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Economics of downscaled climate-induced changes in cropland, with projections to 2050: evidence from Yolo County California

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Abstract This article establishes quantitative relationships between the evolution of climate and cropland using daily climate data for a century and data on allocation of land across crops for six decades in a specific agro-climatic region of California. These relationships are applied to project how climate scenarios reported by the Intergovernmental Panel on Climate Change would drive cropland patterns into 2050. Projections of warmer winters, particularly from 2035 to 2050, cause lower wheat area and more alfalfa and tomato area. Only marginal changes in area were projected for tree and vine crops, in part because although lower, chill hours remain above critical values.

1 Introduction

Hundreds of previous studies have investigated climate effects on agriculture on a global or national basis (Adams et al. 1990; Schlenker et al. 2006; Lobell et al. 2011b). Of course, climate factors relevant to agriculture vary by crop and geography, and for a diverse cropping system regional and crop aggregation is particularly troublesome (Lobell and Field 2011). Our study of Yolo County, California, develops climate-cropland relationships using micro climate information well suited to link to an array of specific crops. Based on 100 years of local climate history and 60 years of county cropland data, we establish statistical relationships between climate change and changes in cropping patterns. These relationships are then applied to assess how down-scaled climate projections constructed under the scenarios of the Intergovernmental Panel on Climate Change (IPCC) affect cropland patterns projected into the future (Trenberth et al. 2007).

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A few studies examining regional-scale data in California may be highlighted. Baldocchi and Wong (2008) and Luedeling et al. (2009) projected substantial loss in chill hours, which are needed for many tree crops, by the end of the century. Lobell and Field (2011) investigated the climate impacts on California perennial crop yields using data with classification of 20 crops and monthly average temperatures. The overall effects of climate have been mixed, with some distinct negative yield effects found for cherries. Deschenes and Kolstad (2011) examined the relationships between profits and climate change for a number of California crops, and projected the overall negative effect of climate change on crop profits by the end of the century. Schlenker et al. (2007) examined implications for farmland values in California, but their results apply much more to those regions with irrigation water supplied by the Sierra Nevada Mountain snow pack.

Our study uncovers crop-climate relationships using detailed characterizations of climate for Yolo County, California. Focusing on a single county allows us to uncover detailed responses of cropland adjustments to detailed climate outcomes and projections that would not be feasible for a larger area. Our choice of Yolo County, California, lets us to investigate historical climate impacts in an especially diverse agricultural environment in which more than a dozen significant crops compete for land and water resources. Cropland in Yolo County, which is almost all irrigated, is devoted to trees and vines, vegetables and field crops with different seasonal cycles. Climate variables are constructed to reflect the specific growing conditions of these crops and include precipitation, growing degree days for spring/summer growing crops, growing degree days for winter/spring growing crops, and winter chill hours. A significant contribution of the present paper is to document that impacts of climate change for cropland patterns may depend on very local conditions and how these climate impacts alone may affect patterns of cropland use across crops over a horizon.

Econometric models can relate the historical cropland of each major crop to changes in market conditions or other relevant factors, including how climate has changed through time. Historical cropland-climate relationships show magnitudes of potential cropland responses caused by climate change. Extrapolating such relationships into the future provides insight on cropland changes that may be induced by climate change. This paper is the first to examine how the long history of climate change has affected crop choice in the context of diverse agriculture with more than a dozen relevant crop alternatives and to show the implications for shifting cropland as climate changes over the next four decades. A recent study by Mehta et al. (2013) explores irrigation water implications of climate change in Yolo County. Focusing on a water district in Yolo County, Mehta et al. develops land use data and projections driven solely by irrigation water allocation and use. Their work is based on an engineering model (and cropland use estimates reported in Jackson et al. (2012)), which evaluates the hydrologic implications of climate change scenarios as well as the water management ramifications of the implied hydrologic changes.

Cropland projections through 2050 are conducted under the two IPCC greenhouse gas (GHG) emission scenarios, B1 (low emissions) and A2 (medium to high emissions). These two scenarios are widely adopted to provide an acceptable range for future climate projections (Lobell and Field 2011; Luedeling et al. 2009; Deschenes and Kolstad 2011; Mehta et al. 2013). Our cropland projections use the climate variables constructed using downscaled daily projections from a global circulation model produced by the National Oceanic and Atmospheric Administration (NOAA) Geophysical Fluid Dynamics Laboratory (GFDL CM2.1) under the IPCC's two scenarios, A2 and B1. Downscaled climate projections were corrected using the Bias Corrected Constructed Analog (BCCA) method (Cayan et al. 2008) which represents local climate in Yolo

County for the period of 2010 to 2050. Our analysis relies on the CMIP3 scenarios, however, after reviewing newer downscaled projections Cayan et al. (2012) state, “In summary… CMIP5 regional climate changes are generally similar to previous generation CMIP3 model results.”

2 Overview of agriculture and historical climate in Yolo County

This section briefly describes agricultural activities and historical climate in Yolo County based on county-specific data collected from *Yolo County Crop Reports* (Yolo County Agricultural Department) and the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA).

2.1 Agriculture in Yolo County

Yolo County is situated in the northwestern part of the Central Valley of California. In 2009, Yolo County farm cash receipts were $461 million from 135 thousand hectares of cultivated cropland. Only 5 % of Yolo farm receipts come from livestock. Crop revenue is diverse with 32 % from vegetables (almost all from processing tomatoes), 27 % from field crops (alfalfa, rice, wheat and others), and 26 % from fruits and tree nuts (winegrapes, almonds and walnuts and others) (Fig. 1). As elsewhere, technological change has increased crop yields per unit of land and per unit of applied water. Some of the trend in cropland changes reflects differential technical change.

