Crops Yield and Harvested Acre Responsiveness to Warming Temperatures in California

Abstract: Drier years over longer period has transformed California's agricultural practices, including crop production outcomes. Here, we document the effects of warmer temperature on 20 major crops yield and harvested acres in California's Central Valley – a major agricultural region. We revisit previous econometric approaches to examine the relationships between crop production outcomes and temperature, with the benefit of a longer time of 1980–2022 of data. The temperature-related yield response appears relatively muted for most major crop groups. In contrast, harvested acres of some of the major crops show negative response signal to warmer temperatures. These results suggest that the direct impacts on crop yield from observed warming have been less sensitive than found in previous studies.

Keywords: climate change, crop production, perennial crops, annual crops, California

1. Introduction

The rise in global temperatures has presented concern for the agricultural sector, particularly in terms of agricultural productivity (Hogan and Schlenker 2024; Lobell and Di Tommaso 2025). Past research suggests that increased temperature during the growing season has a negative direct impact on the production outcomes of cultivated row field crops and specialty crops in California and other globally important agricultural regions (Lobell and Field 2007; S. Chen and Gong 2021a; Miller et al. 2021; Schlenker and Roberts 2009; Welch et al. 2010; J. Lee et al. 2011a). Using the longer study period and more crop groups, we revisit previous econometric approaches applied in California's agricultural setting (e.g., (Lobell et al. 2006, 2007; J. Lee et al. 2011a), to estimate crop yield- and harvested acre- temperature response curves. Specifically, we examine and present a comprehensive empirical estimate of the responsiveness of 20 major crops yield and harvested acre to temperatures in California's Central Valley during 1980–2022 and quantify the estimates in the context of climate change.

Previous studies using different measures of temperature and econometric techniques have produced mixed results on the potential impact of climate change-induced warming on California crops (Deschenes and Kolstad 2011; H. Lee and Sumner 2015; Lobell et al. 2007; Fazli et al. 2025), with yield declines of some specialty crops to warming. Both warmer winters and warmers summers have shown to negatively affect California crops yield (J. Lee et al. 2011b; Kerr et al. 2018; Cordero et al. 2011). In this paper, we employ the 20 crop-group categorization from the California Department of Water Resources (DWR), with the benefit of a longer period 1980–2022 for California's counties in the Central Valley. Specifically, we incorporate the complete temperature distribution, including freezing points (less than 0°C), cooler temperatures (0 – 8°C), growing temperatures (8 – 30°C), and hotter temperatures (above 30°C), and their derived products, such as degree days and heat degree days to estimate the nonlinear relationship between temperature and California's crop production outcomes, such as yield and harvested acres (Snyder 1985; Schlenker et al. 2007).[1] In addition, to capture the effect of climate condition during various plant growth stages, we utilize averages of seasonal weather variables: winter, spring, summer, and fall.

We also examine relationships between crop -specific harvested acres and extreme temperatures to fully capture climate change-induced warming response to crop outcomes (Cui 2020). While harvested acres may not be a first-order function of temperature, planted acreage is a first-order function of water availability which is impacted by temperature variability in California both through the role of winter temperatures in spring snowpack in the Sierra Nevada (e.g., Mote et al. 2005) and indirect influence of warming on increased evaporative demand during the warm season (e.g., Albano et al. 2022). Thus, in addition to the crop yield-temperature response, the estimates of crop-specific acre harvested-temperature response will provide growers a full understanding of farm decisions in response to extreme temperatures.

We employ nonlinear models to represent relationships between the crop production outcomes, such as yield and harvested acres, and temperature consistent with crop-specific agronomy that might be otherwise missed by assuming linear relationships (Schlenker and Roberts 2009; Hogan and Schlenker 2024). For example, climate conditions can impact both the mean crop yields and higher moments of crop yield distribution (C. Chen and Chang 2005). Similarly, plant growth can be affected by temperatures that are higher or lower than a certain threshold. For reference, temperatures above 29°C are harmful to major row crops such as corn and soybean (Schlenker

[1] Degree days are defined as the sum of degrees above a lower baseline and below an upper threshold during the growing season (Schlenker et al. 2007). Degree days are calculated using the daily minimum and maximum temperatures and then summed over the growing season.

and Roberts 2009). Therefore, applying linear models may not adequately capture the nonlinear nature of plant growth. Consequently, several recent studies have used nonlinear models to estimate crop yield-temperature response curve in Chinese (S. Chen and Gong 2021b; Cui and Xie 2022; Cui and Zhong 2024; Du et al. 2025) and American agricultural settings (Miller et al. 2021; Ortiz-Bobea 2020). We build on this literature and estimate the nonlinear relationship between crop production outcomes and temperature.

To estimate statistical relationships between crop production outcomes and temperature, we use county-level data on crop yields and harvested acres obtained from the USDA National Agricultural Statistics Service (NASS) in California's Central Valley counties from 1980 to 2022. We grouped available crop commodities into DWR 20-crop category and estimate changes in crop-group-specific yield and harvested acres as a nonlinear function of seasonal degree days below and above a critical threshold temperature. Our findings indicate that degree days have significant negative association with the yields of almonds, as well as harvested acres of corn, dry beans, cucurbits, and potatoes. In contrast, warming temperatures have positive significant association with pistachios yield. Forage production also decreased, including the yields of alfalfa and corn, in response to warming temperatures in our study region during 1980–2022.

Moreover, to account for growers' expectations about climate in our study region, we examine concurrent seasonal and annual weather data as well as both recent (previous three-year averages) and distant (previous four- to ten-year averages) lagged nonlinear effects of temperature on the crop yield and harvested acres.

Lastly, using our estimated coefficients, we quantify the effects of projected climate change on California's crops yield and harvested acres. Our estimates suggest that the winter degree days in the near-medium term (2031–2055) and in the long term (2056–2080) relative to 1981–2005 will have a negative impact on the projected yields of almonds (5.2% decline in the near-medium term vs. 5.7% decline in the long term). In contrast, summer degree days will increase pistachios yields (14% vs. 15%). In addition, the heat degree days in the near-medium term vs. in the long term relative to 1981–2005 will negatively impact on the projected harvested acres of corn (near-medium term: 45% vs. long term: 49%), dry beans (-28% vs. -30%), cucurbits (-31% vs. -34%), and potatoes (-37.5% vs. 41%).

2. Data

The empirical analysis is based on a county-year panel on crop production outcomes such as yield and harvested acre (as dependent variables) from eighteen counties in the Central Valley, combined with gridded data on historical and future climate patterns.[2] We describe the data sources in the following.

2.1. Data Sources

We compile a county-level panel dataset on crop production outcomes such as crop yield, harvested acre, and weather conditions for our selected DWR 20 major crops groups in California's Central Valley between 1980 and 2022. The county-level crops yield, and harvested acre data are obtained from the USDA National Agricultural Statistics Services (NASS).[3] To categorize reported crops into 20 major crops categories grown in the Central Valley, we rely on

[2] We combine 18 counties to form the Sacramento and San Joaquín Valleys for the analysis. The Sacramento Valley is the northern part of the Central Valley and comprises the counties of Tehama, Glenn, Butte, Colusa, Yolo, Solano, Sutter, Yuba, Placer, and Sacramento. The San Joaquín is divided into northern, central, and southern regions. The northern part of the San Joaquín Valley consists of the counties of San Joaquin, Stanislaus, and Merced. The central part of the San Joaquín Valley includes the counties of Madera, and Fresno. The southern part of the San Joaquín Valley includes the counties of Tulare, Kern, and Kings.

[3] The USDA NASS report is derived from the crop reports that the California County Agricultural Commissioner's compile each year. The data is accessible at https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/, which was accessed on March 7th, 2025.

classifications from the California Department of Water Resources. Crop groups are defined in Online Appendix Table 1. Not all crops are grown in all 18 counties of the Central Valley and within each county over the time period of analysis. Consequently, our panel is unbalanced. Table 1 presents the summary statistics of crop-specific yield and harvested acres across counties in the Central Valley during 1980–2022. Figures A1 and A2 show crop-specific yield and harvested acres scatter plots over the study period.

Next, we obtain climate data from gridMET, a daily surface meteorological dataset with a spatial resolution of approximately 4 km for the years 1979 to 2022 (Abatzoglou 2013).[4] We follow climate-agriculture literature to derive degree-days, seasonal weather variables such as total precipitation levels, mean temperatures, average solar radiation, and average wind speed. We then aggregate daily climate data to the county-year level, weighted by the satellite-derived cropland layer obtained from the 2019 National Land Cover Database (NLCD).[5] This technique masks out any non-crop data when averaging climate data to the county level (Ortiz-Bobea 2021). Table A1 presents the summary statistics of seasonal weather variables used in our analysis. Figures A3a and A3b show spatial and temporal variations in degree days across counties in the Central Valley.

Additionally, for our extended results, we use USDA NASS's crop-specific statewide price information and crop production data for the years 1980 to 2022. We also obtained the acres of

[4] The data is accessible at https://www.climatologylab.org/gridmet.html, which was accessed on February 27th, 2025.
[5] Specifically, to categorize cropland, we utilize pasture/ hay (code: 81) and cultivated crop (code: 82) as the NLCD land cover classification.

irrigated cropped areas (in acres) for specific from the CA-DWR Statewide Agricultural Water Use data for the years 1998–2020.[6]

Lastly, we simulate the potential impacts of future climate change on California's crops yield and harvested acres using the daily downscaled projections from NASA's NEX-GDDP-CMIP6 dataset. Specifically, we use the Goddard Institute of Space Studies (GISS) climate model's downscaled daily weather projections for the socio-economic pathways (SSP245 and SSP585) to calculate degree-days for future years 2031–2080 relative to 1981–2005 (Thrasher et al. 2022, 2021).

3. Empirical Approach

This section details our empirical approach to estimate the nonlinear effects of temperature change on crop production outcomes in California.

Before we apply econometric techniques to the panel dataset, we begin with a simple detrend analysis between crop yield and mean annual temperatures. More specifically, we construct a standardized crop yield and mean annual temperature, which is commonly used in literature to eliminate any spurious correlation due to possible trends in outcomes between crop production and climate. Second, to empirically estimate the responses of crops yield-temperature and harvested acre-temperature, we employ two econometric approaches: (1) a non-parametric temperature-bin approach; and (2) a piecewise-linear approach.

3.1. Detrend analysis between crop yield and annual mean temperature

[6] Statewide Agricultural Water Use Data is available at https://water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use/Agricultural-Land-And-Water-Use-Estimates

Following Troy, Kipgen, and Pal (2015), we construct a standardized measure of crop yield and mean annual temperature that accounts for technological innovations, improvements in seeds and farm management, changes in cultivar practices, and other time varying factors. Specifically, we use a seven-year moving window and the estimating equation is given by

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

where Y_t is the standardized yield for each of the 20 major crops grown across counties in the Central Valley during 1980–2022. The numerator in equation (1) denotes the difference between yield in a year t and a seven-year moving average centered around that year t. The denominator in equation (1) denotes the standard deviation of yield 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 1983 to 2019. Figure A4 shows the detrended time series of crop-specific raw and standardized yields using a seven-year moving window. Next, we will present econometric specifications for the temperature-bin approach and a piecewise-linear approach.

3.2. Panel estimates

Following Du et al. (2025) and Chen and Gong (2021), we first regress the inverse hyperbolic sine (IHS) transformed crop yield and acres harvested on temperature bins, controlling for a set of linear and quadratic terms of other weather conditions, to detect the critical threshold temperature that potentially results in decline of crop yield and harvested acre. The motivation to use the IHS-transformed dependent variable is first to allow for non-positive yield values; second to handle many zeros in harvested acres; and lastly to minimize the influence of outliers in skewed distribution of outcome of interest (Aihounton and Henningsen 2021).

The estimating equation is given by

$$log\ (y_{i,t}) = \sum_s \sum_m \alpha_m Bin_{i,t}^m + \gamma W_{i,t} + \lambda_i + \mu_1 t + \mu_2 t^2 + \varepsilon_{i,t} \qquad (2)$$

where $y_{i,t}$ denotes yearly crop production outcomes such as yield and acres harvested in county i and year t. $Bin_{i,t}^m$ is a set of temperature variables that measure the number of days with daily mean temperature falling into specific bin m in season $s = \{winter, spring, summer, fall\}$ in year t.[7] We set up 3°C bin intervals between 0–33°C to represent the complete temperature distribution across major crops in our study region. As robustness checks, we repeat equation (2) with 4°C and 5°C bin intervals. The [18°C, 21°C) is selected as reference. $W_{i,t}$ is a vector of linear and quadratic terms representing other weather variables, such as total precipitation levels, average solar radiation, and average wind speed in a county i during each season s in year t; λ_i represents county fixed effects that capture time-invariant unobservable county characteristics. $\mu_1 t + \mu_2 t^2$ is a quadratic time trend to represent the effect of technological progress during the sample period and accounting for any time-varying shocks that are common to all counties in the Central Valley. Finally, the expression error terms, $\varepsilon_{i,t}$, represent variations in our outcome variables that are not explained by our model.

Next, to empirically estimate how nonlinear temperature affects crop production outcomes, we create crop-specific growing degree days (GDD) and heat degree days (HDD). To calculate degree days, we set a lower threshold value of 8°C and an upper threshold value of 24°C during

---

[7] Winter: January, February, and March; spring: April, May, and June; summer: July, August, and September; and fall: October, November, and December. The growing season represents months of April through September.

winter, spring (9°C and 30°C), summer (12°C and 30°C), fall (8°C and 30°C), and growing season (9°C and 30°C).[8] We use a piecewise linear approach to measure the effects of GDD and HDD on crop yield and harvested acre. Following Du et al. (2025) and Chen and Gong (2021b), we set up the following model:

$$y_{i,t} = \sum_s \alpha_0 GDD_{i,t} + \alpha_1 HDD_{i,t} + \gamma W_{i,t} + \lambda_i + \mu_1 t + \mu_2 t^2 + \varepsilon_{i,t} \tag{3}$$

where $GDD_{i,t}$ and $HDD_{i,t}$ are growing degree days are calculated within lower and upper threshold temperature and heat degree days above critical threshold temperature in county i during each season s in year t. All other variables are previously defined in Eq. (2). We cluster our standard errors at the year level to account for serial correlation in the error term.

For agricultural purposes, the counties in the Central Valley can plausibly be assumed to be as homogenous as possible with respect to the variables excluded from the explanatory relationship, such as input prices, prevailing agricultural practices. Therefore, our study region offers advantage in reducing omitted variable bias. Because our econometric model only considers climatic constraints to crop production outcomes, we examine the statewide price response to changes in state average crop production and estimate elasticity measures for each crop (Miao et al. 2016). This elasticity measure can allow us to identify the direction of potential bias in estimating impacts of warmer temperatures on projected crop production outcomes.

Lastly, to estimate the potential impacts of projected changes in temperatures on crop production outcomes, 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). Using the estimated

[8] We use a single sine-curve method to calculate annual degree days and degree days during growing season. Specifically, we use the *dd_sng_sine* function available under the *degday* library in R to calculate the degree days.

coefficients from our econometric model, we quantify the changes in the projected climate-driven crops yield and harvested acre 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 degree days (and heat degree days) in 2031–2055 (or 2056–2080 for a measure of long-term impact) and the historical average degree days in 1981–2005.

4. Results and Discussion

The results are divided into five sections. First, we present a simple correlation between standardized measures of crop yields and mean annual temperatures. Second, we present panel estimates of nonlinear effects of temperature on crop production outcomes such as yield and harvested acres. Third, we examine lagged nonlinear effects of temperature on crop yield and harvested acres. Fourth, we explore whether recent past year's crop yields are a good indicator of planted areas, as well as the relationship between crop price and production. Fifth, we use these models to quantify the effects of projected warming on California's crop production outcomes.

4.1. Correlation between annual detrended crop yields and mean annual temperatures

Figure A5 shows the correlation coefficient between standardized yield and standardized mean temperature (mean annual temperature for perennial crops and mean temperature during the growing season for annual crops) between 1983 and 2019. Citrus and subtropical fruit trees, rice, cotton, alfalfa, and cucurbit crops have positive and significant correlations with mean temperatures. The positive correlation between standardized yield and standardized mean temperature suggests that yield responds more to changes in mean temperatures. The relationship between changes in mean annual temperatures and mean yields is shown, but climatic conditions can also impact yields during different plant growth stages. In the next section, we empirically examine the relationship between crop production outcomes and temperature using econometric techniques.

4.2. Nonlinear effects of temperature on crops production outcomes

First, we present the effects of temperature bins on yield and harvested acre. Second, we present the results using a piecewise linear approach.

4.2.1 Impacts of temperature bins on yield and harvested acre

In this section, we present the crop yield- and harvested acres-temperature response curves using the non-parametric temperature-bin approach. We regress the IHS transformed yield of 20 major crops on temperature bins (3-degree temperature interval).

Figures A6a, A6b, and A6c together show the impacts of temperature on yields of 20 major crop groups during 1980–2022. It appears that the yield of perennial crops is more sensitive to warmer temperatures, particularly in the winter, spring, and fall seasons. Importantly, the yield of perennial crops is not as sensitive to summer hot days. Similarly, the yield of major annual crops is not as sensitive to warmer temperatures (above 30°C), except for safflowers, and processing, and fresh tomatoes, for which yield declines less than 1%. In contrast, corn yield is positively associated with lower temperatures (below 9°C) in our study region.

Figures A7a, A7b, and A7c collectively show the impacts of temperature bins on acres harvested of 20 major crops groups in Central Valley. The dependent variable is the IHS-transformed crop harvested acres from 1980 to 2022. The harvested acres of almonds is negatively associated with higher temperatures (above 30°C) in the fall, while the harvested acres of orchards and vineyards are positively associated with higher temperatures (above 30°C) in the fall season. The harvested acres of orchard and vineyards are negatively associated with higher temperatures (above 24°C) in the winter, while the harvested acre of pistachios is positively associated with winter higher temperatures (above 24°C). Moreover, the harvested acre of fresh tomatoes declines with lower temperatures (below 9°C).

