CALIFORNIA PERENNIAL CROPS IN A CHANGING CLIMATE

A Paper From:
California Climate Change Center

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DRAFT PAPER

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Preface

The California Energy Commission's Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

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The California Climate Change Center Report Series details ongoing center-sponsored research. As interim project results, the information contained in these reports may change; authors should be contacted for the most recent project results. By providing ready access to this timely research, the center seeks to inform the public and expand dissemination of climate change information, thereby leveraging collaborative efforts and increasing the benefits of this research to California's citizens, environment, and economy.

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Abstract

Perennial crops are among the most valuable of California's diverse agricultural products. They are also potentially the most influenced by information on future climate, since individual plants are commonly grown for more than 30 years. This study evaluated the impacts of future climate changes on the 20 most valuable perennial crops in California, using a combination of statistical crop models and downscaled climate model projections. County records on crop harvests and weather from 1980–2005 were used to evaluate the influence of weather on yields, with a series of cross-validation and sensitivity tests used to evaluate the robustness of perceived effects. In the end, only four models appear to have a clear weather response based on historical data, with another four presenting significant but less robust relationships. Projecting impacts of climate trends to 2050 using historical relationships reveals that cherries are the only crop unambiguously threatened by warming, with no crops clearly benefiting from warming. Another robust result is that almond yields will be harmed by winter warming, although the effects of summer warming on this crop are less clear. Efforts to shift almond areas or varieties in response to expected temperature changes appear to present limited options for adaptation. Overall, the study has advanced understanding of climate impacts on California agriculture and has highlighted the importance of measuring and tracking uncertainties due to the difficulty of uncovering crop-climate relationships.

Keywords: Global warming, fruits, nuts, climate adaptation, Lasso, Regression Trees

1.0 Introduction

Agriculture is an important component of California's economy, landscape, and culture, and is among the human activities most vulnerable to impending climate changes. Two particularly unique and relevant features of agriculture in California are (1) the diversity of crops grown, with California the leading U.S. producer of over 80 crops, and (2) the substantial fraction of agricultural value (roughly one-third according to the California Agricultural Statistics Service [2006]) derived from long-lived perennial crops, such as grapes and almonds. As perennials typically remain in the ground for over 20 years, climate changes over the next 20–30 years will be relevant to crops that have already been planted, and especially to those that will be planted over the next few years.

The goals of this paper are to assess the potential impacts of climate change on perennial cropping systems in California over the next 20–50 years, and to identify possible adaptation strategies to minimize the potential costs and maximize the potential benefits of climate change. We focus here on effects of changes in average monthly minimum and maximum temperature and precipitation, and therefore our results do not incorporate the potentially important additional effects of changes at sub-monthly time scales, such as increased frequency of extreme events. We consider these latter effects, which are difficult to estimate on a crop-by-crop basis because of data constraints, in a companion report.

While perennial crops provide a unique opportunity to incorporate climate projections into decisions made today, they also present some unique challenges compared to projecting impacts and adaptation options in annual crops. First, the slow growth of perennials makes experimental warming trials difficult. Second, far fewer models exist to describe perennial crop growth compared to annual crops, in part reflecting the lack of experimental data. While annual crop studies can rely on process-based models such as EPIC or CERES, modeling of perennial crops is limited primarily to statistical models developed from historical variations in weather and crop harvests. Third, perennials can be affected by weather at all times of the year, while annual crops are mainly influenced by weather during the summer growing season. Identifying the particular weather variables most relevant to perennial crop growth can therefore be more difficult than with annuals.

2.0 Previous Work

In prior studies, we have attempted to summarize the effects of weather on perennial yields using California statewide average time series of crop harvests since 1980, combined with daily observations of weather that were spatially averaged according to the distribution of each crop throughout the state (Lobell et al. 2007; Lobell et al. 2006a). The relatively small dataset (26 data points corresponding to 1980-2005) dictated that only two to three weather variables be considered for each crop, the selection of which relied inevitably on subjective decisions based on exploratory data analysis and physiological principles. For some crops, the relationships contained too much scatter to say anything very useful about impacts of future warming, but for others the models indicated clear negative responses to warming.

Almonds, in particular, exhibited a strong negative response to nighttime temperatures (Tmin) in February (Figure 1a), and for projections of warming we estimated a roughly 10% loss of almond yields by 2030. We note that the importance of this variable is not likely associated with chilling hour accumulation (CHA), which is often cited as a principal control on nut tree development and growth, because most chilling hours accumulate in November-January, and not in February. Indeed, our computations of CHA, following the method of Balacchi and Wong (2008) for individual stations and then averaging stations based on almond areas, exhibit a much weaker relationship with almond yields than February Tmin (Figure 1b).

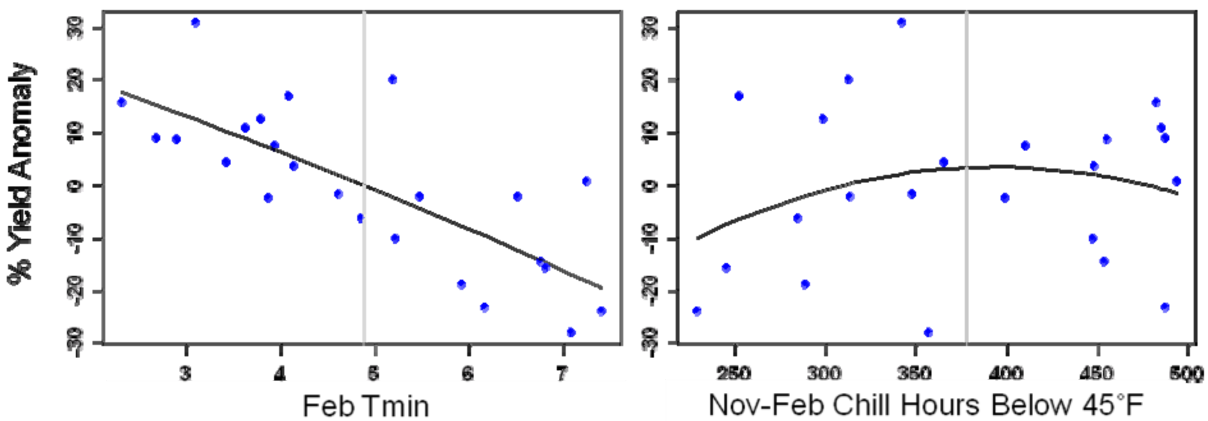


Figure 1. The relationship between California average almond yields (% anomaly from trend) and almond area-weighted state averages of (a) average February Tmin and (b) chill hour accumulation between November-February. The best fit second-order polynomial is shown by gray line, and dashed vertical line indicates average value for 1980–2005.

Instead, we believe the importance of February Tmin relates to the critical period of pollination that occurs in most varieties in mid-late February. The effective period of pollination is longer when temperatures are low during the bloom season, as the stigma is receptive to pollen for longer periods of time (Polito et al. 1996). For example, 2005 had a particularly warm February and the United States Department of Agriculture (USDA) almond production report stated a primary reason for low yield expectations was that "bloom was rapid with an extremely poor set and numerous orchards displayed early petal fall." While poor pollination appears the most likely mechanism, it is impossible to tie a statistical relationship to any single process, which of course causes some concern when applying past empirical relationships to the future. Our perspective is that the major processes linking weather to yields are likely to be similar over the next 20–30 years, when climate is not too different than it is today, and therefore the empirical relationships should be informative in the absence of any more mechanistic predictions.

3.0 Overview of the Current Study

We sought to improve on the past work in three major ways. First and foremost, we analyzed county level crop and weather data to reevaluate the relationship between weather and yields for a wide range of perennial crops. There is no obvious scale at which to model weather-yield relationships. The use of county data has the main advantage that it provides additional data points, as well as access to a wider range of temperatures than when looking at statewide averages. However, there are several potential pitfalls when using county level data. First, data at the county scale are considerably "noisier" than statewide averages, because the number of fields used to estimate production is limited in each individual county. Second, factors other than climate vary between counties, so that comparing yields in a cross-section can be susceptible to omitted variable biases. (Below we evaluate this bias by repeatedly leaving some counties out of the model training and testing predictions for these counties.)

The second objective was to project impacts through 2050 using down-scaled climate projections from six climate models, two downscaling methods, and two emissions scenarios. Third, we sought to assess adaptation options for almonds, which as mentioned above is a very valuable crop in California and one previously identified as susceptible to warming. Specifically, we evaluated (1) whether some almond varieties will be better suited to a warmer climate than others, and (2) whether some counties will be better suited than others. Both of these issues are relevant to decisions made when planning new almond orchards, which are expanding rapidly relative to other crops in California (Figure 2).

