LOW-COST AIR SENSOR STUDY IN THE PASO DEL NORTE

Texas Commission on Environmental Quality

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"TECHNICAL REPORT"

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Chapter 1: Introduction

1.1 PM Pollution in the Paso del Norte Region

The Paso del Norte (PdN) encompasses an area along U.S./Mexico border that includes El Paso County in Texas, Doña Ana County in New Mexico, and Ciudad Juárez in Chihauhua, Mexico, all of which lie in the northern Chihuahuan Desert. The airshed shared by these three neighboring communities is monitored by different entities including the City of El Paso, TCEQ, NMED, and the Ciudad Juárez Ecology and Civil Protection Department DGEPC. These agencies manage several air monitoring systems that are located throughout the area. Air quality in this area has been defined by its geographic characteristics and urban sprawl. Among the criteria air pollutants regulated by different jurisdictionary regulatory agencis, particulate matter (PM) including those particles less than 2.5 µm in aerodynamic diameter ($PM_{2.5}$) and 10 µm (PM_{10}), appears to be the pollutant poses the highest adverse health risk to the public. El Paso was designated as nonattainment for NAAQS for PM_{10} and was classified as a moderate nonattainment area upon enactment of the Federal Clean Air Act Amendments (FCAA) of 1990 (1). During the late fall through winter seasons, the use of fire places and indoor biomass burnings in rural outskirt communities can also be prevalent contributors to PM pollution. Burning of biomass materials during the winter in NW Juarez across the border between El Paso and Juarez (west of Sunset Heights) contributes very heavy PM pollution as evidenced by continuous data collected by TCEQ at CAMS 12 and NMED at SPCY and Desert View School. In PdN, PM_{10} is primarily composed of geologic materials with the PM_{10}-$_{2.5}$ fraction dominating the total mass, whereas $PM_{2.5}$ accounts for approximately 25% of the PM_{10} (2) Road dust from unpaved and paved roads constitutes as one of the most important sources of PM_{10} and $PM_{2.5}$ in the PdN region. Along with unpaved roads, brick kilns are also sources of $PM_{2.5}$, and many studies have also demonstrated that home heating and uncontrolled waste burning are major sources of PM emissions (3).

In Ciudad Juárez, PM from residential heating account for as much as 44% of the annual $PM_{2.5}$ (4). Uncontrollable exceedances of PM_{10} NAAQS caused by natural events lead TCEQ to adopt a Natural Events Action Plan (NEAP) for El Paso in 2007. This plan is used to manage the exceedances of the PM standards that can be attributed to uncontrollable natural events, such as high winds which are common in the area (5). Mexico has implemented the Official Mexican Standard NOM-172-SEMARNAT-2019, which establishes the guidelines for collecting and communicating the Air Quality and Health Risks Index (6). This standard specifies that state and local entities responsible for air quality must make the Air Quality and Health Risks Index known in the zones where they operate said systems. As a result, in 2019, Ciudad Juárez surpassed the Mexican maximum permissible level of 75 $\mu g/m^3$ in daily averages on several occasions for PM_{10}, while for $PM_{2.5}$, the daily limit of 45 $\mu g/m^3$ was surpassed four times, as reported in the 76th meeting of the Joint Advisory Committee (JAC).

It is estimated that approximately 40% of Ciudad Juárez major roadways are unpaved. An even larger percentage of the surface streets in residential neighborhoods through the city are not paved. The unpaved road surfaces provide an unlimited reservoir for dust emissions either by wind erosion or by mechanical disturbance. Fugitive dust emitted from the unpaved road surfaces in Ciudad Juárez has been recognized as a significant source in the PdN. Nevertheless, this type of emissions has not been systematically documented in the PdN's PM emissions inventory. In addition to the fugitive dust emissions from the road surfaces, PM emitted directly from vehicles moving on these unpaved roads (including tail pipe exhaust, brake wear and tire wear), particularly on those surface roads in residential neighborhoods, has not been reported and the contribution to the PM emissions inventory is yet to be determined. Another significant factor contributing to the high levels of PM contamination is the high number of manufacturing industries and factories coupled with uncontrolled vehicular emissions from the buses, trucks, and personal vehicles, primarily due to the staff transfer service the factories offer to their employees, which uses a significant number of old repurposed buses from city bus lines.

As discussed in numerous studies, the success of an air exposure study hinges strongly on the accuracy of the exposure concentrations used for the receptors. The use of the concentrations measured at a central monitoring site relies on the assumption of a steady and homogeneous pollution distribution across the study area. This assumption is likely to introduce exposure misclassification into epidemiological studies and could result in errors in the estimation of adverse effects on public health (7,8). The extent of the misclassification depends on whether an average personal exposure concentration, an average ambient concentration from a central monitoring site, or an actual ambient concentration at a specific receptor location was used to approximate the actual personal exposure concentration (9). In addition, pollutants originated locally tend to be heterogeneously distributed whereas pollutants of regional origins tend to be more ubiquitous. We are concerned about the health impacts of traffic-related and regional industrial pollution on the health of students and community residents in the PdN region. The PdN region has experienced significant population and economic growth since the passage of the North American Free Trade Agreement (NAFTA) in 1994. This region has also seen an increase in the overall number of motor vehicles in the cities, especially at the international border crossings. The PdN represents a paradigmatic exposure-air pollution challenge in an international setting due to its complex terrain, arid weather, frequently occurring temperature inversions, congested roadways, insufficient emission inventory for Ciudad Juarez’s uncontrolled emissions, large number of underserved communities, large migrant population, and rapid growing urban sprawl (2).

1.2 Project Objectives

The goal of this project is threefold: to improve air quality monitoring in the border region; to produce a case study of scientific measurement and analysis of air quality using low-cost air sensors; to foster binational technical exchange between government agencies and research institutions in the PdN. Therefore, this project is designed to collect basin-wide, spatial, and temporal data of the primary pollutant $PM_{2.5}$ in the PdN using low-cost air sensors. In addition, the project will address the air quality issues in the PdN by providing real-time spatial and temporal concentration patterns of PM to the public; and by assessing air quality and emissions associated with transportation by developing an algorithm to predict air pollution for near-road receptors using land-use regression technique.

1.3 Significance of Research

There has been a rise in the use of low-cost sensors over the years. Massive-scale urbanization and population growth have increased traffic, industrialization, and in turn, increased pollutants. There is high complexity in monitoring air quality in an urban environment, as the pollutant concentrations vary widely from place to place. Centralized stations are only able to capture a snapshot of their area. To overcome this, low-cost sensors can be used for robust environmental surveillance. While low-cost sensors may produce lower-quality data than more refined sensors, low-cost sensors can be deployed in high numbers, which will show a higher resolution of pollutant exposure within a city. Low-cost sensors are a promising option that could have a significant impact in increasing city monitoring capabilities. The sensors have produced high-quality data and can allow the public to be rapidly informed of the air quality in their city. Through this collaborative study, researchers can focus on the basin as a whole and monitor both cities as one. This study also fostered a binational technical exchange between the PdN research institutions through working together. This collaboration has allowed fostering a binational technical exchange between both research institutions. As a result, both universities have further their research goals and lay a foundation for future partnerships.

Chapter 2: Background Knowledge

2.1 Near-Road Community Exposures

Residents living near busy streets have a significantly increased risk of adverse health effects and even death (10,11). Impacts of traffic-related pollutant emissions on human respiratory health have been well studied. For instance, Gilliland et al. reported that living within 75 m of a major road was associated with a 1.5-fold increased risk of lifetime asthma and wheeze for children (12). In contrast, the association was not explained by differences in ethnicity or other socio-demographic characteristics. In addition, residential traffic was also reported to increase emergency department visits or hospitalizations for children with asthma by 3.5-fold.

Concerns for the health of populations exposed to traffic-related emissions of particulate matter (PM) and gases have led the US Environmental Protection Agency (EPA) to establish a near-road ambient monitoring program in 2010. As a result, near-road air quality data became more available in the US since 2014; state and local air pollution control agencies began collecting NO2, CO, and $PM_{2.5}$ data and reported to the EPA's Air Quality System (AQS) database. DeWinter et al. (2018) reviewed the air pollutant concentrations measured at 81 near-road sites in 2014-2015 in the US and reported that, for $PM_{2.5}$, the annual and 24-hr $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS) were exceeded at 12 and 5 locations, respectively (13). DeWinter et al. further suggested that proximity to a high traffic roadway results only in a small increment of $PM_{2.5}$ concentrations (an average of 1.2 $\mu g/m^3$ with a standard deviation of 0.3 $\mu g/m^3$) from the background concentration recorded at other urban-scale locations. This increment represents, on average, a 13 to 15 percent increase depending on how close the near-road monitor is to the roadway.

Exposure to the traffic-related pollutants in the PdN could vary spatially and temporally due to the various traffic emission sources and as the result of rapid dispersion from roadways. The time-resolved concentrations used in health outcome studies could mask the short-term effects on people's health. Temporal and spatial characterization of exposure concentrations would fill the data gap between air pollution exposures and health outcome measurements for near-road communities. There is a significant concern about the health impacts of traffic-related and regional industrial pollution on the health of children and community residents in the border cities of PdN. The high urbanization and industrial development rates have led to rapidly deteriorating air quality in the PdN region. Air quality in the PdN represents a paradigmatic challenge in an international setting due to its complex terrain, arid weather, frequently occurring temperature inversions, congested roadways, insufficient emission inventory for Ciudad Juarez, a large number of underserved communities, large migrant population, and rapidly growing urban sprawl.

Unfortunately, to fulfill the purposes of these air pollution regulations, costly air quality monitoring stations are needed, and certified personnel to make use of the equipment. Thus, low-cost monitoring sensors have gained traction in the last years, as there is a possibility that low-cost sensors can further expand the air monitoring capacities of a given city.

2.2 Low-Cost Sensors: PurpleAir literature review

Even though there is a lack of agreed-upon definition, low-cost sensors are described by organizations such as the World Meteorological Organization (WMO) as devices with a smaller initial expense than the acquisition cost of single reference equipment that measures the same atmospheric parameter or a similar one. A defining characteristic of these sensors is that their components allow them to be low-cost, their price range being $100 - $500. Low-cost sensors and their application in atmospheric sciences should be evaluated not only in terms of each device's technical performance but also in analysis frameworks of hardware, software, and data that they can successfully endure for their use in specific sets of tasks

Many goals can become achievable via low-cost sensors, goals such as gaining more spatial data, achieving a higher temporal frequency, and a way to reduce the costs associated with monitoring significantly. An important feature is the possibility of disseminating the data via real time web sites in which the community become aware on the impact of high pollution episodes such as wild fires, industrial fires,etc. As a result, low-cost sensors are rising in popularity as they are a possible way to expand the limited capabilities of a given state. Rapidly growing cities have widely swinging ranges of air pollution; the current monitoring abilities of a city provide low spatial coverage. This low spatial coverage has become a hindrance in quantifying air pollution. Low-cost sensors have grown in popularity in the US as an easy way to identify air pollution concentrations where the sensors are located. Many manufacturers are producing small portable devices for the public. PurpleAir has become one of the most widely used monitors in the US. However, there are many concerns over the reliability and efficacy of these sensors. Many studies have looked into the capabilities of these sensors.

Low-cost sensors can expand a community monitoring area. This, in turn, provides a more expansive geospatial view of how a specific pollutant will behave. For example, in a study by Lu et al., low-cost sensors were utilized to estimate hourly $PM_{2.5}$ concentrations for a neighborhood in the Los Angeles area (14). In addition, an increase in monitoring networks will provide an increased spatial coverage; this data can be used to supplement the data that a regulatory agency would have otherwise provided. Kosmopoulos et al. evaluated the low-cost sensors field capabilities at Patras, a city in the eastern Mediterranean (15). The study utilized PurpleAir sensors to monitor $PM_{2.5}$ in an 8km area. The sensors were evaluated using channels A and B and collocated next to a GRIMM EDM 180. The sensors showed a high correlation with each channel (99%); the hourly measurements appeared to be highly correlated; however, this correlation would decrease slightly with time. In comparison to the GRIMM, the sensors appeared to report 22% lower averaged values. Despite this, the study concluded that they were relatively correlated with one another. Outside meteorological factors played a factor in some of the data collected by the low-cost sensors, such as high wind storms blowing from the Sahara desert. Different calibrations methods were utilized in a study (16) to provide the public with transparency other than just relying on the algorithm that Plantower uses for the sensors PMS 5003 that are utilized in all PurpleAirs. The results were over 433 days, where 33 sensors were used. Their reproducible and alternative (ALT) method, was based on the number of particles per deciliter reported by the PMS 5003 sensors in the PurpleAir instrument for the three size categories less than 2.5 μm in diameter. The method makes no use of either the CF1 or ATM data series which are calculated according to a proprietary and undisclosed algorithm by the Plantower manufacturers of the sensors. The full method can be found in their study. This ALT method to calculating $PM_{2.5}$ showed to be more effective than using the CF1 and ATM that PurpleAir provides.

Low-cost sensors are becoming increasingly valuable for detecting high pollution concentrations in areas that would go unnoticed otherwise. However, at times, the collected and published data must be corrected and evaluated to ensure that they are functioning and in line with regulatory agencies. New methods of calibration and further studies will help pave the way to a cleaner future. As the public begins to utilize these sensors more, regulatory agencies must ask themselves if this supplemental data are relevant and accurate and how these low-cost sensors can alleviate the strain in monitoring. Nevertheless, low-cost sensors are a tool that will become essential in the collection of air quality data.

2.3 EPA Low-Cost Sensor Data Correction

Low-cost sensors are steadily rising as they become lower in cost, are more portable, and are generally easy to operate than regulatory-grade monitors. In addition, the U.S. Environmental Protection Agency (EPA) has developed specific standard operating procedures to help operators perform routine activities consistently. As many sensors enter the market throughout the year, scientists and community scientists face a problem developing extensive operating procedures to ensure the accuracy and efficacy of the sensors. With the growth in low-cost sensors, there is a new opportunity to use these devices for many applications. Some of these applications are for research, personal monitoring, or even supplemental monitoring.

To evaluate each sensor, the EPA has developed a few guidelines that will help ensure the actual performance of the sensor, as well as dictate how the measurements will be analyzed. Nevertheless, no low-cost sensor has been approved to collect regulatory monitoring data (17) which indicates further studies needed when using low-cost monitoring systems or networks. One method that the EPA suggests is to evaluate the low-sensors capabilities by collocating each sensor near a reference monitor (equipped with FRM/FEM designated instrument). Then, the sensor's performance can be evaluated by comparing the sensor's data with the reference monitor's data. The low cost sensors had been manufactured with sensor redundance in order to quickly evaluate the sensor performance (named here as channel A and B). Of course, when reviewing the data, different factors should be considered, such as removing data outliers or channel comparisons for each of the sensors.

Throughout the project, specific criteria were taken into consideration when evaluating the raw data collected from the low-cost sensor, PurpleAir, which is used in this study. EPA ORD correction methods were used when evaluating the data. These methods included removing data where channels A and B differ by more than 5 $\mu g/m^3$, removing extraordinarily high or extremely low (outliers) data, and using a correction factor for humidity and temperature. The agreement between channels A and B help provide confidence in the performance and consistency of the sensors. Data points from channels A and B were averaged to create an hourly mean. Data are removed if data are less than twenty data points or if the length of the data are less than 75%. This is done to ensure a full hour is taken into consideration. If not, the hour does not contain enough information or data to generate an accurate view of the pollutant during that time. These guidelines are provided to ensure a protocol in which the sensor is evaluated to ensure the efficacy and performance of the device.

Chapter 3: Methodology and Study Designs

3.1 Scientific Approach

The air pollutant data are reported and analyzed to implement the two research objectives described previously: 1) provide real-time spatial and temporal concentration patterns of $PM_{2.5}$ to the public, and 2) assess air quality and emissions associated with transportation by developing an algorithm to predict air pollution for near-road receptors using land-use regression technique. Data recorded at each site was transmitted to the data management center at PurpleAir and posted on a publicly accessible website so that community residents could access the data. Data collection was the responsibility of the UTEP-UACJ research team to ensure smooth operations, debug errors, and to interact with school personnel and industry personnel. UTEP and UACJ established an impact zones (500 m and 1,000m) in radius from any measurement location and collected traffic information, such as total length of streets, vehicle miles traveled in the zone, and separate traffic variables such shortest distance to highway, distance to a Port of Entry, and . Land-use regression (LUR) techniques were used to develop regressive correlation for predicting exposure concentrations using traffic data as established in other studies assessing these variables (18).

