Assessment of the Long-Term Impacts of Climate Change on Alfalfa Production in California

Assessment of the Long-Term Impacts of Climate Change on Alfalfa Production in California

Charlie Chen

A Thesis in the Field of Sustainability

for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

November 2021

Abstract

Alfalfa is a crucial feed-supplier for California's livestock and dairy industries, which are among the most profitable commodities in the state. Alfalfa production is projected to be impacted by climate change due to rising temperatures and the increasing frequency and intensity of droughts. As a C3 legume, alfalfa yields are expected to increase as atmospheric concentration of carbon dioxide (CO_2) increases; however, less than optimal irrigation can also reduce alfalfa yields. Therefore, it is still unclear how alfalfa yields in California will ultimately be impacted due to climate change as there is still much uncertainty regarding future greenhouse gas emissions.

To address this, I conducted climate simulations for the near- (2020-2039), mid- (2040-2067), and long- (2072-2095) term using four General Circulation Models (GCMs) under two representative concentration pathway (RCPs) scenarios, RCP4.5 and RCP8.5. The research objectives were to (1) assess performance of DSSAT models built using variety trial data; (2) develop DSSAT models for thirteen counties in California; and (3) assess how increased atmospheric CO_2 concentrations and water stress impact yields under RCP4.5 and 8.5 scenarios. The results align with previous studies that show increases in yields due to increase atmospheric CO_2 concentrations as the average yield is projected to increase through the near (3%), mid- (10%), and long-term (11%) across all thirteen counties. RCP8.5 also had higher increases compared to RCP 4.5 for the near- (4 vs 3%), mid- (13 vs 8%), and long-term (14 vs 7%). The negative impact on yield from a water deficit was minimal and was counterbalanced by the increase in yield from

elevated atmospheric CO_2 concentrations. The larger increases in yield for RCP8.5 was likely due to the expected higher atmospheric CO_2 concentrations for the high emission scenario.

The results from the DSSAT model align with previous studies; however, future studies can incorporate additional crop models and GCMs to achieve more robust results. Overall, the results of this study (based on DSSAT simulation models across four GCMs and two RCPs under water stressed conditions) project an increase in yield for all thirteen counties in California.

Acknowledgements

I would like to thank my parents, Jennifer and Steven Chen, and my fiancée, Jennie Woo, for supporting me during my time in this program. Their constant support was a source of motivation that was invaluable to me.

I want to especially thank Dr. Isaya Kisekka for his support and patience throughout the entire process. His feedback and guidance were indispensable, and I learned so much from him while completing my thesis.

Table of Contents

List of Tables

List of Figures

Definition of Terms

Reference evapotranspiration (ET_0): The reference surface is a hypothetical grass reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m^{-1} and an albedo of 0.23. The reference surface closely resembles an extensive surface of green, well-watered grass of uniform height, actively growing and completely shading the ground. The fixed surface resistance of 70 s m^{-1} implies a moderately dry soil surface resulting from about a weekly irrigation frequency (Allen et al., 1998)

Chapter I

Introduction

Climate change is causing droughts to become more frequent and intense in California (Lobell et al., 2006; Diffenbaugh et al., 2015; Marston & Konar, 2017). The resulting rise in temperatures, increase in atmospheric carbon dioxide (CO_2) concentrations, and reduction in water availability will have profound affects on the state's economy. Agriculture in California is especially susceptible to climate change as weather and water availability are vital factors that can affect crop yields and, therefore, incomes for people in the agricultural sector (CDFA, 2020). Understanding how crops will respond to in the future environment will be vital for all stakeholders.

As the historically largest water user in California, alfalfa has been an important crop in the state. Alfalfa acreage has fluctuated between 0.7 and 1.2 million acres and was, at one point, the largest crop by acreage in the state (CDFA, 2020). Alfalfa production has been closely linked to the state's dairy industry, which is the largest in the country. In 2019, milk was the state's top agricultural commodity, generating $7.34 billion in receipts (CDFA, 2020). However, due to recent droughts, alfalfa acreage has fallen significantly, from 930,000 acres in 2010 to only 580,000 acres in 2019, as freshwater supplies were reduced throughout the state (Orloff et al., 2015). The long-term viability of alfalfa production in California will be highly dependent on how climate change evolves over time.

There is still, however, much uncertainty regarding how our climate will evolve over time. The Intergovernmental Panel on Climate Change (IPCC) established four representative concentration pathways (RCPs) in its fifth Assessment Report (AR) that represent four potential climate futures (IPCC, 2014). The RCPs were defined by the level of greenhouse gas emissions, with RCP4.5 representing an intermediate and RCP8.5 representing a high emission scenario. General circulation models (GCMs) have been developed to simulate how our climate will evolve over time and have been used by researchers to study the long-term impacts of climate change.

Predicting how exactly the climate will look like in the future is a challenge as there is still much uncertainty regarding how much greenhouse gas emissions will be released into the atmosphere. The use of GCMs is a common practice that has been used in past research studies to simulate and assess potential future climate scenarios. Additionally, the use of process-based agricultural models along with GCMs allow researchers to assess how climate change will impact agriculture at various spatial and temporal scales.

Along with GCMs, processed-based agricultural models such as the Decision Support System for Agrotechnology Transfer (DSSAT), have been used to simulate how climate change will impact agriculture under various RCP scenarios without having to do expensive field experiments (Araya et al., 2015; Castaño-Sánchez, 2020). The information provided by these studies can inform decision-making at all levels, from the farm to regional scale.

Research Significance and Objectives

This research focused on how alfalfa production in thirteen counties in California will be impacted under RCP4.5 and 8.5 scenarios from 2020-2095. The results from this research could provide researchers and growers with a better understanding of how alfalfa yields will be impacted due to rising temperatures, increased atmospheric CO_2 concentrations, and reduced water availability in counties throughout California.

My objectives in this study were:

- To assess the performance of DSSAT to model climate change impact on alfalfa yields
- To assess alfalfa yield response across counties throughout California under water stressed conditions for RCP4.5 and 8.5 scenarios from 2020-2095
- To compare yield response across RCPs and regions throughout California

Background

Climate projections indicate average annual temperatures, variability in precipitation patterns such as droughts and floods, and atmospheric concentration of CO_2 will all increase due to human-induced climate change (Lobell et al., 2006; IPCC, 2014; IPCC, 2021). In California, these droughts are projected to become longer and more intense, putting enormous strain on the state's limited freshwater resources (Diffenbaugh et al., 2015; Marston & Konar, 2017). Droughts can negatively impact agriculture by reducing irrigation water availability, precipitation, and crop yields. Yields for some major crops are expected to decline due to increases in temperature and changes in water availability (Reidmiller et al., 2018). In 2021 alone, the damage caused by droughts in California was estimated at 8,745 lost jobs and over $1.7 billion in total economic losses (Medellín-Azuara et al., 2022). This will present numerous challenges as agricultural production in California is highly dependent on weather and water availability.

California is the largest and most agriculturally diverse state in the United States, producing over 400 different commodities and constitutes over a third of the country's vegetables and two-thirds of its fruits and nuts each year (Pathak et al., 2018). Among all the crops, alfalfa has been the single largest user of water due to its extensive acreage and year-round production (Geisseler & Horworth, 2016; Orloff et al., 2015), relying on irrigation to achieve maximum yield throughout the year-round growing season (CDFA, 2020; UCDM, 2022). However, due to water constraints from recent droughts, crop replacement to high value nut trees, and urbanization, alfalfa acreage has fallen from 930,000 acres in 2010 to 580,000 acres in 2019 (Orloff et al., 2015).

Alfalfa production in California plays a vital role in the state's dairy industry and livestock industries. From 2019-2022, California was the thirteenth largest alfalfa producing state in the country and most of the alfalfa grown in the state was used by the dairy industry (USDA, 2022). Milk was the state's number one agricultural commodity in 2019, with $7.34 billion in receipts, while cattle and calves were fifth, with $3.06 billion, and hay (which is mostly alfalfa) fifteenth with $787 million (USDA, 2020).

Although alfalfa has a high annual water demand compared to other crops, it has several advantages that make it a viable crop during droughts in California. Its main advantage is that it is a flexible crop that can survive and produce some yield even under water deficit conditions (Putnam et al., 2018). Alfalfa has been shown to fully recover and potentially increase yields when fully irrigated in the year following deficits (Orloff et al., 2005). Additionally, alfalfa may benefit from the projected increase in atmospheric CO_2 concentration. Previous studies have shown that increased atmospheric CO_2 concentrations and annual temperatures could increase alfalfa yields from 10 to 30% in the United States, given adequate water supplies (De Luis et al., 1999; Aranjuelo et al., 2006; Rotz, 2019; Castaño-Sánchez et al., 2020;). In California, although total acreage has decreased, yield per acre has seen an increase of 4% from 6.80 to 7.10 tons per acre from 2010 to 2019 (CDFA, 2016; CDFA, 2020). With droughts expected to be more frequent and intense in the future, alfalfa growers will have to adopt new strategies besides reducing acreage, such as deficit irrigation (Montazar et al., 2020). What is currently unclear, however, is how the combination of less than maximum water availability (reduce yield) and higher atmospheric CO_2 concentration (increase yield) will are the long-term impact on alfalfa yields in California.

The uncertainty regarding how climate change will impact alfalfa yields is due to the uncertainty regarding how climate change will evolve in the future. The Intergovernmental Panel on Climate Change (IPCC) in its fifth Assessment Report (AR), established four Representative Concentration Pathways (RCPs) (RCP2.6, RCP4.5, RCP6, and RCP8.5) trajectories based on varying future greenhouse gas (GHG) emissions (IPCC, 2014). The RCPs are potential climate futures based on a very stringent (RCP2.6) to high (RCP8.5) emission scenario. Previous studies have compared results under RCP4.5 and RCP8.5 scenarios as they represent an intermediate and extreme scenario (Araya et al., 2015). In the most recent AR, the IPCC updated its projections using Shared Socio-Economic Pathways (SSPs) that look at a far great range of scenarios than the RCPs in the 5th AR (IPCC, 2021). Additional information regarding the RCPs and their representation of greenhouse gas concentrations are available in the IPCC's fifth assessment report (IPCC, 2014) and in Moss et al. (2010).

To understand how climate will change under each RCP scenario, researchers have relied on general circulation models (GCM). GCMs are numerical models that can simulate the global climate by calculating changes in the atmospheric mass, momentum, total energy, and water vapor (Grotch & MacCracken, 1991). Previous studies have used GCMs to study the impact of climate change under various RCP scenarios on yield for crops such as corn (Paul et al., 2020), maize (Sanz-Sáez et al., 2012; Araya et al., 2015; Bao et al., 2017; Castaño-Sánchez et al., 2020), rice (Dias et al, 2016), and soybeans (Paul et al., 2020). There are a multitude of GCMs available today, each with their own unique assumptions. There are many differences between models, and they provide varying results even under the same RCP scenario (Araya et al., 2015).

Along with GCMs, process-based agricultural models have been used to study how climate change will impact agricultural production (Sharda et al., 2020; Dias et al., 2016; Castaño-Sánchez et al., 2020). These models allow researchers to adjust crop properties, management practices and environmental characteristics (e.g., climate variables, soil properties) and examine how crop growth and yield will be impacted under different scenarios (Jing et al., 2020). When locally calibrated, crop models can be used as decision support tools in certain environments (Kisekka et al., 2016; Kim and Kisekka, 2021). These models rely on detailed experimental data to effectively calibrate the model (Sharda et al., 2020). When detailed in-season crop growth observed data is not readily available, the model can also be calibrated using multiyear crop variety trials from different locations (Sharada et al., 2020). These models allow researchers to study how management strategies and environmental factors influence crop growth and development without having to conduct costly field experiments (Malik et al., 2018).

The Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003) can be used to simulate how alfalfa would be affected by climate change. DSSAT is a process-based model that integrates knowledge from various disciplines (e.g., crop physiology, soil hydrology, agronomy) to simulate the interactions between genetics, environment, and management (Hoogenboom, 2000). It has been used in various settings and scales to model climate change impact on crop production and to forecast crop yields (Sharda et al., 2020; Liu et al., 2011).

There is currently limited research available that studies the long-term impact of climate change on alfalfa production in California. Until recently, there was no process-based crop growth model that would accurately predict alfalfa growth and development, in part due to the complexity in simulating perennial crops (Malik et al., 2018). A recent study used DSSAT to examine how elevated atmospheric CO_2 would impact alfalfa to good effect; however, the study area was limited to the Northeastern United States (e.g., Pennsylvania and New York) (Castaño-Sánchez et al., 2020).

Research Questions, Hypotheses, and Specific Aims

My research focused on addressing the following questions:

1) How will alfalfa yields change under RCP 4.5 and RCP 8.5 scenarios from 2020-2095?

2) Under which RCP scenario will alfalfa yields change the most from 2020-2095?
3) Will there be significant differences in how alfalfa yields change between counties?

I hypothesized that alfalfa yields will increase under both the RCP4.5 and 8.5 scenarios from 2020-2095, with higher increases expected under the RCP8.5 scenario. As a C3 legume, alfalfa can take advantage of the higher atmospheric CO_2 concentration to increase yields. Furthermore, I hypothesized that increases in yield will differ between counties, with smaller than average increases in the low desert region and higher than average increases in the intermountain region.

Specific Aims

This research included the following specific aims:

1) Develop an alfalfa model in DSSAT for all thirteen counties in California
2) Simulate changes in alfalfa yields for each county under RCP4.5 and 8.5 scenarios from 2020-2095
3) Compare changes in alfalfa yields between counties under RCP 4.5 and 8.5 scenarios

Chapter II

Methods

Three different types of study sites were used in this research: i) an alfalfa experimental research site near Parlier, California (Parlier site); ii) five alfalfa variety trial locations managed by the University of California Agricultural Experiment Station Cooperative Extension; and iii) thirteen of the top alfalfa producing counties in California.

Parlier Alfalfa Experimental Research Site

Experimental alfalfa research data were generated at the University of California Kearney Agricultural Research Extension Center (KREC) near Parlier, California (Gull, 2021). The study site had a Hanford sandy loam series and a Mediterranean climate, characterized by hot, arid summers and cold, wet winters. The average annual temperature in Parlier fluctuates between 9.6 and 24.9^{o}C. The wet season (October – May) averages 242.4 mm of rainfall annually while the dry season (June – September) only averages 4.8 mm.

The study compared flood irrigation (SI) with sub-surface drip irrigation (SDI) using a cultivar (Ameristand RR835NT RR) with a fall dormancy of eight.
The trial was planted (seeding rate 25 kg ha^{-1}) on October 18th, 2016 and had an emergence date of October 25th, 2016. Dry seeds were planted in rows 20 cm apart with a planting depth of 1.5 cm. There were seven cuttings in 2017, seven in 2018, and six in 2019 with an average of 2,932 kg/ha per harvest and an annual average total harvest of

19,551 kg/ha (Table 1). A detailed description of the experiment can be found in (Gull, 2021).

Table 1. Cutting dates and yields from the Parlier site.

Cutting Dates	**Yield (kg/ha)**
04/27/2017	1566
05/25/2017	3643
06/22/2017	2913
07/20/2017	3057
08/24/2017	2762
09/21/2017	3229
10/27/2017	1684
04/24/2018	3062
05/23/2018	2837
06/21/2018	2979
07/19/2018	3702
08/21/2018	3482
09/19/2018	2254
10/23/2018	2232
06/03/2019	4204
07/02/2019	3918
08/01/2019	3923
08/28/2019	3014
10/02/2019	2347
11/14/2019	1845

Alfalfa Variety Trial

The University of California Agriculture and Natural Resources (UC ANR) Cooperative Extension manages alfalfa variety trials throughout California to help growers select alfalfa varieties based on yield and quality performance in their specific region. Since field data were unavailable, variety trial data was used instead. Previous studies have shown that variety trial data are a viable substitute when detailed field data are unavailable (Sharda et al., 2020). The sites chosen for this study included: 1) Tulelake site located in the Intermountain region of California, 2) Davis site located near Davis, California, 3) Modesto site located near Modesto, California, 4) Kearney site located near Fresno, California, and 5) El Centro site located in the Imperial Valley, California (Figure 1). A more detailed overview of each variety trial site is provided in Table 2.

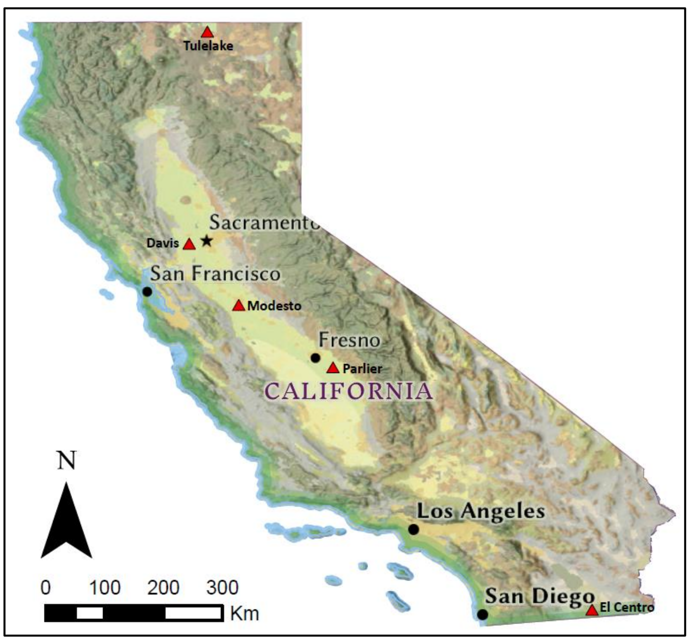


Figure 1. Map of alfalfa variety trial locations in California (Putnam, 2021).

These variety trial locations were chosen due to their proximity to the thirteen counties chosen for this study and to cover the diverse range of agroecological systems, ranging from the Intermountain Region (3-4 cuts) to the Low Desert (8-11 cuts), where alfalfa is grown in California. An overview of the cuttings and yields and provided in Table 3.

Each site featured an average of thirty-eight cultivars with data on cutting schedules and yields provided in an annual progress report (Putnam et al., 2014; Putnam et al., 2015; DeBen et al., 2016; DeBen et al., 2017; DeBen et al., 2018; DeBen & Putnam, 2019; DeBen & Putnam, 2020). Variety trials at each site were planted in different years; however, each trial maintained a four-year cycle from initial planting to last recorded harvest. Four to six replicates of each cultivar were randomly planted in approximately 28 kg/ha (400 plants/m^2) live seeds in plots about 1 m wide by 4-6 m long. Harvests for yield estimation were obtained from a 1m by 5 m area plot using a flail-type or cutter-bar type forage harvester (DeBen, 2016). Cutting schedules were determined by the most common practices for each region and varied from four harvests in the intermountain region (Tulelake) to up to nine cuttings in the low desert region (El Centro). The variety trials were all flood irrigated and did not experience any water stress at any location. The latest completed trial was chosen from each site. Cultivars with representative fall dormancies for each region and that appeared in multiple sites (e.g., CUF101 at Modesto and El Centro) were chosen to allow for accurate representation of each region and comparison of results between locations.

Table 2. Overview of the five variety trial locations.

