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The impact of smart traffic interventions on roadside air quality employing machine learning approaches

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ABSTRACT

In this paper, the impact of smart traffic interventions on air quality was assessed in Thatcham, West Berkshire, UK. The intervention linked NO_2 levels with the cycle time of the traffic lights. When NO_2 levels exceeded a certain threshold, the strategy was triggered, which reduced the traffic congestion by turning the traffic lights green. Eight Earthsense Zephyrs air quality sensors and nine inductive-loop traffic detectors were installed in Thatcham to simultaneously monitor the air quality and traffic flows, respectively. Compared to the pre-intervention period, the observed NO_2 concentrations decreased in June, July and August and increased in September 2021, however, this does not reveal the true effect of smart traffic intervention. Using the observed data on the days with- and without-exceedances, we developed two machine learning models to predict the Business-as-usual (BAU) air quality level, i.e., a generalised additive model for average concentration and a quantile regression model for peak concentration. Our results demonstrated that average predicted concentrations (BAU) were lower than the observed concentrations (with intervention) by 12.45 %. However, we found that peak concentrations decreased by 20.54 %.

1. Introduction

Exposure to poor air quality is causing seven million deaths and the loss of hundreds of thousands healthy years of life every year (WHO, 2021). Air pollution is adversely affecting lung function, causing respiratory infections, aggravating asthma, and resulting in ischaemic heart disease, stroke and neurodegenerative conditions (Landrigan, 2017; WHO, 2021). Exposure to air pollution affects people of all ages and all types of health conditions and air pollution is particularly harmful to young age, old age and people with existing health conditions (Khallaf, 2011). In addition to the clear health impacts, high levels of air pollution may also affect agricultural crops, vegetation, building materials, and reduce visibility in urban and *peri*-urban areas (Khallaf, 2011; Ivaskova et al., 2015). Climatic variables such as temperature, rainfall and wind impact air pollution and, in turn, air pollution can directly affect climate

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change, as several air pollutants and greenhouse gases are highly correlated due to their common emission sources and processes (Balogun et al., 2021; Singh et al., 2021). Although efforts are made at local, national and international levels to cut emissions and improve air quality to reduce short term peaks and long term average pollution levels, pollution levels still exceed air quality standards in many cities in the world, causing adverse health effects (WHO, 2021). Therefore, further interventions are required to cut emissions and manage pollution levels in urban areas.

In this paper, we consider a smart traffic intervention for air quality improvement. The intervention is related to the timing of the traffic light cycle on a single road and the main focus is on how traffic light cycle affects NO_2 levels on roadside locations. This is a unique smart intervention which links NO_2 levels with the traffic light cycle, which was never tried before. Both traffic flow and air quality data are collected before and during the intervention. To extract the effect of the intervention, several approaches are used employing descriptive statistics and machine learning techniques.

According to DEFRA (2020), an air quality intervention is a deliberate measure aimed at improving air quality. An intervention may be primarily aiming at other outcomes (e.g., reducing speed on a particular road for public safety or a lockdown to minimise transmission of COVID-19) but it could also indirectly affect air pollution. Interventions can span a very wide range of temporal scales such as from an hour to a month or longer. Interventions can be implemented at sub-regional or regional levels, national level, or even at global level to cut emissions, improve air quality, reduce exposure and benefit health (Public Health England, 2019). Various transport-related interventions may include such measures as promotion of low emission zones; road pricing; subsidising public transport; abatement retrofit; promotion of walking and cycling; provision of school buses; and increasing fuel duty (Public Health England, 2020). Traffic interventions that promote the uptake of low and zero-exhaust emission vehicles, particularly electric vehicles have also been found as being likely to improve air quality (Public Health England, 2020). Traffic management interventions, such as road pricing and access restrictions, have the potential to improve air quality and encourage the public to consider travel behaviour change and active travel options (Public Health England, 2020). However, active travel interventions on a limited scale do not generally improve air quality significantly, but the added physical exercise benefit makes them very effective for improving public health outcomes (Public Health England, 2019).

Several examples of traffic interventions exist in the UK and other countries. The London Low Emission Zone (LEZ) is probably an example of the most well-known and the most studied intervention (e.g., Ellison et al., 2013; TfL, 2008; Barratt et al., 2009; Kelly et al. 2011). The LEZ brought about a gradual change in the vehicle fleet. When phases 1 and 2 of LEZ were implemented, the interventions did not cause a reduction in measured PM_{10} concentrations, but caused a reduction in black carbon and $PM_{2.5}$ levels. Reductions were rapid and large, when the London Mayor's plan for Ultralow Emission Zone (ULEZ) was announced in 2017 (Air Quality London, 2020). This was a long-term urban level intervention that resulted in significant air quality improvement.

The COVID-19 lockdown was the most recent global intervention aiming at reducing the transmission of COVID-19 among humans, and in many ways acted as a natural intervention experiment to improve outdoor air quality in the UK and elsewhere which has been investigated widely (see, for example, Jephcote et al., 2021; Dacre et al., 2020; Ropkins and Tate, 2021; Shi et al., 2021; Munir et al., 2021). During the first lockdown in the UK (23 March – 10 May 2020), for example, road traffic decreased by about 70 % on the roads in the UK, whereas reductions in NO_2 ranged from 20 to 50 % in different parts of the UK (Munir et al., 2021). In contrast, changes in PM_{10} and $PM_{2.5}$ showed different results in different parts of the world, although the UK experienced higher levels of PM during the lockdown period (Shi et al., 2021; Munir et al., 2021). The levels of O_3 increased almost everywhere globally, most probably due to a reduction in NOx species, which are inversely proportion to O_3, due to their mutual chemical reaction. The COVID-19 lockdown varied spatially from a city to country or even global scale, and ranged temporally within timeframes of days to months.

In the UK under Part IV of the Environment Act 1995 local authorities undertake regular reviews and assessments to determine if the air quality objectives are met. Otherwise, air quality management areas are declared, and interventions are implemented to cut emissions. According to the Department for Environment, Food and Rural Affairs (DEFRA, 2020), most such local-scale interventions generally do not show any clear effects. Some interventions are easy to assess for their impacts on air quality, while others are more challenging. To assess the impact of an intervention several factors should be considered including: The level of change in activity (e.g., how much traffic flow changed); Availability of data for both the activity and air quality; Location of air quality measurement sites (e.g., distance from the road); Conversion of primary to secondary pollutants; Contribution from urban and regional background concentrations (e.g., PM_{10} concentrations in an urban area can be dominated by non-local regional contributions); The influence of meteorological condition; The type of pollutants, and, Uncertainty in measurements (DEFRA, 2020). Uncertainties may be related to the type of sensors, where low-cost sensors have relative higher uncertainties than the reference sensors.

The above literature review showed that most of the interventions carried out in the past were related to long-term intervention and policies. There was no example, where traffic light cycle time was linked to the levels of air pollution. This paper intends to address this gap by using measured traffic and pollution data by employing several machine learning approaches. The paper provides a systematic approach for implementing a smart traffic intervention and how its impact can be assessed on air quality in urban areas. The rest of the paper is organised as below. Section 2 (methodology) provides insights into the study site, traffic data, air quality data and various statistical software and techniques employed. Section 3 (results and discussion) presents the results of the analysis and their discussion. Section 4 (conclusion) concludes the whole study and provides future directions.

2. Methodology

This study aimed to analyse the effect of a smart traffic intervention on air quality in an urban area. For this purpose, air quality and traffic flow data were simultaneously collected before and during the intervention in Thatcham, West Berkshire, UK. Several machine learning approaches (as explained later) were employed to extract the effect of the intervention on air quality. Thatcham is about 5 km east of Newbury and 24 km west of Reading. There are several primary schools and one secondary school in Thatcham. The main east–west road through the town is the A4 Bath Road, which runs between London and Bristol. This is a busy road and is considered the main source of emissions in Thatcham.

2.1. Air quality data

As a part of the project, eight Earthsense Zephyrs (Earthsense, 2021) during the months of June to September 2021(the intervention period) were installed in Thatcham, West Berkshire, UK (Fig. 1). Zephyrs are portable air quality sensors developed by the Earthsense and are able to measure a range of air pollutants including both gaseous and particulate pollutants including NO_2, NO, O_3, PM_1, $PM_{2.5}$ and PM_{10}. Zephyrs weigh from 1.7 to 2 kg and have a size of 23.50 cm × 1.60 cm × 1.14 cm. For NO_2 measurement, its estimated accuracy is $\pm$ 5 μg/m^3 and its measurement range is 0 – 20000 μg/m^3. For more detail on Zephyrs see Earthsense (2021). Some of these sensors were installed in October 2020, while the remaining sensors were installed in April 2021. They also measured the levels of several meteorological parameters, namely, temperature, relative humidity and atmospheric pressure. These sensors did not, however, measure the levels of wind speed, wind direction and solar radiation, and therefore comparable data for these parameters was obtained from the University of Reading Atmospheric Observatory (RAO, 2021). The Zephyr sensors are shown as WB1 to WB8, where WB stands for West Berkshire. Sensors WB1 to WB5 are installed on or near Bath Road, whereas WB6 and WB8 are installed at about 250 m and 180 m distance from the main Bath Road, respectively. NO_2 levels decrease linearly going away from the roadside.

