C – 27C;	0.005	-0.022**	0.037***	0.015	-2.303**
thousands)	(0.007)	(0.009)	(0.017)	(0.014)	(0.813)
HDD (above 27C;	-0.004	0.004	-0.001	0.012**	0.164
hundred)	(0.003)	(0.003)	(0.008)	(0.006)	(0.274)
Observations	172,547	79,988	41,028	63,786	122
R-squared	0.473	0.731	0.644	0.682	0.599

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the IHS-transformed mean number of pesticide applications per hectare per year from 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3b. Panel estimates of the impact of temperature on number of pesticide applications for annual crops

Dependent variable: IHS (Mean Number of Pesticide applications Per Hectare Per Year)	Cucurbits	Berries	Leafy vegetables	Root vegetables	Onions and garlic	Legumes	Other vegetables	Fiber crops	Grain and grasses	Forage and fodder crops	Seeds and oilseeds	Herbs and spices
Panel A1: All Pesticide Usage												
GDD (8C –	-0.004	-0.293	0.126	0.002	-0.055	-0.075*	-0.022*	-0.003	0.022***	0.008*	-0.010	0.066
27C; thousands)	(0.047)	(0.228)	(0.105)	(0.028)	(0.036)	(0.044)	(0.012)	(0.004)	(0.008)	(0.004)	(0.022)	(0.239)
HDD (above	0.018	0.004	-0.100***	-0.005	-0.033**	0.015	0.010***	-0.0004	-0.001	0.001	0.0001	-0.117
27C; hundred)	(0.015)	(0.035)	(0.043)	(0.011)	(0.015)	(0.016)	(0.003)	(0.002)	(0.002)	(0.002)	(0.05)	(0.103)
Observations	45,460	7,898	21,565	50,872	41,331	40,456	171,808	226,507	221,843	342,690	31,641	1,535
R-squared	0.662	0.714	0.819	0.732	0.752	0.751	0.689	0.378	0.451	0.368	0.902	0.862
Panel A2: Insecticide Usage												
GDD (8C –	0.004	-0.167	0.081	-0.044	-0.027	-0.062	-0.043**	0.011*	0.032	-0.002	0.022	0.262
27C; thousands)	(0.053)	(0.271)	(0.118)	(0.046)	(0.055)	(0.053)	(0.022)	(0.006)	(0.020)	(0.06)	(0.039)	(0.576)
HDD (above	0.042**	0.004	-0.089*	0.016	-0.042	0.006	0.012**	-0.007***	-0.003	0.001	-0.0001	-0.361
27C; hundred)	(0.017)	(0.057)	(0.054)	(0.014)	(0.031)	(0.018)	(0.005)	(0.002)	(0.006)	(0.002)	(0.009)	(0.266)
Observations	16,988	2,331	6,321	13,279	6,880	13,377	43,258	58,753	28,759	101,454	7,135	367
R-squared	0.686	0.719	0.830	0.706	0.721	0.765	0.722	0.349	0.663	0.401	0.870	0.848
Panel A3: Fungicide Usage												
GDD (8C –	-0.068	-0.061	0.412***	-0.007	-0.124**	0.189**	-0.010	-0.009	-0.0001	0.009	1.344	-0.145
27C; thousands)	(0.089)	(0.302)	(0.144)	(0.041)	(0.053)	(0.092)	(0.010)	(0.007)	(0.009)	(0.012)	(1.428)	(0.400)
HDD (above	-0.009	0.007	-0.139**	-0.014	-0.016	-0.013	-0.005	0.001	0.002	0.004	-0.484	-0.100
27C; hundred)	(0.032)	(0.054)	(0.044)	(0.017)	(0.019)	(0.032)	(0.004)	(0.002)	(0.003)	(0.004)	(0.404)	(0.170)
Observations	4,235	873	2,018	6,301	9,281	434	36,858	38,169	29,453	21,944	145	163
R-squared	0.672	0.798	0.873	0.882	0.771	0.946	0.651	0.426	0.442	0.460	0.677	0.941
Panel A4: Herbicide Usage												
GDD (8C –	0.081	-0.244	0.200	0.039	-0.004	-0.104	0.012	-0.011*	0.037*	0.014*	-0.112**	0.647
27C; thousands)	(0.153)	(0.224)	(0.179)	(0.042)	(0.039)	(0.117)	(0.019)	(0.007)	(0.019)	(0.007)	(0.045)	(0.625)