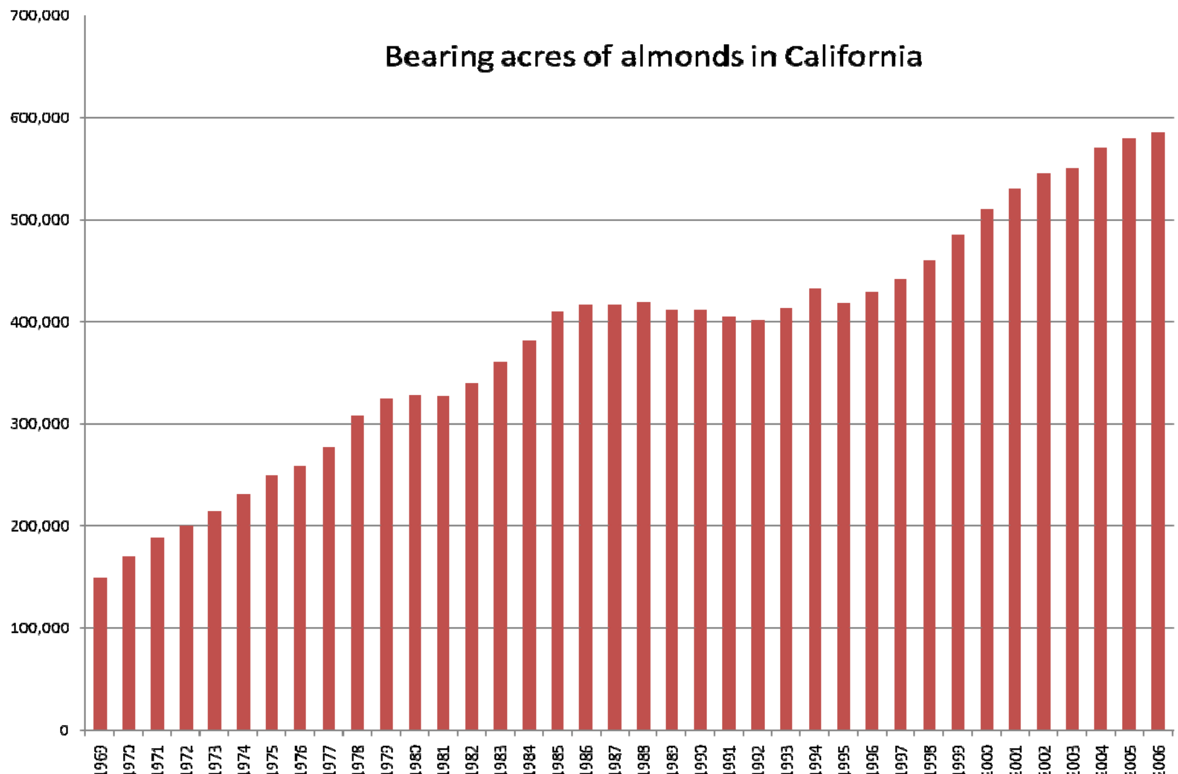


Figure 2. Trend in almond area in California

Source: USDA

4.0 Approach

4.1. Statistical Yield Models Using County Data

County level area and yield data for 1980–2005 were obtained from the Agricultural Commissioners' reports.[1] Measurements of daily minimum and maximum (Tmax) temperatures and precipitation (Prec) were obtained for 382 of the National Weather Service's Cooperative Stations in California (data provided by Mary Tyree of UCSD). For each county, we computed daily and monthly averages of each variable for all stations below 200 meters (656 feet) elevation, to avoid inclusion of high-elevation stations removed from agricultural areas (e.g., in eastern Fresno county). We also computed daily values of chilling hour accumulation following Baldocchi and Wong (2008), equal to the total estimated hours each day below a threshold value of 45˚F (7.22˚C).

This study considers the 20 leading perennial crops, in terms of total state value in 2003–2005 (Table 1). For each crop we consider 72 potential predictor variables: monthly average Tmin, Tmax, and Prec from the September prior to the harvest year through August of the harvest year, along with their squares. We consider Tmin and Tmax separately because they are often not correlated from year-to-year with each other, particularly in winter, and often one but not the other is highly correlated with yields (Lobell et al. 2006a). Combining the two into average temperature would therefore degrade model performance in these situations. We consider both the variable and its square in order to capture nonlinear relationships, as crops often possess an optimal temperature where yields are maximized relative to both cooler and warmer temperatures.

To develop statistical models for perennial crops, we must struggle with the fundamental problem of variable selection. Perennials are affected by weather throughout the year, with each crop potential responsive to different aspects of climate. Moreover, much less research has characterized the weather response of perennial crop growth than for annuals. A priori selection of specific months or climate variables is therefore difficult. At the same time, including all possible months and variables will result in an over-parameterized model that tends to overfit the training sample and give poor predictive performance. For this study, we adopt two statistical procedures commonly used in problems where variable selection is an important criterion.

[1] National Agriculture Statistics Service, County Agricultural Commissioners' Data. www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/indexcac.asp

Table 1. Leading perennial crops in California, ranked by 2003–2005 average total statewide gross cash income, in millions of dollars

Rank	Crop	2003	2004	2005	AVERAGE
1	Almonds	1,600	2,189	2,337	2,042
2	Grapes, Wine	1,543	1,605	2,215	1,787
3	Berries, Strawberries*	1,173	1,206	1,110	1,163
4	Hay, All	544	609	703	618
5	Grapes, Raisin	348	616	567	510
6	Walnuts	378	452	540	457
7	Grapes, Table	407	535	384	442
8	Pistachios	145	465	577	396
9	Oranges, Navel	290	418	363	357
10	Avocados	365	375	280	340
11	Lemons	218	271	319	270
12	Berries, Bushberries	146	209	224	193
13	Oranges, Valencia	131	142	218	164
14	Peaches, Freestone	139	110	157	135
15	Peaches, Clingstone	108	141	122	124
16	Plums, Dried	132	121	81	111
17	Nectarines	119	86	120	109
18	Cherries	107	123	85	105
19	Grapefruit	69	68	130	89
20	Plums	87	74	92	85

*Although strawberries are perennials, they are re-planted each year in most of California
Source: USDA

The first is the least absolute selection and shrinkage operator (Lasso) model, which is a variation on ordinary least square (OLS) regression that "shrinks" the regression coefficient towards zero to avoid overfitting (Hastie et al. 2001). In statistical terms, the Lasso model adds a little bias to the model in return for a larger reduction in variance. In the Lasso, coefficients for many variables can be shrunk to zero, so that resulting model only uses a subset of the initial set of variables. As described in Efron et al. (2004), the Lasso can be viewed in this respect as a form of stagewise variable selection, as opposed to the more unstable method of stepwise variable selection. While the statistical details of the Lasso model are beyond the scope of this report, more information can be found in the previously cited references. Here we implement the Lasso using the "lars" package in R. An important decision in the Lasso is when to stop the stagewise process that shrinks the coefficients. Here we use the common approach of selecting the model with the minimum value of the complexity parameter Cp, which provides an estimate of out-of-sample prediction error.

The second statistical approach we use on the county data is regression tree modeling. Regression trees work by searching for the variable and value of that variable that best splits a dataset into two subsets, where “best” is defined as the split that achieves the maximum difference between the averages of the two subsets. Each split, called a *daughter node,* is then treated as its own dataset and the process is repeated recursively. For this reason, the method is also described as recursive binary partitioning. The resulting tree model uses the mean of each node as the prediction value, so that it effectively fits a piecewise constant function to the data. Regression trees are an increasingly popular tool in data mining, as they possess many attractive features such as automated variable selection, low sensitivity to outliers and missing data, and an ability to capture interactions between variables. Here we implement regression trees using the “rpart” package in R. The tree was grown until no split improved model R^2 by more than 0.01, and then it was pruned by eliminating nodes until R^2 decreased by more than 0.05. The pruning procedure is a common technique to avoid overfitting the model to the calibration dataset.

Both the Lasso and regression tree models are imperfect. For example, the Lasso is a linear model that is incapable of capturing important interactions between weather in different months. Regression trees fit piecewise constant functions and thus provide crude approximations to linear relationships. By employing both techniques, we sought to identify for each crop where the relationships between weather and yields were robust enough that model choice had a relatively small effect on inferred impacts. In such cases, the assumptions that vary for the two methods can be viewed as having a small effect on the results.

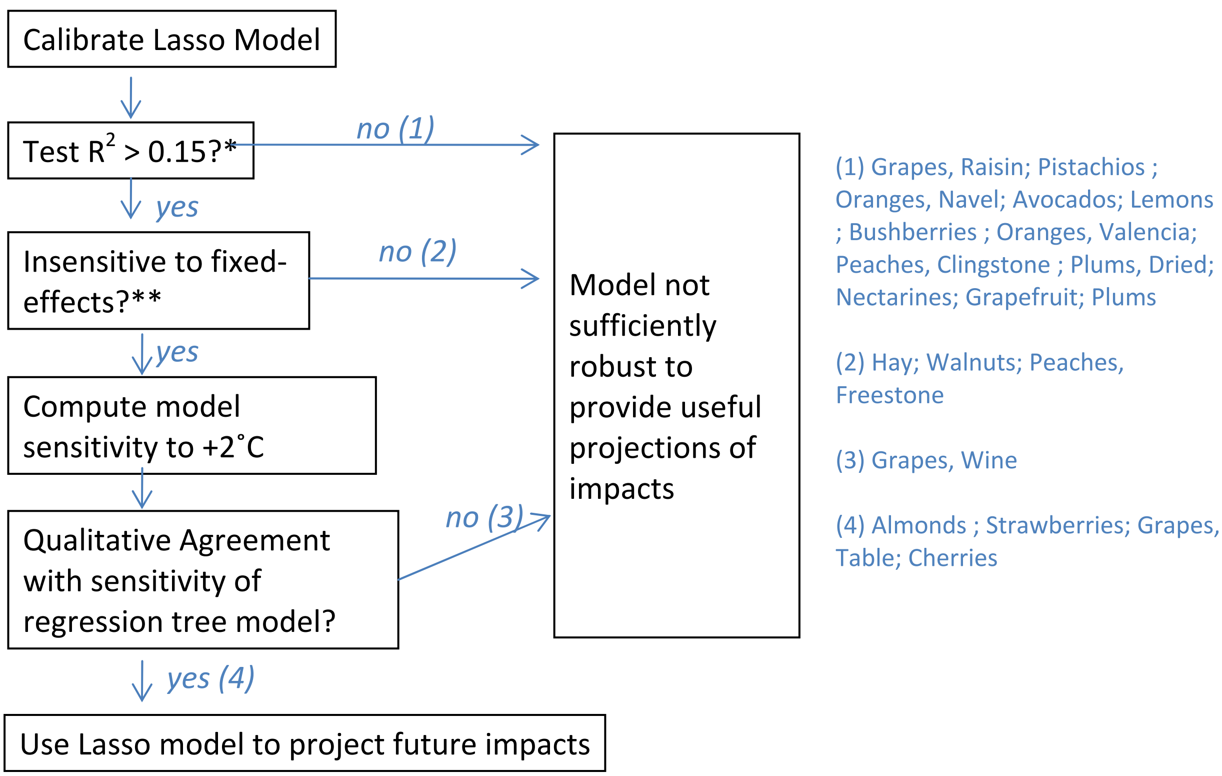
However, comparison of the two methods does not reveal the importance of assumptions that both share. One particular concern is that differences among counties that appear due to weather are, in fact, associated with omitted variables that are correlated with weather. Possible omitted variables include soil quality, topography, and management techniques. To examine sensitivity to omitted variables, we used three approaches.

First, we simply plotted the yield data versus each climate variable identified as important in the Lasso model, with each county coded by a different color. This allowed us to visually examine whether the correlation was driven largely by differences among counties.

Second, we performed a bootstrap analysis of model performance, where for each of 100 iterations we removed one-third of the counties from the calibration procedure. The model calibrated on the other two-thirds of the data was then used to predict yields for the test subset, and the R^2 was computed between predicted and actual yields. Cases where the test R^2 was substantially lower than the training R^2 indicated the possible presence of omitted variable bias.

As a third check against omitted variables, we selected the five most important variables identified from the Lasso analysis and performed an OLS regression with and without a dummy variable for county (i.e., a county fixed-effect). Model predictions for the average statewide impact of a 2˚C (3.6˚F) warming were compared for the two models, and when the answers diverged it indicated the presence of strong county-fixed effects.

