Climate change, pesticide use, and exposure disparities in agricultural communities: A case study of almond orchards in California

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A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2019

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Environmental and Occupational Health Sciences

University of Washington

Abstract

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Anthropogenic climate change is expected to influence pest dynamics and pesticide application timing and rate, but little research has attempted to quantify the relationship or associated health impacts. Changing pesticide applications will impact risk of human exposure, particularly in agricultural communities. A multi-disciplined analysis method is presented here that assesses the association between climate change and agricultural pesticide use, utilizing a combination of climate science, ecological assessment, and public health methods to examine how pesticide use has and is expected to increase with climate change, and what that entails for human health.

Presented here is a spatial and temporal assessment of the impacts of climate change on insecticide use and human health in the California Central Valley. Historical climate data was utilized to estimate degree-days and pest generations for economic pests of concern on the almond crop. Statistically downscaled climate model projections were then used to calculate pest dynamics through 2099. Results indicated an increase of one to two full generations for both pests considered in the analysis by the end of the century. Pesticide use reports were next assessed for trends in insecticide use as well as correlation with degree-days and climate. The modelled relationship was applied to climate projections to project insecticide use through 2099. Insecticide use was found to have a strong seasonal trend, with most applications occurring in the southern region; use was projected to increase throughout the entire valley by the end of the century.

A geospatial assessment of insecticide use intensity and demographics was then used to characterize populations that are more likely to be exposed to insecticides in the Central Valley. This assessment maps areas with the greatest risk of exposure potential, based on use intensity and proximity to orchards, and identifies areas that are disproportionately impacted based on social vulnerability indicators. Those living in the southern region of the valley were found to be at greatest risk of exposure, and these same communities were also found to be the most socially vulnerable. By understanding how climate change impacts vulnerable communities and human health, we can mitigate future exposure and reduce pesticide-induced disease.

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LIST OF ACRONYMS

°C	Degrees Celsius
°D	Degree-Day
°F	Degrees Fahrenheit
ACS	American Community Survey
AI	Active ingredient
CES	CalEnviroScreen
CMIP5	5th Coupled Model Intercomparison Project
CO_2	Carbon dioxide
EDC	Endocrine disrupting chemical
EPA	Environmental Protection Agency
FFDCA	Federal Food, Drug, and Cosmetic Act
FIFRA	Federal Insecticide, Fungicide, and Rodenticide Act
GCM	Global Climate Model
GDD	Growing degree day
GHG	Greenhouse gas
GIS	Geospatial information system
IARC	International Agency for Research on Cancer
ICM	Integrated cropping management
IPCC	International Panel on Climate Change
IPM	Integrated Pest Management
KM	Kilometer
MACA	Multivariate Adaptive Constructed Analogs
NASS	National Agricultural Statistics Service
NCDC	National Climatic Data Center
NIH	National Institutes of Health
NOAA	National Oceanic and Atmospheric Administration
NOW	Navel orangeworm

NTP	National Toxicology Program
PAN(NA)	Pesticide Action Network (of North America)
PBI	Pollution Burden Index
PDSI	Palmer Drought Severity Index
PLSS	Public Land Survey System
PPM	Parts per million
PTB	Peach twig borer
PUR	Pesticide Use Reporting
RCP	Representative Concentration Pathway
SD	Standard deviation
SVI	Social Vulnerability Index
TIGER	Topologically Integrated Geographic Encoding and Referencing
TRI	Toxic Release Inventory
UC	University of California
USDA	United States Department of Agriculture
W/M^2	Watts per meter-squared
WHO	World Health Organization

ACKNOWLEDGEMENTS

No Man is an Island, and no dissertation is completed without a community of support and guidance. First and foremost, I am deeply grateful for those on my doctoral supervisory committee. To my advisor and Committee Chair, Edmund Seto, thank you for your patience, mentorship, practical advice, and continued support these past few years; I would not be standing here today without your help. Michael Yost, your advice to follow my interests rather than the paved road was difficult at times, but I am forever grateful that I listened to your words and forged my own path through the woods. Kristie Ebi always provided kind edits and feedback, and this project turned out better for her excellent guidance and expert knowledge on climate change. Richard Fenske kept this project on the ground from day one, and I am incredibly appreciative for his early direction towards those that would help me successfully complete this dissertation. Joshua Lawler from the College of the Environment served as Graduate School Representative.

This dissertation was supported through various funding sources, but a special thank you is warranted to Charles Stevens, who believed in me and the importance of this project and gave a private donation to the University of Washington School of Public Health and Department of Environmental and Occupational Health Sciences to ensure its completion.

Last, but certainly not least, I would like to thank my family and friends for their support, commiseration, and constant prodding to get this dissertation completed. To my parents, I can’t thank you enough for the gift of education, and the drive to pursue the grandest of dreams. Most importantly, to my wife Ellie, who was my sounding board, editor, and unwavering pillar of support through this entire process – thank you.

DEDICATION

To Ellie – the greatest adventure partner anyone could wish for.

Chapter 1. INTRODUCTION

There is broad scientific consensus that climate change is not only a direct consequence of anthropogenic influences but is a current reality and threat to global ecosystem integrity and public health. Increasing concentrations of carbon dioxide (CO_2) and other greenhouse gases (GHGs) are trapping progressively more solar radiation in the Earth's atmosphere, leading to a net warming of the planet. In 2013, the Intergovernmental Panel on Climate Change (IPCC) released the most recent report on the observations and projections of changes in the global climate, indicating a past and future trend of rapidly increasing global temperature[1]. Global mean temperatures have increased unequivocally and more rapidly over the last three decades compared to all previous decades, with all ten of the warmest years in the global instrumental temperature record occurring since 1998, four of which have occurred since 2014[2].

In 2017, global average warming reached approximately 1°C compared to pre-industrial levels, which has considerable consequences[3]. This trend is expected to continue if largescale mitigation actions are not taken, with future projection models indicating a trend of 1.5°C by 2050 and up to 5.5°C global temperature rise by the end of the 21st century, as CO_2 equivalent concentrations – a measure used to compare emissions of GHGs in a common unit – increase from present day levels of roughly 493 parts per million (ppm) to between 480 ppm and 1,200 ppm[4,5,6]. Rising sea levels, declines in snow and ice extent, changes in precipitation, and more extreme weather events are consistent with this warming and are now evident from observations of the Earth's continents and oceans. These climatic changes are expected to affect human health, through impacts on the incidence, geographic range, and seasonality of a range of climate-sensitive health outcomes, as well as through changes in human behavior and practices.

In particular, climate change is expected to shift the quality and quantity of agricultural products and arable land. Changes in crop type or fallowed fields and longer growing seasons will likely influence pest dynamics and pesticide application timing and rate[7,8]. Agricultural pesticide treatments have the potential to result in non-occupational exposures, such as to farming and non-farming residents in agricultural communities, and to family members of agricultural workers through pesticides brought home on skin, clothing, and work boots[9]. Previous studies have found that pesticide metabolite concentrations in the urine of preschool children in an agricultural community were greater during times of active pesticide spraying than during non-spray months, regardless of proximity to farms[10]. Median dust concentrations of pesticides in the homes of agricultural families and urine metabolite levels have also been found to be several magnitudes higher than non-agricultural families in the community, which were even greater in those living near treated orchards[11]. Children are more vulnerable to pesticide exposure, and those living in agricultural communities bear the burden of higher pesticide exposure compared to the rest of the population.

Agricultural use of modern pesticides has become widespread since the beginning of the Green Revolution, during which global grain production doubled and food shortages were drastically reduced[12]. However, this came at the expense of high use of pesticides, which are now used in such immense quantities that exposure to various mixtures of these chemicals is nearly ubiquitous among the world's populations. It has been hypothesized that climate change will both directly and indirectly affect exposure to these chemicals.

1.1 CLIMATE CHANGE AND AGRICULTURAL PESTICIDE USE

Agriculture and pesticide use are strongly dependent on climate. Crop yields and distribution rely on CO_2, temperature, precipitation, and humidity, all of which are geographically dependent and impacted by changes in the climate[13-17]. Higher temperatures cause temporal shifts in plant growth patterns[13]; the increasing global minimum temperatures expected with climate change will lengthen the growing season of some crops, especially in Mediterranean environments where growth is often limited by low winter temperatures[14]. These temperature changes, along with deviations in rainfall patterns, may alter current land use for agricultural purposes. Farmers may choose to grow crops more suited for the current/future climate, or let fields fallow as water availability fluctuates or becomes scarce. Crops once grown in specific regions due to their favorability of the local climate may redistribute to areas where the climate has become more conducive for their growth and sustainable crop yields.

Additionally, the distribution, abundance and performance of plant pathogens, pests, and invasive species are driven by anthropogenic environmental change. The importance of climate on pathogens and pests has been observed for thousands of years, and it is well understood they have varying responses to factors such as atmospheric CO_2, increased humidity, drought, heavy unseasonal rains and storms, and warmer winter temperatures[14]. Atmospheric CO_2 affects plant transpiration and growth; increased levels are likely to increase leaf waxes and epidermal thickness as well as photosynthetic rate, suggesting better growth and resistance to pests and pathogens[13,14]. However, the same high CO_2 levels (and therefore higher temperatures) may also increase humidity in some areas, providing a better reservoir and favorable conditions for pathogens. Water and temperature stress increases susceptibility for infection, so climate change may consequently allow pre-existing pathogens to emerge as major disease agents or provide the conditions necessary for emerging infectious diseases to thrive[18]. The life cycle of some pathogens and pests are also likely to be affected by climate change. Warmer temperatures may expand or limit the life cycles of pests, or hinder reproduction rates and generation numbers. Greater winter survival rates will correspondingly lead to an abundance of pests in the spring and emergence earlier in the growing season, which will be intensified by extended development times in the summer[18-24]. A warming climate will also expand the areas where pests can establish permanent populations, allowing them to invade agricultural areas outside their historic ranges; the ranges of several important crop pests and pathogens have in fact already expanded northward[25-28]. These changes will require considerable adaptation in existing pest management strategies.

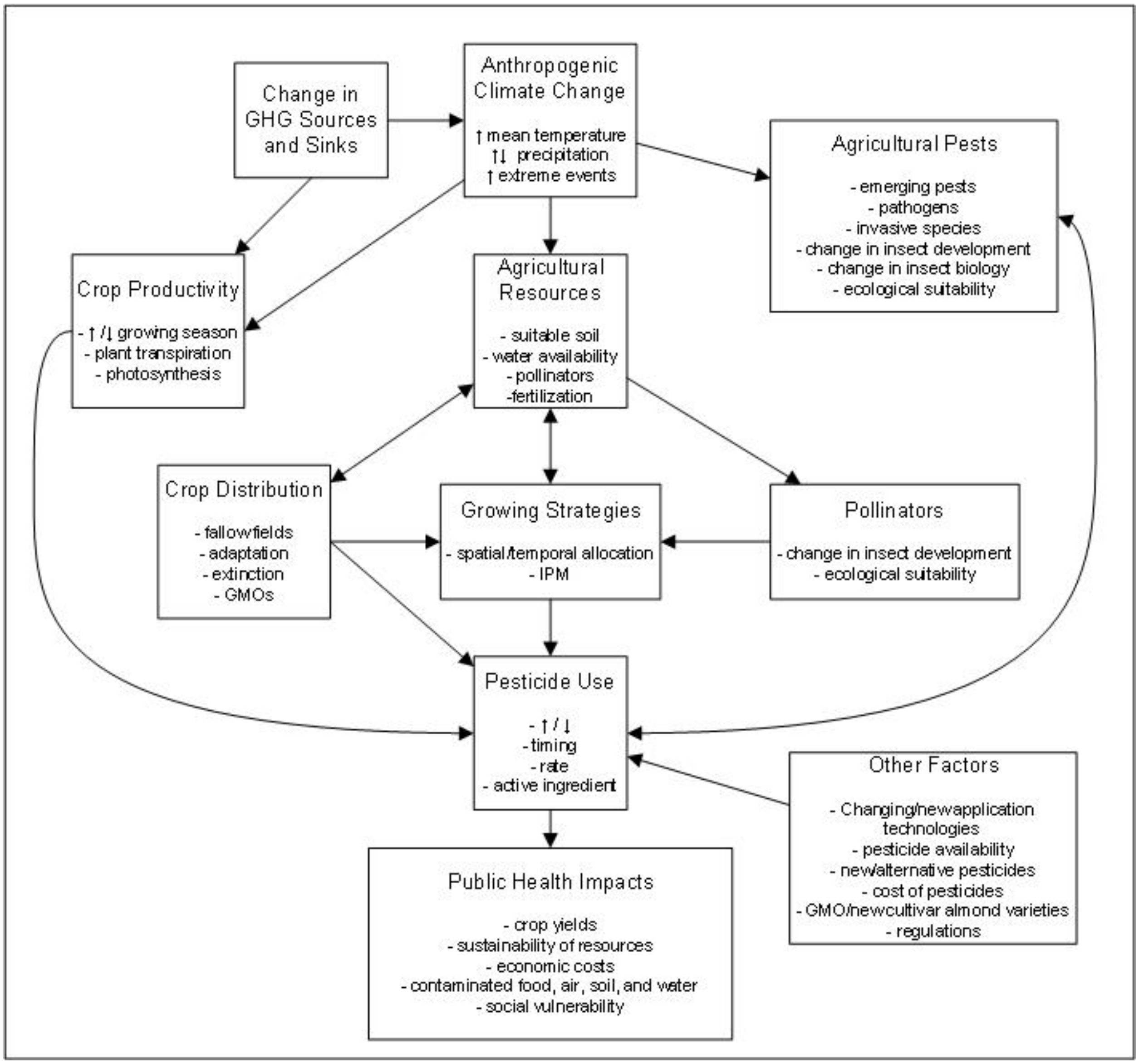


Figure 1.1. Climate change, agriculture, pests, and pesticide relationships.

Changes in ambient temperature have also been found to alter the toxicity of insecticides such as organophosphates, carbamates, and pyrethroid insecticides to insects[29-36] by altering the rate of chemical uptake, metabolism, depuration, and pesticide toxicity[37-42]. Growers will potentially respond to these changes in pests and pesticide efficacy by using more non-chemical pest control methods such as integrated pest management, or by increasing their pest monitoring and pesticide use, possibly switching to more toxic compounds as other chemicals become less effective, or through resistance management strategies. The relationship between climate change and pesticide use is therefore complex and depends on many factors and assumptions (**Figure 1.1**). This has significant implications for the profile of human exposure to pesticides, which warrants investigation of potential impacts in agricultural regions.

1.2 CLIMATE CHANGE AND CALIFORNIA AGRICULTURE

The Central Valley is the most agriculturally rich area of California, as well as one of the most climate sensitive. It stretches 450 miles through the state from Shasta to Kern County and is approximately 40 to 60 miles wide, covering nearly 20,000 spatially diverse square miles[43]. Climate is therefore highly variable across the region and represents a diverse range of climate zones and microclimates, each with its own unique pest complex. It spans through the North Mountains, Sacramento Valley, and San Joaquin Valley, bounded by the Cascade Range to the north, the Sierra Nevadas to the east, the Tehachapi Mountains to the south, and the Coast Ranges and San Francisco Bay area to the west. Geographically, the Central Valley is often divided into northern and southern regions to reflect these differences; the northern third is known as the Sacramento Valley, and the southern two-thirds as the San Joaquin Valley, which is further split into the San Joaquin Basin and Tulare Basin (**Figure 1.2**)[44,45]. The area where the northern and southern portions meet is known as the Delta.

Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Figure 1.2. Map of the Central Valley's major climatic regions in California.

1.2.1 *Climate change impacts in California*

1.2.1.1 Emission scenarios and models

Climate change impacts on California have already been assessed[46,47]. Two Representative Concentration Pathways (RCPs) were used in this assessment – RCP8.5 (higher concentrations of GHGs) and RCP4.5 (moderate concentrations). RCP4.5 is a stabilization scenario and refers to the possible climate future where an additional 4.5 watts per square meter (W/m^2) is trapped in the atmosphere by 2100 relative to pre-industrial conditions from emission of GHGs; total radiative forcing is therefore stabilized after 2100, resulting in a CO_2 concentration of approximately 550 ppm[5]. In order for this scenario to be met, major changes in the energy system would need to occur, such as shifts to electricity over fossil fuels and lower emissions technologies, as well as use of carbon capture and geologic storage technology[48]. On the other hand, RCP8.5 refers to an additional 8.5 W/m^2 trapped in the atmosphere – a future where no action is taken to reduce carbon footprint and emissions consequently increase over time, commonly referred to as the business-as-usual pathway that results in CO_2 concentrations well over 900 ppm. This scenario assumes high population growth and relatively slow income growth, leading to high energy demands and GHG emissions, in a future with no climate change policies[49]. Other standard RCPs include RCP2.6, and RCP6.5, representing increases in end of century radiative forcings of 2.6 and 6.5 W/m^2, respectively. The RCP2.6 scenario is a relatively low GHG emission scenario, but it is favored by countries participating in the Paris Agreement as it would hopefully limit average global warming to 1.5°C; while this target scenario is feasible, it would require aggressive reductions in GHG emissions as well as carbon removal strategies, and participation of all major polluting countries[50].

These two pathways were run with ten global climate models (GCMs) – the ten models were selected by the California Department of Water Resources as being the most suitable for California water resource climate change studies[51]. Climate model sensitivity is a measure to characterize how the global climate system responds to a given forcing (factors that change global temperature directly, such as GHG's, volcanoes, and air pollution), with the response being equilibrated global mean surface temperature following a doubling of atmospheric CO_2. Choosing a set of several models, ideally selecting ten, allows a range of future climate change projections as well as capturing more uncertainty in future concentration pathways. The outputs of these models simulate both historical and projected climate variables, such as temperature and precipitation, and other climate outcomes such as relative humidity and soil moisture.

The climate assessment showed historical trends of warming temperatures, rising sea levels, declining snowpack, and increasing acres burned by wildfires[47]. The projections indicated a continuation of those trends, as well as an increase in intensity of heavy precipitation events, and an increase in the frequency of drought. Annual average temperatures in California have already increased by more than 1°C, with some areas exceeding 2°C. By mid-century, annual average temperature is expected to increase to between 4.4°F and 5.8°F, and up to 5.6°F to 8.8°F towards the end of the century. Precipitation is projected to increase slightly in the northern part of the state, whereas southern regions will become drier. However, precipitation is highly variable in California, and many models project less frequent but more extreme daily precipitation, while the number of drought years increases. These temperature and precipitation variations consequently impact water availability. A decrease in winter precipitation results in less snowpack in the Sierra Nevada Mountains, and an increase in temperature results in earlier runoff, which subsequently decreases stream flow and water storage and supply[52]. The snowpack acts as a natural reservoir during the spring and summer, and its decline effects surface water supplies, forcing a reliance on groundwater.

1.2.1.2 Impacts on irrigation

Despite these projections, California's water system is capable of adapting, although this will come with costs to agriculture: transfers of water rights, new and costly technology, and a shift in how California operates its groundwater storage[53]. Because population growth is expected to increase along with these changes in climate, this puts a significant strain on the system. The Central Valley is very susceptible to future climate changes. The hydrology of the watershed in this region is highly sensitive to changes in precipitation and temperature, and the area has less opportunity to withstand these changes without adaptation. Due to the importance of agriculture in this area, it is likely that farmers will adopt cheaper water management strategies and alter their crops, acreage, or cultural farming techniques in an effort to adapt to the changes in precipitation and temperature, as well as the likelihood of more drought years.

There are four main types of irrigation typically used in agriculture: surface (flood and furrow), sprinkler, drip, and subsurface. Those that are more resilient to drought and climate impacts are non-surface methods, as surface methods lose more water to evaporation. Drip technologies have, in fact, become one of the most popular irrigation technologies over the last decade, as they are exceptionally efficient and easy for growers to transition over to; California's State Water Efficiency Enhancement Program even provides grants for growers looking to switch to more efficient irrigation technologies[54].

1.2.1.3 Impacts on crop yields

One avenue climate change impacts California agriculture is thus through an increasing demand for irrigation, as well as through direct temperature effects on crop yields. Perennial crops are less adaptable and depend on a reliable water supply, which until now has come from the snowpack and available surface water[55]. Periodic droughts lead to large reductions in crop yields, which has large economic implications for many areas in California, as perennial crops are a multi-billion-dollar industry. Despite uncertainties in the climate models, it is likely these changes will decrease yields of almonds, walnuts, avocados, and table grapes between 0% to 40% by 2050 – depending on the crop, emission pathway and global climate model used in the assessment – if no adaptation measures are implemented[55]. It is therefore important for highly agricultural counties and farmers to consider adaptation strategies, such as changing irrigation technologies and crop mix in order to reduce the costs related to climate change. On a similar note, climate change will impact chill hours, the necessary cold temperatures during winter months to break dormancy of fruit and nut trees. Warming temperatures will lead to a decrease in the number of chill hours each season, which may delay pollination and foliation, reduce crop yields, as well as quality of yields[52].

1.2.2 *California agriculture and almonds in the Central Valley*

According to the US Department of Agriculture (USDA), the Central Valley is the largest agricultural producer in the United States, contributing greatly to the state's economy[56]. In 2017, over 77,000 farms operated in California[57], producing over $50 billion in cash receipts, mostly from dairy and specialty crops (almonds, and grapes)[58,59]. Almonds are primarily grown in the Central Valley in the San Joaquin and Sacramento Valley (**Figure 1.3**)[45,60]. Since 2000, the value of almond production increased by over 600% due to increased production and price[61-63], and it continues to increase, primarily due to the increased price of almonds. Price per pound has soared from $0.97 in 2000 to $4.00 in 2014 – nearly doubling in four years[61,62]. Almond production has increased proportionately; between 2000 and 2016, the number of acres planted increased from 610,000 to over 1.6 million[61,63]. California now produces over 80% of the world's almonds.

Because of the recent success of almonds, growers are choosing to invest in the almond crop in the Central Valley, which has significant implications for farming methods given the climate change predictions. Almond production is strongly dependent on weather conditions such as temperature and rainfall. As a perennial crop, they are highly reliant on water, particularly young trees not yet established. For a successful yield, irrigation and amount of water supplied to the trees is significantly important. To help growers manage water resources, the Almond Board of California has developed the Almond Irrigation Improvement Continuum, essentially a manual of responsible and efficient irrigation management practices[64]. Currently, approximately 70% of

California almond orchards self-report they employ microirrigation, assessing evapotranspiration and soil moisture in order to make irrigation decisions. Ideally, all growers will utilize efficient irrigation methods, moving up the continuum to more advanced practices. Besides water resources, almonds are also dependent on receiving enough winter chill hours for a successful crop. Additionally, almond trees persist across multiple growing seasons with a typical lifespan of 30 years, making them less adaptable to climate change[55,65,66]. Given the investment in almonds and their value to the economy, producers therefore have strong incentive to protect the crop[67].

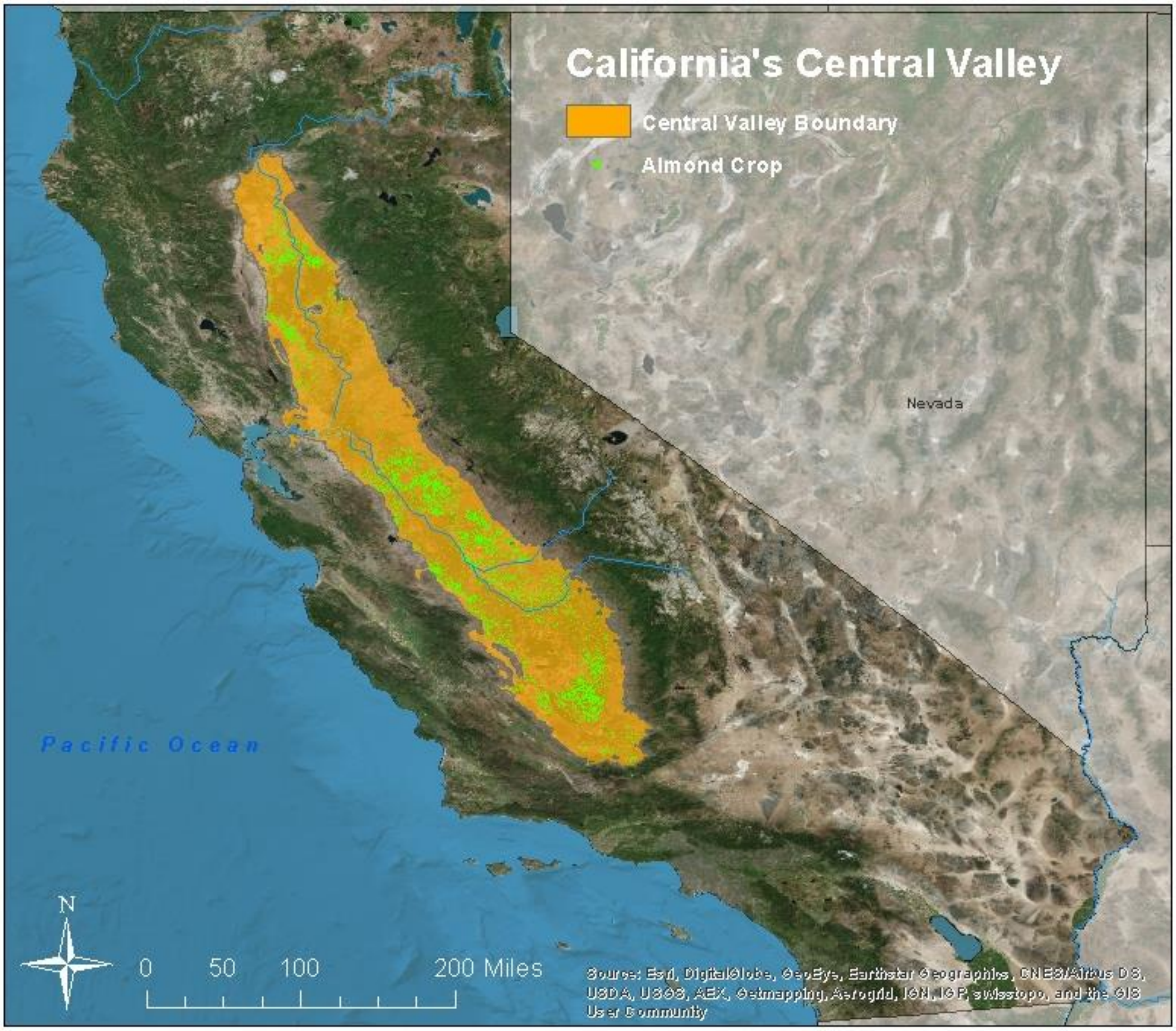


Figure 1.3. Almond acreage in California.

1.3 CALIFORNIA AGRICULTURE, ALMONDS, AND INSECTICIDE USE

1.3.1 *Historical pesticide trends*

Global pesticide production has been steadily increasing since the early 1940's, as has global crop and pasture land[68]. Assuming a continuation of past agricultural practices (fertilization, irrigation, and pesticide application), global pesticide production will be 1.7 times greater than 2000 levels by 2020, and up to 2.7 times greater by 2050[68]. Pesticide use in California varies from year to year, depending on specific pest issues, weather, and crops grown. Past assessments have found only 19 crops account for nearly 85% of all pesticide use (in pounds)[69] most of which are applied on grapes, tomatoes, and almonds. However, pesticide use patterns are changing. This is due to changes in crops and cropping acres, new pests and predators, pesticide resistance leading to an increase or change in use to offset reduced efficacy, how pesticide users make their decisions for application, new application technologies (e.g. unmanned aerial systems, or drone), and new chemical regulations. This complex web of economics, environmental factors, and the decisions of thousands of growers and professional pest managers affects pesticide use trends throughout California and is important to consider when modeling future pesticide use, although potentially difficult to model. By focusing on insect pests on one crop in the Central Valley, some of these confounding factors can be controlled for (e.g. changes in crops), and the relationship applied to other perennial crops. For all other trends, it may only be possible to assume a business-as-usual trend for projecting future use.

Pesticide use has been generally declining in California across all crops. From 1995 to 2010, the total amount of pesticides applied decreased from 211,798,752 pounds in 1995, followed by 187,566,933 pounds in 2000, to 194,310,983 pounds in 2005, and 173,213,823 pounds in 2010[70]. It should be noted that the total pounds of pesticides used is not an accurate indicator of the extent of pesticide use, particularly because it does not consider the amount of changing farmland or the potential increase in planted acres of crop. ‘Pounds per acre’ takes into consideration the size and/or number of fields being treated in each area, which controls for changes in field size and allows for comparison between areas with different numbers of planted crop acres.

Overall, the amount of land being treated with pesticides is also declining in California. This may be due to an increase in organic farming, which touts being pesticide free, an increase in alternative and non-chemical treatments, or changes in state regulations. Of course, the decrease in pesticide use could also be due to shifts in crop patterns and declining yields as a result of climate changes. Farmers may be choosing to grow crops that are less water reliant and require fewer pesticides, or that can withstand the rising temperatures. The introduction of many genetically modified crops may also have slowly decreased the need for chemical management of pests. Cost of pesticides and changes in pesticide application technology are also examples of why pesticide use could have decreased and may possibly continue to decrease in the future.

1.3.2 *Pesticide use trends on almonds*

Pesticide use on almonds has fluctuated in recent years. The total reported pounds of all active ingredients have wavered between 23,222,357 in 2012, 29,958,040 in 2013, 25,925,406 in 2014, 35,620,665 in 2015, to 35,357,726 pounds in 2016[62]. Similarly, the number of acres treated has fluctuated, following the same increase as total pounds applied, suggesting a steady amount applied to increasing acreage. Insecticide use has recently spiked on almonds and is now the most heavily used pesticide type (compared to herbicides, fungicides, and fumigants), in terms of number of acres treated (**Figure 1.4**)[62]. As can also be noted in the figure, a significant increase in pesticide use, particularly insecticides, has occurred since 2005. Insecticide use has more than tripled in 2016 compared to the 1997 – 2005 average. Many of the almond pests have become resistant to certain insecticides[62]; almond growers have therefore tried to diversify the pesticides used on their crops under the advisement of pesticide control management. This has led to the increased use of methoxyfenozide and chlorantraniliprole, as resistance to pyrethroid insecticides has risen (**Figure 1.5**)[62].

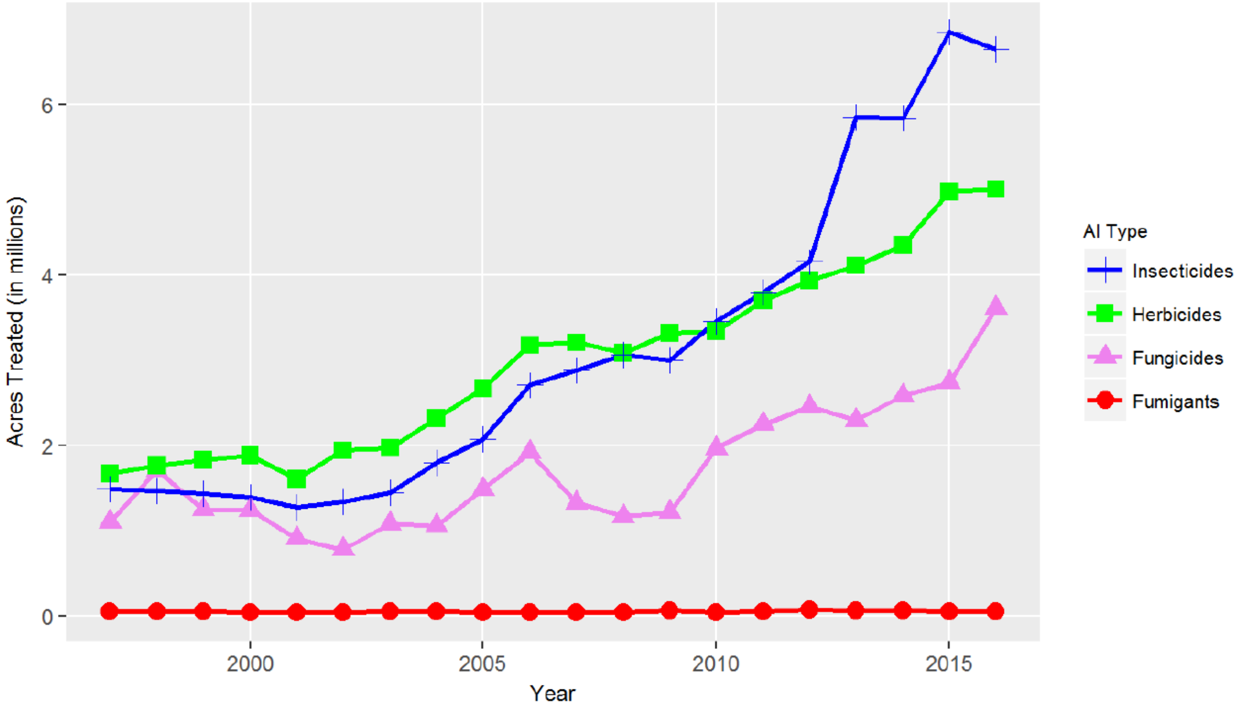


Figure 1.4. Acres of almond treated by active ingredient for all pesticides, 1997 – 2016.

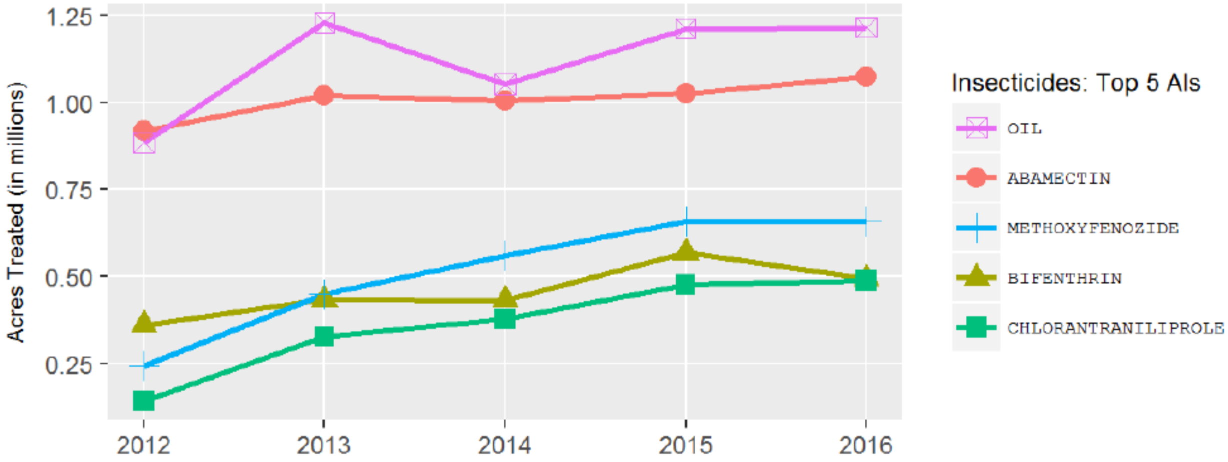


Figure 1.5. Acres of almond treated by active ingredient for top five insecticides, 2012 – 2016.

1.3.3 *Almond pests of concern*

Major almond pests include navel orangeworm (NOW), ants, mites, peach twig borer (PTB), and San Jose scale. NOW is the primary pest of concern, controlled primarily through the use of methoxyfenozide[62]. **Table 1.1** lists recommended insecticides for these pests from the University of California Integrated Pest Management (UCIPM) program[71]. The NOW, PTB, and San Jose scale have previously been assessed for climate change vulnerability in California, and for all it is expected there will be an increase of about one generation per growing season by 2050, and 1.5 generations by the end of the century; a greater increase in generations per season is expected for pests in the south[72]. However, this previous assessment is limited in the choice of phenology models used to estimate number of generations, the use of outdated climate models and scenarios, a limited selection of climate models (three compared to the recommended ten) for the projections, and the choice of using coarse global climate model output. Further study is needed to determine if the use of more (and updated) statistically downscaled climate models might capture more variability in future generation predictions as well as give more fine-scale estimations.

According to the UCIPM, the NOW adult moth is silver-gray and black with a snout like projection on its head. Females begin laying eggs about 2 nights after emergence as an adult on mummy or new crop nuts after hullsplit, and hatch anywhere between four and 23 days depending on environmental conditions. There are currently three to four generations per year (**Figure 1.6**)[73]. Once eggs reach larvae stage, they bore into the nutmeat of the almond, consuming most of the nut and producing webbing and excrement. The pest can largely be controlled for by removing mummy nuts after harvest in order to decrease overwintering, as well as spraying in the spring and at hullsplit, setting egg and pheromone traps, and post-harvest fumigation. The PTB is a steel gray mottled moth. Females lay eggs on twigs, fruit, and leaves, which hatch in four to 18 days. There are four generations per year (**Figure 1.7**)[73]. The larvae damage growing shoots and nuts, leaving shallow channels and grooves on the nutmeat. The pest can be controlled biologically through known natural enemies, organically spraying, or using insecticides at bloom and/or in the spring.

Table 1.1. Most effective insecticides for the navel orangeworm, peach twig borer, and San Jose scale – including dormant, delayed-dormancy, bloom, spring sprays, hullsplit and post-hullsplit sprays, mating disruptants, and postharvest – as recommended by the UCIPM, in order of preference. For PTB and San Jose scale, it is recommended to apply with a dormant oil.

Navel Orangeworm	Peach Twig Borer	San Jose Scale
Methoxyfenozide	Spinosad	Narrow Range oil
Chlorantraniliprole	Spinetoram	Pyriproxyfen
Flubendiamide	Chlorantraniliprole	Buprofezin
Spinetoram	Flubendiamide	Carbaryl
Emamectin benzoate	Narrow Range Oil	Chlorpyrifos
Flubendiamide + Buprofezin	Diflubenzuron	
Spinosad	Acetamprid	
Bacillus Thuringiensis	Esfenvalerate	
Bifenthrin	Bifenthrin	
Lamdba-Cyhalothrin	Cyfluthrin	
Chlorantraniliprole + Lambda-Cyhalothrin	Lambda-Cyhalothrin	
	Methoxyfenozide	
Fenpropathrin	Bacillus Thuringiensis	
Esfenvalerate	Ememectin benzoate	
Chlorpyrifos	Flubendiamide + Buprofezin	
Phosmet	Chlorpyrifos	
Aluminum phosphide		

The San Jose scale is a bright yellow mobile nymph (a type of insect), roughly the size of a pin head. There is no visible egg stage; the crawlers settle at a feeding site, losing their antennae, legs, and eyes. Once immobile they secrete a waxy substance over their body. There are three to four generations per season. The scales suck juice from the twigs and limbs, injecting a toxin which results in loss of tree vigor, growth, and productivity. This often results in death of the tree limb, and if left untreated, an infestation can kill fruit spurs (branches that bear flower buds and fruit) and scaffold wood within one to three years. The pest can be controlled biologically through natural enemies, organically-approved oil sprays, and dormant sprays.

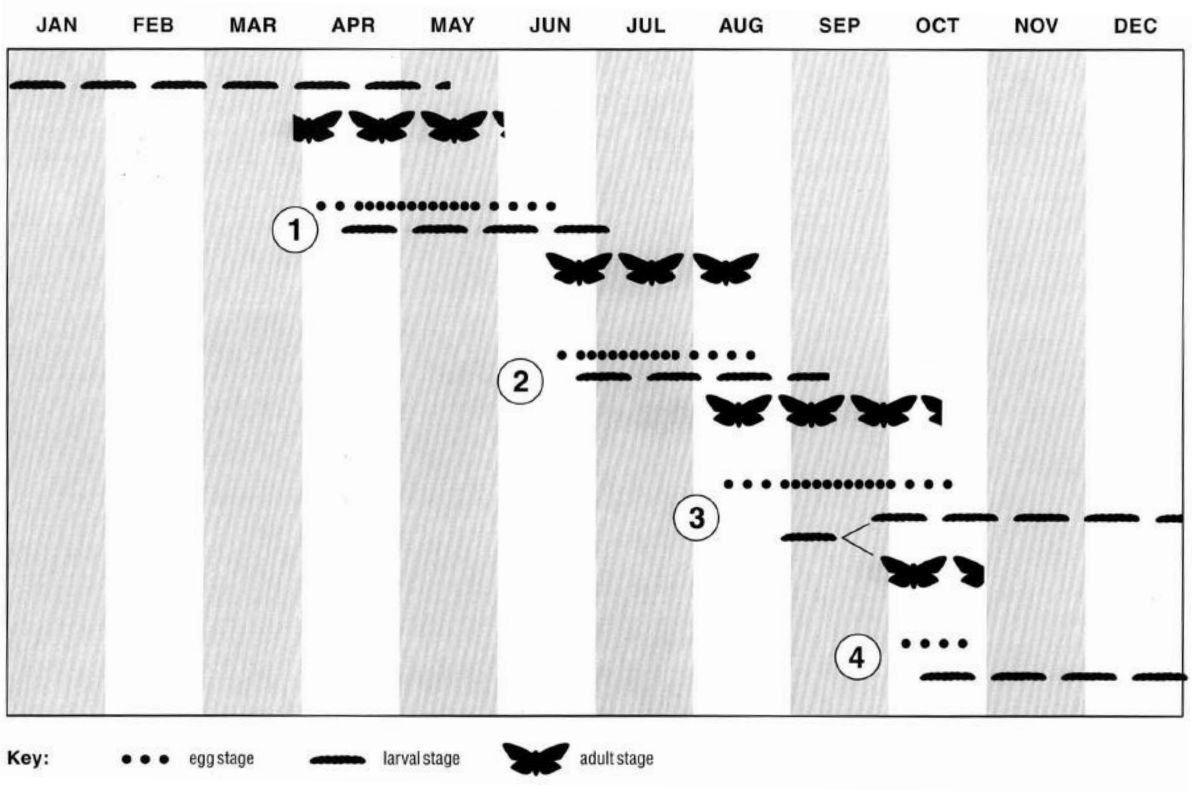


Figure 1.6. Seasonal development of the navel orangeworm.

