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Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties

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Abstract

Most research on the agricultural impacts of climate change has focused on the major annual crops, yet perennial cropping systems are less adaptable and thus potentially more susceptible to damage. In regions where perennial crops are economically and culturally important, improved assessments of yield responses to future climate are needed to prioritize adaptation strategies. These impact assessments, in turn, must rely on climate and crop models that contain often poorly defined uncertainties. We evaluated the impact of climate change on six major perennial crops in California: wine grapes, almonds, table grapes, oranges, walnuts, and avocados. Outputs from multiple climate models were used to evaluate climate uncertainty, while multiple statistical crop models, derived by resampling historical databases, were used to address crop response uncertainties. We find that, despite these uncertainties, climate change in California is very likely to put downward pressure on yields of almonds, walnuts, avocados, and table grapes by 2050. Without CO_2 fertilization or adaptation measures, projected losses range from 0 to >40% depending on the crop and the trajectory of climate change. Climate change uncertainty generally had a larger impact on projections than crop model uncertainty, although the latter was substantial for several crops. Opportunities for expansion into cooler regions were identified, but this adaptation would require substantial investments and may be limited by non-climatic constraints. Given the long time scales for growth and production of orchards and vineyards (~30 years), climate change should be an important factor in selecting perennial varieties and deciding whether and where perennials should be planted.

Keywords: Climate change; Perennial agriculture; Almonds; Grapes; California

1. Introduction

Climate change resulting from human activity has the potential to substantially alter agricultural systems (Adams et al., 1990; IPCC, 2001b; Parry et al., 2004; Rosenzweig and Parry, 1994). Many studies have emphasized the potential for adaptation to reduce costs or increase gains associated with climate change,

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suggesting that systems that are slow to adapt are more vulnerable (Burton and Lim, 2005; Rosenzweig and Hillel, 1998). Yet despite the perceived importance of agricultural adaptation, very little research has focused on impacts in perennial cropping systems, which include long-lived crops and therefore change much more slowly than annual systems. Exceptions include studies of Valencia orange yields in the southern United States (Tubiello et al., 2002) and of wine grape yield (Bindi et al., 1996) and quality (Hayhoe et al., 2004; Jones et al., 2005; White et al., 2006) in major wine-producing regions.

In California, perennial crops represent a multi-billion dollar industry. The fruit, nut, and berry harvest of 2003 was worth US$ 7.8 billion in farm receipts alone (California Agricultural Statistics Service, 2004b), with additional value from manufacturing, tourism, and other related activities likely several times that amount. Models of climate change in California unanimously project warming over the next century, with mixed predictions of precipitation changes (Hayhoe et al., 2004; Snyder et al., 2002). To evaluate the potential impact of these climate changes for perennial crop production, we consider here the six most valuable California perennial food crops: wine grapes, almonds, table grapes, oranges, walnuts, and avocados (Table 1). Each of these crops is typically planted only once every 25 or more years. Therefore, adoption of new varieties – a commonly cited option for climate change adaptation – occurs much more slowly than for annual crops.

Assessments of climate change impacts must consider uncertainties both in future climate and in the response of crops to climate changes. Climate change uncertainties are often evaluated by utilizing projections from multiple climate models, which can each be run with multiple emission scenarios (IPCC, 2001a). Because the probabilities of individual model-emission combinations are generally unspecified, the value of multiple climate model outputs is mainly to define the range of potential outcomes. Model inter-comparisons, however, often cite the percent of models with a certain outcome as a measure of uncertainty, which implicitly assigns equal probability to each model (IPCC, 2001a).

Uncertainties in crop response to climate are often less thoroughly evaluated than climate uncertainty in regional and global assessments. For example, in major global assessments (Fischer et al., 2005; Parry et al., 2005) crop responses are simulated using process-based models that are calibrated for individual sites and then implicitly assumed to be perfectly accurate. Mearns et al. (1999) evaluated impacts of climate change on corn and wheat yields in the central Great Plains using two crop models (CERES and EPIC), and found significant differences between crop models that were comparable to differences obtained when varying climate model resolutions. Aggarwal and Mall (2002) compared the ORYZAIN and CERES rice models in India, and found differences that were nearly as large those due to an optimistic versus pessimistic climate change scenario. Thus, crop model uncertainty appears an important source of overall yield uncertainty that should be explicitly treated in impact assessments.

In this study, we evaluated the responses of California perennial yields to projected changes in temperature and precipitation, with explicit consideration of both climate and crop model uncertainties. Effects of elevated CO_2 and farmer adaptations, both of which may moderate climate impacts, were not explicitly modeled but are discussed with the results. The projections presented in this paper are therefore not intended as predictions of climate change impacts, which will depend not only on climate but factors such as CO_2 and farmer responses. Instead, the primary goal of this study was to quantify (with uncertainties) the sensitivity of major California perennial crops to expected temperature and precipitation changes, which can provide a basis for prioritizing adaptation efforts. A secondary goal was to evaluate the relative contributions of climate and crop uncertainties, as well as their interaction, to total uncertainty.

