Evaluation of air quality effects of the London Ultra-Low Emission Zone by State-Space Modelling

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Abstract

In April 2019, an ultra-low emission zone (uLEZ) was implemented in London to tackle road transport air pollution. In this study, a state-space intervention model is developed for the first time to quantify the effects of this policy on London air quality. For developing this model, hourly NO, NO_2, and NO_x concentrations at 28 monitoring stations across London for 12 months before the uLEZ intervention and 11 months following it were used. Additionally, this model accounts for the influences of the meteorological variables of temperature, wind speed, and humidity, as well as those of the day of the week and calendar month.

The results of this model showed the uLEZ intervention was successful in reducing NO, NO_2, and NO_x concentrations not just within the zone of implementation but also throughout the wider low emission zone (LEZ) and Greater London area. This intervention made the greatest reduction in NO and NO_x in the uLEZ area (19% and 20%, respectively), followed by the LEZ (18% and 17%) and then Greater London (11% and 15%). The reduction in NO_2 in the uLEZ and LEZ is similar (11%-12%), with a larger reduction elsewhere in the Greater London area (13%).

Keywords: state-space modelling, ultra-low emission zone, air quality analysis.

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1. Introduction

Air pollution exposure is a leading risk factor for human health, contributing to 3.4 million premature deaths in 2017 worldwide (Soriano et al., 2017; Stanaway et al., 2018). In addition to human health, air pollution has negative impacts on anthropogenic ecosystems (Ochoa-Hueso et al., 2017) and climate (Shindell et al., 2009).

Road transport is a significant source of pollution in metropolitan areas; it accounted for almost half of NO_x emissions in London during 2016 (*London Atmospheric Emissions Inventory (LAEI) 2016 - Methodology*, 2020). Since 1992, a succession of Euro standards has been created to combat road transport air pollution, with progressively more stringent restrictions to regulate exhaust emissions of new vehicles (Hitchcock et al., 2014). In addition to these regulations, some policies for controlling traffic flow have been developed to reduce air pollution in urban areas. Among these policies, operating and pricing strategies such as low/zero emission zones have the greatest influence on improving urban air quality (York Bigazzi & Rouleau, 2017).

A low emission zone (LEZ) is designed to restrict vehicles based on their pollutant emission in a specific area. The first LEZ was implemented in Sweden in 1996, with others introduced subsequently in other European cities (Settey et al., 2019). There are currently about 260 LEZs in European countries. In Paris, the first LEZ was introduced in 2015, with estimated reductions in road transport NO_x and PM_{10} of 23-44% and 17-25%, respectively (Host et al., 2020). In addition, a recent study (Poulhès & Proulhac, 2021) found this restriction benefits not just LEZ residents, but also people living outside of Paris. In Lisbon, an LEZ was implemented in two phases between 2011 and 2012, and a study looked at the temporal concentrations of several pollutants from 2009 to 2016 (Santos et al., 2019). This analysis showed that the NO_x concentration has decreased by 13% but still exceeds the EU limit which is 40 μgm^{-3} (European Comission, 2017) . Similar studies have been reported for German cities such as Berlin (Gehrsitz, 2017; Poulhès & Proulhac, 2021), and Stuttgart and Munich (Jiang et al., 2017; Poulhès & Proulhac, 2021), which demonstrate a reduction in air pollution concentrations following the implementation of the LEZ. They did, however, emphasise the need for further limitations to avoid EU limits from being exceeded.

According to the London Air Quality Network, nearly all of the monitoring stations in Greater London (GL) exceeded the annual average NO_x limits in 2006 (Fuller & Green, 2006). That report laid the groundwork for the creation of a vehicle emissions-based charge scheme. Based on that, the London low emission zone (LEZ) was established in May 2007 with the goal of reducing emissions by 16% by 2012. This scheme restricted normal access to the greater London area to allow only vehicles with Euro 3 or better emissions standard.

However, according to reports of LAEI in 2016, air pollution concentrations in several London zones continued to exceed the annual mean EU limit values. Figure 1 shows the annual average of NO_2 concentration in London in 2016: this shows that the majority of areas within and near central London, as well as major roads leading there, exceed the EU limit (40 $\mu g/m^3$). To improve air quality in these areas, an ultra-low emission zone (uLEZ) was implemented in April 2019 covering the same area as the existing congestion charge zone in central London. Vehicles are required to meet Euro 4 (petrol), Euro 6 (diesel) or better standards to gain access to the uLEZ.

The restriction of vehicular access to the uLEZ has a variety of effects on traffic volume and emissions-related composition of traffic elsewhere. The volume of traffic entering the uLEZ was expected both to diminish and to improve in composition because of the new restrictions. Although traffic entering the zone will have similar effects nearby, there could be reverse effects on traffic volumes and composition there because of prohibited traffic diverting around the zone. This raises the question of the spatial extent of effects of introduction of the uLEZ, and indeed whether any benefits arise beyond the zone itself.