An overview of the modeling process for the county level models study is given in Figure 3. Only for models that appeared robust, namely with relatively high R^2 and low sensitivity to model structure and fixed-effects, did we then attempt to project impacts of future climate change. Figure 3 indicates which of the 20 crops were considered robust and which were eliminated for each reason. While all model evaluation was based on statistical tests, more qualitative work could be done to verify the model coefficients in the future, for example by surveying growers on their impressions of the most important weather variables.



* Evaluated by calibrating model on 2/3 of counties and testing on remaining 1/3 of counties, repeating 100 times and computing average prediction R^2

** Evaluated by comparing ordinary least square regression model with top 5 Lasso variables , with and without county fixed-effects

Figure 3. Overview of steps taken to model yield responses using county-level data

4.2. Projections of Climate Change Impacts through 2050

The crop models developed here were then combined with climate change projections to assess potential impacts through 2050. We limit our projections to 2050 because temperatures beyond this date are frequently beyond the range of temperatures used to fit the statistical models. We emphasize that these projections are conditional on the assumption of no adaptation, and therefore are unlikely to represent the true future course of yield impacts. However, understanding the potential impacts in the absence of adaptation is a critical step towards planning and prioritizing adaptation options.

We used climate projections from six general circulation models and two emission scenarios (Special Report on Emissions Scenarios [SRES] A2 and B1), which were downscaled using the bias-corrected spatial downscaling (BCSD) method of (Maurer et al. 2002). Average monthly values of Tmin, Tmax, and Prec for 1950–2099 were computed for each of the 12 model simulations and averaged for each county over the portion of the county classified as agriculture in a California map of management landscapes.[2] This latter step was important to ensure that the climate model data were consistent with the extent of observational station data used in the crop model calibration, which were limited to low elevation areas. Their agreement was confirmed by comparing the climatology of simulated and observed temperature and precipitation averages in each county over the observation period of 1980–2005 (not shown).

The county averages of monthly climate model simulations were then fed into the crop models to project yields for each county for 1950–2099, assuming the technology of 2000 (the predictor "year" was held constant at 2000). Statewide average yields were computed by assuming the current distribution of crop area within California. The results are presented as percent changes from the 1995–2005 average yields, and as 21-year moving averages to emphasize the trend rather than year-to-year variability. We present projections only out to 2050 because (1) projections beyond this time period require substantial extrapolation of the statistical models, and are therefore less reliable, and (2) from our perspective most decisions in the agricultural sector have a timeline of 50 years or less.

Finally, to estimate the uncertainty associated with the climate projections, the yield projections were made for each of the 12 climate model simulations (six models x two emission scenarios). To estimate uncertainty associated with the crop models, the projections were repeated using crop models generated from bootstrap samples of the historical data. We present results both for climate uncertainty only and for the combination of climate and crop uncertainty.

4.3. Almond Varieties

As almonds are California's single most valuable perennial and are susceptible to winter warming (see below), we investigated whether different common commercial varieties have differential sensitivity to warming. If so, planting of more heat-tolerant varieties could be pursued as an adaptation strategy. Data on statewide production of individual varieties since 1980 were obtained from the Almond Board of California (courtesy of Sue Olson - Associate Director, Statistics & Compliance). Corresponding data on statewide areas of individual varieties were obtained from the USDA's National Agricultural Statistics Service, California Field Office (courtesy of Jack Rutz, Deputy Director).

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[2] California Department of Forestry and Fire Protection, FRAP. http://frap.cdf.ca.gov.

The time series of each variety were then analyzed separately in an identical manner to the time series of total almond production (Lobell et al. 2007). Briefly, statewide average time series of Tmin, Tmax, and Prec were generated by averaging station data according to the fraction of 2003 statewide area for the specific almond variety that was found in the county. The almond production and yield time series were then detrended using a linear trend, and an autoregressive model was used to remove the autocorrelation that is often present in time series of alternate bearing crops such as almonds. The production and yield anomalies were then regressed against February Tmin. Here we present the results for the production data, since the relationships were slightly stronger and since production statistics are more reliable than area or yield statistics (Jack Rutz, personal communication), although results for the two variables were similar.

5.0 Results

5.1. County Scale Yield Models

5.1.1. Lasso Models

Twelve of the 20 perennial crops considered did not exhibit any clear relationships between weather and yields, with the models able to capture less than 15% of the variation in the yield data not used to calibrate the model. For the remaining eight crops, the models were able to explain more than 46% of the variance in training data, and, with the exception of table grapes, more than 20% of the test data (Figure 4).

The coefficients for the eight successful models, which are useful for understanding which temperature variables most closely relate to yields, are summarized in Figure 5. These coefficients were derived from a single computation of the Lasso using the full dataset (as opposed to the R^2 statistics which were derived by repeated calibrations to subsets of the data). Rather than display in units of absolute yields, these values are expressed in terms of the percent change in statewide average yields that would result from a uniform 2˚C increase in each variable (Tmin and Tmax for each month.) Of course, because each variable is represented by a second-order polynomial, a positive response to 2˚C warming does not necessarily imply a positive response to greater magnitudes of warming. However, we consider 2˚C to be a reasonable approximation for the magnitude of warming expected by 2050 (see below).

For some crops, such as wine grapes, strawberries, and walnuts, the selected Lasso model possessed non-zero coefficients for most temperature variables. For others, such as table grapes and cherries, the majority of coefficients were shrunk to zero, indicating that weather in most months has insignificant effects on yields of these crops.

Several patterns emerge from these models. For some crops, there appear to be parts of the year where warming is beneficial and parts of the year where warming is harmful. For example, warming in January and February significantly reduces yields of almonds, but yields appear to be enhanced by warming in May and July. Wine grapes, strawberries, and walnuts show a qualitatively similar pattern of yield losses for warming throughout the winter but yield gains from warming in summer months. Freestone peaches exhibit an opposite pattern, with winter warming—particularly at night—beneficial, but warming during the summer extremely harmful.

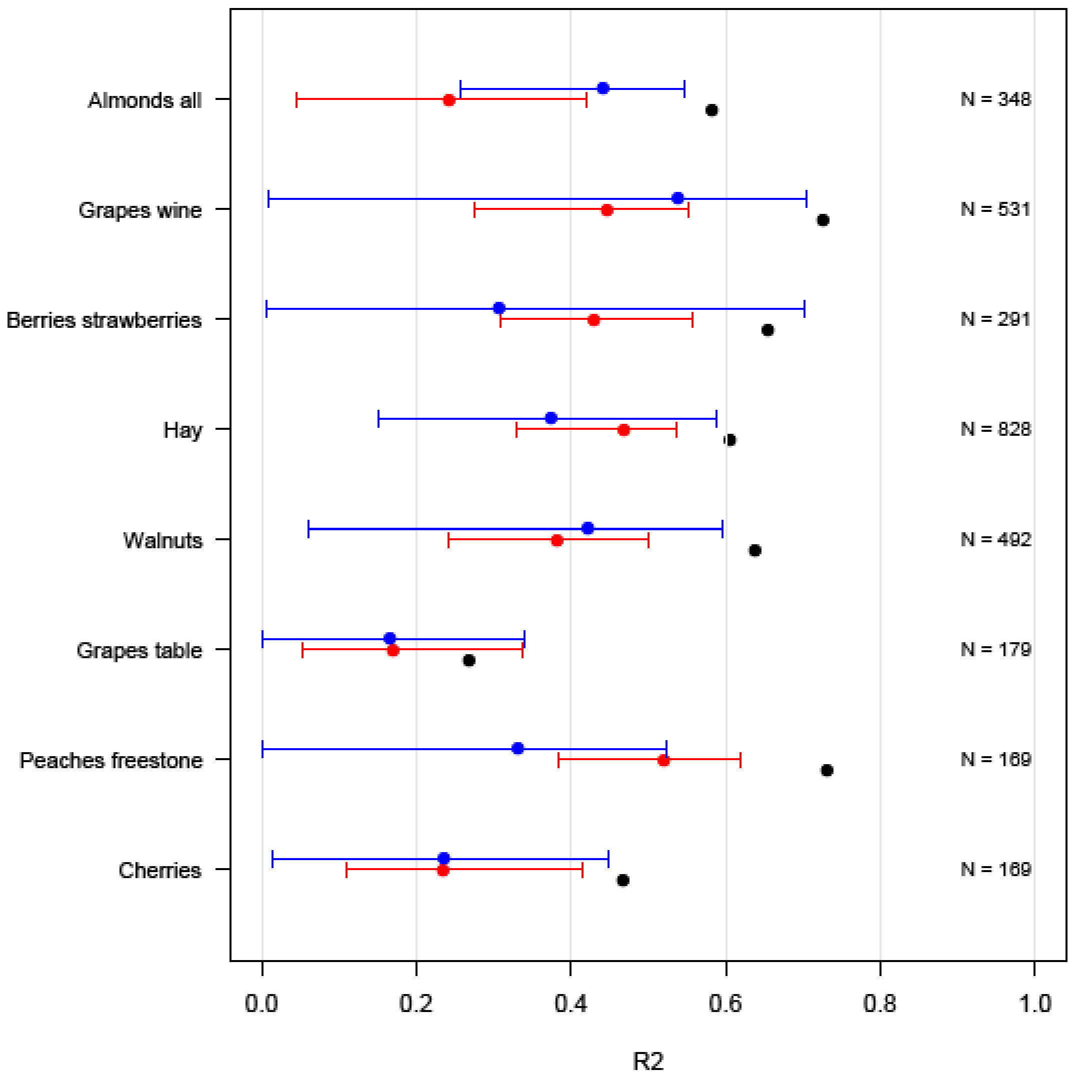


Figure 4. Model R^2 for training and test datasets for each crop with an average test R^2 greater than 0.15. The twelve other crops considered in this study did not meet this criterion. Black point indicates training R^2 for full dataset, red indicates test R^2 when omitting one-third of years from calibration and using these to test the model, and blue indicates test R^2 when omitting one-third of counties. Lines indicate 95% confidence interval based on 100 repeated tests with a different (random) one-third omitted.

Cherries and table grapes exhibit a different pattern, where warming rarely has a benefit at any time of year. The case of cherries is especially stark, with yields harmed by warming throughout November–February, the primary months in which trees accumulate chilling hours. The greater importance of Tmin than Tmax in these months supports the notion that reduced chilling (which occurs mainly at night) is the culprit for yield losses.