Table 1
Life span and trends in area and yield for six major California perennial crops

	Wine grapes	Almonds	Table grapes	Oranges	Walnuts	Avocados
Productive life[a] (years)	25	22–25	25	40	35	30
First harvest (age in years)	3	3	2–3	2–4	4	3
Full production (age in years)	5–6	6	4	12–13	8	7
Area change 1980–2003 (%)	116	69	68	22	26	−12
Yield change 1980–2003 (%)	9	57	25	9	24	−44
Average yields 2000–2003 (ton acre^{-1})	6.9	0.9	8.3	13.0	1.5	2.7

All crops are irrigated.
[a] Life span and production information from http://coststudies.ucdavis.edu/.

2. Methods

2.1. Crop models

The response of yields to temperature and precipitation changes was described for each crop using statistical models developed from 1980–2003 records of state-wide yield and monthly average temperatures (minimum and maximum) and rainfall variations (Lobell et al., in press). The use of statistical yield models was necessitated by a lack of reliable process-based models for the perennial crops considered in this study. One advantage of statistical models is that they intrinsically account for a wide variety of mechanisms that can influence yields in a changing climate. These include not only plant physiological processes but also factors like climate-related influences of pests, pathogens, and air pollution that are omitted from most process-based models. Another advantage is that uncertainties are readily estimated with statistical models, for example using resampling techniques, whereas uncertainties in process-based models are often difficult to measure (see Section 1). However, unlike process-based models, statistical models do not allow explicit consideration of management changes or other factors, such as CO_2 increases, that may alter the effect of climate on yields in the future.

The statistical models used in this study are described in detail by Lobell et al. (in press). Briefly, monthly averages of minimum and maximum temperatures (T_n and T_x) and precipitation (P) were computed for 382 individual meteorological stations throughout the state for 1980–2003. For each crop, a state-wide time series was computed by taking a weighted average of the individual time series, with the weights proportional to the area of the crop in the stations' counties. The most important climate variables and months for each crop were then identified based on exploratory analysis of state yield records (California Agricultural Statistics Service, 2004a) and the climate data for months prior to harvest. Multiple linear regression models to predict yield anomalies were then computed, with linear and quadratic terms for each selected climate variable used as predictor variables.

Table 2 presents the yield functions used for each crop, as well as the adjusted R^2, a common measure of model agreement with observations. As described above, the models were developed from monthly averages aggregated to the state scale, and therefore did not explicitly consider factors such as extreme heat events or spatial variations in crop response to climate. Nonetheless, the models provided a fairly accurate description of historical yield variations, with more than 50% of the variance in yield anomalies explained for all crops.

Fig. 1 shows the historical relationship between yield and the monthly temperature variable that explained the highest proportion of yield variance. All of the crops except almonds have an optimum temperature above and below which yields decline. Interestingly, these optimal temperatures are roughly equivalent to the average values from 1980–2003, illustrating that the current varieties are well suited to the current California climate.

Fig. 1 also provides a clear example of the imperfect empirical relationship between yields and monthly climate, and thus the uncertainty associated with yield projections based on climate. Two aspects of crop model uncertainty were considered here: the uncertainty due to the fact that empirical models are based on finite historical observations, and do not perfectly describe historical yield–climate relationships (referred to as sampling uncertainty), and the added uncertainty due to the fact that simulated future monthly temperature and rainfall may exceed the extremes of the historical record used to generate the empirical models (referred to as extrapolation uncertainty). Sampling uncertainty was estimated using bootstrap resampling of the historical record to generate new estimates of the model coefficients (Efron and Gong, 1983), and then applying these models repeatedly to the

Table 2
Statistical yield models used in this study (from Lobell et al., in press)

Crop	Equation	R^2_{adj}
Wine grapes	$Y = 2.65T_{n,4} - 0.17T^2_{n,4} + 4.78P_6 - 4.93P^2_6 - 2.24P_{-9} + 1.54P^2_{-9} - 10.50$	0.66
Almonds	$Y = -0.015T_{n,2} - 0.0046T^2_{n,2} - 0.07P_1 + 0.0043P^2_1 + 0.28$	0.88
Table grapes	$Y = 6.93T_{n,7} - 0.19T^2_{n,7} + 2.61T_{n,4} - 0.15T^2_{n,4} + 0.035P_1 + 0.024P^2_1 + 1.71P_{-10} - 0.673P^2_{-10} - 73.89$	0.77
Oranges	$Y = 1.08T_{n,-12} - 0.20T^2_{n,-12} + 4.99P_5 - 1.97P^2_5 - 2.47$	0.75
Walnuts	$Y = 0.68T_{x,-11} - 0.020T^2_{x,-11} + 0.038P_2 - 0.0051P^2_2 - 5.83$	0.59
Avocados	$Y = 17.71T_{x,-8} - 0.29T^2_{x,-8} + 3.25T_{n,5} - 0.14T^2_{n,5} + 1.00P_{-10} - 0.31P^2_{-10} - 288.09$	0.73

