UNIVERSITY OF CALIFORNIA,
IRVINE

Mixed-Method Analyses of Climate Change, Episodic Drought, and Vulnerability to Valley Fever Outbreaks in California

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Public Health

by

Melissa Nicole-Renwick Matlock

Dissertation Committee:
Professor Oladele Ogunseitan, Chair
Professor Suellen Hopfer
Professor David Feldman

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DEDICATION

To my wonderful family for supporting me and joining me on this journey, I want to thank you. Standing by my side over these past few years has meant the world to me and I truly appreciate it.

Early to bed and early to rise, makes a man healthy, wealthy, and wise.
- Benjamin Franklin

It does not matter how slowly you go as long as you do not stop.
- Confucius

It always seems impossible until it’s done.
- Nelson Mandela

The way to get started is to quit talking and begin doing.
- Walt Disney

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I would like to thank my committee members, Professor Suellen Hopfer and Professor David Feldman, whose discussions and questions helped shape my analysis and make it be a worthwhile contribution to the academic field.

In addition, a thank you to Water UCI. If I was not selected for the Water UCI fellowship over the summer before I started my Ph.D. program, I would never have traveled to Anza Borrego, where I first learned about Valley Fever.

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ABSTRACT OF THE DISSERTATION

Mixed-Method Analyses of Climate Change, Episodic Drought, and Vulnerability to Valley Fever Outbreaks in California

By

Melissa Nicole-Renwick Matlock

Doctor of Philosophy in Public Health

University of California, Irvine, 2018

Professor Oladele Ogunseitan, Chair

Coccidioidomycosis (Valley Fever) incidence has been steadily increasing in the Southwest United States. In 2017, the highest record number of cases were diagnosed in the state of California, surpassing the previous record in 2016 by 34%, sparking a renewed interest in what is bringing about this increase in incident case counts. *Coccidioides* species of fungi grow in the soil and when the spores become aerosolized, they can be inhaled leading to infection. Previous studies have tried to understand the relationship between Valley Fever exposure and climate.

The goal of this research is to understand the relationship between climate and Valley Fever and how this information can assist local public health agencies in communicating preventive strategies to the vulnerable populations in their local communities. The main research hypothesis is that the relationship with the climate variables and incidence will not behave identically in terms of direction or timing across the study area, except for Precipitation, which is hypothesized to have a positive relationship with cases over the Fall and Winter months.

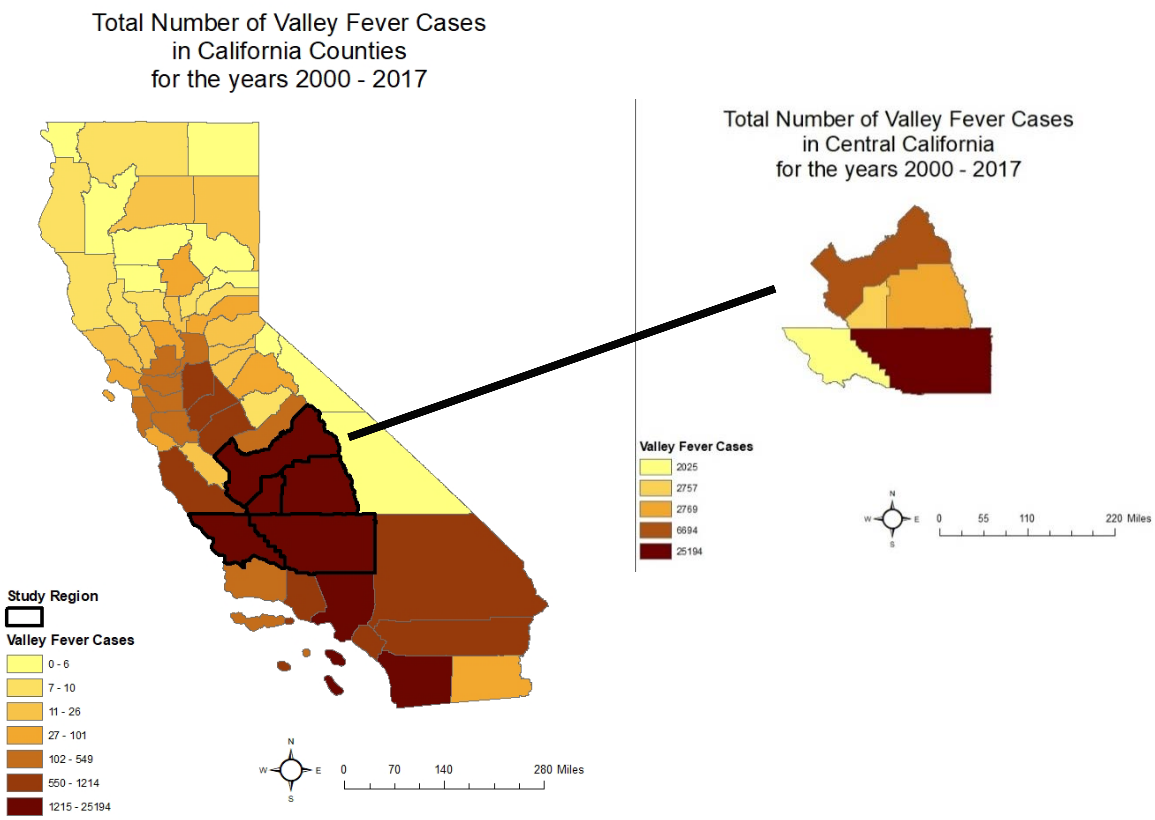
Monthly case data was obtained from the California Department of Public Health, Infectious Disease Branch, for five California Counties (Study area: Fresno, Kern, Kings, San Luis Obispo, and Tulare) for 2000-2015 totaling over 37,000 incident cases. To determine how environmental factors (precipitation, temperature, wind speed, evapotranspiration, Palmer Drought Severity Index, Particulate Matter 2.5 and 10, and El Nino Southern Oscillation Index) were related to diagnosed cases, linear and Poisson regression were used to analyze case counts and incidence rate for 2000-2015. To determine how the relationship between environmental factors and Valley Fever cases changed due to different hypothesized exposure scenarios, ten different exposure scenarios were investigated. To determine how the local public health agencies currently or would like to use climate information in Valley Fever messages, a qualitative survey and interview to representatives from the Public Health agencies in the study area were conducted.

This study verified previous findings that the more total season rainfall that occurs during the Fall and Winter season typically indicates that cases will be higher the following diagnosis season for each county in the study area. Secondly, the Palmer Drought Severity Index, found that the drier the soil was in the months before the peak diagnosis season, the more cases were likely to be diagnosed. Third, most of the cases were diagnosed during La Nina events, which usually indicates a drier weather environment over California. These patterns emerged with the different quantitative methods and the different exposure periods, where the other environmental variables did not have this same consistency. Lastly, the Public Health Agencies in the study area would like to see climate information tailored in a way to allow Behavior Adaptation messaging like bad air quality days or the risk level for the upcoming flu season.

INTRODUCTION

Coccidioidomycosis (Valley Fever) is an illness that develops from breathing in Coccidioidomycosis fungal spores that grow several inches in the soil (Hector (2005), Nguyen (2013)). Disease occurs in most cases when the soil gets disturbed and the fungal spores get aerosolized and inhaled. The spores are endemic to the southwest United States (primarily Arizona and California), parts of Mexico, and parts of South America (Galgiani (1999)). California, the state with the second highest incidence in the United States, does not have equal magnitude of Valley Fever incidence throughout the state. Figure I.1 shows that a majority of the cases occur in Central California and primarily among the counties of Fresno, Kern, Kings, San Luis Obispo, and Tulare.

Figure I.1: Map of Valley Fever Cases in California from 2000 - 2017



Data on Coccidioidomycosis is limited due to variations in state reporting, testing practices, and misunderstanding of the disease. It is estimated that 10-50% of those living in endemic areas have been exposed to some form of the fungal pathogen, *Coccidioides immitis*, or *Coccidioides posadasii* and each year, approximately 150,000 new cases is estimated occur in the United States (Converse (1966), Ampel (1998)).

Listed on the Centers for Disease Control (CDC), Coccidioidomycosis symptoms are similar to the flu; fatigue, cough, fever, headache, rashes, shortness of breath, muscle aches or join pain, and night sweats (CDC). Valley Fever is diagnosed based on symptoms present coupled with a physical exam. Health providers will take a blood sample and send it to a lab and a positive text result will indicate the presence of *Coccidioides* antibodies or antigens (CDC). A chest x-ray may also be required.

The incubation period for Coccidioidomycosis is on average 14 days (Ampel (1998), Kolivras (2003), Park (2005), Comrie (2005), Tamerius (2011)). The symptom onset to diagnosis period is on average 60 days ((Ampel (1998), Kolivras (2003), Park (2005), Comrie (2005), Tamerius (2011)). For approximately 60% of diagnosed cases, the disease will go away in a few months without the need for treatment (Filip (2008), Huang (2012)). However, those with more severe symptoms will typically be treated by their healthcare provider. Although typically treated with various antifungals, such as Amphotericin B deoxycholate (.5-1.5 mg/kg per day), lipid formulations of Amphotericin B, which can be easier to absorb (2-5 mg/kg daily), Ketoconazole (400 mg daily orally), Fluconazole (400-800 mg/day orally), Itraconazole (200 mg twice per day or 3 times orally), there is no cure for the disease (Lawrence (1976), Filip (2008), Huang (2012)). Patients are typically prescribed antifungals for 3-6 months and hospitalizations are common.

2017 had the highest amount of Coccidioidomycosis cases on record, surpassing the previous high year of 2016 by an estimated 34% (Sondermeyer Cooksey (2017)). Many researchers and healthcare providers do not know why the disease has increased incidence (Sondermeyer Cooksey (2017)).

Coccidioidomycosis and Climate

The ecological niche for the fungal causative agents of Coccidioidomycosis is defined by arid, desert areas where spores are found in lower elevations, 4 inches or more under sandy soil ((Hector (2005), Nguyen (2013))). The fungus is endemic in climatic regions with less than 20 inches of rain per year. The most common opportunity for a person to become infected is when the soil is disrupted by construction of civil infrastructure, including roads and building, or by natural environmental events such as earthquakes, landslides, and dust storms; examples of episodic outbreaks following such disruptions are extensively documented in the published literature (Pappagianis (1978), Flynn (1979), Comrie (2007), Sprigg (2014), Benedict (2014)).

The occurrence of dust storms, relatively frequent in the Southwest U.S., has also been linked to increased Coccidioidomycosis incidence. There have been several massive outbreaks of this disease in the last two decades. In 1977, a dust storm, covering 90,000 km^2, originated in Bakersfield and brought the disease to Sacramento, where 115 new cases were diagnosed (Pappagianis (1978), Comrie (2007), Sprigg (2014), Benedict (2014)). In January 1994, the 6.7 Northridge Earthquake in California disturbed the soil and as a result of the magnitude, aftershocks, and subsequent landslides, Coccidioidomycosis fungi became aerosolized and dispersed (Flynn (1979), Sprigg (2014), Benedict (2014)). 203 cases were identified in Ventura County, but Coccidioidomycosis was not the original diagnosis (Benedict (2014)). With further understanding of the relationship between dust exposure and incidence, future impacts could be mitigated through better understanding of the exposure risks and pathways.

From the 1950s, climatic factors, particularly precipitation, were considered to have a “Grow and Blow” Effect on the *Coccidioides immitis* spores (Egeberg (1956), Hugenholtz (1957), Maddy (1965), Jinadu (1995), Stevens (1995)). The “Grow and Blow” Effect hypothesizes that in order for the fungal spores to germinate, there needs to be an increase in soil moisture. Then, a dry period needs to occur to make the soil loose and easily disturbed by wind in order to disperse the spores for inhalation (Egeberg (1956), Hugenholtz (1957), Maddy (1965), Jinadu (1995), Stevens (1995)). Temperature is also said to have a role in the exposure of these spores. During dry, hot periods, temperature is said to sterilize the topsoil, reducing the competition against the *Coccidioides immitis* spores (Maddy (1965), Maddy (1957)). However, statistically analyzing this relationship did not occur until the 2000s. Several of these studies found the roles of climatic factors on incidence to not be fully understood.

Purpose and Research Questions

This dissertation is designed to understand the relationship between climate and Valley Fever and how this relationship can be utilized in Public Health Agencies for the California counties of Fresno, Kern, Kings, San Luis Obispo, and Tulare (study area).

This dissertation will answer the following questions:

- What does the Valley Fever data look like in the California counties of Fresno, Kern, Kings, San Luis Obispo, and Tulare?

- What climate relationships are found to have a significant relationship with Valley Fever cases?
- How do the results regarding the relationship between climate variables and Valley Fever cases change when using local climate information versus averaging county-wide?
- How do the results regarding the relationship between climate variables and Valley Fever cases change when using different published study methodologies regarding Exposure Month?
- How do the results regarding the relationship between climate variables and Valley Fever cases change when using different published study methodologies regarding statistical regression methods?
- How can the information generated in this dissertation be communicated to Public Health agencies regarding the relationship between climate and Valley Fever?

Chapter 1

Climate factors and Coccidioidomycosis: an annotated bibliography and a systematic review of quantitative modeling approaches

Background

Public health preparedness benefits from the development of location-specific models for disease outbreaks and the development of community based education, and interventions that target vulnerable populations to decrease risk. However, when working with data that has seasonal variation, such as climate, crosses governmental boundaries, such as dust, and involves a disease that manifests itself differently and is often misdiagnosed, how does using different methods vary the results? What important factors need to be included?

The purpose of this systematic review is critically to examine the methods used to conduct these analyses on Coccidioidomycosis's relationship with climate and dust. With a focus on research methodologies for developing statistical models on Coccidioidomycosis, this review will focus on the statistical methods involved, the variables that have been studied, key findings, and data issue trends involved in studying the relationship between Coccidioidomycosis and climate.

The objectives of this review are to determine the current standing of Valley Fever research and guide the overall methods and information chosen in the research questions described in the Introduction.

This review will address the following questions:

1. Do study results support the prominent "Grow and Blow" Effect Hypothesis of Coccidioidomycosis incidence?
2. What climate variables are being used to test the Hypothesis?
3. Is there consistency in the methodology used to test the Hypothesis?
4. How do variations in methods, selected environmental parameters, and scale influence the reliability of the study estimates?
5. What are common trends and suggestions for future research?

Methods

The methodology for this systematic review follows the Preferred Reporting Items for Systematic review and Meta-Analysis Protocols (PRISMA-P). The topic of this systematic review was explored in the International Prospective Register of Systematic Reviews (PROSPERO). No reviews on Valley Fever or Coccidioidomycosis have been registered in that system. On May 4, 2018, this review was submitted to PROSPERO, ID # 95737. The submission is under review.

Eligibility Criteria

The eligibility criteria used to develop the inclusion criteria for this study is divided into two main characteristics: Study and Report.

For the study characteristics, all time periods, all populations, all climate variables, and all statistical methods were included. This is due to the small quantity of studies published on this disease related to modeling the disease.

For report characteristics, all years, all languages, and all publication types were included. Although all languages were considered, the search results only showed English articles. For most sources, published reports were only produced in the search results. However, if a presentation or poster related to the disease was found on Google Scholar, further research was conducted to determine if there was a relevant publication. If not, the presentation or poster would be included.

Due to the small quantity of studies conducted on this subject, there were no articles excluded.

Information Sources

A literature search was conducted in December 2016 and a follow-up search was conducted in January 2018.

Using the key words described in the search strategy, Google Scholar, PubMed, and the University of California electronic library system were used to search for literature on modeling climate and Coccidioidomycosis disease.

Search Strategy

A literature search was conducted in December 2016 and a follow-up search was conducted in January 2018.

Keys terms included “Coccidioidomycosis,” “Valley Fever,” “Coccidioidomycosis model,” “Coccidioidomycosis predictive model,” “modeling Coccidioidomycosis incidence,” “Coccidioidomycosis statistics,” “Coccidioidomycosis and climate,” “quantitative modeling approaches,” “Valley Fever model,” “Valley Fever predictive model,” “modeling Valley Fever incidence,” “Valley Fever statistics,” and “Valley Fever and climate.”

Using the key words described above, Google Scholar, PubMed, and the University of California electronic library system were used to search for literature on modeling climate and Coccidioidomycosis disease.

References and citations of the articles identified were checked to ensure that all relevant articles were included. These key terms also highlighted articles focused on risk factors, not related to climate. Articles identified through the search were included if they contained statistical methodology related to estimating relationships between variables.

Study Records

Data Management

Due to the small amount of studies related to this topic (search criteria only produced 45 studies), a simple Microsoft Excel database was used to manage records and data throughout the review.

Selection Process

As there were no exclusion criteria, all articles were selected. There were 45 papers that appear in the search criteria. Out of those 45, only 30 were related to the disease of Cocciodiodomycosis/Valley Fever. The 15 that were excluded shared similar names like Rift Valley Fever or methodological similarities in the search words, but were for other diseases.

Data Collection Process

I developed a list of information needed to accomplish the intended outcomes of this study in Microsoft Excel. Each article was reviewed and their information was placed into the appropriate category in the Microsoft Excel database. The information of interest was an iterative process after the initial list was developed in the beginning.

Data Items

The variables of interest can be divided into three main categories: ecological niche, risk factors related to human traits, and environmental/climate factors. The risk factors related to human traits include variables such as gender, ethnicity, age, immunosuppression, body mass index (BMI), and military profession. The environmental/climate factors include precipitation, wind, dust, temperature, palmer drought severity index, and the normalized difference vegetation index. There were no pre-planned data assumptions and simplifications.

Outcomes and Prioritization

There are four main outcomes of the intended study:

1) Side by side comparison of the studies to highlight the inconsistencies in studying the disease;

2) Highlight the discrepancies of the disease analyses;

3) Discuss the reliability of the results;

4) Discuss how future studies should approach these issues.

Risk of Bias in individual studies
As this review is addressing the methodology of the studies, bias is limited.

Data Synthesis
Results of the studies will be qualitatively synthesized as initial results indicate the studies are non-homogenous. They will be synthesized based on three main criteria:

1) Data Integrity - discussing the location of the analysis, scale of the analysis, and if an exposure estimation was applied for each study;

2) Environmental determinants - discussing the variables used in each study, whether or not the study applied a variable lag, and the findings;

3) Analytical approaches - discussing the different methodologies applied to the studies.

Meta-bias
There is no planned assessment of meta-bias.

Confidence in Cumulative Evidence
The subject materials studied in this review are all observational studies. On several systems used for assessing the body of evidence, these studies automatically start off in the lowest category ("4 Standards for Synthesizing the Body of Evidence" (2011)). This review will utilize the Agency for Healthcare Research and Quality system for assessing the body of this review. There are four categories: high, moderate, low, and insufficient. The high category reflects high confidence that the evidence reflects the true effect. Future research is unlikely to change the estimate of the effect. The moderate category reflects moderate confidence that the evidence reflects the true effect. Further research may change the confidence in the estimate or the estimate itself. The low category reflects low confidence that the evidence reflects the true effect. Further research may change the confidence in the estimate or the estimate itself. The insufficient category states that the evidence is either unavailable or does not permit a conclusion ("4 Standards for Synthesizing the Body of Evidence" (2011)).

Annotated Bibliography

Ecological Niche
Baptista – Rosas *et al.* (2007) used Genetic Algorithm for Rule Set production (GARP) to model the environmental niche for Coccidioidomycosis spores throughout the endemic region of California, Arizona, Texas, Baja California, and Mexico. They utilized 19 climate layers with a square kilometer spatial resolution to understand the niche. These climate variables included seasonality of climate variables, annual precipitation, annual temperature, and quarterly estimates like mean temperature of the warmest quarter.

Lauer *et al.* (2012) and Lauer *et al.* (2014) utilized soil characterization and soil samples around Bakersfield to determine the ecological niche of Coccidioidomycosis spores. They detected the spores at locations that are in non-agricultural land, that have 33% of sand, clay, and silt. They were also said to live in a pH between 7.8 and 8.5.

Vargas - Gastelum *et al.* (2015) studied fungal diversity in two different microhabitats. Their nested Polymerase Chain Reaction (PCR) approach revealed a higher prevalence in burrows as compared to undisturbed soil.

Risk Factors
Gray *et al.* (1998) used hospital case data to determine risk factors of Coccidioidomycosis among Navy and Marine Corps personnel in the United States for 1981-1994. They studied the relationships using univariate risk factor

associations and multiple logistic regression. Using logistic regression, risk factors identified were age group, paygrade, race/ethnicity, and year of service.

Muir Bowers *et al.* (2006) studied the frequency and degree of fatigue associated with Coccidioidomycosis at the Valley Fever Clinic at the Southern Arizona Veterans Affairs Healthcare System utilizing the Mann-Whitney U test, Pearson Chi-Squared test, and Logistic regression. They found that severe fatigue was common with declining BMI.

Chen *et al.* (2007) mailed a survey to 7,608 healthcare providers in October and December of 2007. They used logistic regression to study predictors related to knowledge and treatment practices of Coccidioidomycosis. Their research concluded a significant relationship with healthcare providers receiving continued medical education in Coccidioidomycosis.

Flaherman *et al.* (2007) used hospital data from 1997 – 2002 to understand risk factors in California. Using multivariate Poisson regression, they confirmed well-known risk factors of African Americans, middle and older age, and pregnancy.

Blair *et al.* (2008) compared demographic characteristics, results of diagnostic tests, outcomes of the illness, treatment, and manifestations of Coccidioidomycosis for elderly people. Univariate logistic regression found immunosuppression as the risk factor.

Lee *et al.* (2008) conducted a retrospective epidemiologic study on Coccidioidomycosis incidence at a Naval Base in Kings County from 2002 – 2006. Using Logistic Regression, they found a higher risk among active duty members.

Stern *et al.* (2010) compared case rates for young adults at the University of Arizona, specifically scholarship athletes. They found little susceptibility is attributed to increased exercise or athletic trainings.

Sondermeyer *et al.* (2013) used the California Patient Discharge Data Set for 2000 – 2011 and looked at risk factors associated with patient information. Using negative binomial regression analyses, they found that male sex, African Americans, Hispanics, and older age groups have higher risks for hospitalization.

Guevara *et al.* (2015) studied population surveillance data for Los Angeles County for 1973-2011. They found "being in an area in sight of construction and being in an area in sight of earth excavation had the strongest associations" and the housing boom had an influence.

Predictive Models

Smith *et al.* (1946) found that incidence on four army air fields in the San Joaquin Valley in California were highest during a dry summer and autumn.

Park *et al.* (2005) analyzed the effect of climate factors (precipitation, temperature, Palmer Drought indices, Particulate Matter (PM) 10, and wind speed) on month incidence that was lagged 1 month. Using a Poisson Regression, they found significant relationships with precipitation 7 months prior, temperature 3 months prior, and a proportion of rainfall.

Kolivras *et al.* (2003) utilized temperature, precipitation, and the Palmer Drought Severity Index (PDSI) to estimate incidence in Pima County, AZ. They found that winter climate variables were important and winter temperature and precipitation appeared frequently in their models.

Comrie *et al.* (2005) and (2007) investigated precipitation and PM 10 under a linear regression model to understand monthly exposure in Pima County, AZ. They found that elements of the changes in incidence can be explained by climate variability, the underlying trends do not align with the climate data (Comrie 2007). Comrie *et al.* (2005) found that the four seasonal models explained significantly high proportions of exposure variance. The Wet to Dry sequence did not have the strongest relationships.

Zender *et al.* (2006) utilized the Generalized Autoregressive Moving Average (GARMA) method in Kern County, CA to determine that precipitation anomaly was significant for 8 months, but only explaining 4% of the monthly variability. For data from 1996 – 2002, wind speed 5 months antecedent was significant with incidence.

Talamantes *et al.* (2007) investigated precipitation, temperature, and wind speed under a GARMA methodology to understand weekly incidence. They found that weather was not needed, but knowing incidence at weeks 1, 2, 4, and 26 was significant for Kern County, CA. Another Talamantes *et al.* (2007) study also used GARMA to see if they could predict the stochastic shocks in Coccidioidomycosis incidence in Kern County, CA. They found their model could not predict the incidence.

Stacy *et al.* (2012) conducted stepwise regression analysis for concurrent and lagged Normalized Difference Vegetation Index (NDVI) to Coccidioidomycosis incidence for Pima, Pinal, and Maricopa counties in Arizona. Stacy *et al.* (2012) found incidence peaks in May-July and October-November correspond generally with dry soils.

Sprigg *et al.* (2014) studied the effect of a Haboob dust storm on July 5, 2011 on new cases in Phoenix, AZ. They discovered that increases in Coccidioidomycosis incidence do not require an extreme weather event to occur.

Gorris *et al.* (2018) analyzed Valley Fever incidence across the Southwest United States for 2000-2015. Using a combination of linear and non-linear regression, they looked at temperature, precipitation, surface dust, NDVI, soil moisture, and cropland index and they found that higher Valley Fever incidence in the fall occurs in years with a cool, wet, and productive spring growing seasons.

Table 1.1: Summary of Literature found relating Factors to Coccidioidomycosis						
Study	Time Period	Region	Dependent Variable	Variables of Interest	Methodology	Findings
Gorris (2018)	2000 - 2015	Southwest USA	Incidence	Surface air temperature, precipitation, soil moisture in the top 10 cm, surface dust concentration, normalized difference vegetation index, and cropland area	Linear and non-linear regression	Higher autumn valley fever incidence in years with cool, wet, and productive spring growing seasons
Guevara (2015)	1973 - 2011	Los Angeles County, CA	Surveillance data, uses 1-4 weeks as exposure period	Outdoor exposures, ethnicity, travel, occupation	Pearson correlation coefficients	Significant with construction activities and earth excavation
Vargas – Gastelum (2015)	2015	Baja CA	Soil count	Microhabitats	Repeated Measure ANOVA	Higher prevalence in burrows
Sprigg (2014)	2011	Phoenix, AZ	Cases	July 5th dust storm	DREAM dust model	Extreme weather events do not lead to higher risk of disease
Lauer (2012) (2014)	2008	Kern County, CA	Ecological Niche	Soil parameters	Landsat-5-Thematic-Mapper	Found in the Bakersfield area at locations that are non-agricultural and have about equal parts of sand, clay, and silt (clay loam), a pH between 7.8 and 8.5, an available water capacity of about 0.15– 0.2 cm/cm, a water content of about 30% (1/3 bar), an available water supply (0–25 cm) of 4–5 cm
Sondermeyer (2013)	2000 - 2011	CA	Hospital data	Sex, age group, race/ethnicity, county, region of patient residence	Negative Binomial Regression Analysis	Significant factors: that male sex, older age group, and African American and Hispanic race/ethnicities
Stacy (2012)	1995 - 2006	Pima, Pinal and Maricopa counties, AZ	Monthly incidence estimated with incubation period and further offsets	NDVI	Regression	Incidence peaks in May-July and October-November correspond generally with dry soils
Stern (2010)	1998 - 2006	University of Arizona	Scholarship Athletes	N/A	Incidence rates	Not more susceptible
Blair (2008)	1999 - 2003	Scottsdale, AZ	Elderly people Case data	Patient factors	Logistic Regression	Immunosuppression
Lee (2008)	2002 - 2006	Kings County, CA	Naval Base Case data	Patient factors	Logistic Regression	Active duty members
Flaherman (2007)	1997 - 2002	CA	Hospital discharge data	Patient factors	Poisson regression	Risk Factors identified: African Americans, Middle and older age, pregnancy
Baptista-Rosas (2007)	2007	Endemic Region	Ecological Niche	19 Climate Layers	Genetic Algorithm for Rule Set Production (GARP)	Identified more areas with Coccidioidomycosis spore presence
Talamantes (2007)	1980 - 2002	Kern County, California	Weekly Incidence	Precipitation, Temperature, wind speed	Generalized Autoregressive Moving Average (GARMA)	Weekly incidence at times t-k, where k = 1, 2, 4, 26 weeks
Talamantes (2007)	1995-2003	Kern County, CA	Weekly case data normalized by	Temperature, precipitation, and	GARMA	Model fall short

Table 1.1: Summary of Literature found relating Factors to Coccidioidomycosis						
Study	Time Period	Region	Dependent Variable	Variables of Interest	Methodology	Findings
			population	wind speed		
Comrie (2007)	1991 - 2006	Pima County, Arizona	Monthly case data – with report lag confirmations and disease onset	Precipitation and PM 10	Multiple Linear Regression	Climate variability is not causing incidence trend
Chen (2011)	2007	AZ	Healthcare providers	Knowledge and treatment practices	Logistic Regression	Need for educational campaign for healthcare providers
Zender (2006)	1980 - 2002	Kern County, CA	Monthly cases	Precipitation, Wind speed, Temperature, and Surface Pressure	GARMA	Precipitation anomaly 8 months antecedent
Muir Bowers (2006)	2006	AZ	Fatigue	Patient factors	Mann-Whitney U test, Chi Squared, logistic regression	Severe fatigue in Coccidioidomycosis patients tied to lower BMI.
Comrie (2005)	1992 - 2003	Pima County, AZ	Monthly case data – with report lag confirmations and disease onset	Precipitation and PM 10	Multiple Linear Regression for 4 seasonal models	All 4 models significant
Park (2005)	1998 - 2001	Maricopa County, AZ	Monthly case data – lagged 1 month	Rainfall, drought indices, wind speed, temperature	Poisson Regression	Cumulative rainfall during the previous 7 months, the average temperature during the previous 3 months, dust during the previous month, and the proportion of rainfall during the previous 2 months divided by rainfall during the previous 7 months
Kolivras (2003)	1948 - 1998	Pima County, AZ	Monthly data	Temperature, precipitation, PDSI	Multiple Linear Regression	Winter climate conditions
Gray (1998)	1981-1994	Navy and Marine Corps Personnel	Hospital data	Age group, length of service group, race/ethnicity, year of service, gender, branch of service, paygrade	Logistic Regression and Univariate analyses	Significant risk factors: age group, length of service group, race/ethnicity, and year of service
Smith (1946)	1942 - 1945	San Joaquin Valley, CA	Cases lagged 30 days	Precipitation	Regression	Incidence is highest in a dry summer and autumn

Results

No two studies on understanding the relationship between Coccidioidomycosis and climate are the same and only one study actually supports the highly referenced "Grow and Blow" Effect Hypothesis. From the 1950s, climatic factors, particularly precipitation, were considered to have a "Grow and Blow" Effect on the Coccidioides immitis spores (Egeberg (1956), Hugenholtz (1957), Maddy (1965), Jinadu (1995), Stevens (1995)). In order for the fungal spores to germinate, there needs to be an increase in soil moisture. Then, a dry period needs to occur to make the soil loose and easily disturbed by wind in order to disperse the spores for inhalation (Egeberg (1956), Hugenholtz (1957), Maddy (1965), Jinadu (1995), Stevens (1995)). Temperature is also said to have a role in the exposure of these spores. During dry, hot periods, temperature is said to sterilize the topsoil, reducing the competition against the *Coccidioides immitis* spores (Maddy (1965), Maddy (1957)). The findings in the various research presented are not consistent and do not support that Hypothesis.

Coccidioidomycosis Data Integrity

Table 1.2 lists the 22 published articles that utilize case data in their statistical modelling efforts. The remaining 3 sources out of the total 25 included in this study use Coccidioidomycosis spore counts in their models.

Ten of the publications describe studies conducted in communities in Arizona. Data for Pima County, AZ ranged from 1948 – 2006 and Maricopa County, AZ ranged from 1995 – 2006. Five of the studies estimate case exposure. Two of those studies, by Comrie *et al.*, used two lag periods: the Incubation period lag with a 12.6 day average and the Onset to Report Lag with a 43 day average. Tamerius *et al.* study indicated that the average Onset to Diagnosis average is 209 days (median of 55 days). Incubation period was not used. Stacy *et al.*, used a 14 day incubation period. Diagnosis date reported was also used as an offset for those cases lacking that information. Park *et al.* used one month lag time.

Nine of the articles describe studies conducted in California communities, 4 of which involved military facilities and/or special populations. Only one study, conducted in 1946, accounted for a lag time of 30 days in estimating exposure.

One the major data integrity limitations in the various studies is the estimation of exposure date for the disease cases. Many studies do not address the incubation period of the disease. For those that do, the incubation period is not estimated the same. The same can be said for the symptom to diagnosis lag. How do the results vary by using a 14 day incubation period versus a 1 month period estimate? How do the results vary by adding 58 or 43 days to the incubation period? It leads to questioning how these discrepancies influence the ability to properly estimate the crux of these studies, the dependent variable. The next section discusses climate variables, where all studies lagged their climate variables. Is lagging the climate variables capturing the same relationships as those studies that lagged their data by 43 days and then used climate variables? Does accounting for different incubation and other lags alter the variability of the data sets?

Table 1.2: Summary of the Type of Studies Involving Coccidioidomycosis Case Data

Reference	Time Period	Region	# of Cases Included	Data Type	Notes
			Arizona		
Sprigg (2014)	2010-2011	Phoenix, AZ	N/A	Case	
Stacy (2012)	1995 - 2006	Pima, Pinal, and Maricopa County, AZ	N/A	Monthly incidence	Incubation period and Onset to diagnosis lag included
Tamerius (2011)	1995 - 2006	Pima and Maricopa County, AZ	23,599	Case data	Generated monthly exposure with lag times
Stern (2010)	1998 - 2006	Pima County, AZ	16	Scholarship Athletes	
Talamantes (2007)	1998-2001	Maricopa County, AZ	N/A	Monthly Incidence	
Comrie (2007)	1991-2006	Pima County, AZ	N/A	Monthly summary case counts	Aggregated to seasonal level based on exposure, onset, and report lag times

Reference	Time Period	Region	# of Cases Included	Data Type	Notes
Muir Bowers (2006)	2005	AZ	48	Southern Arizona Veterans Affairs Healthcare System	
Park (2005)	1998-2001	Maricopa County, AZ	5399	Cases	Cohort study of exposure; lagged one month
Comrie (2005)	1992 - 2003	Pima County, AZ	3,283	Seasonal data	Onset lags included
Kolivras (2003)	1948 - 1998	Pima County, AZ	10,000+	Monthly data	
			California		
Guevara (2015)	1973-2011	Los Angeles County, CA	3,338	Population surveillance data	
Sondermeyer (2013)	2000 - 2011	California	25,217	California Patient Discharge Data set	Hospitalization rate per 100,000 population
McCarty (2013)	2010-2011	Children's Hospital Central California	33 children under 17 years old	Cases	
Blair (2008)	1999 - 2003	Scottsdale, AZ	396	Patients > 60	Retrospective review
Lee (2008)	2002-2006	Kings County, CA	82	Naval Base	Retrospective epidemiologic study
Talamantes (2007)	1995-2003	Kern County, CA	N/A	Weekly cases	Incidence
Flaherman (2007)	1997 - 2002	CA State	7,457	Hospital Discharge Data	
Zender (2006)	1980 - 2002	Kern County, CA	N/A	Monthly case data	
Smith (1946)	1941 - 1945	San Joaquin Valley, CA	178	Army Air Forces	Exposure 30 days prior
			United States		
Gorris (2018)	2000-2015	Southwest USA	N/A	Monthly incidence	
Gray (1998)	1981-1994	Navy and Marine Corps personnel	155	Hospital data	

Environmental Determinants of Coccidioidomycosis

Another major limitation of the presented research is the inconsistency in the variables used to understand the climate factors.

Table 1.3 highlights the 16 studies found that try to understand the relationship between Coccidioidomycosis and climate factors. Only 3 of these studies have taken place in California and the two that utilized case data have only been conducted in Kern County, CA.

In comparing the studies, no two studies use the same environmental variables of interest, except two studies that look at the animal microhabitats and the studies conducted by Talamantes *et al.*, both published in 2007.

Only Talamantes *et al.* conducts two studies similarly in California and Arizona. Talamantes *et al.* uses precipitation, temperature, and wind speed as their environmental variables of interest. 6 studies look at how dust affects Coccidioidomycosis cases, but the proxy variables of dust vary from studying PM 10, specific dust events, and wind speed. 3 studies, all taking place in Arizona, studied how soil moisture effects Coccidioidomycosis with one using NDVI and the other two utilizing PDSI. 7 studies researched the relationship between precipitation and Coccidioidomycosis and 6 studies researched the relationship with temperature.

All studies, except those focusing on mapping spores by studying microhabitats, lagged their climate variables. 4 studies found that their variables of interest did not have a significant effect on understanding the relationship with Coccidioidomycosis case data. Only 1 study supported the "Grow and Blow" Effect Hypothesis.

2 studies found a more complex relationship with the lagged variables. For these two studies, the one in California saw a precipitation lag of 8 months prior in Kern County and the one in Arizona saw a precipitation lag of 7 months prior in Maricopa County.

How does trying to prove the "Grow and Blow" Effect limit the ability of these researchers to find new relationships to Coccidioidomycosis exposure? Why are all the climate variables and different measuring methods that cover the study area not included in the research? Does only looking at variables related to the "Grow and Blow" Effect have a sufficient amount of evidence to methodically eliminate other climate variables?

Table 1.3: Summary of the Type of Studies Involving Predicting Coccidioidomycosis Using Environmental Variables

Reference	State	Factors	Variable Lagged?	Findings
Gorris (2018)	Endemic Area	Surface air temperature, precipitation, soil moisture in the top 10 cm, surface dust concentration, normalized difference vegetation index, and cropland area	Yes	Higher autumn valley fever incidence in years with cool, wet, and productive spring growing seasons
Vargas-Gastelum (2015)	Endemic Area	Microhabitats	No	Found in burrows
Sprigg (2014)	Arizona	Haboob event	No	Cases do not require an extreme weather event to cause infection
Lauer (2014) and (2012)	California	Microhabitats	No	Found in the Bakersfield area at locations that are non-agricultural and have about equal parts of sand, clay, and silt (clay loam), a pH between 7.8 and 8.5, an available water capacity of about 0.15– 0.2 cm/cm, a water content of about 30% (1/3 bar), an available water supply (0–25 cm) of 4–5 cm, and a Cation Exchange Capacity (CEC7) of over 20 milliequivalents per 100 grams
Stacy (2012)	Arizona	NDVI	Yes	Incidence peaks in dry soils and low periods of incidence are in wet soils
Tamerius (2011)	Arizona	Temperature, relative humidity, wind speed, mean wind vector, soil temperature, vapor pressure, precipitation, solar radiation	Yes	Corroborates Grow and Blow Effect
Baptista-Rosas (2007)	Endemic Area	19 Climate layers derived from monthly temperature and rainfall	No	Identified more areas with the presence of Coccidioidomycosis spores
Talamantes (2007)	Arizona	Precipitation, temperature, and wind speed	Yes	Weather parameters were not required
Talamantes (2007)	California	Temperature, precipitation, and wind speed	Yes	Model falls short in estimating stochastic shocks
Comrie (2007)	Arizona	Precipitation and PM 10	Yes	Climate variability is not causing incidence trend
Zender (2006)	California	Precipitation, wind speed, temperature, surface pressure	Yes	Precipitation anomaly 8 months prior
Comrie (2005)	Arizona	Precipitation, seasonality, PM 10	Yes	Not a simple wet-dry sequence in the immediate season before a rise in cases
Park (2005)	Arizona	Rainfall, drought indices, dust permits, wind speed, temperature, PM 10	Yes	Cumulative rainfall for previous 7 months, previous 3 month average temperature, previous month dust, portion of rainfall (previous 2/previous 7)
Kolivras (2003)	Arizona	Temperature, precipitation, Palmer Drought Severity Index (PDSI)	Yes	Winter climate conditions appear to be important incidence predictors

Analytical Approaches

A third major limitation of the presented research is the analytical approaches conducted. Out of 22 studies on Coccidioidomycosis and its' relationship to various risk factors, there are 8 different mathematical methodologies applied to the studies. Those that do use the same statistical methods are all coauthors on the other papers using the same methods. Table 1.4 shows the various model methods and the studies that utilize those methods to make their conclusion.

Coccidioidomycosis case data include weekly and monthly sums based on diagnosis date. Climate data is a time series. How do these results vary if we conducted the same study using a different statistical method?

Table 1.4: Summary of the Type of Studies and their Statistical Methodologies

Statistical Methods	Studies
Generalized Autoregressive Moving Average (GARMA)	Talamantes (2007); Talamantes (2007); Zender (2006);
Multiple Linear Regression	Comrie (2007); Comrie (2005); Stacy (2012); Kolivras (2003); Gorris (2018)
Multiple Non-Linear Regression	Gorris (2018)
Multivariate Poisson Regression	Park (2005); Flaherman (2007);
Multiple Logistic Regression	Gray (1998); Chen (2011); Blair (2008); Muir Bowers (2006);
Multivariate Negative Binomial Regression	Sondermeyer (2013);
Bivariate Lag Correlation Matrix	Tamerius (2011)
Univariate risk factor associations	Gray (1998); Guevara (2015); Lee (2008); Muir Bowers (2006);

Discussion

Coccidioidomycosis is a complicated disease to understand and try to predict. Although there are methodological limitations with the results of various studies that limit the strength of the findings, this research provides an attempt to analyze in-depth Coccidioidomycosis and its relationship with then environment. Without these studies bringing the research community's awareness to this disease, the medical community and treatments for the disease would not be where it is today and thousands more people could have been impacted by this disease.

Summarizing the results in terms of the objectives stated at the beginning of the study, these studies show a consensus that the "Grow and Blow" Hypothesis is not the finding from a majority of the studies. There is no consistency between the climate variables used to test the Hypothesis and the statistical methodology involved.

With no true consensus on the results and methods, the reliability and confidence in the evidence of the results is very low. Using the Agency for Healthcare Research and Quality system for assessing the body of this review, the findings would be insufficient, the findings do not permit a conclusion on the relationship between climate and Coccidioidomycosis and it seems that the true effect has not been discovered yet.

Chapter 2

Exploration of Valley Fever Cases and Creating Exposure Period Estimates

This chapter will focus on defining the variability and seasonal patterns of Valley Fever data for the five counties in the study area (Fresno, Kern, Kings, San Luis Obispo, and Tulare). In addition, the results analyzed demographic risk factors for the study area. Lastly, this chapter will discuss the creation and variability of exposure scenarios.

Data Request

This analysis examined Valley Fever cases that occurred between 2000 and 2014 in the California counties of Fresno, Kern, Kings, San Luis Obispo, and Tulare. The Health and Human Services Agency (HHS) collects a two-page description on every case that is diagnosed in each County.

My data request to the California Department of Public Health (CDPH), Infectious Diseases Branch, Surveillance & Statistics Section, provisional infectious diseases Data Requested - November 12, 2017, requested zip code, ethnicity, age, gender, pregnant, country of birth, occupation or job title (not a checklist), occupational or exposure setting (food service, day care, health care, correctional facility, school, other), date of onset, date of first specimen collected, date of diagnosis, reporting health care provider, reporting health care facility, report submitted by, date report submitted, and laboratory test conducted.

Institutional Review Boards

Due to the Personal Identifying Information (PII) of this data request, this research study protocol was submitted and approved by the University of California, Irvine's Institutional Review Board (IRB) (Project Number HS#2016-3231, January 12, 2017) and through the California Department of Public Health's Institutional Review Board (Project Number 2017-014, November 2, 2017).

California Department of Public Health Data

When the California Department of Public Health Surveillance and Statistics Section completed assembly of the surveillance data per my request received on November 12, 2017, they attached an Excel spreadsheet file of summary data for cases of Coccidioidomycosis reported from five specified counties for years 2001 to 2014. Separate worksheets contained data by month/year of onset, case-patient age-group, sex, and race. Cell counts smaller than 11 had been suppressed for tables in compliance with CDPH's policy on potentially individually identifiable health information. Data respective to the other variables of the request—Date of First Specimen Collected, Date of Diagnosis, Reporting Health Care Provider, Reporting Health Care Facility, Report Submitted By, Zip Code, Occupation, Occupation of Exposure Setting, Country of birth, Laboratory Tests—were not included because they were not available, were not amenable to representation in summary tables, or represented potentially individually identifiable health information.

The California Department of Public Health discussed the original data request with other CDPH programs, CDPH management, and the Committee for Protection of Human Subjects (CPHS). All parties agreed that department policy and state and federal law preclude releasing confidential health information to the public, including individual case data such as requested. Only summary data may be released, and only in a manner by which individual patients are not identified or potentially identifiable. Approval of proposed projects by CPHS does not obviate the Department's compliance with the California Information Practices Act (IPA) and the Federal Health Insurance Portability and Accounting Act (HIPAA) to maintain the security and confidentiality of patient health information.

Limits

Originally, I wanted to conduct a case-control survey to investigate exposure. However, the request to contact the cases was denied by each of the Counties' epidemiologists. The California Department of Public Health also denied the request to obtain case information from the Health and Human Services Agency's Two Page Patient Intake

Form. Despite receiving IRB approvals, they have determined that they will not release the information and will only provide summary information.

Additional data requests have been made to the individual counties' public health departments. They all have expressed concerns regarding the release of PII information, and decided not to release the data request.
Since no other data other than summary data can be obtained, the resulting analysis becomes limited from looking at a smaller geographic scale to a county-wide scale for the five counties of interest. All historic research conducted on Valley Fever has been done at the county level, as described in Chapter 1. Although the detailed case data may not be obtained, the results of this study is still comparable to the other studies that have been conducted.
Another limit of the study involves the collapsing of the data by the California Department of Public Health. Categories under 11 were collapsed or left with a (-) in the field. This limits the study results in trying to understand the nuances of the data's relationship to climate.

In partnership with two other Ph.D. candidates at the University of California, Irvine, we developed a database on GitHub (https://github.com/valleyfever/valleyfevercasedata) and are in the process of publishing the results of the report titled, "Coccidioidomycosis (Valley Fever) case data for the southwestern United States" to be submitted to Open Health Data. The purpose of this manuscript is to highlight the availability of the valley fever case data. The California Department of Public Health produced un-collapsed data for this purpose.

Descriptive Statistics

Table 2.1 describes the annual cases that occurred per county during the years 2000 – 2015. Throughout the years, we can see that all counties had an increase in diagnosed cases. Fresno, Kern, Kings, and San Luis Obispo Counties had their highest peak around 2010 – 2011. Tulare County had their highest peak of cases around 2008 – 2009. Fresno and Kern County have the highest amount of cases over time and average monthly. Table 2.2 describes the average monthly cases over time. From this table, we can see that some counties, like Kern, do have more cases getting diagnosed in the second half of the year. However, some counties like Fresno, have a small average change in diagnosed cases per month.

Table 2.1: Annual Case Counts Per County, 2000 - 2015

Year	Cases in Fresno	Cases in Kern	Cases in Kings	Cases in San Luis Obispo	Cases in Tulare
2000	15	375	7	70	61
2001	55	948	37	45	74
2002	73	995	46	45	89
2003	142	1235	50	67	143
2004	130	1468	72	92	158
2005	331	1506	127	90	125
2006	665	1019	231	176	196
2007	400	1394	138	81	172
2008	324	834	183	80	200
2009	489	599	203	78	229
2010	725	1914	384	163	194
2011	724	2567	374	170	128
2012	481	1858	239	106	155
2013	310	1656	97	49	113
2014	155	912	70	22	107
2015	259	1076	52	59	112
Grand Total	**5278**	**20356**	**2310**	**1393**	**2256**

Table 2.2: Average Monthly Cases per County Based on 2000 – 2010 Data					
Month	**Average Monthly Cases Fresno**	**Average Monthly Cases Kern**	**Average Monthly Cases Kings**	**Average Monthly Cases San Luis Obispo**	**Average Monthly Cases Tulare**
Jan	29.1	99.0	11.9	8.7	10.8
Feb	22.6	77.7	9.9	5.3	8.8
Mar	24.1	75.9	9.1	4.9	8.4
Apr	24.8	72.4	8.1	4.9	8.3
May	19.4	79.8	8.2	4.5	10.1
Jun	23.0	92.2	10.1	4.8	10.7
Jul	23.8	100.6	8.0	6.2	12.7
Aug	30.6	133.9	14.3	7.2	13.2
Sep	30.9	141.1	17.4	9.3	13.9
Oct	36.6	155.8	16.9	12.2	16.1
Nov	32.9	139.1	15.8	10.5	13.6
Dec	32.2	104.9	14.7	8.6	14.4
Average per Month	**27.5**	**106.0**	**12.0**	**7.3**	**11.8**

Table 2.3 provides information related to the descriptive statistics of the 5 counties. All the counties have a slight positive skew in their distribution. For Fresno, Kings, and San Luis Obispo, the standard deviation (S.D.) is almost the same size as the mean.

Table 2.3: Monthly Descriptive Statistics of Diagnosed Cases									
Fresno		**Kern**		**Kings**		**San Luis Obispo**		**Tulare**	
Mean	27.49	**Mean**	106.02	**Mean**	12.03	**Mean**	7.26	**Mean**	11.75
S.E.	1.81	**S.E.**	4.88	**S.E.**	0.99	**S.E.**	0.46	**S.E.**	0.48
Median	20.50	**Median**	90.00	**Median**	8.00	**Median**	5.00	**Median**	11.00
Mode	6.00	**Mode**	58.00	**Mode**	3.00	**Mode**	3.00	**Mode**	13.00
S.D.	25.15	**S.D.**	67.57	**S.D.**	13.71	**S.D.**	6.43	**S.D.**	6.71
Kurtosis	1.69	**Kurtosis**	3.62	**Kurtosis**	7.63	**Kurtosis**	4.39	**Kurtosis**	0.76
Skew	1.35	**Skew**	1.51	**Skew**	2.51	**Skew**	1.89	**Skew**	0.80
Range	129	**Range**	431	**Range**	82	**Range**	40	**Range**	37
Min	0	**Min**	12	**Min**	0	**Min**	0	**Min**	1
Max	129	**Max**	443	**Max**	82	**Max**	40	**Max**	38
Sum	5278	**Sum**	20356	**Sum**	2310	**Sum**	1393	**Sum**	2256

Time Series Decomposition

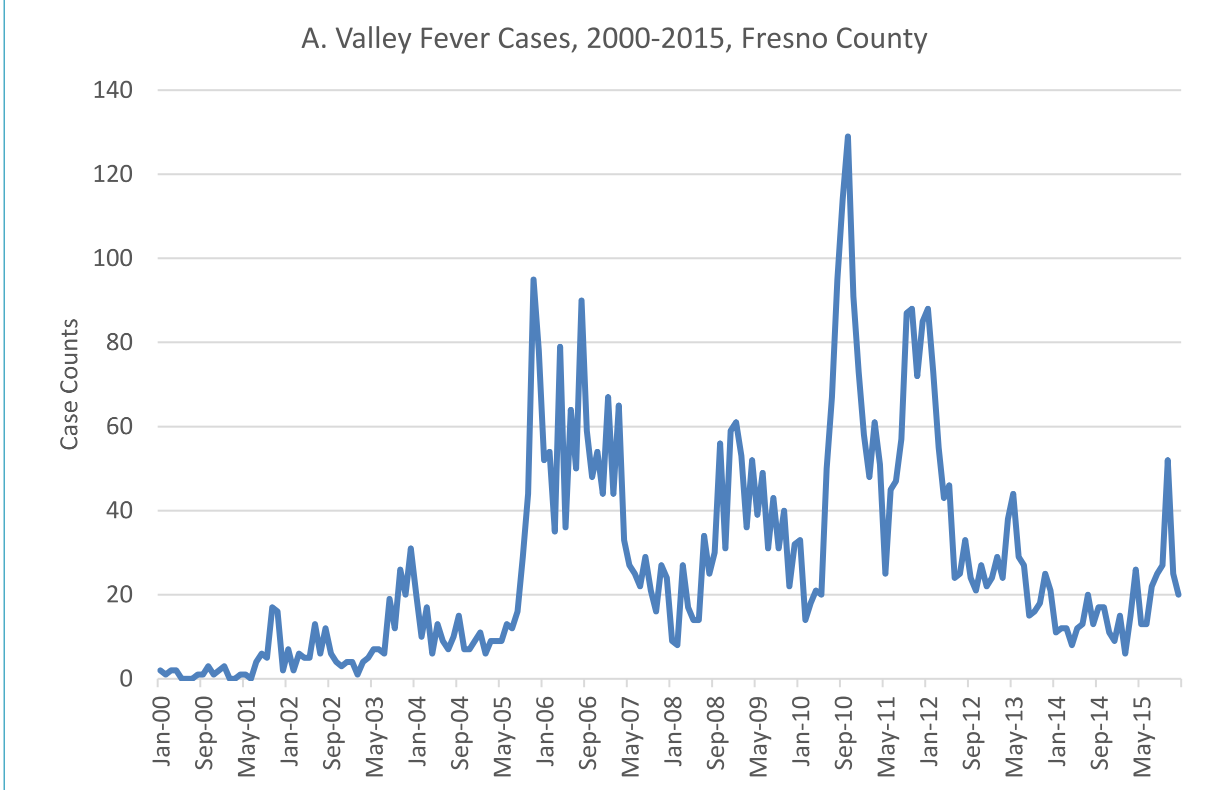
Utilizing R Statistical Program, Time Series (ts) tool, the 5 counties had their time series decompose into four components: observed, trend, seasonality, and random. Table 2.4 highlights the seasonality decomposition. Although most of the months are similar with their seasonality, there are slight variations as to when the diagnoses occur and how many months the season lasts. For example, Fresno and Kern County's season starts in August, but Fresno continues to January and Kern concludes in November. Without a smaller geographical scale to analyze, there does not appear to be a geographical relationship to the location of these counties and their seasonal start. With Figures 2.1 - 2.5, we can also see that the natural trend of the diagnosed cases is not the same, indicating some other factor than location influencing the relationship.

Table 2.4: Time Series Seasonal Decomposition

	Fresno	Kern	Kings	San Luis Obispo	Tulare
Jan	2.58	-4.08	-0.08	1.44	-0.79
Feb	-4.42	-27.45	-2.30	-1.87	-3.15
Mar	-2.96	-28.71	-3.22	-2.35	-3.24
Apr	-2.50	-33.35	-4.22	-2.26	-3.56
May	-8.23	-26.37	-4.16	-2.75	-2.14
Jun	-4.55	-13.85	-2.10	-2.51	-0.83
Jul	-3.95	-4.78	-4.53	-0.84	0.65
Aug	3.07	28.61	2.63	0.04	1.92
Sep	3.22	34.41	5.94	1.77	2.04
Oct	7.58	49.04	5.31	5.04	4.28
Nov	5.35	31.44	3.86	3.24	1.73
Dec	4.81	-4.88	2.88	1.04	3.11

Figure 1 shows the decomposition findings for Fresno County. The trend line shows a potential multi-year variation that is not explained well by the seasonal and random variation.

Figure 2.1: Trend Analysis for Fresno County, 2000 - 2015



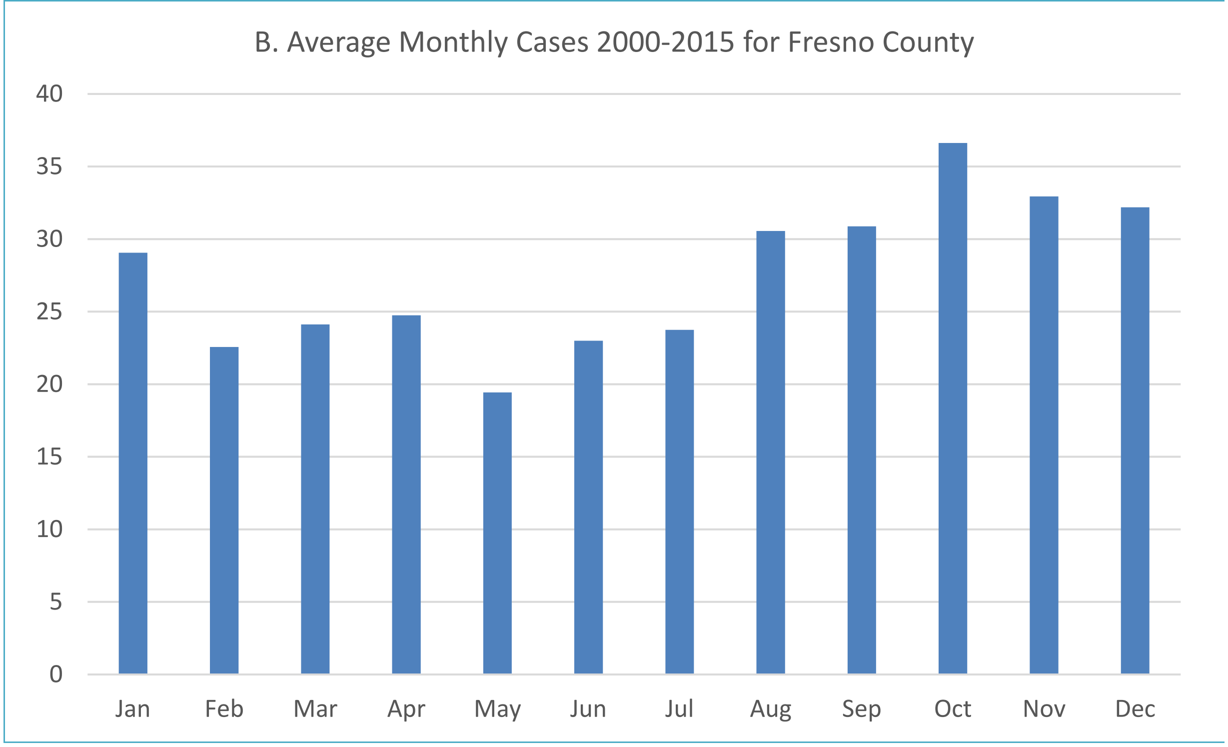


Figure 2.1: Trend Analysis for Fresno County, 2000 - 2015

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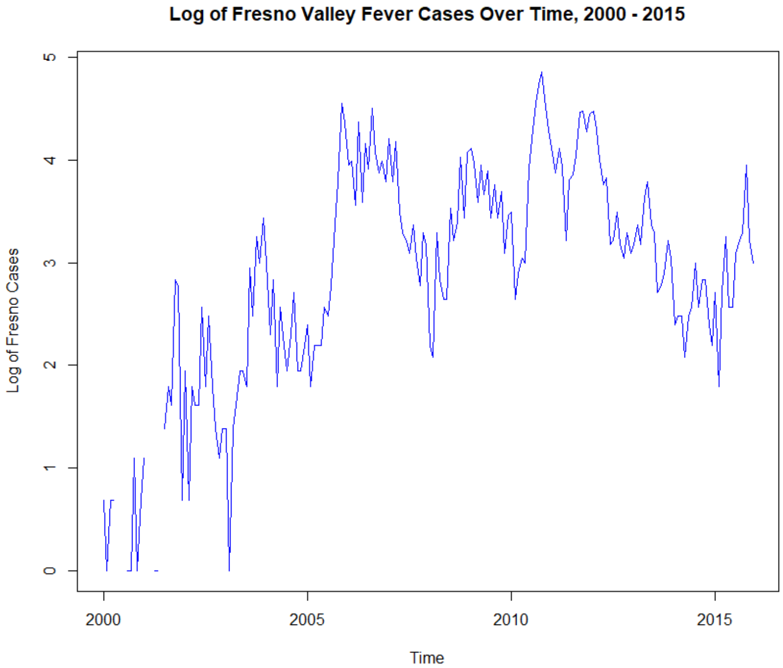

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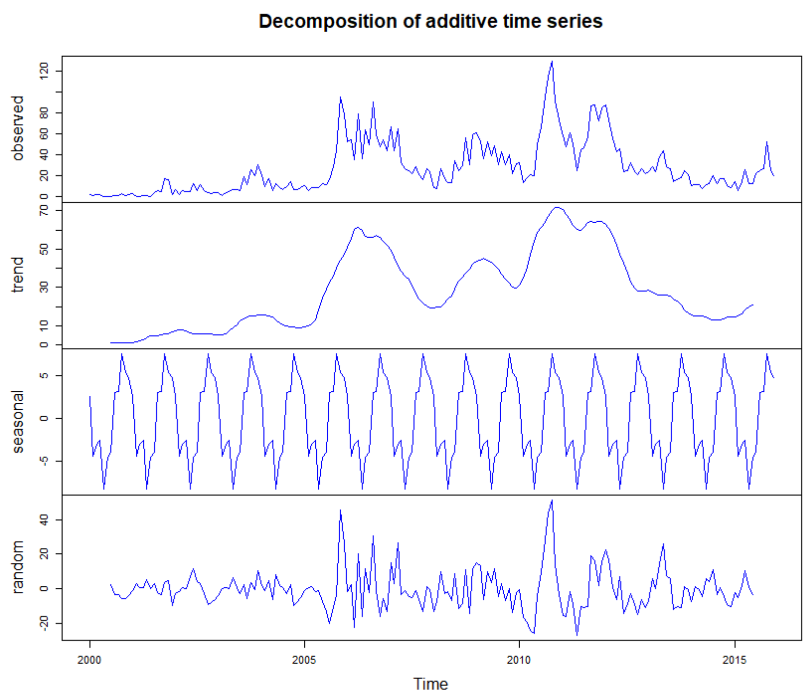
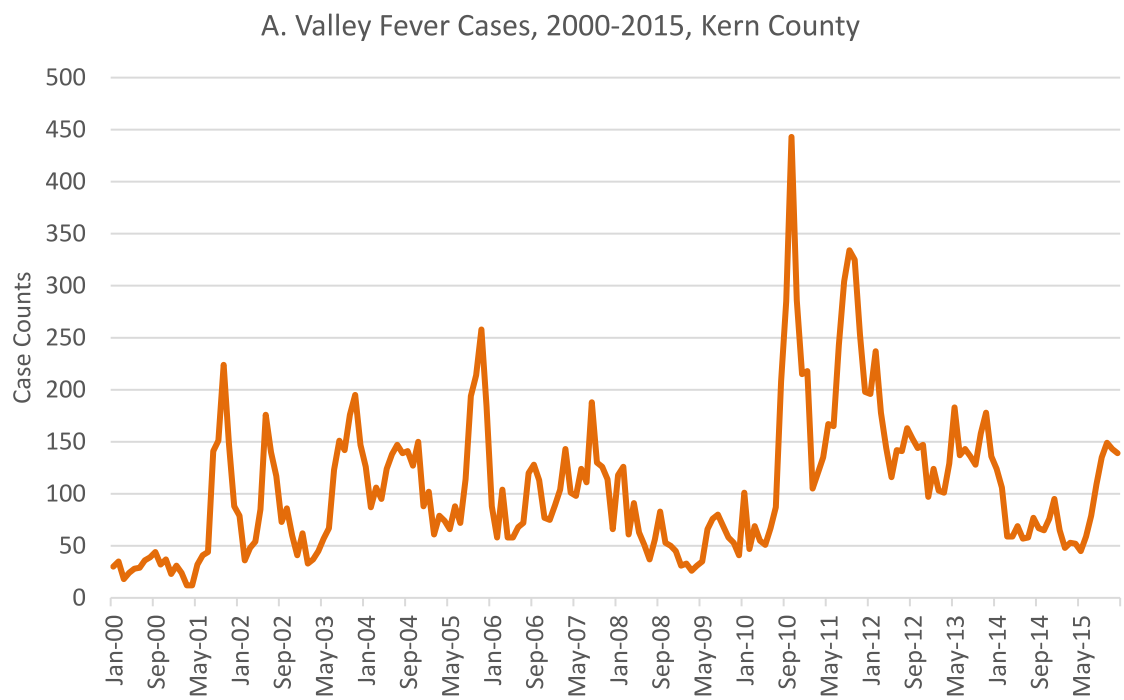


Figure 2.2 shows the decomposition findings for Kern County. The trend line does not show a linear increase, but more of a sudden increase in 2010, with a drop back down in the most recent past years. There seems to be more inter-annual/multi-year fluctuation from 2000 – 2010.

Figure 2.2: Trend Analysis for Kern County, 2000 - 2015



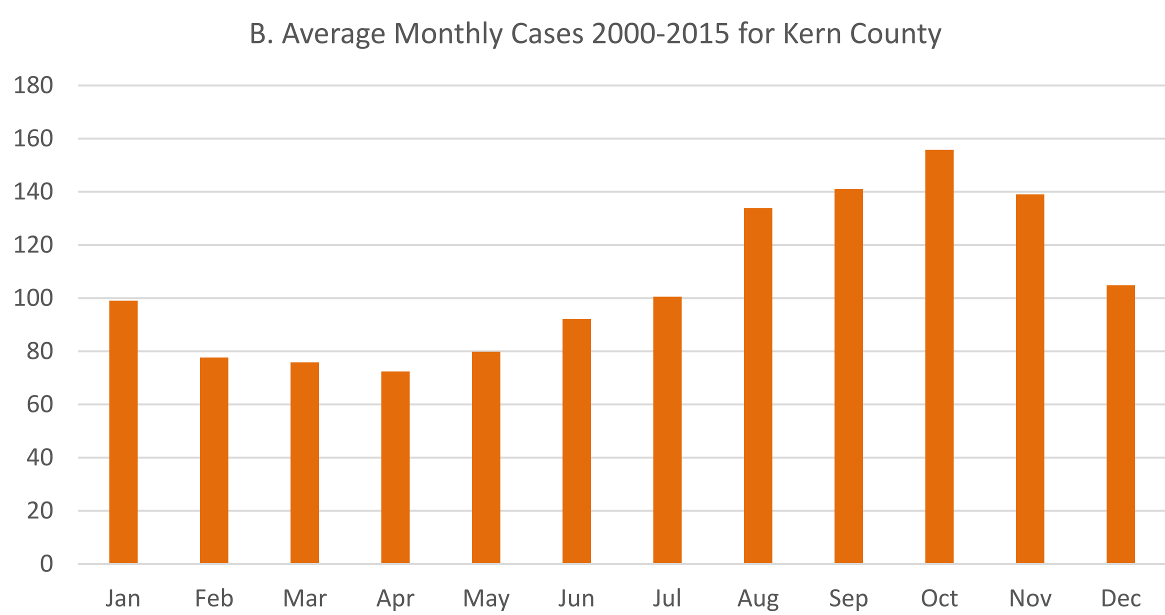


Figure 2.2: Trend Analysis for Kern County, 2000 - 2015

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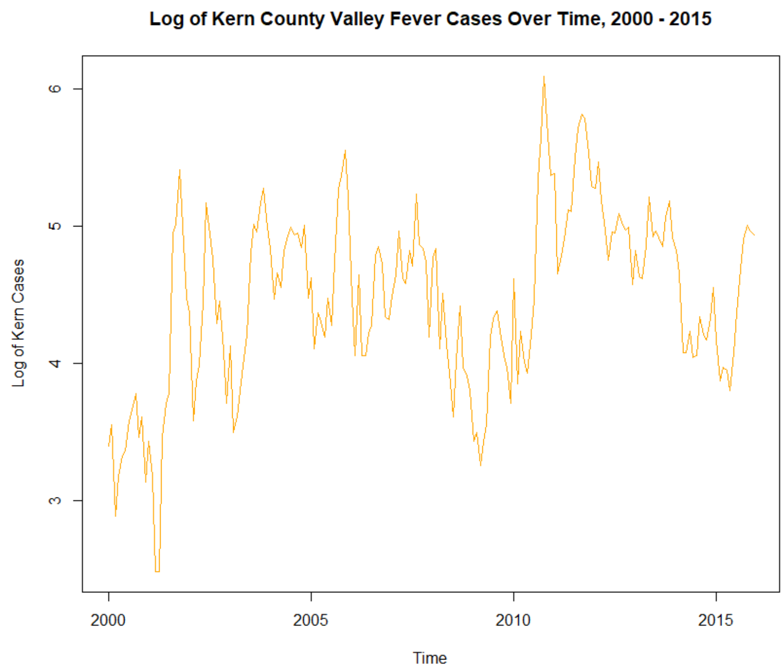

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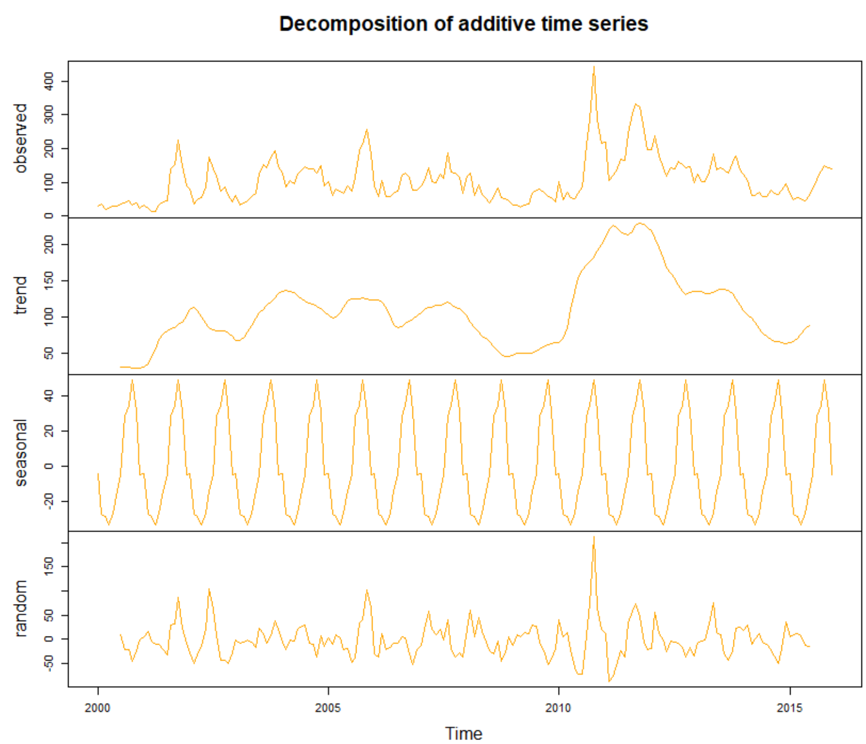


Figure 2.3 shows the decomposition findings for Kings County. The 2010 – 2012 time period seems to be a large uptick in cases, where the decomposition results indicate it is related to some random variation.

Figure 2.3: Trend Analysis for Kings County, 2000 - 2015

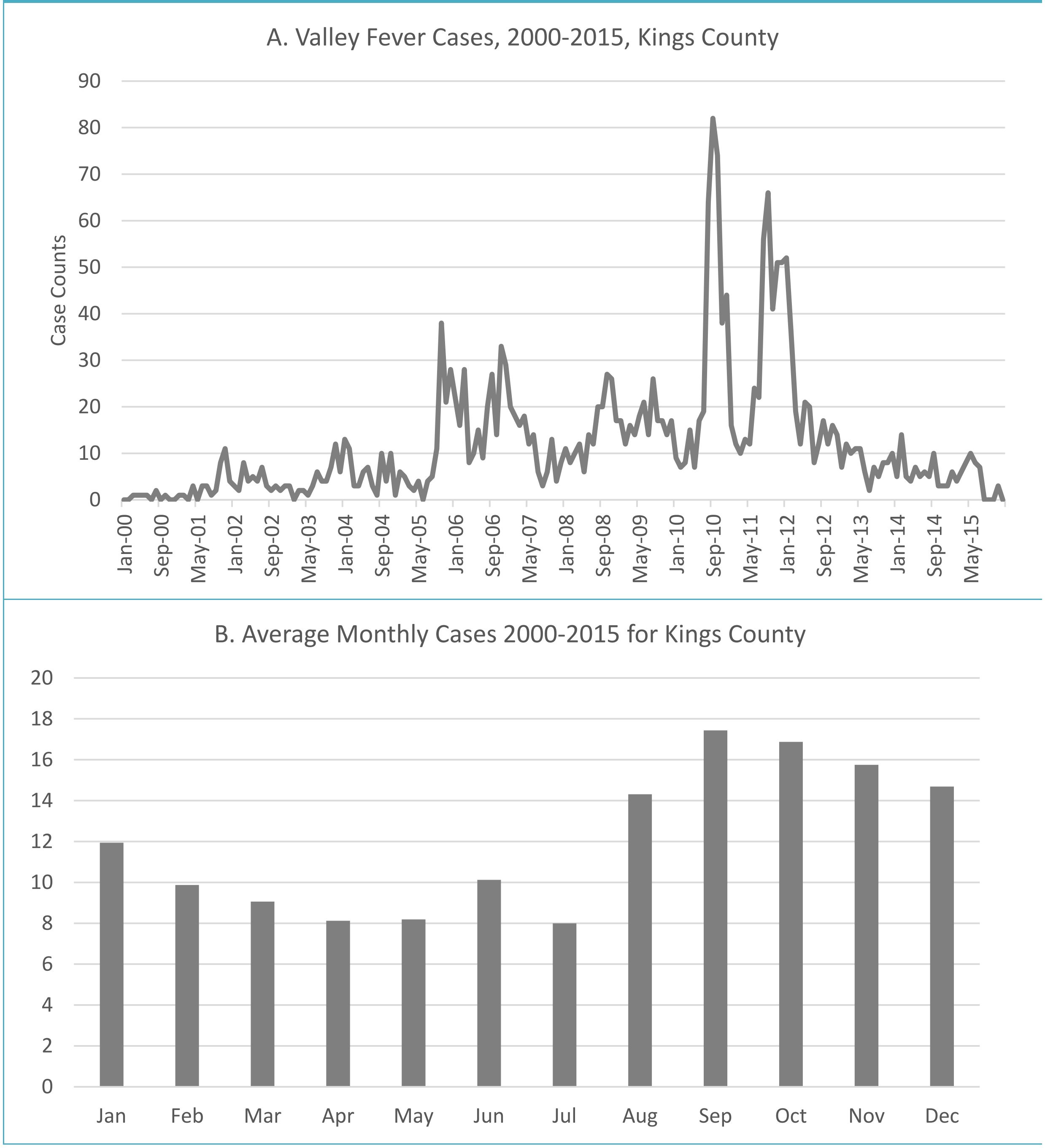
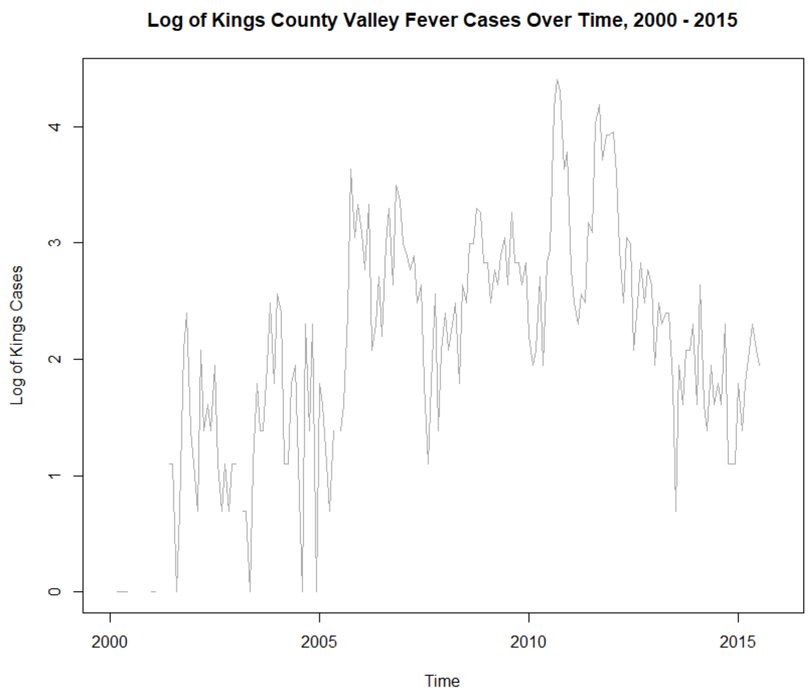


Figure 2.3: Trend Analysis for Kings County, 2000 - 2015

C.



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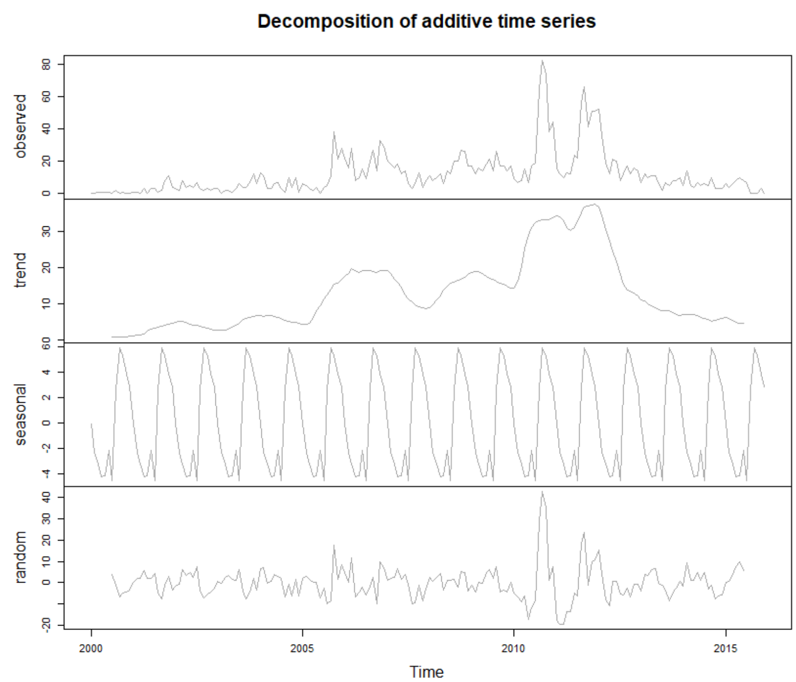
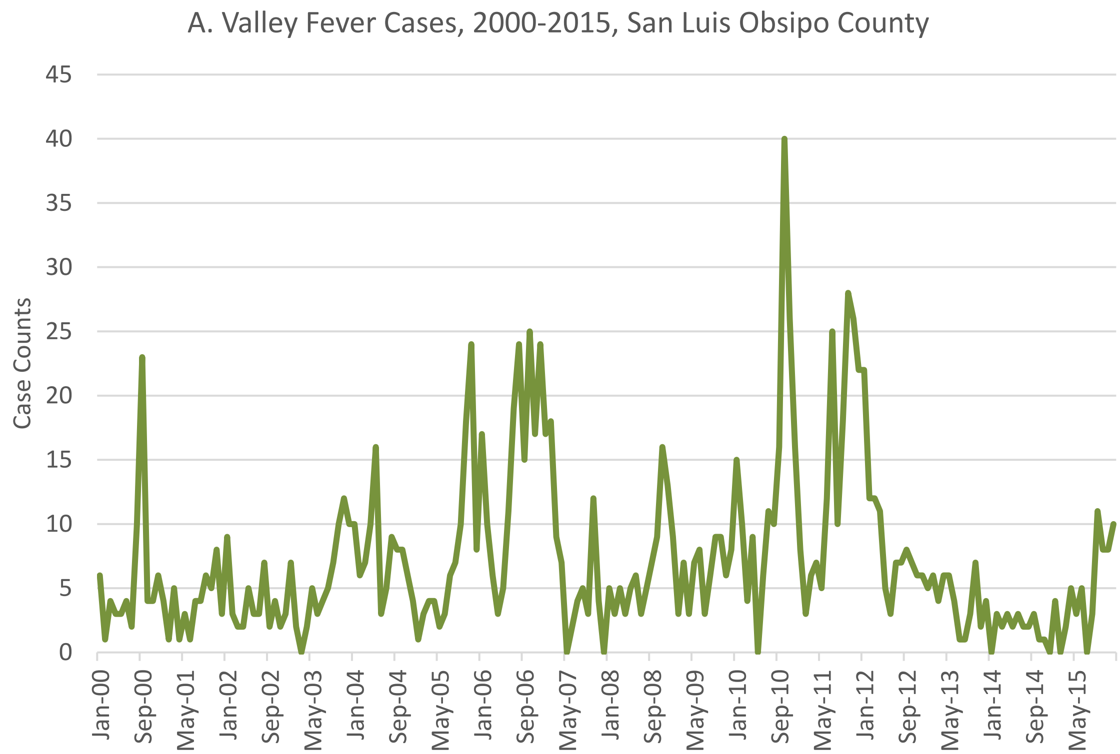


Figure 2.4 shows the decomposition findings for San Luis Obispo County. The trend line picks up two spikes in the data occurring in 2005 and 2010 and lasting for 2 years.