In summary, increased frequency of very hot days are associated with reduced harvested acres of specialty nuts and tree crops.

4.2.2 Panel estimates of nonlinear effects of temperature on yield and harvested acre

Table 2 presents the panel estimates of the impact of temperature on crop yields across counties in the Central Valley. The dependent variable is IHS-transformed crops yield from 1980 to 2022, and the main explanatory variables are degree days below and above threshold temperatures. All regressions include weather controls, as well as linear and quadratic time trends and county fixed effects.

Results suggest that the yield of almonds, orchards, and vineyards is negatively associated with degree days. Specifically, for a hundred unit increase in degree days during winter, the yields of almonds and orchards decline by 6.5% and 3.2% respectively. The negative effect size on vineyards with respect to heat degree days during fall, which is 52.3% outweighs the positive impact during winter (8.7%).

The yield of alfalfa crops is negatively associated with high temperatures during summer. Specifically, a hundred unit increase in heat degree days during summer is associated with a decline in alfalfa yield by 32.2%. Moreover, for a hundred unit increase in degree days, it is associated with a decline in the yield of safflower crop processing tomatoes, onion, and garlic by 2.2%, 2%, and 5.1%. The positive effect of the size of heat degree days on potato yield outweighs the negative impact of increased growing degree days on potato yield (21.1% vs. -3.8%).

Next, in Table 3, we present the panel estimates of the impact of temperature on harvested acres across counties in the Central Valley. The dependent variable is IHS-transformed crops yield from 1980 to 2022. Results suggest that the degree days reduce the harvested acreage of almonds and vineyards. The harvested acre of almonds decreases by 9.2% during winter, while summer heat degree days decrease the harvested acre of vineyards by 33.3%. In contrast, degrees days are positively associated with the harvested acres of pistachios, orchards, citrus, and subtropical fruit trees.

The summer degree days are negatively associated with alfalfa harvested acreage, but the positive effect of heat degree days on alfalfa harvested acreage outweighs this negative effects (63.1% vs. -23.7). Overall, the harvested acre of alfalfa is positively associated with degree days. Moreover, the acre harvested for processing tomatoes, cucurbits, and potatoes is negatively associated with heat degree days. While the harvested acreage of the safflower crop is positively associated with high degree days.

We repeat our main analysis for degree days defined at upper threshold values of 25°C, 26°C, 28°C, 29°C, and 31°C. Although not shown, results are quantitatively the same as the main results.

Finally, to account for spatial variations, we repeat the crop production outcome regressions in equation (3) after applying acreage-weights, and the results are quantitatively similar to our main results.

4.3. Lagged nonlinear effects of temperature on crops yield and harvested acre

This subsection examines the effects of previous years' average temperatures and precipitation as a measure of growers' expectations about climate on contemporaneous crop yields and harvested acres. Specifically, we follow Wimmer et al. (2024), and create lagged degree days from previous years for our study region and considered two different time scales: the more recent (average of degree days between t-3 to t-1 years) and the more distant (average of degree days between t-10 to t-4 years). We include four lagged terms of degree days (two lagged terms of degree days each for more recent and more distant periods) as additional covariates in the right-hand side of our main specification. Additionally, the total precipitation for both near (t-3 to t-1) and far (t-10 to t-4) lagged terms is included in the specification. Taken together, this econometric specification allows us to take into account growers' recent experiences with climate in farming decisions.

Fig 1a and 1b show the impacts of temperature on perennial and annual crop yields. The dependent variable is IHS-transformed yield across Central Valley during 1980-2022. The main explanatory variables are degree days (GDD) and heat degree days (HDD) separate for each season in a year. All regressions include recent (t-3 to t-1) and distant (t-10 to t-4) lagged degree days, recent and distant lagged total annual precipitation, weather controls, as well as linear and quadratic time trends, and county fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Regressions are weighted by 1981-2022 county-average harvested acre. Results suggest that a hundred unit increase in degree days during winter is negatively associated with the yield of almonds, orchards, alfalfa, and other field crops by 7.6%, 7.9%, 7.9%, and 18.3%. While the yield of vineyards is positively associated with the number of degree days. A hundred unit increase in degree days results in a 10.2% increase in vineyard yields. The yield of pistachios, citrus, and subtropical fruit trees is positively associated with high degree days during winter. However, high temperatures during the fall season of the year negatively impact vineyards, citrus, and subtropical fruit trees. The effect size representing negative associations during fall outweighs any gain on vineyard, citrus, and subtropical fruit tree crops during increased degree days during winter.

Degree days have a negative impact on the yield of corn, onions, and garlic. A hundred unit increase in degree days results in a 2.2% decrease in corn yield, and a 4.2% decrease in onions and garlic yield.

Next, we present the panel estimates of the impact of concurrent and lagged climate conditions on harvested acres. The relationship between past years' climate conditions and harvested acreage may not be straightforward. Here, we include concurrent and lagged temperatures to account for growers' expected climate experience during harvesting.

Fig 2a and 2b show the impacts of temperature on perennial and annual crop harvested acres. The dependent variable is IHS-transformed harvested acres across Central Valley during 1980-2022. All regressions include recent (t-3 to t-1) and distant (t-10 to t-4) lagged degree days, recent and distant lagged total annual precipitation, weather controls, as well as linear and quadratic time trends, and county fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Regressions are weighted by 1981-2022 county-average harvested acre.

The harvested acreage of almonds is negatively associated with degree days during winter but positively associated with degrees days during fall. The impact of warming temperatures during fall on almonds harvested acreage outweighs the negative impact during winter. An increase in degree days during summer is positively linked to the harvested acreage of pistachios. The harvested acreage of orchards is negatively associated with degrees during winter and summer, but positively associated with degrees during fall, and with respect to heat degrees during winter and fall. Overall, the impact on orchard harvested acres outweighs the negative impact of rising temperatures. The harvested area of citrus and subtropical fruit trees is positively associated with the degree days during summer. The harvested acreage of vineyards is positively associated with degree days during fall, but negatively associated with heat degree days during spring, outweighing any gains. During winter, grain harvested acreage have a negative impact on degree days. The positive effect size on the harvested acres of other field crops outweighs the negative impact of warming temperatures. In contrast, the negative impact of truck crops harvesting acreage outweighs the positive impact of warming temperatures.

Heat degree days negatively affect the harvested acres of dry beans, cucurbits, and potatoes.

Alfalfa harvested acreage has a positive effect on heat degree days during spring, while corn harvested acreage has a negative effect on heat degree days. Overall, the harvested area of forage production is negative.

In summary, both recent past and distant past lagged heat degree days potentially reduced the yields of some of the major perennial and annual crops in our study region.

4.4. Extended results

As previously mentioned, our empirical estimates only consider climatic constraints to estimate the nonlinear effects of temperature on crop production outcomes. But crop production outcomes are also influenced by external factors, such as output prices. In this subsection, we first explore whether recent year yields are a good indicator of acres planted in our study region. Secondly, to establish a relationship between crop-specific output price information and crop production, we present a simple correlation between statewide crop prices and crop production levels.

Figure A8 shows the slope of regression of irrigated cropped areas in response to recent past 3-year average yield for each major crop during 1998 to 2020. It appears that the estimated correlation coefficient of many major crops is statistically insignificant, except for irrigated cropped areas of sugar beets, potatoes, and dry beans, which has a positive association with the 3-year average yield of sugar beet and a negative association with the yields of potatoes and dry beans.

Figure A9 shows the slope of a regression of IHS-transformed crop price information in response to changes in IHS-transformed crop production for each of the 20 major crops in California. The results can be interpreted as elasticity. Crop production and statewide prices of perennial crops, such as almonds, pistachios, orchards, citrus, and subtropical trees, have a significant positive correlation. Major annual crops, such as grains, rice, corn, processed tomatoes, cucumbers, onion and garlic, potatoes, and truck crops, have positive correlations between crop production and statewide prices. In contrast, cotton, sugar beet, dry beans, and alfalfa show a negative correlation between crop production and statewide prices. Price responsiveness to production changes of perennial and annual crops suggests that the potential impacts of climate change on perennial and annual crops are possibly underestimated, except for cotton, sugar beet, dry beans, and alfalfa, are possibly overestimated.

4.5. Projections of impacts under future climate change

Table A4 presents the estimates of county-level seasonal degree days used in our analysis compared to their averages from 1981 to 2005. The minimum annual temperature is higher by 1.84 (1.95) °C for the near-medium term, and by 2.07 (3.22) °C over the long term for scenario SSP245 (SSP585), compared to the average minimum temperature from 1981 to 2005. Similarly, the average maximum annual temperature under the SSP245 (SSP585) climate scenario is expected to increase by 1.76 (1.95) °C in the near-medium term and by 2.06 (3.22) °C in the long-term in our study region. The degree days during winter, spring, summer, and fall increases under the SSP245 climate scenario by 68, 119, 104, and 117 in the near-medium term, and by 75, 134, 111, 157 degree days in long term. The heat degree days increase under the SSP245 climate scenario by 2, 17, 46, and 4 in the near-medium term, and by 4, 20, 49, and 6 in the long term. In the near-medium term, it is expected that spring temperature days will increase the most, while summer heat days will increase the most. That is, in the near-medium term, 47% more than the historical mean summer heat degree days between 1981 and 2005. Next, using our estimated coefficients, we quantify the effects of projected climate change on California's crops yield and harvested acres.

Figures 3a and 3b show the projected changes in crops yield and harvested acres with respect to degree days and heat degree days under the SSP245 climate scenario. Results suggest that an increase in degree days during winter and fall in the near-medium term and in the long term is expected to increase the yields of vineyards (near-medium term: 6.9% and long term: 7.6%) and citrus, subtropical fruit trees (9% and 12.1%). While the yields of almonds and orchards are expected to decline with respect to degree days during winter (almonds: 5.2% and 5.7% and orchards: 5.4% and 5.9%). The forage production is also expected to decline, including alfalfa

(5.4% and 5.9%) and corn (5.2% and 5.7%). The onion and garlic yield is also expected to decline between 10% and 11% in near-medium term and long term.

Additionally, heat degree days during fall season in the new-medium term (2031–2055) and in the long term (2056–2080) relative to 1981–2005 will have a negative impact on the projected yields of citrus , subtropical fruit trees (6.7% decline in the near-medium term and 10% decline in the long term) and vineyards (4.8% and 7.3%). While pistachio yield is expected to increase with respect to heat degree days during winter between 6.3% and 12.6%.

Next, degree days during spring and fall are expected to increase the harvested acre of vineyards, whereas, degree days during summer and fall are expected to increase the harvested acre of orchards and truck crops (upper panel; Figure 3b). The harvested acreage of almonds, orchards, grain, field and truck crops are expected to decline with respect to degree days during winter. Moreover, the heat degree days in the near-medium term and in the long term relative to 1981–2005 will negatively impact on the projected harvested acres of corn (near-medium term: 45% and long term: 49%), dry beans (28% and 30%), cucurbits (31% and 34%), and potatoes (38% and 41%). Tables A5a and A5b summarize the full results of yield and harvested acre for the projected climate scenarios for SSP245 and SSP585.

Our finding is partly consistent with the observation by (Lobell et al. 2006), which suggests moderate to significant projected yield declines for oranges, avocados, wine grapes, and almonds.[9] Wu et al. (2025) also found a modest loss in almond yields in California due to climate change but suggests that innovations in almond tree crops and changes in cultivar practices may reduce the loss of crop yield due to climate change. Contrarily, we find a small

[9] For reference, Lobell et al. (2006) estimated the upper bound of 3°C for 2050 and 6°C for 2100 using the climate scenarios under the Program for Climate Model Diagnosis and Intercomparison (PCMDI).

decline in almond yields. The net effect of climate change on California's perennial agriculture, especially almonds and pistachios, warrants global trade assessments, which we do not address here due to data limitations and will leave to future research. When interpreting our projected impacts results, one important caveat must be taken into consideration. Conditional on our baseline model, the projections of impacts under future climate change focus only on warming temperatures while holding other weather variables such as total precipitation, average solar radiation, and average wind speed fixed.

5. Conclusion

We have examined the direction and assessed the sensitivity of major groups of perennial and annual crop production outcomes to expected temperature changes in California's Central Valley in the context of climate change. Our results show that the temperature-related yield response appears relatively muted for the most major crop groups for the projected temperature rise horizon (2031–2080), and, at present, have not yet experienced statistically significant declines attributable to warmer temperatures. In contrast, the harvested acreage of almonds, corn, dry beans, cucurbits, and potatoes, suggests a negative response to warmer temperatures.

There are various known climate-cropping system feedback that is not incorporated into this specific analysis. For example, it is anticipated that while atmospheric warming may increase overall crop evapotranspiration in the region (Moyers et al. 2024), warming is likely to accelerate maturation for many crops, thus reducing the growing season and limit the overall impact to crop water demand (Abatzoglou et al. 2025). The latter is likely to affect crop production cycles. Regardless, it is well established that growers often compensate for changing climatic conditions at a variety of spatiotemporal scales and interventions (Cui 2020). Human interventions, particularly sociopolitical ones, are not addressed here but recent changes in groundwater management strategies are affecting lending, profitability, and decision making (Bruno and Jessoe 2024). More inter-disciplinary research is needed between climate-agriculture and trade supply chain logistics to fully understand the interactions between temperature and crop production outcomes.

Tables and Figures

Table 1. Summary statistics

	Yield (ton/acre)		Harvested acre (`000)	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A: Perennial crops				
Almonds	0.76	0.26	42.52	51.02
Pistachios	1.13	0.47	17.96	28.96
Orchard	6.80	5.90	4.65	7.73
Citrus & Subtropical	8.50	5.37	7.99	14.42
Vineyards	8.34	3.43	22.22	30.22
Alfalfa	6.42	1.96	32.70	32.34
Panel B: Annual crops				
Rice	3.64	0.98	28.62	39.20
Cotton	0.72	0.38	63.15	85.12
Sugar beet	26.64	4.22	7.85	7.61
Corn	12.20	9.90	18.64	27.17
Dry beans	1.13	0.74	4.10	4.54
Safflower	1.13	0.33	6.69	8.28
Tomatoes processing	34.18	5.50	23.00	24.98
Tomatoes fresh	15.84	5.71	3.58	3.53
Cucurbits	14.13	7.19	2.57	4.77
Onion & garlic	15.78	7.56	8.86	7.89
Potatoes	15.74	4.95	7.30	8.00
Grain	2.60	1.82	11.71	16.35
Other field crops	2.43	3.67	5.26	11.00
Truck crops	7.89	6.49	3.19	5.45

Notes: Mean values are reported across 18 counties in the Central Valley from 1980 to 2022. To handle outliers, the crop yield data is *winsorized* at the 1st and 99th percentiles. The eighteen counties are as follows: Tehama, Glenn, Butte, Colusa, Yolo, Solano, Sutter, Yuba, Placer, Sacramento, San Joaquin, Stanislaus, Merced, Madera, Fresno, Tulare, Kern, and Kings. The Online Appendix Table 1 provides definitions for crop groups such as grain, other field crops, and truck crops.

Table 2. Panel estimates of the impact of temperature on California's Central Valley crop yields

Dependent variable: IHS (Yield)	Almonds (1)	Pistachios (2)	Orchard (deciduous) (3)	Citrus & subtropical (4)	Vineyards (5)	Alfalfa (6)	Grain (7)	Other field crops (8)	Truck crops (9)
Winter (JFM)									
GDD (8C – 24C; hundred)	-0.065***	0.050	-0.032**	0.026	0.087**	-0.024	-0.018	-0.053	-0.034
	(0.024)	(0.053)	(0.015)	(0.039)	(0.036)	(0.034)	(0.014)	(0.065)	(0.047)
HDD (above 24C; hundred)	0.031	1.106	-0.257	0.276	-0.008	0.088	-0.085	-0.257	-0.099
	(0.115)	(0.936)	(0.262)	(0.302)	(0.154)	(0.263)	(0.090)	(0.250)	(1.014)
Spring (AMJ)									
GDD (9C – 30C; hundred)	0.009	-0.053	0.009	0.093	0.019	0.031	-0.020	-0.021	-0.005
	(0.014)	(0.045)	(0.014)	(0.051)	(0.033)	(0.024)	(0.012)	(0.041)	(0.035)
HDD (above 30C; hundred)	-0.080	-0.167	0.090	0.169	-0.069	-0.051	0.053	0.099	0.102
	(0.077)	(0.237)	(0.115)	(0.183)	(0.116)	(0.094)	(0.079)	(0.185)	(0.264)
Summer (JAS)									
GDD (12C – 30C; hundred)	0.039	-0.040	0.043	0.016	-0.033	0.028	-0.027	0.132**	0.030
	(0.023)	(0.045)	(0.022)	(0.048)	(0.030)	(0.037)	(0.016)	(0.058)	(0.043)
HDD (above 30C; hundred)	0.007	0.234	-0.077	-0.060	-0.019	-0.322***	-0.033	-0.434***	-0.002
	(0.038)	(0.136)	(0.057)	(0.095)	(0.064)	(0.063)	(0.051)	(0.117)	(0.117)
Fall (OND)									
GDD (8C – 30C; hundred)	-0.031	-0.072	-0.016	-0.010	0.001	-0.055	0.012	-0.028	-0.024
	(0.018)	(0.043)	(0.021)	(0.035)	(0.029)	(0.027)	(0.012)	(0.045)	(0.040)
HDD (above 30C; hundred)	-0.046	-0.733	0.214	-0.059	-0.523**	0.054	-0.020	-0.106	0.849
	(0.130)	(0.456)	(0.194)	(0.472)	(0.472)	(0.262)	(0.102)	(0.281)	(0.759)
Observations	692	341	4,357	1,175	1,097	784	2774	528	1,395
R-squared	0.706	0.528	0.181	0.395	0.491	0.252	0.249	0.528	0.252

	Rice (10)	Cotton (11)	Sugar beet (12)	Corn (13)	Dry beans (14)	Safflower (15)	Tomatoes Processing (16)	Tomatoes Fresh (17)	Cucurbits (18)	Onion & garlic (19)	Potatoes (20)
GDD (9C –	0.021**	0.005	-0.002	-0.016	-0.004	-0.022**	-0.019**	-0.009	0.011	-	-
30C; hundred)	(0.009)	(0.012)	(0.009)	(0.008)	(0.008)	(0.011)	(0.007)	(0.018)	(0.014)	0.051**	0.038***
										(0.020)	(0.013)
HDD (above 30C; hundred)	-0.061	0.036	0.022	0.017	-0.025	0.047	0.008	0.087	-0.004	0.234	0.211**
	(0.066)	(0.043)	(0.041)	(0.054)	(0.037)	(0.040)	(0.026)	(0.134)	(0.081)	(0.122)	(0.093)
Observations	763	349	337	1,191	1,125	468	342	306	1,073	241	207
R-squared	0.242	0.288	0.584	0.220	0.266	0.327	0.857	0.361	0.220	0.149	0.779

Notes: Standard errors presented in parentheses are clustered over year. The dependent variable is the IHS-transformed crop yields. All regressions include weather controls, as well as linear and quadratic time trends and county fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: ** $p < 0.05$, *** $p < 0.01$.