Y represents yield anomaly (ton acre^{-1}). Subscript numbers indicate month of climate variable, with negative values denoting a month from the year prior to harvest. T_n, minimum temperature (°C); T_x, maximum temperature (°C); P, precipitation (mm).

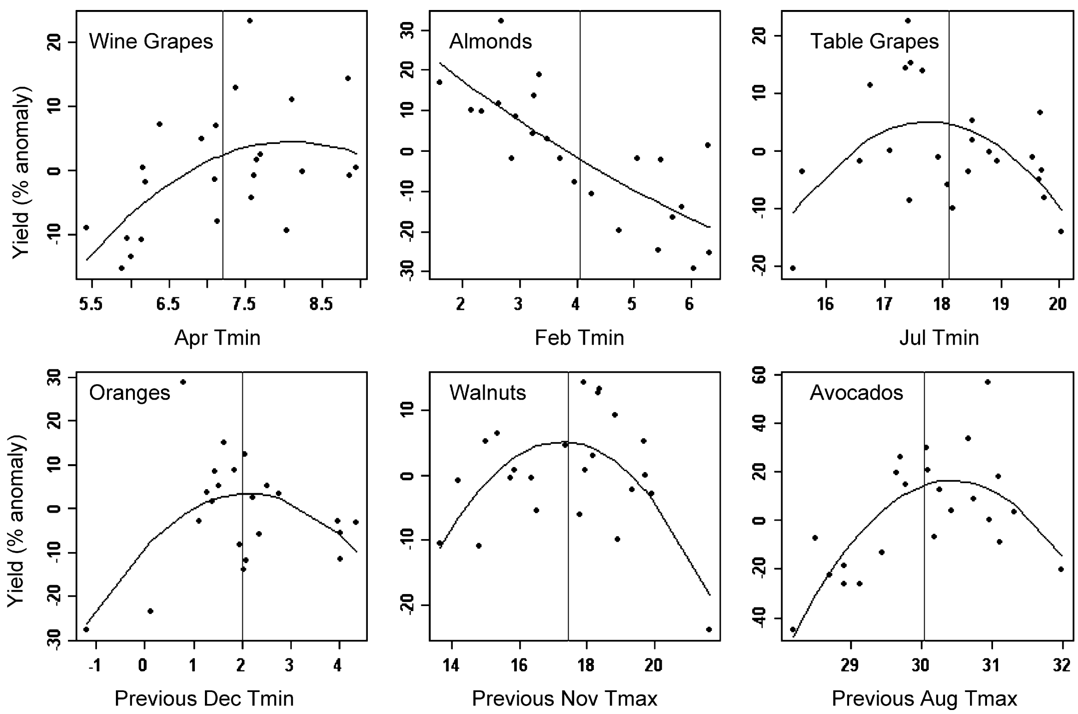

Fig. 1. Observed (points) and modeled (line) yield anomalies for 1980–2003 vs. most important temperature anomaly (°C) for each crop. Vertical line shows 1980–2003 average temperature.

simulated climate. A total of 100 bootstrap replicates were used. Extrapolation uncertainty was evaluated by applying the crop models with and without allowing simulated yields to exceed historical extremes. The latter approach reflects a very conservative assumption that extreme temperatures or rainfalls do not affect yields beyond what has been observed.

Other aspects of crop model uncertainty were not considered here. For example, changes in variables not included in the model are implicitly assumed to not affect future yields. These include extreme temperature or rainfall events, as well as months other than the few selected for each crop based on historical analyses. To the extent that changes in omitted variables are uncorrelated with model variables, their effects introduce an additional source of uncertainty into model projections.

2.2. Climate models

Outputs of 22 coupled ocean–atmosphere general circulation models are archived by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) at Lawrence Livermore National Laboratory (http://www-pcmdi.llnl.gov; Table 3). Three scenarios of emissions trajectories are available for future climate (defined as 2001–2099): the A2 (medium–high), A1b (medium), and B1 (low) emissions scenarios from the IPCC Special Report on Emission Scenarios (SRES) (Nakicenovic et al., 2000). Temperature change projections for California in these models range from ~1 to 3 °C for 2050 and 2 to 6 °C for 2100, while precipitation changes range between −40% and +40% for both 2050 and 2100 (Fig. 2).

