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MINETA TRANSPORTATION INSTITUTE

Spatio-Temporal Analysis of the Roadside Transportation-Related Air Quality (StarTraq 2022): Data-Driven Exposure Analysis by Transportation Modes

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California State University Transportation Consortium

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16. Abstract

Particulate matter (PM) pollution poses significant health risks, influenced by various meteorological factors and seasonal variations. This study investigates the impact of temperature and other meteorological variables on PM_{10} and $PM_{2.5}$ levels in Fresno County, known for high air pollution. Multiple linear regression (MLR) and generalized additive models (GAMs) assess the significance of these relationships. Analyzing data from Fresno County, we examine PM_{10} and $PM_{2.5}$ levels across "hot" (June to August) and "cool" (September to May) seasons. Findings indicate PM_{10}, both MLR and GAM models identify statistically significant variables, excluding temperature and wind direction in each season. However, during the hot season, both temperature and wind direction become statistically significant predictors of PM_{10}. These variables remain insignificant during the cool season. For $PM_{2.5}$, the MLR model suggests that temperature, humidity, and wind direction are not significant throughout the entire season, while the GAM model finds only wind direction to be insignificant. The temperature is highly significant for hot and cool seasons under the MLR model, whereas humidity becomes insignificant under the GAM model. Model performance is evaluated using measures of fit, indicating that MLR outperforms GAM for PM_{10} during the entire and hot seasons, while GAM performs better during the cool season. For $PM_{2.5}$, GAM outperforms MLR during the cool seasons, with no clear distinction in performance during the hot season. The regional air quality $PM_{2.5}$ at Fresno and meteorological conditions were closely related to the concentration of on-road particulate matter. From the intercity monitoring of $PM_{2.5}$ and BC, on-road concentrations were statistically significantly higher than those measured in-vehicle ($p<.001$). Therefore, in-vehicle particle concentrations were safe compared to the on-road concentrations. In most cases, $PM_{2.5}$ on the highways was higher than $PM_{2.5}$ on the local roadways. On-road transportation-related particles measured in the San Joaquin Valley were significantly higher than those measured in the Bay Area. The results from a daily dose of transportation-related $PM_{2.5}$ estimation based on a 2-hour commute and an 8-hour trip demonstrated that children under 11 years of age are more vulnerable than adults. In-vehicle daily doses were significantly lower than the on-road daily doses. This study highlights the importance of considering seasonal variations and meteorological factors when modeling PM pollution. It underscores PM's sensitivity to temperature and wind direction in Fresno County's hot season, offering insights for effective pollution management from transportation and policy implementation to mitigate the adverse health effects.

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Executive Summary

Fresno County, located in California's San Joaquin Valley, is known to have some of the highest levels of air pollution in the United States. The region's main sources of air pollution are transportation, industrial activities, and agriculture. Transportation-related pollution is a major contributor to air pollution in Fresno County. Cars and trucks on the region's roads and highways emit large amounts of particulate matter, nitrogen oxides, and other pollutants into the air. In addition, the county is located near major transportation corridors, including Interstate 5 and State Route 99, which further exacerbates pollution levels. Because of the topographical characteristics of a valley surrounded by high mountain ranges, the pollution generated and transported into the valley slowly disperses when the atmosphere is stagnant, resulting in significantly increased pollution levels. For several decades, emissions from goods movement in the San Joaquin Valley have had detrimental health consequences for the low-income and minority communities adjacent to the truck depots, rail yards, and connecting highways. The previous StarTraq projects provided information, including transportation-related particle pollution data in different modes of transportation, including walking, bicycle riding, and driving; spatial characteristics of particulate matter emitted from traffic sources; and the neighborhood characterization for the built environment infrastructures. The results confirmed that the roadside $PM_{2.5}$, black carbons, and PAHs were significantly elevated compared to the concentrations at the ambient monitoring stations because of the immediate source proximity on or near roadways. This study aims to investigate the impact of meteorological factors such as daily average temperature, humidity, wind speed, and wind direction on PM levels in Fresno, CA. This study also aims to assess the inhalation risk by different age groups and exposure time in on-road and in-vehicle microenvironments by collecting mobile air quality data to explore the spatial variation of the transportation-related $PM_{2.5}$.

To explore the relationships between PM and meteorological factors, multiple linear regression (MLR) and generalized additive models (GAMs) have been utilized. MLR is commonly used in diverse applications due to its simple model interpretations resulting from its linear model structure. However, as many variables exhibit non-linear relationships, GAM is employed to examine these non-linear associations.

To assess the transportation-related exposure to $PM_{2.5}$ during roadway trips, the Average Daily Dose (ADD, μg/kg/day) was estimated from the observed mean $PM_{2.5}$ concentrations in on-road and in-vehicle environments for different age groups and data from NHANES.

Findings

Our key findings are as follows:

1. <u>PM_{10} Analysis using MLR and GAM</u>: During the whole season, humidity and wind speed are significant factors for PM_{10}. During the hot season, temperature, humidity, wind speed, and

wind direction are all significant. During the cool season, humidity and wind speed are significant factors.

2. PM$_{2.5}$ Analysis using MLR: During the whole season, wind speed is the only significant factor for PM$_{2.5}$. During the hot season, temperature and wind speed are both significant. During the cool season, temperature and wind speed are significant factors.

3. PM$_{2.5}$ Analysis using GAM: During the whole season, temperature, humidity, and wind speed are the significant factors for PM$_{2.5}$. During the hot season, temperature and wind speed are both significant. During the cool season, wind speed is the only significant factor.

4. Regional air quality PM$_{2.5}$ measured at Fresno station and meteorological conditions was closely related to the on-road PM$_{2.5}$. PM$_{2.5}$ on the highways was higher than PM$_{2.5}$ on the local roadways. On-road transportation-related particle pollutants measured in the San Joaquin Valley is significantly higher than the concentrations measured in the Bay Area.

5. The average daily dose of transportation-related PM$_{2.5}$ estimation based on a 2-hour commute and an 8-hour trip scenario estimated that the children's average daily dose of PM$_{2.5}$ is significantly higher than the ADDs of adults.

6. In-vehicle average daily doses are significantly lower than the on-road daily doses. The estimation of inhalable exposure to PM$_{2.5}$ on-road can be applied to people who work or live near busy roads.

In this research, we have continued to collect mobile air quality data from transportation-emitted particulate matter, including PM$_{10}$, PM$_{2.5}$, PM$_1$, and BC. The study findings confirmed that personal exposure to transportation related PM$_{2.5}$ varies by spatial variation and in different microenvironments.

This study underscores the importance of considering seasonal variations and meteorological factors when modeling PM pollution. By elucidating the sensitivity of PM levels to temperature and wind direction during the hot season in Fresno County, the findings provide actionable insights for policymakers and stakeholders, such as the need for healthcare providers in the area and school site decisions. These insights can inform the development and implementation of targeted strategies to mitigate the adverse health effects of particulate matter pollution, thereby safeguarding public health and enhancing overall air quality in Fresno County and regions facing similar air pollution challenges.

This comprehensive study significantly advances our understanding of the intricate relationship between meteorological variables and PM pollution. By providing valuable insights and empirical evidence, the study empowers decision-makers with the knowledge needed to formulate evidence-based policies and interventions for effective air quality management and public health protection in Fresno County and beyond.

1. Introduction

Particulate matter (PM; also called particle pollution) is a combination of both solid particles and liquid droplets that can easily be found in the air. PM_{10} refers to inhalable particles with 10 micrometers and smaller diameters, while $PM_{2.5}$ refers to diameters 2.5 micrometers or smaller. To compare the size, human hair has an average diameter of about 70 micrometers, making $PM_{2.5}$ about 28 times smaller. Major PM sources include industrial activities, construction sites, unpaved roads, smoke, and fires (Kassomenos et al., 2014). Particulate matter less than 10 micrometers in diameter can have serious health effects such as asthma, heart attack, and respiratory diseases and potentially enter the human bloodstream.

