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Land Transitioning and Cropping Systems: Buyer Expectations in California's Farm Land Market Amid Climate Change

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Summary:
This paper estimates the impact of climate change on the expectations of buyers in California's farmland market. Focusing on the Central Valley of California and make use of a geo-referenced dataset on farmland, combined with high-resolution spatial data that indicates the distribution of crop types and cropland. We use panel data on repeated farmland sales to estimate a hedonic regression equation with parcel and year of sale fixed effects. The results show a 3% gain in farmland value due to the transition to perennial crops, and a loss of 2.2% of farmland value due to continued farming of annual crops.

Keywords: Hedonic analysis, repeat sales, farm-level adaptation, crop diversity, California

JEL Codes : Q12, Q53, Q54

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Abstract

This paper estimates the impact of climate change on the expectations of buyers in California's farmland market. Focusing on the Central Valley of California and make use of a geo-referenced dataset on farmland, combined with high-resolution spatial data that indicates the distribution of crop types and cropland. We use panel data on repeated farmland sales to estimate a hedonic regression equation with parcel and year of sale fixed effects. The results show a 3% gain in farmland value due to the transition to perennial crops, and a loss of 2.2% of farmland value due to continued farming of annual crops.

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1. Introduction

One of the most climate-vulnerable assets is farmland (Jacoby, Rabassa, and Skoufias 2015), and farmland owners and workers are most affected by climate change (Jackson et al. 2012; Stevens 2017; Jessoe, Manning, and Taylor 2018). The farmer (or an economic agent)[1] knows how the climate is distributed over time and has made investments on the farm (for example, in irrigation technology) to reduce net losses.[2] In addition, when a parcel is sold, the seller may have decided their land offered limited opportunities for private adaptation in the future, or weak effectiveness of current adaptation practices (Mendelsohn and Massetti 2017). However, a buyer could purchase farmland and reoptimize the crop choice in direct response to local climate change. This would allow the new owner to maximize profits so that the drop (irrigation water) per crop is equivalent to the value per crop. Using Hedonic analysis of agricultural land prices for parcels sold repeatedly during periods of drought, we expect to quantify the impact of climate change on the behavior of land buyers.

Our study is set in California during a drought period, which has transformed California agricultural practices. For example, according to California's Department of Water Resources (DWR), a higher proportion of perennial crops associated with the widespread adoption of irrigation practices, including micro- or mini-sprinklers, and surface and buried drip irrigation are being grown in the Central Valley. California's climate is diverse with a wide variety of landscapes that include coastal areas, foothills, and valleys. Farmers in California grow a wide variety of crops throughout the landscape, in different climates (Pathak et al. 2018). Studies have shown that climate change will negatively affect most of California's agricultural sector by

[1]More specifically, an economic agent refers to individuals or enterprises seeking to maximize their profits.
[2] Following (Moore 2019), we define net losses as the difference between the gain in net value in production and the net change in production spending resulting from private adaptation in response to climate change.

reducing the farm profits of certain crops (Deschenes and Greenstone 2007; Deschenes and Kolstad 2011). According to the Intergovernmental Panel on Climate Change (IPCC), climate change will exacerbate the frequency and intensity of future droughts. Changes in precipitation from atmospheric and oceanic signals include El Nino Southern Oscillation (ENSO), and Pacific Decadal Oscillation (PDO) (Mukherji et al. 2023), which increase the challenges for the adaptive capacity of California's agriculture.

Despite a sizeable literature on the impact of climate change on agriculture in California (Lobell, Cahill, and Field 2007; Lobell, Torney, and Field 2011; Deschenes and Kolstad 2011), few studies have quantified the impact of the distributional implications of climate change, which are critical for policy interventions. One reason for the scant research on this issue is the lack of data. Earlier studies based on the Ricardian approach (Prakash et al. 2023) have included limited behavioral responses by farmers to estimate the net impact of adaptation to climate change, and may overestimate the negative impacts (Fezzi and Bateman 2015). Our data on farmland sale values provides few advantages. First, we avoid first aggregation bias by using parcel-level data instead of aggregated data at the county level. Second, we avoid self-reporting bias by using observed sales transactions over self-reported farmland values. Third, our sample is from the Central Valley area, which is as homogenous as possible with respect to the variables excluded from the explanatory relationship, such as input prices, and prevailing agricultural practices, and thus estimates may be not biased due to omitted variables.

In this study, we examine the distributional implications of climate change on California's agriculture using parcel-level repeat-sales transactions and cropland data in California's Central Valley from 2008 to 2021. Specifically, we investigate how and to what extent cropping systems in California's Central Valley explain the buyers' expectation in the farmland market in the context of climate change. We leverage geocoded agricultural parcels and combine them with high-resolution cropland datasets to examine temporal and spatial changes in crop diversity at the local scale. We then explicitly quantify how adaptation to climate change has occurred in the Central Valley in terms of crop distribution.

Researchers have reached a consensus (Blanc and Schlenker 2017; Mendelsohn and Massetti 2017; Deschenes and Kolstad 2011) that the Ricardian approach pioneered by Mendelsohn, Nordhaus, and Shaw (1994; 1996) offers an important empirical strategy for quantifying the impacts of climate change. The value of farmland captures the different climates and makes it possible for researchers to estimate the impact of climate change on agriculture (Mendelsohn and Dinar 2003). Simply put, a Ricardian analysis is a cross-sectional hedonic analysis that quantifies the impacts of climate change on agriculture by regressing farmland values on climatic conditions and parcel hedonic characteristics. However, concerns about omitted variables in the Ricardian analysis may bias the estimates. Based on the expected profit maximization of buyers, our empirical analysis involves estimating a repeat-Ricardian model. A repeat-Ricardian (using parcel-level repeat sales to control for confounding omitted variables, is the basis of a repeat-Ricardian analysis) analysis is more capable of capturing the transition of crops to high-value crops than standard Ricardian analyses (Bareille and Chakir 2023). We hypothesize that property value captures the buyers' expected profit maximization of a potential crop change after the purchase in response to climate change. Our parcel-level data in California over fourteen years (2008–2021) allows us to observe the development of specific on-farm adaptation measures in response to drought conditions. We use farmland transacted values as a dependent variable, and climatic variables (e.g., an indicator of drought severity and their lags) as predictors in a numerical model to understand land buyer expectations to crop choices according to climate conditions. The empirical model provides explicit crop distribution estimates as a response to climate change.

We take advantage of parcels sold several times to different buyers by including fixed effects at the parcel-level and year of sale. Our identification strategy relies on crop variations within the same parcel following the change in ownership. We exploit changes in climate-induced cropping patterns in a parcel that has been sold repeatedly. The results suggest that buyers are growing high-value crops, such as almonds, pistachios, and nuts, and annual crops that have been shown to be less affected by climate change, such as dry beans and grains. We also find that annual crop acreage, such as corn, decreases for purchased parcels that are sold repeatedly.

We also study crop diversity to explore the relationship between cropping patterns and farmland value, and distributional implications across counties in the Central Valley of California. We find that the Herfindahl-Hirschman index, a measure of crop diversity that is widely used in the literature (e.g., Auffhammer and Carleton 2018), is negative and statistically significant for annual crops during our study period, suggesting that farmers are moving to more specialized high-value crops. We also find similar results using an alternative crop diversity index called the Shannon Diversity Index (Aguilar et al. 2015). These findings highlight that Californian farmers are shifting to specialty perennial crops (tree crops), in contrast to diversification, growing annual field crops, as a way to cope with changing climate. We then explore the role of policies, such as the Sustainable Groundwater Management Act (SGMA) affecting agriculture, including cropping patterns and the values of farmlands. We find that the cultivation of perennial crops increased statistically after the introduction of SGMA in 2014.

