Impact of Drought and Institutional Interventions on Adoption of Irrigation Technologies and Agricultural Land Use in California

DIVYA PRAKASH
School of Public Policy
University of California, Riverside

Advisors: Professor Ariel Dinar and Dr. Mehdi Nemati

Abstract

Climate change is expected to exacerbate water scarcity in the agricultural sector, which is already a critical concern. This article investigates the reaction of farmers in California to drought and institutional interventions regarding the adoption of various irrigation technologies and changes in land use. The study employs a fixed effect regression model to analyze data from all 58 California counties from 2000-2020. The results reveal that the adoption of efficient irrigation technologies for all crop categories in the study area increases significantly under extreme or exceptional drought. Furthermore, the results indicate that moderate or severe and extreme or exceptional adversely affect harvested acres of forage crops. We do not find any impact on harvested acres for other crop categories. We find that the passage of the sustainable groundwater management act in 2014 is associated with increased adoption of efficient irrigation technology. Moreover, we find that the act has a negative impact on harvested acres of forage crops. The findings of this study extend the existing literature on farmers' responses to drought and institutional interventions and offer insights to policymakers and stakeholders for enhancing water resource management and agricultural sustainability.

1. Introduction

The concentration of greenhouse gases (GHG) in the atmosphere is expected to increase at an unprecedented rate and scale, significantly affecting agricultural production (Pörtner et al., 2022). According to Thamo et al. (2017), alterations in climate-related aspects, including temperature, precipitation, and atmospheric CO2 concentration, can potentially impact farming yield and profitability. Agriculture's dependence on water supplies and climate renders it more susceptible to the effects of climate change, making it one of the most vulnerable sectors (ERS USDA, 2018a).

Climate change is expected to worsen the issue of water scarcity in the agricultural sector, which is already a pressing concern. This poses a significant challenge for farmers to manage their water resources efficiently and effectively. Farmers in irrigated agricultural production systems can adjust to climate change in numerous ways (i) by reducing the total irrigated acreage or taking land out of production (i.e., leaving it unplanted - fallowed) (Shi & Wu, 2019); (ii) changing crop types and variants from more to less water-intensive crops, or more profitable crops by deciding how much land to allocate for planting as per crop types (i.e., eliminating or reducing the acreage of certain crops and increasing acreage of other crops) (Sumner et al., 2021); (iii) modifying the irrigation technology and the amount of irrigation water used per acre (Dinar et al., 2017); and (iv) any combination of these strategies. Some of these adaptations are short-term reactions that can be changed during the growing season, while others are long-term investments that are almost irreversible and fixed. As a result, adjustments made before the growing season have implications for long-term investments. In contrast, climate and water shortage realizations influence short-term reactions during the growing season (Shi et al., 2022). These adaptive strategies must be implemented efficiently and effectively to ensure the sustainability of the agricultural sector in the face of climate change.

This study investigates how farmers responded to drought and institutional interventions by adopting different irrigation technologies and changing cropping patterns over time and across space in California counties. The majority of the existing literature has focused on broader geographical regions such as US Pacific Northwest (Shi et al 2022), the US West Coast (Shi et al, 2019; Olen et al 2016), US Western states (Frisvold & Deva, 2013) and US Southern region (Cho et al 2021). This study narrows the focus to county-level analysis of the state of California, providing a more granular perspective on the impacts of climate change on agricultural practices.

This paper contributes to the existing literature on California by (i) providing a summary of the changes in the proportions of various irrigation technologies between 2001 and 2016; (ii) summarizing the trends in cropping patterns from 2000 to 2020; (iii) conducting an empirical investigation into the impact of drought on the adoption of different irrigation technologies and the changes of cropping patterns; and (iv) empirically evaluating the consequences of the constraints imposed by the Sustainable Groundwater Management Act (SGMA) on the adoption of different irrigation methods and decisions of land use[1]. To achieve these objectives, we have gathered data on various irrigation methods usage in California for 2001, 2010, and 2016. Additionally, we have compiled twenty-one years of annual crop acreage statistics from 2000 to 2020, as well as weekly U.S. Drought Monitor (USDM) drought data.

The present investigation employs a collection of data obtained by matching the California Department of Water Resources (DWR) Statewide Irrigation Method Survey data and crop acreage data obtained from the annual Crop Reports compiled by the California County Agricultural Commissioners with drought intensity categorizations in the USDM at the county level. The analysis employs panel data models with fixed effects, which account for spatial and temporal variability in drought conditions, adoption of irrigation technologies, and harvested acreage. The study estimates the impact of drought and SGMA on the adoption of irrigation technologies and harvested acreage in California. The investigation also conducts distinct regressions for crop categories, such as field crops, forage, vegetables and melons, and fruits, trees, and nuts, as the impact of drought on harvested acreage and adoption of irrigation technologies is expected to differ across these categories.

The findings suggest that extreme or exceptional drought has a positive and statistically significant influence on the adoption of efficient irrigation technologies. It is observed that the share of sprinklers, drip, and subsurface drip, compared to surface irrigation, increases for all crops, as well as crop categories such as field crops, vegetables and melons, and fruits, trees, and nuts, with each additional week of extreme or exceptional drought. The adoption of efficient irrigation technologies shows a small and significant effect of additional weeks of drought for moderate or severe drought levels. Furthermore, the study reveals adverse and statistically

[1] We could access the latest data for Irrigation technology until the year 2016. Given we do not have the most recent survey data on irrigation technology, our findings need to be interpreted with caution.

significant impacts of drought on forage crops harvested acres for moderate or severe drought and extreme or exceptional drought for each additional week. Additionally, it is found that implementation of SGMA is associated with a statistically significant increase in the adoption of sprinklers, drip, and subsurface irrigation, compared to surface irrigation for all crops, field crops, vegetables and melons, and fruits, trees, and nuts, after controlling for drought levels. Moreover, SGMA leads to a negative estimated coefficient in harvested acres of forage crops after controlling for drought levels. Our findings are robust to alternative drought measures, which yield comparable estimates, reinforcing the reliability of the results.

The rest of this paper is organized as follows. The next section contains a brief review of existing studies on the relationship between droughts and the adoption of irrigation technology and land use patterns. Section 3 develops an analytical framework, and Section 4 discusses the hypothesis. Section 5 presents the estimation strategies, and Section 6 describes the data. Section 7 discusses the results, and Section 8 concludes and provides policy implications.

2. Literature Review

There is a large and well-developed body of literature on adopting irrigation technologies. Many studies that simulate long-term investments reveal that financial and physical factors, including groundwater well depth, water supply, and pricing uncertainty, influence farmers' decisions to embrace new technologies. All of these factors are considered when making long-term investment decisions (Carey and Zilberman, 2002, Caswell and Zilberman, 1986, Li, et al., 2019). Numerous studies have discovered that climate significantly influences the choice of irrigation technology since expectations for the climate (such as temperature and precipitation) indicate varying technological efficacy (Dinar and Yaron, 1990, Fleischer, et al., 2011, Frisvold and Deva, 2013). However, there needs to be more knowledge about how farmers modify water usage and irrigation choices to reduce the effects of climate change, particularly crop loss from extreme weather events. There are a few noticeable exceptions. Using state-level farm-size stratified data, Frisvold and Deva (2013) investigated how climate influences allocating land between the sprinkler and gravity-flow methods. They discovered that climate factors had significantly affected decisions to adopt irrigation technologies. Olen, et al. (2016) examine irrigation decisions made at the farm level and find that producers of orchards and vineyards are more likely to select sprinkler irrigation and apply additional quantities of water to mitigate damage from drought, extreme heat, or freeze. Schuck, et al. (2005) find that in response to droughts, a larger share of farms adopts more technically efficient irrigation systems to maintain crop yield.

Land usage and climate change are associated. Numerous studies have examined this link, which shows that changes in net greenhouse gas emissions, as well as changes in human and natural system land use, are both influenced by climate and policy considerations (Cho and McCarl, 2021). The relationship between climate change and land use has two strands in the literature. One of the themes is how land use affects greenhouse gas emissions, which in turn contribute to climate change. The other strand investigates how land use is impacted by climate change (Mendelsohn and Dinar, 2009). Climate change can influence the yield of agricultural commodities, land value, water availability, infrastructure, and environmental quality. Landowners exposed to such hazards may be motivated to alter land allocations as a climate change adaptation mechanism, which can lead to changes in land use in addition to changes in the natural land cover (Mendelsohn and Dinar, 2009). Reilly, et al. (2003) investigated how climatic and policy variables influenced agricultural land use and expected changes under several future climate change scenarios. Mu, et al. (2013) analyzed how land use changes from crops to grazing when climatic conditions become harsher. Numerous additional studies have focused on how crop mix and agricultural land use are affected by climate change. For instance, a set of studies suggests that acreage allotted to relatively low-value and water-intensive crops is reduced as a result of anticipated climate and water supply fluctuations (Connor, et al., 2009, Manning, et al., 2017, Moore and Negri, 1992, Peck, et al., 2012).