Table 3. Panel estimates of the impact of temperature on California's Central Valley harvested acreage

Dependent variable: IHS (Harvested acre)	Almonds	Pistachios	Orchard (deciduous)	Citrus & subtropical	Vineyards	Alfalfa	Grain	Other field crops	Truck crops		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Winter (JFM)											
GDD (8C –	-0.092**	-0.061	-0.017	-0.035	0.076	-0.037	-0.016	-0.127**	-0.064		
24C; hundred)	(0.040)	(0.061)	(0.028)	(0.025)	(0.056)	(0.066)	(0.038)	(0.050)	(0.072)		
HDD (above	-0.058	1.675	0.190	0.773***	0.168	1.320	0.378	-0.239	0.264		
24C; hundred)	(0.371)	(1.060)	(0.370)	(0.260)	(0.403)	(1.210)	(0.291)	(0.288)	(0.727)		
Spring (AMJ)											
GDD (9C –	0.014	0.072	0.010	0.029	0.096**	0.030	-0.004	0.025	0.035		
30C; hundred)	(0.032)	(0.040)	(0.020)	(0.027)	(0.036)	(0.055)	(0.032)	(0.036)	(0.037)		
HDD (above	-0.055	-0.280	0.095	-0.150	-0.276	-0.103	-0.059	-0.527**	0.109		
30C; hundred)	(0.171)	(0.275)	(0.160)	(0.171)	(0.205)	(0.318)	(0.150)	(0.210)	(0.254)		
Summer (JAS)											
GDD (12C –	0.016	0.132**	0.071**	0.046	0.103	-0.237***	-0.001	-0.043	0.093		
30C; hundred)	(0.039)	(0.056)	(0.027)	(0.032)	(0.061)	(0.081)	(0.042)	(0.052)	(0.056)		
HDD (above	0.100	0.410***	-0.147	0.185	-0.333**	0.631**	0.031	0.398***	-0.124		
30C; hundred)	(0.085)	(0.125)	(0.103)	(0.100)	(0.148)	(0.251)	(0.107)	(0.120)	(0.166)		
Fall (OND)											
GDD (8C –	0.045	0.071	0.067**	0.031	0.057	-0.034	-0.031	-0.030	0.0001		
30C; hundred)	(0.028)	(0.037)	(0.031)	(0.021)	(0.035)	(0.052)	(0.037)	(0.047)	(0.048)		
HDD (above	0.021	-0.638	0.31	0.169	0.094	1.477	0.019	0.844***	1.191***		
30C; hundred)	(0.344)	(0.438)	(0.329)	(0.264)	(0.402)	(1.188)	(0.249)	(0.288)	(0.438)		
Observations	705	345	4,810	1,203	1,096	817	2,783	2,000	1,894		
R-squared	0.945	0.918	0.193	0.480	0.700	0.741	0.262	0.208	0.293		
	Rice	Cotton	Sugar beet	Corn	Dry beans	Safflower	Tomatoes Processing	Tomatoes Fresh	Cucurbits	Onion & garlic	Potatoes
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
GDD (9C –	-0.026	-0.005	-0.010	-0.003	-0.072	-0.019	0.061	-0.038	0.063	-0.022	0.039
30C; hundred)	(0.035)	(0.089)	(0.034)	(0.041)	(0.041)	(0.057)	(0.033)	(0.052)	(0.034)	(0.054)	(0.029)
HDD (above	0.036	-0.705	-0.011	-0.397	-0.255	0.379**	-0.466***	-0.145	-0.647**	-0.215	-0.372**
30C; hundred)	(0.209)	(0.362)	(0.249)	(0.199)	(0.167)	(0.176)	(0.107)	(0.378)	(0.271)	(0.348)	(0.182)
Observations	764	349	358	1,190	1,133	470	490	305	1,080	242	207
R-squared	0.324	0.326	0.793	0.329	0.316	0.653	0.796	0.618	0.356	0.618	0.841

Notes: Standard errors presented in parentheses are clustered over year. The dependent variable is the IHS-transformed harvested acres. All regressions include weather controls, as well as linear and quadratic time trends and county fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Level of significance: ** $p < 0.05$, *** $p < 0.0$

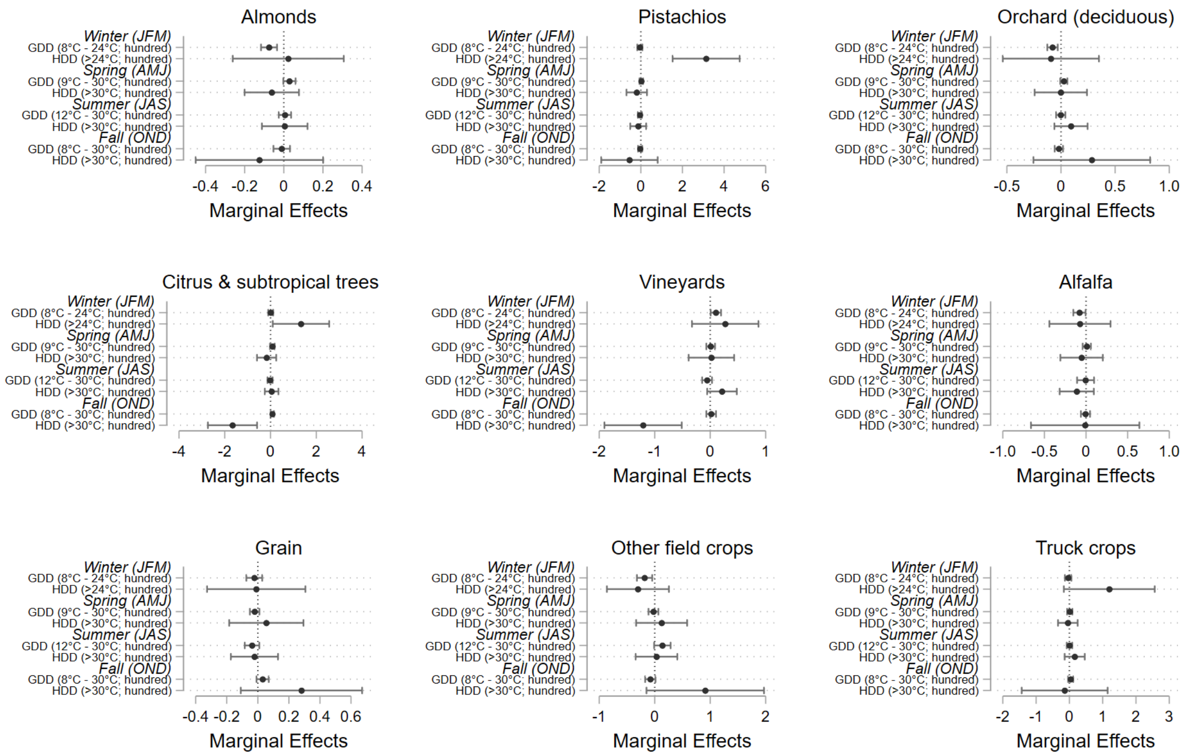

Figure 1a. Impacts of temperature on perennial crop yields, as well as grain, other field crops, and truck crops

Notes: The dependent variable is the IHS-transformed crop yields from 1980 to 2022. The specification includes concurrent and lagged degree days, second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. Regressions are weighted by 1981-2022 county-average harvested acre. The figure plots the point estimate and 95% confidence intervals for each crop. Point estimates were obtained from Table A2. To interpret the point coefficients, we need to multiply them by 100

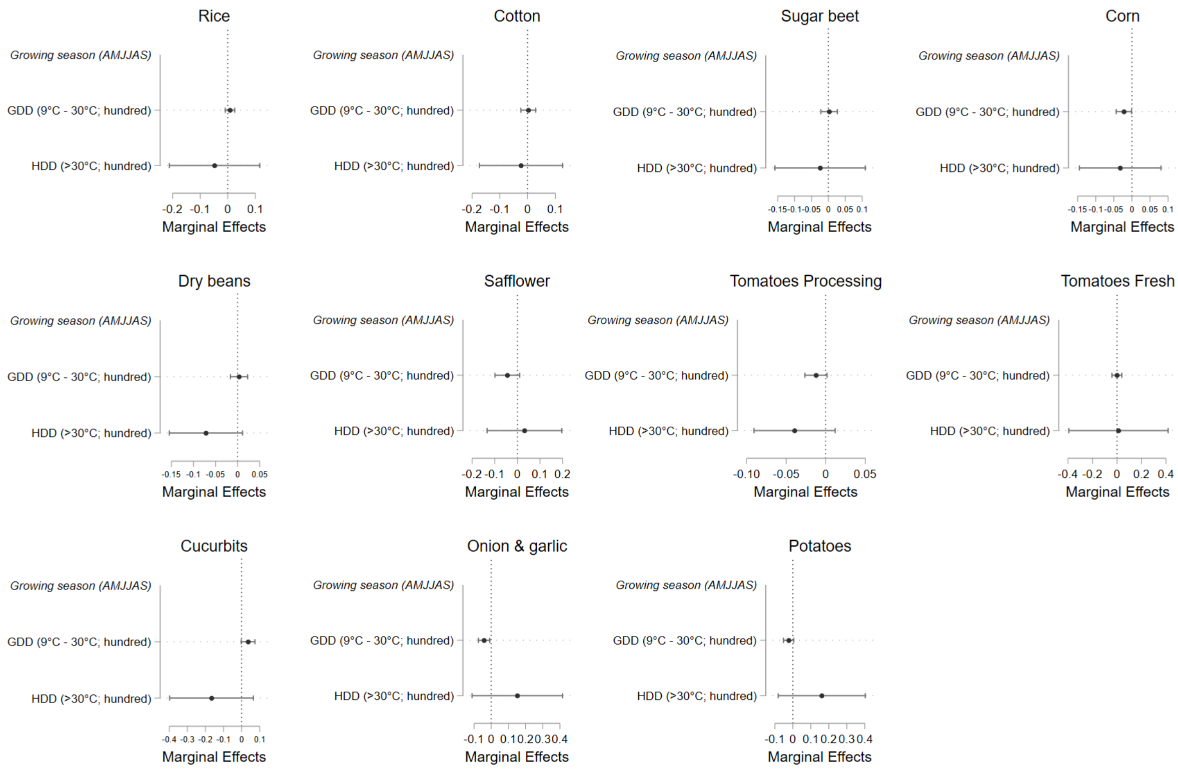

Figure 1b. Impacts of temperature on annual crop yields

Notes: The dependent variable is the IHS-transformed crop yields from 1980 to 2022. The specification includes concurrent and lagged degree days, second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. Regressions are weighted by 1981-2022 county-average harvested acre. The figure plots the point estimate and 95% confidence intervals for each crop. Point estimates were obtained from Table A2. To interpret the point coefficients, we need to multiply them by 100.

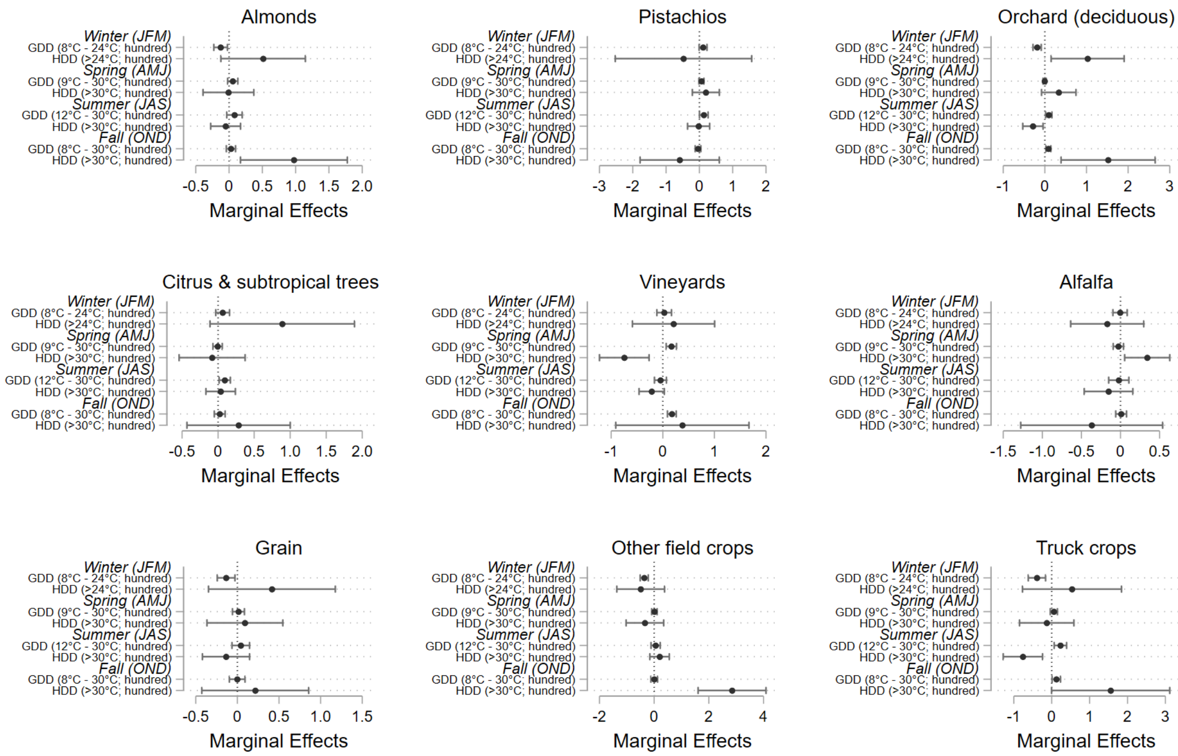

Figure 2a. Impacts of temperature on harvested acre of perennial crops, as well as grain, other field crops, and truck crops

Note: The dependent variable is the IHS-transformed harvested acre from 1980 to 2022. The specification includes concurrent and lagged degree days, second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. Regressions are weighted by 1981-2022 county-average harvested acre. The figure plots the point estimate and 95% confidence intervals for each crop. Point estimates were obtained from Table A3. To interpret the point coefficients, we need to multiply them by 100.

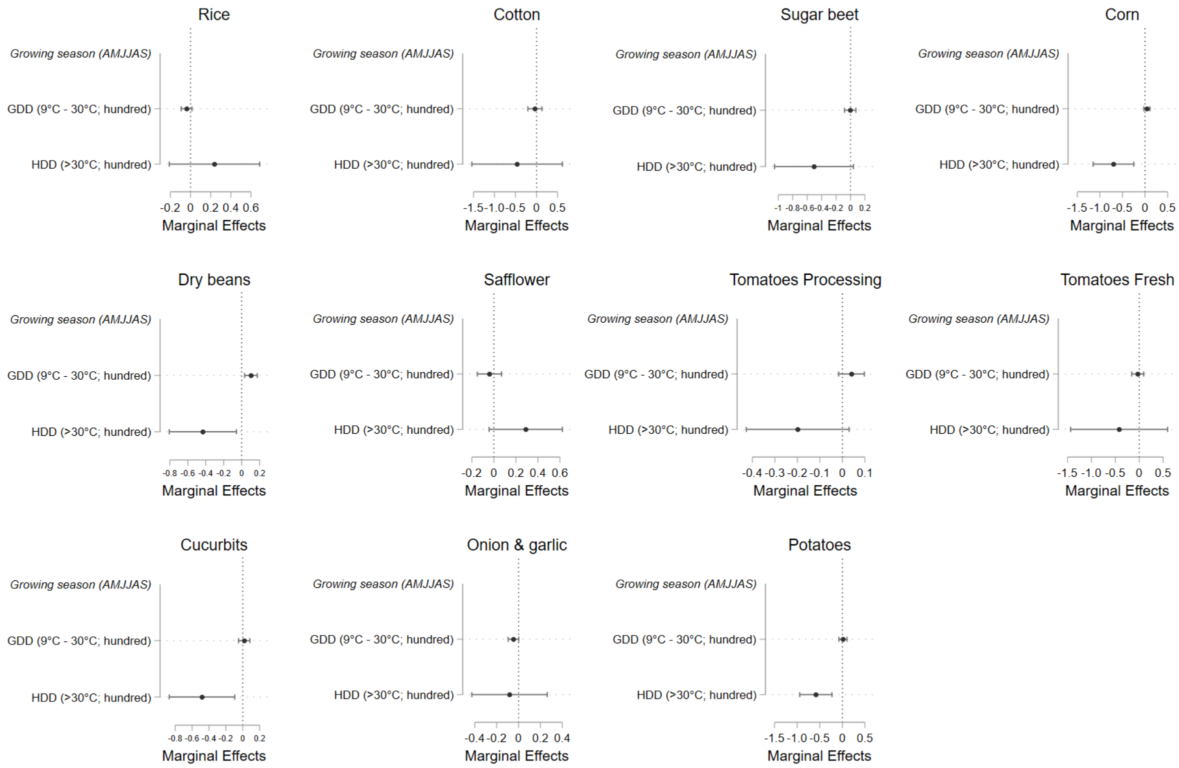

Figure 2b. Impacts of temperature on harvested acre of annual crops

Note: The dependent variable is the IHS-transformed harvested acre from 1980 to 2022. The specification includes concurrent and lagged degree days, second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. Regressions are weighted by 1981-2022 county-average harvested acre. The figure plots the point estimate and 95% confidence intervals for each crop. Point estimates were obtained from Table A3. To interpret the point coefficients, we need to multiply them by 100.

