Drought and Fresh Produce Production in California[*]

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Abstract

California's increasingly frequent and intense drought is a pressing problem for the state's agriculture and the U.S. food supply, as the state is the major producer of many agricultural products. Particularly, California supplies more than half of all fruit and vegetables in the country. This paper examines the severity of the problem by estimating the impacts of the drought on California's fresh fruit and vegetable production. We estimate panel data models using comprehensive, county-level agriculture, irrigation, and weather data from 2000 to 2019. Our findings indicate that droughts significantly reduce total output, ranging from 1.2% to 2.2% for each additional week of drought. The estimated effect is driven by lower yields and fewer harvested acres due to the drought. The drought effects also differ among crops, with thirsty crops and crops with lower economic returns and established insurance programs being disproportionately affected. Results also show the extent to which higher irrigation levels mitigate the adverse effects of drought. Our findings provide insights into the importance of enhancing drought-related risk management and implications for designing cost-effective policies for future adaptation decisions.

Keywords: California drought, fruit and vegetables production, climate change, adaptation
JEL Codes: Q1, Q15, Q25; Q54

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1 Introduction

Global surface temperatures and the frequency and intensity of extreme weather events have been increasing and are predicted to continue to increase due to climate change. (IPCC, 2023; Van Der Wiel and Bintanja, 2021). Droughts are no exception and are expected to become more persistent and extensive in the coming decades (Dai, 2011; Trenberth et al., 2014). While droughts have wide-ranging impacts on regional economies and entire production systems (Fleming-Muñoz, Whitten, and Bonnett, 2023), the agriculture sector is especially vulnerable to drought due to its reliance on precipitation and water supplies. In this paper, we examine the severity of the problem for fruit and vegetable production—a major agricultural sector that is relatively understudied in the context of vulnerability to extreme weather events—in California.

The increasing frequency and intensity of droughts and their impacts on agriculture is particularly concerning for California since it is a major agricultural state and contributor to the U.S. food supply. The state is the largest producer and exporter of produce in the United States,[1] supplying nearly three-quarters of the nation's fruits and more than one-third of its vegetables while exporting about 35% of its total agricultural output internationally.[2] At the same time, California is one of the top states experiencing intense droughts frequently (Pathak et al., 2018).[3] These droughts adversely affect farmers' livelihoods despite advanced technologies and widespread irrigation used in the state's agriculture. For instance, Howitt et al. (2015) estimates that the 2015 drought resulted in about $2.7 billion in losses and 21,000 agriculture-related job cuts. Similarly, the 2021 drought is estimated to result in $1.2 billion in losses and around 8,745 job losses (Medellín-Azuara et al., 2021). Worse still, studies project more frequent and severe

[1] The terms "produce" and "fruit and vegetables" are used interchangeably throughout the text.

[2] Data source: California Agricultural Production Statistics. https://www.cdfa.ca.gov/Statistics/. Accessed on September 5, 2024.

[3] Figure A1 illustrates the total number of weeks that areas in the United States experienced extreme or exceptional drought status from 2000 to 2019. California has spent more than two years in extreme drought or greater.

droughts in the future (Cvijanovic et al., 2017; Swain et al., 2018). Hence, it is imperative to have a full understanding of the consequences of droughts on agriculture to guide the federal and state policies related to drought and future adaptation strategies.

In this article, we examine the impacts of the recent drought on fruit and vegetable (FV) production in California. We use California county-level panel data from 2000-2019 to estimate the effects of an additional week of drought on FV at various intensity levels. California experienced two major drought events during the study period: a shorter one from 2007 to 2009 and a more prolonged, severe drought from 2012 to 2016.[4] This allows us to observe meaningful temporal variation within counties in the sample.

To measure drought severity, we use publicly available vector data from the California Department of Water Resources (DWR) to track farmland use across various fruits and vegetables, and we use vector data from the U.S. Drought Monitor (USDM) to capture drought conditions. The USDM provides weekly updates on the entire distribution of drought severity, ranging from "abnormally dry" to "exceptional drought." We combine these datasets to develop more precise drought metrics that reflect varying drought intensity levels in agricultural areas specific to each crop within a given county. These metrics are aggregated annually to capture cumulative drought effects. We view the intensity of drought levels as a plausibly exogenous treatment. To measure crop production, we obtain annual county crop reports from the California County Agricultural Commissioners, which contain records on total outputs, yield per acre, and harvested acres of FV.

The combined data allows us to use a multi-level panel fixed-effects model that exploits spatial and temporal variation in California's drought conditions and FV production. We use the model to examine how changes in the severity and duration of droughts affect produce production. To identify processes leading to production losses and offer a complete picture of crop production, we decompose our estimates into two compo-

[4]Source: California Department of Water Resources. https://water.ca.gov/drought. Accessed on September 5, 2024.

nents: yield response, which mainly reflects the physical impact of drought on crops, and harvested acreage response, which mainly captures growers' adaptive decisions.

We find robust and statistically significant negative impacts of both low- and high-intensity drought on FV total outputs. At low-intensity levels, each additional week of drought reduces fresh produce total output by an average of 1.2%. This reduction becomes more pronounced at high-intensity levels, with total output declining by 2.2% for an additional week of drought. Further analysis shows that the total output loss is due to decreases in both yield per acre and harvested acreage, with the latter playing a more substantial role. Reduced acreage could be partly driven by growers' adaptive response to drought conditions.

Furthermore, we investigate the heterogeneous effects of droughts by crop growth cycles, water demands, economic returns, and crop insurance coverage. While we find no clear distinction between the responses of annual and perennial crops, we observe that crops with higher water demands and lower economic returns are more sensitive to drought. Additionally, crops covered by established insurance programs exhibit greater vulnerability to drought than those without coverage. Growers can partially mitigate negative drought impacts on FV production when certain adaptation options are available. In particular, we explore the role of irrigation and find that it largely offsets drought-related declines in the total production of FV.

The results remain consistent across several robustness checks. First, we use fixed weights for drought measures in our main analysis, which may raise concerns due to changes in land cover over time. Therefore, as a robustness check, we construct varying weights for the drought measures and find consistent results. Second, we use alternative specifications to account for the non-linear relationship between drought and production outcomes, as well as clustering concerns. Third, we account for potential spillover effects by incorporating spatial lags in the analysis. Finally, although droughts are plausibly exogenous to farm production, there are potential threats to causal identification due to how USDM measures drought severity. Hence, we also estimate the model using an instrumental variables approach to address the concerns about the endogeneity of the drought variables.

This article contributes to the literature in several ways. First, it expands the existing research on the impacts of extreme weather events on agricultural economic outcomes. Drought is a complex extreme climate event characterized by multiple climatological and hydrological parameters (Mishra and Singh, 2010; Mukherjee, Mishra, and Trenberth, 2018). However, most studies rely on precipitation and temperature data or single indices (such as the Palmer Drought Severity Index and the Standardized Precipitation Index) to measure drought severity (Boubacar, 2012; Ding, Schoengold, and Tadesse, 2009; Riebsame, Changnon, and Karl, 2019; Wheaton et al., 2008). Other studies use news articles or government publications to track drought conditions (Lesk, Rowhani, and Ramankutty, 2016), but these sources lack a consistent definition of "drought". In this study, we rely on the U.S. Drought Monitor, a more comprehensive and recently developed tool, for assessing drought conditions. Although USDM has been extensively used by a variety of federal agencies to inform major drought management decisions (Kuwayama et al., 2019; Svoboda, 2015), there is limited evidence linking USDM drought data to observed agricultural outcomes.[5] By estimating the impacts of droughts, as defined by the USDM, on produce production, we fill the gap in the literature.

Second, this article adds to the understanding of how drought affects agricultural production by examining not only its impact on yields but also on harvested acreage—an aspect often overlooked in existing research. Several empirical studies have documented the adverse effects of drought on crop yields at regional (e.g., Bareille and Chakir, 2024; Brás et al., 2021; Kuwayama et al., 2019; Lobell et al., 2014; Schmitt et al., 2022; Tack and Holt, 2016; Zipper, Qiu, and Kucharik, 2016) or global scales (Leng and Hall, 2019; San-

[5]Two exceptions include: Kuwayama et al. (2019), who examine the impact of drought, as measured by the USDM, on corn and soybean yields and farm income in the United States, and Sumner, Li, and Shr (2023), who estimate how USDM-measured drought affects farmers' decisions on corn and soybean acres across crop growing cycles.

tini et al., 2022). However, focusing solely on yields provides an incomplete view of the production process. Changes in harvested acreage can complicate the interpretation of yield responses (Iizumi and Ramankutty, 2015).[6] Moreover, crop production, alongside access and utilization, ultimately determines food security, not just yields. Our study extends the work of Lesk, Rowhani, and Ramankutty (2016) and Sumner, Li, and Shr (2023), expanding the analysis of acreage response to drought by using granular data and rigorous econometric analysis.[7]

Third, this study contributes to the discussion of the impacts of climate change on produce production. While extensive literature focuses on staple crops like wheat, rice, corn, and soybeans (e.g., Schlenker and Roberts, 2009, Miao, Khanna, and Huang, 2016; Cui and Zhong, 2024), much less is known about how climate change and extreme events affect FV production, a sector that is essential for adequate nutrition and dietary diversity (Kerr et al., 2018).[8] Although studies have predicted the effects of rising temperatures on fruit (Baldocchi and Wong, 2008; Luedeling, Zhang, and Girvetz, 2009) and vegetable production (Bisbis, Gruda, and Blanke, 2018; Deschenes and Kolstad, 2011; Lee and Sumner, 2015), research on the impact of changing precipitation remains limited (Lobell, Cahill, and Field, 2007; Lobell and Field, 2011). This is not only due to the difficulty in modeling precipitation at a regional scale (Pierce et al., 2013) but also because available water for fresh produce depends heavily on infrastructure and policy. Taking a step further, Xu et al. (2019) project that global extreme droughts have a stronger impact on vegetation productivity than mild and moderate droughts, but the ex-post estimations

[6]This has been demonstrated in the context of climate change (Cui, 2020a; Cui, 2020b; Obembe, Hendricks, and Tack, 2021) and ozone stress (Liu and Lu, 2023).

[7]Lesk, Rowhani, and Ramankutty (2016) use a statistical model to estimate the effects of drought on cereal production using data aggregated at the country level. Their findings reveal that production losses result from reductions in both harvested areas and yields. In addition, Sumner, Li, and Shr (2023) examine how droughts in the U.S. affect corn and soybean acreage at various stages of the crop cycle, including planned planting, prevented planting, and crop abandonment. Using a two-way fixed effects model, they show that acreage response contributes to 28% of the total drought impact on corn production and 26% for soybeans.

[8]Since 2000, FV production in the United States has declined by 10% and 23.1%, respectively, while imports have grown significantly, posing challenges to the sustainability of the U.S. domestic industry (Ribera and Young, 2024).

of the effects of drought on produce production are still unknown.

Last, this paper contributes to the growing literature on how farmers adapt to climate change. Previous studies have highlighted the significance of temperature and precipitation shocks in driving adaptive behaviors in the agricultural sector (e.g., Burke and Emerick, 2016; Cui and Xie, 2022; Cui and Zhong, 2024; Miller, Tack, and Bergtold, 2021; Ortiz-Bobea, 2021). This study builds on the discussion of the role of irrigation in mitigating production losses due to climate change (Edwards and Smith, 2018; Schlenker, Hanemann, and Fisher, 2005; Schlenker, Hanemann, and Fisher, 2007; Smith and Edwards, 2021), particularly by quantifying how irrigation alleviates drought impacts on produce production. Our findings on the heterogeneity of impacts by economic value of crops align with previous findings that growers' behavioral responses are motivated by the potential for higher revenues (Cui, 2020a). Moreover, our finding of higher drought impact on crops with insurance programs echoes the argument that existing institutions may discourage agricultural adaptation to climate change (Cui, 2020a; Libecap, 2011; Annan and Schlenker, 2015).

The remainder of this paper is structured as follows. Section 2 outlines the background on drought definition and various measures of drought. Section 3 presents a conceptual model that motivates our empirical analysis. Section 4 details the data. In Section 5, we elaborate on the empirical framework used in this study. Section 6 presents the empirical estimations, with an emphasis on explaining the influence of droughts on fresh produce production. Section 7 explores the potential adaptation through irrigation. The last section concludes.

2 Background

2.1 *Drought Definition and Indices*

There is no universally accepted definition of drought (Ault, 2020). Broadly, drought can be considered a climate-related extreme event characterized by a significant reduction in water supply relative to water demand when compared to historical norms. In most cases, drought can persist over prolonged periods and is frequently accompanied by elevated temperatures. Droughts are commonly classified into four types based on their impact (Mishra and Singh, 2010): meteorological, hydrological, agricultural, and socio-economic.[9] In the rest of our paper, we will focus on agricultural drought.

