EFFECT OF CLIMATE CHANGE ON FIELD CROP PRODUCTION IN THE CENTRAL VALLEY OF CALIFORNIA

A Report From:
California Climate Change Center

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FINAL PAPER

DISCLAIMER

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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.

The PIER Program conducts public interest research, development, and demonstration (RD&D) projects to benefit California's electricity and natural gas ratepayers. The PIER Program strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

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- Energy-Related Environmental Research
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- Environmentally Preferred Advanced Generation
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- Renewable Energy Technologies
- Transportation

In 2003, the California Energy Commission's PIER Program established the **California Climate Change Center** to document climate change research relevant to the states. This center is a virtual organization with core research activities at Scripps Institution of Oceanography and the University of California, Berkeley, complemented by efforts at other research institutions. Priority research areas defined in PIER's five-year Climate Change Research Plan are: monitoring, analysis, and modeling of climate; analysis of options to reduce greenhouse gas emissions; assessment of physical impacts and of adaptation strategies; and analysis of the economic consequences of both climate change impacts and the efforts designed to reduce emissions.

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.

For more information on the PIER Program, please visit the Energy Commission's website www.energy.ca.gov/pier/ or contract the Energy Commission at (916) 654-5164.

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Abstract

Climate change under various emission scenarios is highly uncertain but is expected to affect agricultural crop production for the coming century. However, we know very little about future changes in specific cropping systems under climate change in California's Central Valley. Predicting yields requires complex ecosystem modeling that 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 annual 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 five-year moving averages from 1953 to 2097, changes in yield were highly variable depending on the climate change scenarios across times. Furthermore, the variability of crop yield changes tended to increase toward the end of the century. 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, maize, sunflower, and wheat yields decreased by approximately 3% to 8% by 2050 compared to the 2000 average yields. The differences in yield changes between the two emission scenarios were marginal (less than 2%) for the 2001–2050 period. However, it was obvious that all the crop yields, except for alfalfa, significantly declined by 2097 under A2, but less under B1. Under A2, yields decreased in the following order: cotton (29%) > sunflower (26%) > wheat (15%) > maize (12%) > rice (10%) > tomato (9%). Most of the crop yields also tended to decrease under B1 in the same period, but the differences in yield changes between the A2 and B1 emission scenarios ranged from 5% (alfalfa) to 18% (cotton) by 2097. Our results suggest that climate change will decrease crop yields in the long-term, particularly for cotton, unless greenhouse gas emissions and resulting climate change is curbed and/or adaptation of new management practices and improved cultivars occurs.

Keywords: Climate change, California, annual field crops, greenhouse gas, crop yield

1.0 Introduction

1.1 Background and Overview

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 has increased from 280 to 370 parts per million (ppm) over the past 150 years. The change in the atmospheric CO_2 concentration 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).

Global variation in mean precipitation and drought has also increased (Dai et al. 1998; Jones and Mann 2004). This suggests that the increase in atmospheric CO_2 and other greenhouse gases will potentially affect future climate (IPCC 2007). Particularly 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 expected to be sensitive to climate change (Adams et al. 1990), but our understanding of climate change and its impacts on California cropping systems in the coming century is limited. California's Central Valley is considered 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 cropping systems. Therefore, it is pertinent to further explore changes in annual crop yields under changing climate in the Central Valley.

To maintain agricultural crop production under a changing climate, management practices and cultivars will probably have to be adjusted (Cassman 1999). 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). Complex ecosystem modeling represent a 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 crop model uncertainty. First, the crop models have been only calibrated and validated under observed climate conditions (Adams et al. 1990). For example, the responses of crop growth to extreme temperature conditions suggested by the global circulation 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 effect of increasing CO_2 concentration on crop yields were derived from a limited range of growing conditions and may be also overestimated (Long et al. 2006; De Graaff et al. 2006). Regardless of these limitations, process-based crop 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 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, the atmospheric CO_2 concentration is expected to be around 550 ppm by 2050 and 850 ppm by 2100. Under B1, the CO_2 concentration is expected to be 500 ppm by 2050 and then would be stabilized until 2100. Temperatures increase from 1.5°C under B1 to 6°C (2.7°F and 10.8°F) under A2 by the end of the century relative to 1960–1990. Specifically for California, more warming is expected in summer than winter with increasing frequency of heat waves. Annual precipitation shows relatively small changes (10%) in the same period.

1.2 Project Objectives

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.

2.0 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., carbon [C] and nitrogen [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. 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 a major factor that likely affects crop production. Soil-water availability depends on current soil-water, precipitation, irrigation, and potential evapotranspiration (ET). Nutrients (e.g., N) from the soil or fertilizer can also affect potential production depending on crop requirements. In particular, both soil-water and nutrient stresses affect the fraction of C allocated to roots.

2.2 Data Acquisition

2.2.1 Climate Data

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, all the climate 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 kilometers [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 degree grid resolution (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 level of digital soil mapping done by the NRCS in 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. In this study, 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 recently 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. (in press).

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 because a growing degree day submodel was implemented. 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 our own survey data (Howitt et al. in press).

2.3 Modeling Strategies

We selected the six top annual field crops in California based on their harvested area (Figure 1). The selected crops were alfalfa (hay), cotton, maize, winter wheat, tomato, and rice. In addition, sunflower 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 hectares (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 major crops.