Since crops are differentially sensitive to nighttime and daytime temperatures (e.g., Fig. 1), subsequent analysis focused only on the six climate models that provided monthly output on average daily minimum and maximum temperatures in addition to average temperatures and precipitation for both historical and future simulations (CSIRO-Mk3.0, GISS-AOM, INM-CM3.0, MIROC3.2 (hires), MIROC3.2 (medres), and NCAR CCSM3). Three scenario-model combinations were not available in the PCMDI database (Scenario A2 for GISS-AOM, and A1b and A2 for MIROC3.2 (hires)), leaving a total of 15 scenario-model combinations. These six models represent well the range of climate uncertainties seen across the IPCC models since their trends in average temperature and precipitation spanned the range of the entire set of models (Fig. 2). A single time series for 1960–2099 for each scenario-model was generated, using the average for all grid cells over California. Some models provided output from

Table 3
Names of climate models whose output are shown in Fig. 2

Model name	Model description	Country	T_n and T_x
BCCR-BCM2.0	Bjerknes Centre for Climate Research	Norway	
BCC-CM1	Beijing Climate Center	China	
CCSM3	National Center for Atmospheric Research	USA	X
CGCM3.1(T47)	Canadian Centre for Climate Modelling & Analysis	Canada	
CGCM3.1(T63)	Canadian Centre for Climate Modelling & Analysis	Canada	
CNRM-CM3	Météo-France/Centre National de Recherches Météorologiques	France	
CSIRO-Mk3.0	CSIRO Atmospheric Research	Australia	X
ECHAM5/MPI-OM	Max Planck Institute for Meteorology	Germany	
ECHO-G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group.	Germany/Korea	
FGOALS-g1.0	LASG/Institute of Atmospheric Physics	China	
GFDL-CM2.0	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	
GFDL-CM2.1	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	
GISS-AOM	NASA/Goddard Institute for Space Studies	USA	X
GISS-EH	NASA/Goddard Institute for Space Studies	USA	
GISS-ER	NASA/Goddard Institute for Space Studies	USA	
INM-CM3.0	Institute for Numerical Mathematics	Russia	X
IPSL-CM4	Institut Pierre Simon Laplace	France	
MIROC3.2 (hires)	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	X
MIROC3.2 (medres)	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	X
MRI-CGCM2.3.2	Meteorological Research Institute	Japan	
PCM	National Center for Atmospheric Research	USA	
UKMO-HadCM3	Hadley Centre for Climate Prediction and Research/Met Office	UK	
UKMO-HadGEM1	Hadley Centre for Climate Prediction and Research/Met Office	UK	

Only models with T_n and T_x were used for crop yield projections. Description of models available at http://www-pcmdi.llnl.gov.

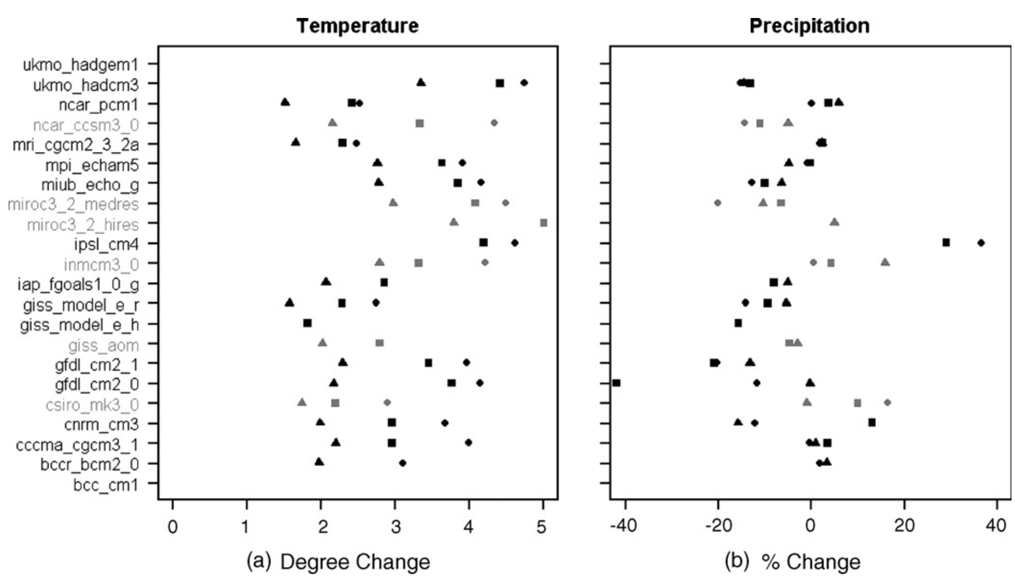

Fig. 2. Change in California annual average temperature (a) and precipitation (b) for 2070–2100 period relative to 1960–1990 for different models and scenarios in PCMDI database. Gray points show models whose output were used in crop models. Scenarios are A1b (square), A2 (circle), and B1 (triangle). See Table 2 for description of model names. Scenarios A2 for GISS-AOM, and A1b and A2 for MIROC3.2 (hires) were not available in the PCMDI database.

multiple realizations, in which case the mean of all realizations was used.