This paper contributes to the literature by examining how farmers react to drought and institutional interventions by analyzing changes in crop mix and irrigation technology adoption over time and across California's counties. The study limits its focus to the county-level examination, thereby offering a more comprehensive perspective on the impact of climate change on agricultural practices. By utilizing panel data for 58 counties over two decades, this study enables the estimation of the impacts of droughts and institutional interventions on agricultural practices, filling a gap in existing literature (Sumner et al 2021, Rodrigue-Flores et al 2021, Carman 2021). Moreover, this study provides causal estimates for both long-run decisions, such as the adoption of efficient irrigation technologies, and short-run responses, such as changes in cropping patterns. Additionally, we contribute to the growing field of agricultural economics by utilizing three different drought measures (described in section 5.4), of which two methods have not been widely used in previous studies on this topic. By employing this methodology, we can provide robust and reliable estimates of droughts' impacts on California's agricultural practices. In turn, this contributes to a better understanding of how farmers respond to drought, which can inform the development of more effective policies to support sustainable and resilient agricultural practices in the face of climate change.

3. Analytical Framework

Consider a representative farmer who is endowed with farmland L. They have to decide on how many acreages of land to harvest in a given year. Assuming that the land can be put to two uses, that is, either to harvest or leave it fallow. Let α denote the share of land used for harvesting, and the remaining share corresponds to the land which is left fallow:

$$L = \alpha L + (1 - \alpha)L \qquad (1)$$

$$Fallow\ land = (1 - \alpha)L \qquad (2)$$

The share α depends on several demand-side factors, such as rising per capita income, rate of urbanization, or consumer demand, and supply-side factors, such as the availability of labor, irrigation technologies, drought incidences, short-run and long-run fluctuations, and exogenous shocks. Earlier literature discusses in great detail that the economic life span of efficient irrigation technologies is several decades (Dinar, et al., 1992). Therefore, we assume that a farmer’s decision to adopt efficient irrigation technologies is a long-term choice and, therefore, remains fixed during the growing season. The choice of harvested acres for annual crops, however, is a short-term response and can be adjusted during the growing season. Similarly, decision-making for perennial crops is a long-term choice and, hence cannot be adjusted during the growing season.

Adopting irrigation technology heavily depends on climatic projections made before the growing season (Shi et al 2022), whereas short-run reactions depend on whether realizations throughout the growing season. Long-term irrigation technology, which is predetermined before making short-run responses throughout the growing season, is also a requirement for short-run responses. According to the standard agronomic literature, our multi-crop production model includes crop-specific equations for the adoption of irrigation technology *(IT)* and for harvested acres *(HA)* and is specified as

$$IT = a(W, S, P) \quad (3)$$

$$HA = b(W, S, P) \quad (4)$$

In equations (3) and (4), the variable W represents water availability, includes temperature and precipitation, and is captured through the inclusion of drought measures. The soil quality variable is denoted by S, and we assume it remains constant in the short run. Therefore, we will not capture changes in soil quality in our estimation equation. The variable *P* encompasses policy shock variables, including taxes, land use constraints, price shocks, and institutional reforms such as implementing the 2014 Sustainable Groundwater Management Act (SGMA). In this article, we are using SGMA as a policy shock variable.

A farmer also incorporates several inputs (*m*) for crop production, such as labor, machinery, fertilizer, etc. Let *X* denote the total input cost used in crop production, and *E(p)* denotes the vector of expected crop prices by the end of the harvesting season. Being a rational (forward-looking) decisionmaker, the representative farmer would be interested in maximizing her utility. Let the utility function be denoted as U. R measures the expected revenue from mixed crop farming operation, and *X* denotes the total input cost used. The utility-maximizing problem for the representative farmer is:

$$Max\ U = R - X \quad (5)$$

Ruling out the corner solution, an optimal solution will be determined.

4. Hypothesis

Based on the literature reviewed and the analytical framework described in section 3, we frame several hypotheses to be inferred using data collected from 58 California countries over the past two decades.

Hypothesis 1: Droughts may result in a reduction in farmland and total cropland, a decline in certain field crop acreage, and an increase in tree nuts and vineyard acreage.

During the period 1980-2021, the state of California experienced five periods of droughts (1987-92, 2001-02, 2007-09, 2012-16, and 2020-23). This has resulted in relative water scarcity in various counties and over-pumping of groundwater with time. Therefore, we expect that the farmers adapt to these changes and must allocate water to the high economic valued crops during drought. Consequently, there might be a reduction of land in farms and total cropland over time and in certain crop acreage, whereas there is an increase in tree crops and vineyard acreage (Sumner et al., 2021). According to the literature, evidence suggests that in California, the expansion of tree nut acreage has outpaced the decline of field crop acreage, implying that tree nuts have been replacing other crops as well. Nonetheless, current trends indicate that although a portion of the land that has shifted away from field crops may have been utilized for the cultivation of vegetables, fruits, or other crops, a significant proportion may have remained unplanted, i.e., fallowed land (Sumner et al., 2021).

Hypothesis 2: Farmers may have substituted less efficient irrigation technologies with more efficient ones.

There are multiple factors that influence the adoption of more efficient irrigation technologies, such as scarcity of irrigation water or being able to expand the irrigated area with the same amount of available water. The rationale underlying the hypothesis is that during drought periods, scarcity of irrigation water increases. Therefore, over time, farmers are likely to adopt technologies that improve irrigation efficiency (Dinar et al., 2017). We expect that farmers may have substituted less efficient irrigation technologies with more efficient ones, especially in more water-scarce counties. We are interested in analyzing the overall trend in the adoption of irrigation technologies and changes in usage across technologies in all fifty-eight California counties.

Hypothesis 3: Implementation of SGMA might

(a) increase fallowed land acreage.

(b) lead to an increase in the utilization of more efficient irrigation systems.

In response to SGMA, we expect more farmers to go out of production. The farmers might have to adapt to the circumstances created by expanding government initiatives and policies. The state legislature passed the Sustainable Groundwater Management Act (SGMA) in 2014. By 2040, groundwater sustainability (which is prevented by avoiding six undesired consequences[2]) must be achieved, according to SGMA, which mandates that local groundwater sustainability agencies (GSAs) create and implement sustainable water management strategies. In many areas of the state, sustainable groundwater use will require replacing present irrigated crops with less water-intensive crops, or land must be removed from cultivation (EDF, 2021). To comply with the sustainability mandate of the SGMA and address the general increase in water shortages, it is predicted that over the next few decades, at least 500,000 to over 1 million acres, largely in the San Joaquin Valley, may need to be taken out of production (Hanak, et al., 2019). Future farming practices, including drip irrigation, water monitoring technologies, and soil moisture sensors, are projected to be adopted by most farmers (Niles and Wagner, 2017). The implementation of SGMA could likely change cropping patterns and increase the use of more efficient irrigation systems. Therefore, we expect an overall increase in fallowed land acreage. We also intend to investigate whether the implementation of SGMA led to the replacement of furrow irrigation with drip, sprinklers, or micro-sprinklers across California counties.

5. Data

5.1. NASS Crop Acreage Data

California-specific statistics are reported annually by the National Agricultural Statistics Service (NASS). The report is based on the California County Agricultural Commissioners' yearly Crop Reports. These publications offer the most comprehensive annual data on agricultural production by county. The Agricultural Commissioners and their staff members compile fundamental data from various sources. The data sources differ from county to county, such as grower surveys, inspection, and regulatory data, shipment data, and industry evaluations. The statistics are coded at a detailed level, varying by county.

[2] chronic lowering of groundwater levels, reduction of groundwater storage, seawater intrusion, land subsidence, water quality degradation, and depletions of interconnected surface water.

We use county-level data on total harvested acres from annual crop reports between 1980 and 2020 to estimate the total harvested acres for given crops in each county. In total, the data covers 442 types of crops harvested across the state of California. We aggregate these into 20 crop categories per the DWR classifications. We further aggregate these 20 crop categories into four different categories, namely field crops, forage, vegetables & melons, and fruit, trees & nuts. Since various county offices report these data, we have noticed inconsistencies in the data on numerous occasions. In such cases, we have dropped 104 observations which are 0.5 percent of the total observations, as part of the data-cleaning exercise. Figure 1 represents the total number of harvested acres, measured in a million acres, within four crop categories in California from 1980 to 2020. The overall trend of harvested acres has been declining over time. However, harvested acres for fruits, trees, and nuts have shown an increase over the same period. The harvested acres for vegetables and melons have remained relatively steady, while there has been a decline in harvested acres for field crops and forage crops.

