Impacts of Modifiable Factors on Ambient Air Pollution: A Case Study of COVID-19 Shutdowns

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Abstract
Modifiable sources of air pollution such as traffic, cooking, and electricity generation emissions can be modulated either by changing activity levels or source intensity. Although air pollution regulations typically target reducing emission factors rather than altering activity, the COVID-19 related closures offered a novel opportunity to observe and quantify the impact of activity levels of modifiable factors on ambient air pollution in real-time. We use data from a network of twenty-seven low-cost Real-time Affordable Multi-Pollutant (RAMP) sensor packages deployed throughout urban and suburban Pittsburgh along with data from EPA regulatory monitors. The RAMP locations were divided into four site groups based on land use (High Traffic, Urban Residential, Suburban Residential, and Industrial). Concentrations of $PM_{2.5}$, CO, and NO_2 following the COVID-related closures at each site group were compared to measurements from "business as usual" periods in March 2019 and 2020. Overall, $PM_{2.5}$ concentrations decreased across the domain by 3 μg/m^3. Intra-day variabilities of the pollutants were computed to attribute pollutant enhancements to specific emission sources (i.e. traffic and industrial emissions). There was no significant change in the industrial related intra-day variability of $PM_{2.5}$ at the Industrial sites following the COVID-related closures. The morning rush hour induced CO and NO_2 concentrations at the High Traffic sites were reduced by 57% and 43%, respectively, which is consistent with the observed reduction in commuter traffic (~50%). The morning rush hour $PM_{2.5}$ enhancement from traffic emissions fell from ~1.5 μg/m^3 to ~0 μg/m^3 across all site groups. This translates to a reduction of 0.125 μg/m^3 in the daily average $PM_{2.5}$ concentration. If $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS) are tightened these calculations shed light on to what extent reductions in traffic related emissions are able to aid in meeting more stringent regulations.

Introduction

Sources of ambient air pollution are generally associated with human activities such as traffic, cooking, and electricity generation. These sources are modifiable factors; emissions can be modulated either by changing activity levels or the source intensity (e.g., emission factor). Air pollution regulation has traditionally relied on reducing emission factors rather than curbing activity. Although previous studies have assessed impacts of event-related step changes in emission sources on air quality[1–4], social distancing measures implemented in response to COVID-19 offer a natural experiment to observe and quantify the impacts of modifiable factors, specifically large shocks to activity, on ambient air pollution in real time with an unprecedented scope, speed, and duration.

In March 2020, 48 U.S. states implemented precautions to limit transmission of COVID-19[5]. In many cases, these measures represented a step-change in activity and accompanying pollutant emissions. This study focuses on data collected in Pittsburgh, PA, which is representative of the rapid changes in activity associated with social distancing measures. A timeline of the closures effecting PA and the upwind state of Ohio can be found in Table S1 in the Supplemental Information (SI) and show that activity was "business as usual" through March 13 [6–10] and rapidly transitioned to lower activity, with the majority of schools and non-essential businesses closed or operating in reduced capacity by March 16.

The closing of schools and businesses has a clear impact on activity levels and therefore air pollutant emissions. In this paper, we use data from both a distributed network of low-cost air pollutant sensors and the Environmental Protection Agency (EPA) regulatory network to examine how changes in activity impacted ambient air pollution. We compare concentrations of fine particulate matter ($PM_{2.5}$), CO, and NO_2 from the post-COVID shutdown period (March 14-31, 2020) to business as usual periods in March 2019 and 2020.

Methods

CO and $PM_{2.5}$ were measured using a distributed network of low-cost sensors. The Real-time Affordable Multi-Pollutant (RAMP) sensor package has been deployed throughout the city of Pittsburgh and surrounding suburbs since 2016[11]. The RAMPs use electrochemical sensors (AlphaSense LLC) to measure CO. $PM_{2.5}$ is measured via light scattering using either MetOne Neighborhood Monitors or PurpleAir PA-IIs. Previous work details the calibration[12,13] and deployment[14–16] of these sensor packages.

In March 2020 there were twenty-seven active RAMP sites in the Pittsburgh region. Figure S2 in the SI shows the locations of the RAMPs. The RAMP sites were grouped into four categories: High Traffic (n = 3), Urban Residential (n = 11), Suburban Residential (n = 8), and Industrial (n = 4). Site groupings were determined according to the same methodology as was used in previous work[14] and are described in detail in the SI.

