ENVIRONMENTAL RESEARCH COMMUNICATIONS

INCLUSIVE PUBLISHING TRUSTED SCIENCE

Part of the ENVIRONMENTAL RESEARCH SERIES

PURPOSE-LED PUBLISHING™

ACCEPTED MANUSCRIPT • OPEN ACCESS

Exploring the Effects of Sheffield's Clean Air Zone on Air Quality and Traffic Volume

To cite this article before publication: Guto Williams *et al* 2025 *Environ. Res. Commun.* in press https://doi.org/10.1088/2515-7620/adf52f

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is **© 2025 The Author(s). Published by IOP Publishing Ltd**.

As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 4.0 licence, this Accepted Manuscript is available for reuse under a CC BY 4.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence https://creativecommons.org/licences/by/4.0

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the article online for updates and enhancements.

This content was downloaded from IP address 185.69.144.154 on 29/07/2025 at 08:14

Exploring the Effects of Sheffield's Clean Air Zone on Air Quality and Traffic Volume

Guto Williams[1], Harry Kai-Ho Chan[2*], Patricio Ortiz[3]

University of Sheffield, United Kingdom
[1]gbwilliams3@sheffield.ac.uk
[2]h.k.chan@sheffield.ac.uk
[3]p.ortiz@sheffield.ac.uk

[*]Author to whom any correspondence should be addressed

Abstract

In the UK, poor air quality is estimated to contribute to 36,000 deaths annually. Since 2021 local authorities have introduced Clean Air Zones (CAZs) to tackle the pollution caused by road traffic. These aim to improve air quality within the CAZ by deterring high polluting vehicles from entering. As of August 2024, there were seven CAZs active in England. This work focuses on Sheffield, UK and explore how the implementation of the CAZ has affected air quality in the city. The impact of Sheffield's CAZ on NO_2 and $PM_{2.5}$ was assessed with data sourced from three DEFRA sites within Sheffield. Weather normalisation was conducted to isolate the impacts of weather. Then the impact of Sheffield's CAZ was evaluated using a Difference-in-Difference (DiD) method. The changes in traffic following the CAZ were also evaluated to assess the potential for spillover. Our results showed that reductions in air pollutions happen both inside and outside the CAZ, but neither $PM_{2.5}$ or NO_2 were significantly reduced within the CAZ. There were no signs of negative spillover with only 5 out of the 33 traffic sensors (16%) showing an increase in traffic post-CAZ. The results were generally in line with the studies on London's ULEZ and Birmingham's CAZ that showed no significant changes in $PM_{2.5}$ and small changes in NO_2. This work differs from literature by suggesting that the CAZ did not drive this NO_2 reduction, with NO_2 concentrations reducing both inside and outside the CAZ. This was likely down to fleet modernisation, with the proportion of non-compliant vehicles across Sheffield reducing by 18% post-CAZ. This highlights how CAZ may be one policy implemented to improve air quality with multiple policies working in conjunction to reduce air pollution.

Accepted Manuscript

1 Introduction

Air pollution is estimated to contribute to 1 out of every 9 deaths globally (4) and poor air quality (AQ) is estimated to contribute to nearly 36,000 deaths per year in the United Kingdom (UK) (1). A significant contributor to air pollution in urban areas is traffic, with vehicles contributing to a range of pollutants such as Nitrogen oxides (NO_x), nitric oxide (NO) nitrogen dioxide (NO_2), Carbon Monoxide (CO) and Sulphur Dioxide (SO_2), and Particulate Matter ($PM_{2.5}$, PM_{10}). The impact of exposure to pollutants has been widely studied and shown to be detrimental to human health. Exposure to air pollution significantly increases the rates of respiratory disease, lung cancer, cardiovascular disease and non-accidental mortality (5–7). Reducing air pollution to meet World Health Organization (WHO) guidelines could prevent up to 327,000 avoidable deaths across the EU (6), highlighting the need to manage and reduce air pollution. The UK government has previously described air pollution as the "*largest environmental risk to public health in the UK*" (8), highlighting the need to manage air pollution.

Local authorities have recently implemented Clean Air Zones (CAZs) which function by charging high-polluting vehicles to enter a designated zone, with the aim being to discourage those with older or higher polluting vehicles from entering certain areas. The first such zone in the UK was London's Low-Emission Zone (LEZ), leading to 13% reductions in PM_{10} (9), and the expanded ULEZ leading to 36% reduction in NO_x (10). There are now seven active CAZs in England as of August 2024 (2), however, there is limited research on the efficacy of these new policies, with studies found for Birmingham's CAZ and London's ULEZ, but none for other CAZs such as Newcastle, Bristol, Bath or Sheffield.

This paper focuses on Sheffield and analyses how the implementation of the CAZ in Sheffield City Centre has impacted air quality and traffic in the city. Sheffield, a city located in South Yorkshire, England, introduced a Class C CAZ in February 2023. This Class C CAZ charges non-compliant buses, taxis, HGVs and vans, but not personal cars or motorcycles. The CAZ was introduced as part of Sheffield City Council's (SCC) 2015 Action Plan (11) which showed that 50% of NO_x pollution and 40% of PM_{10} in the city centre was caused by road traffic. The Sheffield CAZ covers the entire area encircled by the A61 as shown in Figure 1 (12). The A61 ring road is included within the CAZ boundary.

Accepted Manuscript

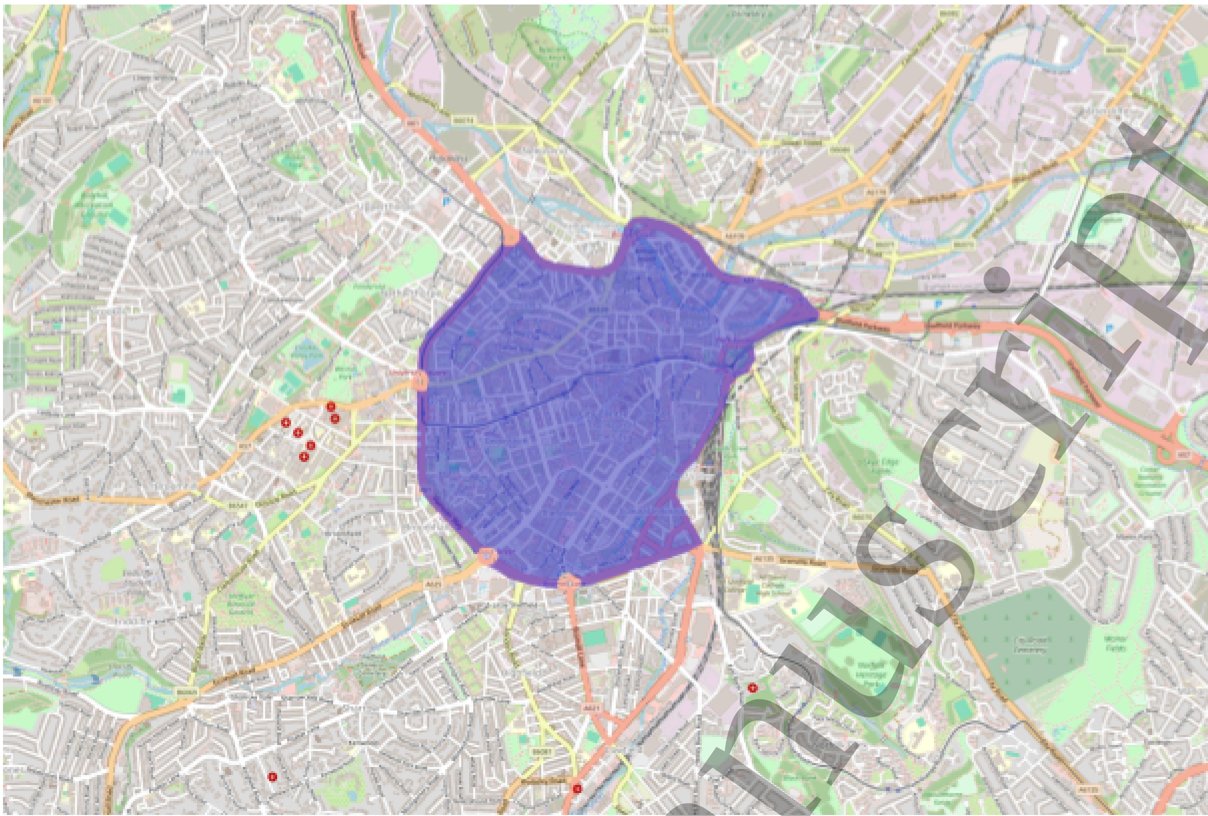


Figure 1. Map showing the area covered by Sheffield's CAZ. Map data from OpenStreetMap, CAZ area boundaries provided by Sheffield City Council[1].

This work presents an exploratory analysis of Sheffield's CAZ using an evidence-based approach. **1.** Air quality data one year before and after the implementation on CAZ was sourced from sensors inside and outside the CAZ. Weather normalisation was then applied to remove the impact of weather on air pollution. Then, the changes in air quality was analysed by employing a difference-in-differences (DiD) based approach, using data from a control group (outside CAZ) and treatment group (inside CAZ) to assess the impact of the intervention. This method has previously been used to analyse air quality policy (13–16). **2.** Traffic volumes were also collected and analysed using a Wilcoxon signed-rank test to provide new insight into the changes in traffic volume pre/post CAZ. We also assess the potential spatial spillover effect, which is a phenomenon that traffic does not reduce, but is instead diverted into other roads surrounding the CAZ.

In short, our results show limited evidence of CAZ-specific effects on air quality within CAZ. This was likely due to pollution generally falling across all sites, regardless of location. However, there is statistically significant reduction of traffic within the CAZ. Our results also suggest that there was no evidence for spatial spillover.

CAZs have been employed across the country to attempt to reduce air pollution, but their efficacy is not yet fully known. With only limited existing studies on evaluating CAZs and LEZs in the UK (17,18), this work aims to build upon these previous studies, adopting an evidence-based approach in exploring the efficacy of policy interventions such as CAZs and LEZs. This study provides initial evidence for the efficacy of Sheffield's CAZ in reducing air pollution and traffic volumes, serving as a foundation for future, more comprehensive evaluations. Better understanding the efficacy of such policy interventions can also better inform future policy

[1] https://www.sheffield.gov.uk/clean-air-zone-sheffield

Accepted Manuscript

decisions, allowing for better informed decisions to be made surrounding public health, sustainability and urban planning.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 details the data sources and methodology. Section 4 reports the analysis results and Section 5 presents the discussion. Section 6 concludes the paper and suggests possible future directions.

2. Related work

2.1 Evaluating impacts of Interventions on Air Quality

Bigazzi & Rouleau (35) conducted a bibliographical review to assess the impact of different policies on air pollution. They found there was a limited evidence base for pre-post evaluations of policies and called for an evidence-based approach to transport systems planning. Multiple studies were found using real-world data (as opposed to simulated data) to evaluate the efficacy of various traffic management policies, with many of the studies occurring after 2017.

In the literature, Regression-discontinuity design (RDD) (28–31) and difference-in-differences (DiD) (13–16,32,33,36,37) are two commonly used methods to evaluate the impacts of intervention, such as the CAZ implementation, and the COVID-19 lockdown restrictions.

In fact, only a few articles and studies were found assessing any of the CAZs active in the UK. Ma et al. (18) analysed the impact of the introduction of the ULEZ in central London. Similar to their previous work analysing the impact of COVID-19 on air quality (34), they conducted weather normalisation and used a sharp RDD model. RDD compares air quality before and after an intervention to estimate the policy's impact, assuming any changes can be attributed to the intervention. They found that the ULEZ had not caused significant reductions in pollution, when considering the context of long-term trends. Reductions in NO_2, O_3 and $PM_{2.5}$ were observed, but their analysis showed that the concentrations did not vary significantly following the ULEZ. However, this analysis was only conducted for a period of three months post-ULEZ. Potentially too short a period for the impacts of behavioural and vehicle fleet changes to be observed.

Conversely, Liu et al. (17) conducted an analysis of the air quality changes for a period of one year after the implementation of Birmingham's CAZ, using a synthetic control method to analyse the impact of the CAZ. This method aims to construct an artificial control group to model the value as if there had been no intervention (Business-as-usual or BAU) (38). The counterfactual BAU case was then compared to the weather-normalised data to assess the impact of the CAZ. Their results indicated significant reductions in pollution both inside and outside the CAZ following its implementation. Liu et al. (17) also analysed the potential for spillover caused by the CAZ. This effect is when air pollution is displaced to other areas by restrictions, rather than an overall reduction in traffic emissions (39). Liu et al. (17) quantified spillover by assessing the changes in pollution, citing that there were no signs of spillover as indicated by the reduction in pollution surrounding the CAZ, however they suggest the potential for future work to include the assessment of traffic volumes when conducting analysis on AQ policy.

No studies were found analysing the impact of Sheffield's CAZ, which is the focus of this work.

Accepted Manuscript

2.2 Traffic and Air Quality

Previous work on source apportionment has shown that traffic contributes to numerous pollutants such as $PM_{2.5}$, NO_x, NO_2 and dust (19–23).

The topic of the relationship between traffic and air policy has been well studied. Siciliano et al. (40) found the decrease of air pollutants was not directly proportional to the vehicular flux reduction, when analysing the impact of lockdowns in Brazil, but other studies seem to suggest a link between traffic and air pollution. Blagoiev et al. (41) analysed the association between traffic and air pollution in Timisoara, Romania. The correlation coefficient was calculated for CO, SO_2, NO_2, and PM. NO_2 was the least correlated, with correlations of -1.2% to -0.58% to, however CO and SO_2 were more strongly correlated. Salama & Zafar (42) investigated the association between traffic and air pollution at a causeway in Saudi Arabia. The correlation coefficient between the mean pollutant concentration and the traffic flow was calculated. The correlations ranged from 0.46 for O_3 to 0.78 for PM, showing that traffic was related to pollutant concentrations.

Several studies were found analysing the impact of interventions similar to CAZ policy on traffic. Boogard et al. (43) found on average, traffic was reduced by 5.1% following interventions. Similarly, Tassinari (44) conducted a pre-post analysis following the introduction of Madrid's LEZ, finding that traffic flow reduced an average of 8.1% within Madrid's LEZ, but saw a small average increase of 3.3% in sites surrounding the LEZ, which is evidence of the spillover effect.

3. Data and Methodology

In this section we detail the data sources and analysis methodology. Section 3.1 gives the data source of air quality data and traffic data. Section 3.2 and 3.3 presents Difference-in-Differences model on air quality data and Wilcoxon Signed-rank Test on traffic volume data, respectively. The data and code used in this paper can be found in our repository[2].

3.1 Data Source

Data was sourced from the Sheffield Urban Flows Observatory (SUFO)[3], a project which collects multiple data streams such as air pollution, traffic flow and meteorological conditions from various sources, including data from Sheffield City Council (SCC), The Department for Energy, Farming and Rural Affairs (DEFRA) and SUFO's own air quality network.

The analysis period was initially defined as February 2022 to February 2024 (one year either side of CAZ implementation in February 2023), with this period later extended to June 2024 to increase the number of samples.

3.1.1 Air Quality (AQ) Data

Hourly air pollution data was collected for NO_2 and $PM_{2.5}$ at 7 sites across Sheffield, including both inside and outside the CAZ. We designate a site to be primary AQ site if it provides

[2] https://anonymous.4open.science/r/Sheffield-CAZ-Analysis

[3] https://urbanflows.ac.uk/

Accepted Manuscript

sufficient data across the period to develop the difference-in-differences model, and to be secondary AQ site otherwise for the additional insights. All sites designated as primary AQ sites were policy-grade sensors, belonging to the Automatic Urban and Rural Monitoring Network (AURN), the UK's main network for compliance reporting. More details of the air quality sites can be found in Appendix A. Missing and inconsistent values were handled through median imputation, given the skewed nature of the data.

Table 1. Descriptions of the Identified AQ Sites.