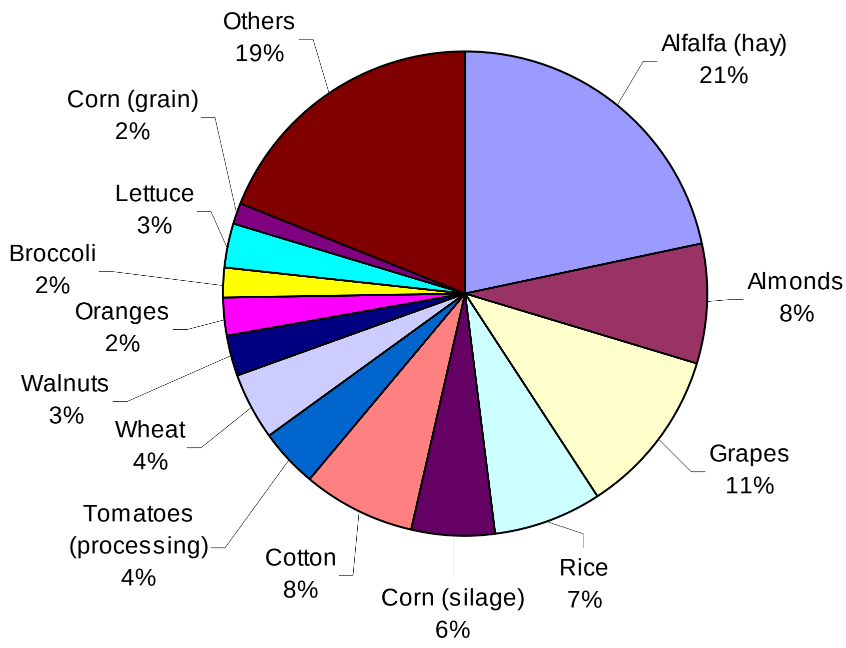

Figure 1. Relative surface area of crops in California for 2006

The historical runs to initialize the model consisted of two periods: (1) grassland with grazing from 0 to 1869, and (2) initiation of cropping between 1870 and 1949. For 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. For the second period, we simulated a rain-fed low input winter wheat with minimal soil disturbance and a fallow year in five years. Since 1900, we assumed introduced diversified crops (e.g., maize in early 1900s, tomatoes in 1945). For rice, we assumed continuous grass until 1911 and cropping started in 1912.

For the model runs for the period 1950–2099, crop rotations were randomly selected based on the acreages of the selected crops (See De Gryze et al., in press). Data on crop rotations were used to calculate the following conditional probabilities for each combination of crops:

$$\Pr(Cr_{t=2})\big|Cr_{t=1} \qquad \text{[Equation 1]}$$

$$\Pr(Cr_{t=3})\big|Cr_{t=1,}Cr_{t=2} \qquad \text{[Equation 2]}$$

where $\Pr(Cr_{t=2})$ is the probability to have a crop, Cr, in the second year; $\Pr(Cr_{t=2})\big|Cr_{t=1}$ is then the probability of having a certain crop in the second year given that this farmer planted crop $Cr_{t=1}$ the year before. The data suggest that a farmer's decision to plant a crop only depends on the crops that were planted two years before, or:

$$\Pr(Cr_{t=4})\big|Cr_{t=1,}Cr_{t=2,}Cr_{t=3} = \Pr(Cr_{t=4})\big|Cr_{t=2,}Cr_{t=3} \qquad \text{[Equation 3]}$$

The crop following the fallow period was selected randomly according to the probabilities from Equation 1. In all subsequent years, the crop planted was selected randomly according to the probabilities from Equation 2. An exception was alfalfa-hay, which was usually grown in a four- to five-year rotation. Therefore, the conditional probabilities for alfalfa-hay were adjusted accordingly. For the period 1950–2099, we considered a high intensity of soil disturbance because conservation tillage had not been extensively practiced in California (Mitchell and Miyao 2002). We also assumed the beginning of irrigation from 1950 and irrigation water supply to attain 95% soil water-holding capacity at the time of irrigation, except for rain-fed winter wheat.

Historically, yields for major annual 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 fertilizer as indicated in the USDA historical records, and also considered different varieties for each period (e.g., maize). Therefore, we did not consider any future adaptations for management practices (e.g., alternative cultivation methods, timing and amount of fertilizer and irrigation use) in response to changes in climate for the period 2000 to 2099.

2.4 Data Analysis

For a combination of crops, climate models, and downscaling methods, annual average yields were calculated from 1950 to 2099, weighted by the acreage of the crop planted in each grid. A five-year moving average was then computed to consider trends in yield variance. In this study, we reported five-year moving averages from 1953 to 2097. Percent changes in yield for each year was relative to the five-year moving averages in 2000, unless otherwise stated. Maps of yield changes in 2050 and 2097 on the county scale for selected crops were produced in ArcGIS 9.1 (ESRI, Redlands, California).

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 (NS), and lack of correlation (LC) (Gauch et al. 2003). First, SB results from two means being different. Second, NS arises when the slope of the least-squared regression of Y on X is not equal to 1. Finally, 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).

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.

3.0 Results and Discussion

3.1 Comparison of Modeled and Observed Yields

At the state-level, the observed crop yields were available from 1953 to 2004, except only from 1975 to 2004 for sunflower. The modeled versus observed yields were generally clustered around the 1:1 line for the A2 and B1 emission scenarios (Figure 2). By comparing the five-year moving average yields, the observed crop yields were reproduced relatively well by DAYCENT. In the period before 1975, the modeled yields deviated on average by 2%–6% from the observed yields. Exceptionally, the maize yields averaged over this period were overestimated by 23 ± 3% (mean ± standard error). Over the period 1975 to 2006, the model overestimated the average tomato yields by 12 ± 1% and the rice yields by 5 ± 0%, whereas the alfalfa, maize, and wheat yields were underestimated by 12 ± 1, 5 ± 1, and 4 ± 1%, respectively. Overall, the differences between the means of modeled and observed yields were in a reasonable range over the period 1953–2004 for all the selected crops.