2.2 Historical surface temperatures in Yolo County for the past decade

We accessed daily maximum and minimum temperatures from the Davis weather station for the years from 1909 to 2009. The annual means of daily temperatures show an unmistakable long-term upward trend (see panel a of Fig. 2). The average annual temperature has risen by 1 °C from approximately 15.15 to 16.1 °C over the past century. Panel b of Fig. 2 presents monthly averages of minimum and maximum temperatures for January and July. We find distinct upward trends for minimum temperatures, with January minimums rising twice as fast as July minimums. In Yolo County, California, climate warming has been due to rising minimum temperatures, especially in the winter. Similar findings are reported by Christy et al. (2006) who attributed their findings of

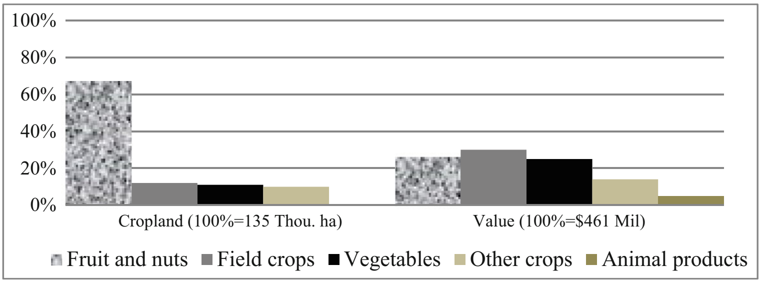


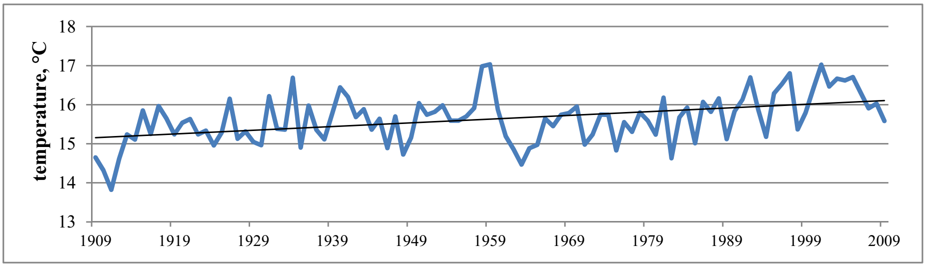
Fig. 1 2009 Yolo County cropland shares (%) and agricultural market value shares (%) by commodity category. Cropland shares are based on the total cropland of 135 thousand hectors and value shares are based on total market value of $461 million. Cropland includes irrigated pasture but excludes non-irrigated (dry) pasture, and other crops include organic crops, nursery products, and seed crops. Source: 2009 Yolo County Agricultural Crop Report

declining maximum temperatures in the San Joaquin Valley of California partially to more irrigation and changes in land use and by Bar-Am (2009) who found rising minimums for winegrapes growing regions for California over the century. (More detailed climate information is shown in Online Resource 1 together with detailed data and comparisons with projections discussed below.)

3 Derivation of climate indexes relevant to crop agriculture

Immediate implications of climate warming for crop agriculture are longer growing seasons for most crops and reduced chill hours needed for deciduous trees and vines. Changes in the duration of a growing season can be quantified by growing degree days (GDD)—a heat accumulation measure, while chill hours can be measured as the number of hours below a threshold minimum temperature. We developed data on GDD and chill hours using past 100 years of data on surface temperatures.

a Annual average temperatures and historical trend inYolo County, California



b Monthly average minimum and maximum temperatures for January and July and historical trends in Yolo County, California

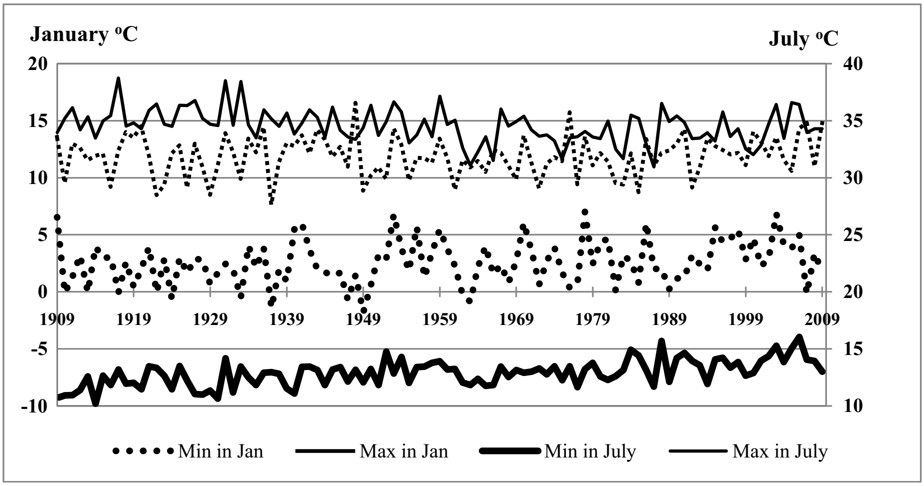


Fig. 2 Historical annual average temperatures and historical minimum and maximum temperatures for January and July in Yolo County, California, derived from actual daily maximum and minimum temperatures for 1909–2009. Solid straight lines indicate linear historical trends. **a**. Annual average temperatures and historical trend in Yolo County, California. **b**. Monthly average minimum and maximum temperatures for January and July and historical trends in Yolo County, California

3.1 Growing degree days (GDD)

Daily GDD are calculated as the difference between the daily average temperature and a lower bound below which plant growth is impaired. Further, the GDD calculation is bounded by temperature above which photosynthetic function is reduced. These two threshold temperatures may differ slightly by plant species and cultivar, but we set these two values for each crop at 8 and 32 °C following Deschenes and Greenstone (2007). Thus, daily mean temperature below 8 °C or above 32 °C contributes no additional GDD. Annual GDD are then calculated by summing up the daily GDD for the relevant growth period.