However, for the cultivation of annual crops, we find no statistical evidence of the influence of SGMA.

Several authors (see the systematic review of Pathak et al. 2018) have studied the impact of climate change on California's agriculture.[3] Researchers agree that California's agricultural sector is vulnerable to climate change. Agriculture in California is mainly irrigated, and the water contractor plays a major role in water resource management for irrigation. Water availability for producers as a production input is tied to the water management capacity of contractors. Climate change poses a threat to water allocation to contractors managing water and, consequently, to producer water availability. One of the ways producers have adapted to uncertainty in water availability is to change cropping patterns, among other adaptation practices (Mendelsohn and Massetti 2017). More permanent crops of relatively high-value, such as almonds, pistachios, citrus, and other tree crops, have replaced seasonal crops of relatively low-value, including alfalfa, corn, cotton, safflower, as part of climatic adaptations (Pathak et al. 2018). This change in cropping patterns on farmland can be expected to be reflected in its value.

The scope of this article is twofold: to quantify changes in climate-induced cropping patterns following a parcel sale, and to examine the extent to which cultivation of land is modified in response to climate change conditions to maximize expected profit to parcel buyers. Using georeferenced parcels, we explore the spatial distribution of crop types and cropland at the parcel level in response to drought conditions. We show that in counties with prolonged drought, the number of farm parcels sold is also higher. These parcels represent a high percentage of the agricultural land that has been transferred.

[3] Also see (Lobell, Cahill, and Field 2007; Lobell, Torney, and Field 2011), (Schlenker, Hanemann, and Fisher 2007), (Deschenes and Kolstad 2011), and (Buck, Auffhammer, and Sunding 2014).

Our analysis makes two main contributions to the literature. First, we show the spatial analysis of the impact of climate change on the state-level agricultural sector using parcel-level data from California. Second, we show the distributional impacts of climate change in 18 agricultural counties in California's Central Valley.

In the remainder of this paper, we propose a conceptual model of buyers' expectations in the context of climate change, and apply the hedonic method to the price of parcels sold repeatedly during long periods of drought between 2008 and 2021 in the Central Valley.

2. Conceptual Model and Testable Hypotheses

2.1. A conceptual model for buyers' expectation in the context of climate change

The hypothesis of our study is that property value captures the buyers' expected profit maximization of a potential crop change after the purchase, in response to climate change. To model this hypothesis, we follow Buck, Auffhammer, and Sunding (2014), and modify the problem of maximizing buyers' profit by including crop choices and climate variables.

Buyers are potentially forward-looking about future land rental flows. The logic follows that a potential buyer purchases land associated with low-value crops and expects to convert it into high-value crops and thus maximize profits. The parcel transition to high-value crops (C^h) from low-value crops (C^l) may be affected by various factors, including a change in the owner's managerial capacity (e.g., a change in ownership from a private owner to a corporate business), or following investment to improve production efficiency.[4] The buyer assumes that the price of the high-value crop, C^h, will be p_t^h in time t. Next, we define the production function as $\sum_{k=0}^{K} f\left(C_{kt}^j, \psi_t, L, W, v_t^j\right)$ where $k = 0, \dots, K$ represents the types of crops to be grown on the

[4] However, the Ricardian approach assumes that landowners are able to move freely (cost less) between land uses (Mendelsohn, Nordhaus, and Shaw 1996).

parcel and $k = 0$ indicates fallowed land; C_{kt}^{j} represents high-value crops ($j = h$) and low-value crops ($j = l$) planted at time t. ψ_t represents an index of drought to track short-term agricultural droughts; L represents land, W represents the water available for the parcel, and v_t^j represents the optimal quantity of variable inputs for crops. We group crop types k into low- and high-value crops and drop the script, j for simplicity. Also similar to Buck, Auffhammer, and Sunding (2014), we assume that total available land in the region does not change over time.

To estimate buyers' expected profit maximization, we further assume that the cost of irrigation water will increase, due to the water availability constraints on the source side. For example, uncertainty about the availability of the parcel's surface water during drought years can be substituted by groundwater, making irrigation more costly.

For multiple crops ($k = 1, \ldots, K$) planted on a parcel, a buyer solves the profit maximization problem at time t:

$$(1) \qquad \max_{\{v_k\}} \sum_{k=1}^{K} p_k \cdot f(C_k, \psi, L, W, v_k) - c \cdot v_k$$

For simplicity, we have suppressed the subscript t. Assume that the land, and water to the parcel do not change during the study period. The term $c \cdot v_k$ is the cost of inputs associated with each crop.

Next, to estimate the climate-induced effects on farm-level choices (such as changes in cropping patterns), we introduce the bid function which is common in the hedonic literature (Sheppard 1999), $\theta(z_i; \alpha)$ in the maximization of buyer profits, where i is a parcel. The bid function describes the amount of money that a buyer is willing to pay for a property i with attributes z at a given utility and income, included in α (Rosen 1974). α is a vector of observed and unobserved characteristics of buyers. We also can think about the attributes of parcels, such as access to water supplies in the form of surface water rights or groundwater, distance from the city center, a parcel located in a low-drought area, and access to market that allow for future adaptation, including shifts in cropping patterns for buyers. A higher bid is then a combination of payment and parcel attribute z, which results in a maximum expected profit for a buyer.

The bidding function associated with the buyer's expectation of converting low-value cropland into high-value cropland as a climate change adaptation measure is given by $\theta\left(C_k^j, \psi; z_{-i}, \alpha\right)$. Where C_k^j, ψ, α are defined similarly to above, and z_{-i} represents other attributes of a parcel.

Combining buyers' expected profit maximization from crop production and the buyers' bidding function yields:

$$\max_{\{v_k\}} \sum_{k=1}^{K} p_k \cdot f\left(C_k, \psi, L, W, v_k\right) - c \cdot v_k - \theta\left(C_k, \psi; z_{-i}, \alpha\right) \tag{2}$$

Under perfect competition, this maximization leads buyers to equate the market price of land to the net income obtained from the land. That is,

$$\sum_{k=1}^{K} p_k \cdot f\left(C_k, \psi, L, W, v_k\right) - c \cdot v_k - \theta\left(C_k, \psi; z_{-i}, \alpha\right) = 0 \tag{3}$$

Rearranging the above equation yields:

$$\theta\left(C_k, \psi; z_{-i}, \alpha\right) = \sum_{k=1}^{K} p_k \cdot f\left(C_k, \psi, L, W, v_k\right) - c \cdot v_k \tag{4}$$

By taking the present value of the rent of the purchased land over an infinite horizon, a potential buyer solves the following profit maximization:

(5) $$\max_{\{v_{kt}\}} \Pi = \sum_{t=0}^{\infty} \sum_{k=1}^{K} \delta^t \cdot (p_{kt} \cdot f(C_{kt}, \psi_t, L, W, v_{kt}) - c_t \cdot v_{kt}) - \theta(C_{kt}, \psi_t; z_{-i}, \alpha)$$

The optimal solution results in the purchase of parcels with a combination of attributes that allow future adaptation. The resultant Π^* is equal to the total economic rent for a combination of crops grown on a parcel adapting to climate-change over a period of time.

The shadow price of climate-induced crop change indicates the additional price that the buyer must pay to get a higher level of attributes that allow the farm to adapt (Rosen 1974). The shadow price is given by the partial derivative with respect to the C_{kt}, with the expression:

(6) $$\frac{\partial f}{\partial C_{kt}} = \lambda_{c_{kt}} = \sum_{t=0}^{\infty} \delta^t \cdot \lambda(C_{kt}, \psi; z_{-i}, \alpha)$$

where $\lambda_{c_{kt}}$ is the shadow price of climate-induced crop switching. The goal of this study is to estimate the marginal value (shadow price) a potential buyer is willing to pay for the attribute that allows for future adaptations at the farm level in the form of crop switching. We capture this form of climate adaptation by estimating the hedonic price equations using the farmland sale price.

