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Effect of climate change on field crop production in California's Central Valley

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Abstract Climate change under various emission scenarios is highly uncertain but is expected to affect agricultural crop production in the 21st century. However, we know very little about future changes in specific cropping systems under climate change in California's Central Valley. Biogeochemical models are a useful tool to predict yields as it integrates crop growth, nutrient dynamics, hydrology, management and climate. For this study, we used DAYCENT to simulate changes in yield under A2 (medium-high) and B1 (low) emission scenarios. In total, 18 climate change predictions for the two scenarios were considered by applying different climate models and downscaling methods. The following crops were selected: alfalfa (hay), cotton, maize, winter wheat, tomato, and rice. Sunflower was also selected because it is commonly included in rotations with the other crops. By comparing the 11-year moving averages for the period 1956 to 2094, changes in yield were highly variable depending on the climate change scenarios across times. Furthermore, yield variance for the crops increased toward the end of the century due to the various degrees of climate model sensitivity. This shows that future climate, suggested by each of the emission scenarios, has a broad range of impacts on crop yields. Nevertheless, there was a general agreement in trends of yield changes. Under both A2 and B1, average modeled cotton, sunflower, and wheat yields decreased by approximately 2% to 9% by 2050 compared to the 2009 average yields. The other crops showed apparently no decreases in yield for the period 2010–2050. In comparison, all crop yields except for alfalfa significantly declined by 2094 under A2, but less under B1. Under A2, yields decreased in the following order: cotton (25%) > sunflower (24%) > wheat (14%) > rice (10%) > tomato and maize (9%). Under A2 compared to B1, the crop yield further decreased by a range of 2% (alfalfa) to 17% (cotton) by 2094, with more variation in yield change in the southern counties than the northern counties. The CO_2 fertilization effects were predicted to potentially offset these yield declines (>30%) but may be overestimated. Our results suggest that climate change will decrease California crop yields in the long-term, except for alfalfa, unless greenhouse gas emissions and resulting climate change is curbed and/or adaptation of new management practices and improved cultivars occurs.

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Abbreviations

GCMs	Global circulation models
analog	Constructed analogues
bcsd	Bias correction and spatial downscaling
MSD	Mean squared deviation
SB	Squared bias
NU	Nonunity slope
LC	Lack of correlation

1 Introduction

Land use change and fossil fuel use have increased the emission of carbon dioxide (CO_2) and other greenhouse gases to the atmosphere at regional and global scales (Janzen 2004). In particular, the atmospheric CO_2 concentration, [CO_2], has increased from 280 to 370 parts per million (ppm) over the past 150 years. The change in [CO_2] has possibly led to an increase in both the mean and variance of the temperature anomaly at the soil surface (Jones and Mann 2004; Porter and Semenov 2005; IPCC 2007). Global variation in mean precipitation and drought has also increased (Dai et al. 1998; Jones and Mann 2004; IPCC 2007).

In agriculture, climate change will likely lead to a major spatial shift and extension of croplands as it will create a favorable or restricted environment for crop growth across different regions (Olesen and Bindi 2002; Smit et al. 1988). Agricultural crop production is fully expected to be impacted by climate change (Adams et al. 1990), but our understanding of climate change and its impacts on California cropping systems in the 21st century is limited (Lobell et al. 2006). California's Central Valley is one of the most productive agricultural regions in the world. It leads national production and sales of many crop commodities, such as almonds, cotton, grapes, hay, rice, and tomatoes (California Agricultural Statistics Service 2008). Lobell et al. (2006) investigated the impact of climate change on perennial crops (e.g., wine grapes), which are high-value commodities in California. However, long-term climate change effects have not been fully tested for major California annual crops and alfalfa (hay). Therefore, it is pertinent to further evaluate potential changes in the production of these systems in California's Central Valley under a changing climate.

Crop growth and development are simultaneously affected by numerous stress factors, which influence crop growth linearly or non-linearly (Hansen et al. 2006; Porter and Semenov 2005). Therefore, a detailed analysis of baseline climate change impacts on cropping systems should precede the development of adaptation scenarios based on alternative management practices under various climate change predictions. Complex ecosystem modeling represents a useful tool for predicting yields as it accounts for a range of interacting conditions in climate, soil, and management. However, there are several factors leading to biogeochemical model uncertainty. First, the process-based biogeochemical models have been only calibrated and validated under observed climate conditions (Adams et al. 1990). Consequently, most biogeochemical models do not predict very well the effects of extreme weather events (e.g., heat waves, floods, etc.) on crop yields. Therefore, the modeled responses of crop growth to temperature and precipitation extremes suggested by the global climate models (GCMs) are often questionable. Second, any change in climatic variables (e.g., temperature and precipitation) at different spatial resolutions and time steps is highly uncertain under any emission scenario (Hansen et al.

2006; Lobell et al. 2006). Third, the fertilization effects of rising [CO_2] on crop yields currently integrated in the biogeochemical models is derived from a limited range of growing conditions and is most likely overestimated (Ainsworth et al. 2008; Long et al. 2005; Long et al. 2006; De Graaff et al. 2006). The magnitude of CO_2 fertilization effects tend to be further reduced when drought stress is minimized by irrigation (Ainsworth et al. 2008; Tubiello et al. 2002). Furthermore, belowground soil respiration (Luo et al. 1996) and weed pressure (Bunce 1995) may increase by elevated [CO_2], which eventually compensate for the potential increase in crop production in the long term. However, current biogeochemical models have limited or no function to account for these factors known to affect crop production under climate change. Regardless of these limitations, process-based biogeochemical models, such as DAYCENT, can effectively integrate crop growth, nutrient dynamics, hydrology, management, and climate for diverse cropping systems and provide a best-estimate of climate change effects on crop yields.

In California, future climate change under A2 and B1 emission scenarios from the IPCC Fourth Assessment Report were evaluated extensively (Cayan et al. 2008). Briefly, the A2 emission scenario predicts medium-high emissions of CO_2 and other greenhouse gases, whereas the B1 emission scenario assumes low emissions. Under A2, [CO_2] is expected to increase exponentially from 352 ppmv in 1990 to 522 ppmv by 2050 and 836 ppmv by 2100. Under B1, [CO_2] is expected to be 482 ppmv by 2050 and then stabilized towards 540 ppmv until 2100. Specifically for California's Central Valley, maximum average temperatures increase from 0.9–3.9°C under B1 to 2.4–5.9°C under A2 by the end of the century relative to 1961–1990. Minimum average temperatures increase from 0.9–3.6°C under B1 to 2.0–6.7°C under A2 in the same period. More warming is expected in summer than winter with increasing frequency of heat waves. Annual precipitation shows relatively small changes (less than 10%) between the 1961–1990 and 2070–2099 periods, but the direction of changes are highly uncertain.