We calculate GDDs for two different growth periods that are relevant for California, from April 1 to August 31 for summer harvested (or spring planted) crops and from November 1 to May 31 for spring harvested (or late fall or winter planted) crops such as fall-sown hard red wheat, labeled as GDD_{summer} and GDD_{winter}, respectively. Panel a of Fig. 3 presents the trends of both GDDs, that have increased over the last century, from 3,223 to 3,516 for GDD_{summer} and from 1,398 to 1,712 for GDD_{winter}. Our results on increasing GDDs are consistent with Feng and Hu (2004) and McKenney et al. (2006) who found the growth season to be lengthening across North America, including California. GDD_{winter} increased by 0.22 % per year, which is more than twice of the rate 0.09 % observed for GDD_{summer}. Importantly, in California, the amount of GDD is rarely a limiting factor for most summer crops. However, for winter crops an increase in GDD_{winter} likely results in positive growth.

3.2 Chill hours

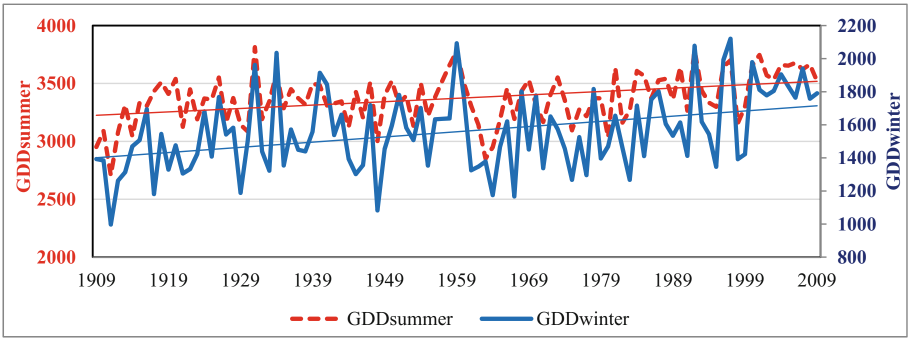
Chill hours are the number of hours below a critical temperature—most commonly 7.22 °C (Aron 1983). Insufficient winter chill provides inadequate physiological stimulation to renew growth, resulting in reduced fruit yield (Aron 1983). We approximated chill hours as a function of daily minimum and maximum temperatures, following Baldocchi and Wong (2008). Their approach assumes that temperature changes over a 24 h period are gradual, and bounded by the daily maximum and minimum temperatures with a linear process in which the daily temperature declines to the minimum, rises to the maximum, and declines again to the minimum the next day. Annual chill hours are the sum of daily chill hours during the plant's dormancy period of November through February.

Panel b of Fig. 3 shows that estimated chill hours have decreased by about 160 h over the last 100 years. Using a shorter time series, Luedeling et al. (2009) also found that winter chill hours in the Central Valley of California had declined. Data in Table 1 show that chill hours requirements in Northern California vary by crop. Table 1 indicates that almonds and grapes require relatively low chill hours, whereas walnuts require considerably more, between 400 and 1500 h. Under the current trends, insufficient chill hours is not yet a major concern in Yolo County, but could become a binding factor over the next century for crops such as pears, plums, pistachios, sweet cherries and perhaps walnuts.

4 Cropland model

Change in climate affects expected crop productivity and therefore farmer allocation of cropland area to specific crops. The economic reasoning is straightforward and will not be derived in any detail. Growers consider the profit potential of crops they plant before weather

a Growing dgree days for winter (Nov 1- May 31), growing degree days for summer (Apr 1- Aug 31), and historical trends



b Chill hours (during Nov 1- Feb 28) and threshold chillh ours for grapes, almonds and walnuts

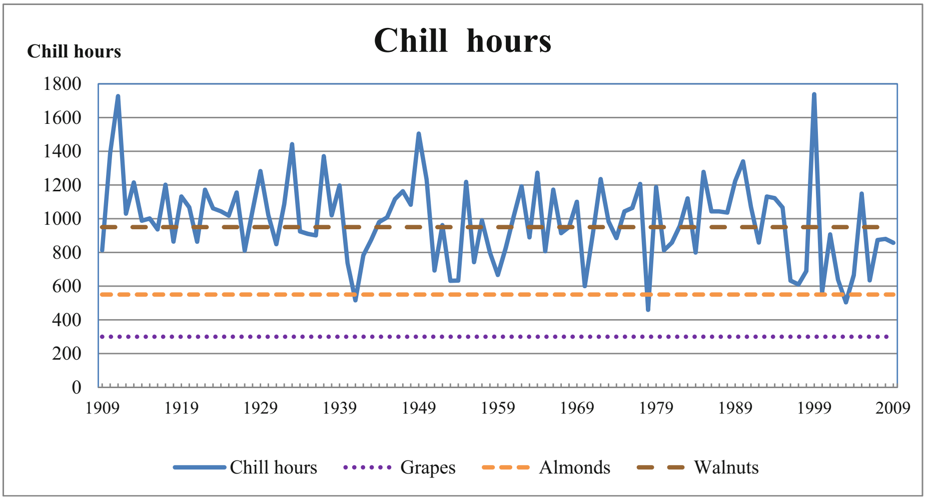


Fig. 3 Historical growing degree days for summer months, growing degree days for winter months, and chill hours in Yolo County, California for the period of 1909–2009, estimated using historical daily minimum and maximum temperatures. Chill hours are compared to threshold chill hours for three important crops in Yolo County, grapes, almonds and walnuts. The threshold chill hours are taken from the mid value of the chill hour range in Table 1. **a**. Growing degree days for winter (Nov 1- May 31), growing degree days for summer (Apr 1- Aug 31), and historical trends. **b**. Chill hours (during Nov 1- Feb 28) and threshold chill hours for grapes, almonds and walnuts

realizations occur. That means they rely on climate to assess likely yields, costs, pest pressures and similar considerations. Farmers face many constraints and incentives likely including relative market prices for outputs and inputs in addition to climate. In this context, econometric analysis in this section is best interpreted as measuring the extent to which local climate information contributes to allocation of cropland among crops, given all the other important factors influencing those decisions. It is, however, important to recognize that such exercise does not fully account for year-to-year fluctuation in cropland or link cropland to the full complement of expected prices and other drivers. That is, we do not attempt to account for all variables in allocation of cropland, rather we focus on how cropland allocation has responded