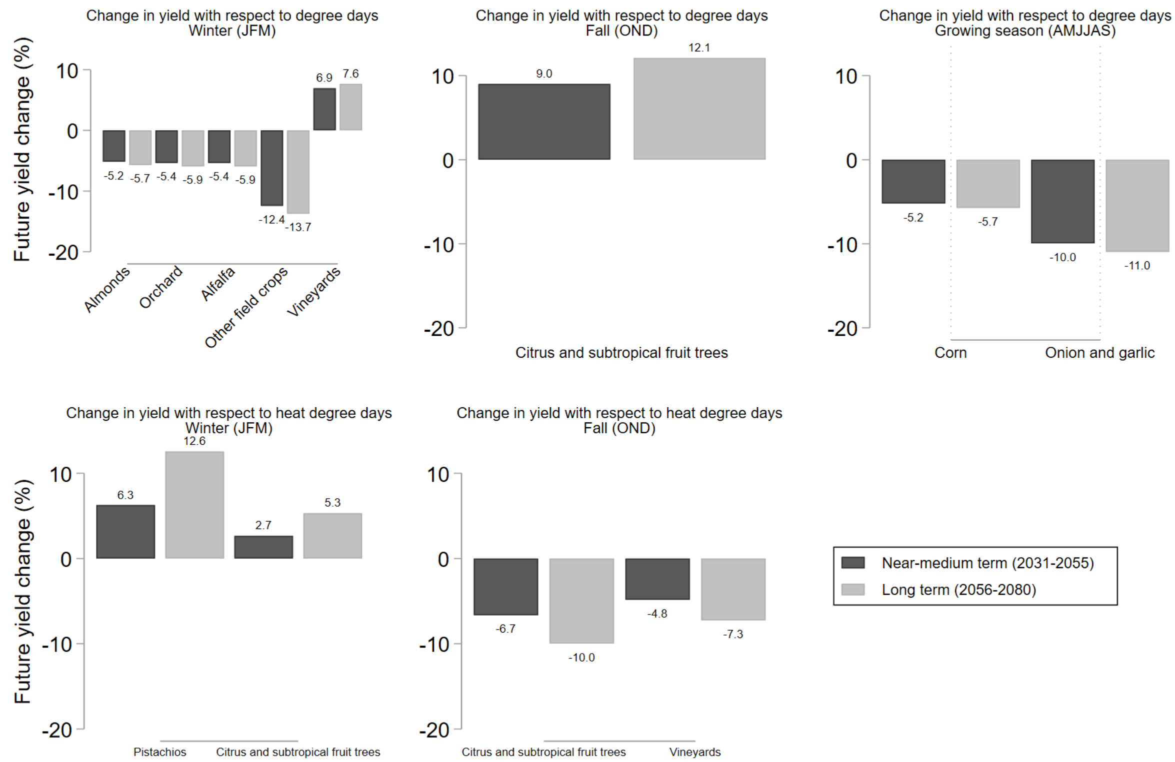

Figure 3a. Percentage change in crop yield across the Central Valley regions over two periods (2031–2055 and 2056–2080) under SSP245.

Notes: The percentage change of projected impacts of climate change on crop yields are reported. These are calculated by multiplying the statistically significant coefficients of average marginal effects (Figure 1) and the difference between the average projected climate in 2031–2055 and the average climate in 1981–2005. Similarly, long-term 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.

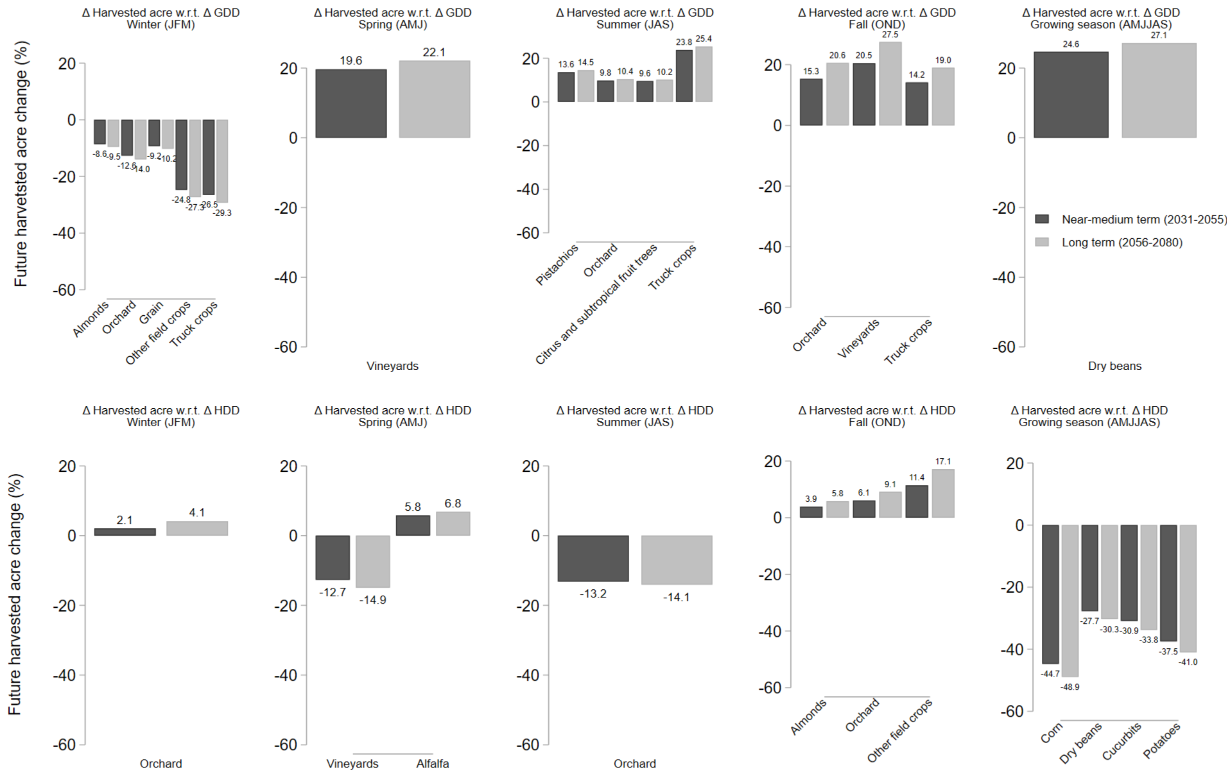

Figure 3b. Percentage change in harvested acres across the Central Valley regions over two periods (2031–2055 and 2056–2080) under SSP245.

Notes: The percentage change of projected impacts of climate change on harvested acres are reported. These are calculated by multiplying the statistically significant coefficients of average marginal effects (Figure 2) and the difference between the average projected climate in 2031–2055 and the average climate in 1981–2005. Similarly, long-term 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.

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.

Abatzoglou, John T., Lauren E. Parker, Joshua H. Viers, et al. 2025. "Shorter Growing Seasons May Moderate Climate Change Effects on Crop Water Demands." *Environmental Research Letters* 20 (3): 034017. https://doi.org/10.1088/1748-9326/adb1f5.

Aihounton, Ghislain B. D., and Arne Henningsen. 2021. "Units of Measurement and the Inverse Hyperbolic Sine Transformation." *The Econometrics Journal* 24 (2): 334–51. https://doi.org/10.1093/ectj/utaa032.

Albano, Christine M., John T. Abatzoglou, Daniel J. McEvoy, et al. 2022. "A Multidataset Assessment of Climatic Drivers and Uncertainties of Recent Trends in Evaporative Demand across the Continental United States." *Journal of Hydrometeorology* 23 (4): 505–19. https://doi.org/10.1175/JHM-D-21-0163.1.

Bruno, Ellen M., and Katrina Jessoe. 2024. "Designing Water Markets for Climate Change Adaptation." *Nature Climate Change* 14 (4): 331–39. https://doi.org/10.1038/s41558-024-01964-w.

Chen, Chi-Chung, and Ching-Cheng Chang. 2005. "The Impact of Weather on Crop Yield Distribution in Taiwan: Some New Evidence from Panel Data Models and Implications for Crop Insurance." *Agricultural Economics* 33 (s3): 503–11. https://doi.org/10.1111/j.1574-0864.2005.00097.x.

Chen, Shuai, and Binlei Gong. 2021a. "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.

Chen, Shuai, and Binlei Gong. 2021b. "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.

Cordero, Eugene C., Wittaya Kessomkiat, John Abatzoglou, and Steven A. Mauget. 2011. "The Identification of Distinct Patterns in California Temperature Trends." *Climatic Change* 108 (1–2): 357–82. https://doi.org/10.1007/s10584-011-0023-y.

Cui, Xiaomeng. 2020. "Beyond Yield Response: Weather Shocks and Crop Abandonment." *Journal of the Association of Environmental and Resource Economists* 7 (5): 901–32. https://doi.org/10.1086/709859.

Cui, Xiaomeng, and Wei Xie. 2022. "Adapting Agriculture to Climate Change through Growing Season Adjustments: Evidence from Corn in China." *American Journal of Agricultural Economics* 104 (1): 249–72. https://doi.org/10.1111/ajae.12227.

Cui, Xiaomeng, and Zheng Zhong. 2024. "Climate Change, Cropland Adjustments, and Food Security: Evidence from China." *Journal of Development Economics* 167 (March): 103245. https://doi.org/10.1016/j.jdeveco.2023.103245.

Deschenes, Olivier, and Charles Kolstad. 2011. "Economic Impacts of Climate Change on California Agriculture." *Climatic Change* 109 (S1): 365–86. https://doi.org/10.1007/s10584-011-0322-3.

Du, Jue, Xiaoguang Chen, and Lingling Hou. 2025. "Cropping Frequency and Crop Acreage in Response to Temperature Change: Evidence from China." *Journal of the Agricultural and Applied Economics Association*, February 17, jaa2.70008. https://doi.org/10.1002/jaa2.70008.

Fazli, Shahryar, Wenzhao Li, Surendra Maharjan, Rejoice Thomas, Aqil Tariq, and Hesham El-Askary. 2025. "Adaptive Crop Switching for Irrigated Agriculture in Response to Climate Change in the Western U.S." *Agricultural Water Management* 318 (September): 109700. https://doi.org/10.1016/j.agwat.2025.109700.

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.

Kerr, Amber, Jake Dialesandro, Kerri Steenwerth, Nathan Lopez-Brody, and Emile Elias. 2018. "Vulnerability of California Specialty Crops to Projected Mid-Century Temperature Changes." *Climatic Change* 148 (3): 419–36. https://doi.org/10.1007/s10584-017-2011-3.

Lee, Hyunok, and Daniel A. Sumner. 2015. "Economics of Downscaled Climate-Induced Changes in Cropland, with Projections to 2050: Evidence from Yolo County California." *Climatic Change* 132 (4): 723–37. https://doi.org/10.1007/s10584-015-1436-9.

Lee, Juhwan, Steven De Gryze, and Johan Six. 2011a. "Effect of Climate Change on Field Crop Production in California's Central Valley." *Climatic Change* 109 (S1): 335–53. https://doi.org/10.1007/s10584-011-0305-4.

Lee, Juhwan, Steven De Gryze, and Johan Six. 2011b. "Effect of Climate Change on Field Crop Production in California's Central Valley." *Climatic Change* 109 (S1): 335–53. https://doi.org/10.1007/s10584-011-0305-4.

Lobell, David B., Kimberly Nicholas Cahill, and Christopher B. Field. 2007. "Historical Effects of Temperature and Precipitation on California Crop Yields." *Climatic Change* 81 (2): 187–203. https://doi.org/10.1007/s10584-006-9141-3.

Lobell, David B., and Stefania Di Tommaso. 2025. "A Half-Century of Climate Change in Major Agricultural Regions: Trends, Impacts, and Surprises." *Proceedings of the National Academy of Sciences* 122 (20): e2502789122. https://doi.org/10.1073/pnas.2502789122.

Lobell, David B., and Christopher B. Field. 2007. "Global Scale Climate–Crop Yield Relationships and the Impacts of Recent Warming." *Environmental Research Letters* 2 (1): 014002. https://doi.org/10.1088/1748-9326/2/1/014002.

Lobell, David B., Christopher B. Field, Kimberly Nicholas Cahill, and Celine Bonfils. 2006. "Impacts of Future Climate Change on California Perennial Crop Yields: Model Projections with Climate and Crop Uncertainties." *Agricultural and Forest Meteorology* 141 (2–4): 208–18. https://doi.org/10.1016/j.agrformet.2006.10.006.

Miao, Ruiqing, Madhu Khanna, and Haixiao Huang. 2016. "Responsiveness of Crop Yield and Acreage to Prices and Climate." *American Journal of Agricultural Economics* 98 (1): 191–211. https://doi.org/10.1093/ajae/aav025.

Miller, Noah, Jesse Tack, and Jason Bergtold. 2021. "The Impacts of Warming Temperatures on US Sorghum Yields and the Potential for Adaptation." *American Journal of Agricultural Economics* 103 (5): 1742–58. https://doi.org/10.1111/ajae.12223.

Mote, Philip W., Alan F. Hamlet, Martyn P. Clark, and Dennis P. Lettenmaier. 2005. "DECLINING MOUNTAIN SNOWPACK IN WESTERN NORTH AMERICA*." *Bulletin of the American Meteorological Society* 86 (1): 39–50. https://doi.org/10.1175/BAMS-86-1-39.

Moyers, Kelley, John T. Abatzoglou, Alvar Escriva-Bou, Josué Medellín-Azuara, and Joshua H. Viers. 2024. "An Invisible Water Surcharge: Climate Warming Increases Crop Water

Demand in the San Joaquin Valley's Groundwater-Dependent Irrigated Agriculture." *PLOS Water* 3 (3): e0000184. https://doi.org/10.1371/journal.pwat.0000184.
Ortiz-Bobea, Ariel. 2020. "The Role of Nonfarm Influences in Ricardian Estimates of Climate Change Impacts on US Agriculture." *American Journal of Agricultural Economics* 102 (3): 934–59. https://doi.org/10.1093/ajae/aaz047.
Ortiz-Bobea, Ariel. 2021. "The Empirical Analysis of Climate Change Impacts and Adaptation in Agriculture." In *Handbook of Agricultural Economics*, vol. 5. Elsevier. https://doi.org/10.1016/bs.hesagr.2021.10.002.
Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. 2007. "Water Availability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California." *Climatic Change* 81 (1): 19–38. https://doi.org/10.1007/s10584-005-9008-z.
Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences* 106 (37): 15594–98. https://doi.org/10.1073/pnas.0906865106.
Snyder, R. 1985. "Hand Calculating Degree Days." *Agricultural and Forest Meteorology* 35 (1–4): 353–58. https://doi.org/10.1016/0168-1923(85)90095-4.
Thrasher, Bridget, Weile Wang, Andrew Michaelis, Forrest Melton, Tsengdar Lee, and Ramakrishna Nemani. 2022. "NASA Global Daily Downscaled Projections, CMIP6." *Scientific Data* 9 (1): 262. https://doi.org/10.1038/s41597-022-01393-4.
Thrasher, Bridget, Weile Wang, Andrew Michaelis, and Ramakrishna Nemani. 2021. "NASA Earth Exchange Global Daily Downscaled Projections - CMIP6." NASA Center for Climate Simulation. https://doi.org/10.7917/OFSG3345.
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.
Welch, Jarrod R., Jeffrey R. Vincent, Maximilian Auffhammer, Piedad F. Moya, Achim Dobermann, and David Dawe. 2010. "Rice Yields in Tropical/Subtropical Asia Exhibit Large but Opposing Sensitivities to Minimum and Maximum Temperatures." *Proceedings of the National Academy of Sciences* 107 (33): 14562–67. https://doi.org/10.1073/pnas.1001222107.
Wimmer, Stefan, Christian Stetter, Jonas Schmitt, and Robert Finger. 2024. "Farm-level Responses to Weather Trends: A Structural Model." *American Journal of Agricultural Economics* 106 (3): 1241–73. https://doi.org/10.1111/ajae.12421.
Wu, Shuaiqi, Prudentia Gugulethu Zikalala, Sequoia Alba, et al. 2025. "Advancing the Modeling of Future Climate and Innovation Impacts on Perennial Crops to Support Adaptation: A Case Study of California Almonds." *Earth's Future* 13 (4): e2024EF005033. https://doi.org/10.1029/2024EF005033.

Appendix Tables and Figures

Table A1. Summary statistics of weather variables

	Mean	Std. Dev.
Winter (JFM)		
GDD (8C – 24C; hundred)	2.37	1.76
HDD (above 24C; hundred)	0.03	0.09
Precipitation (mm)	218.01	137.83
Solar radiation (Watts/m2)	142.62	12.55
Wind speed (m/s)	2.92	0.74
Spring (AMJ)		
GDD (9C – 30C; hundred)	6.65	3.01
HDD (above 30C; hundred)	0.18	0.34
Precipitation (mm)	50.47	41.22
Solar radiation (Watts/m2)	310.12	12.41
Wind speed (m/s)	3.43	0.49
Summer (JAS)		
GDD (12C – 30C; hundred)	8.58	2.77
HDD (above 30C; hundred)	0.63	0.89
Precipitation (mm)	7.89	12.44
Solar radiation (Watts/m2)	303.09	5.45
Wind speed (m/s)	3.19	0.52
Fall (OND)		
GDD (8C – 30C; hundred)	4.05	2.21
HDD (above 30C; hundred)	0.03	0.07
Precipitation (mm)	137.93	97.95
Solar radiation (Watts/m2)	130.44	9.94
Wind speed (m/s)	2.77	0.64
Growing season (AMJJAS)		
GDD (9C – 30C; hundred)	17.75	5.86
HDD (above 30C; hundred)	0.82	1.22
Precipitation (mm)	58.36	44.01
Solar radiation (Watts/m2)	306.55	6.96
Wind speed (m/s)	3.31	0.47

Notes: Mean values are reported across 18 counties in the Central Valley from 1980 to 2022. The eighteen counties are as follows: Tehama, Glenn, Butte, Colusa, Yolo, Solano, Sutter, Yuba, Placer, Sacramento, San Joaquin, Stanislaus, Merced, Madera, Fresno, Tulare, Kern, and Kings.