3.1.1 Selection of Instrument

The PurpleAir Model PA-II-SD Sensor, an optical particle counter, was selected for use in the measurements of $PM_{1.0}$, $PM_{2.5}$ & PM_{10} mass concentrations. This sensor works through a dual monitoring system, in which two sensors—PMS5003 and PMS1003, developed by Plantpower—of particulate matter (PM_{10} and $PM_{2.5}$) are integrated (purpleair.com, s/f). This model was selected as they include an SD card that stores data in case of a failed internet connection. The included SD card has a 16GB capacity. This low-cost sensor has been thoroughly evaluated by the State of California's South Coast AQMD's AQ-SPEC Program with acceptable precision and accuracy, as shown in Table 1 (http://www.aqmd.gov/aq-spec/evaluations).

Table 1 PurpleAir Sensor Evaluation

Sensor	**Model**	**Pollutant**	**Lab** R^2	**Field** R^2
PurpleAir	PA-II	$PM_{1.0}$	0.96-0.98	0.99
		$PM_{2.5}$	0.93-0.97	0.99
		PM_{10}	0.66-0.70	0.95

A similar website for $PM_{2.5}$ data presentation has been developed by Purple Air and shown in the figure below, where the sensor location and real-time $PM_{2.5}$ data are seen in Figure 1

(https://www.purpleair.com/map?opt=1/mAQI/a10/cC0#1/25/-30).

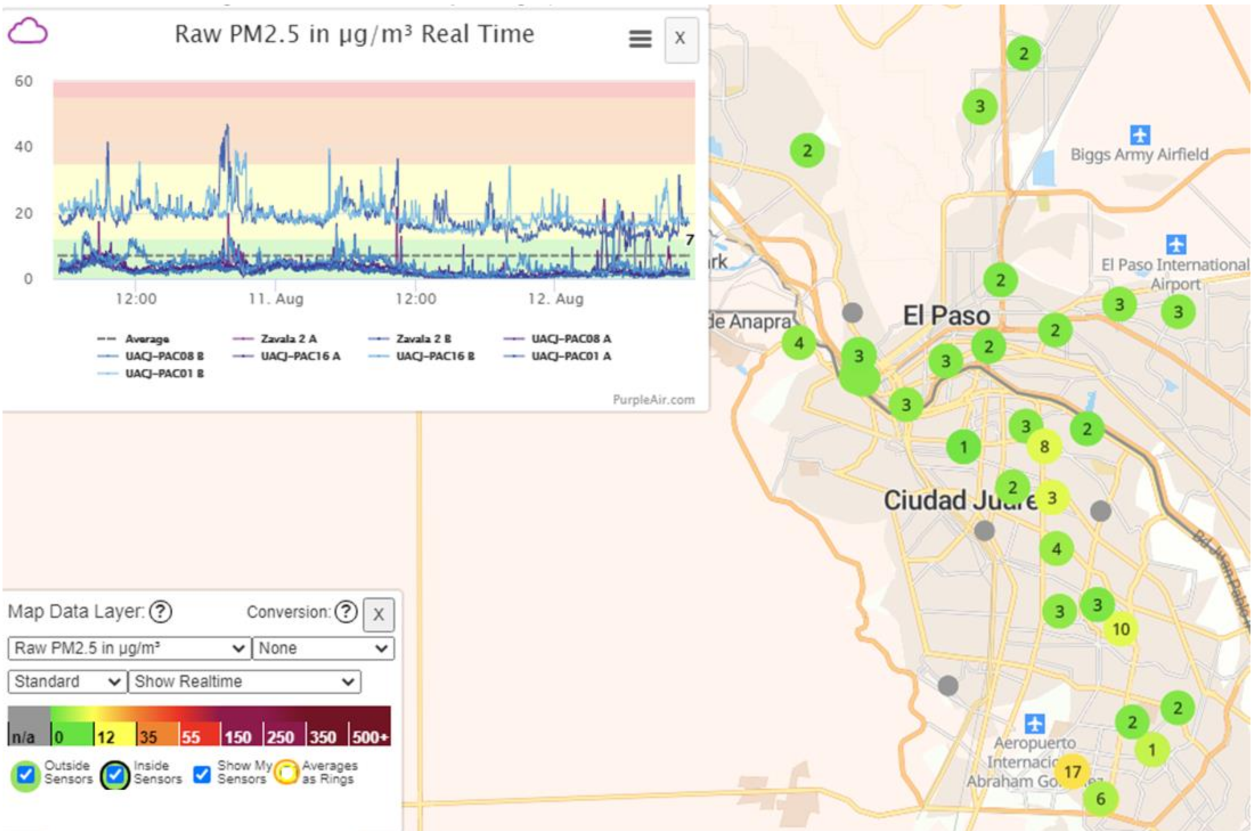


Figure 1 PurpleAir website for $PM_{2.5}$ data presentation

3.1.1 Instrumentation and Setup

The project installed an air monitoring network in the PdN to measure $PM_{2.5}$ at 32 sites in El Paso and Ciudad Juarez plus duplicates located at 12 sites. In total 48 sensors were evaluated at various quality control levels. Task 1 involved monitoring $PM_{2.5}$ levels at selected public elementary schools in the PdN. These sites were 17 elementary schools of high and low traffic exposure based on annual average daily traffic (AADT). These elementary schools encompass 12 sites in El Paso and five sites in Ciudad Juarez. Task 2 involves monitoring PM in the industrial sector in Ciudad Juarez. Again, 14 monitoring sites in industrial zones in Ciudad Juarez were chosen including low and high traffic exposure areas. The sampling project took place over two months, from March through April 2021. The sites chosen for Task 1 (elementary schools) and Task 2 (industrial sites) are shown below in Figure 2.

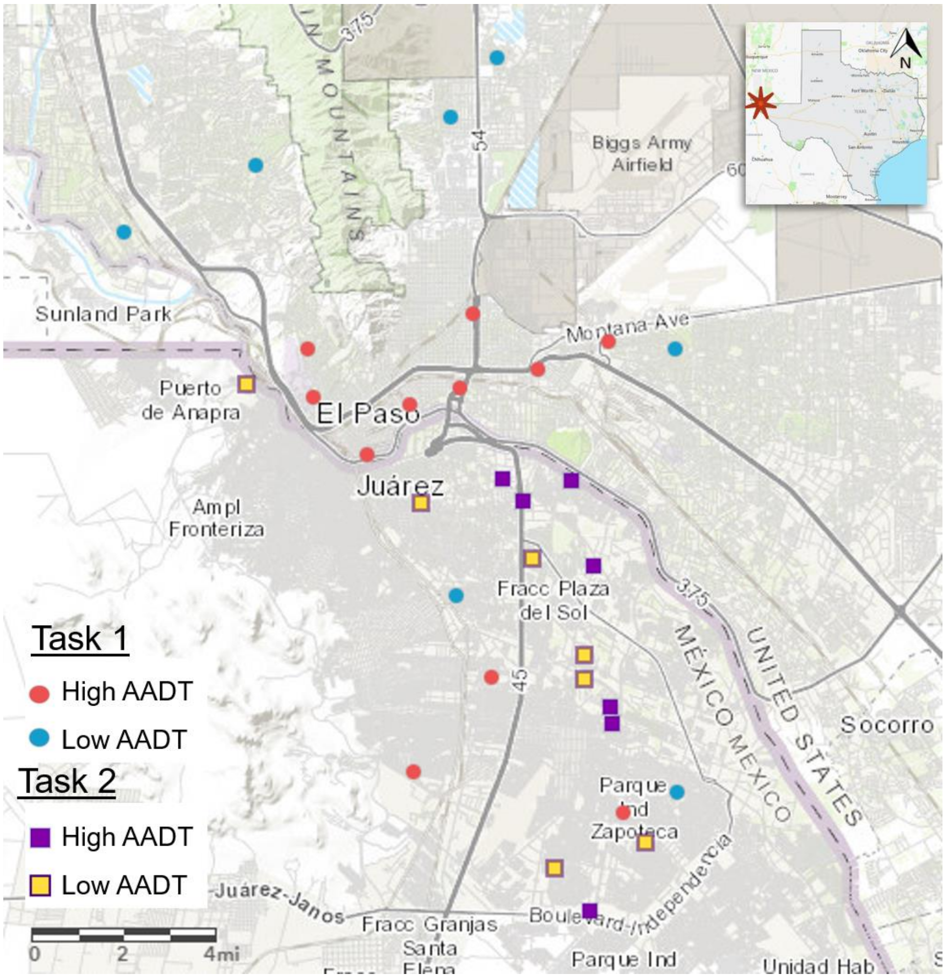


Figure 2 Map of PurpleAir locations for the PdN including AADT

The industrial sector air monitoring network in Ciudad Juarez focuses on the industrial zone in central Ciudad Juarez . According to the National Institute of Statistics and Geography (INEGI), by December 2019, close to 329 maquilas, or manufacturing facilities, employ a workforce in Ciudad Juárez, distributed along industrial zones and parks. The 14 sites for this monitoring network in Task 2 were also selected to designate high and low traffic zones using information from the Municipal Institute for Investigation and Planning (IMIP for its acronym in Spanish). A total of 7 sensors were placed in high traffic zones, which are in industry-related zones. The remaining seven sensors were placed in low traffic areas, residential zones without a *maquila* in a 100m radius. A map of these monitoring sites for Task 2 is shown in Figure 3.

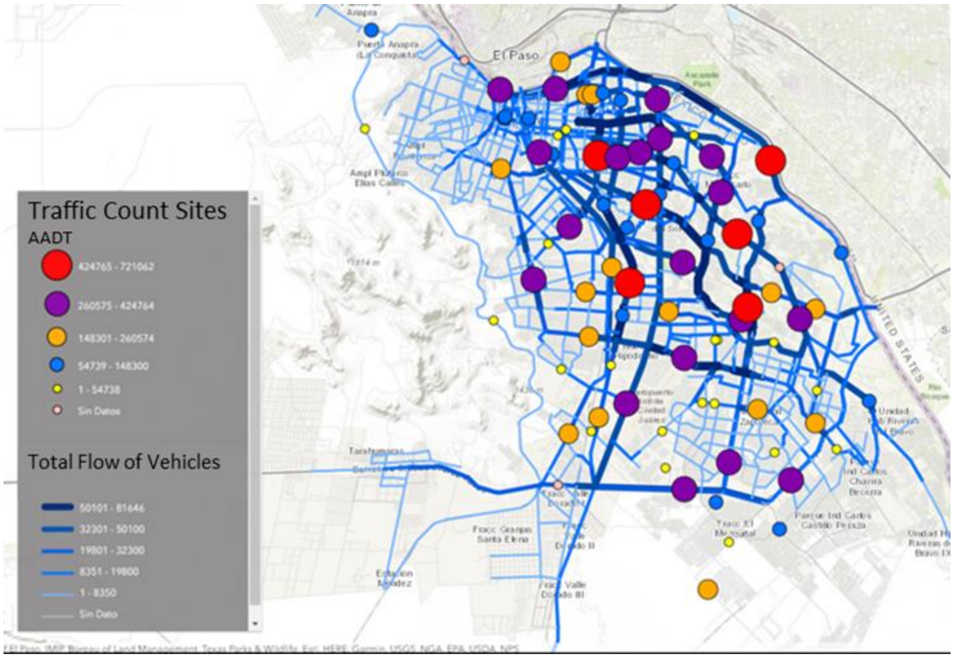


Figure 3 Traffic Count in Sites in Ciudad Juarez

A complete list of all sites and co-located sensors at continuous $PM_{2.5}$ monitoring sites, including their coordinates, are presented in Table 2, along with a naming system to coordinate data presented from each site. 38% of all the sites had a duplicate, collocated sensor, which is shown in bold. Each site is named according to location and type of site. For example, elementary schools were labeled "E" followed by the city identifier "EP" or "CJ," and an ID number. Industrial sector sites were labeled "I," followed by the city identifier "CJ," and an ID number. Sites may also be identified by their names on the PurpleAir website, shown in the second column.

Table 2 Site List for Task 1 and Task 2

ID	Name on PurpleAir Website	Latitude	Longitude	AADT	Type of Site
E-EP1	Zavala	31.7718	-106.4470	High	Elementary School
	Zavala 2				
E-EP2	Hawkins	31.7774	-106.4185	High	Elementary School
E-EP3	Bonham	31.7866	-106.3922	High	Elementary School
E-EP4	Douglass	31.7663	-106.4657	High	Elementary School
E-EP5	Coldwell	31.7951	-106.4424	High	Elementary School
E-EP6	Aoy	31.7508	-106.4815	High	Elementary School
	Aoy 2				
E-EP7	Mesita	31.7839	-106.5037	High	Elementary School
E-EP8	Cielo Vista	31.7840	-106.3676	Low	Elementary School
E-EP9	Park	31.8567	-106.4507	Low	Elementary School
	Park 2				
E-EP10	Whitaker	31.8509	-106.4254	Low	Elementary School
E-EP11	Western Hills	31.8415	-106.5225	Low	Elementary School
E-EP12	Zach White	31.8208	-106.5713	Low	Elementary School
E-CJ1	UACJ-PAC07	31.7383	-106.4311	High	Elementary School
E-CJ2	UACJ-PAC12	31.7210	-106.5218	Low	Elementary School
E-CJ3	UACJ-PAC13	31.7033	-106.4273	High	Elementary School
E-CJ4	UACJ-PAC16	31.6846	-106.4516	High	Elementary School
E-CJ5	UACJ-PAC11	31.6577	-106.4524	High	Elementary School
UTEP 1	UTEP 1	31.7687	-106.5012	High	Calibration Site
	UTEP 2				
	UTEP 3				
I-CJ1	UACJ-PAC08	31.7271	-106.3830	High	Industrial Sector
I-CJ2	UACJ-PAC09	31.7182	-106.4204	Low	Industrial Sector
I-CJ3	UACJ-PAC01	31.6162	-106.4103	Low	Industrial Sector
	UACJ-PAC10				
I-CJ4	UACJ-PAC22			High	Industrial Sector
	UACJ-PAC21	31.7154	-106.3979		
I-CJ5	UACJ-PAC20	31.7363	-106.4238	High	Industrial Sector
	UACJ-PAC19				
I-CJ6	UACJ-PAC15	31.6576	-106.3995	Low	Industrial Sector
I-CJ7	UACJ-PAC04	31.6748	-106.3866	High	Industrial Sector
I-CJ8	UACJ-PAC23	31.6067	-106.3994	High	Industrial Sector
	UACJ-PAC24				
I-CJ9	UACJ-PAC14	31.6878	-106.4015	Low	Industrial Sector
I-CJ10	UACJ-PAC02	31.6285	-106.3770	Low	Industrial Sector
	UACJ-PAC03				
I-CJ11	UACJ-PAC17	31.7355	-106.4616	Low	Industrial Sector
	UACJ-PAC18				
I-CJ12	UACJ-PAC05	31.7716	-106.5573	Low	Industrial Sector
	UACJ-PAC06				
I-CJ13	UACJ-PAC26	31.6662	-106.3912	High	Industrial Sector
	UACJ-PAC25				
I-CJ14	UACJ01	31.7433	-106.4315	High	Industrial Sector

3.1.2 Data Collection

The study installed a low-cost monitoring network with 48 PurpleAir PM sensors (PA-II-SD) at 32 sites. The sensors continuously transmitted data to the PurpleAir website and stored the data locally on an internal memory card. PurpleAir also provides its real-time data through a

JavaScript Object Notation (JSON). PurpleAir transmits data to their servers every 120 seconds and multiple data sets are sent. The data that is included is $PM_{2.5}$ mass concentration, temperature, humidity, and relative pressure. The JSON format allows for data to be transferred from a server to a client. For example, PurpleAir data are stored through "ThingSpeak" servers. Using an R program, this real-time data can be called remotely, and it allows for a seamless process that facilitates the download of many sensors at one time. Downloading multiple sensors allows for the complete data acquisition for the entire network located in the PdN. In addition, data are collected in 120-second intervals, with no further processing or data manipulation. In our study, data were collected via the R program underwent several modifications to make the data readable. First, the program reformatted the JSON format and transformed the existing data into a .csv file, which is easier to read and interpret. Second, the data were changed to the timezone that the user is in; for example, the data were changed from UTC to MST. This step is critical in the data acquisition as it allows the data to be compared to a monitoring station in the area. The collected data underwent a preliminary enhancement to help the data be processed and compared to a central monitoring station. In addition, data were enhanced with geospatial markers, which give the data points a location in time. The markers allow researchers to compare the data to nearby monitoring stations. It is worth mentioning that even though an approximation to the contaminants' concentrations in real-time is sought after, these sensors cannot be used as federally referenced instruments. In addition, the data provided on the PurpleAir website does not undergo any quality control and can contain errors.