Drought lacks a standardized definition, leading to the development of various indices tailored to specific research needs. Mishra and Singh (2010) provide a comprehensive review of a range of drought indices, with newer ones added over time (Hao and AghaKouchak, 2013; Vicente-Serrano, Beguería, and López-Moreno, 2010). These indices can be grouped into two categories: those that measure moisture supply from precipitation alone (e.g., the standardized precipitation index and the rainfall anomaly index) and those that estimate the moisture balance based on precipitation, evapotranspiration, and water storage (e.g., the Palmer drought severity index (PDSI) and the Standardized Precipitation Evapotranspiration Index (SPEI)). Despite its widespread use, the PDSI has notable limitations, including its slow response to emerging droughts and its accuracy depending heavily on the formulation and historical data used for calibration (Mishra and Singh, 2010; Trenberth et al., 2014). While the SPEI has been developed to address some of the PDSI's limitations, it is widely used as a meteorological drought index.[10]

[9] Meteorological drought occurs when rainfall is significantly below historical averages over a period. Hydrological drought refers to a reduction in surface water, reservoir, or groundwater levels relative to the historical levels of the region. Agricultural drought happens when insufficient moisture affects plant growth and yields. Socioeconomic drought arises when water shortages disrupt human activities, linking the effects of the other drought types to broader societal impacts.

[10] Although several other drought indices are discussed in Mishra and Singh (2010), PDSI and SPEI have emerged as the most commonly used in recent research.

2.2 *The U.S. Drought Monitor*

The U.S. Drought Monitor is a tool that considers multiple environmental factors to assess and classify drought intensity. The USDM is a national map depicting areas of the U.S. that are in a drought, produced jointly by the National Drought Mitigation Center (NDMC), the National Oceanic and Atmospheric Administration (NOAA), and the USDA every week.[11] The USDM is not simply an index but rather a composite data product that relies on rich indicators, including a suite of objective climate indices, numerical models, and subjective inputs from a network of experts at the regional and local levels (Svoboda et al., 2002). It provides cumulative weekly information on the percentage of land and the number of weeks in different drought categories at various spatial scales.

The drought intensity is classified in the Drought Monitor into four major categories –moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4) – with a fifth category D0 depicting "abnormally dry" conditions. These drought categories are based on five key objective indicators along with many ancillary indicators.[12] The key indicators are the Palmer Drought Severity Index, CPC Soil Moisture Model Percentiles, U.S. Geological Survey Daily Streamflow Percentiles, Standardized Precipitation Index, and Objective Drought Indicator Blends.[13] Unlike other drought indices, the USDM also relies on input and verification from experts across various fields to enhance its credibility. Experts help verify the drought data with their professional knowledge of regional and local drought conditions and impacts.[14] This

[11]The weekly USDM map can be accessed at https://droughtmonitor.unl.edu/.

[12]Svoboda et al. (2002) detail the supplementary indicators used by the Drought Monitor, including the remotely sensed Satellite Vegetation Health Index, humidity and temperature departure from normal, reservoir and lake levels, surface water supply indices, snowpack, and groundwater levels, etc.

[13]Definitions of these five key indicators and the relationships between the five indicators and the magnitude of drought severity in the U.S. Drought Monitor are available at https://droughtmonitor.unl.edu/About/WhatistheUSDM.aspx. Particularly, the Palmer Drought indices take cumulative events into account so the measured intensity of drought during the current week depends on current weather patterns plus the cumulative patterns of previous weeks.

[14]The USDM primarily relies on physical and objective data related to climate, weather, and hydrology to determine the intensity of drought. Expert input enhances the understanding of drought conditions

collective information is then integrated into a map that categorizes drought intensity based on its historical frequency for a given location and time of year, reflecting local impacts and vulnerabilities (Svoboda et al., 2002).[15] Considering that drought events are often driven by multiple environmental stresses that interact in complex and often unpredictable ways, the USDM serves as the landmark tool for incorporating multivariate drought indicators from various resources and experts' knowledge in information interpretation (Hao and Singh, 2015).

Since the USDM is a versatile and accessible tool providing timely and easily interpretable data, it is widely used for drought management by producers and government agencies. Kuwayama et al. (2019) document how federal and local government agencies, particularly the U.S. Department of Agriculture, and private sector entities utilize the USDM to guide critical decisions regarding drought response. Notably, the USDA uses the USDM map as a trigger for several programs designed to help agricultural producers recover from drought disasters. These programs include the Livestock Forage Disaster Program (LFP), Fast Track USDA Disaster Designations, the Emergency Haying & Grazing – Conservation Reserve Program (CRP), and Emergency Farm Loans.[16]

3 Conceptual Model

Our conceptual model builds on those of Cui (2020a) and Liu and Lu (2023) to illustrate how the effects of drought on produce production are transmitted through changes in harvested acres and yields. Assume a representative FV grower chooses harvested acreages at the end of the growing season to maximize her profit (π). The grower is a price taker in her output market.[17] Hence, given output price p, her total revenue de-

while preserving the objectivity of the assessments.

[15] Table A1 in the appendix lists the percentiles associated with each drought intensity class.

[16] See https://www.farmers.gov/protection-recovery/drought for more details.

[17] According to the 2017 Census of Agriculture, more than 15.6 million acres across approximately 243,000 farms were dedicated to specialty crops (including fruits, vegetables, nuts, and nursery crops), with an average farm size of 64.2 acres.

pends on the level of total output Q, which is a function of harvested acres A. The total output is also affected by drought conditions indexed by D as well as the left skewness of the yield distribution indexed by ξ. The costs include the marginal cost of harvesting c, and the total cost incurred during the entire growing season before harvesting, indexed by S, which is a sunk cost at the time of harvesting. The profit maximization problem can be formalized as follows:

$$\max_{A} \pi = pQ(A; D, \xi) - cA - S \tag{1}$$

Assuming the regularity conditions for the production function hold —that $Q(.)$ is monotonic, twice-continously differentiable, add quasi-concave—the optimal acreage, A^*, exists and is the solution to the first order condition (FOC) given as: $p\frac{\partial Q}{\partial A} - c = 0$.[18] By the implicit function theorem, we derive the drought impact (D) on A^* by differentiating both sides of the FOC with respect to D:

$$\frac{\partial^2 Q}{\partial A^2}\frac{\mathrm{d}A^*}{\mathrm{d}D} + \frac{\partial^2 Q}{\partial A\,\partial D} = 0,\ \forall p \neq 0 \tag{2}$$

Rearranging (2) yields the comparative statics that illustrate how drought influences the optimal harvest levels:

$$\frac{\mathrm{d}A^*}{\mathrm{d}D} = -\frac{\partial^2 Q}{\partial A\,\partial D}\Big/\frac{\partial^2 Q}{\partial A^2} \tag{3}$$

By monotonicity and the law of diminishing returns, $Q(.)$ is assumed to increase with acreage, $\frac{\partial Q}{\partial A} > 0$, at a decreasing rate, $\frac{\partial^2 Q}{\partial A^2} < 0$, which is consistent with higher-yielding land being typically harvested first (Cui, 2020a; Liu and Lu, 2023). Additionally, since drought damages plant growth and reduces yield (Kuwayama et al., 2019; Lesk,

[18] In this context, we rule out corner solutions for simplicity. The first order condition indicates that the grower maximizes profit when the marginal revenue from harvesting an additional acre is equal to the marginal cost of that harvest.

Rowhani, and Ramankutty, 2016), marginal productivity of land decreases as drought severity increases, suggesting $\frac{\partial^2 Q}{\partial A \, \partial D} < 0$. Consequently, $\frac{\mathrm{d}A^*}{\mathrm{d}D}$ would be negative, indicating that drought decreases the optimal harvested acreage.

The conceptual model implies that drought decreases A^* primarily due to not harvesting low-yield acreage, which, in turn, decreases total output. However, reduced yields might also reduce output at the intensive margin. Therefore, our empirical analysis decomposes the effects of drought on output into its effects on acreage and yield, Y. Formally, Q is by definition given as:

$$Q = A(D) \times Y(D) \tag{4}$$

By total differentiation with respect to drought, the marginal change in total production due to drought can be decomposed into marginal changes in harvested acres and yield as:

$$\frac{\partial Q}{\partial D} dQ = \frac{\partial A}{\partial D} dA + \frac{\partial Y}{\partial D} dY. \tag{5}$$

In our empirical analysis, we estimate each of these marginal effects separately.

4 Data Description

The empirical analysis combines county-level data on FV production and drought in California. The drought data is sourced from the USDM for 58 counties between 2000 and 2019. County-level crop data is obtained from the California annual county report, which includes detailed production information for 26 types of fruits and 27 types of vegetables, as listed in Table A2. The dependent variables of interest are county-level total outputs, yields per acre, and harvested acres of FV, while the key explanatory variables are the USDM drought categorizations.

4.1 *USDM Data*

As a composite product, the USDM has several advantages over other drought indices. It integrates multiple data sources, provides timely updates, effectively captures emerging droughts, and is easy to interpret (Mishra and Singh, 2010). However, the USDM drought data have a couple of shortcomings related to our study.

First, the categorization of USDM drought intensity does not necessarily follow county boundaries (Kuwayama et al., 2019). Second, counties experiencing droughts are not necessarily where fruits and vegetables are grown. Hence, to achieve the study's objective of investigating the impact of drought on FV production while minimizing potential measurement errors, we follow a similar approach to that of Schlenker and Roberts (2009) and develop an annual county-level, crop-specific measure of the drought occurrence using a unique combination of dataset obtained from the California Department of Water Resources and the USDM. Our measure captures the degree of drought in agricultural areas that are specific to each crop within counties for each calendar year.[19]

Specifically, we construct our annual, county by crop-specific drought variables using the annual statewide crop mapping GIS information from the DWR and the weekly GIS information for drought categorizations from the USDM. The county and crop-specific drought variables $D_{c,ijt}$ were calculated as follows:

$$D_{c,ijt} = \sum_{w} \left(\frac{\text{Area of crop } j \text{ in county } i \text{ under drought category } c \text{ during week } w}{\text{Total agricultural area of crop } j \text{ in county } i} \right), \quad (6)$$

where w indicates the weeks falling between January and December of year t. To apply the formula, we first use the statewide 2014 Crop Layer[20] to compute the total agri-

[19]Ideally, one would like to account for crops' temporal growing patterns and use crop year instead of the calendar year. However, our production data are reported annually, and the fact that perennial specialty crops have long-term growing cycles limits our ability to define appropriate crop years in our analysis. We address this limitation by adding crop-specific fixed effects in our econometric models.

[20]Data source: California Statewide Crop Mapping. https://data.cnra.ca.gov/dataset/statewide-crop-mapping. Accessed on September 5, 2024. The California DWR has provided the statewide crop layer data since 2014 and updates it every two years. The FV cover layer may indeed change over time, but unfortunately, the earliest layer data we can obtain is the 2014 crop layer. By comparing the available

cultural acreage[21] for each fruit and vegetable within a county. Then, we calculate the percentage of county agricultural acreage affected by each USDM drought for each crop on a weekly basis and aggregate the weekly values for each drought category across a calendar year. Thus, the drought variables are defined as the area-weighted number of weeks during which a county experiences a drought of a given severity level. To avoid a possible multicollinearity problem among USDM intensity levels in the following analyses, we further combine D0, D1, and D2 intensity levels and consider them to be at a low-intensity drought level. Likewise, D3 and D4 are combined to indicate the high-intensity drought level.[22]

Third, a potential concern with using the USDM is that it incorporates remotely sensed satellite vegetation health as a supplementary indicator, which may introduce endogeneity into the regressors. While it is impossible to determine the extent to which vegetation health is emphasized in the construction of the USDM, it is not one of the five key indicators that determine the magnitude of drought. Therefore, the potential issue of endogeneity in the estimation may be limited. To alleviate this concern, we further instrument the drought variable with two objective indicators: annual gross precipitation and annual average maximum temperature at the county level. Both of these indicators play a dominant role in drought occurrence (Mishra and Singh, 2010). We acknowledge that the assumption behind the exclusion restriction—namely, that precipitation and maximum temperature influence crop production only through drought conditions—is quite strong, though it is testable in our study. For this reason, we treat the instrumental variable approach as a robustness check on the coefficient sign.

crop layer information in 2014, 2016, and 2018, we notice that the crop acreages of FV did not change significantly. Furthermore, as discussed below, we conduct a subsample analysis with varying crop layer information over years and find that our main results are robust.

[21] The DWR sought expertise to identify crop types and land uses and quantify crop acreages statewide using remote sensing and associated analytical techniques. Since remote sensing detects active growth, especially early in the growing season, agricultural acreage can be considered as planted acreage.

[22] There are alternative ways to combine the five USDM drought intensity categories. Since drought magnitude is classified into four primary categories (D1 through D4), it makes sense to combine D1 and D2 (plus D0) and combine D3 and D4. In addition, our analyses show this aggregation produces the lowest correlation among drought variables and the best model fit.

Summary statistics for the county-level USDM measures are presented in the upper portion of Table 1. As expected, the average number of weeks assigned to a particular drought intensity is smaller for more intense drought classes, except when the average number of weeks for D4 exceeds that of D3. To visualize the annual variation of drought intensity levels across different counties, Figure 1 illustrates the variability of drought conditions observed from 2000 to 2019. The map reveals a relatively high frequency of drought occurrences in the agricultural land dedicated to growing FV in California over the past twenty years. The map also shows that counties located along the Central Valley, which is home to the majority of fresh produce, exhibit the most variable drought conditions during the study period. Since our primary objective is to determine how drought affects the production of fresh produce, the coefficient estimates will be driven by the relationship between drought conditions and agricultural outcomes in these counties characterized by high variability.