2.2. Traffic data

Nine (9) inductive-loop traffic detectors were installed in Thatcham, West Berkshire, UK to monitor traffic flow in both directions (Fig. 1). These loops measured traffic flows going towards and from Reading and Newbury and within Thatcham, West Berkshire. The traffic loops were installed on Bath Road (A4) in Thatcham around the area where the Zephyrs were installed (Fig. 1). Data were obtained from the nine traffic loops which were named as N36131B (flow31B), N36132A (flow32A), N36141B (flow41B), N36141D (flow41D), N36151E (flow51E), N36151G (flow51G), N36161B (flow61B), N36161D (flow61D), and N36171E (flow71E), with mean traffic flow for January – September 2021 (vehicles/hr) of 258, 258, 212, 224, 265, 243, 303, 290 and 299, respectively.

Fig. 2 visualises box plots (upper-panel), correlation plots (middle-panel) and time variation plots (lower-panel) of traffic flows (flow/hr) measured by different traffic loops from January to September 2021. All data are in hourly resolution. The traffic flows measured by these different loops had a similar trend and demonstrated a very strong correlation with each other ($r > 0.90$). This is further analysed by the time variation plots, which show that traffic flows gradually increased from January to September 2021. Average traffic flow (vehicles/hr) was 192, 215, 242, 266, 271, 286, 293, 293, and 301 in January to September, respectively. Diurnal cycle analysis showed that the highest traffic flow was experienced in the afternoon peak hours (about 5 pm); on a weekly cycle the highest flow was experienced on Friday and lowest on weekend; and, on a monthly basis, the highest traffic flow was experienced in

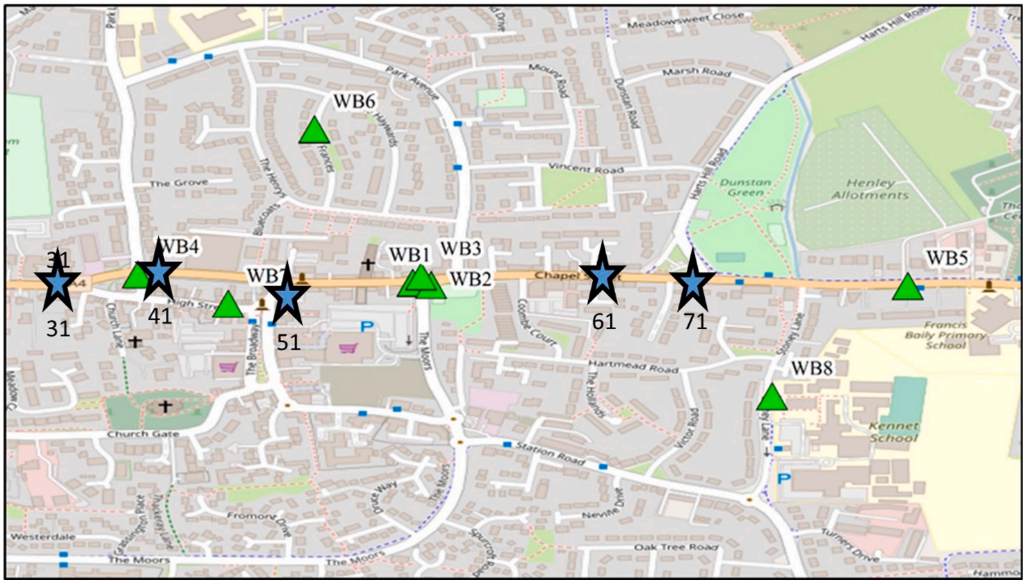


Fig. 1. Green triangles show the locations of eight Earthsense Zephyrs sensors, whereas the stars show the locations of the traffic loops in Thatcham, West Berkshire. WB stands for West Berkshire. Star 31 shows the location of N36131 & N36132, star 41 shows the location of N36141B and N36141D, star 51 shows the location of N36151E and N36151G, star 61 shows the location of N36161B and N36161D, and star 71 shows the location of N36171E. There are four sets of traffic lights in this area: (i) Park lane junction (near WB4), (ii) Broadway junction (near WB7), (iii) the Moor junction (near WB1), and (iv) Harts Hill Rd junction (star 71).

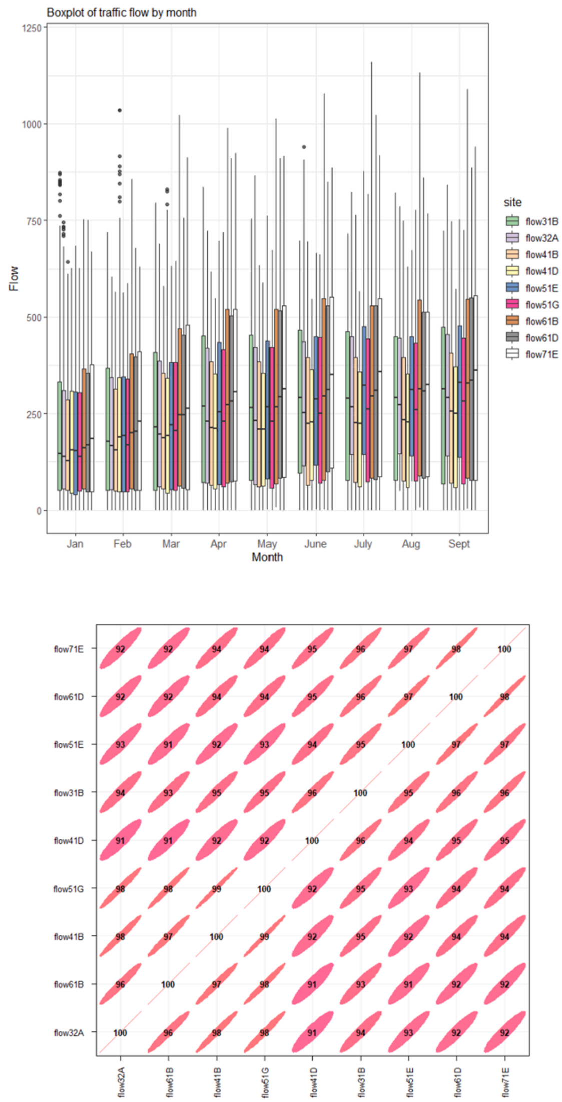


Fig. 2. Box plots (upper-panel), correlation plots (middle-panel), and time variation plots (lower-panel) of traffic flow (vehicles/hr) measured by different traffic loops from January to September 2021 in Thatcham, West Berkshire.

September.

2.3. Correlation between NO_2 and traffic data

This study is based on the assumption that NO_2 concentration is directly correlated with traffic flow and therefore, when traffic flow changes because of the traffic intervention, it affects NO_2 concentration. It is, therefore, important to show how NO_2 concentration correlates with traffic flow at different temporal granularity. When simple correlation was calculated between traffic flow and NO_2 concentration using hourly data from June to September (inclusive), the values of correlation coefficients were very low or even negative (Figure not shown). To explain why the correlation was weak, we visualised the diurnal and weekly cycles of traffic flow and NO_2 concentration (Fig. 3). It should be noted that average traffic flow ranged from 15 to 770 vehicle/hr, whereas NO_2 concentration ranged from 0 to 79 ug/m^3, therefore, to visualise them in the same plot, we used normalised values of both NO_2 and traffic flow. It can be observed in Fig. 3 that the diurnal cycles of NO_2 and traffic flow do not show the same pattern, especially from about 08:00 hr in the morning until 20:00 hr in the evening. On the other hand, the weekly cycles of NO_2 and traffic flow exhibit the same pattern, showing higher levels on weekdays and lower on weekend, as expected. The difference in correlation at different time scales is probably because the diurnal cycle of NO_2 is strongly affected by the meteorological conditions linked with the time of the day, which decouples the association between NO_2 and traffic flow. The weekly cycle of NO_2, on the other hand, is more affected by the emission sources and