Table A2. Panel estimates of the impact of concurrent and lagged temperatures on California's Central Valley crop yields

Dependent variable: IHS (Yield)	Almonds (1)	Pistachios (2)	Orchard (deciduous) (3)	Citrus & subtropical (4)	Vineyards (5)	Alfalfa (6)	Grain (7)	Other field crops (8)	Truck crops (9)
Winter (JFM)									
GDD (8C – 24C; hundred)	-0.076***	-0.049	-0.079***	0.007	0.102**	-0.079**	-0.023	-0.183**	-0.037
	(0.020)	(0.060)	(0.024)	(0.054)	(0.046)	(0.036)	(0.025)	(0.068)	(0.048)
HDD (above 24C; hundred)	0.023	3.138***	-0.094	1.329**	0.271	-0.073	-0.010	-0.303	1.199
	(0.139)	(0.798)	(0.218)	(0.606)	(0.295)	(0.181)	(0.156)	(0.275)	(0.671)
Spring (AMJ)									
GDD (9C – 30C; hundred)	0.029	0.019	0.026	0.079	0.008	0.009	-0.020	-0.023	0.011
	(0.015)	(0.042)	(0.016)	(0.050)	(0.038)	(0.024)	(0.015)	(0.044)	(0.039)
HDD (above 30C; hundred)	-0.062	-0.199	-0.002	-0.171	0.021	-0.053	0.055	0.125	-0.046
	(0.068)	(0.242)	(0.119)	(0.206)	(0.202)	(0.125)	(0.118)	(0.226)	(0.145)
Summer (JAS)									
GDD (12C – 30C; hundred)	0.006	-0.047	-0.003	-0.021	-0.056	-0.006	-0.037	0.138	0.003
	(0.015)	(0.049)	(0.021)	(0.055)	(0.044)	(0.050)	(0.023)	(0.073)	(0.041)
HDD (above 30C; hundred)	0.005	-0.127	0.092	0.047	0.213	-0.111	-0.022	0.032	0.159
	(0.057)	(0.188)	(0.075)	(0.146)	(0.131)	(0.101)	(0.075)	(0.184)	(0.148)
Fall (OND)									
GDD (8C – 30C; hundred)	-0.011	-0.035	-0.020	0.077**	0.017	-0.007	0.031	-0.079	0.038
	(0.021)	(0.049)	(0.019)	(0.035)	(0.043)	(0.027)	(0.019)	(0.046)	(0.038)
HDD (above 30C; hundred)	-0.125	-0.548	0.285	-1.663***	-1.210***	-0.010	0.281	0.911	-0.142
	(0.160)	(0.666)	(0.265)	(0.528)	(0.342)	(0.320)	(0.192)	(0.521)	(0.634)
Observations	552	289	3,370	923	875	601	2,015	335	1,059
R-squared	0.758	0.531	0.186	0.426	0.433	0.280	0.206	0.736	0.364

	Rice (10)	Cotton (11)	Sugar beet (12)	Corn (13)	Dry beans (14)	Safflower (15)	Tomatoes Processing (16)	Tomatoes Fresh (17)	Cucurbits (18)	Onion & garlic (19)	Potatoes (20)
Growing season (AMJJAS)											
GDD (9C – 30C; hundred)	0.008	0.003	0.002	-0.022**	0.003	-0.044	-0.012	-0.001	0.036	-0.042**	-0.023
	(0.009)	(0.013)	(0.012)	(0.010)	(0.010)	(0.027)	(0.007)	(0.020)	(0.019)	(0.016)	(0.014)
HDD (above 30C; hundred)	-0.048	-0.024	-0.024	-0.033	-0.072	0.032	-0.039	0.012	-0.166	0.152	0.161
	(0.081)	(0.074)	(0.064)	(0.055)	(0.041)	(0.081)	(0.025)	(0.199)	(0.114)	(0.129)	(0.119)
Observations	583	289	203	925	844	361	269	225	803	181	157
R-squared	0.267	0.264	0.624	0.239	0.365	0.293	0.845	0.386	0.288	0.095	0.824

Notes: Standard errors presented in parentheses are clustered over year. The dependent variable is the IHS-transformed crop yields. All regressions include recent (t-3 to t-1) and distant (t-10 to t-4) lagged degree days, recent and distant lagged total annual precipitation, weather controls, as well as linear and quadratic time trends, and county fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Regressions are weighted by 1981-2022 county-average harvested acre. Level of significance: $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table A3. Panel estimates of the impact of concurrent and lagged temperatures on California's Central Valley harvested acreage

Dependent variable: IHS (Harvested acre)	Almonds	Pistachios	Orchard (deciduous)	Citrus & subtropical	Vineyards	Alfalfa	Grain	Other field crops	Truck crops
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Winter (JFM)									
GDD (8C –	-0.127**	0.110	-0.186***	0.063	0.027	-0.005	-0.136**	-0.364***	-0.390***
24C; hundred)	(0.050)	(0.058)	(0.049)	(0.047)	(0.070)	(0.045)	(0.052)	(0.073)	(0.112)
HDD (above	0.512	-0.479	1.027**	0.890	0.208	-0.170	-0.415	-0.494	0.535
24C; hundred)	(0.312)	(1.007)	(0.431)	(0.493)	(0.392)	(0.230)	(0.374)	(0.429)	(0.642)
Spring (AMJ)									
GDD (9C –	0.055	0.062	-0.006	-0.007	0.165***	-0.027	0.013	0.009	0.056
30C; hundred)	(0.038)	(0.037)	(0.019)	(0.032)	(0.049)	(0.033)	(0.035)	(0.049)	(0.046)
HDD (above	-0.009	0.193	0.334	-0.083	-0.747***	0.341**	0.090	-0.340	-0.131
30C; hundred)	(0.188)	(0.199)	(0.203)	(0.225)	(0.236)	(0.142)	(0.224)	(0.338)	(0.352)
Summer (JAS)									
GDD (12C –	0.081	0.131**	0.094**	0.092**	-0.046	-0.022	0.041	0.052	0.229***
30C; hundred)	(0.057)	(0.063)	(0.037)	(0.038)	(0.057)	(0.064)	(0.052)	(0.083)	(0.081)
HDD (above	-0.052	-0.024	-0.287***	0.035	-0.215	-0.153	-0.137	0.198	-0.760***
30C; hundred)	(0.110)	(0.163)	(0.120)	(0.100)	(0.120)	(0.153)	(0.139)	(0.174)	(0.255)
Fall (OND)									
GDD (8C –	0.028	-0.041	0.085***	0.022	0.175***	0.008	-0.002	0.002	0.121**
30C; hundred)	(0.034)	(0.041)	(0.029)	(0.037)	(0.042)	(0.034)	(0.046)	(0.061)	(0.054)
HDD (above	0.974**	-0.592	1.519***	0.284	0.380	-0.368	0.215	2.849***	1.555
30C; hundred)	(0.394)	(0.585)	(0.556)	(0.352)	(0.634)	(0.446)	(0.315)	(0.610)	(0.766)
Observations	561	291	3,741	942	874	625	2,025	1,502	1,443
R-squared	0.953	0.958	0.192	0.477	0.696	0.858	0.267	0.243	0.278

	Rice	Cotton	Sugar beet	Corn	Dry beans	Safflower	Tomatoes Processing	Tomatoes Fresh	Cucurbits	Onion & garlic	Potatoes
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Growing season (AMJJAS)											
GDD (9C –	-0.038	-0.038	-0.004	0.042	0.104***	-0.040	0.040	-0.030	0.018	-0.047	0.014
30C; hundred)	(0.026)	(0.083)	(0.038)	(0.033)	(0.035)	(0.054)	(0.028)	(0.062)	(0.033)	(0.024)	(0.044)
HDD (above	0.237	-0.463	-0.506	-0.699***	-0.433**	0.289	-0.199	0.420	-0.483**	-0.082	-
30C; hundred)	(0.220)	(0.529)	(0.262)	(0.221)	(0.184)	(0.163)	(0.112)	(0.499)	(0.191)	(0.169)	0.586***

											(0.175)
Observations	584	293	214	923	851	363	387	226	808	181	157
R-squared	0.324	0.312	0.839	0.334	0.385	0.787	0.849	0.551	0.398	0.095	0.848

Notes: Standard errors presented in parentheses are clustered over year. The dependent variable is the IHS-transformed harvested acres. All regressions include recent (t-3 to t-1) and distant (t-10 to t-4) lagged degree days, recent and distant lagged total annual precipitation, weather controls, as well as linear and quadratic time trends, and county fixed effects. The weather controls include total precipitation, average solar radiation, average wind speed, and their squared terms. Regressions are weighted by 1981-2022 county-average harvested acre. Level of significance: ** $p < 0.05$, *** $p < 0.01$.

Table A4. Projected 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)
Winter (JFM)					
GDD (8C – 24C; hundred)	3.12	3.80	3.87	0.68	0.75
		(3.93)	(4.72)	(0.81)	(1.60)
HDD (above 24C; hundred)	0.02	0.04	0.06	0.02	0.04
		(0.04)	(0.11)	(0.02)	(0.09)
Spring (AMJ)					
GDD (9C – 30C; hundred)	7.38	8.57	8.72	1.19	1.34
		(8.51)	(9.42)	(1.13)	(2.04)
HDD (above 30C; hundred)	0.21	0.38	0.41	0.17	0.20
		(0.42)	(0.55)	(0.21)	(0.34)
Summer (JAS)					
GDD (12C – 30C; hundred)	9.03	10.07	10.14	1.04	1.11
		(9.95)	(10.69)	(0.92)	(1.66)
HDD (above 30C; hundred)	0.98	1.44	1.47	0.46	0.49
		(1.35)	(1.78)	(0.37)	(0.80)
Fall (OND)					
GDD (8C – 30C; hundred)	4.93	6.10	6.50	1.17	1.57
		(6.35)	(7.03)	(1.42)	(2.10)
HDD (above 30C; hundred)	0.05	0.09	0.11	0.04	0.06
		(0.11)	(0.14)	(0.06)	(0.09)
Growing season (AMJJAS)					
GDD (9C – 30C; hundred)	18.83	21.20	21.44	2.37	2.61
		(21.01)	(22.73)	(2.18)	(3.90)
HDD (above 30C; hundred)	1.18	1.82	1.88	0.64	0.70
		(1.77)	(2.33)	(0.59)	(1.15)

Note: The mean climate projection values across Central Valley are reported using different climate scenarios (SSP45 and SSP85). SSP585 is reported in parentheses.

Table A5a. Projected impacts of climate change on selected crop yields under two climate scenarios: [SSP245]/(SSP585)

[near-medium term (2031–2055), long term (2056–2080)]							
Crop Yield	Almonds	Pistachios	Orchards	Citrus & subtropical fruit trees	Vineyards	Alfalfa	Other field crops
Winter (JFM)							
GDD (8C – 24C; hundred)	**[-5.2%, -5.7%] (-6.2%, -12.2%)**	[-3.3%, -3.7%] (-4.0%, -7.8%)	**[-5.4%, -5.9%] (-6.4%, -12.6%)**	[0.5%, 0.5%] (0.6%, 1.1%)	**[6.9%, 7.7%] (8.3%, 16.3%)**	**[-5.4%, -5.9%] (-6.4%, 12.6%)**	**[-12.4%, -13.7%] (-14.8%, -29.3%)**
HDD (above 24C; hundred)	[0.0%, 0.1%] (0.0%, 0.2%)	**[6.3%, 12.6%] (6.3%, 28.2%)**	[-0.2%, -0.4%] (-0.2%, -0.8%)	**[2.7%, 5.3%] (2.7%, 12.0%)**	[0.5%, 1.1%] (0.5%, 2.4%)	[-0.1%, -0.3%] (-0.1%, -0.7%)	[-0.6%, -1.2%] (-0.6%, -2.7%)
	Citrus & subtropical fruit trees	Vineyards					
Fall (OND)							
GDD (8C – 30C; hundred)	**[9.0%, 12.1%] (10.9%, 16.2%)**	**[2.0%, 2.7%] (2.4%, 3.6%)**					
HDD (above 30C; hundred)	[-6.7%, -10.0%] (-10.0%, -15.0%)	[-4.8%, -7.3%] (-7.3%, -10.9%)					
	Corn	Onion and garlic					
Growing season (AMJJAS)							
GDD (9C – 30C; hundred)	**[-5.2%, -5.7%] (-4.8%, -8.6%)**	**[-10.0%, -11.0%] (-9.2%, -16.4%)**					
HDD (above 30C; hundred)	[-2.1%, -2.3%] (-1.9%, -3.8%)	[9.7%, 10.6%] (9.0%, 17.5%)					

Notes: The percentage change of projected impacts of climate change on crop yields are reported. The bold values have statistically significant impacts. The SSP585 climate scenario results are presented in parentheses. These are calculated by multiplying the statistically significant coefficients of average marginal effects (Tables A2) and the difference between the average projected climate in 2031–2055 and the average climate in 1981–2005. Similarly, long-term 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 A5b. Projected impacts of climate change on selected crop harvested acres under two climate scenarios: [SSP245]/(SSP585)

	[near-medium term (2031–2055), long term (2056–2080)]				
Crop Yield	Almonds	Orchards	Grain	Other field crops	Truck crops
Winter (JFM)					
GDD (8C – 24C; hundred)	**[-8.6%, -9.5%]** **(-10.3%, -20.3%)**	**[-12.6%, -14.0%]** **(-15.1%, -29.8%)**	**[-9.2%, -10.2%]** **(-11.0%, -21.8%)**	**[-24.8%, -27.3%]** **(-29.5%, -58.2%)**	**[-26.5%, -29.3%]** **(-31.6%, -62.4%)**
HDD (above 24C; hundred)	[1.0%, 2.0%] (1.0%, 4.6%)	**[2.1%, 4.1%]** **(2.1%, 9.2%)**	[-0.8%, -1.7%] (-0.8%, -3.7%)	[-1.0%, -2.0%] (-1.0%, -4.4%)	[1.1%, 2.1%] (1.1%, 4.8%)
	Vineyards	Alfalfa			
Spring (AMJ)					
GDD (9C – 30C; hundred)	**[19.6%, 22.1%]** **(18.6%, 33.7%)**	[-3.2%, -3.6%] (-3.1%, -5.5%)			
HDD (above 30C; hundred)	**[-12.7%, -14.9%]** **(-15.7%, -25.4%)**	**[5.8%, 6.8%]** **(7.2%, 11.6%)**			
	Pistachios	Orchards	Citrus & subtropical fruit trees	Truck crops	
Summer (JAS)					
GDD (12C – 30C; hundred)	**[13.6%, 14.5%]** **(12.1%, 21.7%)**	**[9.8%, 10.4%]** **(8.6%, 15.6%)**	**[9.6%, 10.2%]** **(8.5%, 15.3%)**	**[14.2%, 25.4%]** **(21.1%, 38.0%)**	
HDD (above 30C; hundred)	[-1.1%, -1.2%] (-0.9%, -1.9%)	**[-13.2%, -14.1%]** **(-10.6%, -23.0%)**	[1.6%, 1.7%] (1.3%, 2.8%)	**[-35.0%, -37.2%]** **(-28.1%, -60.8%)**	
	Almonds	Orchards	Vineyards	Other field crops	Truck crops
Fall (OND)					
GDD (8C – 30C; hundred)	[3.3%, 4.4%] (4.0%, 5.9%)	**[9.9%, 13.3%]** **(12.1%, 17.9%)**	**[20.5%, 27.5%]** **(24.9%, 36.8%)**	[0.2%, 0.3%] (0.3%, 0.4%)	**[14.2%, 19.0%]** **(17.2%, 25.4%)**
HDD (above 30C; hundred)	**[3.9%, 5.8%]** **(5.8%, 8.8%)**	**[6.1%, 9.1%]** **(9.1%, 13.7%)**	[1.5%, 2.3%] (2.3%, 3.4%)	**[11.4%, 17.1%]** **(17.1%, 25.6%)**	[6.2%, 9.3%] (9.3%, 14.0%)
	Corn	Dry beans	Cucurbits	Potatoes	
Growing season (AMJJAS)					
GDD (9C – 30C; hundred)	[10.0%, 11.0%] (9.2%, 16.4%)	**[24.6%, 27.1%]** **(22.7%, 40.6%)**	[4.3%, 4.7%] (3.9%, 7.0%)	[3.3%, 3.7%] (3.1%, 5.5%)	
HDD (above 30C; hundred)	**[-44.7%, -48.9%]** **(-41.2%, -80.4%)**	**[-27.7%, -30.3%]** **(-25.5%, -49.8%)**	**[-30.9%, -33.8%]** **(-28.5%, -55.5%)**	**[-37.5%, -41.0%]** **(-34.6%, -67.4%)**	

Notes: The percentage change of projected impacts of climate change on crop harvested acres are reported. The bold values have statistically significant impacts. The SSP585 climate scenario results are presented in parentheses. These are calculated by multiplying the statistically significant coefficients of average marginal effects (Tables A3) and the difference between the average projected climate in 2031–2055 and the average climate in 1981–2005. Similarly, long-term 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.

