Public Health Research Programme – Rapid Funding Scheme

Rapid Funding Scheme Report – layout and headings

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Project title	Assessing the impact of zero and low emissions control interventions upon air quality in Oxford City; baseline data collection and feasibility study
NETSCC ID number	
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Disclaimer:	
Acknowledgements	The research was funded by the NIHR Public Health Research Programme [Grant number 130095]. The research was undertaken with the support of Oxford City Council and Oxfordshire County Council.
Background	Poor air quality is the largest environmental risk to health in the UK with pollutant levels in many cities regularly exceeding legal limits and health-based guidelines[1]. Air pollution is recognised to exert a mortality burden equivalent to 28,000-36,000 deaths each year in the UK,[2] with estimated economic costs of over £20Bn.[3] Air pollution is consistently ranked in the top five causes of death in urban areas, ahead of road traffic accidents, excess winter deaths and communicable diseases.[4]

	Road transport is widely recognised as the major urban air pollution source and traffic emissions control measures are a key policy intervention option. In 2017, the Government published a framework to support local authority actions to reduce Nitrogen Dioxide (NO_2) levels to below EU legal limits EU legal limits [e.g. 40 μg/m^3 annual mean][5] in the shortest possible timeframe, including introduction of targeted 'Clean Air Zones' in UK cities.[6] In this context, Oxford City Council and Oxfordshire County Council planned to implement Zero Emissions Zone (ZEZ) and Low Emission Zone (LEZ) control interventions from late 2020.[7] Emissions control interventions are primarily focussed upon achieving legal NO_2 compliance within a defined area, with effectiveness to improve population health and wellbeing remaining poorly defined in the UK. Existing LEZ evaluations have concentrated upon large core cities (e.g. ULEZ – London)[8] with limited information from small and medium-sized cities, such as Oxford. This policy context provided a unique and timely opportunity to perform a feasibility study of low- cost sensor technology for pre-intervention data acquisition to enable future quantification of scheme impacts upon air quality, health, local economy and wider society.
Plain English Summary	**Background:** Oxford City has recognised air quality and health inequity challenges, with the equivalent of 1 in 20 deaths due to air pollution. We sought to assess the practicality and viability of using wireless ‘low-cost’ air quality sensors mounted on buildings in the city centre to provide detailed real-time air quality information. This network may also be used to assess the impact of transportation changes (such as those occurring during the COVID-19 pandemic) and introduction of additional pollution control measures, including proposed restrictions on the most polluting vehicles. **Methods:** We set up a network of wireless ‘low-cost’ air quality sensors to capture real-time information on Particulate Matter (PM), Nitrogen Oxide (NO) and Nitrogen Dioxide (NO_2) levels. Three sensors were operational from January to June 2020, throughout the COVID-19 “lockdown” period, with further sensors installed once restrictions were lifted. We applied statistical methods to account for differences in sensor performance and compared our results to those obtained from the Government regulatory air quality monitoring stations. Finally, we assessed changes in average pollutant concentrations before and after introduction of COVID-19 public health restrictions. **Results:** Sensors performed well in laboratory testing. The study team experienced several technical challenges when setting up the network although these have now been overcome. Data analysis of raw outputs before and after the COVID-19 lockdown showed significant reductions in PM (PM_1, $PM_{2.5}$ and PM_{10}) at all three locations. Changes in NO and NO_2 were less marked, with a reduction in NO_2 levels at one site only. Data analysis is ongoing to fully understand the effects of weather conditions and sensor performance upon measured values. **Conclusion**: We report successful establishment of a low-cost air quality sensor network in an urban city environment. Preliminary findings indicate data generated are suitable for assessment of air quality intervention impacts
Scientific Summary	**Background** Poor air quality is the largest environmental risk to health in the UK with pollutant levels in many cities regularly exceeding legal limits and health-based guidelines.[1] Planned emissions control measures in Oxford City

include proposed introduction of a Zero Emissions Zone (ZEZ) and enhanced Low Emission Zone (LEZ). Assessment of the impacts of such measures requires high spatio-temporal resolution air quality data at baseline conditions.