Figure 2.4: Trend Analysis for San Luis Obispo County, 2000 - 2015



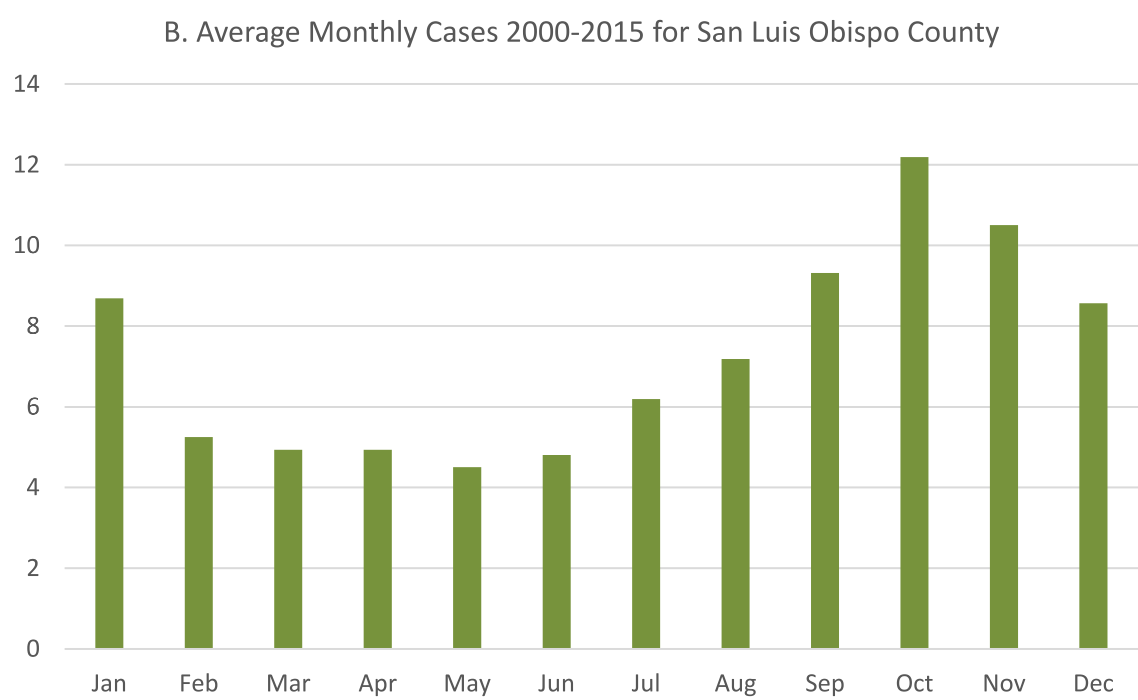


Figure 2.4: Trend Analysis for San Luis Obispo County, 2000 - 2015

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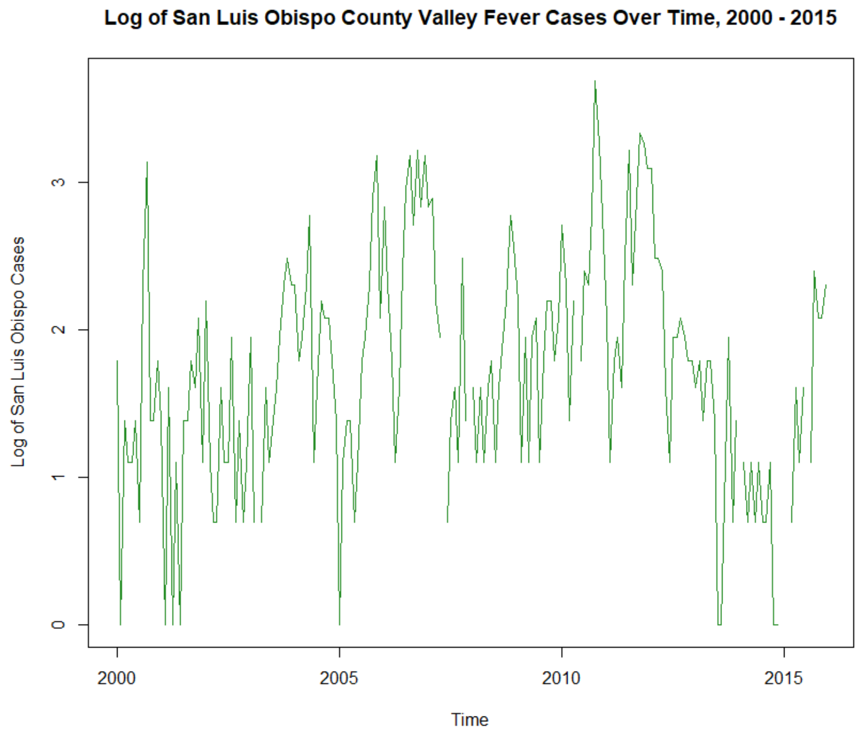

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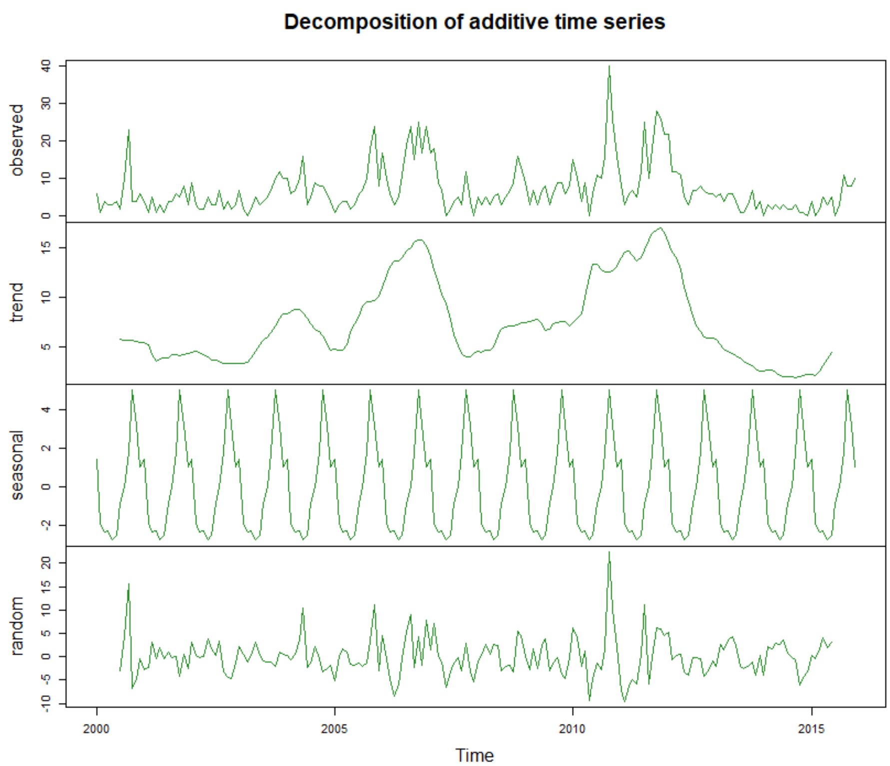


Figure 2.5 shows the decomposition findings for Tulare County. The trend in Tulare has an overall negative quadratic curve with some multi-year fluctuations.

Figure 2.5: Trend Analysis for Tulare County, 2000 - 2015

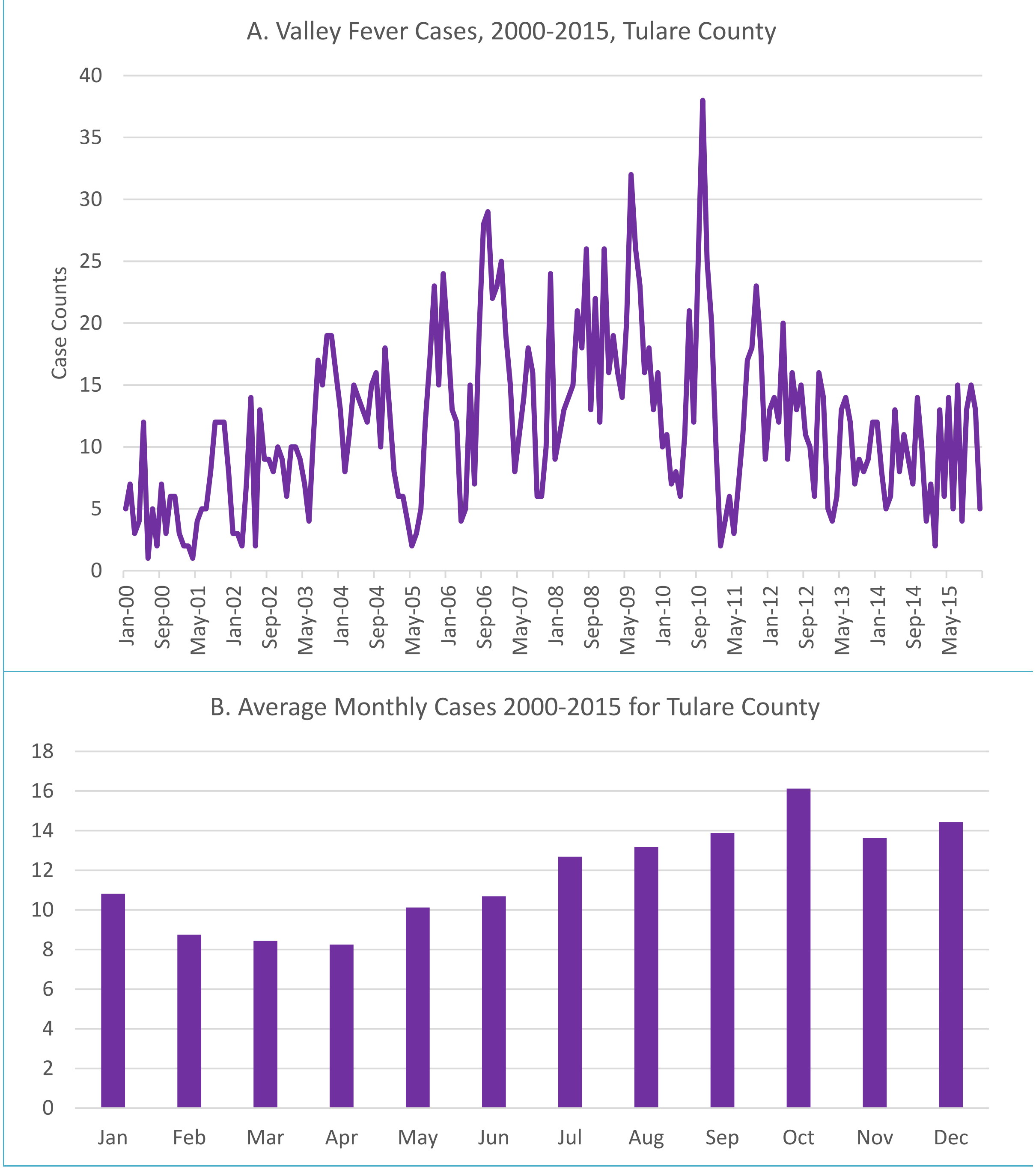
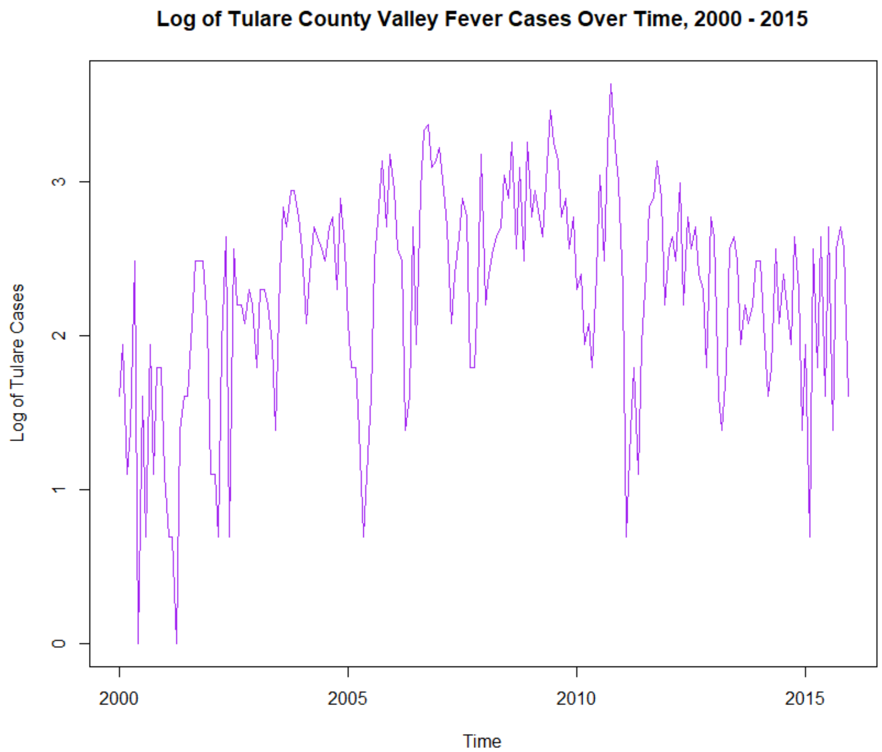


Figure 2.5: Trend Analysis for Tulare County, 2000 - 2015

C.



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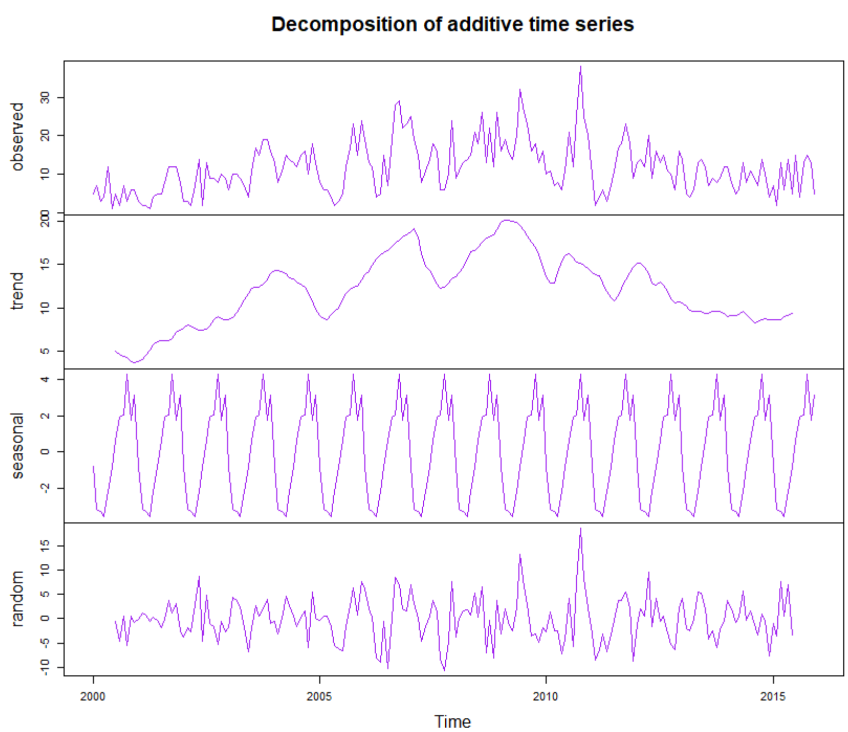
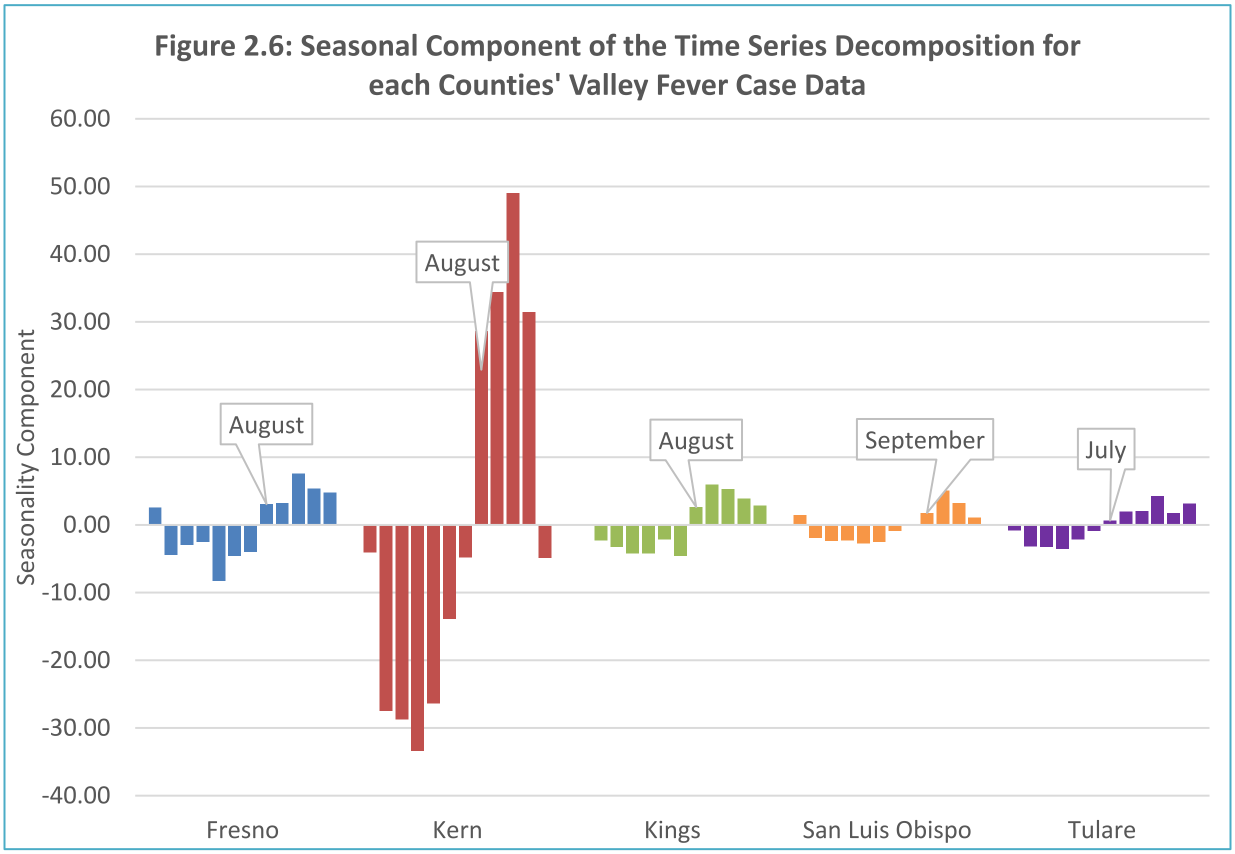


Figure 2.6 shows the seasonality components for each of the counties, side by side. The start of when diagnosed cases are likely to occur is August for Fresno, Kern, and Kings, September for San Luis Obispo, and July for Tulare.



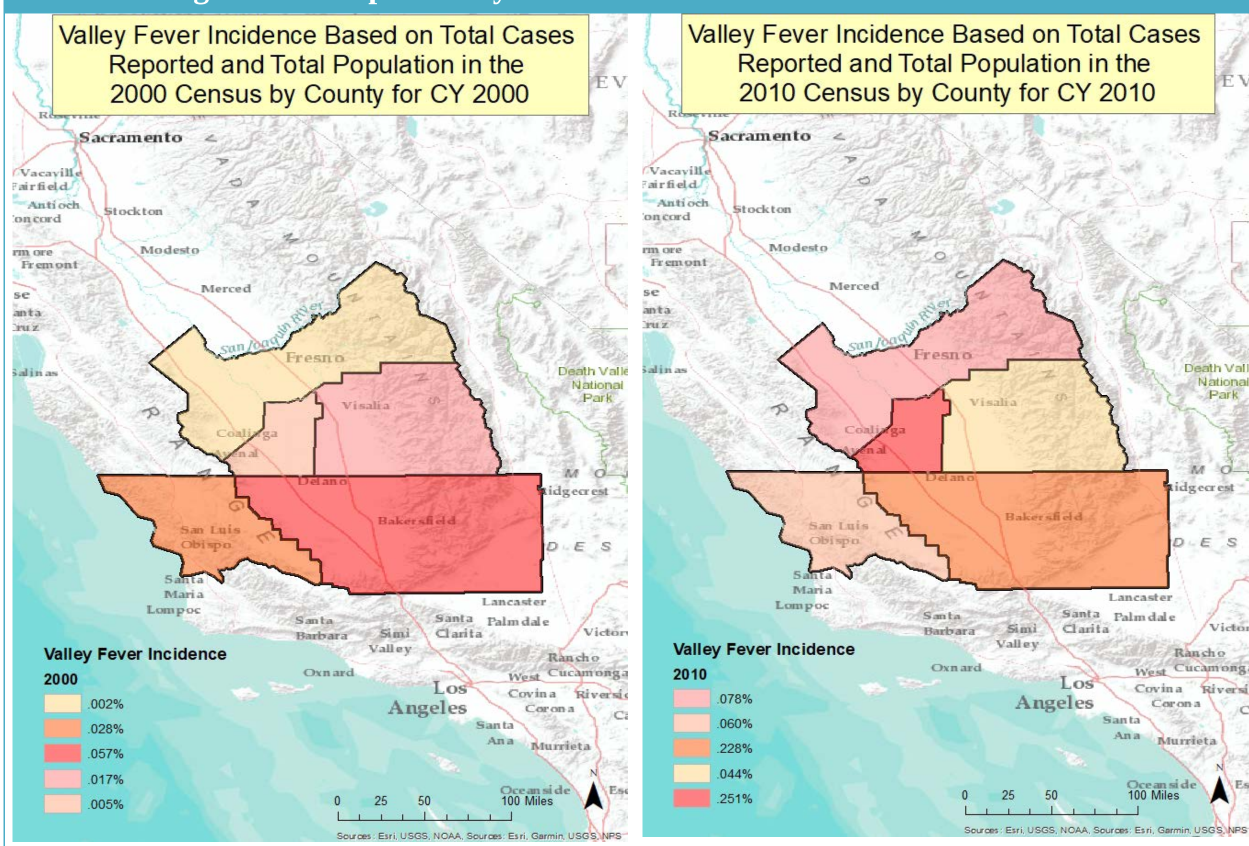
Cases vs. Incidence

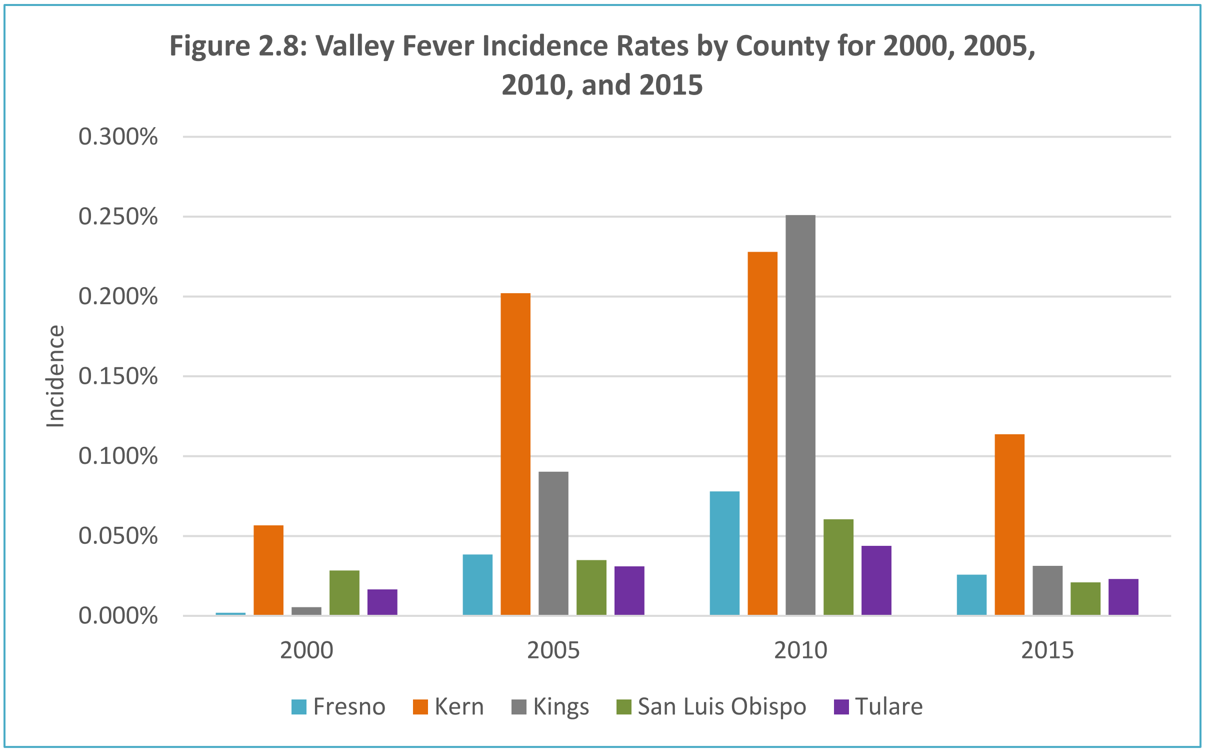
The above analysis was conducted on reported case information. On just the cases alone, we see that Kern and Fresno have the largest amount of cases. However, the human population distribution is different between the counties. Although Fresno has the second highest amount of cases, it also has the highest population in 2010, according to the U.S. Census. Since there is a larger amount of cases in comparison, it may not be a large portion compared to the population. We need to consider the incidence proportion of Valley Fever in each county. Incidence proportion is the number of new cases over the population at risk for a specified time period. Utilizing the population estimates from the U.S. Census, Table 2.5 shows the incidence rates by county for 2000, 2005, and 2010. Figure 2.7 and 2.8 depicts the relationship of these changes spatially and graphically.

From 2000 to 2010, we see that every county's reported incidence rate more than doubled. In 2000, Kern and San Luis Obispo County had the largest incidence rate. However, in 2010, Kern and Kings have the largest incidence rate. In 2015, the incidence decreased for all 5 counties with Kern and Kings having the largest incidence rate, and the other three counties have similar incidence rates. The rate has not increased uniformly across the counties.

Table 2.5: Valley Fever Incidence Rates					
	Fresno	**Kern**	**Kings**	**San Luis Obispo**	**Tulare**
Cases					
2000 Totals	15	375	7	70	61
2005 Totals	331	1506	127	90	125
2010 Totals	725	1914	384	163	194
2015 Totals	259	1076	52	59	112
Population Estimates					
2000 Totals	799,407	661,645	129,461	246,681	368,021
2005 Totals	862,443	745,344	140,731	257,904	403,400
2010 Totals	930,450	839,631	152,982	269,637	442,179
2015 Totals	1,003,819	945,845	166,300	281,904	484,686
% Growth Rate	16%	27%	18%	9%	20%
Incidence					
2000 Estimate	0.002%	0.057%	0.005%	0.028%	0.017%
2005 Estimate	0.038%	0.202%	0.090%	0.035%	0.031%
2010 Estimate	0.078%	0.228%	0.251%	0.060%	0.044%
2015 Estimate	0.026%	0.114%	0.031%	0.021%	0.023%

Figure 2.7: Map of Study Area and Incidence Rates for 2000 and 2010





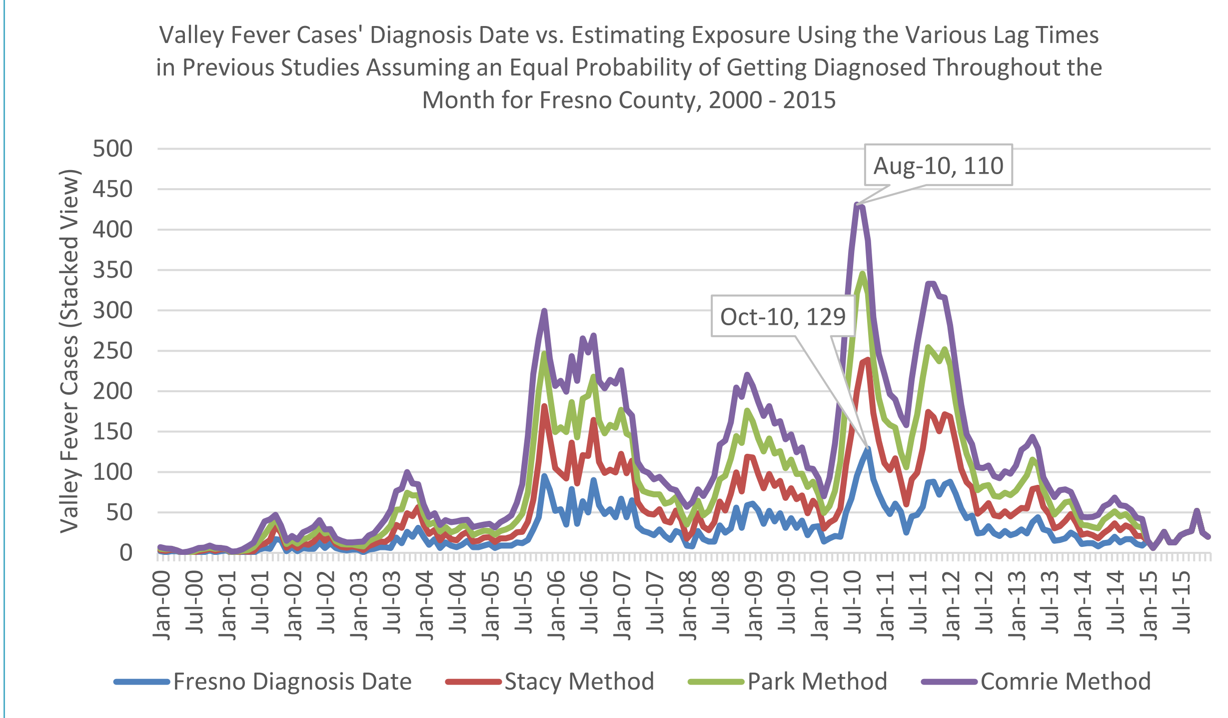
Diagnosed Date vs. Exposure Date

As discussed in Chapter 1, some studies conducted their analysis using diagnosis date and three studies tried to estimate the exposure period of each case. Comrie *et al*., used two lag periods: The Incubation period lag with a 12.6-day average and the Onset to Report Lag with a 43-day average. Tamerius *et al*. study indicated that the average Onset to Diagnosis average is 209 days (median of 55 days). Incubation period was not used. Stacy *et al*, used a 14-day incubation period. Diagnosis date reported was also used as an offset for those cases lacking that information. Park *et al*. used a one-month lag time.

How does using these different diagnosis dates and exposure dates affect the analyses? To answer this question, I created some new case distributions: One for each of the three of the methods - Comrie, Stacey, and Park. Each exposure period for the three methods had different assumptions: Cases were diagnosed equally throughout the month, 75% of the cases were diagnosed in the first part of the month, and 25% of the cases were diagnosed in the first part of the month.

Figures 2.9 – 2.12 show the time-series results of the different exposure estimates on one graph with a graph for each assumption described above for each county. Every graph compares the Exposure date distribution to the original Diagnosis date distribution. Although some of the smaller variations were changed, the overall maximum and minimum peaks maintain their shape and impact. The case quantities per month do vary and the exposure periods do change the months of these peaks by at most 2 months.

Figure 2.9: Diagnosis and Exposure Estimates for Fresno County



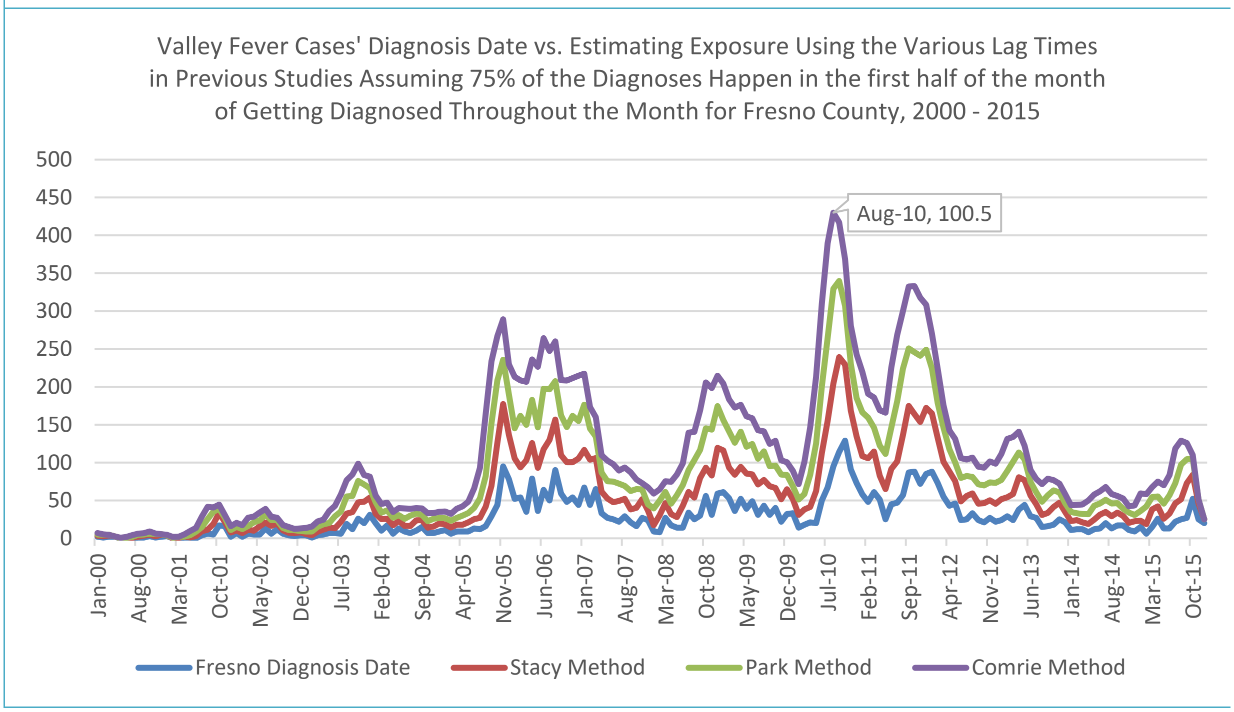


Figure 2.9: Diagnosis and Exposure Estimates for Fresno County

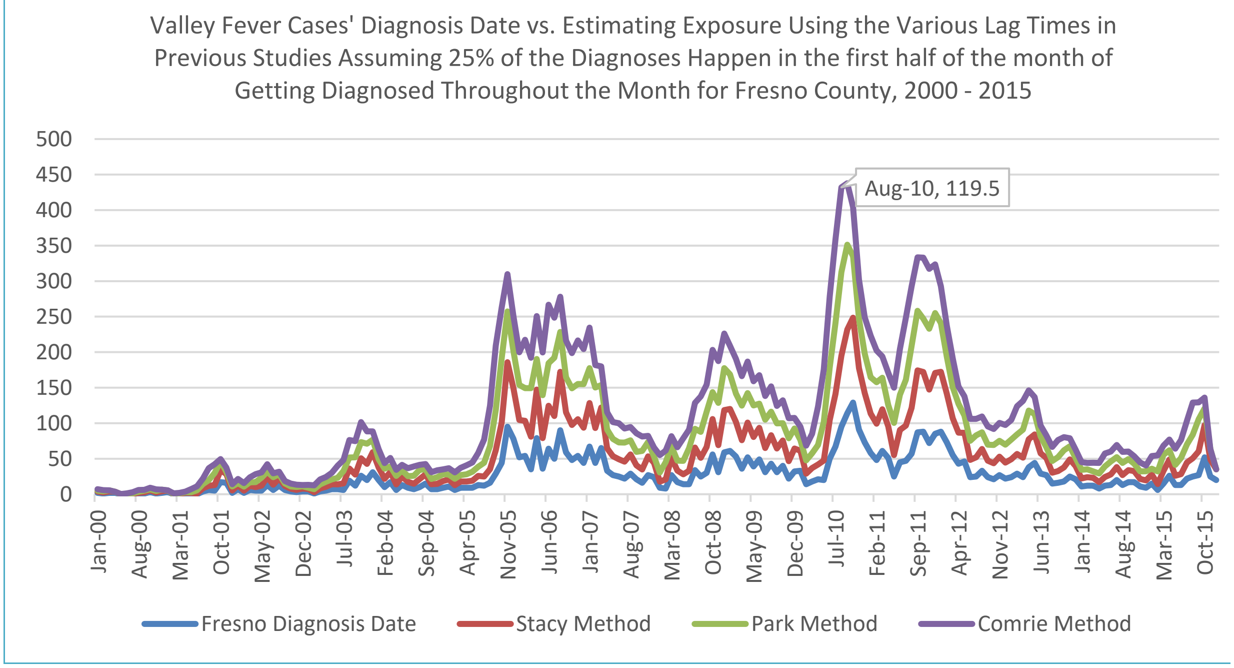


Figure 2.10: Diagnosis and Exposure Estimates for Kern County

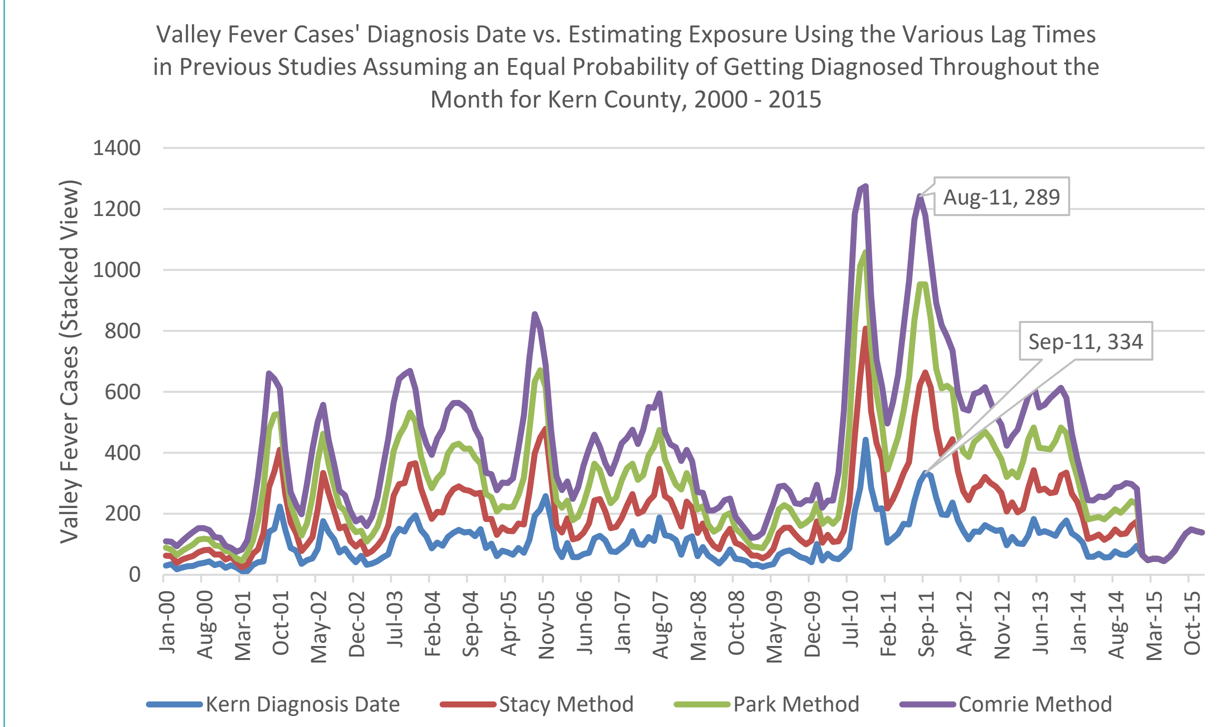
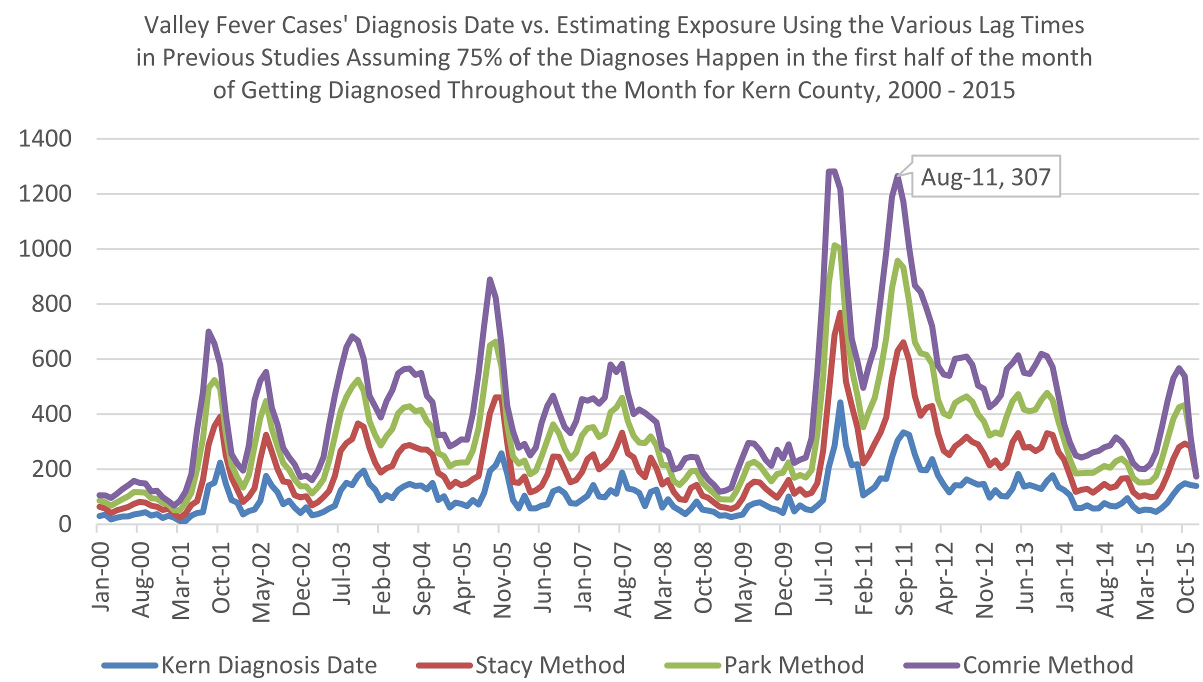


Figure 2.10: Diagnosis and Exposure Estimates for Kern County



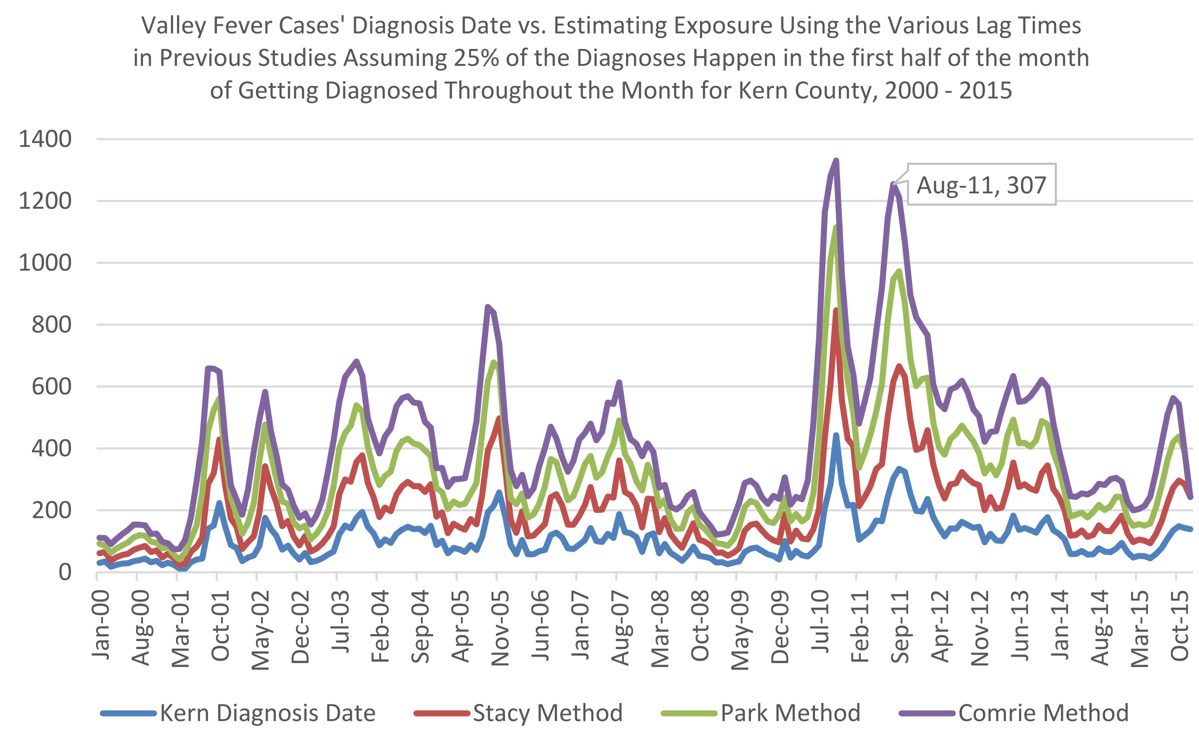
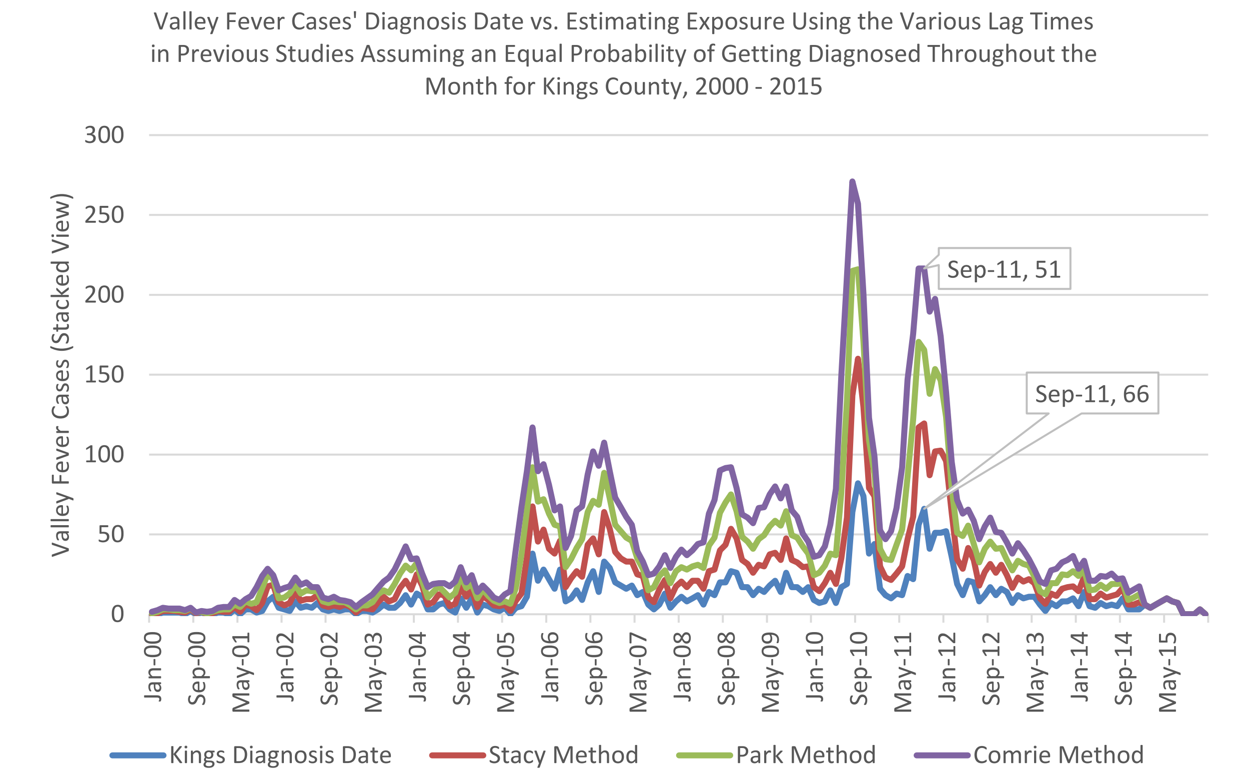


Figure 2.11: Diagnosis and Exposure Estimates for Kings County



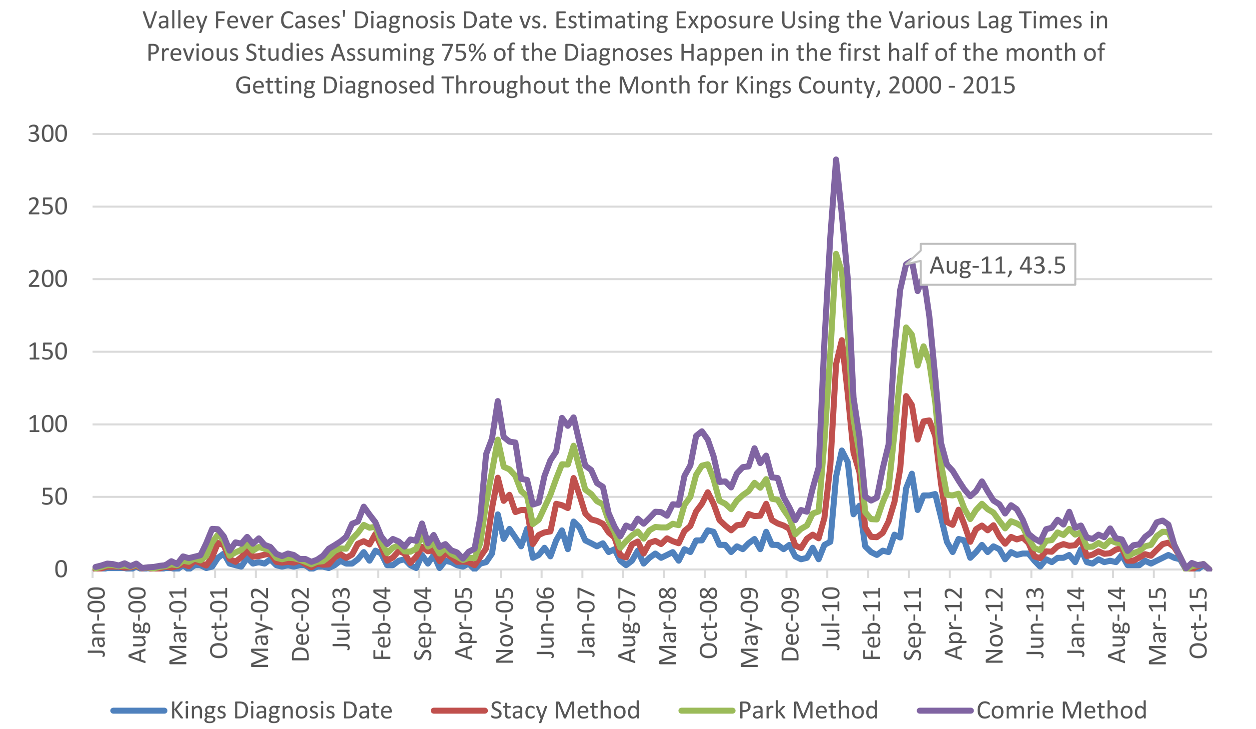


Figure 2.11: Diagnosis and Exposure Estimates for Kings County

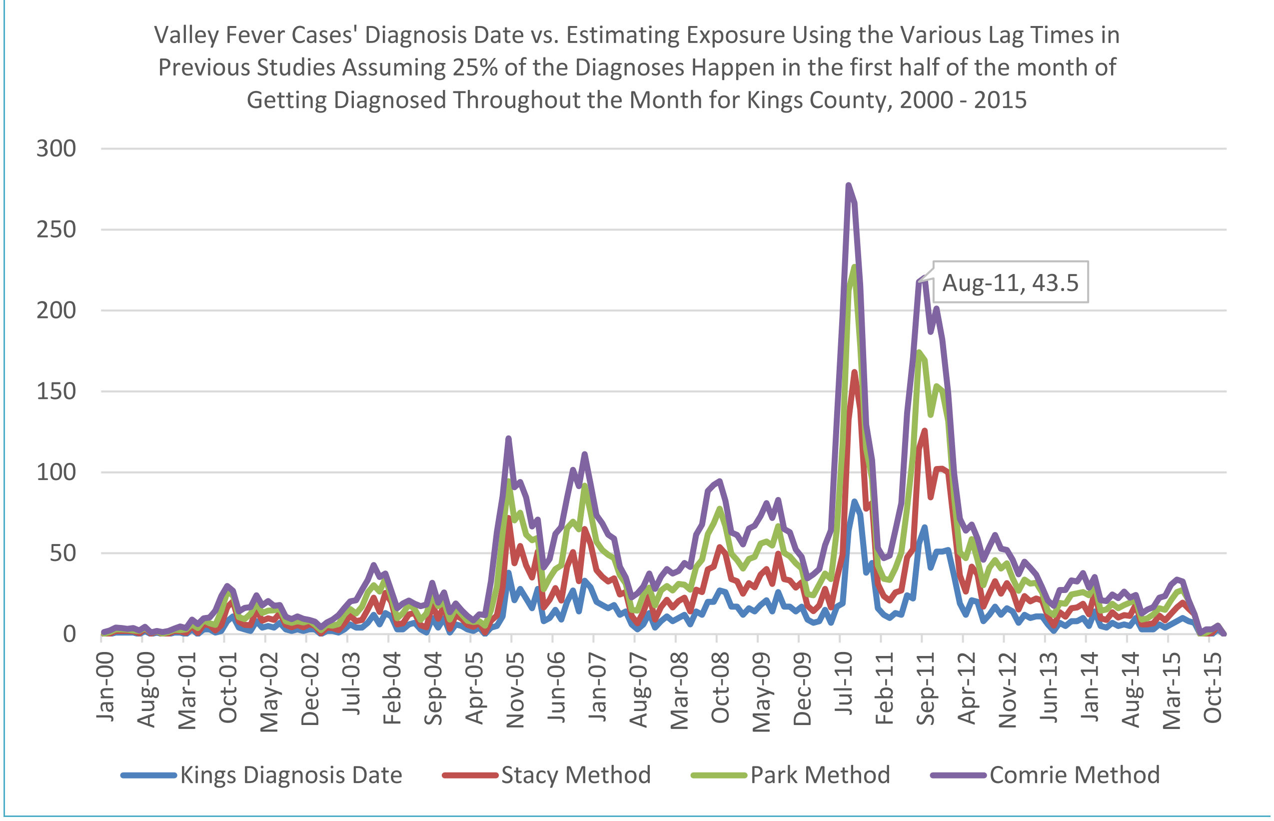
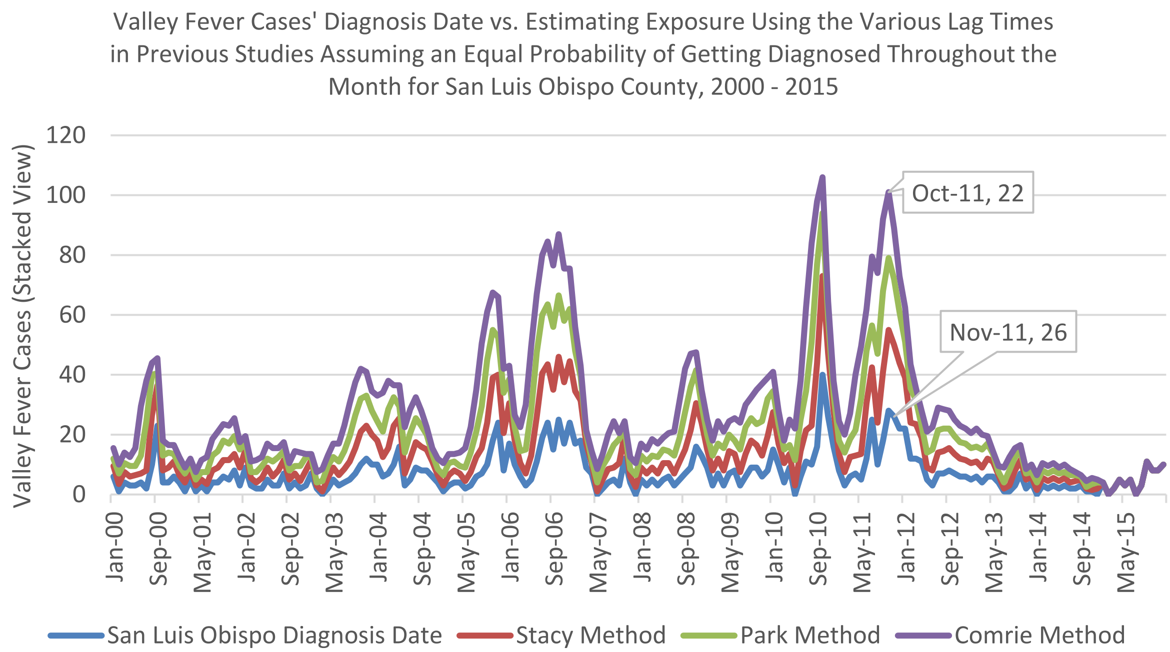


Figure 2.12: Diagnosis and Exposure Estimates for San Luis Obispo County



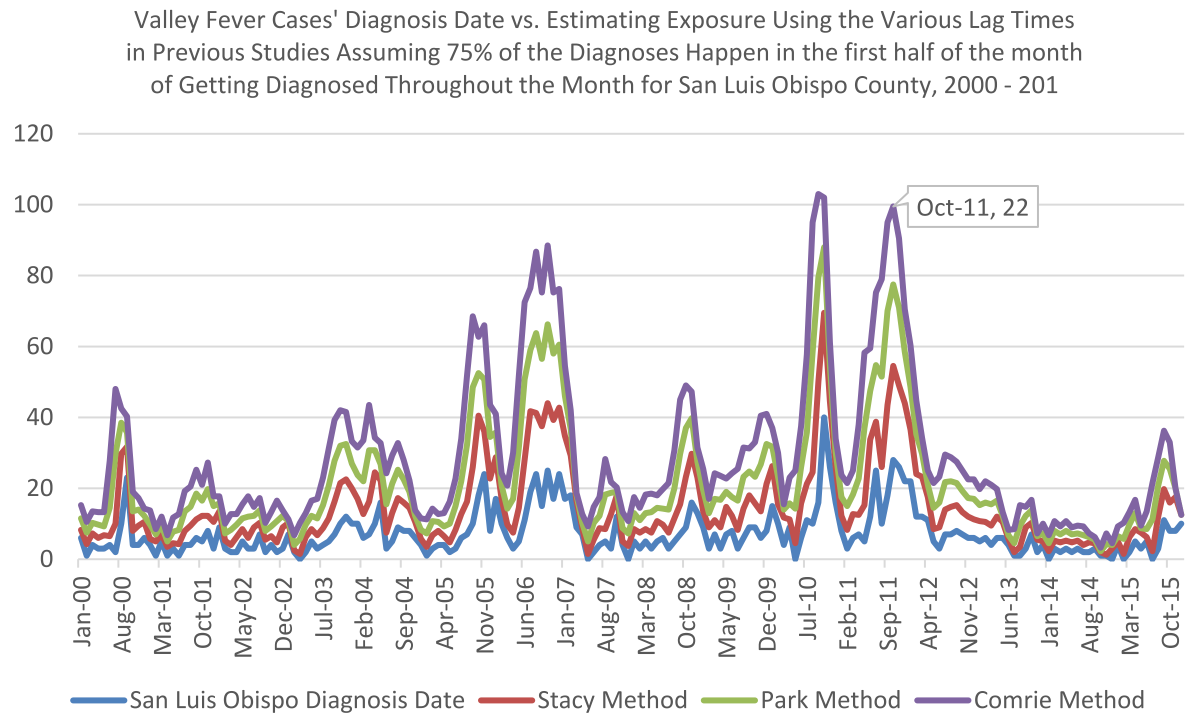


Figure 2.12: Diagnosis and Exposure Estimates for San Luis Obispo County

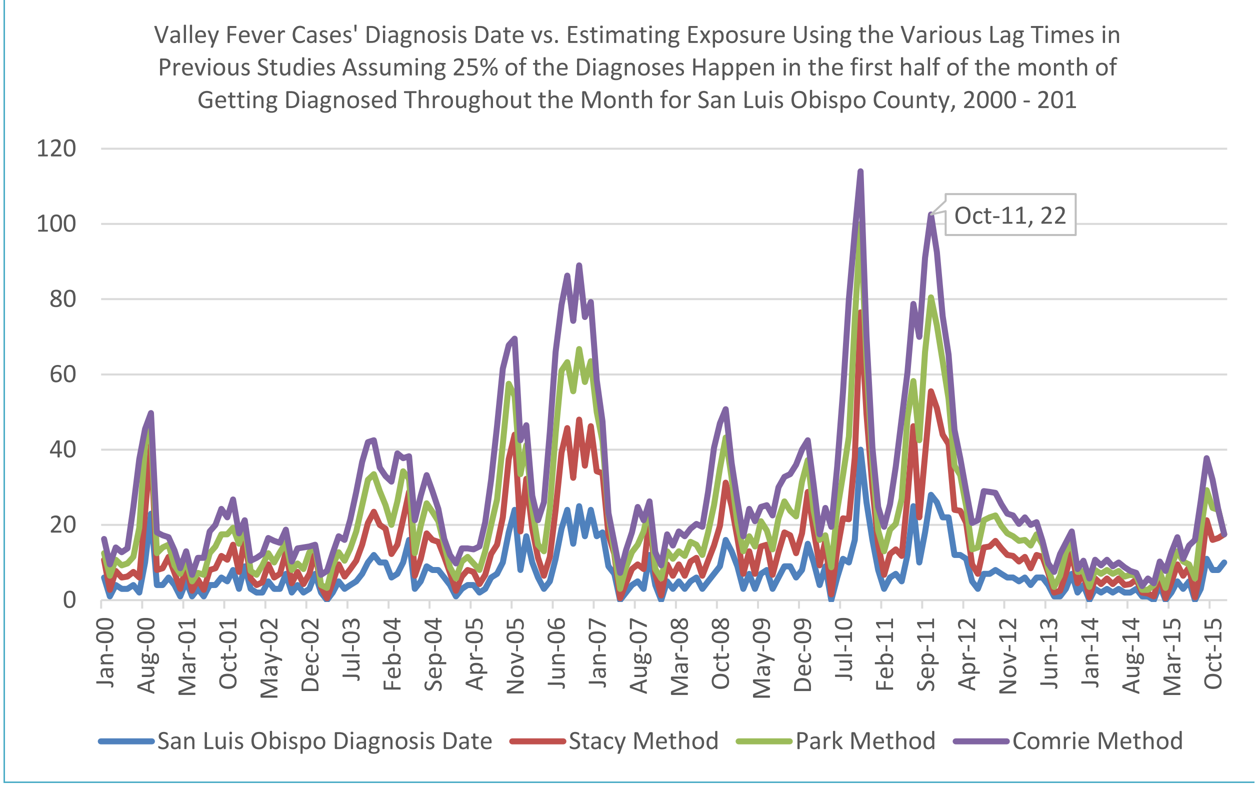
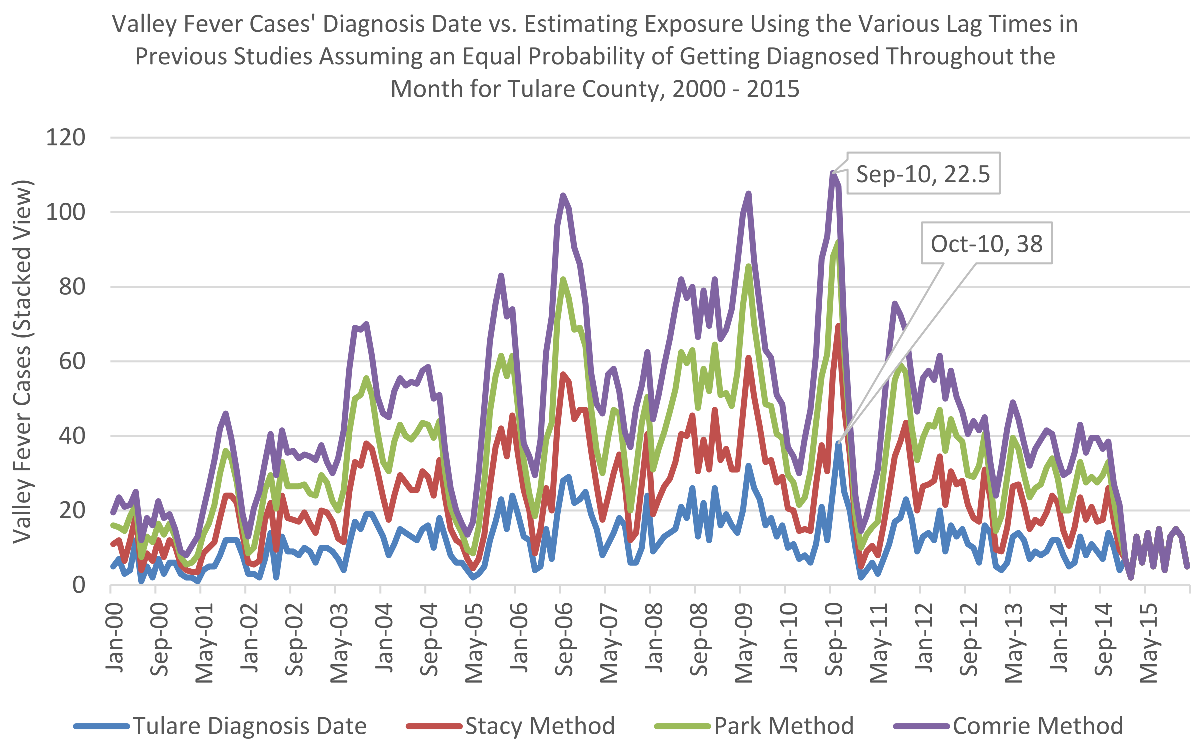


Figure 2.13: Diagnosis and Exposure Estimates for Tulare County



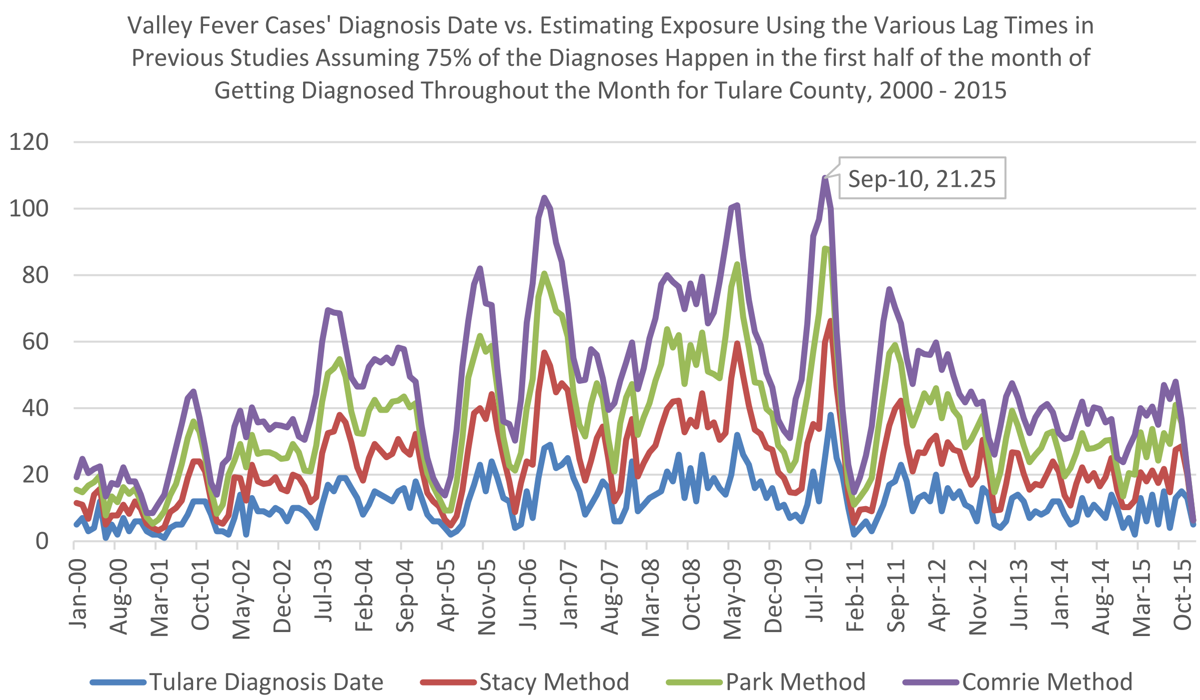
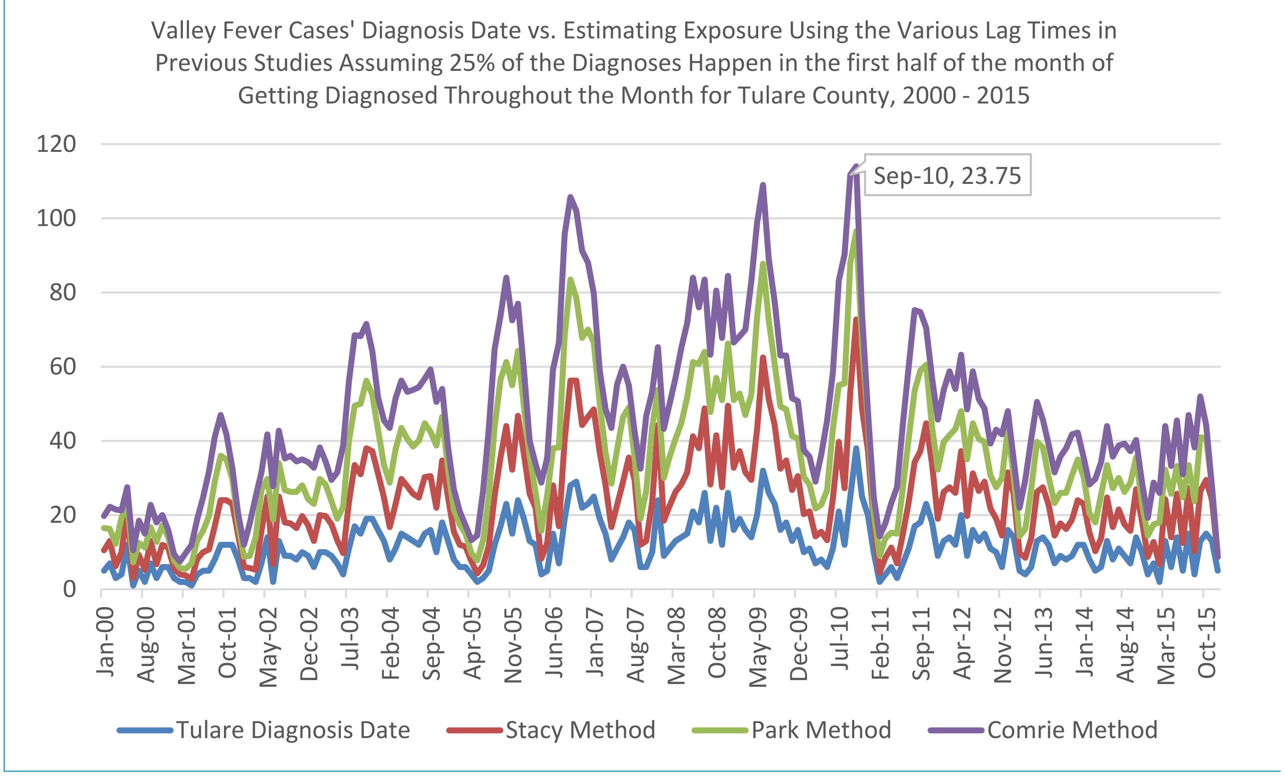


Figure 2.13: Diagnosis and Exposure Estimates for Tulare County



Utilizing ANOVA Single – Factor in Microsoft Excel, the results indicate that there is no statistically significant difference between the distributions in terms of average and variance. The results can be found in the Appendix, Tables A.1 – A.5.

When analyzing the seasonality component of the time-series decomposition of the exposure estimates, there are changes from using the various methods. Figures 2.14 – 2.18 show these components for each estimate. They are organized by County Name_Diagnosis Assumption (Equal – EM, 75% in first half – 75, 25% in first half – 25), Exposure Method (Stacey – ST, Park – PM, Comrie – CM).

With Fresno, Figure 2.14, we see some similarities to the original distribution, called Fresno_Actual. Diagnosis or Exposure is likely to happen six months out of the latter half of the year. Many of the exposure estimates lose the January seasonality and the entire season shifts forward by about two months. Fresno's Equal Diagnosis Assumption and Stacey Method (Fresno_EMST) sees a spike in May followed by a decrease in cases getting exposed for two months until August. With Kern County, Figure 2.15, the equal distribution assumption makes the seasonality become five months instead of four. Other than that, the distributions mirror the Diagnosis date's distribution, just 1-2 months before. The distributions in Kings County, Figure 2.16, mirror the Diagnosis date's distribution, just 1-2 months before as well. With San Luis Obispo, Figure 2.17, the method with only the 25% of cases diagnosed in the first half of the month and the Stacey method, captured the January seasonality that the Diagnosis date distribution saw. Lastly, the distributions in Tulare County, Figure 2.17, mirror the Diagnosis date's distribution, just 1-2 months before.

