Hyperlocal Monitoring of Traffic-Related Air Pollution to Assess Near-Term Impacts of Sustainable Transportation Interventions

December 2022

A Research from the National Center for Sustainable Transportation

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16. Abstract
Traffic and air pollution pose significant challenges to environmental sustainability in the South Coast Air Basin, particularly in urban areas like Riverside, California, where major highways contribute to high levels of background air pollution. This study investigates the impact of traffic-related air pollutants, specifically NO_2 and $PM_{2.5}$, in Riverside's Innovation Corridor, a six-mile roadway serving key urban centers and logistics activities. Utilizing a low-cost, measurement-based approach over a one year period, the researchers employed gradient-boosted regression trees to model pollutant concentrations based on traffic and meteorological conditions. Preliminary findings indicate that background $PM_{2.5}$ and relative humidity are crucial drivers for local $PM_{2.5}$ levels, while NO_2 concentrations are influenced by daily traffic patterns. The study confirms that NO_2, a primary pollutant, is closely linked to daily activity, whereas $PM_{2.5}$ is influenced by regional trends and local meteorology. These insights suggest that pollution reduction strategies should focus on NO_2 emissions while also considering the complex dynamics of $PM_{2.5}$. The study highlights the need for further investigation into the sources of NO_2 and the effectiveness of proposed traffic interventions in improving local air quality. Future analyses will aim to evaluate the impact of modifications in traffic patterns on pollutant levels along the corridor.

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NCST

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Center for Environmental Research & Technology, University of California, Riverside

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Hyperlocal Monitoring of Traffic-Related Air Pollution to Assess Near-Term Impacts of Sustainable Transportation Interventions

EXECUTIVE SUMMARY

Traffic and air pollution are two of the South Coast Air Basin's most difficult challenges for environmental sustainability. This challenge also exists at local levels, such as in the City of Riverside, where two major highways service the area (CA 60/I-215 and CA 91) and background air pollution is high in the afternoons due to pollution transport and photochemistry. The South Coast Air Quality Management District predicts continued increases in VMT in the Basin, while secondary ozone levels are also beginning to increase after decades long reductions. Heavy-duty trips are also increasing due to increasing goods movement activity in inland Southern California. In this project, it was conjectured that traffic-related air pollution would continue to be a challenge for the City of Riverside, whose interstate corridors service a high volume of logistics activity.

To better understand the impacts of interstate vs. local traffic along a highly impacted urban corridor, a low-cost, measurement-based approach was used to assess the potential for sustainable traffic interventions to improve local air quality. Two traffic-related air pollutants, NO_2 and $PM_{2.5}$, were measured for one year along an urban corridor that is currently being tested for smart intersection interventions. Specifically, the chosen corridor is the City of Riverside Innovation Corridor, a six-mile roadway that services downtown Riverside, University of California, Riverside, and several businesses and community organizations.

Gradient boosted regression trees were used to create models to predict hyperlocal $PM_{2.5}$ and NO_2 based on traffic conditions, meteorological conditions, and background concentrations during the months of May and June of 2021. While the applied methods were not used to estimate the exact contribution of a particular variable, partial dependence gave insight into the linearity of influence of variables local pollutant concentrations. Preliminary findings indicate that the key driving variables for modeled traffic-related pollutants were background $PM_{2.5}$ and relative humidity for local $PM_{2.5}$, and day of sample for NO_2. This was determined due to the highly variable nature of partial dependence for these variables, as opposed to the flat signal for the other input variables (Figure ES-1).

The results corroborate *a priori* knowledge that NO_2, a primary pollutant, is driven by day-to-day activity. However, $PM_{2.5}$ is largely driven by regional trends and local meteorology. These results lend direction for improving local air quality in the Riverside area. Pollution reduction strategies should continue to target NO_2 polluters in the area through sustainable interventions. $PM_{2.5}$ is composed of primary and secondary in components and should therefore be monitored for its responses to NO_2 reduction interventions. The findings do not identify local vs. highway sources as driver of NO_2 along the Innovation Corridor. This will be

explored during future efforts to actual modify traffic patterns along the corridor, and a before-after analysis may indicate whether interventions have a significant impact on local NO_2.

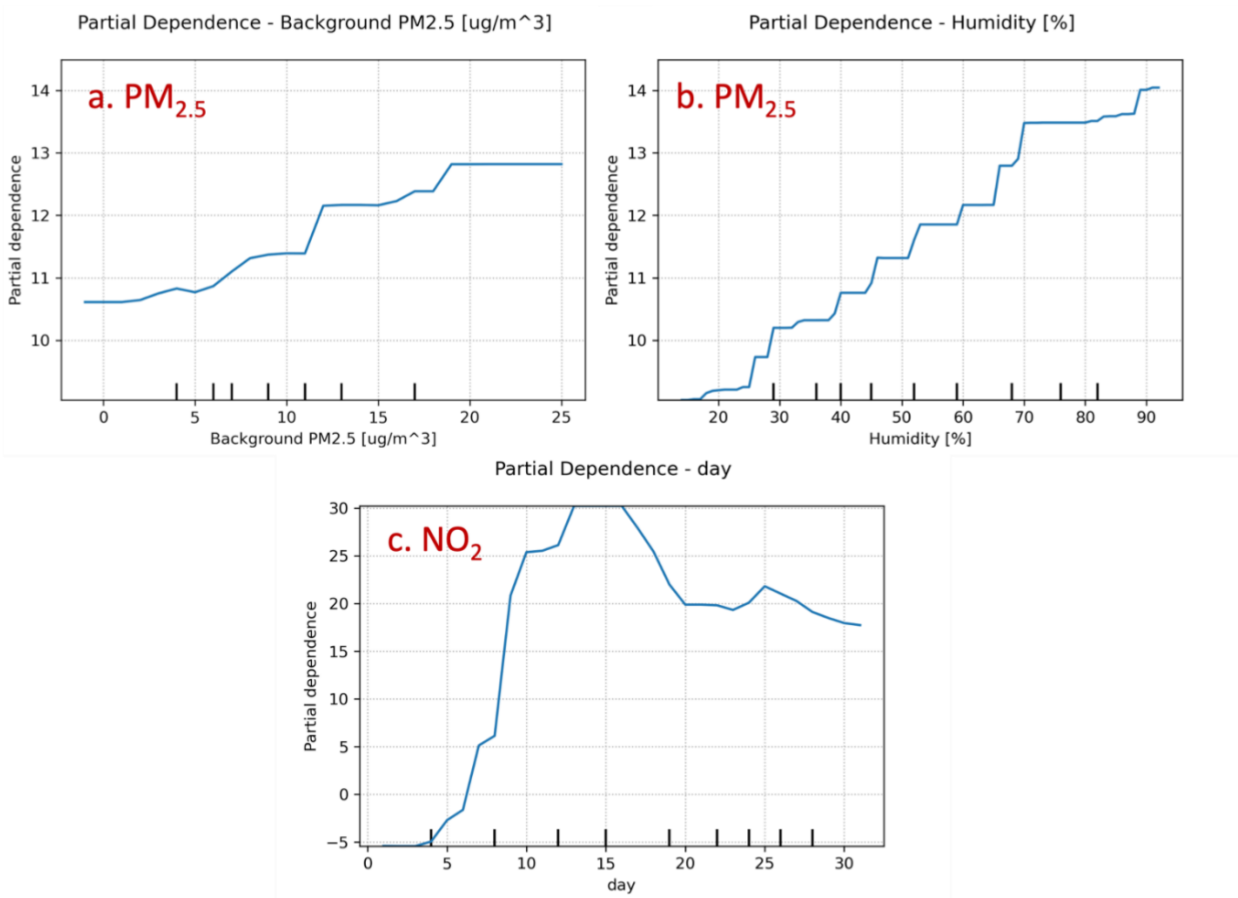

Figure ES-1. Key factors influencing modeled $PM_{2.5}$ and NO_2 presented as the partial dependence of the predicted model outcome on the driving variables. a.) Dependence of predicted local $PM_{2.5}$ on background $PM_{2.5}$. b.) Dependence of predicted local $PM_{2.5}$ on relative humidity. c.) Dependence of predicted local NO_2 on sampling day.

1. Introduction

The South Coast Air Basin (SoCAB) is home to more than 16 million people and is historically a hotspot for poor air quality in the United States. The Inland Empire was recently given the grade of "F" for ozone and $PM_{2.5}$ pollution by the American Lung Association (2020 State of the Air).[1] While tremendous progress has been made to reduce $PM_{2.5}$ and ozone design values for SoCAB, the region is still designated as nonattainment for the annual $PM_{2.5}$ (12 µg m^{-3}) and 8-hour ozone (0.070 ppm) NAAQS. In the last four years, the ozone design value (ODV) reached an inflection point and began to increase, indicating that present-day mitigation strategies are losing effectiveness for bringing SoCAB into attainment. An important question that has not been completely answered is, "What are the main natural or anthropogenic drivers for this reversal?"