Variety Trial	Location	Soil	Mean annual max temp. (C)	Mean annual min temp. (C)	Mean annual Precipitation (mm)	Cultivar	Fall Dormancy	Planting Date	Mean Annual Cuttings	Mean Harvest Yield (kg/ha)	Mean Annual Yield (kg/ha)
Tulelake	Intermountain Research and Extension Center in Tulelake, California	Silty clay loam	16.8	-0.21	235	Hi-Gest 360	3	05/22/17	3	4,386	14,255
Davis	University of California Agronomy Farm in Davis, California	Yolo clay loam	23.8	8.91	419	6R200	6	09/09/14	7	2,752	21,362
Parlier	University of California Kearney Agriculture Center	Hanford fine sandy loam	25.3	9.91	230	6R200	6	10/09/14	6	4,178	27,236
Modesto	Stanislaus Farm Supply in Modesto, California	Stanislaus sandy soil	23.7	7.85	223	CUF101	9	09/18/13	7	3,313	23,881
El Centro	University of California Desert Research and Extension Center in Holtville, California	Imperial clay loam	31.4	14.5	111	CUF101	9	10/19/16	9	2,795	27,022

Table 3. Alfalfa yields from variety trials across major alfalfa producing areas in California (Putnam et al., 2014; Putnam et al., 2015; DeBen et al., 2016; DeBen et al., 2017; DeBen et al., 2018; DeBen & Putnam, 2019; DeBen & Putnam, 2020).

Location	**Year**	**Cut 1 (kg/ha)**	**Cut 2 (kg/ha)**	**Cut 3 (kg/ha)**	**Cut 4 (kg/ha)**	**Cut 5 (kg/ha)**	**Cut 6 (kg/ha)**	**Cut 7 (kg/ha)**	**Cut 8 (kg/ha)**	**Cut 9 (kg/ha)**	**Cut 10 (kg/ha)**	**Total (kg/ha)**
Tulelake	2017	3272	3497									6769
Tulelake	2018	3922	4662	4035								12619
Tulelake	2019	7509	5200	3631	2981							19321
Tulelake	2020	6231	5514	3026	3541							18312
Modesto	2015	6725	5604	5604	5156	3138	3363					29590
Modesto	2016	3497	3138	3923	3901	3250	3833	3901	2062			27505
Modesto	2017	5425	5604	8227	5358							24614
Davis	2015	2914	2914	2914	3138	4035	2914	2241	2242			29590
Davis	2016	1098	2241	2600	3250	3385	3923					16497
Davis	2017	2399	3228	3004	3048	2802	1905	1614				18000
Kearney	2014	5156	3811	4483	4932	3587	4708	2914				29591
Kearney	2015	2242	3587	3587	3138	2914	1793	1793				19054
Kearney	2016	5402	3093	3542	2981	2556	2242	1121				22999
El Centro	2017	2600	2622	4080	4416	2757	2376	1905	1973	749	1771	25249
El Centro	2018	2600	3004	4326	4349	4708	2847	2130	919	1143	2130	28156
El Centro	2019	1816	2825	4125	4483	5380	3026	2488	1793	1726		27662

California Counties

Thirteen of the top alfalfa producing counties in California were chosen for this study (Figure 2). The counties cover a diverse range of climate zones and are divided into five regions based on their geographical locations: the Intermountain Northern California Region (Siskiyou County), the Sacramento Valley Region (Yolo and Solano counties), the San Joaquin Valley Region (San Joaquin, Stanislaus, Merced, and Madera counties), the Southern San Joaquin Valley Region (Fresno, Kings, Tulare, and Kern counties), and the Low Desert Region (Imperial and Riverside counties). An overview of all thirteen counties is provided in Table 4.

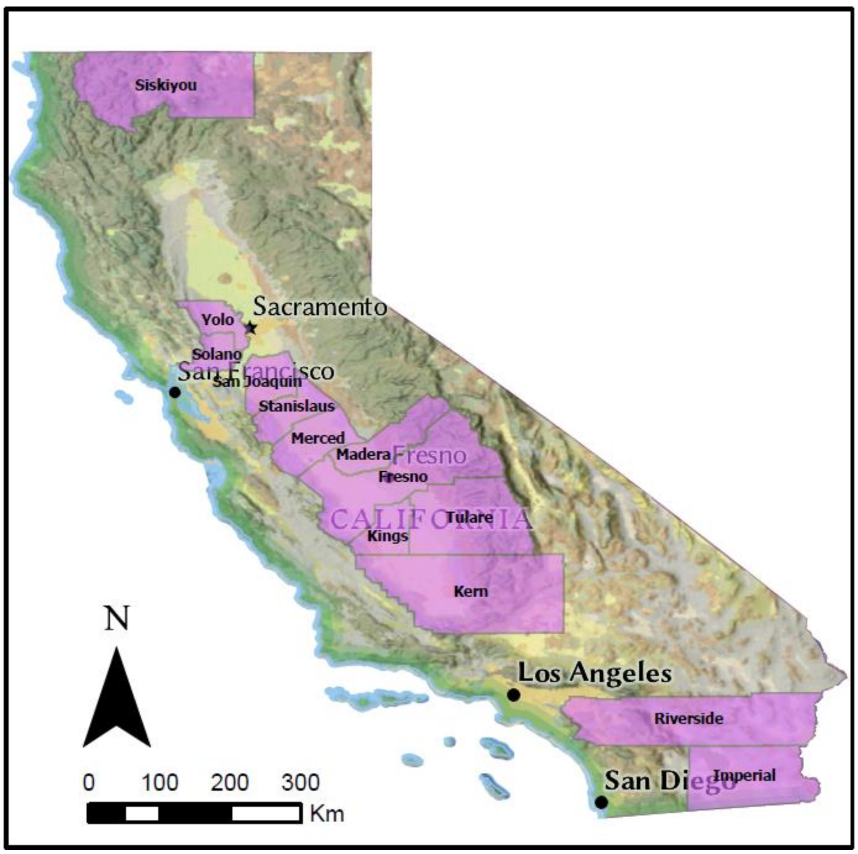


Figure 2. Map of thirteen counties in California examined in this study.

Table 4. Major alfalfa producing counties in California, cultivars, and associated CIMIS weather stations.

County	Weather Station	Latitude	Longitude	Elevation (m)	Location	Years	Mean annual precipitation (mm)	Mean max temp (C)	Mean min temp (C)
Siskiyou	Tulelake FS	41.95887	-121.47237	4035	Tulelake	2017-2020	239	16.7	-0.2
San Joaquin	Manteca	37.83482	-121.22319	38	Modesto	2014-2017	287	23.9	8.3
Stanislaus	Modesto	37.64522	-121.18776	35	Modesto	2014-2017	215	23.6	7.8
Solano	Dixon	38.41556	-121.78691	37	Davis	2014-2017	429	22.9	7.2
Yolo	Davis	38.53579	-121.77639	60	Davis	2014-2017	418	23.7	8.9
Madera	Firebaugh	36.85125	-120.59098	185	Kearney	2013-2016	183	24.8	9.5
Merced	Merced	37.31414	-120.3867	200	Kearney	2013-2016	306	24.7	7.5
Fresno	Fresno State	36.82083	-119.74231	339	Kearney	2013-2016	285	25.1	9.8
Kern	Arvin-Edison	35.20581	-118.77844	508	Kearney	2013-2016	170	25.7	10.7
Kings	Stratford	36.15814	-119.85141	193	Kearney	2013-2016	147	25.8	9.5
Tulare	Porterville	36.08227	-119.09318	400	Kearney	2013-2016	178	25.1	8.4
Imperial	Seeley	32.75958	-115.73207	-38	El Centro	2016-2019	79	31.8	14.2
Riverside	Thermal South	33.59574	-116.15876	-146	El Centro	2016-2019	19	31.1	13.0

Climatic Data and Scenarios

The DSSAT models require data for climatic variables such as average maximum and minimum temperature, solar radiation, and precipitation to run its simulations. Climatic data was collected for each model using different sources.

Parlier Alfalfa Experimental Research Site

Daily evapotranspiration (ET) data between 2017 and 2019 were measured using surface renewal stations (Tule Technologies Inc.) at the study site. Due to the smaller footprint of the Tule station, the reference evapotranspiration (ET_o) from the California Irrigation Management and Information System (CIMIS) multiplied by crop coefficients (k_c) was used to calculate the crop evapotranspiration (ET_c) and compared with actual evapotranspiration (ET_a) from the Tule Daily records. Maximum temperature (T_{max}), minimum temperature (T_{min}), precipitation, and solar radiation for the same period was collected from the Parlier weather station located at the University of California Kearney Agricultural Research Center facility.

Alfalfa Variety Trials

Historical daily records of climatic variables such as maximum temperature (T_{max}), minimum temperature (T_{min}), precipitation, and solar radiation were obtained from nearby weather station managed by the California Irrigation Management Information System (CIMIS) for the duration of each variety trial. Missing data from the daily records was filled using data from nearby weather stations. Daily reference evapotranspiration (ET_o) was calculated using the Penman-Monteith equation in DSSAT (Allen et al., 1998).

Counties in California

Simulated values for climate variables for each county were generated using the MarkSim® DSSAT weather file generator (http://gismap.ciat.cgiar.org/MarkSimGCM/) (ILRI et al., 2014). The program provides a selection of general circulation model (GCM) and can simulate values for maximum and minimum temperature, precipitation, and solar radiation in a format that can be used by DSSAT. Four general circulation models (GCMs) were chosen for this study: BCC-CSM1-1, GFDL-CM3, GISS-EH-H and HadGEM2-ES. Simulated climate variables were collected from each GCM over a seventy-five-year period (2020-2095) for each county. Additionally, atmospheric CO_2 concentrations were adjusted for each year using values established by the Potsdam Institute for Climate Impact Research (Meinshausen et al., 2011).

Soil Data

DSSAT incorporates a soil module that represents the soil as a one-dimensional profile, which is homogenous horizontally and has several vertical soil layers. The module combines information from four separate submodules: soil water, soil temperature, soil carbon and nitrogen, and soil dynamics (Jones et al., 2003). A soil profile was created for each model by gathering soil data using several methods:

A detailed soil profile was not available for the Parlier experimental site. Alternatively, a soil profile for Hanford sandy loam was collected for Parlier using the SoilWeb application (https://casoilresource.lawr.ucdavis.edu/gmap/) managed by the California Soil Resource Lab at the University of California, Davis. By comparing the

SoilWeb profile to those available in DSSAT, a deep sandy loam soil profile provided the closest results and was used to develop the DSSAT model.

Soil profiles for each California county was collected by using the California Department of Water Resources (DWR) Land Use Viewer (https://gis.water.ca.gov/app/CADWRLandUseViewer/) and the Food, Agriculture and Resource Management (FARMs) application (Kim & Kisekka, 2021). The DWR Land Use Viewer combines land use survey data collected over a thirty-year period to classify agricultural land use in California. The application features a virtual GIS map with layers that color code land use by crop type. The application did not have a standalone filter for alfalfa, so plots designated as “grain and hay crops” were chosen to represent alfalfa instead.

Once the plots were identified for each county, soil profiles were then retrieved for each plot using the FARMS web application. The application generates a soil profile in a data format used by DSSAT. The soil profiles for each county are provided in the Appendix 1.

Crop Water Management

Both the Parlier alfalfa experimental research site and the variety trial sites were fully irrigated and provided sufficient water throughout the growing season. The county models, however, simulated a water deficit scenario. Irrigation settings in DSSAT were set to provide an automatic fixed amount, with a management depth of 100 cm, a 40% of maximum available threshold, a 100% maximum available end point, a fixed irrigation amount of 25 mm, and an efficiency fraction of 0.9. Reference evapotranspiration was calculated in DSSAT using the Penman-Monteith equation (Allen et al., 1998).

DSSAT Crop Model

DSSAT is a software application program consisting of crop simulation models. It has additional modules for weather, soil, experiment conditions and measurements, and genotype information (Jones et al., 2003). The models simulate crop growth, development, and yield as a function of soil-plant-atmosphere dynamics using daily weather data, soil surface and profile information, and management details (Hoogenboom et al., 2010). DSSAT integrates the effects of crop phenotype, weather, soil, and management options to simulate multi-year outcomes of different management strategies.

For alfalfa simulations, DSSAT utilizes the CSM-CROPGRO-Perennial-Forage module (CSM-CROPGRO-PFM) (Hoogenboom et al., 2019). The module was adapted from the CSM-CROPGRO module, which was originally designed to be a generic approach to model annual crops with common source code (Jing et al., 2020; Jones et al, 2003). The CSM-CROPGRO-PFM module was adapted to simulate yield, development, and growth for perennial crops such as alfalfa (Malik et al., 2018). The module utilizes a daily time step to simulate biomass accumulation and computes canopy photosynthesis on an hourly time step (Jing et al., 2020). The growth rate is regulated mainly by temperature, solar radiation, and photoperiod with additional constraints for water and nitrogen stress. The dormancy and enhanced allocation to stored reserves are triggered when there is a short photoperiod. Generally, the shortening of the day length starts in the fall, which then prompts the partitioning of assimilates to storage organs to increase while the partitioning to shoots decreases. The vegetative storage organ for alfalfa is the taproot, which acts like a sink and provides a source of nitrogen and carbohydrate for regrowth in the springtime. Freezing of alfalfa is determined by two temperatures: one for leaves at a temperature of -2^{o}C and one for the whole plant at a temperature of -25^{o}C (Jing et al., 2020). A more detailed overview of the CSM-CROPGRO and CSM-CROPGRO-PFM modules is presented in Malik et al. (2018) and Jing et al. (2020).

Calibration and Evaluation of DSSAT Models

Processed-based agricultural models such as DSSAT need to be calibrated and validated so that the parameters accurately represent actual crop characteristics and responses to local soil and atmospheric conditions.

Parlier alfalfa experimental research site. The Parlier site model was calibrated using climate data and crop management practices, including planting date, emergence date, and cutting dates (Table 5). Daily evapotranspiration and yield data from 2018-2019 were divided into two datasets: the first year (2018) was used for calibration and the second year (2019) was used for validation. Cultivar ‘Rugged MG2’ was chosen as the starting point for the calibration process. DSSAT provides fifteen variables for cultivars and the calibration process involved adjusting each variable and combination of variables through trial and error. An overview of the fifteen variables and their calibrated values are provided in Table 6.

Table 5. DSSAT parameters for the Parlier site model.

Parameter	Value
Planting Date	10/01/2016
Emergence Date	10/08/2016
Planting Method	Dry seed
Planting Distribution	Row
Plant Population (m-squared)	400
Row spacing (cm)	10
Planting depth (cm)	1.3
Row direction, degrees from North	0
Irrigation	Automatic when required

Table 6. Overview of calibrated alfalfa cultivar parameters for the CropGro-perennial forage model for an experimental site located near Parlier, California.

Variable	Calibrated value	Definitions
CSDL	12.5	Critical Short-Day Length below which reproductive development progresses with no daylength effect (for shortday plants) (hour)
PPSEN	0.20	Slope of the relative response of development to photoperiod with time (positive for shortday plants) (1/hour)
EM-FL	99.0	Time between plant emergence and flower appearance (R1) (photothermal days)
FL-SH	10.0	Time between first flower and first pod (R3) (photothermal days)
FL-SD	18.0	Time from first flower to seed (R5) (photothermal days)
SD-PM	33.0	Time between first seed (R5) and physiological maturity (R7) (photothermal days)
FL-LF	25.0	Time between first flower (R1) and end of leaf expansion (photothermal days)
LFMAX	1.28	Maximum leaf photosynthesis rate at 30C, 350 vpm CO_2, high light (mg CO_2/m2-s)

SLAVR	250	Specific leaf area of cultivar under standard growth conditions (cm2/g)
SIZLF	2.00	Maximum size of full leaf (three leaflets) (cm2)
XFRT	0.01	Maximum fraction of daily growth that is partitioned to seed + shell
WTPSD	0.02	Maximum weight per seed (g)
SFDUR	15.0	Seed filling duration for pod cohort at standard growth conditions (photothermal days)
SDPDV	2.05	Average seed per pod under standard growing conditions (#/pod)
PODUR	20.0	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)

Alfalfa variety trials. Trials that lasted over a four-year period from planting to last cutting were chosen from each variety trial site. The models were individually calibrated using the planting dates and number of cuttings per year for each site provided in the annual agronomy progress reports (Tables 2 & 3) (Putnam et al., 2014; Putnam et al., 2015; DeBen et al., 2016; DeBen et al., 2017; DeBen et al., 2018; DeBen & Putnam, 2019; DeBen & Putnam, 2020). Simulated yields from the model were compared to reported yields for each cutting over the four-year period using several goodness-of-fit indicators.

Goodness-of-Fit Indicators

To evaluate the model's performance, the following goodness-of-fit indicators were used to determine the models' performance:

Index of Agreement (I):

$$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \ ,0 \leq d \leq 1$$

where O_i is the observation value, P_i is the simulated value, $\bar{O}$ is the average of observation values and $\bar{P}$ is the average of simulated values (AgriMetSoft, 2019).

Root mean squared error (RMSE):

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

where O_i is the observed value, P_i is the simulated value, and n is the sample size. The RSME is used to measure model uncertainty with values close to zero indicating strong agreement and good performance.

Mean absolute error (MAE):

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n}$$

where O_i is the observed value, P_i is the simulated value, and n is the sample size. The MAE is used to measure the magnitude of the errors in the model's values.

Chapter III

Results

The simulated seasonal maximum temperature, minimum temperature, and precipitation were projected to increase under both RCP4.5 and 8.5 scenarios for all counties. These projections were consistent with expectations as atmospheric CO_2 concentration will increase under both scenarios due to human activities (IPCC, 2014). Overall, increases for maximum and minimum temperatures were higher under RCP8.5 scenario, which is to be expected as it represents a higher greenhouse gas emissions scenario compared to RCP4.5.

Assessing the change in yield for each county was conducted by comparing the initial run (2020-2023) with the final run for each future period (e.g., short-term: 2036-2039; mid-term: 2068-2071; and long-term: 2092-2095) Figure 3). Previous studies have indicated that increased atmospheric CO_2 concentration could increase crop yields (Woodrow, 1994; Hatfield et al., 2011; Thivierge et al., 2016; Castaño-Sánchez et al., 2020). More specifically, alfalfa yields have been shown to increase when there are higher concentrations of carbon dioxide in the atmosphere (Castaño-Sánchez et al., 2020). The results align with expectations as counties either had an increase in yield in the short and mid-term followed by a drop in the long term or had increases through all three periods. These trends were applicable for both RCP4.5 and 8.5 scenarios, with yields generally increasing more under the RCP8.5 scenario. A detailed breakdown of the simulated values from each GCM is provided in Appendix 2.