Previous studies have confirmed that seasonal variation and meteorological factors influence the characteristics and behavior of PM (Gvozdić, 2010; Özbay, 2012; González et al., 2018; Ma et al., 2019). Hou et al. (2019) and Shi et al. (2020) have examined the role of meteorological parameters on particulate matter and confirmed the sensitivity and relationship between the two. Additionally, dust storms and wildfires can also contribute to PM pollution. Zhang et al. (2022) examined the impact of a dust storm on PM_{10} levels in Beijing and found that the storm significantly increased PM_{10} concentrations. Similarly, Wu et al. (2020) investigated the impact of wildfires on $PM_{2.5}$ levels in California and found that wildfires resulted in a substantial increase in $PM_{2.5}$.

Fresno County, located in California's San Joaquin Valley, is known to have some of the highest levels of air pollution in the United States. The region's main sources of air pollution are transportation, industrial activities, and agriculture. Transportation-related pollution is a major contributor to air pollution in Fresno County, as cars and trucks on the region's roads and highways emit large amounts of particulate matter, nitrogen oxides, and other pollutants. In addition, the county is located near major transportation corridors, including Interstate 5 and State Route 99, which further exacerbates pollution levels. Industrial activities, including oil and gas production, manufacturing, and power generation also contribute to air pollution in Fresno County. The region is home to several oil and gas fields emitting large amounts of volatile organic compounds (VOCs) and other pollutants into the air. The region's power plants and manufacturing facilities also emit particulate matter and other pollutants into the air. Agriculture is another significant source of air pollution in Fresno County, as the region is known for its large-scale agricultural operations, which use fertilizers, pesticides, and other chemicals that can contribute to air pollution. In addition, the processing and transportation of agricultural products can also generate significant amounts of pollution. The high levels of air pollution in Fresno County have been linked to a range of negative health outcomes, including respiratory problems, cardiovascular disease, and cancer. The county and state have implemented various measures to address pollution levels, including regulations on vehicle emissions and industrial activities, promotion of clean energy sources, and efforts to reduce emissions from agricultural operations. However, air pollution remains a significant challenge for the region, and continued efforts are needed to improve air quality and protect public health.

Fresno County is characterized by hot, dry summers and cool, wet winters. Spring (March to May) in Fresno County is mild and pleasant, with daytime temperatures ranging from the mid-60s to low 80s Fahrenheit (16-27 degrees Celsius). It can be quite windy during this season, with occasional rain showers. Summer (June to August) is hot and dry, with daytime temperatures frequently exceeding 90 degrees Fahrenheit (32 degrees Celsius). Temperatures over 100 degrees Fahrenheit (38 degrees Celsius) are common during the peak of summer. The county is also known for experiencing heat waves lasting several days or weeks. Fall (September to November) is like spring in terms of temperature but with drier conditions. Daytime temperatures typically range from the mid-60s to mid-80s Fahrenheit (16-29 degrees Celsius), and nights are cool and crisp. Winter (December to February) is mild and wet, with occasional frost and fog. Daytime temperatures range from the mid-50s to low-60s Fahrenheit (12-16 degrees Celsius), with nighttime temperatures dropping into the mid-30s to mid-40s Fahrenheit (1-7 degrees Celsius). Rainfall is most common during winter, with occasional snowfall in the higher elevations of the Sierra Nevada mountains.

To further contextualize the investigation into air pollution in Fresno County and the significance of seasonal and meteorological factors, it is essential to understand the broader implications of poor air quality on public health and environmental sustainability. Studies have consistently linked exposure to particulate matter and other air pollutants to adverse health effects, including respiratory and cardiovascular diseases and premature mortality (Cohen et al., 2017; Thurston et al., 2017). Additionally, air pollution can harm ecosystems, contributing to biodiversity loss, soil degradation, and water contamination (Doherty et al., 2017; Wu et al., 2016). Given the multifaceted impacts of air pollution, understanding its drivers and dynamics becomes imperative for effective mitigation strategies and public health interventions.

As climate change exacerbates environmental challenges worldwide, the need for proactive measures to address air pollution becomes even more pressing. Climate-related factors such as rising temperatures, altered precipitation patterns, and increased frequency of extreme weather events can influence air pollutants' formation, dispersion, and concentration, intensifying their adverse effects on human health and the environment (Haines et al., 2019; Jacobson, 2010). Additionally, climate change can interact with local factors such as topography and land use, further complicating the dynamics of air pollution in specific regions like Fresno County (Maji et al., 2018). Integrating climate considerations into air quality modeling and management frameworks becomes essential for building resilience and adaptive capacity in changing environmental conditions.

This study aims to comprehensively understand the complex interplay between seasonal variation, meteorological factors, and air quality in Fresno County by considering the broader implications of air pollution on public health, environmental sustainability, and climate change. By applying multiple linear regression and generalized additive models (GAM), we seek to elucidate the significance of these relationships, offering insights that can inform evidence-based policies and interventions aimed at mitigating air pollution and safeguarding the health and well-being of communities in the region.

The previous StarTraq projects provided information, including transportation-related particle pollution data for different modes of transportation, including walking, bicycle riding, and driving; spatial characteristics of particulate matter emitted from traffic sources; and the neighborhood characterization for the built environment infrastructures. The StarTraq 2020 project focuses on roadside exposure while walking in the Fresno/Clovis neighborhoods. The StarTraq 2021 project added a rich data set of particulate matter concentrations for cycling and driving on different roadways in the Fresno/Clovis area, including State Highway 99. The results from StarTraq 2020 and 2021 have confirmed that the roadside $PM_{2.5}$, black carbons, and PAHs were significantly elevated when compared to the concentrations at the ambient monitoring stations due to the immediate source proximity on or near roadways (Kwon et al., 2021, 2022). Active transportation modes such as cycling and walking, and easy access to transit in communities require consolidating data-driven transportation information. This information is critical to the stakeholders and the public because such data will help urban planning for sustainable growth and promote public health in the region. The CDC defines active transportation as the human-powered mode of transportation. It is directly related to having safe and comfortable sidewalks and bikeways (CDC). U.S. DOT addresses a more fundamental aspect of active transportation, describing its benefits. These benefits include reducing obesity and the risks of developing costly chronic conditions such as diabetes; as well as improving the quality of life for low-income families, minorities, and communities with residents who have no vehicles. Significant issues with active transportation include air pollution, local and regional disparities in environmental properties and social infrastructure and liabilities, and poor dissemination of information about environmental properties and infrastructure to stakeholders for better policies. The StarTraq 2022 project collected additional mobile air quality data to explore the spatial variation of the transportation related $PM_{2.5}$. The meteorological data were analyzed through temporal statistical models, and the inhalation risk for different age groups was assessed based on exposure time in the two microenvironments.

2. Methodology

2.1 Air Quality Data and Study Area

The air quality monitoring station is at latitude 36.7852 and longitude -119.7732 in Fresno, CA. It is surrounded by many residential homes and businesses. This station is shown in Figure 1. The meteorology monitoring station is located near the air quality monitoring station. It is located at latitude 36.7672 and longitude -119.7092 in Fresno, CA. The location is shown in Figure 2. These two stations are approximately four miles apart.

