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Street-scale air quality modelling over the West Midlands, United Kingdom: Effect of idealised traffic reduction scenarios

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ABSTRACT

Air pollution is the major environmental risk to human health. Road transport is one of the major sources for air pollution, particularly nitrogen dioxide, in urban areas, and hence traffic control is an important measure in air quality management. A street-scale air quality model, ADMS-Urban, was configured for a case study of the West Midlands, UK to represent a baseline year (2019). Model outputs were evaluated using hourly air pollutant measurement data, and the model demonstrates good performance overall. This modelling tool was then used to explore the effect of five hypothetical traffic reduction scenarios, ranging from 10% to 90% reduction in traffic activity; scenario impacts were analysed over a range of spatial resolutions. The impacts of traffic reduction are highly dependent on spatial resolution (i.e. street scale, electoral ward level and local authority level), which has to be taken into account when formulating policies for managing air quality on local and city-wide scales. There was an almost linear relationship between the predicted annual concentration and traffic reduction for both NO_2 and $PM_{2.5}$. Traffic reduction would principally reduce NO_2 concentrations, with even very substantial changes in traffic having more limited effects on reducing $PM_{2.5}$ concentrations reflecting the importance of regional and non-traffic $PM_{2.5}$ sources.

1. Introduction

Air pollution is a substantial environmental issue that causes risk to human health (WHO, 2022). Air pollutants such as nitrogen dioxide (NO_2) and particulate matter particles ($PM_{2.5}$ with an aerodynamic diameter smaller than 2.5 μm) are associated with a range of diseases, e.g. respiratory disease, lung cancer, heart disease and stroke (Hu and Guo, 2021). It was estimated by the World Health Organisation (WHO) that poor ambient air quality caused 4.2 million premature deaths globally in 2019 (WHO, 2022). There were 29,000–43,000 estimated premature deaths annually attributable to long term exposure to air pollution in the UK (COMEAP, 2018). The WHO released an update for its Global Air Quality Guidelines in September 2021 (WHO, 2021), which identify potential health risks from exposures at very low levels of air pollution. 99% of the world's population in 2019 was exposed to air pollution levels exceeding the 2021 WHO air quality guidelines (WHO, 2021).

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Air quality monitoring provides direct and continuous information relating to ambient air pollution levels. There are a range of air quality monitoring options, such as the UK's Automatic Urban and Rural Network (AURN) (Defra, 2019), low-cost sensors (Wesseling et al., 2019), and mobile monitoring (Matthaios et al., 2023; Samad and Vogt, 2021). To complement air quality monitoring, air quality modelling has been widely used to reproduce and predict air pollution levels at high spatial and temporal scales (Feng et al., 2021). Air quality modelling adopts mathematical equations to capture the interaction of emissions, chemistry and physical processes in the atmosphere (Lamb and Seinfeld, 1973). Air quality monitoring generates valuable datasets which can be used to validate air quality models. In addition, models commonly use measurement datasets as input, for example as boundary conditions (Simpson et al., 2012), or for calibration purposes (Brookes et al., 2021). The European Directive on Ambient Air Quality and Cleaner Air for Europe encourages the use of air quality modelling in the assessment of emission reduction interventions and air quality forecasting (EUR-Lex, 2015).

Road transport is one of the major sources for air pollution in urban areas. It was estimated that 35% of nitrogen oxide (NO_x) emissions and 13% of $PM_{2.5}$ emissions were generated by the transport sector in the UK (OS, 2021). Traffic control is an important measure in air quality management, particularly during air pollution episodes (Shahbazi et al., 2017). There are a number of studies attempting to investigate the effect of traffic restrictions on air quality, especially during the Covid-19 period with lockdown measures, which serves as a large, if impromptu (and tragic), experimental case study. Xu et al. (2023) explored the air quality changes due to traffic restrictions for four cities in Spain and United States. They found that there was a decrease in NO_2 concentrations by about 50% and an increase in O_3 concentrations by about 40% in response to a traffic volume reduction of 60–90%. Lin et al. (2022) found traffic flow on a motorway in the UK decreased by 7–39% due to the Covid-19 outbreak, and corresponding total non-exhaust PM emissions also reduced by the similar percentage. It was also found that resuspension of road dust was the largest contribution to the non-exhaust emissions (rather than road wear, tyre wear, and brake wear) for the motorway during the studied period. Hwang and Lee (2022) showed that a 1% traffic reduction would lead to 0.94% reduction in $PM_{2.5}$ and 0.74% reduction in NO_2 for Seoul, South Korea. Jephcote et al. (2021) demonstrated that there was a reduction of 69% in the UK monthly average traffic flow in April 2020 (compared with the previous year). Associated air pollution reduction was 38.3% for NO_2 and 16.5% for $PM_{2.5}$. Sánchez et al. (2021) found that the reductions in air pollution concentrations (for NO_x and PM) were around 45% for a 5% traffic reduction scenario and up to 53% for a 20% traffic reduction scenario for Madrid, Spain. Feng et al. (2021) found that removing traffic emissions completely (i.e. 100% traffic reduction) was estimated to cause a decrease in modelled NO_2 and $PM_{2.5}$ concentrations by 18.4% and 9.7%, respectively, for Wuhan, China. These reductions were much less compared with the scenario of removing industrial emissions which led to 65.6% and 48.5% reductions in modelled NO_2 and $PM_{2.5}$ concentrations, respectively. Tanzer-Gruener et al. (2020) used a network of low-cost sensor packages to quantify the impact of traffic activity on air quality in real time in Pittsburgh, USA. They found that the reduction in NO_2 concentration (50%) during the morning peak was consistent with the commuter traffic activity reduction (also 50%) at high traffic-density locations. Kerr et al. (2022) adopted a semi-empirical method (combining measurement and models) to estimate the changes of NO_2 concentrations during the COVID-19 pandemic in 2020 for European cities. They demonstrated a linear regression fit between the change of NO_2 and diesel vehicle shares, reflecting the strong impact of fuel type on NO_2 concentrations. Kumar et al. (2020) investigated the impact of COVID-19 on $PM_{2.5}$ concentrations in five Indian cities using measurement datasets from 2015 to 2020. Their data analysis found a linear correlation between the traffic volume and $PM_{2.5}$ concentrations, although other sector sources may be also impactful. Wang et al. (2021) used ground and satellite observations during the COVID-19 pandemic in 2020 to constrain predictions of a regional chemistry transport model, and found a near-linear relationship between the traffic reduction and NO_2 and $PM_{2.5}$ concentrations for most cities in China. They further built a near-linear model between the traffic reduction and concentration reductions, and extrapolated this model to predict the impact of complete electrification on air quality.Bigazzi and Rouleau (2017) carried out a systematic literature review on the effectiveness of traffic management strategies for improving urban air quality. Traffic management strategies were classified into 5 categories, i.e. traffic flow control, operating restrictions and pricing, lane management, speed management and trip reduction strategies. There was limited evidence for the effects of traffic management strategies on emissions and air quality.

The paper describes the configuration and evaluation of a street-scale air quality model, accounting for dispersion and chemical reactions associated with emissions from major road at high resolution for an approximately 900 km^2 domain covering the West Midlands, UK, and the application of the modelling tool to explore the effect of traffic reduction scenarios, spanning a large dynamic range, on air quality in this region. Section 2 presents the street-scale modelling approach, model configuration and traffic reduction scenarios. Section 3 reports the evaluation of the baseline model and the results of modelling scenarios. Section 4 discusses the modelling results. Section 5 provides brief conclusions.

2. Methods

2.1. Street-scale modelling: ADMS-Urban

ADMS-Urban is an Atmospheric Dispersion Modelling System, which is based on a quasi-Gaussian plume air dispersion model (Carruthers et al., 1994). ADMS-Urban has been widely used to simulate air quality with application of assessing emission-reduction scenarios and interventions (Zhong et al., 2023; Zhang et al., 2022). The dispersion characteristics of the atmospheric boundary layer are governed by a range of meteorological parameters, such as Monin–Obukhov length, boundary layer height, wind speed and wind direction. Hourly meteorological data (wind speed and direction, temperature, cloud cover etc) are processed to generate vertical atmospheric boundary layer profiles which are used to drive dispersion processes within the model. Air flow is inhomogeneous within urban areas, since the upwind flow is displaced by buildings; in-canopy wind speeds are correspondingly reduced. The ADMS-Urban model represents this through use of an 'urban canopy' module (Hood et al., 2014), which calculates turbulence and wind speed profiles that relate to the spatially varying building density at the neighbourhood scale, parameterised via the surface roughness length (e.g. at a resolution of 1 km × 1 km). For local street canyons, the model has an advanced street canyon module to capture the street canyon (both asymmetric and symmetric) effect on in-canyon dispersion, and the channelling and circulation of the in-canyon flow (Hood et al., 2021).

ADMS-Urban can capture the dispersion of a range of emission sources that occur in urban areas, from explicit major road and industrial point emissions to grid-averaged emissions. The model resolves concentration gradients near the local dispersion region of emission sources. The NO_x-O_3-VOC chemistry is captured by the Generic Reaction Set (GRS) chemistry scheme (Venkatram et al., 1994) and the formation of secondary particular matter is represented by sulphate chemistry (CERC, 2021a).