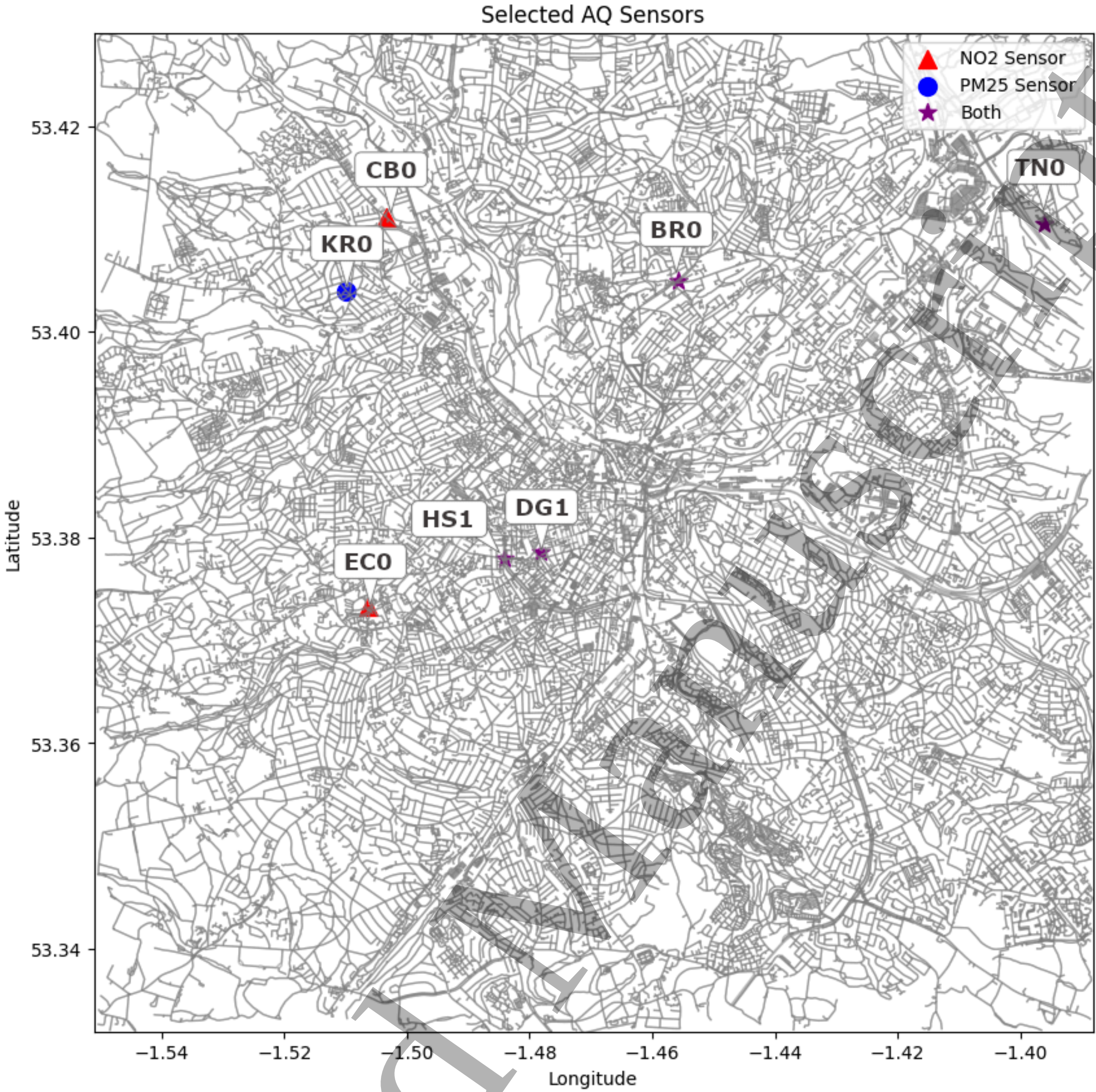
Designation	CAZ Location	Site ID	Site Name	Site Type	Source	Sensor Type	Pollutants
Primary (For DiD Model)	Inside	DG1	Devonshire Green	Background	DEFRA	Policy Grade	NO_2, $PM_{2.5}$
	Outside	BR0	Barnsley Road	Roadside	DEFRA	Policy Grade	NO_2, $PM_{2.5}$
		TN0	Sheffield Tinsley	Background	DEFRA	Policy Grade	NO_2, $PM_{2.5}$
Secondary	Inside	HS1	Hannover Street	Roadside	SUFO	Low-Cost	NO_2, $PM_{2.5}$
	Outside	CB0	Catch Bar Lane	Background	SUFO	Low-Cost	NO_2
		EC0	Endcliffe Crescent	Background	SUFO	Low-Cost	NO_2
		KR0	Kendal Road	Background	Luftdaten	Low-Cost	$PM_{2.5}$

Only one AQ site with suitable data quality for a DiD model was identified. To ensure this site was representative of AQ trends within the CAZ, we compared the readings of DG1 with other sensors in CAZ, the readings are deemed to be following the trends of the whole zone, with further detail on the comparison in the Appendix A.

Figure 2 shows the location of the seven sites, with two sites within the city centre,one to the West, two to the North and two towards the East. Sheffield's topography presents unique challenges to air pollution, with the city characterised by hills rising up from the valleys caused by the rivers Don and Sheaf. These valleys can cause temperature inversions which prevent the dispersal of pollutants and potentially exacerbate air pollution (45). The three primary sites are located out of these valleys, with elevations of 89m for DG1, 82m for BR0 and 90m for TN0.

Accepted Manuscript

Figure 2. Map of the seven identified AQ sensors. Map data from OpenStreetMap.



Weather Normalisation. Weather plays a crucial role in the formation, transport and deposition of air pollution (46), potentially masking fluctuations in pollutant concentration, and thus masking the potential impact of policy interventions. It is therefore important to perform *weather normalisation* to remove the effects of weather conditions on air pollution concentrations. Various ML methods were proposed for weather normalisation, which utilise observed pollution and various weather variables to build models that predict the pollutant concentration without the impact of weather. Ma et al. (18) developed gradient-boosted decision trees, while Grange et al. (47) developed a package *rmweather*[4], a Random Forest model, to conduct weather normalisation to allow for the robust analysis of AQ trends.

Following Liu et al. (17), we use the *rmweather* package to conduct weather normalisation, applying it to the primary AQ sites. The weather variables available were the wind direction, wind speed and air temperature. Details on how this package was applied may be found in Appendix B.

[4] https://github.com/skgrange/rmweather

Accepted Manuscript

3.1.2 Traffic Volume Data

We also explore the changes in traffic volumes and potential spatial spillover post-CAZ. SCC traffic sensors were used to characterise traffic volumes surrounding primary AQ sites, allowing for traffic changes in these areas to be assessed, and for the correlations between traffic volume and AQ made. As seen in previous literature (43), the number of cars per day was used to represent the traffic volume. Thus, the mean of the total number of per day surrounding each AQ site was taken to provide a single value expressing the traffic volume in the area.

Traffic sites within a 0.5km radius of Primary AQ sites were used to characterise the traffic volumes, aside from one site (TN0) which had no sensors within 0.5km, instead a radius of 1km was used. In total, traffic volume data from 25 traffic sites around the AQ sites are aggregated to their corresponding AQ site to compare the traffic volume changes. 33 traffic sites within proximity to but outside the CAZ were used to assess spillover. These sites were located outside of the CAZ, but within 2km of the city centre. The list of traffic sites can be found in Appendix C.

3.2 Difference-in-Differences Model on Air Quality Data

In a similar manner to AQ data reported by DEFRA, changes in AQ were first evaluated by considering the mean annual daily concentration pre and post CAZ, with pre-CAZ defined as 27-Feb-2022 to 26-Feb-2023 and post-CAZ as 27-Feb-2023 to 26-Feb-2024.

The impact of the CAZ was assessed using a Difference-in-Differences (DiD) approach. DiD was chosen over other methods such as RDD for its simplicity to implement, only requiring dummy variables to represent the control variables. Additionally, DiD provides interpretable coefficients that represent the difference between the two groups.

DiD is a statistical method that uses a regression-based analysis, comparing the trends of two groups before and after an intervention, and assessing if they significantly vary, as shown in Figure 3. In the context of analysing the impact of a CAZ, the pollutant concentration Y at time t and location i can be described as:

$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 P_t + \beta_3 (T_i * P_i)$$

where:

- Y_{it} is the concentration for a particular pollutant (e.g. NO_2)
- T_i a binary variable indicating if an observation belongs to the treatment group, inside the CAZ (T_i =1), or the control group, outside the CAZ (T_i =0).
- P_t a binary variable indicating if an observation is pre-CAZ (P_t=0) or post-CAZ (P_t=1).
- $(T_i * P_i)$ an interaction term between treatment and post-CAZ periods. This term only equates to 1 when the observation is inside the CAZ and is post-CAZ, allowing for its impact pollution Y_{it} to be assessed.

The impact of an intervention is assessed by evaluating the magnitude and statistical significance of the coefficient β_3, also called the coefficient of the interaction.

Accepted Manuscript

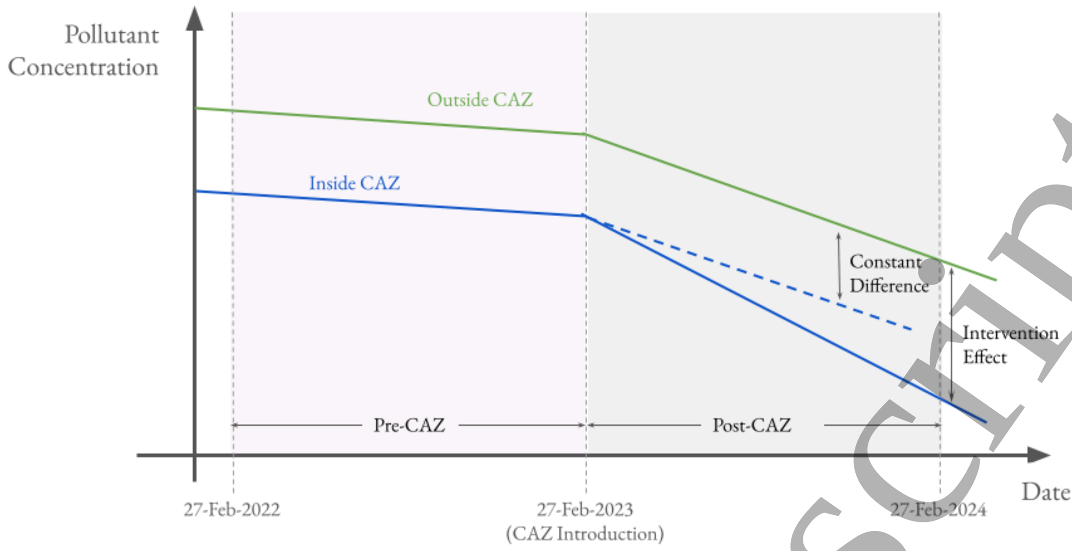


Figure 3. Representation of the Difference-in-Differences model, showing how the model may be used to assess the difference between control and treatment groups Post-CAZ.

While AQ changes could be calculated for both primary and secondary sites, DiD was only conducted on the primary sites, due to DiD requiring sufficient data points one year either side of the CAZ. Three sites were used, two were outside the CAZ and one was inside. Table 2 provides a summary of the DiD models developed. DiD returns the value and statistical significance of each coefficient. A threshold of $\alpha = 0.05$ was used. A negative interaction coefficient would indicate the CAZ led to a greater reduction in pollution.

Table 2. Parameters for each of the 6 DiD Scenarios Evaluated

Scenario	Treatment	Control	Pollutant
1a	DG1	BR0	NO_2
1b	DG1	BR0	$PM_{2.5}$
2a	DG1	TN0	NO_2
2b	DG1	TN0	$PM_{2.5}$
3a	DG1	Mean of BR0 and TN0	NO_2
3b	DG1	Mean of BR0 and TN0	$PM_{2.5}$

3.3 Wilcoxon Signed-rank Test on Traffic Volume Data

Traffic changes pre and post-CAZ were evaluated by considering the total number of vehicles in each period. Additionally, a Wilcoxon signed-rank test was used to evaluate statistically significant differences in traffic pre/post CAZ.

A potential phenomenon of traffic restrictions was *spatial spillover*, where traffic does not reduce, but is instead diverted into other roads surrounding the CAZ. This phenomenon was investigated by acquiring data for sites surrounding the CAZ. The spatial spillover was also assessed using a Wilcoxon signed-rank test. The proportion of traffic sensors that indicated a

Accepted Manuscript

significant increase was considered. If most sensors showed there was no significant increase in traffic volume, then it was concluded that no spillover occurred.

Finally, the correlation between traffic volume and air quality was assessed using methods similar to previous literature (41,42). In particular, the correlation coefficient between the total number of cars in a day and the mean daily pollutant concentration was calculated. Additionally, a linear regression model was developed to assess the relationship. The independent variable was the total number of cars per day and the dependent variable the mean daily pollutant concentration. The adjusted R^2 was used in conjunction with the correlation coefficient to assess the relationship between traffic and air pollution.

4 Results

We report the analysis results in this section. Section 4.1 presents the results of CAZ on air quality and the DiD analysis. Section 4.2 reports the results of CAZ on traffic volume, spatial spillover. Section 4.3 gives the correlation analysis between air quality and traffic volume.

4.1 Effect on Air Quality

4.1.1 Changes in Mean Daily Air Quality Concentration

Figure 4 shows the mean daily de-weathered (i.e., weather normalised) pollutant concentration of NO_2 and $PM_{2.5}$ for the three primary AQ sites throughout the analysis period, where the red dashed line indicates the date of CAZ implementation, and the shaded gray regions indicate the analysis period. We can observe that there is a decline in NO_2, particularly in TN0 and BR0, after the CAZ implementation, while $PM_{2.5}$ generally shows smaller fluctuations.

Based on Figure 4, we also looked at the pre-CAZ data to test the parallel trends assumption in the DiD model. In particular, the pre-CAZ trends for $PM_{2.5}$ appear reasonably parallel across the treatment and control groups, particularly between DG1 and BR0. For NO_2, while the trends are not perfectly parallel, there is no strong evidence of divergent behavior that would invalidate the DiD approach.

Accepted Manuscript

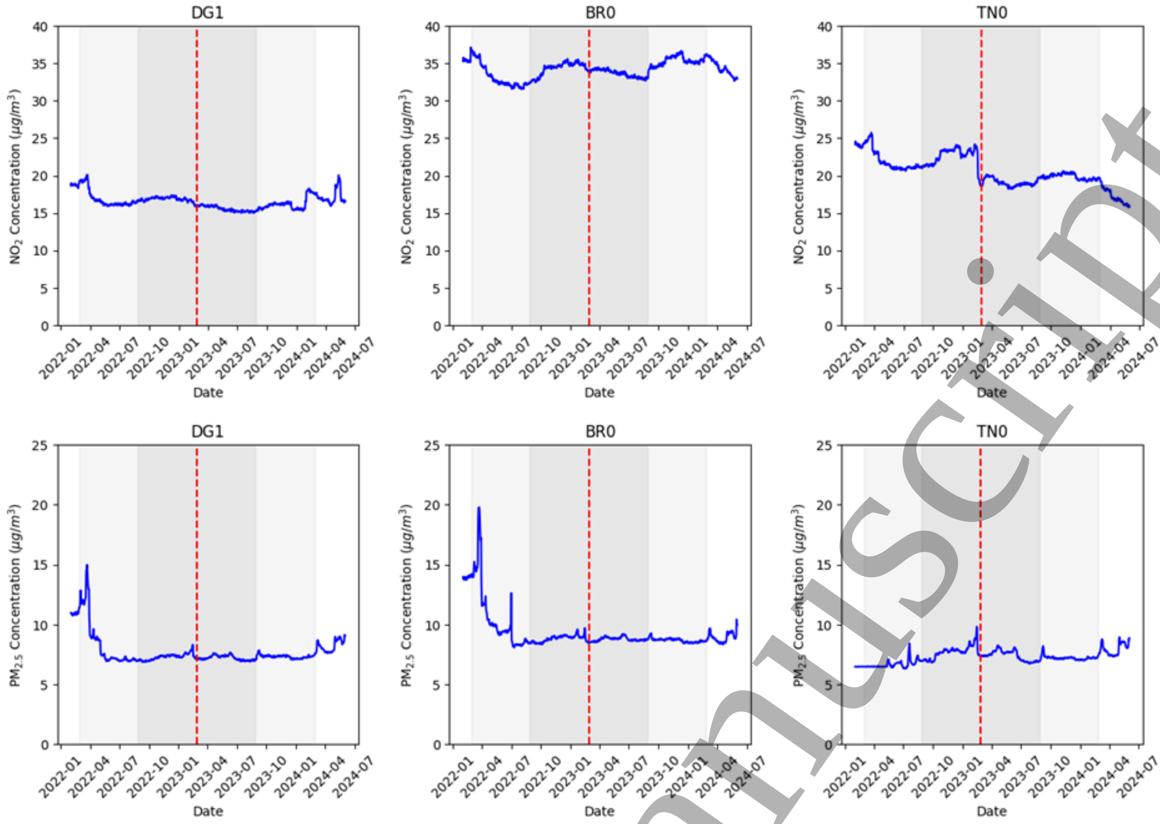


Figure 4. Mean Daily Concentrations of De-Weathered NO_2 and $PM_{2.5.}$ for Primary sites.

To better understand the distribution of the pollutant data, boxplots of the mean daily concentrations for the three primary sites are presented in Figure 5. It shows that for NO_2 there were few outliers, with the data generally grouped together. In contrast, there was a low IQR for $PM_{2.5}$, leading to a large number of outliers. These outliers are potentially genuine events, for example caused by high-traffic events or construction.

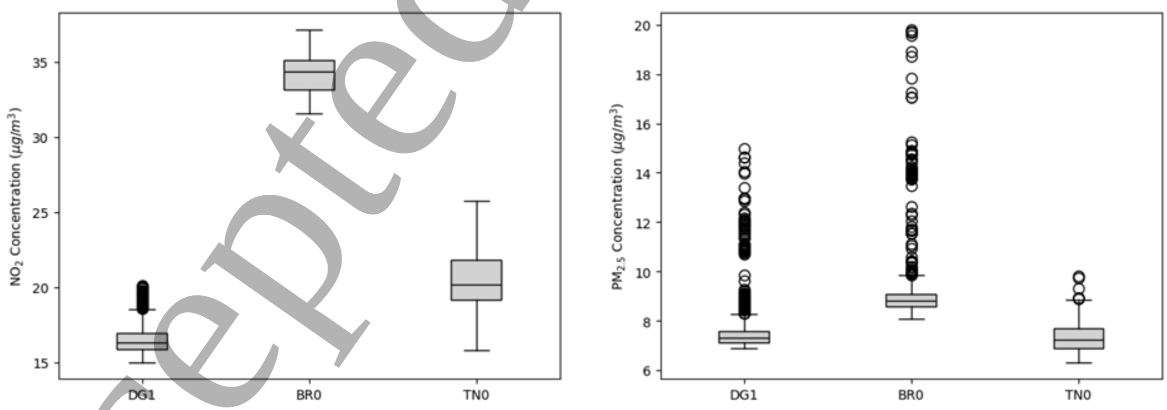


Figure 5. Distribution of De-Weathered NO_2 and $PM_{2.5}$ Concentrations for Primary Sites.

Additional plots and histograms for observed (i.e., non-normalised data) and for secondary sites can be found in the Appendix D. Comparing the distribution of observed and de-weathered data, we observed that performing weather normalisation closer grouped both NO_2 and $PM_{2.5}$, as expected due to the aggregating effect of random forest. For example, the standard deviation for NO_2 at DG1 pre-normalisation was 12.42 $\mu g/m^3$ compared to 1.03 $\mu g/m^3$ post normalisation.

Accepted Manuscript

The mean annual daily concentration of NO_2 and $PM_{2.5}$ were compared one-year pre- and post-CAZ for both sensor-read data and de-weathered data. Table 3 provides the changes in pollutant concentration for the three primary sites. Changes in observed pollution were generally higher than those post-normalisations, with average changes of -10.5% for NO_2 and -7.8% for $PM_{2.5}$. In contrast, de-weathered NO_2 reduced between -12.67% and 2.13%, with a mean change of -5.5%. $PM_{2.5}$ concentrations reduced between -9.86% and 1.65% with a mean change of -5.2%.

