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An Evaluation of Methods and Technology to Estimate Localized Environmental and Health Impacts from Air Pollution and Pesticide Use

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Environmental Science and Engineering

by

Margaret Sandra Isied

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ABSTRACT OF THE DISSERTATION

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Professor Timothy Malloy, Chair

Humans are a product of their environment – the air we breathe, the water we drink, the food we eat, are all in one way or another our "environment", which in turn, impacts our health. Air pollution has been a long-standing issue, from the time humans innovated cooking over fire stoves, to our present-day reliance on transportation, technology, and industry. Exposure to air pollution has been linked to premature deaths, respiratory diseases, such as asthma, chronic obstructive pulmonary disease (COPD), and bronchitis, total body inflammation, and cancer. We are exposed to environmental contaminants everywhere and every day. For example, pesticides are used for farming practices to increase crop yield. With the advancements in commercial farming, any number of highly toxic, highly volatile pesticides are ubiquitously used within the same area. Many communities living near major sources of air pollution, such as freeways,

industrial sites, and agricultural areas, have been demonstrated to be disproportionately burdened by these environmental contaminants.

While environmental conditions have improved drastically since the 1970s, there is high variability of what communities are experiencing at the local level. Recently, there has been a rise in environmental concerns locally; communities are concerned that current environmental monitoring and assessment methods are flawed in two ways. First, these methods are focused on regional impacts not capturing local environmental conditions within smaller communities. Since the 1970s, environmental agencies have evaluated environmental contaminant levels using monitoring and modeling techniques that demonstrate how pollutant concentrations are impacting a region. Many of these methods were developed to demonstrate compliance with state and federal standards. For example, monitoring equipment is strategically placed to understand the impacts of air quality on a region, rather than a local community, and air dispersion modeling has typically been reserved for large industrial operations that are likely to exceed regional air quality standards. Second, these methods do not consider exposure to multiple environmental contaminants which, coupled with social burdens such as low income and limited access to resources, make communities more susceptible to health impacts, ultimately diminishing their quality of life. Single pollutant evaluations are not representative of real-world exposure scenarios.

These concerns highlight a needed call to action to better understand and evaluate environmental pollutants. New or repurposed methods and tools would ultimately provide regulators data at a more granular scale to make decisions in the interest of specific communities, rather than over an entire region. A better understanding of pollution variation in a community would also help regulators know where to focus intervention efforts. My dissertation explores tools and methods with the goal to: (1) recommend how to use new low-cost sensor monitoring technology to successfully understand localized air quality impacts, (2) present a case study using localized air pollution data to better quantify community exposures to air pollution, and (3) explore how air dispersion modeling can be used to evaluate exposure to multiple pesticides at the local level. Results from this dissertation developed new methods for setting up low-cost air quality sensor networks, emphasize variable air pollution concentrations within communities, and demonstrated the feasibility of repurposing modeling tools to evaluate pesticide use. This research is critical to reinforcing the importance of implementing new methods and technologies to understand localized impacts and provide data to regulatory bodies who are responsible for emission control, land use decision making, and public health intervention.

The dissertation of Margaret Sandra Isied is approved.

Alan Irwin Barreca

Lara J. Cushing

Stephanie S. Pincetl

Timothy Malloy, Committee Chair

University of California, Los Angeles

2023

DEDICATION

This dissertation is dedicated to the many people who have supported me along my Doctoral Journey: my immediate family for always supporting me and encouraging the pursuit of higher education: Stephan, Mary, Marlene, Steve, and Roger. My aunts, uncles, and cousins, specifically Margaret and Greg, who have positively encouraged me to work hard, my partner Gus, who has supported and loved me in countless ways, and my friends who have listened to me talk about my degree ad nauseum: Cathy, Vienna, Arely, Bianca, Mandy, Nephty, and so many others.

Two special dedications:

My dad, Dr. Stephan S. Isied, who inspired me to pursue a Doctorate degree, always ask "why does it matter?", and inspired me to teach future generations. My dad is one of the most passionate, dedicated professors that I know, and I hope to follow in his footsteps one day in my own way. My dad always told me: "In this world, anything can be taken away from you: your home, your livelihood, anything material. What can't be taken from you is what's in your mind".

My Teta (grandmother), Lulu Bahou. She was and continues to be my inspiration to study the environment and how it impacts human health. She was taken from us too soon from lung cancer. She was one of the kindest, most generous, and strong women that I ever had the privilege to know. If my work can help even one person to not go through what my family and I went through, this would all be worth it.

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VITA

2010	Diploma
	Leland High School
2015	B.S., Environmental Toxicology with Minor in Human Physiology
	University of California, Davis
2018	M.P.H., Environmental Health Sciences
	Fielding School of Public Health, University of California, Los Angeles
2016-2017	Teaching Assistant
	University of California, Los Angeles
2017-2018	Teaching Associate
	University of California, Los Angeles
2018-2021	Air Quality Specialist
	South Coast Air Quality Management District
2019-2021	Graduate Student Researcher
	University of California, Los Angeles
2021-2022	Pritzker Fellow
	OpenAQ
2021-2022	Senior Air Quality Consultant
	Ramboll Inc
2022-	Environmental Project Manager and Business Development Manager
	Clarity Movement
2023	Teaching Fellow
	University of California, Los Angeles

CHAPTER ONE: INTRODUCTION

Humans are exposed to many environmental contaminants in food, air, water, and soil. There is overwhelming scientific evidence that exposure to environmental contaminants lead to adverse health impacts (US EPA, 2022). Air pollution, a key environmental pollutant, has been associated with respiratory illnesses, such as asthma and chronic obstructive pulmonary disease (COPD), and was responsible for 9 million premature deaths in 2015 (Fuller et al., 2022). Pesticides that have been used to help scale up farming to meet food demands also cause adverse health impacts to workers and surrounding communities. Pesticides can irritate the eyes and skin, and can penetrate the nervous system, hormone and endocrine systems, and has been associated with certain cancers (OCSPP, n.d.). While many strides have been taken to reduce environmental contaminants since the 1970s, there are still many communities globally that continue to be exposed to environmental impacts from air pollutants and pesticide use. Research also suggests that communities of color and areas of low income and low socio-economic status have been disproportionately exposed to higher concentrations of air pollutants and pesticides, when compared with communities with more resources (Bravo et al., 2016; Gochfeld, M., 2011; Johnston & Cushing, 2020).

Advancements in technology have improved environmental monitoring and modeling to estimate impacts from environmental contaminants. To quantify environmental pollutants local, state, and federal agencies employ a number of monitoring and modeling techniques to estimate concentrations of these pollutants:

- Priority Air Pollutants - In the United States, air pollution has been evaluated regionally to determine compliance with the National Ambient Air Quality Standards (NAAQS).

State, regional, or local regulatory agencies are responsible for the necessary monitoring equipment. This equipment has been identified as gold-standard equipment, satisfying regulatory standard operating procedures, known as Federal Reference Method, or Federal Equivalent Method, to evaluate regional air quality. These regulatory monitors (herein referred to as reference monitors) are often costly, require special expertise to maintain, and are cited based on criteria set by the United States Environmental Protection Agency (US EPA) (US EPA, 2016). Reference monitors may or may not be placed in communities where people work, live, and spend their time, suggesting that data collection regionally may not be representative of local conditions. Furthermore, there is overwhelming evidence that air pollution concentrations can vary over space and time, and that reference monitors are not an effective solution in evaluating hyperlocalized air quality. The NAAQS are health-based standards that estimate adverse health impacts beyond a specific pollutant concentration, demonstrating increased respiratory and cardiovascular incidence. The literature has numerous studies that there are adverse health impacts from exposure to air pollution at even lower concentrations that what is deemed to be health protective by the NAAQS standards (Crouse et al., 2012; Hales et al., 2012; Shi et al., 2016).

- Pesticides - Existing environmental evaluation methods can be used to evaluate exposures to environmental contaminants, such as pesticides. Pesticide use varies by crop type among other factors, suggesting that different pesticides can be applied in the same location. However, there is no consistent guidance or regulation from US EPA or the California Environmental Protection Agency (CalEPA) on how to evaluate impacts from multiple pesticide exposures. The US EPA and CalEPA are required to protect human health and the environment. Disproportionately burdened communities would especially benefit from widespread and consistent guidance, ensuring that their community is adequately evaluated for environmental exposures in the same way as other communities. To quantify environmental pollutants local, state, and federal agencies employ a number of monitoring and modeling techniques to estimate concentrations of pesticides. Pesticide exposure can be monitored using air quality monitoring equipment or can be modeled using air dispersion modeling methods and other computational tools. Air dispersion modeling has traditionally been used to understand air dispersion patterns from air pollution sources. There has been some research on modeling pesticides using air dispersion modeling techniques (Costanzini et al., 2018; Teggi et al., 2018; van Wesenbeeck et al., 2019).

California has taken many strides to improve environmental protection: from policy development to financial support, California pioneers' programs that focus on reducing people's exposure to environmental contaminants. Despite these efforts many communities are still disproportionally burdened by environmental pollution sources, such as air quality and pesticide exposure. These communities tend to be communities of color, areas having low socioeconomic status, low education rates, and those that are linguistically isolated (August et al., 2021). Pollution burden and socioeconomic factors combined can make these communities more vulnerable to the adverse health impacts from environmental pollutants, while also having limited capacity to take action to protect their community. CalEPA and the Office of Environmental Health Hazard Assessment (OEHHA) created a map to visualize California's environmentally disadvantaged communities. CalEnviroScreen is a science-based tool that uses publicly available data on pollution, socioeconomic status, and health and quantifies it at the census tract level to identify and track communities that are disproportionately burdened by these factors (August et al., 2021). Communities that have been identified as higher risk communities have been eligible for state programs such as the Community Air Protection Program's Community Air Grants, and DPRs Community Air Monitoring, described in the chapters to follow.

The goal of this dissertation is to leverage innovations in air quality monitoring and modeling to better characterize and quantify exposure to one or more contaminants. This dissertation first examines the potential for low-cost air quality sensors to provide hyperlocal monitoring data. Low-cost air quality sensors (Clements et al., n.d.), have increased spatial coverage of air monitoring, increasing knowledge of local air quality conditions. Low-cost sensors can help provide insights to localized air quality conditions compared to government operated reference grade equipment. These insights can help us understand when these communities are exposed to greater concentrations of pollutants where they live, work, and play than what is being measured at a regional government monitor. This data can be used to make policy recommendations and help empower communities to protect their health when air pollution concentrations are high. However, there is little research on how to effectively set up a low-cost air quality sensor network.

This dissertation also addresses the use of air dispersion modeling coupled with cumulative risk tools to evaluate environmental exposures to multiple pesticides. Humans realistically are exposed to more than one environmental contaminant acutely and chronically. Despite these real-world exposure scenarios, pesticide use and safety is evaluated on a per pesticide basis. Cumulative impact assessment (CIA) is defined as the analysis, characterization, and possible quantification of the combined risks to health and the environment from multiple chemical agents or stressors (Zaunbrecher et al., n.d.). CIA is important to quantify real world exposure scenarios and how those contribute to real environmental conditions and public health outcomes. The goal of this dissertation is to leverage innovations in air quality monitoring and modeling to better characterize and quantify exposure to one or more contaminants. While this dissertation heavily focuses on California data and policy, these methods and recommendations can be adapted to meet other state, federal, and global needs to assess environmental exposure.

This dissertation explores the following topics related to quantifying exposure to environmental contaminants:

- The second chapter explores resources available to effectively use low-cost air quality monitors. It identifies resources that exist on how to set up low-cost sensor networks, makes recommendations on what considerations should be made when designing a sensor network given an example case study, and highlights successes and challenges of using low-cost sensors to achieve air quality goals.
- The third chapter evaluates data from a low-cost sensor network in Richmond, CA to understand pollutant concentration variability within the community that is not captured by the regional reference monitor. The chapter explores co-exposures to $PM_{2.5}$, NO_2, and ozone at a localized scale to identify locations within the community with exposure to more than one pollutant. Using low-cost sensors can provide insights where one or more pollutant concentrations may exceed health-based standards.
- The fourth chapter demonstrates the feasibility of using air dispersion modeling to evaluate local impacts to two or more pesticides applied on the same day. The proposed

tool repurposes an existing air dispersion modeling and health risk assessment tool for use for evaluating pesticide dispersion. The proposed tool supports pesticide regulators in California to better understand local pesticide existing community burdens before approving additional pesticide for use, and further contributing to cumulative exposures of pesticides.

CHAPTER TWO: Evaluation of Techniques and Methods Available to Set Up Low-Cost Sensor Networks

ABSTRACT

Low-cost sensors have gained popularity in recent years and have increased air quality monitoring coverage globally. Low-cost sensors can be used to answer any variety of questions and achieve many project goals, spanning from community-led monitoring to supporting government initiatives. Although the popularity of using low-cost sensor technology has skyrocketed, there is a lack of consistent guidance or research on how to effectively set up a low-cost sensor network to achieve project goals. This chapter aims to explore this knowledge gap in methods available to set up low-cost sensors. I conducted a search of both the academic and grey literature (e.g., UCLA Library, Google Scholar, Engineering Village - Compendex, Inspec, Knovel, etc.), using key words representing air quality sensor network design. The grey literature search uses Google and contacts at government, non-profit, and other sectors that have published guidelines on how to set up a sensor network. I organize the resources into three categories of methods: quantitative, qualitative, and combined qualitative and quantitative methods. I reflect on my experience during my residency in assisting different customers with setting up their sensor networks and use the literature available to create a decision framework that projects can use to design sensor networks. I present two example case studies to demonstrate the use of the decision framework. Results of this chapter suggest methods to design sensor networks require expertise beyond the groups that are actually using low-cost sensor users. Further research is needed to make sensor network designs more accessible. Future work should focus on policy changes to restructure local and regional government air quality landscapes to devote resources for using low-cost sensors.

INTRODUCTION

Poor air quality continues to be a major threat to the environment and public health. Air quality impacts people disproportionately, having greater impacts on low- and middle-income communities (August et al., 2021). Many countries have little or no access to air quality data. As a Pritzker Impact Fellow, I worked with OpenAQ, a non-profit organization that hosts real time global air quality data (OpenAQ, 2022). I contributed to the research of the current state of air quality data globally and accessibility to this data in a report titled Open Air Quality Data: The Global Landscape. Results of the report indicate that 39% of countries globally have no evidence of air quality monitoring (OpenAQ-Team & Community, 2022).

Low-cost air quality sensors are a new technology with a variety of uses such as filling in spatial air quality data gaps, and citizen science projects for community monitoring (Williams, 2019). The United States EPA (US EPA) defines low-cost sensors as devices that use sensor(s) and other components to detect, monitor, and report on specific air pollutants and/or environmental factors such as temperature and humidity (US EPA, n.d.-c). Figures 2.1 and 2.2 shows two leading low-cost air quality sensor platforms: PurpleAir and Clarity Movement, and the density of coverage of low-cost sensor data in California. Low-cost sensors have decreased the barrier to entry for air quality monitoring by giving more people access to air quality monitoring data and information. It is not just important to monitor the air, but to have a specific project goal in mind. Project goals include but are not limited to: filing in air quality data gaps, understanding the air quality impacts of sources on communities, using low-cost sensor data to support the installation of reference monitoring equipment, supporting community-led monitoring and education initiatives, and using air quality data to understand public health and make recommendations.

My professional experience has focused on working with stakeholders using low-cost sensors to achieve specific project goals. I provide technical expertise on low-cost sensors, and work with customers on thinking through how to yield the most useful information for their project. With the increase in popularity of low-cost sensors among air quality and non-air quality experts alike, users are searching for resources to set up low-cost sensor networks. Many countries without any air monitoring at all are using low-cost sensors for preliminary air quality measurements to understand the baseline air pollution levels and are seeking guidance on how to do this effectively with no historic data or knowledge of air quality (OpenAQ-Team & Community, 2022).

Figure 2.1: Purple Air Low-Cost Sensor measurements of ambient fine particulate matter ($PM_{2.5}$) illustrating spatial coverage of sensors in California.

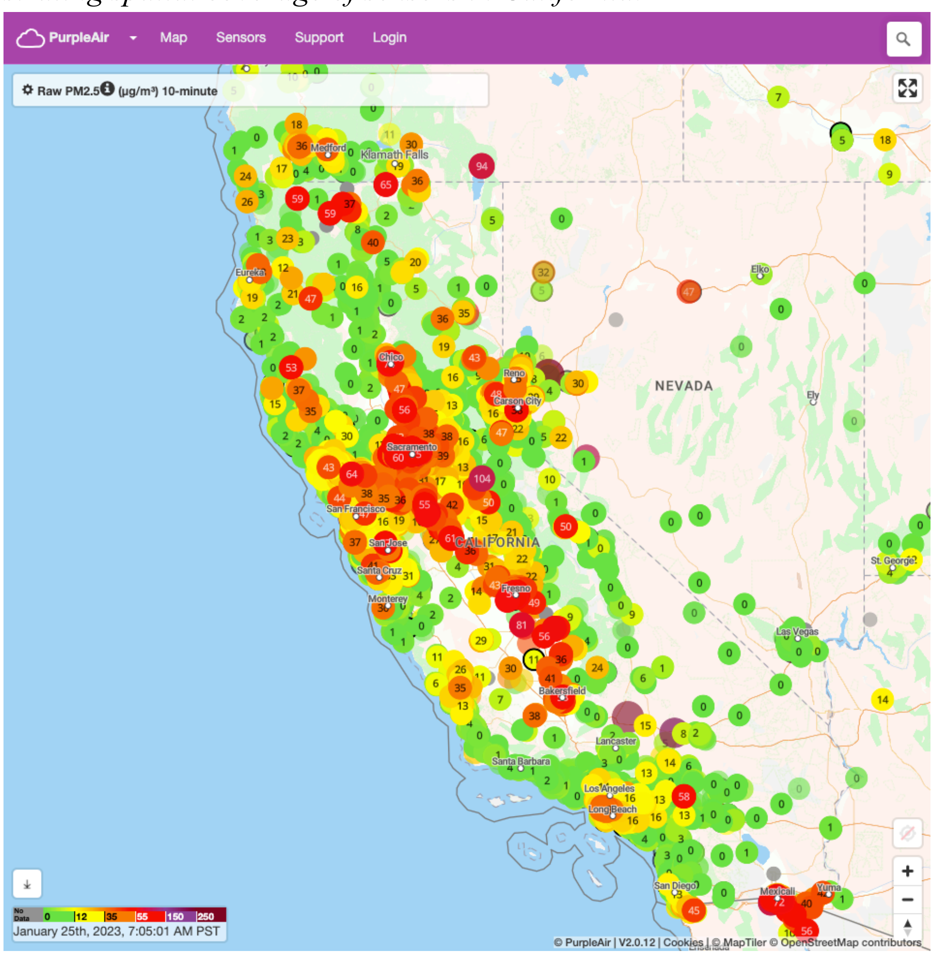
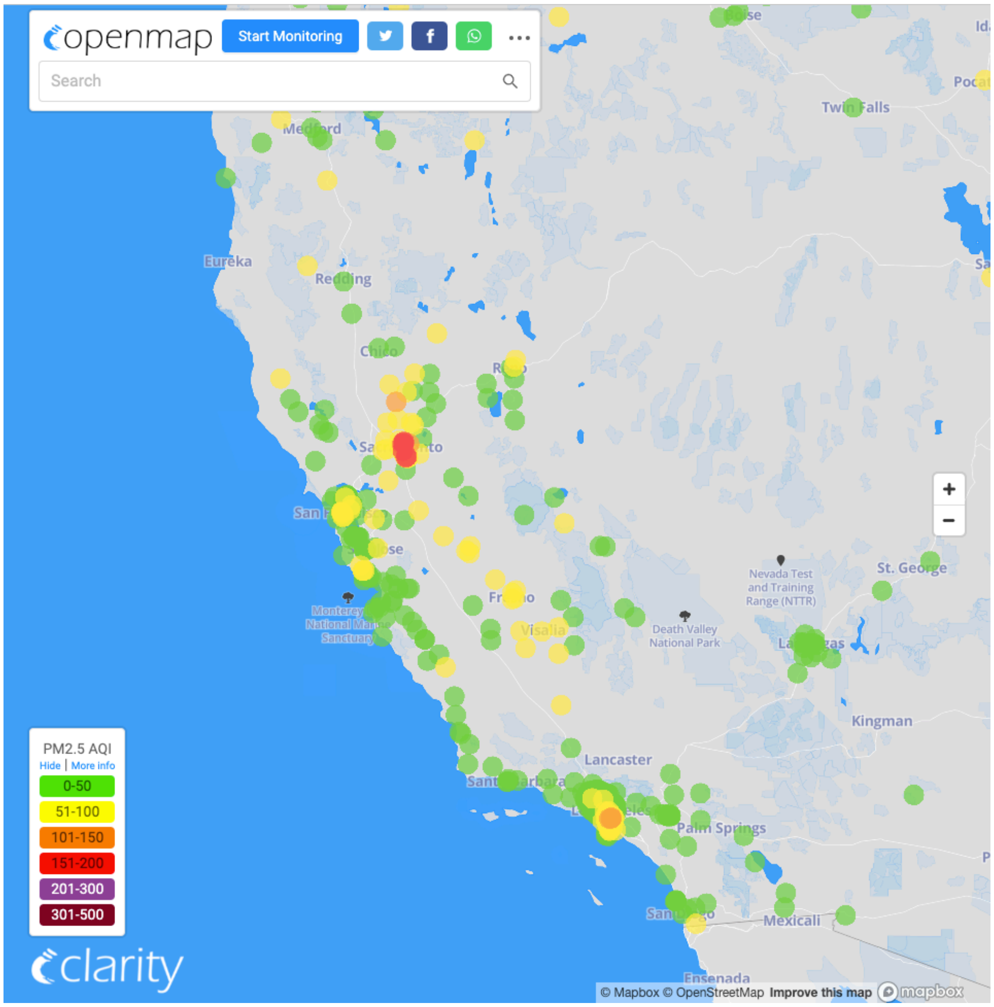


Figure 2.2: Clarity Movement Low-Cost Sensor measurements of ambient fine particulate matter ($PM_{2.5}$) illustrating spatial coverage of sensors in California.



Historically, air pollution has been monitored and regulated at the regional level by government-operated reference monitors. Low-cost air quality sensors have the capacity to supplement regional reference monitoring, but not all regional and local governments have capacity to make use of them (Munir et al., 2019). In the United States, the current funding structure to purchase and deploy low-cost sensors rely on the leadership of local communities. Recent grant funding opportunities from California and United States governments require that a local community-based organization lead the effort or partner with local governments (US EPA Office of Environmental Justice, n.d.).

There is limited literature on how to define and design a low-cost air quality sensor network. The variety in scope of low-cost sensor uses make it challenging to identify consistent variables that any and all projects should use when making sensor network decisions. Currently, there is no universal sensor network design approach that would address all types of projects.

Organizations often defer to low-cost sensor providers to answer challenging questions: What is the optimal number of sensors needed to cover a specific geographic area, what radius beyond the sensor will data be "accurate" for, how many are needed to achieve meaningful results? While these are all valid questions, they are very difficult to answer. First, air quality knows no geographic limits. Second, air pollution concentrations are dependent on many factors, such as temperature, relative humidity, wind, weather, nearby sources, season, and urban development. I have spent my Residency as an Environmental Project Manager with Clarity Movement, a low-cost air quality sensing company that provides both the hardware to monitor air pollutant concentrations, and the software to review and analyze the data. I have worked with customers with diverse needs and have been challenged with assisting them in scoping project goals and network design. This work has highlighted the real-world need for sensor design methods and research.

This chapter aims to (1) provide a review of both the academic and the grey literature to identify what resources currently exist in supporting the design of a low-cost air quality sensors network, (2) develop a decision framework that can be utilized by all projects, and (3) highlight case studies to illustrate how that framework could be applied to design low-cost sensor networks. For this chapter, I define sensor network design as the process to determine the optimal placement of individual air quality sensors to measure pollutant concentrations and answer project specific goals.

METHODS

Literature Search

I conducted a comprehensive literature review of the state of research on sensor network design. Research articles were obtained through scientific databases, including IEEE explorer, Web of Science, and Comprendex. Grey literature was obtained through Google and Google Scholar searches. The searches compromised of the following key words: “low-cost air quality sensor placement”, “(siting OR placement) AND (“low cost”) AND (“air quality” OR “air pollution”) AND (sensor) AND (network) AND (design)”, “("low cost" OR "cost effective") AND ("air quality") AND (sensor OR monitor*) AND (network) AND (design)”.

Exclusions

Interpretation of “sensor network” may be broad. To focus on sources specific to the definition of “sensor network” (defined above), following sources were excluded: (1) sources focusing on the feasibility of low-cost sensor deployment, (2) ongoing projects that are exploring how to deploy sensor networks and have yet to publish their methods or results, (3), duplicates obtained either through similar searches, or between different databases, (4) sources that define “sensor networks” as sensors that communicate with each other and rely on measurements from one another, and (5) sources focusing on calibration models of sensors that were already deployed.

Decision Framework Development

To develop a decision framework, I reviewed the available literature for sensor network design, summarized the available methods, provided example use cases for the methods, and identified data needed to use a specific method. I combine this with real world experience in identifying consistent questions that I have worked through with all projects when designing a sensor network. Considerations for the decision framework included: ease of use, applicability across multiple project types, and inclusion of factors that are critical to setting up a project.

Case Study

To demonstrate the use of the decision framework, I describe two case studies that simulate two real organizations that I have worked with to design an air quality sensor network. The names of the organizations and locations have been anonymized. Each case study represents a different stakeholder group with different project goals, budgets, and expertise levels with the goal demonstrate the utility of the decision framework for different projects.

RESULTS

Literature Review Findings

After applying the search criteria and exclusion criteria, a total of 24 sources were obtained. For each source, Table 2.1 identifies method type (qualitative, quantitative, or mixed), author, title, method name (if applicable), research objectives method/source can support, and data needed.

Table 2.1: Summary of Sensor Network Design Literature Available

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
Quantitative	Grover & Lall, 2021	A Data-Driven Framework for Deploying Sensors in Environment Sensing Application	Universal Kriging: spatially interpolation to predict pollutant concentrations at non-monitored locations. Modeling Residuals: represent spatiotemporal variations, sites with low residuals values mean the sensor is reading similar to the estimated mean	increasing monitoring spatial coverage	-Geographic data – land use regression models broken up by land uses, such as natural land use, commercial, residential, industrial, and nonpolluting areas -Current monitoring data

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
			values and high residuals mean the sensor has different readings than mean values. Data is separated into grids and sites with a higher sum of differences and distances are given higher preferences in initial deployment		
Quantitative	Kelp et al., 2022	A new approach for determining optimal placement of $PM_{2.5}$ air quality sensors: case study for the contiguous United States	Multiresolution Dynamic Mode Decomposition Model: uses pollutant data (in this example, $PM_{2.5}$) temporally to rank locations spatially. Locations are ranked based on spatial patterns and variability; the higher the variability of $PM_{2.5}$ concentrations over space and time, the higher prioritized the location is for monitoring.	prioritization of where to place reference equipment	-Multiple years of daily $PM_{2.5}$ concentrations *Dataset provided through data fusion of machine learning that combines ambient monitoring, satellite aerosol optical depth, and land use data, and chemical transport
Quantitative	Yoo et al., 2020	Adaptive spatial sampling design for environmental field prediction using low-cost sensing technologies	Spatial Fixed Rate Kriging: uses surface prediction uncertainty to look at differences among spatial data	understanding air pollution within a community	-Spatial data
Quantitative	Boghozian, 2021	An Exercise in Selecting Low-Cost Air Quality Sensor Placements within an Urban Environment	Gaussian Process Model Training: Model uses air pollution dispersion to optimize the placement position of sensors that are selected iteratively. The model can be "trained" to define what "good" placement means.	-increasing monitoring spatial coverage	-Historic Air Pollution Measurements at monitoring sites -Defined distances between stationary monitors
Qualitative	Morawska et al., 2018	Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone?	Best Fit for Purpose: -Duration of the project? Months or years? -Continuous monitoring, trend exploration? -Consideration of pollutants measured -Creating a hybrid network – ingesting both reference monitors and low-cost sensors	-increasing monitoring spatial coverage -understanding air quality trends and source impacts	-Duration of Project -Project Scope -Pollutants of Interest
Qualitative	Polidori et al., 2021	Community in Action: A Comprehensive Guidebook on Air Quality Sensors	Factors to consider when setting up a low-cost sensor network. -What questions is the project trying to answer? E.g., placing sensors at	-increasing monitoring spatial coverage -understanding	-Duration of Project -Project Scope -Pollutants of Interest -Locations for sensor placement

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
			the breathing height is important for evaluating exposure. -What pollutants is the project focused on? -Siting decisions, identify the area, and how frequently to collect measurements. For example, ideal places to put sensors include in construction, infrastructure development, near facilities with permits from local reference agencies, pollution sources such as freeways. -To draw comparisons between the sources/areas of interest, consider including background sites – locations away from your sources/areas of interest that are not expected to be impacted by your pollutants -Identify resources the project has access to, what challenges the project faces, and what resources the project will need access to for successful project completion -Are concerns specific to a source within the community that the project wants to study, or is the concern for the overall community? Who are the impacted parties? -How is the data intended to be used? -The more measurements the project can gather, the greater the strength of conclusions that can be drawn -Understanding how environmental factors can impact transportation of air quality. For example, incorporating ways that can increase understanding of wind patterns, if they may be seasonal, temperature, and/or relative humidity. -Consider partnering with a trusted local community group, who can help you frame an	air quality trends and source impacts -understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	(both areas of concern and background) -Intended data uses and temporal scale -Partnership with local community organization

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
			issue through a local lens, provide insight about major sources of air pollution, and what outcomes they would like to see		
Qualitative	TD Environmental Services, n.d.	Designing an Air Sensor Monitoring Network	Sensor placement considerations: -Create a map of the area you're planning to monitor -Consider placing sensors in residential areas, industrial area, commercial areas, traffic locations, recreation spaces, perimeter, references/colocation, comparison sites -Coverage – what areas are not measured, is there a reason, combining this information with sensor locations -Ideally, reference monitors to sensors should be at a ratio of 1:125-35, 5 sensors for every 100,000 residents, or 2-3 sensors every 10 km^2	-increasing monitoring spatial coverage -understanding air quality trends and source impacts -understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	N/A
Both	Kanaroglou et al., 2005	Establishing an air pollution monitoring network for intraurban population exposure assessment: A location-allocation approach	Land Use Regression Modeling: Identify areas where there is higher pollution variability, based on the land use surface distribution. Monitors should be placed in areas with higher pollution variability. Areas where people live and spend time can be defined as high priority areas	-prioritization of where to place reference equipment -increasing monitoring spatial coverage	-Land use data, including transportation and distribution of at-risk populations -High risk population areas and characteristics
Qualitative	Veiga et al., 2021	From a Low-Cost Air Quality Sensor Network to Decision Support Services: Steps towards Data Calibration and Service Development	Sensor Deployment by Government Municipalities: -Placing sensors in areas owned by the municipality, therefore removing the logistics restrictions on the instillation of sensors -Placing sensors in areas with groups that could be at high risk, such as schools, playgrounds, and libraries -Placing sensors in areas with lack of monitoring	-increasing monitoring spatial coverage	N/A
Both	Li et al., 2022	From air quality sensors to sensor networks: Things we need to learn	Considerations: -Calculate the relationship (R squared) between each pair of nearby EPA sites to	-prioritization of where to place reference equipment	N/A

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
			explore homogeneity of various pollutants -results can help provide a spatial area for representation of certain pollutants. For example, Ozone concentrations do not vary drastically over a 10 km^2 spatial area. -Consider which pollutants want to be monitored and what the environmental conditions are at that location. For example, results from studying the Phoenix area suggest that monitors should be installed within 5 km from one another, were as in Detroit, they were recommended to be 1 km apart. -Each local area should conduct an investigation to appropriately determine the optimal sensor placement and distance	-increasing monitoring spatial coverage	
Qualitative	Tracking California, 2018	Guidebook for Developing a Community Air Monitoring Network: Steps, Lessons, and Recommendations from the Imperial County Community Air Monitoring Project	Considerations: -Using input from the community to prioritize locations -Determine where the sensors can be collocated with a reference monitor -Placing in spots that are meaningful to community members -Placement that will increase awareness of air quality issues -Collect information on sites selected by community and set pre-determined criteria for what sites need to have to be eligible. For example, if your sensor needs power or connectivity, is that available? If the project needs siting permission, locate appropriate communication. -Identify areas that may have specific pollutants of concern, minimum number of residents that should be covered, or other project goals -Producing data that community members will use and that will better represent the area	- understanding air quality trends and source impacts - understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	N/A