2.2. Model configuration for West Midlands

The West Midlands, UK region (shown as Fig. 1) was used as a case study for this air quality modelling study. West Midlands covers 7 local authorities (Birmingham, Coventry, Dudley, Sandwell, Solihull, Walsall and Wolverhampton) with a total area of 902 km^2 and a population of 2.9 million. ADMS-Urban requires a range of model input data (such as emissions, background, meteorological data, urban canopy and street canyon data) prior to the running of the model. The model included emissions from explicit point and major road sources, and grid sources for the West Midlands (Fig. 1) for the baseline year of 2019 (the last typical year prior to the Covid 19 pandemic) in this study, which is an update for the modelling year of 2016 presented in Zhong et al. (2021). The EMIT Emissions Inventory Toolkit (CERC, 2021b) was used to pre-process emissions data from all source types and for all scenarios, allowing direct import into the ADMS-Urban model.

Emission rates for point sources (larger industrial sources) for the year of 2019 were obtained from the UK National Atmospheric Emissions Inventory (NAEI, Tsagatakis et al., 2021). Stack parameters (such as stack height and diameter, efflux temperature and exit velocity) for point sources were derived from the Airviro model (Airviro, 2018) through Birmingham City Council (BCC). Major road traffic data combined Transport for West Midlands' PRISM (PRISM, 2019) and BCC's SATURN (BCC, 2018) traffic models, which was used in Zhong et al. (2021). The bus timetable (Remix, 2019) was used to estimate the traffic activity for buses. Traffic fleet composition and emission factors with real-world adjustments (Hood et al., 2018) were derived from the EMIT dataset for the year of 2019. The emission rates for major road sources for 2019 were then automatically calculated in EMIT. Grid emissions for all SNAP (Selected Nomenclature for Air Pollution) sectors at 1 km resolution for the year of 2019 were derived from NAEI (Tsagatakis et al., 2021). For SNAP07 Road Transport sector, the residual between the NAEI derived emissions and explicit major road emissions (aggregated to the 1 km resolution) was taken as unresolved Minor Road emissions, and included in the model as gridded emissions. Table 1 shows a summary of different types of emission sources over the West Midlands computational model domain for the year

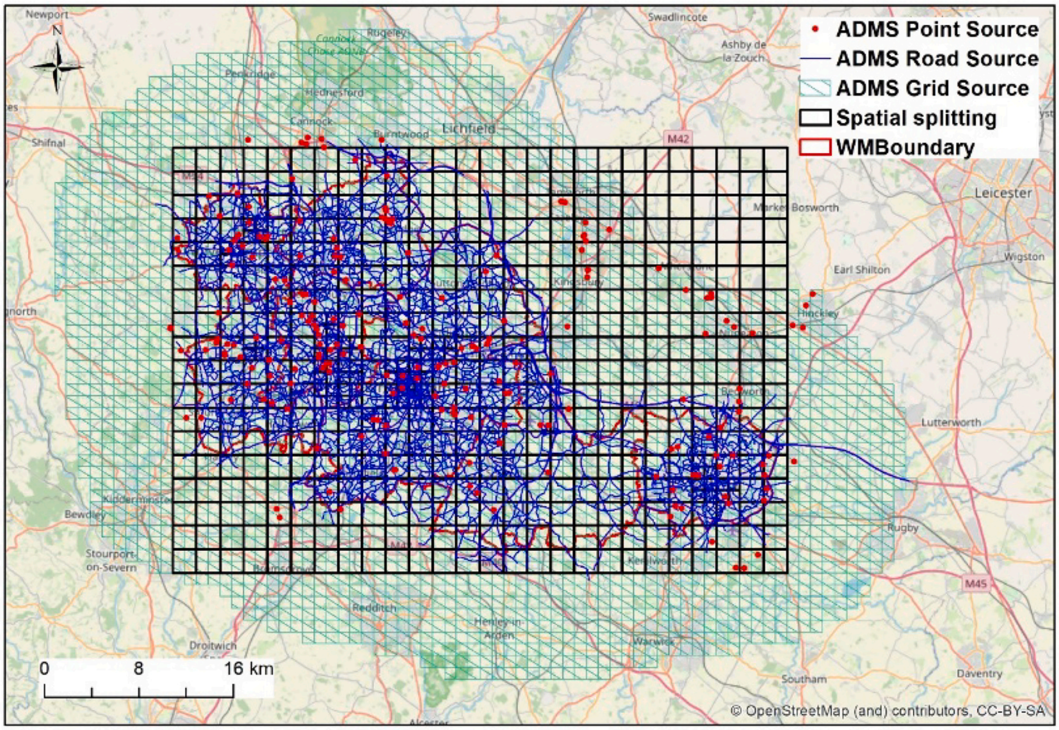

Fig. 1. Emission sources (Point, Road and Grid sources for the year of 2019) and spatial splitting implemented in the model.

2019. The Road Transport sector (SNAP07) is the dominant source for NO_2 and NO_x (Table 1). The Combustion in Commercial, Industrial, Residential and Agriculture (SNAP02) sector is the dominant source for PM_{10}, $PM_{2.5}$, and SO_2, and the Solvent Use (SNAP06) sector is the dominant source for VOCs.

Time varying profiles were also applied to scale annual emissions to hourly emissions. For grid sources, the time varying factors for SNAP sectors were derived from those used in the EMEP model (Simpson et al., 2012). For road sources, the time varying factors were derived from local traffic flows (supplied by Transport for West Midlands). Hourly background data for rural background sites surrounding the West Midlands for the year of 2019 was derived from the Automatic Urban and Rural Network (AURN) (Defra, 2019), and the selection of the upwind sites is dependent on the monitored wind direction at each hour, following the method in Zhong et al. (2021). Hourly meteorological data at Birmingham Airport for 2019 (Met_Office, 2019) was used as a synoptic driver of the dispersion (see the details in Zhong et al. (2021)). The urban canopy parameters (at a resolution of 1 km × 1 km) and street canyon parameters were derived from the local building data and the road network data using an ArcGIS tool (Jackson et al., 2016) developed by Cambridge Environmental Research Consultants. For model evaluation, where model output was required at a limited number of receptor locations (monitors), the Windows version of the ADMS-Urban model (v5.0.0.1) was run in a desktop environment due to the relatively minimal computational resources required for this application. There are 10 air quality sites used for model evaluation, including eight sites from the Defra's Automatic Urban and Rural Network (AURN), one airport site from Air Quality England and one supersite (air pollution research observatory packed with state-of-the-art technology to measure air quality in the atmosphere) located at the University of Birmingham campus (i.e. Birmingham Air Quality Supersite). These sites are classified into three types, i.e. six urban background sites, three roadside sites and one airport site (shown as Fig. 2 and more details are shown in Table S1). It is also noted that not all of these sites have compete datasets available for all pollutants. In order to generate pollution maps for the West Midlands domain, a Linux version of the ADMS-Urban model (v5.0.0.1) was run on the University of Birmingham's BlueBEAR High Performance Computer (HPC). A task farming approach (Zhong et al., 2021) was applied to spatially split the computational domain into 540 sub-domains with varying sizes of 2 km, 1 km and 500 m (Fig. 1). Each sub-domain was computed on a separate core of the HPC, and 540 cores were run in parallel, thus optimising overall model run time.

2.3. Modelling scenarios

In this study, we focus on modelling traffic reduction scenarios and investigate how traffic reductions could influence air quality in the West Midlands region. We used the 2019 model configuration as the baseline/reference case (denoted by Case 2019 BAU). In order to cover the wide range of traffic reduction cases, we further configured five modelling scenarios each with hypothetical traffic reductions of 10% (Case Re0.1), 30% (Case Re0.3), 50% (Case Re0.5), 70% (Case Re0.7) and 90% (Case Re0.9), respectively, which were applied equally across all vehicle types. The lower traffic reduction could represent the near future target of traffic mode changes, such as the use of more public transport rather than cars. The higher traffic reduction could represent the long-term goal towards Net Zero or mode shift.

3. Results

3.1. Model evaluation for the 2019 baseline case

To evaluate the performance of the ADMS-Urban model, a run was configured to include receptor locations corresponding to the air quality measurement recorded during the baseline year of 2019. The computational time for the whole year simulation with hourly outputs of key air pollutants (i.e. NO_x, NO_2, O_3, PM_{10} and $PM_{2.5}$) for these receptors was about 4.6 h. The Model Evaluation Toolkit (Stidworthy et al., 2018) was applied to evaluate the model performance by automatically generating model evaluation statistics and plots.

Table 1
Summary of different type of emission sources (in tonnes/year) over the West Midlands computational domain in the model for the year of 2019. Major Roads represent these explicit roads as resolved by the traffic models, while Minor Roads are unresolved roads represented by the residual between the NAEI derived emissions and explicit major road emissions (aggregated to 1 km resolution).