Figure 1. Air Quality Monitoring Station Location in Fresno, CA

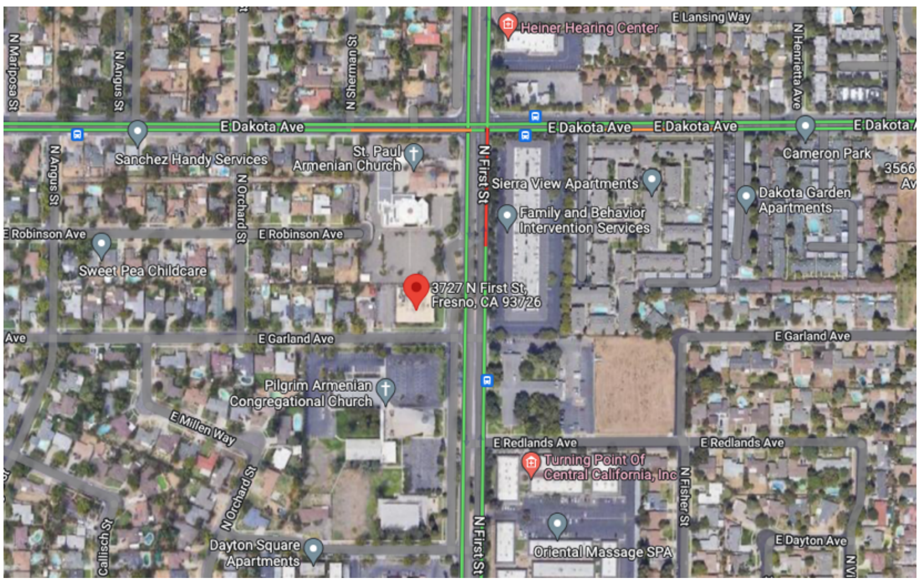
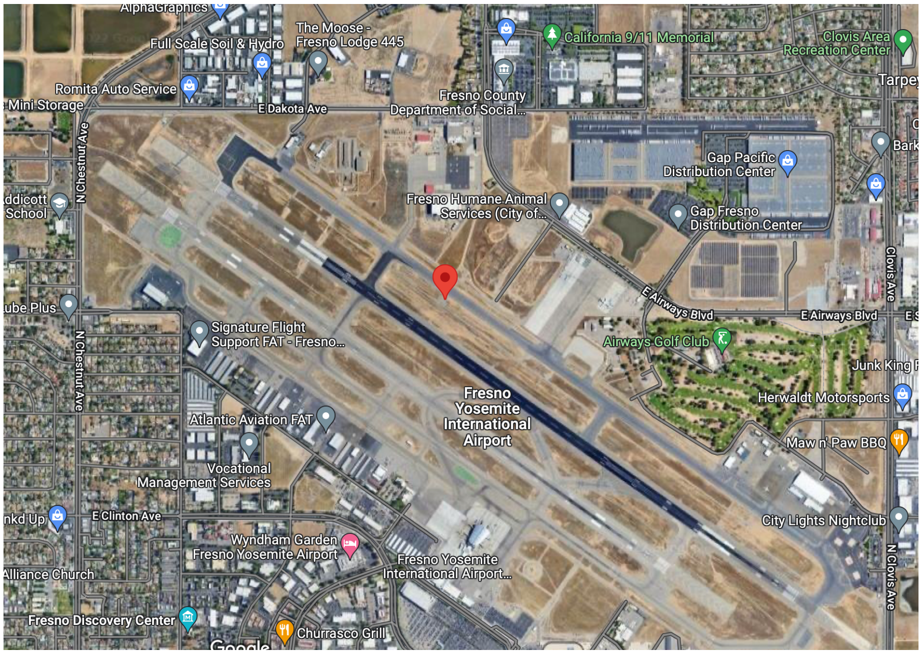


Figure 2. Meteorology Monitoring Station Location in Fresno, CA



Air quality monitoring and meteorology station observations are crucial for understanding air pollution dynamics and its relationship with meteorological factors. These hourly observations provide valuable insight into the daily variations in air quality and weather conditions. These measurements are averaged daily to obtain a more representative picture of the environmental conditions.

The available data covers a substantial period, from January 1, 2015, to December 31, 2020, allowing for comprehensive analyses of long-term trends and seasonal patterns. This extensive temporal coverage allows the assessment of the impact of a range of factors on air quality and meteorological parameters over multiple years.

In developing predictive models, the data from 2015 to 2019 were utilized as a training set. This period was a foundation for understanding the relationships between variables and refining the modeling techniques. Subsequently, the data from 2020 were employed as a testing set to evaluate the performance and generalizability of the developed models.

At the air quality stations, measurements of $PM_{2.5}$ and PM_{10} concentrations are routinely taken, providing essential information on the levels of particulate matter in the atmosphere. These measurements serve as key indicators of air pollution, which can significantly affect public health and environmental quality. Similarly, the meteorology station records various meteorological parameters, including daily average temperature (T), humidity (H), wind speed (WS), and wind direction (WD). These meteorological variables are crucial in influencing atmospheric conditions and the dispersion of air pollutants.

To account for the distinct weather patterns experienced during Fresno's seasons, the data were divided into two distinct seasons—the cool and hot seasons. The cool season, spanning from October to May, is characterized by milder temperatures and higher humidity levels. The hot season, from June to September, is marked by higher temperatures and decreased humidity. Despite the wealth of data available, it is important to note that no imputation was performed for missing data. Instead, any instances of missing data were omitted from the analysis to ensure the integrity and accuracy of the results. This approach maintains the reliability of the findings and prevents potential biases in the analysis.

2.2 Statistical Analyses

The statistical program R was employed for analyses of the data set, allowing for thorough exploration and interpretation of the data. Utilizing this versatile software allowed conduction of in-depth investigations into the characteristics of $PM_{2.5}$ and PM_{10} and the various meteorological variables recorded in the data set. By employing R, summary statistics and graphs could be generated, which provided valuable insights into the distribution, variability, and relationships within the data set.

In addition to examining summary statistics and graphs, various statistical techniques were utilized to further analyze the data and uncover underlying patterns and relationships. Multiple linear regression (MLR) was used to investigate the associations between $PM_{2.5}$ and PM_{10} concentrations and meteorological variables such as temperature, humidity, wind speed, and wind direction. MLR allowed us to assess the impact of each meteorological variable on air pollutant concentrations while controlling for potential confounding factors.

Generalized additive models (GAM) were utilized to explore potentially non-linear relationships between the predictor and response variables. GAM provides a flexible modeling approach that can capture complex relationships not adequately represented by linear models. By incorporating GAM into the analysis, any non-linear associations between meteorological variables and air pollutant concentrations were identified and characterized, thereby enhancing the understanding of the underlying processes driving air quality dynamics.

Multiple Linear Regression (MLR) Analysis

Multiple linear regression (MLR) serves as a versatile statistical method applicable across various fields when investigating the linear relationship between an outcome variable (Y) and multiple predictor variables (Xs). The MLR model equation is as follows:

$$Y = b_0 + \sum_{i=1}^{k} b_i X_i + \epsilon,$$

where b_0 is the intercept parameter, b_i is the coefficient of each X variable, and ϵ is the random error in the model assumed to follow a normal distribution with mean 0 and a constant variance σ^2. The MLR model equation provides the relationships between the outcome variable and each predictor variable. Here, b_0 represents the intercept parameter, signifying the value of Y when all predictor variables are zero. In contrast, b_i denotes the coefficients corresponding to each predictor variable X_i. The model also includes a term for random error, ϵ, which accounts for unexplained variability not captured by the predictor variables. This error term is assumed to follow a normal distribution with a mean of 0 and constant variance σ^2, reflecting the stochastic nature of real-world data and modeling uncertainty. In practical applications, MLR enables assessment of the extent to which changes in the predictor variables are associated with changes in the outcome variable, thereby elucidating the underlying relationships and facilitating predictive modeling. By estimating the regression coefficients (b_i), MLR quantifies the magnitude and direction of the effect of each predictor variable on the outcome, offering valuable insights into the relative importance of different factors influencing the target variable. MLR provides measures of model fit, such as R-squared and adjusted R-squared, which gauge the proportion of variance explained by the predictor variables. These help the investigator evaluate the overall effectiveness of the regression model in capturing the observed data patterns.