The objective of this study is (1) to project long-term field crop yields in California's Central Valley under the A2 and B1 emission scenarios using the DAYCENT model, and (2) to quantify uncertainties in modeled crop yields derived from uncertainties around predicted changes in climate.

2 Methods

2.1 Description of DAYCENT

To assess the impact of climate change on California cropping systems, we selected the DAYCENT model. DAYCENT is described in detail by Del Grosso et al. (2002). In short, it is the daily version of Century, a fully resolved ecosystem model simulating the major processes that affect plant productivity, such as soil organic matter, water flow, nutrient cycling, and soil temperature and water. The crop sub-model simulates crop growth, dry matter production, and yields to estimate the amount and quality of residue (i.e., C and N input) returned to the soil. It also simulates the plant's influence on the soil environment (e.g., water, nutrients). The crop sub-model simulates phenology, C to N ratios, C allocation to roots and shoots, and growth responses to soil temperature and water and nutrient availability. A variety of management options may be specified, including crop type, tillage, fertilization, organic matter (e.g., manure) addition, harvest (with variable residue removal), drainage, irrigation, burning, and grazing intensity. Specifically in DAYCENT, crop production is potentially limited by soil temperature as each crop is regulated by its specific temperature response function. Soil-water availability is also a major factor that affects crop production and is in the model controlled by current soil-water, precipitation, irrigation, and potential evapotranspiration. Nutrients (i.e., N) from the soil or fertilizer affect potential production depending on crop requirements. In particular, both soil-water and nutrient stresses affect the fraction of C allocated to roots. Germination/beginning of growing season is a function of soil temperature and harvest/end of growing season is a function of accumulated growing degree days when the growing degree day submodel is implemented. In addition, the model is able to specify the effects of elevated [CO_2] on net primary production, transpiration rate, and C:N ratio for biomass. The model uses a logarithmic relationship of net primary production and transpiration rate with changes in [CO_2] between 350 and 700 ppmv, and a linear relationship of C:N ratio for biomass.

2.2 Data acquisition

2.2.1 Climate data

Global climate models can simulate contrasting changes in future climate, although they reproduce the historical climate relatively well (Cayan et al. 2008). Consequently, data from various GCMs are essential for uncertainty assessments on the impacts of climate change. For this study, daily precipitation, maximum and minimum temperature, net radiation at the surface, relative humidity, and wind speed data under the A2 and B1 emission scenarios were obtained from the Climate Research Division of Scripps Institution of Oceanography, at the University of California, San Diego. Six GCMs were applied for the two emissions scenarios: (1) CNRM-CM3, (2) GFDL-CM2.1, (3) CCSR-MIROC3.2 (medium resolution), (4) ECHAM5/MPI-OM, (5) NCAR-CCSM3.0, and (6) NCAR-PCM1. A description of the GCMs can be found in Randall et al. (2007). Each climate change scenario was simulated over the time span 1950–2099.

These climate change scenarios were originally projected on a coarse resolution (hundreds of km). However, finer resolution predictions of climate change are typically required to optimize crop simulations under climate change at local and regional scales (Easterling et al. 1998; Mearns et al. 2001). Therefore, we used the downscaled climate change data to a 1/8° grid resolution (approximately 12 km) by two statistical downscaling techniques: a constructed analogues (analog) method and a bias correction and spatial downscaling (bcsd) method (Giorgi and Mearns 1991; Maurer and Hidalgo 2008). Three of the six GCMs did not provide daily data required by the analog method: CCSR-MIROC3.2 (medium resolution), MPI-OM ECHAM5, and NCAR-CCSM3.0. In total, 18 climate change predictions for the two scenarios were considered.

2.2.2 Soil data

We obtained soil data for all climate grids in California from the Soil Survey Geographic Database (SSURGO) of the Natural Resources Conservation Service (NRCS). The SSURGO database is the most detailed digital soil mapping done by the National Cooperative Soil Survey program. Estimates of soil parameters are obtained from the GIS version of the California soil survey maps, available within the SSURGO database. Specifically, soil texture class, bulk density, hydraulic properties (such as field capacity, wilting point, minimum volumetric soil-water content, and saturated hydraulic conductivity), and pH were obtained. If necessary, the hydraulic properties were estimated from texture (Saxton et al. 1986). In the simulations, soil salinity was not considered as a limiting factor for crop yield because DAYCENT does not have the capability to model soil salinity effects.

2.2.3 Crop types and parameters

The land use survey data were obtained from the California Department of Water Resources (DWR). The DWR land use data include GIS information on crop type, which was derived from exhaustive analyses of aerial photos and field surveys (www.water.ca.gov). For agriculture, nine agricultural classes were used to classify land use, such as grain and hay crops, field crops, pasture, and others. The statewide historical data were obtained from the United States Department of Agriculture (USDA)—National Agricultural Statistics Service (NASS).

Crop phenology and growing patterns were calibrated using historical crop yield data from NASS. Biomass C and N data, C allocation to shoots and roots, and N dynamics data were also calibrated from various literature sources. For field crops, these values have been validated for California conditions by De Gryze et al. (2009).

2.2.4 Management data

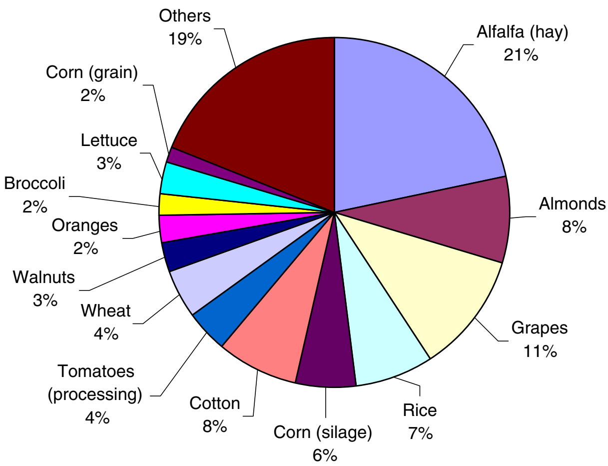
Details on conventional management practices in the region (e.g., planting, fertilization, irrigation, weed control, and harvesting) were obtained from the Agronomy Research and Information Center and Cost and Return Studies (2000–2005) available through the University of California Cooperative Extension. Cost and Return Studies contain details on agricultural inputs, planting and harvesting dates and other operations for crops considered in this study. In DAYCENT, the timing of planting and harvesting events, namely growing season-length, was determined by phenology for a grain-filling crop. The ability of DAYCENT to have various planting and harvesting dates is important for realistic predictions of regional crop yields (Moen et al. 1994). For non-grain crops (e.g., alfalfa and tomato), we considered the same planting and harvesting dates across the Central Valley. Data on crop rotations were derived from pesticide use reports from agricultural commissioners and survey data from Howitt et al. (2009).