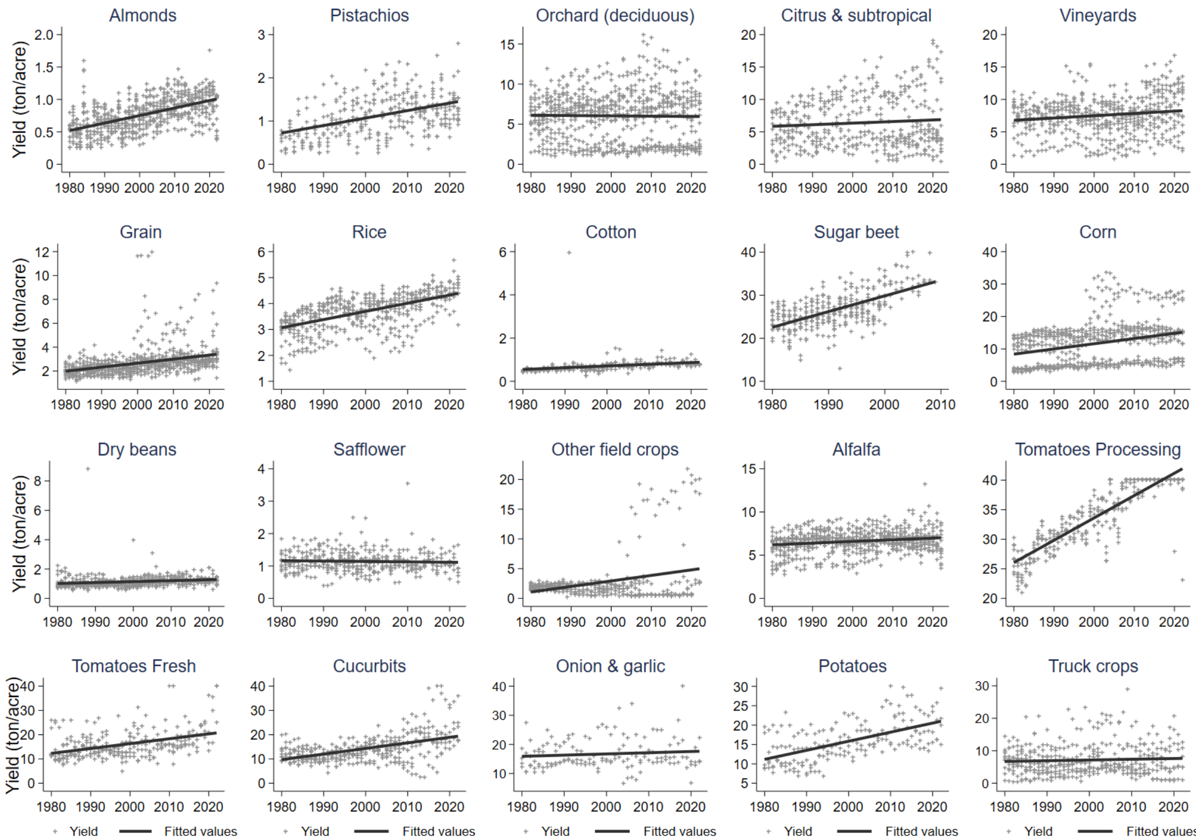

Figure A1. Crop-specific yield scatter plots and fitted linear trends.

Notes: The figure shows scatter plots of crop yields across 18 counties in the Central Valley between 1980 and 2022. To handle outliers, the crop yield data is *winsorized* at the 1st and 99th percentiles.

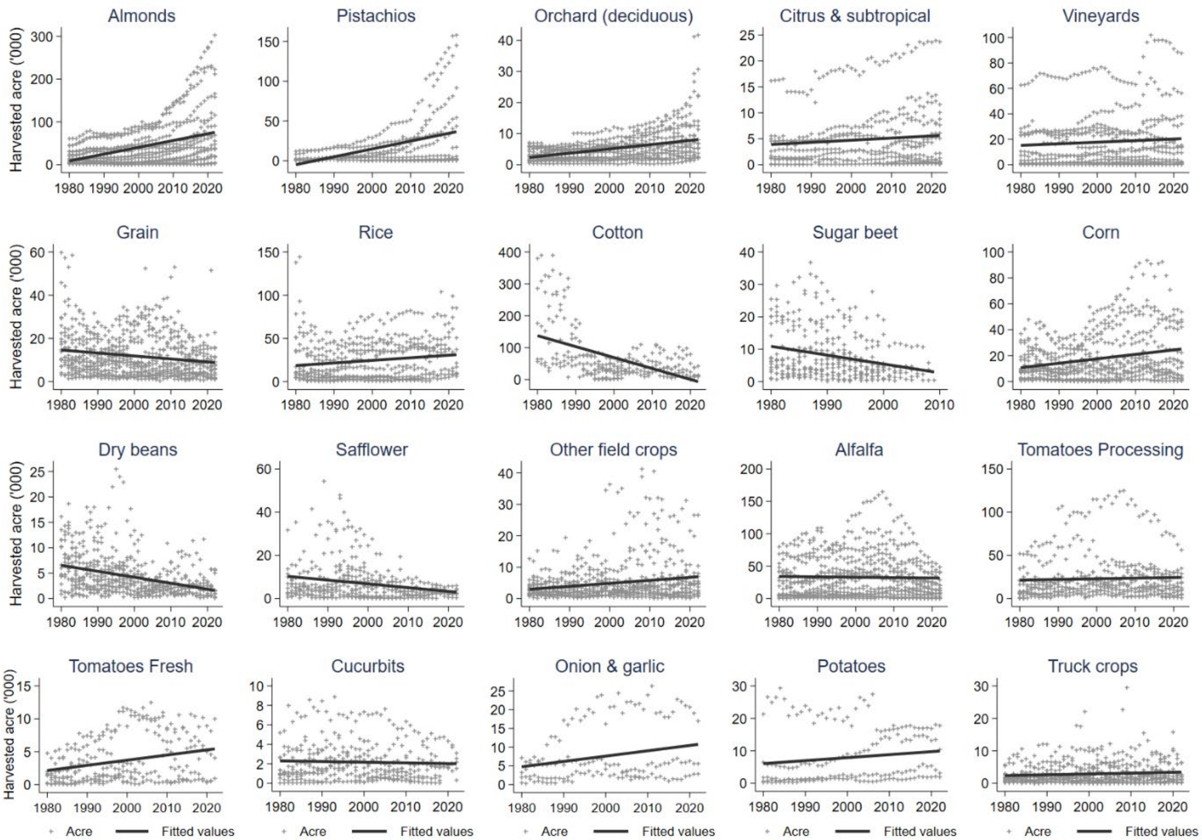

Figure A2. Crop-specific harvested acre scatter plots and fitted linear trends.

Notes: The figure shows scatter plots of harvested acres of crops across 18 counties in the Central Valley between 1980 and 2022. To handle outliers, the harvested acre data is *winsorized* at the 1st and 99th percentiles.

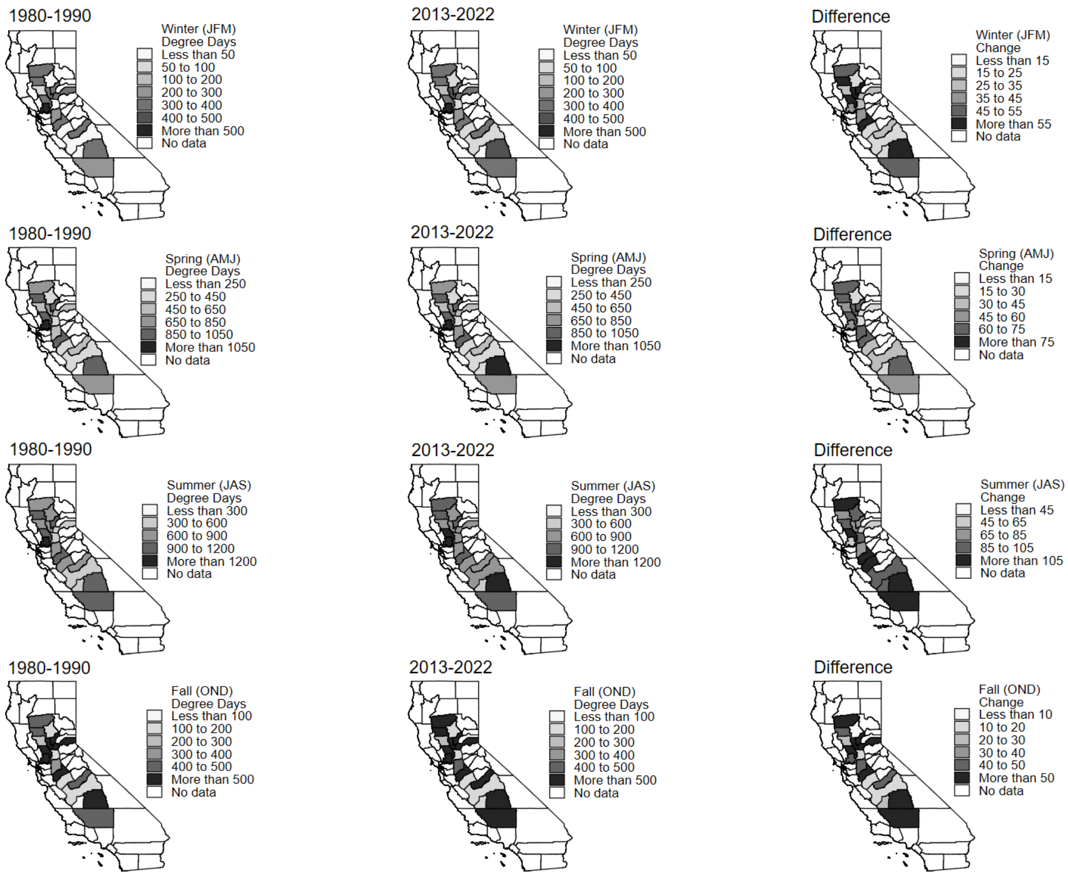

Figure A3a. Spatial and temporal variation in degree days

Note: The first column represents the average mean degree days across Central Valley from 1980 to 1990. The second column represents the average mean degree days across Central Valley from 2013 to 2022. The third column is the difference between the second and first columns. Winter degrees are calculated using the lower threshold temperature of 8areand the upper threshold temperature of 24C. Degree days in spring are calculated using the 9C and 30C; summer degree days are calculated using the 12C and 30C; and fall degree days are calculated using the 8C and 30C.

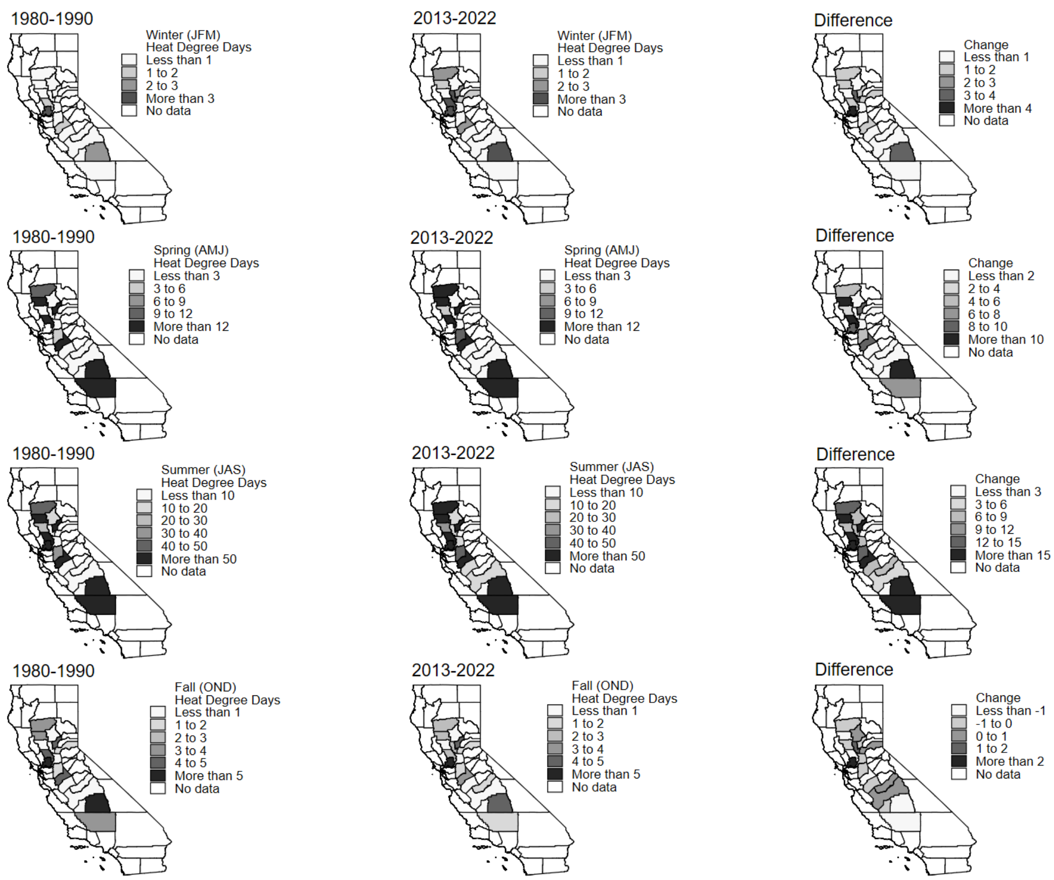

Figure A3b. Spatial and temporal variation in heat degree days

Note: The first column represents the average mean heat degree days across Central Valley from 1980 to 1990. The second column represents the average mean heat degree days across Central Valley from 2013 to 2022. The third column is the difference between the second and first columns. Winter heat degree days are calculated by temperatures above 24C. Heat degree days in spring, summer, and fall are calculated by temperatures above 30C.

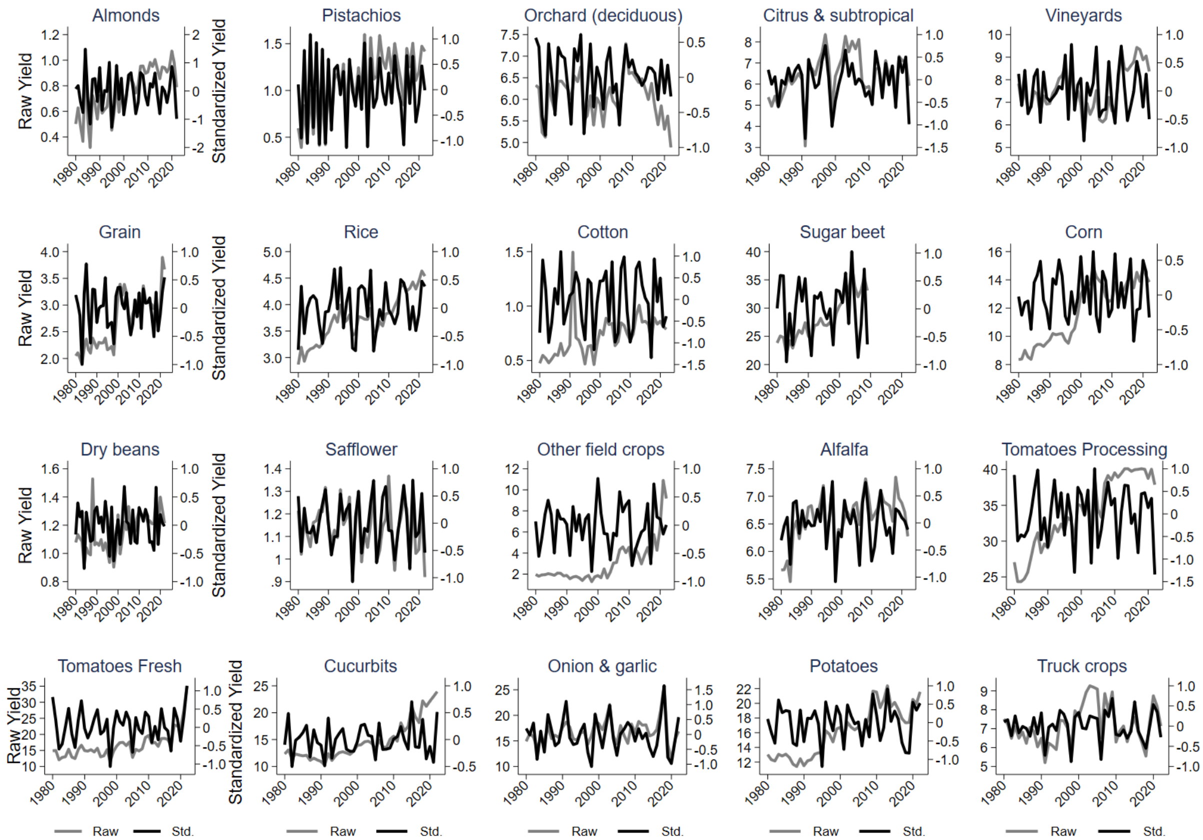

Figure A4. Crop-specific trends in raw and standardized yields

Notes: The dark line represents the crop yields reported in tons/acre, while the gray line represents the standardized yields based on a seven-year moving window. The crop yield time series data is directly obtained from USDA NASS for California.