One potentially significant driver for a reversal in ODV trends is the increase in logistics activity in SoCAB, marked by the expansion of warehouses in the Inland Empire and subsequent increase in heavy-duty trips to and from the warehouses. Ongoing research at the University of California-Riverside's Center for Environmental Research and Technology (CE-CERT) investigates the contributions of heavy-duty trips to annual vehicle miles traveled (VMT) and basin-wide traffic-related emissions. A recent study reported that experimental measurements of NOx from heavy-duty diesel vehicles emitted more than three times the certification standard during real-world operations.[2] The 2016 Air Quality Management Plan for SoCAB estimated that on-road vehicles were responsible for 56% of NOx, 33% of VOC, and 63% of CO emissions (as of 2012).[3] Present-day NOx emissions are estimated to be approximately 40% lower despite reported increases of 5% in population and VMT since 2012.[4] Potential underestimates in District-reported on-road emissions may overestimate the effectiveness of mitigation efforts, which points to a need for real-world assessment of the effectiveness of sustainable transportation interventions for the improvement of in-use traffic-related air pollutant (TRAP) emissions and air quality.

In addition to traffic-related emissions, meteorology also plays an important role in driving air pollutant trends.[5] This was clearly observable during the COVID-19 shutdown where notable reductions in TRAP emissions made meteorological impacts more clearly pronounced.[6,7] Upon comparison with business as usual cases, and after taking background climate trends into account, it was observed that primary NO_2 was reduced during the shutdown while ozone saw large increases during hotter than normal periods in VOC-limited regions of SoCAB. Given the hot and sunny climate of Riverside, ozone and secondary $PM_{2.5}$ formation is favorable.

As such, the short-term goals of the project were to: 1) establish a high-density network of low-cost air pollution monitors along the corridor and 2) carry out hyperlocal monitoring of TRAPs with the consideration of meteorological impacts. Longer-term goals for this effort include 3) quantifying the near-term impacts of the transportation interventions and 4) evaluating the effectiveness of large-scale implementation of the interventions.

1.1. City of Riverside Innovation Corridor

The City of Riverside, CE-CERT and local community organizations are deeply invested in improving local traffic and air quality while maintaining and promoting sustainable economic growth. As a result, the City of Riverside Innovation Corridor was established, a six-mile section of University Avenue between University of California, Riverside and downtown Riverside (Figure 1). The Innovation Corridor is being outfitted with modern traffic signal controllers that broadcast signal phase and timing, employ video analytics, and will be used for future shared, electric, connected and automated vehicle experimentation across different modes (e.g., cars, buses, and trucks). Given the location and the efforts underway, the Innovation Corridor offers an ideal opportunity to test critical technical research questions on how advanced transportation technology can be most effectively deployed.

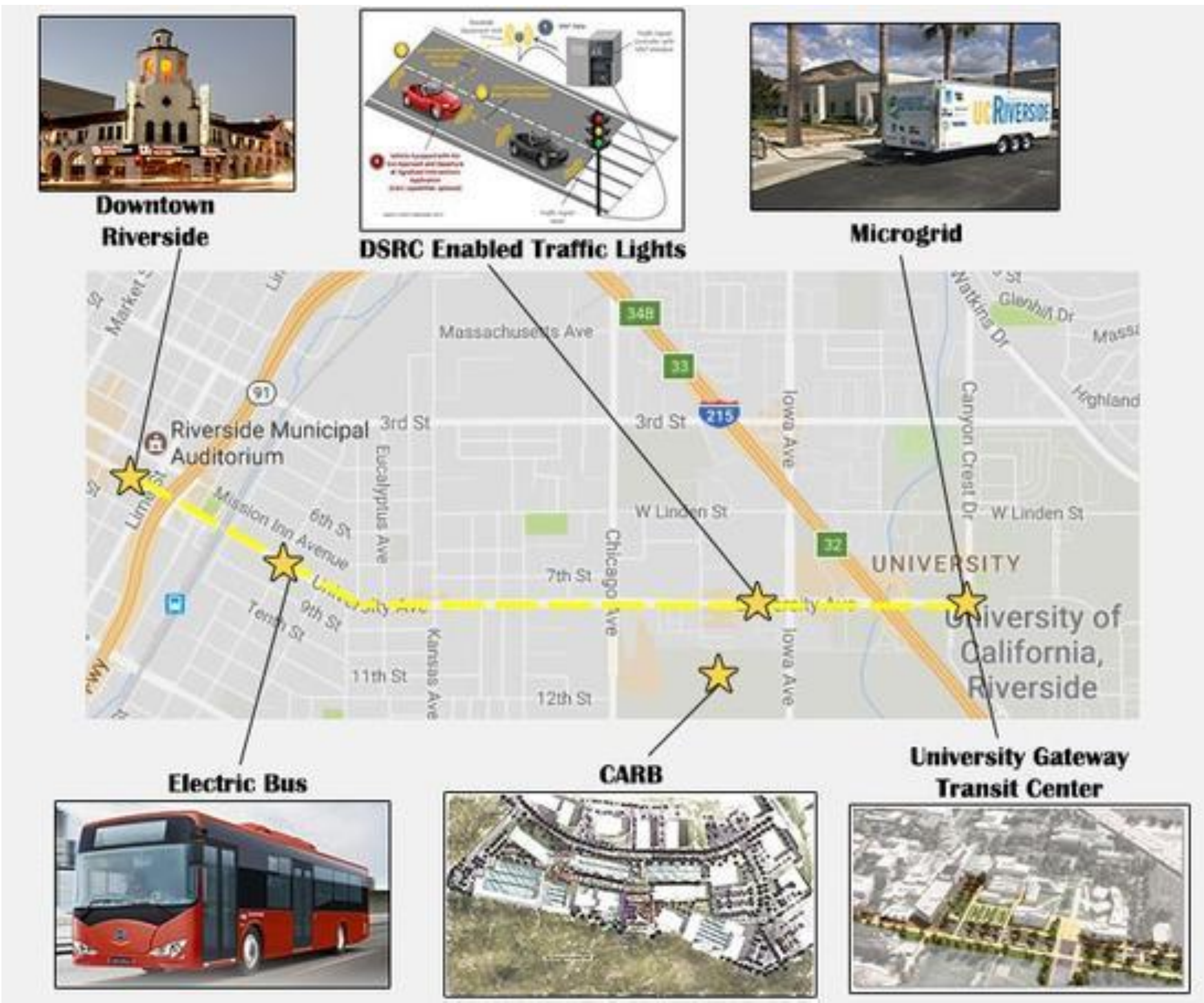

Figure 1. Project site along University Avenue's Innovation Corridor in the City of Riverside.

The research team and the City of Riverside continue to upgrade the infrastructure by expanding other capabilities beyond wireless communications. For example, one of the sensorrich intersections, Iowa Avenue & University Avenue, have been equipped with various infrastructure-based high-resolution traffic and air quality surveillance systems, including GridSmart Fisheye cameras (see figures below) and Ouster LiDAR (Figure 2). These surveillance systems can not only provide object-level trajectory information, accurate vehicular counts or turning movements for different modes, but also detect and track other road users such as pedestrians, bicyclists, and micro-mobility users (e.g., electric scooter riders).

Figure 2. Installation and user interface of GridSmart Fisheye Cameras. a) Researchers at the traffic controller cabinet. b) Installing the camera on a streetlamp post. c) GridSmart user interface.

1.2. Low-Cost Air Monitoring

A recent mobile monitoring study in Oakland, CA demonstrated that ambient concentrations of black carbon and NO_2 vary significantly at the street-level, where gradients were influenced by local pollution sources, such as traffic, warehouses, and small businesses.[8] A cost-effective network of monitors along the Innovation Corridor is useful for capturing the spatial and temporal variability in NO_2 and $PM_{2.5}$ concentrations. NO_2 is a direct tracer for on-road activity, while $PM_{2.5}$ is composed of primary and secondary components. Therefore, we recognize that $PM_{2.5}$ measurements may not have a strong local signal along the corridor, in part due to the inability of the $PM_{2.5}$ sensor within the Node-S to measure ultrafine particles (<100 nm).

To date, we have installed four Clarity Node-S (Berkeley, CA) units on utility poles at three intersections along the Innovation Corridor (University Avenue & Iowa/Cranford/Chicago Aves., between CA-91 and CA-60/I-215) and a partnering site to the south and east of the Corridor (Tyler St. & Magnolia Ave., upwind of CA-91) (Figure 3). The monitored intersections are located along urban commercial corridors that accommodate restaurants, strip malls, gas stations, etc. Google Street view images of all intersection approaches and technical specifications for the Clarity Node-S are provided in the Appendix.