4.2 *Data on Agriculture*

County-level production data are available annually from 2000 through 2019 from the annual Crop Reports from the California County Agricultural Commissioners.[23] These data contain annual records on total outputs, yield per acre, harvested acres, and the Free-on-Board (F.O.B.) packed price per unit of FV. The total output at the county level represents the total production, while yield per acre represents the ratio of total production to the total number of acres harvested. The data are missing for some county-year combinations due to a small number of counties, such as Trinity, Modoc, Lassen, and Humboldt, not submitting or updating their production information. However, none of these counties are major producers of fruits or vegetables. For some crops, the data are recorded at the variety level. To maintain consistency, we use the aggregate crop-level

[23]Data source: California Agricultural Production Statistics. https://www.cdfa.ca.gov/Statistics/. Accessed on September 5, 2024.

values.[24] The data show that out of the 58 counties in California, 48 counties reported production information for fruits or vegetables during the study period.

The two supplementary data sources used in the heterogeneity analyses are the water demand data collected from the DWR and insurance-related data from the USDA Risk Management Agency (RMA). The state-level data from the DWR provides annual information on the amount of water applied to specific crop categories per unit area.[25] Using this dataset, we calculate annual average applied water for each crop category at the state level. We then rank the crop categories based on their water requirements and classify them as either water-intensive or less water-intensive, using the mean applied water as the threshold. Additionally, we utilize RMA data to group FV into two categories: those with individual crop insurance programs during most of the study period and those without such programs.[26]

4.3 *Irrigation Data*

Under drought conditions, when surface water supplies decline, increased groundwater pumping is a common practice in California. Following Edwards and Smith (2018), we define groundwater access based on the physical presence of an underlying aquifer, as identified by the U.S. Geological Survey (USGS, 2003).[27] Figure 2 displays the groundwater storage access and the agricultural area of FV in California. Considering that groundwater use typically occurs near its source, we do not apply any spatial buffer.

[24]For the yield and price variables, the data for different varieties cannot be directly aggregated. Therefore, we estimated the weighted yields and prices for crops with several varieties, where the weight equals the proportion of the outputs of the variety to the total outputs.

[25]Data source: California Department of Water Resources. https://water.ca.gov/Programs/Water-Use-And-Efficiency/Land-And-Water-Use. In this dataset, FV are classified into the following categories: Tomatoes for processing; Tomatoes for market; Cucurbits including melons, squash and cucumbers; onions and garlic; potatoes; other truck crops; other deciduous crops; subtropical crops and vine. Applied water is the quantity of water applied to a specific crop per unit area.

[26]Data source: USDA Risk Management Agency. https://www.rma.usda.gov/about-crop-insurance.

[27]Previous studies rely on previously observed county-level irrigation at a particular time to define areas as irrigated (Cui, 2020a; Kuwayama et al., 2019). However, this approach fails to account for the change of irrigation sources during droughts.

Instead, we calculate the proportion of each county that overlays an aquifer to define its groundwater access. Counties where more than 70% of the area overlays an aquifer are classified as highly irrigated.[28]

4.4 *Weather Data*

To construct instrumental variables, we rely on precipitation and temperature data from the National Oceanic and Atmospheric Administration (NOAA) to determine the annual weather conditions within counties in California. Specifically, we use annual gross precipitation and annual average maximum temperature in each calendar year at the county level.

Summary statistics for agricultural outcomes and other variables are presented in the bottom portion of Table 1. The panel is unbalanced due to the inconsistent availability of crop production statistics across years and variations in specialty crop planting decisions within counties.

5 Empirical Framework

In this section, we discuss our empirical strategy, which leverages panel fixed effects to quantify the net impacts of an additional week of drought at varying intensities on fresh produce production at the county level. This strategy exploits rich spatial and intertemporal variation in agricultural outcomes, drought intensity, and drought duration.

[28] A majority of counties producing FV are located in California's Central Valley, which is covered by an aquifer layer.

5.1 *Main Specification*

We estimate the following equation to identify the relationship between drought and fresh produce production in California:

$$Ln(\text{Output}_{ijt}) = \alpha + \sum_{l \in (L,H)} \beta^l f(\text{Drought}_{ijt,l}) + \theta_{ij} + \phi_{it} + \gamma_{jt} + \epsilon_{ijt} \tag{7}$$

where Output_{ijt} denotes the total output of crop j in county i in year t. The term $f(\text{Drought}_{ijt,l})$ is a general function capturing drought conditions, which indicates the area-weighted number of weeks that agricultural areas growing crop j in county i experienced either low-intensity (L) or high-intensity (H) drought during year t. Crop-by-county fixed effects, θ_{ij}, account for differences in how crops withstand drought and control for time-invariant, crop-specific local factors, such as soil type, quality, and farming practices. Crop-by-year fixed effects, ϕ_{it}, capture crop-specific shocks. For instance, citrus crops in California have been plagued by Huanglongbing disease since 2012, posing a threat to citrus production. County-by-year fixed effects, γ_{jt}, control for county-specific shocks, including variations in institutional changes, market conditions, climatic changes such as ozone stress change, and policy responses. For instance, counties may adopt different water allocation policies to mitigate drought impacts. ϵ_{ijt} represents the idiosyncratic shock. Given the observational nature of our data and research design, we follow the guidelines outlined by Abadie et al. (2023) and MacKinnon, Nielsen, and Webb (2023) and cluster standard errors at the county level throughout. This strategy allows for arbitrary spatial correlation across counties and serial correlation over years within a county.

Following Kuwayama et al. (2019) and Sumner, Li, and Shr (2023), we consider a linear functional form for $f(\text{Drought}_{ijt,l})$ as our main specification:

$$Ln(\text{Output}_{ijt}) = \alpha + \beta^L \text{Drought}_{ijt,L} + \beta^H \text{Drought}_{ijt,H} + \theta_{ij} + \phi_{it} + \gamma_{jt} + \epsilon_{ijt} \tag{8}$$

Conditional on fixed effects, the coefficients of interest, β^L and β^H, capture the uniform effect of an additional week of drought at low intensity and high intensity on fresh produce production outcomes, respectively. We omit a variable that represents the number of weeks in which a county is not indicated as being in any drought status. In doing so, the coefficients of interest can be interpreted as the impact of drought on the total output of fresh produce when the entire agricultural area of a county's crop is affected by an additional week of drought, with particular severity, relative to not experiencing any drought at all.

We estimate β^L and β^H using a multilevel fixed effects approach, because all units in our sample receive continuous "doses" of drought in each period, and we have multiple treatment variables at different intensity levels. β^L and β^H thus represent a dose response to drought at low intensity and high intensity, respectively. According to Callaway, Goodman-Bacon, and Sant'Anna (2024), when the dose-response function is heterogeneous, a stronger parallel trend assumption is needed. Specifically, the average change in crop output across counties at a given level of drought is the same as what all counties would experience, on average, if they all experienced that dose. If this assumption holds and the drought "dose" follows a normal distribution, the fixed effects estimator provides a weighted average of slopes that approximates the average causal response. However, without an established test for the strong parallel trend assumption, our results should be interpreted with caution, as they rely on this strong assumption being valid.

Another important assumption for unbiased estimates of β^L and β^H in Equation (8) is the absence of interference between units, known as the Stable Unit Treatment Value Assumption (SUTVA). This assumption implies that the crop output in county i depends solely on the drought conditions in the same county. To assess potential violations of SUTVA, we model spillovers using a spatial matrix, $\mathbf{W}$. This approach transforms $\text{Drought}_{ijt,L}$ and $\text{Drought}_{ijt,H}$ into a spatially-weighted average of drought conditions around county i, referred to as the "spatial lag of X" (SLX) (Halleck Vega and Elhorst, 2015; Madhok, 2024):

$$\text{SLX}_{ijt,l} = (I_T \otimes \mathbf{W}_D) \cdot \text{Drought}_{ijt,l}, l \in (L, H) \tag{9}$$

Here, $\mathbf{W}_D$ is a symmetric $D \times D$ matrix, where D represents the number of counties in the study sample. I_T is a $T \times T$ identity matrix, with T being the number of years in the study period. The Kronecker product indicates that $\mathbf{W}_D$ is applied to the drought variables for each time period and subsequently stacked into a panel of spatially lagged drought conditions. Specifically, we define $\mathbf{W}_D$ using inverse-distance weighting matrices. By incorporating $\text{SLX}_{ijt,l}$ into Equation (8), we can test and control for spillover bias.

5.2 *Decomposed Specification*

A change in the total output of produce within each drought category involves both the crop yield response and the acreage response to droughts as we discussed in the conceptual section. Understanding these dynamics is crucial for evaluating the overall impact of drought on agricultural production. To analyze how drought affects total output through these two components, we estimate Equation (8) using log yield per acre and log harvested acres as the dependent variables. With the fixed effects model, the impacts of drought on different production components will sum precisely to the overall effect on total production, provided that all regressions include the same independent variables.[29]

[29] According to Equation (5), $\log(\text{total output} Q) = \log(\text{yield} Y) + \log(\text{harvested acres} A)$. The coefficient matrix from the regression $Q = x\beta + e$ is $\widehat{\beta} = (x^{'}x)^{-1}x^{'}Q = (x^{'}x)^{-1}x^{'}(Y + A) = \widehat{\beta_Y} + \widehat{\beta_A}$.

5.3 *Treatment Heterogeneity*

In our primary specification, the estimated impact of an additional week of drought on fresh produce output encompasses all on-farm activities available to agricultural producers that can either help mitigate or exacerbate the biophysical impact of drought on crops. To further examine the heterogeneous impacts of drought on fresh produce production and explore potential adaptive responses by growers that complicate the supply response of crops under drought conditions, we analyze the extent to which the estimated impact varies by the following factors: the type of growth cycle (annual versus perennial crops), water requirements (high-water versus low-water crops), economic returns (low-return versus high-return crops), and the presence of crop insurance (crops with individual insurance programs versus those without). Table A2 in the Appendix lists the specific crop subgroups considered for these four factors. Specifically, we conduct subgroup analyses relying on the main specification and perform Fisher's permutation test to determine the significance of observed differences in coefficient estimates between the two groups.

Growth cycles: Drought effects might vary between annual and perennial crops as farmers may employ different adaptation strategies for crops with different growth cycles given that a drought often persists for months or even years. For instance, on the one hand, annual crops (i.e., most vegetables) have relatively short growth cycles, thereby enabling growers to adjust their production patterns more easily in the event of a long-term drought. Annual crops, however, generally have lower market values than those of perennial crops.[30] The high cost of water during drought may make annual crops less profitable. On the other hand, perennial crops (i.e., most fruits) require a protracted growing cycle before they can be harvested. They are particularly vulnerable to the effects of climate change due to their year-round exposure to fluctuating weather

[30] According to USDA (2024), the average retail price of fresh fruits is higher than that of fresh vegetables. Data source: https://www.ers.usda.gov/data-products/fruit-and-vegetable-prices/.

conditions. Any adaptations taken to mitigate the effects of drought on perennial crops could be costly (e.g., removal, replacement, or irrigation). However, the economic values of perennial crops are generally higher than those of annual crops.

Water requirements: Another source of crop heterogeneity is that different crops have varying water requirements and exhibit a wide range of abilities to withstand droughts. Droughts are often accompanied by water deficits. Crops with high water demands are expected to be most affected in the long run, despite the fact that irrigation might help counteract the effects of drought, at least in the short term (Hornbeck and Keskin, 2014; Pathak et al., 2018).

Economic returns: The severity of drought impacts on water-intensive crops is not solely determined by the crops' biological water needs but can also be exacerbated by farmers' adaptation behaviors under drought stress. In situations of limited water supplies and high water prices, it becomes more economically beneficial to allocate irrigation resources to crops with a high value. To test this hypothesis, we classify fresh produce into two groups: low-return and high-return, based on their annual average unit F.O.B. price and water demand.[31]

Crop insurance: The federal crop insurance program may be another factor influencing regional yield distribution, leading to varying responses in harvested acres and total production. Policymakers have attempted to reduce moral hazard by linking payments to how actual outcomes around harvest time deviate from guaranteed levels. However, substantial subsidies for insurance premiums may have reduced input use intensity and encouraged expansion onto less suitable lands, skewing the yield distribution toward the

[31] The concept of return used here is not in a strict sense. Since we have no information on other agricultural inputs for each crop, we only consider the cost of irrigation. We assume that other input costs will not be significantly affected by drought conditions. If a crop requires a substantial amount of water for growth, the cost of irrigation will be high due to increased expenses associated with pumping during drought periods. For example, Howitt et al. (2015) estimate a 75.5% increase in the costs of additional pumping during the 2015 California drought. We also calculate the annual average unit F.O.B. price for each crop at the state level and classify a crop as high-value if its average price exceeds the mean price of all FV. If a crop is both high-value and low-water-intensive, it is classified as a high-return crop. Otherwise, it is classified as a low-return crop.

left tail and potentially increasing vulnerability to weather shocks (Cui, 2020a). Despite the steady growth of federal crop insurance coverage for specialty crops over the past 15 years, some FV remain uncovered, lacking individual insurance programs. We examine whether drought impacts differ between crops with and without such coverage.[32]

6 Main Results

In this section, we first present the impacts of drought on total production and its components, including yield per acre and harvested acres. We then demonstrate the heterogeneous effects across different groups of crop characteristics. Finally, we discuss the results of robustness checks conducted to validate our main findings.