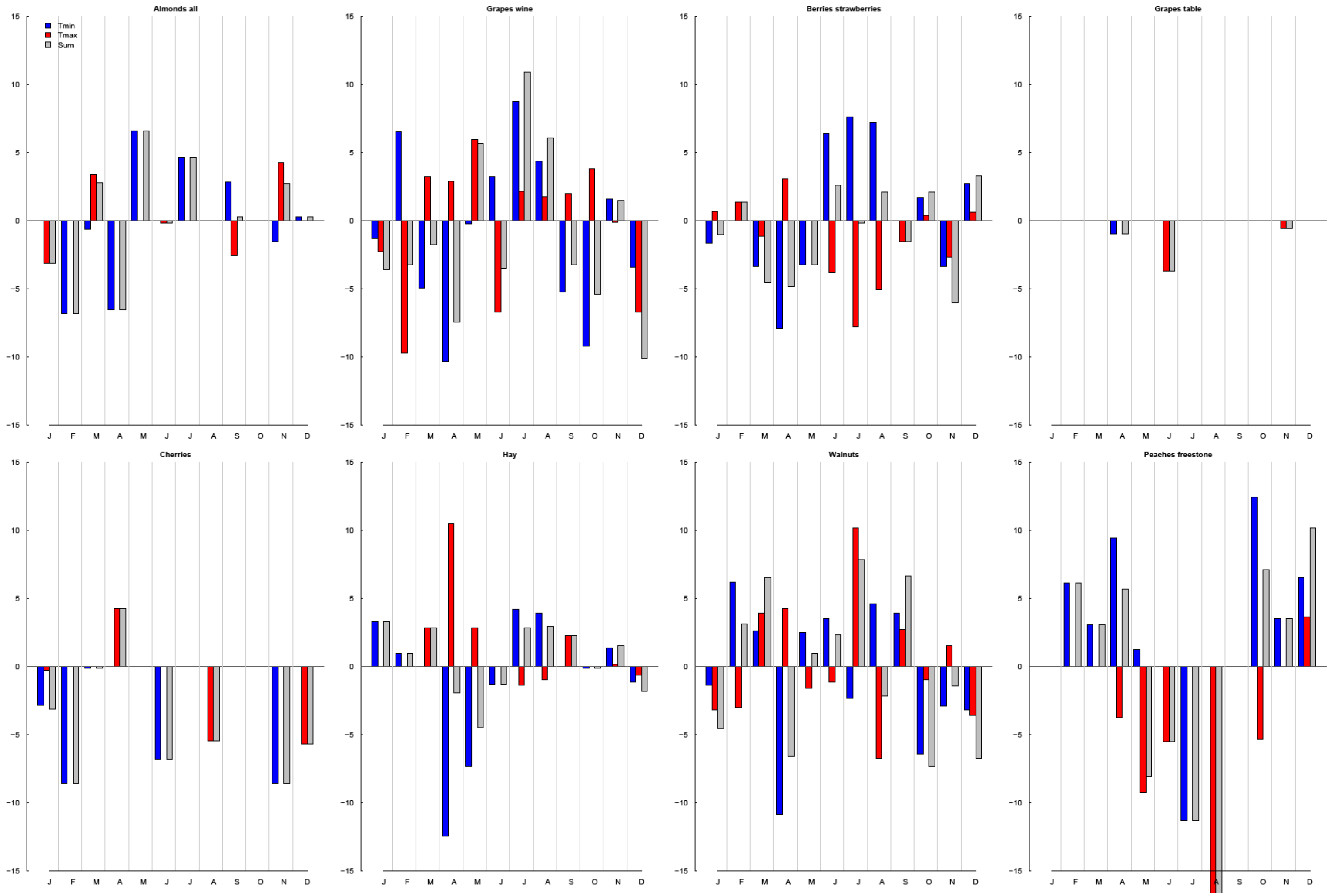


Figure 5. Summary of temperature coefficients for Lasso model, expressed as % change in state average yields for a 2˚C warming. Blue and red bars indicate Tmin and Tmax, respectively, for each month. Coefficients without bars were shrunk to zero by the Lasso model.

5.1.2. Fixed-Effects

Now we consider whether these county-level relationships between weather and yields may be biased by omission of non-climatic variables that vary by county, such as soil quality. This bias was evaluated by selecting the five weather variables with the largest effect in the Lasso model (Figure 5) and running an OLS regression with just these variables and their squares. The OLS regression was then re-run after adding a dummy variable for county. (Dummy variables cannot be entered in a Lasso model, which is why we resort to OLS models in this section.)

The changes in statewide average yields for a 2˚C warming were computed for both OLS regressions, using bootstrap resampling to estimate a confidence interval. The results (Figure 6) demonstrate that five of the eight crops appear very insensitive to inclusion of county fixed-effects, indicating that the Lasso results are not biased by omitted variables. However, three crops (hay, walnuts, and freestone peaches) were significantly different between the two OLS models, with non-overlapping 5%–95% confidence intervals.

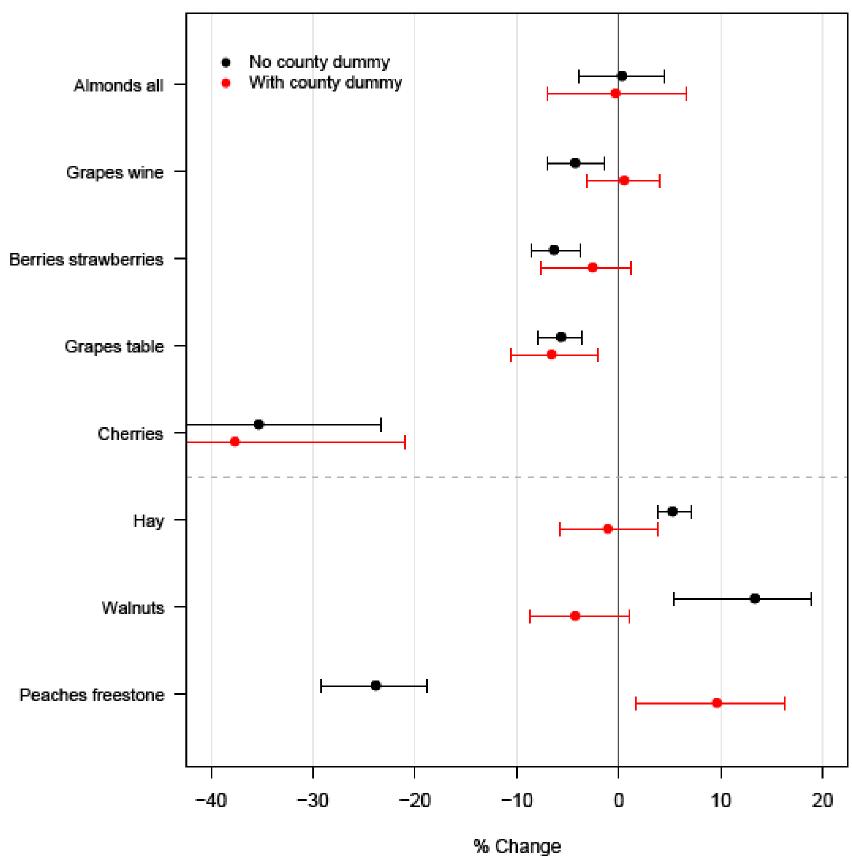


Figure 6. The predicted change in state average yields for a 2˚C warming using ordinary least square regression models without (black) and with (red) county fixed-effects. Error bars indicate 5%–95% confidence interval based on 100 bootstrap replicates. Large differences between the two indicate the potential importance of omitted variables, such as soil quality, that vary by county. The models contained the five temperature variables deemed most important in the Lasso model. Only three variables were used for table grapes since the Lasso model included only three temperature variables.

Figure 7 displays a scatter plot of yields versus an apparently important weather variable for each of these three crops, with each county represented as a different color. The problem of fixed-effects is best exemplified by freestone peaches, where the results from the OLS models with and without fixed-effects diverged most dramatically. A plot of daytime temperature in August and yields reveals that a single county, Riverside, has particularly high temperatures and low yields. (Even when Riverside is removed from the analysis, however, the sensitivity to county-fixed effects remains.)

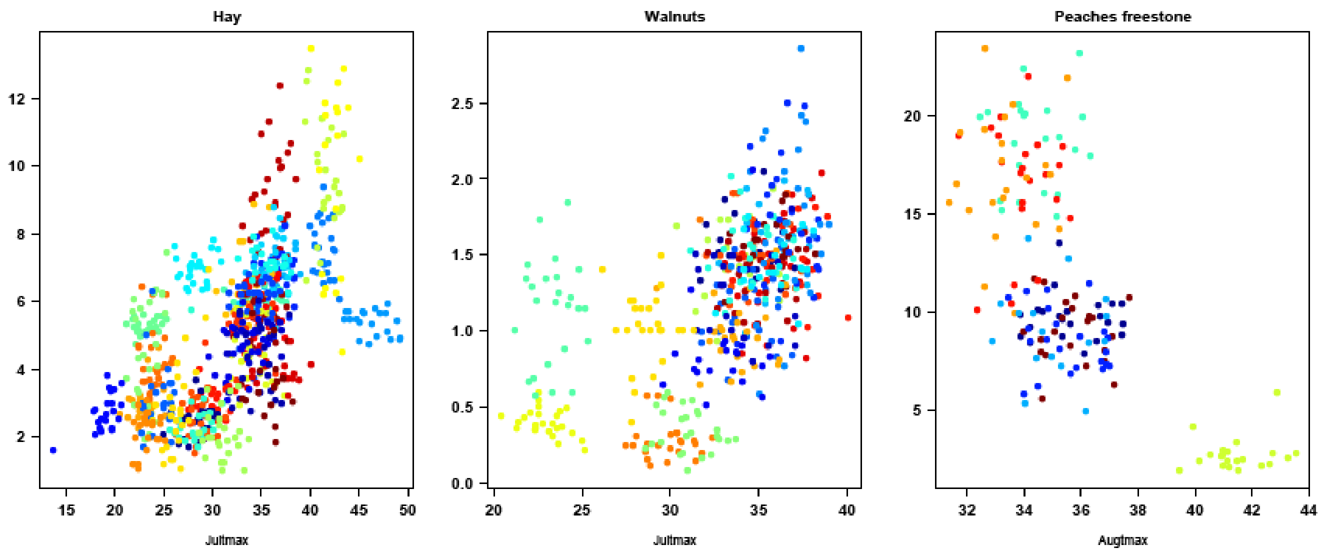


Figure 7. Scatter plots of yields vs. selected temperature variable for three crops with sensitivity to county fixed-effects. Each data point represents an individual county-year, with each county represented by a different color.