The GCM time series for each month and variable were down-scaled to correct for biases in the coarse-scale GCM outputs. First, the trend for the GCM series was computed as a 41-year moving average and subtracted from the original GCM time series. This detrended time series was then divided by the standard deviation over the 1980–2000 period. Observed monthly time series for 1980–2000 were computed separately for each crop by weighting observed values from 382 individual stations by the proportion of crop area in the stations' counties. For each crop, the standardized GCM time series were then multiplied by the standard deviation of the observed climate record for 1980–2000, and then added to the 1980–2000 average difference between observed and GCM simulated values. The previously removed GCM trend was added back to produce a final simulated time series. This downscaling approach ensures that the simulated mean and variance match the observational record for the period 1980–2000, while preserving any simulated trends in mean or variance of each climatic variable for each month (Maurer and Duffy, 2005; Wood et al., 2002).

2.3. Uncertainty analysis

The yield models were applied to the monthly simulations of minimum and maximum temperatures and precipitation for 1980–2099 to assess impacts of climate change on yields. The effect of climate model uncertainty was assessed by applying the yield models to each of the individual climate scenarios, producing a distribution of yields for each simulation year. The results obtained from this analysis are referred to as yield impacts with climate uncertainty only. The combined impact of crop and climate model uncertainty was assessed by creating 100 separate statistical crop models, based on bootstrap resampling of the historical data, and applying each model to each climate time series. These results are referred to as yield impacts with both climate and crop uncertainty. As discussed above, crop models were applied first with and then without truncation of simulated values to historical extremes, as a measure of extrapolation uncertainty.

3. Results and discussion

3.1. Projected yield impacts and uncertainties

Median projections for wine grape yields exhibited very small changes over the next century due to climate change, while the other five crops exhibited moderate to substantial yield declines (Fig. 3). The impact of climate uncertainty on projections was substantial but not overwhelming. For example, the 95th percentile of yield change generally differed from the median projection by less than 10% of current yields for all crops except avocados, in the case without model extrapolation. The uncertainties were slightly larger in the negative direction. The differences in climate uncertainty between crops reflect the fact that each crop responds in different ways to climate.

Crop model sampling uncertainty added significantly to the overall uncertainty in projected yield changes (Fig. 3), although the impact was smaller than for climate uncertainty. When yields were allowed to exceed historical extremes (Fig. 4), three important results were observed. First, the effect of both climate and crop model sampling uncertainty was increased, indicating that uncertainties can interact. For example, estimates of the effect climate uncertainty will depend on the type of crop model used (in this case, whether it allows extrapolation or not). This finding agrees with the observation by Mearns et al. (1999) that the impact of climate model resolution differed greatly depending on the crop model used.

Second, the impact of extrapolation uncertainty was very large for some crops (walnuts, avocados) but relatively small for others (almonds) (compare Figs. 3 and 4). Third, even for crops such as avocados, the impact of extrapolation uncertainty was small until ~2020, after which it became more important. These latter points suggest that while the occurrence of climate conditions outside historical ranges, and the consequent uncertainties associated with extrapolation, may be important for long-term projections, they may be relatively minor for time scales of interest for most adaptation studies. Instead, the most important changes over these time scales are the increasing frequency of warm years for which historical analogues do exist. While a common criticism of empirical models is their inability to extrapolate beyond past climate (e.g., Challinor et al., 2003), this deficiency may be largely irrelevant over the next few decades for many crops.

Even with consideration of both crop and climate model uncertainties and with the conservative estimate that yield changes are limited to historical extremes (Fig. 3), less than 5% of simulations for almonds, table grapes, walnuts, and avocados indicated a non-negative (i.e., zero or positive) response to climate change by mid-century. Two main factors contribute to this result. First, all of these crops are either at or above their optimum temperatures in current climate (Fig. 1), and