Table 1 Winter chill hours required for selected tree and vine crops

Crop	Chill hours (min-max)
Grape	100–500
Peach	200–1,200
Apricot	350–1,000
Kiwi	400–800
Almond	400–700
Walnut	400–1,500
Sweet cherry	600–1,400
European pear	600–1,500
European plum	700–1,800
Pistachio	800–1,000

The range of chill hours reflects different requirements across various varieties of the same crop. This information was previously published in Baldocchi and Wong (2008) which indicated the original source as Australasian Tree Crops Source Book, http://www.aoi.com.au/atcros/LM.html)

to local climate changes alone. Unlike crop yields that depend on realized weather, planted area depends on climate expectations, which is likely formulated based on past climate change.

To investigate this issue quantitatively, we specify statistical models of cropland for each major crop as a function of relevant local climate variables and other relevant variables. We specify 13 equations (see Table 2 for the crop list) with each associated with an individual crop that currently has significant cropland in Yolo County. Since we use these cropland estimates to project over a 40 year horizon, we do not include crops such as apricots or barley, which have ceased to be significant.

Each equation describes cropland of a specific crop and expressed as a linear function of explanatory variables guided by the general formulation:

$$\text{Area of cropland for crop i} = f(\text{market conditions, climate, water availability, agronomic factors})$$

Based on these variable categories, each equation is specified with its own set of variables that are most likely to affect the cropland of that crop. An alternative to our approach is to estimate a set of land share equations, which allows one to impose the property that the shares add to 1.0. However, estimating the full system of cropland allocation equations requires that the same variables appear in each equation. Share equations were estimated by Mu et al. (2013), which considers only three highly aggregated land uses, and Hendricks et al. (2014) where almost all the land is used for one of three few crops (corn, soybeans and an aggregate of other crops). In the context of more than a dozen diverse crops, it is simply not feasible or appropriate to estimate share equations with all common variables included in each equation. For example, for the tree and vine crops we account for chill hours in the specification, whereas we do not include the chill hour variable where that is less relevant.

We categorize explanatory variables and introduce notation here. Estimation details are available in Online Resource 2 (also in Jackson et al. 2012) along with more discussion on data, variable selection, and model specification.

Market conditions Market conditions are represented by own product price and prices of substitute crops. Yolo farmers are price takers, and for most field crops and vegetables, we used one-period lagged prices denoted as $P(\text{crop})_{t-1}$ to represent current own price expectations. For tree and vine crops, to reflect trends and expectations, we use a moving average of multiple lags of own prices expressed as $MP(_{\text{crop}})_{t-i,j,k}$. (for the lags i,j,and k).

Table 2 Econometric estimation of crop acreage equations on selected explanatory variables including own prices, irrigation water variables, growing degree days and chill hours

Fields crops and vegetables									
Variable		Rice	Alfalfa	Wheat	Corn	Safflower	Pasture	Tomatoes	Other veg
Own price	$P(crop)_{t-1}$	620.8***	13.8	95.3***	148.6	3.44	−0.66	121*	
		(3.62)	(0.46)	(4.09)	(0.21)	(0.64)	(−0.41)	(1.69)	
Precipitation	$Prcp_t$			−3.8**					
				(−2.21)					
	$Prcp_{t-1}$	0.86	1.77*	−3.56	−0.23	−2.05**	0.31	1.46	0.34
		(0.8)	(1.88)	(−1.47)	(−0.21)	(−1.92)	(1.25)	(1.25)	(1.43)
	$Prcp_{t-2}$	1.35	1.58*	−3.31**	2.87***	−2.24	0.33	−0.57	0.17
		(0.99)	(1.62)	(−1.96)	(2.66)	(−1.59)	(1.22)	(−0.47)	(0.69)
Moving avg of GDD	$MGDD_s$	−16.9			−6.77	30.5	6.98		6.55
		(−0.62)			(−0.17)	(0.98)	(0.93)		(1.25)
	$MGDD_w$		48.06**	−118.8**				46.6	
			(2.35)	(−2.45)				(1.51)	
Log likelihood		−562	−578.8	−629.9	−571.2	−571.39	−509.7	−582.58	−478.31
Fruits and tree nuts									
					Prunes	Grapes	Almonds	Walnuts	Other fruit
Moving avg of own price		$MP(crop)_{t-i,j,k}$			0.56**	10.5**	404.5	0.08	0.03*
					(2.03)	(2.18)	(0.55)	(0.31)	(1.61)
Moving avg of chill hours		Mchill			1.93**	−3.1	−5.92	4.67*	1.88**
					(2.36)	(−0.7)	(−0.98)	(1.73)	(2.15)
Log likelihood					−363	−246.9	457.4	−438.9	−372.8

$MP(crop)_{t-i,j,k}$ used for tree and vine crops are: $MPprunes_{t-5,6,7}$, $MPgrapes_{t-1,2,3}$, $Pwalnuts_{t-5}$, and $MPofruit_{t-1,2,3}$

Numbers inside parentheses are t-values and the number of asterisks indicates different levels of significance: *** ($P \leq 0.01$), ** ($P \leq 0.05$), and * ($P \leq 0.1$)

Agronomic practices Agronomic practices constrain cropland decisions. Many annual crops require crop rotation to maintain yields. In that case, for a given plot of land, the previous year's crop affects selection of this year's crop. To reflect the effects of rotation crops on this year's cropland decision, we include the one period lagged cropland of rotation crops denoted as $A(crop)_{t-1}$, where it is relevant (Marsh and Jackson 2008).