6.1 *Drought Impacts on Production and Its Components*

Column (1) in Table 2 reports the results of estimating Equation (8), where the dependent variable is the logarithm of total outputs. The key coefficient estimates are all negative and statistically significant, indicating that additional weeks of drought in any severity category are associated with reduced fresh produce outputs. Drought has the expected effect of decreasing outputs, with more severe drought having a greater impact. At a low-intensity level of drought, the average decline in output is 1.2 percent for an additional week, while at a high-intensity level of drought, the magnitude of the decline is 2.2 percent for an additional week. Considering that, on average, counties experience 23 weeks of drought at the low-intensity level and 7 weeks of drought at the high-intensity level within a year, the impact of drought on FV production is considerable compared to periods without drought.

[32]Whether a crop is covered by the federal crop insurance program may be endogenous, influenced by factors such as its economic significance and stakeholder support. Our analysis does not aim to resolve this endogeneity but rather to highlight the differential impacts of drought on crops with and without individual insurance programs.

Furthermore, we estimate the effects of drought on produce yields and harvested acreage separately to identify processes leading to production losses. The results in column (2) indicate a negative association between drought, at both the low-intensity and high-intensity levels, and crop yields. The magnitude of the yield response ranges from a 0.4% loss for an additional week of drought at the low-intensity level to a 0.9% decrease for an additional week of high-intensity drought. The negative relationship between drought and harvested acreage is also evident as shown in column (3) of Table 2. In comparison, the harvested acreage of specialty crops is found to be more responsive to droughts, with a reduction of 0.7% for an additional week of drought at the low-intensity level and a drop of 1.3% for an additional week at the high-intensity level. Our findings slightly differ from previous research, which indicated that the impact of drought on production was more driven by yield responses rather than changes in harvested acreage.[33] This underscores the significance of adaptive harvesting behaviors during drought conditions in FV production.[34] Nonetheless, our results suggest that, as drought worsens, FV production is predicted to decline sharply, primarily due to decreases in both crop yields and harvested acreage.

6.2 *Heterogeneity Analysis*

In the Empirical Framework section, we hypothesize that the growth cycle, water requirements, economic returns, and insurance programs of crops will influence growers' optimal harvesting decisions. To test these predictions, we conduct subgroup analyses and examine the significance of observed differences in coefficient estimates of drought

[33] Lesk, Rowhani, and Ramankutty (2016) find that national cereal production during a drought is reduced by 10.1% on average, with yields declining by 5.1% and harvested area dropping by 4.1%. Similarly, Sumner, Li, and Shr (2023) show that yield accounts for 72% and 74% of drought impacts on corn and soybean production.

[34] Farmers may adjust their harvested acres in response to drought conditions by either reducing the number of acres they plant or decreasing the amount harvested. Unfortunately, the lack of county-level data on planted acres for specific crops makes it difficult to determine which of these strategies they employ.

variables between groups. Figures 3 through 6 present the results for the heterogeneity analysis.

Growth cycles: Figure 3 illustrates the impacts of drought on production outcomes (i.e., total production, yield per acre, and harvested acres) by crop growth cycle. The results show that drought negatively affects both annual and perennial crops, though the effects vary by drought intensity. However, Fisher's permutation test indicates that the differences in drought impacts between annual and perennial crops are not statistically significant. This suggests that drought affects both types of crops in a similar way.

Water requirements: Figure 4 shows the estimated effects of drought on crops with intensive and less intensive water needs. The results indicate a significant negative impact of drought on the output of water-intensive crops, with reductions ranging from 1.2% to 1.9% for each additional week of drought. In contrast, the outputs of crops with lower water demand are less sensitive to drought. None of the drought severity levels show a statistically significant impact on the outputs of crops with lower water demands. The p-values of the tests for differences between coefficients confirm that an additional week of drought at the high-intensity level has a more detrimental effect on the production of thirsty crops relative to less thirsty crops. The figure also reveals that drought impacts harvested acres more than yields for both crop groups. For water-intensive crops, harvested acres decrease significantly—by 0.7% to 1.01% for each additional drought week—while yields show smaller, statistically insignificant reductions. This pattern suggests that during droughts, farmers likely respond by reducing the area harvested, but the yields on remaining acres are relatively stable. Similarly, less water-dependent crops show declines in harvested acres, though these effects are less pronounced, and no significant changes in yield are observed.

Economic returns: In addition to crops' biophysical characteristics, the results presented in Figure 5 reveal differences in the effect of drought on production outcomes between the low-return and high-return groups. The negative impacts of drought on low-return crops are of larger magnitudes as we hypothesized. The significance of these differences is further confirmed by the p-values for testing the differences. For the yield component, low-return crops experience a significant decrease under high-intensity drought, while high-return crops show no significant change. Similarly, harvested acres of low-return crops are more negatively affected by drought, with significant reductions at both intensity levels. These findings support the hypothesis that farmers prioritize water allocation to higher-return crops, potentially worsening the effects of drought on lower-return crops.

Crop insurance: Finally, the results in Figure 6 show how crop insurance programs affect the impact of drought on production outcomes. Crops covered by individual insurance programs experience significantly larger reductions in production under both low- and high-intensity drought conditions, particularly with a decline of 2.73% for each additional week in high-intensity drought. In contrast, crops without individual insurance programs exhibit no statistically significant changes in production under drought conditions. Similarly, yield and harvested acres of insured crops are more negatively affected by drought, with reductions at both intensity levels. These findings suggest that insured crops may experience moral hazard, where farmers reduce their efforts in mitigating drought impacts due to the presence of insurance coverage.

Although the data do not allow us to track the evolution of specific on-farm practices in response to changes in drought circumstances, these findings support the possibility of farmers adopting adaptive behaviors in response to drought.

6.3 *Robustness Checks*

This section demonstrates robustness to drought variable constructions, alternative variants of the main specification, spillover effects, and endogeneity issues.

Alternative aggregation: The main results can be put to further robustness tests by using an alternative way of aggregating levels of drought intensity. In the main specification, drought categories D0 to D2 are combined as the low-intensity drought level, while D3 to D4 are combined as the high-intensity drought level. To examine the robustness of the findings, we alternatively combine D0 to D1 as the low-intensity level and D2 to D4 as the high-intensity level. Table 3 reports the results for the alternative definition. Overall, the significance and magnitude of the results remain similar to the main findings when the definition of aggregated drought intensity levels is replaced with the alternative definition. Under the alternative definition, an additional week of drought in any severity category is associated with lower outputs of specialty crops, as reflected in the decline of yields and harvested acreages.

Varying weights for constructing drought variables: Our primary model uses 2014 Crop Layer data to obtain land coverage of each crop within counties, which serves as weights for constructing crop-specific drought intensity variables such as $D0_{ijt}$. Using fixed weights across the sample period raises potential concerns, as crop acreage may change over time in response to various factors, including drought. To account for this, we also conduct an analysis using a restricted sample from 2012 to 2019, applying available crop layer data from 2014, 2016, and 2018 as weights to build the drought variables. The results, shown in columns 1, 3, and 5 of Table 4 for output, yield, and harvested acres, respectively, align with those using fixed weights (columns 2, 4, and 6), though the coefficient for high-intensity drought is slightly smaller.

Non-linearity function: In our main specification, we consider a linear functional form for $f(\text{Drought}_{ijt,l})$. However, previous literature on weather impacts has demonstrated the usefulness of a quadratic specification of temperature and precipitation (Burke, Hsiang, and Miguel, 2015). To account for the possible non-linear relationship between drought variables and the total outputs of fresh produce, we also consider alternative specifications using the quadratic vector of drought variables. That is, $f(\text{Drought}_{ijt,l}) = \text{Drought}_{ijt,l} + \text{Drought}^2_{ijt,l}$. However, tests for a U-shaped relationship fail to reject the null hypothesis that the true relationship is monotonic over relevant data values (Lind and Mehlum, 2010), which suggests that our main specification is appropriate.[35]

Standard error clustering: Table A7 shows the baseline estimates adjusted for alternative clustering. In columns 1, 3, and 5, we replicate the baseline results, clustering standard errors at the county level to account for potential unobserved shocks. A potential issue arises from clustering at the county level due to the limited number of clusters (Colin Cameron and Miller, 2015). To examine the role of clustering in determining the effects of droughts, we replicate the estimation results by clustering the standard errors at the county $\times$ crop level. The results, shown in columns 2, 4, and 6, remain nearly identical. Similarly, columns 3, 5, and 7 demonstrate that using robust standard errors produces comparable estimates. These consistent findings across various methods confirm the robustness of our results, indicating that clustering is unlikely to pose an issue in our analysis.

Sensitivity to spatial spillovers: Table 5 presents the results of incorporating the spatial lag of explanatory variables to capture potential spillover effects. The findings indicate that spatial spillovers have minimal impact, as the estimated production losses remain consistent even when accounting for influences from neighboring counties.

Instrumental Variable Estimates: As discussed in the Data section, the USDM incorporates remotely sensed satellite vegetation health as a supplementary indicator, which may introduce endogeneity into the regressors. While this potential issue is likely limited, we show that our results are robust to an IV design. We use objective measures—precipitation and maximum temperature—as instruments for the drought variable. Table A8 presents the results from the two-stage least squares (2SLS) specification, where the independent variable is either a simple or weighted summation of weeks in drought at any level, and the independent variable is the total outputs. The F-statistics for weak instrument tests are 103 for the simple summation and 43 for the weighted summation. Hausman tests reveal no evidence of endogeneity, and overidenti-

[35] The p-values from the U-shape test are 0.397 for the Drought_L variable and 0.304 for the Drought_H variable when total outputs are used as the dependent variable.

fication tests confirm the validity of our instruments. Columns 1 and 3 of Table A8 show fixed effects results, while columns 2 and 4 report the 2SLS results. The 2SLS estimates confirm the negative relationship between drought duration and production. While the 2SLS coefficients are smaller than or equal to the fixed effects estimates, comparing them directly would be misleading.[36] What is most important is that both methods show consistent coefficient signs and statistical significance, reinforcing the robustness of the relationship between drought and production loss.

7 Irrigation Adaptation

Irrigation has long been considered an important adaptation tool for mitigating the climatic impacts on crops (e.g., Edwards and Smith, 2018; Smith and Edwards, 2021; Edwards, Sanchez, and Sekhri, 2024). We build on existing discussions about the role of irrigation and examine how it can help reduce the negative effects of drought on crop production. Due to the lack of detailed county-level irrigation data for each crop, we adopt a method similar to that used by Cui (2020a) and Kuwayama et al. (2019). We compare the effects of drought in counties with aquifers and access to groundwater, which typically have higher levels of irrigation, to those that rely on standard irrigation practices without such access.

The results presented in Figure 7 examine the production losses resulting from drought shocks in high-irrigated and standard-irrigated counties. The coefficients for both low- and high-intensity drought levels indicate that drought negatively impacts production output, with high-irrigated counties experiencing smaller losses compared to standard-irrigated counties. Specifically, under low-intensity drought conditions, high-irrigated counties show a production loss of 1.1% per additional week, while standard-irrigated counties face a more substantial loss of 8.3%. Similarly, during high-intensity drought,

[36] 2SLS estimates the LATE, while OLS estimates the ATE. Directly comparing LATE and ATE can be misleading.

the loss for high-irrigated counties is 2.3%, compared to 6.7% for standard-irrigated counties. The Fisher's permutation test indicates that the differences in drought impacts between high-irrigated counties and standard-irrigated counties are statistically significant.

In terms of yield response, high-irrigated counties again demonstrate less sensitivity to drought shocks than their standard-irrigated counterparts. The response of harvested acres follows a similar pattern under low-intensity drought conditions; however, there are no statistically significant differences between the two types of counties during high-intensity drought. These results provide clear evidence that irrigation mitigates the negative impacts of drought shocks on crop production, although the irrigation-related adjustments in yields are more pronounced than those for harvested acres.

8 Discussion and Conclusion

In this section, we discuss our findings by estimating the economic losses in dollar terms and comparing them to the impacts of drought on corn and soybean production in the United States, using the same drought data source. We also extend the comparison to other relevant contexts. Finally, we summarize the key insights of our study and discuss its implications, as well as its limitations.

8.1 *Discussion*

Our main findings show that drought has a clear, negative effect on total fresh produce output. For each additional week of drought, production declines on average by 1.2% to 2.2%, depending on the intensity of the drought conditions. To estimate the dollar value of the losses associated with this percentage reduction in output, we conduct back-of-the-envelope calculations. We first calculate the total annual value of each crop by multiplying its total production quantity by the production-share-weighted price.[37] Subsequently, we derive the annual revenue losses for each crop by multiplying the total value by the percentage reduction. Figure A2 presents the estimates. For example, in the case of grape production, which is the highest-grossing specialty crop cultivated in California, the annual total value ranges from $2,193.85 to $7,344.08 million during the 2000-2019 period. Thus, the losses for grapes range from $26.33 to $88.13 million for an additional week of low-intensity drought, and from $48.26 to $161.57 million for an additional week of high-intensity drought.[38] Given that, on average, California counties experienced varying degrees of drought for several weeks within a year during the study period, the cumulative impact of droughts on crop production is substantial.