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
			where the monitor is located -Define the geographic region that the monitoring network will cover (city, county, neighborhood, etc.) -Consider limitations and prioritizing areas depending on budget		
Qualitative	Environmental Defense Fund, n.d.	How-to Guide for Mapping Hyperlocal Air Pollution	Considerations: -Network should be targeted to collect the kind of data that enables you to achieve your monitoring goals -Consulting with expert partners such as air pollution scientists, local residents and community groups, health scientists, and air monitoring system provides and/or specialists, consultants, and contractors -Identifying and characterizing an air pollution problem -Consider creating awareness and urgency around enforcement, public health , or an advocacy campaign -using block by block data to fine tune actions and policies -accessing the impact of a policy action by measuring pollutant levels before and after an investigation	- understanding air quality trends and source impacts - understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	N/A
Both	Miskell et al., 2017	Low-cost sensors and crowd-sourced data: Observations of siting impacts on a network of air-quality instruments	-Using land use parameters such as distance from emission sources and how sources were mounted to understand if they are measuring pollutants effectively -Understanding the limitations of low-cost sensor data that may not be set up properly to compare to a reference monitor	-prioritization of where to place reference equipment -increasing monitoring spatial coverage	-Data from multiple air pollution measurement equipment
Both	Weissert et al., 2019	Low-cost sensors and microscale land use regression: Data fusion to resolve air quality variations with high spatial and	Land Use Regression: -provide high spatial resolution in the data set to show the short distances in variability of pollutant concentrations on the scale of 100 meters	-prioritization of where to place reference equipment -increasing monitoring spatial coverage	-Land use data -Low-cost air quality data -Focus study area -High Vehicle Traffic Areas -Instruments on different side of roadway between

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
		temporal resolution	-The highest concentrations were found near bus stops, intersections, and under shop awnings		100 meters and 1 kilometer apart -Historic pollutant data to develop microscale land use regression -Permission from store owners to place low-cost sensors
Both	Sun et al., 2019	Optimal Citizen-Centric Sensor Placement for Air Quality Monitoring: A Case Study of City of Cambridge, the United Kingdom	Considerations: -What should the key citizen-centric objectives when deploying an air quality monitoring network throughout the city, in the absence of any prior knowledge in the field? -Given fixed budget constraints, what is the optimal sensor placement strategy to achieve objectives? -When there are multiple objectives to be considered simultaneously, how should we derive a suitable sensor placement strategy to achieve a goal given budget constraints?	-understanding air quality trends and source impacts -understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	-Sensor number constraint, a set of grids with associated percentage of population, distance function, exponential decay parameter -cost constraint, set of grids with associated percentage of population, distance function, exponential decay parameter, and cost function -distance to the nearest sensor, distance between the set of grids (locations in which sensors are placed) -set of locations of interest -number of locations of interest -number of sensors we can place -the set of selected locations for deploying sensors -an indicator denoting whether the location is the nearest to the point of interest (j) -distance between the location (i) and the point of interest -number of candidate locations **If interested in monitoring traffic emissions -all road segments -number of road segments -traffic conditions -defined from google earth as green (no traffic), orange (medium road-based traffic), red -traffic, dark red-high road-based traffic) -fraction of

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
					time in a week that the traffic condition in the road segment is the weight of the parameter -population data
Quantitative	Lerner et al., 2017	Optimal Deployment of a Heterogeneous Air Quality Sensor Network	Based on unit characteristics and land use analysis of the defined region - this is flexible and enables customization based on the defined region - does not consider prior knowledge of pollutant concentrations	-prioritization of where to place reference equipment -increasing monitoring spatial coverage	-land use data
Quantitative	Boubrima et al., 2015	Optimal Deployment of Wireless Sensor Networks for Air Pollution Monitoring	Basic Model: using a dispersion model, we determine for each pollution source the zone which will be polluted, and where the source starts to emit these pollutants	-prioritization of where to place reference equipment	-Gaussian dispersion model. -potential monitoring positions - defined in this study as locations with power (i.e., traffic lights, lamp posts). This can also be a grid of points obtained if you have no placement restrictions -Number of potential positions -Number of pollution sources -Positions for sensors and sinks
Quantitative	Sun, Yu, et al., 2019	Optimal Multi-type Sensor Placements in Gaussian Spatial Fields for Environmental Monitoring	Two criteria for deciding what a good design for placing single-type sensors - entropy and mutual information. 1.entropy seeks to place sensors at the most uncertain places to minimize entropy 2.mutual information seeks to place sensors at locations that most significantly reduce the uncertainty about the estimates in the rest of the space	-prioritization of where to place reference equipment -increasing monitoring spatial coverage	-budget and cost -area of study -hourly air quality monitoring data - determine if the distribution of normalized one-hour difference of pollutants at the monitoring station are normally distributed and thus satisfy the assumptions made by the gaussian process -a number of scenarios to test out the algorithm -expertise to be able to perform such an algorithm
Quantitative	Hao & Xie, 2018	Optimal redistribution of an urban air quality monitoring network using atmospheric	-simulation of pollutant concentration field -definition of network design criteria -application of a Non-dominated Sorting Genetic Algorithm - a	-prioritization of where to place reference equipment	-define a continuous gridded zone/optimal grid squares for deploying sensors -atmospheric dispersion model -

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
		dispersion model and genetic algorithm	multi objective evolutionary algorithm		reproduce detailed concentrations and temporal variations of pollutant -hourly concentrations for pollutant from existing sites
Quantitative	Kouichi et al., 2016	Optimization of sensor networks for the estimation of atmospheric pollutants sources	-goal is to select the best set of X number of sensors with XX number of potential locations, minimizing the cost function	-understanding air quality trends and source impacts -understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	-meteorological data -budget constraints -number of locations -gridded locations -objective of network must be clearly identified
Qualitative	US EPA, n.d.	A Guide to Siting and Installing Air Sensors	Questions to ask when picking a site: -What does the project know about the pollutant sources in the area? -What monitoring location(s) will help me answer my question(s)? -Does the project need to get owner's permission to add a sensor and make measurements at their site? -Will the project be able to access the site for routine checkups or maintenance? -Will the project need AC power? Is there adequate sun exposure? -How does the sensor communicate data? Is Wi-Fi needed and available? -Can the sensor be placed out of reach? Can the sensor be placed in an enclosure? -Will the sensor need materials to be mounted? -Consider siting away from directly building exhaust? -Try to set up sensors with free air flow -Install 3-6 above ground to represent the breathing zone	-understanding air quality trends and source impacts -understanding air pollution exposure at sensitive receptor locations -prioritization of where to place reference equipment	N/A

Qualitative/Quantitative/Both	Author	Title	Method Name (if Applicable) and Description	Research Objectives Method Can Support	Data Needed
Qualitative	X. Li et al., 2021	Using Sensor Network for Tracing and Locating Air Pollution Sources	-Establish a fine particulate matter network of sensors with low cost, high spatiotemporal resolution, flexible distribution, large numbers, and high collection frequency. Also includes designing the network and selecting locations for sensor placement on the basis of local weather, terrain, and land use using software/hardware to ensure consistency. -Data collected from low-cost sensor network to track and locate atmospheric pollutants and identify sources	-prioritization of where to place reference equipment -increasing monitoring spatial coverage	-local weather, terrain, and land use data

Sources discussing sensor network design can be organized into three categories: qualitative, quantitative, and both-qualitative and quantitative. Qualitative models consider a number of factors in determining where and how many monitors to deploy:

- Project goals
- Project budget
- Air quality knowledge
- Local siting, and access to sites (e.g., crowd sourced sites such as residences and reference stations)
- Consultation with expert partners
- Understanding the impacts from sources
- Understanding human exposure, mapping areas, community concerns, and knowledge.

These variables are important for anyone using low-cost sensors but are especially important to engage the communities that low-cost sensors are meant to serve. Qualitative factors are also more likely to be used in a professional setting, as companies providing low-cost sensors often do not have the tools or expertise to conduct sophisticated spatial modeling to precisely locate where each low-cost sensor should be placed. The most important qualitative factors that were identified consistently across literature sources are project goals, pollutants of concern, budget, and location feasibility:

Project Goals: The most important first step to consider when designing a low-cost air quality sensor network is to define the goals of the project: what pollutants to measure, what the data needs are, and how and where monitoring fits in to achieve those goals (Environmental Defense Fund, n.d.). Project goals can be defined by air quality agencies, air quality experts, local communities, and project partners. The ultimate question is "what does the project aim to do with the data?" (Tracking California, 2018). Understanding the project goals will ultimately guide the optimal sensor placement to answer and achieve the goals. For example, if the goal of the project is to investigate the impacts of an air pollution source within a community, the sensor network may be limited to the location around where the source is located. If the goal of the project is to inform public health intervention, sensors may be placed at locations where sensitive populations spend time, such as schools, residences, parks, and other community spaces (Environmental Defense Fund, n.d.; Tracking California, 2018).

Pollutants of concern: There are a limited number of pollutants that can be measured by low-cost sensors (Polidori et al., 2021). Low-cost sensors for pollutants, such as black carbon or ozone often cost more than $PM_{2.5}$. If black carbon is the pollutant of interest, the number of sensors may be limited by the budget (Environmental Defense Fund, n.d.). If multiple pollutants are of interest to the project, the pollutant should be attributed to the location of the low-cost sensor. Identifying the pollutants require that the project revisit the budget to factor in low-cost sensors that may cost more.

Budget: Ideally, projects would have an unlimited budget to purchase all of the equipment and expertise needed to collect, interpret, and present the data. However, budget is among the most constraining factors when considering sensor network design. For example, a project may have a set budget for X number of low-cost sensors that monitor $PM_{2.5}$; however, upon further discussion, the project may also be interested in monitoring other pollutants, such as ozone or black carbon. Since these monitors typically cost more than $PM_{2.5}$ monitors, a project may have to revisit their budget once they have selected their pollutants of interest. This will impact the number and type of sensors that each project will use.

Location Feasibility: To ensure data accuracy and quality, air quality experts recommend that low-cost sensors be collocated with a reference monitoring location for a period of time to perform a calibration that ensures the measurements from the low-cost sensor and the reference monitor are consistent with one another. Calibration models can be applied to the low-cost sensor to ensure that how it's measuring the data is in line with how the reference monitor is measuring the data. The project should determine if they can gain access to a nearby reference monitoring site to calibrate the low-cost sensors.

In addition to gaining access to the reference monitoring site, characteristics about the location where the low-cost sensors will ultimately end up need to be considered. If the low-cost sensors require power and connectivity, are these available at the identified location? If not, this will impact which technology the project will have to select (Environmental Defense Fund, n.d.;

Polidori et al., 2021; Tracking California, 2018). Projects also have to consider whether they have permission at a specific location for a low-cost sensor. Projects may have to request permission from a local government authority if they are interested in placing the low-cost sensor on a light post, local park, or school (Environmental Defense Fund, n.d.; Tracking California, 2018).

In addition to qualitative considerations, quantitative data can also be used to quantify the ideal location for low-cost sensors based on factors like historic air quality, land use, and air pollution sources. Quantitative methods primarily use machine learning, computer modeling, simulations, and statistical estimates. Most quantitative methods use a grid approach – a defined spatial grid will cover the geographic area of interest to estimate pollutant concentrations or source impacts on an specific spatial area (Boubrima et al., 2015; Grover & Lall, 2021; Hao & Xie, 2018; Kouichi et al., 2016; Miskell et al., 2017; Sun, Li, et al., 2019). After assigning spatial grid locations, studies use machine learning patterns of pollution dispersion (Boghozian, 2021), utilize land use data to predict pollutant concentrations, use historic pollutant data to estimate the spatial locations where pollutants concentrations had the highest variability, and combine land use data with pollutant data to identify locations with limited monitoring (Kelp et al., 2022; Lerner et al., 2017). The ultimate goal of these methods is to define the number of locations where sensor placement would fill in pollutant data gaps or provide most optimal data results.

Many quantitative methods use one variable, such as land use, historic pollutant concentrations, or air pollution source locations, and output a number of locations that one would deploy if budget was not a factor. A few quantitative studies incorporate both qualitative and quantitative data: for example, one study incorporated air pollution sources, sensitive land uses, and budget and resource constraints (Lerner et al., 2017). Another study incorporated land use data, existing low-cost air quality sensors, and air pollution to perform land use regression and statistical analysis to identify areas with highest pollutant concentrations (Weissert et al., 2019). Another study utilized population density, cost, and distance from sources to identify locations (Sun, Li, et al., 2019). All of these studies require expertise in modeling, machine learning, spatial analysis, and other technical skills and rely heavily on data to drive where the location of sensors should be, making it inaccessible to the majority of low-cost air quality sensor users.

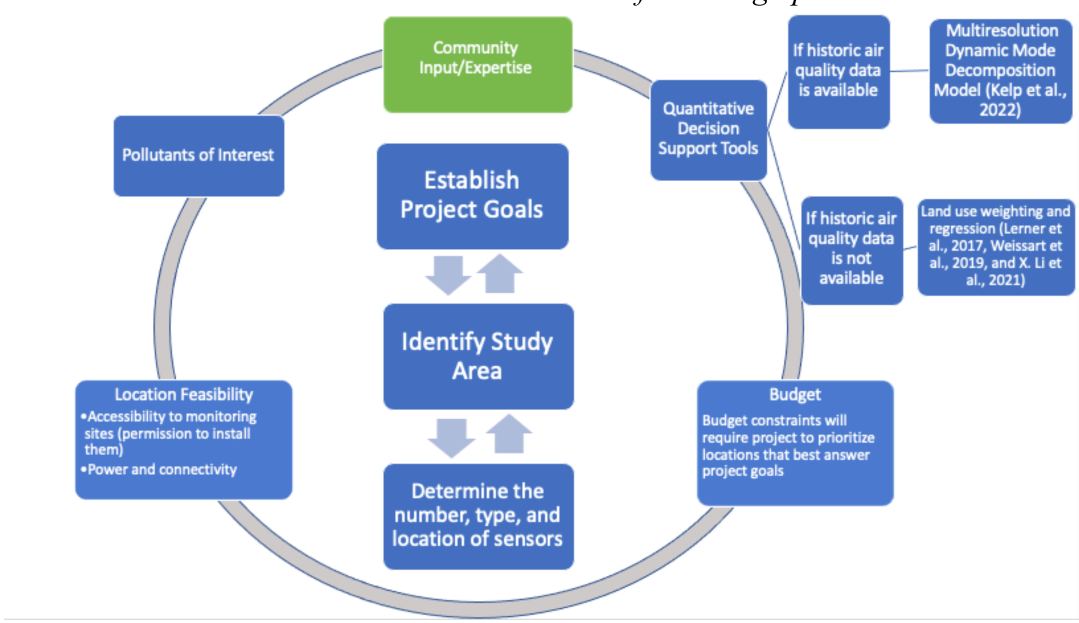
Decision Framework

In addition to the limited number of sensor network design resources, there is no framework that exists that would benefit all project types or factor in project expertise. Based on the literature, the most important elements of sensor network design identified in all projects are listed below:

- What are the research questions or project goals?
- What is the proposed study area?
- What are the pollutants of interest?
- What is the budget?
- What are the prioritized locations for sensor placement?
- How will a project collect information from local community members or air quality experts for locations to place sensors?
- Is the location accessible to place the low-cost sensors?

Based on the literature review and my professional experience, I created a decision framework for setting up low-cost sensor networks. It incorporates both qualitative and quantitative steps that can enhance sensor network design to consider community input and quantitative data. Figure 2.3 shows a diagram of the decision framework. The three steps to designing a sensor network are in the center: establishing project goals, identifying the study area, and determining the number, type, and location for the sensors. The boxes on the outside of the circle (pollutants of interest, community expertise, location feasibility, budget, and quantitative decision support tools) are factors used to inform the network design process. They are placed in a circle outside to represent the iterative nature of designing a sensor network: if one or more factors change, each of these may have to be revisited throughout the process. This decision framework is intended to include considerations for the variety of low-cost sensor project times and provide input that all low-cost sensor projects should review and discuss before designing a low-cost sensor network. To demonstrate the utility of the decision framework, two case studies with different stakeholders and project goals are described below.

Figure 2.3:Decision Framework with considerations for setting up a low-cost sensor network.



Case Study #1

A community organization is interested in better understanding the impacts of warehouses, a rail yard, and industrial facilities on their local community.

Establish Project Goals: The community organization desires to (1) increase air quality transparency to community members, and (2) have data to support local action against further land use development. The community organization does not have expertise to use quantitative decision support tools to identify and prioritize locations spatially, and thus will be relying on community input and expertise. The community organization relied on expertise from local community members and residents submitted during a community meeting where concerned residents and community members identified locations where they would like to see monitoring (*community input/expertise*). Air quality concerns are related to transportation (mobile sources) and impacts from industrial facilities. Pollutants of interest to monitor these sources include $PM_{2.5}$ and Black Carbon for diesel related sources (*pollutants of interest*).

Identify Study Area: The community organization defined their study area as an entire city. Locations for sensors were selected primarily considering access to the site. The community organization has strong ties with residents who are willing to host low-cost sensors close to the identified sources of interest and are currently working with the school district on a separate but relevant monitoring project to place more sensors at schools. The community organization is also dedicated to working with the local government for access to public property where sensors can be collocated for calibration. Due to limitations with power and connectivity, the community organization has decided to select a monitor with solar power and cellular connectivity that provides the flexibility for placement and location. The community identified twelve locations within the city, many of which were near the air pollution sources of concern, with only two of them monitoring Black Carbon and $PM_{2.5}$, and the rest only monitoring $PM_{2.5}$. The community organization has been able to secure access to those locations, either through resident volunteers, or through the local school district (*location feasibility and selecting the type of sensor*).

Determine the number, type, and location of sensors: The community organization submitted a grant to the US EPA for environmental justice related projects. The maximum budget a project could request is $500,000 over three years. The community organization was responsible for determining costs outside of the monitoring hardware and software that they would need to make their project successful, such as hiring additional staff to install and manage monitors and experts to analyze and interpret the data. The community organization determined that they could devote 20% of the budget to monitoring equipment. Based on the number of locations proposed and the budget allocated, the community organization is able to purchase 12 low-cost sensors that measure $PM_{2.5}$, and one black carbon sensor to fulfill their proposed project (*budget and number of sensors*).

Case Study #2

A small country's government with no historic air quality data monitoring is interested in deploying a low-cost sensor network over the entire country.

Establish project goals: The government aims to (1) compare pollution differences across states/provinces in order to know where to focus environmental and project resources and (2) determine where to place reference monitoring equipment. Since $PM_{2.5}$ is both a global air pollutant of concern, and relatively simple and reliable to measure, the government wants to start with monitoring this pollutant.

Identify Study Area: The government organization has the expertise to use quantitative decision support tools. Since the country has no historic air quality data available, the expert can use land use weighting and land use regression as demonstrated in Lerner et al., 2017, Weissart et al., 2019, and C. Li et al., 2021 to identify locations within the country where air pollution sources would carry the most weight over a geographic area. The government organization would define a 10 x 10 kilometer (km) spatial grid over the entire country, as described in Kelp et al., 2022 and Hao & Xie 2018, overlayed with land use data and identify the single highest 10 x 10 km grid cell in each state/province that had the greatest land uses related to air quality.

Identify the number, type, and location of sensors: Since the country will be setting up the sensor network, there are many options for them for placement within the state/providence. When considering the need for power and connectivity, the government is interested in a low-cost sensor solution that would allow them the flexibility of placing it anywhere if they decide to place the sensor in a location that may not have access to power and connectivity. The government organization is working with an undefined budget but would require justification of the project's value add for approval. Because the budget was not a limiting factor, the government organization decided to focus on bandwidth and capacity. Since the country had not previously done air monitoring, there would be a learning curve, limiting the number of sensors the country felt comfortable purchasing initially (*Expertise*). For equality and fairness across the country, the government organization decided on 10 low-cost sensors for $PM_{2.5}$, one for each of the state/provinces.

DISCUSSION

Despite the variety of project goals, and considerations needed to set up a low-cost sensor network, this chapter presents a framework that all projects can follow when designing low-cost sensors network. The decision framework unifies quantitative methods and qualitative factors that are important when considering sensor network design. The literature review demonstrates the limited number of publications on the subject and emphasizes the need for future research to bridge quantitative and qualitative methods together help projects optimize the locations of low-cost sensors and ultimately achieve results that support their project goals.

Low-cost sensors have gained popularity amongst community groups and organizations; one of their intended uses increases data accessibility and empowers communities to be informed of their air quality. However, designing a low-cost air quality sensor network focuses on the first step of the process: how to set up a network, but does not discuss next steps post data collection. The existence of low-cost sensors does not address capacity challenges for interpreting air quality data and making it actionable. Many communities know that there is a problem with air quality through their lived experiences, but do not have the quantitative data to support this.

The literature review also showed that applying quantitative methods would require expertise beyond air quality, such as computational modeling, and machine learning. Users would also have to obtain both air quality and non-air quality datasets, highlighting a limitation to accessibility to the methods used to locate low-cost sensors. Without the skillset to implement these models, and the expertise to work with additional datasets, how can projects ensure they are selecting the most optimal location for the low-cost sensor? To address these fundamental issues, federal and state policy needs to change in two ways. First, research and support should focus on developing a tool that includes both qualitative and quantitative inputs. A graphic user interface tool that would survey users on their project goals, including pre-defined questions and answers, with the technical modeling of the quantitative methods built into the tool, and output a map of the study area and locations where the sensors should be placed to answer the research goals/questions most optimally. For example, a tool that uses qualitative input such as study area/location, research project goals to define a study area, and sources of concern. On the back end, the model would include quantitative inputs, such as historic air pollution measurements (inputs in the Multi-Resolution Dynamic Model Decomposition Method), land use data, and budget constraints as the limiting factor for the number of sensors a project could purchase (inputs in the Microsensing units and Land Use analysis model). Ultimately, tools and considerations can help guide the placement of low-cost sensors, but they cannot replace the importance of community driven input and expertise.

Second, local regulatory agencies across the nation should be given resources for (1) training io agency staff on sensor network design and (2) training community organizations on how to interpret and analyze data. In my experience working with many local and state agencies, their defined roles are to manage and monitor regional air pollution using reference instruments, despite the major shift in monitoring towards low-cost, citizen science solutions. In many conversations with agencies, their largest complaint is that they do not have the funding, capacity, and organization in place to expand their air quality networks to include low-cost sensors, interpret the data, and share those results with the community. Until then, these agencies are doing the job they were intended to do.

There are few success stories for communities working to achieve their air quality goals through low-cost sensor networks. These often require partnership and commitment from air quality experts to analyze, interpret, and preset the results of data in a meaningful way to achieve results. One demonstration of using low-cost sensors to achieve a specific goal is a project in the Pleasantville community within the City of Houston, Texas. Residents had been complaining of increased respiratory problems. The US EPA has estimated that the rate of asthma, chronic obstructive pulmonary disease (COPD), and lung cancer to be at 50 cases per one million people, higher than the national average of 30 cases per one million people. Community members had expressed concerns and requests for environmental scientists to look at the air quality issues, but when complaints fell on deaf ears, community residents decided to take matters into their own hands. The Achieving Community Tasks Successfully (ACTS) nonprofit organization won a community grant to build their own low-cost air quality sensor network in order to quantify community concerns and request that the Texas Commission of Environmental Quality prioritize reference monitoring and resources into their community (One Breath Houston, 2021). TCEQ approved the request and is currently working to schedule deployment of the reference monitor.

CHAPTER THREE: Local Variation in Ambient Air Quality in an Environmental Justice Community: the Richmond Air Monitoring Network

ABSTRACT

Regulatory air quality monitoring is designed to assess regional compliance with federal air quality standards and does not provide information on localized pollution hot spots. Moreover, criteria air pollutants are regulated individually, although cumulative exposures may exacerbate health effects. This chapter uses data from the Richmond Air Monitoring Network (RAMN) - a low-cost air quality sensor network in an industrialized region of Northern California - to illustrate how such a network can aid in the identification of localized variation in air pollutant concentrations. Aeroqual AQY1 micro air quality monitors were used to collect hourly concentrations of particulate matter < 2.5 microns in diameter ($PM_{2.5}$), nitrogen dioxide (NO_2), and ozone (O_3) between December 2019 to March 2022 at 50 locations. I calculated mean daily concentrations from hourly observations for monitors with 75 percent hourly data completeness and assess (1) the degree of correlation between the three pollutants across monitoring sites and (2) the number of days measured concentrations exceed World Health Organization health-based ambient air quality thresholds for one or more of the three pollutants. Results are compared to the reference-grade monitor in the study area. Overall, mean concentrations of $PM_{2.5}$ and ozone from RAMN were similar to that of the reference monitor while the mean NO_2 concentration was double that of the reference monitor. $PM_{2.5}$ and NO_2 concentrations were moderately positively correlated at the reference monitor, while $PM_{2.5}$ and ozone as well as NO_2 and ozone were positively correlated in the summer but negatively correlated in the winter. RAMN monitors revealed significant variation in the degree of correlation across space, with many sites exhibiting inverse correlations to those observed at the

reference monitor. The WHO thresholds for $PM_{2.5}$, NO_2 and ozone were exceeded at 100%, 73%, and 100 % of RAMN monitoring locations respectively; and 90%, 86%, and 88 % RAMN locations exceeded WHO thresholds for $PM_{2.5}$, NO_2 and ozone, respectively, more frequently than the reference monitoring site. My findings indicate that low-cost sensor networks can reveal areas within a community with elevated concentrations of multiple air pollutants that are not being captured at the reference monitor and warrant further investigation.

INTRODUCTION

Air pollution is a major global threat to public health. It is well established that exposure to $PM_{2.5}$, NO_2, and ozone contribute to respiratory illnesses, such as asthma, chronic obstructive pulmonary disease (COPD) (Gao et al., 2020), lung irritation, premature mortality (Faustini et al., 2014; Stieb et al., 2021), and other adverse health impacts (Schwartz et al., 2021). Studies have also associated exposure to air pollutants, such as $PM_{2.5}$, NO_2, and ozone, with inflammatory bodily response (K. Liu et al., 2022; Ostro et al., 2014; Pope et al., 2016; Xia et al., 2021).

In the United States, regulatory air pollution monitors (herein referred to as reference monitors) are used to evaluate regional air quality and to determine compliance with the National Ambient Air Quality Standards (NAAQS) set to protect public health and the environment. Primary NAAQS provide public health protection particularly for sensitive populations such as children, the elderly, and individuals with preexisting health conditions (US EPA, n.d.-d). Regulatory state, regional, or local agencies are responsible for maintaining reference monitors, that follow 'gold-standard' operating procedures, otherwise known as Federal Reference Methods/Federal Equivalent Methods. Reference monitors are costly, require special expertise to maintain, and are located at sites selected to best capture regional conditions using U.S. Environmental Protection Agency (US EPA) criteria (US EPA, 2016). In urban areas, reference monitors are located far apart from one another, and some rural areas lack reference monitors all together. However, recent studies suggest that rural air quality can be just as concerning as urban air quality (Yixiang Wang et al., 2022). Furthermore, regional monitoring is not designed to understand intra-urban spatial variation in air quality conditions and is poorly equipped to shed light on pollution hotspots in places where people work, live, and spend their time.

Although $PM_{2.5}$, NO_2, and ozone are considered to be regional pollutants, numerous studies suggest spatial variability between reference monitor measurements and low-cost monitor measurements (Datta et al., 2020; Feinberg et al., 2019; Morawska et al., 2018; Sadighi et al., 2018). One study deployed 40 $PM_{2.5}$ low-cost monitors over Pittsburgh, Pennsylvania comparing locations near known air pollution sources (within 100 to 1,500 meters), and suburban residential sites (cited 1 mile or more away). Results of the study showed statistically significant differences of $PM_{2.5}$ concentrations within communities that were closest to air pollution sources versus communities that were further away (Tanzer et al., 2019). Another study deployed 40 $PM_{2.5}$ low-cost monitors in locations across Imperial County, California. Low-cost monitors were cited using a combination of regional modeling to identify areas with high $PM_{2.5}$ variability, and community-driven input. Following extensive calibration and data validation (Wong et al., 2018), the study evaluated the performance of the low-cost monitor network by comparing the annual mean $PM_{2.5}$ from the low-cost monitors to the reference monitor from 2015 to 2018. The results suggest that the low-cost monitor annual mean $PM_{2.5}$ concentrations differed statistically from the reference monitor for two out of the four years, suggesting the low-cost air quality monitor network was able to show hyper localized, real-time pollution episodes that were underreported by the reference monitor (English et al., 2020).

While many studies have demonstrated single pollutant variations across space, there are few studies that explore geographic hyperlocal variability of two or more pollutants. The NAAQS and other health-based air quality goals are set at a per pollutant basis, despite the fact that individuals may be exposed to elevated levels of one or more pollutants at a time. The literature has highlighted a need for research that evaluates exposure to multiple pollutants when assessing health impacts; changes in epidemiological and statistical models that represent multiple pollutants; and the need for changes in effective air quality management implemented at the federal level (Vedal & Kaufman, 2012). Furthermore, reports have highlighted the growing concern of the limited data available on simultaneous exposures to multiple air pollutants (i.e., co-exposures), including $PM_{2.5}$ and ozone (Johnson, 2009). The limited data on co-exposures to multiple pollutants, despite its real-world impacts on public health, highlights a fundamental limitation in using the NAAQS to protect public health. This is especially important for communities who are disproportionately burdened by air pollution and other environmental hazards.

Air pollution is an environmental justice issue, with disadvantaged communities facing disproportionate exposure to air pollution. Communities of color or of lower socioeconomic status are more likely to be exposed to higher concentrations of air pollutants. One study quantified the differences in exposure to the six US EPA criteria pollutants: carbon monoxide (CO), sulfur dioxide (SO_2), particulate matter less than or equal to 10 microns in diameter (PM10), $PM_{2.5}$, NO_2, and ozone from 1990 to 2010. Results of the study indicated that racial/ethnic minority groups experienced the highest national average exposure for all years and all pollutants (J. Liu et al., 2021). Another study explored spatial patterns in ambient NO_2 concentrations across US census tracts. Results showed that low-income nonwhite children and elderly people are disproportionately exposed to ambient NO_2, by a population mean-weighted average of 4.6 parts per billion (ppb) higher concentration, which may contribute to development of heart disease (L. P. Clark et al., 2014). Due to the clustering of industry in disadvantaged communities, residents of those communities tend to be exposed to a greater number of air pollution sources, such as freeways, refineries, ports, railyards, and other industrial sources that may contribute to exposure to multiple pollutants. Socially disadvantaged populations may also be more susceptible to health impacts stemming from their exposure due to social stressors and preexisting health conditions (August et al., 2021). Studies have shown that individuals with pre-existing cardiovascular diseases can respond differently to the effects of air pollution. One study demonstrated that long-term exposure to $PM_{2.5}$ can exacerbate heart disease and increase stroke mortality (Hayes et al., 2020). Currently regulatory approaches may be inadequate to protect human health in environmental justice communities facing such cumulative exposures for two reasons: (1) low-spatial coverage of reference monitors poorly captures localized variation in air quality and (2) US EPA NAAQS, European Union, and World Health Organization set health-based air pollutant standards and guidelines on a per-pollutant basis with limited knowledge of the impacts of co-exposures of pollutants, despite its real-world impacts.

New technologies can help fill gaps in our understanding of localized hotspots for one or more pollutants by providing more spatially refined information about air quality. Low-cost air quality sensors have gained popularity over the last decade for providing additional air monitoring, increasing access to real-time data, increasing the spatial density of monitors, reducing the barrier to entry for collecting air quality measurements, and increasing understanding of air pollution attributable to local sources (Considine et al., n.d.; Tanzer et al., 2019; Zuidema et al., 2021). Low-cost sensors can provide more granular air quality conditions than the reference monitors. The comparison between reference monitor data and low-cost air quality sensor data is important for a few reasons: First, low-cost sensors can provide insight to nearby sources that may be underreported by the reference monitor. For example, we may expect to see higher concentrations of pollutants near roadways. Second, reference monitors have to follow specific siting requirements, such as height above ground, spacing from air pollution sources, and pollutant sampling times (US EPA, 2016). Using reference monitors are not useful to measure trends at the local level. Regional reference monitors are used to make decisions on health-based air quality standards, yet due to the specific siting requirements, where they are located may not be representative of what communities are actually exposed to. Third, the quantitative data available for low-cost air quality sensors can support anecdotal experiences that localized air quality conditions are variable, and that regulatory decision making should consider local conditions, not just reference monitors. Quantitative data from low-cost sensors can demonstrate spatial and temporal variation that is useful for governments when deciding where to allocate further monitoring efforts and devote community resources for air pollution mitigation and emission reduction efforts (Shatas & Hubbell, 2022).