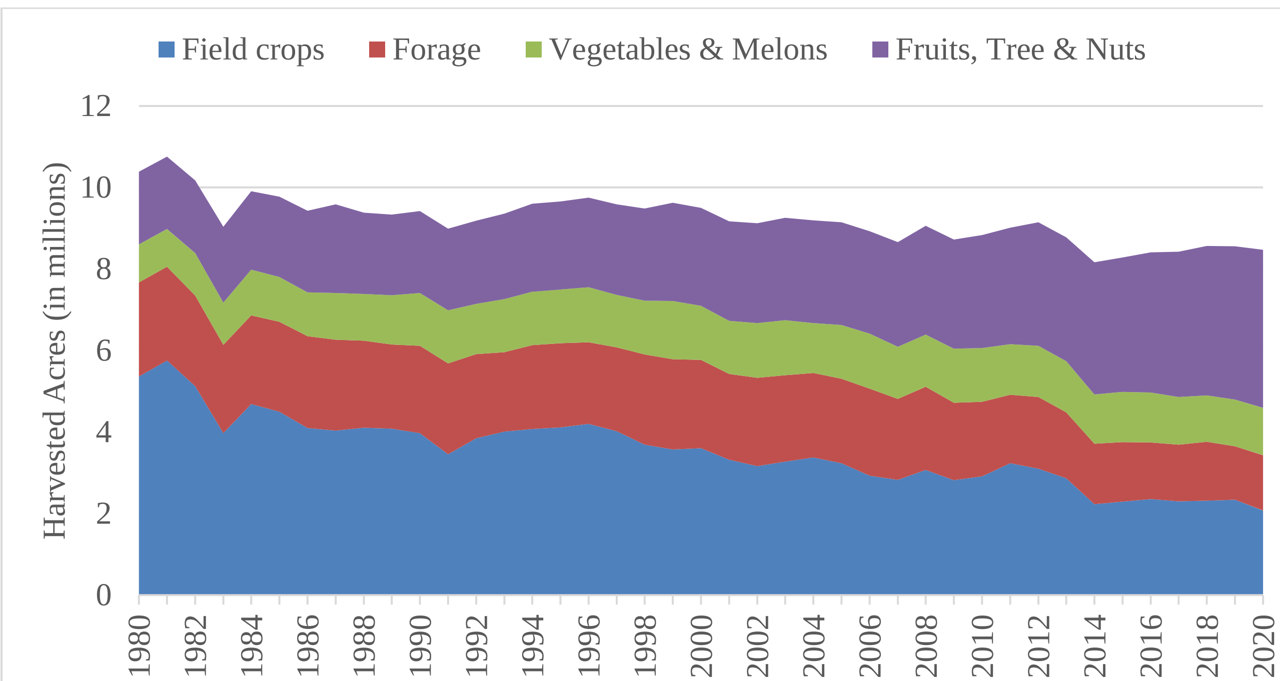

Figure 1. Harvested Acres (in millions) by Crop Categories, 1980 – 2020

5.2. Statewide Irrigation Method Survey (CDWR)

Since 1991, the California Department of Water Resources (CDWR) has performed a survey, typically every ten years, to update California's statistics on crops and irrigation technologies. California producers receive a one-page irrigation survey form in the mail to update records on the types of irrigation systems utilized in the state. Growers were randomly chosen from a list of around 58,000 growers taken from the California Department of Food and Agriculture (CDFA) mail questionnaires as part of the surveys. The list did not include farmers who grew rice, non-irrigated crops, or livestock only. During 2001, 2010, and 2016 surveys, growers were also asked to name the primary county in which they farmed, the acreages they had planted to each of the 20 crop categories, and the related irrigation technology within that county. The number of questionnaires mailed to each county was proportional to the ratio of growers residing in each county to the statewide total.

Surface (i.e., gravity-driven), sprinkler, and low-volume (i.e., drip and micro-sprinkler) irrigation are the primary methods used by growers to irrigate crops within California. There is also a small, irrigated area with subsurface irrigation, in which drain tiles or open channels are blocked to force water into the root zone of crops. However, this area is insignificant relative to the other methods. We have aggregated low-volume and subsurface irrigation into one category.

Figure 2 depicts the trend in the proportion of irrigated land according to the irrigation system category in California. The proportion of micro, drip, and subsurface irrigation technology has significantly increased from 15.8 percent in 1991 to 56.3 percent in 2016. In contrast, the proportion of surface irrigation has experienced a decline from 66.9 percent in 1991 to 30.1 percent in 2016. However, the rate of adoption of sprinkler irrigation has remained relatively constant, with only a slight decrease from 17.3 percent in 1991 to 13.6 percent in 2016. Taken together, these trends suggest that there has been an overall rise in the utilization of efficient irrigation technologies over time, with micro, drip, and subsurface irrigation becoming the predominant technology after 2010.

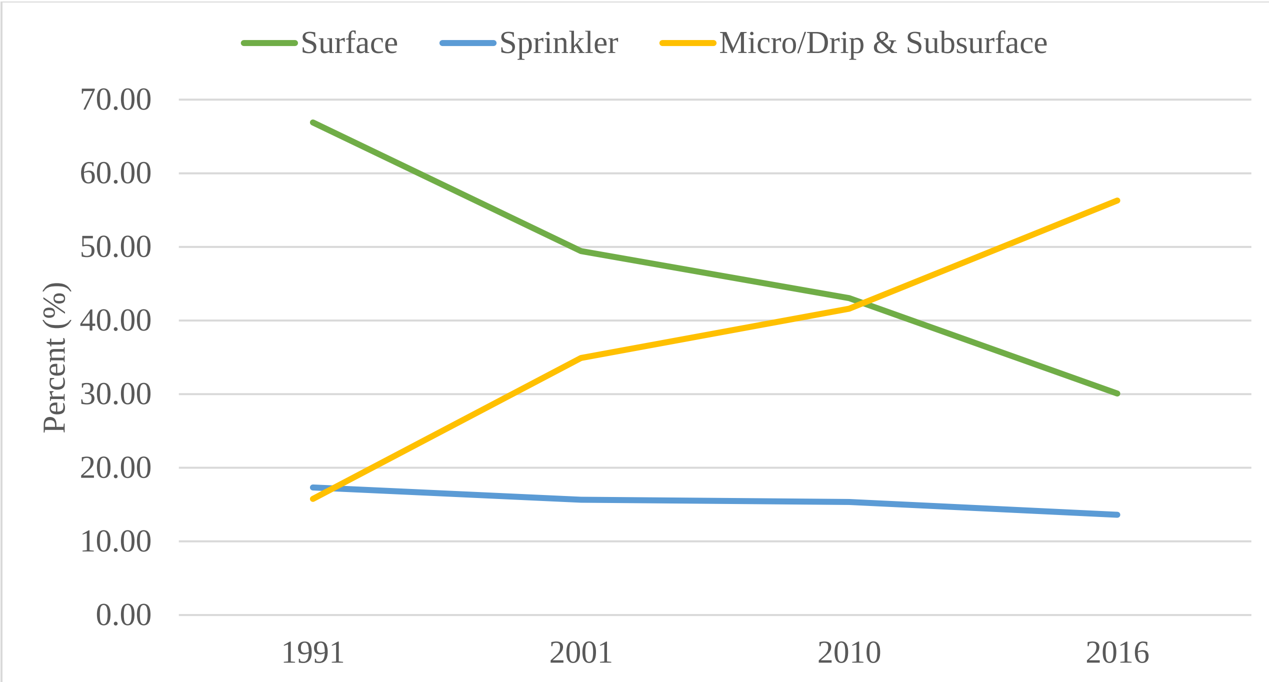

Figure 2. Trends in Irrigated area (%) by Irrigation System Category in California

Figure 3 demonstrates the share of irrigated land based on crop categories and the type of irrigation system used. The use of surface irrigation in field crops has decreased from 91.78 percent in 1991 to 73.82 percent in 2016; nevertheless, it remains the most extensively used method of surface irrigation, closely followed by forage crops at 68.36 percent in 2016. Conversely, fruits, trees, and nuts have the highest percentage of micro, drip, and subsurface irrigation. This grew from 37.97 percent in 1991 to 77.75 percent in 2016, followed by vegetables and melons at 52.38 percent in 2016. Moreover, vegetables and melons have a high percentage of sprinkler irrigation, which increased from 19.83 percent in 1991 to 35.62 percent in 2001 but later decreased to 25.54 percent.