Figure 2.14: Fresno County Seasonality Components for the Exposure Method and Diagnosis Assumption Variables

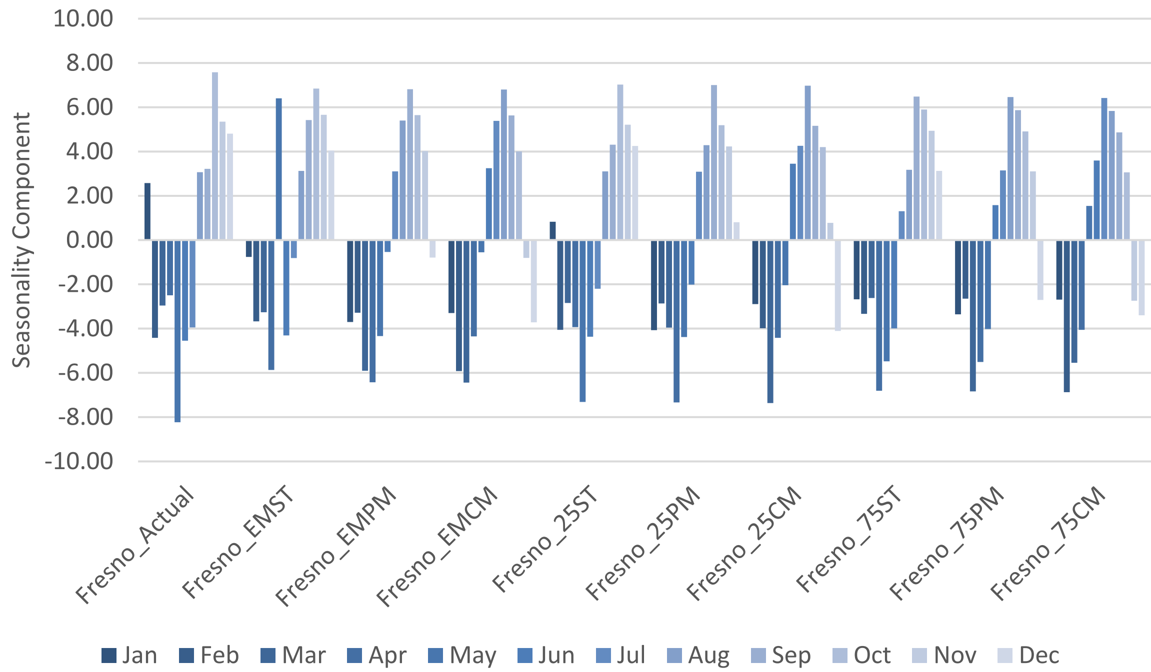


Figure 2.15. Kern County Seasonality Components for the Exposure Method and Diagnosis Assumption Variables

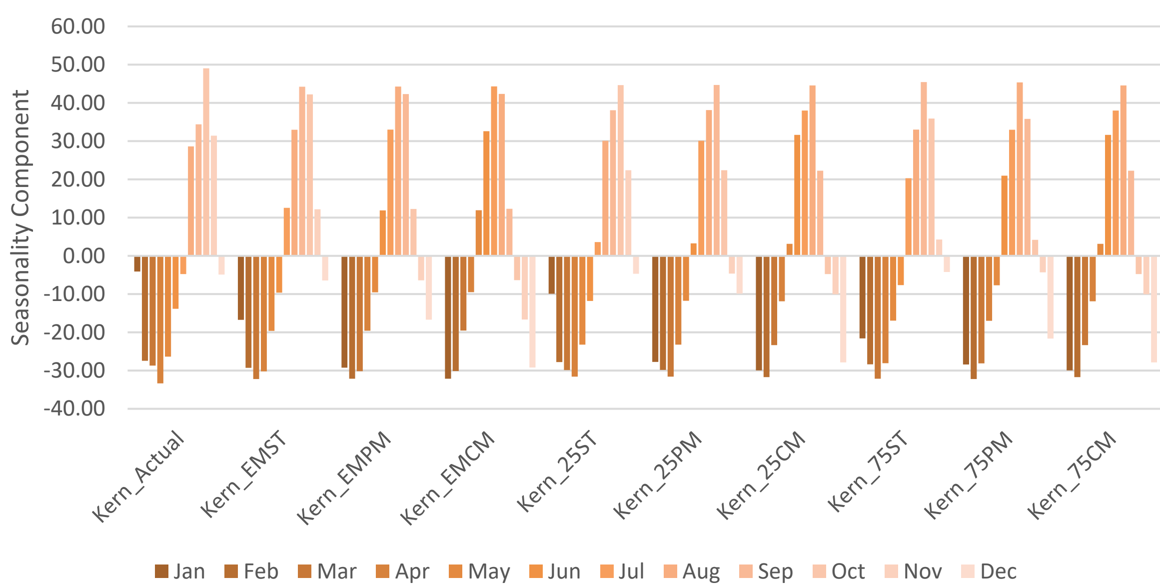


Figure 2.16. Kings County Seasonality Components for the Exposure Method and Diagnosis Assumption Variables

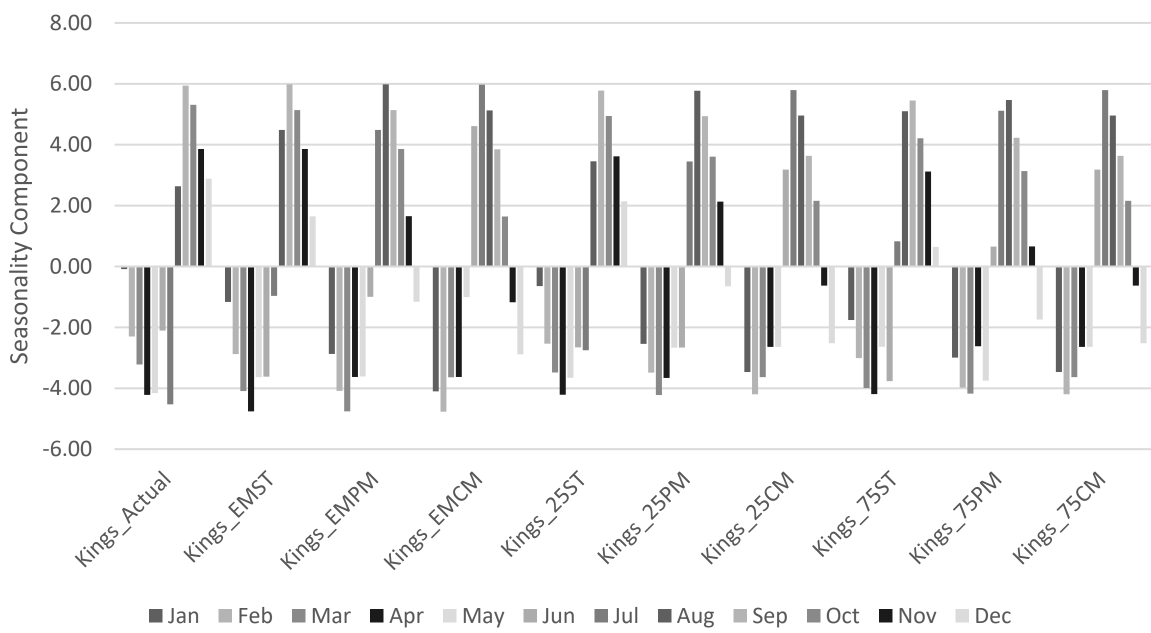
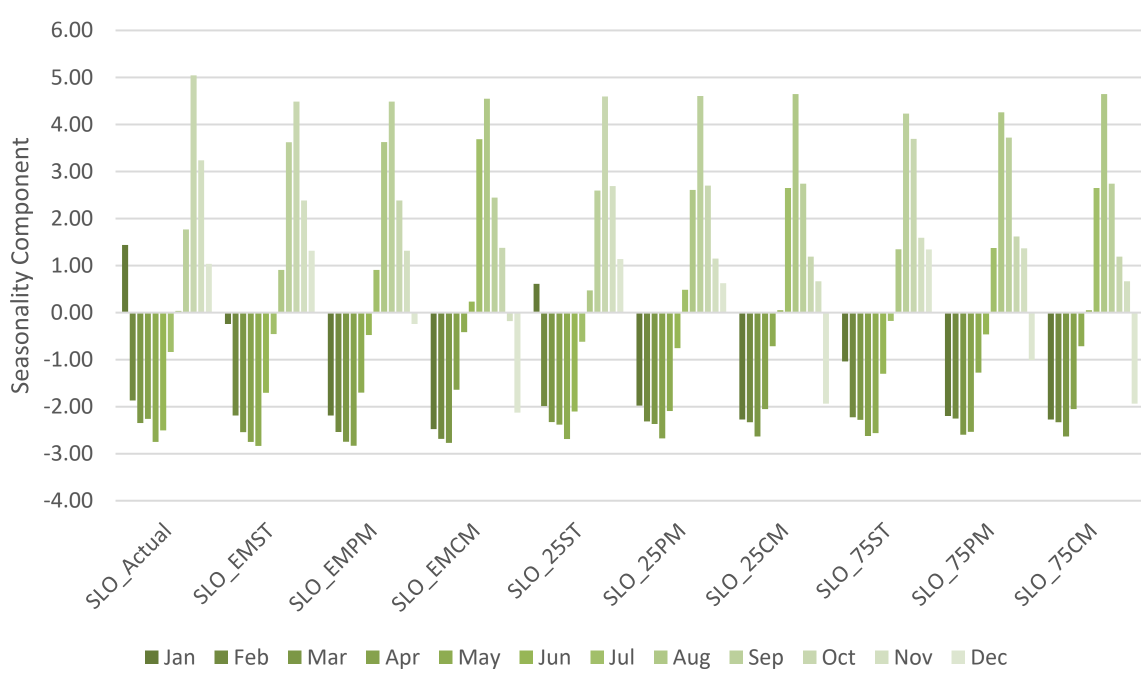
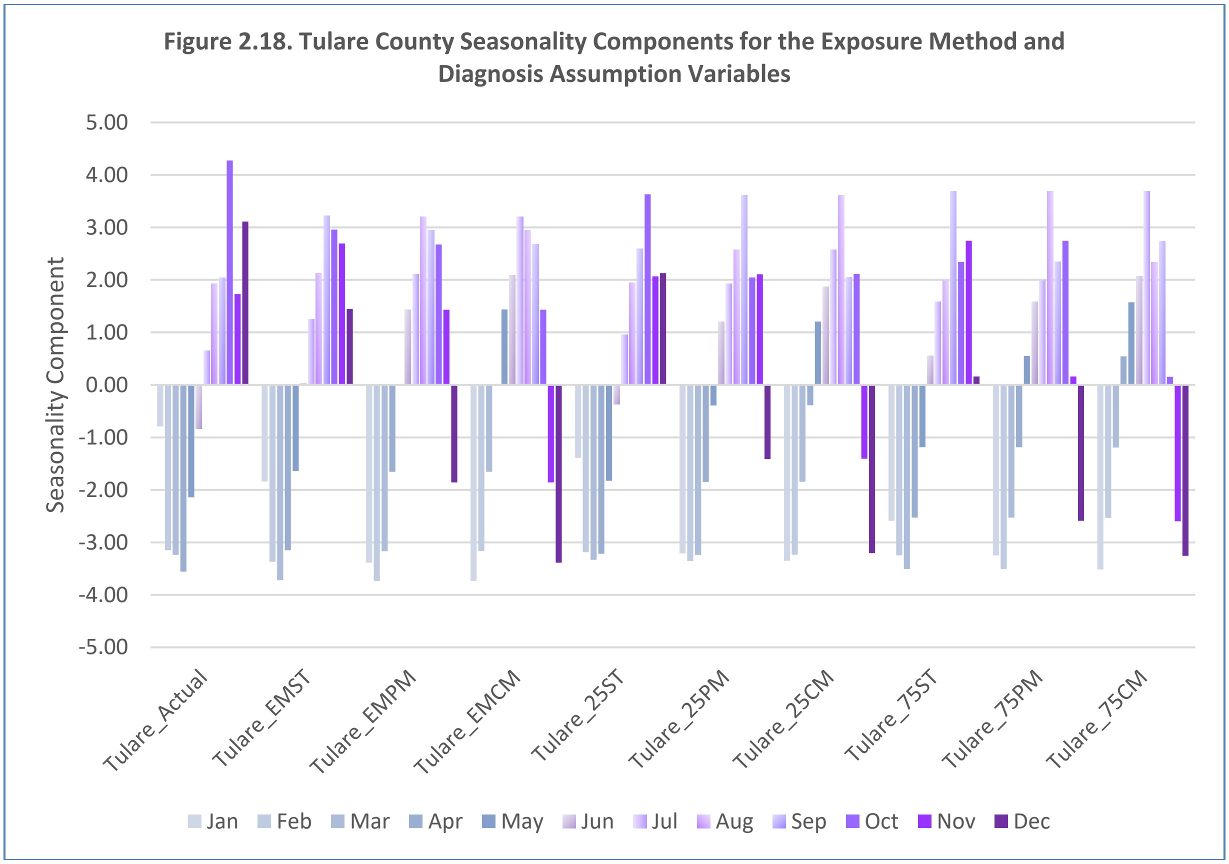


Figure 2.17. San Luis Obispo (SLO) County Seasonality Components for the Exposure Method and Diagnosis Assumption Variables





From this section, we can gather that considering different exposure methods can alter the seasonality of when the cases occur but kept the overall variability of the time-series. We can also see that being limited with diagnosis month of the cases decreases the reliability of exposure estimates. Chapter 4 and 5 will dive further into how these different methods of calculating exposure and case distribution assumptions will impact the relationships to climate and dust variables.

County Census Information

The Census Information summarized in Table 2.6 is sourced from the United States Census Bureau QuickFacts. QuickFacts data are derived from: Population Estimates, American Community Survey, Census of Population and Housing, Current Population Survey, Small Area Health Insurance Estimates, Small Area Income and Poverty Estimates, State and County Housing Unit Estimates, County Business Patterns, Nonemployer Statistics, Economic Census, Survey of Business Owners, Building Permits.

From Table 2.6, we see that the counties are not identical when it comes to the distribution of the population in terms of Age and Ethnicity. Table 6 shows that San Luis Obispo County has more percentage of retirees in their population (age 65+), Kings County has a smaller percentage of women in their population, and Tulare, Kings, Kern, and Fresno County all have over 50% of their population with Hispanic/Latino Ethnicity. Table 2.7 shows the estimated population counts in each of these categories based on 2015 population estimates and the U.S. Census Bureau population percentages. From this we can see that although San Luis Obispo has the smallest percentage of its population being of Hispanic/Latino Ethnicity, the estimated Hispanic/Latino population is larger than Kings and Kern Counties.

Using the census information and the number of cases diagnosed per year in each county, we estimated the number of cases that would have occurred if there were no demographic risk factors to the disease Valley Fever. The results are shown in Table 2.8. This information brings to attention the question of how the demographical makeup of the county effects the published risk factors of the disease. This is explored in the Odd Ratios section of this chapter.

Table 2.6: U.S. Census Bureau QuickFacts							
2012-2016		Tulare	San Luis Obispo	Kings	Kern	Fresno	California
Age	Persons under 5 years, percent	8.40%	4.80%	7.80%	8.10%	8.10%	6.30%
	Persons under 18 years, percent	31.20%	17.90%	27.30%	29.20%	28.60%	23.20%
	Persons 65 years and over, percent	10.90%	18.90%	9.70%	10.40%	11.80%	13.60%
Gender	Female persons, percent	50.00%	49.30%	44.90%	48.70%	50.10%	50.30%
Ethnicity	White alone, percent	88.30%	89.00%	81.30%	82.60%	77.10%	72.70%
	Black or African American alone, percent	2.20%	2.00%	7.20%	6.20%	5.80%	6.50%
	American Indian and Alaska Native alone, percent	2.80%	1.40%	3.10%	2.60%	3.00%	1.70%
	Asian alone, percent	4.00%	3.90%	4.50%	5.20%	10.80%	14.80%
	Native Hawaiian and Other Pacific Islander alone, percent	0.20%	0.20%	0.30%	0.30%	0.30%	0.50%
	Two or More Races, percent	2.50%	3.50%	3.60%	3.10%	3.10%	3.80%
	Hispanic or Latino, percent	64.10%	22.30%	54.20%	52.80%	52.80%	38.90%
	White alone, not Hispanic or Latino, percent	29.20%	69.20%	32.70%	34.80%	30.00%	37.70%

Table 2.7: Demographic Numbers Based on 2015 Population Estimate and U.S. Census Bureau Demographic Percentages						
		Tulare	San Luis Obispo	Kings	Kern	Fresno
Age	Persons under 5 years,	84,321	45,401	12,971	22,834	39,260
	Persons under 18 years,	313,192	169,306	45,400	82,316	138,620
	Persons 65 years and over,	109,416	178,765	16,131	29,318	57,193
Gender	Female persons,	501,910	466,302	74,668	137,287	242,828
Ethnicity	White alone,	886,373	841,802	135,202	232,853	373,693
	Black or African American alone,	22,084	18,917	11,974	17,478	28,112
	American Indian and Alaska	28,107	13,242	5,155	7,330	14,541

Table 2.7: Demographic Numbers Based on 2015 Population Estimate and U.S. Census Bureau Demographic Percentages						
		Tulare	San Luis Obispo	Kings	Kern	Fresno
	Native alone,					
	Asian alone,	40,153	36,888	7,483	14,659	52,346
	Native Hawaiian and Other Pacific Islander alone,	2,008	1,892	499	846	1,454
	Two or More Races,	25,095	33,105	5,987	8,739	15,025
	Hispanic or Latino,	643,448	210,924	90,134	148,845	255,914
	White alone, not Hispanic or Latino,	293,115	654,525	54,380	98,103	145,406

Table 2.8: Expected Case Distribution Based on Population Percentages and Total Cases Diagnosed											
		Fresno		Kern		Kings		San Luis Obispo		Tulare	
		2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
Age	Persons under 5 years,	58	58	155	207	29	29	7	8	15	11
	Persons under 18 years,	206	205	559	747	103	100	27	29	57	39
	Persons 65 years and over,	85	85	199	266	37	36	29	30	20	14
Gender	Female persons,	361	360	933	1246	170	165	74	79	91	63
Ethnicity	White alone,	556	554	1582	2113	307	298	134	143	161	111
	Black or African American alone,	42	42	119	159	27	26	3	3	4	3
	American Indian and Alaska Native alone,	22	22	50	67	12	11	2	2	5	4
	Asian alone,	78	78	100	133	17	17	6	6	7	5
	Native Hawaiian	2	2	6	8	1	1	0	0	0	0

Table 2.8: Expected Case Distribution Based on Population Percentages and Total Cases Diagnosed											
		Fresno		Kern		Kings		San Luis Obispo		Tulare	
		2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
	and Other Pacific Islander alone,										
	Two or More Races,	22	22	59	79	14	13	5	6	5	3
	Hispanic or Latino,	381	379	1011	1351	205	199	34	36	117	81
	White alone, not Hispanic or Latino,	216	215	666	890	124	120	104	111	53	37
	Yearly Totals from CDPH	721	718	1915	2558	378	367	151	161	182	126

Valley Fever Cases by Demographics

The California Department of Public Health, Infectious Diseases Branch, Surveillance & Statistics Section, collapsed cells that had under 11 cases for privacy reasons. Table 2.9 – 2.11 show the actual cases that occurred in each county for 2010 and 2011 by provided demographic information. From the tables 2.9 – 2.11, we can see that more cases occurred for people under 15 years old than for adults older than 65 years, except in San Luis Obispo. All counties have more males being diagnosed than females and the highest amount of cases that occurred were in Hispanics (except in San Luis Obispo County). However, as mentioned when discussing the Census information, a majority of these populations have more males than females and Hispanics are the highest ethnicity. Are the risk factors related to demographics statistically significant given the ethnic composition of the county?

Table 2.9: Valley Fever Cases by County by Age Group for 2010 and 2011										
	Fresno		Kern		Kings		San Luis Obispo		Tulare	
	2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
Under 4	11	16	22	24	*	*	*	*	*	*
Under 15	62	72	169	217	30	18	*	*	12	17
15-64	618	599	1573	2101	342	335	116	136	156	94
65+	41	47	157	240	12	14	35	25	26	17

Table 2.10: Valley Fever Cases by County by Gender for 2010 and 2011										
	Fresno		Kern		Kings		San Luis Obispo		Tulare	
	2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
Female	150	133	773	1049	81	57	51	51	78	52
Male	570	591	1139	1508	303	317	112	119	116	75
Other	*	0	*	*	*	0	0	0	0	0

Table 2.11: Valley Fever Cases by County by Ethnicity for 2010 and 2011										
	Fresno		Kern		Kings		San Luis Obispo		Tulare	
	2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
Black, Non-Hispanic	83	103	51	59	34	33	11	11	0	*
Hispanic	326	266	396	462	96	116	29	47	72	57
White, Non-Hispanic	92	99	181	251	29	37	117	94	44	20

Odds Ratios

Odds ratios are a statistic that is useful at examining effect size (McHugh). An odds ratio (OR) is used to determine the odds of an event and can provide information related to populations at risk in observational studies. The higher the odds, the more at risk a person is with that certain parameter. An Odds Ratio under 1 indicates that the odds are actually less for that parameter. Several studies have been conducted to understand populations at risk in Valley Fever endemic areas. Most of the results are analyzed for specific populations – like elderly, pediatric, and hospitalized patients. For Sondermeyer *et al*., 2013, they found that male sex, older age groups, and Black and Hispanic ethnicities (2.09 and 1.31 ORs compared to Whites) had higher odds of hospitalization in endemic regions in California. For Sondermeyer *et al*., 2016, they found a relative risk of 1.4 for Black children more likely to be hospitalized compared to white children. Flaherman *et al*. found that individuals who were older, Black, Male, and individuals with pregnancy and immosuppressive disorders had higher risk for hospitalizations in California. Noble *et al*. calculated mortality rates and associated demographic risks after controlling for the US Census population estimates. Noble *et al*. found that there were no significant odd ratios when looking at the interaction of race and ethnicity by sex.

Looking at cases that were diagnosed for the five counties, I took the total diagnosed cases for 2010 and calculated the number of cases if there were no relationship between the demographic factors and disease outbreak other than the general population breakdown. As 2010 had the highest amount of cases across all the counties, 2010 has the least collapsed cells and can provide the most reliability with our estimates.

Table 2.12 provides the odd ratio estimates by Gender. For Fresno County in 2010, the odds of Valley Fever in Males is 3 times as much as the estimated number of cases we would expect based on the Census population estimate. The odds of a case being Male are statistically significantly more than what we would expect from the proportion of Males in Fresno County. Fresno, Kern, Kings, and San Luis Obispo Counties all find that the Male gender has greatest odds of getting diagnosed with the disease. Tulare County found that Males had higher odds of getting diagnosed, but it was not significant at the .05 level. One thing to note is that the magnitude of risk for getting diagnosed as a Male is not consistent across the five counties. For example, Males in Fresno are 3-4.8 times more likely to get diagnosed than females in that county, while Males in Kern County are 1.2-1.59 more likely than females to get diagnoses.

Table 2.12: Odd Ratio Estimates for Gender/Sex for 2010						
2010		Males	Females	Odd Ratio	95% Confidence Interval	P value
Fresno	Actual	570	150	3.8106	3.0226 – 4.8039	<.0001
	Population Estimate	360	361			
Kern	Actual	1139	773	1.4000	1.2318 – 1.5910	<.0001
	Population Estimate	982	933			
Kings	Actual	303	81	3.0573	2.2244 – 4.2023	<.0001
	Population Estimate	208	170			
San Luis Obispo	Actual	112	51	2.1105	1.3326 – 3.3426	.0015
	Population Estimate	77	74			
Tulare	Actual	116	78	1.4872	.9885 – 2.2373	.0568
	Population Estimate	91	91			

Table 2.13 provides the odd ratio estimates for Hispanic or Latino ethnicity. For Fresno County, 2010, the odds of Valley Fever in Hispanics are .7365 compared to the estimated number of cases we would expect based on population estimate. The odds of a case being Hispanic are less than what we would expect from the proportion of Hispanics in Fresno County. The odds of a case being Hispanic is less than what we would expect across all counties, which means they are not as likely to get diagnosed and would indicate Hispanic individuals are inherently less at risk. They have a greater number of cases diagnosed because there are more people in the county that are Hispanic. However, San Luis Obispo's odd ratio is not significant at the .05 level. Again, however, we see that the magnitude of the odds is not the same across all counties.

Table 2.13: Odd Ratio Estimates for Hispanic Ethnicity for 2010						
2010		Hispanic	Other	Odd Ratio	95% Confidence Interval	P value
Fresno	Actual	326	395	.7365	.5987 - .9060	.0038
	Population Estimate	381	340			
Kern	Actual	396	1519	.2331	.2022 - .2688	<.0001
	Population Estimate	1011	904			
Kings	Actual	96	282	.2873	.2112 - .3907	<.0001
	Population Estimate	205	173			
San Luis Obispo	Actual	29	122	.8180	.4688 – 1.4271	.4792
	Population Estimate	34	117			
Tulare	Actual	72	110	.3636	.2378 - .5559	<.0001
	Population Estimate	117	65			

Table 2.14 provides the odd ratio estimates for Black (only, non-Hispanic) ethnicity. For Fresno County, 2010, the odds of Valley Fever in Black ethnicity are 2 times higher compared to the estimated number of cases we would expect based on population estimate. The odds of a case being Black are more than what we would expect from the proportion of Blacks in Fresno and San Luis Obispo County and the odds is less than what we would expect in Kern County. Kings and Tulare Counties' odd ratios are not significant at the .05 level.

Table 2.14: Odd Ratio Estimates for Black Ethnicity for 2010

2010		Black	Other	Odd Ratio	95% Confidence Interval	P value
Fresno	Actual	83	638	2.1032	1.4289 – 3.0957	.0002
	Population Estimate	42	679			
Kern	Actual	51	1864	.4129	.2956 - .5769	<.0001
	Population Estimate	119	1796			
Kings	Actual	34	344	1.2849	.7588 – 2.1757	.3509
	Population Estimate	27	351			
San Luis Obispo	Actual	11	140	3.8762	1.0592 – 14.1855	.0407
	Population Estimate	3	148			
Tulare	Actual	0	182	.1087	.0058 – 2.0334	.1375
	Population Estimate	4	178			

Table 2.15 provides the odd ratio estimates for White (only, non-Hispanic) ethnicity. For Fresno County, 2010, the odds of Valley Fever in White ethnicity are .3420 compared to the estimated number of cases we would expect based on population estimate. The odds of a case being White are less than what we would expect from the proportion of Whites in Fresno, Kern, and Kings Counties. San Luis Obispo and Tulare Counties' odd ratios are not significant at the .05 level.

Table 2.15: Odd Ratio Estimates for White Ethnicity for 2010

2010		White	Other	Odd Ratio	95% Confidence Interval	P value
Fresno	Actual	92	629	.3420	.2609 - .4483	<.0001
	Population Estimate	216	505			
Kern	Actual	181	1734	.1958	.1636 - .2343	<.0001
	Population Estimate	666	1249			
Kings	Actual	29	349	.1702	.1101 - .2631	<.0001
	Population Estimate	124	254			
San Luis Obispo	Actual	117	34	1.5551	.9299 – 2.6009	.0924
	Population Estimate	104	47			
Tulare	Actual	44	138	.7760	.4868 – 1.2370	.2865
	Population Estimate	53	129			

Table 2.16 provides the odd ratio estimates for cases that are over 65 years old. For Fresno County, 2010, the odds of Valley Fever in the elderly population are .4511 compared to the estimated number of cases we would expect based on population estimate. The odds of a case being elderly are less than what we would expect from the proportion of the population over 65 in Fresno, Kern, and Kings Counties. San Luis Obispo and Tulare Counties' odd ratios are not significant at the .05 level.

Table 2.16: Odd Ratio Estimates for 65 and Older Age for 2010

2010		65 Years and Older	Other	Odd Ratio	95% Confidence Interval	P value
Fresno	Actual	41	680	.4511	.3060 - .6650	.0001
	Population Estimate	85	636			
Kern	Actual	157	1758	.7701	.6183 - .9592	.0197
	Population Estimate	199	1716			
Kings	Actual	12	366	.3022	.1550 - .5891	.0004
	Population Estimate	37	341			
San Luis Obispo	Actual	35	116	1.2693	.7295 – 2.2087	.3988
	Population Estimate	29	122			
Tulare	Actual	26	156	1.3500	.7240 – 2.5172	.3451
	Population Estimate	20	162			

By having the California Department of Public Health limit access to case data, only provide yearly summary findings on age, gender, and ethnicity, and collapsing any fields with cases under 11, we are limited to our ability to understand the demographic risks associated to cases and this is expanded further in the Conclusion chapter.

Our findings show that the risk of disease is not equal across counties and that African Americans and Males have the highest risk for the disease than what we would expect based on population estimates and previously published risk factors of old age and Hispanics were found to not be at risk, but higher than normal due to the population demographics of the counties. Researchers should work with the California Department of Public Health to highlight the need for more refined and less aggregated data for analyses. The limitations provided by the California Department of Public Health further limit the results and usability of the results for public health preparedness.

Chapter 3

Descriptive Analysis on Environmental Variables and their Spatial Relationship to the Study Area

Introduction

One of the goals of this study is to understand how various environmental variables are related to the disease known as Valley Fever. From the 1950s, different environmental factors were considered to have a "Grow and Blow" Effect on the Coccidioides immitis spores (Egeberg (1956), Hugenholtz (1957), Maddy (1965), Jinadu (1995), Stevens (1995)). The "Grow and Blow" Effect hypothesizes that there is a wet period to "Grow" the spores and then, a dry period that allows the spores to "Blow." (Egeberg (1956), Hugenholtz (1957), Maddy (1965), Jinadu (1995), Stevens (1995)).

As shown in Table 1.1 (Chapter 1), various studies have conducted research attempting to connect climate with Valley Fever diagnoses or exposure. Different variables studied include temperature, precipitation, soil moisture, dust concentrations, vegetation indexes, wind speed, particulate matter (PM) – concentration 10, and drought indices. The studies were also conducted at the County level.

To attempt to understand how environmental variables are linked to disease, it is important to understand the variability within those variables. Since previous analyses were conducted on the county-wide scale, most environmental variables are measured at monitoring stations with a specific latitude and longitude. There is typically more than one station within the county.

The purpose of this chapter is to describe the seasonality and patterns of the various environmental factors and compare those patterns amongst the different monitoring stations within the same geographical area. This information will guide decisions to the variables that show relationships to Valley Fever and provide transparency in the process that the previously conducted studies do not discuss.

The environmental variables included in this study are:

- Precipitation;
- Temperature;
- Wind Speed;
- Evapotranspiration;
- El Niño Southern Oscillation;
- Palmer Drought Severity Index;
- Particulate Matter 10;
- Particulate Matter 2.5;
- Soil Information: Percent clay, percent silt, percent sand, and pH.

Precipitation

Precipitation is the condensation of atmospheric water vapor that falls. The main forms of precipitation include rain, snow, and hail. In the United States, precipitation is measured in inches (in).

<u>Data Source</u>

Precipitation data was obtained several ways. One precipitation source came from Drought Atlas for the years November 1980 to December 2012. Another source was from the National Oceanic and Atmospheric Administration International Research Institute for Climate and Society/ Lamont – Doherty Earth Observatory (NOAA IRI/LDEO) Climate Data Library where satellites average precipitation over NOAA climate divisions 404 and 405 and monthly precipitation was obtained from 2000 – 2013.

Station Location

Figure 3.1 shows the location of the three sources of precipitation data for the study area. San Luis Obispo County is located in three different NOAA zones, but primarily Zone 4. The rest of the study is a part of Zone 5, except the southeast part of Kern County.

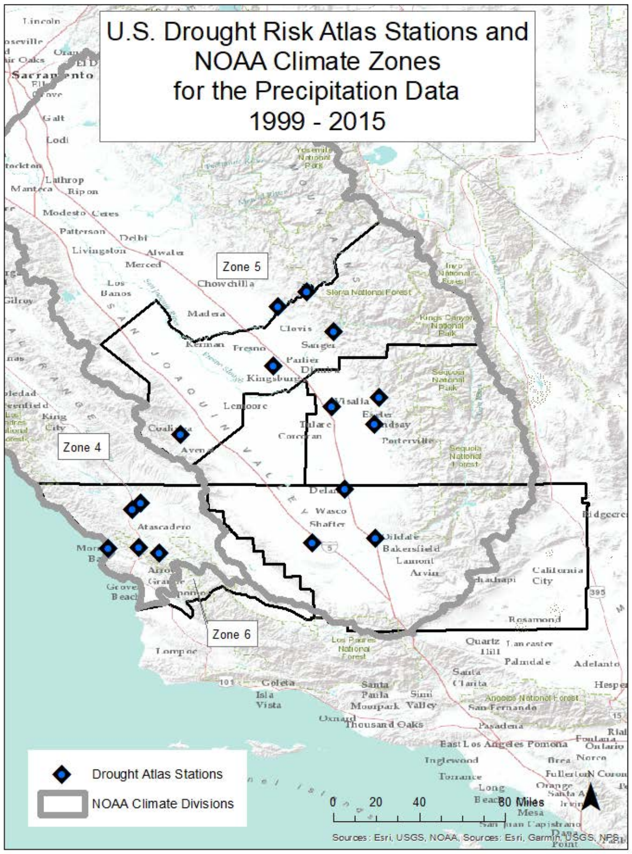
Data Variability

Table 3.1 shows the precipitation variabilities by Station.

In Fresno County, although precipitation measurements vary from Station to Station, all the Stations measured 2010 as the year with the largest amount of precipitation. However, the year with the second largest amount of precipitation and the year with the lowest amount of precipitation are not the same from Station to Station. All the Stations, except Coalinga, measured December as the month with the highest average precipitation over the years and all Stations measured the driest period to be during June – September.

For Kern County, all the Stations, except Delano, measured 2010 as the year with the highest amount of precipitation and 2005 as the second highest. There is no consistency in the year with the lowest amount of precipitation measured ranging from 2007 – 2009. All Stations, except Delano, found December is the month with the highest precipitation over all the years and all Stations measured the driest period to be during June – September.

Figure 3.1: Precipitation Stations for Study Area



For Kings County, there was no Drought Atlas measurement Station located in Kings County. Visalia station was listed as the closest station. Using Visalia and 405 Climate Division, we see that both Stations measured 2010 as the year with the largest amount of precipitation. The year with the second largest amount of precipitation does not match for the Stations. All Stations found December has the month with the highest precipitation over all the years and all Stations measured the driest period to be during June – September.

For San Luis Obispo County, all Stations measured 2010 as the year with the largest amount of precipitation and all Stations, except 404 Division, measured 2001 as second highest precipitation year. All Stations measured 2007 as driest year. All Stations, except 404 Division, measured January as the month with the largest amount of precipitation and June- September as the driest months.

For Tulare County, all Stations measured 2010 as the year with the highest amount of precipitation and all Stations, except 405 Division, measured 2006 as second highest precipitation year. The Stations did not have a consensus on the year with the lowest amount of precipitation. All Stations found December has the month with the highest precipitation over all the years and all Stations measured the driest period to be during June – September.

One observation that can be applied to all the precipitation measurement Stations is that the total amount of precipitation per month varies Station to Station, even in the same county. For many of the Stations, the variation year to year and month to month seem to align but are not one-hundred percent consistent within each county. In addition, the NOAA climate zones have more instances where the data does not align with the individual station data.

Table 3.1: Monthly and Yearly Precipitation by County and Station

Fresno County – Average Monthly Precipitation

Inches	Kfat Station	Coalinga Station	Friant Station	PineFlat Station	Auberry Station	405 Division Station
Jan	2.32	1.90	2.80	3.36	4.48	3.14
Feb	2.28	1.46	2.74	3.43	4.44	3.30
Mar	2.01	1.09	2.33	2.50	3.47	2.53
Apr	1.45	0.73	1.56	2.25	2.58	1.90
May	0.49	0.32	0.55	0.80	1.06	0.83
Jun	0.24	0.03	0.26	0.34	0.32	0.19
Jul	0.03	0.00	0.02	0.02	0.04	0.05
Aug	0.03	0.01	0.01	0.03	0.05	0.05
Sep	0.05	0.07	0.06	0.07	0.14	0.13
Oct	0.91	0.34	1.00	1.20	1.51	1.24
Nov	1.01	0.53	1.19	1.17	1.77	1.65
Dec	2.59	1.67	2.93	3.99	4.80	3.80
Monthly Average	1.12	0.68	1.29	1.60	2.05	1.57

Fresno County – Annual Total Precipitation

Inches	Kfat Station	Coalinga Station	Friant Station	PineFlat Station	Auberry Station	405 Division Station
2000	15.34	5.44	22.58	24.07	32.77	21.57
2001	12	9.96	16.1	20.06	26.71	21.29
2002	6.71	4.26	9.43	14.41	17.4	15.8
2003	9.25	7.47	11.15	14.72	17.35	16.84
2004	9.91	7.49	12.47	15.11	20.2	17.14
2005	12.23	12.2	18.38	20.26	28.39	24.94
2006	14.79	9.55	19.29	24.8	33.21	23.28
2007	7.03	4.51	8.15	11.64	12.47	11.17
2008	8.46	6.56	11.11	16.09	20.82	15.14
2009	15.51	7.1	11.84	17.22	21.39	16.59
2010	28.82	14.38	26.05	33.41	39.14	28.3
2011	17.31	7.04	17.87	18.18	24.56	16.75
2012	17.09	9.99	16.39	19.03	26.14	15.59
Total	174.45	105.95	200.81	249.00	320.55	244.40

Kern County – Average Monthly Precipitation

Inches	Bakersfield Station	Buttonwillow Station	Delano Station	405 Division Station
Jan	0.97	0.98	1.42	3.14

Table 3.1: Monthly and Yearly Precipitation by County and Station

Feb	1.13	1.02	1.71	3.30
Mar	0.81	0.74	1.26	2.53
Apr	0.71	0.60	0.86	1.90
May	0.18	0.16	0.25	0.83
Jun	0.02	0.02	0.07	0.19
Jul	0.01	0.01	0.01	0.05
Aug	0.00	0.01	0.00	0.05
Sep	0.02	0.00	0.03	0.13
Oct	0.32	0.30	0.44	1.24
Nov	0.48	0.47	0.58	1.65
Dec	1.13	1.14	1.27	3.80
Average Monthly	0.48	0.46	0.66	1.57

Kern County – Total Annual Precipitation

Inches	Bakersfield Station	Buttonwillow Station	Delano Station	405 Division Station
2000	5.07	5.08	7.85	21.57
2001	7.38	6.26	8.78	21.29
2002	4.31	4.13	5.28	15.8
2003	5.19	6.89	4.85	16.84
2004	5.07	6.27	6.61	17.14
2005	8.68	7.53	15.1	24.94
2006	6.71	6.57	9.84	23.28
2007	2.98	2.65	4.65	11.17
2008	3.24	2.43	4.38	15.14
2009	5.11	4.09	4.19	16.59
2010	12.51	11.39	13.51	28.3
2011	4.39	4.04	11.46	16.75
2012	4.42	3.87	6.21	15.59
Total	75.06	71.2	102.71	244.4

Kings County - Average Monthly Precipitation

Inches	Visalia Station	405 Division Station
Jan	1.85	3.14
Feb	1.83	3.30
Mar	1.28	2.53
Apr	1.40	1.90
May	0.35	0.83
Jun	0.16	0.19
Jul	0.01	0.05
Aug	0.01	0.05

Table 3.1: Monthly and Yearly Precipitation by County and Station		
Sep	0.03	0.13
Oct	0.62	1.24
Nov	0.90	1.65
Dec	2.02	3.80
Monthly Average	0.87	1.57
Kings County – Total Annual Precipitation		
Inches	**Visalia Station**	**405 Division Station**
2000	12.91	21.57
2001	15.13	21.29
2002	6.34	15.8
2003	8.5	16.84
2004	9.7	17.14
2005	13.1	24.94
2006	16.43	23.28
2007	5.43	11.17
2008	7.54	15.14
2009	7.4	16.59
2010	17.33	28.3
2011	7.39	16.75
2012	8.53	15.59
Total	135.73	244.4

San Luis Obispo County - Average Monthly Precipitation						
Inches	**Morro Bay Station**	**Salinas Dam Station**	**Santa Margarita Station**	**Paso Robles Station**	**Paso Robles Airport Station**	**404 Division Station**
Jan	2.43	4.81	6.30	3.24	2.43	3.70
Feb	2.22	4.45	6.63	2.93	2.22	4.23
Mar	1.69	2.93	3.86	2.13	1.69	2.92
Apr	0.86	1.99	2.33	1.11	0.86	1.71
May	0.29	0.45	0.65	0.42	0.29	0.60
Jun	0.03	0.09	0.19	0.05	0.03	0.20
Jul	0.01	0.01	0.00	0.01	0.01	0.01
Aug	0.02	0.01	0.02	0.03	0.02	0.02
Sep	0.01	0.02	0.03	0.01	0.01	0.09
Oct	0.76	1.52	2.11	1.11	0.76	1.32
Nov	0.79	1.65	2.55	1.11	0.79	2.01
Dec	2.06	4.02	6.12	2.64	2.06	4.95
Monthly Average	0.93	1.83	2.57	1.23	0.93	1.81
San Luis Obispo County – Total Annual Precipitation						

Table 3.1: Monthly and Yearly Precipitation by County and Station						
Inches	**Morro Bay Station**	**Salinas Dam Station**	**Santa Margarita Station**	**Paso Robles Station**	**Paso Robles Airport Station**	**404 Division Station**
2000	11.31	22.64	33.39	13.95	11.31	25.45
2001	16.47	29.49	39.74	18.97	16.47	26.13
2002	7.56	16.17	24.11	9.89	7.56	19.65
2003	7.82	14.28	21.66	10.72	7.82	18.19
2004	13.88	20.78	28.87	16.39	13.88	21.42
2005	13.99	24.09	34.83	17.54	13.99	28.23
2006	14.76	29.19	35.36	18.70	14.76	24.61
2007	4.20	11.06	16.54	7.76	4.20	12.22
2008	7.92	20.60	29.40	13.14	7.92	17.63
2009	8.46	21.83	29.27	14.55	8.46	19.31
2010	16.84	36.85	47.61	22.73	16.84	28.02
2011	12.61	22.70	31.85	15.15	12.61	19.09
2012	9.07	15.43	27.61	12.82	9.07	22.87
Total	144.89	285.11	400.24	192.31	144.89	282.82

Tulare County - Average Monthly Precipitation

Inches	**Visalia Station**	**Lemon Cove Station**	**Lindsay Station**	**405 Division Station**
Jan	1.85	2.47	1.99	3.14
Feb	1.83	2.20	2.04	3.30
Mar	1.28	2.04	1.56	2.53
Apr	1.40	1.79	1.62	1.90
May	0.35	0.58	0.49	0.83
Jun	0.16	0.11	0.06	0.19
Jul	0.01	0.01	0.03	0.05
Aug	0.01	0.00	0.01	0.05
Sep	0.03	0.04	0.06	0.13
Oct	0.62	0.77	0.74	1.24
Nov	0.90	1.19	1.05	1.65
Dec	2.02	2.59	2.40	3.80
Monthly Average	0.87	1.15	1.00	1.57

Tulare County – Total Annual Precipitation

Inches	**Visalia Station**	**Lemon Cove Station**	**Lindsay Station**	**405 Division Station**
2000	12.91	16.55	12.84	21.57
2001	15.13	17.29	12.72	21.29
2002	6.34	9.8	8.98	15.8

Table 3.1: Monthly and Yearly Precipitation by County and Station

2003	8.5	10.99	9.82	16.84
2004	9.7	9.88	9.25	17.14
2005	13.1	15.8	13.04	24.94
2006	16.43	18.72	14.94	23.28
2007	5.43	10.45	8.28	11.17
2008	7.54	10.26	9.5	15.14
2009	7.4	9.6	10.09	16.59
2010	17.33	25.02	23.49	28.3
2011	7.39	11.39	11.41	16.75
2012	8.53	13.78	12.07	15.59
Total	135.73	179.53	156.43	244.4

Temperature

Temperature describes the state of the atmosphere in terms of heat or cold. In the United States, temperature is measured in terms of degrees Fahrenheit (ºF).

<u>Data Source</u>

Temperature data was obtained from three sources. One precipitation source came from Drought Atlas for the years November 1980 to December 2012. Another source was from the IRI/LDEO Climate Data Library where satellites average temperature over climate Divisions 404 and 405 and monthly temperature was obtained from 1996 – 2013.

The last source is from the Department of Water Resources California Irrigation Management Information System (CIMIS) weather station network. They use a Fenwal Thermistor and Rotronic to measure air temperature and relative humidity. Daily temperature is measured.

<u>Station Location</u>

Figure 3.2 shows the station location of the three sources of temperature data for the study area.

Figure 3.2: Temperature Stations for Study Area

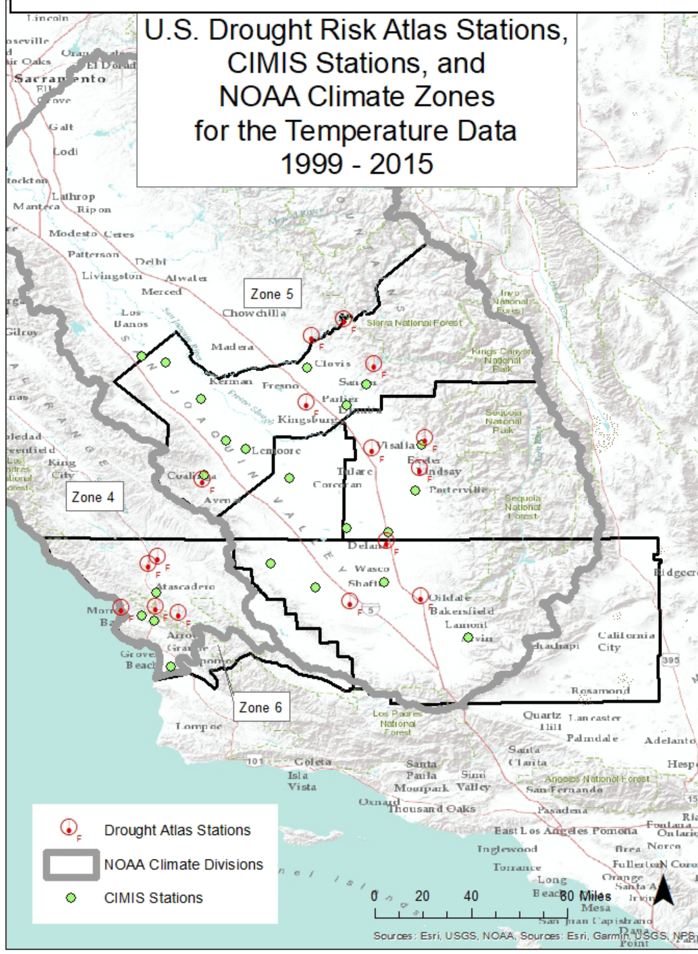


Table 3.2 shows the start and end dates for the CIMIS temperature stations. Out of nine stations in Fresno County, six have data throughout the entire period. Out of five stations in Kern County, three have data throughout the entire period. The only station in Kings County does have data during the entire study period. Out of four stations in San Luis Obispo County, one has data throughout the entire period. Out of four stations in Tulare County, only one has data throughout the entire period.

Table 3.2: CIMIS Stations Start and End Dates by County Location

Station Number	Start Date	End Date
	Fresno County	
2	Before January 1996	After December 2017
7	Before January 1996	After December 2017
39	Before January 1996	After December 2017
80	Before January 1996	December 2002
105	Before January 1996	After December 2017
124	Before January 1996	After December 2017
142	January 1999	After December 2017
190	May 2003	November 2010
205	March 2010	After December 2017
	Kern County	
5	Before January 1996	December 2013
54	Before January 1996	After December 2017
125	Before January 1996	After December 2017
138	September 1997	December 2015
146	October 1998	After December 2017
	Kings County	
15	Before January 1996	After December 2017
	San Luis Obispo County	
52	Before January 1996	After December 2017
160	November 2000	December 2003
163	November 2000	November 2010
202	August 2006	After December 2017
	Tulare County	
86	Before January 1996	After December 2017
169	August 2000	After December 2017
182	March 2002	After December 2017
203	October 2006	December 2016

Data Variability

Table 3.3 shows the temperature variabilities by Station for the Drought Atlas and IRI sources. Table 3.4 shows the temperature variabilities for the CIMIS stations.

For Fresno County, the monthly average temperature over time and across Stations and sources of Stations varies by 5 degrees Fahrenheit. All Stations were consistent in recording July as the consistent average hottest month and January was recorded as the coldest month for the Drought Atlas and IRI Stations. For CIMIS, all Stations registered December as the coldest month. All Stations from all sources with data during that timeframe (2000 – 2016), except Pineflat, found 2006 as the hottest year on record.

For Kern and Kings Counties, the monthly average temperature over time and across Stations varies by 3 degrees Fahrenheit. All Stations from all sources were consistent in recording July as the consistent average hottest month and January/December as the recorded coldest month. All Stations from Drought Atlas and IRI found 2006 as the hottest year on record. However, CIMIS stations found two out of six stations recording 2006 as the hottest year on record, but two stations found 2005 as the hottest and one station found 2003. The CIMIS station in Kings County measured 2014 as the hottest year on record, followed by 2005 and 2006.

For San Luis Obispo County, the monthly average temperature over time and across Stations varies by 2 degrees Fahrenheit for Drought Atlas and IRI sources. The CIMIS stations range on average between 52 – 58 degrees. Most Stations recorded July as the consistent average hottest month. Division 4 and Santa Margarita found August to be the hottest month on average and CIMIS station 202 recorded September and October has the hottest month. All Stations recorded December/January as the recorded coldest month. Most Stations recorded 2006 as the hottest year on record, except Salinas Dam and Santa Margarita which recorded 2012 as the hottest and CIMIS Station 52 and 202 that recorded 2015 as the hottest.

For Tulare County, the monthly average temperature over time and across Stations varies by 4 degrees Fahrenheit. All Stations were consistent in recording July as the consistent average hottest month and December as the recorded coldest month on average. Division 5 and Station 169 recorded January on average as the lowest. All Stations showed 2006 as the hottest year on record, except CIMIS Station 203 that found 2014 has the hottest on record.

Overall, both NOAA climate zones have lower temperatures then all the Stations in every county. However, temperature does not have that much variation by Station within each county and from county to county. Due to this lack of variation and differences across Stations, taking the county-wide temperature for analyses in these areas may show reliable results, however we do see variations between data sources that does change some of the seasonal variability. Chapter 4 will drill further into the topic of a county-wide approach and the differences in results with the various data sources.

Table 3.3: Monthly and Yearly Temperature by County and Station for Drought Atlas and IRI Sources

Fresno County – Average Monthly Temperature						
ºF	Kfat Station	Coalinga Station	Friant Station	PineFlat Station	Auberry Station	405 Division Station
Jan	46.68	48.45	47.58	48.77	45.34	44.84
Feb	50.26	52.32	51.04	50.62	47.92	47.77
Mar	55.45	57.49	54.93	54.61	52.10	52.69
Apr	59.49	61.79	58.48	57.82	56.03	56.42
May	68.78	71.39	67.84	65.63	66.53	64.99
Jun	75.68	78.39	75.26	71.41	74.66	72.11
Jul	81.58	84.64	81.35	76.53	82.14	78.12
Aug	79.97	82.93	80.03	75.81	80.81	76.61
Sep	75.11	77.61	75.36	72.31	75.77	72.13
Oct	64.68	66.78	65.69	63.35	63.47	61.97
Nov	53.81	55.43	54.73	54.79	52.02	51.79
Dec	46.87	49.34	47.86	48.90	45.40	45.01
Monthly Average	63.20	65.55	63.35	61.71	61.85	60.37
Fresno County – Maximum Temperature						
ºF	Kfat	Coalinga	Friant	PineFlat	Auberry	405

Table 3.3: Monthly and Yearly Temperature by County and Station for Drought Atlas and IRI Sources						
	Station	Station	Station	Station	Station	Division Station
2000	81.20	82.76	80.50	74.50	81.40	76.50
2001	81.91	83.30	80.79	73.02	81.86	77.00
2002	84.07	85.50	82.37	73.40	83.30	78.50
2003	86.46	86.31	84.41	75.50	85.58	80.70
2004	83.34	83.89	81.00	73.61	82.19	77.50
2005	86.80	87.31	84.16	75.07	84.68	80.60
2006	87.82	88.23	85.07	77.08	85.36	81.50
2007	83.19	83.62	81.02	74.43	81.25	77.20
2008	84.08	86.05	82.31	78.69	82.30	78.20
2009	74.34	86.73	82.17	75.39	83.28	78.70
2010	77.86	84.92	80.26	83.94	81.25	77.70
2011	76.61	82.81	78.55	82.76	80.36	76.90
2012	77.22	86.02	83.36	85.39	83.81	80.30
Average Maximum	87.82	88.23	85.07	85.39	85.58	81.50

Kern County – Average Monthly Temperature				
ºF	**Bakersfield Station**	**Buttonwillow Station**	**Delano Station**	**405 Division Station**
Jan	48.69	47.70	47.47	44.84
Feb	52.84	52.27	50.34	47.77
Mar	57.96	57.41	55.23	52.69
Apr	61.91	61.67	58.93	56.42
May	71.20	71.03	67.29	64.99
Jun	78.26	77.64	73.61	72.11
Jul	84.57	83.08	78.78	78.12
Aug	82.95	81.05	77.68	76.61
Sep	77.78	75.81	72.71	72.13
Oct	66.79	65.26	63.79	61.97
Nov	55.41	53.65	53.22	51.79
Dec	48.84	47.21	47.28	45.01
Average Monthly	65.60	64.48	62.19	60.37

Kern County – Maximum Temperature				
ºF	**Bakersfield Station**	**Buttonwillow Station**	**Delano Station**	**405 Division Station**
2000	81.92	80.45	76.01	76.50
2001	82.60	81.69	76.43	77.00
2002	85.66	82.89	82.07	78.50

Table 3.3: Monthly and Yearly Temperature by County and Station for Drought Atlas and IRI Sources				
2003	87.44	85.12	77.28	80.70
2004	83.90	82.97	79.19	77.50
2005	87.63	85.97	85.44	80.60
2006	87.90	86.12	87.46	81.50
2007	83.52	82.05	81.85	77.20
2008	85.02	83.89	82.94	78.20
2009	86.45	84.18	72.44	78.70
2010	84.05	82.41	76.64	77.70
2011	83.74	82.13	74.60	76.90
2012	86.95	83.86	78.09	80.30
Average Maximum	87.90	86.12	87.46	81.50

Kings County - Average Monthly Temperature		
ºF	**Visalia Station**	**405 Division Station**
Jan	47.51	44.84
Feb	51.47	47.77
Mar	56.42	52.69
Apr	60.36	56.42
May	69.22	64.99
Jun	75.85	72.11
Jul	81.14	78.12
Aug	79.32	76.61
Sep	74.86	72.13
Oct	65.41	61.97
Nov	54.16	51.79
Dec	47.45	45.01
Monthly Average	63.60	60.37

Kings County – Maximum Temperature		
ºF	**Visalia Station**	**405 Division Station**
2000	79.79	76.50
2001	80.27	77.00
2002	82.16	78.50
2003	83.81	80.70
2004	80.77	77.50
2005	83.06	80.60
2006	83.91	81.50
2007	79.91	77.20
2008	81.02	78.20

Table 3.3: Monthly and Yearly Temperature by County and Station for Drought Atlas and IRI Sources

2009	82.44	78.70
2010	80.81	77.70
2011	79.44	76.90
2012	81.60	80.30
Average Maximum	83.91	81.50

San Luis Obispo County - Average Monthly Temperature

ºF	Morro Bay Station	Salinas Dam Station	Santa Margarita Station	Paso Robles Station	Paso Robles Airport Station	404 Division Station
Jan	47.83	49.62	50.59	47.18	47.83	49.34
Feb	49.76	50.32	51.47	49.22	49.76	50.96
Mar	53.50	53.29	54.14	53.17	53.50	53.74
Apr	56.49	55.69	56.23	55.90	56.49	55.54
May	64.30	61.28	61.30	63.12	64.30	60.20
Jun	69.66	65.65	65.28	68.34	69.66	64.05
Jul	74.11	69.72	68.33	72.15	74.11	66.49
Aug	73.61	69.83	68.62	71.70	73.61	66.62
Sep	70.41	67.80	67.20	69.11	70.41	65.76
Oct	61.80	61.58	62.01	61.16	61.80	60.88
Nov	52.87	54.81	55.60	52.33	52.87	54.39
Dec	47.40	49.41	50.22	46.87	47.40	49.29
Monthly Average	60.15	59.08	59.25	59.19	60.15	58.11

San Luis Obispo County – Maximum Temperature

ºF	Morro Bay Station	Salinas Dam Station	Santa Margarita Station	Paso Robles Station	Paso Robles Airport Station	404 Division Station
2000	75.11	71.63	71.57	71.66	75.11	66.60
2001	73.66	68.29	66.59	71.99	73.66	66.10
2002	73.34	68.61	66.98	71.50	73.34	66.40
2003	76.79	69.78	68.10	72.50	76.79	68.10
2004	73.20	68.29	67.33	70.76	73.20	67.20
2005	77.29	70.02	68.06	74.99	77.29	67.90
2006	78.94	73.53	71.08	78.29	78.94	69.80
2007	74.94	68.58	68.45	73.89	74.94	67.30
2008	75.11	69.93	69.87	74.29	75.11	67.30
2009	75.02	68.50	67.79	73.92	75.02	68.00
2010	71.79	67.70	67.56	69.28	71.79	66.60
2011	72.73	73.44	70.87	71.08	72.73	67.40
2012	77.08	78.52	76.02	76.03	77.08	67.90

Table 3.3: Monthly and Yearly Temperature by County and Station for Drought Atlas and IRI Sources

Average Maximum	78.94	78.52	76.02	78.29	78.94	69.80

Tulare County - Average Monthly Temperature

ºF	Visalia Station	Lemon Cove Station	Lindsay Station	405 Division Station
Jan	47.51	47.99	47.70	44.84
Feb	51.47	52.06	51.46	47.77
Mar	56.42	57.06	56.59	52.69
Apr	60.36	61.01	60.83	56.42
May	69.22	69.79	69.14	64.99
Jun	75.85	76.49	75.76	72.11
Jul	81.14	82.24	81.48	78.12
Aug	79.32	80.47	79.72	76.61
Sep	74.86	75.74	74.86	72.13
Oct	65.41	65.81	64.67	61.97
Nov	54.16	54.85	53.94	51.79
Dec	47.45	47.86	47.52	45.01
Monthly Average	63.60	64.28	63.64	60.37

Tulare County – Maximum Temperature

ºF	Visalia Station	Lemon Cove Station	Lindsay Station	405 Division Station
2000	79.79	81.04	79.57	76.50
2001	80.27	80.79	80.41	77.00
2002	82.16	82.61	81.15	78.50
2003	83.81	84.69	84.49	80.70
2004	80.77	81.46	81.62	77.50
2005	83.06	85.71	84.73	80.60
2006	83.91	86.23	85.04	81.50
2007	79.91	81.20	81.52	77.20
2008	81.02	82.59	82.10	78.20
2009	82.44	83.19	82.34	78.70
2010	80.81	81.79	80.59	77.70
2011	79.44	80.40	79.05	76.90
2012	81.60	82.92	83.18	80.30
Average Maximum	83.91	86.23	85.04	81.50

Table 3.4: Monthly and Yearly Temperature by County and CIMIS Station

Fresno County - Average Monthly Temperature

ºF	Station	Station	Station	Station	Station	Station	Station	Station	Station

Table 3.4: Monthly and Yearly Temperature by County and CIMIS Station

	2	7	39	80	105	124	142	190	205
Jan	43.44	46.19	46.57	46.67	45.88	46.13	45.44	45.00	47.04
Feb	49.60	51.00	50.99	48.82	50.61	50.90	49.01	48.66	51.90
Mar	55.75	56.12	56.27	55.30	56.06	56.03	54.72	55.22	57.48
Apr	60.30	60.18	60.35	57.84	60.82	59.89	59.36	59.56	61.56
May	67.74	67.72	68.42	68.22	69.12	67.39	68.07	68.67	68.79
Jun	74.68	74.25	75.41	74.76	75.84	73.53	76.56	75.48	78.59
Jul	79.13	77.26	80.23	77.95	80.08	76.75	81.60	81.47	83.42
Aug	77.55	76.06	78.20	78.40	78.33	74.49	79.35	78.90	81.81
Sep	73.17	72.33	72.75	73.20	74.02	71.05	74.01	73.72	77.01
Oct	62.32	63.22	62.25	62.26	63.68	62.38	63.31	63.34	65.19
Nov	48.23	52.82	51.79	52.60	52.80	52.54	52.26	52.58	54.37
Dec	41.66	45.23	45.15	45.36	44.89	45.55	45.31	44.68	45.15
Monthly Average	61.13	61.87	62.37	61.78	62.68	61.38	62.42	63.05	64.75

Fresno County - Maximum Temperature

ºF	**Station 2**	**Station 7**	**Station 39**	**Station 80**	**Station 105**	**Station 124**	**Station 142**	**Station 190**	**Station 205**
2000	77.22	75.77	77.31	78.33	75.85	75.34	78.23		
2001	78.20	76.74	78.52	79.07	77.87	75.80	79.56		
2002	79.83	78.22	80.36	81.14	79.59	76.40	81.91		
2003	81.15	81.02	81.69		79.99	79.98	83.69	82.87	
2004	77.82	77.06	79.68		78.95	74.84	81.07	79.14	
2005	82.27	81.30	82.74		83.10	80.04	84.01	83.27	
2006	82.94	81.74	83.29		83.85	80.67	85.02	83.60	
2007	78.17	77.09	79.68		79.81	75.70	80.31	79.84	
2008	79.57	78.09	80.03		80.25	76.37	80.92	81.52	
2009	81.12	79.20	80.87		82.86	77.07	82.33	82.52	
2010	79.36	77.18	79.75		79.57	77.27	80.24	80.95	82.15
2011	77.38	75.40	78.89		78.91	75.38	79.43		80.81
2012	80.18	77.76	80.57		80.69	77.13	81.41		84.24
2013	80.48	79.20	82.26		83.27	78.15	83.35		85.37
2014	81.71	80.18	82.35		81.52	78.61	84.24		84.81
2015	79.40	79.11	80.99		82.18	77.40	81.99		82.44
2016	80.62	79.51	81.24		82.07	75.94	83.17		83.86
2017	81.52	81.20	82.55		84.73	78.34	85.13		86.69
Average Maximum	82.94	81.74	83.29	82.43	84.73	80.67	85.13	83.60	86.69

Kern County - Average Monthly Temperature

ºF	**Station 5**	**Station 54**	**Station 125**	**Station 138**	**Station 146**
Jan	46.04	44.32	46.88	45.97	45.60
Feb	50.25	50.53	52.20	50.29	51.04
Mar	55.51	56.06	56.66	54.54	56.48
Apr	59.70	60.31	61.11	59.04	61.20
May	68.34	68.11	69.83	66.82	68.78
Jun	74.08	75.88	77.30	73.75	76.01
Jul	79.65	81.07	82.73	79.30	80.56
Aug	77.64	79.37	80.83	76.39	78.81
Sep	72.71	74.24	75.41	73.00	73.87
Oct	61.61	63.37	64.07	61.69	62.95
Nov	51.55	52.85	52.86	51.27	53.01

Table 3.4: Monthly and Yearly Temperature by County and CIMIS Station					
Dec	44.71	46.01	46.17	45.24	46.34
Monthly Average	61.73	62.68	63.84	61.44	62.85
Kern County - Maximum Temperature					
ºF	**Station 5**	**Station 54**	**Station 125**	**Station 138**	**Station 146**
2000	76.83	79.26	81.44	78.09	80.78
2001	78.13	80.92	81.63	78.17	80.68
2002	79.46	83.24	83.38	80.77	82.22
2003	80.74	85.20	78.27	82.15	83.47
2004	79.70	81.82	82.82	79.13	81.28
2005	82.54	86.20	85.88	81.16	83.93
2006	82.38	85.17	86.03	81.87	83.06
2007	78.90	80.11	82.10	78.25	79.95
2008	80.86	81.53	83.48	79.04	80.50
2009	80.43	82.95	84.05	79.96	81.09
2010	79.83	80.71	82.48	78.18	78.93
2011	78.29	78.67	81.51	77.05	77.60
2012		82.30	83.49	80.24	79.87
2013	67.89	83.39	84.75	81.62	80.72
2014		83.07	84.54	81.31	81.17
2015		79.79	81.96	78.88	79.01
2016		82.07	83.74		80.68
2017		84.55	87.45		82.93
Average Maximum	82.54	86.20	87.45	82.15	83.93

Kings County - Average Monthly Temperature	
ºF	**Station 15**
Jan	45.70
Feb	50.23
Mar	56.19
Apr	59.59
May	68.91
Jun	76.08
Jul	80.01
Aug	79.29
Sep	74.04
Oct	62.34
Nov	52.78
Dec	45.30
Monthly Average	62.54

Kings County - Maximum Temperature	
ºF	**Station 15**
2000	78.85
2001	78.88
2002	80.83
2003	83.24
2004	80.28
2005	83.53
2006	83.83
2007	79.91
2008	81.66

Table 3.4: Monthly and Yearly Temperature by County and CIMIS Station				
2009		82.85		
2010		77.04		
2011		79.51		
2012		81.47		
2013		83.28		
2014		84.12		
2015		81.96		
2016		82.84		
2017		83.93		
Average Maximum		84.12		
San Luis Obispo County - Average Monthly Temperature				
ºF	**Station 52**	**Station 160**	**Station 163**	**Station 202**
Jan	52.67	50.58	45.05	51.75
Feb	53.16	52.42	43.35	49.65
Mar	54.37	52.82	49.74	53.83
Apr	55.16	40.20	52.71	54.31
May	58.87	56.37	60.13	54.94
Jun	61.35	58.77	64.11	55.34
Jul	63.38	60.24	69.48	57.86
Aug	63.91	58.71	67.37	58.70
Sep	64.22	60.65	63.26	59.24
Oct	61.54	58.25	54.77	59.81
Nov	57.74	46.98	50.07	54.66
Dec	51.59	38.49	44.82	50.21
Monthly Average	58.16	52.34	55.40	55.10
San Luis Obispo County - Maximum Temperature				
ºF	**Station 52**	**Station 160**	**Station 163**	**Station 202**
2000	64.54	53.83	45.57	
2001	63.77	60.68	68.75	
2002	63.11	60.21	68.85	
2003	66.15	61.29	73.61	
2004	64.57		67.72	
2005	62.50		71.58	
2006	66.13		73.92	59.56
2007	63.43		69.76	59.82
2008	63.87		69.62	59.87
2009	64.58		69.51	59.30
2010	64.74		64.66	58.87
2011	62.52			56.38
2012	63.57			61.21
2013	64.52			60.34
2014	67.19			62.08
2015	70.09			66.32
2016	64.98			61.47
2017	67.76			63.12
Average Maximum	**71.02**	**61.29**	**73.92**	**66.32**
Tulare County - Average Monthly Temperature				
ºF	**Station 86**	**Station 169**	**Station 182**	**Station 203**
Jan	45.78	43.98	45.54	42.62
Feb	49.07	48.30	50.02	48.02

Table 3.4: Monthly and Yearly Temperature by County and CIMIS Station				
Mar	55.20	54.52	54.30	55.41
Apr	60.49	58.82	60.82	60.55
May	68.92	67.43	68.77	68.15
Jun	73.98	74.71	76.31	76.07
Jul	80.35	79.60	78.85	78.93
Aug	79.68	77.23	75.60	79.12
Sep	74.36	72.40	72.75	73.93
Oct	63.51	61.74	62.57	62.93
Nov	53.13	50.57	51.91	51.18
Dec	45.64	44.04	41.91	42.87
Monthly Average	62.51	61.33	61.92	61.80
Tulare County - Maximum Temperature				
ºF	**Station 86**	**Station 169**	**Station 182**	**Station 203**
2000	79.76	73.51		
2001	80.41	76.96		
2002	82.63	78.64	82.17	
2003	84.07	80.34	83.49	
2004	81.70	78.19	81.29	
2005	84.76	81.36	83.88	
2006	84.67	82.07	84.66	77.45
2007	81.42	78.06	80.44	79.68
2008	81.47	78.79	80.45	80.41
2009	82.98	76.44	73.47	81.05
2010	81.81	79.50	80.51	76.24
2011	80.99	78.51	77.74	78.93
2012	80.27	80.33	82.72	81.85
2013	84.14	81.38	81.51	83.87
2014	83.55	81.62	83.94	84.76
2015	81.75	80.60	81.51	81.74
2016	82.50	80.74	81.44	83.44
2017	84.08	83.45	82.54	
Average Maximum	**84.76**	**83.45**	**84.66**	**84.76**

Wind Speed

Wind speed is the speed of air moving from a high-pressure to a low-pressure area. It is usually related to changes in temperature.

<u>Data Source</u>

Wind data was obtained from the Department of Water Resources CIMIS weather station network. They use a three-cup anemometer that uses a magnet activated reed switch that reads at a frequency proportional to wind speed. Daily average wind speed is measured. Wind speed is measured in miles per hour (mph).

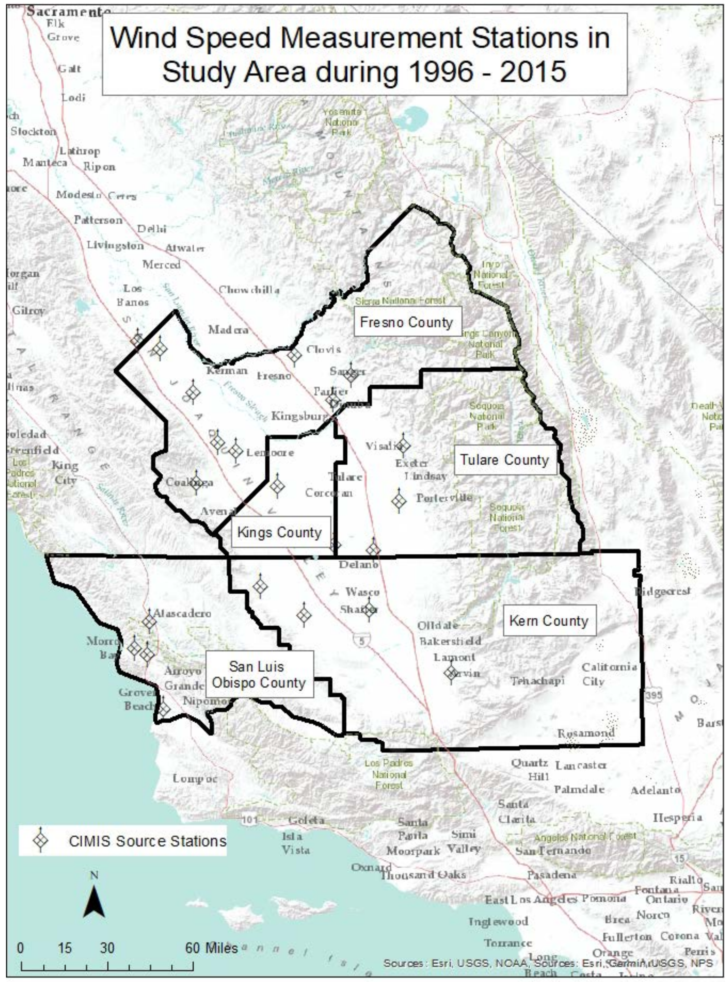
<u>Station Location</u>

Figure 3.3 shows the location of the stations that measure wind speed for the study area.

<u>Data Variability</u>

Table 3.5 shows the wind speed variabilities by Station for the CIMIS stations.

Figure 3.3: Stations Monitoring Wind Speed for Study Area



In Fresno County, the CIMIS stations measure average wind speeds between 3 – 7 mph. All Stations in Fresno County measure peak winds during April – June season, except Station 142's peak wind season appeared to be May – July. All of the CIMIS stations in Fresno County also vary on when their maximum monthly average wind speed is the highest. Station 2 measured peaks in 2000, 2002, and 2013. Station 7 measured a peak in 2000 and shows wind speed gradually decreasing over time. Station 39 measured peaks in 2000, 2008, and 2012. Station 80 measured a peak in 2000. Station 105 measured a peak in 2001 and 2007. Station 124 measured peaks in 2008 and 2010, Station 142 measured peaks in 2004-2005 and 2015, Station 190 measured a peak in 2003, and Station 2012 measured a peak in 2012.

In Kern County, the CIMIS stations measured average wind speeds between 3.5 – 5 mph. All Stations in Kern County measured peak winds during April – June or March – June season. All the CIMIS stations in Kern County also vary on when their maximum monthly average wind speed is the highest. Station 5 measured peaks in 2010 - 2011. Station 54 measured peaks in 2003-2004, 2009, and 2015. Station 125 measured no high peaks. Station 138 measured a peak in 2012 and station 46 measured peaks in 2010-2011. Compared to Fresno County, the range of the maximum wind speeds were higher for Kern County, 4.7 – 9.2 mph.

In Kings County, the CIMIS station measured average wind speeds between 3 – 6 mph. Station 15 saw a higher peak of wind speeds in April – June and saw maximum peaks in 2012 and 2013.

Two Stations in San Luis Obispo County measure peak winds during April – June. Station 52 had a steady 3 mph wind speed per month and Station 160 saw peaks in February/March and again in May/June. All the CIMIS stations in San Luis Obispo County also vary on when their maximum monthly average wind speed is the highest. Station 52 measured a peak in 2000. Station 160 measured a peak in 2002. Station 163 and Station 202 measured no high peaks. Compared to Kern County, the range of the maximum wind speeds were less for San Luis Obispo County, 3 – 5 mph.

All stations in Tulare County measure peak winds during April – June, except Station 86 that measured the peak season between May - July. The stations on average had wind speeds between 2.7 – 4.23 mph.
All the CIMIS stations in Tulare County also vary on when their maximum monthly average wind speed is the highest. Station 86 measured a peak in 2015-2016 and a smaller peak in 2010-2011. Station 169 measured a peak in 2017 and a smaller one in 2011 - 2013. Station 163 measured a peak in 2015 – 2016 and 2003 – 2004 and Station 203 measured peaks in 2008 – 2010. Compared to San Luis Obispo County, the range of the maximum wind speeds were similar for Tulare County, 3.76 – 5.85 mph.

Unlike other variables described in the sections before, there does seem to be more variation and seasonality of the variation between Station within a county and between counties. Although wind speed is said to be directly related to temperature and pressure zones, we see more variability in station to station, than we did with CIMIS temperature data.

Table 3.5: Monthly and Yearly Wind Speed by County and CIMIS Station

Fresno County - Average Monthly Wind

mph	Station 2	Station 7	Station 39	Station 80	Station 105	Station 124	Station 142	Station 190	Station 205
Jan	4.49	3.26	3.20	3.78	4.30	3.94	3.00	3.63	4.25
Feb	5.36	3.73	3.54	4.12	4.95	4.65	3.18	4.51	5.29
Mar	5.98	4.11	4.00	4.56	5.43	5.19	3.67	5.18	5.73
Apr	7.04	4.83	4.60	5.18	6.57	6.26	4.22	5.70	6.17
May	7.20	5.17	4.74	5.88	6.80	6.51	4.74	5.71	6.42
Jun	6.67	5.08	4.60	5.56	6.93	6.08	5.11	5.89	6.38
Jul	5.77	4.46	4.05	5.04	6.21	4.99	4.74	4.97	5.91
Aug	5.71	4.06	3.69	4.59	5.92	4.54	4.35	4.79	5.49
Sep	5.45	3.80	3.39	4.15	5.73	4.42	3.99	4.54	5.48
Oct	5.02	3.55	2.98	3.59	5.08	4.30	3.50	4.35	5.21
Nov	4.12	3.05	2.73	3.43	4.40	3.62	3.12	4.03	4.81
Dec	4.62	3.35	3.03	3.43	4.53	4.04	2.97	4.51	4.44
Monthly Average	5.62	4.04	3.71	4.44	5.57	4.88	3.88	4.82	5.48

Fresno County - Maximum Wind

mph	Station 2	Station 7	Station 39	Station 80	Station 105	Station 124	Station 142	Station 190	Station 205
2000	8.32	6.18	5.15	6.10	6.92	7.08	4.90		
2001	7.52	6.29	4.70	5.96	9.61	7.43	5.23		
2002	8.17	6.58	4.77	5.71	7.76	6.72	5.24		
2003	7.23	5.83	4.75		6.61	6.72	4.99	7.52	
2004	6.89	5.97	4.94		7.43	7.04	5.45	6.23	
2005	7.44	5.82	4.96		7.28	6.63	5.25	5.92	
2006	6.96	5.06	4.56		6.53	5.68	4.93	5.59	
2007	7.54	5.30	4.87		8.07	6.54	5.36	5.65	
2008	7.31	4.98	5.30		7.78	7.36	5.08	5.61	
2009	7.73	4.75	4.77		7.59	6.70	5.09	5.88	
2010	7.54	4.96	4.65		7.71	7.58	5.28	6.74	6.75
2011	7.17	4.48	5.13		6.53	6.88	4.80		6.53
2012	7.76	4.38	5.30		7.61	7.15	5.31		7.13
2013	8.20	4.46	4.92		7.87	6.80	5.28		7.06
2014	7.17	3.98	4.75		7.25	6.86	5.21		6.48
2015	6.65	3.90	4.72		6.21	6.19	5.61		6.20
2016	6.81	3.64	4.31		6.77	6.22	4.90		6.09
2017	7.76	4.47	5.06		6.66	6.15	4.96		6.49

Table 3.5: Monthly and Yearly Wind Speed by County and CIMIS Station

Average Maximum	8.47	7.22	5.49	6.64	9.61	7.58	5.61	7.52	7.13

Kern County - Average Monthly Wind

mph	Station 5	Station 54	Station 125	Station 138	Station 146
Jan	3.38	3.80	3.09	3.37	3.01
Feb	3.74	4.62	3.54	3.81	3.60
Mar	3.75	5.20	3.72	3.86	4.30
Apr	4.27	6.15	4.15	4.02	4.60
May	4.18	6.50	4.33	3.99	4.41
Jun	3.71	6.61	4.20	3.83	4.05
Jul	3.17	6.40	3.77	3.54	3.69
Aug	3.09	5.61	3.60	3.36	3.45
Sep	3.13	5.20	3.41	3.32	3.42
Oct	2.93	4.56	3.31	3.20	3.24
Nov	2.73	3.91	2.96	2.99	3.02
Dec	3.17	3.97	3.04	3.28	3.17
Monthly Average	3.44	5.21	3.59	3.54	3.65

Kern County - Maximum Wind

mph	Station 5	Station 54	Station 125	Station 138	Station 146
2000	4.44	5.09	4.41	4.11	5.79
2001	3.80	8.56	4.37	3.83	5.17
2002	4.34	8.76	4.42	4.07	5.44
2003	4.42	9.11	4.52	3.97	5.26
2004	4.14	8.37	4.60	3.90	4.59
2005	4.14	7.81	4.37	3.82	4.75
2006	4.20	7.10	4.42	3.77	4.39
2007	4.15	7.58	4.47	3.96	4.43
2008	4.41	7.67	4.62	4.15	4.80
2009	4.34	8.34	4.69	4.16	4.84
2010	4.54	6.69	4.16	4.56	4.64
2011	4.54	6.90	3.96	4.56	4.76
2012		7.41	4.72	5.03	4.44
2013		7.71	4.73	4.69	4.35
2014		7.36	4.57	4.39	4.04
2015		9.25	4.31	4.44	4.44
2016		7.38	4.31		4.09
2017		7.44	4.69		4.16
Average Maximum	5.44	9.25	4.79	5.03	5.79

Kings County - Average Monthly Wind

mph	Station 15
Jan	4.05
Feb	4.62
Mar	5.24
Apr	6.14
May	6.59
Jun	6.39
Jul	5.56
Aug	5.38

Table 3.5: Monthly and Yearly Wind Speed by County and CIMIS Station				
Sep	4.94			
Oct	4.31			
Nov	3.86			
Dec	4.06			
Monthly Average	5.09			
Kings County - Maximum Wind				
mph	**Station 15**			
2000	6.84			
2001	6.74			
2002	6.98			
2003	6.35			
2004	6.71			
2005	6.59			
2006	6.62			
2007	6.70			
2008	7.11			
2009	6.86			
2010	7.10			
2011	6.41			
2012	7.33			
2013	7.47			
2014	6.97			
2015	6.30			
2016	6.68			
2017	6.20			
Average Maximum	7.72			
San Luis Obispo County - Average Monthly Wind				
mph	**Station 52**	**Station 160**	**Station 163**	**Station 202**
Jan	3.74	4.48	2.79	3.82
Feb	3.83	4.93	2.68	3.88
Mar	3.76	5.10	3.02	4.03
Apr	3.78	3.84	3.24	4.04
May	3.72	5.35	3.32	4.11
Jun	3.56	5.21	3.15	4.08
Jul	3.33	4.95	2.98	3.96
Aug	3.25	4.88	2.76	3.75
Sep	3.19	4.38	2.59	3.53
Oct	3.45	4.20	2.50	3.63
Nov	3.64	4.01	2.44	3.49
Dec	3.64	3.13	2.69	3.53
Monthly Average	3.58	4.49	2.85	3.81
San Luis Obispo County - Maximum Wind				
mph	**Station 52**	**Station 160**	**Station 163**	**Station 202**
2000	7.17	4.50	2.34	
2001	4.13	5.46	3.42	
2002	3.90	5.59	3.41	
2003	4.01	5.45	3.32	
2004	3.66		3.59	
2005	3.87		3.67	

Table 3.5: Monthly and Yearly Wind Speed by County and CIMIS Station

2006	4.56		3.43	4.40
2007	4.44		3.37	4.32
2008	4.69		3.67	5.03
2009	4.83		3.28	4.52
2010	4.17		3.51	4.32
2011	4.46			4.69
2012	4.07			4.17
2013	4.17			4.20
2014	4.00			4.55
2015	4.39			4.40
2016	5.00			3.64
2017	4.75			3.80
Average Maximum	7.17	5.59	3.67	5.03

Tulare County - Average Monthly Wind

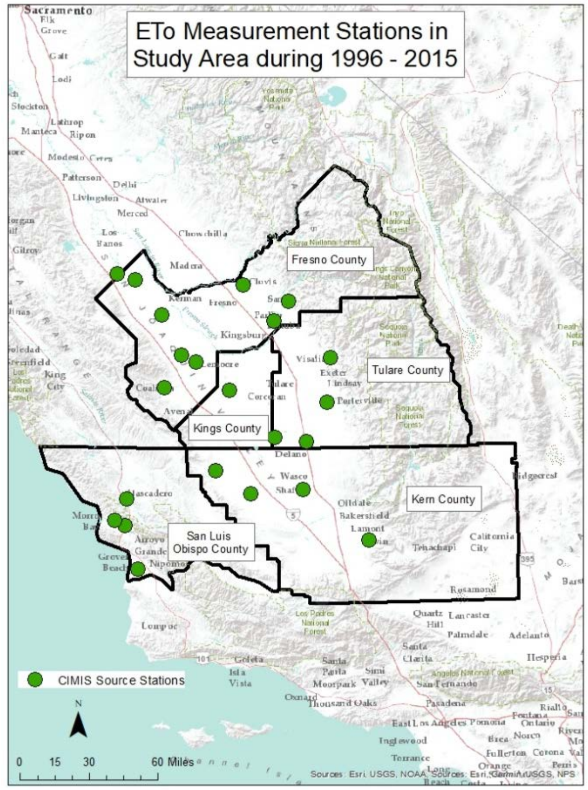
mph	Station 86	Station 169	Station 182	Station 203
Jan	2.22	2.68	2.70	3.37
Feb	2.39	3.02	3.05	3.86
Mar	2.65	3.36	3.28	4.43
Apr	2.99	3.40	3.70	5.03
May	3.24	3.62	3.75	5.41
Jun	3.28	3.41	3.60	5.33
Jul	3.12	3.35	3.16	4.64
Aug	3.01	3.15	3.07	4.38
Sep	2.77	2.81	3.03	4.14
Oct	2.48	2.50	2.75	3.82
Nov	2.15	2.35	2.46	3.20
Dec	2.15	2.50	2.38	3.33
Monthly Average	2.70	3.01	3.08	4.23

Tulare County - Maximum Wind

mph	Station 86	Station 169	Station 182	Station 203
2000	3.17	2.93		
2001	3.15	3.20		
2002	3.20	3.59	3.78	
2003	3.22	3.43	4.00	
2004	3.16	3.63	4.15	
2005	3.07	3.57	3.92	
2006	3.10	3.61	3.81	4.97
2007	3.12	3.69	3.94	5.38
2008	3.10	3.68	3.92	5.84
2009	3.71	3.68	3.89	5.52
2010	3.54	3.98	3.73	5.70
2011	3.46	4.04	3.49	5.06
2012	3.59	4.04	3.64	5.61
2013	3.57	4.04	3.72	5.65
2014	3.55	3.70	3.61	5.52
2015	3.67	3.94	4.15	5.31
2016	3.76	3.77	4.09	5.44
2017	3.56	4.12	3.81	
Average Maximum	3.76	4.12	4.15	5.84

Evapotranspiration (ETo)

Figure 3.4: ETo Stations for Study Area



Evapotranspiration (ETo) is the term used to describe the loss of water to the atmosphere by the combined processes of evaporation (from soil and plant surfaces) and transpiration (from plant tissues). ET is measured in inches. A high ETo value represents more water loss and usually indicates a drier environment.

<u>Data Source</u>
ETo was obtained from the Department of Water Resources CIMIS weather station network.
CIMIS uses the Penman-Monteith equation and a version of Penman's equation modified by Pruitt/Doorenbos (Proceedings of the International Round Table Conference on "Evapotranspiration", Budapest, Hungary. 1977). The Modified Penman employs a wind function developed at UC Davis and is therefore referred to as the CIMIS Penman equation in different literatures. CIMIS uses hourly weather data to calculate hourly ETo and adds them up over 24 hours (midnight to midnight) to estimate daily ETo.

<u>Station Location</u>
Figure 3.4 shows the location of the stations that measure ETo for the study area. Table 3.6 shows the Station Names by county location. Those with smaller number station IDs are the oldest stations and have the longest records.