One concern with low-cost pollutant sensors is uncertainty in the measurements[17–21]. We have previously shown that the mean absolute error relative to a reference measurement in the hourly averaged CO measurements is $\pm$49ppb[11]. Uncertainty in $PM_{2.5}$ is a strong function of averaging time; 1-hr data has a relatively large uncertainty (~4$\mu g/m^3$) that falls to ~1$\mu g/m^3$ after sufficient averaging time[12,19]. In this paper we group sites that have similar land uses in order to increase effective averaging time, thus reducing uncertainty to 1.1$\mu g/m^3$[19].

To supplement the RAMP data, EPA Air Quality System (AQS) data collected by the Allegheny County Health Department (ACHD) was also analyzed. The ACHD network includes two sites with NO_2 measurements. One is a High Traffic site, and the other is a Suburban Residential site; both are shown in Figure S2.

We have also quantified the reduction in traffic. We compared traffic camera data on a main commuter highway in March 2020 (post-closures) to historical vehicle counts on the same roadway during the same time of day (8am: morning rush hour). We estimate that commuter vehicle traffic was reduced by 48%. This estimate is consistent with Google mobility data which estimates that in Allegheny County workplace related mobility decreased by 45%[22].

Results and Discussion

Concentration reductions due to activity changes

In order to control for non-COVID related variables (i.e. weather) we compared post-COVID pollutant measurements in March 2020 to typical March pollutant measurements from March 2019. March 2019 was designated as the “pre-COVID period” for this analysis because of a high frequency of strong temperature inversions during the first two weeks of March 2020, as shown in Figure S6 in the SI. Across the entire RAMP network, pollutant concentrations fell 32% following the COVID-related closures; $PM_{2.5}$ concentrations decreased by ~3 µg/m^3, from 9.5 µg/m^3 (March 2019) to 6.4 µg/m^3 (March 14-31, 2020).

We treat CO as a marker of fresh combustion emissions from vehicular traffic and industrial activity. From Figure 1, during the pre-COVID period, the daily CO pattern is punctuated by occasional spikes. At the High Traffic and Urban Residential sites these spikes are broadly associated with traffic. The daily pattern in CO is evident in the diurnal patterns shown in Figure 2. There is a sharp rise in CO concentrations between an overnight stable period and the morning rush hour (7-8am).