HDD (above 27C; hundred)	0.002	-0.029	-0.150**	-0.014	-0.036**	0.048	0.017***	0.009***	-0.004	0.002	0.007	0.318
	(0.041)	(0.052)	(0.062)	(0.014)	(0.016)	(0.029)	(0.006)	(0.003)	(0.004)	(0.002)	(0.010)	(0.247)
Observations	2,867	1,406	3,133	9,515	7,212	6,219	33,951	58,018	48,879	89,566	6,463	78
R-squared	0.821	0.829	0.850	0.788	0.808	0.810	0.708	0.384	0.607	0.430	0.951	0.933
Panel A5: Other Chemical Usage												
GDD (8C – 27C; thousands)	-0.034	-0.430	0.026	0.002	-0.059	-0.090**	-0.025	-0.002	0.017**	0.011*	0.010	0.042
	(0.061)	(0.269)	(0.107)	(0.035)	(0.040)	(0.042)	(0.018)	(0.006)	(0.008)	(0.006)	(0.023)	(0.312)
HDD (above 27C; hundred)	0.008	0.008	-0.075	-0.013	-0.033*	0.009	0.012***	-0.002	0.002	0.001*	-0.004	-0.100
	(0.020)	(0.035)	(0.046)	(0.013)	(0.017)	(0.014)	(0.005)	(0.002)	(0.002)	(0.002)	(0.006)	(0.100)
Observations	17,294	2,884	8,076	17,946	14,489	16,408	54,183	68,980	109,047	125,933	15,539	621
R-squared	0.662	0.746	0.827	0.746	0.759	0.795	0.733	0.442	0.447	0.421	0.883	0.867

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the IHS-transformed mean number of pesticide applications per hectare per year from 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Regression results for various spatial combinations of fixed effects, including township and range

Dependent variable: Log (Pesticide usage rate)	Baseline [1]	Range [2]	Township [3]
Panel A: Perennial Crops			
GDD (below threshold; thousands)	-0.014	-0.026	-0.0004
	(0.029)	(0.030)	(0.032)
	[0.042]	[0.041]	[0.042]
HDD (above threshold; hundred)	-0.015	-0.024	-0.043***
	(0.012)	(0.012)*	(0.013)
	[0.020]	[0.018]	[0.019]
Observations	1,213,775	1,213,972	1,213,977
R-squared	0.096	0.038	0.023
Panel A: Annual Crops			
GDD (below threshold; thousands)	-0.062	0.059	0.058
	(0.042)	(0.035)*	(0.039)
	[0.076]	[0.055]	[0.055]
HDD (above threshold; hundred)	-0.084***	-0.036	-0.020
	(0.012)	(0.013)***	(0.013)
	[0.023]	[0.021]*	[0.021]
Observations	1,208,932	1,209,657	1,209,679
R-squared	0.083	0.044	0.023
PLS section FEs	Yes	No	No
PLS range FEs	No	Yes	No
PLS township FEs	No	No	Yes
Year FEs	Yes	Yes	Yes

Notes: Standard errors presented in parentheses are clustered at the PLS section level and at the township-range level in square brackets. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. All regressions include weather controls. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. The number of clusters at the sections, range, and township level isLevel of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5a. Panel estimates of the impacts of temperature on crop-specific pesticide use rates in perennial crops using various temperature thresholds