This study makes use of air quality measurements from a low-cost sensor network in Richmond, North Richmond, and San Pablo (Richmond-San Pablo), California. The community is burdened by a number of sources, including industrial facilities (petroleum, chemical, and other manufacturing), and mobile sources, including high volume freeways, and railways/rail yards. The Richmond, North Richmond, and San Pablo communities range from 16 to over 33 percent African America and from 40 to over 56 percent Latinx. Many areas within the community experience social and economic disadvantages, more asthma emergency room visits, higher rates of cardiovascular diseases, and higher incidences of poverty than other areas within the region (BAAQMD, 2018). The California legislature passed Assembly Bill 617 (2017), to begin working to improve air quality for communities disproportionality affected by air pollution (California State Legislature, n.d.). In part due to its high density of complex air pollution sources, the Bay Area Air Quality Management District (BAAQMD) recommended the Richmond-San Pablo community develop and implement an air monitoring plan. Community organizations and residents in the Richmond-San Pablo community worked with BAAQMD to develop a Community Steering Committee, providing a process for knowledgeable community members to raise awareness to the greatest air quality concerns within the community. The Community Steering Committee and BAAQMD used this information to develop a Community Air Monitoring Plan (BAAQMD, 2020).

This chapter analyzes high spatial resolution air pollutant measurements collected via the resulting 27-month low-cost sensor air monitoring campaign in Richmond-San Pablo, CA to better understand intra-urban variation in ambient concentrations of three criteria air pollutants: $PM_{2.5}$, NO_2, and ozone. This chapter builds upon the Richmond Air Monitoring Network (RAMN) Study (Lukanov et al., 2022) by focusing on co-pollutant relationships to better understand differences in trends shown by RAMN monitors compared to the reference monitor. The specific objectives of this chapter are to utilize low-cost sensor data to examine (1) co-exposure patterns and spatial variation and (2) examine divergence from reference monitors with respect to exceedances of health-protective concentrations.

Co-exposure patterns. Except with respect to NO_2 and ozone, the few studies that explore the correlation between multiple pollutants cover only China and India. In those studies, regional measurements of $PM_{2.5}$ and NO_2 concentrations were observed to be positively correlated (as one increases, the other increases) (Ji et al., 2022; Wu et al., 2016). $PM_{2.5}$ and ozone were observed to have a positive relationship in the summer and negative relationship in the winter (Chen et al., 2019; L. Wang et al., 2023). NO_2 and ozone concentrations were observed to have an inverse relationship (CalEPA, CARB, 2007). NO_2 is effectively used to create ozone, and thus NO_2 concentrations are lower in the summer when ozone is the highest. Conversely, less chemical reactivity via sunlight (precursors to ozone formation), and a higher frequency of lower atmosphere inversions in California contribute to higher NO_2 concentrations in the winter (CalEPA, CARB, 2007). NO_2 and ozone typically have an inverse relationship (as one increases, the other decreases) (Pancholi et al., 2018; Soares et al., 2021).

Research revealed no studies in northern California that have explored these relationships between NO2 and ozone, nor the respective relationships between $PM_{2.5}$ and NO_2 or $PM_{2.5}$ and ozone anywhere in California. Furthermore, no studies have examined the degree to which these multiple pollutant relationships at the regional level are consistent at the local level. Variation in proximity to pollutant sources such as roadways, for example, might contribute to higher ambient concentrations of both $PM_{2.5}$ and NO_2 that would be observed at the local level and not observed at the regional level.

Exceedance of Health-Protective Air Quality Thresholds. This study also aims to identify localized exceedances of health-based air quality standards set by the World Health Organization (WHO) by calculating the number of days at each monitoring location for which health-based air quality thresholds were exceeded for each pollutant. The WHO sets Air Quality Guidelines (AQGs), global targets for governments around the world to work towards reducing exposure to harmful air pollutants and improving citizen health overall. WHO sets the AQGs by conducting a systematic literature review, evaluating methods used to better understand the relationship between air quality and public health, and consulting with experts, including researchers and practitioners. The AQGs are updated regularly to consider new and emerging research (Pai et al., 2022). The most recent AQGs were established in 2021(Pai et al., 2022). For short term $PM_{2.5}$ and NO_2 exposures, WHO provides a 24-hour standard. For ozone exposures, WHO provides a standard based on an 8-hour rolling average (Table 3.1).

Table 3.1: WHO AQGs Levels (Pai et al., 2022)

Recommended 2021 AQG levels compared to 2005 air quality guidelines

Pollutant	Averaging Time	2005 AQGs	2021 AQGs
$PM_{2.5}$, μg/m^3	Annual	10	5
	24-hour[a]	25	15
PM_{10}, μg/m^3	Annual	20	15
	24-hour[a]	50	45
O_3, μg/m^3	Peak season[b]	-	60
	8-hour[a]	100	100
NO_2, μg/m^3	Annual	40	10
	24-hour[a]	-	25
SO_2, μg/m^3	24-hour[a]	20	40
CO, mg/m^3	24-hour[a]	-	4

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μg = microgram

[a] 99th percentile (i.e. 3–4 exceedance days per year).

[b] Average of daily maximum 8-hour mean O_3 concentration in the six consecutive months with the highest six-month running-average O_3 concentration.

Note: Annual and peak season is long-term exposure, while 24 hour and 8 hour is short-term exposure.

This chapter focuses upon the AQGs rather than the NAAQS because adverse health impacts from exposure to air pollution appear to occur at lower concentrations than those deemed to be health protective by the NAAQS (Crouse et al., 2012; Hales et al., 2012; Shi et al., 2016). Given evidence of harm at concentrations lower than existing air quality standards, the

US EPA is currently reviewing the $PM_{2.5}$ NAAQS standard (US EPA, n.d.-e). The AQGs are intended to be health protective, and based in scientific rigor, and are more conservative than the NAAQS.

I also identify RAMN locations where concentrations exceeded short-term health-based standards for one or more pollutant and whether the reference monitor also captured the same number of exceedances. I hypothesize that the RAMN will detect more exceedances than the reference monitor due to local influences from air quality sources and highlight potential co-exposures of pollutants that exceed health-protective standards.

This aspect of the chapter examines two hypotheses:

1) On days where $PM_{2.5}$ is higher, NO_2 and ozone will also be higher at most monitoring locations, but that the degree of correlation will vary seasonally and spatially.
2) The RAMN monitors will diverge from the reference monitor in terms of measured pollutant concentrations and correlations between pollutants, especially near air pollution sources, such as roadways.

METHODS

Richmond Air Monitoring Network

In 2018, CARB designated the Richmond-San Pablo community an AB 617 community, making the community eligible for community air monitoring funding. PSE Healthy Energy (PSE) and the Asian Pacific Environmental Network (APEN) received funding through the AB 617 Community Air Grants Program to implement a stationary air monitoring network throughout Richmond-San Pablo, which is characterized as having some of the most disproportionate air pollution and environmental burdens in California. In 2019, PSE, APEN, and University of California, Berkeley received additional funding to expand air monitoring efforts. The 2019 project expanded the 2018 project to add additional pollutants and monitoring equipment, and made use of existing community efforts and monitoring sites (CARB, 2019). Monitoring took place between December 2019 and March 2022, with analysis and preparation of a report drawing the project through the end of 2022; project activities and results are provided in detail in Lukanov et al. (Lukanov et al., 2022).

Data for this chapter was obtained from the RAMN. RAMN aimed to provide the Richmond-San Pablo community with high-resolution air quality monitoring data to promote community engagement, to supplement existing monitoring data within the community, and to inform the development of community emission reduction plan. RAMN was established with key objectives to conduct high density monitoring with data collected every minute; to characterize local ambient concentrations; to detect short-lived pollution; to identify local air pollution hot spots and local sources of pollution; and to provide reliable, local air quality data to the community and regulators to foster actionable change within the local regulatory landscape.

Briefly, PSE procured 50 Aeroqual AQY1 air quality monitors (Aeroqual, n.d.-c), which monitor $PM_{2.5}$, NO_2, ozone, relative humidity, temperature, and dew point. These low-cost sensors transmit data collected to Aeroqual's cloud-based platform. The RAMN included monitors located across 14 neighborhoods with the goal of having at least one air monitor within each neighborhood. RAMN monitor locations were assigned a land use category: residential, commercial, or industrial. PSE assigned land uses for RAMN using the City of Richmond Zoning data and satellite imagery for the San Pablo Area. In total, 29 monitors were deployed at residential land uses, 14 were deployed at commercial land uses, and 7 were deployed at industrial land uses.

PSE collocated the 50 Aeroqual AQY1 air quality monitors near reference monitors at CARB's Monitoring and Laboratory Division in Sacramento, CA between July 2019 and January 2020. The long initial field calibration was meant to study and understand overall sensor drift and inter-device variability and to correct for individual sensor bias. Two monitors were left at the CARB site in Sacramento to continue monitoring for sensor drift. 50 Aeroqual AQY1 air quality monitors were deployed throughout the Richmond-San Pablo community between December 2019 and August 2020. Monitor deployment was significantly delayed in the Spring and Summer of 2020 due to the COVID-19 Pandemic. The network began operating in December 2019 and finished collecting data in March 2022.

Quality Assurance/Quality Control (QA/QC)

PSE used data from the "San Pablo – Rumrill" reference monitor to compare trends between each of the RAMN locations and the reference monitoring location. PSE utilized a multi-step quality assurance process to address known issues with data quality, including sensor drift, sensor failure, sensitivity to environmental conditions, such as temperature and relative humidity, and data incompleteness. Aeroqual AQY1 monitors transmit data directly to the Aeroqual Cloud. PSE built a coding script in R/Python that requested data from the Aeroqual Cloud on a one-minute basis while also looking for any missing data in the last eight weeks and beginning the data request with the first missing one-minute timestamp. The data were then average temporally into 10-minute and 60-minute intervals. Averaging into these temporal intervals was only conducted if the data was defined as being at least 75 percent complete for a given averaging period. If the data were not 75 percent complete, the data were excluded from analysis.

Due to changing meteorological conditions in Richmond-San Pablo, as compared to Sacramento where the devices were collocated, the monitoring network needed ongoing calibration for all pollutants. Calibration parameters were provided each month by Aeroqual. Aeroqual also applied a proprietary relative humidity correction to all $PM_{2.5}$ data to improve data quality. To apply wildfire corrections, PSE identified ground-level wildfire smoke events on an hourly basis. PSE used the Anomaly Detection R Package to detect high $PM_{2.5}$ events for each monitor during deployment. Two of the collocated Aeroqual monitors required data cleaning for ozone to adjust incorrectly calibrated values that were clearly incorrect for specific months. This was done for the collocated monitors because PSE was able to verify the incorrect values as compared to the reference station. Note that it is unknown if this problem persists with the other monitors and for different times. Additional information about the Richmond Air Monitoring Network can be found in the published report *Understanding Air Quality Trends in Richmond-San Pablo, California* (Lukanov et al., 2022).

Analysis – Co-Exposure Patterns

PSE provided air quality concentrations for $PM_{2.5}$, NO_2 , and ozone averaged in 60-minute intervals. Data were provided in units of micrograms per cubic meter ($\mu g/m^3$) for $PM_{2.5}$ and parts per billion (ppb) for NO_2 and ozone. Observations that were negative, zero or flatlined for greater than 24 hours, above the third quartile plus three times the interquartile range for greater than 24 hours, and unexpectedly high concentration events ($X \geqslant 800$ for $PM_{2.5}$, 200 for NO_2, and 150 for ozone) were flagged by as anomalous and thus I excluded them from the analysis. Because my interest was in typical conditions, I excluded wildfire days from the RAMN network using PSE's flags for wildfire smoke events. I also excluded five $PM_{2.5}$ days, and two NO_2 days from the reference monitor where observations were identified as being highly influenced by wildfires. I used R and ESRI's ArcGIS Pro were used to conduct the statistical analysis. Since the data is non-linear, I conducted a Spearman correlation to determine if there were positive or negative relationships between multiple pollutant concentrations.

The 60-minute concentrations were used to calculate a 24 hour mean for $PM_{2.5}$, NO_2 , and ozone only including days where the data were at least 75 percent complete, defined as 18 or more 60 minute measurements within a 24-hour period (US EPA, n.d.-b; US EPA OAQPS, 2017). Since the data do not follow a normal distribution, I then used Spearman correlation coefficients to assess the degree of correlation for three pollutant combinations at each monitoring location: $PM_{2.5}$ and NO_2, $PM_{2.5}$ and ozone, and NO_2, and ozone. Correlation coefficients [ρ] were mapped to visualize spatial variation in the direction and magnitude of correlation between daily mean concentrations of each pair of pollutants over the study period, and during summer and winter seasons. In order to explore the hypothesis that correlations observed at the local scale differ from those observed regionally, I compare pollutant-pair correlation coefficients at each monitoring location to the reference monitor during summer and winter and across the study period for all pollutant combinations. PSE calculated the distance to the nearest roadway, defined from Highway Performance Monitoring System (HPMS) data (FHA, n.d.). I performed a Spearman correlation calculation to demonstrate the relationship between distance to nearest roadway and the co-pollutant correlation coefficients.

Analysis – Exceedances of 2021 WHO AQGs

The 24-hour mean $PM_{2.5}$ and NO_2 values were used to calculate exceedance days. In accordance with the WHO AQGs, an exceedance day was defined when the 24-hour $PM_{2.5}$ mean was greater than 15 μg/m^3,and the 24-hour NO_2 mean was greater than 25 μg/m^3. For ozone, the R "zoo" package was used to calculate the maximum 8-hour ozone rolling average, grouped by day, month, and year. An exceedance day was defined when the maximum 8-hour rolling ozone average was greater than 100 μg/m^3 (Table 3.1).

To calculate the percent of days that the WHO AQGs were exceeded for each of the three pollutants, I divided the number of days that each RAMN monitor and the reference monitor had a defined "exceedance" by the number of days that the RAMN monitor was defined as operational for that pollutant. I define "days operational" to only include the days where 75 percent of data were complete, and thus would have enough data to calculate a 24-hour average or an 8-hour rolling average, respectively. Days operational varied drastically by location and pollutant, due to deployment challenges from the COVID-19 pandemic; intermittent operational data transmission issues; and pollutant specific challenges (see Discussion). The percentage was then classified as an exceedance if the percentage exceeded was greater than 1 percent, or the 99th percentile.

I additionally calculated the number of days where the WHO AQGs were exceeded for two or more pollutants by dividing the number of days the standard was exceeded by the number of days the monitor was operational and then classified it as exceeding if the result was greater 1 percent. Data were filtered to show days with (a) $PM_{2.5}$ and NO_2, (b) $PM_{2.5,}$ and ozone, (c) NO_2 and ozone, and (d) $PM_{2.5}$, NO_2 , and ozone WHO AQGs exceedances. Because the number of days that each monitor and pollutant were operational were different, the denominator selected was the lowest number of days operational between the two or three pollutants.

RESULTS

Correlation Between Daily Mean Ambient Air Quality Concentrations: $PM_{2.5}$ and NO_2, $PM_{2.5}$ and ozone, and NO_2 and ozone

Fifty RAMN locations were operational for a mean of 580 days for $PM_{2.5}$, 316 days for NO_2, and 505 days for ozone (Table 3.2). Mean daily concentrations were 10.4 μg/m^3 for $PM_{2.5}$, 14.4 ppb for NO_2 and 25.5 ppb for ozone, which are similar for $PM_{2.5}$ and ozone on average with analogous concentrations from the reference monitor over the same period (10.1 μg/m^3 for $PM_{2.5}$ and 26 ppb for ozone) but were higher than the average NO_2 concentration at the reference monitor (7.2 ppb) (Table 3.3).

Table 3.2: RAMN Summary Statistics for RAMN monitoring locations (n=50), Richmond-San Pablo, CA, January 2020 – March 2022

	Mean (%)	**Minimum**	**Maximum**	**N**
Land use				
Residential	-	-	-	29
Commercial	-	-	-	14
Industrial	-	-	-	7
Days operational				
$PM_{2.5}$	580	175	791	
NO_2	316	34	551	
O_3	505	268	780	
24-Hour mean concentrations[1]				
$PM_{2.5}$ (μg/m^3)	10.4	0	478.6	28,995
NO_2 (ppb)	14.4	0	161.6	15,821

[1] N=the number of days that all monitors from the RAMN network had 75% data completeness for each pollutant

	Mean (%)	Minimum	Maximum	N
O_3 (ppb)	25.5	0.56	108.4	25,236
Correlation between $PM_{2.5}$ and NO_2 (Rho)				
Study Period	0.000018	-0.31	0.25	23 positive/27 negative
Summer	0.05	-0.54	0.79	27 positive/21 negative
Winter	-0.02	-0.85	0.44	24 positive/24 negative
Correlation between $PM_{2.5}$ and O_3 (Rho)				
Study Period	-0.17	-0.68	0.12	8 positive/42 negative
Summer	-0.01	-0.51	0.59	22 positive/25 negative
Winter	-0.21	-0.68	0.66	8 positive/39 negative
Correlation between NO_2 and O_3 (Rho)				
Study Period	-0.16	-0.31	0.25	12 positive/38 negative
Summer	-0.11	-0.56	0.77	11 positive/35 negative
Winter	-0.03	-0.87	0.67	22 positive/28 negative
Days (%) exceeding WHO standard[2]				
$PM_{2.5}$	105 (18%)	21	192	580
NO_2	124 (40%)	0	252	316
O_3	25 (5.0%)	0	85	505
$PM_{2.5}$ and NO_2	22 (6.7%)	4	57	326
$PM_{2.5}$ and O_3	5 (1.6%)	1	26	316
NO_2 and O_3	4 (1.8%)	1	19	217
$PM_{2.5}$, NO_2 and O_3	2 (0.6%)	1	5	336

[2] N=The denominator used to calculate the percent of days exceeding the WHO thresholds are the minimum number of days that the RAMN monitor was operational and had 75% data completeness.

Table 3.3: Summary Statistics for Richmond-San Pablo Reference monitor (n=811 days), Richmond-San Pablo, CA, January 2020 – March 2022

	Mean (%)	**Rho**
24-Hour mean concentrations		
$PM_{2.5}$ (µg/m^3)	10.1	
NO_2 (ppb)	7.2	
O_3 (ppb)	26	
Correlation between $PM_{2.5}$ and NO_2		
Study Period		0.23
Summer		0.47
Winter		0.51
Correlation between $PM_{2.5}$ and O_3		
Study Period		-0.04
Summer		0.24
Winter		-0.4
Correlation between NO_2 and O_3		
Study Period		-0.44
Summer		0.18
Winter		-0.44
Exceedance Days		
$PM_{2.5}$	97 (12%)	
NO_2	68 (8%)	
O_3	10 (1.2%)	
$PM_{2.5}$ and NO_2	15 (1.8%)	
$PM_{2.5}$ and O_3	4 (0.5%)	
NO_2 and O_3	1 (0.1%)	
All Pollutant	1 (0.1%)	

Over the entire study period, $PM_{2.5}$ and NO_2 were positively correlated at the reference monitor and variably correlated over the RAMN network. Out of 50[3] of RAMN monitoring locations, 27 (54%) were positively correlated, and 23 (46%) were negatively correlated, not entirely in accordance with the degree of correlation observed at the reference monitor (Figure

[3] This includes the two collocated monitors.

3.1a). $PM_{2.5}$ and NO_2 showed similar trends during both summer and winter, trending weakly positively correlated. During summer, out of 48[4] of RAMN monitoring locations, 27 (56%) were positively correlated, and 21 (44%) were negatively correlated, in contrast with the degree of correlation observed at the reference monitor (Table 3.2). Figure 3.2a shows the Rho values in the summer season. In winter, $PM_{2.5}$ and NO_2 correlations between concentrations were both positive and negative (Figure 3.2d). Out of 48 RAMN monitoring locations, 24 (50%) were positively correlated, and 24 (50%) were negatively correlated, half in accordance with the degree of correlation observed at the reference monitor (0.51). The degree of correlation between $PM_{2.5}$ and NO_2 slightly declined on average with distance to roadway. The grey shaded areas on the plots represent the standard error (Figure 3.7).

[4] This excluded the two collocated monitors.

Figure 3.1: Correlation between daily mean ambient air quality concentrations at reference and RAMN monitors during entire study period for: (a) $PM_{2.5}$ and NO_2, (b) $PM_{2.5}$ and O_3 and, (c) NO_2 and O_3

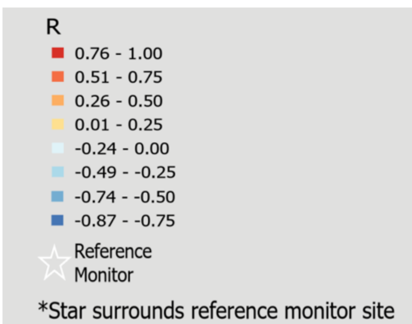
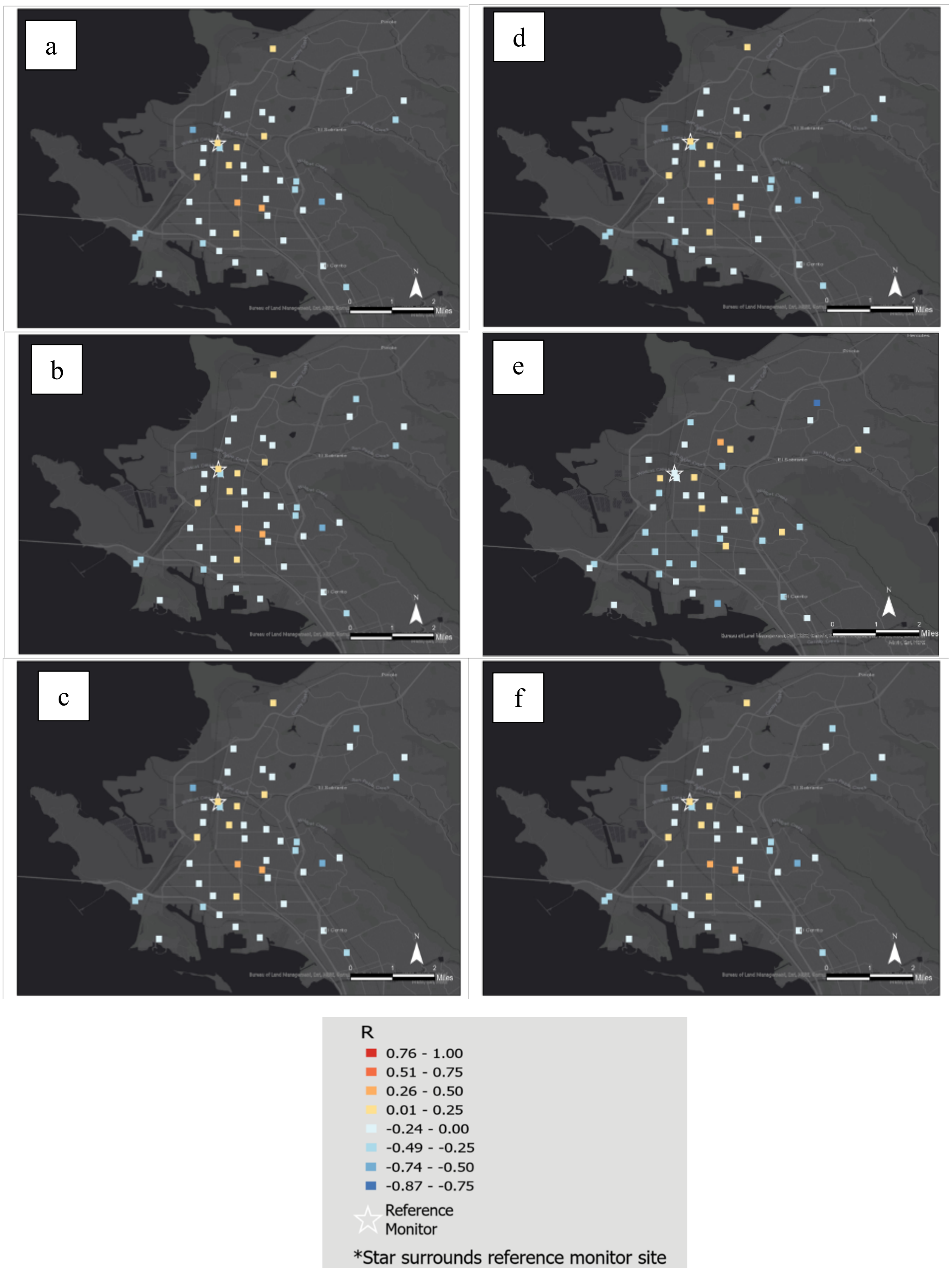


Figure 3.2: Correlation between daily mean ambient air quality concentrations at reference and RAMN monitors during summer for: (a) $PM_{2.5}$ and NO_2, (b) $PM_{2.5}$ and O_3 and, (c) NO_2 and O_3 and winter for (d) $PM_{2.5}$ and NO_2, (e) $PM_{2.5}$ and O_3 and, (f) NO_2 and O_3



Over the entire study period, $PM_{2.5}$ and ozone the correlation was negative at the reference monitor, in accordance with the predominantly negative correlations among the RAMN network (Table 3.2 and 3.3). Out of 50 RAMN monitoring locations, 8 (16%) exhibited a positive correlation and 42 (84%) exhibited a negative correlation, with some areas within the community showing a stronger correlation (Figure 3.1b). $PM_{2.5}$ and ozone showed different seasonal trends, trending both positively and negatively correlated during summer (Figure 3.2b). Out of 47 RAMN monitoring locations, 22 (46%) were positively correlated, and 25 (53%) were negatively correlated, not entirely in accordance with the degree of correlation observed at the reference monitor (Table 3.2 and 3.3). In winter, $PM_{2.5}$ and ozone correlations were predominantly negative (Figure 3.2e). Out of 47 RAMN monitoring locations, 8 (17%) were positively correlated, and 39 (81%) were negatively correlated, in accordance with the degree of correlation observed at the reference monitor. When comparing the nearest roadway to the $PM_{2.5}$ and ozone correlation, there is little evidence of a difference in the strength of correlation between $PM_{2.5}$ and ozone and distance to roadway (ρ=0.048) (Figure 3.7).

Over the entire study period, NO_2 and ozone were negatively correlated at the reference monitor (Table 3.3), in accordance with the RAMN network with predominantly negative correlations (Figure 3.1c). Out of 50 RAMN monitoring locations, 12 (24%) exhibited a positive correlation and 38 (76%) exhibited a negative correlation. NO_2 and ozone showed similar seasonal trends, trending predominantly negative (Figure 3.2c). During summer, out of 48 RAMN monitoring locations 11 were positively correlated, and 35 negatively correlated, in contrast with the degree of correlation observed at the reference monitor (ρ=0.18) (Tables 3.2 and 3.3). In winter, NO_2 and ozone showed similar seasonal trends to what was identified in the literature and at the reference monitor, trending predominantly negative (ρ=-0.44) (Figure 3.2f).

Of the 50 RAMN monitoring locations, 22 (44%) were positively correlated, and 28 (56%) were negatively correlated. When comparing the nearest roadway to the NO_2 and ozone correlation, there is a positive correlation between NO_2 and ozone and distance to roadway (ρ=0.38) (Figure 3.7). Rho values for RAMN monitoring network can be found in Appendix 3A.

WHO AQGs Exceedance Calculations

Figure 3.3 shows the percent of days concentrations exceeded WHO AQGs thresholds for $PM_{2.5}$, NO_2, and ozone. Over the entire study period, the average percent of days exceeded for $PM_{2.5}$, NO_2, and ozone at the RAMN network (18%, 40%, and 5%, respectively) were greater than the percent of days exceeded at the reference monitor (12%, 8%, and 1.2% respectively) (Table 3.2). The WHO thresholds for $PM_{2.5}$, NO_2 and ozone were exceeded at 100%, 73%, and 100 % of RAMN monitoring locations; and 90%, 86%, and 88 % RAMN locations exceeded WHO thresholds for $PM_{2.5}$, NO_2 and ozone more frequently than the reference monitoring site. The proportion of days exceeding threshold was greater at RAMN locations (Figure 3.4) and among residential and commercial locations rather than industrial ones. There is no strong correlation between the percent of days that $PM_{2.5}$, NO_2, or ozone were exceeded and the distance to the nearest roadway (Figure 3.8).

Figure 3.5 shows locations within the community where two or more pollutants exceeded WHO AQGs on the same day. Figure 3.6 shows that most RAMN locations at a higher percent of days exceeding WHO short-term thresholds than the reference monitor. Tables 3.2 and 3.3 show the average percent of days that two or more pollutants exceeded the WHO AQG thresholds. The average percent of days that both $PM_{2.5}$ and NO_2 exceeded at the RAMN network (8.4%) is greater than the percent of days that both $PM_{2.5}$ and NO_2 exceeded at the reference monitor (1.8%). The average percent of days that both $PM_{2.5}$ and ozone exceeded at the RAMN network (1.3%) is greater than the percent of days that both $PM_{2.5}$ and NO_2 exceeded at the reference monitor (0.5%). The average percent of days that both NO_2 and ozone exceeded at the RAMN network (2%) is greater than the percent of days that both $PM_{2.5}$ and NO_2 exceeded at the reference monitor (0.1%). The average percent of days that all three pollutants: $PM_{2.5}$, NO_2 and ozone exceeded at the RAMN network (0.7%) is greater than the percent of days that all three pollutants exceeded at the reference monitor (0.1%) (Tables 3.2 and 3.3). There is no strong correlation between the percent of days that $PM_{2.5}$, NO_2, or ozone were exceeded and the distance to the nearest roadway (Figure 3.9).

