ASSOCIATION OF TRAFFIC AND RELATED AIR POLLUTANTS ON CARDIORESPIRATORY RISK FACTORS FROM LOW-INCOME POPULATIONS IN EL PASO, TX

February 2021

CARTEEH
Center for Advancing Research in
Transportation Emissions, Energy, and Health
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TECHNICAL REPORT DOCUMENTATION PAGE

<table>
<tr><td>1. Report No.</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient’s Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Association of Traffic and Related Air Pollutants on Cardiorespiratory Risk Factors from Low-Income Populations in El Paso, TX</td><td colspan="2">5. Report Date
February 2021</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="2">7. Author(s)
Soyoung Jeon, Juan Aguilera, Leah Whigham, and Wen-Whai Li</td><td colspan="2">8. Performing Organization Report No.
UTEP-03-27</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address:
CARTEEH UTC
The University of Texas at El Paso
500 W. University Ave., El Paso, Texas 79968</td><td colspan="2">10. Work Unit No.</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
69A3551747128</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
Office of the Secretary of Transportation (OST)
U.S. Department of Transportation (USDOT)</td><td colspan="2">13. Type of Report and Period
Final
November 1, 2019–August 31, 2020</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code</td></tr>
<tr><td colspan="4">15. Supplementary Notes
This project was funded by the Center for Advancing Research in Transportation Emissions, Energy, and Health University Transportation Center, a grant from the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology, University Transportation Centers Program.</td></tr>
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16. Abstract

The health effects of air pollution from outdoor environments are of great concern due to the high exposure risk even at relatively low concentrations of air pollutants. Traffic emissions from the El Paso–Ciudad Juarez border crossings make up a sizable portion of the mobile vehicle emissions in El Paso, TX. This project aimed to integrate air quality and traffic data with large epidemiological study results conducted in the El Paso region, and to develop associations between cardiorespiratory outcomes and traffic-related data (air quality and traffic-related activities).

The findings showed respiratory functions could be affected by exposures to various pollutants in previous hours regardless of the wide variations in participants’ metabolic syndrome (MetS) factors. Short-term average exposures of pollutant concentrations of particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$) prior to the participants’ health monitoring were negatively associated with spirometry measures such as forced expiratory volume. Logistic regression modeling found that $PM_{2.5}$ increased likelihoods of high waist circumference and high glucose. Also, increasing nitrogen dioxide (NO_2) concentration was associated with high waist circumference for all exposure periods and high glucose for 72-hr exposure. The likelihood of having MetS closely correlated with increasing 96-hr $PM_{2.5}$ and NO_2, while the odds of having MetS showed associations with decreasing ozone.

Land-use regression models were performed for modeling the spatial variation of MetS based on the significant transportation predictors. The street length within 500 m and vehicle miles traveled have shown to be important traffic predictors to find relationships with lung function. As the total length of street within zones of impact increases, the risks of a high waist circumference, high triglycerides, and low high-density lipoprotein cholesterol were observed. The inverse of the distance to the nearest port of entry was associated with increases in fasting glucose. The increasing likelihood of MetS was also related to the increased street length within 500 m radius zones to each participant’s residential address.

The dissemination of these results can lead to decision making and improve policy related to healthy living in communities close to busy roadways.

<table>
<tr><td colspan="2">17. Key Words
Air pollution, transportation data, traffic volume, land-use regression, respiratory and cardiovascular measures, metabolic syndrome</td><td colspan="2">18. Distribution Statement
No restrictions. This document is available to the public through the CARTEEH UTC website.
http://carteeh.org</td></tr>
<tr><td>19. Security Classif. (of this report)
Unclassified</td><td>20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages
82</td><td>22. Price
$0.00</td></tr>
</table>

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Executive Summary

Problem Statement

People with lower income are more likely to live in communities with higher pollution levels from traffic-related emissions. Traffic-related air emissions have been reported to have strong association with urban air pollution and cause adverse respiratory health effects in near-road communities. Transportation parameters such as traffic density, vehicle miles traveled, and road length, as well as land-use data such as population density, land-use classification, proximity to heavy-traffic roads, distances to major point and area sources, and household income, are important variables for explaining a spatial variation of air quality and health outcomes. However, studies of long-term exposure to traffic-related pollutants with cardiovascular risk factors are less common, and findings remain mixed. None of these studies have been conducted in a border region while considering both cardiovascular and respiratory outcomes.

Technical Objectives

A large health study has been conducted in the El Paso, TX, region in the past five years, collecting data for cardiorespiratory risk from approximately 5,000 participants living in low-income communities. First-year data of health screenings including airway inflammation and lung function measurements were also used to examine the effects of short- and long-term pollution exposure on respiratory health outcomes.

Data extraction and cleanup were performed on participants' home addresses to extract latitude and longitude coordinates. Air quality and meteorological data were acquired from the Texas Commission on Environmental Quality's continuous air monitoring stations including hourly air pollutant data of particulate matter (PM) (including PM less than 2.5 micrometers in diameter [$PM_{2.5}$] and PM less than 10 micrometers in diameter [PM_{10}]), nitrogen dioxide (NO_2), and ozone (O_3). Time-integrated air pollutant exposure data of 24-, 48-, 72-, and 96-hr averages were processed for each subject.

The spatially distributed traffic-related and land-use variables were acquired from the El Paso Metropolitan Planning Organization, the U.S. Census Bureau, and the U.S. Geologic Survey. Two impact zones were established to have radii of 500 m and 1,000 m centered at each participant's address. Data were extracted for the two zones based on the latitude and longitude coordinates of the participant's residence using geographic information system (GIS) mapping.

R code was developed to draw the information from short- and long-term pollution datasets and deliver an average value of pollutant exposure relative to a participant's date of assessment. The land-use regression (LUR) technique was applied to explore the associations between a set of spatially distributed metabolic syndrome (MetS) risk factors collected from 5,000 low-income participants and the transportation and land-use predictors.

Key Findings

Researchers established the following short-term association between cardiorespiratory health outcomes (lung function, inflammation, and MetS risk factors) and traffic-related air pollutants ($PM_{2.5}$, PM_{10}, NO_2, and O_3) in residents of low-income communities of El Paso, TX:

- The forced expiratory volume during one second (FEV_1) was negatively correlated with average concentration levels of $PM_{2.5}$ (24/48/96 hr).
- Negative associations between FEV_1/forced vital capacity and 96-hr $PM_{2.5}$/24-hr NO_2/96-hr NO_2 were also observed.
- MetS risk factors, such as waist circumference, high-density lipoprotein (HDL), and fast blooding glucose, were associated with pollutant measurements.

- Waist circumference, in particular, for females is a significant factor showing strong relationships with $PM_{2.5}$ and NO_2 for all exposure periods.
- Increasing $PM_{2.5}$ and NO_2 concentration was also associated with increasing likelihood of a high waist circumference.
- A significant relationship between 96-hr averaged O_3 and HDL was observed.
- The increase in 24-/48-hr $PM_{2.5}$ and PM_{10} were significantly associated with an increase in the box-cox transformed fasting blood glucose scale. Higher likelihood of having high glucose was associated with increased PM concentrations.
- The MetS classification based on the combination of five risk factors showed significant associations with $PM_{2.5}$, NO_2, and O_3.

Researchers established the following long-term association between cardiorespiratory health outcomes (lung function, inflammation, and MetS risk factors) and spatial transportation data for residents of low-income communities of El Paso, TX:

- The length of the street within the 500-m impact zone has shown to be an important traffic predictor for lung function (peak expiratory flow [PEF] and the best result interpreted by the spirometry software (CareFusion Spirometry PC Software™ 36-SPC1000-STK) for PEF [PEF Best].
- The increase in pulse pressure was associated with the amount of traffic within a 500-m radius and the proximity to the nearest port of entry (POE).
- The increase in the inverse of the distance squared to the POE, which implies a decrease in the distance to the POE, was significantly associated with an increase in fasting glucose.
- The most significant predictor in the LUR models of MetS risk factors was the total length of the street within a 500-m radius.
- The increase in the street length associated with increasing waist circumference and triglycerides and decreasing HDL cholesterol.
- As the total length of the street increases, the risks of a large waist circumference, high triglycerides, and low HDL cholesterol were observed.
- The increasing likelihood of MetS was also related to the increased street length within 500 m.

Project Impacts

Researchers found associations between cardiorespiratory outcomes and traffic-related data for both air quality and traffic-related activities. Aside from the participants receiving their screening results, this project provides relevant air quality information to the participants. Spatial variations of environmental and traffic-related data were informed for the defined impact zones (500 m and 1,000 m). In parallel, this project integrated health outcome data into a GIS map. A predicted map of MetS was produced to show the prediction of the spatial distribution of MetS outcome in El Paso, TX. The dissemination of results can lead to decision making and improve policy related to healthy living in communities close to busy roadways. The research team envisions providing education regarding the detrimental effects of air pollution, which can be combined with the Healthy Living and Traffic-Related Air Pollution initiative to improve participants' health.

Acknowledgments

This research conducted a secondary data analysis that includes low-income participants from El Paso, TX. The participants were recruited as part of an epidemiological study titled Evidence-Based Screening for Obesity, Cardiorespiratory Disease, and Environmental Exposures in Low-Income El Paso Households, funded by the City of El Paso's Department of Public Health.

The research team would also like to acknowledge significant contributions from Dr. Mayra Chavez from the Civil Engineering Department and from Dr. Gabriel Ibarra-Mejia and Dr. Joao Ferreira-Pinto from the College of Health Sciences at The University of Texas at El Paso.

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List of Acronyms

BMI	Body mass index
BP	Blood pressure
CAMS	Continuous Ambient Monitoring Sites
COPD	Chronic obstructive pulmonary disease
DBP	Diastolic blood pressure
eNO	Exhaled nitric oxide
FBG	Fasting blood glucose
FEF_{25-75}	Forced expiratory flow during the two interior quartiles of exhalation
$FEV_{0.5}$	Forced expiratory volume in half a second
FEV_1	Forced expiratory volume in one second
FVC	Forced vital capacity
GIS	Geographic Information System
HbA1c	Glycated hemoglobin
HDL	High-density lipoprotein cholesterol
IQR	Inter-quartile range
LDL	Low-density lipoprotein cholesterol
LUR	Land-use regression
MetS	Metabolic syndrome
NA	Not applicable, missing value
NO_2	Nitrogen dioxide
O_3	Ozone
PBP	Pulse blood pressure
PEF	Peak expiratory flow
PM	Particulate matter
$PM_{2.5}$	Particle with aerodynamic diameters of less than 2.5 µm
PM_{10}	Particle with aerodynamic diameters of less than 10 µm
POE	Ports of entry
Q1	The first quartile
Q3	The third quartile
SD	Standard deviation
SBP	Systolic blood pressure
TC	Total cholesterol
TCEQ	Texas Commission on Environmental Quality
TG	Triglyceride
UTEP	University of Texas at El Paso
VMT	Vehicles miles traveled

Background and Introduction

Introduction

Air pollution is caused by different pollutants in the atmosphere that can harm living organisms and the natural environment. The health effects of air pollution from outdoor environments are of great concern due to the high exposure risk even at relatively low concentrations of air pollutants (Kim et al., 2015). People living in areas with higher exposure to air pollution compared to those in less polluted areas were more likely to die, and stronger associations were found with cardiorespiratory deaths (Dockery et al., 1993; Pope et al., 1995). Several scientific publications have outlined how exposure to these particles is a source of various health problems including heart and lung disease, irregular heartbeat, aggravated asthma, decreased lung function, and increased respiratory symptoms (Atkinson et al., 2010; Cadelis et al., 2014; Correia et al., 2013).

In addition, air pollution may promote the development of several cardiovascular risk factors (e.g., elevated lipids and blood pressure) and lead to type-2 diabetes (Bowe et al., 2018; Pope et al., 2015; Rao et al., 2015). Suggested mechanisms for this interaction include alteration in pathways for control of adipose tissue, the presence of particles in the systemic circulation, release of inflammatory mediators, and the effects on glucose metabolism (Rao et al., 2015; Wellen and Hotamisligil, 2003; Xu et al., 2003). In recent decades, many cardiorespiratory biomarkers have been identified and studied in relation to air pollution exposure (Rom et al., 2013). Even if not all biomarkers are in the causal pathway for development of a disease, they can be considered valuable indices of a change in disease risk of air pollution exposure (Thurston et al., 2017).

Exhaled nitric oxide (eNO) is considered a biomarker of airway/lung inflammation, which is an important determinant of asthma and other lung diseases (Trachsel et al., 2008). eNO measurements have been adopted in large epidemiological studies to elucidate the negative impacts of air pollution on pulmonary inflammation in asthmatic children (Delfino et al., 2006; Holguin et al., 2007; Liu et al., 2009). An elevated eNO value indicates airway inflammation, which translates to an increase in inflammatory processes such as asthma (Holguin et al., 2007; Steerenberg et al., 2003). Lung function measurements are assessed by considering the expiratory flow rate in the amount of time required for a person to exhale. Lung function is usually assessed in terms of forced vital capacity (FVC), forced expiratory volume in one second (FEV_1), peak expiratory flow (PEF), and forced expiratory flow during the two interior quartiles of exhalation (FEF25-75%) (Hankinson et al., 1999).

Metabolic syndrome (MetS) is a known precursor of cardiovascular disease, hypertension, and type-2 diabetes (Chen and Schwartz, 2008), and consists of a group of five risk factors:

- Excess abdominal fat.
- High blood pressure (BP).
- High triglyceride (TG) levels.
- Low high-density lipoprotein (HDL) cholesterol (called good cholesterol) levels.
- High fasting glucose.

Having three or more of these risk factors results in a classification of MetS, which, in itself, is a risk factor for cardiovascular disease, diabetes, hypertension, and dyslipidemia (abnormal lipids). The high prevalence and increasing number of U.S. adults (34 percent) with MetS has become a public health concern that presents a great challenge to health care (Mozumdar and Liguori, 2011).

Traffic-related pollutants include particulate matter (PM) (including PM less than 2.5 micrometers in diameter [$PM_{2.5}$] and PM less than 10 micrometers in diameter [PM_{10}]), nitrogen dioxide (NO_2), and ozone (O_3). A recent review indicated air pollution from traffic sources is a major preventable cause of respiratory disease (Laumbach and Kipen, 2012). Previous studies have linked the short-term effects of traffic-related pollutants to respiratory outcomes such as airway inflammation and decreased lung function (Barraza-Villarreal et al., 2008; Holguin et al., 2007). For example, eNO is an important determinant of respiratory outcomes and disease (Trachsel et al., 2008). Also, lung function can be affected by exposure to air pollutants in healthy adults and those with a preexisting lung disease (Paulin and Hansel, 2016). Moreover, a repeated-measures study found negative associations between daily variations in ambient air pollution and lung function measured by spirometry (Panis et al., 2017).

Furthermore, there is also evidence of a relationship between air pollutant and cardiovascular outcomes. Works by Zanobetti and Schwartz (2005, 2007) showed that yearly average concentrations of PM have been associated with higher hospitalization risks, congestive heart failure, and recurrent heart attack among patients with previous myocardial infarction. Additional studies have looked at the effects of traffic-related air pollutants with components related to MetS, a predictor of cardiovascular disease, which include waist circumference, BP, TG, HDL cholesterol, fasting glucose, and other related factors (low-density lipoproteins [LDL] cholesterol and glycated hemoglobin [HbA1c]) (Clementi et al., 2019).

Short-Term Air Pollution Exposure Assessments

Research on the short-term effects of exposure to air pollutants, such as PM, O_3, and NO_2, has linked them with cardiorespiratory mortality as well (Rückerl et al., 2011). A recent metanalysis suggested that short-term exposure to some air pollutants may increase the risk of hypertension (Cai et al., 2016). Some studies have used time-series or cross-sectional analyses to report associations between elevated air pollutant concentrations over short periods of time (one day or several days) and increased cardiovascular mortality and morbidity (Pope and Dockery, 2006).

However, the precise window of exposure for some biomarkers is not clearly defined and differs by study. Chuang et al. (2010) applied mixed models to examine the associations between air pollutants, BP, and blood biochemistry markers. The exposure variables included levels of PM, NO_2, and O_3 on the same day (24-hr average) and 48- to 144-hr averages before the day of the health measurements, which included systolic blood pressure (SBP), diastolic blood pressure (DBP), HDL cholesterol, LDL cholesterol, fasting glucose, and HbA1c (Chuang et al. 2010). Bell et al. (2017) estimated exposure of ambient $PM_{2.5}$ based on the participant's residential address and used short-term averaging periods on the day of blood draw, the day before, and a moving average of the previous five days with HDL cholesterol measures. One study assigned a daily exposure measure from the monitor nearest to the participant's residence with available data for a given day, and constructed five exposure measures: $PM_{2.5}$ concentration the day before measurement, and average concentrations over the two, seven, 30, and 60 days prior to measurement using MetS as a modifying factor (Park et al., 2010).

Also, the models used to associate air pollution exposure with cardiorespiratory outcomes vary across studies. For example, a study among patients with type-2 diabetes in China considered spline and multiple linear regressions to determine associations between short-term exposure to PM_{10}, sulfur dioxide, NO_2 with total cholesterol (TC), TG, LDL cholesterol, and high HDL cholesterol (Wang et al., 2018). A study in Mexican Americans used short-term exposure considering up to 58 days of cumulative daily averages of $PM_{2.5}$ to find associations with lower insulin sensitivity; HDL-to-LDL ratio; and higher fasting glucose and insulin, TC, and LDL cholesterol using log transformations (Chen et al., 2016).

Long-Term Air Pollution Exposure Assessments

Over the last three decades, large cohort studies have found associations of long-term exposures to air pollutants with increased mortality (Dockery et al., 1993; Pope et al., 1995). Highways and roadways are major sources of air pollutants because of vehicle traffic, which can negatively affect surrounding communities. People with lower income are more likely to live in communities with higher pollution levels from traffic-related air pollution, which in turn can be considered an environmental justice issue (Brulle and Pellow, 2006; Cushing et al., 2015).

Examples of traffic-related air pollutants include $PM_{2.5}$ and PM_{10}, NO_2, and O_3, which pose a risk for cardiorespiratory diseases. Hoek et al. (2013) summarized the effect of long-term exposure to PM and NO_2 on mortality from cardiovascular and respiratory diseases in epidemiological studies, and concluded participants with lower education and obesity had a larger effect estimate for mortality related to fine PM (Hoek et al., 2013). There is also increasing evidence of associations between increased long-term exposure to traffic-related air pollutants with lung function decline in children (Barone-Adesi et al., 2015) and adults (Rhee et al., 2019), as well as attenuation of this decline with reductions in air pollution exposure (Downs et al., 2007). Therefore, identifying zones of increased air pollution exposure can add knowledge to improve the environmental conditions of those living in at-risk areas.

Limitations of Continuous Ambient Monitoring Stations

Located on the U.S.-Mexico border, El Paso, TX, has 12 continuous ambient monitoring stations (CAMSs) monitored by the Texas Commission of Environmental Quality (TCEQ) that measure air pollutants. However, few are equipped to measure all the traffic-related pollutants ($PM_{2.5}$, PM_{10}, NO_2, and O_3), which limits the quantification of air pollutant concentrations at some near-road communities. While previous studies in the region have focused on areas surrounding major highways in the city (Raysoni et al., 2011, 2013), near-road studies for areas farther north of the border are scarce. Furthermore, TCEQ monitoring sites are limited in offering a deep inquiry of the levels of air pollution in El Paso communities.

Other large studies have established the long-term effects of air pollution exposure with respiratory outcomes considering the effect of PM_{10}, $PM_{2.5}$, and NO_2 on lung function using spirometry measures (Köpf et al., 2017). However, long-term studies that consider metabolic factors related to cardiovascular health are less common, and findings remain mixed. A study of Mexican Americans was unable to find long-term associations with metabolic outcomes such as glucose and insulin resistance using spatial interpolation from air quality monitors (Chen et al., 2016). However, another study assessed the long-term effects of air pollution using land-use multivariable linear regression models to estimate the effects with glucose, insulin, HbA1c, and C-reactive protein levels (Wolf et al., 2016). The results suggested an association between long-term exposure to air pollution and insulin resistance.

Incorporation of Geographical Information in Models

A review of 157 studies using various exposure methods concluded that future research would benefit from hybrid models combining the strengths of air pollution exposure assessments and geographic information system (GIS) technologies (Zou et al., 2009). Some studies have shown consistent associations between near-roadway air pollution and cardiorespiratory diseases using traffic density and proximity to roadways (Gan, Koehoorn, et al., 2010; Gan, Tamburic, et al., 2010; Jiang et al., 2016; Kan et al., 2008). Furthermore, Bell et al. (2017) used a hierarchical spatiotemporal model considering traffic-related air pollutant seasonal trends, long-term pollutant averages, and land-use regression. They estimated average pollutant concentrations at each participant's home location during the year of the baseline exam, as well as three months and two weeks prior to each participant's baseline exam. Furthermore, geographic covariates such as distance to roadway and land-use characteristics were used in the universal models to improve prediction (Bell, 2017).

However, none of these studies have been conducted in a border region while considering both cardiovascular and respiratory outcomes. Data modeling of traffic and air quality data associated with the cardiorespiratory factors would allow a better understanding of the impact of these environmental factors on cardiorespiratory health. Therefore, researchers used spatial traffic-related variables to explore the relationship with cardiorespiratory health measures collected in the community.

Pollution Exposure and Health Outcomes in El Paso, TX

El Paso, TX, meets National Ambient Air Quality Standards for NO_2, $PM_{2.5}$, and O_3; the 2015 O_3 standard is currently pending. However, El Paso's desert setting makes attainment of PM_{10} standards difficult and has led to its nonattainment classification. The Paso del Norte air basin is shared by El Paso, TX; Ciudad Juarez, Chihuahua; and Las Cruces, NM. Traffic emissions from the El Paso–Ciudad Juarez border crossings make up a sizable portion of the mobile vehicle emissions in El Paso.

Previous studies have attempted to characterize the air pollution trends in the Paso del Norte air basin. Industrial sources, meteorological conditions, and topography were determined to cause variation in the concentration of air pollutants in the region (Noble et al., 2003). Li et al. (2001) characterized the temporal and spatial variations, along with the composition of PM. PM_{10} and $PM_{2.5}$ were found to increase during the winter months. A study conducted in 2010 across four schools found that PM_{10} was greater in the area near I-10 and the El Paso–Ciudad Juarez border highway (Raysoni et al., 2011). Also, NO_2 has been found to be predominate in central El Paso with lower values in east and west. A winter pilot study showed significant variability in NO_2 concentrations across El Paso where NO_2 concentrations decreased as elevation increased (Gonzalez et al., 2005).

A large health effect study has been under way in the El Paso region for the past five years that has involved collecting data for cardiorespiratory risk factors in almost 5,000 participants from low-income communities. Overall, the Evidence-Based Screening for Obesity, Cardiorespiratory Disease, and Environmental Exposures in Low-Income El Paso Households project aims to evaluate the overall health status of participants who are of uninsured/low-income status and to provide health vouchers for further examination for those who qualify. Individuals who want to participate in the study, which is available to all ages, need to be uninsured/low income and live within El Paso County.

Health screenings conducted include BP, anthropometric measurements (height, weight, and waist), eNO, spirometry, fasting glucose, and a lipid profile (TC, TG, HDL, and LDL). The results are given and interpreted with participants on site. Low-income/free health clinic referrals are given to those with abnormal results. The health professionals who conducted the health assessments and provided the surveys throughout the study consisted of physicians, nurses, graduate and undergraduate students from The University of Texas at El Paso (UTEP), and volunteers. Prevalence rates of each factor have been reported for the first year of the study (N=657) with an overall prevalence of 53 percent in the selected population (Aguilera, 2016).

Modeling of traffic and air quality data association with the MetS factors allows a better understanding of the impact of these environmental factors on cardio-metabolic health. This project aims to integrate air quality and traffic data with large epidemiological study results conducted in the El Paso, TX, region. The main research question is whether there is an association between the concentration levels of traffic-related air pollutants and cardiorespiratory-related risk factors. Air quality and meteorological data were acquired from the centralized TCEQ-operated CAMSs, and the spatial traffic-related variables (e.g., traffic roads, traffic counts, and distances to ports of entry [POE]) were acquired from the El Paso Metropolitan Planning Organization. The dissemination of results can lead to decision making and improve policy related to healthy living in communities close to busy roadways.

Approach

This project integrated air quality and traffic-related data with a large epidemiological study conducted in the El Paso, TX, region, and established a continued partnership for future data collection efforts. The Evidence-Based Screening for Obesity, Cardiorespiratory Disease, and Environmental Exposures in Low-Income El Paso Households project is a large, ongoing study that collects data from low-income participants in El Paso, TX. A team of health professionals conducts a sociodemographic survey and collects health data on site at convenient locations for the participants. The locations include housing authority communities, faith-based organizations, food distribution events by local food banks, community health fairs, Mexican Consulate clinic days, and grocery stores, among others. Data collected include a predictor of cardiovascular risk, MetS, which includes measures of waist circumference, BP, TG, HDL cholesterol, and fasting glucose. During the baseline year of the study, data collected also included respiratory measures of airway inflammation (measured by an eNO test) and lung function (measured by spirometry).

This study conducted a secondary data analysis using health data collected between 2014 and 2020 from the mentioned large study. The larger study protocol and the amendment for conducting this study have been approved by the UTEP Institutional Review Board under study numbers 590300-4 and 1249235-3 with a separate Institutional Review Board review for the secondary analysis under study number 1611345-1

Respiratory Health Measures

The study included measures for height, weight (to calculate body mass index [BMI]), waist circumference, BP, a lipid profile (TG, TC, HDL, and LDL), and fasting glucose. These measures were used to determine the rate of MetS of the participants. Also, a subset of participants were measured for airway inflammation using a NIOX device to determine eNO and lung function measured by spirometry (FVC, FEV_1, and PEF). Participants included in the study were residents living within El Paso County recruited in low-income communities.

Air pollutants that were continuously measured throughout the study in an outdoor environment included measurements for PM_{10}, $PM_{2.5}$, NO_2, and O_3. The data were extracted using publicly available datasets from CAMSs maintained by TCEQ. Each participant was assigned to the most representative CAMS based on residential address (Figure 1). Short-term exposures considered the one-hour average concentration over 24, 48, 72, and 96 hours before the date of examination for each air pollutant.

Traffic-Related Measures

El Paso, TX, is located in the southwest area of the state and borders with Ciudad Juarez, Mexico, to the south and Sunland Park, NM, to the west. For this study, researchers considered data from the participant’s home address to extract latitude and longitude coordinates and create a layer using GIS software (Figure 2).