When comparing our findings to studies on corn and soybean production using the same drought measurement, we observe a significantly greater impact of drought on FV production. Kuwayama et al. (2019) report yield reductions of 0.1% to 1.2% per acre for corn and soybeans in dryland counties for each additional week of drought, and reductions of 0.1% to 0.5% in irrigated counties. In contrast, our analysis shows average yield losses for FV crops ranging from 0.4% to 0.9% per acre, with marginal reductions as high as 6.3% in counties with lower aquifer coverage (below 70%). Similarly, Sumner, Li, and Shr (2023) estimate that a one-percentage-point increase in drought duration decreases total corn output by 0.10% to 0.35% and soybean output by 0.06% to 0.48%. In comparison, our results indicate that each additional week of drought reduces total FV output by 1.2% to 2.2%. These findings emphasize the greater sensitivity of fresh produce to drought conditions compared to staple crops like corn and soybeans.

However, the effects of drought on California's produce are smaller when compared to other contexts. Lesk, Rowhani, and Ramankutty (2016) show that droughts significantly reduced global cereal production by 10%, Brás et al. (2021) find European cereal

[37]The prices reported in county reports are F.O.B. prices. The weight equals the production share of each county. All prices are deflated by U.S. GDP using 2020 as the reference year.

[38]Note that the dollar value of losses associated with percentage reductions in output is roughly estimated.

yields drop by 9% during droughts, and Fleming-Muñoz, Whitten, and Bonnett (2023) provide a summary documenting that Australian crop production falls by 18% to 60% under drought conditions in different study periods. In Tanzania, Kubik and Maurel (2016) estimate that the increase in water deficit by one standard deviation results in a crop production decline by 20% to 30%. This discrepancy may be due to more advanced irrigation systems, agricultural technology, and institutional arrangements in the U.S. Despite these advancements, California's growing groundwater depletion calls for stronger drought risk management strategies to mitigate future impacts.

8.2 *Conclusion*

More frequent severe drought episodes have occurred worldwide in recent decades, coinciding with intensified climate change. Worse yet, these extreme weather events are predicted to have a high probability of occurring in the future. Despite extensive studies on the impacts of weather extremes on crop production, there has been limited focus on quantitatively establishing the connection between drought occurrences and fresh produce production. To fill this gap, this study employs county-level data to estimate the net impacts of the California drought, as defined by the USDM, on fresh produce outputs.

Overall, we find that drought exerts a statistically significant adverse impact on the total outputs of fresh produce. The magnitude of this impact ranges between 1.2% and 2.2% for each additional week of drought. A decomposition of drought impacts on total production shows that this reduction is driven by both lower yields per acre and fewer harvested acres under drought conditions, with the acreage response being more pronounced. Response heterogeneity related to different crop characteristics including growth cycle, water requirement, economic returns, and crop insurance coverage further illustrates the complexity in growers' behavioral response to drought shocks. In addition, we show that irrigation mitigates negative drought impacts on production losses. To strengthen the causal link between drought intensity and produce production outcomes, a series of robustness checks offers additional supporting evidence.

The findings of this study speak directly to the susceptibility of agriculture to climate change. The decline in crop production due to weather-related factors could potentially worsen if the frequency of extreme weather events increases, posing risks to food security given the vulnerability of food systems (Wheeler and Von Braun, 2013). Such declines in crop production could lead to substantial losses in social welfare. Because California has a dominant position in both domestic and international specialty crop markets, droughts in the state can have significant impacts on these markets. These implications highlight the importance of developing risk-reducing measures, such as the introduction of drought-tolerant and high-yielding seed varieties, improving irrigation systems' efficiency, and implementing sustainable water management regulations, to alleviate the impacts of future droughts.

In spite of the contributions and policy implications of this study, there are still limitations that need to be addressed in future investigations. Firstly, there is evidence that crop production is affected not only by the duration and intensity of drought but also by its timing in relation to the growing season (Li and Ortiz-Bobea, 2022; Sumner, Li, and Shr, 2023) and specific growing stage (Rai, Singh, and Upadhyay, 2017). Due to data limitations, we cannot investigate whether droughts have a more pronounced impact during specific times of the year or growth stages. Further research is necessary to explore the effects of these factors in greater detail. Secondly, future research should delve deeper into the distinction between droughts and heat effects. Although the inclusion of county-year fixed effects in this study partially addresses the effects of heatwaves, it remains unclear whether heatwaves contribute to the decline in FV outputs alongside droughts. If high temperatures indeed play a significant role, and considering the projected warming trends in California, relying solely on irrigation alone will not suffice as a solution. More comprehensive and integrated measures are needed to effectively address the challenges posed by the increasingly uncertain climate conditions ahead.

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Tables

Table 1: Summary Statistics of Major Variables

	Mean	Std. Dev.	Min	Max	Obs
# weeks in D0	8.395	10.422	0	46.5	7,223
# weeks in D1	7.876	12.280	0	52	7,223
# weeks in D2	6.439	11.869	0	52	7,223
# weeks in D3	3.368	9.573	0	52	7,223
# weeks in D4	3.958	12.480	0	52	7,223
Total outputs (1000 Tons)	102.442	355.622	0.004	5744	7,223
Yield per acre (Tons)	12.061	14.114	0.11	553.57	7,223
Harvested Acreage (1000 Acres)	7.033	18.203	0.001	254.9	7,223
Price per unit (Dollar)	1076.733	1230.27	6.3	21094.03	7,223
Applied water (Acre-foot per Acre)	2.853	1.598	1.93	4.08	7,223
Annual gross precipitation (Inch)	80.221	51.294	2.57	358.75	7,223
Annual average maximum temperature (F)	73.484	5.224	59.227	90.054	7,223

Notes: Number of weeks in different drought intensities are weighted by % agricultural area affected.

Table 2: Impact of Additional Weeks of Drought on Production Outcomes

Dependent Variable	(1) Ln(output)	(2) Ln(yield)	(3) Ln(harvested acres)
# Weeks at low-intensity level	-0.012***	-0.004*	-0.007***
	(0.003)	(0.002)	(0.002)
# Weeks at high-intensity level	-0.022***	-0.009**	-0.013***
	(0.004)	(0.004)	(0.003)
Constant	9.860***	2.258***	7.611***
	(0.078)	(0.076)	(0.072)
$Drought_L$+$Drought_H$=0 p-val	0.000	0.034	0.000
Crop × County FE	Yes	Yes	Yes
Crop × Year FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Observations	6,985	6,985	6,985
Adj R^2	0.950	0.886	0.958
Within R^2	0.004	0.002	0.003

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) The number of weeks at the low-intensity level (i.e., $Drought_L$) equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level (i.e., $Drought_H$) equals the sum of the number of weeks in D3 and D4 drought. (3) 238 singleton observations are dropped iteratively to avoid biasing the standard errors Correia (2015). (4) *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Estimations in a Different Definition of Aggregate Drought Variables

	(1) Ln(output)	(2) Ln(yield)	(3) Ln(harvested acres)
# Weeks at low-intensity level	-0.012***	-0.004*	-0.007***
	(0.002)	(0.002)	(0.002)
# Weeks at high-intensity level	-0.016***	-0.006*	-0.010***
	(0.004)	(0.003)	(0.002)
Constant	9.841***	2.250***	7.599***
	(0.090)	(0.076)	(0.066)
$Drought_L$+$Drought_H$=0 p-val	0.000	0.034	0.000
Crop × County FE	Yes	Yes	Yes
Crop × Year FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Observations	6,985	6,985	6,985
Adj R^2	0.950	0.886	0.958
Within R^2	0.003	0.001	0.002

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) The number of weeks at the low-intensity level (i.e., $Drought_L$) equals the sum of the number of weeks in D0 and D1 drought. The number of weeks at the high-intensity level (i.e., $Drought_H$) equals the sum of the number of weeks in D2, D3 and D4 drought. (3) Singleton observations are dropped iteratively to avoid biasing the standard errors. (4) *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The Effects of Land Cover Issues on Estimation

	Ln(output)		Ln(yield)		Ln(harvested acres)	
	(1) Varying weights	(2) Fixed weights	(3) Varying weights	(4) Fixed weights	(5) Varying weights	(6) Fixed weights
#Weeks at low-intensity level	-0.008***	-0.007**	-0.002	-0.004	-0.006***	-0.004*
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
#Weeks at high-intensity level	-0.006*	-0.008***	-0.005*	-0.007**	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Constant	9.623***	9.894***	2.286***	2.364***	7.348***	7.544***
	(0.115)	(0.112)	(0.104)	(0.103)	(0.092)	(0.086)
Crop × County FE	Yes	Yes	Yes	Yes	Yes	Yes
Crop × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,983	2,662	3,983	2,662	3,983	2,662
Adj. R^2	0.966	0.968	0.886	0.909	0.974	0.977
Within R^2	0.002	0.002	0.001	0.002	0.004	0.002

Notes: (1) The sample is restricted to the period from 2012 to 2019. (2) Standard errors are clustered at the county level and reported in the parentheses. (3) The number of weeks at the low-intensity level (i.e., $Drought_L$) equals the sum of the number of weeks in D0 and D1 drought. The number of weeks at the high-intensity level (i.e., $Drought_H$) equals the sum of the number of weeks in D2, D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The Effects of Spatial Spillovers

	(1) Ln(output)	(2) Ln(yield)	(3) Ln(harvested acres)
#Weeks at low-intensity level	-0.011***	-0.004*	-0.007***
	(0.002)	(0.002)	(0.002)
#Weeks at high-intensity level	-0.022***	-0.009**	-0.013***
	(0.004)	(0.004)	(0.003)
#Weeks at low-intensity level (County $i \neq d$)	0.014	0.009	0.005
	(0.009)	(0.006)	(0.007)
#Weeks at high-intensity level (County $i \neq d$)	0.028	0.003	0.025
	(0.025)	(0.012)	(0.016)
Constant	9.745***	2.207***	7.548***
	(0.087)	(0.066)	(0.077)
Crop × County FE	Yes	Yes	Yes
Crop × Year FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Observations	6,985	6,985	6,985
Adj R^2	0.950	0.886	0.958
Within R^2	0.005	0.002	0.004

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2)#Weeks at low-intensity level (County $i \neq d$) and #Weeks at high-intensity level (County $i \neq d$) are spatial lags of independent variables. (3) The number of weeks at the low-intensity level (i.e., $Drought_L$) equals the sum of the number of weeks in D0 and D1 drought. The number of weeks at the high-intensity level (i.e., $Drought_H$) equals the sum of the number of weeks in D2, D3 and D4 drought. (4) 238 singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Figures

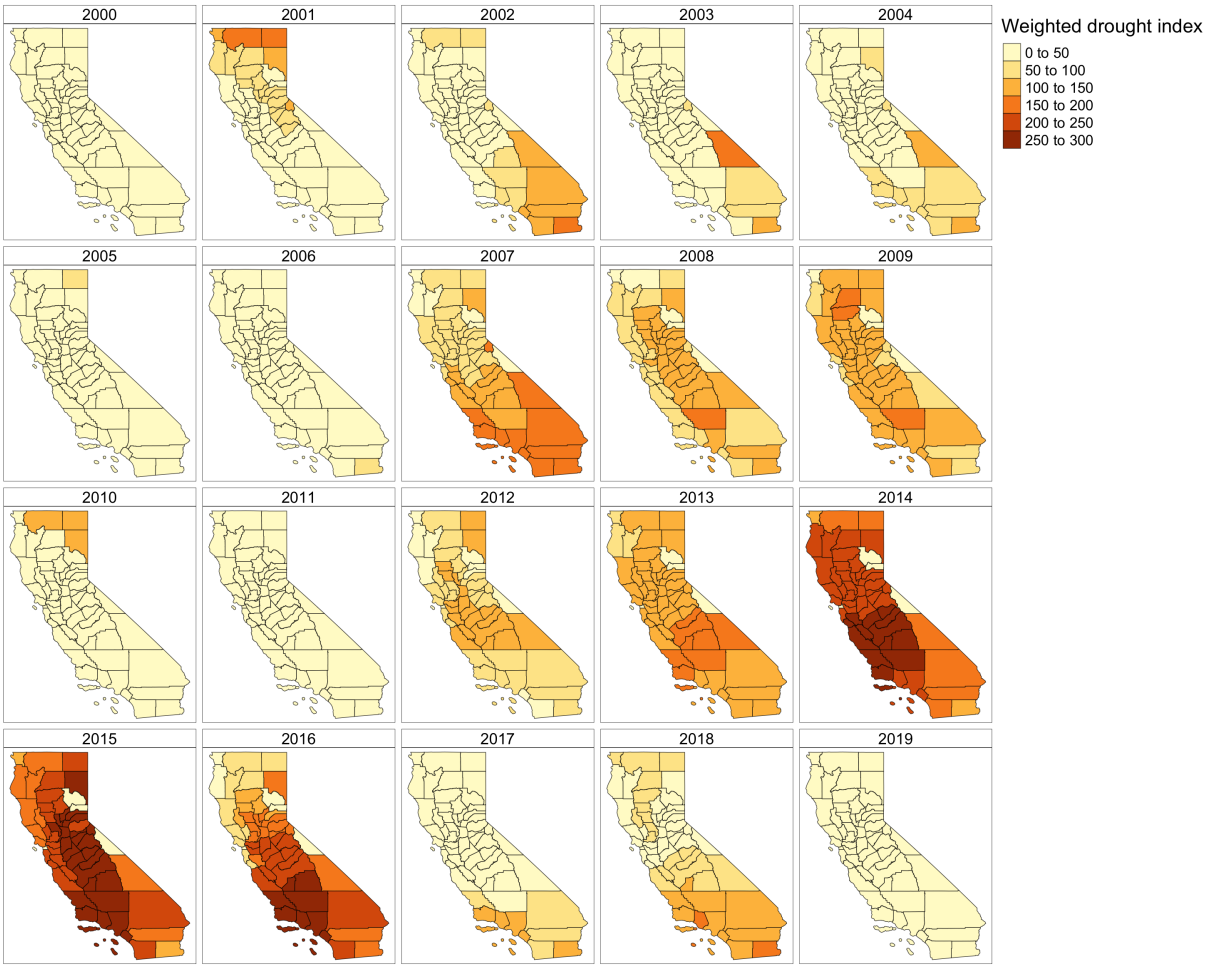

Figure 1: California Map of Weighted Drought Index Based on USDM Drought Classifications during 2000-2019

Notes: Following the suggestions of USDM, for each year, the weighted drought index is calculated by summing weighted weekly drought variables after they have been multiplied by a factor corresponding to severity (e.g., weeks in D0 are the identity and weeks in D4 are multiplied by five). The range of the weighted drought index is from 0 to 260. Here, we aggregated lands for all specialty crops in each county and calculated weights for the vector of drought variables following the same steps as calculating weights for drought variables for each crop. The figure illustrates the variation of drought across counties from 2000 to 2019. The more severe the drought, the darker the shades.