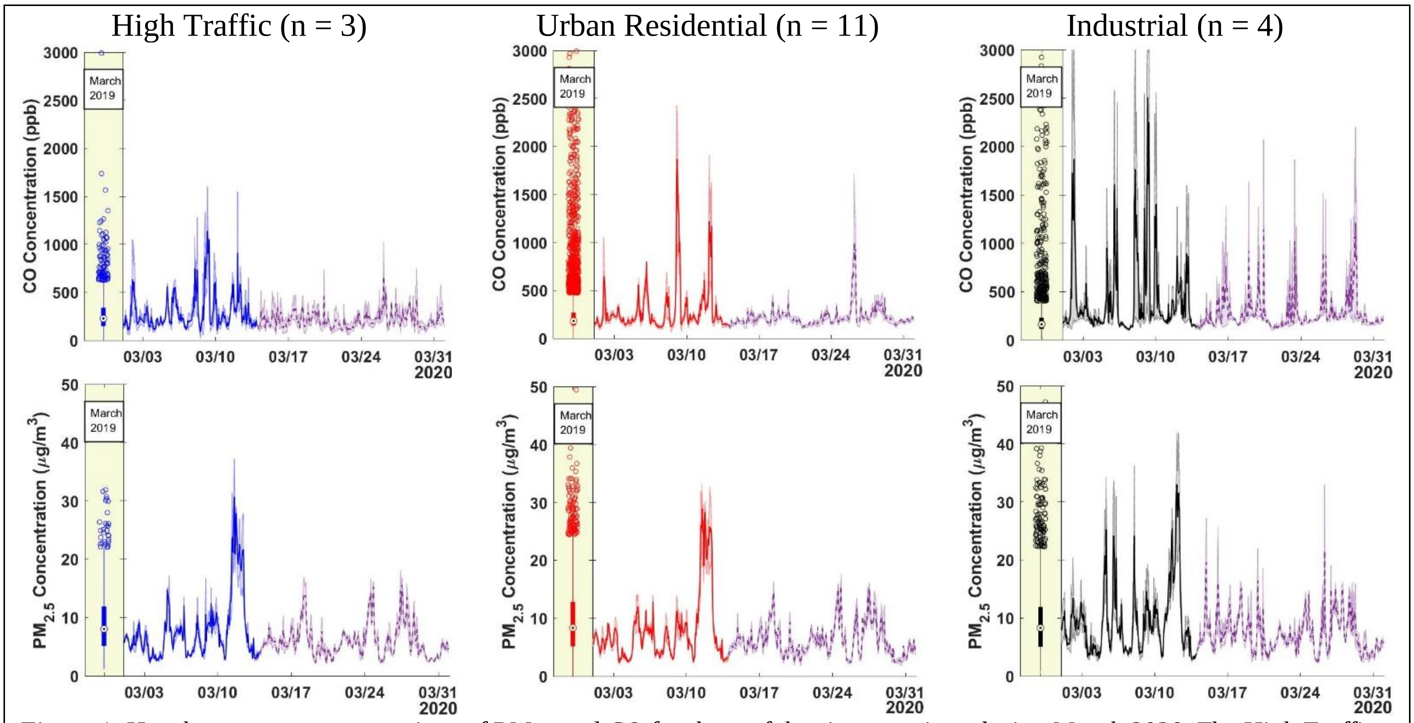


Figure 1. Hourly average concentrations of $PM_{2.5}$ and CO for three of the site groupings during March 2020. The High Traffic, Urban Residential, and Industrial sites are shown while the Suburban Residential sites are shown in Figure S3 in the SI. The solid (pre-COVID closures) and dashed (post-COVID) lines are the mean concentrations for all the sites in each group. The shaded area around each line represent the 25th and 75th percentiles of the data from the site groups. The boxplots show the corresponding March 2019 data for all sites in each site group. The center of the boxes (indicated by a dot) are the median, the

top and bottom of each box represents the 25th and 75th percentiles of the data for all sites over the entire month in that site group. The whiskers of the boxes represent 2.7 standard deviations and the outliers represent the remaining data.

In addition to the daily traffic-driven pattern, the Industrial sites are also impacted by CO emissions from the nearby industrial sources. These emission events generate concurrent spikes of CO and $PM_{2.5}$ that are evident in Figure 1.

The box plots on the left of each panel in Figure 1 show the distribution of CO and $PM_{2.5}$ measurements from March 2019. Overall, CO concentrations in the pre-COVID period in March 2020 are within the instrument uncertainty of 2019 and are therefore indistinguishable from each other. Descriptive statistics comparing the two datasets are shown in table S4 in the SI. This suggests that the main emission sources – countywide traffic and industrial emissions – were similar between 2019 and 2020 before social distancing.

Compared to March 2019 and pre-closure 2020, CO concentrations are both lower and less variable in the post-COVID closure period in 2020. For March 14-31, 2020, the mean concentration at the High Traffic sites fell 19% and the 90th percentile fell 22% when compared to the averages of March 2019 and pre-closures 2020. This is consistent with the large decrease in traffic volume and supported by the diurnal patterns in Figure 2. The morning rush hour peak is significantly smaller in the post-COVID period at the High Traffic sites and seems to have been eliminated completely at the Suburban Residential sites. NO_2, which is also a marker for traffic emissions, shows a similar pattern as CO (Table 1 and S5 in the SI). Concentrations are lower and less variable in the post-COVID period when compared to the March 2019 NO_2 measurements.

Figure 1 and 2 show similar trends for $PM_{2.5}$. Concentrations during the pre-COVID period in 2020 are similar to March 2019. Concentrations in the post-COVID period are lower and less variable. For example, Figure 2 shows that for the High Traffic sites the $PM_{2.5}$ increase associated with the morning rush hour fell from 1.4µg/m^3 in 2019 to zero in the post-COVID period.