Alfalfa and sunflower had relatively high MSD compared to the other crops. Specifically, 54%–56% of errors for alfalfa resulted from LC as indicated by the relatively low r^2 (Table 1). However, the observed mean and trends for alfalfa were reasonably well modeled based on SB and NU, respectively. Sunflower had a high NC because the modeled yields showed a slightly decreasing trend, while the observed yields actually increased. Fortunately, there was no difference in 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. Although cotton had the majority of errors resulting from LC, this may not be a problem because of its intermediate r^2 (= 0.55–0.57). Yield variance for cotton and sunflower was poorly simulated. Only 39%–42% and 29%–30% of the observed range could be simulated for cotton and sunflower, respectively. For alfalfa, approximately 60% of the observed range was simulated. Modeled yields for the other crops accounted for 67%–100% of the observed range.

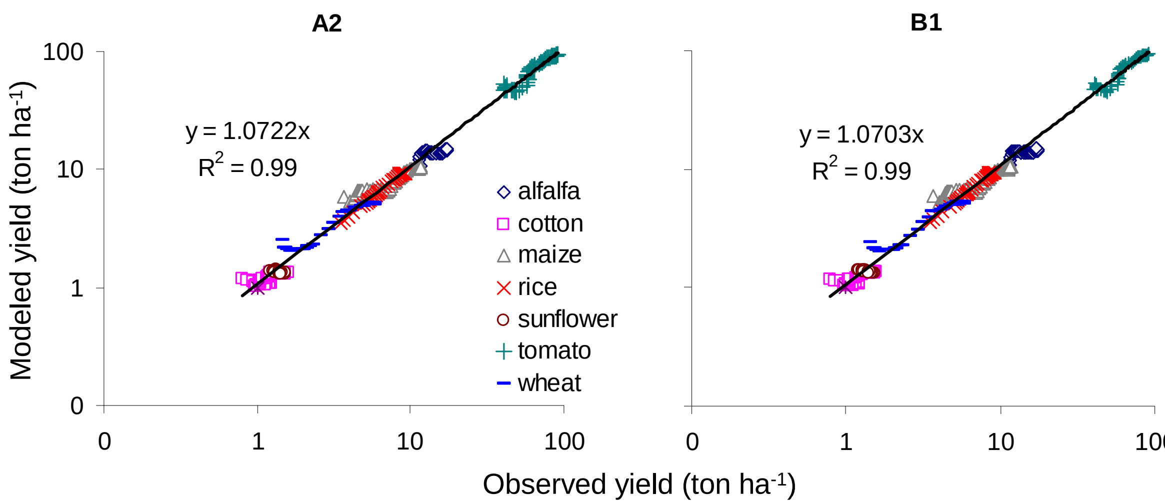

Figure 2. Modeled and observed average crop yields. Five-year moving averages are compared for the period from 1953 to 2004. The yields are plotted on a logarithmic scale.

Table 1. Components (SB = squared bias; NU = nonunity slope; LC = lack of correlation) of mean squared error (MSD) between modeled and observed crop yields (ton 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	14.9		1.2		8.2		7.0		1.4		63.8		4.0	
Modeled mean	14.0	14.0	1.2	1.2	8.4	8.3	7.2	7.2	1.4	1.4	69.2	69.0	4.1	4.1
$b^{\dagger}$	1.68	1.68	1.16	1.14	1.45	1.43	0.92	0.93	-2.29	-2.78	0.88	0.88	1.18	1.17
r^2	0.37	0.37	0.55	0.57	0.94	0.95	0.99	0.99	0.59	0.64	0.93	0.93	0.96	0.96
MSD	2.41	2.52	0.01	0.01	0.73	0.69	0.09	0.09	0.01	0.01	34.64	33.46	0.06	0.05
SB (%)	34.9	37.8	0.0	0.0	2.3	1.7	79.7	81.2	4.6	2.1	83.5	82.2	1.7	1.3
NU (%)	8.7	8.3	4.7	4.7	94.3	94.9	20.1	18.7	83.5	88.1	12.6	13.6	91.7	91.1
LC (%)	56.4	53.9	95.2	95.3	3.4	3.3	0.1	0.1	11.9	9.9	3.9	4.2	6.6	7.7

† The slope of the least-squared regression of observed on modeled yield values.

3.2 Changes in Yield

3.2.1 Within Each Emission Scenario

For a combination of emission scenario and downscaling methods, the crop yields varied greatly between the GCMs for the period 1953 to 2097. For cotton, the mean and maximum differences in yield between the GCMs were up to 0.05 and 0.16 ton ha^{-1} under A2 and 0.04 and 0.16 ton ha^{-1} under B1 when the analog method was used for the period before 2050 (Figure 3). Over the next 50 years, the corresponding mean and maximum differences increased to 0.10 and 0.24 ton ha^{-1} under A2 but were not much changed thereafter under B1. Meanwhile, the mean differences in yield increased two to four times when the bcsd method was used. Therefore, 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.

The crop yields varied greatly depending on the downscaling (analog versus bcsd) methods across times (1953–2097), although overall trends in yield were similar. Maurer and Hidalgo (2008) showed that monthly and seasonal trends of temperature and precipitation produced by both 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 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). Therefore, the model could predict historical crop yields better using the climate change scenarios downscaled by the analog method than the bcsd method.