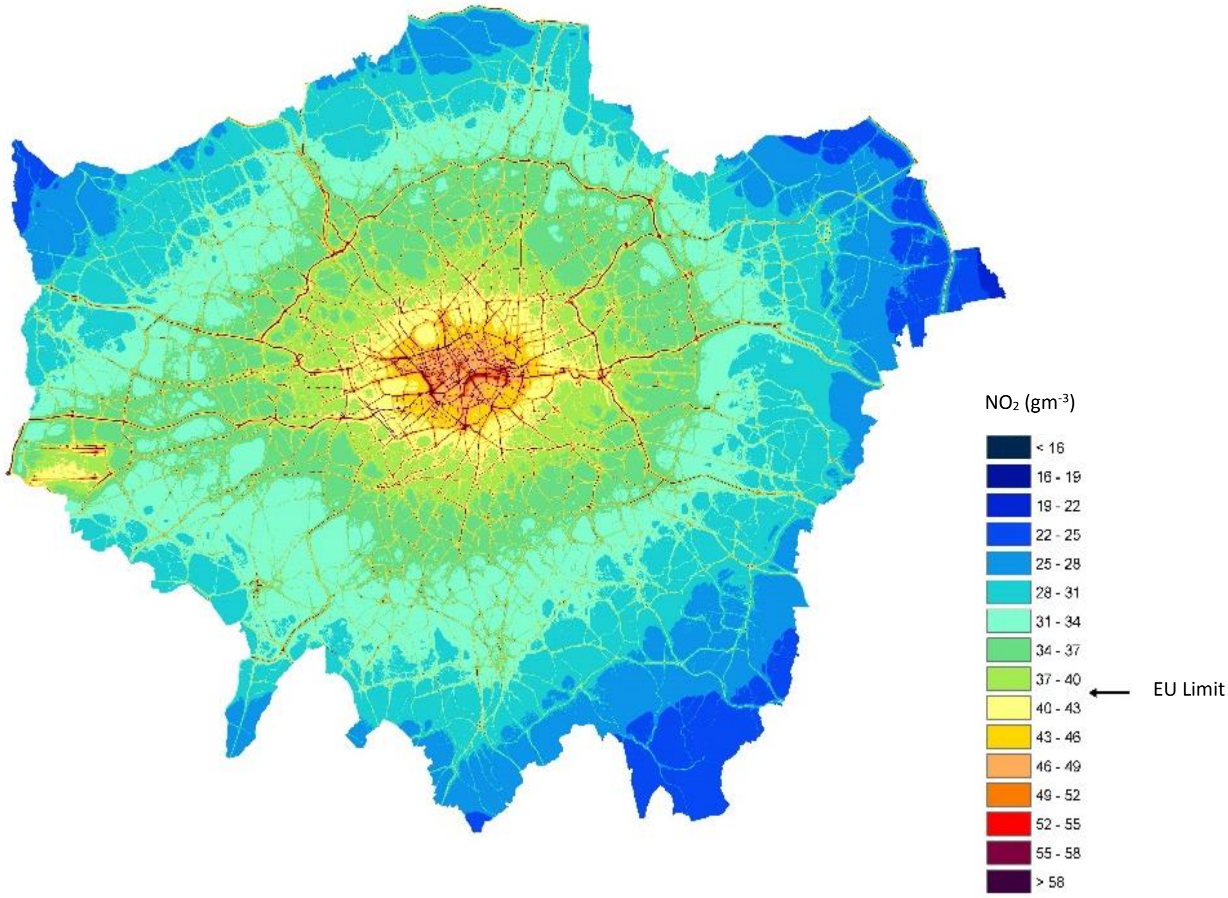

Figure 1: Annual average air pollution concentrations in 2016 for NO_2 from LAEI (*Air Pollution in the UK*, 2018)

There are several approaches to quantify the impacts of these restrictions on road transport air pollution, such as linear regression (Santos et al., 2019), geographically weighted regression models (Poulhès & Proulhac, 2021), mixed effect models (Bernardo et al., 2021) and before-after comparisons with Mann-Whitney statistical test (Tartakovsky et al., 2020). The current study used a state-space intervention method to explore the effects of the uLEZ restriction on London air quality as measured across the broader London area. The main advantage of this model over existing approaches is that it estimates both the temporal and spatial relationship between monitoring stations, and it can incorporate an intervention (such as uLEZ). This model developed based on spatio-temporal modelling of atmospheric pollution (Hajmohammadi & Heydecker, 2021) which is an extension of autoregressive moving average (ARMA) models (G. Box, 2008). In addition, this model evaluates the policy intervention of the uLEZ traffic restrictions in central London on air quality across the Greater London area, implicitly allowing for variations in traffic volumes and composition. Meteorological data including wind speed, temperature and humidity were also used in this model. A series of multivariate state-space models with different specifications were developed and then evaluated by the Bayesian Information Criteria (BIC). The preferred model that results from this was then used to quantify the reduction in pollutant concentrations at each station of the study area, and in each of the uLEZ, the LEZ and greater London.

2. Dataset

2.1. London Air Quality data

The current analysis incorporated data from all of London's 28 air quality monitoring stations extracted from the London Air Quality Network (LAQN)(*London Air Quality*, 2021). Of these, 11 stations are within the uLEZ (located within the London inner ring road, thus including the City of London and the West End), 9 are in the remainder of the London low emission zone (LEZ) and 8 are in greater London (outside of the LEZ). Figure 2 shows the location of each station, along with the boundaries of uLEZ and the LEZ.

This dataset contains hourly measurements of the atmospheric concentration of each of Nitric oxide (NO), Nitrogen dioxide (NO_2) and oxides of Nitrogen (NO_x) at each of these stations. The data was extracted for a period of 23 months, from 1 April 2018 until 28 February 2020. In response to the COVID-19 pandemic and lockdowns from March 2020, traffic flow changed significantly. This prevented us from having a fully balanced design with 12 months during each of the periods before and after uLEZ intervention. Use of calendar month as a categorical covariate ensured that comparisons were made between corresponding months of the year where data were available, so allowing for annual seasonal trends in traffic and meteorological conditions.