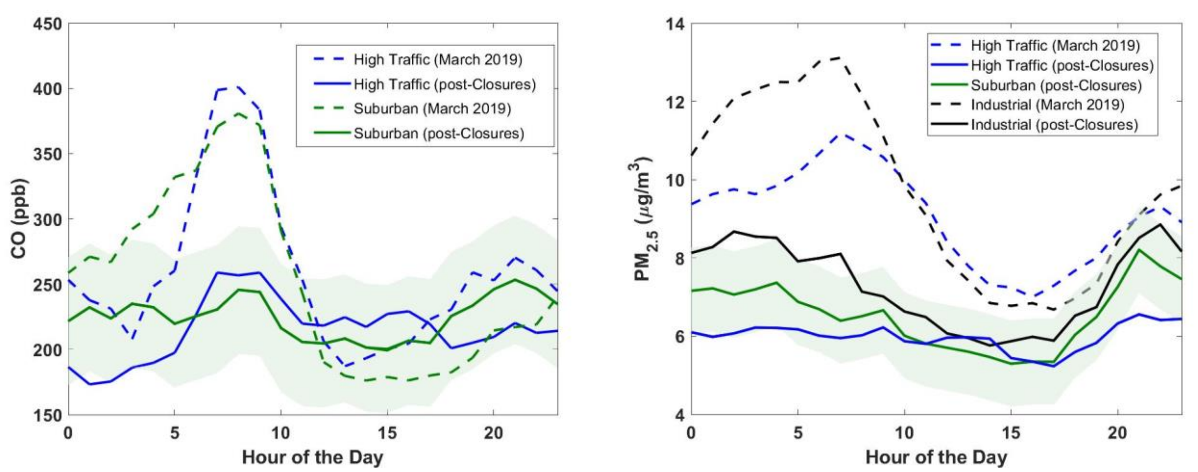


Figure 2. Average diurnal patterns for selected site groups for CO (left) and $PM_{2.5}$ (right). Dashed lines show the pre-closure diurnal patterns from March 2019 and the solid lines show the 2020 post-COVID period. The shaded

area around the line for the Suburban post-closure diurnal indicates the instrument uncertainty for each instrument (1.1 μg/m^3 and 49 ppb for $PM_{2.5}$ and CO, respectively).

Figure 2 shows that the majority of the $PM_{2.5}$ enhancement at the industrially influenced sites occurs at night which is consistent with previous studies[14]. This is because of a combination of emissions and boundary layer height. During overnight hours, the boundary layer is low. Many other sources, such as traffic, have less activity during overnight hours, whereas the industrial sources operate 24 hours per day. Thus, there are local enhancements of $PM_{2.5}$ overnight at the Industrial sites[23,24]. While average $PM_{2.5}$ concentrations were lower at the Industrial sites in the post-COVID compared to pre-COVID periods (25% reduction), these sites still had higher concentrations than all other site groups (1.1μg/m^3). This suggests that the industrial activity was maintained during the shutdown.

One challenge with attributing $PM_{2.5}$ reductions to changes in human activity is that the majority of $PM_{2.5}$ mass is secondary and formed via atmospheric oxidation of precursor vapors[25,26]. Thus, while changes in CO are a good marker for changes in direct combustion emissions, any changes in measured $PM_{2.5}$ concentrations may be driven by several other factors, including upwind emissions, boundary layer height, and weather. In the following section, we compare intra-day variations in enhancements that are associated with local emissions, and therefore should remove influences of these outside factors that may confound comparisons between the pre- and post-COVID periods.

Changes in source-related intra-day variability of pollutant concentrations

We defined two intra-day variations which focus on traffic and industrial-related enhancements. We first define the traffic-related enhancement as the difference between the morning rush hour peak (mean 7-8am) and the overnight stable period (mean 2-3am) for $PM_{2.5}$, CO, and NO_2. Second, we define an industrial enhancement for the sites in the Industrial group as the overnight difference (mean 2-4am) between the four Industrial sites and the five Suburban Residential sites with the lowest concentrations as this is representative of the industrial emissions overnight at those locations when most other emissions sources are reduced. Results are shown in Table 1.