3.1.3 Low-Cost Sensor Management

Once the low-cost equipment was installed in the selected sites, the operation of each of these was reviewed. First, each of the sensors was evaluated and monitored closely by the field team to ensure that the sensors are operational. Next, the team monitored the sensors closely via the PurpleAir website. If a problem was detected at the monitoring point, the field team communicated via telephone with the responsible persons. The field team then went to verify the possible failure (electricity or connectivity) through this communication. Appendix A displays the set-up of selected monitoring sites from the campaign.

3.1.4 Low-Cost Sensor Data Validation

The low-cost sensors by PurpleAir report specific parameters and have certain operating ranges, as seen in Table 3. For example, the PurpleAir sensor reports four parameters that are crucial in identifying each sensor's data validity. In addition, the operating ranges served as a preliminary data cleaning to remove data that is well out of the operating ranges of the sensor.

Table 3 PurpleAir Operation Range and System Parameters

Parameter	Operation Range
Effective Range ($PM_{2.5}$ standard)	0 to 500 µg/m^3
Maximum Range ($PM_{2.5}$ standard)	≥1,000 µg/m^3
Temperature Range	-40 °F to 185 °F (-40°C to 85°C)
Humidity	Response time (τ63%): 1 s Accuracy tolerance: ±3% RH Hysteresis: ≤ 2% RH

The data downloaded via JSON format underwent a preliminary data cleaning to ensure that each parameter is within range. Next, the data that is outside of the operating range was eliminated. For example, if humidity is < 0, the data point is invalidated, and if the humidity is

>100, it is also invalidated. If a $PM_{2.5}$ reading is < 0 or >500, then the data point is invalidated. The remaining data after the preliminary cleaning underwent an averaging and a more stringent process. At the end of this process, a $PM_{2.5}$ column was created by averaging the A and B channel base means. The data passing these specific parameters was validated. For example, if the minimum count is < 20 data points per hour, data would be invalidated if the A/B hourly difference is >5, A/B hourly percent difference is >70%, or the A/B hourly data recovery is <90%. Table 4 shows the total number of invalidated hours of data from March 1-April 30 for each sensor. It can be seen that at least two of the sensors located in Ciudad Juarez had over 50% of operating hours invalidated.

Table 4 Invalidated Hours for each Sensor March 1-April 30

Sensor	Online Hours	Invalidated Hours	Invalidated Hours %
UTEP1	822	56	6.8
UTEP 3	1327	379	28.6
UTEP 2	1327	104	7.8
Cielo Vista	1436	96	6.7
Douglass	1439	122	8.5
Mesita	1435	104	7.2
Park 2	851	55	6.5
Park	1439	211	14.7
Bonham	1426	390	27.3
WesternHills	1312	357	27.2
Whitetaker	1257	370	29.4
ZachWhite	1439	95	6.6
Zavala	1439	106	13.6
Zavala 2	1439	227	15.8
Aoy 2	1364	116	8.5
Aoy	1120	346	30.9
Hawkins	1394	343	24.6
UACJ_PAC01	1418	216	15.2
UACJ_PAC02	1437	98	6.8
UACJ_PAC03	1437	464	32.3
UACJ_PAC04	1429	208	14.6
UACJ_PAC05	1429	78	5.5
UACJ_PAC06	1429	89	6.2
UACJ_PAC08	1438	75	5.2
UACJ_PAC09	1430	110	7.7
UACJ_PAC10	1439	212	14.7
UACJ_PAC11	1433	73	5.1
UACJ_PAC12	1439	75	5.2
UACJ_PAC13	1439	61	4.2
UACJ_PAC14	1365	798	58.5
UACJ_PAC15	1439	1072	74.5
UACJ_PAC16	1437	115	8.0
UACJ_PAC17	1437	67	4.7
UACJ_PAC18	1437	55	3.8
UACJ_PAC19	1162	74	6.4
UACJ_PAC20	1162	72	6.2
UACJ_PAC21	550	36	6.5
UACJ_PAC22	549	34	6.2
UACJ_PAC23	1044	68	6.5
UACJ_PAC24	1044	72	6.9
UACJ_PAC25	883	55	6.2
UACJ_PAC26	883	56	6.3
UACJ_PAC27	930	332	35.7
UACJ_PAC28	829	37	4.5

3.1.6 Multiple Regression Model for calibration

Low-cost sensor could not generate data with the same quality as those monitored at a fixed station. In this case, the data generated by the low-cost sensors were calibrated against side-by-side data measured at a reference station using FRM instrument using Munir et al multiple regression algorithm (19). Multiple regression analysis is a statistical technique that analyzes the relationship between two or more variables and uses the information to estimate the value of the dependent variables. In multiple regression, the objective is to develop a model that describes a dependent variable y to more than one independent variable.

A multiple regression analysis develops corrected slope and offset (intercept) values for a lower-cost sensor which correlate the readings to that monitored by an FRM instrument to improve the accuracy of results. During calibration, the measurements are regressed vs. reference measurements, where readings from the PurpleAir are taken as independent (x-axis) and reference readings as the dependent (y-axis) variable. The multiple regression model was developed, including humidity and temperature variables, based on Equation 1:

$$Ref = \beta_0 + \beta_1(Sensor) + \beta_2(HR) + \beta_3(Temp) + \varepsilon \qquad (1)$$

Equation 1 includes the variables of relative humidity (*HR*) in percentage (%) and temperature (*Temp*) in Celsius degrees (°C). Data that was out of range was eliminated. Data were also eliminated if the difference between channels was more significant than 5 mg/m^3.

Subsequently, the calculation of $\beta_0, \beta_1, \beta_2$ and β_3 for $PM_{2.5}$, was carried out in the R-program. Once these values were obtained, Equation 1 was applied to obtain the corrected $PM_{2.5}$ values. This procedure was carried out with each of the sensors and the regression was used to evaluate the correlations between the low-cost sensor and the reference station.

Chapter 4: Quality of Data and Instrument Calibration

4.1 FRM Correlation and Calibration Multivariate

Before installing the sensors in the field, a monitoring campaign was carried out at a UTEP facility that is immediately adjacent to CAMS 12 for calibration. This campaign was carried out for 15 days in December 2020. In addition, the data generated was subjected to a cleaning and quality control process according to the QAPP. The comparative analysis was carried out with a univariate analysis using the hourly averages of each sensor and the corresponding values from the reference station. The 48 sensors evaluated showed a high correlation ($R^2 > 0.9$) with the data from CAMS12, as seen in Table 5.

Table 5 Correlation analysis for 48 sensors during calibration multivariate

ID	R^2 corrected	Site		ID	R^2 corrected	Site
C1	0.9203	Hawkins		C25	0.9098	UACJ-PAC01
C2	0.9221	Zavala		C26	0.8979	UACJ-PAC22
C3	0.925	Mesita		C27	0.9276	UACJ-PAC21
C4	0.9252	Aoy 2		C28	0.9223	UACJ-PAC20
C5	0.8923	CAMS12		C29	0.9048	UACJ-PAC19
C6	0.9021	CAMS12		C30	0.9254	UACJ-PAC23
C7	0.9119	CAMS 7		C31	0.9201	UACJ-PAC24
C8	0.9223	Whitaker		C32	0.9146	UACJ-PAC17
C9	0.9203	Douglass		C33	0.9191	UACJ-PAC18
C10	0.8848	Aoy		C34	0.924	UACJ-PAC25
C11	0.9284	Park		C35	0.92	UACJ-PAC26
C12	0.9093	Coldwell		C36	0.9252	SPARE
C13	0.9237	Cielo Vista		C37	0.9243	UACJ-PAC15
C14	0.9171	Zach White		C38	0.9225	UACJ-PAC05
C15	0.9201	Western Hills		C39	0.9218	UACJ-PAC06
C16	0.9194	UACJ-PAC07		C40	0.9205	UACJ-PAC08
C17	0.9075	UACJ-PAC11		C41	0.9101	UACJ-PAC28
C18	0.9127	UACJ-PAC27		C42	0.9282	UACJ-PAC02
C19	0.8432	UACJ-PAC12		C43	0.9238	UACJ-PAC03
C20	0.9077	UACJ-PAC13		C44	0.9097	UACJ-PAC09
C21	0.9182	UACJ-PAC16		C45	0.9169	UACJ-PAC10
C22	0.943	Park 2		C46	0.9114	SPARE
C23	0.9172	Zavala 2		C47	0.9241	UACJ-PAC14
C24	0.9243	Bonham		C48	0.9167	UACJ-PAC04

4.2 Channel to Channel Comparison

As previously mentioned, the low-cost sensors used throughout the campaign are equipped with dual Plantower PMS50003; these sensors are named channel A and channel B. These channels generate a two-minute average for each of the sensors. These channel comparisons are used as an indicator of sensor malfunctioning. Channel comparisons also indicate which sensor is about to malfunction. However, not all malfunctions are due to a system malfunction. For example, since the sensors are placed in an outdoor setting, the instrument could be affected by debris settling within the sensor or insects crawling and nesting. Channel comparison plots were developed for each sensor to see how linearly congruent they are with each other. The sensors located in El Paso showed that they have good linearity within channels A and B. It can be noted that some of the sensors showed a slight variation with channels. Most of the sensors remained with a coefficient of determination (R^2) of 0.9 and above. Several other issues can cause the channel sensors to deviate slightly or have a lower R^2. One common issue persistent throughout the campaign is that the sensor's channels may become clogged by outside debris, significantly reducing the instruments' capacity. Similar to the sensors located in El Paso, the sensors that are located in Ciudad Juarez showed a substantial congruity between each of the sensor's channels. Table 6 demonstrates high R^2 values for all sensors.. This can be due to multiple reasons; one trend that is beginning to emerge with this network is that older sensors tend to lose accuracy as they age, most of the sensors that were in Ciudad Juarez were from the newer batch of low-cost sensors, and as such showed more substantial linearity. That is not to say that they are more accurate or precise, as most of the sensors in the network had an R^2 of >0.9. The sensors channel comparison is an early indicator of which sensor will begin to malfunction or a sensor that needs maintenance.

Table 6 Channel to channel correlation for all sensors

Sensor	R^2	Sensor	R^2
UTEP 1	0.9963	UACJ-PAC01	0.9948
UTEP 2	0.968	UACJ-PAC02	0.9922
UTEP 3	0.8879	UACJ-PAC03	0.9378
Bonham ES	0.9946	UACJ-PAC04	0.9854
Park 2	0.9919	UACJ-PAC05	0.9958
Park	0.9245	UACJ-PAC06	0.9898
Whitetaker	0.8798	UACJ-PAC21	0.9734
WesternHills	0.9774	UACJ-PAC10	0.9806
Mesita	0.9928	UACJ-PAC09	0.9971
Douglass	0.9832	UACJ-PAC08	0.9934
Cielo Vista	0.9604	UACJ-PAC11	0.9903
Aoy	0.9157	UACJ-PAC12	0.9944
Aoy 2	0.9961	UACJ-PAC13	0.9971
ZachWhite	0.984	UACJ-PAC14	0.8691
Zavala 2	0.9959	UACJ-PAC15	0.9244
Zavala	0.9935	UACJ-PAC16	0.9916
		UACJ-PAC17	0.9936
		UACJ-PAC18	0.9958
		UACJ-PAC20	0.9961
		UACJ-PAC19	0.9916
		UACJ-PAC22	0.9911
		UACJ-PAC23	0.9902
		UACJ-PAC24	0.9931
		UACJ-PAC25	0.9939
		UACJ-PAC26	0.9966
		UACJ-PAC27	0.8719
		UACJ-PAC28	0.9957
		UACJ-PAC07	0.9991

4.3 Duplicated Sensors (Sensor To Sensor Comparison)

During the monitoring campaign, 12 sites were equipped with duplicates representing around 38% of the monitoring network. These duplicated sensors served as another step of quality assurance. As previously mentioned, the sensors are checked against each other's channels to ensure they are operating correctly. This extra level of quality control ensured that the deployed sensors were performing to the best of their ability. As part of the measurement quality control process, sites were randomly selected where duplicate PurpleAir sensors were placed. It is designed to assure the data quality of the sensors. The validation of the operation of these was evaluated utilizing a correlation analysis. Table 7 shows that the 12 sites showed a correlation greater than 0.97, so it can be deduced that the equipment works correctly, in relation to other PurpleAir sensors.

Table 7 Correlation analysis for Duplicated Sensor Sites Comparison

ID	Name on PurpleAir Website	AADT	Type of Site	R^2
C2	Zavala 2	High	Elementary School	0.9850
C23	Zavala			
C4	Aoy 2	High	Elementary School	0.9555
C10	Aoy			
C22	Park 2	Low	Elementary School	0.9779
C11	Park			
C5	UTEP 3	High	Calibration Site	0.9849
C7	UTEP 1			
C6	UTEP 2		Calibration Site	0.9961
C7	UTEP 1			
C6	UTEP 2		Calibration Site	0.9414
C5	UTEP 3			
C26	UACJ-PAC22	High	Industrial Sector	0.9928
C27	UACJ-PAC21			
C28	UACJ-PAC20	High	Industrial Sector	0.9676
C29	UACJ-PAC19			
C30	UACJ-PAC23	High	Industrial Sector	0.9777
C31	UACJ-PAC24			
C35	UACJ-PAC26	High	Industrial Sector	0.9878
C34	UACJ-PAC25			
C44	UACJ-PAC09	Low	Industrial Sector	0.9798
C45	UACJ-PAC10			
C42	UACJ-PAC02	Low	Industrial Sector	0.9752
C43	UACJ-PAC03			
C32	UACJ-PAC17	Low	Industrial Sector	0.9949
C33	UACJ-PAC18			
C38	UACJ-PAC05	Low	Industrial Sector	0.9699
C39	UACJ-PAC06			

Chapter 5: Results

5.1 Low-Cost Sensor Data Results

The $PM_{2.5}$ monitoring campaign was carried out in 32 sites distributed in both cities. For Task 1, 17 school locations were chosen (12 in El Paso and 5 in Ciudad Juarez), while in Ciudad Juarez, 15 sensors were placed in high and low traffic areas. The data transmitted from the sensors were recorded on the PurpleAir website. Each sensor's operation was monitored daily and any anomaly with the sensor was recorded. During the study, two sensors utilized in Task 2 were found to record anomalous data, possibly due to excessive dust accumulation at the inlets. These two sensors were cleaned and redeployed. However, the sensors were impaired and continued to record inconsistent high values. As a result, these sensors were replaced, in the middle of the campaign, with UACJ-PAC-27 and UACJ-PAC-28.

5.2 Descriptive Statistics

The average $PM_{2.5}$ concentration in the PdN was found to fluctuate between 7.6 and 12.6 $\mu g/m^3$ based on the data collected from the 32 locations. The minimum average recorded was 1.4 $\mu g/m^3$ at Zach White, and the maximum average was found to be 81.9 $\mu g/m^3$ at UACJ-PAC11 (Table 8). Table 8 also shows the descriptive statistics for $PM_{2.5}$ at each of the locations.