2.2. Testable hypotheses

Using this framework, the climate-induced on-farm adaptation, such as changes in cropping patterns of potential buyers, can be further decomposed into the following hypothesis:

HYPOTHESIS 1. *Changing in cropping patterns: transition from annual to perennial crops.*

Assuming that annual crops were cultivated prior to sale. This hypothesis tests whether the buyer changes cropping patterns on the post-sale land to produce a higher net income per unit of land. For our purposes, we have defined tree crops to be high-value perennial crops, because most tree crops are capital-intensive in terms of irrigation technologies, like micro- and buried drip irrigation. Water reliability for growers raising perennial crops is inelastic (requires water regardless of the dry year). It is reasonable to assume that parcels associated with tree crops produce higher net income per unit of water applied, and also higher net income per unit of land. Therefore, we expect that more post-sale land will be allocated to perennial crops, as opposed to annual crops. Mathematically, for perennial crops, the first-order condition is given by $\frac{\partial f}{\partial c_{kt}} > 0$.

3. Study Area and Data Sources

This study examines parcels sold repeatedly in 18 counties in the Central Valley of California over long periods of drought, from 2008 to 2021 (see the map of the study area in the Appendix Figure A1). The Central Valley is composed of the Sacramento and San Joaquin Valleys. [5] The Central Valley is very important for the agricultural sector of California. It grows hundreds of different types of products due to its Mediterranean-like climate, and supports food security of the United States (Jessoe, Mérel, and Ortiz 2021). However, it is also vulnerable to future climate change (Lee, De Gryze, and Six 2011).

Appendix Figure A2 shows the number of parcel transfers, and the farmland area. We see that the number of farm parcels sold during our study period (2008–2021) is above average. The study period also overlaps with California's long-term drought period (Jessoe, Mérel, and Ortiz 2021). These parcels, which were transferred more than twice, represent a large percentage of the farmland transferred.

[5] For our analysis, we combine the counties that make up the Sacramento and San Joaquín Valleys. Sacramento Valley comprises the counties of Tehama, Glenn, Butte, Colusa, Yolo, Solano, Sutter, Yuba, Placer, and Sacramento. The northern part of the San Joaquin Valley consists of the counties of San Joaquin, Stanislaus, and Merced. The central part of the San Joaquín Valley includes the counties of Madera, and Fresno. The southern part of the San Joaquin Valley includes the counties of Tulare, Kern, and Kings.

3.1. Data sources and sample selection

To estimate the changes in the mix of crops and the marginal effect they have on farmland values in the Central Valley, we combine geocoded parcel-level panel data of farmland transactions with a high-resolution spatial cropland data layer from 2008 to 2021.

We obtained all assessed values of farmland and transactions in California between 2008 and 2021 from ATTOM Data Solutions company.[6] The data includes 144,344 unique parcels associated with field-cultivated crops, orchards, and vineyards. We first removed 821 of the 144,344 parcels that are no longer updated and considered inactive by the assessor. Second, we chose only transacted parcel records, which reduced our sample to 123,107 parcels. Third, we followed Buck, Auffhammer, and Sunding (2014), and removed parcels with bedrooms (13,109 parcels) to include only agricultural parcels. Fourth, we removed parcels with a lot size less than 500 square feet (179 parcels). We consider these parcels to be associated with greenhouses that do not necessarily reflect the impacts of climate change. Fifth, we removed records without sales amount information (68,855 parcels). Finally, for the purposes of this analysis, we further restrict the sample to parcels sold in the Central Valley of California between 2008 and 2021. Our final sample includes 30,401 observations (i.e., unique transactions) representing 14,606 parcels and 1.06 million acres of farmland.[7]

For land use data, we rely on annual Cropland Data Layer (CDL) at 30×30 meter resolution for 2008 through 2021.[8] The US Department of Agriculture (USDA) publishes CDL

[6]Seven counties are missing from our sample, due to unavailability of data. The missing counties are Alameda, Amador, Marin, Mariposa, Nevada, Orange, and San Francisco.

7 On an average, the mean lot size is 73 acres with a standard deviation of 127 acres. The minimum area is 0.005 acres while the maximum area is 6,711 acres. Moreover, 75% of the sample has less than 80 acres.

[8] To convert pixel to acres, we use a multiplier, 900*0.0002471054, to pixel values.

products using a combination of satellite imaging and agricultural ground data collected during the growing season.

3.2. Farm sales in the Central Valley of California

We aggregate the value per acre and area of agricultural land by crop type for all agricultural parcels in the California Central Valley that were sold between 2008 and 2021. The average land value per acre (in 2021 dollars) over the study period (2008–2021) is the highest for almonds, pistachios, and nuts at $72,094, followed by citrus, other sub-tropical fruit trees, and other tree crops at $69,789 and $64,669, respectively. Land associated with rice has the lowest average value per acre at $41,344. Dry beans, melons, squash, cucumbers, and safflower also have a low acreage value of approximately $43,000.

In summary, lands with perennial crops in the Central Valley were valued at an average of $67,713 per acre. In contrast, lands that grew annual crops were valued at $54,128 per acre. Natural vegetation and fallowed land are valued at $54,746 and $62,080 per acre, respectively. Figure 1 shows the average value of farmland (left) and area (right) for 18 crops, and two that are not crops, such as fallow land and natural vegetation, produced in the Central Valley of California from 2008 to 2021.[9]

3.3. Variables

We use the transaction sale value of the property, divided by the acreage of the lot to calculate the variable value per acre as a measure of buyers' expectations. All values are adjusted for inflation. The annual Consumer Price Index (CPI) obtained from the Federal Reserve Economic Database is used to convert nominal values to 2021 U.S. dollars. We winsorize the value per acre

[9] CDL data for California is available between 2008 and 2021. Data is available at: https://nassgeodata.gmu.edu/CropScape/

variable at the 1 and 99 percentiles to minimize the impact of outliers. Appendix Figure A3 shows the cumulative percentage distribution of parcels before and after Winsor.

Explanatory variables include vectors of crops grown in a parcel (C_k) to estimate their marginal contribution to farmland value. We construct parcel-weighted acreage area for different types of crops (each non-null crop area within a parcel is divided by the total lot size of that parcel).[10] We control for weather variables in the estimation model. Our main weather indicators are accumulated precipitation (in millimeters) and growing degree days and extreme degree days derived at the parcel-level using the PRISM daily dataset for a growing season (1st April to 30th September) for the years 2008-2021. To account for the non-linear relationship between farmland values and climatic conditions, we include the square terms of precipitation and growing degree days and the square root of extreme degree days.

3.4. Distribution across counties in California's Central Valley

Appendix Figure A4 shows the average value of farmland per acre for parcels sold two or more times between 2008 and 2021 in California's Central Valley. San Joaquin County had the highest price per acre ($194,040), followed by Madera ($124,550), Placer ($103,927), and Kings ($95,484). Sacramento County had the lowest price per acre at $16,322. Other counties where the price was less are Colusa ($16,322), Kern ($26,734), and Glenn ($35,417). Other remaining counties had an average price per acre of between $40,000 and $70,000.