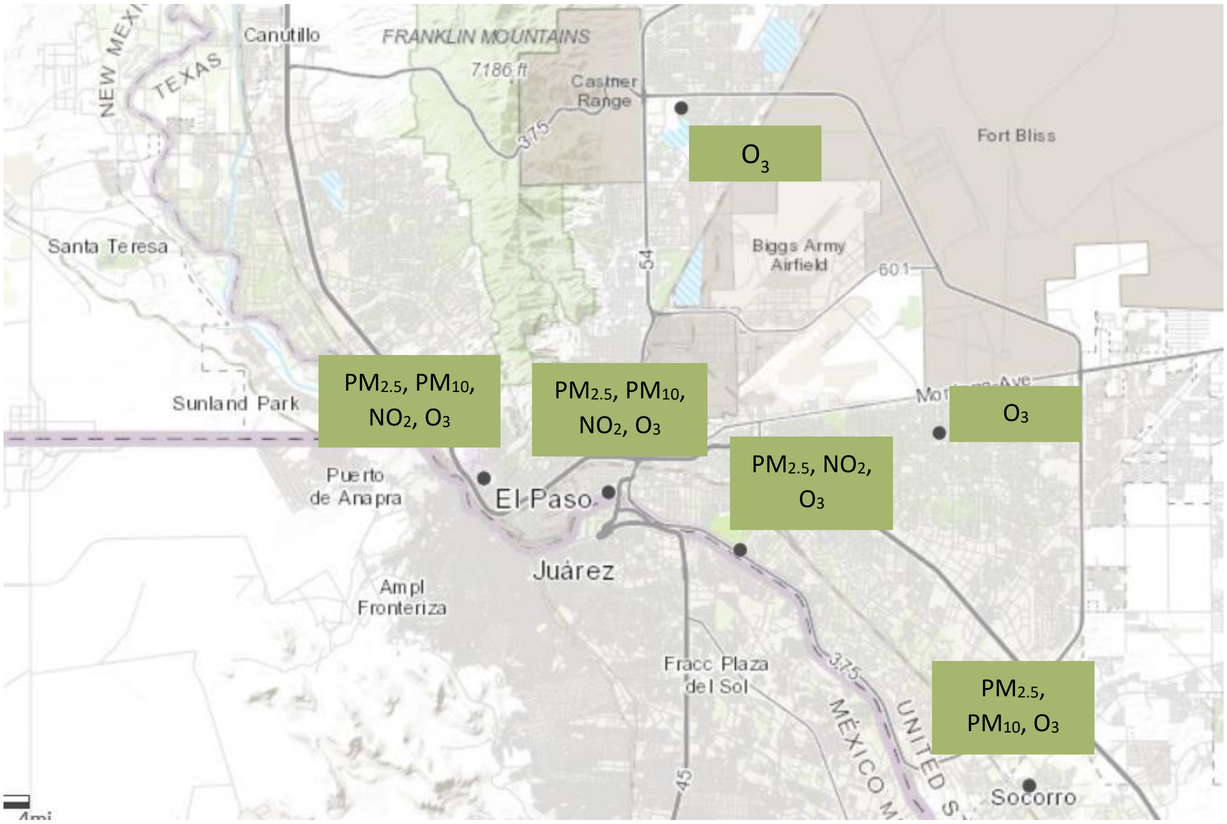

Figure 1. Location of CAMSs in El Paso, TX, for selected air pollutants.

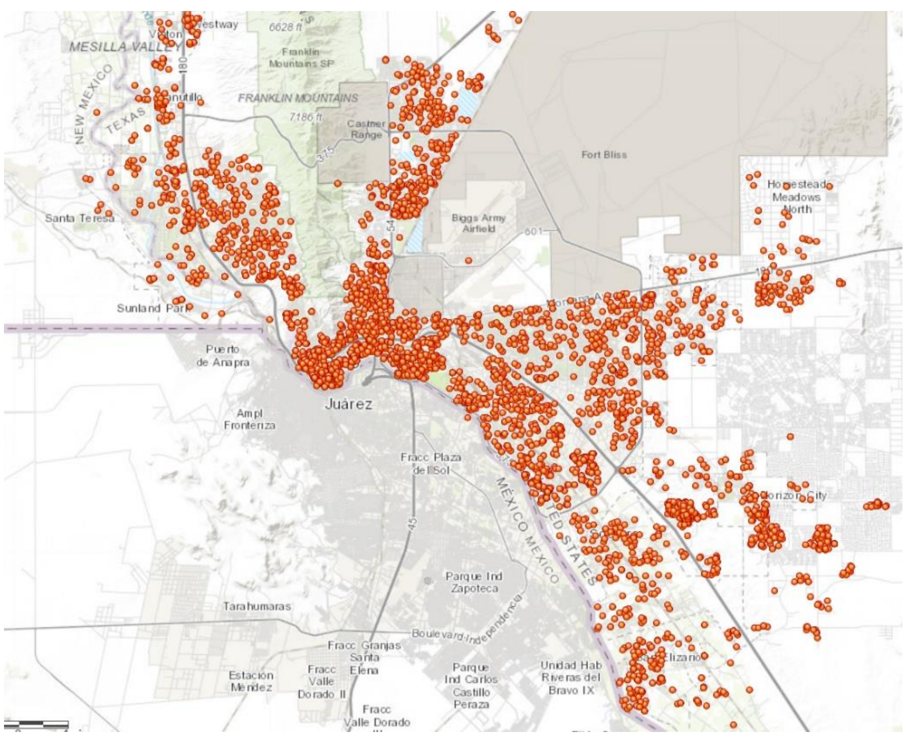

Figure 2. Residential addresses of low-income participants from El Paso, TX.

Researchers used mapping tools (ArcGIS Pro 2.5) to calculate the distance to the nearest major arterial traffic road using a GIS layer developed by the Department of Civil Engineering at UTEP in collaboration with the City of El Paso, TX (available at the PdnMapa website, http://gis.elpasotexas.gov/pdnmapajs/) (Figure 3).

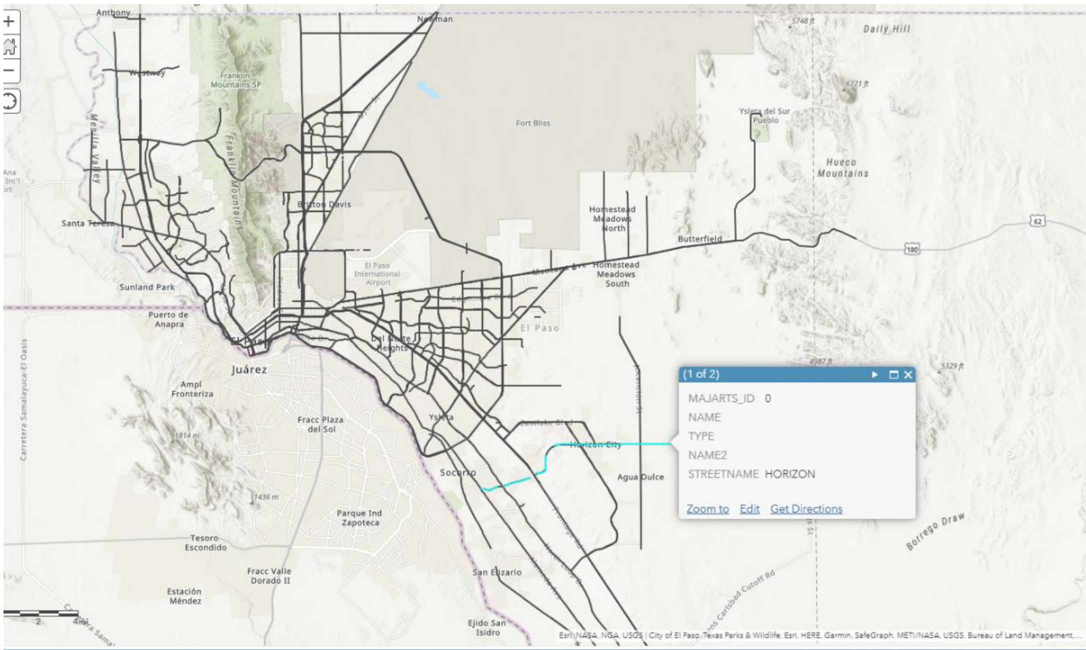

Figure 3. Major arterial roads layer.

Given its border with Mexico, El Paso has three international bridges, which constitute ports of vehicle and pedestrian entry into the United States. Due to the amount of daily traffic and car idling that occur at these points of entry, researchers considered the distance from the participants' home address to the nearest international POE as a layer of interest to explore the association of traffic-related air pollution with cardiorespiratory health outcomes (Figure 4).

Figure 4. Ports of entry in El Paso, TX.

To explore the effects of vehicle traffic using GIS tools, researchers defined zones of impact (500 m and 1,000 m) relative to a participant's residential address. Researchers used a GIS layer developed by the El Paso Metropolitan Planning Organization that included traffic counts from the city's major and minor roads address (Figure 5). This layer allowed calculation of the sum of the yearly vehicles miles traveled (VMT) relative to a participant's residential address.

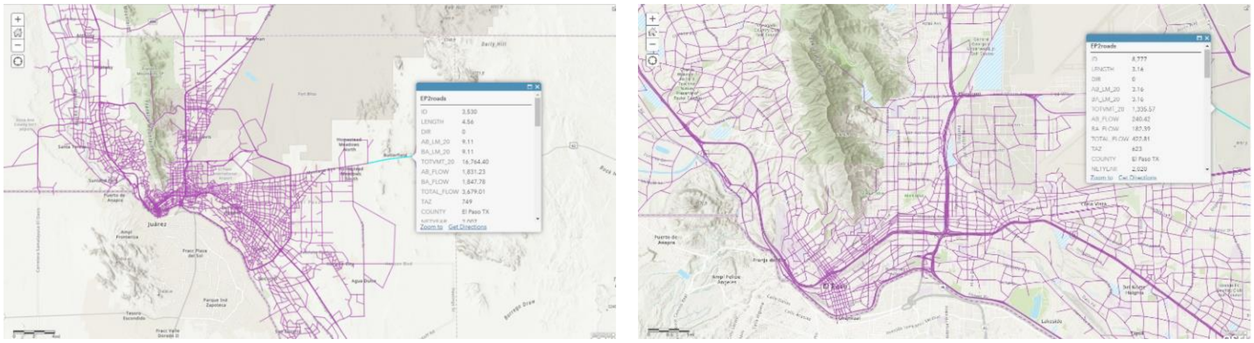

Figure 5. Metropolitan planning organization traffic layer and zoomed version.

Lastly, researchers used a GIS layer available at the Census.gov website that includes all available streets and roads within El Paso County. This layer allowed summarization of the length of roads within 500-m and 1,000-m zones for every participant relative to their residential address (Figure 6). Land-use regression (LUR) was used to explore associations between the mentioned traffic-related variables with the cardiorespiratory outcomes measured for each participant as part of the larger epidemiological study.

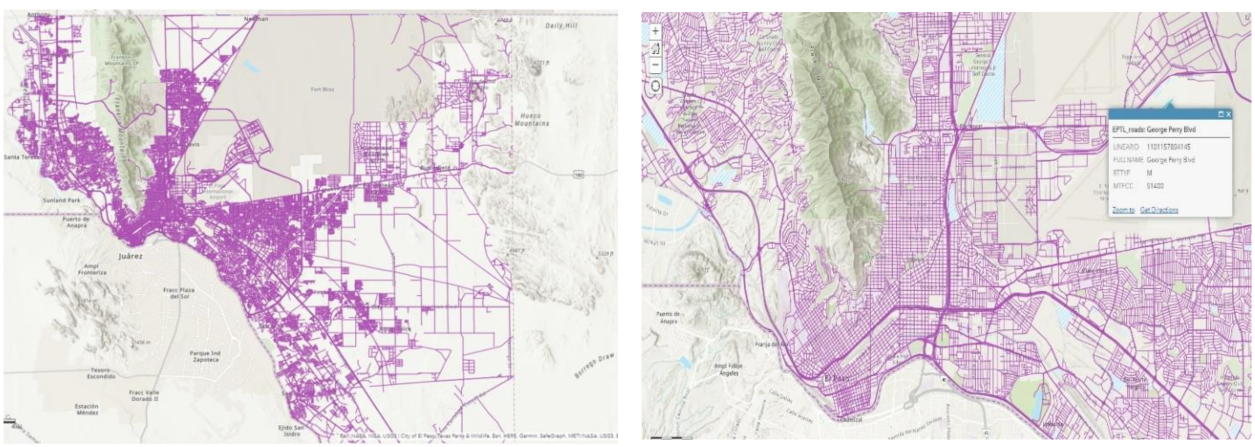

Figure 6. Census.gov street layer and zoomed version.

The analysis established associations between cardiovascular outcome measures using linear models for continuous variables (BMI, waist circumference, BP, TG, HDL cholesterol, and glucose) and logistic models for categorical outcomes (MetS) with spatial transportation data while controlling for known sociodemographic factors.

Researchers also used a subset of participants who had respiratory health outcomes (only available for the first year of the larger study) to establish associations between respiratory health outcome measures using hierarchical models for continuous variables (eNO, FVC, FEV_1, and PEF) with spatial transportation data while controlling for known sociodemographic factors. Furthermore, researchers considered the distribution of the participants that were classified with MetS using the traffic-related variables to determine the geographical areas of higher probability of this diagnosis/classification.

Methodology

GIS Mapping

The use of GIS mapping allowed generation of traffic-related data for every participant as a proxy for traffic-related air pollution exposure. Figure 7 illustrates a subset of distances to the nearest major arterial traffic road relative to participants' GIS coordinates. In a similar way, researchers determined distances to the nearest international POE for each participant.

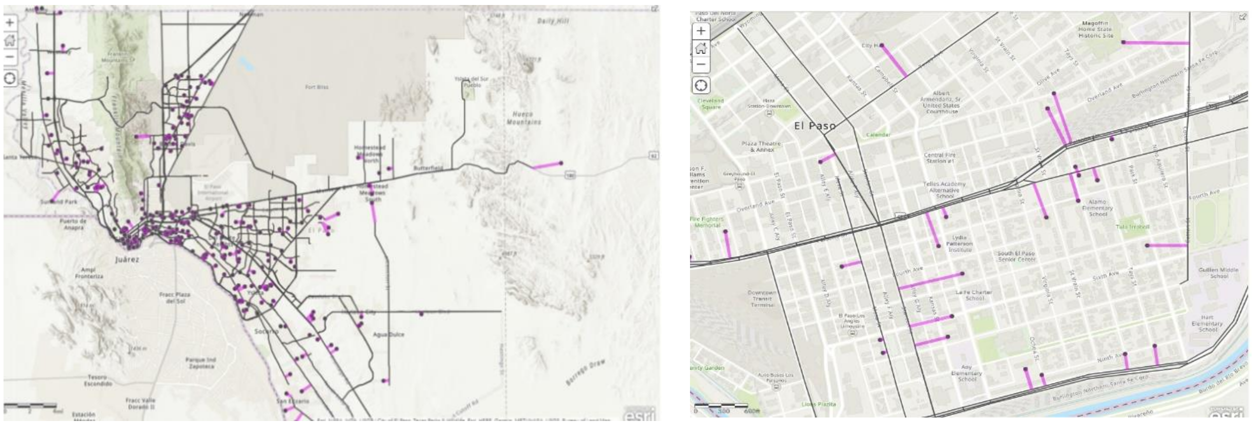

Figure 7. Distance to the nearest major arterial (majart) road and majart layer zoom.

The use of impact zones within 500 m and 1,000 m of each participant's residential address was a key component of the analysis. Researchers used these zones to determine the length of the streets and the amount of VMT by using GIS layers from Census.gov and the El Paso Metropolitan Planning Organization, respectively. Figure 8 and Figure 9 illustrate the calculation of the VMT and the length of the streets within the 500-m impact zone. In a similar way, the variables within a 1,000-m zone were calculated.

Figure 8. Summary of street length within 500 m using the Census.gov layer.

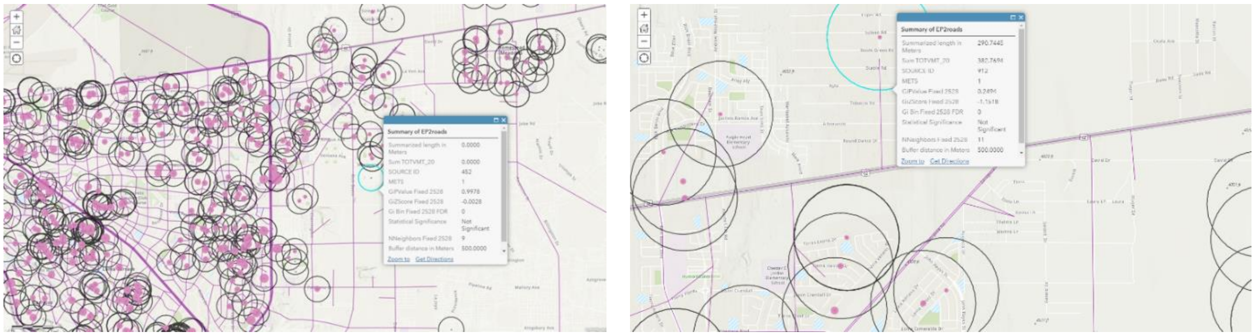

Figure 9. Summary of street length within 500 m using the metropolitan planning organization layer.

Statistical Methods

The continuous variables in this study include waist circumference, SBP, DBP, TG, HDL cholesterol, and fasting blood glucose (FBG). Also, eNO, FVC, FEV_1, and PEF were collected as a subset for those who were measured during the first year of the study (2014–2015).

For further statistical analysis, waist circumference, SBP, DBP, TG, HDL cholesterol, and FBG were coded as binary variables (yes and no) to determine whether a participant has a risk factor for MetS. The recoded variables followed the diagnostic criteria defined by the National Institutes of Health, and the categorical variable "Metabolic Syndrome (MetS)" was constructed by computing the presence of three or more of the previously mentioned risk factors.

Initially, summary statistics of subject demographic information and characteristics were calculated. Correlation analyses using Pearson correlation were conducted to explore relationships between outcome variables and outdoor pollutant concentrations. The associations between pollutant metrics and various health outcomes were analyzed using a linear regression model. Before the correlation and regression analyses, box-cox transformation was applied to the variables to account for the skewness in the distribution, and different power exponents were selected to transform the data. For example, researchers used the log-transformation for the eNO and percent predicted FVC and the exponent of −0.1 for the percent predicted FEV_1 values. The square root transformation was applied to the percent predicted PEF to improve the distribution of the right-skewed PEF data. The power coefficient of −2 was used to transform the glucose value.

Logistic regression analyses were used to examine the relationship between categorical variables for a specified outcome (presence or absence of MetS risk factors and MetS classification) and concentration levels of pollutant variables. Regression models were conducted separately for each pollutant of interest.

To examine the effects of long-term traffic-related pollutions exposures, regression models were conducted separately for each independent variable. Linear regression considered the respiratory and cardiovascular outcomes. Logistic regression analyses were also used to examine the relationship between categorical variables for a specified outcome (the presence or absence of cardiovascular risk factors and MetS classification) and traffic-related measurements. Researchers applied the LUR technique to explore the associations between a set of spatially distributed respiratory factors from 600 participants and MetS risk factors from 5,000 low-income participants with the traffic and land-use predictors. The level of statistical significance was set at a p-value of <0.05 for all tests. The statistical software R (version 3.6.2) was used to perform the statistical analysis portion of the study.

Results

Short-Term Effects of Traffic-Related Air Pollution on Cardiorespiratory Outcomes

Demographics

Table 1 summarizes subject demographic information and health characteristics. A total of 662 subjects participated in the study from September 2014 to May 2015. Most of the participants were female (84.4 percent) and Hispanic (98.2 percent), and subjects have a mean age of 47.8 years with a range of 6–89 years of age (see also Table 2). BMI was an average of 30.56, which ranges from 12.66 to 67.65; 81.1 percent of participants were overweight (35.2 percent) or obese (45.9 percent), and 100 participants (15.1 percent) were normal.

Table 1. Demographic Information for Subjects (N=662)

Characteristic		Frequency	Percent
Sex	Female	559	84.4
	Male	103	15.6
Education	Middle school	162	24.5
	Elementary school	148	22.4
	High school, no diploma	130	19.6
	High school graduate	86	13.0
	Some college, not completed	54	8.2
	Associate degree	26	3.9
	Bachelor’s degree	23	3.5
	Never attended or kindergarten only	14	2.1
	Masters, doctoral, or professional degree	2	0.3
	Not applicable (NA)	17	2.6
Language	Spanish	506	76.4
	Both	126	19.0
	English	21	3.2
	NA	9	1.4
Employed	Homemaker	211	31.9
	Employed part time	146	22.1
	Employed full time	81	12.2
	Not employed for more than 1 year	56	8.5
	Not employed for less than 1 year	51	7.7
	Self-employed	32	4.8
	Student	28	4.2
	Retired	24	3.6
	Unable to work	18	2.7
	NA	15	2.3
Income	$0–$19,999	559	84.4
	$20,000–$29,999	50	7.6
	$30,000–$39,999	9	1.4
	$40,000–$49,999	3	0.5
	$50,000–$69,999	2	0.3
	$70,000–$99,999	2	0.3
	NA	37	5.6

Characteristic		Frequency	Percent
Marital status	Married	232	35.0
	Never married	136	20.5
	Separated	105	15.9
	Divorced	88	13.3
	Widowed	50	7.6
	A member of an unmarried couple	28	4.2
	Civil union	14	2.1
	NA	9	1.4
Ethnicity	Hispanic	650	98.2
	Non-Hispanic	8	1.2
	NA	4	0.6
Race	White	600	90.6
	Black or African American	10	1.5
	American Indian or Alaska Native	3	0.5
	Asian	2	0.3
	NA	47	7.1
Health	Good	253	38.2
	Fair	236	35.6
	Poor	79	11.9
	Very good	50	7.6
	Excellent	21	3.2
	NA	23	3.5
Obesity	Obese	304	45.9
	Overweight	233	35.2
	Healthy	100	15.1
	NA	25	3.8

Table 2. Summary Statistics of Participant Characteristics (N=662)

Characteristic	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR
Age (years)	6	40	49	47.8	57	89	13.8	17
Weight (kg)	18.1	66.0	76.0	77.4	87.0	164.0	17.9	21.0
Height (cm)	115.0	154.0	158.0	159.0	163.5	185.0	8.2	9.5
BMI (kg/m^2)	12.7	26.5	29.7	30.6	34.6	67.7	6.6	8.0

Note: Q1 means quartile 1, Q3 means quartile 3, SD mean standard deviation, and IQR means interquartile range.

Air Pollution Measurements

Hourly concentrations at the nearest CAMS to the subject's residential address (Table 3) were averaged over 24-, 48-, 72-, and 96-hr exposure windows for comparisons. The Chamizal station had the highest frequency as the nearest CAMS relative to subjects' residential address. Other stations were also available for O_3 measurements with valid data during the study period. The averages were aggregated to represent prior pollutant exposure until 10 a.m. during the day when health outcomes were measured. Table 4 summarizes the descriptive statistics for the pollutant measurements for study subjects. Figure 10 shows the boxplots of each pollutant measurement.

Table 3. Spatial Distribution of Subjects to the Nearest CAMS (N=662)

Pollutant	Nearest CAMS	Frequency	Percent
$PM_{2.5}$	Chamizal	298	45.0
	Ascarate	136	20.5
	UTEP	121	18.3
	Socorro	107	16.2
PM_{10}	Chamizal	391	59.1
	Socorro	147	22.2
	UTEP	124	18.7
NO_2	Chamizal	296	44.7
	Ascarate	242	36.6
	UTEP	124	18.7
O_3	Chamizal	194	29.3
	UTEP	115	17.4
	Skyline	111	16.8
	Ascarate	87	13.1
	Socorro	82	12.4
	Ivanhoe	73	11.0

Table 4. Summary Statistics for Pollutant Measurements over Various Window Exposures (N=662)

Metric	Window	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR	NA
$PM_{2.5}$ (µg/m^3)	24 hr	1.737	4.962	7.771	8.932	11.063	30.854	5.555	6.101	4
	48 hr	2.819	5.382	7.849	8.642	9.745	27.292	4.880	4.362	2
	72 hr	3.172	5.859	7.949	8.589	9.497	24.097	4.017	3.637	0
	96 hr	3.174	6.003	7.844	8.435	10.003	20.083	3.380	3.999	0
PM_{10} (µg/m^3)	24 hr	7.268	15.982	24.854	31.820	35.239	101.979	24.156	19.257	7
	48 hr	6.224	17.052	24.374	31.259	37.896	84.665	19.996	20.844	2
	72 hr	9.218	17.040	24.990	30.128	38.962	71.958	15.998	21.922	0
	96 hr	8.185	18.740	25.632	29.376	39.440	64.953	13.571	20.700	0
NO_2 (ppb)	24 hr	0.690	8.788	12.702	14.954	21.435	33.960	8.177	12.646	7
	48 hr	2.420	9.102	12.981	14.580	19.497	31.141	7.037	10.395	7
	72 hr	3.228	10.220	14.088	14.700	18.009	29.650	6.025	7.789	7
	96 hr	5.029	10.994	13.779	14.751	18.793	29.650	5.243	7.798	7
O_3 (ppb)	24 hr	6.250	16.536	24.150	25.159	33.103	51.682	10.747	16.568	0
	48 hr	7.908	17.196	25.261	25.389	31.825	46.996	9.755	14.629	0
	72 hr	8.878	17.493	24.724	25.096	32.395	48.618	9.474	14.902	0
	96 hr	9.619	17.011	24.451	25.176	32.654	47.381	9.270	15.643	0

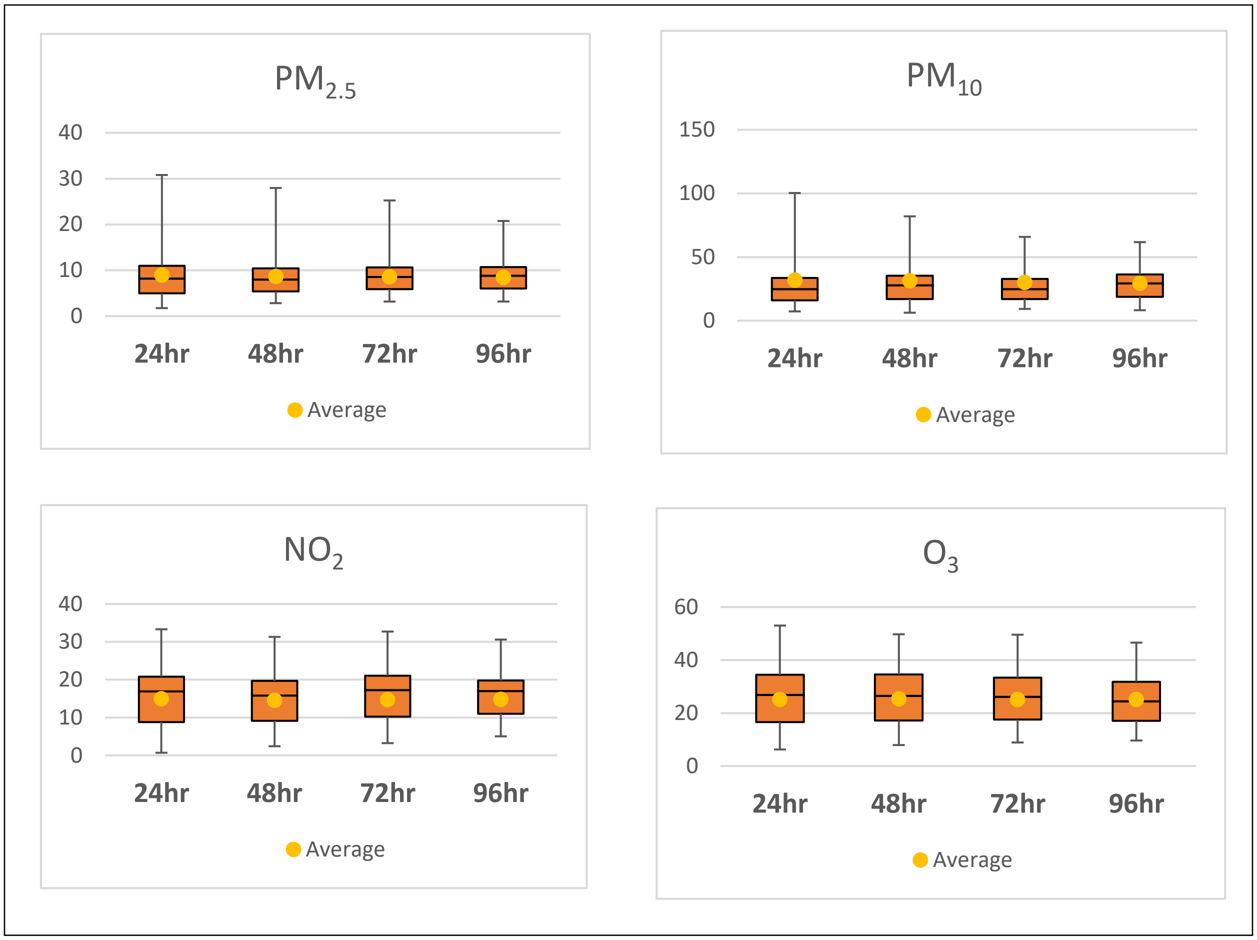

Figure 10. Summary boxplots of air pollution concentrations.