Generalized Additive Model (GAM) Analysis

As shown in the equation above, multiple linear regression provides the "linear" relationship between the outcome variable and predictor variables, which may not adequately capture the complexities of many real-world phenomena. In cases where relationships are nonlinear or exhibit complex interactions, a more flexible modeling approach is warranted. Generalized additive models (GAM) offer a versatile framework that extends beyond the constraints of linear models while preserving the additive structure, allowing for a more nuanced and accurate representation of the data. GAMs allow for the incorporation of smooth, non-linear functions (denoted as f_j) for each predictor variable (X_j) as shown in the following model equation:

$$Y = b_0 + \sum_{j=1}^{j} f_j(X_j) + \epsilon,$$

where f is a (smooth) non-linear function.

This flexibility enables GAMs to capture a wide range of non-linear relationships between the outcome variable and predictors, accommodating complex patterns and interactions that may be missed by traditional linear models. By employing smooth functions, GAMs can effectively model curvilinear relationships, nonlinear trends, and variable interactions, providing a more faithful representation of the underlying data-generating process. Moreover, GAMs offer advantages in handling qualitative and quantitative predictor variables, making them suitable for diverse modeling scenarios. Whether the predictors are continuous, categorical, or a combination, GAMs can accommodate different variables within the same modeling framework. This versatility enhances the applicability of GAMs across various disciplines and research contexts, allowing us to analyze data sets effectively with mixed types of predictors and to uncover intricate relationships between variables. In practical applications, GAMs serve as powerful tools for exploring complex relationships in data, offering insights into the underlying mechanisms driving observed patterns and phenomena. By providing a more flexible and interpretable modeling approach compared to traditional linear regression, GAMs facilitate more accurate predictions, hypothesis testing, and model interpretation.

To assess the performance of multiple linear regression and generalized additive models, several different assessment measures were utilized, as outlined in Table 1, R^2 provides a measure of the model's goodness of fit, ranging from 0 to 1. Prediction Accuracy (PA) also falls from 0 to 1. The Index of Agreement (IA) indicates the ratio of the mean square and potential errors, with a perfect fit indicated when IA = 1. Mean Square Error (MSE) and Mean Absolute Error (MAE) range from 0 to infinity. MSE quantifies the squared average distance between the actual and predicted data, while MAE measures the absolute average distance between the actual and predicted data. It is essential to consider these evaluation metrics comprehensively to gauge the performance of the regression models accurately.

Table 1. Performance Measures

Performance measures	**Equations**
Coefficient of determination (R^2)	$R^2 = \sum_{i=1}^{n} \left[\frac{(y_i - \bar{y}_i)(p_i - \bar{p}_i)}{n\sigma_y \sigma_p} \right]^2$
Mean Square Error (MSE)	$MSE = \sum_{i}^{n} \frac{(y_i - p_i)^2}{n}$
Mean Absolute Error (MAE)	$MAE = \sum_{i}^{n} \frac{\lvert y_i - p_i \rvert}{n}$
Prediction Accuracy (PA)	$PA = \frac{\sum_{i=1}^{n}(p_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Index of Agreement (IA)	$IA = 1 - \frac{\sum_{i=1}^{n}(p_i - \bar{y})^2}{\sum_{i=1}^{n}(\lvert p_i - \bar{y} \rvert + \lvert y_i - \bar{y} \rvert)^2}$

2.3 On-road and in-vehicle PM Air Quality Monitoring

In 2022, particulate matter (PM_{10}, $PM_{2.5}$, and PM_1) and particle-bound black carbon (BC) concentrations were monitored using real-time aerosol monitors, DustTrak DRX II 8533 (TSI, St. Paul, MN), and microAeth AE51 (AethLab, Berkeley, CA), respectively as described in the previous study (Kwon et al., 2022) in four Central Valley to Bay Area round trips. "On-road (outside vehicle)' monitors were installed on the roof of a vehicle. In contrast, 'in-vehicle (inside vehicle)" monitors were installed inside the vehicle to compare the particulate pollution levels in two contrasting microenvironments. The Tracksticks logged the GPS data for trajectories and used them to identify the roadway types and areas of the air pollution data. Before and after driving, collocation sampling was performed for any offsets or drifts of air monitors for quality assurance / quality control. The on-road and in-vehicle PM mean concentrations were compared using t-tests using the statistical program SPSS.

2.4 Exposure Estimation to Transportation-Related $PM_{2.5}$

To assess the transportation-related exposure to $PM_{2.5}$ during roadway trips, the Average Daily Dose (ADD) was estimated from the observed mean $PM_{2.5}$ concentrations in on-road and in-vehicle environments. The $PM_{2.5}$ mean concentrations were pooled from the overall fifteen trips in 2021 (Kwon et al., 2022) and 2022. The NHANES (1999-2006) body weights and inhalation rates by different ages and sexes were referred from the Exposure Factors Handbook (US EPA, 2011). The Average Daily Dose represents human exposure and can be expressed as follows in the equation:

$$\mathrm{ADD} = \frac{\mathrm{C_{AIR}} \times \mathrm{IR} \times \mathrm{ET} \times \mathrm{EF} \times \mathrm{ED}}{\mathrm{BW} \times \mathrm{AT}}$$

where C_{AIR} is pollutant concentration (μg/m³), IR is inhalation rate (m³/hour), ET is exposure time (hours/day), EF is exposure frequency (days/year), ED is exposure duration (years), BW is body weight of children (kg), and AT is averaging exposure time (days). The two scenario assumptions for exposure times (ET) were a 2-hour commute and an 8-hour road trip similar to occupational exposure of vehicle operators and people working 8 hours per day near roadways. The exposure frequency (EF), 250 days/year, was derived from 5 weekdays for 50 weeks per year with a 14-day vacation during a year duration (ED). The ADD (μg/kg-day) values were estimated by the five age groups: Children under 3 years old, children (3 to 11 years old), adolescents and young adults (11 to 21 years old), adults (21 to 59), and adults over 60. The ADD values by age groups in each scenario are compared with the reference dose (RfD) estimated with an assumption of exposure to 12 μg/m³, the annual primary standard of $PM_{2.5}$ of the National Ambient Air Quality Standard (NAAQS). Primary standards provide public health protection, including protecting the health of “sensitive” populations such as asthmatics, children, and the elderly (US EPA, 2023).

3. Results

3.1 Summary Statistics and Graphical Summaries

Separate analyses were conducted for the training period (2015-2019) and the testing period (2020). Tables 2 and 3 present the descriptive statistics for all the variables. It is noticeable that the central tendencies (median and mean) of PM_{10} and $PM_{2.5}$ are higher during 2020 than in 2015-2019. Additionally, the variability (Std Dev) is larger in 2020 than in 2015-2019. These numerical differences are evident in the box plots from Figure 3.

