



Spatial and temporal approaches for differentiating local source and background air quality impacts using low-cost sensor networks

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Abstract. Low-cost sensor (LCS) networks are increasingly used to characterize the impacts of local air pollution sources. Researchers have developed a variety of methods to differentiate local impacts from background influences; however, these methods differ substantially in their definitions, assumptions, and resulting insights. This study compares four spatial and temporal techniques for isolating local influences: Spatial Network, Peak Finding, Fourier Decomposition, and Wavelet Decomposition. We apply these techniques to three pollutants across two LCS networks to assess their strengths, limitations, and suitability for different contexts. The Spatial Network approach performed better for pollutants with spatially localized plumes and low regional background, such as coarse particulate matter, but was sensitive to systematic sensor bias. In contrast, the temporal approaches were more robust to sensor bias but were instead limited by their underlying assumption of the short-lived nature of local impacts. The Peak Finding approach was effective for identifying episodic plume events but struggled to differentiate local impacts for pollutants with strong diurnal variability, such as nitrogen dioxide. Wavelet Decomposition and Fourier Decomposition provided greater flexibility for separating variability across multiple temporal scales, such as diurnal, weekly, and seasonal cycles. Each method also showed distinct tradeoffs in implementation complexity, parameter sensitivity, and data completeness requirements. These findings demonstrate that researchers should select a technique according to the community context, pollutant characteristics, and data quality rather than applying a single approach universally.

1 Introduction

Researchers, local governments, and community groups increasingly employ low-cost sensor (LCS) networks to characterize the air quality impacts of local pollution sources, including construction, industrial facilities, and road traffic (Clements et al., 2017; Commodore et al., 2017; Morawska et al., 2018). The impacts of these localized sources often exhibit substantial spatial and temporal variability (Jaafar et al., 2024; Tchepel et al., 2010), resulting in uneven exposure to pollution in nearby communities and raising concerns about environmental justice (Racz and Rish, 2021).

The high spatial and temporal resolution of LCS networks makes them well suited for capturing these localized pollution patterns to inform effective mitigation strategies (Snyder et al., 2013). However, LCS' utility in this context depends on net-



work operators' ability to differentiate localized pollution impacts from background or regional patterns. Ambient pollution measurements reflect a combination of influences that vary in space and time, including local sources of interest but also chemical transformation and regional transport. The latter are often driven by meteorology and vary by pollutant and geography; for example, large urban zones with regional traffic cycles or areas with significant secondary pollutant production (Dong et al., 2020; Wallace et al., 2010). In such cases, quantifying local pollution contributions is essential for extracting actionable insights from sensor networks that can inform advocacy, policy decisions, and mitigation strategies. Consequently, researchers have developed a variety of methods to distinguish local from background influences in monitoring data. However, the term "background" (e.g., neighborhood background, urban background, regional background) is used inconsistently across existing studies, with its meaning varying with the method applied.

Many strategies define local impacts as isolated in space, relying on this characteristic to differentiate local and background components. A common approach designates a background monitoring site based on factors such as proximity to suspected sources and predominant wind direction. Measurements at this site are then subtracted from other monitors to estimate the local component (Hilker et al., 2019; Deshmukh et al., 2020; Patton et al., 2014). In practice, however, exclusively using a spatial definition of local impacts can be problematic. An ideal background site should remain unaffected by the local source(s) of interest while still experiencing the same regional dynamics and chemical, physical, and meteorological processes that influence pollutant concentrations throughout the study area. Such a site is often difficult to identify, particularly in urban environments with multiple or diffuse emission sources. As an alternative, researchers have also assigned the "background" site dynamically, based on when a site is upwind of a source of interest at any given time (Hilker et al., 2019; Steffens et al., 2017). Other approaches estimate the background as a minimum or low percentile concentration measured across a dispersed sensor network within a time window, which reduces reliance on a single monitor (Shusterman et al., 2018).

Because of these challenges, many studies instead use temporal variability as a proxy for spatial source impacts, assuming that local emissions tend to produce shorter-lived fluctuations than broader background influences (Tchepel et al., 2010). In this framework, the background and local components are separated according to their characteristic temporal frequencies rather than their spatial locations. Temporal frequency-based approaches include Fourier decomposition (Frederickson et al., 2022; Tchepel et al., 2010; Jaafar et al., 2024), wavelet decomposition (Sabaliauskas et al., 2014; Zimmerman et al., 2020), Kolmogorov–Zurbenko (KZ) filtering (Al-Rashidi et al., 2018), rolling minima or percentile-based smoothing (Chen et al., 2024; Hilker et al., 2019; Shairsingh et al., 2018), and other unique algorithms (Ruckstuhl et al., 2012; Vedantham et al., 2015; Heimann et al., 2015). Plume detection is another time-series-based approach that isolates episodic pollution events using peak finding algorithms and concentration thresholds (Brantley et al., 2014; Silberstein et al., 2024; Frischmon et al., 2025a). This method offers a narrower definition for the "local" pollution component, as it typically isolates only the most extreme plumes from the background.

Each of these methods can produce different estimations of local contributions to air quality, impacting source attribution and exposure assessments. Previous work exploring differences in local and background estimation techniques has largely focused on mobile monitoring datasets. For example, Wei et al. (2021) and Pu et al. (2024) found that a temporal smoothing approach was better suited for their data than wavelet decomposition, while Brantley et al. (2014) found that this approach



underestimated the background compared to defining it using mobile measurements from an unaffected area (Wei et al., 2021; Pu et al., 2024; Brantley et al., 2014). Comparisons of local and background estimation techniques using stationary monitoring data are much less common and often focus on near-road contexts. Hilker et al. (2019) found that subtracting concentrations measured at an urban background site produced results consistent with time-series-based approaches for discerning local traffic impacts (Hilker et al., 2019). In contrast, Edwards et al. (2025) cautioned against the use of urban background sites in their comparison of techniques for high-resolution near-road monitoring, particularly during periods heavily influenced by rush hour emissions (Edwards et al., 2025).

None of these comparative studies evaluated techniques for estimating local and background impacts using low-cost sensor data. This omission is notable, given that LCS networks are often deployed by communities and local governments with the explicit goal of characterizing local source impacts, making accurate background estimation critical for interpreting monitoring results. LCS networks also enable novel spatial approaches for estimating these impacts. Specifically, their high spatial coverage makes it possible to dynamically identify background concentrations measured within the network, rather than relying on a single external background site (Shusterman et al., 2018).

In response to this gap, our study compares multiple data processing techniques for estimating local and background impacts using two LCS datasets. The first dataset was collected near a major road construction project, which created intense localized impacts. Conversely, the second dataset was collected in an urban neighborhood with a stronger background influence. We compared four data processing techniques to assess their performance across these two scenarios. The four techniques included three time-series-based approaches—Fourier decomposition, wavelet decomposition, and peak finding plume detection—and one spatial approach, which defined the background using the minimum concentrations measured within the sensor network.

2 Methods

2.1 Data Collection

We applied each data processing technique to two LCS datasets: one of fine particulate matter ($PM_{2.5}$) collected in a Los Angeles (LA), California neighborhood and the other of nitrogen dioxide (NO_2) and coarse particulate matter (coarse PM, or $PM_{10-2.5}$) collected near a construction site in rural northwest Colorado. We chose these datasets to evaluate how the techniques perform in both “strong background” and “weak background” contexts. We expected the data collected in the LA community to be heavily influenced by urban background pollution and the Colorado dataset to have strong local impacts from construction emissions. Both sensor networks were established using sensor platforms, referred to as Pods, developed in the Hannigan Air Quality (HAQ) Lab at University of Colorado, Boulder (github.com/HanniganAirQuality). These platforms use a suite of interchangeable low-cost sensors to measure various pollutants. Details on the specific Pod version and sensor units used, as well as sensor deployment and calibration for each dataset, is provided below.