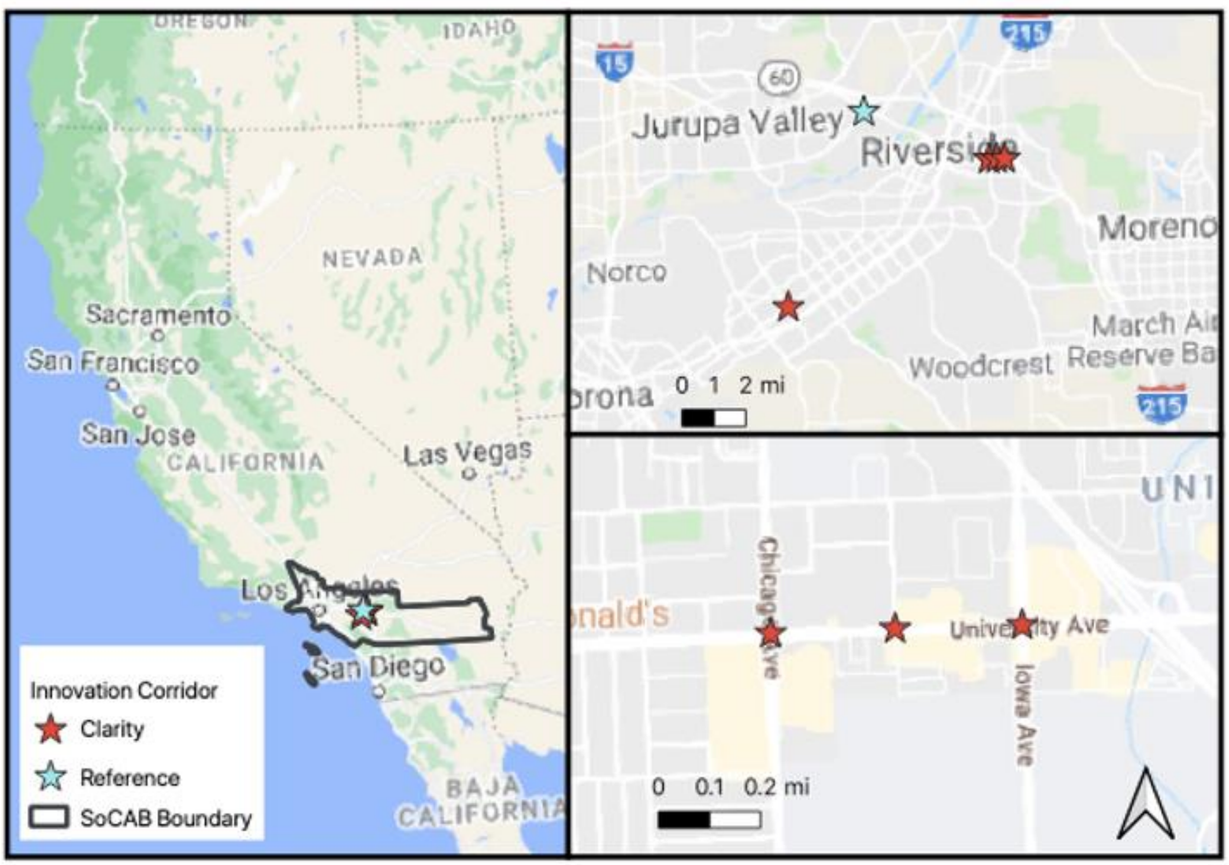

Figure 3. Maps of study location and air pollution monitoring sites. Left: Study site is in Southern California in the South Coast Air Quality Management District. Top right: The study features four low-cost monitoring locations (red) and one SCAQMD reference site (Rubidoux

air monitoring site; blue). Bottom right: Three low-cost monitors are located directly along the Innovation Corridor at the following intersections (west-to-east): University Ave. & Chicago Ave., University Ave. & Cranford Ave., and University Ave. & Iowa Ave. The 4th low-cost monitor is located at the intersection of Magnolia Ave. and Tyler St., south and west of the Innovation Corridor.

2. Data and Methods

2.1. Data Collection

Air Quality & Meteorology. NO_2 and $PM_{2.5}$ concentrations were collected at the four Clarity sites during the year 2021 at approximately 15-minute intervals. The team collaborated with Clarity Inc. to develop near-road correction factors for the sites. Background $PM_{2.5}$ and NO_2 measurements for were obtained from the Rubidoux air monitoring site via the California Air Resources Board AQMIS2 online database. Rubidoux concentrations were available hourly. In order to maintain consistency with measurements obtained from Clarity, the Rubidoux data were up-sampled, and the hourly concentration was assigned to each 15-minute interval of the hour. Historical weather data for the location was obtained from OpenWeather (https://openweathermap.org/) for the year of 2021. Weather variables collected include air temperature (ºC), air pressure (mbar), relative humidity (%), and wind direction (degrees).

Vehicle Miles Traveled. VMT data was obtained from the Caltrans Performance Measurement System (PeMS) for highways surrounding the Innovation Corridor, which are CA-91 (upwind of the Innovation Corridor) and CA-60/I-215 (downwind of the Innovation Corridor) (Figure 4). PeMS records VMT and reports the total sum for the hour. Hourly VMT data were upsampled to 15 minutes, and VMT for the hour was assumed to be consistent.

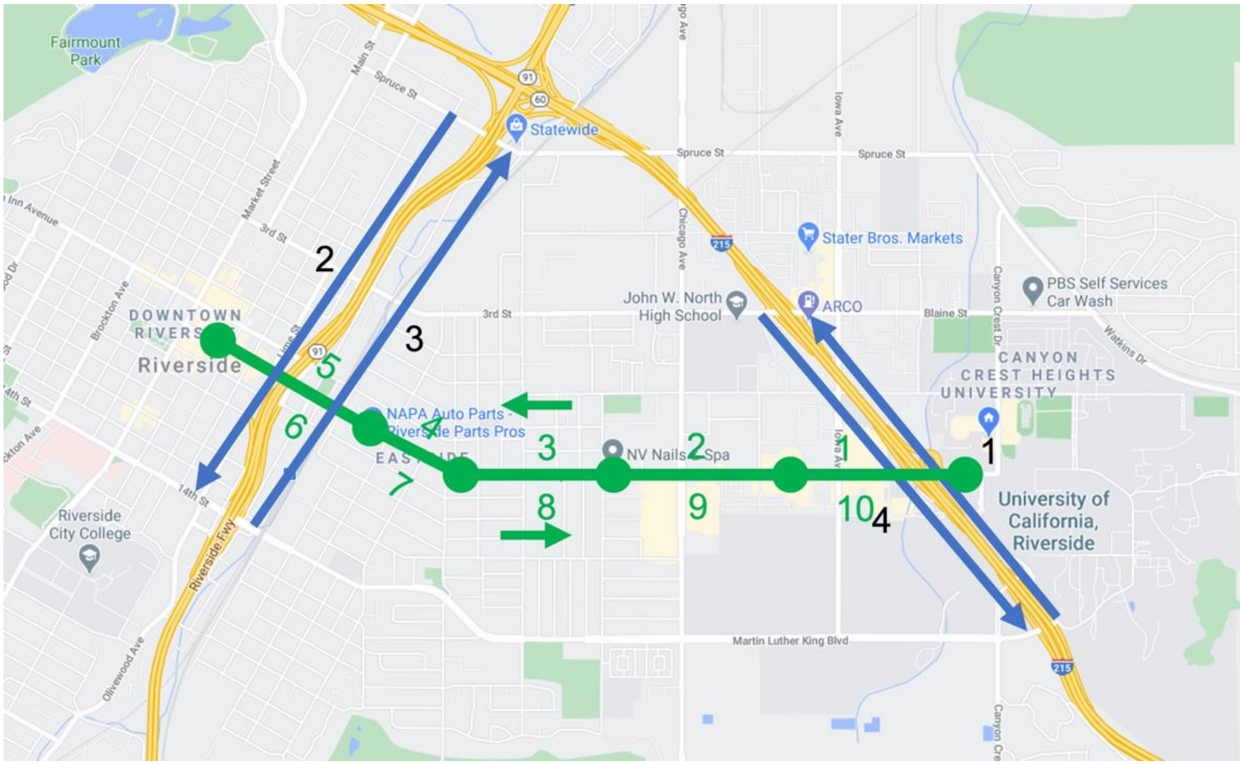

Figure 4. Segment selections used for the retrieval of Google trip time data. Specific segments used in model training include CA-60/I-215 freeway segments 1 and 4 (blue) and Innovation Corridor local segments 2 and 9 (green). Arrows indicate direction of travel.

Traffic Flow. Traffic flow (vehicles per hour) was obtained for the intersection of University Ave. & Iowa Ave. & University from the GridSmart system. The sum of cars passing through the intersection was summed into 15-minute intervals.