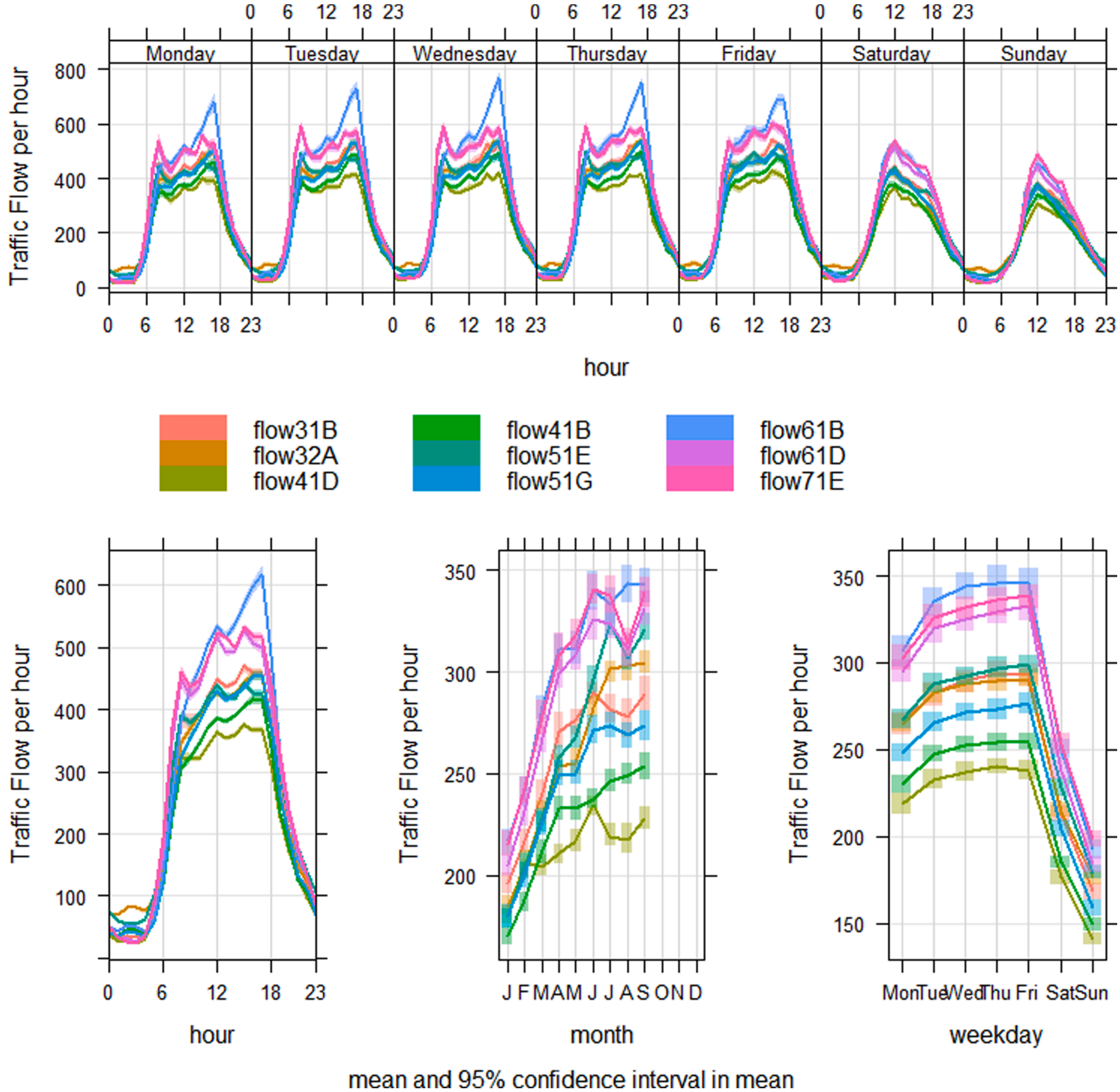


Fig. 2. (*continued*).

their strength, hence a similar weekly pattern can be observed between NO_2 and traffic flow. This analysis shows that simple correlation alone cannot explain the association between traffic flow and air pollution as it changes at different time scales. Therefore, simple correlation should be supported by visualisation and advanced machine learning modelling (as show in later sections).

2.4. Data analysis

Road traffic data from nine traffic loops and air quality data from eight Zephyrs was downloaded in 15 min temporal resolution. Using time average function (timeAverage) of openair package (Carslaw, 2019) in R programming language (R Core Team, 2020), the 15 min average data was converted to hourly average data. Data downloaded from different sites was combined to one file according to the date/time column. Rows with missing values were removed. Furthermore, outliers were identified and removed from the dataset. For example, the range of NO_2 concentration was from 0 to 100 μg/m^3 at most of the monitoring sites. However, WB5 showed a range from 0 to 500 μg/m^3. Not only the range, but also the average value of NO_2 at WB5 was extremely higher, therefore, WB5 was not included in further analysis. All statistical analysis and visualisation were performed in R programming language (R Core Team, 2020). There was no reference air quality monitoring station in Thatcham to compare the Zephyrs measurements with, however, several Zephyrs were collocated with reference sensors in Reading and

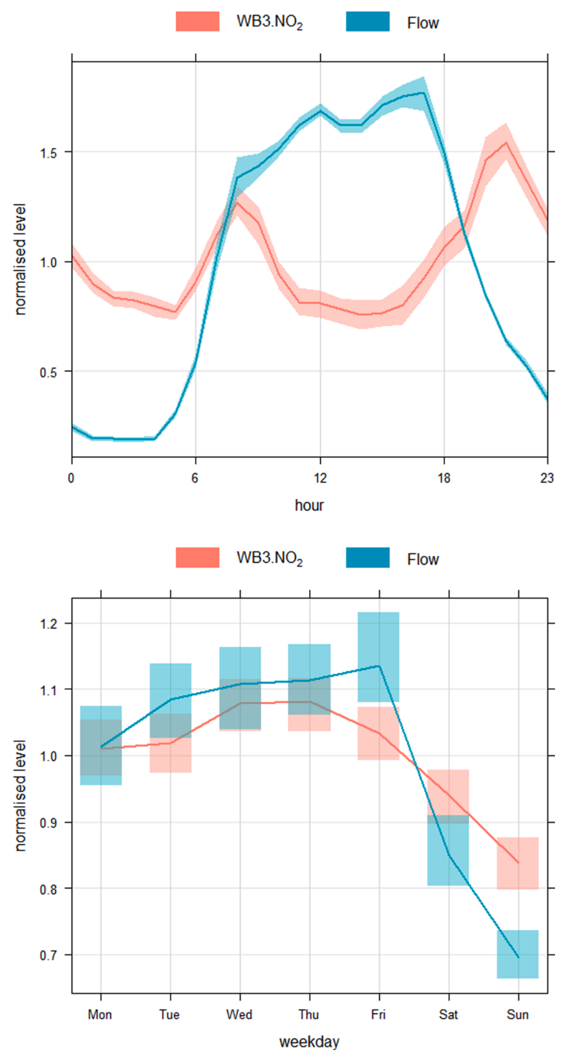


Fig. 3. Diurnal and weekly cycles of NO_2 and traffic flow. NO_2 concentration is used from WB3 site (WB3.NO_2) and traffic flow is the average of all sites. As NO_2 and traffic flow are on the same flow, therefore their levels are normalised.

Wokingham. The data from these collocated sensors was used for Zephyrs calibrations. Data from Reading and Wokingham are not considered in the paper, as these areas were not part of the intervention study.

2.5. Traffic intervention strategy

A smart traffic intervention was implemented in June, July, August and September 2021 at Bath Road (A4) in Thatcham, West Berkshire, UK. The idea was to assess how smart traffic interventions affected air quality on roadside and nearby locations. In this intervention the traffic light cycle time was linked to pollution levels and the aim was that the intervention would help reduce traffic congestion and therefore help reduce NO_2 levels. According to the strategy:

During the peak hours the 'cycle time/the congestion factor strategy' was triggered, based on a 15-minute average and an NO_2 threshold of 43.9 μg/m^3. The cycle time remained triggered (green) until it cleared the traffic congestion and the NO_2 levels reached 29 μg/m^3.
Off peak am (10 am – 12 pm): the strategy dropped to vehicle actuation (VA), which is a mechanism determining the appropriate duration for a traffic signal phase and the SCOOT (Split Cycle Offset Optimisation Technique) facility was turned off. SCOOT is a real time adaptive traffic control system for the coordination and control of traffic signals across an urban road network, adjusting the traffic signal timings to adapt to current traffic conditions.
Off peak pm (1:30 pm – 3:00 pm): a higher cycle time of 94 s was instigated.

The smart traffic intervention was implemented in June and carried on continuously until the end of September 2021. A threshold level of 43.9 μg/m^3 of NO_2 was considered, which is the 90th percentile of May's NO_2 concentrations for WB3, where NO_2 levels were generally higher than the other Zephyrs. The idea was that when NO_2 levels exceed this threshold, it would trigger the traffic strategy and all traffic lights on A4 would turn green, which would clear out traffic congestion.

2.6. 2.6. Machine learning models and software

Several machine learning approaches were employed to predict NO_2 in a Business As Usual (BAU) scenario for the period when the strategy was implemented (June to September 2021). In the first scenario, air quality data was used from three Zephyrs WB1, WB2 and WB3, where data was available from October 2020 to September 2021. The data from October 2020 to May 2021 was used to train (fit) the model, which was then used to predict the levels of NO_2 for the month of June to September 2021 assuming BAU scenario. In the second scenario, days with exceedances (when the strategy was triggered) vs without exceedances (when the strategy was not triggered) in June to September were modelled. Days without-exceedances were used for training the models, which were then used to predict days with-exceedances. It was assumed that days with no exceedances were not affected by the intervention and therefore could be used for training the model to predict NO_2 levels for days affected by the intervention in a BAU scenario. Hence, the difference between the two will show the impact of intervention. It was observed that the range of training data was less than the testing data. Therefore, the training data was extended to increase the range of NO_2 concentrations and predictor variables. For this purpose, April and May were added to the training data, so the training data contained days with no exceedances in June to September plus the months of April and May 2021. Table 1 presents testing and training data for the scenario 2.

Two machine learning approaches, namely Generalised Additive Model (GAM) (Munir et al., 2021; Wood, 2020) and Random Forest (RF) (Grange and Carslaw, 2019), were employed using several meteorological and temporal variables as predictors to fit and validate the model. GAM and RF were good for predicting average NO_2 concentrations but they struggled to predict extreme values. Therefore, for predicting extreme values, a Quantile Regression Model (QRM) was employed, which was more efficient for modelling extremely low or high values of the modelled variable. QRM was implemented in R programming software using its package "quantreg" (Koenker, 2021). The models comparing days with- and without-exceedances were cross-validated using an independent dataset. For cross-validation the data was divided into randomly selected 75 % training and 25 % testing datasets. Several statistical metrics were calculated for model evaluation including coefficient of determination (R^2), Root Mean Squared Error (RMSE), Mean Biased error (MBE), Mena Absolute Error (MAE) and factor of two (FAC2). For predicting NO_2 concentrations in BAU scenario, the model was refitted using the whole training dataset. Predicted concentrations were compared to the observed data to calculate whether NO_2 levels had increased or decreased in BAU scenario.

Predictor variables: *Relative humidity, temperature, atmospheric pressure, wind speed, wind direction, solar radiation, hour of the day, hour of the week, and day of the year.*

Note that road traffic was not included as a predictor because road traffic was affected by the intervention.

All analysis was performed in R programming language (R Core Team, 2020) using 'mgcv" (Wood, 2020) for fitting GAM, "lubridate" (Spinu, 2021) for analysing date and time, "randomForest" (Liaw and Wiener, 2002) for fitting RF and "openair" packages (Carslaw, 2019) for visualising the data.

