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Climate-induced changes in agricultural land use: parcel-level evidence from California's Central Valley

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Abstract
How growers adjust land-use decisions to a changing climate has important consequences for food supplies and environmental impact. In this paper, we examine changes in agricultural land use as an adaptive response to long-term climate impacts, using unique parcel-level data in Central Valley, California – a major agricultural hub worldwide. We combine parcel-specific acreage decisions and climate normal to assess the climate-induced land use transition. We find that growers in the Central Valley are transitioning from annual crops to perennial crops in response to changing climates. Summer degree days and total precipitation increased the share of perennial crops, and projected declines in winter chill hours are also expected to increase the share of perennial crops in the Central Valley. Analysis of land-use with heterogeneous land quality suggests that the share of perennial crops increased 11% in high-quality lands and 7% in low quality lands.

Keywords Climate change adaptation · Land-use modeling · Perennial crops · Annual crops · California

1 Introduction

Climate change has been the subject of much research in agriculture (Lobell et al. 2007; Lobell and Field 2011; Lobell et al. 2011; Deschenes and Kolstad 2011; Lee and Sumner 2015). The majority of work is conducted using county-level data to assess the relationship between acreage decisions and climate (e.g., Cui 2020; Cui and Zhong 2024), with a few notable exceptions that use individual farm-level data (e.g., Ramsey et al. 2021; Wimmer et al. 2024; Ji and Cobourn 2021). Despite the extensive literature on climate-agriculture interactions, there is little empirical evidence on changes in acreage decisions in response to climate change at the micro level. The most recent estimates of climate-induced crop switching in dryland agriculture have been at the county-level scale (e.g., Arora et al. 2020; Mu et al. 2018) and mask significant parcel-level heterogeneity. Using unique parcel-level

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data in an irrigated agriculture context in California's Central Valley, we contribute to the growing literature on assessing climate-induced changes in agricultural land use.

Climate change has a significant impact on agricultural operations and farmers adapt to it in various ways to mitigate its effects. For example, they modify their management practices, they introduce new technologies, such as irrigation technologies, they introduce new varieties, and in many cases, they adjust their land use to new climatic conditions that affect the farm. The focus of this paper is on how climate change has affected the acreage decisions in California's Central Valley. The Central Valley's significant agricultural role and dependence on climate make it a suitable study area. Moreover, the richness of cropping patterns, the large variation in climate conditions across the Central Valley, and the dependence on irrigation water all make this region a microcosm of many other regions worldwide.

Our empirical study calculates the changes in parcel-specific acreage decisions that can be attributed to long-term growing season climate. We exploit the variations in spatial and temporal patterns in our land use and growing season climate. We follow the literature (e.g., Mu et al. (2018); (2017); Cho and McCarl (2017)) to apply fractional multinomial logit land-use model, in which the share of crop types (annual crops, perennial crops, and non-cultivated crops), as a measure of a land-allocation decision variable, is explained by long run historical averages of climate variables (annual precipitation, degree days for summer and winter, and hours of winter chill) and heterogeneous land quality. We also adopt the empirical framework of Cui (2020), which employs panel fixed effects estimation framework to measure the climate impact on county-level aggregate planted area, and adapt it to measure the effect of long-term climate variables on acreage decisions at the parcel level.

Quantitatively, the marginal effects derived from the panel fixed effects model and fractional multinomial logit model are similar. Specifically, our findings indicate that farmers switched to perennial crops from annual crops, particularly due to a higher degree days during summer. We demonstrate that growers are more likely to plant new acres of perennial crops on less suitable land and may potentially shift available irrigation water to high-revenue crops. Analysis of agricultural land-use with heterogeneous land quality suggests that high-quality land has a more than 90% probability of transitioning to perennial crops, while low-quality land has a lower probability (44%) of transitioning to perennial crops.

Next, using econometric estimates, we simulate the impact of climate change on land-use shares in California and evaluate farmers' private adaptation through land-use choices based on their expectations of future climate. Specifically, we predict changes in future land-use shares for 2031–2055 relative to 1981–2005, conditional on soil quality and farmland appraisal value trends. These simulations suggest the direction of farmland adjustment, which serves as a measure of private adaptation to respond to projected climate changes. Our projection results suggest that a potential decrease in winter chill hours could result in an increase in the percentage of perennial crops grown in the Central Valley.

2 Theoretical and empirical framework

We use a simple framework to explain farmers' land-use decision, which is given by $y_{jit} = y_i(\psi_{it}, S_i, A_{it}; \varepsilon_{jit})$ where y_{jit} is the crop-specific land-use share for crop $j = \{1, \ldots, J\}$ (in our analysis $J = 3$), in parcel i, in year t (in our analysis

$t = 2008, \ldots, 2021$). ψ_{it} represents expected climate conditions, including 27-year moving average precipitation, degree-days, and winter chill hours. S_i represents soil quality conditions, including land capability class; A_{it} is the appraisal value of farmland that represents the potential net returns from crop production at the farm level, but it excludes future development returns. The use value assessment of agricultural land in California captures the expectation of long-term operating profits, which translates into net returns to agricultural land-uses.[1] This enables us to include parcel-level observations of net returns in our analysis. Finally, ε_{jit} represents unobserved variables that may influence the farmers' land-use decisions.