Traffic Speed. Specific road segments were selected for collection of Google Maps trip time data (Figure 4). Road segments are specified as local (Innovation Corridor) or freeway. By dividing the length of the paths by the recorded travel times, the average speed of traffic (*v*, miles per hour) was obtained.

Traffic Density. Traffic density (vehicles per mile) is the most commonly used variable for predicting traffic contributions to air pollution. Local roadway traffic density was obtained by using the GridSmart system's traffic flow and dividing it by the traffic speed. Highway traffic density was obtained by first dividing VMT by the length of the highway path to obtain traffic flow. Then traffic flow was divided by the traffic speeds calculated previously to obtain highway traffic density. Specific segments used in model training include CA-60/I-215 freeway segments 1 and 4 (blue) and Innovation Corridor local segments 2 and 9 (Figure 4).

2.2. Machine Learning-based Predictions

The machine learning approach, known as gradient boosted regression trees (GBRT), was to create models to predict hyperlocal $PM_{2.5}$ and NO_2 for the month of May 2021.[9–12] Traffic conditions, meteorological conditions, and background concentrations were used as input variables for the prediction models (Figure 5). While GBRT did not give the exact contribution of a particular variable, calculating partial dependence gave insight into the dependency of local (Innovation Corridor) pollutant concentrations on input variables. To obtain consistent time intervals across all the variables needed for the regression analysis, all data are resampled using cubic interpolation to be available at minutes 00, 15, 30, and 55. All data were also standardized before fitting the models. Preliminarily, the prediction model was fitted for the University Ave. & Iowa Ave. intersection due to it being the only site with a GridSmart system installed. We based modeling methods mainly on a previous study by Sayegh, Tate, and Ropkins[13], and other studies were accessed for further background investigation.[12,14–16]

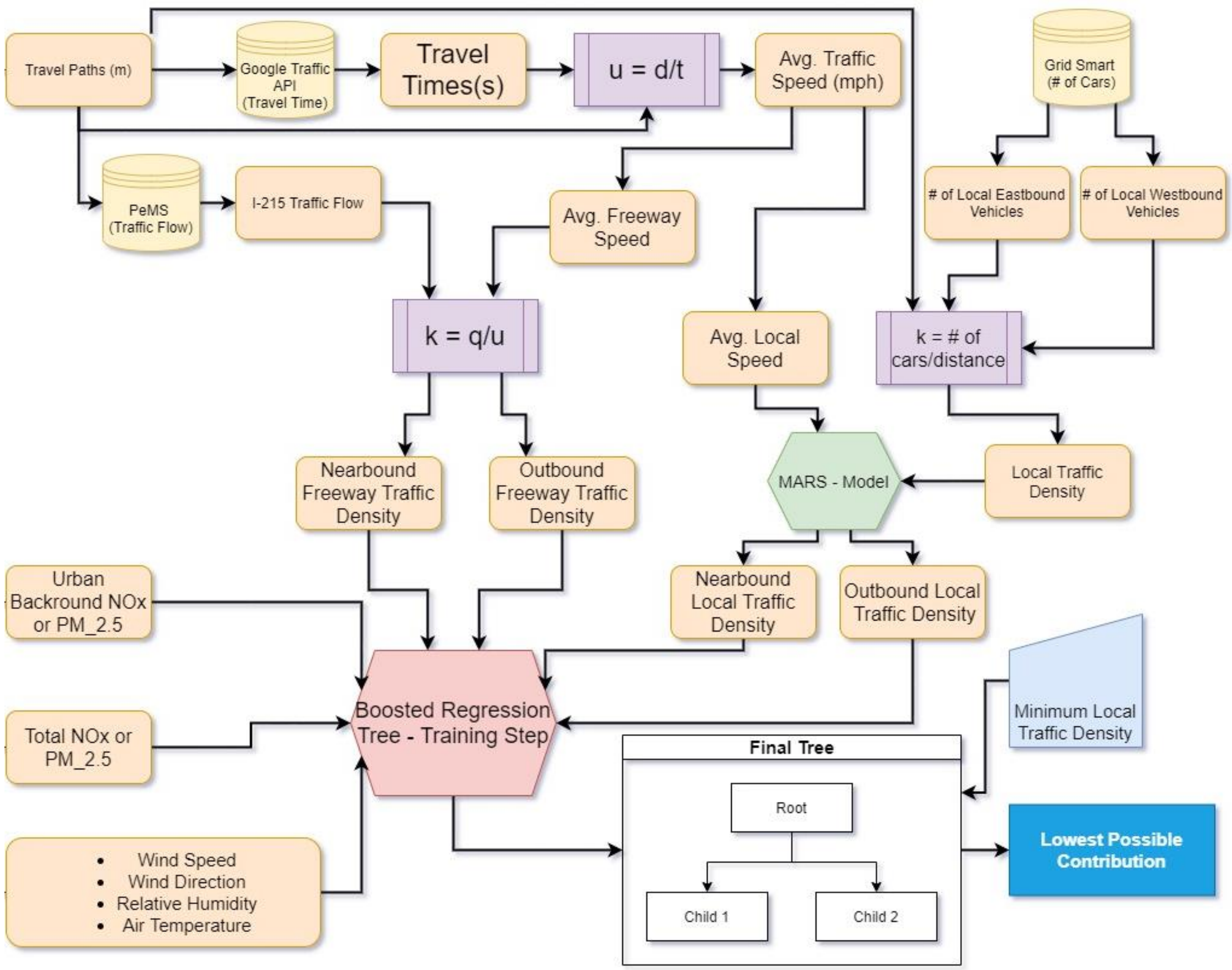

Figure 5. Boosted regression tree flow chart.

3. Results and Discussion

3.1. Traffic Density

As expected, traffic density (vehicles/mile) was much higher along the CA-60/I-215 freeway segments (~65 vehicles/mile) compared to the local segments (~20 vehicles/mile) (Figure 6). The traffic density with the highest probability is larger than the median for the highway segments, while the traffic density with highest probability is lower than the median for the local segments. The northbound segment experienced the overall highest traffic density along the highway corridor, and the westbound segment experience the overall highest traffic density along the local corridor.