2.1.1 Los Angeles Dataset

From 2023 to 2025, the HAQ Lab collected data in a South LA community using the HAQ-Pod model. This community is concerned about the local air quality impacts from a nearby oil extraction site and major highway, yet it also faces regional air quality impacts within the heavily polluted LA air basin (Soleimanian et al., 2019; Jerrett et al., 2005). The HAQ-Pod is an updated version of the Y-Pod used in prior LA-based research (Okorn et al., 2021; Collier-Oxandale et al., 2020). Additional details about the HAQ-Pod and the full suite of sensors inside are available in (Frischmon et al., 2025b, 2026b). In this study, we only included data collected using a Plantower PMS5003 sensor for $PM_{2.5}$ and a Bosch BME 680 sensor for temperature and humidity. The Pods were set up near ground level or on single-story roofs within the West Adams, Jefferson Park, and University Park neighborhoods. A map of the Pod locations used in this study is provided in Figure 1.

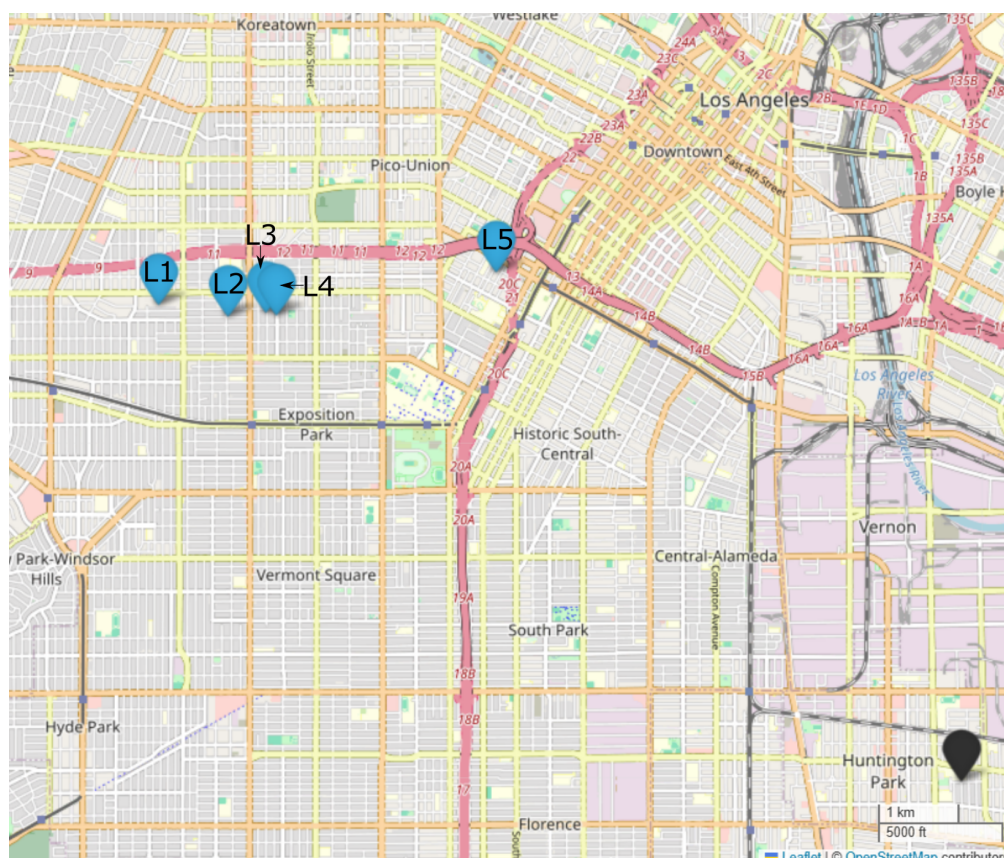


Figure 1. Map of LA Pods included in this study. Blue markers indicate Pod sites and the black marker is the reference site. © OpenStreetMap contributors 2026. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.

The Pods were calibrated using the two-step colocation process detailed in Frischmon et al. (2026a). In this process, we colocated one “secondary standard” Pod with a reference Teledyne T640 instrument managed by the South Coast Air Quality



Management District (South Coast AQMD) in Huntington Park. The South Coast AQMD calibrated the Teledyne T640 every
100 six months and conducted weekly zero and span checks and nightly precision checks. We developed a gradient boosting
machine learning model to calibrate the secondary standard Pod to the Teledyne T640 PM_{2.5} measurements while the remaining
Pods collected field data. Model fit statistics for the calibration are shown in the supplemental materials. The field Pods were
normalized to the secondary standard via pre- and post-deployment colocations with the secondary standard and then calibrated
105 directly with the gradient boosting model. The calibration model inputs included the Plantower PM_{2.5} sensor signal along with
temperature and humidity to correct for environmental sensitivity in the Plantower sensor.

2.1.2 Colorado Dataset

In 2023, Colorado Department of Transportation funded a study to investigate the air quality impacts of road construction in
urban and rural areas. Three highway construction projects were monitored and assessed using a network of HAQ-Pods and
MiniPods. To supplement the suite of pollutants measured by the HAQ-Pods, the MiniPods contain an optical particle counter
110 (Alphasense OPC-R2), which measures the light scattered by particles as they pass through a laser beam. These measurements
are then used to determine the particle bin size and number concentrations for PM₁, PM_{2.5}, and PM₁₀. The full report on this
study can be found online (Coffey et al., 2025). This paper focuses on NO₂ and coarse PM (PM_{10-2.5}) data collected in the
fall of 2024 at the US 40 Passing Lane Project located on US 40 between Kremmling and Steamboat Springs, CO, a semi-arid
rural valley. Construction work included adding eastbound and westbound passing lanes, extending culverts, signing, striping
115 and traffic control. The site also featured a small river valley paralleling the highway north-south just west of the roadway. Pods
were powered with solar panels and batteries and mounted on poles about 5 ft off the ground. They were placed on both sides
of the road, 15-30 ft from the edges of the roadway, in the right-of-way. Two locations were identified outside the immediate
construction zone to capture background: one location a mile north (D9) and another ¾ mile south (D1 and A3). The elevation
change over the network was about 175 ft.

120 A full description of the sensor calibration process is outlined in Coffey et al. (2025). Briefly, we employed a similar two-
step colocation process as described in section 2.1.1 for NO₂, though in this case the NO₂ calibration model was transferred
to the field Pods using the process described in Okorn and Hannigan (2021). The secondary standard Pod was colocated
with a Teledyne-API Model T200 at the I-25 Denver, Colorado Department of Public Health and Environment (CDPHE) air
quality monitoring station. Alphasense's B4 CO, NO, NO₂ and O₃+NO sensor signals along with the BME680 temperature
125 and humidity sensor signals were used in a multi-linear regression to model NO₂ concentrations. The additional sensors were
included in the NO₂ calibration to account for sensor cross-sensitivity to other pollutants.

For coarse PM, the four Pods were each colocated with a GRIMM EDM 180 analyzer at the CDPHE I-25 Denver station
before and after the field deployment at US 40. Here, each Pod had an individual multi-linear regression model developed
between reference coarse PM concentrations and the Alphasense OPC-R2 sensor signals.