Table 3.6: CIMIS Station IDs by County

County	Station IDs
Fresno	2, 7, 39, 80, 105, 124, 142, 190, 205
Kern	5, 54, 125, 138, 146
Kings	15
Tulare	86, 169, 182, 203
San Luis Obispo	52, 160, 163, 202

<u>Data Variability</u>

Table 3.7 shows the ETo variabilities by Station for the CIMIS stations.

For Fresno County, the average monthly ETo values range from 4.45 – 5.70 inches across Stations. All stations found June and July to be the months with the highest ETo, between 8-10 inches. There is no consensus on the year with the highest ETo. The total ETo from 2000 – 2017 does indicate that station 2 and station 105 are in drier parts of the county.

For Kern County, the average monthly ETo values range from 4.6 – 5.3 inches across Stations. All stations found June and July to be the months with the highest ETo, between 7.5-9 inches. There is no consensus on the year with the highest ETo. The total ETo from 2000 – 2017 does indicate that station 54 and station 125 are probably similar climatology and are in the drier parts of the county.

For Kings County, the average monthly ETo values is 5.1. All stations found June and July to be the months with the highest ETo, between 8-9 inches. The highest total ETo for a year was in 2009.

For San Luis Obispo County, the average monthly ETo values range from 3.61 – 4.25 inches across Stations. All stations found June and July to be the months with the highest ETo, between 4 – 6.5 inches. There is no consensus on the year with the highest ETo. Station 202 has consistently ETo values that are 10 inches less than the other Stations.

For Tulare County, the average monthly ETo values range from 4 - 5 inches across Stations. All stations found June and July to be the months with the highest ETo, between 8 – 9 inches. There is no consensus on the year with the highest ETo.

Overall, with ETO, there were similarities with monthly high and lows compared to temperature and precipitation variables described in an earlier section. However, unlike those variables, ETo may do a better job at looking at trends across the years and the data does capture several droughts in 2007 – 2009 and 2013 – 2015.

Table 3.7: Monthly and Yearly ETo by County and CIMIS Station

Fresno County - Average Monthly ETo									
inches	**Station 2**	**Station 7**	**Station 39**	**Station 80**	**Station 105**	**Station 124**	**Station 142**	**Station 190**	**Station 205**
Jan	1.35	1.10	1.07	1.06	1.29	1.27	1.24	1.37	1.89
Feb	2.19	2.00	1.84	1.68	2.17	2.11	1.91	2.11	2.68
Mar	4.30	3.91	3.66	3.63	4.22	4.10	3.65	4.23	4.16
Apr	6.11	5.48	5.14	5.37	6.07	5.82	5.07	5.61	6.22
May	8.26	7.46	7.08	7.44	8.30	7.88	7.35	7.65	8.23
Jun	8.92	8.15	7.91	8.20	9.14	8.68	8.66	8.63	9.52
Jul	9.01	8.17	8.07	8.48	9.38	8.44	9.02	8.85	9.88
Aug	8.26	7.36	7.16	7.66	8.39	7.37	8.07	8.04	8.92
Sep	6.41	5.62	5.35	5.59	6.49	5.73	6.05	6.27	6.97
Oct	4.39	3.84	3.42	3.61	4.39	3.99	3.82	4.11	4.79
Nov	2.13	1.77	1.67	1.68	2.14	1.93	1.93	2.23	2.53
Dec	1.33	1.02	1.06	1.06	1.32	1.26	1.21	1.26	1.84
Monthly Average	5.21	4.66	4.45	4.62	5.27	4.88	4.83	5.10	5.70
Fresno County - Total ETo									
inches	**Station 2**	**Station 7**	**Station 39**	**Station 80**	**Station 105**	**Station 124**	**Station 142**	**Station 190**	**Station 205**
2000	60.51	57.09	53.04	55.53	56.16	56.51	56.15		
2001	65.13	60.04	55.05	58.35	62.94	61.57	59.48		
2002		59.11	53.60	57.70	64.61	59.62	59.02		
2003	60.53	56.64	52.83		61.26	58.18	57.29	49.05	
2004	60.40	57.27	53.18		64.02	59.03	57.56	62.71	
2005	59.95	53.49	51.33		59.55	55.30	54.71	57.46	
2006	60.58	50.56	47.33		59.34	49.72	53.44	50.92	
2007	63.76	56.49	54.47		67.23	57.17	56.67	57.63	
2008	63.18	60.39	57.52		67.40	62.73	60.23	64.56	

Table 3.7: Monthly and Yearly ETo by County and CIMIS Station

2009	65.58	59.09	53.19		68.62	65.19	58.59	65.19	
2010	60.73	53.41	49.75		59.10	57.72	55.62	62.02	57.32
2011	57.56	51.26	51.22		60.51	57.17	55.23		62.58
2012	63.22	54.34	54.58		66.69	61.58	56.98		70.12
2013	67.88	55.18	54.92		70.11	61.71	61.16		72.46
2014	67.95	54.26	57.99		70.67	60.49	63.03		71.54
2015	65.37	54.95	54.48		66.30	57.13	60.50		68.33
2016	65.91	54.93	56.29		65.26	60.99	59.75		67.75
2017	64.12	57.52	53.30		65.04	59.88	60.06		66.14
Total	1,318.44	1,229.76	1,174.85		1,392.33	1,288.79	1,101.83		

Kern County - Average Monthly ETo

inches	Station 5	Station 54	Station 125	Station 138	Station 146
Jan	1.26	1.56	1.49	1.38	1.42
Feb	2.11	2.28	2.29	2.09	2.28
Mar	3.96	4.34	4.11	3.80	4.18
Apr	5.37	5.97	5.58	5.13	5.56
May	7.28	8.05	7.63	6.86	7.46
Jun	7.86	9.01	8.71	7.80	8.18
Jul	8.07	9.69	9.15	7.93	8.40
Aug	7.31	8.64	8.54	7.43	7.60
Sep	5.67	6.45	6.19	5.59	5.80
Oct	3.74	4.21	4.13	3.65	3.81
Nov	1.90	2.14	2.07	1.88	2.04
Dec	1.27	1.48	1.43	1.32	1.46
Monthly Average	4.65	5.32	5.11	4.57	4.80

Kern County - Total ETo

inches	Station 5	Station 54	Station 125	Station 138	Station 146
2000	55.55	59.68	57.78	53.13	62.75
2001	56.44	67.58	62.56	53.81	22.02
2002	55.60	68.85	63.37	55.34	62.36
2003	54.07	64.27	59.25	53.85	58.81
2004	56.96	67.10	63.86	56.36	60.51
2005	53.97	65.12	58.92	52.24	56.33
2006	53.12	64.18	58.02	47.99	53.17
2007	56.83	66.02	60.22	53.89	56.78
2008	57.48	66.71	64.04	56.35	59.24
2009	57.82	65.96	62.06	57.65	58.70
2010	54.98	60.43	58.64	55.42	54.96
2011	54.04	60.03	60.07	54.62	52.39
2012		67.94	63.53	58.31	57.18
2013		68.18	63.16	59.73	58.93
2014		69.41	66.10	61.03	61.27
2015		66.66	61.10	58.42	58.26
2016		67.72	62.77		58.44
2017		64.96	63.43		56.21
Total		1,404.17	1,349.23		1,075.43

Kings County - Average Monthly ETo

inches	Station 15
Jan	1.258

Table 3.7: Monthly and Yearly ETo by County and CIMIS Station				
Feb	2.125			
Mar	4.180			
Apr	5.937			
May	8.138			
Jun	8.947			
Jul	9.091			
Aug	8.226			
Sep	6.265			
Oct	4.190			
Nov	2.093			
Dec	1.286			
Monthly Average	5.145			
Kings County - Total ETo				
inches	Station 15			
2000	59.45			
2001	63.15			
2002	63.35			
2003	61.26			
2004	61.21			
2005	59.56			
2006	53.16			
2007	64.96			
2008	65.46			
2009	67.05			
2010	60.60			
2011	58.94			
2012	65.55			
2013	67.24			
2014	66.67			
2015	63.54			
2016	65.42			
2017	65.17			
Total	1,358.18			
San Luis Obispo County - Average Monthly ETo				
inches	Station 52	Station 160	Station 163	Station 202
Jan	2.29	2.06	1.67	2.15
Feb	2.48	2.42	2.15	2.46
Mar	3.91	3.85	3.73	3.59
Apr	4.82	4.30	4.65	4.59
May	5.71	5.81	6.19	4.98
Jun	6.07	6.09	6.64	4.94
Jul	6.22	6.04	6.91	4.90
Aug	5.74	5.48	6.42	4.37
Sep	4.83	4.59	5.05	3.74
Oct	3.96	3.52	3.50	3.34
Nov	2.65	2.43	1.99	2.38
Dec	2.16	1.95	1.52	1.94
Monthly Average	4.24	3.95	4.18	3.61
San Luis Obispo County - Total ETo				
inches	Station 52	Station 160	Station 163	Station 202

Table 3.7: Monthly and Yearly ETo by County and CIMIS Station				
2000	47.11	5.20	1.78	
2001	49.46	47.34	52.69	
2002	50.66	49.40	52.52	
2003	48.11	48.05	50.84	
2004	49.29		52.25	
2005	47.27		46.68	
2006	45.68		44.36	
2007	49.87		50.46	44.14
2008	52.61		52.51	45.03
2009	50.02		51.13	43.48
2010	48.79		50.45	41.66
2011	51.18			43.58
2012	51.59			43.78
2013	54.58			44.63
2014	53.73			42.33
2015	53.84			43.49
2016	52.20			41.36
2017	52.81			42.87
Total	1,118.11			
Tulare County - Average Monthly ETo				
inches	**Station 86**	**Station 169**	**Station 182**	**Station 203**
Jan	1.17	1.24	1.19	1.37
Feb	1.75	1.96	2.03	2.09
Mar	3.49	3.71	3.83	3.99
Apr	4.83	4.92	5.18	5.58
May	6.81	6.88	7.00	7.39
Jun	7.78	7.80	7.97	8.63
Jul	8.09	8.01	8.18	9.02
Aug	7.25	7.22	7.44	8.17
Sep	5.36	5.37	5.49	6.10
Oct	3.43	3.41	3.40	3.90
Nov	1.74	1.81	1.78	2.06
Dec	1.11	1.17	1.19	1.28
Monthly Average	4.40	4.44	4.59	4.94
Tulare County - Total ETo				
inches	**Station 86**	**Station 169**	**Station 182**	**Station 203**
2000	53.32	17.96		
2001	54.74	52.94		
2002	52.85	54.64	47.85	
2003	51.72	54.75	53.8	
2004	54.05	53.59	55.71	
2005	48.43	51.2	52.97	
2006	49.86	46.12	48.34	
2007	55.07	51.2	54.72	59.76
2008	54.48	54.89	55.48	59.68
2009	55.37	54.85	54.13	59.93
2010	51.3	50.95	53.05	53.99
2011	50.88	51.77	51.68	59.42
2012	51.89	52.77	54.47	56.03
2013	56.27	56.15	57.51	63.23

Table 3.7: Monthly and Yearly ETo by County and CIMIS Station				
2014	56.26	58.36	58.58	64.45
2015	53.64	56.79	57.23	61.31
2016	54.98	56.3	57.65	
2017	53.05	53.1	54.7	
Total	1161.58	928.33		

El Niño Southern Oscillation Index

El Niño and the Southern Oscillation, also known as ENSO is an inter-seasonal fluctuation (i.e., every 2–7 years) in sea surface temperature and the air pressure of the atmosphere over the equatorial Pacific Ocean. The presence of an El Niño, or its opposite – La Niña –modifies the flow of the atmosphere and affects normal weather conditions. A weak El Niño occurs when the peak Oceanic Niño Index (ONI) is greater than or equal to 0.5 degrees Celsius (°C) and less than or equal to 0.9°C. A moderate El Niño occurs when the peak Oceanic Niño Index (ONI) is greater than or equal to 1.0°C and less than or equal to 1.4°C. A strong El Niño occurs when the peak Oceanic Niño Index (ONI) is greater than or equal to 1.5°C (Halbert, M).

Over California and the Southwest, the relationship between El Niño and more than average rainfall is dependent on the strength of the El Niño. The stronger the El Niño signal, the more reliable of an impact on weather occurs. Typically, when El Niño occurs, there is more precipitation than normal and other related events like floods and landslides.

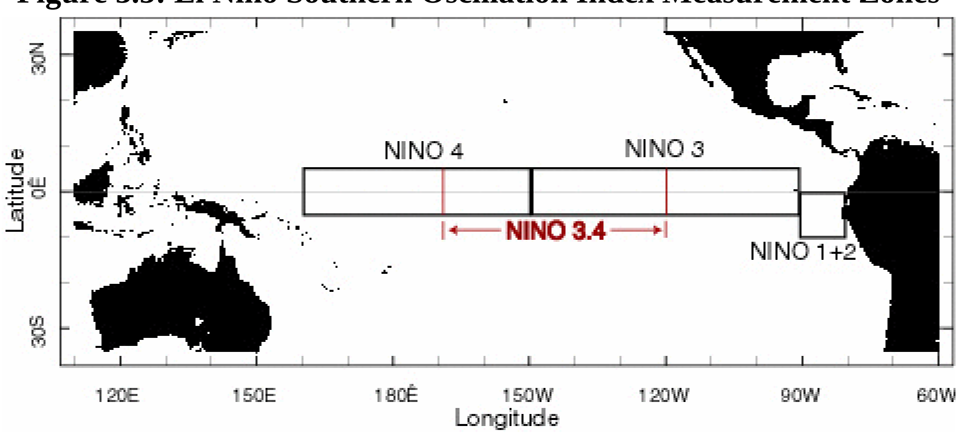
Data Source

The ENSO index was obtained from the National Oceanic and Atmospheric Administration - National Centers for Environmental Information. Monthly sea surface temperatures (ºC) and their anomalies from the average were provided for 4 zones in the equatorial Pacific Ocean from 1982 – 2015.

Station Location

Figure 3.5 shows the areas of the ocean where the sea surface measurements are averaged.

Figure 3.5: El Niño Southern Oscillation Index Measurement Zones



Source (www.ncdc.noaa.gov)

Data Variability

Major El Niño events occurred in 1997, 2002, 2009-2010, and 2015 as shown in Figure 3.6. Major La Niña events occurred in 1999, 2003, 2008, and 2011. Table 3.8 highlights that each station has a different range in sea surface temperatures and Table 3.9 shows that the seasonality changes per station. NIÑO 1+2 is more likely to have their negative anomaly (La Niña) during October – February. NIÑO 3.4 is more likely to have their negative anomaly (La Niña) during January – May.

According to Table 3.10, there is a pattern of more Valley Fever cases occurring per month during La Niña events. However, this is based on diagnosis date. The relationship between ENSO events and case exposures under the various scenarios will be explored in the next chapter.

Figure 3.6: El Nino Southern Oscillation Index Anomalies, Jan 1996 - Dec 2015

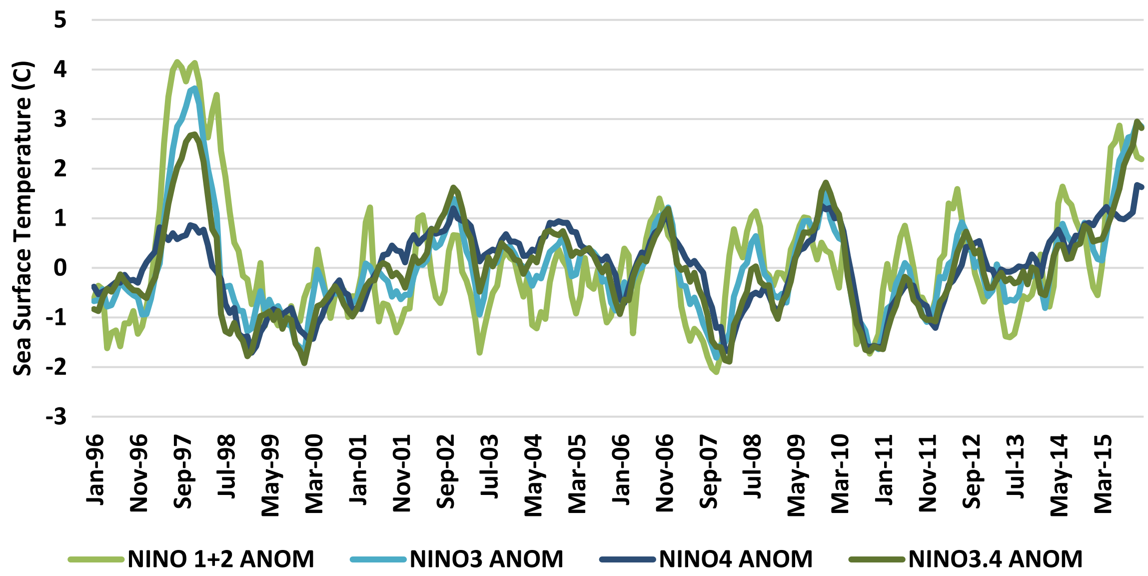


Table 3.8: Descriptive Statistics on the El Niño Southern Oscillation Index Stations

Degrees C	NIÑO 1+2	NIÑO 3	NIÑO 4	NIÑO 3.4
Average	23.18	25.91	28.55	27.00
Standard Error	.158	.085	.052	.069
Standard Deviation	2.45	1.33	.820	1.07
Skewness	.132	.093	-.538	-.037
Minimum	18.57	23.17	26.43	24.65
Maximum	29.15	29.14	30.3	29.6

Table 3.9: Average Monthly Anomalies by ENSO station

Degrees C	Average of NIÑO 1+2 ANOM	Average of NIÑO3 ANOM	Average of NIÑO4 ANOM	Average of NIÑO3.4 ANOM
Jan	-0.102	-0.232	-0.199	-0.313
Feb	-0.034	-0.209	-0.148	-0.271
Mar	0.053	-0.100	-0.073	-0.183
Apr	0.138	-0.005	0.003	-0.094
May	0.225	0.001	0.024	-0.037
Jun	0.210	0.084	0.057	0.033
Jul	0.136	0.185	0.035	0.086
Aug	0.138	0.178	0.060	0.097
Sep	0.057	0.129	0.057	0.099

Table 3.9: Average Monthly Anomalies by ENSO station				
Oct	-0.005	0.094	0.065	0.081
Nov	-0.059	0.109	0.113	0.137
Dec	-0.064	0.077	0.004	0.024
Average	0.058	0.026	0.000	-0.028

Table 3.10: ENSO Occurrences with Total Number of Valley Fever Cases by Diagnosis Date

	LA NIÑA	NUETRAL	EL NIÑO
Monthly Occurrences	70	76	46
Total Number of Cases in Fresno County (Average)	2,034 (29)	1,960 (25)	1,284 (27)
Total Number of Cases in Kern County (Average)	9,245 (132)	7,273 (95)	3,838 (83)
Total Number of Cases in Kings County (Average)	970 (13)	822 (10)	518 (11)
Total Number of Cases in San Luis Obispo County (Average)	543 (7)	523 (6)	327 (7)
Total Number of Cases in Tulare County (Average)	795 (11)	828 (11)	633 (13)
Total Number of Cases	13,587	11,406	6,600
Average Number of Cases per Month	194	150	143

Soil Moisture

Palmer Drought Severity Index (PDSI)

The Palmer Drought Severity Index (PDSI) combines temperature and precipitation to estimate regional dryness and drought. PDSI looks at the water balance and quantifies drought on a longer-term scale. Negative values indicate drought and positive values indicate wet periods. It is a monthly value that indicates the severity of a wet and dry spell. PDSI values of 0 to -.5 are considered normal; -0.5 to -1.0 are incipient drought; -1.0 to -2.0 are mild drought; -2.0 to -3.0 are moderate drought; -3.0 to -4.0 are severe drought; anything over -4.0 is considered extreme drought. The same categories (normal – extreme) are applied to the wet years, with positive values.

Data Source

The PDSI was obtained monthly from Drought Atlas from November 1980 to December 2012. The Visalia station was used for Tulare County, Bakersfield station was used for Kern County, Morro Bay Station was used for San Luis Obispo County, Fresno station was used for Fresno County, and Visalia station was used for Kings County as there was no station in the region.

Station Location

Figure 3.7 shows the locations of the four PDSI monitoring Stations.

Data Variability

The variability in the PDSI index per county seems to be similar across stations, where there is a peak in the index; it is reflected across all stations. For example, January 2005 and January 2011 show a strong peak across all stations, as shown in Figure 3.8. For all four stations, the index has a larger negative value in August and September (Table 3.11). However, the magnitude of the peak is not similar. For example, the station in Fresno County starts off with one of the more extreme drought indexes in 2002-2004, but then becomes the wettest station from 2010 to 2012. The opposite relationship is true for San Luis Obispo County.

In Table 3.12, we can see that Kern County has 85% of the months on record in a drought versus Fresno County with 66% of the months being a drought. Spatially, the percentage of drought decreases as you move north and towards the coast. This indicates that looking at variables at a spatial level larger than a county may be inappropriate. We also see a pattern emerging with how many cases would be expected to occur during a PDSI < 0, based on the percentage of drought events. This pattern indicates that those counties with less drought events during the time period show that the number of cases is less than expected. Again, this is based on diagnosis date. The relationship between PDSI and case exposures under the various scenarios will be explored in the next chapter.

Figure 3.7: PDSI Stations for Study Area

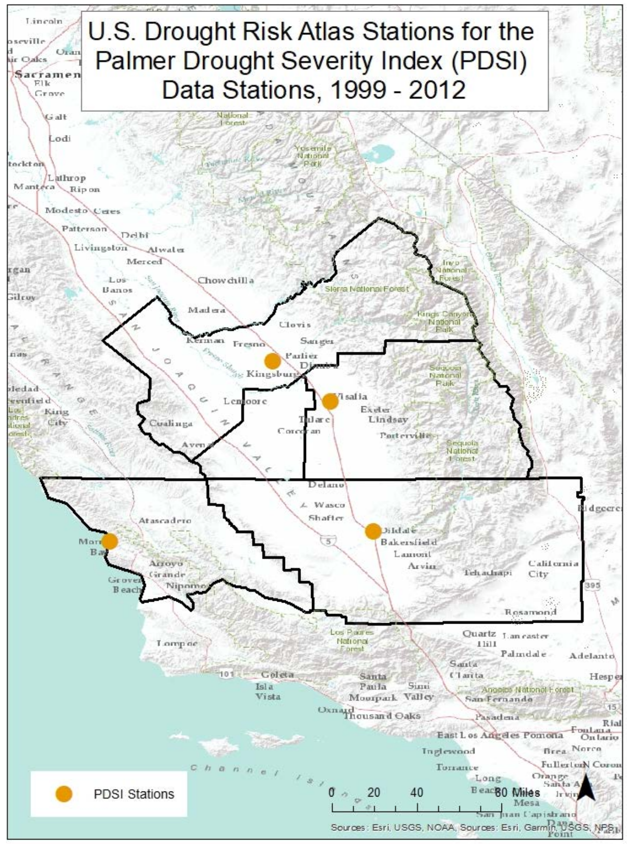


Figure 3.8: Palmer Drought Severity Index Based on Drought Atlas Stations Over Time

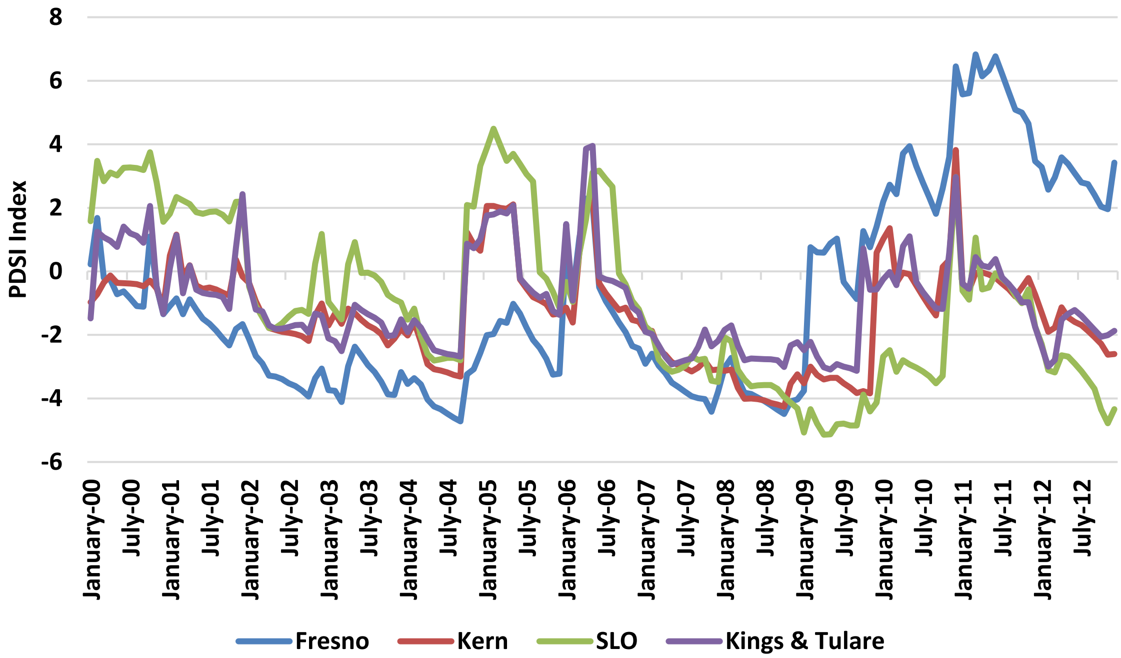


Table 3.11: Palmer Drought Severity Index Over Time and by County Station				
		PDSI Yearly Average		
PDSI Index	**Fresno County**	**Kern County**	**Counties of Kings & Tulare**	**San Luis Obispo County**
2000	-0.31	-0.51	0.62	2.93
2001	-1.52	-0.14	-0.07	1.97
2002	-3.24	-1.56	-1.49	-1.00
2003	-3.35	-1.70	-1.74	-0.48
2004	-3.82	-1.83	-1.47	-1.14
2005	-2.09	0.33	0.32	2.23
2006	-0.46	-0.45	0.43	0.85
2007	-3.56	-2.74	-2.42	-2.82
2008	-3.84	-3.78	-2.51	-3.44
2009	0.14	-3.16	-2.17	-4.68
2010	3.16	0.21	0.04	-2.28
2011	5.61	-0.38	-0.39	-0.52
2012	2.85	-1.86	-1.92	-3.38
Average	-0.80	-1.35	-0.98	-0.90
		PDSI Monthly Average		
PDSI Index	**Fresno County**	**Kern County**	**Counties of Kings & Tulare**	**San Luis Obispo County**

Table 3.11: Palmer Drought Severity Index Over Time and by County Station				
Jan	-0.79	-0.99	-0.90	-0.81
Feb	-0.41	-0.93	-0.86	-0.70
Mar	-0.47	-1.14	-0.96	-0.87
Apr	-0.29	-1.01	-0.61	-0.87
May	-0.28	-1.11	-0.61	-0.77
Jun	-0.60	-1.59	-1.15	-0.79
Jul	-0.96	-1.72	-1.29	-0.84
Aug	-1.22	-1.87	-1.37	-0.90
Sep	-1.47	-1.99	-1.47	-1.45
Oct	-1.12	-1.54	-0.91	-1.12
Nov	-1.21	-1.44	-0.95	-0.96
Dec	-0.81	-0.89	-0.70	-0.78
Average	-0.80	-1.35	-0.98	-0.90

Table 3.12: Number of Actual Cases during a Drought Compared to Expected Number of Cases Related to the PDSI

	Percentage of Occurrences for Drought (PDSI < 0 / Total Months)	Total of Cases PDSI > 0	Total of Cases PDSI < 0	Expected Number of Cases Based on Percentage of Occurrences of Drought
Fresno County	66%	2,461	2,093	3,005
Kern County	85%	2,315	14,397	14,205
Kings County	77%	310	1,781	1,610
San Luis Obispo County	68%	291	972	858
Tulare County	77%	27	37	49
Total	74%	5,404	19,280	18,266

Dust

PM 10

<u>Data Source</u>
PM 10 comes from EPA's Air Quality System (AQS). Particulate Matter (PM, also called particle pollution) is the term for a mixture micrometers and smaller (ug/m3). Particles that make up PM could be dust, dirt, soot, smoke, or even smaller particles of solid particles and liquid droplets found in the air. PM 10 are particles with the diameter of 10. The EPA Air Quality Standard for PM 10 is 150 ug/m3 in a 24-hour period.

<u>Station Location</u>
Figure 3.9 shows the PM 10 monitoring Stations in the study area. There are three Stations in Fresno County, six in Kern County, three in Kings County, four in San Luis Obispo County, and one in Tulare County. The start and end times for the various Stations are shown in Table 3.13. Not every Station has data for the entire time frame (2000 -2015) and some Stations have gaps/missing values.

Figure 3.9: PM 10 Stations for Study Area

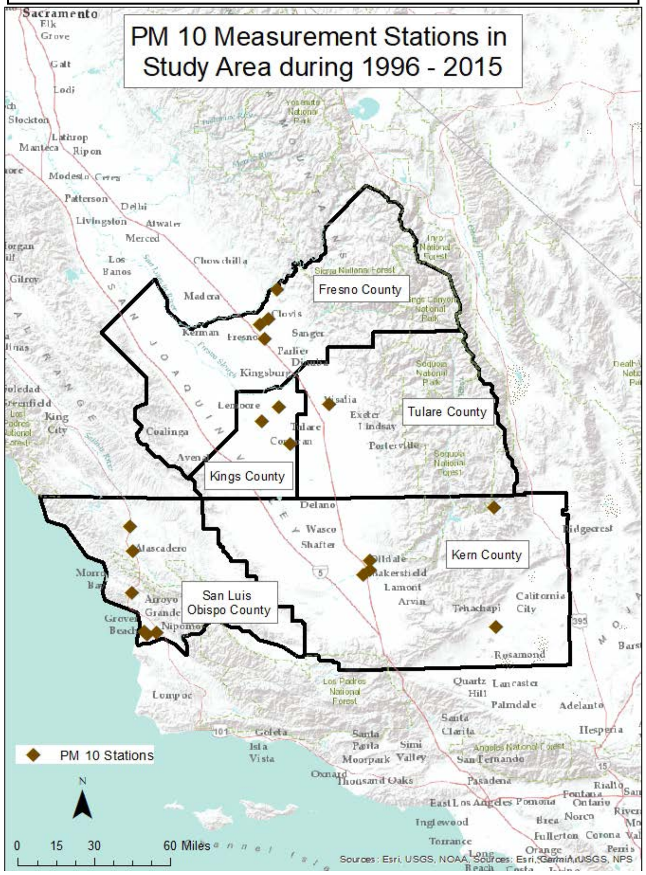


Table 3.13: PM 10 Monitoring Stations and Start and End Dates for the Stations	
Counties	**PM 10 Monitoring Station and Timeframes**
Fresno County	Station 1*: January 2000 – December 2015 *Missing January – June 2002 Station 2: January 2000 – December 2011 Station 3: January 2000 – December 2015
Kern County	Station 1: January 2000 – January 2010 Station 2: January 2000 – June 2011 Station 3: August 2006 – September 2013 Station 4: January 2000 – July 2004 Station 5: January 2000 – December 2005 Station 6: August 2006 – December 2015
Kings County	Station 1: January 2000 – May 2011 Station 2: January 2000 – December 2015 Station 3: August 2006 – October 2014
San Luis Obispo County	Station 1: January 2000 – July 2009 Station 2: January 2000 – December 2010 Station 3*: January 2000 - June 2010 *Missing January and February 2002 Station 4: January 2000 – May 2010
Tulare County	Station 1: January 2000 – March 2007

Data Variability
Table 3.14 shows the PM 10 pollution by Station per county and Figure 3.10 shows the PM 10 time series.

For Fresno County, PM 10 has a seasonal trend, where PM 10 is lower during winter months and higher during summer months. Stations 2 & 3 are relatively similar in variability, but Station 1's peaks are larger.

For Kern County, Stations 1 & 3 have much larger spikes compared to stations 4, 5, & 6. The two Stations in Kings County are almost identical with their pattern and PM 10 quantities.

In the early 2000s, variability in average monthly PM 10 is much larger than the average monthly concentration in 2010 for San Luis Obispo County. The Stations do not appear to have similar seasonality's. With one Station in Tulare County, it appears that PM 10 peaks in September.

Figure 3.10: Average Monthly PM 10 Time-Series

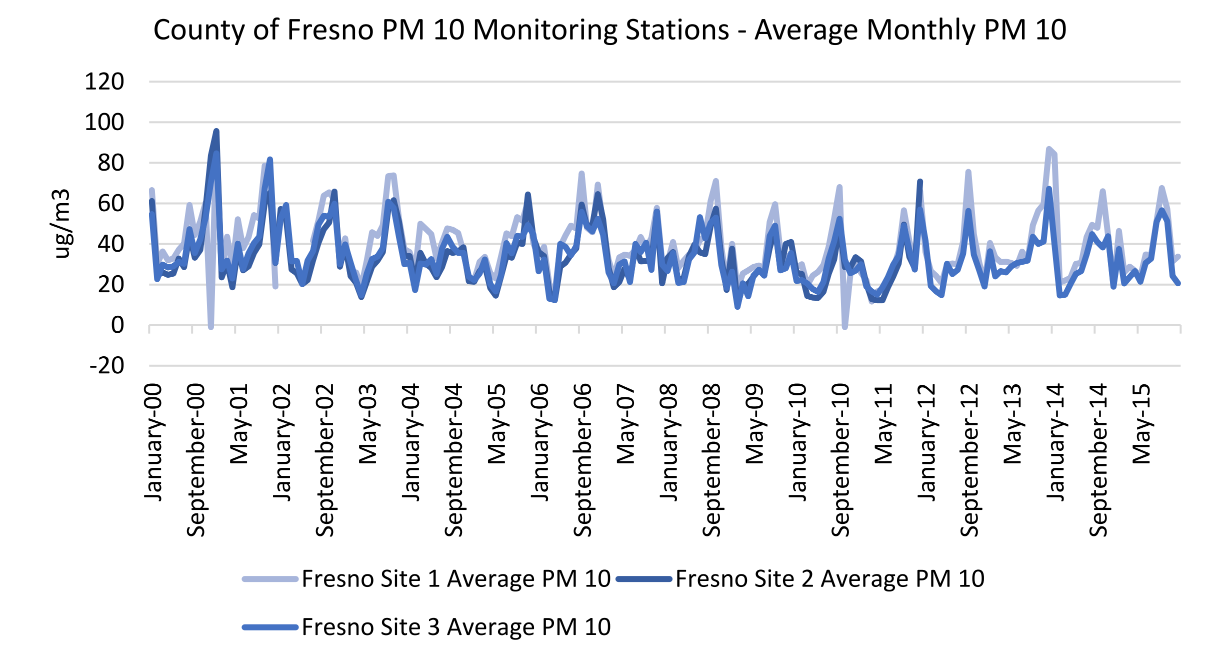
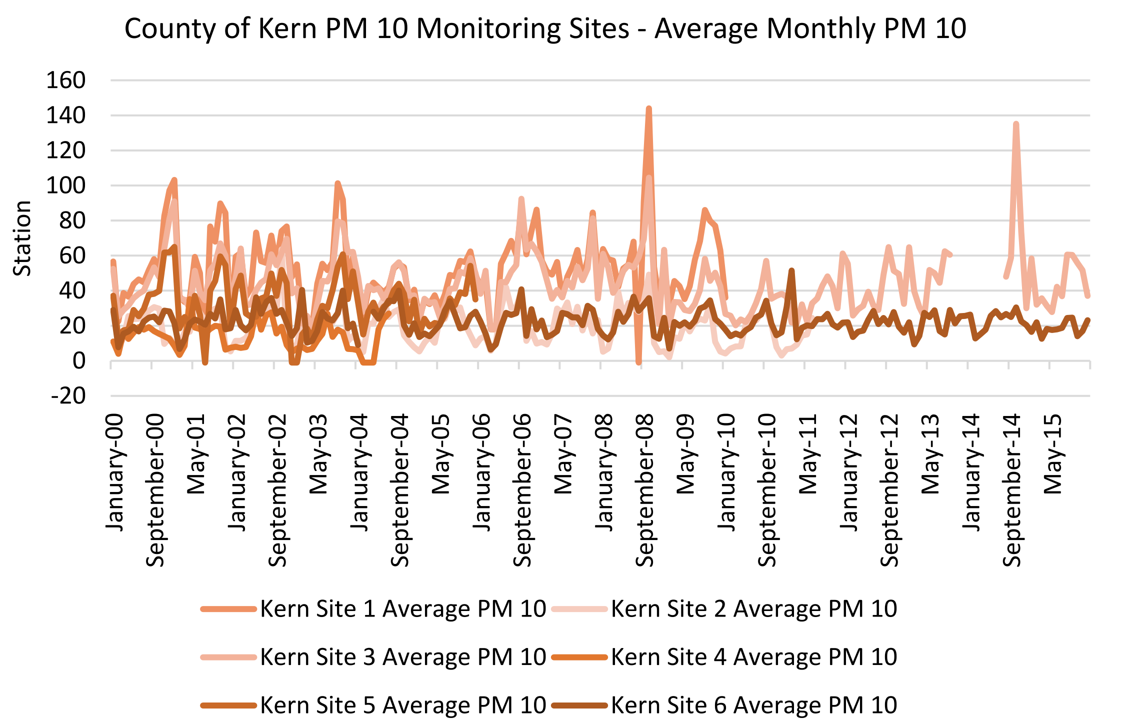


Figure 3.10: Average Monthly PM 10 Time-Series



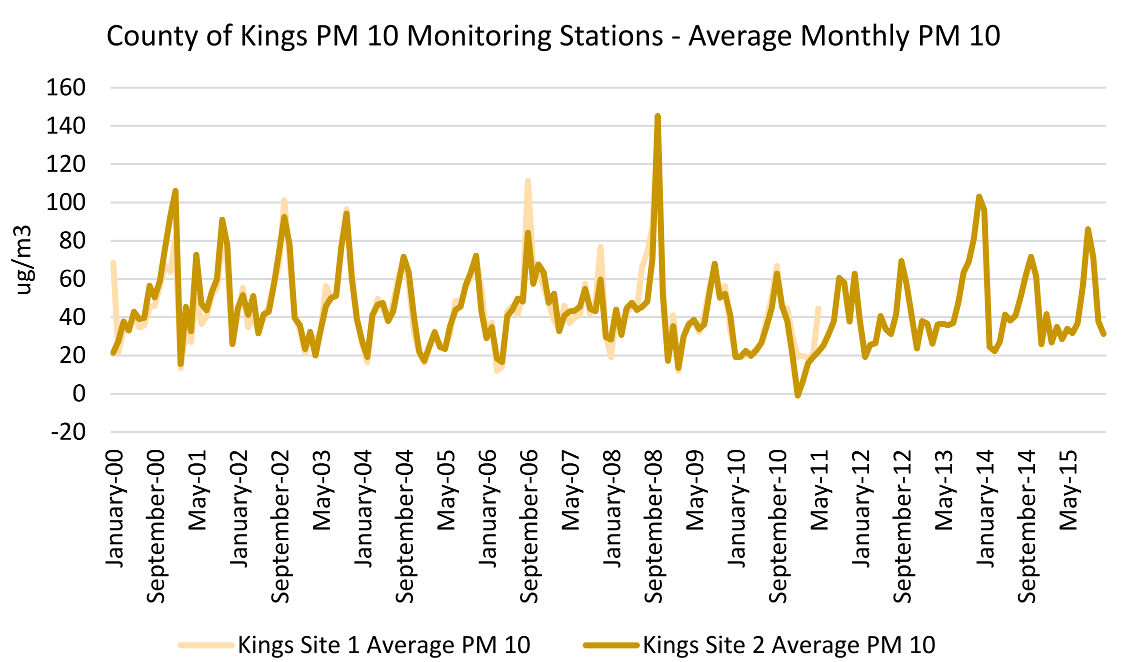
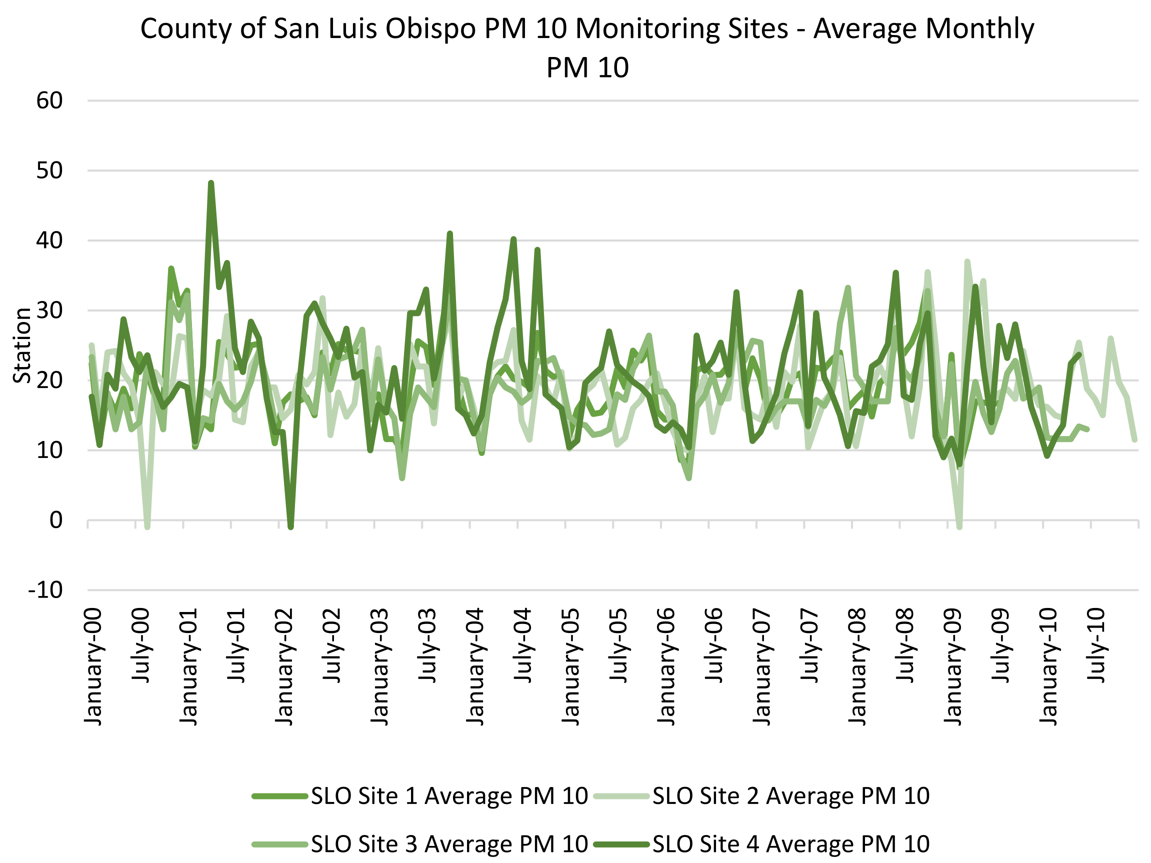


Figure 3.10: Average Monthly PM 10 Time-Series



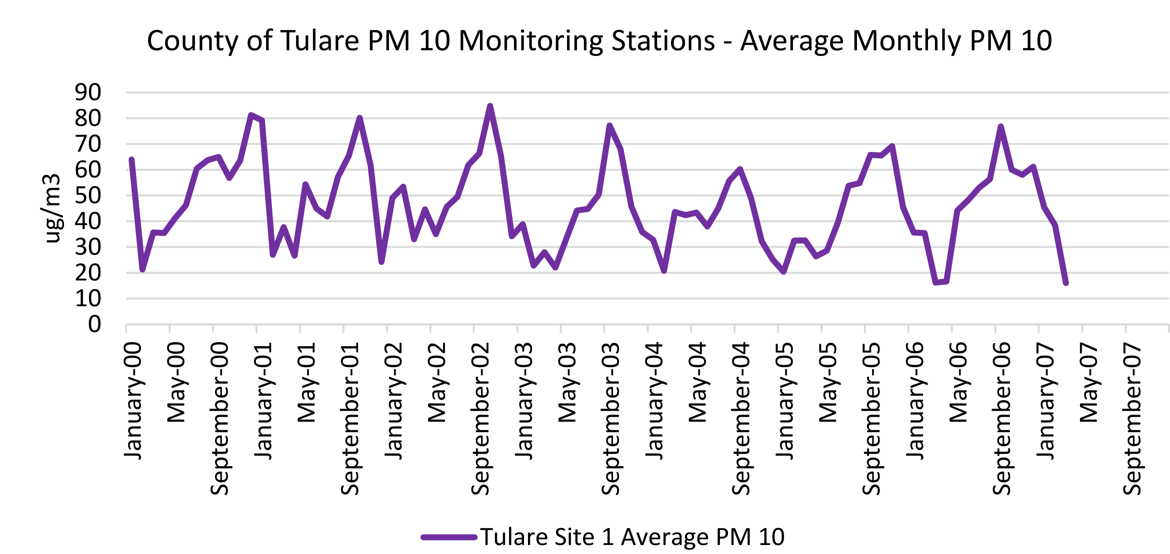


Table 3.14: Monthly and Yearly Average PM 10 by County and Station

Fresno County - Average Annual PM 10

ug/m3	Fresno Station 1	Fresno Station 2	Fresno Station 3
2000	40.74	39.89	39.53
2001	50.20	41.09	44.51
2002	52.82	39.17	42.50
2003	43.30	34.98	35.77
2004	39.66	30.84	31.72
2005	38.69	32.48	33.24
2006	43.80	37.73	36.62
2007	38.15	31.70	33.60
2008	40.00	34.59	34.98
2009	34.28	29.77	27.48
2010	30.98	25.49	27.58
2011	31.21	28.67	29.74
2012	34.23		28.92
2013	43.01		35.63
2014	40.09		30.28
2015	38.54		33.03
Average	39.57	33.87	34.07

Fresno County - Average Monthly PM 10

ug/m3	Fresno Station 1	Fresno Station 2	Fresno Station 3
Jan	44.88	43.75	38.50
Feb	28.47	27.22	25.33
Mar	28.27	22.78	23.24
Apr	26.94	19.52	21.61
May	32.00	23.94	27.06
Jun	33.93	26.12	28.35
Jul	38.84	30.61	34.65
Aug	47.13	35.94	40.87
Sep	58.29	44.92	48.18
Oct	51.80	42.75	43.08
Nov	46.42	48.05	41.98
Dec	35.17	40.81	35.98
Average	39.57	33.87	34.07

Kern County - Average Annual PM 10

ug/m3	Kern Station 1	Kern Station 2	Kern Station 3	Kern Station 4	Kern Station 5	Kern Station 6	Kern Station 7
2000	52.57	20.09	45.45	14.59	34.08	21.36	
2001	54.68	19.67	48.70	15.00	34.16	20.90	
2002	59.22	22.86	49.28	15.59	35.08	25.95	
2003	52.38	20.88	46.94	11.90	30.92	23.32	
2004	42.49	19.93	42.65	10.29	31.59	25.58	
2005	43.21	18.48	39.38		30.06	21.76	
2006	56.43	21.09	50.53			21.37	
2007	54.21	21.66	47.58			22.59	
2008	59.93	23.75	54.53			23.27	
2009	56.99	15.81	39.80			23.19	14.51
2010	36.00	15.50	32.19			19.66	12.88
2011		12.77	35.63			24.11	12.95
2012			40.77			20.90	13.05
2013			47.71			21.67	13.03

Table 3.14: Monthly and Yearly Average PM 10 by County and Station

2014			69.13			23.01	16.31
2015			44.15			18.91	13.43
Average	53.07	19.66	44.98	13.76	32.65	22.31	13.74

Kern County - Average Monthly PM 10

ug/m3	Kern Station 1	Kern Station 2	Kern Station 3	Kern Station 4	Kern Station 5	Kern Station 6	Kern Station 7
Jan	53.95	8.58	50.91	8.10	31.72	21.29	4.17
Feb	39.05	9.56	35.03	4.35	22.35	17.48	4.94
Mar	37.65	13.42	30.67	7.59	22.57	14.38	8.21
Apr	37.38	18.22	31.03	13.50	21.79	18.96	12.81
May	47.22	24.52	36.76	18.80	26.99	22.55	20.79
Jun	49.22	28.48	39.38	18.89	29.19	24.69	24.58
Jul	49.04	25.76	40.35	22.64	27.31	25.61	21.38
Aug	54.82	27.78	51.07	19.68	39.99	26.34	22.05
Sep	70.58	29.00	60.36	17.59	42.91	27.91	22.28
Oct	75.97	30.83	62.79	17.64	48.06	26.07	14.72
Nov	67.45	11.74	55.73	9.05	45.43	21.38	5.87
Dec	54.40	9.41	44.21	7.94	33.48	20.31	3.04
Average	53.07	19.66	44.98	13.76	32.65	22.31	13.74

Kings County - Average Annual PM 10

ug/m3	Kings Station 1	Kings Station 2	Kings Station 3
2000	45.70	48.07	
2001	46.85	55.88	
2002	52.48	53.85	
2003	48.37	46.85	
2004	41.91	43.09	
2005	41.04	40.28	
2006	47.63	46.18	84.28
2007	44.87	44.76	46.27
2008	55.21	51.46	51.78
2009	41.36	40.69	36.81
2010	33.83	31.41	33.45
2011	24.62	31.37	33.52
2012		37.34	37.15
2013		50.90	47.67
2014		46.78	44.36
2015		43.08	
Average	44.63	44.50	43.48

Kings County - Average Monthly PM 10

ug/m3	Kings Station 1	Kings Station 2	Kings Station 3
Jan	36.93	39.06	36.72
Feb	26.72	27.48	23.55
Mar	29.33	30.58	24.24
Apr	32.08	31.44	31.41
May	38.26	38.62	36.21
Jun	38.78	37.72	37.81
Jul	45.22	40.78	42.71
Aug	55.02	50.28	52.26

Table 3.14: Monthly and Yearly Average PM 10 by County and Station

Sep	67.67	66.37	67.93
Oct	72.51	70.84	67.06
Nov	60.82	58.27	54.28
Dec	37.64	42.54	40.49
Average	44.63	44.50	43.48

San Luis Obispo County - Average Annual PM 10

ug/m3	San Luis Obispo Station 1	San Luis Obispo Station 2	San Luis Obispo Station 3	San Luis Obispo Station 4
2000	20.63	18.88	18.78	19.77
2001	20.18	19.85	18.29	25.07
2002	20.38	18.90	20.69	20.58
2003	19.71	21.01	18.77	23.16
2004	19.49	18.67	18.67	23.38
2005	18.41	16.30	17.09	18.70
2006	18.44	16.10	18.06	19.21
2007	19.23	17.70	19.45	19.76
2008	21.29	20.45	20.30	20.59
2009	15.71	19.83	17.17	20.12
2010		18.20	12.17	16.13
2011				
2012				
2013				
2014				
2015				
Average	19.51	18.72	18.38	20.84

San Luis Obispo County - Average Monthly PM 10

ug/m3	San Luis Obispo Station 1	San Luis Obispo Station 2	San Luis Obispo Station 3	San Luis Obispo Station 4
Jan	19.28	16.65	20.67	13.68
Feb	13.19	13.14	13.42	11.56
Mar	14.61	19.93	15.13	19.43
Apr	15.34	20.14	14.04	24.73
May	19.53	22.55	16.19	27.38
Jun	21.18	24.16	17.42	28.85
Jul	21.05	15.03	17.22	23.17
Aug	21.50	13.21	18.84	22.35
Sep	24.17	19.67	21.23	25.30
Oct	25.43	22.80	23.54	24.32
Nov	22.33	19.73	23.33	16.98
Dec	17.83	17.59	20.55	13.06

Table 3.14: Monthly and Yearly Average PM 10 by County and Station				
Average	19.51	18.72	18.38	20.84

Tulare County - Average Annual PM 10	
ug/m3	**Tulare Station 1**
2000	52.88
2001	50.04
2002	51.88
2003	42.57
2004	40.71
2005	44.53
2006	46.79
2007	33.30
2008	
2009	
2010	
2011	
2012	
2013	
2014	
2015	
Average	46.58

Tulare County - Average Monthly PM 10	
ug/m3	**Tulare Station 1**
Jan	45.65
Feb	31.46
Mar	30.35
Apr	30.57
May	39.96
Jun	43.81
Jul	49.77
Aug	57.14
Sep	68.09
Oct	66.36
Nov	56.56
Dec	43.88
Average	46.58

PM 2.5

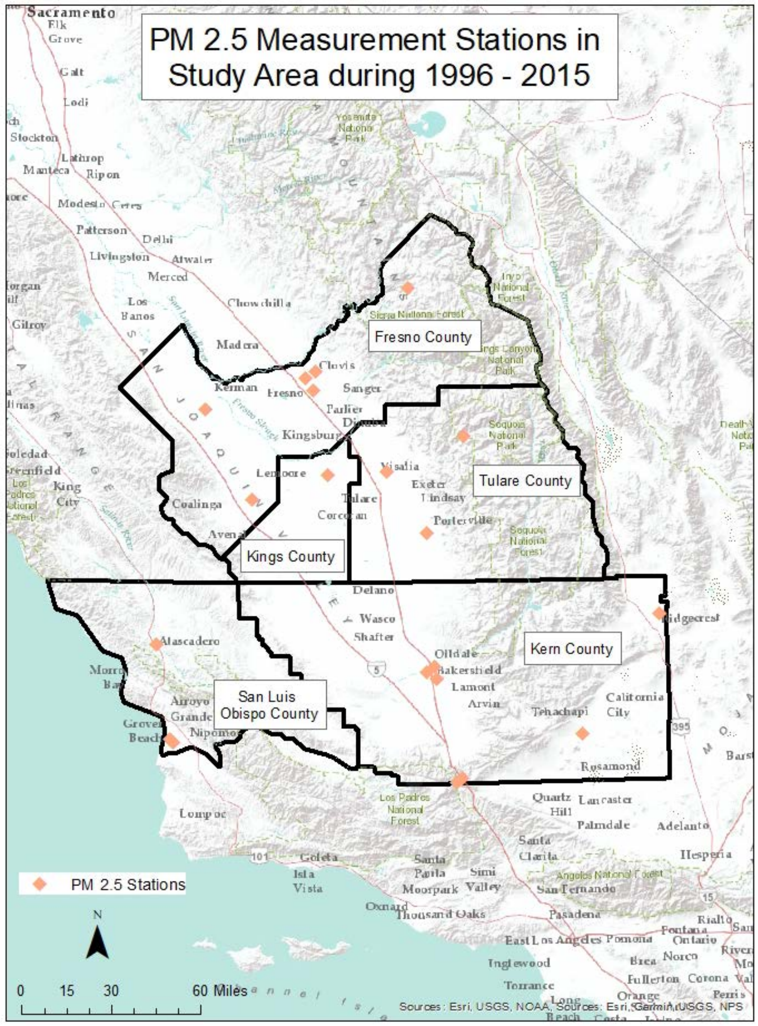
Data Source

PM 2.5 comes from EPA's Air Quality System (AQS). Particulate Matter (PM, also called particle pollution) is the term for a mixture micrometers and smaller (ug/m3). Particles that make up PM could be dust, dirt, soot, smoke, or even smaller particles of solid particles and liquid droplets found in the air. PM 2.5 are particles with the diameter of 2.5. The EPA Air Quality Standard for PM 2.5 is 35 ug/m3 in a 24-hour period or 12.0 ug/m3 annually.

Station Location

Figure 3.11 shows the PM 2.5 monitoring Stations in the study area. There are six Stations in Fresno County, eight in Kern County, three in Kings County, five in San Luis Obispo County, and two in Tulare County. The start and end times for the various Stations are shown in Table 3.15. Not every Station has data for the entire time frame (2000 -2015) and some Stations have gaps/missing values.

Figure 3.11: PM 2.5 Stations for Study Area



Data Variability

Table 3.16 shows the PM 2.5 pollution by Station per county and Figure 3.12 shows the PM 2.5 time series.

For Fresno County, the variability between the sites is similar, except for Station 4, where the average concentrations of PM 2.5 are 2-5x lower than the rest of the stations. Also, Station 4 appears to have a different seasonality compared to the other stations, the month that Station 4 has a low concentration, the other stations have a high concentration. For Stations 1, 2, 3, and 5, PM 2.5 peaks during the winter season, November – February.

For Kern County, three stations have an average PM 2.5 concentration between 18-20 ug/m^3 and the other four stations have an average concentration between 5-6 ug/m^3. The stations with larger PM 2.5 concentrations have concentration peaks during November – February, while the other stations peak during summer.

For Kings County, that station has an average PM 2.5 concentration between 18-20 ug/m^3 and a seasonality peaking during the winter months.

For San Luis Obispo, all stations have average PM 2.5 concentrations between 6-12 ug/m3. Although there is not a large difference between the highest monthly concentration and the lowest, approximately 2-5 ug/m^3, there does appear to be consistent high concentration peaks in April and May.

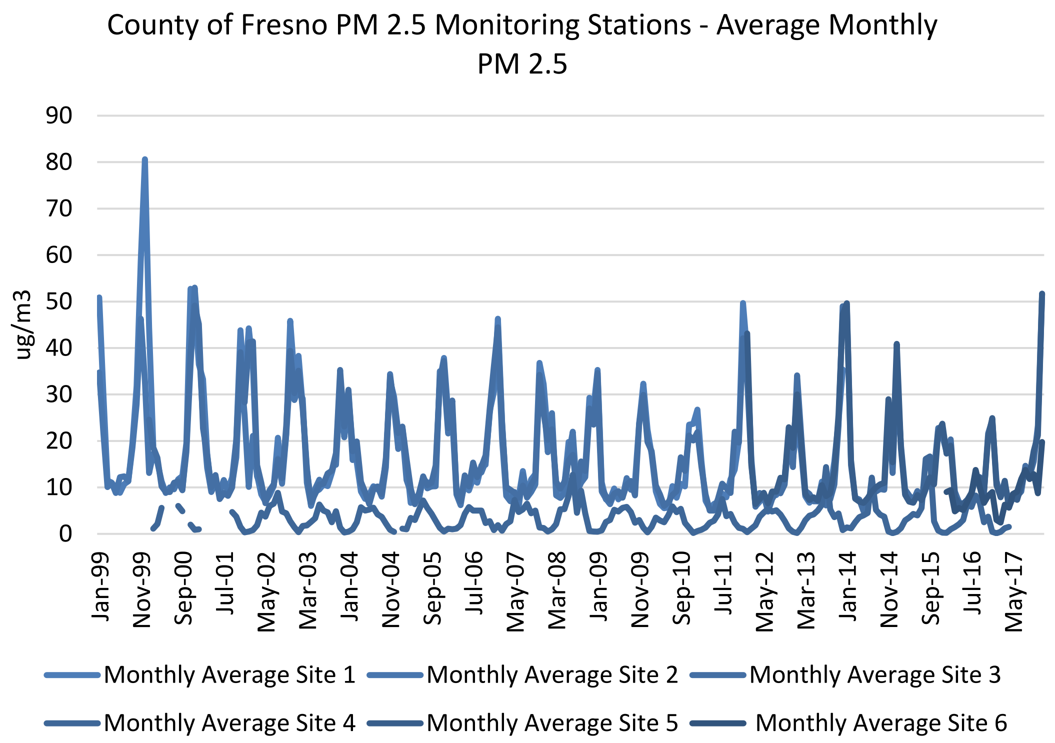
Table 3.15: PM 2.5 Monitoring Stations and Start and End Dates for the Stations

Counties	**PM 2.5 Monitoring Station and Timeframes**
Fresno County	Station 1: January 1999 – December 2013 Station 2: January 1999 – September 2009 Station 3: January 2000 – December 2017 Station 4: February 2000 – April 2017 Station 5: January 2012 – December 2017 Station 6: January 2016 – December 2017
Kern County	Station 1*: January 1999 – December 2017 No data between November 2009 – July 2014 Station 2: January 1999 – June 2012 Station 3: January 1999 – December 2017 Station 4: January 1999 – December 2017 Station 5: February 2000 – December 2017 Station 6: March 2000 – December 2004 Station 7: November 2005 – April 2017 Station 8: November 2017 – December 2017
Kings County	Station 1*: January 1999– March 2015 *Missing data from January 2011 – October 2012
San Luis Obispo County	Station 1: January 1999 – September 2005 Station 2: January 1999 – March 2010 Station 3: September 2005 – March 2011 Station 4: July 2009 – December 2017 Station 5: August 2010 – November 2017
Tulare County	Station 1: January 1999 – April 2017 Station 2: January 1999 – December 2017

For Tulare County, one station has an average PM 2.5 concentration of 7-8 ug/m^3 and peaks in July and August. The other station has an average 18-19 ug/m^3 and has high concentration peaks in November – February.

It should be evident that the PM 2.5 concentrations and the seasonality of those concentrations are different based on where the stations are located. In the mountains, the concentrations are lower. Being able to know geographically where the cases where exposed would help narrow down the relationship between PM 2.5 concentration and exposure.

Figure 3.12: Average Monthly PM 2.5 Time-Series



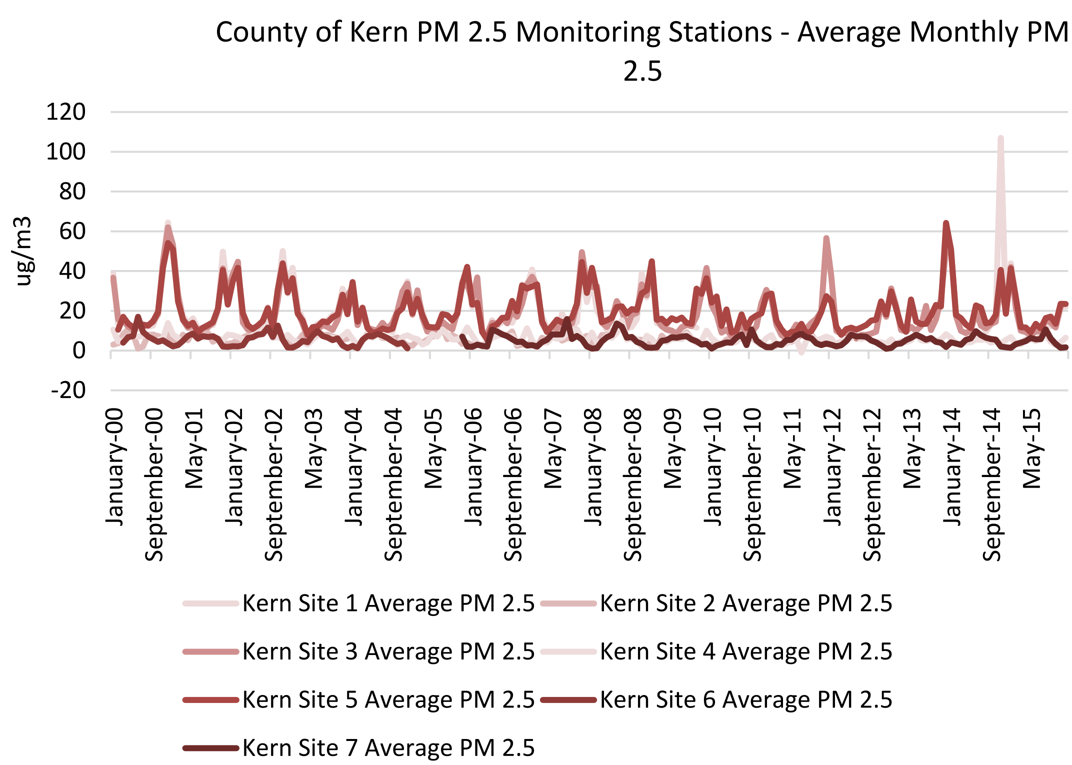
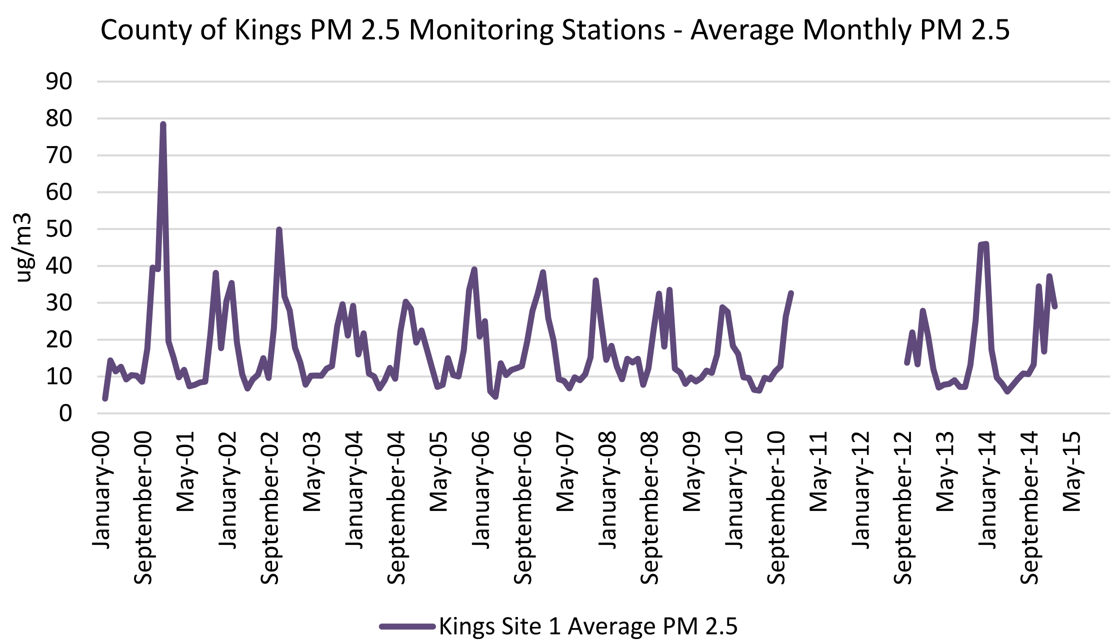


Figure 3.12: Average Monthly PM 2.5 Time-Series



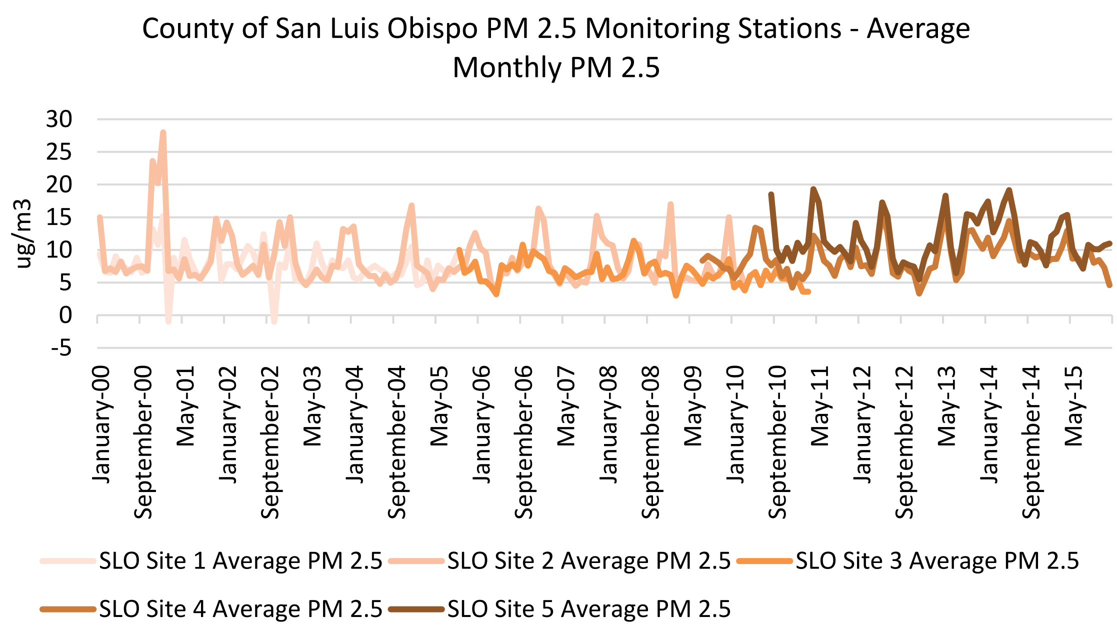


Figure 3.12: Average Monthly PM 2.5 Time-Series

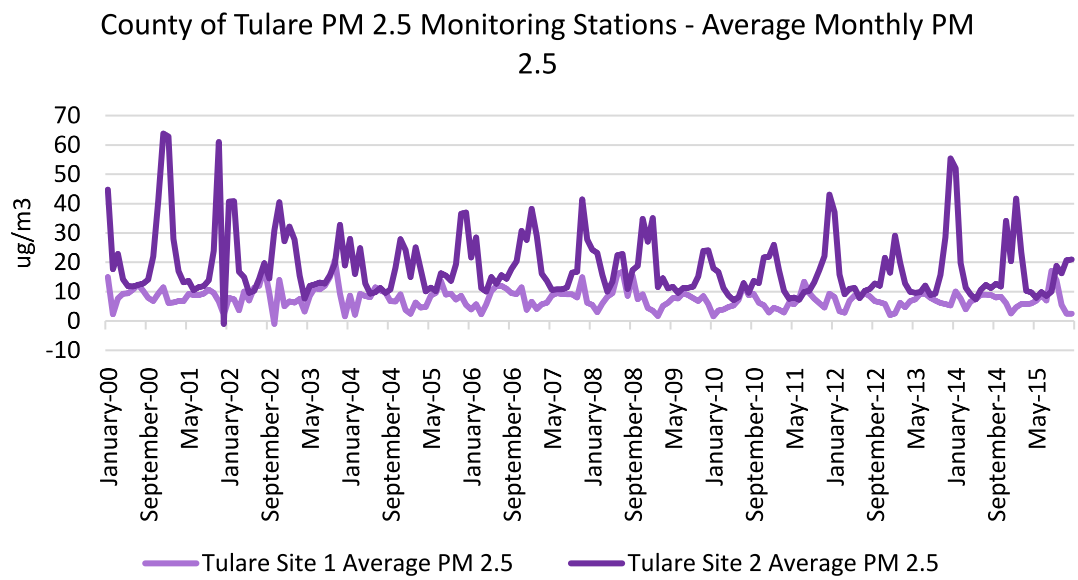


Table 3.16: Monthly and Yearly Average PM 2.5 by County and Station

Fresno County - Average Annual PM 2.5					
ug/m3	**Fresno Station 1**	**Fresno Station 2**	**Fresno Station 3**	**Fresno Station 4**	**Fresno Station 5**
2000	25.46	17.79	18.85		
2001	20.41	18.20	19.13	2.56	
2002	21.74	16.09	21.30	3.85	
2003	17.83	13.53	17.93	2.91	
2004	16.46	16.18	16.82	3.08	
2005	16.63	15.53	17.07	2.88	
2006	16.60	16.47	17.69	3.01	
2007	18.33	16.25	17.13	3.60	
2008	17.10	15.78	16.40	4.54	
2009	14.57	11.05	14.11	3.30	
2010	12.71		13.19	2.88	
2011	15.00		14.64	2.72	
2012	13.22	17.13	12.25	2.96	14.22
2013	14.60	14.86	16.04	4.35	16.18
2014		14.57	14.06	3.58	14.96
2015		13.04	14.48	4.86	14.61
Average	17.04	15.45	16.32	3.45	14.99
Fresno County - Average Monthly PM 2.5					
ug/m3	**Fresno Station 1**	**Fresno Station 2**	**Fresno Station 3**	**Fresno Station 4**	**Fresno Station 5**
Jan	32.58	26.80	32.08	0.54	40.93
Feb	22.00	19.61	21.12	1.09	17.10
Mar	10.98	10.86	11.74	2.15	7.75
Apr	7.37	8.44	8.69	3.52	7.14

Table 3.16: Monthly and Yearly Average PM 2.5 by County and Station

May	8.40	8.82	8.24	4.26	7.51
Jun	8.78	9.38	8.55	5.24	7.45
Jul	11.16	10.63	10.35	6.79	9.00
Aug	10.29	9.82	10.14	6.74	9.26
Sep	11.77	9.32	11.23	5.56	10.90
Oct	15.10	13.73	15.07	3.32	11.76
Nov	31.92	29.39	29.13	1.66	24.86
Dec	32.38	28.61	29.46	0.66	26.21
Average	17.04	15.45	16.32	3.45	14.99

Kern County - Average Annual PM 2.5

ug/m3	**Kern Station 1**	**Kern Station 2**	**Kern Station 3**	**Kern Station 4**	**Kern Station 5**	**Kern Station 6**	**Kern Station 7**
2000	22.49	6.22	22.28	7.26	20.14	7.04	
2001	22.28	6.08	21.63	6.87	20.83	5.24	
2002	24.01	7.86	22.90	8.34	23.61	6.19	
2003	19.43	6.48	16.67	6.11	17.68	4.99	
2004	17.99	6.17	18.15	6.03	16.87	4.89	
2005	19.28	5.90	18.14	6.94	20.28		4.50
2006	18.56	5.42	19.29	6.19	19.09		5.15
2007	19.92	6.23	22.07	6.07	21.70		6.30
2008	18.12	6.73	21.75	6.84	23.40		5.81
2009	14.68	5.12	18.71	5.69	21.79		4.78
2010		4.57	14.49	5.05	17.78		4.42
2011		4.84	16.65	4.74	14.48		4.80
2012		5.17	12.92	5.16	14.62		4.54
2013			19.50	5.41	22.27		4.72
2014	30.07		18.52	4.62	21.58		5.09
2015	16.64		15.73	5.14	18.26		4.53
Average	19.94	5.93	18.73	6.00	19.65	5.62	5.01

Kern County - Average Monthly PM 2.5

ug/m3	**Kern Station 1**	**Kern Station 2**	**Kern Station 3**	**Kern Station 4**	**Kern Station 5**	**Kern Station 6**	**Kern Station 7**
Jan	36.92	3.11	35.03	6.88	34.45	2.04	1.93
Feb	24.32	3.38	23.15	3.87	22.43	2.19	2.60
Mar	15.80	5.82	12.42	3.96	14.49	4.36	3.55
Apr	10.80	6.11	9.71	5.02	11.71	6.41	4.90
May	11.04	7.37	10.77	6.11	12.65	7.44	6.94
Jun	10.81	7.39	12.04	6.94	13.45	9.85	8.24
Jul	12.88	7.90	12.77	7.41	15.14	7.95	7.95
Aug	13.10	7.87	13.04	7.44	14.33	7.66	7.60
Sep	12.67	6.94	13.00	6.18	15.61	5.94	6.43
Oct	18.17	6.28	17.16	5.06	20.21	6.48	4.67
Nov	43.79	4.56	31.43	5.19	30.79	3.89	3.59
Dec	31.06	4.21	35.24	8.02	31.40	1.86	2.10
Average	19.94	5.93	18.73	6.00	19.65	5.62	5.01

Kings County - Average Annual PM 2.5

ug/m3	**Kings Station 1**
2000	16.10
2001	20.37
2002	20.95

Table 3.16: Monthly and Yearly Average PM 2.5 by County and Station

2003	16.44
2004	17.18
2005	17.62
2006	16.42
2007	17.84
2008	15.97
2009	15.64
2010	14.02
2011	
2012	16.35
2013	15.93
2014	15.84
2015	33.11
Average	17.14

Kings County - Average Monthly PM 2.5

ug/m3	**Kings Station 1**
Jan	32.44
Feb	19.99
Mar	14.05
Apr	9.10
May	9.67
Jun	8.62
Jul	10.53
Aug	10.49
Sep	10.37
Oct	18.01
Nov	32.44
Dec	27.74
Average	17.14

San Luis Obispo County - Average Annual PM 2.5

ug/m3	**San Luis Obispo Station 1**	**San Luis Obispo Station 2**	**San Luis Obispo Station 3**	**San Luis Obispo Station 4**	**San Luis Obispo Station 5**
2000	8.30	10.22			
2001	8.03	9.58			
2002	7.68	9.30			
2003	7.49	8.16			
2004	6.91	8.32			
2005	6.87	7.31	7.93		
2006		8.24	7.07		
2007		7.96	6.73		
2008		8.31	7.45		
2009		7.65	6.16	8.06	
2010		6.00	5.47	8.20	11.08
2011			4.23	8.28	11.84
2012				8.05	9.63
2013				9.67	12.46
2014				10.18	12.79
2015				8.71	11.13
Average	7.58	8.44	6.55	8.79	11.53

San Luis Obispo County - Average Monthly PM 2.5

Table 3.16: Monthly and Yearly Average PM 2.5 by County and Station					
ug/m3	**San Luis Obispo Station 1**	**San Luis Obispo Station 2**	**San Luis Obispo Station 3**	**San Luis Obispo Station 4**	**San Luis Obispo Station 5**
Jan	8.99	13.88	6.18	7.53	12.12
Feb	4.88	7.98	4.84	7.45	11.18
Mar	7.08	6.27	4.96	8.28	11.53
Apr	6.76	5.26	5.60	11.34	15.27
May	8.62	6.59	7.37	13.15	16.43
Jun	8.37	6.55	7.12	10.67	12.12
Jul	6.88	6.79	7.01	7.48	8.52
Aug	7.77	6.69	6.24	7.85	10.60
Sep	7.58	6.65	7.97	9.08	10.89
Oct	5.76	7.41	6.78	8.66	10.27
Nov	10.00	13.29	7.50	7.99	10.08
Dec	8.47	13.67	7.16	6.82	10.43
Average	**7.58**	**8.44**	**6.55**	**8.79**	**11.53**

Tulare County - Average Annual PM 2.5		
ug/m3	**Tulare Station 1**	**Tulare Station 2**
2000	9.39	24.08
2001	7.61	22.21
2002	8.77	23.35
2003	9.41	18.35
2004	7.88	16.88
2005	7.48	18.99
2006	8.07	18.79
2007	8.11	20.27
2008	9.16	20.06
2009	6.60	15.92
2010	5.93	13.55
2011	6.79	16.03
2012	6.41	14.67
2013	6.53	18.43
2014	7.31	17.72
2015	7.20	16.53
Average	7.67	18.49

Tulare County - Average Monthly PM 2.5		
ug/m3	**Tulare Station 1**	**Tulare Station 2**
Jan	6.13	34.17
Feb	4.73	22.54
Mar	5.17	14.84
Apr	6.66	10.84
May	8.03	10.61
Jun	9.91	10.87
Jul	11.00	12.84
Aug	10.42	11.94
Sep	9.60	14.15
Oct	7.51	18.18
Nov	8.20	32.45
Dec	4.64	28.43
Average	7.67	18.49

Soil Criteria

Data Source
Information about the soil type, percentage of clay, silt, and sand in the soil at the monitor place, as well as soil pH was obtained from the National Cooperative Soil Survey.

Station Location
Within the 5-county study area, there were 357 soil surveys conducted. The location of these surveys is shown in Figure 3.13. More than 50% of these soil surveys were conducted in the Sierra Nevada and coastal mountain ranges.

Data Variability

Percentage of Clay
Figure 3.14 shows the station distribution based on the percent of clay in the soil. The soil in the Sierra Nevada Mountain Range seems to have consistently low percentage of clay in the region. As we look at the stations west of the range, almost all of them indicate that the percent of clay in the soil is above 11%.

Percentage of Silt
Figure 3.15 shows the station distribution based on the percent of silt in the soil. The lowest percent of silt in the soil seem to be located mostly in the southeast corner of Kern County.

Percentage of Sand
Figure 3.16 shows the station distribution based on the percent of sand in the soil. The lowest percent of silt in the soil seem to be located mostly in the East of the Sierra Nevada Mountains.

pH
Figure 3.17 shows the station distribution based on the pH in the soil. Any pH below 7 is said to be acidic and any pH above 7 is said to be alkaline. We can see that the mountain ranges tend to have more acidic soil and the valley/low areas tend to have more alkaline soil.