Table 3. One-year Pre-/Post-CAZ Changes in NO_2 and $PM_{2.5}$ Concentrations for Primary Sites

	Site	Site location (wrt CAZ)	Observed (μg/m³)			De-Weathered (μg/m³)		
			Pre-CAZ	*Post-CAZ*	*Changes*	*Pre-CAZ*	*Post-CAZ*	*Changes*
NO_2	DG1	Inside	17.256	14.812	**-13.82%**	16.873	15.853	**-6.04%**
	BR0	Outside	34.203	33.750	**-1.32%**	33.765	34.486	**+2.13%**
	TN0	Outside	22.604	18.882	**-16.47%**	22.277	19.455	**-12.67%**
$PM_{2.5}$	DG1	Inside	8.017	6.874	**-14.26%**	7.848	7.261	**-7.48%**
	BR0	Outside	9.329	8.520	**-8.67%**	9.685	8.730	**-9.86%**
	TN0	Outside	6.946	6.912	**-0.49%**	7.186	7.305	**+1.65%**

Secondary site data allowed for further insight into concentration changes. These sites however were not de-weathered due to the lack of localised meteorological data. Table 4 shows larger fluctuations in NO_2, with changes varying from -53.77% to 76.77%, while that of $PM_{2.5}$ are more stable. Large variability was seen for CB0 and EC0. We investigated the potential reasons. These sensors did not function from July 2022 to April 2024[5], with readings significantly different following their refurbishment. This was not seen with other sensors, for instance when data from pre-normalised BR0 was filtered for the same time periods used for EC0, the percentage changes were a more modest +6.3%. The large swings and difference in readings could be caused by sensor calibration or servicing that occurred during the downtime.

Table 4. One-year Pre-/Post-CAZ Changes in NO_2 and $PM_{2.5}$ Concentrations for Secondary Sites

	Site	Site location (wrt CAZ)	Observed (μg/m³)		
			Pre-CAZ	*Post-CAZ*	*Changes*
NO_2	CB0	Outside	16.563	7.657	**-53.77%**
	EC0	Outside	5.361	9.476	**+76.77%**
	HS1	Inside	5.265	4.185	**-20.52%**
$PM_{2.5}$	KR0	Outside	5.309	5.319	**+0.19%**
	HS1	Inside	215.955	207.181	**-4.06%**

4.1.2 Difference-in-Differences Results

Difference-in-Differences was conducted to determine if there was a significant difference in air quality post-CAZ. Six DiD models were developed (in Table 2) to compare the pollutant concentrations. Table 5 shows the results of the DiD analysis for the six de-weather ed scenarios.

[5] Because of this data availability issue, we use them as secondary sites to provide additional information.

Accepted Manuscript

Table 5. Results of the Six DiD Scenarios Showing the Magnitude and Significance of DiD Coefficients.

Scenario	Treatment	Control	Pollutant	Post	Treatment	Interaction
1a	DG1	BR0	NO_2	0.59 (<0.000)	-16.89 (<0.000)	-1.45 (<0.000)
1b	DG1	BR0	$PM_{2.5}$	-1.19 (<0.000)	-1.91 (<0.000)	0.59 (<0.000)
2a	DG1	TN0	NO_2	-3.39 (<0.000)	-5.40 (<0.000)	2.53 (<0.000)
2b	DG1	TN0	$PM_{2.5}$	0.30 (<0.000)	0.91 (<0.000)	-0.90 (<0.000)
3a	DG1	Outside Mean	NO_2	-1.40 (<0.000)	-11.15 (<0.000)	0.55 (<0.000)
3b	DG1	Outside Mean	$PM_{2.5}$	-0.45 (<0.000)	-0.50 (<0.000)	-0.15 0.120

There were significant changes in NO_2 caused by the CAZ in *every* scenario. However, the direction of change varied. Scenario 1a indicated a -1.45 $\mu g/m^3$ greater reduction in NO_2 due to the CAZ. Yet, comparing Scenario 2a that the CAZ led to a 2.53 $\mu g/m^3$ lesser reduction in NO_2. This was also observed with $PM_{2.5}$, with scenario 1b indicating a lesser reduction in $PM_{2.5}$, while 2b indicated a -0.9 $\mu g/m^3$ greater reduction. Overall, the analysis shows a lesser reduction of 0.55 $\mu g/m^3$ in NO_2 within the CAZ, and no significant change for $PM_{2.5}$.

4.2 Traffic Volumes

Building upon previous work, the changes in traffic pre-/post-CAZ were analysed to determine if traffic volumes varied significantly post-CAZ (Section 4.2.1), if there were any indications of negative spillover caused by the CAZ (Section 4.2.2), and the correlation between traffic volume and air quality (Section 4.2.3).

4.2.1 Changes in Traffic volumes

Figure 6 shows the histograms of the mean number of cars per day surrounding each site. All three sites show similar patterns, with most counts clustered around 7,500 cars per day.

Accepted Manuscript

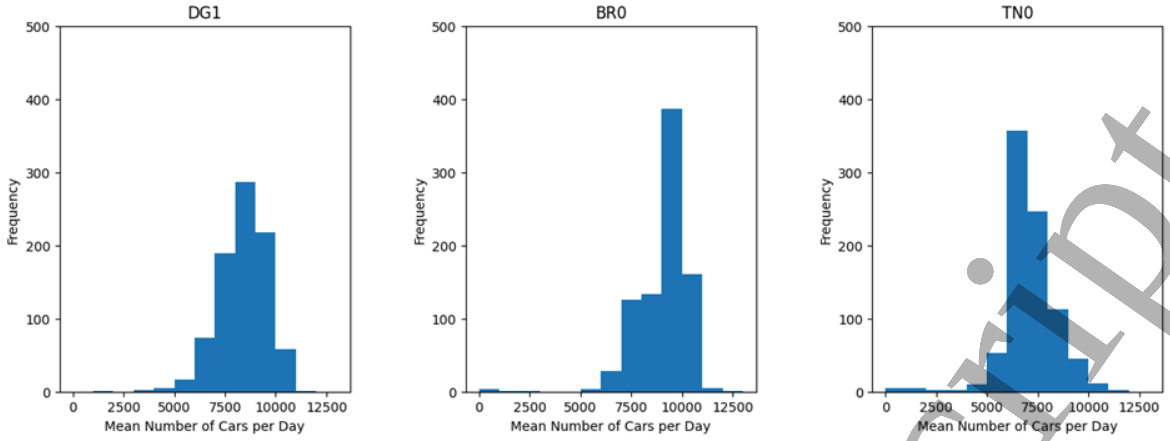


Figure 6. Distribution of the Mean Number of Cars per Day Surrounding Each Primary AQ Site.

Figure 7 shows a boxplot describing the distribution of the number of cars per day for the three sites. Traffic surrounding each site was broadly similar, with TN0 presenting the lowest median and IQR, potentially due to many sensors being located on access points to a shopping centre (Meadowhall), rather than commuter or other types of roads. However, this value was not significantly lower than DG1 and BR0. All distributions presented a significant number of outliers, however this was expected for numerous reasons, such as sensor calibration, road closures, and one-off traffic events (e.g. extreme weather) all affecting traffic volumes.

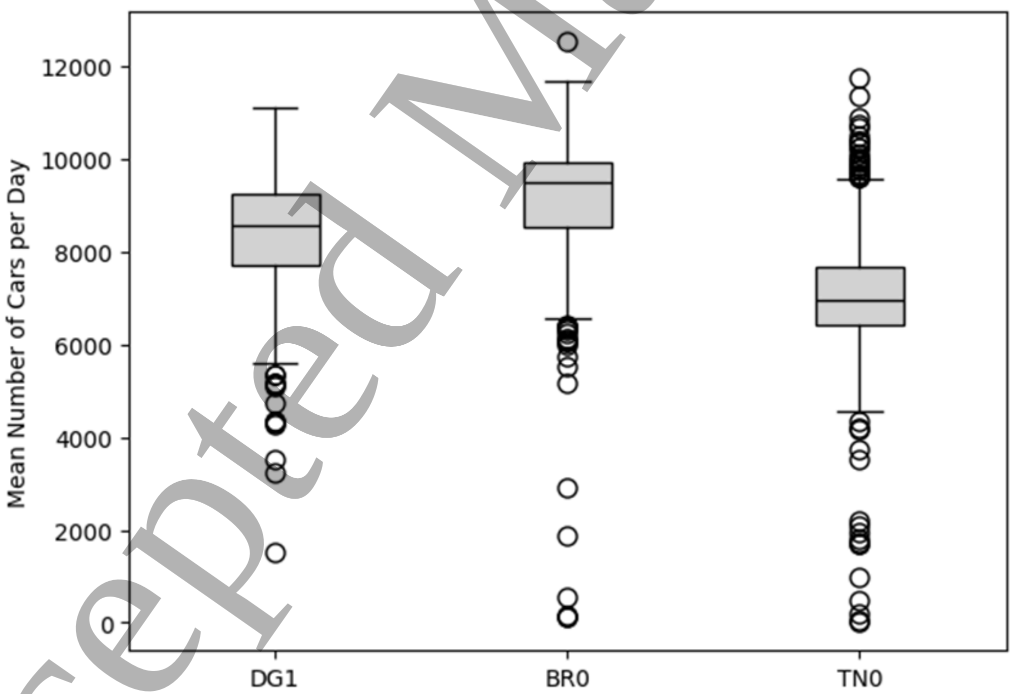


Figure 7. Boxplots Describing the Mean Number of Cars per Day Surrounding Each Primary AQ Site.

A Kolmogorov-Smirnoff test was conducted to determine if the data was normally distributed. The null hypothesis was that the data is normally distributed, and the alternative hypothesis that the data was not with a threshold of $\alpha = 0.05$. Before performing the KS test, the data was

Accepted Manuscript

normalised with Z-score normalisation. The results of the KS test are shown in Table 6. All KS tests returned a significance of less than 0.05 indicating that none of the distributions were normally distributed, therefore Wilcoxon signed-rank tests were used to assess the changes in traffic volume.

Table 6. Results of Kolmogorov-Smirnoff tests conducted to test normal distribution.

Site	Test Stat	*p-value*	Normally distributed?
DG1	0.048	0.036	No
BR0	0.138	<0.000	No
TN0	0.112	<0.000	No

The changes in traffic volumes pre/post CAZ were evaluated using a Wilcoxon signed-rank test with the null hypothesis that there was no difference in the median number of cars per day before and after the CAZ. The alternative hypothesis was that there was a difference in the median number of cars. The median of the difference was also calculated to provide an indication of the directions of any significant changes. The results are shown in Table 7. Traffic volumes outside the CAZ did *not* significantly vary, with traffic volumes surrounding BR0 and TN0 showing a significance of 0.580 and 0.193, respectively. Traffic surrounding DG1 however showed a significant change, with a median difference of -618.6 cars/day, suggesting that traffic volume reduced within the CAZ following its introduction.

Table 7. Results of the Wilcoxon Signed-Rank Test used to assess the significance of traffic changes pre/post CAZ for traffic surrounding primary AQ sites. ($\alpha = 0.05$)

Site	Wilcoxon Statistic	*p-value*	Statistical Significance	Median Difference
DG1	20210	<0.000	**Yes**	**-618.6**
BR0	32281	0.580	No	96.1
TN0	30769	0.193	No	93.1

This can also be seen when estimating the total number of cars pre-/post-CAZ. Table 8 shows the estimated total number of cars one year either side of the CAZ. YoY there was a 6% reduction in traffic inside the CAZ. On the other hand, while traffic slightly increased outside, this was shown to not be statistically significant.

Table 8. Changes in the total number of cars pre-/post- CAZ for traffic surrounding primary AQ sites.

Site	Total Cars Pre-CAZ	Total Cars Post-CAZ	Change
DG1	3,142,491	2,953,353	**-6.02%**
BR0	3,285,294	3,332,921	1.11%
TN0	2,581,818	2,595,856	0.54%

Accepted Manuscript

4.2.2 No evidence of spatial spillover

Spillover effect was further assessed by considering a further 33 traffic sensors within a 2km radius of Sheffield City Centre (Sheffield Peace Gardens), providing data in proximity to, but not within the CAZ. Again, a Wilcoxon signed-rank test was used to assess the significance of difference in means pre-/post-CAZ. The full test results may be found in Appendix E. Table 9 shows a summary of the number of sites which displayed significant or non-significant changes in traffic volume. In total, there were 19 sensors that indicated a significant change in traffic volume. Of those, 14 showed a significant decrease, and only 5 a significant increase, resulting in only 5 out of the 33 sensors (16%) showing a significant increase in traffic post-CAZ. This therefore suggests there was no evidence of negative spatial spillover caused by the CAZ.

Table 9. Assessing Spatial Spillover Effect

Wilcoxon signed-rank test outcome	**Number of traffic sites within 2km of City Centre but outside CAZ**
Significant Decrease Traffic	14 (42.4%)
Significant Increase Traffic	5 (15.2%)
Non-Significant Change	14 (42.4%)
Total	33

4.3 Correlation between Traffic Volume and Air Quality

The correlation between traffic and air quality was evaluated by considering the mean daily pollutant concentration and the total of cars per day. The results of this analysis are shown in Figure 8. For readability the Pearson Correlation Coefficient and Adjusted-R^2 values are shown in Table 10. The correlation analysis shows a weak correlation between $PM_{2.5}$ concentration and traffic surrounding DG1 and shows a weak association for NO_2. There were no associations between either NO_2 or $PM_{2.5}$ for BR0 and TN0.

Accepted Manuscript

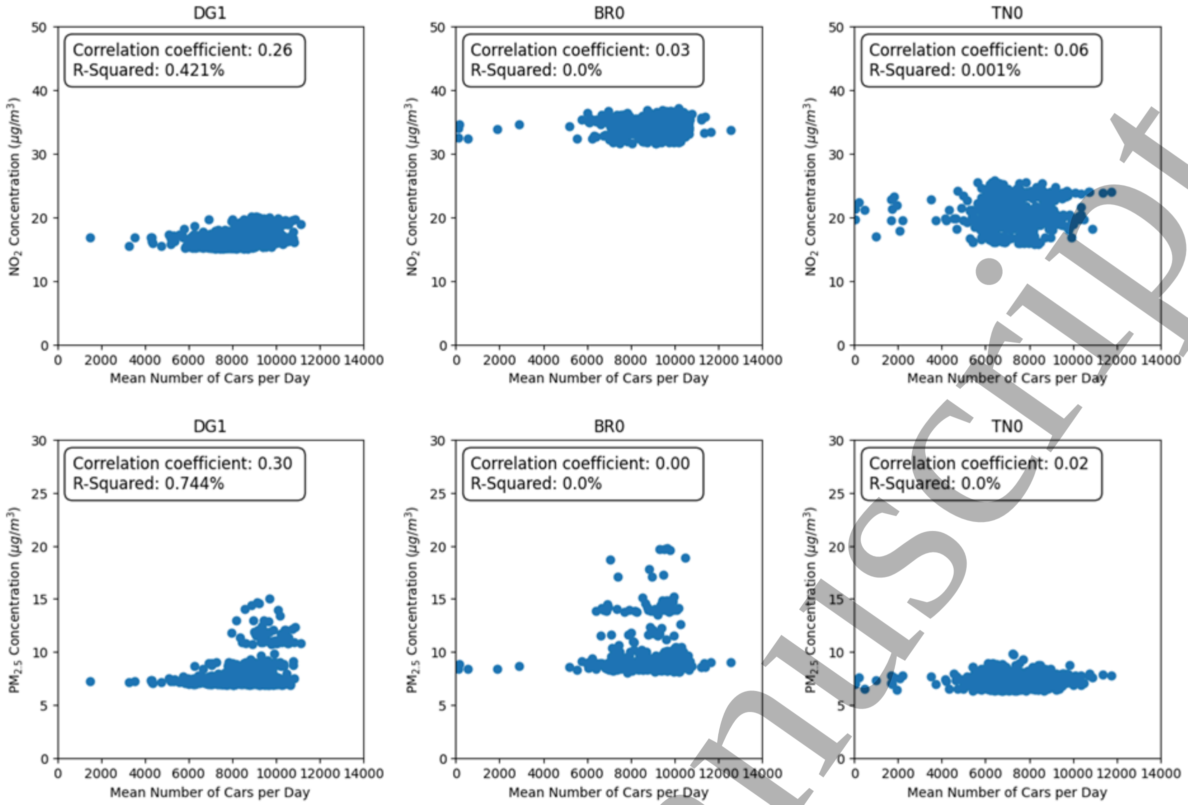


Figure 8. Scatter Plots Showing the Correlation Between the Mean Number of Cars Per Day Surrounding Primary AQ Sites, and the De-Weathered Pollutant Concentration.

Table 10. Correlation coefficients and adjusted R-Square for the association between the mean number of cars per day and NO_2 or $PM_{2.5}$ concentration.

Site	Traffic Volume to NO_2		Traffic Volume to $PM_{2.5}$	
	Coefficient	Adj-R^2 (%)	Coefficient	Adj-R^2 (%)
Non-Normalised				
DG1	0.06	0.2%	0.06	<0.000%
BR0	0.14	0.037%	0.01	<0.000%
TN0	0.10	0.007%	-0.02	<0.000%
De-Weathered				
DG1	0.26	0.421%	0.30	0.744%
BR0	0.03	<0.000%	<0.00	<0.000%
TN0	0.06	0.001%	0.02	<0.000%

Accepted Manuscript

5 Discussion

5.1 Air Quality

The analysis results showed that the concentrations of both $PM_{2.5}$ and NO_2 fell post-CAZ. The average reductions for de-weathered data were 5.53% and 5.23% for NO_2 and $PM_{2.5}$, respectively. The reductions in NO_2 are broadly in line with those observed in literature that analyses other cities. Ma et al. (18) found average reductions in NO_2 of less than 3% across all of London following the ULEZ. Similarly Liu et al. (17) found average NO_2 reductions of 3.4% in Birmingham's CAZ. Neither of these studies found significant changes in $PM_{2.5}$.