Group	NO_2	NO_x	VOC	PM_{10}	$PM_{2.5}$	SO_2
Major Roads	1959	9605	374	892	371	22
Point Sources	152	3040	1974	356	244	179
SNAP01 Combustion in Energy Production and Transformation	1	10	2	5	5	71
SNAP02 Combustion in Commercial, Industrial, Residential and Agriculture	152	3030	2014	1977	1923	1691
SNAP03 Combustion in Industry	166	3313	138	339	334	495
SNAP04 Production Processes	10	203	1140	2020	321	564
SNAP05 Extraction and Distribution of Fossil Fuels	0	0	1555	0	0	0
SNAP06 Solvent Use	0	3	16,900	137	88	2
SNAP07 Road Transport (Minor Roads)	1464	7305	1396	456	390	54
SNAP08 Other Transport and Mobile Machinery	250	5001	2300	363	362	93
SNAP09 Waste Treatment and Disposal	1	18	250	121	112	3
SNAP10 Agriculture, Forestry and Landuse Change	21	417	983	194	30	0
SNAP11 Nature (Other)	1	20	671	87	80	0

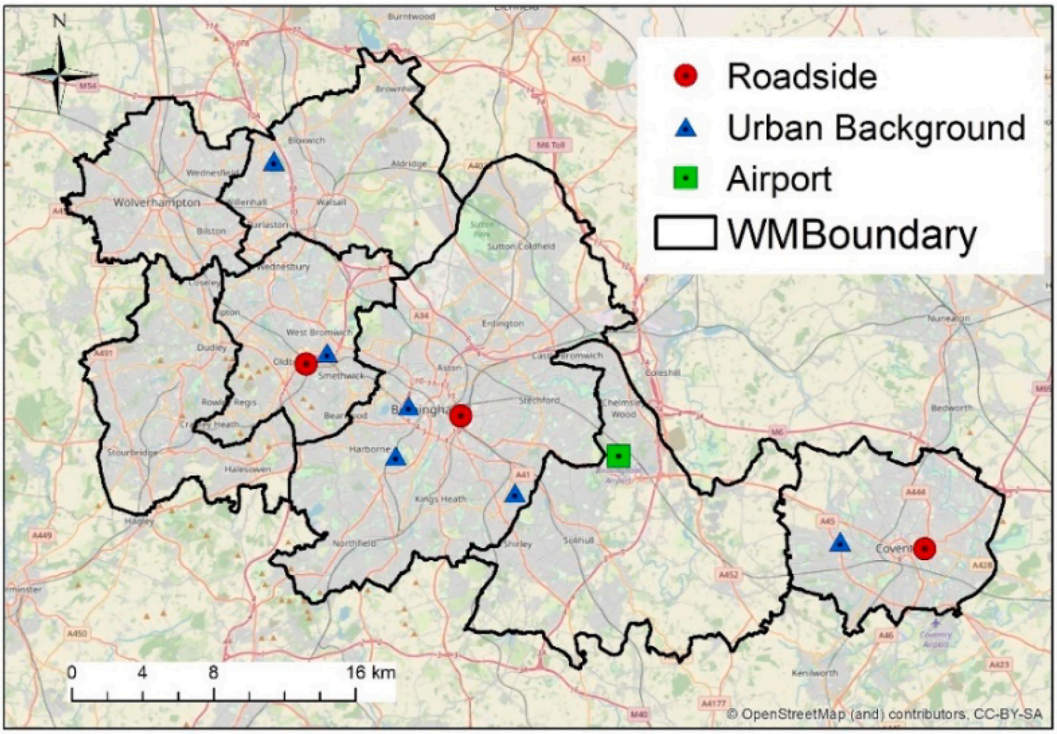

Fig. 2. Different types of monitoring sites (i.e., six urban background sites, three roadside sites and one airport site) in the West Midland for the model evaluation of the 2019 baseline model configuration. It is also noted that not all of these sites have compete datasets available for all pollutants.

Fig. 3 shows scatter plots of daily averages (annual averages shown in Fig. S1a-c) of NO_x, NO_2 and O_3 comparing modelled and measured data for three types of sites (airport, roadside and urban background) for the baseline year of 2019. For NO_x and NO_2, the model has a small overestimation for the airport site, a slight tendency to underestimate at roadside sites; agreement is good on average at the urban background sites. For O_3, the model performs well for all three types of sites, although this relates in part to that O_3 is not a primary pollutant and the background measurements of O_3 were used to represent the long-range pollutant transport. Fig. 4 shows the corresponding comparisons of modelled and observed daily averages (annual averages shown in Fig. S1d-e) of PM_{10} and $PM_{2.5}$. For PM_{10}, there is a good agreement for the airport site between the model and the measurement. The model performs well for all site types, with a slight overestimation at urban background. The model takes air quality measurements as model inputs for background to represent the long-range pollutant transport for PM_{10} and $PM_{2.5}$, which influences model performance.

The model performance has been also assessed using evaluation statistics calculated based on full year hourly time series of modelled and measured data for different types of sites, as shown in Table 2. The measured average (Obs) and modelled average (Mod) of NO_x, NO_2, O_3, PM_{10} and $PM_{2.5}$ for each type of sites reflect the results shown in the scatter plots in Figs. 3 and 4. Fb (Fractional bias) measures the mean difference of the modelled and measured data. Fb (ideal value is 0) varies within (−0.25, 0.29) for NO_x, (−0.08, 0.21) for NO_2, (−0.05, 0.09) for O_3, (0.01, 0.08) for PM_{10}, and (0.06, 0.13) for $PM_{2.5}$. Fac2 reflects the fraction of modelling data within a factor of 2 of measured data. Fac2 (ideal value is 1.0) shows that 66%–76% of modelled NO_x, 78%–82% of modelled NO_2, 72%–81% of modelled O_3, 82%–83% of modelled PM_{10}, 79%–80% of modelled $PM_{2.5}$ are within a factor of 2 of measured data. NMSE (normalised mean square error) measures normalised mean difference between the modelled and measured data. NMSE (ideal value is 0) varies within (1.05, 1.40) for NO_x, (0.28, 0.41) for NO_2, (0.12, 0.19) for O_3, (0.35, 0.43) for PM_{10}, and (0.43, 0.47) for $PM_{2.5}$. R (correlation coefficient) measures the correlation between the modelled and measured data. R (ideal value is 1.0) varies within (0.49, 0.54) for NO_x, (0.63, 0.66) for NO_2, (0.77, 0.79) for O_3, (0.61, 0.65) for PM_{10}, and 0.72 for $PM_{2.5}$.

Fig. 5 shows time variation of modelled and measured NO_2 (See Fig. S2 for other pollutants) at a selected site, i.e. Birmingham A4540 Roadside site, for the baseline year of 2019. The diurnal cycle of NO_2 reflects the morning and evening traffic related peaks, generally captured by the model. There is a smaller peak of NO_2 around midday, which is possibly driven by the stronger photochemistry at this time. The model slightly overestimates the evening peaks, possibly because the potential evening congestions and urban heat islands (Biggart et al., 2020) are not well captured. The model generally captures the monthly variation and there is a good agreement of overall annual average between the model and measurement. The day of the week profile between the model and measurement matches very well, and the typical traffic pattern (weekday tends to have more traffic than Saturday and Sunday) is captured by the model.

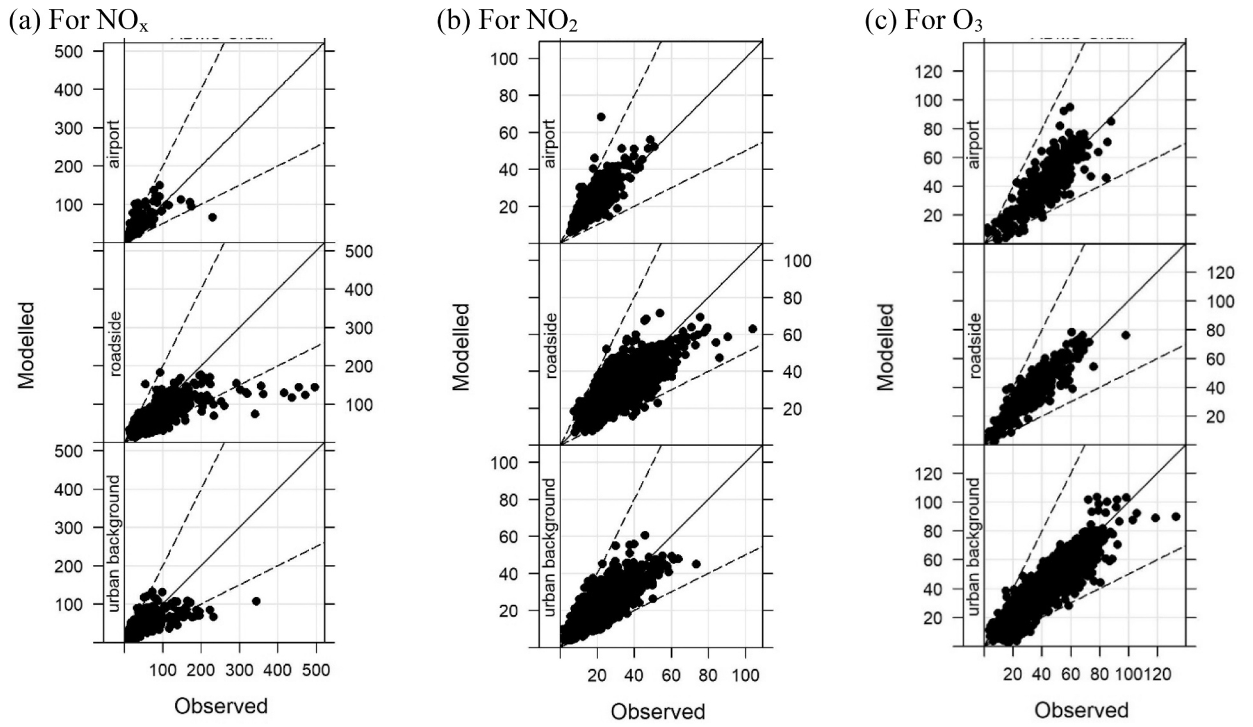

Fig. 3. Scatter plots of daily averages between the modelled and measured data for 3 types of sites (airport, roadside and urban background): (a) for NO_x (in μg m^{-3}), (b) for NO_2 (in μg m^{-3}) and (c) for O_3 (in μg m^{-3}) for the baseline year of 2019. These dashed lines represent the slopes of 0.5 and 2 respectively (indicating a factor of 2 between the modelled and measured data).

