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The effect of workplace mobility on air pollution exposure and its inequality in the UK

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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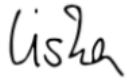

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Abstract

A large number of epidemiological studies have identified air pollution as a major risk to human health. Short-term and long-term exposures to air pollutants such as $PM_{2.5}$, NO_2 and O_3 cause cardiovascular and respiratory diseases, cancer and other adverse health effects. These lead to decreased quality of life, increased hospital visits and premature mortality. Due to a high spatial and temporal variability of air pollution exposure, exposure inequalities exist within the society. Published studies suggest that it is often the most deprived and susceptible who are disproportionately exposed to the highest concentrations of some of the most ubiquitous air pollutants.

However, most epidemiological and exposure studies do not take into account the spatio-temporal variability of air pollutants and population mobility within their assessments which is likely to lead to exposure misclassification and, consequently, a bias in the associated health effects. Several modelling approaches have been developed to improve estimates of population exposure. Either statistical or deterministic models are now commonly used to predict air pollution concentrations. Deterministic models include atmospheric chemistry transport models (ACTMs), which tend to be used for larger study areas on a regional or higher scale, and Gaussian dispersion models, which on a local – urban – scale are able to predict concentrations at very high spatial resolutions. The aim of this thesis is to investigate how workplace-related population mobility and spatio-temporal variability of air pollution affect population exposure and its inequality in the UK.

Firstly, the effect of exposure to ambient air pollution at the place of work or study on overall population exposure in the UK is examined using publicly available data from Census 2011. The analysis is conducted for the whole of the UK (England, Wales, Scotland and Northern Ireland), and separately for Scotland only. The residential population distribution and daytime population distribution data are combined with concentration fields of key air pollutants ($PM_{2.5}$, NO_2 and O_3) generated by the EMEP4UK atmospheric chemistry transport model at relatively high spatial (approximately 1.5 km × 2 km) and

temporal (hourly) resolutions to calculate population exposure of stay-at-home 'static' population and a 'dynamic' population which spends a proportion of time on weekdays at the place of work or study. The calculated exposures of static and dynamic populations are compared, and sensitivity studies of different working hours of the dynamic population are conducted. The highest difference between dynamic and static population exposures is observed for NO_2 (0.28 µg m^{-3} or 2.0% increase in the UK, 0.29 µg m^{-3} or 23.1% increase in Scotland) for working hours between 08:00 and 18:00. The calculated differences for $PM_{2.5}$ and O_3 are much smaller. Whilst at the population level the exposure difference is small, a case study using virtual individuals suggests a potential large variation between individuals.

Secondly, the exposure of dynamic population and population subgroups to air pollution is examined in a case study of the Central Belt of Scotland region. Additionally, the two largest and demographically contrasting urban areas within the region – Glasgow and Edinburgh – are considered separately. For the analysis, anonymised personal data of the participants of the Scottish Longitudinal Study (SLS), which is a representative sample of the Scottish population, are linked at the postcode unit level with air pollution concentrations generated by EMEP4UK (approximately 0.8 km × 1.4 km spatial resolution). The SLS participants are stratified by age, ethnicity and socio-economic status (SES) for the population subgroup exposure assessment. Exposures at residential address and the place of work or study are considered using three different work pattern scenarios and the results are compared with exposures of the 'static' population. Exposure gradients are observed across all demographic characteristics. Young people between 21 and 30 years of age tend to have the highest exposure to NO_2 and $PM_{2.5}$, and lowest to O_3; however, those aged 31 to 50 tend to be most affected by inclusion of exposure at workplace. The patterns for SES and ethnicity are complex and study area specific; however, people in the two least deprived deciles consistently have the lowest residential and residential-workplace exposure to NO_2 and $PM_{2.5}$ but tend to see the highest increase in exposure due to workplace mobility. Overall, including exposure at place of work in

exposure estimates tends to alleviate some of the exposure inequalities observed in the static population exposure assessments.

Thirdly, the effect of using different air pollution models on 'dynamic' population exposure estimates and its inequalities is investigated. The city of Edinburgh is chosen as the study area. Two models are considered: EMEP4UK and a Gaussian plume dispersion model, ADMS-Urban. Detailed traffic emission data for all major and some minor roads in the city, and gridded emissions from other sources, are used in the ADMS-Urban modelling. The model output is verified against available monitoring data. Differences in modelled output are observed between the models which are subsequently translated into differences in population exposure estimates. The effect of workplace exposure on overall population exposure to NO_2 is larger for the ADMS-Urban model than for the EMEP4UK model; however, the magnitude is still very small (≤ 1.6%). For O_3 and $PM_{2.5}$, the effects are smaller and largely comparable between the models. With some notable exceptions, both models show similar patterns in both exposure inequality and the influence of workplace mobility on it.

Lastly, the overall findings and their implication for assessment of exposure and exposure inequality are discussed. This work suggests that inclusion of the place of work or study in exposure assessments makes only a small difference for population-scale burden assessment, particularly for those pollutants with secondary contributions such as O_3 and $PM_{2.5}$. This conclusion is not particularly sensitive to the atmospheric chemistry/dispersion model used.

Lay Summary

Air pollution is a major worldwide problem affecting human health, as well as ecosystems and the built environment. Air pollution causes or worsens many diseases including cancer and leads to increased hospital visits and premature deaths. It is estimated that in 2015 long-term exposure to outdoor air pollution contributed to 4.2 million (equivalent to 7.6%) of deaths globally. In the United Kingdom (UK) alone, the number of estimated premature deaths due to outdoor air pollution ranges between 28,000 and 36,000 annually.

Epidemiologists who investigate and quantify the effect of air pollution on specific health outcomes rely on accurate estimates of the concentrations of the different air pollutants to which the people taking part in their studies are exposed. Obtaining those is, however, very challenging as air pollution concentrations vary in time and space, and people move through that space in their daily lives. As a consequence, epidemiological studies have traditionally not considered population mobility and instead assumed that air pollution concentrations outside a person's home are representative of that person's exposure. While the assumption is largely valid for less mobile people such as the very young or very old, a school or working age individual may spend a substantial proportion of his or her day away from their home. This in turn may lead to errors in exposure estimates and ultimately errors in health impacts calculations. The variability of air pollution concentrations in time and space also means that some people are exposed to higher levels of air pollution than others. Studies, which are also based on exposure at home only, show that it is usually those of low socio-economic status that are exposed disproportionally to poorer air quality.

Therefore, the overall aim of this thesis is to investigate the effect of workplace-related population mobility on estimates of population exposure to air pollution and its inequality in the UK. The work focuses on three key pollutants with widespread exposure and a rather contrasting spatial variability: particulate matter of diameter < 2.5 µm ($PM_{2.5}$), ozone (O_3) and nitrogen dioxide (NO_2). Of these, $PM_{2.5}$ tends to be the least and NO_2 the most spatially variable.

Continuous and accurate measurements of air pollution concentrations are expensive and therefore there are only a few hundred monitoring stations covering the whole of the UK. This is not enough to capture the spatial variability of the studied pollutants. Hence, this work, like many others, relies on pollution concentrations calculated by computer models that simulate the 'life journey' of pollutants in the atmosphere from their release to their removal. The information on the location of people's home and their place of work or study is obtained from both publicly available and restricted access data from the last UK census which took place in March 2011. It was the first UK census to ask where people work or study.

The effect of workplace-related mobility on population exposure is first investigated on a large (national) scale; the whole of the UK is considered, and then additionally Scotland only. Concentrations of pollutants are taken from an atmospheric chemistry transport model (called EMEP4UK) and it is assumed that people are at their place of work or study from Monday to Friday for up to 40 hours a week and at home at all other times. Considering workplace exposure in exposure estimates leads to only a small increase in exposure compared with residential-only based estimates. For NO_2, there is an increase of 2.0% in the UK, and 3.1% in Scotland. Changes in exposure for the other two pollutants are an order of magnitude smaller than for NO_2. However, it is observed that the population mean masks some potentially very large differences between the solely residential and the combined residential-workplace exposures of some individuals.

The population exposure assessment then focuses on regional and urban spatial scales. The Central Belt of Scotland and its two largest cities of Glasgow and Edinburgh are chosen as the study areas. EMEP4UK pollution concentration data are used again, however, the population data are anonymised personal data of the participants of the Scottish Longitudinal Study which is a representative sample of the Scottish population. The data allow for an investigation of exposures across population subgroups. It is found that at the population level the impact of workplace exposure on overall

exposure is comparable to that observed at the national level. At the sub-population level it is estimated that in general the white ethnic group, children and people over 60 years of age, and people of the highest socio-economic status have the lowest residential and combined residential-workplace exposure to NO_2 and $PM_{2.5}$, and highest exposures to O_3. Considering exposure at the place of work or study, however, tends to decrease but not eliminate the differences in exposure to air pollution between population subgroups.

Several different types of model are used for predicting air pollution concentrations. Each model type has its advantages and disadvantages. One disadvantage of the EMEP4UK model is that it tends to underestimate concentrations of pollutants near their sources and in densely built-up areas, particularly of those pollutants that are highly spatially variable. This may potentially lead to underestimation of exposure of workers and students who commute to urban city centres. Therefore another type of model – called a Gaussian plume dispersion model (ADMS-Urban) – which better simulates concentrations in urban areas is used to predict air pollution concentrations in Edinburgh. A comparison of exposure estimates between the two models is undertaken. The analysis demonstrates that the effect of workplace exposure on overall population exposure to NO_2 is larger for the ADMS-Urban model than for the EMEP4UK model, but the magnitude is still very small (≤ 1.6%) and both models mostly show similar patterns in exposure inequality between population subgroups.

Finally, the findings and implication of this work on exposure assessments are discussed. Including place of work or study in population exposure assessments makes only a small impact on estimates of exposure and its inequality, particularly to those pollutants that are less spatially variable. This finding does not seem to be very sensitive to the type of air pollution model used.

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Chapter 1 Introduction

1.1 Air pollution

Over the last several decades a large and continuously growing body of evidence has demonstrated that air pollution has a detrimental effect on human health. Historically, only short-term exposure to air pollution was considered to have a negative impact on public health as the effects of poor air quality episodes, such as the infamous London smog event in the winter of 1952, were coincident with clear increases in respiratory diseases and deaths (Bell and Davis, 2001). The recognition of adverse health impacts due to long-term exposure to air pollution was slower (WHO, 2017). However, following two ground-breaking studies published in the 1990s (Dockery *et al.*, 1993; Pope *et al.*, 1995) which clearly associated long-term exposure to ambient air pollution with premature mortality, it is now accepted that long-term exposure has a much larger impact and is, in fact, one of the leading risk factors for premature mortality. The Global Burden of Disease study estimated that in 2015 long-term exposure to ambient fine particulate matter (described in more detail in 1.2.1) contributed to 4.2 million (7.6%) of deaths globally (Cohen *et al.*, 2017). It has been suggested that this figure might still be an underestimate by more than a factor of two (Burnett *et al.*, 2018).

Air pollution is a widespread issue; it is largely caused by anthropogenic activities of power generation, manufacturing, heavy industry, domestic combustion, farming and transport. Consequently, it is currently a much larger issue in the rapidly industrialising countries in Asia than in the more economically developed western societies. However, the burden of air pollution in Europe is still substantial (Cohen *et al.*, 2017). In the UK, where concentrations of most pollutants have been decreasing for the last several decades (Carnell *et al.*, 2019), it is estimated that 28,000 to 36,000 people die prematurely each year due to long-term exposure to air pollution, which is equivalent to the loss of 328,000 to 416,000 life-years (COMEAP, 2018), placing a substantial financial burden on society (Pimpin *et al.*, 2018).

The accumulating scientific evidence linking air pollution and public health issues in the second half of the 20th century led the World Health Organization (WHO) to publishing air quality guidelines for many air pollutants in 1987 (WHO, 2017). The most recent update to the guidelines in 2005 (WHO, 2006) focused on four key pollutants which were widespread and had been recognised to have substantial health impacts – sulphur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3) and particulate matter (PM). The latter was separated into particulate matter with aerodynamic diameter < 2.5 µm ($PM_{2.5}$, also termed fine PM) and with aerodynamic diameter < 10 µm (PM_{10}). The European Union (EU) also recognised there was a need to protect public health. The Ambient Air Quality Directive set limit and target values of ambient air pollutant concentrations (not always corresponding to the WHO guidelines) applicable in all member states (EU, 2008). Subsequently, the EU legislation, which also allowed more stringent limits to be introduced by individual member states, was transposed to the UK law as national air quality objectives (*The Air Quality Standards Regulations 2010*).

Following successful mitigation strategies to decrease SO_2 emissions across Europe the focus of epidemiological and exposure studies has been on the remaining three air pollutants with widespread ambient exposure – PM, O_3 and NO_2 (Brunekreef and Holgate, 2002; Royal College of Physicians, 2016). Their EU limit and target values, and UK air quality objectives are presented in Table 1.1.

Table 1.1 National air quality objectives and European Directive limit and target values for the protection of human health.

Pollutant	Applies	Objective	Measured as	Achieved by (and maintained thereafter)	European Obligations	Achieved by (and maintained thereafter)
PM_{10}	UK	50 µg/m^3 not to be exceeded more than 35 times a year	24 hour mean	31 December 2004	50 µg/m^3 not to be exceeded more than 35 times a year	1 January 2005
		40 µg/m^3	annual mean	31 December 2004	40 µg/m^3	1 January 2005
	Indicative 2010 objectives for PM_{10} (from the 2000 strategy and Addendum) have been replaced by an exposure reduction approach for $PM_{2.5}$ (except in Scotland – see below)					
	Scotland	50 µg/m^3 not to be exceeded more than 7 times a year	24 hour mean	31 December 2010	50 µg/m^3 not to be exceeded more than 35 times a year	1 January 2005
		18 µg/m^3	annual mean	31 December 2010	40 µg/m^3	1 January 2005
$PM_{2.5}$	UK (except Scotland)	25 µg/m^3	annual mean	2020	Target value - 25 µg/m^3	2010
	Scotland	10 µg/m^3		31 December 2020	Limit value - 25 µg/m^3	1 January 2015
	UK urban areas	Target of 15% reduction in concentrations at urban background		Between 2010 and 2020	Target of 20% reduction in concentrations at urban background.	Between 2010 and 2020
Nitrogen dioxide	UK	200 µg/m^3 not to be exceeded more than 18 times a year	1 hour mean	31 December 2005	200 µg/m^3 not to be exceeded more than 18 times a year	1 January 2010
		40 µg/m^3	annual mean	31 December 2005	40 µg/m3	1 January 2010
Ozone	UK	100 µg/m^3 not to be exceeded more than 10 times a year	8 hour mean	31 December 2005	Target of 120 µg/m^3 not to be exceeded by more than 25 times a year averaged over 3 years	31 December 2010

1.2 Key pollutants

1.2.1 Particulate matter

Solid, liquid or solid and liquid particles suspended in the air are referred to as particulate matter. There can be >100,000 of these particles per cm^3 of ambient air in a polluted urban area (Kaur *et al.*, 2005; Seinfeld and Pandis, 2006). Particles can be emitted into the atmosphere either directly (referred to as primary PM) or they can form in the atmosphere from precursor gases (referred to as secondary PM) in nucleation or condensation processes (Heal *et al.*, 2012).

There are many natural and anthropogenic sources of airborne particles and their precursor gases; consequently, the chemical composition of PM is diverse. Major natural sources of primary PM are oceans, arid regions and the biosphere which emit sea salt (mostly Na^+ and Cl^-), dust (composed of crustal elements Si, Al, Fe and others) and various biological material (e.g. pollen, bacteria), respectively. Forest fires are a source of elemental carbon. Volcanic eruptions are episodic events which emit volcanic ash as well as sulphur-containing precursor gases.

Primary anthropogenic PM emissions are mostly associated with stationary or mobile combustion sources and biomass burning producing elemental and organic carbon particles, and agricultural, industrial and transport activities causing emission and resuspension of particles from the surface. Sources of secondary PM are those that emit the precursor gases NO_x ($NO + NO_2$), SO_2, NH_3, and volatile organic compounds (VOCs) – mainly combustion processes and agricultural activities (Seinfeld and Pandis, 2006; Wallace and Hobbs, 2006). The former group of gases form secondary inorganic aerosol (SIA) which consists mainly of NH_4NO_3, $NaNO_3$ and $(NH_4)_2SO_4$. VOCs form secondary organic aerosol (SOA) which consists of many different organic species (Heal *et al.*, 2012). Particles containing NH_4^+, SO_4^{2-}, elemental and organic carbon are mostly within the fine fraction, whilst sea-salt and dust particles from the Earth's surface and biological material are predominantly in

the coarse fraction. Particles containing NO_3^- can be found in both fractions (Seinfeld and Pandis, 2006).

Once airborne, particles are subject to physical and chemical processes that may change their composition and/or size. For example, water vapour and other gases condense on existing particles and increase their size. Particles are removed from the atmosphere through coagulation with other particles, or through the processes of dry or wet deposition. Dry deposition refers to gravitational or turbulence-induced settling of particles on vegetation, either on their own or in cloud droplets. Wet deposition is a removal through precipitation (AQEG, 2012).

The diversity of particle sources, formation processes and physical and chemical transformations result in a large range of PM sizes which spans five orders of magnitude from a few nanometres to approximately 100 micrometres in diameter. Four modes are observed from the particle size distribution. Nucleation (diameter < ~10 nm), Aitken (~10 nm - ~100 nm), accumulation (~100 nm - 2 μm) and coarse (> ~ 2μm) (Seinfeld and Pandis, 2006).

Whilst the vast majority of particles are in the nucleation and Aitken modes, their total mass is negligible in comparison with the other two modes. Particle size largely determines the atmospheric lifetime of PM. Nucleation and Aitken mode particles coalesce readily with others and grow into the accumulation mode on the time scale of minutes to hours. At the other end of the scale, the lifetime of coarse particles is also on the scale of hours due to efficient gravitational settling. However, the lifetime of particles in the accumulation mode is several days since growth and removal mechanisms are least efficient for this mode (Heal *et al.*, 2012).

In health studies, however, PM size is classified according to how deeply it can penetrate into the airways. PM_{10} (particulate matter with aerodynamic diameter < 10 μm) penetrates beyond the larynx whereas $PM_{2.5}$ (particulate matter with aerodynamic diameter < 2.5 μm) penetrates to the unciliated airways, i.e. the

alveoli. The $PM_{2.5}$ fraction, which by definition is a subgroup of PM_{10}, has a stronger link with adverse health effects than PM_{10} (AQEG, 2012) therefore this work is concerned with that particle size fraction.

Particulate matter with aerodynamic diameter < 100 nm (referred to as ultrafine particles - UFP) has also been subject of interest from public health researchers. UFP have a potential to be very damaging to health due to their small size and large surface area which is believed to increase particle toxicity (HEI, 2013). There is however still insufficient evidence on their impact on public health (AQEG, 2018; Schraufnagel, 2020).

The diversity of PM size, composition and properties is also responsible for difficulties in both measuring and modelling of PM concentrations. In particular, semi-volatility and hygroscopicity of some particles are a significant problem (AQEG, 2012).

1.2.2 Nitrogen dioxide

NO_2 is both a primary and secondary gaseous pollutant. It is directly emitted to the atmosphere together with NO (collectively referred to as NO_x) from stationary and mobile combustion sources or formed via oxidation of NO by O_3. Traffic is the largest source of NO_x emissions in Europe, contributing approximately 39% in the EU countries in 2017 (European Environmental Agency, 2019). In the presence of O_3 and sunlight of wavelength < ~400 nm a photochemical NO_x cycle (1.1-1.3) is quickly established and the interconversion between the two NO_x species takes only a few minutes.

$$NO + O_3 \rightarrow NO_2 + O_2 \quad (1.1)$$

$$NO_2 + h\upsilon \rightarrow NO + O \quad (1.2)$$

$$O + O_2 + M \rightarrow O_3 + M \quad (1.3)$$

Oxidation to HNO_3 is the principal sink of NO_x from the troposphere either in a reaction with OH radical during daylight (1.4) or via production of N_2O_5 at night time (1.5-1.7), although a small proportion of NO_x is lost in the formation of organic nitrates such as peroxyacetyl nitrate (PAN) (Bloss, 2009).

$$NO_2 + OH + M \rightarrow HNO_3 + M \quad (1.4)$$

$$NO_2 + O_3 \rightarrow NO_3 + O_2 \quad (1.5)$$

$$NO_2 + NO_3 + M \leftrightarrow N_2O_5 + M \quad (1.6)$$

$$N_2O_5 + H_2O \rightarrow 2HNO_3 \quad (1.7)$$

NO_2 emissions are affected by both overall NO_x emissions and the magnitude of the fraction of NO_x emitted as NO_2. NO_2 has become a major pollutant of concern in Europe in the last two decades due to a rise in popularity of diesel vehicles, which emit more NO_x than their petrol equivalents, and the technology implemented in them to decrease their emissions of CO, hydrocarbons and particulates. The fitted particle traps and oxidation catalysts use excess NO_2 which may potentially increase the proportion of NO_x emitted as NO_2 up to 70% (Carslaw, 2005; Alvarez *et al.*, 2008; Anttila *et al.*, 2011). As a result, reductions in observed NO_x concentrations did not translate into reductions of NO_2 until the last few years when technologies to limit NO_x emissions from light duty vehicles were introduced (Carslaw *et al.*, 2016, 2019; European Environmental Agency, 2019). Despite the decreasing trend in NO_2 concentrations, around 10% of monitoring stations across the EU reported exceedances of the annual mean NO_2 limit value of 40 µg m^{-3} in 2017 (European Environmental Agency, 2019).

1.2.3 Ozone

Tropospheric O_3 is a secondary pollutant formed in a set of reactions involving NO_x and peroxy radicals derived from CO and VOCs in the presence of sunlight. The reaction chain, which is initiated with the production of OH radicals by O_3 photolysis, is shown in Figure 1.1. The OH radical reacts with VOCs or CO to produce organic peroxy (RO_2) and hydroperoxy (HO_2) radicals, respectively. In low NO_x environments these radicals react with one another resulting in O_3 loss. However, in environments with higher NO_x concentrations a propagation of radicals occurs as organic RO_2 and HO_2 radicals react with NO to produce NO_2. RO_2 radicals in this chain of reactions themselves cause formation of another HO_2 radical and, consequently, another NO_2 molecule. Since OH is regenerated in the process, if there are sufficient NO_x and VOC or CO concentrations in the environment the reaction cycle continues. Each molecule of NO_2 produced can lead to O_3 formation as shown in reactions 1.2 and 1.3. In urban areas, where NO_x concentrations are high, O_3 production is limited by the relative concentrations of VOCs and the 'titration' removal of O_3 by reaction (1.1) can dominate. Conversely, in rural areas O_3 production is NO_x-limited. Termination of the reaction chain occurs when NO_2 and OH react to produce HNO_3 as in reaction (1.4) (Seinfeld and Pandis, 2006; Bloss, 2009).

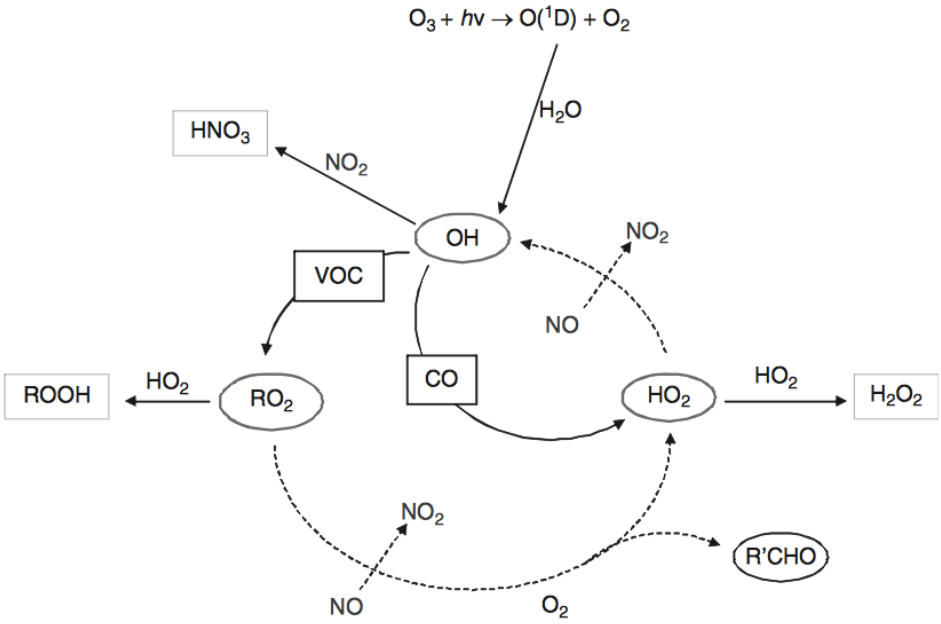

Figure 1.1 Oxidation of VOCs and CO in low NOx (solid lines) and high NOx (solid and dashed lines), the latter leading to O_3 formation. Reproduced from: Bloss (2009).

1.3 Spatio-temporal variability of $PM_{2.5}$, NO_2 and O_3

Factors affecting air pollutant concentrations in time and space are the emission rates of pollutants and their precursors, the proximity of emission sources of primary pollutants, the rates of chemical reactions and the meteorological conditions responsible for air pollution dispersion, deposition, advection from elsewhere, amount of short-wave radiation and air temperature. These factors vary on a range of spatial and/or temporal scales from local to regional and from minutes to years (Salmond and McKendy, 2009) and cause a high spatial and/or temporal variability of air pollutants. This is particularly the case in urban areas where complex geography and variety of sources (both in terms of strength and spatial distribution) may lead to substantial spatial concentration gradients. However, common patterns of air pollutant concentrations can be observed.

The lifetime of NO_2 is short hence NO_2 concentrations are closely linked with local sources and are highly spatially and temporally variable (Cyrys *et al.*, 2012). For example, of the 10% of sites reporting NO_2 concentrations above

the EU limit in 2017, 86% were traffic stations (European Environmental Agency, 2019). NO_2 concentrations tend to peak in the winter season when emissions from heating add to those from traffic and diurnally tend to have two peaks associated with increased traffic volumes during rush hour (Bloss, 2009).

O_3 concentrations tend to be elevated in rural (low NO_x emissions) and coastal areas (elevated ozone concentrations over the ocean), and higher altitudes (downward transfer of O_3 from the stratosphere exceeding the loss rate through dry deposition). In urban areas and particularly near NO_x sources concentrations tend to be suppressed due to titration by NO (The Royal Society, 2008) resulting in potentially high spatial gradients in mean concentrations (Lin *et al.*, 2016). Seasonally, O_3 concentrations tend to peak in the spring and early summer and in the autumn. Diurnally, the highest concentrations tend to occur in the afternoon and the lowest at night time (The Royal Society, 2008).

In most developed countries a large proportion of $PM_{2.5}$ is made of secondary aerosol hence regional sources tend to be more important drivers of $PM_{2.5}$ concentrations than local sources (e.g. AQEG, 2012). This causes $PM_{2.5}$ to be spatially more homogeneous than the other two pollutants with only relatively small increment in concentrations in urban areas. Seasonally and diurnally, the trend in $PM_{2.5}$ concentrations is similar to that of NO_2 but with smaller gradients (AQEG, 2012).

1.4 Health effects of $PM_{2.5}$, NO_2 and O_3

Epidemiological studies investigate whether there is a causal relationship between an incidence rate of a specific health outcome and air pollution exposure whilst accounting for confounding variables such as sex, age, smoking habits and body mass. The result is a concentration-response function, which is then used in health burden calculations. Much of the epidemiological evidence comes from single-pollutant models where the health effect is attributed to just one pollutant even though individuals are

exposed to a mixture of air pollutants in the ambient air at any given time. This approach may attribute all of the health effect to the pollutant studied when some of it may be due to exposure to another pollutant or pollutants, or even another environmental factor such as noise pollution. Two- and multi-pollutant models, where health effects of one pollutant are adjusted for those of correlated pollutants, are being increasingly used to try to address this issue. However, if pollutants are highly correlated (e.g. traffic related pollution), it is difficult to establish independent health associations using even multi-pollutant models (COMEAP, 2018). It is likely that some of the associations attributed to the pollutants below are partially due to other pollutants as well and therefore adding health burdens of correlated pollutants would lead to overestimations. Nonetheless, the evidence for adverse health effects of air pollution is extensive and continually growing. It also suggests that for many air pollutants there are no concentration thresholds below which the pollutants cause no harm (WHO, 2013).

The link between adverse health effects and exposure to $PM_{2.5}$ is particularly strong. Studies have shown that both short and long-term exposure to $PM_{2.5}$ contribute to cardiovascular and pulmonary diseases such as ischaemic heart disease, stroke, chronic obstructive pulmonary disease and chronic bronchitis, and lung cancer leading to increased hospital visits and premature mortality (WHO, 2013). Other health effects associated with exposure to $PM_{2.5}$ include development of chronic kidney disease and renal function decline (Wu *et al.*, 2020), pre-term birth and low birth weight (Li *et al.*, 2017), and decreased development of lungs and lower lung function (WHO, 2013). Traffic related air pollution, of which $PM_{2.5}$ is a component, contributes to the development and exacerbation of asthma (Khreis *et al.*, 2017). Links have also been emerging between $PM_{2.5}$ exposure and increased risk of neurological diseases such as dementia (Carey *et al.*, 2018), Autism Spectrum Disorder and Alzheimer's and Parkinson's diseases (Fu *et al.*, 2019).

Short-term exposure to O_3 has been associated with increased hospital visits and mortality due to respiratory diseases such as asthma and COPD and some

cardiovascular diseases as well (WHO, 2013). The link between long-term exposure to O_3 and mortality is less clear. A meta-analysis by Atkinson *et al.* (2016) found no association of long-term exposure to O_3 and mortality, however the authors noted a limited number of studies available. Since then two large cohort studies in the USA have suggested an association of long-term O_3 exposure and all-cause, cardiovascular and respiratory mortality (Turner *et al.*, 2016) and ischaemic heart disease, COPD disease, cardiovascular and respiratory mortality (Lim *et al.*, 2019). Compared with $PM_{2.5}$, the burden of exposure to O_3 is thought to be much smaller. Exposure to O_3 is estimated to have been responsible for 254,000 deaths globally in 2015 (Cohen *et al.*, 2017).

There is strong evidence of association of short-term exposure to NO_2 and increased mortality and hospital admissions due to respiratory diseases (WHO, 2013). Long-term exposure to NO_2 has also been associated with mortality, however the magnitude of the effect is a more contentious issue as NO_2 is strongly correlated with other pollutants, particularly those from traffic.

The relative risks coefficients for the effects of short- and long-term exposure to the key air pollutants derived from epidemiological studies are presented in Table 1.2 and Table 1.3, respectively.

Table 1.2 Relative Risk (RR) coefficients for the effects of short-term (daily) exposure to air pollution.

Pollutant	Metric	Outcome	RR (95% CI) per 10 µg m^{-3} (%)	Source
PM_{10}	daily mean	mortality, cardiovascular, all ages	0.9 (0.7 – 1.2)	COMEAP (2006)
	daily mean	hospital admissions, cardiac & IHD	0.8 (0.6 – 1.1)	COMEAP (2006)
$PM_{2.5}$	daily mean	mortality cardiovascular, all ages	1.4 (0.7 – 2.2)	COMEAP (2006)
	daily mean	mortality, all cause, all ages	1.23 (0.45 – 2.01)	WHO (2013)
	daily mean	hospital admissions, cardiovascular, all ages	0.91 (0.17 – 1.66)	WHO (2013)
	daily mean	hospital admissions, respiratory, all ages	1.90 (-0.08 – 4.02)	WHO (2013)
O_3	daily max 8-h mean > 20 µg m^{-3}	mortality, all cause, all ages	0.29 (0.14 – 0.43)	WHO (2013)
	daily max 8-h mean > 20 µg m^{-3}	mortality, cardiovascular, all ages	0.49 (0.13 – 0.85)	WHO (2013)
	daily max 8-h mean > 20 µg m^{-3}	mortality, respiratory, all ages	0.29 (-0.11 – 0.70)	WHO (2013)
	daily max 8-h mean	mortality, all cause, all ages	0.34 (0.12 – 0.56)	COMEAP (2015)
	daily max 8-h mean	mortality, cardiovascular, all ages	0.11 (-0.06 – 0.27)	COMEAP (2015)
	daily max 8-h mean	mortality, respiratory, all ages	0.75 (0.30 – 1.20)	COMEAP (2015)
NO_2	daily max 1-h mean	mortality, all cause, all ages	0.27 (0.16 – 0.38)	WHO (2013)
	daily max 1-h mean	hospital admissions, respiratory, all ages	0.15 (-0.08 – 0.38)	WHO (2013)

Table 1.3 Relative risk (RR) coefficients for the effects of long-term (annual) exposure to air pollution.