For our empirics, we follow previous studies to model land allocation shares for each usage type j in parcel i in year t, which is y_{jit}, where $y_{jit} \in [0,1]\, \forall i, t$ and $\sum_{j=1}^{J} y_{ji} = 1$. The total share of perennial crops, annual crops, and non-cultivated crops on each parcel equals one for every year during our study period. Following Mu et al. (2018) and Cho and McCarl (2017), we apply a fractional multinomial logit model to estimate the impact of long-run climate change on agricultural land use in California's Central Valley. The estimating equation is

$$E\left(y_{jit}|W, X, \overline{Z}; \varepsilon_{jit}\right) = \frac{exp(\sum_{k=1\in K}\beta_{jk}f_k\left(W_{kit}\right) + \gamma_j X_i + \tau_j T_{it} + \phi_j \overline{Z_i} + \varepsilon_{jit})}{\sum_J exp(\sum_{k=1\in K}\beta_{jk}f_k(W_{kit}) + \gamma_j X_i + \tau_j T_{it} + \phi_j \overline{Z_i} + \varepsilon_{jit})} \quad (1)$$

where y_{jit} denotes the agricultural land use shares for usage types j in parcel i in time t . X_i is a vector representing observable determinants of land use decisions, such as the parcel-specific land capability class (LCC). LCC has eight land capability classes: from class I through VIII, the constraints on soil suitability for crop cultivation increase from I to VIII. In our analysis, we utilize an indicator for high-quality land (LCC12) as well as two indicators for low-quality land (LCC34 and LCC5678). We follow previous literature from the California study area (e.g., Lee and Sumner 2015) to include climate normals for degree days during both summer and winter, total annual precipitation, and chill winter hours. We define climate normal over 27 years.[2] $f_k(.)$ represents non-linearities such as squared terms in precipitation, degree days, and chill hours. $k = 1,2,3, \ldots, K$ represents various measures of climate variables. β_{jk} are long-term climate coefficients to be estimated for each land use share j and represents our variable of interest. T_{it} represents a set of year dummies that captures the changes in commodity output prices and input prices of production.

Following Mu et al. (2018) and Mundlak (1978), we include the vector of $\overline{Z_i}$, which is climate variables averaged over time for each parcel i, to overcome the difficulty of including fixed effects in the fractional multinomial logit model. This Chamberlain-Mundlak approach allows for correlation between unobserved heterogeneity and observed time-varying covariates (Wooldridge 2019). ε_{jit} denotes error terms, representing variations in farmers' acreage decisions that are not explained by our model. Our identification strategy exploits the variations in spatial and temporal patterns of agricultural land use and growing season climate. To account for spatial correlation in the error term, we cluster the standard

[1] In the Appendix, we provide a brief introduction to the use-value assessment of agricultural land in California.

[2] We acknowledge that climate normals are typically 30 years long (e.g., the 1981-2010 normal covers 30 years). However, our cropland data starts in 2008. Therefore, to include cropland in 2008 and 2009, we define a climate normal covering 27 years (1981-2007).

errors at the regional level, which is the combination of irrigation districts and counties.[3] We also present standard errors clustered at the county level. Due to the small sample size (11 counties in our analysis), we bootstrapped standard errors with 100 repetitions.[4] We use a built-in package, *fmlogit*, to estimate the fractional multinomial logit model in Stata (Buis 2008).

The marginal effect of agricultural land use share with respect to climate normal is expressed as

$$ME\left(y_{ji}|W_i\right) = \frac{\partial E(y_{ji}|W_i)}{\partial W_i} = E\left[y_{ji}|W_i\right]\left(\beta_{jW} - \sum\nolimits_{j=1\in J}\beta_{jW}E[y_{ji}|W_i]\right) \tag{2}$$

where $E(y_{ji}|W_i) = \frac{\exp(\beta_j W_i)}{\sum_J \exp(\beta_j W_i)}$, represents a simple expression of Eq. (1), after dropping subscript t, non-climate covariates, and error terms.

In addition to above fractional multinomial logit model, we also adopt the empirical framework of Cui (2020), which employs panel fixed effects estimation framework to measure the climate impact on county-level aggregate planted area, and adapt it to measure the effect of long-term climate variables on acreage decisions at the parcel level. The estimating equation is as follows:

$$y_{it} = \alpha_i + \delta_t + g\left(\widetilde{T}_{it};\beta\right) + h\left(\widetilde{P}_{it};\gamma\right) + \varepsilon_{it} \tag{3}$$

where y_{it} is agricultural land use share (the share of perennial and annual crops) in parcel i in year t. $\widetilde{T}_{it}$ and $\widetilde{P}_{it}$ represents derived degree days, chill hours, and annual precipitation normal from temperature and precipitation, respectively. $g(.)$ and $h(.)$ represents non-linear functions of climate variables such as squared terms in degree days, chill hours, and precipitation. ε_{it} represents idiosyncratic shock.

While the interpretation of estimated coefficients obtained from the panel fixed effects model is straightforward, this model lacks the ability to explain the probability of switching crop types. The results section of the paper includes combined regression results (i.e., panel fixed effects model and fractional multinomial logit model) to examine changes in parcel-specific crop types and the probability of switching between crop types.

[3] To achieve this, we associate each georeferenced parcel with irrigation districts in our study region. Out of 49,175 parcels, 10,410 (21.19% of parcels) are not part of any of the 230 irrigation districts. Therefore, to retain the full sample, we combined irrigation districts and counties, so that parcels outside of irrigation districts would fall within the non-irrigated districts section of the county. The combined number of counties and irrigation districts is 255.

[4] Bootstrap technique involves repeating a sample within the panel data. However, when the panel ID is set at the parcel level, it is not feasible to reset the time values within the panel. As a result, our bootstrap with 100 repetition is restricted to only fractional multinomial logit mode.