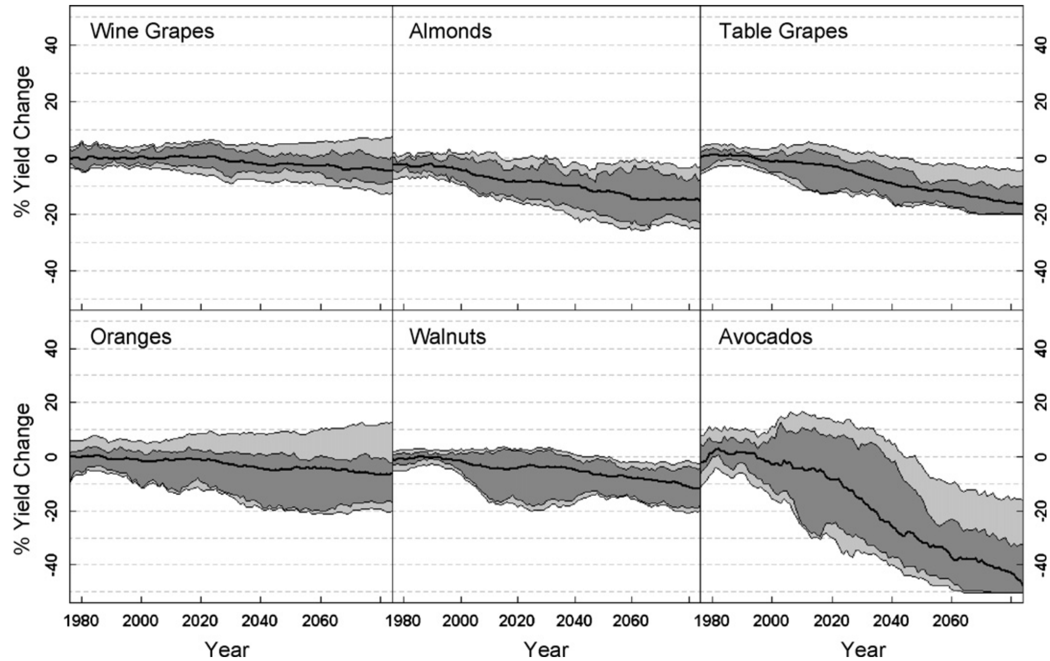

Fig. 3. Crop yield changes associated with future climate scenarios, with yield anomalies constrained to historical extremes. Yields are expressed in units of percent anomaly from 2000–2003 average yields, and are plotted as 19-year running averages to highlight trends rather than year-to-year variability. Black line shows median projections, dark shaded area shows 90% confidence interval after accounting for climate uncertainty, and light shaded area shows 90% confidence interval after accounting for both climate and crop uncertainty.

all climate models project at least some warming (Fig. 2). Second, all of these crops are irrigated, so that the large uncertainties in precipitation projections (Fig. 2) have a relatively minor effect.

3.2. Potential impacts of shifts in growing regions

The simulated impacts are based on the assumption that producers do not move to other locations with more

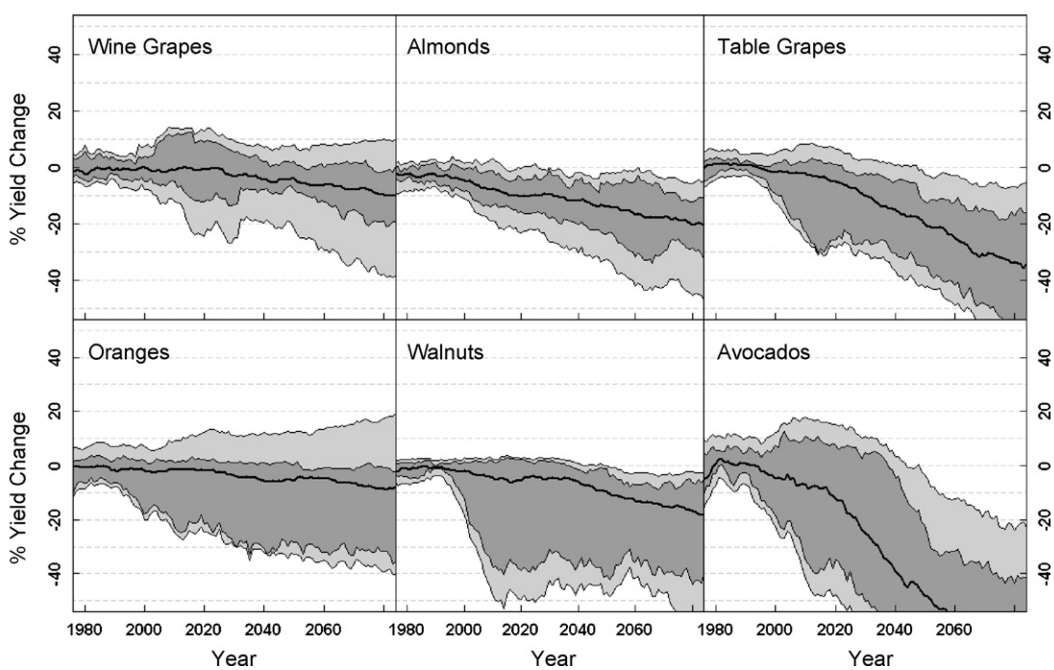

Fig. 4. Same as Fig. 3 except yields were allowed to exceed historical extremes.