2.3 Modeling strategies

We selected the six top field crops in California based on their harvested area (Fig. 1). The selected crops were alfalfa-hay (*Medicago sativa* L.), cotton (*Gossypium hirsutum* L.), maize (*Zea mays* L.), winter wheat (*Triticum aestivum* L.), tomato (*Solanum lycopersicum* L.), and rice (*Oryza sativa* L.). In addition, sunflower (*Helianthus annuus* L.) was selected because this crop is commonly included in cropping rotations. We modeled approximately 50% of California's Central Valley, currently covering 1.4×10^6 ha. A typical field crop is assumed to be grown on any soil conditions within each grid. For rice, however, the majority of soils are clayey and poor drained, which makes them generally unsuitable for other crops. Therefore, we intersected the climate, land use, and soil data on each downscaled climate grid for rice, the other field crops, or both by county. The total number of grids used was 110 for rice and 537 for the other crops.

The historical runs to initialize the size of soil organic matter pools in the model consisted of three periods: (1) temperate C_3 grassland with grazing from 0 to 1869 (Paruelo and Lauenroth 1996), (2) initiation of cropping between 1870 and 1884, and (3) pre-modern agriculture

Fig. 1 Relative surface area of crops in California for 2006



between 1885 and 1949. In the first period, a medium-yield variety grass was simulated, which began growing in November and ended growing in April. Low-intensity grazing was assumed to affect 10% of the live shoots and 5% of the aboveground dead biomass. In the second period, we simulated a rain-fed low input winter wheat with minimal soil disturbance and a fallow year in 5 years. In the third period, we assumed a shift to diversified crops to include maize. For rice, we assumed continuous C_3 grass until 1911 and cropping started in 1912.

For the simulations for years 1950–2099, crop rotations were randomly selected based on the acreages of the selected crops (See De Gryze et al. 2009). The data on crop rotations were used to calculate the following conditional probabilities for each combination of crops:

$$\Pr(\mathrm{Cr_t}) \tag{1}$$

$$\Pr(\mathrm{Cr_t}|\mathrm{Cr_{t-1}}) \tag{2}$$

$$\Pr(\mathrm{Cr_t}|\mathrm{Cr_{t-1},}\mathrm{Cr_{t-2}}) \tag{3}$$

where $\Pr(\mathrm{Cr_t})$ is the probability to have a crop in the current year $\mathrm{Cr_t}$; $\Pr(\mathrm{Cr_t}|\mathrm{Cr_{t\text{-}1}})$ is the probability of having a certain crop in the current year given that a farmer planted a certain crop the year before $\mathrm{Cr_{t\text{-}1}}$; $\Pr(\mathrm{Cr_t}|\mathrm{Cr_{t\text{-}1}}, \mathrm{Cr_{t\text{-}2}})$ is the probability to have a crop in the current year conditioned on previous year's crop $\mathrm{Cr_{t\text{-}1}}$ and the crop from 2 years before $\mathrm{Cr_{t\text{-}2}}$. The survey data suggest that a farmer's decision to plant a crop only depends on the crops that were planted 2 years before. The crop following the fallow period was selected randomly according to the probabilities from Eq. (2). In all subsequent years, the crop planted was selected randomly according to the probabilities from Eq. (3). An exception was alfalfa-hay, which was typically grown in a four- to five-year rotation. Therefore, the conditional probabilities for alfalfa-hay were adjusted accordingly. For the whole simulated period 1950–2099, we considered a high intensity of soil disturbance because conservation tillage had not been extensively and will probably not be practiced in California (Mitchell et al. 2007). We also assumed the beginning of irrigation from 1950 and automatic irrigation up to field capacity was used when soil-water content dropped below 95% of available water holding capacity in the 0–1.5 m depth except for rain-fed winter wheat.

Historically, yields for major crops were relatively low until the mid 1940s. Crop production then started to significantly increase over the past 60 years due to improved mechanical, genetic, and chemical (pesticide and fertilizer) technologies (Johnson et al. 2006). In particular, commercial fertilizer nutrient inputs account for at least 30–50% of the crop yield increase since 1940 (Stewart et al. 2005). The effect of fertilization has been closely related to other improvements for most crops during the same period, such as genetic modifications (Johnson et al. 2006). To account for these effects, we simulated the increasing use of N fertilizer as indicated in NASS survey data from 1964 to 2006 that were found in Tyler (1994) and NASS' Agricultural Chemical Usage Report series. We also introduced different varieties for each period (e.g., low yielding vs. high yielding maize varieties). To maintain agricultural crop production under a changing climate, management practices and cultivars will probably have to be adjusted (Cassman 1999; Lobell et al. 2008). However, it is questionable whether or not the rate of yield improvements will continue in the 21st century (Ainsworth and Ort 2010). In this study, we did not fully consider any future adaptations for management practices (e.g., adjustment of crop variety, alternative cultivation methods, timing and amount of fertilizer and irrigation use, etc.) in response to projected climate change for years 2007–2099. We used the growing degree day submodel to control plant phenology and growing-season length. This option allowed changes in planting and harvest dates, hence providing limited adaptation to climate change. We did not directly simulate several field conditions, such as weed and pest problems.

To evaluate the effects of rising [CO_2] on crop yields, we selected the climate data from the CNRM-CM3 model downscaled by the bcsd method. These climate data represent the multi-model average climate change considered in this study. We assumed that (1) the increase in [CO_2] from 350 (i.e., 1990 [CO_2] levels) to 700 ppmv enhanced net primary production by 10% (Long et al. 2005) and C:N ratio for biomass by 25% (Poorter et al. 1997), but decreased transpiration rate by 23% (Cure and Acock 1986); and (2) the effects of elevated [CO_2] on production, transpiration, and C:N ratio for biomass were proportional to the magnitude of [CO_2] changes over time. We assumed no stimulation in alfalfa and maize production by elevated [CO_2] (Bunce 1995; Kim et al. 2006; Long et al. 2005).