Table 8 Descriptive Statistics for $PM_{2.5}$ obtained during the monitoring campaign

$PM_{2.5}$							
ID	**Name on PurpleAir Website**	**AADT**	**Type of Site**	**Average**	**Standard deviation**	**Minimum**	**Maximum**
C2	Zavala	High	Elementary School	9.1	3.0	3.8	31.1
C23	ZavalaEs	High	Elementary School	8.7	3.1	2.3	31.5
C1	Hawkins	High	Elementary School	8.4	2.8	2.6	32.9
C24	Bonham	High	Elementary School	9.4	3.1	2.3	33.7
C9	Douglass	High	Elementary School	9.2	3.3	2.6	30.3
C12	Coldwell	High	Elementary School	8.9	2.8	3.1	27.9
C4	Aoy	High	Elementary School	10.1	3.8	3.7	36.2
C10	AoyES	High	Elementary School	10.2	4.7	2.3	36.5
C3	Mesita	High	Elementary School	8.7	2.7	3.4	28.6
C13	Cielo Vista	Low	Elementary School	8.7	2.7	2.8	31.1
C22	Park2	Low	Elementary School	8.8	2.6	2.7	26.9
C11	ParkES	Low	Elementary School	8.7	2.8	2.7	31.6
C8	Whitaker	Low	Elementary School	7.6	2.9	3.7	33.7
C15	Western Hills	Low	Elementary School	8.8	2.9	3.2	29.5
C14	Zach White	Low	Elementary School	9.3	3.5	1.4	29.0
C5	UTEP 3	High	Calibration Site	9.6	3.3	3.6	31.3
C6	UTEP 2	High	Calibration Site	8.8	2.9	2.9	27.7
C7	UTEP 1	High	Calibration Site	9.7	2.6	6.2	24.9
C16	UACJ-PAC07	High	Elementary School	-	-	-	-
C20	UACJ-PAC13	High	Elementary School	11.0	4.7	3.2	50.4
C21	UACJ-PAC16	High	Elementary School	11.3	5.6	2.6	57.9
C17	UACJ-PAC11	High	Elementary School	12.7	7.5	3.2	82.0
C40	UACJ-PAC08	High	Industrial Sector	9.6	3.5	3.6	40.4
C26	UACJ-PAC22	High	Industrial Sector	8.9	2.9	4.0	34.1
C27	UACJ-PAC21	High	Industrial Sector	8.9	3.3	3.2	39.5
C28	UACJ-PAC20	High	Industrial Sector	9.0	3.0	4.2	32.2
C29	UACJ-PAC19	High	Industrial Sector	10.4	3.1	4.5	30.5
C48	UACJ-PAC04	High	Industrial Sector	9.8	4.4	3.5	53.1
C30	UACJ-PAC23	High	Industrial Sector	10.0	2.8	4.3	24.7
C31	UACJ-PAC24	High	Industrial Sector	10.5	3.0	4.6	25.9
C35	UACJ-PAC26	High	Industrial Sector	9.0	3.0	5.5	29.3
C34	UACJ-PAC25	High	Industrial Sector	9.0	3.0	5.5	29.3
	UACJ01	High	Industrial Sector	9.4	2.8	3.7	25.6
C19	UACJ-PAC12	Low	Elementary School				
C44	UACJ-PAC09	Low	Industrial Sector	9.2	4.1	2.4	47.7
C45	UACJ-PAC10	Low	Industrial Sector	8.9	3.9	2.8	42.7
C25	UACJ-PAC01	Low	Industrial Sector	11.7	5.2	2.7	54.7
C37	UACJ-PAC15**	Low	Industrial Sector	12.3	7.1	3.4	43.7
C41	UACJ-PAC28	Low	Industrial Sector	9.6	3.1	5.3	25.7
C47	UACJ-PAC14**	Low	Industrial Sector	10.6	5.2	3.3	39.6
C18	UACJ-PAC27	Low	Industrial Sector	8.5	3.3	4.0	31.2
C42	UACJ-PAC02	Low	Industrial Sector	10.3	3.7	2.9	30.7
C43	UACJ-PAC03	Low	Industrial Sector	10.9	4.6	3.1	45.3
C32	UACJ-PAC17	Low	Industrial Sector	9.4	4.1	4.5	47.6
C33	UACJ-PAC18	Low	Industrial Sector	10.0	4.5	2.9	50.6
C38	UACJ-PAC05	Low	Industrial Sector	9.9	4.9	2.6	60.1
C39	UACJ-PAC06	Low	Industrial Sector	9.6	5.2	3.7	61.0

** Sensors that were changed due to technical problems

For temperature (Table 9), the average for the season ranged between 66.9 ºF and 73.7ºF (19.4-23.1 ºC), with a maximum of 116.5ºF (46.9 ºC) and a minimum of 33.5ºF (0.9 ºC).

Table 9 Descriptive statistics for temperature obtained during the monitoring campaign

Temperature							
ID	**Name on PurpleAir Website**	**AADT**	**Type of Site**	**Average**	**Standard deviation**	**Minimum**	**Maximum**
C2	Zavala 2	High	Elementary School	68.5	12.4	39.3	99.6
C23	ZavalaEs			69.8	13.8	39.8	111.2
C1	Hawkins	High	Elementary School	70.9	13.0	40.3	102.2
C24	Bonham	High	Elementary School	68.7	13.2	38.3	103.8
C9	Douglass	High	Elementary School	70.5	11.7	42.9	98.7
C12	Coldwell	High	Elementary School	69.0	13.4	41.6	101.2
C4	Aoy 2	High	Elementary School	73.0	13.0	42.0	104.9
C10	AoyES			67.0	12.0	39.7	98.1
C3	Mesita	High	Elementary School	71.6	13.3	41.3	103.7
C13	Cielo Vista	Low	Elementary School	70.5	14.2	37.0	105.0
C22	Park 2	Low	Elementary School	68.9	11.6	38.0	92.6
C11	ParkES			68.5	12.1	38.7	97.5
C8	Whitaker	Low	Elementary School	70.2	12.2	42.9	99.7
C15	Western Hills	Low	Elementary School	69.4	13.9	36.3	104.7
C14	Zach White	Low	Elementary School	69.6	14.0	39.2	108.2
C5	UTEP 3	High	Calibration Site	67.8	12.7	38.7	100.4
C6	UTEP 2			68.2	12.4	39.5	100.2
C7	UTEP 1			72.0	11.9	47.0	101.6
C16	UACJ-PAC07	High	Elementary School	-	-	-	-
C20	UACJ-PAC13	High	Elementary School	69.9	14.5	35.6	110.6
C21	UACJ-PAC16	High	Elementary School	68.2	13.1	35.5	99.4
C17	UACJ-PAC11	High	Elementary School	71.4	13.4	40.2	105.0
C40	UACJ-PAC08	High	Industrial Sector	69.3	14.1	36.3	104.4
C26	UACJ-PAC22	High	Industrial Sector	68.1	12.2	40.6	97.1
C27	UACJ-PAC21			66.9	11.7	40.2	95.0
C28	UACJ-PAC20	High	Industrial Sector	70.0	12.6	39.7	98.7
C29	UACJ-PAC19			69.1	12.5	39.3	98.3
C48	UACJ-PAC04	High	Industrial Sector	68.8	13.4	36.3	101.8
C30	UACJ-PAC23	High	Industrial Sector	70.8	12.4	42.6	98.9
C31	UACJ-PAC24			69.7	12.6	40.5	98.5
C35	UACJ-PAC26	High	Industrial Sector	73.7	13.6	44.9	104.5
C34	UACJ-PAC25			73.7	13.6	44.9	104.5
	UACJ01	High	Industrial Sector	69.8	14.7	38.7	116.5
C19	UACJ-PAC12	Low	Elementary School	69.6	12.7	38.2	99.9
C44	UACJ-PAC09	Low	Industrial Sector	69.0	13.1	38.3	102.1
C45	UACJ-PAC10			68.8	13.4	37.8	102.4
C25	UACJ-PAC01	Low	Industrial Sector	70.1	14.1	37.2	104.4
C37	UACJ-PAC15**	Low	Industrial Sector	69.2	13.2	36.6	101.1
C41	UACJ-PAC28			73.1	12.0	48.0	99.5
C47	UACJ-PAC14**	Low	Industrial Sector	70.5	14.2	38.6	105.3
C18	UACJ-PAC27			67.8	12.7	38.7	100.4
C42	UACJ-PAC02	Low	Industrial Sector	68.4	13.7	36.0	102.7
C43	UACJ-PAC03			68.4	13.5	35.9	100.7
C32	UACJ-PAC17	Low	Industrial Sector	68.5	13.2	37.2	100.9
C33	UACJ-PAC18			68.7	13.1	37.6	101.1
C38	UACJ-PAC05	Low	Industrial Sector	66.9	12.9	35.5	98.3
C39	UACJ-PAC06			67.2	13.2	37.1	99.9

** Sensors that were changed due to technical problems

For humidity, shown in Table 10, average values were recorded between 14.6 and 19.2%. The minimum value was 0%, and the maximum was 70.6%

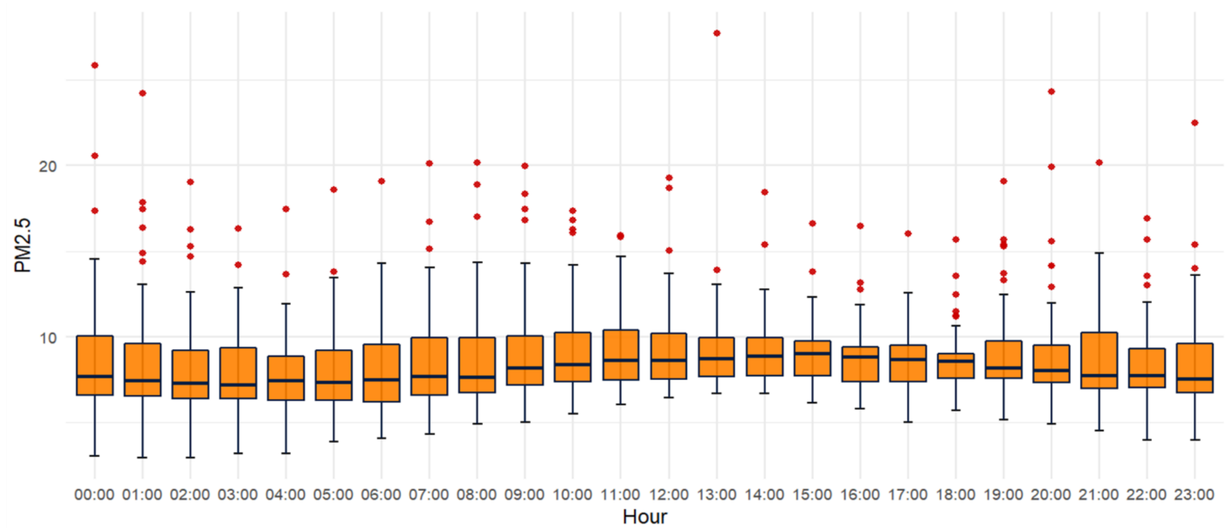
Table 10 Descriptive statistics for temperature obtained during the monitoring campaign

ID	Name on PurpleAir Website	AADT	Type of Site	Humidity Average	Humidity Standard deviation	Humidity Minimum	Humidity Maximum
C2	Zavala	High	Elementary School	17.0	11.5	0.0	66.1
C23	ZavalaEs			17.3	12.2	0.0	66.0
C1	Hawkins	High	Elementary School	16.0	11.3	0.1	64.3
C24	Bonham	High	Elementary School	16.2	12.2	0.0	65.9
C9	Douglass	High	Elementary School	17.7	10.5	2.0	63.2
C12	Coldwell	High	Elementary School	17.4	12.1	0.0	62.4
C4	Aoy	High	Elementary School	15.7	11.0	0.0	59.4
C10	AoyES			17.9	11.4	0.0	63.2
C3	Mesita	High	Elementary School	16.3	11.0	0.1	57.6
C13	Cielo Vista	Low	Elementary School	16.8	11.8	0.0	63.5
C22	Park2	Low	Elementary School	18.3	12.7	1.0	69.1
C11	ParkES			17.0	11.4	0.8	59.4
C8	Whitaker	Low	Elementary School	16.8	11.4	1.0	64.3
C15	Western Hills	Low	Elementary School	17.7	12.1	0.0	64.2
C14	Zach White	Low	Elementary School	19.2	11.2	1.2	58.1
C5	UTEP 3	High	Calibration Site	18.9	12.3	1.0	70.2
C6	UTEP 2			18.1	12.1	1.0	69.0
C7	UTEP 1			19.0	11.2	3.0	65.7
C16	UACJ-PAC07	High	Elementary School	-	-	-	--
C20	UACJ-PAC13	High	Elementary School	16.5	12.4	0.0	64.1
C21	UACJ-PAC16	High	Elementary School	16.3	12.1	0.0	66.0
C17	UACJ-PAC11	High	Elementary School	15.3	11.2	0.0	62.7
C40	UACJ-PAC08	High	Industrial Sector	17.3	12.5	0.0	68.2
C26	UACJ-PAC22	High	Industrial Sector	18.1	12.6	0.1	64.7
C27	UACJ-PAC21			17.8	12.2	0.1	63.0
C28	UACJ-PAC20	High	Industrial Sector	16.1	12.4	0.0	70.4
C29	UACJ-PAC19			16.7	12.1	0.0	65.5
C48	UACJ-PAC04	High	Industrial Sector	16.9	11.8	0.0	66.7
C30	UACJ-PAC23	High	Industrial Sector	16.8	12.4	0.2	69.6
C31	UACJ-PAC24			16.5	12.9	0.0	69.0
C35	UACJ-PAC26	High	Industrial Sector	16.4	12.3	0.0	60.1
C34	UACJ-PAC25			16.4	12.3	0.0	60.1
	UACJ01	High	Industrial Sector	16.9	11.9	0.0	62.7
C19	UACJ-PAC12	Low	Elementary School	16.7	11.1	0.3	65.4
C44	UACJ-PAC09	Low	Industrial Sector	17.3	12.5	0.0	70.6
C45	UACJ-PAC10			17.4	12.4	0.0	69.3
C25	UACJ-PAC01	Low	Industrial Sector	15.8	11.8	0.0	67.8
C37	UACJ-PAC15**	Low	Industrial Sector	17.0	11.8	0.0	63.6
C41	UACJ-PAC28			14.6	11.6	0.0	62.9
C47	UACJ-PAC14**	Low	Industrial Sector	17.2	12.3	0.0	66.4
C18	UACJ-PAC27			18.9	12.3	1.0	70.2
C42	UACJ-PAC02	Low	Industrial Sector	17.3	12.3	0.0	65.7
C43	UACJ-PAC03			17.3	12.6	0.0	66.6
C32	UACJ-PAC17	Low	Industrial Sector	16.4	12.4	0.0	68.3
C33	UACJ-PAC18			16.8	12.4	0.0	68.1
C38	UACJ-PAC05	Low	Industrial Sector	17.4	12.0	0.1	66.9
C39	UACJ-PAC06			18.3	12.7	0.0	65.8

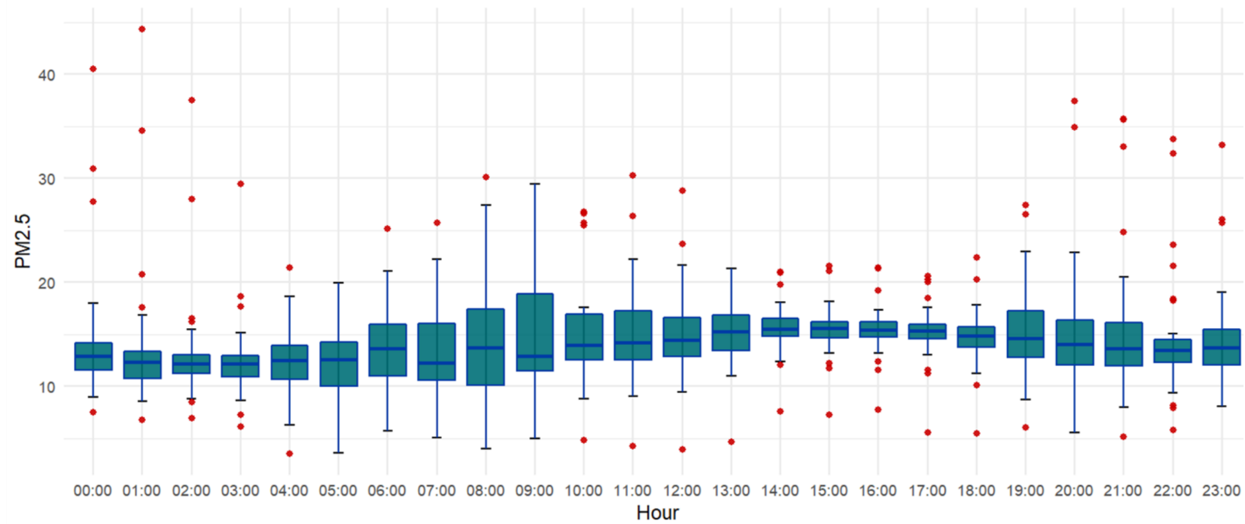
** Sensors that were changed due to technical problems

5.2.1 Daily $PM_{2.5}$ Variation

Hourly $PM_{2.5}$ data observed during the study period are summarized to show the diurnal variation at each sensor location in the PdN. Most of the sensors showed that $PM_{2.5}$ concentration peaks in the afternoons or early evenings before 8:00 p.m. Figure 4 shows the diurnal $PM_{2.5}$ variation at two representative locations, UTEP1 and UACJ01. Low $PM_{2.5}$ were observed during the nights before the vehicle flow started to increase (6:00 h). The Hourly average $PM_{2.5}$ boxplots for all sensors are presented in Appendix B.



a) Hourly Boxplot for $PM_{2.5}$ during the study period: UTEP 1



b) Hourly Boxplot for $PM_{2.5}$ during the study period: UACJ01

Figure 4 Hourly Boxplot for $PM_{2.5}$ during the study period: a) UTEP 1, b) UACJ01

General information on weekly trends can be seen in Table 11. $PM_{2.5}$ data were averaged per day of the week for each sensor during the study period. From these daily averages the day of the week with the highest average was identified in order to asses weekly trends of $PM_{2.5}$. Days of the week that recorded the highest and lowest are presented for each individual sensor. Weekly averaged time series' are shown for each sensor in Appendix C.