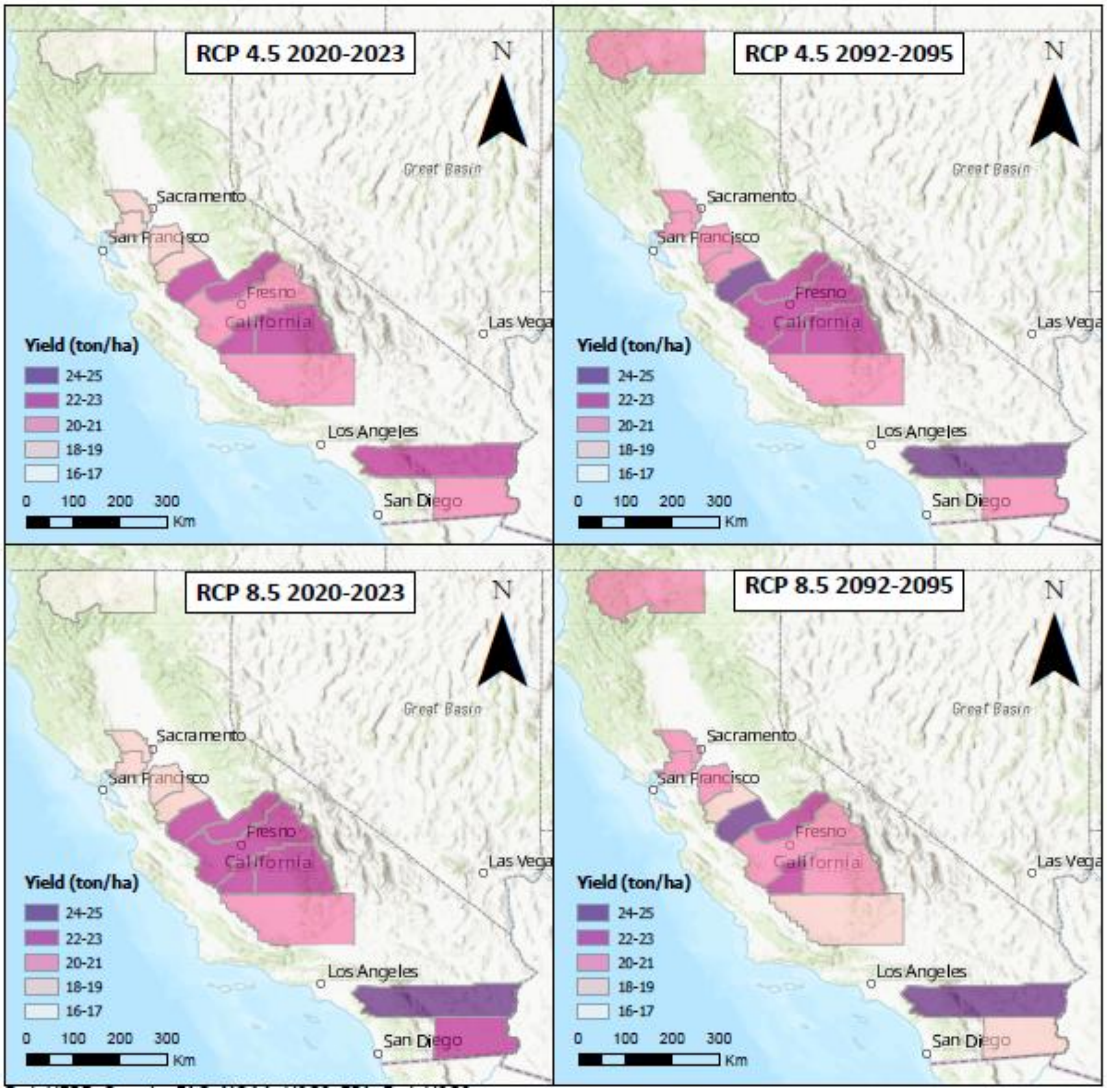


Figure 3. Average simulated alfalfa yields (four GCMs) for 2020-2023 and 2092-2095 under both RCP 4.5 and RCP 8.5 scenarios for all thirteen counties.

Intermountain Northern California Region

The simulated mean seasonal (mid-May – September) maximum temperature, minimum temperature, and precipitation for the Intermountain Northern California region increased by an average of 1.4 and 2.3°C, 1.1 and 1.8 °C and 5.9 and 1.6 mm in the mid-and long-term across both RCP scenarios, respectively (Table 7). Yields for Siskiyou County is estimated to increase in the near- (7 and 11%), mid- (16 and 31%), and long- (17 and 38%) for RCP4.5 and 8.5 scenarios across all four GCMs, respectively (Figure 4).

Table 7. Simulated seasonal (mid-May to September) climatic changes (max. and min. temperature, precipitation (P_n)) for the near- (2020-2039), mid- (2040-2071), and long-term (2072-2095) under RCP 4.5 and RCP 8.5 scenarios for Siskiyou County in the Intermountain Northern California Region.

				RCP 4.5			**RCP 8.5**	
County	**Period**	**GCM**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**
Siskiyou	Near	BCC-CM1-1	29.1	8.3	63.4	29.4	8.5	68.9
		GFDL-CM3	29.5	8.5	81.2	29.7	8.7	77.9
		GISS-E2-H	28.2	7.8	75.6	28.4	7.9	74.7
		HadGEM2-ES	29.4	8.6	67.0	29.4	8.7	78.6
		Average	29.0	8.3	71.8	29.2	8.5	75.0
	Mid	BCC-CM1-1	29.4	8.3	69.5	30.6	9.5	92.1
		GFDL-CM3	31.3	9.6	91.3	31.9	10.3	89.8
		GISS-E2-H	28.9	8.5	100.7	29.6	9.0	57.7
		HadGEM2-ES	30.6	9.8	63.7	31.6	10.9	69.1
		Average	30.1	9.1	81.3	30.9	9.9	77.2
	Far	BCC-CM1-1	29.3	8.3	83.8	31.8	10.3	79.8
		GFDL-CM3	31.8	9.9	62.6	34.0	11.7	56.0
		GISS-E2-H	28.5	8.2	90.3	30.5	9.8	65.6
		HadGEM2-ES	30.8	10.1	77.0	34.0	13.5	84.9
		Average	30.1	9.1	78.4	32.6	11.3	71.6

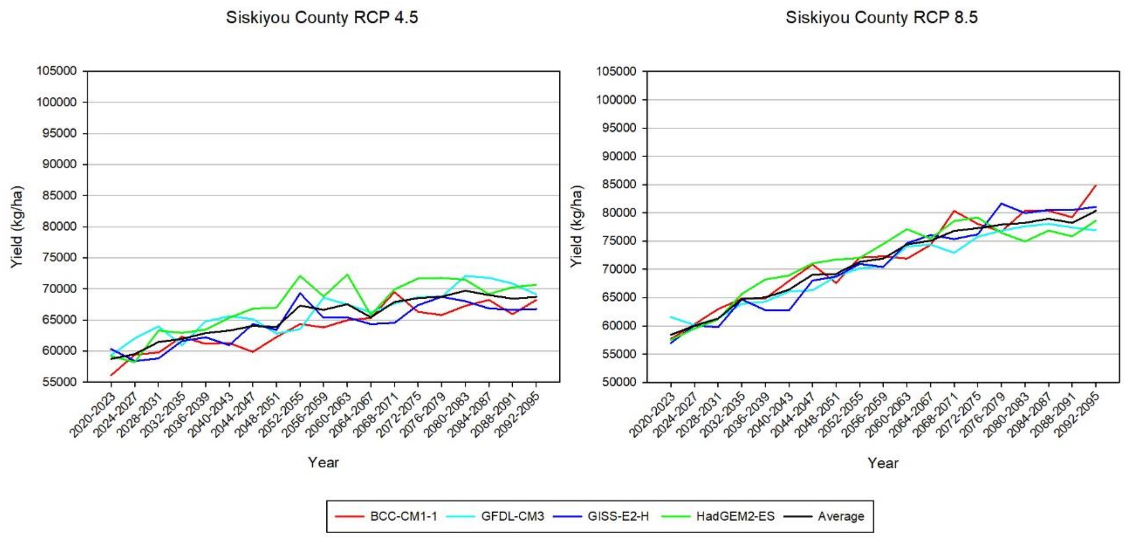


Figure 4. Simulated alfalfa yields (four GCMs and average) for the intermountain northern California region under RCP4.5 and RCP8.5 scenarios from 2020-2095.

Sacramento Valley Region

The simulated mean season (mid-March – October) maximum temperature, minimum temperature, and precipitation for the Sacramento Valley region counties increased by an average of 1.6 and 3.1^{o}C, 1.4 and 2.7 ^{o}C, and 40.6 and 47.0 mm in the mid- and long-term across both RCP scenarios, respectively. The changes were about the same for both counties, with Solano County experiencing a slightly larger increase across both time periods than Yolo County (Table 8).

Yields also increased for both counties, with an average increase of 3, 12 and 14% across both counties for the near-, mid-, and long-term, respectively. Overall, yields increase for both counties for both RCP scenarios; however, Yolo County increased more than Solano County in the near- and long-term while Solano County increase more in the mid-term (Figure 5).

Table 8. Simulated seasonal (mid-March to October) climatic changes (max. and min. temperature, precipitation (P_n)) for the near- (2020-2039), mid- (2040-2071), and long-term (2072-2095) under RCP 4.5 and RCP 8.5 scenarios for Yolo and Solano counties in the Sacramento Valley Region.

			RCP 4.5			**RCP 8.5**		
County	**Period**	**GCM**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**
Yolo	Near	BCC-CM1-1	29.7	11.6	113.0	29.8	12.0	151.3
		GFDL-CM3	30.5	12.1	129.7	30.7	12.2	94.8
		GISS-E2-H	29.3	11.7	190.5	29.4	11.8	196.2
		HadGEM2-ES	30.1	12.0	159.0	30.2	12.2	151.8
		Average	29.9	11.9	148.0	30.0	12.0	148.5
	Mid	BCC-CM1-1	30.0	12.0	182.0	30.9	12.9	199.8
		GFDL-CM3	31.6	12.8	181.7	32.1	13.4	120.3
		GISS-E2-H	30.0	12.3	187.5	30.6	12.8	201.2
		HadGEM2-ES	31.1	12.9	137.4	31.9	13.8	132.4
		Average	30.7	12.5	172.1	31.4	13.2	163.4
	Far	BCC-CM1-1	30.6	12.7	202.1	32.8	14.5	182.1
		GFDL-CM3	32.4	13.4	181.4	34.3	15.0	170.9
		GISS-E2-H	30.4	12.7	196.6	31.7	13.8	215.3
		HadGEM2-ES	31.7	13.5	136.3	33.9	15.8	138.6
		Average	31.3	13.0	179.1	33.2	14.8	176.7
Solano	Near	BCC-CM1-1	29.4	12.1	128.8	29.6	12.5	175.6
		GFDL-CM3	30.0	12.0	153.0	29.7	11.9	98.6
		GISS-E2-H	29.2	12.3	186.0	29.3	12.4	179.1
		HadGEM2-ES	29.7	12.2	151.1	29.9	12.4	139.4
		Average	29.6	12.2	154.7	29.6	12.3	148.2
	Mid	BCC-CM1-1	29.7	12.4	191.1	30.6	13.3	184.7
		GFDL-CM3	31.6	13.4	175.5	31.0	12.8	136.8
		GISS-E2-H	29.6	12.6	181.2	30.2	13.1	220.0
		HadGEM2-ES	30.7	13.2	137.0	31.5	14.1	151.6
		Average	30.4	12.9	171.2	30.8	13.3	173.3
	Far	BCC-CM1-1	30.2	12.8	159.0	32.4	14.6	155.0
		GFDL-CM3	33.7	15.1	168.3	31.9	13.5	171.9
		GISS-E2-H	29.9	12.8	209.5	31.2	14.0	227.6
		HadGEM2-ES	31.2	13.8	145.9	33.3	16.1	151.1
		Average	31.3	13.6	170.7	32.2	14.5	176.4

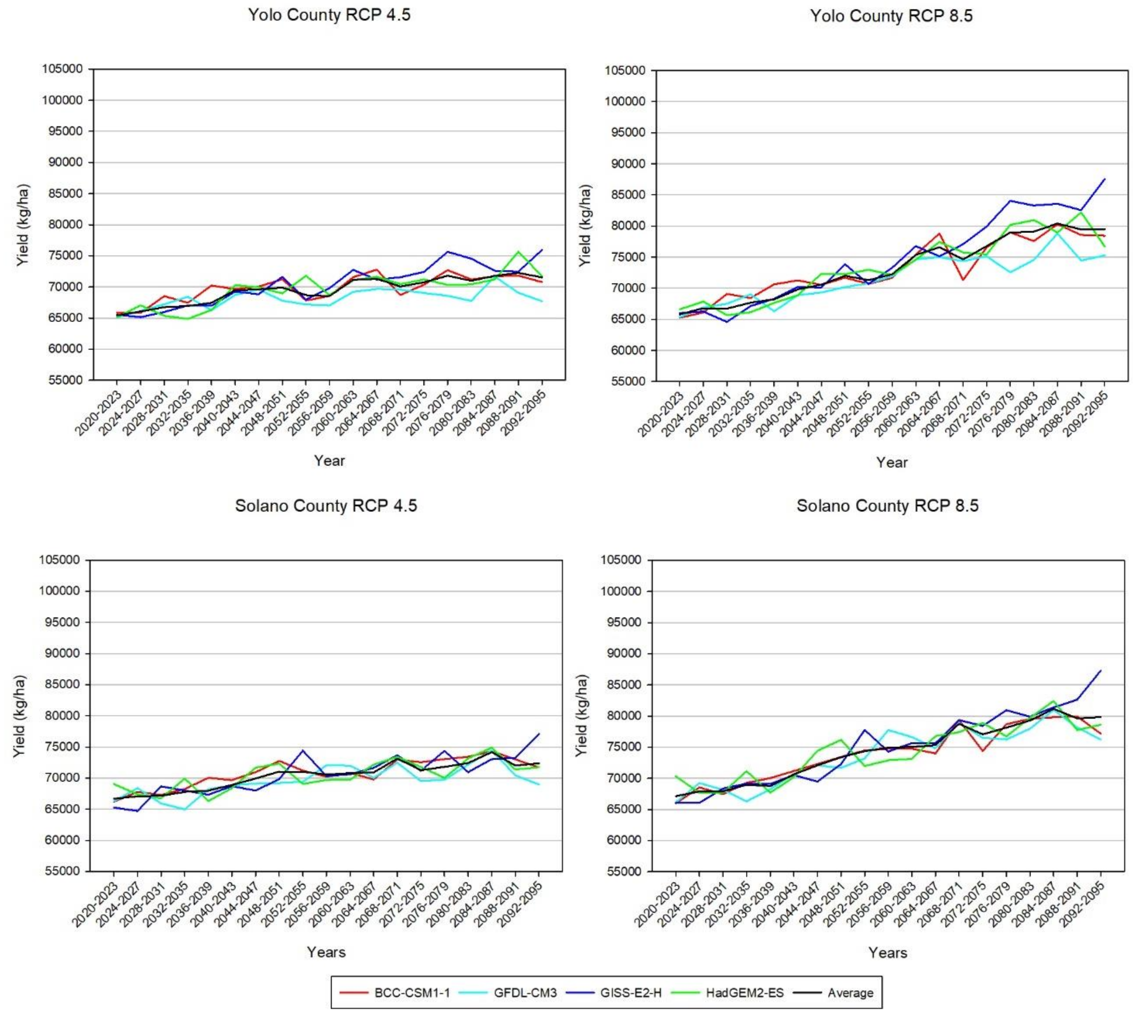


Figure 5. Simulated alfalfa yields (four GCMs and average) for the Sacramento valley region under RCP4.5 and RCP8.5 scenarios from 2020-2095.

San Joaquin Valley Region

There are two distinct growing seasons among the four counties that makeup the San Joaquin Valley Region with San Joaquin and Stanislaus (mid-March – September) and Merced and Madera (mid-February – October). Each growing season will be addressed separately.

San Joaquin and Stanislaus counties. Both San Joaquin and Stanislaus counties are projected to experience minimum increases in the maximum (1.0 and 2.2 ^{o}C) and minimum (0.9 and 1.8 ^{o}C) temperatures for both RCP scenarios. However, simulated precipitation differed significantly among both counties. Precipitation for San Joaquin County is projected decrease in the mid- (-8.4 mm) and long-term (-19.9 mm) for RCP4.5 while increasing by 19.4 and 11.8 mm in the mid- and long-term, respectively, for RCP8.5. Stanislaus, on the other hand, will see an increase in precipitation in the mid- (2.5 mm) and long-term (13.5mm) for RCP4.5 but will see a slight increase in the mid- (2.6 mm) followed up a slight decrease (-0.6 mm) in the long-term (Table 9). Yield for both counties follow a similar as other regions with average increases in the near- (5%), mid- (14%), and long-term (16%) across both RCP scenarios. Increases were again larger for RCP8.5, which is to be expected as higher atmospheric CO_2 concentrations can stimulate biomass production (De Luis, 1999) (Figure 6).

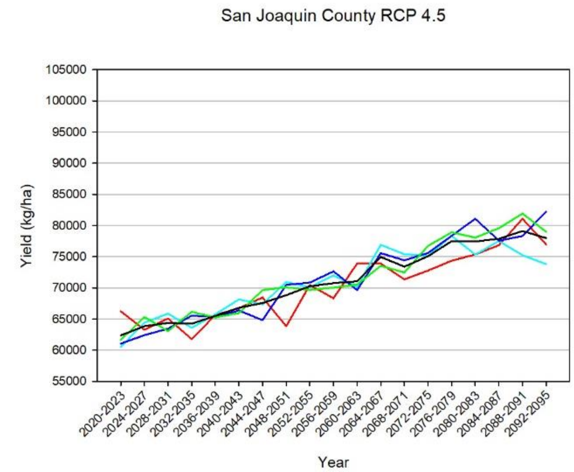
Merced and Madera counties. Merced and Madera counties follow a similar trend as both counties are projected to experiences minimal increases in maximum (1.1 and 2.4 ^{o}C) and minimum (0.9 and 1.9 ^{o}C) temperatures across both RCP scenarios but have different precipitation trends for each scenario. For Merced County, precipitation is projected to decrease in both the mid- (-8.7 mm) and long-term (-10.7 mm) for RCP4.5 but increase by 15.5 and 1.0 mm, respectively, for RCP8.5. Precipitation for Madera County, on the other hand, is expected to increase, with higher increases for RCP8.5, in the mid- (11.1 and 22.4 mm) and long-term (19.8 and 32.1 mm), respectively. Yields for both counties are projected to experience a similar but slightly smaller increase compared to San

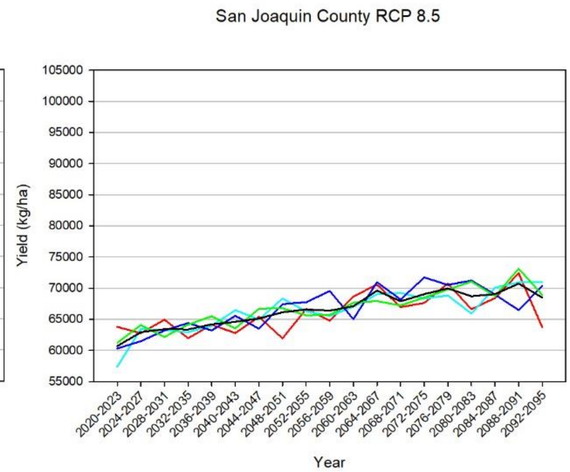
Table 9. Simulated seasonal (mid-March to September) climatic changes (max. and min. temperature, precipitation (P_n)) for the near- (2020-2039), mid- (2040-2071), and long-term (2072-2095) under RCP 4.5 and RCP 8.5 scenarios for San Joaquin and Stanislaus counties in the San Joaquin Valley Region.