Water availability All major crops in Yolo County are irrigated. Unlike much of the Central Valley, which relies on watersheds fed by the Sierra Nevada snow pack, about 70 % of irrigation water in Yolo County is supplied by local rain fed surface water storage, with the rest pumped from groundwater (Water Resources Association 2005). Given the lack of appropriate time series data, we use lagged precipitation denoted as $Prcp_{t-i}$ (for lag i) as a proxy for surface water availability.[1] We also use a dummy variable indicating new water storage (Indian Valley Reservoir) operated since 1976 by the local water district. Precipitation accumulates mainly from January through March, and the local water district authority announces availability of

[1] The amount of rainfall may differ in the valley region of Yolo County and the upper watershed where reservoirs are located. Hence, our rainfall data may under represent surface water availability. However, as long as the rainfall in the valley and upper watershed is correlated (likely so), using rainfall in the valley is expected to make little difference in the regression results.

surface irrigation water in April (Mehta et al. 2013). Thus, current year's rainfall is included in the equations for the fall-planted crops, but not for the spring planted crops. (See Online Resource 3 for more details about irrigation water availability.)

Climate (surface temperature) variables Climate variables represent the trends not year-to-year short-term changes in weather. We construct 10 years moving averages of annual climate indexes and adopt those as climate variables in cropland equations. We use 10 years averages rather than longer moving averages (say 30 years) to reflect climate expectations over a period in which farmers have observed and expect relatively steady changes. Ten-year moving averages are denoted as Mchill for chill hours, $MGDD_w$ for GDD_{winter} and $MGDD_s$ for GDD_{summer}, and we use Mchill for tree and vine crops, $MGDD_w$ for wheat, tomatoes and alfalfa, and $MGDD_s$ for all other annual crops.[2] Even though tomatoes and alfalfa are mostly summer-harvested crops, tomatoes intended for early harvest are planted as early as February, and the first cut of alfalfa after winter also occurs in April. For these crops, warm temperature during the winter growth period is particularly relevant.

5 Data and estimation

5.1 Data

Cropland estimations outlined above require data from two broad sources, agriculture and climate. For agriculture we have time series data on Yolo County cropland available from *Yolo County Crop Reports* (Yolo County Agricultural Department). The longest consistent time series available for the crops we considered start from the early 1950s (the starting year varies slightly by crop), and our data end in 2008. We also obtained time series crop prices for California from the National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). The state represents the smallest geographic unit for any consistent price data. Given markets tend to be spatially integrated statewide, we use state prices in place of county prices. All prices are converted into real prices using the gross domestic product deflator (Bureau of Economic Analysis).

Climate data needed for estimation were obtained from the time series data for the past hundred years by subsetting the period of the early 1940s though 2008. To construct moving averages, climate data start 10 years earlier than crop data. Our climate data also provide annual precipitation for the same time series.

5.2 Estimation

Given we use time series data, statistical properties of all time series data had to be tested before the model estimation (Enders 2004). In particular, we test for a unit root using the augmented Dickey-Fuller method (the presence of a unit root implies data nonstationarity). Given the failure to reject unit roots by most variables, the next step is to test for cointegration

[2] GDD_{winter} likely affects the growth of annuals as well as perennials as shown in Lobell and Field (2011) recent findings that the low minimum temperature in February adversely affects almond yields. Nevertheless, in our study, the climate variable for tree crops is represented by Mchill alone, due to the considerable negative correlation between chill hours and GDD_{winter}.

which allows for the use of an error correction model. Given no strong evidence of cointegration, we transformed all variables into first differences and regressed first-differences on first-differences (test results are provided in Online Resource 4). Estimations were conducted using STATA time series routines.

Recent studies and reviews have emphasized nonlinear impacts of climate change in a variety of outcomes, including field crop yields (Auffhammer et al. 2013; Dell et al. 2014; Schlenker and Roberts 2009). We do not document effects of highly nonlinear changes in the distribution of climate extremes because parameters for such impacts are much more difficult to measure empirically with historical data (Bar-Am 2009; Lobell et al. 2011a). We have tested a simple nonlinear relationship by adding the squared term of relevant climate variable in each equation. Our results indicate that the nonlinear term did not improve the overall fit for any of our crops except for walnuts, suggesting no significant nonlinear impacts over the range of data in the California context (see Online Resource 2).

We also investigated the robustness of the model specifications for prediction accuracy. We conduct out of sample robustness checks by splitting the sample into sub-samples before and after 1980. We use the pre-1980 sample for estimations and reserve the post 1980 sample for prediction tests. To provide a relative measure for prediction accuracy, the benchmark model is specified as a univariate time series ARIMA model (Clark and West 2006). Both benchmark and our models are estimated using the pre-1980 subsample. Using the estimated results, we predicted "Y" values for the out of sample period. We compute the root of mean squared error (MSE) from each prediction. The comparison of these values indicates that our model improves the out-of-sample forecast accuracy for two thirds of the crops relative to the benchmark model (Online Resource 2). Even if our model underperformed for one third of the crops, it is important to bear in mind that the focus in this paper is not "forecasting," but rather isolating the climate effects in the multivariate framework.

6 Estimation results and interpretation

Table 2 reports estimation results for selected regressors, including own prices and climate variables with full estimation results presented in Online Resource 2. In addition, we report results for the water availability variable only for annual crops given that recent water availability would be more important in year-to-year cropland decisions for annuals than for perennials. (We found that none of the recent water supply variables were statistically significant for perennials.)

Own prices are important for rice and wheat land. Increased availability of irrigation water (represented by variable Prcp) expands alfalfa and corn, and contracts wheat and safflower ($P \leq 0.06$). The results on wheat and safflower are consistent with their relatively low dependence on irrigation and low per-land revenue.