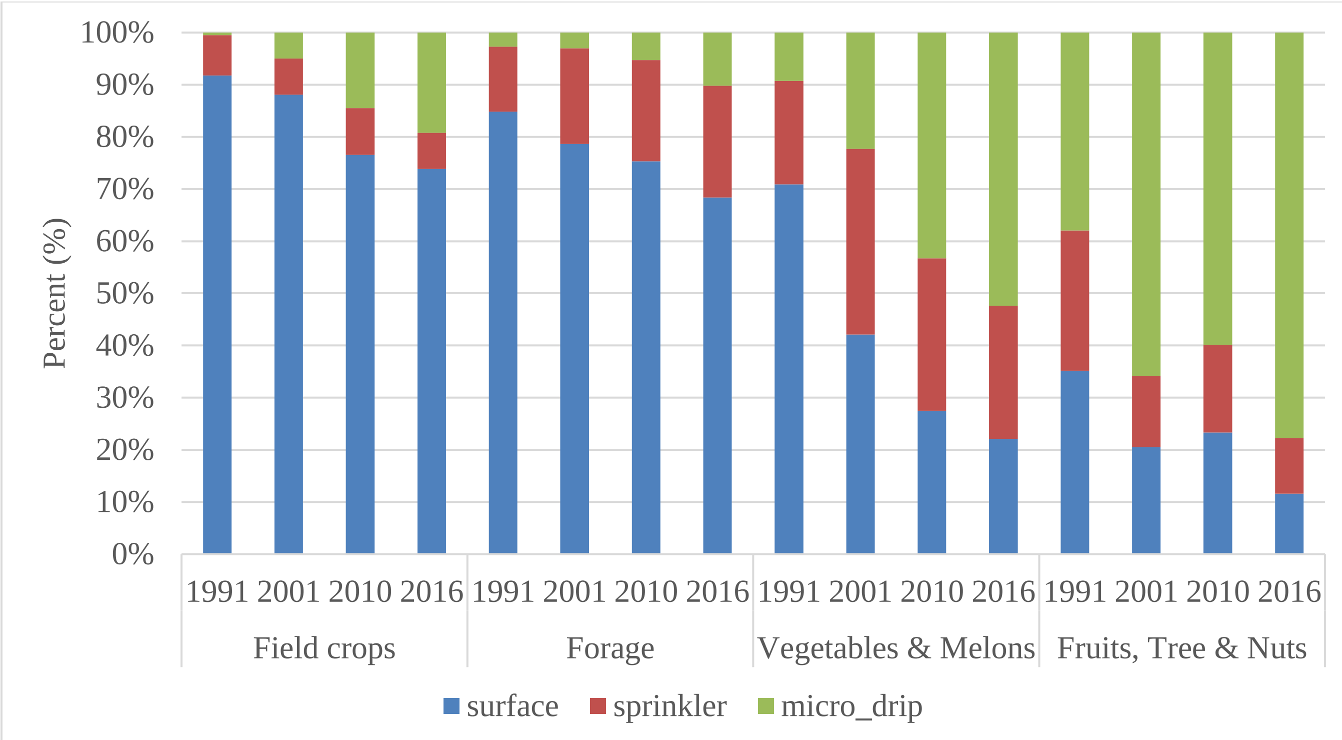

Figure 3. Trends in Irrigated area (%) by Crop Categories and Irrigation System Category in California

5.3. Summary Statistics

Table 1 displays summary statistics for the analyzed sample comprising 19,707 observations for all crops intended for harvest and 7,030 words for different irrigation technologies. The mean estimated total harvested acres is 9.2 million annually, with a minimum of 8.1 million and a maximum of 10.7 million acres over time. Field crops occupy the most harvested acres, approximately 3.5 million, while fruits, trees, and nuts account for 2.5 million acres. On the other hand, vegetables & melons, and forage have the least harvested acres coverage—1.2 million and 1.9 million acres, respectively. In California, 44.1 percent of all crops utilize surface irrigation, while 55.9 percent apply sprinkler, drip, micro, and subsurface irrigation. Forage crops exhibit the highest rate of surface irrigation, at 67.5 percent, followed by field crops, at 66.8 percent. In contrast, fruits, trees, and nuts have the highest sprinkler, drip, micro, and subsurface irrigation rate, at 85.2 percent, followed by vegetables and melons at 62.8 percent.

Table 1: Summary Statistics

	Number of observations	Mean	Std. Dev.	Min	Max
Harvested Acreage					
All crops	19,707	9,216,123.2	562,436.0	8,163,926	10,756,627
Field Crops	7,180	3,520,609.6	874,310.4	2,076,759	5,756,756
Forage	3,541	1,964,444	298,129.7	1,306,735	2,311,920
Vegetables & Melons	4,351	1,228,455	115,694.2	923,809	1,429,167
Fruits, Trees & Nuts	4,635	2,502,614.7	584,683.7	1,777,373	3,878,906
Irrigation Technology (in percent)					
All crops					
Surface	7,030	44.1	42.3	0	100
Sprinkler, Micro & Drip	7,030	55.9	42.3	0	100
Field Crops					
Surface	1,899	66.8	40.1	0	100
Sprinkler, Micro & Drip	1,899	33.2	40.1	0	100
Forage					
Surface	1,399	67.5	37.3	0	100
Sprinkler, Micro & Drip	1,399	32.5	37.3	0	100
Vegetables & Melons					
Surface	1,509	37.2	42.3	0	100
Sprinkler, Micro & Drip	1,509	62.8	42.3	0	100
Fruits, Trees & Nuts					
Surface	2,233	14.8	22.8	0	100
Sprinkler, Micro & Drip	2,233	85.2	22.8	0	100
Additional Weeks of Drought (count)					
No Drought	9,395	35.4	18.6	0	53
Severe Drought	9,395	20.1	18.4	0	53
Extreme Drought	9,395	7.8	16.1	0	53
Drought Intensity Index	9,395	54.2	71.3	.0009	461

5.4. Constructing Drought Measures

We use three different methods to construct a drought variable, which is a crucial explanatory factor in our analysis. First, we generate an indicator drought variable, where the variable takes a value of 1 in drought years and 0 in non-drought years. However, there are caveats to this measure, such as potential biases and limitations in accurately identifying and defining drought events (Heim, 2002).

To address these issues, we then constructed two different drought measures using the U.S. Drought Monitor (USDM) data. The USDM is a map generated collaboratively by the United States Department of Agriculture (USDA), the National Oceanic and Atmospheric Administration (NOAA), and the National Drought Mitigation Center (NDMC), which provides weekly information about drought conditions across the country. The map identifies general drought areas in five different levels of intensity ranging from D0 to D4 (explained below). Each intensity level is linked with a probability of occurrence expressed as a percentile, derived from the 1932-2001 record of drought indicators. When an area doesn't fall into any of the drought categories, it is classified as "None" or having no drought. The USDM uses a five-category system, labeled Abnormally Dry (D0) (a precursor to drought, not actually drought), and Moderate (D1), Severe (D2), Extreme (D3), and Exceptional (D4). The USDM is not a strict drought index but is a composition of climate indices, numerical models, and expert input. The USDM uses six key physical indicators, including a drought index, percentiles from a soil moisture model, daily streamflow percentiles, the percent of normal precipitation, a standardized precipitation index, and a remotely sensed vegetation health index. This dataset gets updated every week to show the country's location and intensity of drought[3].

5.4.1 Drought as an indicator variable

One way to assess the occurrence of drought events over time is by constructing drought indicator variables that assign a value of one to drought years and a value of zero otherwise. During our analysis period, the drought-affected years are 1987-92, 2000-01, 2007-09, 2012-16 and 2020.

[3] Note that there are other methods to measure drought. For example, the Palmer Drought Severity Index (PDSI), which utilizes accessible temperature and precipitation data to estimate relative dryness. PDSI is a standardized index that usually ranges from -10 (dry) to +10 (wet), and it has county-level data available since 1885. Another example is using the California Irrigation Management Information System (CIMIS) data to measure drought. CIMIS data enables the calculation of the deficit of evapotranspiration (ET), a measure of drought or water scarcity. However, for the sake of expediency, we concentrate on the other two methods described above to establish our drought variable.