2.4 Data analysis

All yields were expressed on a wet matter basis at harvest. The field crop moisture content at harvest was assumed to be 19% for alfalfa, 15% for cotton, 15% for maize, 14% for rice, 9% for sunflower, 94% for tomato, and 12% for wheat (Perez-Quezada et al. 2003; Wilks et al. 1993). For a combination of crops, climate models, and downscaling methods, annual average yields were calculated from 1951 to 2099, weighted by the acreage of the crop planted in each grid. A five-year moving average was computed to consider trends in yield variance. In this study, we reported 11-year moving averages from 1956 to 2094. Percent changes in yield for each year was relative to the 11-year moving averages in 2009, unless otherwise stated.

The model was validated using the observed statewide crop yield data for the period 1951–2006, except for sunflower, which was only available from 1975 to 2006. To assess model performance, we computed the mean squared deviation (MSD) between modeled and observed yield values, X and Y. The mean squared deviation was then partitioned into three components: squared bias (SB), nonunity slope (NU), and lack of correlation (LC) (Gauch et al. 2003). The SB results from two means being different, whereas the NU arises when the slope of the least-squared regression of Y on X is not equal to 1. The LC arises when the square of the correlation is not equal to 1. These MSD components are additive. The equations for these components can be found in Gauch et al. (2003). In addition, we evaluated the ability of the model to mimic crop yield response to variation in climate. At the regional scale, we described the historical climate-crop yields relationships using modeled and observed annual crop yield and annual averages for maximum/minimum temperature and precipitation. The observed data for annual mean maximum/minimum temperature and precipitation at the regional scale were obtained from Western Region Climate Center's California Climate Tracker (www.wrcc.dri.edu/monitor/cal-mon/frames_version.html). The modeled values were multi-model averages based on each emission scenario. All time series were detrended when necessary.

For this study, we focused on changes in modeled crop yields under the different climate change scenarios. We compared modeled yields by different GCMs and downscaling methods for uncertainty analysis.

3 Results and discussion

3.1 Comparison of modeled and observed yields

The modeled versus observed yields were generally clustered around the 1:1 line for the A2 and B1 emission scenarios (data not shown). By comparing the annual average yields, the observed crop yields were reproduced relatively well by DAYCENT. This is in agreement with De Gryze et al. (2009), showing that the model reliably simulated general yield trends under California conditions. In the period before 1975, the modeled yields deviated on average by 2–14% from the observed yields. Except, the maize and wheat yields averaged over this period were overestimated by 37±4% (mean±standard error) and 31±3%, respectively. Over the period 1975 to 2006, the maize, rice, tomato and wheat yields were overestimated in the range of 5–16%, whereas the alfalfa yields were underestimated by 3±1%. Overall, the differences between the means of modeled and observed yields were in a reasonable range over the period 1951–2006 for all the selected crops.

Alfalfa and sunflower had relatively high MSD compared to the other crops. Specifically, 89–91% of errors for alfalfa resulted from LC (Table 1). However, the observed mean and trends for alfalfa were reasonably well modeled based on SB and NU, respectively. Similarly, cotton had the majority of errors resulting from LC. Sunflower had a high NU because the modeled yields slightly decreased from 1975 to 2006, while the observed yields actually increased over the same period. There was no difference between the modeled and observed means for sunflower. For the other crops, errors from LC were almost negligible, except for cotton, as indicated by the intermediate to high r^2. Yield variance for cotton and sunflower was poorly simulated, presumably due to a limited model representation of these crops (Ogle et al. 2006). Only 35–38% and 27–29% of the observed range could be simulated for cotton and sunflower, respectively. Modeled yields for the other crops accounted for 78–100% of the observed range.

At the regional scale, both modeled and observed annual mean maximum and minimum temperatures were approximately 24°C and 9°C, respectively, showing significant ($P<0.001$) increasing trends (data not shown). We found no trends in annual precipitation, which was 408 mm on average. Yield changes over time showed sigmoidal (e.g., maize) or linear (e.g., cotton) trends during the historical period. The same trends were also found in the modeled yields, except for alfalfa. In general, detrended variation in annual mean maximum/minimum temperature ranged between −1 and 1°C. The model simulated the range of crop yield

Table 1 Components (SB = squared bias; NU = nonunity slope; LC = lack of correlation) of mean squared error (MSD) between modeled and observed annual crop yields (Mg ha^{-1}) for A2 and B1 emission scenarios

	Alfalfa		Cotton		Maize		Rice		Sunflower		Tomato		Wheat	
	A2	B1	A2	B1	A2	B1	A2	B1	A2	B1	A2	B1	A2	B1
Observed mean	13.5		1.2		7.5		6.9		1.4		58.4		3.7	
Modeled mean	13.9	13.9	1.2	1.2	8.4	8.3	7.2	7.2	1.4	1.4	66.3	66.1	4.1	4.1
b[a]	0.85	0.84	1.17	1.16	1.27	1.25	0.93	0.93	−1.76	−1.92	0.86	0.86	1.04	1.02
r^2	0.31	0.30	0.35	0.38	0.90	0.90	0.98	0.97	0.17	0.18	0.89	0.89	0.90	0.90
MSD	1.74	1.72	0.02	0.02	1.09	1.03	0.09	0.09	0.04	0.03	70.88	69.02	0.19	0.19
SB (%)	9.3	6.8	0.0	0.0	68.0	69.8	75.2	76.5	1.5	0.6	87.4	86.8	87.7	87.3
NU (%)	1.8	1.9	1.7	1.8	25.3	23.6	22.7	21.1	37.2	38.5	8.4	8.8	1.4	0.6
LC (%)	88.9	91.2	98.3	98.2	6.7	6.5	2.1	2.4	61.3	60.9	4.2	4.4	10.9	12.1

[a] The slope of the least-squared regression of observed on modeled yield values

response to climate reasonably. However, there was no apparent relationship between yield deviations from the trend and climatic variation over the period 1951–2006 for both modeled and observed (Fig. 2). Historical crop yields may show increasing sensitivity to monthly changes in temperature or precipitation (Lobell et al. 2007). Nevertheless, the model would show more sensitivity to increasing temperatures above the range observed because daily production and the duration of crop growth until maturity are quite sensitive to temperature (Stehfest et al. 2007). Overall, we found no effects of precipitation changes on irrigated crop yields.