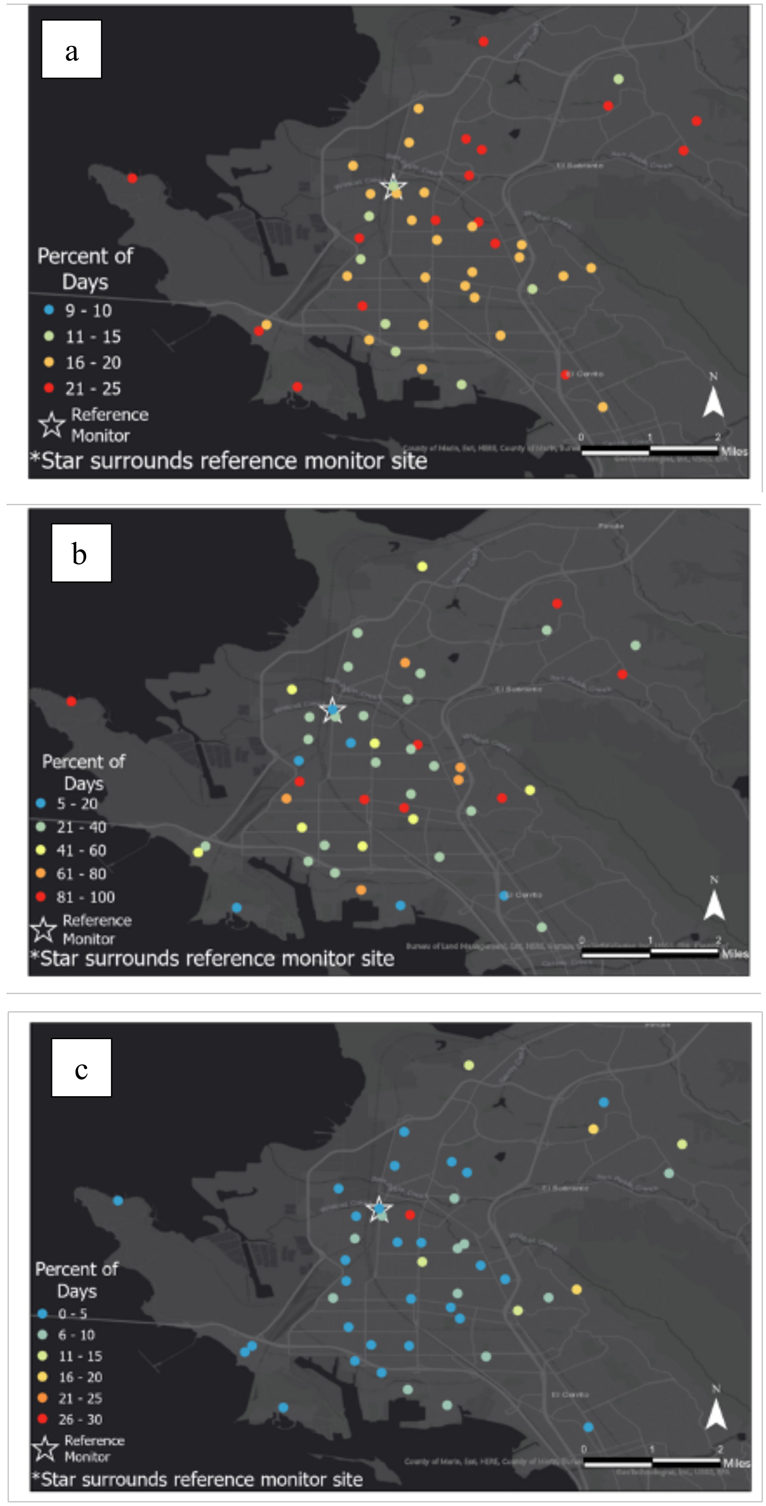
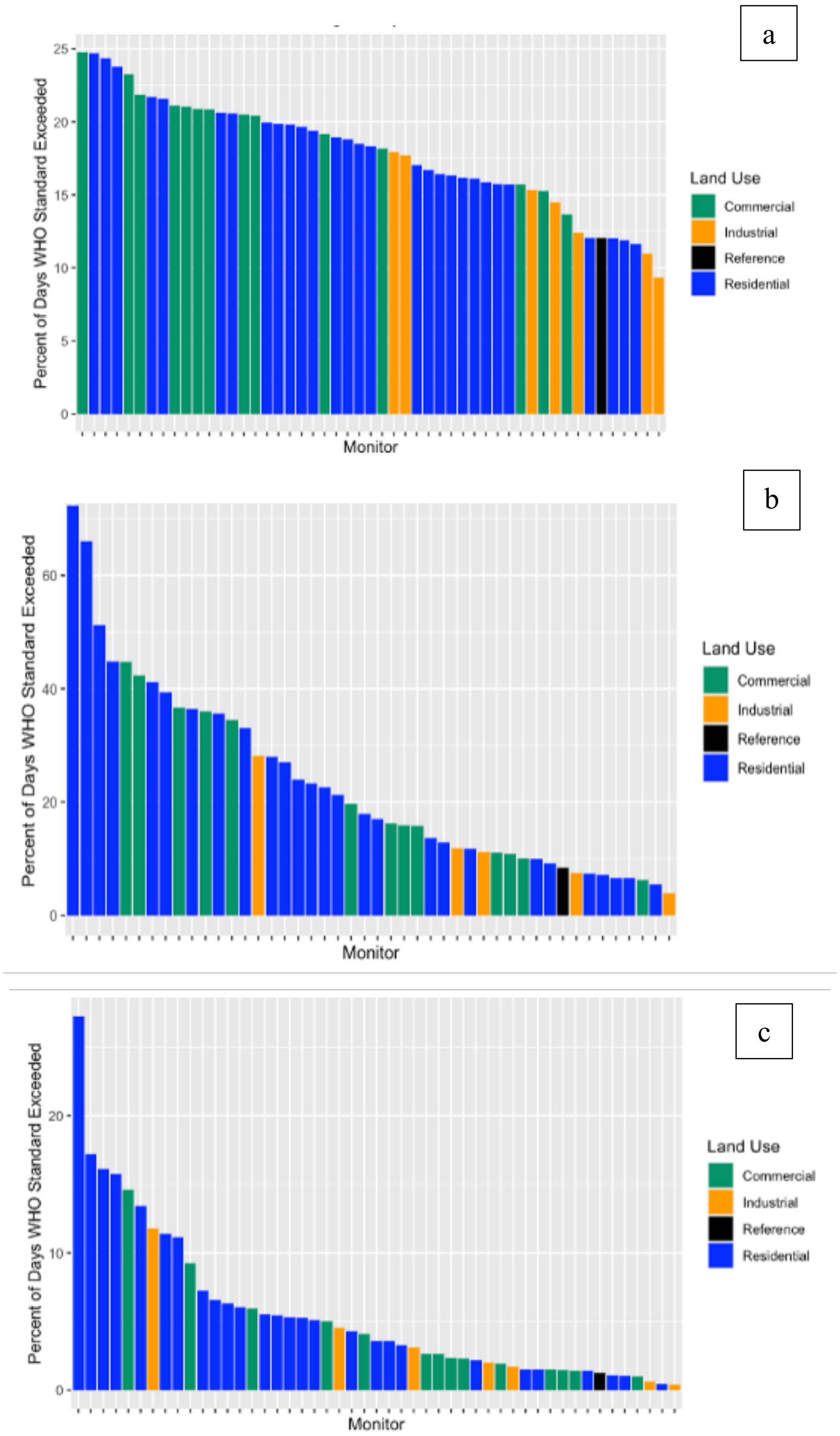


Figure 3.3: Percent of days concentrations exceeded WHO Air Quality Goals for: (a) $PM_{2.5}$, (b), NO_2, and (c) O_3.

Figure 3.4: Percent of days concentrations exceeded WHO Air Quality Goals for: (a) $PM_{2.5}$ (b)NO_2 (c) O_3. "Reference" in black refers to the reference monitor.



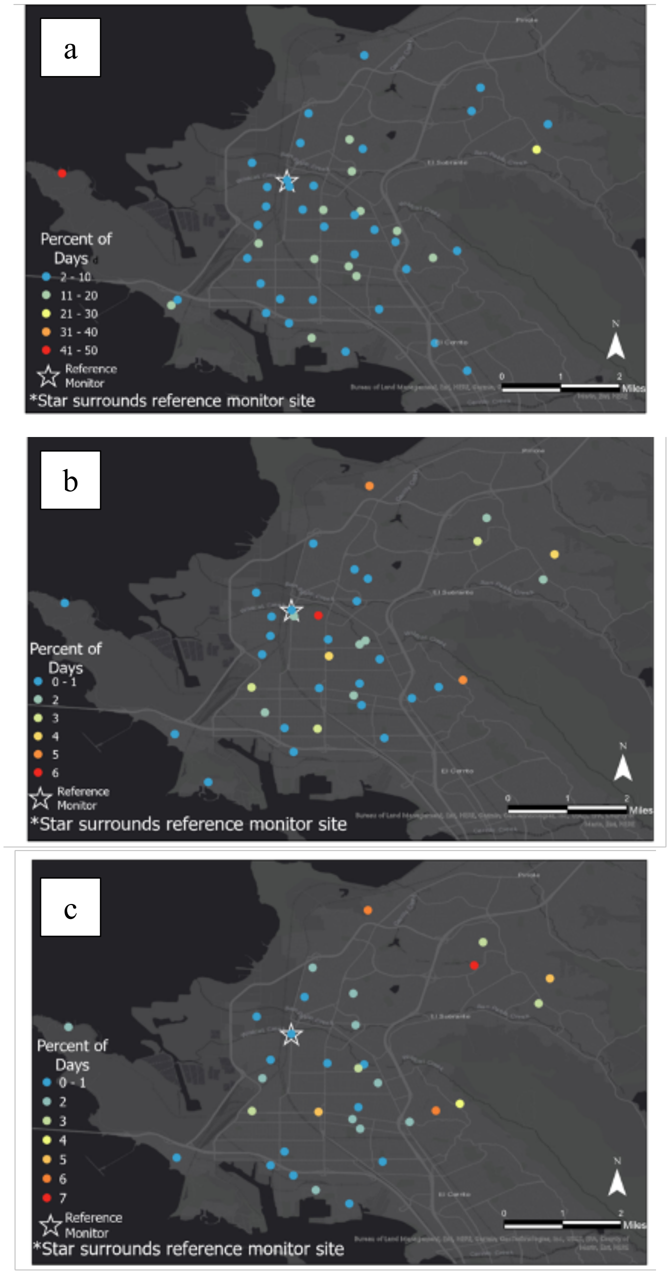


Figure 3.5: Percent of days concentrations exceeded WHO Air Quality Goals for: (a) $PM_{2.5}$ and NO_2, (b)$PM_{2.5}$ and O_3, and (c) NO_2 and O_3

Figure 3.6: Percent of days concentrations exceeded WHO Air Quality Goals for: (a) $PM_{2.5}$ and NO_2, (b)$PM_{2.5}$ and O_3, (c) NO_2 and O_3, and (d) $PM_{2.5}$, NO_2 and O_3

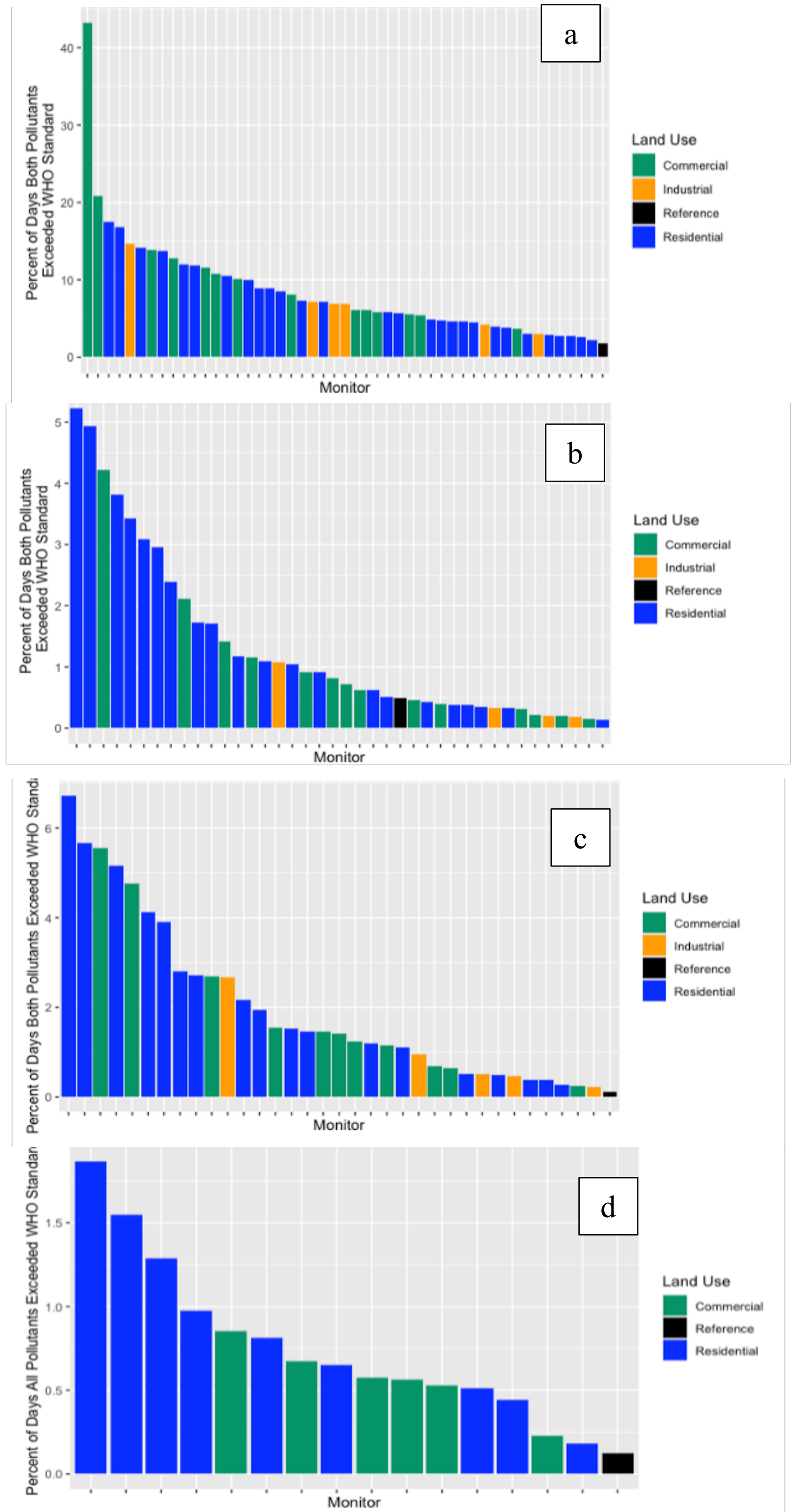


Figure 3.7: Relationship between pollutant Rho values and distance to roadway

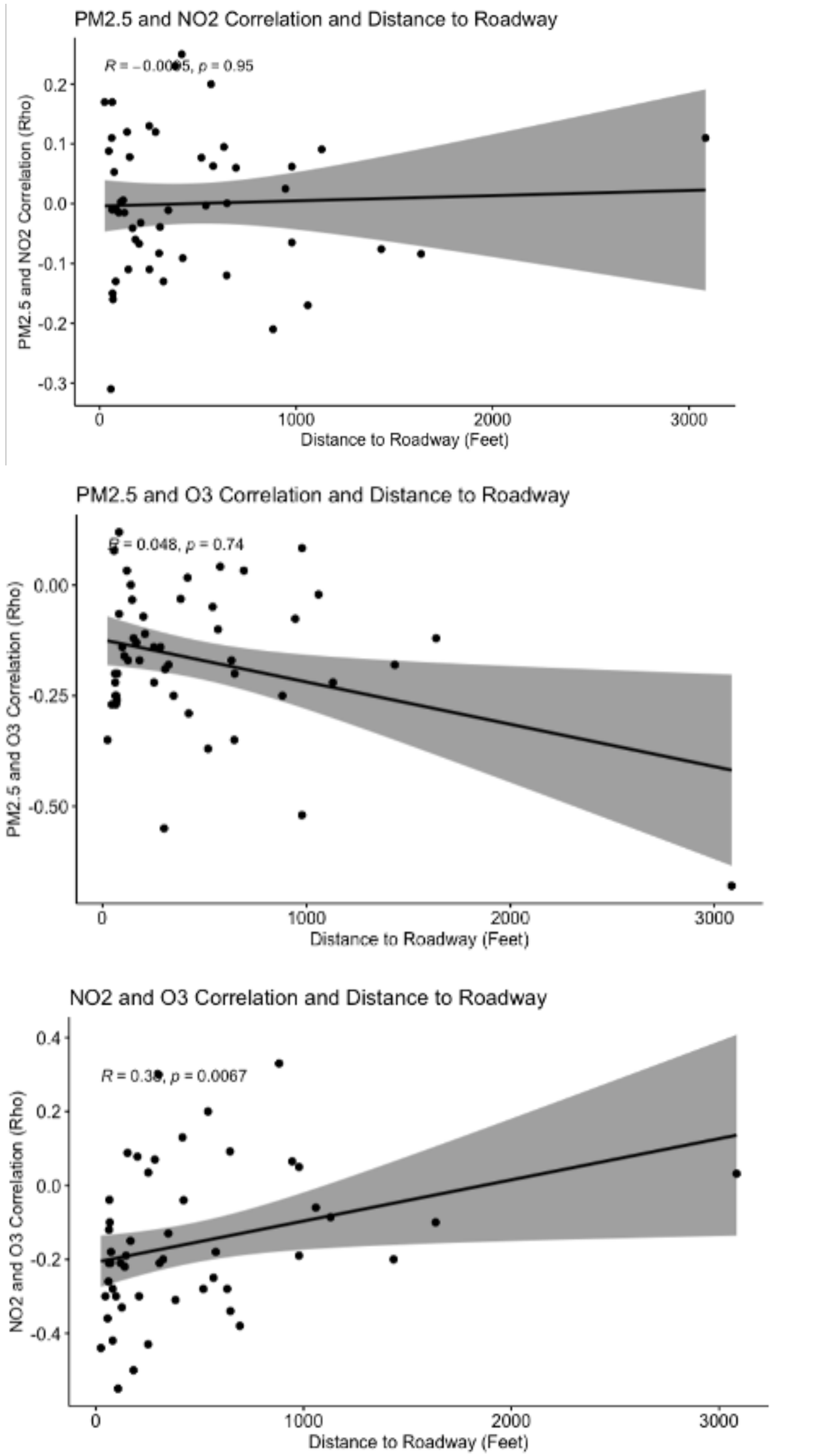


Figure 3.8: Relationship between pollutant exceedance days and distance to roadway

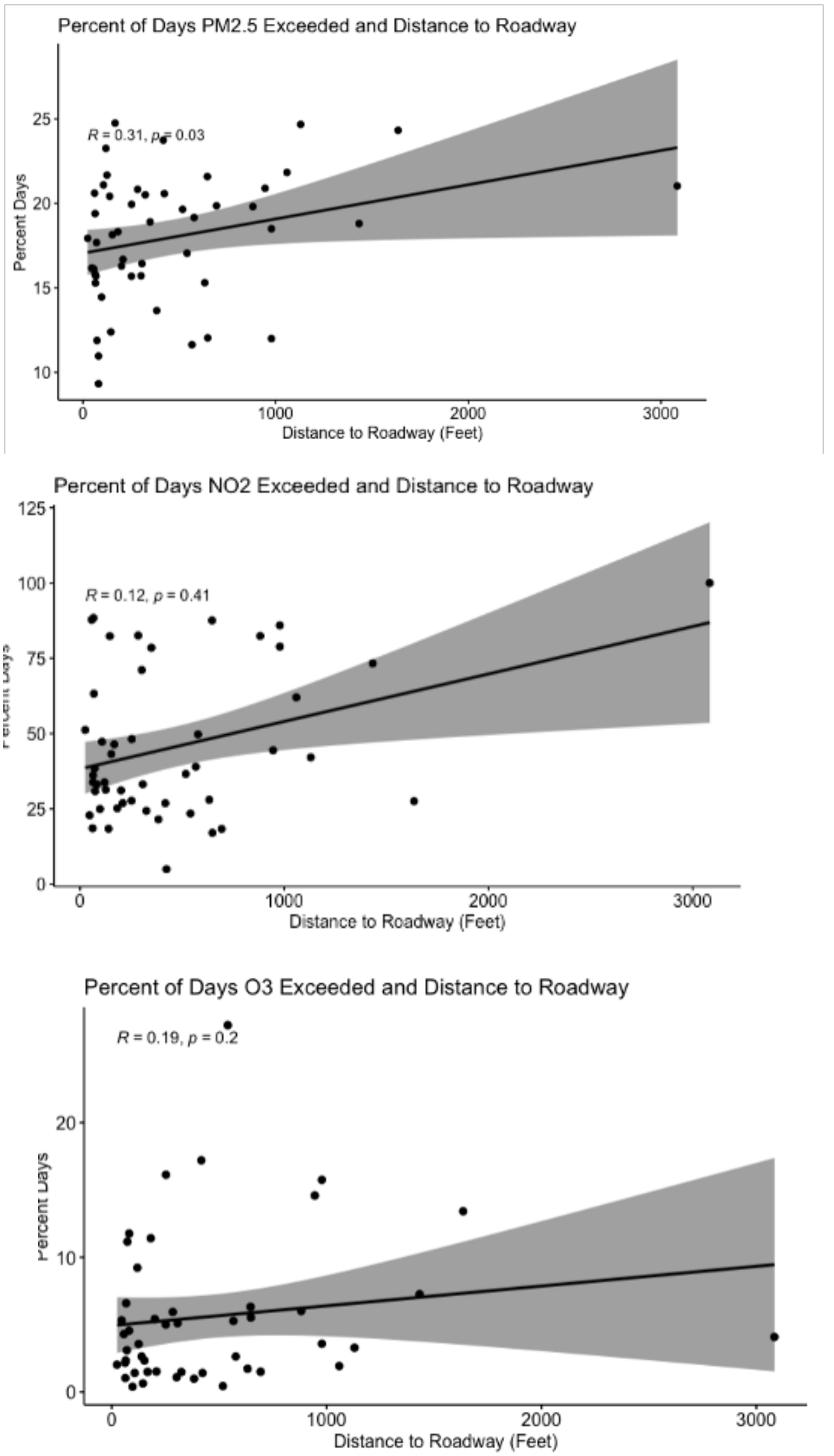
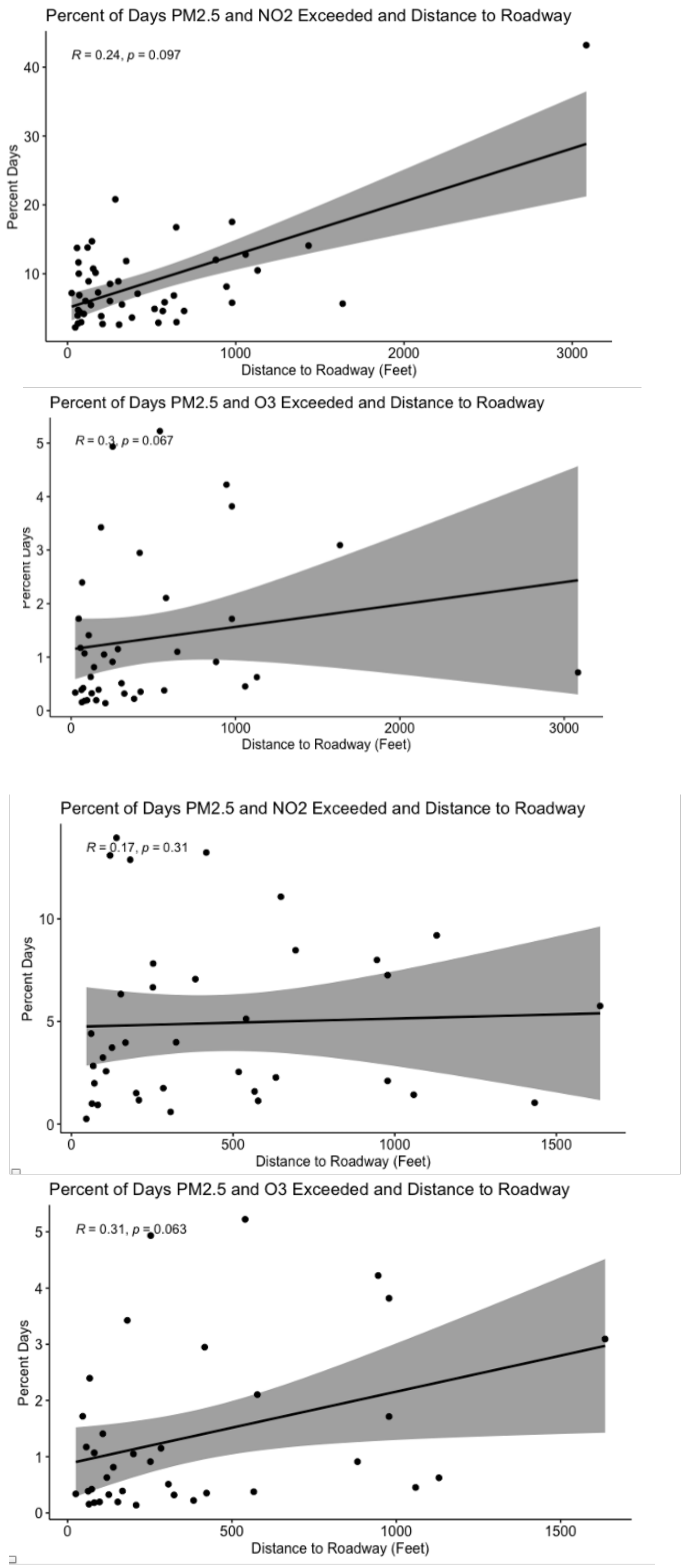


Figure 3.9: Relationship between multiple pollutant exceedance days and distance to roadway



DISCUSSION

Mean daily concentrations were 10.4 μg/m^3 for $PM_{2.5}$, 14.4 ppb for NO_2 and 25.5 ppb for ozone, which are similar for $PM_{2.5}$ and ozone on average with analogous concentrations from the reference monitor over the same period (10.1 μg/m^3 for $PM_{2.5}$ and 26 ppb for ozone) but were higher than the average NO_2 concentration at the reference monitor (7.2 ppb). Since there was no strong correlation between NO_2 concentrations and distance to roadways, higher NO_2 concentrations can likely be attributed to the electrochemical sensors known and studied susceptibility to variability in performance (Cross et al., 2017; Zuidema et al., 2021). Despite these challenges, results of this study confirm the hypothesis that there would be a varying degree of correlation of multiple pollutants between the RAMN monitors and the reference monitor. $PM_{2.5}$ and ozone, and NO_2 and ozone correlation trends typically tracked well with the reference monitor, whereas most $PM_{2.5}$ and NO_2 correlations were negative, suggesting that the degree of correlation between pollutants differs from the reference monitor. Results of this portion of the study suggest that there may be variable co-exposures to pollutants within the Richmond-San Pablo community. Results also suggest that seasonal correlations track well with the reference monitor, but still show variability across the RAMN monitors (Tables 3.2 and 3.3).

The results of this study did not support the hypothesis that if one pollutant increases, the other will increase. For example, I would expect to see that pollutant concentrations and distance to roadways to be correlated, but this was not always the case (Figures 3.6 through 3.8). However, these results suggest that community is still impacted by these pollutants, even when they are not right next to the sources, suggesting that there are other sources of emissions in the community that are being captured by RAMN.

The RAMN network also suggests that there are locations within the Richmond-San Pablo community with concentrations of $PM_{2.5}$, NO_2, and ozone that exceed health-based thresholds far more often than the reference monitor (Figures 3.4 and 3.6). Furthermore, results of the study also suggest that exceedances of two or more pollutants occur more frequently in the community than they do at the reference monitor (Figures 3.3 and 3.5), suggesting that there are locations of the community that are experiencing co-exposures of multiple pollutants that are not being captured by the reference monitor.

Results of this study illustrate that relying on reference monitors to determine compliance with health-based air quality standards is not protective of the entire community. (Figures 3.4 and 3.6 show that RAMN monitors have higher percentages of exceedance days than the reference monitors (labeled in black) suggesting that much more of the community is exposed to levels that exceeded health-based goals than what is being measured at the reference monitor. The number of exceedance days captured by the RAMN monitors highlight two key points. First, the exceedance of health-based standards for single pollutants demonstrate that the reference monitor is not capturing community variation and that communities may experience more adverse health impacts than anticipated or projected by the reference monitor's concentrations, suggesting that there may be underreported health impacts from air pollution. Second, exceedances of two or more pollutants on the same day further demonstrate the concern with co-exposures of multiple pollutants, supporting the urgent need for more research and action into the health impacts of co-exposures and policy reform.

The desire to correlate low-cost sensors to the reference monitor is not the goal. The goal of using low-cost sensor data is to identify air pollution patterns at a specific location away from the reference monitor. If the low-cost sensors have been collocated with the reference monitor and calibrated to account for over- or underestimation and/or sensor drift, we should expect to see differences between the reference monitor and the low-cost sensor since the low-cost sensor are not designed to measure what is happening regionally. The results of this study support the expectation of seeing different pollutant trends at different areas within the community. The significance of the finding of the differences in correlation between the regional monitor and the low-cost sensors provide evidence to support the hypothesis that air pollution variability within a community should be accounted for in air pollution management practices. Air quality management should work to include data from both reference monitoring equipment and low-cost sensors to better characterize the entire community landscape and make effective decision that serve entire communities.

There are limited studies demonstrating a positive correlation between co-exposures of multiple pollutants (Dedoussi et al., 2020; Ma et al., 2022; Riches et al., 2022; VN et al., 2015; Wei et al., 2020). A recent literature review of the health effects of co-exposures of pollutants showed an increase of non-accidental mortality observed with elevated concentrations of both $PM_{2.5}$ and NO_2. Furthermore, respiratory disease mortality, specifically by pneumonia and lung cancer was associated with a synergistic effect between $PM_{2.5}$ and NO_2 concentrations. Another study exploring short term simultaneous exposure to $PM_{2.5}$ and NO_2 concluded that NO_2 exposure may produce and exacerbate acute cardiovascular effects of $PM_{2.5}$ (Huang et al., 2012).

Multiple studies exploring simultaneous exposures between $PM_{2.5}$ and ozone found an increase between short-term exposure and increased deaths (Di et al., 2017; Yan Wang et al., 2017; Wei et al., 2020). One study concluded that mortality associated with long-term $PM_{2.5}$ and ozone exposure increased substantially at levels that were even below the NAAQS (Wei et al., 2020). Another study explored the contributions to mortality from $PM_{2.5}$ and ozone, suggesting that future policies reducing $PM_{2.5}$ and ozone are projected to reduce mortality from cardiovascular and respiratory related diseases, suggesting that current exposures to $PM_{2.5}$ and ozone are contributing to mortality from cardiovascular and respiratory related diseases (VN et al., 2015).

There are limited studies assessing the impact of NO_2 and ozone co-exposures. One study explored the short-term effects of NO_2 and ozone and their combined oxidant capacity. Results suggested that short term exposures to NO_2 and ozone were associated with mortality, especially in warmer seasons. Combined oxidative capacity were associated with high cerebrovascular and respiratory mortality, and slightly associated with cardiac mortality versus each individual pollutant (Faustini et al., 2019). Another study concluded that short term exposure to NO_2 and ozone was positively associated with emergency room visits for respiratory diseases, especially in younger people (defined as less than 18 years of age). Exposure to NO_2 and ozone its intermediary indicators (oxides) was positively associated with emergency room visits for total respiratory diseases and upper respiratory infections (Fu et al., 2022).

Further research is needed to understand the health effects of exposure to multiple pollutants. For example, a literature review of exploring co-exposures of $PM_{2.5}$ and NO_2 identified only eight studies that explored the relationship between $PM_{2.5}$ and NO_2 (Mainka & Żak, 2022). Public health impacts of air pollutants are well known at the single pollutant level, yet are not being evaluated and regulated at the local level. Furthermore, despite the real-world exposure scenario that air always contains more than one pollutant at varying concentrations, regulatory structure is only addressing one pollutant at a time, identifying a fundamental need for assessment of real-world exposure scenarios. There are very few studies that have explored multi-pollutant evaluation approaches (Dominici et al., 2010; Johnson, 2009). One study found short and long term $PM_{2.5}$, ozone, and NO_2 exposures were all associated with increased mortality risk (Wei et al., 2020). Studies cited by US EPA have even suggested that when exploring adverse health impacts from ambient $PM_{2.5}$, NO_2 and other gaseous components should also be considered (Huang et al., 2012). Furthermore, multiple studies have identified adverse health impacts at concentrations below the current NAAQS, suggesting that all standards need to be reevaluated at both an individual pollutant, and a co-pollutant basis (Di et al., 2017; Wei et al., 2020). New models are being explored in the literature for simultaneous evaluation of multiple pollutants, but nothing has been implemented to date (Gorrochategui et al., 2022).

This study contributes to environmental and public health fields in in two ways: (1) it utilizes high resolution measurements with dense spatial coverage to estimate co-exposures of pollutants at the local level, and (2) it uses highly spatially dense data to explore exceedances using WHO AQGs for individual pollutants, and combinations of two three pollutants, an analysis that has not been done previously. Variable relationships could be suggestive of different trends between pollutants at the local level where they may be closer to air pollutant emission sources. Areas where there is a measured positive relationship between pollutant concentrations may be exposing community members to multiple elevated ambient air pollutant concentrations over time, which have been studied exacerbate cardiovascular and respiratory illnesses, and contribute to increased mortality from co-exposures. This information is valuable to understanding where more community and regulatory enforcement efforts may be necessary and provides preliminary data to support prioritization of said efforts.

Limitations

Air quality professionals have raised concerned related to the data accuracy and variable data quality from low-cost sensors relative to reference monitoring. Limitations include siting errors, low-shelf life of low-cost sensor and thus concerns with performance, and no standard guidelines for how to interpret results (Idaho Department of Environmental Quality, n.d.). While performance of low-cost sensors can vary widely, users can take actions to ensure accurate data quality, such as collocating the low-cost sensor with a reference monitor for a short period of time before the low-cost sensor is deployed. The data from the reference monitor can be used to track the accuracy of the low-cost sensor, and provide a calibration to the low-cost sensor such that when it is in the field, it is providing measurements as closely to the reference monitor as feasibly possible (Carvlin et al., 2017). Low-cost sensors have proven useful for hot spot analysis, better understanding where further monitoring and investigation can be helpful, and for citizen science projects. In a study evaluating the use of low-cost sensors for hot spot analysis, results suggested that the accuracy of low-cost sensors is sufficient to achieve the goal of identifying increased air quality concentrations to alert regulators to an area (Lagerspetz et al., 2019).

The results of this study rely on calibration, QA/QC, and data cleaning, such that the resulting dataset used this study are actionable and useful. The results of this study assume data accuracy based on the QA/QC done to the data before it was analyzed.

These data provide many localized insights in Richmond, North Richmond, and San Pablo, California, but not without some challenges: (1) Not all monitors were deployed at the same time due to delays related to COVID-19 pandemic shelter-in-place restrictions. Thus, not all monitors had the same number of measurements. (2) Low-cost sensors can be more sensitive to atypical readings. For example, when calculating the 24-hour average for $PM_{2.5}$, NO_2, and ozone, I used the US EPA data completeness method to only include days with at least 75 percent hourly data points. This excluded many measurements and ultimately, days with limited data available were excluded. The 75 percent data completeness method was also used to define the number of days that the RAMN monitor was considered “operational” (Appendix 3B). For comparison, percent of days exceeded were also calculated by defining an “operational” day as a day having at least one measurement. However, in staying consistent with the fact that exceedance days were calculated using the 75 percent completeness assumption, I used the 75 percent completeness to define the number of days that the RAMN monitor was operational. This comparison resulted in minor differences for $PM_{2.5}$ and ozone, and more drastic differences with NO_2. Similarly, exceedances of two or more pollutants were calculated using the least common value between the two pollutants as the numerator, and the number of days that two or three pollutants exceeded the WHO in the numerator. This comparative analysis resulted in minor changes with $PM_{2.5}$ and ozone, and more drastic changes with NO_2 (Appendix 3B), suggesting a higher variability of NO_2 data when compared to the reference monitor.