Objectives:
(a) Assess feasibility of low-cost sensor deployment for obtaining high spatio-temporal resolution air quality data (NO_2, particles (PM)) in Oxford City
(b) Produce micro-scale AP exposure estimates at key City Centre locations
(c) Calculate pre-intervention impacts of AP exposure upon: (i) premature mortality; (ii) lifetime economic costs; (iii) health inequalities in Oxford City.
(d) Assess modelled impacts of future intervention measures (e.g. ZEZ/LEZ)

The originally stated baseline data collection and analysis activities were disrupted considerably due to the COVID-19 pandemic and associated public health measures, with delays in sensor deployment date due to resource and building access restrictions. The focus of this report is therefore objectives (a) and (b) as (c) and (d) were not possible under the circumstances.

Setting: Oxford City (population ~155,000).

Methods
Data Collection
Eight South Coast Science (SCS) Praxis Urban air quality sensors were procured to measure four gaseous pollutants (Carbon Monoxide – CO, Nitrogen Oxide – NO, Nitrogen Dioxide – NO_2, Ozone – O_3) by electrochemical sensor and Particulate Matter (PM_1, $PM_{2.5}$, PM_{10}) by optical particle counter (Alphasense OPC-N3). Air quality sensors were laboratory tested for four days prior to field deployment to assess dependence of gaseous and PM measurements upon temperature and humidity. Sensor offsets from baseline were subsequently assessed by co-location of selected units at the Defra Automatic Urban and Rural Monitoring Network (AURN) sites at roadside (High Street) and urban background (St Ebbes) locations.

Sensor Deployment
Air quality sensors were wall-mounted on public and privately-owned building assets at selected City Centre locations at distances 1.1-9.7 metres from roadside and heights 1.2-9.5 metres. Site locations were originally selected to measure impacts across the proposed LEZ/ZEZ intervention areas; and detailed placement was decided by power availability, sensor security, and proximity to breathing height.

Data Processing and Statistical Analysis
Data filters were applied to remove data observations (temperature, humidity, pollutant concentrations) outside the expected performance bounds. The *Iteratively Reweighted Penalised Least Squares* regression analysis (AirPLS) method was adopted for sensor baseline estimation and offset adjustment using data comparison to AURN measurements (urban background). An alternative machine learning Random Forest data processing technique was applied, utilising an algorithm ensemble of Decision Trees developed during a sensor "training period, removing the need for AURN comparison data.

Patient and Public Involvement
Three public involvement sessions were held during the study, involving cycling campaigners, commercial bus drivers and members of the wider general public respectively. A research poster detailing study methods was presented to academic, commercial and policy representatives at the 2020 Oxford Air Quality Meeting.

	Results Sensor performance and internal comparability for PM measurement was acceptable (uncorrected errors were <10% for all sensors) in laboratory testing. Technical challenges encountered during sensor deployment included temperature and humidity board (SHT) failure (four units), and 4G modem replacement (two units). All sensors required software upgrades (provided by the manufacturer) but the majority have proved robust under field conditions, with three operational sensors performing continuous data collection for a study period of >3 months. Examination of uncorrected values for daily pollutant values from three operational SCS study sensors (Feb – end May 2020) revealed significant reductions in PM concentrations associated with the COVID-19 "lockdown" period (mean concentration change -44% $PM_{2.5}$, -43% PM_{10}) with few significant changes observed in NO_2 levels. **Conclusions** We report our experience of deployment of a low-cost sensor network in Oxford City and the generation of high spatio-temporal resolution point estimates at multiple sensor locations. We have identified and addressed multiple logistical and technical challenges associated with low-cost sensor deployment in an urban setting. Further detailed analyses of fully processed and adjusted data will be required to understand relative changes in pollutant concentrations at specified city centre locations to generate further insights regarding impacts of the COVID-19 lockdown period upon NO_2 and PM concentrations. Changes in population level exposures and therefore health impacts associated with these changes are more uncertain and estimates were not undertaken due to health behavioural and service access changes during the COVID-19 lockdown period. The data collected are not representative of (the previous) business-as-usual scenario as originally planned due to impacts of the COVID-19 pandemic. However, the established sensor network provides valuable monitoring capability to quantify air quality impacts of these natural experimental changes and forthcoming COVID-19 recovery transport measures within the city. As a result of this study we recommend the following future research priorities: 1. Undertake further investigation and comparison of ML algorithms for correcting data obtained from networks of low-cost air quality sensors 2. Estimate pre-intervention (business-as-usual) impacts of air pollution exposure upon: (i) premature mortality; (ii) lifetime economic costs; (iii) health inequalities in Oxford City. 3. Assess modelled impacts of future intervention measures (e.g. ZEZ/LEZ measures) 4. Assess air quality and health impacts of COVID-19 recovery emergency active travel and transport interventions (e.g. Low Traffic Neighbourhoods, bus gates) 5. Undertake comparisons of sensor performance characteristics, calibration methods and air quality measurements to those obtained using comparable low-cost sensor technology in other settings.
Study aims,	The overarching aim of this feasibility study was to obtain detailed baseline air