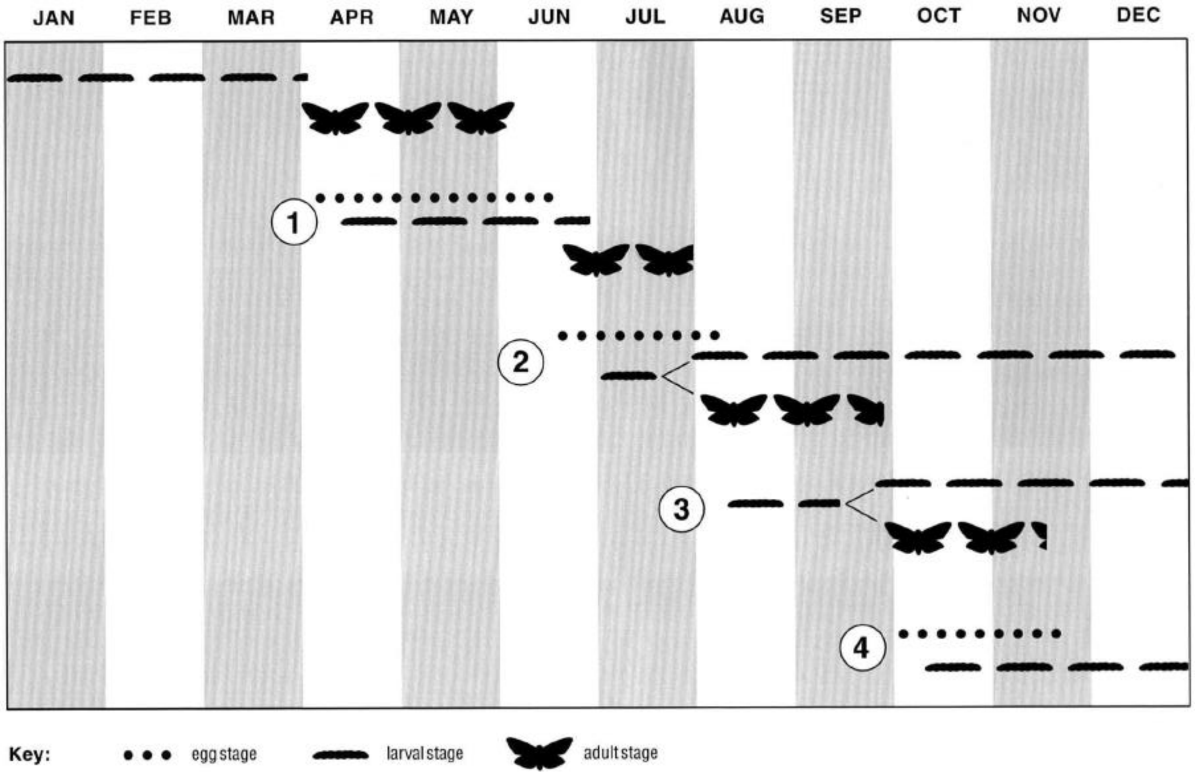


Figure 1.7. Seasonal development of the peach twig borer.

1.3.4 *Pest development*

The developmental rates of these agricultural pests are controlled through temperature. There is a total amount of heat accumulation needed, between a lower and upper threshold, for an organism to develop from one life-cycle stage to another; this combination of temperature and time is known as the degree-day (°D). Degree days are the accumulation of heat and time between developmental thresholds for each day – one degree day is accumulated when the temperature is above the lower threshold by one degree for 24 hours (**Figure 1.8**)[74]. Each organism typically has its own developmental thresholds, determined through laboratory and field experiments. Below the lower threshold, development of the organism typically stops; this value is directly related to the organism's physiology. The upper threshold is the temperature above which development begins to slow or stops completely, depending on the cut-off method used to calculate the degree-days. These days accumulate throughout the growing season, each organism requiring a specific number of accumulated degree days to complete its developmental cycle.

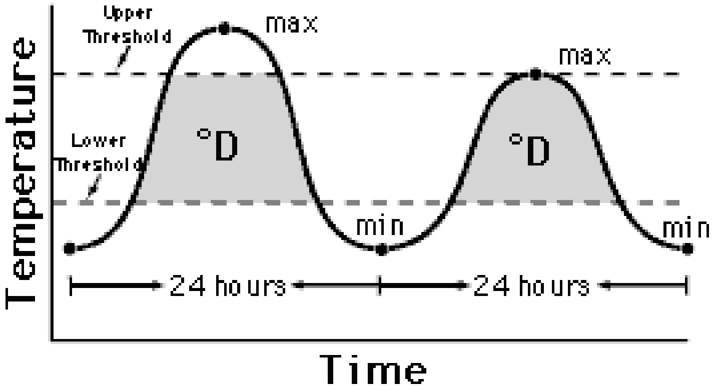


Figure 1.8. Pest temperature thresholds and accumulated degree-days.

There are several methods to calculate a degree-day – single and double sine, and single and double triangle (**Figure 1.9**)[74]. Each method approximates the number of degree-days based on daily temperatures and upper and lower developmental thresholds. Triangle methods draw a straight line between the daily minimum and maximum temperature, and then assumes the following day's minimum temperature is the same in order to draw another straight line, forming a triangle. The double triangle method uses two half-day calculations, drawing a straight line between the daily minimum and maximum temperature, and a second line vertically through the maximum temperature to form two sides of a triangle; the same triangle is then created for the second half-day. Degree-days are calculated by summing the area within the triangles, and between the upper and lower thresholds. Sine methods use the daily maximum and minimum temperatures to create a sine curve over the day's temperatures, calculating the degree-days by summing the area above the lower threshold and below the curve. The double sine method fits two sine curves – one from the minimum to maximum daily temperature, and a second from the maximum daily temperature to the minimum temperature of the following day.

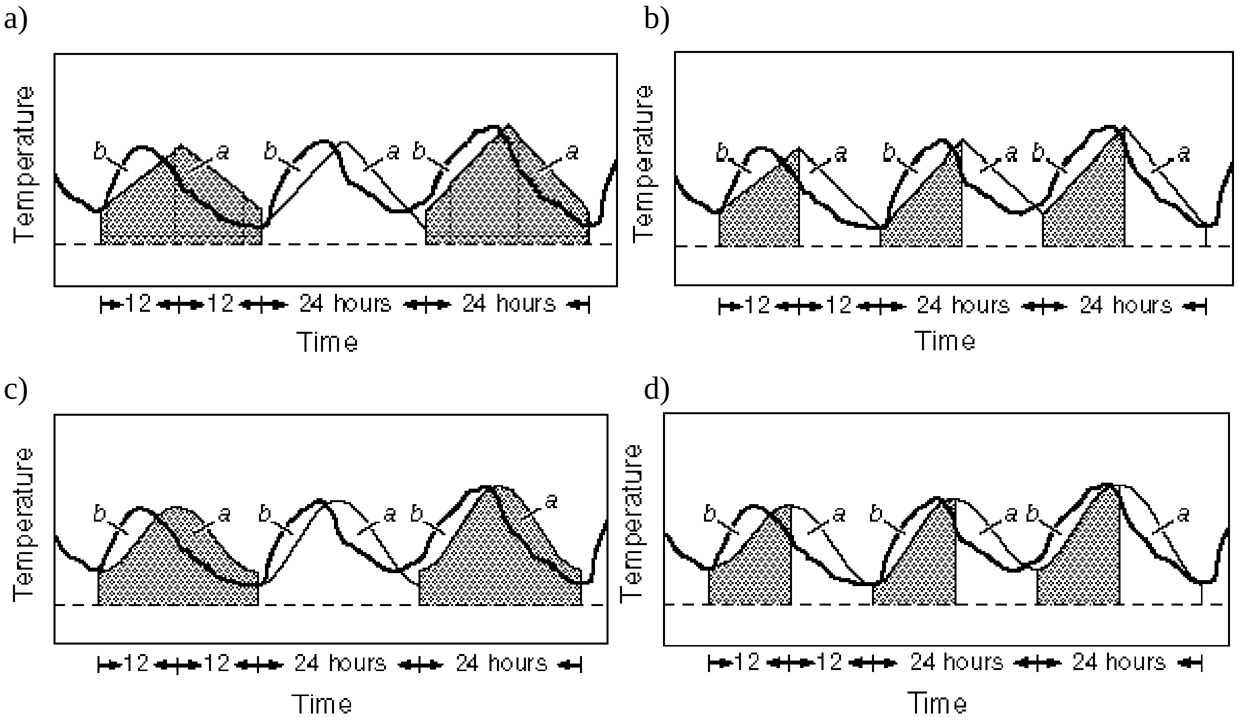


Figure 1.9. a) Single and b) double triangle method of accumulating degree-days. c) Single and d) double sine method of accumulating degree-days.

Once the calculation method is determined, there are three developmental cutoff methods to choose from, which refer to how the upper temperature threshold is treated in relation to the triangle or sine curve around the diurnal temperature (**Figure 1.10**)[74]. The horizontal method assumes that pest development continues at a constant rate at temperatures above the upper threshold. The intermediate method assumes that pest development slows at temperatures above the upper threshold but does not stop. The vertical cutoff method assumes that no pest development occurs at temperatures above the upper threshold.

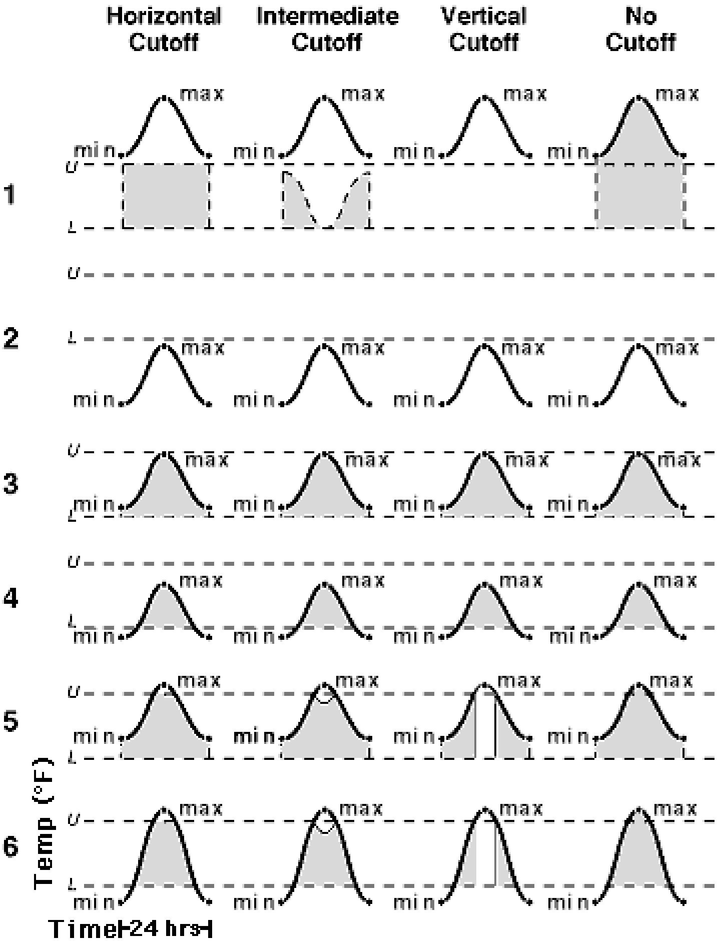


Figure 1.10. Cutoff method relationship between diurnal temperature cycle and the upper and lower thresholds. 1) Above both thresholds, 2) below both thresholds, 3) between both thresholds, 4) intercepted by the lower threshold, 5) intercepted by the upper threshold, and 6) intercepted by both thresholds.

In order to begin accumulating degree-days to use in pest phenology models, a starting date must be defined. This date is often an observed biological event, such as a planting date, first trap catch, or the first noted occurrence of a pest[74]. When a biological event is used, it is referred to as a biological fix point, or 'biofix'; this date varies with the species of pest. Alternatively, a calendar date can be used to begin the accumulation of degree-days. This date is often early in the season, before degree-day accumulation typically begins due to cooler daily maximum temperatures. Using a biofix date rather than a calendar date usually gives a better prediction of when a developmental state will be reached for the pest, as it better synchronizes the phenology model to differing environmental and field conditions that affect pest emergence and developmental rate.

1.4 PESTICIDE EXPOSURE AND HUMAN HEALTH

Investigation and quantification of the link between pesticide use and climate change has substantial public health relevance, as pesticide use is extensive and popular. Many of the chemicals are persistent, meaning they do not break down into safer compounds but rather remain intact in the environment for prolonged periods of time, making them readily accessible for human exposure. This environmental persistence can be illustrated by the fact that biomonitoring studies have revealed detectable levels of previously banned pesticides in the majority of people living in the United States[75]. By their very nature, pesticides are designed to kill certain organisms, and thusly pose a continuous human health hazard. Some pesticides may affect the nervous system, they may be carcinogens, they may affect the hormone or endocrine system in the body, or they may simply be irritants to the skin and eyes. But for the most part, pesticides are toxic and persistent, and are often extremely harmful to human health.

Many health geography studies have linked proximity of residents to pesticides with certain neurological diseases or cancer. In one California study, pesticides were found to play a role in the neuro-degenerative process that leads to Parkinson's disease, with those living in agricultural counties showing an increased mortality rate from the disease[76]. Pesticides may also cause an increased risk of cancer through various toxicokinetic properties, resulting in mutagenicity, tumor promotion, immunotoxicity, or hormonal disruption. Germ cell tumors, non-Hodgkin's lymphoma, and Burkitt Lymphoma have been seen at elevated levels in those living at closer residential proximity to cropland[77,78], and similar relationships have been found for leukemia[79,80]. Mothers living near cornfields during gestation or at delivery are more likely to give birth to babies with limb malformations, neural tube defects, and congenital malformations that result in death[78]. Likewise, maternal residence has been linked to autism spectrum disorders in children living in agricultural areas of the Central Valley of California[81].

1.4.1 *Pesticide classification and regulation*

The health effects of pesticides depend on the type and active ingredient. Each pesticide can be placed into one of four general types: insecticides for controlling insect pests, rodenticides for controlling rodents, herbicides for controlling weeds or desiccating plants, and fungicides for controlling pathogens[82]. Insecticides include organochlorines (such as DDT, aldrin, dieldrin, endrin, lindane, and chlordane among others, which are typically not acutely toxic but may interfere with natural hormonal activities), anti-esterases (organophosphates and carbamates, which were derived from nerve gases developed in World War I and typically affect the nervous system with varying toxicity), and synthetic analogs of 'naturally' occurring insecticides such as pyrethrins and pyrethroids, that are of lower toxicity to mammals[83]. Herbicides account for over 50% of all pesticide use in the US and world-wide, and most act on metabolic processes specific to plants, so are generally safe to humans[84]. However, this class of pesticides does include chlorophenoxy acid herbicides and the dioxin contaminant, which is a known carcinogen, bipyridil herbicides such as paraquat and diquat, which damage the lungs, and triazines such as atrazine, which has been linked to birth defects and malformations via endocrine disruption[85-88]. Fungicides include a wide variety of chemical compounds used in vastly different ways; prolonged exposure can cause neural and visual disturbances such as in ziram, may contribute to medication resistance in humans for treating the aspergillus fungus infections, or can reprogram the DNA and impact generations decades later[89].

These potential human health effects, as well as potential impacts on the environment, are assessed during a pesticide's registration process. This process essentially permits what pesticides may be used for, their quality, usage rates, and labelling and packaging requirements[90]. Additionally, there is the intention to prove that proper use of the pesticide does not promote adverse human health effects or negatively impact the environment[91]. This is done through thorough examination of the ingredients of the pesticide, the site or crop it is intended to be used on, the amount/frequency/timing of its use, and storage and disposal practices[92]. Risk assessments for each pesticide are done to evaluate potential harm to humans, wildlife, fish and plants, and particularly endangered species or non-target organisms; these assessments also evaluate the potential for groundwater contamination from leaching, runoff, or spray drift. The potential human health risks consider both short-term/acute and long-term/chronic exposure effects, such as cancer and reproductive system disorders. Language and labelling are also assessed in order to ensure that directions and safety precautions can easily be followed[90].

Human health risks from exposure to pesticides are evaluated based on sensitive groups, such as children and individuals that are immuno-compromised, during the registration process[93,94]. This includes looking at aggregated risks through food and water consumption, and potential residential uses[90,94]. Cumulative risks are also assessed – different pesticides with the same effects may lead to greater human health impacts if exposure to multiple chemicals occurs[90]. Additionally, the risk to occupational groups such as operators and farm workers is evaluated in order to ensure that those applying the product during their work are not inordinately exposed[90]. A comprehensive risk assessment is then developed that examines and reviews human health and environmental risks, which undergoes peer review[90]. Based on these risk assessments, risk management and regulatory decisions are made, where alternative pesticides are researched, measures to mitigate risks are reviewed, new food tolerances are established, and the registration of the product is granted[90]. Throughout a pesticide's use, the registering authority also ensures that the pesticide continues to meet the highest standards of safety in order to protect human health and the environment, as standards become stricter due to better scientific advances; older pesticides are continuously reviewed to ensure they meet current scientific and regulatory standards[90]. This re-registration process has led to many active substances being banned, especially in the European Union[95].

Pesticides in the United States are regulated under two major laws – the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), and the Federal Food, Drug, and Cosmetic Act (FFDCA). FIFRA requires that all pesticides sold or distributed in the US be registered by the US Environmental Protection Agency (EPA) based on evaluation of scientific data and risk assessments, proper labelling, training and certification of workers using the pesticides, and the potential suspension or cancellation of a product's registration[96]. The FFDCA then requires pesticide tolerances (maximum permissible level) to be set for all pesticides used in or on food in a manner that may result in residue in or on food or animal feed; the law includes strong provisions for protecting vulnerable and sensitive populations[97]. These laws are further amended by the Food Quality Protection Act of 1996 and the Pesticide Registration Improvement Act. Under the Food

Quality Protection Act, a pesticide must be found to pose “a reasonable certainty of no harm” before it can be registered for use on food or feed, and must be reviewed at least once every 15 years[98].

1.4.2 *Health effects and exposure to pesticides*

The authorization for pesticide regulation and use requires data on the potential adverse human health effects of the active ingredients. The US EPA requires several tests focused on acute, sub-chronic, and chronic toxicity, developmental and reproductive toxicity, mutagenicity, and hormone disruption[90]. Acute toxicity information is used for the calculation of the median lethal dose (LD_{50}) of the pesticide – the amount of ingested pesticide that kills 50 percent of the test sample; this is calculated for all possible exposure routes, such as oral, dermal absorption, and inhalation. The lethal concentration (LC_{50}) is also determined – this refers to the concentration of the pesticide in air that kills 50 percent of the test sample over a set period (usually four hours). These endpoints are then used by the EPA as well as the World Health Organization (WHO) to classify pesticides based on their toxicity[90,92]. The reference point below which no adverse effects occur is also determined through these tests. The No Observed Adverse Effect Level (NOAEL) or No Observed Effect Level (NOEL) is then used to derive the acceptable daily intake for humans – i.e. the amount of chemical that can be ingested on a daily basis, over a lifetime, without an appreciable health risk.

Many pesticides work on controlling pests by targeting the nervous system; therefore, many pesticides are also found to be neurotoxic in humans. Organophosphate pesticide poisoning in particular leads to adverse peripheral nervous system functioning[99,100]. Permanent residual damage may occur after acute poisoning events, or through chronic exposure through pesticide application. More moderate exposures to neurotoxic pesticides have been found to impair cognition, autonomic and motor function, and vision[101]. Pesticides have also been found to be marginally associated with development of Parkinson's disease[76,102-104].

In addition to toxicity, pesticides are classified based on their carcinogenicity, or ability to damage the human genome and/or disrupt cellular metabolic processes, leading to development of cancer. This classification is based on the principles of the International Agency for Research on Cancer (IARC)[105]. Pesticides are classified as either carcinogenic to humans (Group 1), probably carcinogenic to humans (Group 2A), possibly carcinogenic to humans (Group 2B), not classifiable as to its carcinogenicity to humans (Group 3), or probably not carcinogenic to humans (Group 4). The EPA has similarly classified chemicals as either carcinogenic to humans, likely to be carcinogenic, suggestive evidence of carcinogenic potential, inadequate information to assess carcinogenic potential, and not likely to be carcinogenic to humans[106]. Cancer research to date has found pesticide exposures to be linked to multiple cancer types, including childhood cancers, leukemia, lymphoma, brain, kidney, breast, prostate, pancreas, liver, lung, and skin cancers[107-111].

Many pesticides are also known to be endocrine disrupting chemicals (EDC), a group of chemicals that may interfere with the body's endocrine system and produce adverse reproductive and sexual development, neurological, and immune effects; they were developed to similarly act on the endocrine systems of pests for their control[112,113]. This occurs due to their ability to interfere with the signaling and transport/metabolism of hormones such as estrogens and androgens. Exposure to a known EDC – diethylstilbestrol – has been shown to result in higher rates of preterm and spontaneous delivery, ectopic pregnancy, as well as uterine leiomyomata in females, and male offspring may be at risk from testicular or prostate cancer and often have reduced testosterone levels and fertility[114-117]. However, nearly 50% of known EDCs are insecticides[87]. Their effects have been largely noted in wildlife such as invertebrates, reptiles, and fish, but effects have also been seen at the human level. Those most sensitive to exposure are human fetuses, infants, and children, as most of the damage caused by EDCs occurs during early development and through greater doses via maternal fat reserves and breastfeeding[118]. Geographic studies have noted that residential proximity to agricultural activity is associated with developmental abnormalities, fetal death, and childhood cancers[79,119,120]. Furthermore, in areas with high agricultural activity and in children of agricultural workers, a higher prevalence of cryptorchidism and hypospadias has been found[121-123]. In adults, EDC pesticide exposure has been linked to higher rates of breast cancer, immune system damage, and prostate cancer[124-134]. Co-exposures to these types of substances may even be working in additive, synergistic, or antagonistic ways[135].

The toxicity information for current and previously registered pesticides has been collected by the Pesticide Action Network of North America (PANNA)[136]. This database brings together a diverse array of information on pesticides including human toxicity (chronic and acute), ecotoxicity, and regulatory information for over 5,000 pesticide active ingredients. Most information used by PANNA comes from the US EPA, WHO, National Toxicology Program (NTP), National Institutes of Health (NIH), IARC, the European Union, and the State of California (California's Proposition 65 list). Based on this information, PANNA has classified each pesticide based on its carcinogenicity, acute toxicity, reproductive and developmental toxicity, and endocrine disruption ability.

1.4.3 *Pesticides of concern in treatment of almonds*

The top insecticides used on almonds from 2010 to 2014, by acres treated, include oil, abamectin, methoxyfenozide, bifenthrin, and chlorantraniliprole[136]. Abamectin is a botanical/macrocyclic lactone insecticide, and acts on insects by interfering with neural and neuromuscular transmission. It is both acutely toxic, a reproductive or developmental toxicant, and a suspected endocrine disruptor[137-143]. Bifenthrin, a pyrethroid insecticide, is both an insecticide and acaricide, acting on insects by affecting their nervous system and causing paralysis. Bifenthrin has moderate acute toxicity, is a possible carcinogen, a reproductive or developmental toxicant, and a suspected endocrine disruptor[144-151]. Oil, particularly paraffin-based and unclassified petroleum oil, has a physical mode of action – they kill insects on contact by disrupting gas exchange (respiration), cell membrane function or structure; they also kill insects by disrupting their feeding on oil-covered surfaces. It has slight acute toxicity, and is a known carcinogen[152,153]. Methoxyfenozide, a diacylhydrazine insecticide, is a molting accelerator that is an agonist of the hormone 10-hydroxyecdysone. There are no known human health effects from exposure to this insecticide. Similarly, chlorantraniliprole, an anthranilic diamide insecticide, has relatively few known human health effects.

1.4.4 *Pesticide exposure – environmental and occupational*

The general population is exposed to pesticides mainly through pesticide residue on food or drinking contaminated water. These exposures tend to be low-dose and chronic or semi-chronic; and with negligible health effects noted, have not been found to be a significant issue. However, those who live in agricultural communities may be more substantially exposed through drift events, or children of farmworkers may be exposed through the take-home pathway[154-156]. Infants and young children are uniquely sensitive to environmental contaminants such as pesticides, as their organs, neurologic, and immunologic systems are still developing[157]. Compounding this susceptibility is their behavior, which puts them at greater risk of exposure and adverse health effects in the proximity of pesticides. Young children often play and crawl on the floor and have frequent hand-to-mouth contact. This leads to ingestion of pesticide contaminated soil or house dust. Their skin to body weight ratio is also several times greater than that of adults. Exposure to pesticides by dermal absorption is thus greater, as it leads to a larger dose per unit of body weight compared to that of an adult. Lastly, children have higher respiratory rates than adults, so airborne pesticides (among other pollutants) are inhaled at a greater frequency.

Occupational exposure to pesticides is also of concern. These exposures may occur during production, transportation, preparation and application, or while working in treated fields[158]. These activities have led to many accidental acute poisonings from spills or faulty equipment, in addition to repeated low-dose exposures[159-161]. With higher amounts of pesticides being applied, at potentially higher doses and types of products applied, the human exposure potential to workers during agricultural activities is high. Those at greatest risk are those involved in activities related to the application of pesticides, such as mixing/loading the pesticide into the application device/machinery, operation of the applicator, and maintenance of the application machinery. Increasing this risk is the poor knowledge many workers have regarding the risks associated with pesticides, or the correct application techniques and precautions[162-165]. Most exposures occur when workers do not pay attention to instructions on use and/or safety guidelines on the use of personal protective equipment and sanitation practices. Weather conditions during the time of application, such as temperature and humidity, may also affect the chemical volatility of the product, the perspiration rate of the worker, and the use of personal protection equipment, increasing exposures[166-168]. Wind may increase spray drift, and low humidity/high temperature causes more rapid evaporation of the pesticide between the applicator device and the target.

1.4.5 *Pesticide use and environmental justice*

These known health effects could disproportionately affect low-income and minority populations as well as children as the climate continues to change[169,170]. Most jobs in the agricultural sector are held by low-income people of color. Latinos comprise approximately 77% of the US agricultural workforce, and most of these jobs are seasonal, paying low wages with no health benefits or job security[171]. Not only are these susceptible populations responsible for working in the fields and where they contact pesticides while at work, but their families and those in the nearby community are at risk as well through take-home pathways, drift events, and environmental spread. It is therefore important to consider social vulnerability when examining the relationship between climate change, pesticide use, and human health.

Climate change is an important factor for human rights, public health, and environmental justice because of its diverse consequences and its disproportionate impact on the agricultural community. Implementing a geographic information system (GIS)-based assessment of potential pesticide exposure that utilizes global climate models is therefore necessary. This will allow for a broader physical area of study and will identify high-risk sites where targeted risk management strategies can be used. Transferability of findings will be greater and will therefore have a potentially larger impact. Local governments will be able to plan for better pesticide use regulations as well as allocating their resources to the most vulnerable communities, and health communication messages can be tailored to specific ethnic or demographic groups.

The biggest challenge to the public health community over the coming years will be to respond to the various effects of climate change and make sure we are adequately protecting our vulnerable and socially marginalized populations. Federal and state agencies are currently developing climate change mitigation and adaptation strategies to protect public health[172]. By understanding how climate change impacts our agricultural practices, and consequently human health, we can mitigate potential future exposures through regulation measures and ultimately reduce pesticide-induced disease. This project will inform public health officials and researchers on the risks of pesticide exposure in a changing climate, how these exposures are likely to change, and how to quantify this often-overlooked health threat related to climate change. Finally, it will result in valuable information to almond producers and stakeholders, and other fruit and nut tree growers.

1.5 SPECIFIC AIMS

To date, little research has attempted to quantify the association between climate change and pesticide use, and the associated human health impacts from exposure[173]. Previous studies have separately used GIS to map and model changes in climate, track pesticide application, and identify communities vulnerable to pesticide pollution in agricultural areas[11,174-177]. Yet these studies have not linked agricultural pesticide use with climate change to identify temporal and spatial shifts in human exposures. The proposed research will utilize existing climate, pesticide, and agricultural data to address this missing link and assess whether climate change may influence pest dynamics and pesticide use.

This project focuses on the almond crop in California, and tests two important hypotheses: (1) Climate variables have been historically associated with insect pest population and pesticide use; and (2) Assuming agricultural regions and pest management practices remain the same, climate change will result in increased insect pest populations and pesticide use in future projections to mid- and end-of 21st century. Specifically, the project will:

1) Using a GIS analysis approach, quantify the historical and future relationship between weather/climate variables and pest populations on almond crops. Historical observed weather data will be used to model the historical relationship between temperature and almond pest population dynamics. Future pest populations will be modeled using a group of ten climate model projections to mid- and end-of 21st century, to cover the range of future changes in climate and uncertainty in the climate scenarios.

2) Historical pesticide use reports will be assessed for temporal and spatial trends, as well as correlation to growing degree days, estimated pest generations, and climate. Future insecticide use projections will be based on historical trends and will be estimated using the ensemble of climate models to mid- and end-of 21st century.
3) Identify and map geographical areas with higher risk of exposure to pesticides by mid-21st century – specifically insecticides used on almond crops – and identify areas with the greatest human health hazard that would benefit from more wide-spread alternative pest management strategies.

Chapter 2. HISTORICAL AND PROJECTED CLIMATE CHANGE EFFECTS ON ALMOND PESTS IN CALIFORNIA'S CENTRAL VALLEY

2.1 ABSTRACT

Climate change, most notably increasing minimum and maximum temperatures, is likely to impact agricultural pests. Increasing pest pressure due to changes in voltinism and phenology represents a potential economic loss to growers, in terms of nut damage and cost of control measures; if control measures such as the use of insecticides increases, this may lead to an increase in occupational and environmental exposure and is therefore an important public health issue to consider. Previous studies of the impact of climate change on agricultural pests in the Central Valley have been limited by their use of outdated climate models, often choosing a minimum of three to project future pest pressure, and averaging results across models[23,72]. To our knowledge, no study has focused on pests specific to the almond industry or assessed changes in both phenology and voltinism using a suite of ten down-scaled climate models suitable for California using the latest IPCC scenarios. This study aims to assess changes to pest pressure in California's $5.2 billion almond industry due to recent historic and projected future temperature changes. For two past historical observation periods (1965 and 1995) and ten future climate modeled periods (2025, 2055, and 2085), 150 years of daily maximum and minimum temperatures were obtained. Degree-day models were then used to estimate the number of accumulated growing degree days per season using two different biofix/start dates. Mean generation numbers and date of first flight for the overwintering generations were projected using the accumulated growing degree days for both the navel orangeworm and peach twig borer, two of the most economically important pests for the almond industry in California.

This chapter addresses the following sub-aims:

- Establish the extent of historical climate change in California's Central Valley using the extensive National Climatic Data Center weather station data
- Determine the best statistically down-scaled GCMs to use in California, and utilize them to project future temperature changes for California's Central Valley in the next century
- Estimate accumulated growing degree days to calculate generation numbers and changes in phenology to ascertain if these number will change significantly with climate

2.2 INTRODUCTION

Overwhelming evidence suggests not only is climate change a current reality, but that anthropogenic forces are to blame[1]. Such evidence shows that global temperatures are increasing, precipitation patterns are changing, and extreme events are increasing in frequency and magnitude. Climate change is therefore considered one of the most serious challenges facing mankind, as it has the potential to impact every aspect of our well-being, from where we live, to how our food is grown. An overall warming will lead to the prolongation of growing seasons in temperate regions, as has already been detected in the United States; most notably, the growing season has lengthened by nearly two weeks since the beginning of the 20th century which has been occurring more rapidly in Southwestern states such as California, where a large percentage of the country's food is grown and produced[178]. The warmer temperatures are also expected to expand almond acreage in the Central Valley[179]. Similarly, agricultural pest control is strongly dependent on climate as pressure from plant pests is likely to change with climate[180].

Many insects are ectotherms, relying on the ambient temperature of their environment for body heat and growth and development. They are therefore likely to respond rapidly to changes in climate, as both maximum and minimum temperatures increase. Different species respond differently to temperature changes, depending on their physiological traits, seasonal life-cycles, and bioclimatic region. With a changing climate, many species may shift or expand their geographical range, increase in abundance or generations per season (voltinism), alter and prolong the timing of their life-cycles and active development time (phenology), or change their behavior or population structure when faced with greater temperature extremes[181]. Many such effects have already been detected in several insects[20,22-24,72,182-188]. How much these pests respond to the changing climate will depend on the extent and rate of warming.

As a result of this temperature dependence, it is important to consider how changes in climate will impact human exposure to pesticides due to the probable change in their use. Increasing temperatures will result in enhanced winter survival leading to higher initial populations in the spring, as well as through changes in voltinism and phenology such as earlier flight periods and acceleration of development rates[187,189-191]. Climate change is therefore of utmost importance when considering pest management strategies, both historically and in the future. Insect development can be modeled using degree-day models, a simple function of threshold temperatures for insect development, accumulated to predict insect life cycles. These models are widely used by growers to time pest management[74,192-194]. However, they can also be used to estimate the number of pest generations that may occur during a season, as well as timing for emergence of the first flight.

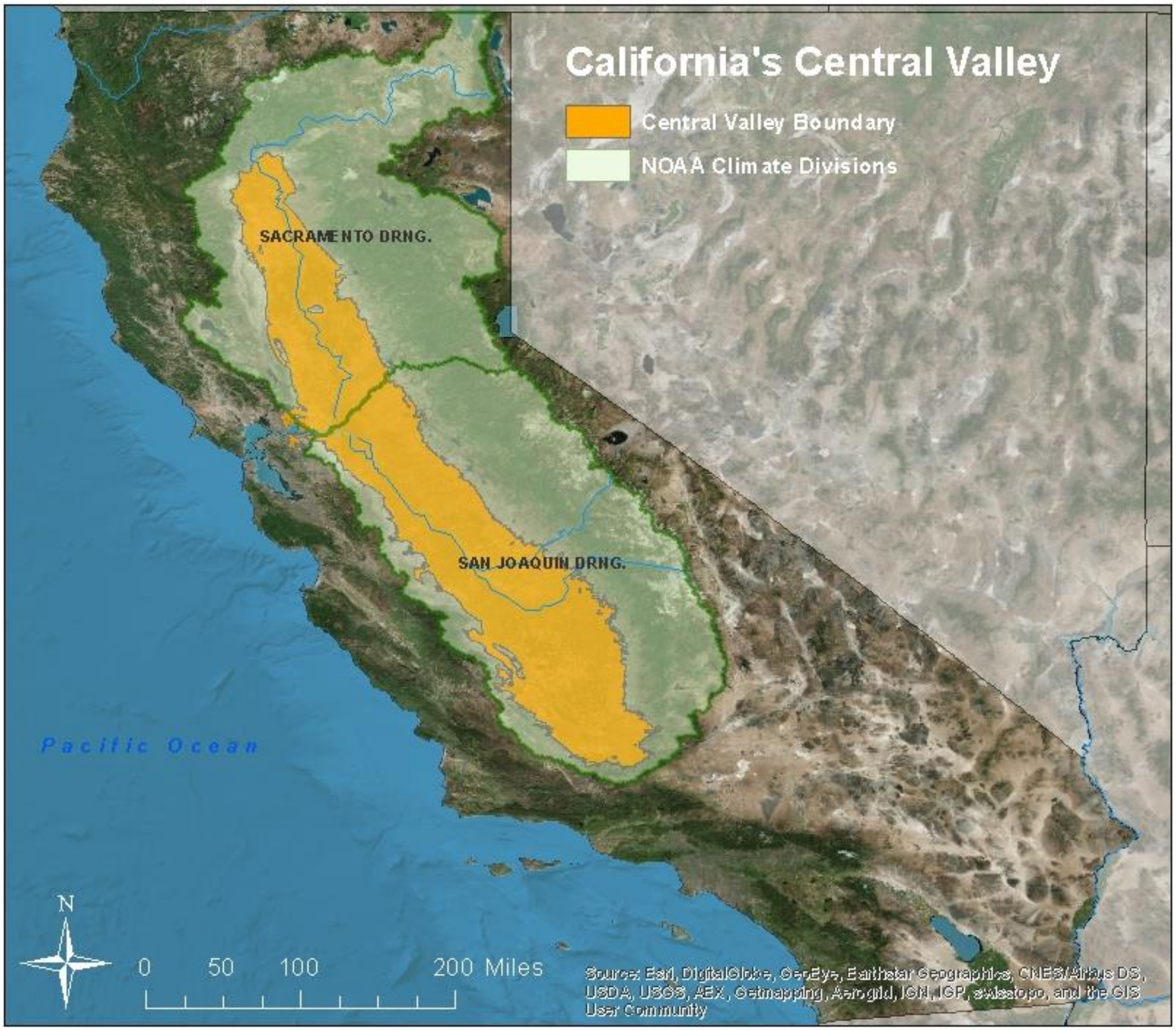
The purpose of this study is to quantify the historical and project the future relationship between climate and pest populations for two important pests of almonds in the California Central Valley. The Central Valley is one of the most important producers of almonds in the United States as well as the world, contributing 80% of the global supply[63]. The annual crop value has been estimated at $5.2 billion, with nearly the entire crop produced in the Central Valley[60,61]. Previous assessments have shown the valley will remain thermally suitable for almond cultivation by mid-

21st century, with bloom and harvest occurring several weeks earlier than historic normals[195]. The major pests of economic concern include the navel orangeworm (NOW; *Amyelois transitella*), ants, webspinning mites, peach twig borer (PTB; *Anarsia lineatella*), and San Jose scale (*Quadraspidiotus perniciosus*). The navel orangeworm, peach twig borer, and San Jose scale have previously been assessed for climate change vulnerability in California, where temperature was found to be the major factor impacting pest development and number of generations per season[72]; this study expands upon these previous analyses by using the appropriate number of climate models in order to handle uncertainty in the projections, as well as projecting date of emergence. Under current pest management practices, the San Jose scale is controlled for once a season using a dormant spray, so was therefore not considered in this analysis as it is expected climate change will not have as great an impact on the control strategies growers will use to control the pest.

2.3 MATERIALS AND METHODS

2.3.1 *Climate divisions*

Given the diversity in climate across the Central Valley, the region was categorized into climate divisions used by the National Oceanic and Atmospheric Administration (NOAA) for regional forecasting[196]. These divisions have been used over the past century to generate climate analyses and regional monitoring of climate-related variables (such as drought, temperature, precipitation, and degree day values) within the United States. Naturally, they have been used for agricultural applications; in fact, the divisions were initially created for agriculture, irrigation, and forestry and are largely defined by drainage basins and crops[197]. There are 344 climate divisions within the continental United States. In California, there are seven regions: North Coast Drainage, Sacramento Drainage, Northeast Interior Basins, Central Coast Drainage, San Joaquin Drainage, South Coast Drainage, and Southeast Desert Basin. The areas that encompass the Central Valley are the Sacramento and San Joaquin Drainages (**Figure 2.1**). As climate may vary significantly between climate regions, these regions were included in the analysis in order to account for any differences in the relationship between climate and pest development, by region. In order to simplify the analyses, the historical climate data was spatially aggregated by climate region, into a North (Sacramento Drainage) and South (San Joaquin Drainage) Central Valley.



Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Figure 2.1. Location of California NOAA climate divisions for the Central Valley.

2.3.2 *Weather data*

For long-term temperature records, the National Climatic Data Center (NCDC) records were used[198]. This network contains daily records from 1951 to 2016 for most stations in California and is maintained by the US Department of Commerce/NOAA. All available data for the 136 (active and inactive) stations of the California NCDC network were obtained, through the University of California weather database[199]. This database stores current daily and hourly data throughout California, as well as long-term data for climate stations. Using a Geographic Information System (ArcGIS 10.5.1, ESRI, Redlands, CA, USA), the NCDC stations were narrowed down to 36 within the Central Valley boundary (**Figure 2.2**). Of those 36, three stations without complete records dating back to 1951 were not included, leaving 33 stations for the historical climate analysis.

The observational NCDC climate data included dates, observation time, daily precipitation amount (inches) and type, daily maximum and minimum air temperature (°F), daily observed temperature (°F), weather conditions, wind direction and speed, wet and dry bulb temperature, minimum and maximum soil temperature (°F), pan evaporation (inches), solar radiation (Langleys), reference evapotranspiration (inches), and minimum and maximum relative humidity (%). Only minimum and maximum air temperature were chosen for historical analysis, due to their relevance to pest development.

For stations where requested data were not complete, backup and long-term average stations were used to fill in missing data. The default backup stations and long-term averages used by the University of California weather database were chosen to fill in missing data[200]. Backup stations are those nearby that can be used to fill in data gaps for specific variables – for some variables, no backup stations are recommended if values will not be similar enough to the selected station. The first recommended backup station was used first to supply the missing data, and in the case of missing data at that station for the same date, the second recommended backup station was used. In the event a date had missing values at all backup stations, the long-term average for the date was used. The historical minimum and maximum temperatures for each of the 33 NCDC stations was then classified as ‘North’ or ‘South’ Central Valley based on the weather station’s location within the NOAA climate divisions (**Table 2.2**). The historical observations were obtained to establish two historical ‘baseline’ periods (1951 – 1980, 1981 – 2009) for climate and growing degree days – these are observed periods from which to base changes in future climate on.