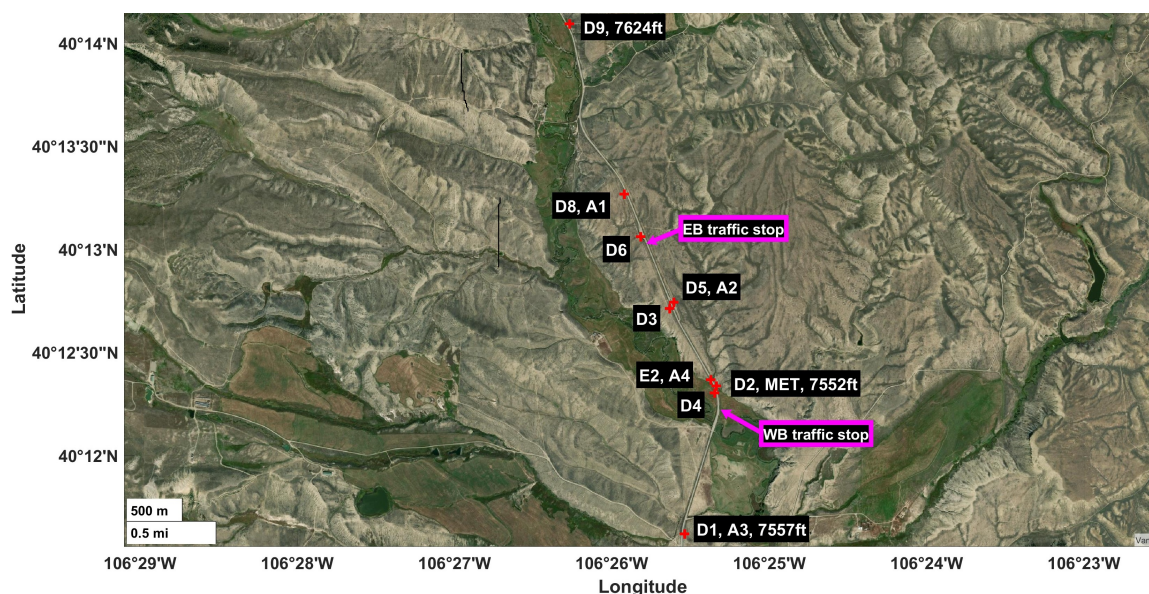


Figure 2. Map of CO Pods included in this study as well as the locations of eastbound (EB) and westbound (WB) traffic stops. Imagery © 2025 Vantor generated using MATLAB R2024a

130 2.2 Data Cleaning

For the purposes of this analysis, we selected one- to two-month subsets from each dataset that minimized missing data and maximized the number of measurement sites. Data were time-averaged using 15-min medians to reduce noise. The resulting Los Angeles PM_{2.5} dataset spanned 10-24-23 to 12-20-23 and included five Pods with an average 99.8% data completeness. The resulting Colorado dataset spanned 9-17-24 to 10-16-24 and included four Pods for coarse PM and nine Pods for NO₂, with
 135 an average data completeness of 92.6% and 99.7%, respectively. We imputed missing data with each Pod's diurnal median; i.e., a missing 10:30 am data point was filled with the Pod's series median 10:30 am measurement.

2.3 Techniques for Estimating Background and Local Impacts

We evaluated four data processing techniques on each dataset. These techniques included a spatial network approach, a peak finding approach, and two temporal frequency-based techniques—wavelet and Fourier decomposition. These techniques are
 140 based on existing methods for estimating background or local impacts and vary widely in their complexity and suitability for different applications. We chose them to provide a representative range of approaches available to researchers and community monitoring practitioners.

2.3.1 Spatial Network Approach

The Spatial Network approach assumes that, at any given time interval, at least one sensor in the monitoring network best represents the ambient background concentration. This assumption can be bolstered by the deliberate positioning of a subset of sensors to be either more distant from or upwind of known pollution sources.

The network background concentration for each time interval is estimated dynamically as the minimum or low-percentile sensor measurement within the network during that interval. The minimum represents the simplest estimate of the background, whereas the percentile can be used to reduce the influence of sensor uncertainty and transient outliers (Shusterman et al., 2018). The background value is then subtracted from the corresponding concentration at each sensor in the network to calculate enhancements above the background. As the simplest form for comparison, we set the background concentration as the minimum among all sensors for each hourly interval.

2.3.2 Peak Finding Approach

The temporal methods used in this study assume a close relationship between spatial and temporal scales of air pollution phenomena to differentiate local impacts. Peak finding algorithms determine local maxima within a time series by comparing each data point to its neighboring data points (Virtanen et al., 2020). In air quality research, these algorithms have been applied to identify short-term concentration spikes associated with local emission plumes (Orkin et al., 2013; Hui et al., 2025). The peak finding approach we used here builds on this foundation, using peak identification as a temporal approach to isolating local source impacts from background concentrations.

We applied Python's `find_peaks` algorithm from the Scipy library to each dataset (Virtanen et al., 2020). We set two parameters for each pollutant: distance, the minimum number of data points required between peaks, and prominence, the minimum height a peak must rise above the surrounding baseline points. Additionally, when determining the peak widths, we set `rel_height`, defining the fractional depth of the prominence at which the peak width is measured. Parameter values were individualized for each pollutant and dataset (Table 1), and were determined through a sensitivity analysis detailed in the supplementary materials.

Table 1. Peak Finding approach parameters for each pollutant.

Pollutant	distance	prominence	rel_height
Coarse PM	2	8	0.7
NO ₂	12	4	0.7
PM _{2.5}	16	4	0.7

Importantly, parameter selection is both dataset- and pollutant-dependent; different pollutants or contexts may require different parameter values or additional parameters to effectively capture peaks of interest. This flexibility adds complexity and subjectivity, as parameters can be tuned to target more or less extreme peaks depending on the research interest.



After peaks were identified, background concentrations were estimated by applying a 2-hour rolling average on data points not contained within the width of the peaks. To determine the background within the peaks, linear interpolation was performed between the points immediately preceding and following the peak. Finally, local impact concentrations were calculated by subtracting the background from the total measured concentration. Importantly, because the non-peak background is a smoothed rolling average rather than the raw measurement, the components do not sum to the total concentration measured during non-peak periods, though the residual is only a fraction of a percent.

2.3.3 Fourier Decomposition

Analyzing air pollution data in the frequency domain enables an understanding of the layered periodic processes that together form an overall pollution signal; thus, it can be utilized to differentiate between short-term and long-term variability. For example, high-frequency oscillations may indicate a localized emission source or rapid chemical transformation, whereas seasonal changes or regional transport are represented by low-frequency components. One method of converting a pollution time series into the frequency domain is Fourier decomposition, which decomposes a series into a sum of constituent sine and cosine waves with varying frequencies, amplitudes, and phases (Hies et al., 2000; Marr and Harley, 2002; Frederickson et al., 2022; Tchepel et al., 2010). This decomposition is commonly performed using the Fast Fourier Transform (FFT), an efficient algorithm for calculating the discrete Fourier transform $X(k)$. A periodogram at frequencies k is calculated by squaring the magnitude of $X(k)$ (Eq. 1):

$$\phi(\nu_k) = |X(k)|^2 = \left| \frac{1}{\sqrt{N}} \sum_{t=0}^{N-1} x_{t,\text{orig}} e^{(-2\pi i \nu_k t)} \right|^2 \quad (1)$$

Where $k = 0, 1, \dots, N-1$, N is the number of observations, x_t , orig is the original time series, and $k = k/N$. The periodogram plots the strength of the signal (spectral power, (k)) against frequency, providing insight into the frequencies that dominate the overall signal. In the example periodogram below, spectral power peaks can be observed at frequencies corresponding to 12-hour and 24-hour oscillations (Figure 3).