Pollutant	Metric	Outcome	RR (95% CI) per 10 µg m^{-3} (%)	Source
$PM_{2.5}$	annual mean	all-cause mortality	6 (4 – 8)	COMEAP (2009)
	annual mean	cardiopulmonary mortality	9 (3 – 16)	COMEAP (2009)
	annual mean	lung cancer mortality	8 (0 – 16)	COMEAP (2009)
	annual mean	all-cause mortality, ages 30+	6.2 (4.0 – 8.3)	WHO (2013)
O_3	Apr–Sep average daily max 8-h mean > 70 µg m^{-3}	mortality, respiratory, ages 30+	1.4 (0.5 – 2.4)	WHO (2013)
	annual mean	mortality	No recommendation	COMEAP (2015)
NO_2	annual mean > 20 µg m^{-3}	mortality, all cause, ages 30+	5.5 (3.1 – 8.0)	WHO (2013)
NO_2 as marker of traffic air pollution mixture	annual mean	mortality, all cause	2.3 (0.8 – 3.7)	COMEAP (2018)
NO_2 for NO_2 alone	annual mean	mortality, all cause	0.6 – 1.3 [a]	COMEAP (2018)

[a] no central estimate, only a plausible range for the relative risk coefficient

1.5 Advancements in exposure assessment

Aside from issues with double counting of health effects of correlating air pollutants, a major difficulty for epidemiological studies lies in accurately assigning exposure to air pollution by the study's subjects. Ideally, personal monitoring would provide the desired air pollution exposure data. This is, however, not feasible in epidemiological studies whose study subjects are in their thousands or more in order to provide enough statistical power.

The two seminal studies published in the 1990s (Dockery *et al.*, 1993; Pope *et al.*, 1995) used air pollution data measured at fixed monitoring stations in the investigated cities as a proxy of population exposure in each urban area since

no better exposure data were available to them. However, such a simple approach fails to account for

1. the spatio-temporal variability of air pollution discussed already in Section 1.3

2. the fact that people move around in those spatio-temporally variable pollution fields and are likely to experience different levels of exposure in different places

3. indoor sources of air pollution and the modifying effect of the building envelope on ambient concentrations penetrating indoors where people tend to spend most of their time

All three issues may result in exposure misclassification and bias in health associations.

A large amount of progress has been made addressing issue #1 above. The various approaches which attempt to account for the spatio-temporal variability of exposure in urban areas where concentration gradients are strongest were reviewed by Jerrett *et al.* (2005). They include rather crude methods such as using distance to sources as a proxy of exposure or interpolation of measurements from monitoring stations. The more sophisticated approaches may use data derived from satellite observations, statistical models such as land-use regression (LUR) models, Gaussian plume dispersion models or a combination of those.

One of the most popular methods is LUR statistical modelling which uses supervised stepwise regression to predict concentrations from potential predictor variables at locations with known air pollution concentrations, e.g. at fixed monitoring stations or purposefully deployed air pollution monitors. The built model is then used to predict concentrations at the desired receptor points in the study area (Briggs *et al.*, 1997). The predictor variables almost always

include a variable related to traffic (intensity, road length, distance) and population density. Other frequently used variables include land use (e.g. proximity to green space), meteorology and altitude (Hoek *et al.*, 2008). An advantage of LUR models is a relatively cheap computational cost as they do not require complex computation or proprietary software. Costs can, however, mount up if extensive monitoring campaigns are needed for the model build. Gillespie *et al.* (2016) and Basagaña *et al.* (2012) argue that at least 60 and 80 monitoring sites, respectively, are needed to train the model to minimise the risk of overfitting. There is also an issue of transferability between study areas (e.g. Jerrett *et al.*, 2005) with dissimilar land use, and temporal resolution. The latter can be addressed by scaling the calculated long-term averages by more temporally resolved data from monitoring stations or developing individual models for each desired period (e.g. Dons *et al.*, 2013).

Dispersion models are deterministic models. They range in complexity from Gaussian plume models to computational fluid dynamics models. Gaussian plume models assume that on average the distribution of pollutant concentrations in a plume released from a point source is Gaussian in the plane perpendicular to the mean wind direction provided the wind direction and speed are constant. In the downwind (x) direction the plume is diluted by the wind. In the crosswind (y) and vertical (z) directions the plume is diluted by turbulent motions. It is also necessary that the mean wind speed >> turbulent motions in the x direction. Under those assumptions and in the absence of boundaries concentrations in the plume can be calculated as:

$$C = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right) \exp\left[-\frac{(z-h)^2}{2\sigma_z^2}\right] \quad (1.8)$$

where C is the concentration at a given point (g m^{-3}), Q is the emission rate (g s^{-1}), u is the downwind speed (m s^{-1}), σ_y is the dispersion parameter in the horizontal direction (m), σ_z is the dispersion parameter in the vertical direction (m), h is the effective source height (m), y is the horizontal direction perpendicular to the wind (m) and z is the vertical direction (m) (De Visscher,

2014). Additional terms may be included in equation 1.8 to account for reflections of the plume off the surface and inversion layers, respectively. The dispersion parameters (σ_y, σ_z) depend on the stability of the boundary layer and vary with source and plume heights. In Gaussian plume dispersion models non-point sources such as line, area and volume sources are decomposed to a small number of point source elements whose contributions are then summed to calculate the concentration (De Visscher, 2014). The advantages of using a Gaussian plume dispersion model are high spatial and temporal resolution, and transferability. They can also be used for source apportionment or impact assessment of changes in emissions. The models may also include simple chemistry, for example simplified O_3 or sulphate chemistry. On the other hand, they require detailed emission and meteorological input data and a substantially larger amount of computational power when the number of modelled emission sources and/or receptor points is large compared to LUR models (Jerrett *et al.*, 2005). Moreover, the assumptions on which Gaussian plume dispersion models are based break down within just a few tens of kilometres, therefore these models are limited to local and urban scale assessments (De Visscher, 2014).

For large geographic scale (regional, national and higher) air pollution exposure studies Eulerian grid-based atmospheric chemistry transport models (ACTMs) are generally used (Colette *et al.*, 2014; Cohen *et al.*, 2017; Milojevic *et al.*, 2017). ACTMs are driven by input meteorological data and predict concentrations by solving the continuity equation for mass conservation of air pollutants. They are capable of modelling complex chemistry, however they are not suited to capture fine intra-urban scale concentration gradients and are computationally very expensive (De Visscher, 2014). The spatial resolution of ATCMs is limited by the available computational power, resolution of input emission data and the physical theories utilised in the models. Still, spatial resolution in low single figures of km has been achieved (e.g. Colette *et al.*, 2014; Reis *et al.*, 2018).

Whilst large improvements have been made in the spatial and temporal resolution of exposure assessments, still relatively little has been done to address the issue of population mobility and exposure in microenvironments outside home. This is particularly the case at large (national) scale level. The importance of including exposure at workplace was demonstrated for example by Ragettli *et al.* (2015) who calculated that ignoring workplace exposure to NO_2 resulted in potential 12% underestimation of health effects. Similarly, Nyhan *et al.* (2019) estimated a 9% bias towards the null in exposure to $PM_{2.5}$. To account for population mobility in exposure studies several approaches have been adopted. These include utilising Census data (Shafran-Nathan *et al.*, 2017, 2018), time-activity or travel surveys (Setton *et al.*, 2011; Ragettli *et al.*, 2015; Smith *et al.*, 2016), synthetic populations (Beckx, Int Panis, Arentze, *et al.*, 2009; Dhondt *et al.*, 2012) or data from mobile phone networks (Dewulf *et al.*, 2016; Nyhan *et al.*, 2016, 2019). The results in the aforementioned studies generally show an increase in exposure to nitrogen oxides and/or PM of the 'dynamic' populations compared with the 'static' ones.

Very few population exposure studies have addressed issue #3 which requires detailed information on the building type and material used and the building condition as well as ventilation habits of the studied population. Due to the lack such data this issue is not considered in this work.

1.6 Differential effects of air pollution on human health

Due to its ubiquity everyone in society is to some degree impacted by air pollution. However, some population subgroups are more vulnerable to it than others due to biological (e.g. genetics, age, pre-existing disease) and/or environmental factors (e.g. deprivation, diet, smoking habit) (Royal College of Physicians, 2016). For example, children are more affected by air pollution as their lungs are still in development and they generally have higher baseline ventilation rates than the adult population (Bateson and Schwartz, 2007). Older people are also more vulnerable, largely because of other co-morbidities and weaker immune systems associated with older age (Royal College of

Physicians, 2016). People of low socio-economic status (SES) have been shown to be disproportionally affected by air pollution compared with those less deprived.

The effect of increased susceptibility to air pollution on health may be further exacerbated by increased exposure to air pollution, in other words through differential exposure. Whilst the evidence is not straightforward and appears to be area specific, in general most deprived people tend to experience the highest levels of exposure to PM and NO_2 (Hajat *et al.*, 2015; Fairburn *et al.*, 2019). Evidence of differential exposure of ethnic minorities in Europe is even more mixed (Fairburn *et al.*, 2019). However, as with the majority of exposure studies, only few published studies consider subjects' exposure away from home in their analysis.

1.7 Aims of this work

The overarching goal of this thesis is to improve and investigate estimates of population exposure and its inequality in the UK to the key air pollutants of NO_2, $PM_{2.5}$ and O_3. The specific aims are as follows:

1. Improve estimates of population exposure to the air pollutants in the UK by considering exposure to ambient air at the place of work or study in addition to place of residence.

2. Investigate how exposure of various population subgroups is affected by workplace exposure using a case example of the Central Belt of Scotland and its major urban areas - Glasgow and Edinburgh. Specifically, age, ethnicity and SES are considered.

3. Investigate the impact of model choice (ACTM vs Gaussian plume dispersion model) on estimated exposure of the population and population subgroups in Edinburgh.

Additional introductory and methodological information relevant to each of the following three chapters are contained within that chapter.

Chapter 2 The influence of workplace mobility on population exposure to air pollution in the UK

Part of this chapter is based on a research paper published in Environment International (Reis, S., Liška, T., Vieno, M., Carnell, E. J., Beck, R., Clemens, T., Dragosits, U., Tomlinson, S. J., Leaver, D. and Heal, M. R. 2018. The influence of residential and workday population mobility on exposure to air pollution in the UK. Environment International. 121, pp.803-813.). Stefan Reis, Mat Heal, Massimo Vieno and I conceived the methodology. Stefan Reis undertook the mapping of population datasets from census geographies onto the British National Grid. Massimo Vieno undertook EMEP4UK modelling. I mapped the EMEP4UK output onto the British National Grid, combined the population and pollution datasets, calculated the population- and individual-level exposures, conducted sensitivity analyses and calculated the mortality impacts.

2.1 Introduction

Many epidemiological studies have identified associations between exposure to air pollution with adverse effects on human health, particularly on the cardiovascular and respiratory systems, leading to increased morbidity and premature mortality (e.g. WHO, 2013). A particular challenge for epidemiologists investigating the associations and quantifying their health impacts is to accurately estimate exposure levels of the study subjects as they move in spatio-temporally variable air pollution fields in their daily activities.

In the absence of low-cost, high-accuracy and high-reliability personal monitors that could be deployed on a large scale, the common practice in epidemiological studies has been an indirect approach of assigning to the study subjects ambient air pollution concentrations obtained from air pollution models or derived from measurements in the study area (Özkaynak *et al.*, 2013). Increasingly sophisticated methods in air pollution modelling have enabled air pollution concentrations to be predicted well at fine spatial scales (Beelen *et al.*, 2014; Barone-Adesi *et al.*, 2015). Mainly due to the lack of reliable time-activity data many cohort studies still do not account for the

mobility of the study subjects and simply rely on ambient concentrations at the subjects' place of residence as a reasonable proxy of their exposure. However, small-scale personal exposure studies have shown that personal exposure integrated over all personal activities in various microenvironments may substantially differ from exposure at the residential address only, and that there can be a substantial variability in personal exposure within the population when personal mobility is accounted for (Dons *et al.*, 2011; de Nazelle *et al.*, 2013; Steinle *et al.*, 2015). Whilst small-scale personal exposure studies are useful in investigating the potential impact of different microenvironments on overall exposure, deriving population level exposure estimates from such studies is challenging as the study participants are not necessarily a representative sample of the population.

In recent years, several studies have investigated the impact of population mobility on population-level exposure, mostly to NO_2 and $PM_{2.5}$, and on urban to regional scales. The methods used to account for individuals' mobility included travel surveys (Ragettli *et al.*, 2015; Smith *et al.*, 2016), simulated populations (Setton *et al.*, 2008; Beckx, Int Panis, Uljee, *et al.*, 2009; Dhondt *et al.*, 2012), censuses (Shafran-Nathan *et al.*, 2017, 2018) and mobile phone tracking (Dewulf *et al.*, 2016; Nyhan *et al.*, 2016, 2019).

Most of those studies found a relatively small change (several percent) in population exposure compared to estimates based on residential exposure only. However, Nyhan et al. (2019), Ragettli et al. (2015) and Setton et al. (2011) have shown that even small underestimates in population exposure may lead to potentially substantial underestimates in health effects, thus demonstrating the importance of considering exposure in other microenvironments, particularly at the place of work (Ragettli *et al.*, 2015). The magnitude of the bias was shown to increase with distance between home and workplace, and with higher spatial resolution of modelled pollution concentrations (Setton *et al.*, 2011).

A large-scale national exposure assessment of a mobile population is rare in the literature (Beckx, Int Panis, Arentze, *et al.*, 2009; Dewulf *et al.*, 2016) as it places substantial demands on both air pollution and population mobility data coverage. Considering the former, aside from adequate spatial resolution there is an additional requirement on the model to simulate the temporal variability of air pollutants well too. In practice, a good agreement with the observed diurnal profile of air pollution concentrations will often suffice since many regular daily activities such as work tend to take place at set times of the day. Atmospheric chemistry transport models (ACTMs) have achieved a substantial progress in spatial and temporal accuracy and can provide consistent spatio-temporal air pollution concentration fields for both individual and population levels of exposure assessment where personal or stationary observations are not available (including for historic and future exposure estimates). Considering population data, national censuses are a rich source of information on population characteristics with exceptional population coverage. At an individual level census data are normally inaccessible due to privacy issues, however data aggregated to coarser spatial units are available to researchers and the wider public.

This study takes an advantage of a new and publicly available Workday Population dataset in the most recent UK Census (2011) which estimates the spatial distribution of the population during the working day. Together with the standard Residential Population dataset and using the state-of-the-art ACTM EMEP4UK this study's aim is to investigate the effect of workday mobility on population exposure to air pollution on a national scale and in the process derive a more realistic exposure estimates of the UK population. Whilst EMEP4UK is capable of modelling a large suite of air pollutants the analysis focuses on the key pollutants NO_2, O_3 and $PM_{2.5}$ due to their widespread presence, well-documented health impacts, and mutually contrasting spatio-temporal variability.

2.2 Methods

2.2.1 Study areas

The analysis was conducted for the whole of the UK (England, Wales, Scotland and Northern Ireland). An additional analysis was also conducted for Scotland only. The are several reasons to treat Scotland separately in addition to the main analysis concerning the whole of the UK. From a policy perspective, environment and health related matters are devolved in the UK which means that the Scottish Government and Parliament are responsible for policy in these areas and would benefit from a standalone analysis of air pollution exposure in the country should the results be substantially different from the whole of the UK. From a science perspective, Scotland makes up about one third of the UK landmass yet its population of about 5.3 million contributed only about 8% to the total UK population in 2011 (ONS, 2013). Consequently, Scotland is a much less densely populated country than the UK as a whole - 68 vs 216 people km^{-2} on average (ONS, 2013). Furthermore, due to its location within the UK it is subject to different levels of air pollution than the rest of the UK, and particularly England which makes up the majority of the UK population (see Section 2.3.1).

2.2.2 Population mapping

The methodology used to derive the high-resolution population distribution maps is shown in Figure 2.1. Data on population distribution for usually resident (referred to as 'residential') and workday populations for the UK is available to the public from statistical offices in England & Wales, Northern Ireland and Scotland, e.g. via the Office for National Statistics (ONS). The ONS defines a usual resident of the UK as

"anyone who, on census day, was in the UK and had stayed or intended to stay in the UK for a period of 12 months or more, or had a permanent UK address and was outside the UK and intended to be outside the UK for less than 12 months" (ONS, 2014a).

The workday population in an area then represents

"all usual residents aged 16 and above who are in employment and whose workplace is in the area, and all other usual residents of any age who are not in employment but are resident in the area. People who work mainly at or from home, or do not have a fixed place of work, are included in the area of their usual residence" (ONS, 2014a).

The workday dataset therefore excludes workers not resident in the UK, short-term residents and residents working offshore. It also excludes individuals working in one country of the UK but living in another except for England and Wales which are administered together by one statistical office (ONS, 2014a).

The geographical areas for which census estimates are provided reflect different levels of administrative boundaries, from Devolved Administration (i.e. England, Wales, Scotland and Northern Ireland) to Output Areas (OA) as the smallest. The minimum OA size was 40 resident households and 100 resident people, with recommended sizes being larger at 125 households. Since they are population based, the OAs are polygons with highly variable sizes and shapes. As the model output of atmospheric concentrations is provided on a regular grid (Section 2.2.3), the population distribution was also mapped onto a regular grid for merging with the modelled air pollution concentration fields. This allows for a more uniform spatial analysis based on a regular grid, whereas mapping pollution fields onto OA shapes may lead to spreading pollutant concentrations across larger areas in sparsely populated regions. The dataset used for this study therefore combines 2011 UK Census population data at the OA level with land cover data (Land Cover Map 2015) (Rowland *et al.*, 2017). The categories 'Urban' and 'Suburban' were aggregated to create a consistent gridded population data product to provide a population density surface at 1 km × 1 km spatial resolution. The mapping products are based on the British National Grid (OSGB36 datum). Both residential and workday population datasets have been published and are publicly available (Reis *et al.*, 2017).

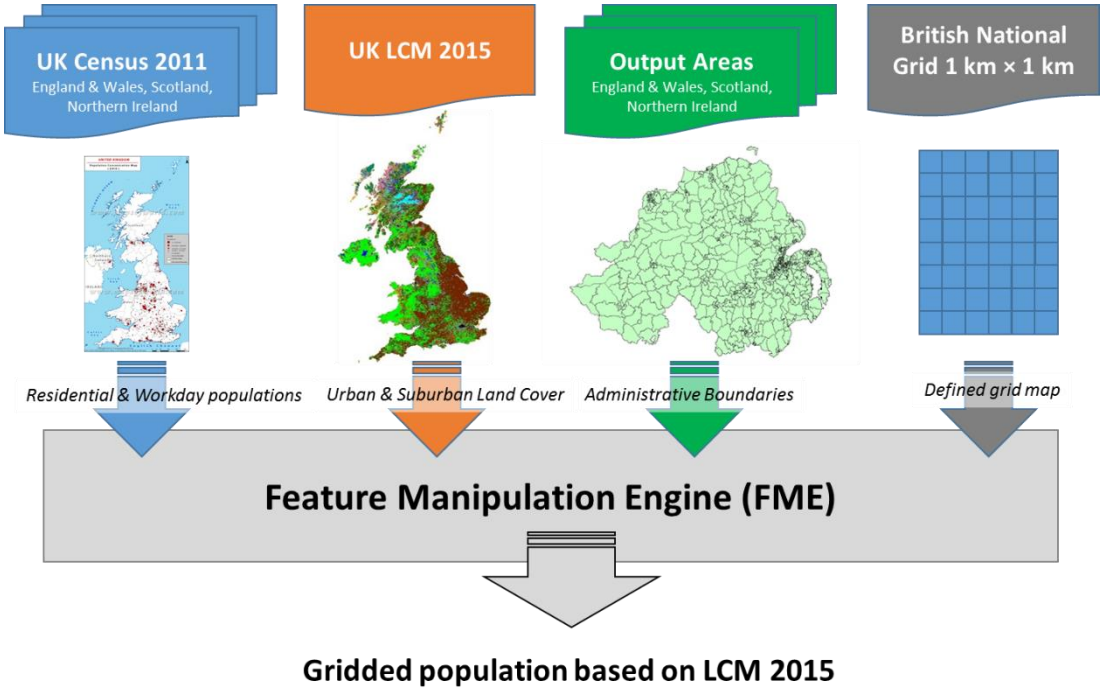

Figure 2.1 Flowchart for the production of high resolution population maps (FME © Safe Software; LCM = Land Cover Map). (Reis et al., 2018).

The total population number in each dataset for the whole of the UK and for Scotland only are shown in Table 2.1. All grid cells which at least partially lie within Scotland were selected for the Scotland only analysis. The difference between the two populations in Scotland is caused by the omission of workers working in other nations of the UK or offshore in the Workday Population dataset. There are 125,456 populated grid cells in the UK of which 323 have residential population only and 206 workday population only. In total, in the UK there are 83,719 grid cells in which residential population is larger than workday population, 34,560 grid cells where the opposite is true, and 7,177 grid cells where the two populations are equal. This indicates that the workday population is focused on fewer grid cells of high workday population densities compared with the residential population which is distributed more uniformly. In approximately 47% of the populated grid cells the difference between the two populations is < 10 people.

Table 2.1 Total population numbers in mapped residential and workday datasets, and their difference (workday – residential) from Census 2011.

Country	Residential	Workday	Difference	Difference (%)
UK	63,184,827	63,185,286	459	0
Scotland	5,111,641	5,092,320	-19,321	-0.4

The spatial distribution of the gridded residential population is shown in Figure 2.2. Urban areas are clearly the most densely populated, however it is worth noting there is also variability in population densities within urban areas as demonstrated by the ring of the highest observed residential population densities up to 22,620 people per km^2 surrounding the city centre of London. Figure 2.3 also highlights the difference in population density between Scotland (to the north of the internal border shown in purple) and the rest of the UK.

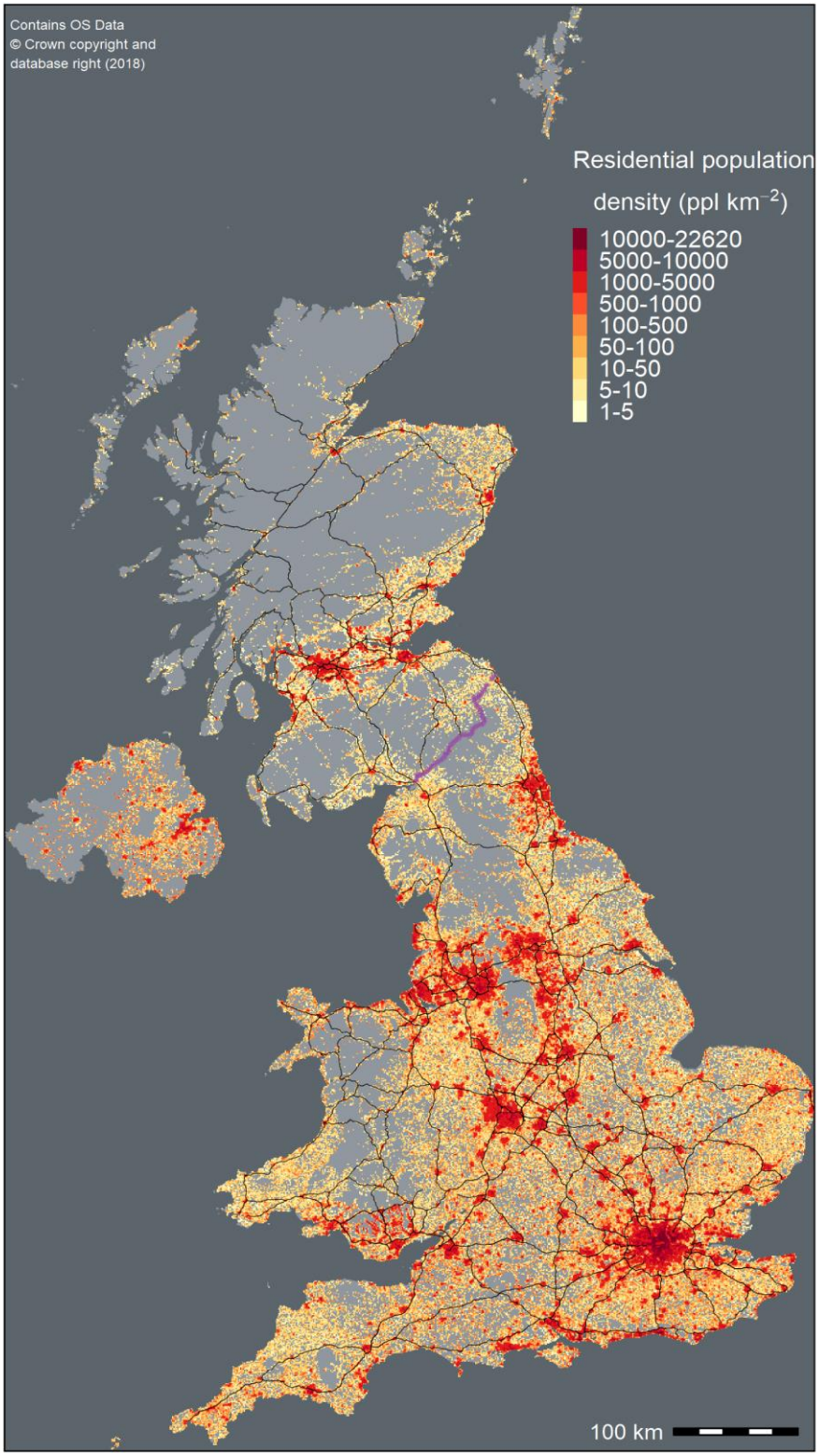

Figure 2.2 Spatial distribution of residential population in the UK mapped on 1 km x 1 km British National Grid. The purple line shows the internal UK border between Scotland to the north, and England and Wales to the south. Contains OS Data © Crown copyright and database right (2021).

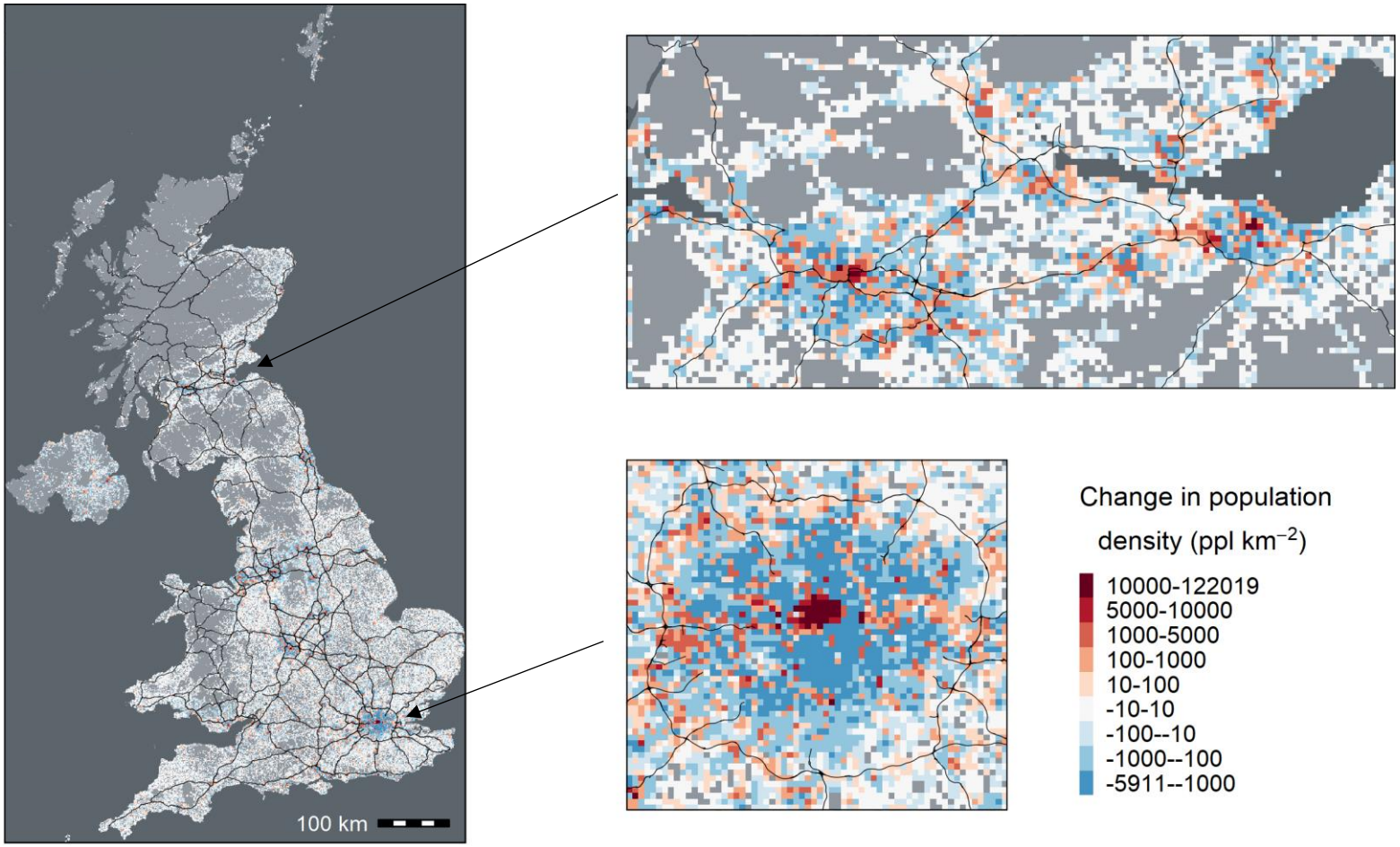

Figure 2.3 Difference between UK workday and residential population densities (km^{-2}) (left). Positive values represent workday population > residential population. The Central Belt of Scotland and Greater London regions are shown in greater detail at the top right and bottom right, respectively. Contains OS Data © Crown copyright and database right (2021).

The spatial distribution of the difference between the two population datasets (workday – residential) is shown in Figure 2.3. The figure shows that out in the countryside the difference between the two populations tends to be small, however in urban areas and their adjacent regions (i.e. the commuter belt) the difference in population numbers is often very large. This is highlighted in the right panels of Figure 2.3 which show a more detailed view of the Glasgow and Edinburgh (also referred to as the Central Belt) region in Scotland and Greater London area. The panels highlight that urban centres gain population during working days due to commuting, while population density in suburbs is reduced. The most striking effect is observed in central London where the residential population is very low compared with the workday population. During working hours, population densities exceed 120,000 km^{-2} with 10 to 20-fold increases in the local population density, for example, in the City of London.

2.2.3 Air pollution data

The regional atmospheric chemistry transport model (ACTM) EMEP4UK was used for quantifying atmospheric pollutant concentrations. The model is based on version rv4.10 of the European Monitoring and Evaluation Programme (EMEP) Meteorological Synthesizing Centre - West (MSC-W) model (www.emep.int), which is described in Simpson et al. (2012). A detailed description of the EMEP4UK model is provided in Vieno et al. (2016a, 2016b, 2014, 2010). The model produces hourly concentrations of a wide range of gaseous and particulate matter species. The EMEP4UK model's meteorological driver is the Weather Research and Forecast (WRF) model version 3.7.1 (Skamarock *et al.*, 2005). The EMEP4UK and WRF model domain uses a one-way nested approach with a latitude/longitude grid at a horizontal resolution of 0.5° × 0.5° (~55.5 km at the equator) for an extended European domain, ~0.055° × ~0.055° (~6.2 km at the equator) for the British Isles nested domain (UK & Republic of Ireland), and ~0.018° × ~0.018° (~2 km at the equator) for the innermost domain covering the United Kingdom. The boundary conditions at the edge of the European domain are prescribed

concentrations in terms of latitude and adjusted for each year as described in Simpson et al. (2012). Emission data and meteorology for 2015 were used. Land-based anthropogenic emissions for the UK were obtained from the National Atmospheric Emission Inventory (NAEI, http://naei.beis.gov.uk/). Elsewhere, the EMEP emission estimates provided by the Centre for Emission Inventories and Projections (CEIP, http://www.ceip.at/) were used. Estimates for shipping emissions were derived from Jalkanen et al. (2016) and were for the year 2011.

2.2.4 Exposure analysis

Firstly, the EMEP4UK NO_2, O_3 and $PM_{2.5}$ concentration fields, which were generated in geographical coordinates, were remapped onto the British National Grid to match the spatial reference system of the population data (OSGB36 datum). Then three annual mean population exposures were calculated for each pollutant in each grid cell from the hourly concentrations during the year: Residential only (RE_i), Workday only (WE_i) and combined Residential-Workday (RWE_i).

The RE_i and WE_i exposures represent scenarios in which the whole UK population stays all the time at their place of residence and work, respectively, while the RWE_i represents a more realistic scenario in which people spend some time at home and some time at work.

The RE_i and WE_i were calculated as

$$E_i = P_i \times \bar{C}_i \tag{2.1}$$

where E_i (either RE_i for residential or WE_i for workday) is the annual mean population exposure in grid cell i, P_i is the respective population number in grid cell i and $\bar{C}_i$ is the annual mean concentration of the pollutant in grid cell i.