3.2 Changes in yield

3.2.1 Within each emission scenario

For a combination of emission scenarios and downscaling methods, the crop yields varied greatly between the GCMs for the period 2009 to 2094. For cotton and rice, the average differences in yield were 0.2–0.4 Mg ha^{-1} and 0.2–0.5 Mg ha^{-1} (Fig. 3), with substantial variation in projected temperature (1.0–2.1°C), precipitation (22–33 cm), and relative humidity (5–8%) between the GCMs (data not shown). The average differences in yield between the GCMs were 0.9–1.8 Mg ha^{-1} for alfalfa, 0.7–1.0 Mg ha^{-1} for maize, 0.1–0.2 Mg ha^{-1} for sunflower, 1.8–4.1 Mg ha^{-1} for tomato, and 0.2–0.4 Mg ha^{-1} for wheat (data not shown). These differences were equivalent to 3–17% changes in yield in 2009 for A2 and 2–12% for B1. Despite climate model uncertainty, the average differences in yield by GCM or downscaling method mostly showed increasing temporal trends. As a result, yield variance for the crops increased toward the end of the century due to the various degrees of climate model sensitivity. Hence, future climate change suggested by each of the emission scenarios has a broad range of impacts on crop yields. Therefore, the magnitude of changes in yield under climate change was highly uncertain for most crops.

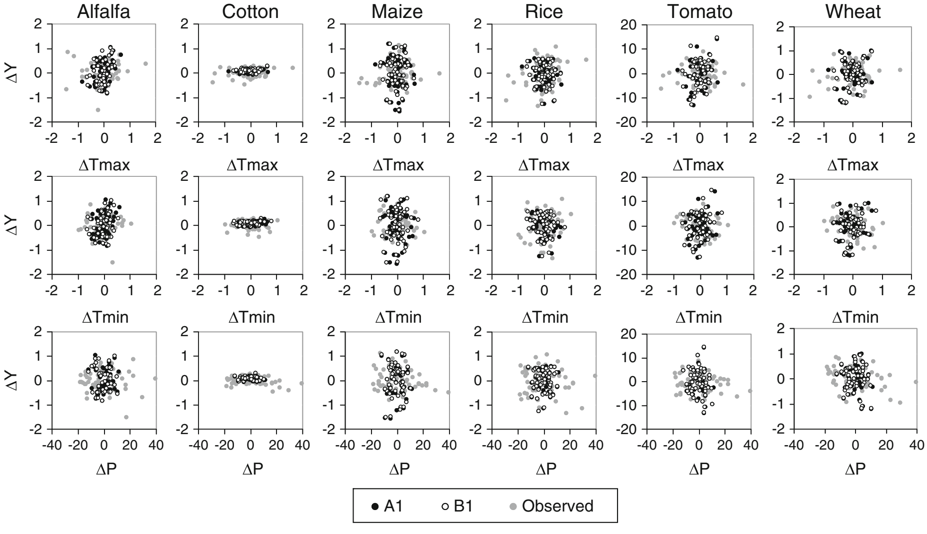


Fig. 2 Scatter plots of yield deviations from trend (ΔY) and detrended variation in annual mean maximum temperature (ΔTmax), annual mean minimum temperature (ΔTmin) and annual precipitation (ΔP). The units for yield, temperature, and precipitation are Mg ha^{-1}, °C, and cm, respectively

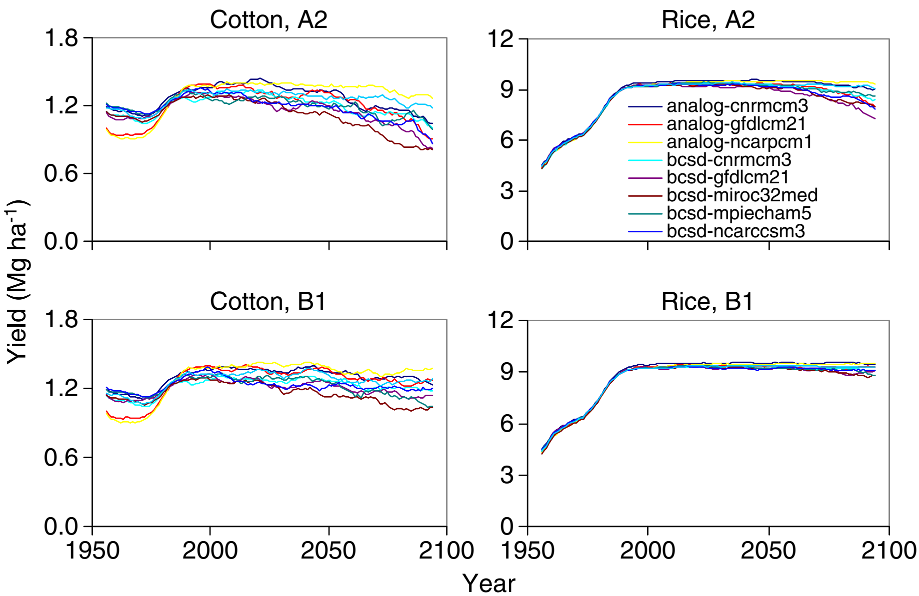


Fig. 3 Multi-model variation in modeled yield under A2 (medium-high) and B1 (low) emission scenarios. Lines are 11-year moving averages that are calculated over the period 1956 to 2094. Analog and bcsd are two methods used to downscale the original climate data from three and six climate models, respectively, for each emission scenario