Respiratory Associations

Table 5 summarizes descriptive statistics for eNO and spirometry measurements. The range for eNO was from 4.9 to 113 ppb with a mean average of 21.37 ppb. The FEV_1 ranged from 0.76 to 4.86 L with an average of 2.4 L, the FVC ranged from 0.82 to 6 L with an average of 2.65 L, and the PEF ranged from 1.59 to 11.48 L/minute with an average of 5.29 L/minute.

Table 5. Descriptive Statistics for eNO, FEV_1, FVC, and PEF Metrics (N=662)

Metric	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR	NA
eNO (ppb)	4.900	13.000	18.000	21.369	24.000	113.000	14.006	11.000	121
FEV_1 (L)	0.755	2.005	2.340	2.399	2.747	4.863	0.623	0.742	163
FVC (L)	0.820	2.179	2.553	2.646	3.023	6.020	0.732	0.844	163
PEF (L/min)	1.590	4.181	5.128	5.290	6.230	11.477	1.688	2.049	163
FEV_1 %Pred	18.00	83.000	92.000	95.872	101.000	360.000	30.532	18.000	163
FVC %Pred	16.000	73.000	82.000	84.645	91.000	266.000	24.289	18.000	163
PEF %Pred	14.000	80.500	95.000	95.786	109.500	267.000	26.984	29.000	163
FEV_1/FVC	0.570	0.880	0.920	0.914	0.970	1.000	0.070	0.090	163
$FEV_{0.5}$Best (L)	0.290	1.720	1.940	1.993	2.260	3.940	0.502	0.540	163
FEV_1Best (L)	0.420	2.130	2.440	2.509	2.820	5.060	0.640	0.690	163
FVCBest (L)	0.450	2.285	2.680	2.768	3.185	6.020	0.770	0.900	163
PEFBest (L/min)	0.800	5.070	6.050	6.107	7.075	12.230	1.732	2.005	163

Table 6 presents pollutant effect estimates on respiratory outcomes using linear regression models and corresponding p-values. Regression analysis showed that short-term pollutant concentrations of $PM_{2.5}$ were negatively associated with spirometry measures such as FEV_1: $\beta_1 = -0.011$ for 24-hr $PM_{2.5}$ (p-value = 0.038), $\beta_1 = -0.014$ for 48-hr $PM_{2.5}$ (p-value = 0.018), and $\beta_1 = -0.017$ for 96-hr $PM_{2.5}$ (p-value = 0.032). FEV_1Best value showed similar associations with 24- and 48-hr PM2.5_z $\beta_1 = -0.011$ for 24-hr $PM_{2.5}$ (p-value = 0.043), and $\beta_1 = -0.013$ for 48-hr $PM_{2.5}$ (p-value = 0.034). Negative $PM_{2.5}$-$FEV_{0.5}$Best associations were also significant for the 24-, 48-, and 96-hr window exposure (p-values < 0.05).

The PEF was also negatively correlated with $PM_{2.5}$ for all time exposure periods: $\beta_1 = -0.048$ for 24-hr $PM_{2.5}$, $\beta_1 = -0.058$ for 48-hr $PM_{2.5}$, $\beta_1 = -0.054$ for 72-hr $PM_{2.5}$, and $\beta_1 = -0.068$ for 96-hr $PM_{2.5}$; p-values < 0.01. Researchers found that the relatively longer the participants were exposed to $PM_{2.5}$ concentrations, the more lung function decreased, represented by PEF. The 24-, 48-, and 96-hr averaged NO_2 had negative association with PEF: $\beta_1 = -0.023$ for 24-hr NO_2 (p-value = 0.013), $\beta_1 = -0.028$ for 48-hr NO_2 (p-value = 0.011), and $\beta_1 = -0.028$ for 96-hr NO_2 (p-value = 0.047). Only 48-hr PM_{10} particle showed relevance to the PEF Best value with $\beta_1 = -0.008$ (p-value = 0.043). The log-transformed eNO, FVC, percent predicted values in FEV_1, FVC, and PEF did not show any significant relationship with pollutant measurements.

The negative relationships were also found between FEV_1/FVC and pollutant measurements. Using generalized linear regression modeling, researchers observed a negative association between FEV_1/FVC and 96-hr $PM_{2.5}$ ($\beta_1 = -0.023$, p-value = 0.040). The ratio was also negatively associated with 24-hr NO_2 ($\beta_1 = -0.011$, p-value = 0.020) and 96-hr NO_2 ($\beta_1 = -0.019$, p-value = 0.011). However, 24-hr O_3 data showed a positive correlation with the sFEV_1/FVC value ($\beta_1 = 0.008$, p-value = 0.040).

Table 6. Association between Respiratory Outcome and Pollutant Metrics (N=662)

Respiratory Outcome	Pollutant	Window	Estimate	Std. Error	t value	p-value
log(eNO)	$PM_{2.5}$	24 hr	−0.003	0.004	−0.678	0.498
		48 hr	−0.002	0.005	−0.382	0.702
		72 hr	−0.001	0.006	−0.216	0.829
		96 hr	0.001	0.007	0.159	0.873
	PM_{10}	24 hr	0.000	0.001	−0.100	0.920
		48 hr	0.001	0.001	0.485	0.628
		72 hr	0.001	0.001	0.920	0.358
		96 hr	0.002	0.002	1.165	0.244
	NO_2	24 hr	−0.005	0.003	−1.693	0.091
		48 hr	−0.003	0.003	−0.879	0.380
		72 hr	−0.002	0.004	−0.502	0.616
		96 hr	−0.001	0.004	−0.339	0.735
	O_3	24 hr	0.002	0.002	0.937	0.349
		48 hr	0.001	0.002	0.294	0.769
		72 hr	0.000	0.002	0.031	0.975
		96 hr	0.000	0.002	0.021	0.983

Respiratory Outcome	Pollutant	Window	Estimate	Std. Error	t value	p-value
FEV_1	$PM_{2.5}$	**24 hr**	−0.011	0.005	−2.080	**0.038***
		48 hr	−0.014	0.006	−2.381	**0.018***
		72 hr	−0.012	0.007	−1.725	0.085
		96 hr	−0.017	0.008	−2.148	**0.032***
	PM_{10}	24 hr	−0.001	0.001	−1.205	0.229
		48 hr	−0.001	0.001	−1.047	0.295
		72 hr	−0.001	0.002	−0.743	0.458
		96 hr	−0.002	0.002	−1.088	0.277
	NO_2	24 hr	−0.002	0.003	−0.551	0.582
		48 hr	−0.006	0.004	−1.577	0.115
		72 hr	−0.006	0.005	−1.190	0.235
		96 hr	−0.009	0.005	−1.758	0.079
	O_3	24 hr	0.000	0.003	0.101	0.920
		48 hr	0.002	0.003	0.863	0.389
		72 hr	0.001	0.003	0.293	0.770
		96 hr	0.001	0.003	0.449	0.654
FVC	$PM_{2.5}$	24 hr	−0.010	0.006	−1.594	0.111
		48 hr	−0.013	0.007	−1.860	0.064
		72 hr	−0.008	0.008	−0.969	0.333
		96 hr	−0.011	0.010	−1.147	0.252
	PM_{10}	24 hr	−0.002	0.001	−1.150	0.251
		48 hr	−0.001	0.002	−0.693	0.489
		72 hr	−0.001	0.002	−0.261	0.794
		96 hr	−0.001	0.002	−0.366	0.715
	NO_2	24 hr	0.001	0.004	0.364	0.716
		48 hr	−0.005	0.005	−1.017	0.310
		72 hr	−0.003	0.006	−0.454	0.650
		96 hr	−0.005	0.006	−0.788	0.431
	O_3	24 hr	−0.002	0.003	−0.642	0.521
		48 hr	0.001	0.003	0.251	0.802
		72 hr	−0.001	0.003	−0.325	0.746
		96 hr	−0.001	0.003	−0.236	0.813
PEF	$PM_{2.5}$	**24 hr**	−0.048	0.015	−3.289	**0.001***
		48 hr	−0.058	0.016	−3.555	**0.000***
		72 hr	−0.054	0.019	−2.883	**0.004***
		96 hr	−0.068	0.022	−3.120	**0.002***
	PM_{10}	24 hr	−0.005	0.003	−1.509	0.132
		48 hr	−0.007	0.004	−1.964	0.050
		72 hr	−0.007	0.005	−1.522	0.129
		96 hr	−0.009	0.005	−1.637	0.102
	NO_2	**24 hr**	−0.023	0.009	−2.496	**0.013***
		48 hr	−0.028	0.011	−2.561	**0.011***
		72 hr	−0.023	0.013	−1.787	0.075
		96 hr	−0.028	0.014	−1.987	**0.047***
	O_3	24 hr	0.007	0.007	0.961	0.337
		48 hr	0.009	0.008	1.148	0.251
		72 hr	0.004	0.008	0.475	0.635
		96 hr	0.004	0.008	0.534	0.593

Respiratory Outcome	Pollutant	Window	Estimate	Std. Error	t value	p-value
Transformed FEV_1 %Pred	$PM_{2.5}$	24 hr	0.000	0.001	−0.072	0.943
		48 hr	0.000	0.002	−0.081	0.935
		72 hr	0.001	0.002	0.519	0.604
		96 hr	0.001	0.002	0.248	0.804
	PM_{10}	24 hr	0.000	0.000	0.705	0.481
		48 hr	0.000	0.000	0.129	0.897
		72 hr	0.000	0.000	0.283	0.778
		96 hr	0.000	0.001	0.262	0.794
	NO_2	24 hr	0.000	0.001	0.099	0.922
		48 hr	0.000	0.001	0.451	0.652
		72 hr	0.000	0.001	0.374	0.708
		96 hr	0.000	0.001	0.029	0.977
	O_3	24 hr	−0.001	0.001	−1.415	0.158
		48 hr	−0.001	0.001	−1.564	0.118
		72 hr	−0.001	0.001	−1.630	0.104
		96 hr	−0.001	0.001	−1.462	0.144
Transformed FVC %Pred	$PM_{2.5}$	24 hr	0.000	0.002	0.216	0.829
		48 hr	0.000	0.002	0.179	0.858
		72 hr	0.003	0.003	0.953	0.341
		96 hr	0.002	0.003	0.722	0.470
	PM_{10}	24 hr	0.000	0.000	0.355	0.723
		48 hr	0.000	0.001	0.269	0.788
		72 hr	0.000	0.001	0.547	0.585
		96 hr	0.000	0.001	0.525	0.600
	NO_2	24 hr	0.001	0.001	1.078	0.281
		48 hr	0.001	0.002	0.800	0.424
		72 hr	0.002	0.002	0.917	0.360
		96 hr	0.001	0.002	0.669	0.504
	O_3	24 hr	−0.002	0.001	−1.861	0.063
		48 hr	−0.002	0.001	−1.619	0.106
		72 hr	−0.002	0.001	−1.704	0.089
		96 hr	−0.002	0.001	−1.569	0.117
Transformed PEF %Pred	$PM_{2.5}$	24 hr	−0.357	0.237	−1.508	0.132
		48 hr	−0.444	0.262	−1.694	0.091
		72 hr	−0.354	0.304	−1.167	0.244
		96 hr	−0.522	0.350	−1.491	0.136
	PM_{10}	24 hr	−0.001	0.049	−0.011	0.991
		48 hr	−0.054	0.059	−0.911	0.363
		72 hr	−0.054	0.073	−0.744	0.457
		96 hr	−0.068	0.086	−0.799	0.424
	NO_2	24 hr	−0.214	0.147	−1.453	0.147
		48 hr	−0.124	0.176	−0.706	0.480
		72 hr	−0.095	0.204	−0.468	0.640
		96 hr	−0.106	0.225	−0.469	0.639
	O_3	24 hr	−0.014	0.111	−0.124	0.901
		48 hr	−0.073	0.124	−0.589	0.556
		72 hr	−0.101	0.127	−0.797	0.426
		96 hr	−0.101	0.128	−0.791	0.429

Respiratory Outcome	Pollutant	Window	Estimate	Std. Error	t value	p-value
FEV_1/FVC	$PM_{2.5}$	24 hr	−0.006	0.008	−0.765	0.445
		48 hr	−0.007	0.009	−0.877	0.381
		72 hr	−0.015	0.010	−1.563	0.119
		96 hr	−0.023	0.011	−2.062	**0.040***
	PM_{10}	24 hr	0.002	0.002	1.148	0.251
		48 hr	0.000	0.002	0.056	0.955
		72 hr	−0.001	0.002	−0.379	0.705
		96 hr	−0.002	0.003	−0.837	0.403
	NO_2	**24 hr**	−0.011	0.005	−2.342	**0.020***
		48 hr	−0.007	0.006	−1.170	0.243
		72 hr	−0.013	0.007	−1.963	0.050
		96 hr	−0.019	0.007	−2.540	**0.011***
	O_3	**24 hr**	0.008	0.004	2.057	**0.040***
		48 hr	0.005	0.004	1.242	0.215
		72 hr	0.006	0.004	1.338	0.182
		96 hr	0.006	0.004	1.453	0.147
$FEV_{0.5}$ Best	$PM_{2.5}$	**24 hr**	−0.009	0.004	−2.126	**0.034***
		48 hr	−0.012	0.005	−2.400	**0.017***
		72 hr	−0.010	0.006	−1.811	0.071
		96 hr	−0.014	0.006	−2.114	**0.035***
	PM_{10}	24 hr	−0.001	0.001	−1.003	0.316
		48 hr	−0.001	0.001	−1.113	0.266
		72 hr	−0.001	0.001	−0.829	0.407
		96 hr	−0.002	0.002	−0.982	0.327
	NO_2	24 hr	−0.003	0.003	−1.004	0.316
		48 hr	−0.006	0.003	−1.813	0.070
		72 hr	−0.005	0.004	−1.402	0.161
		96 hr	−0.007	0.004	−1.790	0.074
	O_3	24 hr	0.000	0.002	0.207	0.836
		48 hr	0.002	0.002	0.877	0.381
		72 hr	0.001	0.002	0.404	0.687
		96 hr	0.001	0.002	0.488	0.626
FEV_1 Best	$PM_{2.5}$	**24 hr**	−0.011	0.006	−2.027	**0.043***
		48 hr	−0.013	0.006	−2.123	**0.034***
		72 hr	−0.011	0.007	−1.521	0.129
		96 hr	−0.015	0.008	−1.774	0.077
	PM_{10}	24 hr	−0.001	0.001	−1.254	0.210
		48 hr	−0.002	0.001	−1.082	0.280
		72 hr	−0.001	0.002	−0.806	0.421
		96 hr	−0.002	0.002	−0.962	0.336
	NO_2	24 hr	−0.002	0.004	−0.526	0.599
		48 hr	−0.006	0.004	−1.442	0.150
		72 hr	−0.005	0.005	−1.079	0.281
		96 hr	−0.008	0.005	−1.564	0.118
	O_3	24 hr	0.000	0.003	0.106	0.915
		48 hr	0.003	0.003	0.852	0.395
		72 hr	0.001	0.003	0.462	0.644
		96 hr	0.002	0.003	0.613	0.540

Respiratory Outcome	Pollutant	Window	Estimate	Std. Error	t value	p-value
FVC Best	$PM_{2.5}$	24 hr	−0.012	0.007	−1.755	0.080
		48 hr	−0.014	0.007	−1.858	0.064
		72 hr	−0.009	0.009	−1.046	0.296
		96 hr	−0.011	0.010	−1.077	0.282
	PM_{10}	24 hr	−0.002	0.001	−1.497	0.135
		48 hr	−0.002	0.002	−1.019	0.309
		72 hr	−0.001	0.002	−0.599	0.550
		96 hr	−0.001	0.002	−0.568	0.570
	NO_2	24 hr	0.001	0.004	0.240	0.811
		48 hr	−0.005	0.005	−1.061	0.289
		72 hr	−0.003	0.006	−0.460	0.646
		96 hr	−0.004	0.006	−0.692	0.489
	O_3	24 hr	−0.002	0.003	−0.560	0.576
		48 hr	0.001	0.004	0.390	0.696
		72 hr	0.000	0.004	−0.019	0.985
		96 hr	0.000	0.004	0.078	0.938
PEF Best	$PM_{2.5}$	**24 hr**	−0.048	0.015	−3.154	**0.002***
		48 hr	−0.055	0.017	−3.317	**0.001***
		72 hr	−0.050	0.019	−2.583	**0.010***
		96 hr	−0.062	0.022	−2.752	**0.006***
	PM_{10}	24 hr	−0.005	0.003	−1.614	0.107
		48 hr	−0.008	0.004	−2.026	**0.043***
		72 hr	−0.008	0.005	−1.623	0.105
		96 hr	−0.009	0.005	−1.562	0.119
	NO_2	**24 hr**	−0.020	0.009	−2.104	**0.036***
		48 hr	−0.024	0.011	−2.169	**0.031***
		72 hr	−0.018	0.013	−1.372	0.171
		96 hr	−0.021	0.014	−1.434	0.152
	O_3	24 hr	0.005	0.007	0.658	0.511
		48 hr	0.007	0.008	0.844	0.399
		72 hr	0.002	0.008	0.227	0.821
		96 hr	0.002	0.008	0.212	0.832

*All significant pollutant time exposures and corresponding p-values are expressed in bold.

Cardiovascular Associations

Table 7 presents descriptive statistics for cardiovascular measurements. The mean average for BMI was 30.56 and for waist circumference was 95.45 cm. Waist circumference ranged from 49 to 151 cm with an average of 95 cm. Blood pressure (SBP/DBP) measurements ranged from 74/35 to 211/128 with an average of 127/76 mmHg. TG levels ranged from 45 to 650 mg/dL with an average of 186 mg/dL. HDL cholesterol ranged from 15 to 100 mg/dL with an average of 49 mg/dL. Glucose levels ranged from 50 to 477 mg/dL with an average of 109 mg/dL. Other variables of interest of cardiovascular risk that are not components of MetS but could potentially offer more information related to cardiovascular risk included BMI, pulse blood pressure (PBP), TC, and LDL cholesterol. The lipid profile measures indicated an average total cholesterol of 190 mg/dL and a fasting glucose average of 108.7 mg/dL.

Table 7. Descriptive Statistics for MetS Risk Factors (N=662)

Risk Factor	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR	NA
BMI (kg/m^2)	12.660	26.520	29.690	30.560	34.560	67.650	6.580	8.040	11
Waist	49.000	86.000	94.000	95.456	104.000	151.000	14.414	18.000	7
SBP (mmHg)	74.000	113.000	125.000	127.772	140.250	211.000	20.626	27.250	22
DBP (mmHg)	35.000	69.000	75.000	76.178	82.000	128.000	11.409	13.000	22
PBP (mmHg)	6.000	42.000	49.000	51.594	59.000	107.000	14.476	17.000	22
TC (mg/dL)	99.900	161.000	187.500	189.952	215.000	350.000	38.774	54.000	8
TG (mg/dL)	44.900	107.250	161.000	186.043	224.000	650.100	114.664	116.750	8
HDL (mg/dL)	14.900	40.000	48.000	49.714	58.000	100.100	14.583	18.000	18
LDL (mg/dL)	12.000	84.000	102.000	106.088	127.000	220.000	31.896	43.000	63
TC/HDL	1.400	3.100	3.800	4.169	4.800	22.000	1.709	1.700	31
FBG (mg/dL)	49.900	86.250	94.500	108.682	108.000	477.000	46.478	21.750	8

Correlation and regression analyses showed that the continuous types of MetS risk factors, such as waist circumference, HDL, and fast blooding glucose, were associated with pollutant measurements. Table 8 and Table 9 show detailed results of the correlation and regression analyses, respectively. Waist circumference, in particular for females, is a significant factor showing strong relationships with most of the pollutants: positive correlation with $PM_{2.5}$ and NO_2 for all exposure periods (p-values < 0.005), and negative correlation with all O_3 measurement (p-values < 0.050). The relationship between waist circumference and $PM_{2.5}$ may be due to a strong correlation observed between BMI and waist circumference with a high correlation coefficient of 0.856 (0.870 for females and 0.893 for males). The 72-hr $PM_{2.5}$ concentration was found to be positively associated with BMI ($\beta_1 = 0.132$, p-value = 0.042).

A significant relationship was found between 96-hr averaged O_3 and HDL, showing positive correlation with $\beta_1 =$ 0.136 (p-value = 0.028). The increase in 24- and 48-hr $PM_{2.5}$ and PM_{10} were significantly associated with an increase in the box-cox transformed FBG scale (p-values < 0.05) but not for the original scale of FBG. The transformation of FBG was suitable to find linear relationships with air pollution measurement.

Table 8. Correlation Analysis (N=662)

Risk Factor	Pollutant	24 hr	48 hr	72 hr	96 hr
BMI	$PM_{2.5}$	0.070	0.064	**0.080***	0.069
	PM_{10}	0.022	0.018	0.017	0.009
	NO_2	0.048	0.065	0.065	0.052
	O_3	−0.010	−0.018	−0.024	−0.015
Waist (overall)	$PM_{2.5}$	**0.113***	**0.121***	**0.134***	**0.129***
	PM_{10}	0.031	0.043	0.045	0.045
	NO_2	**0.126***	**0.149***	**0.158***	**0.142***
	O_3	**−0.098***	**−0.112***	**−0.117***	**−0.107***
• Waist (female, N=559)	$PM_{2.5}$	**0.148***	**0.161***	**0.179***	**0.171***
	PM_{10}	0.050	0.068	0.076	0.077
	NO_2	**0.126***	**0.157***	**0.164***	**0.141***
	O_3	**−0.100***	**−0.118***	**−0.123***	**−0.108***
• Waist (male, N=103)	$PM_{2.5}$	−0.036	−0.060	−0.084	−0.063
	PM_{10}	−0.056	−0.086	−0.127	−0.124
	NO_2	0.150	0.126	0.130	0.155
	O_3	−0.118	−0.109	−0.112	−0.128

Risk Factor	Pollutant	24 hr	48 hr	72 hr	96 hr
SBP	$PM_{2.5}$	−0.053	−0.053	−0.034	−0.030
	PM_{10}	−0.049	−0.065	−0.053	−0.037
	NO_2	−0.030	0.003	0.008	0.022
	O_3	0.021	0.013	0.013	0.010
• SBP < 130 (N=377)	$PM_{2.5}$	**−0.112***	−0.090	−0.025	−0.015
	PM_{10}	**−0.106***	**−0.124***	−0.076	−0.062
	NO_2	**−0.106***	−0.062	−0.020	0.011
	O_3	0.026	0.002	−0.023	−0.044
• SBP ≥ 130 (N=263)	$PM_{2.5}$	−0.033	−0.087	−0.102	−0.120
	PM_{10}	−0.028	−0.055	−0.066	−0.053
	NO_2	−0.006	−0.021	−0.049	−0.078
	O_3	0.039	0.070	0.087	0.094
DBP	$PM_{2.5}$	−0.075	−0.076	−0.069	−0.069
	PM_{10}	−0.051	−0.050	−0.047	−0.045
	NO_2	−0.015	−0.022	−0.032	−0.021
	O_3	0.054	0.059	0.063	0.060
• DBP < 85 (N=509)	$PM_{2.5}$	−0.062	−0.042	−0.009	0.017
	PM_{10}	−0.052	−0.048	−0.026	0.000
	NO_2	−0.034	−0.029	−0.014	0.020
	O_3	0.044	0.033	0.016	0.007
• DBP ≥ 85 (N=131)	$PM_{2.5}$	0.016	−0.040	−0.054	−0.070
	PM_{10}	−0.032	−0.036	−0.046	−0.057
	NO_2	0.002	−0.062	−0.120	−0.126
	O_3	−0.080	−0.015	0.015	0.011
PBP	$PM_{2.5}$	−0.016	−0.016	0.006	0.012
	PM_{10}	−0.029	−0.054	−0.038	−0.018
	NO_2	−0.031	0.021	0.036	0.047
	O_3	−0.013	−0.028	−0.031	−0.033
TC	$PM_{2.5}$	−0.042	−0.009	−0.005	0.000
	PM_{10}	−0.011	0.005	0.020	0.033
	NO_2	−0.039	−0.034	−0.020	−0.017
	O_3	−0.004	−0.006	−0.010	−0.009
TG	$PM_{2.5}$	−0.006	−0.008	0.002	0.009
	PM_{10}	−0.033	−0.046	−0.040	−0.033
	NO_2	0.004	−0.005	0.007	0.027
	O_3	−0.065	−0.062	−0.053	−0.053
log.TG	$PM_{2.5}$	−0.004	−0.005	0.016	0.021
	PM_{10}	−0.026	−0.039	−0.027	−0.020
	NO_2	0.009	0.011	0.027	0.046
	O_3	−0.059	−0.063	−0.061	−0.062
HDL	$PM_{2.5}$	0.038	0.040	0.026	0.023
	PM_{10}	0.049	0.042	0.043	0.045
	NO_2	−0.031	−0.024	−0.037	−0.047
	O_3	0.072	0.069	0.077	**0.087***
LDL	$PM_{2.5}$	−0.066	−0.016	−0.026	−0.019
	PM_{10}	−0.048	−0.009	−0.011	0.000
	NO_2	−0.028	−0.004	0.000	−0.006
	O_3	0.008	−0.006	−0.013	−0.015

Risk Factor	Pollutant	24 hr	48 hr	72 hr	96 hr
TC/HDL	$PM_{2.5}$	−0.064	−0.038	−0.028	−0.016
	PM_{10}	−0.044	−0.033	−0.027	−0.025
	NO_2	−0.005	0.015	0.027	0.027
	O_3	−0.013	−0.012	−0.011	−0.009
log.TC/HDL	$PM_{2.5}$	−0.075	−0.042	−0.027	−0.018
	PM_{10}	−0.060	−0.041	−0.033	−0.029
	NO_2	0.006	0.024	0.039	0.042
	O_3	−0.037	−0.039	−0.042	−0.044
bc.TC/HDL[1]	$PM_{2.5}$	−0.076	−0.041	−0.024	−0.016
	PM_{10}	−0.065	−0.043	−0.035	−0.030
	NO_2	0.012	0.029	0.045	0.049
	O_3	−0.044	−0.048	−0.053	−0.055
FBG	$PM_{2.5}$	0.019	0.024	−0.002	−0.012
	PM_{10}	0.024	0.027	0.012	0.016
	NO_2	0.004	0.006	−0.005	−0.017
	O_3	0.008	−0.005	0.003	0.011
log.FBG	$PM_{2.5}$	0.048	0.050	0.022	0.012
	PM_{10}	0.051	0.050	0.032	0.036
	NO_2	0.027	0.033	0.018	0.005
	O_3	−0.011	−0.030	−0.023	−0.015
bc.FBG[2]	$PM_{2.5}$	**0.087***	**0.087***	0.065	0.059
	PM_{10}	**0.091***	**0.084***	0.070	0.075
	NO_2	0.054	0.064	0.052	0.043
	O_3	−0.029	−0.052	−0.051	−0.045

* All significant correlations are expressed in bold.