We also compare our results with the information released by Sheffield City Council. In July 2024, SCC reported there had been a 16% reduction in NO_2 concentrations within the CAZ, and a 21% reduction across the wider Sheffield area (3, 48). This report does not describe the methodology used, however it is broadly similar to our result of 14% reductions NO_2 in the case without weather-normalisation.

The previous work conducted by Ma et al. (18) and Liu et al. (17) showed that policy interventions led to significant reductions in NO_2, but had no impact on $PM_{2.5}$. The DiD analysis conducted in this study shows that the CAZ did not significantly reduce $PM_{2.5}$ concentrations, in line with results from previous work. Additionally, the DiD analysis showed that NO_2 was significantly changed following post-CAZ, again similar to other work. However, the coefficient of interaction, as seen previously in Table 5 was 0.55 ($p<0.000$). This positive coefficient suggests that following the CAZ, the concentrations of NO_2 within the CAZ were reduced *less than* pollutant concentrations outside the CAZ. While this finding is contrary to previous work, this can be consistent with SCC's press release (3). They estimated (pre-weather normalised) reductions in NO_2 of -16% within the CAZ, and -21% across the wider Sheffield area. These figures corroborate the results of the DiD analysis, showing that NO_2 reduced both inside and outside the CAZ, but with greater reductions outside.

As Liu et al. (17) points out, while CAZs and LEZs are one form of policy implemented to improve air quality, they are not the only ones. Policies work in conjunction to reduce air pollution. This can be seen in the analysis conducted. The *post* term indicates the trend in air pollution following the intervention, for NO_2 was -1.40 ($p<0.000$), indicating that overall NO_2 levels fell inside and outside the CAZ, with NO_2 levels not reduced to the same extent inside the CAZ as they were outside.

We additionally consider the compliance of AQ sites to regulatory requirements. These requirements, set out by DEFRA, detail the limits for air pollution (49). They are defined in Table 11 and define a maximum annual mean concentration.

Table 11. Air Quality Limits for NO_2 and $PM_{2.5}$

Pollutant	Limits(s)
NO_2	Mean annual daily concentration below 20 µg/m^3
	200 µg/m^3 not to be exceeded more than 18 times a year (1 hour mean)
$PM_{2.5}$	Mean annual daily concentration below 40 µg/m^3

Accepted Manuscript

The compliance to these regulations pre- and post-CAZ was evaluated. All sites met the mean annual daily NO_2 concentration of 20 μg/m^3. Additionally, there were no instances where primary NO_2 sites exceeded 200 μg/m^3. Some secondary sites exceeded this limit. CB0 exceeded the limit for an equivalent of 84 times pre-CAZ, and 0 times post-CAZ. Additionally, EC0 exceeded 200 μg/m^3 of NO_2 at an annual equivalent of 42 times pre-CAZ, and 4 post-CAZ.

All sites but one met the mean annual $PM_{2.5}$ limit of 40 μg/m^3. The site in breach of this was HS1, which saw mean $PM_{2.5}$ levels of 200 μg/m^3. While still breaching this limit post-CAZ, the $PM_{2.5}$ levels were reduced by 4.06% post-CAZ.

The high pollutant concentrations shown by HS1 led to further analysis. Figure 9 shows the$PM_{2.5}$ concentrations at HS1 overlaid with another site, DG0, a policy-grade sensor approximately 200m away. Figure 9 shows that PM2.5 at HS1 was significantly higher than that at DG0, while these sits differ in nature, HS1 is a roadside site and DG0 a background site, the concentrations at HS1 were on average 40 times larger than those at DG0. Additionally, such high levels of PM2.5 concentration were not seen in any other sensors, regardless of position, suggesting the readings seen above were the result of sensor issues. However, it does not significantly impact our analysis, as our focus is to compare the differences before and after CAZ.

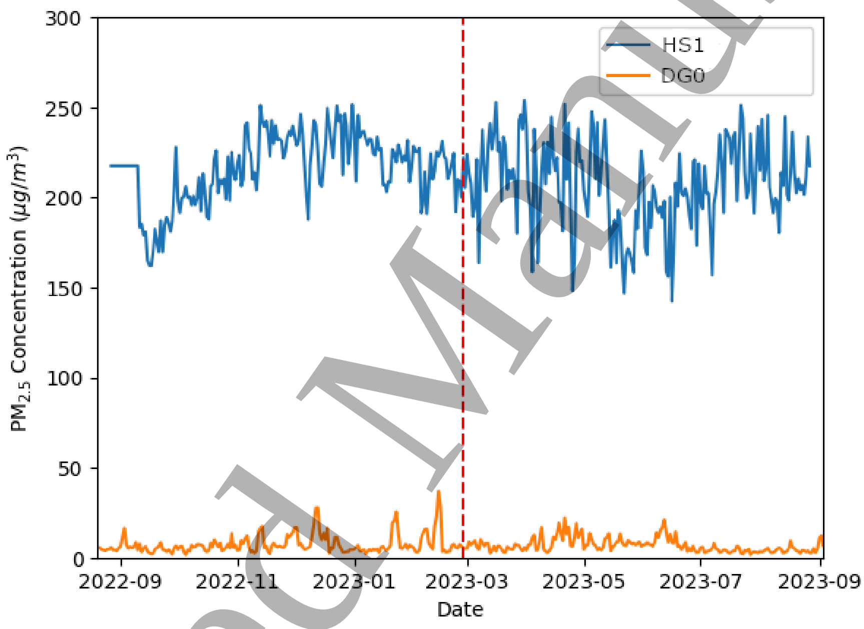


Figure 9. $PM_{2.5}$ concentrations at DG0 and HS1 for the whole analysis period.

Comparing this result to the traffic composition during the same period of time, that is, the share of vehicles that were non-compliant. SCC data (3), shows that pre-CAZ 37% of journeys inside the CAZ were non-compliant, and 39% across Sheffield. Post-CAZ, this number fell to 13% within the CAZ, and interestingly to 32% across Sheffield. This change in traffic composition highlights the knock-on effect of policy interventions.

We also compared our result with the observed traffic composition data released by Sheffield City Council (3), which reported the proportion of non-compliant vehicles at two different time points, November 2022 (pre-CAZ) and October 2023 (post-CAZ), both outside and inside CAZ, as shown in Table 12. The non-compliance percentages of both inside and outside CAZ have been reduced. This reduction could be partly attributed to the CAZ policy, but could also be influenced by other relevant policies such as the financial assistance schemes for vehicle

Accepted Manuscript

upgrades[6], as well as the implementation of bus gate on Arundel Gate which is inside the CAZ[7]. This shows how a policy such as a CAZ works in conjunction with other policies to improve overall air quality, but at the same time it shows a limitation of this study, that the 'Control' groups used in the DiD analysis may not be true control groups, as despite being significantly outside the CAZ are still subject to its impact.

Table 12. Proportion of non-compliant fleet (Source: Sheffield City Council (3))

Non-compliance percentage	Nov 2022 (Pre-CAZ)	Oct 2023 (Post-CAZ)	Percentage reduction
Inside CAZ	37%	13%	64%
Outside CAZ	39%	32%	18%

The impact of weather normalisation on the results also provided points for discussion. The difference between pre- and post-CAZ concentrations were reduced, and in some instances reversed with increases reported post-normalisation for some sites. Isolating the impacts of weather on pollutant concentrations plays a key part in understanding the impact of interventions. For example, the analysis initially suggested that for DG1 and BR0, there was no significant change in NO_2. However, post-normalisation there was a significant decrease in NO_2 within the CAZ. However, the impacts of weather normalisation did not affect the overall (combined) results.

5.2 Traffic

Analysis showed that the changes in traffic surrounding DG1 was statistically significant, with a 6.02% decrease in the total number of cars post-CAZ. This change is in line with the 5.1% decrease observed by Boogaard et al. (43) across 5 Dutch cities, and the 8.1% reduction found by Tassinari (44) following Madrid's LEZ. Tassinari (2024), however, found that traffic increased surrounding the CAZ, indicating the possible effects of spillover.

Our research assessed the spillover effect utilising the traffic sensors surrounding Sheffield's CAZ, and found *no evidence for spillover*. Of the 33 outside-CAZ traffic sites analysed, 14 showed no significant changes, and only 5 (16%) indicated a significant increase in traffic post-CAZ. Liu et al. (17) also found no evidence of spillover following Birmingham's CAZ citing reductions in air pollution both inside and outside.

There was no significant association found between traffic volume and air quality, the highest correlation was shown for NO_2 and $PM_{2.5}$ for DG1 with correlations of 0.26 and 0.3, respectively.

Previous studies have found associations between traffic and air pollution (41,42); the difference between these studies and this work could be attributed to measurement criteria. Salama & Zafar (42) analysed the correlation on a singular stretch of highway, providing extremely localised data. In contrast, traffic readings in our study were taken near to AQ sites, but not directly from. For example, the nearest traffic sensor to DG1 was located approximately 380m away, on a major road. This could potentially influence the results, as the traffic measurement taken may not reflect the traffic conditions directly from each AQ sensor.

[6]https://www.sheffield.gov.uk/clean-air-zone-sheffield/apply-financial-support-upgrade-or-replace-polluting-vehicle
[7] https://www.sheffield.gov.uk/travel-transport/bus-lanes-gates

Accepted Manuscript

6 Conclusion

This study offered an exploratory analysis on the efficacy of Sheffield's Clear Air Zone (CAZ) as a tool for improving air quality. We used an evidence-based approach, utilising data before and after CAZ from sites throughout Sheffield. Our analysis showed that air quality within the CAZ did not significantly differ from the trends in air pollution outside the CAZ. Reductions of 6.04 % in NO_2 and 7.48% in $PM_{2.5}$ were observed inside the CAZ, and 5.27% in NO_2 and 4.1% in $PM_{2.5}$ outside the CAZ. The lack of difference between the control and treatment group found in this study could be explained by traffic composition, with the number of high-polluting vehicles reducing both inside and outside the CAZ. We also assessed traffic changes post-CAZ. There were no significant differences at sites outside the CAZ, with traffic volumes reducing 6% YoY within the CAZ. Spillover was then assessed using 33 sensors surrounding the CAZ, in which 28 or 84% showed no significant change, or a significant decrease, indicating there were no negative spillover effects caused by the CAZ.

This study serves as the foundation for understanding the impact of Sheffield's CAZ and inform future research, which we suggest several directions as follows.

First, additional sensors (and thus data) should be made available for analysis. One limitation in our analysis was the availability of data and the number of sites used in the analysis. 46 potential sites were identified reporting either NO_2 or $PM_{2.5}$, however only three of these sites provided sufficient data to be primary sites for complete analysis, with an additional four with sufficient data to be secondary sites for partial analysis. In contrast, similar literature used more sites, with Ma et al. (18) using 58 sites across four pollutants, and Liu et al. (17) using 16 sites for two pollutants. Additional sites were identified, however these either provided insufficient data for analysis, or were not paired to meteorological conditions. Analysis conducted with a limited number of sensors risk skewing results by inadvertently focusing on local trends rather than broader contextual changes. Therefore, future research would benefit from an increased density of both AQ and meteorological sensors, both background and roadside, both within and outside CAZ, to more effectively and comprehensively assess and understand CAZ. The AQ sensors could also be deployed alongside meteorological sensors in order to provide weather variables for normalisation.

Second, in this research, the weather variables used were wind speed, wind direction and air temperature, since these were the only weather parameters available. Previous research however has considered additional variables such as pressure and relative humidity (17,20). In the future, additional weather variables could be included, for example the Met Office provides weather station archive data[8], or using NOAA data.

Third, a promising direction for future research is to strengthen the casual analysis of the CAZ impact, possibly through the synthetic control method (17). Our study employed the difference-in-differences approach and used sites outside CAZ as "Control" group, but as highlighted in the discussion, these areas may also be have been indirectly influenced by CAZ. The advantage of the synthetic control method is that it creates control sites from unaffected regions (or other cities) to mirror the pre-CAZ trends, and thus provide a more accurate baseline for comparison and enable a more robust casual inference.

Fourth, while Sheffield's CAZ does not charge private vehicles, the electrification of cars should not be ignored. As of 2024, there are an estimated 1,000,000 electric vehicles on the UK roads (50). These vehicles do not emit exhaust gases such as CO and NO_2, but they do emit particulate matter (51). We have discussed in this research the changes in traffic volumes and number of compliant vehicles, but future work could also analyse the changes in the number of private EVs

[8] https://www.metoffice.gov.uk/research/climate/maps-and-data/data/index

Accepted Manuscript

or other vehicle types on the road, and the impact of this on air pollution. For example, sensors with Automatic Number-Plate Recognition (ANPR) so we can cross correlate plate number with DVLA, so and could know the kind of vehicle passing the camera, including engine type.

Fifth, future studies can take a comparative approach by examining other cities' CAZ or low-emission zone to assess their impact, providing additional insights, such as why some CAZs appear more effective than others, and what factors drive success. It would also be interesting to compare the results of different classes of CAZs.

Funding Information.

This work is supported by Engineering and Physical Sciences Research Council, UK Research and Innovation (EP/R013411/1).

Accepted Manuscript

References

1. GOV.UK [Internet]. 2022 [cited 2024 Mar 19]. Air pollution: applying All Our Health. Available from: https://www.gov.uk/government/publications/air-pollution-applying-all-our-health/air-pollution-applying-all-our-health
2. GOV.UK [Internet]. 2024 [cited 2024 Mar 19]. Clean air zones. Available from: https://www.gov.uk/guidance/driving-in-a-clean-air-zone
3. Clean Air Zone air quality data | Sheffield City Council [Internet]. [cited 2024 Aug 18]. Clean Air Zone air quality data. Available from: https://www.sheffield.gov.uk/clean-air-zone-sheffield/clean-air-zone-air-quality-data
4. Air Pollution and Health in Cities | State of Global Air [Internet]. 2022 [cited 2024 Aug 18]. Available from: https://www.stateofglobalair.org/resources/health-in-cities
5. Bălă GP, Râjnoveanu RM, Tudorache E, Motișan R, Oancea C. Air pollution exposure—the (in)visible risk factor for respiratory diseases. Environ Sci Pollut Res Int. 2021;28(16):19615–28.
6. European Environment Agency [Internet]. 2024 [cited 2024 Aug 20]. Harm to human health from air pollution in Europe: burden of disease 2023. Available from: https://www.eea.europa.eu/publications/harm-to-human-health-from-air-pollution/harm-to-human-health-from
7. Huang W, Zhou Y, Chen X, Zeng X, Knibbs LD, Zhang Y, et al. Individual and joint associations of long-term exposure to air pollutants and cardiopulmonary mortality: a 22-year cohort study in Northern China. Lancet Reg Health West Pac. 2023 May 4;36:100776.
8. UK plan for tackling roadside nitrogen dioxide concentrations: Detailed plan [Internet]. Joint Air Quality Unit; 2017 Jul. Available from: https://assets.publishing.service.gov.uk/media/5a81d37540f0b623026995e7/air-quality-plan-detail.pdf
9. Fichera E, Beshir H, Serna-Castaño A. Low Emission Zones improve air quality, physical health and mental well-being [Internet]. Zenodo; 2023 Nov [cited 2024 Aug 18]. Available from: https://zenodo.org/doi/10.5281/zenodo.8360285
10. ULEZ reduces 13,500 cars daily & cuts toxic air pollution by a third [Internet]. 2019 [cited 2024 Aug 18]. Available from: https://www.london.gov.uk/press-releases/mayoral/ulez-reduces-polluting-cars-by-13500-every-day
11. Air quality in Sheffield [Internet]. Sheffield City Council; 2015 [cited 2024 Mar 19]. Available from: https://www.sheffield.gov.uk/pollution-nuisance/air-quality
12. Clean Air Zone [Internet]. 2024 [cited 2024 Mar 20]. Available from: https://sheffieldcc.maps.arcgis.com/apps/webappviewer/index.html?id=209bfe53e5b34c06878e0f0d6c39ee88
13. Liu H, Wang C, Zhang M, Wang S. Evaluating the effects of air pollution control policies in China using a difference-in-differences approach. Sci Total Environ. 2022 Nov 1;845:157333.
14. Son JY, Fong KC, Heo S, Kim H, Lim CC, Bell ML. Reductions in mortality resulting from reduced air pollution levels due to COVID-19 mitigation measures. Sci Total Environ. 2020 Nov 20;744:141012.
15. Wang M, Liu F, Zheng M. Air quality improvement from COVID-19 lockdown: evidence from China. Air Qual Atmosphere Health. 2021 Apr 1;14(4):591–604.
16. Zhang T, Tang M. The Impact of the COVID-19 Pandemic on Ambient Air Quality in China: A Quasi-Difference-in-Difference Approach. Int J Environ Res Public Health. 2021 Jan;18(7):3404.