To analyse how the traffic intervention affected air quality, in this paper the air quality data was analysed by using different approaches as given below:

i. Comparing measured NO_2 concentration before and during the intervention:
   - Exceedances of the threshold (43.9 μg/m^3) using 15-minutes averages.
   - Comparison of hourly NO_2 levels observed before and during the intervention.

ii. Prediction of NO_2 in BAU scenario employing machine learning modelling:
   - Modelling long-term data (October 2020 – September 2021).
   - Modelling days with-exceedances vs without-exceedances (June to September 2021).
   - Predicting NO_2 concentrations for extreme values - top ten % NO_2 concentrations.

Table 1
Days with-exceedances of the NO_2 threshold of 43.9 μg/m^3 and without-exceedances in the month of June to September 2021 at WB1 to WB8 in Thatcham.

Days with exceedances (**testing data**)		Days without exceedances (**training data**)	
June dates	July dates	June dates	July dates
1, 2,4, 7, 8, 14, 15, 16, 17, 23, 24, 25, 26, 30	1, 2, 8, 10, 11, 12, 13, 16, 17, 18, 19, 20, 21, 22, 24, 26	3, 5, 6, 9, 10, 11, 12, 13, 18, 19, 20, 21, 22, 27, 28, 29	3, 4, 5, 6, 7, 9, 14, 15, 23, 25, 27, 28, 29, 30, 31
August dates	September	August dates	September dates
1,2,3,4,6,9,10,15,16, 19, 20, 21, 22, 23, 24, 26, 28, 29	1,2,3,4,5,6,7,8, 10, 11, 13, 14, 15, 16, 17, 18, 20, 21, 22, 23, 24, 28, 29, 30	5, 7, 8, 11, 12, 13, 14, 17, 18, 25, 27, 30, 31	9, 12, 19, 25, 26, 27

3. Results and discussion

3.1. Comparing measured NO_2 concentration before and during the intervention

In this section measured NO_2 concentrations from the eight Zephyrs are analysed using visual presentation and descriptive statistics, and both 15 min and hourly concentrations are analysed.

3.1.1. Exceedances of the threshold (43.9 μg/m^3) using 15 min averages

Average 15 min NO_2 concentrations (μg/m^3) were compared with the threshold value of 43.9 μg/m^3 at different monitoring sites during the month of May (black), June (green), July (blue), August (cyan) and September (magenta) 2021 (Fig. 4). Fig. 4 also showed exceedances (red colour) of the threshold levels at different monitoring sites in different months. The NO_2 measurement of WB5 did not seem to be correct as the concentration was too high compared to the other monitoring sites (Fig. 4), and this was found to be caused by a faulty sensor having a problem with power. Therefore, WB5 was excluded from any further analysis. The total number of exceedances during the month of May to September were 426, 126, 61, 75 and 547, respectively. This showed a significant reduction in the number

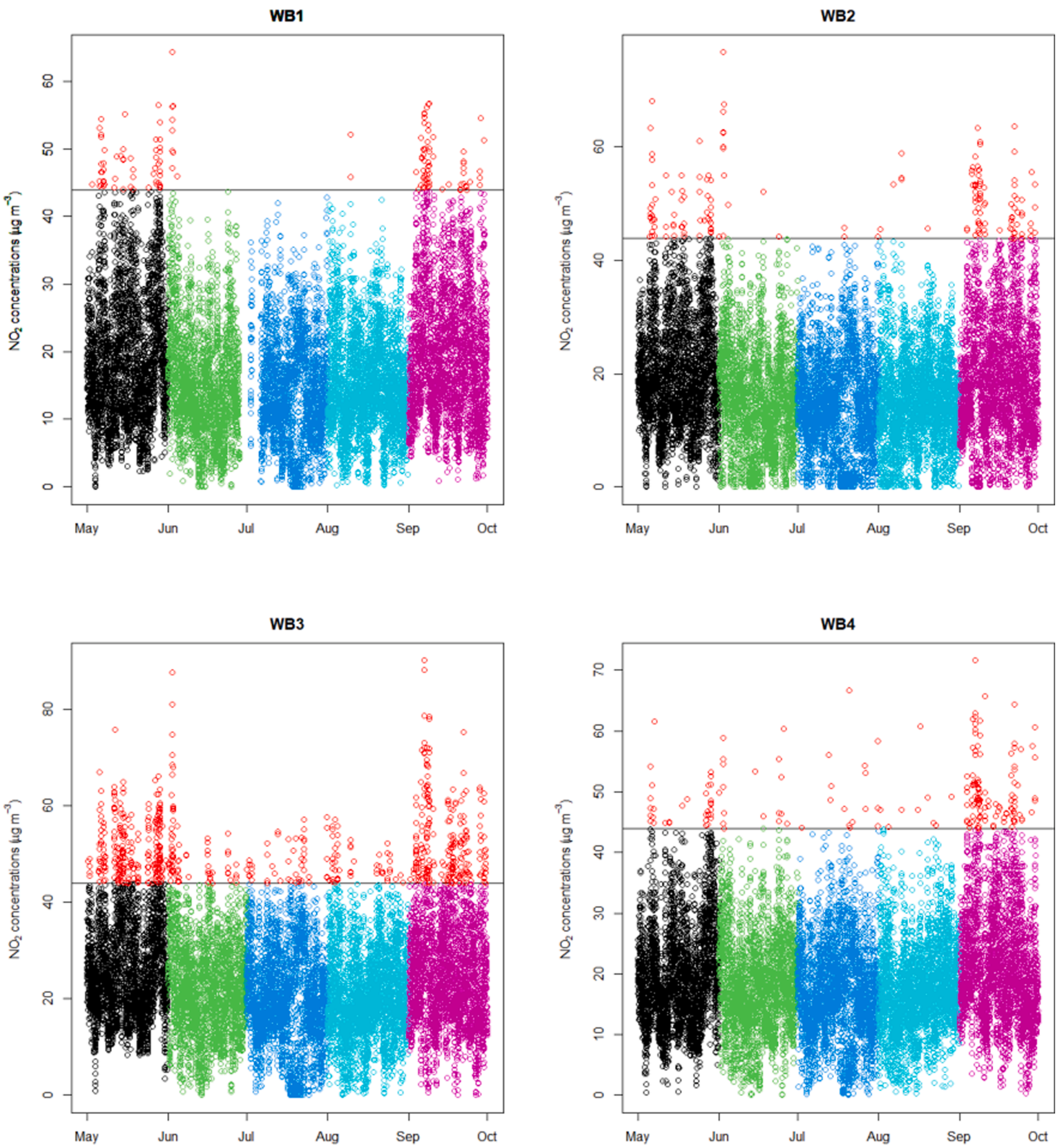


Fig. 4. Depicting exceedances (red) of 43.9 μg/m^3 NO_2 threshold during May (black), June (green), July (blue), August (cyan) and September (magenta) 2021 at different monitoring sites in Thatcham, West Berkshire. The horizontal lines show the threshold of 43.9 μg/m^3.