USDM data offers a more comprehensive and nuanced measure of drought conditions in comparison to a drought indicator variable. Furthermore, it has a much finer spatial resolution, providing county-level data, which facilitates a more detailed analysis of drought variation across diverse regions, accounting for microclimates and fluctuation of weather patterns. In addition, the weekly update feature of USDM data enables the construction of a continuous measure of drought severity, which captures the dynamic nature of drought conditions over time. The data amalgamate various indicators, including precipitation, soil moisture, streamflow, and vegetation health, resulting in a more comprehensive measure of drought conditions. In contrast, a drought year indicator variable solely indicates the occurrence of a drought in a specific year without providing any information regarding the severity, duration, or spatial extent of the drought. Researchers, policymakers, and stakeholders widely employ USDM data to monitor drought conditions in the United States (Kuwayama et al, 2018). Utilizing this data ensures consistency and comparability across different studies and analyses, and results are based on a standardized and widely accepted measure of drought severity.

5.4.2 Construction of the Drought Intensity Index (USDM)

The categorizations of drought intensity in the weekly USDM updates do not necessarily align with county boundaries. Therefore, to ensure accurate drought assessment, annual county-level measures were developed that reflect drought occurrence within agricultural areas in a county. To achieve this, we National Land Cover Database (NLCD) 2019 data and a geographic information system (GIS) to identify agricultural and non-agricultural areas by county. By excluding non-agricultural parcels from the analysis for all California counties, we match weekly USDM data with the NLCD agricultural parcels for each county, creating data that measures the impact of drought solely on agricultural areas. As a result, we construct USDM data for each week and the percentage of county agricultural areas experiencing drought, defined as per USDM drought category. This methodology allows us to assess the impact of drought on agricultural outcomes, at the county level, with higher accuracy. We take the summation of values corresponding to every level of drought between October of the preceding year and September of the ongoing year. This time frame is typically considered a general window during which drought adversely affects crops. Further details about the drought variables are discussed in Table 2.

Table 2: USDM Drought Severity Levels

Category	Drought Intensity Level	% of Normal Conditions
None	Normal or wet conditions	31 or above
D0	Abnormally dry	21 to ≤ 30
D1	Drought, moderate	11 to ≤ 20.99
D2	Drought, severe	6 to ≤ 10.99
D3	Drought, extreme	3 to ≤ 5.99
D4	Drought, exceptional	0 to ≤ 2.99

The drought intensity index is created using the U.S. Drought Monitor data, which provides information on drought levels ranging from D0 (abnormally dry) to D4 (exceptional drought) for each county in the U.S. When an area doesn't fall into any of the drought categories, it is classified as "None" or having no drought. The drought intensity index measures the severity or strength of a drought event in a particular area. It considers the extent of coverage of drought conditions and the intensity of those conditions. This formula calculates the weighted average of the values for each drought level based on the proportion of the county area experiencing each drought level per week. By doing so, the formula considers the extent and intensity of drought conditions in a particular area and assigns a single value that represents the overall severity of drought conditions in that area for that particular week. We created an annual county-level drought intensity index by taking yearly averages. The weights assigned to each drought level reflect the relative ranking of the severity of each level, with a higher rank assigned to more severe levels of drought. This means counties with larger areas experiencing more severe drought conditions have a higher drought intensity score. The weights assigned to each drought level (I_1, I_2, I_3, I_4, I_5, and I_6) give higher importance to more severe drought levels. For example, I_5, and I_6 have higher values than I_1, I_2, I_3, and I_4. In that case, it means that the drought intensity variable is more sensitive to severe drought conditions (D3 and D4) than to moderate, mild or no drought conditions (None, D0, D1, and D2). The drought intensity index takes a single value for each county and each year. Overall, the drought intensity variable provides a valuable metric for assessing the severity of drought conditions in different areas and can be used to compare drought conditions over time and across regions.

$$Drought\ Intensity\ Index = \frac{County\ Drought\ Area\ (None)}{Total\ County\ Agricultural\ Area} * I_1 + \frac{County\ Drought\ Area\ (D0\ Level)}{Total\ County\ Agricultural\ Area} * I_2 + \frac{County\ Drought\ Area (D1\ Level)}{Total\ County\ Agricultural\ Area} * I_3 + \frac{County\ Drought\ Area (D2\ Level)}{Total\ \ County\ Agricultural\ Area} * I_4 + \frac{County\ Drought\ Area\ (D3\ Level)}{Total\ County\ Agricultural\ Area} * I_5 + \frac{County\ Drought\ Area (D4\ Level)}{Total\ County\ Agricultural\ Area} * I_6$$

where $I_1 = 1$, $I_2 = 2$, $I_3 = 3$, $I_4 = 4$, $I_5 = 5$, and $I_6 = 6$

5.4.3 Impact of Additional Weeks of Drought (USDM)

The drought variable is defined as the number of weeks a county experiences a given severity level of drought, weighted by the percentage of the county's agricultural area. To investigate the impact of drought on agriculture, we condensed all six drought intensity levels into three categories, where the first category consists of None and D0. The second category consists of D1, and D2. And the third category consists of D3 and D4. There are three variables based on this new categorization of USDM drought intensity levels:

$$D0: No\ Drought\ \&\ Abnormally\ Dry$$
$$D1: Moderate\ \&\ Severe\ Drought$$
$$D2: Extreme\ \&\ Exceptional\ Drought$$

The coefficient associated with this variable can be used to assess the effect of an additional week of drought covering all of the agricultural areas in the county when used as an explanatory variable in a regression.

$$DX_{it} = \sum \text{agricultural area in county } i \text{ experiences drought of intensity level } X \text{ in time } t \quad (6)$$

$$\forall\ X \ \in \{0, 1, 2\}$$

where DX_{it} represents a vector consisting of three variables These variables indicate the area-weighted number of weeks in year t, where the agricultural areas of county i were classified as experiencing each of the three levels of drought intensity.

6. Estimation Strategy

The goal of this analysis is to estimate the effect of drought and SGMA, in our study, on the rate of adoption of efficient irrigation technologies and the changes in cropping choice. To obtain reliable estimates, we employ the county fixed-effects model. Incorporating fixed effects at the county level facilitates the control of unobservable time-invariant factors that might systematically impact the variables of interest. Additionally, the county fixed-effect model captures the within-county variations over time. The utilization of this model increases the robustness of the findings and provides reliable and meaningful results.

6.1 Main Specification: Impact of Additional Weeks of Drought

These estimation strategies are adapted from Kuwayama et al, 2018. The dependent variable is the share of adoption of irrigation technology for county *c* in year *t*:

$$IT_{ct} = \alpha + DX'_{ct} * \mathit{\Gamma} + \beta * SGMA_{ct} + \eta_i + \epsilon_{ct} \qquad (7)$$

where surface irrigation is the reference category and ε_{ct} is an idiosyncratic error term. The vector $\mathit{\Gamma}$ corresponds to the coefficients of interest for drought, and the β corresponds to the coefficients of interest for SGMA. County fixed effects (η_i) help obtain unbiased estimates in the presence of unobserved time-invariant characteristics of counties that affect their agricultural outcomes in the face of drought. We will estimate equation 7 for all crops and for different crop categories, namely field crops, forage, vegetables and melons, fruits, trees, and nuts separately. The irrigation technology data that is currently obtainable is not gathered on an annual basis, as the survey examining it is only conducted periodically. This lack of regular data collection may, in turn, create certain constraints that could limit its usefulness in certain contexts.

In another specification, the dependent variable is log of harvested acres for county c in year t:

$$log(HA)_{ct} = \alpha + DX'_{c(t-k)} * \ \Gamma + \ \beta * \ \ SGMA_{ct} \ + \ \eta_i \ + \epsilon_{ct} \qquad (8)$$

where k takes the value from 0 to 3 for field crops; forage; vegetables and melons, and it takes the value from 0 to 5 for fruits, tree, and nuts. ε_{ct} is an idiosyncratic error term. The vector Γ corresponds to the coefficients of interest for drought, and β is the coefficient of interest for SGMA. We will estimate equation 8 for all crops and for different crop categories, namely field crops, forage, vegetables and melons, fruits, tree, and nuts separately.

We incorporate two additional drought measures into our analysis, namely the drought intensity index (*DI*) and the drought indicator (D_t). These measures will serve as the variables of interest in equation 7 to assess the influence of drought on the adoption rate of irrigation technologies and in equation 8 to evaluate the impact of drought on the logarithm of harvested acres. The inclusion of these measures enables us to take into account both the severity and duration of drought conditions, thereby providing us with a holistic understanding of their effects on both irrigation technology adoption and harvested acreage. By incorporating these measures into our analysis, we aim to enhance the accuracy and robustness of our findings.