1. Box-cox transformation: bc.TC/HDL = [(TC/HDL)^(−0.5)−1]/(−0.5).

2. Box-cox transformation: bc.FBG = [FBG^(−2)−1]/(−2).

Table 9. Association between Cardiovascular Outcome and Pollutant Metrics (N=662)

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
BMI	$PM_{2.5}$	24 hr	0.086	0.048	1.792	0.074
		48 hr	0.089	0.055	1.631	0.103
		72 hr	0.132	0.065	2.036	**0.042***
		96 hr	0.135	0.077	1.756	0.080
	PM_{10}	24 hr	0.006	0.011	0.564	0.573
		48 hr	0.006	0.013	0.449	0.654
		72 hr	0.007	0.016	0.431	0.666
		96 hr	0.004	0.019	0.218	0.828
	NO_2	24 hr	0.040	0.032	1.231	0.219
		48 hr	0.062	0.037	1.654	0.099
		72 hr	0.072	0.044	1.660	0.097
		96 hr	0.066	0.050	1.323	0.186
	O_3	24 hr	−0.006	0.024	−0.254	0.799
		48 hr	−0.012	0.027	−0.469	0.639
		72 hr	−0.017	0.027	−0.605	0.545
		96 hr	−0.011	0.028	−0.384	0.701

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
Waist (overall)	$PM_{2.5}$	**24 hr**	0.301	0.104	2.901	**0.004***
		48 hr	0.365	0.117	3.114	**0.002***
		72 hr	0.486	0.141	3.459	**0.001***
		96 hr	0.554	0.166	3.332	**0.001***
	PM_{10}	24 hr	0.019	0.024	0.783	0.434
		48 hr	0.031	0.028	1.100	0.272
		72 hr	0.041	0.035	1.154	0.249
		96 hr	0.048	0.042	1.153	0.249
	NO_2	**24 hr**	0.225	0.070	3.238	**0.001***
		48 hr	0.309	0.081	3.833	**0.000***
		72 hr	0.382	0.094	4.060	**0.000***
		96 hr	0.393	0.108	3.636	**0.000***
	O_3	**24 hr**	−0.132	0.052	−2.527	**0.012***
		48 hr	−0.166	0.058	−2.870	**0.004***
		72 hr	−0.179	0.059	−3.014	**0.003***
		96 hr	−0.167	0.061	−2.754	**0.006***
● Waist (female, N=559)	$PM_{2.5}$	**24 hr**	0.386	0.110	3.508	**0.000***
		48 hr	0.473	0.124	3.820	**0.000***
		72 hr	0.625	0.147	4.262	**0.000***
		96 hr	0.712	0.175	4.077	**0.000***
	PM_{10}	24 hr	0.029	0.025	1.172	0.242
		48 hr	0.048	0.030	1.595	0.111
		72 hr	0.067	0.037	1.799	0.073
		96 hr	0.079	0.044	1.805	0.072
	NO_2	**24 hr**	0.221	0.075	2.953	**0.003***
		48 hr	0.321	0.087	3.702	**0.000***
		72 hr	0.392	0.101	3.868	**0.000***
		96 hr	0.388	0.116	3.331	**0.001***
	O_3	**24 hr**	−0.132	0.056	−2.351	**0.019***
		48 hr	−0.171	0.061	−2.781	**0.006***
		72 hr	−0.184	0.063	−2.900	**0.004***
		96 hr	−0.166	0.065	−2.558	**0.011***
● Waist (male, N=103)	$PM_{2.5}$	24 hr	−0.104	0.287	−0.361	0.719
		48 hr	−0.202	0.336	−0.602	0.549
		72 hr	−0.368	0.434	−0.848	0.399
		96 hr	−0.316	0.498	−0.635	0.527
	PM_{10}	24 hr	−0.040	0.071	−0.566	0.573
		48 hr	−0.075	0.086	−0.868	0.387
		72 hr	−0.137	0.107	−1.284	0.202
		96 hr	−0.150	0.119	−1.258	0.211
	NO_2	24 hr	0.273	0.180	1.517	0.132
		48 hr	0.270	0.212	1.275	0.205
		72 hr	0.318	0.243	1.307	0.194
		96 hr	0.438	0.280	1.566	0.121
	O_3	24 hr	−0.164	0.137	−1.194	0.235
		48 hr	−0.176	0.161	−1.099	0.274
		72 hr	−0.186	0.163	−1.136	0.259
		96 hr	−0.215	0.165	−1.301	0.196

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
SBP	$PM_{2.5}$	24 hr	−0.205	0.154	−1.331	0.184
		48 hr	−0.234	0.175	−1.337	0.182
		72 hr	−0.180	0.209	−0.862	0.389
		96 hr	−0.185	0.246	−0.752	0.452
	PM_{10}	24 hr	−0.043	0.035	−1.228	0.220
		48 hr	−0.069	0.042	−1.651	0.099
		72 hr	−0.069	0.052	−1.334	0.183
		96 hr	−0.057	0.060	−0.942	0.347
	NO_2	24 hr	−0.077	0.102	−0.752	0.453
		48 hr	0.008	0.119	0.072	0.943
		72 hr	0.028	0.138	0.202	0.840
		96 hr	0.086	0.157	0.548	0.584
	O_3	24 hr	0.040	0.076	0.523	0.601
		48 hr	0.028	0.084	0.331	0.741
		72 hr	0.029	0.086	0.332	0.740
		96 hr	0.022	0.088	0.245	0.807
● SBP (<130, N=377)	$PM_{2.5}$	**24 hr**	−0.222	0.102	−2.167	**0.031***
		48 hr	−0.203	0.115	−1.756	0.080
		72 hr	−0.067	0.139	−0.482	0.630
		96 hr	−0.048	0.161	−0.297	0.766
	PM_{10}	**24 hr**	−0.047	0.023	−2.039	**0.042***
		48 hr	−0.066	0.028	−2.410	**0.016***
		72 hr	−0.050	0.034	−1.468	0.143
		96 hr	−0.048	0.040	−1.197	0.232
	NO_2	**24 hr**	−0.140	0.068	−2.059	**0.040***
		48 hr	−0.098	0.081	−1.204	0.229
		72 hr	−0.035	0.094	−0.377	0.706
		96 hr	0.022	0.105	0.210	0.834
	O_3	24 hr	0.026	0.051	0.497	0.620
		48 hr	0.002	0.057	0.043	0.966
		72 hr	−0.026	0.058	−0.441	0.659
		96 hr	−0.051	0.060	−0.857	0.392
● SBP (≥130, N=263)	$PM_{2.5}$	24 hr	−0.092	0.173	−0.532	0.595
		48 hr	−0.283	0.201	−1.410	0.160
		72 hr	−0.396	0.238	−1.664	0.097
		96 hr	−0.553	0.284	−1.947	0.053
	PM_{10}	24 hr	−0.018	0.040	−0.454	0.650
		48 hr	−0.042	0.048	−0.882	0.379
		72 hr	−0.063	0.059	−1.064	0.288
		96 hr	−0.060	0.070	−0.856	0.393
	NO_2	24 hr	−0.010	0.115	−0.091	0.928
		48 hr	−0.044	0.130	−0.340	0.734
		72 hr	−0.119	0.152	−0.782	0.435
		96 hr	−0.221	0.176	−1.257	0.210
	O_3	24 hr	0.053	0.084	0.628	0.531
		48 hr	0.106	0.093	1.141	0.255
		72 hr	0.134	0.095	1.413	0.159
		96 hr	0.147	0.097	1.517	0.130

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
DBP	$PM_{2.5}$	24 hr	−0.162	0.085	−1.906	0.057
		48 hr	−0.185	0.097	−1.913	0.056
		72 hr	−0.202	0.116	−1.745	0.082
		96 hr	−0.239	0.136	−1.758	0.079
	PM_{10}	24 hr	−0.025	0.019	−1.276	0.203
		48 hr	−0.029	0.023	−1.264	0.207
		72 hr	−0.034	0.029	−1.197	0.232
		96 hr	−0.038	0.033	−1.129	0.259
	NO_2	24 hr	−0.021	0.056	−0.376	0.707
		48 hr	−0.035	0.065	−0.541	0.588
		72 hr	−0.061	0.076	−0.800	0.424
		96 hr	−0.045	0.086	−0.525	0.600
	O_3	24 hr	0.058	0.042	1.374	0.170
		48 hr	0.070	0.046	1.504	0.133
		72 hr	0.076	0.048	1.591	0.112
		96 hr	0.074	0.049	1.518	0.130
● DBP (<85, N=509)	$PM_{2.5}$	24 hr	−0.088	0.063	−1.394	0.164
		48 hr	−0.068	0.072	−0.944	0.345
		72 hr	−0.018	0.087	−0.210	0.834
		96 hr	0.039	0.103	0.381	0.703
	PM_{10}	24 hr	−0.017	0.015	−1.171	0.242
		48 hr	−0.019	0.018	−1.088	0.277
		72 hr	−0.013	0.022	−0.576	0.565
		96 hr	0.000	0.026	0.007	0.995
	NO_2	24 hr	−0.033	0.044	−0.759	0.448
		48 hr	−0.033	0.051	−0.646	0.518
		72 hr	−0.019	0.060	−0.309	0.757
		96 hr	0.031	0.067	0.456	0.648
	O_3	24 hr	0.033	0.033	1.000	0.318
		48 hr	0.027	0.036	0.742	0.458
		72 hr	0.013	0.037	0.360	0.719
		96 hr	0.006	0.038	0.160	0.873
● DBP (≥85, N=131)	$PM_{2.5}$	24 hr	0.028	0.161	0.176	0.861
		48 hr	−0.087	0.190	−0.456	0.649
		72 hr	−0.130	0.213	−0.611	0.542
		96 hr	−0.193	0.240	−0.801	0.425
	PM_{10}	24 hr	−0.012	0.032	−0.364	0.716
		48 hr	−0.015	0.037	−0.409	0.683
		72 hr	−0.024	0.046	−0.520	0.604
		96 hr	−0.034	0.053	−0.644	0.521
	NO_2	24 hr	0.002	0.082	0.023	0.982
		48 hr	−0.065	0.093	−0.702	0.484
		72 hr	−0.146	0.106	−1.367	0.174
		96 hr	−0.180	0.126	−1.426	0.156
	O_3	24 hr	−0.055	0.061	−0.915	0.362
		48 hr	−0.012	0.068	−0.173	0.863
		72 hr	0.012	0.070	0.167	0.868
		96 hr	0.009	0.073	0.120	0.904

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
PBP	$PM_{2.5}$	24 hr	−0.042	0.108	−0.393	0.695
		48 hr	−0.049	0.123	−0.399	0.690
		72 hr	0.021	0.147	0.145	0.885
		96 hr	0.054	0.173	0.311	0.756
	PM_{10}	24 hr	−0.018	0.024	−0.741	0.459
		48 hr	−0.040	0.029	−1.356	0.176
		72 hr	−0.035	0.036	−0.956	0.339
		96 hr	−0.019	0.042	−0.452	0.652
	NO_2	24 hr	−0.056	0.072	−0.775	0.439
		48 hr	0.044	0.083	0.527	0.599
		72 hr	0.089	0.097	0.915	0.360
		96 hr	0.131	0.110	1.193	0.233
	O_3	24 hr	−0.018	0.053	−0.336	0.737
		48 hr	−0.042	0.059	−0.712	0.477
		72 hr	−0.047	0.061	−0.778	0.437
		96 hr	−0.052	0.062	−0.846	0.398
TC	$PM_{2.5}$	24 hr	−0.298	0.280	−1.064	0.288
		48 hr	−0.069	0.318	−0.217	0.828
		72 hr	−0.052	0.382	−0.135	0.893
		96 hr	0.004	0.452	0.008	0.994
	PM_{10}	24 hr	−0.018	0.064	−0.287	0.775
		48 hr	0.010	0.076	0.135	0.893
		72 hr	0.049	0.095	0.518	0.604
		96 hr	0.093	0.112	0.831	0.406
	NO_2	24 hr	−0.184	0.188	−0.981	0.327
		48 hr	−0.189	0.219	−0.864	0.388
		72 hr	−0.132	0.255	−0.515	0.607
		96 hr	−0.128	0.293	−0.439	0.661
	O_3	24 hr	−0.015	0.141	−0.108	0.914
		48 hr	−0.023	0.156	−0.147	0.883
		72 hr	−0.040	0.160	−0.247	0.805
		96 hr	−0.038	0.163	−0.230	0.819
TG	$PM_{2.5}$	24 hr	−0.136	0.829	−0.165	0.869
		48 hr	−0.197	0.939	−0.210	0.834
		72 hr	0.072	1.129	0.064	0.949
		96 hr	0.302	1.337	0.226	0.821
	PM_{10}	24 hr	−0.159	0.189	−0.845	0.399
		48 hr	−0.264	0.226	−1.171	0.242
		72 hr	−0.287	0.280	−1.022	0.307
		96 hr	−0.280	0.330	−0.849	0.396
	NO_2	24 hr	0.053	0.557	0.096	0.924
		48 hr	−0.075	0.648	−0.116	0.907
		72 hr	0.126	0.756	0.167	0.868
		96 hr	0.600	0.866	0.693	0.489
	O_3	24 hr	−0.697	0.417	−1.673	0.095
		48 hr	−0.732	0.460	−1.594	0.111
		72 hr	−0.642	0.473	−1.359	0.175
		96 hr	−0.658	0.483	−1.362	0.174

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
log.TG	$PM_{2.5}$	24 hr	0.000	0.004	−0.110	0.913
		48 hr	−0.001	0.005	−0.117	0.907
		72 hr	0.002	0.006	0.402	0.688
		96 hr	0.003	0.007	0.530	0.597
	PM_{10}	24 hr	−0.001	0.001	−0.655	0.513
		48 hr	−0.001	0.001	−0.997	0.319
		72 hr	−0.001	0.001	−0.678	0.498
		96 hr	−0.001	0.002	−0.508	0.611
	NO_2	24 hr	0.001	0.003	0.216	0.829
		48 hr	0.001	0.003	0.275	0.783
		72 hr	0.002	0.004	0.674	0.501
		96 hr	0.005	0.004	1.161	0.246
	O_3	24 hr	−0.003	0.002	−1.511	0.131
		48 hr	−0.004	0.002	−1.611	0.108
		72 hr	−0.004	0.002	−1.550	0.122
		96 hr	−0.004	0.002	−1.594	0.111
HDL	$PM_{2.5}$	24 hr	0.102	0.106	0.962	0.336
		48 hr	0.121	0.120	1.008	0.314
		72 hr	0.094	0.144	0.651	0.515
		96 hr	0.101	0.171	0.589	0.556
	PM_{10}	24 hr	0.030	0.024	1.233	0.218
		48 hr	0.031	0.029	1.062	0.289
		72 hr	0.039	0.036	1.098	0.273
		96 hr	0.048	0.042	1.129	0.259
	NO_2	24 hr	−0.056	0.071	−0.792	0.428
		48 hr	−0.050	0.083	−0.610	0.542
		72 hr	−0.090	0.096	−0.938	0.349
		96 hr	−0.129	0.110	−1.173	0.241
	O_3	24 hr	0.098	0.053	1.838	0.066
		48 hr	0.104	0.059	1.763	0.078
		72 hr	0.117	0.060	1.946	0.052
		96 hr	0.136	0.062	2.206	**0.028***
LDL	$PM_{2.5}$	24 hr	−0.391	0.241	−1.622	0.105
		48 hr	−0.109	0.273	−0.399	0.690
		72 hr	−0.203	0.326	−0.624	0.533
		96 hr	−0.181	0.386	−0.469	0.639
	PM_{10}	24 hr	−0.062	0.054	−1.157	0.248
		48 hr	−0.014	0.065	−0.218	0.827
		72 hr	−0.022	0.080	−0.273	0.785
		96 hr	−0.001	0.095	−0.010	0.992
	NO_2	24 hr	−0.110	0.161	−0.680	0.497
		48 hr	−0.021	0.188	−0.109	0.913
		72 hr	−0.002	0.219	−0.009	0.992
		96 hr	−0.034	0.251	−0.137	0.891
	O_3	24 hr	0.024	0.121	0.200	0.842
		48 hr	−0.021	0.134	−0.159	0.874
		72 hr	−0.042	0.137	−0.308	0.758
		96 hr	−0.050	0.140	−0.355	0.723

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
TC/HDL	$PM_{2.5}$	24 hr	−0.020	0.013	−1.591	0.112
		48 hr	−0.014	0.014	−0.953	0.341
		72 hr	−0.012	0.017	−0.707	0.480
		96 hr	−0.008	0.020	−0.389	0.697
	PM_{10}	24 hr	−0.003	0.003	−1.096	0.274
		48 hr	−0.003	0.003	−0.823	0.411
		72 hr	−0.003	0.004	−0.676	0.499
		96 hr	−0.003	0.005	−0.621	0.535
	NO_2	24 hr	−0.001	0.008	−0.124	0.902
		48 hr	0.004	0.010	0.368	0.713
		72 hr	0.008	0.011	0.662	0.508
		96 hr	0.009	0.013	0.672	0.502
	O_3	24 hr	−0.002	0.006	−0.338	0.735
		48 hr	−0.002	0.007	−0.308	0.758
		72 hr	−0.002	0.007	−0.288	0.774
		96 hr	−0.002	0.007	−0.234	0.815
log.TC/HDL	$PM_{2.5}$	24 hr	−0.005	0.003	−1.873	0.062
		48 hr	−0.003	0.003	−1.059	0.290
		72 hr	−0.002	0.003	−0.681	0.496
		96 hr	−0.002	0.004	−0.452	0.651
	PM_{10}	24 hr	−0.001	0.001	−1.501	0.134
		48 hr	−0.001	0.001	−1.016	0.310
		72 hr	−0.001	0.001	−0.835	0.404
		96 hr	−0.001	0.001	−0.717	0.473
	NO_2	24 hr	0.000	0.002	0.152	0.879
		48 hr	0.001	0.002	0.596	0.552
		72 hr	0.002	0.002	0.963	0.336
		96 hr	0.003	0.003	1.059	0.290
	O_3	24 hr	−0.001	0.001	−0.918	0.359
		48 hr	−0.001	0.001	−0.977	0.329
		72 hr	−0.002	0.001	−1.057	0.291
		96 hr	−0.002	0.001	−1.109	0.268
bc.TC/HDL	$PM_{2.5}$	24 hr	−0.002	0.001	−1.904	0.057
		48 hr	−0.001	0.001	−1.037	0.300
		72 hr	−0.001	0.002	−0.606	0.545
		96 hr	−0.001	0.002	−0.409	0.683
	PM_{10}	24 hr	0.000	0.000	−1.616	0.107
		48 hr	0.000	0.000	−1.067	0.286
		72 hr	0.000	0.000	−0.870	0.384
		96 hr	0.000	0.000	−0.743	0.458
	NO_2	24 hr	0.000	0.001	0.292	0.770
		48 hr	0.001	0.001	0.728	0.467
		72 hr	0.001	0.001	1.126	0.261
		96 hr	0.002	0.001	1.228	0.220
	O_3	24 hr	−0.001	0.001	−1.115	0.265
		48 hr	−0.001	0.001	−1.209	0.227
		72 hr	−0.001	0.001	−1.323	0.186
		96 hr	−0.001	0.001	−1.394	0.164

Risk Factor	Pollutant	Window	Estimate	Std. Error	t value	p value
FBG	$PM_{2.5}$	24 hr	0.166	0.336	0.495	0.621
		48 hr	0.237	0.381	0.622	0.534
		72 hr	−0.025	0.458	−0.054	0.957
		96 hr	−0.163	0.542	−0.300	0.764
	PM_{10}	24 hr	0.047	0.076	0.614	0.539
		48 hr	0.064	0.092	0.697	0.486
		72 hr	0.034	0.114	0.298	0.766
		96 hr	0.053	0.134	0.398	0.690
	NO_2	24 hr	0.024	0.225	0.105	0.917
		48 hr	0.042	0.262	0.160	0.873
		72 hr	−0.040	0.306	−0.132	0.895
		96 hr	−0.153	0.350	−0.438	0.662
	O_3	24 hr	0.034	0.169	0.200	0.841
		48 hr	−0.025	0.187	−0.135	0.893
		72 hr	0.012	0.192	0.064	0.949
		96 hr	0.054	0.196	0.274	0.784
log.FBG	$PM_{2.5}$	24 hr	0.003	0.002	1.211	0.226
		48 hr	0.003	0.002	1.273	0.203
		72 hr	0.002	0.003	0.557	0.578
		96 hr	0.001	0.003	0.313	0.754
	PM_{10}	24 hr	0.001	0.000	1.294	0.196
		48 hr	0.001	0.001	1.269	0.205
		72 hr	0.001	0.001	0.809	0.419
		96 hr	0.001	0.001	0.920	0.358
	NO_2	24 hr	0.001	0.001	0.678	0.498
		48 hr	0.001	0.002	0.832	0.406
		72 hr	0.001	0.002	0.450	0.653
		96 hr	0.000	0.002	0.122	0.903
	O_3	24 hr	0.000	0.001	−0.280	0.780
		48 hr	−0.001	0.001	−0.754	0.451
		72 hr	−0.001	0.001	−0.585	0.558
		96 hr	0.000	0.001	−0.375	0.708
bc.FBG	$PM_{2.5}$	**24 hr**	0.000	0.000	2.220	**0.027***
		48 hr	0.000	0.000	2.225	**0.026***
		72 hr	0.000	0.000	1.673	0.095
		96 hr	0.000	0.000	1.517	0.130
	PM_{10}	**24 hr**	0.000	0.000	2.324	**0.020***
		48 hr	0.000	0.000	2.162	**0.031***
		72 hr	0.000	0.000	1.794	0.073
		96 hr	0.000	0.000	1.924	0.055
	NO_2	24 hr	0.000	0.000	1.369	0.171
		48 hr	0.000	0.000	1.632	0.103
		72 hr	0.000	0.000	1.330	0.184
		96 hr	0.000	0.000	1.097	0.273
	O_3	24 hr	0.000	0.000	−0.750	0.453
		48 hr	0.000	0.000	−1.318	0.188
		72 hr	0.000	0.000	−1.294	0.196
		96 hr	0.000	0.000	−1.146	0.252

*All significant pollutant time exposures and corresponding p-values are expressed in bold.

Table 10 shows the classification of MetS risk factors (binary outcomes) based on current guidelines. Table 11 summarizes the associations between classification of MetS factors and pollutant metrics. Table 11 also shows effect estimates using logistic regression models, corresponding p-values, odds ratios, and 95 percent confidence intervals of the odds ratio. In logistic regression modeling, increasing $PM_{2.5}$ and NO_2 concentrations were associated with increasing likelihoods of a high waist circumference (p-values < 0.05 for 48-, 72-, and 96-hr $PM_{2.5}$; p-values < 0.01 for all windows of NO_2 concentration). However, the odds of having a high waist circumference decrease as the O_3 level increases (p-values < 0.05 for 24-, 48-, 72-, and 96-hr O_3). The O_3 increase was also associated with less likelihood of having low HDL status (p-values < 0.05 for 24-, 48-, 72-, and 96-hr O_3), and more exposures to O_3 led to a lower odds ratio of having low HDL (0.983 for 24-hr O_3, 0.980 for 48- and 72-hr O_3, and 0.976 for 96-hr O_3).

Table 10. Summary of MetS Risk Factors (N=662)

Variable	Value	Frequency	Percent
HighWaist	1	411	62.1
	0	244	36.9
	NA	7	1.1
HighBP	0	363	54.8
	1	277	41.8
	NA	22	3.3
HighTC	0	410	61.9
	1	244	36.9
	NA	8	1.2
HighTG	1	363	54.8
	0	291	44.0
	NA	8	1.2
LowHDL	1	329	49.7
	0	315	47.6
	NA	18	2.7
HighFBG	0	423	63.9
	1	231	34.9
	NA	8	1.2
MetS	1	336	50.8
	0	307	46.4
	NA	19	2.9

Table 11. Associations between MetS Risk Factors and MetS Classification and Pollutant Metrics (N=662)

Variable	Pollutant	Window	Estimate	Std. Error	z value	p-value	Odds Ratio	Lower 95% CI	Upper 95% CI
HighWaist	$PM_{2.5}$	24 hr	0.030	0.016	1.902	0.057	1.031	1.000	1.065
		48 hr	0.038	0.018	2.084	**0.037***	1.039	1.003	1.078
		72 hr	0.060	0.022	2.697	**0.007***	1.062	1.018	1.112
		96 hr	0.070	0.026	2.697	**0.007***	1.072	1.020	1.130
	PM_{10}	24 hr	0.003	0.003	0.859	0.390	1.003	0.996	1.010
		48 hr	0.004	0.004	0.897	0.370	1.004	0.996	1.012
		72 hr	0.006	0.005	1.105	0.269	1.006	0.996	1.016
		96 hr	0.006	0.006	1.044	0.296	1.006	0.995	1.018
	NO_2	**24 hr**	0.027	0.010	2.641	**0.008***	1.027	1.007	1.048
		48 hr	0.036	0.012	3.028	**0.002***	1.037	1.013	1.062
		72 hr	0.048	0.014	3.399	**0.001***	1.050	1.021	1.080
		96 hr	0.055	0.016	3.373	**0.001***	1.056	1.023	1.091

Variable	Pollutant	Window	Estimate	Std. Error	z value	p-value	Odds Ratio	Lower 95% CI	Upper 95% CI
	O_3	**24 hr**	–0.016	0.008	–2.079	**0.038***	0.984	0.970	0.999
		48 hr	–0.019	0.008	–2.238	**0.025***	0.981	0.965	0.998
		72 hr	–0.021	0.009	–2.465	**0.014***	0.979	0.963	0.996
		96 hr	–0.022	0.009	–2.485	**0.013***	0.978	0.962	0.995
HighBP	$PM_{2.5}$	24 hr	–0.012	0.015	–0.781	0.435	0.988	0.958	1.018
		48 hr	–0.007	0.017	–0.410	0.682	0.993	0.959	1.027
		72 hr	–0.009	0.021	–0.417	0.677	0.991	0.952	1.032
		96 hr	–0.007	0.024	–0.300	0.764	0.993	0.946	1.041
	PM_{10}	24 hr	–0.002	0.003	–0.585	0.559	0.998	0.991	1.005
		48 hr	–0.002	0.004	–0.525	0.600	0.998	0.990	1.006
		72 hr	–0.003	0.005	–0.620	0.535	0.997	0.987	1.007
		96 hr	–0.003	0.006	–0.471	0.637	0.997	0.986	1.009
	NO_2	24 hr	–0.002	0.010	–0.213	0.832	0.998	0.979	1.018
		48 hr	0.004	0.012	0.379	0.705	1.004	0.982	1.027
		72 hr	0.004	0.013	0.301	0.763	1.004	0.978	1.031
		96 hr	0.010	0.015	0.649	0.517	1.010	0.980	1.041
	O_3	24 hr	0.005	0.007	0.719	0.472	1.005	0.991	1.020
		48 hr	0.003	0.008	0.331	0.741	1.003	0.987	1.019
		72 hr	0.004	0.008	0.489	0.625	1.004	0.988	1.021
		96 hr	0.004	0.009	0.519	0.603	1.004	0.988	1.022
HighTG	$PM_{2.5}$	24 hr	0.001	0.015	0.061	0.951	1.001	0.973	1.030
		48 hr	0.000	0.016	0.020	0.984	1.000	0.969	1.033
		72 hr	0.012	0.020	0.615	0.538	1.012	0.974	1.053
		96 hr	0.016	0.024	0.668	0.504	1.016	0.970	1.064
	PM_{10}	24 hr	0.001	0.003	0.378	0.705	1.001	0.995	1.008
		48 hr	–0.001	0.004	–0.181	0.857	0.999	0.992	1.007
		72 hr	0.001	0.005	0.207	0.836	1.001	0.991	1.011
		96 hr	0.002	0.006	0.342	0.732	1.002	0.991	1.013
	NO_2	24 hr	0.005	0.010	0.478	0.633	1.005	0.986	1.024
		48 hr	0.009	0.011	0.796	0.426	1.009	0.987	1.032
		72 hr	0.021	0.013	1.568	0.117	1.021	0.995	1.048
		96 hr	0.027	0.015	1.770	0.077	1.027	0.997	1.059
	O_3	24 hr	–0.011	0.007	–1.435	0.151	0.990	0.975	1.004
		48 hr	–0.014	0.008	–1.690	0.091	0.986	0.971	1.002
		72 hr	–0.016	0.008	–1.874	0.061	0.985	0.968	1.001
		96 hr	–0.016	0.009	–1.919	0.055	0.984	0.967	1.000
LowHDL	$PM_{2.5}$	24 hr	–0.012	0.015	–0.837	0.403	0.988	0.960	1.016
		48 hr	–0.006	0.016	–0.364	0.716	0.994	0.962	1.027
		72 hr	0.005	0.020	0.271	0.786	1.005	0.967	1.045
		96 hr	0.007	0.023	0.311	0.756	1.007	0.962	1.055
	PM_{10}	24 hr	–0.003	0.003	–1.057	0.291	0.997	0.990	1.003
		48 hr	–0.003	0.004	–0.651	0.515	0.997	0.990	1.005
		72 hr	–0.004	0.005	–0.747	0.455	0.996	0.987	1.006
		96 hr	–0.005	0.006	–0.807	0.420	0.995	0.984	1.007
	NO_2	24 hr	0.010	0.010	1.066	0.286	1.010	0.991	1.030
		48 hr	0.013	0.011	1.109	0.267	1.013	0.990	1.036
		72 hr	0.017	0.013	1.252	0.211	1.017	0.991	1.044
		96 hr	0.027	0.015	1.765	0.078	1.027	0.997	1.058