We transformed each Pod's time series using MATLAB's fft function. Before the transformation, we subtracted the linear trend but left the mean intact to facilitate easier comparisons between techniques. For the purposes of this study, we then defined three subset frequency bins to characterize fluctuations in the signal at different time scales, similar to those outlined in Frederickson et al. (2022): localized (short-term, period ≤ 4 hours), diurnal or meteorological (4 hours $<$ period ≤ 32 hours), and background or regional (period > 32 hours). These bin sizes were chosen to match those used in the Wavelet Decomposition approach and are based on prior work that experimented with suitable bin sizes for isolating background and diurnal influence (Frischmon et al., 2026b). Frequency-filtered signals x_t , filtered for each bin were then reconstructed in the time domain using the Inverse Fast Fourier Transform (IFFT) (Eq. 2) function in MATLAB, ifft.

$$x_{t,\text{filtered}} = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X(k) e^{(2\pi i \nu_k t)} \quad (2)$$

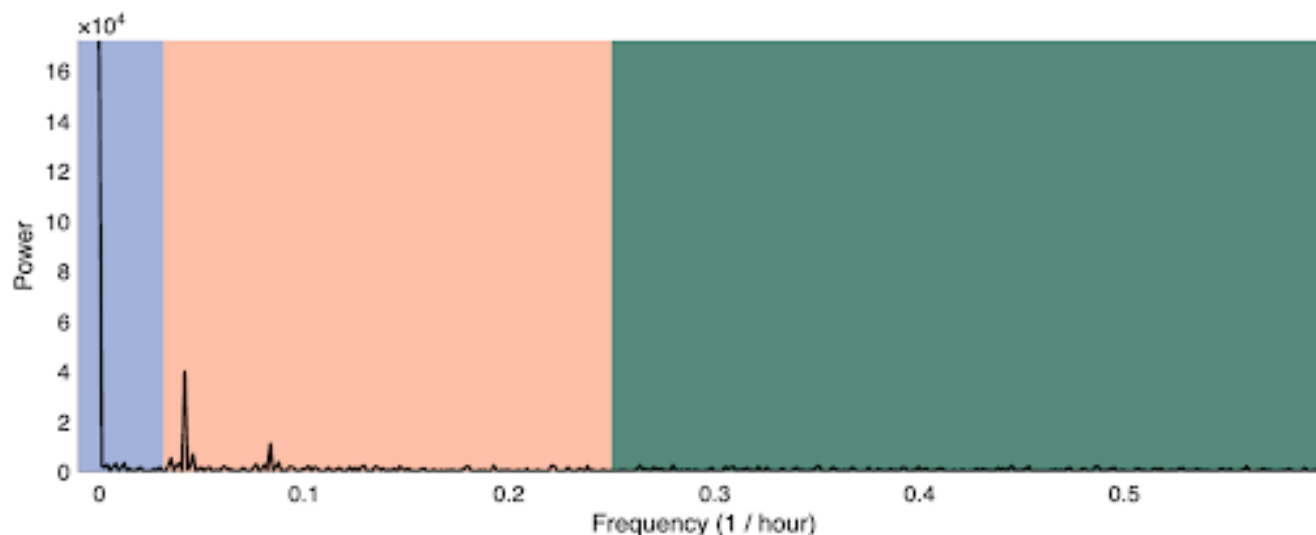


Figure 3. Example periodogram for a coarse PM time series. The large spike at the 0 frequency corresponds to the series mean, which was not subtracted for this analysis. Background shading corresponds to the local (green), diurnal (pink), and background (blue) frequency bins defined below.

This reconstruction results in three time series components, one for each frequency bin, which sum to the original signal. It is important to note that because we did not subtract the mean from the original series before transforming it, the background component is dominated by the mean. In this context the localized and diurnal components can be conceptualized as anomalies from the background, containing positive and negative components.

2.3.4 Wavelet Decomposition

Wavelet decomposition is another method to break down a time series based on the frequencies of underlying oscillations. Instead of sine and cosine waves, this method decomposes a signal using a set of wavelet basis functions, which are localized in time and frequency. Wavelet decomposition iteratively decomposes data in multiple steps. In the first step, the original signal passes through a high- and low- frequency filter. The low-frequency component isolated from the filter continues to pass through the filter in the subsequent steps, removing the higher-frequency details until the desired low-frequency baseline is reached. Each level of decomposition changes the timescale of the low-frequency baseline by 2^n . We implemented wavelet decomposition using the methods described in detail in Frischmon et al. (2026b), which uses the `baseline_dwt` function from the `scikit-ued` Python package with the default parameters and the commonly-used Daubechies 4 (db4) wavelet function (Liu et al., 2025).

We reconstructed the data into background, diurnal, and short-lived components using the low-frequency baselines obtained at different levels of decomposition (Zimmerman et al., 2020). We used the 7-level decomposition baseline to isolate background changes on a timescale of 32 hours or greater ($15 \text{ min} * 2^7 = 1920 \text{ min} = 32 \text{ h}$). We identified the diurnal component



as the difference between the 4-level and 7-level decomposition baselines, as this captured variability on the scale of 4 to 32 hours ($15 \text{ min} * 2^4 = 240 \text{ min} = 4 \text{ h}$). Finally, the difference between the original signal and the 4-level decomposition baseline captured the short-lived component, as this isolated any concentration variability on a timescale less than 4 hours.

3 Results

220 Each technique's results are impacted by the subjective tuning and implementation decisions we made (see the supplemental materials and Frischmon et al. (2026b)). With this in mind, we try to extract transferable insights that transcend those decisions, focusing instead on the suitability of each technique depending on the pollutant context, desired use case, and dataset limitations.

Figure 4 shows a time series snapshot of a single measurement site within each network to orient the reader to the way
225 each approach decomposes the total series into background, local, and sometimes diurnal components. Although these short snapshots are not suitable for quantitative analysis, the timeframes shown are representative of the typical dynamics of each pollutant and highlight several distinct features of each technique.

All approaches estimate a local component, capturing the short-lived or spatially distinct variability in pollutant concentration, and a background component. One key difference in these estimations is that the Peak Finding and Spatial Network
230 approaches isolate only these two components, while Fourier and Wavelet Decomposition can isolate multiple, in this case a diurnal component. Additionally, the Fourier Decomposition estimates are particularly unique, as the background component is dominated by the concentration mean. The diurnal and short-lived components represent positive or negative deviations from the mean, limiting its interpretability in the time domain.

Figure 4 shows that the Peak Finding approach appears well-suited for coarse PM, where short-duration spikes dominate
235 the time series. However, for pollutants with more persistent enhancements or diurnal variability, such as NO_2 , the distinction between baseline and peaks becomes less evident and the background is built from longer interpolations. Because the Spatial Network approach determines background spatially as the minimum measurement taken by the Pod for each hour, its background component retains more high-frequency variability than is physically realistic, particularly for NO_2 .