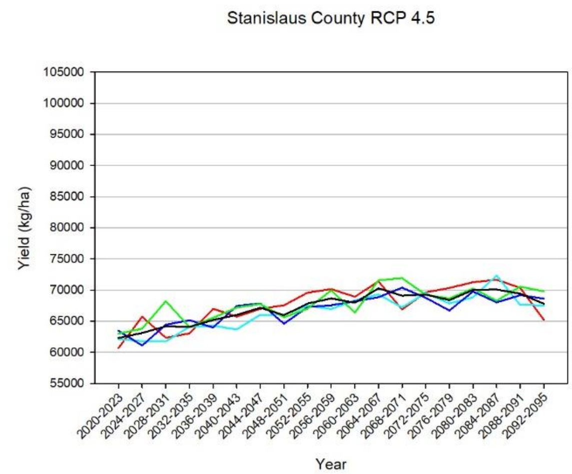
			RCP 4.5			RCP 8.5		
County	**Period**	**GCM**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**
San Joaquin	Near	BCC-CM1-1	30.5	13.2	96.7	30.7	13.5	107.1
		GFDL-CM3	30.9	13.2	107.1	31.2	13.3	69.6
		GISS-E2-H	30.0	13.0	132.0	30.1	13.2	127.9
		HadGEM2-ES	30.8	13.4	152.8	30.9	13.6	101.8
		Average	30.5	13.2	122.1	30.7	13.4	101.6
	Mid	BCC-CM1-1	30.7	13.6	143.5	31.7	14.5	150.9
		GFDL-CM3	32.1	13.9	75.3	32.6	14.3	80.6
		GISS-E2-H	30.4	13.5	103.3	31.0	14.0	120.7
		HadGEM2-ES	31.3	14.2	132.9	32.1	15.1	131.7
		Average	31.1	13.8	113.7	31.9	14.5	121.0
	Far	BCC-CM1-1	31.0	13.8	143.0	33.4	15.8	128.7
		GFDL-CM3	32.9	14.3	86.1	34.7	15.8	135.8
		GISS-E2-H	30.8	13.7	91.5	32.2	15.0	109.2
		HadGEM2-ES	32.3	15.0	88.5	34.4	17.1	80.0
		Average	31.7	14.2	102.3	33.7	15.9	113.4
Stanislaus	Near	BCC-CM1-1	30.4	12.9	87.4	30.7	13.4	129.3
		GFDL-CM3	31.0	13.1	93.1	31.4	13.0	52.7
		GISS-E2-H	30.1	12.9	90.6	30.2	13.0	112.2
		HadGEM2-ES	30.7	13.0	100.5	30.8	13.1	106.9
		Average	30.6	13.0	92.9	30.8	13.1	100.3
	Mid	BCC-CM1-1	30.9	13.3	98.3	31.9	14.3	121.1
		GFDL-CM3	32.2	13.8	81.4	32.8	14.1	73.5
		GISS-E2-H	30.6	13.4	119.5	31.2	13.9	122.3
		HadGEM2-ES	31.8	14.2	82.6	32.6	15.0	94.8
		Average	31.4	13.7	95.4	32.1	14.3	102.9
	Far	BCC-CM1-1	31.4	13.8	115.6	33.7	15.8	95.6
		GFDL-CM3	32.8	13.9	94.7	34.7	15.4	123.7
		GISS-E2-H	30.9	13.7	111.2	32.3	14.9	102.8
		HadGEM2-ES	32.4	15.0	104.2	34.7	17.2	76.8
		Average	31.9	14.1	106.4	33.9	15.8	99.7

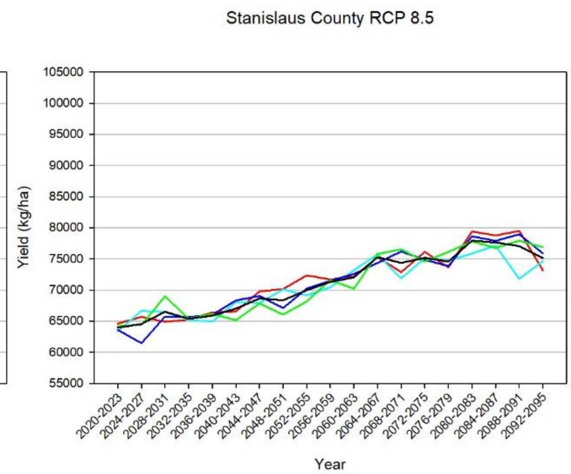
Table 10. Simulated seasonal (mid-February to October) climatic changes (max. and min. temperature, precipitation (P_n)) for the near- (2020-2039), mid- (2040-2071), and long-term (2072-2095) under RCP 4.5 and RCP 8.5 scenarios for Merced and Madera counties in the San Joaquin Valley Region.

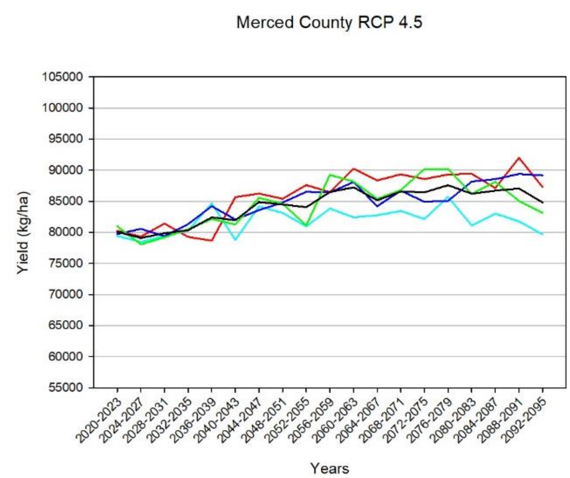
			RCP 4.5			RCP 8.5		
County	**Period**	**GCM**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**
Merced	Near	BCC-CM1-1	29.2	12.0	189.7	29.4	12.3	216.3
		GFDL-CM3	30.0	12.2	169.3	30.2	12.3	109.5
		GISS-E2-H	29.1	12.1	215.4	29.3	12.2	221.2
		HadGEM2-ES	29.8	12.4	161.1	29.8	12.5	188.0
		Average	29.5	12.2	183.9	29.7	12.3	183.8
	Mid	BCC-CM1-1	30.0	12.5	144.5	30.7	13.4	228.5
		GFDL-CM3	31.4	13.1	141.0	32.1	13.5	154.2
		GISS-E2-H	29.6	12.4	225.9	30.2	13.0	241.4
		HadGEM2-ES	30.6	13.2	189.4	31.5	14.2	173.2
		Average	30.4	12.8	175.2	31.1	13.5	199.3
	Far	BCC-CM1-1	30.4	13.0	173.8	32.7	15.0	147.5
		GFDL-CM3	32.1	13.5	143.7	34.4	15.0	200.9
		GISS-E2-H	30.0	13.0	223.9	31.6	14.3	250.6
		HadGEM2-ES	31.5	14.1	151.5	33.9	16.4	140.2
		Average	31.0	13.4	173.2	33.2	15.2	184.8
Madera	Near	BCC-CM1-1	29.6	11.9	124.4	29.8	12.3	140.8
		GFDL-CM3	30.2	12.1	78.6	30.6	12.1	45.6
		GISS-E2-H	29.3	11.8	151.7	29.4	12.0	180.0
		HadGEM2-ES	30.0	12.2	100.1	30.0	12.4	107.3
		Average	29.8	12.0	113.7	29.9	12.2	118.4
	Mid	BCC-CM1-1	30.0	12.3	121.8	30.8	13.2	163.5
		GFDL-CM3	31.3	12.7	98.4	32.0	13.0	89.7
		GISS-E2-H	30.0	12.5	152.7	30.5	12.9	175.1
		HadGEM2-ES	30.9	13.1	126.4	31.7	14.0	135.2
		Average	30.6	12.6	124.8	31.3	13.3	140.9
	Far	BCC-CM1-1	30.5	12.6	145.0	32.6	14.6	121.5
		GFDL-CM3	31.9	12.8	114.6	34.1	14.4	198.2
		GISS-E2-H	30.3	12.8	155.4	31.8	14.2	167.0
		HadGEM2-ES	31.6	13.7	118.8	34.0	16.0	115.3
		Average	31.1	13.0	133.5	33.1	14.8	150.5

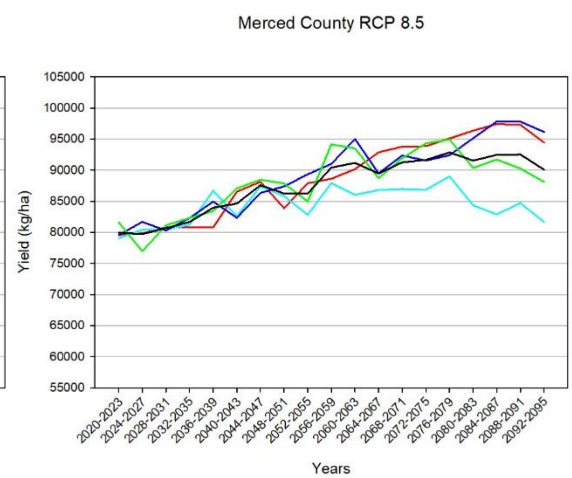

San Joaquin County RCP 4.5
Yield (kg/ha)
105000
100000
95000
90000
85000
80000
75000
70000
65000
60000
55000
2020-2023
2024-2027
2028-2031
2032-2035
2036-2039
2040-2043
2044-2047
2048-2051
2052-2055
2056-2059
2060-2063
2064-2067
2068-2071
2072-2075
2076-2079
2080-2083
2084-2087
2088-2091
2092-2095
Year


San Joaquin County RCP 8.5
Yield (kg/ha)
105000
100000
95000
90000
85000
80000
75000
70000
65000
60000
55000
2020-2023
2024-2027
2028-2031
2032-2035
2036-2039
2040-2043
2044-2047
2048-2051
2052-2055
2056-2059
2060-2063
2064-2067
2068-2071
2072-2075
2076-2079
2080-2083
2084-2087
2088-2091
2092-2095
Year


Stanislaus County RCP 4.5
Yield (kg/ha)
105000
100000
95000
90000
85000
80000
75000
70000
65000
60000
55000
2020-2023
2024-2027
2028-2031
2032-2035
2036-2039
2040-2043
2044-2047
2048-2051
2052-2055
2056-2059
2060-2063
2064-2067
2068-2071
2072-2075
2076-2079
2080-2083
2084-2087
2088-2091
2092-2095
Year


Stanislaus County RCP 8.5
Yield (kg/ha)
105000
100000
95000
90000
85000
80000
75000
70000
65000
60000
55000
2020-2023
2024-2027
2028-2031
2032-2035
2036-2039
2040-2043
2044-2047
2048-2051
2052-2055
2056-2059
2060-2063
2064-2067
2068-2071
2072-2075
2076-2079
2080-2083
2084-2087
2088-2091
2092-2095
Year


Merced County RCP 4.5
Yield (kg/ha)
105000
100000
95000
90000
85000
80000
75000
70000
65000
60000
55000
2020-2023
2024-2027
2028-2031
2032-2035
2036-2039
2040-2043
2044-2047
2048-2051
2052-2055
2056-2059
2060-2063
2064-2067
2068-2071
2072-2075
2076-2079
2080-2083
2084-2087
2088-2091
2092-2095
Years


Merced County RCP 8.5
Yield (kg/ha)
105000
100000
95000
90000
85000
80000
75000
70000
65000
60000
55000
2020-2023
2024-2027
2028-2031
2032-2035
2036-2039
2040-2043
2044-2047
2048-2051
2052-2055
2056-2059
2060-2063
2064-2067
2068-2071
2072-2075
2076-2079
2080-2083
2084-2087
2088-2091
2092-2095
Years

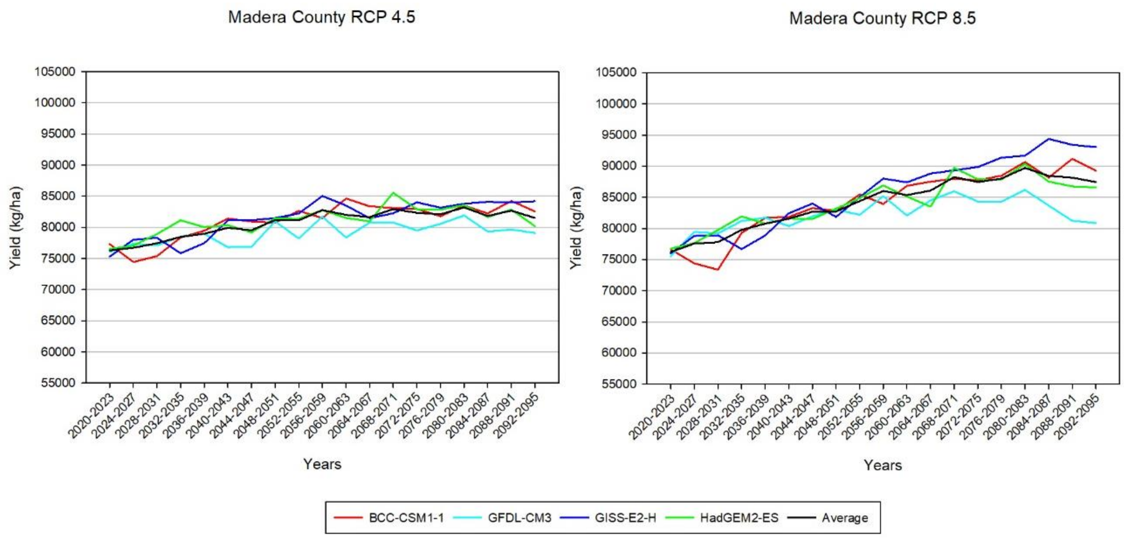


Figure 6. Simulated alfalfa yields (four GCMs and average) for counties in the San Joaquin valley region under RCP4.5 and RCP8.5 scenarios from 2020-2095.

Joaquin and Stanislaus counties. Overall, the average increase in yield among both counties' yields will be 4, 12, and 10% in the near-, mid-, and long-term, respectively. Increases were higher for RCP8.5, which is consistent with other counties and regions.

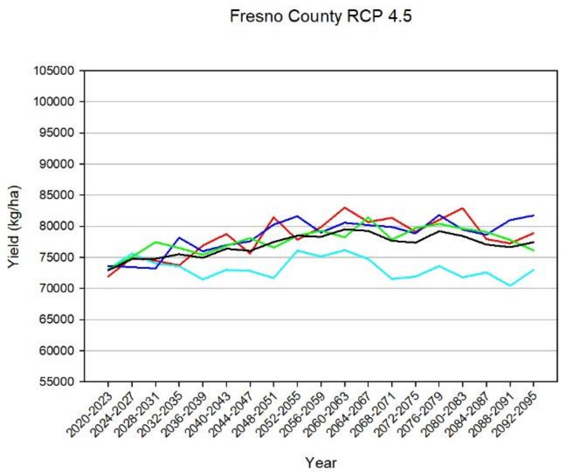
Southern San Joaquin Valley Region

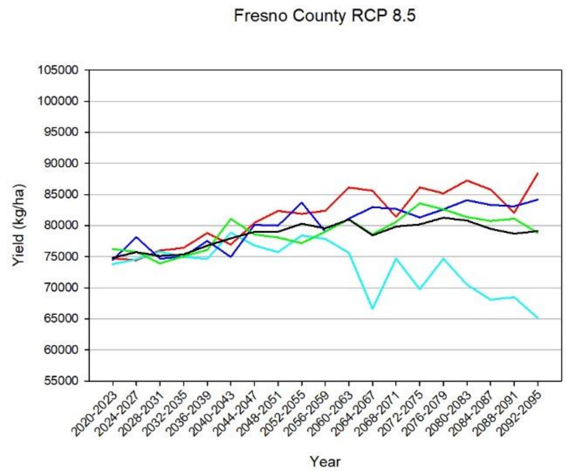
Collectively, the simulated mean season (mid-February – October) maximum temperature, minimum temperature, and precipitation for the four counties that make up the Southern San Joaquin Valley region are projected to slightly increase in the mid- (1.1°C, 1.0°C, and 7.8 mm) and long-term (2.4°C, 2.1°C, and 6.4 mm) (Table 11). There is not much variation among counties regarding increases in maximum and minimum temperatures for both RCP scenarios; however, there is much larger range regarding precipitation. For RCP4.5, precipitation for Fresno and Tulare counties are projected to increase in the mid- and long-term, while it will decrease for Kern County over both periods. Kings County is in the middle, with an increase in the mid-term (3.2 mm) followed by a decrease in the long-term (-7.1 mm). For RCP8.5, on the other hand, things change with precipitation in Tulare, Kings, and Kern counties increasing in the mid- and long-term while Fresno County is on its own with an increase in the mid-term (1.7 mm) followed by a decrease in the long-term (-13.9 mm). Overall, yield for the region will increase in all three periods (3, 8, and 5%) among all four counties (Figure 7). For all counties except Tulare County in the long-term (3% vs 5%), yield increases were slightly higher for RCP8.5 when compared to RCP4.5. These results follow the trend in other regions.

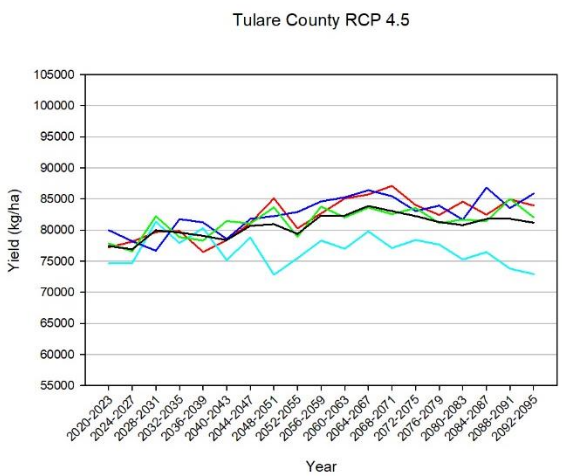
Table 11. Simulated seasonal (mid-February to October) climatic changes (max. and min. temperature, precipitation (P_n)) for the near- (2020-2039), mid- (2040-2071), and long-term (2072-2095) under RCP 4.5 and RCP 8.5 scenarios for Fresno, Tulare, Kings, and Kern counties in the Southern San Joaquin Valley Region.