objectives and research question	quality data (NO_2, $PM_{1,2.5,10}$) for Oxford City to enable subsequent environmental, health and economic impact assessment. The originally stated objectives of this baseline study were to: (a) Assess feasibility of low-cost sensor deployment for obtaining high spatio-temporal resolution air quality data (NO_2, particles (PM)) in Oxford City (b) Produce micro-scale AP exposure estimates at key City Centre locations (c) Calculate pre-intervention impacts of AP exposure upon: (i) premature mortality; (ii) lifetime economic costs; (iii) health inequalities in Oxford City. (d) Assess modelled impacts of future intervention measures (e.g. ZEZ/LEZ) The originally stated baseline data collection and analysis activities were disrupted considerably due to the COVID-19 pandemic and associated public health measures, with delays in sensor deployment due to resource and building access restrictions. The focus of this report is therefore objectives (a) and (b) as (c) and (d) were not possible under the circumstances.
Methods	**Sensor validation and calibration** Eight South Coast Science (SCS) Praxis Urban air quality sensors were procured within the study. The SCS Praxis Urban unit measures four gaseous pollutants (Carbon Monoxide – CO, Nitrogen Oxide – NO, Nitrogen Dioxide – NO_2, Ozone – O_3) sensor and Particulate Matter (PM_1, $PM_{2.5}$, PM_{10}). Gases are measured by electrochemical sensors and the particulates by optical particle counter (Alphasense OPC-N3) (Appendix A). Air quality sensors were laboratory tested for four days prior to field deployment to assess dependence of gaseous and PM measurements upon temperature and humidity. Sensor offsets from baseline were subsequently assessed by co-location of selected units at the Defra Automatic Urban and Rural Monitoring Network (AURN) sites at roadside (High Street) and urban background (St Ebbes) locations. **Sensor deployment** Air quality sensors were wall-mounted on public and privately-owned building assets at selected City Centre locations at distances 1.1-9.7 metres from roadside and heights 1.2-9.5 metres (Table 1). Locations were chosen to measure the impact across the LEZ/ZEZ intervention areas; and detailed placement was decided by power availability, sensor security, and proximity to breathing height. Table 1. Air quality sensor site characteristics and deployment dates

Sensor No.	Deployment Date	Site type	Distance from roadside (m)	Height (m)
536	In storage[a]	Roadside, cul-de- sac	N/A	N/A
537	30/01/2020	Close to busy road, near railway station	TBC	9.5
538	04/06/2020[a]	AURN Station Urban background	8	2.7

539	28/01/2020	Roadside, cul-de- sac, waiting area for delivery mopeds	1.1	3.3
541	24/02/2020	Roadside, arterial route into central Oxford	9.7	1.2
542	23/01/2020	Roadside, arterial route into central Oxford	-	4.7
543	25/01/2020	Roadside, main arterial route into central Oxford	3.5	5.5
552	04/06/2020[a]	AURN Station Roadside, main arterial route into central Oxford	3.7	1.4

[a]Deployment delayed due to COVID-19 restrictions.

Data processing and analysis

Data cleaning was performed by applying filters to remove observational data observations (temperature, humidity) outside the expected performance bounds. Short-term peaks in NO_2 concentrations exceeding 1000 ppb were excluded, considered to reflect uncorrected interferences from environmental influences upon sensor performance.

The *Iteratively Reweighted Penalised Least Squares* regression analysis *(AirPLS)* method[9] was adopted for sensor baseline estimation and offset adjustment, targeting corrections in sensor drift by iteratively changing weights of sum squares errors (SSEs) between the fitted baseline and original signals, with weights of SSE obtained adaptively using the difference between the previously fitted baseline and original signals. External offset correction was performed by attenuating the sensor baseline relative to the data series for the corresponding time-period obtained from the St Ebbes AURN urban background station. Finally, residual negative sensor observations were removed.