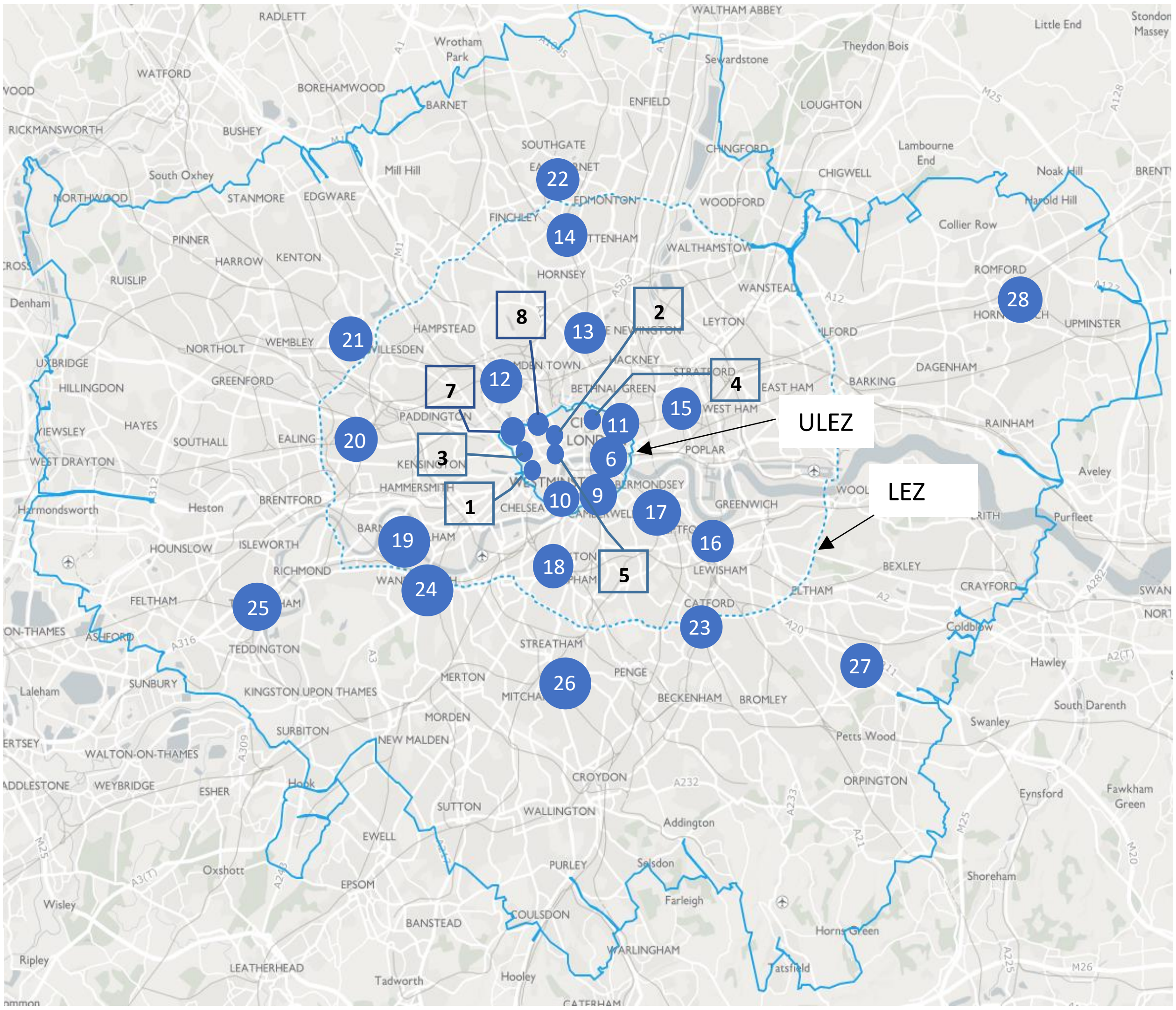

Figure 2: Location of each monitoring station across London

The total number of observations available was 1,336,344, which was less than the maximum possible of 1,409,184: this shortfall was due to detector outages in about 5% of hours. The concentrations of each of the pollutants varied substantially across the stations, and also with each of hour of the day, day of the week, and month of the year. Each of these relationships has a high level of statistical significance in a one-way analysis of variance (p < 0.01) because of the large number of observations. The number of observations, and the typical size of each pollutant together with these variations, expressed as the standard deviation among the classified means, is given in Table 1. The variation among stations constituted a substantial proportion of the total squared deviations, amounting to $R^2 \approx 1/4$ for each of the pollutants. The distribution of the mean of the concentration of the pollutants is shown in Figure 3.

Table 1: Statistics of pollutants (μgm-3)

	NO	*NO_2*	*NO_x*
Number	445,451	445,446	445,447
Mean	34.33	44.83	97.48
Standard deviation	48.5	28.7	98.3
SD (Station)	23.7	16.3	52.1
SD (Hour)	11.0	7.3	23.1
SD (Day)	7.11	4.12	15.00
SD (Month)	7.42	3.89	14.03

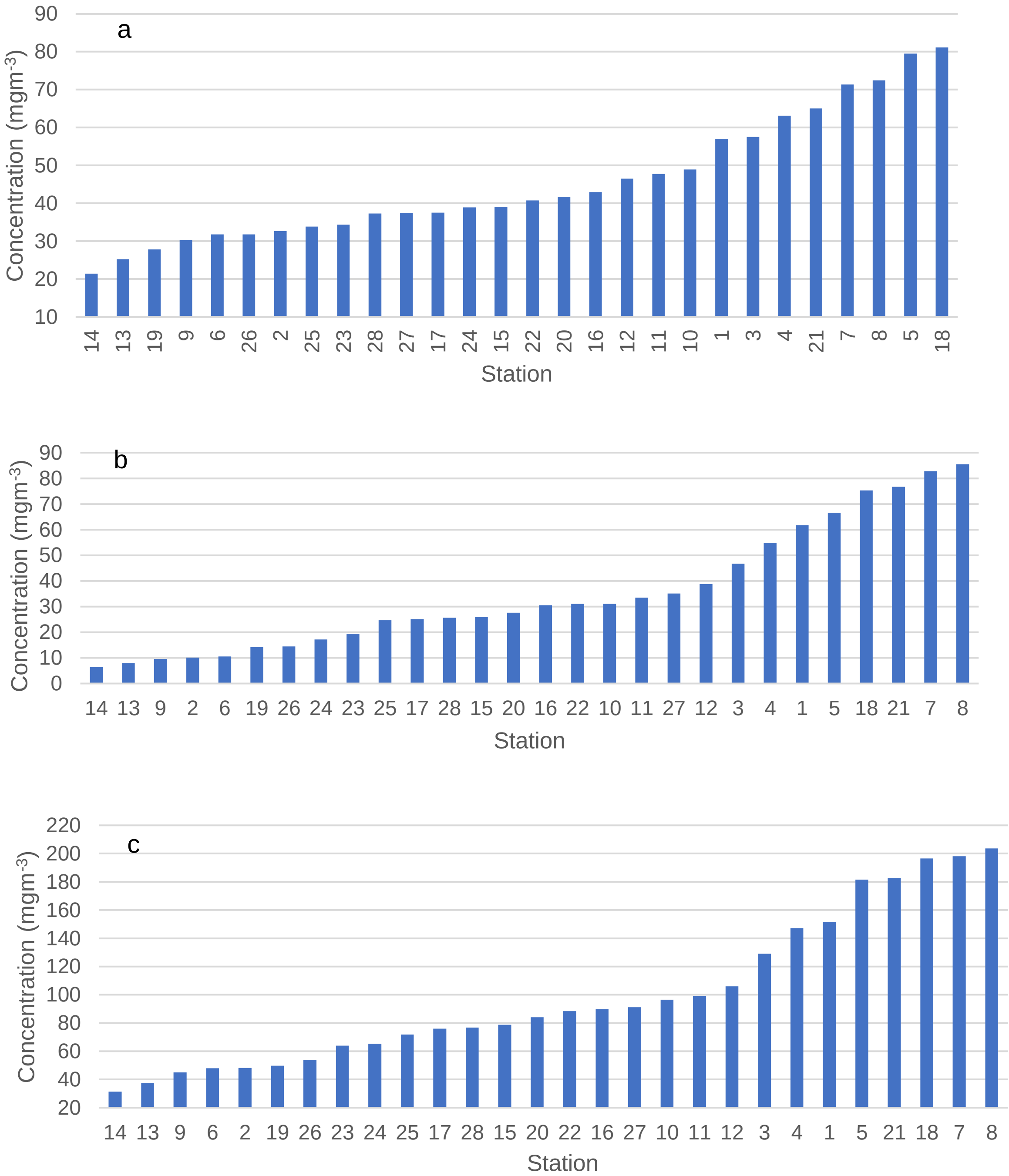

Figure 3: Mean concentrations of a) NO, b) NO_2 and c) NO_x at the studied monitoring stations

2.2. Meteorological Data

Hourly observations of ambient temperature $T\,(\mathrm{C}^{\circ})$, relative humidity h (%) and wind speed s (ms^{-1}) were extracted from London Heathrow airport located in west London. This data is provided by the National Centres for Environmental Information (National Oceanic and Atmospheric Administration, 2019). These meteorological measurements were taken to apply throughout the study area. They were used in the present analysis to allow for the effects on the pollution measurements of differences in weather between the periods before and after implementation of the uLEZ.