Accepted Manuscript

17. Liu B, Bryson JR, Sevinc D, Cole MA, Elliott RJR, Bartington SE, et al. Assessing the Impacts of Birmingham's Clean Air Zone on Air Quality: Estimates from a Machine Learning and Synthetic Control Approach. Environ Resour Econ. 2023 Oct 1;86(1):203–31.
18. Ma L, Graham DJ, Stettler MEJ. Has the ultra low emission zone in London improved air quality? Environ Res Lett. 2021 Nov;16(12):124001.
19. Almeida SM, Manousakas M, Diapouli E, Kertesz Z, Samek L, Hristova E, et al. Ambient particulate matter source apportionment using receptor modelling in European and Central Asia urban areas. Environ Pollut. 2020 Nov 1;266:115199.
20. Battista G. Analysis of the Air Pollution Sources in the city of Rome (Italy). Energy Procedia. 2017 Sep 1;126:392–7.
21. Lu X, Yao T, Li Y, Fung JCH, Lau AKH. Source apportionment and health effect of NOx over the Pearl River Delta region in southern China. Environ Pollut. 2016 May 1;212:135–46.
22. Nguyen CV, Soulhac L, Salizzoni P. Source Apportionment and Data Assimilation in Urban Air Quality Modelling for NO2: The Lyon Case Study. Atmosphere [Internet]. 2018 Jan 1 [cited 2024 Aug 18];9(8). Available from: https://www.mdpi.com/2073-4433/9/1/8
23. Zhu Y, Huang L, Li J, Ying Q, Zhang H, Liu X, et al. Sources of particulate matter in China: Insights from source apportionment studies published in 1987–2017. Environ Int. 2018 Jun 1;115:343–57.
24. GOV.UK [Internet]. 2021 [cited 2024 Aug 18]. The impact of lockdown on reported road casualties Great Britain, final results: 2020. Available from: https://www.gov.uk/government/statistics/reported-road-casualties-great-britain-annual-report-2020/the-impact-of-lockdown-on-reported-road-casualties-great-britain-final-results-2020
25. Giani P, Castruccio S, Anav A, Howard D, Hu W, Crippa P. Short-term and long-term health impacts of air pollution reductions from COVID-19 lockdowns in China and Europe: a modelling study. Lancet Planet Health. 2020 Oct 1;4(10):e474–82.
26. Pei Z, Han G, Ma X, Su H, Gong W. Response of major air pollutants to COVID-19 lockdowns in China. Sci Total Environ. 2020 Nov 15;743:140879.
27. Berman JD, Ebisu K. Changes in U.S. air pollution during the COVID-19 pandemic. Sci Total Environ. 2020 Oct 15;739:139864.
28. Cai WJ, Wang HW, Wu CL, Lu KF, Peng ZR, He HD. Characterizing the interruption-recovery patterns of urban air pollution under the COVID-19 lockdown in China. Build Environ. 2021 Nov 1;205:108231.
29. Dang HAH, Trinh TA. The Beneficial Impacts of COVID-19 Lockdowns on Air Pollution: Evidence from Vietnam. J Dev Stud. 2022 Oct 3;58(10):1917–33.
30. Song Y, Li Z, Liu J, Yang T, Zhang M, Pang J. The effect of environmental regulation on air quality in China: A natural experiment during the COVID-19 pandemic. Atmospheric Pollut Res. 2021 Apr 1;12(4):21–30.
31. Xu S qing, He H di, Yang M ke, Wu C lin, Zhu X hang, Peng Z ren, et al. To what extent the traffic restriction policies can improve its air quality? An inspiration from COVID-19. Stoch Environ Res Risk Assess. 2023 Apr 1;37(4):1479–95.
32. Liu S, Kong G, Kong D. Effects of the COVID-19 on Air Quality: Human Mobility, Spillover Effects, and City Connections. Environ Resour Econ. 2020 Aug 1;76(4):635–53.
33. Zhang R, Li H, Khanna N. Environmental justice and the COVID-19 pandemic: Evidence from New York State. J Environ Econ Manag. 2021 Oct 1;110:102554.
34. Ma, Graham D, Settler M. Using Explainable Machine Learning to Interpret the Effects of Policies on Air Pollution: COVID-19 Lockdown in London | Environmental Science & Technology. Environ Sci Technol. 2023 Aug 11;57(46):18271–81.
35. Bigazzi AY, Rouleau M. Can traffic management strategies improve urban air quality? A review of the evidence. J Transp Health. 2017 Dec 1;7:111–24.
36. Lu KF, Wang HW, Li XB, Peng ZR, He HD, Wang ZP. Assessing the effects of non-local traffic restriction policy on urban air quality. Transp Policy. 2022 Jan 1;115:62–74.
37. Qiu LY, He LY. Can Green Traffic Policies Affect Air Quality? Evidence from A

Accepted Manuscript

Difference-in-Difference Estimation in China. Sustainability. 2017 Jun;9(6):1067.
38. Gilchrist D, Emery T, Garoupa N, Spruk R. Synthetic Control Method: A tool for comparative case studies in economic history. J Econ Surv. 2023;37(2):409–45.
39. Fang D, Chen B, Hubacek K, Ni R, Chen L, Feng K, et al. Clean air for some: Unintended spillover effects of regional air pollution policies. Sci Adv. 2019 Apr 24;5(4):eaav4707.
40. Siciliano B, Carvalho G, da Silva CM, Arbilla G. The Impact of COVID-19 Partial Lockdown on Primary Pollutant Concentrations in the Atmosphere of Rio de Janeiro and São Paulo Megacities (Brazil). Bull Environ Contam Toxicol. 2020 Jul 1;105(1):2–8.
41. Blagoiev M, Gruicin I, Ionascu ME, Marcu M. A Study on Correlation Between Air Pollution and Traffic. In: 2018 26th Telecommunications Forum (TELFOR) [Internet]. 2018 [cited 2024 Jan 19]. p. 420–5. Available from: https://ieeexplore.ieee.org/abstract/document/8612084?casa_token=rSJgTSwHXgwAAAAA:2bAoM7t2fOHVagZrI5TXgnrp7AoHn6W4C_DQkGPCecFhYnDnxmuw41z8HzB-ZJ0tEQ2EojTuPg
42. Salama K, Zafar M. Air Pollution from Traffic at Major Causeway Al-Khobar, Saudi Arabia. J Ecophysiol Occup Health. 2020 Jun 25;20:1–5.
43. Boogaard H, Janssen NAH, Fischer PH, Kos GPA, Weijers EP, Cassee FR, et al. Impact of low emission zones and local traffic policies on ambient air pollution concentrations. Sci Total Environ. 2012 Oct 1;435–436:132–40.
44. Tassinari F. Low emission zones and traffic congestion: Evidence from Madrid Central. Transp Res Part Policy Pract. 2024 Jul 1;185:104099.
45. Wallace J, Corr D, Kanaroglou P. Topographic and spatial impacts of temperature inversions on air quality using mobile air pollution surveys. Sci Total Environ. 2010 Oct 1;408(21):5086–96.
46. Ceballos-Santos S, González-Pardo J, Carslaw D, Santurtún A, Santibáñez M, Fernández-Olmo I. Meteorological Normalisation Using Boosted Regression Trees to Estimate the Impact of COVID-19 Restrictions on Air Quality Levels. Environ Res Public Health. 2021 Dec 18;18(24):13347.
47. Grange SK, Carslaw DC, Lewis AC, Boleti E, Hueglin C. Random forest meteorological normalisation models for Swiss PM_{10} trend analysis. Atmospheric Chem Phys. 2018 May 3;18(9):6223–39.
48. Thake S. BBC News. 2024 [cited 2024 Aug 26]. Sheffield Clean Air Zone: Pollution levels in city fall after a year. Available from: https://www.bbc.com/news/articles/c6p2076k6nko
49. Department for Environment F and RA (Defra) webmaster@defra gsi gov uk. UK Air Quality Limits- Defra, UK [Internet]. Department for Environment, Food and Rural Affairs (Defra), Nobel House, 17 Smith Square, London SW1P 3JR helpline@defra.gsi.gov.uk; [cited 2024 Mar 19]. Available from: https://uk-air.defra.gov.uk/air-pollution/uk-limits.php
50. The road to electric - the UK's adoption of electric cars in charts and data | RAC Drive [Internet]. [cited 2024 Nov 14]. Available from: https://www.rac.co.uk/drive/electric-cars/choosing/road-to-electric/
51. Timmers VRJH, Achten PAJ. Non-exhaust PM emissions from electric vehicles. Atmos Environ. 2016 Jun 1;134:10–7.

Accepted Manuscript

Appendices

A - AQ Site Locations

Figure A1 shows the map of chosen sites for NO_2 and $PM_{2.5}$. HS1 and DG1 were both located within the CAZ and within 200m of each other, while all other sensors were outside and located more sparsely.

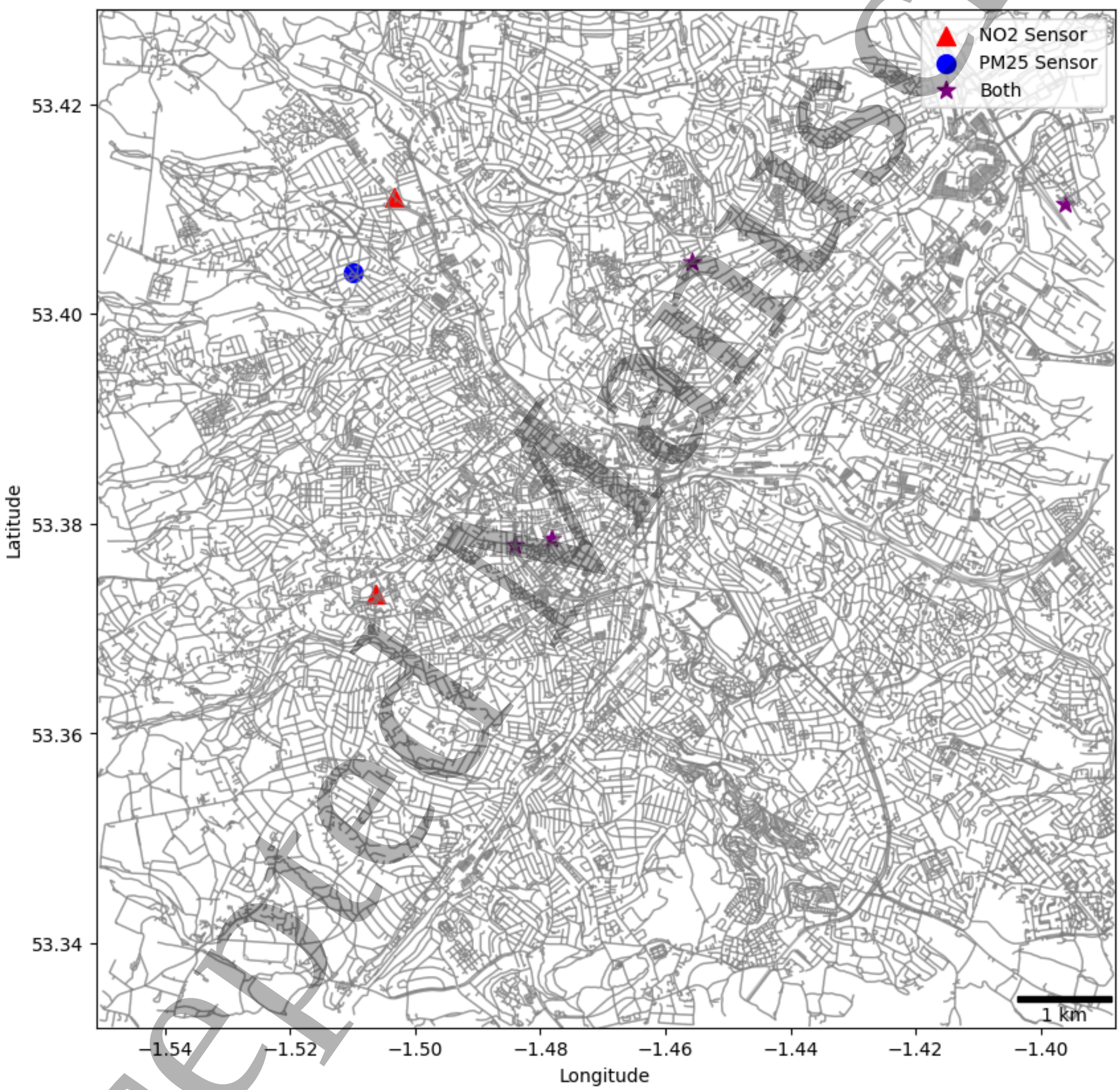


Figure A1. Location of all identified AQ sites reporting NO_2, $PM_{2.5}$ of both. Map data from OpenStreetMap.

Sensors from three families were used, DEFRA, SUFO and Luftdaten (also called Sensor. Community). DEFRA and SUFO have been discussed previously, and Luftdaten is a community

Accepted Manuscript

sensor network that allows anyone to purchase a simple AQ monitoring kit. This means the network has over 9000 sensors globally (*About Sensor.Community*, n.d.).

Only one site was provided sufficient data for the entire analysis period. To ensure this sensor was a suitable representation of the air quality within the CAZ, this sensor was compared to other sensors. These alternate sensors presented data up to March 2023.

Figure A2 presents boxplots showing the distribution of the mean daily concentration for the sensors within the CAZ. These boxplots are based on a period of 1 year Pre-CAZ. It shows that DG1, our primary site, have readings fall into the range of typical values among the sensors.

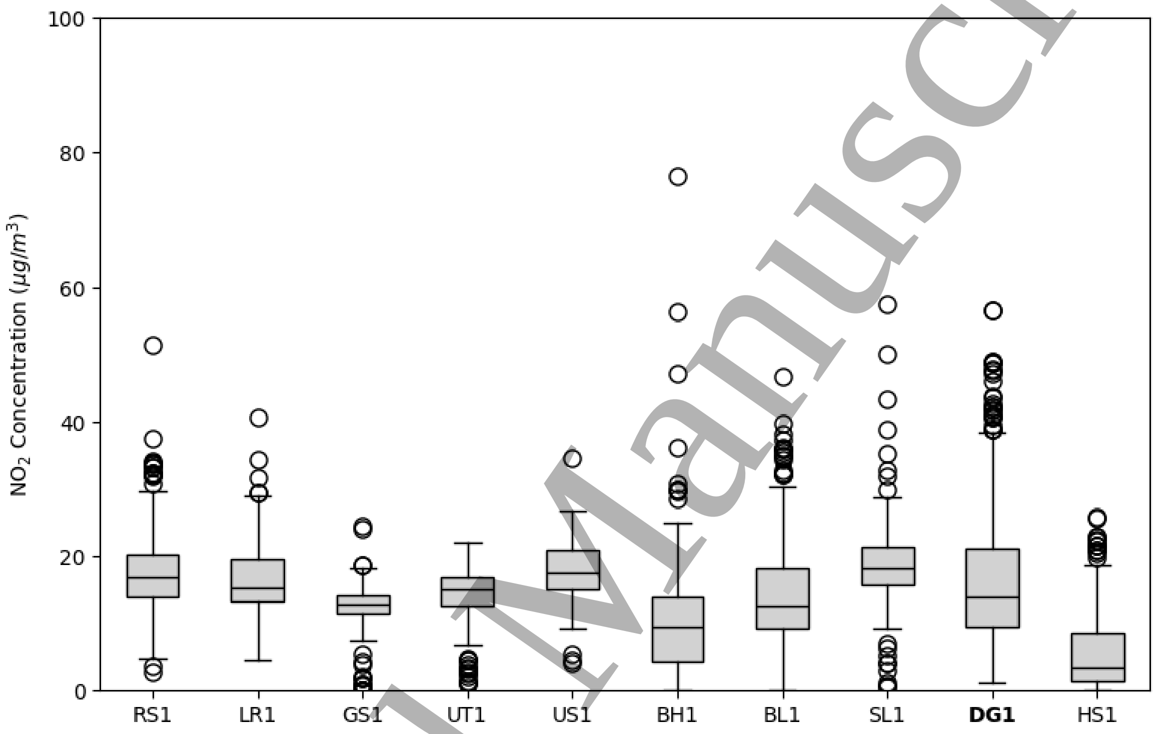


Figure A2. Boxplots showing pre-CAZ NO_2 concentration for the 10 sites within the CAZ.

We conducted further analysis on the representativeness of DG1 for the air quality within the CAZ, focusing on the pre-CAZ period from February 2022 to February 2023, during which more sensor data were available. Table A1 lists 10 sensors located within the CAZ and three metrics:

- **% Data Available:** The proportion of NO_2 readings recorded by the sensor.
- **Correlation coefficient with daily mean:** We first calculate the overall daily mean NO_2 concentration, and then measure the correlation between the site's daily readings and the overall daily mean. A higher value indicates stronger alignment with the overall trend and thus better representativeness.
- **MAE:** We calculate the Mean Absolute Error between the site's daily NO_2 readings and the corresponding overall daily mean, reflecting the average size of deviation. A lower value indicates smaller deviation and thus better representativeness.

DG1 recorded the fourth highest NO_2 concentration among the ten sensors, showed a moderate correlation with the daily mean, and a reasonable MAE, making it to be a reasonable representative of air quality within the CAZ.

Accepted Manuscript

Table A1. Site IDs, locations and representativeness study for sites within the CAZ from 27/02/2022 to 27/02/2023

Site ID	Site Name	% Data Available	NO_2 Mean Concentr-ation	Correlation Coefficient with Daily Mean	MAE
DG1	Devonshire Green	98.47%	17.31	0.590	6.095
RS1	Regent Street	47.30%	17.87	0.571	4.171
LR1	Leavygreave Road	21.60%	16.93	0.838	2.841
GS1	Gell Street	23.83%	12.36	0.322	3.320
UT1	UoS Tram Stop	18.78%	14.34	0.149	3.806
US1	University Square	10.92%	17.98	0.005	4.776
BH1	Brook Hill	18.31%	13.80	0.755	9.720
BL1	Broad Lane	30.40%	13.70	0.320	6.908
SL1	Surrey Lane	18.31%	18.72	0.703	4.003
HS1	Hannover Street	41.08%	8.86	0.472	6.879

Accepted Manuscript

B - Weather Normalisation

Weather normalisation is a process of removing the effect of weather conditions on air pollution concentrations. Weather plays a crucial role in the formation, transport and deposition of air pollution (Ceballos-Santos et al., 2021), potentially masking fluctuations in pollutant concentration. This can result in the effectiveness of an intervention being obscured by the wider conditions.

Various methods exist to perform weather normalisation, but each method functions similarly. Models are developed to use meteorological variables to explain variation in the pollutant concentration. Ceballos-Santos et al. (2021) and Ma et al. (2021) performed this process using boosted regression trees, while Grange et al. (2018) used a random forest model. Following this work Grange developed a package for the weather normalisation of air pollution, named *rmweather*.

This package allows a user to provide air pollution and meteorological variables and quickly de-weather the data. The package develops 300 decision trees with each tree using an 80/20 split of training to test data. Each tree then develops its own model to predict the pollutant concentration given the meteorological conditions. This is applied to each observation with the de-weathered pollutant concentration calculated through aggregate voting, taking the mean of all decision trees. A Tibble with the timestamp and de-weather pollutant concentration was returned. This package was observed in the literature, used by B. Liu et al. (2023) when analysing the effectiveness of the Birmingham CAZ among other uses in air-pollution research (Lin et al., 2022; Lv et al., 2022; Yao & Zhang, 2024).