A sensitivity of results to fixed-effects indicates that much of the perceived effect of weather is obtained by comparing yields across counties, rather than by comparing across years. It does not necessarily indicate that weather is not the true reason causing yields to differ among counties. However, one cannot rule out the possibility that other differences among counties explain at least part of the yield differences. There is therefore no obvious choice between a model with and without fixed-effects, and here we simply point to the crops that are sensitive to this choice. For crops that are insensitive to this choice, such as almonds and grapes, the models utilize differences between counties but are not entirely dependent on them, as evidenced by the similar results when the model is limited to using only differences across years.

5.1.3. Comparison of Lasso and Regression Tree Models

We next consider the importance of model structural assumptions. In particular the OLS and Lasso models assume that yield response to weather can be represented as a second-order polynomial, with no interactions among variables. In contrast, the regression tree models use piecewise constant fits and are capable of capturing interactions and higher order nonlinearities. Figure 8 compares the inferred sensitivity of statewide average yields to a 2˚C warming for the Lasso and regression tree models for each crop. For many of the crops the two models provided predictions that were qualitatively consistent, with overlapping confidence intervals. An important exception was wine grapes, where the Lasso predicts on average a statewide loss of roughly 15% for 2˚C warming while the regression tree predicts a 5% increase. The regression tree model can choose different variables for each bootstrap iteration, so it is difficult to describe exactly why it shows an increase. However, when fit to the entire dataset for wine grapes, the regression tree chose as predictor variables only August Tmin and Tmax, which tend to be higher in the Central Valley counties with higher yields.

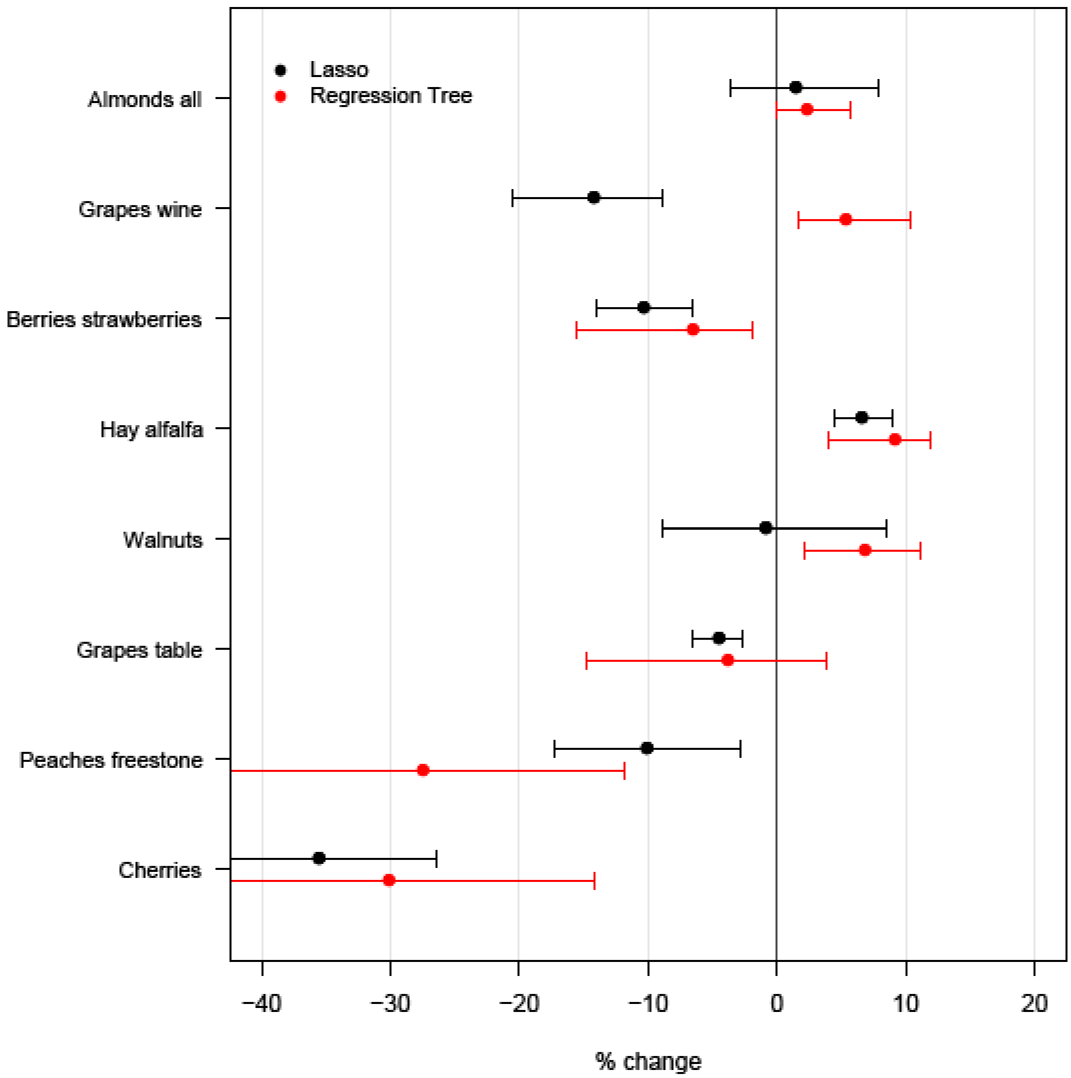


Figure 8. The predicted change in state average yields for a 2˚C warming using the Lasso (black) and regression tree models (red). Error bars indicate 5%–95% confidence interval based on 100 bootstrap replicates. Large differences between the two indicate the potential importance of structural assumptions in the models.

Of course, for wine grapes the major concern is not total production but the quality of the grapes for winemaking. While coastal counties have varieties with lower yields, they produce wine with much greater economic value. Therefore, a shift to Central Valley yields and varieties would likely reduce, not increase, total agricultural value. While this study does not focus on climate change and wine quality, previous studies have concluded that wine quality could suffer from more frequent summer heat extremes (Hayhoe et al. 2004; White et al. 2006).

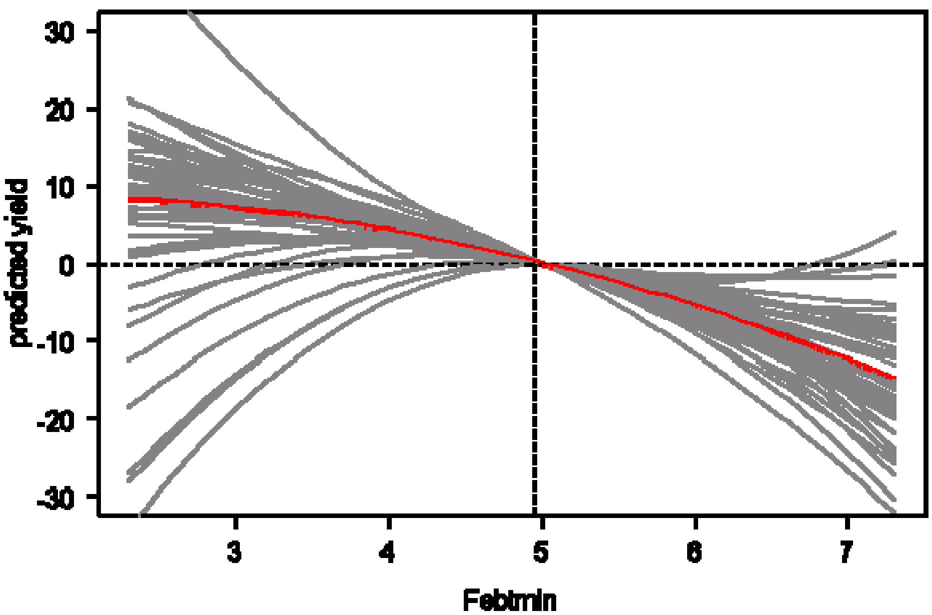
To summarize, the regression tree models generally support the Lasso results, with the exception of wine grapes. We therefore do not place great confidence in the Lasso predictions of lower wine grape yields with warming. At the same time, the yields of wine grapes in a future climate will be far less important than the quality of grapes that can be grown.

5.1.4. Comparison with Previous Studies

Of the eight crops with significant models using county-scale data, four were also considered in previous work using statewide averages. Table 2 shows the variables and coefficients used for these crops. Of these crops, the model for table grapes agreed well at the two scales, with both the county and state models indicating modest declines in statewide average yields for warming. For walnuts the model from county data was ambiguous because of the sensitivity to fixed-effects. In the state model, walnuts showed a modest decline because of sensitivity to November temperatures. The county OLS model with fixed-effects showed similar declines for warming (Figure 6), while the OLS model without fixed-effects and the Lasso model exhibited a positive response to warming.

As shown in Figure 8, the estimated response of wine grape yields to warming with county data was negative when using the Lasso but positive for a regression tree model. The state model exhibited a very small sensitivity to warming, falling between the predictions of the two county level models. A reasonable estimate for wine grapes may therefore be little change in statewide average yields for warming.

The most striking difference between the state and county models was for almonds, the single most valuable perennial crop in California. The county models indicate a very low sensitivity to a uniform warming of 2˚C throughout the year, with the result apparently robust to omitted variables and structural assumptions. The state model, which relied solely on February Tmin for temperature response, shows instead a negative response to warming. Importantly, the county model also shows a strong negative effect of February warming (Figure 5). In fact, the inferred effect of February Tmin on yields is nearly identical when using the county or state average data over the range of temperatures seen in the state model (Figure 9). The county model possesses a larger range of temperatures, and thus is also able to capture the reduction of yields at very cold temperatures.