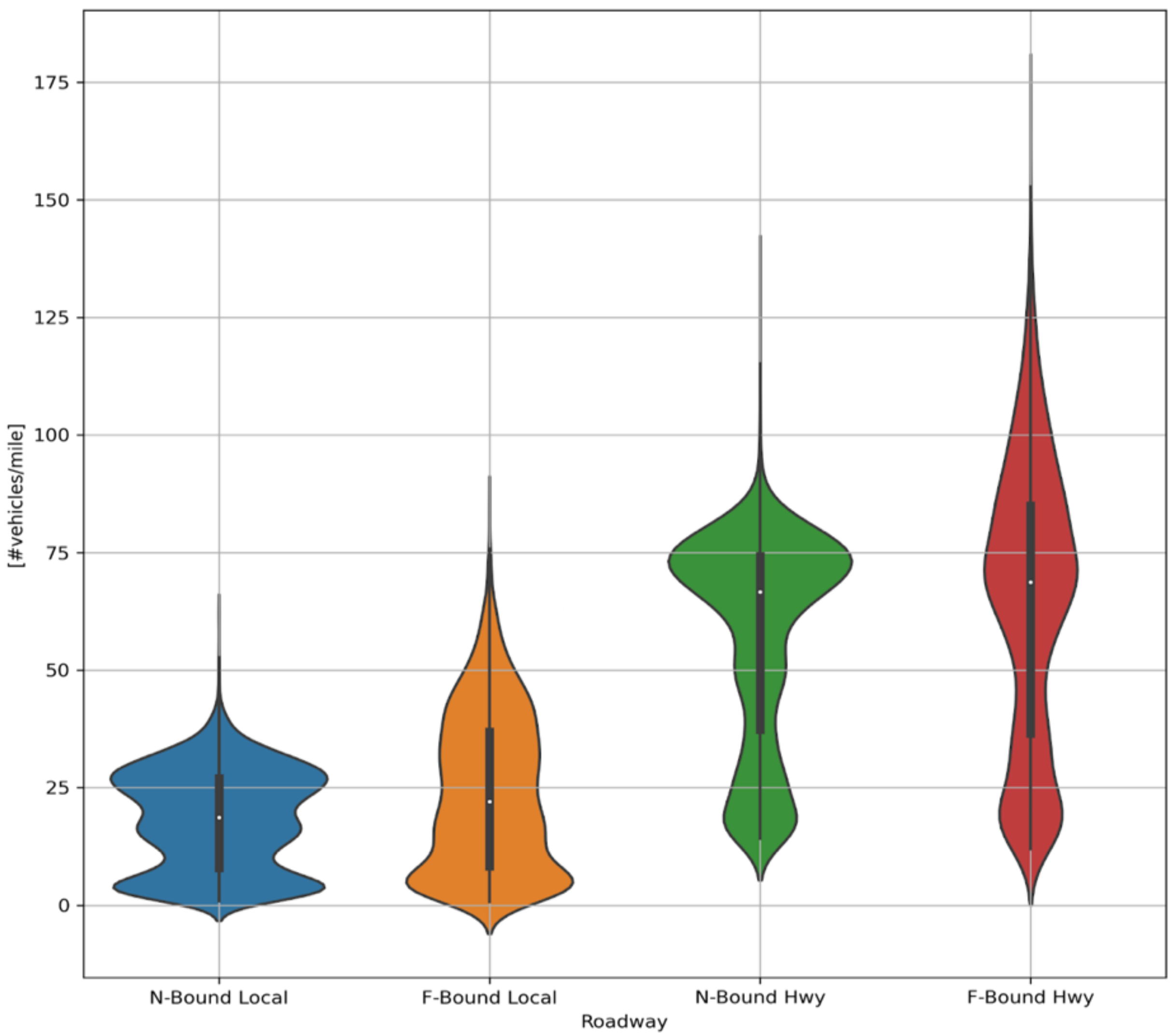

Figure 6. Traffic density (vehicles/mile) distributions for segments (left-to-right): local 9 (blue, eastbound), local 2 (orange, westbound), freeway 4 (green, southbound), and freeway 1 (red, northbound). The median value is indicated by the central white dots of the inner box plots.

3.2. Fine Particulate Matter ($PM_{2.5}$)

Year-long distributions of $PM_{2.5}$ concentrations were relatively similar at all four low-cost monitoring locations, where maximums were near the 24-hour standard $PM_{2.5}$ of 35 µg/m³ (Figure 7). This indicates that $PM_{2.5}$ concentrations are spatially smooth with tens of miles in the Riverside Area.

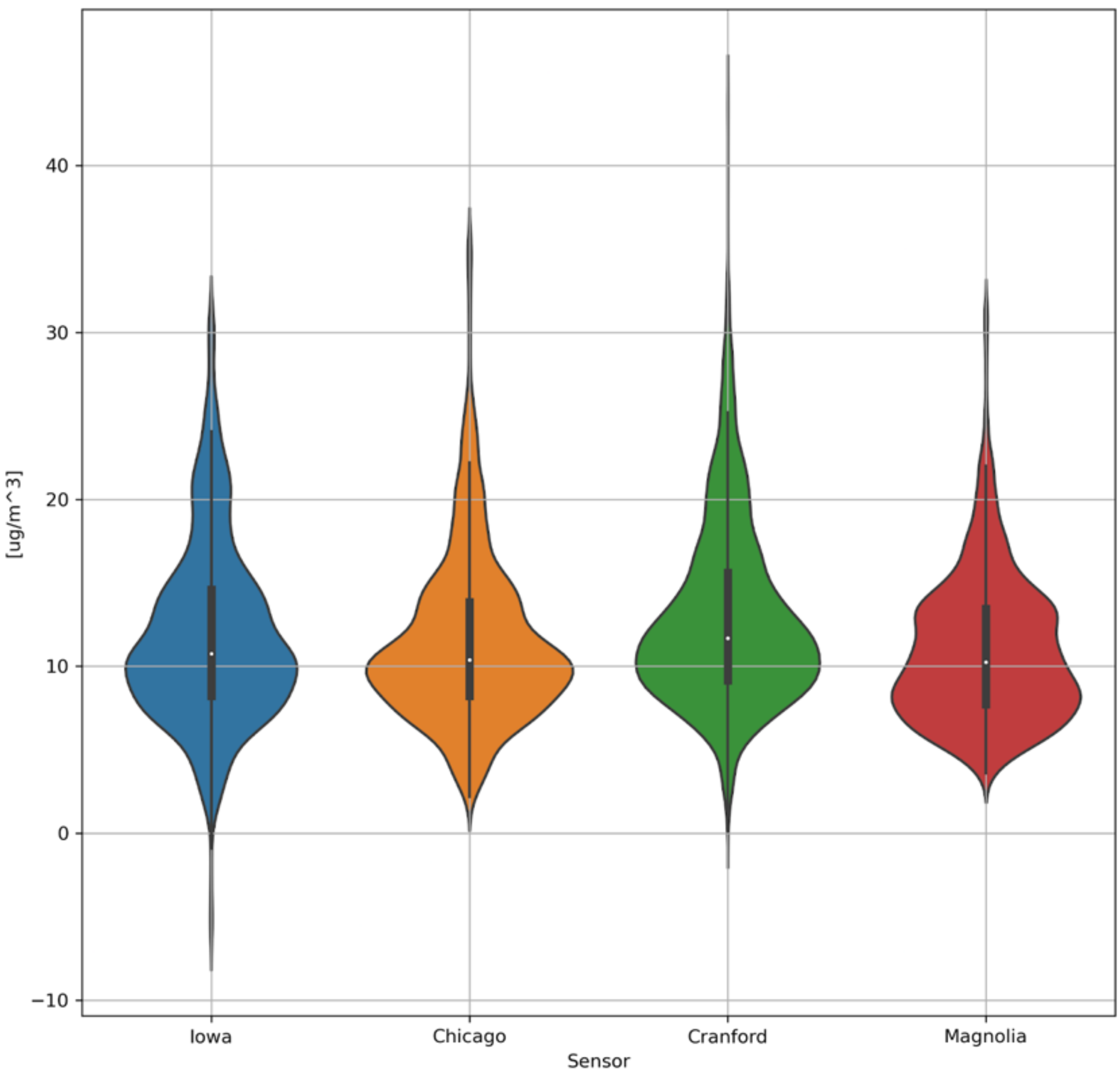

Figure 7. $PM_{2.5}$ concentration (µg/m³) distributions for low-cost monitoring locations.

The $PM_{2.5}$ model was evaluated using cross-validation, and the model explained approximately 75% of the variance in the data (Table 1). Partial dependence analysis identified background $PM_{2.5}$ and relative humidity as significant drivers of model variability (Figure 8). This indicates strong regional, meteorological, and diurnal influences on $PM_{2.5}$ along the Innovation Corridor.

Sampling day and hour was also significant, but the trends were non-linear. Partial dependence plots for all other input variables can be found in the Appendix.

Table 1. Cross-validation metrics for the $PM_{2.5}$ model and testing data subset.

Model Metrics:	**Scores**
Fit Time:	70.8678
Score Time:	0.0447
Avg. Test R2:	0.756
Avg. Test MSE:	7.3134
Avg. Test RMSE:	2.7036
Avg. Test Explained Variance:	0.7575

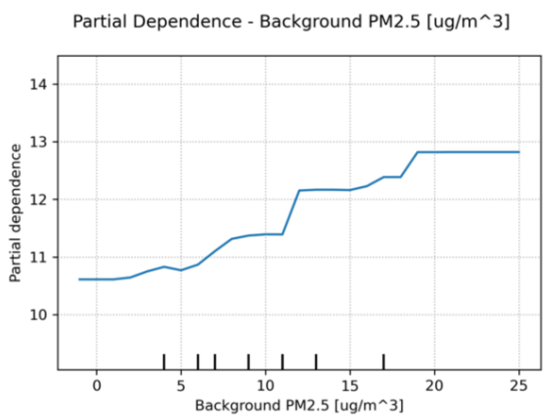

Figure 8. Dependence of predicted local $PM_{2.5}$ on background $PM_{2.5}$ (left) and relative humidity (right).

3.3. Nitrogen Dioxide (NO_2)

NO_2 mixing ratio distributions were similar across all low-cost monitors, except for the monitor at University Ave. & Cranford Ave. due to sensor drift (data included for transparency) (Figure 9). The distributions are bimodal at both along the Innovation Corridor, and mixing ratios were generally less than 50 ppb. The Tyler St. & Magnolia Ave (red) distribution saw highest probabilities near the upper end of the distribution; this corridor is more heavily used by heavy-duty vehicles than the Innovation Corridor. Therefore, it is likely that despite more heavy-duty traffic along Tyler Street, NO_2 mixing ratios along the Innovation Corridor are similar to Tyler Street due to significant influence from nearby highway corridors.