3 Data and descriptive statistics

3.1 Data sources

Our empirical study, which is based on 49,175 parcels in California's Central Valley, combines agricultural data with climate data.[5] We use parcel boundaries to derive crop-specific acreage and long-term moving averages of climate data for the years 2008-2021. These parcels located in the Central Valley are associated with field crops, orchards, and vineyards. The Central Valley is a vital part of California's agricultural sector as it produces hundreds of different types of products due to its Mediterranean-like climate, and supports food security of the United States (Jessoe et al. 2021). However, this region is also vulnerable to future climate change (Lee et al. 2011). The study area map is shown in Appendix Figure A1.

3.1.1 Cropland data

Our outcome variables are the land use shares of perennial, annual, and non-cultivated crops (fallowed or idle land and natural vegetation) at the parcel level in our study region.[6] To determine these agricultural land use, we rely on Cropland Data Layer (CDL), a raster-based land-use map, at 30×30 meter resolution for 2008 through 2021. The USDA, National Agricultural Statistic Service (NASS) publishes CDL products using a machine learning model based on a combination of satellite imaging and agricultural ground data collected during the growing season (Boryan et al. 2011). CDL products are available for the contiguous United States at a 30 m spatial resolution annually since 2008.[7] Despite the widespread use of CDL data in agriculture-climate research, CDL data has inherent errors that could potentially lead to uncertainty in land-use change calculations (Reitsma et al. 2016; Laingen 2015). Although there are limitations, the CDL data is still the primary source of land use information at the micro-level and is frequently used in the literature to influence land use policies (e.g., Boser et al. 2024; Ramsey et al. 2021; Jiang et al. 2021). We are cautious in the use of CDL data in our study region and take the following steps to minimize any potential errors that may arise from using CDL data.

First, following Lark et al. (2017) and Reitsma et al. (2016), we combine CDL classes into perennial, annual, and non-cultivated to minimize any errors related to CDL ability to distinguish spectrally similar land cover classes.[8]

Second, we use time-series CDL data for a given parcel to derive parcel-specific crops.

[5] The dataset consists of parcels situated in 11 counties in the Central Valley. Fresno County accounts for the largest number of parcels with 13,639 (27.74%), while Tulare County has 10,359 (21.07%), Kern County has 5,742 (11.68%), Merced has 5,890 (11.98%), San Joaquin has 4,146 (8.43%), Butte has 2,925 (5.95%), and Glenn County has 2,642 (5.37%). Counties that contribute less than 5% of the sample in our analysis are Yolo (2,337; 4.75%), Placer (352; 0.72%), Yuba (619; 1.26%), and Solano (524; 1.07%).

[6] To determine the share of perennial, annual, and non-cultivated crops in a parcel, we divide these crop types by the total cropland in that parcel.

[7] CDL can be accessed through CropScape at http://nassgeodata.gmu.edu/CropScape/. To convert pixel to acres, we use a multiplier, 900*0.0002471054, to pixel values.

[8] Appendix Table A1 provides a definition of land cover types and mapping used to classify crop types in our study.

Third, we compare the construction validity of the derived crop acreage in our sample by taking the ratio of the parcel area derived from the geographic information system (GIS) to the parcel area reported in the assessor's data. Any value greater than one means that the area of the parcel from the GIS exceeds the area reported in the assessor's table. We drop observations above 95% of the distribution of measurement errors.[9]

Fourth, we compare aggregated crop types acreages obtained from CDL data to administrative data at the county level. To compare the satellite-derived Cropland Data Layer (CDL) with administrative data, we obtained the county-specific annual crop statistics for California from the National Agricultural Statistics Services (NASS). The NASS report is based on the yearly crop reports of the California County Agricultural Commissioners. Specifically, we use county-level data on total harvested acres from annual crop reports between 2008 and 2021 to estimate the total harvested acres for particular crops in each county of California.[10] We present two comparison plots using the CDL and NASS dataset that has been aggregated. First, a time series of total cropland from perennial and annual crop acreage obtained from the CDL and harvested acres from the NASS datasets. Second, we present the time series of the detrended CDL cropland area and detrended time series of NASS cropland area. These figures are shown in Appendix Figure A2. We find that CDL cropland acreage data reflects NASS harvested acres from 2008 to 2021, except for 2009, 2018 and 2019. In 2009, the aggregated acreage obtained from CDL data had a substantial drop, while in 2018 and 2019, NASS harvested acres had a significant rise. Overall, we find that the CDL data in our sample is most comparable to the NAAS data for the years 2010 through 2017. In our robustness checks, we perform regression analysis on the main specifications for the years 2010 to 2017.

Lastly, we take advantage of a stable climate regime and homogeneous biophysical characteristics of our study region, which also reduce false positives, which reduce inaccuracy in cropland data.

3.1.2 Climate variables

Our main climate variables are growing degree days (GDD) during summer (April through August) and winter (November through March of the next year), the accumulated annual precipitation, and accumulated chill hours during winter (November through February of the next year) derived at the parcel-level using the PRISM daily dataset for the years 2008–2021. For the purposes of our analysis and to preserve complete cropland data from 2008-2021, we define the climate normals over 27 years.[11] The PRISM data is a high-resolution dataset that is suitable for agricultural-climate analysis and is utilized by researchers to design climate policy for California (Jessoe et al. 2021).

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

[10] The data covers 442 crops that were harvested in California. We classify these into 20 crop categories using the classifications from the California Department of Water Resources (DWR). For our purposes, we further classify these categories as perennial and annual crops. Finally, to compare with the parcel-specific CDL data, we use only 11 counties in California's Central Valley from the NASS dataset that matches with CDL data in our sample. We aggregate the parcel-specific CDL data at the county level.