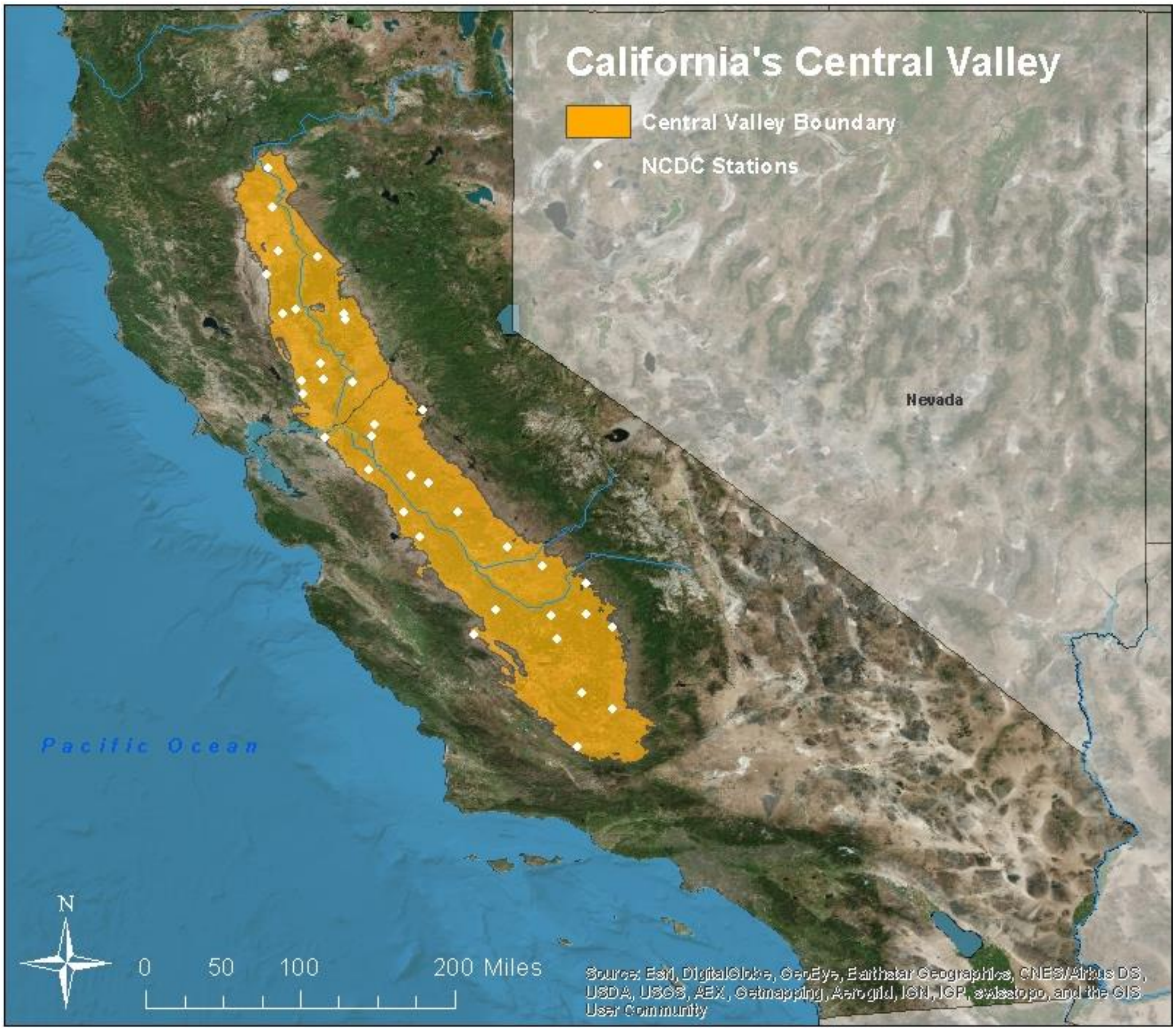


Figure 2.2. Location of NCDC stations within the California Central Valley.

Table 2.2. NCDC stations in the northern (Sacramento drainage) and southern (San Joaquin drainage) regions of the Central Valley.

North: Sacramento drainage	California State University (CSU) Chico University Farm (NCDC #1715), Colusa (NCDC #1948), Davis (NCDC #2294), Marysville (NCDC #5385), Orland (NCDC #6506), Red Bluff Municipal Airport (NCDC #7292), Redding Weather Service Office (WSO) (NCDC #7304), Sacramento Federal Aviation Administration (FAA) Airport (NCDC #7630), Vacaville (NCDC #9200), Willows (NCDC #9699), Winters (NCDC #9742), Woodland (NCDC #9781)
South: San Joaquin drainage	Bakersfield Weather Service Office Airport (NCDC #0442), Camp Pardee (NCDC #1428), Coalinga (NCDC #1864), Corcoran Irrigation District (NCDC #2012), Denair (NCDC #2389), Five Points (NCDC #3083), Fresno Yosemite International Airport (NCDC #3257), Hanford (NCDC #3747), Lindsay (NCDC #4957), Lodi (NCDC #5032), Los Banos (NCDC #5118), Madera (NCDC #5233), Maricopa (NCDC #5338), Merced (NCDC #5532), Modesto (NCDC #5738), Newman (NCDC #6168), Orange Cove (NCDC #6476), Stockton Fire Station (NCDC #8560), Tracy-Carbona (NCDC #8999), Visalia (NCDC #9367), Wasco (NCDC #9452)

2.3.3 *Climate scenarios and models*

Climate model projections (2006 – 2099) were utilized from statistically downscaled GCMs coordinated by the 5th Coupled Model Inter-Comparison Project (CMIP5)[201]. CMIP is a global project containing over 40 climate models; in its latest phase it provides significant corrections over previous models and the most up-to-date view of future changes in climate[202]. Projections include future trajectories based on human actions – Representative Concentration Pathways (RCPs) – which establish a range of changes in radiative forcing from which possible environmental consequences can be derived. These assumed scenarios consider future global GHG emissions, land use, population growth, technology, and other factors.

Statistically downscaled projections, using the newest version of the Multivariate Adaptive Constructed Analogs (MACA)[203] method, were available for 20 of the CMIP5 models (**Table 2.3**). MACA is a method for statistically downscaling GCMs from their native coarse global resolution to a fine-scale spatial resolution that better captures and reflects observed patterns of daily regional meteorology. It uses the Livneh[204] observational dataset as training data for the Western US and is preferable in regions of complex terrain due to its multivariate approach. It is a multi-step procedure that uses bias correction procedures and constructed analogs – this approach produces forecasts that are a linear combination of past predictand values; the large-scale GCM patterns are matched on a smaller scale using historical/observed patterns to produce more fine-scale features. The observational dataset variables are at a resolution of 1/16th degree (~6 kilometer – km), and after the downscaling process, the final downscaled climate projection data from the GCMs matches this resolution. Statistical downscaling is a simpler method, as compared to dynamic downscaling, which performs better if considering extreme events. The MACA method was chosen over others, as more CMIP5 models were downscaled using this method compared to other similar methods, and dynamic downscaling was not necessary for the scope of this project.

The MACA downscaling method considers RCP4.5 and RCP8.5 using the GCM model output for the years 2006 – 2099. Before 2050, changes in radiative forcing are not significantly different between the four RCP scenarios, but they diverge significantly by the end of the century[205]. When considering which RCP to use in projections to 2050 or 2099 for this analysis, it was decided to choose the scenario that is most similar to the trajectory the world is on. Recent assessments show that we are on or past the RCP8.5 trajectory, a business-as-usual scenario, despite global efforts to follow RCP2.6[206]. Therefore, the RCP8.5 MACA downscaled model output for the chosen GCMs was used in the projection of temperature to mid- and end-of 21st century.

Table 2.3. 20 MACA downscaled models considered for the projection analysis.

Model Name	**Country**	**Agency**
bcc-csm1-1	China	Beijing Climate Center, China Meteorological Administration
bcc-csm1-1	China	Beijing Climate Center, China Meteorological Administration
BNU-ESM	China	College of Global Change and Earth System Science, Beijing Normal University, China
CanESM2	Canada	Canadian Centre for Climate Modeling and Analysis
CCSM4	USA	National Center of Atmospheric Research, USA
CNRM-CM5	France	National Centre of Meteorological Research, France
CSIRO-Mk3-6-0	Australia	Commonwealth Scientific & Industrial Research Organization/ Queensland Climate Change Centre of Excellence, Australia
GFDL-ESM2M	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA
GFDL-ESM2G	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA
HadGEM2-ES	UK	Met Office Hadley Center, UK
HadGEM2-CC	UK	Met Office Hadley Center, UK
inmcm4	Russia	Institute for Numerical Mathematics, Russia
IPSL-CM5A-LR	France	Institut Pierre Simon Laplace, France
IPSL-CM5A-MR	France	Institut Pierre Simon Laplace, France
IPSL-CM5B-LR	France	Institut Pierre Simon Laplace, France
MIROC5	Japan	Atmosphere & Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MIROC-ESM	Japan	Japan Agency for Marine-Earth Science & Technology, Atmosphere & Ocean Research Institute, and National Institute for Environmental Studies
MIROC-ESM-CHEM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MRI-CGCM3	Japan	Meteorological Research Institute, Japan
NorESM1-M	Norway	Norwegian Climate Center, Norway

From the 20 MACA-downscaled climate models, ten were chosen to best represent the Central Valley of California. Using a group of at least ten models is standard practice in climate modeling, as the group of models can then be used to characterize consensus about projected mean climate variables, as well as the range and variability; using less than ten is not suggested as it provides a limited sample[207]. Regional climate projection uncertainty arises from anthropogenic forcing and the drivers of change, climate sensitivity (i.e. how the climate system responds to those drivers), the manifestation of change to regional scales, and the future trajectory of natural variability[208].

Mote et al., 2011[207] suggests that while evaluating how well models perform is useful, previous studies indicate that projections from a randomly selected group of models will yield results similar to a group of the ‘best’ models. It is therefore not necessary to choose models based on a central tendency or ‘good’ performance. Instead, they recommend choosing at least ten models and evaluating them against observations just to be aware of model biases. Evaluation of the GCMs was previously conducted to assess how well they simulate the climate of California[209]. A suite of statistics was calculated to evaluate how well each GCM performed (reproduced) the observed metrics. Using a multi-factor historical climate evaluation scheme for the Southwestern US, each GCM was ranked by total relative error of the ensemble mean of each metric (such as correlation and variance of mean seasonal spatial patterns, amplitude of seasonal cycle, diurnal temperature range, etc.) for each CMIP5 GCM (where total relative error is the sum of relative errors from all metrics, excluding the diurnal temperature range metrics). Based on this analysis, the top models with the least amount of bias for the region were: MIROC5, CCSM4, CNRM-CM5, CanESM2, IPSL-CM5A-MR, HadGEM2-ES, NorESM1-M, GFDL-ESM2M, HadGEM2-CC, and CSIRO-M3-6-0. GFDL-ESM2G was used instead of CSIRO-M3-6-0, as it performed better than some of the other top models in terms of the southwestern US mean seasonal amplitude in temperature.

Daily minimum and maximum temperature projections for RCP8.5 were downloaded for each of the ten MACA downscaled CMIP5 models for the years 2006 to 2099. The latitude and longitude for each of the 33 NCDC stations was used to select the point locations from which to download the data; the extracted data corresponds to the average over the grid cell that contains the selected point (1/16th degree Livneh grid cell). Future degree days were estimated based on the minimum and maximum daily temperature for each NCDC station location, for all ten climate models. 30-year periods were averaged to give a robust estimate of temperatures around 2025 (2010 to 2039), 2055 (2040 to 2069) and 2085 (2070 to 2099).

2.3.4 *Insect physiology models*

As most insects are ectothermic, temperature controls their growth and developmental rate – typically there is an optimal temperature range defined by an upper and lower threshold for each insect in which they will grow and develop rapidly, accumulating heat known as physiological time[74]. No development will occur below the lower threshold, and above the upper threshold development typically slows or stops as determined by the cutoff method, and/or the insect no longer survives. The life cycle of agricultural pests can therefore reliably be predicted using this accumulation of heat and time often expressed as the degree-day; these daily accumulations (accumulated degree days) are added over time and used to predict insect development. Phenology models are used by farmers and growers to predict pest development in order to time their use of insecticides or other pest control methods, so that treatment is applied when the pest is most vulnerable and when treatment will be most effective.

The University of California's Agricultural and Natural Resources, Cooperative Extension's Statewide Integrated Pest Management Program has developed an internet-based tool that models insect pest development based on temperature (UCIPM)[210]. The models use previous research on insect development and geographical area to estimate pest development stages[71]. The online tool can be used in a variety of ways; the user can run models and methods recommended by the UC Cooperative Extension for the region the information is to be used, or thresholds and methods of calculation can be individually specified by the user. Additionally, weather data can be uploaded via a file, entered online, or the UCIPM weather database for stations within California can be chosen for the input.

For each pest, there are multiple phenology models available, that help predict the organisms' development based on accumulated growing degree days. The models differ based on their recommended location and/or region of study, as well as predicted stage of development for the pest. The UCIPM has also developed their own phenology model for each organism. For the navel orangeworm, there are four models available. Model one[193] was developed and studied in Butte, Kern, and Tulare counties for generation time adult to adult; model two[211] and model three[212] were developed in Kern County for generation time egg to adult and for eggs, and model four was developed by the UCIPM. Only development on mummy almonds was considered for generation number calculations. For the peach twig borer, there are four models available, as well as a UCIPM model[192,213-215]. All were developed in California, and model two was specifically developed in the Central Valley.

For both pests, the default UCIPM recommended models were chosen as well as two additional models that assessed generation time (egg to adult or adult to adult), and the NCDC observational daily temperature records as well as the MACA projected daily temperatures for all

Central Valley weather stations and locations were used as inputs for the degree-day models. Two almond pests of economic importance in California were chosen for this analysis: navel orangeworm and peach twig borer. For both pests, the single sine/horizontal cut-off setting was used to approximate growing degree-days, as recommended by UCIPM; there are no advantages to using more complicated methods, and no additional error is introduced to the growing degree day estimates when using the horizontal cut-off[194]. The degree days were then accumulated by adding up daily contributions of degree-days between the beginning and end of the season. For each pest and model (climate and phenology), the number of generations per growing season were calculated using the accumulated degree days and lower and upper thresholds set by the phenology models, for both climate divisions. The insect-specific parameters used in calculating the insect development are listed in **Table 2.4**.

Table 2.4. Parameters and calculation methods for the degree-day pest phenology models.

Pest	**Model/Generation Parameters**	**Degree-Day/Lower/ Upper Threshold (°F)**
Navel orangeworm	Model 1: Mummy Almonds (adult to adult)	1092.6/55.0/93.9
	Model 1: New Crop Almonds (adult to adult)	738.0/55.0/93.9
	Model 2: Mummy Almonds (egg to adult)	1121.4/55.0/93.9
	Model 2: New Crop Almonds (egg to adult)	765.9/55.0/93.9
	UCIPM: Mummy Almonds	1056/55/94
	UCIPM: New Crop Almonds	723/55/94
Peach twig borer	Model 1: Generation time (adult to adult)	1080.0/50.0/88.0
	Model 2: Generation time (adult to adult)	1060.0/50.0/88.0
	UCIPM: Generation time (adult to adult)	1030/50/88

The beginning of the season for pests is known as the biofix, a calendar date after which degree-day totals start accumulating and accounting toward pest development. For some pests, this occurs on January 1st, whereas for others it is dependent on insect development as noted in the field or orchard. For the navel orangeworm, the biofix is typically the beginning of a consistent increase in egg laying on egg traps; when at least 75% of the egg traps in a given location show increases in the number of eggs on two consecutive monitoring dates, the biofix is the first of those two dates. For the peach twig borer, the biofix is the first date that male moths are consistently found in pheromone traps placed throughout the orchard. The UCIPM does not specify a biofix or start or end date for the accumulation of degree days for either pest in this assessment. One impact of climate change on agricultural pests is that the growing season is likely to start earlier and/or end later, due to temperature and precipitation effects on host plants and insect physiology. By not accounting for this potential change through flexibility in the biofix, such impacts of climate change on pest development would be missed.

Therefore, in this study the degree-day models were run on both a calendar year basis (January 1st start date through the end of December) as well as an estimated biofix and end date; previous studies found minimal differences in accumulated growing degree days between the two biofix/start date methods[72]. April 1st was chosen as the estimated biofix for both pests, as historically this date would capture most start dates in the study period (for navel orangeworm, the first oviposition has historically been noted in mid- to late-April; for the peach twig borer, the first male in traps has historically been noted in early- to mid-April), and October 31st was chosen as an end date, as most almonds are typically harvested by the end of October yet the pests of concern often inflict damage well into the month[216]. Degree-days were added cumulatively for each year and station as well as model, and then averaged by climate division for each year. Data analyses were performed in R, a free open-source and adaptable statistical analysis platform[217].

2.4 RESULTS

2.4.1 *Historical and projected climate change*

Throughout the Central Valley, temperature varies widely for both historical and projected periods (**Table 2.5** and **Table 2.6**). During the first historically observed baseline period (1951 to 1980) maximum daily temperature averaged 75.76 ºF (ranging between 5 ºF and 119 ºF throughout and between all years), and minimum daily temperature averaged 48.01 ºF (ranging between 0 ºF and 92 ºF throughout and between all years) for the entire valley. The northern Sacramento drainage was on average one-degree (ºF) cooler than the southern San Joaquin drainage (75.04 ºF compared to 76.17 ºF), and there was an even smaller difference in the average minimum temperatures observed between the northern and southern regions (47.97 ºF compared to 48.04 ºF).

During the second historically observed baseline period (1981 – 2010), maximum daily temperature was less than one degree (ºF) warmer for the entire valley compared to the first baseline – average maximum temperatures were 76.12 ºF (ranging between 26 ºF and 121 ºF). Similarly, the northern and southern regions saw an increase in maximum temperature of half a degree (ºF). However, minimum temperatures increased by over a full degree (49.17 ºF) throughout the valley, with similar increases seen in the northern and southern regions; the southern region of the valley saw a larger increase in minimum temperature compared to the northern region.

For future projection periods, there is an approximately three degree (ºF) increase in both maximum and minimum temperatures between each period. Average maximum temperatures increase to 78.45 ºF by 2025, 81.27 ºF by 2055, and 84.48 ºF by 2085. The same increase is seen in both the northern and southern regions of the Central Valley. Average minimum temperatures increase at approximately the same rate, to 50.94 ºF by 2025, 53.44 ºF by 2055, and 56.61 ºF by

2085. Again, the rate of increase in minimum temperatures is greater for the southern region of the Central Valley, compared to the north.

Table 2.5. Historic average minimum and maximum temperatures of the Central Valley for baseline periods 1965 (1951 – 1980) and 1995 (1981 – 2010). The average temperature and range of temperatures for each baseline period are shown.

	Central Valley		**North Central Valley**		**South Central Valley**	
	Maximum Temp (°F)	**Minimum Temp (°F)**	**Maximum Temp (°F)**	**Minimum Temp (°F)**	**Maximum Temp (°F)**	**Minimum Temp (°F)**
1965 **Average (Range)**	75.76 (5.00, 119.00)	48.01 (0.00, 92.00)	75.04 (7.00, 119.00)	47.97 (13.00, 87.00)	76.17 (5.00, 116.00)	48.04 (0.00, 92.00)
1995 **Average (Range)**	76.12 (26.00, 121.00)	49.17 (11.00, 90.00)	75.48 (27.00, 121.00)	48.85 (11.00, 89.00)	76.49 (26.00, 116.00)	49.36 (11.00, 90.00)

Table 2.6. Projected average minimum and maximum temperatures of the Central Valley for future conditions in 2025 (2010 – 2039), 2055 (2040 – 2069), and 2085 (2070 – 2099). Averages between all ten climate models are shown; ranges represent full yearly and model differences.

	Central Valley		**North Central Valley**		**South Central Valley**	
	Maximum Temp (°F)	**Minimum Temp (°F)**	**Maximum Temp (°F)**	**Minimum Temp (°F)**	**Maximum Temp (°F)**	**Minimum Temp (°F)**
2025 **Average (Range)**	78.45 (16.63, 127.31)	50.94 (-2.91, 95.71)	77.79 (16.70, 127.31)	50.78 (-2.91, 94.87)	78.82 (16.63, 126.10)	51.04 (-0.7879, 95.71)
2055 **Average (Range)**	81.27 (19.22, 132.71)	53.44 (0.29, 105.83)	80.54 (19.22, 132.49)	53.27 (0.29, 101.82)	81.69 (21.45, 132.71)	53.54 (2.78, 105.83)
2085 **Average (Range)**	84.48 (18.67, 136.22)	56.61 (2.96, 107.06)	83.80 (24.55, 136.22)	56.47 (11.19, 104.06)	84.86 (18.67, 133.44)	56.69 (2.96, 107.06)

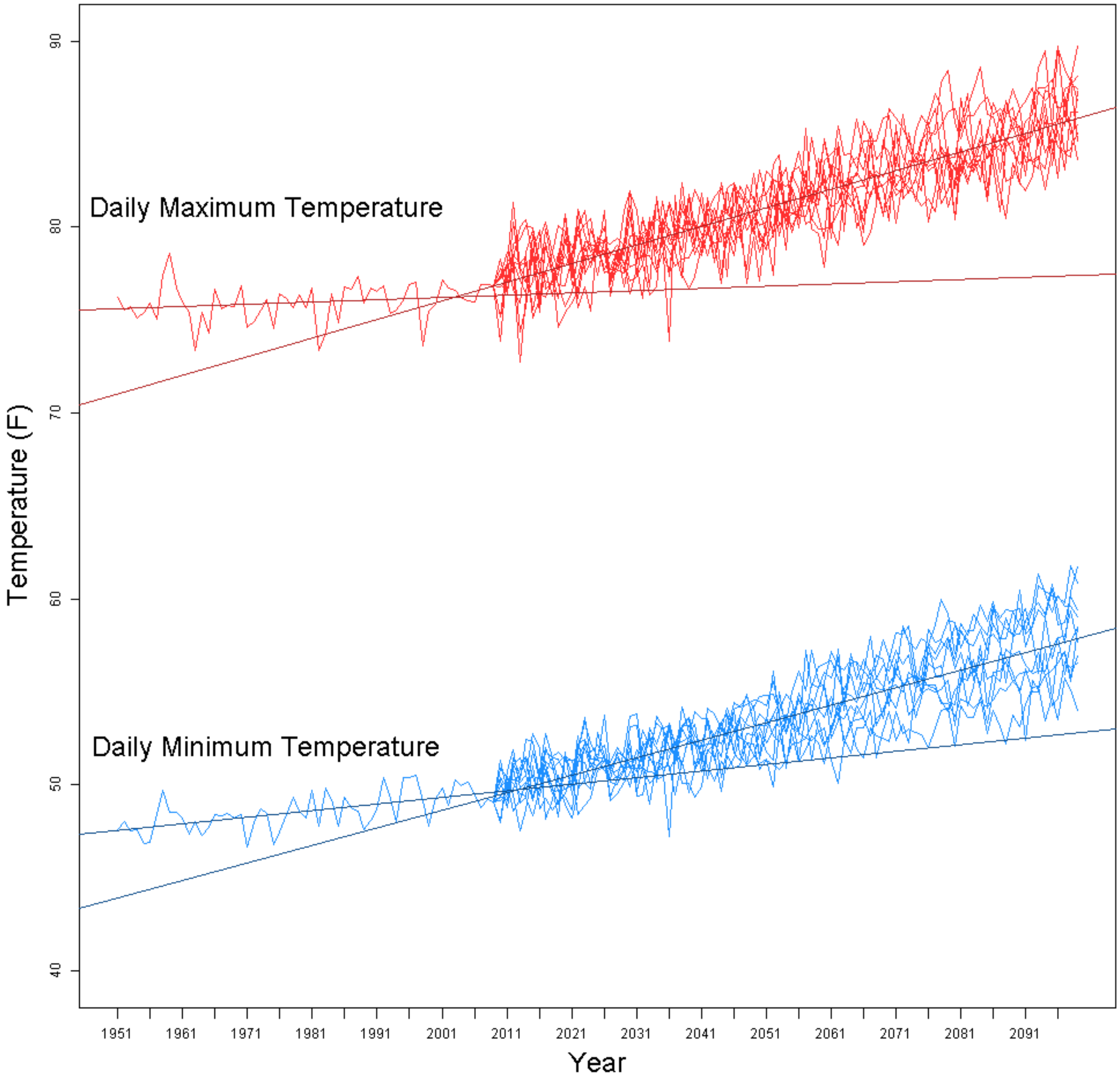


Figure 2.3. Average yearly maximum and minimum daily temperature in the California Central Valley, 1951-2099. The single line represents historical observations (1951 – 2009), and the group of lines represent each of the ten climate model projections (2010 – 2099).

Figure 2.3 shows the average yearly temperature over the study period for the entire Central Valley. The historical trend lines indicate a slight trend in maximum temperature over time (°F) (slope = 0.0123, R^2 = 0.00016, p-value < 0.001), whereas a much greater trend can be seen in minimum temperature (°F) (slope = 0.0354, R^2 = 0.00320, p-value < 0.001). These trends indicate that maximum temperature is not increasing as fast as minimum temperature. The projection trend lines indicate a much stronger increasing trend in both maximum and minimum temperatures (ºF) from 2010 to 2099 (maximum temperature: slope = 0.1003, R^2 = 0.02787, p-value < 0.001; minimum temperature: slope = 0.0940, R^2 = 0.05907, p-value < 0.001). This suggests an increase of approximately one degree (ºF) in both maximum and minimum temperature every ten years, or three degrees (ºF) every 30 years. The trend in projected temperatures prior to 2006 represent what the historical temperature would have looked like were the trend linear over time. These suggest the rate of increase will rise dramatically from historical trends, assuming an RCP8.5 pathway.

2.4.2 *Climate impact on growing degree days*

2.4.2.1 Navel orangeworm

Throughout the Central Valley, the mean number of navel orangeworm generations calculated by the number of degree days varied by year as well as phenology model (**Table 2.7**). When using a biofix of April 1st and estimating the number of generations on October 31st, there were less than half a generation fewer during the first baseline period, but still less than one generation fewer by 2085, compared to the calendar year estimations. The difference of generation numbers between the northern and southern regions of the valley did not differ significantly; across all models, the difference between generations of navel orangeworm was less than half between the two regions.

Assuming a biofix date of January 1st, during the first baseline period of 1965 (1951 to 1980), number of navel orangeworm generations for the Central Valley ranged between 3.4 and 3.6, depending on phenology model; the UCIPM model typically gave the highest estimates, whereas model two typically gave the lowest estimates. During the 1995 baseline period (1981 to 2010), number of navel orangeworm generations increased to 3.5 to 3.7. For future projection periods, the number of navel orangeworm generations increased from 3.8 to 4.1 for 2025 (2010 to 2039), 4.4 to 4.7 for 2055 (2040 – 2069), to 5.1 to 5.4 in 2085 (2070 to 2099) – a full 50% increase from the first baseline period. These numbers assume a start date of January 31st, allowing for potential earlier development of pests. This is an increase of approximately two *full* generations of navel orangeworm by the end of the century (**Figure 2.4**).

Table 2.7. Mean number (and range) of generations of navel orangeworm throughout the Central Valley for 1951-2016, for both biofix/start and end of season dates. The mean is an average between the ten climate models during the 30-year period: 1965 (1951 – 1980), 1995 (1981 – 2010), 2025 (2010 – 2039), 2055 (2040 – 2069), and 2085 (2070 – 2099).

	Central Valley			**North Central Valley**			**South Central Valley**		
	Model 1	**Model 2**	**UCIPM Model**	**Model 1**	**Model 2**	**UCIPM Model**	**Model 1**	**Model 2**	**UCIPM Model**
January 1st-December 31st									
1965	3.5 (2.5, 4.9)	3.4 (2.4, 4.8)	3.6 (2.6, 5.1)	3.3 (2.5, 4.3)	3.3 (2.4, 4.2)	3.5 (2.6, 4.5)	3.5 (2.5, 4.9)	3.4 (2.5, 4.8)	3.6 (2.6, 5.1)
1995	3.6 (2.4, 5.8)	3.5 (2.3, 5.6)	3.7 (2.5, 6.0)	3.4 (2.4, 4.2)	3.4 (2.3, 4.1)	3.6 (2.5, 4.3)	3.7 (2.5, 5.8)	3.6 (2.4, 5.6)	3.8 (2.6, 6.0)
2025	3.9 (2.7, 5.2)	3.8 (2.7, 5.1)	4.1 (2.8, 5.4)	3.9 (3.2, 4.7)	3.8 (3.1, 4.5)	4.0 (3.3, 4.8)	4.1 (3.2, 5.2)	4.0 (3.1, 5.1)	4.3 (3.3, 5.4)
2055	4.5 (3.3, 6.0)	4.4 (3.2, 5.8)	4.7 (3.4, 6.2)	4.5 (3.7, 5.4)	4.4 (3.6, 5.3)	4.7 (3.9, 5.6)	4.7 (3.7, 6.0)	4.6 (3.6, 5.8)	4.9 (3.9, 6.2)
2085	5.2 (4.0, 6.8)	5.1 (3.9, 6.6)	5.4 (4.1, 7.0)	5.2 (4.5, 6.0)	5.1 (4.3, 5.9)	5.4 (4.6, 6.2)	5.4 (4.5, 6.8)	5.3 (4.3, 6.6)	5.6 (4.6, 7.0)
April 1st-October 31st									
1965	3.2 (2.3, 4.3)	3.1 (2.2, 4.2)	3.3 (2.3, 4.5)	3.1 (2.3, 4.0)	3.0 (2.2, 3.9)	3.2 (2.4, 4.2)	3.2 (2.3, 4.3)	3.1 (2.2, 4.2)	3.3 (2.3, 4.3)
1995	3.3 (2.2, 5.3)	3.2 (2.2, 5.1)	3.4 (2.3, 5.5)	3.1 (2.3, 3.7)	3.0 (2.3, 3.6)	3.2 (2.4, 3.9)	3.3 (2.2, 5.3)	3.2 (2.2, 5.1)	3.4 (2.3, 5.5)
2025	3.5 (2.5, 4.5)	3.4 (2.5, 4.4)	3.6 (2.6, 4.7)	3.5 (2.9, 4.2)	3.4 (2.9, 4.1)	3.6 (3.0, 4.4)	3.7 (2.9, 4.5)	3.6 (2.8, 4.4)	3.8 (3.0, 4.7)
2055	4.0 (2.9, 5.0)	3.9 (2.8, 4.9)	4.1 (3.0, 5.2)	4.0 (3.3, 4.7)	3.9 (3.2, 4.6)	4.1 (3.4, 4.9)	4.1 (3.3, 5.0)	4.0 (3.2, 4.9)	4.3 (3.4, 5.2)
2085	4.5 (3.4, 5.5)	4.4 (3.3, 5.3)	4.6 (3.5, 5.7)	4.5 (3.9, 5.2)	4.4 (3.8, 5.0)	4.6 (4.0, 5.3)	4.6 (3.8, 5.5)	4.5 (3.7, 5.3)	4.8 (4.0, 5.7)

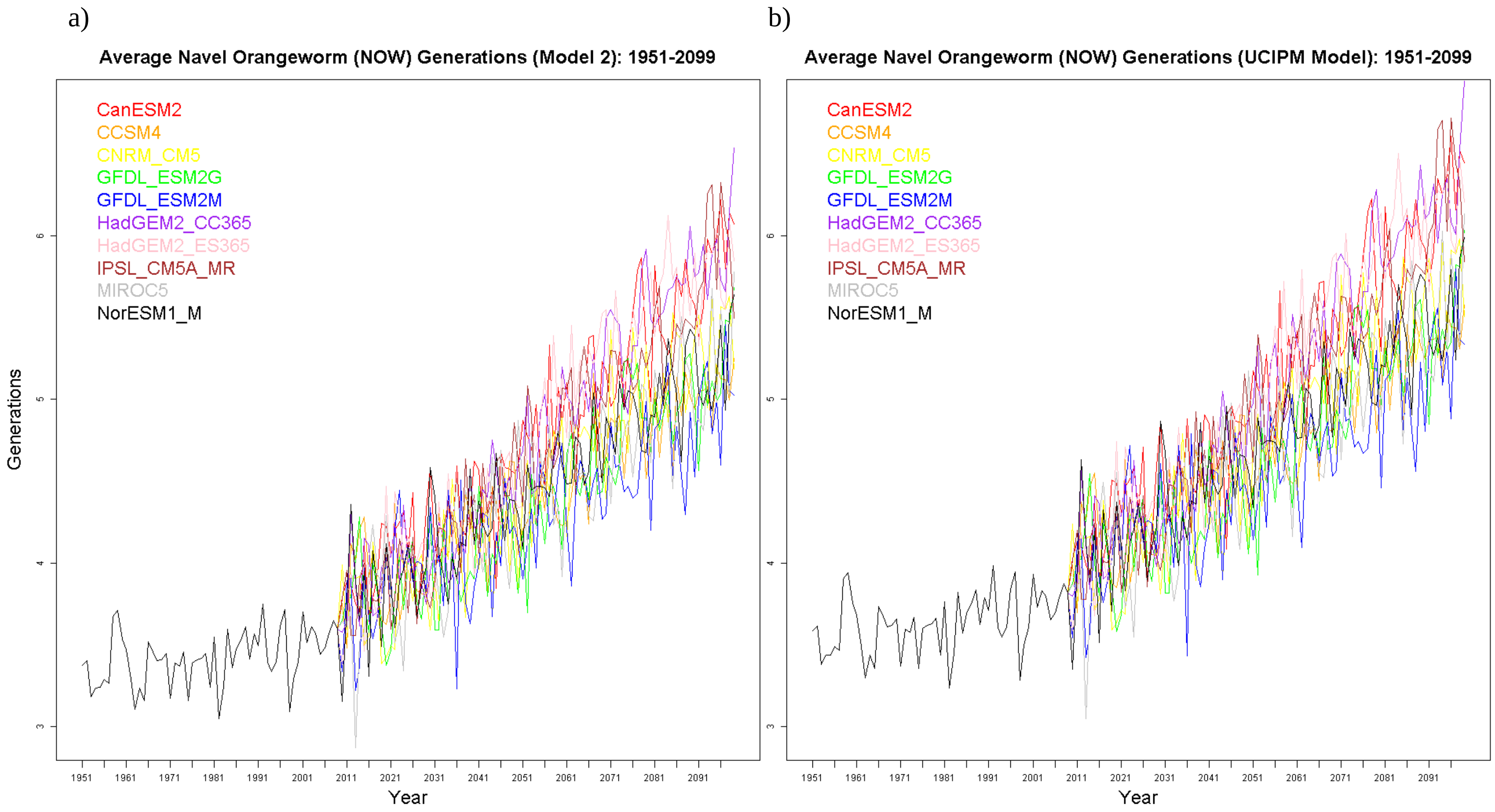


Figure 2.4. Number of navel orangeworm generations for a) model two and b) the UCIPM model, January 1st start date, 1951 – 2099. The black line represents generations calculated from estimated growing degree days using historical temperature observations. The colored lines represent generations calculated from estimated growing degree days using the ten climate model projections.

Overwintering adult flight (first flight, overwintering generation) shifts considerably over the study period (**Figure 2.5**). Using 99.9°D as the number of required GDD for egg development, the first flight date can be approximated. During the baseline periods, first flight averaged the second or first week of March. By 2055 the date averaged mid-February, and by 2095 the date averaged during the first week of February.

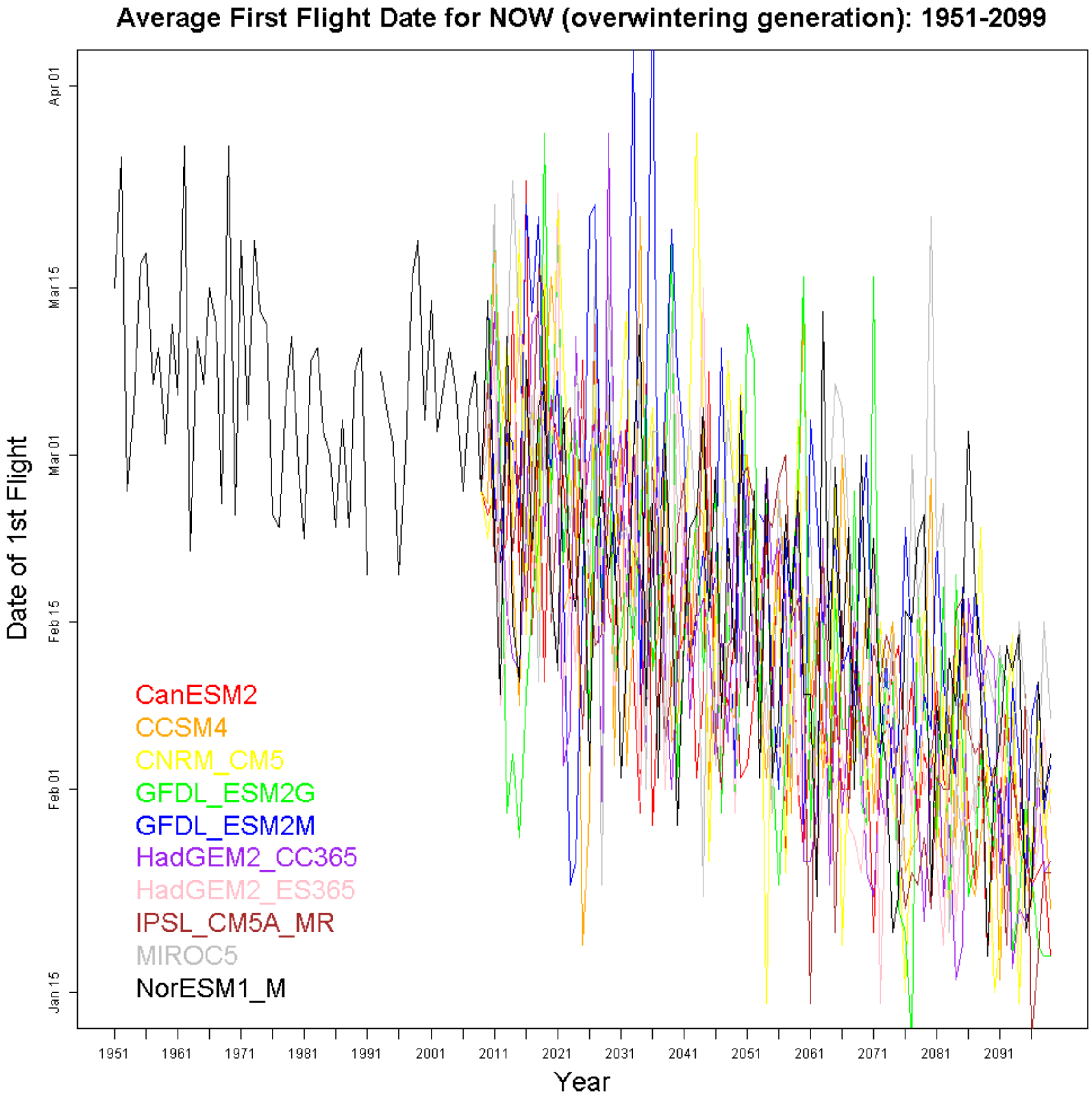


Figure 2.5. Average yearly first flight (for the overwintering generation) of the navel orangeworm based on accumulated growing degree days and egg development, January 1st start date, 1951 – 2099.

2.4.2.2 Peach twig borer

Throughout the Central Valley, the mean number of peach twig borer generations calculated by the number of degree days varied by year as well as phenology model (**Table 2.8**). When using a biofix of April 1st and estimating the number of generations on October 31st, there were approximately half a generation fewer peach twig borer during the first baseline period, but over one generation fewer by 2085, compared to using a start date of January 1st and estimating number of generations on December 31st. The difference of generation numbers between the northern and southern regions of the valley did not differ significantly; during most of the study period and across all models, the difference between generations of peach twig borer was less than half a generation between the two regions.

Assuming a biofix date of January 1st, during the first baseline period of 1965 (1951 to 1980), number of peach twig borer generations for the Central Valley ranged between 4.5 and 4.7, depending on phenology model; the UCIPM model typically gave the highest estimates, whereas model one typically gave the lowest estimates. During the 1995 baseline period (1981 to 2010), number of peach twig borer generations increased to 4.7 to 4.9. For future projection periods, the number of peach twig borer generations further increased from 5.0 to 5.3 for 2025 (2010 to 2039), 5.7 to 5.9 for 2055 (2040 to 2069), to 6.4 to 6.7 in 2085 (2070 to 2099) – a 37% increase from the first baseline period. These numbers assume a start date of January 31st, allowing for potential earlier development of pests. This is an increase of approximately two *full* generations of peach twig borer by the end of the century (**Figure 2.6**).

Overwintering adult flight (first flight, overwintering generation) shifts considerably over the study period (**Figure 2.7**). Using 752.6°D as the number of required GDD for larva and pupa development, the first flight date can be approximated. During the baseline periods, first flight averaged the first week of May or last week of April. By 2055 the date averaged early April, and by 2095 the date averaged during the last week of March.

Table 2.8. Mean number (and range) of generations of peach twig borer throughout the Central Valley for 1951-2016, for both biofix/start and end of season dates. The mean is an average between the ten climate models during the 30-year period: 1965 (1951 – 1980), 1995 (1981 – 2010), 2025 (2010 – 2039), 2055 (2040 – 2069), and 2085 (2070 – 2099).