In Table 3, we list the relevant variables and their expected sign on harvested acres of each crop category and adoption of irrigation technology. We also describe each variable and how it is measured in this study.

Table 3: Description of Variables and Expected Signs

Name of Variable	Acronym	Description	Units	Type of Variable	Expected Sign
Dependent Variable					
Harvested Acres	HA	Acreage harvested per year	Acres	Continuous	
Irrigation Technology	IT	Share of efficient irrigation methods used for irrigation	Percent	Continuous	
Surface irrigation (reference category)		Share of surface irrigation used for irrigation	Percent	Continuous	
Sprinkler, micro, drip and Subsurface		Share of sprinkler, drip, micro and subsurface used for irrigation	Percent	Continuous	
Independent Variable					
Additional Week of Drought	DX_{it}	number of weeks in a year a county experiences a given severity level of drought			- for HA and + for IT
Moderate or Severe drought	Severe	This includes moderate (D1) and severe (D2) drought category of USDM	count	Discrete	- for HA and + for IT
Moderate or Severe drought one-year lag	Severe lag1	Additional weeks in drought in previous year			- for HA and + for IT
Moderate or Severe drought two-year lag	Severe lag2	Additional weeks in drought 2 years ago			- for HA and + for IT
Moderate or Severe drought three-year lag	Severe lag3	Additional weeks in drought 3 years ago			- for HA and + for IT
Extreme or Exceptional drought	Extreme	This includes extreme (D3) and exceptional (D4) drought category of USDM	count	Discrete	- for HA and + for IT
Extreme or Exceptional drought one-year lag	Extreme lag1				- for HA and + for IT
Extreme or Exceptional drought two-year lag	Extreme lag2				- for HA and + for IT
Extreme or Exceptional drought three-year lag	Extreme lag3				- for HA and + for IT

Sustainable Groundwater Management Act	SGMA	The county that has implemented SGMA after the year 2014 gets a value of 1 and all other counties without SGMA after 2014 get a value of 0 and all counties prior to 2014 get a value of 0.	Discrete	- for HA and + for IT
Drought Intensity Index	DI	It is an index to measure the severity of drought in a county in a year. For detail refer data section	Continuous	- for HA and + for IT
Drought Intensity Index one-year lag	DI lag1			- for HA and + for IT
Drought Intensity Index two-year lag	DI lag2			- for HA and + for IT
Drought Intensity Index three-year lag	DI lag3			- for HA and + for IT
Drought Indicator Variable	drought	The variable takes the value 1 for the drought year in California such as 1987-92, 2001-02, 2007-09, 2012-16 and takes the value 0 for remaining years.	Discrete	- for HA and + for IT
Drought Indicator Variable one-year lag	drought lag 1			- for HA and + for IT
Drought Indicator Variable two-year lag	drought lag2			- for HA and + for IT
Drought Indicator Variable three-year lag	drought lag3			- for HA and + for IT

7. Results

7.1. Irrigation Technology

Table 4 (Model 1) presents the results of our analysis using equation (7), wherein the dependent variable is the share of efficient irrigation technologies, with surface irrigation as the reference category. The coefficients in the table indicate the positive relationship between additional weeks of drought and the adoption rate of efficient irrigation technologies for varying drought severity levels. The coefficient estimates for all crops category in column 1 suggest that moderate or severe drought has a more pronounced significant effect on the adoption of efficient irrigation technologies. In other words, the adoption of sprinkler, drip or subsurface irrigation is higher during moderate or severe drought relative to extreme or exceptional drought.

The specification in column 2 includes county-fixed effects, which reveals a modest but positive and significant effect of moderate or severe drought (at a 10% significance level) on the adoption of efficient irrigation technologies, indicating that farmers are somewhat responsive to these drought conditions. The county fixed-effects control for within-county variations over time. The finding suggests that as drought becomes intense, there is a slight increase in the adoption rate of these technologies across all crops. Furthermore, the estimated coefficients are positive and statistically significant at 1% as drought conditions become more extreme or exceptional. This indicates a positive association between drought severity and the adoption rate of efficient irrigation technologies. Hence, farmers are more likely to invest in technologies such as sprinklers, micro, and drip irrigation as the severity of drought rises. The positive relationship reflects farmers' need to cope with water scarcity and maintain or improve crop productivity.

The magnitude of this positive impact is 0.05 and 0.11 percentage point surge in the adoption rate of efficient irrigation technologies compared to surface irrigation for every additional week of moderate or severe and extreme or exceptional drought, respectively. In other words, for every week of extreme or exceptional drought, there is a 0.11 percentage point increase in the likelihood that farmers adopt efficient irrigation technologies over surface irrigation. Overall, these findings demonstrate that farmers are responsive to drought conditions when making decisions regarding irrigation technology adoption as the adoption rate of efficient irrigation technologies rises with increasing drought severity. It reflects their recognition of the need to adapt to water scarcity and maximize water-use efficiency.

In columns 3, 4, 5, and 6 of Table 4, we present the findings for four crop categories: field crops, forage, vegetables and melons, and fruits, trees, and nuts. For field crops, vegetables and melons, and fruits, trees, and nuts, the results indicate a positive and statistically significant association between the rate of adoption of irrigation technology and additional weeks of extreme or exceptional drought. This means that as the severity of drought worsens, the likelihood of farmers adopting efficient irrigation technologies increases for these crop categories. Specifically, for each additional week of extreme or exceptional drought, the adoption rate of sprinkler, drip, and subsurface irrigation increases by 0.13 percentage points for field crops, 0.12 percentage points for vegetables and melons, and 0.08 percentage points for fruits, trees, and nuts as compared to surface irrigation. However, the findings for forage crops differ. Extreme or exceptional drought has a negative impact on the adoption of irrigation technologies for forage crops, although the coefficient estimate is statistically insignificant. The reasons for this could be related to the economic value or water-use efficiency associated with these particular crop categories.

Overall, the positive coefficients indicate that the rate of adoption of irrigation technologies increases with additional weeks of extreme or exceptional drought for field crops, vegetables and melons, and fruits, trees, and nuts. However, for forage crops, extreme drought has a negative impact, although not statistically significant. The specific dynamics of each crop category and the varying factors influencing farmers' decisions contribute to these findings.

In Table 4 (Model 2), the outcomes are presented wherein the dependent variable is the share of efficient irrigation technologies, with surface irrigation as the reference category. The variable of interest is SGMA while controlling for the additional weeks of drought. This enables the isolation of SGMA's specific impact on irrigation technology adoption while taking into account the influence of drought conditions. Such control measures allow us to distinguish the effect of SGMA from the impact of drought on farmers' irrigation choices.

The results indicate that there is an upsurge in the adoption rate of efficient irrigation technology after SGMA's implementation for all crops. Counties with SGMA program implementation are, on average, 11.21 percentage points more likely to adopt sprinklers, drip or subsurface drip than counties without SGMA implementation (column 8). For field crops, vegetables and melons, and trees, fruits, and nuts, there is a positive and statistically significant effect, with corresponding coefficient estimates being 10.6 percent, 21.14 percent, and 2.8 percent, respectively. For forage crops, on the contrary, there is a positive but insignificant effect on the adoption of irrigation technologies.

A positive coefficient for SGMA indicates that its implementation is associated with a higher share of sprinklers, drip, or subsurface irrigation compared to surface irrigation. This suggests that the adoption of SGMA regulations and practices encourages farmers to invest in more efficient irrigation technologies, which can potentially lead to improved water management and conservation.

Table 4: Impact of Expectation of SGMA and Additional Weeks of Drought on Percent of Adoption of Efficient Irrigation Technologies

	Model 1						Model 2					
	All crops	All Crops	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts	All crops	All Crops	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts
SGMA							11.66***	11.21***	10.60***	2.741	21.14***	2.807**
							(1.148)	(1.099)	(1.412)	(1.831)	(2.254)	(1.327)
Severe	0.104***	0.050*	0.049	0.011	0.101*	0.002	0.116***	0.047*	0.045	0.010	0.059	0.001
	(0.0266)	(0.0267)	(0.0350)	(0.0411)	(0.0585)	(0.0333)	(0.0265)	(0.0266)	(0.0347)	(0.0411)	(0.0536)	(0.0332)
Extreme	0.083***	0.109***	0.126***	-0.043	0.125*	0.079**	-0.068**	-0.049	-0.025	-0.079	-0.147**	0.040
	(0.0308)	(0.0285)	(0.0374)	(0.0443)	(0.0678)	(0.0347)	(0.0341)	(0.0323)	(0.0421)	(0.0504)	(0.0669)	(0.0394)
County FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Sample size	8610	8610	2718	1604	1968	2320	8610	8610	2718	1604	1968	2320
Adjusted R2	0.00287	0.186	0.388	0.458	0.00273	0.325	0.0146	0.196	0.400	0.459	0.305	0.326

***Indicate statistical significance at the 1% levels.

**Indicate statistical significance at the 5% levels.

*Indicate statistical significance at the 10% levels.