Appendix Figure A5 shows the average percentage of perennial and annual crops between 2008 and 2021 in the Central Valley of California. These percentages were derived by

[10] The minimum mapping unit for CDL database is 30 m pixels. As a result, the cultivated area computed from this dataset can exceed the total lot size of a parcel.

taking the ratio between the percentage area of perennial and annual crops in a parcel and the lot size. In the southern San Joaquin Valley, a large proportion of parcels had perennial crops, while parcels with more annual crops were located in the central San Joaquin Valley. For example, farmlands in San Joaquin and Madera counties had the highest share of perennial crops, at 65% and 62% on average. Farmland in Fresno, Butte, Kings, and Tulare counties, which are south of the San Joaquin Valley, represents about 50% of perennial crops. The smallest share of perennial crops was found in the counties of Placer (less than 1%), and Kern (less than 5%). Sacramento County had less than 10% agricultural land with perennial crops, and over 75% with annual crops. Merced County had approximately 50% agricultural land with annual crops. The counties of Tehama (below 5%), and Kern and Sutter (below 15%) account for the smallest share of annual crops.

The bottom left of Appendix Figure A5 shows the average percentage of non-cultivated crops between 2008 and 2021 in the Central Valley for parcels that have been sold two or more times. The counties of San Joaquin and Tehama consist of less than 5% of non-cultivated crops, including fallow land and natural vegetation on parcels that have been sold more than twice. The counties of Madera, Merced, and Sacramento consist of less than 10% of non-cultivation within a parcel. Kern county had no crops planted on 21% of its farmland. Placer County had the largest percentage of non-cultivation in a parcel (64%), followed by Sutter County (38%), and Colusa County (33%).[11]

[11] Here, to note that the percentage of perennial, annual, and no crops was derived by taking the ratio between the percentage area of perennial, annual, and no crops in a parcel, and the lot size. This may mean that the percentage may not equal to one.

4. Empirical Strategy

We are interested in explaining the rent from land, measured as value per acre, in terms of acreage of crops, C_k grown in the land where $k = 0, \ldots, K$ represents the types of crops to be grown on the parcel, and $k = 0$ indicates fallowed land. To assess the impact of climate change on California's Central Valley agriculture, we use a panel fixed effects model to account for time-invariant unobserved heterogeneities that are both correlated with climate and the farmland value (Blanc and Schlenker 2017).

The Ricardian method captures farmers' choice of crops that maximize their profits in response to the climate (Mendelsohn, Nordhaus, and Shaw 1996). Using parcel-level data from California's Central Valley, we apply the Ricardian approach to model climate-induced crop switching as an adaptation at the farm level. The estimated equation is:

(7) $$\left(\frac{Value}{Acre}\right)_{it} = \beta_0 + \sum_{k=0}^{K} \beta_k C_{ikt} + \gamma f\left(W_{it}\right) + \mu_i + \tau_t + \varepsilon_{it}$$

where i indicates the parcel; t indicates the year of sale; C_{ikt} represents the share of crop k planted in parcel i in year t. Note that *K* indicates universe of crops planted in the study area, and $k = 0$ indicates the fallowed land. $f(W_{it})$ is non-linear function of precipitation and temperature at the parcel-level, such as squared terms of precipitation and growing degree days and square root of extreme degree days.

We include parcel fixed effects, μ_i, to control for time-invariant unobservable effects that may affect the farmland values (Buck, Auffhammer, and Sunding 2014). For example, we rely on parcel-level fixed effects to absorb most parcel-level characteristics, such as constant spatial location variables (e.g., distance to a city and major highway or type of water rights), and biophysical characteristics (e.g., soil quality). We also include the year-fixed effects, τ_t, to control for time varying shocks, such as changes in global agricultural prices that may have an impact on farmland values.[12] The expression ε_{it} is an error term, representing the variations in farmland values that are not explained by our model. We are limited in our selection of crop types, because many crops do not have any cultivated area on a parcel. We apply the inverse hyperbolic sine transformation on explanatory variables to adjust for many zero-valued observations (Aihounton and Henningsen 2021). We cluster the standard errors at the parcel level. The coefficient of interest is β_k, which gives the shadow price of climate-induced crop switching.

Additionally, to assess the market response to crop diversification after each sale, based on the farmland value, we estimate a regression model that includes the interactions between the crop diversity indicator, H_i and an indicator of perennial crops, $C_i^{j=h}$and annual crops, $C_i^{j=l}$ and the H_i:

$$(8) \qquad \left(\frac{Value}{Acre}\right)_{it} = \beta_0 + \beta_1 H_i + \beta_2 (H_i * C_i^j) + \gamma f\left(W_{it}\right) + \mu_i + \tau_t + \varepsilon_{it}$$

The coefficient β_1 measures the direct relationship between crop diversity and the value of agricultural land. The coefficient β_2 measures the relationship between high concentration of a specialty crop (lower diversity) and the agricultural land values. The sign is ambiguous and depends on whether crop diversity is used as a mechanism for drought resistance, or to generate high-value agricultural land from the cultivation of high-value crops during droughts. The identification comes from the variation inside the parcel after several sales, conditional on year-of-sale fixed effects. One of the main contributions of this study concerns our ability to exploit

[12] We attempted both the year of sale and the year of appraisal as time-fixed effects in a separate regression. The results remain the same.

the crop variation within the parcel after the change of ownership over time under drought conditions.

4.1. Identification strategy

The validity of our estimates is based on the assumption that the choice of crop for new buyers of agricultural land is exogenous. This may not be the case, since cropland can be measured in error or be correlated with omitted variables. A measurement error may occur if cropland detected by the remote-sensing data is not credible. Thus measurement error can be a major challenge for panel models (Blanc and Schlenker 2017). Endogeneity in the crop distribution on land with farmland values could also result from correlation with omitted variables. For example, if a policy has induced growers to raise certain types of crops, then not taking these variables into account may lead to spurious correlations between crop choice and farmland values. Following Ifft, Bigelow, and Savage (2018), we correct this endogeneity by using the generalized difference-in-differences technique.

4.2. Threats to identification strategy: Measurement errors

Our main explanatory variables – different types of crop acreage are derived from remote sensing-based CDL data and may be erroneous. [13] Measurement errors result from the inevitable nonclassical misclassification errors associated with satellite data products, such as land cover and crop classifications (Alix-Garcia and Millimet 2022), and may therefore bias our regression estimates (Jain 2020). This implies that the measurement error will cause a downward bias in our outcome coefficients. To minimize measurement errors, we derive CDL data within the boundaries of parcels for a given year. We use alternative measures of crop patterns: the share of

[13] It is not clear whether CDL data uniquely captures young tree crops (e.g., almond, pistachio, etc.), and this is a limitation of our study.

perennial and annual crops, to show that our results are robust. In addition, to compare the construction validity of the derived crop acreage, we take the ratio of the parcel area derived from the geographic information system (GIS) to the parcel area reported in the assessor's table. Any value greater than one means that the area of the parcel from the GIS exceeds the area of the parcel reported in the assessor's table. Appendix Figure A6 shows the density for the measurement error. We drop observations above 95% of the distribution of measurement errors (1.08).[14]

4.3. *Functional forms*

We present three main specifications of hedonic regression: linear-linear, log-linear, and log-log models. Given the data, our preferred hedonic regression model is a log-log model, with a natural logarithm of farmland value per acre regressed on the vectors of transformed (inverse hyperbolic sine) independent variables, such as different types of crop types.

5. Results

We report different types of results. First, we check whether the value of parcels sold repeatedly differ statistically from all other parcels (external validity test). Table 1 shows different characteristics of parcels that were sold repeatedly compared to all other parcels. Second, we present the ordinary least squares (OLS) estimations of the hedonic regression equation that estimated the shadow price of climate-induced crop change in the Central Valley of California. Third, we present the impact of crop diversity using the Herfindahl-Hirschman Index (HHI), a measurement of crop diversity, on farmland value. Finally, we present the effect of a policy

[14] Dropping all the observations with a ratio higher than one does not change our main results.

variable, such as the Sustainable Groundwater Management Act (SGMA), on the value of farmland in California's Central Valley.