	Central Valley			**North Central Valley**			**South Central Valley**		
	Model 1	**Model 2**	**UCIPM Model**	**Model 1**	**Model 2**	**UCIPM Model**	**Model 1**	**Model 2**	**UCIPM Model**
January 1st-December 31st									
1965	4.5 (3.5, 6.1)	4.6 (3.6, 6.3)	4.7 (3.7, 6.4)	4.4 (3.5, 5.5)	4.5 (3.6, 5.6)	4.6 (3.7, 5.8)	4.6 (3.5, 6.1)	4.7 (3.6, 6.3)	4.8 (3.7, 6.4)
1995	4.7 (3.4, 5.9)	4.8 (3.5, 6.0)	4.9 (3.6, 6.2)	4.5 (3.4, 5.3)	4.6 (3.5, 5.4)	4.8 (3.6, 5.6)	4.8 (3.5, 5.9)	4.9 (3.5, 6.0)	5.0 (3.7, 6.2)
2025	5.0 (3.7, 6.4)	5.1 (3.7, 6.5)	5.3 (3.9, 6.7)	5.0 (4.3, 5.8)	5.1 (4.4, 5.9)	5.3 (4.5, 6.0)	5.3 (4.3, 6.4)	5.4 (4.4, 6.5)	5.5 (4.5, 6.7)
2055	5.7 (4.3, 7.2)	5.8 (4.3, 7.3)	5.9 (4.5, 7.5)	5.7 (4.9, 6.6)	5.8 (5.0, 6.7)	5.9 (5.1, 6.9)	5.9 (4.9, 7.2)	6.0 (5.0, 7.3)	6.2 (5.1, 7.5)
2085	6.4 (5.1, 8.0)	6.5 (5.2, 8.1)	6.7 (5.3, 8.4)	6.4 (5.6, 7.2)	6.6 (5.8, 7.3)	6.7 (5.9, 7.6)	6.6 (5.7, 8.0)	6.8 (5.8, 8.1)	7.0 (6.0, 8.4)
April 1st-October 31st									
1965	3.9 (3.0, 5.1)	4.0 (3.0, 5.2)	4.1 (3.1, 5.4)	3.9 (3.1, 4.8)	3.9 (3.1, 4.9)	4.0 (3.2, 5.1)	4.0 (3.0, 5.1)	4.1 (3.0, 5.2)	4.2 (3.1, 5.4)
1995	4.1 (3.0, 5.0)	4.1 (3.1, 5.1)	4.3 (3.2, 5.3)	3.9 (3.1, 4.5)	4.0 (3.2, 4.6)	4.1 (3.3, 4.7)	4.1 (3.0, 5.0)	4.2 (3.1, 5.1)	4.3 (3.2, 5.3)
2025	4.3 (3.3, 5.3)	4.4 (3.3, 5.4)	4.5 (3.4, 5.6)	4.3 (3.7, 5.0)	4.4 (3.8, 5.1)	4.5 (3.9, 5.2)	4.5 (3.7, 5.3)	4.5 (3.8, 5.4)	4.7 (3.9, 5.6)
2055	4.7 (3.7, 5.7)	4.8 (3.8, 5.8)	5.0 (3.9, 6.0)	4.7 (4.1, 5.4)	4.8 (4.2, 5.5)	5.0 (4.3, 5.7)	4.9 (4.1, 5.7)	5.0 (4.2, 5.8)	5.1 (4.3, 6.0)
2085	5.2 (4.2, 6.1)	5.3 (4.3, 6.2)	5.4 (4.4, 6.4)	5.2 (4.6, 5.8)	5.3 (4.7, 5.9)	5.5 (4.9, 6.1)	5.3 (4.6, 6.1)	5.4 (4.7, 6.2)	5.6 (4.8, 6.4)

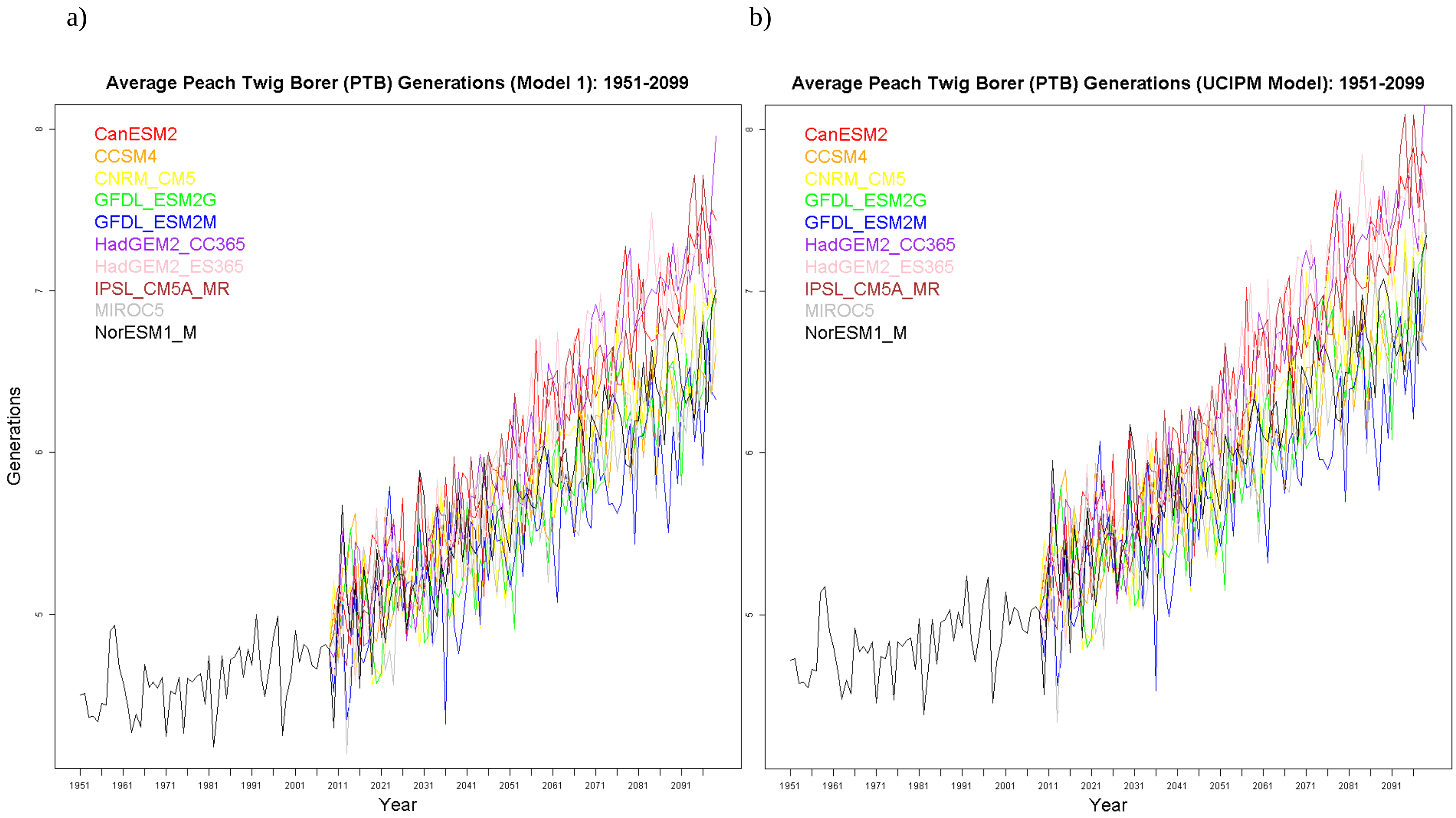


Figure 2.6. Number of peach twig borer generations for a) model two and b) the UCIPM model, January 1st start date, 1951 – 2099. The black line represents generations calculated from estimated growing degree days using historical temperature observations. The colored lines represent generations calculated from estimated growing degree days using the ten climate model projections.

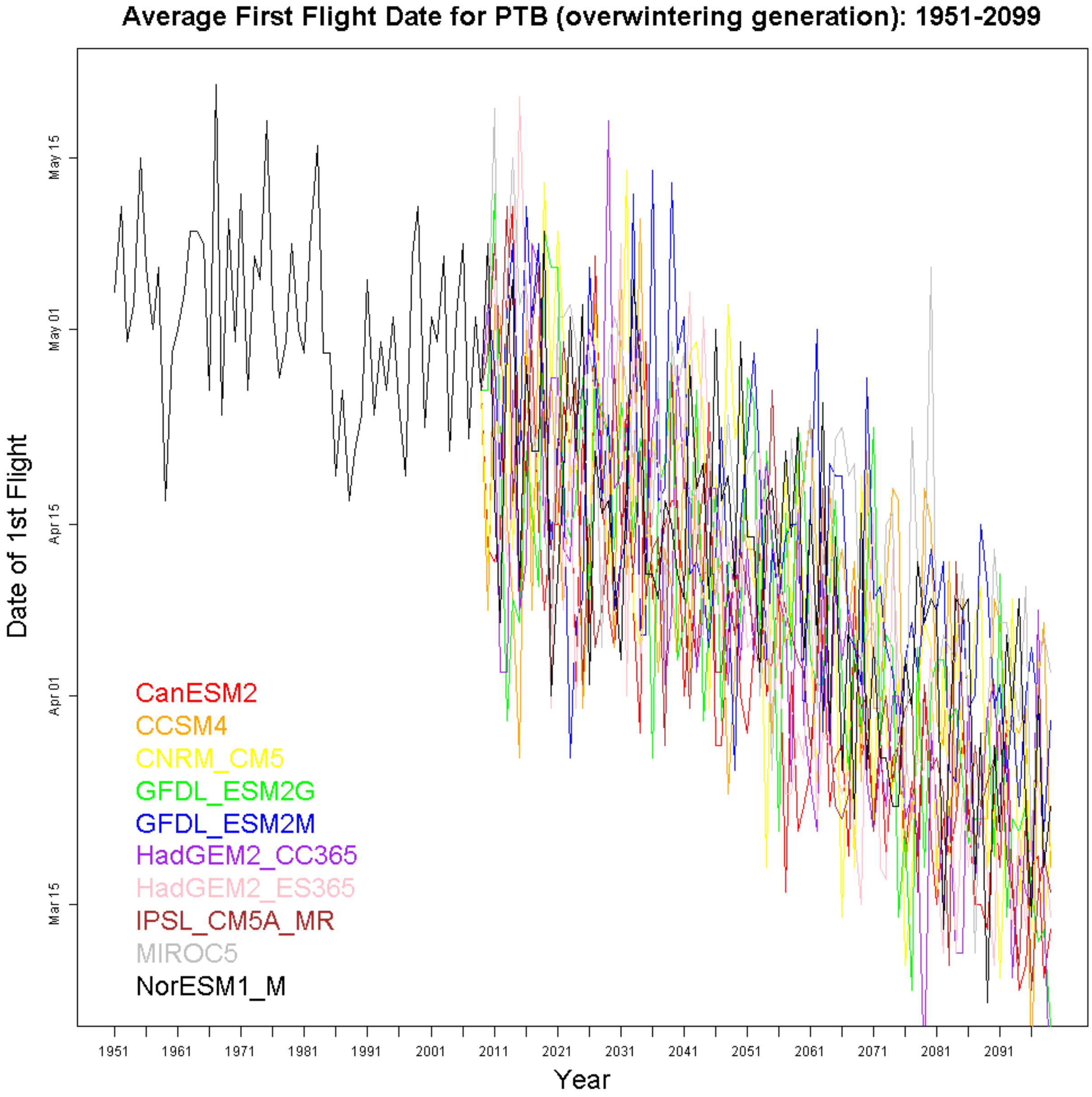


Figure 2.7. Average yearly first flight (for the overwintering generation) of the peach twig borer based on accumulated growing degree days and egg development, January 1st start date, 1951 – 2099.

2.5 DISCUSSION

The climate change model projections clearly indicate an average increase in temperature of approximately six to ten degrees by mid- and end of the 21st century, under RCP8.5 in California's Central Valley. Because growing degree days are based on temperature, it is expected that daily growing degree days will also increase in number. In this study, the accumulated growing degree days per year increased over the 21st century for both pests, under all ten climate models. Compounding the increased heat during the traditional growing season is the shift in phenology, where the first flights of the overwintering generations occur earlier every season. These early flights will lay first-generation eggs earlier in the year as well, and it is expected that each development step and consequently generation of pests thereafter will be shifted earlier in the season.

The insect physiology results clearly indicate that numbers of pest generations will rise for both the navel orangeworm and peach twig borer. The estimated baseline number of generations for both pests using the models were similar to what is currently observed – approximately three and sometimes four generations of navel orangeworm, and four generations of peach twig borer. The results following a biofix date of April 1st are more closely aligned with current observations. By mid-century, the results suggest that navel orangeworm will consistently experience a fourth generation and peach twig borer will start to see a potential fifth generation. By the end of the 21st century, it is likely that the navel orangeworm will have approximately four and often five full generations per season, whereas the peach twig borer will have approximately five if not six full generations. For both pests this is an increase of one if not two more generations per season, which is similar to results of previous studies of climate change impacts on these pests[23,72]. This of course has potential consequences not only for potential crop loss, but pest management practices as well.

Previous assessments of climate change impacts on pest species in California found similar results, despite differences in methods and climate models used. Luedeling et al. assessed the navel orangeworm (in addition to several different pests) and found the pest was expected to increase by roughly one generation by the end of the century[23]. However, besides seeing an increase in pest generations, there are very few similarities between this work and the Luedeling study. Luedeling et al. only considered three climate models, averaging between them before calculating the estimated number of degree days and generation numbers, so there is no range provided across climate models; cooler or warmer models may have strongly influenced their climate predictions and therefore had a significant impact on the estimated degree days, which is not discussed in their results. While they did consider multiple scenarios and provided a range based on these, the scenarios and climate models used in the analyses are outdated and no longer supported by the IPCC. Luedeling et al. also only used phenology model calculations based on new crop almonds to calculate number of generations, whereas in this analysis, degree days based on mummy crop almonds were used. Therefore, it is not possible to make more quantitative comparisons between the two studies.

Similarly, Ziter et al. recently conducted an assessment of climate change on 13 different pest species in California[72]. Their results more closely align to the results here, although the presentation makes it difficult to determine actual number of generations predicted. Ziter et al. found that for both the navel orangeworm and peach twig borer, number of generations are projected to increase by 1.0 to 1.5 for both species by the 2050s and 2090s. They do not provide numbers for baseline generations, nor do they provide numbers for the projections – predicted increase is only displayed in a bar graph, as compared to numbers predicted under baseline conditions. Similar to the Luedeling et al. study, only three climate models were used in Ziter et al. study, and all models and scenarios are no longer recommended for climate research implications. Again, they averaged across all models and scenarios, so it is not possible to see the range predicted by each climate model and scenario. The Ziter study also did not statistically downscale the climate model output, instead using coarse global climate model output for their projections. Based on the considerable differences between this analysis and the Ziter et al. study, it is not possible to make further comparisons.

Both previous studies discussed above had significant limitations that warranted a further assessment of the impacts of climate change on both the navel orangeworm and peach twig borer. The assessment here utilized three different phenology models, all of which projected different generation numbers by 2055 and 2085. Additionally, ten climate models were used for the projections, which is the recommended number of models to use in order to account for model uncertainty as well as provide a full consensus about the mean of projected values. Longer baseline periods were used here, each averaging across 30-year time periods; likewise, 30-year projection periods were used in order to give robust estimates that average over interannual variability, which is longer than the periods used in the other two studies. Finally, two different biofix/start dates were used in this analysis in order to fully assess the potential impacts of climate change on both phenology and voltinism. Luedeling et al. noted that the timespan for development of the pests was a limitation in their study, so two different methods were used here. Number of generations estimated by the two methods differed by 10%; while insignificant, when in addition to the estimations generated by using ten climate models and three phenology models, these differences are worthy of noting and doing a third analysis of the impacts of climate change on these pests.

The choice of biofix date is a potential source of over- or under-estimation. By choosing a historical average for biofix, this does not allow for shifts in phenology as the climate warms earlier in the season. Estimates based on this date are likely to underestimate the potential accumulated growing degree days in the future, as it is likely that the biofix will occur earlier in the season under a warming climate. However, estimates based on a January 1st start date are likely to over-estimate the accumulated growing degree days. While the accumulation of heat does allow for an insect to develop, there are other factors involved in the emergence of the overwintering generation into the first flight, as well as egg-laying for subsequent generations. Such factors include night-time minimum temperatures and crop phenology and physiology. When night temperatures drop low enough, no eggs are laid by the navel orangeworm; as long as night-time temperatures remain below the lower development threshold, the progression of future generations will be limited. However, higher minimum daily temperatures are suggested by the climate models and have been estimated by previous national climate assessments[47], which does favor pest development. The phenology of the almond crop is also dependent on climate and temperature, in particular winter chilling and spring heat. There are significantly fewer studies looking at the impact of climate change on almond phenology, but there is some suggestion that there will be a delay in chill accumulation and an advance in the timing of bloom and harvest in the Central Valley[195]. It is possible that these factors will limit how early the biofix may shift; while future temperatures may be favorable for earlier pest development, almond phenology may be a limiting factor for pest development. By assessing both an April 1st biofix and a January 1st start date, this study is able to parse out some of these differences and provide a range of potential outcomes.

How the upper pest development threshold is considered also plays a role in predicting how many generations of pests there will be by the end of the century. The horizontal cut-off method chosen for this analysis is the simplest, assuming development continues at the same rate as the upper threshold temperature when temperatures are above it. However, it does not consider the deleterious effects of high temperatures on pest development. It may be that future temperatures will exceed the upper development threshold for both pests with enough frequency to delay their development during the hottest periods of the growing season. Using a different method such as the vertical cut-off method may produce more conservative results for future generation number estimations, as it assumes that no development occurs when temperature is above the upper threshold and subtracts that time from the accumulated growing degree days.

Similarly, the phenology models for the navel orangeworm are more complicated than simply using the same growing degree day accumulations for each generation of pest. The overwintering and first generations of navel orangeworm (first and second flight) develop on mummy nuts; these generations require more accumulated growing degree days for development. However, later generations develop on new crop almonds; because they are a much better and plentiful food source than mummy nuts from the previous year, these generations grow more rapidly and require fewer accumulated growing degree days to advance in development. It was not possible to account for this effect in this study, as this would require modeling almond phenology in addition to the insect phenology to know what future generations will develop on new crop versus mummy crop. By only calculating generation numbers based on mummy crop, we are potentially underestimating future generations on new crop almonds.

The primary limiting factor in estimating degree days and using them to approximate pest development and numbers of pest generations is accurate temperature readings. If a weather station location is not representative of the environment in which the insect occurs, the resulting degree days will not mirror the actual development of the insect. It is possible that conditions just a few miles away from the weather station are not reflective of the temperature readings. This was observed when assessing differences in the northern and southern regions of the Central Valley. While actual conditions in the valley vary greatly between north and south, the averages of the weather stations in the regions did not demonstrate large differences in climate. Averaging climate over these regions suppresses the localized climates and may lead to over- or under-estimations of pest pressures throughout the valley, depending on whether the local climate is over- or under-estimated by the regional average. Use of different metrics to divide the region into zones that better reflect the difference in climate is recommended, or potentially using a much finer geospatial scale to average climate and growing degree days. This analysis was limited in doing so due to the computing power required to handle more granular datasets.

Climate models are not predictions or forecasts, rather they are simply a potential trajectory of future climate change, simulating what the future may look like. A limitation of using climate models is the inherent uncertainty in the factors they are based on. This uncertainty comes from 1) the drivers of anthropogenic change associated with GHGs, aerosols, and land use change; 2) the sensitivity of the climate system to these changes; and 3) natural unforced variability. Due to the uncertainty in the drivers of the anthropogenic change, such as changes in demography, socioeconomic development and technological development, using multiple scenarios or pathways is often recommended. By only using RCP8.5 climate model output, this analysis is limited in its ability to predict the full spectrum of possible futures and their resulting changes in climate. However, one strength of the study is the inclusion of an ensemble of ten climate models. This allowed for the accounting of model uncertainty and gave a more comprehensive projection that is not model dependent.

Climate change is likely to result in both increasing minimum and maximum temperatures, having a direct impact on pest dynamics in the Central Valley of California. According to all climate models analyzed, the accumulation of growing degree days will increase in conjunction with increasing temperatures. Generation numbers of navel orangeworm and peach twig borer are likely to increase by at least one generation per season, creating a new challenge for almond growers. More research into how other climate scenarios and pest modeling methods may affect these predictions is needed, as is research into how the agricultural ecosystem as a whole will be affected by climate change, in order to project the impacts of climate change on pest dynamics and pressure with greater certainty. The validity of current pest development models under a much warmer climate should also be investigated, as they were developed under current conditions and may not accurately reflect how the pests will react to more frequent extreme temperatures during the height of the growing season.

Chapter 3. HISTORICAL AND PROJECTED CLIMATE CHANGE EFFECTS ON INSECTICIDE USE IN CALIFORNIA'S CENTRAL VALLEY

3.1 ABSTRACT

Increasing temperatures, changes in precipitation, and more variable weather patterns are expected to be the norm under a changing climate[1,3,218]. It is predicted that these same changes will result in impacts to agricultural pests and, consequently, pesticide use to combat the likely increase in pest pressure[8,180,186]. This has the potential for considerable impact on the environment and human health. Previous studies of the impact of climate change on pesticide use have generally focused on one part of this equation, assessing how climate will impact certain pest populations and speculating how pesticide use is likely to follow suit[23,72]. To our knowledge, no study has focused on pests specific to the almond industry or quantified the changes in insecticide use.

This study aims to assess historical seasonal and temporal trends in insecticide use and predict that relationship using climate model projections to mid- and end-of the 21st century. Historical (2005 – an average of 1990 to 2016) and future (2025, 2055, and 2085 – an average of the periods from 2006 to 2099) daily weather variables were previously obtained for California's Central Valley. For the climate projections, a suite of ten statistically downscaled models suitable for use in California were chosen, using output from one representative concentration pathway (RCP8.5). Degree-day models were previously used to estimate growing degree days for both the navel orangeworm and peach twig borer. California pesticide use reports for the years 1990 to 2016 were then assessed for seasonal and temporal trends, as well as correlation to weather variables (temperature and precipitation) and degree-days. This relationship was estimated and then

predicted on the climate model projections for daily weather and calculated degree-days through the end of the 21st century (at averaged time points for 2025, 2055 and 2085).

This chapter addresses the following sub-aims:

- Understand historical trends and seasonality in insecticide use from observed pesticide use reports for the years 1990 to 2016
- Determine the relationship between insecticide use and weather variables, such as minimum and maximum temperature and precipitation, and growing degree days; develop a multi-variate linear regression model based on the historical observed data to estimate insecticide use
- Estimate future insecticide use in California's Central Valley to mid- and end-of century, utilizing the model developed from historical observations of temperature, precipitation, and degree-days on climate model projections and estimated future degree-days

3.2 INTRODUCTION

Agriculture and climate change are deeply intertwined[55,179,219-222]. Climate is, simply, the average of the weather over an extended time period; under a changing climate, weather will be more variable and extreme. Because agriculture is dependent on weather variables such as temperature and precipitation, overall warming will affect both plant and insect species and communities in connection with physiology and species distributions[20,72,181,185]. Many insect species are predicted to respond strongly and quickly to changes in climate, as their growth and development is determined by temperature and accumulation of heat over time. Such responses to climate change likely include changes in phenology, such as earlier start dates for development, and in voltinism, such as increasing numbers of generations per growing season.

One concern of increasing pest pressure on agriculture is the potential increase in pesticide use to combat the issue. The US EPA defines pesticides as a substance or mixture of substances intended to prevent, destroy, repel, or mitigate any species designated as a pest[223]. Historically, this included heavy metals and naturally occurring plant derivatives. However, synthetic pesticides, developed and introduced in the 20th century (often times for original use in warfare), have quickly spread in use[224-226]. Pesticides are now widely used across all agricultural sectors to reduce losses by pests, thereby improving yield and quality of the produce; they are considered by many to be an economic and efficient tool of pest management and are regularly used as part of major management actions for pests. Global crop loss due to insect pests is astounding; similarly, expenditure on agricultural insect control can be estimated in the billions of dollars[180,184,227].

In order to combat this loss, farmers have historically employed broad spectrum chemical insecticides to control against insect pests, as well as targeted insecticides during susceptible developmental phases. This widespread and oft indiscriminate use (and abuse) has led to pesticide resistance as well as harmful effects on human health and the surrounding environment[226-228]. While genetically modified crops and integrated pest management – which takes into account the ecological implications of insect control – have increased in order to combat this issue, and there has been an overall decrease in pesticide use, the emerging issue of climate change points to an increase in pest pressure, and subsequently an increase in crop losses due to insect pests in a warming climate[180,220].

Most almond pests are controlled with organophosphates, pyrethroids, growth-regulating insecticides and oils[67]. Many of the chemicals used to reduce insect pests on almonds have been restricted or banned over the last 50 years, and many that are presently in use are currently being evaluated by regulatory bodies, such as chlorpyrifos. Concerns about the impacts of pesticide use on human health may lead to new legislation that may restrict the array of available pesticides in the future. Alternative crop management systems such as biological control is thus becoming increasingly important for California almond growers[229]. Integrated Crop Management (ICM) is a system of crop production that conserves and enhances natural resources, following a set of guidelines that enforce safe agricultural practices with simultaneous respect to the environment; this includes careful selection of planting sites, soil management, seed and planting material, crop rotation, crop nutrition, water and landscape management, and pest management.

For control of pests, ICM encourages using complementary methods such as biological, cultural, mechanical and physical, and chemical controls; pesticide use is only permitted through an Integrated Pest Management (IPM) program[230,231]. The principles of IPM include identifying pests and establishing monitoring guidelines for each pest species including natural enemies, establishing an action threshold for when management action is needed, evaluate and implement control tactics to find those that are most effective and have the least amount of impact on non-target species and the environment, and to monitor, evaluate, and document the results of the pest management strategies used[232,233]. Pesticides are only used when absolutely needed under IPM and are selected and applied in a way that minimizes their negative impacts on humans and the environment. Similarly, the limited pesticide use under IPM ensures that overuse will not lead to pest resistance to broadly applied insecticides. Each major crop type has a set of management guidelines for pest management and biological control – a seasonal checklist of major management actions broken down by season, highlighting when pests should be monitored and controlled for (**Table 3.9**)[216]. Use of degree days (a measure of heat accumulation related to the rate of insect development) to time treatments is an important component of IPM and allows growers to pinpoint specific treatment dates that will have the most impact on the pest.

Table 3.9. Seasonal checklist of major management actions for almond orchards.

WINTER MANAGEMENT ACTIONS (Nov – Jan)

Remove mummy nuts from trees and destroy; prune trees

Monitor prunings for scales and mite eggs

Apply dormant treatment as needed for peach twig borer, San Jose Scale, and mite eggs OR apply dormant oil for scales and mite eggs followed by bloom treatment for peach twig borer

Monitor winter annual and perennial weed seedlings

Monitor pocket gophers, control if needed

Arrange to have beehives placed in orchard prior to bloom

SPRING MANAGEMENT ACTIONS (Feb – Apr)

Protect against frost as needed

Mow ground cover prior to bloom and thereafter as needed

Bloom and post bloom disease control

Apply Bt or Spinosad bloom sprays if no dormant sprays were applied for peach twig borer

Begin irrigation as needed

Apply nitrogen fertilizer in April

Begin monitoring insect and mite pests:

1) Count mummy nuts remaining in trees
2) Monitor peach twig borer emergence from hibernacula
3) Set out egg traps for NOW and calculate degree-days
4) Set out pheromone traps for peach twig borer and calculate degree-days
5) Set out pheromone traps or sticky tape traps for San Jose scale if needed and calculate degree-days
6) Set out pheromone traps for oriental fruit moth if needed

Monitor vertebrates, control if needed

SUMMER MANAGEMENT ACTIONS (May – Jul)

Irrigate as needed

Monitor summer annual weed seedlings and perennials

Continue monitoring insects and mites

Have leaf analysis done

Monitor vertebrate activity (ground squirrels, birds, gophers), control if needed

Monitor hullsplit for spray and earliest harvest date, and apply sprays for navel orangeworm if needed

Apply spray for San Jose scale and peach twig borer as needed, if not treated earlier in the season

Prepare orchard floor for harvest

Apply nitrogen fertilizer in July

FALL MANAGEMENT ACTIONS (Aug – Oct)

Monitor webspinning mites

Harvest early to avoid third navel orangeworm flight

Pick up nuts as quickly as possible to minimize ant damage

Have hulls analyzed for boron

Monitor for shot hole lesions and fruiting structures

Monitor vertebrates, and control if needed

Apply potassium (soil) if needed

Apply zinc spray at leaf fall if needed

Irrigate if needed following harvest

Apply preemergence herbicides

Monitor for peach tree borer

Remove weak trees, backhoe, and fumigate tree sites

Seed fall/winter cover crop if needed

The future of pest control will depend largely on how climate and other factors affect the ecological balance between pests and control organisms in almond orchards in the coming years[216]. Previous studies have assessed how climate change may impact pests (i.e. insect pests) and crop yields as well as food security, yet few have made the extra step to quantifiably link pesticide use to a changing climate[8,173,234-237]. The purpose of this study is to evaluate historical use trends of insecticides on the almond crop in California's Central Valley, to determine if there are seasonal and temporal trends or correlation to climate variables, and to project these trends to the middle and end of the 21st century using an ensemble of climate model projections. The ectothermic nature of insects makes their population dynamics highly sensitive to both average annual temperatures and intra-annual variations. To consider the combined effect of temperature on insect development, growing degree days should also be considered when determining overall pest pressure and insecticide use. A framework that links historical weather and pest population dynamics to predict insecticide use is used in this analysis.

3.3 MATERIALS AND METHODS

3.3.1 *Study area*

Analyzing historical changes in almond pests and insecticide use requires historical almond acreage and increases in orchard size and number to be accounted for. National crop distribution data from the National Agricultural Statistics Service (NASS), which has produced a GIS layer using satellite imagery during the growing season and validated using farmer reported data on crop type and location, has been reported at a spatial resolution of 30 meters since 2007[60]. Because this data does not go back in time far enough to analyze long-term trends in crop distribution, the NASS data was used only to confirm the location of almond orchards in California. Historical pesticide use, described below, was instead used to determine the total number of almond acres planted and treated in order to consider changing acreage over time.

3.3.2 *Climate divisions*

Given the diversity in climate across the Central Valley, the region was categorized into climate divisions used by the National Oceanic and Atmospheric Administration (NOAA) for regional forecasting[196]. These divisions have been used over the past century to generate climate analyses and regional monitoring of climate-related variables within the United States[197]. In California, there are seven climate regions: North Coast Drainage, Sacramento Drainage, Northeast Interior Basins, Central Coast Drainage, San Joaquin Drainage, South Coast Drainage, and Southeast Desert Basin. The areas that encompass the Central Valley are the Sacramento and San Joaquin Drainages. As climate and growing practices may vary significantly between climate regions, these regions were included in the analysis in order to account for any differences in the relationship between climate and pest development and insecticide use by climate region.

3.3.3 *Historical weather data*

Historical climate records were obtained previously from the NCDC from 1950 to 2016[198]. Daily records of minimum and maximum air temperature (°F) and precipitation amount (inches) were selected for the 33 stations within the Central Valley from 1990 to 2016 through the University of California weather database[199]. For stations where requested data was not complete, backup and long-term average stations were used to fill in missing data, as described previously[200]. The historical minimum and maximum temperatures for each of the 33 NCDC stations were then classified as 'North' or 'South' Central Valley based on the weather stations location within the NOAA climate divisions.

3.3.4 *Climate scenarios and models*

Climate model projections (2006 to 2099) were utilized from statistically downscaled GCMs coordinated by CMIP5[201]. Of the 40 models included in CMIP5, 20 were statistically downscaled using the newest version of the MACA method[203]. From this group of 20, ten were chosen to best represent the Central Valley region of California, based on a previous assessment: MIROC5, CCSM4, CNRM-CM5, CanESM2, IPSL-CM5A-MR, HadGEM2-ES, NorESM1-M, GFDL-ESM2M, HadGEM2-CC, and GFDL-ESM2G[209]. A suite of ten models was chosen, as using a group of climate models allows for a more thorough characterization of the range and variability of the future climate[207].

The MACA downscaling considers RCP4.5 and RCP8.5, two assumed scenarios representing potential future global GHG emissions, land use, population growth, technology, and other factors. As RCP4.5 is a stabilization scenario and RCP8.5 represents a future where no action is taken to reduce carbon emissions, RCP8.5 output was chosen for the analysis, as recent assessments show the world is on or past the RCP8.5 trajectory[48,49,206]. Daily minimum and maximum temperature and precipitation projections for RCP8.5 were downloaded for each of the ten MACA downscaled CMIP5 models for the years 2006 to 2099. The latitude and longitude for each of the 33 NCDC stations was used to select the point locations from which to download the data; the extracted data corresponds to the average over the grid cell that contains the selected point (1/16th degree Livneh grid cell).

3.3.5 *Insect physiology and modelled growing degree days*

Established growing degree-day models used by the University of California’s Agricultural and Natural Resources, Cooperative Extension’s Statewide Integrated Pest Management Program were used to predict insect pest development using degree-days based on historically observed and future projected weather and climate data[210]. Degree-days are a measure of physiological time – the amount of heat needed for an organism to develop – and are commonly used by IPM as they generate important information on insect development.

The navel orangeworm and peach twig borer were chosen for this analysis, as they both have great potential for economic impact on the almond crop throughout the Central Valley and were previously found to be sensitive to climatic changes[66,72]. For both pests, the default UCIPM recommended models were chosen, and were run using the NCDC historical observational daily temperature records as well as the MACA projected daily temperatures for all Central Valley weather station locations from 1990 to 2099 to calculate degree-days for each day throughout the year. Degree-days are a measurement of heat units over time, between a lower and upper development threshold, needed for pest development. They are an important component of an Integrated Pest Management program, as they can be used to determine timing for insecticide treatments. Certain life stages of insects are more susceptible to chemical treatment, such as young larvae, and degree days are used to predict when those life stages will occur.

3.3.6 *Pesticide use and properties*

California has the most comprehensive agricultural pesticide use reporting (PUR) database in the country[238]. Since 1990, the California Department of Pesticide Regulation has required full reporting of pesticide use on agricultural land. The PUR database provides detailed information on each pesticide use at the field level (township and section, by county), including name and active ingredients included in the product, concentration and quantity applied, time and date of application, number of acres and crop treated, and location (to the square mile) of all agricultural pesticide applications[239]. Each year of the PUR database contains more than 2.5 million individual records of pesticide use, documenting the application of more than 1,000 different pesticides used, and the crops on which they were applied.

All available PUR records were downloaded from the publicly available database from 1974 to 2016. Chemical use data was joined with the records, including product and formula information, chemical codes, and Chemical Abstracts Service Registry Numbers. Records without an application date or chemical code/name were dropped. The use data was first restricted by counties within the Central Valley, and then further by township and section; only those sections within the Central Valley boundary were analyzed. The list of chemicals included over 4,600 active ingredients. The records were then merged into two separate files – one for pesticide use report data from 1974 to 1989, and one for pesticide use report data from 1990 to 2016.

Data prior to 1990 represent applications of restricted materials only that required a permit and application to be made by licensed pest control operators and businesses. The amount of product reported differed (rate per acre) and did not reflect the actual amount of product that was used. Many of the pre-1990 data contain errors, and the old use reports contained limited documentation. These records were obtained to determine if any temporal trends could be assessed in insecticide use on almonds prior to 1990. However, limited and poor-quality data prevented any meaningful analysis. For the remaining years 1990 to 2016, nearly 35 million complete pesticide application records were retrieved for the Central Valley, and over 4.25 million of those records noted the site code for almonds.

All active and inactive chemical ingredients found in pesticide products used in California were queried from the California Department of Pesticide Regulation database on chemical ingredients[240]. Chemicals were selected by pesticide type (algaecide, anti-foulant, antimicrobial, avicide, bactericide, defoliant, desiccant, disinfectant, fertilizer, fungicide, growth regulator, herbicide, insecticide, miticide, molluscicide, nematicide, repellent, slimicide, virucide, vertebrate control, special activity, and insect growth regulator), and each list of chemicals was joined to create a dataset of all 1,691 active and inactive ingredients found in pesticide products in California. This data was then joined to the PUR dataset by chemical code and chemical name, coding each chemical as either a single or combination pesticide type (e.g. used as both an insecticide and an herbicide). From this join, only use records that contained chemicals classified as insecticides were selected for analysis, representing 241 active ingredients (AI's). There were 1,906,281 insecticide use records with a chemical designated as an insecticide. Each of the 241 chemicals were assessed for its primary function, and only those that are primarily used as an insecticide were kept for further analysis. 959,725 pesticide use records were remaining in the dataset for insecticide use on almonds in the Central Valley between 1990 and 2016.

Errors and outliers were either fixed or removed from the dataset. There were several records with erroneous dates; a few years were entered as 1901, 1902, 1922, and 1989. Because it could not be determined which year the records represented, these records were removed. Further, nearly all use records were reported as acres planted and treated (99.999%); those records that noted unit planted and/or treated as square feet, cubic feet, thousand cubic feet, pounds, tons, or miscellaneous were removed, as they would not allow comparison to or combination with acres treated.

Finally, because pesticide use is non-normally distributed, the definition for an outlier set by the California Department of Pesticide Regulation was used to identify potential outliers. Three different criteria were applied by CDPR for outlier flagging: 1) a single use rate (pounds of chemical used per number of acres treated) higher than 200 pounds of active ingredient per acre, 2) use rates that are 50 times larger than the median rate for all uses with the same pesticide product, crop treated, unit treated, and record type, and 3) use rates higher than a value determined by a procedure that approximated what a 'group of scientists' believed to be obvious outliers[241]. Of the nearly one million use reports from 1990 to 2016, only 61 had use rates above 200 pounds per acre and greater than 50 times the median use, and only 41 had use rates above 300 pounds per acre. The records greater than 300 pounds per acre were dropped from the dataset, as they were determined to likely be outliers. The final dataset contained 959,516 records, representing 139 insecticide active ingredients.

To evaluate the pesticide use data for basic patterns and trends in use, the reports were aggregated by chemical name to determine which chemicals have been applied the most in terms of pounds of active ingredient and acres treated. Next, pounds of active ingredient per acre treated was calculated to better understand 'use intensity' and account for changes in almond acreage over time. The pesticide use reports were then aggregated to month-year (e.g. January-1990, February-1990, March-1990,…, December-2016 etc.), as well as year in order to look for seasonal and annual trends. The mean and standard deviation in monthly use intensity was calculated to assess the variability in monthly insecticide use. Monthly use intensity (pounds per acre treated) was used in the analyses rather than daily, as it more accurately reflects seasonal trends in use.

3.3.7 *Trend analysis*

The trend analysis was performed in R, a free open-source and adaptable statistical analysis platform[217]. Because pest dynamics are modeled directly on growing degree-days, they are explicitly associated with weather variability. The analysis therefore concentrated on modeling temporal trends in monthly-yearly insecticide use intensity (pounds of active ingredient per acre treated) for each region of the Central Valley against pest dynamics (growing degree days) and climate (temperature and precipitation). Trends were detected with the Mann-Kendall test implemented in the package Kendall in R, to statistically assess if there is a monotonic upward or downward trend in insecticide use intensity over time[242,243]. The Mann-Kendall test was preferred, as the trend in insecticide use intensity was hypothesized to be non-linear, and it does not require the assumption that the residuals from a fitted regression be normally distributed. Daily, weekly, monthly, and yearly insecticide use intensity was analyzed for trend, and while all were statistically significant, aggregated monthly-yearly use intensity showed the most significant trend over time.

To analyze historical pesticide use intensity trends in relation to climate and growing degree days, insecticide application per acre (pounds of active ingredient applied per treated acre) was regressed on climate and weather variables (maximum and minimum temperature, and precipitation) and growing degree days. In order to determine what climate variables to include in the analysis, stepwise model selection by Akaike information criterion was performed, using package MASS in R[244]. Linear regression was used to predict month-year pesticide use intensity as a function of the predictor variables. Regression is often used to model and forecast seasonal data, accounting for the seasonal and long-term patterns in the outcome by including an indicator variable for each time interval in the model (i.e. month).

Precipitation was considered as both average annual precipitation (in order to account for dry or wet years) as well as a monthly average. Precipitation is used here as a proxy for more specific agricultural variables such as evapotranspiration and drought index, which are more difficult to model and not possible to project given the climate variables available in the MACA downscaled models. Temperature data were considered as both average annual maximum and minimum temperature, as well as a monthly-yearly average of maximum and minimum temperature. Degree days were modeled as the total number of degree days per year-month, in order to capture differences in warmth accumulation by season, and as the total accumulated growing degree days per year, to capture differences in warmth accumulation by year. Climate division was included in the selection, in order to detect differences in insecticide use intensity between the northern and southern region of the Central Valley. Monthly dummy variables were included in the model selection in order to capture monthly-seasonal differences in insecticide use intensity; month is included strictly as a dummy variable, indexed across all years (with 11 degrees of freedom). A lag to determine whether insecticide use intensity in a given month was related to insecticide use intensity in preceding months was not used, as it was previously found to be non-significant in the almond crop, and would not be applicable to predicting use intensity based on climate model projections, which only include temperature and precipitation variables for predictions[245]. Using lagged dependent variables has also been found to lead to severe bias. Year was also considered in the model, in order to control for immeasurable factors associated with time, such as insecticide resistance (which occurs over time), regulations (new regulations adopted over time due to new research), development of new application technology (technology advances over time), and adoption of better pest management practices (may be due to cost of pesticides over time, or potentially due to adaptation to pest and climate impacts over time).

Multiple models were developed – including only climate variables as well as the addition of growing degree days – for the relationship between climate and insecticide use intensity. The first model included only temperature and precipitation variables as found statistically significant through the stepwise selection process; year was not significant and forcing it into the model did not lead to a better fit. Climate division was also found to be non-significant, implying that pesticide use practices do not differ between regions for reasons other than number of almond orchards; records were averaged across division to reflect this. The climate-only model can be written as,

$$I_t = \beta_0 + \beta_1 tmin_y + \beta_2 tmax_y + \beta_3 tmin_t + \beta_4 tmax_t + \beta_5 prcp_y + month + \varepsilon$$

where I is the total insecticide use intensity (pounds per acre treated), t is the month-year of observation, y is the year of observation, *tmin* is minimum temperature averaged by year and by month-year (°F), *tmax* is maximum temperature averaged by year and by month-year (°F), *prcp* is precipitation averaged by year, m is the month (defined as a dummy variable), and ε are the idiosyncratic errors.

When adding growing degree days into the model, the result from the stepwise regression only included temperature, precipitation, and total accumulated degree days by year; accumulated degree days by month were found to be non-significant. The final selected model for the addition of degree days can be written as,

$$I_t = \beta_0 + \beta_1 tmin_y + \beta_2 tmax_y + \beta_3 tmin_t + \beta_4 tmax_t + \beta_5 prcp_y + \beta_6 add_y + month + \varepsilon$$

where *add* is accumulated growing degree days for the navel orangeworm per year and/or accumulated growing degree days for the peach twig borer per year (the model was run with each pest's accumulated degree days separately, as well as with both pests accumulated growing degree days included in the model); all other variables are defined the same as the previous model. The Breusch-Pagan test was used to test for non-constant variance and was found to be significant ($p < 0.001$); therefore, the null hypothesis was rejected, and heteroscedasticity assumed. To account for heteroscedasticity, Huber-Eicker-White robust standard errors were estimated[246-248].