An alternative approach to data analysis was also attempted for the first time, using the machine learning (ML) *Random Forest* (RF) technique, which is an algorithm ensemble of Decision Trees. This approach removes the need to have comparison data from the AURN, after an initial "training" period. In this work the splitting criterion used for each branch of the decision tree was the mean squared error. In order to find the optimum parameter and value to perform a split at each node, a greedy algorithm was used. Mean absolute errors (MAE) from before and after the use of the RF approach for NO2 for three sensors are shown in Table 2.

Table 2. NO_2 Mean Absolute Error before and after the use of RF models

NO2 Mean absolute error ($\mu g/m^3$)		
Sensor	Before	After

539	14.8	5.7
541	47.4	7.4
542	66.3	5.5

Data adjustment for temperature and humidity

Adjustment for the effect of humidity on the PM and NO_2 readings is ongoing. In order to understand such effects, the approach adopted focuses on data taken for the month of April, when the lockdown was in full effect, with the hypothesis that the measured values between the AURN roadside and background readings will converge or at least show the same patterns. As such the background AURN data from the St Ebbe's station will be used as the reference signal for this analysis.

All data processing and analysis was performed using Python and R.

Public and patient Involvement

The study team adopted a targeted approach for public involvement, comprising three interactive group sessions: (i) active travel campaigners; (ii) commercial bus drivers; (iii) public webinar event. The former two sessions included question prompts to explore perceptions of local air quality and preferences for air quality research priorities and outcome measures. The final session comprised a focussed question and answer session exploring impacts of the COVID-19 pandemic upon local air quality.

In addition, a dissemination event, the Oxford Air Quality Meeting, was held on Jan 10 2020, with over 160 attendees from the public, policy, industry, and academic communities. A project poster was displayed and the project team members discussed the project with the attendees (it was too early in the project to give a formal presentation).

Results

Feasibility assessment

Technical challenges encountered during sensor deployment included temperature and humidity board (SHT) failure (four units), and 4G modem replacement (two units). All sensors have also required software upgrades (provided by the manufacturer) but the majority have proved robust under field conditions, with three operational sensors performing continuous data collection for a study period of >3 months. The learning obtained by the first field deployment has demonstrated the feasibility of the data gathering approach and following these initial teething problems the authors' now have no concerns about the viability of this approach.

Sensor performance

In laboratory testing sensor performance and internal comparability for PM measurement was acceptable (uncorrected errors were <10% for all sensors and subsequent analysis and processing reduces this even further). Electrochemical sensor measurements (for gases) showed greater variability than for PM. The effect of humidity on PM and NO_2 observations under field conditions is subject to ongoing further detailed investigation using the methods previously described.

$PM_{2.5}$ and NO_x assessment

Analysis of regulatory data obtained from the Oxford High Street AURN station (NO, NO_2, PM_{10}) indicates a marked reduction in average daily roadside

NO/NO_2 concentrations following introduction COVID-19 restrictions from late March 2020 (Table 2). Average daily NO_2 concentrations decreased from 32.1 to 15.6 μgm^{-3}, a reduction to 49% of original levels (Table 3).

Table 3. Comparison of average (mean, 95% CI) roadside values of pollutant concentrations (NO/NO_2) measured at Oxford High Street (AURN) before and after introduction of COVID-19 emergency public health measures.

Pollutant	*1 Jan – 23 Mar ($\mu g/m^3$)*		*24 Mar – 31 May 2020 ($\mu g/m^3$)*	
	Mean	95 % CI	Mean	95% CI
NO	22.8	21.3 – 24.3	5.4	5.0 – 5.8
NO_2	32.1	31.3 - 33.1	15.6	15.0 – 16.1

There was no statistically significant change in overall PM_{10} concentrations (although the mean increases), with a notable PM episode occurring in early-mid April 2020 (Figure 1)