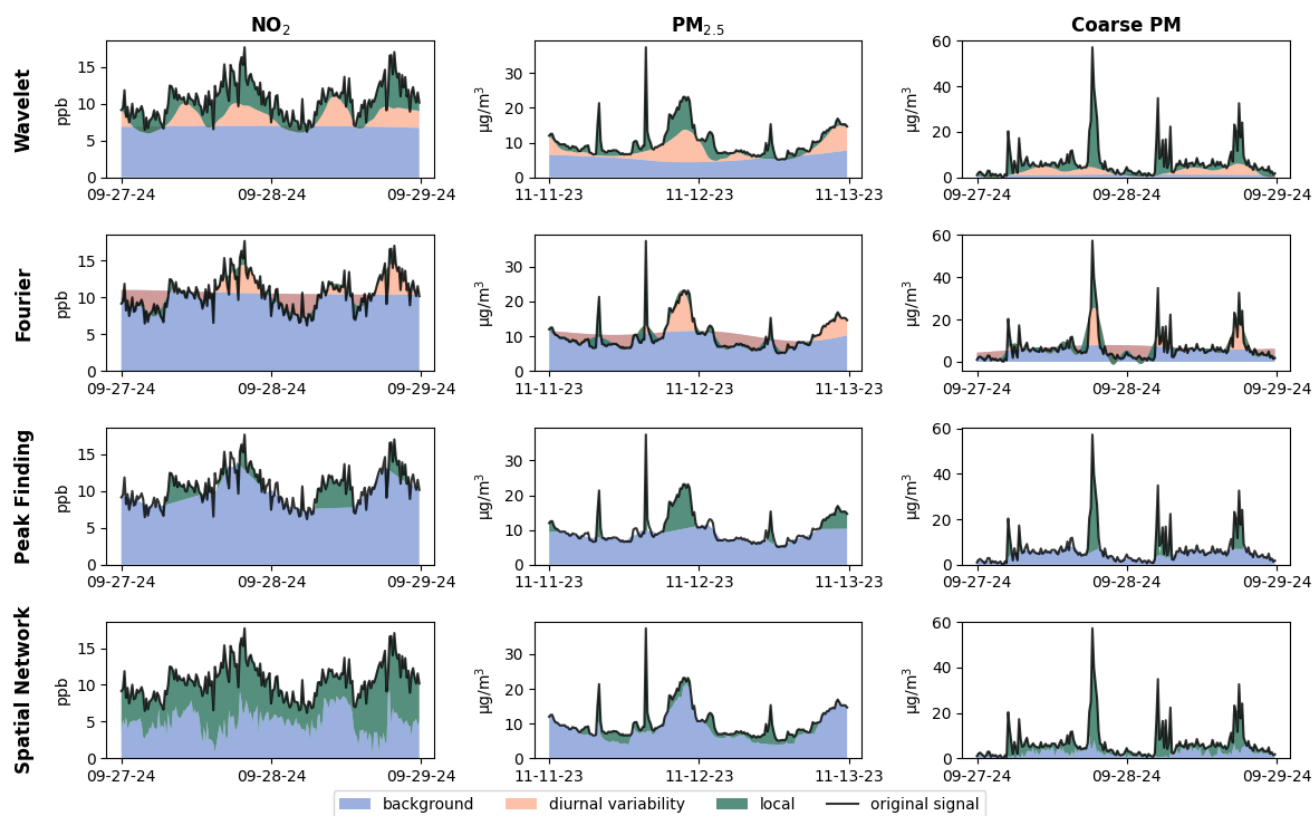


Figure 4. Stack plot time series snapshot showing the components differentiated by each technique for a single Pod. Left to right: Pods D1, L3, A3.

3.1 Diurnal Trends

Figure 5 compares the network-average diurnal cycle of the components produced by each technique, computed by averaging the measurements from all Pods at a given hour of day. Each approach partitions the signal differently. For example, the background estimated by the Fourier and Wavelet Decomposition approaches remains relatively constant. This is because these approaches isolate a diurnal component distinct from the background that captures recurring daily patterns.

For both NO_2 and $\text{PM}_{2.5}$, the diurnal component follows atmospheric dispersion patterns with lower concentrations during the afternoon when atmospheric mixing is highest. Similarly, the average background component estimated by the Peak Finding approach is near-constant, partitioning most of the diurnal cycle into the local component. In contrast, because the Spatial Network approach estimates the background for each hourly interval using measurements from all sensors in the network, a larger portion of the diurnal cycle is incorporated into the background estimate.

For coarse PM, all approaches showed peaks in the local component during daytime hours that closely follow the overall signal, suggesting that local emissions, such as from construction operations, drive overall concentrations. For the decompo-



sition approaches, some of this impact is partitioned as the diurnal component, likely because construction occurred each day during typical work hours.

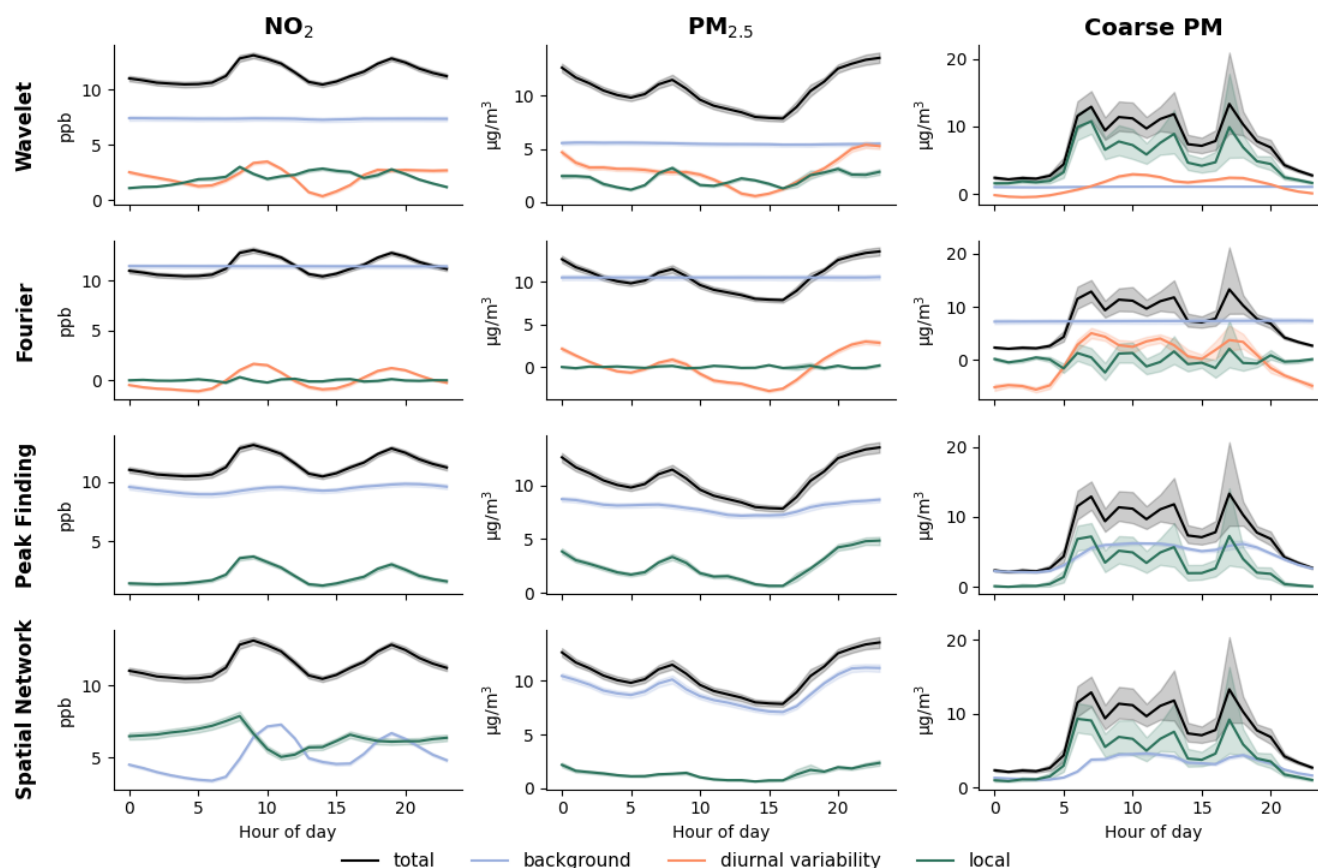


Figure 5. Diurnal network average of each component estimated by each technique.

3.2 Network Analysis

The ultimate goal of differentiating a local component is often to quantify its relative contribution to the overall signal, either of the same pollutant across a network (enabling an intra-network or spatial comparison of local impacts) or between two pollutants at one location. This can shed light on the drivers of spatial variation and overall exposure, revealing targets for local intervention. Figure 6 depicts the percentage of the total signal attributed to each component resolved by the four approaches, quantified either as the contribution to concentration or the contribution to variance. The Wavelet Decomposition and Spatial Network approaches isolate positive components that sum to the overall concentration but do not conserve variance. Peak Finding produces positive components that nearly sum to the total (though as noted earlier have marginal discrepancies during non-peak periods due to temporal smoothing) and similarly do not conserve variance, so this method is represented as a relative contribution to concentration as well. Because Fourier Decomposition defines the diurnal and local components as positive and



negative anomalies from the background, instead we show the contribution of each component to overall variance, which is conserved by this technique.