3.4 RESULTS

3.4.1 *Characterization of overall insecticide use*

Overall, an average of 11,003,101 pounds of insecticide active ingredients are used on almonds annually throughout the Central Valley, representing approximately 5.16 pounds of pesticide active ingredients per treated almond acre per year. Throughout the year, the distribution of average total insecticide use varies, with peaks in January, May, July, and December (**Figure 3.1 - Figure 3.3**). The growing season peaks roughly coincide with recommended treatment times – typically a spring spray or at the beginning of hullsplit – for navel orangeworm (during egg laying) and peach twig borer (during larval development) – which suggests that most growers are using insecticide treatments following recommended IPM management guidelines. The winter peaks coincide with dormancy sprays, which is a traditional time to treat for the peach twig borer as well as scales and mites. Typically, these are oil sprays that contain small amounts of insecticide and are used in higher amounts to fully coat the bark of the tree to physically kill overwintering pests as well as mites and scales.

Use and variability of insecticides varied by month as well as metric considered. Numbers of acres treated peaked in July, but had smaller peaks in January, May, and June (**Table 3.10**). The same seasonal peaks of acres treated was seen when looking at the northern and southern regions of the Central Valley separately. There are considerably more acres of almond orchards in the southern Central Valley than the northern Central Valley. This difference is also seen in pounds of active ingredients applied, but the differences in acres treated and pounds of applied active ingredients by region appear to be related, and not attributable to other unmeasured factors related to region that would account for differences in use (**Table 3.11**). January has the highest peak of insecticide use in terms of total pounds applied, with smaller peaks seen in May and July, and other peaks in February, June, and December. However, these metrics do not control for increasing almond acreage and therefore do not capture the use intensity of insecticides, as they do not tell how heavily insecticides are being applied to almond orchards.

Table 3.10. Mean monthly number of acres treated (and SD) of insecticides, 1990 to 2016.

	Central Valley		**N Central Valley**		**S Central Valley**	
	Mean	**SD**	**Mean**	**(SD)**	**Mean**	**(SD)**
January	364,529.5	90,277.5	15,762.1	10,466.9	348,767.3	91,199.3
February	119,530.4	47,542.3	8,016.4	5,105.5	111,513.9	46,174.7
March	57,095.0	41,983.6	2,561.9	2,446.5	54,533.1	40,607.4
April	177,158.4	277,787.5	3,473.9	5,791.5	173,684.5	273,148.0
May	480,868.7	385,455.8	15,995.6	20,144.3	464,873.2	369,969.0
June	395,767.9	469,892.1	17,178.1	22,833.5	378,589.8	448,643.1
July	708,441.6	484,710.2	44,622.3	28,654.2	663,819.3	458,369.8
August	141,617.6	112,414.0	7,312.0	4,988.4	134,305.6	108,533.2
September	19,347.4	17,889.9	447.3	601.8	18,916.6	17,676.2
October	4,178.8	4,598.3	400.1	661.4	3,852.8	4,324.5
November	4,870.6	2,308.8	247.3	427.3	4,678.3	2,231.3
December	62,220.9	36,364.7	1,574.5	2,248.9	60,763.1	35,518.1

Table 3.11. Mean monthly pounds of active ingredient applied (and SD), 1990 to 2016.

	Central Valley		**N Central Valley**		**S Central Valley**	
	Mean	**SD**	**Mean**	**(SD)**	**Mean**	**(SD)**
January	5,145,271.0	1,246,320.3	206,694.0	136,805.6	4,938,577.0	1,254,941.6
February	833,710.4	357,291.5	55,692.2	64,439.8	778,018.2	316,496.6
March	145,452.4	77,703.6	4,098.5	4,160.1	141,353.9	77,346.2
April	460,693.4	549,470.2	6,410.8	18,012.6	454,282.6	549,137.3
May	1,277,067.1	1,034,283.8	18,811.5	19,955.7	1,258,255.6	1,023,957.4
June	698,224.3	787,115.9	19,345.2	27,258.7	678,879.1	773,677.7
July	1,201,299.2	852,552.9	43,216.4	21,327.5	1,158,082.7	840,295.9
August	334,910.3	324,605.2	8,643.1	9,096.2	326,267.2	320,979.3
September	48,644.1	51,774.7	490.5	700.9	48,171.8	51,452.9
October	5,602.6	6,204.9	1,476.7	2,873.3	4,399.3	4,700.9
November	6,111.9	8,784.1	235.9	508.6	5,928.4	8,764.5
December	846,114.6	469,149.5	17,532.7	24,769.4	829,880.6	458,860.9

Pounds of active ingredients per treated acre of almond orchard is a much better metric for determining use intensity (**Table 3.12**). Use intensity peaks in January and December, over ten times the use intensity during the growing season months, suggesting high use of dormancy sprays across all almond orchards. February is also a high use intensity month, likely a carryover of dormancy sprays used during the winter months. The next largest peak in use intensity appears to be during early spring, coinciding with spring and bloom sprays. Generally, the southern Central Valley applied insecticides more heavily than the northern Central Valley, except for what appears to be a higher use rate in October for the northern region. Months with higher use of insecticides also had above average variability. However, the amount used was substantially higher than the standard deviation in use, indicating that the amount of insecticides used monthly is consistent. The exception is the month of April and some of the fall months.

Table 3.12. Mean monthly pounds of active ingredient per acres treated (and SD) of insecticides, 1990 to 2016.

	Central Valley		**N Central Valley**		**S Central Valley**	
	Mean	**SD**	**Mean**	**(SD)**	**Mean**	**(SD)**
January	14.21	1.57	13.16	3.22	14.26	1.57
February	7.60	3.02	6.41	4.49	7.65	3.03
March	2.85	1.11	2.14	1.81	2.89	1.10
April	3.09	1.60	1.57	1.61	3.09	1.61
May	2.57	0.54	1.87	1.50	2.60	0.54
June	1.91	0.36	1.50	0.73	1.92	0.37
July	1.69	0.18	1.10	0.34	1.73	0.20
August	2.18	0.63	1.16	0.81	2.24	0.68
September	2.32	1.02	1.40	2.78	2.37	1.05
October	1.81	1.68	1.69	1.81	1.72	1.73
November	1.44	1.54	1.57	2.99	1.50	1.62
December	13.82	2.63	12.13	16.57	13.87	2.63

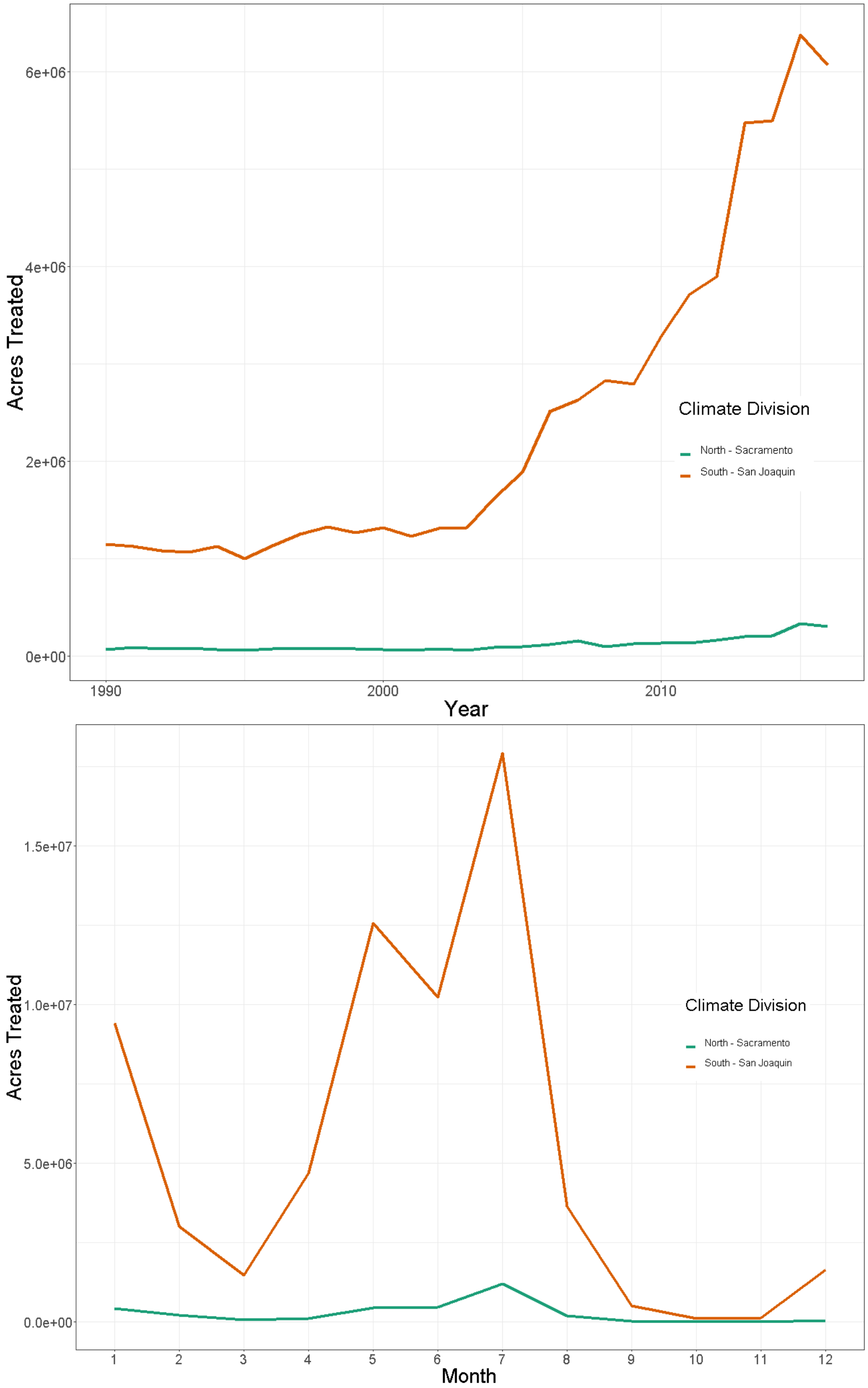


Figure 3.1. Yearly and monthly trends (total acres treated with insecticides) by climate division, 1990 to 2016. The northern Central Valley is in green, and the southern Central Valley is in orange.

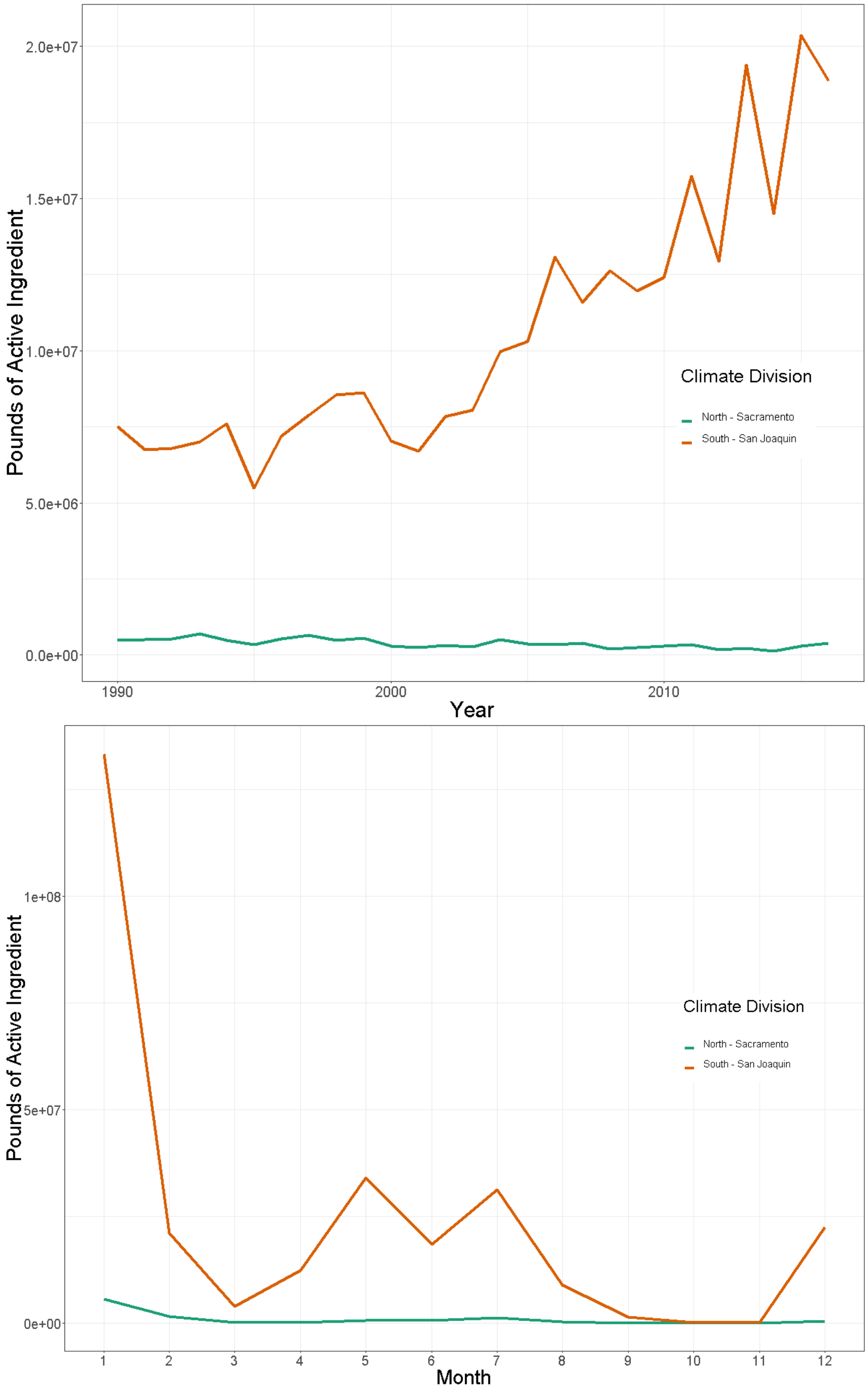


Figure 3.2. Yearly and monthly trends (total pounds of active ingredient) by climate division, 1990 to 2016. The northern Central Valley is in green, and the southern Central Valley is in orange.

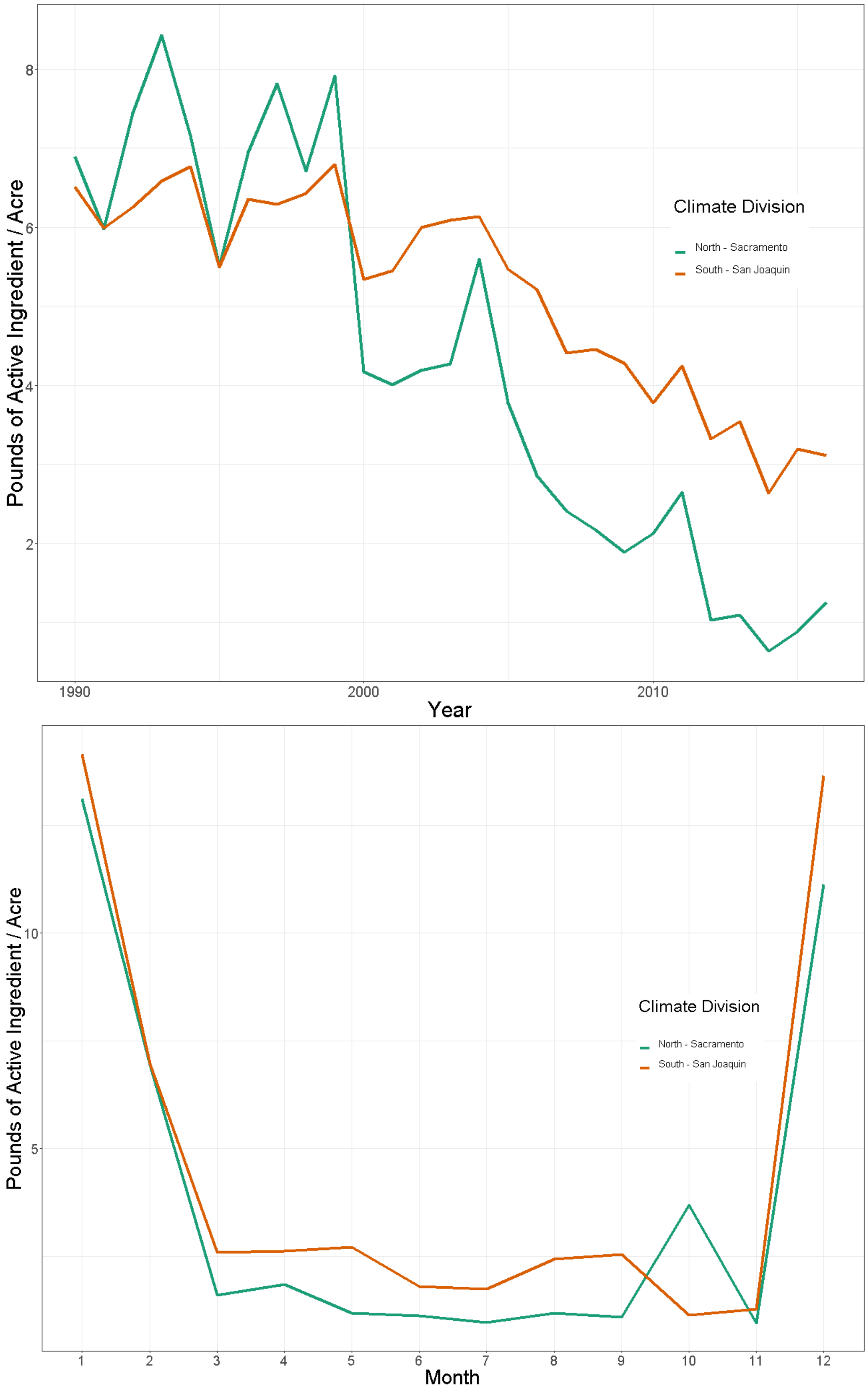


Figure 3.3. Yearly and monthly trends (use intensity: pounds of active ingredient per acre treated) by climate division, 1990 to 2016. The northern Central Valley is in green, and the southern Central Valley is in orange.

The region-wide top ten active ingredients by number of acres treated included (in order) abamectin, unclassified petroleum oil, mineral oil, methoxyfenozide, chlorpyrifos, esfenvalerate, propargite, bifenthrin, chlorantraniliprole, and pyriproxyfen (**Table 3.13**). However, over the historical record period of 1990 to 2016, some pesticides have been banned and others have lost effectiveness, halting or decreasing their use. This is reflected in the top insecticides used by acre treated for the last ten years of the record period (2007 to 2016) (**Table 3.14**). Most recently, the top ten insecticides include (in order) abamectin, unclassified petroleum oil, mineral oil, methoxyfenozide, bifenthrin, esfenvalerate, chlorantraniliprole, etoxazole, pyriproxyfen, and chlorpyrifos. The use of chlorpyrifos and propargite has decreased dramatically, whereas other insecticides such as bifenthrin increased in use. By peak months, January saw the highest number of acres treated with unclassified petroleum oil, methoxyfenozide, and mineral oil (**Figure 3.4**). These same insecticides also peaked in May and July, but the insecticide with the highest number of acres treated during the growing season was abamectin, used for controlling mites.

Table 3.13. Insecticide use (total acres treated) for California almonds from 1990 to 2016 for region-wide top ten insecticides (by total acres treated).

	Central Valley	**N Central Valley**	**S Central Valley**
Abamectin	10,262,807.26	765,855.24	9,694,746.43
Petroleum oil, unclassified	9,259,307.30	336,823.53	9,043,562.26
Mineral oil	5,619,431.81	173,919.83	5,496,676.35
Methoxyfenozide	3,800,273.91	179,403.23	3,661,581.34
Chlorpyrifos	3,743,973.58	342,700.61	3,537,476.64
Esfenvalerate	3,455,321.49	455,738.19	3,204,231.52
Propargite	2,987,979.19	374,222.52	2,794,728.09
Bifenthrin	2,897,052.63	258,360.24	2,710,214.23
Chlorantraniliprole	1,980,784.82	213,391.07	1,811,350.08
Pyriproxyfen	1,965,673.30	31,293.17	1,934,380.13

Table 3.14. Insecticide use (total acres treated) for California almonds from 2007 to 2016 for region-wide top ten insecticides (by total acres treated).

	Central Valley	N Central Valley	S Central Valley
Abamectin	8,049,466.05	513,817.44	7,535,648.61
Petroleum oil, unclassified	5,160,638.30	32,177.95	5,128,460.35
Mineral oil	4,321,923.93	27,074.96	4,294,898.47
Methoxyfenozide	3,435,718.53	117,218.21	3,318,500.32
Bifenthrin	2,869,138.97	184,253.30	2,684,885.67
Esfenvalerate	2,170,803.80	146,803.24	2,024,000.56
Chlorantraniliprole	1,980,784.82	169,434.74	1,811,350.08
Etoxazole	1,760,517.70	17,832.17	1,742,685.53
Pyriproxyfen	1,606,183.38	27,108.27	1,579,075.11
Chlorpyrifos	1,510,921.42	112,169.35	1,398,752.07

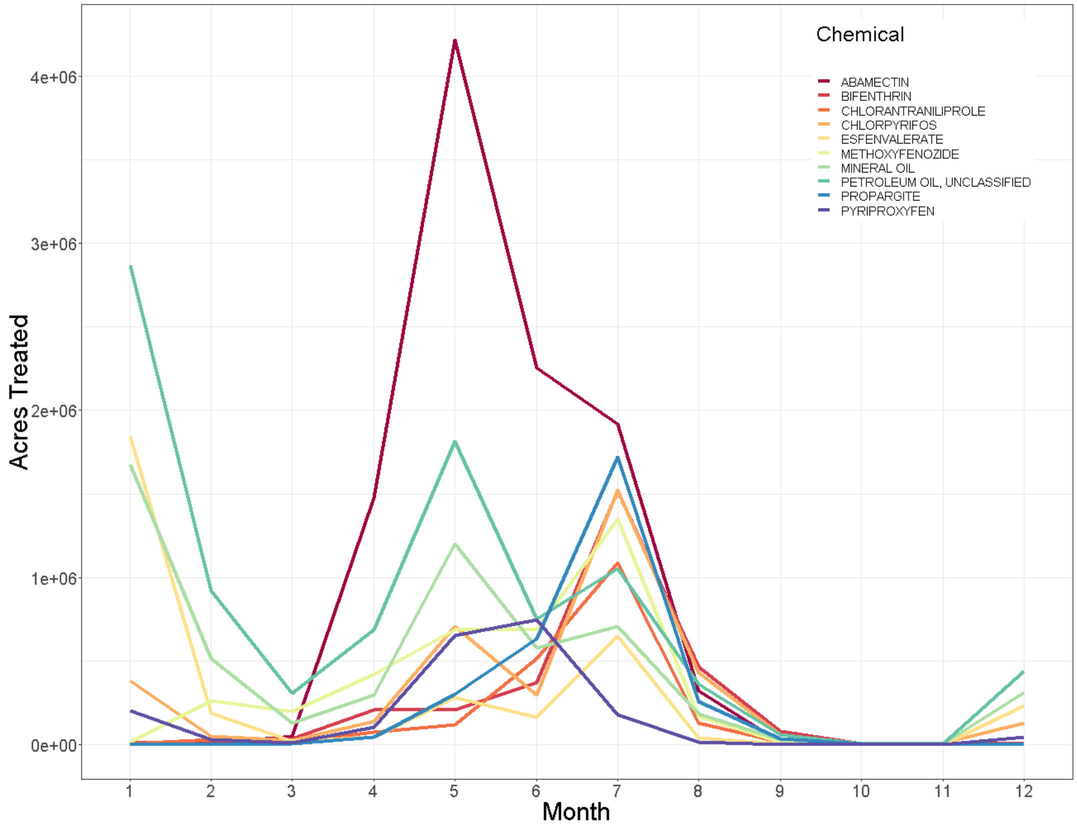


Figure 3.4. Monthly trend in total acres treated with insecticides, by active ingredient, 1990 to 2016.

The region-wide top ten active ingredients by total pounds of active ingredient applied included (in order) unclassified petroleum oil, mineral oil, chlorpyrifos, sulfur, propargite, phosmet, diazinon, paraffin-based petroleum oil, azinphos-methyl, and methoxyfenozide (**Table 3.15**). Most recently, the top ten insecticides by total pounds of active ingredient applied include (in order) unclassified petroleum oil, mineral oil, sulfur, chlorpyrifos, paraffin-based petroleum oil, methoxyfenozide, propargite, bifenthrin, phosmet, and bifenazate (**Table 3.16**). Again, propargite decreased in total amount used, as did phosmet; not surprisingly, azinphos-methyl also decreased in use, as the US EPA began a phase-out in 2005 and completed the phase-out in 2012 due to acute and short-term occupational exposures of concern. By peak months, January saw the highest amount of active ingredients applied by pound with mineral oil and unclassified petroleum oil (**Figure 3.5**). These same insecticides also peaked in May and July and were by far applied in the greatest amounts compared to all other insecticides used.

Table 3.15. Insecticide use (total pounds applied) for California almonds from 1990 to 2016 for region-wide top ten insecticides (by total pounds applied).

	Central Valley	**N Central Valley**	**S Central Valley**
Petroleum oil, unclassified	168,918,700.0	4,498,826.0	164,576,400.0
Mineral oil	91,964,180.0	2,825,355.0	89,225,590.0
Chlorpyrifos	6,885,338.0	363,142.5	6,536,325.0
Sulfur	6,037,710.0	1,468,444.0	4,649,196.0
Propargite	6,036,548.0	252,247.5	5,918,869.0
Phosmet	2,364,908.0	64,738.0	2,325,170.0
Diazinon	2,320,608.0	191,477.7	2,135,438.0
Petroleum oil, paraffin based	1,993,765.0	120,944.6	1,890,674.0
Azinphos-Methyl	1,957,216.0	118,331.2	1,838,885.0
Methoxyfenozide	1,048,826.0	40,478.62	1,008,347.0

Table 3.16. Insecticide use (total pounds applied) for California almonds from 2007 to 2016 for region-wide top ten insecticides (by total pounds applied).

	Central Valley	**N Central Valley**	**S Central Valley**
Petroleum oil, unclassified	75,315,590.0	467,026.1	74,848,570.0
Mineral oil	64,711,770.0	593,181.7	64,153,630.0
Sulfur	3,255,622.0	1,138,566.0	2,194,437.0
Chlorpyrifos	2,855,469.0	204,788.6	2,650,680.0
Petroleum oil, paraffin based	1,293,082.0	68,165.7	1,224,916.0
Methoxyfenozide	955,583.5	35,210.6	920,373.0
Propargite	680,719.7	26,251.8	654,467.9
Bifenthrin	591,871.6	27,733.6	564,138.0
Phosmet	414,347.4	762.5	413,584.9
Bifenazate	348,352.0	6,040.9	342,311.1

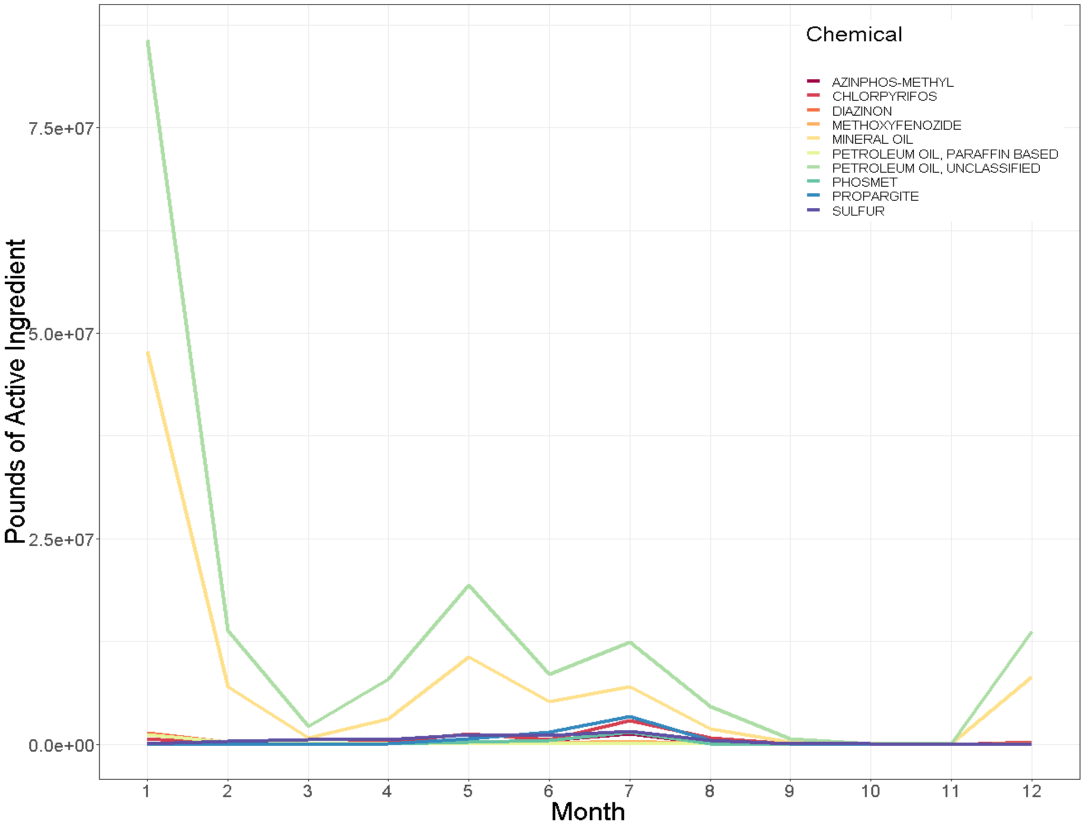


Figure 3.5. Monthly trend in total pounds applied, by active ingredient, 1990 to 2016.

The region-wide top ten active ingredients by use intensity (pounds of active ingredient per acre treated) included (in order) kaolin, refined petroleum distillates, unclassified petroleum oil, mineral oil, dienochlor, soybean oil, ethoprop, sulfur, potash soap, and aromatic petroleum distillates (**Table 3.17**). Most recently, the top ten insecticides include (in order) fenamiphos, paraffin-based petroleum oil, kaolin, refined petroleum distillates, mineral oil, unclassified petroleum oil, soybean oil, limonene, sulfur, and cryolite (**Table 3.18**). Kaolin decreased in use, as did the use of dienochlor and ethoprop. The sale and use of dienochlor was banned in California in 1998, and a risk assessment of ethoprop done in 1995 determined that its use was leading to unacceptable exposures and thus its use was mitigated. By peak months, January and December saw the largest use intensity of unclassified and paraffin-based petroleum oil (**Figure 3.6**). These same insecticides also peaked in April and late summer/early fall. Sulfur was also used heavily throughout the year, with use peaking during the growing season.

Table 3.17. Insecticide use (pounds of active ingredient per acre treated) for California almonds from 1990 to 2016 for region-wide top ten pesticides (by pounds/acre).

	Central Valley	**N Central Valley**	**S Central Valley**
Kaolin	19.33	13.15	19.38
Petroleum distillates, refined	18.30	21.62	18.22
Petroleum oil, unclassified	18.24	2.08	18.20
Mineral oil	16.37	22.98	16.23
Dienochlor	16.18	-	16.18
Soybean oil	9.05	12.96	8.99
Ethoprop	8.00	-	8.00
Sulfur	7.62	8.67	7.46
Potash soap	4.93	4.59	4.93
Petroleum distillates, aromatic	4.58	0.04	4.97

Table 3.18. Insecticide use (pounds of active ingredient per acre treated) for California almonds from 2007 to 2016 for region-wide top ten pesticides (by pounds/acre).

	Central Valley	**N Central Valley**	**S Central Valley**
Fenamiphos	51.43	-	51.43
Petroleum oil, paraffin based	21.94	24.55	21.81
Kaolin	19.73	13.15	19.80
Petroleum distillates, refined	15.14	20.87	15.03
Mineral oil	14.97	21.91	14.94
Petroleum oil, unclassified	14.59	14.51	14.59
Soybean oil	12.65	-	12.65
Limonene	8.33	-	8.33
Sulfur	7.97	8.77	7.87
Cryolite	5.32	-	5.32

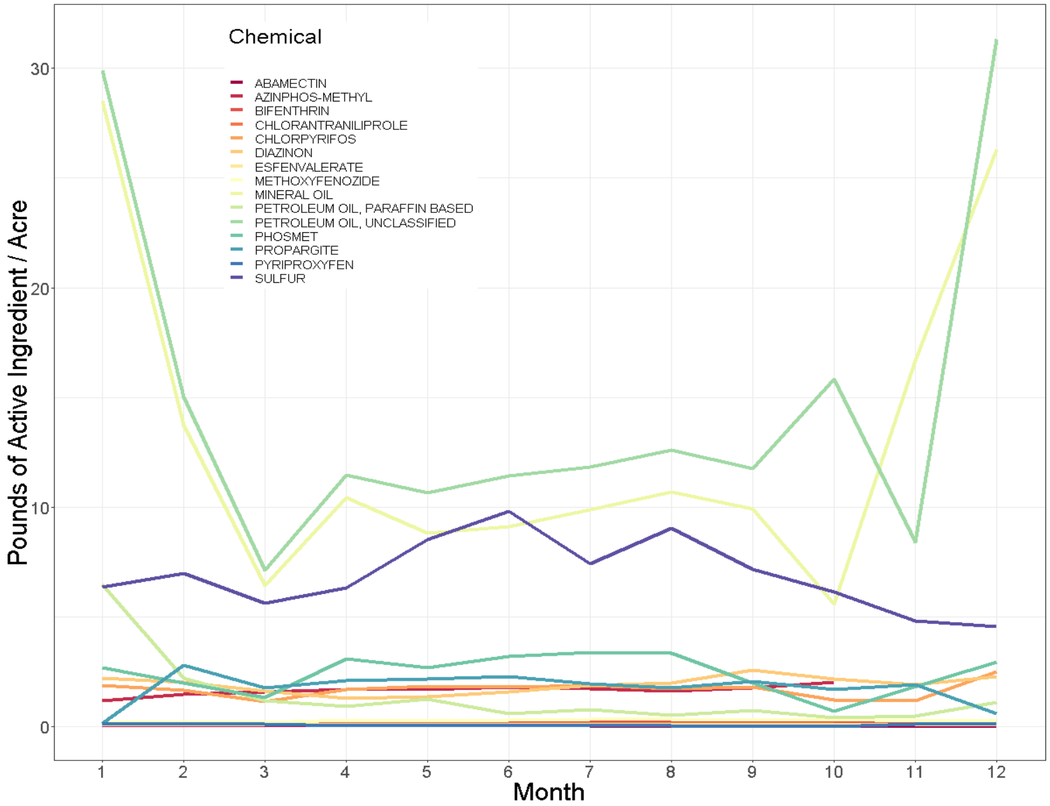


Figure 3.6. Monthly trend in average pounds of active ingredient per acre treated, by active ingredient, 1990 to 2016.

3.4.2 *Trends in insecticide use*

Overall, the number of almond acreage has increased, which is reflected in the number of acres treated (**Figure 3.7**). While the most heavily used insecticides by pounds of active ingredient applied were petroleum and mineral oils (**Figure 3.8**), they do not appear to be used as extensively as abamectin. Others with dramatic increases in use include methoxyfenozide, bifenthrin, and chlorantraniliprole – all insecticides listed as acceptable for the treatment of navel orangeworm and peach twig borer by the University of California's IPM program. Conversely, there does not appear to be a strong temporal pattern in pounds of active ingredient used per acre, except for a decrease in the use of petroleum and mineral oils (**Figure 3.9**). These trends appear to be largely driven by the trends in the southern region of the valley compared to the north (**Figure 3.10** - **Figure 3.12**).

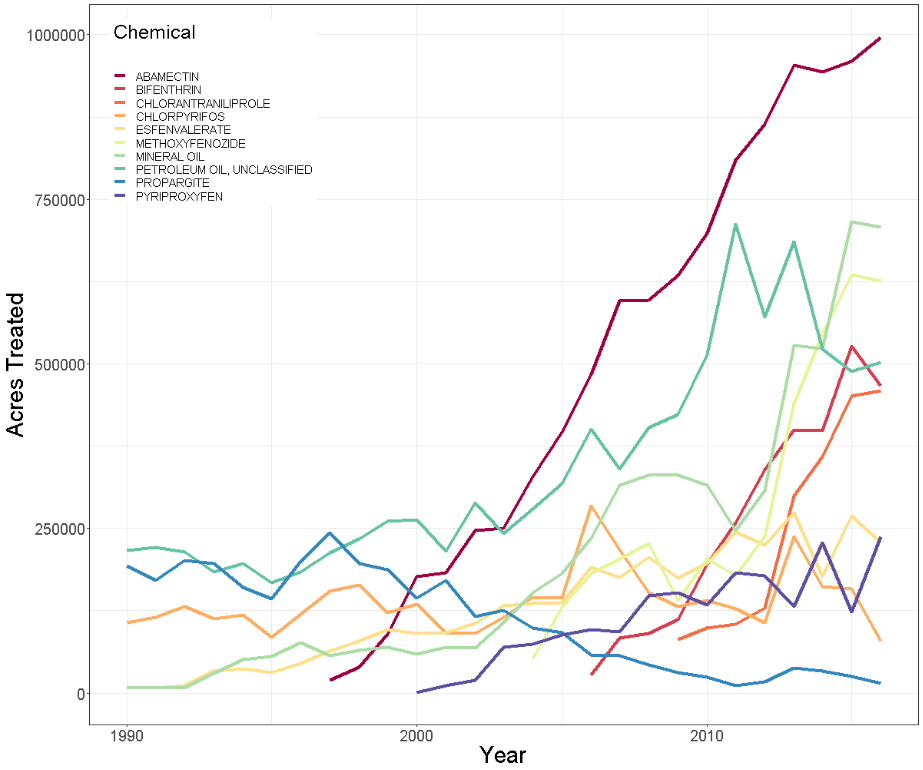


Figure 3.7. Yearly trend in acres treated with insecticides, by active ingredient, 1990 to 2016.

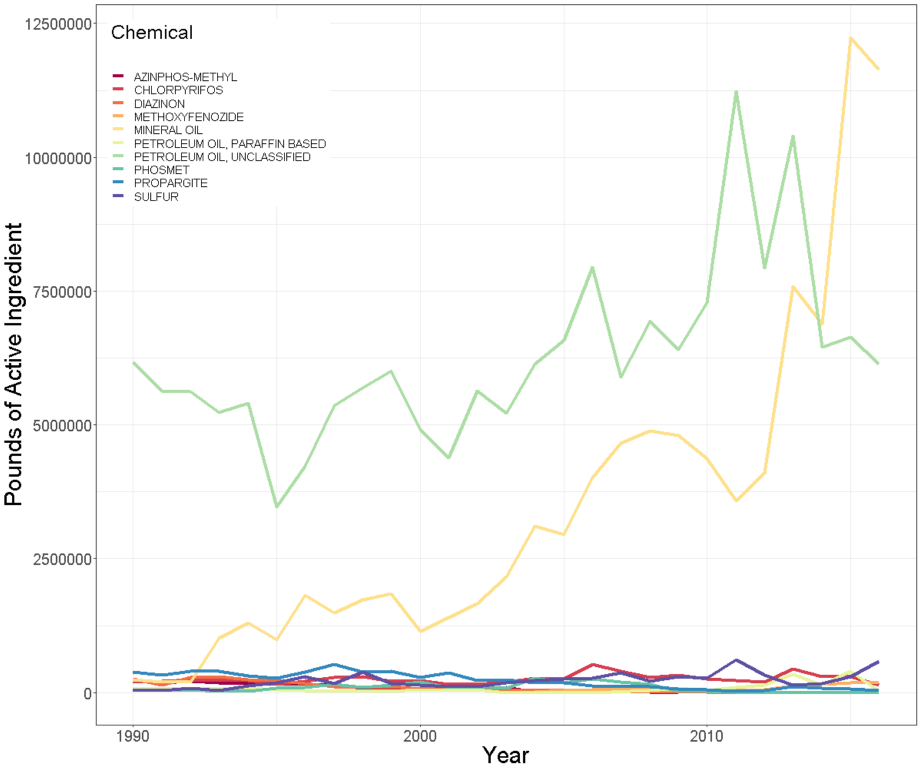


Figure 3.8. Yearly trend in total pounds of active ingredient applied, 1990 to 2016.

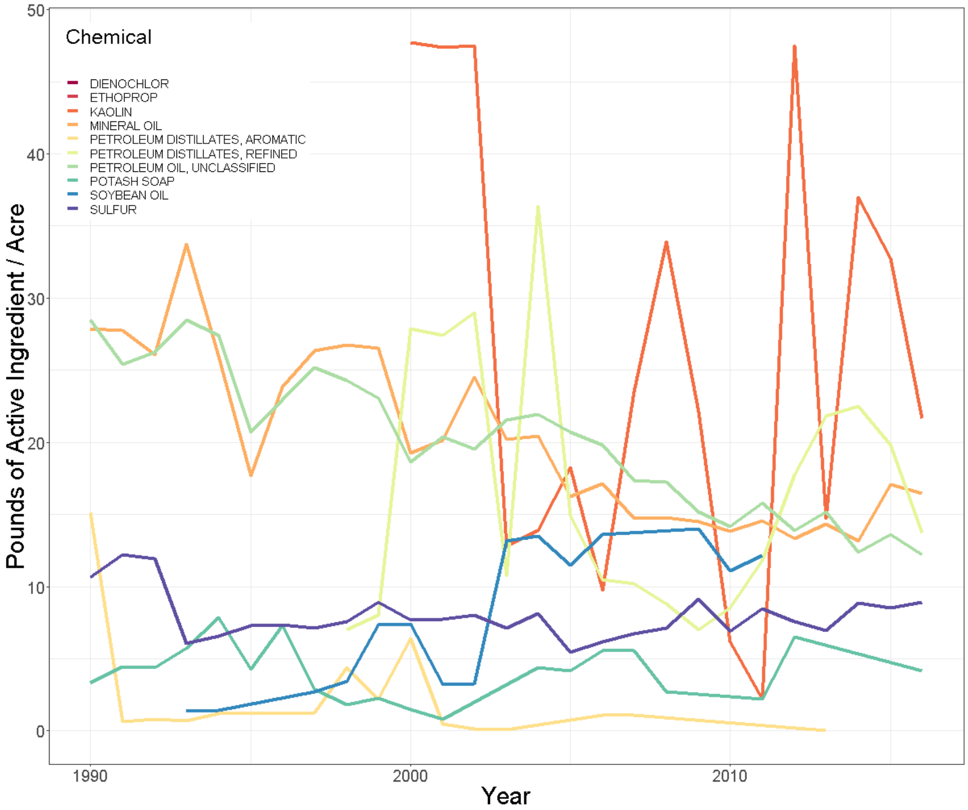


Figure 3.9. Yearly trend in total pounds of active ingredient per acre treated, 1990 to 2016.