Since this package used R, a conversion between Python and R was required using the *rpy2* library. This allowed for both R and Python to be accessed and converted within the same Jupyter notebook. The merged data containing air pollution and meteorological variables was converted from a Pandas DF to an R DF, the weather normalisation performed, then the output converted back into a Pandas DF.

The meteorological variables used to perform weather normalisation were wind speed, wind direction and ambient temperature. Additional variables relevant to the formation and dispersion of pollutants such as pressure and relative humidity were not available for the selected sensors through data retrieved from DEFRA.

Figure A3 presents a scatter plot of the observed against predicted mean daily concentration for either NO_2 or $PM_{2.5}$, alongside the R^2 for the six weather normalisation models.

Accepted Manuscript

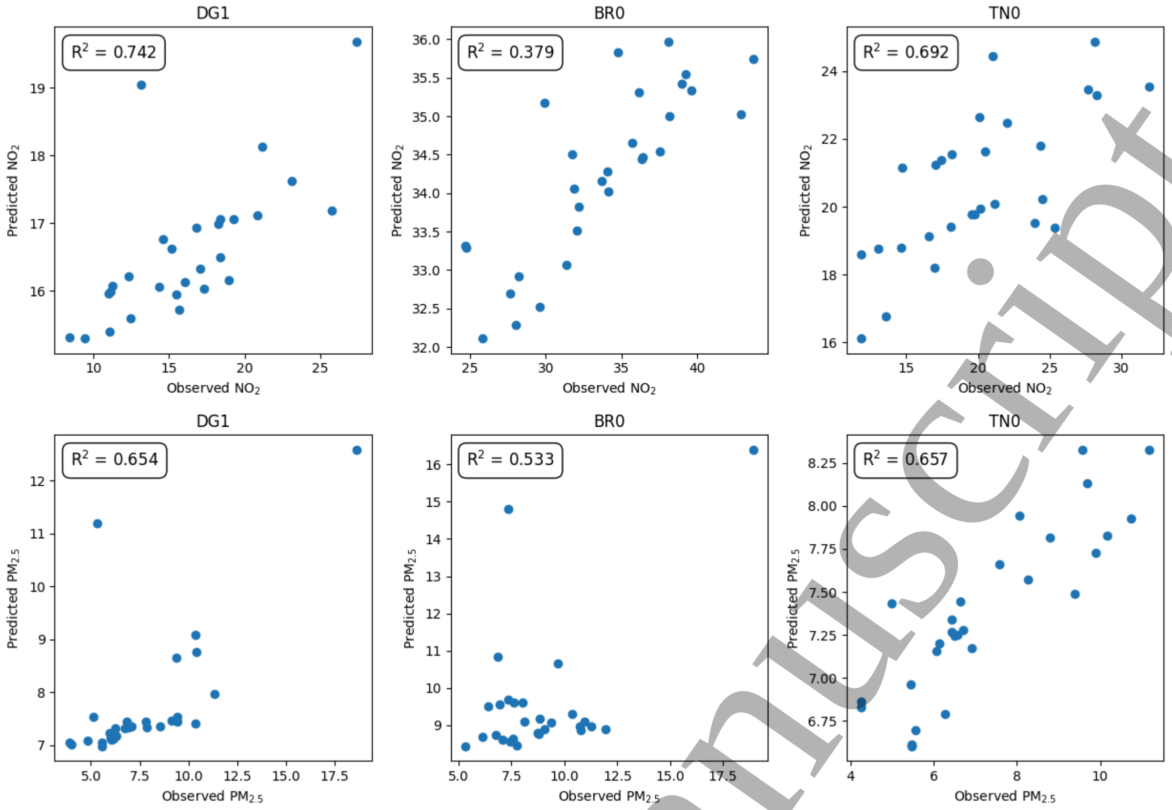


Figure A3. Weather normalisation model performance with scatter plots showing the observed vs predicted pollutant concentrations (mean monthly).

(18) found their model performed with between 30% and 90% agreement depending on the pollutant and site location. The models developed in this paper present R^2 in the range of 38% to 75%, within those observed by (18), but with marginally lower performance. The lower performance may be due to the number of weather variables used, and future work could include additional variables, but the performance of the weather normalisation models are still suitable for use in further analysis.

Accepted Manuscript

C - Traffic Data Description

Primary Sites

Traffic sites were initially selected for areas surrounding the primary AQ sensors. A 0.5 km radius was considered and the traffic data surrounding the sites assessed. Figure A4 shows the number of traffic sites identified in relation to DG1.

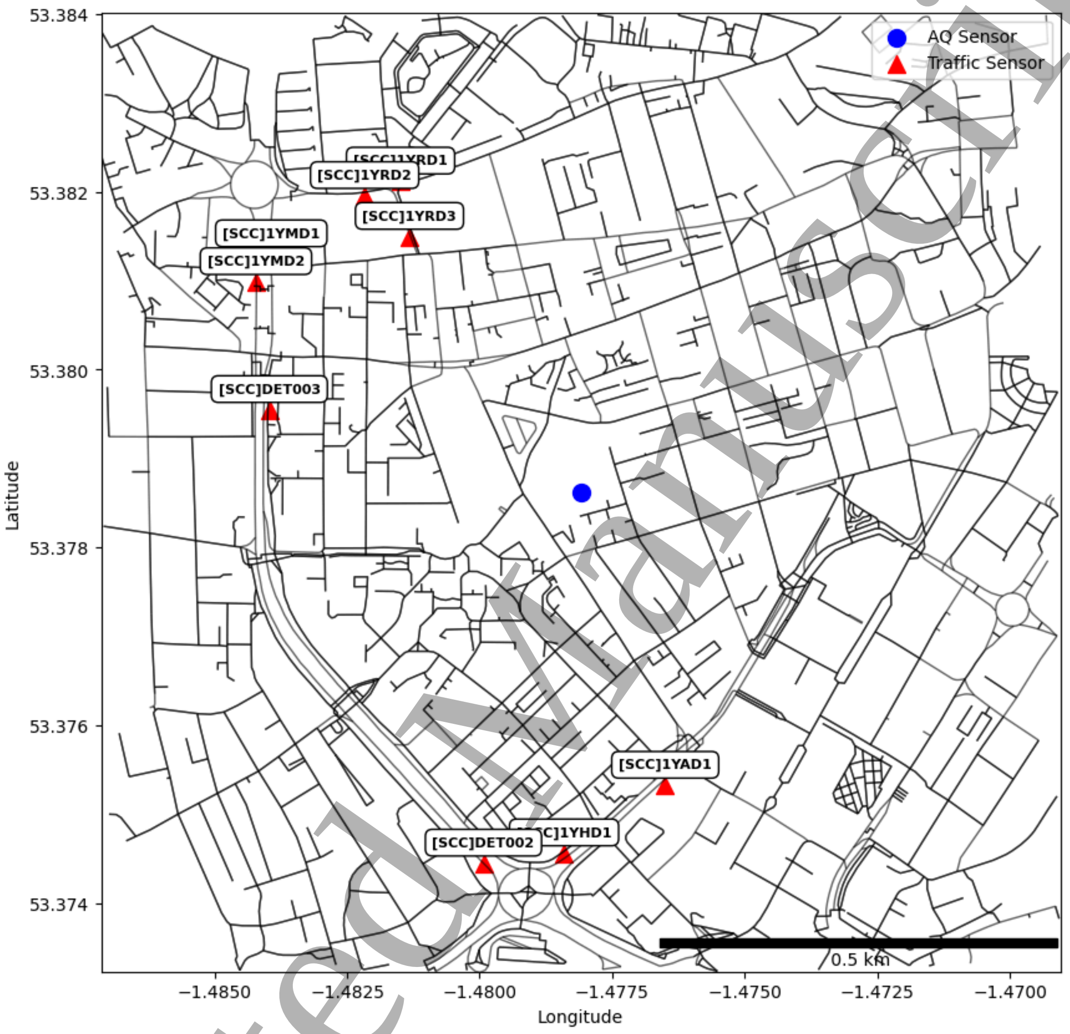


Figure A4. Map showing the locations of traffic sites identified within 0.5 km of primary sites DG1. Map data from OpenStreetMap.

Accepted Manuscript

Nine sensors were identified within 0.5 km of this site. Their data between February 2022 and June 2024 was downloaded. Figure A5 shows the traffic flow per minute for the sensors surrounding this site with the CAZ introduction shown as a vertical line and shading denoting 12 and 24 month windows surrounding this date. The missing number of values for each site was also calculated. As seen in Figure A5, DET002 presented the highest number of missing values at 86.81% of all data. Sensors with a high proportion of missing values (>10%) were removed from analysis. The sensors removed from analysis were DET002, DET003 and 1YRD3.

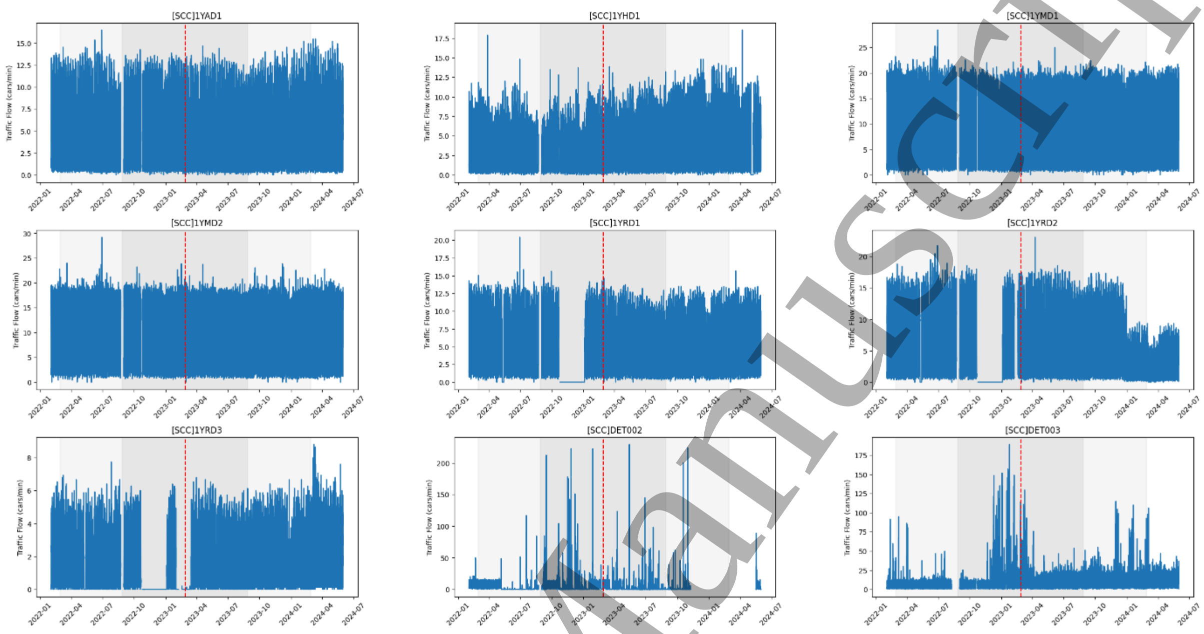


Figure A5. Sensor-Read Traffic Flow for the nine traffic sites surrounding DG1 with the CAZ introduction shown as a vertical line and shaded regions representing 12 and 24 month spans

The same process was conducted for BR0, Figure A6 shows the traffic sites surrounding this AQ sensor. There were only four traffic sensors within 0.5 km of BR0 (note that the AQ sensor is obscured by the label for 1BND2 on the above map). Figure A7 shows the sensor-read flow for each of these sites. The largest proportion of missing values for these sensors was 2.34%, however as can be seen in Figure A7, 1BUD1 presented values much lower when compared to its sensor pair 1BUD2. This raised concerns regarding sensor calibration and thus 1BUD2 was removed from further analysis. Therefore, three sensors were used for this site.

Accepted Manuscript

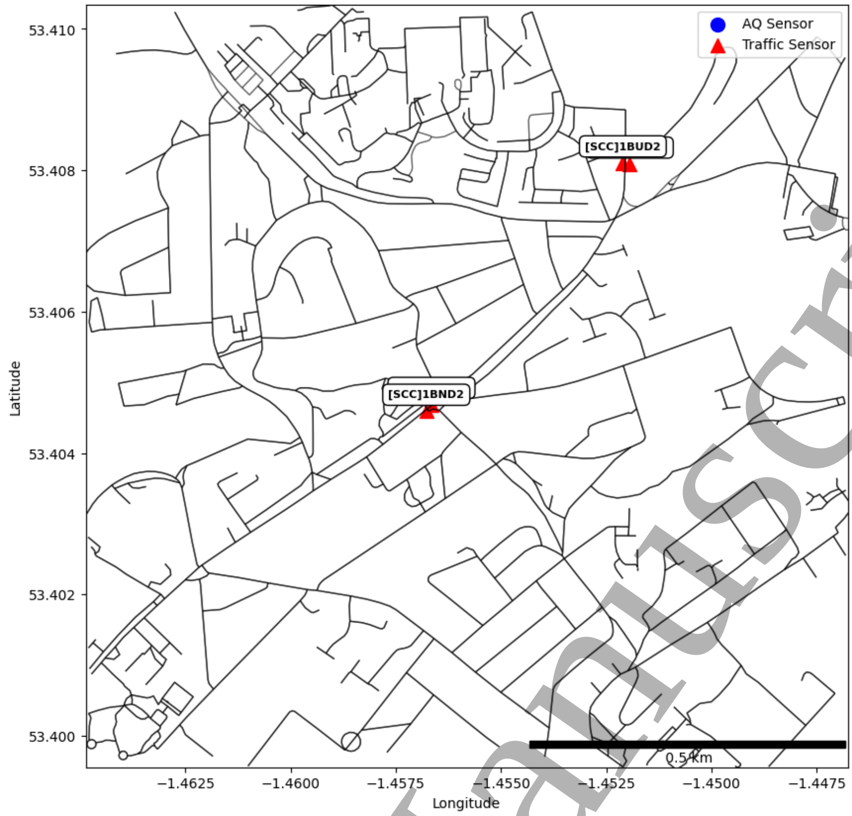


Figure A6. Map showing the locations of traffic sites identified within 0.5 km of primary site BR0. Map data from OpenStreetMap.

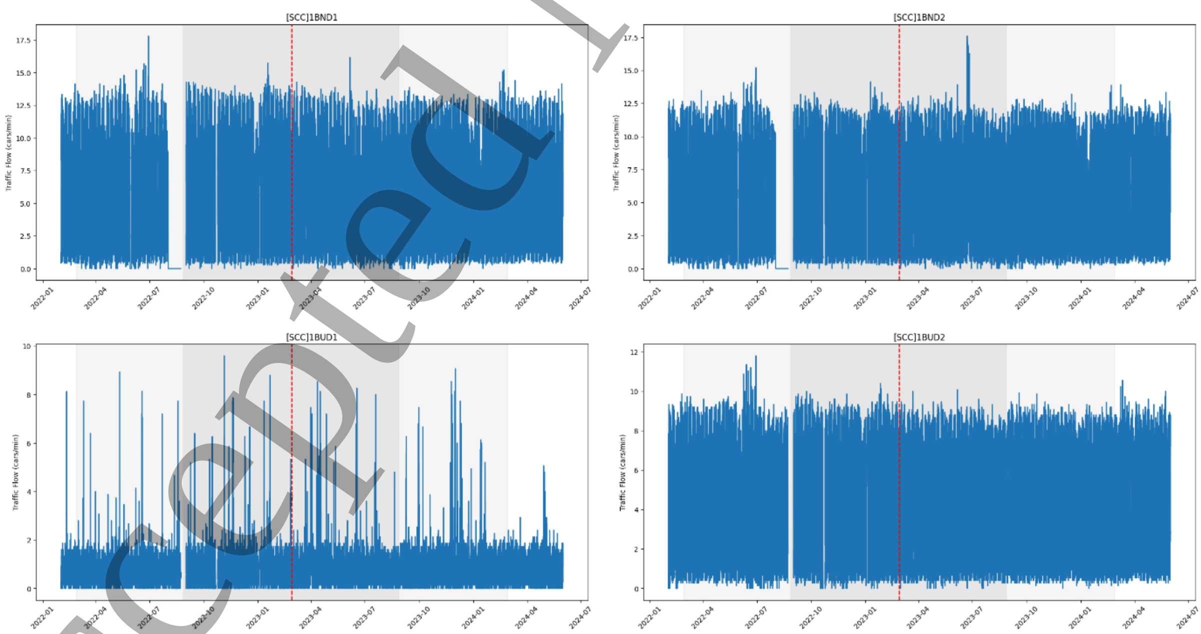


Figure A7. Traffic Flow for the four traffic sites surrounding BR0 with the CAZ introduction shown as a vertical line and shaded regions representing 12 and 24 month spans.

Accepted Manuscript

There were no traffic sensors within 0.5 km of the TN0 site, the search was widened to 1 km and Figure A8 shows the traffic sensors identified. There were 16 sensors identified within 1 km of this site with the majority of sensors surrounding Meadowhall Shopping Centre and its connections to the M1. Figure A9 shows the sensor-read flows for the 16 sensors. The largest number of missing values was 3.22% therefore no sensors were removed from further analysis resulting in 16 sensors being included.