Threshold (degrees Celsius)	(26)	(27)	(28)	(29)
Panel A1: All pesticide usage				
GDD (below threshold; thousands)	-0.014	-0.014	-0.020	-0.034
	(0.027)	(0.029)	(0.031)	(0.031)
HDD (above threshold; hundred)	-0.015	-0.015	-0.016	-0.011
	(0.010)	(0.012)	(0.014)	(0.018)
Observations	1,213,775	1,213,775	1,213,775	1,213,775
R-squared	0.096	0.096	0.096	0.096
Panel A2: Insecticide usage				
GDD (below threshold; thousands)	-0.011	0.027	0.042	0.043
	(0.053)	(0.056)	(0.059)	(0.060)
HDD (above threshold; hundred)	-0.004	-0.008	-0.014	-0.020
	(0.018)	(0.021)	(0.025)	(0.031)
Observations	302,817	302,817	302,817	302,817
R-squared	0.196	0.196	0.196	0.196
Panel A3: Fungicide usage				
GDD (below threshold; thousands)	0.169^{***}	0.129^{***}	0.081	0.038
	(0.046)	(0.048)	(0.050)	(0.051)
HDD (above threshold; hundred)	-0.087^{***}	-0.105^{***}	-0.124^{***}	-0.142^{***}
	(0.018)	(0.021)	(0.025)	(0.033)
Observations	239,568	239,568	239,568	239,568
R-squared	0.236	0.236	0.236	0.236
Panel A4: Herbicide usage				
GDD (below threshold; thousands)	-0.132^{***}	-0.108^{***}	-0.090^{**}	-0.091^{**}
	(0.038)	(0.041)	(0.044)	(0.045)
HDD (above threshold; hundred)	0.039^{***}	0.051^{***}	0.062^{***}	0.087^{***}
	(0.014)	(0.015)	(0.018)	(0.023)
Observations	311,096	311,096	311,096	311,096
R-squared	0.309	0.309	0.309	0.309
Panel A5: Other chemical usage				
GDD (below threshold; thousands)	-0.036	-0.074^{**}	-0.098^{***}	-0.114^{***}
	(0.033)	(0.035)	(0.036)	(0.037)
HDD (above threshold; hundred)	-0.026^{**}	-0.017	-0.007	0.013
	(0.012)	(0.013)	(0.016)	(0.020)
Observations	358,483	358,483	358,483	358,483
R-squared	0.166	0.166	0.166	0.166

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A5b. Panel estimates of the impacts of temperature on crop-specific pesticide use rates in annual crops using various temperature thresholds

Threshold (degrees Celsius)	(26)	(27)	(28)	(29)
Panel B1: All pesticide usage				
GDD (below threshold; thousands)	0.066**	0.008	-0.041	0.068**
	(0.029)	(0.030)	(0.032)	(0.032)
HDD (above threshold; hundred)	-0.096***	-0.094***	-0.087***	-0.080***
	(0.011)	(0.012)	(0.015)	(0.018)
Observations	1,208,932	1,208,932	1,208,932	1,208,932
R-squared	0.083	0.083	0.083	0.083
Panel B2: Insecticide usage				
GDD (below threshold; thousands)	0.187***	0.069	-0.017	-0.075
	(0.051)	(0.053)	(0.056)	(0.056)
HDD (above threshold; hundred)	-0.219***	-0.221***	-0.228***	-0.213***
	(0.020)	(0.022)	(0.026)	(0.033)
Observations	309,207	309,207	309,207	309,207
Adj. R-squared	0.204	0.204	0.204	0.204
Panel B3: Fungicide usage				
GDD (below threshold; thousands)	-0.249***	-0.338***	-0.453***	-0.541***
	(0.065)	(0.068)	(0.070)	(0.070)
HDD (above threshold; hundred)	-0.094***	-0.099***	-0.089***	-0.069*
	(0.023)	(0.027)	(0.032)	(0.040)
Observations	156,538	156,538	156,538	156,538
Adj. R-squared	0.258	0.258	0.258	0.258
Panel B4: Herbicide usage				
GDD (below threshold; thousands)	-0.026	-0.092	-0.095	-0.093
	(0.060)	(0.062)	(0.065)	(0.065)
HDD (above threshold; hundred)	-0.044**	-0.022	-0.004	-0.006
	(0.021)	(0.025)	(0.031)	(0.039)
Observations	277,034	277,034	277,034	277,034
Adj. R-squared	0.194	0.194	0.194	0.194
Panel B5: Other chemical usage				
GDD (below threshold; thousands)	0.180***	0.211***	0.193***	0.194***
	(0.036)	(0.039)	(0.041)	(0.041)
HDD (above threshold; hundred)	-0.017	-0.034**	-0.040**	-0.048*
	(0.014)	(0.016)	(0.019)	(0.024)
Observations	462,684	462,684	462,684	462,684
Adj. R-squared	0.169	0.169	0.169	0.169