Growing degree days for summer harvested crops ($MGDD_s$) did not directly affect the allocation of cropland in Yolo County. However, $MGDD_w$ for alfalfa and wheat which grow through the winter had significant effects on their cropland ($P \leq 0.01$ and $P \leq 0.02$, respectively) but with different signs, positive for alfalfa and negative for wheat. A warm winter is expected to provide favorable conditions for alfalfa production (consistent with Lobell and Field (2011)). The negative effect on wheat may be because many wheat varieties require a period of cool growing conditions known as vernalization (Chouard 1960).[3]

Prunes and grapes also have significant own price effects ($P \leq 0.05$). None of precipitation variables were significant for any tree crop. Winter chill hours are statistically significant for prunes, miscellaneous fruits ($P \leq 0.05$), and walnuts ($P \leq 0.08$), indicating that continuing warming in winter would reduce the land area for these crops in the future. A 1 % reduction in chill hours (in 10 years moving average terms or equivalently a permanent 1 % reduction) induces a reduction in cropland by about 1 % for prunes and walnuts. Recall walnuts and prunes are among the crops that require relatively high chill hours (Table 1).

Overall, these parameter estimates indicate moderate influences of climate variables and the effects on individual cropland of each climate variable are dictated largely by two facts, whether the crop requires cooling periods and whether the crop grows over the winter season. Other climate-related factors that affect Yolo County cropland, such as irrigation water impacts caused by lower snow pack (outside Yolo County) or potential impacts of statewide or global climate change on relative prices, are beyond the scope of this study. To the extent that Yolo precipitation and temperature are correlated with snowpack these variables also capture some expectations of irrigation water availability from outside the county.

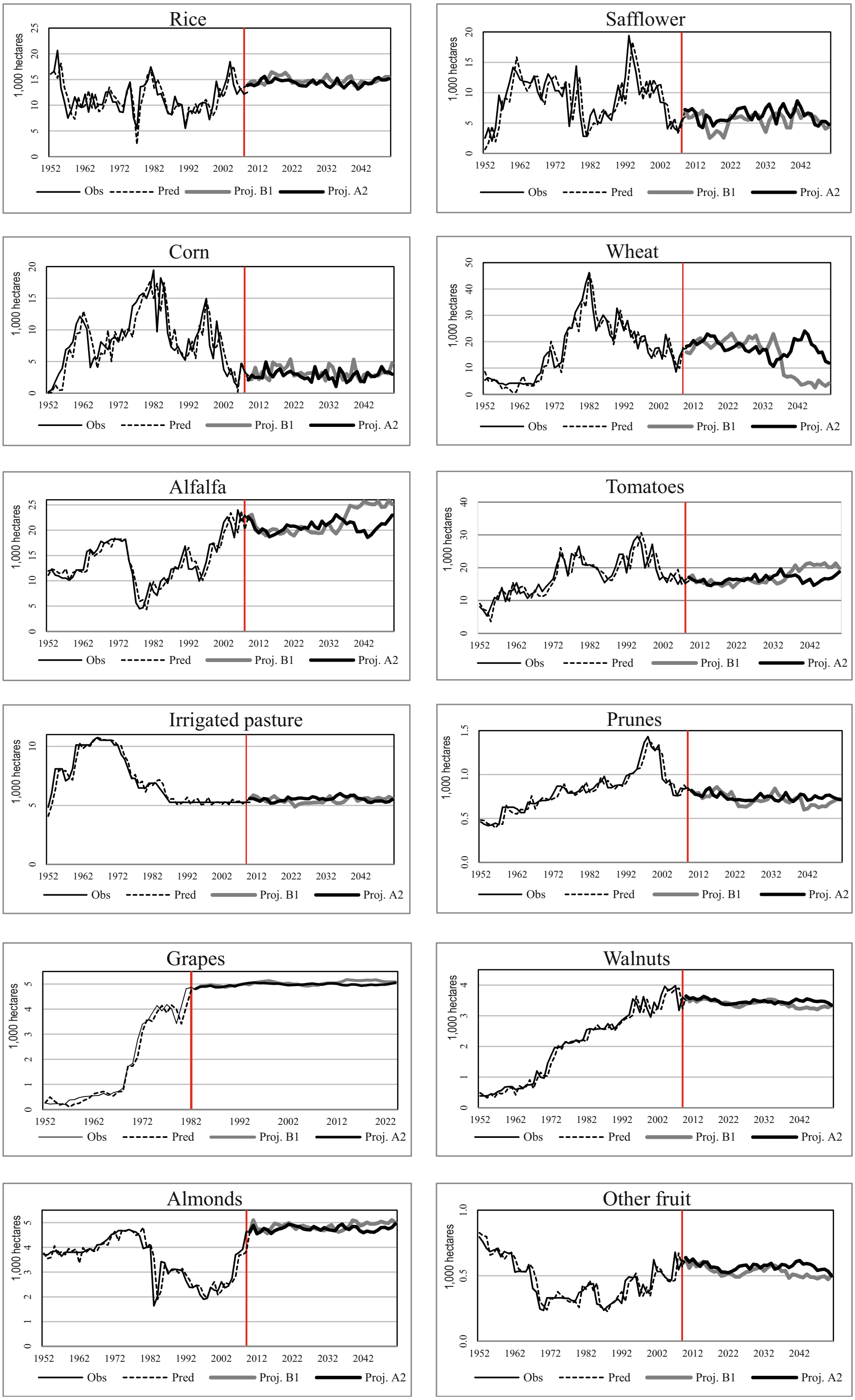
7 Cropland projections

We now use the estimates of climate-related parameters to project how local climate change alone may affect allocation of Yolo County cropland for the period of 2010–2050. We focus on the horizon ending 2050 to avoid extrapolating beyond the usefulness of the historical relationships. Under the two IPCC scenarios, A2 and B1, which are based on storylines for higher and lower GHG emissions, respectively, we obtained downscaled climate projections from the GFDL model (Cayan et al. 2008) to represent future climates.