Figure 3.13: National Cooperative Soil Survey Station Locations Area

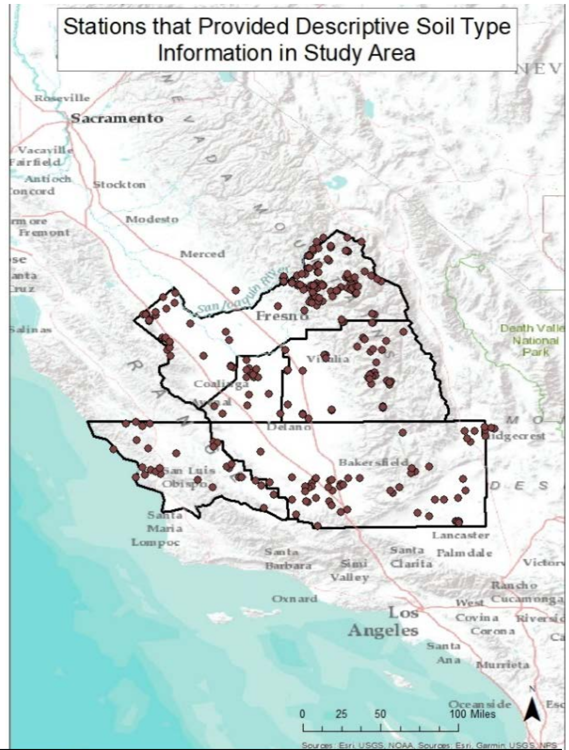


Figure 3.14: Percent of Clay

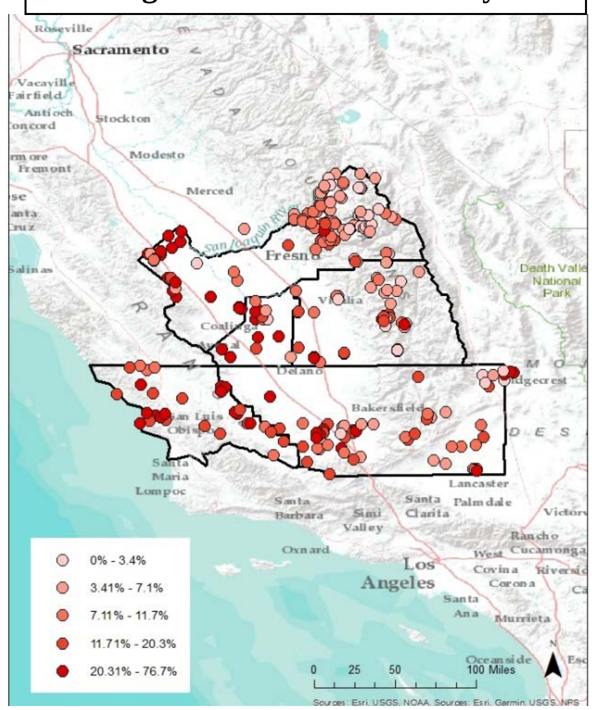


Figure 3.15: Percent of Silt

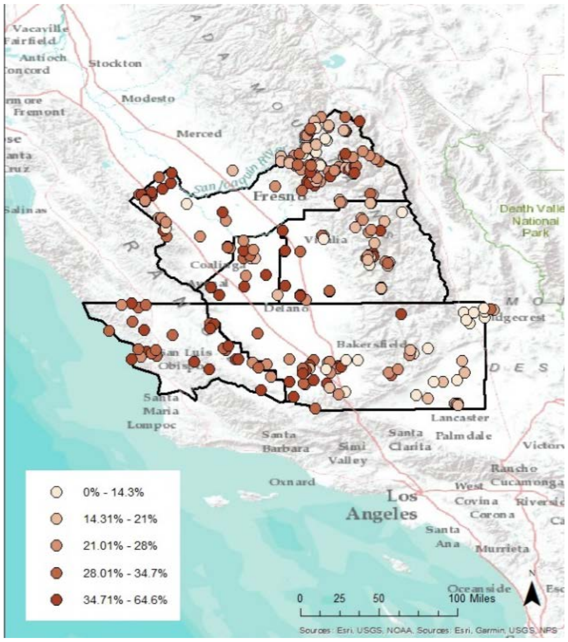


Figure 3.16: Percent of Sand

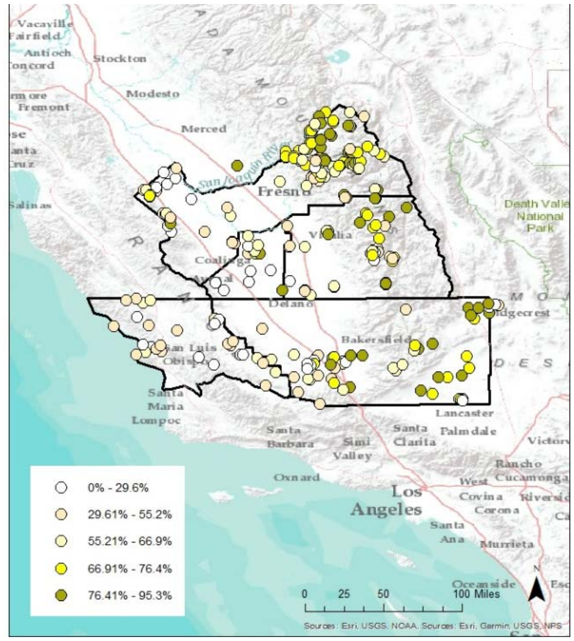
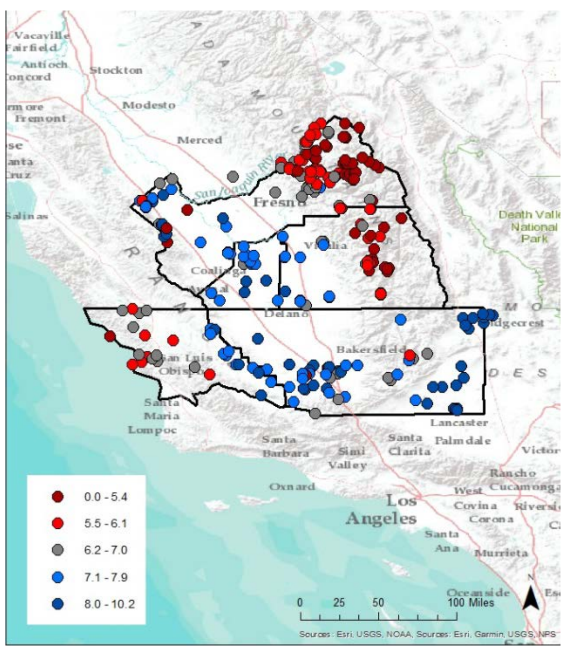


Figure 3.17: Soil pH



Ecological Niche Theories

Lauer et al. (2012) and Lauer et al. (2014) utilized soil characterization and soil samples around Bakersfield to determine the ecological niche of Coccidioidomycosis spores. They detected the spores at locations that are in non-agricultural land, that have 33% of sand, clay, and silt. They were also said to live in a pH between 7.8 and 8.5. Using this Hypothesis, Figure 3.18 and 3.19 demonstrate the soil surveys that meet the 33% clay characterization and the soil with a slight alkaline pH. If Coccidioidomycosis spores require a niche to have both 33% clay and 7.8-8.5 pH, the ecological niche would be very small and centered on Northwest of Fresno County and the North part of Kings County.

Although zip code and individual level data could not be provided, this would be a prime example of how that information can benefit the research on the disease. If researchers could know where diagnosed cases lived generally and where they worked, researchers might be able to test these ecological niche theories and other climate variables like PDSI and further refine the endemic zone of these spores.

It should now be evident that the soil is not the same throughout each county and not the same across the counties. Taking a county-wide evaluation of the relationship between disease exposure and the environment may not be appropriate.

Figure 3.18: Ecological Niche Theory Locations Based on Percent of Clay

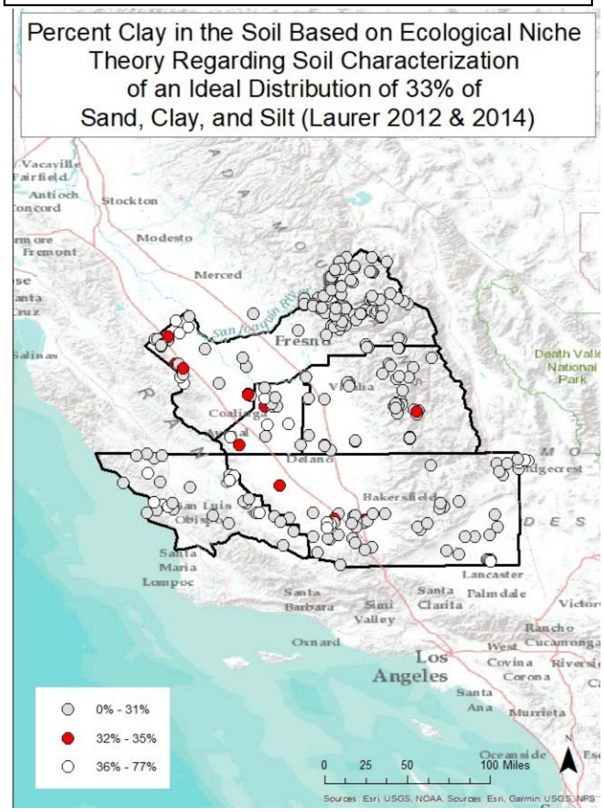
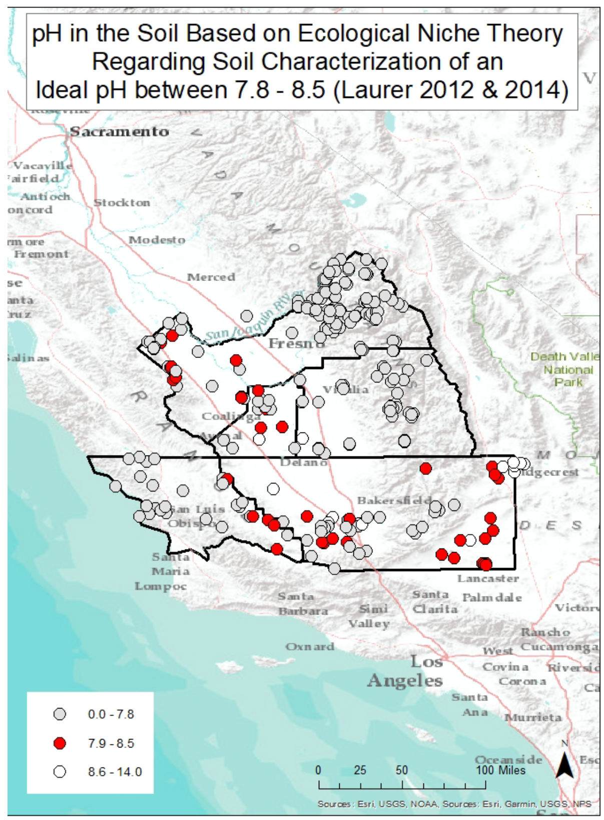


Figure 3.19: Ecological Niche Theory Locations Based on Soil pH



Conclusion

This chapter should highlight that environmental factors are not homogenous within manmade governmental boundaries of a county. The homogeneity is not just in the monthly quantities of the variable being measured per station, but even the seasonality of the peak concentrations of those variables.

Without knowing a smaller geographical region where cases are exposed, what stations should researchers use? Should researchers average all the stations together? How do the differences in the choices that researchers make influence the results?

The next chapter will explore more of these concepts.

Chapter 4

Exploratory Analysis on the Relationship of Various Climate Explanatory Variables and their Monthly Lags to Various Valley Fever Exposure Methods

Introduction

This chapter will explore analyses conducted between the climate variables discussed in Chapter 3 and the case data discussed in Chapter 2. Univariate and multivariate analyses will be conducted in this chapter for the five counties of interest to this study: Fresno, Kern, Kings, San Luis Obispo, and Tulare.

More specifically, this chapter will discuss the results of exploring:

1) How does averaging site information over the county differ from using site specific information?
2) How does the analysis change when looking at the climate variables to diagnosis date versus other exposure scenarios?
3) How do the results change by using different mathematical regression methods?
4) How do these initial results compare to the “Grow and Blow” Effect Hypothesis?
5) Are there any similarities or patterns emerging across the entire study area?

Methods

R Statistical Program and library packages of MASS, HMISC, MICE, and MEMISC was used for the calculations and organization of the results in this chapter.

Naming Conventions

Ten (10) exposure scenarios were analyzed as the dependent variables. Table 4.1 lists the names of these 10 scenarios and what they describe. Further details of these scenarios can be found in Chapter 2. Every county uses these 10 exposure scenario estimates.

Table 4.1: Dependent Variable Exposure Variables and their Description

Naming Convention	Description
Actual	This is the Diagnosis Month of the Cases (what was received by the researchers).
EMST	Exposure was calculated using Stacy *et al*’s exposure method that exposure occurs ½ a month before diagnosis and that 50% of cases get diagnosed in the first half of the month.
75ST	Exposure was calculated using Stacy *et al*’s exposure method that exposure occurs ½ a month before diagnosis and that 75% of cases get diagnosed in the first half of the month.
25ST	Exposure was calculated using Stacy *et al*’s exposure method that exposure occurs ½ a month before diagnosis and that 25% of cases get diagnosed in the first half of the month.
EMPM	Exposure was calculated using Park *et al*’s exposure method that exposure occurs 1 month before diagnosis and that 50% of cases get diagnosed in the first half of the month.
75PM	Exposure was calculated using Park *et al*’s exposure method that exposure occurs 1 month before diagnosis and that 75% of cases get diagnosed in the

Table 4.1: Dependent Variable Exposure Variables and their Description	
	first half of the month.
25PM	Exposure was calculated using Park *et al*'s exposure method that exposure occurs 1 month before diagnosis and that 25% of cases get diagnosed in the first half of the month.
EMCM	Exposure was calculated using Comrie *et al*'s exposure method that exposure occurs 2 months before diagnosis and that 50% of cases get diagnosed in the first half of the month.
75CM	Exposure was calculated using Comrie *et al*'s exposure method that exposure occurs 2 months before diagnosis and that 75% of cases get diagnosed in the first half of the month.
25CM	Exposure was calculated using Comrie *et al*'s exposure method that exposure occurs 2 months before diagnosis and that 25% of cases get diagnosed in the first half of the month.

To simplify the displays in the table, the climate and environmental variables described in Chapter 3 were also renamed for the analysis. Their new naming conventions can be found in Table 4.2.

Table 4.2: Renamed Climate Variables by County	
Fresno County	
Old Name	**New Name**
Kfat	Fresno_Precip_Site1 & Temp
Coalinga	Fresno_Precip_Site2 & Temp
Friant	Fresno_Precip_Site 3 & Temp
PineFlat	Fresno_Precip_Site 4 & Temp
Auberry	Fresno_Precip_Site 5 & Temp
NOAA Division 5	Fresno_Precip_Site 6 & Temp
CIMIS Station 2	Fresno_Temp_Site7
CIMIS Station 7	Fresno_Temp_Site8
CIMIS Station 39	Fresno_Temp_Site9
CIMIS Station 105	Fresno_Temp_Site10
CIMIS Station 124	Fresno_Temp_Site11
CIMIS Station 142	Fresno_Temp_Site12
CIMIS Station 2	Fresno_Wind_Site1 & ETO
CIMIS Station 7	Fresno_Wind_Site2 & ETO
CIMIS Station 39	Fresno_Wind_Site3 & ETO
CIMIS Station 105	Fresno_Wind_Site4 & ETO
CIMIS Station 124	Fresno_Wind_Site5 & ETO
CIMIS Station 142	Fresno_Wind_Site6 & ETO
PM 10 Site 1 **PM 10 Site 2** **PM 10 Site 3**	Fresno_PM10Average_Site1 Fresno_PM10Average_Site2 Fresno_PM10Average_Site3
PM 2.5 Site 1 **PM 2.5 Site 2**	Fresno_AveragePM2.5_Site1 Fresno_AveragePM2.5_Site2
Kern County	
Old Name	**New Name**
Bakersfield	Kern_Precip_Site1 & Temp
Buttonwillow	Kern_Precip_Site2 & Temp

Table 4.2: Renamed Climate Variables by County	
Delano	Kern_Precip_Site3 & Temp
NOAA Division 5	Kern_Precip_Site4 & Temp
CIMIS Station 5	Kern_Temp_Site5
CIMIS Station 54	Kern_Temp_Site6
CIMIS Station 125	Kern_Temp_Site7
CIMIS Station 138	Kern_Temp_Site8
CIMIS Station 146	Kern_Temp_Site9
CIMIS Station 5	Kern_Wind_Site1 & ETO
CIMIS Station 54	Kern_Wind_Site2 & ETO
CIMIS Station 125	Kern_Wind_Site3 & ETO
CIMIS Station 138	Kern_Wind_Site4 & ETO
CIMIS Station 146	Kern_Wind_Site5 & ETO
PM 10 Site 1	Kern_PM10Average_Site1
PM 10 Site 2	Kern_PM10Average_Site2
PM 10 Site 3	Kern_PM10Average_Site3
PM 10 Site 4	Kern_PM10Average_Site4
PM 10 Site 5	Kern_PM10Average_Site5
PM 2.5 Site 1	Kern_AveragePM2.5_Site1
PM 2.5 Site 2	Kern_AveragePM2.5_Site2

Kings County

Old Name	New Name
Kings	Kings_Precip_Site1 & Temp
NOAA Division 5	Kings_Precip_Site 2 & Temp
CIMIS Station 15	Kings_Temp_Site3
CIMIS Station 15	Kings_Wind_Site1 & ETO
PM 10 Site 1	Kings_PM10Average_Site1
PM 10 Site 2	Kings_PM10Average_Site2
PM 2.5 Site 1	Kings_AveragePM2.5_Site1

San Luis Obispo County

Old Name	New Name
Morro Bay	SLO_Precip_Site1 & Temp
Salina Dam	SLO_Precip_Site2 & Temp
Santa Margarita	SLO_Precip_Site 3 & Temp
PasoRobles	SLO_Precip_Site 4 & Temp
PasoRobles Airport	SLO_Precip_Site 5 & Temp
NOAA Division 4	SLO_Precip_Site 6 & Temp
CIMIS Station 52	SLO_Temp_Site7
CIMIS Station 52	SLO_Wind_Site1 & ETO
PM 10 Site 1	SLO_PM10Average_Site1
PM 10 Site 2	SLO_PM10Average_Site2
PM 10 Site 3	SLO_PM10Average_Site3
PM 10 Site 4	SLO_PM10Average_Site4
PM 2.5 Site 1	SLO_AveragePM2.5_Site1
PM 2.5 Site 2	SLO_AveragePM2.5_Site2

Tulare County

Old Name	New Name
Visalia	Tulare_Precip_Site1 & Temp
LemonCove	Tulare_Precip_Site2 & Temp
Lindsay	Tulare_Precip_Site 3 & Temp
NOAA Division 5	Tulare_Precip_Site 4 & Temp
CIMIS Station 86	Tulare_Temp_Site5
CIMIS Station 86	Tulare_Wind_Site1 & ETO
PM 10 Site 1	Tulare_PM10Average_Site1
PM 2.5 Site 1	Tulare_AveragePM2.5_Site2
PM 2.5 Site 2	Tulare_AveragePM2.5_Site1

The nine (9) El Niño Southern Oscillation (ENSO) indices described in Chapter 3 have also been renamed. Their new names are found in Table 4.3.

Table 4.3: Naming Convention for the ENSO Indices

Old Name	New Name
INO1+2	ENSO1
NINO 1+2	ENSO2
NINO3	ENSO3
NINO3 Anom	ENSO4
NINO4	ENSO5
NINO4 Anom	ENSO6
NO3.4	ENSO7
NINO3.4 ANOM	ENSO8
EL Nino/La Nina	ENSO9

Quantitative Methods

There are three quantitative methods conducted in this chapter: Correlation, Linear Regression, and Poisson Regression. Correlation is a technique that provides a number that is used to determine how strongly pairs of variables are related. The results of the Correlation used in this study, called the Pearson's Correlation Coefficient (r) ranges from -1 to 1. The closer to -1 or 1, the variables are closely related. If the coefficient is near 0, the variables are not related. Statistical significance was determined at the .05 level.

Linear Regression, known as the best fitting line, is a linear approach to modelling the relationship between our climate variables and our case data. The best fitting line summarizes the relationship between two quantitative variables.

Poisson Regression is a generalized linear model regression analysis that typically models count data. In this chapter, Poisson was observed as a rate, using population data as an offset. Yearly population data for each county was obtained from the State of California's Department of Finance. The offset is the log of the population. For the exposure scenarios that were estimated from the diagnosis date, their ending result may not have been whole numbers. For Poisson, the dependent variables were transformed to whole numbers using an as.interger() command in R. A characteristic of the Poisson distribution is that the mean equals the variance. If this is not the case with actual data, then overdispersion occurs and the Poisson model is not appropriate. Typically, overdispersion problems can be solved by using a Quasipossion or a Negative Binomial distribution. Poisson utilizes a link function that defines the relationship between the linear predictor and the distribution function's mean. The Log link was utilized in this analysis.

Examples of the regression codes can be found in Table 4.4.

Table 4.4: Example R code for the Quantitative Methods	
R Code	**Description**
lmFresno_Actual_Precip_Average = lm(Fresno_Actual ~ Fresno_Precip_Average)	Linear Regression Equation between Diagnosis Date of Cases in Fresno County and the Precipitation Site Average for Fresno County
glmFresno_Actual_Precip_Average = glm(Fresno_Actual ~ Fresno_Precip_Average + offset(Fresno_PopL), family=(poisson(log)))	Poisson Regression Equation between Diagnosis Date of Cases in Fresno County and the Precipitation Site Average for Fresno County utilizing a population offset factor and a log link

These regression statistical methods were chosen because they represent over 50% of the methodologies utilized in the previous studies described in Chapter 1. Table 4.5 shows the relevant studies and their statistical methods.

Table 4.5: Examples of Previous Relevant Studies and Their Statistical Methodologies	
Statistical Methods	**Studies**
Multiple Linear Regression	Comrie (2007); Comrie (2005); Stacy (2012); Kolivras (2003); Gorris (2018)
Multivariate Poisson Regression	Park (2005); Flaherman (2007);
Multiple Logistic Regression	Gray (1998); Chen (2011); Blair (2008); Muir Bowers (2006);
Multivariate Negative Binomial Regression	Sondermeyer (2013);

Since the Valley Fever case data occurs over a period, 2000 – 2015, the dependent variables were lagged monthly for 12 prior months. Lagging variables is used to predict values of a dependent variable by using current and past values of the explanatory variable. With the purpose of determining what variables are linked to exposure, lagging variables helps test the “Grow and Blow” Effect hypothesis described in Chapter 1.

For part of the analysis described in this chapter, stepwise selection methods were used. Stepwise selection fits models by choosing variables in an automated process. Stepwise selection adds and subtracts variables based on a defined criterion. The criterion used in this study is Akaike Information Criterion (AIC). The model with the highest AIC was selected. AIC estimated the information lost by a given model while balancing how good the model fits (goodness of fit) and the simplicity of the model. When looking at the relationship between the various sites and the site average for the exposure scenarios, stepwise regression was selected. Stepwise selection provides some background for developing multivariate analyses on what climate lags should be explored further. It also provided a standardized way to see how different sites and lags were related to the different exposure methods. There are limitations to this method. One limitation is that stepwise regression tends to select too many variables where all of them may not be needed in the model. For this reason, stepwise selection was just used for a portion of the univariate exploratory analysis.

Time Series Comparisons

To help visual how climate varies over time with the number of cases diagnosed in each county, Figure 4.1 shows a time series of the average monthly climate variables compared to the cases that occurred by diagnosis date per county. From these time series, we can see that there are some patterns emerging where peaks in a climate variable match a peak in case counts. We can also see that some peaks appear to be offset and if we lag those months, a significant relationship might appear.

Figure 4.1 Time Series of the Average Climate Indicator and Monthly Diagnosis by County

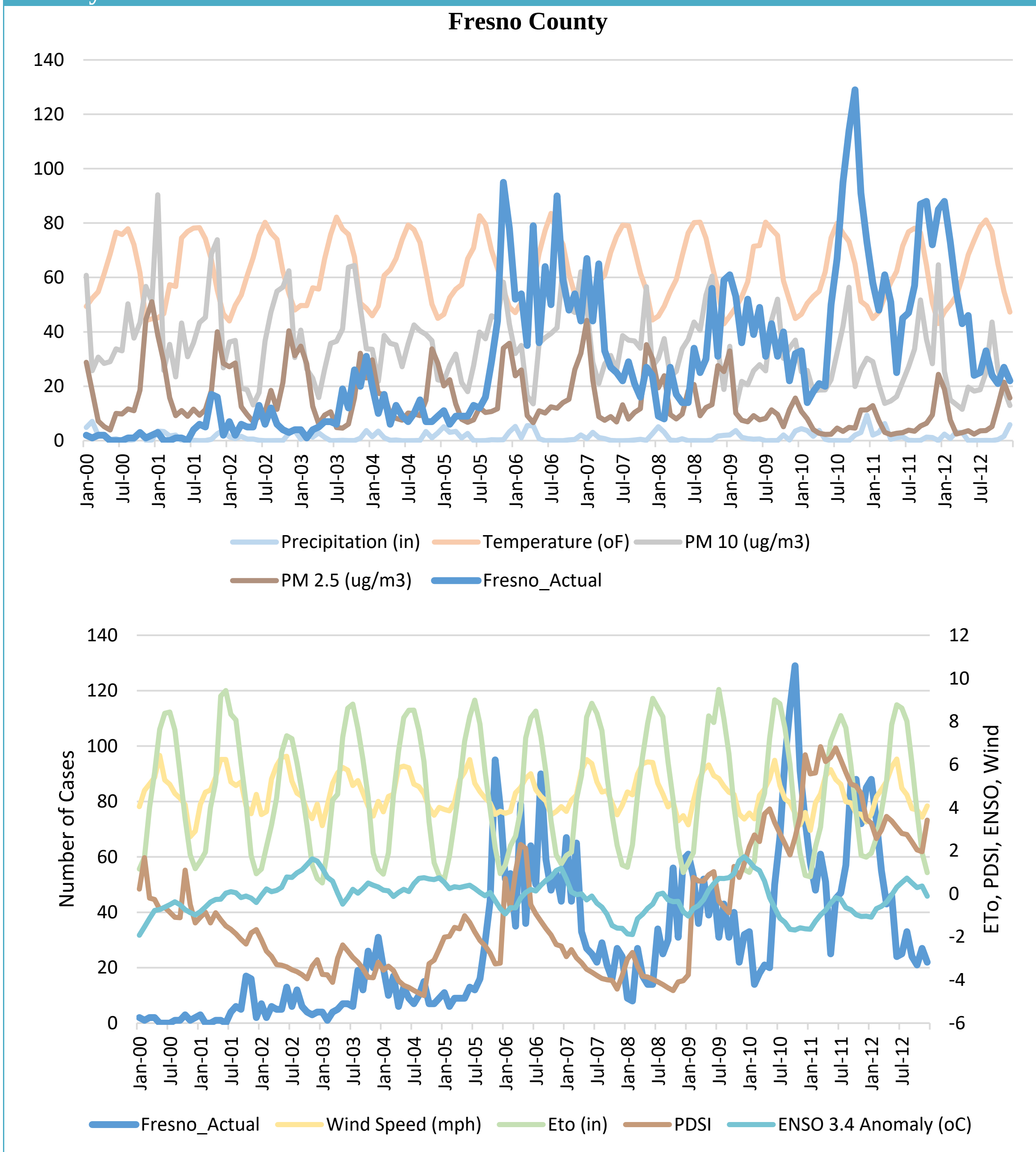
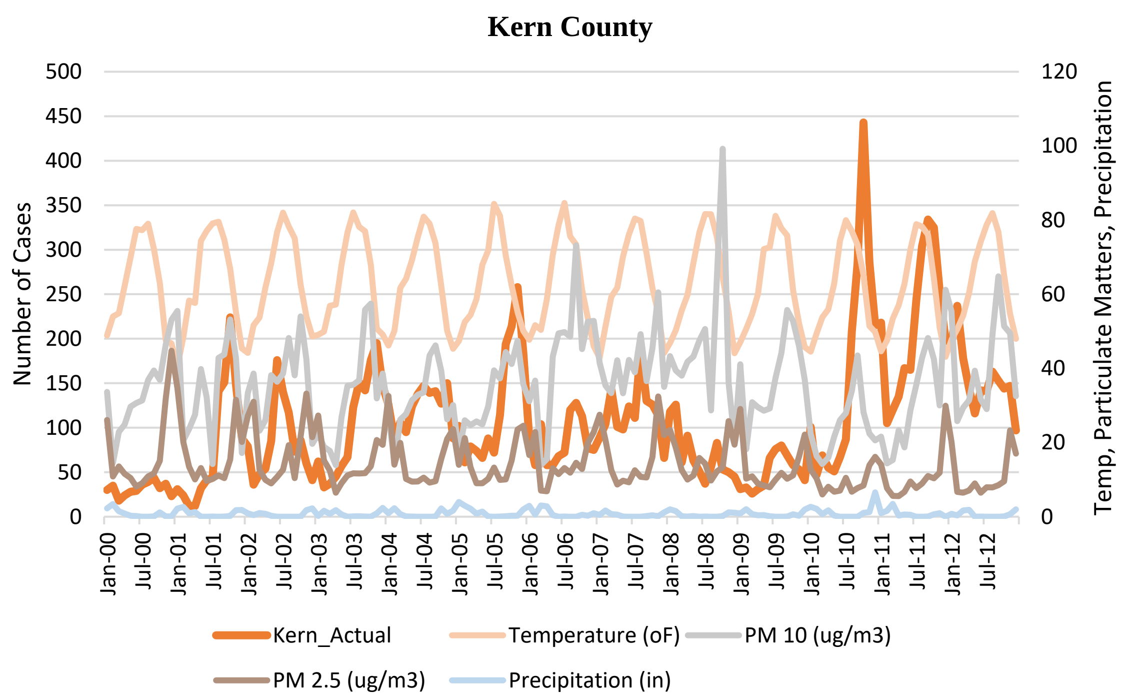


Figure 4.1 Time Series of the Average Climate Indicator and Monthly Diagnosis by County



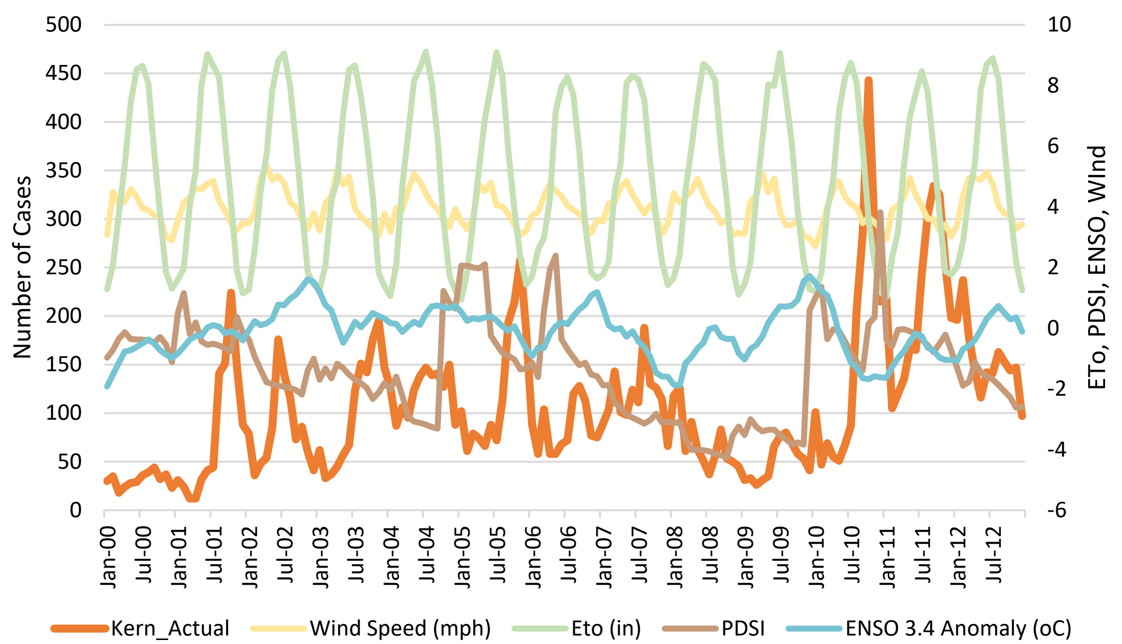


Figure 4.1 Time Series of the Average Climate Indicator and Monthly Diagnosis by County

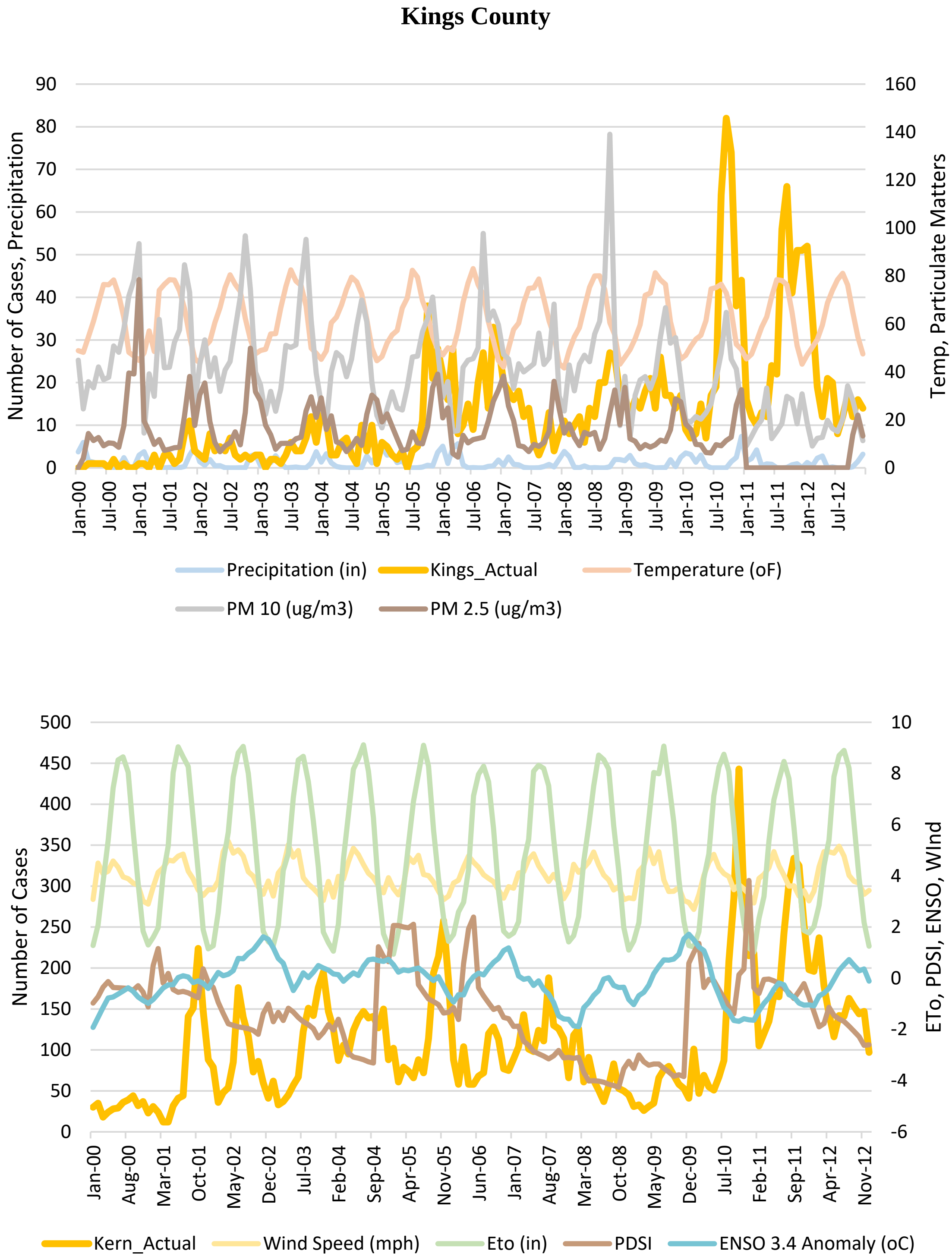
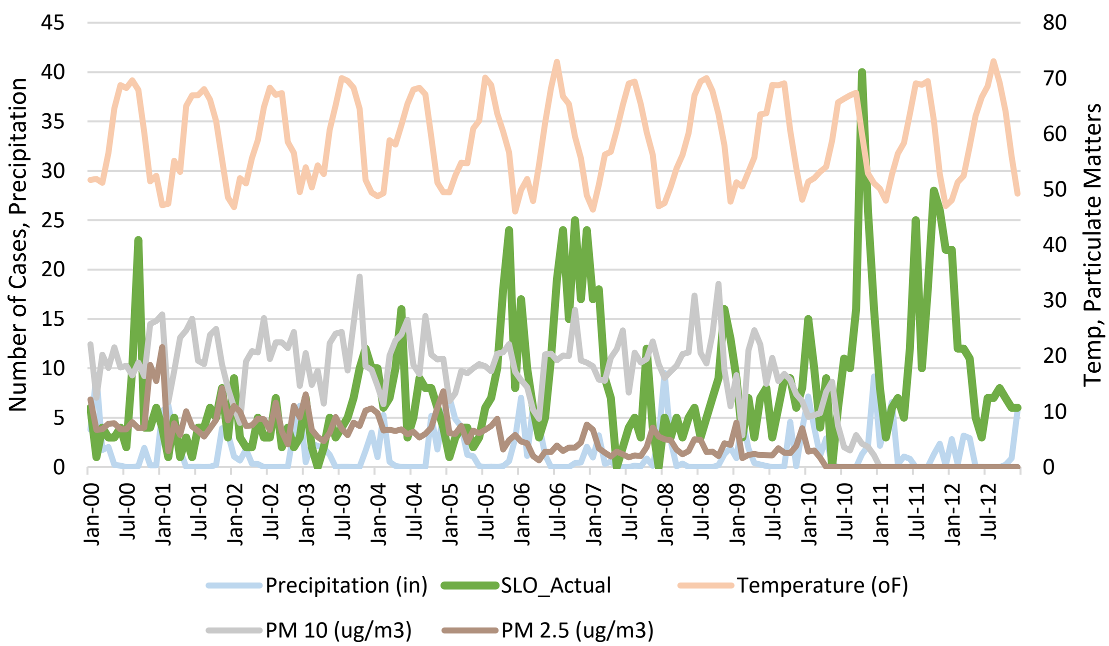


Figure 4.1 Time Series of the Average Climate Indicator and Monthly Diagnosis by County

San Luis Obispo County



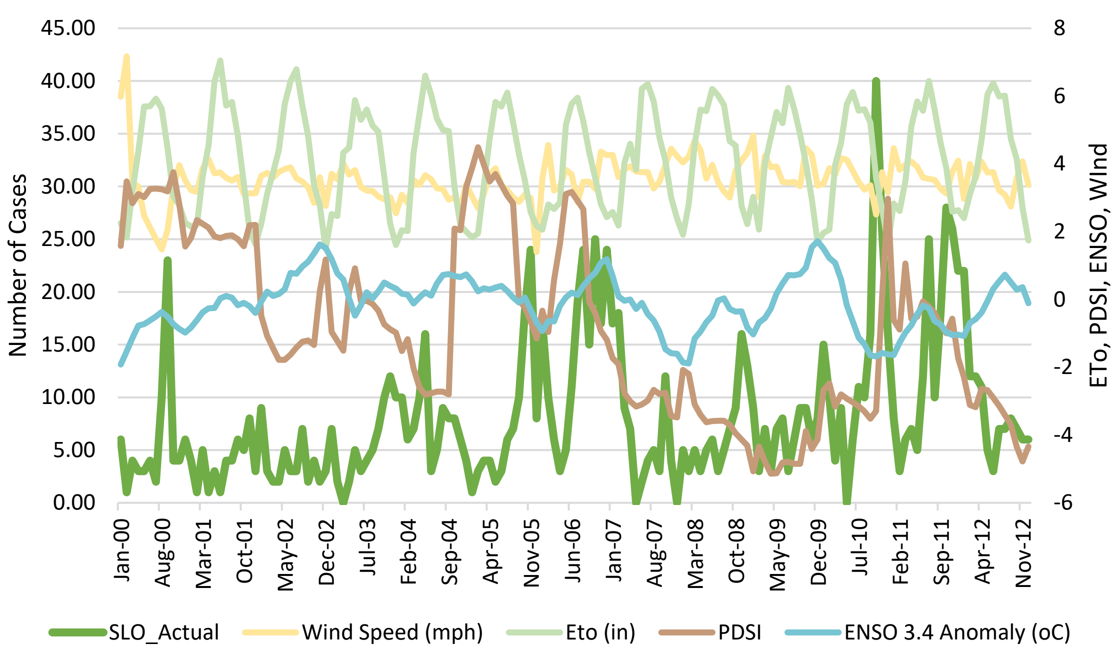
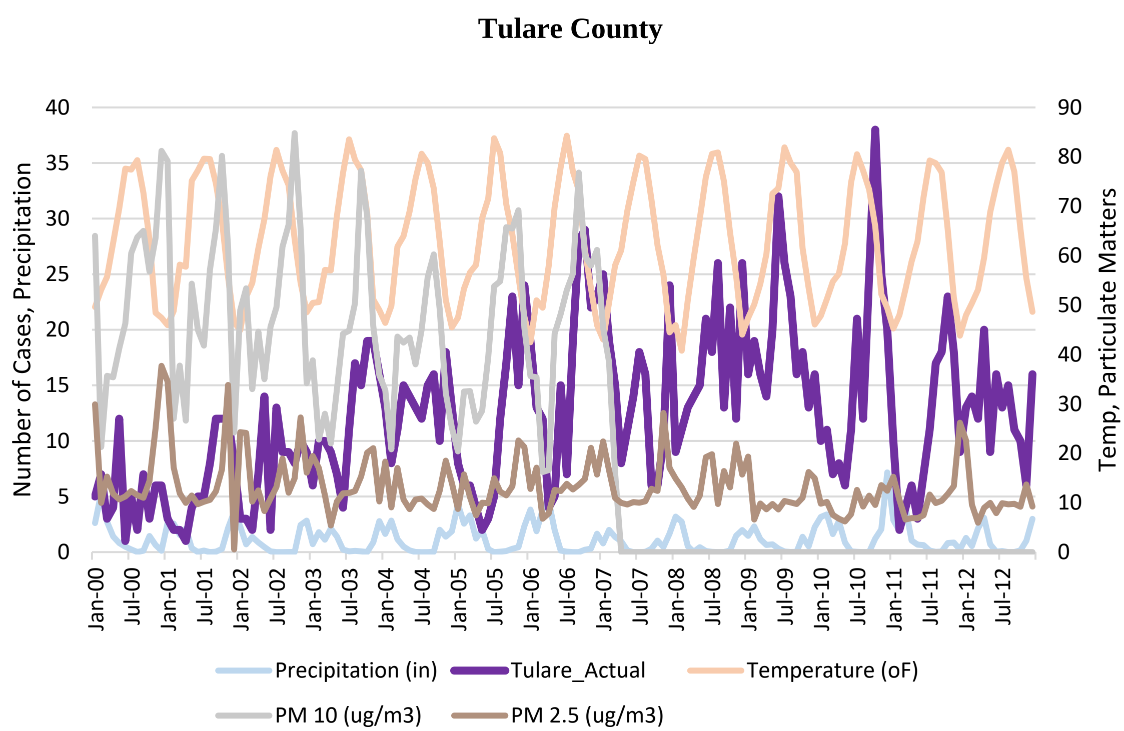
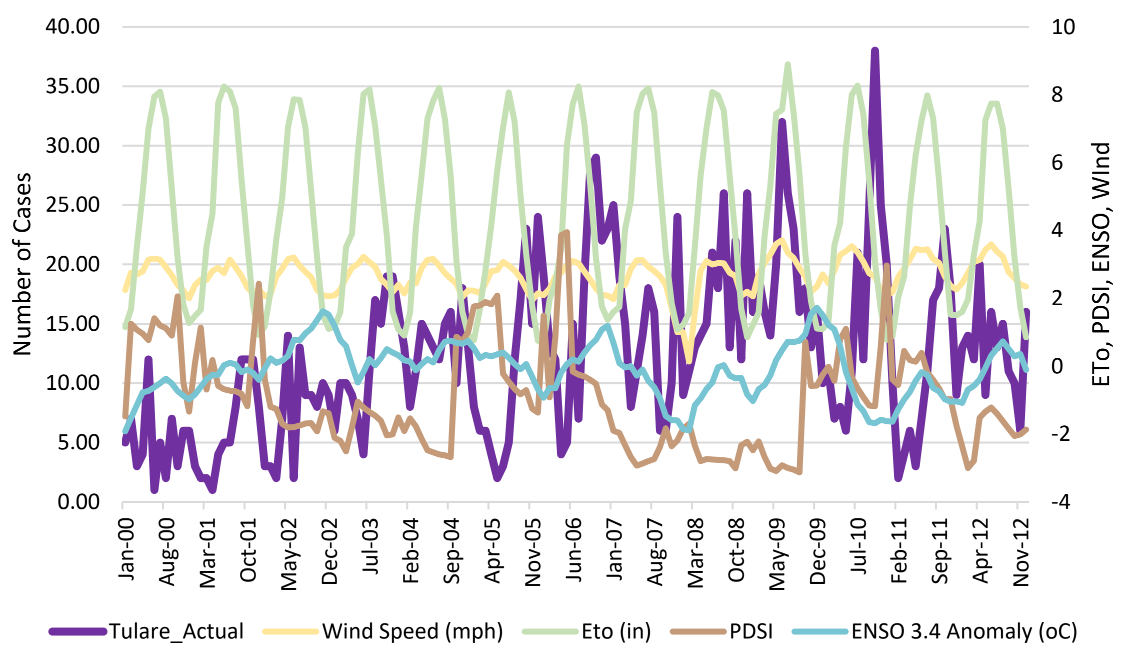


Figure 4.1 Time Series of the Average Climate Indicator and Monthly Diagnosis by County





Correlation Results

Table 4.6 shows the sites that are statistically significant correlations to the various exposure methods for each of the five counties. The numbers in the table represent the significant sites that were measured at current time, no lags are displayed.

For Fresno County, although there are similar patterns across the sites being selected, there are some notable differences. Diagnosis date found Precipitation Site 1 to be significantly correlated, but none of the other exposure scenarios found that. For the Park Method, all sites were selected similarly except for one ETo site. The variables selected between methods is also not the same. For example, sites between Stacy method and Comrie method are not the same.

The other four counties of Kern, Kings, San Luis Obispo, and Tulare have similar results. Across counties, it is interesting to note that the direction of the relationship is not the same for the climate factors selected. For example, Fresno county has a positive significant correlation between Precipitation Sites and Exposure scenario, but Kern, San Luis Obispo, and Tulare have a negative relationship. Temperature Sites across counties all have the same directionality.
In addition, sites within a county do not have the same directionality. For example, in Kern County, Wind Sites 1, 3, and 4 have a negative significant correlation with their corresponding exposure scenarios, but Site 2 has a positive significant correlation.

Table 4.6: Sites with Significant Correlations to the Various Exposure Methods by County
(Information in Parentheses represent directionality of the Correlations (*p*<.05)

Fresno County

Exposure Scenario	Precip (all have + #)	Temp (all have + #)	Wind (all have - #)	Eto (all have + #)	PDSI	PM 10	PM 2.5 (all have - #)	ENSO (all have - #)
Actual	1	None	2, 3, 4, 5, 6	None	None	None	2	1, 3, 4, 5, 6, 7, 8
EMST	None	None	2, 3, 5	None	None	None	2	1, 3, 4, 5, 6, 7, 8
75ST	None	4	2, 3, 5	None	None	None	2	1, 3, 4, 5, 6, 7, 8
25ST	None	None	2, 3, 5	None	None	None	2	1, 3, 4, 5, 6, 7, 8
EMPM	None	2, 3, 4, 5, 6	2, 5	None	None	None	2	1, 3, 4, 5, 6, 7, 8
75PM	None	2, 3, 4, 5, 6	2, 5	1	None	None	2	1, 3, 4, 5, 6, 7, 8
25PM	None	2, 3, 4, 5, 6	2, 5	None	None	None	2	1, 3, 4, 5, 6, 7, 8
EMCM	None	1, 2, 3, 4, 5, 6	2	1	None	None	2	1, 3, 4, 5, 6, 7, 8
75CM	None	1, 2, 3, 4, 5, 6, 7	2	1	None	None	2	1, 3, 4, 5, 6, 7, 8

Table 4.6: Sites with Significant Correlations to the Various Exposure Methods by County (Information in Parentheses represent directionality of the Correlations (p<.05))								
25CM	None	1, 2, 3, 4, 5, 6	2	1	None	None	None	1, 3, 4, 5, 6, 7, 8
				Kern County				
Exposure Scenario	**Precip (all have - #)**	**Temp (all have + #)**	**Wind (1, 3, 4 = -#)**	**Eto (all have + #)**	**PDSI**	**PM 10 (all have - #)**	**PM 2.5 (all have - #)**	**ENSO (all have - #)**
Actual	None	4, 9	1, 3, 4	None	None	1, 2	1	1, 2, 3, 4, 6, 7, 8, 9
EMST	None	4, 6, 7, 8, 9	1, 3	None	None	1, 4	1, 3	1, 2, 3, 4, 6, 7, 8, 9
75ST	4	4, 6, 7, 8, 9	3	3, 4, 5	None	1, 4	1, 3	1, 2, 3, 4, 6, 7, 8, 9
25ST	None	4, 9	1, 3	None	None	1, 4	1, 3	1, 2, 3, 4, 6, 7, 8, 9
EMPM	1, 4	1, 2, 3, 4, 6, 7, 8, 9	2	1, 2, 3, 4, 5	None	1, 4	1, 3	1, 2, 3, 4, 6, 7, 8, 9
75PM	1, 3, 4	1, 2, 3, 4, 6, 7, 8, 9	2	1, 2, 3, 4, 5	None	1, 4	1, 3	1, 2, 3, 4, 6, 7, 8, 9
25PM	4	1, 2, 4, 6, 7, 8, 9	2, 3	2, 3, 4, 5	None	1, 4	1, 3	1, 2, 3, 4, 6, 7, 8, 9
EMCM	1, 4	1, 2, 3, 4, 6, 7, 8, 9	2	1, 2, 3, 4, 5	None	1, 4, 5	1, 3	1, 2, 3, 4, 8, 9
75CM	1, 2, 3, 4	1, 2, 3, 4, 6, 7, 8, 9	2	1, 2, 3, 4, 5	None	1, 4, 5	1, 3	1, 2, 3, 4, 6, 8, 9
25CM	1, 2, 3, 4	1, 2, 3, 4, 6, 7, 8, 9	2	1, 2, 3, 4, 5	None	1, 4, 5	1, 3	1, 2, 3, 4, 6, 8, 9
				Kings County				
Exposure Scenario	**Precip**	**Temp (all have + #)**	**Wind (all have - #)**	**Eto (all have + #)**	**PDSI**	**PM 10**	**PM 2.5 (all have - #)**	**ENSO (all have - #)**
Actual	None	None	1	None	None	None	1	1, 3, 4, 5, 6, 7, 8
EMST	None	1, 2	None	None	None	None	1	1, 3, 4, 5, 6, 7, 8
75ST	None	1, 2	None	None	None	None	1	1, 3, 4, 5, 6, 7, 8

Table 4.6: Sites with Significant Correlations to the Various Exposure Methods by County
(Information in Parentheses represent directionality of the Correlations (p<.05)

25ST	None	1	None	None	None	None	1	1, 3, 4, 5, 6, 7, 8
EMPM	None	1, 2	None	None	None	None	1	1, 3, 4, 5, 6, 7, 8
75PM	None	1, 2	None	None	None	None	1	1, 3, 4, 5, 6, 7, 8
25PM	None	1, 2	None	None	None	None	1	1, 3, 4, 5, 6, 7, 8
EMCM	None	1, 2, 3	None	1	None	None	1	1, 3, 5, 6, 7, 8
75CM	None	1, 2, 3	None	1	None	None	1	1, 3, 4, 5, 6, 7, 8
25CM	None	1, 2, 3	None	1	None	None	1	1, 3, 4, 5, 6, 7, 8
San Luis Obispo County								
Exposure Scenario	**Precip (all have - #)**	**Temp (all have + #)**	**Wind (all have - #)**	**Eto (actual - #)**	**PDSI**	**PM 10**	**PM 2.5 (all have - #)**	**ENSO (all have - #)**
Actual	None	1, 2, 3, 4, 5, 6	None	1	None	None	1	1, 3, 5, 6, 7, 8
EMST	None	1, 2, 3, 4, 5, 6	None	None	None	None	1	1, 3, 6, 7
75ST	None	1, 2, 3, 4, 5, 6	1	None	None	None	1	1, 3, 6, 7
25ST	None	1, 2, 3, 4, 5, 6	None	None	None	None	1	1, 3, 5, 6, 7, 8
EMPM	None	1, 2, 3, 4, 5, 6	1	None	None	None	1	1, 3, 6, 7
75PM	None	1, 2, 3, 4, 5, 6	None	None	None	None	1	1, 3, 6, 7
25PM	None	1, 2, 3, 4, 5, 6	1	None	None	None	1	1, 3, 6, 7
EMCM	6	1, 2, 3, 4, 5, 6, 7	None	1	None	None	1, 2	1, 3
75CM	6	1, 2, 3, 4, 5, 6, 7	None	1	None	None	1	1, 3, 6, 7
25CM	6	1, 2, 3, 4, 5, 6, 7	None	1	None	None	1	1, 3, 6, 7
Tulare County								

Table 4.6: Sites with Significant Correlations to the Various Exposure Methods by County (Information in Parentheses represent directionality of the Correlations (p<.05)								
Exposure Scenario	**Precip (all have - #)**	**Temp (all have + #)**	**Wind (all have + #)**	**Eto (all have + #)**	**PDSI (all have - #)**	**PM 10**	**PM 2.5 Site 1 (+)**	**ENSO (1, 3 have - #)**
Actual	None	1, 2, 3, 4	None	None	Yes	None	None	1, 3
EMST	None	1, 2, 3, 4	None	None	Yes	None	1	1, 3, 9
75ST	1, 4	1, 2, 3, 4, 5	None	None	Yes	None	1	1, 3
25ST	None	1, 2, 3, 4	None	None	Yes	None	None	1, 3
EMPM	1, 2, 3, 4	1, 2, 3, 4, 5	1	1	Yes	None	1, 2	1, 3, 9
75PM	1, 2, 3, 4	1, 2, 3, 4, 5	1	1	Yes	None	1, 2	1
25PM	1, 2, 3, 4	1, 2, 3, 4, 5	None	1	Yes	None	1	1, 3
EMCM	1, 2, 3, 4	1, 2, 3, 4, 5	1	1	Yes	None	1, 2	1, 3, 9
75CM	1, 2, 3, 4	1, 2, 3, 4, 5	1	1	Yes	None	1, 2	1
25CM	1, 2, 3, 4	1, 2, 3, 4, 5	1	1	Yes	None	1, 2	1

Linear Regression Results

Univariate Stepwise Selection

Table 4.7 shows the monthly lags selected by stepwise, univariate, Linear Regression for the various precipitation sites in Fresno County. Across sites, the months selected are not the same for each exposure scenario or for the site averages. Across exposure scenarios, the months selected are not the same for each site.

Table 4.7: Example of the Months Selected by Stepwise Linear Regression for the Precipitation Sites Located in Fresno County (p<.05)										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Site 1	6, 7, 8, 10, 11, 12	7, 8, 9, 10, 11	7, 8, 9, 10, 11, 12	5, 6, 7, 9, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	5, 6, 7, 8	3, 4, 5, 6, 7, 8, 9, 10, 11	4, 5, 6, 7, 8, 9, 10, 11

Table 4.7: Example of the Months Selected by Stepwise Linear Regression for the Precipitation Sites Located in Fresno County (p<.05)

Site 2	0, 6, 7, 9, 10, 11, 12	0, 6, 8, 9, 10, 11, 12	0, 5, 6, 8, 9, 10, 11, 12	0, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 9, 10, 11, 12	0, 5, 7, 8, 9, 10, 11, 12	0, 5, 6, 8, 9, 10, 11, 12	4, 5, 6, 7	4, 6, 7, 8, 9, 11	0, 4, 5, 7, 8, 9, 10, 11, 12
Site 3	6, 7, 9, 10, 11, 12	6, 8, 10, 12	6, 8, 10, 12	6, 8, 10, 11, 12	0, 5, 6, 7, 8, 10, 11, 12	4, 6, 8, 9, 10	5, 6, 8, 10, 12	4, 6, 8, 10	4, 6, 8, 10	4, 5, 7, 8, 9, 11
Site 4	6, 8, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	5, 6, 7, 9, 10, 11, 12	0, 3, 5, 6, 7, 8, 9, 10, 11, 12	0, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 3, 5, 7, 8, 9, 10, 11, 12	4, 5, 6, 7, 8, 9, 10, 11	3, 5, 6, 7, 8, 10, 12	4, 5, 6, 7, 8, 9, 10, 11
Site 5	6, 8, 10, 11, 12	5, 6, 7, 8, 10, 11, 12	5, 6, 7, 8, 10, 11, 12	5, 6, 7, 9, 10, 11, 12	5, 6, 7, 8, 10, 11, 12	4, 5, 6, 7, 9, 10, 11	5, 6, 7, 8, 10, 11, 12	4, 5, 6, 8, 9	3, 4, 5, 6, 7, 8, 10, 12	4, 5, 6, 7, 9, 10, 11
Site 6	4, 6, 8, 10,11, 12	3, 5, 6, 7, 8, 9, 10, 11, 12	5, 6, 7, 8, 10, 11, 12	4, 6, 8, 10, 11, 12	0, 3, 5, 6, 7, 8, 9, 10, 11, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 3, 5, 7, 8, 9, 10, 11, 12	3, 4, 5, 6, 7, 8, 9, 10, 11, 12	3, 4, 5, 6, 7, 8, 9, 10, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
Average across Sites	6, 7, 8, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 10, 11, 12	5, 6, 7, 9, 10, 11, 12	0, 3, 5, 6, 7, 8, 9, 10, 11, 12	0, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 10, 11, 12	4, 5, 6, 7, 8, 9, 10, 11	3, 4, 5, 6, 7, 8, 9, 10	0, 4, 5, 6, 7, 8, 10, 11

Table 4.8 shows the monthly lags selected by stepwise Linear Regression for each climate variable averaged by site. As discussed in sections above, the months selected are not the same across exposure scenarios by county.
In addition, between counties, the months selected are not the same for the same exposure period and climate variable.

Table 4.8: Months Selected by Stepwise Linear Regression for the Climate Explanatory Variables Averaged by Site per County

Fresno County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	6, 7, 8, 10, 11, 12	5, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 10, 11, 12	5, 6, 7, 9, 10, 11, 12	0, 3, 5, 6, 7, 8, 9, 10, 11, 12	0, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 10, 11, 12	4, 5, 6, 7, 8, 9, 10, 11	3, 4, 5, 6, 7, 8, 9, 10	0, 4, 5, 6, 7, 8, 10, 11
Temp	4	3	3	3	2	2	3, 12	1	1	2, 11
Wind	6	0, 5, 12	0, 5, 12	0, 5, 12	0, 4, 12	0, 4, 12	3	0, 3, 12	0, 3, 12	0, 4, 12

Table 4.8: Months Selected by Stepwise Linear Regression for the Climate Explanatory Variables Averaged by Site per County

ETo	1, 7, 11	2, 7	0, 7, 10	3, 7	0, 6, 10	6, 10, 12	0, 7, 10	6, 9, 12	6, 9, 12	6, 9, 12
PDSI	5, 10, 12	4, 6, 9, 12	4, 9, 12	3, 5, 8, 12	2, 4, 9, 12	1, 4, 8, 12	4, 9, 12	1, 3, 5, 12	2, 4, 12	1, 5, 12
PM 10	0, 1	0, 1	0, 1	0, 1	0	0	0	0	0	0
PM 2.5	0	0	0, 8	0	9	9	0, 8	9	8	9
ENSO 1	6, 10	5, 8, 12	5, 9	6, 10	4, 6, 9, 12	4, 9	4, 9	3, 5, 8, 12	0, 3	0, 4, 11
ENSO 2	6, 12	5, 9, 12	5, 10	6, 12	4, 9	9	9	3, 9	9	9
ENSO 3	0, 6, 12	0, 12	0, 5, 12	0, 6, 12	0, 5, 12	0, 4, 12	0, 5, 12	0, 4, 12	0, 3, 12	0, 4, 12
ENSO 4	0, 12	0, 6	0, 12	0, 12	0, 4	0, 4	0, 5	0, 3	0, 8	0, 8
ENSO 5	0, 4, 8, 12	0, 2, 8, 12	0, 2, 8, 12	0, 2, 8, 12	0, 1, 8, 12	0, 1, 8, 12	0, 2, 8, 12	0, 1, 8, 12	0, 1, 8, 12	0, 1, 8, 12
ENSO 6	0, 4	0, 4	0, 3	0, 4	0, 2	0, 2	0, 3	0, 1	0, 2, 9, 12	0, 2, 10, 12
ENSO 7	0, 6, 9, 11	0, 7, 8, 12	0, 5, 12	0, 6	0, 1, 12	0, 4, 10, 12	0, 5, 8, 12	0, 1, 12	0, 3, 9, 12	0, 4, 10, 12
ENSO 8	0, 11	0	0, 5	0, 10	0, 1	0, 2	0, 3	0, 3	0, 3	0, 2
ENSO 9	6, 12	4, 8, 12	4, 6, 10, 12	6, 12	4, 6, 9, 12	4, 9, 12	5, 9, 12	4, 8, 12	3, 10	4, 8, 12
Kern County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	All	All	All	All	All	All	All	All	All	All
Temp	2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	All	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12
Wind	9, 12	8, 9, 12	7, 9, 12	9, 12	7, 8, 11	7, 8, 11	7, 9, 12	6, 7, 10, 11	6, 8, 11	6, 8, 11
ETo	4, 6, 9, 11, 12	4, 6, 8, 10, 12	4, 5, 8, 11, 12	4, 6, 9, 11, 12	4, 5, 8, 10, 12	4, 5, 8, 9, 12	4, 5, 8, 10, 12	3, 4, 8, 9, 12	3, 4, 7, 8, 9, 12	3, 4, 7, 8, 9, 12
PDSI	8, 10, 12	7, 8, 9, 12	7, 9, 12	8, 9, 12	6, 8, 12	6, 8, 12	7, 8, 12	5, 6, 7, 10, 12	6, 7, 10, 12	6, 7, 10, 12
PM 10	All	All	All	All	All	All	All	All	All	All
PM 2.5	2, 3, 4, 5, 7, 11, 12	2, 3, 4, 5, 6, 7, 10, 12	2, 3, 4, 5, 6, 7, 10, 12	2, 3, 4, 5, 6, 7, 9, 12	2, 3, 4, 5, 6, 9, 10, 12	2, 3, 4, 5, 6, 9, 11, 12	2, 3, 4, 5, 6, 7, 10, 12	2, 3, 4, 5, 8, 9, 11, 12	2, 3, 4, 5, 7, 9, 11, 12	2, 3, 4, 5, 7, 9, 11, 12
ENSO 1	0, 3, 7, 10, 12	0, 3, 10, 12	0, 12	0, 7, 12	0, 5, 12	0, 5, 8, 12	0, 9, 12	0, 4, 12	0, 5, 7, 12	0, 5, 7, 12

Table 4.8: Months Selected by Stepwise Linear Regression for the Climate Explanatory Variables Averaged by Site per County										
ENSO 2	0	0	0, 12	0	0	0, 12	0, 12	0, 12	0, 12	0, 12
ENSO 3	0, 7, 8, 12	0, 6, 8, 12	0, 6, 8, 12	0, 6, 8, 12	0, 3, 11, 12	0, 2, 5, 7, 12	0, 5, 8, 12	0, 2, 12	0, 2, 5, 7, 12	0, 2, 5, 7, 12
ENSO 4	0, 1, 12	0, 1, 12	0, 1, 12	0, 1, 12	0, 12	0, 12	0, 12	0, 2, 12	0, 12	0, 12
ENSO 5	0, 4, 8, 12	0, 1, 5, 7, 12	0, 2, 7, 12	0, 4, 8, 12	0, 1, 6, 12	0, 2, 6, 12	0, 2, 6, 12	0, 1, 5, 11	0, 1, 5, 10, 12	0, 1, 5, 10, 12
ENSO 6	0, 12	0, 2, 12	0, 4, 12	0, 12	0, 1, 12	0, 2, 12	0, 2, 12	0, 2, 12	0, 2, 12	0, 2, 12
ENSO 7	0, 4, 7, 8, 12	0, 4, 11, 12	0, 4, 8, 11, 12	0, 4, 10, 12	0, 3, 11, 12	0, 3, 8, 12	0, 3, 8, 12	0, 2, 8, 12	0, 2, 8, 12	0, 2, 8, 12
ENSO 8	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12	0, 7, 12	0, 7, 12	0, 7, 12
ENSO 9	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12	0, 12
Kings County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	1, 6, 8, 9, 10, 12	0, 6, 8, 10, 12	0, 5, 7, 8, 10, 11, 12	0, 6, 8, 10, 12	0, 6, 7, 8, 10, 12	0, 6, 7, 8, 10, 12	0, 6, 7, 8, 10, 12	5, 6, 7, 8, 12	6, 7, 8, 12	6, 7, 8, 12
Temp	2, 10	2, 10	1, 9	2, 11	1, 9	0, 8	1, 9	0, 8	0, 7	0, 7
Wind	1, 9	0, 7, 9	0, 7, 9	1, 8, 9	0, 7, 10	7, 10	0, 7, 10	7, 10	7, 10	7, 10
ETo	2, 8, 11	2, 8, 11	1, 7, 10	2, 8, 11	1, 7, 10	1, 6, 10	1, 7, 10	1, 3, 9, 12	1, 6, 9	1, 6, 9
PDSI	1, 8, 12	0, 7, 9, 12	0, 7, 9, 12	1, 5, 8, 12	0, 6, 8, 12	0, 6, 8, 12	0, 7, 9, 12	6, 8, 12	6, 8, 12	6, 8, 12
PM 10	4, 6, 8	5, 7, 9	5, 7	4, 6, 8	3, 5, 7	4, 6	3, 5, 7	2, 4, 6	4, 6	4, 6
PM 2.5	1, 2, 5, 7, 12	0, 2, 4, 6, 12	0, 2, 4, 6, 12	0, 2, 5, 7, 12	0, 3, 5, 10	0, 3, 5, 10	0, 1, 4, 6, 10	1, 3, 4	1, 3, 5	1, 3, 5
ENSO 1	7	6, 9	0	7	5, 9	0	0	4, 8	0, 4	0, 4
ENSO 2	0	3, 7	0	0	5	None	0	4	None	None
ENSO 3	0	0	0	0	0, 3	0, 10, 12	0, 5, 7	0, 2	0, 2, 9, 12	0, 2, 9, 12
ENSO 4	0	0, 4	0, 4	0	0, 3	0, 2	0, 3	0, 2	0, 2	0, 2
ENSO 5	0, 1, 6, 8, 10	0, 2, 8, 12	0, 1, 5, 7, 12	0, 2, 6, 8, 12	0, 1, 7, 12	0, 1, 7, 11	0, 1, 7, 12	0, 1, 5, 9, 11	0, 1, 6, 9, 12	0, 1, 6, 9, 11
ENSO 6	0, 6, 8	0, 5, 8	0, 5, 7	0, 5, 8	0, 1, 11, 12	0, 1, 10, 12	0, 2, 11, 12	0, 1, 10, 12	0, 1, 10, 12	0, 1, 10, 12
ENSO 7	0, 7, 8	0, 5, 8	0, 5, 10, 12	0, 5, 8	0, 3, 10, 12	0, 3, 9, 12	0, 5, 6, 10, 12	0, 1, 9, 12	0, 3, 9, 12	0, 3, 9, 12

Table 4.8: Months Selected by Stepwise Linear Regression for the Climate Explanatory Variables Averaged by Site per County										
ENSO 8	0	0, 3	0, 3	0	0, 2	0, 2, 10, 12	0, 3	0, 1	0, 3, 9, 12	0, 3, 9, 12
ENSO 9	7	3, 6, 12	6	7	2, 5, 12	5	6	2, 4, 12	5	5
San Luis Obispo County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	6, 7, 9, 10, 11, 12	0, 5, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 9, 10, 11, 12	6, 7, 8, 9, 10, 11, 12	4, 5, 6, 7, 8, 9, 10, 11	4, 5, 6, 7, 8, 9, 10, 11	0, 5, 6, 7, 8, 9, 10, 11, 12	3, 4, 5, 6, 7, 8, 9, 10	4, 5, 6, 7, 8, 9, 10	4, 5, 6, 7, 8, 9, 10
Temp	3, 9	3, 9, 12	2, 8	3, 9	2, 8, 12	2, 7, 12	2, 8	1, 7, 11	1, 7	1, 7
Wind	1, 7	1, 6	0, 6	0, 7	1, 5	0, 5	1, 6	3, 5, 12	5	5
ETo	3, 4, 8, 9, 10, 11	3, 4, 7, 9, 10, 11	3, 4, 8, 9, 10	3, 4, 7, 9, 10, 11	2, 3, 6, 8, 9, 10	1, 2, 3, 7, 8, 9	2, 3, 6, 8, 9, 10	1, 2, 6, 7, 8, 9	1, 2, 6, 7, 8, 9	1, 2, 6, 7, 8, 9
PDSI	1, 7, 12	0, 6, 12	0, 6, 12	1, 7, 12	0, 5, 12	0, 5, 12	0, 6, 12	4, 12	5, 12	5, 12
PM 10	9, 12	8, 12	8, 12	8, 12	6, 7, 12	6, 7, 12	6, 8, 12	1, 6, 11, 12	1, 6, 12	1, 6, 12
PM 2.5	1, 3, 6, 11, 12	0, 3, 5, 6, 10, 11	0, 2, 5, 10, 11	3, 5, 6, 10, 11	2, 4, 5, 9, 10	1, 4, 9, 10	2, 5, 9, 10	1, 3, 4, 8, 9	1, 4, 8, 9	1, 4, 8, 9
ENSO 1	4, 5	5, 8	3, 4, 12	3, 12	7, 11	2, 3, 12	3, 4, 11	3, 12	2, 3, 10	2, 3, 10
ENSO 2	5, 12	5	3, 4, 11	5, 12	4	2, 3, 10	4, 11	3	10	10
ENSO 3	0, 4, 6, 8	0, 6, 11	0, 3, 5, 8	0, 4, 6, 8	0, 5, 7	0, 4, 10	0, 5, 7	0, 4, 10, 12	0, 4, 6, 10	0, 4, 6, 10
ENSO 4	0, 1	0, 5, 8	0, 5, 8	0, 5, 8	11, 12	0, 4, 7	0, 4, 7	10, 12	10, 12	10, 12
ENSO 5	0, 3, 9, 12	0, 3, 8, 12	0, 2, 8, 12	0, 3, 9, 11	0, 2, 8, 12	0, 2, 7, 12	0, 2, 8, 12	0, 1, 7, 12	0, 1, 7, 12	0, 1, 7, 12
ENSO 6	0	0, 2, 9	0, 2, 8	0, 3, 9	0, 1, 11, 12	0, 1, 11, 12	6, 2, 8, 12	0, 10, 12	0, 11, 12	6, 11, 12
ENSO 7	0, 7, 8	0, 6, 8	0, 3, 6, 8	0, 4, 7, 8	0, 5, 7, 11, 12	0, 4, 7, 11, 12	0, 5, 7, 11, 12	0, 4, 6, 10, 12	0, 4, 6, 11, 12	0, 4, 6, 11, 12
ENSO 8	0, 1	0	0	0, 1	0, 11, 12	0, 11, 12	0, 11, 12	0, 10, 12	0, 11, 12	0, 11, 12
ENSO 9	5	5	4	5	4	3	4	3	3	3
Tulare County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	2, 5, 8,	1, 7, 8,	1, 7, 8,	2, 5, 8,	0, 6, 7,	0, 6, 7,	0, 1, 4,	0, 3, 5,	0, 3, 5,	0, 3, 6,

Table 4.8: Months Selected by Stepwise Linear Regression for the Climate Explanatory Variables Averaged by Site per County

	9, 10	9	9	9, 10	8	8	7, 8, 9	6, 7	7	7, 8
Temp	0, 1	2, 8	2, 5, 11	0, 1, 9	0, 10, 12	0, 6, 7, 8	2, 5	0, 3, 9	0, 3, 9	0, 3, 6, 7, 8
Wind	2, 8, 12	1, 5, 10, 12	1, 7, 10, 12	2, 5, 10, 12	1, 4, 9, 11	0, 6, 9, 11	0, 4, 9, 12	0, 5, 8, 12	0, 5, 8, 12	0, 3, 8, 11
ETo	5, 8, 12	5, 8, 12	0, 5, 9, 12	5, 8, 12	4, 7, 8, 11, 12	4, 7, 8, 11	0, 4, 7, 8, 11, 12	3, 6, 7, 10, 11	3, 6, 10	3, 6, 8, 11
PDSI	1, 3, 5, 8, 12	0, 2, 5, 8, 12	0, 1, 3, 4, 7, 12	1, 3, 5, 8, 12	0, 1, 4, 7, 12	0, 2, 3, 6, 12	0, 2, 4, 7, 12	0, 6, 10, 12	0, 6, 10, 12	0, 6, 10, 12
PM 10	1, 5, 8	1, 4, 8	1, 4, 8	1, 5, 8	0, 4, 7	0, 5, 7	0, 4, 8	0, 5	0, 4	1, 5
PM 2.5	2, 4, 5, 7	2, 4, 7	2, 4, 6	2, 4, 7	1, 3, 6, 12	2, 3, 5, 12	1, 3, 6	2, 5, 12	2, 4, 11, 12	2, 3, 5, 12
ENSO 1	7	4, 7, 9	4, 9, 11	4, 7	3, 6, 8	11	0, 3, 7	2, 5, 7	1, 2	0, 2
ENSO 2	4	0, 4, 9	None	4	0, 3, 8	None	None	2, 8	None	None
ENSO 3	0, 1, 7	0, 5	0, 6, 11, 12	0, 5	5, 11, 12	0, 4, 11, 12	0, 4, 11, 12	4, 10, 12	0, 4, 6, 10, 11	0, 5, 7, 10, 12
ENSO 4	11	1, 12	10	11	12	None	10	8	6, 7	None
ENSO 5	0, 2, 9, 12	0, 2, 9, 12	0, 2, 8, 12	0, 2, 9, 12	8, 11	7, 11	0, 2, 8, 11	7, 10	4, 8, 10	7, 10
ENSO 6	None	12	0, 12	0, 12	11	0, 12	0, 12	11	0	0
ENSO 7	0, 1, 7, 8, 12	0, 3, 7, 9, 12	0, 3, 6, 8, 12	0, 3, 7, 9, 12	0, 2, 5, 8, 12	0, 2, 5, 8, 12	0, 2, 5, 8, 12	4, 7, 12	0, 4, 7, 12	0, 4, 7, 12
ENSO 8	0, 1, 5, 11	12	12	0, 1, 5, 11	12	4, 9	12	12	0	3, 9
ENSO 9	2, 6, 11	0, 2, 6, 10	1, 5, 10	2, 6, 10	0, 4, 9, 12	0, 4, 9	1, 5, 10	0, 4, 8, 12	0, 8	0, 9

Univariate Regression on the Averages of the Sites for the Explanatory Variables

A Linear Regression model and equation was created for each monthly lag for each climate variable for four of the exposure scenarios for the five counties. Table 4.9 shows the months that were significant in this approach.
For Fresno County, we do see patterns emerge, but the patterns are not consistent. For example, for the average of the precipitation sites, the Actual exposure scenario and the EMST scenario found significant relationships between precipitation that occurs during 6-12 months prior. Since EMPM is 1 month ahead for the exposure period, we would expect this lag to shift from 5-11. Table 4.9 shows that it does. Since EMST was the same in Precipitation as Actual, we might expect that pattern to persist in the other climate variables. It does not, perhaps because converting the diagnosis distribution to a new distribution under a different exposure estimate changes the inherent variability.

The same patterns emerging but lack of consistency in those patterns is evident for the other four counties: Kern, Kings, San Luis Obispo, and Tulare.

However, generally, for Fresno County, we do see that Precipitation is significant several months in advance of exposure, Temperature is significant around exposure and the 1-2 months before, Wind is significant around exposure and during a similar period when Precipitation is, and ETo is significant during the middle part of Temperature and Wind's significant months. PM 10, 2.5, and PDSI are significant for most of the year.

For Kern County, we do see that Precipitation is significant several months in advance of exposure and around the month of exposure, Temperature is significant similarly to Precipitation, Wind is significant around exposure and during a similar period when Precipitation is, and ETo is significant during the middle part of Temperature and Wind's significant months. PM 10, 2.5, and PDSI are significant for about half of the year. Overall, almost each variable seems to have two peaks of significance.

For Kings County, we do see that Precipitation is significant several months in advance of exposure, Temperature is significant several months during potential exposure, Wind has about two peaks of significance about 4 months apart, and ETo is similar to Wind's patterns. PM 10 and PDSI are significant for about half of the year. PM 2.5 concentration is significant for the months around exposure.

For San Luis Obispo County, we do see that Precipitation is significant around 6 months in advance of exposure, Temperature is significant several months during potential exposure, Wind has about two to three months that are significant with no consistent pattern among the exposure scenarios, and ETo has two to three peaks. No months are significant for PM 10 and PDSI. PM 2.5 concentration is significant for the months around exposure.

For Tulare County, we do see that Precipitation, Temperature, Wind, ETo, and PDSI have two peaks of significance, where all of the variables have one peak occurring in the four months before exposure/diagnosis date. PM 2.5 concentration is significant for the months around exposure.