The RWE_i was calculated as

$$RWE_i = \frac{R_i \times \sum C_{Ri} + W_i \times \sum C_{Wi}}{8760} \tag{2.2}$$

where RWE_i is the combined mean population exposure in grid cell i, R_i is the residential population in grid cell i, $\sum C_{Ri}$ is the sum of all hourly concentrations of the pollutant in grid cell i outside working hours, W_i is the workday population in grid cell i, $\sum C_{Wi}$ is the sum of all hourly concentrations of the pollutant in grid cell i during working hours and 8760 is the number of hours in 2015.

Finally, the population-weighted mean exposure to a pollutant was calculated as

$$E = \frac{\sum_{i=1}^{n} E_i}{P} \tag{2.3}$$

where E is the population-weighted mean exposure for a population (residential, workday, combined), n is the number of populated grid cells by a population, E_i is the mean exposure in grid cell i for a population and P is the respective total population. Residential population was used for the calculation of RWE, as the difference between the total Residential and Workday populations in the UK is negligible (minor differences occur due to cross-border and offshore commuting).

For the calculation of RWE, uniform working hours across the population were used and two main scenarios were considered: $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$, whereby everyone is at their place of work between 09:00 and 17:00, and 08:00 and 18:00, respectively, from Monday until Friday. Outside the prescribed working hours everyone was considered to be at their place of residence. The scenarios were based on standard working ('office') hours in the UK. Exposures while in transit and mode of commuting between work and home were not considered as there was no link on an individual level between the two population datasets. The $RWE_{8\text{-}18}$ scenario, however, includes transit time spent not at their place of residence for much of the population, whilst the $RWE_{9\text{-}17}$ scenario is likely more appropriate for those with short commuting distances. Overall, 23.8% and 29.8% of the time is spent at work in the $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$ scenario, respectively.

In the analysis, clock changes to British Summer Time (BST) in March and back to Greenwich Mean Time (GMT) in October were accounted for in the RWE scenario. However, the 8 days of public holiday in the year are treated as weekdays, as their dates vary between the nations of the UK.

The exposure analysis was conducted in Python programming language using the NumPy and the UK Met Office's Iris (version 2.0) libraries. Both the EMEP4UK hourly output for each studied pollutant and the populations datasets were loaded into Iris 'cube' objects. The pollutant cubes were mapped to the British National Grid using the Iris cube.regrid method with the regridding scheme argument set to 'linear'. Subsequently, a mask based on the two population datasets was applied to the pollutant cubes using the numpy.ma module so that pollution concentration data only in populated grid cells were used in the exposure analysis.

For the calculations of RE_i and WE_i, the mean annual concentrations were calculated using the Iris cube.collapsed method applied to the time coordinate with the aggregator argument set to 'MEAN'. The resulting annual mean pollutant concentration cube was then multiplied by the relevant population cube.

For the calculation of RWE_i, the pollutant concentration cube was split into a 'work' cube and a 'home' cube using the Iris cube.extract method with the constraint argument on the time coordinate set to include designated working hours for the work cube and exclude working hours for the home cube. Each of the work and home cubes was then collapsed on the time coordinate with the aggregator argument set to 'SUM' and multiplied by the workday and residential population cube, respectively. Those were then summed and divided by 8,760.

For the population-weighted mean exposure calculation, the RE_i, WE_i, RWE_i and population cubes were further collapsed on the spatial coordinates with the aggregator argument set to 'SUM' to give the total UK population-exposure

and population scalar cubes, respectively. The population-exposure cubes were then divided by the relevant population cube.

EMEP4UK output is generated in Coordinated Universal Time (UTC). To address the change to daylight saving time, after loading the air pollution data into a cube, the cube was further divided into two cubes; one covering the period of GMT (referred to as the GMT cube) and the other covering the BST period (referred to as the BST cube) using the cube.extract method with the constraint argument on the time coordinate set to the start and end of the BST in 2015. Designated working hours in the BST cube were then shifted back by one hour compared to the GMT cube, as BST = GMT + 1.

Health burden calculations

The calculated change in total population-weighted exposure to $PM_{2.5}$ and NO_2 is used to estimate the impact of workplace exposure to these pollutants on premature mortality as described in Walton *et al.* (2015) using the relative risk coefficient for long-term exposure presented in Table 1.3. The coefficient is scaled using the following relationship:

$$RR_{scaled} = RR^{\frac{RWE-RE}{10}}$$

The RR_{scaled} is then converted to the attributable fraction (AF) using:

$$AF = \frac{RR_{scaled} - 1}{RR_{scaled}}$$

The AF is then multiplied by the number of deaths in the UK in 2015, of which there were 601,634 in 2015 (ONS, 2020). For NO_2, COMEAP published a range for the relative risk of exposure to NO_2, however, the Committee stated that

> "Neither the unadjusted single pollutant summary estimate nor an adjusted coefficient can be used with confidence to reflect the mortality burden on the UK population due to NO_2 itself" (COMEAP, 2018).

Therefore, whilst the health burden of the change in exposure to NO_2 is calculated, it should only be viewed as an indicative figure.

Exposure sensitivity analysis

The sensitivity of estimated population exposure to the choice of working hours was investigated using other uniformly prescribed working hours between Monday and Friday. Since ~ 70% of people in employment work over 30 hours a week (ONS, 2014b) part-time working patterns were not considered.

2.2.5 Individual exposure case studies

The lack of origin – destination links in the population datasets used in this study also prevents an investigation of exposure variability within the population and what effect exposure at the place of work may have on it. Therefore, the potential impact of exposure at the place of work at an individual level is examined on virtual individuals working in a city centre but living in mutually contrasting urban areas – inner urban and outer urban (suburban). The motivation is not to obtain an accurate assessment of the range of potential exposures differences due to workplace exposure but to

a. demonstrate that the substantial variability in the difference between RWE and RE at an individual level exists within an urban setting and can be captured in this modelling approach
b. give examples of a potential magnitude of change in personal exposure of those workers who live in the areas that lose a large amount of residential population due to work (dark blue grid cells in Figure 2.3).

For this, Edinburgh, Greater Manchester and Greater London urban areas were selected (top, middle, and bottom panel in Figure 2.4, respectively). In each area, a pair of individuals work in a central location (denoted as 3 in Figure 2.4). One of the pairs lives further away from the city centre in an outer urban area (denoted as 1 in Figure 2.4), whilst the other individual lives much closer to their place of work (denoted as 2 in Figure 2.4). The location selection

was largely arbitrary, however it was also informed by the change in population densities shown in Figure 2.3.

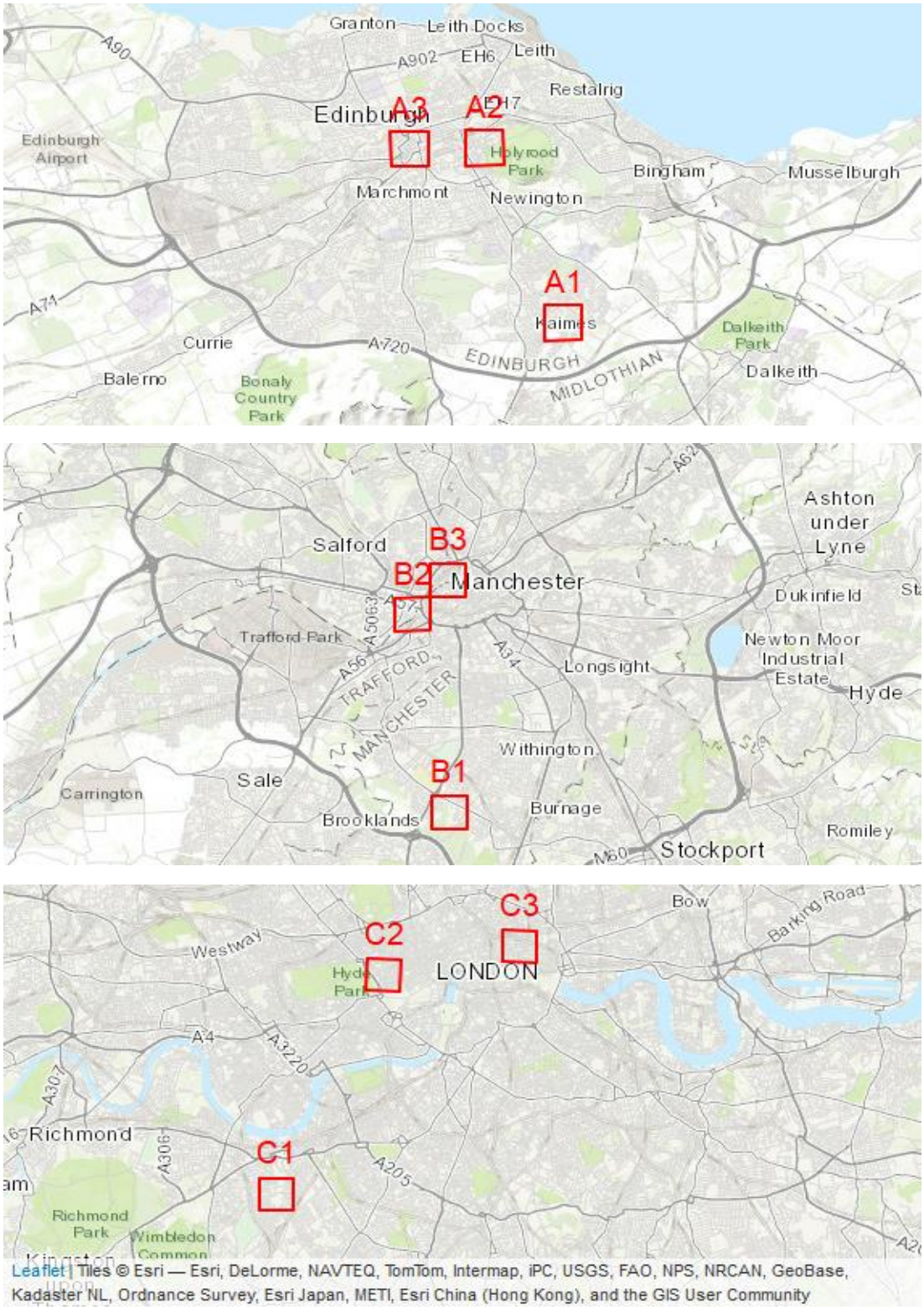

Figure 2.4 Location of 1 km × 1 km grid cells selected for model assessment of virtual individuals living in either outer urban (1) or an inner urban (2) location and working in a city centre (3) location in Edinburgh (A1–A3), Manchester (B1–B3) and London (C1–C3). Adapted from Reis at al., 2018.

2.3 Results

2.3.1 Air pollution concentrations

The EMEP4UK modelled annual mean NO_2, O_3 and $PM_{2.5}$ concentrations following the re-gridding onto the British National Grid are shown in Figure 2.5. Only those grid cells where at least one of residential or workday population > 0 are shown. The map for NO_2 clearly shows that the highest concentrations and gradients of NO_2 are associated with urban agglomerations, busy ports, airports and major roads. On the other hand, high O_3 concentrations occur in rural communities, particularly in the west of the country, whilst in urban areas O_3 concentrations are comparatively lower. The rural - urban gradient of O_3 concentrations is largely masked in Figure 2.5 as rural areas are scarcely populated. A spatial anti-correlation between O_3 and NO_2 can be seen, particularly in the London area. This is the corollary of the reaction between NO and O_3 that leads to enhanced NO_2 in areas of high NO_x emissions simultaneously reducing concentrations of urban O_3. Similarly to NO_2, $PM_{2.5}$ concentrations are elevated in urban areas, ports and roads. However, these local increments are superimposed on a background southeast – northwest $PM_{2.5}$ concentration gradient caused by import of secondary PM from continental Europe. The range of annual mean $PM_{2.5}$ concentrations is substantially smaller than those of NO_2 and O_3.

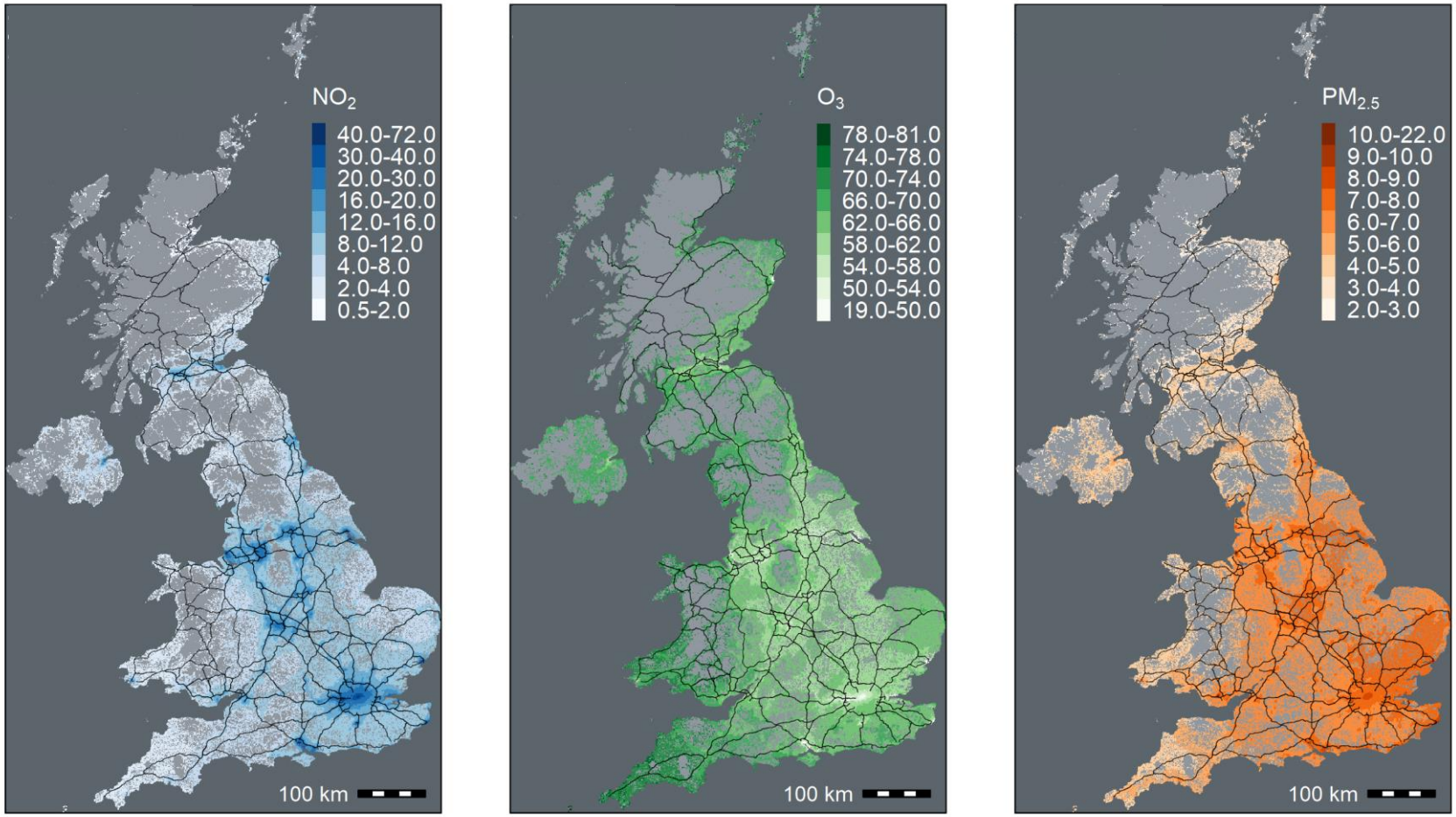

Figure 2.5 Modelled annual mean NO_2, O_3 and $PM_{2.5}$ concentrations in the UK for the year 2015 in grid cells where at least one of residential or workday populations > 0. All units are μg m^{-3}. Contains OS Data © Crown copyright and database right (2021).

2.3.2 Population exposure estimates

The population-weighted mean exposures to NO_2, O_3 and $PM_{2.5}$ in the UK and Scotland, respectively, calculated for RE, WE, $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$ scenarios are shown in Table 2.2. Residential population-weighted mean exposures to NO_2 and $PM_{2.5}$ are ~ 36% lower in Scotland than in the UK. However, for O_3, the exposures are marginally higher in Scotland. For NO_2, the results show only modest increase of 0.90 µg m^{-3} and 0.96 µg m^{-3} in population exposure when comparing the WE scenario with the RE scenario in the UK and Scotland, respectively. For O_3, the change is negative and equals 0.50 µg m^{-3} in both cases. For $PM_{2.5}$ the difference between WE and RE is positive but at 0.06 µg m^{-3} and 0.08 µg m^{-3} in the UK and Scotland, respectively, virtually negligible.

The magnitude and direction of change in exposure to the three pollutants clearly reflect the combination of population mobility to urban centres (Figure 2.3) and the spatial distribution of each pollutant (Figure 2.5). For example, results for both NO_2 and $PM_{2.5}$ show that WE is larger than RE as concentrations of those pollutants tend to be higher in urban centres but the magnitude of NO_2 change is an order of magnitude larger than that of $PM_{2.5}$.

Table 2.2 Residential (RE), workday (WE) and combined residential-workday (RWE) population-weighted mean exposures to NO_2, O_3 and $PM_{2.5}$ in the UK and Scotland for 9-17 and 8-18 Monday to Friday working hours scenarios. Also shown are the respective RWE/RE ratios. Exposure units are µg m^{-3}.

Pollutant	Country	RE	WE	$RWE_{9\text{-}17}$	$RWE_{9\text{-}17}$/RE	$RWE_{8\text{-}18}$	$RWE_{8\text{-}18}$/RE
NO_2	UK	14.28	15.18	14.49	1.014	14.56	1.020
	Scotland	9.09	10.05	9.30	1.023	9.38	1.031
O_3	UK	62.45	61.95	62.33	0.998	62.28	0.997
	Scotland	64.68	64.18	64.49	0.997	64.43	0.996
$PM_{2.5}$	UK	6.71	6.77	6.72	1.002	6.73	1.003
	Scotland	4.30	4.38	4.32	1.003	4.32	1.005

The RE and WE represent the boundary values of population exposure estimates in this assessment and any RWE based on an arbitrary choice of working hours will lie between the RE and WE exposure estimates. Therefore,

the maximum potential increase in population exposure to NO_2 when accounting for exposure at the place of work is 6.3% in the UK and 10.6% in Scotland. For the other two pollutants the magnitude of the maximum potential change is less than 1.0 % except for $PM_{2.5}$ in Scotland (1.7%). Table 2.2 shows that the increase in population-weighted mean exposure to NO_2 only amounts to 2.0% and 3.1% in the UK and Scotland, respectively, for the $RWE_{8\text{-}18}$ scenario. The increases for the $RWE_{9\text{-}17}$ scenario are smaller still. The changes in population exposure to O_3 and $PM_{2.5}$ due to accounting for exposure at work are less or equal to 0.5%.

The additional estimated $PM_{2.5}$ exposure of 0.02 µg m^{-3} when including workplace mobility may contribute to additional 72 (95% CI 47 – 96) premature mortalities per year across the UK. The estimated additional mortality due to increased exposure to NO_2 is approximately 101 – 218. As already pointed out, the additional premature mortality due to increased exposure to NO_2 is only an indicative figure due to low confidence in the magnitude of the relative risk. Furthermore, the calculated additional mortalities due to exposure to $PM_{2.5}$ and NO_2, respectively, should not be added together, as this would overestimate the effects (COMEAP, 2018).

The results of the sensitivity study on the effect of assigned duration and start time of working hours on the change in potential population exposure to NO_2 in the UK are presented in Figure 2.6. The figure shows that the length of assigned work hours has a larger effect on the population exposure estimate than the work start time. The differences caused by varying the work start time are small between 06:00 and 10:00 after which they rise rather more sharply. It is worth noting that the standard working hours of 09:00-17:00 (Parton, 1980) used in the $RWE_{9\text{-}17}$ scenario result in the smallest increase in NO_2 exposure estimate.

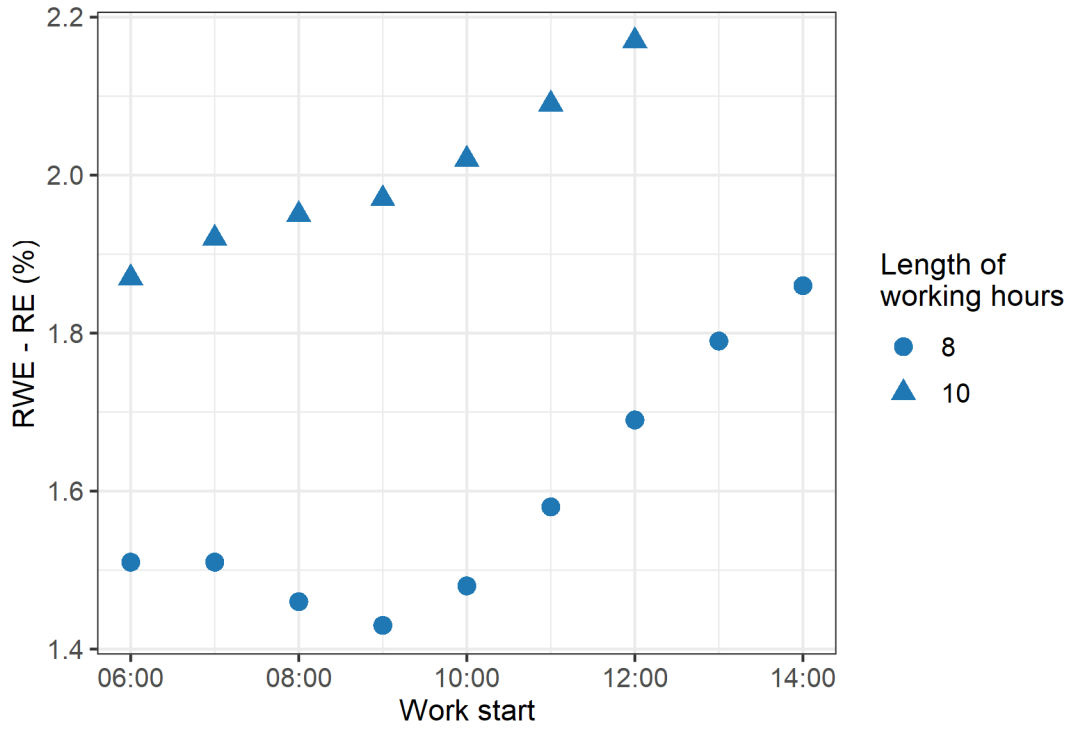

Figure 2.6 Relative increase (%) in population exposure to NO_2 in the UK according to assigned work start time and length of working hours per day (Monday to Friday). The earliest start time is 06:00 and the latest finish time is 22:00.

The relationship between assigned working hours and the magnitude of the change in population exposure estimate is directly related to the weekday diurnal profile of modelled pollutant concentrations. An example of such profiles from a grid cell that contains the urban background monitoring station London North Kensington for each pollutant is shown in Figures 2.7-2.9. The profiles, which only include weekday data, show that the $RWE_{9\text{-}17}$ scenario largely excludes both the morning and evening peaks of NO_2 and $PM_{2.5}$ concentrations whereas the $RWE_{8\text{-}18}$ scenario captures at least part of those peaks, particularly of the morning one. Similarly for O_3, $RWE_{8\text{-}18}$ contains more of the lower values observed in the morning and evening compared with $RWE_{9\text{-}17}$. Concurrent observed concentrations at the monitoring station are also plotted in Figures 2.7-2.9 for a reference of the temporal model agreement with observations relevant for this study (hour of the day). The figures suggest the model simulates the daily profile in urban background setting well for NO_2 and O_3 but less well for $PM_{2.5}$. A comprehensive evaluation of the EMEP4UK

model (v4.3) with monitoring data across the UK and site classification was conducted in Lin et al. (2017).

The modelled mean NO_2 concentration on weekdays for the time period between 09:00 and 17:00 at London North Kensington is 5.9 µg m^{-3} less than the modelled mean on weekdays for the full 24-hour period. For the 08:00-18:00 period the mean is 1.3 µg m^{-3} less than the modelled 24-hour mean. This means that the temporal variability of NO_2 concentration partially counteracts the effect of the spatial variability in the overall effect on population exposure. In other words, if temporal variability of NO_2 was ignored in this assessment the difference between RWE and RE at the population level would be larger.

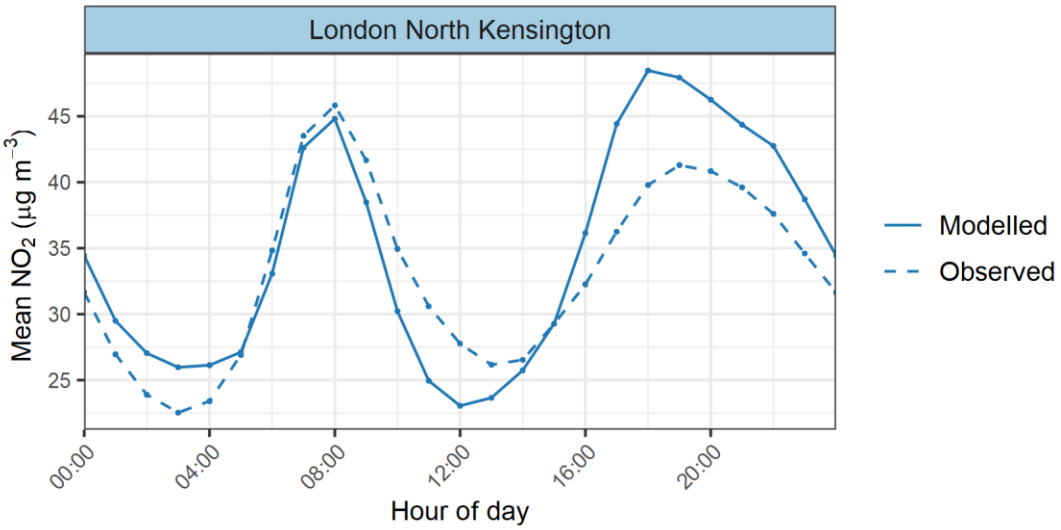

Figure 2.7 Annual mean diurnal profile of modelled and observed NO_2 on weekdays at London North Kensington urban background monitoring station.

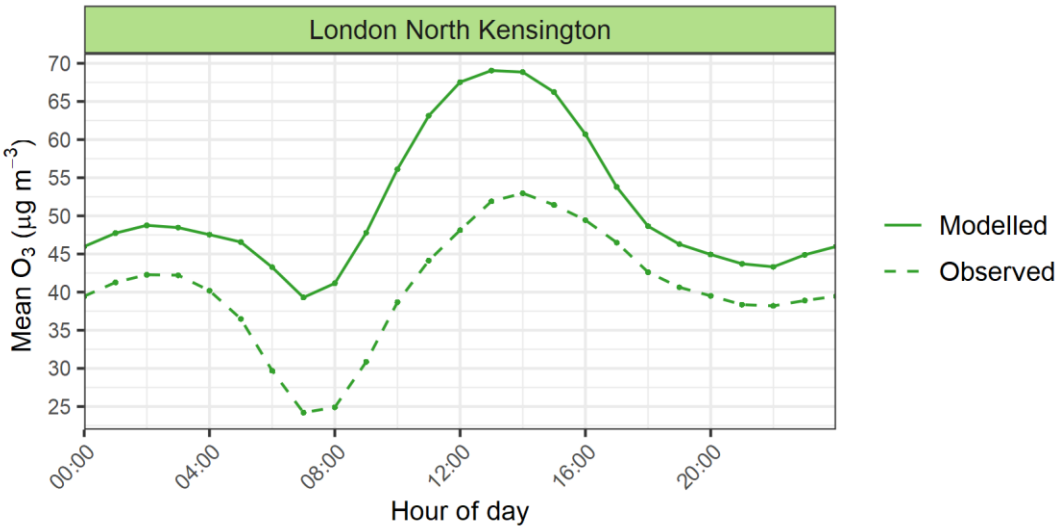

Figure 2.8 Annual mean diurnal profile of modelled and observed O_3 on weekdays at London North Kensington urban background monitoring station.

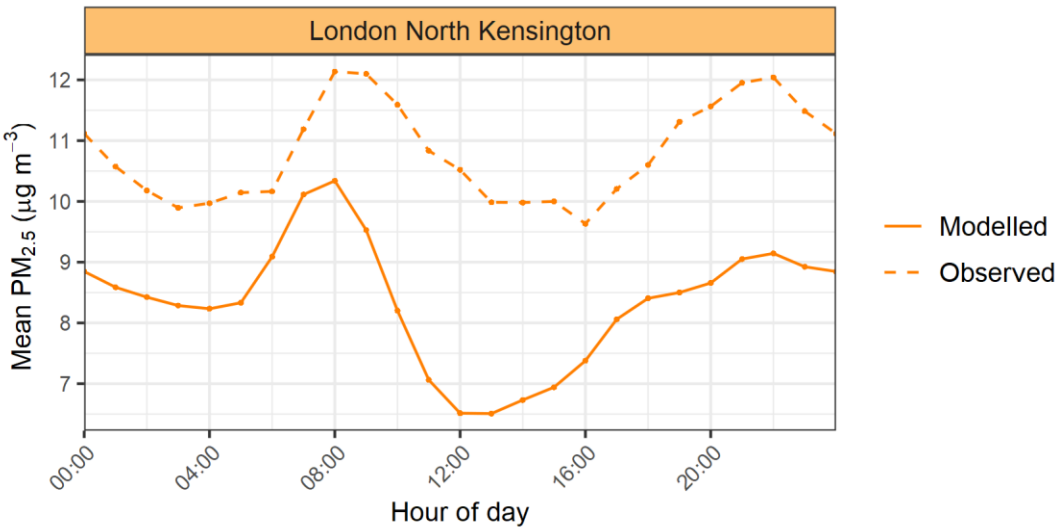

Figure 2.9 Annual mean diurnal profile of modelled and observed $PM_{2.5}$ on weekdays at London North Kensington urban background monitoring station.

2.3.3 Case studies of modelled individual-level exposure differences

The previous section indicates a comparatively small population-level difference in exposures to NO_2, O_3 and $PM_{2.5}$ between solely using residential

locations, or accounting for workplace locations also. However, the concentration maps in Figure 2.5 indicate the potential for the rather marked differences that accounting for workplace exposure can have on exposure of individuals. Therefore, the impact of workplace exposure on overall exposure was examined on individuals described in Section 2.2.5 whose residence and place of work are shown in Figure 2.4. The results are summarised and shown in Figure 2.10 and Table 2.3. For simplicity, only results for $RWE_{8\text{-}18}$ scenario, which has a larger population-level impact than $RWE_{9\text{-}17}$, are shown.

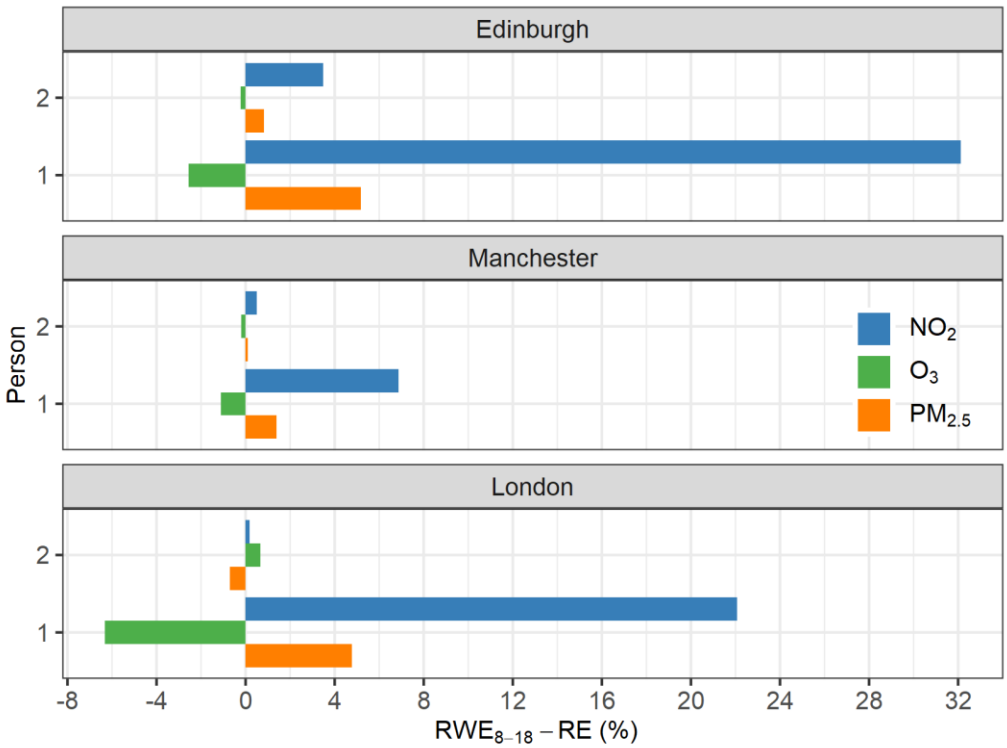

Figure 2.10 Relative $RWE_{8\text{-}18}$ – RE differences for simulated virtual individuals per pollutant and city. Adapted from Reis at al., 2018.

