UC RIVERSIDE School of Public Policy

UCR SPP Working Paper Series

August 2024 – WP#24-03

TABLE OF CONTENTS

Parcel-Level Agricultural Land Use and Climate Change: Evidence from California's Central Valley

Siddharth Kishore,[1] Mehdi Nemati,[1] Ariel Dinar,[1] Cory L. Struthers,[2] Scott MacKenzie,[3] Matthew S. Shugart[3]

[1]*School of Public Policy, University of California, Riverside, CA*

[2]*Evans School of Public Policy and Governance, University of Washington, WA*

[3]*Department of Political Sciences, University of California, Davis, CA*

Summary:

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-level characteristics data with cropland data and long-run historical climate variables 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. 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.

Acknowledgements: The research leading to this paper was funded by the National Institute of Food and Agriculture, USDA.

Parcel-Level Agricultural Land Use and Climate Change: Evidence from California's Central Valley

Siddharth Kishore, Mehdi Nemati, Ariel Dinar, Cory L. Struthers, Scott MacKenzie, Matthew S. Shugart

Authors:

Siddharth Kishore is Postdoctoral Scholar at the School of Public Policy, UC Riverside, Email: siddhark@ucr.edu

Mehdi Nemati is Assistant Professor of Environmental Economics and Policy at the School of Public Policy, UC Riverside, Email: mehdin@ucr.edu

Ariel Dinar is Distinguished Professor Emeritus at the School of Public Policy, UC Riverside, Email: adinar@ucr.edu

Cory L. Struthers is Assistant Professor of Administration and Policy at the Evans School of Public Policy and Governance, University of Washington, Email: cstruth@uw.edu

Scott MacKenzie is Professor of Political Science at UC, Davis, Email: samackenzie@ucdavis.edu

Matthew S. Shugart is Distinguished Professor Emeritus in the Department of Political Science at UC, Davis, Email: msshugart@ucdavis.edu

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-level characteristics data with cropland data and long-run historical climate variables 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. 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, Cahill, and Field 2007; Lobell and Field 2011; Lobell, Torney, and Field 2011; Deschenes and Kolstad 2011; H. Lee and Sumner 2015). Most works use county-level data, and some works use individual farm-level data (Ramsey, Bergtold, and Heier Stamm 2021; Wimmer et al. 2024). Our work also uses regional-level parcel level data in irrigated agriculture to assess the climate-induced land-transition. Recent estimates of climate-induced crop switching in dryland agriculture are at the county-level scale (e.g., Arora et al. (2020); Mu et al. (2018)) and mask significant parcel-level heterogeneity of attributes. The literature on climate-agriculture interaction lacks empirical evidence on shifts in agricultural land use at the micro level, such as determining whether and to what extent farmers are shifting from annual to perennial crops. This paper fills this gap by combining parcel-level agricultural land-use data and long run historical climate variables to assess climate-induced land-use transition in California's Central Valley

Climate change has significant impact on agricultural operations. Agriculture is one of the most vulnerable sectors to climate change. Farmers adapt to climate change in different ways. 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. In this paper we focus on land use changes as an adaptation to climate change. The Central Valley is an excellent area for studying because of the significant role of agriculture and its reliance on climate (Pathak et al. 2018). 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 to many other regions anywhere.

The research asks how and to what extent farmers make land-use decisions in irrigated agricultural production in response to various long run (normal) measures of climates to capture long-run adaptation. We provide empirical estimates on expected land-use changes in the Central Valley of California using parcel-level panel data and detailed time series cropland data, conditional on heterogeneous land quality. This study exploits parcel-level variations in crop types to estimate the impact of climate change on irrigated agriculture by shifting crops, which captures growers' behavioral response in long-run adaptation. 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 (accumulated annual precipitation, degree days for summer and winter, and accumulated hours of winter chill) and heterogeneous land quality.

We find that growers are switching to perennial crops from annual crops in response to changing climates. The parcel-level shares of perennial crops show a U-shaped relationship with long-term degree days during summer and cumulative chill winter hours, negatively associated with degree days during winter, and with annual precipitation. In contrast, the parcel-level land-use shares of annual crops show an inverse U-shape relationship with long-term degree days, while they show a U-shape relationship with long-term precipitation. Analysis of agricultural land-use with heterogeneous land quality suggests that transitioning land to perennial crops has a probability of more than 50% in high-quality land, while the probability of transitioning to perennial crops in the next period is below 50% in low-quality land. Results from this analysis help play a key role in understanding potential climate adaptation options and, thus, impact on food supply trends from a major food producing region at present and in the future under climate change.

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. The simulations predict changes in land allocation at the parcel level due to exogenous changes in projected climate variables. 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. The predicted agricultural land-use change favors annual crops over perennial crops based on future climate projections.

2. Theoretical and Empirical Framework

A simple framework explaining farmers' land-use decision is given by $y_{jit} = y_i(\psi_{it}, S_i, A_{it}, Z_{it}; \varepsilon_{jit})$ where y_{jit} is the crop-specific land-use share for crop $j = \{1, \dots, J\}$ (in our analysis $J = 3$), in parcel i, at year t (in our analysis $t = 2008, \dots, 2021$). ψ_{it} represents expected climate conditions, including 27-year moving average precipitation, degree-days, and winter chill hours. S_i is soil quality conditions; $A_{it}$is the annual appraisal value of farmland, a hypothetical value, which potentially reflects the net returns from crop production at the farm-level and does not include future development returns; Z_{it} includes other variables, such as population density and time trend, and ε_{jit} represents unobserved variables that may influence the farmers land-use decisions. We assume that the annual appraisal value of farmland captures the expectation of long-term operating profits, and therefore net returns to agricultural land-uses.

We take advantage of the observed use value assessment of agricultural land in California to account for parcel-level observations of net returns in our analysis.

For our empirics, we follow previous studies (e.g., Mu et al. (2018); Cho and McCarl (2017)) to model land allocation shares for each usage type j in parcel i and year t, y_{jit}, where $y_{jit} \in [0,1]\ \forall\ i, t$ and $\sum_{j=1}^{J} y_{ji} = 1$. In our analysis, there are four types of use: perennial crops, annual crops, non-cultivated crops, and no cropland. For the purposes of our analyses, we apply a fractional multinomial logit model to estimate the impact of climate change on land-use shares in the Central Valley of California.[1] The estimated equation is

$$E\left(y_{jit} \middle| W, X, \bar{Z}; \varepsilon_{jit}\right) = \frac{exp(\sum_{k=1\in K} \beta_{jk} f_k(W_{kit}) + \gamma_j X_i + \phi_j \bar{Z}_i + \varepsilon_{jit})}{\sum_J exp(\sum_{k=1\in K} \beta_{jk} f_k(W_{kit}) + \gamma_j X_i + \phi_j \bar{Z}_i + \varepsilon_{jit})} \tag{1}$$

where y_{jit} denotes the land use shares for usage types j in parcel i at time t. X_i is a vector representing observable determinants of land use decisions, such as the parcel-specific land capability class. We use an indicator for high-quality land (LCC12) and two indicators for low-quality land (LCC34 and LCC5678). $k = 1,2,3, \dots, K$ denotes various measures of climate variables. We follow previous literature from the California study area (e.g., see Lee and Sumner (2015)) to include climate normals from 27-year moving averages for degree days (in summer and winter), total annual precipitation, and chill winter hours. $f_k(.)$ represents non-linearities such as squared terms in precipitation, degree days, and chill hours. β_{jk} are long-term climate coefficients to be estimated for each land use share j and represents our variable of interest. Following Mu et al. (2018), 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

[1] We use the FMLOGIT Stata package to estimate the fractional multinomial logit model (Buis 2008).

multinomial logit model (Mundlak 1978). This approach is basically an extension of Chamberlain-Mundlak approach or correlated random effects that allows for unobserved heterogeneity to be correlated with observed time varying covariates (Wooldridge 2019). ε_{jit} represents error terms. Standard errors are clustered at the parcel level.

We assume that all climate variables are strictly exogenous, $(E[W\varepsilon] = 0)$. There may be a concern that the inclusion of the appraisal value of land as a regressor may be correlated with the error terms, such as soil quality, and therefore is endogenous, $(E[X\varepsilon] \neq 0)$. We control for this by including the land capability class (as a measure of soil quality). Growers can reduce cost expenditure with high-quality land, while low-quality land may increase cost expenditure for crop production. Crop cultivation in high-quality land is characterized by few limitations: physical (such as soil fertility, water-holding capacity, and topsoil depth), topographical, and meteorological. However, low-quality land is characterized by more physical constraints on crop productions. We would expect growers to maximize their returns from crop production by allocating more land shares to perennial crops on high-quality land with minimal cost expenditures and on low-quality lands with maximum cost expenditures.

The marginal effect of land-use shares with respect to climate normal is expressed as

(2) $$ME\left(y_{ji}|W_i\right) = \frac{\partial E(y_{ji}|\,W_i)}{\partial W_i} = E\left[y_{ji}\middle|W_i\right](\beta_{jW} - \textstyle\sum_{j=1\in J}\beta_{jW}E[y_{ji}|W_i])$$

where $E(y_{ji}|\,W_i) = \frac{\exp(\beta jW_i)}{\sum_J \exp(\beta_j W_i)}$, represents a simple expression of Eq. (1), after dropping subscript t, non-climate covariates, and error terms. In the same way, we calculate the marginal effects of land-use shares with respect to land quality.

3. Data and Descriptive Statistics

3.1. Data Sources

The empirical analysis combines cropland data and climate data at the farm-level. The boundaries of farmland land data are sourced from ATTOM data. Our analysis is based on 49,175 farm parcels in California's Central Valley, spanning 11 counties.[2] These parcels are associated with field crops, orchards, and vineyards 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. 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 (J. Lee, De Gryze, and Six 2011). For the purposes of our analysis, we take advantage of the reported appraisal value of farmland to include as a regressor in our econometric specification. In the subsequent subsection, we provide a brief introduction to the use-value assessment of agricultural land in California.

3.1.1. Cropland Data

To determine land use changes, we rely on the annual Cropland Data Layer (CDL), a raster-based land-use map, at 30×30 meter resolution for 2008 through 2021.[3] The USDA, National Agricultural Statistic Service (NASS) publishes CDL products using a machine learning model

[2] The panel dataset consists of farm parcels 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%).