[11] In our robustness checks, we define our climate normal over 30 years (1981-2010) using a restricted sample of cropland data from 2010 to 2017. Quantitatively, the results are similar to when the climate normal is defined over 27 years.

The winter chill hour is a critical climate variable in the fruit and nut growing region of the Central Valley. We follow Jackson et al. (2012) to calculate the daily chill hours using the daily minimum temperature, mean temperature, daily maximum temperature, and the reference temperature (7.22 degrees Celsius). Winter chill hours are the sum of daily chill hours during plant's dormancy period of November through February. Depending on the variety, a tree crop can require anywhere from 200 and 1500 chill hours during winter to produce flowers and fruits (Baldocchi and Wong 2008).[12] Appendix Figure A5 highlights the spatial variations in growing season used in our study region. During summer, there are significant variations in degree days in the central and southern parts of Central Valley, while there are small variations in degrees days in winter in the southern parts of Central Valley (as shown in upper panel Appendix Figure A5). In the northern and southern parts of the Central Valley, the change in average annual precipitation over a long period is greater, whereas in the central part, there is a decrease in average annual precipitation. The northern and central parts of the Central Valley experience a greater increase in winter chills hours. Overall, there are enough variations in our study region to identify long-term climatic impacts in our empirical design.

3.1.3 Land capability class

To assess parcel's suitability for agricultural production, we link the parcel-level cropland data to the dominant land capability class (LCC), an integrated measure of soil quality and agricultural potential, which is widely used in literature to measure land quality. We obtained LCC data for California from the California Soil Resource Lab at UC Davis, which is available in grid cells of 800 meters (Walkinshaw et al. 2023). We construct one indicator for high-quality land (LCC12: combined classes 1 and 2) and two indicators for low-quality land (LCC34: combined classes 3 and 4 and LCC5678: combined classes 5 through 8). On average, more than half of the sample is on high-quality land (56%), while 40% of the sample is on low-quality land, and only 4% of the sample is on the lowest-quality land.

3.2 Descriptive statistics

Table 1 presents the descriptive statistics of 657,554 observations (49,175 parcels representing 3.78 million acres) from 2008 to 2021. Perennial crops have the highest land-use shares on average at 0.52, followed by annual crops (0.32), and non-cultivated crops (0.16). About 21% of parcels do not have any share of perennial crops, while 34% and 41% of parcels do not have any share of annual crops and non-cultivated crops, respectively.

In Appendix Table A2, we present the annual composition of our dependent and explanatory variables. The share of perennial crops increased by 29 percent from 0.48 in 2008 to 0.62 in 2021, while the share of annual crops declined by 32 percent from 0.38 in 2008 to 0.26 in 2021. The non-cultivated crop shares, which include fallowed/idle land and natural vegetation, varied between 0.11 to 0.20, with more fallowed land during drought years. Overall, these descriptive statistics demonstrate that perennial crops have replaced annual crops.

[12] If the chilling received is higher than the needs of a variety, it can cause the tree to bloom too early and then be hit by frost or not have warm enough temperatures during its early fruit/nut development period. In addition, Appendix B, provides more details on the formulas that we used to create climate variables.

Table 1 Descriptive statistics ($N = 657{,}554$)

Variable	Mean	Std. Dev.	Minimum	Maximum
Dependent variable: Agricultural land-use shares				
Perennial crops share	0.52	0.44	0	1
Annual crops share	0.33	0.41	0	1
Non-cultivated crops share	0.15	0.31	0	1
Long-term climate normals from 27-year moving averages				
Growing Degree Days (thousands, summer)	2.08	0.15	0.59	2.34
Growing Degree Days (thousands, winter)	0.42	0.05	0.002	0.62
Annual Precipitation (100 mm)	3.49	2.11	0.92	21.06
Chill Hours (100 hours, winter)	9.65	1.41	5.26	26.89
Soil Attributes				
Land Capability Class (class 1 or 2)	0.56	0.50	0	1
Land Capability Class (class 3 or 4)	0.40	0.49	0	1
Land Capability Class (class 5 through 8)	0.04	0.20	0	1
Use-value assessment of agricultural land in California				
Appraisal value of land (thousand dollars per acre)	7.36	8.23	0.03	53.37

The dependent variable is agricultural land-use shares that add up to 1. Mean values are calculated for a sample of 49,175 from 2008 to 2021. The non-cultivated crops share includes fallow/idle land as well as natural vegetation. To create land-use shares, we divide the shares for each crop type within a parcel by the total cropland data in that parcel. A parcel from our sample may be associated with one or more crops. Appraisal value of agricultural land is adjusted for inflation (base year is 2017) and is *winsorized* at the 1 and 99 percentiles

We explore further to examine crop-specific variations over time. For illustration purposes, we randomly split the sample into two periods: the first period from 2008 to 2014 and the second period from 2015 to 2021 (as shown in Appendix Table A3). The land share allocated to perennial crops, particularly almonds, pistachios, and nuts, increased by 8% in the second period. This increase was predominantly in high-quality land (with a 10% increase in LCC12) and in low-quality land (with an 8% increase in LCC34 and 2% in LCC5678). The land share allocated to annual crops declined by 12%, with a reduction of 10% in high-quality land and a 6% and 2% decline in low-quality land (LCC34 and LCC5678). Together, the trends in agricultural land use shares indicate further that substitution of annual crops for perennial crops, particularly allocation to almonds, pistachios, and nuts, has occurred on both high-quality (LCC12) and low-quality land (LCC34 and LCC5678).