Table 2. Summary Statistics of the Variables from 2015 to 2019

Variables	Min	Q1	Median	Mean	Q3	Max	Std Dev	N
PM_{10}	2.708	20.764	31.822	36.491	47.021	322.146	23.438	1820
$PM_{2.5}$	0.778	6.6424	9.9546	13.4970	16.0927	95.7271	11.1425	1820
Daily Avg. Temp	20.00	42.00	46.00	45.87	51.00	64.00	6.8001	1820
Humidity	17.00	38.00	50.00	53.64	70.00	94.00	18.1839	1820
Wind Speed	0.00	3.5	5.90	5.961	7.80	20.00	2.9251	1820
Wind Direction	10	220.00	300	260.4	310.0	350.00	81.3916	1820

Table 3. Summary Statistics of the Variables from 2020

Variables	Min	Q1	Median	Mean	Q3	Max	Std Dev	N
PM_{10}	1.688	20.958	34.326	47.463	54.618	294.208	43.26	365
$PM_{2.5}$	1.126	6.887	11.334	18.399	23.162	170.238	20.432	365
Daily Avg. Temp	26	39.00	45.00	45.05	51.00	63.00	7.506	365
Humidity	24.00	37.00	46.50	51.08	62.75	95.00	16.938	365
Wind Speed	1	3.30	5.300	5.596	7.200	16.700	2.745	365
Wind Direction	30	262.5	300	266.9	310.0	350.0	78.526	365

Figure 3. Boxplots of PM_{10} (left) and $PM_{2.5}$ (right) from 2015 to 2020

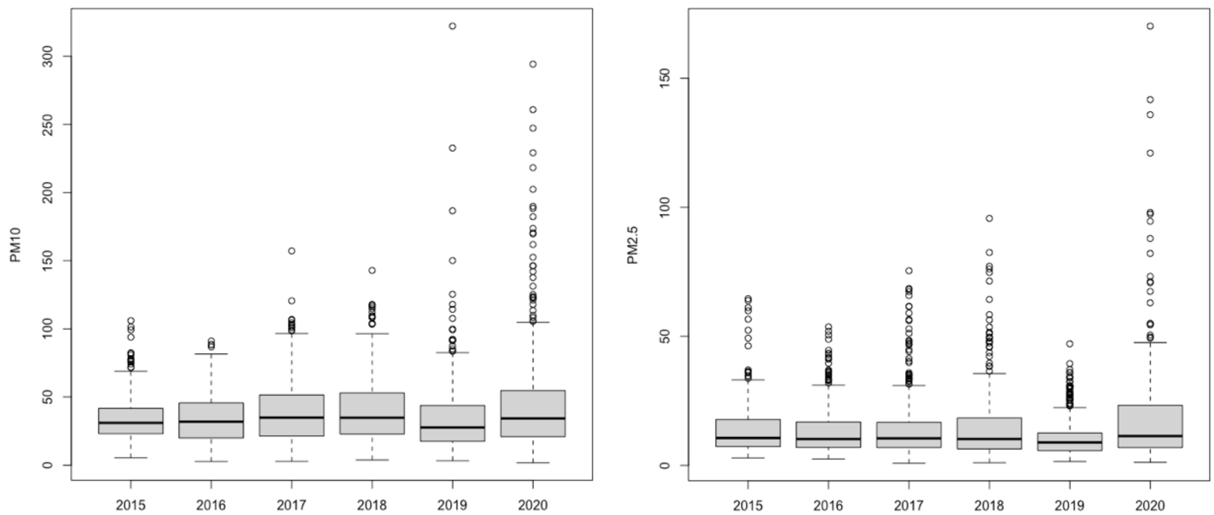
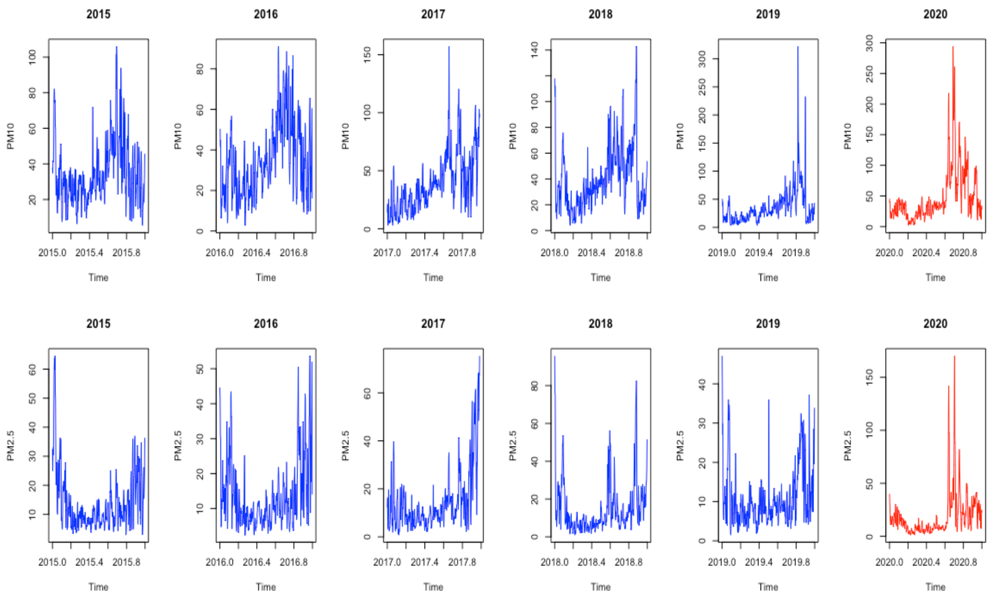


Figure 3 displays the boxplots of PM_{10} (left) and $PM_{2.5}$ (right) by year. Notably, in 2019, the average levels clearly decreased. Furthermore, the variability in PM_{10} increased during 2019 and 2020, while $PM_{2.5}$ decreased during 2019. These trends are apparent in the boxplots, highlighting the temporal variations in particulate matter concentrations over the years.

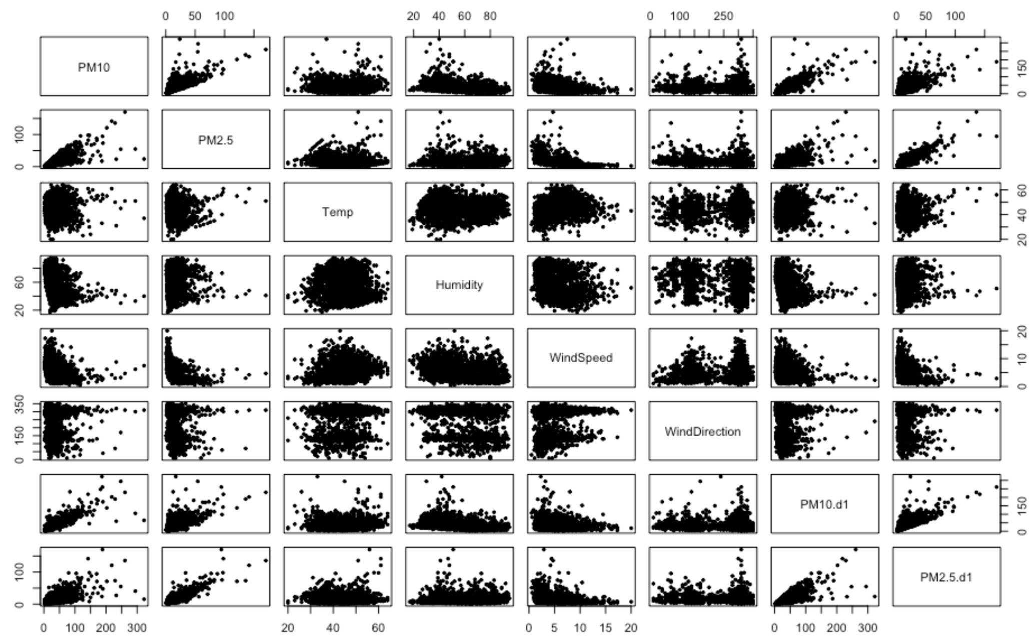
In Figure 4, the time series plots depict the variations in PM_{10} and $PM_{2.5}$ levels over time. For PM_{10}, it is evident that the concentrations peak during the fall seasons, influenced by factors such as increased agricultural activities and atmospheric conditions. Conversely, $PM_{2.5}$ levels exhibit higher concentrations in early spring and winter, potentially attributed to increased combustion activities for heating purposes and atmospheric inversions trapping pollutants closer to the surface. These temporal patterns provide valuable insights into the region's seasonal dynamics of particulate matter pollution.