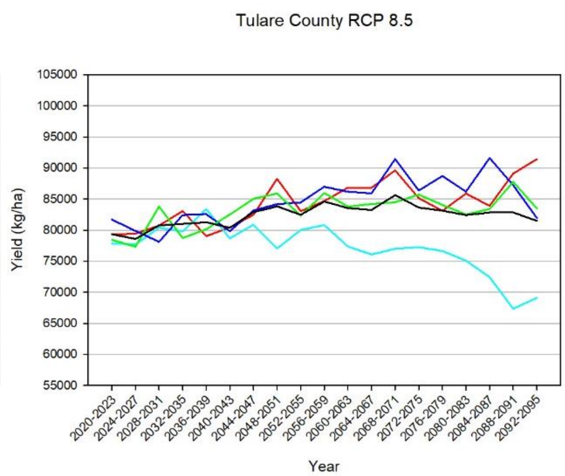
			RCP 4.5			**RCP 8.5**		
County	**Period**	**GCM**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**
		BCC-CM1-1	29.8	12.5	156.6	29.3	12.4	199.3
		GFDL-CM3	31.0	12.9	151.2	31.2	13.0	111.9
	Near	GISS-E2-H	29.8	12.6	180.9	29.8	12.7	238.5
		HadGEM2-ES	30.5	13.3	179.3	30.5	13.5	191.7
		Average	30.2	12.8	167.0	30.2	12.9	185.3
		BCC-CM1-1	29.9	12.6	132.6	30.7	13.5	176.3
		GFDL-CM3	32.0	13.5	136.0	32.8	14.0	148.4
Fresno	Mid	GISS-E2-H	30.5	13.4	226.2	31.1	13.9	242.0
		HadGEM2-ES	31.4	14.1	188.1	32.2	15.0	181.5
		Average	30.9	13.4	170.7	31.7	14.1	187.1
		BCC-CM1-1	30.1	13.1	200.7	33.1	15.6	180.8
		GFDL-CM3	32.9	14.2	139.6	35.4	15.7	195.3
	Far	GISS-E2-H	30.8	13.7	223.8	32.6	15.1	187.9
		HadGEM2-ES	32.1	14.7	167.3	34.7	17.2	121.8
		Average	31.5	13.9	182.8	34.0	15.9	171.4
		BCC-CM1-1	30.6	13.2	157.4	30.8	13.5	163.4
		GFDL-CM3	31.5	13.2	119.3	31.7	13.4	83.7
Tulare	Near	GISS-E2-H	30.3	13.1	169.3	30.5	13.3	186.6
		HadGEM2-ES	31.3	13.9	145.0	31.4	14.0	149.7
		Average	30.9	13.4	147.7	31.1	13.5	145.8

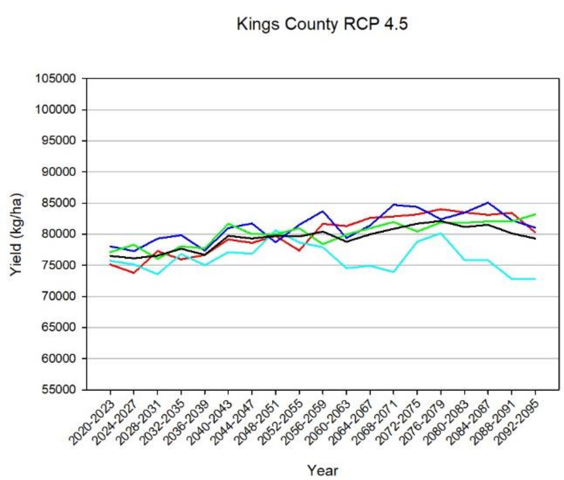
		BCC-CM1-1	31.2	13.6	170.0	32.1	14.5	179.9
		GFDL-CM3	32.9	14.3	141.4	33.5	14.8	165.3
	Mid	GISS-E2-H	31.1	13.9	147.6	31.7	14.4	197.4
		HadGEM2-ES	31.9	14.6	154.8	32.7	15.4	142.2
		Average	31.8	14.1	153.4	32.5	14.8	171.2
		BCC-CM1-1	31.6	14.2	165.3	33.9	16.2	162.3
		GFDL-CM3	33.4	14.5	122.8	35.9	16.2	181.6
	Far	GISS-E2-H	31.6	14.3	166.6	33.2	15.8	173.6
		HadGEM2-ES	32.5	15.2	179.8	35.0	17.7	159.8
		Average	32.3	14.6	158.6	34.5	16.5	169.3
		BCC-CM1-1	30.6	13.0	120.8	30.8	13.3	172.9
		GFDL-CM3	31.5	13.0	105.2	31.8	13.2	67.0
	Near	GISS-E2-H	30.3	12.5	112.2	30.4	12.7	146.5
		HadGEM2-ES	31.3	13.4	95.6	31.4	13.5	97.2
		Average	30.9	13.0	108.5	31.1	13.2	120.9
		BCC-CM1-1	31.4	13.5	124.8	32.1	14.3	168.7
		GFDL-CM3	32.7	13.8	89.8	33.3	14.2	118.2
Kings	Mid	GISS-E2-H	31.2	13.5	120.3	31.8	14.0	149.8
		HadGEM2-ES	32.0	14.1	111.9	32.8	15.0	118.6
		Average	31.8	13.7	111.7	32.5	14.4	138.8
		BCC-CM1-1	32.0	14.0	112.1	34.3	16.1	110.9
		GFDL-CM3	33.3	14.4	67.0	35.5	16.1	143.4
	Far	GISS-E2-H	31.7	13.9	124.6	33.1	15.2	156.2
		HadGEM2-ES	32.8	14.8	101.7	35.1	17.0	101.7
		Average	32.4	14.3	101.3	34.5	16.1	128.1
		BCC-CM1-1	31.4	15.2	123.4	31.6	15.4	116.2
		GFDL-CM3	32.3	15.3	93.5	32.4	15.5	70.5
	Near	GISS-E2-H	30.9	15.1	159.9	31.2	15.3	168.7
		HadGEM2-ES	31.7	15.8	150.9	31.8	15.9	172.2
		Average	31.6	15.4	132.0	31.7	15.5	131.9
		BCC-CM1-1	31.9	15.8	137.7	32.7	16.6	147.3
		GFDL-CM3	33.6	16.2	97.8	34.1	16.7	99.7
Kern	Mid	GISS-E2-H	31.7	15.8	146.6	32.4	16.4	171.7
		HadGEM2-ES	32.4	16.7	135.8	33.2	17.5	136.2
		Average	32.4	16.1	129.5	33.1	16.8	138.7
		BCC-CM1-1	32.2	15.9	147.3	34.4	18.0	156.6
		GFDL-CM3	34.3	16.6	92.4	36.6	18.6	168.7
	Far	GISS-E2-H	32.1	16.2	126.6	33.4	17.5	169.1
		HadGEM2-ES	33.0	17.2	143.9	35.4	19.6	111.7
		Average	32.9	16.5	127.5	34.9	18.4	151.5

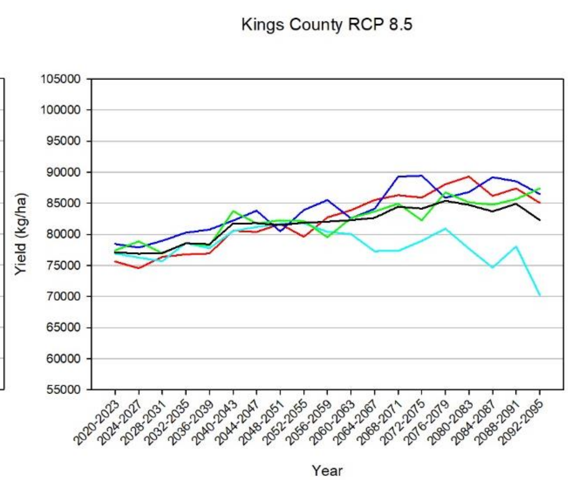

Fresno County RCP 4.5
Yield (kg/ha)
Year


Fresno County RCP 8.5
Yield (kg/ha)
Year


Tulare County RCP 4.5
Yield (kg/ha)
Year


Tulare County RCP 8.5
Yield (kg/ha)
Year


Kings County RCP 4.5
Yield (kg/ha)
Year


Kings County RCP 8.5
Yield (kg/ha)
Year

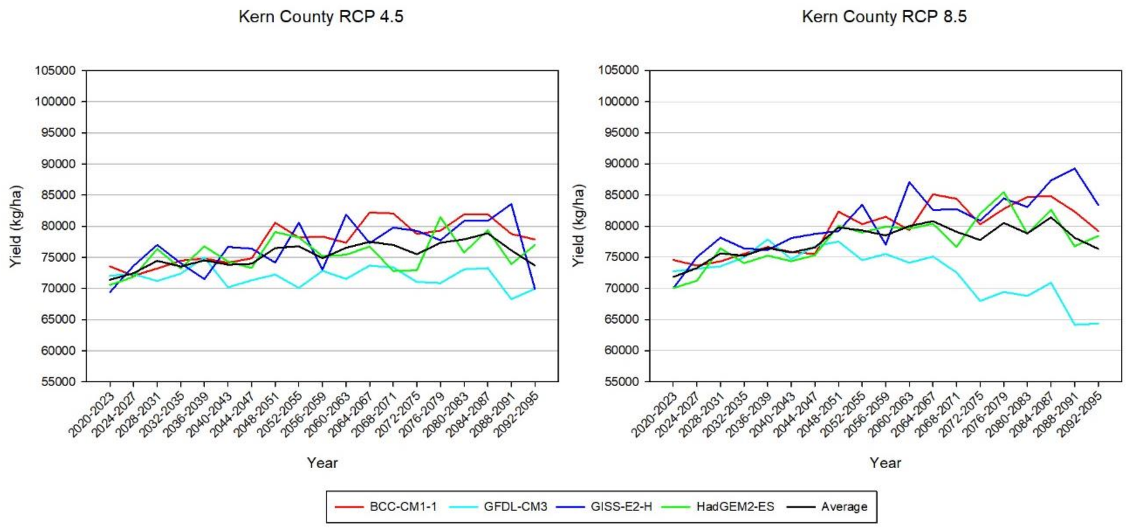


Figure 7. Simulated alfalfa yields (four GCMs and average) for counties in the southern San Joaquin valley region under RCP4.5 and RCP8.5 scenarios from 2020-2095.

Low Desert Region

For the Low Desert region, the simulated mean season (mid-February – November) maximum and minimum temperatures is projected to slightly increase in the mid- (1.1 and 0.9°C) and long-term (2.3 and 2.1°C) across both RCP scenarios and counties (Table 12). However, precipitation is significantly different between RCP scenarios. For RCP4.5, precipitation is expected to increase by 26.5 and 42.0mm in the mid- and long-term, respectively. On the other hand, precipitation is expected to drop by 26.4 mm in the mid-term and then recover to slightly increase by 5.7 mm in the long-term for RCP8.5. At the county level, Riverside County is projected to experience a decrease in both the mid- (-18.9mm) and long-term (-1.3mm) while Imperial County will only experience a decrease in the mid-term (-33.9mm) followed by an increase in the long-term (12.7mm) (Table 12).

Yield changes for counties in the Low Desert region follow two separate trends (Figure 8). For Riverside County, average yield increase across both RCP scenarios will increase in the near- (3%), mid- (5%), and long-term (8%). For Imperial County, on the other hand, average yield is projected to initially decrease in the near-term (-2%), followed by slight increases in the mid- (1%) and long-term (2%). The minimal changes in yield in the Low Desert region could be due to the higher average temperatures in the region as higher temperatures could negate the positive increases in yield resulting from increased atmospheric CO_2 concentrations (Hatfield et al., 2011).

Table 12. Simulated seasonal (mid-February to November) climatic changes (max. and min. temperature, precipitation (P_n)) for the near- (2020-2039), mid- (2040-2071), and long-term (2072-2095) under RCP 4.5 and RCP 8.5 scenarios for Riverside and Imperial counties in the Lower Desert Region.

			RCP 4.5			**RCP 8.5**		
County	**Period**	**GCM**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**	**T_{max} (C)**	**T_{min} (C)**	**P_n (mm)**
Riverside	Near	BCC-CM1-1	35.3	17.7	45.5	35.5	17.8	64.8
		GFDL-CM3	36.2	18.0	105.0	36.4	18.3	31.6
		GISS-E2-H	34.7	17.5	82.6	34.0	17.4	258.0
		HadGEM2-ES	35.5	18.1	45.8	35.8	18.4	47.3
		Average	35.4	17.8	69.7	35.4	17.9	100.4
	Mid	BCC-CM1-1	35.8	18.0	36.8	36.8	19.0	84.9
		GFDL-CM3	37.4	19.0	99.9	38.2	19.9	27.9
		GISS-E2-H	34.9	18.1	170.6	35.6	18.7	161.9
		HadGEM2-ES	36.4	19.0	67.2	37.4	19.9	51.5
		Average	36.1	18.5	93.6	37.0	19.4	81.5
	Far	BCC-CM1-1	35.8	18.3	125.5	38.1	20.2	58.5
		GFDL-CM3	38.1	19.7	54.6	40.7	21.9	43.8
		GISS-E2-H	35.3	18.3	193.8	36.6	19.7	221.4
		HadGEM2-ES	37.1	19.7	55.8	39.2	22.0	72.9
		Average	36.6	19.0	107.4	38.6	21.0	99.1
Imperial	Near	BCC-CM1-1	33.9	17.3	182.0	34.4	17.6	155.1
		GFDL-CM3	35.0	17.9	126.0	35.0	18.2	152.1
		GISS-E2-H	33.3	17.2	174.9	33.5	17.4	286.4
		HadGEM2-ES	34.0	17.9	251.4	34.0	18.0	280.3
		Average	34.1	17.5	183.6	34.2	17.8	218.5
	Mid	BCC-CM1-1	34.3	17.9	227.9	35.4	18.7	240.6
		GFDL-CM3	35.9	18.8	236.1	36.9	19.6	155.1
		GISS-E2-H	34.2	17.8	188.6	34.9	18.2	127.6
		HadGEM2-ES	34.7	18.1	198.4	35.5	18.8	215.2
		Average	34.8	18.1	212.7	35.7	18.8	184.6
	Far	BCC-CM1-1	34.9	18.2	267.2	37.1	20.0	267.9
		GFDL-CM3	36.9	19.4	165.1	39.5	21.7	129.4
		GISS-E2-H	34.4	18.0	240.9	35.9	19.3	196.5
		HadGEM2-ES	35.6	19.3	245.9	37.9	21.8	331.0
		Average	35.4	18.7	229.8	37.6	20.7	231.2

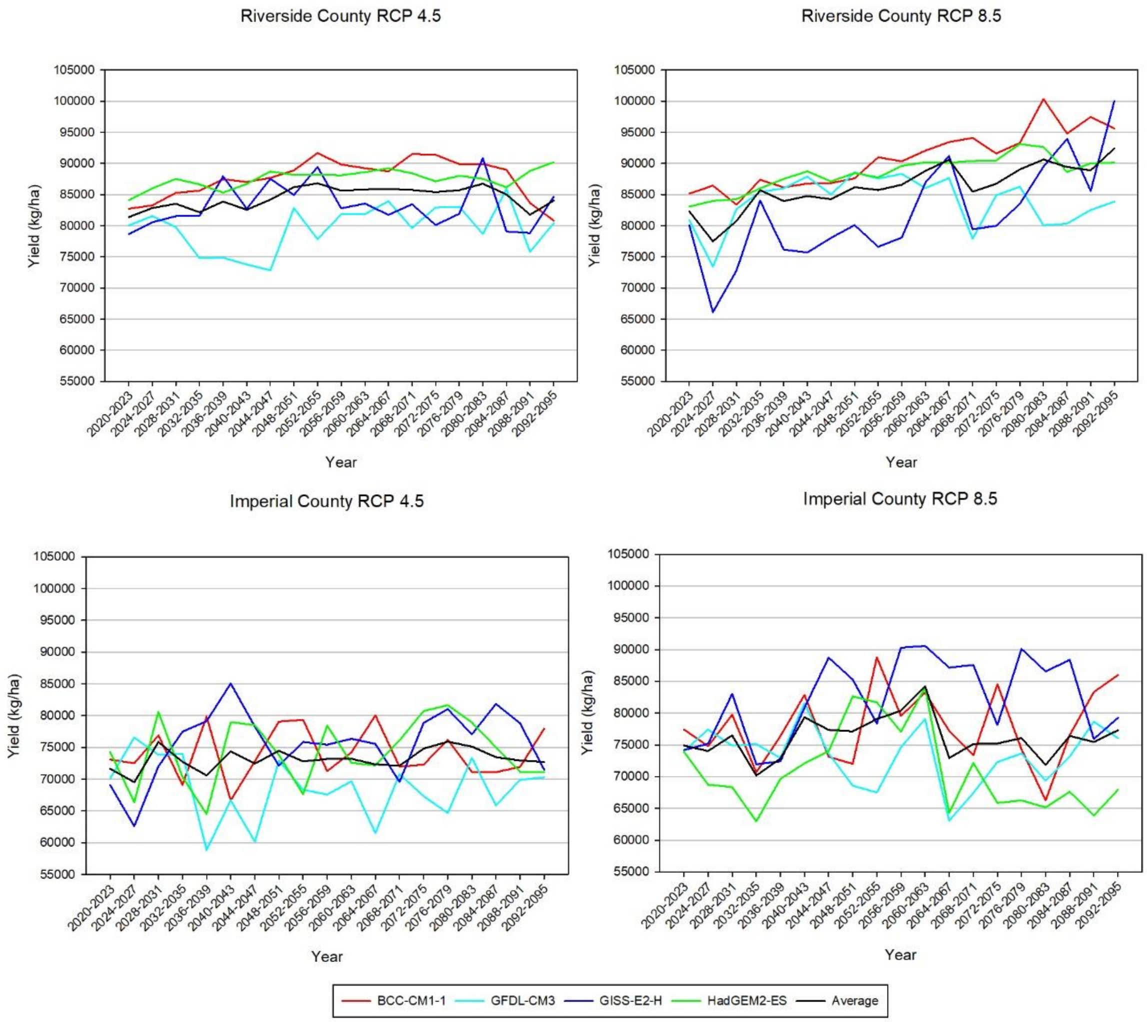


Figure 8. Simulated alfalfa yields (four GCMs and average) for counties in the lower desert region under RCP4.5 and RCP8.5 scenarios from 2020-2095.

Model Performance

The performance of the models developed for the Parlier experiment site and county models were compared using the goodness-of-fit indicators.

For the Parlier alfalfa experimental site, the model showed good performance for daily evapotranspiration and crop yields when compared to observed ET and yields. The goodness-of-fit for evapotranspiration were 902, 0.661, and 0.931 for RMSE, MAE and index of agreement respectively. Except for one outlier, the model performed well in predicting yield with goodness-of-fit of 540, 390, and 0.866 for RMSE, MAE and index of agreement respectively.

The models for each county showed good simulation performances based on the goodness-of-fit as shown in Table 13. The average RMSE, MAE, and Index of Agreement values for all the models were 917, 1100, and .82, respectively. Overall, model performance decreased from northern to southern California, with Siskiyou County (Intermountain Northern California region) showing the best performance with the lowest RMSE and MAE values and the highest index of agreement value. On the other hand, low desert region (Imperial and Riverside counties) had the worst performance with the lowest index of agreement values of 0.77 and 0.73, respectively.

Table 13. Evaluation of the DSSAT CropGro Alfalfa model performance for the thirteen counties in California.