3.2. Effect of traffic reduction scenarios on air quality

To generate air quality maps for the region, the ADMS-Urban model was then configured and run to generate air pollutant concentration maps with dense output points (~0.61 million) covering the West Midlands using the method described previously. The computational domain was split into 540 subdomains (Fig. 1) using a task farming approach (Zhong et al., 2021). We executed the Linux version of the ADMS-Urban model in parallel with 540 cores on the University of Birmingham's HPC. The overall computational time for a typical whole year simulation with hourly outputs was about 34 h. ADMS-Urban model utilities (CERC, 2021a) were used to combine and interpolate the netcdf files output from each core. Another utility facilitated the post-processing of hourly outputs to generate annual averages. Air quality map data was created using Surfer (GoldenSoftware, 2023) and then visualised in ArcGIS (ESRI, 2023). Pollution maps were generated for the 2019 baseline model (Case 2019 BAU) in addition to the five hypothetical traffic reduction scenarios (i.e. Case Re0.1, Case Re0.3, Case Re0.5, Case Re0.7 and Case Re0.9 with corresponding traffic reductions of 10%, 30%, 50%, 70%, and 90% respectively). In this study, we focus on the analysis of legally regulated air pollutants in the UK, i.e. NO_2 and $PM_{2.5}$, at different spatial resolutions (i.e. street scale, electoral ward level and local authority level).

Fig. 6a presents an annual air quality map of NO_2 at 10 m × 10 m resolution for the baseline scenario (Case 2019 BAU). The annual NO_2 concentrations are higher than the UK objective value of 40 μg m^{-3} (Defra, 2023c) are indicated by the legend in red. The exceedance of 40 μg m^{-3} mostly occurred in regions close to motorways and in city centre areas with more traffic (especially in Birmingham). The highest value (up to 97 μg m^{-3}) of modelled annual NO_2 concentration for Case 2019 BAU was smaller than that (up to 139 μg m^{-3}) in 2016 modelling for the same region (Zhong et al., 2021). The influence of traffic emissions was reflected in the spatial pattern of annual NO_2 concentrations with a larger gradient near road sources. In rural areas (with less influence from road sources), there were lower annual NO_2 concentrations (11–15 μg m^{-3}). Fig. 6b-f depicts the predicted annual NO_2 concentrations for different hypothetical traffic reduction scenarios at 10 m × 10 m resolution (percentage reductions compared to Case 2019 BAU were shown in Fig. S4). It was found that the more the traffic activity was reduced, the more the annual NO_2 concentration decreased. With 90% traffic reduction (Case Re0.9), the annual NO_2 concentration in the West Midlands region decreased by up to 54–74% for regions near the motorway and city centre areas. With less traffic reduction, the pattern observed for Case Re0.9 gradually faded out. With 10% traffic reduction (Case Re0.1), the annual NO_2 concentration decreased by up to 8%. A near-linear relationship between the annual NO_2 concentration and the traffic reduction (Fig. S5) was found for these 10 m × 10 m grids averages where selected roadside and urban background sites were located (in Fig. 2). The spatial distribution of O_3 concentrations (Fig. S3) shows that O_3 concentrations have a smaller response in the modelling scenarios (as the same amount of background including O_3 was adopted). The generation of NO_2 is determined by primary emissions, and titration of O_3 by NO, limited by overall NO_x emissions.

Fig. 7a shows an annual air quality map of $PM_{2.5}$ at 10 m × 10 m resolution for Case 2019 BAU. Areas where the annual $PM_{2.5}$

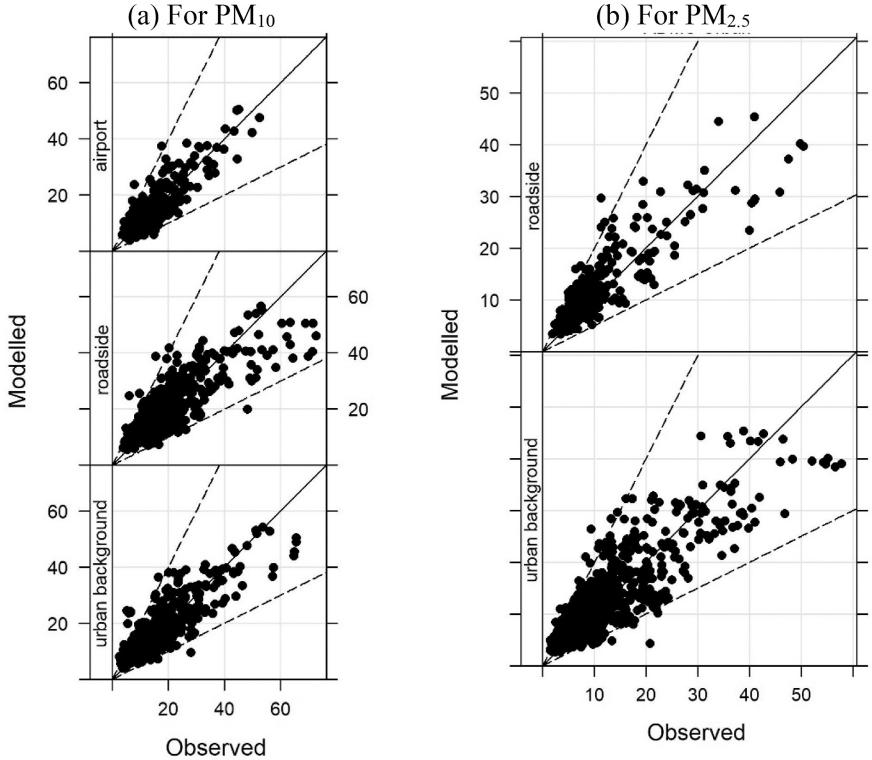

Fig. 4. Scatter plots of daily averages between the modelled and measured data for 3 types of sites (airport, roadside and urban background): (a) for PM_{10} (in μg m^{-3}) and (b) for $PM_{2.5}$ (in μg m^{-3}). These dashed lines represent the slopes of 0.5 and 2 respectively (indicating a factor of 2 between the modelled and measured data).

Table 2
Model evaluation statistics calculate based on annual hourly series of modelled and measured data (for the period both the model and measurement have data) for different types of sites. It is noted that not all of these sites have compete datasets available for all pollutants. Obs: measured average; Mod: modelled average; Fb: fraction bias; Fac2: proportion of modelling data within a factor of 2 of measured data; NMSE: normalised mean square error; R: correlation coefficient.

Pollutants	Site Type	nSites	Obs (μg m^{-3})	Mod (μg m^{-3})	Fb	Fac2	NMSE	R
NO_x	urban background	5	27.7	27.4	−0.01	0.76	1.40	0.54
NO_x	roadside	3	71.8	56.0	−0.25	0.72	1.05	0.54
NO_x	Airport	1	28.5	38.3	0.29	0.66	1.32	0.49
NO_2	urban background	5	18.4	19.0	0.03	0.80	0.41	0.65
NO_2	roadside	3	32.1	29.5	−0.08	0.82	0.28	0.63
NO_2	Airport	1	18.6	22.9	0.21	0.78	0.37	0.66
O_3	urban background	5	47.5	45.0	−0.05	0.81	0.12	0.79
O_3	roadside	1	34.7	37.8	0.09	0.72	0.19	0.77
O_3	Airport	1	42.8	41.8	−0.02	0.78	0.14	0.77
PM_{10}	urban background	4	13.0	14.1	0.08	0.82	0.43	0.61
PM_{10}	roadside	2	17.4	17.6	0.01	0.83	0.38	0.63
PM_{10}	Airport	1	13.9	14.0	0.01	0.83	0.35	0.65
$PM_{2.5}$	urban background	4	9.3	9.9	0.06	0.79	0.47	0.72
$PM_{2.5}$	roadside	1	9.8	11.1	0.13	0.80	0.43	0.72

concentrations were modelled to be higher than the (England) annual mean concentration target of 10 μg m^{-3} for $PM_{2.5}$ (to be achieved by 2040, Defra (2023c)) are indicated by the legend in orange and red. Similar to NO_2, there were some exceedances of 10 μg m^{-3} $PM_{2.5}$ occurring in the vicinity of the motorways and in city centre areas. This was due to the exhaust and non-exhaust $PM_{2.5}$ emissions from traffic (Defra, 2023b). Higher $PM_{2.5}$ concentrations were also found in the vicinity of industrial areas. In rural areas, there were lower annual $PM_{2.5}$ concentration (8.1–8.9 μg m^{-3}). Figs. 7b-f shows the predicted annual $PM_{2.5}$ concentrations for different hypothetical traffic reduction scenarios at 10 m × 10 m resolution (percentage reductions compared to Case 2019 BAU were shown in Fig. S6). With 90% traffic reduction (Case Re0.9), the annual $PM_{2.5}$ concentration decreased by up to 25–45% in the vicinity of motorways and major roads with relatively more traffic, which reflected the non-negligible contribution from traffic emissions for