The total number of observations available was 50,274, which was 0.25% less than the maximum possible of 50,400. A number of observations together with the typical value and standard deviation are given in Table 2 for each of these measurements.

Table 2: Meteorological data

	Temperature $T\,(\mathrm{C}^{\circ})$	*Relative humidity* *h (%)*	*Wind speed* w *(m/s)*
Number of Observations	16,758	16,758	16,758
Mean	12.52	76.02	4.02
Standard deviation	6.21	17.20	2.22

Each of the three pollutants, NO, NO_2 and NO*x* is negatively correlated with each of temperature and wind speed. However, whilst each of NO and NO_x is positively correlated with relative humidity, NO_2 is negatively correlated with it. These results are summarised in Table 3.

Table 3: Correlation of pollutants with meteorological data

Pollutant	*Temperature* $T\,(\mathrm{C}^{\circ})$	*Relative humidity* *h (%)*	*Wind speed* w *(m/s)*
NO	-0.22	0.11	-0.33
NO_2	-0.08	-0.11	-0.46
NO_x	-0.19	0.05	-0.39

3. Methodology

3.1. Introduction

The effects of the uLEZ intervention on air quality across London, both within the uLEZ zone and beyond, were quantified using a state-space modelling approach. State-space models are dynamic statistical analysis techniques that estimate the state of a system at the current time indirectly through observed time series data (Durbin & Koopman, 2000; Tsay & Chen, 2018).

The observed time series, $\mathbf{y}_t$, depends on an underlying or state process, $\mathbf{x}_t$, through an inexact observation process: $\mathbf{y}_t = \mathbf{a}(\mathbf{x}_t) + \boldsymbol{\varepsilon}_t$ whilst the state evolves in a way that reflects the structure of the system being observed: in the simplest case, without any exogenous influences, this can be expressed as $\mathbf{x}_t = \mathbf{B}(\mathbf{x}_{t\text{-}1}) + \mathbf{w}_t$ where $\mathbf{w}_t$ is a random disturbance to development of the system, typically with a white noise distribution. Here we adopt time-invariant linear formulations $\mathbf{a}(.)$ for the observation and $\mathbf{B}(.)$ for the system processes.

3.2. Modelling the uLEZ Intervention

The policy intervention that is of primary interest is the introduction of uLEZ in April 2019. This can be represented through a vector of covariates:

$$\mathbf{c}_t = \Theta(t - t_0) \tag{1}$$

where t_0 is the time of introduction uLEZ, and $\Theta(t) = \begin{cases} 0 & (t \le 0) \\ 1 & (t > 0) \end{cases}$.

3.3. Air Quality Space-State (AQSS) Model

In the state-space model used for London air quality, the observed time series vector $\mathbf{y}_t$ is a measurement of atmospheric concentration of pollutant (observation vector) and the state time series vector $\mathbf{x}_t$ is the corresponding vector of the atmospheric concentration of pollutants. This value at time t is connected to the value at t-1 (1 hour lag) at the same station as well as other stations by the process matrix, $\mathbf{B}$. This matrix shows the spatio-serial relationship of pollutant concentrations as they develop over time and location.

To accommodate seasonal variation of pollutant concentrations over the 12 calendar months, the covariate vector δ_{mt} with coefficients $\mathbf{M}_m$ was included in the model to represent effects of month m. Similarly, to represent systematic variation within each week, the day-of-week effect was modelled by covariate vector α_{dt} with coefficients $\mathbf{D}_d$. These two covariates are defined as:

$$\delta_{mt} = \begin{cases} 1 & \text{if time } t \text{ is during calendar month } m \ (1 \le m \le 12) \\ 0 & \text{otherwise} \end{cases}$$
$$\alpha_{dt} = \begin{cases} 1 & \text{if time } t \text{ is during day } d \ (1 \le d \le 7) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

These covariates will generate separate coefficients for 12 months (January to December) and 7 days (Monday to Sunday) in the model, so the effects each month and day will be estimated.

The meteorological variables including temperature, T, relative humidity, h and wind speed, s, were added to the model as covariates with coefficients P, R and W, respectively. Hence, the air quality state-space (AQSS) model is:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{x}_t + \boldsymbol{\varepsilon}_t \\ \mathbf{x}_t &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{c}_t + \sum_{m=1}^{12} \mathbf{M}_m \delta_{mt} + \sum_{d=1}^{7} \mathbf{D}_d \alpha_{dt} + PT_t + Rh_t + Ws_t + \mathbf{w}_t \end{aligned} \tag{3}$$

where $\boldsymbol{\varepsilon}_t$ and $\mathbf{w}_t$ are uncorrelated white noise representing observation (respectively process) error.

3.4. Model development and Evaluation

For the evaluation of the London ultra-low emissions zone, several different state-space model formulations were investigated in this study. Model development started from a “basic” state-space model with process matrix ($\mathbf{B}$), intervention term ($\mathbf{C}$) and increment ($\mathbf{u}$), which allows for systematic drift in the state:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{x}_t + \boldsymbol{\varepsilon}_t \\ \mathbf{x}_t &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{c}_t + \mathbf{u} + \mathbf{w}_t \end{aligned} \tag{4}$$

We note that the drift in the state, represented by the offset $\mathbf{u}$, will accommodate any long-term trends in traffic volumes and fleet composition through the study period.