5.1. Comparison of parcels sold repeatedly to all other parcels

Approximately 46% (5,241) of parcels changed ownership at least once and less than four times in our 14-year time frame analysis (2008–2021). Less than 0.7% (73) of the parcels changed ownership four times or more. The average value of land sold four times or more is $33,908 per acre, compared to $70,717 per acre on land sold less than four times. The mean value of agricultural land that is sold repeatedly is approximately 10% lower than that of all other parcels. This might suggest that land of lesser value is sold more often. To determine if farmland that is repeatedly sold differs systematically from farmland that is not sold, we follow Buck, Auffhammer, and Sunding (2014), and keep only the first transaction for every repeated parcel so that the prices reflect the beginning of our study period. Table 1 compares parcels sold at least twice or more, parcels sold once, and parcels that were not sold during our study period (2008–2021).

Column 1 of Table 1 presents summary statistics of parcels sold twice or more. The average land value per acre for parcels sold twice or more is $65,971, which is about $5,750–$6,772 less than the parcels sold once or not at all. The percentage share of almonds, pistachios, and nuts cultivated within parcels that are sold more than twice is 39%, which is on average higher than grapes (26%), and citrus and other subtropical fruits (21%). The average percentage share of other tree crops within a parcel is 10%.

Of the annual crops, on average, within a parcel, 17% of the parcel is grown with alfalfa, 20% of the parcel with grains, 15% of the parcel with maize, 18% of the parcel with cotton, and 13% of parcel with tomatoes. Hay, safflower, onion, garlic, melon, squash, cucumbers, dry beans, potatoes, other vegetables, and other field crops are less than 10% altogether. The proportion of fallow land in a parcel is 22%, and 19% of the parcel is related to natural vegetation, on average.

Weather variables are averaged over all parcels and years, the growing degree days from April to September amount to 2625.8 days, and the average sum of precipitation is 44 mm. The average value of the HHI (crop diversity index) is 0.75 for all types of parcels – parcels sold multiple times, or not sold. The standard deviation for the crop diversity index is 0.25. This may suggest that a major crop is grown in a larger proportion, and that other crops are grown in a smaller proportion in a parcel.

In summary, perennial crops (the collective category includes tree crops, such as almonds, pistachios, walnuts, grapes, citrus fruits, other subtropical fruits and other tree crops) make up a significant proportion of the crops grown in a parcel (42% of parcels), compared to annual crops (22% of parcels). The collective category of annual crops include alfalfa, hay, corn, cotton, tomatoes, safflower, melon, squash, cucumber, rice, potatoes, cereals, onions, garlic, dry beans, berries, and other field crops. The average proportion of fallow land and native vegetation is 14% of parcels, and higher than that of many annual crops. Columns 4 and 5 in Table 1 show the p-value of a t-test for equality in means, and suggests that the value of parcels sold repeatedly differs statistically from that of all other parcels. Specifically, the value of parcels associated with perennial crops sold twice or more differ statistically from parcels sold once or not sold. However, the value of parcels associated with annual crops and uncultivated crops, such as fallow land and natural vegetation, sold twice or more do not differ statistically from the value of parcels sold once or not sold. This means that for our results, the lack of external validity of perennial crops can be implicit for parcels sold twice or more. However, our results related to annual crops hold external validity.

5.2. *Empirical results*

Our focus is on estimating the implicit price of climate-induced crop changes. Table 2 presents the hedonic regression results for three main specifications. Columns 1–3 present the results for the linear-linear, log-linear, and log-log models. The comparison of the three models suggests that the linear-linear model results in an R-square (0.80) slightly higher than the log-linear and log-log (0.75) models. Column 3 is obtained after adjusting the vector of independent variables for too many zeros using the inverse hyperbolic sine (IHS) transformation (Aihounton and Henningsen 2021), which is our preferred model. The dependent variable in columns 3 and 4 are the log of value per acre for a parcel that has been sold repeatedly (twice or more) in the Central Valley of California. The explanatory variables are in log terms using the IHS transformation, which represents the parcel area weighted area of the various crop types grouped into perennial, annual, and non-cultivated crops in a parcel for the years 2008 to 2021. For interpretation purposes, we use annual crops (% of the parcels) as a baseline for hedonic regression models.[15]

The results suggest that perennial crops, including tree crops, such as almonds, pistachios, walnuts, grapes, citrus fruits, other subtropical fruits, and other tree crops, increase land values by 0.7% for each 10% increase in their proportional share. In addition, we present hedonic regression results on disaggregated crop types in Appendix Table A1. The results suggest that almonds, pistachios, and nuts raise land prices by 0.4% for every 10% increase in its proportionate share. The increased share of other tree crops, which represent the collective

[15] We regress the log value of farmland per acre on the percentage of perennial, annual, and non-cultivated crops within a parcel – first separately and then the percentage of perennial crops compared to first non-cultivated and second annual crops as a base. Appendix Table A2 in the appendix presents the results of these specifications.

category of tree crops, increases the price of land by 0.05%, although it is insignificant at 95% level. The share of grapes and citrus, and other subtropical tree crops in a parcel is positively associated with the land prices, but is not statistically significant.

Among annual crops, the share of dry beans in a parcel significantly increases the land price by 0.25%. The share of cultivated grains and other cultivated field crops, which are a collective category of cultivated field crops, within a parcel increases the land prices by 0.05% and 0.13%, respectively. In contrast, the share of corn in a parcel reduces the price of land by 0.08%. Moreover, the results also suggest that annual crops, such as alfalfa, cotton, safflower, melon, squash, cucumbers, rice, tomatoes, potatoes, and hay are negatively associated with land price, although they are not statistically different from zero. The price effects associated with perennial crops are likely due to high-value crops, and the price effects associated with annual crops are likely due to crops that are less susceptible to climate, such as dry beans. Finally, the share of fallowed land within a parcel is negatively associated with the price of land, and the share of natural vegetation is positively associated with the price of land; however, it's insignificant at the conventional level of value. Figure 2 shows the coefficients (95% confidence interval) derived from the hedonic log-log regression model.

5.3. Herfindahl-Hirschman Index

Using the parcel-level database, we generate a crop diversity indicator to investigate temporal and spatial changes in crop diversity. We create a simple yet widely used concentration indicator, the Herfindahl-Hirschman Index (HHI), based on different crops grown in a parcel that is sold repeatedly.[16] Here, we define HHI as the sum of the squared crop shares grown in an individual

[16] We are limited in our selection of diversity index, because many crops do not have any information on cultivated area of a parcel.

parcel. HHI for parcels sold repeatedly enables us to examine the market response to diversification through the value of farmland after each sale.

Our HHI for parcel i defined as follows:

$$HHI_i = \sum_{k=1}^{K} s_{ik}^2 \quad (9)$$

where $s_{ik} = \frac{c_{ik}}{\sum_{k=1}^{K} c_{ik}}$ is the share of total cropped area for crops $k = 1, \ldots, K$ grown in parcel i. K is the total number of crops, which is 18 in our data set. HHI values range between 0 and 1, where 1 indicates the concentration towards one crop. Figure 3 shows the HHI of crop diversification for parcels sold twice or more and parcels sold once or unsold. We see an increasing trend in crop concentration, possibly into high-value crops. With more years of drought, parcels sold twice or more are comparatively more specialized than parcels sold one time.