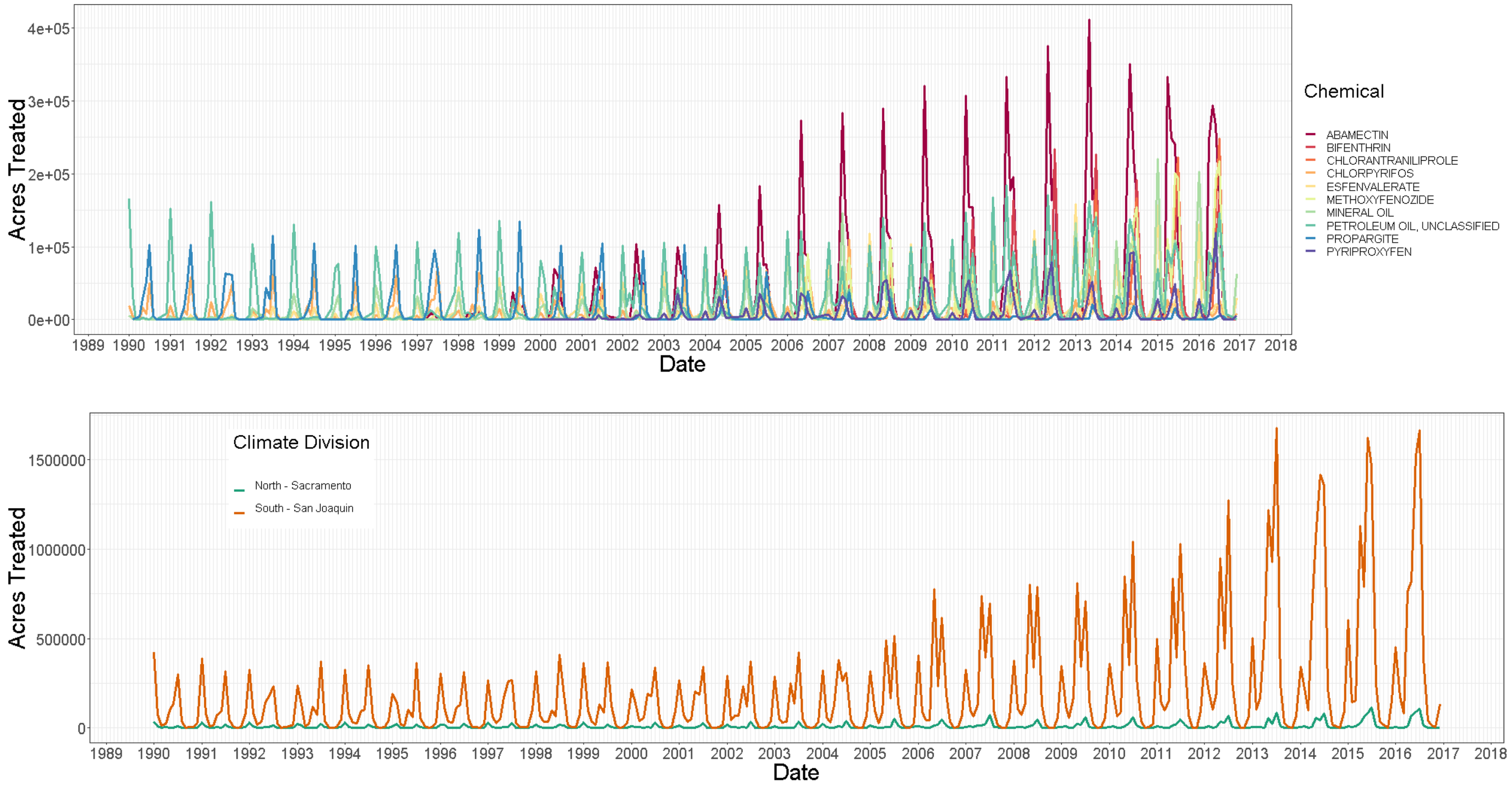


Figure 3.10. Time trend (month-year) in total number of acres treated with insecticides, 1990 to 2016.

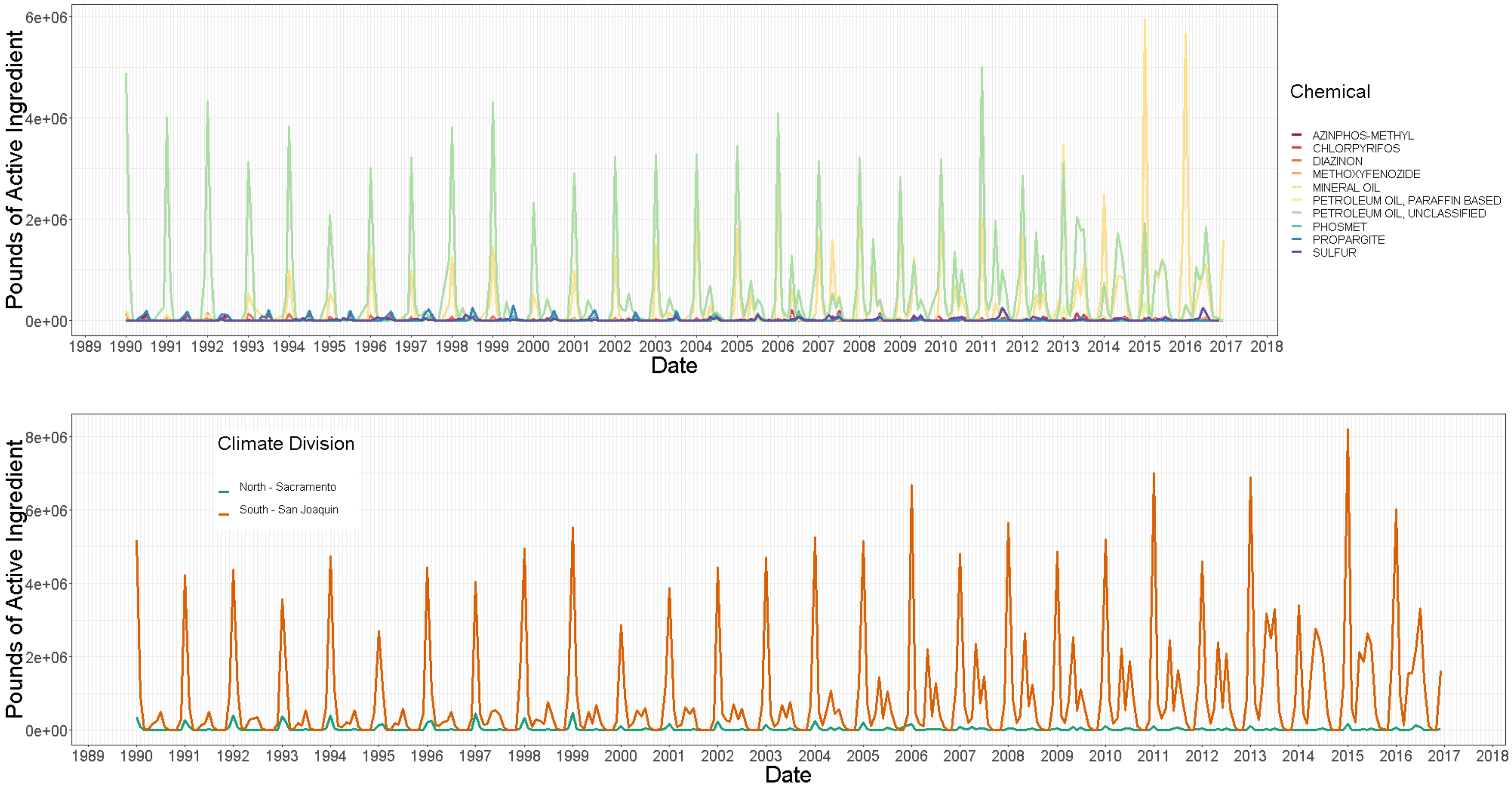


Figure 3.11. Time trend (month-year) in total pounds of active ingredient, 1990 to 2016.

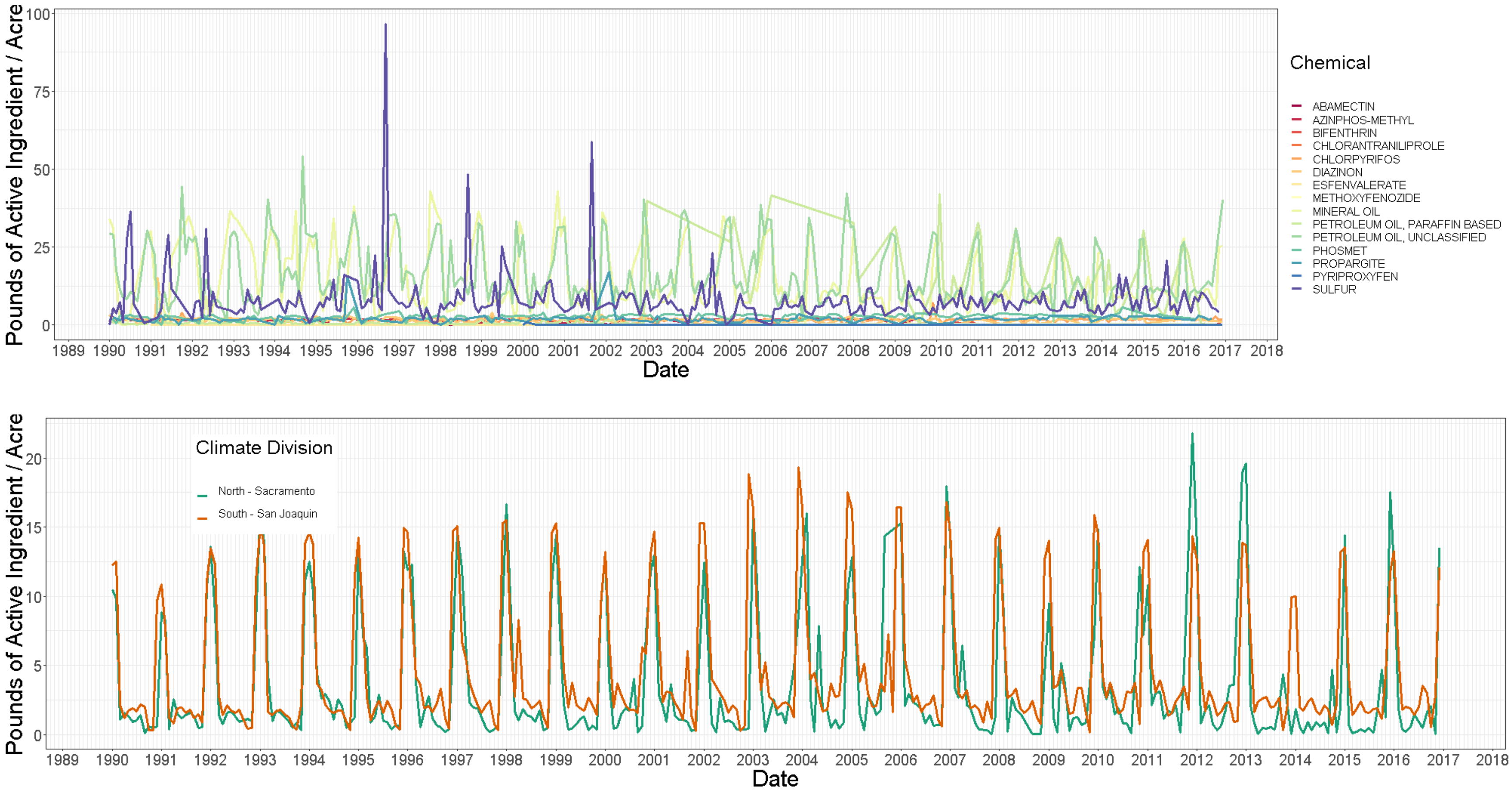


Figure 3.12. Time trend (month-year) in pounds of active ingredient per acre treated, 1990 to 2016.

Use intensity of insecticides decreased over time. The Mann-Kendall trend tests suggest a statistically significant decrease of pounds per acre (use intensity) over time. The multi-variate regression model showed a decrease in use intensity for all months in comparison to January (**Table 3.19**). The regression results also indicate that insecticide use is moderately related with variations in temperature (both monthly and annual averages), precipitation (annual averages reflecting dry/wet years), and accumulated growing degree days, although the impact is different for each variable (**Table 3.20**). Model fit suggests that there are no non-linear patterns in the residuals (**Figure 3.13**); residuals are roughly equally spread around the horizontal line, with a clustering effect seen in the fitted values, and a slight increase in residuals as fitted values increase. The Q-Q plot shows that residuals are not exactly normally distributed; residuals deviate from the straight line on both ends of the plot, suggesting heteroscedasticity, which was detected with the Breusch-Pagan test. The spread-location plot suggests that residuals are spread equally along the ranges of predictors, with the same clustering effect seen in the residuals vs fitted plot. Finally, the residuals vs leverage plot does not suggest there are any influential cases (outliers) in the data.

For the climate-only model, for each degree (°F) increase in annually averaged minimum temperature, insecticide use intensity increases by 0.607 pounds per acre; yet for each degree increase in annually averaged maximum temperature, insecticide use intensity decreases by 0.459 pounds per acre. The same relationship can be seen for month-year minimum and maximum temperatures. For each degree (°F) increase in minimum temperature (over time, by month-year), insecticide use intensity increases by 0.130 pounds per acre; yet for each degree increase in maximum temperature (over time, by month-year), insecticide use intensity decreases by 0.115 pounds per acre. This suggests that while pesticide use is associated with temperature, the decrease in use during warmer maximum temperatures indicated by the model may be related to the influence of winter dormant sprays or more likely due to thermally unsuitable conditions for the pests, limiting their numbers and development. On the other hand, the increase in insecticide use for increasing minimum temperatures suggests a true link to climate factors; higher use during warmer winters may be linked to a need for more control of overwintering generations due to the increased pest pressure throughout the warmer growing season, or because warmer winter temperatures lead to the potential for accumulation of growing degree days for the pests during months that were historically the dormant season.

Table 3.19. Multivariate regression estimates for climate only predictors, predicting monthly total insecticide use (pounds of active ingredient per acre treated), White's robust standard errors, and t test of coefficients.

Variables	**Estimate**	**SE**	**t**	**Pr(>|t|)**
Intercept	22.150	6.634	3.34	0.001
February	-6.328	0.697	-9.07	< 0.001
March	-10.789	0.545	-19.79	< 0.001
April	-10.264	0.752	-13.65	< 0.001
May	-10.620	0.991	-10.72	< 0.001
June	-11.119	1.271	-8.75	< 0.001
July	-11.221	1.481	-7.58	< 0.001
August	-10.651	1.424	-7.48	< 0.001
September	-10.550	1.283	-8.22	< 0.001
October	-11.367	0.946	-12.02	< 0.001
November	-12.275	0.565	-21.73	< 0.001
December	-0.312	0.522	-0.60	0.550
Annual Minimum Temperature	0.607	0.201	3.03	0.003
Annual Maximum Temperature	-0.459	0.168	-2.74	0.007
Annual Average Precipitation	-30.997	13.289	-2.33	0.020
Monthly Minimum Temperature	0.130	0.063	2.05	0.041
Monthly Maximum Temperature	-0.115	0.043	-2.68	0.008

R^2 = 0.90, Adjusted R^2 = 0.90, F-statistic = 179.6 on 16 and 307 DF, p-value < 0.001

Finally, annual average precipitation was found to have a negative impact on insecticide use intensity. For every increase in precipitation (inches) per year, insecticide use intensity decreases by 30.997 pounds per acre. This suggests that growers apply more insecticides during drier years, possibly a result of increased pest pressure due to the adverse impacts of drought on almonds.

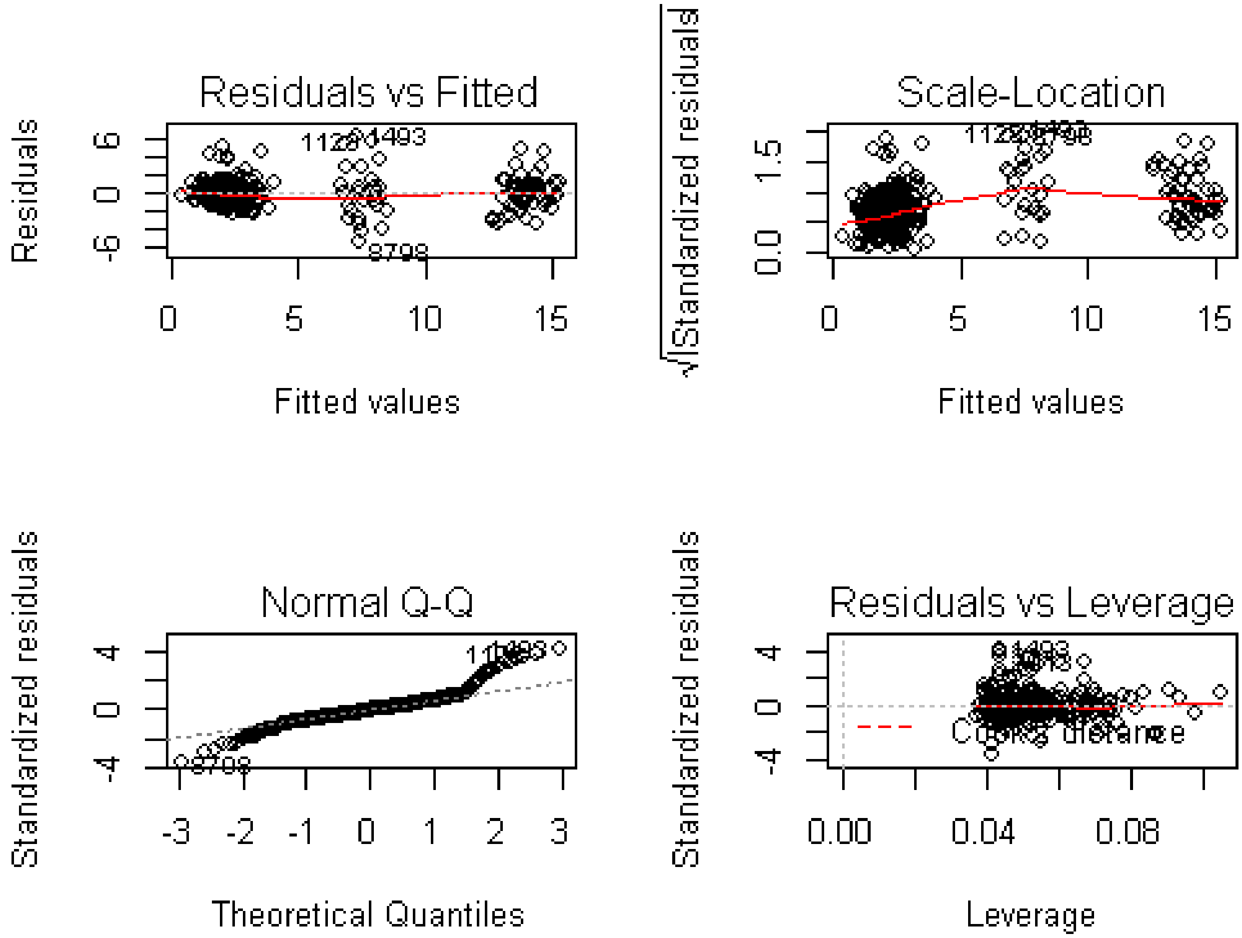


Figure 3.13. Model diagnostic plots for the climate-only model – residuals vs fitted, normal Q-Q, scale-location, and residuals vs leverage.

The addition of year into the above model did not increase fit of the model, nor did it imply there were any unaccounted-for factors that vary over time which might affect insecticide use intensity. The R-squared value decreased slightly, and year was found to be non-significant (p-value = 0.63). The relationship across month with year added to the model was similar to the model without year, as were the relationships between annual and monthly minimum and maximum temperature and annual precipitation to insecticide use intensity. Due to indications from the residual and Q-Q plots (**Figure 3.13**), a few different transformations were applied to the dependent variable (insecticide use intensity). After re-running alternative models with a few transformations of the dependent variable, none of the transformations considered improved fit of the model or reduced heteroscedasticity. This included Tukey's ladder of powers (λ = - 0.075), square root, and log transformations (natural and base 10). In all cases, the results were observed to generally have the same results in regard to year (non-significant), month (January and December have higher use intensity compared to other months), temperature (minimum temperature increases insecticide use intensity whereas maximum temperature decreases insecticide use intensity), and precipitation (use intensity decreases with increasing annual precipitation).

With the addition of accumulated growing degree days into the model, only accumulations for the navel orangeworm increase insecticide use intensity (**Table 3.20**). For each additional accumulated degree day for the navel orangeworm at the end of the year, insecticide use intensity increases by 0.008 pounds per acre. However, for each accumulated degree day for the peach twig borer at the end of the year, insecticide use intensity decreases by nearly the same amount (0.011 pounds per acre). Due to the physiological model for the peach twig borer, degree days accumulate at a greater rate than for the navel orangeworm, so for any given month or year, the accumulated growing degree days will be higher for the peach twig borer than for the navel orangeworm; this suggests an actual overall decrease in pesticide use intensity for increase in accumulated growing degree day when both pests are considered. With the addition of growing degree days for both pests in the model, annual average maximum temperature was no longer found to be significant, but it was kept in the model for comparison to the climate-only model. When considering accumulated growing degree days for each pest separately, the regression coefficients for the accumulated degree days were similar (0.001 increase in use intensity for each increase in NOW growing degree days; -0.002 decrease in use intensity for each increase in PTB growing degree days); however, neither metric was statistically significant, and led to a decrease in model fit as measured by the R-squared value.

Table 3.20. Multivariate regression estimates including growing degree days, predicting monthly total insecticide use (pounds of active ingredient per acre treated), White's robust standard errors, and t test of coefficients.

Variables	**Estimate**	**SE**	**t**	**Pr(>|t|)**
Intercept	-8.830	26.477	-0.33	0.739
February	-6.328	0.695	-9.11	< 0.001
March	-10.789	0.526	-20.51	< 0.001
April	-10.264	0.731	-14.05	< 0.001
May	-10.620	0.971	-10.93	< 0.001
June	-11.119	1.244	-8.94	< 0.001
July	-11.221	1.450	-7.74	< 0.001
August	-10.651	1.396	-7.63	< 0.001
September	-10.550	1.255	-8.41	< 0.001
October	-11.367	0.928	-12.25	< 0.001
November	-12.275	0.563	-21.80	< 0.001
December	-0.312	0.497	-0.63	0.531
Monthly Minimum Temperature	0.130	15.805	2.11	0.036
Monthly Maximum Temperature	-0.115	0.323	-2.73	0.007
Annual Minimum Temperature	1.027	0.368	3.18	0.002
Annual Maximum Temperature	-0.017	0.062	-0.05	0.963
Annual Average Precipitation	-42.131	0.042	-2.67	0.008
Yearly Accumulated DD (NOW)	0.008	0.004	3.23	0.004
Yearly Accumulated DD (PTB)	-0.011	0.003	-2.93	0.001

$R^2 = 0.91$, Adjusted $R^2 = 0.90$, F-statistic = 164.5 on 18 and 305 DF, p-value < 0.001

3.4.3 *Projected insecticide use*

The previous analysis, where changes in climate demonstrated an impact on the use of insecticides, substantiates the further prediction of insecticide use intensity over time to the end of the century. The regression results were applied to the maximum and minimum temperatures and precipitation projected by the ten climate models, again averaging by month-year and year, through 2099. Average insecticide use intensities were predicted for the years 2025, 2055, and 2085; for each projected time period, 30-year averages of the weather variables were taken to account for natural variability (2010 to 2039, 2040 to 2069, and 2070 to 2099).

Results show increases in insecticide use intensity through the end of the century (**Figure 3.14**). By 2025, insecticide use intensity is projected to be 4.49 (range 3.75 – 5.26) pounds per acre, increasing to 4.75 (range 4.27 – 5.64) pounds per acre by mid-century, and 5.10 (range 4.33 – 5.72) pounds per acre by the end of the century; this is an increase of roughly 0.60 pounds per acre across the projection period. While these projections show an increase in insecticide use intensity over time in relation to climate, the projected use intensities are considerably less than the average use intensity noted from the historical observations (5.16 pounds per acre, range 2.57 – 6.86). This is likely due to the strong negative influence of precipitation on the model. Half of the CMIP5 climate models show a positive bias for precipitation compared to historical observations, with CanESM2 showing the strongest positive bias, followed closely by CNRM_CM5; the others are only slightly positively biased. For models with a negative bias for precipitation, most are very small. These biases are exaggerated when projecting precipitation to 2099 using RCP8.5. Because of the large positive biases of several models, it is likely they are strongly influencing the mean precipitation (suggesting a wetter than normal future), and therefore negatively affecting insecticide use intensity projections in comparison to historical observations.

Figure 3.15 through **Figure 3.17** show model projections for temperature and precipitation.

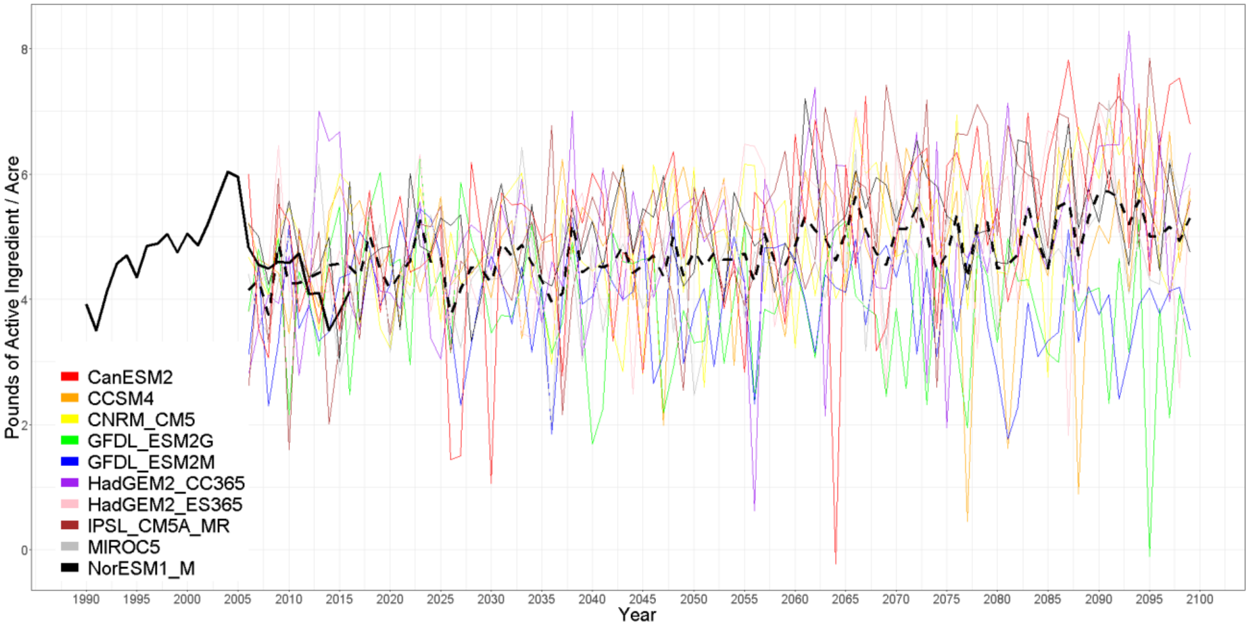


Figure 3.14. Annual trend in insecticide use intensity (pounds of active ingredient per acre) for ten climate models, 2010 to 2099. Historical observations are in bold black, 1990 to 2016. Average climate projected use intensity is in bold, dashed line.

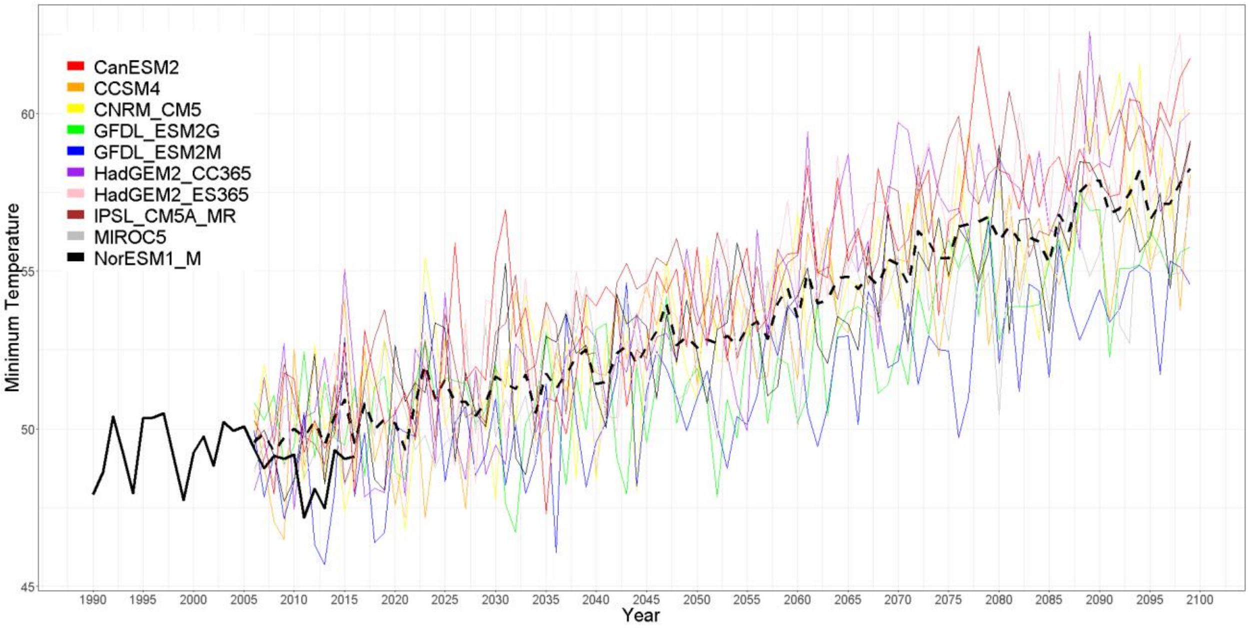


Figure 3.15. Annual average minimum temperature for ten climate models, 2010 to 2099. Historical observations are in bold black, 1990 to 2016. Average projected minimum temperature is in bold, dashed line.

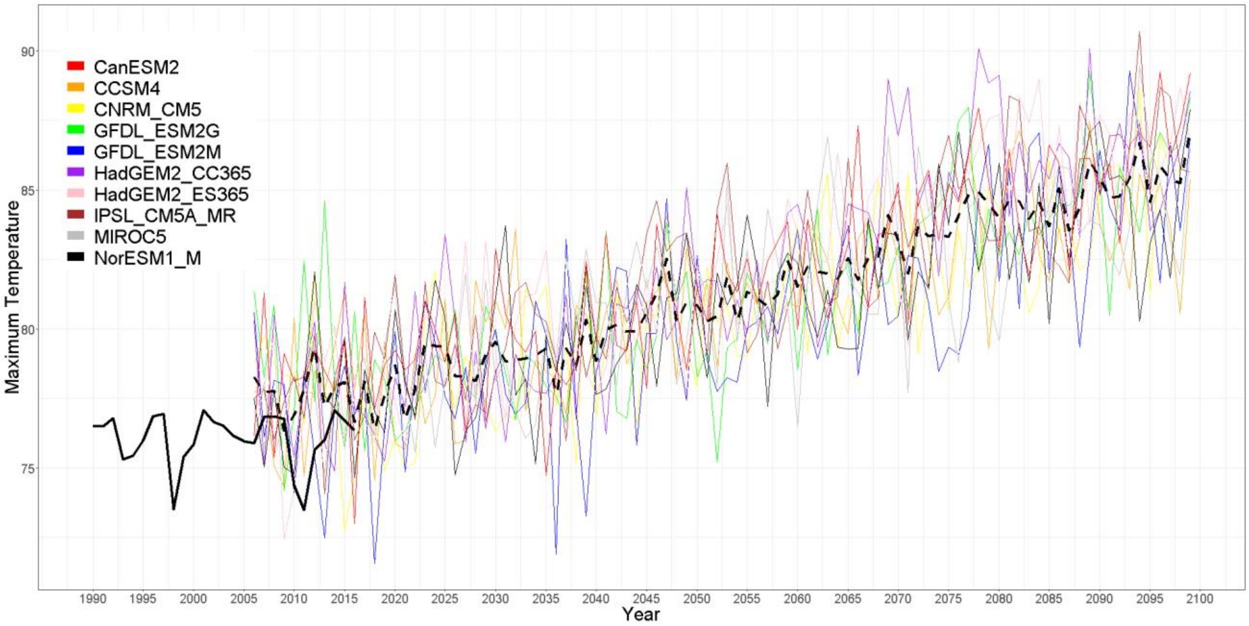


Figure 3.16. Annual average maximum temperature for ten climate models, 2010 to 2099. Historical observations are in bold black, 1990 to 2016. Average projected maximum temperature is in bold, dashed line.

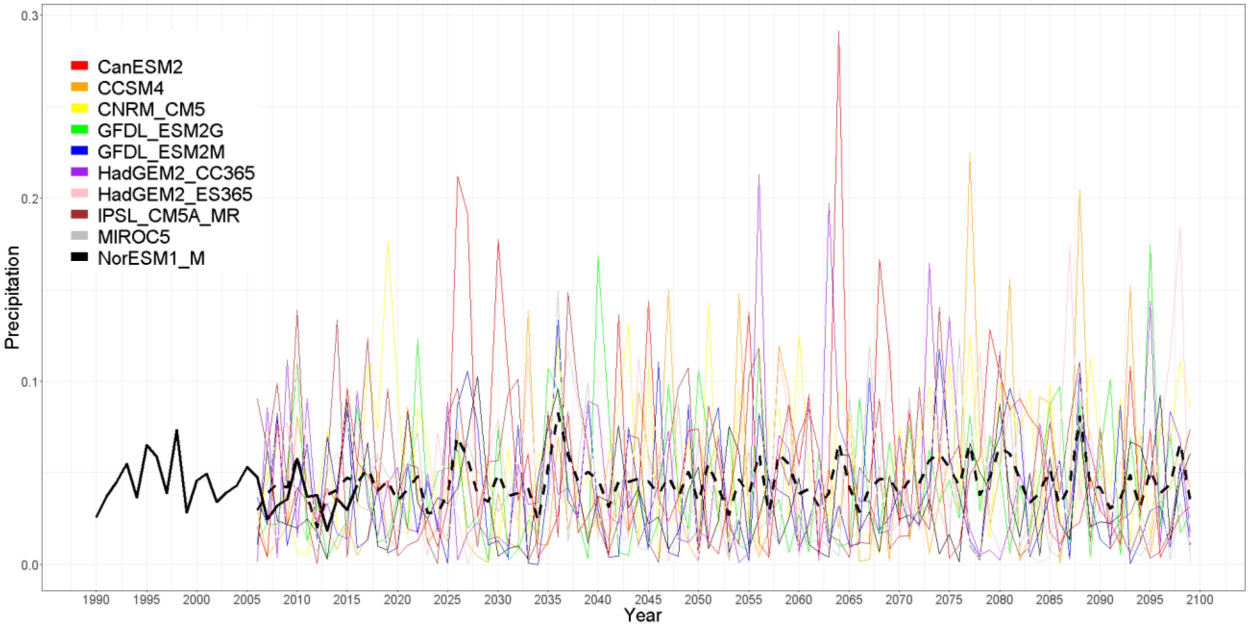


Figure 3.17. Annual average precipitation for ten climate models, 2010 to 2099. Historical observations are in bold black, 1990 to 2016. Average projected precipitation is in bold, dashed line.

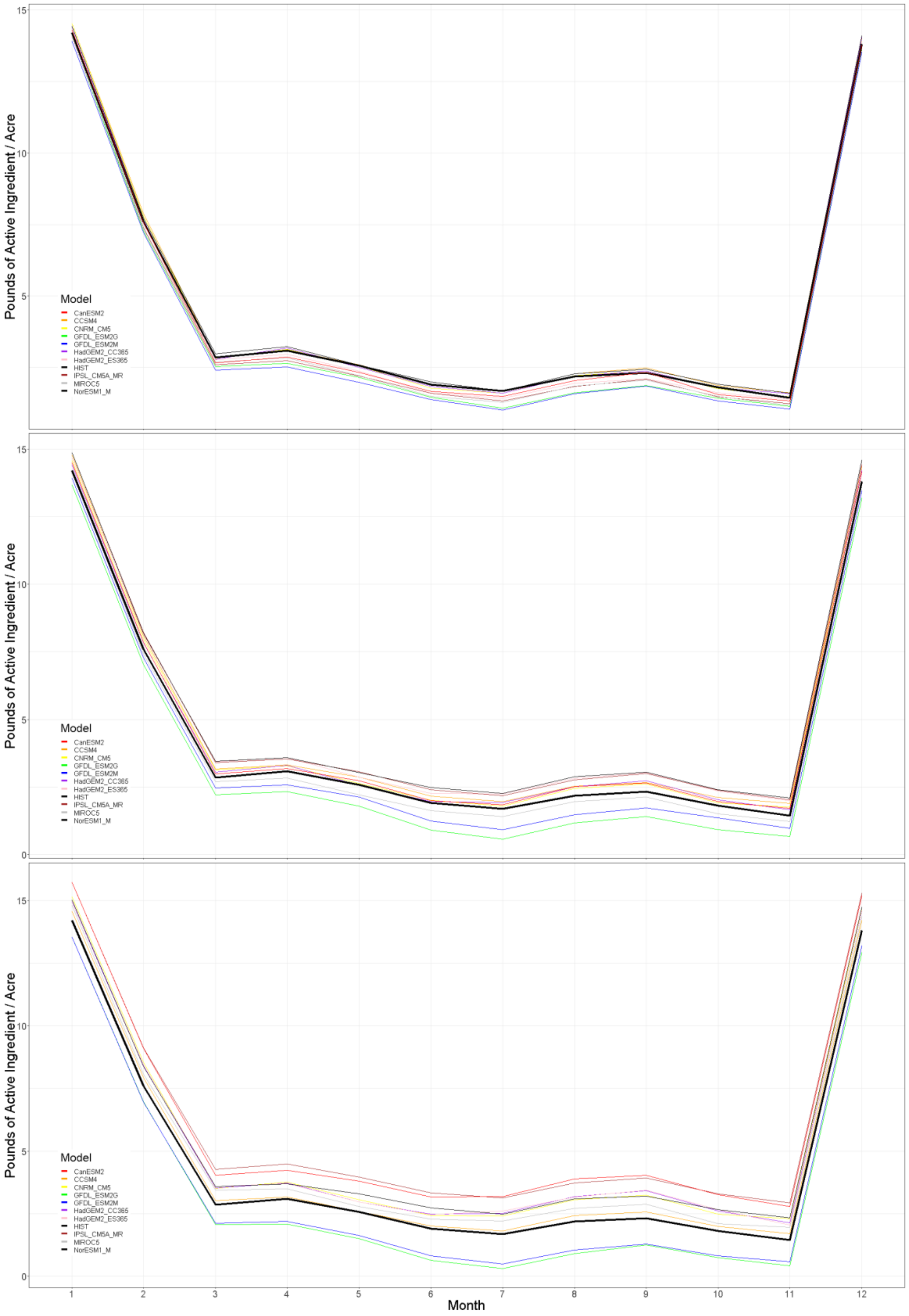


Figure 3.18. Monthly/seasonal trend in insecticide use for historical observations (bold black), 2025 (top), 2055 (middle) and 2085 (bottom) for ten climate models.

The model predicted monthly and seasonal patterns similar to the historically observed trends (**Figure 3.18**). Use intensity is projected to be highest in the winter months (December through February), with smaller peaks in use intensity in April and September. There is less variability between the models during the first projection period, but this increases towards the end of the century. The CanESM2 and IPSL_CM5A_MR models predicted higher insecticide use intensities; whereas the GFDL_ESM2G and GFDL_ESM2M models predicted lower insecticide use intensities compared to the average value across all models.

3.5 DISCUSSION

Application timing and rate of insecticides on the almond crop ebbs and flows throughout the year due to both pest and plant life cycles. Pest management guidelines recommend spraying for insect pests only during specific time points of both the insect's development cycle and the trees (egg laying in the spring or at hullsplit for the navel orangeworm, and larvae development during dormancy, bloom, or throughout the season as needed for the peach twig borer). The monthly-seasonal analysis showed that almonds have high intra-annual variability, but low inter-annual variability in insecticide use, indicating regular seasonal use patterns that are consistent year to year. Use intensity was markedly different between seasons, peaking at an average of 13.82 pounds per acre in December and 14.21 pounds per acre in January, then declining to 7.60 pounds per acre in February and remaining less than 2 pounds per acre for four months of the year. These seasonal peaks suggest that a large portion of the insecticides being used on almonds are routine and follow IPM guidelines, preferring dormant sprays to control for pests as they can control for a wide range of insect pests, are not likely to lead to resistance due to their mode of action, and are less harmful to beneficial insects, birds, and humans and other mammals.

Many of the temporal trends in insecticide use are the result of pest management practices, such as a focus on integrated pest management, government regulations, availability of new pesticides, and phasing out of insecticides known to adversely impact human health and the environment. Several insecticides decreased in use over the study period (e.g. chlorpyrifos), and others were phased out (e.g. azinphos-methyl); because of these shifts due largely to factors unrelated to climate and insect pest pressure, it is difficult to assess pesticides on an individual compound level. By aggregating all insecticide use, it becomes possible to assess general use trends, but it becomes difficult to look for trends in specific insecticides (such as non-oil sprays) without removing these insecticides from the dataset and doing a secondary analysis, or to assess how individual insecticides or insecticide types may change over time and with climate change.