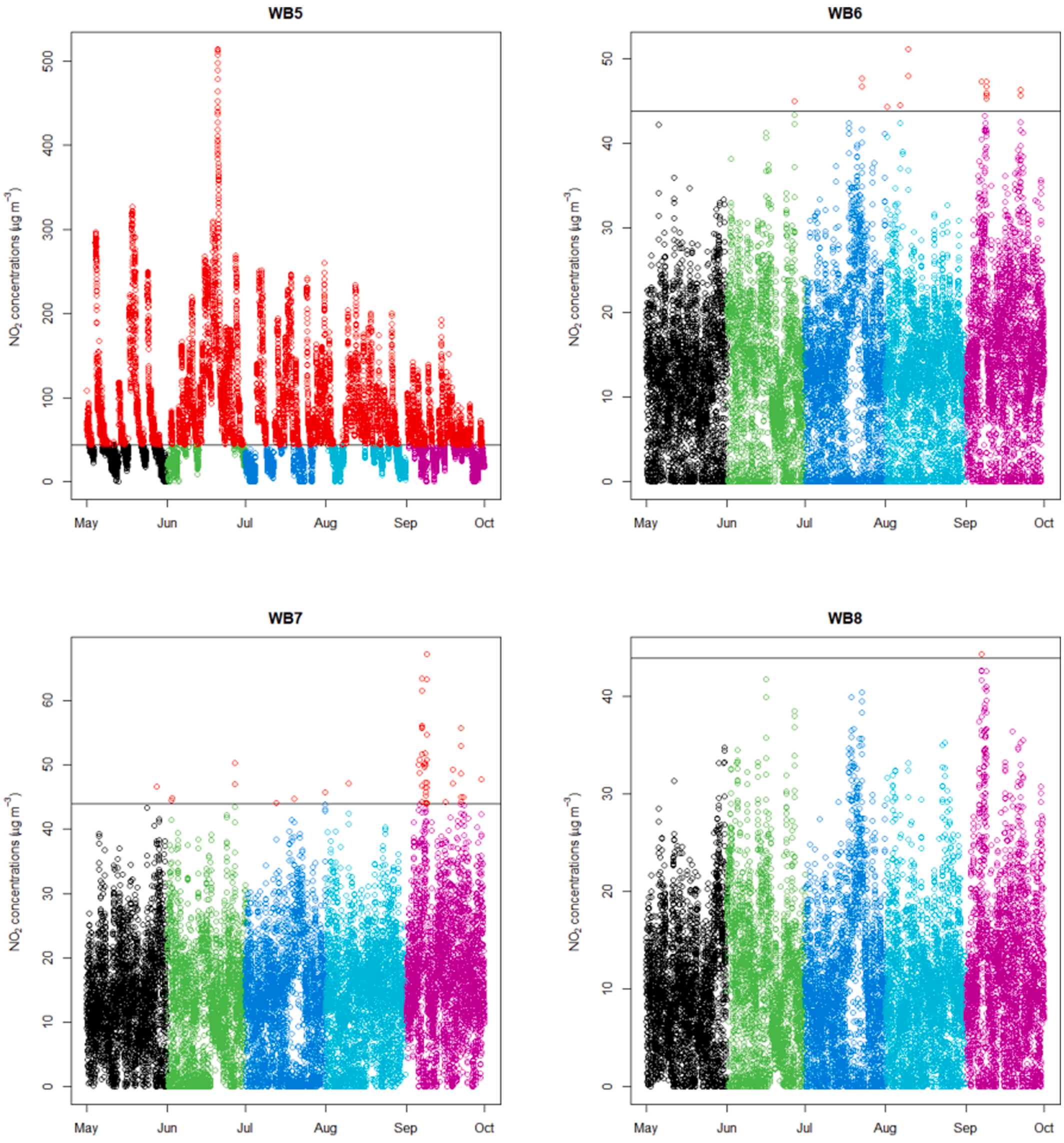
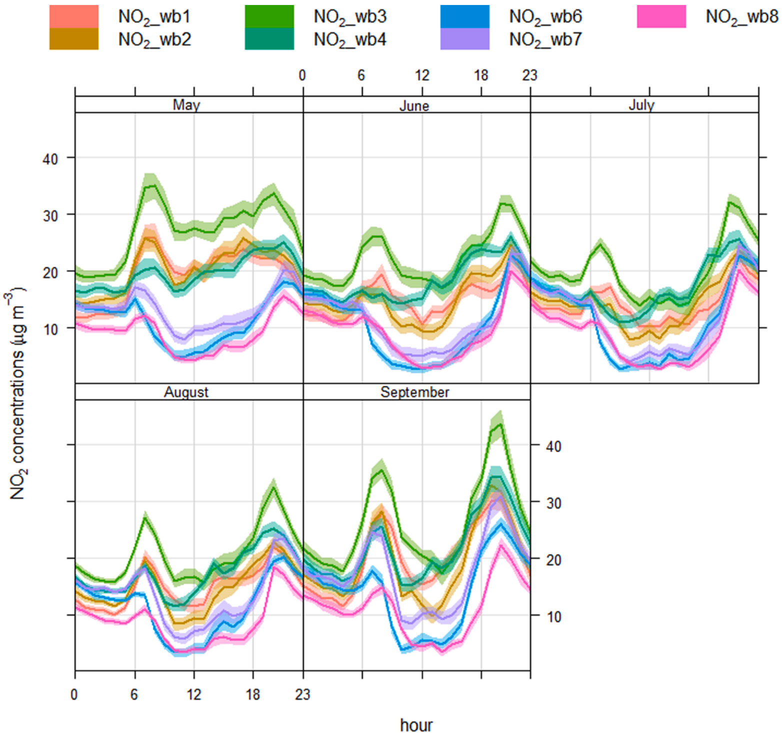


Fig. 4. (*continued*).

of exceedances in June, July and August and increase in the month of September compared to the month of May. The decreasing number of exceedances in the first three months and increasing number in September are due to the typical annual cycle of NO_2 in the UK, which shows higher levels in winter and lower in the summer.

On average, WB3 experienced the highest number of exceedances (695), followed by WB4 (182) and WB2 (162). In contrast, WB8, WB6 and WB7 experienced the least number of exceedances, which were 1, 17 and 47, respectively. Zephyrs WB1, WB2, WB3 and WB4 were deployed in the busy area of the Town, which experienced the most traffic congestion and where the road was surrounded by buildings, which hindered the dispersion of locally emitted pollutants. WB3 experienced higher levels of NO_2, which was probably due to the fact that: (a) WB3 was installed next to a busy traffic light; and, (b) the sensor was installed on the north side of the road covered by buildings, which hindered the dispersion and helped recirculate the emissions. In contrast, the southern side was open, having a park and open area, which encouraged pollution dispersion. Analysis of meteorological data showed no atypical condition that stood out that could have caused the exceedances (figures not shown for brevity).

Although traffic flow data were analysed above, we had no data to show if traffic congestion decreased or increased during these hours when the threshold was exceeded. For further analysis, 15 min data of 1st, 2nd and 3rd June were analysed (figure not shown for brevity) as these three days experienced the most exceedances in June. The main anomaly on June 2 was that solar radiation levels and wind speed decreased abruptly at about 12 pm. This probably caused a reduction in the dispersion of locally emitted NO_2 and as a result NO_2 levels increased at several sensors in Thatcham, which showed how important the meteorological parameters were in controlling the levels of air pollution in urban areas.



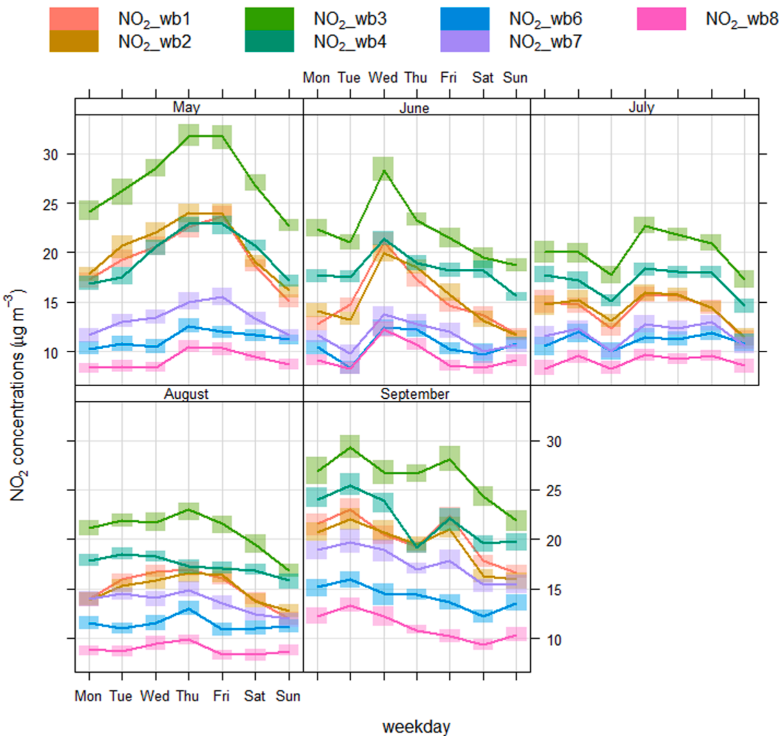


Fig. 5. Diurnal and weekly cycles of NO_2 for the month of May to September 2021 at different air quality monitoring stations in Thatcham, West Berkshire.

3.1.2. Comparison of hourly NO_2 levels measured before and during the intervention

Measured hourly air quality data from the eight Zephyrs during the months of May to September 2021 were analysed. Diurnal and weekly cycles showing concentrations of NO_2 for the months of May to September are depicted in Fig. 5 (upper and lower panels). NO_2 levels demonstrated clear reductions in June and July compared to May. However, NO_2 concentrations increased at most of the sites in September. More details are provided in Table 2, which shows absolute change and percent change in NO_2 concentrations. NO_2 levels decreased by 21.29 %, 24.53 % and 17.82 % in June and by 27.23 %, 29.50 % and 25.74 % in July at WB1, WB2 and WB3, respectively (Table 2). In September NO_2 levels increased by 3.69 %, 11.76 %, 25.42 %, 32.18 % and 23.12 % at WB1, WB4, WB6, WB7 and WB8, respectively, whereas the levels decreased at WB2 (4.62 %) and WB3 (3.51 %).

To investigate this further, NO_2 data from automatic urban and rural network (AURN) operated by DEFRA in Reading was analysed (data not shown for brevity), which showed a typical annual cycle of NO_2 in the UK and demonstrated lower levels of NO_2 in June and July and higher levels of NO_2 in the colder months. Generally, NO_2 levels were higher in May than in June, July and August, which demonstrated that probably the reductions in June and July were due to the seasonality effect rather than the intervention effect, otherwise the reductions would have been observed in September as well. This is a general trend found throughout the UK. NO_2 levels are normally higher in winter due to atmospheric conditions (for example, high pressure and low temperature), which hinder the dispersion of locally emitted air pollutants. The boundary layer is also shallow and the atmosphere is relatively stagnant in winter, both of which discourage horizontal and vertical movement of the pollutants. Ideally, we should compare the concentrations of NO_2 in 2020 with the same months in 2021, but as we did not have measured data in June to September 2020 in Thatcham, it was challenging to assess the effect of the intervention to draw conclusive results. The atmosphere is a very complex system and air quality is affected by numerous confounding factors, therefore pollutant levels demonstrate significant spatial and temporal variability. In this respect, the diurnal cycle is controlled by meteorological conditions and the levels of emissions, the weekly cycle is predominantly controlled by emission levels (e.g., road traffic), and the annual cycle is mainly controlled by meteorological conditions.

3.2. Prediction of NO_2 in BAU scenario employing machine learning modelling

In this section, different machine learning approaches are employed to predict NO_2 in BAU scenario for the period when the strategy was implemented in June to September 2021.

3.2.1. Machine learning modelling using long-term data (October 2020 – September 2021)

In this section, air quality data was used from three Zephyrs WB1, WB2 and WB3, where data was available from October 2020 to September 2021. The data from October 2020 to May 2021 was used to train (fit) the model, which was then used to predict the levels of NO_2 for the month of June to September 2021 assuming BAU scenario. Here GAM and RF machine learning models were employed.