County	RMSE	MAE	Index of Agreement
Siskiyou	739	556	0.92
Imperial	1110	847	0.77
Riverside	1151	927	0.73
Merced	838	635	0.83
Tulare	757	597	0.86
Fresno	846	671	0.78
Madera	774	589	0.84
Kings	797	638	0.84
Kern	751	584	0.85
Yolo	833	2536	0.77
Solano	871	4048	0.76
Stanislaus	1218	815	0.88
San Joaquin	1237	853	0.86

Chapter IV

Discussion

Since DSSAT is better suited to model annual crops, there were limited studies available that examined how climate change would impact alfalfa yields. The results from the thirteen county models project yield increases through 2095, even under water-stressed conditions. These results are consistent with previous studies regarding alfalfa's response to increased atmospheric CO_2 concentration. De Luis et al. (1999) showed that elevated CO_2 concentrations were a counterbalance to the negative effects of soil water deficit on alfalfa plant growth. Elevated CO_2 concentrations not only delayed the onset of drought stress by decreasing transpiration rates but also stimulated carbon fixation and biomass production. More specifically, increased atmospheric CO_2 concentration causes the stomata in C3 plants to partially close, which results in improved water use efficiency (Hatfield et al., 2011). Ergon et al. (2018) also examined how forage production in the Mediterranean and Nordic regions of Europe would be impacted by climate change and found that, although droughts pose a major future challenge in the Mediterranean, elevated atmospheric CO_2 concentrations would make up for any deficiencies caused by droughts on forage photosynthesis and growth.

Both Thivierge et al. (2016) and Castaño-Sánchez et al. (2020) assessed how climate change would impact alfalfa yields under two future climate conditions and elevated atmospheric CO_2 concentrations in Quebec, Canada, and Northeastern United States, respectively, and achieved similar results. Thivierge et al. (2016) utilized the

Integrated Farm System Model (IFSM) along with three GCMs for two RCPs (4.5 and 8.5) and two time periods (2020-2040 and 2050-2079). Their findings indicated that alfalfa yields increased when combining climate change impact with elevated atmospheric CO_2 concentrations, except for the most extreme case (RCP8.5, 2050-2079). Likewise, Castaño-Sánchez et al. (2020) used a combination of three process-based agricultural models (CropSyst, DSSAT, and IFSM) to assess the impact of climate change on maize and alfalfa yields in six counties of Pennsylvania and New York, using 25 years of weather data and two different atmospheric CO_2 concentrations (350 and 550 ppm). All three models simulated an increase in alfalfa yields, with a 20% increase from the DSSAT-A and IFSM models and a 32% increase from the Cropsyst model.

The average yield increase in this study across all thirteen counties was only 3, 10, and 11% in the near, mid, and long term, respectively. These increases were much smaller than the ones from Castaño-Sánchez et al. (2020)'s study; however, that could be a result of the difference in the climate of the study location. The six counties in the Castaño-Sánchez et al. (2020) study were located in Pennsylvania and New York, which have climates that can be characterized as cold with no dry season. This contrasts from California's Mediterranean climate, which is characterized by dry summers and mild, wet winters. However, if we looked at individual counties, Siskiyou County had the most similar climate to Pennsylvania and New York and had increases that were more consistent with Castaño-Sánchez et al. (2020)'s study. Siskiyou County had projected yield increases of 7, 16, and 17% and 11, 31, and 38% for the near-, mid-, and long-term under RCP4.5 and 8.5 scenarios, respectively. While our study projected slightly higher increases under RCP8.5, the results in the mid- and long-term are close to their results

(20% increase from the DSSAT-A and IFSM models; 32% increase from the Cropsyst model).

Research Limitations

Limitations to this study include the use of only four GCMs and one process-based agricultural model. Since it is unclear how climate change will unfold in the future, it is generally assumed that climate change will fall within a range of possible conditions (Tao et al., 2009). Climate change impact assessments based on multi-model climate projections, therefore, will provide more robust results than a single model approach (Tao et al., 2009; Araya et al., 2015). The use of only four GCMs in this study provides a limited range and could be improved in future studies by utilizing either more GCMs or a different combination of GCMs. Araya et al. (2015), for example, utilized twenty GCMs to examine the impact of climate change on maize yield in Ethiopia. Utilizing more GCMs could only improve the robustness of the results as each GCM has their own differences that can contribute to differences in results.

Additionally, the use of only one process-based agricultural model, DSSAT, limits our ability to compare results to better understand how the choice in crop model and climate scenario impacts our results (Challinor et al., 2013; Araya et al., 2015). However, although this research was limited to only using one process-based agricultural model, DSSAT, the results could be used to compare results in future studies that utilize different or multiple models. Castaño-Sánchez et al. (2020) showed that DSSAT could provide similar results to other process-based agricultural models when comparing only two potential atmospheric CO_2 concentration scenarios. Araya et al. (2015) also showed that DSSAT provided similar results to the APSIM model when examining how maize yields in Ethiopia would be impacted under future climate scenarios. Future research could explore using different process-based agricultural models such as AQUACROP or Soil and Water Assessment Tool (SWAT) (Arnold et al., 2012) to further validate the results from this study.

Conclusions

Climate change is projected to heavily impact agriculture in California as temperatures rise and droughts increase in frequency and intensity. Farmers will have to adapt and make important decisions regarding what crops to grow in a hotter and less water secure environment. The DSSAT models for all thirteen counties indicate that alfalfa yields are expected to increase in yield through 2095 for both RCP4.5 and 8.5 scenarios, even under water-stressed conditions. The study results are consistent with previous studies that have also shown alfalfa yields to increase due to increase atmospheric concentration of CO_2.

The viability of alfalfa production in California will play a significant role in the long-term health of the state's dairy and livestock industries. The increasing trend in yield is a positive sign that overall yields of alfalfa could be maintain even if total alfalfa acreage is reduced. With climate change possibly negatively impacting yields for other crops, the positive change for alfalfa can ensure that alfalfa production remains an integral part of California's agricultural economy.

Appendix 1

DSSAT Soil Data Results

Table 14. DSSAT Soil Module variables and definition.

Soil Variable	Description
SLB	Depth, base of layer, cm
SLLL	Lower limit, cm3 cm-3
SDUL	Upper limit, drained, cm3 cm-3
SSAT	Upper limit, saturated, cm3 cm-3
SRGF	Root growth factor, soil only, 0.0 to 1.0
SSKS	Sat. hydraulic conductivity, macropore, cm h-1
SBDM	Bulk density, moist, g cm-3
SLOC	Organic carbon, %
SLCL	Clay (<0.002 mm), %
SLSI	Silt (0.05 to 0.002 mm), %
SLNI	Total nitrogen, %
SLHW	pH in water
SCEC	Cation exchange capacity, cmol kg-1

Table 15. DSSAT's default deep sandy loam soil profile values.

SLB [1]	SLLL [2]	SDUL [3]	SSAT [4]	SRGF [5]	SBDM [6]	SLOC [7]	SLCL [8]	SLSI [9]	SLNI [10]	SLHW [11]
5	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
15	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
45	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
75	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
105	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
135	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
165	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1
195	.070	.270	.390	1.00	-1.61	0.70	10	30	.070	7.1

[1] SLB: Depth, base of layer, cm
[2] SLLL: Lower limit, cm3 cm-3
[3] SDUL: Upper limit, drained, cm3 cm-3
[4] SSAT: U pper limit, saturated, cm3 cm-3
[5] SRGF: Root growth factor, soil only, 0.0 to 1.0
[6] SBDM: Bulk density, moist, g cm-3
[7] SLOC: Organic carbon, %
[8] SLCL: Clay (<0.002 mm), %
[9] SLSI: Silt (0.05 to 0.002 mm), %
[10] SLNI: Total nitrogen, %
[11]SLHW: pH in water

Table 16. Soil profiles for each county generated by the FARMs application.

Siskiyou County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.062	0.127	0.28	1	15.62	1.59	2.75	16.18	34.54	0.12	6.17	18
15	0.062	0.127	0.28	0.85	15.62	1.59	2.33	17.86	33.75	0.09	6.24	15.7
30	0.058	0.157	0.28	0.7	10.42	1.6	1.78	20.18	32.61	0.07	6.34	15.2
60	0.053	0.149	0.26	0.5	14.66	1.64	1.14	22.26	31.47	0.06	6.45	15.9
100	0.041	0.084	0.17	0.38	14.66	1.76	0.66	22.22	30.8	0.05	6.59	16
200	0.124	0.237	0.392	0.05	1.03	1.51	0.38	20.59	30.47	0.05	6.77	15.9
Solano County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.12	0.24	0.392	1	0.95	1.51	1.28	19.78	35.13	0.12	7.02	23
15	0.131	0.252	0.395	0.85	0.79	1.53	1.08	21.63	34.31	0.09	7.09	20.2
30	0.145	0.268	0.4	0.7	0.62	1.56	0.82	24.08	33.03	0.07	7.19	19.5
60	0.158	0.281	0.404	0.5	0.5	1.61	0.53	26.29	31.73	0.06	7.3	20.4
100	0.158	0.28	0.404	0.38	0.38	1.67	0.3	26.21	31.16	0.05	7.44	20.6
200	0.148	0.267	0.399	0.05	0.05	1.72	0.19	24.59	30.92	0.05	7.61	20.5
Yolo County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.118	0.239	0.392	1	0.98	1.53	1.35	19.44	35.51	0.12	6.93	22.6
15	0.129	0.25	0.395	0.85	0.82	1.55	1.14	21.29	34.65	0.09	7	19.8
30	0.144	0.267	0.4	0.7	0.63	1.58	0.88	23.88	33.37	0.07	7.1	19.2
60	0.157	0.28	0.404	0.5	0.51	1.63	0.57	26.09	32.13	0.06	7.2	20.1
100	0.157	0.279	0.404	0.38	0.51	1.69	0.33	26.08	31.46	0.05	7.34	20.2
200	0.146	0.266	0.399	0.05	0.63	1.74	0.2	24.3	31.1	0.05	7.52	20.1
Fresno County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.086	0.182	0.37	1	3.24	1.65	0.86	18.71	34.5	0.08	7.1	21.4
15	0.086	0.182	0.37	0.85	3.24	1.65	0.73	20.51	33.7	0.06	7.16	18.8
30	0.079	0.175	0.38	0.7	3.23	1.65	0.56	22.92	32.51	0.05	7.25	18.2
60	0.079	0.175	0.38	0.5	3.24	1.65	0.36	25.3	31.18	0.04	7.37	19
100	0.079	0.175	0.39	0.38	10.04	1.62	0.21	25.23	30.5	0.04	7.51	19.1
200	0.142	0.259	0.397	0.05	0.7	1.83	0.11	23.65	30.33	0.05	7.69	19.1
Merced County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.118	0.235	0.392	1	1.11	1.52	1.23	19.55	19.55	0.12	7.31	23.3
15	0.129	0.246	0.395	0.85	0.93	1.54	1.04	21.34	21.34	0.09	7.38	20.5
30	0.143	0.262	0.4	0.7	0.73	1.57	0.79	23.73	23.73	0.07	7.47	19.8
60	0.157	0.277	0.404	0.5	0.58	1.62	0.51	26.15	26.15	0.06	7.59	20.6
100	0.157	0.275	0.404	0.38	0.59	1.68	0.3	26.08	26.08	0.05	7.72	20.8
200	0.146	0.262	0.399	0.05	0.73	1.73	0.17	24.31	24.31	0.05	7.9	20.7
Tulare County												

SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
5	0.117	0.237	0.391	1	1.02	1.55	1	19.38	34.77	0.08	7.18	24.5
15	0.128	0.248	0.394	0.85	0.85	1.57	0.84	21.17	33.94	0.06	7.25	21.5
30	0.143	0.264	0.399	0.7	0.7	1.6	0.64	23.63	32.76	0.05	7.34	20.8
60	0.157	0.279	0.404	0.5	0.5	1.65	0.41	26.09	31.38	0.04	7.45	21.8
100	0.156	0.277	0.403	0.38	0.38	1.71	0.24	25.96	30.76	0.04	7.6	21.9
200	0.146	0.264	0.398	0.05	0.05	1.77	0.13	24.22	30.58	0.05	7.78	21.8

Kings County

SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
5	0.128	0.248	0.394	1	0.85	1.49	0.99	21.09	34.19	0.08	7.7	24.8
15	0.139	0.26	0.397	0.85	0.7	1.51	0.83	23	33.36	0.06	7.77	21.7
30	0.154	0.276	0.402	0.7	0.54	1.54	0.63	25.47	32.19	0.05	7.87	21
60	0.168	0.291	0.408	0.5	0.43	1.59	0.41	27.85	30.77	0.04	7.98	22
100	0.168	0.289	0.407	0.38	0.43	1.65	0.25	27.85	30.17	0.04	8.12	22.2
200	0.157	0.277	0.403	0.05	0.53	1.71	0.14	26.15	29.9	0.05	8.3	22.1

Madera County

SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
5	0.133	0.255	0.396	1	0.75	1.47	1.19	21.91	34.96	0.08	7.77	24.8
15	0.144	0.268	0.4	0.85	0.62	1.49	1	23.84	34.06	0.06	7.84	21.7
30	0.158	0.283	0.405	0.7	0.49	1.52	0.77	26.27	32.83	0.05	7.94	21
60	0.174	0.299	0.411	0.5	0.38	1.57	0.49	28.84	31.43	0.04	8.05	22
100	0.173	0.297	0.41	0.38	0.38	1.63	0.29	28.84	30.88	0.04	8.19	22.1
200	0.163	0.284	0.405	0.05	0.47	1.68	0.17	27.03	27.03	0.05	8.37	22.1

Kern County

SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
5	0.131	0.251	0.395	1	0.81	1.55	0.95	21.74	33.28	0.08	7.85	27.6
15	0.143	0.263	0.398	0.85	0.67	1.57	0.81	23.63	32.38	0.06	7.92	24.2
30	0.157	0.279	0.403	0.7	0.52	1.6	0.62	26.12	31.06	0.05	8.02	23.5
60	0.172	0.294	0.409	0.5	0.4	1.65	0.39	28.6	29.78	0.04	8.13	24.5
100	0.172	0.293	0.408	0.38	0.41	1.71	0.23	28.57	29.23	0.04	8.26	24.6
200	0.161	0.28	0.403	0.05	0.5	1.76	0.12	26.8	28.87	0.05	8.45	24.6

Riverside County

SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
5	0.072	0.155	0.38	1	5.62	1.63	0.58	18.42	31.53	0.03	7.85	21.8
15	0.072	0.155	0.38	0.85	5.62	1.63	0.49	20.27	30.65	0.02	7.91	19.1
30	0.074	0.167	0.37	0.7	5.62	1.63	0.37	22.77	29.41	0.02	8	18.6
60	0.074	0.167	0.37	0.5	5.52	1.63	0.24	24.91	28.15	0.02	8.13	19.4
100	0.074	0.167	0.37	0.38	5.62	1.63	0.13	24.88	27.61	0.02	8.27	19.5
200	0.139	0.249	0.394	0.05	0.8	1.86	0.1	23.09	27.19	0.05	8.45	19.5

Imperial County

SLB	SLLL	SDUL	SSAT	SRGF	SSKS	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
5	0.126	0.243	0.392	1	0.91	1.58	0.27	20.87	32.22	0.03	8.06	21.3
15	0.138	0.255	0.396	0.85	0.75	1.6	0.22	22.81	31.32	0.02	8.13	18.6

30	0.153	0.271	0.401	0.7	0.58	1.63	0.19	25.33	30.12	0.02	8.23	18.1
60	0.167	0.286	0.406	0.5	0.45	1.68	0.1	27.75	28.97	0.02	8.34	18.9
100	0.167	0.285	0.405	0.38	0.46	1.74	0.1	27.72	28.34	0.02	8.48	19
200	0.132	0.235	0.39	0.05	0.96	1.79	0.1	25.96	27.89	0.05	8.66	19
Stanislaus County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.111	0.229	0.389	1	1.13	1.49	1.07	18.28	34.48	0.08	7.07	22.9
15	0.121	0.241	0.392	0.85	0.94	1.51	0.9	20.06	33.65	0.06	7.14	20.1
30	0.136	0.256	0.396	0.7	0.74	1.54	0.69	22.59	32.49	0.05	7.23	19.4
60	0.151	0.271	0.401	0.5	0.58	1.59	0.44	25.04	31.15	0.04	7.35	20.3
100	0.15	0.269	0.4	0.38	0.59	1.65	0.26	24.58	30.58	0.04	7.49	20.4
200	0.141	0.257	0.396	0.05	0.72	1.71	0.13	23.33	30.27	0.05	7.67	20.4
San Joaquin County												
SLB	**SLLL**	**SDUL**	**SSAT**	**SRGF**	**SSKS**	**SBDM**	**SLOC**	**SLCL**	**SLSI**	**SLNI**	**SLHW**	**SCEC**
5	0.102	0.213	0.387	1	1.5	1.42	1.63	16.86	32.22	0.12	6.96	23.7
15	0.112	0.223	0.389	0.85	1.27	1.44	1.38	18.56	31.36	0.09	7.04	20.9
30	0.126	0.239	0.393	0.7	1	1.47	1.05	20.92	30.24	0.07	7.13	20.1
60	0.139	0.253	0.396	0.5	0.8	1.52	0.67	23.16	28.89	0.06	7.24	21.1
100	0.14	0.252	0.396	0.38	0.81	1.59	0.39	23.26	28.3	0.05	7.39	21.2
200	0.13	0.239	0.392	0.05	0.98	1.64	0.22	21.59	27.85	0.05	7.56	21.1

Appendix 2

Breakdown of Simulated GCM Results

Table 17. Simulated alfalfa yields under different climate change scenarios in the near, mid, and long term for alfalfa major producing counties in California.