Table 11 Weekly trends of $PM_{2.5}$

ID	Name on PurpleAir Website	AADT	Type of Site	Highest Weekday	Lowest Weekday
C2	Zavala	High	Elementary School	Saturday	Thursday
C23	ZavalaEs				
C1	Hawkins	High	Elementary School	Saturday	Wednesday
C24	Bonham	High	Elementary School	Saturday	Thursday
C9	Douglass	High	Elementary School	Sunday	Thursday
C12	Coldwell	High	Elementary School		
C4	Aoy	High	Elementary School	Sunday	Thursday
C10	AoyES				
C3	Mesita	High	Elementary School	Sunday	Thursday
C13	Cielo Vista	Low	Elementary School	Saturday	Thursday
C22	Park2	Low	Elementary School	Sunday	Thursday
C11	ParkES				
C8	Whitaker	Low	Elementary School	Sunday	Wednesday
C15	Western Hills	Low	Elementary School	Sunday	Thursday
C14	Zach White	Low	Elementary School	Saturday	Thursday
C5	UTEP 3	High	Calibration Site	Sunday	Thursday
C6	UTEP 2				
C7	UTEP 1				
C16	UACJ-PAC07	High	Elementary School		
C20	UACJ-PAC13	High	Elementary School	Saturday	Thursday
C21	UACJ-PAC16	High	Elementary School	Sunday	Thursday
C17	UACJ-PAC11	High	Elementary School	Sunday	Thursday
C40	UACJ-PAC08	High	Industrial Sector	Saturday	Thursday
C26	UACJ-PAC22	High	Industrial Sector	Sunday	Wednesday
C27	UACJ-PAC21				
C28	UACJ-PAC20	High	Industrial Sector	Saturday	Wednesday
C29	UACJ-PAC19				
C48	UACJ-PAC04	High	Industrial Sector	sunday	Friday
C30	UACJ-PAC23	High	Industrial Sector	Saturday	Thursday
C31	UACJ-PAC24				
C35	UACJ-PAC26	High	Industrial Sector	Saturday	Thursday
C34	UACJ-PAC25				
	UACJ01	High	Industrial Sector	Saturday	Wednesday
C19	UACJ-PAC12	Low	Elementary School	Sunday	Thursday
C44	UACJ-PAC09	Low	Industrial Sector	Sunday	Thursday
C45	UACJ-PAC10				
C25	UACJ-PAC01	Low	Industrial Sector	Saturday	Thursday
C37	UACJ-PAC15	Low	Industrial Sector	NA	NA
C41	UACJ-PAC28				
C47	UACJ-PAC14	Low	Industrial Sector	NA	NA
C18	UACJ-PAC27				
C42	UACJ-PAC02	Low	Industrial Sector	Saturday	Thursday
C43	UACJ-PAC03				

C32	UACJ-PAC17	Low	Industrial Sector	Sunday	Thursday
C33	UACJ-PAC18				
C38	UACJ-PAC05	Low	Industrial Sector	Saturday	Thursday
C39	UACJ-PAC06				

5.2.2 PM Heat Map

Pollutant heat maps are used extensively to understand the risks a specific pollutant may pose in each area. The collected pollutant data can be mapped on a plane coordinate system to identify pollutant hot spots over a period average or throughout the day. The relationship between the pollutant data and their colors can be seen in the bottom left-hand corner of the following figures. A darker shade will represent a high concentration of the pollutant.

This study utilizes heats maps to visualize the spatial variation of the PM pollutant concentrations in PdN. All period average was plotted in the heat map, as shown in Figure 5,which shows a higher concentration in Ciudad Juarez than in El Paso, Texas. The all period average is helpful as it shows the concentration average over a defined period.

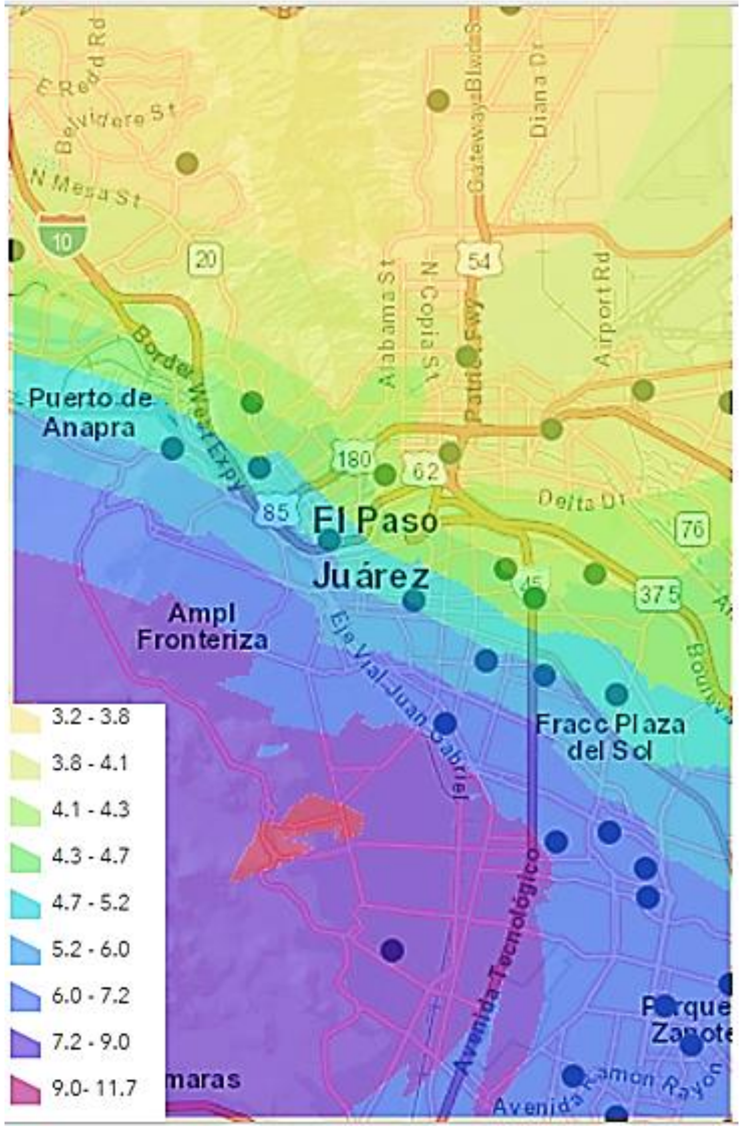


Figure 5 Heat map of $PM_{2.5}$: Period Average

The maximum 1-hr and maximum 24-hr $PM_{2.5}$ concentrations for the PdN during the study period are displayed in Figure 6. The heat map shows how the 24-hr average PM concentration varied throughout the basin. The max pollutant concentration for the 24-hour average showed the pollutant varied slightly, having higher concentrations in the southern regions of Ciudad Juarez.

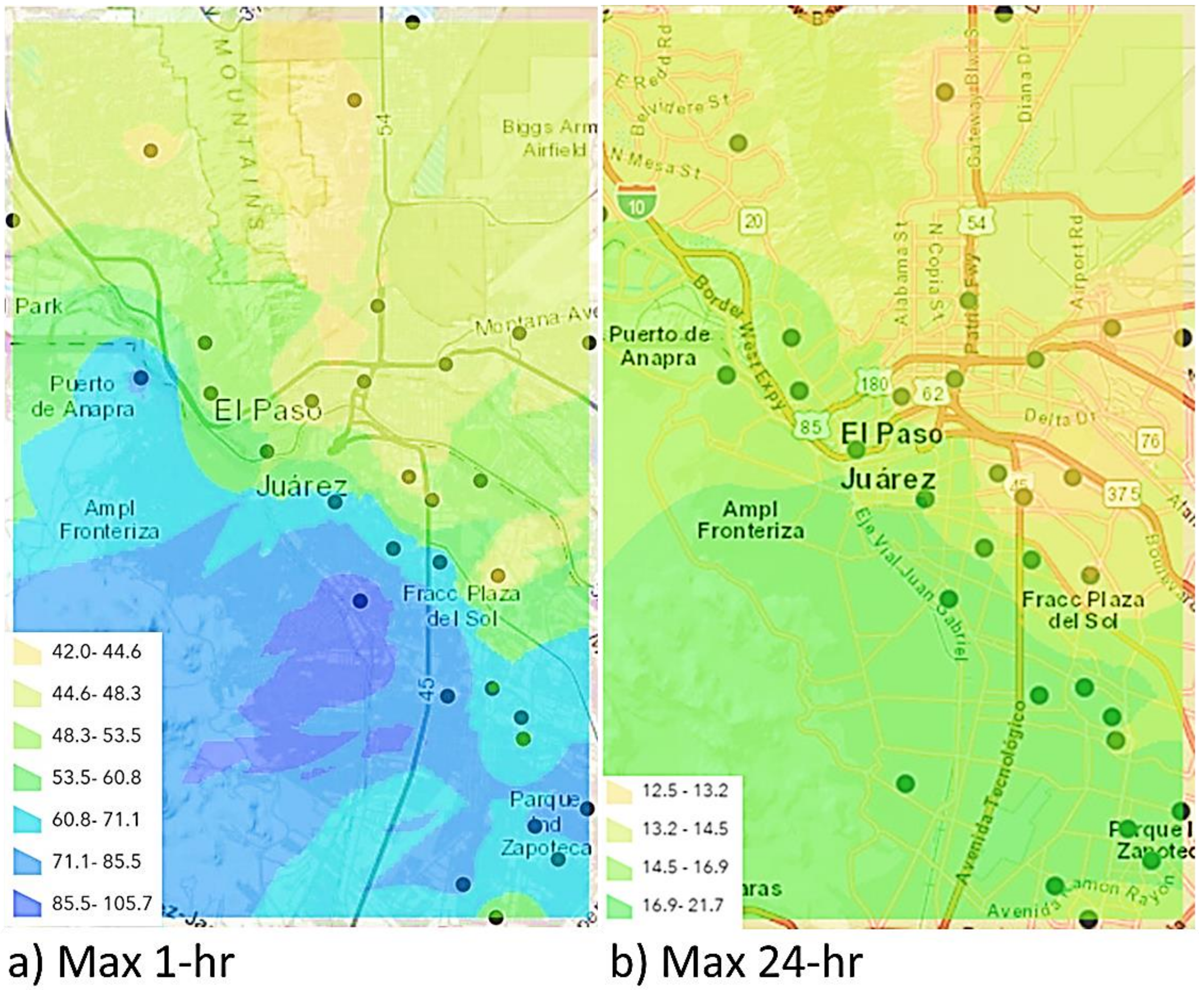


Figure 6 Heat Map of $PM_{2.5}$ in PdN a) Max 1-hr, b) Max 24-hr

5.2.3 Surface Meteorological Conditions

Surface meteorological conditions (wind direction and wind speed) during the study period are illustrated with wind rose plots. The wind rose plot is a graphical presentation of the frequency of occurrence of wind direction and wind speed categories. It is used to identify prevailing winds for air pollution study. Figure 7 shows the wind conditions for several locations in the PdN region during March and April 2021. Windrose is presentedin spokes; each spoke represents the frequency of winds that are coming from the direction of the spoke and the wind speed category is representd by the color code provided in the figure. During this period, westerly winds prevailed consistently throughout the PdN air basin.

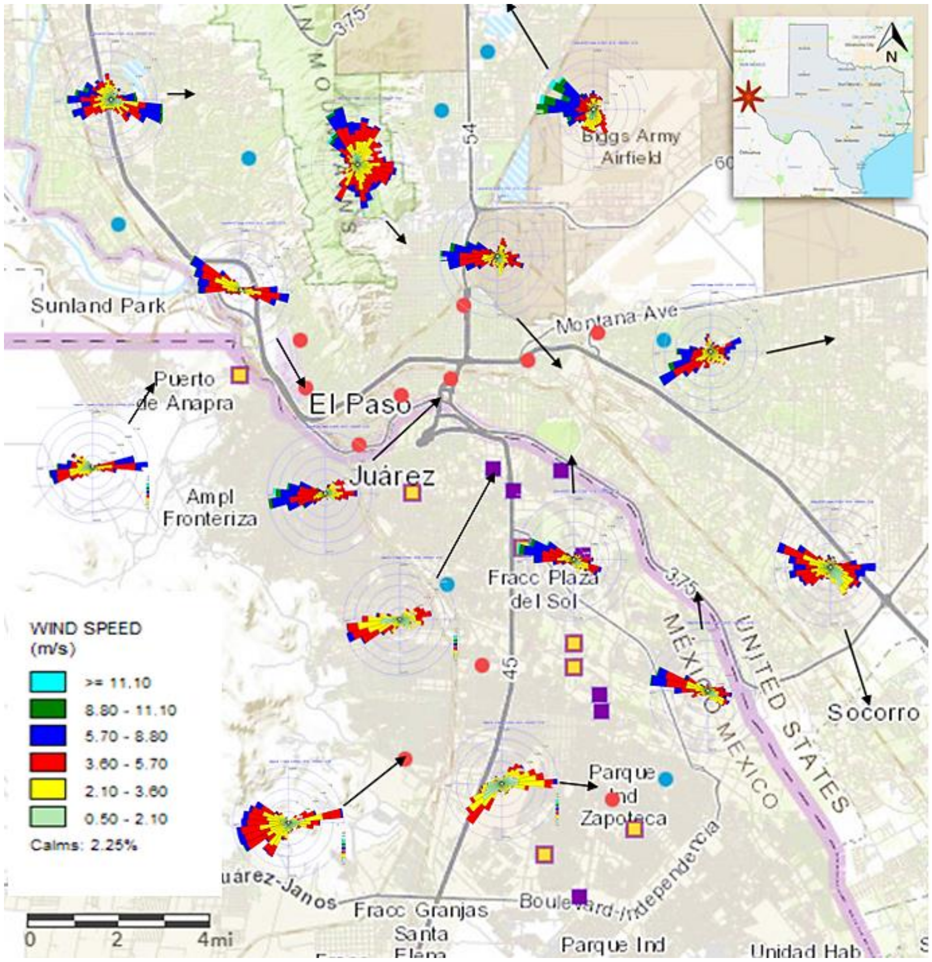


Figure 7 Map of study area with windrose

5.3 Land-Use Linear Regression

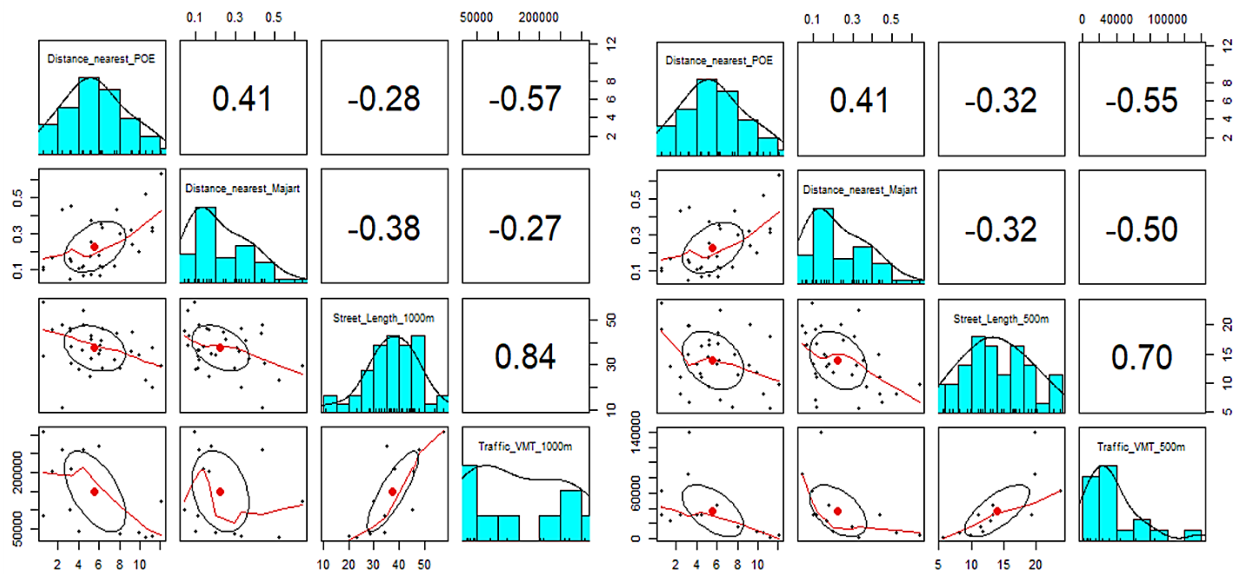
The land-use linear regression model is an algorithm that is developed to analyze pollution in relation to many predictor variables associated with land use of an area. Multiple regression equations are utilized to represent the relationships between the pollutant data and the predictors, this relied heavily on environmental variables and geographic information systems (GIS). The multivariate regression can be used to quantify the relationships between different types of traffic variables and air pollution.