Predicted and observed concentrations were compared and various statistical metrics were calculated to assess the models' performance for predicting the concentrations of NO_2 for the fitted model using training data (Table 3). Correlation coefficient was higher for GAM (0.79 to 0.82) than for RF (0.71 to 0.76), showing better performance of GAM.

Estimated NO_2 concentrations for the BAU scenario using testing data and observed concentrations are visually compared in Fig. 6. It is clearly shown that observed concentrations in June and July were lower than the BAU scenario predicted by both GAM and RF. This means that the models predicted that the observed concentration was lower than expected under BAU scenario in June and July. The models showed slightly different results in August and September. GAM predicted that in September the NO_2 concentration was higher than expected, although in August the observed concentration was higher at WB1 and lower at WB2 and WB3 (Table 4). According to the GAM model outputs, observed NO_2 levels were lower than the predicted concentrations by 67.40 %, 63.45 % and 26.33 % in June, and 56.30 %, 55.22 % and 27.60 % in July at WB1, WB2 and WB3, respectively in BAU scenario. In August the observed concentrations were higher at WB1 (30.48 %), and lower at WB2 (9.12 %) and WB3 (13.72 %). In September the observed concentration was higher by 56.14 %, 11.52 % and 5.09 % at WB1, WB2 and WB3, respectively. Further details are provided in Table 4, which also shows the outcome of RF model.

Here it should be noted that the training dataset did not cover the whole annual cycle of NO_2; for example, the months of June to September were not included in the training data, therefore the model struggled to predict these months accurately, as the model failed to capture the effect of seasonality on NO_2 levels. Furthermore, NO_2 levels were much higher in the training data (October 2020 – May 2021) than in June, July, August and September 2021. Therefore, the results were not reliable. To address this issue and to avoid the effect of seasonality, only data from the months of June to September were modelled in the coming sections.

Table 2
Change in the concentrations of NO_2 between before (May) and during intervention (June, July, August and September), where June_diff = June – May, and % June_diff = (June_diff/May)*100.

Site	%June_diff	% July_diff	%Aug_diff	%Sept_diff
WB1	−21.29	−27.23	−22.76	3.69
WB2	−24.53	−29.50	−27.34	−4.62
WB3	−17.82	−25.74	−24.01	−3.51
WB4	−6.96	−13.41	−11.58	11.76
WB6	−6.11	−1.32	0.94	25.42
WB7	−12.93	−11.66	2.24	32.18
WB8	4.36	−0.36	−2.47	23.12

Table 3
Values of different statistical metrics for assessing the performance of GAM and RF models for estimating different pollutants using training data at the three monitoring sites.

Model	Metrics	WB1	WB2	WB3
GAM	FAC2	0.73	0.91	0.96
	MBE	2.44e-12	4.22e-13	−1.802–12
	RMSE	6.69	7.16	7.11
	MAE	5.06	5.41	5.46
	R	0.82	0.79	0.81
RF	FAC2	0.68	0.88	0.95
	MBE	0.003	0.002	0.002
	RMSE	8.09	8.64	8.76
	MAE	6.10	6.49	6.63
	R	0.76	0.71	0.73

3.2.2. Modelling days with exceedances vs Without exceedances

Seasonality had a significant effect on NO_2 levels, therefore, NO_2 levels were much lower in warmer months (for example in June and July) than the other months (October 2020 – May 2021). The models trained in colder months struggled to predict the warmer months correctly. In this section, only the data for the months of June to September 2021 are used to avoid the effect of seasonality.

Model validation: In this section, we analysed how the model was validated to see how good the model was in predicting an independent dataset.

For model validation, the training data (April, May and days with no exceedances) was further split into two subsets: sub-training (75 %) and sub-testing (25 %) datasets. It was shown in the previous section that GAM outperformed RF, therefore here we employed GAM only. The GAM was fitted on the sub-training data and then used to predict the sub-testing data. Predicted and observed values were compared for assessing the model performance. Correlation coefficient (r), MBE and RMSE values are provided for both training and testing dataset (Table 5). The model showed a good fit at all three sites. Correlation coefficients were 0.72, 0.74 and 0.79 for the sub-testing data at WB1, WB2 and WB3, respectively. Hence, the model performance was satisfactory at all sites.

Fig. 7 compares the GAM predicted and observed NO_2 concentrations for both sub-training and sub-testing data at WB1 (WB2 and WB3 were not shown for brevity, which showed almost similar results). It can be observed from Fig. 7 that the model struggled to predict the extreme values and therefore was under predicting the higher values of NO_2 concentrations. To quantify how much the model was under or over predicting, we calculated percent difference between observed and predicted concentrations. The model successfully predicted average NO_2 concentrations for the testing data and the difference was negligible between predicted and observed concentrations. The percentage difference for the testing data was 1.39 %, 1.18 % and −3.40 % and for the training data was 0.12 %, 0.06 % and −3.23 % at WB1, WB2 and WB3, respectively. This showed that the model performed well in predicting the training and testing data.

4. Predicting NO_2 concentrations for BAU scenario

After having validated the model and showed that the model was predicting an independent dataset well, we fitted the model again using the whole training data (April, May and days with no exceedances in June to September) and then used it to predict the testing data (days with exceedances in June to September) in the BAU scenario. The absolute difference and percent difference between observed and predicted NO_2 concentrations for the testing data were calculated. The GAM model demonstrated an increase in NO_2 levels: i.e., the model prediction was lower than the observed concentrations, which meant that according to the model the observed levels were higher than what would be expected. The percentage increase predicted by GAM was 12.06 %, 13.97 % and 11.33 % at WB1, WB2 and WB3, respectively. Fig. 8 compares predicted and observed concentrations for the testing data, which shows again that the predicted values were lower than the observed levels, especially for the peak values.

To analyse how the difference between observed and predicted NO_2 concentration varied with the number of exceedances for each day, we analysed data from WB3, which experienced more exceedances than the other sites. Daily average observed and predicted NO_2 concentrations and the number of exceedances for each day were calculated. Fig. 9 shows how the exceedances are related to the difference (observed minus predicted daily NO_2 concentrations), which shows that overall the difference increases with the increasing number of exceedances. Therefore, there was a positive correlation between them. Spearman's correlation coefficient was 0.60 between the number of exceedance and differences. This indicated that the model showed larger difference for the days with higher number of exceedances. This probably meant that the levels increased when the intervention was triggered. However, we also believe that the model struggled to predict atypically high values of NO_2, therefore other approaches should be tried to further improve the model prediction of the extreme values.

4.1. Predicting NO_2 concentrations for extreme values - top ten % NO_2 concentrations

The aim of this section was to see how extreme values (top 10 %) of NO_2 changed due to the intervention. For this purpose, in addition to GAM, a QRM was developed using the data described in the previous section. Firstly, both models were validated to show how good these models were in predicting the levels of NO_2 concentrations. For this purpose, estimated and observed concentrations

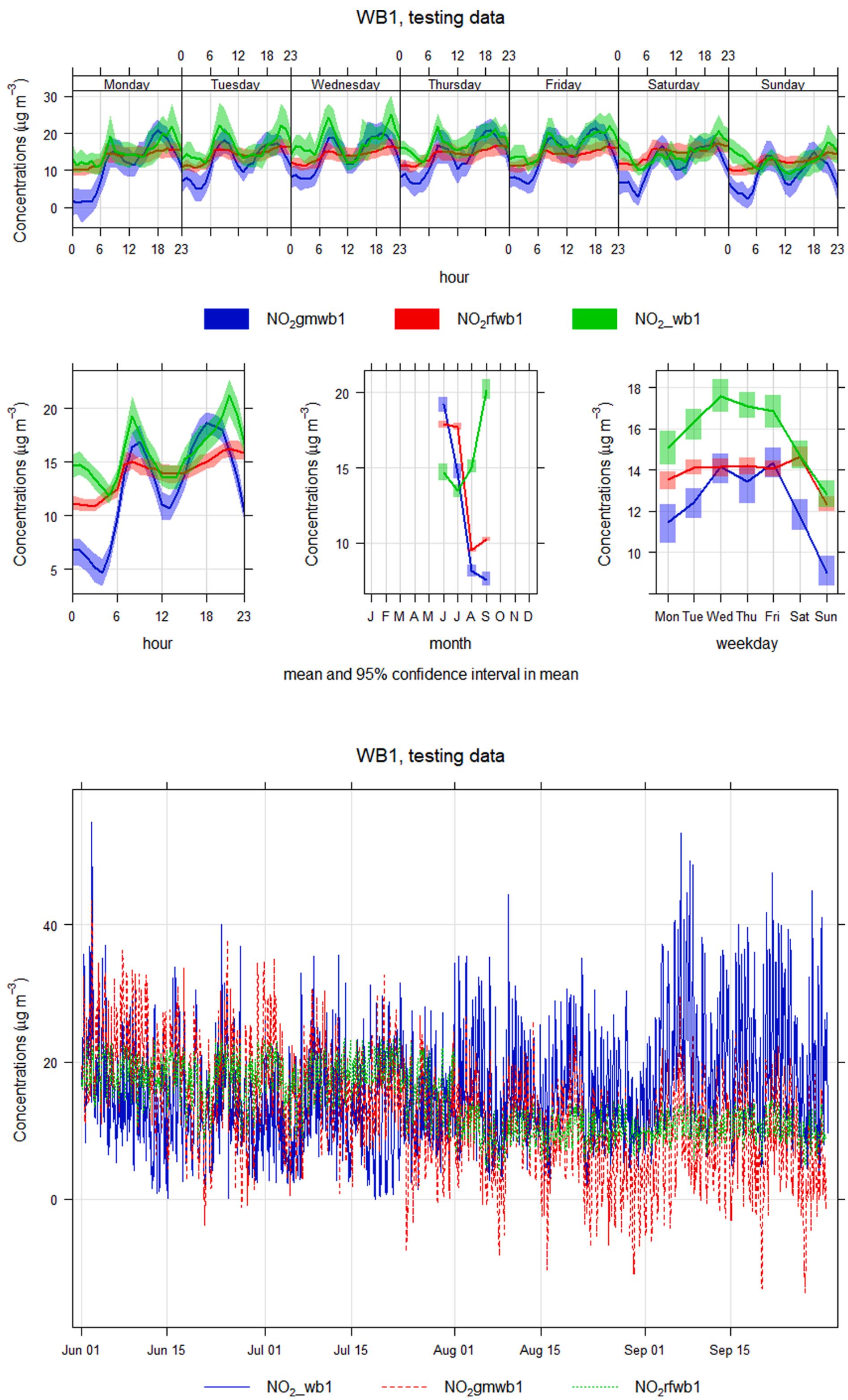


Fig. 6. Comparing predicted NO_2 for the BAU scenario using GAM (NO_2gmwb1) and RF models (NO_2rfwb1) with the observed NO_2 concentrations (NO_2_wb1) at WB1 site for the month of June to September 2021 using the testing dataset.