Next, we examine whether a higher concentration of specialty crops within a parcel is more resilient to duration of drought. Table 3 presents the estimated results for Equation 8. The dependent variable is log of value per acre of a parcel that has been sold twice or more in the Central Valley. Column 1 of Table 3 shows the HHI (a measure of crop diversity) as the main explanatory term. We find negative yet statistically insignificant parameter estimates on the diversity index, conditional on parcel-level and year of sale fixed effects. The coefficient on perennial is statistically zero. The interaction between the HHI indicator and the perennial crops dummy is also statistically insignificant. However, the annual crops are negatively associated with farmland values, and the interaction between the HHI indicator and the annual crops is negative and statistically significant. A one standard deviation increase in the HHI for annual crops would result in a 2.2% (0.25*(-0.576+0.485) = -0.022)[17] decline in the value per acre for that parcel. This further implies that farmland in the Central Valley during the study period has been increasingly homogeneous towards perennial cropping systems. These results support our hypothesis of a new buyer switching to perennial crops to maximize profits.

As a sensitivity check, we also present the results of the effective number of crop species as an alternative measure of crop diversity based on the Shannon Diversity Index (SDI). We calculate the crop species diversity for each parcel using SDI expressed as follows:

(10) $$SDI_i = \sum_{k=1}^{K} s_{ik} \ln{(s_{ik})}$$

where s_{ik} is defined same as in the Equation (9). Following Aguilar et al. (2015), we transform the SDI into a more easily interpretable index of crop species diversity, the effective number of crop species (ENCS). The ENCS is computed as:

(11) $$ENCS = e^{-SDI}$$

A higher value of the ENCS represents a higher diversity of crop species, while a lower value of the ENCS represents a lower diversity of crop species. For example, the ENCS value of seven indicates that more crops dominate production on an agricultural land, whereas the ENCS value of two indicates fewer crops dominating production. Appendix Figure A7 shows the ENCS trend in the Central Valley. We see a gradual downward trend in the ENCS for all parcels sold repeatedly, or not.

[17] HHI standard deviation is 0.25.

We notice that HHI and SDI are different, and they measure different aspects of crop diversity. We use them to strengthen our evidence that shows a growing trend towards homogenizing the cropping system in California's Central Valley.

5.4. *Effect of SGMA on crop selection*

Growers are concerned that the implementation of the SGMA in 2014 in the context of protecting groundwater exploitation may affect how crop selection is capitalized in the value of agricultural land. The SGMA can influence the irrigation capacity derived from groundwater for growers, establishing a lower baseline for agricultural water use for growers. Growers can respond to these changing expectations of the permanency of irrigation restriction through SGMA by changing cropping patterns. Thus, not taking into account the effect of SGMA can cause a potential endogeneity problem in the analysis. For example, new buyers would change their cropping pattern as a result of SGMA-induced uncertainties in water use rather than climate. Therefore, hedonic regression without explicit policy variable (such as SGMA) provides us the net impact of policy and climate change. Following Kuminoff, Parmeter, and Pope (2010), we employ a generalized difference-in-differences (DID) estimation to address this potential endogeneity of SGMA in land value panel regression models. In our context, a DID estimation that includes the interaction terms between the policy variable (the SGMA) and year of sale takes the form of event-study regression. The specification for an event-study regression is given by

$$\left(\frac{Value}{Acre}\right)_{it} = \sum_{j=-6,j\neq-1}^{8} \beta_j int_{it}^{j} + \mu_i + \tau_t + \varepsilon_{it} \qquad (12)$$

where j denotes leads and lags of the event of interest. int_{it}^{j} represents an interaction term between the percentage of perennial and annual crops and the year of sale. The terms are defined as in Equation (7). We group the explanatory variables based on the percentage of perennial crops, the percentage of annual crops, and the percentage of uncultivated crops per parcel, i. The reference group is the percentage of crops not grown on a parcel. If SGMA influenced cropping patterns, we would expect that the post-2014 β coefficient would be statistically significant.

Appendix Figure A8 shows an event-study regression for percentage of perennial crops and annual crops. We find that the percentage of perennial crops is statistically significant after the introduction of SGMA in 2014 for three lag periods. We find no evidence that SGMA affects the share of annual crops. Our results for perennial crops must be interpreted with caution.

5.5. *Types of crops and land allocation matrix*

Our results suggest that farmland associated with annual crops suffer loss after the sale. However, we do not know if the loss in land value is due to continued farming of annual crops or the transition of fallow land or natural vegetation to annual crops. In this sub-section, we quantify the amount of land that will be allocated to perennial and annual crops in the future for various sets of parcels: parcels not sold, sold once, and sold more than twice. We construct a matrix that presents a forecast of the percentage of land in a parcel that will be allocated to perennial and annual crops based on data from previous years. This matrix is derived from a fourth-order autoregressive AR (4) model, in which the percentage share of perennial (annual) crops is regressed on its own lagged values.

Table 4 provides estimates of how much land will be allocated to perennial and annual crops in the future. We find that in the future, less land will be allocated to annual crops conditional on annual crops grown in previous years for all types of parcels.

6. Conclusion and Policy Implications

Farmland value is a long-term estimate of expected farm productivity in the future. This study assessed buyers' responses in cropping systems to changing climate. The theoretical framework shows that prolonged periods of drought affect the rent from the land, and buyers' expectation to maximize rent from farmland. One option is to switch from low-value crops to high-value crops. In this context, farmland in the central valley of California is transitioning to perennial specialty crops. Using parcel-level data from farm parcels sold repeatedly in the Central Valley of California, we apply the Ricardian approach to model buyer expectations through crop selection in response to climate change in the California farmland market. Our empirical results suggest that California's Central Valley is shifting to more specialized crops in response to climate change. We find that the increased share of perennial crops on a parcel significantly increases the value of the land by 3%. The share of annual crops is positively associated with land values, but is not statistically significant. Specifically, perennial tree crops, in particular almonds, pistachios, and nuts are driving our results. Annual crops, such as alfalfa, hay, corn, cotton, tomatoes, safflower, melon, squash, cucumber, rice, and potatoes are negatively associated with farmland value. In contrast, cereals, onions, garlic, dry beans, berries, and other vegetables are positively associated with farmland values. Among uncultivated crops, fallowing land is negatively associated, and natural vegetation is positively associated with farmland values in the Central Valley.

The results show a 3% gain in farmland value due to the transition to perennial crops and a loss of 2.2% of farmland value due to continued production of annual crops. Overall, the extent of welfare measurement from climate-induced crop change in the Central Valley of California is marginally positive. We show evidence of our hypothesis that buyers change cropping patterns on the farmland after sale, in order to produce a higher net income per unit of land from parcels sold repeatedly. Our conclusion stands in contrast with previous literature (Pathak et al. 2018) that argue perennial crops make the agricultural system less flexible and therefore less able to adapt to climate risks. This indicates that potential new buyers have greater resource capacity to maintain uncertainty in the face of climate change. However, we leave a detailed study on future research projects. Farmlands associated with annual crops are part of the food security story in California and the United States. From a policy point of view, the loss to buyers and farmers in terms of land value due to the continuation of growing annual crops can be a concern.

We also find that the Herfindahl index (a measure of crop diversity) is negative and statistically significant for annual crops during our study period, suggesting that farmers are moving to more specialized high-value crops. This contrasts with climate change literature on crop yields in developing countries, such as India, where crop diversification improves resilience during drought periods (Auffhammer and Carleton 2018). This shows the differences in the management of for-profit agricultural operations in developed countries like the U.S., and subsistence agricultural operations in low- and middle-income countries like India. In the Californian context, agricultural operations benefit from economies of scale and the level of specialization, including irrigation technology, required for crop specialization. We also explore the presence of policies like SGMA that affect agriculture, including cropping patterns and the value of farmlands. We find that the cultivation of perennial crops increased statistically after the introduction of SGMA in 2014. However, for the cultivation of annual crops, we find no statistical evidence of the impact of SGMA.

This paper has limitations. First, the weak external validity of our results of perennial crops. Second, the presence of a measurement error in the derived spatial data that implies that our results are biased downwards. Nonetheless, the paper provides insight into California's agricultural diversity and resilience to climate change.