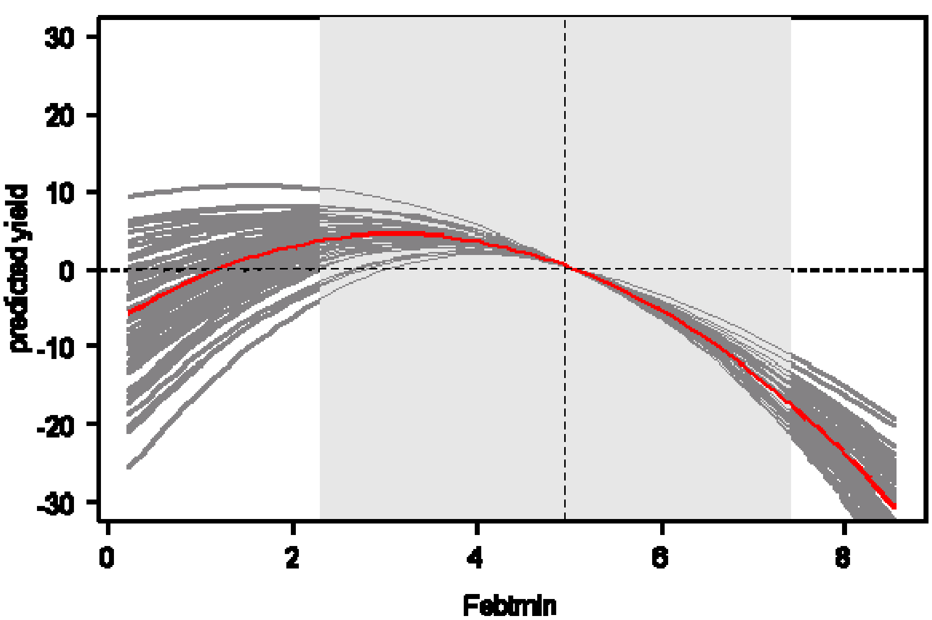


Figure 9. The inferred relationship between February Tmin and state average almond yields using (a) state-wide average yields and (b) county-level data. The shaded area in (b) indicates the range of temperatures for the state model in (a). The red lines show the relationship when using all data, and black lines show the relationship for 50 bootstrap samples. The units of yields are the percentage above the value of yield at the average statewide temperature, which is indicated by vertical dashed line.

As discussed above, the small net effect of temperature on almonds in the county model arises from a beneficial effect of spring and summer warming that cancels the effect of winter warming. To test whether the state model would also exhibit this response if summer temperatures were included in the model, we performed a stepwise OLS regression where we added variables to the original state model (Table 3). The variables added are the two that had the biggest positive effect in the Lasso model: May and July Tmin.

Table 3 displays the model R^2, as well as the predicted response to uniform 2˚C warming for a model using only statewide averages and a model using county-level data. The county and state models give nearly identical results of ~13% yield loss when using the original two variables of the state model: February Tmin and January Prec. When May Tmin is added, the county model R^2 improves substantially, while the projected loss is reduced by half to 6%. In the state model, the R^2 also improves but the mean projected impact changes very little. In addition, the confidence interval becomes wider because with six variables (three weather variables plus their squares) and 26 data points, the model exhibits a higher variance for bootstrap resampling that is symptomatic of overfitting.

When July Tmin is added, both the county and state model impacts are reduced by roughly 3%. Here the state model becomes very variable and the confidence interval widens further. The main difference between the two models is thus the strong beneficial effect of May Tmin warming in the county model that is simply not evident in the statewide average time series. According to Kester et al. (1996), May is the critical month of embryo growth and hardening, and "adverse conditions and stress in this period can seriously lower quality and reduce weight of the mature nut" (p. 96). Thus, it is at least plausible that warming in May does substantially benefit almond yields.

A possible explanation for the lack of this effect in statewide time series is that it is too short to accurately measure this effect. To assess this, we obtained weather records and average almond yield data back to 1960 and repeated the OLS analysis at the state scale, with results shown in the right columns of Table 3. When using this longer record, the model agrees remarkably well with the county model that showed a significant benefit of May warming. Thus, the balance of evidence leads us to believe that spring warming will, in fact, benefit almond yields enough to offset much of the losses incurred from winter warming.

Table 2. Models developed from statewide average data for four perennial crops (ref). Y represents yield anomaly (ton acre^{-1}). Subscripts indicate month of climate variable, with negative values denoting a month from the year prior to harvest. Tn = minimum temperature (ºC), Tx = maximum temperature (ºC), P = precipitation (mm).

Crop	Equation	R^2_{adj}
Wine grapes	$Y = 2.65\ Tn_4 - 0.17\ Tn_4^2 + 4.78\ P_6 - 4.93\ P_6^2 - 2.24\ P_{-9} + 1.54\ P_{-9}^2 - 10.50$	0.66
Almonds	$Y = -0.015\ Tn_2 - 0.0046\ Tn_2^2 - 0.07\ P_1 + 0.0043\ P_1^2 + 0.28$	0.88
Table grapes	$Y = 6.93\ Tn_7 - 0.19\ Tn_7^2 + 2.61\ Tn_4 - 0.15\ Tn_4^2 + 0.035\ P_1 + 0.024\ P_1^2 + 1.71\ P_{-10} - 0.673\ P_{-10}^2 - 73.89$	0.77
Walnuts	$Y = 0.68\ Tx_{-11} - 0.020\ Tx_{-11}^2 + 0.038\ P_2 - 0.0051\ P_2^2 - 5.83$	0.59

Table 3. Ordinary Least Square models for almond yields using statewide average or county level data from 1980–2005 and using statewide average data for 1960–2006. Model R^2 and the estimated impact of 2˚C warming is shown for four models of increasing complexity.

	State, 1980–2005				County, 1980–2005				State, 1960–2006			
Variables	R^2	Estimated sensitivity to +2˚C			R^2	Estimated sensitivity to +2˚C			R^2	Estimated sensitivity to +2˚C		
		mean	5th %tile	95th %tile		mean	5th %tile	95th %tile		mean	5th %tile	95th %tile
Feb Tmin	0.55	-14.9	-23.0	-5.5	0.25	-15.7	-19.6	-12.2	0.35	-14.5	-21.6	-7.9
Feb Tmin, Jan Prec	0.74	-13.5	-20.2	-7.4	0.32	-12.6	-14.8	-9.9	0.43	-12.4	-19.7	-6.2
Feb Tmin, Jan Prec, May Tmin	0.81	-14.5	-28.2	-5.4	0.41	-6.3	-9.9	-3.1	0.47	-5.7	-13.4	0.9
Feb Tmin, Jan Prec, May Tmin, Jul Tmin	0.86	-11.8	-24.0	0.3	0.46	-3.1	-9.5	2.3	0.48	-1.4	-14.4	14.8

5.2. Projected Impacts of Climate Change

The climate model projections indicated similar patterns in each county, with temperatures for Fresno displayed in Figure 10 as an example. The two emission scenarios give similar average temperature changes until roughly 2040, indicating that the next 30+ years of climate change are "locked-in" because of inertia in the climate and energy systems (Meehl et al. 2007). Temperature changes are slightly more rapid in summer months than in winter months, a result that likely reflects a simulated warming feedback from soil moisture decreases in summer months. As discussed in Lobell et al. (2006b), the representation of soil moisture feedbacks in general circulation models is questionable in agricultural areas, since none represent the irrigated conditions that exist in the Central Valley. Nonetheless, we use these climate scenarios in the current study without adjustment for this potential bias and discuss the potential implications of the bias below.

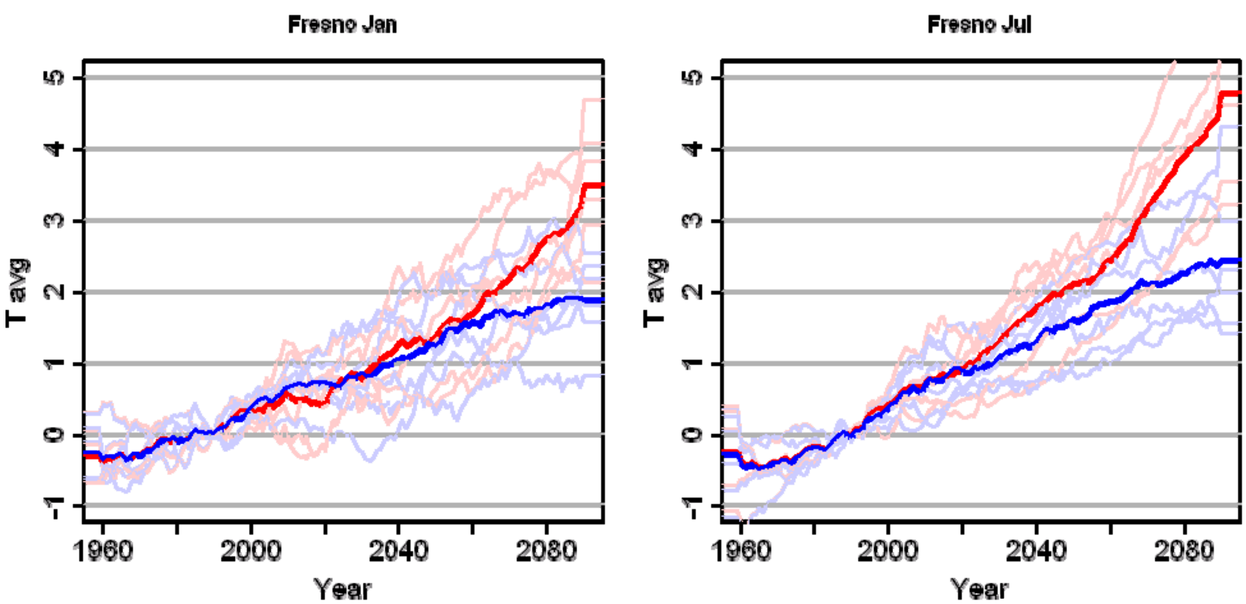


Figure 10. Projected change in average monthly temperature for (a) January and (b) February. Each thin line shows an individual model projection, with red representing an A2 emission scenario and blue representing B1. Thick lines show the model average for each emission scenario. The results are presented as changes (˚C) from the 1980–1999 climatology, and as 21-year moving averages to emphasize the trend, rather than year-to-year variability.

The simulated impact of climate change on statewide average yields for the four crops with the most reliable crop models are shown in Figure 11, assuming no shift in crop areas. For almonds, the trend is slightly positive with a projected increase of less than 5% by 2050 relative to current climate. As seen above (Figure 8), the impact of a uniform 2˚C increase was a very small net change in yield. The slight positive impact of the actual climate projections indicates the greater warming of summer months relative to winter, with the former benefiting and the latter harming almond yields in the model.