Table 4.9: Statistically Significant Months Selected by Univariate Linear Regression Analysis for the Climate Explanatory Variables Averaged by Site per County (*p*<.05)

		Fresno County		
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	6-12	6-12	5-11	4-10
Temp	2-5	1-4	0-4	0-3, 12
Wind	0-1, 9-12	0-1, 8-12	0, 8-11	7-8
ETo	3-4, 9-11	3-4, 9-10	2-3, 8-9	1-2, 7-8
PDSI	ALL	ALL	ALL	ALL
PM 10	4-11	4-11	3-10	2-9
PM 2.5	1-10, 12	1-12	ALL	ALL
ENSO 1	1, 2, 7-9	0, 1, 6-9	5-8	4 - 7
ENSO 2	5-10	5-10	4-9	4-8
ENSO 3	0-2, 6-8,	0-2, 6-8	0, 1, 5-7	0, 4, 5
ENSO 4	0, 1,	0, 1	0, 1	0
ENSO 5	0, 1, 2	0-2	0, 1	0, 1
ENSO 6	0-4	0-3	0-3	0-2
ENSO 7	0, 1, 2	0-2	0, 1	0
ENSO 8	0-3	0-3	0-2	0, 1
ENSO 9	4-12	4-12	3-12	2-11
		Kern County		
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	2, 3, 6-11	1, 2, 5-10	0, 1, 4 -9	0, 3 – 8
Temp	1-4, 6-10	0-3, 6-10	0-2, 5-9, 11, 12	0, 1, 4-8, 10-12

Table 4.9: Statistically Significant Months Selected by Univariate Linear Regression Analysis for the Climate Explanatory Variables Averaged by Site per County (p<.05)				
Wind	0, 3-6, 8-12	2-5, 8-12	1-4, 7 – 11,	0-3, 6-10
ETo	1-5, 7-11	1-4, 7-10	0 – 3, 6-9, 12	0-2, 5-8, 11, 12
PDSI	4-11	3-10	2-9	1-8
PM 10	5-8	5-8	3-8	2-6
PM 2.5	1-7	0-6, 12	0-5, 11, 12	0 – 4, 10-12
ENSO 1	0-3, 5-8, 11, 12	0-2, 5-8, 11, 12	0-1, 4-7, 10-12	0, 3-6, 9-11
ENSO 2	0-3	0-2	0, 1	0, 1, 12
ENSO 3	0-2, 5-8	0-1, 4-7, 11	0, 1, 3-6, 10	0, 3-5, 9
ENSO 4	0-2, 10-12	0-2, 9-12	0, 1, 8-12	0, 1, 7-12
ENSO 5	11, 12	10-12	9-12	8-12
ENSO 6	0, 1, 9-12	0, 1, 8-12	0, 8-12	7-12
ENSO 7	0, 1, 5	0, 1, 5	0, 4, 12	11, 12
ENSO 8	0-2, 9-12	0, 1, 8-12	0-1, 7-12	0, 7 -12
ENSO 9	0-2	0-2	0-1, 12	1, 11, 12
Kings County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	7-11	6-11	5-10	4-9
Temp	1-5, 9-10	0-4, 9	0-3, 8, 12	0-3, 11, 12
Wind	0, 4-5, 9-12	3-5, 8-11	2-4, 7-10	1-3, 7-9
ETo	2-5, 8-11	2-4, 8-11	1-3, 7-10	0-2, 6-9, 12
PDSI	6-9	5-9	4-8, 12	3-7, 12
PM 10	4-10	3-9	3-8	2-7
PM 2.5	0-7	0-7	0-6	0-5
ENSO 1	0-2, 6-9, 12	0-2, 5-8, 12	0,1, 4-7, 11, 12	0, 3-6, 10-12
ENSO 2	4-7	4-6	5	None
ENSO 3	0-2, 5-7, 11, 12	0-2, 5-7, 11, 12	0, 1, 4, 5, 6, 10-12	0, 3, 4, 5, 9, 10, 11
ENSO 4	0, 1	0, 1	None	None
ENSO 5	0-2, 8	0, 1, 8	0, 1, 6-8	0, 5, 6, 7
ENSO 6	0-3	0-3	0-2	0, 1
ENSO 7	0-2	0-2, 11	0, 1, 9-10	0, 9
ENSO 8	0-3	0-2	0-2	0, 1
ENSO 9	4-8	3-8	2-6	1-5
San Luis Obispo County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	6-12	6-11	5-11	4-10
Temp	0-6, 12	0-6, 12	0-5, 11, 12	0-4, 10-12
Wind	1, 7	1, 6, 7	0, 5, 6	4, 5
ETo	0, 3-5, 9-12	2-5, 7-11	0-4, 6-10	0-3, 5-9, 12
PDSI	None	None	12	12

Table 4.9: Statistically Significant Months Selected by Univariate Linear Regression Analysis for the Climate Explanatory Variables Averaged by Site per County (p<.05)				
PM 10	None	None	None	None
PM 2.5	1-7	0-7	0-6	0-5
ENSO 1	0-3, 6-9, 12	0-3, 5-9, 11, 12	0-2, 4-8, 10 -12	0, 1, 3-7, 9-12
ENSO 2	5, 6	4-6	3, 4	3
ENSO 3	0-2, 5-8, 11-12	0-2, 4-7, 10-12	0, 1, 3-6, 9-12	0, 3-5, 8-11
ENSO 4	None	None	None	None
ENSO 5	0, 7-10	7-9	5-8	5-8
ENSO 6	0-1	0-1	0	None
ENSO 7	0-1, 10-12	0-1, 9-12	0, 8-11	7-10
ENSO 8	0	None	None	None
ENSO 9	5-7	4-6	3-5	2-4
Tulare County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	1-4, 6-10	0-3, 6-10	0-2, 5-9, 12	0, 1, 4-8, 11, 12
Temp	0-5, 8, 9	0-4, 8, 9, 12	0-3, 11, 12	0-2, 10-12
Wind	2-4, 8-12	1-4, 7-12	0-3, 6-10	0-2, 5-10
ETo	1-5, 7-11	1-4, 7-10	0-3, 6-9, 12	0-2; 5-8, 11, 12
PDSI	0-4, 11-12	0-4, 11-12	0-3, 10-12	0-2, 9-12
PM 10	3-12	2-12	2-12	1-10, 12
PM 2.5	2-5	2-6	1, 4, 12	0-3, 11, 12
ENSO 1	0-2, 5-9, 11-12	0-2, 4-8, 11, 12	0, 1, 3-7, 10-12	0, 2-6, 9-12
ENSO 2	4-5	2-5	3,	None
ENSO 3	0, 1, 4-8, 11-12	0, 3-7, 10-12	3-6, 10, 11	2-5, 8-10
ENSO 4	None	None	None	None
ENSO 5	12	12	11, 12	10-12
ENSO 6	None	None	None	None
ENSO 7	None	4, 5	3, 4	2, 12
ENSO 8	None	None	None	None
ENSO 9	1-7, 10, 11	0-11	0-6, 9, 10	0-4, 8-9

Multivariate Linear Regression

The Multvariate analysis was conducted for the following scenarios: Actual, EMST, EMPM, and EMCM.

Fresno County

Linear Regression shows that about 40-55% of the variation in Valley Fever cases and Exposure scenarios can be explained by several climate variables and their lags for Fresno County (Table 4.10).

For cases estimated on their month of diagnosis, climate factors were identified to occur approximately 6 – 12 months prior to diagnosis, except El Niño. The amount of cases diagnosed in a month increases on average of 4.22 for every inch of precipitation that occurs 12 months prior. When wind speed increases 9 months before diagnosis, the amount of cases is expected to decrease by 5 people on average. The Palmer Drought Severity Index has two effects on cases based on diagnosis month. If PDSI is in a wet period 5 months prior to diagnosis, cases on average will increase. If PDSI increases its drought category one year prior to diagnosis, cases are estimated to increase on average. If a La Niña increases in strength, more cases on average are expected to be diagnosed that same month.

Using Stacy *et al.*'s method for exposure, precipitation in months 9-12 before exposure, wind speed during the month of exposure and 5 months prior to exposure, ETo measured 7 months prior, PDSI 4 and 9 months prior, PM 2.5 concentration during the month of exposure, and ENSO stage during the month of exposure were found to have a significant additive relationship on what effects the amount of diagnosed cases estimated to be exposed to Valley Fever. The variables in EMST scenario have the same directionality as the Fresno_Actual Scenario. A new variable, PM 2.5 is related to EMST exposure by every micrometer increase in PM 2.5 concentration, the average number of cases exposed that month decreases.

For Exposure Methods Park *et al.* and Comrie *et al.*, similar relationships occur. The more precipitation in 6-12 months prior lead to more cases estimated to be exposed. For the ENSO anomaly the month of, the directionality is the same. However, these two scenarios also include the ENSO anomaly a couple months prior (10 months for EMPM and 3 months for EMCM). These months have an opposite relationship than the month of exposure.

These results are from linear regression analysis. When exploring model validity, many linear regression assumptions are violated for the Fresno scenarios.

Table 4.10: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Fresno California, 2000 - 2014

			Actual			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	48.86	8.94	5.462	<.0001	31.33	66.38
Precipitation Month 12	4.22	1.03	4.080	<.0001	2.20	6.23
Wind Month 9	-5.27	2.02	-2.601	.0101	-9.22	-1.31
PDSI Month 5	5.76	.83	6.909	<.0001	4.13	7.38
PDSI Month 12	-2.88	.83	-3.469	.0006	-4.50	-1.25
ENSO 3.4 Anomaly	-8.20	2.10	-3.893	.0001	-12.31	-4.08
R^2 (Adjusted)			.4004 (.383)			
			EMST			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	118.02	24.58	4.801	<.0001	69.84	166.20
Precip Month 9	3.31	1.02	3.226	.0015	1.31	5.31
Precip Month 10	3.25	1.01	3.209	.0015	1.27	5.23

Table 4.10: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Fresno California, 2000 - 2014						
Precip Month 11	3.09	.99	3.093	.0023	1.15	5.03
Precip Month 12	2.73	1.04	2.609	.0098	0.69	4.77
Wind (no lag)	-10.01	2.90	-3.443	.0007	-15.69	-4.33
Wind Month 5	-7.31	2.56	-2.856	.0048	-12.33	-2.29
ETO Month 7	-2.44	.77	-3.148	.0019	-3.95	-0.93
PDSI Month 4	3.21	.85	3.734	.0002	1.54	4.88
PDSI Month 9	-2.07	.85	-2.445	.0155	-3.74	-0.40
PM 2.5 (no lag)	-.88	.20	-4.266	<.0001	-1.27	-0.49
ENSO 3.4 Anomaly	-6.58	1.86	-3.523	.0005	-10.23	-2.93
R^2 (Adjusted)			.5233 (.4919)			
EMPM						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	104.13	20.5164	5.076	<.0001	63.92	144.34
Precip Month 8	1.98	.9812	2.021	.0448	0.06	3.90
Precip Month 9	3.88	1.0177	3.818	.0001	1.89	5.87
Precip Month 10	3.13	.9889	3.173	.0017	1.19	5.07
Precip Month 11	2.95	1.0170	2.904	.0041	0.96	4.94
Wind (no lag)	-12.23	3.2383	-3.777	.0002	-18.58	-5.88
Wind Month 4	-8.54	2.3117	-3.694	.0002	-13.07	-4.01
ETO (no lag)	3.59	.9929	3.623	.0003	1.64	5.54
PDSI Month 4	4.12	.8664	4.761	<.0001	2.42	5.82
PDSI Month 9	-2.59	.8461	-3.069	.0025	-4.25	-0.93
PM 2.5 (no lag)	-.68	.2071	-3.285	.0012	-1.09	-0.27

Table 4.10: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Fresno California, 2000 - 2014						
ENSO 3.4 Anomaly	-5.31	1.8082	-2.942	.0037	-8.85	-1.77
ENSO 3.4 Anomaly (Month 10)	5.37	1.7873	3.007	.0030	1.87	8.87
R^2 (Adjusted)			.5486 (.5159)			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	50.08	7.24	6.915	<.0001	35.89	64.27
Precip Month 7	2.29	.98	2.332	.0208	0.37	4.21
Precip Month 8	2.53	.98	2.582	.0106	0.61	4.45
ETO Month 6	-1.51	.55	-2.749	.0066	-2.59	-0.43
ETO Month 9	-1.60	.74	-2.171	.0313	-3.05	-0.15
PDSI Month 1	4.66	.66	7.018	<.0001	3.37	5.95
PDSI Month 12	-2.15	.62	-3.442	.0007	0.00	0.00
PM 2.5 Month 9	-.701	.18	-3.855	.0001	-3.37	-0.93
ENSO 3.4 Anomaly	-13.29	2.55	-5.208	<.0001	-1.05	-0.35
ENSO 3.4 Anomaly Month 3	10.68	2.50	4.256	<.0001	-18.29	-8.29
R^2 (Adjusted)			.5216 (.4961)			

Kern County

Linear Regression shows that about 60-70% of the variation in Valley Fever cases and Exposure scenarios can be explained by several climate variables and their lags for Kern County (Table 4.11).

For Kern County, the number of cases based on diagnosis month found a significant additive relationship to average precipitation at time of diagnosis, 2 months before diagnosis, and 8 and 9 months prior to diagnosis. Unlike Fresno County, the relationship between cases and precipitation is not consistent for every month in the model. There is a significant relationship that the more precipitation that occurs during the month of diagnosis and two months before, the less cases will occur. The more precipitation that occurs in months 8 and 9 before diagnosis, the more cases tended to occur. Temperature has a consistent relationship, with less cases occurring when temperatures increase in months 6 and 12 prior to diagnosis. The PDSI for month 10 saw increased cases when it was a wet period, but saw decreased cases when month 12 was wet. In the several months selected for Particulate Matter 10 and 2.5, the more concentrations occurs in those months, there are less cases. ENSO 3.4 anomalies share a similar relationship to Kern County as it did to Fresno.

For Stacy *et al.*'s exposure period, similar climate variables were selected. PM 2.5 has months slightly offset when compared to Diagnosis Date months selected. The directionality and magnitude of those months selected are similar to diagnosis date scenario.

For Park and Comrie *et al.*'s exposure period, similar climate variables were selected, with the months offset. The one variable consistently in each model for the same month and direction is ENSO 3.4 anomaly at the time of exposure. Other consistencies include that the earlier precipitation months have a negative relationship to cases, but the later months have a positive relationship to cases. Temperature and particulate matters have a negative relationship. The first PDSI month included has a positive relationship and the second month included has a negative relationship. The same occurs for ENSO 3.4 Anomaly.

These results are from linear regression analysis. When exploring model validity, many linear regression assumptions are violated for the Kern scenarios.

Table 4.11: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014

	Actual					
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	617.35	105.22	5.867	<.0001	411.12	823.58
Precip (no lag)	-10.51	3.85	-2.729	.0070	-18.06	-2.96
Precip Month 2	-11.16	3.76	-2.964	.0035	-18.53	-3.79
Precip Month 8	11.48	3.97	2.891	.0043	3.70	19.26
Precip Month 9	11.86	3.99	2.971	.0034	4.04	19.68
Temp Month 6	-2.94	.88	-3.326	.0010	-4.66	-1.22
Temp Month 12	-2.50	.87	-2.869	.0046	-4.21	-0.79
PDSI Month 10	15.34	3.11	4.919	<.0001	9.24	21.44
PDSI Month 12	-7.22	3.00	-2.400	.0175	-13.10	-1.34
PM 10 Month 12	-.55	.27	-2.021	.0449	-1.08	-0.02
PM 2.5 Month 2	-1.10	.55	-1.995	.0477	-2.18	-0.02
PM 2.5 Month 4	-1.41	.52	-2.701	.0076	-2.43	-0.39
PM 2.5 Month 5	-1.58	.57	-2.774	.0061	-2.70	-0.46
PM 2.5	-2.44	.52	-4.624	<.0001	-3.46	-1.42

Table 4.11: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014						
Month 7						
PM 2.5 Month 11	-2.53	.49	-5.092	<.0001	-3.49	-1.57
ENSO 3.4 Anomaly	-13.98	4.54	-3.080	.0024	-22.88	-5.08
ENSO 3.4 Anomaly Month 12	19.21	4.15	4.624	<.0001	11.08	27.34
R^2 (Adjusted)			.666 (.6332)			
			EMST			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	378.46	33.66	11.241	<.0001	312.49	444.43
Precip Month 2	-14.20	3.47	-4.090	<.0001	-21.00	-7.40
Precip Month 8	10.92	3.49	3.124	.0021	4.08	17.76
Temp Month 6	-1.35	.49	-2.733	.0069	-2.31	-0.39
PDSI Month 9	13.45	2.04	6.569	<.0001	9.45	17.45
PM 2.5 Month 2	-1.52	.50	-3.011	.0030	-2.50	-0.54
PM 2.5 Month 4	-1.84	.42	-4.371	<.0001	-2.66	-1.02
PM 2.5 Month 6	-1.86	.51	-3.620	.0003	-2.86	-0.86
PM 2.5 Month 7	-2.25	.50	-4.459	<.0001	-3.23	-1.27
PM 2.5 Month 10	-2.03	.42	-4.732	<.0001	-2.85	-1.21
PM 2.5 Month 12	-1.43	.49	-2.863	.0047	-2.39	-0.47
ENSO 3.4 Anomaly	-12.24	4.13	-2.959	.0035	-20.33	-4.15
ENSO 3.4 Anomaly Month 12	16.67	3.84	4.340	<.0001	9.14	24.20
R^2 (Adjusted)			.6688 (.645)			
			EMPM			
			Statistical Significance Information			

Table 4.11: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014						
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	365.64	35.21	10.39	<.0001	296.63	434.65
Precip Month 1	-14.34	3.61	-3.97	.0001	-21.42	-7.26
Precip Month 7	15.57	3.60	4.32	<.0001	8.50	22.63
Temp Month 5	-1.90	0.49	-3.90	.0001	-2.85	-0.94
PDSI Month 8	13.04	2.22	5.87	<.0001	8.68	17.39
PM 2.5 Month 5	-2.59	0.53	-4.88	<.0001	-3.63	-1.55
PM 2.5 Month 6	-1.94	0.53	-3.63	.0003	-2.99	-0.89
PM 2.5 Month 9	-2.08	0.44	-4.75	<.0001	-2.93	-1.22
PM 2.5 Month 12	-1.40	0.58	-2.42	.0167	-2.53	-0.26
ENSO 3.4 Anomaly	-9.88	4.43	-2.23	.0270	-18.56	-1.20
ENSO 3.4 Anomaly Month 12	19.68	4.10	4.80	<.0001	11.65	27.71
R^2 (Adjusted)			.6065 (.5832)			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	440.68	44.26	9.96	<.0001	353.94	527.42
Precip (no lag)	-9.15	3.24	-2.83	.0053	-15.50	-2.80
Precip Month 6	12.57	3.25	3.87	.0001	6.20	18.94
Temp Month 3	-3.17	0.98	-3.23	.0014	-5.10	-1.25
ETO Month 3	15.30	4.86	3.15	.0019	5.76	24.83
PDSI Month 7	14.64	2.50	5.86	<.0001	9.74	19.53
PDSI Month 10	-6.02	2.55	-2.36	.0196	-11.02	-1.01
PM 10	-0.87	0.24	-3.66	.0003	-1.33	-0.40

Table 4.11: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014						
Month 10						
PM 2.5 Month 2	-1.80	0.45	-3.99	.0001	-2.69	-0.92
PM 2.5 Month 3	-1.18	0.49	-2.42	.0166	-2.13	-0.22
PM 2.5 Month 5	-2.05	0.42	-4.84	<.0001	-2.87	-1.22
PM 2.5 Month 8	-1.54	0.47	-3.30	.0011	-2.45	-0.62
PM 2.5 Month 9	-1.37	0.50	-2.75	.0067	-2.34	-0.39
PM 2.5 Month 11	-1.34	0.52	-2.55	.0116	-2.36	-0.31
PM 2.5 Month 12	-1.88	0.51	-3.65	.0003	-2.89	-0.87
ENSO 3.4 Anomaly	-15.60	3.92	-3.97	.0001	-23.29	-7.91
ENSO 3.4 Anomaly Month 7	23.45	3.69	6.36	<.0001	16.23	30.68
R^2 (Adjusted)			.7265 (.6996)			

Kings County

Linear Regression shows that about 40-55% of the variation in Valley Fever cases and Exposure scenarios can be explained by several climate variables and their lags for Kings County (Table 4.12).

For cases based on diagnosis date, Kings County found significant relationships to precipitation 8-10 months prior, wind 1 month before diagnosis, ETo 11 months prior, PDSI one month prior, PM 10 4 months prior, PM 2.5 7 months prior, and ENSO 3.4 anomaly during the month of diagnosis. The precipitation in the later months and ETo have a positive relationship with cases diagnosed. The other variables have a negative relationship.

For Stacy *et al.*'s exposure period, similar climate variables were selected with some of them being a different month that the diagnosis date scenario. More months from PM 2.5 were selected. Overall, the variables maintain similar directions as the diagnosis exposure results.

For Park and Comrie *et al.*'s exposure periods, PM 2.5 in a later month (10 and 12) were included in the models, but their directionality is opposite than the PM 2.5 pattern that occurred.

These results are from linear regression analysis. When exploring model validity, many linear regression assumptions are violated for the Kings scenarios.

Table 4.12: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014						
			Actual			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence	Upper 95% Confidence

Table 4.12: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014

					Level	Level
Intercept	23.78	6.41	3.71	.0003	11.21	36.35
Precip Month 8	2.62	0.66	3.94	.0001	1.32	3.92
Precip Month 9	2.50	0.76	3.29	.0012	1.01	3.99
Precip Month 10	1.72	0.74	2.32	.0216	0.27	3.17
Wind Month 1	-3.42	1.42	-2.41	.0169	-6.20	-0.64
ETO Month 11	1.40	0.56	2.50	.0134	0.30	2.50
PDSI Month 1	-1.72	0.62	-2.79	.0059	-2.92	-0.51
PM 10 Month 4	-0.18	0.04	-4.08	.0001	-0.27	-0.09
PM 2.5 Month 7	-0.22	0.08	-2.71	.0074	-0.37	-0.06
ENSO 3.4 Anomaly	-5.00	1.12	-4.47	<.0001	-7.20	-2.81
R^2 (Adjusted)				.4009 (.3691)		

EMST						
Statistical Significance Information						
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	7.60	4.26	1.79	.0758	-0.74	15.94
Precip Month 8	3.43	0.58	5.96	<.0001	2.30	4.56
Precip Month 10	2.27	0.66	3.45	.0007	0.98	3.56
Precip Month 12	1.94	0.65	2.97	.0034	0.66	3.22
ETO Month 11	1.39	0.53	2.64	.0091	0.36	2.42
PDSI (no lag)	-1.28	0.55	-2.31	.0220	-2.37	-0.20
PDSI Month 12	-1.20	0.57	-2.10	.0371	-2.32	-0.08
PM 10 Month 5	-0.15	0.04	-3.93	.0001	-0.23	-0.08
PM 10 Month 9	-0.09	0.04	-2.16	.0324	-0.18	-0.01
PM 2.5 (no lag)	-0.24	0.09	-2.81	.0055	-0.41	-0.07

Table 4.12: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014						
PM 2.5 Month 6	-0.20	0.08	-2.43	.0161	-0.36	-0.04
PM 2.5 Month 12	0.23	0.08	2.80	.0057	0.07	0.39
ENSO 3.4 Anomaly	-4.88	1.04	-4.71	<.0001	-6.91	-2.84
R^2 (Adjusted)			.4794 (.442)			
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	15.59	4.81	3.24	.0014	6.17	25.02
Precip Month 6	2.12	0.60	3.54	.0005	0.95	3.30
Precip Month 7	1.91	0.63	3.02	.0029	0.67	3.15
Precip Month 8	2.28	0.64	3.57	.0005	1.03	3.54
Precip Month 10	2.43	0.72	3.37	.0009	1.02	3.85
Precip Month 12	3.74	0.69	5.45	<.0001	2.40	5.09
Temp Month 9	-0.37	0.12	-3.06	.0026	-0.61	-0.13
ETO Month 10	2.59	0.79	3.28	.0013	1.04	4.13
PDSI Month 12	-1.96	0.55	-3.56	.0005	-3.04	-0.88
PM 10 Month 3	-0.13	0.04	-3.05	.0027	-0.21	-0.05
PM 2.5 (no lag)	-0.23	0.08	-2.78	.0060	-0.39	-0.07
PM 2.5 Month 5	-0.23	0.08	-2.93	.0039	-0.38	-0.07
PM 2.5 Month 10	0.17	0.08	2.18	.0307	0.02	0.32
ENSO 3.4 Anomaly	-8.16	1.76	-4.64	<.0001	-11.61	-4.71
ENSO 3.4 Anomaly Month 2	4.16	1.79	2.33	.0212	0.65	7.66
R^2 (Adjusted)			.5215 (.4809)			

Table 4.12: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014						
EMCM						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	24.67	6.73	3.67	0.0003	11.48	37.85
Precip Month 5	1.31	0.66	2.00	0.0467	0.03	2.60
Precip Month 6	2.15	0.66	3.27	0.0013	0.86	3.43
Precip Month 7	1.59	0.61	2.60	0.0102	0.39	2.79
Precip Month 12	3.73	0.80	4.65	0.0000	2.16	5.30
Temp Month 8	-0.25	0.10	-2.59	0.0103	-0.44	-0.06
ETO Month 1	-2.47	0.82	-3.02	0.0029	-4.08	-0.87
ETO Month 12	2.33	0.77	3.03	0.0028	0.83	3.84
PDSI Month 8	1.56	0.63	2.47	0.0146	0.32	2.79
PDSI Month 12	-3.53	0.61	-5.76	0.0000	-4.74	-2.33
PM 2.5 Month 1	-0.30	0.08	-3.70	0.0003	-0.47	-0.14
PM 2.5 Month 4	-0.20	0.08	-2.60	0.0103	-0.36	-0.05
ENSO 3.4 Anomaly	-12.16	2.95	-4.13	0.0001	-17.94	-6.38
ENSO 3.4 Anomaly Month 1	8.61	2.95	2.92	0.0039	2.84	14.39
R^2 (Adjusted)	.4968 (.4574)					

San Luis Obispo County

Linear Regression shows that about 50-65% of the variation in Valley Fever cases and Exposure scenarios can be explained by several climate variables and their lags for San Luis Obispo County (Table 4.13).

The results of San Luis Obispo County are different than the rest of the counties. Precipitation is a dominate relationship and not many more variables are needed in the model to gain the R^2 values. For every exposure scenario, approximately 6 months of precipitation are selected that start around 6 months prior to diagnosis date. For all the exposure periods, precipitation selected has a positive relationship to the number of cases. With more precipitation in these months, there is a significant relationship with more cases occurring.

Another commonality between the models is that PM 2.5 concentration is significant around the month of exposure. When PM 2.5 concentration increases, the amount of cases is estimated to decrease.

Unlike the other counties, ENSO 3.4 anomaly is not selected in any of the models.

These results are from linear regression analysis. When exploring model validity, many linear regression assumptions are violated for the San Luis Obispo scenarios.

Table 4.13: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, San Luis Obispo California, 2000 - 2014

Actual						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	4.08	0.60	6.84	<.0001	2.91	5.25
Precip Month 6	0.50	0.19	2.72	.0071	0.14	0.87
Precip Month 7	0.75	0.19	4.06	.0001	0.39	1.11
Precip Month 9	0.60	0.18	3.28	.0013	0.24	0.96
Precip Month 10	0.96	0.19	4.95	<.0001	0.58	1.34
Precip Month 11	0.70	0.19	3.65	.0003	0.32	1.08
Precip Month 12	0.55	0.19	2.98	.0033	0.19	0.92
PM 2.5 Month 1	-0.51	0.08	-6.28	<.0001	-0.67	-0.35
R^2 (Adjusted)	.5244 (.505)					

EMST						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	7.42	1.59	4.66	<.0001	4.30	10.54
Precip Month 5	0.52	0.16	3.23	.0015	0.20	0.83
Precip Month 6	0.67	0.17	3.97	.0001	0.34	1.00
Precip Month 7	0.60	0.17	3.63	.0004	0.28	0.93
Precip Month 8	0.47	0.16	2.88	.0045	0.15	0.78
Precip Month 9	0.85	0.16	5.26	<.0001	0.53	1.16
Precip	0.79	0.16	4.96	<.0001	0.48	1.10

Table 4.13: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, San Luis Obispo California, 2000 - 2014						
Month 10						
Precip Month 11	0.59	0.16	3.67	<.0003	0.27	0.90
Precip Month 12	0.46	0.15	3.02	<.0029	0.16	0.76
Temp Month 12	-0.08	0.03	-2.52	<.0125	-0.14	-0.02
Month 12 PM 2.5 (no lag)	-0.48	0.07	-7.21	<.0001	-0.62	-0.35
R^2 (Adjusted)			.627 (.605)			
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	11.31	2.94	3.85	.0002	5.55	17.07
Precip Month 4	0.43	0.17	2.50	.0132	0.09	0.76
Precip Month 5	0.59	0.16	3.64	.0004	0.27	0.92
Precip Month 6	0.56	0.16	3.43	.0008	0.24	0.88
Precip Month 7	0.64	0.17	3.81	.0002	0.31	0.97
Precip Month 8	0.89	0.17	5.16	<.0001	0.55	1.23
Precip Month 9	0.88	0.17	5.28	<.0001	0.55	1.20
Precip Month 10	0.65	0.17	3.93	.0001	0.33	0.98
Precip Month 11	0.53	0.16	3.29	.0012	0.22	0.85
Temp Month 8	-0.11	0.03	-3.30	.0012	-0.17	-0.04
Wind Month 5	1.04	0.48	2.16	.0324	0.10	1.98
ETO Month 3	-1.56	0.36	-4.30	<.0001	-2.28	-0.85
PM 2.5 Month 5	-0.41	0.07	-5.79	<.0001	-0.55	-0.27
R^2 (Adjusted)			.6293 (.6027)			
			EMCM			
			Statistical Significance Information			

Table 4.13: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, San Luis Obispo California, 2000 - 2014						
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	3.95	0.53	7.39	<.0001	2.90	4.99
Precip Month 3	0.52	0.16	3.17	.0018	0.20	0.83
Precip Month 4	0.54	0.17	3.26	.0013	0.22	0.87
Precip Month 5	0.47	0.17	2.83	.0053	0.14	0.79
Precip Month 6	0.43	0.17	2.59	.0106	0.10	0.76
Precip Month 7	0.65	0.17	3.90	.0001	0.32	0.97
Precip Month 8	0.68	0.17	4.08	.0001	0.35	1.00
Precip Month 9	0.48	0.17	2.87	.0047	0.15	0.80
Precip Month 10	0.51	0.16	3.17	.0018	0.20	0.83
PM 2.5 Month 1	-0.21	0.10	-2.14	.0342	-0.41	-0.02
PM 2.5 Month 4	-0.28	0.10	-2.81	.0055	-0.48	-0.09
R^2 (Adjusted)				.5967 (.5728)		

Tulare County

Linear Regression shows that about 50-60% of the variation in Valley Fever cases and Exposure scenarios can be explained by several climate variables and their lags for Tulare County (Table 4.14).

For cases based on diagnosis date, Precipitation has a negative relationship to cases when it occurs 2 months prior and a positive relationship when it occurs 10 months prior. Temperature has a positive relationship when it occurs 1 month prior to diagnosis and Wind has a negative relationship when it occurs 12 months prior to diagnosis. ETo for Month 5, PDSI for month 3, and PM 10 for month 8 all have a negative relationship to cases diagnosed. ENSO 3.4 anomaly is included in this model, but for 11 months prior. Similar to the other counties where a lag is included, the relationship is positive. If an El Niño increases in strength during month 11, more cases are estimated to occur.

For Stacy *et al*.'s exposure scenario, Precipitation and ENSO 3.4 anomaly in the later months have a positive relationship with cases estimated to be exposed. All other variables included have a negative relationship.

For Park and Comrie *et al.*'s exposure scenarios, the months change, but the overall relationships maintain. Except in Comrie *et al.*'s exposure scenario, ENSO 3.4 Anomaly is no longer included, at any monthly lag. For Park *et al.*'s exposure scenario, Precipitation and Temperature at no lag are included in the model, but they have an opposite relationship than they did in later lag months.

These results are from linear regression analysis. When exploring model validity, many linear regression assumptions are violated for the Tulare scenarios.

Table 4.14: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Tulare California, 2000 - 2014						
Actual						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	26.61	4.79	5.56	<.0001	17.23	35.99
Precip Month 2	-1.59	0.31	-5.04	<.0001	-2.20	-0.97
Precip Month 10	1.36	0.38	3.59	.0004	0.62	2.10
Temp Month 1	0.13	0.02	6.10	<.0001	0.09	0.18
Wind Month 12	-5.55	1.26	-4.39	<.0001	-8.02	-3.07
ETO Month 5	-1.18	0.29	-4.08	.0001	-1.74	-0.61
PDSI Month 3	-0.83	0.28	-2.93	.0039	-1.38	-0.27
PM 10 Month 8	-0.10	0.02	-6.69	<.0001	-0.13	-0.07
ENSO 3.4 Anomaly Month 11	1.77	0.49	3.63	.0004	0.82	2.73
R^2 (Adjusted)	.4913 (.4675)					
EMST						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	51.16	6.59	7.76	<.0001	38.24	64.09
Precip Month 7	0.81	0.31	2.61	.0098	0.20	1.42
Precip Month 9	0.93	0.31	2.99	.0032	0.32	1.54
Wind Month 12	-5.10	1.12	-4.53	<.0001	-7.30	-2.89
ETO Month 5	-2.58	0.46	-5.67	<.0001	-3.48	-1.69
ETO Month 8	-1.55	0.33	-4.75	<.0001	-2.19	-0.91
ETO Month 12	-1.87	0.53	-3.53	.0005	-2.91	-0.83
PDSI (no lag)	-0.86	0.28	-3.05	.0026	-1.42	-0.31

Table 4.14: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Tulare California, 2000 - 2014						
PDSI Month 2	-0.72	0.28	-2.55	.0118	-1.27	-0.17
PM 10 Month 8	-0.08	0.01	-6.79	<.0001	-0.11	-0.06
ENSO 3.4 Anomaly Month 12	1.15	0.40	2.87	.0046	0.36	1.93
R^2 (Adjusted)			.5941 (.57)			
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level
Intercept	52.86	7.51	7.04	<.0001	38.14	67.59
Precip (no lag)	-0.96	0.34	-2.88	.0045	-1.62	-0.31
Precip Month 8	1.04	0.33	3.15	.0019	0.39	1.69
Temp (no lag)	0.13	0.03	3.91	.0001	0.07	0.20
Temp Month 12	-0.11	0.04	-2.37	.0187	-0.19	-0.02
Wind Month 11	-5.05	1.13	-4.46	<.0001	-7.27	-2.83
ETO Month 4	-2.74	0.46	-5.89	<.0001	-3.65	-1.83
ETO Month 7	-1.46	0.38	-3.88	.0001	-2.20	-0.72
ETO Month 11	-1.95	0.53	-3.69	.0003	-2.98	-0.91
PDSI Month 1	-1.01	0.24	-4.29	<.0001	-1.47	-0.55
PM 10 Month 7	-0.10	0.01	-7.35	<.0001	-0.12	-0.07
ENSO 3.4 Anomaly Month 12	1.30	0.41	3.19	.0017	0.50	2.11
R^2 (Adjusted)			.5973 (.5709)			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level	Upper 95% Confidence Level

Table 4.14: Results of a Linear Regression of Valley Fever Exposure Scenarios by Climate Factors, Tulare California, 2000 - 2014						
Intercept	64.63	7.37	8.77	<.0001	50.18	79.08
Precip Month 5	0.80	0.33	2.44	.0156	0.16	1.44
Wind Month 8	-3.23	1.18	-2.73	.0070	-5.54	-0.91
Wind Month 12	-4.11	1.22	-3.37	.0009	-6.50	-1.72
ETO Month 3	-1.81	0.33	-5.49	<.0001	-2.46	-1.17
ETO Month 6	-3.02	0.52	-5.85	<.0001	-4.03	-2.01
ETO Month 11	-2.61	0.54	-4.87	<.0001	-3.66	-1.56
PDSI (no lag)	-1.14	0.26	-4.44	<.0001	-1.65	-0.64
PM 10 Month 5	-0.08	0.01	-6.23	<.0001	-0.11	-0.06
R^2 (Adjusted)			.5244 (.5022)			

Poisson Results

Stepwise Selection

Table 4.15 shows the monthly lags selected by stepwise Poisson Regression for each climate variable averaged by site. As discussed in sections above, the months selected are not the same across exposure scenarios by county. In addition, between counties, the months selected are not the same for the same exposure period and climate variable.

For Kern, Precipitation and PM 10 have the same months selected, but that appears to just occur for Kern County.

Table 4.15: Months Selected by Stepwise Poisson Regression (link = Log) for the Climate Explanatory Variables Averaged by Site per County (p<.05)										
					Fresno County					
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	ALL	ALL	ALL	ALL
Temp	1, 4, 9, 10	0, 3, 5, 8, 10, 12	0, 3, 5, 8, 9, 11, 12	0, 3, 4, 8, 10, 12	2, 5, 7, 9, 12	2, 4, 7, 8, 10, 11, 12	0, 3, 5, 8, 9, 11, 12	1, 3, 6, 8, 11	1, 3, 6, 7, 9, 10, 11	2, 6, 8, 11
Wind	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	ALL	All	All

Table 4.15: Months Selected by Stepwise Poisson Regression (link = Log) for the Climate Explanatory Variables Averaged by Site per County (p<.05)

	11	11	11	11	11	11				
ETo	1, 4, 6, 8, 11, 12	4, 6, 10, 11	0, 3, 4, 5, 8, 10, 11	4, 6, 8, 10, 11, 12	3, 4, 5, 9, 10	3, 4, 5, 9, 10	0, 3, 5, 8, 10, 11	2, 3, 4, 8, 9, 10, 12	1, 2, 3, 4, 8, 9, 10, 12	2, 4, 8, 9, 10, 12
PDSI	5, 10, 12	4, 6, 9, 12	4, 9, 12	3, 5, 8, 12	2, 4, 6, 12	1, 4, 8, 12	4, 9, 12	1, 4, 12	0, 4, 12	1, 5, 12
PM 10	0, 1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12	ALL	0, 1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12	ALL	0, 1, 3, 4, 5, 6, 8, 9, 10, 11, 12	0, 1, 3, 4, 5, 6, 8, 9, 10, 11, 12	0, 1, 3, 4, 5, 6, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12	0, 3, 4, 5, 6, 8, 9, 10, 11, 12
PM 2.5	0, 2, 3, 4, 5, 6, 7, 8, 10, 12	ALL	0, 1, 2, 3, 4, 5, 6, 7, 9, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 10, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 8, 10, 11, 12	0, 1, 2, 3, 4, 5, 6, 7, 9, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 7, 9, 10, 11, 12	1, 2, 3, 4, 6, 8, 10, 11, 12
ENSO 1	0, 1, 4, 6, 8, 10, 12	0, 1, 5, 7, 9, 10, 12	0, 1, 4, 5, 7, 9, 11, 12	0, 1, 4, 6, 7, 9, 10, 12	0, 1, 4, 6, 7, 9, 11, 12	3, 4, 6, 8, 9, 11, 12	0, 1, 4, 5, 7, 9, 11, 12	3, 5, 7, 9, 11	3, 5, 7, 9, 10, 12	2, 4, 6, 8, 11
ENSO 2	0, 1, 4, 6, 8, 12	0, 1, 4, 6, 7, 9, 12	0, 1, 5, 7, 9, 11, 12	0, 1, 4, 6, 7, 11, 12	4, 5, 7, 9, 11, 12	4, 6, 9, 11	0, 1, 4, 5, 7, 9, 11, 12	3, 4, 7, 9, 12	3, 4, 7, 9, 12	2, 4, 6, 8, 9, 11
ENSO 3	0, 2, 3, 4, 5, 6, 7, 12	0, 1, 3, 6, 8, 9, 12	0, 1, 2, 4, 5, 8, 9, 12	0, 2, 3, 6, 12	0, 1, 5, 12	0, 1, 4, 9, 12	0, 1, 2, 5, 8, 9, 12	0, 1, 4, 12	0, 1, 3, 12	0, 1, 4, 9, 10, 12
ENSO 4	0, 2, 3, 4, 5, 6, 9, 12	0, 1, 6, 12	0, 1, 5, 9, 11, 12	0, 2, 6, 12	0, 1, 4, 9, 11, 12	0, 1, 4, 7, 9, 10, 12	0, 1, 5, 8, 9, 11, 12	0, 1, 3, 8, 11, 12	0, 1, 3, 6, 8, 11, 12	0, 2, 4, 5, 9, 11, 12
ENSO 5	0, 1, 4, 6, 8, 12	0, 1, 2, 6, 8, 10, 12	0, 1, 6, 7, 12	0, 1, 3, 6, 8, 12	0, 1, 2, 8, 12	0, 1, 8, 12	0, 1, 2, 8, 12	0, 1, 8, 12	0, 1, 5, 6, 8, 11, 12	0, 1, 8, 12
ENSO 6	0, 4, 8, 9, 11, 12	0, 3, 9, 11, 12	0, 1, 3, 9, 11, 12	0, 4, 11, 12	0, 1, 2, 8, 10, 11, 12	0, 1, 2, 7, 10, 11, 12	0, 1, 3, 8, 11, 12	0, 1, 2, 7, 9, 11, 12	0, 1, 2, 7, 9, 11, 12	0, 1, 2, 7, 10, 11, 12
ENSO 7	0, 2, 3, 6, 8, 10, 11	0, 1, 4, 5, 9, 12	0, 1, 4, 5, 9, 10, 11, 12	0, 6, 9, 12	0, 1, 5, 8, 10, 12	0, 1, 5, 6, 10, 12	0, 1, 5, 8, 11, 12	0, 1, 4, 9, 12	0, 1, 3, 9, 12	0, 1, 4, 10, 12
ENSO 8	0, 2, 5, 6, 11	0, 1, 7, 11, 12	0, 1, 7, 10, 11, 12	0, 2, 7, 12	0, 1, 3, 9, 10, 11, 12	0, 1, 3, 9, 10, 12	0, 1, 7, 11, 12	0, 1, 3, 6, 7, 10, 12	0, 1, 3, 5, 7, 8, 9, 11, 12	0, 1, 3, 6, 7, 9, 10, 12
ENSO 9	1, 4, 6, 8, 9, 10, 12	3, 4, 5, 6, 7, 8, 10, 12	3, 4, 5, 6, 7, 9, 10, 12	3, 4, 6, 7, 8, 10, 12	2, 3, 4, 5, 6, 8, 9, 11, 12	2, 4, 6, 8, 9, 11, 12	2, 3, 4, 5, 6, 7, 9, 10, 12	1, 2, 3, 4, 5, 8, 10, 12	1, 3, 4, 5, 7, 8, 10, 12	2, 4, 5, 6, 8, 9, 11, 12
Kern County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11	0, 1, 2, 11
Temp	2, 3, 4, 5, 6, 7,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	1, 2, 3, 4, 5, 6,	0, 1, 2, 3, 4, 5,	0, 1, 2, 3, 4, 5,	0, 1, 2, 3, 4, 5, 6, 7,	ALL	ALL	ALL

Table 4.15: Months Selected by Stepwise Poisson Regression (link = Log) for the Climate Explanatory Variables Averaged by Site per County (p<.05)

	8, 9, 10, 11, 12	7, 8, 9, 10, 11, 12	7, 8, 9, 10, 11, 12	7, 8, 9, 10, 11, 12	6, 7, 8, 9, 10, 11, 12	6, 7, 8, 9, 10, 11, 12	8, 9, 10, 11, 12			
Wind	1, 2, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 4, 7, 8, 9, 10, 12	1, 4, 7, 8, 9, 11, 12	1, 2, 5, 7, 8, 9, 10, 12	0, 3, 6, 7, 8, 9, 11, 12	0, 3, 5, 6, 7, 8, 9, 10, 11, 12	1, 3, 6, 7, 8, 9, 11, 12	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 2, 5, 6, 7, 8, 10, 11, 12	0, 1, 2, 5, 6, 7, 8, 10, 11, 12
ETo	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	ALL	ALL
PDSI	1, 2, 4, 5, 6, 7, 8, 9, 10, 12	0, 1, 2, 5, 6, 7, 8, 9, 10, 12	0, 1, 3, 5, 6, 7, 8, 9, 11, 12	0, 2, 4, 5, 6, 7, 8, 9, 10, 12	1, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 3, 5, 6, 7, 8, 10, 12	1, 5, 6, 7, 8, 9, 11, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 12
PM 10	0, 9	0, 9	0, 9	0, 9	0, 9	0, 9	0, 9	0, 9	0, 9	0, 9
PM 2.5	1, 2, 3, 4, 5, 6, 7, 8, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12
ENSO 1	0, 3, 4, 5, 7, 8, 10, 12	0, 3, 5, 7, 8, 10, 12	0, 1, 2, 4, 6, 9, 12	0, 3, 5, 7, 8, 10, 12	0, 3, 5, 8, 9, 11, 12	0, 3, 5, 8, 11, 12	0, 1, 2, 4, 6, 7, 9, 12	0, 1, 3, 4, 6, 8, 11, 12	0, 2, 3, 4, 5, 6, 8, 11, 12	0, 2, 3, 4, 5, 6, 8, 11, 12
ENSO 2	0, 3, 4, 5, 7, 8, 10, 11, 12	2, 1, 2, 5, 6, 8, 10, 11, 12	0, 1, 2, 4, 6, 7, 9, 11, 12	0, 3, 4, 5, 7, 8, 10, 11, 12	0, 4, 5, 7, 11, 12	0, 2, 3, 5, 6, 8, 11, 12	0, 1, 2, 6, 7, 9, 11, 12	0, 1, 3, 4, 7, 11, 12	0, 2, 3, 4, 5, 6, 8, 11, 12	0, 2, 3, 4, 5, 6, 8, 11, 12
ENSO 3	0, 1, 2, 3, 4, 7, 8, 10, 12	0, 1, 2, 4, 6, 8, 11, 12	0, 1, 2, 3, 5, 6, 8, 10, 11, 12	0, 1, 3, 4, 7, 8, 11, 12	0, 3, 5, 8, 9, 11, 12	0, 2, 5, 8, 9, 11, 12	0, 1, 2, 3, 5, 6, 8, 10, 11, 12	0, 1, 2, 4, 5, 7, 11, 12	0, 2, 5, 7, 11, 12	0, 2, 5, 7, 11, 12
ENSO 4	0, 1, 2, 3, 4, 5, 11, 12	0, 1, 3, 4, 5, 10, 11, 12	0, 1, 2, 3, 10, 11, 12	0, 1, 3, 4, 5, 11, 12	0, 1, 3, 8, 9, 11, 12	0, 2, 9, 11, 12	0, 1, 2, 3, 4, 7, 8, 9, 11, 12	0, 1, 2, 8, 11, 12	0, 2, 9, 11, 12	0, 2, 9, 11, 12
ENSO 5	0, 1, 2, 4, 6, 7, 8, 9, 10, 11, 12	0, 1, 2, 5, 7, 11, 12	0, 1, 3, 5, 7, 8, 9, 11, 12	0, 1, 2, 4, 6, 7, 8, 9, 10, 11, 12	0, 1, 2, 6, 9, 10, 12	0, 1, 2, 6, 7, 8, 10, 12	0, 1, 3, 6, 7, 8, 9, 10, 11, 12	0, 1, 2, 5, 6, 8, 9, 11	0, 1, 2, 5, 7, 8, 10, 12	0, 1, 2, 5, 7, 8, 10, 12
ENSO 6	0, 2, 5, 8, 9, 10, 11, 12	0, 2, 4, 5, 7, 9, 11, 12	0, 1, 4, 7, 8, 11, 12	0, 2, 5, 7, 8, 9, 10, 11, 12	0, 1, 2, 4, 6, 8, 10, 11, 12	0, 1, 2, 4, 6, 7, 10, 11, 12	0, 1, 4, 6, 7, 8, 9, 10, 12	0, 1, 2, 3, 5, 6, 9, 10, 12	0, 1, 2, 4, 5, 6, 7, 8, 9, 11, 12	0, 1, 2, 4, 5, 6, 7, 8, 9, 11, 12
ENSO 7	0, 2, 3, 4, 7, 8, 10, 12	0, 1, 2, 4, 5, 8, 11, 12	0, 1, 2, 3, 4, 8, 9, 10, 11, 12	0, 1, 2, 3, 4, 7, 8, 11, 12	0, 1, 3, 4, 8, 11, 12	0, 2, 3, 4, 6, 7, 8, 11, 12	0, 1, 2, 3, 4, 7, 9, 10, 11, 12	0, 2, 4, 5, 8, 10, 12	0, 2, 3, 8, 10, 12	0, 2, 3, 8, 10, 12
ENSO 8	0, 2, 3, 4, 6, 7,	0, 1, 4, 5, 6, 7,	0, 1, 4, 5, 8,	0, 1, 2, 6, 7, 9,	0, 1, 3, 5, 7, 9,	0, 2, 5, 7, 9, 11,	0, 1, 2, 3, 5, 7, 8,	0, 2, 4, 7, 8, 10,	0, 2, 5, 7, 9,	0, 2, 5, 7, 9,

Table 4.15: Months Selected by Stepwise Poisson Regression (link = Log) for the Climate Explanatory Variables Averaged by Site per County (p<.05)										
	9, 12	9, 11, 12	10, 11, 12	12	11, 12	12	10, 11, 12	12	10, 11, 12	10, 11, 12
ENSO 9	0, 1, 3, 5, 7, 8, 10, 12	0, 1, 4, 7, 8, 10, 12	0, 4, 7, 8, 9, 12	0, 1, 3, 7, 8, 10, 12	0, 6, 8, 11, 12	0, 5, 8, 9, 11, 12	0, 6, 8, 11, 12	0, 4, 7, 12	0, 5, 7, 8, 9, 10, 12	0, 5, 7, 8, 9, 10, 12
Kings County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	1, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 5, 6, 7, 8, 9, 10, 11, 12	0, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 5, 6, 7, 8, 9, 10, 11, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
Temp	0, 2, 10, 12	0, 2, 6, 9, 11	0, 1, 6, 9, 11	0, 2, 7, 9, 12	0, 1, 5, 8	0, 1, 5, 8	0, 1, 6, 8, 11	0, 5, 7	0, 5, 7	0, 5, 7
Wind	1, 2, 7, 8, 9, 10, 12	0, 1, 2, 6, 7, 8, 9, 10, 12	0, 1, 2, 6, 7, 8, 9, 10, 12	0, 1, 2, 7, 8, 9, 10, 12	0, 1, 5, 6, 7, 8, 9, 10, 11, 12	0, 5, 6, 7, 8, 9, 10, 11, 12	0, 1, 6, 7, 8, 10, 11, 12	0, 4, 5, 6, 7, 8, 9, 10, 11	0, 5, 6, 7, 8, 9, 10, 11	0, 5, 6, 7, 8, 9, 10, 11
ETo	0, 1, 2, 3, 5, 6, 8, 11, 12	2, 3, 4, 7, 8, 10, 11	0, 1, 2, 4, 7, 8, 10, 11, 12	2, 4, 5, 7, 8, 10, 11	1, 2, 4, 6, 7, 9, 10, 12	0, 1, 2, 4, 6, 7, 9, 10, 11, 12	1, 2, 3, 5, 7, 9, 10, 11, 12	0, 1, 2, 3, 5, 6, 8, 9, 12	0, 1, 2, 4, 6, 8, 9, 10, 11, 12	0, 1, 2, 4, 6, 8, 9, 10, 11, 12
PDSI	0, 1, 3, 5, 6, 8, 10, 12	0, 2, 5, 6, 7, 8, 9, 10, 12	0, 2, 4, 5, 6, 7, 8, 9, 12	0, 1, 2, 5, 6, 8, 10, 12	0, 4, 6, 7, 8, 9, 12	0, 4, 6, 8, 12	0, 2, 3, 5, 6, 7, 8, 9, 12	0, 3, 5, 6, 8, 10, 12	0, 3, 5, 6, 8, 12	0, 3, 5, 6, 8, 12
PM 10	1, 4, 5, 6, 7, 8, 9, 11, 12	0, 4, 5, 6, 7, 8, 10, 12	0, 4, 5, 6, 7, 8, 9, 12	0, 4, 5, 6, 7, 8, 9, 11, 12	0, 1, 3, 4, 5, 6, 7, 8, 12	3, 4, 5, 6, 7, 9, 10, 12	0, 1, 3, 4, 5, 6, 7, 9, 12	2, 3, 4, 5, 6, 7, 10, 12	2, 3, 4, 5, 6, 7, 10, 12	2, 3, 4, 5, 6, 7, 10, 12
PM 2.5	0, 2, 3, 5, 6, 7, 8, 9, 10, 12	0, 1, 2, 4, 5, 6, 7, 9, 10, 12	0, 1, 2, 4, 5, 6, 7, 8, 10, 11, 12	0, 2, 4, 5, 6, 7, 9, 10, 12	0, 1, 2, 3, 4, 5, 6, 8, 10, 12	0, 1, 2, 3, 4, 5, 6, 7, 10, 12	0, 1, 2, 3, 4, 5, 6, 8, 10, 11, 12	0, 1, 2, 3, 4, 5, 7, 10, 11, 12	0, 1, 2, 3, 4, 5, 7, 10, 11, 12	0, 1, 2, 3, 4, 5, 7, 10, 11, 12
ENSO 1	4, 7, 10, 12	3, 6, 7, 9, 12	3, 6, 9, 12	4, 7, 10, 12	2, 5, 6, 9	2, 5, 8, 12	3, 6, 9, 12	1, 4, 5, 8, 12	2, 5, 8, 12	2, 5, 8, 12
ENSO 2	0, 4, 5, 7, 11, 12	0, 3, 6, 7, 11, 12	0, 3, 6	0, 4, 7, 11, 12	0, 2, 5, 12	0, 2, 5, 12	0, 2, 3, 6, 12	0, 1, 4, 11, 12	2, 5, 11, 12	2, 5, 11, 12
ENSO 3	0, 3, 4, 7, 8	0, 5, 8	0, 5, 8	0, 3, 4, 7, 8	0, 3, 11, 12	0, 2, 5, 6, 11, 12	0, 3, 10, 12	0, 2, 10, 12	0, 2, 9, 11, 12	0, 2, 9, 11, 12
ENSO 4	0, 4, 8, 10, 11, 12	0, 4, 8, 9, 11, 12	0, 3, 11, 12	0, 4, 8, 9, 11, 12	0, 1, 3, 11, 12	0, 2, 3, 6, 11, 12	0, 3, 7, 9, 10, 11, 12	0, 1, 2, 8, 11, 12	0, 2, 9, 11, 12	0, 2, 9, 11, 12
ENSO 5	0, 1, 3, 6, 8, 10, 12	0, 2, 5, 7, 8, 12	0, 1, 2, 5, 7, 8, 12	0, 2, 6, 8, 10, 12	0, 1, 2, 7, 9, 11	0, 1, 4, 6, 9, 11	0, 1, 4, 7, 12	0, 1, 2, 5, 9, 11	0, 1, 2, 6, 9, 11	0, 1, 2, 6, 9, 11
ENSO 6	0, 3, 6, 8, 10, 11, 12	0, 2, 5, 8, 11, 12	0, 2, 5, 7, 11, 12	0, 3, 6, 8, 11, 12	0, 1, 2, 4, 6, 10, 11, 12	0, 1, 2, 4, 6, 10, 12	0, 2, 4, 7, 9, 10, 11, 12	0, 1, 3, 5, 9, 11, 12	0, 1, 3, 4, 5, 9, 11, 12	0, 1, 3, 4, 5, 9, 11, 12

Table 4.15: Months Selected by Stepwise Poisson Regression (link = Log) for the Climate Explanatory Variables Averaged by Site per County (p<.05)										
ENSO 7	0, 2, 5, 7, 8, 9, 11, 12	0, 5, 8, 11, 12	0, 3, 5, 7, 10, 12	0, 5, 8, 11, 12	0, 3, 5, 6, 10, 12	0, 1, 3, 5, 6, 7, 9, 10, 12	0, 3, 5, 7, 10, 12	0, 1, 3, 5, 7, 8, 9, 12	0, 2, 6, 7, 9, 12	0, 2, 6, 7, 9, 12
ENSO 8	0, 1, 2, 3, 7, 8, 9, 11, 12	0, 3, 9, 11, 12	0, 3, 9, 10, 11, 12	0, 3, 9, 11, 12	0, 2, 3, 6, 8, 10, 12	0, 2, 5, 6, 7, 10, 12	0, 3, 6, 8, 10, 11, 12	0, 1, 3, 5, 7, 8, 10, 12	0, 1, 3, 6, 7, 9, 10, 12	0, 1, 3, 6, 7, 9, 10, 12
ENSO 9	1, 3, 4, 5, 7, 9, 12	1, 2, 3, 4, 6, 8, 12	1, 2, 3, 4, 6, 8, 12	0, 3, 4, 5, 7, 9, 12	2, 3, 5, 6, 8, 12	2, 3, 5, 7, 9, 12	0, 2, 3, 4, 6, 8, 12	1, 2, 4, 5, 8, 12	1, 2, 4, 5, 7, 9, 12	1, 2, 4, 5, 7, 9, 12
San Luis Obispo County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	4, 5, 6, 7, 8, 9, 10, 11, 12	4, 5, 6, 7, 8, 9, 10, 11, 12	3, 4, 5, 6, 7, 8, 9, 10, 11, 12	4, 5, 6, 7, 8, 9, 10, 11, 12	3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 6, 7, 10, 12	0, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	2, 3, 4, 5, 6, 7, 8, 9, 10, 11	2, 3, 4, 5, 6, 7, 8, 9, 10, 11	2, 3, 4, 5, 6, 7, 8, 9, 10, 11
Temp	0, 3, 6, 9	3, 9, 12	2, 6, 8	3, 9, 12	2, 8, 12	1, 5, 7, 12	2, 8, 12	1, 7, 11	1, 4, 7, 11	1, 4, 7, 11
Wind	1, 6, 7, 8, 12	1, 5, 6, 7, 12	1, 5, 6, 7, 12	1, 5, 7, 12	0, 4, 5, 6, 12	1, 4, 5, 6, 12	0, 4, 5, 6, 12	0, 3, 4, 5, 12	0, 3, 4, 5, 12	0, 3, 4, 5, 12
ETo	2, 3, 4, 5, 7, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	2, 3, 4, 5, 7, 8, 9, 10, 11, 12	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	1, 2, 3, 4, 6, 7, 8, 9, 10, 11	0, 1, 2, 3, 5, 6, 7, 8, 9, 10	0, 1, 2, 3, 5, 6, 7, 8, 9, 10	0, 1, 2, 3, 5, 6, 7, 8, 9, 10
PDSI	1, 4, 7, 12	0, 4, 6, 12	0, 3, 6, 12	1, 4, 7, 12	0, 3, 5, 12	0, 2, 5, 12	0, 3, 6, 12	0, 1, 4, 12	0, 3, 5, 12	0, 3, 5, 12
PM 10	1, 2, 3, 8, 9, 12	0, 7, 8, 9, 11, 12	0, 7, 8, 11, 12	0, 2, 7, 8, 9, 11, 12	6, 7, 8, 11, 12	1, 6, 7, 10, 12	0, 6, 7, 8, 11, 12	1, 5, 6, 7, 10, 11, 12	1, 5, 6, 7, 10, 11, 12	1, 5, 6, 7, 10, 11, 12
PM 2.5	1, 3, 5, 6, 7, 8, 10, 11, 12	0, 3, 5, 6, 9, 10, 11, 12	0, 2, 4, 5, 6, 9, 10, 11, 12	0, 3, 5, 6, 10, 11, 12	0, 1, 2, 4, 5, 8, 9, 10, 11, 12	1, 3, 4, 5, 8, 9, 10, 12	0, 2, 4, 5, 7, 9, 10, 11, 12	0, 1, 3, 4, 7, 8, 9, 10, 12	1, 3, 4, 8, 9, 12	1, 3, 4, 8, 9, 12
ENSO 1	4, 5, 6, 8	3, 5, 8, 12	3, 4, 7, 10, 11	3, 5, 8	2, 3, 6, 12	2, 3, 9, 10	2, 4, 7, 11	1, 2, 10, 12	1, 3, 12	1, 3, 12
ENSO 2	0, 4, 5, 12	0, 5, 12	0, 3, 4, 11	0, 5, 12	2, 3, 4, 11	1, 3, 10	0, 4, 11	1, 2, 3, 10	1, 3, 10	1, 3, 10
ENSO 3	0, 1, 2, 4, 6, 8, 10, 11	0, 2, 6, 8, 9, 11	0, 3, 5, 8, 9, 11, 12	0, 1, 2, 6, 8, 10, 11	0, 5, 7, 11, 12	0, 5, 6, 8, 10, 12	0, 3, 5, 7, 9, 11, 12	3, 4, 6, 10, 12	0, 4, 6, 8, 9, 11, 12	0, 4, 6, 8, 9, 11, 12
ENSO 4	0, 1, 6, 9, 10, 11	0, 1, 5, 8, 10, 11, 12	0, 1, 5, 8, 9, 11, 12	0, 1, 6, 8, 10, 11	0, 4, 7, 11, 12	0, 4, 7, 8, 10, 11, 12	0, 4, 7, 9, 11, 12	0, 3, 6, 7, 10, 12	0, 3, 6, 8, 10, 12	0, 3, 6, 8, 10, 12
ENSO 5	0, 3, 9, 11	0, 2, 3, 8, 12	0, 2, 8, 12	0, 3, 5, 9, 11	0, 2, 7, 8, 12	0, 1, 7, 12	0, 2, 8, 12	0, 1, 7, 12	0, 1, 7, 12	0, 1, 7, 12
ENSO 6	0, 3, 5, 8, 9, 12	0, 2, 9, 12	0, 2, 8, 12	0, 3, 9, 12	0, 1, 8, 11, 12	0, 1, 7, 11, 12	0, 2, 8, 11, 12	0, 1, 10, 12	0, 1, 7, 11, 12	0, 1, 7, 11, 12
ENSO 7	0, 1, 2, 4, 7, 8	0, 3, 6, 8, 11,	0, 3, 6, 8, 11,	0, 1, 2, 3, 7, 8	0, 2, 5, 7, 11,	0, 5, 6, 11, 12	0, 5, 7, 11, 12	0, 4, 6, 10, 12	0, 4, 6, 10, 11,	0, 4, 6, 10, 11,

Table 4.15: Months Selected by Stepwise Poisson Regression (link = Log) for the Climate Explanatory Variables Averaged by Site per County (p<.05)

		12	12		12				12	12
ENSO 8	0, 1, 9, 10, 12	0, 1, 8	0, 1, 8, 10, 11, 12	0, 1, 8	0, 2, 7, 9, 11, 12	0, 2, 7, 8, 11, 12	0, 2, 8, 9, 11, 12	0, 2, 6, 7, 10, 12	0, 2, 6, 8, 10, 11, 12	0, 2, 6, 8, 10, 11, 12
ENSO 9	5, 8	4, 5, 7	4, 5, 7	5, 8	4	3, 4	4, 6	3	3	3
Tulare County										
	Actual	**EMST**	**75ST**	**25ST**	**EMPM**	**75PM**	**25PM**	**EMCM**	**75CM**	**25CM**
Precip	2, 4, 5, 7, 8, 9, 10	1, 2, 5, 7, 8, 9, 10	1, 3, 4, 5, 7, 8, 9, 11	2, 5, 7, 8, 9, 10	0, 1, 4, 6, 7, 8, 9	0, 2, 3, 4, 6, 7, 8, 10	0, 1, 4, 6, 7, 8, 9, 11	0, 3, 5, 6, 7, 8	0, 3, 5, 6, 7	0, 3, 5, 6, 7, 8
Temp	0, 1, 3, 6, 12	1, 3, 5, 11	0, 2, 5, 11	1, 3, 6, 12	0, 2, 4, 10	1, 4, 10	0, 2, 5, 11, 12	0, 3, 9	0, 3, 9	1, 4
Wind	2, 5, 8, 9, 10, 12	2, 5, 7, 10, 12	1, 5, 7, 10, 12	2, 5, 7, 10, 12	1, 4, 6, 9, 10, 12	0, 1, 4, 6, 9, 10, 12	0, 5, 9, 10, 12	0, 3, 5, 8, 9, 12	0, 3, 5, 8, 9, 12	0, 4, 8, 9, 11
ETo	3, 6, 8, 10, 12	0, 4, 5, 8, 9, 12	0, 4, 5, 8, 9, 12	3, 5, 8, 9, 12	0, 3, 4, 7, 8, 11, 12	0, 3, 4, 6, 7, 8, 11, 12	0, 4, 7, 8, 11, 12	3, 6, 7, 10, 11	0, 2, 3, 5, 6, 7, 10, 11, 12	3, 4, 6, 7, 8, 11, 12
PDSI	0, 1, 2, 3, 5, 8, 12	0, 1, 2, 5, 8, 12	0, 1, 2, 3, 4, 7, 9, 10, 12	0, 1, 2, 3, 5, 8, 12	0, 2, 3, 6, 7, 10, 12	0, 2, 3, 6, 8, 11, 12	0, 1, 2, 4, 7, 12	0, 3, 6, 10, 12	0, 1, 2, 5, 7, 10, 12	0, 1, 3, 6, 10, 12
PM 10	1, 5, 8	0, 1, 4, 7, 8	0, 4, 7, 8	1, 5, 8	0, 4, 7	0, 5, 7, 10	0, 4, 6, 8	0, 3, 5, 6, 9	0, 4, 6, 9	0, 3, 5, 6, 9
PM 2.5	1, 2, 4, 5, 7	0, 2, 3, 4, 5	0, 1, 2, 3, 4, 6	2, 3, 4, 5, 7	2, 3, 6, 9, 12	2, 3, 5, 9, 12	0, 1, 2, 3, 4, 6, 12	1, 2, 5, 8, 12	1, 2, 4, 8, 11, 12	2, 3, 5, 9, 12
ENSO 1	4, 7, 10	4, 7, 9	4, 6, 9	4, 7, 9	3, 6, 8	3, 6, 8, 11, 12	3, 6, 9, 11	2, 5, 7	2, 5, 7	2, 5, 8, 10
ENSO 2	0, 4, 10	0, 4, 9	0, 4, 9	0, 4, 10	0, 3, 8	0, 3, 8	0, 3, 9	2, 8	2, 8	2, 8
ENSO 3	0, 2, 3, 5, 7	0, 1, 5, 7, 11, 12	0, 1, 6, 11, 12	0, 1, 5, 7	4, 6, 11, 12	5, 11, 12	0, 5, 11, 12	4, 10, 12	4, 10, 11	1, 4, 10, 12
ENSO 4	0, 1, 12	1, 10	1, 10	0, 1, 12	0, 9, 12	0, 9, 12	1, 10	0, 8, 11	0, 8, 11	0, 8, 12
ENSO 5	0, 2, 9, 12	0, 2, 6, 9, 12	0, 1, 8, 12	0, 2, 7, 9, 12	0, 1, 8, 11	1, 7, 11	0, 1, 8, 11	7, 10	1, 6, 11, 12	7, 11
ENSO 6	0, 2, 7, 12	0, 1, 6, 12	0, 1, 6, 12	0, 2, 7, 12	9, 11	9, 11	0, 1, 6, 11	8, 10	2, 11	3, 10
ENSO 7	0, 1, 4, 7, 10, 12	0, 3, 7, 8, 11, 12	0, 3, 6, 9, 11, 12	0, 1, 7, 8, 12	0, 2, 5, 8, 11, 12	0, 2, 5, 8, 12	0, 2, 5, 8, 11, 12	0, 1, 4, 8, 12	0, 1, 4, 7, 12	0, 2, 4, 8, 12
ENSO 8	0, 1, 6, 7, 12	12	12	0, 1, 5, 12	12	12	2, 4, 10	11	11	3, 9
ENSO 9	0, 2, 5, 7, 10, 12	0, 2, 4, 6, 10, 12	0, 2, 4, 6, 10, 12	0, 2, 5, 8, 10, 12	0, 4, 9, 12	0, 4, 9, 12	0, 4, 9, 12	0, 4, 8, 12	0, 2, 4, 8, 12	0, 4, 8, 12

Univariate Regression on the Averages of the Sites for the Explanatory Variables

A Quasipoisson Regression model and equation was created for each monthly lag for each climate variable for four of the exposure scenarios for the five counties. Table 4.16 shows the months that were significant in this approach. For Fresno County, we do see patterns emerge, but the patterns are not consistent. For example, for the average of the temperature sites, the Actual exposure scenario found significant relationships between temperature that occurs during the 0-7 months prior and 9-11 month prior. Since EMPM is 1 month ahead for the exposure period, we would expect this lag to shift from 0-6, 8-10, and potentially 12. Table 4.16 shows that it does. This pattern of lag shift is more consistent than it was for Linear Regression results.

Kern, Kings, San Luis Obispo, and Tulare Counties do not have this same consistency and pattern.

Generally, for Fresno County, we do see that Precipitation is significant for about 9 months of the year, Temperature is significant in three peaks, Wind is significant in three peaks but different peaks than Temperature, and ETo is not consistent. PM 10, 2.5, and PDSI are significant for most of the year.

For Kern County, we do see that Precipitation is significant several months in advance of exposure and around the month of exposure and the rest of the variables are significant for most of the year.

For Kings County, we do see that Precipitation is significant in two peaks: one several months in advance of exposure and the other around exposure, Temperature, Wind, ETo, and PDSI are significant almost the entire year. PM 10 is not significant around months 10-11 and PM 2.5 is not significant around months 6-9, depending on the exposure method.

For San Luis Obispo County, we do see that Precipitation is significant in two peaks, Temperature is significant in two offset peaks compared to Precipitation, Wind has some similarity in its peak months compared to Precipitation, and ETo's peaks are similar to temperature. PM 10 and PDSI have significant months about 4-7 months prior to exposure. PM 2.5 concentration is significant for the months around exposure.

For Tulare County, we do see that Precipitation, Temperature, Wind, ETo, and PDSI have two peaks of significance, where all of the variables have one peak occurring in the four months before exposure/diagnosis date. PM 2.5 concentration is significant for the months around exposure.

Table 4.16: Statistically Significant Months Selected by Univariate Quasipoisson Regression (Link = log) Analysis for the Climate Explanatory Variables Averaged by Site per County (*p*<.05)

Fresno County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	0-2, 4-12	0, 4-12	3-12	2-12
Temp	0-7, 9-11	0-6, 8-10, 12	0-5, 8-9, 11-12	0-5, 7-8, 10-12
Wind	0-2, 4-6, 8-12	0-2, 4-5, 7-12	0-1, 3-4, 6-12	0, 2-3, 5-11
ETo	0, 2-6, 8-12	0-5, 7-12	ALL	0-10, 12
PDSI	ALL	ALL	ALL	ALL
PM 10	1, 3-12	0, 3-12	0, 2-12	1-12
PM 2.5	ALL	ALL	ALL	ALL
ENSO 1	0-3, 5-10, 12	0-3, 5-10, 12	0-2, 4-9, 11-12	0-1, 3-8, 10-12
ENSO 2	0-1, 3-12	0-1, 3-12	0, 2-12	1-12
ENSO 3	0-3, 5-10, 12	0-9, 11-12	0-8, 10-12	0-7, 9-12
ENSO 4	0-4, 6-12	0-3, 5-12	0-2, 4-12	0-2, 4-12

Table 4.16: Statistically Significant Months Selected by Univariate Quasipoisson Regression (Link = log) Analysis for the Climate Explanatory Variables Averaged by Site per County (*p*<.05)				
ENSO 5	0-9	0-9, 12	0-8, 12	0-8, 11-12
ENSO 6	0-6	0-6, 12	0-6, 12	0-5, 12
ENSO 7	0-9	0-3, 5-8	0-2, 4-8,	0-1, 3-6, 12
ENSO 8	0-5, 7-12	0-5, 8-12	0-4, 6-12	0-3, 6-12
ENSO 9	0, 2-12	2-12	1-12	All
Kern County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	1-11	0-3, 5-12	0-2, 4-12	0-9, 11, 12
Temp	ALL	ALL	ALL	ALL
Wind	0-6, 8-12	0, 2-12	1-12	ALL
ETo	1-12	ALL	ALL	ALL
PDSI	ALL	ALL	0-11	0-10
PM 10	0-2; 4-10, 12	0-9, 11-12	0-8, 10-12	0-7, 9-12
PM 2.5	ALL	0-7, 9, 11-12	0-6, 8, 10-12	0-5, 7-8, 10-12
ENSO 1	0-3, 5-12	ALL	ALL	ALL
ENSO 2	0-5, 7-9, 11-12	0-5, 7-8, 11-12	0-4, 9-12	0-3, 8-12
ENSO 3	0-8, 10-12	ALL	ALL	ALL
ENSO 4	0-5, 7-12	0-5, 7-12	0-4, 6-12	0-3, 5-12
ENSO 5	0-1, 4-5, 9-12	0-1, 3-4, 8-12	0, 2-3, 7-12	6-12
ENSO 6	0-3, 5-12	0-3, 5-12	0-2, 4-12	0-1, 3-12
ENSO 7	0-9, 11-12	0-8, 10-12	0-7, 9-12	0-6, 8-12
ENSO 8	0-5, 7-12	0-4, 6-12	0-3, 5-12	ALL
ENSO 9	0-5, 7-9, 11-12	0-4, 6-12	0-4, 10-12	0-3, 8-12
Kings County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	1-4, 6-12	1-3, 5-12	0-2, 4-11	0-1, 3-10, 12
Temp	0-6, 8-11	0-5, 7-10, 12	0-9, 11-12	0-4, 6-8, 10-12
Wind	0-1, 3-6, 8-12	ALL	0-11	0-10, 12
ETo	ALL	1-5, 7-11	0-4, 6-10, 12	0-3, 5-9, 11-12
PDSI	0-2, 4-11	0-1, 3-10, 12	0, 2-12	1-9, 11-12
PM 10	2-11	2-10, 12	1-9, 12	0-8
PM 2.5	0-8, 10-12	0-7, 9-11	0-6, 8-10	0-5, 7-9, 12
ENSO 1	0-3, 5-12	0-9, 11-12	0-8, 10-12	0-7, 9-12
ENSO 2	0-1, 4-9	0, 2-9	1-8	0-6
ENSO 3	0-8, 10-12	0-2, 4-8, 10-12	0-1, 3-7, 9-12	0, 2-6, 8-12
ENSO 4	0-3, 6-7	0-3, 6	0-2	0-1
ENSO 5	ALL	0-11	0-11	0-10, 12
ENSO 6	ALL	ALL	ALL	0-11

Table 4.16: Statistically Significant Months Selected by Univariate Quasipoisson Regression (Link = log) Analysis for the Climate Explanatory Variables Averaged by Site per County (*p*<.05)				
ENSO 7	0-3, 5-7, 9-12	0-2, 4-6, 8-12	0-5, 7-12	0-4, 6-11
ENSO 8	0-5, 11-12	0-5, 11	0-4, 9-11	0-3, 8-10
ENSO 9	0, 2-12	2-12	1-12	ALL
San Luis Obispo County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	0, 2-3, 6-12	1-3, 5-12	0-2, 4-11	0-1, 3-10, 12
Temp	0-8, 11-12	0-7, 11-12	0-7, 9-12	0-6, 8-12
Wind	0-3, 5-8, 12	0-2, 5-8, 12	0-1, 4-7, 11-12	0, 3-6, 10-12
ETo	0, 2-6, 8-12	0-5, 7-12	0-4, 6-12	0-3, 5-12
PDSI	4-8	4-7, 12	3-7, 11-12	1-6, 10-12
PM 10	7-9	7-9	6-7, 11-12	6, 10-12
PM 2.5	0-9	0-8	0-7	0-6
ENSO 1	0-3, 5-12	0-3, 5-9, 11-12	0-2, 4-8, 10-12	0-1, 3-7, 9-12
ENSO 2	4-8, 11-12	3-7, 11-12	3-6, 10-12	2-4, 9-12
ENSO 3	0-8, 10-12	0-2, 4-8, 10-12	0-1, 3-7, 9-12	0, 2-6, 8-12
ENSO 4	0, 9, 11-12	0, 10-11	0, 7-11	6-10
ENSO 5	0-1, 6-11	0-1, 5-11	0, 4-10	0-9, 12
ENSO 6	0-11	0-10	0-10	0-9
ENSO 7	0-2, 4-7, 9-12	0-1, 4-6, 8-12	0-1, 3-5, 8-12	0, 2-4, 6-11
ENSO 8	0-2, 8-9	0-2, 7-9	0-8	0-9
ENSO 9	3-8	3-8	2-6	0-5
Tulare County				
	Actual	**EMST**	**EMPM**	**EMCM**
Precip	1-11	0-3, 5-10	0-2, 4-9, 12	0-1, 3-8, 11-12
Temp	0-5, 8-10, 12	0-5, 8-9, 11-12	0-4, 7-8, 10-12	0-3, 9-12
Wind	0, 2-5, 7-12	1-4, 7-12	0-3, 5-11	0-2, 4-10, 12
ETo	1-5, 7-11	0-11	0-10, 12	0-9, 11-12
PDSI	0-4, 11-12	0-4, 10-12	0-3, 9-12	0-2, 8-12
PM 10	4-11	3-10	3-9	2-8
PM 2.5	2-7, 10-11	2-6, 9-11	1-5, 8-10, 12	0-4, 7-9, 11-12
ENSO 1	0-9, 11-12	0-2, 4-12	0-1, 3-12	0, 2-12
ENSO 2	0-10	0-10	0-5, 7-9	0-3, 7-8
ENSO 3	0-1, 3-8, 10-12	0-1, 3-8, 10-12	0, 2-7, 9-12	1-6, 8-11
ENSO 4	0-3, 9-12	1-2, 8-12	8-12	8-12
ENSO 5	2, 11-12	11-12	6, 10-12	5-6, 9-12
ENSO 6	10-12	10-12	10-12	9-12
ENSO 7	0, 3-7, 10	2-6, 9-10	1-5, 8-9, 12	1-4, 7-8, 11-12
ENSO 8	10-12	9-12	8-12	8-12

Table 4.16: Statistically Significant Months Selected by Univariate Quasipoisson Regression (Link = log) Analysis for the Climate Explanatory Variables Averaged by Site per County (*p*<.05)				
ENSO 9	ALL	ALL	ALL	ALL

Multivariate Poisson Regression

To use Poisson Regression, several assumptions must be true. Your dependent variable must be count data. You have one or more independent variables. Your observation should be independent. The distribution of counts follows a Poisson distribution. Assumption 5 is that the mean and variance are identical.

In checking that the data follows assumption 5, it was determined that overdispersion has occurred. Quasipoisson regression was used to account for the dispersion parameter.

Fresno County

Quasipoisson Regression shows that not all the variables identified in the linear regression were needed in the Quasipoisson method for Fresno County. The significant variables are included in Table 4.17.

There is 95% confidence that for every inch increase in precipitation, the incidence of cases is multiplied by a factor between 1.03 and 1.15. PDSI during month 5 has this same positive relationship. ENSO 3.4 Anomaly during the month of diagnosis has a negative relationship. For every degree increase towards El Niño, the incidence decreases by being multiplied by a factor between .69 and .91 on average.

For the variables included in the various exposure models, the directionality stays the same as it does during the linear regression results.

The dispersion parameter for Fresno county is high, between 10-14 for the various models. Although the other assumptions are met, this high dispersion could be related to the need for other variables to be included in the model. In addition, using diagnostic plots, Cook's distance did identify some outliers for these county models.