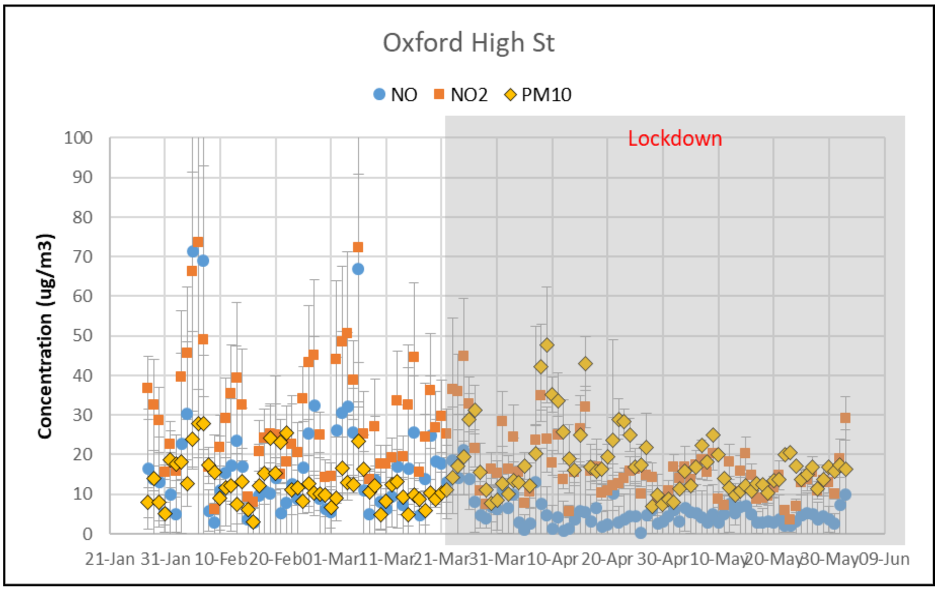

Figure 1. NO, NO_2, and PM_{10} daily means from the AURN Oxford High St site (error bars correspond to ±σ).

Examination of uncorrected values for daily pollutant values from three operational SCS study sensors (Feb – end May 2020) also reveals a noticeable drop in PM concentrations associated with the COVID-19 “lockdown” period with few significant changes observed in NO_2 levels (Figures 2-4, Table 4). All sensors exhibit trends similar to background levels, which are the focus of ongoing investigation.

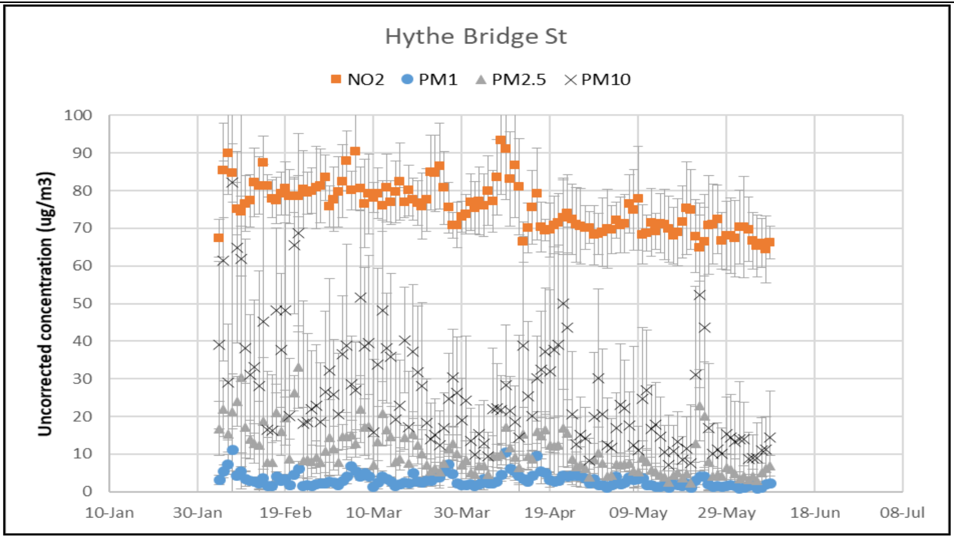

Figure 2 Uncorrected NO_2 and PM $_{(1, 2.5, 10)}$ values from Hythe Bridge Street (SCS Sensor 542) (error bars correspond to ±σ)