		RCP 4.5				RCP 8.5			
County	**GCM**	**2020-2023**	**2036-2039**	**2068-2071**	**2092-2095**	**2020-2023**	**2036-2039**	**2068-2071**	**2092-2095**
Siskiyou	BCC-CSM1-1	55914	60725	69833	67894	57838	64711	80364	85471
Siskiyou	GFDL-CM3	59048	64481	67362	69097	61109	64340	73347	77341
Siskiyou	GISS-E2-H	60138	61968	64263	66331	56581	62614	75226	81303
Siskiyou	HadGEM2-ES	59055	63455	69964	72928	57135	68025	79005	80424
Imperial	BCC-CSM1-1	73739	81965	73067	78369	79315	77619	76492	88597
Imperial	GFDL-CM3	71697	58808	73512	71513	75081	73281	67487	78466
Imperial	GISS-E2-H	69328	80976	69854	71619	74482	72445	88148	78870
Imperial	HadGEM2-ES	75476	64948	77348	71947	74393	70570	72524	70223
Riverside	BCC-CSM1-1	87264	92182	96459	85000	89976	91878	100542	101694
Riverside	GFDL-CM3	84585	78858	83382	83704	85701	90484	85321	87171
Riverside	GISS-E2-H	83472	93165	91109	89681	84078	78924	82779	107209
Riverside	HadGEM2-ES	88567	90277	94441	96386	88424	92436	96215	95311
Stanislaus	BCC-CSM1-1	61397	67345	67784	65858	65023	66714	74301	73960
Stanislaus	GFDL-CM3	64407	65146	67832	68261	64041	65576	72105	74756
Stanislaus	GISS-E2-H	63872	64388	71580	69063	64862	66227	77535	76053
Stanislaus	HadGEM2-ES	63817	65612	72238	70269	64487	66394	76827	77254
San Joaquin	BCC-CSM1-1	64751	64584	66790	63642	66833	66226	71838	77164
San Joaquin	GFDL-CM3	57626	64128	69368	69171	60636	65973	76246	74352
San Joaquin	GISS-E2-H	60222	63493	68019	70851	61127	65238	74308	82477
San Joaquin	HadGEM2-ES	61618	65485	67310	68774	61844	65361	72481	79135
Kings	BCC-CSM1-1	75728	76958	82691	80664	76637	77236	86556	87184

Kings	GFDL-CM3	76217	75398	74813	73618	77548	79505	79065	70106
Kings	GISS-E2-H	78974	78233	85227	81917	78616	81151	89589	86806
Kings	HadGEM2-ES	78391	79086	82650	84557	78841	79042	85977	89272
Kern	BCC-CSM1-1	74252	74752	82414	77637	75325	76579	85029	79927
Kern	GFDL-CM3	74058	76013	76350	71348	73296	78890	77001	66921
Kern	GISS-E2-H	70055	71233	80744	71348	70217	76260	83128	83485
Kern	HadGEM2-ES	70791	77887	73614	76859	70421	76089	79479	78631
Madera	BCC-CSM1-1	77784	79932	83334	82690	76961	81948	87981	90752
Madera	GFDL-CM3	76734	80389	81596	79402	76145	83293	86512	80389
Madera	GISS-E2-H	75538	77778	82622	84682	76141	79214	87844	92970
Madera	HadGEM2-ES	77171	80418	86546	80938	77312	81221	91596	90072
Fresno	BCC-CSM1-1	72369	77383	81158	79691	72667	78070	84145	87330
Fresno	GFDL-CM3	72496	74796	76850	72285	72445	79760	79052	71246
Fresno	GISS-E2-H	73583	79527	82775	81194	72681	80894	87459	84828
Fresno	HadGEM2-ES	74611	76227	80444	74576	74775	77775	84460	78383
Merced	BCC-CSM1-1	79771	77544	88590	86235	80035	79141	92922	94965
Merced	GFDL-CM3	78516	83821	82207	78307	78661	85936	85777	81603
Merced	GISS-E2-H	78207	83190	85936	88647	77775	84076	92216	96682
Merced	HadGEM2-ES	80285	81405	86633	82352	80933	82417	91536	87853
Tulare	BCC-CSM1-1	77717	76861	88363	84327	79489	79107	91620	93439
Tulare	GFDL-CM3	75144	80862	78194	73069	78295	84442	77844	70051
Tulare	GISS-E2-H	80375	80468	86052	84535	82012	82300	91567	82836
Tulare	HadGEM2-ES	78235	78786	82811	82205	79224	80436	84738	83266
Solano	BCC-CSM1-1	66523	67867	72410	69787	66412	68433	78054	74566
Solano	GFDL-CM3	65047	68553	69778	66733	66342	68698	76335	75655
Solano	GISS-E2-H	64497	67417	73489	75002	65191	69219	79098	83953
Solano	HadGEM2-ES	69810	66190	71466	70220	70556	67913	75468	83953
Yolo	BCC-CSM1-1	65040	70851	69901	71721	65812	71294	71693	78331
Yolo	GFDL-CM3	64372	66984	69887	68674	66789	67178	74672	76351
Yolo	GISS-E2-H	64945	67228	72348	76447	66676	69229	77972	87681
Yolo	HadGEM2-ES	64976	66672	71824	72711	67362	68647	77007	77002

Table 18. Averages of four GCMs for climate variables under RCP4.5 and 8.5 scenarios for Intermountain Northern California region.

			RCP 4.5			RCP 8.5		
County	**GCM**	**Period**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**
Siskiyou	BCC	Near	29.1	8.3	63.4	29.4	8.5	68.9
Siskiyou	GFD	Near	29.5	8.5	81.2	29.7	8.7	77.9
Siskiyou	GIS	Near	28.2	7.8	75.6	28.4	7.9	74.7
Siskiyou	HAD	Near	29.4	8.6	67.0	29.4	8.7	78.6
Average	Total	Near	29.0	8.3	71.8	29.2	8.5	75.0
Siskiyou	BCC	Mid	29.4	8.3	69.5	30.6	9.5	92.1
Siskiyou	GFD	Mid	31.3	9.6	91.3	31.9	10.3	89.8
Siskiyou	GIS	Mid	28.9	8.5	100.7	29.6	9.0	57.7
Siskiyou	HAD	Mid	30.6	9.8	63.7	31.6	10.9	69.1
Average	Total	Mid	30.1	9.1	81.3	30.9	9.9	77.2
Siskiyou	BCC	Long	29.3	8.3	83.8	31.8	10.3	79.8
Siskiyou	GFD	Long	31.8	9.9	62.6	34.0	11.7	56.0
Siskiyou	GIS	Long	28.5	8.2	90.3	30.5	9.8	65.6
Siskiyou	HAD	Long	30.8	10.1	77.0	34.0	13.5	84.9
Average	Total	Long	30.1	9.1	78.4	32.6	11.3	71.6

Table 19. Averages for four GCMs for climate variables under RCP4.5 and 8.5 climate change scenarios for San Joaquin Valley Region.

			RCP 4.5			RCP 8.5		
County	**GCM**	**Period**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**
Madera	BCC	Near	29.6	11.9	124.4	29.8	12.3	140.8
Madera	GFD	Near	30.2	12.1	78.6	30.6	12.1	45.6
Madera	GIS	Near	29.3	11.8	151.7	29.4	12	180
Madera	HAD	Near	30	12.2	100.1	30	12.4	107.3
Average	Total	Near	29.8	12	113.7	29.9	12.2	118.4
Madera	BCC	Mid	30	12.3	121.8	30.8	13.2	163.5
Madera	GFD	Mid	31.3	12.7	98.4	32	13	89.7
Madera	GIS	Mid	30	12.5	152.7	30.5	12.9	175.1
Madera	HAD	Mid	30.9	13.1	126.4	31.7	14	135.2
Average	Total	Mid	30.6	12.6	124.8	31.3	13.3	140.9
Madera	BCC	Far	30.5	12.6	145	32.6	14.6	121.5
Madera	GFD	Far	31.9	12.8	114.6	34.1	14.4	198.2

Madera	GIS	Far	30.3	12.8	155.4	31.8	14.2	167
Madera	HAD	Far	31.6	13.7	118.8	34	16	115.3
Average	Total	Far	31.1	13	133.5	33.1	14.8	150.5
Merced	BCC	Near	29.2	12	189.7	29.4	12.3	216.3
Merced	GFD	Near	30	12.2	169.3	30.2	12.3	109.5
Merced	GIS	Near	29.1	12.1	215.4	29.3	12.2	221.2
Merced	HAD	Near	29.8	12.4	161.1	29.8	12.5	188
Average	Total	Near	29.5	12.2	183.9	29.7	12.3	183.8
Merced	BCC	Mid	30	12.5	144.5	30.7	13.4	228.5
Merced	GFD	Mid	31.4	13.1	141	32.1	13.5	154.2
Merced	GIS	Mid	29.6	12.4	225.9	30.2	13	241.4
Merced	HAD	Mid	30.6	13.2	189.4	31.5	14.2	173.2
Average	Total	Mid	30.4	12.8	175.2	31.1	13.5	199.3
Merced	BCC	Long	30.4	13	173.8	32.7	15	147.5
Merced	GFD	Long	32.1	13.5	143.7	34.4	15	200.9
Merced	GIS	Long	30	13	223.9	31.6	14.3	250.6
Merced	HAD	Long	31.5	14.1	151.5	33.9	16.4	140.2
Average	Total	Long	31	13.4	173.2	33.2	15.2	184.8
Stanislaus	BCC	Near	30.4	12.9	87.4	30.7	13.4	129.3
Stanislaus	GFD	Near	31	13.1	93.1	31.4	13	52.7
Stanislaus	GIS	Near	30.1	12.9	90.6	30.2	13	112.2
Stanislaus	HAD	Near	30.7	13	100.5	30.8	13.1	106.9
Average	Total	Near	30.6	13	92.9	30.8	13.1	100.3
Stanislaus	BCC	Mid	30.9	13.3	98.3	31.9	14.3	121.1
Stanislaus	GFD	Mid	32.2	13.8	81.4	32.8	14.1	73.5
Stanislaus	GIS	Mid	30.6	13.4	119.5	31.2	13.9	122.3
Stanislaus	HAD	Mid	31.8	14.2	82.6	32.6	15	94.8
Average	Total	Mid	31.4	13.7	95.4	32.1	14.3	102.9
Stanislaus	BCC	Long	31.4	13.8	115.6	33.7	15.8	95.6
Stanislaus	GFD	Long	32.8	13.9	94.7	34.7	15.4	123.7
Stanislaus	GIS	Long	30.9	13.7	111.2	32.3	14.9	102.8
Stanislaus	HAD	Long	32.4	15	104.2	34.7	17.2	76.8
Average	Total	Long	31.9	14.1	106.4	33.9	15.8	99.7
San Joaquin	BCC	Near	30.5	13.2	96.7	30.7	13.5	107.1
San Joaquin	GFD	Near	30.9	13.2	107.1	31.2	13.3	69.6
San Joaquin	GIS	Near	30	13	132	30.1	13.2	127.9
San Joaquin	HAD	Near	30.8	13.4	152.8	30.9	13.6	101.8
Average	Total	Near	30.5	13.2	122.1	30.7	13.4	101.6
San Joaquin	BCC	Mid	30.7	13.6	143.5	31.7	14.5	150.9
San Joaquin	GFD	Mid	32.1	13.9	75.3	32.6	14.3	80.6

San Joaquin	GIS	Mid	30.4	13.5	103.3	31	14	120.7
San Joaquin	HAD	Mid	31.3	14.2	132.9	32.1	15.1	131.7
Average	Total	Mid	31.1	13.8	113.7	31.9	14.5	121
San Joaquin	BCC	Long	31	13.8	143	33.4	15.8	128.7
San Joaquin	GFD	Long	32.9	14.3	86.1	34.7	15.8	135.8
San Joaquin	GIS	Long	30.8	13.7	91.5	32.2	15	109.2
San Joaquin	HAD	Long	32.3	15	88.5	34.4	17.1	80
Average	Total	Long	31.7	14.2	102.3	33.7	15.9	113.4

Table 20. Averages for four GCMs for climate variables under RCP4.5 and 8.5 climate change scenarios for Sacramento Region.

				RCP 4.5			**RCP 8.5**	
County	**GCM**	**Period**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**
Solano	BCC	Near	29.4	12.1	128.8	29.6	12.5	175.6
Solano	GFD	Near	30	12	153	29.7	11.9	98.6
Solano	GIS	Near	29.2	12.3	186	29.3	12.4	179.1
Solano	HAD	Near	29.7	12.2	151.1	29.9	12.4	139.4
Average	Total	Near	29.6	12.2	154.7	29.6	12.3	148.2
Solano	BCC	Mid	29.7	12.4	191.1	30.6	13.3	184.7
Solano	GFD	Mid	31.6	13.4	175.5	31	12.8	136.8
Solano	GIS	Mid	29.6	12.6	181.2	30.2	13.1	220
Solano	HAD	Mid	30.7	13.2	137	31.5	14.1	151.6
Average	Total	Mid	30.4	12.9	171.2	30.8	13.3	173.3
Solano	BCC	Long	30.2	12.8	159	32.4	14.6	155
Solano	GFD	Long	33.7	15.1	168.3	31.9	13.5	171.9
Solano	GIS	Long	29.9	12.8	209.5	31.2	14	227.6
Solano	HAD	Long	31.2	13.8	145.9	33.3	16.1	151.1
Average	Total	Long	31.3	13.6	170.7	32.2	14.5	176.4
Yolo	BCC	Near	29.7	11.6	113	29.8	12	151.3
Yolo	GFD	Near	30.5	12.1	129.7	30.7	12.2	94.8
Yolo	GIS	Near	29.3	11.7	190.5	29.4	11.8	196.2
Yolo	HAD	Near	30.1	12	159	30.2	12.2	151.8
Average	Total	Near	29.9	11.9	148	30	12	148.5
Yolo	BCC	Mid	30	12	182	30.9	12.9	199.8
Yolo	GFD	Mid	31.6	12.8	181.7	32.1	13.4	120.3

Yolo	GIS	Mid	30	12.3	187.5	30.6	12.8	201.2
Yolo	HAD	Mid	31.1	12.9	137.4	31.9	13.8	132.4
Average	Total	Mid	30.7	12.5	172.1	31.4	13.2	163.4
Yolo	BCC	Long	30.6	12.7	202.1	32.8	14.5	182.1
Yolo	GFD	Long	32.4	13.4	181.4	34.3	15	170.9
Yolo	GIS	Long	30.4	12.7	196.6	31.7	13.8	215.3
Yolo	HAD	Long	31.7	13.5	136.3	33.9	15.8	138.6
Average	Total	Long	31.3	13	179.1	33.2	14.8	176.7

Table 21. Averages for four GCMs for climate variables under RCP4.5 and 8.5 climate change scenarios for the Southern San Joaquin Valley Region.

			RCP 4.5			**RCP 8.5**		
County	**GCM**	**Period**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**	**Max Temp (ºC)**	**Min Temp (ºC)**	**Precipitation (mm)**
Fresno	BCC	Near	29.8	12.5	156.6	29.3	12.4	199.3
Fresno	GFD	Near	31	12.9	151.2	31.2	13	111.9
Fresno	GIS	Near	29.8	12.6	180.9	29.8	12.7	238.5
Fresno	HAD	Near	30.5	13.3	179.3	30.5	13.5	191.7
Average	Total	Near	30.2	12.8	167	30.2	12.9	185.3
Fresno	BCC	Mid	29.9	12.6	132.6	30.7	13.5	176.3
Fresno	GFD	Mid	32	13.5	136	32.8	14	148.4
Fresno	GIS	Mid	30.5	13.4	226.2	31.1	13.9	242
Fresno	HAD	Mid	31.4	14.1	188.1	32.2	15	181.5
Average	Total	Mid	30.9	13.4	170.7	31.7	14.1	187.1
Fresno	BCC	Far	30.1	13.1	200.7	33.1	15.6	180.8
Fresno	GFD	Far	32.9	14.2	139.6	35.4	15.7	195.3
Fresno	GIS	Far	30.8	13.7	223.8	32.6	15.1	187.9
Fresno	HAD	Far	32.1	14.7	167.3	34.7	17.2	121.8
Average	Total	Far	31.5	13.9	182.8	34	15.9	171.4
Kern	BCC	Near	31.4	15.2	123.4	31.6	15.4	116.2
Kern	GFD	Near	32.3	15.3	93.5	32.4	15.5	70.5
Kern	GIS	Near	30.9	15.1	159.9	31.2	15.3	168.7
Kern	HAD	Near	31.7	15.8	150.9	31.8	15.9	172.2
Average	Total	Near	31.6	15.4	132	31.7	15.5	131.9
Kern	BCC	Mid	31.9	15.8	137.7	32.7	16.6	147.3
Kern	GFD	Mid	33.6	16.2	97.8	34.1	16.7	99.7
Kern	GIS	Mid	31.7	15.8	146.6	32.4	16.4	171.7
Kern	HAD	Mid	32.4	16.7	135.8	33.2	17.5	136.2
Average	Total	Mid	32.4	16.1	129.5	33.1	16.8	138.7
Kern	BCC	Far	32.2	15.9	147.3	34.4	18	156.6

Kern	GFD	Far	34.3	16.6	92.4	36.6	18.6	168.7
Kern	GIS	Far	32.1	16.2	126.6	33.4	17.5	169.1
Kern	HAD	Far	33	17.2	143.9	35.4	19.6	111.7
Average	Total	Far	32.9	16.5	127.5	34.9	18.4	151.5
Kings	BCC	Near	30.6	13	120.8	30.8	13.3	172.9
Kings	GFD	Near	31.5	13	105.2	31.8	13.2	67
Kings	GIS	Near	30.3	12.5	112.2	30.4	12.7	146.5
Kings	HAD	Near	31.3	13.4	95.6	31.4	13.5	97.2
Average	Total	Near	30.9	13	108.5	31.1	13.2	120.9
Kings	BCC	Mid	31.4	13.5	124.8	32.1	14.3	168.7
Kings	GFD	Mid	32.7	13.8	89.8	33.3	14.2	118.2
Kings	GIS	Mid	31.2	13.5	120.3	31.8	14	149.8
Kings	HAD	Mid	32	14.1	111.9	32.8	15	118.6
Average	Total	Mid	31.8	13.7	111.7	32.5	14.4	138.8
Kings	BCC	Far	32	14	112.1	34.3	16.1	110.9
Kings	GFD	Far	33.3	14.4	67	35.5	16.1	143.4
Kings	GIS	Far	31.7	13.9	124.6	33.1	15.2	156.2
Kings	HAD	Far	32.8	14.8	101.7	35.1	17	101.7
Average	Total	Far	32.4	14.3	101.3	34.5	16.1	128.1
Tulare	BCC	Near	30.6	13.2	157.4	30.8	13.5	163.4
Tulare	GFD	Near	31.5	13.2	119.3	31.7	13.4	83.7
Tulare	GIS	Near	30.3	13.1	169.3	30.5	13.3	186.6
Tulare	HAD	Near	31.3	13.9	145	31.4	14	149.7
Average	Total	Near	30.9	13.4	147.7	31.1	13.5	145.8
Tulare	BCC	Mid	31.2	13.6	170	32.1	14.5	179.9
Tulare	GFD	Mid	32.9	14.3	141.4	33.5	14.8	165.3
Tulare	GIS	Mid	31.1	13.9	147.6	31.7	14.4	197.4
Tulare	HAD	Mid	31.9	14.6	154.8	32.7	15.4	142.2
Average	Total	Mid	31.8	14.1	153.4	32.5	14.8	171.2
Tulare	BCC	Far	31.6	14.2	165.3	33.9	16.2	162.3
Tulare	GFD	Far	33.4	14.5	122.8	35.9	16.2	181.6
Tulare	GIS	Far	31.6	14.3	166.6	33.2	15.8	173.6
Tulare	HAD	Far	32.5	15.2	179.8	35	17.7	159.8
Average	Total	Far	32.3	14.6	158.6	34.5	16.5	169.3

Table 22. Averages for four GCMs for climate variables under RCP4.5 and 8.5 climate change scenarios for the Lower Desert Region.