Table 4
Comparing BAU with observed NO_2 concentrations for the month of May, June, July, August and September 2021 at WB1, WB2 and WB3 in Thatcham (Diff = observed – BAU, and % Diff = (diff/observed)*100) using GAM and RF machine learning models.

Model	Site	June		July		August		September	
		Diff	%Diff	Diff	%Diff	Diff	%Diff	Diff	%Diff
GAM	wb1	−9.89	−67.40	−7.58	−56.30	4.58	30.48	11.36	56.14
	wb2	−9.70	−63.45	−8.00	−55.22	−1.36	−9.12	2.25	11.52
	wb3	−5.87	−26.33	−5.59	−27.60	−2.84	−13.72	1.34	5.09
RF	wb1	−4.53	−30.87	−0.48	−3.57	6.15	40.93	10.45	51.80
	wb2	−6.36	−41.59	−6.58	−45.43	−6.28	−42.23	−3.02	−15.47
	wb3	−4.47	−20.06	−5.76	−28.44	−5.19	−25.07	−1.04	−3.94

Table 5
Metrics for assessing model performance for both training and testing dataset at WB1, WB2 and WB3.

Site	Metrics	Training data	Testing data
WB1	R	0.74	0.72
	RMSE	5.85	6.25
	MBE	3.11e-11	−0.23
WB2	R	0.75	0.74
	RMSE	6.08	6.47
	MBE	2.91e-11	−0.20
WB3	R	0.79	0.79
	RMSE	6.37	6.58
	MBE	4.23e-12	0.38

were compared and different metrics calculated. The values of R, RMSE and MBE were 0.91, 3.99 and 1.42 for QRM, and 0.39, 7.87 and −2.18 for GAM, respectively. This clearly demonstrated that QRM outperformed GAM in predicting the extreme values of NO_2. The fitted models were then used to predict NO_2 for the BAU scenario. As an example, scatter plots of observed NO_2 versus the predictions of GAM and QRM are shown in Fig. 10 for WB1, where it can be observed that QRM was able to predict the extreme values more efficiently than the GAM. Percent difference between observed and predicted NO_2 for the top 10 % data was calculated (Table 6). The % difference was 42.28 %, 44.89 % and 36.64 % for GAM and −20.85 %, –22.34 % and −18.43 % for QRM at WB1, WB2 and WB3, respectively (Table 6). Hence, GAM showed an increase whereas QRM showed a decrease in the top 10 % NO_2 levels during the interventions. Hence, according to the QRM extreme NO_2 levels decreased during the intervention.

We conclude that such interventions are helpful in reducing peaks of NO_2 concentrations, which can be helpful in avoiding the acute health effects of air pollution. However, average pollution levels may not decrease or even further increase, which require further investigations over an extended period of time and large spatial scale. Therefore, it is hard to decide whether such interventions could be recommended for improving air quality in urban areas. Further investigations are also required to study the impact of such interventions on the surrounding areas including both local and regional scales. This study highlights some of the shortcomings in assessing the effect of interventions on air quality, which are discussed in detailed in Munir et al. 2021.

Some possible analyses of the results presented are as follows: (1) Given that increasing the duration of the green light may result in increased traffic flows, hence the average observed NO_2 concentrations are higher than those predicted for the BAU scenario. (2) The trigger of the traffic intervention strategy may result in increased road speed and reduced congestion, and thus peak NO_2 concentrations caused by congestion are decreased. In the UK local transport authorities in England are required to produce Local Transport Plans (LTPs) under the Local Transport Act 2008. Local authorities follow a number of measures to reduce levels of pollutants from vehicles, either directly or indirectly. These measures include: (a) Reducing traffic levels, e.g., through controls on the most polluting vehicles; (b) behaviour change programmes to encourage travel alternatives and improved loading/occupancy of vehicles; (c) Improving traffic flows, e.g., through traffic management including junction design; and (d) Cleaner vehicle technology, e.g., promoting the use of low emission vehicles. It is challenging to clearly identify the impacts of a single intervention against a backdrop of the diversity of policies that have been implemented to improve air quality and reduce population exposure across the UK and beyond. Therefore, several authors have suggested the concept of policy intervention packages, which exploit the potential synergetic relationships between certain policy interventions and thus greatly increase the effectiveness and efficiency of resultant policy interventions (e.g., Givoni et al., 2013; Thaller et al., 2021).

5. Conclusion

In this paper, the effect of smart traffic interventions on air quality was investigated using several approaches:

- Analysis of measured data using descriptive statistics: (a) Using 15-minutes average exceedances of 43.9 μg/m^3 of NO_2 threshold, and (b) comparing hourly NO_2 data in May (pre-intervention period) with June to September 2021(intervention period).

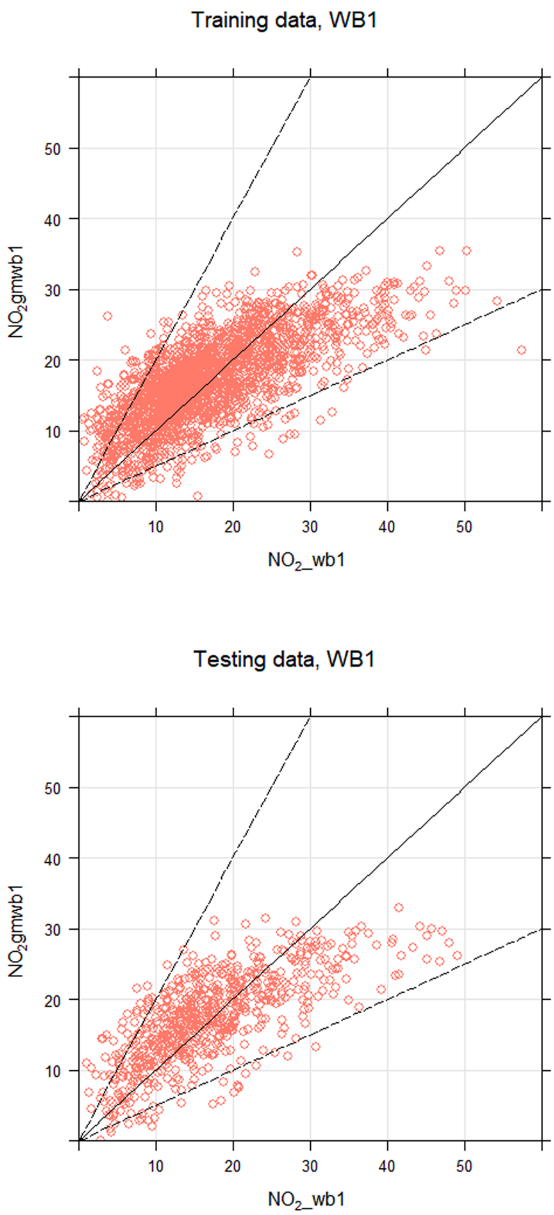


Fig. 7. Scatter plots comparing predicted and observed NO_2 concentrations of both training and testing dataset employing GAM at WB1 site. The 1:1 line is the solid black and the 1:0.5 and 1:2 lines are the dashed black lines. Together these lines help show how close a group of points are to a 1:1 relationship and also show the points that are within a factor of two (FAC2). Most of the point within the FAC2 show good model fit.

- Machine learning modelling: (a) modelling long-term hourly NO_2 concentrations (October 2020 – September 2021), (b) comparing days with-exceedances vs no-exceedances (June – September 2021), and (c) predicting the top 10 % NO_2 concentrations.