This model was developed to “Basic+W” by adding the meteorological data including temperature, T, relative humidity, h, and wind speed, s:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{x}_t + \boldsymbol{\varepsilon}_t \\ \mathbf{x}_t &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{c}_t + \mathbf{u} + PT_t + Rh_t + Ws_t + \mathbf{w}_t \end{aligned} \tag{5}$$

Further development to this model results in AQSS model (3) with meteorological data and additionally daily ($\mathbf{D}$) and monthly ($\mathbf{M}$) effects: This model does not require the increment $\mathbf{u}$ because its effect is absorbed into the daily term. The final step in model investigation was to add an hourly effect ($\mathbf{H}$) (AQSS+H) to allow for systematic effects over the 24 hours the day, modelled by covariate vector η_{ht} with coefficients $\mathbf{H}_h$; this covariate is defined as:

$$\eta_{ht} = \begin{cases} 1 & \text{if time } t \text{ is during hour of the day } h \ \left(1 \le h \le 24\right) \\ 0 & \text{otherwise.} \end{cases}.$$

Hence, this extension (AQSS+H) to the air quality state-space model is:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{x}_t + \boldsymbol{\varepsilon}_t \\ \mathbf{x}_t &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{c}_t + \sum_{m=1}^{12}\mathbf{M}_m\delta_{mt} + \sum_{d=1}^{7}\mathbf{D}_d\alpha_{dt} + PT_t + Rh_t + Ws_t + \sum_{h=1}^{24}\mathbf{H}_h\eta_{ht} + \mathbf{w}_t \end{aligned} \tag{6}$$

These models were developed in the R programming software using the MARSS (Holmes et al., 2012) package. Because the response variable x_t of these models could not be negative, the logarithm of pollutant concentration is used. The resulting model form for concentration of pollution is consequently log-linear with lognormal error structure.

The performance of models (3) – (6) was compared using the Bayesian Information Criterion (BIC) (Pandis, 2016):

$$\mathrm{BIC} = -2\mathcal{L} + \log_e(n)\,p \tag{7}$$

where p is the number of free parameters in the model, n is the number of observations and $\mathcal{L}$ is the log-likelihood of the fitted model. According to this criterion, the introduction of further parameters can be justified by a sufficiently large increase in likelihood of the fitted model, taking into account the number of observations used. In the present form (7), models with smaller values of BIC are preferred.

4. Results

The results of fitting state-space models to the London air quality dataset (atmospheric concentration of NO_2, NO and NO_x) and model evaluation are presented in this section.

4.1. Model testing and evaluation

The performance of several models introduced in section 3.4 was evaluated by Bayesian Information Criterion (BIC) (7). The BIC of each of these models is presented in Table 4. Models with smaller values of BIC are preferred, with use of additional parameters justified by sufficient improvement in model likelihood.

Table 4: BIC of the developed models (smaller is better)

Model (Equation number)	Parameters							BIC (in millions)		
	u	$\mathbf{B}$	C	Meteorology (P, R, W)	$\mathbf{D}$	$\mathbf{M}$	$\mathbf{H}$	NO	NO_2	NO_x
Basic (4)	✓	✓	✓	-	-	-	-	2.212	2.222	2.112
Basic+W (5)	✓	✓	✓	✓	-	-	-	2.018	2.048	2.024
AQSS (3)	-	✓	✓	✓	✓	✓	-	2.015	2.042	2.021
AQSS+H (6)	-	✓	✓	✓	✓	✓	✓	2.412	2.451	2.415

According to the results of model performance, the AQSS model (3) is preferred for each of the three pollutants over the others as it has the smallest BIC values. The BIC values in Table 4 show that inclusion of meteorological data improves the performance of the Basic model substantially. Inclusion of month and day of week effects also improves model performance, but further inclusion of hourly effects does not. Based on this, the AQSS model (3) was selected to estimate the intervention effects, $\mathbf{C}$, of the uLEZ intervention.

4.2. Analysis of residuals

The residuals in a statistical model of time series data of this type should be serially uncorrelated (Washington et al., 2020). Failure of this weakens the model due to lack of independence in the residuals, and it might be a sign of inadequate modelling. Two diagnostics that are used to check the residuals are the autocorrelation function (ACF) and the partial autocorrelation function (PACF). ACF and PACF of the residuals of the AQSS models are shown in Figure 4. From this figure, the residuals of the AQSS model are largely clear from significant lags, so that no temporal structure remains.

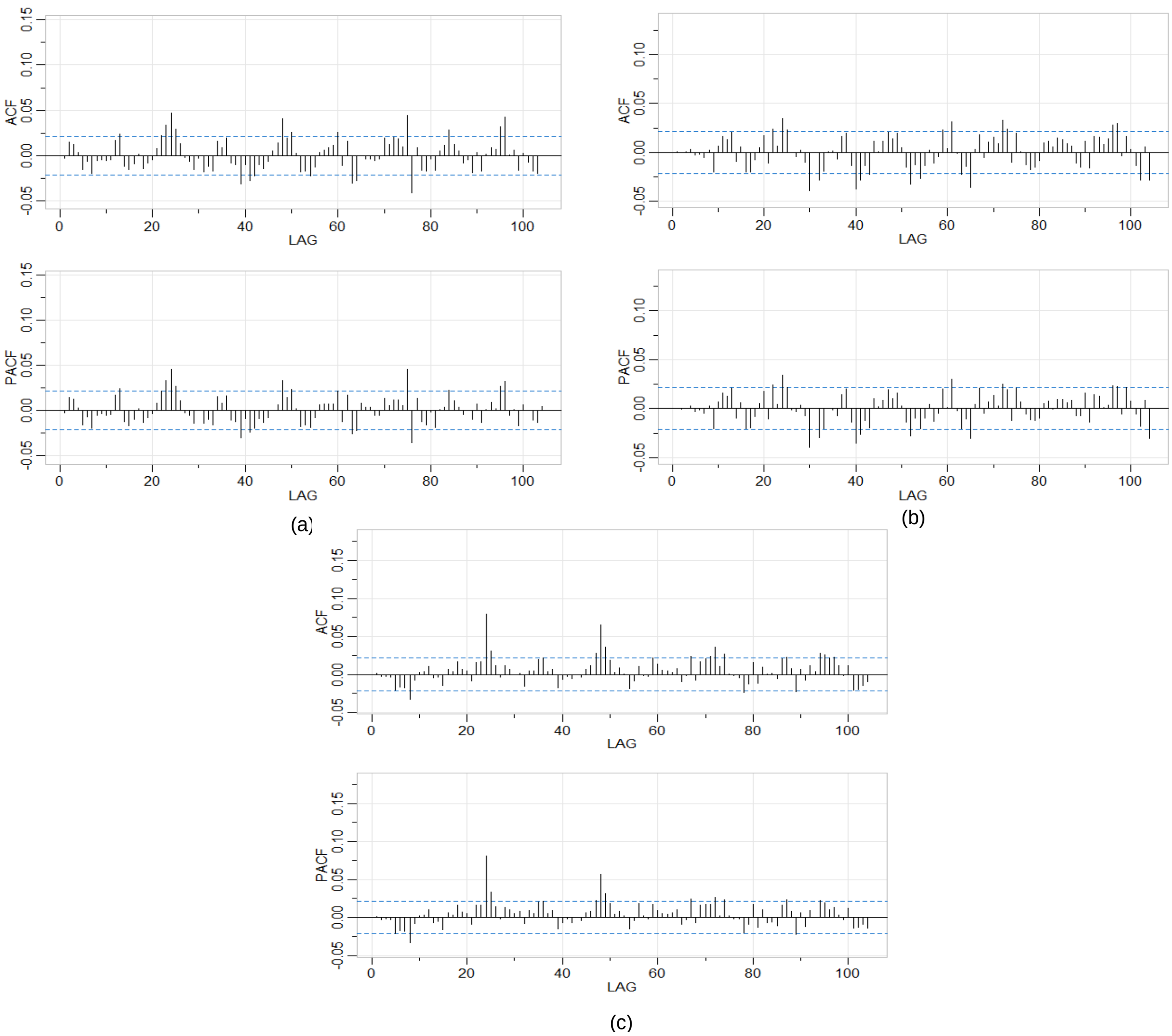

Figure 4: ACF and PACF plots of residuals in the AQSS model: a) NO, b) NO=, c) NO_x