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Table 1. Comparison of parcels sold at least twice or more, parcels sold once, and parcels that were not sold, 2008–2021.

	(1) Parcel sold twice or more	(2) Parcel sold once	(3) Parcel not sold	(4) Diff. (1)-(2)	(5) Diff. (1)-(3)
Value per acre (dollars)	65,971 (109343.90) [4.72, 429083.80]	71,721 (113130.80) [2.97, 429083.80]	72,743 (113725.90) [1.64, 429083.80]	- 5750***	- 6772***
Perennial crops (% of parcel)					
Almonds, pistachios and nuts	38.58 (37.17) [0.03, 107.56]	37.42 (36.98) [0.03, 107.42]	36.25 (37.36) [0.05,107.60]	1.16***	2.33***
Grapes	26.28 (34.55) [0.03, 101.62]	26.76 (34.80) [0.02, 105.66]	28.43 (35.67) [0.02,107.61]	-0.48	-2.15
Citrus, other subtropical fruit	21.18 (29.11) [0.03, 101.36]	26.85 (32.93) [0.02, 106.11]	26.56 (33.19) [0.03,105.62]	-5.58	-5.38*
Other tree crops	9.89 (17.91) [0.03, 99.47]	11.84 (20.82) [0.03,102.17]	13.65 (24.37) [0.04,106.73]	-1.95	-3.76*
Annual crops (% of parcel)					
Alfalfa	16.64 (27.48) [0.05, 100.95]	17.64 (27.93) [0.02,106.73]	17.92 (28.18) [0.03,107.35]	-1.00	-1.28***
Grains	19.26 (28.38) [0.03, 100.81]	21.56 (30.42) [0.04,106.73]	22.48 (30.50) [0.02,106.91]	-2.30	-3.22*
Corn	14.80 (27.66) [0.04, 102.00]	11.26 (21.52) [0.02,102.95]	12.87 (23.97) [0.01,102.53]	3.54	1.93
Cotton	17.18 (27.80) [0.05, 98.66]	21.32 (32.64) [0.03,106.73]	22.4^{4} (33.56) [0.01,107.27]	-4.14**	-5.22*
Tomatoes	13.53 (26.16) [0.04, 104.64]	13.34 (25.87) [0.04,102.29]	14.09 (25.98) [0.03,107.05]	018	-0.56
Safflower	7.19 (16.47) [0.04, 90.23]	6.84 (16.31) [0.04,97.49]	6.40 (16.84) [0.03,99.67]	0.35	0.79*
Onions, garlic	5.68 (14.40) [0.03, 74.49]	8.28 (20.14) [0.02,106.73]	7.78 (19.16) [0.03,96.73]	-2.60	-2.10

Melons, squash, cucumbers	6.48 (16.05) [0.03, 84.22]	4.71 (12.66) [0.03,88.83]	4.71 (11.66) [0.03,93.63]	1.77	1.77*
Rice	38.96 (42.03) [0.03, 102.29]	51.78 (43.30) [0.03,104.86]	48.29 (43.43) [0.03,107.41]	-12.82	-9.33
Dry beans	8.99 (20.74) [0.05,95.62]	5.34 (14.63) [0.04,94.10]	7.47 (18.31) [0.01,94.13]	3.65***	1.52*
Potatoes	9.02 (13.03) [0.51, 43.72]	9.66 (20.41) [0.18,98.72]	10.99 (18.46) [0.02,90.01]	-0.64*	-1.97
Other vegetables, berries	4.44 (9.86) [0.03,95.62]	6.24 (12.67) [0.03,95.97]	6.16 (13.28) [0.03,107.02]	-1.80**	-1.72*
Other field crops	3.75 (9.37) [0.05,66.22]	4.87 (13.15) [0.02,95.30]	5.22 (31.30) [1,142]	-1.12	-1.47
Hay	5.42 (10.68) [0.03,82.10]	7.43 (15.27) [0.03,97.83]	8.60 (17.12) [0.01,98.93]	-2.01	-3.18**
Not crops (% of parcel)					
Fallow	22.21 (28.53) [0.03,105.72]	22.93 (30.58) [0.03,106.73]	19.95 (28.81) [0.03,107.29]	-0.72	2.26**
Natural vegetation	19.32 (30.04) [0.03,102.57]	20.26 (32.54) [0.03,106.85]	30.38** (40.42) [0.03,107.66]	-0.94	-11.06**
Weather variables					
Precipitation (mm)	43.92 (30.66) [0,253.40]	41.54 (30.35) [0,488.72]	43.91 (37.78) [0,416.83]	2.38*	0.01
Growing degree days (8-32)	2625.76 (248.46) [1137.34,3264.49]	2661.15 (225.40) [1205.09,3256.18]	2644.32 (264.02) [661.45,3415.96]	-35.39***	-18.56***
Extreme degree days (32+)	0.80 (2.48) [0,55.17]	0.84 (2.24) [0,36.35]	0.91 (2.56) [0,89.95]	-0.04***	-0.11***
Crop diversity					
HHI	0.74 (0.25) [2166]	0.75 (0.25) [8,542]	0.75 (0.25) [16,385]	-0.01***	0.00***
Number of parcels	751	4,515	17,508		

Notes: Mean value is reported. Standard deviation is presented in parentheses. The minimum and maximum are shown in square brackets. Land values are winsorized at the 1 and 99 percentiles. The difference in observation is because we take summary statistics for parcels with a non-zero crop value. A parcel from our sample may be associated with one or more crops. Column (4) is the difference, and the p-value of a t-test for equality in means in columns 1 and 2. Similarly, column (5) is the difference and the p-value of a t-test for equality in means in columns 1 and 3. Following Buck, Auffhammer, and Sunding (2014), we keep the first observation per parcel to estimate the p-value in column (4)-(5). The maximum percent is more than 100 for some crops because of discrepancy between the parcel size reported in the table and the cultivated area derived from the GIS.

Table 2. Hedonic regression results

	(1)	(2)	(3)	(4)
Specification:	Linear-Linear	Log-Linear	Log-Log	Log-Log
Dependent variable:	value per acre	Log (value per acre)	Log (value per acre)	Log (value per acre)
(% of parcel)				
Perennial crops	86.543	0.002^{*}	0.067^{***}	0.066^{***}
	(86.598)	(0.001)	(0.025)	(0.024)
Not cultivated	37.217	-0.0004	-0.007	-0.005
	(90.918)	(0.002)	(0.027)	(0.027)
Parcel-level FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Polynomial functions	No	No	No	Yes
Mean dep. variable	65996.384	9.893	9.893	9.893
SD dep. variable	109459.837	1.775	1.775	1.775
Observations	2358	2358	2358	2358
Number of clusters	764	764	764	764
R-squared	0.800	0.751	0.752	0.752

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. Each column results from a separate regression. The dependent variable is the value per acre in column 1 and the log value per acre for a parcel in columns 2 and 3 that has been repeatedly sold in the Central Valley of California. The explanatory variables represent the parcel's weighted-acreage area of different crop types in a given year. The explanatory variables in columns 3 and 4 are in log terms using the IHS transformation. The proportion of annual crops is the reference. Weather controls include precipitation (in mm) and growing degrees days (8-32) and extreme degrees days (32+). Polynomial functions include squared terms of precipitation and growing degree days and square root of extreme degrees days.