Linear Regression

The linear regression model was utilized in this study as it is a simple regression model; it only utilizes one independent variable and assumes a linear function. This modified version has been adjusted for the number of predictors within the model. To make an accurate prediction using the regression model, the standard error of the regression is more meaningful than the R^2 because the standard error provides an idea of how precise the prediction is. The level of statistical significance was set at p-value of < 0.05 for all tests in this study. We used the statistical software R (version 3.6.2) to perform the statistical analysis portion of the study.

For the LUR modeling, we applied multivariate linear regression including 4 traffic variables; distance to the nearest major arterial road, street length within 500m impact zone, street length within 1000m impact zone, distance to the nearest port of entry (POE), traffic vehicle miles traveled within 500m zone and traffic vehicle miles traveled within 1000m zone. Distance to the nearest major arterial road (Dist_nearest_Majart), street length within 500m and 1,000m impact zone (Street_Length_500m, Street_Length_1000m), and distance to the nearest port of entry (Distance_nearest_POE) are measured in kilometers. Traffic counts were calculated from the average daily amount of vehicle miles traveled (VMT) within 500m and 1,000m zone of impact (Traffic_VMT_500m and Traffic_VMT_1000m) and converted to the unit in thousands.

In Figure 8, the scatterplot matrix presented for the pairs of traffic variables to explore the distribution of each variable and collinearity between variables.



a) Scatterplot Matrix of Pairs of Four Traffic Variables: 500 m radius b) Scatterplot Matrix of Pairs of Four Traffic Variables: 1000 m radius

Figure 8 Scatterplot Matrix of Pairs of Four Traffic Variables: a) 500 m radius, b) 1000 m radius

In the correlation analysis and univariate linear regression modeling, shown in Table 12, distance to nearest POE was found to be the only significant traffic variable in modeling of $PM_{2.5}$ for the period average ($\beta_1 = -0.190$, p-value=0.024). This indicates a relationship where high $PM_{2.5}$ is associated with a shorter distance to a POE. In other words, in this first regression model, we observed a significant negative association between Distance_nearest_POE and $PM_{2.5}$ Period Average, which implies that $PM_{2.5}$ value increases by 0.190 μg/m3 per one-unit decrease of Distance_nearest_POE.

Table 12 Correlation Analysis between $PM_{2.5}$ and traffic variables (unit: km, in thousands).

Yvar		Traffic Variables	Estimate	Std. Error	t value	Pr(>|t|)
$PM_{2.5}$ Period Average	500m Traffic Variables	(Intercept)	4.222	0.180	23.411	0.000
		Distance_nearest_Majart	-1.091	1.589	-0.687	0.504
		Street_Length_1000m	-0.049	0.037	-1.336	0.204
		Distance_nearest_POE	**-0.190**	**0.075**	**-2.545**	**0.024**
		Traffic_VMT_1000m	-0.001	0.003	-0.281	0.783
$PM_{2.5}$ Period Average	1000m Traffic variables	(Intercept)	4.205	0.200	20.975	0.000
		Distance_nearest_Majart	-1.807	1.750	-1.032	0.321
		Street_Length_500m	-0.037	0.072	-0.508	0.620
		Distance_nearest_POE	-0.140	0.085	-1.640	0.125
		Traffic_VMT_500m	-0.008	0.008	-0.984	0.343

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

Chapter 6: Discussion and Conclusions

6.1 Low-Cost Sensor Overall Performance

The use of low-cost sensors has grown over the last years, these sensors offer a cheap alternative for institutions and the general public, and in this way, they can be involved in the monitoring of contaminants, such as $PM_{2.5}$. However, there are some doubts regarding their functionality and reliability of their measurements compared to those of reference stations. Low-cost sensors can be a useful tool for the measuring and evaluation of certain events, but it is of vital importance to constantly monitor the equipment, as to reduce variations in its measuring. During the winter calibration campaign, the sensors demonstrated certain similitude in behavior with the CAMS 12 reference station. During the correlation analysis, R^2 values were superior (>0.9), which indicated that the equipment made the measuring in the same magnitudes as the reference station.

For the monitoring campaign, 32 PurpleAir sites were installed, 12 in El Paso, Texas sites, and 20 in Ciudad Juárez. These sites were chosen according to their Annual Average Daily Traffic, choosing sites with high AADT and sites with low AADT. The PurpleAir sensors worked adequately during the campaign, but it was noted that they are sensitive to dust storms events, minimizing real $PM_{2.5}$ concentration levels. Six PurpleAir sensors were affected by contamination originated from dust storms, and for this reason, a maintenance campaign took place. The functionality of only 3 of these sensors could be restored. Regarding measuring, the equipment behaved consistently, showing very similar mean $PM_{2.5}$ values throughout the campaign and steady connectivity.

In the case of sensors collocated in school zones in El Paso, it was observed that high AADT sites presented a slightly higher average (9.26±0.59) µg/m^3 than that presented in low AADT sites (8.63±0.54) µg/m^3. On the other hand, in Ciudad Juarez there were two site categories: 1) school zones, and 2) industrial zones. In school zones, high AADT sites registered values of 11.66±0.87 µg/m^3, while unfortunately there was only one monitor placed in a low AADT site, and it presented values outside of the ones established for the project, UACJ-PAC12. In the industrial zones, values are somewhat different from the previously stated: In high AADT sites, the registered values were a little below (9.48±0.61) µg/m^3 from those registered on low AADT sites (10.06±1.07) µg/m^3. This, due to a series of street alterations currently taking place in the city, which generates an atypical vehicular flow. The behavior of the contaminant in both communities can be observed in Figure 5, where it is shown that $PM_{2.5}$ concentrations are lower in El Paso, Texas, than those in Ciudad Juárez. On the other hand, to perform the $PM_{2.5}$ data correction, sensors' temperature and humidity data were used. With this, it was observed that the PurpleAir sensors usually overestimate temperature, reaching levels as high as 116 °F (46.66 °C), especially during summer days. During the winter season, the sensors reported temperature values which were highly consistent with those registered at the reference station. With respect to humidity, minimum levels stayed in the range below 5% and maximum levels in the range from 50 to 70%. The sensors' weekly behavior showed that the days where the maximum levels were reported are the weekend, while Wednesday and Thursday were the days with the lowest concentration levels. An example of weekly trends is shown in Figure 9. Weekly trend time series, with hourly averages, for all sensors are shown in Appendix C.

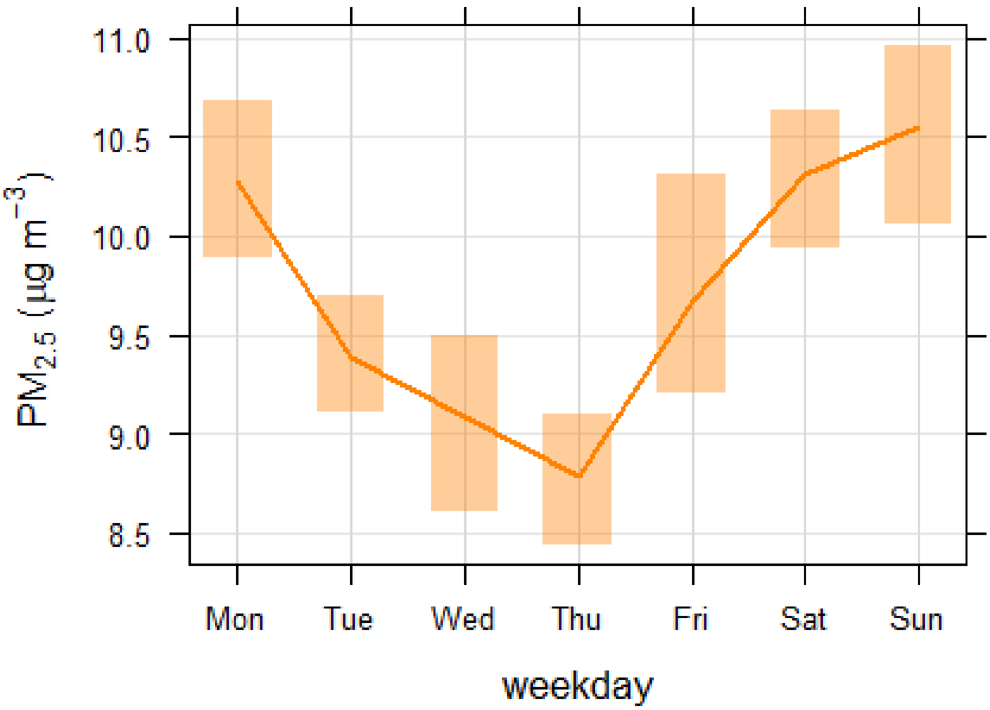


Figure 9 Example of Weekly trends during the study period

This situation was consistent for both cities. With this study, it can be concluded that PurpleAir low-cost sensors can be considered as a useful tool for the monitoring of $PM_{2.5}$. They should not , however, be used for regulatory compliance study.

6.2 Land Use Regression

For the LUR modeling, applying multivariate linear regression using the 6 traffic variables; distance to the nearest major arterial road, street length within 500m impact zone, street length within 1,000m impact zone, distance to the nearest port of entry (POE), traffic vehicle miles traveled within 500m zone and traffic vehicle miles traveled within 1,000m zone, provided some significant relationships. Distance to nearest POE was a significant traffic variable in modeling of $PM_{2.5}$ for the period average ($\beta_1 = -0.190$, p-value=0.024). This indicates a relationship where high $PM_{2.5}$ is associated with a shorter distance to a POE, as may be expected due to high wait times and congestion experienced near ports of entry in the PdN region. However, this weak statistical association requires further investigation due to the short period of study time used for the average $PM_{2.5}$ concentrations in comparison to that used for other predictor variables in the analysis.

6.2.1 Limitations and Future studies

Application of the LUR model in this study requires further exploration considering the number of traffic and geographic variables that can be identified.In addition, these traffic variables are based on long-term measurements as well as the Travel Demand model that projects VMT for certain target future years. This presents a data inconsistency issue when the $PM_{2.5}$ pollutant data are only averaged over a two-month period. Furthermore, these traffic-related variables are currently unavailable in Ciudad Juarez, as well as other data such as street length, distance to POE, and distance to major arterial roads.

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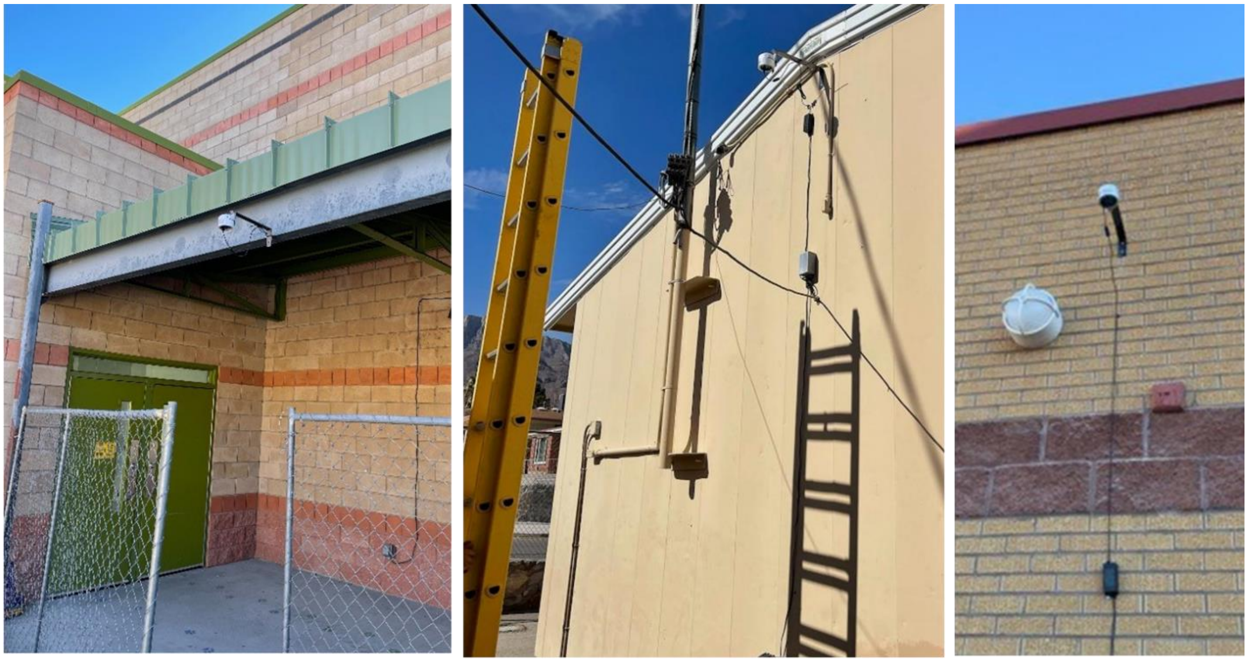
Appendix A – Site Photos



a) Aoy b) Cielo Vista c) Mesita

Figure 10 Selected Task 1 Site Photos: a) Aoy, b) Cielo Vista, c) Mesita

a) UACJ-PAC04 b) UACJ-PAC18 c) UACJ-PAC06

Figure 11 Selected Task 2 Site Photos: a) UACJ-PAC04, b) UACJ-PAC18, c) UACJ-PAC06

Appendix B – Hourly Boxplots

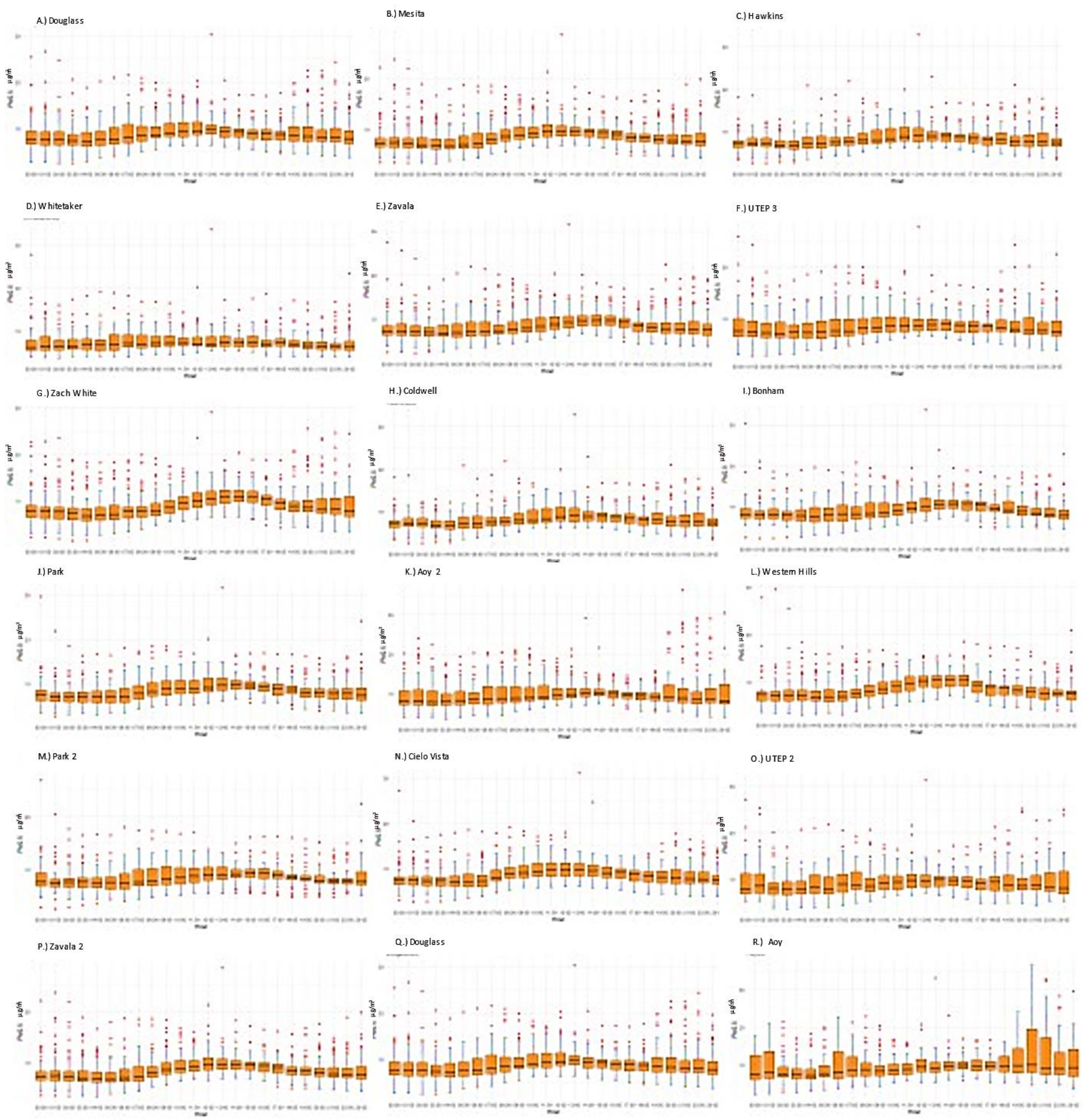


Figure 12 Hourly Averages shown as boxplots, during the study period for sites a) Douglass, b) Mesita, c) Hawkins, d) Whitetaker, e) Zavala, f) CAMS 6, g) Zach White, h) Coldwell, i) Bonham, j) Park, k) Aoy 2, l) Western Hills, m) Park 2, n) Cielo Vista, o) CAMS 5, p) Zavala 2, q) Douglasss, r) AOY