It was shown that generally NO_2 levels were higher in May than in June, July, and August due to the annual cycles of pollutants and seasonal variations. A comparison of May with June to September using both exceedances of the threshold and hourly concentrations showed a reduction in NO_2 concentrations during June, July and August and an increase in September. For further analysis, various machine learning modelling approaches were used to predict NO_2 concentrations in the BAU scenario. Firstly, the models were applied to long-term data (October 2020 to September 2021). However, as the data was not available for a whole year, the results were biased by the seasonal variations. To avoid the issue of the seasonal variability, only the air quality data collected in June to September 2021 was modelled. For this purpose, days with no exceedances and days with-exceedances were compared, which showed no reduction due to interventions. In fact, it was shown that average NO_2 levels had increased during the intervention period. Furthermore, according to the model results, days with more exceedances demonstrated a higher positive difference between observed and predicted concentrations, which showed that average NO_2 levels had increased during the days that experienced exceedances. GAM was very good at

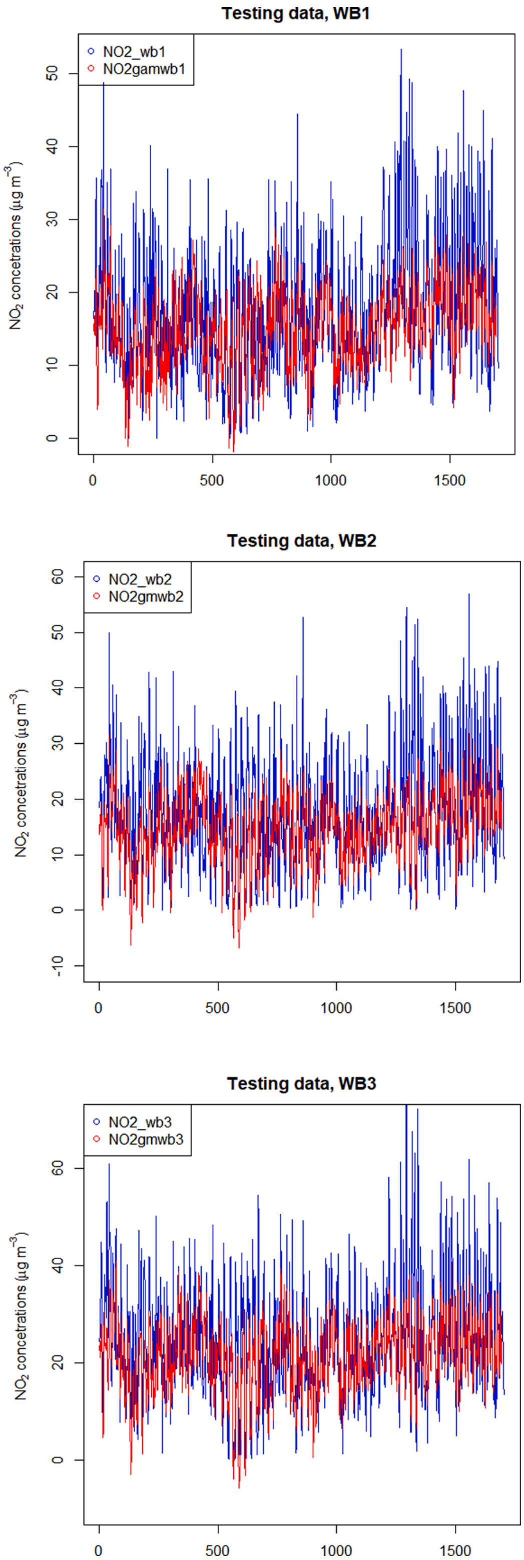


Fig. 8. Comparing observed and GAM predicted NO_2 concentrations in BAU scenario at WB1, WB2 and WB3.

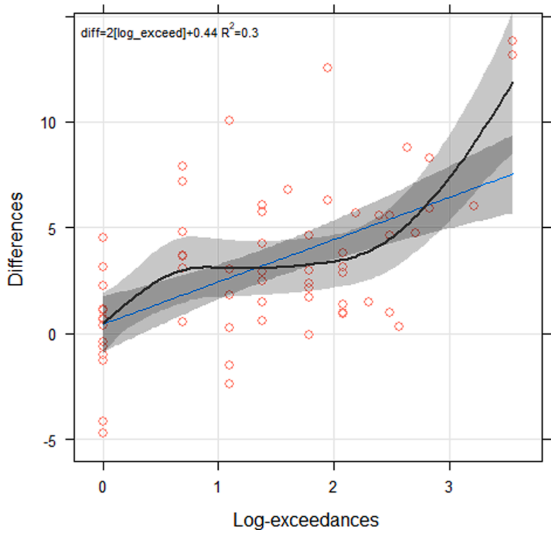


Fig. 9. Showing how difference between observed and predicted concentrations varied with the number of exceedances at WB3, which experienced most exceedances during the intervention period 2021. The blue solid curve shows the linear line and the black curve shows the smooth line (nonlinear). The grey area show the confident intervals of the data. On the x-axis, the log of the exceedances is displayed (log-exceedances).

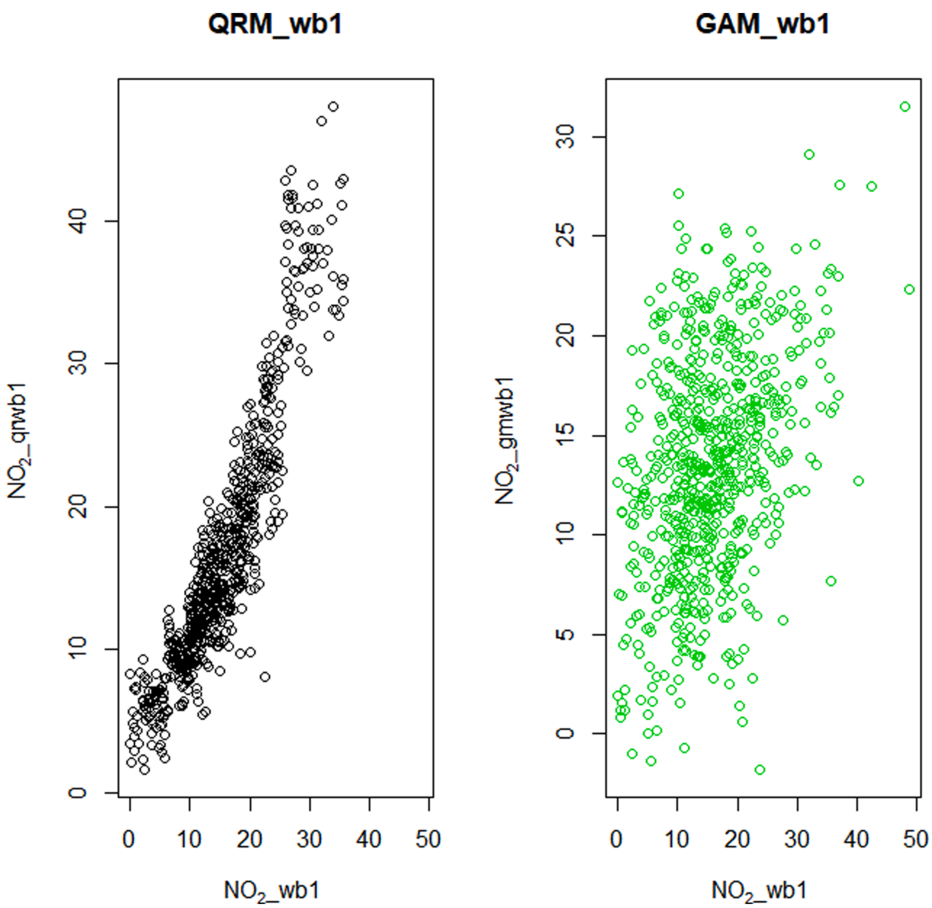


Fig. 10. Comparing observed and predicted concentrations for the QRM and GAM model using testing data at WB1.

Table 6
Comparing observed and predicted NO_2 concentrations for top ten % data using GAM and QRM at WB1, WB2 and WB3.

Model	Site	Observed	BAU	Diff	%Diff
GAM	wb1	30.94	17.86	13.08	42.28
	wb2	32.99	18.18	14.81	44.89
	wb3	43.20	27.37	15.83	36.64
QRM	wb1	30.94	37.39	−6.45	−20.85
	wb2	32.99	40.36	−7.37	−22.34
	wb3	43.20	51.16	−7.96	−18.43

predicting average concentrations and outperformed RF, but it struggled to accurately predict atypically high NO_2 concentrations. As a result, a QRM model was employed to predict the top 10 % NO_2 concentrations, which showed a reduction in extreme values. Therefore, according to the modelling results, average NO_2 levels increased and extreme levels decreased due to the traffic intervention. How the intervention affected traffic flow and NO_2 concentrations on other roads nearby, was not analysed due to data unavailability for the adjacent area. Furthermore, data are analysed only for a limited period of time. In future long-term, at least a year data should be analysed. Every approach has its limitations, but our study provides great insight on choosing appropriate approaches for evaluating the impact of interventions on air quality in urban environment.

This paper demonstrated a detailed methodology for assessing the impact of smart intervention on air quality in urban areas. It is suggested that several approaches should be employed for the evaluation of the intervention. Simply, comparison of the raw data before and during the intervention would not produce reliable results (Munir et al., 2021). For robust analysis several factors should be considered, including: (1) Adjust for the effect of meteorological parameters; (2) Adjust for the effect of seasonal variations; (3) Make sure the air quality monitoring site is representative of the local area where intervention is implemented; (4) Consider the uncertainties of the air quality monitoring sensors; (5) Account for the contribution of background concentrations, which also include the formation of secondary pollutants; and (6) In addition to descriptive statistics, employ advance machine learning techniques, which are more capable of extracting changes in the levels of air pollutants.

This analysis showed that adjustment of the traffic light cycles can induce changes in NO_2 concentrations, especially in extreme levels on roadside locations. To enhance its effectiveness further, the traffic light adjustment can be integrated with other types of transport-related interventions (intervention packages). Other transport-related interventions may include such measures as promotion of low emission zones; road pricing; subsidising public transport; abatement retrofit; promotion of walking and cycling; provision of school buses; road pricing and access restrictions; and increasing fuel duty (Public Health England, 2020). Traffic interventions that promote the uptake of low and zero-exhaust emission vehicles, particularly electric vehicles have also been found as being likely to improve air quality (Public Health England, 2020).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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