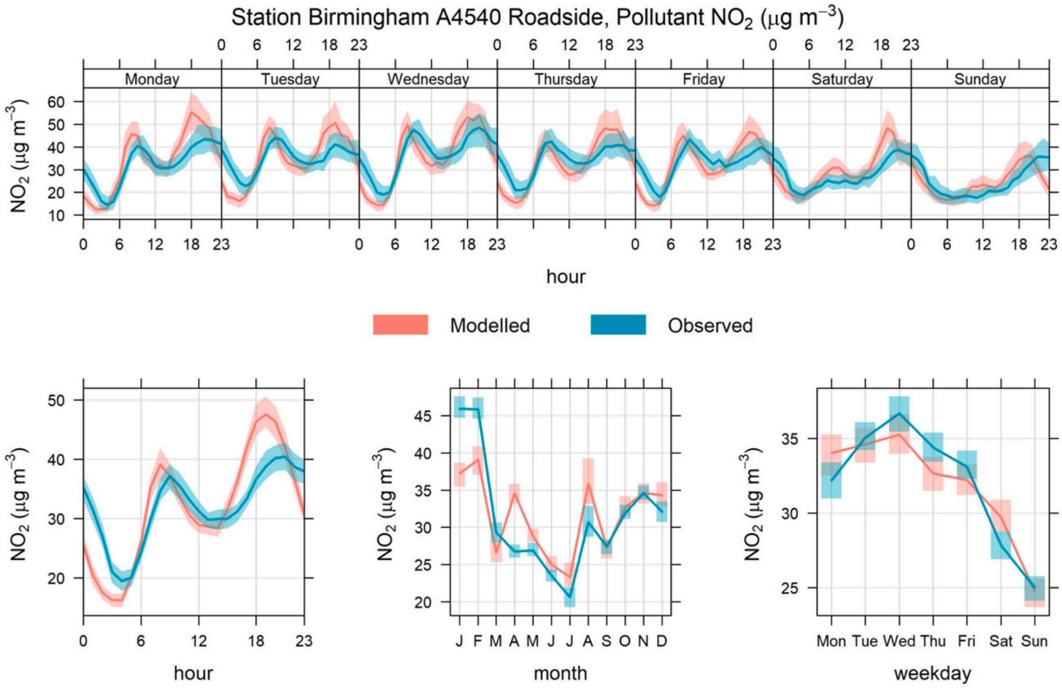

Fig. 5. Time variation of modelled and measured NO_2 at Birmingham A4540 Roadside site for the baseline year of 2019. The shading areas indicate the 95% confidence intervals of the mean (plus and minus the variation). Plots were generated using the timeVariation function of the Openair package in R (Carslaw and Ropkins, 2012).

roadside locations. With less traffic reduction, the annual $PM_{2.5}$ concentration decreased less. There was a decrease of $PM_{2.5}$ of up to 4% for the 10% traffic reduction scenario (Case Re0.1). A nearly linear relationship between the annual $PM_{2.5}$ concentration and the traffic reduction (Fig. S7) was also found for these 10 m × 10 m grids averages where selected roadside and urban background sites were located (in Fig. 2).

Apart from the high spatial resolution maps (Figs. 6 and 7), the electoral ward level (spatially aggregated based on 10 m × 10 m resolution map) maps are also of interest, which can be linked to socio-demographic data for the health assessment of clean air interventions (Hall et al., 2023). Fig. 8a shows an annual air quality map of NO_2 at the electoral ward level for Case 2019 BAU. There are higher concentrations for wards close to city centre areas and lower concentrations for wards in rural areas. Fig. 8b-f shows the impact of different hypothetical traffic reduction scenarios on annual NO_2 concentration at the ward level (percentage reductions compared to Case 2019 BAU were shown in Fig. S8). Similarly, the annual NO_2 concentration would decrease more with the decrease in the traffic activity. The range of the predicted percentage change (reduction in %) of annual NO_2 concentration for all scenarios at the ward level is 2–43%, which is smaller and narrower than that (8–74%) at the 10 m × 10 m resolution.

Fig. 9a shows an annual air quality map of $PM_{2.5}$ at the ward level for Case 2019 BAU. Most of the ward averages across the West Midlands region (indicated by the light green to red colour range) are above the England annual mean concentration target of 10 μg m^{-3} for $PM_{2.5}$. Fig. 9b-f shows the impact of different hypothetical traffic reduction scenarios on annual $PM_{2.5}$ concentration at the ward level (percentage reductions compared to Case 2019 BAU were shown in Fig. S9). The annual $PM_{2.5}$ concentration at the ward level would slightly decrease with the reduction in traffic activity. The range of the predicted percentage change (reduction in %) of annual $PM_{2.5}$ concentration for all scenarios at the ward level is 0.2–10%, which is smaller and narrower than that (1–45%) at the 10 m × 10 m resolution.

Fig. 10 shows predicted annual NO_2 and $PM_{2.5}$ concentrations for different hypothetical traffic reduction scenarios compared to Case 2019 BAU (percentage reductions were shown in Fig. S10) at the local authority level. For NO_2, with 90% traffic reduction (Case Re0.9), predicted relative concentration reductions were in the range of 25–32% (Sandwell and Walsall would benefit the most with up to a reduction of up to 6.8 μg m^{-3}). With 10% traffic reduction (Case Re0.1), the annual NO_2 concentrations reduced by 2.7–3.3%. There was a near-linear relationship between the predicted annual NO_2 concentration and traffic reduction for the studied scenarios, but with the response of the NO_2 concentrations much lower than the (proportional) change in traffic levels. For $PM_{2.5}$, with 90% traffic reduction (Case Re0.9), there would be a reduction of 3.6–5.4% in annual concentrations. With 10% traffic reduction (Case Re0.1), the annual $PM_{2.5}$ concentrations only decreased by 0.41–0.60%. A close linear relationship between predicted annual $PM_{2.5}$ concentration and traffic reduction was also found. The results clearly show that traffic reduction would have a limited effect on controlling $PM_{2.5}$ concentrations (with a reduction up to 0.6 μg m^{-3} or 5.4% compared to the baseline levels), in the absence of any other changes.