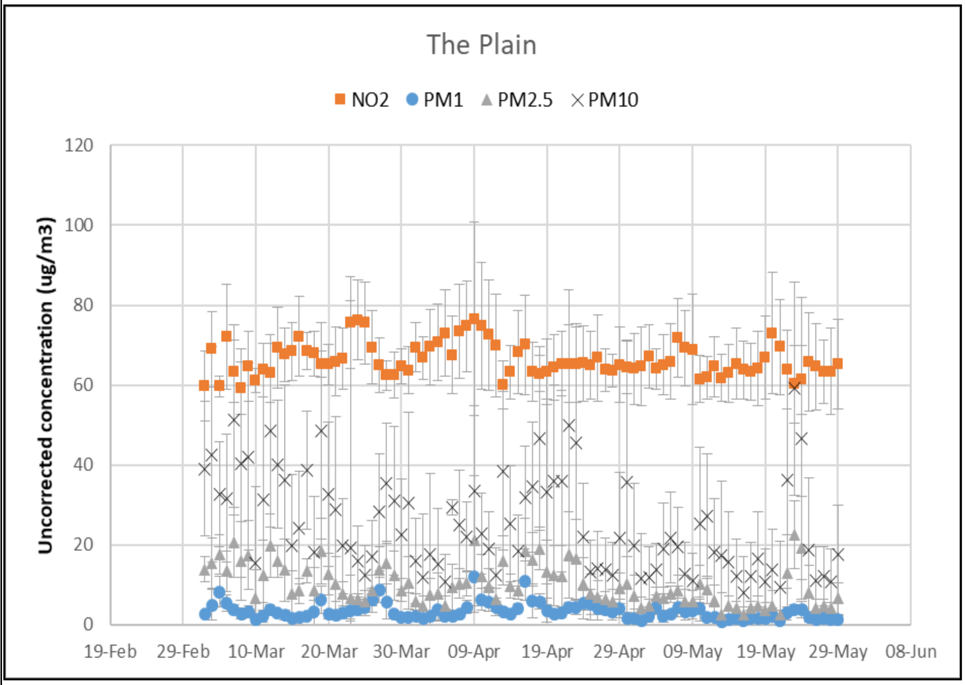

Figure 3 Uncorrected NO_2 and PM $_{(1, 2.5, 10)}$ values from The Plain (SCS Sensor 541) (error bars correspond to ±σ)

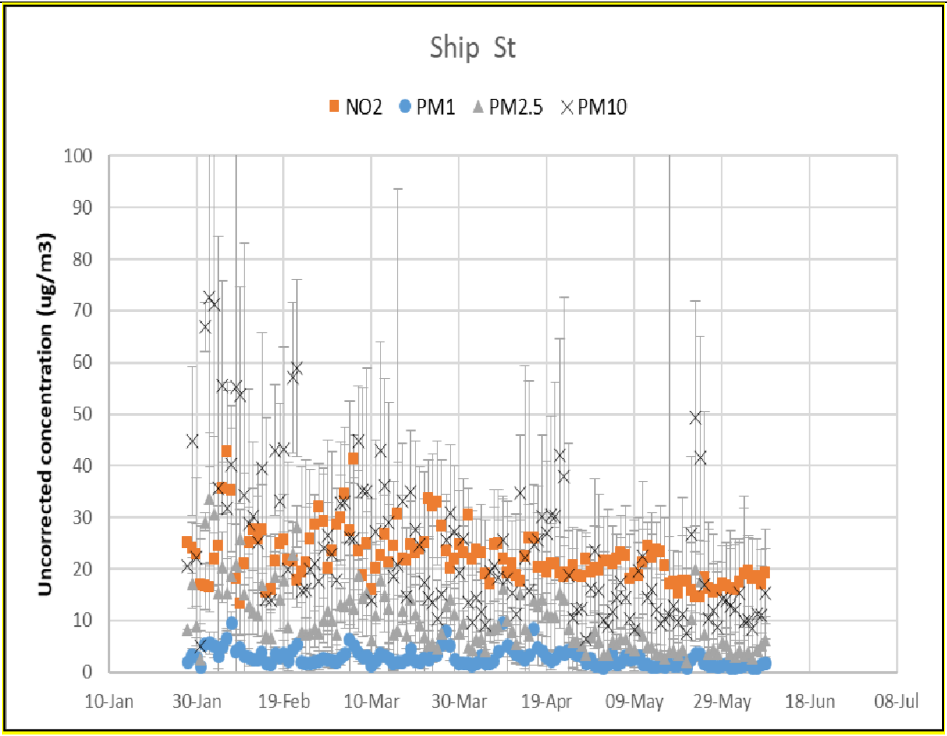

Figure 4 Uncorrected NO_2 and PM $_{(1, 2.5, 10)}$ values from Ship Street (SCS Sensor 539) (error bars correspond to ±σ)

Table 4. Percentage change in pollution readings prior to and after introduction of COVID-19 emergency public health measures.