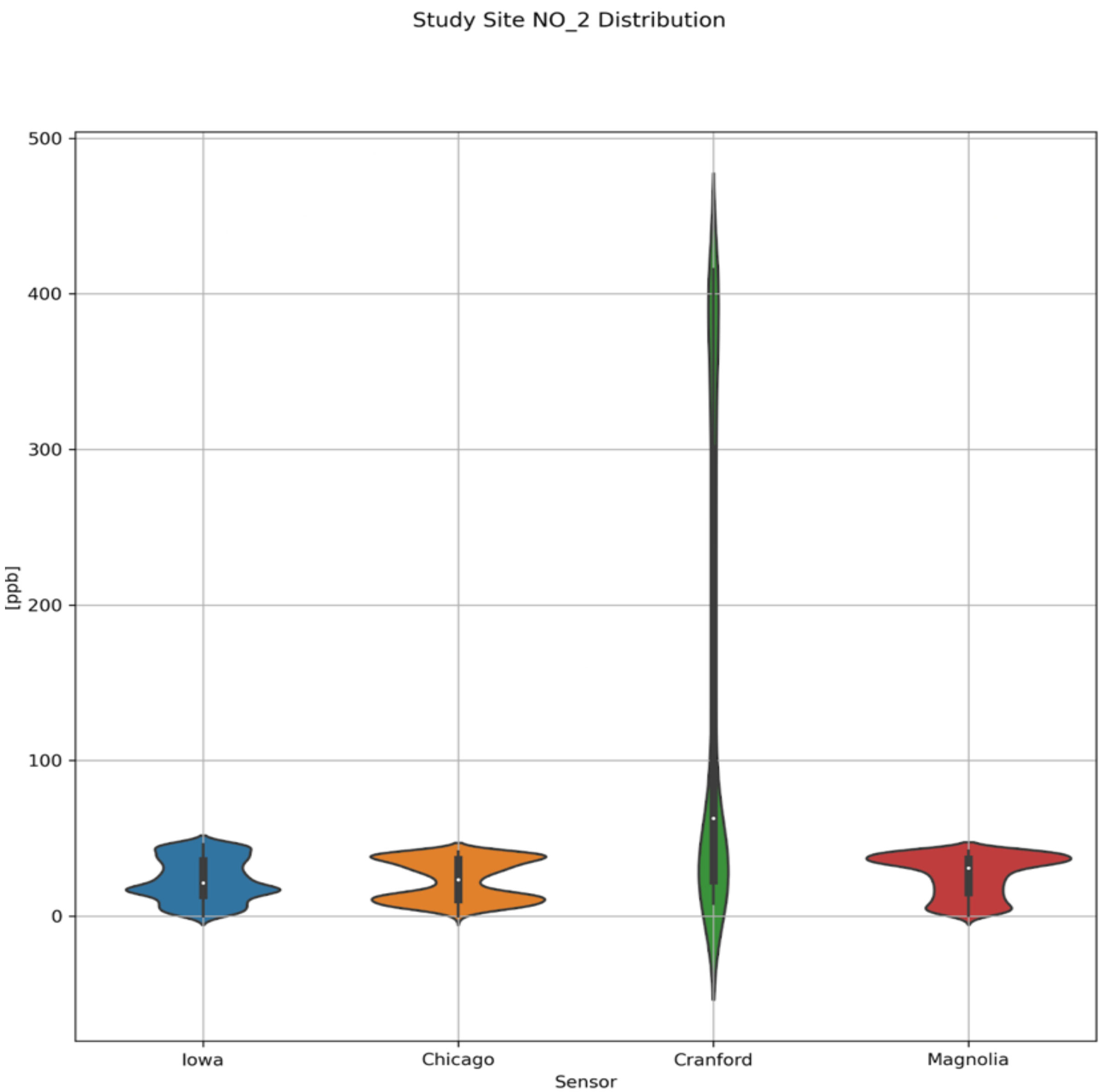

Figure 9. NO_2 concentration (ppb) distributions for low-cost monitoring locations.

The NO_2 model was evaluated using cross-validation, and the model explained approximately 99% of the variance in the data (Table 2). The NO_2 model did not exhibit strong dependence on traffic data or meteorology. Partial dependence analysis identified sampling day as the most significant driver of model variability (Figure 10). This indicates that day-to-day changes in traffic activity is the most significant predictor of modeled NO_2 along the Innovation Corridor. In future tests, the upwind highway corridor traffic (CA-91) will be used as input to further test local model dependence on upwind highway activity. Partial dependence plots for all other input variables can be found in the Appendix.

Table 2. Cross-validation metrics for the NO_2 model and testing and training data subsets.

Model Metrics	Scores
Fit Time:	53.1859
Score Time:	0.0382
Avg. Test R2:	0.9928
Avg. Test MSE:	2.2159
Avg. Test RMSE:	1.4881
Avg. Test Explained Variance	0.9928
Avg. Train R2:	0.9935
Avg. Train MSE:	2.0092
Avg. Train RMSE:	1.4164
Avg. Train Explained Variance	0.9935

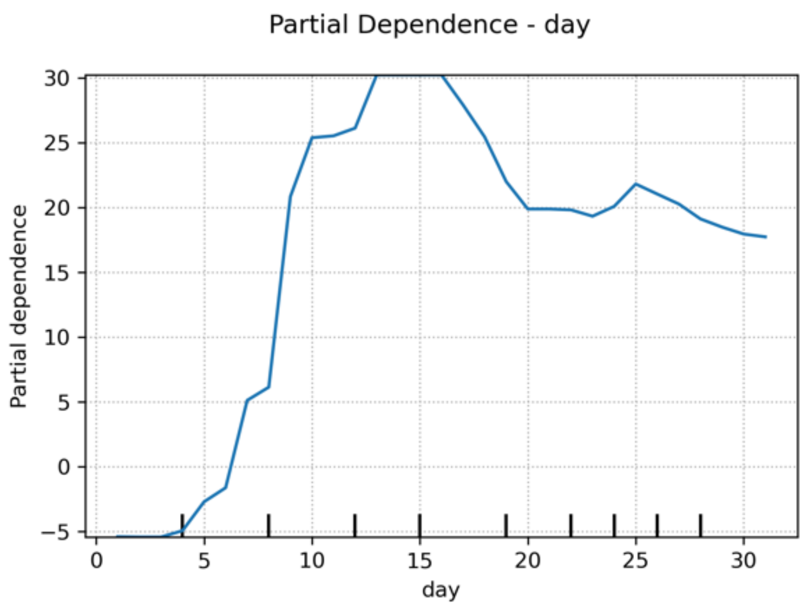

Figure 10. Dependence of predicted local NO_2 on sampling day.

3.4. Limitations

The analysis presented here is preliminary in nature due to the limited availability of GridSmart data during our air monitoring sampling period. The one-month modeling analysis did not span the entire year and therefore does not accurately represent seasonal variability. Partial dependence does directly calculate the variables' contributions to local pollutant concentrations, but the analysis is useful to elucidate the relationship between pollutants and their environmental drivers. The models both performed well in cross-validation tests, and RMSEs for the tests were low (2.7 for $PM_{2.5}$ and 1.5 for NO_2). While these are important metrics for measuring the accuracy of the model on a given dataset, they are potentially subject to overfitting bias.

4. Future Work

In future efforts, the time period of analysis will be extended to determine seasonal trends. We will also seek to quantify NO_2 impacts from the surrounding highways vs. local impacts by isolating the effects of transportation interventions along the innovation corridor. Traffic data and signal timing data will be continuously collected from the innovation corridor to support the future research. Advanced roadside sensors including camera, LiDAR and radar will be further deployed to monitor the traffic volume and vehicle speed. The vehicle activity data from Connected Vehicles will be also utilized in future analysis.

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Data Summary

Products of Research

In this project, we collected vehicle speed trajectories and energy consumptions data for all the host vehicles from all the numerical and micro-simulation experiment. Those data are used to validate the proposed algorithms and estimate the performance on energy savings.

Data Format and Content

The data were saved in CSV files in the format of second-by-second trajectories. For each time stamp, the vehicle's dynamic state, e.g. location, speed and acceleration rate, the signal timing information and the traffic information are archived along with the estimate energy consumption calculated by the specific models for gasoline vehicles or electric vehicles.

Data Access and Sharing

The data are publicly available via Dryad, which is in compliance with the USDOT Public Access Plan. The data can be accessed at https://doi.org/10.6078/D1K992.

Reuse and Redistribution

The data are restricted to research use only. If the data are used, our work should be properly cited:

> Ivey, Cesunica, Alexander Nguyen, Ruoming Xu, Khanh Do, Peng Hao, and Matthew Barth. (2023). Hyperlocal monitoring of traffic-related air pollution to assess near-term impacts of sustainable transportation interventions [Dataset]. Dryad. https://doi.org/10.6078/D1K992.

Appendix

A.1. Low-Cost Monitoring Locations

All intersection images were sourced from the Google Maps Street View tool.

Figure 11. Iowa Ave. and University Ave.

Figure 12. Cranford Ave. and University Ave.

Figure 13. Chicago Ave. and University Ave.