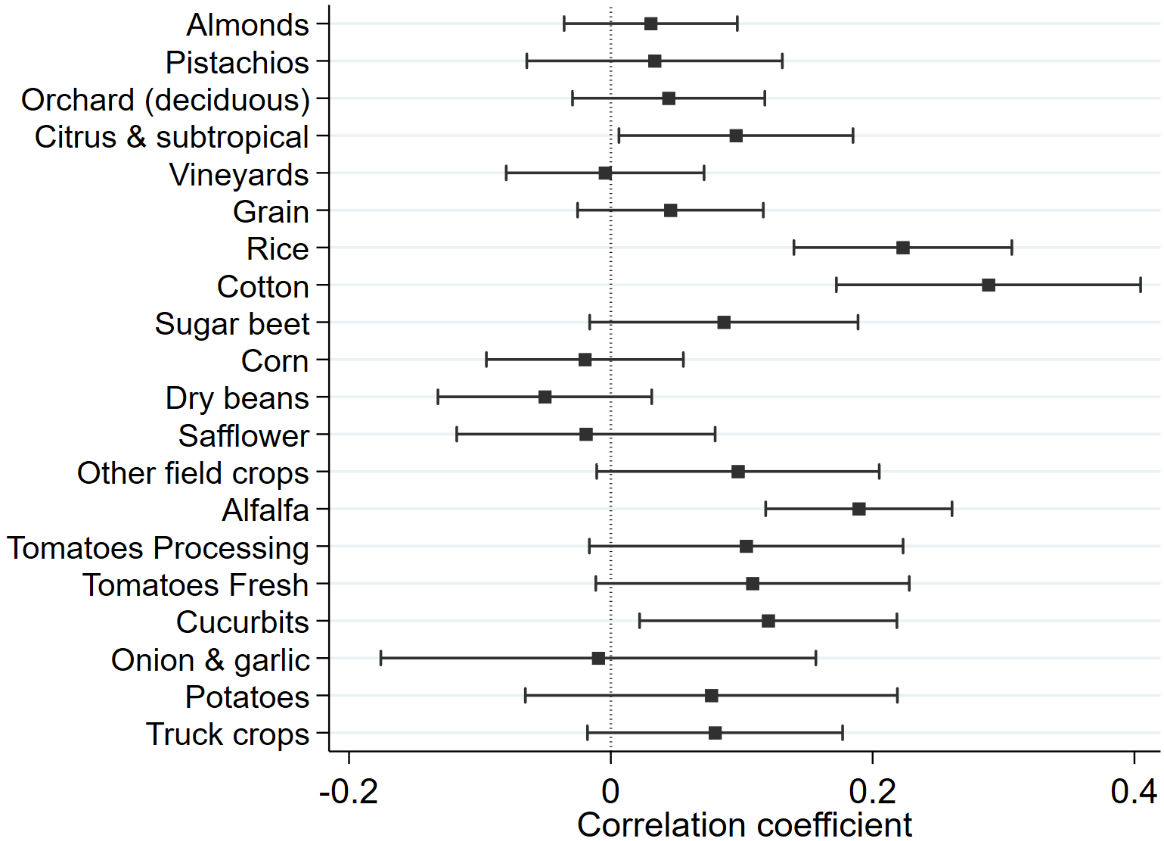

Figure A5. Pearson's correlation coefficient between annual detrended crop yields and mean annual temperatures across the Central Valley during 1983-2019

Notes: The x-axis represents the estimated correlation coefficient. The Pearson correlation is computed between the standardized crop yields (seven-year moving average) 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.

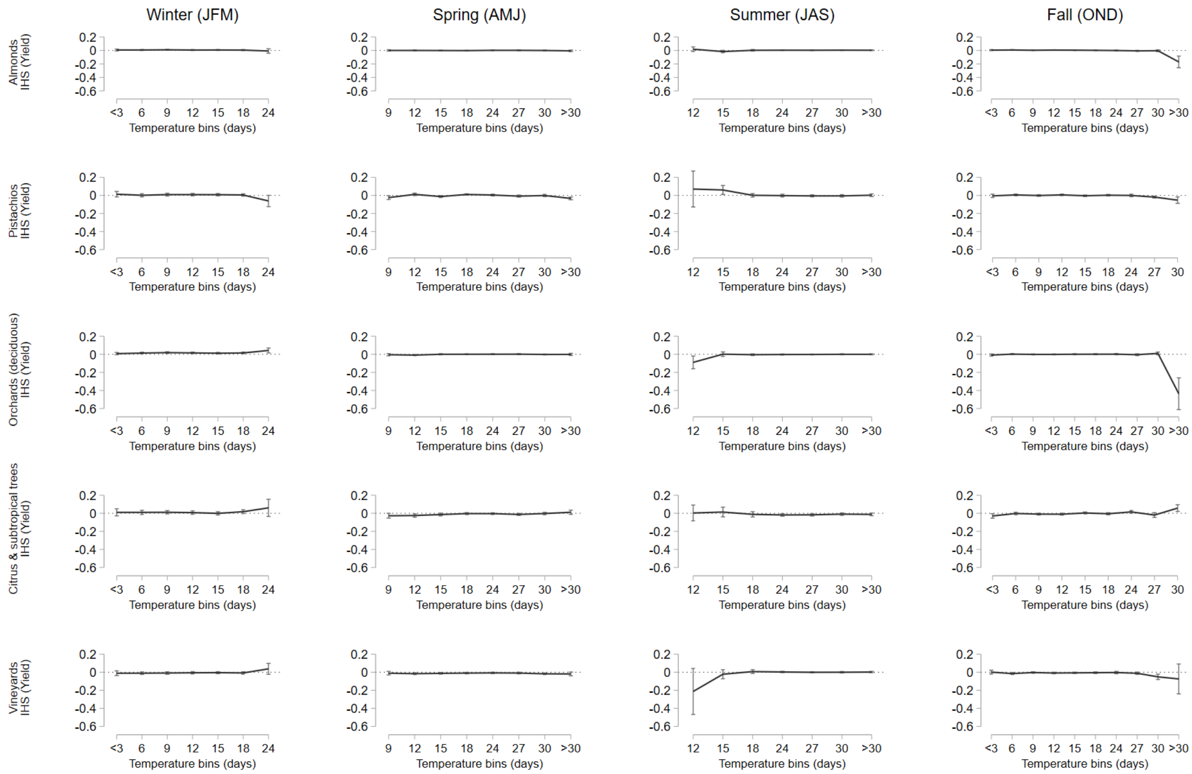

Figure A6a. Impacts of temperature bins on specialty nuts and tree crop yields

Notes: The dependent variable is the IHS-transformed crop yields from 1980 to 2022. To interpret the point coefficients, we need to multiply them by 100. Temperature bins measure the number of days with daily mean temperature falling into that specific bin. The specification includes second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. The [18°C, 21°C) is selected as reference. The figure plots the point estimate and 95% confidence intervals for each crop. The crop yield data is directly obtained from USDA NASS for California, and temperature bins are derived from gridMET daily data.

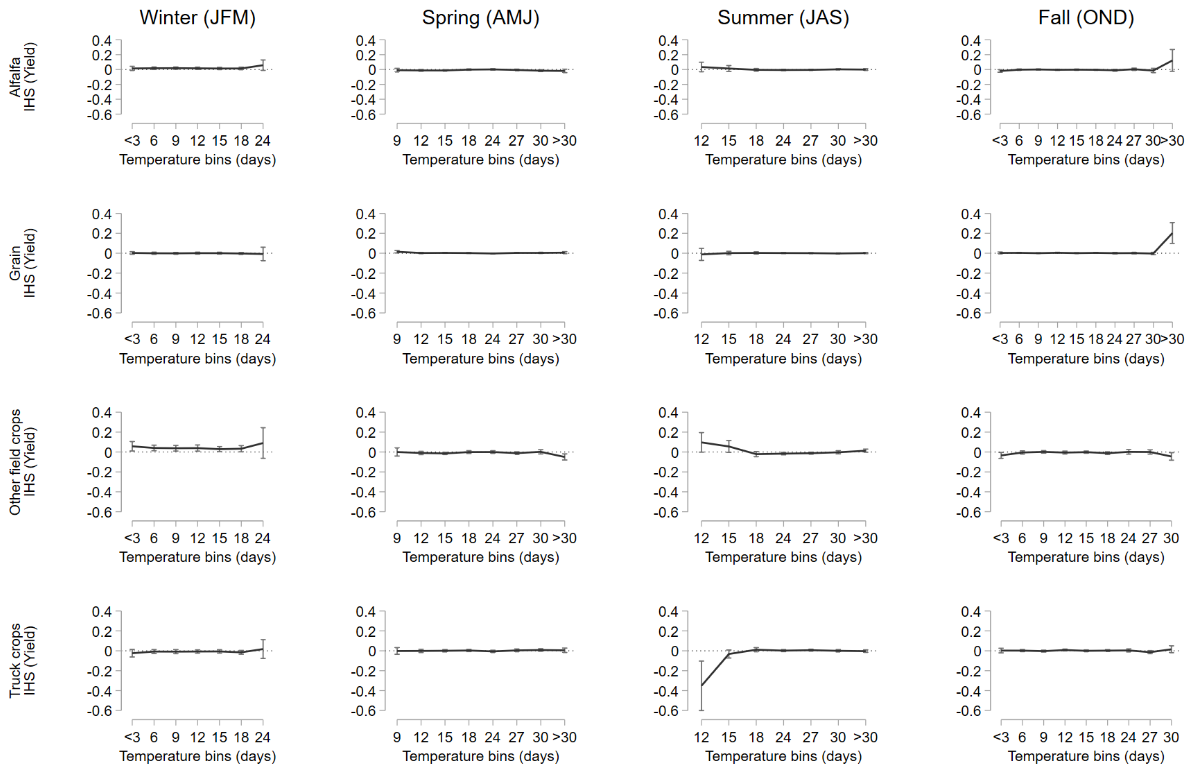

Figure A6b. Impacts of temperature bins on alfalfa, grain, other field, and truck crop yields

Notes: The dependent variable is the IHS-transformed crop yields from 1980 to 2022. To interpret the point coefficients, we need to multiply them by 100. Temperature bins measure the number of days with daily mean temperature falling into that specific bin. The specification includes second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. The [18°C, 21°C) is selected as reference. The figure plots the point estimate and 95% confidence intervals for each crop. The crop yield data is directly obtained from USDA NASS for California, and temperature bins are derived from gridMET daily data.

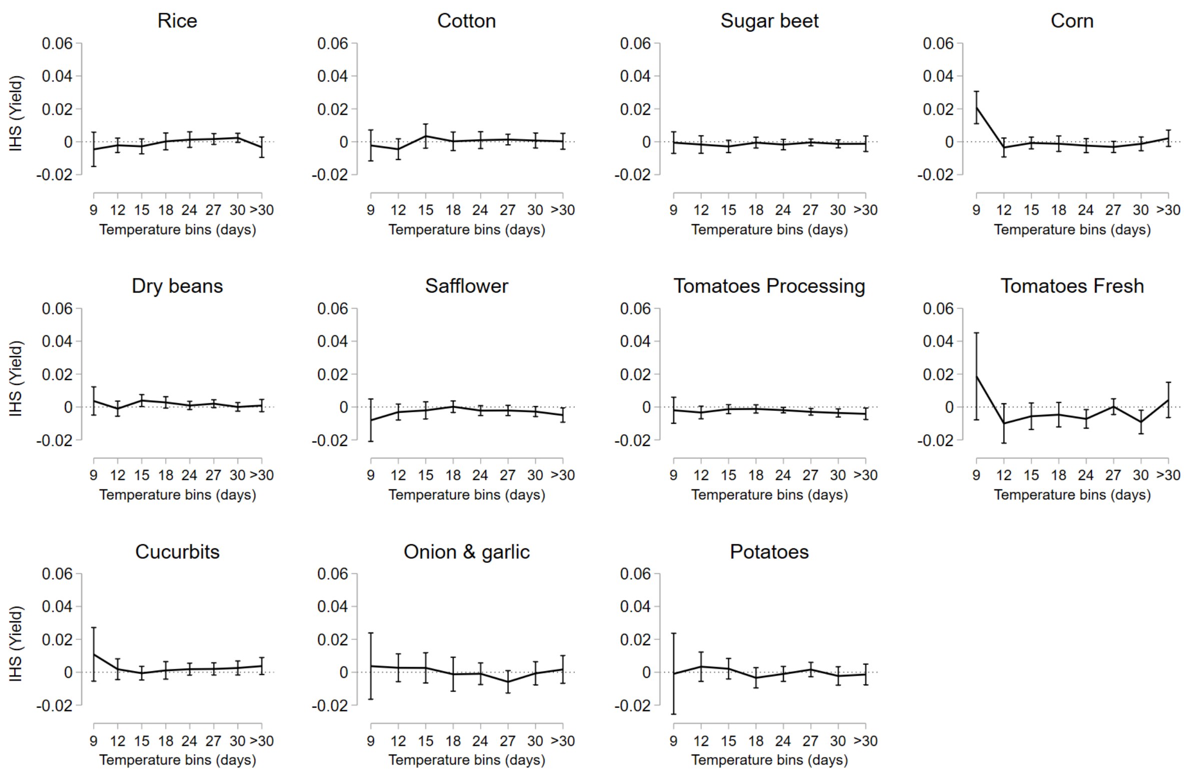

Figure A6c. Impacts of temperature bins on annual crop yields

Notes: The dependent variable is the IHS-transformed crop yields from 1980 to 2022. To interpret the point coefficients, we need to multiply them by 100. Temperature bins measure the number of days with daily mean temperature falling into that specific bin. The specification includes second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. The [18°C, 21°C) is selected as reference. The figure plots the point estimate and 95% confidence intervals for each crop. The crop yield data is directly obtained from USDA NASS for California, and temperature bins are derived from gridMET daily data.

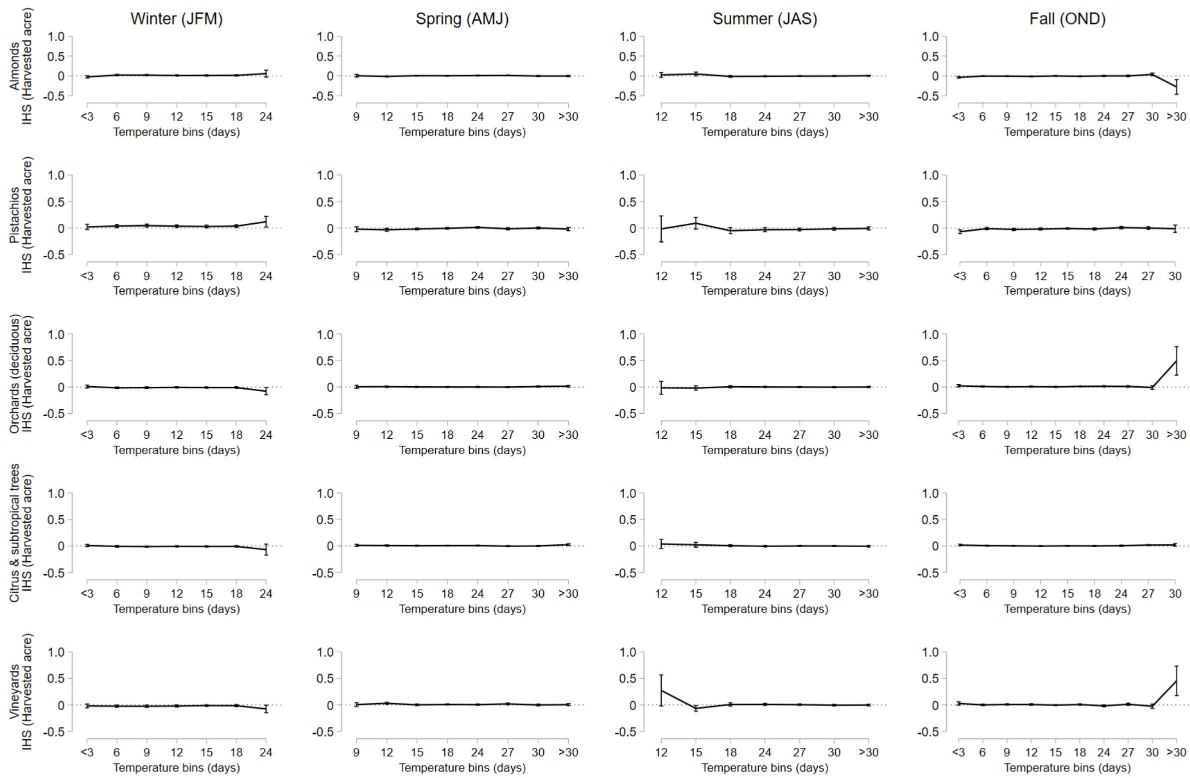

Figure A7a. Impacts of temperature bins on acres harvested of specialty nut and tree crops

Notes: The dependent variable is the IHS-transformed acres harvested from 1980 to 2022. To interpret the point coefficients, we need to multiply them by 100. Temperature bins measure the number of days with daily mean temperature falling into that specific bin. The specification includes second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. The [18°C, 21°C) is selected as reference. The figure plots the point estimate and 95% confidence intervals for each crop. The crop yield data is directly obtained from USDA NASS for California, and temperature bins are derived from gridMET daily data.

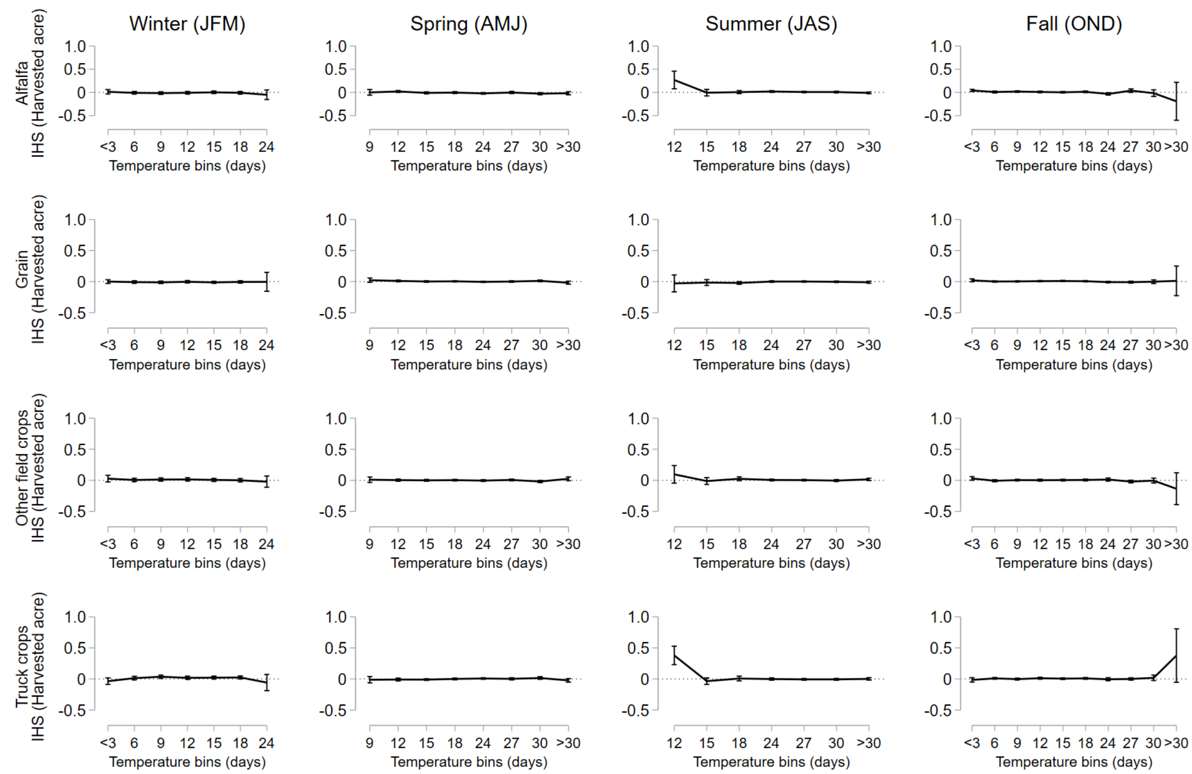

Figure A7b. Impacts of temperature bins on acres harvested of alfalfa, grain, other field crops, and truck crops

Notes: The dependent variable is the IHS-transformed acres harvested from 1980 to 2022. To interpret the point coefficients, we need to multiply them by 100. Temperature bins measure the number of days with daily mean temperature falling into that specific bin. The specification includes second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. The [18°C, 21°C) is selected as reference. The figure plots the point estimate and 95% confidence intervals for each crop. The crop yield data is directly obtained from USDA NASS for California, and temperature bins are derived from gridMET daily data.