The literature has identified challenges with using low-cost NO_2 sensors. Some studies suggest that the correlation between NO_2 measurements with low-cost sensors and reference monitors is poor (Zuidema et al., 2021). The electrochemical sensor used in NO_2 low-cost sensor technology is more suspectable to variability in performance based on environmental conditions, such as temperature, relative humidity, competing gas molecules that also undergo oxidation-reduction reactions, and season, making it difficult to rely on specific concentration differences versus relative differences across sensors (Cross et al., 2017; Zuidema et al., 2021). As noted in Table 3.2, NO_2 was operational for less days when compared to $PM_{2.5}$ and ozone. To minimize these sensitivities, sensors must be collocated with a reference monitor in a location that is representative of the NO_2 conditions for the study and undergo a robust calibration process to correct for potential interferences. One limitation of this study was that the sensors were initially collocated with a reference monitor in Sacramento, CA (due to initial reference site access restrictions in the study area),which has different temperature, relativity, and pollutant conditions. This may have contributed to the accuracy of the sensors for use in Richmond and San Pablo, CA and thus the reliability of the NO_2 data. While the frequency of calibration is essential to correct for the data, it does not account for all limitations of low-cost NO_2 monitoring, such as the reliability of the monitor to measure small NO_2 concentration changes. This study relies on the performance of the NO_2 sensor to estimate pollutant concentrations at ~12-13 ppb (25 $\mu g/m^3$), the WHO AQG for 24-hour NO_2. Aeroqual's specification sheet notes that the precision of NO_2 readings is 8 ppb, suggesting that some of the NO_2 data may be overreporting or underreporting exceedances and may skew the pollutant correlations (Aeroqual, n.d.-a). Electrochemical sensors can respond to other pollutants that undergo oxidation reduction reactions. If there are more oxidation reduction reactions with gases other than NO_2, the sensors detect higher concentrations due to all reactions present, not necessarily NO_2. Conversely, if there are less reactions occurring, the sensors may show lower or negative concentrations, which are filtered out. The cross-interference of NO_2 may skew the concentrations, particularly underrepresenting concentrations if they are close to zero (Aeroqual, n.d.-b). Among the three pollutants evaluated in this study, the performance of NO_2 was the most limiting, which should be taken into account when considering the results of this study.

Concluding Paragraph/Path Forward

This study contributes to existing research supporting spatial variability of air pollutants within a community and enhances it by relating the data to health-based standards and examining co-pollutant exposures. Regional air monitoring does not provide representative coverage of air pollutant concentrations within a community and some areas within a community are more likely to experience pollutant concentrations that exceed health-based standards, therefore increasing the risk of adverse health outcomes. These results support policy needs to reform ambient air monitoring approaches that consider localized impacts and changes. Future policy development should focus on using a hybrid network of regional and low-cost air monitors to help inform locations for additional reference air quality monitoring equipment. The US EPA's strict siting requirements for reference monitors would also need to be reformed to enable reference monitoring in additional locations. This could provide insight regarding hyperlocal community air quality landscapes as a whole, and be used to drive public health intervention, such as biomonitoring studies.

Appendix 3A: Co-exposures Rho values for RAMN Network (n=50)

ID	Land_Use	PM2.5/NO2 -R	PM2.5/O3 - R	NO2/O3 - R	Summer PM2.5/NO2 - R	Summer PM2.5/O3 - R	Summer NO2/O3 - R	Winter PM2.5/NO2 -R	Winter PM2.5/O3 - R	Winter NO2/O3 - R
AQY BB-607	Commercial	0.11	-0.68	0.032	-0.54	-0.48	0.38	-0.48	0.2	-0.051
AQY BB-608	Commercial	-0.041	-0.13	-0.15	0.2	-0.31	0.15	-0.31	-0.024	-0.12
AQY BB-609	Residential	-0.21	-0.25	0.33	-0.024	-0.36	0.38	-0.36	n/a	0.3
AQY BB-610	Residential	-0.12	-0.35	0.092	n/a	-0.18	n/a	-0.32	-0.18	0.5
AQY BB-611	Residential	-0.16	-0.25	-0.1	0.1	-0.061	-0.14	-0.19	-0.24	0.12
AQY BB-633	Industrial	-0.0082	0.12	-0.42	0.18	0.37	-0.45	0.14	-0.2	0.075
AQY BB-634	Industrial	-0.0099	-0.26	-0.21	-0.16	-0.065	-0.025	-0.041	-0.37	-0.19
AQY BB-635	Residential	0.088	-0.27	-0.3	0.18	-0.12	-0.34	-0.14	-0.31	0.027
AQY BB-636	Residential	0.077	-0.37	-0.28	-0.23	0.099	-0.34	-0.27	-0.49	0.24
AQY BB-637	Residential	-0.039	-0.19	-0.21	0.16	0.094	-0.26	0.039	-0.26	-0.15
AQY BB-638	Residential	0.2	-0.1	-0.25	-0.22	0.14	-0.24	0.15	-0.22	-0.063
AQY BB-639	Residential	0.091	-0.22	-0.086	0.099	0.24	-0.051	-0.85	-0.39	-0.025
AQY BB-640	Residential	-0.01	-0.22	-0.21	-0.059	-0.00068	-0.21	-0.18	-0.26	0.13
AQY BB-641	Residential	0.0007	-0.2	-0.34	0.18	-0.1	-0.3	0.031	-0.54	-0.22
AQY BB-642	Industrial	-0.13	-0.065	-0.28	0.048	0.21	-0.56	-0.28	-0.32	-0.0078
AQY BB-643	Residential	-0.032	-0.11	-0.3	-0.035	0.12	-0.52	-0.14	-0.36	-0.023
AQY BB-644	Residential	-0.067	-0.071	0.078	0.087	-0.0042	-0.26	0.044	-0.066	0.096
AQY BB-645	Residential	-0.083	-0.55	0.3	n/a	n/a	n/a	-0.083	-0.67	0.27
AQY BB-646	Residential	-0.076	-0.18	-0.2	0.32	0.051	0.77	-0.05	-0.61	-0.22
AQY BB-647	Residential	-0.011	-0.25	-0.13	-0.052	-0.25	-0.34	0.38	-0.31	-0.35
AQY BB-648	Residential	0.17	-0.25	-0.12	0.084	-0.097	-0.09	0.15	-0.61	-0.36
AQY BB-649	Residential	-0.11	-0.22	0.035	0.28	-0.37	0.2	-0.32	-0.27	0.14
AQY BB-650	Commercial	0.0026	-0.16	-0.55	-0.13	0.12	-0.3	0.31	-0.34	-0.87
AQY BB-651	Residential	-0.31	0.078	-0.36	0.014	0.54	-0.17	-0.33	-0.059	-0.19
AQY BB-652	Commercial	-0.15	-0.27	-0.039	-0.19	0.12	-0.079	-0.29	-0.37	0.046
AQY BB-787	Commercial	0.0058	0.033	-0.21	0.028	0.3	-0.14	0.26	-0.28	0.11
AQY BB-788	Residential	-0.06	-0.17	-0.5	-0.19	-0.006	-0.39	0.4	-0.43	-0.33
AQY BB-789	Commercial	0.13	-0.14	-0.43	0.23	0.13	-0.56	0.21	-0.42	-0.43
AQY BB-790	Commercial	0.23	-0.031	-0.31	0.37	0.46	0.1	0.32	-0.29	-0.52
AQY BB-791	Residential	-0.0031	-0.049	0.2	-0.37	0.11	-0.11	0.069	0.28	0.67
AQY BB-792	Commercial	0.025	-0.076	0.065	0.23	0.18	0.21	-0.22	-0.3	0.33
AQY BB-793	Residential	0.11	-0.2	-0.26	0.039	0.022	-0.12	0.34	-0.68	-0.52
AQY BB-794	Residential	-0.015	-0.17	-0.33	0.097	-0.2	-0.36	0.089	-0.14	0.22
AQY BB-795	Residential	-0.084	-0.12	-0.1	0.29	-0.44	-0.28	-0.31	-0.21	0.37
AQY BB-796	Residential	0.25	0.017	0.13	0.45	0.17	0.26	0.15	-0.2	-0.14
AQY BB-797	Commercial	0.12	-0.14	0.07	-0.1	n/a	n/a	-0.12	-0.12	-0.075
AQY BB-798	Industrial	0.17	-0.35	-0.44	0.19	-0.32	0.11	0.11	-0.31	0.097
AQY BB-799	Industrial	-0.015	-0.14	-0.3	-0.17	0.36	-0.091	0.03	-0.38	-0.28
AQY BB-800	Industrial	-0.11	-0.033	-0.19	-0.28	0.58	0.56		n/a	n/a
AQY BB-801	Commercial	-0.17	-0.021	-0.06	-0.052	-0.19	-0.32	-0.0016	-0.16	0.56
AQY BB-802	Residential	0.062	0.084	0.05	0.23	0.59	-0.1	0.089	-0.36	0.022
AQY BB-803	Residential	-0.065	-0.52	-0.19	-0.017	n/a	n/a	-0.05	-0.53	-0.35
AQY BB-804	Commercial	0.078	-0.12	0.088	0.14	0.14	0.086	-0.036	-0.34	0.14
AQY BB-805	Residential	-0.091	-0.29	-0.04	0.79	-0.19	-0.034		0.18	n/a
AQY BB-806	Commercial	0.12	0.00074	-0.22	0.34	-0.21	-0.069	0.44	0.22	-0.33
AQY BB-807	Residential	0.06	0.033	-0.38	-0.16	-0.25	-0.00029	0.3	0.032	-0.49
AQY BB-808	Commercial	-0.13	-0.18	-0.2	-0.28	-0.43	-0.22	0.056	0.66	-0.024
AQY BB-809	Residential	0.053	-0.2	-0.18	0.72	-0.27	-0.56	0.22	0.29	0.1
AQY BB-810	Industrial	0.095	-0.17	-0.28	-0.37	-0.33	-0.27	0.24	0.48	-0.017
AQY BB-811	Commercial	0.063	0.042	-0.18	-0.039	-0.51	-0.15	-0.2	n/a	0.16
Regulatory Monitor		0.23	-0.04	-0.44	0.47	0.24	0.18	0.51	0.4	-0.44

Appendix 3B: Exceedances Data

Appendix 3B.1: Exceedances for $PM_{2.5}$ and Comparative analysis with data completeness

		75% Data Completeness Days				All Days Operational		
RAMN ID	Land Use	Days Exceeding PM2.5 Standard	Total Days	Percent Days Exceeded	Exceeds 99th (1=yes, 0=no)	Total Days_	Percent Days Exceeded_	Exceeds 99th (1=yes, 0=no)_
AQY BB-607	Commercial	118	561	21.0	1	568	20.8	1
AQY BB-608	Commercial	127	513	24.8	1	525	24.2	1
AQY BB-609	Residential	151	762	19.8	1	778	19.4	1
AQY BB-610	Residential	125	579	21.6	1	590	21.2	1
AQY BB-611	Residential	124	790	15.7	1	797	15.6	1
AQY BB-633	Industrial	42	383	11.0	1	383	11.0	1
AQY BB-634	Industrial	93	526	17.7	1	533	17.4	1
AQY BB-635	Residential	120	742	16.2	1	774	15.5	1
AQY BB-636	Residential	124	631	19.7	1	645	19.2	1
AQY BB-637	Residential	130	791	16.4	1	804	16.2	1
AQY BB-638	Residential	86	739	11.6	1	743	11.6	1
AQY BB-639	Residential	192	778	24.7	1	790	24.3	1
AQY BB-640	Residential	123	777	15.8	1	780	15.8	1
AQY BB-641	Residential	69	573	12.0	1	576	12.0	1
AQY BB-642	Industrial	55	590	9.3	1	590	9.3	1
AQY BB-643	Residential	128	767	16.7	1	773	16.6	1
AQY BB-644	Residential	116	712	16.3	1	720	16.1	1
AQY BB-645	Residential	66	420	15.7	1	429	15.4	1
AQY BB-646	Residential	63	335	18.8	1	336	18.8	1
AQY BB-647	Residential	128	677	18.9	1	688	18.6	1
AQY BB-648	Residential	116	598	19.4	1	604	19.2	1
AQY BB-649	Residential	150	752	19.9	1	764	19.6	1
AQY BB-650	Commercial	77	365	21.1	1	372	20.7	1
AQY BB-651	Residential	113	701	16.1	1	708	16.0	1
AQY BB-652	Commercial	105	687	15.3	1	702	15.0	1
AQY BB-787	Commercial	127	546	23.3	1	559	22.7	1
AQY BB-788	Residential	131	715	18.3	1	739	17.7	1
AQY BB-789	Commercial	88	561	15.7	1	566	15.5	1
AQY BB-790	Commercial	62	454	13.7	1	463	13.4	1
AQY BB-791	Residential	66	387	17.1	1	396	16.7	1
AQY BB-792	Commercial	121	579	20.9	1	580	20.9	1
AQY BB-793	Residential	143	694	20.6	1	696	20.5	1
AQY BB-794	Residential	137	632	21.7	1	651	21.0	1
AQY BB-795	Residential	118	485	24.3	1	499	23.6	1
AQY BB-796	Residential	104	438	23.7	1	441	23.6	1
AQY BB-797	Commercial	115	552	20.8	1	552	20.8	1
AQY BB-798	Industrial	125	697	17.9	1	701	17.8	1
AQY BB-799	Industrial	85	588	14.5	1	593	14.3	1
AQY BB-800	Industrial	29	234	12.4	1	240	12.1	1
AQY BB-801	Commercial	145	664	21.8	1	675	21.5	1
AQY BB-802	Residential	84	454	18.5	1	458	18.3	1
AQY BB-803	Residential	21	175	12.0	1	184	11.4	1
AQY BB-804	Commercial	98	540	18.1	1	551	17.8	1
AQY BB-805	Residential	71	345	20.6	1	351	20.2	1
AQY BB-806	Commercial	136	666	20.4	1	674	20.2	1
AQY BB-807	Residential	114	574	19.9	1	580	19.7	1
AQY BB-808	Commercial	129	629	20.5	1	642	20.1	1
AQY BB-809	Residential	58	488	11.9	1	508	11.4	1
AQY BB-810	Industrial	88	575	15.3	1	582	15.1	1
AQY BB-811	Commercial	110	574	19.2	1	581	18.9	1
Reference	Reference	97	806	12.0	1	806	12.0	1

Appendix 3B.2: Exceedances for NO_2 and Comparative analysis with data completeness

		75% Data Completeness Days				All Days Operational			
RAMN ID	**Land Use**	**Days Exceeding NO2 Standard**	**Total Days**	**Percent Days Exceeded**	**Exceeds 99th (1=yes, 0=no)2**	**Total Days**	**Percent Days Exceeded**	**Exceeds 99th (1=yes, 0=no)**	**Difference in Percent Exceedance**
AQY BB-607	Commercial	81	81	100.0	1	111	73.0	1	27.0
AQY BB-608	Commercial	306	142	46.4	1	356	39.9	1	6.5
AQY BB-609	Residential	233	192	82.4	1	271	70.8	1	11.6
AQY BB-610	Residential	209	183	87.6	1	224	81.7	1	5.9
AQY BB-611	Residential	370	234	63.2	1	402	58.2	1	5.0
AQY BB-633	Industrial	220	0	0.0	0	345	0.0	0	0.0
AQY BB-634	Industrial	393	151	38.4	1	432	35.0	1	3.5
AQY BB-635	Residential	547	125	22.9	1	628	19.9	1	2.9
AQY BB-636	Residential	410	150	36.6	1	476	31.5	1	5.1
AQY BB-637	Residential	386	128	33.2	1	441	29.0	1	4.1
AQY BB-638	Residential	372	145	39.0	1	438	33.1	1	5.9
AQY BB-639	Residential	544	229	42.1	1	721	31.8	1	10.3
AQY BB-640	Residential	470	159	33.8	1	539	29.5	1	4.3
AQY BB-641	Residential	270	46	17.0	1	421	10.9	1	6.1
AQY BB-642	Industrial	338	112	33.1	1	393	28.5	1	4.6
AQY BB-643	Residential	409	110	26.9	1	533	20.6	1	6.3
AQY BB-644	Residential	392	122	31.1	1	487	25.1	1	6.1
AQY BB-645	Residential	45	32	71.1	1	74	43.2	1	27.9
AQY BB-646	Residential	206	151	73.3	1	212	71.2	1	2.1
AQY BB-647	Residential	321	252	78.5	1	335	75.2	1	3.3
AQY BB-648	Residential	551	199	36.1	1	637	31.2	1	4.9
AQY BB-649	Residential	411	198	48.2	1	532	37.2	1	11.0
AQY BB-650	Commercial	315	149	47.3	1	320	46.6	1	0.7
AQY BB-651	Residential	131	115	87.8	1	179	64.2	1	23.5
AQY BB-652	Commercial	189	167	88.4	1	215	77.7	1	10.7
AQY BB-787	Commercial	355	120	33.8	1	506	23.7	1	10.1
AQY BB-788	Residential	413	104	25.2	1	551	18.9	1	6.3
AQY BB-789	Commercial	415	115	27.7	1	492	23.4	1	4.3
AQY BB-790	Commercial	442	95	21.5	1	531	17.9	1	3.6
AQY BB-791	Residential	209	49	23.4	1	269	18.2	1	5.2
AQY BB-792	Commercial	234	104	44.4	1	367	28.3	1	16.1
AQY BB-793	Residential	383	71	18.5	1	470	15.1	1	3.4
AQY BB-794	Residential	450	141	31.3	1	546	25.8	1	5.5
AQY BB-795	Residential	461	127	27.5	1	628	20.2	1	7.3
AQY BB-796	Residential	268	72	26.9	1	423	17.0	1	9.8
AQY BB-797	Commercial	149	123	82.6	1	394	31.2	1	51.3
AQY BB-798	Industrial	209	107	51.2	1	242	44.2	1	7.0
AQY BB-799	Industrial	433	108	24.9	1	521	20.7	1	4.2
AQY BB-800	Industrial	34	28	82.4	1	142	19.7	1	62.6
AQY BB-801	Commercial	258	160	62.0	1	305	52.5	1	9.6
AQY BB-802	Residential	194	153	78.9	1	304	50.3	1	28.5
AQY BB-803	Residential	277	238	85.9	1	361	65.9	1	20.0
AQY BB-804	Commercial	345	149	43.2	1	421	35.4	1	7.8
AQY BB-805	Residential	141	7	5.0	1	239	2.9	1	2.0
AQY BB-806	Commercial	348	64	18.4	1	559	11.4	1	6.9
AQY BB-807	Residential	262	48	18.3	1	361	13.3	1	5.0
AQY BB-808	Commercial	489	119	24.3	1	608	19.6	1	4.8
AQY BB-809	Residential	337	104	30.9	1	382	27.2	1	3.6
AQY BB-810	Industrial	425	119	28.0	1	464	25.6	1	2.4
AQY BB-811	Commercial	171	85	49.7	1	347	24.5	1	25.2
Reference	Reference	808	68	8.4	1	808	8.4	1	0.0

Appendix 3B.3: Exceedances for ozone and Comparative analysis with data completeness

		75% Data Completeness Days				All Days Operational			
RAMN ID	Land Use	Days Exceeding NO2 Standard	Total Days	Percent Days Exceeded	Exceeds 99th (1=yes, 0=no)2	Total Days	Percent Days Exceeded	Exceeds 99th (1=yes, 0=no)	Difference in Percent Exceedance
AQY BB-607	Commercial	81	81	100.0	1	111	73.0	1	27.0
AQY BB-608	Commercial	306	142	46.4	1	356	39.9	1	6.5
AQY BB-609	Residential	233	192	82.4	1	271	70.8	1	11.6
AQY BB-610	Residential	209	183	87.6	1	224	81.7	1	5.9
AQY BB-611	Residential	370	234	63.2	1	402	58.2	1	5.0
AQY BB-633	Industrial	220	0	0.0	0	345	0.0	0	0.0
AQY BB-634	Industrial	393	151	38.4	1	432	35.0	1	3.5
AQY BB-635	Residential	547	125	22.9	1	628	19.9	1	2.9
AQY BB-636	Residential	410	150	36.6	1	476	31.5	1	5.1
AQY BB-637	Residential	386	128	33.2	1	441	29.0	1	4.1
AQY BB-638	Residential	372	145	39.0	1	438	33.1	1	5.9
AQY BB-639	Residential	544	229	42.1	1	721	31.8	1	10.3
AQY BB-640	Residential	470	159	33.8	1	539	29.5	1	4.3
AQY BB-641	Residential	270	46	17.0	1	421	10.9	1	6.1
AQY BB-642	Industrial	338	112	33.1	1	393	28.5	1	4.6
AQY BB-643	Residential	409	110	26.9	1	533	20.6	1	6.3
AQY BB-644	Residential	392	122	31.1	1	487	25.1	1	6.1
AQY BB-645	Residential	45	32	71.1	1	74	43.2	1	27.9
AQY BB-646	Residential	206	151	73.3	1	212	71.2	1	2.1
AQY BB-647	Residential	321	252	78.5	1	335	75.2	1	3.3
AQY BB-648	Residential	551	199	36.1	1	637	31.2	1	4.9
AQY BB-649	Residential	411	198	48.2	1	532	37.2	1	11.0
AQY BB-650	Commercial	315	149	47.3	1	320	46.6	1	0.7
AQY BB-651	Residential	131	115	87.8	1	179	64.2	1	23.5
AQY BB-652	Commercial	189	167	88.4	1	215	77.7	1	10.7
AQY BB-787	Commercial	355	120	33.8	1	506	23.7	1	10.1
AQY BB-788	Residential	413	104	25.2	1	551	18.9	1	6.3
AQY BB-789	Commercial	415	115	27.7	1	492	23.4	1	4.3
AQY BB-790	Commercial	442	95	21.5	1	531	17.9	1	3.6
AQY BB-791	Residential	209	49	23.4	1	269	18.2	1	5.2
AQY BB-792	Commercial	234	104	44.4	1	367	28.3	1	16.1
AQY BB-793	Residential	383	71	18.5	1	470	15.1	1	3.4
AQY BB-794	Residential	450	141	31.3	1	546	25.8	1	5.5
AQY BB-795	Residential	461	127	27.5	1	628	20.2	1	7.3
AQY BB-796	Residential	268	72	26.9	1	423	17.0	1	9.8
AQY BB-797	Commercial	149	123	82.6	1	394	31.2	1	51.3
AQY BB-798	Industrial	209	107	51.2	1	242	44.2	1	7.0
AQY BB-799	Industrial	433	108	24.9	1	521	20.7	1	4.2
AQY BB-800	Industrial	34	28	82.4	1	142	19.7	1	62.6
AQY BB-801	Commercial	258	160	62.0	1	305	52.5	1	9.6
AQY BB-802	Residential	194	153	78.9	1	304	50.3	1	28.5
AQY BB-803	Residential	277	238	85.9	1	361	65.9	1	20.0
AQY BB-804	Commercial	345	149	43.2	1	421	35.4	1	7.8
AQY BB-805	Residential	141	7	5.0	1	239	2.9	1	2.0
AQY BB-806	Commercial	348	64	18.4	1	559	11.4	1	6.9
AQY BB-807	Residential	262	48	18.3	1	361	13.3	1	5.0
AQY BB-808	Commercial	489	119	24.3	1	608	19.6	1	4.8
AQY BB-809	Residential	337	104	30.9	1	382	27.2	1	3.6
AQY BB-810	Industrial	425	119	28.0	1	464	25.6	1	2.4
AQY BB-811	Commercial	171	85	49.7	1	347	24.5	1	25.2
Reference	Reference	808	68	8.4	1	808	8.4	1	0.0

Appendix 3B.4: Exceedances for $PM_{2.5}$ and NO_2 and Comparative analysis with data completeness

RAMN ID	Land Use	Total Days Monitor Operational for PM2.5	Total Days Monitor Operational for NO2	Number of days PM2.5 and NO2 Exceeded	Percent PM2.5 and NO2 Exceeded (smaller denominator)	Exceeds 99th percentile defined by WHO? (1=yes, 0=no)	Percent PM2.5 and NO2 Exceeded (larger denominator)	Exceeds 99th percentile defined by WHO? (1=yes, 0=no)2	Difference in Percent Exceedance
AQY BB-607	Commercial	568	81	35	43.2	1	6.2	1	-37.0
AQY BB-608	Commercial	525	306	31	10.1	1	5.9	1	-4.2
AQY BB-609	Residential	778	233	28	12.0	1	3.6	1	-8.4
AQY BB-610	Residential	590	209	35	16.7	1	5.9	1	-10.8
AQY BB-611	Residential	797	370	37	10.0	1	4.6	1	-5.4
AQY BB-633	Industrial	383	220	0	0.0	1	0.0	1	0.0
AQY BB-634	Industrial	533	393	27	6.9	1	5.1	1	-1.8
AQY BB-635	Residential	774	547	12	2.2	1	1.6	1	-0.6
AQY BB-636	Residential	645	410	20	4.9	1	3.1	1	-1.8
AQY BB-637	Residential	804	386	10	2.6	1	1.2	1	-1.3
AQY BB-638	Residential	743	372	17	4.6	1	2.3	1	-2.3
AQY BB-639	Residential	790	544	57	10.5	1	7.2	1	-3.3
AQY BB-640	Residential	780	470	13	2.8	1	1.7	1	-1.1
AQY BB-641	Residential	576	270	8	3.0	1	1.4	1	-1.6
AQY BB-642	Industrial	590	338	10	3.0	1	1.7	1	-1.3
AQY BB-643	Residential	773	409	11	2.7	1	1.4	1	-1.3
AQY BB-644	Residential	720	392	15	3.8	1	2.1	1	-1.7
AQY BB-645	Residential	429	45	4	8.9	1	0.9	1	-8.0
AQY BB-646	Residential	336	206	29	14.1	1	8.6	1	-5.4
AQY BB-647	Residential	688	321	38	11.8	1	5.5	1	-6.3
AQY BB-648	Residential	604	551	26	4.7	1	4.3	1	-0.4
AQY BB-649	Residential	764	411	35	8.5	1	4.6	1	-3.9
AQY BB-650	Commercial	372	315	19	6.0	1	5.1	1	-0.9
AQY BB-651	Residential	708	131	18	13.7	1	2.5	1	-11.2
AQY BB-652	Commercial	702	189	22	11.6	1	3.1	1	-8.5
AQY BB-787	Commercial	559	355	49	13.8	1	8.8	1	-5.0
AQY BB-788	Residential	739	413	30	7.3	1	4.1	1	-3.2
AQY BB-789	Commercial	566	415	25	6.0	1	4.4	1	-1.6
AQY BB-790	Commercial	463	442	16	3.6	1	3.5	1	-0.2
AQY BB-791	Residential	396	209	6	2.9	1	1.5	1	-1.4
AQY BB-792	Commercial	580	234	19	8.1	1	3.3	1	-4.8
AQY BB-793	Residential	696	383	15	3.9	1	2.2	1	-1.8
AQY BB-794	Residential	651	450	40	8.9	1	6.1	1	-2.7
AQY BB-795	Residential	499	461	26	5.6	1	5.2	1	-0.4
AQY BB-796	Residential	441	268	19	7.1	1	4.3	1	-2.8
AQY BB-797	Commercial	552	149	31	20.8	1	5.6	1	-15.2
AQY BB-798	Industrial	701	209	15	7.2	1	2.1	1	-5.0
AQY BB-799	Industrial	593	433	18	4.2	1	3.0	1	-1.1
AQY BB-800	Industrial	240	34	5	14.7	1	2.1	1	-12.6
AQY BB-801	Commercial	675	258	33	12.8	1	4.9	1	-7.9
AQY BB-802	Residential	458	194	34	17.5	1	7.4	1	-10.1
AQY BB-803	Residential	184	277	16	5.8	1	8.7	1	2.9
AQY BB-804	Commercial	551	345	37	10.7	1	6.7	1	-4.0
AQY BB-805	Residential	351	141	0	0.0	1	0.0	1	0.0
AQY BB-806	Commercial	674	348	19	5.5	1	2.8	1	-2.6
AQY BB-807	Residential	580	262	12	4.6	1	2.1	1	-2.5
AQY BB-808	Commercial	642	489	27	5.5	1	4.2	1	-1.3
AQY BB-809	Residential	508	337	15	4.5	1	3.0	1	-1.5
AQY BB-810	Industrial	582	425	29	6.8	1	5.0	1	-1.8
AQY BB-811	Commercial	581	171	10	5.8	1	1.7	1	-4.1
Reference	Reference	811	811	15	1.8	1	1.8	1	0.0

Appendix 3B.5: Exceedances for $PM_{2.5}$ and ozone and Comparative analysis with data completeness

RAMN ID	Land Use	Minimum Number of Days between PM2.5 and O3	Maximum Number of Days between PM2.5 and O3	Number of days PM2.5 and O3 Exceeded	Percent PM2.5 and O3 Exceeded (smaller denominator)	Exceeds 99th percentile defined by WHO? (1=yes, 0=no)3	Percent PM2.5 and O3 Exceeded (larger denominator)	Exceeds 99th percentile defined by WHO? (1=yes, 0=no)6	Difference in Percent Exceedance3
AQY BB-607	Commercial	561	612	4	0.71	1	0.65	1	-0.059
AQY BB-608	Commercial	513	536	2	0.39	1	0.37	1	-0.017
AQY BB-609	Residential	549	762	5	0.91	1	0.66	1	-0.255
AQY BB-610	Residential	364	579	4	1.10	1	0.69	1	-0.408
AQY BB-611	Residential	668	790	16	2.40	1	2.03	1	-0.370
AQY BB-633	Industrial	374	383	4	1.07	0	1.04	0	-0.025
AQY BB-634	Industrial	0	0	0	0.00	1	0.00	1	0.000
AQY BB-635	Residential	640	742	11	1.72	1	1.48	1	-0.236
AQY BB-636	Residential	0	0	0	0.00	1	0.00	1	0.000
AQY BB-637	Residential	587	791	3	0.51	1	0.38	1	-0.132
AQY BB-638	Residential	531	739	2	0.38	1	0.27	1	-0.106
AQY BB-639	Residential	640	778	4	0.63	1	0.51	1	-0.111
AQY BB-640	Residential	777	780	3	0.39	1	0.38	1	-0.001
AQY BB-641	Residential	0	0	0	0.00	1	0.00	1	0.000
AQY BB-642	Industrial	549	590	1	0.18	1	0.17	1	-0.013
AQY BB-643	Residential	723	767	1	0.14	1	0.13	1	-0.008
AQY BB-644	Residential	572	712	6	1.05	1	0.84	1	-0.206
AQY BB-645	Residential	0	0	0	0.00	1	0.00	1	0.000
AQY BB-646	Residential	0	0	0	0.00	1	0.00	1	0.000
AQY BB-647	Residential	0	0	0	0.00	1	0.00	1	0.000
AQY BB-648	Residential	0	0	0	0.00	1	0.00	1	0.000
AQY BB-649	Residential	527	752	26	0.00	1	3.46	1	3.457
AQY BB-650	Commercial	355	365	5	1.41	1	1.37	1	-0.039
AQY BB-651	Residential	512	701	6	1.17	1	0.86	1	-0.316
AQY BB-652	Commercial	640	687	1	0.16	1	0.15	1	-0.011
AQY BB-787	Commercial	477	546	3	0.63	1	0.55	1	-0.079
AQY BB-788	Residential	438	715	15	3.42	1	2.10	1	-1.327
AQY BB-789	Commercial	439	561	4	0.91	1	0.71	1	-0.198
AQY BB-790	Commercial	454	508	1	0.22	1	0.20	1	-0.023
AQY BB-791	Residential	268	387	14	5.22	1	3.62	1	-1.606
AQY BB-792	Commercial	521	579	22	4.22	1	3.80	1	-0.423
AQY BB-793	Residential	0		0	0.00	1	0.00	1	0.000
AQY BB-794	Residential	618	632	2	0.32	1	0.32	1	-0.007
AQY BB-795	Residential	485	544	15	3.09	1	2.76	1	-0.335
AQY BB-796	Residential	407	438	12	2.95	1	2.74	1	-0.209
AQY BB-797	Commercial	522	552	6	1.15	1	1.09	1	-0.062
AQY BB-798	Industrial	593	697	2	0.34	1	0.29	1	-0.050
AQY BB-799	Industrial	515	588	1	0.19	1	0.17	1	-0.024
AQY BB-800	Industrial	0		0	0.00	1	0.00	1	0.000
AQY BB-801	Commercial	664	675	3	0.45	1	0.44	1	-0.007
AQY BB-802	Residential	419	454	16	3.82	1	3.52	1	-0.294
AQY BB-803	Residential	175	363	3	1.71	1	0.83	1	-0.888
AQY BB-804	Commercial	515	540	1	0.19	1	0.19	1	-0.009
AQY BB-805	Residential	284	345	1	0.35	1	0.29	1	-0.062
AQY BB-806	Commercial	493	666	4	0.81	1	0.60	1	-0.211
AQY BB-807	Residential	0		0	0.00	1	0.00	1	0.000
AQY BB-808	Commercial	629	674	2	0.32	1	0.30	1	-0.021
AQY BB-809	Residential	475	488	2	0.42	1	0.41	1	-0.011
AQY BB-810	Industrial	0		0	0.00	1	0.00	1	0.000
AQY BB-811	Commercial	380	574	8	2.11	1	1.39	1	-0.712
Reference	Reference	811	811	4	0.49	1	0.49	1	0.000