Table 2.3 The RE, $RWE_{8\text{-}18}$ and their absolute and relative difference for individuals living in an outer and inner urban area, respectively, and working in a city centre. Exposure units are µg m^{-3} unless stated otherwise.

Pollutant	City	Person	RE	$RWE_{8\text{-}18}$	$RWE_{8\text{-}18}$ - RE	$RWE_{8\text{-}18}$ – RE (%)
NO_2	Edinburgh	A1	8.95	11.82	2.87	32.1
		A2	17.52	18.13	0.61	3.5
	Manchester	B1	21.90	23.40	1.50	6.9
		B2	26.31	26.45	0.13	0.5
	London	C1	25.49	31.11	5.63	22.1
		C2	41.63	41.71	0.07	0.2
O_3	Edinburgh	A1	65.11	63.43	-1.68	-2.6
		A2	58.89	58.75	-0.14	-0.2
	Manchester	B1	56.65	56.03	-0.63	-1.1
		B2	55.46	55.35	-0.11	-0.2
	London	C1	57.89	54.23	-3.65	-6.3
		C2	46.00	46.30	0.30	0.7
$PM_{2.5}$	Edinburgh	A1	4.26	4.48	0.22	5.2
		A2	4.89	4.93	0.04	0.8
	Manchester	B1	7.13	7.23	0.10	1.4
		B2	7.33	7.34	0.01	0.1
	London	C1	7.64	8.01	0.37	4.8
		C2	8.80	8.74	-0.06	-0.7

The results show that, for individuals commuting for work to city centres from suburban areas, accounting for exposure at the place of work can substantially change their overall exposure, way above the values seen at the population level. Similarly to the population-level assessment, the largest differences in exposure are seen for NO_2. In the case of person A1 and C1 their change in exposure is an order of magnitude larger than the national population average change. Person B1 in Manchester experiences smaller changes in personal exposure than Persons A1 and C1. A closer inspection of Table 2.3 and Figure 2.4 reveal that the differences between residential exposures of Person B1 and Person B2 are much smaller compared with the equivalent differences seen in the pairs of individuals in Edinburgh and London. This is likely the result of Person B1 living in close proximity and generally downwind of the M60

motorway underlining the fact that distance between home and place of work is just one of many factors affecting the observed change in estimated personal exposure. An interesting observation emerging from this case study is that accounting for workplace exposure seems to reduce the exposure inequality seen in residential exposure between each pair of the virtual individuals.

2.4 Discussion

In this study the impact of workday population mobility on estimates of population exposure to NO_2, O_3 and $PM_{2.5}$ on a national scale was investigated using modelled air pollution concentrations and publicly available population data collected in the 2011 UK Census. The study encompassed virtually the whole population of the UK (approximately 63 million people), and, separately of Scotland – a nation within the UK (approximately 5 million people) and as such addressed the issue of study subjects' representativeness of the population encountered in many smaller scale studies. Accounting for exposure at the place of work resulted in only small increases in estimated NO_2 exposure and almost negligible changes in estimated exposure to O_3 and $PM_{2.5}$ in the UK. When considering Scotland separately, in absolute terms the changes in estimated exposure were comparable to those in the whole of the UK except for O_3. However, relative changes were larger in Scotland due to lower population-weighted mean concentrations. Therefore at the population level there seems to be no substantial benefit in treating Scotland separately.

Few exposure studies have considered population mobility in exposure assessment on a national scale. Those that did also reported a modest change in population exposure to air pollution relative to residential exposure albeit only slightly larger than estimated here. Beckx et al. (2009) estimated a 4% increase in population exposure to NO_2 in the Netherlands using modelled pollution concentrations (3 km horizontal resolution) and a synthetic population. Their estimated increase in population exposure to NO_2 is twice as much as calculated here. However, aside from residential and workplace exposures, they also considered exposures during travelling and other

activities in their assessment and reported that on average the highest exposure occurred during travelling. In Belgium, Dewulf et al. (2016) utilised mobile phone data to account for population mobility in their NO_2 exposure study. They found a 4.3% and 0.4% increase in exposure to NO_2 in the mobile population compared with the static population on a weekday day and a weekend day, respectively. Provided those two days are representative of weekday and weekend exposures in Belgium, annualization of the increases results in overall 3.2% increase in NO_2 exposure for the population of Belgium. Through tracking of individuals' movements, Dewulf et al. (2016) accounted for exposure in all microenvironments including travelling which may explain the slightly larger estimate of exposure increase than was found in this study. Similarly to this study, Shafran-Nathan et al. (2017) considered the place of residence and place of work or study based on census data in their exposure assessment. They used a temporally static LUR model over an area of Israel where 88% of the country's population lived. They found that on average exposure to NO_x increased by 5-10 ppb when exposure at both home and work (school for children) microenvironments were included although the exposure of 70% of children and 57% of adults changed by less than 5 ppb.

Other studies that have considered population mobility in population exposure assessment on regional or city scales also reported similar changes in population exposures to the pollutants investigated here. Results in Ragettli et al. (2015) suggested a 2.0% increase in population exposure to NO_2 when exposure at the place of work or study was accounted for in the assessment. In Boston, Nyhan et al. (2019) estimated a 0.23% increase in population exposure to $PM_{2.5}$ which is comparable to the increase estimated here. A 1.8% decrease in 1-hour daily maximum exposure of a 'mobile' population to O_3 in the summer months observed in Flanders and Brussels (Dhondt *et al.*, 2012) is substantially larger than the results for O_3 in this study, however given the different metric and averaging period their results are not directly comparable. One exception to the results reported above is a London-based exposure study by Smith et al. (2016). The authors accounted for infiltration of outdoor

pollution indoors in their assessment and as a result reported substantial decreases in mean exposure to $PM_{2.5}$ and NO_2 for their mobile population compared to the static (based on ambient concentrations at home) one.

From Figures 2.3 and 2.5 it is clear that the population increase in city and town centres due to workplace locations creates hotspots of NO_2 exposure and to a lesser extent $PM_{2.5}$ exposure and those are more intense than if only residential exposure is considered. This is in agreement with the findings of Nyhan et al. (2016) who compared population-weighted exposure to $PM_{2.5}$ in New York City. They reported that population-weighted exposure for the Active scenario was statistically significantly different to the Home scenario for most NYC districts and areas of Active Population Exposure were more centralised than Home Population Exposure areas. It follows then that even a small improvement in air quality in areas of high-density workday population would decrease the exposure of many more people than would be achieved by focussing on residential density areas. In general, interventions with a focus on achieving compliance with air quality limit values at a small number of existing air quality monitoring sites cannot be expected to automatically achieve the most effective reductions in population exposures and hence a substantial improvement of public health. A nuanced approach to air pollution mitigation is needed as vulnerable populations (e.g. children and the elderly) that would most benefit from decreased exposure are likely to be less mobile than the less vulnerable. In their case, they would be better represented by the residential spatial distribution. Furthermore, intervention policies should consider air pollution as a mixture. Changes in exposure to O_3 are in the opposite direction to NO_2 and $PM_{2.5}$ because of the tendency for O_3 to be higher in rural areas and lower in urban areas. This study has highlighted the importance of a holistic approach to consideration of the impacts on population mobility on exposure to air pollution.

The differences in estimated population-level exposure, as a result of including the workplace microenvironment in the assessment observed here, and in the studies discussed above, mask much larger potential differences in exposure

on a personal level reported, for example, in de Nazelle et al. (2013). The range and distribution of those differences could not be investigated in this study due to the nature of the population datasets used. An indicative assessment carried out on pairs of individuals in three UK cities situated in the south, middle and north of the country suggested the potential for a difference in personal exposure of an order of magnitude larger than the population average. Given that person '1' in Section 2.3.3 represents a large swathe of workers commuting between their home in a residential suburban area and their workplace in the city centre (as indicated in Figure 2.3) it is perhaps surprising that at the population level the effect of workplace exposure on overall population exposure is so small. There are a number of factors that affected the results, however. Firstly, the 'Workday Population' excludes children below 16 years old and people over the age of 74 who together represent ~ 26.5% of the UK population (ONS, 2014b). Excluding the latter group does not affect this analysis in a meaningful way as the vast majority of those are retired. However, 14% of the total population are school-age children (ONS, 2014b). The distance between home and school is likely to be on average shorter than the distance between home and place of work (Shafran-Nathan *et al.*, 2017) and hence it is likely that, including children, mobility would have had a small effect. Nonetheless, it would have been larger than zero. Of the remaining approximately 46 million UK residents who were between 16 and 74 years old just under 33 million were in employment or students. That represents just ~ 52% of the UK population. Of those another ~ 18% workers and students stated that they worked or studied mainly at home or had no fixed place of work (in which case their workday address was the same as their residential one) (ONS, 2014b). Altogether this left less than 50% of the population commuting to the place of work. Additionally, some of those commuting may have their places of work or study away from their home but within the same EMEP4UK grid cell in which case no difference in exposure would have been estimated in this modelling approach.

2.4.1 Limitations

The study has several limitations which in turn point to a direction of further research. Firstly, due to the nature of the population datasets, exposure during commuting between home and workplace could not be accounted for. Secondly, assumptions had to be made regarding the period of time spent at the place of work. The selected fixed working hours were based on the usual working pattern of an office-based worker in full-time employment. As shown in Figure 2.6, the number of hours spent in workplace has an impact on the estimated exposure. In the UK, data show that ~58% of individuals aged 16-74 and in employment worked 31-48 hours per week in 2011. Further ~13% worked 49 hours or more (ONS, 2014b). This suggests that for at least ~29% of workers the time spent at work was overestimated in this study, even after allowing for additional time spent at the place of work due to midday breaks, whilst less than 13% of workers work longer than the prescribed number of hours in the $RWE_{8\text{-}18}$ scenario. Furthermore, no consideration in this work was given for those working outside the standard office hours, e.g. evenings, weekends or variable shifts. Thirdly, the lack of links between home and workplace on an individual level in the datasets also prevented a more detailed exposure assessment beyond reporting the population-weighted exposure means. If such information were available the variability in personal exposure could be investigated as demonstrated by the examples of virtual individuals in Section 2.3.3. Finally, both spatially and temporally accurate modelled air pollution concentrations are essential to decrease exposure misclassification. The spatial resolution of the model used here is high for an ACTM model, yet it is still too coarse to capture high spatial gradients of NO_2 and even O_3 (Lin *et al.*, 2016) observed near busy roads. This may potentially mask even larger impacts of workplace exposure on overall population exposure.

2.5 Conclusion

This study demonstrates the utility of using publicly available UK Census products comprising information on workday population densities, in combination with high spatio-temporal resolution atmospheric model output, to

derive more realistic estimates of population exposure to air pollution on a national scale. Taking workday location into account had the largest impact on population exposure to NO_2, with an estimated 0.3 µg m^{-3} (equivalent to 2%) increase in population-weighted annual exposure to NO_2 across the whole population of the UK. Population-weighted exposure to O_3 and $PM_{2.5}$ decreased and increased by 0.3%, respectively, when including workday population distribution, reflecting the different atmospheric processes contributing to the spatio-temporal distributions of these three pollutants. Largely similar results were obtained for Scotland treated as a separate study area despite differences in population density and geography between Scotland and the UK as a whole. These findings are in line with other studies, which identified that accounting for a combination of temporal and microenvironmental adjustments led to the most pronounced contrasts in population-level and individual exposures.

Chapter 3 The effect of workplace mobility on air pollution exposure inequality – a case study in the Central Belt of Scotland

For this chapter, EMEP4UK modelling was conducted by Massimo Vieno. I devised, with Mat Heal and Stefan Reis's contribution, the methodology of the research. I extracted the relevant pollution data, summarised the population and pollution data and calculated and analysed the population exposures. Population data extraction and linking to the provided pollution data conducted by LSCS staff.

3.1 Introduction

Numerous exposure studies have shown that spatial variability of air pollution leads to differential exposure at both individual and community levels resulting in environmental inequality among various population strata (e.g. Bell and Ebisu, 2012; Hajat et al., 2015; Mitchell and Dorling, 2003; Moreno-Jiménez et al., 2016). Unlike in the USA, where research into environmental inequality began and predominantly focused on links with ethnicity (Bolte *et al.*, 2011), in Europe the emphasis has been largely placed on the relationship between air quality and a level of deprivation. The relationship between socio-economic status (SES) and air pollution exposure is not simple. It has been shown to vary between investigated areas (Padilla *et al.*, 2014; Temam *et al.*, 2017), study types (individual vs ecological) (Temam *et al.*, 2017), metrics of SES (Samoli *et al.*, 2019) and pollutants (Milojevic *et al.*, 2017). However, at the small area level the most deprived neighbourhoods are often exposed to the highest concentrations of nitrogen oxides and PM (Fairburn *et al.*, 2019). Few studies in Europe have explored relationships with other demographic characteristics such as age and ethnicity. Most of those investigating ethnicity and air pollution exposure suggest higher exposures of ethnic minorities or immigrants; however results vary by ethnic groups (Padilla *et al.*, 2014; Fecht *et al.*, 2015; Moreno-Jiménez *et al.*, 2016; Tonne *et al.*, 2018). Studies of

exposures of the very young and the very old show mixed results depending on the study area (Mitchell and Dorling, 2003; Cesaroni *et al.*, 2010; Fecht *et al.*, 2015; Moreno-Jiménez *et al.*, 2016).

Higher levels of exposure to air pollution in socially disadvantaged and vulnerable communities contravene the concept of environmental justice which aims for environmental burdens and benefits to be shared reasonably equally within the population regardless of individuals' social characteristics. Worse still, high exposures to air pollution by vulnerable and low social class communities may exacerbate some adverse health outcomes which already disproportionally occur in such communities (Bolte *et al.*, 2011; Brunt *et al.*, 2017).

Nearly all studies that have investigated differential exposure to air pollution relied on the assumption that residential exposure is a satisfactory proxy of personal exposure across the communities. Whilst this may be true for some subgroups such as the very young and very old, those of working age may spend a substantial proportion of their time away from home. The findings of the study described in the previous chapter and other similar studies (e.g. Ragettli et al., 2015) show that, at the population scale, accounting for a place of work or study in quantifying overall exposure results only in relatively small changes in exposure to NO_2, O_3 and $PM_{2.5}$ when compared to residential exposure only. However, as the example of the virtual individuals in Section 2.2.5 demonstrates, the effect on some individuals can be substantially larger than the population average, particularly for those whose residence and place of work are situated in contrasting built-up environments (suburban or rural vs inner urban). Such differences may affect the inequalities observed through residential exposure only.

The aim of this study is to contribute to the growing literature on air pollution exposure inequality by investigating how including the place of work or study in exposure assessment affects exposure inequalities observed from only residential exposure. Firstly, the impact of exposure to ambient NO_2, O_3 and

$PM_{2.5}$ at the place of work or study on the study population is explored. Secondly, the study population is stratified by age, ethnicity and SES and the impact of the more comprehensive residential + workplace exposure estimate on exposure inequality is examined. The Central Belt region of Scotland is selected as the study area. Earlier studies have already shown that environmental inequality related to SES in Scotland exists (Fairburn *et al.*, 2005; Morrison *et al.*, 2014); however other social characteristics have not been examined. Data from Census 2011 suggest that Scotland is not ethnically very diverse, but diversity in the country has been rapidly increasing. For example, the number of people who identified as African ethnicity in the Census grew by a factor of 5, and those who identified as Chinese or Indian more than doubled between 2001 and 2011 (Smith and Simpson, 2015). Potential clustering of ethnic communities on a local scale may result in developing exposure inequalities.

In addition to the regional scale analysis, the two largest Scottish cities, Glasgow and Edinburgh, which lie within the Central Belt are investigated separately for an urban scale assessment, as urban areas have been shown to mostly be responsible for the observed air pollution exposure inequalities on larger scales (Fecht *et al.*, 2015). Furthermore, the two cities have some contrasting demographic characteristics. The Glasgow City council area has the highest level of deprivation in the country. Data from Census 2011 show that 63.6% and 2.2% of its population were in the most and least deprived quintiles of the Carstairs deprivation index (Carstairs and Morris, 1989), respectively, compared with 23.5% and 24.0%, respectively, for the City of Edinburgh council area population (Brown *et al.*, 2014). Edinburgh is also the most ethnically diverse urban area in Scotland with all its wards exceeding the national average in diversity in 2011. In comparison, 68% of Glasgow wards exceeded the national average in 2011 (Smith and Simpson, 2015).

3.2 Methods

3.2.1 Study area and population

The Central Belt of Scotland region chosen as the study area refers to the central region of Scotland encompassing the two largest cities of Glasgow and Edinburgh and the surrounding commuter belt. There are however no strictly defined boundaries of the region. In this study, the Central Belt area, which is shown in Figure 3.1, extends from Inverclyde in the west to western parts of East Lothian in the east. To the north it includes the city of Stirling, Clackmannanshire and south-western parts of Fife, and to the south it extends to the southernmost tip of East Renfrewshire. The study area covers ~4,000 km^2 and had approximately 2.9 million residents in 2011 which represented ~56% of the Scottish population. The extents of Glasgow and Edinburgh urban areas were taken from the Settlements 2012 data (https://www.nrscotland.gov.uk/statistics-and-data/geography/our-products/settlements-and-localities-dataset) which group together adjacent urban areas. For example, Glasgow is joined with neighbouring smaller cities and towns of Paisley, Clydebank and others to form the 'Greater Glasgow' settlement.

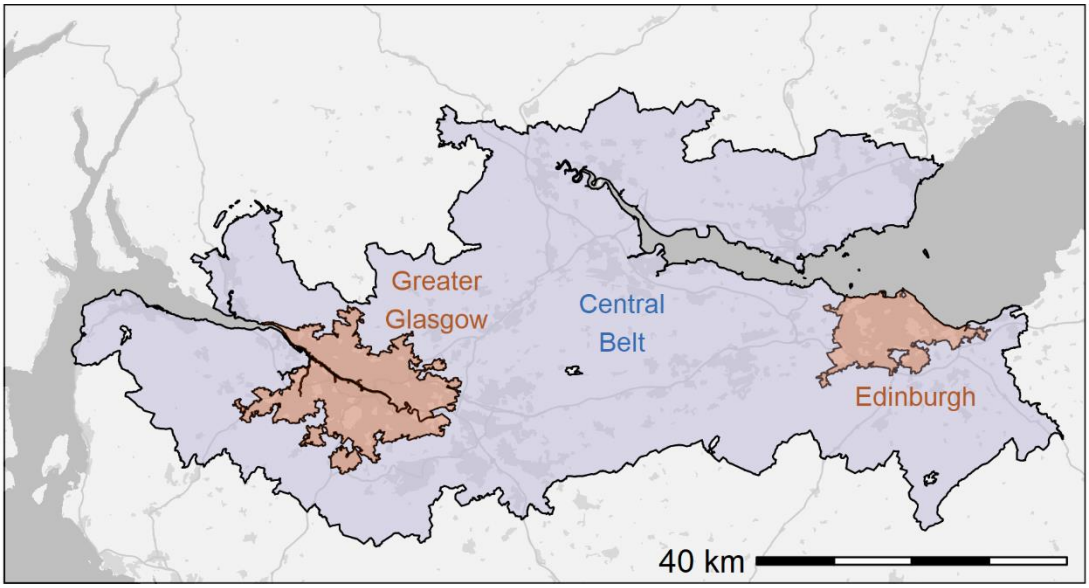

Figure 3.1 The extents of the Central Belt region, and Greater Glasgow and Edinburgh urban areas. Contains OS Data © Crown copyright and database right (2021).

The population data used were anonymised personal data based on responses in the UK Census in March 2011 by the participants of the Scottish Longitudinal Study (SLS) (Boyle *et al.*, 2009) whose place of residence and place of work or study were situated within the study area, or whose place of residence was within the area but they were either economically inactive or not in education. Workers or students resident in the area but with no fixed place of work or study were excluded, with the exception of drivers and other workers resident in the study area with no fixed place of work but reporting to a depot within the area.

The locations of SLS participants' places of residence and work or study were available at the unit postcode level (but see Section 0 below) which is on average shared by 15 and never more than 100 individual addresses. To determine which postcodes lay within the study area the unit postcode coordinates of all postcodes in use at the time of the census were downloaded from the UK Data Service (https://borders.ukdataservice.ac.uk/pds.html). The coordinates of each postcode unit were the coordinates of the postal delivery address nearest to the mean position of all delivery points in the postcode unit. As a result, any SLS participants whose address lay within the study area but whose unit postcode coordinates lay outside the area would not be included in the analysis. Conversely, those SLS participants whose address lay just outside the study area but whose unit postcode coordinates lay within the area were included.

The SLS has linked census data from 1991 onwards, also linked to other vital events, migration and school census data for an approximately 5.3% representative sample of the Scottish population (Boyle *et al.*, 2009). The extracted personal data included SLS participants' age, ethnicity and data related to economic activity. Additionally, the Carstairs deprivation score (Carstairs and Morris, 1989) decile was obtained to represent each member's socio-economic status. Unlike all the other personal data, which were extracted at an individual level, the Carstairs Index decile was an averaged value of all households within an Output Area – a Census geography

containing at least 20 households and on average 114 residents (Brown *et al.*, 2014). The Carstairs Index is an unweighted score calculated from four variables derived from the Census – no car ownership, male unemployment, overcrowding and low social class.

3.2.2 Air pollution data

Hourly air pollution data were taken from EMEP4UK model version rv4.17. The model is described in greater detail in the previous chapter. This version of the model has a horizontal resolution ~0.124º × ~0.124º which is equivalent to ~0.8 km × ~1.4 km in the study area. The temporal resolution is 1 hour. The model is driven by meteorology provided by WRF model version 3.9.1 and the modelled year is 2015.

3.2.3 Exposure analysis

For the exposure analysis each postcode within the study area was assigned concentrations from its nearest EMEP4UK grid point. No area averaging was applied. As in the case of the national scale analysis in the previous chapter, the effect of exposure to ambient air at workplace in addition to exposure at the place of residence was compared with exposure at the place of residence only. In addition to the exposure scenarios used previously (RE, $RWE_{9\text{-}5}$, $RWE_{8\text{-}6}$), an hours-worked based combined exposure scenario (RWE_{hw+}) was also calculated. The scenario is a weighted mean of residential and workplace concentrations weighted by the number of typical hours per week worked. For full-time students the number of hours at the place of study was set as 30 hours. For part-time students it was assumed that their answer to the place of work/study and typical hours per week questions in the Census related to their place of work rather than place of study and the number of hours worked was used. It was also assumed that all of the typical hours per week worked were spent at the workplace address provided. For every seven hours worked an additional hour was added to the total hours worked to allow for breaks. For example, a person whose typical hours per week worked were between 35

and 41 inclusive was assigned an additional five hours at the workplace for the exposure analysis.

The exposure scenarios were used to estimate exposure of the total population as well as population sub-groups based on age, ethnic group and Carstairs index decile. The age variable was grouped into 5-year wide bins except for the youngest (0 to 5 years inclusive) and oldest (76 years and over) age groups. The ethnicity variable was grouped based on the main sections in the Census form to White, Asian, African, Caribbean or Black, Arab, Mixed, and other ethnic groups. Descriptive statistics of exposures for each group, air pollution model and exposure scenario were calculated.

The Python language Iris library and the R language raster, sf, and tidyverse libraries were used for the data processing and analysis. Specifically, the Iris library was used to extract EMEP4UK pollutant concentration data in the study area and to calculate the mean concentrations (and the length of the period for time-weighted overall exposure mean) for each exposure scenario investigated (e.g. between 08:00 and 18:00 on weekdays) using methods described in Section 2.2.4. The raster library was then used to read these datasets in R, and the sf library was subsequently used to convert the raster data into a spatial dataframe of polygons and to spatially overlay postcode points and pollutant polygons in order to assign pollutant concentrations for every exposure scenario and every postcode in the study area. Once the pollutant concentrations were linked with the population data (see below), functions within the tidyverse suite of libraries were used to calculate, summarise and plot the exposures presented in Section 3.3.

3.2.4 Data access and dissemination restrictions

Due to the high sensitivity of the population data used in this study several restrictions were placed on access and dissemination of the data in order to prevent disclosure. The requested population data were extracted and linked with the pollution data by staff at the SLS Development and Support Unit. There was never access to the SLS participants' home or workplace postcode

unit data by the researchers. This restriction also prevented the inclusion of exposure during commuting in the study which is discussed in 3.4.4.

Results of the analysis can only be reported if the result datum is shared by at least 10 SLS participants. As a consequence, no exposure extremes are reported and exposure distribution bins may have different widths in the figures of exposure distributions to ensure at least 10 SLS participants are in each bin. This, however, does not affect the calculated exposures.

3.3 Results

3.3.1 SLS sample summary

The number of SLS participants living in the Central Belt study area during the Census who fulfilled the inclusion criteria is 124,659. This SLS subsample is hereinafter referred to in the text as ‘the Central Belt sample’ or ‘Central Belt SLS participants’. Similarly, Greater Glasgow and Edinburgh SLS subsamples are referred to as the (Greater) Glasgow sample (SLS participants) and the Edinburgh sample (SLS participants), respectively. The Central Belt, Glasgow and Edinburgh sample demographic characteristics are presented in Table 3.1. Just over 54% of the Central Belt SLS participants are female and 95.4% are white. 45,283 of the Central Belt SLS participants over the age of 16 are economically inactive and 7,580 of those working or studying do so at their home address. This, together with most children under the age of 5 also staying at home only, results in only 51.7% of the Central Belt SLS participants working or studying in a different place from their home address. The median (mean) distance between the place of residence and place of work/study, derived from the postcode centroids and calculated as the length of the straight line between those, is 4 (7) km with the Q1 and Q3 distances equating to 1 km and 9 km, respectively. The Carstairs Index deciles are calculated from the whole Scottish population; however, as the Central Belt sample is a subsample, the deciles are not represented equally in the sample. The decile with the largest number of the Central Belt SLS participants is the most

deprived decile 10 (14,132 or 11.3%), whilst the least populated decile 4 has 11,427 (9.2%) SLS participants.

The Glasgow sample contains around twice as many SLS participants as the Edinburgh sample and together they represent 45.5% of the Central Belt sample. Similarly to the Central Belt sample, only around a half (46.4% and 53.2%) of the Glasgow and Edinburgh SLS participants, respectively, commute to their place of work/study. It is clear from Table 3.1 that ethnic minorities within the Central Belt mostly live in the two urban areas. Whilst the age and ethnicity characteristics are comparable between the Glasgow and Edinburgh samples, substantial differences are found in the Economic Activity and, consequently, the Carstairs index variables. In Glasgow 33.7% of the SLS participants are in employment whereas in Edinburgh 39.6% are employed. Conversely, the unemployed together with the economically inactive represent 18.8% of the Glasgow sample and 12.6% of the Edinburgh sample. In Glasgow, the most deprived decile contains 20.7% of the sample which is considerably above the Central Belt's value of 11.3%. On the other hand, in Edinburgh the most deprived decile contains only 7.5% of the SLS participants and is the least populated decile. Furthermore, the least deprived decile contains 13.6% of the sample and is the most populated one.

Table 3.1 Demographic characteristics of the SLS participants in the Central Belt, Glasgow and Edinburgh study areas. Source: Scottish Longitudinal Study.

		Central Belt		Greater Glasgow		Edinburgh	
		SLS participants	%	SLS participants	%	SLS participants	%
All SLS participants	-	124659	100.0	37884	100.0	18850	100.0
Sex	Male	56944	45.7	16999	44.9	8706	46.2
	Female	67715	54.3	20885	55.1	10144	53.8
Age Group	0-5	9115	7.3	2833	7.5	1291	6.8
	6-10	5922	4.8	1731	4.6	798	4.2
	11-15	6825	5.5	1902	5.0	908	4.8
	16-20	7974	6.4	2546	6.7	1281	6.8
	21-25	7977	6.4	2755	7.3	1616	8.6
	26-30	8098	6.5	2570	6.8	1569	8.3
	31-35	7511	6.0	2124	5.6	1317	7.0
	36-40	8059	6.5	2279	6.0	1208	6.4
	41-45	8857	7.1	2507	6.6	1215	6.4
	46-50	9252	7.4	2737	7.2	1181	6.3
	51-55	8345	6.7	2577	6.8	1136	6.0
	56-60	7297	5.9	2124	5.6	961	5.1
	61-65	7699	6.2	2203	5.8	1114	5.9
	66-70	6437	5.2	1953	5.2	841	4.5
	71-75	5614	4.5	1778	4.7	813	4.3
	76+	9677	7.8	3265	8.6	1601	8.5
Ethnic Group	White	118979	95.4	35013	92.4	17476	92.7
	Asian	4080	3.3	2162	5.7	929	4.9
	African	609	0.5	334	0.9	144	0.8

		Central Belt		Greater Glasgow		Edinburgh	
		SLS participants	%	SLS participants	%	SLS participants	%
Ethnic Group	Arab	256	0.2	124	0.3	83	0.4
	Caribbean or Black	107	0.1	42	0.1	27	0.1
	Mixed	492	0.4	162	0.4	146	0.8
	Other	136	0.1	47	0.1	45	0.2
Economic Activity	Employed FT	36928	29.6	9500	25.1	5720	30.3
	Employed PT	11828	9.5	3247	8.6	1758	9.3
	Student Employed PT	2605	2.1	929	2.5	586	3.1
	Student Employed FT	350	0.3	120	0.3	78	0.4
	Student	5803	4.7	2098	5.5	1362	7.2
	Unemployed	5828	4.7	2133	5.6	726	3.9
	Inactive	12846	10.3	5016	13.2	1636	8.7
	Retired	26609	21.3	8375	22.1	3987	21.2
	Children under 16 y	21862	17.5	6466	17.1	2997	15.9
Carstairs Index Decile	1 (least deprived)	13291	10.7	3058	448.1	2569	13.6
	2	12117	9.7	2745	7.2	1686	8.9
	3	11661	9.4	2785	7.4	2051	10.9
	4	11427	9.2	3018	8.0	1782	9.5
	5	11579	9.3	3029	8.0	2090	11.1
	6	11713	9.4	3063	8.1	1838	9.8
	7	12664	10.2	3440	9.1	1849	9.8
	8	12589	10.1	3916	10.3	1820	9.7
	9	13486	10.8	4991	13.2	1748	9.3
	10 (most deprived)	14132	11.3	7839	20.7	1417	7.5
Place of Work/Study	At Home	7580	6.1	2471	6.5	1410	7.5

	Central Belt		Greater Glasgow		Edinburgh	
	SLS participants	%	SLS participants	%	SLS participants	%
Elsewhere	64452	51.7	17562	46.4	10032	53.2
Not Applicable	52627	42.2	17851	47.1	7408	39.3

3.3.2 Modelled air pollution concentrations

Table 3.2 presents the summary of the modelled annual mean concentrations of the three pollutants by EMEP4UK in the Central Belt study area and the two urban areas within it for those grid cells where postcode point coordinates are located. The spatial distributions of the annual mean modelled concentrations are shown in Figures 3.2-3.4. In the Central Belt annual mean NO_2 concentrations range from 2.0 µg m^{-3} in the rural southeast of the study area to 23.9 µg m^{-3} in central Glasgow. Glasgow, as a larger city than Edinburgh with two motorways running through its urban area, has higher mean and wider range of concentrations of NO_2 and $PM_{2.5}$ than Edinburgh but lower mean concentrations of O_3. However, Edinburgh still has the smallest range of O_3 concentrations. The NO_2 mean concentration is 11.2 µg m^{-3} in the Central Belt, 13.8 µg m^{-3} in Glasgow and 12.9 µg m^{-3} in Edinburgh. The mean O_3 concentration across the Central Belt is 58.3 µg m^{-3}, in Edinburgh it is 58.6 µg m^{-3} and in Glasgow it is 55.3 µg m^{-3}.

Table 3.2 Summary statistics of modelled annual mean concentrations (µg m^{-3}) of NO_2, O_3 and $PM_{2.5}$ in the Central Belt, Glasgow and Edinburgh study areas. Only those grid cells which contain postcode point coordinates are included.