Figure 4. Time Series Plot of PM_{10} and $PM_{2.5}$ from 2015 to 2020



In Figure 5, the linear relationship among the variables is explored. PM_{10} and PM_{10}.d1 (previous day) exhibit a high correlation, indicating a strong influence of the previous day's PM_{10} levels on the current day's values. Similarly, $PM_{2.5}$ and $PM_{2.5}$.d1 (previous day) also demonstrate a high correlation, suggesting a significant impact of preceding $PM_{2.5}$ concentrations on the current day's measurements. These observed correlations highlight the persistence of particulate matter pollution over consecutive days, indicating the potential for carryover effects from previous days' pollution levels. Understanding these relationships is crucial for accurately predicting and managing air quality, as past pollution levels can be valuable predictors for future concentrations. Additionally, these strong correlations underscore the interconnected nature of atmospheric processes and the importance of considering temporal dynamics when analyzing air quality data.

Figure 5. Scatterplot Matrix of the Variables



3.2 Multiple Linear Regression (MLR) and Generalized Additive Model (GAM) Results

Tables 4 and 5 represent the relationship between multiple linear regression and the generalized additive model for PM_{10}, while Tables 6 and 7 display the results for $PM_{2.5}$. Fresno County experiences hot, dry summers and cool, wet winters. Understanding the influence of temperature on particulate matter in this area is of interest, therefore we have considered both seasons. The "hot" season refers to June through August, while the "cool" season refers to September through May. These distinctions allow for a more nuanced analysis of the seasonal variations in particulate matter concentrations and their relationship with temperature.

For PM_{10}, both MLR and GAM analyses indicate that temperature and wind direction are statistically insignificant, while other variables are. During the hot season, both temperature and wind direction become statistically significant predictors. However, they remain insignificant during the cool season. This suggests that the influence of temperature and wind direction on PM_{10} levels varies depending on the season, with these factors playing a more prominent role during the hot season.

Turning to $PM_{2.5}$, the MLR model shows that temperature, humidity, and wind direction are not significant predictors, whereas only wind direction is insignificant under the GAM model throughout the entire season. However, temperature emerges as highly significant during both hot and cool seasons under the MLR model. Conversely, humidity becomes insignificant during hot and cool seasons under the GAM model. These findings underscore the complex relationships between meteorological variables and $PM_{2.5}$ concentrations, with different models yielding varying results across different seasons.

The distinction between hot and cool seasons allows for a more comprehensive understanding of how meteorological factors influence particulate matter levels in Fresno County. By examining these seasonal variations, the underlying mechanisms driving air pollution dynamics can be elucidated, and targeted strategies can be developed to mitigate their adverse effects on public health and the environment. Further research into the interplay between meteorology and air quality is essential for informing effective pollution control measures and improving overall air quality in the region.

Table 4. Multiple Linear Regression Model (MLR) Output for PM_{10}

	Entire Season		**"Hot" Season**		**"Cool" Season**	
Variable	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	35.795	0	23.578	0	42.554	0
PM_{10} (d-1)	0.685	0	0.706	0	0.667	0
Temperature	0.069	0.169	0.304	0.003	-0.083	0.236
Humidity	-0.27	0	-0.178	0.017	-0.265	0
Wind Speed	-1.833	0	-1.584	0	-1.87	0
Wind Direction	-0.007	0.102	-0.025	0.037	-0.007	0.192

Table 5. Generalized Additive Model (GAM) Output for PM_{10}

	Entire Season		**"Hot" Season**		**"Cool" Season**	
Variables	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	36.552	0	44.519	0	32.582	0
PM_{10} (d-1)	4.38	0	2.085	0	3.831	0
Temperature	1.905	0.075	1	0.008	3.548	0.691
Humidity	4.818	0	2.341	0.007	4.703	0
Wind Speed	4.188	0	2.225	0	5.058	0
Wind Direction	1	0.23	5.372	0.007	1	0.431

Table 6. Multiple Linear Regression Model (MLR) Output for $PM_{2.5}$

	Entire Season		“Hot” Season		"Cool" Season	
Variable	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
Intercept	11.107	0.000	3.118	0.123	13.777	0.000
$PM_{2.5}$ (d-1)	0.750	0.000	0.697	0.000	0.740	0.000
Temperature	-0.009	0.626	0.147	0.000	-0.103	0.000
Humidity	-0.013	0.096	-0.031	0.242	0.016	0.173
Wind Speed	-1.012	0.000	-0.679	0.000	-1.089	0.000
Wind Direction	-0.002	0.194	-0.004	0.365	-0.002	0.226

Table 7. Generalized Additive Model (GAM) Output for $PM_{2.5}$

	Entire Season		“Hot” Season		"Cool" Season	
Variables	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
Intercept	13.469	0.000	10.620	0.000	14.888	0.000
$PM_{2.5}$ (d-1)	3.302	0.000	3.017	0.000	3.293	0.000
Temperature	6.292	0.000	1.000	0.000	4.878	0.145
Humidity	7.472	0.000	1.400	0.193	4.779	0.164
Wind Speed	5.891	0.000	6.806	0.000	4.275	0.000
Wind Direction	4.521	0.459	4.002	0.374	1.000	0.435

Tables 8 and 9 present the measures of how the MLR and GAM models fit the PM_{10} and $PM_{2.5}$ data. For PM_{10}, MLR demonstrates superior performance compared to GAM during the hot seasons, while GAM performs better during the cool season. This suggests that MLR may be more effective in capturing the relationship between predictor variables and PM_{10} concentrations overall, particularly during periods of elevated temperatures. However, during cooler seasons, the flexibility of the GAM model allows it to capture the variability in PM_{10} levels better.

For $PM_{2.5}$, GAM outperforms MLR throughout the period and during the cool seasons. This indicates that the GAM model's ability to capture nonlinear relationships and account for complex interactions between variables makes it more suitable for modeling $PM_{2.5}$ concentrations, especially during cooler periods. Interestingly, during the hot season, it is unclear which model performs better, suggesting that the performance of MLR and GAM may be comparable under certain conditions.

These findings highlight the importance of considering linear and nonlinear modeling approaches when analyzing air quality data. The choice of model may depend on a range of factors, such as the season, the specific pollutant being studied, and the characteristics of the data. By comparing the performance of different modeling techniques, valuable insights can be gained into the underlying processes driving air pollution and improve the accuracy of air quality predictions. Continued research in this area is essential for developing robust modeling frameworks that effectively inform air quality management strategies and protect public health.