Next, we discuss the climate variables used in the study. As previously mentioned, we define climate normal over 27 years. During our study period, on average, there were 2,083 degree days in summer and 415 degree days in winter. The long-term average total precipitation was 346 mm. Moreover, in winter, the Valley accumulates 962 hours of long-term chill hours, on average. The average degree days for both summer and winter are fairly uniform over the study period, with the summer average values between 2000 and 2200 degree days and the winter average between 400 and 4300 degree days (as shown in Appendix Table A2 and graphically in Appendix Figure A3). The precipitation levels in the long run fluctuated between 350 and 370 millimeters, but in 2009, they decreased significantly to almost 291 millimeters from 363 millimeters the previous year. The winter chill hours have decreased over time, from 1006 cumulative hours in 2008 to 892 cumulative hours in 2021. Although winter chill hours have decreased, the values for most tree crops are still above the upper bound thresholds.

Finally, we use the appraisal value of farmland, divided by the acreage of the lot, to calculate the variable appraisal value per acre as a measure of net returns from the farmland. On average, the appraised value of farmland in the study area and period (2008–2021) is 7.31 thousand dollars per acre. The dollar values are adjusted for inflation. The annual Gross Domestic Product (Chain-Type Price Index) obtained from the Federal Reserve Economic Database is used to convert nominal values to 2017 U.S. dollars (U.S. Bureau of Economic Analysis 2024).

4 Results and discussion

We first present a simple correlation analysis between agricultural land-use shares and the climate variables. Second, we present the transition probabilities among major crops grown in the Valley. Third, we present combined regression results (i.e., panel fixed effects model and fractional multinomial logit model) to examine changes in parcel-specific crop types and the probability of switching between crop types. Fourth, we perform two robustness checks: (a) we use restricted sample (2010–2017) to address measurement error in land use change CDL data; and (b) we include an additional regressor for distance to control for the correlation between the proximity of parcels to one another. Lastly, using the estimated coefficients from our econometric models, we simulate the changes in parcel-specific agricultural land-use shares across northern, central, and southern parts of the Central Valley in response to future climate projections.

4.1 Correlation between agricultural land-use shares and climate variables

Appendix Figure A4 (a) and (b) present scatter plots that show a correlation between the share of perennial and annual crops and climate variables such as degree days in summer and winter, annual precipitation, and winter chill hours. During the summer, the share of perennial crops increases at an increasing rate, while it decreases during winter. The relationship between perennial crops and total annual precipitation shows a flat to downward slope, suggesting that excess precipitation may decrease the share of perennial crops. The association between perennial crops and winter chill hours is negative. The relationship between annual crop shares and summer degree days and total precipitation decreases, but it increases with winter degree days.

4.2 Transition probabilities

We present a probability estimate for the likelihood of a crop being grown in the next period among the major crops by land quality in our study region. In order to do that, we split the land-use shares of perennial and annual crops into crop-specific land-use shares by land quality and year in the study region, as shown in the Appendix Table A3. The changes in land-use shares are displayed for two periods (Period I: 2008–2014 and Period II: 2015–2021) to maintain readability.[13]

[13] We choose the years ad hoc so that there is the same number of years for both periods. The following is a detailed discussion from Appendix Table A3. The land shares allocated to perennial crops increased by an average of nearly 10% within a farm parcel. This increase in perennial crops shares is significant in high-

Appendix Table A4 displays the probability that a typical grower in our study region will continue to grow the same crop in the next period (2015-2021).[14] The probability of a grower cultivating almonds, pistachios, and nuts in the next period is 92% (as shown in column 1 of Appendix Table A4). Furthermore, growers are 63% and 37% likely to cultivate grapes, citrus, and other subtropical fruits respectively in the next period. The probability of annual crops growing in the next period is low (less than 50%), with the exception of alfalfa (55%). Lastly, land that was fallowed or idled in the first period has an 80% probability of continuing to be fallowed or idled.

We repeat the assessment of transition probabilities to examine how crops transition between different land classes (High quality: LCC12, Low quality: LCC34, and Poor quality: LCC5678). Columns 2, 3, and 4 of Appendix Table A4 report the results. The key findings are as follows. Almonds, pistachios, nuts, and crops like alfalfa have a very high probability (91% for almonds and 61% for alfalfa) of being grown in low quality land in the next period. While rice crops have the least probability of being grown on high quality land in the next period (8%).

4.3 Empirical results

Table 2 presents combined regression results (i.e., panel fixed effects model and fractional multinomial logit model) to examine changes in parcel-specific crop types and the probability of switching between crop types (for economical purposes, we may expect a switch from annual to perennial crop types).[15] Quantitatively, the marginal effects derived from the panel fixed effects model and fractional multinomial logit model are alike, expect for annual precipitation. The fractional multinomial logit model indicates that perennial crops are more likely to increase in response to annual precipitation. However, the panel fixed effects model shows a negative relationship between the share of perennial crops and annual precipitation, but it is not significant. Both models have consistent climate-induced acreage decisions for remaining climate normal. For instance, on average, the growing degree days during summer (winter) is positively (negatively) associated with an increase in perennial crop shares. The average winter chill hours have a negative association with the share of perennial crops, as shown by both models.

In Fig. 1, we present the estimated marginal effects calculated at various levels of the climate normal distribution, such as the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles. During the summer, the share of perennial crops peak at between 50 (2147 degree days) and

quality land, with an increase of about 10%, followed by an increase of 8% in LCC34 and 2% in LCC5678 low-quality land. Almonds, pistachios, and nuts are the perennial crops that feature in such increases. In contrast, the percentage of annual crops decreased by 8%. The greatest decrease occurs in high-quality land, which accounts for nearly 10% of the loss, and LCC34 (approximately 8%). Notably, alfalfa's shares fell by nearly 5% in both high-quality land (LCC34) during the second period. Lastly, the non-cultivated crop shares experienced a modest decrease of 1% from high-quality land.