Pollutant	Area	Mean	SD	Min	Q1	Median	Q3	Max
NO_2	Central Belt	11.2	4.3	2.0	7.7	10.9	14.1	23.9
	Glasgow	13.8	4.3	4.9	10.6	13.7	16.3	23.9
	Edinburgh	12.9	3.1	4.1	10.9	13.5	15.0	18.7
O_3	Central Belt	58.3	4.2	46.6	55.5	58.5	61.4	69.3
	Glasgow	55.3	4.1	46.6	52.8	55.2	58.4	64.7
	Edinburgh	58.6	2.9	52.8	56.5	58.1	60.2	65.9
$PM_{2.5}$	Central Belt	7.6	0.7	5.7	7.2	7.7	8.1	15.4
	Glasgow	8.0	0.4	6.6	7.8	8.1	8.4	10.1
	Edinburgh	7.7	0.5	6.2	7.4	7.8	8.0	8.6

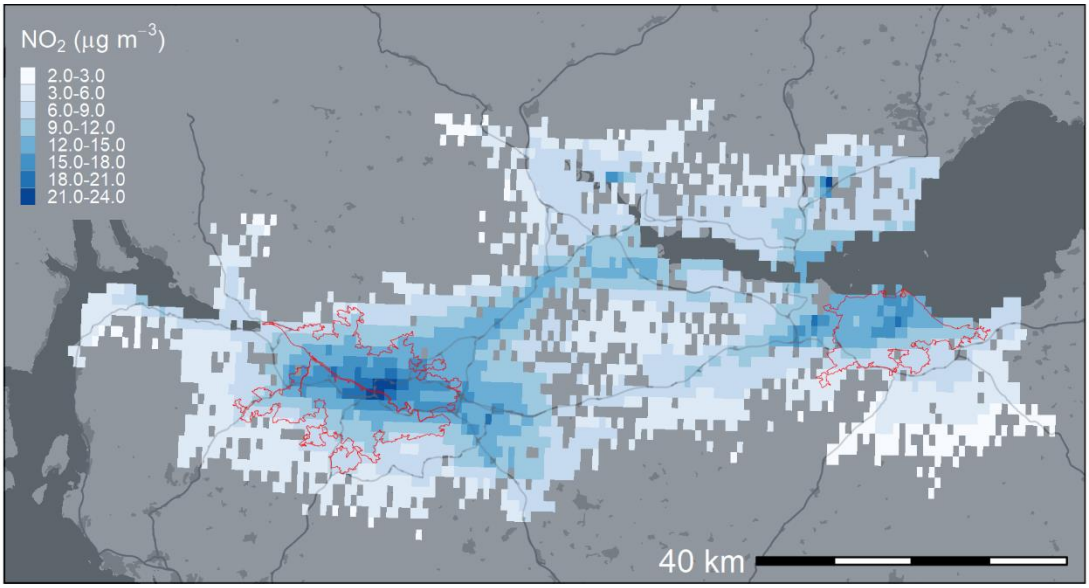

Figure 3.2 Modelled annual mean NO_2 concentrations in the study area. Only the grid cells containing postcode locations are shown. Red lines represent the boundaries of the Glasgow and Edinburgh urban areas. Contains OS Data © Crown copyright and database right (2021).

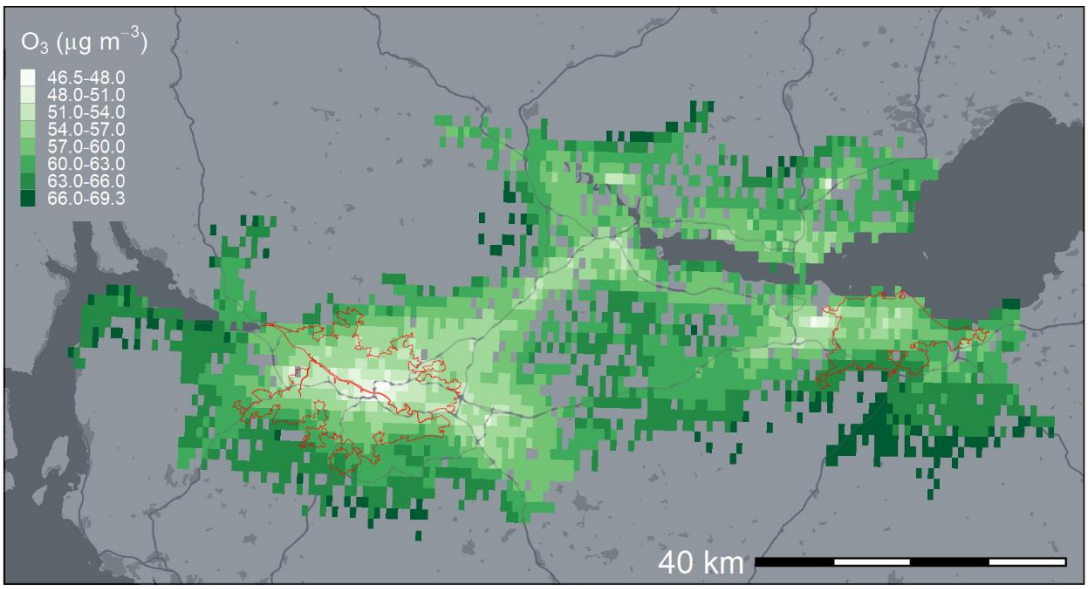

Figure 3.3 Modelled annual mean O_3 concentrations in the study area. Only the grid cells containing postcode locations are shown. Red lines represent the boundaries of the Glasgow and Edinburgh urban areas. Contains OS Data © Crown copyright and database right (2021).

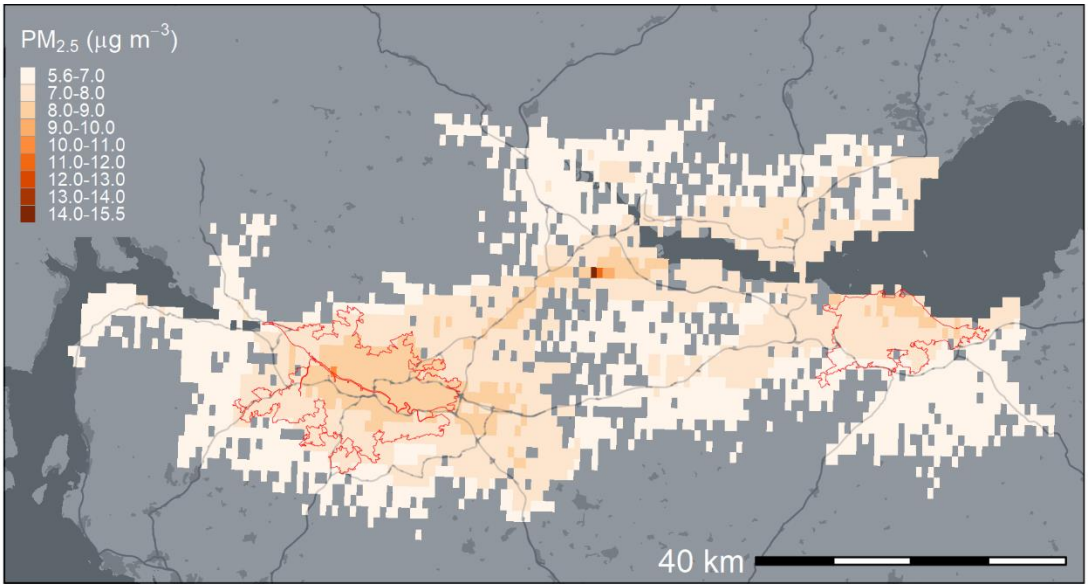

Figure 3.4 Modelled annual mean $PM_{2.5}$ concentrations in the study area. Only the grid cells containing postcode locations are shown. Red lines represent the boundaries of the Glasgow and Edinburgh urban areas. Contains OS Data © Crown copyright and database right (2021).

For $PM_{2.5}$, the highest mean modelled concentrations occur in the central region of the Central Belt at the vicinity and downwind in the predominant south-westerly and westerly winds of a manufacturing facility. Except for that area, the mean modelled $PM_{2.5}$ concentrations in the rest of the Central Belt are much more homogeneous than those of the other two pollutants. Therefore, there is a much larger range of modelled $PM_{2.5}$ concentrations in the Central Belt than in the two urban areas. Despite that, the means of the mean modelled $PM_{2.5}$ concentrations of all three areas are comparable ranging from 7.6 µg m^{-3} to 8.0 µg m^{-3}.

3.3.3 Residential vs. combined residential-workplace population exposure

The descriptive statistics of the residential exposure (RE) and combined residential-workplace exposure (RWE) scenarios in all three study areas and for all three pollutants are presented in Table 3.3. Also presented in the table are the absolute and relative differences (means and medians) between each of the RWE scenarios compared with the baseline RE scenario. In general, the $RWE_{8\text{-}18}$ scenario has the highest impact on annual mean exposures. The

RWE_{hw+} scenario tends to show similar or in many cases the same values of mean exposures as the $RWE_{9\text{-}17}$ scenario despite using fundamentally different assumptions of working patterns. As expected from the pollution concentration data shown in Figures 3.2-3.4, the largest changes in the mean population exposures are observed for NO_2, and in the Greater Glasgow urban area. For example, in Glasgow the mean NO_2 exposure of the $RWE_{8\text{-}18}$ scenario is higher by 0.44 µg m^{-3} (3.2%) than that of the RE scenario. In the other study areas for the same pollutant and exposure scenario the mean population exposure increase is 0.33 µg m^{-3} (2.9%) in the Central Belt and 0.19 µg m^{-3} (1.5%) in Edinburgh. The change in mean exposure to O_3 is negative and an order of magnitude smaller in relative terms than the change in exposure to NO_2 for all RWE scenarios. The observed increases in mean $PM_{2.5}$ population exposure are less than 0.05 µg m^{-3} in the Central Belt and Greater Glasgow and negligible in Edinburgh.

Table 3.3 Descriptive statistics of population exposures for each pollutant, study area and exposure scenario. Also shown are the absolute and relative differences in the means and medians between each of the RWE scenarios and the RE scenario. Units are µg m^{-3}. Source: Scottish Longitudinal Study.

Pollutant	Area	Exposure Scenario	Mean	SD	Median	Q1	Q3	RWE* - RE (means)	RWE* - RE (means) %	RWE* - RE (medians)	RWE* - RE (medians) %
NO_2	Central Belt	RE	10.92	3.96	10.65	7.63	13.73	-	-	-	-
		RWE_{9-17}	11.16	3.86	10.93	8.01	13.93	0.24	2.2	0.28	2.6
		RWE_{8-18}	11.25	3.86	11.02	8.14	14.00	0.33	3.0	0.37	3.5
		RWE_{hw+}	11.17	3.85	10.97	8.06	13.92	0.25	2.3	0.32	3.0
	Glasgow	RE	13.39	3.95	13.56	10.45	15.67	-	-	-	-
		RWE_{9-17}	13.71	3.83	13.79	10.69	16.05	0.32	2.4	0.23	1.7
		RWE_{8-18}	13.83	3.83	14.03	10.79	16.31	0.44	3.3	0.47	3.5
		RWE_{hw+}	13.71	3.82	13.80	10.71	16.04	0.32	2.4	0.24	1.8
	Edinburgh	RE	12.71	3.02	13.41	10.62	14.99	-	-	-	-
		RWE_{9-17}	12.85	2.86	13.48	10.88	14.99	0.14	1.1	0.07	0.5
		RWE_{8-18}	12.90	2.83	13.49	11.02	15.02	0.19	1.5	0.08	0.6
		RWE_{hw+}	12.85	2.84	13.48	10.91	14.97	0.14	1.1	0.07	0.5
O_3	Central Belt	RE	58.50	3.95	58.58	55.66	61.48	-	-	-	-
		RWE_{9-17}	58.31	3.86	58.44	55.60	61.19	-0.19	-0.3	-0.14	-0.2
		RWE_{8-18}	58.24	3.85	58.39	55.56	61.08	-0.26	-0.4	-0.19	-0.3
		RWE_{hw+}	58.29	3.84	58.41	55.61	61.12	-0.21	-0.4	-0.17	-0.3
	Glasgow	RE	55.72	3.83	55.46	53.20	58.66	-	-	-	-
		RWE_{9-17}	55.47	3.71	55.15	52.95	58.36	-0.25	-0.4	-0.31	-0.6
		RWE_{8-18}	55.37	3.70	55.05	52.88	58.27	-0.35	-0.6	-0.41	-0.7
		RWE_{hw+}	55.44	3.68	55.10	52.94	58.30	-0.28	-0.5	-0.36	-0.6
	Edinburgh	RE	58.78	2.87	58.36	56.78	60.46	-	-	-	-
		RWE_{9-17}	58.66	2.72	58.16	56.8	60.19	-0.12	-0.2	-0.20	-0.3

Pollutant	Area	Exposure Scenario	Mean	SD	Median	Q1	Q3	RWE* - RE (means)	RWE* - RE (means) %	RWE* - RE (medians)	RWE* - RE (medians) %
		$RWE_{8\text{-}18}$	58.62	2.69	58.15	56.76	60.14	-0.16	-0.3	-0.21	-0.4
		RWE_{hw+}	58.65	2.68	58.16	56.84	60.15	-0.13	-0.2	-0.20	-0.3
$PM_{2.5}$	Central Belt	RE	7.63	0.66	7.66	7.17	8.08	-	-	-	-
		$RWE_{9\text{-}17}$	7.65	0.63	7.69	7.22	8.08	0.02	0.3	0.03	0.4
		$RWE_{8\text{-}18}$	7.66	0.63	7.69	7.23	8.09	0.03	0.4	0.03	0.4
		RWE_{hw+}	7.65	0.63	7.69	7.22	8.08	0.02	0.3	0.03	0.4
	Glasgow	RE	8.02	0.44	8.09	7.75	8.32	-	-	-	-
		$RWE_{9\text{-}17}$	8.04	0.42	8.11	7.78	8.33	0.02	0.2	0.02	0.2
		$RWE_{8\text{-}18}$	8.05	0.41	8.12	7.8	8.34	0.03	0.4	0.03	0.4
		RWE_{hw+}	8.05	0.42	8.11	7.78	8.32	0.03	0.4	0.02	0.2
	Edinburgh	RE	7.70	0.48	7.75	7.41	8.00	-	-	-	-
		$RWE_{9\text{-}17}$	7.70	0.44	7.75	7.43	7.98	0.00	0.0	0.00	0.0
		$RWE_{8\text{-}18}$	7.70	0.43	7.75	7.43	7.97	0.00	0.0	0.00	0.0
		RWE_{hw+}	7.70	0.44	7.74	7.43	7.98	0.00	0.0	-0.01	-0.1

The relatively modest changes in the mean population exposure due to the exposure at place of work/study compared to the baseline scenario can be explained by investigating the personal exposure of individual SLS participants and its changes. As an example, the left-hand panels of Figures 3.5-3.7 show the distributions of personal RE and $RWE_{8\text{-}18}$ and the means of those distributions for all study areas and pollutants, respectively. Whilst not every postcode in the study area may have any SLS participants living or working in them, the ranges of exposures shown in the panels clearly reflect the ranges of concentrations in each study area including the comparatively very high $PM_{2.5}$ concentrations in the central region of the Central Belt.

The left-hand panels of Figures 3.5-3.7 show there is a substantial overlap (shown in grey) of the two distributions in all presented cases. For NO_2 the RE tends to dominate in the left tail of the observed exposures and on the right-hand side extremes. O_3 concentration distributions are spatially anti-correlated with NO_2 distributions. In the case of $PM_{2.5}$ the RE tends to be larger at the extremes of the distributions.

The $RWE_{8\text{-}18}$ distributions are generally narrower than the RE distributions, which is a consequence of at least some of those SLS participants living in the cleanest (most polluted) areas working or studying in the more (less) polluted ones and vice versa.

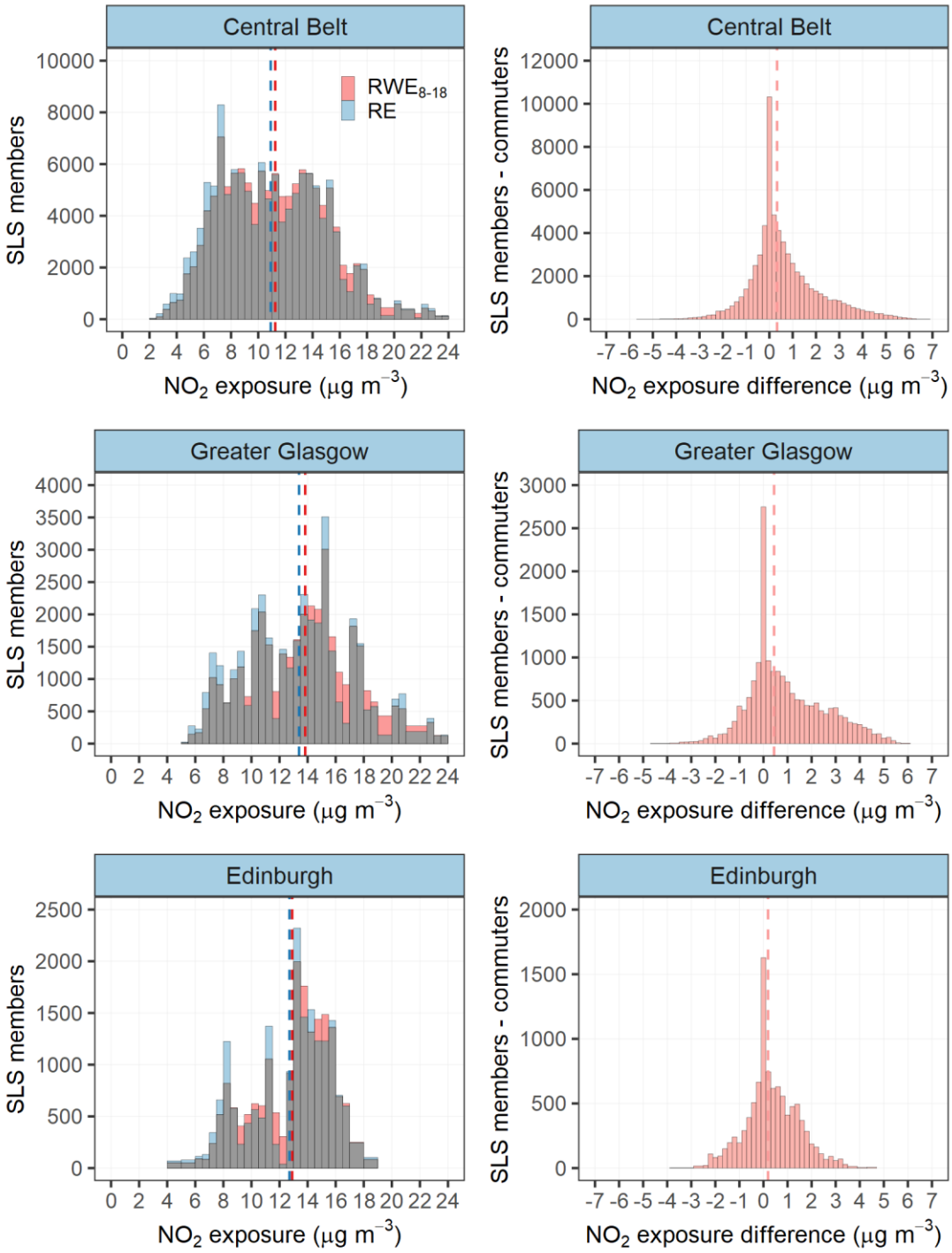

Figure 3.5 Distributions of NO_2 RE and $RWE_{8\text{-}18}$ of the SLS participants in the study areas (left panels) and the NO_2 $RWE_{8\text{-}18}$ – RE exposure differences of the SLS participants who commute to place of work and study (right panels). Grey shading in the left panels represents the distribution overlap. Dashed lines represent the means of the distributions. Bins with fewer than 10 SLS participants are aggregated with a neighbouring bin and the aggregated participant number is normalised by the aggregated bin width. Source: Scottish Longitudinal Study.

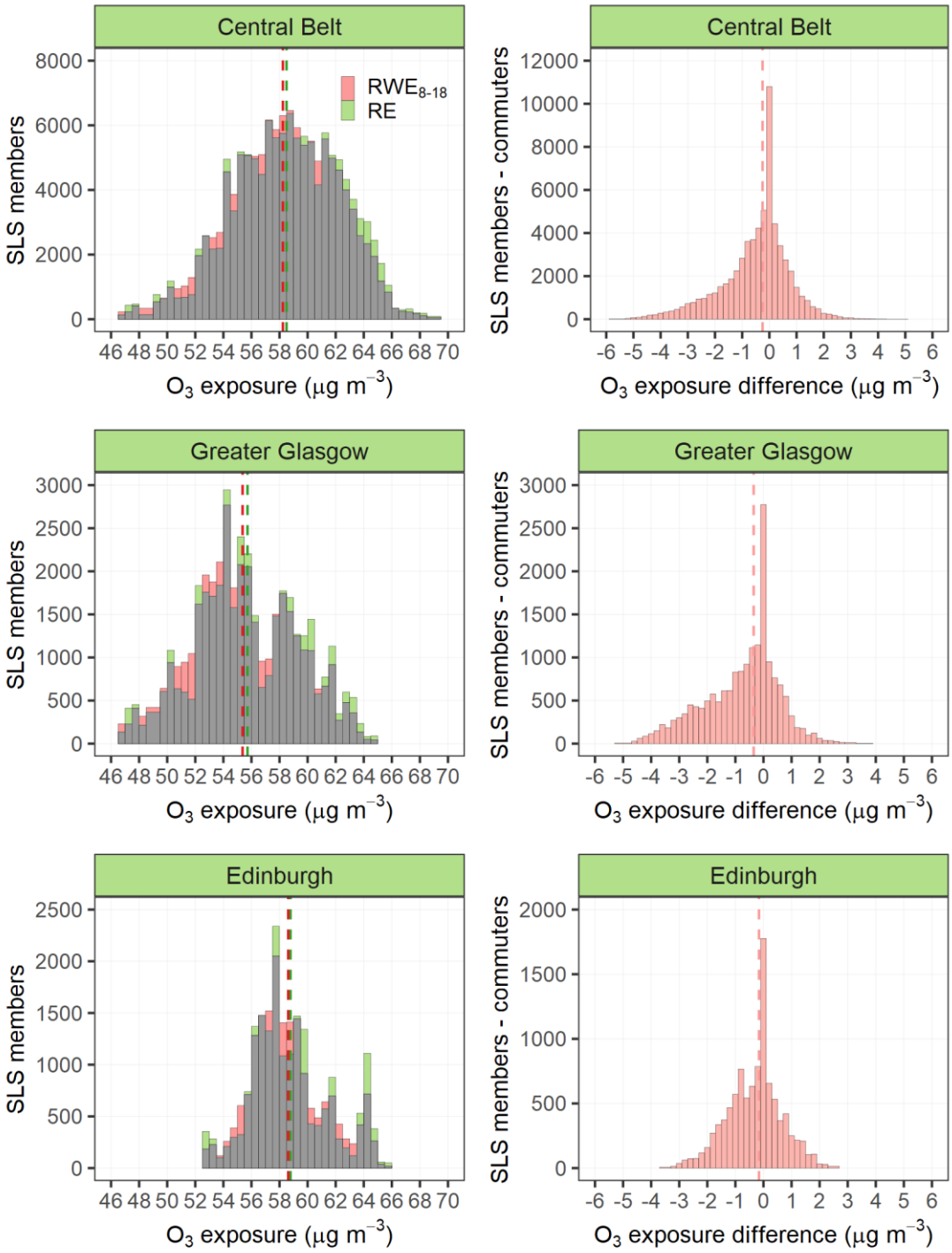

Figure 3.6 Distributions of O_3 RE and $RWE_{8\text{-}18}$ of the SLS participants in the study areas (left panels) and the O_3 $RWE_{8\text{-}18}$ – RE exposure differences of the SLS participants who commute to place of work and study (right panels). Grey shading in the left panels represents the distribution overlap. Dashed lines represent the means of the distributions. Bins with fewer than 10 SLS participants are aggregated with a neighbouring bin and the aggregated participant number is normalised by the aggregated bin width. Source: Scottish Longitudinal Study.

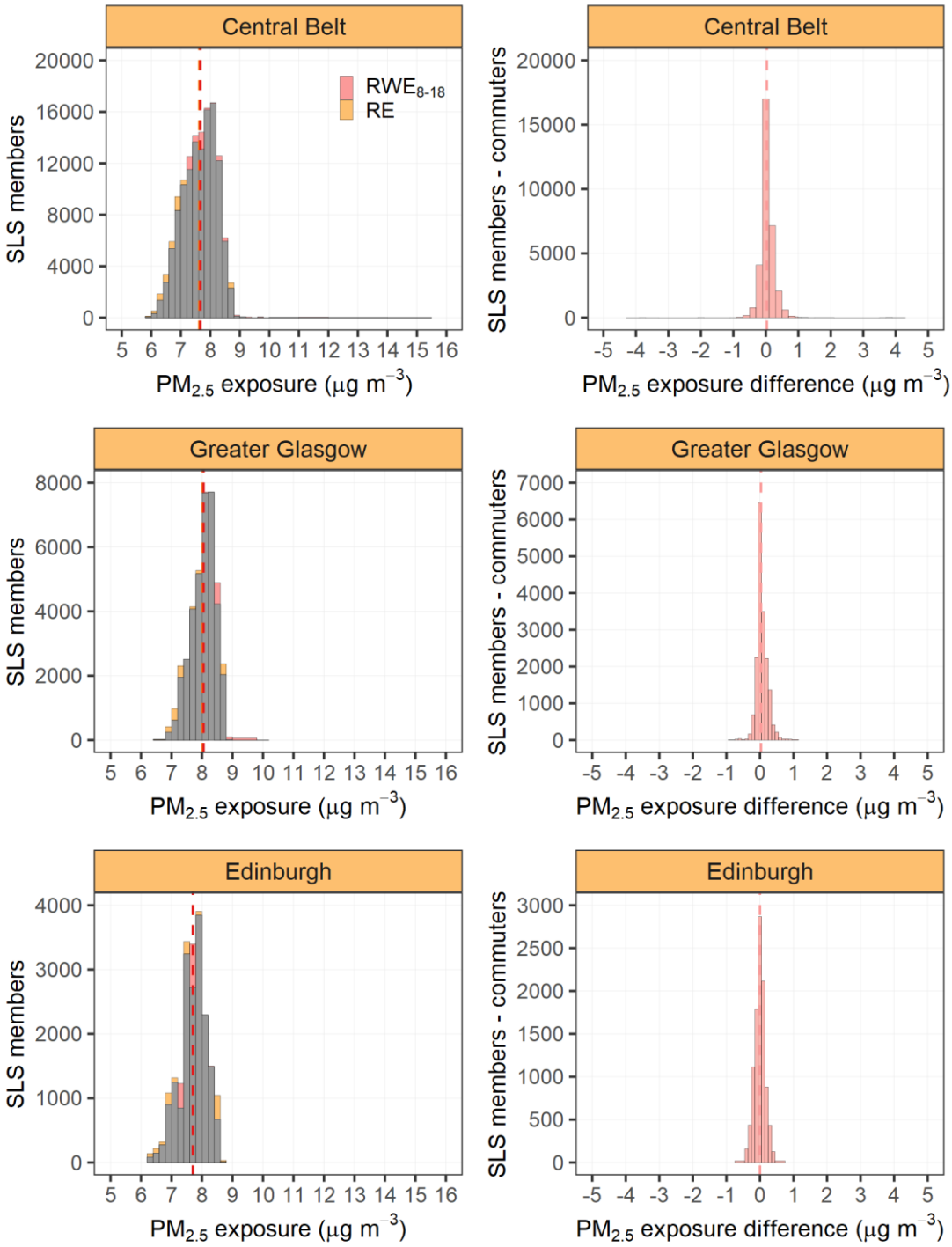

Figure 3.7 Distributions of $PM_{2.5}$ RE and $RWE_{8\text{-}18}$ of the SLS participants in the study areas (left panels) and the $PM_{2.5}$ $RWE_{8\text{-}18}$ – RE exposure differences of the SLS participants who commute to place of work and study (right panels). Grey shading in the left panels represents the distribution overlap. Dashed lines represent the means of the distributions. Bins with fewer than 10 SLS participants are aggregated with a neighbouring bin and the aggregated participant number is normalised by the aggregated bin width. Source: Scottish Longitudinal Study.

As mentioned previously, approximately 50% of the SLS participants either do not work or study or do so at their home and therefore their personal exposure change is zero. Furthermore, a large proportion of the remaining individuals who commute for work/study away from home experience a tiny change in personal exposure as a result. This is demonstrated in the right-hand panels of Figures 3.5-3.7 which show the distributions of the change in exposure of the commuters between the $RWE_{8\text{-}18}$ and RE scenarios for all pollutants and study areas. In the case of NO_2 and O_3 the magnitude of exposure change, whether positive or negative, is 0.1 µg m^{-3} or less for approximately 16% of the commuters in all three study areas. In the case of $PM_{2.5,}$ 27.3% commuters in the Central Belt experience a change ≤ 0.1 µg m^{-3}, whilst 17.0% in Greater Glasgow and 14.2% in Edinburgh experience a change of 0.05 µg m^{-3} or less.

Whilst the exposure changes tend to cluster around zero, there are some large differences in personal exposure for a small number of individuals, and as the right-hand panels of Figures 3.5-3.7 show the NO_2 and O_3 distributions are skewed. This is further demonstrated in Table 3.4 which shows the number of SLS participants whose magnitude of difference between their combined residential-workplace exposure ($RWE_{8\text{-}18}$) and just residential exposure to either NO_2 or O_3 exceeds a threshold. For example, in the Central Belt there are 14,088 (11.3%) SLS participants whose combined residential-workplace exposure is larger by at least 1.5 µg m^{-3} than their residential exposure only. In contrast, only around 2,700 (2.2%) SLS participants in the Central Belt experience a decrease in personal exposure of at least 1.5 µg m^{-3} when exposure to NO_2 at their workplace location is considered.

Table 3.4 Number of SLS participants whose difference between personal $RWE_{8\text{-}18}$ and RE to NO_2 and O_3, respectively, is larger in magnitude than Difference D. Source: Scottish Longitudinal Study

Pollutant	Difference	Central Belt		Greater Glasgow		Edinburgh	
	(D) (µg m^{-3})	≤ -D	≥ D	≤ -D	≥ D	≤ -D	≥ D
NO_2	0.5	13,308	27,522	3,118	8,955	2,323	3,847
	1.5	3,545	14,088	768	5,520	707	1,372
	2.5	896	7,490	207	3,279	73	313
	3.5	197	3,461	44	1,479	18	37
O_3	0.5	30,216	10,538	9,575	2,353	4,324	1,763
	1.5	13,587	2,127	5,254	435	1,436	319
	2.3	7,342	548	3,084	111	350	26

At the extremes of the distributions, a particularly striking result is the 29 Central Belt SLS participants who experience an increase in $PM_{2.5}$ exposure in the region of 3.9-4.3 µg m^{-3} and 17 Central Belt SLS participants who experience an increase in NO_2 exposure in the region of 6.3-6.9 µg m^{-3}. When scaled up those figures would translate into approximately 550 and 320 Central Belt residents whose $PM_{2.5}$ and NO_2 exposure change would be within those two categories of magnitude. At the same time, 10 and 16 Central Belt SLS participants have personal exposure that is smaller by 3.9-4.3 µg m^{-3} and 4.7-5.7 µg m^{-3} for $PM_{2.5}$ and NO_2, respectively.

3.3.4 Residential vs. combined residential-workplace exposure of population subgroups

The exposure means, medians and interquartile ranges are shown in the top panels of Figures 3.8-3.16. The panels show that most exposure distributions, particularly in Edinburgh, are skewed either left (NO_2 and $PM_{2.5}$) or right (O_3). Therefore, differences in median exposures which are shown in the bottom panels of Figures 3.8-3.16 are used to compare the exposures of population sub-groups. The summary statistics for each exposure distribution shown in Figures 3.8-3.16 are presented in Tables A1-A36 in Appendix A.1.