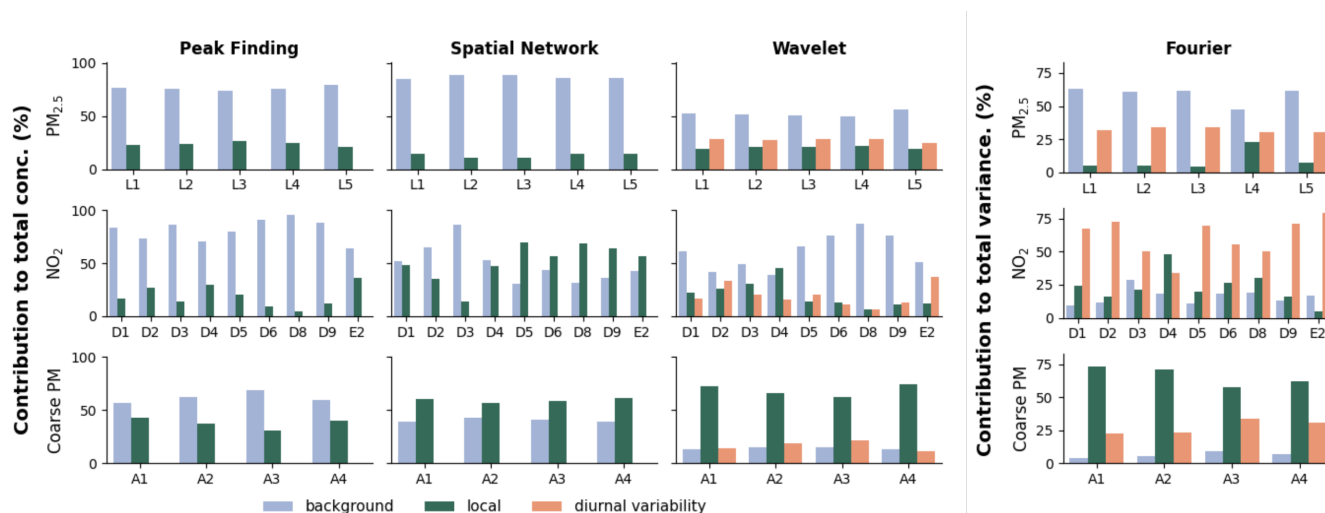


Figure 6. Contribution to total concentration (Peak Finding, Spatial Network, and Wavelet Decomposition) and to total variance (Fourier Decomposition) for each Pod.

Figure 6 indicates that for NO₂, the contribution patterns from each component are not consistent across techniques. In particular, the Spatial Network approach is the only technique where the local component contributes the most to overall concentrations (for all except Pod D3) (Figure 6). The time series snapshot shown in Figure 7 helps reveal a possible sensor bias issue that leads to the high local contribution for this technique. In this figure, it is easy to see that D3 has a lower baseline than the rest of the network, including D5, which is located just across the roadway from D3 (Figure 2). It is physically unlikely that D3 and D5 would experience substantially different concentrations in close proximity, suggesting that D3 may be experiencing sensor bias issues. If D3 is biased low, it could lower the background component resolved by the Spatial Network approach for the entire network, since it is based on only one Pod. This highlights a weakness of using the Spatial Network approach with LCS, as significant bias is a common problem with LCS measurements (Hayward et al., 2024).

Furthermore, because NO₂ has a very strong diurnal cycle, the attribution issue highlighted in Figure 5, where diurnal effects are assigned to either the background or local components, appears to drive discrepancies in the NO₂ results. For example, the Peak Finding approach identified E2 as having the largest local contribution, likely because it classified much of the diurnal oscillation as local by interpolating between successive minima (Figure 7). In contrast, Wavelet and Fourier Decomposition both identified D4 as having the largest local contribution across the network for NO₂ (Figure 6), consistent with the pronounced high-frequency concentration spikes observed at this site in Figure 7. For other Pods in the network, including D2 and D4, Peak Finding appears to instead assign more of the diurnal oscillation to the background component. This inconsistent attribution limits Peak Finding's ability to resolve differences in the local contribution by Pod. Although the technique could be further tuned to reduce this behavior, its underlying assumption that local impacts manifest as distinct



peaks limits its application for pollutants such as NO_2 , where concentrations are dominated by diurnal cycles rather than discrete plume events.

285 For $\text{PM}_{2.5}$, the estimated component contributions are fairly consistent across Pods and methods, particularly for the Peak Finding and Spatial Network approaches (Figure 6). However, examining the time series in Figure 8 reveals that these similar aggregate contributions arise from very different definitions of the local component. In particular, Peak Finding again interpo-
 290 lates between successive minima that span the broader diurnal cycle, rather than isolating the finer-scale, localized variability captured by the other techniques. This highlights the importance of evaluating multiple metrics and visualizations when com-
 295 paring techniques to isolate local and background components, as similar summary statistics can mask substantial differences in how these components are isolated. Fourier Decomposition estimates greater intra-network differences in the local compo-
 300 nents' variance. This may indicate that extreme pollution spikes, which variance is sensitive to, vary more between Pods than can be estimated in their contribution to concentration.

Across all techniques, coarse PM exhibits a larger local contribution than NO_2 and $\text{PM}_{2.5}$, consistent with the highly lo-
 295 calized nature and short lifetime of emissions. Compared with the other techniques, the Peak Finding approach estimates a relatively small local contribution because it is tuned to isolate only the most prominent concentration spikes. As noted in Figure 5, Wavelet and Fourier Decomposition both resolve a meaningful diurnal component despite the highly local nature of coarse PM. The diurnal component peaks during the day, which likely reflects recurrent daytime construction activity. This illustrates a limitation of temporal frequency-based methods: they assume that local impacts are confined to high-frequency
 300 variability, whereas local emissions can also produce regular diurnal cycles (e.g., workday industrial activity or rush-hour traffic) or sustained concentration enhancements. Consequently, these methods require context-informed interpretation to dis-
 305 tinguish between temporally recurring local emissions and broader background variability.

The Spatial Network and Peak Finding approaches appear better suited for coarse PM than for NO_2 or $\text{PM}_{2.5}$ because coarse particle plumes are more spatially isolated (Figure 9) and occur against a relatively low, stable background. Most methods
 305 identify site A3 as having the smallest local contribution, which is consistent with its location as a relative “background” site located away from construction activity (Figure 2). The Spatial Network approach is the notable exception, as it does not identify A3 as the least locally impacted site. The reason for this discrepancy is not immediately apparent and warrants further investigation.