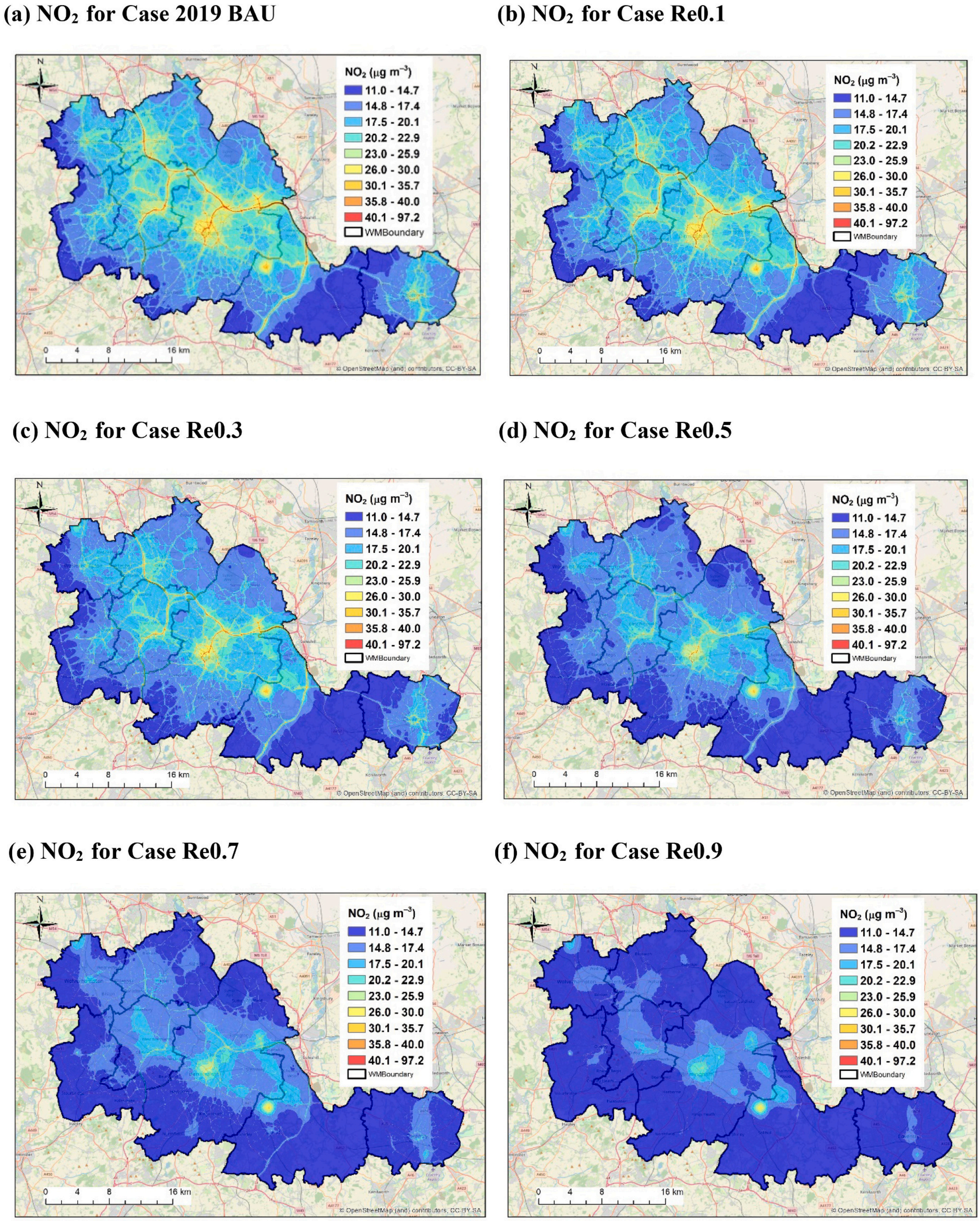

Fig. 6. Annual air quality map of NO_2 (in μg m^{-3}) at 10 m × 10 m resolution for (a) Case 2019 BAU, and percentage change (reduction in %) of NO_2 for (b) Case Re0.1, (c) Case Re0.3, (d) Case Re0.5, (e)Case Re0.7, and (f) Case Re0.9, relative to Case 2019 BAU.

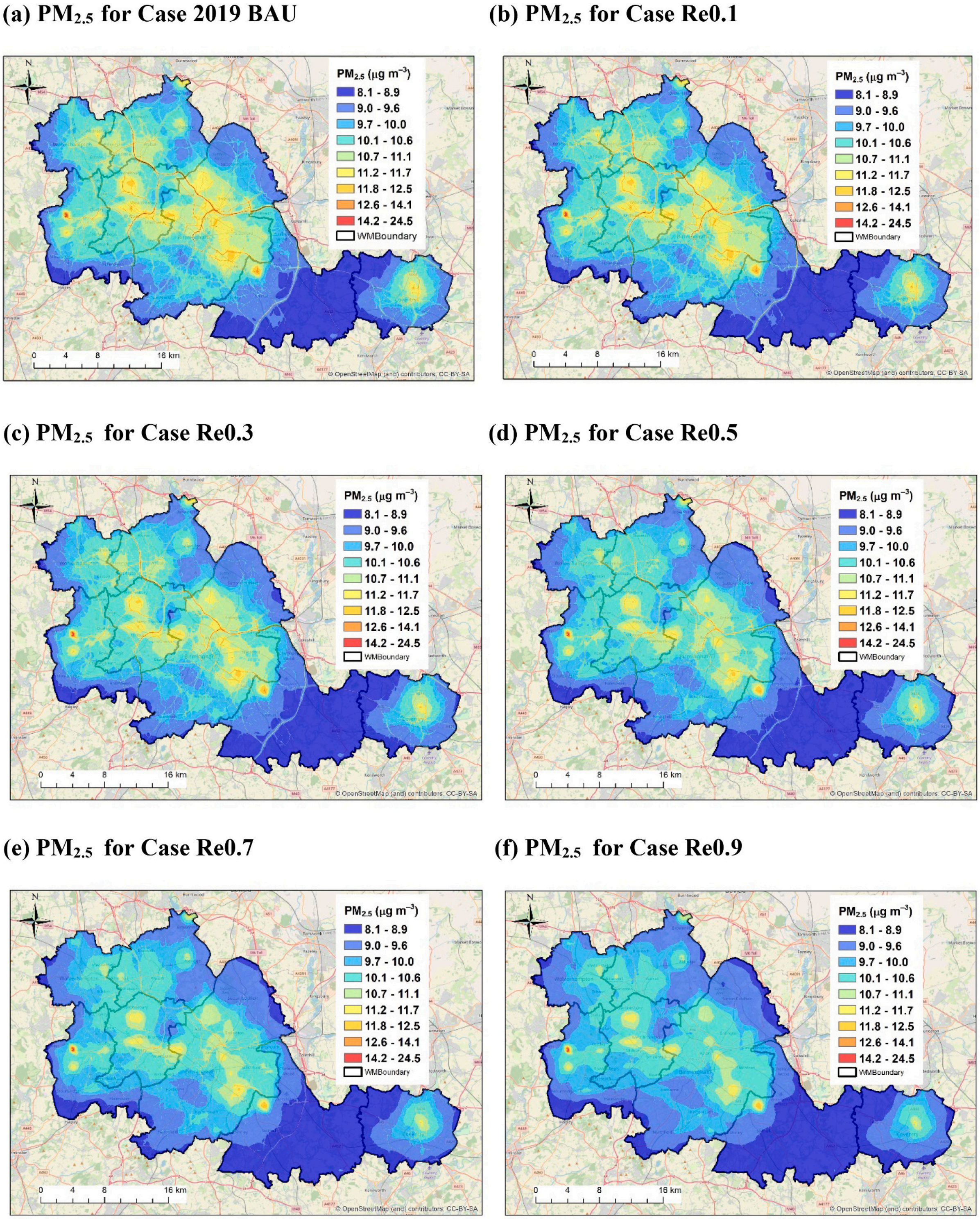

Fig. 7. Annual air quality map of $PM_{2.5}$ (in μg m^{-3}) at 10 m × 10 m resolution for (a) Case 2019 BAU, and percentage change (reduction in %) of $PM_{2.5}$ for (b) Case Re0.1, (c) Case Re0.3, (d) Case Re0.5, (e)Case Re0.7, and (f) Case Re0.9, relative to Case 2019 BAU.