	RCP 4.5	RCP 8.5

County	GCM	Period	Max Temp (ºC)	Min Temp (ºC)	Precipitation (mm)	Max Temp (ºC)	Min Temp (ºC)	Precipitation (mm)
Imperial	BCC	Near	33.9	17.3	182	34.4	17.6	155.1
Imperial	GFD	Near	35	17.9	126	35	18.2	152.1
Imperial	GIS	Near	33.3	17.2	174.9	33.5	17.4	286.4
Imperial	HAD	Near	34	17.9	251.4	34	18	280.3
Average	Total	Near	34.1	17.5	183.6	34.2	17.8	218.5
Imperial	BCC	Mid	34.3	17.9	227.9	35.4	18.7	240.6
Imperial	GFD	Mid	35.9	18.8	236.1	36.9	19.6	155.1
Imperial	GIS	Mid	34.2	17.8	188.6	34.9	18.2	127.6
Imperial	HAD	Mid	34.7	18.1	198.4	35.5	18.8	215.2
Average	Total	Mid	34.8	18.1	212.7	35.7	18.8	184.6
Imperial	BCC	Long	34.9	18.2	267.2	37.1	20	267.9
Imperial	GFD	Long	36.9	19.4	165.1	39.5	21.7	129.4
Imperial	GIS	Long	34.4	18	240.9	35.9	19.3	196.5
Imperial	HAD	Long	35.6	19.3	245.9	37.9	21.8	331
Average	Total	Long	35.4	18.7	229.8	37.6	20.7	231.2
Riverside	BCC	Near	35.3	17.7	45.5	35.5	17.8	64.8
Riverside	GFD	Near	36.2	18	105	36.4	18.3	31.6
Riverside	GIS	Near	34.7	17.5	82.6	34	17.4	258
Riverside	HAD	Near	35.5	18.1	45.8	35.8	18.4	47.3
Average	Total	Near	35.4	17.8	69.7	35.4	17.9	100.4
Riverside	BCC	Mid	35.8	18	36.8	36.8	19	84.9
Riverside	GFD	Mid	37.4	19	99.9	38.2	19.9	27.9
Riverside	GIS	Mid	34.9	18.1	170.6	35.6	18.7	161.9
Riverside	HAD	Mid	36.4	19	67.2	37.4	19.9	51.5
Average	Total	Mid	36.1	18.5	93.6	37	19.4	81.5
Riverside	BCC	Long	35.8	18.3	125.5	38.1	20.2	58.5
Riverside	GFD	Long	38.1	19.7	54.6	40.7	21.9	43.8
Riverside	GIS	Long	35.3	18.3	193.8	36.6	19.7	221.4
Riverside	HAD	Long	37.1	19.7	55.8	39.2	22	72.9
Average	Total	Long	36.6	19	107.4	38.6	21	99.1

References

AgriMetSoft (2019). Online Calculators. Retrieved from https://agrimetsoft.com/calculators/Index%20of%20Agreement.

Allen, R. G., & Food and Agriculture Organization of the United Nations (Eds.). (1998). Crop evapotranspiration: Guidelines for computing crop water requirements. Food and Agriculture Organization of the United Nations.

Anderson, R., Bayer, P. E., & Edwards, D. (2020). Climate change and the need for agricultural adaptation. *Current Opinion in Plant Biology*, *56*, 197–202. https://doi.org/10.1016/j.pbi.2019.12.006

Aranjuelo, I., Irigoyen, J. J., Perez, P., Martinez-Carrasco, R., & Sanchez-Diaz, M. (2006). Response of nodulated alfalfa to water supply, temperature and elevated CO2: Productivity and water relations. *Environmental and Experimental Botany*, *55*(1–2), 130–141. https://doi.org/10.1016/j.envexpbot.2004.10.007

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K. M., Kisekka, I., & Martorano, L. G. (2015). Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. *Agricultural and Forest Meteorology*, *214–215*, 252–265. https://doi.org/10.1016/j.agrformet.2015.08.259

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., van Griensven, A., Van Liew, M.W., Kannan, N., & Jha, M.K. (2012). SWAT: Model use, calibration, and validation. *Transactions of the ASABE*, *55*(4), 1491–1508. https://doi.org/10.13031/2013.42256

Bao, Y., Hoogenboom, G., McClendon, R., & Vellidis, G. (2017). A comparison of the performance of the CSM-CERES-Maize and EPIC models using maize variety trial data. *Agricultural Systems*, *150*, 109–119. https://doi.org/10.1016/j.agsy.2016.10.006

California Department of Food and Agriculture (CDFA). (2016). California Agricultural Statistics Review, 2015-2016. https://www.cdfa.ca.gov/Statistics/PDFs/2016Report.pdf

California Department of Food and Agriculture (CDFA). (2020). California Agricultural Statistics Review, 2019-2020. https://www.cdfa.ca.gov/Statistics/PDFs/2020_Ag_Stats_Review.pdf

Castaño-Sánchez, J. P., Rotz, C. A., Karsten, H. D., & Kemanian, A. R. (2020). Elevated atmospheric carbon dioxide effects on maize and alfalfa in the Northeast US: A comparison of model predictions and observed data. *Agricultural and Forest Meteorology*, *291*, 108093–. https://doi.org/10.1016/j.agrformet.2020.108093

Challinor, A. J., Smith, M. S., & Thornton, P. (2013). Use of agro-climate ensembles for quantifying uncertainty and informing adaptation. *Agricultural and Forest Meteorology*, *170*, 2–7. https://doi.org/10.1016/j.agrformet.2012.09.007

DeBen, C., Maciel, F., Orloff, S., Culp, D., Pattigan, D., Putnam, D.H. (2016). *Agronomy Progress Report: 2016 California Alfalfa Variety Trial Results* (Report No. 323). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR323-2016-FINAL.pdf.

DeBen, C., Maciel, F., Orloff, S., Culp, D., Pattigan, D., Putnam, D.H. (2017). *Agronomy Progress Report: 2017 California Alfalfa Variety Trial Results* (Report No. 325). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR325-2017-FINAL.pdf.

DeBen, C., Bachi, O., Putnam, D.H. (2018). *Agronomy Progress Report: 2018 California Alfalfa Variety Trial Results* (Report No. 326). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR326-2018-DHP.pdf.

DeBen, C., & Putnam, D.H. (2019). *Agronomy Progress Report: 2019 California Alfalfa Variety Trial Results* (Report No. 327). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR-2019.pdf.

DeBen, C., & Putnam, D.H. (2020). *Agronomy Progress Report: 2020 California Alfalfa Variety Trial Results* (Report No. 328). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR-2020%20CMD.pdf.

De Luis, I., Irigoyen, J. J., & Sánchez-Díaz, M. (1999). Elevated CO2 enhances plant growth in droughted N2-fixing alfalfa without improving water status. *Physiologia Plantarum*, *107*(1), 84–89. https://doi.org/10.1034/j.1399-3054.1999.100112.x

Dias, M. P. N. M., Navaratne, C. M., Weerasinghe, K. D. N., & Hettiarachchi, R. H. A. N. (2016). Application of DSSAT crop simulation model to identify the changes of rice growth and yield in Nilwala river basin for mid-centuries under changing climatic conditions. *Procedia Food Science*, *6*, 159–163. https://doi.org/10.1016/j.profoo.2016.02.039

Diffenbaugh, N. S., Swain, D. L., Touma, D., & Lubchenco, J. (2015). Anthropogenic warming has increased drought risk in California. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(13), 3931–3936. https://doi.org/10.1073/pnas.1422385112

Ergon, Seddaiu, G., Korhonen, P., Virkajärvi, P., Bellocchi, G., Jørgensen, M., Østrem, L., Reheul, D., & Volaire, F. (2018). How can forage production in Nordic and Mediterranean Europe adapt to the challenges and opportunities arising from climate change? *European Journal of Agronomy*, *92*(November 2017), 97–106. https://doi.org/10.1016/j.eja.2017.09.016

Geisseler, D., & Horwath, W.R. (2016). *Alfalfa production in California* [Fact sheet]. https://apps1.cdfa.ca.gov/FertilizerResearch/docs/Alfalfa_Production_CA.pdf

Grotch, S. L., & MacCracken, M. C. (1991). The use of general circulation models to predict regional climatic change. *Journal of Climate*, *4*(3), 286–303. https://doi.org/10.1175/1520-0442(1991)004<0286:TUOGCM>2.0.CO;2

Gull, U. (2021). Quantifying the forage yield, quality, water productivity in Alfalfa under surface irrigation (SI) and sub-surface drip irrigation (SDI). Ph.D. Dissertation. University of California Davis.

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., Thomson, A. M., & Wolfe, D. (2011). Climate impacts on agriculture: Implications for crop production. *Agronomy Journal*, *103*(2), 351–370. https://doi.org/10.2134/agronj2010.0303

Hoogenboom, G. (2000). Contribution of agrometeorology to the simulation of crop production and its applications. *Agricultural and Forest Meteorology*, *103*(1–2), 137–157. https://doi.org/10.1016/S0168-1923(00)00108-8

Hoogenboom, G., C.H. Porter, V. Shelia, K.J. Boote, U. Singh, J.W. White, L.A. Hunt, R. Ogoshi, J.I. Lizaso, J. Koo, S. Asseng, A. Singels, L.P. Moreno, & J.W. Jones. (2019). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7.5 (https://DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA

International Livestock Research Institute (ILRI), International Center for Tropical Agriculture (CIAT), CGIAR Research Program on Climate Change, Agriculture, and Food Security (CCAFS). (2014). MarkSim® DSSAT weather file generator. http://gisweb.ciat.cgiar.org/MarkSimGCM/

Intergovernmental Panel on Climate Change (IPCC). (2014). Climate Change 2014: Synthesis Report. Retrieved from https://www.ipcc.ch/site/assets/uploads/2018/02/SYR_AR5_FINAL_full.pdf.

Intergovernmental Panel on Climate Change (IPCC). (2022). Summary for Policymakers. *In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Citation.pdf

Jing, Q., Qian, B., Bélanger, G., VanderZaag, A., Jégo, G., Smith, W., Grant, B., Shang, J., Liu, J., He, W., Boote, K., & Hoogenboom, G. (2020). Simulating alfalfa regrowth and biomass in eastern Canada using the CSM-CROPGRO-perennial forage model. *European Journal of Agronomy, 113*, 125971. https://doi.org/10.1016/j.eja.2019.125971

Jones, J.W., Hoogenboom, G., Porter C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., and Ritchie, J.T. (2003). The DSSAT Cropping System Model. *European Journal of Agronomy, 18 (3)*: 235–65.

Kim, J. S., & Kisekka, I. (2021). Farms: A geospatial crop modeling and agricultural water management system. *ISPRS International Journal of Geo-Information, 10*(8). https://doi.org/10.3390/ijgi10080553

Kimball, B. A. (2016). Crop responses to elevated CO2 and interactions with H2O, N, and temperature. *Current Opinion in Plant Biology, 31*, 36–43. https://doi.org/10.1016/j.pbi.2016.03.006

Kisekka, I., Aguilar, J. P., Rogers, D. H., Holman, J., O'Brien, D. M., & Klocke, N. (2016). Assessing deficit irrigation strategies for corn using simulation. *Transactions of the ASABE, 59*(1), 303–317. https://doi.org/10.13031/trans.59.11206

Lee, Juhwan, De Gryze, Steven, & Six, Johan. (2011). Effect of climate change on field crop production in California's Central Valley. *Climatic Change, 109*(Suppl 1), 335–353. https://doi.org/10.1007/s10584-011-0305-4

Liu, H. L., Yang, J. Y., Tan, C. S., Drury, C. F., Reynolds, W. D., Zhang, T. Q., Bai, Y. L., Jin, J., He, P., & Hoogenboom, G. (2011). Simulating water content, crop yield and nitrate-N loss under free and controlled tile drainage with subsurface irrigation using the DSSAT model. *Agricultural Water Management, 98*(6), 1105–1111. https://doi.org/10.1016/j.agwat.2011.01.017

Lobell, D. B., Field, C. B., Cahill, K. N., & Bonfils, C. (2006). Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. *Agricultural and Forest Meteorology, 141*(2–4), 208–218. https://doi.org/10.1016/j.agrformet.2006.10.006

Malik, W., Boote, K. J., Hoogenboom, G., Cavero, J., & Dechmi, F. (2018). Adapting the CROPGRO Model to Simulate Alfalfa Growth and Yield. *Agronomy Journal*, *110*(5), 1777–1790. https://doi.org/10.2134/agronj2017.12.0680

Marston, & Konar, M. (2017). Drought impacts to water footprints and virtual water transfers of the Central Valley of California. *Water Resources Research*, *53*(7), 5756–5773. https://doi.org/10.1002/2016WR020251

Medellín-Azuara, J., Escriva-Bou, A., Abatzoglou, J.A., Viers, J.H., Cole, S.A., Rodríguez-Flores, J.M., & Sumner, D.A. (2022). Economic impacts of the 2021 drought on California agriculture: preliminary report. Retrieved from https://wsm.ucmerced.edu/wp-content/uploads/2022/02/2021-Drought-Impact-Assessment_20210224.pdf

Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M. L. T., Lamarque, J.-F., Matsumoto, K., Montzka, S. A., Raper, S. C. B., Riahi, K., Thomson, A., Velders, G. J. M., & van Vuuren, D. P. P. (2011). The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change*, *109*(1–2), 213–241. https://doi.org/10.1007/s10584-011-0156-z

Montazar, A., Bachie, O., Corwin, D., & Putnam, D. (2020). Feasibility of moderate deficit irrigation as a water conservation tool in California's Low Desert Alfalfa. *Agronomy*, *10*(11). https://doi.org/10.3390/agronomy10111640

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., & Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment. *Nature*, *463*(7282), 747–756. https://doi.org/10.1038/nature08823

O'Green, T. (2022). *SoilWeb apps*. California Soil Resources Lab. https://casoilresource.lawr.ucdavis.edu/soilweb-apps/

Orloff, S., Putnam, D.H., Hanson, B., Carlson, H. (2005). Implications of deficit irrigation management on alfalfa. *California Alfalfa and Forage Symposium*. Visalia, CA. https://alfalfa.ucdavis.edu/+symposium/proceedings/2005/05-25.pdf

Orloff, S., Putnam, D.H., & Bali, K. (2015). Drought strategies for alfalfa. University of California Extension. ANR Publication 8522. https://anrcatalog.ucanr.edu/pdf/8522.pdf

Pathak, T., Maskey, M., Dahlberg, J., Kearns, F., Bali, K., & Zaccaria, D. (2018). Climate change trends and impacts on California agriculture: A detailed review. *Agronomy*, *8*(3), 25. https://doi.org/10.3390/agronomy8030025

Paul, M., Dangol, S., Kholodovsky, V., Sapkota, A. R., Negahban-Azar, M., & Lansing, S. (2020). Modeling the impacts of climate change on crop yield and irrigation in the Monocacy river watershed, USA. *Climate, 8*(12), 1–20. https://doi.org/10.3390/cli8120139

Putnam, D. H. (1996). History, Importance, and Production Dynamics of Alfalfa in California. Retrieved from https://alfalfa.ucdavis.edu/+symposium/proceedings/1996/96-01.pdf.

Putnam, D. H. (2015). Why alfalfa is the best crop to have in a drought. Retrieved from https://ucanr.edu/blogs/blogcore/postdetail.cfm?postnum=17721

Putnam, D.H. (2021). Variety Selection. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/index.aspx.

Putnam, D. H., Summers, C. G., Orloff, S. B. (2007). Alfalfa Production Systems in California. IN (C.G. Summers and D.H. Putnam, eds.), Irrigated alfalfa management for Mediterranean and Desert Zones. Chapter 1. Oakland: University of California Agriculture and Natural Resources

Putnam, D. H., Giannini, C., Maciel, F., Orloff, S., Culp, D., DeBen, C., Pattigan, D. (2014). *Agronomy Progress Report: 2014 California Alfalfa Variety Trial Yield Results, Including Round-Up Ready Varieties* (Report No. 320). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR320-2014.pdf.

Putnam, D. H., Giannini, C., Maciel, F., Orloff, S., Culp, D., DeBen, C., Pattigan, D. (2015). *Agronomy Progress Report: 2015 California Alfalfa Variety Trial Yield Results, Including Round-Up Ready Variety* (Report No. 322). Agricultural Experiment Station Cooperative Extension. Retrieved from https://alfalfa.ucdavis.edu/+producing/variety/apr/APR322-15.pdf.

Putnam, D.H., Gull, U., Radawich, J., Montazar, A., Bali, K. (2018). Deficit irrigation strategies: why alfalfa is the best crop to have in a drought. *Proceedings of Second World Alfalfa Congress*, Cordoba, Argentina

Rankin, M. (2022). Alfalfa suits a water-challenged future. Retrieved from https://hayandforage.com/article3786-Alfalfa-suits-a-water-challenged-future.html.

Reidmiller, D. R., Avery, C. W., Easterling, D. R., Kunkel, K. E., Lewis, K. L. M., Maycock, T. K., & Stewart, B. C. (2018). *Impacts, Risks, and Adaptation in the United States: The Fourth National Climate Assessment, Volume II*. U.S. Global Change Research Program. https://doi.org/10.7930/NCA4.2018

Rotz, C.A. (2019). Implications of climate predictions on forage production in western states. Paper presented at the 49th California Alfalfa Symposium, Reno, Nevada. https://alfalfa.ucdavis.edu/+symposium/proceedings/2019/Articles/ClimateChange_Rotz_Article.pdf

Sanz-Sáez, Á., Erice, G., Aguirreolea, J., Muñoz, F., Sánchez-Díaz, M., & Irigoyen, J. J. (2012). Alfalfa forage digestibility, quality and yield under future climate change scenarios vary with *Sinorhizobium meliloti* strain. *Journal of Plant Physiology*, *169*(8), 782–788. https://doi.org/10.1016/j.jplph.2012.01.010

Sharda, V., Mekonnen, M. M., Ray, C., & Gowda, P. H. (2020). Use of multiple environment variety trials data to simulate maize yields in the Ogallala Aquifer region: A two model approach. *Journal of the American Water Resources Association*, 1752-1688.12873. https://doi.org/10.1111/1752-1688.12873

Tanaka, S. K., Zhu, T., Lund, J. R., Howitt, R. E., Jenkins, M. W., Pulido, M. A., Tauber, M., Ritzema, R. S., & Ferreira, I. C. (2006). Climate warming and water management adaptation for California. *Climatic Change*, *76*(3–4), 361–387. https://doi.org/10.1007/s10584-006-9079-5

Tao, F., Zhang, Z., Liu, J., & Yokozawa, M. (2009). Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection. *Agricultural and Forest Meteorology*, *149*(8), 1266–1278. https://doi.org/10.1016/j.agrformet.2009.02.015

Thivierge, M.-N., Jégo, G., Bélanger, G., Bertrand, A., Tremblay, G. F., Rotz, C. A., & Qian, B. (2016). Predicted yield and nutritive value of an alfalfa-timothy mixture under climate change and elevated atmospheric carbon dioxide. *Agronomy Journal, 108(2),* 585–603. https://doi.org/10.2134/agronj2015.0484

United States Department of Agriculture (USDA). (2022). Crop Production 2021 Summary. Retrieved from https://downloads.usda.library.cornell.edu/usda-esmis/files/k3569432s/sn00c1252/g158cj98r/cropan22.pdf

University of California Division of Agriculture and Natural Resources (UCANR). (1997). Intermountain Alfalfa Management. https://cesiskiyou.ucanr.edu/files/117595.pdf

University of California Drought Management (UCDM). (2022). Alfalfa. https://ucmanagedrought.ucdavis.edu/Agriculture/Crop_Irrigation_Strategies/Alfalfa/

Vanuytrecht, E., Raes, D., Steduto, P., Hsiao, T. C., Fereres, E., Heng, L. K., Garcia Vila, M., & Mejias Moreno, P. (2014). AquaCrop: FAO's crop water productivity and yield response model. *Environmental Modelling & Software*, *62*, 351–360. https://doi.org/10.1016/j.envsoft.2014.08.005

Woodrow, I. E. (1994). Optimal acclimation of the C3 photosynthetic system under enhanced CO2. *Photosynthesis Research*, *39*(3), 401–412. https://doi.org/10.1007/BF00014594

Zaccaria, D., Carrillo-Cobo, M. T., Montazar, A., Putnam, D. H., & Bali, K. (2017). Assessing the viability of sub-surface drip irrigation for resource-efficient alfalfa production in central and Southern California. *Water (Switzerland)*, *9*(11), 1–21. https://doi.org/10.3390/w9110837