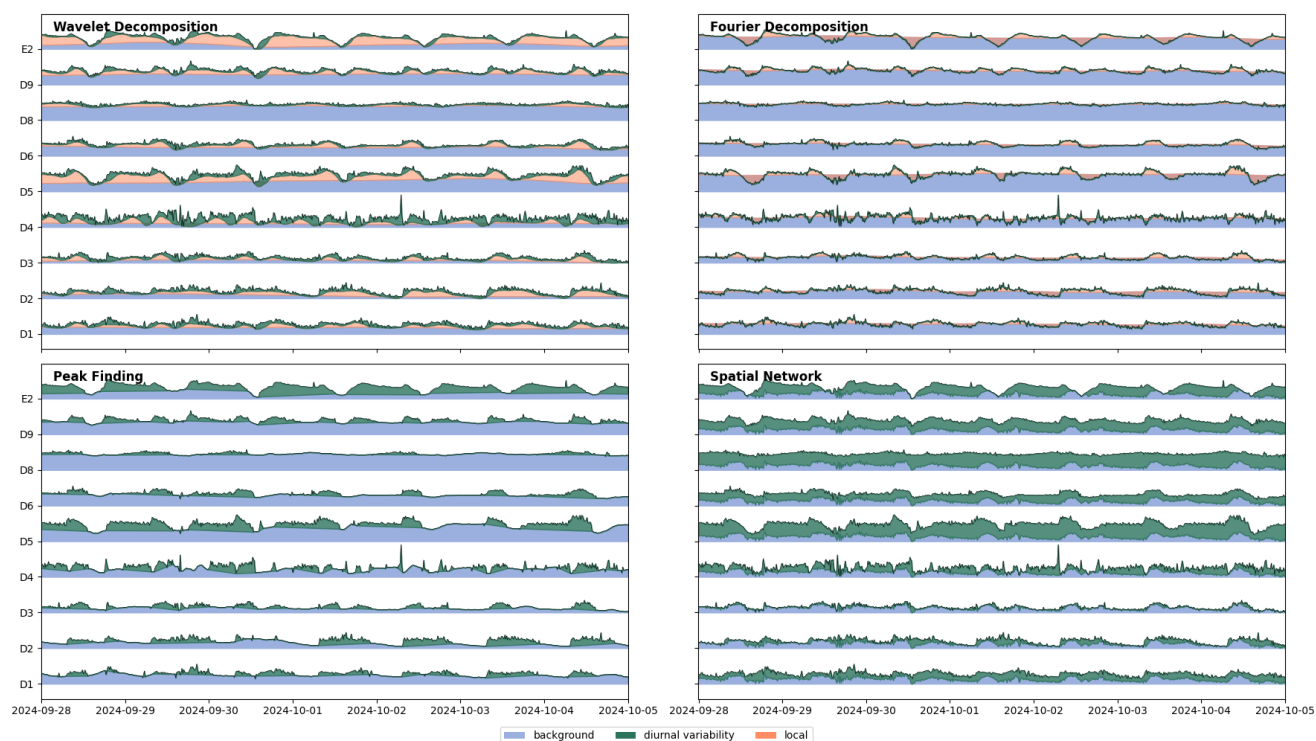


Figure 7. NO₂ stack plot time series showing the components differentiated by each technique separated by Pod. We selected a one week period representative of the whole time series.

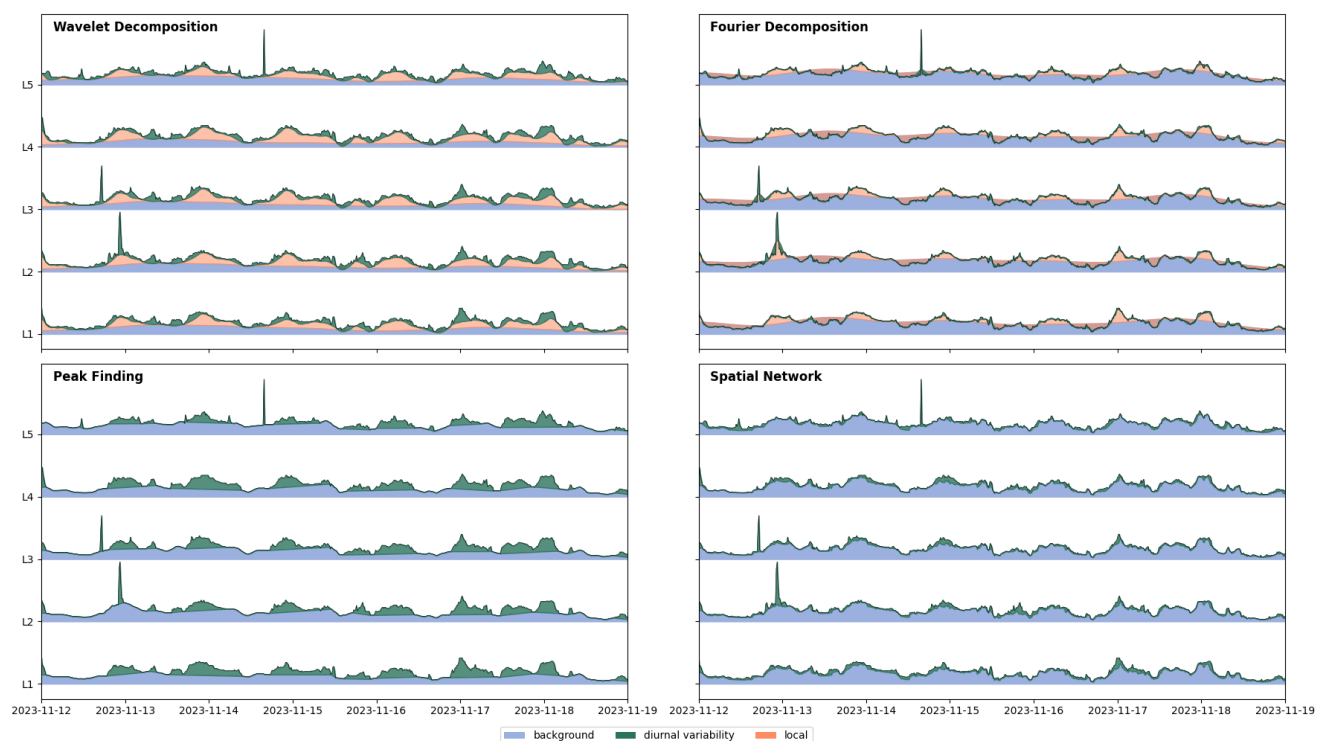


Figure 8. PM_{2.5} stack plot time series showing the components differentiated by each technique separated by Pod. We selected a one week period representative of the whole time series.

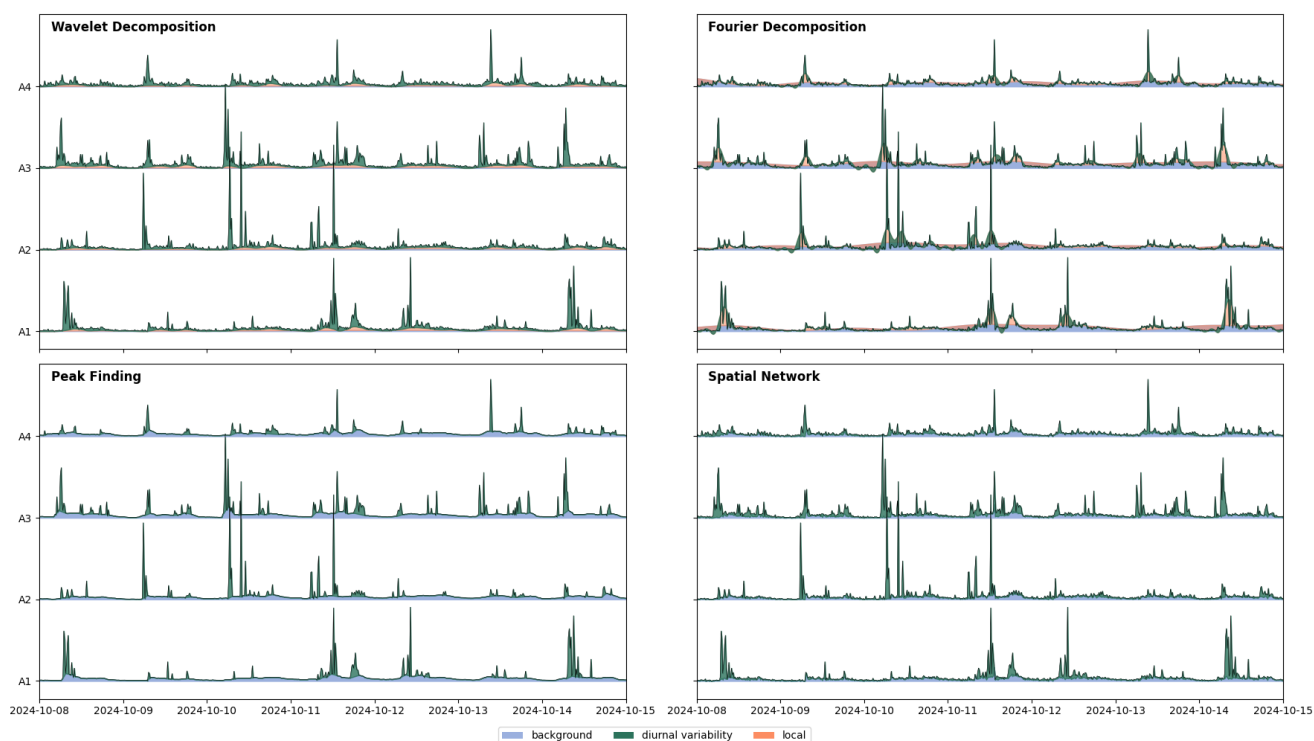


Figure 9. Coarse PM stack plot time series showing the components differentiated by each technique separated by Pod. We selected a one week period representative of the whole time series.