Table 8. Model Comparisons PM_{10}

Seasons (PM_{10})	**R^2**	**RMSE**	**MAE**	**PA**	**IA**
Entire season (MLR)	0.818	19.515	10.386	0.574	0.806
Entire season (GAM)	0.802	21.346	10.428	0.479	0.824
Hot Season (MLR)	0.785	27.1	13.825	0.572	0.804
Hot Season (GAM)	0.786	29.3	14.879	0.461	0.827
Cool Season (MLR)	0.82	13.576	8.412	0.641	0.795
Cool Season (GAM)	0.829	12.92	7.589	0.729	0.78

Table 9. Model Comparisons for $PM_{2.5}$

Seasons ($PM_{2.5}$)	**R^2**	**RMSE**	**MAE**	**PA**	**IA**
Entire season (MLR)	0.775	9.792	5.024	0.65	0.79
Entire season (GAM)	0.774	9.676	4.747	0.742	0.774
Hot Season (MLR)	0.753	15.59	7.219	0.542	0.809
Hot Season (GAM)	0.756	15.754	7.152	0.506	0.816
Cool Season (MLR)	0.809	5.534	3.991	0.78	0.772
Cool Season (GAM)	0.839	5.084	3.512	0.769	0.774

3.3 Transportation-Related PM Measured On-road, In-vehicle, and Regional Air During the Intercity Trips

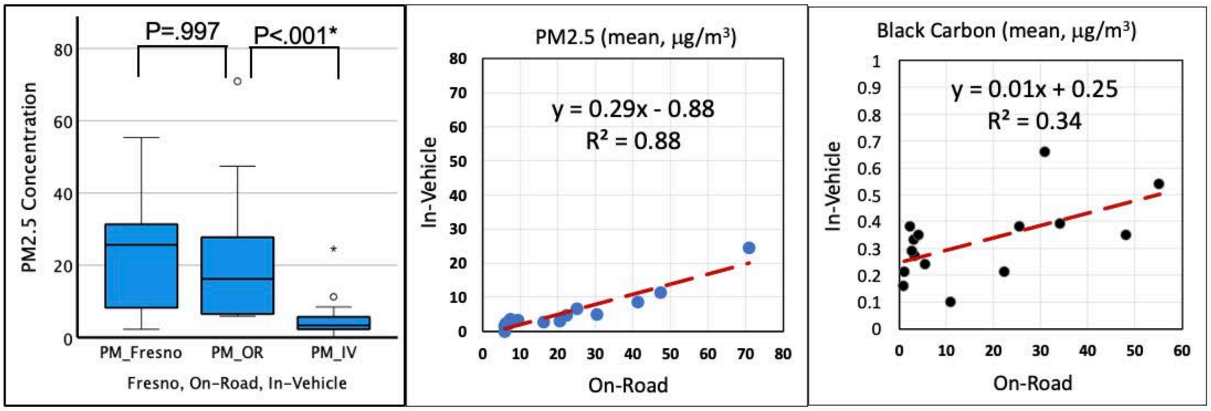
Table 10 summarizes the mean $PM_{2.5}$ and Black Carbon (BC) measured on-road and in-vehicle as markers of Fresno's air quality. On-road $PM_{2.5}$ and BC concentrations were statistically significantly higher than those measured in-vehicle using a t-test. On-road concentrations were almost 6 times higher than in-vehicle concentrations for $PM_{2.5}$ and nearly 10 times higher for BC. Therefore, in-vehicle concentrations were at a safer level, 16% for $PM_{2.5}$ and 11% for BC, respectively, compared to the on-road concentrations. Compared to the previous StarTraq 2021 study, on-road black carbon was significantly decreased in 2022 data. Therefore, the I/O ratio increased from 4% to 11%, although the in-vehicle black carbon levels remained similar to the 2021 levels.

Table 10. Average $PM_{2.5}$ and Black Carbon Concentrations (μg/m^3) Measured On-road and In-vehicle During the Four Intercity Trips Between the San Joaquin Valley and Bay Area in 2022

Trip ID	$PM_{2.5}$		Black Carbon		$PM_{2.5}$ at Fresno
	On-Road	In-Vehicle	On-Road	In-Vehicle	
Trip 12 F-B-F*	5.9	0.01	3.23	0.27	5.4
Trip 13 F-B-F	22.3	4.6	2.26	0.38	34.0
Trip 14 F-B-F	20.5	3.1	2.68	0.29	28.5
Trip 15 F-B-F	30.5	4.8	4.04	0.35	32.0
Average	19.8	3.1	3.1	0.3	25.0
On-Road/In-Vehicle	6.3		9.5		
In-Vehicle/On-Road		16%		11%	

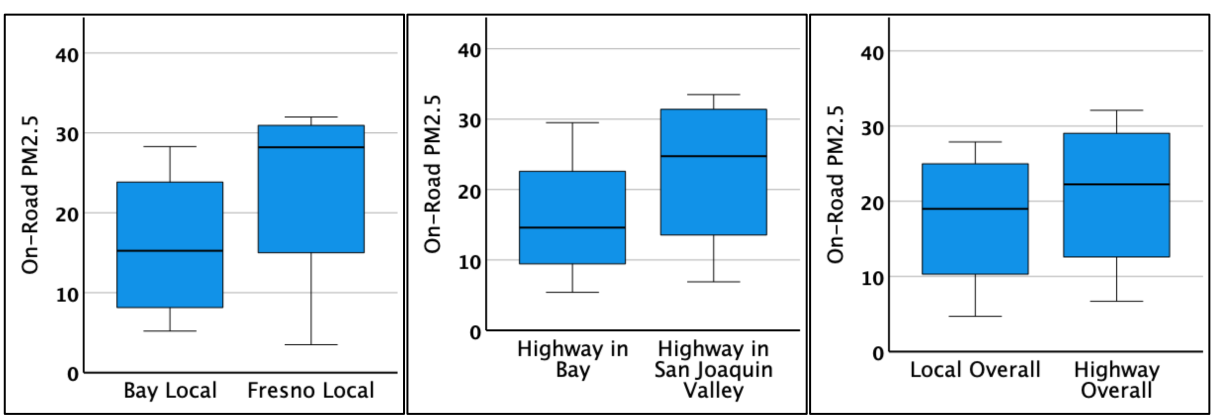
**F-B-F: Fresno to Berkeley to Fresno trip*

Figure 6. $PM_{2.5}$ Concentration by Microenvironments (left: box plot), 1:1 Scatter Plots of On-road and In-vehicle $PM_{2.5}$ (middle) and Black Carbon (right), Fifteen Trips Were Combined from the StarTraq 2021 and 2022



The on-road $PM_{2.5}$ means were not statistically significantly different from the $PM_{2.5}$ means measured at the Fresno monitoring station by a t-test when the overall fifteen trips were sampled in 2021 and 2022. The p-value was 0.997. The on-road $PM_{2.5}$ means were statistically significantly higher than the in-vehicle $PM_{2.5}$ means, as shown in Figure 6 (on the left, $p < 0.001$*). The scatter plots of the on-road and in-vehicle $PM_{2.5}$ (middle) and BC (right) illustrate positive relationships between the on-road and in-vehicle mean concentrations. There is a strong positive relationship between on-road and in-vehicle $PM_{2.5}$. For $PM_{2.5}$, 88% of the variability in in-vehicle $PM_{2.5}$ can be explained by on-road $PM_{2.5}$ ($R^2 = 0.88$). For BC, the relationship between on-road and in-vehicle was positive but not as strong as that of $PM_{2.5}$. For BC, 34% of the variability in in-vehicle BC can be explained by on-road BC ($R^2 = 0.34$). The results indicate that in-vehicle transportation-related particle exposure was at safer levels (11 to 16 %) compared to the on-road exposure for both $PM_{2.5}$ and BC.

Figure 7. $PM_{2.5}$ on the Local Roads in the Bay Area and in Fresno (left); $PM_{2.5}$ on the Highways in the Bay Area and in the San Joaquin Valley (middle); $PM_{2.5}$ on the Local Roads and Highways in Overall Trips (right) in 2022 Intercity Monitoring (trips 12 to 15)



The geographical locations impacted by topography and roadway classes are also significant determinants of air quality. As illustrated in Figure 7, regardless of the roadway types, on-road $PM_{2.5}$ means were higher in the San Joaquin Valley than in the Bay area. The $PM_{2.5}$ was higher on the highways than the $PM_{2.5}$ on the local roads in the Bay area. Notably, the median of $PM_{2.5}$ in Fresno local was higher than that of $PM_{2.5}$ on highways in the San Joaquin Valley. When overall data were combined by roadway class, highway concentrations were higher than local roadways.