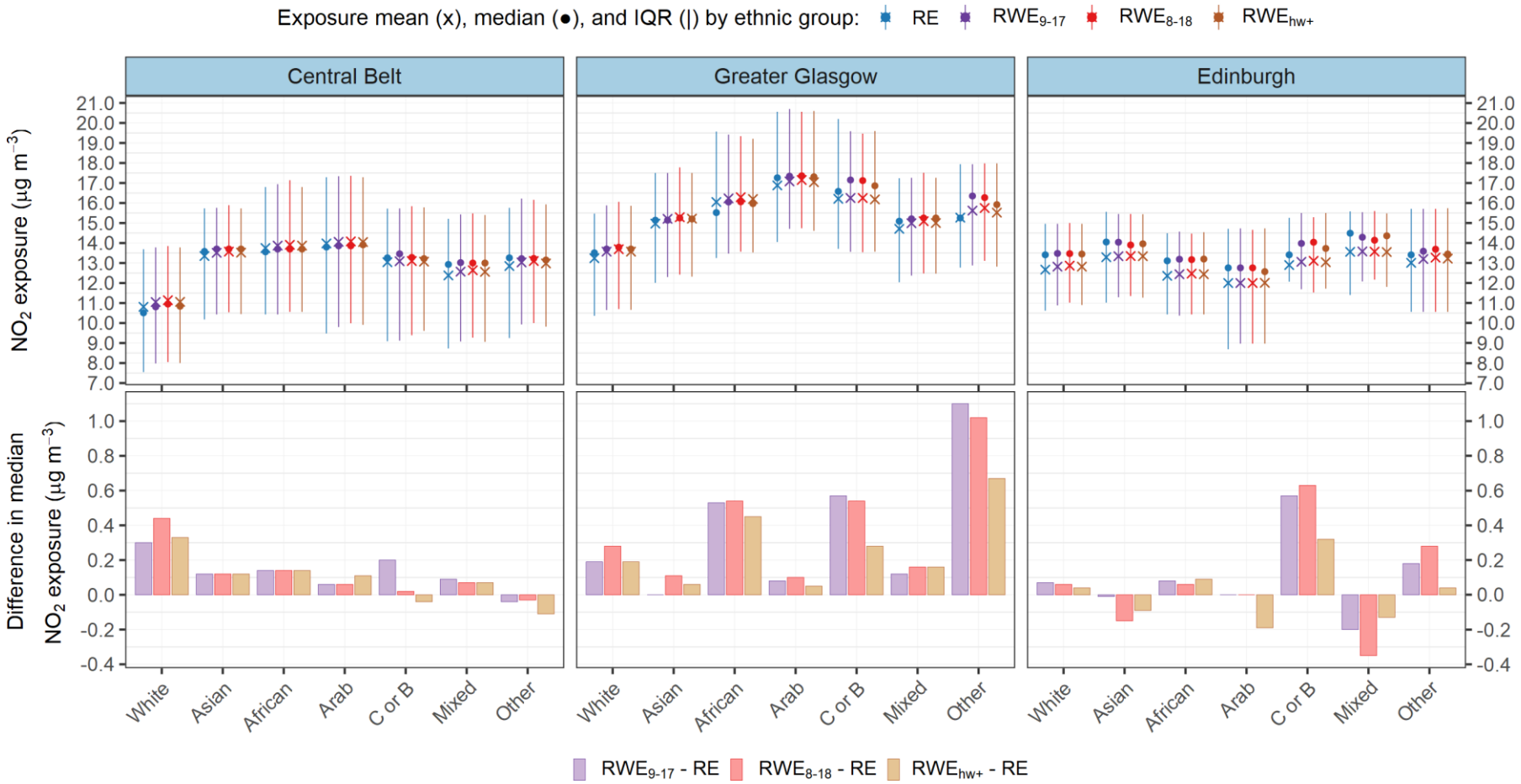

Figure 3.8 NO_2 exposure means, medians and interquartile ranges by ethnic group, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). C or B = Caribbean or Black. Source: Scottish Longitudinal Study.

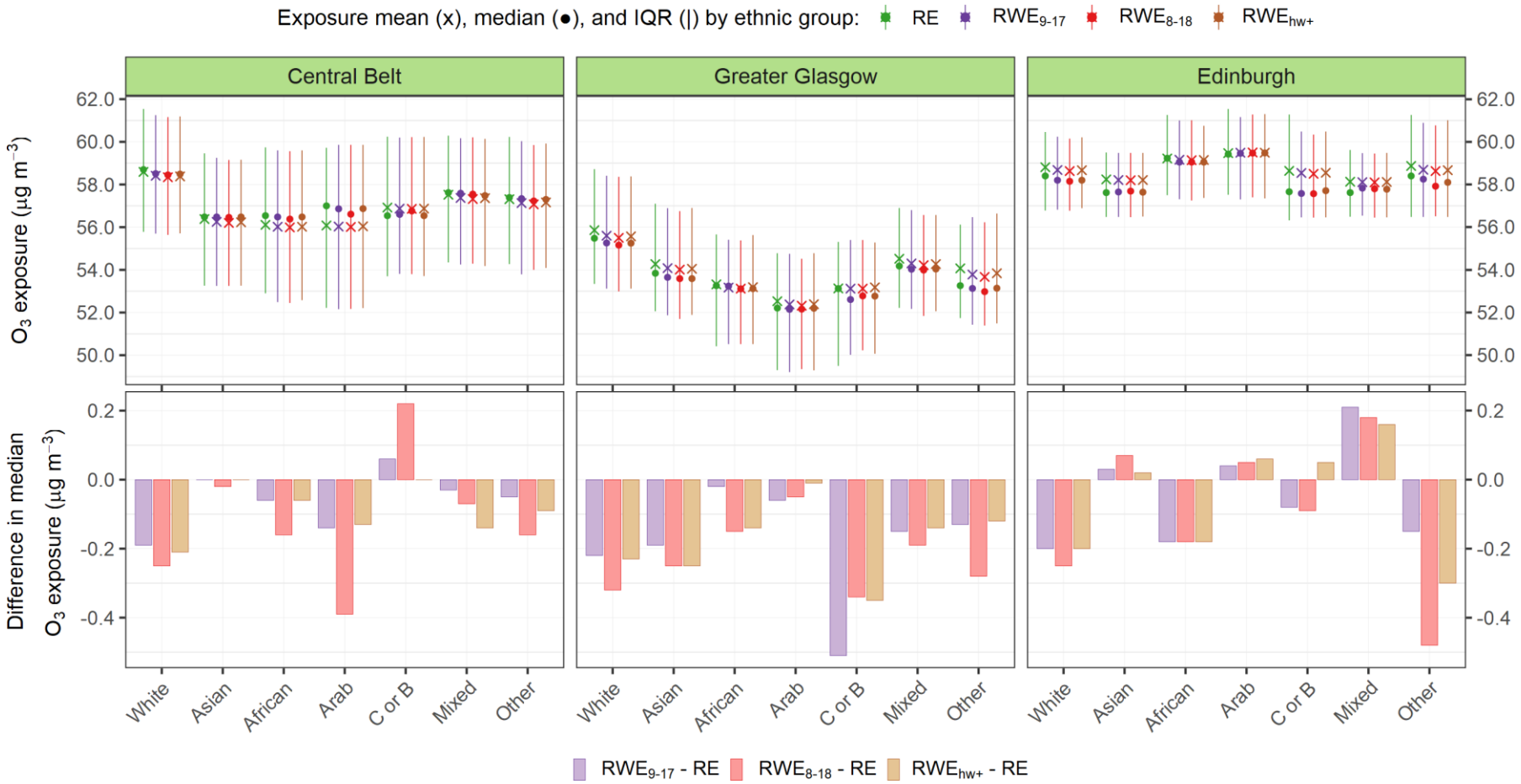

Figure 3.9 O_3 exposure means, medians and interquartile ranges by ethnic group, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). C or B = Caribbean or Black. Source: Scottish Longitudinal Study.

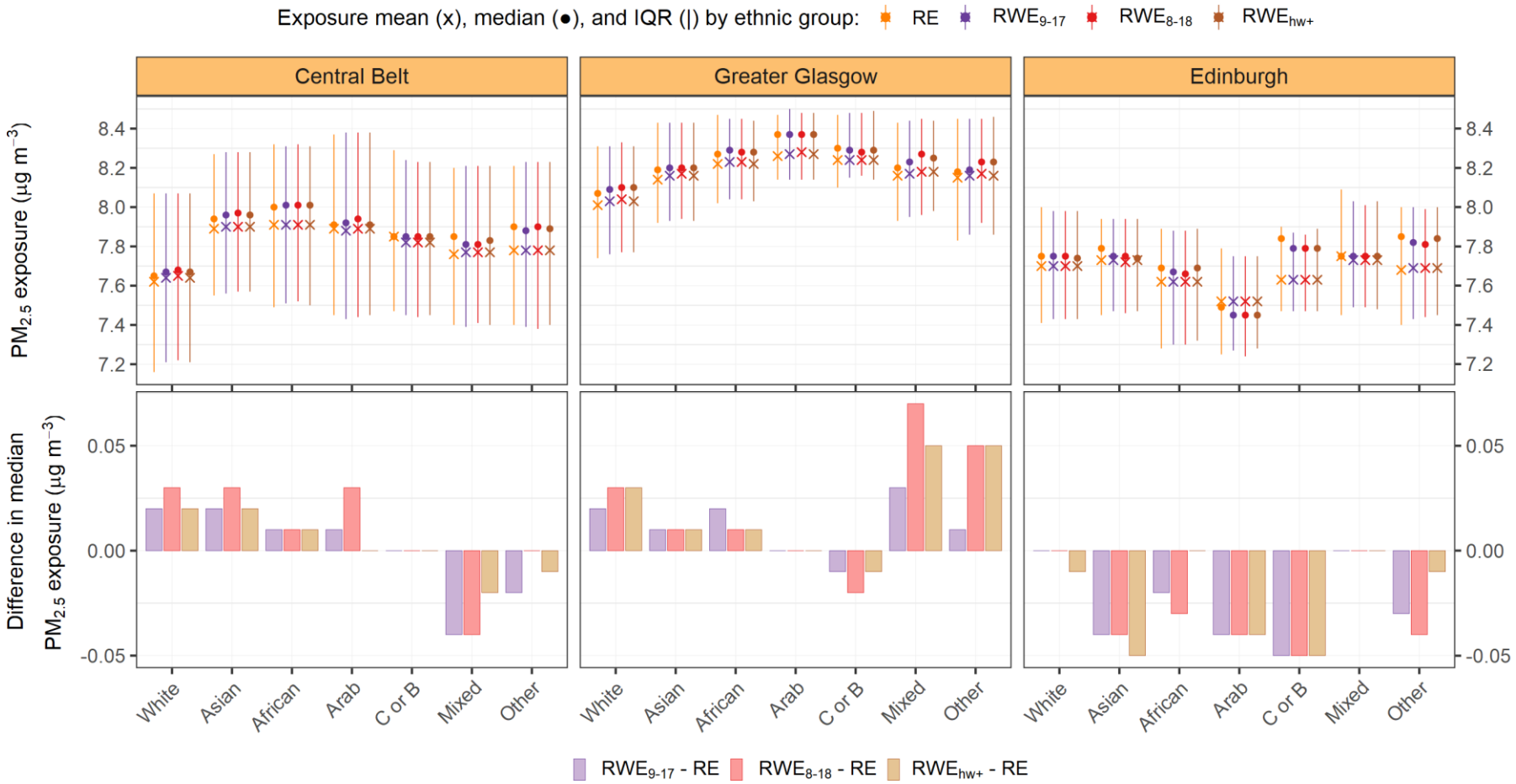

Figure 3.10 $PM_{2.5}$ exposure means, medians and interquartile ranges by ethnic group, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). C or B = Caribbean or Black. Source: Scottish Longitudinal Study.

Ethnic Group

The relationship between ethnicity and air pollution exposure is rather complex across both the study areas and ethnic groups (Figures 3.8-3.10) There is no consistency regarding which ethnic group is exposed to the worst or best air quality for a given pollutant. This is largely due to Edinburgh displaying different patterns of exposure compared to the other study areas. For example, the Arab ethnic group is exposed to the highest NO_2 concentrations in the Central Belt and Glasgow but the lowest NO_2 concentrations in Edinburgh. Generally the magnitude and direction of change in exposure due to workplace exposure also varies across ethnic groups, study areas and even exposure scenarios.

Overall in the Central Belt region, the White ethnic group has the lowest NO_2 and $PM_{2.5}$ residential exposure and the highest O_3 residential exposure of all the ethnic groups. The gap in median residential exposure between the White ethnic group and all the minority groups is largest in the regional domain compared with the urban domains. For NO_2, the White group is most affected by exposure at the place of work/study in the Central Belt. There, the increase in median NO_2 exposure ranges from 0.30 µg m^{-3} in the $RWE_{9\text{-}17}$ scenario to 0.44 µg m^{-3} in the $RWE_{8\text{-}18}$ scenario compared with the RE scenario. Changes in O_3 exposure are less than 0.5 µg m^{-3} for everyone except for the $RWE_{9\text{-}17}$ scenario in the Caribbean and Black minority in Glasgow. Changes in $PM_{2.5}$ exposure are less than 0.1 µg m^{-3} everywhere.

Age

The pattern of NO_2 and $PM_{2.5}$ exposure in all exposure scenarios according to the age grouped into 5-year wide bins shown in Figures 3.11-3.13 is almost the same across all three study areas. O_3 exposure patterns are effectively mirror images of the other two pollutants. The median NO_2 and $PM_{2.5}$ RE rapidly increases from a comparatively low level in childhood and peaks for young adults in the 21-25 or 26-30 years old groups before quickly decreasing again up to the age group 36-40 years old after which the RE is either constant or slowly decreasing depending on the study area and pollutant. In all three

areas, children up to the age of 5 have a slightly higher NO_2 and $PM_{2.5}$ RE than children between 6 and 15 years old.

In the Central Belt and Greater Glasgow domains, accounting for exposure at the place of work/study results in a similar pattern of an increase of NO_2 exposure for all age groups except for the oldest age group in which virtually everyone is retired and therefore their exposure change is zero. The increase in NO_2 exposure is also marginal for those younger than 11 years old and older than 65. The exposure increase rises rapidly between the 11-15 and 16-20 age groups and peaks between the ages of 30-40 before slowly subsiding again. In Edinburgh, the NO_2 exposure change pattern is different for the 16-25 age groups, however. Those age groups experience a decrease in NO_2 exposure compared with the RE scenario of up to 0.23 µg m^{-3} in the $RWE_{8\text{-}18}$ scenario. Admittedly, the $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$ scenarios are somewhat unrealistic for those age groups in which a large proportion of SLS participants are students. However, even the more realistic RWE_{hw+} scenario, which assigns 30 hours per week at the place of study to full time students, shows a decrease in NO_2 exposure of 0.05-0.1 µg m^{-3}. Correspondingly, the 16-25 years of age groups experience an increase in median O_3 exposure which is not observed in the other study areas. The only other age group that also sees an increase in O_3 exposure is the 11-15 age group in Greater Glasgow. The patterns of differences between the median $PM_{2.5}$ RWE and RE scenarios are less clear however the magnitude of the difference is again very small for $PM_{2.5}$. Most groups in the Central Belt and Greater Glasgow experience a small increase in exposure. On the other hand, most groups in Edinburgh experience a decrease or the same levels of exposure.

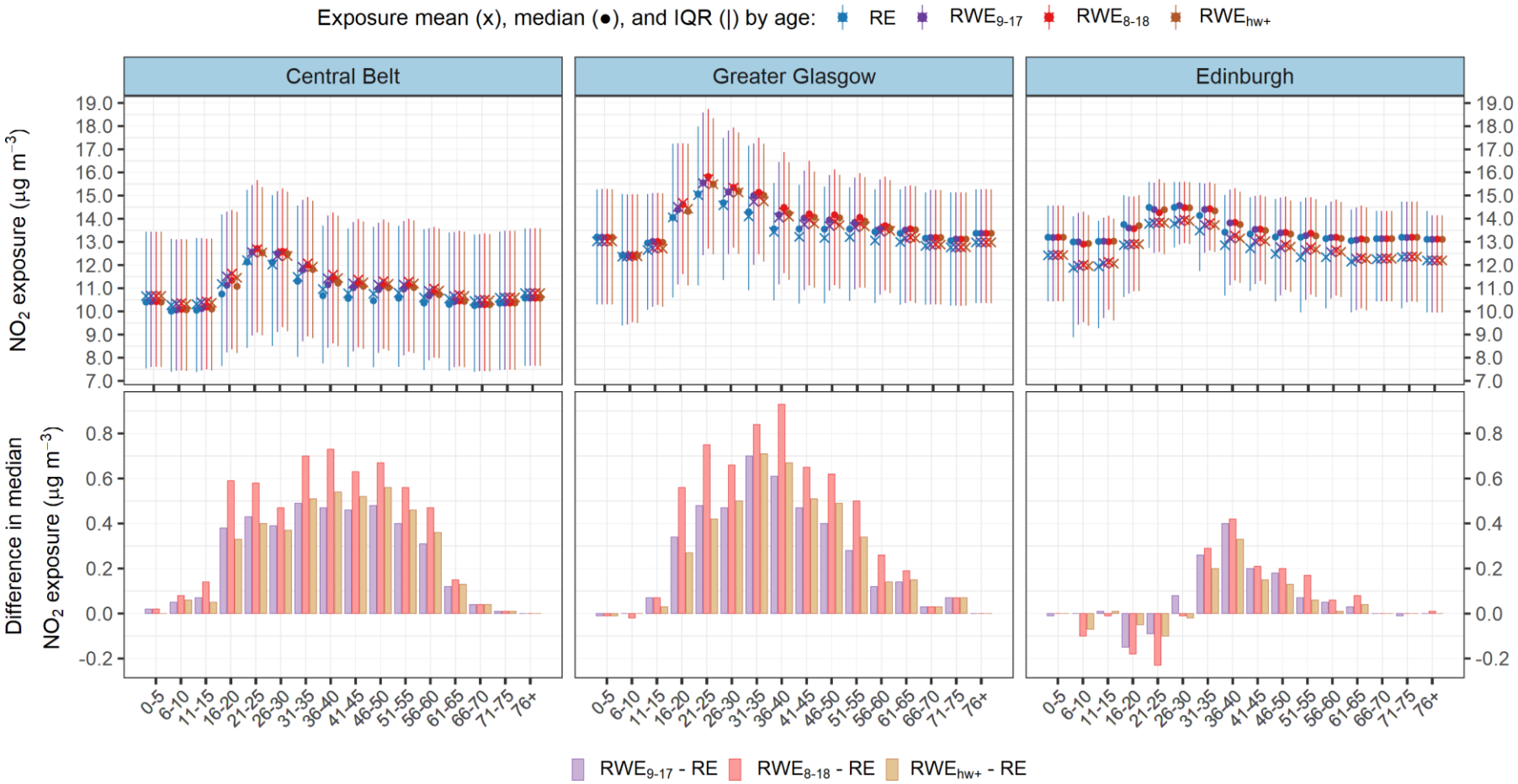

Figure 3.11 NO2 exposure means, medians and interquartile ranges by age group, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Source: Scottish Longitudinal Study.

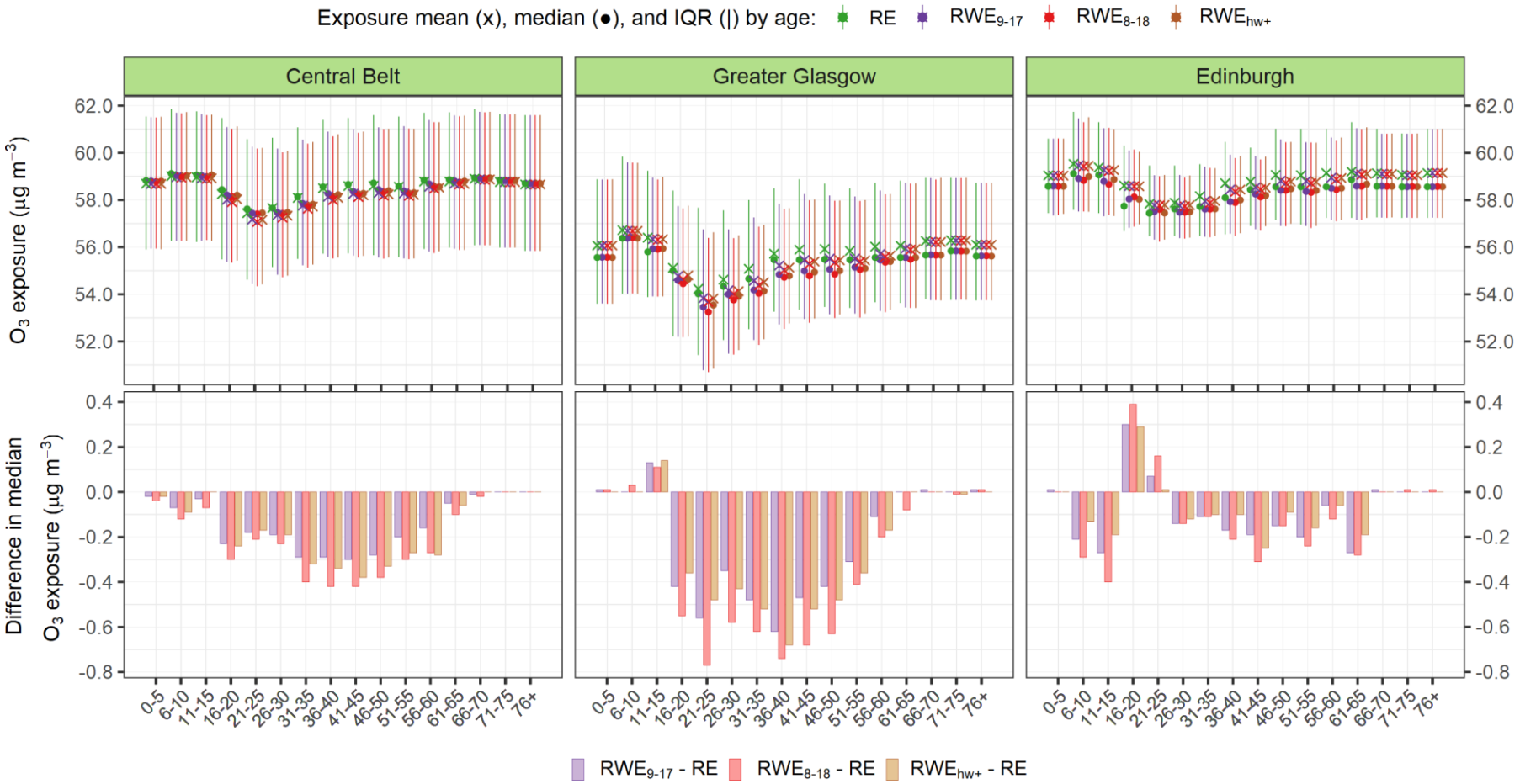

Figure 3.12 O_3 exposure means, medians and interquartile ranges by age group, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Source: Scottish Longitudinal Study.

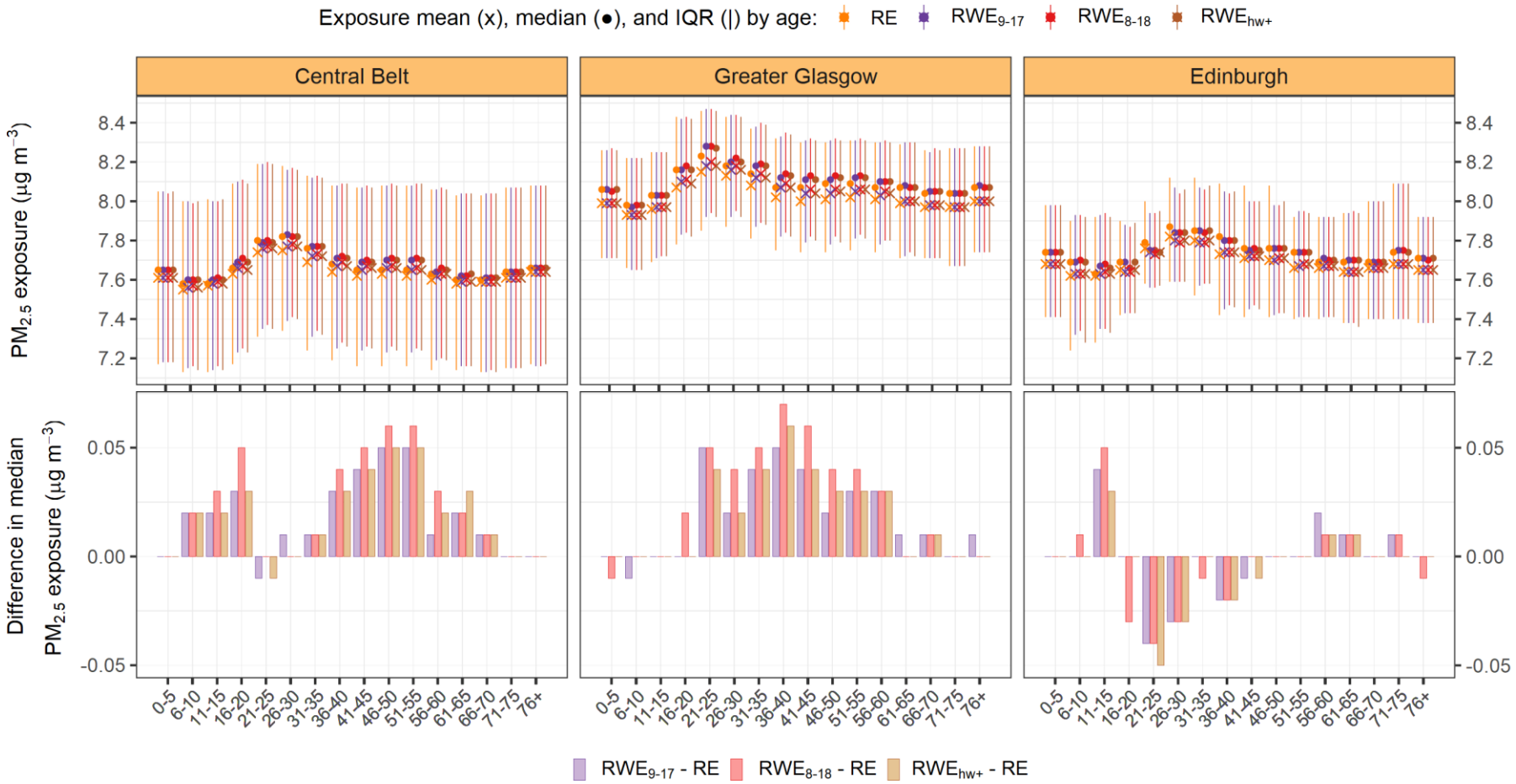

Figure 3.13 $PM_{2.5}$ exposure means, medians and interquartile ranges by age group, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Source: Scottish Longitudinal Study.

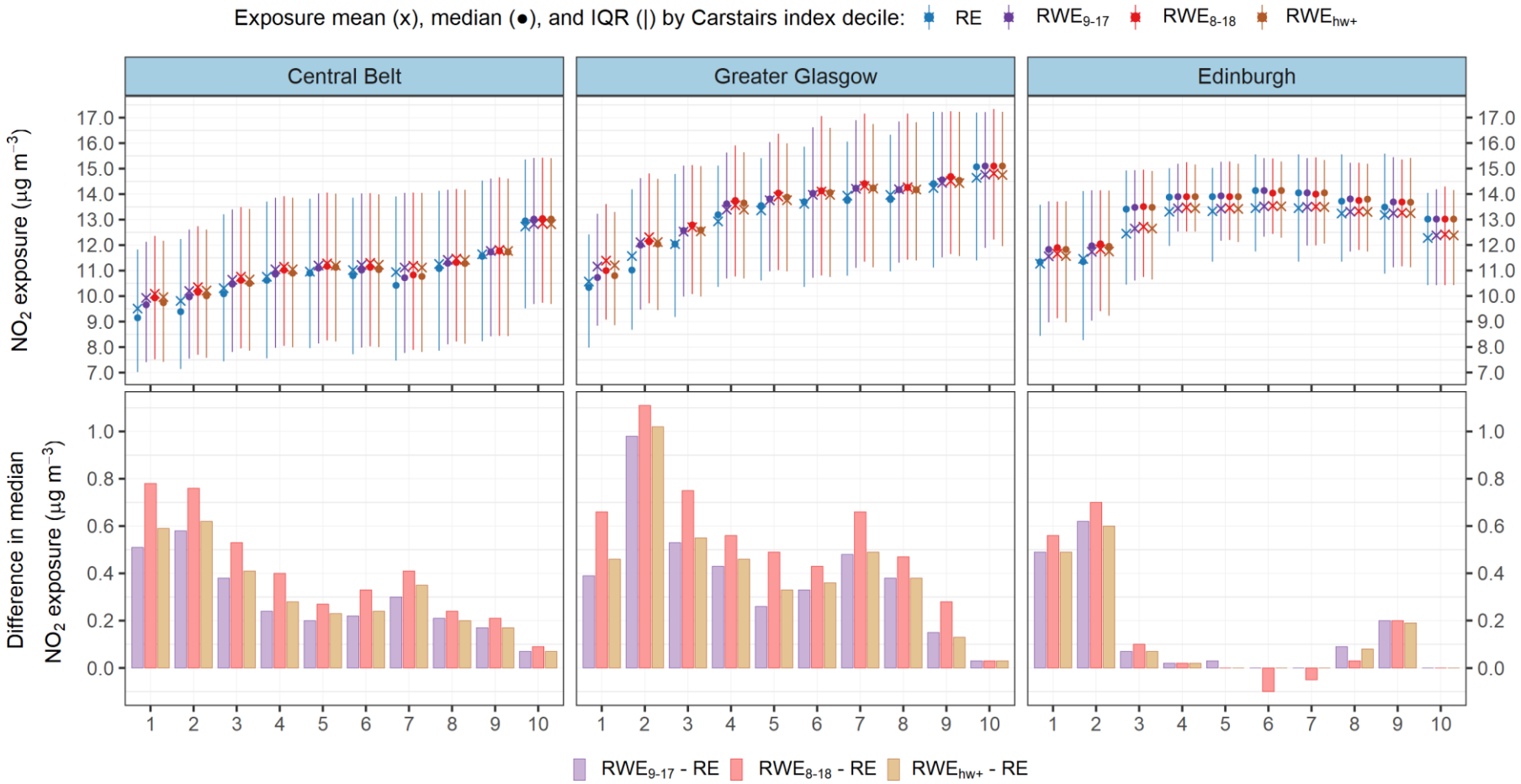

Figure 3.14 NO_2 exposure means, medians and interquartile ranges by socioeconomic status, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Decile 1 is the least deprived. Decile 10 is the most deprived. Source: Scottish Longitudinal Study.

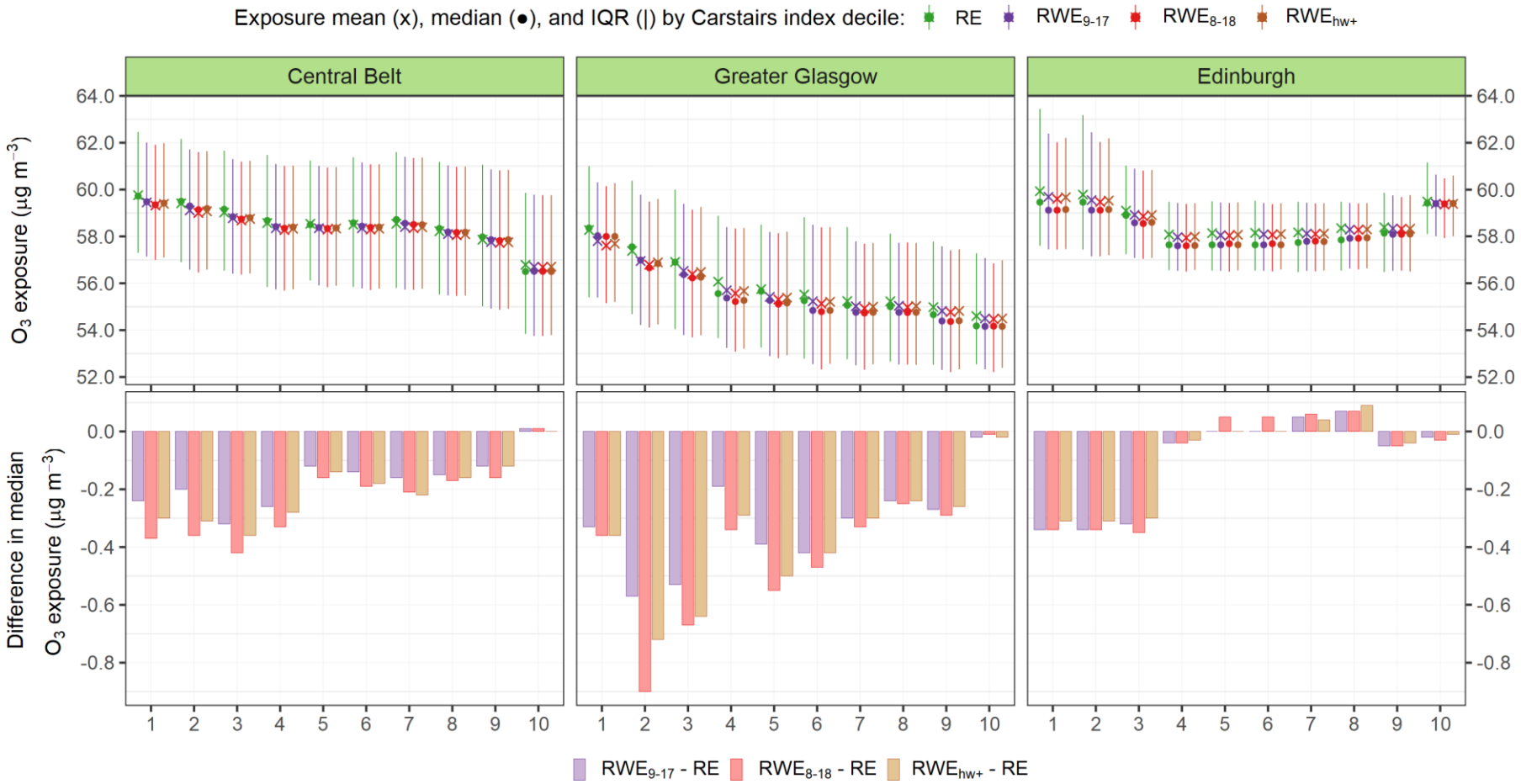

Figure 3.15 O_3 exposure means, medians and interquartile ranges by socioeconomic status, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Decile 1 is the least deprived. Decile 10 is the most deprived. Source: Scottish Longitudinal Study.