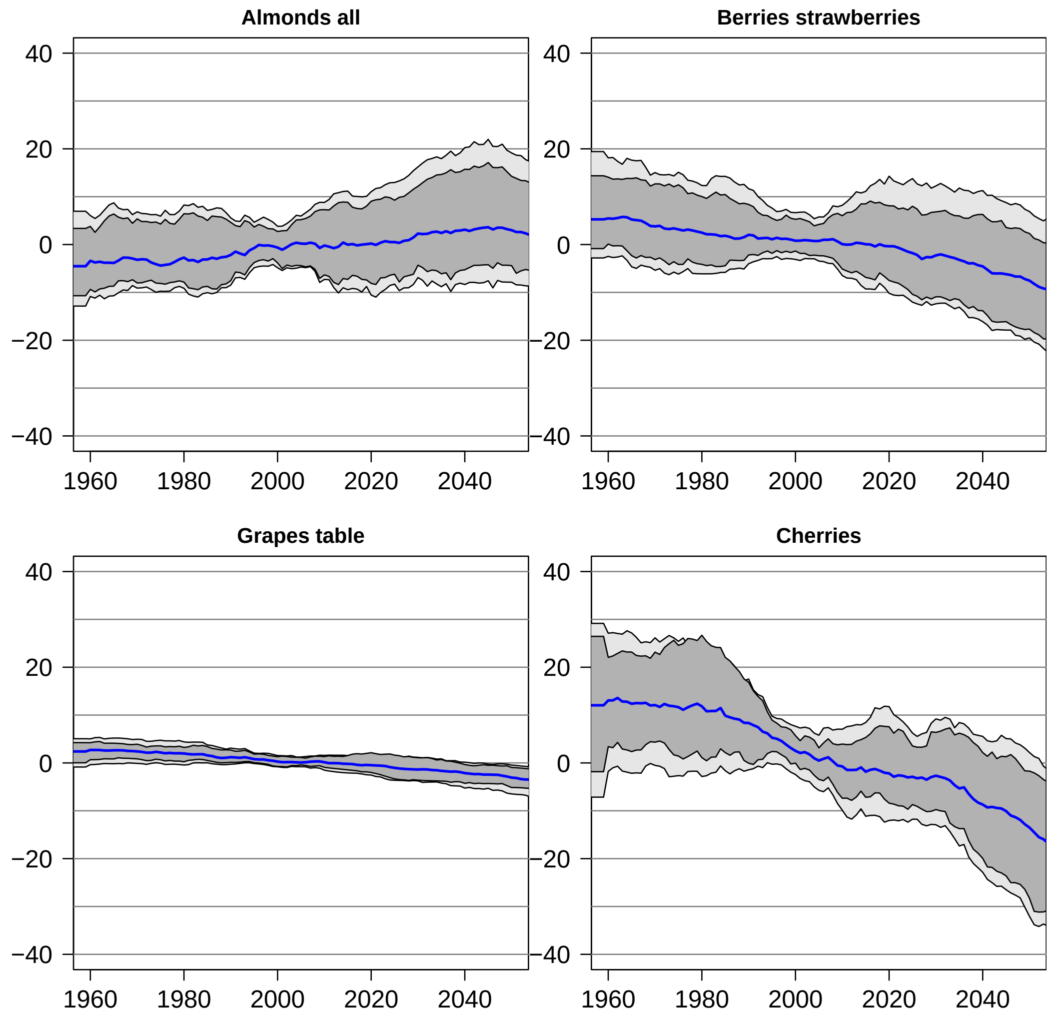


Figure 11. Simulated change in crop yields for four crops with most reliable crop models. The thick blue line shows the average of all projections, the dark shaded area shows 5%–95% range of projections when using multiple climate models, and the light shaded area shows 5%–95% range when using multiple climate models and multiple crop models (based on bootstrap resampling). The results are presented as percent changes from the 1995–2005 average yields, and as 21-year moving averages in order to emphasize the trend rather than year-to-year variability.

Average projections for the other three crops indicate negative trends out to 2050, ranging from less than 5% decreases for table grapes to nearly 20% average loss for cherries by 2050. The shaded areas indicate substantial uncertainties associated with these projections, arising from both the climate and crop models. For example, average statewide cherry yields may be reduced by as much as 30% or as little as 0% by 2050 relative to the climate of 2000.

The average projected impacts for 2030–2050 relative to current climate in each county are illustrated in Figure 12 for the four most reliable crop models. Overall, the simulated impacts were fairly uniform throughout California, suggesting limited potential benefits from changing the spatial distribution of crops within their current growing areas. Slightly more negative impacts were simulated in the southern part of the state for strawberries and cherries. Again, these results have the caveat that the models used here do not consider effects of weather variables other than monthly averages.

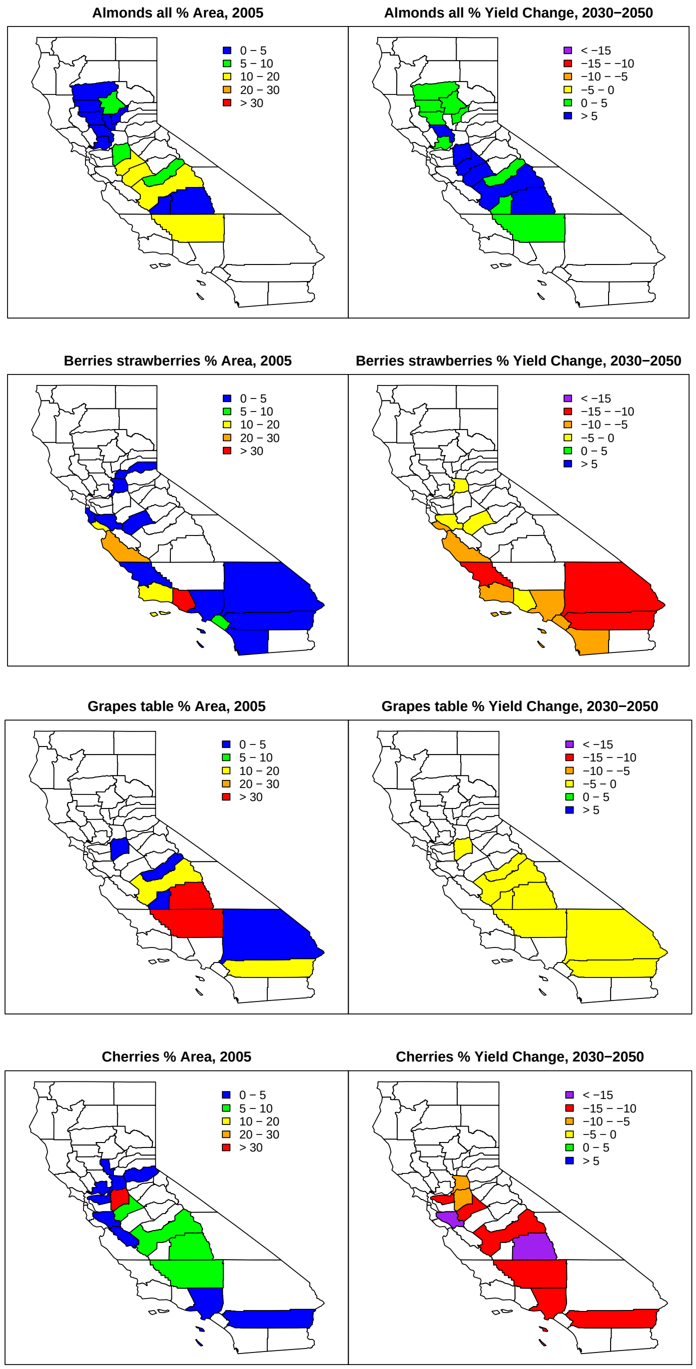


Figure 12. Current % of crop area in each county (left) and average projected changes in county yields (right) for four perennial crops. Yield changes are expressed as percentage difference between average yields in 2030–2050 and those in 1995–2005.

Figure 13 displays projections for the four less reliable crop models, with a slight yield increase projected for hay, little change for walnuts, a slight decrease for wine grapes, and considerable decrease for freestone peaches. As discussed above, these results should be treated with more caution because of the sensitivity of the crop model to treatments of county fixed-effects or structural assumptions (Lasso vs. regression tree).

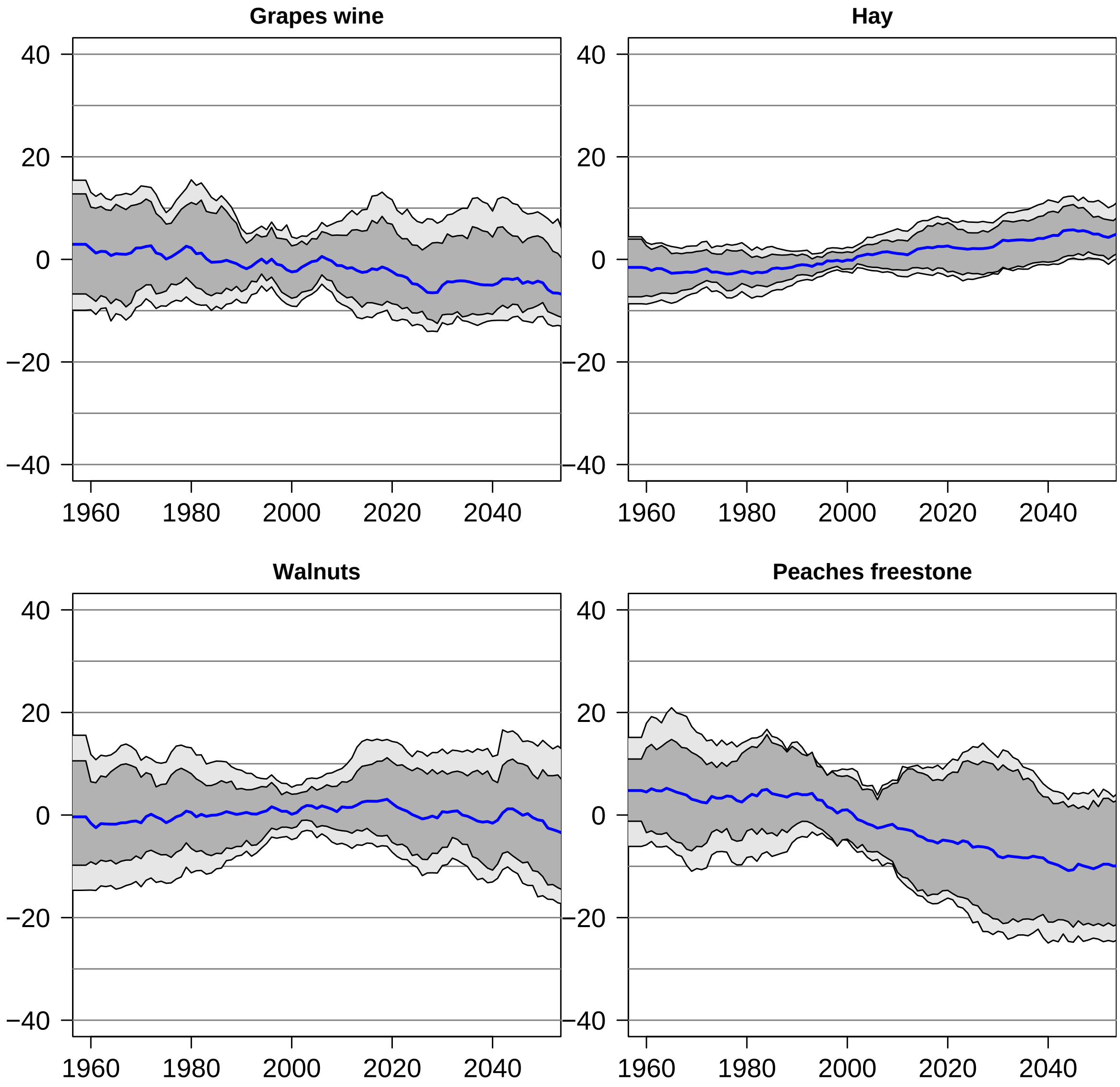


Figure 13. Same as Figure 11, but for four crops with less reliable models, due to sensitivity to fixed-effects or significant differences between lasso and regression tree models