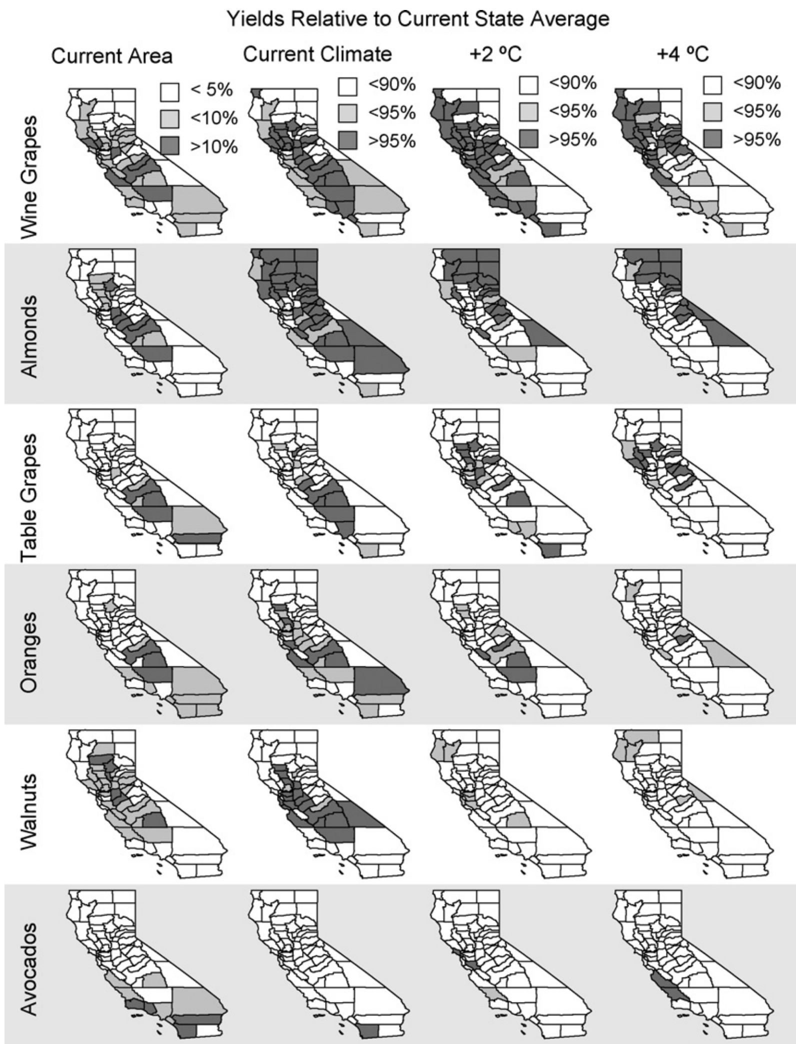

Fig. 5. County maps of California, showing (from left to right) the percent of current statewide area in each county, modeled yields for each county under current climate (expressed as a percentage of current statewide average yields), and modeled yields for a 2 or 4 °C warming above current temperatures. Summary statistics are given in Table 4.

favorable climates. Especially with long-lived perennial plants, moving to another region within California is a limited option. Still, we assessed the potential impact of shifting production toward counties with more favorable climate by simulating, for each county, the expected yields under current climate and scenarios of 2 and 4 °C warming (Fig. 5, Table 4). These simple climate change scenarios approximate the low and high end of projected temperature changes by late century (Fig. 2).

Much of the current crop area is in counties that have among the highest simulated yields, indicating that producers have selected regions appropriate for each crop as well as varieties well suited to the regions of current production. Under 2 °C warming, there are no counties in California in which walnut yield reaches 95% of the current state average (Table 4). For almonds, table grapes, and avocados in a climate 2 °C warmer, some areas in the state have climate conditions consistent with yields near or even above current levels. These are, however, sufficiently disjoint from the areas with the bulk of current production that the necessary shifts in production could be difficult, expensive, or culturally challenging. In addition, as our model considers only climatic constraints to yields, some of the counties may be less suitable in reality than predicted here.

For 4 °C warming, fewer counties exhibit yields at least 95% of current averages, and all crops except wine grapes have less than 5% of current area in these

Table 4
The number of counties in different climate scenarios with average simulated yields of at least 95% of the current state average, and the percentage of current crop area within those counties (%current area)

Crop	Current climate		+2 °C		+4 °C	
	No. of counties	Current area (%)	No. of counties	Current area (%)	No. of counties	Current area (%)
Wine grapes	25	80.9	38	76.9	26	32.5
Almonds	31	70.0	18	8.0	13	1.3
Table grapes	7	83.7	10	38.3	10	4.4
Oranges	7	67.3	4	70.5	1	0.0
Walnuts	18	64.8	0	0.0	0	0.0
Avocados	1	40.8	2	0.0	2	2.9

counties. For oranges, walnuts, and avocados, not only are the areas with the potential for high yields dramatically reduced—the areas with appropriate climate tend to be in dry or mountainous regions with limited opportunities for agriculture. As future climate will significantly change the relative suitability of counties within California for perennial agriculture, opportunities may exist to shift production in response to climate change. The feasibility of these shifts would, however, depend on a range of other factors, including topography, soils, irrigation infrastructure, transportation infrastructure, and competing land uses.