[3] CDL can be accessed through CropScape at http://nassgeodata.gmu.edu/CropScape/

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. We acknowledge that inherent CDL errors can cause uncertainty in land-use change calculations (Reitsma et al. 2016; Laingen 2015). Despite these limitations, the CDL data is a primary source of land use information at the micro-level and is widely used in the literature to influence land use policies (e.g., Boser et al. 2024; Ramsey, Bergtold, and Heier Stamm 2021; Jiang et al. 2021). To reduce errors when distinguishing spectrally similar land cover classes, we combine CDL classes into perennial, annual, and non-cultivated crops and utilize time-series cropland data, following recommendations from the literature (e.g., Lark et al. (2017)).[4] In addition, a stable climate regime and homogeneous biophysical characteristics, such as our study area in the Central Valley, also reduce the false positives, which lowers inaccuracy in cropland data (Reitsma et al. 2016). For the purposes of our analysis, we require associations between specific crop types (crop-specific identification and acreage estimates) and farm parcels (Appendix Table A1). We extract crop types at the parcel level in the Central Valley of California and then we construct the share of perennial, annual, and non-cultivated crops within a parcel.[5] [6] Appendix Figure A2 presents a comparison between CDL cropland acreage and USDA NASS acreage for the study area from 2008 to 2021.[7] CDL cropland acreage data follows NASS harvested acres for the years

---

[4] 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. We drop observations above 95% of the distribution of measurement errors. Dropping all the observations with a ratio higher than one does not change our main results.

[5] The percentage of perennial, annual, and uncultivated crops was derived by taking the ratio between the area of perennial, annual, and non-cultivated crops in a parcel and the total cropland.

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

[7] We compare CDL crop-specific land cover data with NASS survey data from 2008–2021. We obtain the NASS dataset from the USDA's NASS California Field Office, which is operated in cooperation with the California

2008 through 2021, except for 2009, 2018 and 2019. In 2009, CDL data acres saw a sharp decline, but in 2018 and 2019, NASS harvested acres saw a sharp increase. In our robustness checks, we perform regression analysis on the main specifications after excluding these years (i.e., shares of land use for the period of 2010 to 2017).

3.1.2. Climate variables

Our main climate variables are growing degree days (GDD) during summer (April through August) and winter (November through May of the next year), the total annual accumulated 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 our analysis, we compute the 27–year normal for all our climate variables. The PRISM data is a high-resolution dataset suitable for analyzing the heterogeneous landscape of California (Jessoe, Mérel, and Ortiz 2021).

Next, 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 (below 7.2 degrees Celsius) during winter to produce flowers and fruits (Baldocchi and Wong 2008). Appendix B provides more details on variable construction. The winter chill hour is a critical climate variable in the fruit and nut growing region of the Central Valley of California. Climate change induced warming is expected to reduce the accumulated number of chill hours in the Central Valley of California (Baldocchi

Department of Food and Agriculture. NASS survey data can be accessed through https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/index.php.

and Wong 2008). This may pose a potential threat to the production of high-value nuts, fruits, and other tree crops, and could have an economic and culinary impact on California.

3.1.3. Land Capability Class

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 the 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, O'Green, and Beaudette 2023). LCC data includes values for both irrigated and non-irrigated agriculture. Our focus is on irrigated LCC because the majority of farmland in the Central Valley is irrigated. Irrigated LCC has eight classes. As we move along the land capability classes, from class I through VIII, the constraints on soil suitability for crop cultivation also increases. The constraints in LCC are characterized by soil erosion and runoff, excess water, root zone depth, climate limitations, and limitations on mechanized farming activity. Class I has a few limitations that restrict their use for crop cultivation, while class VIII has severe limitations that reduce the choice of plants and need special conservation practices.

3.1.4. Background: Use-value assessment of agricultural land in California

In our theoretical framework, we assume that growers' land use decisions are based on the expected returns from the land in its optimal use. In the absence of data on the economic returns to land at the farm level, we use the appraisal value of land to capture the net returns to land from crop production. In this subsection, we first present the background of the use-value assessment of agricultural land in California and then discuss the relevance of the appraisal value of land in capturing the net returns to lands.

The Uniform Standards of Professional Appraisal Practice (USPAP) defines the practice of valuation as the act or process of developing a value opinion for estimating the value of property (USPAP 2010). In California and nationwide, local assessors assess farmland based on its use value in agriculture. To assess the agricultural land for tax purposes, the land is valued in its agricultural (current) use and ignores future development potential and non-agricultural land uses (Anderson and Griffing 2000). The use-value assessment of agricultural land is usually lower than its full market value due to the lower agricultural use value, other things being equal. A primary motivation of significantly lower assessment value is to provide a more equitable distribution of the property tax burden between agricultural and non-agricultural landowners. Additionally, the lower farmland assessment values compared to market value serves as the basis for property tax relief for farmland owners. The aim is to reduce the tax burden on farmers and prevent the conversion of farmland to developed areas.

Licensed or certified appraisers employed by government agencies, such as county appraiser's office and/or professional agencies, such as American Society of Farm Managers and Rural Appraisers (ASFMRA) to appraise taxable properties, including agricultural land. An assessor in a California jurisdiction is required to estimate the value of farmland based on agricultural use. Typically, when a property is purchased, the county appraiser assigns an assessment value of land equal to the purchase price. Each year after that, the property's assessed value goes up by 2 percent or the rate of inflation, whichever is less. The assessment is not necessarily done every year, and in some cases, assessment is done in the year following the sale. This process continues until the property is resold and the assessed value is adjusted in accordance with the current purchase price. This reassessment does not apply in the case of certain exceptions, for example, properties damaged by a disaster, transfers with the same family, etc.[8] California Land Conservation Act of 1965 (also known as the Williamson Act Program, an agricultural preserve program), [9] another land program, enables local government to enter into contracts with private landowners for a long-term commitment to conserve farmland.[10] Proposition 13 (an annual 2% increase in assessment value for unsold properties) and the Williamson Act (encourages landowners to keep their land in agriculture) govern land appraisers in California.

Based on personal communication with an assessor in Merced County, California, the assessment value is based on historical data and may not be used to predict land values. In contrast, the sale prices are forward-looking. Moreover, assessor's valuation by Williamson Act can also cause an annual increase greater than 2%. In particular, variables which effect Williamson Act valuation include, but not limited to land rents, crop yields, commodity prices, and statutory cap rates provided to Assessor by State Board of Equalization.

The assessed value of agricultural land may not exceed the market value of all parcels (sold or not). In addition, following cases where the assessed value may differ from Proposition 13's 2% annual increase:

[8] A detailed summary is provided in the brief report by Understanding California's Property Taxes. Available at: https://lao.ca.gov/reports/2012/tax/property-tax-primer-112912.aspx

[9] The agricultural preserve program encourages landowners to continue to use their lands for agricultural purposes rather than converting them to non-agricultural purposes. Other examples in California include Farmland Security Zone contracts which offer a property tax reduction of 65% of its Land Conservation Act or 65% of the Proposal 13 assessment, whichever is lower.

[10] The assessment is based on agricultural production rather than full market value to reduce the property tax. According to the California Department of Conservation, the Land Conservation Act is expected to save agricultural property owners 20-75% in property taxes each year. For a detailed discussion, see https://www.fresnocountyca.gov/Departments/Assessor/Williamson-Act

Case 1: For unsold parcels, where improvements (e.g., crop switch, installation of irrigation pipeline, construction of buildings, and other structures) have been made to the parcel.

Case 2: For unsold parcels, if the market value of parcels with similar characteristics (e.g., location, land size, soil quality, irrigation district, improvements, crop types) is lower than the historic assessed value. The assessed value may have a lower value than the base value.

In California, farm managers and agricultural consultants assess farm parcels and may influence agricultural inputs and other crop production and marketing decisions. For our purposes, we use the appraisal value of land to capture the net returns from the farmland.

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. The farmlands are located in 11 counties of the Central Valley. We construct land-use shares by dividing the shares for each crop type within a parcel by the total cropland data of that parcel. Our sample may contain a parcel that is linked to one or more crops. 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). The non-cultivated crops share includes fallow/idle land as well as natural vegetation. About 21% of parcels do not have a share of perennial crops, while 34% and 41% of parcels do not have a share of annual crops and non-cultivated crops, respectively.

Appendix Table A2 present the composition of our dependent and explanatory variables over years in the study region. 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 fallow/idle land and natural vegetation, varied between 0.11 to 0.20, with an upper bound during drought years. Over the years, the variation shows that perennial crops are substituting annual crops, and the proportion of non-cultivated crops has remained the same, with higher lands being fallowed or idled during drought periods.

Appendix Table A3 present crop-specific land shares and land quality 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. 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 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 shown in Appendix Figure A3). We use 27-year moving averages to create long-term climate normals. The degree days in summer are more than twice as high as those in winter. During our study period, on average, there were 2,086 degree days in summer and 984 degree days in winter. The long-term average total precipitation was 346 mm. In winter, the valley accumulates 962 hours of long-term chill hours, on average.[11] The average degree days of both summer and winter have remained constant throughout the years, with the summer average being slightly over 2000 days and the winter average being almost 1000 days (Appendix Table A2). The long-term precipitation levels tend to be around 350 to 370 millimeters, with the exception of 2009 when they fell drastically to nearly 300 millimeters from 370 millimeters. Over time, the cumulative chill hours during winter have decreased, from 1006 cumulative hours in 2008 to 892 cumulative hours in 2021. Although there has been a decrease in the number of chill hours accumulated during winter, the values for most tree crops still exceed the upper bound thresholds.

To assess parcel's suitability for agricultural production, we utilize a composite class category called land capability class (LCC: classes 1 through 8) and 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.

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).

[11] This and the other climate data are averaged over a suite of stations from all 11 counties in the valley.

4. Results and Discussion

We first present the correlation between agricultural land-use shares and the climate variables. Second, we present the transition probabilities derived from the logit model conditional on parcel-level characteristics. Third, we present our empirical results from Eq. (1). Specifically, we present the average marginal effects from the fractional multinomial logit regression. Fourth, we perform robustness checks: (1) to address measurement error in land use change CDL data, we limit the sample size for the years 2010–2017; and (2) 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 model, we simulate the changes in land-use shares of perennial and annual crops at the parcel-level to respond future climate projection.