3.4 Exposure Assessment to Transportation-Related $PM_{2.5}$

The Average Daily Dose (ADD, μg/kg/day) was estimated from the observed mean $PM_{2.5}$ concentrations in on-road and in-vehicle environments to assess the transportation-related exposure to $PM_{2.5}$ during roadway trips. Two scenario assumptions for exposure times were used. The first scenario estimated transportation-related $PM_{2.5}$ exposure in vehicles (in-vehicle) and near roadsides (on-road) from a 2-hour daily commute every weekday for a year with a 2-week vacation (50 weeks per year). The second scenario estimated transportation-related $PM_{2.5}$ exposure in vehicles (in-vehicle) and near roadsides (on-road) from an 8-hour daily road trip every weekday for a year, excluding a 2-week vacation (50 weeks per year). The 8-hour daily road trip scenario can be applied for 8-hour occupational exposure of transportation workers and people who work for 8 hours per day near the roadways. The ADD estimations were divided into five age groups: Children under 3 years old, children (3 to 11 years old), adolescents and young adults (11 to 21 years old), adults (21 to 59), and adults over 60.

As illustrated in Figures 8 and 9, the average daily doses for the children's groups were significantly higher than those in the adults' groups because of the children's smaller size. The median ADD of children under 3 in in-vehicle exposure (0.36 μg/kg/day) was higher than the average reference dose (RfD, 0.32 μg/kg/day), a value derived from the same frequency and duration of exposure for all age groups (that is, the annual $PM_{2.5}$ standard of 12 μg/m^3). The results illustrate that $PM_{2.5}$ exposure at safe levels during the daily commute can still significantly expose infants and children under 3. For two-hour daily exposure to near-road environments, the ADDs of children under 11 were higher than the RfD of the other age groups. This result may concern schools and daycare facilities next to busy traffic areas.

Despite the higher average daily dose of transportation-related $PM_{2.5}$ in the on-road air quality, if people consistently close the window and recirculate their in-vehicle air, the ADD is reduced significantly in in-vehicle cabin air. People can use cabin air filters and recirculate in-vehicle air to protect themselves from $PM_{2.5}$ penetrating from on-road transportation or even from elevated $PM_{2.5}$ driven by wildfire. Figure 9 shows that an 8-hour driving scenario is equivalent to daily exposure for people who operate vehicles occupationally or for those who work on or near roadways. Due to the increase in exposure duration, increased ADD is observed in all age groups. The ADDs of adult groups were lower than the RfD-8hr (1.26 μg/kg/day) even in the on-road environments. However, the ADDs of groups of children under 11 were higher than RfD-8hr. The scenario may be applied to estimate inhalation exposure of children who live near busy roadways or in downwind locations and play outside frequently.

Figure 8. Transportation-related Exposure to $PM_{2.5}$ Estimated
from a 2-hour Daily Commute In-vehicle and On-road Environments by Age Groups

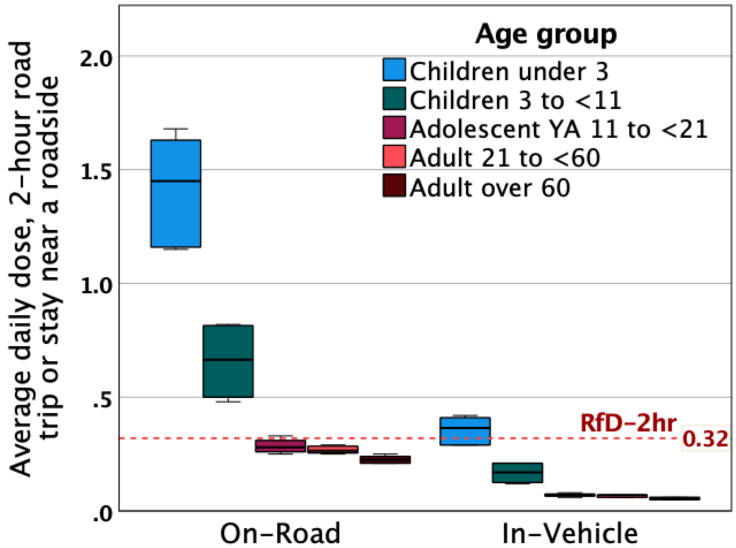
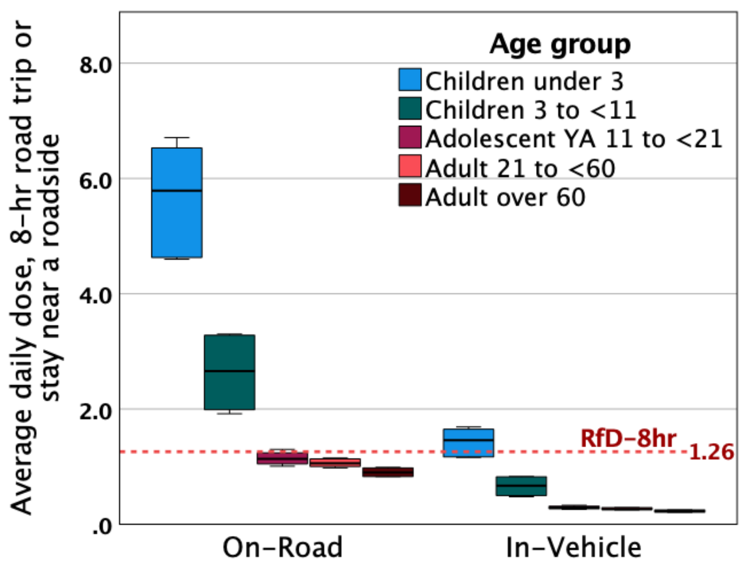


Figure 9. Transportation-related Exposure to $PM_{2.5}$ Estimated
from an 8-hour Daily Exposure In-vehicle and On-road Environments by Age Groups



4. Summary & Conclusions

Analysis suggests that the relationship between temperature and particulate matter (PM_{10} and $PM_{2.5}$) in Fresno County is influenced by the season, temperature, and wind direction. These meteorological factors significantly impact PM_{10} levels during the hot season but not during the cool season. Conversely, temperature emerges as a highly significant predictor for $PM_{2.5}$ concentrations during both hot and cool seasons under the MLR model. The choice between MLR and GAM for modeling depends on the specific season and pollutant, with MLR outperforming GAM for PM_{10} and GAM performing better for $PM_{2.5}$ during the cool season.

The regional air quality $PM_{2.5}$ measured at Fresno station and meteorological conditions were closely related to the concentration of on-road particulate matter. Through intercity monitoring of $PM_{2.5}$ and BC, it was observed that on-road concentrations were statistically significantly higher than the particle concentrations measured in-vehicle ($p<.001$), indicating that in-vehicle particle concentrations were at a safe level compared to on-road concentrations. Additionally, $PM_{2.5}$ concentrations on highways were higher than those on local roadways in most cases. Furthermore, transportation-related particle pollutants measured on-road in the San Joaquin Valley were significantly higher than the concentrations measured in the Bay Area.

The results from an average daily dose of transportation-related $PM_{2.5}$, based on a 2-hour commute and an 8-hour trip scenario, estimated that the children's average daily dose of $PM_{2.5}$ is significantly higher than the ADDs of adults' age groups. In-vehicle average daily doses were significantly lower than the on-road daily doses. The estimation of inhalable exposure to $PM_{2.5}$ on-road can be applied to people who work or live near busy traffic areas.

These findings underscore the complex dynamics of air pollution and the importance of considering a range of factors such as seasonality, location, and transportation patterns when assessing air quality. Continued research in this area is crucial for developing effective strategies to mitigate air pollution and safeguard public health in Fresno County and beyond. By understanding the interplay between meteorological conditions, transportation emissions, and particulate matter concentrations, policymakers can make informed decisions to improve air quality and promote environmental sustainability.

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