7.2. Harvested Acres

Table 5 (Model 1) illustrates the results of estimating equation (8), which incorporates drought lags into the estimation equation and uses the logarithm of harvested acres as the dependent variable. The coefficients presented in the table provide the association between the harvested acres and drought levels, including moderate or severe and extreme or exceptional droughts, in the same year and various lag periods.

The results demonstrate the impact of additional weeks of drought on the harvested acres of different crop categories. Specifically, for forage crops, a significant negative effect of additional weeks of moderate or severe and extreme or exceptional drought at three-year lags is observed, resulting in a reduction in harvested acres. The magnitude of this adverse impact is 0.3 percent for moderate or severe drought levels and 0.4 percent for extreme or exceptional drought levels for an additional week of drought. Thus, prolonged periods of drought have a deleterious effect on forage crop production, leading to a decline in the harvested acres.

Table 5 (Model 2) presents the results of our analysis, which focuses on the relationship between the implementation of the SGMA and the log of harvested acres while accounting for additional weeks of drought. We find a significant negative effect of SGMA on harvested acres for forage crops. Specifically, we observe a substantial decline of 27.69 percent in harvested acres for counties with SGMA program implementation than counties without SGMA (column 10). The observed negative coefficient indicates that the incorporation of SGMA regulations and practices has resulted in an unfavorable impact on the extent of agricultural land used for the production of forage crops. This decrease in harvested acres can be attributed to the measures enacted under SGMA, such as the necessity to acquire additional water supplies and a reduction in groundwater pumping. When faced with water shortages, farmers frequently resort to idling or fallowing land, which involves leaving certain irrigated croplands unplanted. This adaptive strategy serves to mitigate revenue losses during periods of water scarcity. Typically, farmers prioritize idling less profitable crops as a means to minimize financial impacts (PPIC, 2021).

Table 5: Impact of Expectation of SGMA and Additional Weeks of Drought on Log Harvested Acres

	Model 1				Model 2			
	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts
SGMA					-0.0814	-0.284***	0.153	-0.0548
					(0.0817)	(0.0731)	(0.115)	(0.122)
Severe	0.0003	-0.0006	-0.0003	-0.0010	0.0004	0.0001	-0.0007	-0.0010
	(0.00181)	(0.00147)	(0.00244)	(0.00224)	(0.00182)	(0.00147)	(0.00246)	(0.00224)
Extreme	-0.0008	-0.0027	-0.0013	-0.0014	0.0005	0.0015	-0.0038	-0.0006
	(0.00241)	(0.00194)	(0.00329)	(0.00320)	(0.00275)	(0.00221)	(0.00379)	(0.00366)
Severe lag1	0.0018	-0.0014	-0.0016	-0.0016	0.0017	-0.0014	-0.0015	-0.0016
	(0.00198)	(0.00160)	(0.00267)	(0.00234)	(0.00198)	(0.00159)	(0.00267)	(0.00235)
Extreme lag1	-0.0008	0.0006	0.0009	-0.0012	-0.0007	0.0008	0.0008	-0.0011
	(0.00321)	(0.00256)	(0.00442)	(0.00393)	(0.00321)	(0.00255)	(0.00442)	(0.00394)
Severe lag2	0.0002	0.0001	0.0009	-0.0004	0.0003	0.0006	0.0007	-0.0002
	(0.00203)	(0.00164)	(0.00279)	(0.00246)	(0.00204)	(0.00164)	(0.00279)	(0.00250)
Extreme lag2	0.0018	-0.0001	0.001	0.0014	0.0019	0.0001	0.0008	0.0018
	(0.00317)	(0.00254)	(0.00430)	(0.00381)	(0.00317)	(0.00253)	(0.00430)	(0.00391)
Severe lag3	0.0014	-0.003**	-0.0017	-0.0012	0.0014	-0.0029**	-0.0017	-0.0012
	(0.00182)	(0.00147)	(0.00248)	(0.00248)	(0.00182)	(0.00146)	(0.00248)	(0.00248)
Extreme lag3	-0.0011	-0.004**	-0.0003	-0.0007	0.0002	0.0002	-0.0028	-0.0004
	(0.00242)	(0.00196)	(0.00329)	(0.00406)	(0.00273)	(0.00223)	(0.00376)	(0.00412)
Severe lag4				-0.0011				-0.0011
				(0.00248)				(0.00248)
Extreme lag4				-0.0011				-0.0009
				(0.00412)				(0.00416)
Severe lag5				-0.0002				-0.0001
				(0.00252)				(0.00255)
Extreme lag5				0.0008				0.0014

				(0.00340)				(0.00369)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	2522	1406	1675	1788	2522	1406	1675	1788
Adjusted R2	0.463	0.779	0.380	0.618	0.463	0.781	0.380	0.617

***Indicate statistical significance at the 1% levels.

**Indicate statistical significance at the 5% levels.

*Indicate statistical significance at the 10% levels.

7.3. Robustness Check

As a means of conducting a robustness check, we employ two distinct methods to define drought variables in addition to our preferred specification. These methods consist of a drought intensity index and a drought indicator variable. Specifically, the results are reported in Table A1. In this instance, the dependent variable is the rate of adoption of irrigation technologies, the independent variable is the drought intensity index, and the reference category is surface irrigation. Notably, the estimated coefficient is positive and statistically significant, suggesting that an increase in the drought intensity index is associated with a corresponding increase in the rate of adoption of sprinklers, drip or subsurface drip in comparison to surface irrigation for all crops. Furthermore, Table A3 reports the results, where the dependent variable is the rate of adoption of irrigation technologies, and the independent variable is the drought indicator. Here, the coefficient estimate is negative but statistically insignificant.

Table A2 presents findings where the log harvested acres as the dependent variable, and drought intensity index as the independent variable. The obtained negative coefficient estimate is statistically insignificant, regardless of the presence or absence of lag. Furthermore, Table A4 portrays the outcomes where the log harvested acres as the dependent variable and drought indicator as the independent variable. The negative coefficient estimate is statistically insignificant without lag. The same is true for the negative estimated coefficient with lag.

8. Conclusion and Policy Implications

This paper has examined how farmers respond to drought and institutional interventions in terms of the adoption of different irrigation technologies and changes to cropping patterns, over time and across California counties. The article uses three different methods to measure the drought namely (i) the impact of additional week of drought; (ii) the drought intensity index; and (iii) the drought indicator variable. To analyze this question, the article employs a fixed effect regression model to analyze data gathered from 58 California counties in the past two decades.

The findings of this article demonstrate the significant impact of drought on the adoption of efficient irrigation technologies. Specifically, each additional week of extreme or exceptional drought has a positive and statistically significant effect on the adoption of efficient irrigation technologies across all crops. In contrast, prolonged drought periods at moderate or severe drought shows a small but positive effects influence on the adoption of efficient irrigation technologies for all crops. The phenomenon observes that farmers are possibly more inclined to invest in efficient irrigation technologies during extreme or exceptional drought situations, but not during moderate or severe drought conditions which raises a fascinating question regarding their decision-making processes. Therefore, it is imperative to consider the underlying factors that influence farmers' investment decisions during different drought scenarios.

One plausible explanation for this phenomenon is the perception of risk and urgency. Farmers may perceive a higher level of risk and urgency during extreme or exceptional droughts to adopt efficient irrigation technologies to mitigate the immediate impacts of water scarcity and maintain crop productivity. In contrast, during moderate or severe droughts, farmers might perceive a lower level of risk, or facing a sense of resilience based on their past experiences or the availability of alternative coping mechanisms, such as groundwater extraction or changing cropping patterns. Other possible explanations could be that efficient irrigation technology is expensive to install and maintain. Farmers may be hesitant to invest in this technology during moderate or severe droughts for certain crops. However, during extreme or exceptional droughts, the opportunity cost of not investing in efficient irrigation technology may be too high, as farmers may have no other way to water their crops with dwindling amounts of water.