Table 4.17: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Fresno California, 2000 - 2014

			Actual			
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-10.55	.0744	-141.85	<.0001	0.0000	0.0000
Precipitation Month 12	.0906	.0290	3.122	.0021	1.0343	1.1589
PDSI Month 5	.1830	.0251	7.273	<.0001	1.1432	1.2614
PDSI Month 12	-.1047	.0286	-3.654	.00034	0.8515	0.9525
ENSO 3.4 Anomaly	-.2298	.0713	-3.219	.0015	0.6910	0.9139
Dispersion Parameter			13.76			
			EMST			

Table 4.17: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Fresno California, 2000 - 2014

	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-7.55	0.90	-8.37	<.0001	0.0001	0.0031
Precip Month 9	0.10	0.03	3.21	.0016	1.0406	1.1788
Precip Month 10	0.10	0.03	3.17	.0018	1.0376	1.1689
Precip Month 11	0.09	0.03	3.10	.0023	1.0341	1.1603
Precip Month 12	0.08	0.03	2.35	.0200	1.0130	1.1540
Wind (no lag)	-0.30	0.11	-2.73	.0070	0.5977	0.9188
Wind Month 5	-0.29	0.10	-3.03	.0028	0.6220	0.9030
ETO Month 7	-0.08	0.03	-2.61	.0100	0.8745	0.9812
PDSI Month 4	0.09	0.03	3.01	.0031	1.0316	1.1589
PDSI Month 9	-0.08	0.03	-2.65	.0090	0.8669	0.9790
PM 2.5 (no lag)	-0.02	0.01	-3.03	.0028	0.9631	0.9920
ENSO 3.4 Anomaly	-0.16	0.07	-2.37	.0189	0.7436	0.9723
Dispersion Parameter	10.91					

EMPM

	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-8.22	0.81	-10.14	<.0001	0.0001	0.0013
Precip Month 9	0.14	0.03	4.44	<.0001	1.0804	1.2211
Precip Month 10	0.11	0.03	3.64	.0004	1.0526	1.1864
Precip Month 11	0.12	0.03	3.67	.0003	1.0580	1.2042
Wind (no lag)	-0.38	0.13	-2.87	.0047	0.5291	0.8872
Wind Month 4	-0.30	0.09	-3.42	.0008	0.6286	0.8814

Table 4.17: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Fresno California, 2000 - 2014						
ETO (no lag)	0.14	0.04	3.65	.0004	1.0682	1.2451
PDSI Month 4	0.13	0.03	4.65	<.0001	1.0809	1.2107
PDSI Month 9	-0.10	0.03	-3.37	.0009	0.8546	0.9592
PM 2.5 (no lag)	-0.02	0.01	-2.14	.0337	0.9666	0.9985
ENSO 3.4 Anomaly (Month 10)	0.17	0.06	2.89	.0044	1.0551	1.3232
Dispersion Parameter			11.06			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-10.57	0.07	-156.41	<.0001	0.0000	0.0000
Precip Month 7	0.07	0.02	2.72	.0072	1.0190	1.1232
Precip Month 8	0.06	0.02	2.30	.0224	1.0087	1.1125
PDSI Month 1	0.15	0.02	6.85	<.0001	1.1112	1.2091
PDSI Month 12	-0.06	0.02	-2.80	.0058	0.8972	0.9811
ENSO 3.4 Anomaly	-0.34	0.08	-4.17	<.0001	0.6040	0.8338
ENSO 3.4 Anomaly Month 3	0.28	0.08	3.43	.0007	1.1255	1.5418
Dispersion Parameter			11.31			

<u>Kern County</u>

Quasipoisson Regression shows that not all the variables identified in the linear regression were needed in the Quasipoisson method for Kern County. The significant variables are included in Table 4.18.

There is 95% confidence that for every inch increase in precipitation, the incidence of cases is multiplied by a factor between 1.03 and 1.15 for months 8 and 9. These are the same factors found in Fresno County. PDSI during month 10 has this same positive relationship.

For the variables included in the various exposure models, the directionality stays the same as it does during the linear regression results.

The dispersion parameter for Kern county is high, between 11-16 for the various models. Although the other assumptions are met, this high dispersion could be related to the need for other variables to be included in the model.

However, using diagnostic plots, Cook's distance did not identify outliers for these county models. Overall, Quasipoisson was found to be an acceptable model method to use.

Table 4.18: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014

Actual						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-7.15	0.26	-27.75	<.0001	0.0005	0.0013
Precip Month 2	-0.09	0.04	-2.56	.0114	0.8497	0.9787
Precip Month 8	0.09	0.03	3.18	.0017	1.0353	1.1569
Precip Month 9	0.09	0.03	3.31	.0011	1.0379	1.1565
Temp Month 6	-0.01	0.00	-3.95	.0001	0.9809	0.9935
PDSI Month 10	0.11	0.02	5.82	<.0001	1.0764	1.1600
PM 2.5 Month 4	-0.02	0.00	-4.41	<.0001	0.9716	0.9890
PM 2.5 Month 7	-0.03	0.00	-5.77	<.0001	0.9645	0.9824
PM 2.5 Month 11	-0.01	0.00	-3.44	.0007	0.9769	0.9936
ENSO 3.4 Anomaly Month 12	0.18	0.03	5.43	<.0001	1.1246	1.2842
Dispersion Parameter			15.87			

EMST						
	Statistical Significance Information					
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-6.84	0.28	-24.55	<.0001	0.0006	0.0018
Precip Month 2	-0.10	0.03	-3.09	.0023	0.8475	0.9636
Precip Month 8	0.08	0.02	3.09	.0023	1.0286	1.1344
Temp Month 6	-0.01	0.00	-2.54	.0122	0.9805	0.9975
PDSI Month 9	0.12	0.02	6.99	<.0001	1.0889	1.1636

Table 4.18: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014

PM 2.5 Month 2	-0.01	0.01	-2.24	.0262	0.9787	0.9986
PM 2.5 Month 4	-0.02	0.00	-3.98	.0001	0.9754	0.9916
PM 2.5 Month 6	-0.01	0.00	-3.00	.0032	0.9765	0.9951
PM 2.5 Month 7	-0.02	0.00	-3.46	.0007	0.9751	0.9930
PM 2.5 Month 10	-0.01	0.00	-3.52	.0006	0.9794	0.9941
PM 2.5 Month 12	-0.01	0.00	-2.45	.0155	0.9788	0.9976
ENSO 3.4 Anomaly Month 12	0.17	0.03	5.473	<.0001	1.1156	1.2604
Dispersion Parameter				12.80		
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-6.92	0.28	-24.27	<.0001	0.0006	0.0017
Precip Month 1	-0.10	0.03	-3.12	.0021	0.8480	0.9630
Precip Month 7	0.11	0.02	4.23	<.0001	1.0580	1.1664
Temp Month 5	-0.01	0.00	-3.55	.0005	0.9772	0.9934
PDSI Month 8	0.12	0.02	6.75	<.0001	1.0890	1.1677
PM 2.5 Month 5	-0.02	0.00	-4.28	<.0001	0.9705	0.9890
PM 2.5 Month 6	-0.01	0.00	-2.99	.0032	0.9769	0.9951
PM 2.5 Month 9	-0.01	0.00	-3.67	.0003	0.9792	0.9936
PM 2.5 Month 12	-0.02	0.01	-2.63	.0093	0.9741	0.9962
ENSO 3.4 Anomaly Month 12	0.20	0.03	5.99	<.0001	1.1459	1.3082
Dispersion Parameter				13.76		
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard	t-statistic	*P* - value	Lower 95%	Upper 95%

Table 4.18: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kern California, 2000 - 2014						
		Error			Confidence Level of Effect on Incidence Rate	Confidence Level of Effect on Incidence Rate
Intercept	-7.45	0.14	-52.82	<.0001	0.0004	0.0008
Precip Month 6	0.09	0.02	3.67	.0003	1.0428	1.1481
PDSI Month 7	0.11	0.02	6.74	<.0001	1.0829	1.1561
PM 10 Month 10	-0.01	0.00	-2.69	.0079	0.9907	0.9985
PM 2.5 Month 2	-0.02	0.00	-3.43	.0008	0.9753	0.9932
PM 2.5 Month 3	-0.01	0.00	-2.52	.0127	0.9791	0.9974
PM 2.5 Month 5	-0.01	0.00	-3.50	.0006	0.9815	0.9948
PM 2.5 Month 11	-0.02	0.00	-3.98	.0001	0.9725	0.9906
PM 2.5 Month 12	-0.02	0.01	-4.58	<.0001	0.9659	0.9862
ENSO 3.4 Anomaly Month 7	0.21	0.03	7.00	<.0001	1.1611	1.3042
Dispersion Parameter				11.92		

<u>Kings County</u>

Quasipoisson Regression shows the significant variables included in the Kings County models in Table 4.19.

There is 95% confidence that for every inch increase in precipitation, the incidence of cases is multiplied by a factor between 1.1 and 1.2 for months 8 and 9. ENSO 3.4 Anomaly during the month of diagnosis has a negative relationship. For every degree increase towards El Niño, the incidence decreases by being multiplied by a factor between .61 and .81 on average.
The dispersion parameter for Kings County is much lower than the previous methods, between 4-6 for the various models. Although the other assumptions are met, this high dispersion could be related to the need for other variables to be included in the model. However, using diagnostic plots, Cook's distance did not identify outliers for these county models. Overall, Quasipoisson was found to be an acceptable model method to use.

Table 4.19: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014						
			Actual			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence	Upper 95% Confidence Level of Effect on Incidence

Table 4.19: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014

					Rate	Rate
Intercept	-8.89	0.42	-21.07	<.0001	0.0001	0.0003
Precip Month 8	0.17	0.03	5.18	<.0001	1.1124	1.2663
Precip Month 9	0.17	0.04	4.53	<.0001	1.1011	1.2753
Precip Month 10	0.11	0.04	2.87	.0046	1.0353	1.2020
Wind Month 1	-0.22	0.09	-2.39	.0179	0.6662	0.9606
ETO Month 11	0.09	0.04	2.60	.0100	1.0234	1.1777
PDSI Month 1	-0.16	0.04	-3.64	.0004	0.7774	0.9272
PM 10 Month 4	-0.01	0.00	-3.79	.0002	0.9819	0.9942
PM 2.5 Month 7	-0.01	0.01	-2.45	.0154	0.9761	0.9973
ENSO 3.4 Anomaly	-0.35	0.07	-5.04	<.0001	0.6140	0.8068
Dispersion Parameter				5.92		
			EMST			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-10.28	0.27	-38.78	<.0001	0.0000	0.0001
Precip Month 8	0.20	0.03	6.85	<.0001	1.1558	1.2981
Precip Month 10	0.17	0.04	4.64	<.0001	1.1019	1.2702
Precip Month 12	0.15	0.04	3.50	.0006	1.0676	1.2617
ETO Month 11	0.11	0.03	3.91	.0001	1.0579	1.1848
PDSI (no lag)	-0.13	0.04	-3.18	.0017	0.8092	0.9509
PDSI Month 12	-0.10	0.04	-2.39	.0180	0.8368	0.9826
PM 10 Month 5	-0.01	0.00	-4.72	<.0001	0.9795	0.9915
PM 2.5 Month 6	-0.02	0.01	-3.36	.0010	0.9688	0.9917
PM 2.5 Month 12	0.01	0.01	2.47	.0146	1.0027	1.0234
ENSO 3.4 Anomaly	-0.36	0.06	-5.64	<.0001	0.6134	0.7891

Table 4.19: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014						
Dispersion Parameter			5.21			
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-9.80	0.17	-58.44	<.0001	0.0000	0.0001
Precip Month 6	0.15	0.03	4.83	<.0001	1.0946	1.2387
Precip Month 7	0.14	0.03	4.56	<.0001	1.0857	1.2292
Precip Month 8	0.13	0.03	4.25	<.0001	1.0749	1.2165
Precip Month 12	0.25	0.04	5.97	<.0001	1.1809	1.3896
PDSI Month 12	-0.18	0.04	-4.79	<.0001	0.7728	0.8976
PM 10 Month 3	-0.01	0.00	-4.40	<.0001	0.9825	0.9933
PM 2.5 Month 5	-0.02	0.01	-3.00	.0031	0.9747	0.9947
ENSO 3.4 Anomaly	-0.36	0.06	-5.65	<.0001	0.6189	0.7924
Dispersion Parameter			4.68			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-9.85	0.15	-67.05	<.0001	0.0000	0.0001
Precip Month 5	0.11	0.03	3.43	.0008	1.0491	1.1928
Precip Month 6	0.15	0.03	4.71	<.0001	1.0914	1.2361
Precip Month 7	0.10	0.03	3.17	.0018	1.0383	1.1731
Precip Month 12	0.25	0.04	6.03	<.0001	1.1823	1.3892
PDSI Month 8	0.08	0.03	2.31	.0223	1.0118	1.1556
PDSI Month 12	-0.27	0.04	-6.94	<.0001	0.7044	0.8220

Table 4.19: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Kings California, 2000 - 2014						
PM 2.5 Month 1	-0.03	0.01	-4.60	<.0001	0.9645	0.9855
PM 2.5 Month 4	-0.01	0.01	-2.82	.0054	0.9753	0.9955
ENSO 3.4 Anomaly	-0.64	0.18	-3.64	.0004	0.3747	0.7449
ENSO 3.4 Anomaly Month 1	0.40	0.18	2.181	.0305	1.0413	2.1313
Dispersion Parameter			4.24			

San Luis Obispo County

Quasipoisson Regression shows the significant variables included in the San Luis Obispo County models in Table 4.20. There is 95% confidence that for every inch increase in precipitation, the incidence of cases is multiplied by a factor between 1.02 and 1.14 for months 6-12.

The dispersion parameter for San Luis Obispo County is much lower than the previous methods, between 1.5-2.4 for the various models. Quasipoisson was found to be an acceptable model method to use.

Table 4.20: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, San Luis Obispo California, 2000 - 2014						
			Actual			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-11.09	0.09	-121.73	<.0001	0.0000	0.0000
Precip Month 6	0.07	0.02	3.28	.0013	1.0303	1.1260
Precip Month 7	0.09	0.02	4.52	<.0001	1.0551	1.1455
Precip Month 9	0.06	0.02	3.46	.0007	1.0283	1.1063
Precip Month 10	0.10	0.02	5.12	<.0001	1.0625	1.1456
Precip Month 11	0.09	0.02	4.73	<.0001	1.0563	1.1417
Precip Month 12	0.07	0.02	3.33	<.0011	1.0288	1.1159
PM 2.5 Month 1	-0.05	0.01	-4.85	<.0001	0.9325	0.9708
Dispersion Parameter			2.42			
			EMST			

Table 4.20: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, San Luis Obispo California, 2000 - 2014						
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-11.25	0.08	-133.64	<.0001	0.0000	0.0000
Precip Month 5	0.06	0.02	3.15	.0020	1.0241	1.1081
Precip Month 6	0.08	0.02	4.07	.0001	1.0419	1.1242
Precip Month 7	0.06	0.02	3.47	.0007	1.0276	1.1030
Precip Month 8	0.05	0.02	2.88	.0045	1.0160	1.0867
Precip Month 9	0.08	0.02	4.93	<.0001	1.0504	1.1208
Precip Month 10	0.09	0.02	5.52	<.0001	1.0612	1.1330
Precip Month 11	0.08	0.02	4.77	<.0001	1.0506	1.1252
Precip Month 12	0.06	0.02	3.49	.0006	1.0280	1.1031
PM 2.5 (no lag)	-0.05	0.01	-5.55	<.0001	0.9380	0.9699
Dispersion Parameter			1.63			
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-11.21	0.25	-44.91	<.0001	0.0000	0.0000
Precip Month 4	0.05	0.02	2.57	.0111	1.0130	1.1013
Precip Month 5	0.08	0.02	4.22	<.0001	1.0425	1.1205
Precip Month 6	0.06	0.02	3.50	.0006	1.0279	1.1025
Precip Month 7	0.07	0.02	3.96	.0001	1.0369	1.1131
Precip Month 8	0.09	0.02	5.10	<.0001	1.0576	1.1341
Precip Month 9	0.10	0.02	5.95	<.0001	1.0693	1.1420
Precip Month 10	0.09	0.02	4.95	<.0001	1.0528	1.1263

Table 4.20: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, San Luis Obispo California, 2000 - 2014						
Precip Month 11	0.06	0.02	3.44	.0007	1.0273	1.1032
Wind Month 5	0.12	0.06	2.13	.0346	1.0098	1.2650
ETO Month 3	-0.12	0.04	-2.90	.0043	0.8217	0.9628
PM 2.5 Month 5	-0.05	0.01	-5.45	<.0001	0.9346	0.9687
Dispersion Parameter			1.55			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-11.40	0.09	-133.33	<.0001	0.0000	0.0000
Precip Month 3	0.06	0.02	2.87	.0045	1.0197	1.1089
Precip Month 4	0.08	0.02	3.89	.0001	1.0405	1.1278
Precip Month 5	0.06	0.02	3.34	.0010	1.0270	1.1075
Precip Month 6	0.05	0.02	2.91	.0040	1.0176	1.0934
Precip Month 7	0.08	0.02	4.34	<.0001	1.0424	1.1161
Precip Month 8	0.09	0.02	5.07	<.0001	1.0561	1.1311
Precip Month 9	0.08	0.02	4.14	<.0001	1.0408	1.1184
Precip Month 10	0.07	0.02	3.60	.0004	1.0318	1.1121
Dispersion Parameter			1.83			

Tulare County

Quasipoisson Regression shows the significant variables included in the Tulare County models in Table 4.21.

There is 95% confidence that for every inch increase in precipitation, the incidence of cases is multiplied by a factor between 1.05 and 1.17 for month 10.

The dispersion parameter for Tulare County is much lower than the previous county models, between 1.29-2 for the various models. Quasipoisson was found to be an acceptable model method to use.

Table 4.21: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Tulare California, 2000 - 2014

Actual						
Statistical Significance Information						
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-9.52	0.35	-27.5140	<.0001	0.0000	0.0001
Precip Month 2	-0.14	0.03	-4.7230	<.0001	0.8165	0.9196
Precip Month 10	0.11	0.03	3.6630	.0003	1.0510	1.1784
Temp Month 1	0.01	0.00	6.1430	<.0001	1.0077	1.0150
Wind Month 12	-0.42	0.09	-4.7880	<.0001	0.5495	0.7781
ETO Month 5	-0.09	0.02	-3.8530	.0002	0.8766	0.9580
PDSI Month 3	-0.08	0.02	-3.2570	.0014	0.8790	0.9684
PM 10 Month 8	-0.01	0.00	-4.9960	<.0001	0.9907	0.9959
ENSO 3.4 Anomaly Month 11	0.15	0.04	3.8920	.0001	1.0751	1.2453
Dispersion Parameter			2.01			
EMST						
Statistical Significance Information						
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-7.48	0.52	-14.3910	<.0001	0.0002	0.0016
Precip Month 7	0.07	0.02	2.9940	.0032	1.0253	1.1274
Precip Month 9	0.08	0.02	3.3020	.0012	1.0328	1.1349
Wind Month 12	-0.39	0.08	-4.8940	<.0001	0.5791	0.7915
ETO Month 5	-0.21	0.04	-5.5600	<.0001	0.7542	0.8737
ETO Month 8	-0.13	0.03	-4.8400	<.0001	0.8336	0.9258
ETO Month 12	-0.16	0.04	-3.7290	.0003	0.7834	0.9269
PDSI (no lag)	-0.09	0.03	-3.4130	.0008	0.8656	0.9617

Table 4.21: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Tulare California, 2000 - 2014						
PDSI Month 2	-0.08	0.03	-2.8430	.0050	0.8808	0.9769
PM 10 Month 8	-0.01	0.00	-5.1190	<.0001	0.9924	0.9966
ENSO 3.4 Anomaly Month 12	0.12	0.03	3.6800	.0003	1.0570	1.1992
Dispersion Parameter			1.29			
			EMPM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence Rate	Upper 95% Confidence Level of Effect on Incidence Rate
Intercept	-7.29	0.60	-12.0750	<.0001	0.0002	0.0022
Precip (no lag)	-0.10	0.03	-2.9940	.0032	0.8535	0.9675
Precip Month 8	0.08	0.03	3.2480	.0014	1.0331	1.1409
Temp (no lag)	0.01	0.00	4.2600	<.0001	1.0070	1.0189
Temp Month 12	-0.01	0.00	-2.4460	.0155	0.9820	0.9980
Wind Month 11	-0.41	0.08	-5.0210	<.0001	0.5688	0.7808
ETO Month 4	-0.22	0.04	-5.8770	<.0001	0.7426	0.8618
ETO Month 7	-0.12	0.03	-3.6410	.0004	0.8333	0.9467
ETO Month 11	-0.16	0.04	-3.8190	.0002	0.7808	0.9235
PDSI Month 1	-0.11	0.02	-4.9590	<.0001	0.8612	0.9373
PM 10 Month 7	-0.01	0.00	-5.8370	<.0001	0.9913	0.9957
ENSO 3.4 Anomaly Month 12	0.14	0.03	4.1280	<.0001	1.0766	1.2303
Dispersion Parameter			1.31			
			EMCM			
			Statistical Significance Information			
	Coefficient	Standard Error	t-statistic	*P* - value	Lower 95% Confidence Level of Effect on Incidence	Upper 95% Confidence Level of Effect on Incidence

Table 4.21: Results of a Quasipoisson Regression of Valley Fever Exposure Scenarios by Climate Factors, Tulare California, 2000 - 2014

					Rate	Rate
Intercept	-6.18	0.59	-10.5570	<.0001	0.0007	0.0065
Precip Month 5	0.07	0.03	2.9540	.0036	1.0254	1.1322
Wind Month 8	-0.20	0.08	-2.4830	.0140	0.6956	0.9582
Wind Month 12	-0.35	0.08	-4.1540	.0001	0.5956	0.8303
ETO Month 3	-0.15	0.03	-5.3490	<.0001	0.8168	0.9104
ETO Month 6	-0.29	0.04	-6.6080	<.0001	0.6907	0.8181
ETO Month 11	-0.24	0.04	-5.2980	<.0001	0.7244	0.8622
PDSI (no lag)	-0.12	0.02	-4.9760	<.0001	0.8497	0.9316
PM 10 Month 5	-0.01	0.00	-4.3500	<.0001	0.9926	0.9972
Dispersion Parameter			1.53			

Discussion

Overall, a couple of themes emerge in this analysis. First, site specific climate factors differ in their relationship to exposure methods than the county-wide averages. What is the right one to use? How would the results change if a site-specific climate variable could be used with a zip code level of case data aggregate?

Although there are still minor differences in the results between the estimate of when diagnosis occurs in the month (EM, 75, 25), the results are generally similar across the counties and variables. However, patterns are not consistent between exposure periods and the diagnosis date. How do these inconsistencies change the result? Can researchers assume this pattern occurs in other exposure estimates not included in this study? Without more information and research conducted on understanding the incubation period and symptom onset to diagnosis lag, what is the right method to use?

There are several climate variables that have a significant relationship with Valley Fever cases across the five counties and the general summary can be found in Table 4.22. Overall, Precipitation was found to be significant in every county. Typically, 6-12 months prior to diagnosis, the more precipitation that occurs, incidence increases. 0-2 months to diagnosis, the more precipitation that occurs, the trend is that incidence decreases. This pattern is found to occur in all five counties.

It was found that the total amount of cases diagnosed during the peak season (August – December), determined in Chapter 2, is positively correlated to the total precipitation 7-12 months prior for all 5 counties. This can be seen in Figure 4.2. If peak season starts in August, then 7-12 months prior is estimating precipitation that occurs during Fall-Winter the year before. This pattern is consistent across exposure scenarios.

For Kern and Tulare Counties, Precipitation occurring during the months surrounding diagnosis/exposure has a negative relationship. Aside from San Luis Obispo County, ENSO 3.4 Anomaly did find a significant relationship with cases being diagnosed and exposed in every county and almost every exposure period. The same describes PDSI. These two variables are not like Precipitation where they are measured at a specific geographic area and represent impacts to that geographical area. ENSO and PDSI have a wider interannual scale and impacts the region in a similar manner. San Luis Obispo County is the only county in NOAA Climate zone 4, the other counties are in

Climate Zone 5. Therefore, perhaps when looking at the NOAA climate zones described in Chapter 3, these variables impact zone 5 and the overall climate patterns for the region.

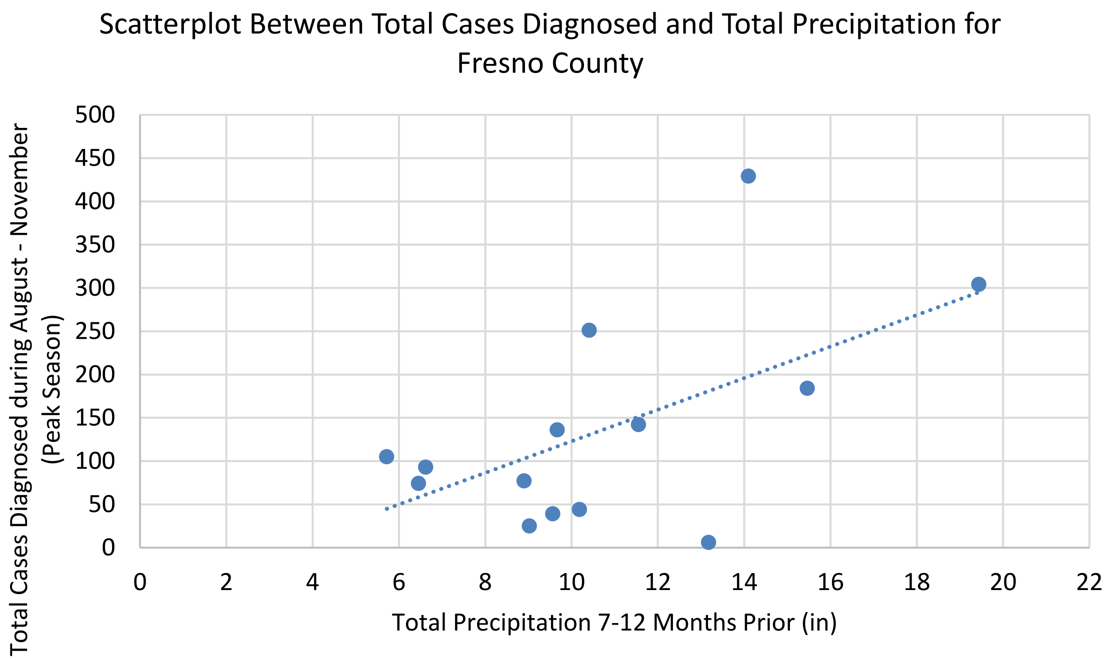
Table 4.22: Summary of Significant Climate Variables Identified in Quasipoisson Analysis for the Scenarios by County (Direction of Relationship)

			Actual		
	Fresno	Kern	Kings	San Luis Obispo	Tulare
Precipitation	12 (+)	2 (-), 8 (+), 9 (+)	8, 9, 10 (+)	6, 7, 9, 11, 11, 12 (+)	2 (-), 10 (+)
Temperature	N/A	6 (-)	N/A	N/A	1 (+)
Wind	N/A	N/A	1 (-)	N/A	12 (-)
ETo	N/A	N/A	11 (+)	N/A	5 (-)
PDSI	5 (+); 12 (-)	10 (+)	1 (-)	N/A	3 (-)
PM 10	N/A	N/A	4 (-)	N/A	8 (-)
PM 2.5	N/A	4, 7, 11 (-)	7 (-)	1 (-)	N/A
ENSO 3.4 Anomaly	0 (-)	12 (+)	0 (-)	N/A	11 (+)
			EMST		
	Fresno	Kern	Kings	San Luis Obispo	Tulare
Precipitation	9, 10, 11, 12 (+)	2 (-), 8 (+)	8, 10, 12 (+)	5, 6, 7, 8, 9, 10, 11, 12 (+)	7, 9 (+)
Temperature	N/A	6 (-)	N/A	N/A	N/A
Wind	0, 5 (-)	N/A	N/A	N/A	12 (-)
ETo	7 (-)	N/A	11 (+)	N/A	5, 8, 12 (-)
PDSI	4 (+); 9(-)	9 (+)	0, 12 (-)	N/A	0, 2 (-)
PM 10	N/A	N/A	5 (-)	N/A	8 (-)
PM 2.5	0 (-)	2, 4, 6, 7, 10, 12 (-)	6 (-), 12 (+)	0 (-)	N/A
ENSO 3.4 Anomaly	0(-)	12 (+)	0 (-)	N/A	12 (+)
			EMPM		
	Fresno	Kern	Kings	San Luis Obispo	Tulare
Precipitation	9, 10, 11 (+)	1 (-), 7 (+)	6, 7, 8, 12 (+)	4, 5, 6, 7, 8, 9, 10, 11 (+)	0 (-), 8 (+)
Temperature	N/A	5 (-)	N/A	N/A	0 (+), 12 (-)
Wind	0, 4 (-)	N/A	N/A	5 (+)	11 (-)
ETo	0 (+)	N/A	N/A	N/A	4, 7, 11 (-)
PDSI	4 (+), 9 (-)	8 (+)	12 (-)	3 (-)	1 (-)
PM 10	N/A	N/A	3 (-)	N/A	7 (-)
PM 2.5	0 (-)	5, 6, 9, 12 (-)	5 (-)	5 (-)	N/A
ENSO 3.4 Anomaly	10 (+)	12 (+)	0 (-)	N/A	12 (+)
			EMCM		
	Fresno	Kern	Kings	San Luis Obispo	Tulare
Precipitation	7, 8 (+)	6 (+)	5, 6, 7, 12 (+)	3, 4, 5, 6, 7, 8, 9, 10 (+)	5 (+)
Temperature	N/A	N/A	N/A	N/A	N/A
Wind	N/A	N/A	N/A	N/A	8, 12 (-)
ETo	N/A	N/A	N/A	N/A	3, 6, 11 (-)
PDSI	1 (+), 12 (-)	7 (+)	8 (+)	N/A	0 (-)
PM 10	N/A	10 (-)	N/A	N/A	5 (-)
PM 2.5	N/A	2, 3, 5, 11, 12 (-)	1, 4 (-)	N/A	N/A

Table 4.22: Summary of Significant Climate Variables Identified in Quasipoisson Analysis for the Scenarios by County (Direction of Relationship)

ENSO 3.4 Anomaly	0 (-); 3 (+)	7 (+)	0 (-), 1 (+)	N/A	N/A

Figure 4.2: Scatterplots Between Total Cases Diagnosed During Peak Season (August – November) and Total Precipitation 7-12 Months Prior for 5 Counties, 2000 - 2013



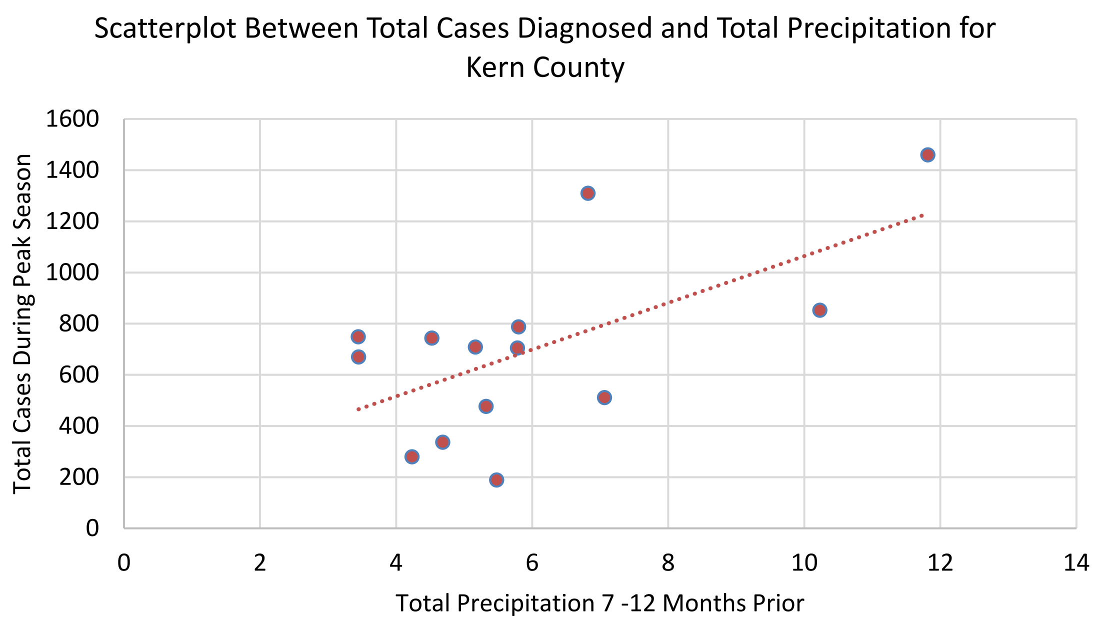
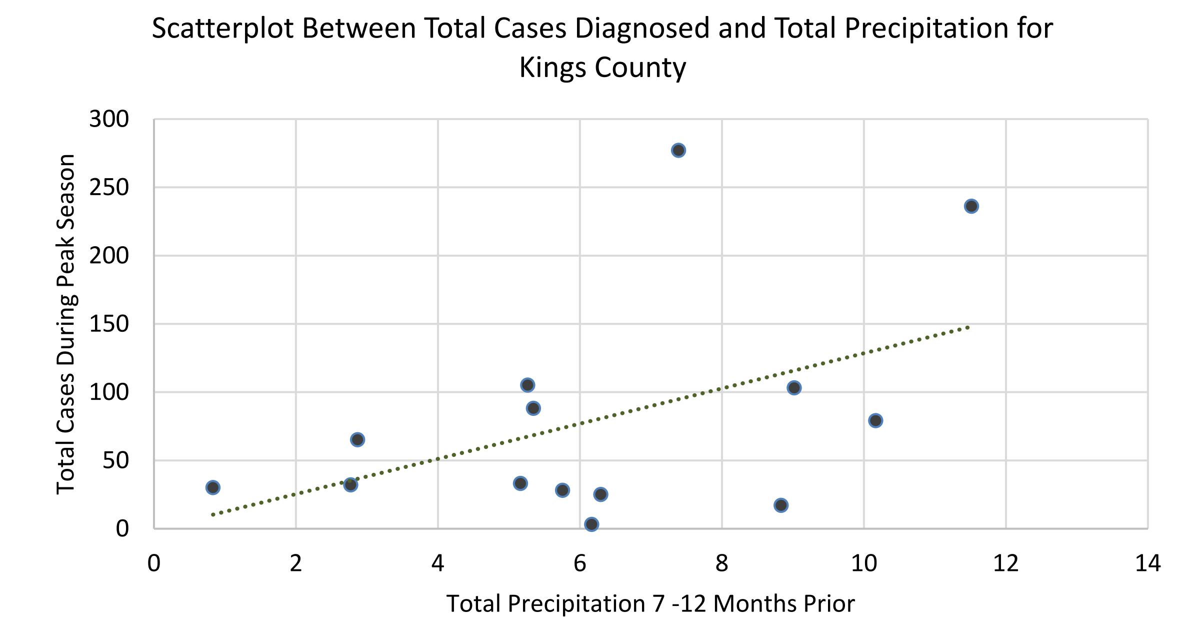


Figure 4.2: Scatterplots Between Total Cases Diagnosed During Peak Season (August – November) and Total Precipitation 7-12 Months Prior for 5 Counties, 2000 - 2013



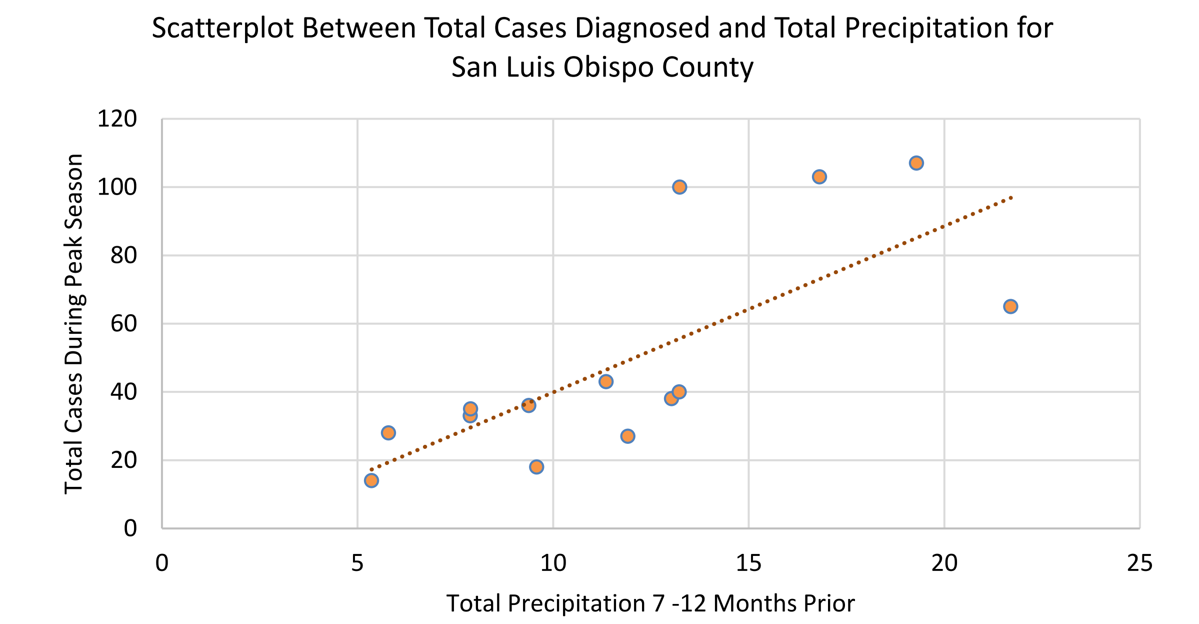
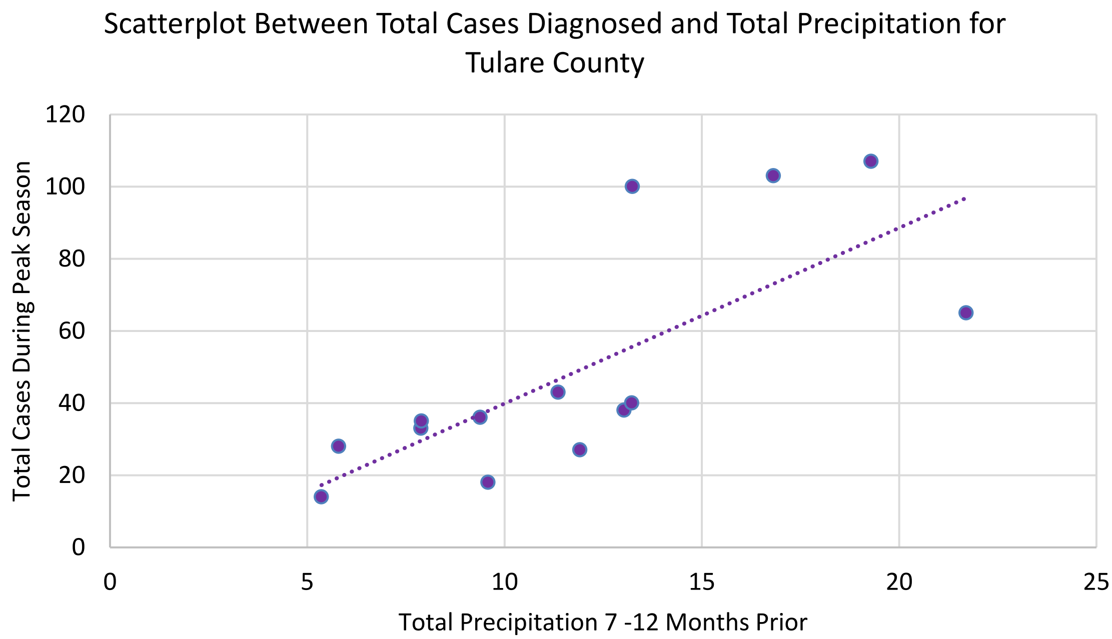


Figure 4.2: Scatterplots Between Total Cases Diagnosed During Peak Season (August – November) and Total Precipitation 7-12 Months Prior for 5 Counties, 2000 - 2013



When looking at mathematical methods, it becomes clear that the data violates linear regression. When using Poisson regression, not all the variables that were significant in the linear model were significant in the Poisson and Quasipoisson model. Common variables that were not significant were Temperature, Wind, and PM 10. The directionality of the relationships stays the same when the quantitative method changed. Overall, there is a general trend across the study area with the climate impacts, but the months are not the same and there are also some notable differences. With only 50% of the data being explained by the variables included in this chapter, there still leaves more room for confounding variables and other variables not examined like occupation, construction activities, or other forms of soil moisture measurements.

With 50% of the data explained by the climate variables, one consistent pattern that appears is the cumulative rain occurring 7-12 months prior to the start of the exposure period for each county. This does align with the “Grow” portion of the “Grow and Blow” Effect Hypothesis. However, the information presented here does not provide enough evidence to support or disprove the Hypothesis. The information presented in this study indicate that although tendencies of this Hypothesis appear, there is a more complicated relationship occurring that needs to be explored further. There is no pattern indicating that one Hypothesis is applicable to the entire region. They all appear to have their own climate effect. How does land movement and changing land use patterns influence the results? Is there a confounding variable covering up the “Grow and Blow” Effect from appearing? How will interaction between different climate variables like Precipitation and Temperature enhance or damper this Hypothesis?

Limitations

Until exposure estimates are defined further, a consensus on the relationship of climate factors is only appropriate. A Bonferroni adjustment as a procedure to correct a researcher's test for significant effects, relative to how many repeated analyses are being done and repeated hypotheses are being tested was not conducted in this analysis. By running the model analysis with multiple predictors, we choose an "alpha" and by doing so, choose a percentage of error we are willing to live with. The most common amount of error that is accepted is 5% (as in $p < .05$). That is to say, we expect that 19 out of 20 times we find significant effects it will be without error. However, in model development we will test different potential predictors and the likelihood of finding an erroneous significant effect (purely by random chance) increases. A Bonferroni correction will adjust for this. A Bonferroni adjustment was not conducted in this analysis because *p*-values closer to .05 may be more likely to be erroneous, but it could also be because of the new exposure distribution highlighting a new climate relationship. The researchers found value to keep all significant values into the analysis as a comparison with the understanding that more research is needed to understand the different exposure and geographical distributions.

Chapter 5

Qualitative Research on Valley Fever Communication in Public Health Agencies

Introduction

So far, this dissertation has analyzed results under different exposure methods, climate variables, geographical boundaries, and different mathematical methods. The analytics conducted are just one piece in addressing and lowering the Central California's risk to Valley Fever. It is also important to understand what public health agencies would do with this information and what would be the best way to provide the findings to the county agencies and ultimately benefit the community.

This chapter connects the statistical findings from the previous protocol by exploring the need of the local agencies.

Qualitative research consisting of a survey and interview were conducted from the public health agencies in Fresno, Kern, Kings, San Luis Obispo, and Tulare Counties. The purpose of this qualitative research was to identify the needs of Public Health agencies to communicate risk and preventive strategies about Valley Fever infection and symptoms and to discover the levels of access of Public Health agencies to different levels of disease case data, time of infection, and if additional information will improve disease prevention strategies for eliminating seasonal Valley Fever prevalence.

My hypothesis is that most agencies do not have the staff time or resources to expand their information on Valley Fever and currently focus their efforts on reminding their community to get tested for Valley Fever if they have the familiar, known symptoms.

Some of the questions to be addressed are:
1) What Valley Fever information do the 5 public agencies of interest have access to?
2) How do these agencies use this information for communicate Valley Fever to the public?
3) If these agencies had access to more specific Valley Fever information, how would they want to use it/what type of more specific information would be of interest?

Methods

Data Collection

The five Central California public health agencies from the counties in this study were approached about being interviewed to better understand current and desired public health risk communication and prevention messaging employed to address Valley Fever as a public health issue. There were two main Specific Aims in this qualitative research:

Aim 1: Survey 5 public health agencies (Fresno, Kern, Kings, San Luis Obispo, and Tulare counties) to assess their access to epidemiological data and their in-house resources towards the communication of Valley Fever;

Aim 2: Interview representatives from the 5 public health agencies (Fresno, Kern, Kings, San Luis Obispo, and Tulare counties) to understand their methodology and communication measures towards Valley Fever and what information could be used to improve the current strategies.

The principal investigator collected all data for this investigation. Eligibility criteria for participants included staff members in a position to be representative of the agency and have knowledge of the operations, resources, and budget of the agency. These individuals had titles such as Public Health Director, Assistant Director, Division

Manager, Program Manager, and/or Health Officer. At least 1 staff member from each of the 5 central California public health agencies most impacted by Valley Fever (Fresno, Kern, Kings, San Luis Obispo, and Tulare counties) participated in this study (n=8). All interviews were conducted in English and interviews ranged in length between 25 minutes and 45 minutes. San Luis Obispo and Tulare counties had two people participate in a group interview. Interviews were audio-recorded and transcribed verbatim. This research study protocol was approved by the University of California, Irvine's Institutional Review Board (IRB) (Project Number HS#2018-4860, January 29, 2019). Anonymity was kept by referencing the interviewees as representatives of the county.

The survey was emailed out to staff at these agencies using GoogleForm. The survey took approximately 10 minutes for each agency to complete. After the agency staff took the survey, they were scheduled for a phone call interview that lasted about 30-45 minutes each.

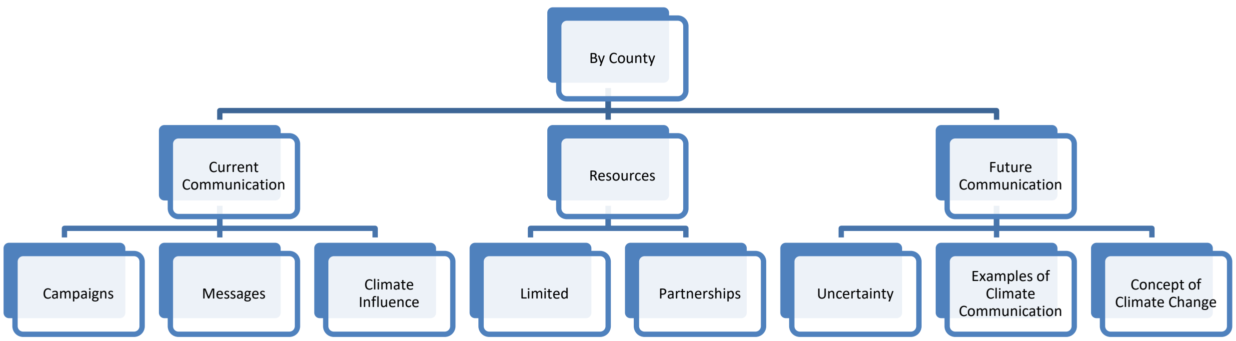
The following research questions guided this study:
Research Question 1: What Valley Fever information do the 5 public health agencies of interest have access to?
Research Question 2: How do these agencies use information to communicate Valley Fever to the public?
Research Question 3: If these agencies had access to more specific Valley Fever information, how would they want to use it/what type of more specific information would be of interest?

Specific questions asked to address the research questions were derived from the Local Public Health System Performance Assessment Instrument (Local Public Health System Performance Assessment Instrument, 2013). The questions were adapted to be open-ended and tailored to ask about Valley Fever and climate information. The open-ended, semi-structured, interview guide was written to include questions exploring (a) what information public health agency current practices to communicate Valley Fever health risks (b) whether public health prevention messages and strategies incorporated climate information, and (c) perceived challenges to communicating Valley Fever risk (see Appendix A-6 for Interview Guide). The interview guide was organized and questions were grouped to address Valley Fever data, evaluation, and communication. Interviews were semi structured and conducted over the phone, audio-recorded, and transcribed verbatim. The principle investigator conducted all the interviews. Detailed notes were taken during the interview to verify the transcribed interviews.

Data Analysis

Two coders independently read all transcripts becoming familiar with the data, and then proceeded with primary, iterative, open coding, coding transcripts for each of the 5 public health agencies, first within and then across agencies. Constant comparison was subsequently also done comparing incidents applicable to each category of codes across the five public health agencies for emergent themes (secondary coding). Primary coding identified meaningful units of data, tagging, and naming segments of data with codes (Tracy 2013). A codebook of these codes was developed. Subsequently, secondary coding grouped and organized the codes, synthesizing and categorizing them into higher order themes. Themes were examined for answering the research questions: What messages were used for communicating Valley Fever risk, How were messages adapted to existing risk environments, How was climate information integrated, and What were continued challenges for communicating Valley Fever risk. Coders examined the data for saturation of codes and discussed emerging themes (Morse 2015). Discrepancies were discussed to ensure coding consistency. Figure 5.1 shows the first and second level codes of the analysis.

Figure 5.1: Qualitative Data Analysis – First and Second Level Codes



Results

What Valley Fever information do the 5 public agencies of interest have access to?

Overall Lack of Resources and Limited Reporting Accuracy

Overall, the public health agencies get newly diagnosed cases from health providers and laboratory reports. Cases being reported can include those that were previously diagnosed, but had a relapse in symptoms. With cases in the several hundred a month, importing this data can be a huge workload for staff at these agencies. According to a representative from Kern County, "Because Valley fever is a chronic illness and you only get reported once, we have to de-duplicate a lot of it. And so people who've been reported in the past, we take them out of our data sets. So it takes a little bit of effort to sort of filter through all of those."

The laboratory reports typically only comes with birthdate and zip code of the diagnosed patient. Other demographic information is absent and the agencies do not have enough resources to ask for more information. In terms of demographics, a representative from Fresno County stated, "with Valley Fever, if it's included on the initial report, we will go in and enter it as such. So when we enter it into the state database, it's not going to allow us not to upload if we don't have that information since Valley Fever isn't really a funded disease here in California and we've got other diseases that we have to meet certain criteria and actually follow up with the provider. So if it's initially included, we will upload it. If it's not, we try our best to reach out to the physician. But if we're not able to capture it from the physician, if they're not responsive, we will still upload it. So if it's given to us and we're able to get it off our first attempt with a doc, we'll upload it. So I can't say that every case would have race/ethnicity on it." Only Fresno and San Luis Obispo County follow-up with the providers. According to Kern County, "In the past, typically we would try to contact the lab and have them submit it to us. We don't do that currently. It's just the amount really is too high and we just didn't get a lot of feedback from that." San Luis Obispo County, a county with a lower incidence that many of the other counties, takes getting demographics and risk factors a step further by making "three attempts to contact the person who's been infected to receive information regarding their risk factor and any types of exposures to dirt and dust that they might have had. We generally have a pretty good response rate. I'd say 60 to 75%."

Overall, staff at each agency spends 10-20 hours a month on Valley Fever related workloads like imputing in the lab forms into the CALREADY database, following up with providers, and de-duplicating the data. Kern County spends an estimated 40 hours a month on Valley Fever related work. With approximately a .125 full-time equivalent staff person working on Valley Fever a month, it is no surprise that 75% of counties are neutral about the statement: Systems are in place to ensure Accurate reporting, Timely reporting, and Unduplicated reporting for Valley Fever.

All of the agencies get individual files and they use ArcGIS™ to analyze data spatially. In addition, all of the counties believe/ are unsure if their agency has the necessary resources to support health problems and health hazard surveillance and investigation activities towards Valley Fever. Only one agency, Kings County, has resources set aside for staff to pilot test or conduct studies to determine new solutions for Valley Fever. However, the staff member that was the resident expert on Valley Fever in Kings County recently retired and the position has not been filled.

Agencies are Reactive Towards Valley Fever

When it comes to learning more about Valley Fever, these agencies take a reactional approach. The agencies do not partner with research organizations to have Valley Fever included in their research, but do meet with these agencies to hear their findings. According to a representative from Kern County, "Our staff probably-- we do a couple of things. We're very well known to and with the California Department of Public Health. So we get a lot of information from them about what's going on statewide. We do have some relationships with places like the Valley Fever Institute which is at Kern Medical Center here in Kern County. They're doing some research on-- the clinical research as well as Dr. Lauer at Cal State University Bakersfield has also been doing some environmental research regarding Valley Fever. So because they're located nearby as we tend to work with them."

The agencies do attend a Valley Fever coalition to discuss Valley Fever needs and get other data from the state. However, attending these meetings is more reactionary than proactive. According to Fresno County, "I mean, right now, you're talking to me, and I don't just manage Cocci disease. I manage labs. I manage clinics. Every one of us has 20 things we do. And so without the focus and the resources, the funding for that specificity, it is just something that's going to take a university to come in with the resources and provide those resources locally, as well, to be able to get it to come together and do the study."

How do these agencies use information to communicate Valley Fever to the public?

Evolution of Media

Each agency has limited resources to spend on media campaigns, but these campaigns have evolved over the years.

For Fresno County, "My first year here five years ago it was more just TV only, so we would just do TV really and maybe a local newspaper. We now have evolved into going on Pandora, using Pandora, using Facebook. YouTube Spanish got a huge hit and some of our other campaigns. So a YouTube Spanish Valley Fever is something we'll be doing in the upcoming year, and so we learned on what is the Spanish-speaking population in Fresno County, specifically western Fresno County, how are they accessing our campaigns?"

For Kern County, "it's just education and awareness. Our public health department has a contract with the electronic billboard companies in our county and we cycle through different diseases depending on the season. So coming up in spring/summertime, we'll probably run through the Valley Fever billboards again. Last year, I think-- I think last summer, we partnered with our county sheriff to new PSAs (public service announcements) that were run on television. We have some that have gone on radio media. We're constantly putting things out on social media. We have a Facebook and a Twitter where we talk about Valley Fever. So it's not so much a campaign. It's sort of ongoing education that we expect to continue to use for multiple years, now that all the stuff has been created."

For Tulare County, outreach visits make up a majority of their media campaign. "We do work with our PIO (Public Information Officer), our media specialist here, and we provide her, on a periodic basis, numbers of valley fever reported and compare to the years before. And then also, we usually try to do something around Valley Fever Awareness Month, which is in August… I think last year we had maybe 15 to 20 outreach events. And they're in some higher rate cities, towns in the county. But, yeah. We do that year-round, whenever we're invited. And we try to reach out. Especially to folks who are labor workers, construction workers. And oftentimes people are, "Oh yeah. Somebody did get valley fever. They were working in this." Just kind of give them education on when the risk is higher. When it's dusty out. What kind of occupation they have, and such.

For San Luis Obispo County, their media strategy is geared around their community relationships. “So we developed some pretty concise messages around Valley Fever and developed a schedule and pretty regularly throughout the year kind of remind the media of this issue hooking onto different things that make it timely or relevant at different parts of the year. Often, that relates to just releasing more data as the year goes on. And that kind of complements an overall approach with our-- we're kind of in a small community. So our media strategy is really built on having these ongoing relationships.”

Campaigns

All of the agencies stated that they tailor their media campaigns based on culture, language, and occupation.

Campaigns for the Planning Department

All of the counties partner with their planning departments to hand out Valley Fever awareness documents to construction projects. Kern County stated, “But their planning department, it's part of all of their environmental health assessments. Is that they have to have pieces of dust mitigation and specific they must have Valley Fever education. So that's stuff that has been in place for a while now. But we know it's a known risk and it's a known hazard in Kern County and that construction and any other of those planning elements need to take that into account and to take steps for mitigation and for employee education.”

For San Luis Obispo County, “We have become much more focused in attempting to get occupational information, for one, which is due in large part to the solar farm construction and other construction outbreaks we've had in our county. So we work really hard to understand what occupational risks are in regards to Valley Fever.”

At Risk Community Campaigns

Public Health agencies all stated that they target their messaging to at-risk communities. These might include construction workers, farmers, and the prison population. Educational materials were often provided in at least two languages, English and Spanish. However, their approach to messaging differed depending on audience.

For construction workers, messaging focused on dust containment and wetting of soil. All counties partnered with their planning departments to hand out Valley Fever awareness documents to construction projects with messaging related to keeping the dust down. Kern County stated, “But we know it's a known risk and it's a known hazard in Kern County and that construction and any other of those planning elements needed to take that into account and to take steps for mitigation and for employee education.” In San Luis Obispo County, prevention procedures were even integrated as conditional mechanisms of administrative approval on construction projects: “we worked very hard to make sure the conditions of approval for big projects, there is most definitely language inserted into the conditions of approval that talk about high wind days and the need to use water truck to keep the dirt down.”

Prevention messages for farmers included more frequent and routine tilling of soil to prevent excessive fungal spores from growing. Fresno County had a hypothesis that water allocations to the farmers are linked to Valley Fever outbreaks and that prevention for farmers could occur by controlling the moisture in the soils. However, this is an informal hypothesis that has not been researched.

> Because we have a less stable water allocation, what does that do? Our farmers on our side then aren't planting crops because their water allocation is unstable. What that means is they're not tilling the ground, they're not working the land as much to disturb the potential growth of the spores, so-- of the fungus. So with us, going through years, you're letting the-- the ground is not being tilled. And then, we get a wet year. The wet year loves to feed the fungus even more. So that first tilling in your wet year, when everybody's going back to work. Now, your expectation here is you're going to give more admission of that fungus out

> into the air. And so because of the unstable water allocation, our farmers aren't tilling the ground as often as they could to actually prevent this. - Fresno County

In addition to frequent tilling, wearing proper protective equipment during peak risk times was another focus of Valley Fever messaging for farmers. Fresno County, Kings and San Luis Obispo County reported these messaging strategies. From the Kings County representative, “We tell them they should be wearing N95 respirators when they're out there, especially people that are not endemic to the area and come in from other areas.”

Certain living conditions, especially places of confinement such as prisons, where a special population is concentrated in one location and consequently, have exacerbated risk for acquiring Valley Fever. Kings County mentioned that they have a high incidence of Valley Fever among correctional facilities. “So a wind comes out of the northwest and goes southeast, right, and that tends to be where our concentration of cases are. And then, of course, and you may have found this out too, but then confinement. Hence prisons. We've got three prisons here and then all three has been an issue.” However, the struggle for Kings County is what to do to prevent the high-risk season from being exposed. They are working on it but do not have an answer. Kings County struggled with the messaging to prisons because the prisoners are confined in the endemic zone and avoiding exposure for long-lengths of time is not practical.

Current Messages

“Get Tested” Valley Fever Prevention Messages

Most public health agencies focused their Valley Fever prevention messages on getting tested if you exhibit symptoms. Tulare County focused on “Just kind of give them education on when the risk is higher. When it's dusty out. What kind of occupation they have, and such.”

Timing of “get tested” campaigns for most counties were geared around or launched in August or end of summer. This coincided with August being Valley Fever Awareness Month. For example, Tulare County launched awareness campaigns during this time “…that's kind of the peak, or the beginning of the peak, of the season with all the dryness and dust.” Fresno County reported two phases of messaging.

> When we look at our data set, for us, when are we going to actually do TV, do radio, do social media, do all of that, the data drives us to do that and we like doing that around this time of year. We'll do it right around February, March. We'll do it around also-- I've done one in the summertime a little bit but that's kind of a little bit late and we'll do it again in I think fall if there's any funding available. – Fresno County

Absence of Explicit Discussion about Valley Fever as a Climate Sensitive Disease

Overall, participants did not currently incorporate climate information into their Valley Fever communication, but they were aware that there is a relationship to climate. To keep messaging simple and avoid information overload, public health agencies had not integrated explicit climate information into Valley Fever messaging. Climate factors such as wind however, were discussed, but were not incorporated into explicit Valley Fever risk messages.

> But from a climate perspective, we understand that hot, dry weather will promote the spread of cocci when the wind blows. We also are aware of the fact that valley fever does seem to have some linkages to weather change patterns. After a long period of drought, we know that the fungus does not proliferate as well in the soil and so case rate goes down. And then when you get a really wet period like half a couple of years ago, case rate go skyrocketing. That tends to be a definite correlation… We don't pass along all the research. We really try to keep-- we understand that the people we're trying to reach face an information overload in every aspect of life and so we really try to defer down to simple messages and occasionally a different point of view which is really relevant which shows up sort of as a way to pique interest. – San Luis Obispo County

Climate Influences on Valley Fever Discussed as Wind Messages.

When asked about climate's relationship to spore growth, all agencies discussed rain. When asked about climate's relationship to Valley Fever outbreaks, all agencies discussed wind. Public health agencies perceive the scientific evidence correlating fungal growth with Valley Fever cases was as of yet too unreliable and not specific enough to use in risk messaging strategies and awareness strategies.

> We always kind of talk about it. We make the joke after windy days. Like, 'Well, in a month, we're going to get a bunch of Valley fever cases.' No one's so far been able to give me a really good sense of predicting Valley fever and of course, predicting fungal growth doesn't predict the number of cases you're going to see. But we like to assume there's some kind of correlation there. – Kern County

If these agencies had access to more specific Valley Fever information, how would they want to use it/what type of more specific information would be of interest?

Valley Fever as an Under-funded Disease

All five agencies echoed the sentiment that more resources of increased budget and staff are needed to further the research on Valley Fever. According to Fresno County, the departments needs an increased budget of 150-200 thousand dollars a year to run the kind of analysis the department wants. "It's a matter of what would we actually expand into. Because, right now, we could easily look at better surveillance so you know how I said if we make one attempt to see whether or not the provider is going to be responsive? If we had more surveillance dollars, we would actually make more of an attempt to get a more thorough record of treatment and have more of that there. So there would have to be an increase in surveillance and then we would have to see-- what else? We don't run a primary care clinic here in Fresno County, so for treatment and that, I don't see us going down that route. And then prevention dollars would be my second. So primary, surveillance, second would be prevention, and just doing outreach, expanding on what we do now because it's a very small budget on what we do now."

Kern County echoed a similar sentiment. "If I had an ideal situation and specified funding for it, we would love to be able to dig a little bit more into the cases to do more followup, to do not research on patients but just more in-depth surveillance, more enhanced surveillance because we're limited on what we can do and none of it is mandated by any state or federal funding that it, unfortunately, kind of falls to the wayside. You know Valley Fever's also not communicable person to person and so that plays a role in sort of its priority at the Public Health Department of trying to do immediate disease transmission interruption with things like STDs versus Valley Fever. A lot of it has to do with environmental aspects and a lot of those exposures have already come and gone by the time those cases are reported. And so if we could I would love to be able to look more into those exposures to find out more about where and how people are getting exposed kind of in that perfect world. A lot of resources starting with funding to be able to fund a person to be in charge of something like that, that's dedicated. What happens, unfortunately, is when we all have limited resources we tend to have to reallocate them versus if there's dedicated funding to something like Valley Fever and we know that those funds must be spent in that activity, then you can make sure that it gets spent in that activity and those certain kinds of projects get done. Then aside from having that funding we'd have to have the people to do it, a dedicated person or a part of an FTE (full-time equivalent) to be specific to Valley Fever would be great and to have somebody who's well-knowledgeable about is always something that takes a little bit of time."

San Luis Obispo County shared that more can always be done. "We are a small health department with extremely limited resources. We are doing more, I happen to know, than most health departments do for investigating Valley Fever. But we simply don't have additional resources to apply to that."

Climate Information

Two main themes arose: metaphor communication and risk communication. The biggest challenge the agencies experienced with communicating climate information was how to apply that information into messaging that does not result in message fatigue and target audiences discounting public health Valley Fever risk messages.

Comparisons with Warning Messages Already Familiar to the Public

Public health agencies discussed communicating Valley Fever risk by drawing analogies to Poor Air Quality Days or Red Flag or "red" days surpassing thresholds. Target audiences living and working in these counties are already familiar with public health risk messaging about poor air quality and attend to these kind of messages. One strategy then, is to couple or piggy back Valley Fever messaging jointly with poor air quality risk messaging. This "kills two birds with one stone" so to speak given the agencies' minimal resources and the public's limited attention to health risk messages. Furthermore, Valley Fever risk messaging cannot ask the public to avoid the environment in which they routinely work and live; they can at best, ask people to adapt to their environment to minimize risks to their health. This message concept draws on the behavior adaptation model (BAM) (Parrott, 1998). Kern County suggested "We cannot tell people, 'Don't go outside if it's windy or dusty for the entire Valley Fever season,' if there is a Valley Fever season. But that's just really hard for people to maintain."

To address this issue, Kern County made the analogy to Poor Air Quality.

> What I'd like to find out is what does windy mean? Does that mean winds of 5 mph, winds of 35 mph? So that we could more accurately warm people about their risk of Valley Fever. In my head-- I've told this to a couple of people I think-- the same way we have air quality flags and so this is a red day for air quality. If you're in a sensitive group, you need to stay indoors. But I'd like to see if we had something like that for Valley Fever. If it was something as simple as correlating it with air quality. That if it's a poor air quality day, it's probably a poor day for Valley Fever. That people could use that as a gauge of their risk. Right now, it's very general if you-- if it's windy or dusty, go inside. But how windy, how dusty? – Kern County

Using Analogies with Health Conditions Familiar to the Public

Another form of climate communication of interest to the health agencies employed a message strategy that addresses the uncertainty inherent to Valley Fever and the agencies' prevention measures. In discussing successful communication strategies for the agencies, all agencies made comparisons between flu and Valley Fever.

> So what I would hope for is that we could say, 'Windy days increase your risk and when the wind is over 50 miles an hour, you're at increased risk of Valley Fever.' You should always take precautions but since it's an increasing windy day, then you might think about it more often. You're much more likely to do it. Just like when it's a 'bad flu season', people are going to run off to get their flu shot. – Kern County

Kings County also made a comparison to allergies. "We know this year especially is going to be bad for allergies because of all the rain. We need the rain, but the rains-- it's awesome. But it's also going to have a collateral effect with the allergies, right? And the same thing with these kind of a fungus, right? If the temperatures are right, they're in these spores, well they become active."

The Challenge of Message Fatigue

When discussing their media campaign, San Luis Obispo County believed their media market is fairly saturated with Valley Fever messaging. For them, "We understand that the people we're trying to reach face an information overload in every aspect of life and so we really try to defer down to simple messages and occasionally a different point of view which is really relevant which shows up sort of as a way to pique interest." For Tulare County, "We certainly don't do a media release every single month. I think people wouldn't pay much attention in that case."

Fresno County discussed how messaging needs to phrased a certain way in order to avoid fatigue in the messaging.

> Hey, there's a windstorm coming," that media message will die out so fast. It's kind of like crying wolf all the time. And so all it's going to do is really be-- it'd be exciting, and you'll effect change immediately, but that's not a sustainable media campaign because we really can't connect the two, right? And so is it 20 mile-an-hour winds? Is it 10? Is it 30, or is it 60? Without having not seen the research, that's a little tough to do. And so people are going to be like, "Wind? There's wind all the time." And so it has to be something else besides something like that. – Fresno County

Limitations

Participants pointed towards four themes: (a) the uncertainty inherent in accurately diagnosing Valley Fever – making it a challenge to disseminate clear, simple Valley Fever risk messages, (b) the politically conservative target audience that is unreceptive to Valley Fever climate messages, (c) the low geographical impact of Valley Fever, and (d) the misinformation being spread regarding Valley Fever and how it spreads.

Uncertainty Inherent in Valley Fever Diagnosis Presents Prevention Challenges

There is still so much that is unknown about Valley Fever, how it is exposed, the connection between climate, and how to prevent it. All the counties discussed how there was not a real action piece involved for preventing Valley Fever. For Kern County, this is where they saw flu and Valley Fever messaging diverge. For flu, they advertised to come get your flu shot.

> But now, we're kind of in that last piece where there's not a lot of action we can have people take and behavior change they can do because if your job is an outside job and you have to work, then there's going to be exposure that happens. – Kern County

Tulare County echoed the same sentiments. "A lot of people don't want to wear a mask all day long if they're working outside. It's very hot here during the valley fever risk period. You can't really tell people, 'Just sit inside all day.' So it's very hard to-- I mean, some of the effective strategies are, if you're disturbing dirt, to maybe wet it down ahead of time. But we were in a really long-term drought and water usage was restricted during that time. So it depends. There's limited really good preventative measures for valley fever at this point."

Political Considerations in Valley Fever Messaging

The relationship of Valley Fever fungi to climate also has a political connotation. With Fresno County, the representative spoke about how the topic of climate change with farmers is too abstract with them. The message hits a dead wall. Kings County also saw this as a limitation.

> And then they're not buying in, politics, right? Because they're not buying into climate-- a lot of places aren't buying into climate. The coastal counties, coastal areas, they're buying in. Your value areas that tend to be more conservative are not buying into climate change. So it's going to be-- I would say we have the difficult spot of education. And a lot of people need to, hopefully-- recent events, with the freezes and things, maybe that's, right there, a pretty good little indicator of climate change, right? Man, they never had these freezes like they're having there now. So we'll see what happens. A lot of it-- it's a challenge, and I'm sure you're running into that. With climate now, it's a big challenge. Bay area, places that are a little more open to understand it more. Or you get into areas that are more conservative that they don't. – Kings County

Fresno County believes if the climate communication could be relayed into how it impacts the Farmer's livelihood might be a better approach. For example, Fresno discussed how climate affects the water allocation and how the water allocation may influence Valley Fever. "I think if we had a more stable water allocation in the Central Valley, that could potentially reduce the amount of Valley Fever cases" and Fresno found that this could be used to help farmers see the benefit of purchasing more expensive, imported water.

However, on the topic of climate change, San Luis Obispo County saw it as an unnecessary addition.
It's not so much that there are topics we stay away from but there are really a few specific messages that we do focus in on. So we really try to exclude a lot of information in order to have those few messages come through clearly. We really want people to understand their risk and possible diagnostic things. And I think they've done some study that says that you remember maybe 15% of what a doctor or a professional tells you in any given educational session. So we really try to get into them a few key messages. If you're coughing for more than two weeks, you should ask your health care provider about getting tested for valley fever. If you're out and it's windy and gusty, you should either make sure that the dust and the dirt gets watered down or you should get out of the dust and dirt. So we don't find that there are taboo topics in valley fever. We just find that we want to focus in on the ones that will help our population the most. – San Luis Obispo County

Not in my Backyard Themed Rhetoric

Most of the counties found that people do not see Valley Fever as a priority because it is not something every agency has to deal with, or as the saying goes, "if it's not in my backyard, it is not my problem." The representative from Kings County stated "It's very difficult to have people buy in. Because even in California, it doesn't affect everybody. And so it only becomes a low priority because if it's not a hotbed in their area, then they have their own agenda, and they have their own priorities. But in the valley and anything maybe south, and then again towards Arizona, are having issues. The coastal areas that I know about, like the city of San Luis Obispo and those areas, south Ventura, it hasn't really been an issue until recently. And they're starting to see cases now, and so they're starting to get onboard, and they're starting to get more-- unfortunately, a lot of the stuff with Valley Fever I'm finding is fairly new. People are just trying to get into it at this point in time, which is unfortunate."

Misinformation is High

Another limitation described by Kern County and echoed by Tulare County is misinformation and biases. For Kern County, "I'd like to know the extent of that misinformation so that we can start correcting it and helping people understand what their real risks to Valley Fever are. Even this morning, I had somebody call that said, "My husband has Valley Fever. We want to move somewhere that doesn't have Valley Fever. Where should we move?" And part of my conversation was like, "Hey. If your husband's already got Valley Fever, he's not going to get it again. So if that's why you want to move, then that's not the right reason. If you're worried that you're going to get it or your kids are going to get it, then you might need to think about whether or not you've already been exposed and are already immune to it." And so those are just kinds of the things that people are reacting to Valley Fever. And they just don't know as much as they could about it. And so part is just trying to figure out what people know about Valley Fever and what they think they know but don't know so that we could help with that education, help people make good decisions. Obviously, we're not going to vacate the entire Central Valley. But part of that balance has always been how much do we tell people about Valley Fever without scaring off business, without scaring off visitors? And letting people know their true risk without downplaying it too much. Because there's that other balance that says, "Hey. Everybody gets Valley Fever. It's not a big deal." But you have people who are very sick and can be sick for the-- maybe on medication for the rest of their life. So you don't want to downplay it too much as saying there's no risk or it's not a risk you have to worry about because if you're an unlucky person and you end up with Cocci Meningitis, then you will be on meds for the rest of your life. And that might play a role if you're someone who's immunocompromised if you do want to move and live here or if you want to move out of here. And we just want to make sure that people have the information they need to make the best decisions."

For Tulare County, a major limitation can be found in the research. "It's a disease that's only specific to certain areas of the country. So the funds and the actual research attention has been fairly limited. A lot of what we do know is from very old studies. And even some of the studies that are more recent, they're a bit limited by being able to detect cases. A lot of people aren't symptomatic, or they have a very mild infection. So I think a lot of the research-- sometimes I look at it, I wonder how biased the results are because you're only really seeing the more severe cases. So it's hard to do it if you're not doing kind of a more intense perspective type of study. And those kinds of resources haven't really been put into Valley Fever very much."

Future of Valley Fever

Changes in Reporting

The California Department of Public Health Infectious Disease Branch, effective in 2019, changed the definition of what counts as a Valley Fever diagnosis. Starting in 2019, Valley Fever is only laboratory reportable, where they test positive in a lab report, but no longer need to exhibit symptoms. All five agencies discussed that the entire state of California will see an uptick in cases moving forward, but lab reporting means a decrease in information related to ethnicity and the date when symptoms started. For Fresno County, this can be seen as a step in the right direction. "When you look at Valley Fever data in prior years, counties classify cases differently. Some just used labs. Others used symptoms plus labs to confirm whether or not it was a Valley Fever case. So it's now the state has said, "You know? You could just call it a case based on lab results only." At least we'll get some standardization on everybody, and more than likely it's going to increase our number of cases just because of that change alone in itself. But regardless of that, at least we'll have a consistent way throughout California on classifying these cases."

Inherent Uncertainty Coupled with Valley Fever Diagnosis makes Public Health Messaging Challenging

Valley Fever is a disease that does not have a good prevention metric and uncertainty that makes agencies strive away from messages that are outside of "Get Tested." To combat this, the research fields need to communicate more with specifics and use these specifics in a form of a Behavior Adaptation Model.

> So it's always going to deal with uncertainty. We're always going to be talking about an increased risk or a lower risk so that it's not necessarily going to say that, "Today it's a windy day. You're going to get Valley Fever today." But you just need to kind of keep these things in mind. Take additional precaution. I know it'll be really hard for us to ever kind of prove this causes that with something like Valley Fever, but if those correlations are strong and really if they make sense to people, hopefully, they will kind of follow those recommendations to stay indoors if they can. Something like schools that say, "If it's a super windy day, we're going to treat it like it's a bad air quality day. We're not going to have sporting events. We're not going to have all the kids out there exposed to all this dust at this time." And luckily, at least in sort of metro Bakersfield, we don't get a ton of windy days. We don't see what Arizona sees where they get the big haboob's that blow over. Those things are very rare for us. And so hopefully if we could quantify the winds at one point, or even winds and temperature and just all of that stuff, that we could pick those days. It's a running joke in Kern County that we have so many bad air quality days that kids should just stay inside all summer. If we could pick out the ones that are worse for others that we could alert people to then hopefully, people would listen and take extra precautions on those days. For most people, it's going to be the only time they take precautions because they just are so used to that baseline of risk. – Kern County

Tulare County finds that just a prevention method for Valley Fever will not be enough. “It's hard to really have a good prevention method. And a lot of these folks live really deep into the county, so even when I tell them, when I'm doing outreach, like, "If you're having these signs and symptoms and they haven't gone away for two weeks [a month?], go to your doctor." But a lot of these folks can't just go to the doctor whenever they're feeling sick. So a lot of them end up in the ER once the infections have gotten complicated. So maybe that's another barrier that we have to getting folks to get screened earlier.”

Keep it Local

Although a direct tie to these agencies getting more resources is for the state to intervene, the counties do not share this sentiment. For Fresno County, Valley Fever research should be a focus for local partners. Valley Fever has “never risen to the amount of, "Hey, we have a pharmaceutical company who wants to invest in better treatment and a potential vaccine and so forth." So, unfortunately, it's just-- it doesn't impact enough people in the United States or in the world for it to get the notice and the funding that it should like other diseases. So I think for California we're just going to have to work with our partners to figure this out on our own as far as prevention strategies and how we can-- and so this whole water allocation thing or other studies that would inform our policies and inform how we actually do outreach I think are more important now in what we need to work on in the next five years versus trying to get somebody at the federal level to listen to us and give us funding to find a cure or a vaccine for it. I think there have been ample attempts to do that. It just never has really happened. So I'd rather see us focus more on what can we do here with our local partners to get us to a better place where we're at than we are today.”

Discussion

The results from the interviews point to several findings:

Need for Funding

The Public Health agencies are at capacity with their staff hours and budget. Right now and in the near future, not much more can be done without an increase in budget and an increase in staff. If additional funding is not earmarked specifically for Valley Fever, then there needs to be staff on-site that has a passion for Valley Fever.

Cases in 2019

These public health agency officials predict that the number of cases diagnosed in 2019 will be one of the highest on records because of the new lab reporting policies. There will be a need to control the media’s interpretation of this uptick. According to my relationships described in previous chapters, fall and winter wet season for 2019 is on track to be the highest out of the past several years, indicating that cases could be higher. It is important to emphasize correlation is not causation and there are several reasons bringing about the 2019 anticipated uptick in cases.

Media Strategies
Current media strategies focus on bringing awareness to the symptoms and when to get tested for Valley Fever and these strategies begin around August. A proactive approach done year round is working with the planning department to hand out Valley Fever exposure flyers to construction projects. However, there is currently no mandated stop-work policy related to Valley Fever and construction. In addition, media strategies are not evaluated and there are no resources to allocate towards Valley Fever media evaluation.

Research and Researchers
Currently, research that is published is typically not specific for Central California. Most of the past publications are outdated, over 7 years old. Public Health staff are also aware of publication biases influencing the findings.

In addition, the scientific research is not relatable for media strategies. There is a need to communicate the research to the end-user, being aware of the Public Health Agency's staff time (or lack thereof) and how the information could be used for the timing or content of the media strategy.

Future research should be looked at to address thresholds. For the Public Health Agencies, stating wind has a relationship with disease outbreak is not helpful. Stating that wind under 5 mph is linked to increase exposure is more helpful. It provides more content for the media strategy. However, Public Health Agencies should be aware that to get more specific in terms of mph threshold and links, daily and monthly case data should be provided to researchers. In addition, if the goal is to develop a program where on a high exposure day, construction activities are halted, more information than general relationships would need to be provided to justify the economic impacts related to a stop day.

Limitations
Aside from funding and time limitations, Public Health Agencies should understand that they can be their own stopping block for the Valley Fever research. The agencies do not have staff to conduct these analyses in house, but they also do not partner with educational institutions to get Valley Fever on their research agenda or to provide interested researchers with access to their data. Currently, requests for Valley Fever data go to the agency's legal counsel and ultimately denied.

Another limitation involves uncertainties. Since there are so many uncertainties around exposure to diagnosis date, more research should be focused on understanding this relationship.

Conclusion

Quality Criteria
According to an article by Tracy (2010), there are eight criteria for excellence in qualitative research: worthy topic, rich rigor, sincerity, credibility, resonance, significant contribution, ethical, and meaningful coherence. Valley Fever is expected to increase over the next coming years and there is little that is known about the disease. Developing qualitative research that looks into how climate can be utilized for risk communication of Valley Fever is a relevant and timely topic of research. This qualitative research was conducted with only 8 people, typically one staff member per county agency, but was designed to coincide with the dissertation's study area. However, the findings in this study are consistent between the California agencies, the breadth of the interview sample is wide enough to meet the goals of the study. The original research foci of interviews was to determine how agency's process Valley Fever data, their resources, and how they communicate Valley Fever and climate. A self-reflective analysis to bring transparency was conducted after the interviews were completed. In this analysis, the researcher discovered the inclination towards a code related to research and partnerships. This inclination is based on a bias related from attempts to get case data described in an earlier chapter. With the help of a second coder, the foci of the research changed and allowed for the opening of ideas related to media campaigns and target audiences. With the findings, especially related to methods to communicate climate, many of the transcripts include dialog where the agency representative states they are thinking out loud and the idea they propose comes from this internal brainstorm. These findings should allow future researchers to find the research trustworthy enough to act and make decisions with. In terms of resonance, the themes in this study should show transferability from fellow public health agencies that share similar struggles and experiences related to the management of Valley Fever or similar climate sensitive diseases. This research follows a heuristic significance, asking people to further explore and act on

research in the future. Currently, the relationship between climate and Valley Fever is not included in risk communication. This study suggests that future researchers partner their findings with their local agencies to provide this relationship in a way that can be utilized in a beneficial way. By connecting the research with the Behavior Adaptation Model, this research achieves meaningful coherence by connecting past occupation adaptation methods with the findings.

Limitations

This study was conducted for Central California and extrapolation to other counties or states may not be appropriate. For the study area, the findings are consistent among the counties' health agencies. This increases the validity of the findings towards the idea of incorporating climate communication to the disease known as Valley Fever.

By using a developed and tested survey instrument for the basis of the interview guide, unconscious bias from the researcher that may be evident in questions and design and may warp findings was minimized, increasing the validity of the findings.

Summary

Given the limited resources, public health agencies are disseminating tailored prevention messages to at-risk groups. First, general "get tested" messages are disseminated during peak seasons of Valley Fever to a broad audience, also disseminating such campaigns in Spanish to reach a broader at-risk group. Furthermore, prevention messages are adapted for at-risk groups including construction workers, farmers, and prison populations to emphasize mitigation strategies of dust containment, wetting and tilling soils, and enforcing these behaviors with protocols integrated into policy approval processes of construction jobs. Valley Fever risk messages capitalize on heightened recognition of familiar poor air quality or red flag days as a strategy for increased attention to these prevention messages. While generic wind messages seem to be ineffective, specific wind messages indicating threshold effects stand a higher likelihood of message acceptance and compliance.