4. Conclusions

Despite uncertainties in emission scenarios, climate responses, and crop behavior, the unambiguous effect of warming from climate change will be to reduce yields for several major perennials. Our approach did not explicitly account for non-climatic trends that affect yields, such as increased atmospheric CO_2 and management or technological changes, and therefore cannot estimate net changes in yields from present. The yield trends since 1980 for these crops (Table 1) are negative for avocados but positive for the other crops, ranging from 9% to 57% over 24 years. Analysis of historical climate trends indicate that little if any of these yield trends can be attributed directly to climate (Lobell et al., in press). Thus, past changes in technology and atmospheric CO_2 improved yields as much or more than the median anticipated effect of climate change over the next two decades.

In the future, actual yield changes will reflect the combined influence of the (generally negative) effects of warming and the potentially positive effects of management, technology, and atmospheric CO_2. The effects of elevated atmospheric CO_2 on perennial crops are not well known, as few experiments have been conducted (e.g., Bindi et al., 2001; Idso and Kimball, 2001). A recent meta-analysis of free-air CO_2 enrichment (FACE) experiments with various (mostly annual) crops concluded that yield increases under elevated CO_2 ($\sim$475–600 ppm) average roughly 17% (Ainsworth and Long, 2005). While climate change is only one of several factors that will significantly influence future yields, it appears that future gains from improved management, varieties, and elevated CO_2 and technology will need to be roughly as large as in the past simply to offset the reductions from warming.

The economic impacts of climate related yield losses will be distributed between producers and consumers through effects of yield changes on prices (Adams et al., 1990; Mjelde et al., 2000; Reilly et al., 2003). Three of the crops studied here – almonds, oranges, and avocados – exhibited a highly significant ($p < 0.001$) negative correlation between statewide production and price anomalies since 1980 (Table 5). For example, a 50% decline in almond yields from 1994 to 1995 corresponded to roughly a doubling of almond prices over the same time period. Thus, yield declines may incur much higher

Table 5
Correlation between California production anomalies (%) and price anomalies (%), and the slope of a regression of price response to production changes for each crop

	Wine grapes	Almonds	Table grapes	Oranges	Walnuts	Avocados
Correlation	0.06	−0.71	0.06	−0.91	−0.20	−0.89
Slope	0.06	−1.04	0.05	−0.90	−0.28	−1.02
p-Value	0.78	<0.001	0.79	<0.001	0.34	<0.001

Calculated from state averages for 1980–2003 (California Agricultural Statistics Service, 2004a).

costs to consumers than producers, whose profits may be helped by higher prices.

In addition, given the increasing globalization of food production, the net effect of climate change on California growers and consumers may depend as much or more on what happens in other regions as what happens locally. Thus, global assessments of perennial crop impacts, such as those that have been attempted for annual crops, appear warranted. Such assessments would ideally also consider trends in demand and technologies, which can interact with climate changes. The approach presented in this paper, namely to use statistical crop models derived from historical yield and spatially aggregated climate data, and apply these models to a range of future climate scenarios, may provide a useful foundation for studies of perennial crops in other regions. As discussed above, consideration not only of climate change uncertainty but of uncertainty in the response of crops to climate change should be a central component of such an analysis.

The projections presented in this study may be used to guide future adaptation efforts, for example by focusing efforts on developing heat tolerant almond varieties. The full potential of adaptation to reduce impacts of climate change are currently unclear and indeed may be large, but as several authors have noted (e.g., Reilly, 1999; Schneider et al., 2000), realizing the potential benefits of adaptation may involve substantial costs, risks, and additional research. Moreover, some of the negative effects were simulated to occur within the lifetime of trees and vines that are currently in the ground, especially for almonds. Therefore, short-term losses may largely be unavoidable.

The long time horizon of perennial agriculture creates special challenges in a changing climate. Favorable areas may become unfavorable during the life of a single orchard or vineyard. The choice of a variety is complicated by the risk that the best variety for the current climate may be poorly suited for future climates. In addition, the perennial habit slows the process of developing new varieties, potentially limiting the options for shifting varieties to cope with a changing climate (Koski, 1996). While these factors do not necessarily mean that perennial agriculture is more vulnerable than other sectors, they argue for effective integration of climate science with agricultural practice.

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