4.1. Correlation between agricultural land-use shares and climate variables

Appendix Figure A4 (a) and (b) present scatter plots showing correlation between the share of perennial and annual crops and climate variables. The correlation between the land use share of perennial crops and climate variables suggests a distinct relationship. For example, the relationship between the share of perennial crops and the degree-days suggests that the share of perennial crops will increase at an increasing rate during summer, while the share of perennial crops will increase at a decreasing rate during winter degree days. The correlation between the share of perennial crops and total annual precipitation is flat for most of the time, but then decreases with an increase in total precipitation. The relationship between perennial crops shares and the accumulated chill hours during winter suggests a decline with an increase in additional chill hours. This may seem counterintuitive. The reason for this may be that the long-term cumulative chill hours for tree crops have already potentially reached their maximum, and any additional chill hours may cause a decrease in yields.[12] In contrast, the land use share of annual crops has decreased in relation to all climate variables. This may indicate that the share of annual crops may decrease more rapidly in the future due to an increase in growing degree days during winter.

4.2. *Transition probabilities*

We disaggregate 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. We choose the years ad hoc so that there is the same number of years for both periods. 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-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.

Appendix Table A4 displays the probability of continuing to grow the same crop in the second period (2015-2021). Average marginal effects are reported from the logit model conditional on an indicator of crops grown in the first period (2008–2014), and current parcel-level characteristics such as climate variables that include degree-days (in summer and winter), total annual

[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.

precipitation, chill hours during winter, and soil quality (an indicator of LCC34 and LCC5678).[13] Column (1) of Appendix Table A4 reports the probability of crops staying in the same state in the second period. The likelihood of a grower cultivating almonds, pistachios, and nuts in the second period is 92%. Similarly, growers are likely to cultivate grapes, citrus, and other subtropical fruits with a probability of 63% and 37%, respectively. In contrast, annual crops have a probability of less than 50% of growing in the second period, except for alfalfa (55% probability of continuing to grow alfalfa). It can be inferred from this that several annual crops have a greater than 50% probability of transitioning to perennial crops. Lastly, land that was fallowed or idled in the first period have an 80% probability of continuing to be fallowed or idled. The likelihood of natural vegetation being in the same state is only 27%.

We repeat the analysis for each land class (LCC12, LCC34, and lCC5678) to construct transition probabilities. Columns 2, 3, and 4 of Appendix Table A4 report the results. The transition probability of high-quality (LCC12) and low-quality (LCC34) land for perennial crops shares is similar to the transition probability for all lands. The transition probability of the lowest quality land (LCC5678) shows that perennial crops have less than 50% probability of continuing to grow the same crop. In the case of grapes, the probability decreased to 10%. Non-cultivated crops (fallowed or idled, and natural vegetation) have more than 50% probability of remaining fallowed or in natural vegetation.

4.3. Empirical Results

Table 2 presents the marginal effects from fractional multinomial logit regression (Eq. 1) evaluated at the mean values. We use the share of non-cultivated crops as the base case. The non-

[13] Using the Stata command *margins*, we obtain the marginal effects evaluated on mean of all covariates used in the analysis.

cultivated crops share includes fallow/idle land as well as natural vegetation. Columns 2 and 4 show marginal effects after the inclusion of the appraisal value of land to account for net returns from the land, and these are our preferred specifications (see Appendix Table A5 for full results). Results suggest that a thousand-units increase in degree days in summer, all else equal, is associated with an average decrease of 50%, and an average increase of 119% for land allocated to perennial and annual crops, respectively. The degree-days in winter are negatively associated with both perennial and annual crop shares, with a 66% decrease in land use share for perennial crops and 53% for annual crops. Long-term annual accumulated precipitation leads to an average increase of 20% in share of perennial crops, while annual crops see an average increase of 6%. The importance of chill hours during winter is greater for perennial crops, and the results indicate that hundred-unit increase in long-term chill winter hours is associated with an average decrease of 12% in land allocated to perennial crops.

The estimated coefficients of dummy variables for low-quality land, which are less suitable for agricultural production, LCC34 and LCC5678, can be interpreted relative to high-quality land. LCC34 and LCC5678 are low-quality lands that show an average of 2% and 29% less land allocated to perennial crops than high-quality land. The allocation of annual crops rises when compared to high-quality land in low-quality lands: 19% in LCC5678. Low-quality lands (LCC34 and LCC5678) are more likely to have fallowed/idled land or natural vegetation.

Figure 1 shows the non-linear relationship between predicted land use shares and changes in long-term degree-days (in summer and winter), total precipitation, and chill hours in winter. Perennial crops' land share has an upward slope for degrees days in summer, while it has a downward slope for degrees days in winter, following the 25th percentile distribution of degrees days. Moreover, perennial crops demonstrate a negative relationship with long-term annual precipitation, as indicated by a downward slope. In contrast, the land shares of annual crops have an inverse U-shaped relationship with degrees of day in summer and winter, and U-shape relationship with long-term annual precipitation. Tree crops experience significant variations in chill hours during winter, where they require 200 and 1500 hours below 7.2 degrees Celsius to produce flowers and fruits. The marginal effects of long-term chill hours on perennial crops, evaluated at various intervals, are negative, and statistically significant. This outcome may be partially influenced by almonds and pistachios, as opposed to other tree crops. Pistachios are quite low-chill, and almonds are not too high (about 500 hours). Other tree crops that have higher chill hours requirements, we would expect them to decline. Dividing perennial crops into almonds, pistachios, nuts, and other tree crops will allow us to examine this hypothesis. Appendix Table A6 presents the average marginal effects of fractional multinomial logit regression. The results suggest that share of almonds, pistachios, and nuts have a negative and statistically significant relationship with long-term degree days in winter, annual precipitation, and chill hours.

4.4. Robustness checks and sensitivity analyses

As mentioned in the data section, the changes in agricultural land use in the CDL cropland time series are more reliable and less uncertain for the years 2010 - 2017. Using the restricted years sample (2010–2017), average partial effects from the fractional multinominal logit regression results, shown in column 1 and 3 of Table 3, suggest that land use shares of perennial crops are positively and negatively associated with long-term degree-days during summer and winter, respectively. The main results show that the share of perennial crops is negatively linked to degree-days in both seasons, which is contrary to this. The estimates of long-term precipitation and chill hours during winter are both positive and negative and are in line with the main results.

In addition, the estimated coefficients of soil attributes and the appraisal value of land are the same as the main results. While the land use shares of annual crops are positively associated with long-term degree days during summer and winter, they are statistically insignificant during summer. The estimated coefficients in the remaining covariates are the same in sign and significance, but larger in magnitude compared to the main results.

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, Plantinga, and Stavins (2008)) have addressed the issue by removing observations that are close together. We address this concern by utilizing parcel locations to establish the average distance between parcels of the five closest neighbors. Then, add this variable to the main specification. Columns 2 and 4 of Table 3 provide an average marginal effect derived from fractional multinomial regression results in columns 2 and 4. The estimated coefficients are similar to the main results in sign, size, and significance.

4.4. 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 land use at the parcel level in the Central Valley of California. 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). We take advantage of georeferenced parcel-level data to project the impacts of climate change on land use decisions at the farm-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. The predictions for climate variables used in our analysis relative to their averages during 1981–2005 are presented in Appendix Table A6. In the Central Valley, the SSP45 and SSP85 scenarios applied shows that the average degree-days in summer and winter in 2031–2055 may be higher than in 1981–2005 by 206 (or 10.06% over the historical mean between 1981 and 2005) and 291 (or 25.94%) days, respectively. The total average annual precipitation in 2031–2055 may increase by 39.4 mm (or 10.37%) relative to 1981–2005. In contrast, the accumulated 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 land-use change 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 gain or loss in the projected climate-driven land use shares of perennial and annual crops: $\left(\frac{\partial E(y_{ji}|\, W_i)}{\partial W_i} * \Delta\overline{W}\right)$; where $\frac{\partial E(y_{ji}|\, W_i)}{\partial W_i}$ is the average marginal effect from fractional multinomial logit regression with respect to climate variables, such as degree-days in summer and winter, annual precipitation, and accumulated chill hours during winter. $\Delta\overline{W}$ represents the difference between the average projected climate variables in 2031–2055 and the average climate variables in 1981–2005 (as shown in the Appendix Table A7).

Table 4 presents the predicted changes in farm-level land-use shares of perennial and annual crops in the SSP45 and SSP585 projected climate scenario. The land-use share of perennial crops decreases by 10% and 19% during summer and winter respectively for projected degree days in the SSP45 climate scenario. The biggest change in the percentage of perennial crops is caused by the accumulation of chill hours in winter, which leads to a 33% increase in land use. This result is puzzling, given the projected decline in cumulative chill hours during winter. However, this result can be explained by the negative correlation between long-term winter chill hours and perennial crops. The shares of annual crops increase for all climate variables except for degree-days during winter. The largest increase in the share of annual crops comes from changes in the degree-days during summer (25%). The smallest decrease in land use shares of annual crops is attributed to an increase in projected total annual precipitation (2%). To sum up, these predicted changes in land-use shares suggest prospects for adaptation to climate change through adjustments in land use.

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 farm-level data, this study provides microlevel evidence of the impact of climate change on land-use shares. This study exploits farm-level variations in crop types to estimate the impact of climate change on irrigated agriculture by shifting crops, which captures growers' behavioral response to long-run adaptation. We developed an econometric model to account for the determinants of land-use decisions at fine spatial scales. We find that growers are switching to perennial crops from annual crops in response to changing climates. Specifically, land-use shares of perennial crops have a negative association with long-term degree-days and winter chill hours, while they have a positive association with precipitation. 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). Land-use shares of annual crops are positively associated with all climate variables, except for degrees-days during winter. By empirically quantifying climate-induced changes in land use shares at farm-level scales, we evaluate the costly adaptation strategies, such as crop switching and fallowing, and contribute to literature on agricultural-climate interactions for California and other water stressed agricultural regions globally.