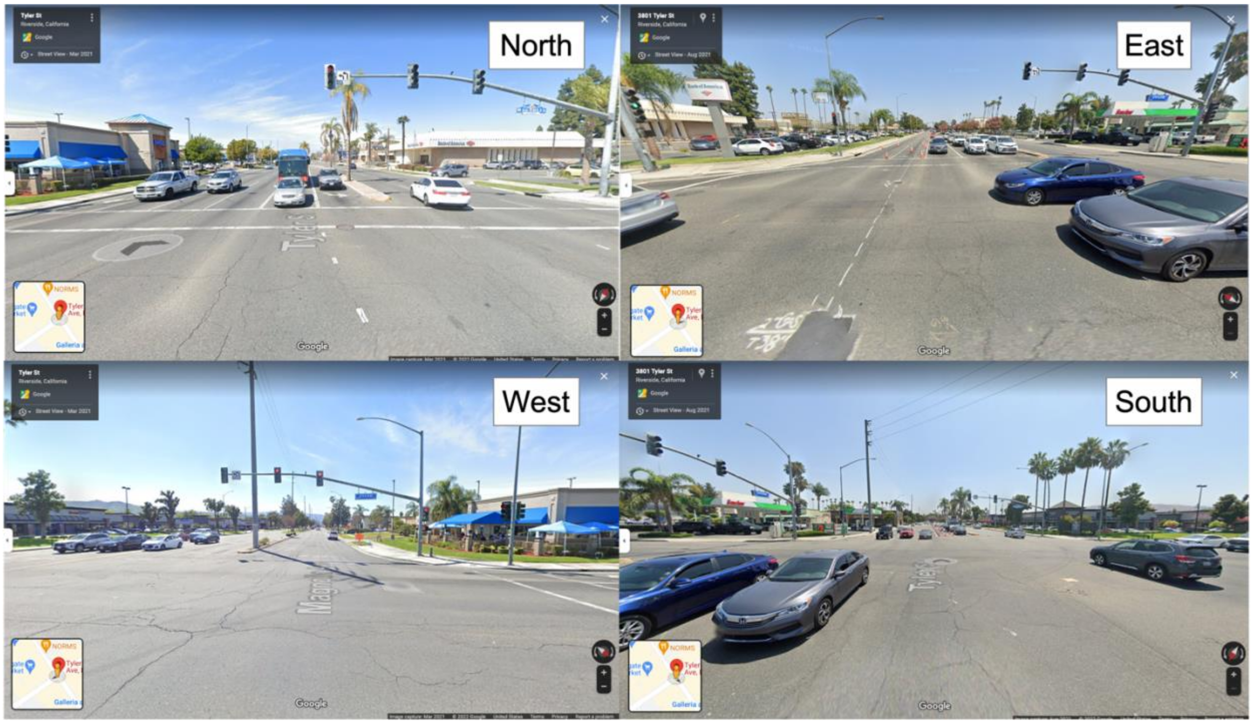


Figure 14. Tyler St. and Magnolia Ave.

A.2. Clarity Node-S

AIR QUALITY MEASUREMENTS

PARAMETER	TECHNOLOGY	RANGE	ACCURACY (Typical)
$PM_{2.5}$ [1]	Laser Light Scattering with Smart Calibration	0–1000 µg/m³ 1 µg/m³ resolution	Correlation (R2) with FRM instrument > 0.8 95% Confidence interval: < 100 µg/m³: ± 10 µg/m³ ≥ 100 µg/m³: within ± 10% of measured value
Nitrogen Dioxide	Electrochemical Cell with Smart Calibration	0–3000 ppb 1 ppb resolution	Correlation (R2) with FRM instrument > 0.7 95% Confidence interval: < 200 ppb: ± 30 ppb ≥ 200 ppb: ± 15%
Carbon Dioxide [2]	Metal Oxide Semiconductor	0–1000 ppm	Within ± 7% of measured value
Total VOC [3]	Metal Oxide Semiconductor	0–1000 ppm	Within ± 14% of measured value
Temperature [4]	Band-gap	-20–70° C	± 0.2° C
Humidity [5]	Capacitive	0–100% RH	Within ± 2% of measured value
AQI (US EPA Standard)	–	0–500	Calculations based on $PM_{2.5}/NO_2$

Figure 15. Clarity Node-S hardware and technical specifications (https://www.clarity.io/products/clarity-node-s).

A.3. Rubidoux Air Monitoring Site

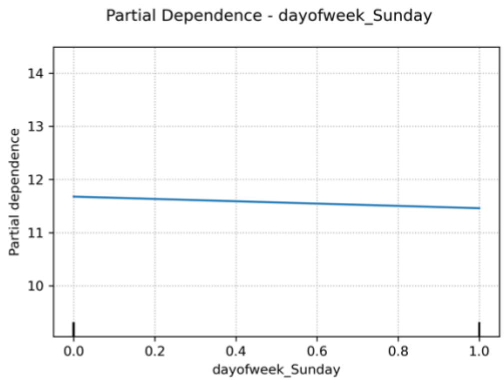
Table 3. Rubidoux Site Information

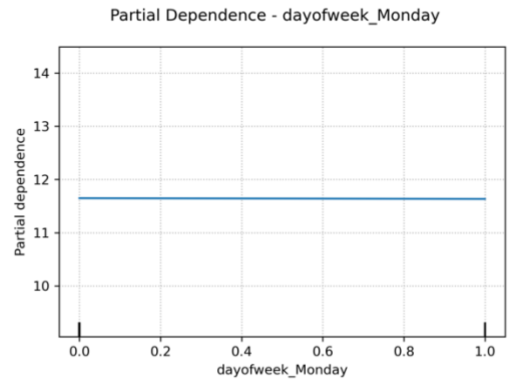
Attribute	Data
AQS Number	06-065-8001
CARB Number	33144
Site Address	5888 Mission Bl, Riverside, CA 92509
County	Riverside
Air Basin	South Coast
Latitude	33.99952
Longitude	-117.41595
Elevation	248 m

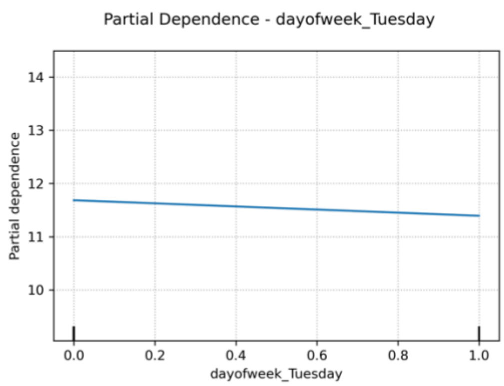
A.4. $PM_{2.5}$ Partial Dependence Plots

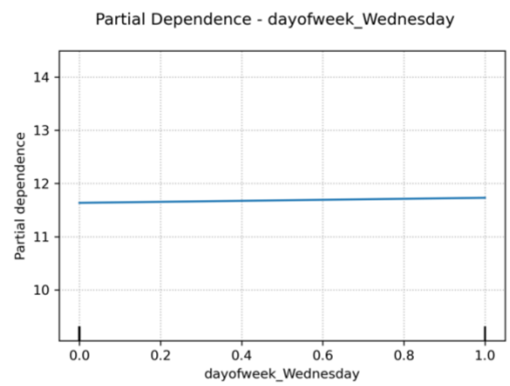
$PM_{2.5}$ Partial dependence plots are included below for the following input variables:

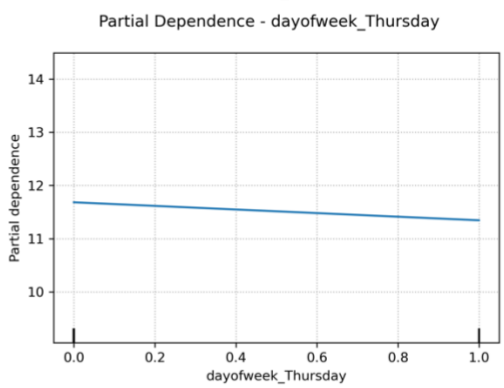
- Sampling day (day of month)
- Day of week
- Hour of day
- Sampling minute
- Sampling month
- Air pressure (mbar)
- Temperature (ºC)
- Traffic density of local and interstate corridors (vehicles/mile)
- Wind direction (degrees)
- Wind speed (miles per hour)