Appendix 3B.6: Exceedances for NO_2 and ozone and Comparative analysis with data completeness

RAMN ID	Land Use	Minimum Number of Days between NO2 and O3	Maximum Number of Days between NO2 and O3	Number of days NO2 and O3 Exceeded	Percent NO2 Exceeded (smaller denominator)	Exceeds 99th percentile defined by WHO? (1=yes, 0=no)5	Percent NO2 and O3 Exceeded (larger denominator)	Exceeds 99th percentile defined by WHO? (1=yes, 0=no)4	Difference in Percent Exceedance 2
AQY BB-607	Commercial	81	612	1	1.23	1	0.16	1	-1.07
AQY BB-608	Commercial	306	536	2	0.65	1	0.37	1	-0.28
AQY BB-609	Residential	233	549	12	5.15	1	2.19	1	-2.96
AQY BB-610	Residential	209	364	1	0.48	1	0.27	1	-0.20
AQY BB-611	Residential	370	668	10	2.70	1	1.50	1	-1.21
AQY BB-633	Industrial	0	0	0	0.00	1	0.00	1	0.00
AQY BB-634	Industrial	393	517	2	0.51	1	0.39	1	-0.12
AQY BB-635	Residential	0	0	0	0.00	1	0.00	1	0.00
AQY BB-636	Residential	0	0	0	0.00	0	0.00	0	0.00
AQY BB-637	Residential	386	587	2	0.52	1	0.34	1	-0.18
AQY BB-638	Residential	372	531	1	0.27	1	0.19	1	-0.08
AQY BB-639	Residential	544	640	2	0.37	1	0.31	1	-0.06
AQY BB-640	Residential	0	0	0	0.00	1	0.00	1	0.00
AQY BB-641	Residential	270	380	1	0.37	1	0.26	1	-0.11
AQY BB-642	Industrial	338	549	9	2.66	1	1.64	1	-1.02
AQY BB-643	Residential	409	723	6	1.47	1	0.83	1	-0.64
AQY BB-644	Residential	392	572	11	2.81	1	1.92	1	-0.88
AQY BB-645	Residential	0	0	0	0.00	0	0.00	1	0.00
AQY BB-646	Residential	206	303	4	1.94	1	1.32	1	-0.62
AQY BB-647	Residential	0	0	0	0.00	0	0.00	0	0.00
AQY BB-648	Residential	0	0	0	0.00	0	0.00	1	0.00
AQY BB-649	Residential	411	527	16	3.89	1	3.04	1	-0.86
AQY BB-650	Commercial	0	0	0	0.00	1	0.00	1	0.00
AQY BB-651	Residential	131	512	2	1.53	1	0.39	1	-1.14
AQY BB-652	Commercial	189	640	9	4.76	1	1.41	1	-3.36
AQY BB-787	Commercial	355	477	5	1.41	1	1.05	1	-0.36
AQY BB-788	Residential	0	0	0	0.00	1	0.00	1	0.00
AQY BB-789	Commercial	415	439	1	0.24	1	0.23	1	-0.01
AQY BB-790	Commercial	442	508	3	0.68	0	0.59	0	-0.09
AQY BB-791	Residential	0	0	0	0.00	1	0.00	1	0.00
AQY BB-792	Commercial	234	521	13	5.56	1	2.50	1	-3.06
AQY BB-793	Residential	0	0	0	0.00	0	0.00	0	0.00
AQY BB-794	Residential	450	618	5	1.11	1	0.81	1	-0.30
AQY BB-795	Residential	461	544	19	4.12	1	3.49	1	-0.63
AQY BB-796	Residential	268	407	18	6.72	1	4.42	1	-2.29
AQY BB-797	Commercial	149	522	4	2.68	1	0.77	1	-1.92
AQY BB-798	Industrial	209	593	2	0.96	1	0.34	1	-0.62
AQY BB-799	Industrial	433	515	1	0.23	0	0.19	0	-0.04
AQY BB-800	Industrial	0	0	0	0.00	0	0.00	0	0.00
AQY BB-801	Commercial	258	675	4	1.55	1	0.59	1	-0.96
AQY BB-802	Residential	194	419	11	5.67	1	2.63	1	-3.04
AQY BB-803	Residential	277	363	6	2.17	1	1.65	1	-0.51
AQY BB-804	Commercial	345	515	5	1.45	1	0.97	1	-0.48
AQY BB-805	Residential	0	0	0	0.00	1	0.00	1	0.00
AQY BB-806	Commercial	348	493	4	1.15	1	0.81	1	-0.34
AQY BB-807	Residential	0	0	0	0.00	1	0.00	1	0.00
AQY BB-808	Commercial	0	0	0	0.00	1	0.00	1	0.00
AQY BB-809	Residential	337	475	4	1.19	1	0.84	1	-0.34
AQY BB-810	Industrial	425	581	2	0.47	1	0.34	1	-0.13
AQY BB-811	Commercial	0	0	0	0.00	1	0.00	1	0.00
Reference	Reference	811	811	1	0.12	1	0.12	1	0.00

Appendix 3B.7: Exceedances for $PM_{2.5}$, NO_2, and ozone and Comparative analysis with data completeness

RAMN ID	Land Use	Minimum Number of Days between PM2.5 NO2 and O3	Maximum Number of Days between PM2.5 NO2 and O3	Number of days PM2.5 NO2 and O3 Exceeded	Percent PM2.5 NO2 and O3 Exceeded (smaller denominator)	Percent PM2.5 NO2 and O3 Exceeded (larger denominator)	Difference in Percent Exceedance3
AQY BB-607	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-608	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-609	Residential	233	762	3	1.29	0.39	-0.89
AQY BB-610	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-611	Residential	370	790	3	0.81	0.38	-0.43
AQY BB-633	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-634	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-635	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-636	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-637	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-638	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-639	Residential	544	778	1	0.18	0.13	-0.06
AQY BB-640	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-641	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-642	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-643	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-644	Residential	392	712	2	0.51	0.28	-0.23
AQY BB-645	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-646	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-647	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-648	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-649	Residential	411	752	4	0.97	0.53	-0.44
AQY BB-650	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-651	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-652	Commercial	189	687	1	0.53	0.15	-0.38
AQY BB-787	Commercial	355	546	2	0.56	0.37	-0.20
AQY BB-788	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-789	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-790	Commercial	442	508	1	0.23	0.20	-0.03
AQY BB-791	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-792	Commercial	234	579	2	0.85	0.35	-0.51
AQY BB-793	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-794	Residential	450	632	2	0.44	0.32	-0.13
AQY BB-795	Residential	461	544	3	0.65	0.55	-0.10
AQY BB-796	Residential	268	438	5	1.87	1.14	-0.72
AQY BB-797	Commercial	149	552	1	0.67	0.18	-0.49
AQY BB-798	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-799	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-800	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-801	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-802	Residential	194	454	3	1.55	0.66	-0.89
AQY BB-803	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-804	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-805	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-806	Commercial	348	666	2	0.57	0.30	-0.27
AQY BB-807	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-808	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-809	Residential	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-810	Industrial	n/a	n/a	n/a	n/a	n/a	n/a
AQY BB-811	Commercial	n/a	n/a	n/a	n/a	n/a	n/a
Reference	Reference	811	811	1	0.12	0.12	0.00

CHAPTER FOUR: Using Air Dispersion Modeling and Health Risk Assessment Methods to Evaluate Cumulative Impacts from Pesticides in California

ABSTRACT

California is one of the largest agricultural economies in the United States. To maintain production and crop yield, California uses pesticides, many of which are toxic, and highly volatile, and pose health risks to farmers and local communities. In California, the Department of Pesticide Regulation (DPR) is responsible for registering pesticides for sale in California at the state level, including restrictions. The County Agricultural Commissioners (CACs) are responsible for localized safe use of pesticides by growers. A CAC has the authority to impose restrictions and mitigation measures in pesticide permits based on local conditions if the CAC determines that pesticide use may harm public health and the environment. One such local condition is the use of other pesticides at or near the application site identified in a permit application.

Although multiple pesticides are often applied within a community over the same day or week, neither DPR nor the CACs evaluate local community impacts from the resulting cumulative exposures. A review of the literature indicates there are multiple challenges to establishing tractable cumulative impact assessment methods for cumulative pesticide exposure. This chapter proposes applying air dispersion modeling and health risk assessment methods currently utilized for air pollution and air toxics to estimate pesticide dispersion and impacts. I demonstrate how DPR could use similar methods to estimate statewide impacts of pesticides, identifying specific areas of high concern for cumulative exposure. In reviewing permit applications relating to such areas, CACs could estimate localized cumulative impacts based on

local pesticide use data and , where appropriate, require additional mitigation or risk reduction strategies to minimize cumulative impacts. To demonstrate the feasibility of such an approach, I focus on 1x1 square mile grid cell in Merced County to perform air dispersion modeling and health risk assessment.

INTRODUCTION

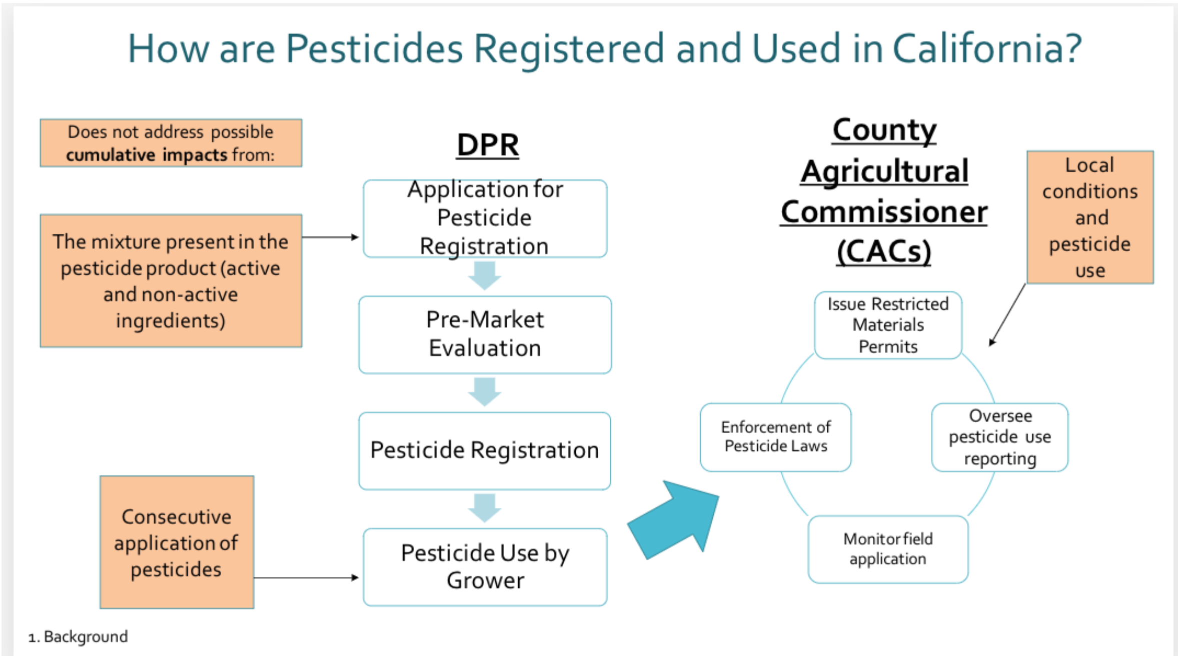
California is one of the largest agricultural economies in the United States, supplying over a third of the country's vegetables and two-thirds of the country's fruits and nuts (*CDFA - Statistics*, n.d.). California uses a large number and quantity of pesticides with the goal of maintaining production and increasing efficiency of crop yield. In California, there are two entities that regulate pesticide registration and use: The California Department of Pesticide Regulation (DPR), and County Agricultural Commissioners (CACs).

Before a pesticide can be sold or used in California, it must undergo a registration process through the DPR, the statewide regulatory body responsible for the public health and safety of pesticide use. DPR receives applications for pesticide registration, conducts a pre-market evaluation of the pesticide, registers the pesticide, and then the pesticide can be used by the grower. Before DPR registers a pesticide for use, staff conduct a premarket evaluation of the pesticide to determine if it can safely be used, including human health and ecological risk assessment for pesticides that present concern. Where necessary to protect human health or the environment, DPR may impose risk management requirements on the pesticide including use restrictions, buffer zones and worker protection standards. Existing pesticides that are already in use are also subject to reevaluation under certain circumstances (DPR, 2017).

The role of the CACs is to enforce the laws and regulations of the California Food and Agricultural Code (*Agricultural Commissioner > Home*, n.d.). Among many other roles, the CACs are responsible for pesticide use enforcement, with the goal to provide safe use of pesticides for the production of food and protection of public health. If a grower would like to use a pesticide, they must submit a restricted materials permit to their respective CAC prior to use. The CAC must evaluate the proposed restricted material use to decide if application of that pesticide has the potential to cause harm to public health or the environment. Permits, which are typically issued at the beginning of the year, do not specify timing of use and are active for one year. When the grower is ready to apply the permitted pesticide, the grower will submit a notice of intent (NOI) to the CAC prior to application of the pesticide in the field (Malloy et al., 2017). The NOI must include the location, address of the applicator, crop, acres to be treated, the method of application, what pesticides will be applied, application rate, date/time of intended application, and identify neighboring properties (e.g., schools, houses, water sources) and who could be adversely impacted by the application (Santa Cruz County Agricultural Commissioner, 2015). The NOI gives the CACs another chance to review the proposed pesticide and provide additional restrictions. County staff can also do pre-site inspections to make sure the information is accurate (DPR, n.d.-b). Figure 4.1 provides a visual representation of the relationship between DPR and the CACs.

Many pesticides used are toxic, and highly volatile, posing a health risk to workers applying the pesticides, nearby residents, and local communities. Cumulative exposures can occur in multiple ways: (1) exposure to both the pesticide's active and non-active ingredients, (2) pesticides where there are multiple active ingredients, (3) pesticides that are mixed in a tank by certified pesticide applicators before they are applied to a field, and (4) pesticide applications that occur close in space and time. This chapter focuses on pesticide applications that are close in space and time. Impacts from any mixture of these pesticide exposures may be additive (where the effect of two or more chemicals is equal to the sum of each of the agents when it is alone) (Christen et al., 2014; Zaunbrecher et al., n.d.), greater than additive (which assumed that the health response is greater than is observed when interaction is additive) (Rizzati et al., 2016), and independent (where exposure impacts different target sites) (Hernández et al., 2013). A meta-analysis revealed that 47% of complied studies reported an additive effect between pesticides, ultimately leading to adverse health effects to the brain, endocrine, and lymphatic systems (Rizzati et al., 2016). One study highlighted from the meta-analysis suggests that certain fungicides interact in an additive-fashion that may disrupt the endocrine system (Christen et al., 2014). Another study explored the combination of herbicides impacting the lymphatic system (Demsia et al., 2007). A literature review studying the toxicological evidence of interactions between multiple pesticides suggests that a number of commonly combined pesticides have been found to elicit greater than additive effects (Rizzati et al., 2016). A literature review by Hernandez et. al. compiled and reviewed research focusing on toxicological interactions in pesticide mixtures. Their research reported several examples of adverse health effects attributed to multiple insecticide exposure, such as the more than additive effects between two commonly applied pesticides, malathion and pyrethroids, neurotoxins that target the acetylcholinesterase enzyme responsible for regulating voluntary muscle movement (Hernández et al., 2013). Many communities in California continue to bear a disproportionate burden of environmental impacts from nearby sources, such as air pollution sources and agricultural sources. These communities also experience the additional burden of socioeconomic stressors and health conditions that make them more vulnerable to environmental impacts (August et al., 2021). This chapter focuses on the impacts from chemical stressors only.

Figure 4.1: The California Pesticide Regulatory Process



Cumulative impact assessment (CIA) is defined as the analysis, characterization, and possible quantification of the combined risks to health and the environment from multiple chemical agents or stressors (Zaunbrecher et al., n.d.). In most cases across programs and countries, regulators do not engage in cumulative risk assessment. Thus, current regulatory risk assessment methods do not represent real-world exposure scenarios; humans are continuously exposed to contaminants in environmental media such as air, water, and food. To date, the United States federal regulators have only recognized and adopted the Common Mechanism Group (CMG) method to assess cumulative impacts of pesticides (Zaunbrecher et al., n.d.). The CMG method groups two or more chemicals that have been identified to elicit the same toxic effect by the same, or similar biochemical events. Other agencies, such as the European Union uses Cumulative Assessment Groups (CAGs) to identify the specific impacts on organ systems, hazard characteristics, and selection of index compounds allowable in food residues (Crivellente et al., 2019). Canada uses a Tiered Approach to estimate conservative assumptions for exposures and hazards to multiple pesticides. Depending on data available, higher tiers require more information to make cumulative impact decisions (Moretto et al., 2017).

At present, neither DPR nor the CACs systematically engage in cumulative risk assessment. (Malloy et al., 2017; Zaunbrecher et al., n.d.). A National Academy of Science review of DPR practices concluded that it is unclear how DPR is considering cumulative impacts, and recommended that DPR stay up to date in current trends of exposure assessment (The National Academies Press, 2015). In registering new pesticides, DPR only evaluates risk from exposure to the new active ingredient contained in the product. The agency does not consider cumulative risks associated with the presence of other previously approved active ingredients or inert ingredients. DPR has conducted pesticide monitoring and modeling but has not developed consistent guidelines that it or CACs can use to evaluate the use of multiple pesticides. DPR has explored using air dispersion modeling as a first step in assessing concentrations of one pesticide, not for health risk assessment, and not for regulatory purposes (Luo, 2019). At the county level, in approving a restricted materials permit application, the CAC does not assess cumulative impacts associated with other pesticides applied by the applicant or nearby growers. CACs have limited capacity to effectively evaluate all permits consistently and need a simple, effective, and consistent method to evaluate cumulative impacts.

Cumulative risk assessment methods are inherently complex; they require accounting of exposure to multiple environmental stressors, understanding the relationship between the stressors, and providing a clear explanation of how they translate into health impacts. In a previous literature review, I identified four challenges with implementing CIA into regulatory processes such as registration and permitting. First, there are significant data gaps in toxicological and health effects data essential to evaluate pesticide pairings or groups. This is often the rationale to explain why cumulative impact assessment is not always feasible. Second, technological integration, such as geographic information systems, air dispersion modeling, or other computational methods have yet to be widely used to make the cumulative impact assessment process more efficient. Third, integration of principles, tools, and methods from various disciplines, including public health, epidemiology, predictive toxicology, and data science, to address pervasive data gaps and develop of widely accepted cumulative impact assessment methods is challenging. Finally, a lack of inclusion of a broad range of stakeholders, such as business interests, policy makers, and social groups, may be a major barrier to CIA development (C. F. Clark et al., 2003; Meek et al., 2011; Sexton & Linder, 2010, 2011). This chapter aims to fill a need from the second data gap/challenge: How can existing technologies be leveraged by local and state regulatory agencies to evaluate cumulative risks meaningfully and efficiently?

This chapter focuses on the cumulative impacts the active pesticide ingredients when application occurs over close space and time. There are two important pieces to be considered: exposure and risk. It is important to note that exposure is modeled rather than measured, since this is used to assess the use of pesticides prior to application. The risk from exposure will depend on the pesticide applied and the local conditions. Additionally, since the toxicological testing of the ambient mixture is not practical, the risk is characterized using existing toxicological data regarding the active ingredients of the pesticide mixture.

Air dispersion modeling is the gold-standard method for evaluating impacts from air pollution. Air dispersion modeling is currently being widely implemented at other local, state, and federal agencies to estimate dispersion and concentration of pollutants and is cost-effective method that can be leveraged to estimate impacts from multiple pesticides. The South Coast Air Quality Management District uses air dispersion modeling to evaluate impacts from toxic air contaminants under Rule 1401 (South Coast AQMD, 2017). Air dispersion modeling is being implemented at the federal, state, and regional level, and thus is not foreign to pesticide regulators for pollution estimation, dispersion, or evaluation. DPR has also used air dispersion monitoring tools to estimate pollutant dispersion, but have not implemented this method for regulatory requirements (Reiss & Griffin, 2006) According to the State Legislature (Assembly Bill 1807, Food & Agricultural Code sections 14021-14027 (DPR, n.d.-c)), pesticides are also considered toxic air contaminants, suggesting that existing methods used to evaluate air toxics can translate into evaluating pesticide dispersion. Air dispersion modeling would provide conservative estimates of pesticides concentrations locally, which can be used to (1) estimate health risks from use of multiple pesticides and (2) identify locations where the CAC should recommend mitigation.

The United States Environmental Protection Agency (US EPA) recognizes the American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) as the preferred regulatory atmospheric model. AERMOD is a Gaussian steady-state plume model that incorporates dispersion based on geographical boundary structure, elevation, and terrain. AERMOD can provide both pollutant and non-pollutant specific air concentrations (Tao & Vidrio, 2019). Using non-pollutant specific AERMOD model outputs make it desirable for modeling pesticides, since the locations are unlikely to change, but the pesticide uses vary by location, season, and crop. The AERMOD output can be post-processed to calculate pollutant-specific ground level concentrations to decrease model run time and increase efficiency (CARB, 2015). The US EPA's Office of Pesticide Programs has used AERMOD to model concentrations of individual pesticides in ambient air to estimate human exposure and risk assessment (van Wesenbeeck et al., 2019), but has not provided guidance for regulatory implementation at the federal, state, or local level.

Practices and tools used in complying with California's Toxic Hot Spots program provide a model that can be implemented in the pesticide area. To conduct air dispersion modeling and health risk assessment for air toxics in California, many air quality experts use the California Air Resources Board's Hot Spots Analysis and Reporting Tool (HARP2), an air dispersion modeling and risk assessment tool. HARP2 combines the US EPA's AERMOD model using non-pollutant specific concentrations, and health risk assessment methods into a user-friendly software that walks the user (1) estimating non-pollutant specific air dispersion patterns, (2) calculating pollutant specific concentrations, and (3) using the pollutant specific concentrations to estimate health risk from one or more pollutants. HARP2 uses component-based risk characterization for non-carcinogenic pollutants. Component-based risk characterization assumes that chemicals with similar mode actions, or have closely related chemical structures, and occur together are combined to estimate a risk. This approach is best suited when quantitative information on toxicological interactions is available (Choudhury et al., 2000). Although the initial intent for the development for HARP2 was to support the Air Toxics Hot Spots Information and Assessment Act (1987), HARP2 can also be utilized for preparing risk assessments for other air related programs, such as ambient monitoring evaluations, or air toxics control measure development (CARB, 2015). The risk assessment methods in HARP2 would satisfy the National Academy of

Sciences recommendation for DPR and the CACs to (1) perform quantitative health risk assessments and (2) consider the risk of multiple pesticides (The National Academies Press, 2015).

My research proposes to (1) provide a framework for the role that DPR and the CACs would take to implement air dispersion modeling and risk assessment methods to conduct CIA, (2) demonstrate the feasibility of using air dispersion modeling to estimate pesticide dispersion by discussing both current practice and literature discussion, and (3) use the modeling results to conduct a cumulative health risk assessment using HARP2. To demonstrate the feasibility of using existing air dispersion modeling techniques and risk characterization tools for permitting decisions by CACs, I use historical pesticide use data from DPR to visualize how this tool could work. I demonstrate the capabilities of the tool assuming two pesticides that have been applied on the same day within a 1x1 square mile grid.

This chapter will walk through how to identify communities of concern, estimate pesticide use spatially, set up an air dispersion model, use the air dispersion modeling results to calculate pesticide-specific ground-level concentrations, and estimate health risks to nearby communities.

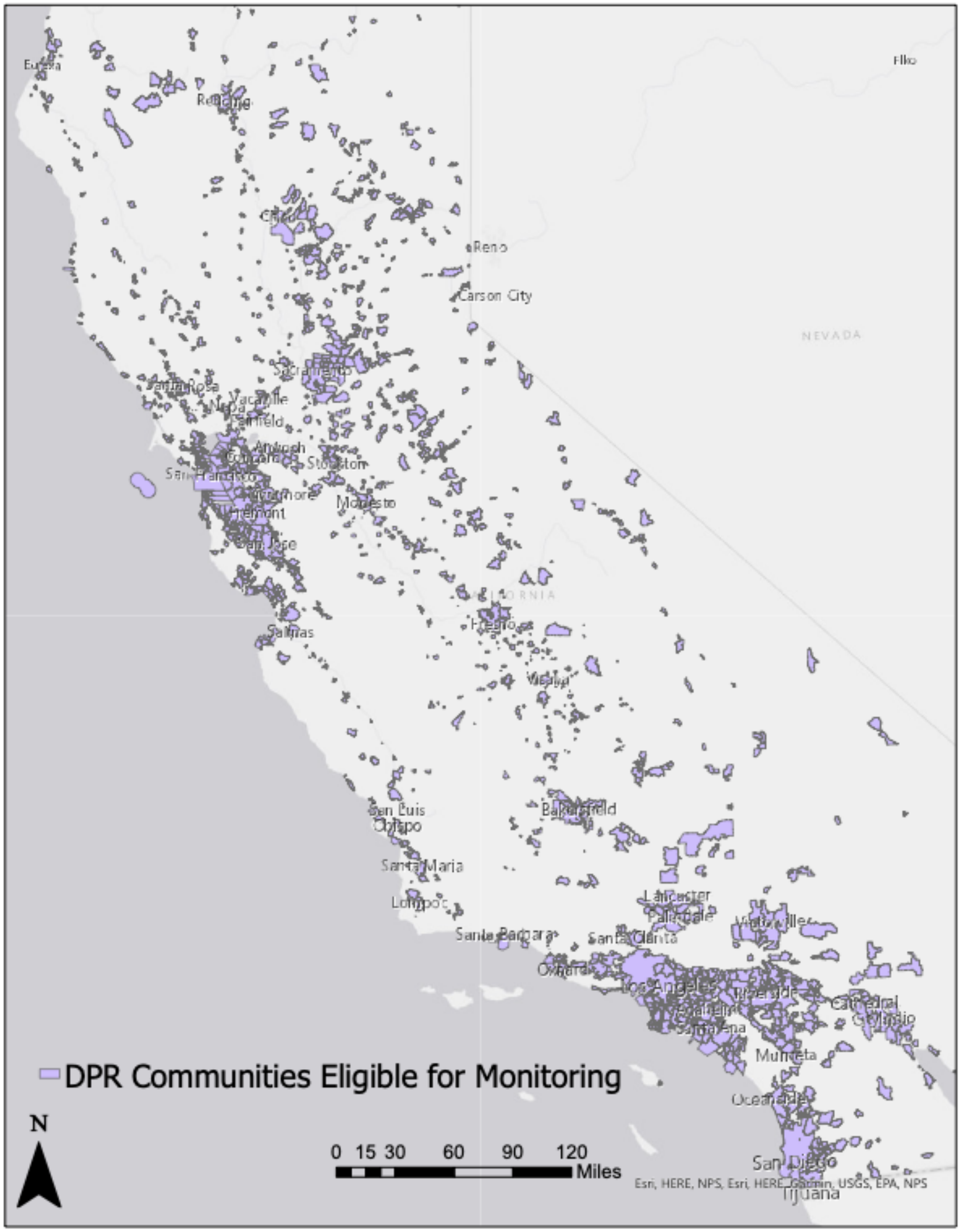
METHODS

Identification of Communities with Multiple Pesticide Use

The first task is to identify communities of concern. DPR had previously evaluated and ranked communities impacted by pesticide use by using geographic information systems (GIS) analysis to calculate the amount of each pesticide applied within the community, within one mile of the community, and within one to five miles of the community. (For this analysis, DPR used geographic boundaries from the US Census Bureau's 2015 TIGER/Line Place shapefile.) DPR used density in pounds per square mile (lbs/sq mi) determined by the pesticide, year, and zone, data from nearest California Irrigation Management Information System to understand wind speed, and Environmental Justice (EJ) factors from CalEnviroScreen 2.0 to select and prioritize these communities (DPR Identified Community) (DPR Environmental Monitoring Branch, 2017). I requested the Shapefile for the DPR Identified Communities from staff at DPR, which were provided as a GIS file (Figure 4.2). The DPR Identified Communities were used as the receptor locations where the air dispersion model would estimate pesticide concentrations (Segawa et al., 2014).

To estimate pesticide use spatially, I obtained data from DPR's Pesticide Use Reporting (PUR) system that allows users to query historical pesticide use data, including the pesticide used, the date applied, the pounds applied per day in location only for agricultural use, and the user-designated spatial scale. PUR data from 2018 was retrieved at the highest spatial scale available by the US Bureau of Land Management: The Public Land Survey System (PLSS) sections (from herein referred to as "sections"), a grid of 1x1 square mile sections of land (CalPIP DPR, n.d.). For reference, California DPR refers to these as County code, Meridian, Township, Range and Section (COMTRS), and this is how the data is spatially identified from PUR (DPR, n.d.-a)). PUR data was joined with the section data in GIS to create a map.

Figure 4.2: DPR Identified Communities in California



Statewide Air Dispersion Modeling

There are limited resources on using AERMOD and other air dispersion modeling techniques to evaluate pesticide dispersion, concentration, and risk assessment (De Leeuw et al., 2000; Luo, 2019; van Wesenbeeck et al., 2019). DPR previously evaluated AERMOD to simulate ambient concentrations of a single pesticide by modeling how well air dispersion modeling performs in comparison to ambient monitoring stations (Luo, 2019). Other studies evaluate models that estimate pesticide exposure, such as the Soil Fumigant Exposure Assessment (SOFEA) modeling system, and the AERFUM, integrated air dispersion modeling system for soil fumigants (Luo, 2019; van Wesenbeeck et al., 2019). However, these studies share several limitations for purposes of my research: a focus on a single pesticide – 1,3-dichloropropene, failure to address air dispersion modeling on one specific day or time, and lack of integration with risk characterization. Furthermore, it is not clear how the studies accounts for variable emission rates, used to estimate how much pesticide may be applied during a single day (Luo, 2019). Existing studies are helpful to understand how to scale up estimation of pesticide concentrations in multiple locations but are limited in providing solutions to model cumulative exposures. Research revealed no studies that used multiple pesticide concentrations derived from air dispersion modeling as input for risk characterization software. To demonstrate how DPR could implement such an approach, I selected one section in Merced County to conduct an air dispersion modeling model run and health risk assessment.

Demonstration of Air Dispersion Modeling Inputs and Outputs

Air dispersion modeling estimates how pollutants will disperse and predict concentrations at specific locations. The model must include information about the source: (type, size, emissions profile), receptors (where the model will estimate pollutant concentrations), meteorological information (temperature, relative humidity, wind speed and direction), and terrain (elevation will estimate potential dispersion and pollutant deposition) (CARB, 2015). For statewide air dispersion modeling, the 1 x 1 square mile sections will be used as the sources in the air dispersion model, and the DPR Identified Communities will be used as the receptors. I selected four counties in Central California: Merced, Kings, Fresno, and Kern Counties and filtered sections within one mile of a DPR identified community (Figure 4.5) to demonstrate how DPR would model pesticide use.

Sources: One section grid cell was selected and modeled as an area source to estimate pesticide emissions (Tao & Vidrio, 2019). To simulate ground field application, I set the release height to zero (Tao & Vidrio, 2019). To account for the fact that pesticides are applied over a shorter time than continuous emission sources, I used the variable emissions section to estimate the months in which these pesticides were applied. Variable emissions allows the model to weight when the emissions would occur and estimates dispersion modeling concentrations accordingly. The literature is not consistent on how to most effectively model dispersion for a single day. Based on my professional experience and assessment of air dispersion modeling, I used the Hour of Day, Day of Week emission profile. Between 7 AM and 7 PM were used to weight any pollutant emissions. Since not all of the pesticide will volatilize, assumptions were made to estimate the amount of pesticide emitted. See "Estimated Pesticide Specific Concentrations" section below. AERMOD is run at a default emission rate of 1 gram/second of emissions.

Receptors: DPR Identified Communities represent the receptors where pollutant concentrations will be calculated. To reduce modeling runtime, sensitive receptor points were placed around the perimeter of each receptor community. If the edge of the receptor community is impacted by pesticides, and the edge is assumed to be the most vulnerable location of the community, it would demonstrate the potential maximum exposure from nearby pesticide use.