Tables and Figures

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	0.32	0.41	0	1
Non-cultivated crops share	0.16	0.31	0	1
Long-term climate normals from 27-year moving averages				
Growing Degree Days (thousands, summer)	2.09	0.15	0.59	2.34
Growing Degree Days (thousands, winter)	0.98	0.11	0.04	1.27
Annual Precipitation (100 mm)	3.46	2.09	0.92	21.06
Chill Hours (100 hours, winter)	9.63	1.41	5.26	26.86
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	0.19	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

Notes: 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 list of perennial crops includes almonds, pistachios, and nuts, grapes, citrus, other subtropical fruits, and other tree crops. The list of annual crops includes alfalfa, hay, grains, corn, cotton, tomatoes, safflower, onions, garlic, melons, squash, cucumbers, rice, dry beans, potatoes, other vegetables, berries, and other field crops. 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.

Table 2. Average marginal effects from fractional multinomial logit regression

	Perennial crops		Annual crops	
	[1]	[2]	[3]	[4]
Long-term climate normals from 27-year moving averages				
Growing Degree Days (thousands, summer)	-0.668***	-0.498***	1.253***	1.193***
	(0.051)	(0.051)	(0.053)	(0.052)
Growing Degree Days (thousands, winter)	-0.804***	-0.654***	-0.235***	-0.532***
	(0.065)	(0.065)	(0.063)	(0.063)
Annual Precipitation (100 mm)	0.228***	0.198***	0.033***	0.058***
	(0.005)	(0.005)	(0.005)	(0.004)
Chill Hours (100 hours, winter)	-0.164***	-0.117***	0.111***	0.074***
	(0.002)	(0.002)	(0.002)	(0.002)
Soil Attributes				
Land Capability Class (class 3 or 4)	-0.023***	-0.016***	-0.018***	-0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
Land Capability Class (class 5 through 8)	-0.353***	-0.289***	0.246***	0.189***
	(0.015)	(0.014)	(0.012)	(0.012)
Use-value assessment of agricultural land in California				
Appraisal value of land (dollars per acre)		0.009***		-0.005***
		(0.0003)		(0.0002)
Mean of dependent variable	0.521	0.524	0.325	0.320
Log Likelihood	-571942.54	-527844.16	-571942.54	-527844.16
Number of parcels	49,175	49,175	49,175	49,175
Observations	685,716	657,554	685,716	657,554

Notes:

[1] The dependent variable is agricultural land-use shares (perennial crops are represented in columns 1–2, and annual crops are represented in columns 3–4), with non-cultivated crops being the base case. The list of perennial crops includes almonds, pistachios, and nuts, grapes, citrus, other subtropical fruits, and other tree crops. The list of annual crops includes alfalfa, hay, grains, corn, cotton, tomatoes, safflower,

onions, garlic, melons, squash, cucumbers, rice, dry beans, potatoes, other vegetables, berries, and other field crops.
[2] The explanatory variable includes degree-days, precipitation, and chill hours during winter (and their square terms), and indicators of LCC34 and LCC5678. See Appendix Table A5 for full results.
[3] We follow Chamberlain-Mundlak's approach to estimate fixed effects using the parcel-level averages of each climate and non-climate variable.
[4] Standard errors in parentheses are derived from delta-method and are clustered at the parcel level.
[5] Level of significance: $^{***}p < 0.01$.

Table 3. Robustness checks.

	Perennial crops		Annual crops	
	Restricted sample [1]	Include distance [2]	Restricted sample [3]	Include distance [4]
Long-term climate normals from 27-year moving averages				
Growing Degree Days (thousands, summer)	0.167**	-0.370***	0.045	1.104***
	(0.080)	(0.051)	(0.085)	(0.052)
Growing Degree Days (thousands, winter)	-1.347***	-0.732***	1.942***	-0.487***
	(0.132)	(0.065)	(0.138)	(0.063)
Annual Precipitation (100 mm)	0.158***	0.168***	0.133***	0.073***
	(0.007)	(0.005)	(0.007)	(0.004)
Chill Hours (100 hours, winter)	-0.186***	-0.114***	0.191***	0.072***
	(0.003)	(0.002)	(0.005)	(0.002)
Soil Attributes				
Land Capability Class (class 3 or 4)	-0.018***	-0.010***	-0.028***	-0.030***
	(0.003)	(0.003)	(0.003)	(0.003)
Land Capability Class (class 5 through 8)	-0.273***	-0.272***	0.183***	0.180***
	(0.014)	(0.014)	(0.012)	(0.011)
Use-value assessment of agricultural land in California				
Appraisal value of land (dollars per acre)	0.008***	0.009***	-0.004***	-0.005***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Average distance between parcels of the five nearest neighbors				
Distance (meter)		-0.0002***		0.0001***
		(5.80e-06)		(4.77e-06)
Mean of dependent variable	0.500	0.524	0.331	0.320
Log Likelihood	-331034.73	-518204.40	-331034.73	-518204.40
Number of parcels	50,730	49,175	50,730	49,175

Observations	403,805	657,554	403,805	657, 554

Notes:

[1] The dependent variable is agricultural land-use shares, with non-cultivated crops being the base case. See Table 2 for more details.

[2] Column 1 and 3 represent the average marginal effects for the years 2010-2017. Column 2 and 4 include the average distance between parcels of the five closest neighbors.

[2] Standard errors in parentheses are derived from delta-method and are clustered at the parcel level.

[3] Level of significance: $^{***}p < 0.01$, $^{**}p < 0.05$.

Table 4. 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
Growing Degree Days (thousands, summer)	-10.22%	24.58%	-9.32%	22.43%
Growing Degree Days (thousands, winter)	-19.26%	-15.48%	-21.32%	-17.13%
Annual Precipitation (100 mm)	7.84%	2.29%	8.06%	2.35%
Chill Hours (100 hours, winter)	33.26%	21.04%	38.77%	24.52%

Note: 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 and the difference between the average projected climate in 2031-2055 and the average climate in 1981-2005.

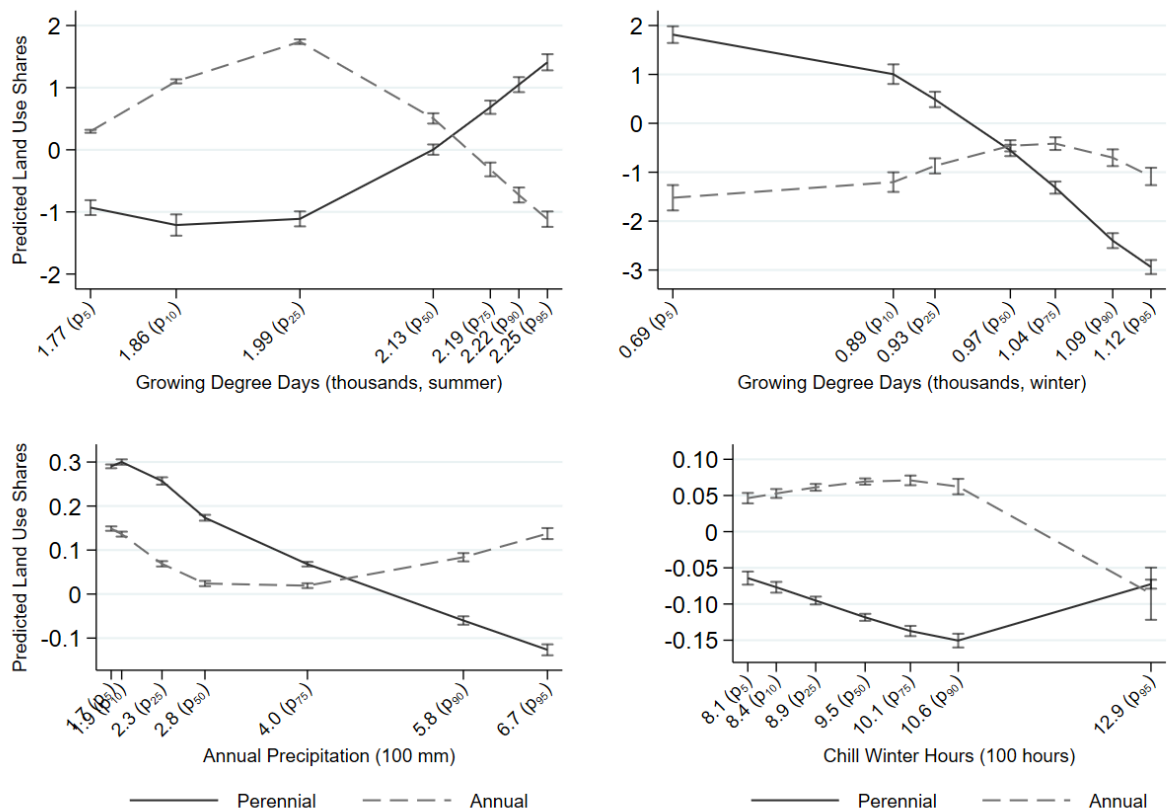


Figure 1. Relationship between predicted land use shares and long-term climate variables.

Note: 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 cap represents the 95% confidence intervals. The x-axis has brackets representing the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles

References

Anderson, John E, and Marlon F Griffing. 2000. "Use-Value Assessment Tax Expenditures in Urban Areas." *Journal of Urban Economics* 48 (3): 443–52. https://doi.org/10.1006/juec.2000.2175.

Arora, Gaurav, Hongli Feng, Christopher J. Anderson, and David A. Hennessy. 2020. "Evidence of Climate Change Impacts on Crop Comparative Advantage and Land Use." *Agricultural Economics* 51 (2): 221–36. https://doi.org/10.1111/agec.12551.

Baldocchi, Dennis, and Simon Wong. 2008. "Accumulated Winter Chill Is Decreasing in the Fruit Growing Regions of California." *Climatic Change* 87 (S1): 153–66. https://doi.org/10.1007/s10584-007-9367-8.

Boryan, Claire, Zhengwei Yang, Rick Mueller, and Mike Craig. 2011. "Monitoring US Agriculture: The US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program." *Geocarto International* 26 (5): 341–58. https://doi.org/10.1080/10106049.2011.562309.

Boser, Anna, Kelly Caylor, Ashley Larsen, Madeleine Pascolini-Campbell, John T. Reager, and Tamma Carleton. 2024. "Field-Scale Crop Water Consumption Estimates Reveal Potential Water Savings in California Agriculture." *Nature Communications* 15 (1): 2366. https://doi.org/10.1038/s41467-024-46031-2.

Buis, Maarten L. 2008. "FMLOGIT: Stata Module Fitting a Fractional Multinomial Logit Model by Quasi Maximum Likelihood." https://ideas.repec.org/c/boc/bocode/s456976.html.