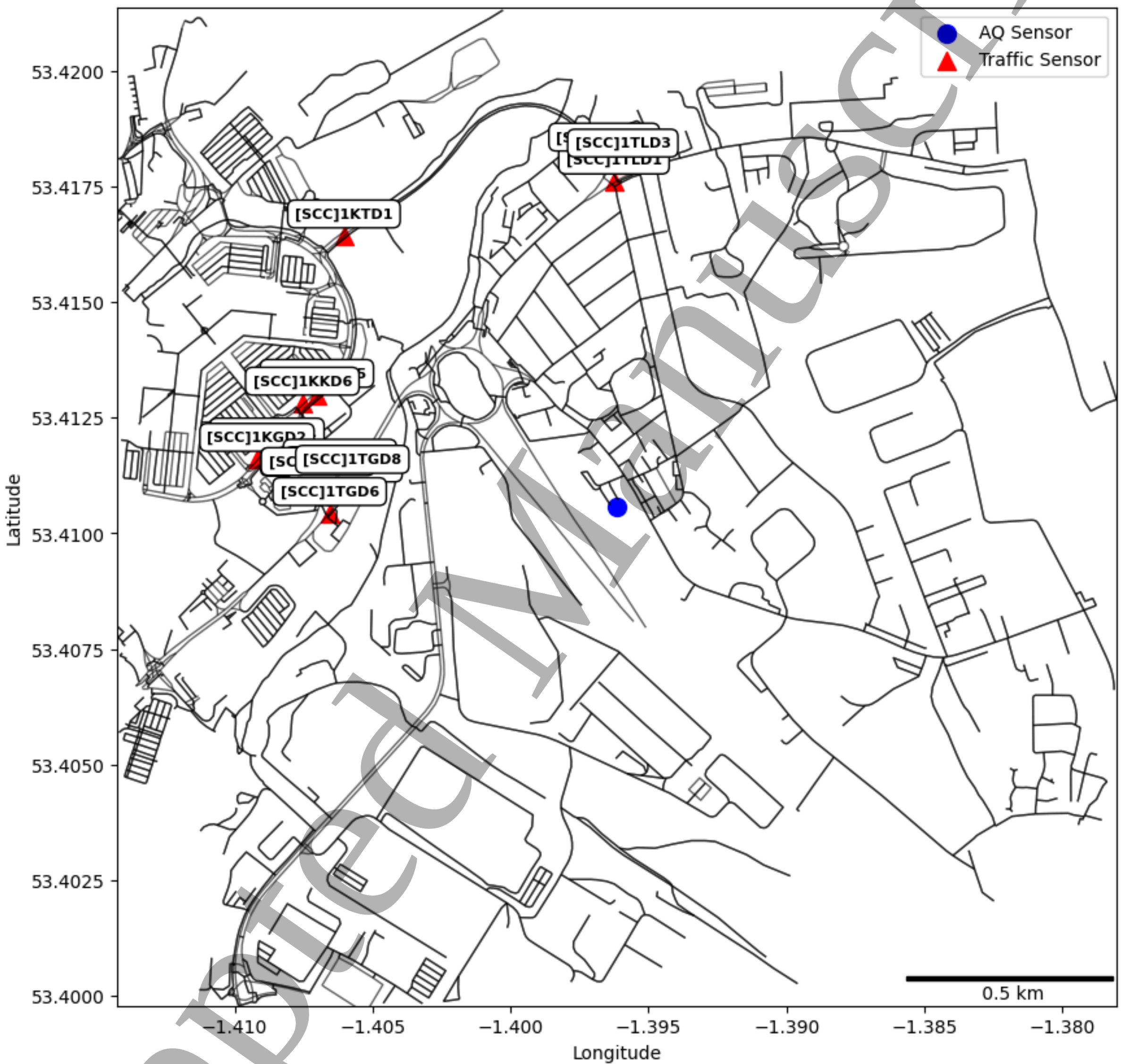


Figure A8. Map showing the locations of traffic sites identified within 1 km of primary site TN0. Map data from OpenStreetMap.

Accepted Manuscript

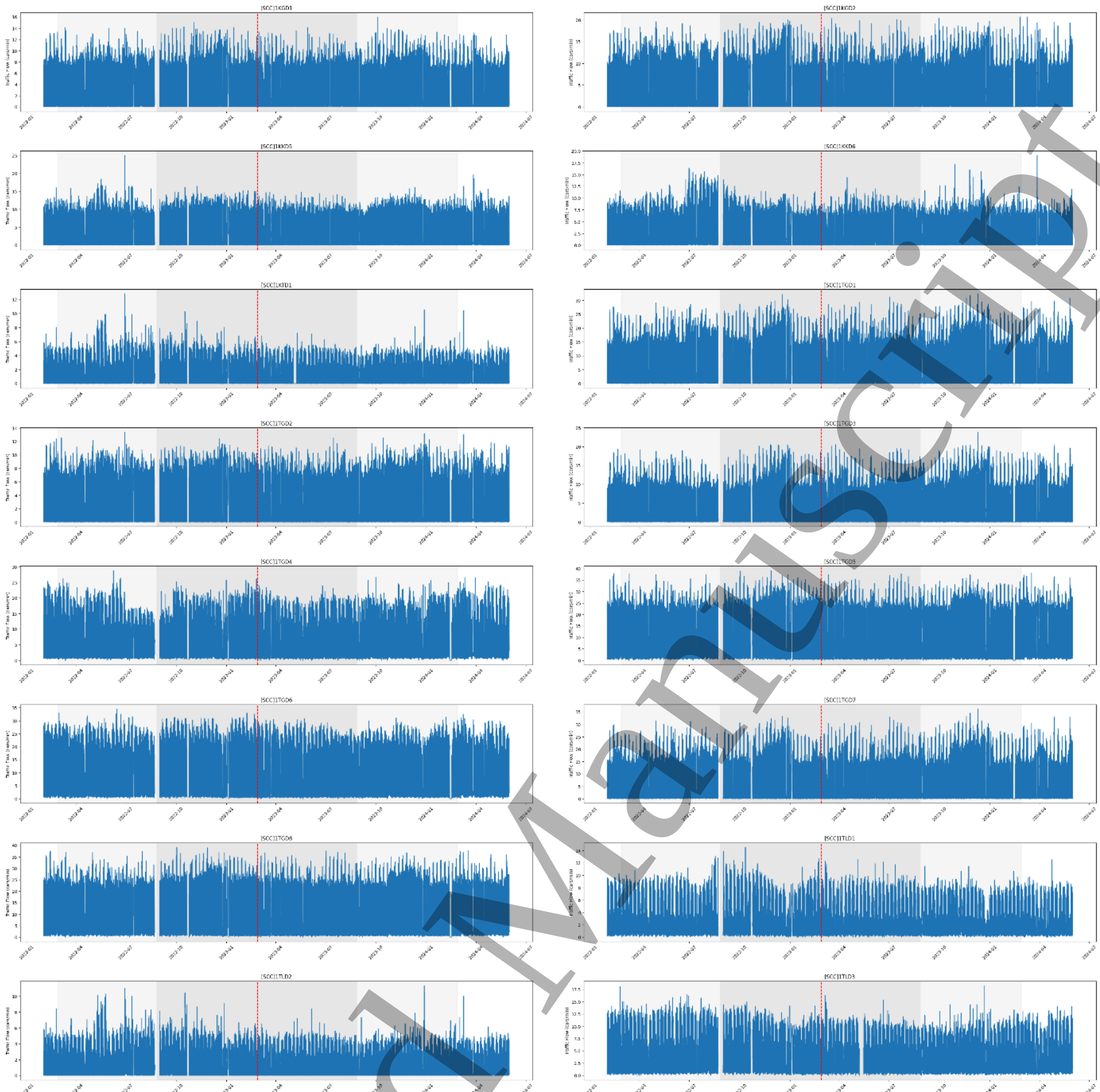


Figure A9. Traffic Flow for the sixteen traffic sites surrounding TN0 with the CAZ introduction shown as a vertical line and shaded regions representing 12 and 24 month spans.

Accepted Manuscript

Accessing Spillover

Traffic sites surrounding the CAZ were used to assess spillover. Figure A10 shows 39 identified sites. Of those, 33 sites were used to evaluate if spatial spillover had occurred due to the CAZ with six removed due to a large number of missing values or poor data quality. Similar to the traffic surrounding Primary AQ sites, the total number of cars per day was calculated and Wilcoxon signed-rank tests were used to determine if the CAZ significantly changed traffic volumes surrounding the CAZ (see Appendix E for plots showing traffic flows).

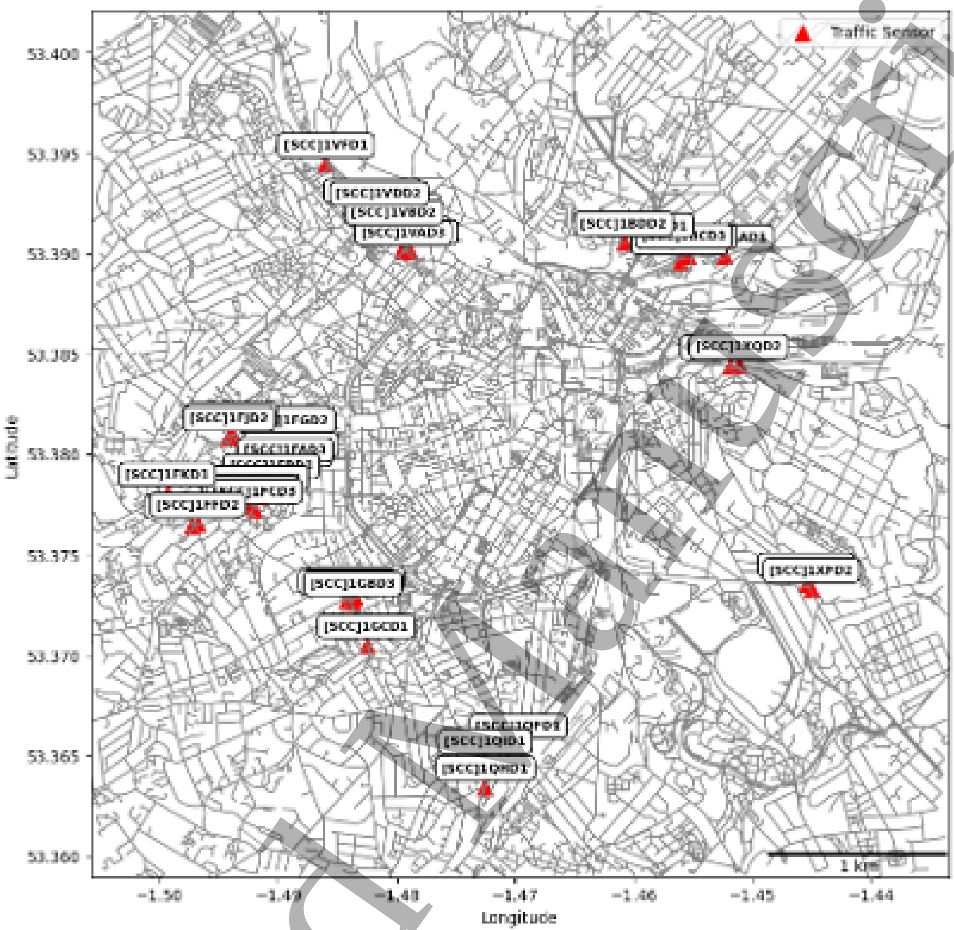


Figure A10. Map showing the traffic sensors located outside the CAZ, but within proximity to the City Centre used to evaluate spillover. Map data from OpenStreetMap.

Accepted Manuscript

D - Air Quality Histograms

Figures A11 and A12 show the distribution of AQ data for all sites. As can be seen the data was skewed, therefore, median imputation was used to handle missing values.

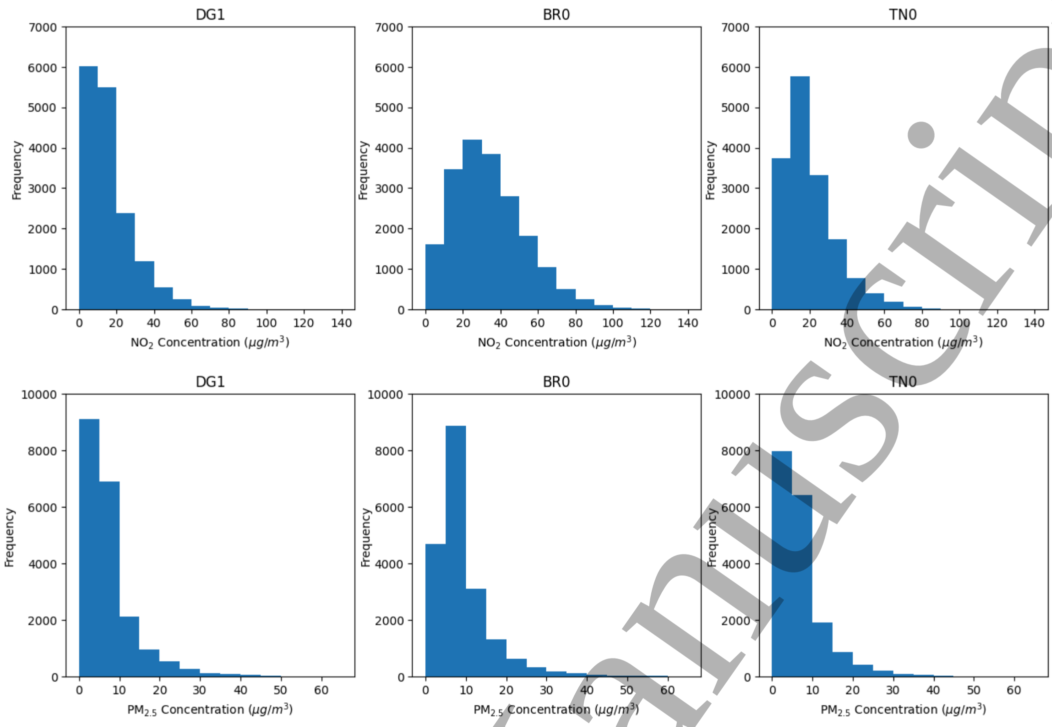


Figure A11. Histogram showing the distribution of sensor-read NO_2 and $PM_{2.5}$ concentrations for Primary AQ Sites.

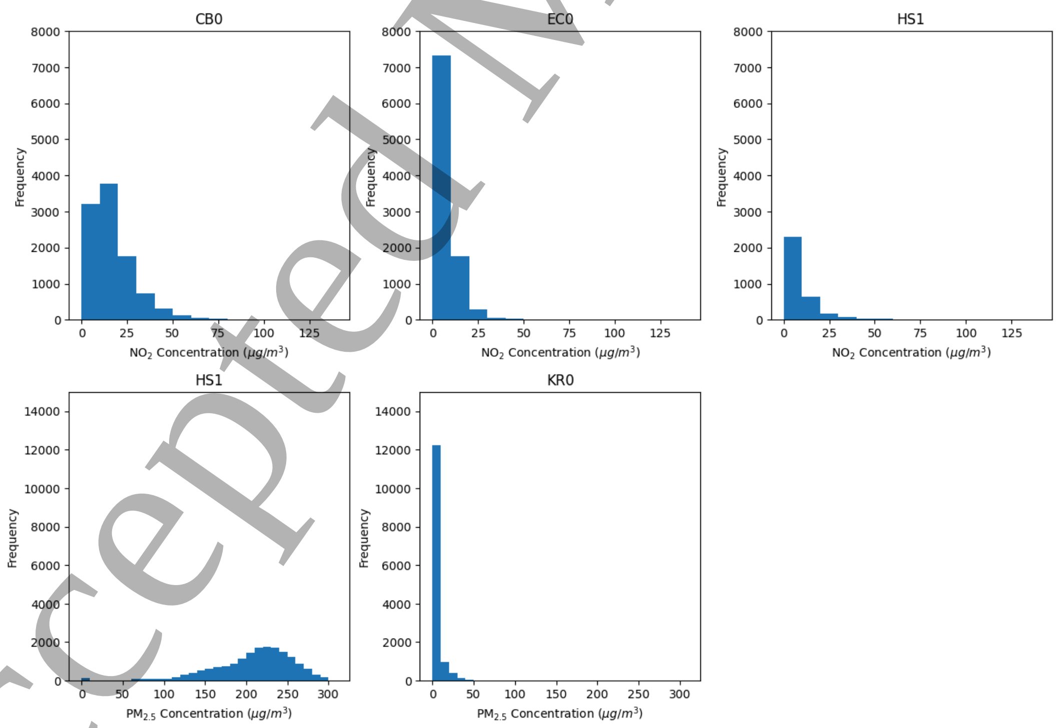


Figure A12. Histogram showing the distribution of sensor-read NO_2 and $PM_{2.5}$ concentrations for Secondary AQ Sites.

Accepted Manuscript

The mean daily pollutant concentration was then calculated for each site and pollutant. The mean daily concentration can be seen for the primary sites in Figure A13 and secondary sites in Figure A14. Secondary sites CB0 and EC0 only provided data for six months, hence the large gap between data points shown in Figure A6.

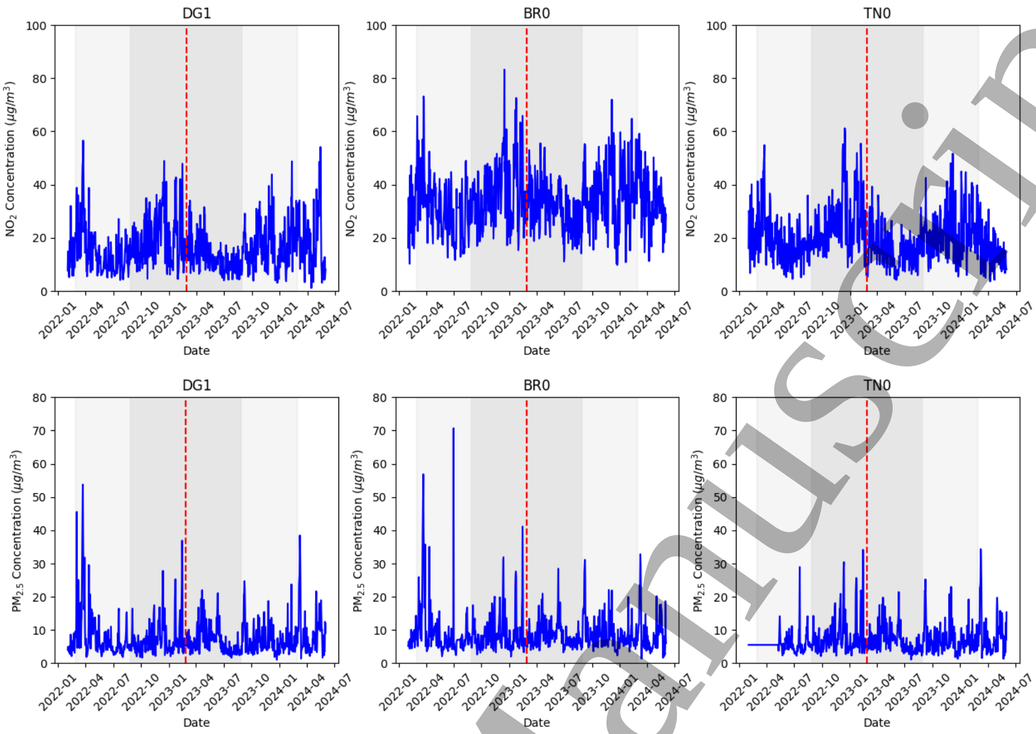


Figure A13. Mean daily concentrations of NO_2 and $PM_{2.5}$ for primary AQ sites with the CAZ introduction and 12 and 24 month windows annotated.