For example, when we used the climate data downscaled by the analog method only, the difference in the cotton yields between the emission scenarios was on average up to 0.4 ton ha^{-1} over the period 1950–2000 (Figure 3). However, the difference increased up to 0.8 ton ha^{-1} with the bcsd method. Alfalfa, maize, and tomato yields also tend to follow this trend (data not shown). In comparison, the other crops, such as rice (Figure 3) and wheat (data not shown), had a small difference in yields between the downscaling methods. These differences in the crops' sensitivity to climate variation were mostly due to specific crop temperature thresholds (Porter et al. 2005). In DAYCENT, base and maximum temperatures for rice growth were specifically set to 2°C and 45°C (35.6°F and 113°F), whereas it was 5°C and 45°C (41°F and 113°F) for cotton. Due to a broader average temperature range for crop growth, rice was potentially less affected by daily temperature extremes than cotton was.

Thus, the choice of the downscaling methods can be a source for uncertainties in predicting future crop yields under climate change. For cotton, the yields between the downscaling methods differed by 0.16–0.30 ton ha^{-1} for the period before 2050 when the same GCM was used (Figure 3). This was equivalent to 11%–21% changes from the observed yields in 2000 (= 1.42 ton ha^{-1}). In the period 2051 to 2097, the differences in yield between the downscaling methods ranged from 0.01 to 0.16 ton ha^{-1}. Regardless of the emission scenarios, the modeled changes in yield were generally lower by the analog method than the bcsd method for the period until 2050, but the opposite trend was observed for the period after 2050. This was because the magnitude of changes in yield was generally higher with the analog method than the bcsd method, suggesting a larger crop sensitivity to climate change.

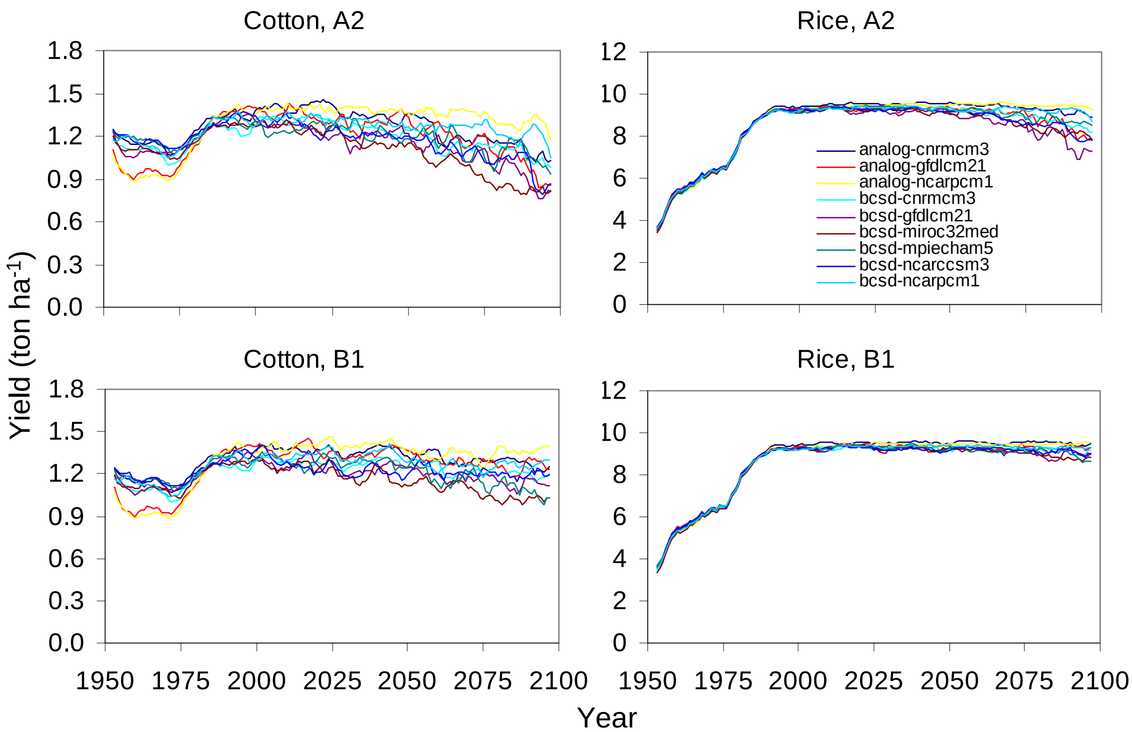

Figure 3. Average simulated yields under A2 (medium-high) and B1 (low) emission scenarios. Lines are five-year moving averages that are calculated over the period 1953 to 2097. Analog and bcsd are two methods used to downscale the original climate data. Three and six climate models are used for the A2 and B1 emission scenarios, respectively.

3.2.2 Between the Emission Scenarios

In the period 2001 to 2025, changes in yield relative to the 2000 averages were highly variable for some crops (Figure 4). Relative changes in yield for alfalfa ranged from -7% to 22%, followed by maize (= -6%–16%). Cotton, sunflower, and wheat yield changes also varied within a range of 6%–7%. The exceptions were rice and tomato yields that remained closely to the 2000 crop yield level. These trends for yield variance seem to last over the next period 2026 to 2050. Under both A2 and B1, cotton, sunflower, and wheat yields started to slightly decrease from the year 2026 with expected yield losses of approximately 3%–8% by 2050 (Figure 5). Meanwhile, our results suggest that the yield for alfalfa, rice, and tomato slightly increased over the same period, ranging from 1% to 5%. By 2050, the differences in yield changes between the two emission scenarios were marginal (less than 1%), except for sunflower and wheat (≈ 2%). This suggests that the effects of climate change on crop yields will generally not be noticeable by 2050.