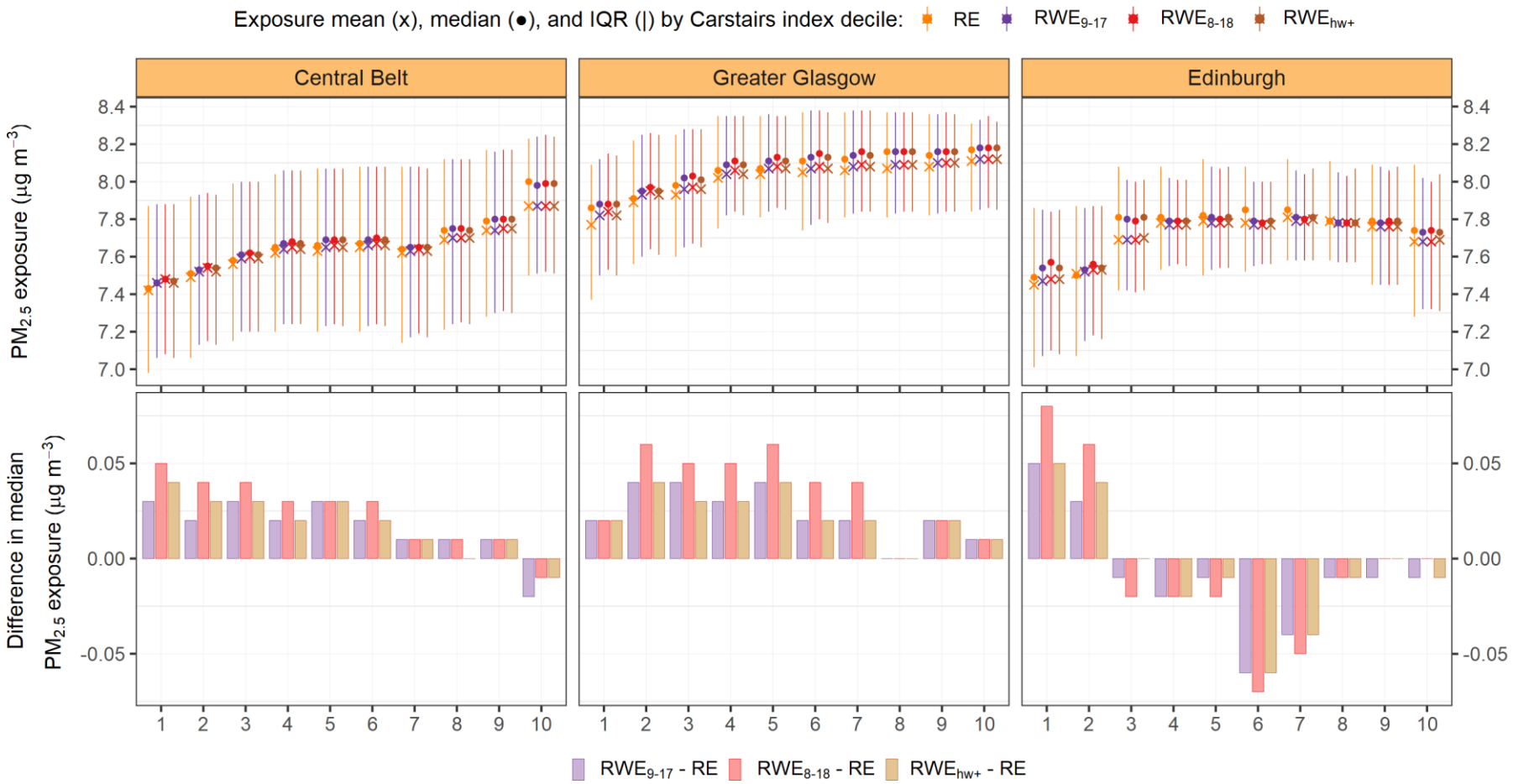

Figure 3.16 $PM_{2.5}$ exposure means, medians and interquartile ranges by socioeconomic status, study area and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Decile 1 is the least deprived. Decile 10 is the most deprived. Source: Scottish Longitudinal Study.

Socio-economic status

Figures 3.14-3.16 show a pattern of generally increasing NO_2 and $PM_{2.5}$ exposures as the level of deprivation increases in the Central Belt and Greater Glasgow study areas. More substantial increases between neighbouring deciles tend to occur between the lower (least deprived) deciles whilst in the upper deciles the increases tend to be smaller except for NO_2 and $PM_{2.5}$ in the Central Belt where the largest increase occurs between the two most deprived deciles 9 and 10 (1.39 µg m^{-3} and 0.21 µg m^{-3}, respectively). In contrast, the pattern in Edinburgh is of an upside-down U-shape. The median exposure to NO_2 and $PM_{2.5}$ increases from decile 1 to decile 6 before slowly decreasing again as the level of deprivation increases. There is a substantial, and the largest observed in any study area, increase in NO_2 and $PM_{2.5}$ RE exposure of 2.06 µg m^{-3} and 0.31 µg m^{-3}, respectively, between deciles 2 and 3. The patterns observed for O_3 exposure are opposite to those of NO_2 and $PM_{2.5}$ in all three study areas.

The differences in median exposures between the RWEs and RE scenarios shown in the bottom panels of Figures 3.14-3.16 show that generally the largest differences in median exposure occur in deciles 1 and 2 and then tend to decrease with the exception of a small secondary peak around the 7^{th} decile for NO_2 in the Central Belt and Greater Glasgow. In Edinburgh, the change in NO_2 and O_3 exposures is virtually nil in the middle deciles, and the change in $PM_{2.5}$ exposure is negative which is not observed in the other two study areas. The smallest, and in most cases almost zero, change tends to occur in the most deprived decile.

3.4 Discussion

In this study, exposure to NO_2, O_3 and $PM_{2.5}$ at the place of work or study was accounted for in assessing air pollution exposure and its inequalities of the population living and working in the Central Belt of Scotland region using anonymised personal data. Since no data on specific times at workplace were available three scenarios were used to estimate the potential impact on

population exposure – two ($RW_{8\text{-}18}$, $RWE_{9\text{-}17}$) were based on prescribed fixed hours and one (RWE_{hw+}) on typical hours worked. The $RWE_{8\text{-}18}$ scenario can be considered as the more impactful scenario since it assigns workplace exposure for 50 hours per week and partially covers weekday morning and evening rush hour concentration peaks (NO_2 and $PM_{2.5}$) and troughs (O_3), as previously shown in Figures 2.7-2.9. The impacts of the other two scenarios were smaller in comparison. The $RWE_{9\text{-}17}$ excludes essentially all of the morning and evening concentration extremes and better represents those workers with very short commuting distances. The RWE_{hw+} ignores temporal variability of concentrations but better represents part time workers and workers working variable shifts. Consequently, all three scenarios together provide a plausible range of population exposures whilst accounting for exposure at the place of work or study.

3.4.1 The effect of exposure at the place of work or study on population exposure in the study areas

Compared with the estimates of residential exposure only, the changes in exposure to NO_2, O_3 and $PM_{2.5}$ in the Central Belt study area are small and comparable to those for the whole of the UK as described in Chapter 2 and published in Reis et al. (2018) . There is, however, a variability in exposure change within the area demonstrated by the substantially different impacts seen in Glasgow and Edinburgh. In Glasgow, the mean NO_2 increment due to exposure at workplace is at least twice larger in magnitude for all RWE scenarios compared with Edinburgh, despite the range of NO_2 concentrations being 19.0 µg m^{-3} in the former and 14.6 µg m^{-3} in the latter (Table 3.2). The difference in medians is larger still. $RWE_{8\text{-}18}$ - RE in Glasgow (3.5%) is almost six times larger than its equivalent in Edinburgh (0.6%). On the other hand, the ranges of change in individual exposures reflect the ranges in concentrations much better. This suggests that large centres of employment and education in Edinburgh are situated further away from the most polluted city centre area, compared to Glasgow. This may have important implications for health impacts in the cities. The O_3 and $PM_{2.5}$ show similar differences between the

cities albeit the changes are at least an order of magnitude smaller. It is worth noting that approximately 50% of the population in the study areas do not work or work from home, hence the changes in exposure for the commuting half of the population are approximately twice the estimated exposure change for the whole population.

3.4.2 Analysis of residential exposure inequalities

A direct comparison of this study's findings with other studies is not straightforward due to inconsistency in air pollution and population data resolutions between studies. Therefore trends rather than absolute values are considered for comparison. Considering residential exposure only of the study population stratified by ethnicity, age and SES the following patterns have emerged.

The White ethnic group has a substantially lower exposure to NO_2 and $PM_{2.5}$, and higher exposure to O_3, than any other ethnic group in the Central Belt region which is likely due to minority ethnic groups predominantly living in the cities and towns, whilst the rural (less NO_2 and $PM_{2.5}$ polluted, more O_3 polluted) areas are traditionally inhabited by the White population. The observation is in agreement with Fecht et al. (2015) who found that in England and the Netherlands, at regional level, neighbourhoods with <20% non-White ethnic individuals had lower concentrations of NO_2 than those with >20% non-White ethnic individuals. Fecht et al. (2015) observed a similar trend in the case of PM_{10} in the majority (but not all) of the regions too. At the city level there is a contrast in findings between Glasgow and Edinburgh. The pattern in Glasgow of lowest NO_2 and $PM_{2.5}$ exposures experienced by the White ethnic group is again in agreement with findings of Fecht et al. (2015) and Tonne et al. (2018), and those of Moreno-Jiménez et al. (2016) and Padilla et al. (2014), who considered immigrants rather than ethnic groups per se. In Edinburgh, however, the mean and median exposures of the White ethnic group tend to rank in the middle of the mean and median exposures of the other ethnic groups which points to a different pattern of ethnic minority clustering than found in the other cities in the UK and across Europe. Given the small numbers

of ethnic minorities in the population samples in this study there is, however, a possibility that some of the observations may not be truly representative of the exposure of the minority groups.

In contrast with the findings for ethnicity, the pattern of exposure vs age is clear and is virtually the same across all study areas. There is a peak in exposure to NO_2 and $PM_{2.5}$ (and trough for O_3) that occurs approximately between the ages of 16 and 35. As discussed in Mitchell and Dorling (2003), this is due to the trend of young adults moving to inner urban areas for work, university and socialising purposes before starting a family and moving out into the suburban areas to raise their children. The explanation is further supported by the youngest age group (<6 years old) having on average slightly higher NO_2 and $PM_{2.5}$ exposure than older children (between 6 and 16 years old). The observed peak in exposure of young adults in this study agrees with the study of Mitchell and Dorling (2003) who considered age related exposure inequality to NO_2 at the neighbourhood level across the whole of Great Britain. However, in contrast with their above-average exposure of children up to the age of about 10, in this study, children always had a lower than average exposure to NO_2. Moreno-Jiménez et al. (2016) also found lower exposure to NO_2 of children under the age of 5 than the population average in Madrid and Barcelona. However, they observed above-average exposures of the 80+ age group in the former and approximately average in the latter which is not the case in this study. In England, Fecht et al. (2015) found mixed results when comparing NO_2 exposures between neighbourhoods with lowest and highest proportion of children, but lower NO_2 exposure in neighbourhoods with the largest proportion of the over 65s. The advantage of this study compared with the others is that it uses individual level data and as such is not subject to modifiable area unit problem.

Across all study areas the least deprived are exposed to the lowest NO_2 and $PM_{2.5}$ concentrations and the highest O_3 concentrations. However, in Edinburgh the highest NO_2 and $PM_{2.5}$ (and lowest O_3) concentrations were observed in the middle Carstairs index deciles as opposed to the most

deprived decile in Glasgow. Overall in the Central Belt region the pattern resembles that seen in Glasgow. The complex relationship between the SES and residential exposure observed here is in agreement with other studies in Europe which also argue that the relationship between air pollution and SES is area specific (e.g. Fecht et al., 2015; Temam et al., 2017). Unlike the other investigated social characteristics in this study, the SES variable was only available as an Output Area average which may have masked higher gradients in exposure inequalities between people of differential SES.

3.4.3 Analysis of combined residential-workplace exposure inequalities

As shown in Figures 3.8-3.16 considering exposure at the place of work or study has a differential impact on exposure inequalities across population subgroups and pollutants. The impact on $PM_{2.5}$ exposure tends to be very small; it is rarely larger in magnitude than 0.05 µg m^{-3}.

In the population stratified by ethnicity, the impact of exposure at workplace is very variable and, as mentioned before, due to the low numbers in most ethnic minorities, any conclusion would be unlikely to be robust.

The picture is much clearer for the age and SES based strata. The largest observed changes in exposure are seen in the working age population between approximately 31 and 50 years of age with some minor variations across study areas and pollutants. This is clearly a result of a large proportion of suburban dwelling adults commuting to urban centres for work. A positive finding of this study is that young children's exposure appears to be largely unaffected by the exposure at school which is likely due to the distance between the home and school being short. Using a higher spatial resolution model could however produce more substantial differences. The exposure of the very old is also unaffected since the vast majority of those are in retirement. There is evidence in this study that exposure at the place of work/study tends to attenuate but not cancel out the inequalities in exposure between people of differential SES. Despite this mitigating effect on exposure inequality, in the

regional study area the most deprived subgroup still experiences an increase in NO_2 exposure when exposure at work or school is considered.

Few studies have investigated differential population exposure in a socially stratified population. Dhondt et al. (2012) stratified population by age and gender whilst considering mobility of a synthetic population. In their study annual exposure to NO_2 and 1 h max O_3 was comparable between males and females whilst 18-34 and 35-54 year-old groups had higher exposure to NO_2 and lower exposure to O_3 than older age groups. The authors did not investigate exposure of children under the age of 18. In London, Tonne et al. (2018), using a comprehensive exposure model (Smith *et al.*, 2016), found differences in exposure according to age and area-level income deprivations. However, since they included data for infiltration rates of outdoor to indoor concentrations, which yielded large reductions in personal exposures, their results are not easily comparable with the findings of this study.

3.4.4 Limitations

A limitation of this study is the inability to include exposure in other potentially important microenvironments in the assessment, particularly exposure during commuting between home and place of work or study. The access restrictions to the SLS participants' personal data meant no access to the actual postcode information was possible. In order to estimate exposure during commuting, it was necessary to provide estimated exposure for journeys between a combination of any two postcodes within the study area with the relevant connections then being assigned to matching SLS participants by the SLS-DSU staff. Additionally, several likely routes between each pair of postcodes would have had to be considered in order to account for commuters using different modes of transport. Given the large number of postcodes and potential routes in the study area it was not feasible to fulfil such a requirement.

However, data presented by Ragettli et al. (2015) suggest that in the Basel region on average commuting increases exposure to NO_2 by approximately 0.8% compared to home only scenario. Shafran-Nathan et al. (2018) also

argue that contribution of commuting to overall exposure to NO_2 is small. On the other hand, de Nazelle et al. (2013) suggest an 11% contribution of commuting to NO_2 exposure based on a small sample in Barcelona. Whilst on average the contribution of commuting to overall exposure may be small (particularly to NO_2 but to some extent to $PM_{2.5}$), for some individuals commuting longer distances and/or on busy roads it may be substantial. It is also likely that due to clustering of communities with similar social characteristics and propensity to use a specific mode of transport (i.e. least deprived and private cars, more deprived and buses) it may further affect the observed exposure inequalities (Tonne *et al.*, 2018).

Another limitation of the study is the spatial resolution of the EMEP4UK model. Despite the model grid being very fine for an ACTM, it is nonetheless still unable to resolve high spatial concentration gradients in the vicinity of air pollution sources. This issue is likely to have resulted in smaller calculated differences in exposure to NO_2 in particular and is further addressed in the next chapter.

Finally, some types of jobs which are mostly done by low skilled and more deprived people, such as cleaners, handymen, taxi drivers, delivery drivers etc. do not have a fixed place of work and were excluded from the analysis. Furthermore, it is unlikely that those who do report to a depot, and were therefore included in the analysis, were during work exposed to the same air pollution concentrations as those observed at the depot location which potentially introduces bias of unknown direction for the lower ranking SES groups.

3.5 Conclusions

In this study, the exposure at the place of work or study was considered alongside residential exposure in the assessment of population exposure and its inequalities to key air pollutants – NO_2, O_3 and $PM_{2.5}$ on regional and urban scales. On the population level, accounting for the place of work or study results in only small adjustments to estimated residential only exposures to

NO_2 and O_3 and negligible changes to estimated exposures to $PM_{2.5}$. The changes are in all cases not shared equally among groups of different social characteristics affecting the exposure inequalities based only on residential exposure. Whilst the pattern between various social characteristics and exposure is complex and is strongly affected by the investigated area, accounting for exposure at the place of work or study seems to attenuate but not cancel exposure gradients between subgroups of different ethnicity and socio-economic status.

Chapter 4 The effect of air pollution model type on estimates of exposure

For this chapter, I devised the methodology of the research with assistance from Mat Heal, Stefan Reis and Chun Lin. EMEP4UK modelling was conducted by Massimo Vieno. I collated the data for ADMS-Urban modelling, ran the ADMS-Urban model and evaluated its output. I summarised the pollution data, calculated the population and population subgroup exposures, and analysed the differences in exposure estimates. Population data extraction and linking with the provided pollution datasets conducted by LSCS staff.

4.1 Introduction

So far in this work the model used in the exposure analyses was a regional Eulerian ACTM whose spatial resolution is approximately 1 km × 1.5 km. As a result, the model is unable to capture high spatial gradients in air pollution concentrations occurring in the vicinity of emission sources. This is particularly the case for highly spatially heterogenous pollutants, for example NO_2.

In urban areas these concentration gradients may be further enhanced due to the complexity of the built environment as streets are often lined by buildings, walls and other obstacles that affect the air flow and dispersion of pollutants. Such street configurations are termed street canyons. Depending on wind speed and direction, and other meteorological conditions, air pollution can build up in certain locations within the street canyon, for example on the leeward side when the wind is perpendicular to the canyon axis (Vardoulakis *et al.*, 2003). Consequently, ACTMs such as EMEP4UK tend to perform substantially less well when evaluated against roadside measurements than at background locations (Lin *et al.*, 2017; Hood *et al.*, 2018). Furthermore, emission input in ACTMs comes from gridded national or international emission inventories such as the UK's National Atmospheric Emission Inventory (NAEI) that may capture national scale emission well, however the

uncertainty in the data is much larger when spatially disaggregated onto individual grid cells in the inventory.

The limitations of ACTMs in predicting air pollution concentrations within urban areas are well documented and several approaches have been developed to address the issue (Jerrett *et al.*, 2005; Özkaynak *et al.*, 2013). One such approach is a Gaussian plume dispersion model that calculates concentrations of a pollutant in the plume emitted from a particular modelled source. The concentration of the pollutant at a receptor point is then derived by summing concentrations in the plumes from all contributing sources at that receptor point plus the background concentration (often obtained from a monitoring station upwind from the modelling domain). One advantage of such an approach is the ability to utilise detailed local emission data if such data are available. Another is the ability of modern, advanced Gaussian dispersion models to account for the effects of street canyons on pollution dispersion.

The aim of this chapter is to investigate whether and by how much using a local, Gaussian plume dispersion model for air pollution concentrations predictions affects the impact of workplace mobility on population exposure to air pollution and its inequality based on the EMEP4UK data. As such, this chapter addresses the limitations associated with the model resolution in the analyses in Chapters 2 and 3. The analysis is conducted for a single urban area within the Central Belt of Scotland due to the local model constraints. Edinburgh was selected as good local knowledge of the modelling domain was deemed beneficial. As in the previous chapters, the three major air pollutants NO_2, O_3 and $PM_{2.5}$ are the subject of the analysis.

4.2 Methods

4.2.1 Study area and population

The study area encompasses the urban area of Edinburgh, UK, and some surrounding suburban and rural communities lying between 317000 and 333000 Easting and north of 666000 Northing coordinates of the British

National Grid (BNG). To the north the study area is bounded by the Firth of Forth (Figure 4.1). It covers approximately 168 km^2 of land.

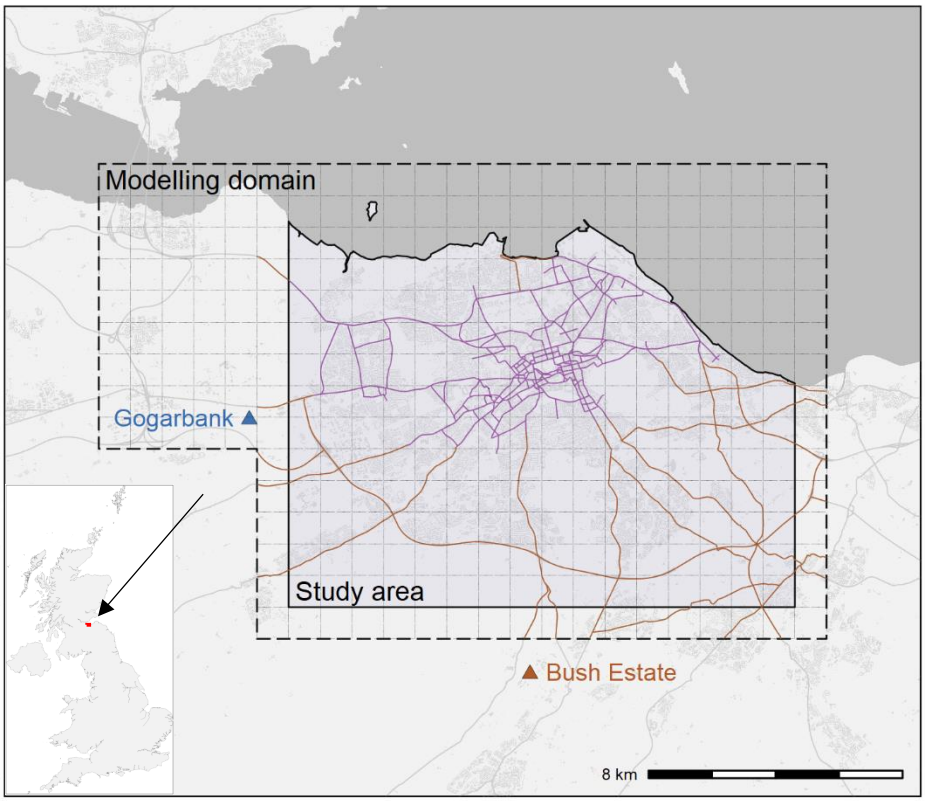

Figure 4.1 Map of the study area and ADMS-Urban modelling domain. Also shown are the network of explicitly modelled roads split by traffic data source (brown = DfT, purple = SEPA) and locations of Gogarbank meteorological and Bush Estate air quality monitoring stations supplying data used in ADMS-Urban modelling. Contains OS Data © Crown copyright and database right (2021).

The source of the population data – the Scottish Longitudinal Study (Boyle *et al.*, 2009) – is the same as in the previous chapter (Section 3.2.1) and the SLS participants' selection criteria and extracted variables are also the same.

4.2.2 Air pollution modelling

Models used

The EMEP4UK version used here is the same as in the previous chapter - the model's horizontal resolution is ~ 0.124º × ~0.124º which is equivalent to ~0.8 km × ~1.4 km in the study area. The temporal resolution is 1 hour. The EMEP4UK model is described in detail in Vieno et al. (2010) and a

comprehensive technical description of the underlying EMEP model can be found in Simpson et al. (2012). The following sections are therefore primarily concerned with data input and modelling strategy for the Gaussian plume dispersion model - ADMS-Urban. The modelled years were 2015 and 2016. The former to match the EMEP4UK model output for a direct comparison of pollutant concentrations and exposures, and the latter for model verification purposes.

The ADMS-Urban model, a member of the ADMS model suite, is a proprietary Gaussian plume dispersion model developed by Cambridge Environmental Research Consultants (Carruthers *et al.*, 1994). The ADMS models are widely used in air pollution exposure assessments either on their own or in combination with regional-scale models (e.g. Beevers *et al.*, 2012; Gulliver *et al.*, 2018; Hood *et al.*, 2018). The ADMS-Urban model simulates dispersion of pollutants from sources typically found in urban environments – industrial, transport, commercial and domestic – and is capable of simulating simplified ozone and sulphate particle chemistry.

Emissions

Emission sources can be modelled in ADMS-Urban either explicitly as point, line, area or volume sources if source and emission characteristics are well defined, or are aggregated onto a regular grid (‘grid source’) in the case of diffuse or poorly-defined emissions. An example of the former would be a road on which vehicle number, type and speed are known whereas areas with residential housing would represent the latter. Emission rates from explicitly modelled sources are then calculated as emission activity × emission factors. In this study, traffic data on roads shown in Figure 4.1 were available and were modelled explicitly. All other sources were modelled as a grid source.

Road network

The geometry of the modelled road network is based on the Ordnance Survey (OS) Open Roads and MasterMap datasets. The roads were modified where necessary and their widths were calculated as described below. An example

of the method is shown in Figure 4.2. The original road network (panel A, shown as blue lines) was simplified by removing roundabouts and slip roads at major junctions and by removing road vertices deviating less than 1 m from a straight line between its neighbouring vertices. The modelled roads were then overlaid on the detailed OS MasterMap Topography Layer and additional vertices were added to the network to ensure the modelled roads lay as close as possible to the centre of the carriageways (panel B, shown as thick orange lines).

In order to calculate the road width the road network was split into simple geometry road segments (exactly 2 vertices). On each road segment a perpendicular line was drawn from kerb to kerb at four regularly spaced points along the segment. Perpendicular lines which did not fulfil the minimum or maximum length (= road width) criteria of 5 m and 22 m, respectively, were discarded (panel C). This was necessary to avoid erroneous results caused by, for example, traffic islands or widening of roads at junctions as can be seen at the junction at the bottom of Figure 4.2, panel C. From the remaining perpendicular segments the median length was then selected as the road segment's width (panel D, shown as orange shading). Finally, visual checks were performed on the assigned road widths in ArcMap (Esri) and manual corrections made in those instances where the assigned width substantially deviated from the true width.

Figure 4.2 Example of modelled road geometry modification and width assignment strategy. See section 'Road network' for a detailed description. ©Crown copyright/MasterMap 2021. Ordnance Survey/Edina supplied service.

Emissions from explicitly modelled road sources were calculated from traffic data that had been obtained from the Scottish Environment Protection Agency (SEPA) and the Department for Transport (DfT). The data provided by SEPA were collected in the form of origin-destination junction turn counts at 113 junctions, mainly in the city centre and northern section of the study area (Figure 4.1). At 29 junctions the counting took place for 24 hours on Tuesday 29th November 2016 and at the remaining junctions for 12 hours between 07:00 and 19:00 on the same day. The counted vehicles were split into 11 vehicle categories and summed for every 15-minute period.

In order to calculate annual emissions the junction counts were converted to annual average daily traffic flow (AADF) values on the roads leading to the junctions following the DfT methodology for manual vehicle count conversion to AADF (DfT, 2016). For each vehicle category the total number of vehicles passing through each junction arm in both traffic flow directions (unless one-way road) between 07:00 and 19:00 was calculated. These totals were then multiplied by appropriate expansion factors provided by the DfT based on the vehicle and road category for 29th November 2016. The expansion factors are shown in Table 4.1. There was no hard and fast rule how far away from the

junction the calculated AADFs were applicable. In the approach adopted, each AADF was generally assigned to the nearest major junction along the road. However, the length of the road between the junctions and the number of side streets branching from the road were also taken into account.

Table 4.1 Expansion factors for each vehicle class and road category in the modelling domain. MC = motorcycle, R = rigid HGV, A = articulated HGV. Source: DfT.

Road category	Vehicle Class					
	MC	**CAR**	**BUS**	**LGV**	**R**	**A**
Urban A roads (AADF < 20k)	1.845	1.148	1.110	1.056	0.879	1.063
Urban A roads (AADF ≥ 20k)	1.750	1.174	1.145	1.096	0.964	0.923
Minor urban roads	1.800	1.166	1.488	1.099	0.838	1.042

The calculated AADFs were complemented in the rest of the modelled road network by adjusted 2016 AADF data published by the DfT (https://roadtraffic.dft.gov.uk/downloads) that was available for major road links (A roads and motorways). Each link in the DfT network is assigned an AADF derived from one count point located somewhere along the corresponding road. Due to logistical and economic reasons the counting does not take place on every link every year and on some links may not take place for several years. In such years the AADF is estimated by multiplying the AADF data from the previous year by a growth factor. To update the DfT counts, some of which had not taken place since 2006, adjustment factors for each vehicle category were calculated as follows. Firstly, DfT count points situated in the proximity of SEPA count junctions were identified. From those, two points where traffic had only ever been estimated were removed. An additional count point was also removed due to permanent vehicle restrictions implemented after the last count had taken place. The adjustment factors were then calculated from the remaining 29 count point pairs using ordinary least-square regression through the origin between the corresponding DfT AADFs and SEPA AADFs. Scatterplots of DfT AADFs vs SEPA AADFs are shown in Figure 4.3 and the derived adjustment factors are presented in Table 4.2

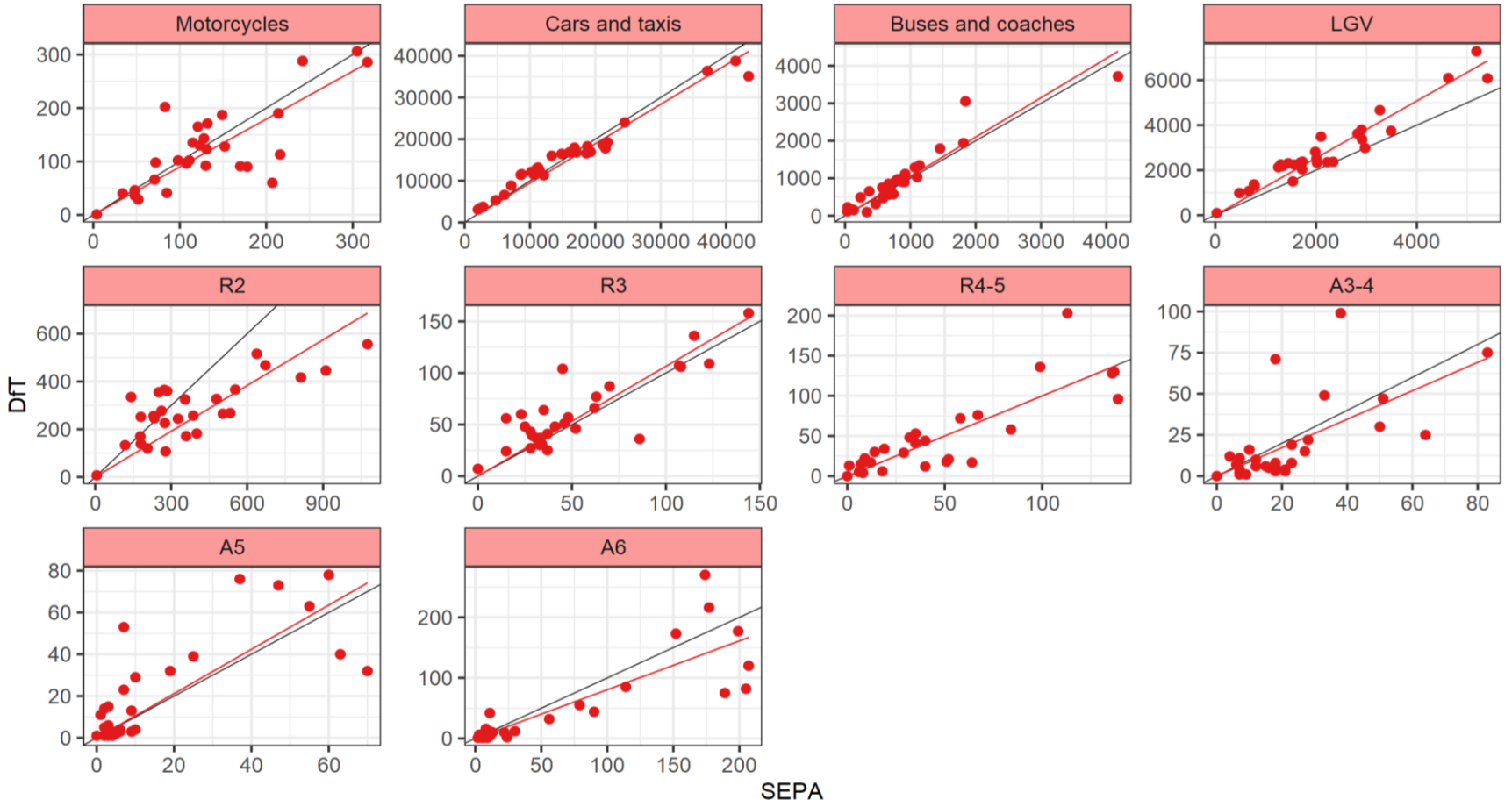

Figure 4.3 Relationship between DfT and SEPA annual average daily flows per vehicle category. Regression line forced through origin is shown in red, 1:1 relationship is represented by the black line. 'R' = rigid HGV, 'A' = articulated HGV, numbers next to 'R' or 'A' refer to the number of axles.