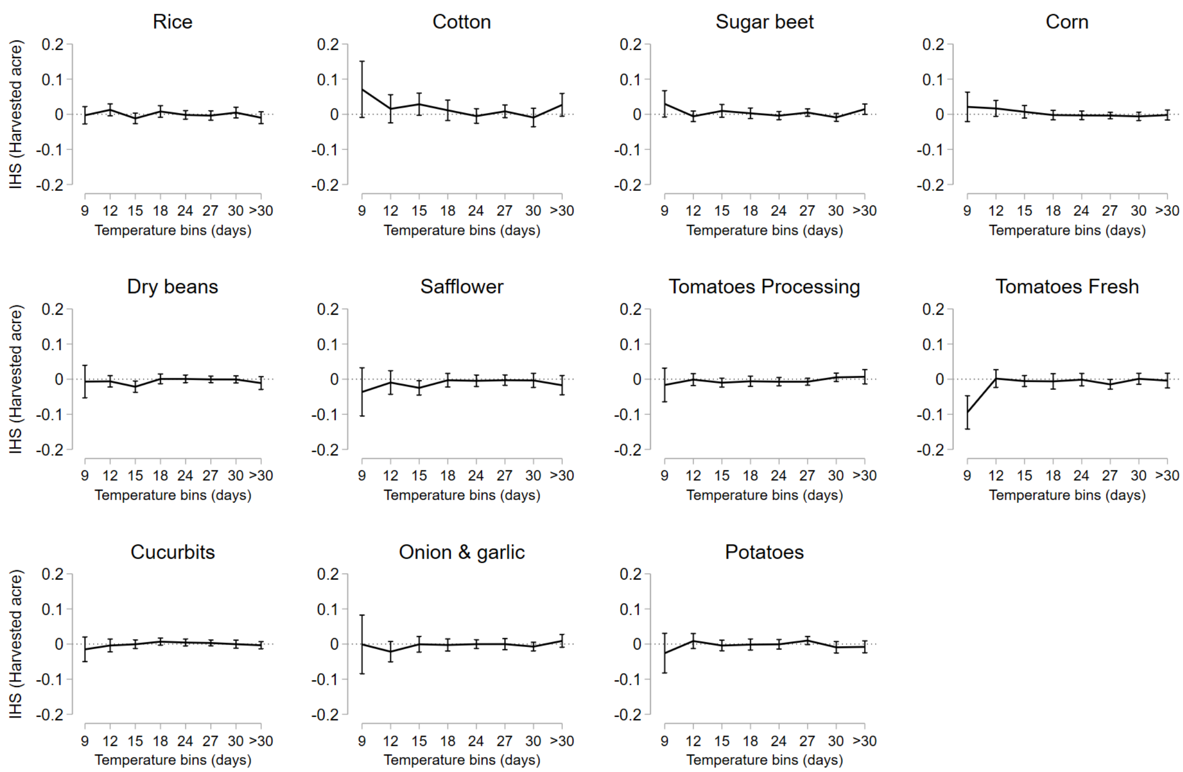

Figure A7c. Impacts of temperature bins on acres harvested of annual crops

Notes: The dependent variable is the IHS-transformed acres harvested from 1980 to 2022. To interpret the point coefficients, we need to multiply them by 100. Temperature bins measure the number of days with daily mean temperature falling into that specific bin. The specification includes second order polynomials for other weather variables, including total precipitation, average solar radiation, and average wind speed, quadratic time-trend, as well as county fixed effects. The [18°C, 21°C) is selected as reference. The figure plots the point estimate and 95% confidence intervals for each crop. The crop yield data is directly obtained from USDA NASS for California, and temperature bins are derived from gridMET daily data.

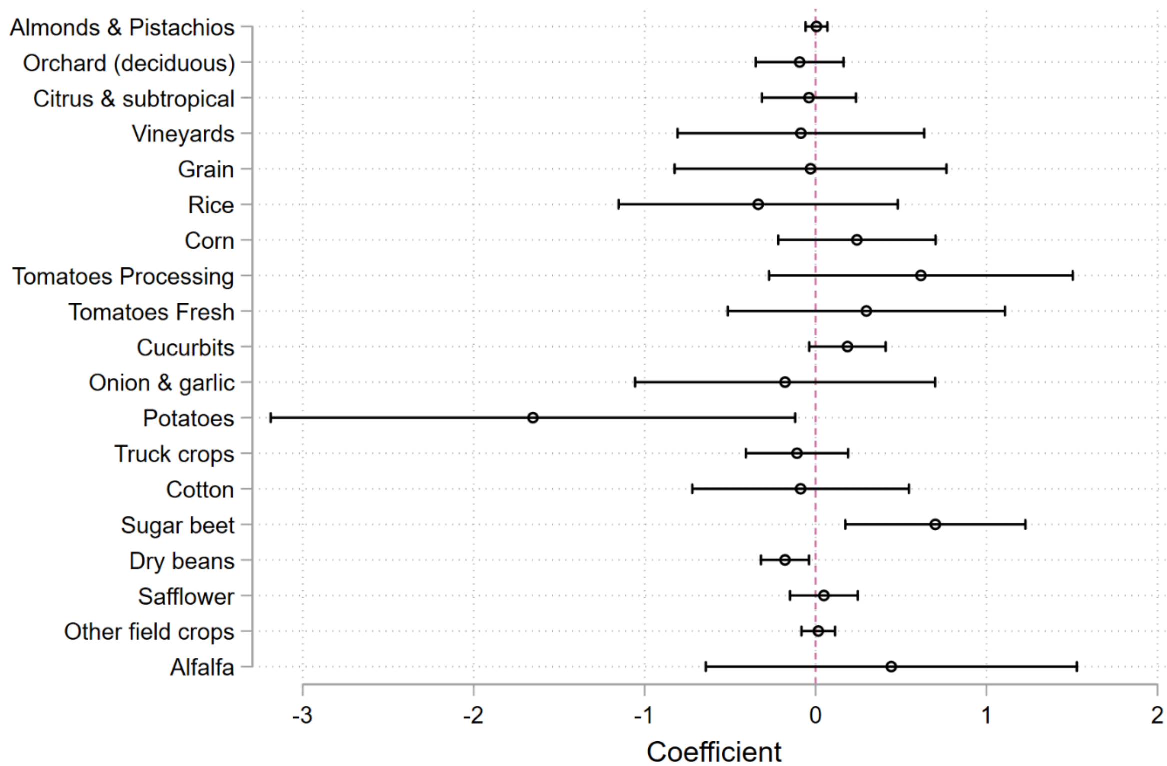

Figure A8. Irrigated cropped area response to recent past 3-year average changes for each crop yield

Notes: The x-axis shows the slope of a regression of acres planted responses to recent past 3-year average changes for each crop yield. The coefficient is obtained by regressing IHS-transformed irrigated cropped area on IHS-transformed recent past 3-yaer average change for each crop yield since 1998. The figure plots the point estimate and 95% confidence intervals for each crop. The irrigated cropped area for each crop from 1998 to 2020 is obtained from the California Department of Water Resources, and crop yield data for the years 1980 to 2022 is directly obtained from USDA NASS.

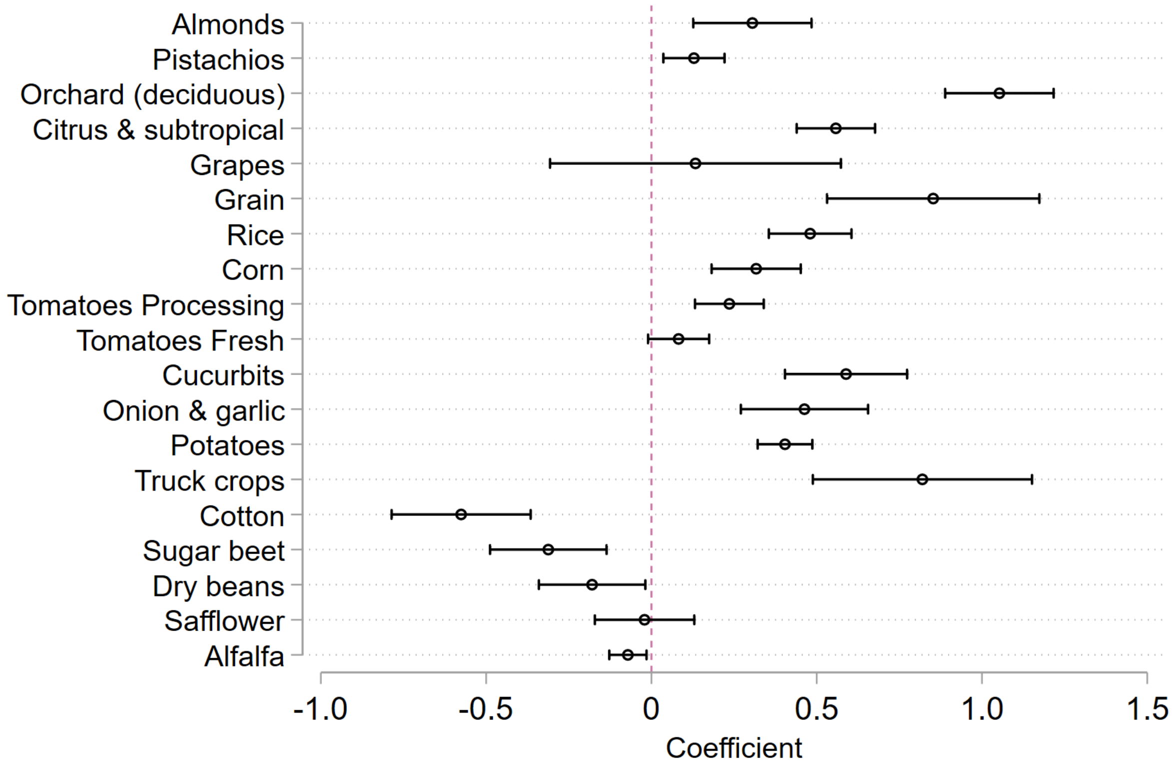

Figure A9. Price response to production changes for each crop.

Notes: The x-axis shows the slope of a regression of price responses to production changes for each crop. The coefficient is obtained by regressing IHS-transformed statewide prices on IHS-transformed state average production for each crop since 1981. The figure plots the point estimate and 95% confidence intervals for each crop. The prices and production data for each crop in California from 1981 to 2022 are directly obtained from USDA NASS.

Online Appendix Table

Online Appendix Table 1. Definition of crop groups

CROP CATEGORY	CROPS
Alfalfa	Hay Alfalfa, Seed Alfalfa
Almonds	Almonds All
Citrus & Subtropical	Avocados All, Cherimoyas, Citrus By-Products Miscellaneous, Citrus Unspecified, Dates, Feijoa, Grapefruit All, Guavas, Jojoba, Lemons All, Limes All, Nectarines, Olives, Oranges Navel, Oranges Unspecified, Oranges Valencia, Pomelo, Tangelos, Tangerines & Mandarins
Corn	Corn Crazy, Corn Grain, Corn Popcorn, Corn Popcorn Seed, Cord Seed, Corn Silage, Corn Sweet All, Corn White, Silage
Cotton	Cotton Lint Pima, Cotton Lint Unspecified, Cotton Seed Planting, Cottonseed
Cucurbits	Chayotes, Cucumbers, Cucumbers Greenhouse, Melons Cantaloupe, Melons Casaba, Melons Honeydew, Melons Unspecified, Melons Watermelon, Pumpkins, Squash
Dry Beans	Beans Blackeye (Peas), Beans Dry Edible Unspecified, Beans Fava, Beans Fresh Unspecified, Beans Garbanzo, Beans Kidney Red, Beans Lima Baby Dry, Beans Lima Green, Beans Lima Large Dry, Beans Lima Unspecified, Beans Pink, Beans Pinto, Beans Red Small, Beans Seed, Beans White Small, Beans White Small Flat, Soybeans
Grain	Barley Feed, Barley Malting, Barley Seed, Barley Unspecified, Hay Grain, Hay Green Chip, Hay Other Unspecified, Oats Grain, Rye Grain, Rye Seed, Triticale, Wheat All, Wheat Seed
Onion & Garlic	Garlic All, Onions, Onions Green & Shallot
Orchard (Deciduous)	Apples All, Apricots All, Cherries Sweet, Chestnuts, Figs, Figs Dried, Filberts, Fruits & Nuts Unspecified, Kiwifruit, Kumquats, Macadamia Nuts, Peaches Clingstone, Peaches Freestone, Peaches Unspecified, Peanuts All, Pears Asian, Pears Bartlett, Pears Prickly, Pears Unspecified, Pecans, Persimmons, Plumcots, Plumcots & Other Hybrid Stone Fruit, Plums, Plums Dried, Pomegranates, Quince, Walnuts Black, Walnuts English
Other Field Crops	Field Crop By-Products, Field Crops Seed Miscellaneous, Field Crops Unspecified, Hay Sudan, Hay Wild, Hemp Unspecified, Hops, Seed Legumes All Other, Seed Other (No Flowers), Seed Vegetable & Vinecrop, Seed Vetch, Seeds Miscellaneous Oil Unspecified, Sesame, Sorghum Grain, Sorghum Seed, Sorghum Silage, Sunflower Seed, Sunflower Seed Planting, Yucca
Pasture	Pasture Forage Miscellaneous, Pasture Irrigated, Pasture Range, Ryegrass Perennial All, Seed Bermuda Grass, Seed Clover Unspecified, Seed Grass Unspecified, Seed Ladino Clover, Seed Sudan Grass, Straw
Pistachios	Pistachios
Potatoes	Potatoes All, Potatoes Irish All, Potatoes Seed, Potatoes Sweet
Rice	Rice Milling, Rice Seed, Rice Sweet, Rice Wild
Safflower	Safflower, Safflower Seed Planting
Sugar Beet	Beets, Beets Garden, Sugar Beets

Tomato Fresh	Tomatillo, Tomatoes Cherry, Tomatoes Fresh Market, Tomatoes Greenhouse, Tomatoes Unspecified
Tomato Processing	Tomatoes Processing
Truck Crops Miscellaneous	Anise (Fennel), Artichokes, Asparagus Fresh Market, Asparagus Processing, Asparagus Unspecified, Beans Snap Fresh Market. Beans Snap Processing, Beans Snap Unspecified, Berries Blackberries, Berries Blueberries, Berries Boysenberries, Berries Bushberries Unspecified, Berries Loganberries, Berries Olallieberries, Berries Raspberries, Berries Strawberries All, Berries Strawberries Fresh Market, Berries Strawberries Processing, Berries Strawberries Unspecified, Broccoli Food Service, Broccoli Fresh Market, Broccoli Processing, Broccoli Unspecified, Brussels Sprouts, Cabbage Chinese & Specialty, Cabbage Head, Cabbage Red, Cactus Fruits, Cardoon, Carobs, Carrots Food Service, Carrots Fresh Market, Carrots Processing, Carrots Unspecified, Cauliflower Food Service, Cauliflower Fresh Market, Cauliflower Processing, Cauliflower Unspecified, Celery Food Service, Celery Fresh Market, Celery Processing, Celery Unspecified, Chives, Cilantro, Collard Greens, Eggplant All, Endive All, Escarole All, Greens Turnip & Mustard, Guar, Horseradish, Jerusalem Artichokes, Kale, Kohlrabi, Leeks, Lettuce Bulk Salad Products, Lettuce Head, Lettuce Leaf, Lettuce Romaine, Lettuce Unspecified, Mint, Mushrooms, Mustard, Okra, Parsley, Parsnips, Peas Cowpea & Blackeye, Peas Dry Edible, Peas Edible Pod (Snow), Peas Green Fresh Market, Peas Green Processing, Peas Green Unspecified, Peas Seed, Peppers Bell, Peppers Chili Hot, Pimentos, Radicchio, Radishes, Rappini, Rhubarb, Rutabagas, Salad Greens Miscellaneous, Salad Greens Not Elsewhere Classified., Spices and Herbs, Spinach Food Service, Spinach Fresh Market, Spinach Processing, Spinach Unspecified, Spouts Alfalfa & Bean, Swiss Chard, Taro Root, Turnips All, Vegetables Asian, Vegetables Baby, Vegetables Greenhouse, Vegetables Unspecified, Watercress
Vineyards	Grapes Raisin, Grapes Table, Grapes Unspecified, Grapes Wine