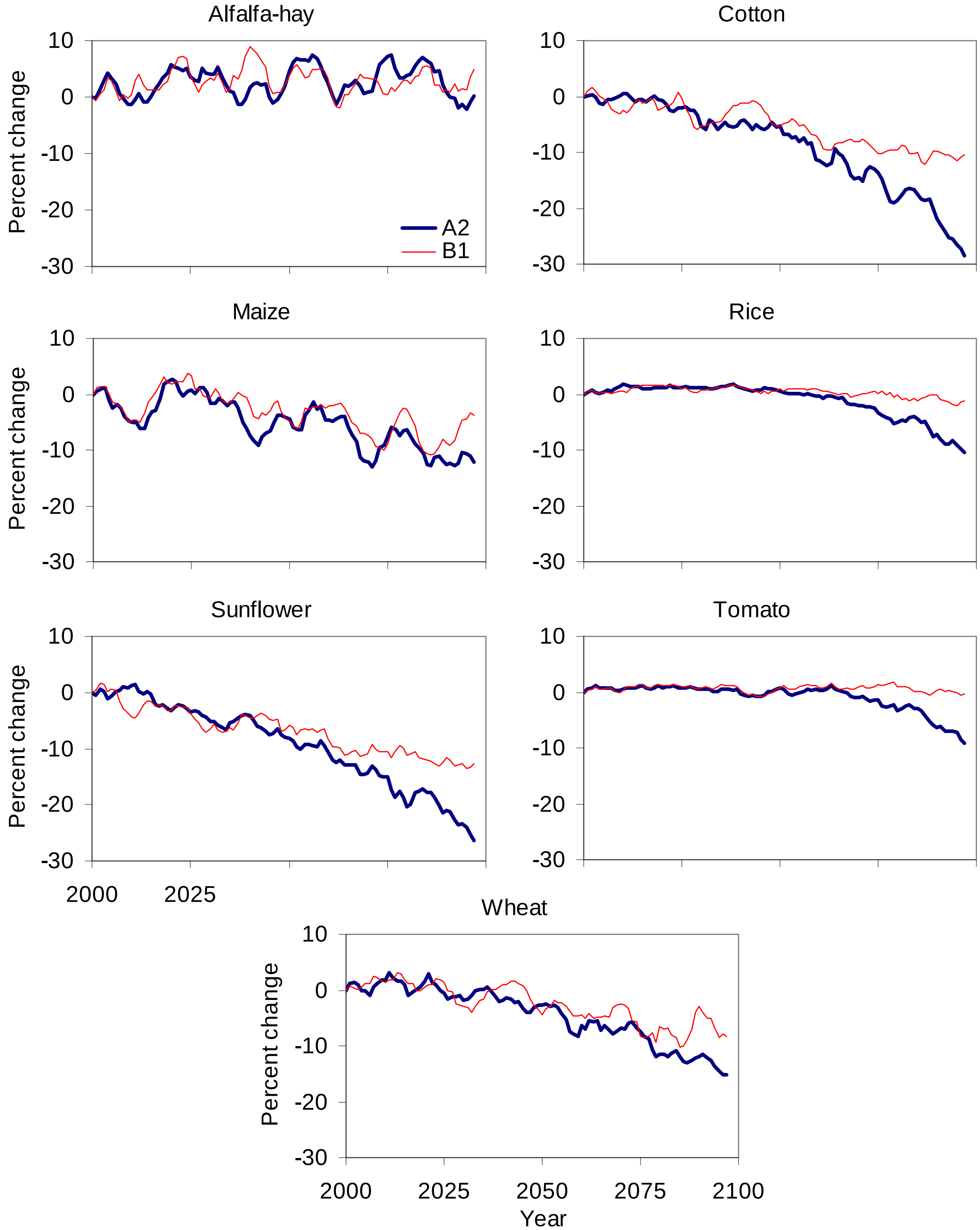

Figure 4. Changes in yield under A2 (medium-high) and B1 (low) emission scenarios. Five-year moving averages are calculated for the period 2000–2097. Yield changes are then expressed as percent deviation from the five-year moving averages in 2000.