Using these localized daily climate projections, we constructed scenario-specific climate indexes, GDD_{summer}, GDD_{winter}, and chill hours, and then 10 years moving averages of these indexes. We used these climate "data" and downscaled precipitation projections in our estimated cropland equations to obtain cropland projections, holding all other independent variables constant at the value in the last year (2008) of actual data. Using these climate related variables as sole drivers for cropland changes, we isolate the effects on future land exclusively of the changes in specific climate related variables. (See Online Resource 1 for more details on the climate projections.)

The crop-by-crop panels in Fig. 4 present the climate-change induced future cropland as well as the observed and fitted values over the historical period. The fitted cropland tracks the actual land of each crop well over the historical period. The cropland projections into the future use the estimates obtained in our regressions, which are based on historical data. They do not incorporate unanticipated shocks, such as new pests, unanticipated technologies or changes in relative prices that may affect cropland directly and through adjustment to climate change (Gutierrez et al. 2006). Our projected cropland varies much less from year to year than does the historical cropland. This smoothing follows because future cropland was projected by varying only future climate (temperature and precipitation, holding all other variables constant).

[3] Wheat varieties planted in California these days do not require a cool period. However, the plausibility of vernalization is based on the fact that our data period extends more than a half century.


Rice
1,000 hectares
0 5 10 15 20 25
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Safflower
1,000 hectares
0 5 10 15 20
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Corn
1,000 hectares
0 5 10 15 20
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Wheat
1,000 hectares
0 10 20 30 40 50
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Alfalfa
1,000 hectares
0 5 10 15 20 25
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Tomatoes
1,000 hectares
0 10 20 30 40
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Irrigated pasture
1,000 hectares
0 5 10
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Prunes
1,000 hectares
0.0 0.5 1.0 1.5
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Grapes
1,000 hectares
0 1 2 3 4 5
1952 1962 1972 1982 1992 2002 2012 2022
Obs Pred Proj. B1 Proj. A2
Walnuts
1,000 hectares
0 1 2 3 4
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Almonds
1,000 hectares
0 1 2 3 4 5
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2
Other fruit
1,000 hectares
0.0 0.5 1.0
1952 1962 1972 1982 1992 2002 2012 2022 2032 2042
Obs Pred Proj. B1 Proj. A2

◀ **Fig. 4** Cropland projections (thousand hectares) into 2050 by crop under A2 and B1 scenarios in Yolo County, California when climate changes following GFDL projections while all other factors held constant at 2008 levels. Abbreviated notation above is: *Obs* observed, *Pred* predicted, *Proj.B1* projected under B1, and *Proj.A2* projected under A2

We only mention some of the main results here. Future rice land rises slightly. Recall from our regression results that the own price of rice is a more significant determinant of rice land than climate. Wheat area decreases significantly under the warming of the B1 scenario in the final 15 years of the projection period. The opposite is true for alfalfa. Increasing GDD in winter is favorable for alfalfa, and alfalfa area increases significantly during this warming period.

Safflower land fluctuates over a wider range than other crops during the projection period. Our regressions showed that safflower increases when water availability is restricted. The increasing trend of tomato land in the latter half of the projection period under the B1 scenario may be related to the increase in GDD_{winter} as a warmer climate in the late winter or early spring allows early planting.

Projected prune land shows a downward trend under both scenarios–a result of the projected reduction in winter chill hours. However, prune fluctuates more under the B1 scenario than under A2. Grape land is almost constant over the projected period; changes in grape land are induced by changes in factors other than climate. Almond, unlike other tree and vine crops, increases in the latter half of the projected period when winter warming occurs under the B1 scenario. The almond crop has a relatively low winter chill hour requirement, and

Table 3 Yolo County cropland in 2008 and projected acreage in 2050 with the projections induced by climate change alone and the range in projected cropland is provided by the projections under B1 and A2 scenarios

	2008 (historical) 1,000 ha	2050 (projection)
Total (Land in listed crops)	98.1	101.7–102.2
Major field crops	66.3	65.5–66.2
Rice	12.2	15.1–15.5
Alfalfa	22.9	26.2–28.7
Wheat	17.2	7.4–12.9
Corn	3.3	2.5–4.3
Safflower	5.5	4.2–4.4
Irrigated Pasture	5.3	5.1–5.2
Vegetables	17.2	20.8–21.9
Proc. Tomatoes	15.2	18.7–19.8
Other vegetables	2.0	2.1
Fruits and tree nuts	14.6	14.7–14.8
Prune	0.8	0.8
Grapes	4.9	5.1
Walnut	3.6	3.3
Almond	4.7	5–5.1
Other fruits	0.6	0.4–0.5

Cropland projections obtained under scenarios B1 and A2 provide the range in 2050 cropland. Field crops include only the listed crops and the total cropland refers only to crops listed in the table. Land use above does not include minor field crops, seeds, organic crops, and nursery crops is affected relatively little by the projected lower chill hours. For walnut and other fruit crops, reduced chill hours are found to be a contributing factor, and their land tends to fall more under the B1 scenarios.

8 Summary, implications and limitations

Table 3 summarizes projections of crop area performed under the two alternative climate scenarios to 2050 compared with area by crop in 2008, the base year of projections. Yolo County climate change has played a moderate role in the evolution of cropland in the past 60 years. Even though the warmer winter under the B1 scenario increases alfalfa planting, this increase cannot offset the loss in wheat land, leading to a slight decline in field crop area. The projected increase in alfalfa relative to wheat presents an interesting implication for water use. A significant shift from wheat to alfalfa would increase regional irrigation water demand.

Our results suggest climate change has been less important for the crop area allocation across trees and vines in Yolo County. In the second half of the projection period, cropland reductions for prunes, walnuts, and other fruits under B1 are offset by the increase for almond and grape land. Reduction in winter chill hours does not appear to be a major factor, at least through 2050. We stress that our projections are *not* cropland forecasts. They are driven solely by projections of local climate variables with no other drivers of cropland included over the projection period. That is, no attempt is made to forecast relative prices, technical changes, new markets, or other factors that will also surely affect how much of each crop is planted.