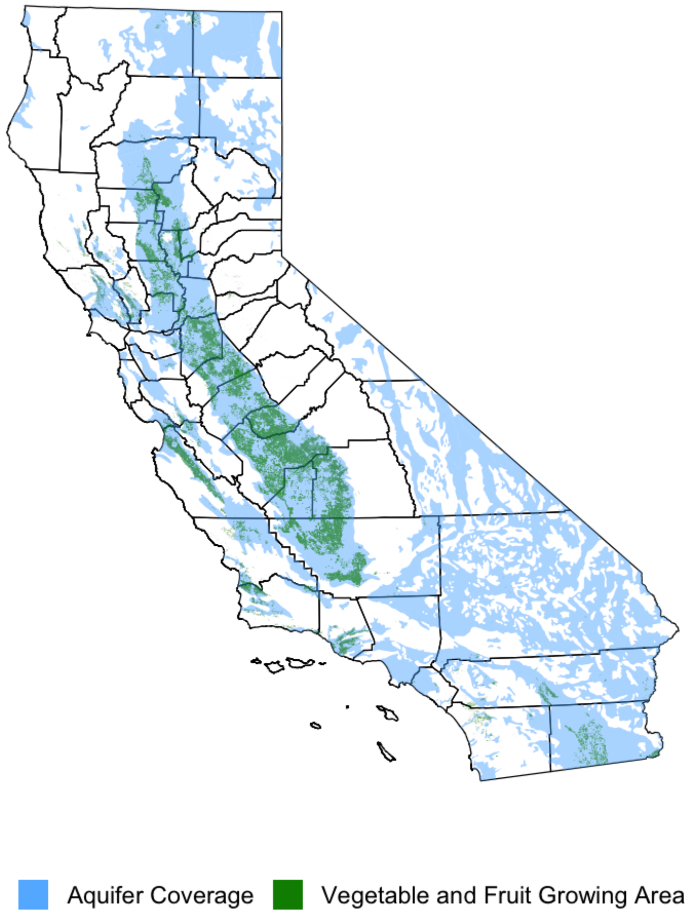

Figure 2: Groundwater Storage Access and Produce Growing Areas in California

Notes: This figure presents the locations of aquifers alongside the major fruit and vegetable growing regions in California. The data are sourced from the USGS (2003) and California statewide 2014 Crop Layer.

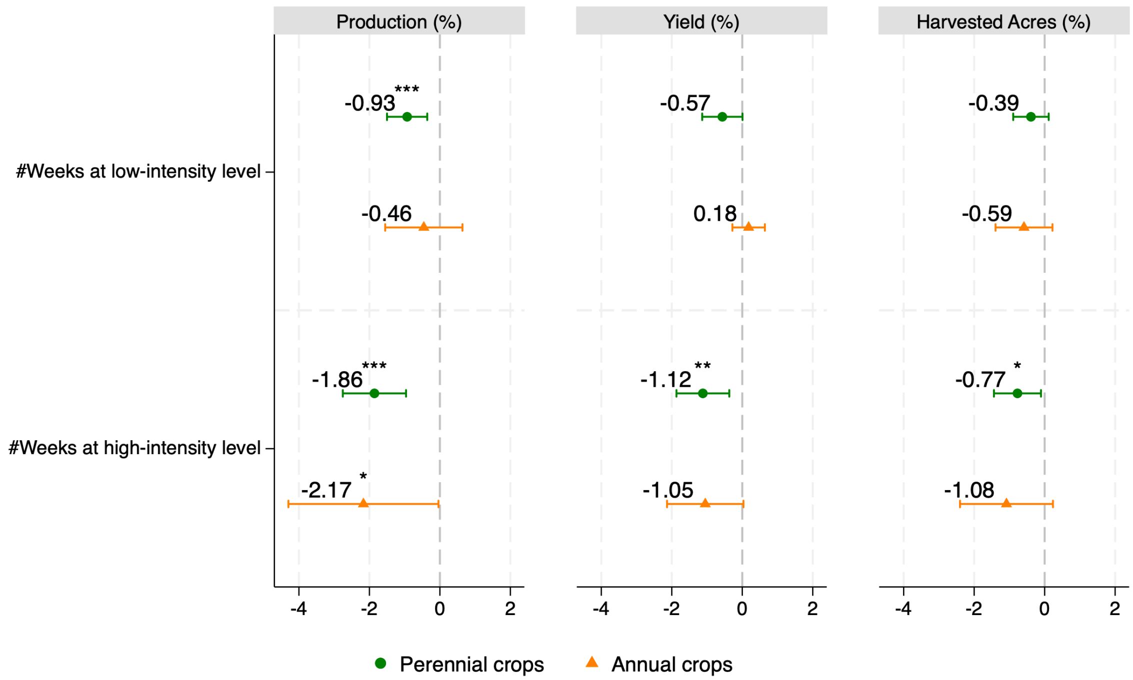

Figure 3: Heterogeneous Supply Responses to Drought by Growth Cycles

Notes: This figure illustrates the estimated coefficient for drought on production outcomes by crop growth cycles. The bars represent 95 percent confidence intervals, and standard errors are clustered at the county level. Table A3 provides detailed information.

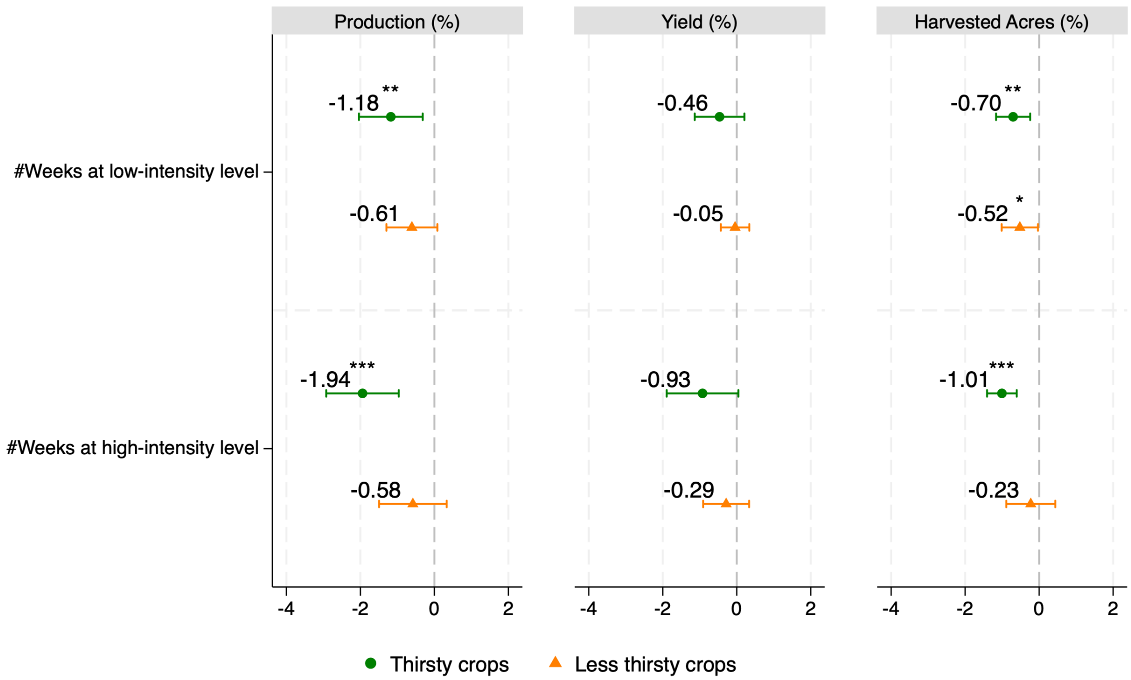

Figure 4: Heterogeneous Supply Responses to Drought by Water Requirements

Notes: This figure illustrates the estimated coefficient for drought on production outcomes by crop water requirements. The bars represent 95 percent confidence intervals, and standard errors are clustered at the county level. Table A4 provides detailed information.

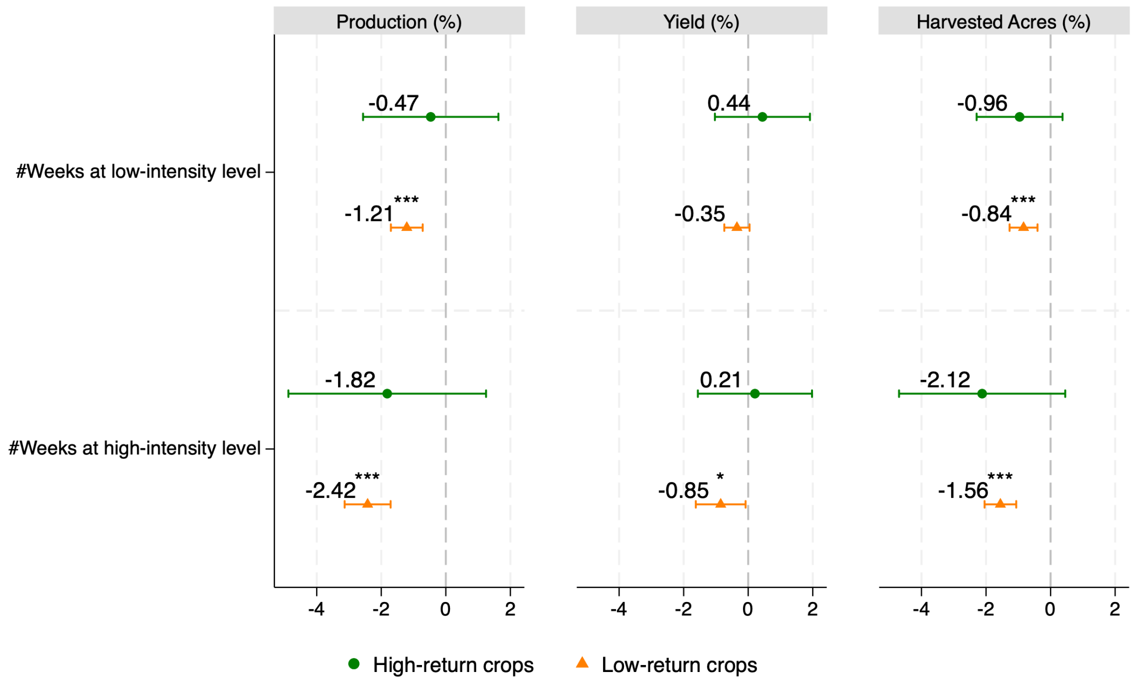

Figure 5: Heterogeneous Supply Responses to Drought by Economic Returns

Notes: This figure illustrates the estimated coefficient for drought on production outcomes by crop economic returns. The bars represent 95 percent confidence intervals, and standard errors are clustered at the county level. Table A5 provides detailed information.

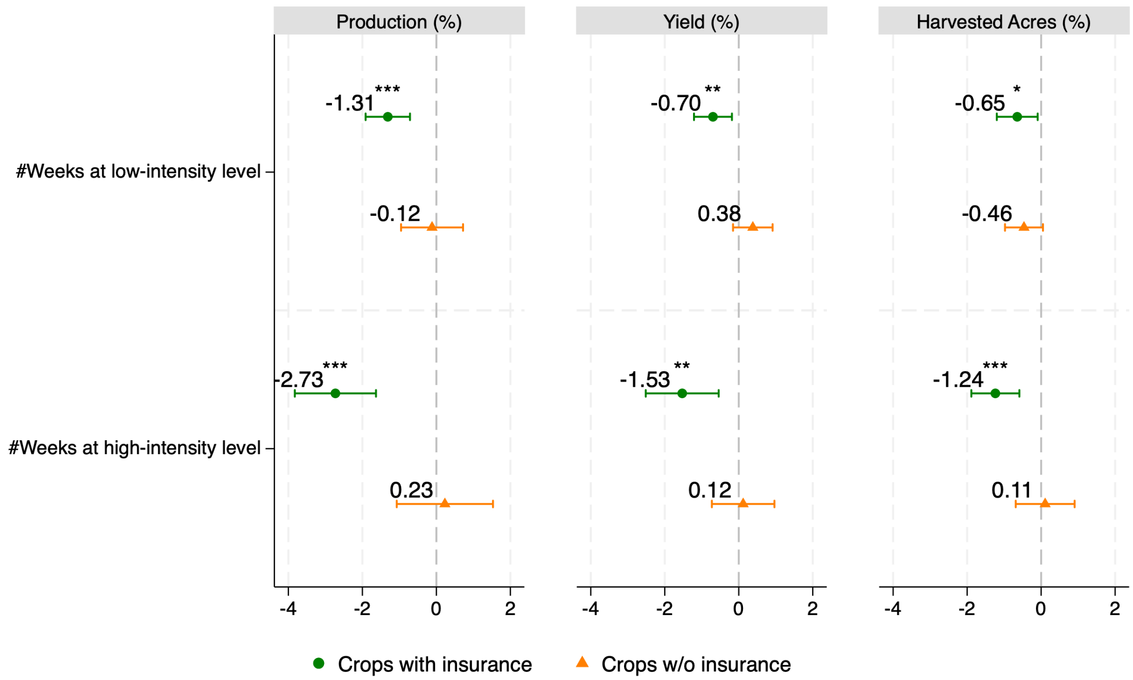

Figure 6: Heterogeneous Supply Responses to Drought by Insurance

Notes: This figure illustrates the estimated coefficient for drought on production outcomes, distinguishing between crops with and without established individual programs. The bars represent 95 percent confidence intervals, and standard errors are clustered at the county level. Table A6 provides detailed information.