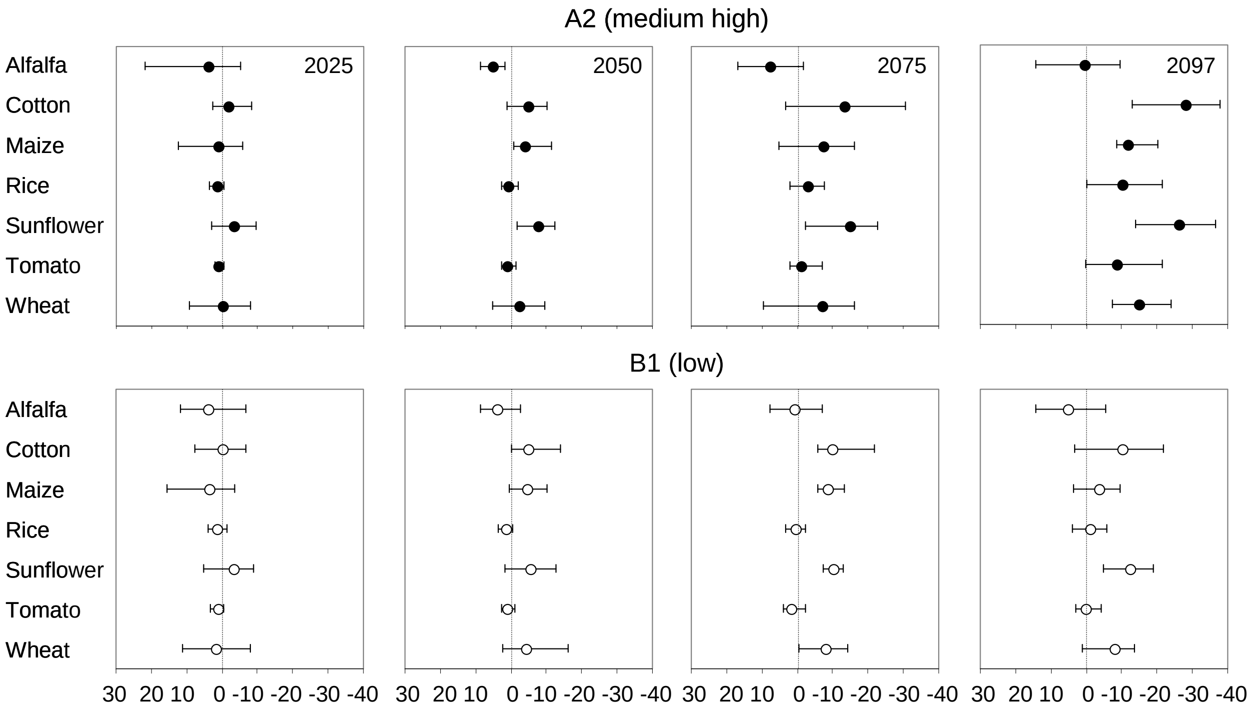

Figure 5. Percent changes in crop yield in California under the A2 and B1 climate scenarios. Five-year moving averages are calculated for the period from 2000 to 2097. Changes in yield are expressed as percent mean deviations from 2000 average yields. Error bars indicate the range of simulated values.

In the period 2051 to 2097, all the crop yields except for alfalfa were significantly declining under A2 (Figure 4). Maize and sunflower yields tended to steadily decrease from 2051 on. However, declining rates for cotton, rice, tomato, and wheat yields were even further accelerated over the period 2075 to 2097. The yields under A2 decreased by 2097 in the following order: cotton (≈ 29%) > sunflower (≈ 26%) > wheat (≈ 15%) > maize (12%) > rice (≈ 10%) > tomato (≈ 9%) (Figure 5). The yields also tended to decrease under B1 in the same period, but they were less than the ones under A2. These yield decreases were mainly because high temperatures under climate change shorten the duration of phenological phases (Adams et al. 1990; Porter and Semenov 2005). As temperature increases, daily ET generally increases. As a result, irrigation demand could substantially increase in this period, although seasonal ET was possibly reduced due to the shorter growing season (Howell et al. 1997). However, we did not consider limitations related to water supply to irrigated croplands (Anderson et al. 2008). This suggests that the modeled yield losses for the irrigated crops were possibly underestimated. Variability wheat yield could be partly affected by winter precipitation, but it was highly uncertain. The differences in yield changes between the emission scenarios ranged from 5% (alfalfa) to 18% (cotton) by 2097. Our results suggest that uncontrolled climate change will decrease crop yields in the long-term, particularly for cotton and sunflower.

3.2.3 Changes and Differences in County-Level Yield Patterns

The magnitude and direction of modeled yield changes under climate change varied considerably between counties. The county-level yield responses to climatic variation were in part associated with soil variability in the region (Schimel et al. 1997). Relative to the 2000 average yields, the differences in yield changes between the A2 and B1 emission scenarios ranged from -10% to 10% in the southern counties of San Joaquin Valley and from -4% to 2% in the northern counties of Sacramento Valley by 2050. Accordingly, the range of county-level yield changes was greater in the southern counties than the northern counties. Under A2, for example, alfalfa yields varied from 1% to 8% in the northern counties, but had a range of -3%–14% in the southern counties. For the crops whose state-level yields decreased under both emission scenarios (i.e., maize, sunflower, and wheat), the yields decreased more progressively in the southern counties than the northern counties (Figure 6). This shows that the state-level changes in yield were generally more affected by the regional yield changes of the San Joaquin Valley than the Sacramento Valley. At the county-level scale, the differences in yield changes between the emission scenarios for sunflower ranged from -4% to -1% across the counties. However, modeled sunflower yields decreased in all of the nine counties by 2050 under A2 when compared under B1.

Table 2. Percent changes in crop yield in California under the A2 and B1 climate scenarios. Five-year moving averages are calculated for the period from 2000 to 2097. Changes in yield are expressed as percent mean deviations from 2000 average yields.