Variable	Pollutant	Window	Estimate	Std. Error	z value	p-value	Odds Ratio	Lower 95% CI	Upper 95% CI
	O_3	**24 hr**	–0.017	0.007	–2.317	**0.021***	0.983	0.969	0.997
		48 hr	–0.020	0.008	–2.465	**0.014***	0.980	0.964	0.996
		72 hr	–0.021	0.008	–2.462	**0.014***	0.980	0.964	0.996
		96 hr	–0.024	0.009	–2.822	**0.005***	0.976	0.960	0.993
HighFBG	$PM_{2.5}$	**24 hr**	0.034	0.015	2.269	**0.023***	1.034	1.005	1.065
		48 hr	0.037	0.017	2.197	**0.028***	1.037	1.004	1.072
		72 hr	0.030	0.020	1.487	0.137	1.030	0.990	1.072
		96 hr	0.026	0.024	1.073	0.283	1.026	0.979	1.076
	PM_{10}	**24 hr**	0.008	0.003	2.294	**0.022***	1.008	1.001	1.014
		48 hr	0.008	0.004	2.011	**0.044***	1.008	1.000	1.016
		72 hr	0.008	0.005	1.661	0.097	1.008	0.998	1.018
		96 hr	0.009	0.006	1.466	0.143	1.009	0.997	1.021
	NO_2	24 hr	0.014	0.010	1.421	0.155	1.014	0.995	1.035
		48 hr	0.023	0.012	1.925	0.054	1.023	1.000	1.047
		72 hr	0.027	0.014	1.975	**0.048***	1.027	1.000	1.055
		96 hr	0.024	0.016	1.551	0.121	1.025	0.994	1.057
	O_3	24 hr	–0.008	0.008	–1.030	0.303	0.992	0.977	1.007
		48 hr	–0.014	0.008	–1.686	0.092	0.986	0.969	1.002
		72 hr	–0.017	0.009	–1.899	0.058	0.983	0.967	1.000
		96 hr	–0.015	0.009	–1.690	0.091	0.985	0.968	1.002
MetS	$PM_{2.5}$	24 hr	0.022	0.015	1.422	0.155	1.022	0.992	1.053
		48 hr	0.029	0.017	1.692	0.091	1.030	0.996	1.066
		72 hr	0.037	0.021	1.772	0.076	1.037	0.997	1.081
		96 hr	0.049	0.024	2.025	**0.043***	1.051	1.002	1.103
	PM_{10}	24 hr	0.003	0.003	0.922	0.357	1.003	0.997	1.010
		48 hr	0.003	0.004	0.746	0.456	1.003	0.995	1.011
		72 hr	0.003	0.005	0.692	0.489	1.003	0.994	1.013
		96 hr	0.005	0.006	0.883	0.377	1.005	0.994	1.017
	NO_2	24 hr	0.019	0.010	1.888	0.059	1.019	0.999	1.039
		48 hr	0.027	0.012	2.305	**0.021***	1.027	1.004	1.051
		72 hr	0.039	0.014	2.877	**0.004***	1.040	1.013	1.068
		96 hr	0.054	0.016	3.475	**0.001***	1.056	1.024	1.089
	O_3	**24 hr**	–0.018	0.007	–2.470	**0.014***	0.982	0.968	0.996
		48 hr	–0.025	0.008	–3.010	**0.003***	0.975	0.960	0.991
		72 hr	–0.026	0.008	–3.008	**0.003***	0.975	0.959	0.991
		96 hr	–0.027	0.009	–3.079	**0.002***	0.974	0.957	0.990

*All significant pollutant time exposures and corresponding p-values are expressed in bold.

Note: CI means confidence interval.

The likelihood of having high glucose was associated with increased PM concentrations: 1.034 and 1.037 times higher odds of having high glucose per a one-unit increase in 24- and 48-hr $PM_{2.5}$, respectively (p-values < 0.05). A one-unit increase in both 24- and 48-hr PM_{10} results in 1.008 times higher odds of being high glucose (p-values < 0.05). The 72-hr NO_2 concentration was also a significant factor in prediction of the high-glucose status, showing an increased likelihood of having high glucose as NO_2 increases (odds ratio = 1.027; p-value = 0.048).

The MetS classification based on the combination of five risk factors showed significant associations with $PM_{2.5}$, NO_2, and O_3. More precisely, the odds of having MetS is 1.051 times higher with a unit increase in 96-hr $PM_{2.5}$ (p-value = 0.043). The associations of MetS classification with NO_2 concentrations are also positive, showing the increased odds ratio of 1.027 (p-value = 0.021), 1.040 (p-value = 0.004), and 1.056 (p-value = 0.001) for 48-, 72-, and 96-hr exposure windows, respectively. However, the increased O_3 was correlated with a decreased likelihood of having MetS (p-values < 0.05 for all time exposures).

Long-Term Effects of Transportation Data on Cardiorespiratory Outcomes

Demographics

Using the full dataset, which contains data from participants from the last five and a half years (September 2014 to January 2020), researchers identified 4,959 participants with an age range of 18 to 94 years old (an average of 45.5 years old). Most of the participants were female (79.5 percent) and Hispanic (95.5 percent), and 54.8 percent of participants were overweight (23.9 percent) or obese (30.9 percent), whereas 13.7 percent of participants were not overweight. Table 12 shows summary statistics of subject demographic information and health characteristics.

Table 12. Demographic Information for Subjects (N=4,959)

Characteristic		Frequency	Percent
Sex	Female	3,941	79.5
	Male	954	19.2
	NA	64	1.3
Education	Middle school	896	18.1
	High school graduate	832	16.8
	High school, no diploma	723	14.6
	Elementary school	680	13.7
	Some college, not completed	636	12.8
	Bachelor's degree	532	10.7
	Associate degree	319	6.4
	Masters, doctoral, or professional degree	119	2.4
	Never attended or kindergarten only	72	1.5
	NA	150	3.0
Language	Spanish	3,408	68.7
	Both	1,050	21.2
	English	396	8.0
	Other	8	0.2
	NA	97	2.0
Employed	Homemaker	1,606	32.4
	Employed part time	1,025	20.7
	Employed full time	795	16.0
	Student	313	6.3
	Retired	290	5.8
	Not employed for more than 1 year	232	4.7
	Not employed for less than 1 year	228	4.6
	Self-employed	197	4.0
	Unable to work	126	2.5
	Seasonal worker	17	0.3
	NA	129	2.6

Characteristic		Frequency	Percent
Income	$0–$19,999	3,532	71.2
	$20,000–$29,999	603	12.2
	$30,000–$39,999	237	4.8
	$50,000–$69,999	142	2.9
	$40,000–$49,999	133	2.7
	$70,000–$99,999	62	1.3
	$100,000 or more	51	1.0
	NA	199	4.0
Marital status	Married	2,248	45.3
	Never married	905	18.2
	Divorced	453	9.1
	Separated	407	8.2
	Single/never married	313	6.3
	Widowed	313	6.3
	A member of an unmarried couple	148	3.0
	Civil union	70	1.4
	NA	102	2.1
Ethnicity	Hispanic	4,738	95.5
	Non-Hispanic	79	1.6
	White	41	0.8
	Black or African American	9	0.2
	Asian	4	0.1
	American Indian or Alaska Native	3	0.1
	Native Hawaiian	2	0.0
	Other	1	0.0
	NA	82	1.7
Race	White	3,302	66.6
	Black or African American	40	0.8
	American Indian or Alaska Native	16	0.3
	Asian	14	0.3
	Native Hawaiian	3	0.1
	NA	1,584	31.9
Health	Good	2,072	41.8
	Fair	1,457	29.4
	Very good	575	11.6
	Poor	400	8.1
	Excellent	339	6.8
	NA	116	2.3
Obesity	Obese	1,534	30.9
	Overweight	1,185	23.9
	Healthy	681	13.7
	NA	1,559	31.4

Traffic-Related Measurements

Table 13 summarizes the descriptive statistics of traffic-related measurements using the first-year subset of data (N=662). Distance to the nearest major arterial road (Dist_nearest_Majart), street length within the 500-m and 1,000-m impact zones (Street_Length_500m and Street_Length_1000m), and distance to the nearest POE (Distance_nearest_POE) are measured in kilometers. Due to the exponential decay of distance measurements, researchers also considered the inverse of distance to the nearest POE (InvDist_POE) and the inverse of the distance squared (InvSqDis_POE) as alternatives. Traffic counts were calculated from the average daily amount of VMT within the 500-m and 1,000-m zones of impact (Traffic_VMT_500m and Traffic_VMT_1000m) and converted to the unit in thousands.

Table 13. Descriptive Statistics of Traffic Variables (N=662; Unit: km, in Thousands)

Variable	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR	NA
Distance_nearest_Majart	0.00	0.09	0.20	0.24	0.32	2.26	0.22	0.23	3
Street_Length_500m	3.04	8.46	10.96	11.48	14.16	24.85	3.97	5.70	4
Street_Length_1000m	14.09	34.32	44.42	43.60	50.36	81.15	12.76	16.04	4
Distance_nearest_POE	0.25	2.16	6.60	6.85	11.15	25.36	5.12	8.99	3
InvDist_POE	0.04	0.09	0.15	0.35	0.46	4.05	0.42	0.37	3
InvSqDist_POE	0.00	0.01	0.02	0.29	0.21	16.44	1.09	0.21	3
Traffic_VMT_500m	0.00	13.82	21.98	26.56	33.57	152.94	21.99	19.75	3
Traffic_VMT_1000m	0.31	61.73	110.53	126.45	164.79	412.10	85.01	103.06	3

Figure 11 shows the scatterplot matrix for the pairs of traffic variables to explore the distribution of each variable and collinearity between variables. Based on the scatterplot, researchers decided to choose the impact zone with a 500-m radius to use multivariate regression models.

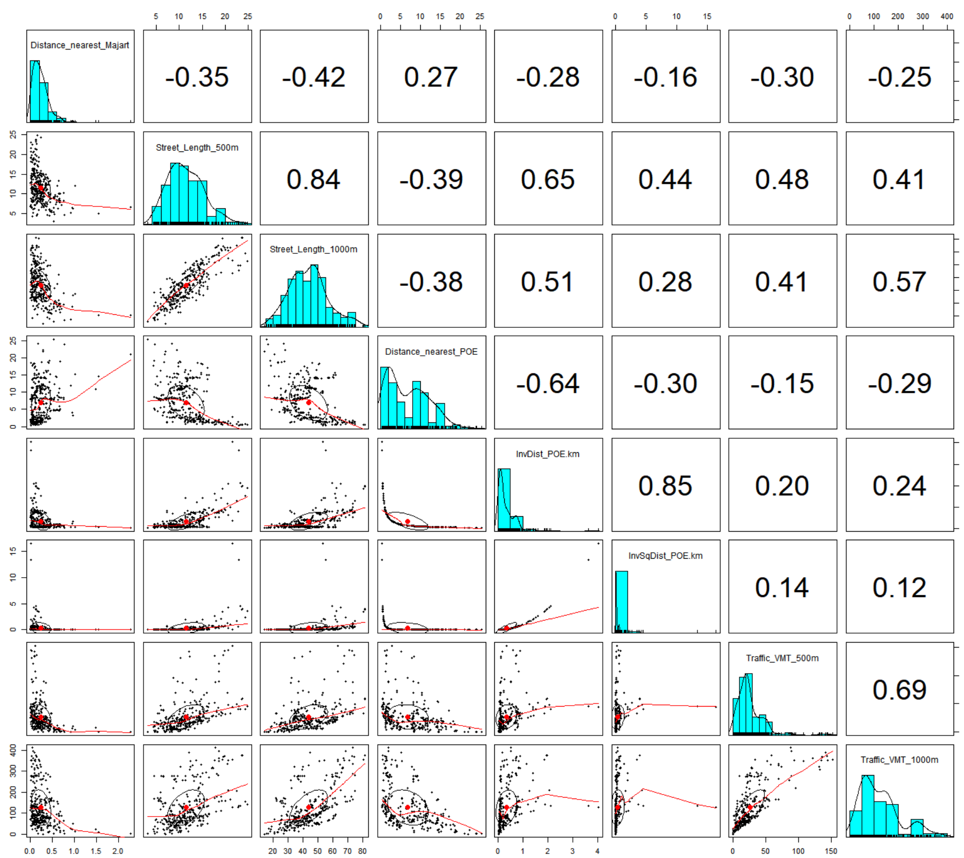

Figure 11. Scatterplot matrix of pairs of eight traffic variables (N=662).

Table 14 summarizes the descriptive statistics of traffic-related measurements for the whole study period (N=4,959). Figure 12 presents the scatterplot matrix for the pairs of traffic variables to explore the distribution of each variable and collinearity between variables. Based on the scatterplot, researchers decided to choose the impact zone with a 500-m radius to use in multivariate regression models.

Table 14. Descriptive Statistics of Traffic Variables (N=4,959; Unit: km, in Thousands)

Variable	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR	NA
Distance_nearest_Majart	0.00	0.10	0.22	0.33	0.43	3.35	0.34	0.32	152
Street_Length_500m	0.28	7.84	10.23	10.73	13.18	25.51	4.23	5.34	174
Street_Length_1000m	0.20	28.88	36.95	39.20	48.29	83.04	15.40	19.41	168
Distance_nearest_POE	0.16	3.39	8.62	9.48	13.81	37.58	7.00	10.42	152
InvDist_POE.km	0.03	0.07	0.12	0.28	0.29	6.15	0.46	0.22	152
InvSqDist_POE.km	0.00	0.01	0.01	0.29	0.09	37.78	1.70	0.08	152
Traffic_VMT_500m	0.00	6.92	15.49	23.34	27.69	178.54	27.47	20.77	319
Traffic_VMT_1000m	0.17	33.96	65.65	102.38	136.48	437.44	100.86	102.52	176

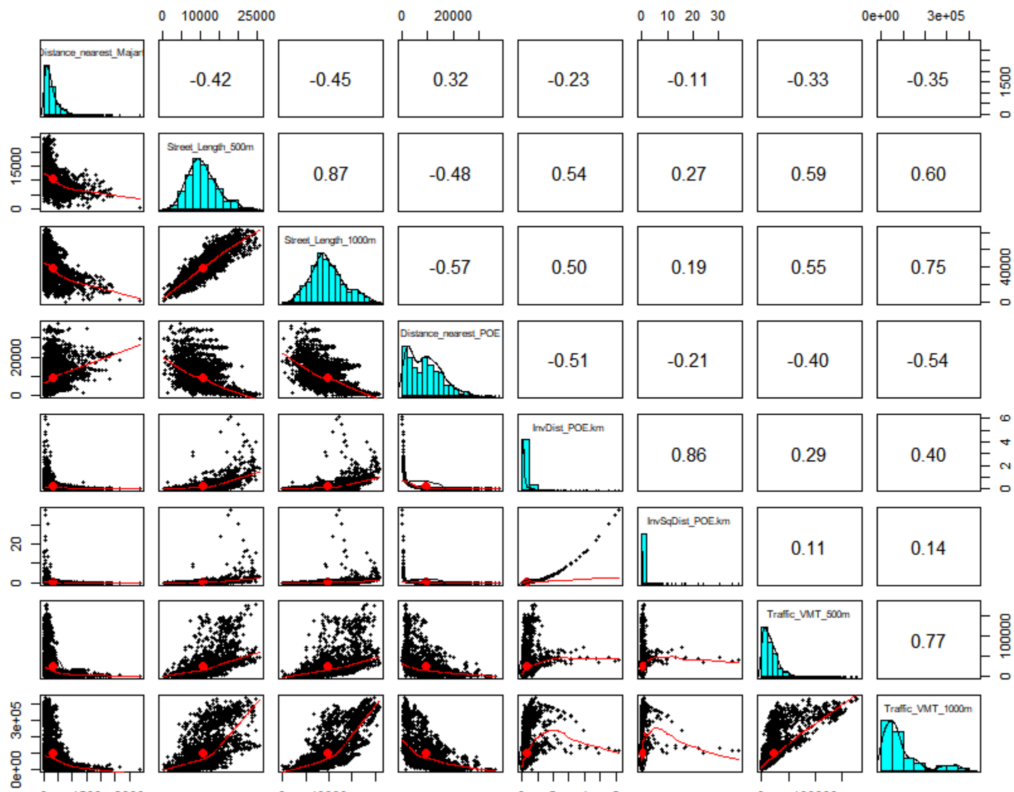

Figure 12. Scatterplot matrix of pairs of eight traffic variables (N=4,959).

Respiratory Associations Using First-Year Subset of Data

In the correlation analysis and univariate linear regression modeling, the length of the street and VMT have shown to be important traffic predictors to find relationships with lung function (see Table 15). Increases in the length of the street within the 500-m radius zone were associated with decreased lung function: $\beta_1 = -0.017$ for FEV_1 (p-value = 0.016), $\beta_1 = -0.017$ for FVC (p-value = 0.045), $\beta_1 = -0.049$ for PEF (p-value = 0.011), and $\beta_1 = -0.046$ for PEF Best (p-value = 0.021). The founding was similar in the relationships between FEV_1/FVC/PEF/PEF Best and street length within a bigger zone of a 1,000-m radius.

Table 15. Correlation Analysis between Respiratory Outcome and Traffic Variables (N=662)

Variable	Distance_ nearest_ Majart	Street_ Length_ 500m	Street_ Length_ 1000m	Distance_ nearest_ POE	InvDist_ POE	InvSqDist _POE	Traffic_ VMT_ 500m	Traffic_ VMT_ 1000m
log(eNO)	0.008	0.036	0.003	−0.052	0.025	−0.007	0.034	0.013
FEV_1	0.071	**−0.108***	**−0.108***	0.021	0.010	0.055	**−0.125***	−0.048
FVC	0.072	**−0.090***	**−0.091***	0.047	−0.014	0.032	**−0.116***	−0.051
PEF	**0.090***	**−0.114***	**−0.141***	−0.006	−0.006	0.027	**−0.097***	−0.017
FEV_1 %Pred	0.031	0.010	0.009	**−0.105***	**0.134***	**0.118***	−0.054	0.001
bc.FEV %Pred[1]	0.040	0.010	0.006	**−0.115***	**0.118***	**0.095***	−0.052	0.006
FVC %Pred	0.041	0.007	0.013	−0.077	**0.101***	**0.093***	−0.066	−0.009
log.FVC %Pred	0.038	0.006	0.012	−0.082	**0.088***	0.069	−0.062	−0.002
PEF %Pred	0.047	−0.046	−0.063	**−0.108***	0.075	0.065	−0.060	0.013
sqrt.PEF %Pred	0.053	−0.050	−0.066	**−0.112***	0.072	0.063	−0.053	0.024
FEV_1/FVC	−0.001	−0.024	−0.033	−0.086	0.066	0.061	−0.019	−0.001
$FEV_{0.5}$ Best	0.054	−0.079	−0.086	−0.014	0.041	0.070	**−0.116***	−0.037
FEV_1 Best	0.048	−0.079	−0.075	0.005	0.025	0.055	**−0.116***	−0.046
FVC Best	0.051	−0.068	−0.060	0.039	−0.006	0.027	**−0.100***	−0.043
PEF Best	0.064	**−0.103***	**−0.127***	−0.016	0.010	0.045	**−0.096***	−0.015

* All significant correlations are expressed in bold.

1. Box-cox transformation: bc.FEV1.%Pred = [(FEV1.%Pred)^(−0.1)−1]/(−0.1)

Traffic density within the 500-m impact zone was also negatively correlated with most of the spirometry measures: $\beta1 = -0.004$ for FEV_1 (p-value = 0.005), $\beta1 = -0.004$ for FVC (p-value = 0.010), $\beta1 = -0.008$ for PEF (p-value = 0.031), $\beta1 = -0.003$ for $FEV_{0.5}$ Best and FEV_1 Best (p-values = 0.010), $\beta1 = -0.004$ for FVC Best (p-value = 0.026), and $\beta1 = -0.008$ for PEF Best (p-value = 0.033). The traffic amount within the 1,000-m zone, in contrast, did not correlate with any respiratory measures. In addition to street length and VMT variables, distance to the nearest major road was another significant predictor, showing a positive correlation with PEF (ρ= 0.09, $\beta1 = 0.663$; p-value = 0.045).

For the LUR modeling as shown in Table 16, researchers applied multivariate linear regression including five traffic variables: distance to the nearest major arterial road, street length within the 500-m impact zone, distance to the nearest POE, inverse of the distance to the POE squared, and traffic VMT within the 500-m zone. As with findings from the univariate regression, street length within the 500-m zone was a significant traffic variable in modeling of PEF ($\beta1 = -0.056$, p-value = 0.026) and PEF Best ($\beta1 = -0.057$, p-value = 0.025). A measure of traffic volume (Traffic_VMT_500m) had negative associations with $FEV_{0.5}$ Best and FEV_1 Best, though it reported insignificant p-values < 0.1.

Table 16. Summary and Parameter Estimates of Multivariate Regression Models for Respiratory Outcomes (N=662)

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
log.eNO	(Intercept)	2.913	0.023	128.220	0.000
	Distance_nearest_Majart	0.043	0.139	0.308	0.758
	Street_Length_500m	0.003	0.008	0.368	0.713
	Distance_nearest_POE	−0.005	0.005	−1.124	0.261
	InvSqDist_POE	−0.014	0.022	−0.645	0.519
	Traffic_VMT_500m	0.001	0.001	0.525	0.599
FEV_1	(Intercept)	2.396	0.028	86.197	0.000
	Distance_nearest_Majart	0.110	0.134	0.820	0.413
	Street_Length_500m	−0.017	0.009	−1.843	0.066
	Distance_nearest_POE	0.000	0.006	−0.014	0.989
	InvSqDist_POE	0.059	0.026	2.302	**0.022***
	Traffic_VMT_500m	−0.002	0.001	−1.584	0.114
FVC	(Intercept)	2.642	0.033	80.533	0.000
	Distance_nearest_Majart	0.147	0.158	0.926	0.355
	Street_Length_500m	−0.012	0.011	−1.074	0.283
	Distance_nearest_POE	0.004	0.007	0.614	0.540
	InvSqDist_POE	0.050	0.030	1.665	0.097
	Traffic_VMT_500m	−0.003	0.002	−1.633	0.103
PEF	(Intercept)	5.279	0.075	69.972	0.000
	Distance_nearest_Majart	0.399	0.364	1.096	0.274
	Street_Length_500m	−0.056	0.025	−2.235	**0.026***
	Distance_nearest_POE	−0.015	0.016	−0.914	0.361
	InvSqDist_POE	0.113	0.070	1.623	0.105
	Traffic_VMT_500m	−0.003	0.004	−0.724	0.470
FEV_1%Pred	(Intercept)	96.021	1.370	70.071	0.000
	Distance_nearest_Majart	6.931	6.617	1.048	0.295
	Street_Length_500m	−0.250	0.452	−0.553	0.580
	Distance_nearest_POE	−0.611	0.290	−2.103	**0.036***
	InvSqDist_POE	2.997	1.265	2.369	**0.018***
	Traffic_VMT_500m	−0.076	0.072	−1.044	0.297
bc.FEV_1%Pred	(Intercept)	3.641	0.007	510.238	0.000
	Distance_nearest_Majart	0.044	0.034	1.285	0.199
	Street_Length_500m	−0.001	0.002	−0.394	0.693
	Distance_nearest_POE	−0.004	0.002	−2.476	**0.014***
	InvSqDist_POE	0.012	0.007	1.749	0.081
	Traffic_VMT_500m	0.000	0.000	−0.976	0.330
FVC %Pred	(Intercept)	84.733	1.093	77.489	0.000
	Distance_nearest_Majart	6.554	5.280	1.241	0.215
	Street_Length_500m	−0.034	0.361	−0.094	0.925
	Distance_nearest_POE	−0.362	0.232	−1.561	0.119
	InvSqDist_POE	1.869	1.009	1.852	0.065
	Traffic_VMT_500m	−0.078	0.058	−1.348	0.178

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
log.FVC %Pred	(Intercept)	4.407	0.011	391.189	0.000
	Distance_nearest_Majart	0.064	0.054	1.171	0.242
	Street_Length_500m	0.000	0.004	0.017	0.987
	Distance_nearest_POE	−0.004	0.002	−1.772	0.077
	InvSqDist_POE	0.013	0.010	1.243	0.214
	Traffic_VMT_500m	−0.001	0.001	−1.297	0.195
PEF %Pred	(Intercept)	95.949	1.204	79.693	0.000
	Distance_nearest_Majart	5.796	5.814	0.997	0.319
	Street_Length_500m	−0.652	0.397	−1.641	0.101
	Distance_nearest_POE	−0.700	0.255	−2.743	**0.006***
	InvSqDist_POE	1.770	1.111	1.593	0.112
	Traffic_VMT_500m	−0.035	0.064	−0.557	0.578
sqrt.PEF %Pred	(Intercept)	9.702	0.060	160.660	0.000
	Distance_nearest_Majart	0.338	0.292	1.160	0.247
	Street_Length_500m	−0.036	0.020	−1.812	0.071
	Distance_nearest_POE	−0.037	0.013	−2.915	**0.004***
	InvSqDist_POE	0.088	0.056	1.575	0.116
	Traffic_VMT_500m	−0.001	0.003	−0.303	0.762
FEV_1/FVC	(Intercept)	0.915	0.003	290.795	0.000
	Distance_nearest_Majart	−0.002	0.015	−0.137	0.891
	Street_Length_500m	−0.002	0.001	−1.518	0.130
	Distance_nearest_POE	−0.001	0.001	−1.966	**0.050***
	InvSqDist_POE	0.004	0.003	1.402	0.162
	Traffic_VMT_500m	0.000	0.000	0.035	0.972
$FEV_{0.5}$Best	(Intercept)	1.991	0.022	88.556	0.000
	Distance_nearest_Majart	0.064	0.109	0.592	0.554
	Street_Length_500m	−0.011	0.007	−1.499	0.134
	Distance_nearest_POE	−0.003	0.005	−0.586	0.558
	InvSqDist_POE	0.047	0.021	2.266	**0.024***
	Traffic_VMT_500m	−0.002	0.001	−1.683	0.093
FEV_1Best	(Intercept)	2.505	0.029	87.041	0.000
	Distance_nearest_Majart	0.064	0.139	0.461	0.645
	Street_Length_500m	−0.012	0.009	−1.269	0.205
	Distance_nearest_POE	−0.001	0.006	−0.166	0.868
	InvSqDist_POE	0.052	0.027	1.964	0.050
	Traffic_VMT_500m	−0.003	0.002	−1.765	0.078
FVCBest	(Intercept)	2.762	0.035	79.642	0.000
	Distance_nearest_Majart	0.100	0.167	0.595	0.552
	Street_Length_500m	−0.008	0.011	−0.680	0.497
	Distance_nearest_POE	0.004	0.007	0.570	0.569
	InvSqDist_POE	0.041	0.032	1.289	0.198
	Traffic_VMT_500m	−0.003	0.002	−1.549	0.122
PEFBest	(Intercept)	6.099	0.077	78.796	0.000
	Distance_nearest_Majart	0.220	0.374	0.588	0.557
	Street_Length_500m	−0.057	0.026	−2.241	**0.025***
	Distance_nearest_POE	−0.016	0.016	−0.945	0.345
	InvSqDist_POE	0.137	0.071	1.920	0.055
	Traffic_VMT_500m	−0.004	0.004	−0.868	0.386

*All significant predictors and corresponding p-values are expressed in bold.