Cho, Sung Ju, and Bruce A. McCarl. 2017. "Climate Change Influences on Crop Mix Shifts in the United States." *Scientific Reports* 7 (1): 40845. https://doi.org/10.1038/srep40845.

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

Jackson, Louise, Van R Haden, Stephen M Wheeler, Allan D Hollander, Josh Perlman, Toby O'Geen, Vishal K Mehta, Victoria Clark, and John Williams. 2012. "VULNERABILITY AND ADAPTATION TO CLIMATE CHANGE IN CALIFORNIA AGRICULTURE." *UC Berkeley: California Institute for Energy and Environment (CIEE)*, Climate Change, .

Jessoe, Katrina, Pierre Mérel, and Ariel Ortiz. 2021. "Chapter 16. Climate Change and California Agriculture." *University of California: Giannini Foundation and Division of Agriculture and Natural Resources*.

Jiang, Chongya, Kaiyu Guan, Madhu Khanna, Luoye Chen, and Jian Peng. 2021. "Assessing Marginal Land Availability Based on Land Use Change Information in the Contiguous United States." *Environmental Science & Technology* 55 (15): 10794–804. https://doi.org/10.1021/acs.est.1c02236.

Laingen, Chris. 2015. "Measuring Cropland Change: A Cautionary Tale." *Papers in Applied Geography* 1 (1): 65–72. https://doi.org/10.1080/23754931.2015.1009305.

Lark, Tyler J., Richard M. Mueller, David M. Johnson, and Holly K. Gibbs. 2017. "Measuring Land-Use and Land-Cover Change Using the U.S. Department of Agriculture's Cropland Data Layer: Cautions and Recommendations." *International Journal of Applied Earth Observation and Geoinformation* 62 (October):224–35. https://doi.org/10.1016/j.jag.2017.06.007.

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

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

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

Lobell, David B., and Christopher B. Field. 2011. "California Perennial Crops in a Changing Climate." *Climatic Change* 109 (S1): 317–33. https://doi.org/10.1007/s10584-011-0303-6.

Lobell, David B., Angela Torney, and Christopher B. Field. 2011. "Climate Extremes in California Agriculture." *Climatic Change* 109 (S1): 355–63. https://doi.org/10.1007/s10584-011-0304-5.

Lubowski, Ruben N, Andrew J Plantinga, and Robert N Stavins. 2008. "What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions." *Land Economics*.

Mu, Jianhong E., Bruce A. McCarl, Benjamin Sleeter, John T. Abatzoglou, and Hongliang Zhang. 2018. "Adaptation with Climate Uncertainty: An Examination of Agricultural Land Use in the United States." *Land Use Policy* 77 (September):392–401. https://doi.org/10.1016/j.landusepol.2018.05.057.

Mu, Jianhong E., Benjamin M. Sleeter, John T. Abatzoglou, and John M. Antle. 2017. "Climate Impacts on Agricultural Land Use in the USA: The Role of Socio-Economic Scenarios." *Climatic Change* 144 (2): 329–45. https://doi.org/10.1007/s10584-017-2033-x.

Mundlak, Yair. 1978. "On the Pooling of Time Series and Cross Section Data." *Econometrica* 46 (1): 69. https://doi.org/10.2307/1913646.

Pathak, Tapan, Mahesh Maskey, Jeffery Dahlberg, Faith Kearns, Khaled Bali, and Daniele Zaccaria. 2018. "Climate Change Trends and Impacts on California Agriculture: A Detailed Review." *Agronomy* 8 (3): 25. https://doi.org/10.3390/agronomy8030025.

Ramsey, Steven M., Jason S. Bergtold, and Jessica L. Heier Stamm. 2021. "Field-Level Land-Use Adaptation to Local Weather Trends." *American Journal of Agricultural Economics* 103 (4): 1314–41. https://doi.org/10.1111/ajae.12157.

Reitsma, Kurtis D., David E. Clay, Sharon A. Clay, Barry H. Dunn, and Cheryl Reese. 2016. "Does the U.S. Cropland Data Layer Provide an Accurate Benchmark for Land-Use Change Estimates?" *Agronomy Journal* 108 (1): 266–72. https://doi.org/10.2134/agronj2015.0288.

Thrasher, Bridget, Weile Wang, Andrew Michaelis, Forrest Melton, Tsengdar Lee, and Ramakrishna Nemani. 2022. "NASA Global Daily Downscaled Projections, CMIP6." *Scientific Data* 9 (1): 262. https://doi.org/10.1038/s41597-022-01393-4.

Thrasher, Bridget, Weile Wang, Andrew Michaelis, and Ramakrishna Nemani. 2021. "NASA Earth Exchange Global Daily Downscaled Projections - CMIP6." NASA Center for Climate Simulation. https://doi.org/10.7917/OFSG3345.

"U.S. Bureau of Economic Analysis." 2024. , Gross domestic product (chain-type price index)retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/A191RG3A086NBEA.

USPAP. 2010. *Uniform Standards of Professional Appraisal Practice*. 2010/2011 ed. Washington, DC: Appraisal Standards Board, The Appraisal Foundation.

Walkinshaw, Mike, A.T. O'Green, and D.E. Beaudette. 2023. "Soil Properties." California Soil Resource Lab. casoilresource.lawr.ucdavis.edu/soil-properties/.

Wimmer, Stefan, Christian Stetter, Jonas Schmitt, and Robert Finger. 2024. "Farm-level Responses to Weather Trends: A Structural Model." *American Journal of Agricultural Economics* 106 (3): 1241–73. https://doi.org/10.1111/ajae.12421.

Wooldridge, Jeffrey M. 2019. "Correlated Random Effects Models with Unbalanced Panels." *Journal of Econometrics* 211 (1): 137–50. https://doi.org/10.1016/j.jeconom.2018.12.010.

Appendix A: Tables and Figures

Appendix Table A1. Definition of land cover types

Category	Crops	CDL code and land cover type
Perennial	Almonds, pistachios, and nuts	74 Pecans, 75 Almonds, 76 Walnuts, 204 Pistachios
	Grapes	69 Grapes
	Citrus, other subtropical fruit	72 Citrus, 215 Avocados, 212 Oranges
	Other tree crops	70 Christmas Trees, 71 Other Tree Crops, 211 Olives, 223 Apricots, 66 Cherries, 67 Peaches, 68 Apples, 77 Pears, 210 Prunes, 220 Plums
Annual	Alfalfa	36 Alfalfa
	Grains	4 Sorghum, 5 Soybeans, 6 Sunflowers, 12 Sweet Corn, 13 Pop or Orn Corn, 21 Barley, 22 Durum wheat, 23 Spring wheat, 24 Winter wheat, 25 Other small grains, 26 Dbl Crop Win wht/Soy, 27 Rye, 28 Oats, 29 Millet, 30 Speltz, 31 Canola, 32 Flaxseed, 34 Rape seed, 35 Mustard, 38 Camelina, 39 Buckwheat, 51 Chick Peas, 52 Lentils, 53 Peas, 225 Dbl Crop Win wht/corn, 226 Dbl Crop Oats/Corn, 228 Dbl Crop Triticale/Corn, 230 Dbl Crop lettuce/Durum wht, 234 Dbl Crop Durum wht/Sorghum, 235 Dbl Crop Barley/Sorghum, 236 Dbl Crop Winwht/Sorghum, 237 Dbl Crop Barley/Corn, 238 Dbl Crop Winwht/Cotton, 239 Dbl Crop Soy/Cotton, 240 Dbl Crop Soy/Oats, 241 Dbl Crop Corn/Soy, 254 Dbl Crop Barley/Soy
	Corn	1 Corn
	Cotton	2 Cotton
	Tomatoes	54 Tomatoes
	Safflower	33 Safflower
	Onions, garlic	49 Onions, 208 Garlic
	Melons, squash, cucumbers	48 Watermelon, 50 Cucumbers, 213 Honeydew, 209 Cantaloupes, 222 Squash
	Rice	3 Rice
	Dry beans	42 Dry beans
	Potatoes	43 Potatoes
	Other vegetables, berries	14 Mint, 41 Sugar beets, 46 Sweet Potatoes, 47 Misc Vegs&Fruit, 55 Caneberries, 57 Herbs, 206 Carrots, 207 Asparagus, 214 Broccoli, 216 Peppers, 217 Pomegranates, 218 Nectarines, 219 Greens, 220 Plums, 221 Strawberries, 227 Lettuce, 229 Pumpkins, 242 Blueberries, 243 Cabbage, 244

		Cauliflower, 245 Celery, 246 Radishes, 247 Turnips, 248 Eggplants, 249 Gourds, 250 Cranberries
	Other field crops	10 Peanuts, 11 Tobacco, 44 Other Crops, 45 Sugarcane, 56 Hops, 205 Triticale, 224 Vetch, 232 Dbl Crop Lettuce/cotton, 233 Dbl Crop Lettuce/Barley
	Hay	37 Other hay/non Alfalfa, 58 Clover/Wildflowers, 59 Sod/Grass Seed, 60 Switchgrass
Non-cultivated crops	Fallow/Idle	61 Fallow/Idle cropland
	Natural vegetation	62 Pasture/Grass, 63 Forest, 64 Shrubland, 141 Deciduous Forest, 142 Evergreen Forest, 143 Mixed Forest, 152 Shrubland

Appendix Table A2. Agricultural land-use share, climate normals, soil attributes, use-value assessment, and year in the study region

Variable	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Perennial crops share	0.48	0.47	0.43	0.46	0.47	0.51	0.52	0.52	0.54	0.57	0.54	0.56	0.62	0.62
Annual crops share	0.38	0.33	0.42	0.36	0.36	0.34	0.32	0.28	0.28	0.28	0.29	0.30	0.27	0.26
Non-cultivated crops share	0.14	0.20	0.15	0.18	0.17	0.15	0.16	0.20	0.18	0.15	0.17	0.14	0.11	0.12
GDD (thousands, summer)	2.08	2.14	2.08	2.08	2.07	2.07	2.07	2.08	2.08	2.09	2.09	2.10	2.10	2.11
GDD (thousands, winter)	0.98	1.01	0.98	0.97	0.97	0.97	0.97	0.98	0.99	0.99	1.00	0.99	1.00	1.00
Precipitation (100 mm)	3.63	2.91	3.49	3.43	3.47	3.51	3.42	3.41	3.39	3.46	3.53	3.51	3.55	3.44
Chill Hours (100 hours, winter)	10.06	10.04	10.02	10.07	9.98	10.00	9.88	9.70	9.54	9.37	9.25	9.14	9.03	8.92
LCC12	0.56	0.53	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
LCC34	0.40	0.44	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
LCC5678	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Appraisal value of land (thousand dollars per acre)	5.15	4.67	5.31	5.49	5.94	6.19	6.57	7.04	7.59	8.15	8.68	9.45	10.04	11.16
Observations	48,932	21,037	48,579	49,051	48,972	48,906	48,966	48,982	48,977	48,971	49,020	48,976	49,029	49,082

Appendix Table A3. Crop-specific land-use shares by land quality and period in the study region.