Including oil sprays in the analysis of projected insecticide use may have biased the results, as they account for a large proportion of insecticide use. Due to their heavy use intensity, the models developed to assess the relationship between insecticide use intensity and climate change are strongly influenced by oil spray insecticides, and therefore do not likely model the use intensity of other insecticides very well. While this is a potential issue for the projections, it does suggest that the model likely demonstrates what will occur in the future; if oil insecticides are currently applied in great amounts and high rates, it may be assumed that this is likely to continue in the future, particularly if oil insecticides are less likely to lead to resistance. Future research might focus on modelling insecticide use intensity by type (such as carbamates, pyrethroid/pyrethrins, organophosphates, etc.) or individual insecticide (active ingredient) to further explore the relationship with climate change.

Additionally, oil sprays are typically used to control for mites and scales, as well as overwintering peach twig borer. They are not typically used for control of navel orangeworm.

Other insecticides included in this analysis may also not be used for control of the two pests considered in this analysis. However, restricting to insecticides used only to treat the navel orangeworm and peach twig borer may not be the best choice, as the UCIPM recommended pesticides are purely recommendations. Growers may certainly choose to use different insecticides. One insecticide may also be used to treat more than one pest, or several pests may be controlled for at the same time with one spray. It is not possible to parse out what each insecticide use was applied for; for example, a chlorpyrifos use report may have been for control of the San Jose scale, a pest not included in this analysis, or it may have been for control of peach twig borer or navel orangeworm or both at the same time. The UCIPM recommends using chlorpyrifos for control of each of those pests (and potentially others). Until pesticide use reports include specific pests, it is best to use all insecticide use reports when modelling the relationship between insecticide use intensity and climate change.

Due to past and future regulations, as well as the development of insecticide resistance in pests, individual insecticide use has and will continue to change for reasons completely unrelated to climate change. For example, each insecticide has recommended application rates that vary widely by chemical. Therefore, a change in use intensity may be due to a transition to insecticides with lower or higher suggested application rates. This suggests that even though insect pest pressure is projected to increase, insecticide use intensity may not follow suit if insecticides chosen in the future are those with lower suggested application rates. In addition, changes in application technology, such as to more efficient drone technologies, may also lead to decreases in use and use intensity. These potential changes may affect the results by increasing use intensity (insecticides used in the future may have higher recommended application rates) or decreasing use intensity (lower recommended application rates or more efficient application technologies).

Therefore, this analysis makes the large assumption that insecticide use will continue in the future under a business-as-usual scenario in regards to insecticide use intensity and application.

The two models developed in this study, as well as the alternative models considering transformations and accumulated growing degree days (separately), all had generally identical findings. January and December were found to have the highest insecticide use intensity compared to other months. Higher average annual precipitation corresponded to lower pesticide use rates. Higher maximum temperature (both annual averages and month-year averages) always correspond to lower insecticide use intensity, while higher minimum temperature (both annual averages and month-year averages) always correspond to higher insecticide use intensity, irrespective of month. These results suggest that the increase in use intensity in relation to minimum temperature is strong and supports a link to climate; higher use of insecticides is linked to warmer minimum temperatures, which may be related to the need for more control of overwintering pests during warmer winters, or more control throughout the year due to increased numbers and generations throughout the growing season. The decrease in use intensity with higher maximum temperature, irrespective of month, suggests that high maximum temperatures near or above developmental thresholds may be negatively impacting pests during the growing season and resulting in less need for pest control; alternatively, it is recommended to not apply insecticides when temperatures are higher than recommended maximum temperatures for the specific insecticide. Spraying during cooler temperatures and lower humidity reduces the chance of pesticide drift due to temperature inversions or evaporation; similarly, spraying within weather parameters increases target deposition and coverage. Finally, the decrease in insecticide use intensity during years with higher precipitation suggests that there are fewer days during wet years for optimal application. Precipitation may wash the insecticide product from leaves and reduce the level of protection against pests. Additionally, the increase in insecticide use during dry years may be related to drought stress on the almond tree; drought renders the tree more vulnerable to insect pests.

The results found in this study are similar to other recent studies assessing the impact of climate on insecticides[234,237,249]. Chen and McCarl[234] assessed the impact of climate and per acre pesticide costs as a proxy for investigating the consequence for pest populations, finding an overall increase in pesticide use cost with increasing rainfall and an increase in pesticide cost with increasing temperature (increases seen for corn, cotton, potatoes, and soybeans, while decreases were seen for wheat). They also found that warmer temperatures are associated with increased pesticide cost variance, while increasing precipitation is associated with an overall decrease. Their results suggest that more pesticides are used when precipitation and temperature increase. Similarly, the Nikolinka et al. working paper assessed pesticide use and climate through an economics lens, considering marginal revenue in addition to climate[237]. They found that pesticide application (in kilograms) generally increases with precipitation, although it was found to decrease for berries, citrus fruits, and leafy vegetables. Temperature was found to have similar mixed results. Finally, Ruiz assessed the relationship between pesticide use and climate, considering land area and selling price in addition to climate[249]. They assessed several crop types, but for the fruit crop they did find an increase in pesticides with increasing temperature and a decrease with increasing precipitation.

None of these previous studies used similar methods to the assessment performed here; most considered an economics analysis with a focus on several different crops and pesticide types at once. Therefore, it is not possible to compare the results with the study here, except to note similarities. In all studies, climate variables were found to be significantly associated with pesticide use. All found that pesticide use increases with increasing temperature; however, none of the studies assessed minimum and maximum temperature separately. Precipitation was found to both increase and decrease pesticide use, but those that considered crops similar to almonds (such as stone fruits), a decrease in pesticide use with increasing precipitation was found. None of the studies considered how growing degree days might impact the relationship between climate and pesticide/insecticide use.

Including growing degree days for different pests of concern may help explain insecticide use; however, there are drawbacks to this method as well. The inclusion of growing degree days in this analysis showed that overall, higher accumulated growing degree days across both pests actually results in less insecticide use. While this does imply that insecticide use has a negative relationship with overall favorable heat accumulation for pest development, this may be an artifact of the method used to calculate growing degree days as well as the pests chosen to model. Only degree days for the navel orangeworm and peach twig borer were included in the model, whereas there are several other important pest species that are typically controlled for using insecticides, such as mites and San Jose scale. A secondary analysis may be needed that includes accumulated growing degree days for all pests that are of importance to the almond crop – the UCIPM lists 18. However, the increase seen with the navel orangeworm and simultaneous decrease seen with the peach twig borer, both in combination and when assessed separately, suggests that using individual pest growing degree days may not be appropriate. Growers often spray for navel orangeworm and peach twig borer at the same time, so it is unlikely that an individual pests accumulated growing degree days would have more impact over another if their treatments are usually applied simultaneously. It may be more useful to create a different metric that measures heat accumulation, which could be applied across all pests.

It may also be possible that insecticide use intensity favors accumulated growing degree days for pests that hit specific developmental milestones earlier compared to other pests. Growers may choose to spray insecticides at this earlier time point to control for multiple pests at once. In this case, consideration of multiple pest growing degree days should also examine timing of pest development stages associated with accumulated degree days, such as egg laying or newly hatched larvae. Another factor that may be impacting the growing degree day results is a potential lag in insecticide use related to certain pest or climatic factors. It may be possible that insecticide use intensity is more strongly correlated with the previous months accumulated growing degree days or temperatures. A distributed lag model might be able to decipher whether this is occurring. However, it is unlikely that a lag is impacting this relationship, as general insecticide use is strongly associated with seasonal application. If a lag was introduced into the model, it is more likely that it would pick up the possible relationship of insecticide use and pest development stage associated with growing degree days, rather than an actual lag of insecticide use and growing degree days.

Another level of uncertainty comes from the use of climate models to project the relationship between insecticide use and climate into the future. Not only is the use of RCP8.5 leading to potential overestimations of the future climate (as discussed in chapter two), but there is inherent uncertainty in the climate models themselves. According to Hawkins and Sutton, these uncertainties arise from several sources, including the drivers of anthropogenic change associated with GHGs, aerosols, and land use change, which becomes more important by the late 21st century; uncertainty may arise from climate sensitivity and statistically downscaling models, both of which are model dependent; finally, uncertainty may also be due to internal variability as well as natural unforced variability[208]. In order to control for these uncertainties, Mote et al. suggests considering which climate aspects are important, obtaining climate projections based on as many simulations and models as possible (recommending using at least ten models), evaluating the climate variables used from model projections in order to be cognizant of model biases, and using the ensemble of models chosen for the analysis to characterize consensus and range around the projected mean[207]. All of these suggestions were taken into account in these analyses – using ten models, evaluating model bias for climate variables used, and using the ensemble of models to generate a range and mean for the projections. Models were chosen based on the amount of bias and error in their performance in California; Mote et al. also suggests that most studies have found little to no difference in choosing or weighting model output based on potential bias, so the level of bias in temperature and precipitation for the ten models used was not quantifiably described here.

Finally, there is significant uncertainty in assuming that all other factors regarding insecticide use on almonds remain static. It is impossible to predict future pesticide regulations, whether some pesticides will be banned or phased out, whether non-chemical and organic pest management strategies will significantly change, and what future pesticide application technologies will be developed which may make application more efficient (and therefore decrease in total amount applied). While there are no currently known transgenic almond species, it is certainly a possibility for a pest-resistant species to be developed in the future, decreasing the need for insecticides. Additionally, climate change may impact crop yields, leading to decreases in almond size and harvests as temperatures lead to unfavorable nut development; this decrease in yield may impact growers investment decisions for the almond crop, leading to a decrease in almond acreage and consequently insecticide use on almonds. This assessment of insecticide use projections assumes a business-as-usual future, where no new regulations or technologies are introduced that might affect the use intensity of insecticides – it is an example of what insecticide use may look like in the future if current practices do not change. The assumption of business-as-usual is likely incorrect, and most likely leads to overestimation of future insecticide use intensity as technology and cultivation and management practices advance and change over time.

Finally, water availability is likely to dramatically alter almond production in the future, potentially more so than pest pressure. If climate change leads to increases in extreme precipitation events such as increasing frequency and magnitude of droughts, the agricultural system in California will need to reassess water allocation and water rights. Almond production is water intensive, and cultivation may not be sustainable at the current growth rate or even extent. It may be likely that almond production will decrease given the probable water availability issues that will be exacerbated with a changing climate. Ideally, such extreme events would be considered in the analysis of the impacts of climate change on insecticide use intensity for almonds. In order to fully model drought, soil moisture and evapotranspiration need to be considered, in addition to simply temperature and rainfall. Soil moisture is the amount of water held in between soil particles, whereas evapotranspiration is the process by which water evaporates from the soil back into the atmosphere. Using approximations of these variables, such as computed in the Palmer Drought Severity Index (PDSI), is problematic and not appropriate for climate projections. The PDSI is primarily driven by temperature so is highly sensitive to warming associated with climate change; this results is large overestimations of drought. It would be better to model soil moisture and evapotranspiration directly, but these metrics are not included in MACA downscaled climate model projections, so it is not possible to model at this time.

Historically, California has experienced several droughts throughout the PUR data timespan. These include 1987 to 1992, 2001 to 2002, 2007 to 2009, and 2012 to 2016[250]. Visually, it does not appear that insecticide use intensity differed in these years compared to non-drought years. Future research should consider how to incorporate drought into the analysis of climate change impacts on insecticide use. Until then, incorporation of a range of climate models that incorporate wet and dry models among the ensemble will have to suffice in the consideration of drought. The models used in this analysis covered a wide range of performance in relation to precipitation. Approximately half of the models projected a wet future in comparison to historically observed precipitation, and the other half projected a dry future. Dry models will more closely resemble a future with considerably more drought. Therefore, the results found in this study should portray a range of potential futures, including an increase in the frequency and magnitude of drought (as well as the opposite).

Insecticides are an essential component to agriculture, and with a changing climate it is likely that their use will increase, potentially leading to greater environmental and human health risks than exist today. The initial assessment into the relationship between insecticide use and climate on almond pests suggests a substantial increase in insecticides by the end of the century, particularly in comparison to current use intensity. While end of century projections are in the distant future and not likely to be of interest to most growers or policy makers, even the mid-century projections indicate an increase in use that should be of concern. However, due to the highly seasonal application patterns, it is unlikely that the trend will continue to increase at the rate indicated in the models. In general, it appears that more almond growers are choosing to implement better pest management strategies, as evidenced in the overall decline in insecticide use. This analysis suggests that furthering these practices should be of utmost importance. Future analyses should focus on improving the regression model, or perhaps focus on crops that do not follow such seasonal patterns in use.

Chapter 4. DISPROPORTIONATE RISKS OF INSECTICIDE EXPOSURE IN CALIFORNIA'S CENTRAL VALLEY

4.1 ABSTRACT

Climate change has the potential to harm human health through multiple avenues, but one that has been studied the least is the potential increase in environmental contaminants such as pesticides. With increasing temperatures comes longer growing seasons and intensified pest pressure; insecticide use has been found to correspondingly rise as temperatures warm and heat accumulation increases[234,237,249]. As more pesticides such as insecticides are used, this raises the risk of potential exposure to these harmful chemicals, as they will be used more frequently throughout the growing season to combat additional generations of insect pests, and in greater amounts to combat larger and more widespread populations of pests. While potential exposure increases, it is possible that this will result in more adverse health outcomes in those who live in the vicinity of agricultural fields where insecticides are used, as many insecticides are acutely toxic and have been associated with a range of acute and chronic illnesses.

Previous studies have speculated about the potential for pesticide use to increase, but very few – if any – have quantified this increase and superimposed the potential for exposure on the demography of agricultural communities[8,173]. To our knowledge, no study has then determined the impact of potential exposure on vulnerable populations that often comprise large proportions of agricultural communities. This study aims to assess the disproportionate impacts of potential insecticide exposure in agricultural communities surrounding the billion-dollar almond industry, through development of an impact score that considers both potential exposure burden and social vulnerability. The results are then discussed through the lens of a future where insecticide use increases in response to climatic changes.

This chapter addresses the following sub-aims:

- Understand the demographics of California's Central Valley, particularly those that live near almond orchards and in townships and sections with high insecticide use
- Develop an Impact Score that will incorporate both potential burden of insecticide exposure, defined as total amount of insecticides used by weight per square kilometer, and social vulnerability factors such as socioeconomic status, household composition and disability, minority status and language, and housing and transportation; this will identify areas that would benefit from promotion of alternative pest management strategies

4.2 INTRODUCTION

Climate change will impact human health in more ways than simple physical hazards such as heat and extreme weather events[251-253]. A changing climate is also likely to alter human exposures to chemical pollutants such as pesticides[8,173]. Warmer temperatures, particularly warming minimum temperatures, not only lengthen the growing season for many crops, but they also have a direct impact on the physiology of agricultural pests[55,254]. Insects are exothermic, meaning they have limited ability to regulate their own body temperatures and rely instead on the environment; warm temperatures lead to heat accumulation (known as a degree day) that speeds along their physical development. Climate change will likely increase growing degree days for pests, resulting in earlier emergence, more generations per growing season, and larger overwintering populations[23,72,180,185,187,188]. Consequently, insecticide use is likely to increase in tandem, as growers make pest management choices to protect against potential crop and consequent monetary loss[7,234,237,255]. In areas of high agricultural activity, communities are therefore at risk from unintended environmental exposures to pesticides as concentrations of these harmful chemicals increase in environmental media such as air and water. This exposure is therefore likely to increase in the future with a changing climate.

Many exposures to pesticides are unintentional or accidental. Humans may be exposed to these chemicals through several routes, including consumption of foods, livestock, or fish that have been treated with insecticides or have bioaccumulated the contaminants through the food chain and environment, or consumption of contaminated drinking water sources. Exposure may also occur directly, via aerial transport (spray drift, volatilization, and transport of dust particles) and inhalation or direct contact with contaminated environmental media. Agricultural workers have the greatest chance of exposure, but residential proximity to pesticide applications is also an important source of unintended environmental exposures among agricultural communities through a phenomenon known as drift.

Pesticide drift is the unintentional movement of pesticide dust or droplets through the air from the application site to areas nearby, and is influenced by the type of spraying equipment, type and height of crop, weather conditions such as inversion layers and wind, and chemical properties of the active ingredient and spray liquid. Both aerial and ground application of pesticides have been observed to drift from treatment sites, often detected at measurable concentrations nearly a half to full kilometer away[256-258]. Chemicals that are still airborne may be inhaled into the lungs of adults or children nearby, while those that deposit on surfaces or water bodies may eventually be ingested[259]. When sprays and dusts are deposited on other areas, such as nearby homes, schools, and playgrounds, pesticide exposures may be high and related illnesses could result, potentially even leading to death [260,261].

Communities in agriculturally rich areas are most at risk from unintentional exposure to pesticides. California is the largest agricultural producer in the United States, growing over a third of the country's vegetables and two-thirds of the country's fruits and nuts[58]. In California alone, over 82,300 insecticide exposures were reported from 2000 to 2014, and 35,557 of those were in children[262]. Pesticides are consistently one of the top substances most frequently involved in human and pediatric exposures and deaths. Those most often implicated in poisonings, injuries, and pesticide illnesses include fumigants (aluminum phosphide, methyl bromide, sulfuryl fluoride, and others), fungicides (carbamates, copper compounds, phthalimides, and others), herbicides (chlorophenoxy herbicides, diquat, glyphosate, paraquat, triazines, and others), insecticides (carbamates, chlorinated hydrocarbon insecticides, insect growth regulators, metaldehyde, organophosphates, piperonyl butoxide, pyrethrins, pyrethroids, and rotenone), and miscellaneous pesticides and repellents (arsenic pesticides, borates and/or boric acid, metam sodium, and others)[263]. From 2000 to 2014, the environmental tracking network detected and followed 12,188 carbamate/organophosphate exposures, 1,129 organochlorine exposures, 39,366 pyrethroid/ pyrethrin/piperonyl exposures, 4,576 boric acid exposures, and 25,043 exposures to other pesticides[262].

Health impacts related to these exposures are broad and dependent on many factors, such as type of chemical, exposure dose and/or length, and age of the exposed. Each pesticide has a different mode of action, and will therefore have different effects dependent on the chemicals properties, such as neurotoxicity, endocrine disruption, carcinogenicity, and other health effect pathways[264]. Insecticides such as organophosphates and carbamates are cholinesterase inhibitors, leading to sensory and behavioral disturbances, incoordination, muscle twitching, motor function and respiratory depression, seizures, and loss of consciousness or death[265]. Organochlorines, while largely banned in the United States, are still found in some products; they mostly impact the nervous system, causing sensory disturbances and convulsions[265]. Pyrethrins and pyrethroids act by paralyzing the nervous system, and boric acid mostly causes irritation to the skin or mucous membranes and gastroenteritis[265]. Exposure to these insecticides can cause adverse health effects ranging from minor to major illness or even death. From 2000 to 2014, there were over 150,000 reported pesticide illnesses, resulting in 16 deaths; over 50% of those were in children (**Table 4.21**)[262]. Almost 95% of pesticide exposures leading to illness occurred at home, largely due to general unintentional exposures. Chronic, long-term exposure to pesticides has been linked to a wide range of adverse health impacts and chronic illnesses including cancer, reproductive and developmental problems, Parkinson's disease, and adverse birth outcomes[76,77,79,80,99,102,103,107-109,117,120,124-129,131-134,137,266].

Table 4.21. 2000 – 2014 pesticide related illnesses and deaths from exposure to all pesticides in California. Children are those aged 17 years old and younger. Pesticide exposures that were unable to be followed are potentially toxic illnesses. Environmental, occupational, general, and misuse exposures are unintentional. Pesticide illnesses enumerated in the 'All' column can have more than one characteristic.

	All	Child	Home	Work	Enviro	Occup	General	Misuse
Deaths	16	NA	NA	NA	NA	NA	NA	NA
Major	110	27	96	11	10	10	76	10
Minor	97,162	42,972	91,120	4,400	12,582	2,867	75,611	5,631
Moderate	2,715	431	2,249	421	724	325	1,341	306
No effect	58,142	36,766	56,400	1,117	4,659	765	50,659	1,834
Potential	3,762	1,080	3,346	323	647	237	2,615	234
TOTAL	161,907	81,276	153,211	6,272	18,622	4,204	130,302	8,015

Not all exposures to pesticides are created equal – some populations are more vulnerable to exposure and are also disproportionately exposed to environmental contaminants such as pesticides. Vulnerable populations include those with low socio-economic status, communities of color, uninsured, children and the elderly, homeless, and those with pre-existing chronic health conditions. These factors impact an individual or community's resilience – their ability to recover from external stresses on their health such as environmental exposure to pesticides – as they have fewer social, political and economic resources to mitigate the potential health effects and advocate for themselves; these factors may also lead to situations in which exposure is more likely to occur. This environmental injustice is a systemic driver of health disparities; inequities exist that create higher exposures to environmental contaminants such as pesticides, and these same inequities make it more difficult for these vulnerable populations to seek help or recover. The purpose of this study is to assess the impact of agricultural insecticide use for the almond crop on agricultural communities in California's Central Valley. Almonds serve as a useful example for the state because they are a major economic crop for which large amounts of pesticides are applied, with orchards widely distributed in the valley. A geospatial assessment of historical insecticide use, and a social vulnerability index will evaluate disparities in exposure.

4.3 MATERIALS AND METHODS

4.3.1 *Study area and crop*

California's Central Valley, where nearly all the almonds grown in California are cultivated, was selected as the study area. It was defined using the boundary of alluvial deposits in the Central Valley, encompassing the Sacramento, San Joaquin, and Tulare Lake groundwater basins, defined by California's Department of Water Resources[45]. The boundary encompasses approximately 20,000 square miles, and has been used to define the boundary of the area simulated by the transient Central Valley Hydrologic Model, the most recent regional-scale model of the Central Valley developed by the United States Geological Survey as part of the Groundwater Resources Program[267]. This boundary was chosen for the Central Valley as it reflects areas where crops are most often grown, particularly perennial crops such as almonds, due to their significant reliance on groundwater for irrigation and successful crop yields.

4.3.2 *Demographics and Social Vulnerability Index*

US Census Bureau data was used to describe the demographics of the Central Valley, including total population and percent breakdown of race and ethnicity, using Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line shapefiles[268]. Census tracts were used as a geographic unit, as they do not often change and are therefore useful for combining and mapping data. Because the Central Valley is not defined by census tract, all tracts that intersected or were within the boundary of the valley were included. This resulted in 1,457 out of 8,041 census tracts across 29 counties in California. The 2016 five-year estimates for the 2012 – 2016 American Community Survey (ACS) were then used to assess demographics and factors that contribute to vulnerable populations, such as race and ethnicity, limited English speaking skills (linguistic isolation), low educational attainment, and poverty[269]. By definition, this information only included individuals who were captured by census records; stationary and non-stationary migrant farm workers and their families are historically undercounted in these reports[270].

A California-specific vulnerability index based on the Social Vulnerability Index (SVI), developed by the US Center for Disease Control and Prevention and the Geospatial Research, Analysis and Services Program at the Agency for Toxic Substances and Disease Registry, was employed to further identify and rank vulnerable communities[271]. This index utilizes 2012 – 2016 US Census Bureau ACS variables to determine the relative social vulnerability of every census tract by ranking each tract on 15 social factors and grouping them into four themes (**Table 4.22**). These rankings are based on percentiles, ranging from zero to one, with higher values indicating greater vulnerability. For each tract, the percentile ranking was generated for each of the 15 individual variables, based on population proportions. The percentiles were then summed within each of the four themes and ordered to determine the theme-specific percentile rankings. Finally, the overall vulnerability was determined by similarly summing the four themes, ordering by census tract, and calculating the overall percentile rankings. This determined the overall tract summary ranking for all census tracts within California. It was decided to use all four themes and 15 variables to evaluate vulnerability in the Central Valley, as this is a common metric created for and used across the United States to determine social vulnerability within communities. Those tracts that intersect the Central Valley boundary were then selected to assess vulnerability of Central Valley communities relative to each other and the rest of the state.

Table 4.22. Overall vulnerability of a census tract is determined by 15 US census ACS variables, categorized into four social vulnerability themes.

Socioeconomic status	Below poverty Unemployed Low Income No high school diploma
Household composition and disability	Aged 65 or older Aged 17 or younger Civilian with a disability Single-parent households
Minority status and language	Minority Speak English “less than well”
Housing and transportation	Multi-unit structures Mobile homes Crowding No vehicle Group quarters

ACS definitions were used to determine estimates for each variable included in the index, with variables defined as the percentile percentage of persons for each estimate. Poverty was defined as the estimate of persons below the Federal poverty level. Unemployment was defined as civilians aged 16 and older that were unemployed. Income was defined as the per capita income estimate. No high school diploma was defined as persons aged 25 and older with no high school diploma (including those with education below the high school level). The two age groups were defined as either persons aged 65 and older or persons aged 17 and younger, respectively. Disability was defined as the civilian noninstitutionalized population with a disability. Single-parent household was defined as single parent households with children under 18 years of age. Minority was defined as all persons except white, non-Hispanics. Limited English-speaking capabilities were defined as persons aged five and older who speak English “less than well”. Multi-unit structures were defined as housing in structures with 10 or more units. Mobile homes were defined as the number of mobile home units. Crowding was defined at the household level (occupied housing units), with more people than available rooms. No vehicle was defined as households with no vehicle available. Group quarters was defined as persons in institutionalized group quarters.

4.3.3 *Pesticide use and insecticide Pollution Burden Index*

Pesticide-use reports (PUR) collected by the California Department of Pesticide Regulation were used to evaluate insecticide use in the Central Valley[238]. Each record documents the active ingredients contained in the specific pesticide product applied, the amount of product used and percent of active ingredient by weight (in pounds), the crop and total planted and treated acreage of the field, application method (aerial or ground), and the date of the pesticide application[239]. Each record is contained within a township and section as defined by the Public Land Survey System (PLSS); townships comprise an area of six square miles, divided into sections which comprise an area of one square mile[272]. Each pesticide use report notes the county, baseline meridian, township and township direction, range and range direction, and section the pesticide was applied in; from these location details, a variable was created that describes each section's geospatial location that matches the PLSS sections.

The PUR data was then linked to the California PLSS sections, and only records that fell within the Central Valley boundary were used in the analyses. For each PLSS section, the pounds of active ingredients for all insecticide use reports on almonds between 2012 and 2016 were summed to find a value for total applied pounds of insecticide active ingredients used on almonds within the Central Valley. The years 2012 to 2016 were used, as these data would match the years for the ACS demographics and vulnerability index, and more accurately represent potential exposure among communities during that time period.

Like the SVI, an insecticide Pollution Burden Index (PBI) was calculated for each census tract within the Central Valley. For this index, each PLSS section was joined to the corresponding census tract based on its geospatial location. For every tract within the valley, the total pounds of insecticide active ingredients from each PLSS section within its boundary was summed to find the total pounds of insecticide active ingredients used within the census tract, between the years 2012 and 2016. Heavy use was defined as total pounds applied during this period, greater than the 75th percentile for all summed use reports.

Although the PUR system records detailed pesticide use, the spatial resolution does not allow for an assessment of exposures from residential proximity, as most of these exposures occur at distances less than one kilometer, significantly shorter than the square mile of the PLSS sections[257,273,274]. When aggregated at the census tract level, this further dilutes exposure potential, as many census tracts are considerably larger than one square mile, and it becomes difficult to determine if location of residence is near the pesticide application site or miles away. In order to account for this spatial dispersion, the total pounds of applied insecticides were divided by the area of the census tract (in square kilometers) to standardize the use intensity within each tract. Several recent studies have demonstrated the validity of assessing pesticide exposure this way, using application rate and number of acres treated as a proxy for potential exposure[273,275-277]. The census tracts were then ordered and ranked to determine the percentile ranking for insecticide use intensity per square kilometer, known as the insecticide Pollution Burden Index. As this value is based on percentiles ranging from zero to one, higher values indicate census tracts where use intensity of insecticides is relatively high compared to use throughout the rest of the valley.

4.3.4 *Impact Score*

The Social Vulnerability Index and insecticide Pollution Burden Index were combined to create an Impact Score, an index that reflects potential for insecticide exposure among vulnerable agricultural communities. Similar indices have previously been calculated to determine effects of environmental exposures on vulnerable populations[169,170,278]. The Impact Score was determined by multiplying the SVI by the PBI, as the scientific literature suggests that vulnerability factors are effect modifiers, meaning they amplify the risk of both exposure and adverse health impacts; multiplication also accounts for potential human sensitivity to exposures, and is often used by emergency response organizations to determine risk (Risk = Threat x Vulnerability)[279]. In this Impact Score, the social vulnerability indicators are identified as modifiers of the insecticide pollution burden.

4.3.5 *Pesticide properties*

Separate from development of the Impact Score, in order to place almond-related insecticide use in California within the context of human health risk, the toxicological properties of the pesticides were reviewed. Previous analyses (see chapter three, section 4.1 and 4.2) established which insecticides were used most heavily on almond crops over the span of the PUR program and the last five to ten years, in terms of total pounds applied, acres treated, and use intensity (pounds per acre). Information regarding the potential for causing adverse health effects for each of the top active ingredients was obtained from the Pesticide Action Network (PAN). This database includes information on each chemical, such as regulatory status, US EPA hazardous air pollutant and California Toxic Air Contaminant status, ground water contamination potential, acute or chronic aquatic toxicity, acute toxicity in humans, carcinogenicity, developmental and reproductive toxicity, endocrine disruption, physical properties of the chemical, and water quality standards. Properties considered for this analysis were the acute toxicity summary, which combines the WHO acute hazard rankings, the US EPA acute toxicity rankings, the US EPA Toxic Release Inventory (TRI) rankings, and the US NTP acute toxicity rankings; the final summary categorizes each chemical as extremely, highly, moderately, slightly, and not acutely toxic.

The PAN cancer rating is based on the US EPA Office of Pesticide Programs carcinogen list and TRI carcinogen list, IARC carcinogen list, and US NTP carcinogen list; it is categorized as known, probable, possible, unclassifiable, or not likely to be carcinogenic. The developmental or reproductive toxicity rating is based on the California Proposition 65 list, which includes pesticides determined by the state of California to cause reproductive and environmental harm; the US EPA TRI list also includes a list of chemicals known to cause reproductive and developmental toxicity. The endocrine disruptor rating is based on several sources of information, as no official database exists that fully lists chemicals known to be an EDC; these include the Illinois EPA list, the Danish EPA report on the health effects of selected pesticide coformulants, the European Union prioritization list, the Colborn list[112], the Keith list[280], and the Benbrook list[113].

4.4 RESULTS

4.4.1 *Demography and social vulnerability of the Central Valley*

Overall, California is predominantly white, with 38.56% identifying as Hispanic/Latinx (**Table 4.23**). Approximately 10% of the population speaks English ‘less than well’, and nearly 18% have less education than a high school diploma. 15.84% of the state is below the Federal poverty level, with a median household income of $72,227. Within the Central Valley, the proportion of the population identifying as white increases while the Hispanic/Latinx population increases to 39%. Interestingly, the proportion of the population that speaks English ‘less than well’ decreases to 9.10%. However, individuals with less than a high school education increases to 19.96%, and those below poverty level increases to 19.82% while median household income decreases to $57,349. This indicates a trend in socioeconomic and racial vulnerability, as the minority population comprises a greater fraction of the total population, and economic indicators deteriorate.

Among communities living in census tracts with heavy insecticide use (total pounds applied greater than the 75th percentile), these trends continue more dramatically. The proportion of the population that is white increases to 75% – an increase of nearly 10% compared to the rest of the valley; likewise, the Hispanic/Latinx population increases by nearly 20% to over 56% of the population. Linguistic isolation (those who speak English ‘less than well’) increases moderately to 13.85%, while those with less than a high school education increases by over 10% to just over 30%. Socioeconomic indicators continue to decline, as those living below the Federal poverty level increases to over 20%, while the median income drops to $52,383. These indicators suggest there is a potential environmental justice issue occurring in areas within the Central Valley, particularly those with heavy insecticide use on almonds. Socioeconomic and minority and language status appear to be the largest indicators of social vulnerability, followed by low educational attainment.

Table 4.23. 2012 – 2016 demographics of California and the Central Valley (as percent of the population) by census tract, in relation to proximity to insecticides – heavy (greater than 4th quartile) use – measured as total pounds of active ingredients applied, 2012 – 2016.

	California	**Central Valley**	**Heavy Use**
White	61.26	66.46	74.99
Black/African American	5.85	5.80	3.06
American Indian/Alaska Native	0.74	0.90	0.85
Asian	13.85	9.74	5.01
Native Hawaiian/Pacific Islander	0.39	0.50	0.19
Other race	13.28	11.12	12.71
Two races +	4.62	5.48	3.19
Hispanic or Latinx	38.56	38.93	56.13
Limited English	10.29	9.10	13.85
Less than Highschool Education	17.90	19.96	31.45
Below Poverty	15.84	19.82	20.31
Median Household Income	$72,227	$57,349	$52,383

The four Social Vulnerability Index themes demonstrate similar findings as the selected ACS indicators, revealing uneven geographic distribution for the valley compared to California, and similar uneven distribution within the Central Valley (**Figure 4.1**). The socioeconomic status theme indicates the southern region of the valley has the highest scores for socioeconomic vulnerability, as measured through those living below the Federal poverty level, unemployment, low median income, and low educational attainment. This theme, while unevenly distributed throughout the valley, does show similar distributions throughout the rest of the state. The household composition and disability theme (**Figure 4.1**), as measured through vulnerability related to age (children aged 17 and younger, and the elderly aged 65 and older), disability, and single-parent households does not appear to be unevenly distributed. However, the northern region does indicate a slightly higher vulnerability level as compared to the rest of the valley.

The minority status and language theme (**Figure 4.2**), as measured through racial/ethnic minority and linguistic isolation, clearly indicates a very large uneven geographic distribution for the Central Valley as compared to the rest of California. Nearly all census tracts that rank high in this Social Vulnerability Index theme are within the boundary of the Central Valley. Within the Central Valley, there is further uneven distribution of this theme; those most vulnerable are clustered in the southern two-thirds of the valley, and those in the highest percentile ranking for vulnerability are in the most southern one-third of the Central Valley. Finally, the housing and transportation theme (**Figure 4.2**), as measured through the number of multi-unit structures, number of mobile homes, crowding within living spaces, and percentage of homes with no access to a vehicle, does not indicate any differences in vulnerability within the Central Valley or compared to the rest of California. While there are clusters of high vulnerability related to this theme, they are evenly distributed throughout the state as well as throughout the Central Valley. This theme likely does not contribute significantly to the overall Social Vulnerability Index.

The overall Social Vulnerability Index indicates that the trends noted in the selected ACS indicators and each of the four individual SVI themes were correct in suggesting high social vulnerability among communities within the Central Valley (Figure 4.3). While a few pockets of socially vulnerable communities exist outside of the valley, such as near the Salton Sea and the Mojave National Preserve, and in northern California near the border with Oregon, a large proportion are congregated in the southern region of the Central Valley, a region known as the San Joaquin Valley. Nearly 33% of the census tract areas with the highest Social Vulnerability Index scores (a percentile ranking greater than 75%) are within the Central Valley. Again, most of these census tracts are clustered within the southern region of the valley, with a few tracts interspersed throughout the northern Central Valley.

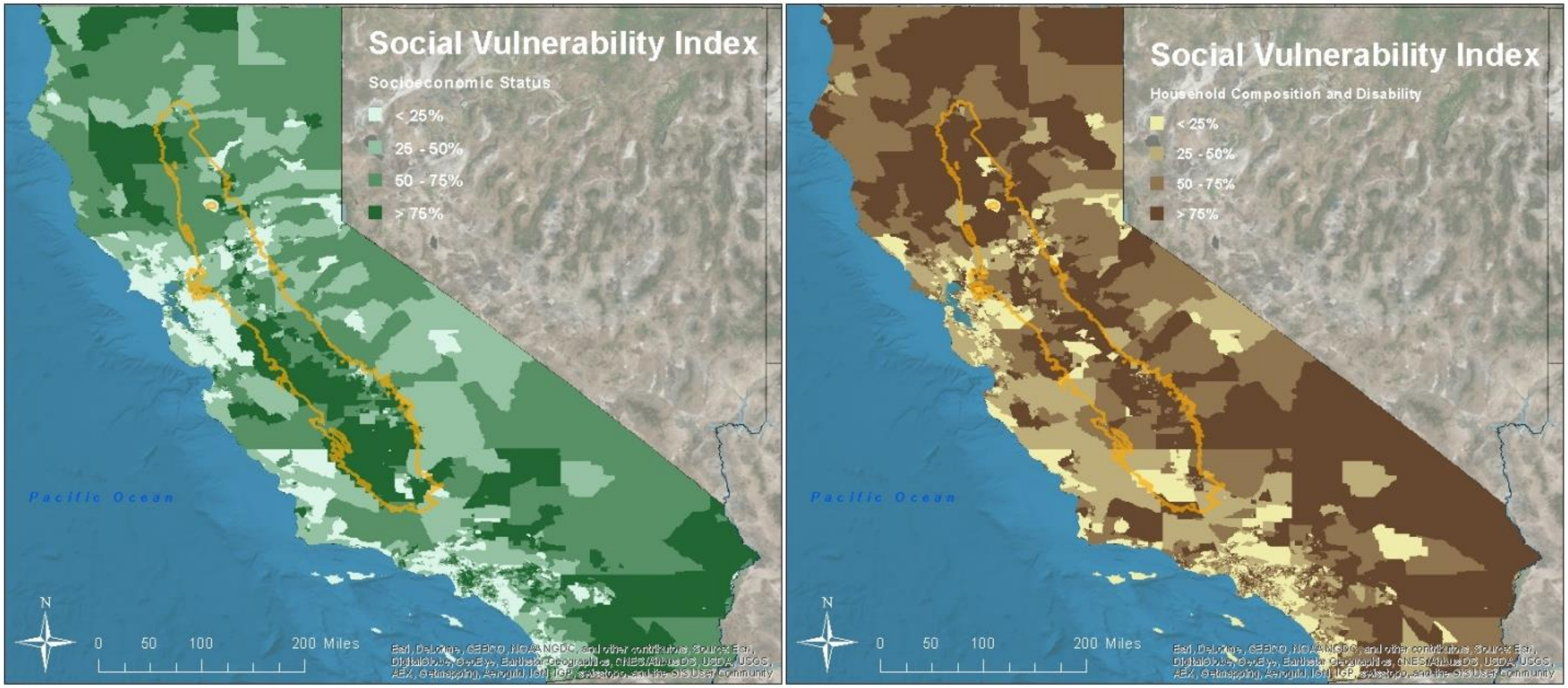


Figure 4.1. Social Vulnerability Index for each theme – socioeconomic status and household composition and disability. Themes are displayed as quantile ranks – less than 25%, 25 to 50%, 50 to 75%, and greater than 75%.