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Correlation and univariate regression analyses showed that a few MetS risk factors were associated with the inverse distance and inverse squared distance to the nearest POE (see Table 17). The inverse of the distance to the nearest POE was associated with increases in fasting glucose and TG ($\rho = 0.153$, $\beta_1 = 17.124$, p-value < 0.001; $\rho = 0.081$, $\beta_1 = 22.351$, p-value = 0.039, respectively). The inverse of the distance squared to the POE also showed positive correlations with fasting glucose and TG ($\rho = 0.217$, $\beta_1 = 9.209$, p-value < 0.001; $\rho = 0.134$, $\beta_1 = 14.086$, p-value = 0.001, respectively), implying that the metabolic risk related to fasting glucose and TG decreases as subjects live farther away from the POE. BMI calculation and waist circumference are also health outcomes correlated with inverse squared distance to the POE ($\rho = 0.077$, $\beta_1 = 0.462$, p-value = 0.050; $\rho = 0.095$, $\beta_1 = 1.251$, p-value = 0.015, respectively). In particular, female waist circumference was associated with the street length for both impact zones ($\beta_1 = 0.313$, p-value = 0.047 for the 500-m zone; $\beta_1 = 0.108$, p-value = 0.024 for the 1,000-m zone), as well as the inverse squared distance to the POE ($\beta_1 = 2.187$, p-value = 0.007).

Table 17. Correlation Analysis (N=662)

Characteristic	Distance_ nearest_ Majart	Street_ Length_ 500m	Street_ Length_ 1000m	Distance_ nearest_ POE	InvDist_ POE	InvSqDist _POE	Traffic_ VMT_ 500m	Traffic_ VMT_ 1000m
BMI	0.063	0.031	0.042	0.014	0.046	**0.077***	−0.020	0.003
Waist	0.033	0.064	0.075	0.015	0.068	**0.095***	0.023	0.045
• Female	0.004	**0.085***	**0.096***	0.011	0.081	**0.115***	0.026	0.031
• Male	0.111	−0.043	−0.013	0.010	0.005	0.058	0.020	0.115
SBP	0.023	0.008	0.016	0.028	0.024	0.054	0.038	0.030
• SBP < 130	0.086	−0.079	−0.091	**0.102***	−0.053	−0.010	−0.016	−0.019
• SBP ≥130	0.107	−0.073	−0.085	0.024	−0.024	−0.012	−0.004	−0.027
DBP	0.007	0.005	0.015	0.069	0.015	0.044	0.048	0.018
• DBP < 85	−0.060	−0.048	−0.017	0.051	−0.022	0.010	0.039	0.003
• DBP ≥ 85	0.016	0.122	0.070	0.003	0.031	−0.026	0.087	−0.028
PBP	0.028	0.007	0.012	−0.014	0.023	0.042	0.017	0.028
TC	0.053	−0.035	−0.069	−0.017	0.024	0.070	−0.018	−0.046
TG	**0.078***	0.056	−0.015	0.025	**0.081***	**0.134***	−0.030	**−0.080***
log.TG	**0.087***	0.049	−0.003	0.036	0.053	**0.100***	−0.033	−0.069
HDL	0.004	−0.032	−0.020	−0.026	−0.024	−0.033	−0.028	0.009
LDL	0.013	−0.039	−0.061	−0.032	−0.035	−0.057	0.030	−0.017
TC/HDL	0.015	0.012	0.003	0.006	0.031	0.071	0.016	−0.035
log.TC/HDL	0.042	0.015	−0.003	0.013	0.024	0.060	0.017	−0.031
bc.TC/HDL[1]	0.053	0.013	−0.006	0.014	0.018	0.049	0.013	−0.027
FBG	−0.036	0.074	0.054	−0.039	**0.153***	**0.217***	0.010	0.006
log.FBG	−0.024	0.059	0.058	−0.053	**0.127***	**0.166***	0.003	0.023
bc.FBG[2]	−0.006	0.040	0.068	−0.059	**0.084***	**0.095***	−0.004	0.045

* All significant correlations are expressed in bold.

1. Box-cox transformation: bc.TC/HDL = [(TC/HDL)^(−0.5) −1]/(−0.5).

2. Box-cox transformation: bc.FBG = [FBG^(−2) −1]/(−2).

Separate logistic regression models were run for each traffic variable of interest to evaluate the binary outcome of the MetS factors. Table 18 summarizes the associations between the classification of MetS factors and traffic variables. The logistic regression models showed that the street length within the 1,000-m impact zone was also a significant factor related to a higher risk of high BP (odds ratio = 1.013, p-value = 0.048). The increase in the length of the street within the 1,000-m zone was also associated with the risk of high SBP_1 (odds ratio = 1.014, *p*-value = 0.030), and the high value in SBP_1 may play a role in determining high BP.

Table 18. Univariate Associations between MetS Risk Factors and MetS Classification and Traffic Variables (N=662)

Y	Traffic Variable	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI	Upper 95% CI
HighWaist	Distance_nearest_Majart	−0.220	0.364	−0.605	0.545	0.802	0.391	1.663
	Street_Length_500m	0.009	0.021	0.422	0.673	1.009	0.969	1.051
	Street_Length_1000m	0.007	0.006	1.115	0.265	1.007	0.995	1.020
	Distance_nearest_POE	0.017	0.016	1.031	0.303	1.017	0.985	1.050
	InvDist_POE.km	−0.042	0.193	−0.217	0.828	0.959	0.658	1.417
	InvSqDist_POE.km	0.012	0.076	0.162	0.871	1.012	0.877	1.202
	Traffic_VMT_500m	0.000	0.004	0.054	0.957	1.000	0.993	1.008
	Traffic_VMT_1000m	0.001	0.001	0.844	0.398	1.001	0.999	1.003
HighBP	Distance_nearest_Majart	−0.449	0.385	−1.166	0.244	0.638	0.290	1.326
	Street_Length_500m	0.030	0.020	1.495	0.135	1.031	0.991	1.073
	Street_Length_1000m	0.013	0.006	1.977	**0.048***	1.013	1.000	1.025
	Distance_nearest_POE	0.004	0.016	0.266	0.790	1.004	0.974	1.035
	InvDist_POE.km	0.228	0.193	1.182	0.237	1.256	0.862	1.852
	InvSqDist_POE.km	0.146	0.093	1.567	0.117	1.157	0.988	1.445
	Traffic_VMT_500m	0.005	0.004	1.301	0.193	1.005	0.998	1.012
	Traffic_VMT_1000m	0.001	0.001	1.103	0.270	1.001	0.999	1.003
HighTC	Distance_nearest_Majart	0.612	0.394	1.552	0.121	1.843	0.854	4.058
	Street_Length_500m	−0.036	0.021	−1.716	0.086	0.965	0.926	1.005
	Street_Length_1000m	−0.016	0.007	−2.405	**0.016***	0.984	0.972	0.997
	Distance_nearest_POE	0.007	0.016	0.454	0.650	1.007	0.976	1.039
	InvDist_POE.km	0.040	0.194	0.206	0.837	1.041	0.704	1.517
	InvSqDist_POE.km	0.088	0.076	1.159	0.246	1.092	0.945	1.295
	Traffic_VMT_500m	−0.003	0.004	−0.910	0.363	0.997	0.989	1.004
	Traffic_VMT_1000m	−0.002	0.001	−2.196	**0.028***	0.998	0.996	1.000
HighTG	**Distance_nearest_Majart**	0.919	0.424	2.168	**0.030***	2.507	1.124	5.931
	Street_Length_500m	0.015	0.020	0.762	0.446	1.015	0.976	1.056
	Street_Length_1000m	0.000	0.006	−0.014	0.989	1.000	0.988	1.012
	Distance_nearest_POE	0.021	0.016	1.327	0.185	1.021	0.990	1.053
	InvDist_POE.km	0.107	0.193	0.558	0.577	1.113	0.767	1.646
	InvSqDist_POE.km	0.149	0.106	1.403	0.161	1.161	0.978	1.503
	Traffic_VMT_500m	−0.003	0.004	−0.929	0.353	0.997	0.990	1.004
	Traffic_VMT_1000m	−0.001	0.001	−1.423	0.155	0.999	0.997	1.000
LowHDL	Distance_nearest_Majart	0.055	0.386	0.143	0.886	1.057	0.494	2.276
	Street_Length_500m	0.025	0.020	1.226	0.220	1.025	0.985	1.067
	Street_Length_1000m	0.009	0.006	1.489	0.137	1.009	0.997	1.022
	Distance_nearest_POE	0.009	0.016	0.581	0.561	1.009	0.979	1.041
	InvDist_POE.km	0.123	0.191	0.643	0.520	1.131	0.779	1.664
	InvSqDist_POE.km	0.067	0.079	0.856	0.392	1.070	0.925	1.284
	Traffic_VMT_500m	0.002	0.004	0.640	0.522	1.002	0.995	1.009
	Traffic_VMT_1000m	0.000	0.001	0.389	0.697	1.000	0.999	1.002

Y	Traffic Variable	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI	Upper 95% CI
HighFBG	Distance_nearest_Majart	0.463	0.394	1.176	0.240	1.589	0.730	3.474
	Street_Length_500m	−0.001	0.021	−0.051	0.960	0.999	0.959	1.040
	Street_Length_1000m	0.002	0.006	0.348	0.728	1.002	0.990	1.015
	Distance_nearest_POE	−0.013	0.016	−0.799	0.424	0.987	0.956	1.019
	InvDist_POE.km	0.170	0.193	0.880	0.379	1.185	0.806	1.734
	InvSqDist_POE.km	0.078	0.074	1.056	0.291	1.081	0.935	1.273
	Traffic_VMT_500m	−0.003	0.004	−0.725	0.468	0.997	0.990	1.005
	Traffic_VMT_1000m	0.000	0.001	0.397	0.692	1.000	0.998	1.002
MetS	Distance_nearest_Majart	0.133	0.387	0.343	0.732	1.142	0.534	2.477
	Street_Length_500m	0.031	0.020	1.541	0.123	1.032	0.992	1.074
	Street_Length_1000m	0.010	0.006	1.629	0.103	1.010	0.998	1.023
	Distance_nearest_POE	0.011	0.016	0.726	0.468	1.011	0.981	1.043
	InvDist_POE.km	0.197	0.196	1.007	0.314	1.218	0.835	1.814
	InvSqDist_POE.km	0.158	0.106	1.488	0.137	1.171	0.986	1.514
	Traffic_VMT_500m	−0.001	0.004	−0.271	0.787	0.999	0.992	1.006
	Traffic_VMT_1000m	0.000	0.001	0.111	0.912	1.000	0.998	1.002

* All significant correlations are expressed in bold.

The LUR model included the five traffic-related variables within the 500-m impact zone in a multivariate regression model. The most significant predictor in the LUR models of MetS risk factors was the inverse squared distance to the nearest POE (see Table 19). The increase in the inverse of the distance squared to the POE, implying a decrease in the distance to the POE, was significantly associated with increases in waist circumference (β_1 = 1.216, p-value = 0.037; β_1 = 2.116, p-value = 0.026 for female), total cholesterol (β_1 = 3.689, p-value = 0.019), TG (β_1 = 15.063, p-value = 0.001), and fasting glucose (β_1 = 9.805, p-value < 0.001).

Table 19. Summary and Parameter Estimates of Multivariate Regression Models for Continuous MetS Risk Factors (N=662)

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
BMI	(Intercept)	30.579	0.258	118.571	0.000
	Distance_nearest_Majart	2.682	1.318	2.035	**0.042***
	Street_Length_500m	0.082	0.087	0.941	0.347
	Distance_nearest_POE	0.041	0.057	0.727	0.468
	InvSqDist_POE.km	0.492	0.266	1.847	0.065
	Traffic_VMT_500m	−0.008	0.014	−0.558	0.577
Waist	(Intercept)	95.510	0.563	169.567	0.000
	Distance_nearest_Majart	4.409	2.883	1.529	0.127
	Street_Length_500m	0.223	0.190	1.170	0.243
	Distance_nearest_POE	0.144	0.124	1.166	0.244
	InvSqDist_POE.km	1.216	0.582	2.087	**0.037***
	Traffic_VMT_500m	0.005	0.030	0.162	0.872
• Waist (female, N=559)	(Intercept)	94.806	0.603	157.111	0.000
	Distance_nearest_Majart	2.131	3.290	0.648	0.518
	Street_Length_500m	0.256	0.212	1.211	0.227
	Distance_nearest_POE	0.191	0.135	1.410	0.159
	InvSqDist_POE.km	2.116	0.948	2.233	**0.026***
	Traffic_VMT_500m	−0.004	0.031	−0.117	0.907

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
● Waist (male, N=103)	(Intercept)	99.403	1.502	66.195	0.000
	Distance_nearest_Majart	10.719	6.031	1.777	0.079
	Street_Length_500m	−0.326	0.471	−0.692	0.491
	Distance_nearest_POE	−0.087	0.318	−0.275	0.784
	InvSqDist_POE.km	0.775	0.815	0.950	0.344
	Traffic_VMT_500m	0.070	0.091	0.765	0.446
SBP	(Intercept)	127.671	0.816	156.374	0.000
	Distance_nearest_Majart	3.606	4.172	0.864	0.388
	Street_Length_500m	−0.126	0.276	−0.457	0.648
	Distance_nearest_POE	0.157	0.178	0.883	0.378
	InvSqDist_POE.km	1.391	0.836	1.664	0.097
	Traffic_VMT_500m	0.052	0.043	1.208	0.228
● SBP (<130, N=377)	(Intercept)	114.051	0.549	207.899	0.000
	Distance_nearest_Majart	2.820	2.841	0.993	0.322
	Street_Length_500m	−0.302	0.204	−1.479	0.140
	Distance_nearest_POE	0.212	0.125	1.692	0.092
	InvSqDist_POE.km	2.108	1.385	1.522	0.129
	Traffic_VMT_500m	0.030	0.036	0.848	0.397
● SBP (≥130, N=263)	(Intercept)	147.381	0.910	162.039	0.000
	Distance_nearest_Majart	7.348	4.596	1.599	0.111
	Street_Length_500m	−0.345	0.309	−1.118	0.265
	Distance_nearest_POE	−0.080	0.198	−0.404	0.687
	InvSqDist_POE.km	0.310	0.645	0.481	0.631
	Traffic_VMT_500m	0.032	0.039	0.805	0.422
DBP	(Intercept)	76.136	0.449	169.455	0.000
	Distance_nearest_Majart	0.364	2.296	0.159	0.874
	Street_Length_500m	−0.057	0.152	−0.378	0.706
	Distance_nearest_POE	0.198	0.098	2.026	**0.043***
	InvSqDist_POE.km	0.741	0.460	1.611	0.108
	Traffic_VMT_500m	0.032	0.024	1.356	0.176
● DBP (<85, N=509)	(Intercept)	71.994	0.350	205.512	0.000
	Distance_nearest_Majart	−3.725	1.943	−1.917	0.056
	Street_Length_500m	−0.250	0.122	−2.053	**0.041***
	Distance_nearest_POE	0.092	0.079	1.162	0.246
	InvSqDist_POE.km	0.651	0.524	1.241	0.215
	Traffic_VMT_500m	0.027	0.020	1.356	0.176
● DBP (≥85, N=131)	(Intercept)	92.411	0.668	138.441	0.000
	Distance_nearest_Majart	1.873	2.723	0.688	0.493
	Street_Length_500m	0.365	0.230	1.589	0.115
	Distance_nearest_POE	0.074	0.135	0.547	0.585
	InvSqDist_POE.km	−0.375	0.403	−0.930	0.354
	Traffic_VMT_500m	0.012	0.028	0.415	0.679
PBP	(Intercept)	51.535	0.575	89.652	0.000
	Distance_nearest_Majart	3.242	2.938	1.104	0.270
	Street_Length_500m	−0.069	0.194	−0.353	0.724
	Distance_nearest_POE	−0.041	0.125	−0.329	0.742
	InvSqDist_POE.km	0.650	0.589	1.104	0.270
	Traffic_VMT_500m	0.020	0.030	0.656	0.512

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
TC	(Intercept)	190.077	1.516	125.367	0.000
	Distance_nearest_Majart	9.553	8.363	1.142	0.254
	Street_Length_500m	−0.834	0.514	−1.622	0.105
	Distance_nearest_POE	−0.222	0.332	−0.670	0.503
	InvSqDist_POE.km	3.689	1.566	2.356	**0.019***
	Traffic_VMT_500m	0.037	0.080	0.465	0.642
TG	(Intercept)	186.352	4.443	41.944	0.000
	Distance_nearest_Majart	63.169	24.507	2.578	**0.010***
	Street_Length_500m	2.310	1.506	1.534	0.126
	Distance_nearest_POE	1.491	0.972	1.535	0.125
	InvSqDist_POE.km	15.063	4.589	3.282	**0.001***
	Traffic_VMT_500m	−0.243	0.235	−1.035	0.301
log.TG	(Intercept)	5.068	0.022	232.742	0.000
	Distance_nearest_Majart	0.328	0.120	2.729	**0.007***
	Street_Length_500m	0.013	0.007	1.789	0.074
	Distance_nearest_POE	0.008	0.005	1.595	0.111
	InvSqDist_POE.km	0.054	0.022	2.396	**0.017***
	Traffic_VMT_500m	−0.001	0.001	−1.056	0.291
HDL	(Intercept)	49.662	0.572	86.764	0.000
	Distance_nearest_Majart	−3.169	3.152	−1.005	0.315
	Street_Length_500m	−0.157	0.195	−0.807	0.420
	Distance_nearest_POE	−0.137	0.126	−1.091	0.276
	InvSqDist_POE.km	−0.414	0.588	−0.705	0.481
	Traffic_VMT_500m	−0.012	0.030	−0.404	0.686
LDL	(Intercept)	106.017	1.308	81.072	0.000
	Distance_nearest_Majart	2.814	7.747	0.363	0.717
	Street_Length_500m	−0.501	0.457	−1.096	0.274
	Distance_nearest_POE	−0.451	0.290	−1.557	0.120
	InvSqDist_POE.km	−2.582	2.113	−1.222	0.222
	Traffic_VMT_500m	0.091	0.069	1.329	0.184
TC/HDL	(Intercept)	4.171	0.068	61.072	0.000
	Distance_nearest_Majart	0.212	0.374	0.567	0.571
	Street_Length_500m	−0.010	0.023	−0.428	0.668
	Distance_nearest_POE	0.007	0.015	0.459	0.646
	InvSqDist_POE.km	0.134	0.070	1.929	0.054
	Traffic_VMT_500m	0.002	0.004	0.559	0.576
log.TC/HDL	(Intercept)	1.366	0.014	100.898	0.000
	Distance_nearest_Majart	0.096	0.074	1.298	0.195
	Street_Length_500m	0.000	0.005	−0.046	0.963
	Distance_nearest_POE	0.002	0.003	0.538	0.591
	InvSqDist_POE.km	0.023	0.014	1.634	0.103
	Traffic_VMT_500m	0.000	0.001	0.616	0.538
bc.TC/HDL	(Intercept)	0.976	0.007	145.985	0.000
	Distance_nearest_Majart	0.057	0.037	1.551	0.121
	Street_Length_500m	0.000	0.002	0.066	0.948
	Distance_nearest_POE	0.001	0.001	0.448	0.654
	InvSqDist_POE.km	0.009	0.007	1.358	0.175
	Traffic_VMT_500m	0.000	0.000	0.583	0.560

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
FBG	(Intercept)	108.802	1.789	60.832	0.000
	Distance_nearest_Majart	−3.955	9.866	−0.401	0.689
	Street_Length_500m	−0.199	0.606	−0.328	0.743
	Distance_nearest_POE	0.230	0.391	0.588	0.556
	InvSqDist_POE.km	9.805	1.847	5.307	**0.000***
	Traffic_VMT_500m	−0.030	0.095	−0.322	0.748
log.FBG	(Intercept)	4.635	0.011	405.152	0.000
	Distance_nearest_Majart	−0.013	0.063	−0.201	0.841
	Street_Length_500m	−0.001	0.004	−0.290	0.772
	Distance_nearest_POE	−0.001	0.003	−0.200	0.842
	InvSqDist_POE.km	0.046	0.012	3.891	**0.000***
	Traffic_VMT_500m	0.000	0.001	−0.364	0.716
bc.FBG	(Intercept)	0.500	0.000	652753	0.000
	Distance_nearest_Majart	0.000	0.000	0.061	0.951
	Street_Length_500m	0.000	0.000	−0.082	0.935
	Distance_nearest_POE	0.000	0.000	−0.884	0.377
	InvSqDist_POE.km	0.000	0.000	2.005	**0.045***
	Traffic_VMT_500m	0.000	0.000	−0.383	0.702

* All significant predictors and corresponding p-values are expressed in bold.

In logistic regression modeling, researchers also found that increasing the inverse distance squared to the POE was associated with an increased likelihood of high TC (odds ratio = 1.221; p-value = 0.055) (see Table 20). The LUR model was found to have a weak correlation between MetS classification and street length within the 500-m zone, which implies more likelihood of having MetS with increased street length around the residential area (odds ratio = 1.050, p-value = 0.082). However, as shown in the previous univariate models, the larger impact zone within the 1,000-m distance may be more appropriate than the 500-m zone when modeling the binary risk factors of MetS.

Table 20. Summary and Parameter Estimates of Multivariate Logistic Regression Model for Binary MetS Factors (N=662)

Y	Traffic Variable	Estimate	Std. Error	z value	p-value	Odds Ratio	Lower 95% CI	Upper 95% CI
HighWaist	(Intercept)	0.534	0.081	6.563	0.000	1.706	1.456	2.003
	Distance_nearest_Majart	−0.193	0.414	−0.467	0.641	0.824	0.367	1.900
	Street_Length_500m	0.021	0.028	0.745	0.456	1.021	0.967	1.078
	Distance_nearest_POE	0.026	0.018	1.416	0.157	1.026	0.990	1.064
	InvSqDist_POE	0.012	0.087	0.134	0.893	1.012	0.859	1.238
	Traffic_VMT_500m	−0.002	0.004	−0.359	0.719	0.998	0.990	1.007
HighBP	(Intercept)	−0.280	0.081	−3.478	0.001	0.756	0.645	0.885
	Distance_nearest_Majart	−0.253	0.418	−0.604	0.546	0.777	0.332	1.743
	Street_Length_500m	0.014	0.027	0.497	0.619	1.014	0.960	1.070
	Distance_nearest_POE	0.021	0.018	1.224	0.221	1.022	0.987	1.058
	InvSqDist_POE	0.138	0.108	1.285	0.199	1.148	0.960	1.504
	Traffic_VMT_500m	0.003	0.004	0.604	0.546	1.003	0.994	1.011

Y	Traffic Variable	Estimate	Std. Error	z value	p-value	Odds Ratio	Lower 95% CI	Upper 95% CI
HighTC	(Intercept)	−0.518	0.082	−6.337	0.000	0.596	0.507	0.699
	Distance_nearest_Majart	0.358	0.443	0.809	0.419	1.430	0.599	3.457
	Street_Length_500m	−0.057	0.028	−2.034	**0.042***	0.944	0.893	0.998
	Distance_nearest_POE	−0.001	0.018	−0.033	0.974	0.999	0.965	1.035
	InvSqDist_POE	0.200	0.104	1.916	0.055	1.221	1.023	1.577
	Traffic_VMT_500m	0.001	0.004	0.306	0.760	1.001	0.993	1.010
HighTG	(Intercept)	0.237	0.081	2.933	0.003	1.267	1.082	1.485
	Distance_nearest_Majart	1.296	0.499	2.598	**0.009***	3.653	1.416	9.979
	Street_Length_500m	0.044	0.028	1.553	0.121	1.045	0.988	1.104
	Distance_nearest_POE	0.033	0.018	1.829	0.067	1.033	0.998	1.071
	InvSqDist_POE	0.204	0.150	1.362	0.173	1.226	0.982	1.785
	Traffic_VMT_500m	−0.004	0.004	−0.956	0.339	0.996	0.988	1.004
LowHDL	(Intercept)	0.046	0.079	0.584	0.559	1.047	0.897	1.224
	Distance_nearest_Majart	0.332	0.443	0.749	0.454	1.393	0.590	3.391
	Street_Length_500m	0.033	0.027	1.218	0.223	1.034	0.980	1.090
	Distance_nearest_POE	0.020	0.017	1.132	0.258	1.020	0.986	1.056
	InvSqDist_POE	0.049	0.088	0.556	0.578	1.050	0.891	1.293
	Traffic_VMT_500m	0.001	0.004	0.138	0.891	1.001	0.992	1.009
HighFBG	(Intercept)	−0.603	0.082	−7.328	0.000	0.547	0.465	0.642
	Distance_nearest_Majart	0.431	0.446	0.966	0.334	1.539	0.636	3.727
	Street_Length_500m	−0.007	0.028	−0.255	0.799	0.993	0.940	1.049
	Distance_nearest_POE	−0.016	0.018	−0.858	0.391	0.985	0.950	1.020
	InvSqDist_POE	0.088	0.084	1.045	0.296	1.092	0.927	1.321
	Traffic_VMT_500m	−0.002	0.004	−0.416	0.677	0.998	0.989	1.007
MetS	(Intercept)	0.092	0.080	1.150	0.250	1.096	0.937	1.283
	Distance_nearest_Majart	0.383	0.449	0.853	0.394	1.466	0.617	3.623
	Street_Length_500m	0.048	0.028	1.739	0.082	1.050	0.994	1.109
	Distance_nearest_POE	0.029	0.018	1.614	0.106	1.029	0.994	1.066
	InvSqDist_POE	0.142	0.123	1.150	0.250	1.152	0.949	1.583
	Traffic_VMT_500m	−0.004	0.004	−0.980	0.327	0.996	0.988	1.004

* All significant predictors and corresponding p-values are expressed in bold.

Cardiovascular Associations Using Five-Year Data

Table 21 summarizes descriptive statistics for cardiovascular risk measurements (MetS) using the five-year dataset (N=4.959). Waist circumference ranged from 56 to 154 cm with an average of 95 cm. Blood pressure (SBP/DBP) measurements ranged from 71/35 to 232/151 mmHg with an average of 123/76 mmHg. TG levels ranged from 45 to 650 mg/dL with an average of 186 mg/dL. HDL cholesterol ranged from 15 to 100 mg/dL with an average of 48.5 mg/dL. Glucose levels ranged from 50 to 500 mg/dL with an average of 113 mg/dL. Other variables of interest of cardiovascular risk that are not a component of MetS but could potentially offer more information related to cardiovascular risk included BMI, PBP, TC, and LDL cholesterol.