	All lands		High-Quality LCC12		Low-Quality LCC34		Low-Quality LCC5678	
	2008–2014	2015–2021	2008–2014	2015–2021	2008–2014	2015–2021	2008–2014	2015–2021
A. Land shares allocated to perennial crops (%)								
Almonds, pistachios, and nuts	22.27	30.16	26.42	35.33	18.13	25.20	6.64	8.10
Grapes	12.04	13.34	13.46	14.57	11.16	12.83	1.11	1.46
Citrus, other subtropical fruit	9.25	8.94	4.46	4.38	16.57	15.98	1.37	1.39
Other tree crops	4.25	4.25	4.10	4.35	4.75	4.38	1.15	1.56
Total perennial crops	**47.81**	**56.68**	**48.45**	**58.62**	**50.63**	**58.39**	**10.27**	**12.52**
B. Land shares allocated to annual crops (%)								
Alfalfa	9.88	5.71	11.66	6.78	8.36	4.76	0.64	0.47
Grains	10.24	8.29	11.81	9.52	8.98	7.34	1.22	0.74
Corn	2.22	1.34	2.76	1.62	1.67	1.07	0.33	0.20
Cotton	3.38	2.47	4.18	2.98	2.60	2.00	0.06	0.02
Tomatoes	2.62	2.52	3.37	3.21	1.85	1.81	0.05	0.08
Safflower	0.38	0.25	0.44	0.27	0.34	0.25	0.08	0.03
Onions, garlic	0.41	0.44	0.52	0.51	0.30	0.39	0.001	0.007
Melons, squash, cucumbers	0.26	0.32	0.35	0.39	0.17	0.24	0.04	0.01
Rice	3.57	3.30	0.99	0.81	4.56	4.26	29.40	28.18
Dry beans	0.12	0.13	0.16	0.16	0.08	0.08	0.01	0.01
Potatoes	0.16	0.12	0.17	0.13	0.16	0.13	0.01	0.007
Other vegetables, berries	1.72	1.82	1.87	2.03	1.62	1.65	0.57	0.67
Other field crops	0.25	0.39	0.26	0.40	0.25	0.40	0.17	0.07
Hay	0.89	1.10	0.89	1.13	0.89	1.12	0.77	0.60
Total annual crops	**36.11**	**28.21**	**39.44**	**29.96**	**31.83**	**25.51**	**33.34**	**31.11**
C. Non-cultivated land shares (%)								
Fallow/Idle	10.81	10.03	10.24	9.71	11.67	10.35	10.04	11.31
Natural vegetation	5.26	5.08	1.87	1.71	5.87	5.76	46.35	45.06

Total non-cultivated crops	**16.08**	**15.11**	**12.11**	**11.42**	**17.54**	**16.12**	**56.39**	**56.38**
Parcel size (in acre)	77.14	77.09	69.77	69.48	76.92	77.25	182.24	181.08
Number of parcels	49,175	49,175	27,391	27,391	19,822	19,822	1,962	1,962
Observations	314,432	343,122	174,492	191,057	127,421	138,333	12,519	13,732

Notes: Mean value is reported. Land-use shares are formed by dividing each crop's share within a parcel by its total cropland. A parcel from our sample may be associated with one or more crops. The natural vegetation consists of pastures/grass, deciduous and evergreen forest covers, and shrubland.

Appendix Table A4. Transition probabilities for crop choice

	Crop in 2015–2021			
	Probability of continuing to grow the same crop			
		High-Quality	Low-Quality	
Crop in 2008–2014	All Lands	LCC12	LCC34	LCC5678
	[1]	[2]	[3]	[4]
A. Perennial crops				
Almonds, pistachios, and nuts	0.917***	0.953***	0.914***	0.443***
	(0.001)	(0.001)	(0.001)	(0.007)
Grapes	0.625***	0.675***	0.608***	0.098***
	(0.002)	(0.002)	(0.003)	(0.005)
Citrus, other subtropical fruit	0.369***	0.349***	0.423***	0.101***
	(0.002)	(0.002)	(0.003)	(0.007)
Other tree crops	0.623***	0.661***	0.607***	0.253***
	(0.002)	(0.002)	(0.003)	(0.005)
B. Annual crops				
Alfalfa	0.552***	0.606***	0.506***	0.262***
	(0.002)	(0.002)	(0.003)	(0.008)
Grains	0.693***	0.732***	0.673***	0.345***
	(0.002)	(0.002)	(0.003)	(0.008)
Corn	0.394***	0.436***	0.360***	0.160***
	(0.002)	(0.003)	(0.003)	(0.007)
Cotton	0.308***	0.323***	0.268***	0.059***
	(0.002)	(0.002)	(0.003)	(0.005)
Tomatoes	0.385***	0.401***	0.330***	0.302***
	(0.002)	(0.002)	(0.002)	(0.007)
Safflower	0.169***	0.174***	0.150***	0.104***
	(0.001)	(0.002)	(0.002)	(0.006)
Onions, garlic	0.163***	0.180***	0.156***	0.033***
	(0.001)	(0.002)	(0.002)	(0.005)
Melons, squash, cucumbers	0.166***	0.182***	0.153***	0.068***
	(0.001)	(0.002)	(0.002)	(0.005)
Rice	0.106***	0.081***	0.112***	0.409***
	(0.001)	(0.001)	(0.001)	(0.004)
Dry beans	0.114***	0.120***	0.106***	0.111***
	(0.001)	(0.002)	(0.002)	(0.006)
Potatoes	0.034***	0.040***	0.030***	0.016***
	(0.001)	(0.001)	(0.001)	(0.003)
Other vegetables, berries	0.590***	0.643***	0.554***	0.222***
	(0.002)	(0.002)	(0.003)	(0.006)
Other field crops	0.252***	0.268***	0.242***	0.125***
	(0.002)	(0.002)	(0.003)	(0.007)
Hay	0.340***	0.359***	0.324***	0.221***
	(0.002)	(0.002)	(0.003)	(0.007)
C. Non-cultivated crops				
Fallow/Idle	0.795***	0.820***	0.785***	0.537***
	(0.001)	(0.002)	(0.002)	(0.004)
Natural vegetation	0.270***	0.241***	0.279***	0.559***

	(0.002)	(0.002)	(0.003)	(0.005)
Observations	49,175	27,391	19,822	1,962

Note:
[1] The dependent variables are the binary crop choices grown on average from 2015 to 2021 in the Central Valley.
[2] Average marginal effects are reported from the logit model conditional on an indicator of crops grown in the previous period (2008–2014), and current parcel-level characteristics such as climate variables that include degree-days (in summer and winter), total annual precipitation, and chill hours during winter and soil quality (an indicator of LCC34 and LCC5678).
[3] Standard errors in parentheses are clustered at parcel-level and derived from delta-methods.
[4] Level of significance: $^{***}p < 0.01$.

Appendix Table A5. Coefficients from fractional multinomial logit regression

	Perennial crops		Annual crops	
	[1]	[2]	[3]	[4]
Long-term climate normals from 27-year moving averages				
Growing Degree Days (thousands, summer)	-47.924***	-53.980***	134.4173***	138.557***
	(5.074)	(5.167)	(4.963)	(5.009)
Growing Degree Days (thousands, winter)	60.339***	65.738***	16.151***	6.486***
	(4.329)	(4.485)	(4.499)	(4.484)
Annual Precipitation (100 mm)	4.952***	4.679***	3.363***	3.428***
	(0.088)	(0.089)	(0.077)	(0.078)
Chill Hours (100 hours, winter)	2.851***	2.407***	1.280***	1.666***
	(0.247)	(0.253)	(0.207)	(0.207)
Growing Degree Days square (thousands, summer)	12.290***	13.982***	-30.021***	-30.761***
	(1.208)	(1.227)	(1.184)	(1.191)
Growing Degree Days square (thousands, winter)	-35.559***	-38.734***	-12.787***	-9.063***
	(2.167)	(2.228)	(2.285)	(2.267)
Annual Precipitation square (100 mm)	-0.333***	-0.302***	-0.156***	-0.159***
	(0.008)	(0.008)	(0.007)	(0.007)
Chill Hours square (100 hours, winter)	-0.197***	-0.165***	-0.074***	-0.096***
	(0.013)	(0.014)	(0.011)	(0.011)
Soil Attributes				
Land Capability Class (class 3 or 4)	-0.485***	-0.441***	-0.479***	-0.496***
	(0.021)	(0.021)	(0.021)	(0.021)
Land Capability Class (class 5 through 8)	-1.781***	-1.631***	-0.139***	-0.228***
	(0.075)	(0.077)	(0.054)	(0.055)
Use-value assessment of agricultural land in California				
Appraisal value of land (dollars per acre)		0.056***		0.015***
		(0.002)		(0.002)
Parcel-level mean of time varying variables				
Growing Degree Days mean (thousands, summer)	-6.056***	-5.867***	-39.029***	-40.157***
	(0.674)	(0.707)	(0.785)	(0.795)
Growing Degree Days mean (thousands, winter)	28.397***	26.976***	70.887***	72.688***
	(1.206)	(1.251)	(1.417)	(1.424)
Annual Precipitation mean (100 mm)	-1.632***	-1.672***	-1.572***	-1.624***
	(0.040)	(0.041)	(0.042)	(0.043)
Chill Hours mean (100 hours, winter)	1.945***	1.617***	2.916***	2.921***
	(0.054)	(0.057)	(0.062)	(0.063)
Mean of appraisal value of land (dollars per acre)		0.019***		-0.034***
		(0.003)		(0.002)
Mean of dependent variable	0.521	0.524	0.325	0.320
Log Likelihood	-571942.54	-527844.16	-571942.54	-527844.16
Number of parcels	49,175	49,175	49,175	49,175
Observations	685,716	657,554	685,716	657,554

Notes:

[1] The dependent variable is agricultural land-use shares (perennial crops are represented in columns 1–2, and annual crops are represented in columns 3–4), with non-cultivated crops being the base case.