Yield differences were less affected by downscaling (analog versus bcsd) method. However, we found constantly slightly higher yields for all crops with the analog method than with the bcsd method across time (2009–2094). The average yields were higher by 0.1 Mg ha^{-1} for cotton and by 0.1–0.3 Mg ha^{-1} for rice with the analog method than with the bcsd method (Fig. 3). The average differences in yield by downscaling method were 0.3–1.2 Mg ha^{-1} for alfalfa, 0.5–1.3 Mg ha^{-1} for maize, 0–0.1 Mg ha^{-1} for sunflower, 1.4–3.2 Mg ha^{-1} for tomato, and 0.2 Mg ha^{-1} for wheat (data not shown). Overall trends over time in yield were, nevertheless, similar between the downscaling methods. Maurer and Hidalgo (2008) showed that monthly and seasonal trends of temperature and precipitation produced by both downscaling methods were compatible. In addition, the observed wet and dry extremes were poorly reproduced by both methods and the difference in daily precipitation between the downscaling methods was not significant. However, when compared to observed temperatures, daily temperature extremes were effectively better reproduced by the analog method than the bcsd method (Maurer and Hidalgo 2008); partly leading to uncertainties in the model predictions of crop yields under climate change. We found lower maximum and minimum temperature (0.1–0.5°C), lower solar radiation (34–44 langleys day^{-1}), and higher relative humidity (1–2%) with the analog method than with the bcsd method (data not shown). In comparison, there was an inconsistent trend for precipitation and wind speed by downscaling method. For irrigated crops, these differences in the crops' sensitivity to climate variation were primarily due to specific crop temperature thresholds (Porter and Semenov 2005) that may affect daily production and tolerance to temperature extremes. Phenological development of a crop is strongly determined by changes in temperature. Lower solar radiation and higher relatively humidity likely resulted in less potential evapotranspiration, but changes in evapotranspiration did not affect crop yields due to the use of irrigation. Thus, the choice of the downscaling methods is a major source for uncertainties in predicting future crop yields under climate change.

3.2.2 Between the emission scenarios

Under both A2 and B1, changes in yield relative to the 2009 averages tend to increase for alfalfa (−2–+4%) and for maize (−1–+6%) in the period 2010 to 2025 (Fig. 4). Cotton (−2–+1%), sunflower (−4–0%), and wheat yields (−2–+1%) started to decrease over the same period. The exceptions were rice and tomato yields that remained closely to the 2009 crop yield level. These trends for yield variance seem to last over the next period: 2026 to 2050 (Fig. 4). Regardless of emission scenarios, cotton, sunflower, and wheat yields consistently decreased over time with expected yield losses of approximately 0–6%, 2–9%, and 1–4%, respectively. Meanwhile, our results suggest that the yield for alfalfa slightly increased toward 2050, ranging from −0.3% to 4%. In contrast, there was still no apparent change in rice and tomato yields in this period. By 2050, the average differences in yield changes between the two emission scenarios were marginal: less than 1% for all crops, except for cotton (4%) and sunflower (5%). This suggests that the differences in crop yield between the emission scenarios will generally not be noticeable until 2050.

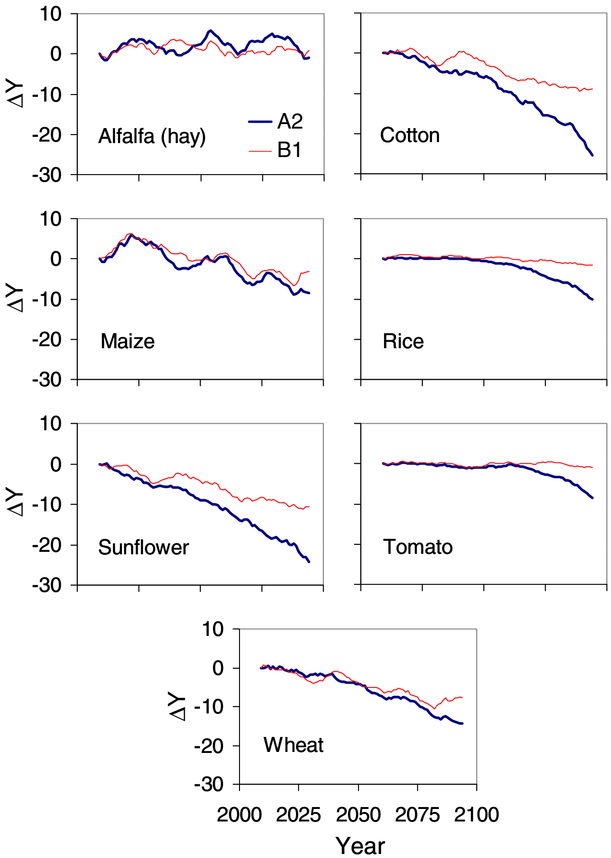


Fig. 4 Changes in yield (ΔY) under A2 (medium-high) and B1 (low) emission scenarios. 11-year moving averages are calculated for the period from 2009 to 2094. Changes in yield are then expressed as percent deviation from the 11-year moving averages in 2009

In the period 2051 to 2094, all the crop yields except for alfalfa were substantially declining under A2 (Fig. 4). Relative to the 2009 averages, the yields under A2 decreased by 2075 in the following order: sunflower (17%) > cotton (15%) > wheat (9%) > maize (6%) > rice (4%) > tomato (3%). The yields further decreased by 2094 in the following order: cotton (25%) > sunflower (24%) > wheat (14%) > rice (10%) > tomato and maize (9%). This suggests that the yields appeared to steadily decrease from 2051 on. The yields also tended to decrease under B1 in the same period, but the yield decreases were less than the ones under A2. Under A2 compared to B1, additional yield decreases were 0% to 17% depending on crop over this period. However, alfalfa yields further increased up to 5% under A2. Therefore, our results suggest that uncontrolled climate change will decrease crop yields in the long-term.

These regional yield decreases were mainly related to the increases in (maximum and minimum) temperature among the climate variables (Fig. 5). In the period 2010 to 2050, the crop yields significantly decreased with increasing temperatures for all crops, except alfalfa under A2 (data not shown) and sunflower under B1. Both emission scenarios had similar crop-specific yield responses to a range of temperature changes (0–1.1°C for A2 and 0–0.8°C for B1). In the period 2051 to 2094, we found similar temperature-crop yield relationships under A2 with the increases in temperature of 1.1–3.3°C. Under B1, all the crop yields except for alfalfa and tomato were significantly affected by increasing temperatures (0.8–1.7°C). Generally, increasing temperatures under climate change shortened the duration of phenological phases until maturity (Adams et al. 1990; Porter and Semenov 2005). As temperature increases, irrigation demand could substantially increase under climate change, although seasonal evapotranspiration was possibly reduced due to the shorter growing season (Howell et al. 1997). However, we did not consider any limitations related to water supply to irrigated croplands, which are expected to occur under climate change conditions in California (Anderson et al. 2008). Although current predictions for reductions in irrigation water supply are highly uncertain (Joyce et al. 2009), the modeled yield losses for the irrigated crops are possibly underestimated. Annual variability of crop yield could partly be affected by winter precipitation (Fig. 5) and relative humidity (data not shown), but the relationships were also highly uncertain. Daily