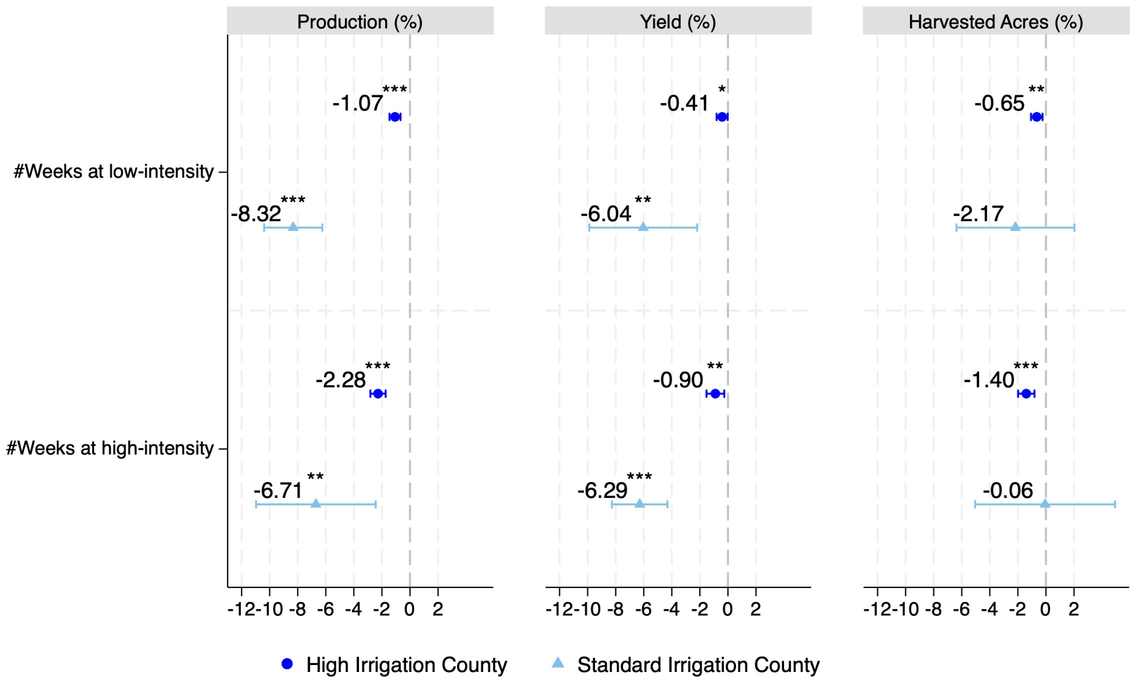

Figure 7: Production Losses from Drought Shocks: High Irrigated Counties versus Standard Irrigated Counties

Notes: This figure illustrates the estimated coefficient for drought on production outcomes, distinguishing between high irrigation counties and standard irrigation counties. The bars represent 95 percent confidence intervals, and standard errors are clustered at the county level. Table A9 provides detailed information.

Appendix

Table A1: Drought Intensity Classification by the U.S. Drought Monitor

Category	Drought Intensity	Percentile
D0	Abnormally Dry	20 to $\leq$ 30
D1	Moderate Drought	10 to $\leq$ 20
D2	Severe Drought	5 to $\leq$ 10
D3	Extreme Drought	2 to $\leq$ 5
D4	Exceptional Drought	$\leq$ 2

Notes: The table outlines the percentile ranges for each drought intensity level in the U.S. Drought Monitor. These levels are determined by their likelihood of occurrence, based on drought indicator data collected between 1932 and 2001.

Table A2: List of Fresh Produce Subgroups

No.	Crop name	Perennial	Water-intensive	High return	Insured
1	Apples	1	1	0	1
2	Apricots	1	1	0	1
3	Artichokes	1	0	1	0
4	Asparagus	1	0	1	0
5	Avocados	1	1	0	1
6	Snap beans	0	0	1	0
7	Blueberries	1	0	1	1
8	Raspberries	1	0	1	0
9	Strawberries	1	0	1	0
10	Broccoli	0	0	0	0
11	Brussels Sprouts	0	0	0	0
12	Cabbage	0	0	0	0
13	Carrots	0	0	0	0
14	Cauliflower	0	0	0	0
15	Celery	0	0	0	0
16	Cherries	1	1	0	1
17	Citrus	1	1	0	1
18	Sweet corn	0	0	0	0
19	Cucumbers	0	0	0	0
20	Dates	1	1	0	0
21	Eggplant	0	0	0	0
22	Endive	0	0	0	0
23	Dried figs	1	1	0	0
24	Garlic	0	1	0	0
25	Grapefruit	1	1	0	1
26	Grape	1	0	1	1
27	Horseradish	1	0	0	0
28	Kale	1	0	1	0
29	Kiwifruit	1	1	0	0
30	Leeks	0	0	1	0
31	Lemons	1	1	0	1
32	Lettuce	0	0	0	0
33	Melons	0	0	0	0
34	Nectarines	1	1	0	1
35	Olives	1	1	0	1

Table A2: List of Fresh Produce Subgroups (Countinued)

No.	Crop name	Perennial	Water-intensive	High return	Insured
36	Onions	0	1	0	1
37	Orange	1	1	0	1
38	Parsley	0	0	0	0
39	Peaches	1	1	0	1
40	Pears	1	1	0	1
41	Peppers	0	0	0	0
42	Persimmons	1	1	0	0
43	Plums	1	1	0	1
44	Pomegranates	1	1	0	0
45	Potatoes	0	0	0	1
46	Pumpkins	0	0	0	0
47	Quince	1	1	0	0
48	Radishes	0	0	0	0
49	Spinach	0	0	0	0
50	Squash	0	0	0	0
51	Tangelos	1	1	0	0
52	Tangerines & Mandarins	1	1	0	1
53	Tomatoes	0	0	0	1

Notes: TThe table provides a list of 53 fruits and vegetables analyzed in our study, along with binary indicators representing key crop characteristics. A value of "1" signifies that a crop belongs to a specific subgroup, such as "perennial," "water-intensive," "high-return," or "insured," while a value of "0" indicates that the crop is not part of those categories.

Table A3: Heterogeneous Supply Responses to Drought by Growth Cycles

	Ln(output)			Ln(yield)			Ln(harvested acres)		
	(1) Perennial	(2) Annual	(3) Diff-test	(4) Perennial	(5) Annual	(6) Diff-test	(7) Perennial	(8) Annual	(9) Diff-test
#Weeks at low-intensity level	-0.009***	-0.005	-0.005	-0.006	0.002	-0.008	-0.004	-0.006	0.002
	(0.003)	(0.006)	[0.315]	(0.003)	(0.003)	[0.155]	(0.003)	(0.005)	[0.440]
#Weeks at high-intensity level	-0.019***	-0.022*	0.003	-0.011**	-0.010	-0.001	-0.008*	-0.011	0.003
	(0.005)	(0.012)	[0.459]	(0.004)	(0.006)	[0.480]	(0.004)	(0.008)	[0.467]
Constant	9.395***	10.245***		1.924***	2.677***		7.485***	7.568***	
	(0.104)	(0.227)		(0.104)	(0.101)		(0.093)	(0.160)	
Crop $\times$ County FE	Yes	Yes		Yes	Yes		Yes	Yes	
Crop $\times$ Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
County $\times$ Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	4,102	2,728		4,102	2,728		4,102	2,728	
Adj. R^2	0.953	0.938		0.848	0.848		0.969	0.942	
Within R^2	0.003	0.003		0.002	0.006		0.001	0.001	

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) We use the Fisher's permutation test to determine the significance of observed differences in coefficient estimates between two groups. The number of bootstrap repetitions is 1000. P-values for the group coefficients difference are reported in the square brackets. (3) The number of weeks at the low-intensity level equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level equals the sum of the number of weeks in D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Heterogeneous Supply Responses to Drought by Water Requirements

	Ln(output)			Ln(yield)			Ln(harvested acres)		
	(1) Thirsty	(2) Less Thirsty	(3) Diff-test	(4) Thirsty	(5) Less Thirsty	(6) Diff-test	(7) Thirsty	(8) Less Thirsty	(9) Diff-test
#Weeks at low-intensity level	-0.012**	-0.006	-0.06	-0.005	-0.000	-0.005	-0.007**	-0.005*	-0.002
	(0.005)	(0.004)	[0.197]	(0.004)	(0.002)	[0.235]	(0.003)	(0.003)	[0.417]
#Weeks at high-intensity level	-0.019***	-0.006	-0.013	-0.009	-0.003	-0.006	-0.010***	-0.002	-0.008
	(0.006)	(0.005)	[0.071]	(0.006)	(0.004)	[0.147]	(0.002)	(0.004)	[0.119]
Constant	9.340***	10.123***		1.941***	2.481***		7.401***	7.643***	
	(0.148)	(0.128)		(0.126)	(0.076)		(0.074)	(0.089)	
Crop × County FE	Yes	Yes		Yes	Yes		Yes	Yes	
Crop × Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
County × Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	3,180	3,440		3,180	3,440		3,180	3,440	
Adj. R^2	0.945	0.952		0.850	0.889		0.961	0.957	
Within R^2	0.004	0.001		0.002	0.000		0.003	0.001	

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) We use the Fisher's permutation test to determine the significance of observed differences in coefficient estimates between two groups. The number of bootstrap repetitions is 1000. P-values for the group coefficients difference are reported in the square brackets. (3) The number of weeks at the low-intensity level equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level equals the sum of the number of weeks in D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Heterogeneous Supply Responses to Drought by Economic Returns

	Ln(output)			Ln(yield)			Ln(harvested acres)		
	(1) High-return	(2) Low-return	(3) Diff-test	(4) High-return	(5) Low-return	(6) Diff-test	(7) High-return	(8) Low-return	(9) Diff-test
#Weeks at low-intensity level	-0.005	-0.012***	0.007	0.004	-0.003	0.007	-0.010	-0.008***	-0.002
	(0.012)	(0.003)	[0.003]	(0.008)	(0.002)	[0.000]	(0.008)	(0.003)	[0.000]
#Weeks at high-intensity level	-0.018	-0.024***	0.006	0.002	-0.009*	0.011	-0.021	-0.016***	-0.005
	(0.018)	(0.004)	[0.059]	(0.010)	(0.005)	[0.258]	(0.015)	(0.003)	[0.052]
Constant	9.543***	9.907***		1.737***	2.314***		7.833***	7.596***	
	(0.424)	(0.094)		(0.281)	(0.080)		(0.298)	(0.076)	
Crop × County FE	Yes	Yes		Yes	Yes		Yes	Yes	
Crop × Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
County × Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	748	5,722		748	5,722		748	5,722	
Adj. R^2	0.961	0.946		0.876	0.885		0.975	0.952	
Within R^2	0.004	0.005		0.001	0.002		0.007	0.004	

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) We use the Fisher's permutation test to determine the significance of observed differences in coefficient estimates between two groups. The number of bootstrap repetitions is 1000. P-values for the group coefficients difference are reported in the square brackets. (3) The number of weeks at the low-intensity level equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level equals the sum of the number of weeks in D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Heterogeneous Supply Responses to Drought by Insurance

	Ln(output)			Ln(yield)			Ln(harvested acres)		
	(1) Insured	(2) Uninsured	(3) Diff-test	(4) Insured	(5) Uninsured	(6) Diff-test	(7) Insured	(8) Uninsured	(9) Diff-test
#Weeks at low-intensity level	-0.013***	-0.001	-0.012	-0.007**	0.004	-0.011	-0.006*	-0.005	-0.001
	(0.004)	(0.005)	[0.153]	(0.003)	(0.003)	[0.066]	(0.003)	(0.003)	[0.439]
#Weeks at high-intensity level	-0.027***	0.002	-0.029	-0.015**	0.001	-0.016	-0.012***	0.001	-0.013
	(0.007)	(0.008)	[0.039]	(0.006)	(0.005)	[0.069]	(0.004)	(0.005)	[0.123]
Constant	9.962***	9.466***		2.156***	2.290***		7.824***	7.179***	
	(0.119)	(0.165)		(0.105)	(0.107)		(0.100)	(0.099)	
Crop $\times$ County FE	Yes	Yes		Yes	Yes		Yes	Yes	
Crop $\times$ Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
County $\times$ Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	3,983	2,863		3,983	2,863		3,983	2,863	
Adj. R^2	0.959	0.940		0.895	0.847		0.967	0.943	
Within R^2	0.007	0.000		0.005	0.001		0.003	0.001	