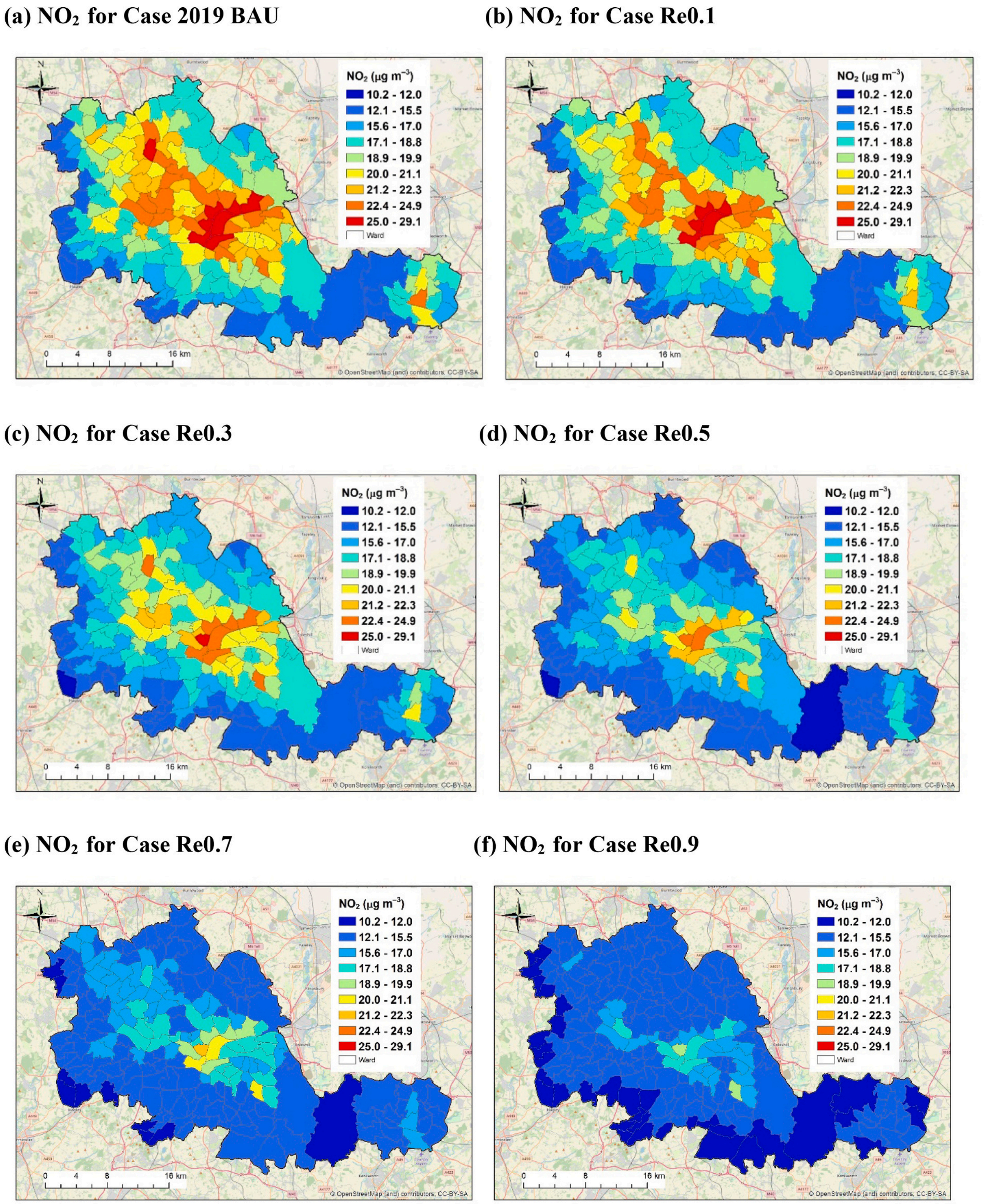

Fig. 8. Annual air quality map of NO_2 (in μg m^{-3}) at the ward level for (a) Case 2019 BAU, and percentage change (reduction in %) of NO_2 for (b) Case Re0.1, (c) Case Re0.3, (d) Case Re0.5, (e)Case Re0.7, and (f) Case Re0.9, relative to Case 2019 BAU.

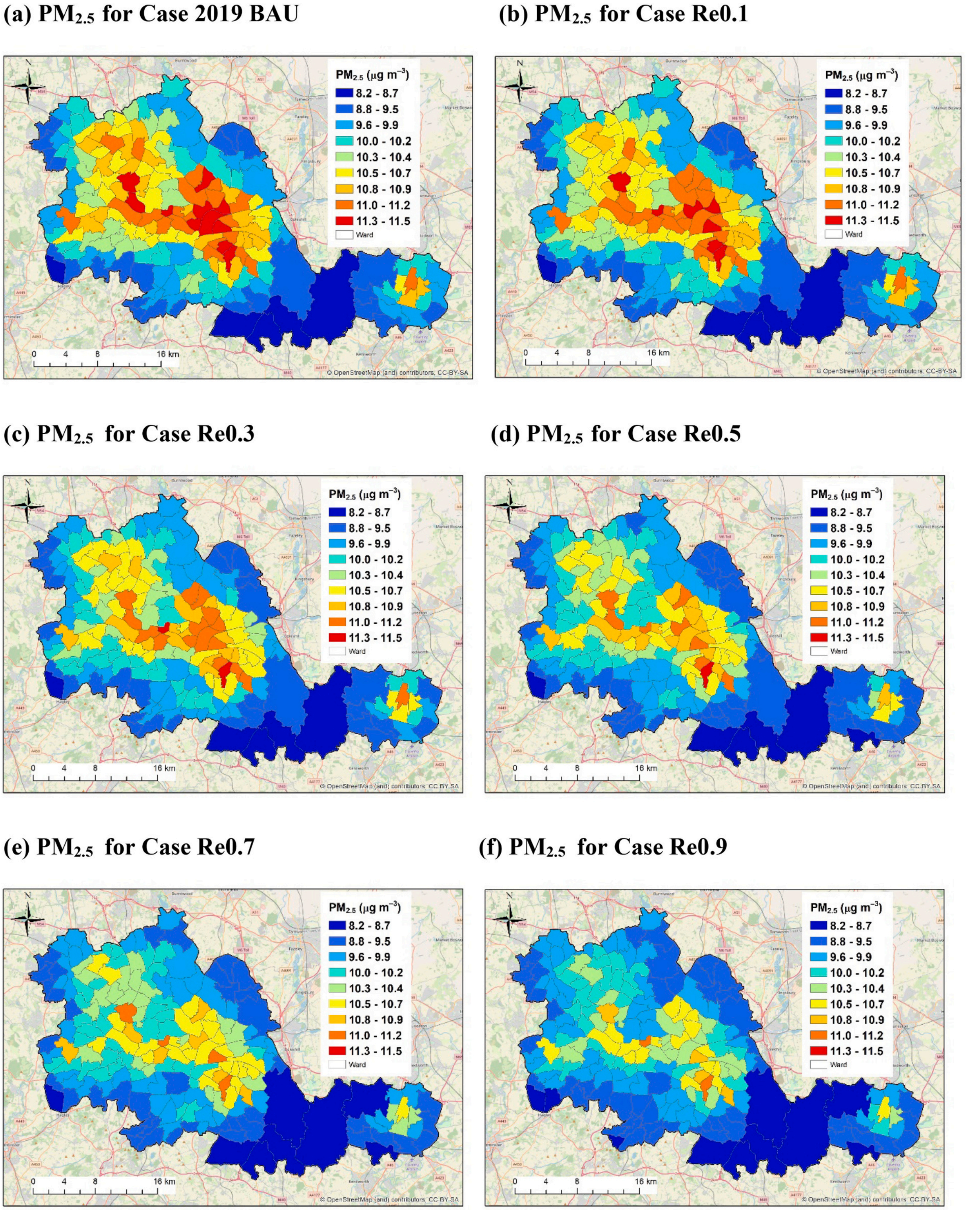

Fig. 9. Annual air quality map of $PM_{2.5}$ (in μg m^{-3}) at the ward level for (a) Case 2019 BAU, and percentage change (reduction in %) of $PM_{2.5}$ for (b) Case Re0.1, (c) Case Re0.3, (d) Case Re0.5, (e)Case Re0.7, and (f) Case Re0.9, relative to Case 2019 BAU.

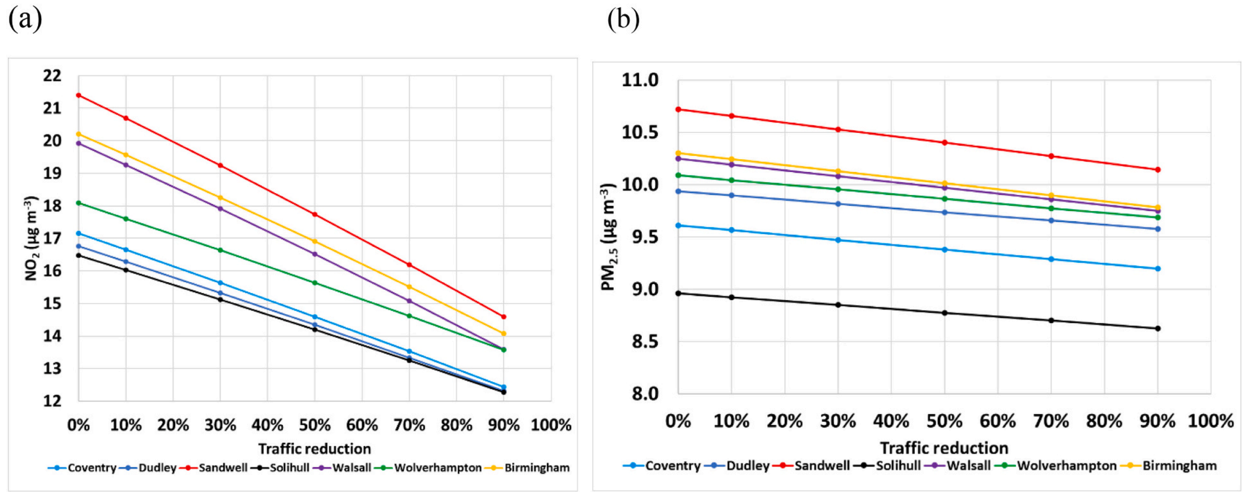

Fig. 10. (a)NO_2 and (b)$PM_{2.5}$ at local authority levels (averages calculated based on 10 m × 10 m resolution maps). "0%" represents the 2019 baseline BAU case. Traffic reductions of "10%", "30%", "50%", "70%", and "90%" represent Case Re0.1, Case Re0.3, Case Re0.5, Case Re0.7 and Case Re0.9, respectively.

4. Discussion

ADMS-Urban applications commonly involve generating modelled pollutant concentration time series corresponding to air quality monitor locations prior to creating pollutant concentration maps over the whole area of interest (Zhong et al., 2021; Zhong et al., 2023). An evaluated model configuration can be used as a robust baseline for modelling scenarios. Model evaluation is dependent on the number of available sites in the region, and ideally includes evaluation at a range of site types (e.g. urban background, roadside, industrial, airport etc). In this 2019 study, we used ten air quality measurement sites for evaluation, from the AURN and Birmingham University's supersite. The Model Evaluation Toolkit (Stidworthy et al., 2018) has been specifically developed and designed for the evaluation of air quality model performance, especially for the ADMS-Urban model. The model evaluation results demonstrated overall good performance of the baseline model for the West Midlands. For NO_x and NO_2, the model can well capture annual averages well at the urban background sites, which indicates a good representation of local emissions sources. The overestimation for the airport site may be due to a complex traffic pattern near the airport and because the emissions from the airport were not explicitly resolved as elevated sources. The slight underestimation for roadside sites may be due to the challenges associated with vehicular emissions calculations, for instance in relation to real world traffic emission factor adjustments (Hood et al., 2018). The better agreement for annual O_3 concentrations for all types of sites indicated good representation of the chemistry and local NO_x emissions (contributing to NO titration). For PM_{10} and $PM_{2.5}$, the model predicts concentrations that are similar to the measurements on average with a correlation coefficient between 0.61 and 0.72. It is noted that the increment (between the urban background and roadside sites) associated with local PM emission sources is much lower than the urban background levels. This indicates a limited effect (compared with the background contributions) of changing local PM emissions on PM levels.