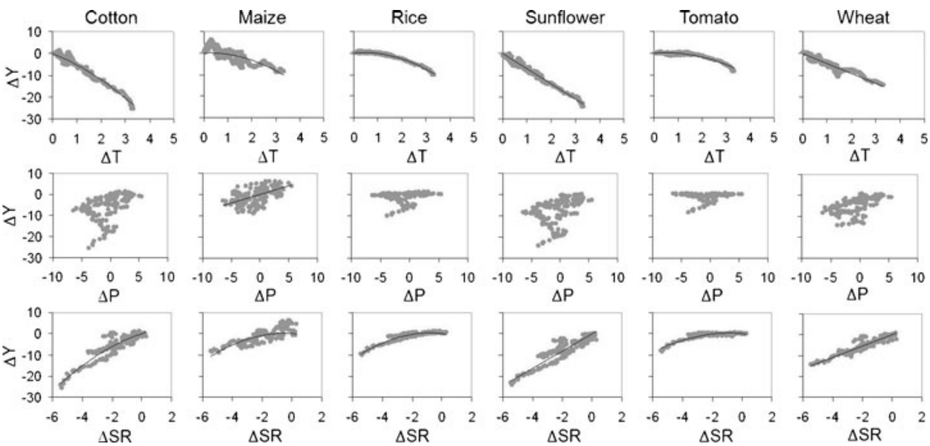


Fig. 5 Scatter plots of percent changes in crop yield (ΔY) and projected changes in annual mean temperature (ΔT), annual precipitation (ΔP), and annual mean solar radiation (ΔSR). Trend lines are shown if significant at P=0.05. The units for temperature, precipitation, and solar radiation are °C, cm, and langleys day^{-1}, respectively

production may decrease with decreasing solar radiation, further decreasing crop yields under climate change (Fig. 5).

3.2.3 Changes and differences in county-level yield patterns

The magnitude and direction of modeled yield changes under climate change varied considerably among counties. The county-level yield responses to climatic variation were in part associated with soil variability in the region, as has been found by Schimel et al. (1997). Across all the crops, the differences in yield changes between the A2 and B1 emission scenarios ranged from −6% to +10% in the southern counties of San Joaquin Valley and from −6% to +2% in the northern counties of Sacramento Valley by 2050 relative to the 2009 average yields (Fig. 6). Under A2, for example, alfalfa yield changes varied from +1% to +7% in the northern counties, but had a range of −10–+14% in the southern counties. Except for tomato and rice, variation in yield changes increased more progressively in the southern counties than the northern counties. This shows that the region-level changes in yield under climate change were generally more affected by the county-level changes in yield of the San Joaquin Valley than those of the Sacramento Valley. For sunflower, on the other hand, the region-level yields decreased under both emission scenarios and the changes in yield differed by −6% to −2% by emission scenario

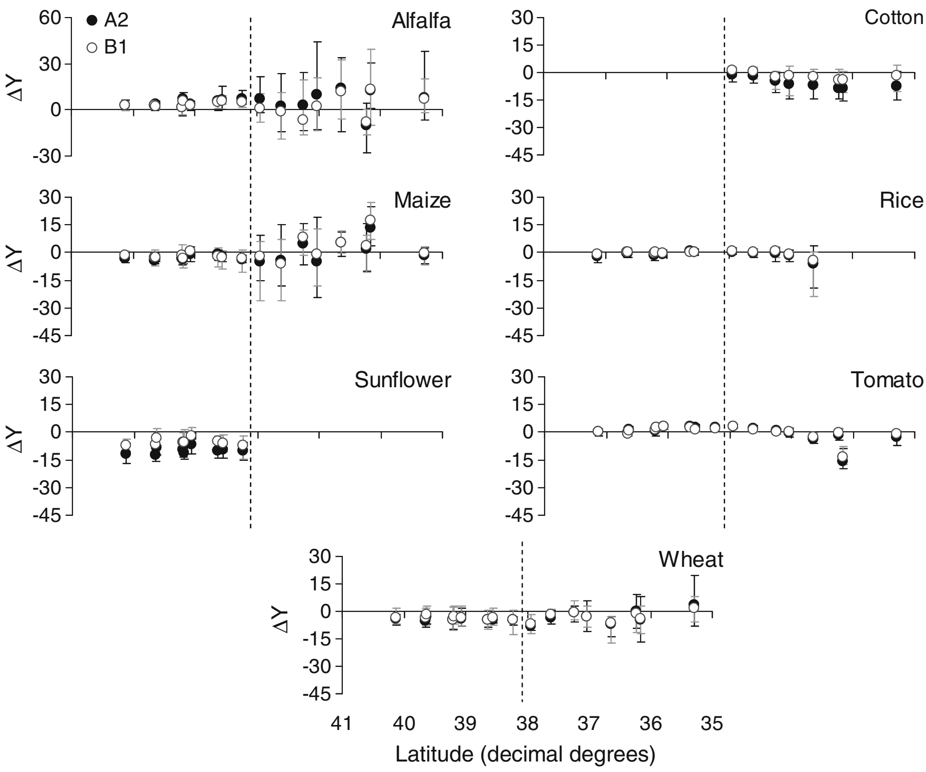


Fig. 6 Percent deviations of the 11-year moving averages in 2050 from the 2009 averages under A2 (medium-high) and B1 (low) emission scenarios. Error bars indicate the range of variation in county-level averages due to climate uncertainty. *Dotted vertical lines* indicate the boundary between the northern Sacramento and southern San Joaquin Valleys

across the counties. However, there was no obvious pattern for changes in sunflower yield by 2050 under A2 and B1. This suggests that the risk of these crops for yield losses will likely increase in response to early climate change particularly in the San Joaquin Valley, presumably due to its relatively low environmental suitability for the crops (Lobell et al. 2006).