	Site Group	Pre-COVID Traffic Related Variability	Post-COVID Traffic Related Variability		Pre-COVID Industrial Related Variability	Post-COVID Industrial Related Variability
$PM_{2.5}$ (μg/m^3)	*High Traffic*	**1.4**	-0.2		n/a	n/a
	Urban Residential	**1.4**	-0.1		n/a	n/a
	Suburban	**1.2**	-0.7		n/a	n/a
	Industrial	0.4	-1		**2.8**	**1.8**
CO (ppb)	*High Traffic*	**180.2**	**77.1**		n/a	n/a
	Urban Residential	**85.9**	42.1		n/a	n/a
	Suburban	**96.2**	8.8		n/a	n/a
	Industrial	**103.8**	-22.3		**272**	**290.2**
NO_2 (ppb)	*High Traffic*	**7.4**	4.2			
	Suburban	**0.2**	0.1			

Table 1. Intra-day source specific concentration changes associated with traffic and industrial emissions. The traffic enhancements were calculated for all four site groups (only two site groups were available with NO_2 measurements). Industrial enhancements were only computed for the Industrial sites. Differences larger than the instrumental uncertainties are shown in bold font.

For all site groups, the pre-COVID traffic enhancements of NO_2 and CO generally scale with traffic intensity. CO enhancements are largest at the High Traffic sites, nearly double the enhancement at the other site groups. Traffic CO enhancements at the Industrial, Urban Residential, and Suburban Residential sites are all similar (85-104ppb ±49ppb). The correlation between land use (i.e., traffic volume) and traffic-related CO enhancements, along with the fact that CO is non-reactive, supports the use of CO as a tracer for traffic emissions in these locations. NO_2 enhancements at the high traffic ACHD site were 7.4 ppb (±0.05ppb) compared to 0.2 ppb at the Suburban site.

The traffic enhancements fell post-COVID closures. Enhancements of CO and NO_2 fell at high traffic sites by 57% and 43%, respectively; this is consistent with the observed ~50% reduction in commuter traffic. Morning CO enhancements fell to nearly zero in Suburban areas (96.2 to 8.8ppb), suggesting a larger fractional reduction in traffic volumes in those areas, consistent with people working and schooling from home. The traffic CO enhancement became negative in Industrial areas, meaning that concentrations at 7-8am were lower than 2-3am. This is consistent with our observations that although traffic emissions in the mornings have decreased, the overnight industrial emissions have persisted.

$PM_{2.5}$ enhancements during the morning rush hour in the pre-COVID period were more uniform across site groups. For High Traffic, Urban Residential, and Suburban Residential groups, the morning rush hour $PM_{2.5}$ enhancement was 1.2-1.4μg/m^3, suggesting that traffic is broadly distributed. As a result there is a regional increase in morning $PM_{2.5}$, consistent with the more regional nature of $PM_{2.5}$[25–28].

Morning traffic enhancements in $PM_{2.5}$ were smaller at the Industrial Sites. This may be a consequence of already-enhanced concentrations during the overnight hours at these sites because of nearby industrial emissions. The overnight Industrial $PM_{2.5}$ enhancement relative to Suburban Residential sites was 2.8μg/m^3 in the pre-COVID period. The smaller apparent traffic enhancement at the Industrial sites may also be an artifact of how we determine this enhancement (mean 7-8am minus the mean 2-3am). However, our sensitivity analysis in the SI (Figure S7) shows that the general pattern is robust to the specific sets of hours we use when calculating the enhancements.

In the post-COVID period the morning traffic enhancements for all site groups are within instrument uncertainty of zero, indicating there is no longer a $PM_{2.5}$ enhancement during the morning rush hour. For all site groups, the morning increase in $PM_{2.5}$ fell by 0.5-1.5μg/m^3, suggesting that the impact of reduced traffic on morning $PM_{2.5}$ is more regional.

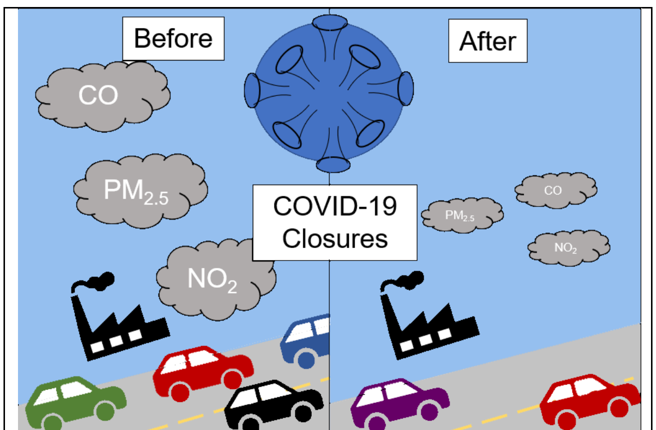
Our analysis suggests that the activity at the industrial sources continued after social distancing was enacted. The industrial $PM_{2.5}$ enhancement fell from 2.8 (pre-COVID) to 1.8μg/m^3 (post-COVID). However, the uncertainty of the $PM_{2.5}$ measurements are 1.1μg/m^3, suggesting that this decrease may not be significant. Similarly, although the corresponding CO industrial enhancement slightly increased in the post-COVID period the increase was once again within the instrument uncertainty suggesting that there was no significant change in industrial CO enhancement between the pre- and post-COVID time periods as well.