Table 21. Descriptive Statistics for MetS Risk Factors (N=4,959)

Characteristic	Min.	Q1	Median	Mean	Q3	Max.	SD	IQR	NA
BMI (kg/m^2)	15.318	25.748	29.149	29.942	33.218	67.650	6.136	7.470	1,538
Waist (cm)	56.000	84.000	93.000	93.953	103.000	154.000	14.559	19.000	1038
SBP (mmHg)	71.000	110.000	121.000	123.183	134.000	232.000	19.266	24.000	776
DBP (mmHg)	35.000	69.000	75.000	76.400	83.000	151.000	11.438	14.000	776
PBP (mmHg)	3.000	37.000	45.000	46.783	54.000	133.000	14.103	17.000	776
TC (mg/dL)	100.000	160.000	186.000	189.646	214.000	500.010	41.868	54.000	1,349
TG (mg/dL)	44.900	110.000	164.000	186.642	233.000	650.100	108.203	123.000	1,324
HDL (mg/dL)	14.900	38.000	47.000	48.555	57.000	100.100	15.319	19.000	1,365
LDL (mg/dL)	14.000	81.000	102.000	105.278	127.000	314.000	34.746	46.000	1,621
TC/HDL	1.400	3.100	3.900	4.254	5.000	15.500	1.647	1.900	1,441
FBG (mg/dL)	49.900	90.000	99.000	113.795	116.000	500.010	48.971	26.000	1,336

As Table 22 shows, linear relationships were found between traffic variables and a few MetS risk factors. Waist measurement significantly correlated with the street length within the 500-m area ($\rho = 0.045$, $\beta_1 = 0.155$), inverse of the distance to the nearest POE ($\rho = 0.046$, $\beta_1 = 1.426$), and inverse squared distance ($\rho = 0.033$, $\beta_1 = 0.270$). BP monitoring showed that traffic variables were more associated with PBP, rather than SBP or DBP. The PBP increases related to an increase in street length within the 500- and 1,000-m zones ($\rho = 0.035$, $\beta_1 = 0.115$; $\rho = 0.050$, $\beta_1 = 0.046$, respectively), decrease in the distance to the nearest POE ($\rho = -0.059$, $\beta_1 = -0.118$), rise in the inverse of the distance to the POE ($\rho = 0.040$, $\beta_1 = 1.227$), and increase in traffic amount within 500 and 1,000 m ($\rho = 0.051$, $\beta_1 = 0.026$; $\rho = 0.055$, $\beta_1 = 0.008$, respectively). Log-transformed and box-cox transformed glucose levels showed similar correlation results.

Log-transformed TG was significantly associated with the street length within the 500-m zone ($\beta_1 = 0.005$, p-value = 0.036). The fasting glucose showed significant relationships with the POE-related distance variables: negative association with the distance to the nearest POE ($\rho = -0.036$, $\beta_1 = -0.257$), and positive associations with the inverse of the distance ($\rho = 0.064$, $\beta_1 = 6.723$) and the inverse of the distance squared ($\rho = 0.051$, $\beta_1 = 1.380$).

Table 23 summarizes the frequency of the five MetS risk factors (binary outcomes) and the MetS classification. Researchers also included the classification of high cholesterol. The univariate associations between the binary classification of MetS risk factors and traffic variables were examined using logistic regression modeling (see Table 24). The risk of low HDL cholesterol was found to be higher as the street length within the impact zone (odds ratio = 1.023, p-value = 0.006 for the 500-m zone) and the inverse distance to the POE increase (odds ratio = 1.212, p-value = 0.012) get larger. The effect of street length is more substantial for the smaller region, that is, the 500-m zone, than for the 1,000-m zone. The street length within the 500-m impact zone was also an important factor correlated with a higher risk of MetS (odds ratio = 1.020, 95% CI = [1.003, 1.037]). Increase in the inverse distance to the nearest POE, implying a decrease in the distance to the POE, related to the higher risk in MetS ($\beta_1 = 0.192$, p-value = 0.012).

Table 22. Correlation Analysis (N=4,959)

Characteristic	Distance_ nearest_ Majart	Street_ Length_ 500m	Street_ Length_ 1000m	Distance_ nearest_ POE	InvDist_ POE	InvSqDist _POE	Traffic_ VMT_ 500m	Traffic_ VMT_ 1000m
BMI	0.022	0.005	−0.010	**0.039***	−0.002	0.000	**−0.043***	**−0.042***
Waist	−0.001	**0.045***	0.031	−0.002	**0.046***	**0.033***	0.002	0.006
• Female	−0.004	**0.059***	**0.046***	−0.009	**0.054***	0.024	0.013	0.017
• Male	0.045	−0.018	−0.054	0.065	−0.001	0.028	−0.050	−0.062
SBP	0.012	0.008	0.018	**−0.031***	0.018	0.013	0.028	0.021
• SBP < 130	**0.041***	−0.021	−0.015	0.029	−0.011	0.012	0.006	−0.007
• SBP ≥ 130	0.031	−0.001	−0.001	−0.022	0.033	0.031	0.041	0.020
DBP	0.022	−0.029	**−0.032***	0.020	−0.020	−0.006	−0.016	**−0.033***
• DBP < 85	0.021	−0.025	−0.025	0.027	**−0.040***	−0.022	0.010	−0.020
• DBP ≥ 85	−0.033	0.030	0.009	0.008	0.013	−0.010	−0.004	−0.018
PBP	−0.002	**0.035***	**0.050***	**−0.059***	**0.040***	0.023	**0.051***	**0.055***
TC	**0.036***	−0.026	**−0.040***	0.022	−0.015	0.002	−0.012	−0.031
TG	0.012	0.028	0.006	−0.010	0.023	0.017	0.014	−0.019
log.TG	0.013	**0.035***	0.009	−0.007	0.025	0.019	0.011	−0.027
HDL	0.016	**−0.046***	**−0.046***	0.001	**−0.041***	−0.027	−0.025	−0.021
LDL	0.023	−0.026	−0.032	0.026	−0.024	−0.007	−0.011	−0.020
TC/HDL	0.013	0.011	0.000	0.012	0.013	0.018	0.021	−0.003
log.TC/HDL	0.011	0.019	0.009	0.010	0.020	0.024	0.021	−0.003
bc.TC/HDL[1]	0.010	0.021	0.013	0.010	0.022	0.025	0.020	−0.004
FBG	0.003	0.032	0.021	**−0.036***	**0.064***	**0.051***	0.018	0.006
log.FBG	0.001	**0.037***	0.023	**−0.035***	**0.066***	**0.049***	0.017	0.004
bc.FBG[2]	0.001	**0.043***	0.025	−0.031	**0.061***	**0.040***	0.016	0.001

* All significant correlations are expressed in bold.

1. Box-cox transformation: bc.TC/HDL = [(TC/HDL)^(−0.5)−1]/(−0.5).

2. Box-cox transformation: bc.FBG = [FBG^(−2)−1]/(−2).

Table 23. Summary of MetS Risk Factors (N=4,959)

Variable	Value	Frequency	Percent
HighWaist	1	2,307	46.5
	0	1,603	32.3
	NA	1,049	21.2
HighBP	0	2,561	51.6
	1	1,622	32.7
	NA	776	15.6
HighTC	0	2,247	45.3
	1	1,363	27.5
	NA	1,349	27.2
HighTG	1	2,047	41.3
	0	1,588	32.0
	NA	1,324	26.7
LowHDL	1	1,835	37.0
	0	1,750	35.3
	NA	1,374	27.7

Variable	Value	Frequency	Percent
HighFBG	0	1,827	36.8
	1	1,795	36.2
	NA	1,337	27.0
MetS	1	1,851	37.3
	0	1,626	32.8
	NA	1,482	29.9

Table 24. Univariate Associations between MetS Risk Factors and MetS Classification and Traffic Variables (N=4,959)

Y	Traffic Variable	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI	Upper 95% CI
HighWaist	Distance_nearest_Majart	−0.012	0.095	−0.129	0.898	0.988	0.820	1.192
	Street_Length_500m	0.010	0.008	1.276	0.202	1.010	0.995	1.026
	Street_Length_1000m	0.000	0.002	−0.065	0.948	1.000	0.996	1.004
	Distance_nearest_POE	0.009	0.005	1.834	0.067	1.009	0.999	1.018
	InvDist_POE.km	0.014	0.070	0.204	0.838	1.014	0.885	1.166
	InvSqDist_POE.km	0.000	0.019	−0.024	0.981	1.000	0.964	1.038
	Traffic_VMT_500m	0.000	0.001	−0.319	0.750	1.000	0.997	1.002
	Traffic_VMT_1000m	0.000	0.000	−1.370	0.171	1.000	0.999	1.000
HighBP	Distance_nearest_Majart	0.005	0.093	0.051	0.959	1.005	0.836	1.205
	Street_Length_500m	0.002	0.008	0.225	0.822	1.002	0.987	1.017
	Street_Length_1000m	0.002	0.002	0.733	0.463	1.002	0.997	1.006
	Distance_nearest_POE	−0.008	0.005	−1.706	0.088	0.992	0.983	1.001
	InvDist_POE.km	0.038	0.068	0.550	0.583	1.038	0.907	1.186
	InvSqDist_POE.km	−0.001	0.019	−0.027	0.978	0.999	0.962	1.036
	Traffic_VMT_500m	0.000	0.001	0.380	0.704	1.000	0.998	1.003
	Traffic_VMT_1000m	0.000	0.000	0.341	0.733	1.000	0.999	1.001
HighTC	Distance_nearest_Majart	0.146	0.102	1.429	0.153	1.157	0.946	1.412
	Street_Length_500m	−0.012	0.008	−1.413	0.158	0.988	0.972	1.005
	Street_Length_1000m	−0.004	0.002	−1.516	0.130	0.996	0.992	1.001
	Distance_nearest_POE	0.006	0.005	1.223	0.221	1.006	0.996	1.016
	InvDist_POE.km	0.011	0.075	0.148	0.882	1.011	0.871	1.169
	InvSqDist_POE.km	0.019	0.019	0.998	0.318	1.019	0.981	1.058
	Traffic_VMT_500m	−0.001	0.001	−0.532	0.595	0.999	0.997	1.002
	Traffic_VMT_1000m	0.000	0.000	−1.035	0.301	1.000	0.999	1.000
HighTG	Distance_nearest_Majart	0.090	0.101	0.894	0.371	1.094	0.899	1.336
	Street_Length_500m	0.011	0.008	1.297	0.195	1.011	0.995	1.027
	Street_Length_1000m	0.001	0.002	0.621	0.534	1.001	0.997	1.006
	Distance_nearest_POE	0.002	0.005	0.467	0.640	1.002	0.993	1.012
	InvDist_POE.km	0.034	0.073	0.468	0.640	1.035	0.898	1.197
	InvSqDist_POE.km	0.004	0.019	0.216	0.829	1.004	0.968	1.044
	Traffic_VMT_500m	0.000	0.001	−0.104	0.917	1.000	0.997	1.002
	Traffic_VMT_1000m	−0.001	0.000	−1.612	0.107	0.999	0.999	1.000

Y	Traffic Variable	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI	Upper 95% CI
LowHDL	Distance_nearest_Majart	0.002	0.100	0.022	0.982	1.002	0.823	1.221
	Street_Length_500m	0.023	0.008	2.756	**0.006***	1.023	1.007	1.039
	Street_Length_1000m	0.006	0.002	2.696	**0.007***	1.006	1.002	1.011
	Distance_nearest_POE	0.001	0.005	0.244	0.808	1.001	0.992	1.011
	InvDist_POE.km	0.192	0.076	2.523	**0.012***	1.212	1.047	1.413
	InvSqDist_POE.km	0.037	0.021	1.787	0.074	1.038	0.999	1.085
	Traffic_VMT_500m	0.002	0.001	1.248	0.212	1.002	0.999	1.004
	Traffic_VMT_1000m	0.000	0.000	1.152	0.249	1.000	1.000	1.001
HighFBG	Distance_nearest_Majart	0.033	0.100	0.329	0.742	1.033	0.849	1.257
	Street_Length_500m	0.004	0.008	0.478	0.633	1.004	0.988	1.020
	Street_Length_1000m	−0.001	0.002	−0.622	0.534	0.999	0.994	1.003
	Distance_nearest_POE	0.004	0.005	0.866	0.387	1.004	0.995	1.014
	InvDist_POE.km	0.136	0.074	1.843	0.065	1.145	0.993	1.327
	InvSqDist_POE.km	0.025	0.020	1.285	0.199	1.025	0.988	1.068
	Traffic_VMT_500m	0.000	0.001	−0.247	0.805	1.000	0.997	1.002
	Traffic_VMT_1000m	−0.001	0.000	−1.586	0.113	0.999	0.999	1.000
MetS	Distance_nearest_Majart	−0.047	0.102	−0.460	0.645	0.954	0.781	1.166
	Street_Length_500m	0.020	0.008	2.368	**0.018***	1.020	1.003	1.037
	Street_Length_1000m	0.004	0.002	1.598	0.110	1.004	0.999	1.008
	Distance_nearest_POE	0.002	0.005	0.355	0.722	1.002	0.992	1.012
	InvDist_POE.km	0.150	0.076	1.964	**0.050***	1.162	1.003	1.355
	InvSqDist_POE.km	0.016	0.019	0.802	0.423	1.016	0.979	1.057
	Traffic_VMT_500m	0.000	0.001	−0.052	0.959	1.000	0.997	1.002
	Traffic_VMT_1000m	0.000	0.000	−0.802	0.422	1.000	0.999	1.000

* All significant correlations are expressed in bold.

Five traffic variables (i.e., distance to the nearest major arterial road, street length within the 500-m impact zone, distance to the nearest POE, inverse of the distance to the POE squared, and traffic VMT within the 500-m zone) were included in LUR modeling for multivariate analyses of the five-year data. As Table 25 shows, the most significant predictor in the LUR models was the total length of the street within a 500-m radius. The increase in the street length associated with increasing MetS factors, in particular BMI (β_1 = 0.110, p-value = 0.002), waist circumference (β_1 = 0.294, p-value < 0.001), log-transformed TG (β_1 = 0.007, p-value = 0.025), and box-cox transformed fasting glucose (β_1 = 2.218e-07, p-value = 0.049). However, the fasting glucose and log-transformed glucose showed positive relationships with the inverse squared distance to the POE (β_1 = 1.156, p-value = 0.015; β_1 = 0.007, p-value = 0.023, respectively). In the modeling of PBP, the increase in PBP was associated with an increase in the amount of traffic within a 500-m radius (β_1 = 0.021, p-value = 0.048) and the proximity to the nearest POE (β_1 = −0.095, p-value = 0.013). Researchers also found the effect of traffic volume within the 500-m zone on the DBP measurement for the participants whose DBP was less than 85 mmHg.

Logistic regression models, including the five traffic predictors, also showed the significance of the length of the street within the 500-m impact zone (see Table 26). As the total length of the street increases, the risks of a large waist circumference (β_1 = 0.034, p-value = 0.002), high TG (β_1 = 0.024, p-value = 0.034), and low HDL cholesterol (β_1 = 0.032, p-value = 0.004) were observed. The significance of the street length variable in predicting three MetS risk components may have influenced the prediction of MetS classification. The increasing likelihood of MetS was related to the increased street length within the impact zone (β_1 = 0.038, p-value = 0.001, odds ratio = 1.039 [1.016, 1.062]).

Table 25. Summary and Parameter Estimates of Multivariate Regression Models for Continuous MetS Risk Factors (N=4,959)

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
BMI	(Intercept)	29.961	0.108	277.530	0.000
	Distance_nearest_Majart	0.562	0.394	1.426	0.154
	Street_Length_500m	0.110	0.035	3.122	**0.002***
	Distance_nearest_POE	0.044	0.018	2.382	**0.017***
	InvSqDist_POE.km	0.002	0.061	0.040	0.968
	Traffic_VMT_500m	−0.013	0.005	−2.647	**0.008***
Waist	(Intercept)	93.875	0.241	389.725	0.000
	Distance_nearest_Majart	0.462	0.878	0.526	0.599
	Street_Length_500m	0.294	0.077	3.793	0.000
	Distance_nearest_POE	0.054	0.041	1.329	0.184
	InvSqDist_POE.km	0.176	0.140	1.255	0.210
	Traffic_VMT_500m	−0.020	0.011	−1.801	0.072
• Waist (female, N=3941)	(Intercept)	92.889	0.267	347.822	0.000
	Distance_nearest_Majart	0.322	0.953	0.338	0.736
	Street_Length_500m	0.351	0.086	4.097	**0.000***
	Distance_nearest_POE	0.049	0.045	1.099	0.272
	InvSqDist_POE.km	0.053	0.196	0.269	0.788
	Traffic_VMT_500m	−0.019	0.012	−1.548	0.122
• Waist (male, N=954)	(Intercept)	97.755	0.536	182.392	0.000
	Distance_nearest_Majart	2.616	2.139	1.223	0.222
	Street_Length_500m	0.190	0.178	1.065	0.287
	Distance_nearest_POE	0.173	0.098	1.762	0.079
	InvSqDist_POE.km	0.231	0.202	1.145	0.253
	Traffic_VMT_500m	−0.022	0.025	−0.886	0.376
SBP	(Intercept)	123.202	0.308	399.361	0.000
	Distance_nearest_Majart	1.804	1.122	1.608	0.108
	Street_Length_500m	−0.054	0.099	−0.542	0.588
	Distance_nearest_POE	−0.084	0.052	−1.610	0.107
	InvSqDist_POE.km	0.110	0.183	0.600	0.549
	Traffic_VMT_500m	0.021	0.014	1.518	0.129
• SBP (<130, N=2801)	(Intercept)	112.606	0.207	542.694	0.000
	Distance_nearest_Majart	1.764	0.754	2.340	**0.019***
	Street_Length_500m	−0.027	0.066	−0.402	0.688
	Distance_nearest_POE	0.044	0.034	1.285	0.199
	InvSqDist_POE.km	0.131	0.119	1.094	0.274
	Traffic_VMT_500m	0.015	0.010	1.509	0.131
• SBP (≥130, N=1382)	(Intercept)	144.678	0.396	365.337	0.000
	Distance_nearest_Majart	1.123	1.449	0.775	0.438
	Street_Length_500m	−0.143	0.130	−1.102	0.271
	Distance_nearest_POE	−0.069	0.071	−0.979	0.328
	InvSqDist_POE.km	0.294	0.253	1.162	0.246
	Traffic_VMT_500m	0.029	0.018	1.648	0.100

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
DBP	(Intercept)	76.386	0.183	417.888	0.000
	Distance_nearest_Majart	0.445	0.665	0.669	0.503
	Street_Length_500m	−0.053	0.059	−0.897	0.370
	Distance_nearest_POE	0.011	0.031	0.360	0.719
	InvSqDist_POE.km	0.013	0.108	0.120	0.905
	Traffic_VMT_500m	0.001	0.008	0.108	0.914
• DBP (<85, N=3246)	(Intercept)	71.840	0.140	514.876	0.000
	Distance_nearest_Majart	0.644	0.516	1.249	0.212
	Street_Length_500m	−0.046	0.045	−1.019	0.308
	Distance_nearest_POE	0.030	0.024	1.284	0.199
	InvSqDist_POE.km	−0.056	0.085	−0.658	0.511
	Traffic_VMT_500m	0.013	0.006	1.972	**0.049***
• DBP (≥85, N=937)	(Intercept)	92.209	0.247	373.154	0.000
	Distance_nearest_Majart	−1.092	0.856	−1.275	0.203
	Street_Length_500m	0.087	0.080	1.077	0.282
	Distance_nearest_POE	0.036	0.042	0.848	0.397
	InvSqDist_POE.km	−0.071	0.135	−0.529	0.597
	Traffic_VMT_500m	−0.008	0.012	−0.723	0.470
PBP	(Intercept)	46.816	0.227	206.456	0.000
	Distance_nearest_Majart	1.359	0.825	1.648	0.099
	Street_Length_500m	−0.001	0.073	−0.014	0.989
	Distance_nearest_POE	−0.095	0.038	−2.481	**0.013***
	InvSqDist_POE.km	0.097	0.135	0.720	0.472
	Traffic_VMT_500m	0.021	0.010	1.978	**0.048***
TC	(Intercept)	189.327	0.720	263.063	0.000
	Distance_nearest_Majart	2.711	2.649	1.023	0.306
	Street_Length_500m	−0.195	0.233	−0.837	0.403
	Distance_nearest_POE	0.038	0.123	0.308	0.758
	InvSqDist_POE.km	0.236	0.409	0.578	0.564
	Traffic_VMT_500m	0.012	0.033	0.369	0.712
TG	(Intercept)	187.067	1.867	100.215	0.000
	Distance_nearest_Majart	12.724	6.868	1.853	0.064
	Street_Length_500m	0.901	0.603	1.494	0.135
	Distance_nearest_POE	0.094	0.319	0.295	0.768
	InvSqDist_POE.km	0.730	1.055	0.692	0.489
	Traffic_VMT_500m	0.026	0.085	0.312	0.755
log.TG	(Intercept)	5.078	0.010	528.973	0.000
	Distance_nearest_Majart	0.068	0.035	1.917	0.055
	Street_Length_500m	0.007	0.003	2.236	**0.025***
	Distance_nearest_POE	0.001	0.002	0.636	0.525
	InvSqDist_POE.km	0.004	0.005	0.734	0.463
	Traffic_VMT_500m	0.000	0.000	−0.151	0.880
HDL	(Intercept)	48.563	0.263	184.810	0.000
	Distance_nearest_Majart	−0.220	0.971	−0.227	0.821
	Street_Length_500m	−0.222	0.085	−2.616	**0.009***
	Distance_nearest_POE	−0.059	0.045	−1.318	0.188
	InvSqDist_POE.km	−0.151	0.148	−1.024	0.306
	Traffic_VMT_500m	0.000	0.012	0.002	0.998

Y	Traffic Variable	Estimate	Std. Error	t value	Pr(>|t|)
LDL	(Intercept)	104.895	0.624	168.048	0.000
	Distance_nearest_Majart	−0.419	2.311	−0.181	0.856
	Street_Length_500m	−0.130	0.202	−0.645	0.519
	Distance_nearest_POE	0.037	0.106	0.346	0.729
	InvSqDist_POE.km	−0.025	0.349	−0.073	0.942
	Traffic_VMT_500m	0.000	0.029	0.015	0.988
TC/HDL	(Intercept)	4.247	0.029	147.650	0.000
	Distance_nearest_Majart	0.077	0.106	0.727	0.467
	Street_Length_500m	0.005	0.009	0.492	0.622
	Distance_nearest_POE	0.005	0.005	1.046	0.296
	InvSqDist_POE.km	0.017	0.016	1.065	0.287
	Traffic_VMT_500m	0.002	0.001	1.198	0.231
log.TC/HDL	(Intercept)	1.382	0.006	224.893	0.000
	Distance_nearest_Majart	0.013	0.023	0.586	0.558
	Street_Length_500m	0.002	0.002	0.950	0.342
	Distance_nearest_POE	0.001	0.001	1.143	0.253
	InvSqDist_POE.km	0.004	0.003	1.284	0.199
	Traffic_VMT_500m	0.000	0.000	0.907	0.364
bc.TC/HDL	(Intercept)	0.982	0.003	320.741	0.000
	Distance_nearest_Majart	0.006	0.011	0.530	0.596
	Street_Length_500m	0.001	0.001	1.148	0.251
	Distance_nearest_POE	0.001	0.001	1.185	0.236
	InvSqDist_POE.km	0.002	0.002	1.330	0.184
	Traffic_VMT_500m	0.000	0.000	0.751	0.453
FBG	(Intercept)	113.656	0.841	135.214	0.000
	Distance_nearest_Majart	3.365	3.096	1.087	0.277
	Street_Length_500m	0.261	0.271	0.962	0.336
	Distance_nearest_POE	−0.200	0.144	−1.395	0.163
	InvSqDist_POE.km	1.156	0.474	2.438	**0.015***
	Traffic_VMT_500m	−0.005	0.038	−0.143	0.886
log.FBG	(Intercept)	4.678	0.005	908.585	0.000
	Distance_nearest_Majart	0.019	0.019	1.027	0.305
	Street_Length_500m	0.002	0.002	1.395	0.163
	Distance_nearest_POE	−0.001	0.001	−1.161	0.246
	InvSqDist_POE.km	0.007	0.003	2.279	**0.023***
	Traffic_VMT_500m	0.000	0.000	−0.368	0.713
bc.FBG	(Intercept)	0.500	0.000	1436139	0.000
	Distance_nearest_Majart	0.000	0.000	1.086	0.278
	Street_Length_500m	0.000	0.000	1.973	**0.049***
	Distance_nearest_POE	0.000	0.000	−0.839	0.401
	InvSqDist_POE.km	0.000	0.000	1.641	0.101
	Traffic_VMT_500m	0.000	0.000	−0.596	0.551

*All significant predictors and corresponding p-values are expressed in bold.

Table 26. Summary and Parameter Estimates of Multivariate Logistic Regression Model for Binary MetS Factors (N=4,959)

Y	Traffic Variable	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI	Upper 95% CI
HighWaist	(Intercept)	0.359	0.034	10.612	0.000	1.431	1.340	1.529
	Distance_nearest_Majart	−0.037	0.123	−0.302	0.763	0.964	0.758	1.227
	Street_Length_500m	0.034	0.011	3.157	**0.002***	1.035	1.013	1.058
	Distance_nearest_POE	0.016	0.006	2.677	**0.007***	1.016	1.004	1.027
	InvSqDist_POE.km	−0.006	0.019	−0.291	0.771	0.994	0.957	1.034
	Traffic_VMT_500m	−0.002	0.002	−1.326	0.185	0.998	0.995	1.001
HighBP	(Intercept)	−0.459	0.033	−13.944	0.000	0.632	0.592	0.674
	Distance_nearest_Majart	0.106	0.119	0.886	0.376	1.112	0.879	1.403
	Street_Length_500m	0.000	0.011	−0.002	0.998	1.000	0.979	1.021
	Distance_nearest_POE	−0.010	0.006	−1.801	0.072	0.990	0.979	1.001
	InvSqDist_POE.km	−0.006	0.020	−0.311	0.756	0.994	0.954	1.032
	Traffic_VMT_500m	0.000	0.002	−0.133	0.894	1.000	0.997	1.003
HighTC	(Intercept)	−0.515	0.036	−14.438	0.000	0.598	0.557	0.641
	Distance_nearest_Majart	−0.009	0.131	−0.066	0.947	0.991	0.766	1.280
	Street_Length_500m	−0.013	0.012	−1.115	0.265	0.987	0.965	1.010
	Distance_nearest_POE	0.003	0.006	0.424	0.671	1.003	0.991	1.015
	InvSqDist_POE.km	0.028	0.020	1.414	0.157	1.028	0.989	1.070
	Traffic_VMT_500m	0.000	0.002	0.305	0.760	1.000	0.997	1.004
HighTG	(Intercept)	0.253	0.035	7.291	0.000	1.288	1.203	1.379
	Distance_nearest_Majart	0.146	0.128	1.136	0.256	1.157	0.901	1.491
	Street_Length_500m	0.024	0.011	2.120	**0.034***	1.024	1.002	1.047
	Distance_nearest_POE	0.005	0.006	0.875	0.381	1.005	0.994	1.017
	InvSqDist_POE.km	−0.001	0.020	−0.061	0.951	0.999	0.961	1.039
	Traffic_VMT_500m	−0.001	0.002	−0.763	0.446	0.999	0.996	1.002
LowHDL	(Intercept)	0.049	0.035	1.398	0.162	1.050	0.981	1.124
	Distance_nearest_Majart	0.129	0.128	1.006	0.314	1.138	0.885	1.464
	Street_Length_500m	0.032	0.011	2.862	**0.004***	1.033	1.010	1.056
	Distance_nearest_POE	0.010	0.006	1.645	0.100	1.010	0.998	1.022
	InvSqDist_POE.km	0.028	0.021	1.319	0.187	1.028	0.988	1.075
	Traffic_VMT_500m	0.000	0.002	0.039	0.969	1.000	0.997	1.003
HighFBG	(Intercept)	−0.013	0.034	−0.371	0.710	0.987	0.923	1.056
	Distance_nearest_Majart	0.095	0.127	0.744	0.457	1.099	0.857	1.412
	Street_Length_500m	0.009	0.011	0.782	0.434	1.009	0.987	1.031
	Distance_nearest_POE	0.009	0.006	1.490	0.136	1.009	0.997	1.021
	InvSqDist_POE.km	0.028	0.020	1.371	0.170	1.028	0.989	1.073
	Traffic_VMT_500m	0.000	0.002	−0.119	0.906	1.000	0.997	1.003
MetS	(Intercept)	0.127	0.035	3.589	0.000	1.135	1.059	1.216
	Distance_nearest_Majart	0.022	0.130	0.169	0.866	1.022	0.793	1.319
	Street_Length_500m	0.038	0.011	3.309	**0.001***	1.039	1.016	1.062
	Distance_nearest_POE	0.009	0.006	1.564	0.118	1.009	0.998	1.022
	InvSqDist_POE.km	0.006	0.020	0.283	0.777	1.006	0.968	1.047
	Traffic_VMT_500m	−0.002	0.002	−1.538	0.124	0.998	0.994	1.001

* All significant predictors and corresponding p-values are expressed in bold.