Commodity	Emission scenario	Year							
		2025		2050		2075		2097	
		Average	Range	Average	Range	Average	Range	Average	Range
Alfalfa	A2	3.7	-5 / 21.9	4.7	1.7 / 8.5	7.3	-1.8 / 16.8	0.1	-9.7 / 14.2
	B1	3.8	-6.8 / 11.8	3.7	-2.6 / 8.6	0.4	-7 / 7.7	4.8	-5.6 / 14.2
Cotton	A2	-2.1	-8.3 / 2.6	-5.2	-10.3 / 1	-13.7	-30.6 / 3.4	-28.5	-37.9 / -13.1
	B1	-0.3	-6.6 / 7.8	-5.3	-14.1 / -0.2	-10.3	-21.8 / -5.7	-10.5	-21.8 / 3.2
Maize	A2	0.7	-5.9 / 12.5	-4.4	-11.3 / -0.9	-7.6	-16.2 / 5.2	-12.2	-20.2 / -8.7
	B1	3.3	-3.7 / 15.5	-4.8	-10.3 / 0.4	-9.0	-13.4 / -5.9	-3.9	-9.6 / 3.7
Rice	A2	1.2	-0.3 / 3.6	0.6	-2 / 2.7	-3.3	-7.6 / 2	-10.5	-21.5 / -0.1
	B1	1.0	-1.4 / 4	1.0	-0.5 / 3.6	0.2	-2.2 / 3.3	-1.2	-5.9 / 4.1
Sunflower	A2	-3.4	-9.6 / 3	-8.1	-12.4 / -1.6	-15.1	-22.7 / -2.4	-26.4	-36.6 / -14.9
	B1	-3.6	-8.9 / 5.2	-5.8	-12.8 / 1.7	-10.5	-13 / -7.3	-12.6	-18.9 / -4.7
Tomato	A2	0.8	-0.4 / 2.1	0.7	-1.4 / 2.6	-1.4	-7 / 2	-9.1	-21.6 / 0.3
	B1	0.9	-0.4 / 3.2	0.8	-1.2 / 2.6	1.5	-2.2 / 4	-0.2	-4.1 / 3
Wheat	A2	-0.5	-8.1 / 9.4	-2.6	-9.6 / 5.3	-7.4	-16.1 / 9.5	-15.3	-24.1 / -7.2
	B1	1.4	-7.9 / 11.1	-4.5	-16.2 / 2.5	-8.3	-14.2 / -0.4	-8.3	-13.7 / 1.2

This indicates that the risk of these crops for yield losses will increase in response to early climate change, presumably due to decreasing "relative suitability of counties" (Lobell et al. 2006). For the other crops, the regional patterns of yield changes seem not to be negatively affected by climate change across the counties in the same period.

For the period 2051 to 2097, the differences in yield changes between the emission scenarios across all the crops ranged from -5% to 20% in Sacramento Valley and from -24% to 7% in San Joaquin Valley (Figure 7). The yields of cotton, maize, rice, sunflower, tomato, and wheat generally decreased across the counties. Hence, crop production seems to be negatively affected by climate change. It has been suggested that crop production will be mostly affected by increasing climatic variation, including extreme weather events (Porter and Semenov 2005). In contrast to the other crops, the effects of climate change on alfalfa seem to be not spatially consistent at the county level scale because its yields were improved in five out of the 17 counties under A2. Difference between water delivery target and actual delivery in agriculture is currently approximately 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 (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 by 2097.

4.0 Summary and Conclusions

There is a lack of understanding of how future climate change affects specific cropping systems in California. The data are scarce that are required to develop adaptation scenarios and management strategies that maintain or increase yields while mitigating emissions of major biogenic greenhouse gases (e.g., CO_2). In this study, we assessed the effects of climate change on crop productivity of alfalfa, cotton, maize, rice, sunflower, tomato, and wheat under current management conditions in the 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 1953 to 2004, although crop variance for some crops (i.e., cotton and sunflower) were not well reproduced. In general, the effects of climate change on changes in yield (relative to the 2000 average yields) were not obvious in the period 2001 to 2050. However, in the next period (2051–2097), relative crop yield changes were different between the two emission scenarios. In this period, the crop yields were negatively affected by climate change, particularly for cotton and sunflower. The exception was alfalfa because its yields did not consistently respond to climate change across the counties. In conclusion, climate change will decrease crop yields in the long-term, unless one slows climate change and/or adapts new management practices and improved cultivars.