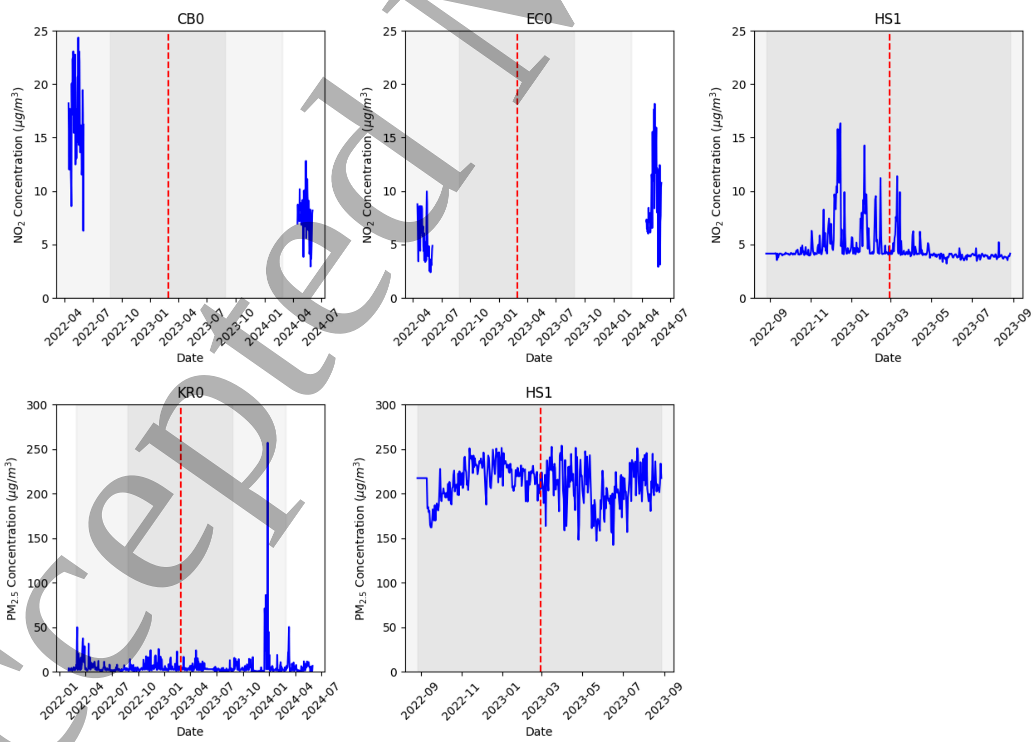


Figure A14. Mean daily concentrations of NO_2 and $PM_{2.5}$ for secondary AQ sites with the CAZ introduction and 12 and 24 month windows annotated.

Accepted Manuscript

Figure A15 and A16 present descriptive statistics for mean daily concentration of NO_2 and $PM_{2.5}$ for both primary and secondary AQ sites pre-normalisation.

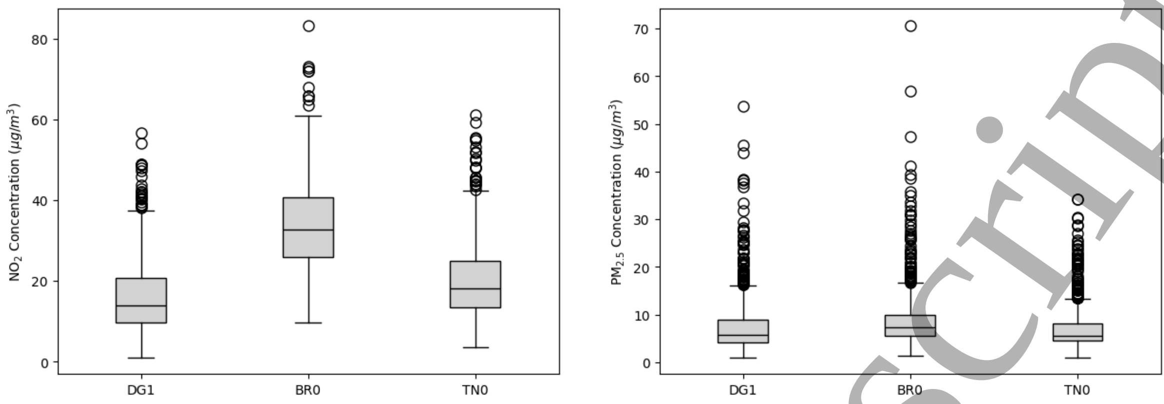


Figure A15. Boxplots showing the pre-normalised NO_2 and $PM_{2.5}$ concentrations for primary sites.

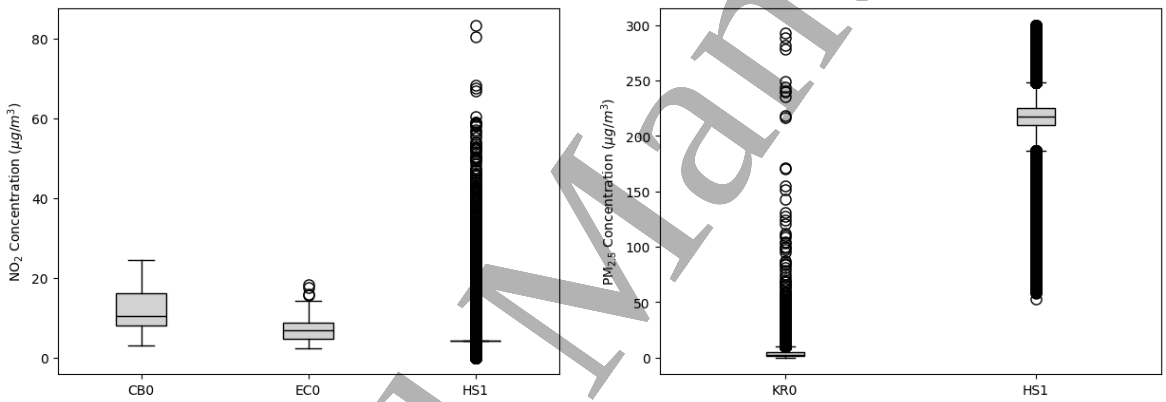


Figure A16. Boxplots showing the pre-normalised NO_2 and $PM_{2.5}$ concentrations for secondary sites.

Accepted Manuscript

E - Spillover Full Results

Below is a series of Figures showing the sensor-read traffic flow for the 39 sites initially assessed for spillover analysis. Of these sites, the six that were removed were [SCC]1FBD1, [SCC]1FGD2, [SCC]1FJD1, [SCC]1AAD1, [SCC]1VAD2, [SCC]1VFD1 leaving 26 sites for further analysis. Three were removed for not providing data in the analysis period, with [SCC]1AAD1 ,[SCC]1VAD2 and [SCC]1VFD1 removed for their large gaps of missing values.

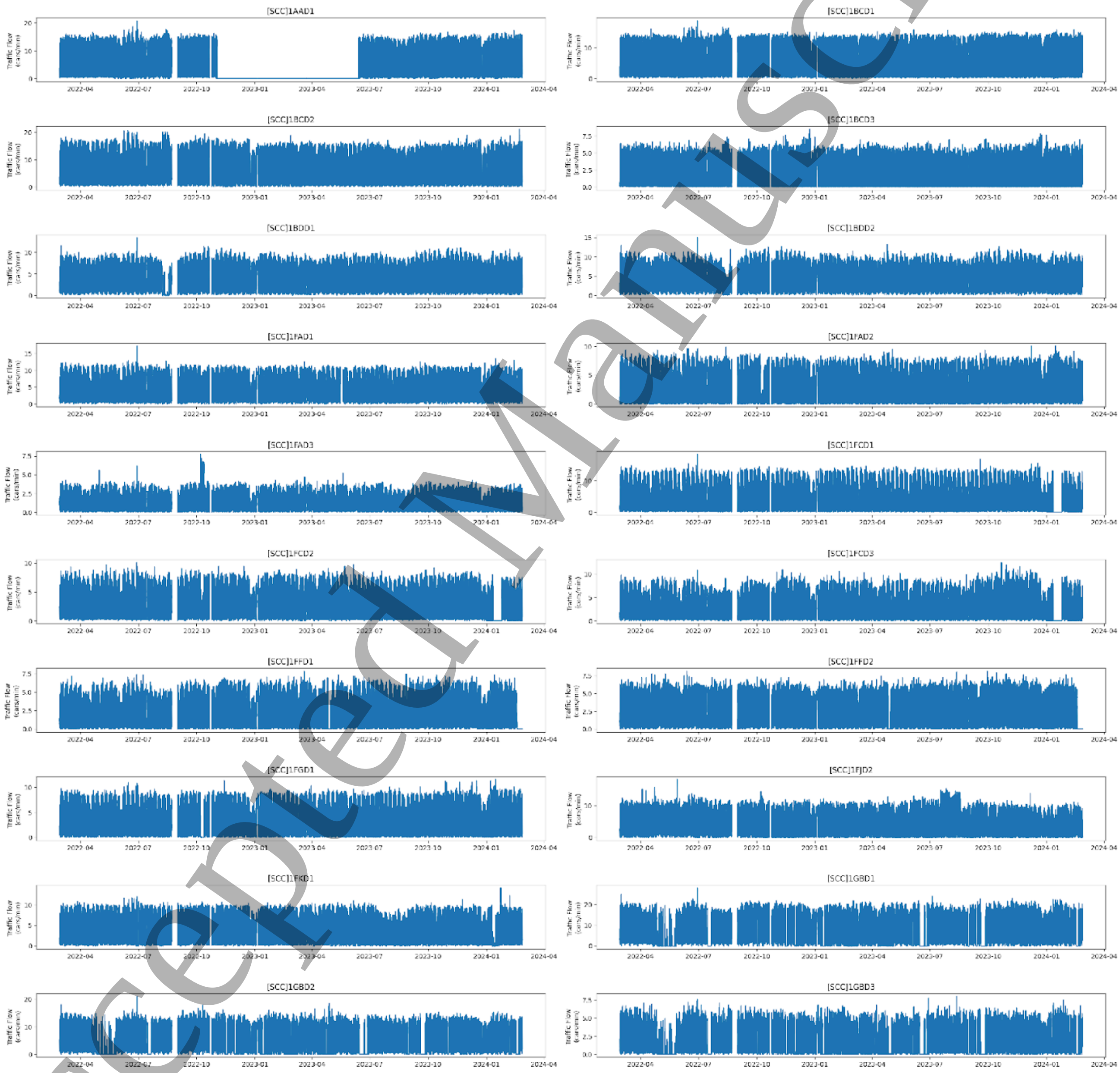


Figure A17. Traffic Flow for 20 out of the 36 Traffic sensors identified for spillover analysis.

Accepted Manuscript

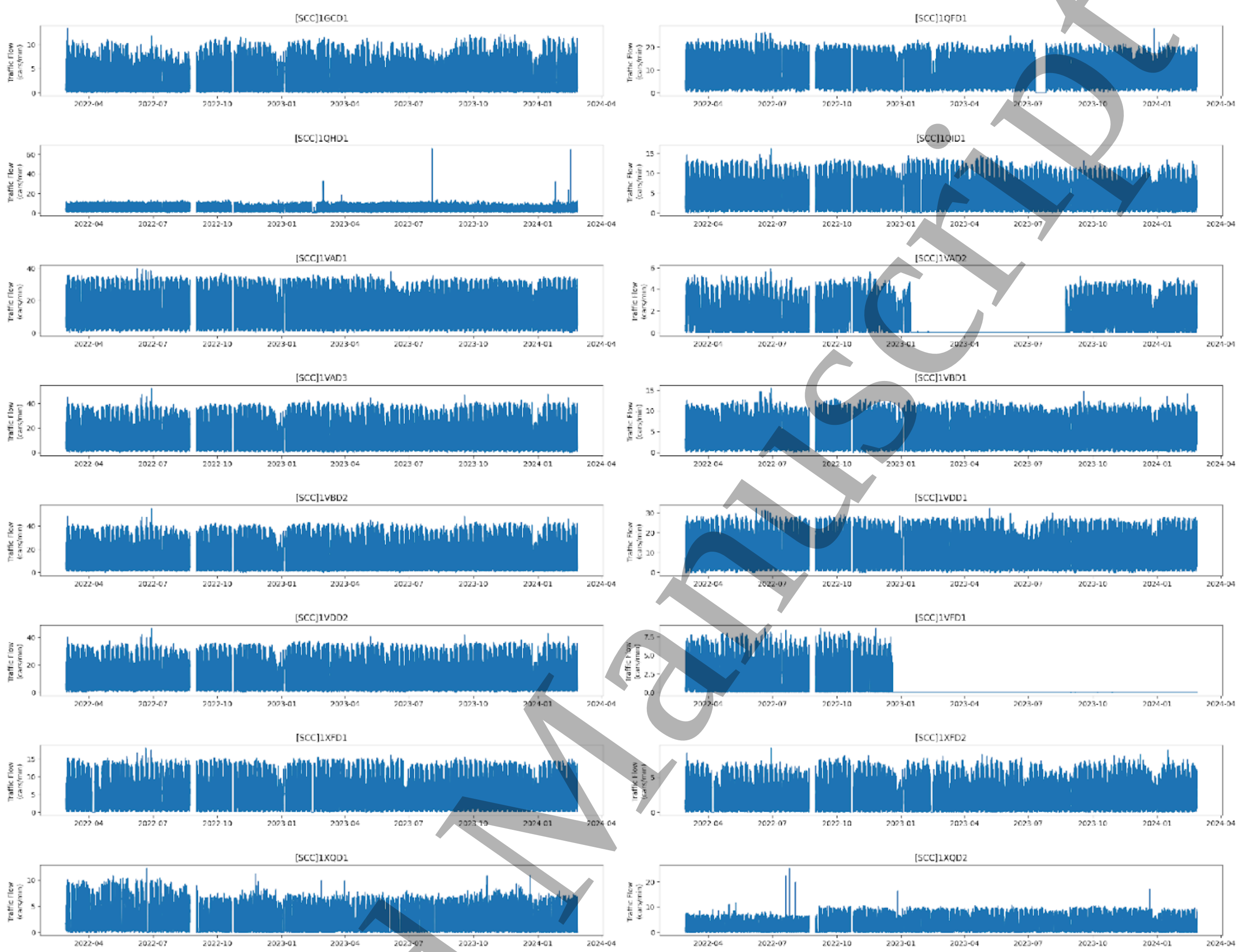


Figure A18. Traffic Flow for the remaining 16 out of the 36 Traffic sensors identified for spillover analysis.

For each of the sites, below Table A2 containing the Wilcoxon Signed Rank Test outcome for the 33 sites used in spillover analysis. Of those, 14 showed a significant decrease, and only 5 a significant increase, resulting in only 5 out of the 33 sensors (16%) showing a significant increase in traffic post-CAZ. This therefore suggests there was no evidence of negative spatial spillover caused by the CAZ.

Accepted Manuscript

Table A2. Wilcoxon Signed Rank Test for each traffic sensor used in spillover analysis.

Site	Test Statistic	p-value	< 0.05	Median Difference
[SCC]1BCD1	24436.5	8.9E-06	Yes	-200
[SCC]1BCD2	20255	7.25E-11	Yes	-656.8
[SCC]1BCD3	22192.5	2.78E-08	Yes	-200.8
[SCC]1BDD1	32477.5	0.648327	No	4
[SCC]1BDD2	32468.5	0.645122	No	5.6
[SCC]1FAD1	33095.5	0.880989	No	24
[SCC]1FAD2	31245	0.285929	No	46.4
[SCC]1FAD3	32477	0.648149	No	17.94286
[SCC]1FCD1	23124	3.52E-07	Yes	-266.4
[SCC]1FCD2	23394.5	7.09E-07	Yes	-106.4
[SCC]1FCD3	30243	0.117857	No	262.4
[SCC]1FFD1	20735	3.44E-10	Yes	308.8
[SCC]1FFD2	26047.5	0.000269	Yes	177.6
[SCC]1FGD1	30200.5	0.112988	No	64.8
[SCC]1FJD2	20196	5.97E-11	Yes	-701.6
[SCC]1FKD1	17016.5	4.63E-16	Yes	-383.2
[SCC]1GBD1	33179	0.913741	No	178.4
[SCC]1GBD2	31229	0.282363	No	-275.2
[SCC]1GBD3	31093	0.253268	No	-87.2
[SCC]1GCD1	25119.5	4.06E-05	Yes	219.2
[SCC]1QFD1	17061	5.55E-16	Yes	-935.657
[SCC]1QHD1	14126.5	1.25E-21	Yes	-794.4
[SCC]1QID1	20287.5	8.07E-11	Yes	-321.143
[SCC]1VAD1	26432.5	0.000735	Yes	-277.6
[SCC]1VAD3	28613.5	0.017709	Yes	-344
[SCC]1VBD1	32991	0.840291	No	83.2
[SCC]1VBD2	30649.5	0.173099	No	-93.6
[SCC]1VDD1	26871	0.001214	Yes	-178.4
[SCC]1VDD2	31480	0.34181	No	-15.2
[SCC]1XFD1	29734	0.069344	No	236
[SCC]1XFD2	28720	0.020403	Yes	144
[SCC]1XQD1	24697.5	1.61E-05	Yes	-348.8
[SCC]1XQD2	21334.5	2.23E-09	Yes	643.2

Accepted Manuscript