[2] Standard errors in parentheses are clustered at the parcel level. Level of significance: $^{***}p < 0.01$.

Appendix Table A6. Average marginal effects from fractional multinomial logit regression: The share of perennial crops is divided into almonds, pistachios, nuts, and other tree crops

	Almonds, pistachios, and nuts [1]	Other tree crops [2]	Annual crops [3]
Long-term climate normals from 27-year moving averages			
Growing Degree Days (thousands, summer)	0.048	-0.488***	1.098***
	(0.049)	(0.044)	(0.051)
Growing Degree Days (thousands, winter)	-1.325***	0.335***	-0.274***
	(0.062)	(0.047)	(0.063)
Annual Precipitation (100 mm)	-0.156***	0.348***	0.063***
	(0.005)	(0.005)	(0.004)
Chill Hours (100 hours, winter)	-0.113***	-0.013***	0.078***
	(0.002)	(0.002)	(0.002)
Soil Attributes			
Land Capability Class (class 3 or 4)	-0.061***	0.035***	-0.021***
	(0.003)	(0.002)	(0.003)
Land Capability Class (class 5 through 8)	-0.306***	0.030**	0.185***
	(0.014)	(0.014)	(0.011)
Use-value assessment of agricultural land in California			
Appraisal value of land (dollars per acre)	0.006***	0.002***	-0.005***
	(0.0002)	(0.0001)	(0.0002)
Mean of dependent variable	0.264	0.261	0.319
Log Likelihood	-717262.23	-717262.23	-717262.23
Number of parcels	49,175	49,175	49,175
Observations	658,830	658,830	658,830

Notes:

[1] The dependent variable is agricultural land-use shares (perennial crops are represented in columns 1–2, and annual crops are represented in columns 3), with non-cultivated crops being the base case.

[2] The explanatory variable includes degree-days, precipitation, and chill hours during winter (and their square terms), and indicators of LCC34 and LCC5678.

[3] We follow Chamberlain-Mundlak's approach to estimate fixed effects using the parcel-level averages of each climate and non-climate variable.

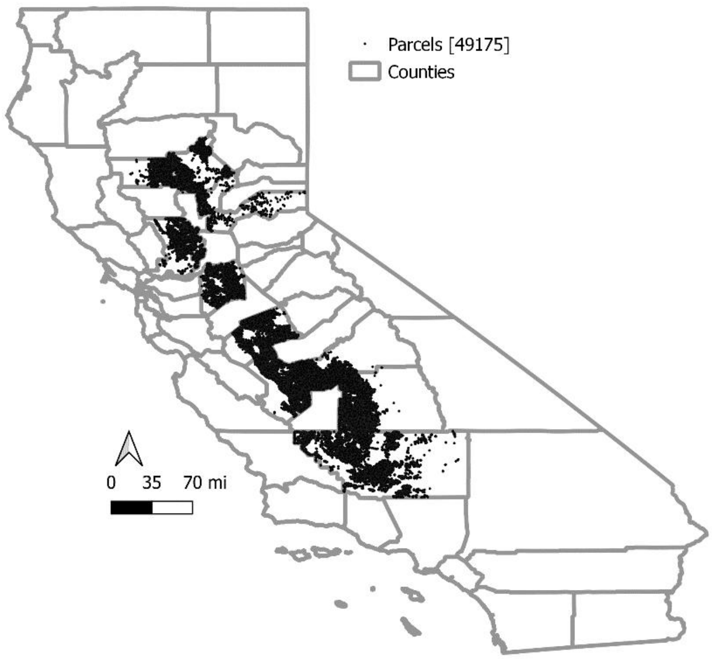
[4] Standard errors in parentheses are derived from delta-method and are clustered at the parcel level.

[5] Level of significance: $^{***}p < 0.01$ and $^{**}p < 0.05$.

Appendix Table A7. Predicted changes in climate variables compared to the average during 1981–2005.

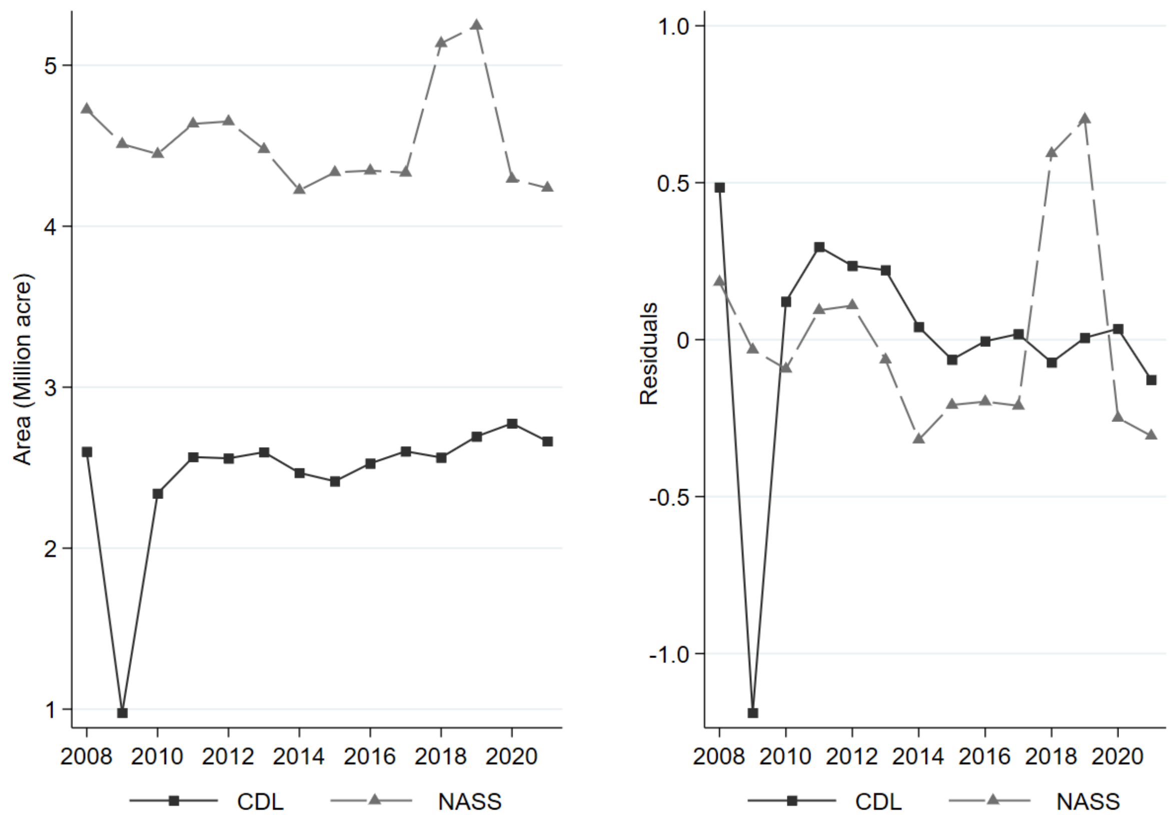
	SSP45			SSP585	
	1981–2005 (1)	2031–2055 (2)	Difference (2) - (1)	2031–2055 (3)	Difference (3) - (1)
Growing Degree Days (thousands, summer)	2.048	2.254	0.206	2.236	0.188
Growing Degree Days (thousands, winter)	1.122	1.413	0.291	1.444	0.322
Annual Precipitation (100 mm)	3.801	4.195	0.394	4.206	0.405
Chill Hours (100 hours, winter)	7.357	4.514	-2.843	4.043	-3.314

Note: Mean values are reported.



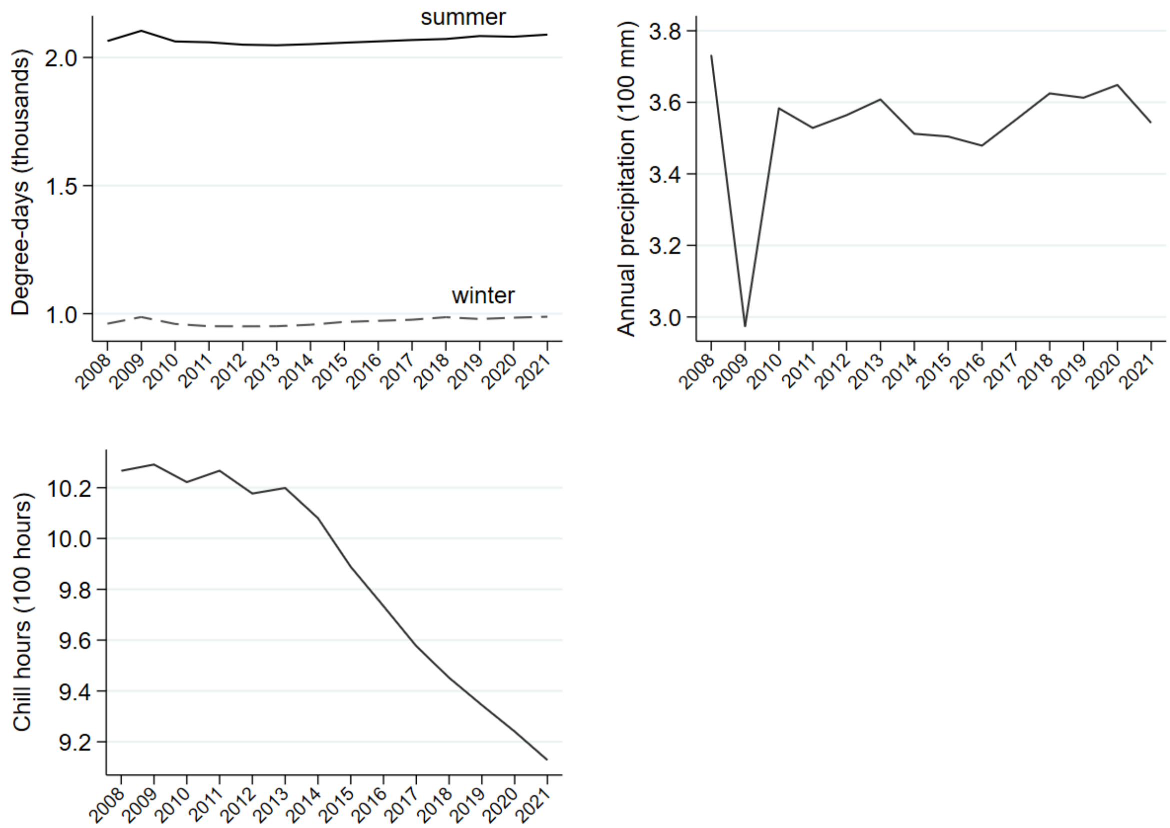
Appendix Figure A1: Selected parcels from 2008 to 2021 in the Central Valley of California.