Chapter 6

Climate Thresholds and Scenario Modeling on the Understanding of the Valley Fever Risk Season

Introduction

This chapter will tie the multivariate relationships between climate and diagnosis date conducted in this dissertation to the qualitative research findings in Chapter 5. Chapter 5 findings indicate that Public Health agencies want to see what an example of climate information would look like incorporated into their media strategies. They also have some concerns about the data being too vague or actions based on those data are too unrealistic. An example of this is that the data says to stay inside during windy days. Construction people cannot stay indoors during all windy days. Therefore, this type of message is not sustainable.

This leads to the question, how can climate information and its relationship to Valley Fever diagnoses be presented to Public Health Agencies? How can the information generated in this dissertation be communicated to Public Health agencies regarding the relationship between climate and Valley Fever? Based on feedback from the interviews conducted in Chapter 5 of this dissertation, example information on how climate can be used in Valley Fever communication will be presented in two ways.

Analysis will be conducted on whether there are patterns on climate thresholds and diagnosis amount. The second method of communication is developing a scenario-based tool that can answer the question, what type of Valley Fever season will the upcoming season be?

The final communication method will be a research brief developed by Melissa Matlock. This brief will contain summary information from this dissertation, tailored to each county, with the public health agency as the audience.

Methods

The analysis looking at patterns between diagnosis month and climate variables will be conducted looking at correlations between the averages, across the estimated exposure months, of the climate variables to the amounts of cases diagnosed during the high diagnosis periods.

The model used to develop the scenario-based tool is hosted on the program called GoldSim^{TM}. GoldSim^{TM} is a Monte Carol simulation software, typically used for dynamic and static modeling of complex systems. GoldSim^{TM} is a risk-analysis and decision-making tool that incorporates dashboards and limited interactive version that is perfect for summary information and those without programming knowledge. The data fueling the model are multi-variate linear regression results, where all the variables in the model are significant and are easier for the public health agencies to use and interpret.

The model output is a dashboard, where each agency can input a couple of climate variables and the result will determine if that season, starting in August, will be a low-risk, "normal", high-risk, or highest on record season. This information can then be used to inform resources towards media messaging.

Limitations

The methods and results in this study are meant to be used as an example of how communication can be made. With limited years of data and data aggregated into months, it becomes difficult to ascertain the significance of the thresholds determined in this analysis.

With the new policy established in 2019 to accept lab reports only for Valley Fever cases, all of the public health agencies in this study expressed statements indicating that this action will cause an uptick in the number of cases. The magnitude of this uptick has not been determined yet and could affect the reliability of the estimates in this model.

Results

Patterns and Thresholds

Fresno

Based on the findings in the previous chapters for Fresno County, patterns and thresholds were examined for climate variables of PM 2.5, Wind, Palmer Drought Severity Index (PDSI), and Precipitation.

PM 2.5, Wind, and PDSI was averaged over August to November and was compared to total annual cases for the year. Total precipitation for the 12 to 6-month prior were averaged over August to November.

From Table 6.1, cases appear to be highest when precipitation is over 12 inches during the previous Fall and Winter. When the Palmer Drought Severity Index is wet and PM 2.5 is around 4 ug/m^3, cases appear to be higher than average. High cases also appear when PDSI is neutral and PM 2.5 is higher than average, over 10 ug/m^3.

Average Wind speed stays consistent between 4-5 mph. Without weekly or daily data, relationships between wind and amount of cases cannot be determined for Fresno County.

Table 6.1: Average Climate Values Compared to Annual Total Cases for Fresno County

	Cases Total	PM 2.5	Wind	PDSI	Precipitation
2000	6	12.78	4.58	-0.45	12.85
2001	44	12.66	4.87	-1.23	9.90
2002	25	15.45	4.57	-3.22	9.65
2003	77	7.80	4.76	-3.03	9.75
2004	39	11.01	4.68	-4.05	9.28
2005	184	11.23	4.63	-1.38	15.78
2006	251	13.37	4.33	1.24	14.07
2007	93	10.81	4.74	-3.33	6.56
2008	142	13.81	4.52	-3.76	10.67
2009	136	8.57	4.92	0.78	9.49
2010	429	4.38	4.35	3.35	14.35
2011	304	4.76	4.33	6.52	21.44
2012	105	6.34	4.34	3.26	7.50

Kern

Based on the findings in the previous chapters for Kern County, patterns and thresholds were examined for climate variables of PM 2.5, Wind, Palmer Drought Severity Index (PDSI), and Precipitation.

PM 2.5, Wind, and PDSI was averaged over August to November and was compared to total annual cases for the year. Total precipitation for the 12 to 6-month prior were averaged over August to November.

From Table 6.2, cases appear to be highest when precipitation is over 10 inches during the previous Fall and Winter. When the Palmer Drought Severity Index is neutral and PM 2.5 is below average around 10 ug/m^3, cases appear to be higher than average.

Average Wind speed stays consistent between 3-4 mph. Without weekly or daily data, relationships between wind and amount of cases cannot be determined for Kern County.

Table 6.2: Average Climate Values Compared to Annual Total Cases for Kern County					
	Cases Total	PM 2.5	Wind	PDSI	Precipitation
2000	152	17.37	3.56	-0.43	6.62
2001	664	17.13	3.69	-0.41	6.09
2002	336	21.12	3.75	-1.90	5.68
2003	664	14.42	3.38	-2.06	6.25
2004	557	13.85	3.75	-1.12	6.36
2005	780	14.68	3.56	-1.03	11.61
2006	438	14.80	3.56	-1.21	8.16
2007	558	17.46	3.68	-3.03	3.87
2008	242	15.28	3.49	-4.03	4.83
2009	260	12.35	3.35	-3.78	5.24
2010	1222	9.21	3.65	-0.50	7.80
2011	1216	10.54	3.46	-0.52	12.56
2012	607	12.31	3.70	-2.21	3.89

Kings

Based on the findings in the previous chapters for Kings County, patterns and thresholds were examined for climate variables of PM 2.5, Wind, Palmer Drought Severity Index (PDSI), and Precipitation.

PM 2.5, Wind, and PDSI was averaged over August to November and was compared to total annual cases for the year. Total precipitation for the 12 to 6-month prior were averaged over August to November.

From Table 6.3, cases appear to be highest when precipitation is over 12 inches during the previous Fall and Winter.

Without weekly or daily data, relationships between the other climate variables and amount of cases cannot be determined for Kings County.

Table 6.3: Average Climate Values Compared to Annual Total Cases for Kings County					
	Cases Total	PM 2.5	Wind	PDSI	Precipitation
2000	3	18.99	4.71	-0.90	10.76
2001	22	19.22	4.26	0.50	9.21
2002	10	24.40	4.28	1.66	11.18
2003	27	19.57	4.95	1.78	9.13
2004	25	18.60	4.78	0.93	9.49
2005	75	17.77	4.67	0.87	15.42
2006	94	18.08	4.61	0.59	14.26
2007	26	17.73	4.95	2.33	5.69
2008	93	18.84	4.44	2.73	8.99
2009	74	16.82	4.96	1.51	8.63
2010	258	14.90	4.68	0.67	11.50
2011	214	-1.00	4.49	0.75	16.33
2012	57	8.44	4.56	1.88	5.04

San Luis Obispo
Based on the findings in the previous chapters for San Luis Obispo County, patterns and thresholds were examined for climate variables of PM 2.5, Wind, Palmer Drought Severity Index (PDSI), and Precipitation.

PM 2.5, Wind, and PDSI was averaged over August to November and was compared to total annual cases for the year. Total precipitation for the 12 to 6-month prior were averaged over August to November.

From Table 6.4, cases appear to be highest when precipitation is over 14 inches during the previous Fall and Winter and the PDSI for the time period is not wet.

Without weekly or daily data, relationships between the other climate variables and amount of cases cannot be determined for San Luis Obispo County.

Table 6.4: Average Climate Values Compared to Annual Total Cases for San Luis Obispo County

	Cases Total	PM 2.5	Wind	PDSI	Precipitation
2000	41	10.15	2.70	3.25	13.76
2001	23	8.79	3.34	1.86	14.28
2002	15	8.28	3.31	-0.89	10.07
2003	34	7.84	3.05	-0.52	13.79
2004	31	7.28	2.98	-0.35	10.42
2005	59	6.03	2.99	0.48	24.05
2006	81	3.58	3.64	0.32	15.64
2007	24	3.70	3.79	-2.91	6.51
2008	37	2.95	3.52	-3.84	15.48
2009	30	3.08	3.88	-4.50	8.99
2010	92	-1.00	3.22	-2.52	18.87
2011	82	-1.00	3.42	-0.68	20.95
2012	28	-1.00	3.37	-4.06	8.90

Tulare
Based on the findings in the previous chapters for Tulare County, patterns and thresholds were examined for climate variables of PM 2.5, Wind, Palmer Drought Severity Index (PDSI), and Precipitation.

PM 2.5, Wind, and PDSI was averaged over July to November and was compared to total annual cases for the year. Total precipitation for the 12 to 6-month prior were averaged over July to November.

From Table 6.5, cases appear to be above average when total precipitation is between 7 and 11 inches for the Fall and Winter season. Cases also appear to be higher when PM 2.5 is above average and PDSI is neutral. Cases also appear to be higher when PM 2.5 is below average and PDSI is neutral. In one instance, cases are high when PDSI is in extreme drought and PM 2.5 is above average. Cases are higher than average when wind speed is above 2.7 mph.

Without weekly or daily data, relationships between the other climate variables and amount of cases cannot be determined for Tulare County.

Table 6.5: Average Climate Values Compared to Annual Total Cases for Tulare County

	Cases Total	PM 2.5	Wind	PDSI	Precipitation
2000	23	14.87	2.67	0.96	7.98
2001	49	16.73	2.64	-0.54	6.73
2002	49	17.28	2.54	-1.67	9.18
2003	81	16.16	2.63	-1.69	7.86
2004	71	12.03	2.55	-1.26	7.50
2005	72	14.92	2.52	-0.78	11.36

Table 6.5: Average Climate Values Compared to Annual Total Cases for Tulare County					
	Cases Total	PM 2.5	Wind	PDSI	Precipitation
2006	105	15.21	2.55	-0.52	9.69
2007	56	14.72	2.50	-2.42	4.82
2008	91	16.20	2.71	-2.73	7.59
2009	96	11.47	2.85	-1.81	6.80
2010	121	11.27	2.81	-0.66	9.78
2011	87	11.41	2.93	-0.64	15.57
2012	55	10.45	2.88	-1.79	4.67

Predicting Valley Fever Seasons

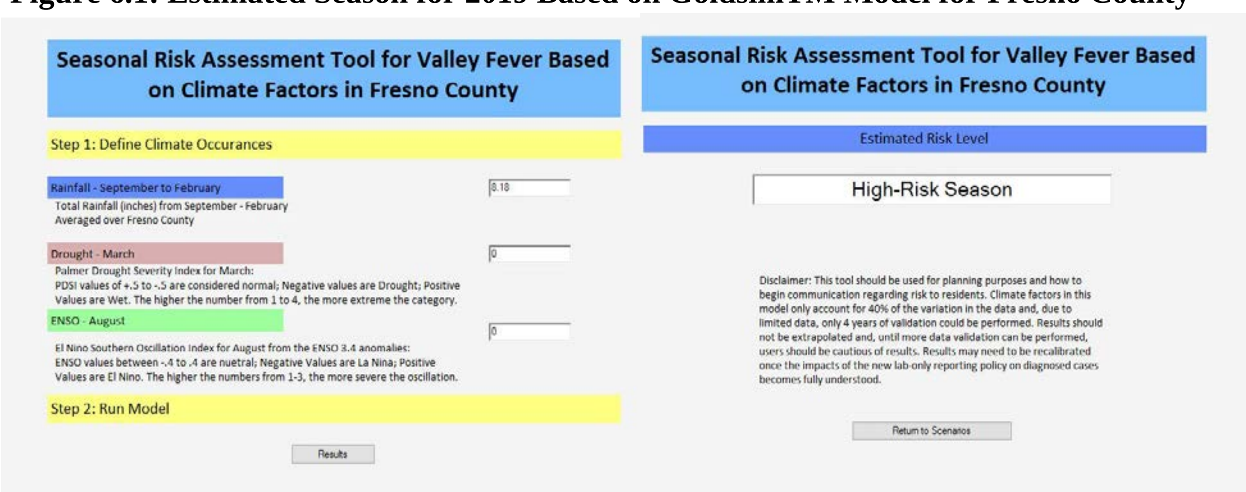
<u>Fresno</u>

Using Goldsim™, the number of monthly cases is set up around the average number of monthly cases for Fresno plus the amount of total September to February rainfall multiplied by the rainfall coefficient in Table 6.6 plus the PDSI value multiplied by the PDSI coefficient plus the sea surface temperature anomaly for ENSO 3.4 region multiplied by the ENSO coefficient. When the equation equals plus or minus 1 standard deviation from the average number of cases, the model changes the output to a different risk category.

Table 6.6: Fresno County Model for Scenario Tool		
Climate Variable	Coefficient	P-Value
Rainfall – September to February	1.3137	<.0001
PDSI in March	3.236	<.0001
El Nino in August	-6.8116	<.0001

Figure 6.1 shows the interface for the Goldsim™ model for Fresno County. The current input values for this model are set up to estimate the 2019 Valley Fever season. Currently, there has been 8.18 inches of rainfall from September 2018 to February 2019. Drought in March is looking to be Neutral and ENSO is estimated to be Neutral in the Fall season of 2019. This together estimated that 2019 will be a high-risk season.

Figure 6.1: Estimated Season for 2019 Based on GoldsimTM Model for Fresno County



The model was validated from 2014–2017 and accurately estimated the season for this time frame. However, this tool should be used for planning purposes and how to begin communication regarding risk to residents. Climate factors in this model only account for 40% of the variation in the data and, due to limited data, only 4 years of validation could be performed. Results should not be extrapolated and, until more data validation can be performed, users should be cautious of results. Results may need to be recalibrated once the impacts of the new lab-only reporting policy on diagnosed cases becomes fully understood.

Kern

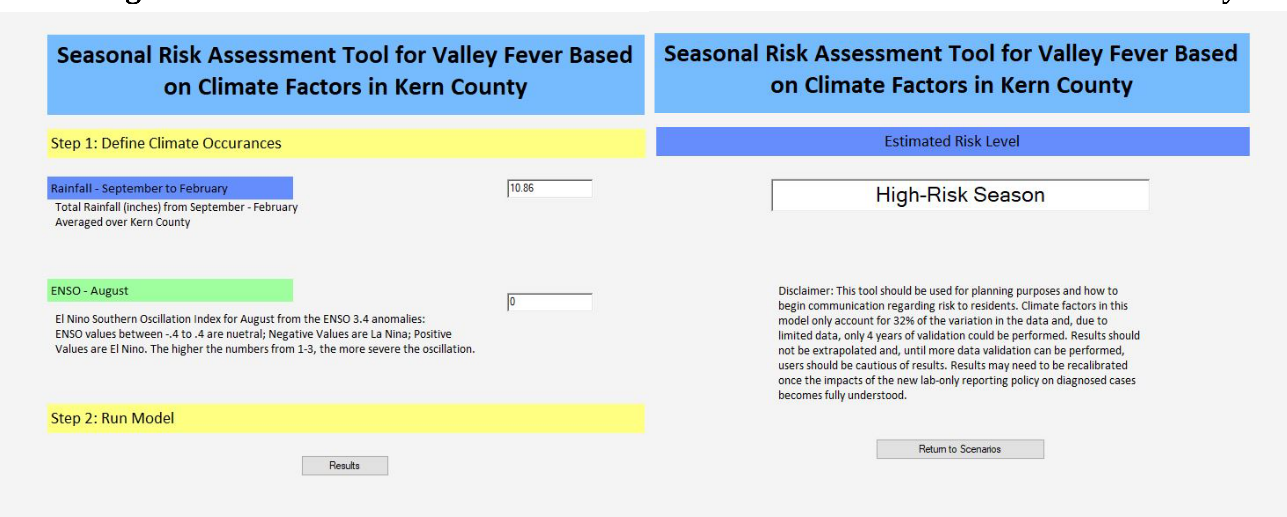
Using Goldsim™, the number of monthly cases is set up around the average number of monthly cases for Kern County plus the amount of total September to February rainfall multiplied by the rainfall coefficient in Table 6.7 plus the sea surface temperature anomaly for ENSO 3.4 region multiplied by the ENSO coefficient. When the equation equals plus or minus 1 standard deviation from the average number of cases, the model changes the output to a different risk category.

Table 6.7: Kern County Model for Scenario Tool

Climate Variable	Coefficient	P-Value
Rainfall – September to February	10.214	<.0001
El Nino in August	-16.288	<.0001

Figure 6.2 shows the interface for the Goldsim™ model for Kern County. The current input values for this model are set up to estimate the 2019 Valley Fever season. Currently, there has been over 10 inches of rainfall from September 2018 to February 2019. ENSO is estimated to be Neutral in the Fall season of 2019. This together estimated that 2019 will be a high-risk season.

Figure 6.2: Estimated Season for 2019 Based on Goldsim™ Model for Kern County



The model was validated from 2014–2017 and accurately estimated the season for this time frame. However, this tool should be used for planning purposes and how to begin communication regarding risk to residents. Climate factors in this model only account for 32% of the variation in the data and, due to limited data, only 4 years of validation could be performed. Results should not be extrapolated and, until more data validation can be performed, users should be cautious of results. Results may need to be recalibrated once the impacts of the new lab-only reporting policy on diagnosed cases becomes fully understood.

Kings

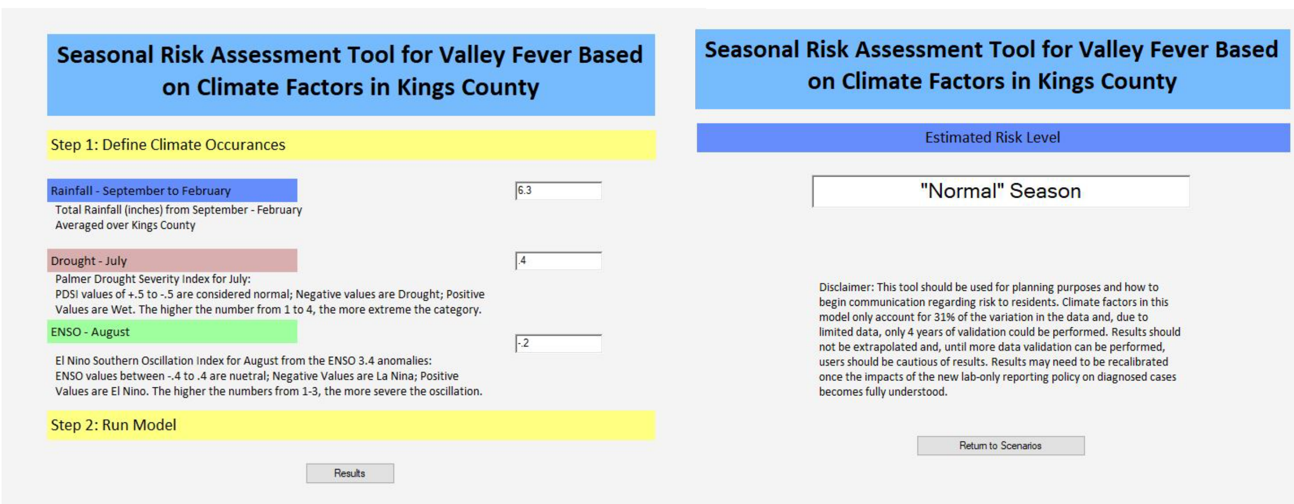
Using Goldsim™, the number of monthly cases is set up around the average number of monthly cases for Kings County plus the amount of total September to February rainfall multiplied by the rainfall coefficient in Table 6.8 plus the PDSI value multiplied by the PDSI coefficient plus the sea surface temperature anomaly for ENSO 3.4

region multiplied by the ENSO coefficient. When the equation equals plus or minus 1 standard deviation from the average number of cases, the model changes the output to a different risk category.

Table 6.8: Kings County Model for Scenario Tool		
Climate Variable	Coefficient	P-Value
Rainfall – September to February	1.1766	<.0001
PDSI in March	-1.4009	<.0001
El Nino in August	-5.2741	<.0001

Figure 6.3 shows the interface for the Goldsim™ model for Kings County. The current input values for this model are set up to estimate the 2019 Valley Fever season. Currently, there has been 6.3 inches of rainfall from September 2018 to February 2019. Drought in July is looking to be Neutral and ENSO is estimated to be Neutral in the Fall season of 2019. This together estimated that 2019 will be a normal season. However, this scenario tool can be used to play some "what-if" scenarios. For example, this model can answer "What if the Drought Level in July will be at a Level 2?"

Figure 6.3: Estimated Season for 2019 Based on Goldsim™ Model for Kings County



The model was validated from 2014-2017 and accurately estimated the season for this time frame. However, this tool should be used for planning purposes and how to begin communication regarding risk to residents. Climate factors in this model only account for 31% of the variation in the data and, due to limited data, only 4 years of validation could be performed. Results should not be extrapolated and, until more data validation can be performed, users should be cautious of results. Results may need to be recalibrated once the impacts of the new lab-only reporting policy on diagnosed cases becomes fully understood.

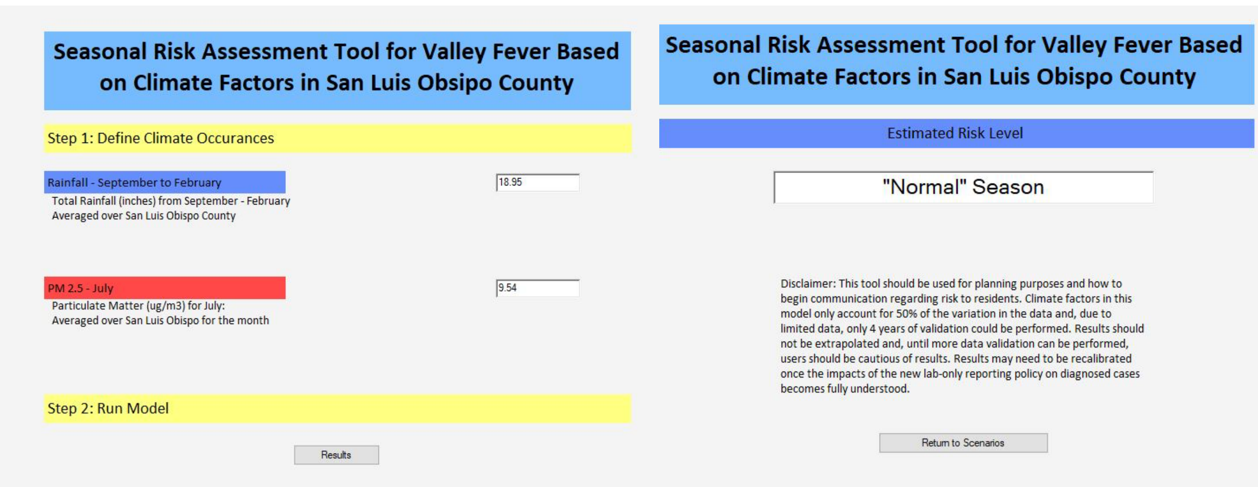
San Luis Obispo

Using Goldsim™, the number of monthly cases is set up around the average number of monthly cases for San Luis Obispo County plus the amount of total September to February rainfall multiplied by the rainfall coefficient in Table 6.9 plus the PM 2.5 concentration for July multiplied by the PM 2.5 coefficient. When the equation equals plus or minus 1 standard deviation from the average number of cases, the model changes the output to a different risk category.

Table 6.9: San Luis Obispo County Model for Scenario Tool		
Climate Variable	Coefficient	P-Value
Rainfall – September to February	.59174	<.0001
El Nino in August	-.47655	<.0001

Figure 6.4 shows the interface for the Goldsim™ model for San Luis Obispo County. The current input values for this model are set up to estimate the 2019 Valley Fever season. Currently, there has been over 19 inches of rainfall from September 2018 to February 2019. Average PM 2.5 concentration for July is around 9 ug/m^3. This together estimated that 2019 will be a normal season.

Figure 6.4: Estimated Season for 2019 Based on GoldsimTM Model for San Luis Obispo County



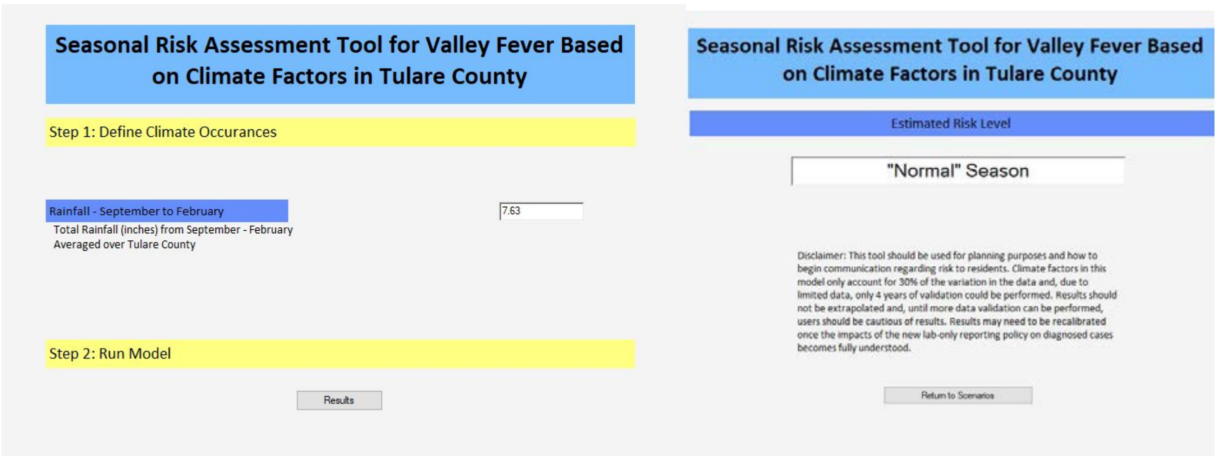
The model was validated from 2014–2017 and accurately estimated the season for this time frame. However, this tool should be used for planning purposes and how to begin communication regarding risk to residents. Climate factors in this model only account for 50% of the variation in the data and, due to limited data, only 4 years of validation could be performed. Results should not be extrapolated and, until more data validation can be performed, users should be cautious of results. Results may need to be recalibrated once the impacts of the new lab-only reporting policy on diagnosed cases becomes fully understood.

<u>Tulare</u>
Using Goldsim™, the number of monthly cases is set up around the average number of monthly cases for Tulare County plus the amount of total September to February rainfall multiplied by the rainfall coefficient in Table 6.10. When the equation equals plus or minus 1 standard deviation from the average number of cases, the model changes the output to a different risk category.

Table 6.10: Tulare County Model for Scenario Tool		
Climate Variable	Coefficient	P-Value
Rainfall – September to February	.5199	<.0001

Figure 6.5 shows the interface for the Goldsim™ model for Tulare County. The current input values for this model are set up to estimate the 2019 Valley Fever season. Currently, there has been over 7 inches of rainfall from September 2018 to February 2019. This estimated that 2019 will be a normal season.

Figure 6.5: Estimated Season for 2019 Based on GoldsimTM Model for Tulare County



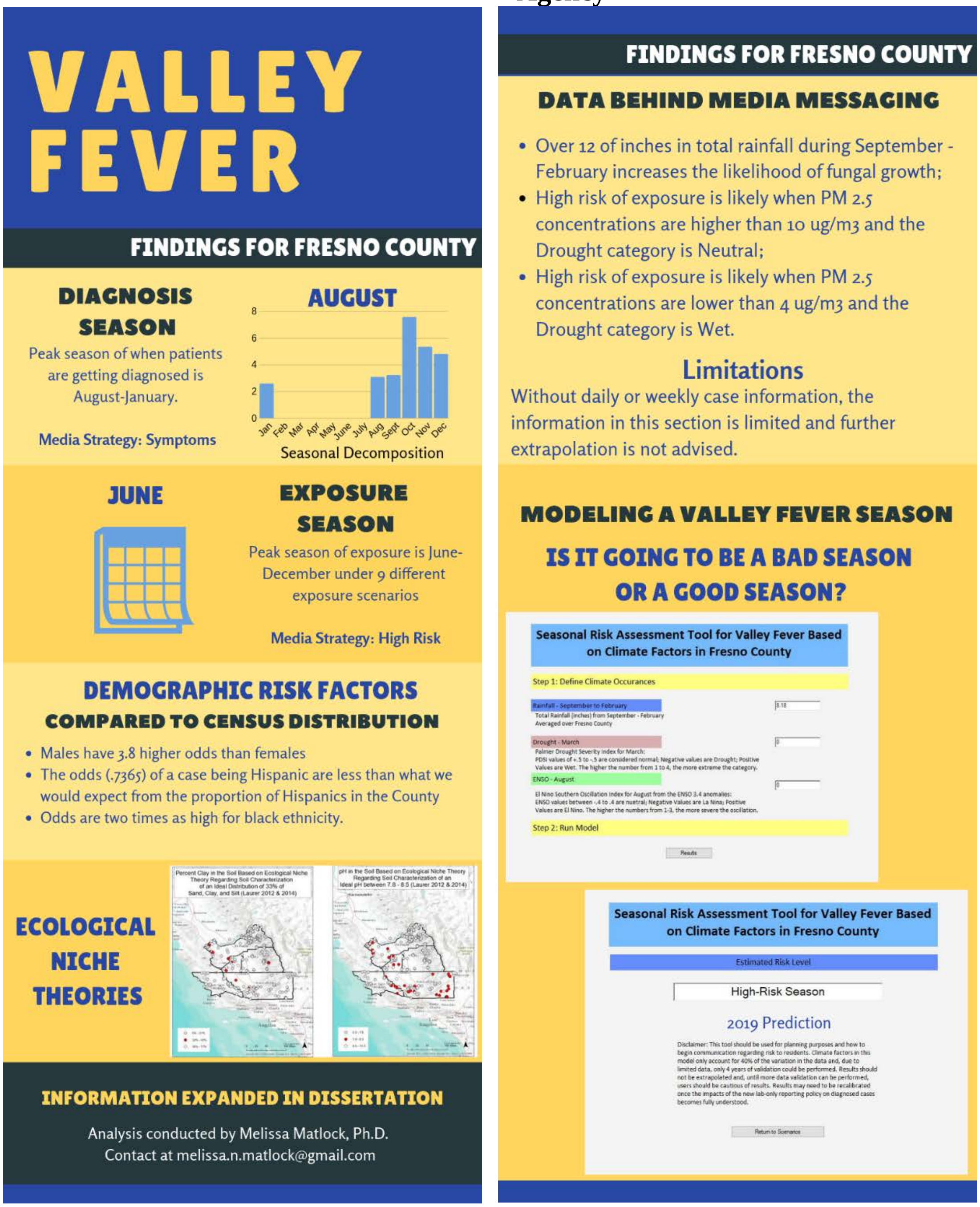
The model was validated from 2014–2017 and accurately estimated the season 50% of the time for this time frame. The model tended to gravitate towards Normal Season when the season was actually Lower than Normal. Climate factors in this model only account for 30% of the variation in the data and, due to limited data, only 4 years of validation could be performed. Results should not be extrapolated and, until more data validation can be performed, users should be cautious of results. Results may need to be recalibrated once the impacts of the new lab-only reporting policy on diagnosed cases becomes fully understood.

Communication Research Briefs for Public Health Agencies as the Audience

Taking all the information and analysis of chapters 1 through 6, a research brief for each county's public health agency was developed that summarizes the main findings. The following subsections show examples of the briefs for each county. The brief is double-sided single page document. In the images below, the left side is page one, and the right side is page two.

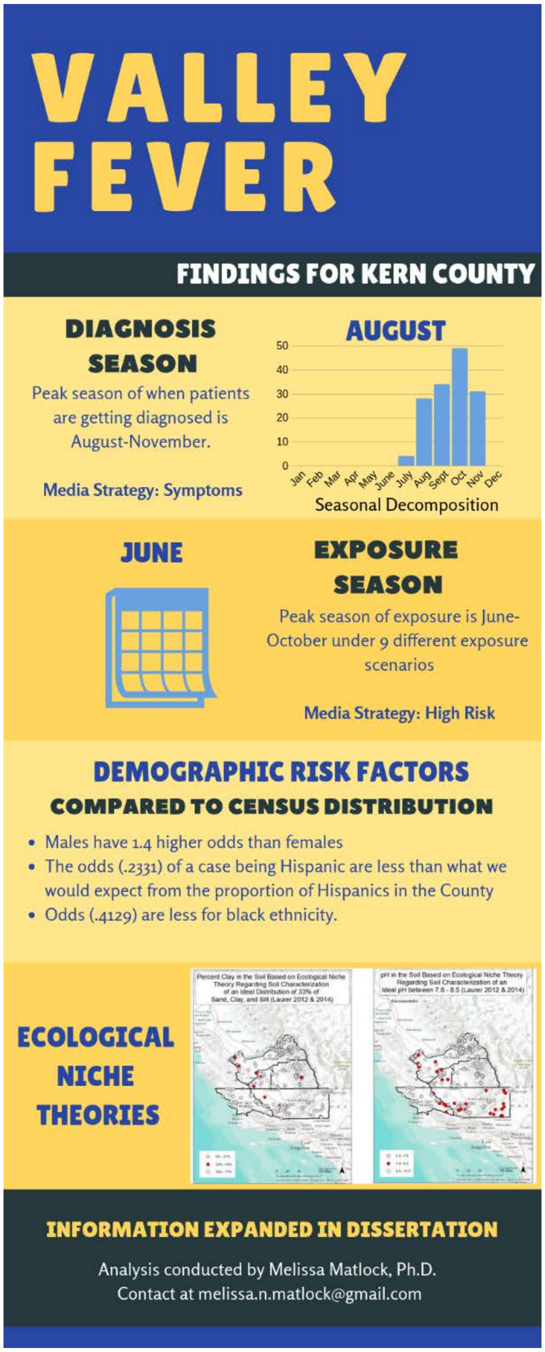
Fresno

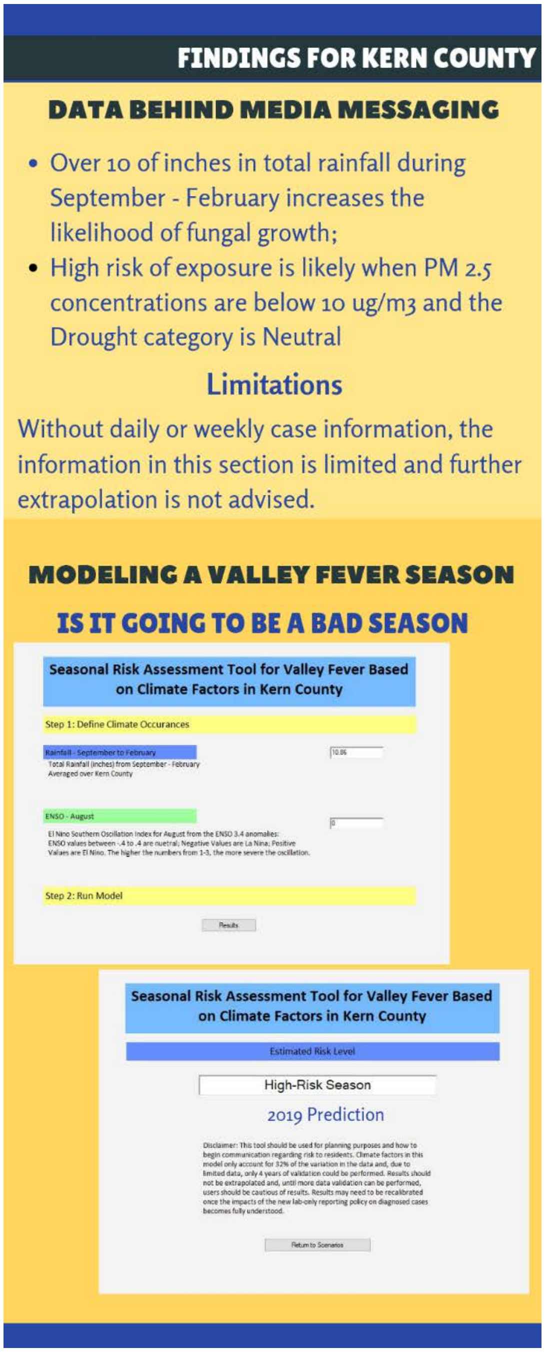
Figure 6.6: Valley Fever Research Communication Brief for Fresno County Public Health Agency



Kern

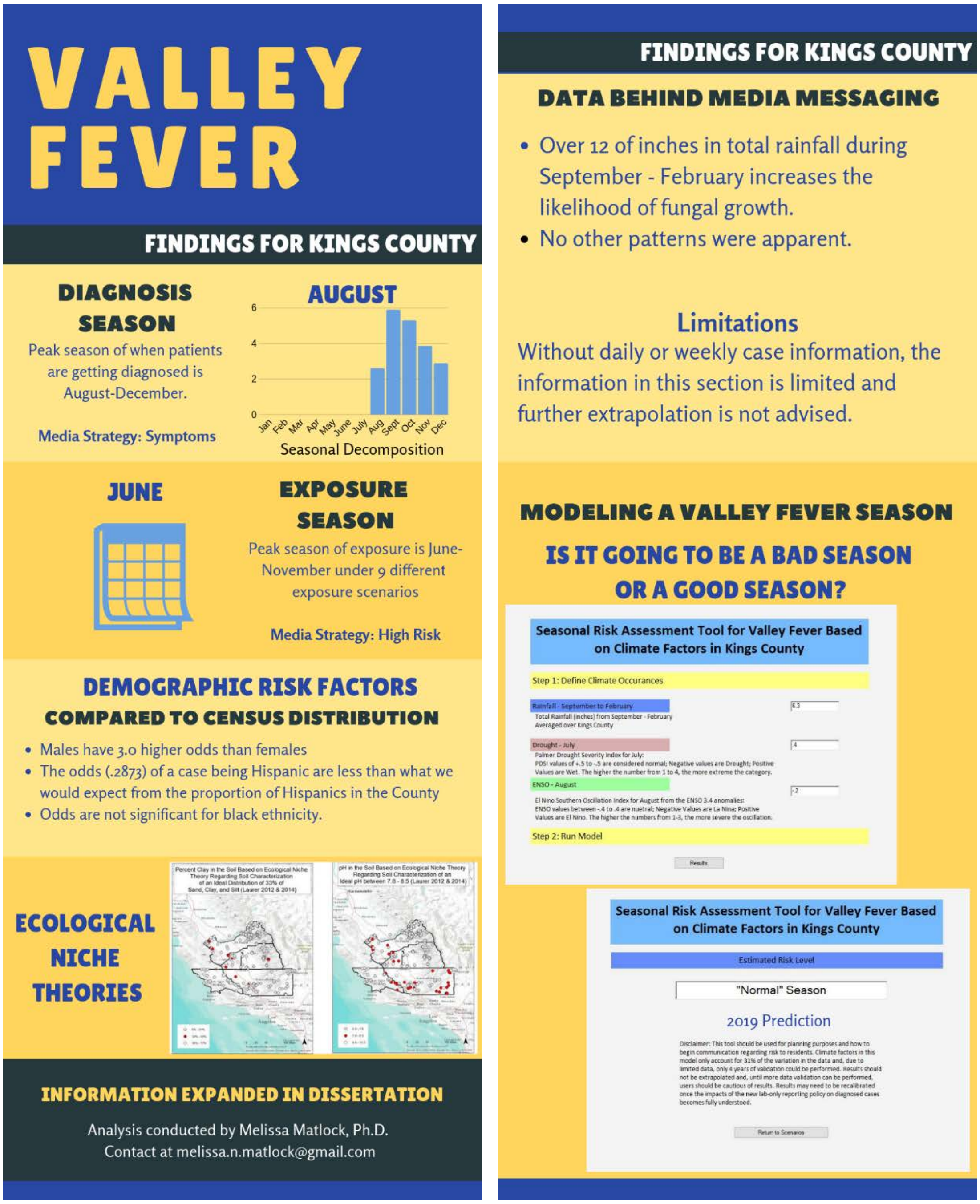
Figure 6.7: Valley Fever Research Communication Brief for Kern County Public Health Agency





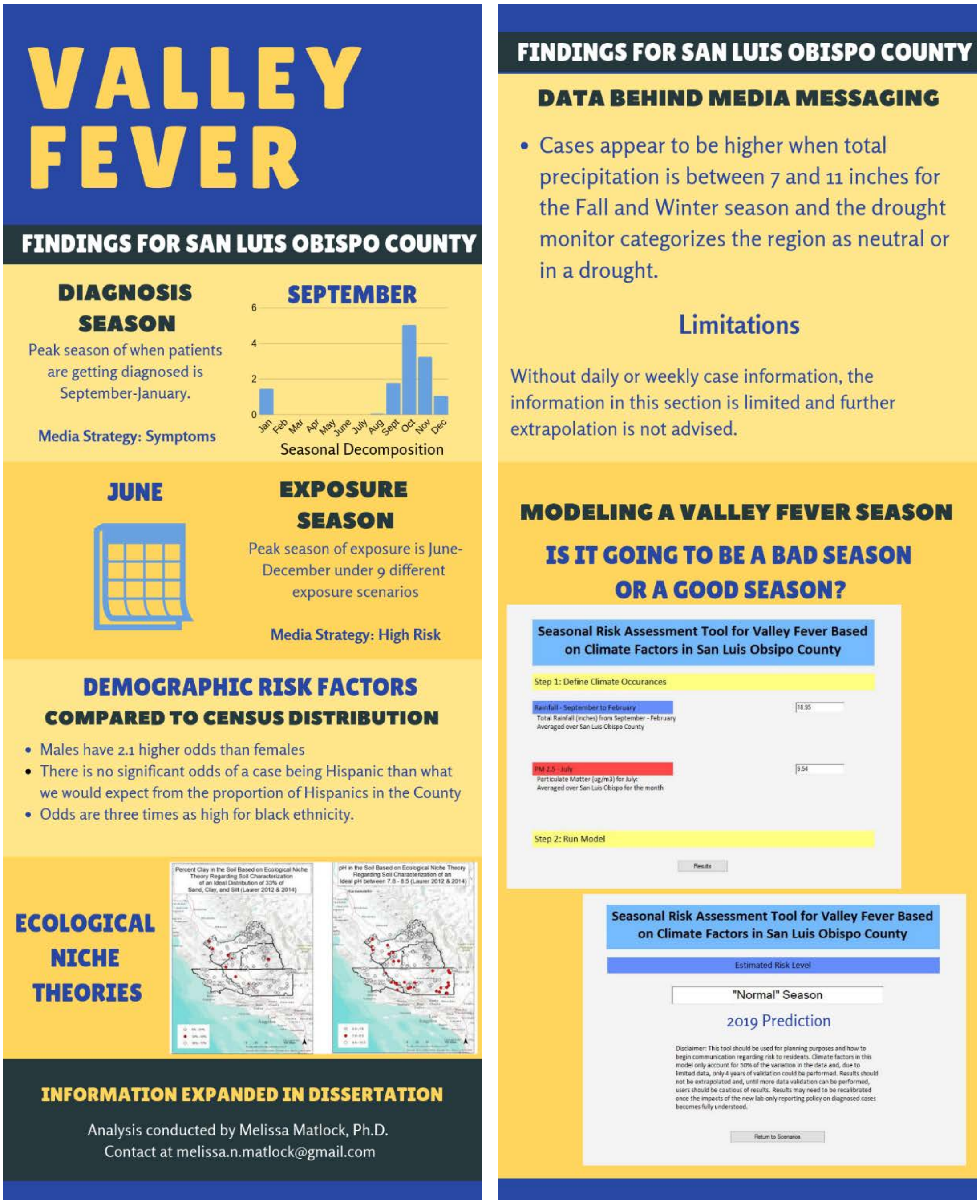
Kings

Figure 6.8: Valley Fever Research Communication Brief for Kings County Public Health Agency



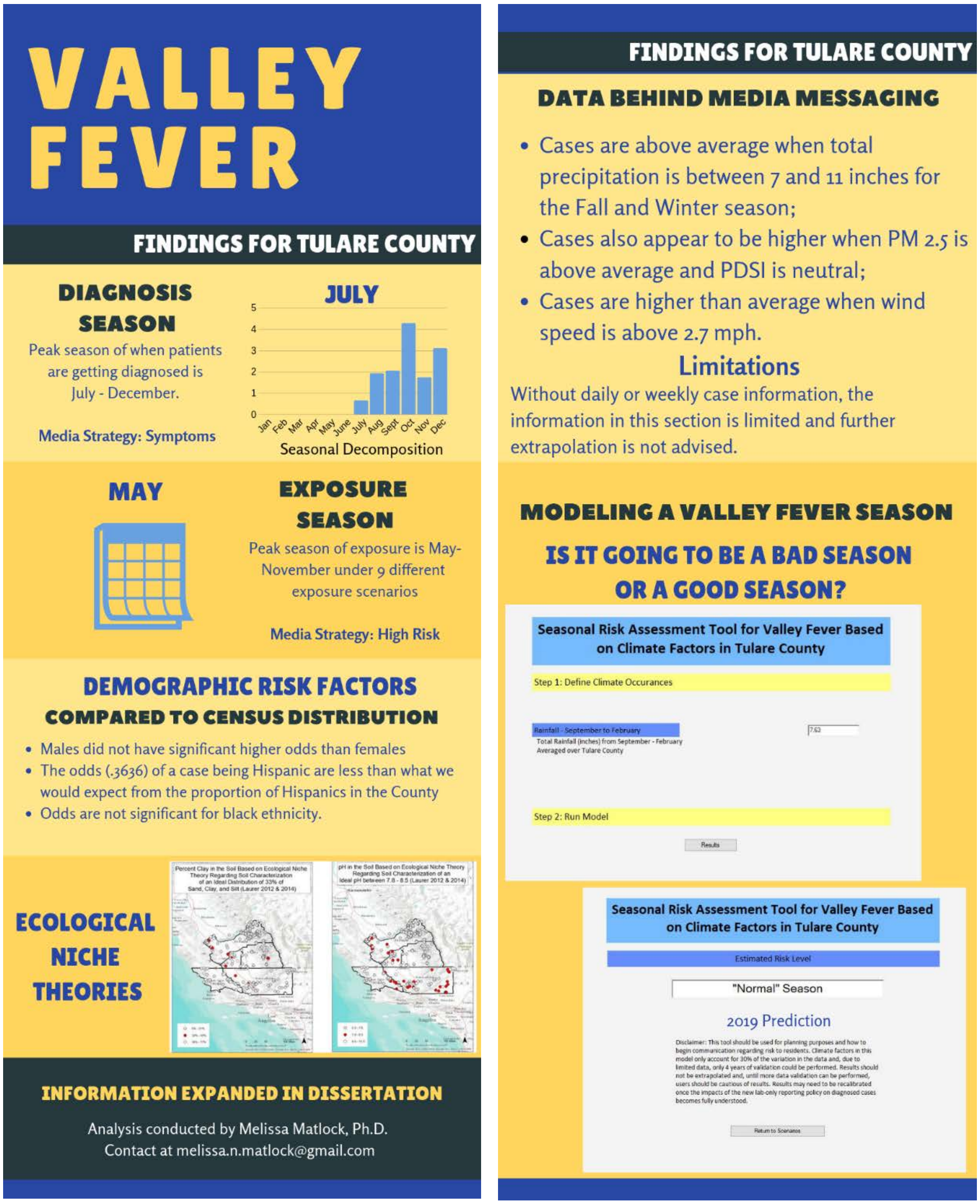
San Luis Obispo

Figure 6.9: Valley Fever Research Communication Brief for San Luis Obispo County Public Health Agency



Tulare

Figure 6.10: Valley Fever Research Communication Brief for Tulare County Public Health Agency



Discussion

The research conducted in this dissertation shows what questions can be answered with the data provided and provides tailored information for the five counties in California with the highest incidence. It is the hope that if public health agencies could grant researchers access to case data, researchers could provide further refined information, furthering the Valley Fever communication efforts. An example of this can be seen in the risk scenario models. If data provided from the counties included zip codes, the analysis could be conducted looking at the relationships between local climate factors and case diagnosis. From that, a risk model could be developed to describe when a certain zip code is at higher risk. This information could be used to provide further education and safety requirements to construction workers that have plans to disturb soils during the certain time of the year and in the zip code that’s at risk.

Conclusion

Summary

This dissertation sought out to understand the relationship between climate factors and Valley Fever cases in Central Californian counties of Fresno, Kern, Kings, San Luis Obispo, and Tulare.

<u>What does the Valley Fever data look like in the California counties of Fresno, Kern, Kings, San Luis Obispo, and Tulare?</u>

Patterns of Valley Fever outbreak and exposures are not homogenous across the counties. Although most of the counties have their diagnosis season begin in August, the length of the season is not the same. According to a time series decomposition, Tulare County's season starts in July and San Luis Obispo County's season starts in September.

In addition, demographic risk factors are not the same across the counties. All the counties, except Tulare County, the analysis found that males had a higher odds than females of getting the disease. This is likely confounded by occupation although that hypothesis could not be analyzed in this study.

These five counties have a large Hispanic population. However, the odds of a case being Hispanic are less than what we would expect to have happened based on the demographic distribution of the counties. San Luis Obispo County found no significant odds of a Hispanic case.

When looking at a black ethnicity, Fresno and San Luis Obispo Counties found that the odds of a case being black were higher than expected, but Kern County found the odds to be less than expected. Kings and Tulare found the odds to be not significant.

These results indicate that each county should be analyzed separately and outreach designed for one county may not be appropriate for another county.

<u>What climate relationships are found to have a significant relationship with Valley Fever cases considering local versus county-wide averages, different exposure scenarios, and different mathematical methods?</u>

This study analyzed climate relationships on eight climate variables. These variables include Precipitation, Temperature, Wind Speed, ETo, PDSI, ENSO, PM 2.5, and PM 10. Lags were incorporated to observe if a previous month's climate has a significant relationship on disease numbers. In addition, three Exposure Scenarios were modeled in this study. However, timing and distribution assumptions were also modeled in this study, making a total of ten scenarios. Lastly, two quantitative methods, linear regression and Poisson regression were used to conduct the analysis.

When comparing climate sites to each other with a county, the general findings are that sites within a county do not have the same directionality. One example, in Kern County, average monthly wind speed for Wind Sites 1, 3, and 4 have a negative significant correlation with their corresponding exposure scenarios, but Site 2 has a positive significant correlation. Further details of this example is presented in chapter 4. When averaging the sites together, the extreme variability that is present in some sites becomes minimized.

When comparing climate variables to different exposure scenarios, some patterns emerge that would be what someone might expect, like a relationship with month 1 precipitation in one scenario might suggest that month of diagnosis would be significant for a exposure scenario based on a 30 day incubation and symptom lag period. However, this does not occur for every variable. An example of this can be seen in Fresno County. For the average of the precipitation sites, the Actual exposure scenario and the EMST scenario found significant relationships between precipitation that occurs during 6-12 months prior. Since EMST was the same in Precipitation as Actual, we might expect that pattern to persist in the other climate variables. It does not. Overall similar patterns do emerge but there is a lack of consistency in those patterns.

When using Poisson regression, not all the variables that were significant in the linear model were significant in the Poisson and Quasipoisson model. Common variables that were not significant were Temperature, Wind, and PM 10. However, the directionality of the relationships stays the same when the quantitative method changed.

Overall, there is a general trend across the study area with the climate impacts, but the months are not the same and there are also some notable differences. With only 50% of the data being explained by significant climate variables, there still leaves more room for confounding variables and other variables not looked at.

Overall, Precipitation was found to be significant in every county. Typically, 6-12 months prior to diagnosis, the more precipitation that occurs, incidence increases. 0-2 months to diagnosis, the more precipitation that occurs, the trend is that incidence decreases. This pattern is found to occur in all five counties.

Aside from San Luis Obispo County, ENSO 3.4 Anomaly did find a significant relationship with cases being diagnosed and exposed in every county and almost every exposure period. The same describes PDSI. These two variables are not like Precipitation where they are measured at a specific geographic area and represent impacts to that geographical area. ENSO and PDSI have a wider interannual scale and impacts the region in a similar manner.

With 50% of the data explained by the climate variables, one consistent pattern that appears is the cumulative rain occurring 7-12 months prior to the start of the exposure period for each county. This does align with the “Grow” portion of the “Grow and Blow” Effect Hypothesis. However, the information presented here does not provide enough evidence to support or disprove the Hypothesis. The information presented in this study indicate that although tendencies of this Hypothesis appear, there is a more complicated relationship occurring that needs to be explored further.

<u>How can the information generated in this dissertation be communicated to Public Health agencies regarding the relationship between climate and Valley Fever?</u>

Public Health Agencies of Fresno, Kern, Kings, San Luis Obispo, and Tulare Counties are interested in incorporating climate thresholds and seasonal risk estimations into their communication and media strategies. These agencies made analogies to bad air quality days and flu risk season. However, they also addressed the need for better prevention strategies and action items for their community.

Future Research

The results of this dissertation should be a bridge between what previous research by others has shown what has been done currently and the needs for additional knowledge and understanding regarding climate’s relationship to Valley Fever and the communication dialog between researchers and public health agencies. There are many obstacles, such as bureaucratic policies, in the study of Valley Fever and its relationship to climate. Researchers are currently at an impasse with providing new theories or research results until these obstacles are addressed.

Ecological Fallacy

Ecological inferences are inferences about individual behavior drawn from data about aggregates. The exposure and response variables are measured in aggregates and are typically common for ecological studies (Piantadosi (1988), Schwartz (1994), Freedman (1999)). The differences between findings at the individual level compared to the aggregate level can be attributed to bias related to confounding variables and aggregation. The ecological fallacy is when relationships at the aggregate level are assumed to occur at the individual level. This can lead to incorrect conclusions. This study was conducted at the county-wide aggregate level due to limitations in data access. There were several forms of aggregation (case location, date of diagnosis, and climate averages) in this study that impacts the ecological fallacy. Due to the concept of the ecological fallacy, the results of this study would be inappropriate to extrapolate to an individual level.

Stability of Findings

Overall, this study has several large limitations that stem from the level of data able to be accessed. When trying to analyze a relationship to climate, it is understood that climate varies with time and poses spatial challenges, especially when applied to small regions. For example, temperature varies by season, where it is typically cooler in the winter months and warmer in the summer months. In addition to variation between seasons, temperature can also vary drastically within the same month. For example, a week long heat wave could occur during a month, raising the temperature for that week by over 10 degrees. In addition to variation within a season, climate can also vary over a timescale of a day. For example, temperature is higher in the middle of the day and cooler in the mornings and evenings. When you look at climate, aggregating the shorter timescales into a larger timescale, like daily climate into an average of the climate for the month, variability is inherently decreased.

Although patterns did arise with climate and Valley Fever in the five counties of interest, the analysis was conducted on a monthly timescale. When looking at thresholds discussed in chapter 6, these thresholds are based on an average monthly value, when some climate relationships might be stronger on a smaller time-scale like a week. This limits the overall validity of the findings.

In addition, the counties vary widely in terms of climate and geography. By averaging across all climate sites to get an overall climate value for the county for the month, the data was limited. Future researchers need to look at each individual diagnosed case and link them to a specific geographic-based climate station. This could be an explanation for why climate variables that impact the region on a larger geographical scale were more likely to have a significant relationship in this study.

There is consistency in this research study and the inferences and patterns that emerged were consistent across different methodological scenarios. However, the limited access to data at a disaggregated level did limit the scale of the research progress related to this field of study.

Methodology Concerns and Best Practices

The initial studies conducted on Valley Fever have provided a helpful first step in the understanding of Valley Fever. The findings in this study should be used to help researchers become aware and address methodological limitations, such as quantitative methodology and exposure lags, in their future research. Until research on the incubation period and symptom to diagnosis lag is fully developed, researchers should include several attempts to understand the exposure period of their cases in their analyses and how it changes with climate lags. Researchers should also conduct a broader climate analysis in understanding the environment's relationship with Coccidioidomycosis exposure. Instead of just focusing on precipitation and temperature, analysis should also include different methods of accounting for soil moisture and dust exposure.

Research should also be conducted on a smaller spatial scale and for more endemic regions. Although Kern County has the highest Coccidioidomycosis incidence in California, research conducted in that county is not appropriate to apply to other counties in California. In addition, conducting analyses at the county level may not be appropriate. For example, Los Angeles County saw a spike in incidence of Coccidioidomycosis in 2016 and 2017. However, most of those cases are from the Antelope Valley, a small portion of Los Angeles County. Future research should consider doing analysis at zip code level, census blocks, and/or climate microzones.

Finally, how does the study of Coccidioidomycosis exposure and climate change based on different methodologies? What do the results look like under Poisson regression? How do those same results look under Logistic regression? Would a time series approach capture the complicated relationships? Until a consensus can be developed among researchers, future studies should consider comparing their results across the different statistical methodologies.

Estimating Coccidioidomycosis exposure is an important research step to prevent future outbreaks of the disease. For the relationship between the research community and the general population, it is critical for future research to try to minimize the limitations presented in this study.

This study suggests the following protocol as a best practice until the scientific community can get together to address the fundamental issues related to the study of Valley Fever. The best practices include:

- Analyze data at a smaller spatial scale with climate more closely tied to that geography;
- Include several attempts to understand how different incubation periods and symptom onset to diagnosis lags affect the results;
- Analyses should include different methods of accounting for soil moisture and dust exposure;
- Include several attempts to understand how results change under different quantitative modeling efforts;

- Partner with public health agencies on how to apply a future study's results and conclusions;
- Control for confounding variables like occupation and nearby construction activities;
- Conduct analyses on case files and include several attempts to understand how aggregating the data at different temporal and spatial scales affect the results and the ecological fallacy.

Resources and Capacity

Valley Fever is a challenge for Californian Public Health Agencies because there are limited resources and capacity to accommodate proper diagnosis, treatment, and surveillance. Valley Fever is a challenge for public health management. Current the onus of the Valley Fever research and management is put on the individual county agencies. Why should each county carry the burden of this management, when they have no resources or capacity to change their current limited management of the disease, when the disease does not respect the geo-political boundaries? This disease should be a statewide problem and provided dedicated resources from the state. Possibly, a larger effort from agencies like the National Institutes of Health – Infectious Disease Branch or Environmental Health Branch - should be made to provide funding and support to local agencies in the entire United States endemic region.

However, providing dedicated dollars to these agencies for increased surveillance will not solve the entire problem, because it is not just about resources. There are bureaucratic barriers in place that limit research partnerships. For example, when the Principle Investigator received Institutional Review Board Approval to conduct this analysis using case data, the California Department of Public Health changed their data sharing policy. When reaching out to the individual county agencies, the legal departments rejected the request because there is no statement addressing that a Valley Fever diagnosed patient's data may be used for research. Even when the research was deemed to be minimal risk and the proper safety protocols in place, data was not able to be shared.

When reaching out to one county's public health agency where the principal investigator had more rapport with the staff to see if that county's data could be used as a comparison county analysis, the principal investigator was told by the staff that they did not feel any conclusions could be drawn so they would not provide the data. However, even with the summary data that was provided, months with cases under 10 were collapsed, so even analyzing demographic risks were limited to 2010 and 2015, as those were the years with no collapsed fields. Due to the collapsed fields, this study was unable to identify if there were confounding risks when we look at the interaction of Age and Ethnicity and Gender. We were unable to aggregate the data differently to align with population estimates. We were unable to verify the findings in previous studies to see if one ethnicity or age group is proportionately getting hospitalized over another. With collapsed fields, we were unable to look at how the odds may have changed over time, all forms that should be a valuable resource of information for the public health agencies.

Until the state and/or national government provides dedicated funding for addressing Valley Fever, the best course of action is to target resources and target capacity into partnerships with research institutions. These partnerships would create an open dialog between the researchers and the agencies where the research can be guided by the agencies' need as well as creating memorandum of understanding and data sharing policies and agreements so the data can be done in the "Gold Standard" best practice with health data analysis. Another suggestion would be to create a Valley Fever registry, similar to the cancer registry, where researchers with approved protocols and permissions can download data for analysis.

Behavior Adaptation

The public health agencies discussed individuals avoiding going outside when it is dusty or windy to avoid getting Valley Fever. These agencies understood that this type of health campaign is unrealistic because the behavior cannot be avoided as it is usually tied to occupation. These agencies utilize a Behavior Adaptation Model (BAM) to provide adoption of a specific practice so that their community member's risk is reduced (Parrott, 1998).Currently, these agencies discuss wearing N95 respirators during the Valley Fever season. However, these agencies still see construction workers and farmers being diagnosed with Valley Fever. It is unrealistic to ask people to wear the mask all day. It is too hot.

With no confirmed theory relating climate to Valley Fever exposure, these agencies are interested in an approach that can handle uncertainties but can provide specific actions the agency can take – like poor Valley Fever day – stay inside/ stop construction work. Perhaps incorporating climate into a BAM, farmers can understand that they are at a higher risk because of the low water allocation and to wear the mask and pay for the water to keep the fields wet.

Instead of a message geared for protection the whole season, the message can be made when the climate threshold is triggered.

However, in order to do that, the scientific research is not currently relatable for media strategies. There is a need to communicate the research to the end-user, being aware of the Public Health Agency's staff time (or lack thereof) and how the information could be used for the timing or content of the media strategy.

Current research does not identify climate thresholds and future research should be undertaken at to address thresholds. For the Public Health Agencies, stating wind speed is correlated with disease outbreak was suggested that it was not a helpful statement. As an example, not related to the data – just used for demonstration purposes, these agencies found that a statement like windspeed that is under 5 mph is linked to increase exposure is more helpful. It provides more content for the media strategy. However, Public Health Agencies should be aware that to get more specific in terms of mph threshold and links, daily and monthly case data should be provided to researchers. In addition, if the goal is to develop a program where on a high exposure day, construction activities are halted, more information than general relationships would need to be provided to justify the economic tradeoffs between work stoppages to avert Valley Fever versus the work-time losses from contracting the illness.

Future Exploration

A true partnership between researchers and public health agencies needs to focus on constant communication and open-ended efforts, not about just getting published or creating a research brief and calling the work done. However, as these agencies do not currently have partnerships and data use memoranda with research institutions, researchers studying Valley Fever are limited in their results. Many of the agencies did not know the benefits of climate information and how it could be used in their media strategies. Many of the agencies look to research conducted in other counties and investigations that are over five years old for their Valley Fever information.

More research should focus on occupation as a confounding variable. Additionally, researchers need to partner with local agencies to get Valley Fever on research agendas and to determine how their results can be applied to the region's understanding and communication strategies regarding its prevention, diagnosis, and prediction. Future researchers should run sensitivity analyses on their results with regards to different exposure assumptions and quantitative methods. Public health agencies should work with researchers to provide data that can help shed light on these relationships.

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Appendix

Table A.1 ANOVA: Single – Factor Results for Fresno County Diagnosis Date and Exposure Estimates Organized by County Name_Diagnosis Assumption (Equal – EM, 75% in first half – 75, 25% in first half – 25)_Exposure Method (Stacey – ST, Park – PM, Comrie – CM).

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Fresno_Actual	192	5278	27.48958	632.2931
Fresno_EMST	180	5025.5	27.91944	617.5703
Fresno_EMPM	180	5034.5	27.96944	615.3636
Fresno_EMCM	180	5043.5	28.01944	613.1519

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	33.51482	3	11.17161	0.018024	0.996706	2.617136
Within Groups	451217.3	728	619.804			
Total	451250.8	731				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Fresno_Actual	192	5278	27.48958	632.2931
Fresno_75ST	192	5276.5	27.48177	598.8275
Fresno_75PM	192	5275.25	27.47526	599.179
Fresno_75CM	192	5273.5	27.46615	599.6664

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.056885	3	0.018962	3.12E-05	1	2.616558
Within Groups	464123.5	764	607.4915			
Total	464123.6	767				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Fresno_Actual	192	5278	27.48958	632.2931
Fresno_25ST	192	5277.5	27.48698	598.5502
Fresno_25PM	192	5275.75	27.47786	599.0378
Fresno_25CM	192	5274.5	27.47135	599.3892

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.040609	3	0.013536	2.23E-05	1	2.616558
Within Groups	463990.6	764	607.3176			
Total	463990.7	767				

Table A.2 ANOVA: Single – Factor Results for Kern County Diagnosis Date and Exposure Estimates Organized by County Name_Diagnosis Assumption (Equal – EM, 75% in first half – 75, 25% in first half – 25)_Exposure Method (Stacey – ST, Park – PM, Comrie – CM).

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Kern_Actual	192	20356	106.0208	4566.199
Kern_EMST	180	19297.5	107.2083	4358.237
Kern_EMPM	180	19321.5	107.3417	4341.404
Kern_EMCM	180	19345.5	107.475	4322.925

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	253.5041	3	84.50137	0.019205	0.996381	2.617136
Within Groups	3203183	728	4399.977			
Total	3203437	731				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Kern_Actual	192	20356	106.0208	4566.199
Kern_75ST	192	20333.5	105.9036	4302.357
Kern_75PM	192	20299.75	105.7279	4333.788
Kern_75CM	192	20286.5	105.6589	4346.709

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	15.65649	3	5.218831	0.00119	0.999943	2.616558
Within Groups	3351869	764	4387.263			
Total	3351885	767				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Kern_Actual	192	20356	106.0208	4566.199
Kern_25ST	192	20348.5	105.9818	4288.072
Kern_25PM	192	20317.25	105.819	4317.613
Kern_25CM	192	20286.5	105.6589	4346.709

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	15.82576	3	5.275255	0.001204	0.999942	2.616558
Within Groups	3346051	764	4379.648			
Total	3346067	767				

Table A.3 ANOVA: Single – Factor Results for Kings County Diagnosis Date and Exposure Estimates Organized by County Name_Diagnosis Assumption (Equal – EM, 75% in first half – 75, 25% in first half – 25)_Exposure Method (Stacey – ST, Park – PM, Comrie – CM).

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Kings_Actual	192	2310	12.03125	187.9467
Kings_EMST	180	2261	12.56111	177.4879
Kings_EMPM	180	2266	12.58889	176.925
Kings_EMCM	180	2270.5	12.61389	176.4297

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	44.14911	3	14.71637	0.081833	0.969908	2.617136
Within Groups	130918.6	728	179.8333			
Total	130962.8	731				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Kings_Actual	192	2310	12.03125	187.9467
Kings_75ST	192	2310	12.03125	175.4401
Kings_75PM	192	2310	12.03125	175.4401
Kings_75CM	192	2309.75	12.02995	175.4713

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.000244	3	8.14E-05	4.56E-07	1	2.616558
Within Groups	136431	764	178.5745			
Total	136431	767				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Kings_Actual	192	2310	12.03125	187.9467
Kings_25ST	192	2310	12.03125	175.4401
Kings_25PM	192	2310	12.03125	175.4401
Kings_25CM	192	2309.75	12.02995	175.4713

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.000244	3	8.14E-05	4.56E-07	1	2.616558
Within Groups	136431	764	178.5745			
Total	136431	767				

Table A.4 ANOVA: Single – Factor Results for San Luis Obispo County Diagnosis Date and Exposure Estimates Organized by County Name_Diagnosis Assumption (Equal – EM, 75% in first half – 75, 25% in first half – 25)_Exposure Method (Stacey – ST, Park – PM, Comrie – CM).

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
SLO_Actual	192	1393	7.255208	41.3429
SLO_EMST	180	1333	7.405556	35.90723
SLO_EMPM	180	1331.5	7.397222	35.98519
SLO_EMCM	180	1330	7.388889	36.07976

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	2.881574	3	0.960525	0.025686	0.994435	2.617136
Within Groups	27223.52	728	37.39494			
Total	27226.4	731				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
SLO_Actual	192	1393	7.255208	41.3429
SLO_75ST	192	1388.5	7.231771	36.36354
SLO_75PM	192	1386.25	7.220052	36.50728
SLO_75CM	192	1385	7.213542	36.58832

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.193604	3	0.064535	0.001712	0.999902	2.616558
Within Groups	28803.19	764	37.70051			
Total	28803.38	767				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
SLO_Actual	192	1393	7.255208	41.3429
SLO_25ST	192	1391.5	7.247396	36.23036
SLO_25PM	192	1386.75	7.222656	36.47209
SLO_25CM	192	1385	7.213542	36.58832

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.225505	3	0.075168	0.001996	0.999877	2.616558
Within Groups	28771.03	764	37.65842			
Total	28771.26	767				

Table A.5 ANOVA: Single – Factor Results for Tulare County Diagnosis Date and Exposure Estimates Organized by County Name_Diagnosis Assumption (Equal – EM, 75% in first half – 75, 25% in first half – 25)_Exposure Method (Stacey – ST, Park – PM, Comrie – CM).

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Tulare_Actual	192	2256	11.75	44.98429
Tulare_EMST	180	2145	11.91667	38.07123
Tulare_EMPM	180	2143.5	11.90833	38.18289
Tulare_EMCM	180	2146	11.92222	38.02464

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	3.908424	3	1.302808	0.032651	0.992075	2.617136
Within Groups	29047.9	728	39.90096			
Total	29051.81	731				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Tulare_Actual	192	2256	11.75	44.98429
Tulare_75ST	192	2252.25	11.73047	39.01434
Tulare_75PM	192	2245.75	11.69661	39.59039
Tulare_75CM	192	2241.75	11.67578	39.9961

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.638916	3	0.212972	0.005208	0.999483	2.616558
Within Groups	31244.76	764	40.89628			
Total	31245.4	767				

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Tulare_Actual	192	2256	11.75	44.98429
Tulare_25ST	192	2254.75	11.74349	38.77254
Tulare_25PM	192	2249.25	11.71484	39.28966
Tulare_25CM	192	2243.25	11.68359	39.83621

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.531494	3	0.177165	0.004351	0.999605	2.616558
Within Groups	31110.6	764	40.72067			
Total	31111.13	767				

A.6: Qualitative Research on Valley Fever Communication in Public Health agencies

Purpose: To identify the needs of Public Health agencies to communicate risk and preventive strategies about Valley Fever infection and symptoms. To discover the levels of access of Public Health agencies to different levels of disease case data, time of infection, and if additional information will improve disease prevention strategies for eliminating seasonal Valley Fever prevalence.
Participants of Interest:

First Approach

Survey of the 5 Public Health agencies servicing regions endemic for Valley Fever to assess their access to epidemiological data and how they use the data for public communication.

Method: SurveyMonkey for Survey Distribution to Participants

Source: Local Public Health System Performance Instrument

Background

1. Name of Local Health Department:
2. Address:
3. Name of Director of Public Health:
4. Your Name:
5. Your Title:
6. Your Phone:
7. Your Email:
8. What is the population size of your jurisdiction?
    a. Population:
    b. Year of population estimate:

9. How many people are employed by your local health department?
10. To which agency does your local public health officer report directly?
    a. Local board of health
    b. City council / county council
    c. County commissioner / county executive
    d. City or town manager
    e. Regional or district health director
    f. State health director or commissioner
    g. Other

11. Does your organization conduct a community health assessment?
    a. How often?
    b. Is data from the assessment compared to data from other areas or populations (like neighboring counties)?

c. Is information obtained on Valley Fever cases?

12. Do any of the following contribute data and/or resources to the development of the Valley Fever Assessments:

(a) Local health department
(b) University or academic institution(s)
(c) Private consultant(s), Health/hospital system(s)
(d) Managed care organization(s)
(e) Other public sector agency or governmental entity(ies)
(f) State level agency or organization(s)
(g) National level agency or organization(s)
(h) Community-based organization(s)
(i) The general public?

Valley Fever Data

1. Does your agency collect Valley Fever health information?
2. How does your agency conduct Valley Fever Assessments?
    a. Resident staff
    b. Consultants
    c. State
    d. Other:
3. What level of geographical access does your agency have towards Valley Fever Case data?
    a. Hospital files
    b. County Summation
    c. Zip Code level
    d. Census tract level
4. What level of temporal access does your agency have towards Valley Fever Case data?
    a. Daily
    b. Weekly
    c. Monthly
    d. Annual
5. Is Valley Fever health data compared with data from peer (demographically similar) communities?
    a. Neighboring counties?
    b. The region?
    c. The state?
    d. The nation?

1. How many hours per month does the agency spend on workloads related to Valley Fever?
2. Are there standards and standard operating procedures for data collection of Valley Fever data?
3. Are there standards and standard operating procedures for analysis of Valley Fever data?

4. Is technology (e.g. GIS, electronic filing systems, database management) utilized to make Valley Fever health data available electronically?
    a. How many years of Valley Fever electronic health data does your agency have access to?
    b. Does the agency have access to geocoded Valley Fever health data?
    c. Does the agency use geographic information systems (GIS) for Valley Fever Health data?
    d. Is there a staff member on site with GIS experience?
6. Does the agency use computer-generated graphics to identify trends and/or compare data by relevant categories (i.e., race, gender, age group)?
    a. Does the agency do this for Valley Fever?
7. Are there standards and standard operating procedures for data collection of Valley Fever data?
    a. Are there established processes for reporting Valley Fever health events?
    b. Are systems in place to ensure: Accurate reporting? Timely reporting? Unduplicated reporting?
8. Does the agency operate or participate in surveillance system(s) designed to monitor health problems and identify health threats for Valley Fever?
9. Does the agency use the surveillance system(s) to monitor changes in the occurrence of health problems and hazards for Valley Fever?
10. Does the agency have necessary resources to support health problems and health hazard surveillance and investigation activities in the field of Valley Fever?
11. Does the agency use information technology for surveillance activities (e.g., geographic information systems, word processing, spreadsheets, database analysis, and graphics presentation software)?
12. Does the agency have (or have access to) Masters or Doctoral level epidemiologists and/or statisticians to assess, investigate and analyze public health threats and health hazards related to Valley Fever?

Evaluation

1. Does your agency evaluate its research activities?
2. Does your agency provide time and/or resources for staff to pilot test or conduct studies to determine new solutions for Valley Fever?
3. During the past two years, has the agency proposed Valley Fever to research organizations for inclusion in their research agenda?
4. Does your agency identify and stay current with best practices developed by other public health agencies or organizations?
    a. Are the following used to identify best practices:
        i. Scientific publications?
        ii. Professional associations?
        iii. National and state conferences?
5. Does the agency partner with at least one institution of higher learning and/or research organization to conduct research related to Valley Fever?
6. Does the agency encourage collaboration between the academic and practice communities related to Valley Fever?

7. Does the agency have access to researchers (either on staff or through other arrangements) that conduct analytics on Valley Fever?

8. Is there access to resources to facilitate Valley Fever research within the agency?

9. Does the agency disseminate findings from their Valley Fever research?

10. Does the agency evaluate Valley Fever health education and health promotion activities on an ongoing basis?

    a. Do evaluations take into account the: Comorbid health issues? Populations served? Partners involved? Settings for health education activity (e.g., school, worksite, religious institution, or community-at-large)? Communication mechanisms used (e.g., print, radio, television, Internet, or face-to-face group encounters)? Program quality? Achievement of intended outcomes?

11. Are evaluation results used to revise and strengthen the programs?

Communication

1. Is there a public media strategy (e.g. radio, TV, newspaper, billboards) in place to promote use of the Valley Fever health data?

2. Does the agency provide the general public, policymakers, and public and private stakeholders with information on Valley Fever health status?

3. Does your organization use Valley Fever health data currently to inform health policy and planning decisions?

4. Does the agency plan and conduct health education and/or health promotion campaigns?

    a. Are these campaigns based on sound theory, evidence of effectiveness, and/or best practice?

    b. Are campaigns tailored for populations with higher risk of negative health outcomes?

        i. Are campaigns appropriate to identified populations:

            1. Culture? Age? Language? Gender? Socioeconomic status? Race/ethnicity? Occupation? Sexual Orientation? Are campaigns designed to reach populations in specific settings? Is there cooperation on data between different county agencies?

        ii. Do these settings include:

            1. Personal health care delivery locations (e.g., doctor’s offices, clinics, hospitals)? Worksites? Schools? Neighborhoods? Recreational facilities (e.g., public parks, health clubs)? Places of worship? Correctional facilities?

5. Do nearby county organizations work together to plan, conduct, and implement health education and promotion activities related to Valley Fever?

6. Do entities work with community advocates and local media outlets to publicize Valley Fever health promotion activities?

7. In regards to Valley Fever, does the agency monitor:

    a. The media’s use of information?

    b. Whether or not press releases generate stories or follow-up inquiries from media outlets?

    c. If public health stories provoke inquiries from the public?

8. Do community health professionals submit reportable disease information in a timely manner to the state or agency?

Second Approach

Interview at least 1 staff member (holding a position of Director of Public Health, Public Health Officer, or equivalent) from each of the 5 public health agencies and the California Department of Public Health. The interview questions will expand on the Survey Questions and ask about how they would use more specific Valley Fever information.

Background

1. How does your agency obtain Valley Fever health information? Describe the process that the data information goes from the hospital record to your agency.
2. Describe your Valley Fever "database."
3. What does the data look like once your agency gets access to it?
    a. Access to ethnicity? Gender? Age?
4. How many agencies have access to this data?
5. What diseases are most resources currently allocated to?
    a. What additional resources are needed by the agency to further expand their work on Valley Fever?
        i. If in survey question states that they don't have enough resources

Valley Fever Data

1. Can you describe the standards and standard operating procedures for data collection of Valley Fever data?
    a. How is it combined?
    b. Incubation period or Symptom On-set reporting?
2. Can you describe the standards and standard operating procedures for data analysis of Valley Fever data?
    a. Is the analysis done by agency staff?
        i. What are their qualifications?
3. What is the process to determine risks to specific populations? (Compared to census distributions of the county?)
4. Is there a process to understand climate influences (like Precipitation, Temperature, Wind, El Nino events) related to Valley Fever in your department?
    a. Can you describe the process? How do you relate climate influences to Valley Fever disease outbreak?

Evaluation

1. How do staff stay up to date on Valley Fever research?
2. What would an ideal partnership with research organizations look like for Valley Fever collaboration?
3. How has your agency's approach to studying and reporting on Valley Fever changed in the past 10 years? 5 years?
4. How has your agency evaluated the effectiveness of Valley Fever health education and health promotion activities?
    a. What were the findings?
    b. What were the approaches to improve the effectiveness?
5. What limitations do you currently see for the study of Valley Fever?
6. What limitations do you currently see for the reporting of Valley Fever?

Communication

1. Is there a media strategy in place to promote use of the Valley Fever health data? Can you describe the strategy and processes currently in place?
    a. Is there a communication on how the weather/climate impacts the disease?
2. What limitations do you currently see for the communication of Valley Fever?
3. Does your organization use Valley Fever health data currently to inform health policy and planning decisions? Can you describe how you use the data to inform these decisions?
4. Does the agency plan and conduct health education and/or health promotion campaigns for Valley Fever?
    a. Are these campaigns based on sound theory, evidence of effectiveness, and/or best practice? How so?

    b. How are campaigns tailored for populations with higher risk of negative health outcomes from Valley Fever?
    c. How do agencies get information on who is high risk for Valley Fever? How often is this updated?
5. What disease in your agency has a very effective media strategy?
    a. Why do you think it’s effective?
    b. What are the differences in the resources between that disease and Valley Fever?
    c. What are the differences in the type of data provided to your agency between that disease and Valley Fever?
6. What are your thoughts on incorporating climate/weather information into your media strategy for Valley Fever?
7. What information do you need to have in order to develop an effective Valley Fever media strategy?
    a. Resources?
    b. Partnerships?
    c. Types of data?
    d. Weather communication?
    e. Dealing with uncertainties in the data?