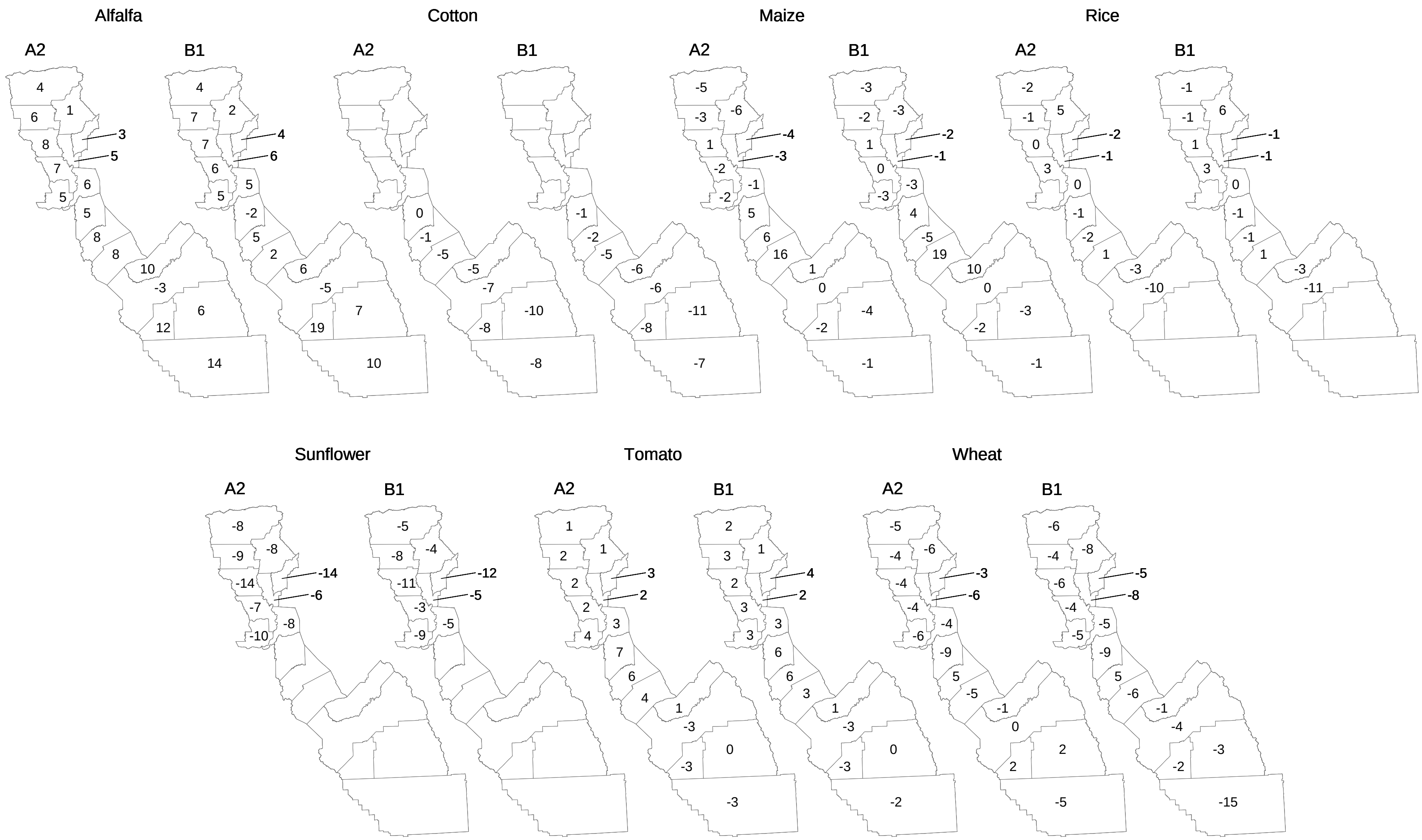

Figure 6. County maps showing the percent deviations of the five-year moving averages in 2050 from the 2000 averages under A2 (medium-high) and B1 (low) emission scenarios

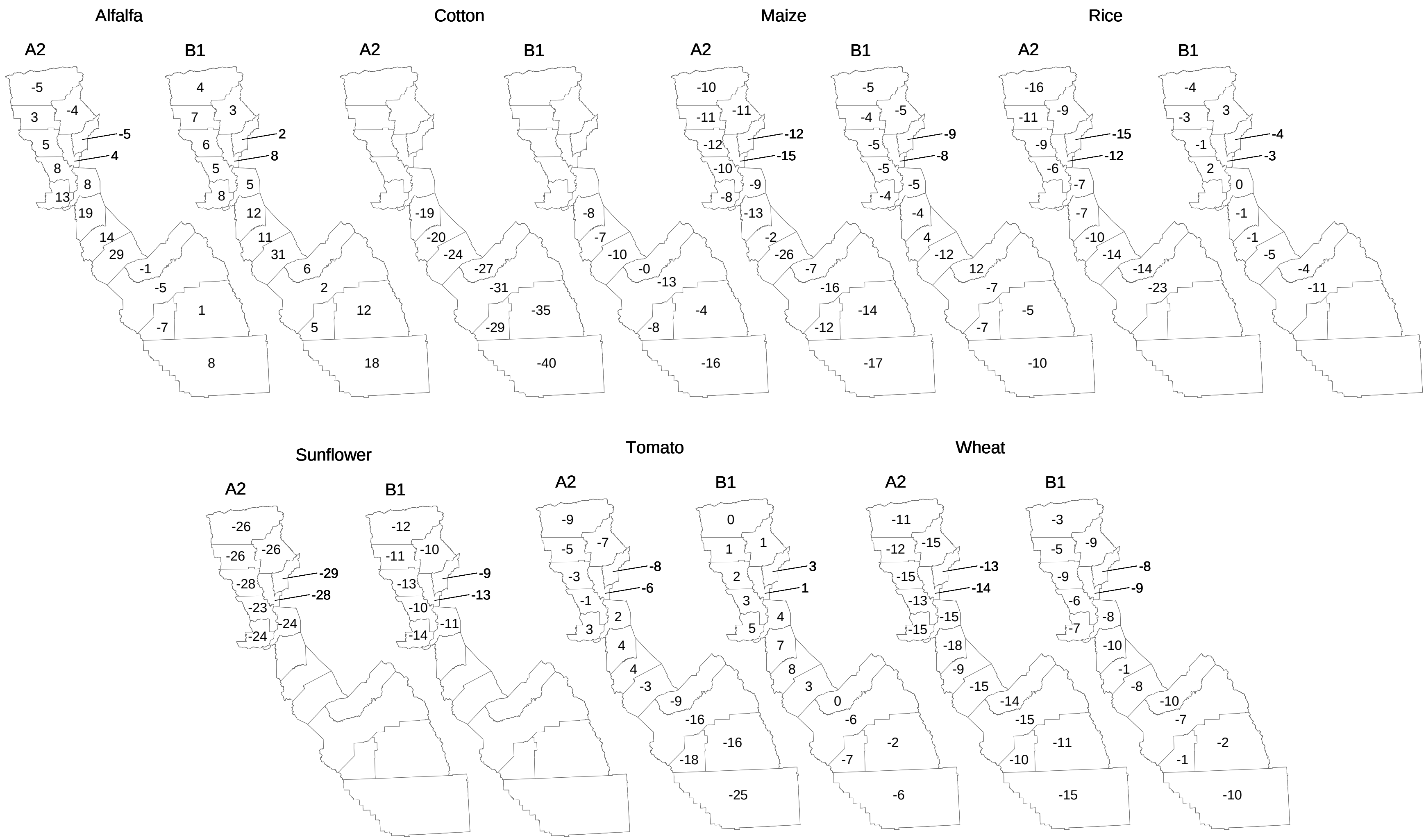

Figure 7. County maps showing the percent deviations of the five-year moving averages in 2097 from the 2000 averages under A2 (medium-high) and B1 (low) emission scenarios

5.0 References

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