4 Discussion

310 A "true" local pollution impact is, by definition, localized in space. It is often also assumed to be localized in time, reflecting the close coupling between spatial and temporal scales in atmospheric processes. Most approaches for isolating local air quality impacts exploit one of these characteristics, choosing either a temporal or spatial basis to define the local component. Our comparison of both types of approach applied in multiple contexts revealed important considerations for each.

When using a spatial approach, it is difficult to identify a true background location that experiences the same chemical and meteorological processes as the study area but remains unaffected by local emission sources. To address this challenge, 315 the Spatial Network approach assumed that at least one sensor within the network would remain outside the influence of a local plume at any given time while still experiencing conditions representative of the study area. This approach was most successful for coarse PM, which has a low background and more spatially isolated plumes. It also produced reasonable results for $PM_{2.5}$, as the dynamic "background" site was subject to the same meteorological influences as the rest of the network 320 and thus most shared diurnal variability was assigned to the background component. However, the NO_2 results revealed an important limitation of the method. Because the background is defined as the minimum concentration across the network, this



approach is particularly sensitive to sensor bias; systematic differences between sensors can influence which site is selected as the background and consequently bias both the estimated background and local components. This also results in a more variable background than is physically realistic.

325 The temporal methods are less sensitive to sensor bias; instead, their limitations arise from their underlying assumption of the short-lived nature of local impacts. Inherently, temporal methods do not disentangle drivers of fluctuations, only their timescale. For example, the diurnal component captures variation due to regional movements of the boundary layer but also daily commuter traffic and workday construction emissions, which in some contexts may be more appropriate to resolve into a local component. Peak Finding, which only resolves two components, inconsistently assigns diurnal variability to either the background or local components for each Pod. This greatly changes the conclusions that would be drawn from the sensor network, such as which site experiences the greatest local impacts. Its use of interpolation to construct the background also results in physically unrealistic time series for pollutants with strong diurnal cycles. In contrast, Wavelet and Fourier Decomposition can partition the signal into multiple temporal components, allowing recurring oscillations such as the diurnal cycle to be isolated separately from both short-lived variability and longer-term background trends. This flexibility is not limited to diurnal cycles; depending on the length of the time series, it is also possible to isolate weekly, seasonal, or any other oscillatory period of interest. However, the decomposition methods still only define phenomena temporally.

Ultimately, the most suitable technique—and the interpretation of its results—depends on the contextual definition of “local” and “background.” Is your expected local impact plume-sized, affecting only a subset of the sensor network, or is it network- or community-sized, affecting most or all sensors? Are you interested in traffic-driven NO₂ emissions as a local or regional impact? Do you have a constant local source (i.e. a 24/7 facility) or a sporadic source (i.e. a port)? Is it reasonable to define your local impact by its spatial or temporal characteristics alone? The answers to these questions are highly specific to the goals and structure of the sensor network.

Beyond their outputs, there are also tradeoffs in the ease-of-implementation and suitability of each method depending on the dataset’s constraints and desired use case (2). For example, Wavelet and Fourier Decomposition are more conceptually complex to implement and interpret, but have fewer parameters to tune (only which frequency bins to isolate). The Spatial Network and Peak Finding approaches are the inverse, requiring several user-defined parameters, such as the network background statistic or peak detection thresholds. These parameter choices can substantially influence the resulting background and local estimates.



Table 2. Comparison of implementation considerations for each approach

	Spatial Network (Spatial)	Peak Finding (Temporal)	Fourier Decomposition (Temporal)	Wavelet Decomposition (Temporal)
Complexity to implement	Low	Medium	High	High
Complexity to tune/optimize	Medium	Medium	Low	Low
Sensitivity to temporal incompleteness	Low	Low	High	Medium
Sensitivity to spatial incompleteness	High	Low	Low	Low
Isolates more than two components	No	No	Yes	Yes

Each method also varies in its sensitivity to data incompleteness depending on its underlying approach. For the sake of comparing method outputs, we selected data subsets with high spatiotemporal completeness (>95%) to minimize imputation. However, for many sensor networks this threshold is not realistic, and analysts must take into account their dataset completeness when determining which method is most suitable or feasible. For example, the Spatial Network approach requires a minimum number of functioning sensors—spatial completeness—at any given timestep in order to calculate a dynamic background. Missing data does not necessarily need to be imputed; instead, the resulting background-subtracted series will have temporal gaps. In contrast, Wavelet and Fourier Decomposition can be implemented on a single time series, but require higher temporal completeness for the decomposition to be solved. For Fourier Decomposition, all missing data in the time series must be imputed, making it highly sensitive to temporal gaps. Wavelet Decomposition also requires more complete data chunks, but only up to the oscillatory period of interest, making this method slightly less sensitive. The Peak Finding approach is unique in that it can be implemented on a single incomplete series without imputing missing data.

Lastly, the approaches vary in how the relative contribution of each component can be quantified. As noted previously, Fourier Decomposition results cannot be expressed as contribution to concentration and the Spatial Network, Peak Finding, and Wavelet Decomposition results cannot be expressed as contribution to variance. These metrics both provide valuable but distinct insights. Concentration is useful for understanding which component drives overall exposure, while variance is useful for understanding which component drives overall fluctuations in pollution levels.

Future work could explore hybrid approaches that combine spatial and temporal definitions of local and background impacts, which may help minimize the limitations of their respective assumptions. For example, Zimmerman et al. (2020) used wavelet decomposition to isolate low-frequency background components across a sensor network, then introduced a spatial aspect by selecting the lowest value for each time interval as the overall network background. The Spatial Network approach presented here could be augmented by temporally smoothing the spatially-defined background to reduce the influence of short-term fluctuations and measurement noise. Due to their potential for high spatiotemporal resolution data collection, low-cost sensor networks are uniquely able to leverage both definitions of local impacts, opening the door to other potential hybrid approaches worth developing and exploring.



5 Conclusions

Low-cost sensor networks' ability to identify pollution drivers and inform targeted mitigation interventions depends on being able to isolate local source impacts from background influence. In this study, we compared four techniques of separating these components, spanning both time-series- and space-based options, to understand how the technique choice affects estimates of local and background contributions.

Our analysis did not aim to reveal a universally optimal technique across the four we tested, which included Fourier Decomposition, Wavelet Decomposition, Peak Finding, and a Spatial Network approach. Instead, we argue that the appropriate choice depends on multiple application-specific factors. Important considerations include whether the monitoring network is susceptible to sensor bias (a key limitation of the Spatial Network approach), whether local impacts are expected to occur as distinct plume events (suitable for Peak Finding) or as more gradual changes, and whether separating the signal into more than two components would provide additional insight (favoring Wavelet or Fourier Decomposition). Most importantly, the choice of technique depends on how "local" is defined. Local impacts may be conceptualized as spatially isolated concentration enhancements, short-lived temporal fluctuations, or recurring oscillatory patterns associated with nearby emission sources. Each method implicitly adopts one of these definitions, leading to different estimates of local and background contributions.

None of these definitions is inherently more correct than the others; rather, each is appropriate for different analytical contexts. Consequently, studies should clearly define what is meant by "local" and "background" influence and select a technique that is consistent with that definition and the scientific question being addressed.

Data availability. The sensor data are available at <https://doi.org/10.17632/5f2gzyzdjy.1>

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