Predictive Probability Model

The multivariate regression analysis quantified the relationships between different types of traffic variables and risk factors for MetS. Using a stepwise selection technique, researchers built a multivariate logistic regression model that showed the best performance in estimating the likelihood of MetS. Based on the modeling, the selected variables were the length of street in the 500-m zone, distance to the nearest POE, and traffic VMT in the 500-m zone (see Table 27).

Table 27. Summary of Variable Selection for Multivariate Logistic Regression Models Using a Stepwise Selection Technique

Health Variable	Traffic Variable[1]	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI	Upper 95% CI
Metabolic syndrome	(Intercept)	0.126	0.035	3.586	0.000	1.134	1.059	1.215
	Street_Length_500m	0.038	0.011	3.459	**0.001***	1.039	1.017	1.062
	Distance_nearest_POE	0.009	0.006	1.569	0.117	1.009	0.998	1.021
	Traffic_VMT_500m	−0.003	0.002	−1.597	0.110	0.997	0.994	1.001

* All significant predictors and corresponding *p* are expressed in bold.

1. Traffic variable units: km, in thousands

The multivariate regression model estimated the coefficients of the selected traffic variables that were used to predict the probabilities of occurring in El Paso, TX, for MetS. The length of street within 500 m was positively associated with the likelihood of having MetS (p-value = 0.001). The distance to the nearest POE was positively associated with the likelihood of MetS, while traffic VTM within 500 m was negatively correlated with MetS; both were not significant. Using these estimates, a land-use map was made for each traffic variable. The land-use maps show the length of streets within 500 m, distance to the nearest POE, and traffic VMT within 500 m with the values grouped into different areas for visual interpretation (Figure 13).

The maps show that the areas with the highest street length are located in the central part of the city, while the areas with the most traffic are located in the vicinity of the major freeways. The distance to the POE is associated with the outer west and northeast and the far east of the city. Each map provides spatial variations, especially with regard to spatial patterns of street length and traffic.

Lastly, researchers used the coefficient estimates from the multivariate logistic regression modeling to calculate a predicted probability for MetS. The predicted probability can be obtained from the following equation:

$$\hat{p} = \frac{\exp\{0.126 + 0.038(Strlength_{500m} - 10.731) + 0.009(Dist_{POE} - 9.482) - 0.003(TrafVMT_{500m} - 23.337)\}}{1 + \exp\{0.126 + 0.038(Strlength_{500m} - 10.731) + 0.009(Dist_{POE} - 9.482) - 0.003(TrafVMT_{500m} - 23.337)\}}$$

The predicted values were applied to a gridded map representative of areas in El Paso, TX, in which the resulting layer (Figure 14) shows areas of higher and lower probability of MetS.

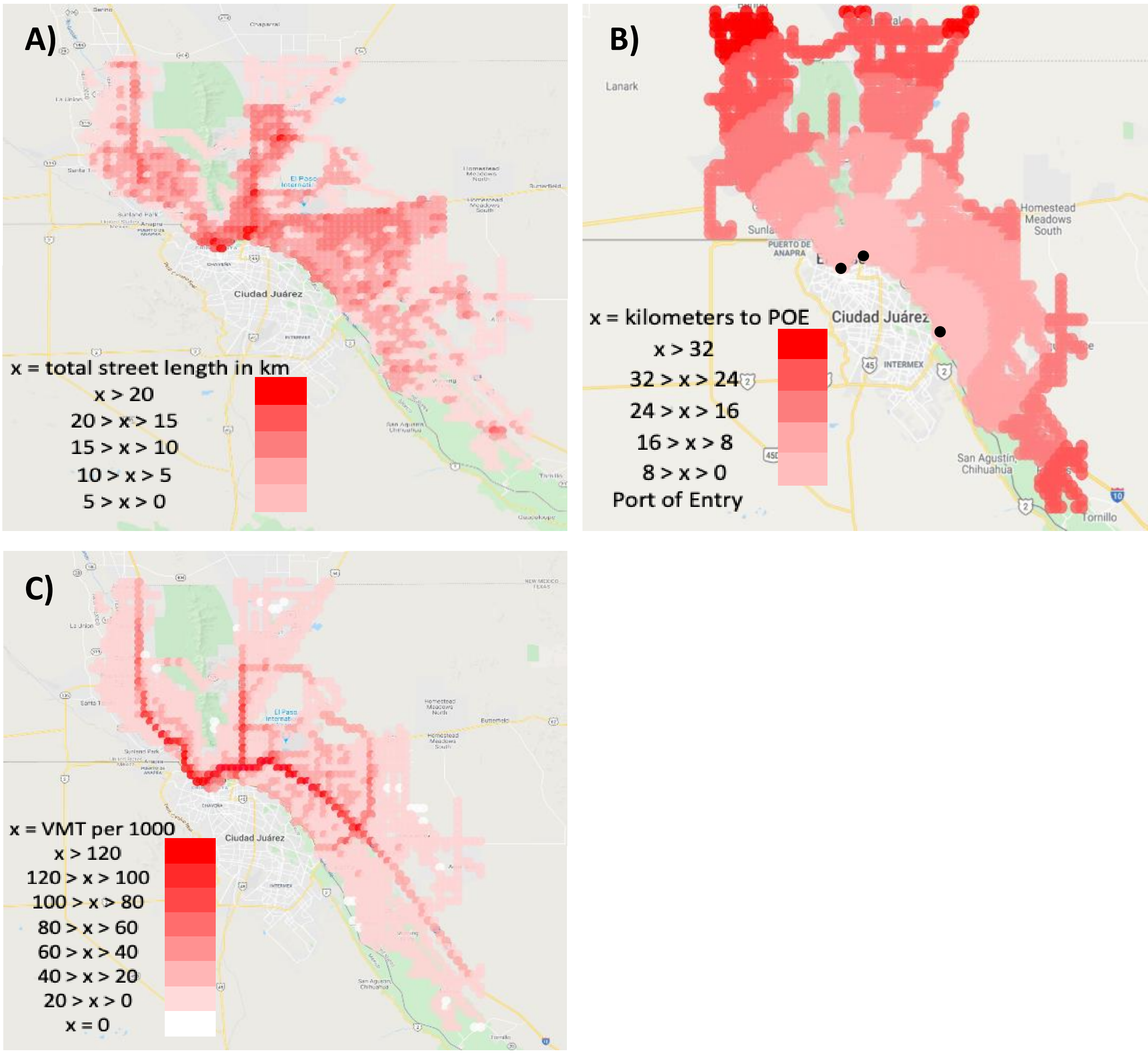

Figure 13. Traffic-related variables applied to a city grid for (A) street length within 500 m, (B) distance to the nearest port of entry, and (C) VMT within 500 m.

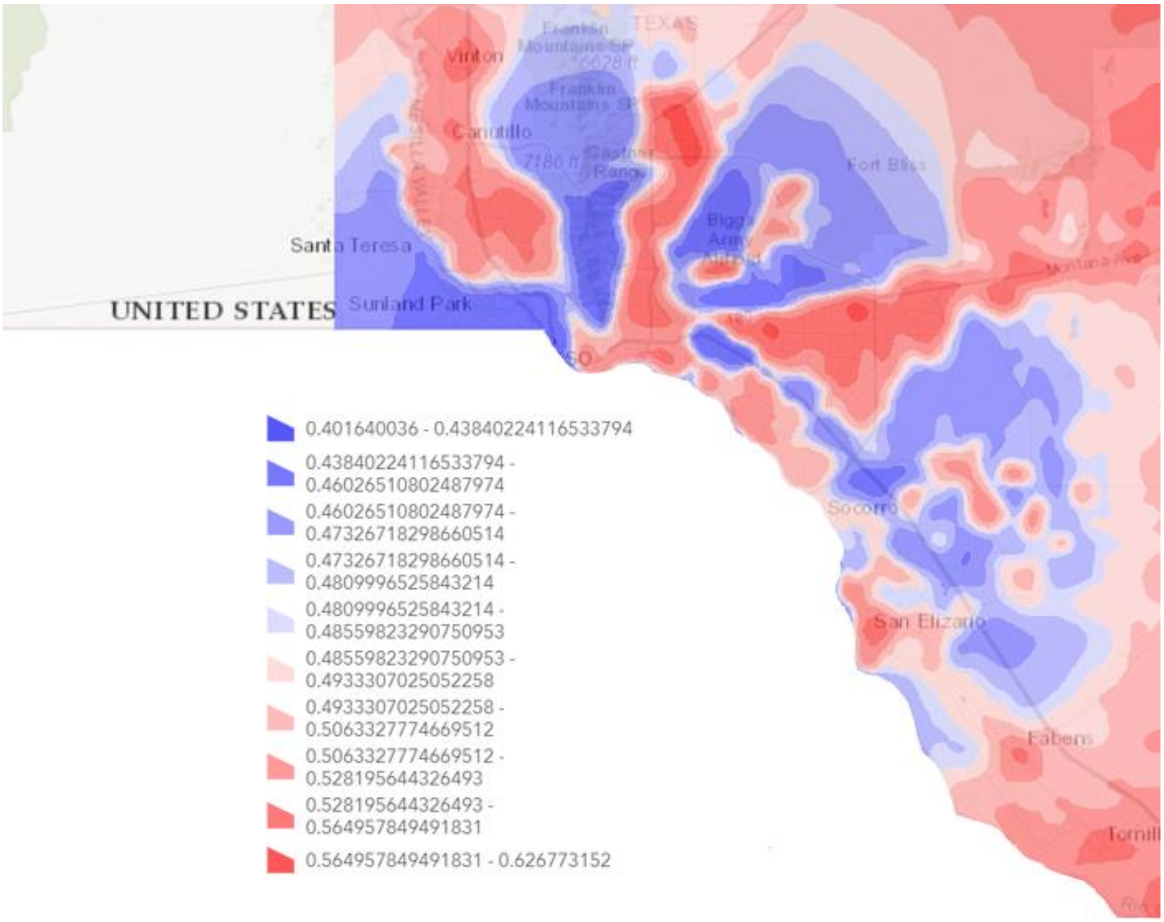

Figure 14. Predictive model of higher risk of MetS based on the land-use regression model.

Conclusions and Recommendations

Short-Term Effects of Traffic-Related Air Pollution on Cardiorespiratory Outcomes

This study examined the short-term associations (24-, 48-, 72-, and 96-hr averages) of traffic-related air pollutants ($PM_{2.5}$, PM_{10}, NO_2, and O_3) with biomarkers of respiratory and cardiovascular disease in a group of uninsured participants from low-income communities in El Paso, TX. Researchers found associations of short-term air pollutant concentrations with respiratory outcomes, which was expected. However, researchers also found associations with metabolic risk factors such as BMI, waist circumference, and fasting glucose.

FEV_1 was negatively correlated with average concentration levels of $PM_{2.5}$ (24, 48, and 96 hr), indicating a relationship between lung function and ambient $PM_{2.5}$ before the measurement. Specifically, this respiratory indicator represents an increase of risk to developing chronic obstructive pulmonary disease (COPD). Furthermore, PEF, which is also an indicator of the respiratory risk of COPD, was negatively correlated not only with $PM_{2.5}$ but also NO_2. However, researchers did not see an influence by coarse particles (PM_{10}), which might indicate the significant effects came from smaller particles, which affect the lower respiratory tract and can further cause obstructive disease. Further analysis using the best results available for respiratory indicators (FEV_1, FVC, and PEF), as interpreted by the spirometry software (CareFusion Spirometry PC Software™ [36-SPC1000-STK]), further confirmed the associations with $PM_{2.5}$ air pollutants and NO_2.

eNO is a measure of airway inflammation and useful in the treatment and adherence of asthma treatment but was not correlated with concentration levels of air pollutants in the selected population. Given that the inclusion methods do not ask if a participant has asthma, researchers cannot subset the data to explore if a relationship exists in this subgroup. Also, based on the lung function parameter and related associations with air pollutants, researchers can infer the patterns align more with an obstructive respiratory disease (like COPD) than restrictive respiratory diseases like asthma.

Researchers also considered the percent predicted values of lung function. However, the analyses did not show any significant correlation with air pollutant concentration levels; however, there were associations with the FEV_1/FVC ratio, which is a clinical marker that can differentiate lung obstruction from restriction. A ratio of 0.7 is indicative of lung obstruction. Given the negative correlations found with $PM_{2.5}$ and NO_2 in different time windows, lung obstruction seems to be more prevalent in the selected population.

The short-term associations with risk factors related to obesity (BMI and waist circumference) both in linear and logistic models were not expected as part of this study. Moreover, the relationship was present across a majority of average air pollution average values before the date of examination. Researchers do not assume a causal effect between a short-term exposure to air pollution and obesity but do theorize this is due to the lack of variation of air pollution exposure in the short term. This could be reflective of the medium to long exposure, which can be also representative of the environmental conditions, neighborhoods where participants live, and locations of the CAMSs assigned to them.

Researchers did not find associations with other metabolic outcomes such as high BP or an altered lipid profile but did find associations with FBG. In linear models, researchers normalized the values and further confirmed this relationship in logistic models by looking into participants with high glucose levels. Possible reasons for this increase include oxidative stress and inflammation cause by air pollution exposure (Bowe et al., 2018; Eze et al., 2015; Wolf et al., 2016). Also, it is possible that measures related to obesity such as waist circumference can be considered better predictors of air pollution exposure since a unit change in waist (cm) is metabolically more important than unit changes in lipid profile and glucose (mg/dl).

Strengths and Limitations

The present study considered measures of ambient air pollution at nearby CAMSs. However, there could be some variation in the participants' indoor environment. It is beyond the scope of this research to consider measurements of indoor air pollution; however, from pilot data, there is a direct relationship between ambient and indoor air pollution, which is further confirmed by the literature (Andersen, 1972; Raysoni et al., 2013; Zora et al., 2013).

The measurements of air pollution exposure rely on CAMSs with available data. In some cases, the stations were far from certain areas in El Paso County, which led to exclusion of some participants from the analysis. Furthermore, not all CAMSs had measurements available for every traffic-related pollutant. However, the number of CAMSs that measured O_3 was at least two times more than those that measured the other pollutants, and researchers still observed associations similar to those for the other pollutants.

Comparison with Other Studies

Respiratory outcomes have been associated with air pollution exposure in other epidemiological studies. The Framingham study found that moderate exposure measured by the Environmental Protection Agency's Air Quality Index for $PM_{2.5}$, NO_2, and O_3 was associated with lower FEV_1 considering 24- and 48-hr pollutant concentration averages before the measurement (Rice et al., 2013). A study among 1,694 female non-smokers from Wuhan-Zhuhai, China, found that in a city with high pollutant levels, the moving average of $PM_{2.5}$, PM_{10}, NO_2, and O_3 exposures were significantly associated with FEV_1 reductions. Also, in a low-level air pollution city, PM_{10} (72-, 96-, and 120-hr), O_3 (72-hr), and $PM_{2.5}$ (96- and 144-hr) exposures were significantly associated with reduced FEV_1 (Zhou et al., 2016). The Zhou et al. study also found associations with FVC. However, in the current study, the relatively low levels of exposure in this study could be the reason why these associations were not found.

Furthermore, a repeated measures study from Belgium found that an increase in PM_{10} on the day of the clinical examination was associated with lower FVC, FEV_1, and PEF. Also, an increase of NO_2 was associated with a reduction in PEF on the day of the examination (Panis et al., 2017). A study of ambient air pollution with lung function in adults at very low levels in Europe did not observe an association of air pollution with longitudinal change in lung function but did observe that an increase in NO_2 exposure was associated with lower levels of FEV_1 and FVC (Adam et al., 2015). Also, an increase of PM_{10}, but not other PM metrics ($PM_{2.5}$, the coarse fraction of PM, and PM absorbance), was associated with a lower level of FEV_1. The associations were particularly strong in obese persons.

Regarding metabolic outcomes, Chuang et al. (2010) observed increased PM_{10} was marginally ($p < 0.10$) associated with elevated SBP (24 hr) and TG (24 to 120 hr), and statistically associated with hemoglobin A1c (72 hr) and reduced HDL (24 hr). Also, O_3 was associated with DBP (72 and 120 hr) and hemoglobin A1C (24, 72, and 120 hr) and marginally associated with TG and fasting glucose (Chuang et al., 2010). Unfortunately, this study did not consider $PM_{2.5}$ measurements, which further showed some associations in the current study. Also, a study conducted in China showed a positive correlation between PM_{10}, NO_2, and O_3 and BMI (Li et al., 2015), which further aligns with some of the associations from the current study, although the time window Li et al. considered for the association was based on the medium term instead of short term. Furthermore, a 2014 review by Weichenthal el al. (2014), which considered 14 studies of short-term effects, suggested that "the consistent pattern of stronger associations among obese subjects suggests that obesity may modify the impact of $PM_{2.5}$ on cardiovascular health."

Long-Term Effects of Transportation Data on Cardiorespiratory Outcomes

Researchers examined the association of respiratory and cardiovascular risk factors with the long-term effects of air pollution related to vehicle traffic (VMT and street length) and distance to air pollution sources (major arterial roads and international POEs) using LUR models and GIS measures, in a large dataset of adults residing in low-income in El Paso, TX. This study found expected associations with respiratory outcomes caused by long-term exposure using the available data subset from the first year of the larger health study. Researchers found correlations of length of street within the 500-m and 1000-m impact zone as well as the VMT with measures of lung function (FEV_1, FVC, and PEF). Furthermore, multivariate models showed the length of street within 500 m was an important traffic predictor for lung function based on the peak expiratory flow (PEF and PEF Best).

Regarding the cardiovascular outcomes, the most significant predictor in the LUR models of MetS risk factors was the total length of the street within a 500-m radius. The increase in the street length was associated with increasing waist circumference and TG and decreasing HDL in multivariate models. Furthermore, the increase in the inverse of the distance squared to the POE (which implies a decrease in the distance to the POE) was significantly associated with an increase in glucose levels. The modeling also considered the PBP, a measure of the difference between SBP and DBP, which showed that an increase in PBP was associated with the increase in the amount of traffic within a 500-m radius and the proximity to the nearest POE.

These results were further confirmed in logistic regression models, which found that as the total length of the street increases, the risks of a large waist circumference, high TG, and low HDL cholesterol were observed. Finally, models considering those participants with MetS (three or more risk factors) showed an increasing likelihood of MetS was also related to the increased street length within 500 m.

Strengths and Limitations

This study provides a large sample of low-income participants from El Paso, TX, representing the population distribution living all over the county. Also, the use of LUR models allowed further exploration considering measures of vehicle traffic, which complements other studies that have relied on concentration levels of air pollutants from CAMSs, which are not always available or are located far from the participants' neighborhoods.

However, this study has limitations. Variations are assumed between the indoor environment and the ambient air pollution exposure. It is beyond the scope of this research to consider measurements of indoor air pollution; however, other studies in the region have shown there is a direct relationship between ambient and indoor air pollution.

Also, the measurements of traffic rely on GIS layers from the El Paso Metropolitan Planning Organization, Census, and PdnMapa. However, data from participants that lived farther from certain areas in El Paso County were not covered by the layers, and researchers excluded them from the analysis. Furthermore, for participants living less than 1000 m from the border area, this analysis did not include the traffic variables or GIS layers from Ciudad Juarez in Mexico. Researchers expect the lack of information did not have much influence since not many participants lived close to neighborhoods in Ciudad Juarez; however, future studies would benefit from including information from GIS layers with data from Mexico.

Comparison with Other Studies

Studies about the impact of long-term exposure to outdoor air pollution on health outcomes have played a crucial role in recent decades (Amini et al., 2017; Hoek et al., 2008). Other studies have used LUR to factor exposure of traffic-related air pollution. In 1999, an LUR model was developed to predict concentrations of NO_2 and other related pollutants; the study found the most useful variables were elevation, population density, distance to an international POE, and distance to a petroleum facility considering two monitoring sites (Smith et al., 2006). This was further evaluated in 2006–2007 using a series of mixed model LURs, which confirmed the mentioned variables as useful predictors of NO_2 even when considering seasonal variation (Gonzales et al., 2012).

A study modeling the PM concentrations along I-10 in El Paso, TX, considered dispersion and LUR models that considered wind speed and daily traffic counts, which suggested particle concentrations impact within a 1,000-m buffer along the interstate (Olvera et al., 2014). A further study focusing on $PM_{2.5}$ considered surrogate variables of traffic emission at four monitoring sites such as land use, traffic intensity, population density, and property value to estimate pollutant concentrations; however, results were heavily influenced by climate-specific meteorological events (Alvarez et al., 2018). Furthermore, a $PM_{2.5}$ LUR study incorporated a principal component analysis to optimize the model, which found a combination of traffic variables (VMT, speed, traffic demand, road length, and time) to be a good predictor (Olvera et al., 2012).

However, few studies have correlated the use of LUR with air pollution and health outcomes. A 2015 study tested relationships for residential pest and $PM_{2.5}$ exposures with children's self-reported wheezing severity based on socioeconomic factors and a previously developed LUR model (Grineski et al., 2015).

Outputs, Outcomes, and Impacts

Short-term exposure to traffic-related pollutants was correlated with respiratory outcomes related to pulmonary obstruction, which could be explain by inflammation of the respiratory tract. Future studies should consider clinical classifications of obstructive respiratory outcomes such as COPD and consider the effects on FEV_1 and PEF. Researchers also found relationships of fasting glucose levels with short-term effects of air pollution exposure. Researchers further recommend studies that not only look at high levels of fasting glucose but also expand on levels of glycated hemoglobin and diabetes diagnosis.

This study might be the first to find associations of short-term exposure to air pollutants with obesity, which might be more related to the neighborhood locations of participants and socioenvironmental conditions. In future studies, it is recommended to consider obesity as an outcome for air pollution exposure and consider extended windows of time to assess long-term exposure. Furthermore, the use of LUR models can further elucidate this relationship with the characteristics of the neighborhoods surrounding the participants.

The long-term effects of traffic-related air pollution were found to be associated with respiratory and cardiovascular health outcomes. The length of the streets within the 500-m radius was the most significant predictor for lung function measurements (PEF and PEF Best). The LUR models showed the total length of the street within the 500-m impact zone was also an important traffic-related variable to predict MetS risk factors (waist circumference, TG, and HDL cholesterol). The final selected model for MetS classification produced a predicted probability map showing El Paso areas of higher and lower probability of MetS.

The dissemination of results can lead to decision making and improve policy related to healthy living in communities close to busy roadways. Furthermore, the use of predictive models based on LUR can allow further identification of communities at risk for cardiorespiratory health outcomes. Future studies should focus on models that integrate LUR with other types of data in the region to complement existing studies, which can further allow more accurate predictors of cardiorespiratory disease. Furthermore, the use of such models can be paired with clinical health outcomes to improve strategies aimed to reduce the effects of air pollution exposure on health and associated diseases.

Research Outputs, Outcomes, and Impacts

Peer-reviewed publications include:

- Aguilera, J., Jeon, S., Raysoni, A., Rangel, A., Li, W. W., and Whigham, L. (2020). Moderate to vigorous physical activity levels negatively correlate with traffic related air pollutants in children with asthma attending a school near a freeway. (Manuscript in preparation.)
- Aguilera, J., Jeon, S., Chavez, M. C., Ibarra-Mejia, G., Ferreira-Pinto, J., Whigham, L., and Li, W. W. (2020). Land use regression of long-term transportation data on metabolic syndrome risk factors in low-income communities. (Manuscript submitted to the Transportation Research Board.)

Conference papers submitted include:

- Aguilera, J., Jeon, S., Chavez, M. C., Ibarra-Mejia, G., Ferreira-Pinto, J., Li, W. W., and Whigham, L. D. (2020). Associations of traffic and related air pollutants with obesity in low-income populations in El Paso, TX. (Abstract submitted to the Obesity Society's Annual Conference: ObesityWeek, Atlanta, GA, November 2020.)
- Aguilera, J., Jeon, S., Chavez, M. C., Ibarra-Mejia, G., Ferreira-Pinto, J., Whigham, L., and Li, W. W. (2020). Short-term associations of traffic-related air pollutants on cardiorespiratory risk factors from low-Income

populations in El Paso, TX. (Abstract submitted to the Transportation, Environment, and Energy: An Integrated Research Symposium, Transportation Research Board, Denver, CO, July 2020.)

- Aguilera, J., Jeon, S., Chavez, M. C., Ibarra-Mejia, G., Ferreira-Pinto, J., Whigham, L., and Li, W. W. (2020). Land use regression modeling to assess effects of long-term transportation data on metabolic syndrome risk factors of low-income communities, TX. (Abstract submitted to the Transportation, Environment, and Energy: An Integrated Research Symposium, Transportation Research Board, Denver, CO, July 2020.)
- Aguilera, J., Jeon, S., Chavez, M. C., Ibarra-Mejia, G., Ferreira-Pinto, J., Whigham, L., and Li, W. W. (2020). Short-term associations of traffic-related air pollutants on cardiorespiratory risk factors from low-income populations in El Paso, TX. (Abstract submitted to and accepted by the second Transportation, Air Quality, and Health Symposium, Riverside, CA, May 2020.)

Presentations at conferences and technical meetings include:

- Aguilera, J. (October 2019). Moderate to vigorous physical activity levels negatively correlate with traffic related air pollutants in children with asthma attending a school near a freeway. Stanford Postdoctoral Recruitment Initiative in Sciences and Medicine presentation, Stanford, CA.
- Aguilera, J. Association of traffic and related air pollutants on cardiorespiratory risk factors from low-income populations in El Paso. The University of Texas at El Paso, El Paso, TX.
- Aguilera, J. (March 2020). General aspects of COVID-19: Airborne transmission, immune response, and chronic disease risk. Health Clinic Day, Consulate General of Mexico in El Paso, El Paso, TX.
- Aguilera, J. (July 2020). Short-term effects of traffic related air pollution on cardiorespiratory outcomes among low-income residents from El Paso, TX. Joint Advisory Committee for the Improvement of Air Quality in the Ciudad Juárez, Chihuahua/El Paso, Texas/Doña Ana County, New México Air Basin (virtual).
- Jeon, S. (July 2020). Land use regression modeling to assess effects of long-term transportation data on metabolic syndrome risk factors of low-income communities in El Paso, TX. Joint Advisory Committee for the Improvement of Air Quality in the Ciudad Juárez, Chihuahua/El Paso, Texas/Doña Ana County, New México Air Basin (virtual).
- Aguilera, J. (August 2020). Land use regression of long-term transportation data on metabolic syndrome risk factors in low-income communities. Fundación Best monthly seminar in Ciudad Juarez.
- Results and main findings (the predicted probability map for MetS) were shared with the public in a virtual Joint Advisory Committee meeting.

Technology Transfer Outputs, Outcomes, and Impacts

This project had the following technology transfer outputs, outcomes, and impacts:

- Air quality data were acquired from TCEQ’s CAMSs, including hourly air pollutant data.
- Time-integrated air pollutant data of 24-, 48-, 72-, and 96-hr averages were processed for each subject.
- Short-term pollution exposures and long-term transportation data were extracted using GIS mapping.
- GIS layers from Census.gov and the El Paso Metropolitan Planning Organization were used.
- Statistical code for LUR modeling was developed.
- The interpolation technique was applied to produce a predicted probability map.
- Software was used as part of this study including R and ArcGIS Pro.

Education and Workforce Development Outputs, Outcomes, and Impacts

This project had the following education and workforce development outputs, outcomes, and impacts:

- This project supported a doctoral student from Health Science at UTEP as a research associate.

- The project was conducted as part of a doctoral dissertation in the Interdisciplinary Health Sciences program at UTEP.
- An undergraduate student from the Department of Civil Engineering at UTEP was involved in the project.
- Training and education in application of GIS information to transportation data were conducted.

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