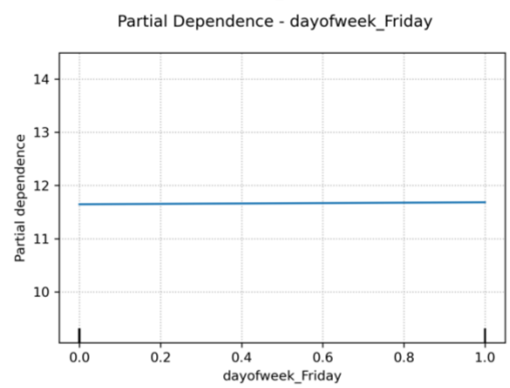

Partial Dependence - dayofweek_Sunday
Partial dependence
dayofweek_Sunday

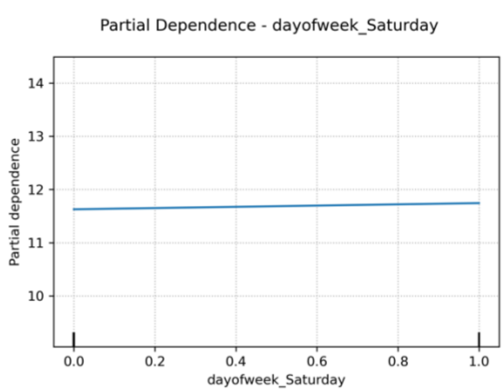

Partial Dependence - dayofweek_Monday
Partial dependence
dayofweek_Monday

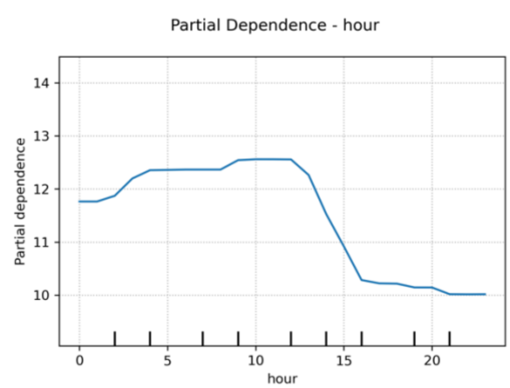

Partial Dependence - dayofweek_Tuesday
Partial dependence
dayofweek_Tuesday

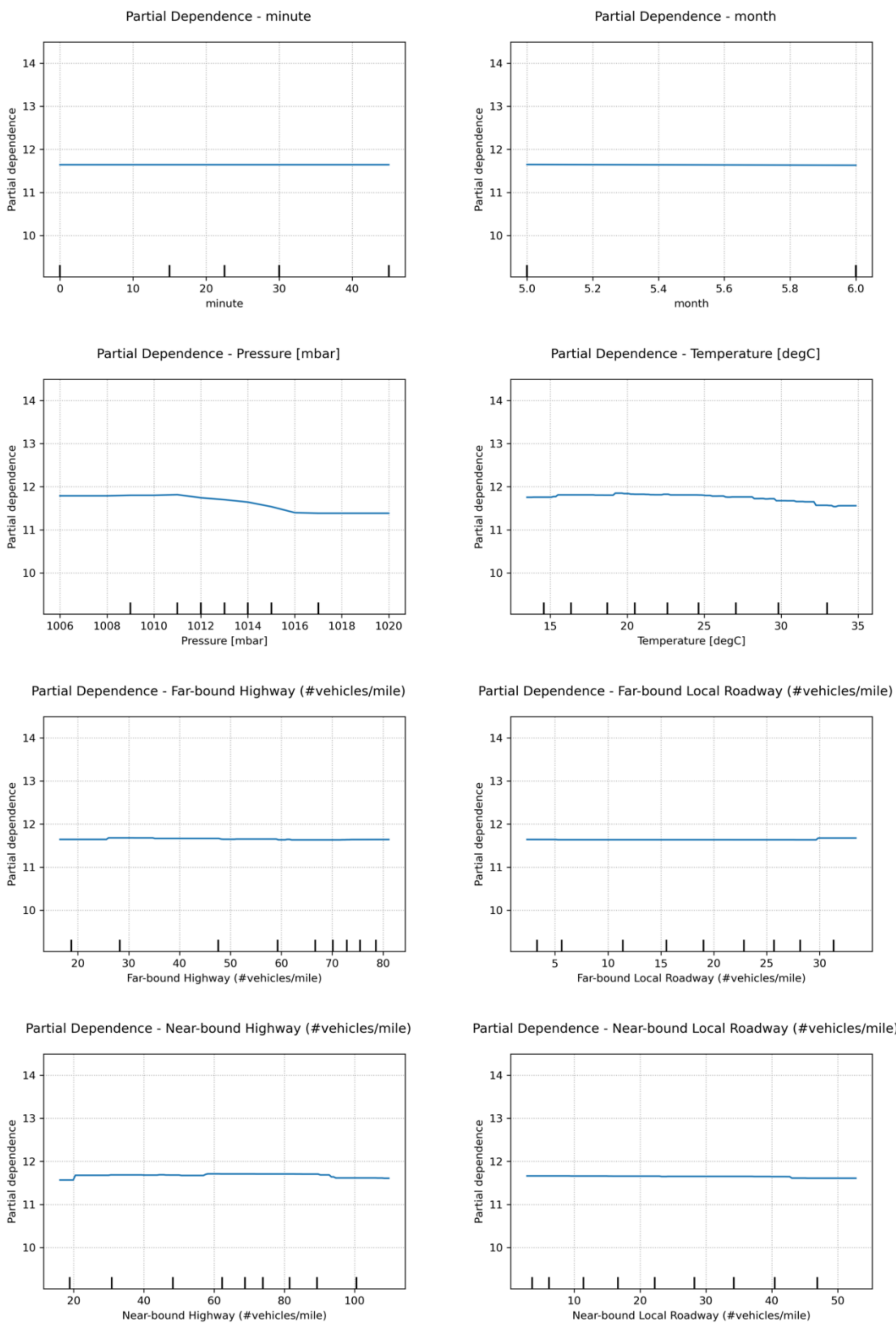

Partial Dependence - dayofweek_Wednesday
Partial dependence
dayofweek_Wednesday

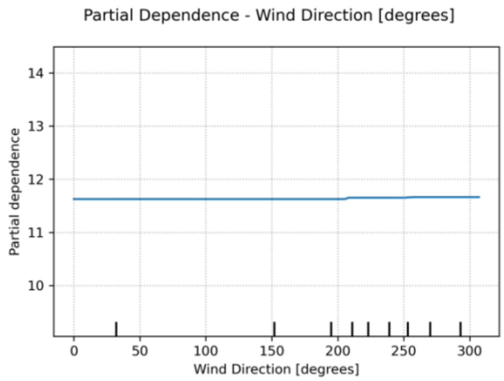

Partial Dependence - dayofweek_Thursday
Partial dependence
dayofweek_Thursday

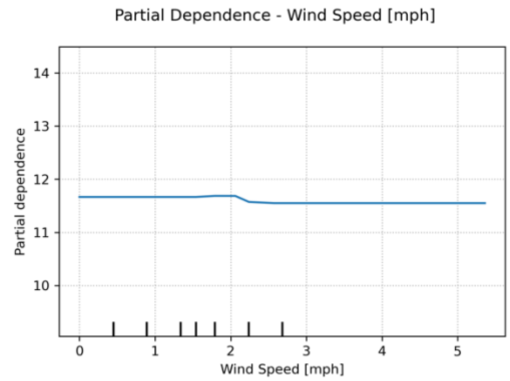

Partial Dependence - dayofweek_Friday
Partial dependence
dayofweek_Friday


Partial Dependence - dayofweek_Saturday
Partial dependence
dayofweek_Saturday


Partial Dependence - hour
Partial dependence
hour


Partial Dependence - minute
Partial dependence
14
13
12
11
10
0
10
20
30
40
minute
Partial Dependence - month
Partial dependence
14
13
12
11
10
5.0
5.2
5.4
5.6
5.8
6.0
month
Partial Dependence - Pressure [mbar]
Partial dependence
14
13
12
11
10
1006
1008
1010
1012
1014
1016
1018
1020
Pressure [mbar]
Partial Dependence - Temperature [degC]
Partial dependence
14
13
12
11
10
15
20
25
30
35
Temperature [degC]
Partial Dependence - Far-bound Highway (#vehicles/mile)
Partial dependence
14
13
12
11
10
20
30
40
50
60
70
80
Far-bound Highway (#vehicles/mile)
Partial Dependence - Far-bound Local Roadway (#vehicles/mile)
Partial dependence
14
13
12
11
10
5
10
15
20
25
30
Far-bound Local Roadway (#vehicles/mile)
Partial Dependence - Near-bound Highway (#vehicles/mile)
Partial dependence
14
13
12
11
10
20
40
60
80
100
Near-bound Highway (#vehicles/mile)
Partial Dependence - Near-bound Local Roadway (#vehicles/mile)
Partial dependence
14
13
12
11
10
10
20
30
40
50
Near-bound Local Roadway (#vehicles/mile)


Partial Dependence - Wind Direction [degrees]
Partial dependence
14
13
12
11
10
0
50
100
150
200
250
300
Wind Direction [degrees]


Partial Dependence - Wind Speed [mph]
Partial dependence
14
13
12
11
10
0
1
2
3
4
5
Wind Speed [mph]