4.3. Effects of uLEZ intervention

The vector of coefficients **C** in the AQSS model quantifies the uLEZ intervention effect at the measurement sites. Table 4 shows the values of $\mathrm{Exp}(\mathrm{C})$ and reduction percentage (calculated as $100[1\text{-}\ \mathrm{Exp}(\mathrm{C})]\%$) for each station and pollutant type. It should be noted that the AQSS model uses a logarithmic transformation of the concentration of pollutants.

We note from these results that the estimates of reduction in NO_2 concentration are smaller than the corresponding ones in NO and NO_x. Reasons for this include that road vehicles tend to emit more NO than NO_2, so the primary effect of changes in traffic will be on the former.

The two main pathways for NO are oxidation to NO_2 and dispersion, whilst there are other sources of NO_2 in urban areas, so that changes in NO concentration will lead to smaller ones in NO_2. Other sources of NO_2 in urban areas will reduce the proportional effect of changes in NO concentrations.

Generally, these values show a reduction in NO, NO_2, and NO_x concentrations at all stations across London after the uLEZ intervention. The average reductions of NO and NO_x in the uLEZ zone are greater (19% and 20%, respectively) than in the LEZ (17.9% and 17.1%, respectively) and Greater London (10% and 15.1%). However, in the case of NO_2, the average reduction is similar at 11.6% for uLEZ and 11.4% for LEZ, while it is slightly larger in Greater London (13.4%).

In addition, annual mean of NO_2 in London (average of all monitoring stations) shows that London reached the EU limit for NO_2 (40 µg/m^3) in 2020. The annual mean of NO_2 was 47.5 µg/m^3 in 2018 (before introducing uLEZ) which reduced to 43.8 µg/m^3 in 2019 and 38.9 µg/m^3 in 2020.

4.4. Spatial distribution of effects of the uLEZ intervention

Heat maps of the $\mathrm{Exp(C)}$ values at the stations across London for NO, NO_2 and NO_x are shown in Fig. 3-5, respectively, to highlight the geographical distribution of the intervention value. (Note that the neutral value of $\mathrm{Exp(C)}$ in this form is 1).

Table 5: Exp (C) and reduction (percentage) at each station, along with average reduction in each zone

Zone	Code	Station	NO exp (*C*)	NO reduction %	NO_2 exp (*C*)	NO_2 reduction %	NO_x exp (*C*)	NO_x reduction %
ULEZ	1	WM6	0.78	22	0.93	7	0.60	40
	2	BM0	0.79	20	0.92	8	-	-
	3	IM1	0.74	26	0.87	13	0.77	23
	4	CT4	0.78	21	0.91	9	0.82	18
	5	NB1	0.80	20	0.93	7	0.90	10
	6	CT3	0.77	23	0.84	16	0.80	20
	7	MY1	0.83	16	0.87	13	0.82	18
	8	CD9	0.77	23	0.86	14	0.71	29
	9	SK6	0.96	3	0.84	16	0.88	12
	10	LB5	0.89	10	0.95	5	0.93	7
	11	HK6	0.79	20	0.81	19	0.76	24
LEZ	12	CD1	0.79	21	0.87	13	0.81	19
	13	IS6	0.86	13	0.96	4	0.91	9
	14	HG4	0.91	8	0.96	4	0.86	14
	15	TH2	0.61	39	0.73	27	0.70	30
	16	LW4	0.94	5	0.91	9	0.90	10
	17	SK5	0.80	19	0.91	9	0.77	23
	18	LB4	0.97	3	0.87	13	0.90	10
	19	RI1	0.67	32	0.83	17	0.77	23
	20	EA8	0.83	16	0.93	7	0.82	18
Greater London	21	BT4	0.82	18	0.81	19	0.83	17
	22	EN5	0.68	32	0.89	11	0.74	26
	23	LW1	0.94	6	0.92	8	0.92	8
	24	WA2	0.97	2	0.85	15	0.84	16
	25	RHG	0.94	5	0.91	9	0.84	16
	26	LB6	0.93	6	0.72	28	0.91	9
	27	GN4	0.94	6	0.86	14	0.81	19
	28	HV3	0.94	6	0.97	3	0.91	9

Zone	average reduction % NO	average reduction % NO_2	average reduction % NO_x
ULEZ	19.0	11.6	20.2
LEZ	17.9	11.4	17.1
Greater London	10.6	13.4	15.1

Figure 5: Heat map of reduction in air pollution at stations across London: a) NO, b) NO_2 and c) NO_x

4.5. Monthly, Daily and meteorological effects

In the AQSS model (3), parameters **M** and **D** represent monthly (respectively daily) effects on London air quality. The variation among months has standard deviations a, b, c (NO, NO_2, NO_x, respectively) with corresponding values among days of the week e, f, g. These effects are supposed to remain unaffected by introduction of the uLEZ. The parameter values are plotted in Fig. 6 and 7, respectively.