[14] We present average marginal effects in Appendix Table A4 that are conditional on an indicator of crops grown during 2008–2014, and current parcel-level characteristics such as climate variables that include degree-days (in summer and winter), total annual precipitation, chill hours during winter, and soil quality (an indicator of LCC34 and LCC5678) in the logit model. After running logit model regression, we utilize Stata command *margins* to evaluate the marginal effects on the mean of all covariates used in the analysis.

[15] Appendix Table A8 exhibits a variety of fractional multinomial logit specifications. Specifically, with and without the appraisal value of agricultural land, and the Chamberlain-Mundlak approach incorporates climate variables averaged over time for each parcel and region in the regression.

Table 2 Marginal effects evaluated at the mean value of the climate normal

	Panel Fixed Effects Model		Fractional Multinomial Logit Model	
	Perennial crops	Annual crops	Perennial crops	Annual crops
	[1]	[2]	[3]	[4]
Long-term climate normals from 27-year moving averages				
Growing Degree Days (thousands, summer)	2.037	-1.659	1.296	-1.434
	(0.528)***	(0.583)***	(0.629)**	(0.602)**
	[0.906]**	[1.132]	[0.835]	[0.808]*
Growing Degree Days (thousands, winter)	-4.433	4.413	-6.525	9.843
	(0.708)***	(0.684)***	(3.159)**	(3.189)***
	[0.863]***	[1.100]***	[4.543]	[4.784]**
Annual Precipitation (100 mm)	-0.024	0.044	0.156	-0.146
	(0.053)	(0.054)	(0.049)***	(0.044)***
	[0.062]	[0.068]	[0.065]**	[0.059]**
Chill Hours (100 hours, winter)	-0.085	0.131	-0.310	0.436
	(0.036)**	(0.036)***	(0.150)**	(0.142)***
	[0.043]**	[0.049]***	[0.195]	[0.201]**
Mean of dependent variable	0.524	0.320	0.524	0.320
Log Likelihood	n.a.	n.a.	-511957.32	-511957.32
Number of parcels	49,175	49,175	49,175	49,175
Observations	660,147	660,147	657,554	657,554

Level of significance: ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$. Standard errors in parentheses are derived from the delta method and are clustered at the level of combined irrigation district and county. The number of counties and irrigation districts combined is 255. Squared parentheses are standard errors that are clustered at the county level with a 100 bootstrap repetitions. In all regressions, dummies are included for year. See Appendix Table A5 for full results

75 (2194 degree days) percentiles of degree days, and then decline at higher percentiles of 90 (2230) and 95 (2255) percentiles of degree days (as shown in the upper left panel of Fig. 1). During winter, the share of perennial crops decreases at all levels of degree day distribution (upper right). In contrast, annual crop shares decrease during the summer and increase with an increase in winter degree days. These plots suggest that increased degree days during summer favor planting perennial crops rather than annual crops. The share of perennial crops increases when annual precipitation is below or at the median (285 mm) distribution of annual precipitation, but decreases when annual precipitation is above the median distribution (bottom left). While the annual crop share increases at all levels of annual precipitation, as indicated by the upward slope of marginal effects of annual crops shares. Finally, perennial crops shares decrease at higher levels of distribution of chill hours during winter, particularly sharply between the 25th (893 hours) and 75th (1002 hours) percentile of distribution of chill hours (bottom right).[16]

To estimate the long-term climate effects on acreage decisions for almonds, pistachios, and nuts, the widespread cash crops in the Valley, we divided the perennial crops in our

[16] Chill hours for tree crops vary significantly during winter, requiring 200 and 1500 hours below 7.2 degrees Celsius to produce flowers and fruits. For instance, pistachios and almonds need moderate chilling, while other tree crops with higher chilling requirements will experience a decline. The marginal effects of long-term chill hours on perennial crops, evaluated at various intervals, are negative, and statistically significant.

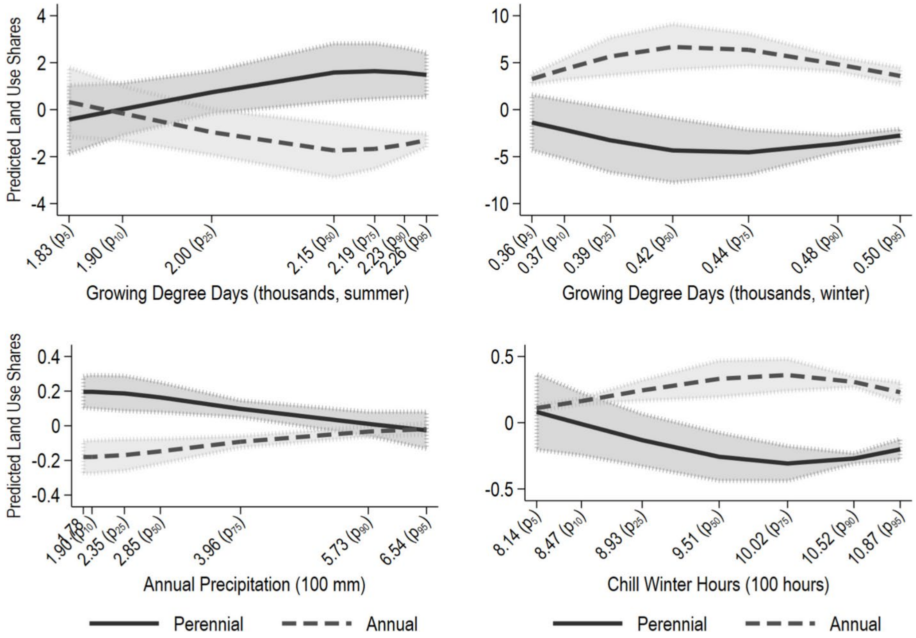

Fig. 1 Relationship between predicted land use shares and long-term climate variables. *Notes*: These graphs are obtained by calculating the average marginal effects from the fractional multinomial logit regression at different intervals of degree days, precipitation, and chill hours. The gray area represents the 95% confidence intervals. The x-axis has brackets representing the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles

sample into (a) almonds, pistachios, and nuts, and (b) other tree crops. Appendix Table A6 presents the marginal effects assessed using average climate normal for the shares of almonds, pistachios, nuts, and other tree crops separately. The acreage decision of almonds, pistachios, and nuts crops on average has a negative association with chill hours during winter and degree days. While degree days during summer and annual precipitation positively correlate with an increase in the share of other tree crops.

Next, we explore spatial heterogeneity in how climate-induced acreage decisions are made in different parts of the Central Valley. To explore spatial heterogeneity empirically, we ran separate fractional multinomial logit regressions for the northern, central, and southern parts of the Central Valley to obtain the average marginal effects.[17] Appendix Table A7 reports the results. The results indicate that the share of perennial crops increases (decreases) in response to growing degree days during summer (winter) in the northern parts of the Central Valley. An increase in annual precipitation is positively associated with the share of perennial crops grown in all parts (northern, central, and southern) of the Central Valley. Winter chill hours only affect the central and southern parts of the Central Valley, resulting in a decrease in perennial crop shares. In contrast, the share of annual crops decreases in response to the growing degree days during summer only in the northern parts of the Valley. An increase in winter degrees days is positively associated with the share of annual crops

[17] We classify the northern parts of the Central Valley using parcels in our sample that are in Butte, Glenn, Yolo, Placer, Yuba, Merced, San Joaquin, and Solano counties. We combined the central and southern parts of the Central Valley, which consist of parcels in our sample located in Fresno, Kern, and Tulare.

grown in all parts of the Central Valley. Lastly, an increase in precipitation is negatively associated with the share of annual crops in the northern parts of the Central Valley.

4.4 Robustness checks and sensitivity analyses

As mentioned in the data section, the changes in crop type acreage derived from cropland data layer (CDL) are more reliable during 2010-2017 than during all the study periods (2008-2021). We test the robustness of our main results by limiting our study period to 2010-2017 and defining our climate normal over 30 years. Quantitatively, marginal effects evaluated at mean values of climate normal are comparable to the main results with full sample for the years 2008-2021 and climate normal defined over 27 years (results shown in columns 1 and 3 of Appendix Table A8). For instance, the share of perennial crops is positively (negatively) associated with long-term degrees days during summer (winter) and annual precipitation. Contrarily, during summer (winter), degrees days and annual precipitation have a negative (positive) impact on the share of annual crops. Finally, an increase in winter chill hours has a negative association with the planting of perennial crops.

Next, there may be a concern about farmland parcels near each other that may have unobserved characteristics that are correlated across space and may potentially influence growers' land-use decisions. Previous studies (e.g., Lubowski et al. (2008)) have addressed the issue by removing observations (e.g., fields) that are close together. We address this concern by utilizing geo-referenced parcel locations to create a new variable, the average distance between a parcel and its five closest neighbors, then use this variable as an additional regressor in our main specification. The new distance variable could be used as a proxy for acreage decisions in nearby parcels, which could impact planting decisions within the own parcel. We report the marginal effect of crop type shares evaluated at mean values of climate normal in columns 2 and 4 of Appendix Table A8. The estimated coefficients are comparable to the main results in Table 2, suggesting that unobserved characteristics related to neighboring parcels are not a major concern in our study region.

4.5 Changes in land-use shares under future climate projection

Using the daily downscaled projections from NASA's NEX-GDDP-CMIP6 dataset, we simulate the impacts of future climate change on agricultural land use in Central Valley. Specifically, we utilize the Goddard Institute of Space Studies (GISS) climate model's downscaled daily weather projections for the socio-economic pathways (SSP45 and SSP85) to calculate degree-days, chill hours, and precipitation for future years 2031–2055 relative to 1981–2005 (Thrasher et al. 2021; 2022). The predictions for climate variables used in our analysis relative to their averages during 1981–2005 are presented in Appendix Table A10.[18] The SSP45 and SSP85 scenarios applied to the Valley shows that the degree-days in summer and winter in 2031–2055 are expected to be higher compared to historical averages of 1981–2005 by 206 degree days (or 10.06% over the historical mean between 1981 and 2005) and 291 (or 25.94%), respectively. The total annual precipitation in 2031–2055 is also expected to increase by 39.4 mm (or 10.37%) relative to 1981–2005. In contrast, the accu-

[18] We use georeferenced parcel-level data to project the impacts of climate change on land use decisions at the parcel level. However, downscaling climate models at the farm level also introduces more noise and less accuracy, and therefore readers must be cautious when interpreting our results.