AERMOD was run using unit emission rates to estimate non-pollutant specific (herein referred to as pesticide specific concentrations). Running a non-pesticide specific model reduces modeling run time. All the inputs used for the demonstration can be found in Table 4.1. Pesticide specific ground-level concentrations are calculated using the output of the model run, described in further detail below.

Table 4.1: AERMOD Inputs

AERMOD Pathway Inputs	**Pathway Input**	**Input**	**Explanation**
Project Information	Facility/Project Origin	Coordinates representing centroid of sections	Set the center of the Modeling Domain
Control Pathway	Dispersion Options	Regulatory Default Options	Regulatory Default refers to the outputs of the model (concentration), the averaging times (1 hour and annual), as applicable to the project.
Source Pathway	Source Type	AREAPOLY	Area sources are used to model pollutant emissions that occur over an area(Cobbs & Mountain, 2020).
	Polygon Vertices	Four corners of the sections	Define the size of the area source
	Non-pollutant Specific Unit Rate Emission Factor	4.01E-07 g/s*m^2	Pollutant emission rate divided by the area of the AREAPOLY source to calculate the emissions over the area(OEHHA, 2015a).
	Variable Emission Rates	Emissions were weighted to only occur on one day of the week (e.g., Saturday).	Emission rates can vary by month, hour of day, and day of the week. Currently, there is no way to designate a specific day of the year. This Variable Emission was used to estimate as close as possible to a single day.
Receptor Pathway	Receptor Types	-Cartesian Receptor Grid -Sensitive Receptor	The Cartesian Receptor Grid was drawn to determine where the greatest impacts to the community were. The sensitive receptors line the perimeter of the

AERMOD Pathway Inputs	Pathway Input	Input	Explanation
			DPR Designated Communities. If the concentrations are elevated at the perimeter of the community, it is assumed that the entire community would be impacted
Meteorology Pathway	Meteorology Data	Surface Met Data and Profile Met Data used	Data used to estimate the atmospheric conditions, and layer parameters used in the dispersion calculations. Atmospheric conditions include wind speed, wind direction, temperature, and cloud cover (CARB, n.d.-a). Meteorological data was obtained from the San Joaquin Valley Air Pollution Control District(San Joaquin APCD, n.d.).
Terrain Options	Terrain/AERMAP	Digital Elevation Model (DEM) Files for: Cressy, Atwater, Arena, Stevinson, Winton, Turlock, Turlock Lake, Monpeller, and Denair	DEM files are used to calculate the elevation at the source and receptor locations, which will impact pollution dispersion. More than one DEM was needed to cover the entire modeling domain. DEM files were obtained from the California Air Resources Board(CARB, n.d.-b).

Estimating Pesticide Specific Concentrations: To calculate the pesticide specific ground-level concentrations at each receptor, HARP2 uses the AERMOD Output to calculate and sum the concentrations into one file for each pollutant. For example, if two adjacent sections impacting the receptors were using the same pollutant, the calculation of pollutant-specific ground-level concentrations would be summed to estimate the risk from both of the sections, resulting in a single set of data used to estimate risk. Note that in this example at this section location, these specific pesticides were not applied at the same time (See Discussion section below). However, for demonstration purposes, the health risk assessment assumes that these pesticides were applied on the same day.

The PUR data, retrieved in pounds per year (lbs/yr), was used to calculate the Max Hourly Emission (max lbs/hr). Although pesticides do not have a Max Hourly Emission, HARP2 uses this calculation to estimate acute impacts (see Discussion section below for recommendation how HARP2 can be reformed to include pesticide use specific temporal parameters). HARP2 includes pollutant-specific information, such as molecular weight, and reference exposure levels. There are four pesticides that are currently co-listed as air toxics in HARP2: Acrolein, Methyl Bromide, Pentachlorophenol, and Phosphine. Since these are already incorporated into HARP2, Methyl Bromide and Pentachlorophenol were used to demonstrate feasibility of estimating risk from more than one pesticide at or near a location. It was assumed that both Methyl Bromide and Pentachlorophenol were applied on the same day.

Total pounds of pesticide applied per day within the sections was used to set the emissions rate. To estimate the pesticide emissions, it was assumed that pesticides could be applied any time between 7 AM and 7 PM. A conservative estimate was made that the maximum amount of pesticide emitted in one hour was the total pounds of pesticide applied in a day divided by 12 hours (7 AM and 7PM). This value was used to estimate acute exposure and short-term emission rates. Table 4.2 includes the pounds of Methyl Bromide and Pentachlorophenol applied in a specific day.

Table 4.2: Pounds of Pesticide Applied and Assumed provided from DPR PUR

Pesticide/Pollutant	**PUR (lbs/day)**	**Maximum Hourly Emissions (lbs/hr)**
Methyl Bromide	15,008.1	1, 250.7
Pentachlorophenol	0.0634	0.00528

Health Risk Assessment

To estimate potential non-cancer health impacts from short-term, one-hour peak exposures to pollutants inhalation at a specific receptor, the Hazard Index Approach is incorporated into HARP2. The health impact calculation for a single substance is called the Hazard Quotient (HQ). Acute Reference Exposure Levels (RELs) are defined as acceptable exposure that is not likely to cause adverse health outcomes in human populations (OEHHA, 2015b). The Acute HQ is calculated by dividing the concentration of the pesticide at the receptor by the REL. If the HQ is greater than 1, the probability of adverse human health impacts increases (OEHHA, 2015a). Because pesticides are applied over a short amount of time, using the acute hazard index calculation is the best estimate to assess exposure using HARP2. See Discussion section for recommendations to adapt this tool to assess pesticide use.

$$Acute\ HQ_{Pesticide} = \frac{1\ Hour\ Max\ Concentration\ \left(\frac{\mu g}{m^3}\right)}{Acute\ REL\ \left(\frac{\mu g}{m^3}\right)}$$

To estimate the health risks from multiple pesticides, the HQs for all target organs are summed to calculate the Hazard Index (HI). For acute exposure, HARP2 only estimates health risk from inhalation to the respiratory pathway. The HQ for Methyl Bromide and Pentachlorophenol were summed to estimate the HI.

$$Hazard\ Index = HQ_{Methyl\ Bromide} + HQ_{Pentachlorophenol}$$

RESULTS

Results of this chapter visualize the issue with multiple pesticide use. I use 2018 historical PUR data to show the location and prevalence of multiple pesticide uses, and the frequency in which it occurred in Merced County. I also visualize the air dispersion modeling results, and how the results are used to estimate risk to nearby communities.

Visualization of Multiple Pesticide Uses within Merced County

Figure 4.3 shows the locations adjacent or overlapping communities where at least two pesticides were applied on the same day in Merced County, California. Figure 4.4 shows section locations and the frequency of days where two or more pesticides were applied on the same day.

Figure 4.3: Sections in Merced County with two or more pesticides applied on the same day in 2018.

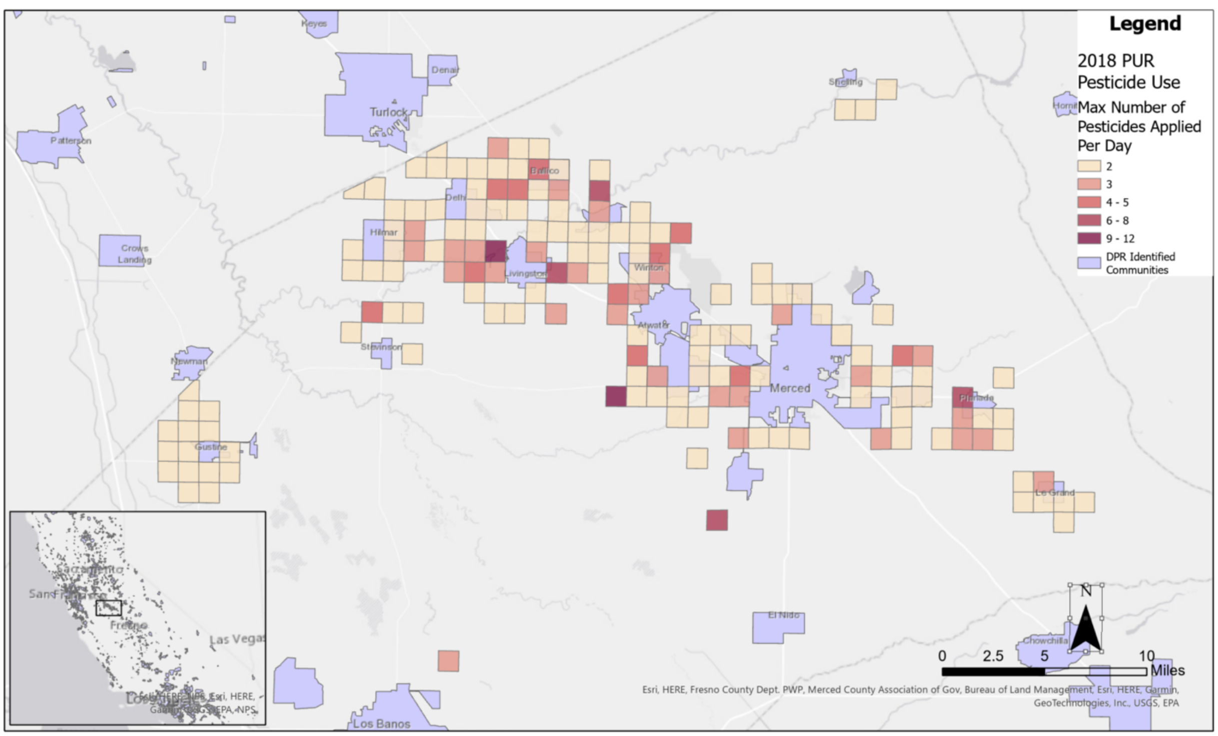
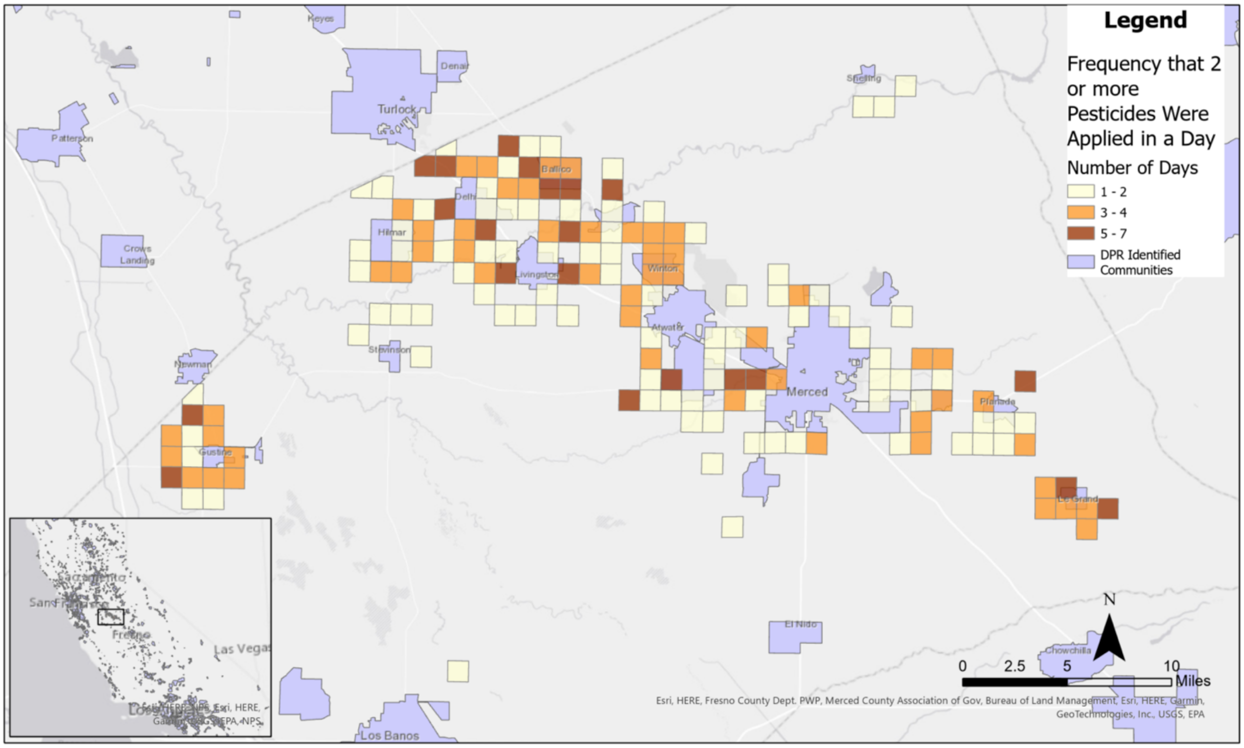


Figure 4.4: Frequency of days where two or more pesticides were applied in the same sections on the same day in 2018.



Air Dispersion Modeling Results

Figure 4.5 shows non-pesticide specific concentration estimates of dispersion and community impact from pesticide use, demonstrating that the highest estimated pesticide concentrations will overlap with a DPR designated community. Figures 4.6a and 4.6b show the maximum 1-hour pollutant-specific ground-level concentrations for Methyl Bromide and Pentachlorophenol, respectively from the single section. The highest concentration estimates (shown in Red and Orange) impact the nearby DPR Designated Community of Ballaco (to the northwest of the section).

Figure 4.5: Non-pesticide specific dispersion estimates

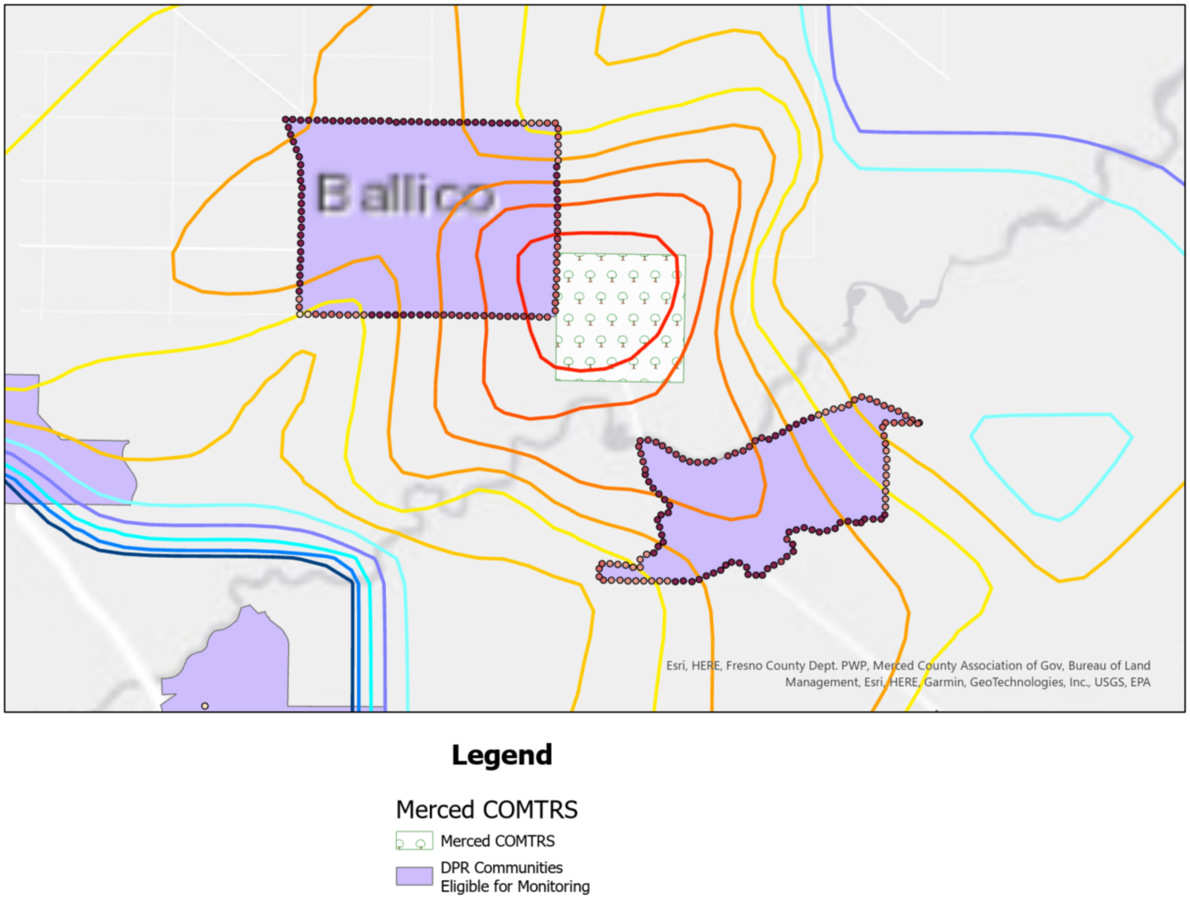
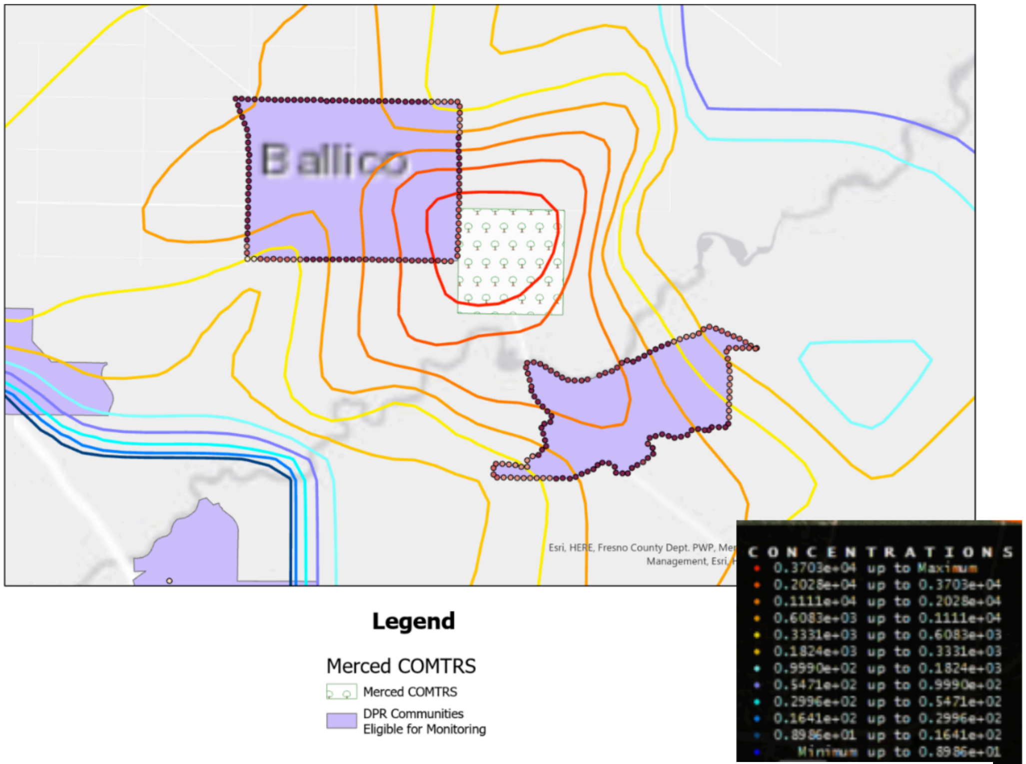
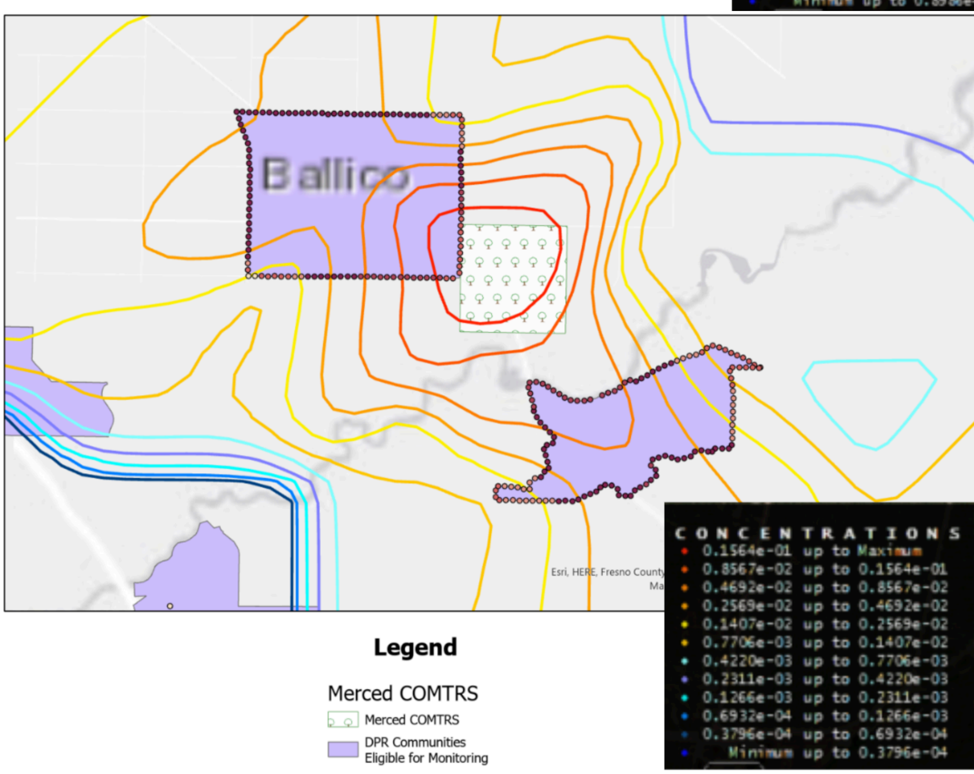


Figure 4.6: Maximum 1-hour ground level concentration estimates of (a) Methyl Bromide and (b) Pentachlorophenol.

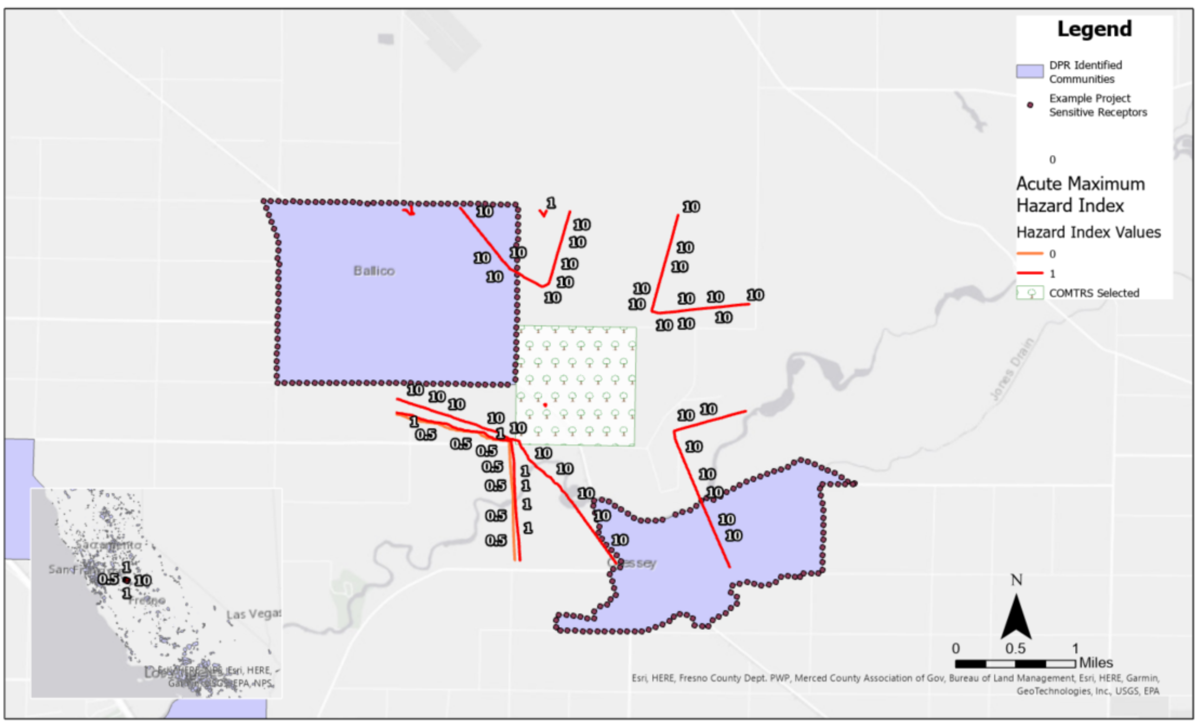




Health Risk Assessment Results

Figure 4.7 shows the Hazard Index risk to communities adjacent to the section. The numbers represent Acute HI's. Both adjacent communities estimate Acute HIs at 10, which is 10 times higher than the OEHHA recommended HI threshold of 1 (OEHHA, 2015a). Since the REL is the concentration at which populations are not expected to see adverse health outcomes, a, HI of 10 means that the concentration exceeds this "safe" level and may expose community members to higher pesticide concentrations. These results suggest that even the use of two pesticides in a single day significantly exceeds health risk reduction values.

Figure 4.7: Acute Maximum Hazard Index. HI greater than 1 suggests a significant impact on the community from pesticide use.

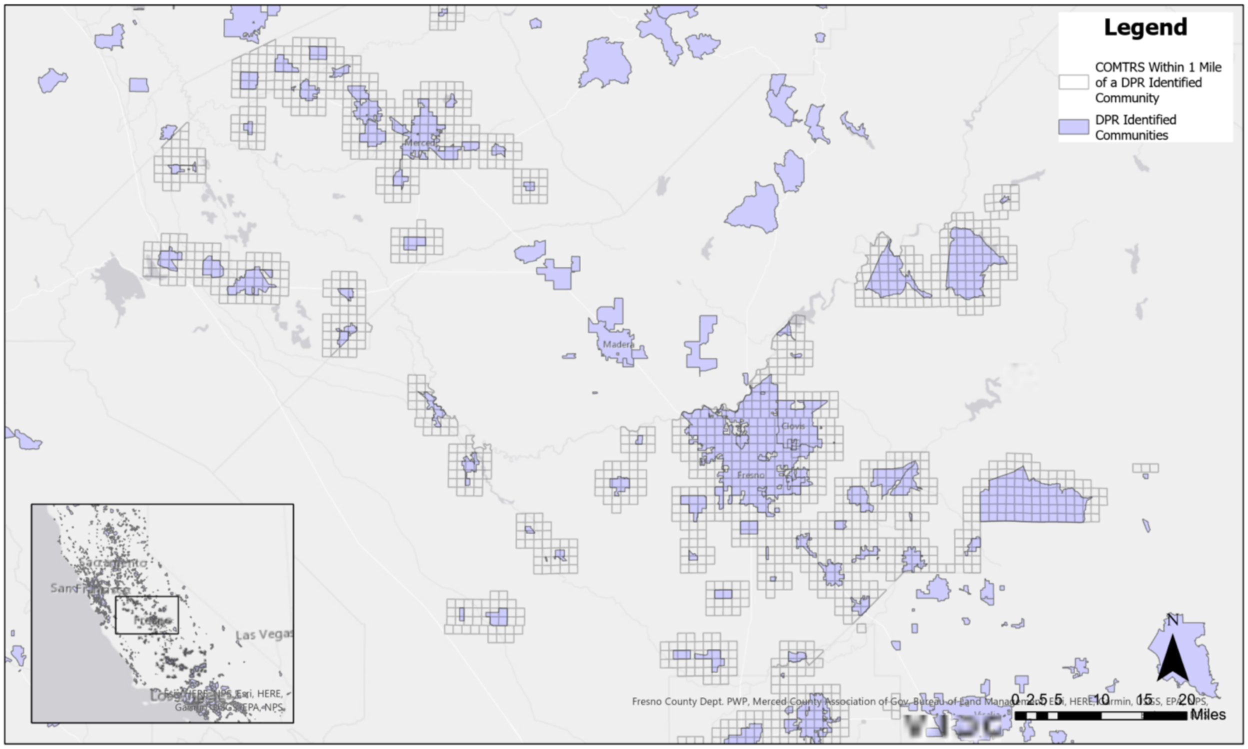


DISCUSSION

This chapter demonstrates how available modeling tools could be repurposed to meet DPR and CACs needs. The results showing elevated acute risk above the OEHHA recommended threshold justify the need for CIA methods that CACs can use when evaluating NOIs. This approach takes resource constraints and institutional competence into account to create a first-generation CIA approach which can be further developed by the regulatory agencies as experience, technology and resources grow.

To conduct such an approach state and local level, DPR could use its air dispersion modeling experience to run AERMOD to model default non-pesticide specific exposures from pesticides from sources nearby to vulnerable communities. DPR would use the default 1 gram/second emission rate to generate non-pesticide specific concentrations from the relevant sections. DPR would provide a map of the model outputs: visualizing 1 x 1 square mile areas where pesticides would be applied and the estimated impacts to adjacent DPR identified communities. Figure 4.8 shows all of the sections within one mile of a DPR identified community and Figure 4.6 shows the non-pesticide specific concentrations that would be modeled for each section.

Figure 4.8: Sections within one mile of DPR Designated Communities in Merced, Kings, Kern, and Fresno counties. A visual representation of the area that DPR would conduct non-pesticide specific dispersion modeling.



The CACs would then insert pesticide specific use data from the NOI to generate pesticide specific concentrations and use this visualization tool to identify where new pollutants plan to be used. Instead of using historic pesticide data, as was used in the demonstration, the NOIs include pesticide use within the area, what quantity be applied over a day or week, and at what location. Multiple NOIs would provide insight to the different pesticides applied over adjacent spatial areas. The CACs would enter pesticide uses in lbs/day to calculate pollutant-specific ground-level concentrations (CARB, 2015). Using the built-in risk characterization tool, CACs would use ground-level concentrations to calculate risk from multiple pesticides. If the risk exceeds the Hazard Index/Hazard Quotient values determined by OEHHA, CACs would be responsible for requesting mitigation from the grower, and/or consulting with DPR as needed on how to proceed. The CAC is required to determine if "a substantial adverse environmental impact may result from the use of such pesticides" and have the authority to deny applications or issue conditional approvals with required mitigation measures. The CACs can use this method to make data-driven decisions reduce the risk to localized communities, such as mitigation. Mitigation measures can include: buffer zones, use limits, personal protective equipment, or potential alternatives to use of that pesticide (Malloy et al., 2017).

For future NOIs, CACs can quickly use this to visualize where multiple pesticides are already being used, and areas where pesticide use may have already. The CACs can identify instances where cumulative exposures to pesticides are already happening, and effectively assist them in making more informed decisions in advance of issuing NOIs (Malloy et al., 2017). This method acknowledges the capacity challenges CACs experience and provides them a consistent way to evaluate all NOIs.

Implementing this method would require training and a dedicated team of air dispersion modeling experts at the state level. Conducting air dispersion modeling at this level requires expertise, time, and resources. While DPR would have access to many of these resources through other California state agencies, it would still require an investment to implement this process. One way to offset these costs would be to levy an additional expense on the pesticide companies or farmers/growers who would be submitting permits for their use. These costs would be used to establish and implement a program like this at the state level.

In addition to DPR expertise and resources, HARP2 would need to be significantly revised to account for the challenges and limitations discussed. HARP2 is designed for use for continuously emitting sources. Because pesticides are applied only during a specific period of time, HARP2 would have to be updated to account for pesticide application characteristics. For example, HARP2 should include a temporal scale that estimates 24-hour acute exposures or chronic exposures. Beyond methyl bromide and pentachlorophenol, HARP2 does not include other pesticides or their characteristics, such as chemical properties, and RELs. HARP2 would have to include all registered pesticide specific health reference exposure levels. To support this effort, DPR has published Health Screening Levels and Regulatory Targets for certain pesticides (see Table 4.3 below) (DPR Environmental Monitoring Branch, 2017). Screening levels could be used to calculate reference exposure levels that can then be input into a revised HARP2.

Further research is needed to formalize AERMOD inputs for pesticide air dispersion modeling. There is still limited research on using AERMOD to estimate pesticide concentrations on a large spatial scale. To use existing air dispersion modeling techniques, I used my professional judgment to make assumptions about pesticide air emissions. For example, to calculate the maximum 1-hour pesticide emissions, I divided the daily amount of pesticides (in lbs/day) by the 12 hours during which pesticides were assumed to be applied. This is a both a conservative, and non-conservative estimate: it is conservative in that it assumes that the maximum amount of pesticide “emitted” in a single hour would impact the community but is not conservative in that it does not account for all exposure pathways, such as soil and water, and it does not estimate the risk after acute exposure. This further supports the need to revise HARP2 to factor other exposure pathways for acute impacts from pesticides. To best assess short term pesticide use, only the Maximum 1-hour pesticide concentration was used to evaluate impacts. This does not conservatively estimate pesticide impacts that occur at 24-, 48- or 72 hours after application.