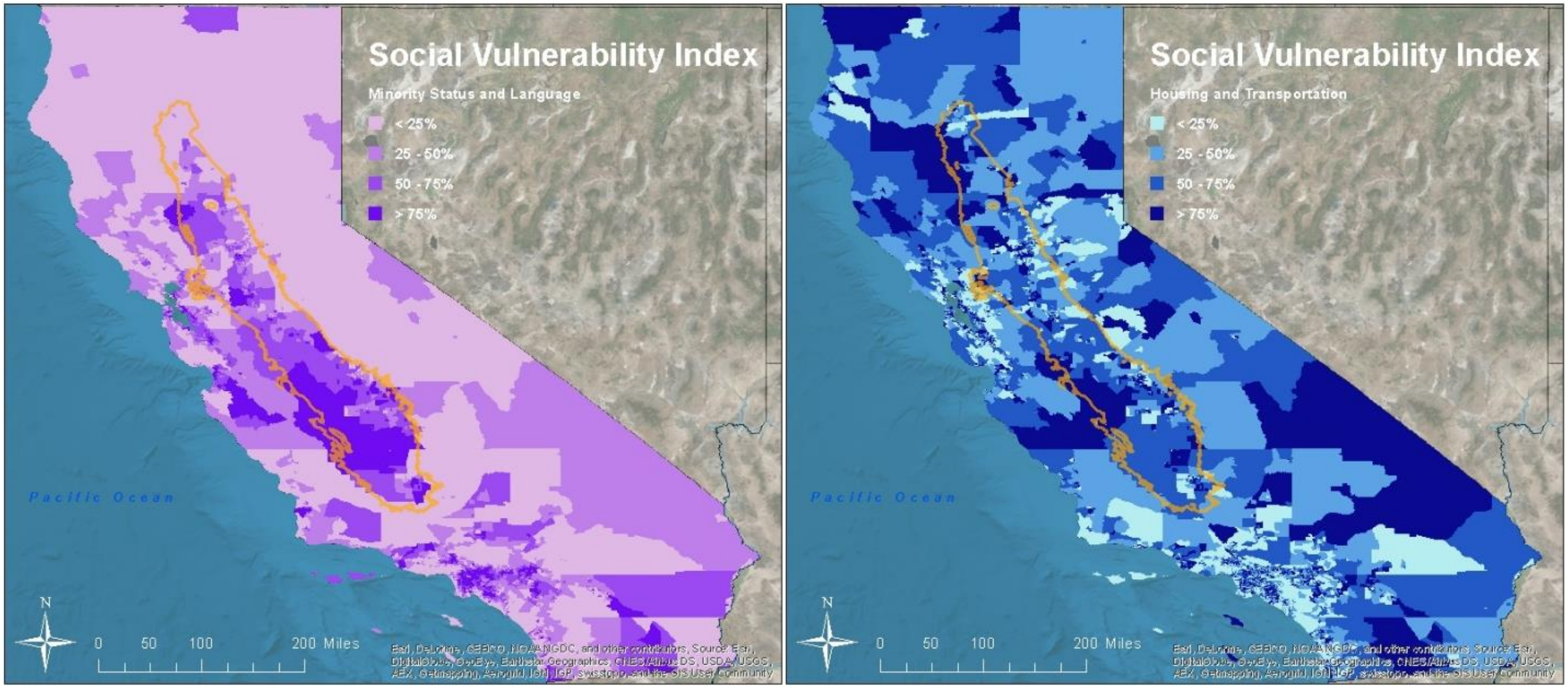
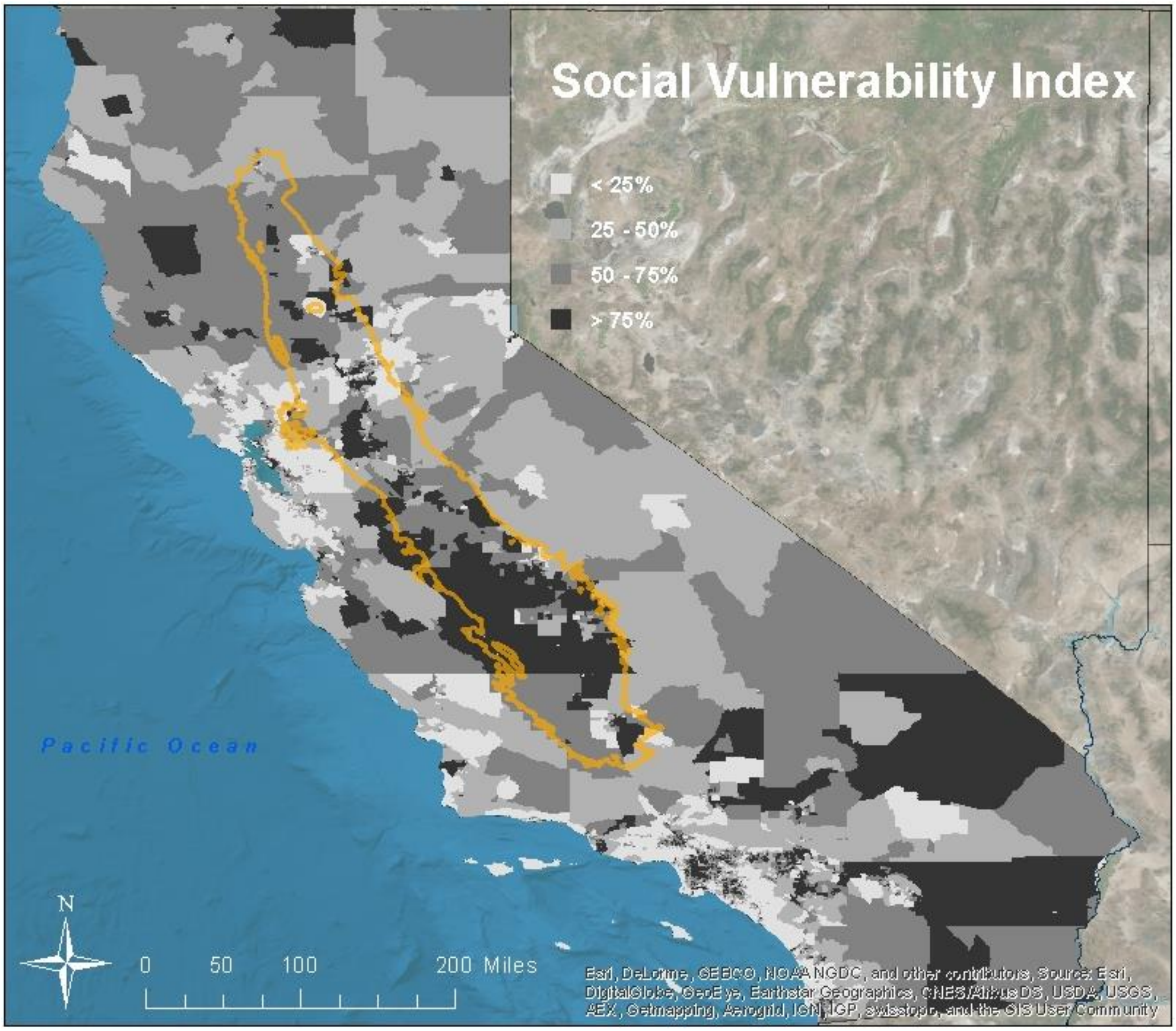


Figure 4.2. Social Vulnerability Index for each theme – minority status and language, and housing and transportation. Themes are displayed as quantile ranks – less than 25%, 25 to 50%, 50 to 75%, and greater than 75%.



Esri, DeLorme, GEBCO, NOAA NGDC, and other contributors, Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Figure 4.3. Overall Social Vulnerability Index by census tract in California, a combination of all four themes. SVI is displayed as quantile ranks.

4.4.2 *Pesticide use and potential for exposure*

Between the years 2012 and 2016, the total pounds of active ingredient applied for insecticides on almonds ranged between 0.000315 and 272,160 within the PLSS sections, and 0.257 to 12,610,675 pounds by census tract (**Figure 4.4**). Most use is concentrated in the lower two-thirds of the valley. The southern region also applies relatively greater amounts of insecticide, particularly in the bottom third of the valley, as use appears to mostly fall above the 50th percentile in this region. Use also varied by season (**Figure 4.5**). During the winter months, nearly 36 million pounds of insecticides were applied between 2012 and 2016. This drops to closely 12 million pounds in the spring months, followed by an increase to almost 36 million pounds in the summer, and decreasing again to only approximately four million pounds during the fall months. These differences in use suggest that the potential for almond-related insecticide exposure among agricultural communities in the Central Valley will differ by season, with the greatest risks occurring during the winter and summer months, coinciding with dormant spraying and the busy growing season.

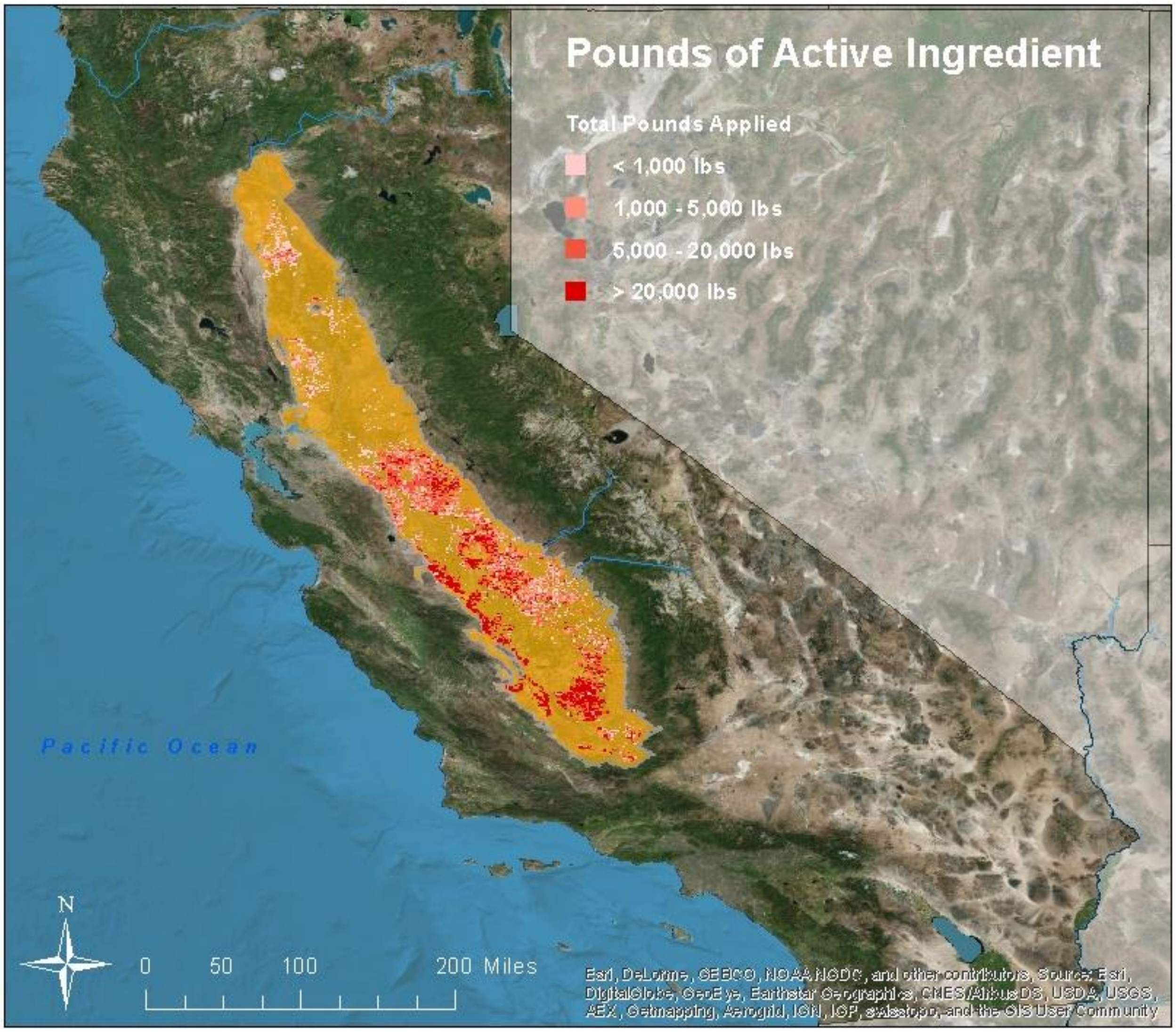


Figure 4.4. Total pounds of applied active ingredients found in insecticides used on almond orchards (2012 – 2016) in California’s Central Valley, by PLSS section.

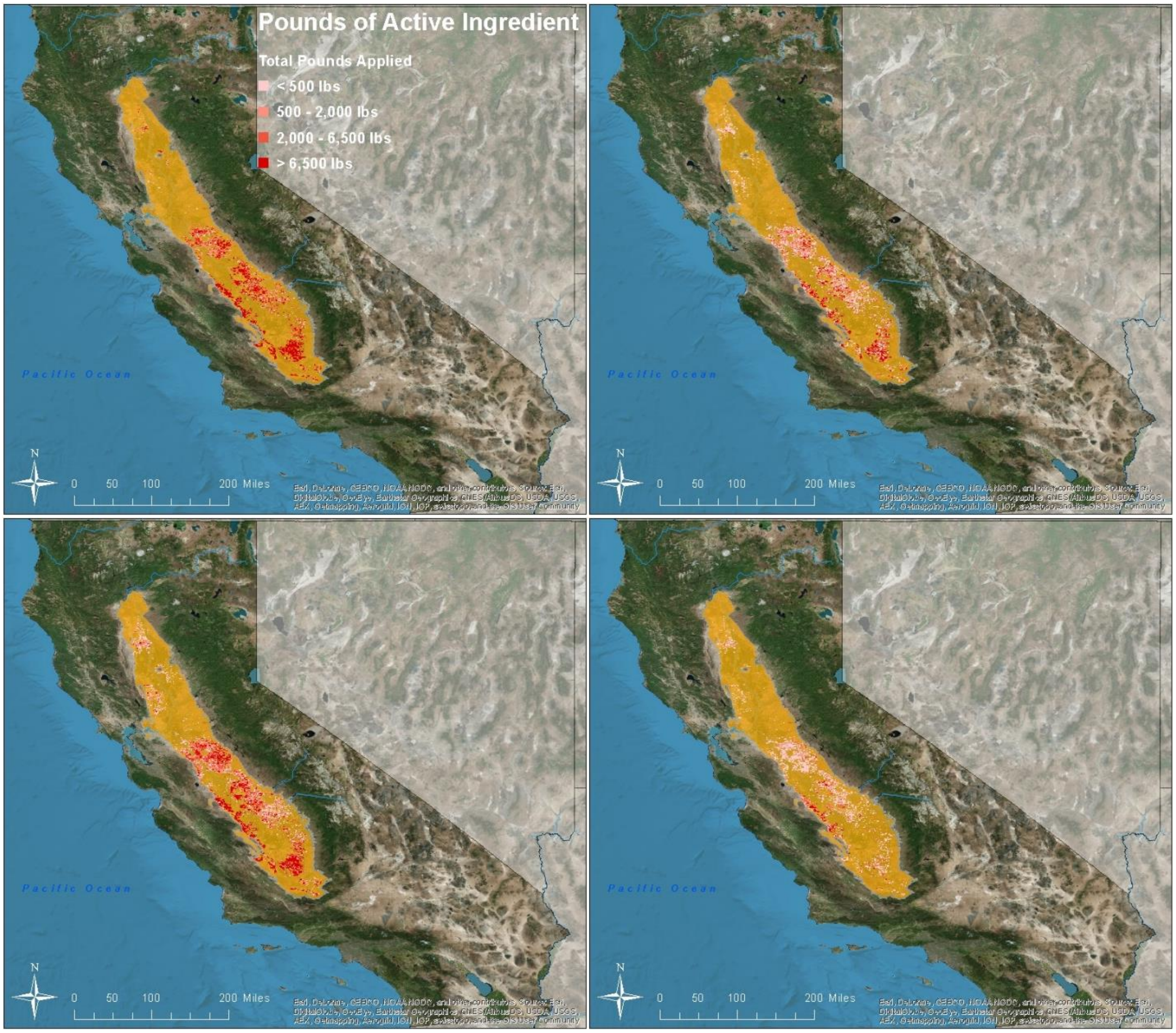


Figure 4.5. Seasonal differences in insecticide use on the almond crop in California’s Central Valley 2012 – 2016, measured as total pounds of active ingredient within each PLSS section. From top left to bottom right: winter, spring, summer, and fall.

The Pollution Burden Index reflects the heavy insecticide use noted in the southern Central Valley (**Figure 4.6**). All census tracts that had high PBI scores greater than 75% were in the lower two-thirds of the valley. Some tracts did not contain PLSS sections with reported pesticide use, and therefore had a PBI score of zero. Of the 1,457 tracts within the Central Valley, only 427 (29.3%) had reported insecticide use on almonds between 2012 and 2016. Despite the small percentage of tracts with recorded insecticide use, those that had PBI scores comprise much of the land area of the Central Valley. Approximately 65% of the land encompassed by the census tracts that intersect the Central Valley is accounted for in the 427 tracts with reported insecticide use on almonds. This suggests that rural areas with larger census tracts and fewer people per square mile experience the most insecticide use. This is particularly true in the southwest region of the valley, where census tracts are typically larger, and more insecticides are applied by total pounds of active ingredient. So, while there may be fewer people in these census tracts, insecticide use is widespread.

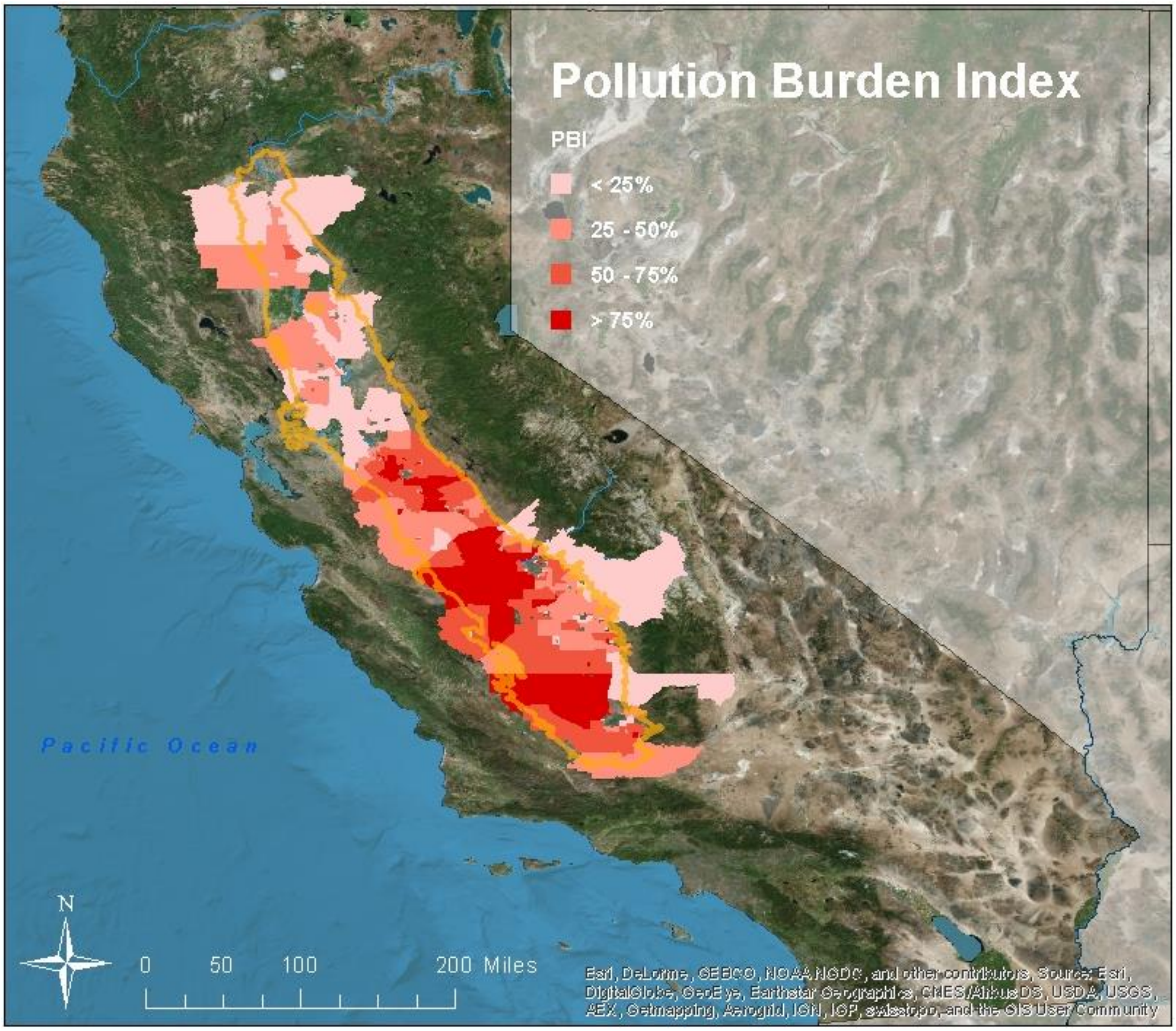


Figure 4.6. Insecticide Pollution Burden Index, by census tract, for census tracts intersecting the boundary of California's Central Valley.

4.4.3 *Impact Score*

The total Impact Score exhibits the same trends seen in the individual SVI and PBI scores (**Figure 4.7**). The cumulative impact scores are unevenly distributed throughout the Central Valley, with the southern two-thirds of the valley experiencing the greatest environmental justice impacts. There is a small pocket in the northern region of the valley between Chico and Sacramento that also has a high impact score, more likely related to social vulnerability than heavy insecticide use.

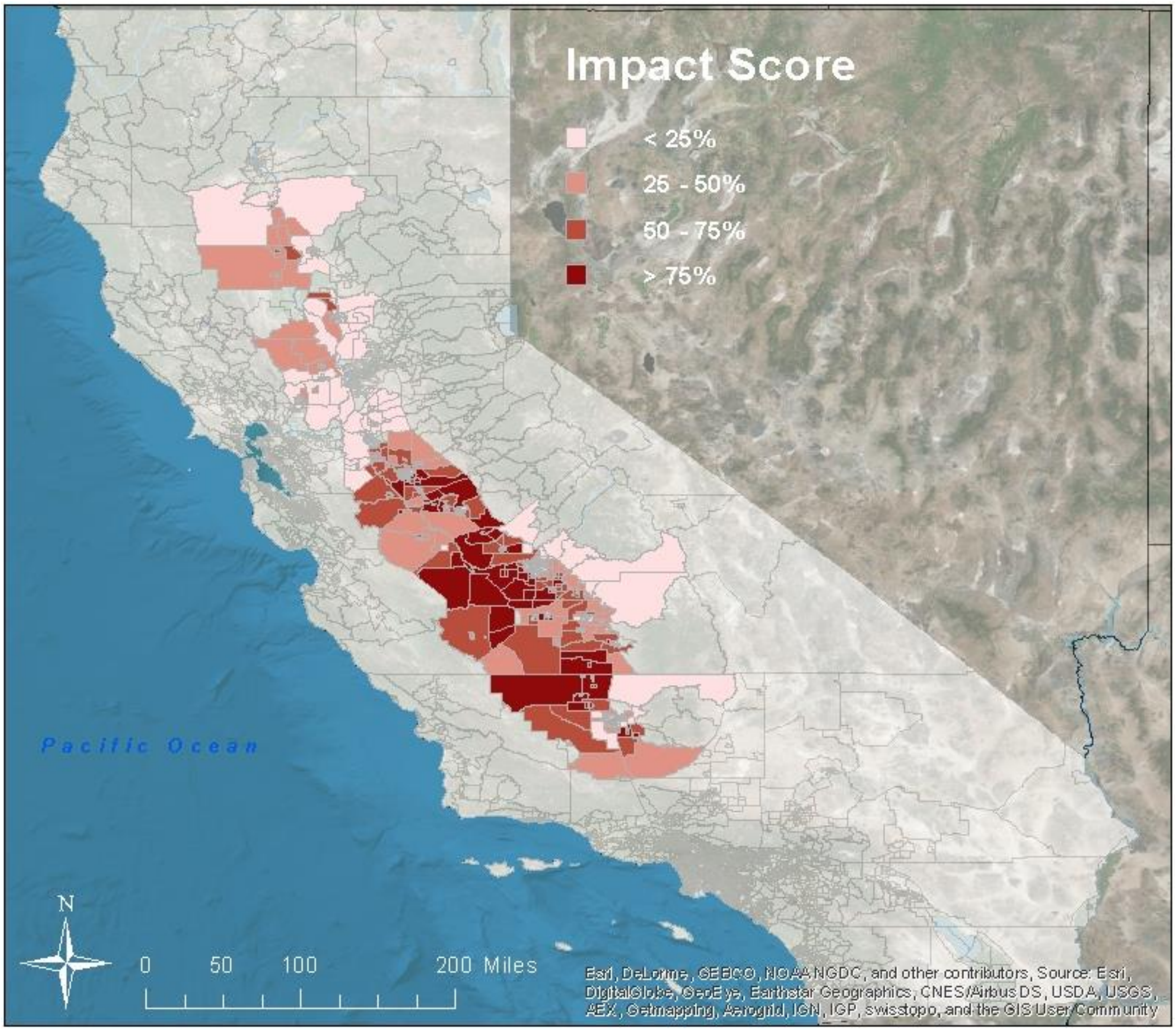


Figure 4.7. Total Impact Score, reflecting social vulnerability and insecticide pollution burden among communities in California’s Central Valley between 2012 and 2016, by census tract.

4.4.4 *Pesticide toxicity*

Of the 139 different active ingredients applied to almond orchards between 1990 and 2016, PAN data was available for 82 of the chemicals. Of those 82 chemicals, seven were rated as extremely toxic, 19 as highly toxic, 20 moderately toxic, eight not acutely toxic, and 28 slightly toxic; for 34 chemicals, a toxicity rating was not available (**Table 4.24**). One of the chemicals was a known carcinogen, but 10 were known carcinogens according to California Proposition 65 and the EPA TRI list. 42 chemicals were not likely carcinogenic, 16 were possible carcinogens, and 44 chemicals were not listed or were unclassifiable. 12 chemicals were listed as developmental and reproductive toxicants, and 30 were suspected endocrine disruptors. Of the top 15 most heavily used insecticides during this 27-year period, none were rated as extremely toxic, only one was rated as highly toxic, four moderately toxic, two not acutely toxic, and three slightly toxic; for one chemical, a toxicity rating was not available. One of the chemicals was a known carcinogen according to California Proposition 65 and the EPA TRI list. Seven chemicals were not likely carcinogenic, two were possible carcinogens, and one chemical was not listed. Two chemicals were listed as developmental and reproductive toxicants, and three were suspected endocrine disruptors.

Over the last ten years of the PUR records, fewer chemicals were used, likely due to regulations and changes in pesticide effectiveness. Between 2007 and 2012, only 104 active ingredients were applied to almond orchards. Of these chemicals, four were rated as extremely toxic, 12 as highly toxic, 17 as moderately toxic, six as not acutely toxic, and 20 as slightly toxic; a toxicity rating was not available for 24 of the chemicals. Six of the chemicals were known carcinogens according to the California Proposition 65 and EPA TRI lists, 36 were not likely, 13 were possible, 3 were probable carcinogens, and 21 of the chemicals were not listed. Nine chemicals were known developmental and reproductive toxicants, and 23 were suspected endocrine disruptors. Of the top 15 most heavily used insecticides during this period, none were rated as extremely toxic; two were rated as highly toxic, five as moderately toxic, two as not acutely toxic, and two as slightly toxic. One of the chemicals was a known carcinogen according to the California Proposition 65 and EPA TRI lists, seven were not likely, two were possible carcinogens, and one was not listed. Three of the chemicals were known developmental and reproductive toxicants, and five were suspected endocrine disruptors. This decline in the number of active ingredients suggests a possible decline in insecticide use, or potential legislation related to the toxicity of the chemicals previously used.

Table 4.24. Toxicity of insecticides used on the almond crop over the PUR reporting history (1990 – 2016), the last ten years (2006 – 2016), and the last five years (2012 – 2016). Numbers reflect the total number of active ingredients with available information on toxicity, carcinogenicity, developmental or reproductive toxicity, and potential endocrine disruption.

	1990-2016	**2006-2016**	**2012 – 2016**
Extremely Toxic	7	4	2
Highly Toxic	19	12	7
Moderately Toxic	20	17	17
Not Acutely Toxic	8	6	5
Slightly Toxic	28	20	18
Known Carcinogen	11	6	5
Not Likely Carcinogenic	42	36	32
Possible or Probable Carcinogen	16	16	14
Developmental/Reproductive Toxicant	12	9	9
Endocrine Disruptor	30	23	18
TOTAL CHEMICALS APPLIED	139	104	87

Even fewer chemicals were used between the years 2006 and 2012, with only 87 active ingredients applied to almond orchards. Of these chemicals, only two were rated as extremely toxic, seven as highly toxic, 17 moderately toxic, five not acutely toxic, and 18 slightly toxic; a toxicity rating was not available for 19 of the chemicals. Five of the chemicals were known carcinogens according to the California Proposition 65 and EPA TRI lists, 32 were not likely, 11 were possible, three were probably carcinogenic, and 14 were not listed. Nine of the chemicals were known developmental and reproductive toxicants, and 18 were suspected endocrine disruptors. Of the top 15 most heavily used insecticides during this period, none were rated as extremely toxic; one was rated as highly toxic, three as moderately toxic, two as not acutely toxic, and three as slightly toxic. One of the chemicals was a known carcinogen according to the California Proposition 65 and EPA TRI lists, seven were not likely, and one was possibly carcinogenic. Two of the chemicals were known developmental or reproductive toxicants, and three were suspected endocrine disruptors.

Overall, there has been a decreasing trend not only in the use of insecticides, but in the total number of chemicals used as well. Those active ingredients that are currently still in use are considerably less toxic than the chemicals used 30 years ago, suggesting legislation has likely played a heavy role in reducing the number of toxic and carcinogenic chemicals being used in an effort to protect human health and the environment.

4.5 DISCUSSION

Insecticide use on almond orchards within California’s Central Valley is not geographically uniform. Use is highest among the southern region of the valley, particularly in the southwest. Consequently, the Pollution Burden Index indicates a high risk of exposure to insecticides for individuals living near almond orchards in this region, particularly during the summer and winter months, when most insect control is typically employed. These differences in exposure potential, as measured by the PBI, become an environmental justice issue when those at greatest risk of exposure are also the most vulnerable. The Social Vulnerability Index suggested that this is the case. Of the four themes, socioeconomic status, as well as minority and language indicators, had the greatest concentration of vulnerability within the southern Central Valley. The overall SVI agreed with these individual themes, implying that some of the most vulnerable populations not only live within the Central Valley, but also reside in the southern regions of the valley, where exposure potential is greatest.

The total Impact Score revealed that this is occurring; the most vulnerable populations are those that live in agricultural communities with the greatest chance of exposure to insecticides due to heavy application rates. The individual SVI themes further suggest that what makes these communities most vulnerable is low socioeconomic status and income, low educational attainment, high racial minority composition, and limited English speaking skills. It is possible that these disparities would be even larger if the census were able to fully capture the migrant population living within these agricultural communities.

Under a changing climate, it is likely that the potential for exposure to insecticides will increase; population projections would help in examining if the current disparities in exposure will continue as well. Warmer temperatures throughout the year, particularly increasing minimum temperatures, will increase pest pressure[23,72,181]. In response to this change in pest dynamics, insecticide use is also projected to increase, as growers respond and adapt to a changing climate[8,173,234,237,249]. While population projections have been developed, both with a global focus, and downscaled projections to a regional level, the projections are limited in their estimates of demography[281-285]. These projections were developed using the new Shared Socioeconomic Pathways (SSPs), downscaled to produce projections of population change that are consistent with national projections (considering both rural and urban populations) on a spatial scale. However, what is lacking in the projections are information on race/ethnicity, age, and other vulnerability indicators such as socioeconomic status and linguistic isolation. Limited information is available on SSPs that focus on individual country – these are mostly large-scale population projection scenarios, using different indicators for vulnerability (e.g. global definition of poverty rather than US specific indicators such as Federal poverty level) than were used in this analysis. Therefore, to model future potential exposures to insecticides under a changing climate, it is currently only possible to do so assuming a business-as-usual scenario for Central Valley demographics, while also considering general population projections.

California's population is projected to grow approximately 0.76% per year from 2016 to 2036, and by 2051 is expected to have more deaths than births while migration keeps the population growth positive[284,285]. By 2060, the population in California is expected to grow by 30%, from 39.4 million in 2016 to 51.1 million in 2060. Basic demographic projections suggest that the Hispanic/Latinx population will continue to grow as well, from 39% in 2016 to 46% by 2060. The Central Valley region, as well as the San Francisco Bay Area, greater Sacramento region, and Inland Empire regions of California are projected to grow more quickly. This suggests that the number of people who may potentially be exposed to insecticides will increase, especially with the larger increase in population expected in the Central Valley compared to the rest of the state. In addition, it is also likely that social vulnerability will increase in the future, in relation to racial minority status, as the Hispanic/Latinx population will increase as well. These projections indicate that the likely increase in Pollution Burden Index from projected increase in insecticide use related to climatic changes, combined with the potential increase in the Social Vulnerability Index from population projection estimations of racial minority and assuming business-as-usual for all other indicators, will most likely result in an increased Impact Score. This is, of course, assuming all other factors related to insecticide use on almonds within the Central Valley do not change, such as the range of almond cultivation and suitability of climate for continued agricultural production.

The Social Vulnerability and Pollution Burden Indices used in this analysis were far from perfect. Some census tracts did not have a reported value for the SVI, so it was not possible to determine social vulnerability for these communities; this was due to unavailable census data for these tracts. Unfortunately, due to partially incomplete census records, further calculations on the SVI were not completed. While this only occurred in a limited number of census tracts, it does mean that vulnerability was not able to be captured for all communities in the Central Valley. Similarly, some census tracts within the Central Valley did not report any insecticide use between the years 2012 to 2016. This resulted in a PBI ranking of zero, and therefore a total impact score of zero. While this should reflect exposure for these communities, it is possible that some of the pesticide use reports were incomplete or contained errors, and so were therefore not included in the pesticide use analysis. This also does not reflect the potential exposure of those who live on or near the boundaries of the census tracts, and whose potential exposure may more closely align with a neighboring census tract than the one containing their residence location.

By combining all pesticide use reports and treating all insecticide active ingredients the same, it is not possible to assess how individual insecticides or insecticide types may be impacting exposure and human health. As discussed previously, each chemical differs in its toxicity and exposure potential; some chemicals are more harmful to human health than others and may also be more likely to move through the environment and enter the human body. Aggregation of chemicals as done in these analyses assumes that all insecticides used on almonds within the

Central Valley will lead to potential exposure as well as adverse human health impacts, and this may lead to over-estimation of the potential exposure and health effects, as well as impact score.

In addition, regarding potential exposures from climate change, the aggregation of chemicals leads to uncertainty in future use intensity as well. Due to past and future regulations, as well as the development of insecticide resistance in pests, individual insecticide use has and will continue to change for reasons completely unrelated to climate change. For example, each insecticide has recommended application rates that vary widely across chemical. So, a change in use intensity may be due to a transition to insecticides with lower or higher suggested application rates. This suggests that even though insect pest pressure is projected to increase, insecticide use intensity may not follow suit. In addition, changes in application technology, such as to more efficient drone technologies, may also lead to decreases in use and use intensity. Therefore, this discussion makes the large assumption that insecticide use will continue in the future under a business-as-usual scenario regarding insecticide use intensity and application. It is likely that future technologies will reduce insecticide use; however, it is not possible to hypothesize what insecticides may be used in the future, so use intensity related to active ingredient may either increase or decrease, especially in relation to pest resistance or potential increase in insecticide cost. These potential changes may affect the results by increasing (insecticides used in the future may have higher recommended application rates) or decreasing use intensity (lower recommended application rates or more efficient application technologies) and the resulting exposure potential.

Due to the spatial limitations of the datasets used, it was not possible to calculate more specific exposure potentials for the agricultural communities. The main limiting factor is the resolution of the census information. Census tracts vary widely in size, depending on the density of the population in the area. In rural neighborhoods with fewer people per square mile, the census tracts become quite large. This makes it impossible to assess potential for pesticide exposure based on residential proximity to a field or orchard. While census block groups are smaller in size, they are still not drawn on a fine enough spatial scale. Additionally, more detailed census information, such as indicators included in the ACS, are not available on the census block group scale. So, while the block groups would allow a potentially better estimate of pesticide exposure potential, there would be less information available to determine social vulnerability of agricultural communities captured within the census block groups. Future studies attempting a similar methodology would be better suited to incorporate land parcel information to determine actual proximity of residence to almond orchard and insecticide use. While this information would not inform the vulnerability of those living in the residences, it would allow a calculation of the number of residences that have high potential of insecticide exposure, and this value could be incorporated into the overall index.

The indicators used in both the SVI and PBI could be further adjusted to fine tune the measures of vulnerable communities and exposure potential. For the SVI, indicators could be added that would reflect populations that are more likely to be exposed to pesticides, such as farm workers. For example, an indicator that measured the number of agricultural workers per square kilometer of cropland within each census tract could be used to capture potential occupational exposures in addition to residential. On the same note, the percent of each census tract dedicated to agricultural fields could be incorporated into the index. Further, the census tracts could be broken down not only into percent agricultural land, but percent urban or residential as well. For the PBI, the area of each PLSS reporting insecticide use could be used to determine the percent of land within each census tract that had reported pesticide use. Or, instead of dividing the total amount of insecticides used by the area of each census tract, the mean value of the use intensity (pounds per square mile of PLSS or even pounds per acre treated) could be used instead for each census tract, to determine the pesticide density.

Additionally, the Social Vulnerability Index created by the CDC may not be the best representation of vulnerability. The indicator variables used are simply proxies and are often seen as insufficient in correctly measuring the different aspects of what makes a community vulnerable. For example, individuals living near but just above the poverty level would not be considered when determining socioeconomic vulnerability. Likewise, those living well below the poverty level are not counted any differently than others falling into the poverty indicator, when they should perhaps be weighted more heavily. When considering racial minorities, all racial groups are grouped together, without considering the differences in vulnerability among different racial and ethnic groups. Again, a weight could be used for each race and ethnicity identifier, rather than comparing the group as a whole to the white population. Among the same theme, the SVI indicator for English speaking capabilities may not depict the full extent of linguistic isolation in these communities, as individuals may have different definitions of what it means to speak English “less than well.” There are potential issues with each of the indicators, which could all be better defined, with classifications within each indicator weighted differently.

The Pollution Burden Index developed here, while similar to other indices such as CalEnviroScreen (CES), is unique in that it focuses on one environmental exposure hazard. The CES looks at cumulative impacts from many environmental hazards, including ozone, fine particulate matter, diesel particulate matter, drinking water contaminants, pesticides, toxic releases, traffic, toxic cleanups, and groundwater contamination. Pesticides are aggregated in the CES, so it is not possible to look at how specific pesticide types such as insecticides may be negatively impacting human health and vulnerability within communities. The approach used here is novel in that it looks specifically at the impact from insecticides used on a specific agricultural sector (perennial almond crop). Therefore, the score seen here is a much more targeted ‘attributable’ impact score. Future research may continue to focus on individual exposures, leading to analyses that show the different yet specific population health impacts of individual agricultural sectors.

Regarding a community’s potential for exposure to pesticides, the analyses done here do not fully capture the pollution burden of pesticide use within agricultural communities. While almonds make up a large portion of the crops grown in the Central Valley, there are other crops to consider as well, on which insecticides are being used. Some of these crops may even use insecticides in greater amounts and on a more frequent basis. Different crops also tend to have different seasonal fluxes in use, so while the analysis of insecticides used on almonds suggest a high potential for exposure during the summer and winter months, if other crops were included in the analysis, the exposure potential could be just as high or even higher for other seasons. Additionally, there are several other types of pesticides that are frequently used in agricultural settings, including fumigants, herbicides, and rodenticides. If the total use of all pesticides were considered in the PBI, it is likely that the values would be much greater across the entirety of the Central Valley. Fumigants tend to be used in very large amounts; they are also more volatile than other pesticides and therefore more likely to lead to potential unintentional residential exposures in nearby agricultural communities.

Chapter 5. CONCLUSIONS

5.1 KEY FINDINGS

This dissertation assessed the relationship between global climate change and potential exposure to insecticides among vulnerable communities. Several key steps were necessary to come to the final assessment, including an evaluation of how climate change will impact pest physiology in order to understand how and when insecticide use might increase. Next, it was essential to attempt to define the relationship between climate, pest dynamics – such as voltinism and phenology – and insecticide use in order to create projections of insecticide use for a changing climate. The final part of the puzzle, determining whether there are disparities in pesticide exposure among the communities living in these agricultural communities, completed the picture of the full impact of climate change on exposure to insecticides.

Part one of this assessment determined that climate change has significant impacts on insect pests of concern to the almond industry. For both of the investigated pests, it was found that climate change will not only increase the number of generations of the pests per growing season, but that the pests will begin emerging earlier in the season. By 2050, it was predicted that one to two additional generations of pests can be expected, with pests emerging approximately two weeks earlier than historical averages. The main driver of this finding was the increase in minimum temperatures over the last century and projected to the end of this century. It would then be presumed that insecticide use would reflect these changes in pest dynamics, showing earlier applications of insecticides as well as potentially more frequent applications in greater amounts, in order to counteract larger populations of pests.

Part two of this assessment found that while insecticide use is likely to increase in the future with a changing climate, it was difficult to relate this to pest dynamics. Overall, pesticide and insecticide use has been decreasing over the years, as more impact studies show the adverse effect these chemicals have on human health and the environment. Regulations have phased out and banned many of the pesticides used during the early part of the century and even at the start of the pesticide reporting program in California. The highly seasonal use of insecticides on almond crops was also found to strongly dictate the timing and rate of insecticide applications. However, a slight trend in insecticide use and increasing minimum temperatures was found. It was this relationship that allowed projections of insecticide use to the end of the century. These projections suggest an average increase in use between 20 and 40% by 2050, depending on location within the Central Valley.

Finally, part three of this assessment found that a significant environmental justice issue exists surrounding insecticide use and vulnerable populations. Not only does the Central Valley have a disproportionately higher number of vulnerable communities compared to the rest of California, but these same communities are located in regions where insecticide use is greatest. Further, those that live in areas that experience particularly heavy uses of insecticides rank even higher on the vulnerability index, particularly related to socioeconomics, education, race, and linguistic isolation. It is likely that these measured disparities would be even greater if the most vulnerable population of all in agricultural communities, migrant workers and their families, were more fully captured in the vulnerability indicators.

Ultimately, the findings of the individual parts of this dissertation suggest that climate change will have a disproportionate impact on vulnerable communities and their potential exposure to insecticides, exacerbating the current disparities. These communities already experience a greater pesticide pollution burden, and the potential exposure is only projected to increase with the warming temperatures of climate change. Populations are also expected to grow, which indicates that an even larger number of individuals living within agricultural communities will potentially be exposed to the harmful chemicals found within insecticides. Consequently, acute and chronic illnesses related to pesticide exposures can be expected to increase as well. Therefore, it is highly recommended that growers within the Central Valley fully adopt alternative pest management practices and follow Integrated Pest Management guidelines, only using insecticides when absolutely necessary to protect their crop from imminent destruction due to pests.

5.2 LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Main limitations of this analysis have been previously discussed, however, it is worth noting that the major limitations are related to spatial resolution and the choice of crop and pesticide used in the analyses. Ideally, the assessment of climate change on insect pests would include all potential pests of concern, not limited to those associated with almonds. In addition, a full assessment should include all pesticide types, not just insecticides, to fully capture both the relationship between pesticide use and climate, and the potential for exposure among agricultural communities. Lastly, data available on a finer scale than census tracts would allow a more accurate prediction of exposure due to residential proximity to pesticide use. Future studies looking to assess how climate change impacts pesticide use and exposure among agricultural communities should focus on these questions in order to more accurately depict the disparities exposed in this dissertation.

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VITA

Katie Fellows was born and raised outside of Seattle in the small town of Edgewood, WA. She earned a Bachelor of Science degree in Environmental Health at the University of Washington in Seattle, WA in 2008. She then went on to earn a Master of Science degree in Epidemiology with a focus on Environmental Health from the Harvard University T.H Chan School of Public Health in Boston, MA in 2009. While at Harvard, Katie was introduced to climate change and public health issues, and conducted her Master's thesis on the impacts of climate change on mortality across the United States. Returning to Seattle in 2012, Katie began working towards her Doctor of Philosophy in Environmental and Occupational Hygiene from the Department of Environmental and Occupational Health Sciences at the University of Washington, earning this degree in 2018. In addition to her PhD, Katie completed a graduate Certificate in Climate Science through the University of Washington Program on Climate Change, in which she focused on developing a course that teaches graduate students about climate risk in the Pacific Northwest. She also completed the University of Washington's Institute for Risk Analysis and Risk Communication Risk Emphasis program. Katie is also a Pacific Science Center Science Communication Fellow, where she continues to volunteer and educate the public on climate change and human health issues.