Several limitations of this study suggest further research. First, our specific results apply to a single county and replication for other regions is in order. Second, assessing potential effects across even more alternative variable definitions and econometric specifications, such as share equations estimated with more aggregate data would be useful. In keeping with our focus on local climate, we did not explore the influence of out-of-region climate changes such as those related to snowpack. A more detailed treatment of irrigation water availability from outside the county may provide a useful clarification of these results. One important item on the agenda is to examine projection results under alternative GCMs or climate change scenarios. The approach of this paper may be enhanced by using the most recent climate forecasts from a range of GCMs and scenarios including the potential impact of climate extremes and those consistent with downscaled CMIP5 projections. That would usefully consider more than one location to compare local responses to local climate changes. This would likely include comparing local regions in California that grow similar crops but may have different climate responses. Cross section time series data may also be more likely to reveal non-linear impacts.

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References

Adams RM, Rosenzweig C, Peart RM et al (1990) Global climate change and U.S. agriculture. Nature 345:219–224, 17 May 1990

Aron R (1983) Availability of chilling temperatures in California. Agric Meteorol 28:351–363

Auffhammer M, Hsiang S, Schlenker W, Sobel A (2013) Global climate models: a user guide for economists. Rev Environ Econ Policy 7:181–198
Baldocchi D, Wong S (2008) Accumulated winter chill is decreasing in the fruit growing regions of California. Clim Chang 87(Suppl 1):S153–S166
Bar-Am C (2009) The economic effects of climate change of the California winegrape industry. Unpublished doctoral dissertation, University of California, Davis
Cayan DR, Maurer EP, Dettinger MD, Tyree M, Hayhoe K (2008) Climate change scenarios for the California region. Clim Chang 87(Suppl 1):S21–S42
Cayan DR, Polade S, Gershunov A, Dettinger M, Pierce D (2012) Climate change model simulations: new CMIP5 projections. Southwest CSC Meeting, Tucson, Arizona, June 13, 2012
Chouard P (1960) Vernalization and its relations to dormancy. Annu Rev Plant Physiol 11:191–238
Christy JR, Norris WB, Redmond K, Gallo KP (2006) Methodology and results of calculating central California surface temperature trends: evidence of human-induced climate change? J Clim 19:548–563
Clark TE, West KD (2006) Using out-of-sample mean squared prediction errors to test the martingale difference hypothesis. J Econ 135:155–186
Dell M, Jones B, Olken B (2014) What do we learn from the weather? The new climate-economy literature. J Econ Lit 52(3):740–798
Deschenes O, Greenstone M (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Am Econ Rev 97(1):354–385
Deschenes O, Kolstad C (2011) Economic impacts of climate change on California agriculture. Clim Chang 109(suppl 1):365–386
Enders W (2004) Applied econometric time series, 2nd edn. John Wiley & Sons, Hoboken, New Jersey
Feng S, Hu Q (2004) Changes in agro-meteorological indicators in the contiguous United States: 1951–2000. Theor Appl Climatol 78:247–264
Gutierrez AP, Ponti L, Ellis CK, d'Oultremont T (2006) Analysis of climate effects on agricultural systems, CEC-500–2005–188-SF. California Climate Change Center, Sacramento
Hendricks NP, Smith A, Sumner DA (2014) Crop supply dynamics and the illusion of partial adjustment. Am J Agric Econ 96(5):1469–1491
Jackson L, Haden VR, Hollander AD et al (2012) Adaptation strategies for agricultural sustainability in Yolo County, California. California Energy Commission. Publication number: CEC-500-2012-032
Lobell DB, Field C (2011) California perennial crops in a changing climate. Clim Chang 109:317–333
Lobell DB, Schlenker WS, Costa-Roberts J (2011a) Climate trends and global crop production since 1980. Science 333:616–20
Lobell DB, Torney A, Field C (2011b) Climate extremes in California agriculture. Clim Chang 109:355–363
Luedeling E, Zhang M, Girvetz EH (2009) Climatic changes lead to declining winter chill for fruit and nut trees in California during 1950–2099. PLoS ONE 4(7):e6166. doi:10.1371/journal.pone.0006166
Marsh B, Jackson L (2008) Small grain production manual part 12: small grains in crop rotations, publication 8175. University of California, Division of Agriculture and Natural Resources
McKenney DW, Pedlar JH, Papadopol P, Hutchinson MF (2006) The development of 1901–2000 historical monthly climate models for Canada and the United States. Agric For Meteorol 138:69–81
Mehta VK, Haden VR, Joyce BA, Purkey DR, Jackson LE (2013) Irrigation demand and supply, given projections of climate and land-use change, in Yolo County, California. Agric Water Manag 117:70–82
Mu JE, McCarl BA, Wein AM (2013) Adaptation to climate change: changes in farmland use and stocking rate in the U.S. Mitig Adapt Strateg Glob Chang 18(6):713–730
National Oceanic Atmospheric Administration (NOAA) U.S. Department of Commerce National Climatic Data Center. URL: http://cdo.ncdc.noaa.gov/CDO/cdo
Schlenker W, Roberts MJ (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc Natl Acad Sci 106(37):15594–15598
Schlenker W, Hanemann M, Fisher AC (2006) The impact of global warming on U.S. agriculture: an econometric analysis of optimal growing conditions. Rev Econ Stat 88(1):113–125
Schlenker W, Hanemann M, Fisher AC (2007) Water availability, degree days, and the potential impact of climate change on irrigated agriculture in California. Clim Chang 81(1):19–38
Trenberth KE, Jones PD, Ambenje P et al (2007) Observations: surface and atmospheric climate change. In: Solomon SD, Qin M (eds) Climate change 2007: the physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, UK
Water Resources Association (2005) Yolo County integrated regional water management plan backgroun data and information appendix. URL: www.yolowra.org/irwmp_documents_a.html
Yolo County Agricultural Department. Agricultural crop reports, issues for 1937–2008, URL: http://www.yolocounty.org/Index.aspx?page=486