Table 4.3: DPR Health Screening Levels and Regulatory Targets for a Subset of Registered Pesticides (DPR Environmental Monitoring Branch, 2017)

Pesticide	24-hour acute screening level (ng/m^3)	Subchronic Screening Level (ng/m3)	Chronic screening level (ng/m3)
1,3-Dichloropropene	505,000*	14,000	9,000
Acephate	12,000	8,500	8,500
Bensulide	259,000	24,000	24,000
Chloropicrin	491,000*	2,300	1,800
Chlorothalonil	34,000	34,000	34,000
Chlorpyrifos	1,200	850	510
Chlorpyrifos OA	1,200	850	510
Chlorthal-dimethyl (DCPA)	23,500,000	470,000	47,000
Cypermethrin	113,000	81,000	27,000
DDVP	11,000	2,200	770
Diazinon	130	130	130
Diazinon OA	130	130	130
Dimethoate	4,300	3,000	300
Dimethoate OA	4,300	3,000	300
Diuron	170,000	17,000	5,700
Endosulfan	3,300	3,300	330
Endosulfan Sulfate	3,300	3,300	330
EPTC	230,000	24,000	8,500
Iprodione	939,000	286,000	286,000
Malathion	112,500	80,600	8,100
Malathion OA	112,500	80,600	8,100
Methidathion	3,100	3,100	2,500
Methyl Bromide	820,000*	19,400*	3,900
Metolachlor	85,000	15,000	15,000
MITC	66,000*	3,000	300
Norflurazon	170,000	26,000	26,000
Oryzalin	420,000	230,000	232,000
Oxydemeton methyl	39,200	610	610
Oxyfluorfen	510,000	180,000	51,000
Permethrin	168,000	90,000	90,000
Phosmet	77,000	26,000	18,000
pp-Dicofol	68,000	49,000	20,000
Propargite	14,000	14,000	14,000
Simazine	110,000	31,000	31,000
SSS-tributyltriphosphorotrithioate (DEF)	8,800	8,800	**
Trifluralin	1,200,000	170,000	41,000

*Regulatory target

**Pesticides have seasonal use only, so there is no chronic exposure.

There are limitations to using air dispersion modeling techniques to estimate dispersion of pesticides. This paper makes assumptions that pesticides are applied over a 1x1 square mile grid area, when the application is often times more granular than this. Additionally, this proposed method highlights the uncertainty in variable emission rates that can be used to estimate pesticide concentrations on the same day. It is challenging to estimate variable emissions – previous work has found unique ways to estimate short term and annual concentrations to pesticides (Costanzini et al., 2018; Tao & Vidrio, 2019; Teggi et al., 2018). Since this study focuses on cumulative exposures, it is imperative that the pesticide uses be modeled within a short amount of time between applications. Furthermore, air dispersion modeling does not address deposition, or exposures after initial dispersion. The dispersion of the chemical emitted is evaluated as an inert compound and does not model any reactions that may occur in the atmosphere or following deposition (OEHHA, 2015a).

Finally, there are uncertainties of the environmental conditions during and after pesticide application. This method does not account for further volatility after application (Luo, 2019). Further research needs to be done on the downstream effects of pesticide use that may occur away from where humans would be exposed, as this is beyond the scope of this dissertation chapter.

The intent of this chapter was to demonstrate that existing methods and tools can be harnessed to address cumulative risk. The approach is relatively simple and utilizes expertise from state agencies that DPR would have access to. Despite the fact that the method presented in this chapter relies on a set of assumptions, it is a transparent and meaningful approach that can be implemented now to protect public health and the environment as more refined tools and methods are developed and implemented at the regulatory level.

Appendix 4A: CIA Literature Review

Appendix 4A.1: CIA Literature Review

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Chemical Risk Assessment: Traditional vs Public Health Perspectives	Maureen R. Gwinn PhD, Daniel A. Axelrad MPP, Tina Bahadori ScD, David Bussard BA, Wayne E. Cascio MD, Kacee Deener MPH, David Dix PhD, Russell S. Thomas PhD, Robert J. Kavlock PhD, and Thomas A. Burke PhD, MPH		Health Impact Assessment	Systems approach, integrating data sources and analytic methods, and considers input from stakeholders to determine	-organize various data streams that can influence our understanding of a health effect -inform potential multiple contributors to adverse health outcomes -provide recommendations to decision-makers for monitoring and managing these outcomes.	-incorporating these approaches, which are typically used in epidemiology, to animal and advanced toxicity testing data can be challenging -Requires training on how to communicating risk in a way that acknowledges the influence of nonregulated factors.	Any single health outcome may be influenced by multiple factors beyond chemical exposures, such as nutrition, genetics, and social stressors. Because those factors are not regulated, it is important for environmental regulatory agencies to understand what fraction of the
Racial/Ethnic Disparities in Cumulative Environmental Health Impacts in California: Evidence From a Statewide Environmental Justice Screening Tool (CalEnviroScreen 1.1)	Lara Cushing, MPH, MA, John Faust, PhD, Laura Meehan August, MPH, Rose Cendak, MS, Walker Wieland, BA, and George Alexeeff, PhD	Methods are used to better reflect the cumulative impacts of environmental exposures and population vulnerabilities and provide assessments that can support the incorporation of equity and environmental justice goals into policymaking.	CalEnviroScreen	- A screening tool that considers both pollution burden and population vulnerability in assessing the potential for cumulative impacts across California zip codes. It was	The tool identifies communities that warrant further attention and can help policymakers and decision makers prioritize their activities to the benefit of communities disproportionately burdened by multiple environmental health hazards	-The tool does not quantify the probability of harm or health risk. –The tool does not utilize local data, since it is a statewide tool. S6	-Improve methods for addressing the sensitivity of environmental justice screening tools to the geographic unit of analysis; inform the approach to relative scoring, including the way variables are standardized, weighted, and combined; and, most importantly, identify specific ways that cumulative impact assessment can be most
Tools and perspectives for assessing chemical mixtures and multiple stressors	Hans Løkkea,∗, Ad M.J. Ragasb,c,1,2, Martin Holmstrupa,	EU NoMiracle	Mixture Experiments to explore Concentration Addition and Independent Action	Explore the application of two predictive models: concentration addition and	Data from these models can be used to assess the probability that the two reference models fail to correctly describe the joint effects of chemicals, which is relevant information for risk assessors	Practically infeasible to test all mixture combinations. -Dose–response relationship of a certain combination is likely to depend on the dose ratios.	
Tools and perspectives for assessing chemical mixtures and multiple stressors	Hans Løkkea,∗, Ad M.J. Ragasb,c,1,2, Martin Holmstrupa,	EU NoMiracle	The Receptor Oriented Approach	This approach focuses on the receptor as an integrator of exposure and effects over space and time. Two Approaches for Description of Activity Patterns 1. Descriptive Approach -- data about	Description Approach Advantage: simulates realistic activity and movement patterns and preserves correlations of different activities Predictive Approach Advantages: large explanatory power of these models ,the activity pattern is an emergent property that depends on the characteristics of the rceptor, environment, and behavior rules	Description Approach Disadvantage: the exposure predictions only apply to the conditons reflected in the database and does not account for changes that may inflence the activity patterns such as the introduction of a new transport system or new food product on the market Predictive Approach Disadvantages: the accuracy of the predictions strongly depends on the quality of the behavioral rules which rarely have been validated Challenges include	Wild life behavioral models can be a source of inspiration for human models when it comes to simulation of emergent activity patterns.

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
International experience in addressing combined exposures: Increasing the efficiency of assessment.	M.E. (Bette) Meek*	Updates to the WHO/IPCS Methodology (above)		Following publication of the WHO Framework, an international workshop was convened by WHO, the Organization for Economic hazardCooperation and			
Review Article: Cumulative Risk Assessment Toolbox: Methods and Approaches for the Practitioner	Margaret M. MacDonell,1Lynne A. Haroun,2Linda K. Teuschler,3Glenn E. Rice,3Richard C.		PESTAN, Pesticide Analytical Model	A dose zone modeling of the transport of organicpestici	Location- and time-specific predictions for single chemicals can be overlain for CRA groupings.	It does not predict interactions in environmental media.	
Review Article: Cumulative Risk Assessment Toolbox: Methods and Approaches for the Practitioner	Margaret M. MacDonell,1Lynne A. Haroun,2Linda K. Teuschler,3Glenn E.		STF, Soil Transport and Fate Database	Provides data on the behavior of organic/some	This general-use tool can be used to evaluate the physicochemical properties of environmental contaminants for CRAs.	The focus is one chemical at a time; interactions are not addressed.	
Review Article: Cumulative Risk Assessment Toolbox: Methods and Approaches for the Practitioner	Margaret M. MacDonell,1Lynne A. Haroun,2Linda K. Teuschler,3Glenn E. Rice,3Richard C. Hertzberg,4James P. Butler,1Young-Soo Chang,1Shanna L. Clark,5Alan P. Johns,6Camarie S. Perry,7Shannon S. Garcia,8John H. Jacobi,1and Marcienne A. Scofield17		Exposure Factors Handbook	Provides extensive values and underlying bases for many factors that affect exposures.Examples include exposure duration,frequency, surface area, inhalation rate peractivity			

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Review Article: Cumulative Risk Assessment Toolbox: Methods and Approaches for the Practitioner	Margaret M. MacDonell,1Lynne A. Haroun,2Linda K. Teuschler,3Glenn E. Rice,3Richard C. Hertzberg,4James P. Butler,1Young-Soo Chang,1Shanna L. Clark,5Alan P. Johns,6Camarie S. Perry,7Shannon S. Garcia,8John H. Jacobi,1and Marcienne A. Scofield19		E-FAST, Exposure and Fate Assessment Screening Tool (EPA)	Provides screening-level estimates for general population, consumer, and environmental exposures to concentrations of chemicals released to air, surface water, and landfills and released from	Default exposure parameters are available, but the use of site-specific values is recommended. Can predict exposure concentrations for comparison to media-specific standards.		*possibly adaptable to pesticides
Review Article: Cumulative Risk Assessment Toolbox: Methods and Approaches for the Practitioner	Margaret M. MacDonell,1Lynne A. Haroun,2Linda K. Teuschler,3Glenn E. Rice,3Richard C. Hertzberg,4James P. Butler,1Young-Soo Chang,1Shanna L. Clark,5Alan P. Johns,6Camarie S. Perry,7Shannon S. Garcia,8John H. Jacobi,1and Marcienne A. Scofield23		Pesticides: Health and Safety, Common MechanismGroups; Cumulative Exposure and Risk Assessment;	Identifies health information to assess pesticide groups that share common mechanisms of toxicaction, with links for quantitative approaches(e.g., RPF values) and qualitative	Can be used to assess indexchemical-equivalent doses and risksassociated with specific pesticide groupsthat share a common toxic mode ofaction.		
Cumulative Risk Assessment (CRA): Transforming the Way We Assess Health Risks	Pamela R. D. Williams,*G. Scott Dotson, and Andrew Maier	US EPA Cumulative Risk Assessment Method				limitation of screening-level risk assessments that rely on the default assumption of additivity of dose or risk for mixed stress or exposure, because in reality, interactions that increase the risk(i.e., synergism) or decrease the risk (i.e., antagonism) are possible	CRAs should follow a tiered approach, in which more refined data and sophisticated techniques are invoked only when simpler health-protective methods and assumptions indicate a concern or impact decision-making For higher-tiered assessments

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Cumulative Risk Assessment (CRA): Transforming the Way We Assess Health Risks	Pamela R. D. Williams,*G. Scott Dotson, and Andrew Maier	US EPA Cumulative Risk Assessment Method	Mixture-Based Approach	Combining the effects of chemicals in the same toxicological class based on the potencyof			1. identifying relevant risk modifying factors and common effects, 2. integrating nonoccupational and occupational exposures and 3. developing and implementing a cohesive
The Environmental Protection Agency's Community-Focused Exposure and Risk Screening Tool (C-FERST) and Its Potential Use for Environmental Justice Efforts	Valerie G. Zartarian, PhD, Bradley D. Schultz, MS, Timothy M. Barzyk, PhD, MaryBeth Smuts, PhD, Davyda M. Hammond, PhD, Myriam Medina-Vera, PhD, and Andrew M. Geller, PhD	Provide to communities and individuals tools for advancing the science and understanding cumulative risk	US EPAs Community-Focused Exposure and Risk Screening Tool (C-FERST)	-It incorporates what is known about high-priority environmental issues, provides a venue for communicating cutting-edge science and solutions to communities, and helps to identify knowledge gaps. -The C-FERST is a geographic information system and resource access Web tool that supports multimedia	-C-FERST could provide information for assessments of cumulative impact -C-FERST links to and builds on other community-focused tools, and it provides science approaches to charaterizing community exposures to environmental contaminants that lead to cumulative risks -Where cumulative research is not yet available, C-FERST will contain the best available information and science on environmental sources, concentrations, exposures, and risks for individual issues of concern - it is an umbrella tool that organizes EPA information and science by linking to, building on, or including these other tools to assist with conducting community environmental assessments (including within-the-interface ''cross-walks'' with available step-by-step community assessment guidance	Assessing health risks from multiple sources is challenging on the basis of the level of information available and difficulties in accessing, integrating, and interpreting data	-EPA scientists are working on additional research that can populate C-FERST: developing a new census-tract level, multimedia childhood lead exposure screening tool; expanding previous research21 to generate local-scale estimates for residential pesticide -Information for community and environmental justice assessments on many issues is still considerably lacking **To fully develop C-FERST to inform EJ assessments, researchers need to - research and disseminate cumulative risk approaches and nonchemical stressors' impacts on environmental stressors for vulnerable populations; - research approaches for fostering sustainable
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD	How to prioritize integrating existing data to evaluate health risks from chemical mixtures	2006 US EPA Guidelines for Evaluating Health Risks from Chemical Mixtures	First Priority: use evidence for the mixture of concern when it existed Second Priority: Use information about a similar			

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		Interactive Hazard Index Approach (most extensive data necessary)	Modifies the hazard index based on a specified function to describe empirical data for the			
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		Toxicity equivalency factor (TEF) approach (moderate data requirements)	Sums the toxicity of the individual mixture			
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		Margin of exposure (MOE) approach (moderate data requirements)	uses toxicity equivalency factors to calculate the			
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		HI approach using NOAEL or BMD;	Assumes additivity of effects for mixture constituents. NOAELs and BMDs used for			
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		HI approach using RfD or RfC (RfC=reference concentration; RfD=reference dose;)	Assumes additivity of effects for mixture constituents.	Simplest approach with least resource requirements,	-Depends on scientific judgment to translate NOAELs or LOAELs into RfDs or RfCs. -Not a true quantitative risk assessment, just a single comparison value that obscures	

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		US EPAs Community-Focused Exposure and Risk Screening Tool (C-FERST)	The EPA's C-FERST is a web-based tool—with links to existing EPA information and techniques—that is being developed or use by communities in identifying and prioritizing combined risks from chemical and	C-FERST offers legitimate promise as an accessible, transparent, and practical assessment tool for use by members of affected communities. A workable system for assessing the severity of cumulative health risks in complicated, real-world situations	It necessarily requires assumptions to sustain it	
Cumulative Risk Assessment for Combined Health Effects from Chemical and Nonchemical Stressors	Ken Sexton ScD, and Stephen H. Linder, PhD		US EPAs Office of Enforcement and Compliance Assistance: Environmental Justice Strategic Enforcement Screening Tool (EJSEAT)	The EJSEAT is intended to provide consistent identification of geographic areas with disproportionately higher burdens of harmful environmental features.It is composed of 18 indicator variables divided into four categories:			Recommend a coordinated research effort on targeted populations including laboratory field research aimed at 1. elucidating the magnitude, duration, frequency and timing of relevant exposures 2. determining whether mixture-related health effects are additive, antagonistic, or synergistic 3. explicating important interactive mechanisms of toxicity among mixtures of components

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach *Tier 1: summation of deterministic estimates of exposure for all components of the assessment group based on measured or modeled data, or both may suffice as a basis for comparison *Tier 2: refined with incorporation of increasing numbers of measured values. Definition of assessment group refined through considering more specific information on mode of action or modeling ○ Tier 3: exposure estimates are probabilistic in nature § Account for distributions of exposure factors or exposure data § Often include multiple-source pollutants § Includes more refined information on mode of action, including both kinetic and dynamic aspects Physiologically based and biologically based dose response Additional Information • Include terminology to describe various aspects of exposure ○ Single chemical all routes-exposure to same substance by multiple pathways =	Combined Exposure Assessment (Tiers)	• Questions to ask: ○ What is the nature of exposure ○ Is there a likelihood of co-exposure within a relevant timeframe § Do the compounds have short half-lives or effects of short duration § Is the time between initial and subsequent exposure ○ What is the rationale for considering compounds in an assessment		***a variety of additional case studies would further illustrate, test, and develop the framework which is expected to evolve ***lack of regulatory requirement to consider combined exposure, or to a lack of their publication, need for advancement in this area is emphasized by stakeholders	
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 0: Exposure Assessment	When margins between conservative estimates of exposure and points of	Semiquantitative estimates may be additionally refined through inclusion of information on physicochemical properties (e.g., information on vapor pressure provides an indication of whether or		
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 0:Hazard Assessment	As a conservative early assumption, based on an indication that components of an assessment group should			

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 0: Risk Characterization	-Incorporate the individual health-based guidance values (e.g., reference dose, allowable operator exposure level, acceptable			
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 1: Exposure Assessment	For a Tier 1 assessment, summation of deterministic estimates of exposure for all components of the assessment group based unmeasured			
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 1: Hazard Assessment	Incorporates additional information on the potency of individual			
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 1: Risk Characterization	Risk characterizatio n can be undertaken by calculating the hazard index (i.e., sum of the ratios of estimated exposures to reference values for			
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 2: Exposure Assessment	In Tier 2 assessments, the deterministic estimation of exposures	Models may incorpo-rate additional parameters, and, although estimates are still con-sidered conservative, they are believed to be more realistic, incorporating more data. Multiple sources are often taken into ac-count		

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 2: Hazard Assessment	In Tier 2 assessments, the definition of an assessment group may be additionally refined through consideration of increasingly more specific information on mode of action or other factors on which to base the grouping (e.g.,			
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers	Tier Phase Approach	Tier 2: Risk Characterization	Where it is possible to derive relative potency factors, risk is determined by expressing the sum of the relative potency factor-adjusted exposures to all substances in the group as		while the limited availability of case examples maybe a function of the lack of regulatory requirement to consider combined exposure or, alternatively, to a lack of their publication, the need for additional advancement in this area continues to be emphasized by stakeholders.	
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers		Tier 3: Exposure Assessment	In Tier 3 assessments, estimates of exposure are probabilistic in nature,	Models at this level of complexity often include multiple-source exposures.	This approach requires representative information on exposure for the scenarios of interest for the relevant populations for different uses and across populations.	

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers		Tier 3: Hazard Assessment	Tier 3 assessments of hazard incorporate increasingly refined information on mode of action, including both kinetic and dynamic aspects. These can include both	These models, which incorporate both chemical-specific and more generic information on comparative physiology, biochemistry, etc., improve the characterization of interspecies differences and human variability (i.e., as a basis for extrapolation across species and among humans).		
Risk assessment of combined exposure to multiple chemicals: A WHO/IPCS framework	M.E. (Bette) Meeka, Alan R. Boobisb, Kevin M. Croftonc, Gerhard Heinemeyerd, Marcel Van Raaije,Carolyn Vickers		Tier 3: Risk Characterization	In probabilistic assessments, risk can be estimated as the per-centile of the population exceeding the reference value, as the maximum exceedance of the reference value or as the percentage of the			
The Role of Cumulative Risk Assessment in Decisions about Environmental Justice	Ken Sexton and Stephen H. Linder	•Focus on multiple stressors •Inclusion of both chemical and nonchemical (e.g., biological, radiological,physical, psychological, work life, lifestyle) stressors •Assessment of aggregate exposures and risks (i.e., exposure to a single stressor by multiple routes) •Assessment of combined risks for common effects (e.g., chemicals or stressorsthat have a common mechanism of toxicity) •Population-based focus (i.e., assessment starts with the receptors orpopulations of interest and then determines which	US EPA Cumulative Risk Assessment Framework Phase 1: Planning, Scoping and Problem Formulation	In the first phase, risk assessors, risk managers, and interested stakeholders work together to determine the goals, scope, and focus of the assessment. The products			

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
The Role of Cumulative Risk Assessment in Decisions about Environmental Justice	Ken Sexton and Stephen H. Linder		US EPA Cumulative Risk Assessment Framework Phase 2: Information and Data Analysis	The second phase involves technical/scientific activities such as developing exposure profiles, examining the nature and extent of			
The Role of Cumulative Risk Assessment in Decisions about Environmental Justice	Ken Sexton and Stephen H. Linder		US EPA Cumulative Risk Assessment Framework Phase 3: Interpolation and Risk Characterization	In the third phase, risk estimates are explained and their significance described in terms of			
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism	Hazard Index	Based on the simple ratio between the exposure level and reference toxicity value			
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism	Cumulative Risk Index (CRI)	Sum of the reciprocal hazard quotients for chemicals compromising			
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism of mammalian toxicity, common specific toxic effects.	Reference Point Index (RPI)	Uses uncorrected point of departure, such as Benchmark Dose 10 or No Observed Adverse Effect Level, rather than the			

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism	Margin of Exposure (MOE)	Similar to the relationship of CRI and hazard index, the MOE is the reciprocal of			
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism of mammalian toxicity, common specific toxic effects.	Target-organ Toxicity Dose (TTD)	refined method of hazard index, developed to accommodate the assessment of mixtures of chemical compounds that do not share the same critical toxic effect. this is calculated using appropriate			
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism of mammalian toxicity, common specific toxic effects.	Weight of Evidence (WOE)	Addresses the need for information on interactions among components of a mixture. This method incorporates an uncertainty factor (UF) to modify the hazard index to account for synergistic, potentiating or antagonistic	This method is best used for predicting whether hazard may be greater or less than indicated by the HI determined assuming additivity. The BINWOE indicates the expected direction of an interaction (i.e., greater than additive, less than additive, additive, or indeterminate). It also scores the data qualitatively using an alphanumeric scheme that takes into account mechanistic understanding, toxicological significance, and relevance of the exposure duration, sequence, bioassay (i.e., in vivo versus in vitro), and route of exposure.	Previous experiences using the algorithm for specific mixtures to generate the interaction-adjusted Hazard Index have revealed that the method does not generally handle changes in proportions of mixture components.	

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism of mammalian toxicity, common specific toxic effects.	Relative Potency Factor (RPF) OR Potency Equivalency Factor (PEF)	Potencies of all chemicals in the common assessment group are normalized to a single potency scale relative to the index chemical. Once RPF has been determined for individual chemicals, the activity of the	General , used for compounds such as polycyclic aromatic hydrocarbons and pesticides such as organophosphates. RPF and other component-based approaches are considered "bottom-up" because they are built by incorporating data from individual chemicals into additivity models. Because data for the complex mixture or a sufficiently similar mixture is rarely available, the Relative Potency Factor (RPF) method of dose additivity may be the rule, not the exception with the current state of	as shown that risk assessments for some classes of toxic organic compounds, such as the polycyclic aromatic hydrocarbons (PAHs), may not accurately predict the potential for genotoxicity and immunotoxicity.	
Common Mechanism Groups, Cumulative Assessment Group, and Methods for Cumulating Toxicity (Appendix A)	Tim Brown, Ph. D., Susan Kegley, Ph. D.	Common Mechanism Group (CMG) - compounds acting at the same molecular target belong to the same CMG. US EPA States - CMG should be based on: similarities in chemical structures, mechanisms of pesticidal action, general mode/mechanism	Physiologically Based Pharmokinetic/pharma codynamic (PBPK/PD) Model	Model can be used to describe the mechanisms of action and tissue		Although progress has been made in this area, relatively few examples of PBPK/PD models for pesticide mixtures exist in the peer-reviewed literature.	
Review of California's Risk-Assessment Process for Pesticides	National Research Council		California Pesticide Use Reporting Program (PUR)	All agricultural pesticide use must be reported monthly to county agricultural commissioners , who report the data to DPR. The reporting requirements also include pesticide	PUR and ARB data have been used by DPR and other researchers to evaluate the agricul-tural use of pesticides and ambient concentrations (e.g., Harnly et al. 2005; Li et al. 2005) and to evaluate the predictive capability of exposure models (e.g., Cryer 2005; van Wesenbeeck et al. 2011). Most recently, the California Environmental Health Tracking Program studied agricultur-al pesticide use near public schools (CEHTP 2014). PUR data have also been used by researchers to investigate the relationship between pesticide exposure and a variety of	Pesticide applica-tions in home and garden use and in most industrial and institutional uses are excluded from the reporting requirements (DPR 2013). Although it would be difficult to obtain accurate infor-mation on personal home use, it might be possible to collect some information by expanding PUR reporting requirements to cover all licensed pesticide appliers, including those who perform applications for nonagricultural purposes at homes, institutions, and industries. There appears to be	

Article Title	Author(s)	Risk Assessment Method/Goal/Question	Method/Framework/ Tool/Database	Short Description	Advantages	Disadvantages (gaps, etc.)	Next Steps
Critical assessment and integration of separate lines of evidence for risk assessment of chemical mixtures	Antonio F. Hernandez, Aleksandra Buha, Carolina Constantin, David R. Wallace, Dimosthenis Sarigiannis, Monica Neagu, Biljana Antonijevic, A. Wallace Hayes, Martin F. Wilks,Aristidis Tsatsakis	These include new in vitro models: omics-related tools, organs-on-a-chip and 3D cell culture, and in silico methods. Taken together, all these modern methodologies improve the understanding of the multiple toxicity pathways associated with adverse outcomes (e.g., adverse outcome pathways), thus allowing investigators to better predict risks linked to exposure to chemical mixtures.	Component Based Approach	requires identifcation of the chemicals present in the mixture of concern (e.g., concentration, mode of action (MoA) and toxicity of	A robust body of experimental evidence indicates that the basic assumption of additivity ofers a reasonable expectation of mixture toxicity <u>assuming that the components of the mixture do not interact with each other, which can modify the magnitude and even the nature of the toxic efect</u>	However, component-based approaches can potentially lead to underestimations of hazard when the composition of a mixture is not fully known, which is usually the case, except for clearly defned, intentionally manufactured products (e.g., pesticide formulations), or chemicals present in foodstuf (e.g., multiple residues of	
Critical assessment and integration of separate lines of evidence for risk assessment of chemical mixtures	Antonio F. Hernandez, Aleksandra Buha, Carolina Constantin, David R. Wallace, Dimosthenis Sarigiannis, Monica Neagu, Biljana Antonijevic, A. Wallace Hayes, Martin F. Wilks,Aristidis Tsatsakis	New methodological developments that improve the scope and quality of epidemiological data on chemicals	1. hypothesis-free, environment-wide association studies (EWAS) 2. pooled data from multiple existing studies 3. markers of disease processes as an outcome (SAPEA (Science Advice for Policy by European Academies	1. EWAS assess simultaneously the relationships between health outcomes and a wide range of chemicals, thus allowing the identifcation of chemical mixtures			

Appendix 4B: 2018 DPR PUR Data

Appendix 4B.2: 2018 DPR PUR Data at Sections Selected

DATE	COUNTY NAME	SECTIONS	CHEMICAL_NAME	POUNDS CHEMICAL APPLIED
4/25/18	MERCED	24M05S11E35	METHYL BROMIDE	1172.5
4/26/18	MERCED	24M05S11E35	METHYL BROMIDE	2814
9/19/18	MERCED	24M05S11E35	METHYL BROMIDE	1172.5
9/21/18	MERCED	24M05S11E35	METHYL BROMIDE	2814
4/30/18	MERCED	24M05S11E35	METHYL BROMIDE	1688.4
3/29/18	MERCED	24M05S11E35	METHYL BROMIDE	4020
9/19/18	MERCED	24M05S11E35	METHYL BROMIDE	1172.5
9/21/18	MERCED	24M05S11E35	METHYL BROMIDE	2814
3/30/18	MERCED	24M05S12E35	METHYL BROMIDE	8832
10/3/18	MERCED	24M05S13E17	METHYL BROMIDE	6541.32
9/27/18	MERCED	24M05S13E22	METHYL BROMIDE	1765.86
10/29/18	MERCED	24M05S13E31	METHYL BROMIDE	3154.95
10/31/18	MERCED	24M05S13E31	METHYL BROMIDE	1008.9
4/3/18	MERCED	24M05S13E35	METHYL BROMIDE	1872.45
4/23/18	MERCED	24M06S10E03	METHYL BROMIDE	1172.5
4/25/18	MERCED	24M06S10E03	METHYL BROMIDE	1172.5
4/27/18	MERCED	24M06S10E03	METHYL BROMIDE	2345
4/25/18	MERCED	24M06S10E12	METHYL BROMIDE	11585.64
5/3/18	MERCED	24M06S11E01	METHYL BROMIDE	46.9
4/14/18	MERCED	24M06S11E01	METHYL BROMIDE	1172.5
4/23/18	MERCED	24M06S11E01	METHYL BROMIDE	1172.5
4/16/18	MERCED	24M06S11E01	METHYL BROMIDE	1172.5
4/21/18	MERCED	24M06S11E01	METHYL BROMIDE	1172.5
4/28/18	MERCED	24M06S11E02	METHYL BROMIDE	1641.5
4/26/18	MERCED	24M06S11E02	METHYL BROMIDE	1172.5
5/7/18	MERCED	24M06S11E02	METHYL BROMIDE	70.35
4/24/18	MERCED	24M06S11E02	METHYL BROMIDE	1102.15
3/27/18	MERCED	24M06S11E02	METHYL BROMIDE	1172.5
5/3/18	MERCED	24M06S11E02	METHYL BROMIDE	398.65
5/7/18	MERCED	24M06S11E02	METHYL BROMIDE	4690
5/4/18	MERCED	24M06S11E02	METHYL BROMIDE	1172.5
4/30/18	MERCED	24M06S11E02	METHYL BROMIDE	2345
3/29/18	MERCED	24M06S11E02	METHYL BROMIDE	1172.5

3/30/18	MERCED	24M06S11E05	METHYL BROMIDE	3172.05
4/21/18	MERCED	24M06S11E05	METHYL BROMIDE	2171.7
3/26/18	MERCED	24M06S11E12	METHYL BROMIDE	1172.5
3/28/18	MERCED	24M06S11E12	METHYL BROMIDE	1172.5
3/30/18	MERCED	24M06S11E12	METHYL BROMIDE	1407
5/30/18	MERCED	24M06S11E15	METHYL BROMIDE	522.08
6/1/18	MERCED	24M06S11E15	METHYL BROMIDE	682.72
11/6/18	MERCED	24M06S12E05	METHYL BROMIDE	407.55
8/28/18	MERCED	24M06S12E05	PENTACHLOROPHEN OL	0.0634248
10/31/18	MERCED	24M06S12E05	METHYL BROMIDE	4911.12
5/7/18	MERCED	24M06S12E05	METHYL BROMIDE	5057.04
4/20/18	MERCED	24M06S12E05	METHYL BROMIDE	15008.1
4/18/18	MERCED	24M06S12E07	METHYL BROMIDE	1172.5
4/20/18	MERCED	24M06S12E07	METHYL BROMIDE	539.35
3/29/18	MERCED	24M06S13E05	METHYL BROMIDE	114
11/9/18	MERCED	24M07S11E16	METHYL BROMIDE	36441.3
2/16/18	MERCED	24M07S11E23	METHYL BROMIDE	5172.75
3/30/18	MERCED	24M07S11E24	METHYL BROMIDE	5360

CONCLUSION

As presented, this dissertation identified technologies and tools available to evaluate environmental impacts at the local level. Understanding environmental impacts are critical to taking action to protect public health and the environment. This dissertation contributes to the literature by combining real-world experiences with environmental work with research/analytical methods that provide real world solutions to tackle environmental science challenges.

The work presented in this dissertation requires further research to enhance and optimize the findings. Further research is needed to enhance or reform policy to address these localized impacts, to better understand the health impacts from exposure to multiple pollutants and how it contributes to cumulative health impacts, and implementation of research findings into practice.

For low-cost sensor network design, it will be important to develop a better understanding of how low-cost sensors can be used to supplement reference monitoring. This will support policy development that considers the data that low-cost sensors can provide in making regulatory decisions and reforming current environmental monitoring regulations to include new technologies that provide hyper localized air quality data.

For health impacts from co-exposures to multiple pollutants, it will be important to conduct further research on how exposure to multiple air pollutants can further exacerbate health outcomes, and how these co-exposures should be factored into regulatory decision-making. Future work should focus on how co-exposures play a role in protecting public health.

For air dispersion modeling pesticide use, further research should focus on implementation and operationalization of both new and repurposed methods to better evaluate local impacts from pesticides. Furthermore, future research should focus on better understanding health impacts from multiple pesticide exposure, which should play a role in how pesticides are registered, and permitted for use.

DISCLAIMER

The views, conclusions, opinions, and positions expressed are my own, and do not necessarily represent the views, position or opinions of the South Coast Air Quality Management District, Clarity Movement, or any of their components.

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