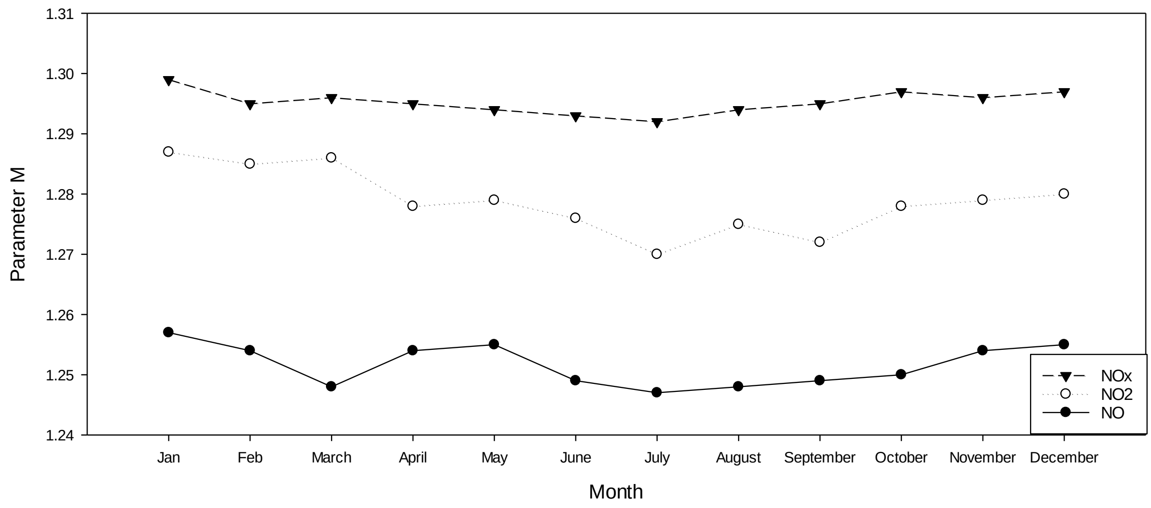

*Figure 6: Monthly (**M**) variations of NO, NO_2 and NO_x from the AQSS model (3)*

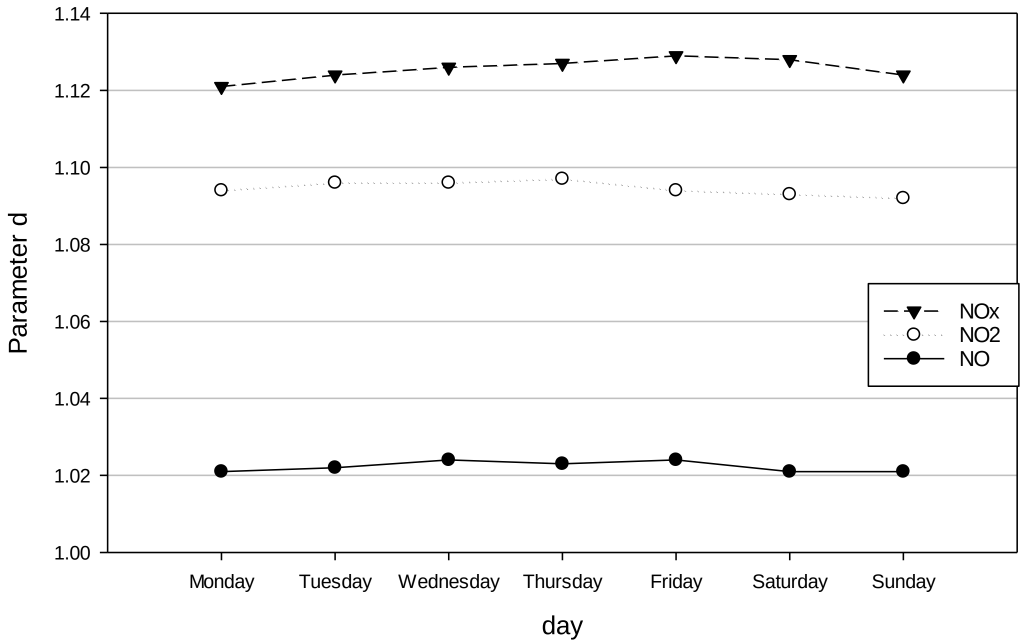

*Figure 7: daily (**D**) variations of NO, NO_2 and NO_x from the AQSS model (3)*

From these results, the variations of NO, NO_2 and NO_x concentrations over calendar months are small, with a greater reduction from March to October in NO_2 and NO_x and from June to October for NO.

Estimations of the parameter $\mathbf{D}$ show also some slight variations in NO, NO_2 and NO_x concentrations over the 7 days of the week, with a greater value for Wednesday and Thursday compared to Saturday and Sunday.

5. Discussion

The BIC values of several state-space models (Table 4) show that meteorological data (temperature, humidity and wind speed), along with month and day effects (model AQSS) are key variables that improve the performance of the "Basic" model, which has the intervention effect and the process matrix only. The AQSS model (3) also was checked by ACF and PACF plots (Figure 4) to see if any temporal structure remained in the residuals, and they revealed mostly white noise.

As shown in Table 5, the uLEZ intervention was successful in reducing NO, NO_2, and NO_x concentrations not just within the target zone but also throughout the LEZ and Greater London areas. This intervention makes the greatest reduction in NO and NO_x in the uLEZ area, followed by the LEZ and Greater London. The reduction in NO_2 in the uLEZ and LEZ zones is similar, with a slightly greater reduction elsewhere in the Greater London area.

Estimation of month and day effects covariates (Figure 6 and 7, respectively) in the AQSS model showed that while the variation over calendar months and days of the week are small, there is a reduction in the NO, NO_2 and NO_x concentrations from June to October, and over the weekends (Saturday and Sunday).

The AQSS model (3) shows that the uLEZ intervention reduced NO, NO_2, and NO_x concentrations in London (uLEZ, LEZ and Greater London areas). This model quantifies the reduction after allowing for meteorological conditions before and after the intervention, as well as the effects of the day of the week and calendar month.

6. Conclusions

Low emission zone and ultra-low emission zone are traffic policies that have been introduced in London to tackle road transport air pollution. A state-space time series model was developed in this work to quantify the effects of ultra-low emission zone policy. This model used hourly NO, NO_2, and NO_x concentrations from 28 monitoring stations across London for 12 months before and 10 months after the intervention. Furthermore, meteorological data including temperature, wind speed and humidity, as well as the influence of the day of the week and calendar month were considered in this model. The results of this model showed that the ultra-low emission intervention successfully reduced the NO, NO_2, and NO_x concentrations in all monitoring stations studied. Notable in this is that the spatial extent of these reductions is beyond the uLEZ itself, which could be due in part to each of reduction in traffic volume, change in fleet composition in response to introduction of the uLEZ, and atmospheric convection of pollutant.

Future work for this research will be using the presented model to quantify the effects of the intervention on other pollutant types, such as particular matter (PM_n).

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References

Air Pollution in the UK. (2018).

Bernardo, V., Fageda, X., & Flores-Fillol, R. (2021). Pollution and congestion in urban areas: The effects of low emission zones. *Economics of Transportation*, *26–27*, 100221. https://doi.org/https://doi.org/10.1016/j.ecotra.2021.100221

Box, G. (2008). *Time Series Analysis: Forecasting and Control, Fourth Edition / Box, George.* (1st editio).

Box, G. E. P., & Jenkins, G. (1990). *Time Series Analysis, Forecasting and Control*. Holden-Day, Inc.