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) We use the Fisher's permutation test to determine the significance of observed differences in coefficient estimates between two groups. The number of bootstrap repetitions is 1000. P-values for the group coefficients difference are reported in the square brackets. (3) The number of weeks at the low-intensity level equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level equals the sum of the number of weeks in D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Robustness Checks-Alternative Standard Errors

	Ln(output)			Ln(yield)			Ln(harvested acres)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
#Weeks at low-intensity level	-0.012***	-0.012***	-0.012***	-0.004*	-0.004*	-0.004*	-0.007***	-0.007***	-0.007***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
#Weeks at high-intensity level	-0.022***	-0.022***	-0.022***	-0.009**	-0.009***	-0.009***	-0.013***	-0.013***	-0.013***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Constant	9.860***	9.860***	9.860***	2.258***	2.258***	2.258***	7.611***	7.611***	7.611***
	(0.077)	(0.107)	(0.101)	(0.076)	(0.064)	(0.069)	(0.072)	(0.085)	(0.072)
Crop × County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,985	6,985	6,985	6,985	6,985	6,985	6,985	6,985	6,985
Adj. R^2	0.950	0.950	0.951	0.886	0.887	0.888	0.958	0.959	0.959
Within R^2	0.004	0.004	0.004	0.002	0.002	0.002	0.003	0.003	0.003

Notes: (1) The standard errors are clustered at different levels across the columns. For columns 1, 3, and 5, the standard errors are clustered at the county level. In columns 2, 4, and 7, they are clustered at the county × crop level. For columns 3, 6, and 9, robust standard errors are used. (3) The number of weeks at the low-intensity level equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level equals the sum of the number of weeks in D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Robustness Checks-Instrumental Variable Design

	Unweighted		Weighted	
	(1) Fixed effects	(2) 2SLS	(3) Fixed effects	(4) 2SLS
#Weeks in D0–D4 (unweighted)	-0.012***	-0.008*		
	(0.002)	(0.004)		
#Weeks in D0–D4 (weighted)			-0.004***	-0.004*
			(0.001)	(0.002)
Crop FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County-specific time trend	Yes	Yes	Yes	Yes
First-stage F-statistic		103.302		43.424
Hansen J statistic		0.2543		0.2469
Endogeneity test		0.3908		0.4051
Observations	6,985	6,988	6,985	6,988

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) The number of weeks in D0 D4 (unweighted) is calculated by summing the five drought variables. The number of weeks in D0 D4 (weighted) is calculated by summing the five drought variables after they have been multiplied by a factor corresponding to severity (i.e., weeks in D0 are identity, and weeks in D4 are multiplied by 5). Note that the number of weeks in different drought intensity levels is all weighted by agricultural areas. (3) In the fixed-effects models, singleton observations are dropped iteratively to avoid biasing the standard errors. (4) *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Production Losses from Drought Shocks: High Irrigation versus Standard Irrigation

	Ln(output)			Ln(yield)			Ln(harvested acres)		
	(1) High-irrigated	(2) Standard-irrigated	(3) Diff-test	(4) High-irrigated	(5) Standard-irrigated	(6) Diff-test	(7) High-irrigated	(8) Standard-irrigated	(9) Diff-test
Weeks at low-intensity level	-0.011***	-0.083***	0.072	-0.004*	-0.060**	0.056	-0.007**	-0.022	0.015
	(0.002)	(0.011)	[0.000]	(0.002)	(0.021)	[0.000]	(0.002)	(0.023)	[0.000]
Weeks at high-intensity level	-0.023***	-0.067**	0.044	-0.009**	-0.063***	0.054	-0.014***	-0.001	-0.013
	(0.003)	(0.023)	[0.000]	(0.004)	(0.011)	[0.000]	(0.003)	(0.027)	[0.479]
Constant	10.160***	9.012***		2.341***	2.875***		7.830***	6.088***	
	(0.070)	(0.282)		(0.076)	(0.489)		(0.075)	(0.629)	
Crop × County FE	Yes	Yes		Yes	Yes		Yes	Yes	
Crop × Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
County × Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	6,018	514		6,018	514		6,018	514	
Adj. R^2	0.950	0.858		0.886	0.721		0.959	0.902	
Within R^2	0.005	0.016		0.002	0.018		0.003	0.008	

Notes: (1) Standard errors are clustered at the county level. Standard errors are reported in the parentheses. (2) We use the Fisher's permutation test to determine the significance of observed differences in coefficient estimates between two groups. The number of bootstrap repetitions is 1000. P-values for the group coefficients difference are reported in the square brackets. (3) The number of weeks at the low-intensity level equals the sum of the number of weeks in D0, D1, and D2 drought. The number of weeks at the high-intensity level equals the sum of the number of weeks in D3 and D4 drought. (4) Singleton observations are dropped iteratively to avoid biasing the standard errors. (5) *** p<0.01, ** p<0.05, * p<0.1.

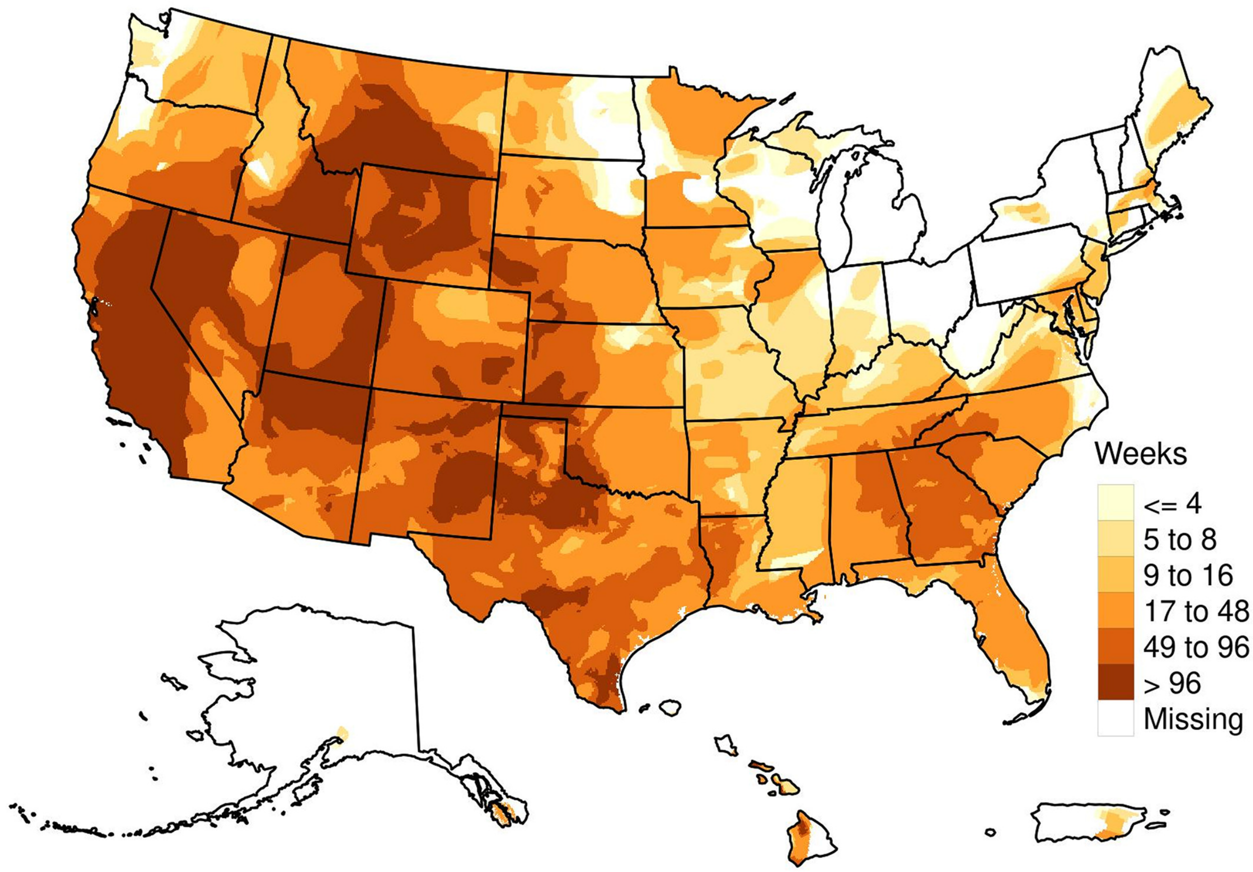

Figure A1: Total Number of Drought Weeks at Extreme and Exceptional Drought Status from 2000 to 2019

Notes: Based on USDM data, this figure illustrates the total number of weeks that areas experienced extreme drought (D3) or exceptional drought (D4) from 2000 to 2019. Areas with no drought weeks exceeding D3 status are marked as missing. Source: Leeper et al. (2022).

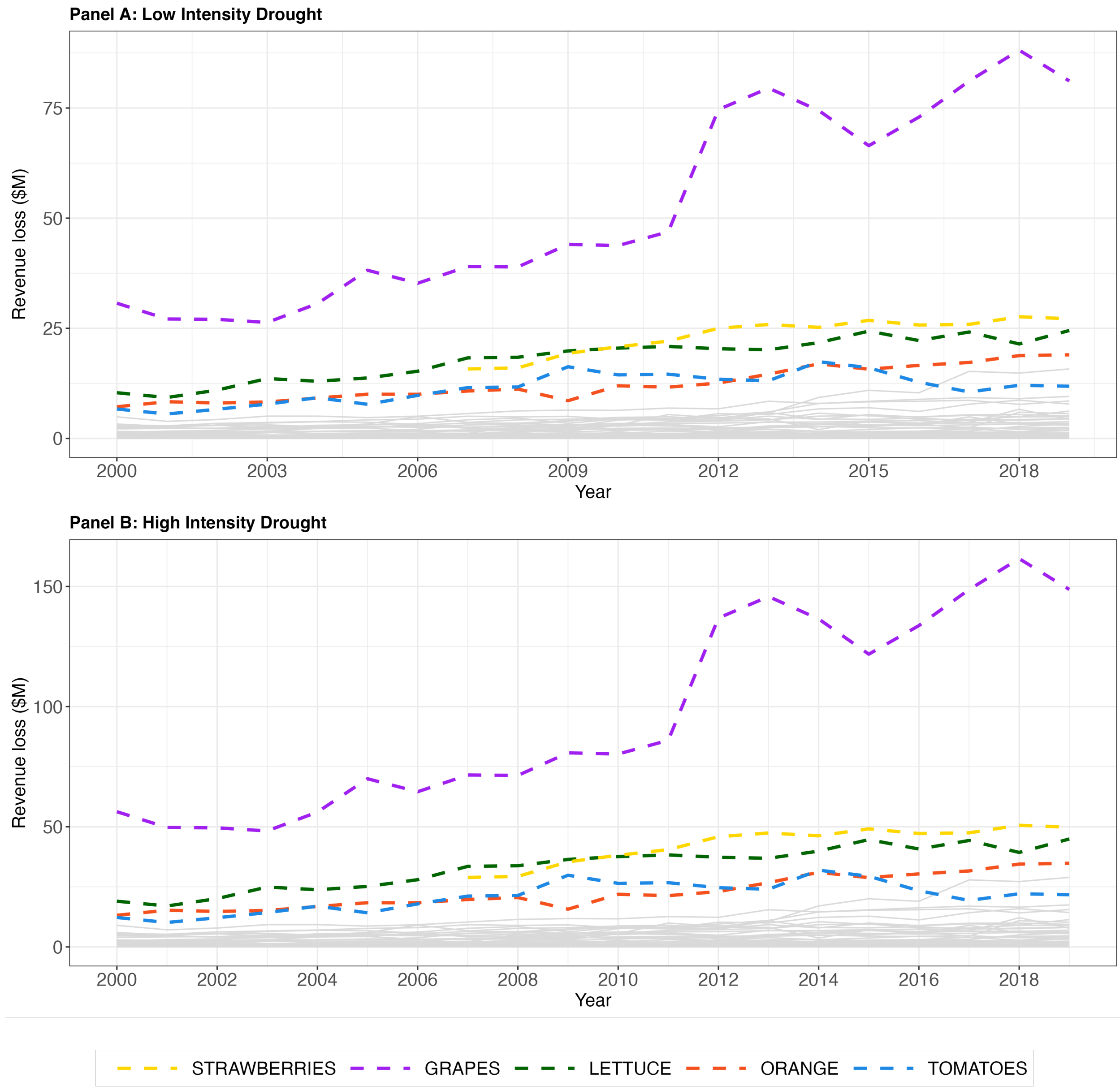

Figure A2: The Revenue Losses for Each Produce for an Additional Week of Drought

Notes: This figure illustrates the estimated revenue losses for each fruit and vegetable resulting from an additional week of drought, compared to no drought at all. Panel A represents the effects of low-intensity drought, while Panel B reflects high-intensity drought. The highlighted crops are those with high market values, while the remaining crops, shown in grey, are included for comparison.