Additionally, the results indicate noteworthy negative and statistically significant effects of drought on harvested acres of forage crops. This negative impact is observed for each additional week of both moderate or severe and extreme or exceptional drought conditions. The reduction in harvested acres of forage crops due to drought can be attributed to multiple factors. Specifically, forage crops typically have greater watering needs relative to other crops, making them more vulnerable to water scarcity caused by drought conditions. This can lead to a decrease in planted area and harvested acres as farmers struggle to meet the water needs of forage crops. Additionally, farmers may prioritize their water usage for higher-value or essential food crops, resulting in a strategic shift away from forage crops. This shift can lead to a reduction in the cultivation of forage crops in favor of other crops that offer better economic returns or have higher water-use efficiency. Therefore, the negative impact of drought on forage crop production is a multifaceted issue that requires careful consideration of water management strategies and crop allocation decisions.

Moreover, the study reveals that the implementation of the SGMA has led to a notable increase in the adoption rate of irrigation technology, while controlling for additional weeks of drought. This means that areas that have implemented SGMA are more likely to introduce efficient irrigation technologies, such as sprinklers, drip, or subsurface drip, compared to surface (furrow) irrigation during drought conditions. This finding is consistent with the goals of SGMA, which aims to promote sustainable groundwater management practices and reduce reliance on unsustainable groundwater extraction. Overall, this finding suggests that SGMA has been successful in promoting sustainable groundwater management practices and encouraging the use of efficient irrigation technologies during drought conditions. Policymakers can consider this as an encouraging sign that institutional interventions, such as SGMA, can effectively incentivize the adoption of sustainable agricultural practices in response to water scarcity.

Furthermore, the analysis uncovers a negative and statistically significant relationship between SGMA and harvested acres for forage crops, while controlling for additional weeks of drought. The implementation of SGMA has had a remarkable detrimental effect on the harvested acres of forage crops. Our analysis reveals that following the adoption of SGMA, there has been a substantial reduction in the extent of agricultural land utilized for forage crop production.

The purpose of SGMA is to guarantee sustainable groundwater management, which has necessitated diverse measures such as enhancing water supplies and curtailing groundwater pumping. These actions have resulted in noteworthy shifts in land use patterns and agricultural practices. Farmers, who are confronted with water scarcities, have resorted to leaving land idle or fallow as a mechanism to tackle limited water availability. This method involves abstaining from planting certain irrigated croplands, specifically forage crops. By idling less profitable crops, farmers aim to mitigate revenue losses and optimize resource allocation. The adverse impact of SGMA on the harvested acres of forage crops underscores the difficulties encountered while adapting to new water management regulations and practices. It emphasizes the necessity for farmers to revise their agricultural activities to align with sustainable groundwater management objectives.

Our findings are robust to alternative drought measures, which yield comparable estimates, thereby reinforcing the reliability of our results. Overall, policymakers can leverage the insights from this article to inform their decision-making processes regarding the promotion of efficient irrigation technologies, managing the impacts of drought on cropping patterns, and shaping effective institutional interventions to enhance water management in California's agricultural sector.

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Appendix

Table A1: Impact of Expectation of SGMA and Log Drought Intensity Index on Adoption of Irrigation Technologies

	Model 1						Model 2					
	All crops	All Crops	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts	All crops	All Crops	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts
SGMA							12.05***	10.11***	10.96***	1.398	17.78***	2.587**
							(1.132)	(1.082)	(1.450)	(1.824)	(2.120)	(1.319)
Log DI	1.751*	3.796***	3.744***	-0.784	3.760*	2.290**	-2.158**	0.0205	-0.103	-1.199	-1.679	1.259
	(0.944)	(0.872)	(1.161)	(1.385)	(2.042)	(1.050)	(0.971)	(0.914)	(1.218)	(1.487)	(1.805)	(1.125)
County FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Sample size	7920	7920	2432	1524	1841	2123	8390	8390	2527	1524	2064	2275
Adjusted R2	0.0003	0.187	0.393	0.451	0.001	0.330	0.013	0.192	0.399	0.451	0.291	0.413

***Indicate statistical significance at the 1% levels.

**Indicate statistical significance at the 5% levels.

*Indicate statistical significance at the 10% levels.

Table A2: Impact of Expectation of SGMA and Log Drought Intensity Index on Log Harvested Acres

	Model 1				Model 2			
	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts
SGMA					-0.0685	-0.258***	0.0987	-0.1800
					(0.0781)	(0.0675)	(0.101)	(0.116)
Log DI	-0.0529	-0.0617	-0.0791	-0.0415	-0.0297	0.0153	-0.0709	-0.0092
	(0.0635)	(0.0538)	(0.105)	(0.0843)	(0.0688)	(0.0572)	(0.0895)	(0.0868)
Log DI lag1	0.0752	-0.0242	-0.0124	-0.0520	0.0780	-0.0104	-0.0169	-0.0176
	(0.0780)	(0.0657)	(0.132)	(0.0970)	(0.0780)	(0.0655)	(0.102)	(0.0994)
Log DI lag2	-0.0279	0.00782	-0.0166	0.0050	-0.0134	0.0569	0.0232	0.0644
	(0.0782)	(0.0655)	(0.132)	(0.0944)	(0.0800)	(0.0665)	(0.104)	(0.102)
Log DI lag3	0.0360	-0.136***	-0.0964	-0.0168	0.0561	-0.0676	-0.0648	-0.0040
	(0.0627)	(0.0528)	(0.104)	(0.0953)	(0.0668)	(0.0555)	(0.0864)	(0.0956)
Log DI lag4				-0.0214				-0.0028
				(0.0986)				(0.0992)
Log DI lag5				0.0079				0.0818
				(0.0865)				(0.0988)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	2254	1334	1568	1631	2254	1334	1568	1631
Adjusted R2	0.465	0.766	-0.0008	0.616	0.465	0.769	0.408	0.616

***Indicate statistical significance at the 1% levels.
**Indicate statistical significance at the 5% levels.
*Indicate statistical significance at the 10% levels.

Table A3: Impact of Expectation of SGMA and Drought Indicator on Adoption of Irrigation Technologies

	Model 1						Model 2					
	All crops	All Crops	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts	All crops	All Crops	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts
SGMA							6.70***	6.74***	6.54	-2.56	32.23***	0.03
							(1.088)	(0.924)	(4.905)	(4.162)	(6.002)	(2.671)
drought	-0.65	-0.74	-13.52***	2.49	-12.20**	-3.43	-0.120	-0.22	-7.45	0.25	17.15**	-3.40
	(1.009)	(0.830)	(3.759)	(4.244)	(5.166)	(2.538)	(1.010)	(0.830)	(5.901)	(5.592)	(7.488)	(3.477)
County FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Sample size	7030	7030	1899	1399	1509	2123	7030	7030	1899	1399	1509	2123
Adjusted R2	-0.00008	0.324	0.599	0.570	0.472	0.330	0.005	0.329	0.599	0.570	0.482	0.331

***Indicate statistical significance at the 1% levels.

**Indicate statistical significance at the 5% levels.

*Indicate statistical significance at the 10% levels.

Table A4: Impact of Expectation of SGMA and Drought Indicator on Log Harvested Acres

	Model 1				Model 2			
	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts	Field Crops	Forage	Vegetables & Melons	Fruits Trees & Nuts
SGMA					-0.0761	-0.255***	0.0764	-0.0677
					(0.0582)	(0.0514)	(0.0801)	(0.0812)
drought	0.0136	-0.0185	-0.0715	-0.0357	0.0172	-0.0080	-0.0745	-0.0371
	(0.0609)	(0.0513)	(0.0826)	(0.0803)	(0.0609)	(0.0509)	(0.0826)	(0.0803)
drought lag1	0.0498	-0.0305	-0.0124	-0.0552	0.0567	-0.0089	-0.0202	-0.0423
	(0.0709)	(0.0596)	(0.0958)	(0.0905)	(0.0711)	(0.0593)	(0.0960)	(0.0918)
drought lag2	-0.0038	0.0116	-0.0108	-0.0200	0.0057	0.0401	-0.0202	0.0035
	(0.0675)	(0.0566)	(0.0911)	(0.0863)	(0.0678)	(0.0564)	(0.0916)	(0.0910)
drought lag3	0.0929	-0.0860*	-0.0144	-0.0203	0.110*	-0.0352	-0.0312	-0.0044
	(0.0595)	(0.0502)	(0.0808)	(0.0855)	(0.0609)	(0.0508)	(0.0825)	(0.0875)
drought lag4				-0.0219				-0.0177
				(0.0894)				(0.0896)
drought lag5				-0.0244				0.0074
				(0.0756)				(0.0848)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	2521	1406	1671	1787	2521	1406	1671	1787
Adjusted R2	0.463	0.777	0.378	0.618	0.463	0.781	0.379	0.618

***Indicate statistical significance at the 1% levels.

**Indicate statistical significance at the 5% levels.

*Indicate statistical significance at the 10% levels.