Durbin, J., & Koopman, S. J. (2000). Time series analysis of Non-Gaussian observations based on state space models from both classical and Bayesian perspectives. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*. https://doi.org/10.1111/1467-9868.00218

European Comission. (2017). *Standards - Air Quality - Environment - European Commission*. Europa. https://ec.europa.eu/environment/air/quality/standards.htm

Fuller, G., & Green, D. (2006). *Air Quality In London 2005 and mid 2006 – Briefing*.

Gehrsitz, M. (2017). The effect of low emission zones on air pollution and infant health. *Journal of Environmental Economics and Management*, *83*, 121–144. https://doi.org/https://doi.org/10.1016/j.jeem.2017.02.003

Hajmohammadi, H., & Heydecker, B. (2021). Multivariate time series modelling for urban air quality. *Urban Climate*, *37*, 100834. https://doi.org/https://doi.org/10.1016/j.uclim.2021.100834

Hitchcock, G., Conlan, B., Kay, D., Brannigan, C., & Newman, D. (2014). *Air quality and road transport, impacts and solutions*.

Holmes, E. E., Ward, E. J., & Wills, K. (2012). MARSS: Multivariate autoregressive state-space models for analyzing time-series data. *R Journal*. https://doi.org/10.32614/rj-2012-002

Host, S., Honoré, C., Joly, F., Saunal, A., Le Tertre, A., & Medina, S. (2020). Implementation of various hypothetical low emission zone scenarios in Greater Paris: Assessment of fine-scale reduction in exposure and expected health benefits. *Environmental Research*. https://doi.org/10.1016/j.envres.2020.109405

Jiang, W., Boltze, M., Groer, S., & Scheuvens, D. (2017). Impacts of low emission zones in Germany on air pollution levels. *Transportation Research Procedia*. https://doi.org/10.1016/j.trpro.2017.05.217

London Air Quality. (2021). https://maps.london.gov.uk/air-quality/

London Atmospheric Emissions Inventory (LAEI) 2016 - Methodology. (2020). Transport for London.

National Oceanic and Atmospheric Administration. (2019). *Data Access | National Centers for Environmental Information (NCEI) formerly known as National Climatic Data Center (NCDC)*. Department of Commerce. https://www.ncdc.noaa.gov/isd

Ochoa-Hueso, R., Munzi, S., Alonso, R., Arróniz-Crespo, M., Avila, A., Bermejo, V., Bobbink, R., Branquinho, C., Concostrina-Zubiri, L., Cruz, C., Cruz de Carvalho, R., De Marco, A., Dias, T., Elustondo, D., Elvira, S., Estébanez, B., Fusaro, L., Gerosa, G., Izquieta-Rojano, S., … Theobald, M. R. (2017). Ecological impacts of atmospheric pollution and interactions with climate change in terrestrial ecosystems of the Mediterranean Basin: Current research and future directions. *Environmental Pollution*, *227*, 194–206. https://doi.org/https://doi.org/10.1016/j.envpol.2017.04.062

Pandis, N. (2016). Multiple linear regression analysis. In *American Journal of Orthodontics and Dentofacial Orthopedics* (Vol. 149, Issue 4, p. 581). John Wiley & Sons, Inc. https://doi.org/10.1016/j.ajodo.2016.01.012

Poulhès, A., & Proulhac, L. (2021). The Paris Region low emission zone, a benefit shared with residents outside the zone. *Transportation Research Part D: Transport and Environment*, *98*, 102977. https://doi.org/https://doi.org/10.1016/j.trd.2021.102977

Santos, F. M., Gómez-Losada, Á., & Pires, J. C. M. (2019). Impact of the implementation of Lisbon low emission zone on air quality. *Journal of Hazardous Materials*. https://doi.org/10.1016/j.jhazmat.2018.11.061

Settey, T., Gnap, J., & Beňová, D. (2019). Examining the impact of the deployment of low emission zones in Europe on the technological readiness of road freight transport. *Transportation Research Procedia*, *40*, 481–488. https://doi.org/https://doi.org/10.1016/j.trpro.2019.07.070

Shindell, D. T., Faluvegi, G., Koch, D. M., Schmidt, G. A., Linger, N., & Bauer, S. E. (2009). Improved attribution of climate forcing to emissions. *Science*, *326*(5953), 716–718. https://doi.org/10.1126/science.1174760

Soriano, J. B., Abajobir, A. A., Abate, K. H., Abera, S. F., Agrawal, A., Ahmed, M. B., Aichour, A. N., Aichour, I., Eddine Aichour, M. T., Alam, K., Alam, N., Alkaabi, J. M., Al-Maskari, F., Alvis-Guzman, N., Amberbir, A., Amoako, Y. A., Ansha, M. G., Antó, J. M., Asayesh, H., … Vos, T. (2017). Global, regional, and national deaths, prevalence, disability-adjusted life years, and years lived with disability for chronic obstructive pulmonary disease and asthma, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. *The Lancet Respiratory Medicine*, *5*(9), 691–706. https://doi.org/10.1016/S2213-2600(17)30293-X

Stanaway, J. D., Afshin, A., Gakidou, E., Lim, S. S., Abate, D., Abate, K. H., Abbafati, C., Abbasi, N., Abbastabar, H., Abd-Allah, F., Abdela, J., Abdelalim, A., Abdollahpour, I., Abdulkader, R. S., Abebe, M., Abebe, Z., Abera, S. F., Abil, O. Z., Abraha, H. N., … Murray, C. J. L. (2018). Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks for 195 countries and territories, 1990-2017: A systematic analysis for the Global Burden of Disease Stu. *The Lancet*, *392*(10159), 1923–1994. https://doi.org/10.1016/S0140-6736(18)32225-6

Tartakovsky, D., Kordova – Biezuner, L., Berlin, E., & Broday, D. M. (2020). Air quality impacts of the low emission zone policy in Haifa. *Atmospheric Environment*, *232*, 117472. https://doi.org/https://doi.org/10.1016/j.atmosenv.2020.117472

Tsay, R. S., & Chen, R. (2018). Nonlinear time series analysis. In *Nonlinear Time Series Analysis*. https://doi.org/10.1002/9781119514312

Washington, S., Karlaftis, M., Mannering, F., & Anastasopoulos, P. (2020). Statistical and Econometric Methods for Transportation Data Analysis. In *Statistical and Econometric Methods for Transportation Data Analysis*. https://doi.org/10.1201/9780429244018

York Bigazzi, A., & Rouleau, M. (2017). Can traffic management strategies improve urban air quality? A review of the evidence. In *Journal of Transport and Health*. https://doi.org/10.1016/j.jth.2017.08.001