For the period 2051 to 2094, the differences in yield changes between the emission scenarios across all the crops ranged from −16% to +6% in Sacramento Valley and from −21% to +8% in San Joaquin Valley (Fig. 7). The yields of cotton, maize, rice, sunflower, tomato, and wheat generally decreased across the counties. It has been suggested that crop production will be mostly affected by increasing climatic variation, including extreme weather events (Porter and Semenov 2005). Hence, crop production seems to be negatively affected by climate change, but the magnitude of the yield reduction was highly uncertain due to the limited model ability to simulate crop responses to extreme weather conditions. In contrast to the other crops, the effects of climate change on alfalfa seem to be not spatially consistent at the county level scale. Water delivery target in agriculture is currently approximately higher than actual delivery by 2% in the Sacramento Valley and 20% in the San Joaquin Basin (Medellín-Azuara et al. 2008). It is expected, however, to further increase by 20–25% by the year 2050 under A2 unless adaptations for water management are made. As a result, climate change will likely decrease annual water deliveries and increase water supply risk in agriculture

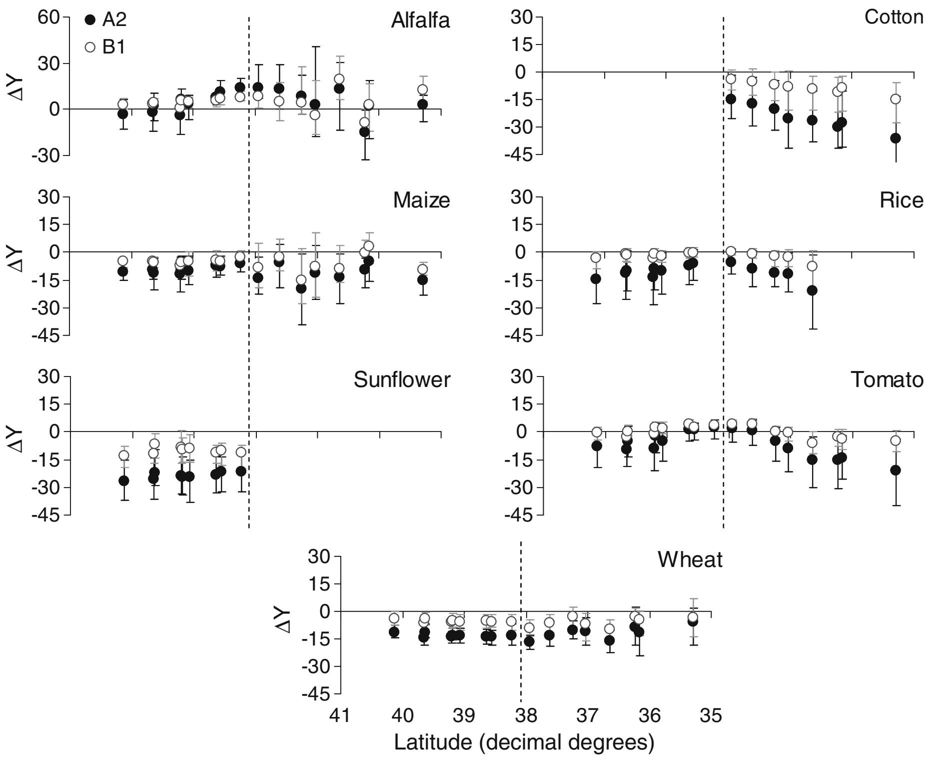


Fig. 7 Percent deviations of the 11-year moving averages in 2094 from the 2009 averages under A2 (medium-high) and B1 (low) emission scenarios. Error bars indicate the range of variation in county-level averages due to climate uncertainty. *Dotted vertical lines* indicate the boundary between the northern Sacramento and southern San Joaquin Valleys

(Anderson et al. 2008). As irrigation demand and evapotranspiration during the growing season are potentially greater in San Joaquin Valley than Sacramento Valley under climate change, the risk of the crops grown on the southern counties is expected to further increase toward the end of the century.

3.2.4 Elevated CO_2 effects on changes in yield

In theory, the negative effect of climate change on yields could be counterbalanced by the increased rate of crop production under elevated [CO_2], particularly for C3 crops (Long et al. 2006). In our simulation study, the effects of climate change and CO_2 fertilization increased crop yields by 2–16% more than the yields under climate change only under A2 in 2094 (data not shown). In comparison, there were smaller yield increases (1–8%) due to CO_2 fertilization effects under B1. The effects of elevated [CO_2] mitigated approximately 30–100% of the yield declines for all crops by 2094. However, regardless of emission scenario, this stimulation of yield seems to be overestimated in comparison to current field data from FACE experiments (Ainsworth et al. 2008). In addition, the direction and magnitude of modeled yield changes vary among climate data and crop models. Tubiello et al. (2002) showed that increasing [CO_2] up to 660 ppmv did not mitigate yield declines from baseline (1951–1994) for irrigated maize under climate change in 2090. Rain-fed winter wheat yields increased (13% to 48%) or decreased (−4% to −30%) in 2090, respectively, with increasing or decreasing precipitation (Tubiello et al. 2002). For rice, changes in [CO_2] from 330 ppmv to 660 ppmv increased yields by 9% or 15% depending on crop models (Bachelet and Gay 1993). Therefore, we have less confidence in the model to accurately predict the potential stimulation of crop yields in response to increasing [CO_2] and focused on the temperature and precipitation effects on yield in a future changed environment.

4 Conclusions

In this simulation study, we assessed the effects of future climate change on crop productivity of alfalfa (hay), cotton, maize, rice, sunflower, tomato, and wheat under current management conditions in California's Central Valley. Our study area includes 17 counties and represents approximately 50% of the crop land in California. In total 18 different climate change scenarios for both A2 (medium-high) and B1 (low) emission scenarios were used to establish a baseline for the period 1950 to 2099. We also evaluated uncertainties in modeled yields from the choice of GCMs and the downscaling methods. The model simulated the observed yields relatively well for all crops in the period 1951 to 2006, although yield variance for some crops (i.e., cotton and sunflower) was not very well reproduced. In the historical period, the range of yield deviations from the trend in response to variation in temperature and precipitation was properly simulated but did not show any trend. In the period 2010 to 2050, there were effects of climate change on changes in yield (11-yr moving average; relative to the 2009 average yields) under both emission scenarios but the differences by emission scenario were not obvious. However, in the next period (2051–2094), relative crop yield changes were different between the two emission scenarios and showed strong spatial patterns across the counties. Overall, the crop yields were negatively affected by the increase in temperature with greater precipitation variation, except alfalfa yields did not consistently respond to climate change. In part, the yields may further decrease with decreasing solar radiation over time. However, we also found that

CO_2 fertilization will potentially offset future yield declines under climate change but crop responses to elevated [CO_2] should be further validated before strong conclusions are made. Furthermore, other global change factors, such as elevated ozone and N deposition should also be considered because they could enhance or counterbalance the effects of climate change on crop yields. With respect to climate change, we conclude that California crop yields will be negatively affected in the long-term, unless there are statewide adaptation scenarios and management strategies to climate change that maintain or increase yields while mitigating emissions of greenhouse gases.

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