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Impacts of mean temperature on pesticide use

Dependent variable: Log (Pesticide usage rate)	All Pesticide Use	Insecticide Use	Fungicide Use	Herbicide Use	Other Chemical Use
Panel A: Perennial crops					
Mean annual temperature	0.411***	0.143	1.348***	1.234***	-0.698***
	(0.118)	(0.213)	(0.186)	(0.187)	(0.132)
Mean annual temperature squared	-0.012***	-0.006	-0.038***	-0.034***	0.019***
	(0.003)	(0.006)	(0.005)	(0.005)	(0.004)
Observations	851,567	215,381	175,031	219,030	240,273
R-squared	0.141	0.298	0.338	0.394	0.285
Panel B: Annual crops					
Mean seasonal temperature	0.288***	-0.127	0.649***	-0.052	1.076***
	(0.086)	(0.199)	(0.157)	(0.155)	(0.115)
Mean seasonal temperature squared	-0.005***	0.006	-0.015***	0.004	-0.024***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
Observations	803,769	205,624	126,583	203,563	264,419
R-squared	0.110	0.301	0.308	0.254	0.314

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The dependent variable is the log transformed pesticide usage rates (in kg/ha) during 1993 to 2022. Mean annual temperature for perennial crops and mean temperature during the growing season for annual crops. All regressions include weather controls, as well as year and PLS section level fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7. Temperature effects on crop-specific land-use shares

	Almonds	Pistachios	Walnuts	Grapes	Orchards	Subtropical fruit trees	Young perennial	Field and grain	Corn	Cotton	Cucurbits
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
GDD (8C – 27C; thousands)	0.028**	0.028*	-0.008	-0.066***	-0.020**	0.027**	-0.018	-0.005	0.003	0.068	0.012
	(0.011)	(0.016)	(0.010)	(0.012)	(0.008)	(0.014)	(0.015)	(0.020)	(0.022)	(0.064)	(0.037)
HDD (above 27C; hundred)	-0.014***	-0.010	-0.000	0.027***	0.007**	-0.003	0.006	-0.003	-0.007	-0.030	-0.009
	(0.004)	(0.007)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.021)	(0.008)
Mean dep. var.	0.434	0.351	0.300	0.355	0.179	0.361	0.101	0.193	0.328	0.323	0.141
Observations	48,111	18,880	24,316	24,028	21,855	14,311	17,674	30,362	26,076	8,169	5,372
R-squared	0.908	0.931	0.940	0.938	0.944	0.955	0.642	0.749	0.802	0.606	0.701

	Rice	Dry beans	Berries	Lettuce	Onions and garlic	Potatoes	Tomatoes	Safflower	Sunflower	Truck crops	Alfalfa
	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
GDD (8C – 27C; thousands)	-0.040	-0.112*	-0.038	-0.269**	0.041	-0.085	0.066*	0.281**	0.016	0.004	-0.015
	(0.040)	(0.066)	(0.039)	(0.120)	(0.082)	(0.093)	(0.037)	(0.115)	(0.055)	(0.026)	(0.024)
HDD (above 27C; hundred)	-0.011	0.003	0.000	-0.001	-0.044	0.002	-0.020**	-0.032	-0.004	-0.011	0.007
	(0.010)	(0.013)	(0.007)	(0.043)	(0.028)	(0.027)	(0.009)	(0.022)	(0.017)	(0.007)	(0.006)
Mean dep. var.	0.678	0.152	0.092	0.196	0.201	0.239	0.265	0.237	0.177	0.114	0.224
Observations	10,540	2,587	1,701	987	2,781	2,586	13,137	2,419	3,932	7,587	24,578
R-squared	0.897	0.677	0.919	0.677	0.570	0.754	0.626	0.574	0.399	0.778	0.715

Notes: Standard errors presented in parentheses are clustered at the PLS section level. The weather controls include total precipitation, total solar radiation, average wind speed, and their squared terms. Degree days are accumulated in a year for perennial crops, while they are accumulated during the growing season (April through September) for annual crops. Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8. Predicted changes in climate variables compared to the average during 1981–2005.