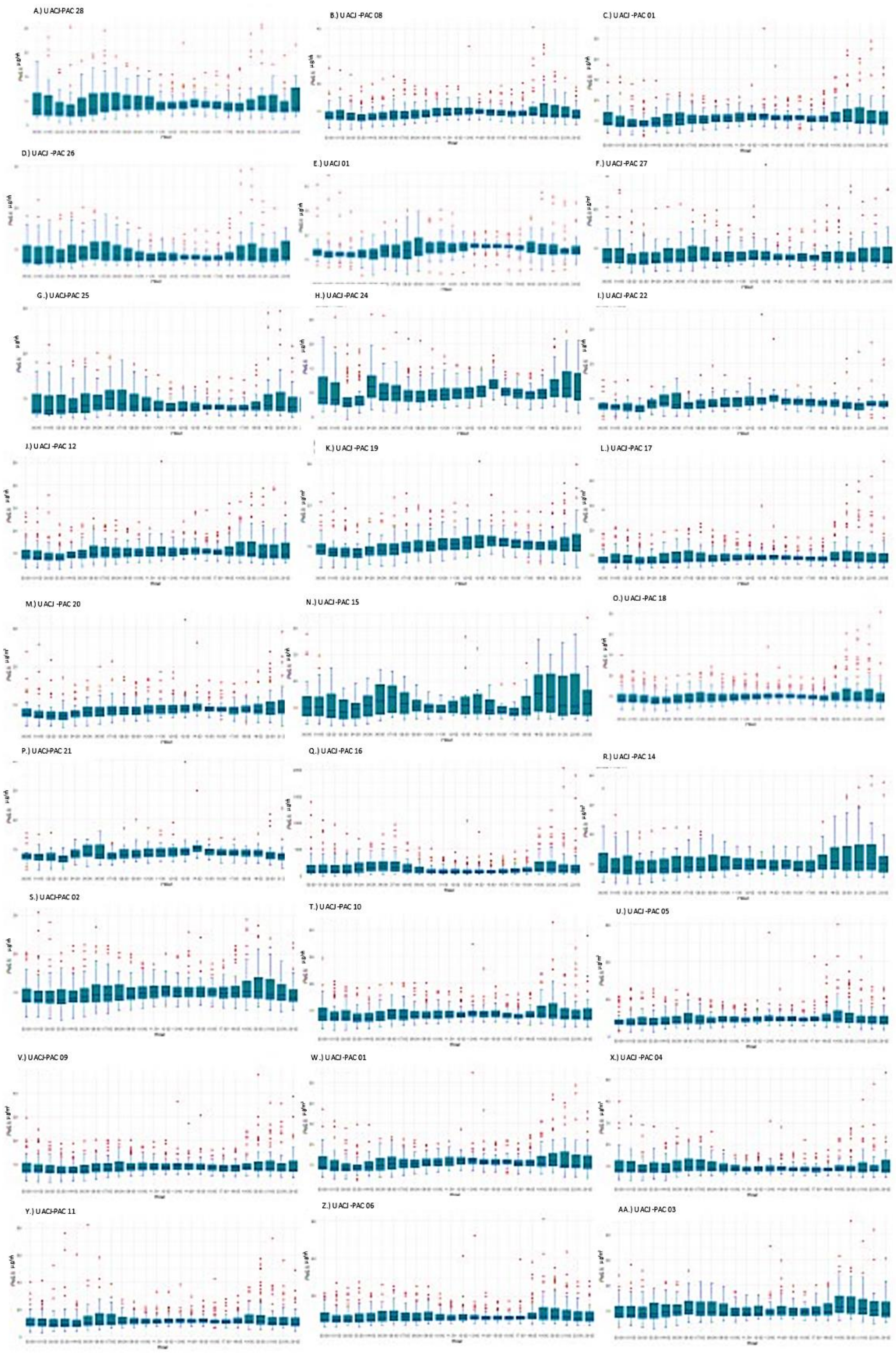


Figure 13 Hourly Averages shown as boxplots, during the study period for sites a) UACJ-PAC 28, b) UACJ-PAC 08, b)UACJ-PAC 01, d) UACJ-PAC 26, e) UACJ 01, f) UACJ-PAC 27, g) UACJ-PAC 25, h) UACJ-PAC 24, i) UACJ-PAC 22, j) UACJ-PAC 12, k) UACJ-PAC 19, l)UACJ-PAC 17,

Appendix C – Weekly Trends with hourly averages

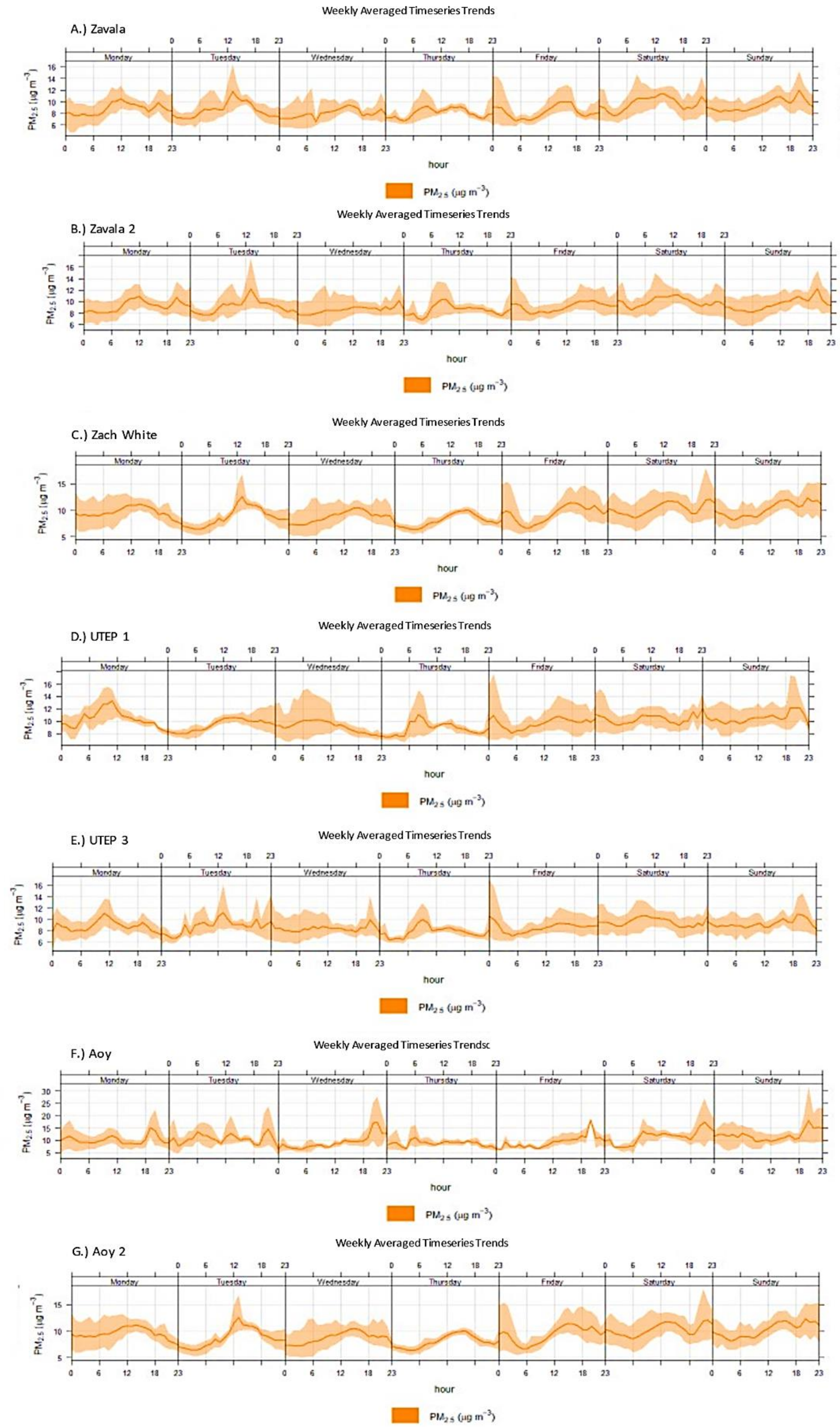


Figure 14 Weekly averaged Time series during the study period for a) Zavala, b) Zavala 2, c) Zach White, d) UTEP 1, e) UTEP 3, f) Aoy, g) Aoy 2

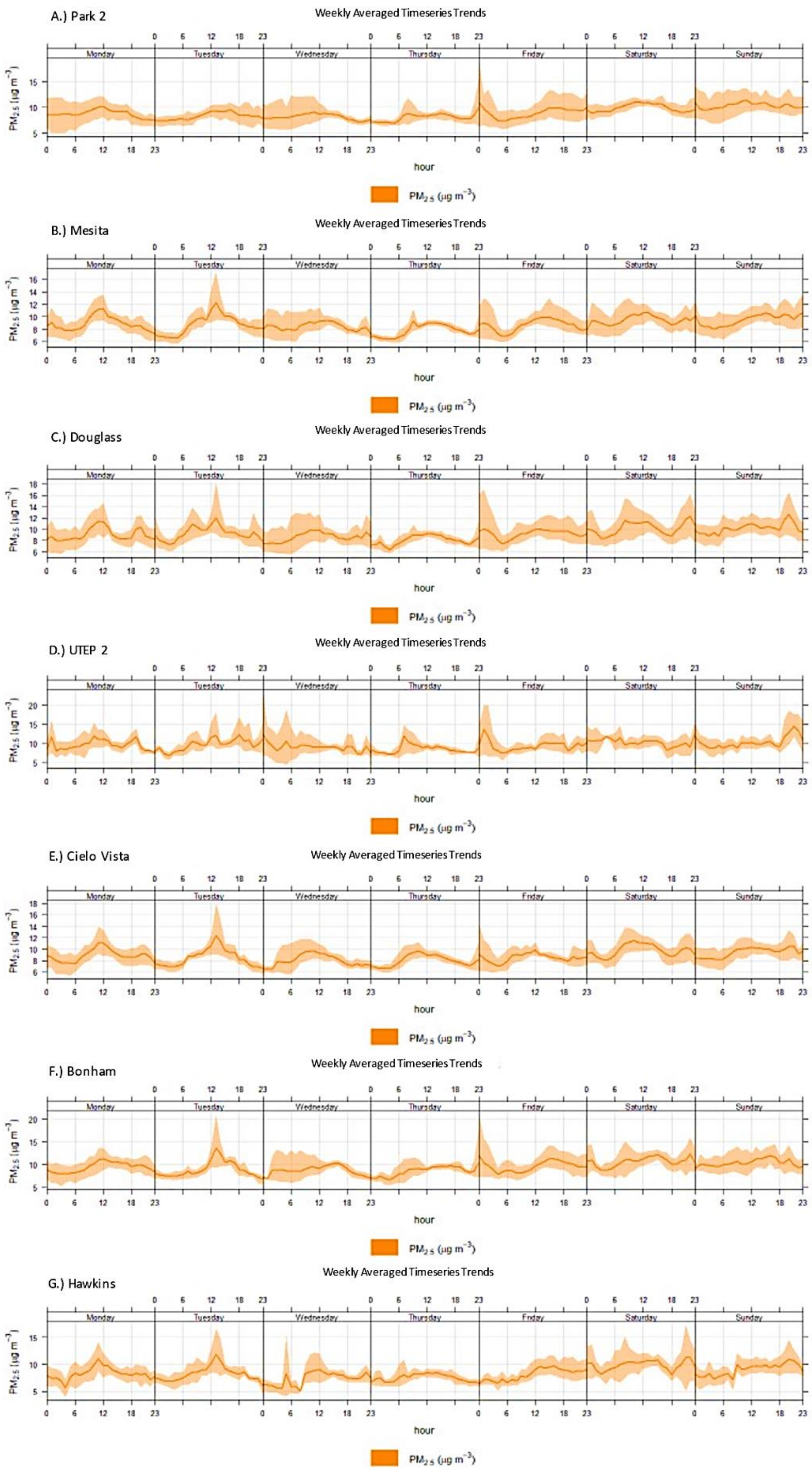


Figure 15 Weekly averaged Time series during the study period for a) Park 2, b) Mesita, c) Douglass, d) CAMS 5, e) Cielo Vista, f) Bonham, g) Hawkins

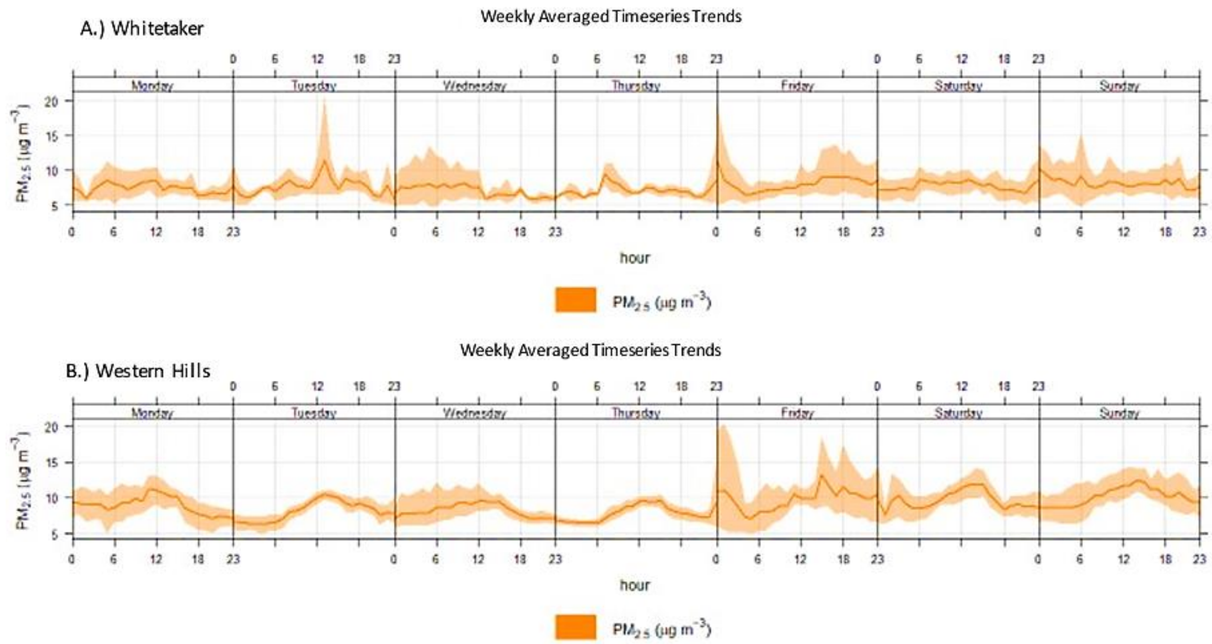


Figure 16 Weekly averaged Time series during the study period for a) Whitetaker, b) Western Hills