Notes: The figure shows the selected parcels as dots. The county boundaries are shown in gray lines.



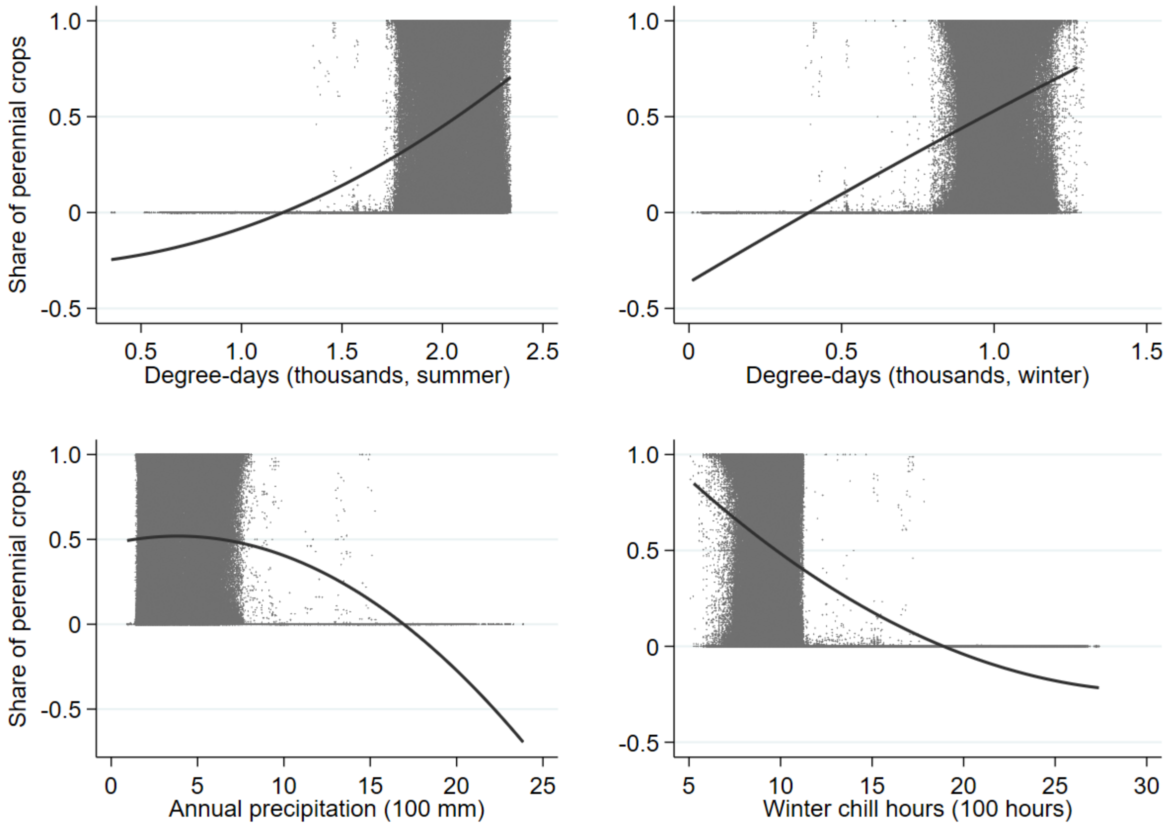
Appendix Figure A2. Cropland acreage trends in CDL and NASS datasets from 2008 to 2021.

Note: We present a time series of total cropland from perennial and annual crops acreage from the CDL and harvested acres from the NASS datasets on the left. On the right, we present the time series of detrended CDL cropland area and detrended time series of NASS cropland area.



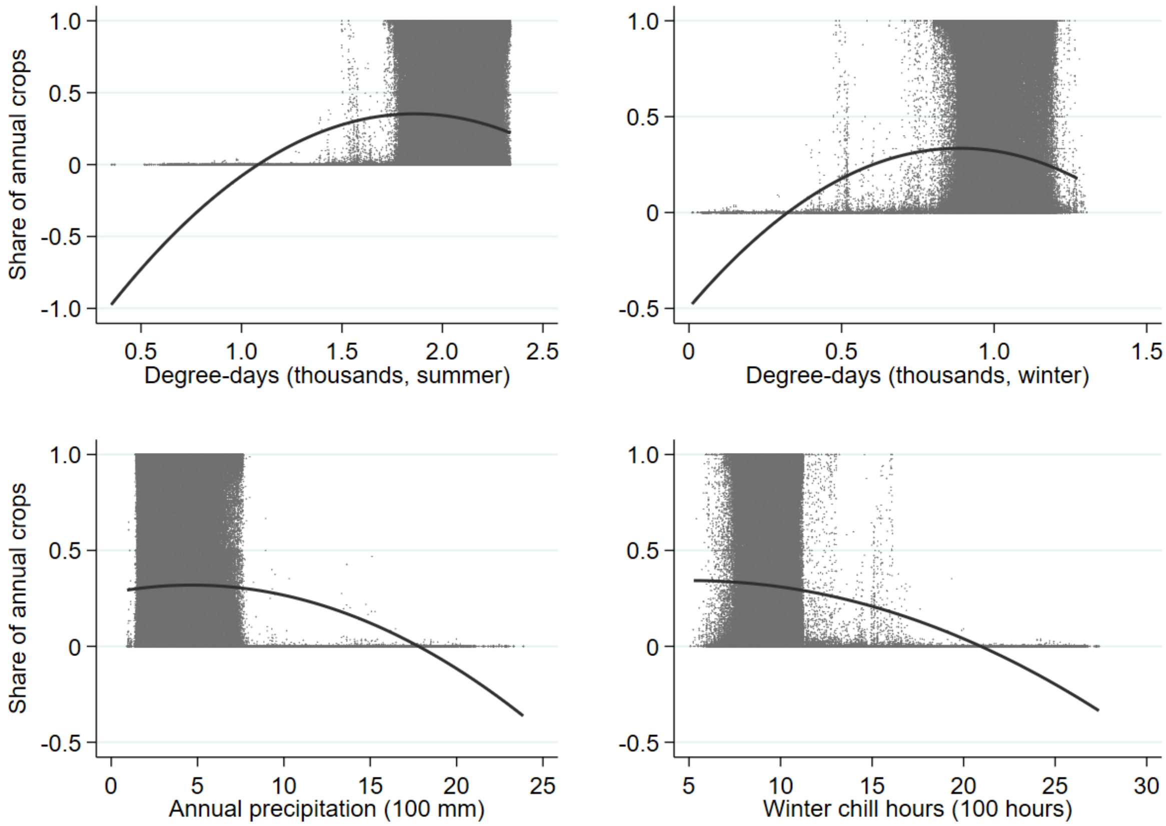
Appendix Figure A3: Trends in the long-term climate variables.

Notes: We aggregated the long-term (27-years moving average) climate variables and reported the mean values by year.



Appendix Figure A4a: Scatter plot for the correlation between the share of perennial crops and climate variables.

Notes: The dots represent the share of perennial crops, and the dark line represents the quadratic fit values. The farmlands are located in 11 counties of the Central Valley.



Appendix Figure A4b: Scatter plot for the correlation between the share of annual crops and climate variables.

Notes: The dots represent the share of perennial crops, and the dark line represents the quadratic fit values. The farmlands are located in 11 counties of the Central Valley. The correlation between the long-term accumulated chill hours during winter and the share of annual crops has no agronomic significance, we present them only to finish the graphs.

Appendix B: Variable Construction

Agricultural Land use share:

Mathematically, the share of land use S of parcel i for each crop type $k \in K = \{perennial, annual, noncultivated\}$ at time $t \in \{2008, \dots, 2021\}$ is calculated as: $S_{it}^{k} = \frac{l_{it}^{k}}{\sum_k l_{it}^{k}}$ where l_{it}^{k} is the land in acres of parcel i for crop type k at time t. The value of land share can vary between zero and one.

Growing Degree Days:

Following the previous literature, we calculate growing degree days as follows:

$$\sum_{d}^{D} GDD(T_{mean,d}) = \begin{cases} 0, if\ T_{mean,d} \leq 8 \\ T_{mean,d} - 8, if\ 8 < T_{mean,d} \leq 32 \\ 0, if\ T_{mean,d} > 32 \end{cases}$$

where $T_{mean,d}$ is the mean daily temperature in degree Celsius. The subscript, d indicates the days of different seasons. Winter starts on November 1 and ends on February 28 of the next year, and summer starts on April 1 and ends on August 31.

Chill Hours:

We follow Jackson et al., (2012) to calculate the daily chill hours using the daily minimum temperature ($tmin$), mean temperature ($tavg$), daily maximum temperature ($tmax$), and the reference temperature ($t_{ref} = 7.22$ degrees Celsius). The daily chill hour for parcel i in time t is calculated as follows:

$Chillhour_{it} = 0\ if\ t_{ref} < tmin$ or

$ChillHour_{it} = 12 * \left(\frac{t_{ref} - tmin}{tavg - tmin}\right)\ if\ t_{ref} < tavg$ or

$ChillHour_{it} = 12 + 12 * \left(\frac{t_{ref} - tavg}{tmax - tavg}\right)\ if\ t_{ref} > tavg$ or

$ChillHour_{it} = 24\ if\ t_{ref} > tmax.$

We then sum up the daily chill hours during the winter (November through February) in a given year. We calculate the 27-year normal for chill hours during winter for our analysis.