Location	*Pollutant*			
	NO_2	PM_1	$PM_{2.5}$	PM_{10}
Ship St	Not significant	Not significant	-48%	-46%
The Plain	Not significant	Not significant	-39%	-39%
Hythe Bridge St	-8%	Not significant	-45%	-44%

Conclusions and Recommendations

We report our experience of deployment of a low-cost sensor network in Oxford City and the generation of high spatio-temporal resolution point estimates at multiple sensor locations. We have identified and addressed multiple logistical and technical challenges associated with low-cost sensor deployment in an urban setting. Our analytical approaches to data analyses for NO_2 data are described including use of the AirPLS algorithm for baseline offset correction and application of machine learning as an alternative data processing technique, which is not reliant upon regulatory station data.

Preliminary analyses of regulatory air quality data obtained during the COVID-19 lockdown period has identified marked roadside reductions in NO_2 concentrations associated with reductions in vehicle traffic, with limited changes and greater variation in average daily PM concentrations. These findings are consistent within those reported within the Defra Air Quality Expert Group (AQEG) rapid evidence review undertaken in June 2020, which identified the most pronounced changes in air quality to be within the urban environment with typical reductions in mean NO_2 concentrations of 20-39% over the lockdown period. Such changes typically correspond to decreases in concentrations of 10-20μgm^{-3} if expressed relative to annual averages and are broadly consistent with a 50-60% reduction in traffic as observed in Oxford.

Further detailed analyses of fully processed and adjusted data will be required to understand these relative changes in pollutant concentrations at specified

	city centre locations and generate further insights regarding the impacts of the lockdown period upon PM concentrations, measures (transport contributes to 18% of PM_{10} and 21% $PM_{2.5}$ emissions in the city).[10] The sensor network provides novel monitoring capability for PM assessment; of value for informing policy recommendations including those within the Oxford City Council Air Quality Action Plan. Changes in population level exposures and therefore health impacts associated with these changes are more uncertain compared to estimates of changes in ambient concentration; notably due to widespread health and behavioural changes during the COVID-19 lockdown period. The data are a very useful starting point, but the authors hesitate to say whether they form an appropriate baseline. At the time of writing the proposed ZEZ/LEZ intervention is postponed and uncertain, and the data that have been gathered are not representative of (the previous) business as usual due to the COVID-19 pandemic. However, it remains to be seen what business as usual will look like going forwards. The authors continue to monitor the situation.
Appendices	Appendix A: South Coast Science Praxis Unit – Detailed specification

Appendix A: SCS Urban Praxis Unit – Detailed Specification
Sensing

- Alphasense analogue front-end (AFE) supporting up to four A4 electrochemical sensors
  - Ozone, model no. OX-A431
  - Nitrogen dioxide, model no. NO2-A43F
  - Nitric oxide, model no. NO-A4
  - Carbon monoxide, model no. CO-A4
- Ultra low-noise circuitry maximises repeatability of electrochemical sensing.
- Particulate monitoring via Alphasense OPC-N3 particle counters.
- Temperature and relative humidity via Sensirion (SHT) device.

Communications

- Wired: ethernet via waterproof RJ45 connector.
- Wireless: 4G cellular modem.

Processor

- Raspberry Pi Zero.

Clock

- Real time clock with battery backup.
- Time synchronisation is via GPS receiver, network time protocol or real time clock, as available.

Power

- 90 to 240 V AC Mains or 7 to 24 V DC input.
- Internal battery backup for up to 2 hours operation. ● Environment Operating range: -10 to 50 Centigrade.

Data infrastructure

- Sensed data messaging, control messaging via MQTT
- Data storage using Amazon Web Services (DynamoDB) with Python based API libraries and data dashboard.
- The SCS Praxis Urban logs at 0.1 Hz and transmits its data over the 4G network. The units are relatively easy to install requiring 12-24V DC or 240V AC (mains) power.

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