<u>Implications</u>

Our data show a clear decrease in air pollution driven in large part by reductions in vehicle traffic. While the COVID-related shutdowns are unprecedented and do not likely represent the new status quo, they can offer insights into air pollution under future emissions scenarios (e.g., large-scale adoption of electric vehicles). Figure 2 and Table 1 suggest that a ~50% adoption of electric vehicles would essentially eliminate the morning rush hour peak in $PM_{2.5}$, CO, and NO_2. This could reduce acute exposures, especially in high traffic or near-road environments.

In addition to traffic activity reductions, we also estimated reductions in restaurant activity (by anonymous survey, shown in S8 in the SI) and in electricity related emissions (by calculating the decrease in the metered hourly electricity load supplied by Duquesne Light Company, which provides electricity for ~600,000 customers in the region). We found that the activity of these sources reduced by 63% and 8%, respectively. However, determining the impacts of reductions in restaurant emissions and electricity generation on measured pollutant concentrations are more difficult. Neighborhoods with high restaurant impacts have an additional ~1μg/m^3 of $PM_{2.5}$ compared to areas with low restaurant activity[29]. Our estimated change in restaurant activity would drop this impact to ~0.4μg/m^3. However, the RAMP network does not have sufficient sites in high- and low-restaurant areas to examine this impact in greater detail. Impacts of changes in electricity demand are also difficult to determine directly from our data, as much of the $PM_{2.5}$ from power plants is in the form of secondary sulfate[30]. Upwind changes in power plant emissions would therefore be convolved with changes in other upwind emissions and weather patterns. Reductions in electricity generation and restaurant emissions may contribute to the lower overnight background concentrations observed in the post-COVID period.

The most recent policy assessment review for the $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS) recommended a revision to the annual $PM_{2.5}$ NAAQS to as low as 9µg/m^3. Such a reduction is estimated to reduce the $PM_{2.5}$ related mortality rate by 21-27%[31]. The Pittsburgh domain considered here has an annual average $PM_{2.5}$ concentration of 9.5µg/m^3. While evaluating the full impact of vehicle traffic on $PM_{2.5}$ requires a more thorough assessment of impacts on primary and secondary $PM_{2.5}$, we can use the observed changes in the morning rush hour peak to make a first-order estimate for the impacts of major changes to vehicle emissions on the annual average $PM_{2.5}$. We observe that the morning rush hour peak enhancement from 7-8am fell from 1.4µg/m^3 to ~0µg/m^3. This translates to a reduction of 0.125µg/m^3 in the daily average $PM_{2.5}$ concentration, which would account for a third of the necessary reduction to reach a hypothetical 9µg/m^3 standard. Thus, reductions beyond morning rush-hour traffic emissions may be needed to reach 9µg/m^3 in urban areas.



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Associated Content

Supporting Information
Additional details, figures, and tables outlining the timeline for COVID-19 related closures, measurement site groupings and locations, CO and $PM_{2.5}$ measurements for the Suburban Residential sites, overall CO and $PM_{2.5}$ measurements for the entire domain, NO_2 measurements from Allegheny County Health Department, boundary layer height during measurement periods, sensitivity analysis for traffic enhancement calculations, and emissions activity reduction for restaurant cooking and electricity consumption.

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The authors declare no competing financial interest.

Acknowledgements

This work is part of the Center for Air, Climate and Energy Solution (CACES, www.caces.us). This publication was developed under Assistance Agreement no. RD83587301 awarded by the U.S. Environmental Protection Agency (EPA). This publication has not been reviewed by the EPA. The views expressed in this manuscript do not necessarily represent those of the funding agency. The authors would also like to thank Aliaksei Hauryliuk for maintaining the RAMP sensor network.

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