5.3. Almond Variety Switching as a Possible Adaptation?

For almonds, the most valuable perennial crop in California, the results from the county-scale model presented above suggested that previous estimates based only on statewide data may have overestimated warming-induced losses. However, the county model agrees with the state model in predicting that winter warming, by itself, will be harmful in the absence of adaptation. An ability to adapt to this warming could thus substantially improve future yields of almond growers, even if the net effect of climate change without adaptation is small.

Different varieties of almonds have different chilling requirements and blooming periods. A reasonable hypothesis is therefore that some varieties exhibit lower sensitivity to winter temperatures than others. Alternatively, because almond varieties are self-sterile and require other adjacent varieties for successful pollination, the response of any individual tree to weather reflects the behavior of a collection of varieties, and therefore may not exhibit unique sensitivities to warming. For example, average annual yields for common varieties (Figure 14a) exhibit strong correlations over the 1980–2005 period.

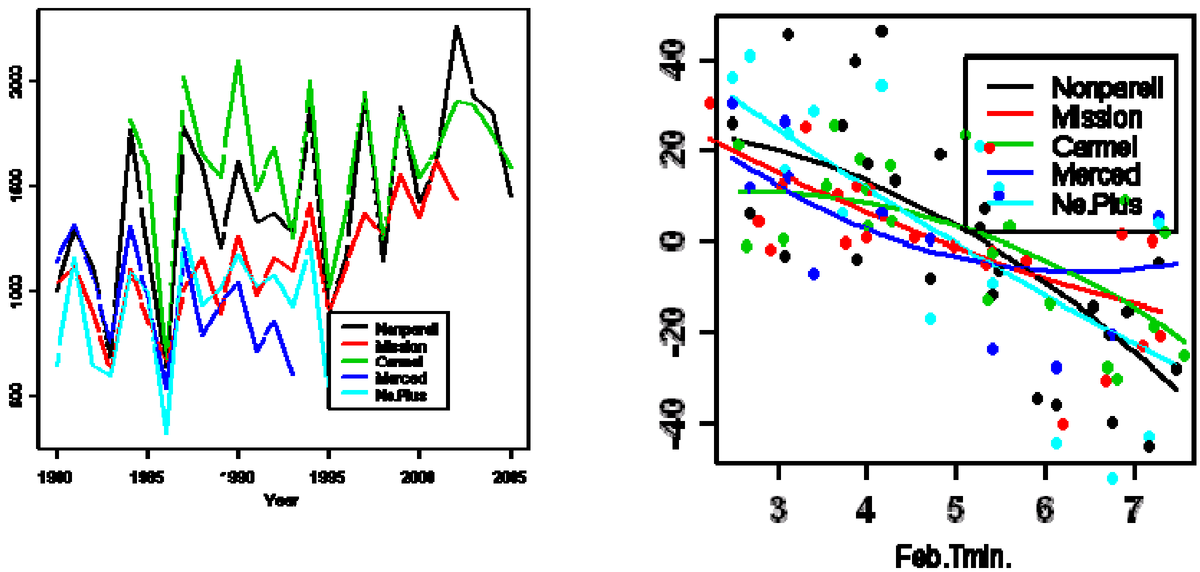


Figure 14. (a) Time series of statewide average almond yields for five major varieties. (b) The relationship between production anomalies and February Tmin for five major varieties. Lines indicate best fit second-order polynomial. No significant differences in the response of different varieties to February Tmin are evident.

A comparison of production anomalies (in percentage of recent production) with February Tmin offers little support for the hypothesis that varieties exhibit significantly different responses to winter warming, as all of the five varieties with sufficiently long records exhibit a similar negative relationship with February Tmin (Figure 14b). As a result, this study found little evidence that switching among the current commercial varieties offers a promising pathway towards climate adaptation.

Given the self-sterile nature of almonds, it is more likely that a holistic approach to adaptation is needed, with selection of a group of varieties that are less sensitive to warming. As discussed above, the most likely explanation for sensitivity to February Tmin is a shortening of the critical bloom period in warmer years, although this claim deserves further scrutiny. Thus, emphasis on traits controlling successful pollination may be warranted in variety development and selection.

6.0 Discussion and Conclusions

The potential impacts discussed above considered the direct effects of temperature and rainfall on perennial crop yields. Importantly, several other factors related to climate change were not addressed. First, it was assumed that historical management practices that affect the response of yields to weather remained constant. Specifically, all of these crops are irrigated in the entirety of their area, and while they would not be grown without irrigation, declining water resources related to climate change may force reductions in the acreage grown or the amount of irrigation applied. Thus, the omission of water resources likely creates an overly optimistic view of net impacts on the agricultural economy, although decreased water availability will more heavily impact lower value annual crops than the higher value perennials considered here (Tanaka et al. 2006).

Second, we did not consider the direct fertilization effect of higher carbon dioxide (CO_2) levels, which according to the SRES scenarios will reach between roughly 450–600 parts per million (ppm) by 2050. The magnitude of CO_2 fertilization for perennials is not well known. Open-top chamber experiments with sour orange trees showed substantial yield increases of up to 80% for a 300 ppm CO_2 increase, even after 13 years (Idso and Kimball 2001) but studies on other tree species show substantially lower rates. While the fertilization effect of CO_2 is relevant to projections of net yield changes, we argue that this effect is likely to be similar across the range of perennial species considered here, all of which possess the C3 photosynthetic pathway. The relative priorities for adapting California crops to climate change therefore should not depend greatly on the exact magnitude of CO_2 fertilization.

Third, we also omitted analysis of detrimental effects of high ozone levels, which may become more frequent and extreme in the next 50 years. Studies with annual crops suggest that losses from ozone may more than offset the gains from CO_2 fertilization (Long et al. 2006).

One of the main conclusions of this study is that, among the 20 most valuable perennials crops, cherries are likely be the most negatively affected by warming over the next decades. This likely relates to a loss of chilling, but again empirical models cannot unambiguously identify mechanisms. While cherries rank only eighteenth by average value for 2003–2005 (Table 1), they are rapidly increasing in popularity. For example, bearing acres of cherries hovered around 10,000 from 1920 to the early 1990s, before increasing to 20,000 in 2000 and 28,000 in 2008.[3] We do not consider here whether the economic decisions to maintain existing or establish new

[3] California Sweet Cherries, 1920-2006.
www.nass.usda.gov/Statistics_by_State/California/Historical_Data/Cherries.pdf

cherry orchards would be affected by consideration of lower yields in future climates, but this is a topic deserving of future study.

Another robust result is that almond yields will be harmed by warming of February temperatures, as this effect is revealed in both state- and county-level analyses (Figure 9). Less certain is the beneficial effect of warmer springs and summers, which appear to cancel the losses from winter warming in the county-level model but not in the state model (Table 3). Regardless of the summer effect, adaptation of almonds to warmer winters represents a substantial economic opportunity. Almonds are the single most valuable perennial crop and are also experiencing a surge in popularity and planted acreage (Figure 2).

7.0 References

Baldocchi, D., and S. Wong. 2008. "Accumulated winter chill is decreasing in the fruit growing regions of California." *Clim Change 87*: 153–166.

California Agricultural Statistics Service. 2006. California Agricultural Statistics 2005: Overview. 10 pp, USDA-NASS, Sacramento.

Efron, B., et al. 2004. "Least angle regression." *Annals of Statistics 32*: 407–499.

Hastie, T., et al. 2001. *The elements of statistical learning: Data mining, inference, and prediction*. 533 pp., Springer, New York.

Hayhoe, K., et al. 2004. "Emissions pathways, climate change, and impacts on California." *Proc. Natl. Acad. Sci. U. S. A. 101*: 12422–12427.

Idso, S. B., and B. A. Kimball. 2001. "CO_2 enrichment of sour orange trees: 13 years and counting." *Environ Exp Bot 46*: 147–153.

Kester, D. E., et al. 1996. Growth and development, in *Almond Production Manual*, edited, pp. 90–97, University of California.

Lobell, D. B., et al. 2006a. "Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties." *Agric For Meteorol 141*: 208–218.

Lobell, D. B., et al. 2006b. "Potential bias of model projected greenhouse warming in irrigated regions." *Geophysical Research Letters 33*. L13709, doi:13710.11029/12006GL026770.

Lobell, D. B., et al. 2007. "Historical effects of temperature and precipitation on California crop yields." *Clim Change 81*: 187–203.

Long, S. P., et al. 2006. "Food for Thought: Lower-Than-Expected Crop Yield Stimulation with Rising CO_2 Concentrations." *Science 312*: 1918–1921.

Maurer, E. P., et al. 2002. "A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States." *J. Clim. 15*: 3237–3251.

Meehl, G. A., et al. 2007. Global Climate Projections, in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Edited by S. Solomon, et al., Cambridge University Press, Cambridge, United Kingdom and New York, New York, USA.

Polito, V., et al. 1996. Bud development, pollination and fertilization, in *Almond Production Manual. University of California Publication* edited, pp. 98–102.

Tanaka, S. K., et al. 2006. "Climate Warming and Water Management Adaptation for California." *Clim Change 76*: 361–387.

White, M. A., et al. 2006. Extreme heat reduces and shifts United States premium wine production in the 21st century, *Proceedings of the National Academy of Sciences*. *103*: 11217.