Table 3. Impact of crop diversity index on farmland value

	(1) Log (value per acre)	(2) Log (value per acre)
HHI	-0.180	0.412
	(0.137)	(0.625)
Perennial crops (dummy)		0.204
		(0.409)
Annual crops (dummy)		0.508**
		(0.238)
HHI x Perennial crops		-0.022
		(0.559)
HHI x Annual crops		-0.604**
		(0.278)
Parcel-level FEs	Yes	Yes
Year of sale FEs	Yes	Yes
Weather Controls	Yes	Yes
Polynomial functions	Yes	Yes
P-val: HHI + HHI x Annual crops		0.625
Mean dependent variable	10.038	10.038
SD dependent variable	1.662	1.662
Number of clusters	675	675
Observations	2030	2030
R-squared	0.743	0.744

Notes: Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses are clustered at the parcel level. The dependent variable is the log of value per acre of a parcel that has been repeatedly sold in the Central Valley. HHI = Herfindahl-Hirschman Index (calculated on the cultivated area for 18 crops). The baseline is the share of uncultivated crops, such as fallow land, and natural vegetation. Weather controls include precipitation (in mm) and growing degrees days (8-32) and extreme degrees days (32+). Polynomial functions include squared terms of precipitation and growing degree days and square root of extreme degrees days.

Commented [AD1]: Is it Ln or Log?

Table 4. Crop types and land allocation for parcels that are not sold, sold once, and sold twice or more

	Not sold	Sold once	Sold twice or more
$\%\boldsymbol{\Delta}P_{t+1}\vert\sum_{j=1:4}\%\Delta P_{t-j}$	1.14%	0.20%	-0.86%
$\%\boldsymbol{\Delta}A_{t+1}\vert\sum_{j=1:4}\%\Delta A_{t-j}$	-4.00%	-3.00%	-4.00%

Note: The values in the table provide estimates of how much land will be allocated to perennial and annual crops in the future. The canonical form represents the autoregressive model in which percent share of perennial (annual) crops is regressed against its own lagged values. Each element is derived separately from the fourth-order autoregressive AR(4) model: $\%\Delta P_t = \beta_0 + \beta_1\%\Delta P_{t-1} + \beta_2\%\Delta P_{t-2} + \beta_3\%\Delta P_{t-3} + \beta_4\%\Delta P_{t-4} + \tau + \lambda + u_t$ where $\Delta\%P_t$ is the difference between the percentage share of perennial crops in a parcel in time t and $t-1$. τ denotes the linear time trend. λ are the county effects, and u_t is the forecast error terms. Similarly, ΔA_trepresents the difference between percent share annual crops in a parcel in time t and $t-1$. Standard errors are clustered at the parcel level. See Appendix Table A3 for full results.

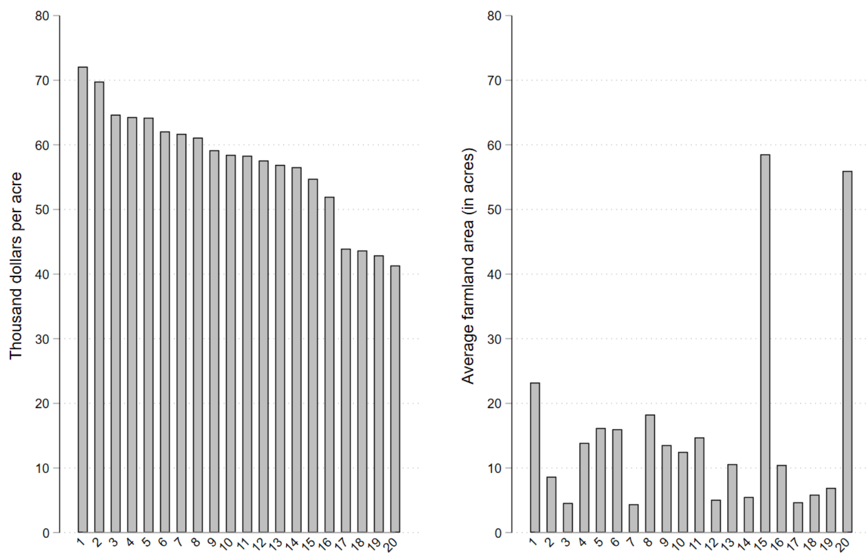

Figure 1. The average value of farmland (left) and area (right) for 18 crops and two uncultivated crops. The sample includes only farm parcels from the California's Central Valley that were sold between 2008 and 2021. The x-axis represents various crop types (18 crop types and two non-cultivated crops) by numbers. To avoid overcrowding of graphics, we define the crop types below in the notes.

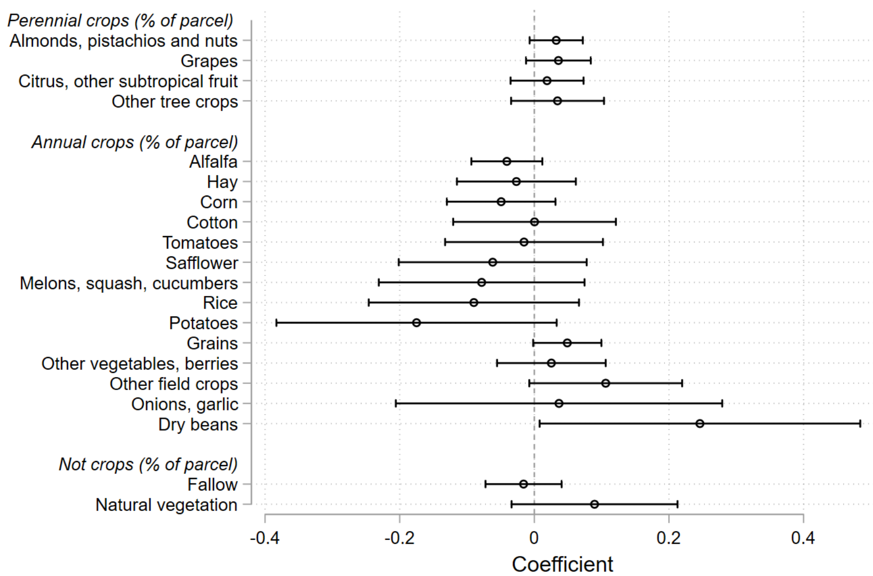

Figure 2. The coefficients (95% confidence interval) were derived from the hedonic log-log regression model. See appendix A1 for full results.

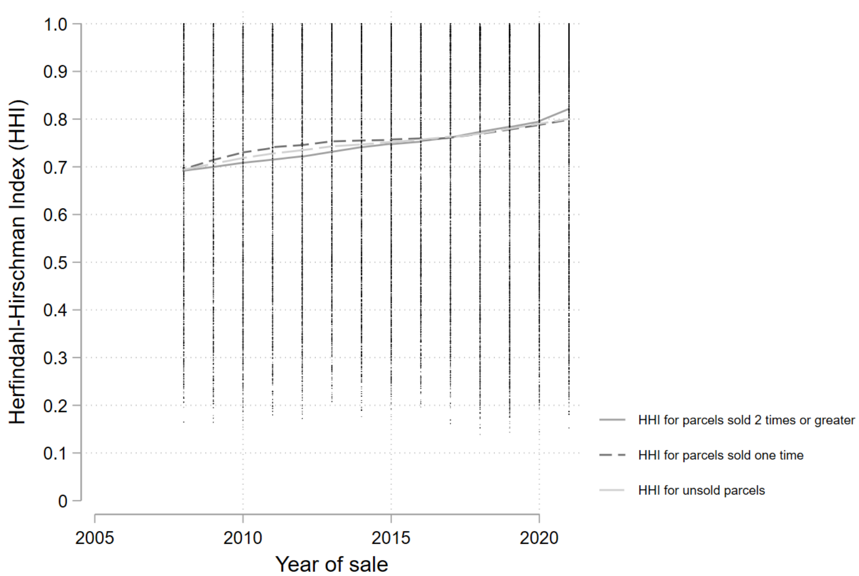

Figure 3. Crop diversity index for parcels sold twice or more, parcels sold once, and parcels unsold. HHI = Herfindahl-Hirschman Index (calculated on cultivated area for 18 crops).