Generating of air quality maps over the region requires considerable resources. Street scale air quality maps at 10 m × 10 m resolution have been generated to capture the concentration gradient in the vicinity of road sources. The street scale resolution air quality maps can be further aggregated to population-related coarser resolutions (ward level and local authority level), potentially for the assessment of health impacts such as the ward-level Air Quality Life Assessment Tool (AQ-LAT, Hall et al., 2023; Hall et al., 2024). Coarser resolution air quality maps smooth out the local traffic induced hotspots, but may be useful to inform the local air quality action plans at the ward level and local authority level. Clean air actions have been undertaken at national, regional and local levels to improve air quality in the UK. In February 2023, a Defra air quality grant scheme (Defra, 2023a) has provided a share of £10.7 million to local councils across England to help improve air quality in local communities, while the West Midlands Combined Authority (including 7 constituent local authorities) was allocated almost £1 million (WMCA, 2023). At the local level, Birmingham has introduced the Brum Breathes Fund to help individual wards to improve air quality (BrumBreathes, 2023).

We have simulated five hypothetical traffic reduction (from 10% to 90%) modelling scenarios to cover the widest range of possible situations, noting that at the higher levels, these changes are unlikely to be plausible. With the greatest modelled traffic reduction of 90%, there was a decrease of 74% in annual NO_2 concentrations (vs a maximum reduction of 50% for traffic reductions of 60–90% for four cities in Spain and United States as found by Xu et al. (2023)) and 45% in annual $PM_{2.5}$ concentrations (vs a reduction of 16.5% for a traffic reduction of 69% as found by Jephcote et al. (2021)) at the street scale (10 m × 10 m) resolution for regions near motorway and city centre areas. This was due to the traffic activity on the motorways and in the city centre areas being higher, and hence dominating emissions / concentrations, and so the traffic reduction affected overall concentrations to a greater extent than other roads with less traffic, which is consistent with Tang et al. (2020). The exhaust and non-exhaust $PM_{2.5}$ emissions from traffic also play a key role for street scale $PM_{2.5}$ concentrations (Defra, 2023b). The concentration range derived at the ward level is narrower across the region compared with the 10 m × 10 m resolution map, since the highest concentrations in the vicinity of road sources and the lowest concentrations in rural areas are not represented (rather, are averaged out) at this lower spatial resolution. With the greatest traffic reduction of 90%, there was a decrease of 43% in annual NO_2 concentrations and 10% in annual $PM_{2.5}$ concentrations when averaged to ward level. At coarser resolution (local authority level), this decrease was up to 32% for annual NO_2 concentrations and 5.4% for annual $PM_{2.5}$ concentrations. Coarser spatial resolution leads to reduced detail in terms of the influence of local traffic on modelled concentrations. Regional air quality models are commonly run at coarse resolution (typically 1 km or larger grids), which do not resolve near-source dispersion of local traffic emissions. Regional modelling scenarios conducted by Feng et al. (2021) indicated a reduction of 18.4% in annual NO_2 concentration and 9.7% in annual $PM_{2.5}$ concentration while all traffic emissions were removed for Wuhan, China; part of the difference to our results may reflect these resolution differences. There was an almost linear relationship between the predicted annual concentration and traffic reduction for both NO_2 and $PM_{2.5}$ in this study, which is consistent with Kerr et al. (2022) for NO_2, Kumar et al. (2020) for $PM_{2.5}$, and Wang et al. (2021) for both NO_2 and $PM_{2.5}$. The ADMS-Urban applied a relatively simple chemistry, i.e. the Generic Reaction Set (GRS) chemistry scheme (Venkatram et al., 1994), to capture the interaction of NO_x-O_3-VOC chemistry. For NO_2, near-source chemical reactions are important and non-linear. However, in the UK for most of time, photochemistry is insufficiently active to generate much NO_2, beyond ozone titration reactions. All modelling scenarios assume the same amount of background (including O_3), therefore a reduction in NO_x results in a corresponding near-linear reduction in NO_2, although there is a slight downward bend to the line for NO_2. For $PM_{2.5}$, regional background and residential combustion (both kept unchanged for modelling scenarios while only changing traffic emissions) have much greater contributions than the traffic emission sources. Therefore, we see the smaller changes in $PM_{2.5}$ with nearly a linear relationship. The effects derived from the model simulations for $PM_{2.5}$ are influenced by the model approach to deriving the background levels. As the incoming baseline does not change, only local emissions, the overall shift inferred might underestimate that obtained for a national (rather than regional) traffic reduction scenario.

This modelling study required a range of model input data and model parameters, which may have uncertainties. The traffic activity and speed data were from the local traffic models, which would not well represent the real-world driving behaviour (Ghaffarpasand et al., 2022). The time varying profiles for traffic were derived from the limited number of traffic flow measurement sites across the West Midlands, which may not fully capture the traffic characteristics (e.g. speed variations and changes in fleet during the day) for the whole region. The real-world emission factor adjustment (Hood et al., 2021) used in the study may be uncertain to fully reflect the local traffic fleet for the West Midlands and the wide range of Euro 6 vehicle standards was not captured by the current model. The modelling scenarios in this study were limited to five hypothetical traffic reductions with uniform values applied to the whole region and traffic fleet, which do not reflect the spatial variation and traffic redistribution, or differential changes between the various vehicle classes. The background inputs used in the baseline model were also kept unchanged for the traffic reduction scenarios modelling, in order to isolate the investigation of traffic reduction. However, the possible change to background concentrations as a result of potential wider traffic reduction measures was not captured. Regional O_3 background concentrations tend to increase while NO_x emissions decrease under traffic reduction scenarios. This is attributed to a weakened titration by NO (Zhong et al., 2023; Wang et al., 2022; Liu et al., 2023).

5. Conclusions

This study configured and evaluated a street-scale air quality model over the West Midlands, UK using the ADMS-Urban model. ADMS-Urban had an overall good performance for the West Midland baseline case. This modelling tool was then used to explore the effect of five hypothetical traffic reduction, ranging from 10% to 90% reduction in traffic activity. Scenario impacts were analysed over differing spatial resolution. Close to roads (within 10 m), the decrease in annual concentrations was up to 74% for NO_2 and 45% for $PM_{2.5}$ for near motorway and city centre areas for the largest traffic reduction scenario (90%). For the same case, this decrease was up to 43% for annual NO_2 concentrations and 10% for annual $PM_{2.5}$ concentrations at the ward level. At the local authority level, this reduction was in the range of 2.7–32% for NO_2 and 0.41–5.4% for $PM_{2.5}$ for all traffic reduction scenarios. The modelled impact of air pollution response to traffic reductions is heavily dependent on model spatial resolution. These results illustrate the dynamic range in response of city-wide air pollution exposure to different traffic changes, including extreme reductions, highlighting the contrast in responses for NO_2 and $PM_{2.5}$, the different and sub-unit response for both pollutants, and the impact of simulation resolution upon the changes predicted. This study also indicated that substantial traffic reductions alone, with no changes to other air pollution sources, would mainly reduce NO_2 concentration with limited impact on reducing $PM_{2.5}$ concentrations. If similar changes were applied also nationally, there would be reduced background aerosol (e.g. less NO_x emissions forming nitrate).

Future studies would be 1) to explore the impact of the real-world emission reduction scenarios on air quality, 2) to investigate other traffic management options (such as traffic speed limit, traffic fleet changes), 3) to explore the impact of the Covid-19 induced local traffic reductions on air quality, 4) to apply traffic demand model for the better spatial varying representation of traffic changes, and 5) to conduct the assessment of health impacts of traffic reduction scenarios using the AQ-LAT health tool.

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CRediT authorship contribution statement

Jian Zhong: Writing – original draft, Visualization, Software, Methodology, Formal analysis. **Jenny Stocker:** Writing – review & editing, Software, Methodology. **Xiaoming Cai:** Writing – review & editing, Supervision, Conceptualization. **Roy M. Harrison:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **William James Bloss:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Air quality measurement data from AURN are available via Defra UK-Air website, https://uk-air.defra.gov.uk/networks/network-info?view=aurn. The UK NAEI emission data are available in http://naei.beis.gov.uk/data. Met Office MIDAS meteorological data are available in Centre for Environmental Data Analysis, http://catalogue.ceda.ac.uk/uuid/dbd451271eb04662beade68da43546e1. EMEP time-variation data are available in https://www.emep.int/. The building data are available in https://digimap.edina.ac.uk.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2024.101961.

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