Table 3 Projected impacts of climate change on land-use shares for perennial and annual crops under two climate scenarios

	SSP45		SSP585	
	Perennial crops	Annual crops	Perennial crops	Annual crops
Panel A: All observations				
Growing Degree Days (thousands, summer)	24.9%	-27.5%	22.4%	-24.8%
Growing Degree Days (thousands, winter)	-125.9%	190.0%	-158.2%	237.2%
Annual Precipitation (100 mm)	5.9%	-5.5%	6.0%	-5.6%
Chill Hours (100 hours, winter)	87.0%	-122.4%	100.7%	-141.6%
Panel B: Northern parts of Central Valley				
Growing Degree Days (thousands, summer)	33.7%	-43.5%	31.1%	-40.2%
Growing Degree Days (thousands, winter)	-181.5%	283.9%	-235.5%	368.3%
Annual Precipitation (100 mm)	6.5%	-5.9%	7.4%	-6.7%
Chill Hours (100 hours, winter)	73.1%	-134.6%	86.9%	-160.0%
Panel C: Central and southern parts of Central Valley				
Growing Degree Days (thousands, summer)	-1.2%	-8.0%	-1.1%	-7.1%
Growing Degree Days (thousands, winter)	-45.9%	145.4%	-56.0%	177.5%
Annual Precipitation (100 mm)	17.1%	-8.7%	3.8%	-2.0%
Chill Hours (100 hours, winter)	56.2%	-108.8%	63.6%	-123.1%

The percentage change of projected impacts of climate change on land use shares of perennial and annual crops are reported. These are calculated by multiplying the coefficients of average marginal effects (Columns 2 and 4 of Table 2 in panel A, columns 1 and 2 for Panel B, and 3 and 4 for Panel C in Table 3) and the difference between the average projected climate in 2031-2055 and the average climate in 1981-2005

mulated chill hours during winter in 2031–2055 may significantly decrease by 284 hours (or 38.64%) relative to 1981–2005.

Using the estimated coefficients from our econometric model, we estimate the change in agricultural land use that can be attributable to changes in crops' comparative yield advantage due to projected climate change– certain crops will perform better than others in future climates. We follow literature to estimate the predicted changes in the projected climate-driven agricultural land use and is given by the expression $\left(\frac{\partial E(y_{ji}|W_i)}{\partial W_i} * \Delta\overline{W}\right)$; where $\frac{\partial E(y_{ji}|W_i)}{\partial W_i}$ is the marginal effect from fractional multinomial logit regression with respect to climate normal. $\Delta\overline{W}$ represents the difference between the average projected climate variables in 2031–2055 and the average climate variables in 1981–2005 (as shown in column 3 of Appendix Table A10 under SSP45 scenario and column 5 of Appendix Table A10 under SSP85 scenario).

Table 3 presents the predicted changes in agricultural land-use under the SSP45 and SSP585 projected climate scenarios. Under the SSP45 (SSP85) climate scenario, the shar eof perennial crops is expected to increase by around 25% (22%) during summer and decrease by 126% (158%) during winter (as shown in Panel A of Table 3). A decrease in projected chill hours is expected to increase perennial crop shares by 87% (or 100% under the SSP85 scenario). An increase in projected total precipitation is expected to increase the share of perennial crops in the Central Valley.

From a policy perspective, we explore the spatial heterogeneity of our projection results. Panel B and C of Appendix Table A10 report the results. We observe that projected degree days and total precipitation have different effects on the share of agricultural land use in the northern, and central and southern parts of the Central Valley. The projected increase in degrees during summer (winter), on average, negatively (positively) affects perennial crops in the northern parts of the Central Valley. The perennial crop shares in the central and southern parts of the Central Valley is expected to be negatively affected during both summer and winter due to projected increase in degree days. The annual crop share is expected to be negatively impacted by the degree days during summer in all parts of the Central Valley, but positively impacted by the degree days during winter. A decrease in projected chill hours in winter is expected to increase planting of perennial crops throughout the Central Valley, with a higher percentage in the northern parts. Finally, projected total precipitation is expected to increase the share of perennial crops and decrease the share of annual crops in the Central Valley.

Overall, the projection results suggest that growing degree days are expected to favor the share of perennial crops in the northern part of the Central Valley. An increase (and or decrease) in projected annual precipitation (and or chill hours) will also increase perennial crop shares, especially in the central and southern parts of the Valley. In contrast, the annual crop share is expected to decrease in all parts of the Central Valley in response to projected growing degree days and total precipitation.

5 Conclusions

This paper examines growers' revealed adaptation in land-use adjustments and changing cropping patterns (to capture long-term adjustments) in California in response to climate change. We provide estimates of long-run adaptive responses to climate-induced changes in California's agriculture. Using parcel-level data, we provide microlevel evidence of the impact of climate change on agricultural land use. This study exploits parcel-level variations in crop types to estimate the impact of climate change on irrigated agriculture by shifting crops, which capture growers' behavioral response to long-run adaptation. We find that growers in the Central Valley are transitioning from annual crops to perennial crops in response to changing climates. Specifically, perennial crops have a positive (negative) association with long-term degree-days in summer (winter) and total precipitation, while negative association with winter chill hours. We demonstrate that growers are more likely to plant new acres of perennial crops on less suitable land and may potentially shift available irrigation water to high-revenue crops. Moreover, our projection results suggest that an increase in total precipitation and decrease in winter chill hours in northern and central and southern parts of Central Valley will potentially be associated with an overall increase in perennial crop shares. From a policy perspective, switching to high-value crops, which are also long-term water-demanding crops, may be in contrast to the potential water savings of a crop-switching strategy (Boser et al. 2024). This study quantifies the changes in climate-induced agricultural land use, including crop switching, and contribute to the literature on agricultural-climate interactions in California and other water stressed agricultural regions globally.

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