	1981–2005 (1)	2031–2055 (2)	2056–2080 (3)	Diff. (2) - (1)	Diff. (3) - (1)
Annual:					
Mean temperature (degrees Celsius)	17.18	18.93	19.19	1.75	2.01
		(19.02)	(20.31)	(1.84)	(3.13)
GDD (8C – 27C)	3494.88	4150.46	4255.08	655.58	760.20
		(4179.78)	(4663.48)	(684.90)	(1168.60)
HDD (> 27C)	40.66	107.02	116.56	66.36	75.9
		(100.33)	(186.39)	(59.67)	(145.73)
Growing season: April through September					
GDD (8C – 27C)	2596.46	2993.41	3035.27	396.95	438.81
		(2963.50)	(3243.49)	(367.04)	(647.03)
HDD (> 27C)	40.35	105.59	112.53	65.24	72.18
		(97.53)	(181.57)	(57.18)	(141.22)

Notes: The mean climate projection value from SSP245 scenario is reported. The SSP585 scenario is reported in parentheses.

Table A9. Projected impacts of climate change on pesticide use rate under two climate scenarios SSP245 (SSP585)

	Panel A: Near-medium term (2031–2055)											
	Almonds, pistachios, and other nuts	Grapes	Citrus, other subtropical fruit trees	Other fruit trees	Cucurbits	Leafy vegetables	Root vegetables	Fiber crops	Grain and grass	Forage and fodder crops	Seeds and oilseeds	Herbs and spices
GDD (8C – 27C)	**-5.7%** **(-6.0%)**	**12.7%** **(13.3%)**	1.3% (1.4%)	**15.9%** **(16.6%)**	-2.5% (-2.3%)	**45.6%** **(42.2%)**	**18.9%** **(17.4%)**	-2.9% (-2.7%)	**14.2%** **(13.1%)**	-2.1% (-1.9%)	**-24.2%** **(-22.4%)**	-28.1% (-25.9%)
HDD (above 27C)	-1.4% (-1.3%)	**-3.3%** **(-3.0%)**	**-5.6%** **(-5.1%)**	2.3% (2.1%)	**-14.0%** **(-12.3%)**	**-24.2%** **(-21.1%)**	**-13.8%** **(-12.0%)**	**-7.4%** **(-6.4%)**	-0.3% (-0.3%)	**-6.9%** **(-6.0%)**	**8.9%** **(7.8%)**	**66.3%** **(58.0%)**
	Panel B: Long-term (2056–2080)											
	Almonds, pistachios, and other nuts	Grapes	Citrus, other subtropical fruit trees	Other fruit trees	Cucurbits	Leafy vegetables	Root vegetables	Fiber crops	Grain and grass	Forage and fodder crops	Seeds and oilseeds	Herbs and spices
GDD (8C – 27C)	**-6.6%** **(-10.2%)**	**14.7%** **(22.7%)**	1.5% (2.3%)	**18.5%** **(28.4%)**	-2.8% (-4.1%)	**50.4%** **(74.3%)**	**20.9%** **(30.7%)**	-3.2% (-4.7%)	**15.7%** **(23.1%)**	-2.3% (-3.4%)	**-26.8%** **(-39.5%)**	-31.0% (-45.7%)
HDD (above 27C)	-1.6% (-3.1%)	**-3.8%** **(-7.3%)**	**-6.5%** **(-12.4%)**	2.7% (5.1%)	**-15.5%** **(-30.3%)**	**-26.7%** **(-52.3%)**	**-15.5%** **(-29.8%)**	**-8.1%** **(-15.9%)**	-0.4% (-0.7%)	**-7.6%** **(-14.9%)**	**9.9%** **(19.3%)**	**73.2%** **(143.4%)**

Notes: The percentage change of projected impacts of climate change on pesticide use rate are reported. The SSP585 climate scenario results are presented in parentheses. The bold values have statistically significant impacts. These are calculated by multiplying the statistically significant coefficients of average marginal effects (Tables A3a and A3b) and the difference between the average projected climate in 2031-2055 and the average climate in 1981–2005. Similarly, long-term predicted climate impacts are calculated by multiplying the coefficients of average marginal effects and the difference between the average projected climate in 2056–2080 and the average climate in 1981–2005.