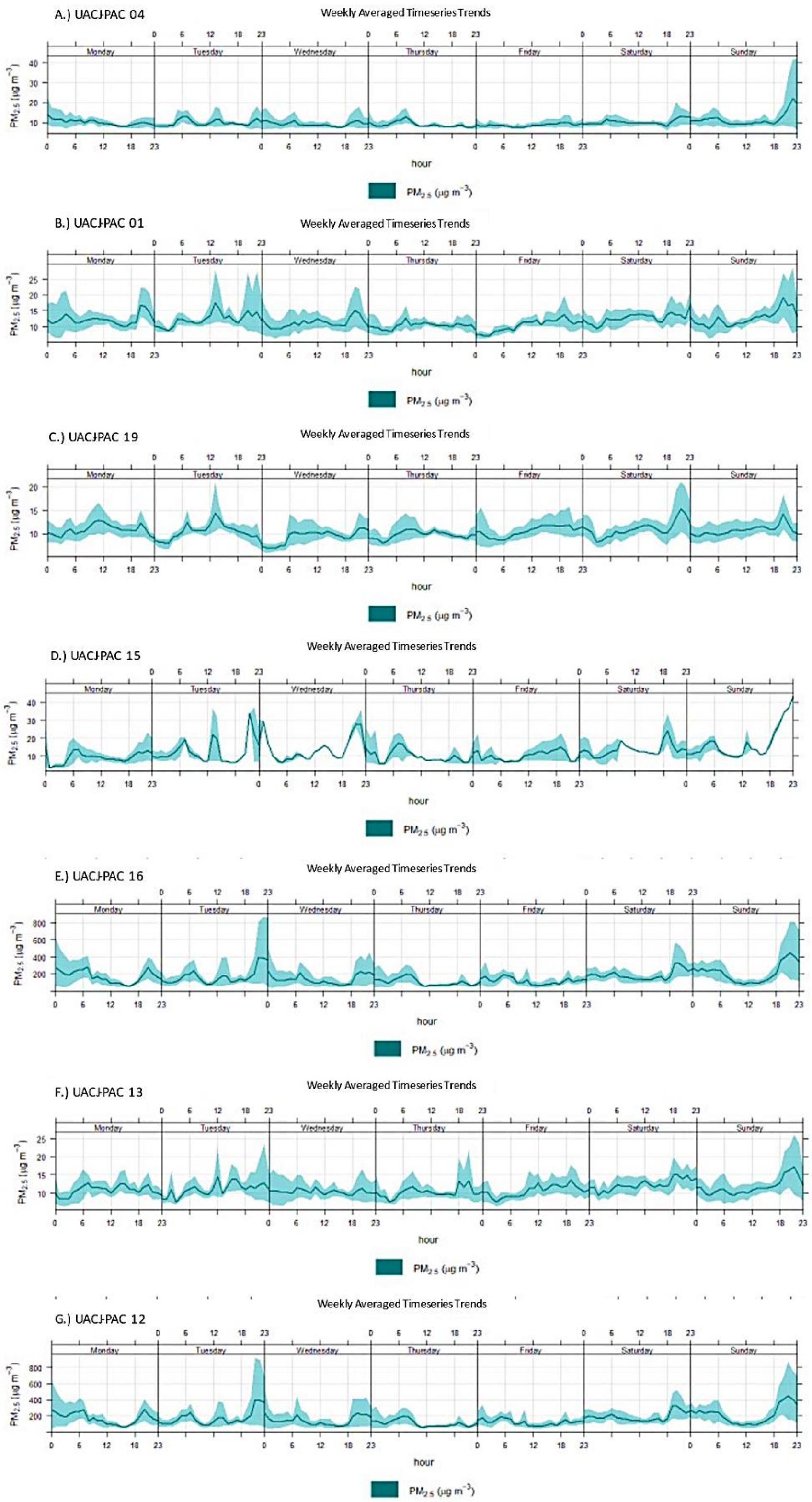


Figure 17 Weekly averaged Time series during the study period for a) UACJ-PAC 04, b) UACJ-PAC01, c) UACJ-PAC19, d) UACJ-PAC 15, e) UACJ-PAC 16, f) UACJ-PAC 13, g) UACJ-PAC12

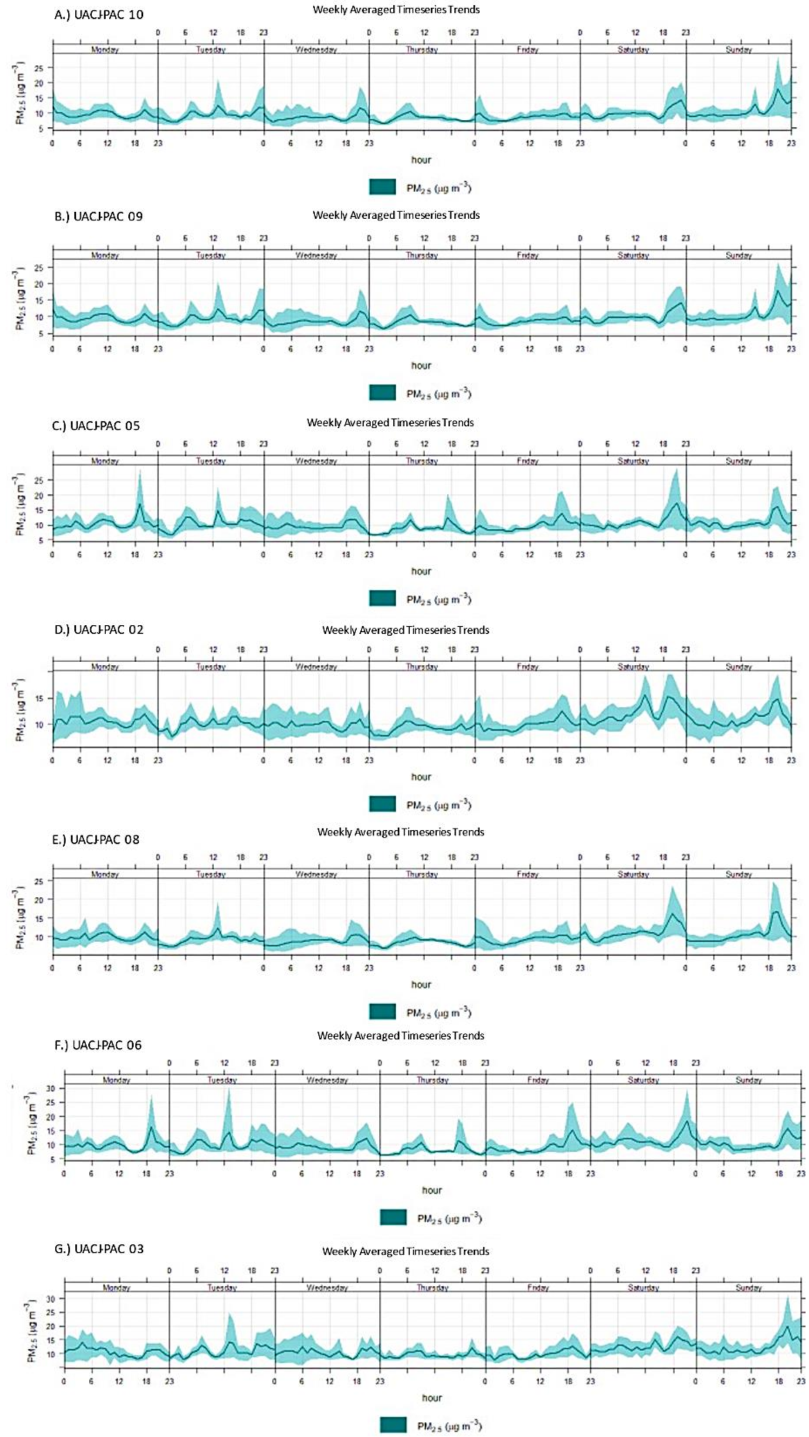


Figure 18 Weekly averaged Time series during the study period for a) UACJ-PAC 10, b) UACJ-PAC09, c) UACJ-PAC05, d) UACJ-PAC 02, e) UACJ-PAC 08, f) UACJ-PAC 06, g) UACJ-PAC03

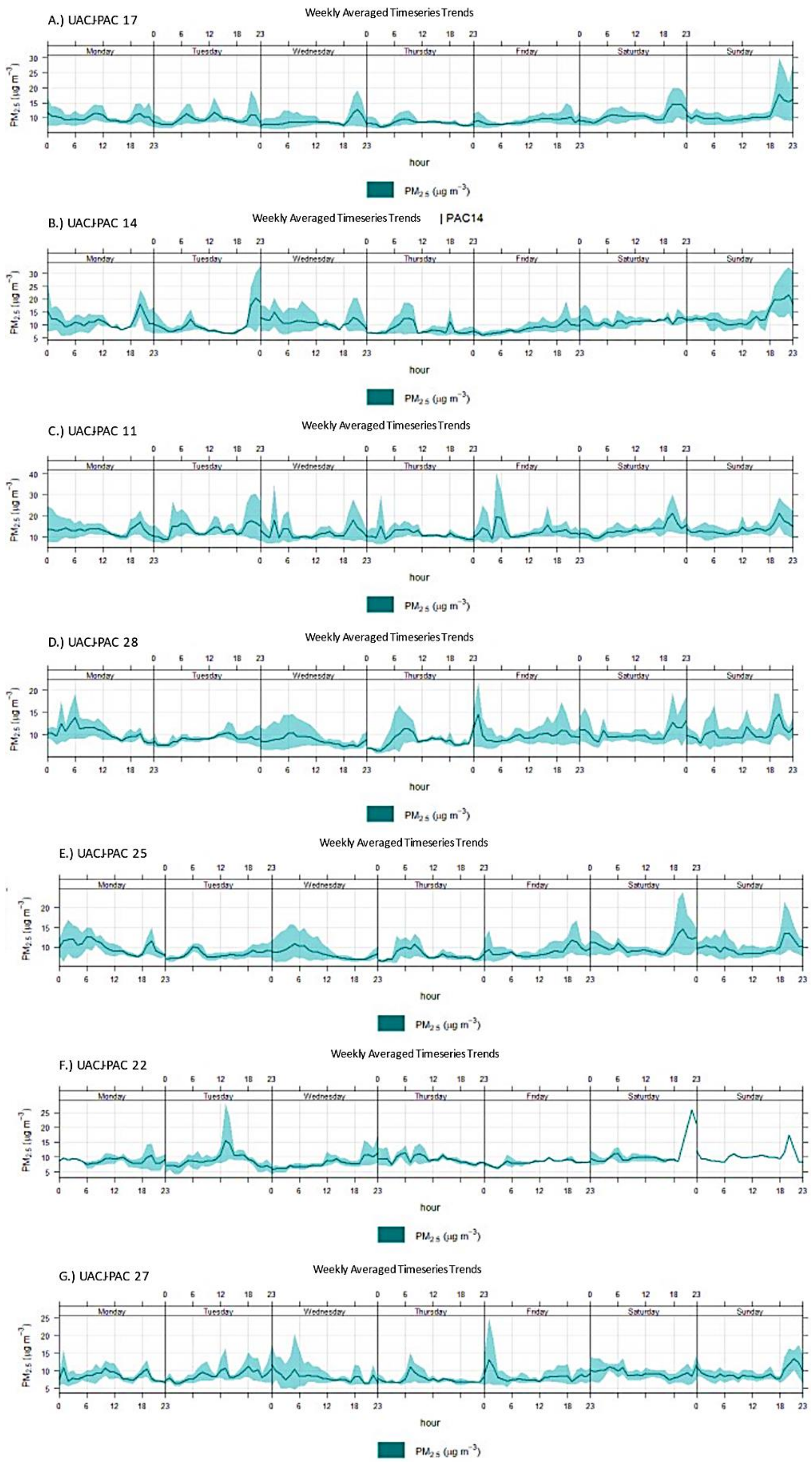


Figure 19 Weekly averaged Time series during the study period for a) UACJ-PAC 17, b) UACJ-PAC14, c) UACJ-PAC11, d) UACJ-PAC 28, e) UACJ-PAC 25, f) UACJ-PAC 22, g) UACJ-PAC27

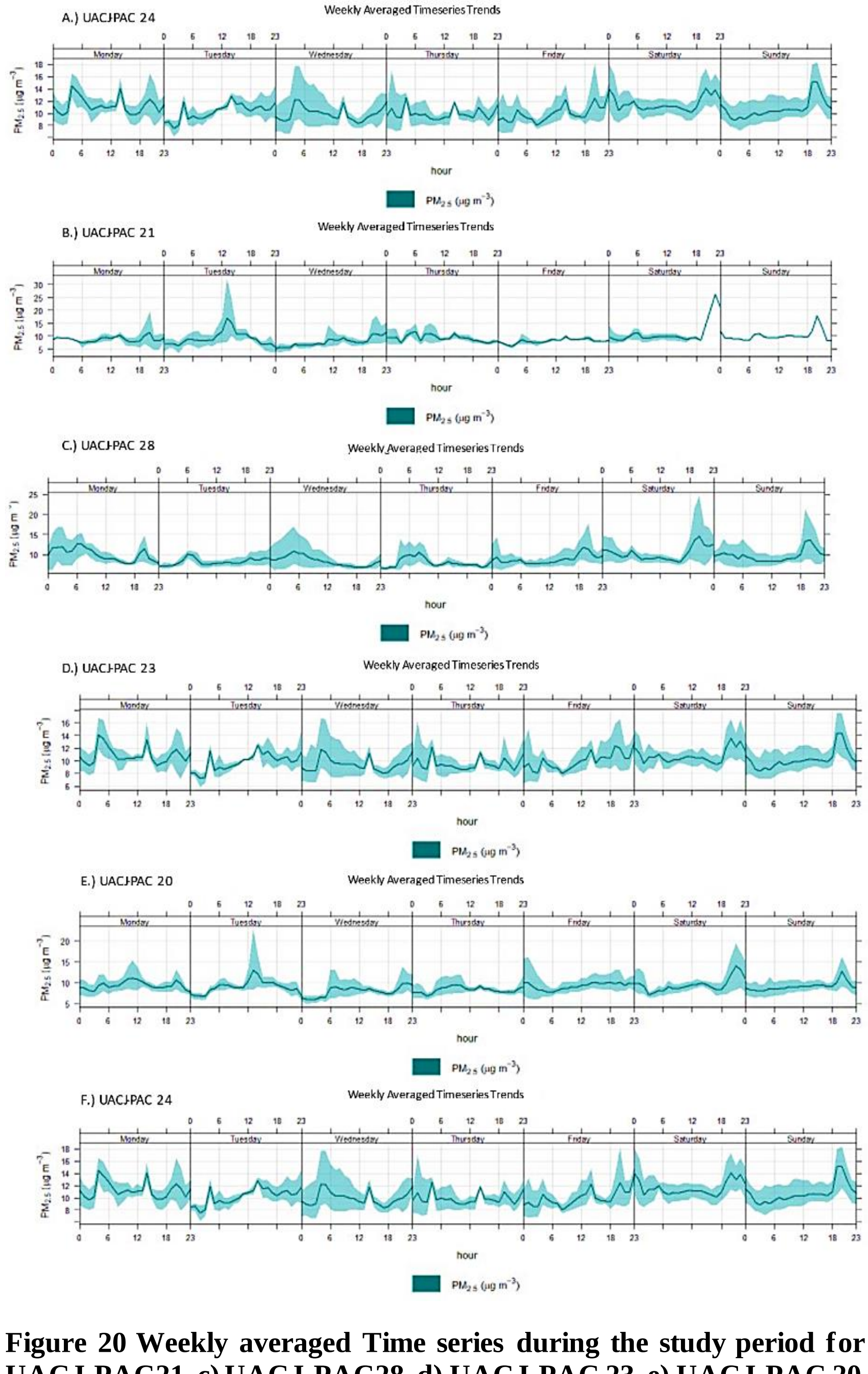


Figure 20 Weekly averaged Time series during the study period for a) UACJ-PAC 24, b) UACJ-PAC21, c) UACJ-PAC28, d) UACJ-PAC 23, e) UACJ-PAC 20, f) UACJ-PAC 24