Table 4.2 Derived adjustment factors for DfT traffic counts. R = Rigid HGV, A = Articulated HGV, numbers next to 'R' or 'A' refer to the number of axles.

Vehicle class	Slope
Motorcycles	1.116
Cars and taxis	1.058
Buses and coaches	0.953
LGV	0.788
R2	1.566
R3	0.939
R4-5	1.002
A3-4	1.158
A5	0.944
A6	1.242

All original DfT 2016 AADF data were multiplied by the adjustment factors with the exception of the M8 motorway and the A720 bypass road which are transit routes on the western and southern edges of the city, respectively. When the year 2015 was modelled the derived 2016 AADFs were scaled by the reciprocal of the 2016 growth factors. As no information was available on the average traffic speed on each road segment the speed was estimated as 90% of the speed limit taken from OpenStreetMap data downloaded in November 2017 (OpenStreetMap contributors, 2017). To simulate slower traffic movements near junctions, the assigned average speed was set to 60% of the speed limit within a 50-metre radius of a junction with traffic lights or a roundabout.

The assigned AADFs and average traffic speed data for all 3,422 explicitly modelled road segments were imported to the Emission Inventory Toolkit (EMIT) software (CERC, 2015b) which calculated NO_x and $PM_{2.5}$ emission rates for each road segment using Emissions Factors Toolkit version 8.0. The pre-defined urban Scotland route type option in EMIT was used to disaggregate the traffic into vehicle sub-categories, i.e. by fuel type, Euro standard and engine size.

Aggregated sources

Emissions from aggregated sources were taken from the 2015 and 2016 emissions data in the National Atmospheric Emission Inventory (NAEI) (https://naei.beis.gov.uk). The inventory disaggregates total emissions of pollutants spatially on a 1 km × 1 km grid and by source sector according to the Selected Nomenclature for Air Pollution (SNAP). To avoid double counting of traffic emissions, in each grid cell the calculated emissions from explicitly modelled roads were summed and subtracted from the NAEI Road Transport sector (SNAP 7) emissions. In several grid cells where the vast majority of roads were modelled explicitly the calculated emissions exceeded road transport emissions in the inventory and the subtraction resulted in negative aggregated emissions from the sector. In such grids the aggregated road transport emissions were set to zero. The fraction of NO_x that is NO_2 (fNO_2) for SNAP 7 sector was set at 23.5% and for all the other sectors at 5% as per the defaults in the EMIT software (CERC, 2015b).

Temporal disaggregation of emissions

Both explicitly modelled roads and aggregated emissions were temporally distributed using hourly factors for each day of the week and monthly factors. The time factors for emissions from explicitly modelled roads were derived by combining information on traffic distribution from the SEPA traffic counts, road traffic statistics from the DfT (DfT, 2018) and the magnitude of emissions from seven vehicle classes (motorcycle, car, taxi, bus, LGV, rigid HGV and articulated HGV) calculated by EMIT. For weekday hourly profiles, the 24-hour junction counts from SEPA were summed for each hour of the day and normalised per vehicle class as shown in Figure 4.4. Distinctive diurnal patterns per vehicle class can clearly be seen. For example, evening peaks only occur for cars and motorcycles. Buses/coaches and LGVs profiles have a top hat shape and HGVs have one wide peak between 09:00 and 13:00. Taxis have the smallest diurnal cycle.

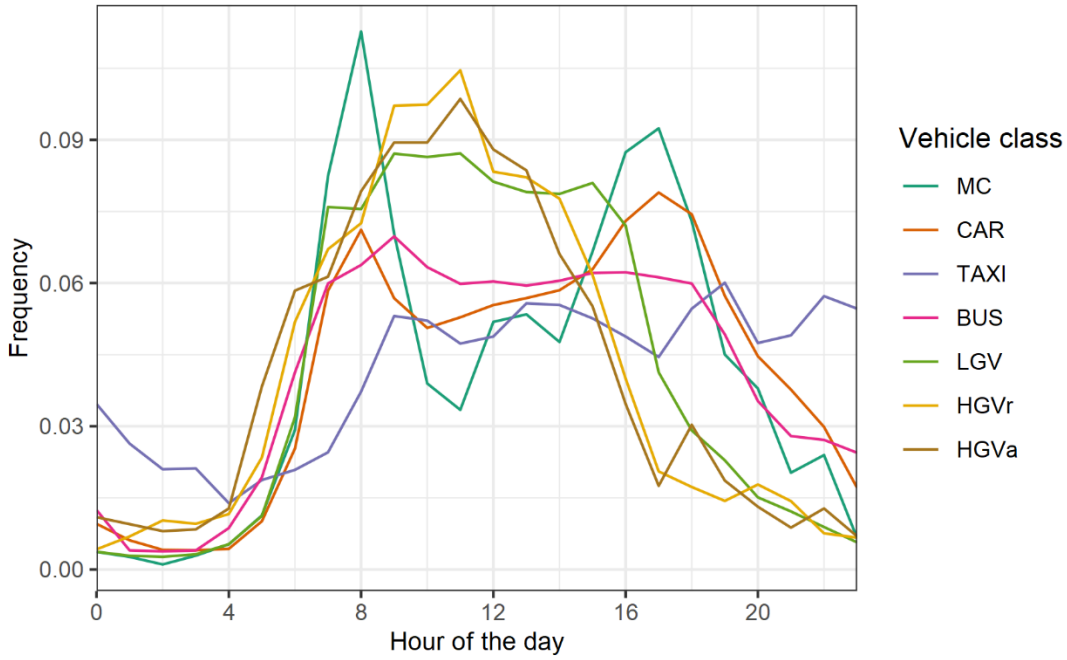

Figure 4.4 Diurnal profile of vehicle frequency by vehicle class. MC = motorcycle, HGVr = rigid HGV, HGVa = articulated HGV.

The diurnal profiles were then weighted by NO_x emissions per vehicle class calculated by EMIT and normalised to create one set of hourly factors for all modelled roads on weekdays. An example of the impact of accounting for differential emission rates and temporal variability per vehicle class on emission time factors compared to just raw traffic counts is shown in Figure 4.5. Data for Tuesday are shown. The emission weighting resulted in an almost flat profile in emissions from traffic in the middle of the day and no distinctive evening rush hour peak.

DfT hourly and daily road traffic statistics were used for weekends and to scale the hourly traffic factors derived from SEPA counts by the day of the week, respectively. Monthly traffic data from DfT were also weighted by NO_x emissions per vehicle class to create the monthly emission factors that are shown in Figure 4.6.

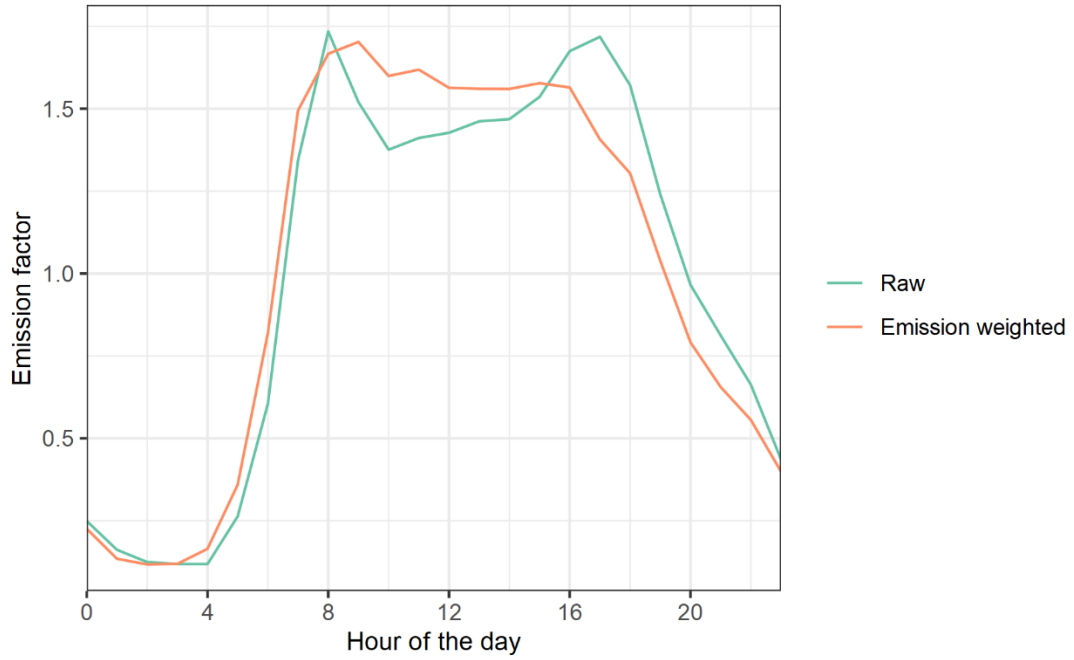

Figure 4.5 Hourly traffic emission factors derived from raw traffic counts (SEPA) and after weighting by NO_x emissions per vehicle category. Tuesday profile shown.

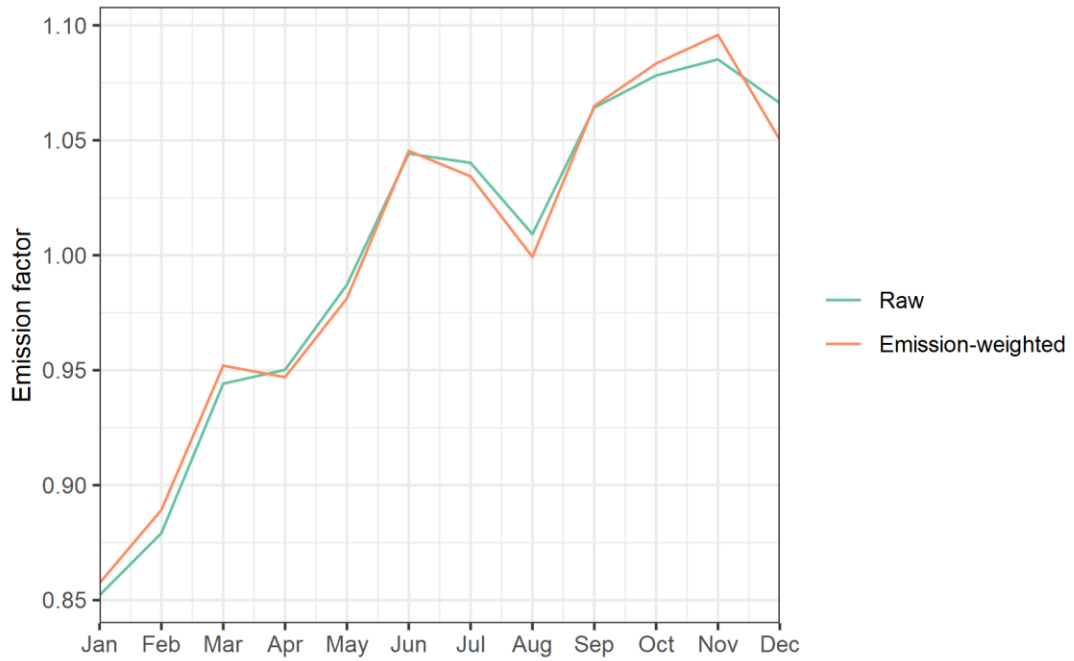

Figure 4.6 Monthly traffic emission factors from raw traffic counts (DfT) and after weighting by NO_x emissions per vehicle category.

A variety of emission source types, which are likely to have distinctive emission time profiles, were included in the modelled grid source. However, the ADMS-Urban version used in this study allowed only one emission time profile for the grid source. Therefore, emission profiles from the majority contributing SNAP sectors to overall NO_x emissions within the modelling domain were considered. Of those, SNAP 7 (Road transport) and SNAP 2 (Combustion in commercial, institutions, residential and agricultural sectors) emissions occurred in most grid cells, whereas the SNAP 8 (Other Transport and Machinery) sector contributed substantially in only a few (e.g. the railway station and railway lines, harbour). Consequently, only SNAP 7 and SNAP 2 sectors were selected and both sectors contributed equally to the single time-varying grid source profile. The derivation of SNAP 7 factors was described in the previous section. For SNAP 2 emissions the local gas demand hourly data for a representative week in winter obtained from Dr Grant Wilson (University of Birmingham, personal communication) were used (Figure 4.7).

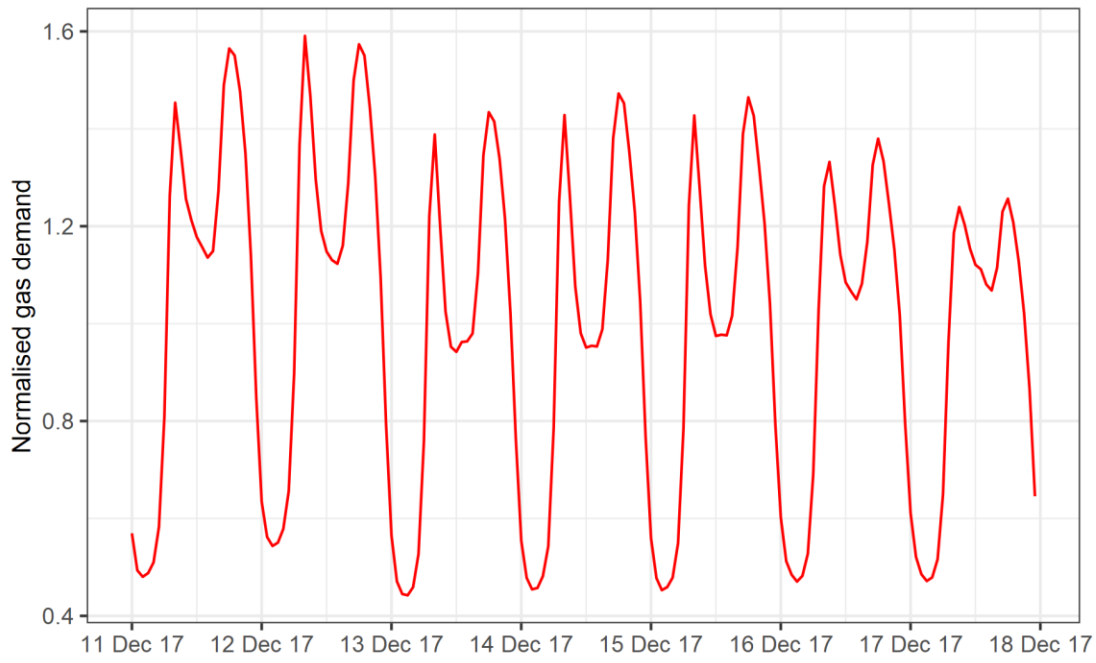

Figure 4.7 Normalised gas demand data for the week commencing Monday 11th December 2017. From Dr Grant Wilson (University of Birmingham).

The data in Figure 4.7 show low gas usage at night, and clear morning and evening peaks, both of which are less pronounced over the weekend. The inter-day variability was likely due to changing heating demands as air temperature changed as well as different population behaviour on weekdays and weekends. It was not possible to determine how much each factor contributed to the gas demand variability from one week's data. Therefore Saturday and Sunday hourly factors were retained to represent weekend emission profiles and Friday factors were used to represent the emission profile for every weekday. The profiles were scaled to ensure the factors added to unity. Monthly emission factors for SNAP 2 sector in the UK were taken from those used in the EMEP4UK model which originated from the GENEMIS project (Friedrich and Reis, 2004), and are shown in Figure 4.8.

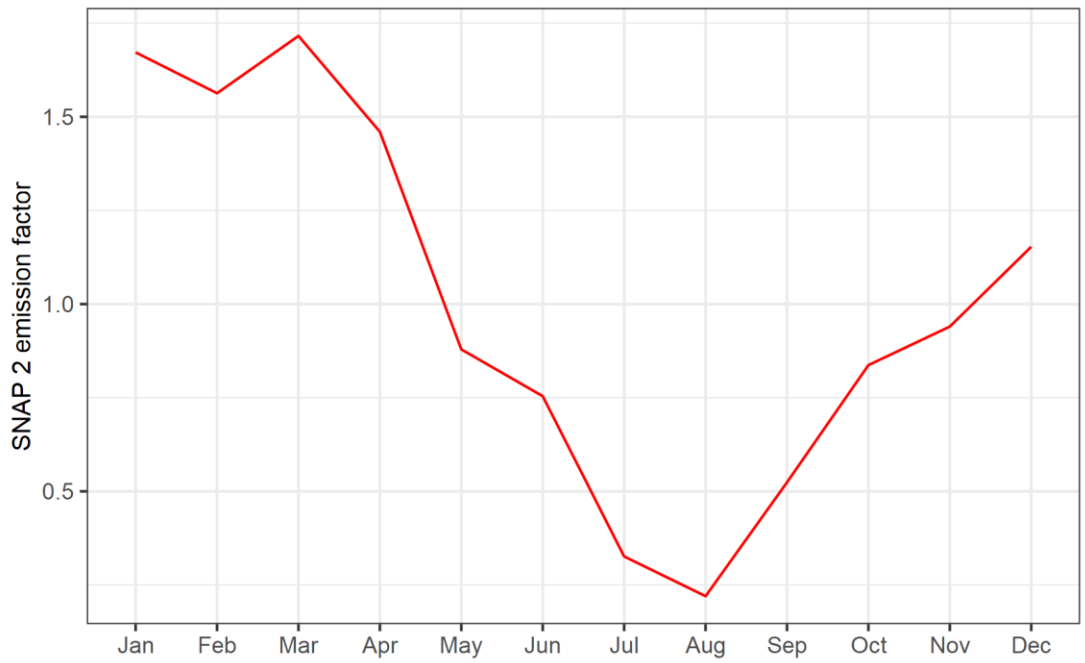

Figure 4.8 Monthly SNAP 2 emission factors in the UK.

Meteorological and background pollution concentrations data

Hourly meteorological data from Gogarbank meteorological station located to the west of the study area (Figure 4.1) were downloaded from the Centre for Environmental Data Analysis (Met Office, 2006). The meteorological variables used were air temperature, wind speed, wind direction and total cloud cover

amount. There were only 15 and 14 hourly observations in 2015 and 2016, respectively, where the value of at least one variable was missing. Those were filled in with the last previous measured value of the variable.

Measured air pollution data were downloaded from automatic monitoring networks using the openair library in R (Carslaw and Ropkins, 2012). Hourly background pollution concentration data were taken from the stations at Bush Estate (NO_x, NO_2 and O_3) (Figure 4.1) and at Auchencorth Moss ($PM_{2.5}$ and SO_2). The Auchencorth Moss site is located approximately 17 km to the south of Edinburgh city centre (not shown). ADMS-Urban stops running if 24 consecutive hours of input background pollution data are missing therefore gaps in the data had to be filled in. At Bush Estate the data capture for all downloaded pollutants exceeded 99% in 2015 but was around 89% in 2016. At Auchencorth Moss the data capture was more than 95% in 2015 and 87% in 2016 for $PM_{2.5}$ but only around 65% for SO_2 in both years. Except for SO_2, for which the missing values were set to zero, the missing values were filled in using a relationship calculated through ordinary least-square regression between the pollutant measured at one of the stations above and the nearest other automatic monitoring station which also measured that pollutant. The suburban monitoring station at Currie (Figure 4.9) was nearest in the case of NO_x and NO_2, Auchencorth Moss station in the case of O_3 and the urban background monitoring station at St Leonard's (Figure 4.9) in the case of $PM_{2.5}$. The summary of the relationships is presented in Table 4.3.

Table 4.3 Summary of relationships between hourly measurements at Bush Estate and Currie (NO_x and NO_2), Bush Estate and Auchencorth Moss (O_3), and Auchencorth Moss and St Leonards ($PM_{2.5}$). The relationships were used to fill in missing background concentration data.

	2015				2016			
	NO_x	NO_2	O_3	$PM_{2.5}$	NO_x	NO_2	O_3	$PM_{2.5}$
Slope	0.37	0.61	1.05	-0.95	0.39	0.63	1.03	-1.07
Intercept (μg m^{-3})	4.23	1.93	-3.52	0.60	4.82	1.81	-1.97	0.57
Adjusted R^2	0.43	0.59	0.76	0.63	0.45	0.63	0.79	0.47

Where both stations' data were missing during the same time period, and the period was less than three consecutive hours, linear interpolation was used to fill the gap. For the period of up to 24 consecutive missing data, the data from the previous day were used. Finally, for the period of up to one week of consecutive missing data, the data from the previous week were used.

Other model parameters and methods

In the model runs in this study the Advanced Street Canyon modelling option version 1 (Jackson et al., 2016) was used to model street canyons in the study area. Since the Advanced Street Canyon Module accounts for porosity (the ratio of gaps between buildings and street canyon length), all modelled roads were modelled as street canyons. Street canyon parameters were calculated using building placement and height data in OS MasterMap. Aside from the Advanced Street Canyon module, other modelling options used were ozone chemistry modelling, night-time chemistry modelling and a shift in emission temporal distribution due to change between GMT and BST and back again in March and October each year, respectively.

Neither dry nor wet deposition of any pollutant was modelled. Other modelling options such as Urban Canopy Flow option and Complex Terrain option were also tested. However, despite substantially increasing the model run time, those options had little impact on modelled concentrations and were not used in the final modelling strategy.

Due to the size of the domain and licence limit on the number of explicitly modelled sources, the domain was split into four modelling sub-domains which were run separately and the individual run outputs were subsequently combined for the final output.

ADMS-Urban output and verification

For the exposure analysis the model calculated mean hourly concentrations of NO_x, NO_2, O_3 and $PM_{2.5}$ at every postcode within the study area. The height of all modelled receptor points was set to 1.5 m.

For model verification purposes hourly mean concentrations of the above pollutants were calculated at seven fixed-site automatic air quality monitoring stations operational in 2015 and 2016 in the study area (Figure 4.9). Of those, four sites were classified as roadside sites (Gorgie Road, Salamander Street, Queen Street, Queensferry Road), the remaining three were classified as suburban (Currie), urban background (St Leonards) and kerbside (St John's Road). The St Leonards station's NO_x instrument was offline for all of 2015 and early 2016. The year 2016 was therefore also modelled in order to verify the model output at a site type which is representative of the majority of the receptor points in the study.

Additionally, NO_2 concentrations were calculated at over 100 locations of diffusion tube monitoring sites in the study area. The locations of automatic monitoring stations and diffusion tubes were inspected using Google Street View and, where necessary, the locations were adjusted so that the distance of the modelled site from the modelled road reflected the true distance between those in the real world. The receptor height at the monitoring stations was set to the height of the inlets obtained from the City of Edinburgh Air Quality Annual Progress Report (The City of Edinburgh Council, 2016). No information on the height of the diffusion tubes was available, therefore the height of 2 m was assigned to all of the tubes.

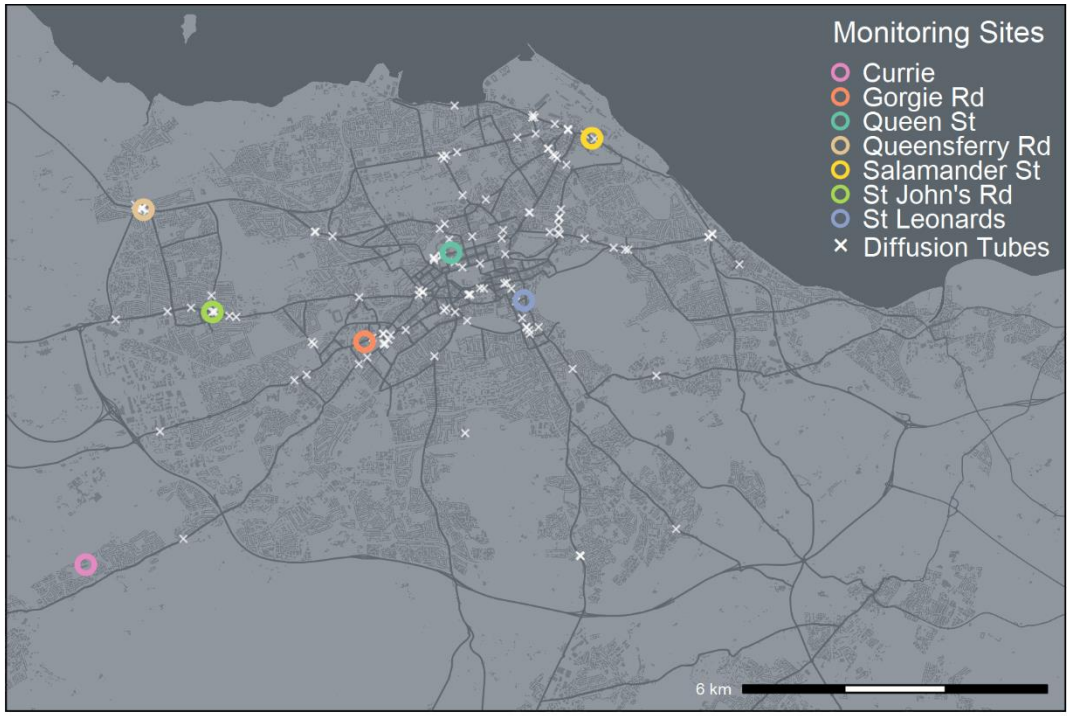

Figure 4.9 Locations of automatic monitoring stations and diffusion tubes in the study area. Contains OS Data © Crown copyright and database right (2021).

4.2.3 Exposure analysis

The exposure analysis strategy is the same as in the previous chapter (Section 3.2.3). Briefly, four exposure scenarios were considered – residential exposure only (RE) and three scenarios that considered exposure at place of work or study ($RWE_{9\text{-}17}$, $RWE_{8\text{-}18}$ and RWE_{hw+}) reflecting a potential range of time people spend there. The exposure scenarios were used to estimate exposure of the total population as well as population sub-groups based on age, sex, ethnic group and Carstairs index decile. Summary statistics of exposures for each group, air pollution model and exposure scenario were calculated. The same Python and R libraries and methods described in Section 3.2.3 were used for the exposure calculations, analysis and presentation. The same dissemination restrictions as described in Section 3.2.4 also apply here.

4.3 Results and Discussion

4.3.1 ADMS-Urban verification

Automatic monitoring stations

The results of commonly used statistics for model verification comparing ADMS-Urban hourly concentration predictions with observations at the automatic monitoring stations in the study area are presented in Tables 4.4 and 4.5, for 2015 and 2016 respectively. Only St Leonards station measured O_3 and $PM_{2.5}$ in 2015 and 2016 therefore the model verification of those pollutants is limited to that station. Scatter plots of observed versus modelled hourly concentrations for all pollutants measured at St Leonards station ($PM_{2.5}$ in 2015; O_3, NO_x and NO_2 in 2016) are shown in Figures 4.10-4.13. Due to a large number of displayed points (> 8000) that often overlap the plot areas in Figures 4.10-4.13 are divided into hexagons. A colour scale is then used to show the number of points within each hexagon. The model performs reasonably well at St Leonards for all pollutants, particularly for O_3 where the model underestimates mean concentrations by only 3%, and 83% of the modelled concentrations are within a factor of two (FAC2). The model underpredicts $PM_{2.5}$ concentrations by 16%. The high observed $PM_{2.5}$ concentrations of >60 µg m^{-3} seen in Figure 4.11 occurred on 5th November when fireworks are traditionally set off in the UK. This event and the corresponding increase in emissions was not included in the model setup. In the case of NO_x and NO_2 the model overpredicts the mean concentration of the former by 7% and underpredicts those of the latter by 5%. Over 70% of the modelled NO_x and NO_2 values lie within FAC2.

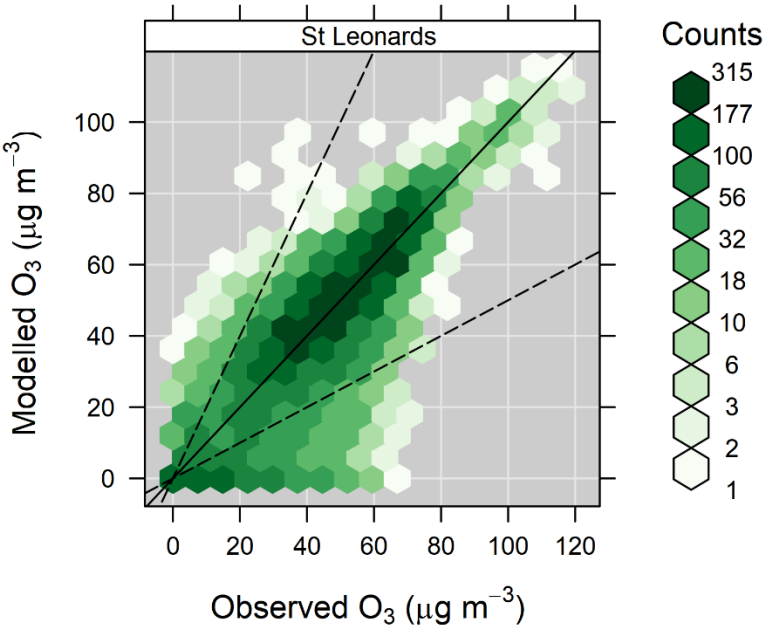

Figure 4.10 Scatter plot of modelled vs observed hourly O_3 concentrations at St Leonards urban background station in 2016. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationships.

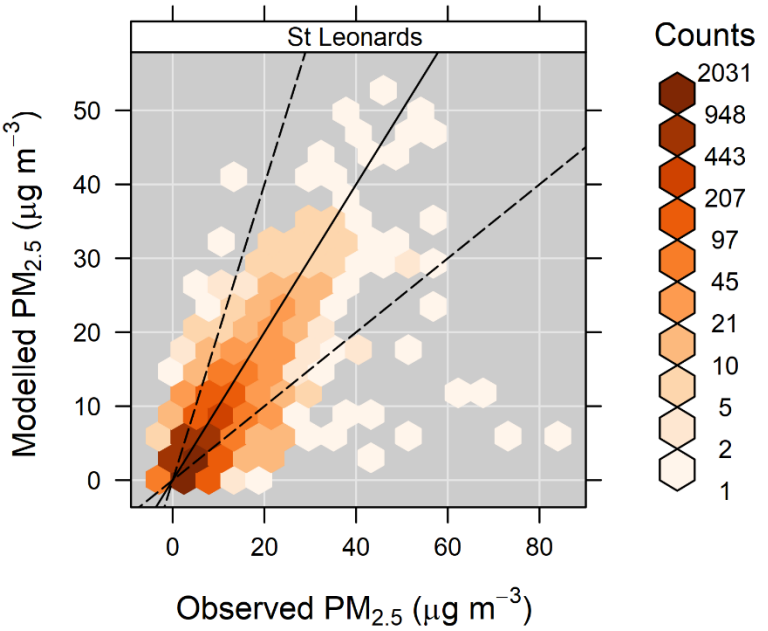

Figure 4.11 Scatter plot of modelled vs observed hourly $PM_{2.5}$ concentrations at St Leonards urban background station in 2015. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationship.

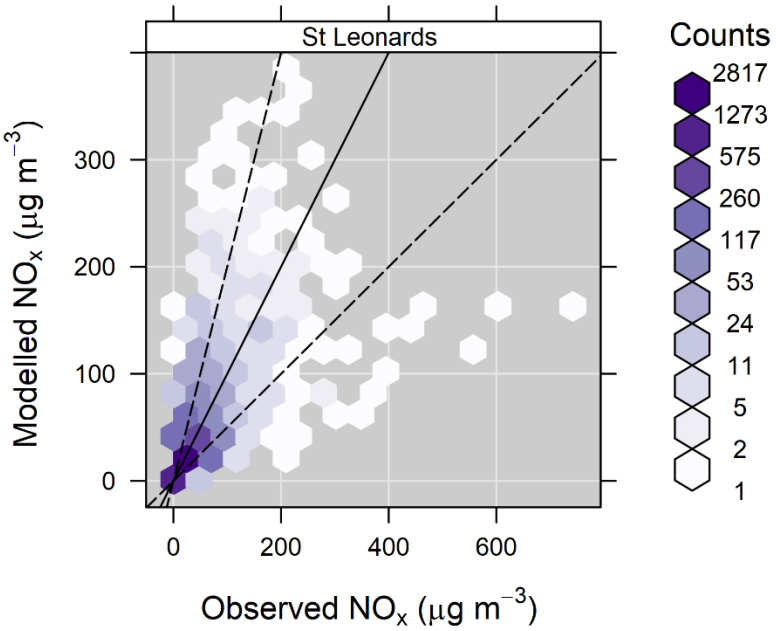

Figure 4.12 Scatter plot of modelled vs observed hourly NO_x concentrations at St Leonards urban background station in 2016. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationships.

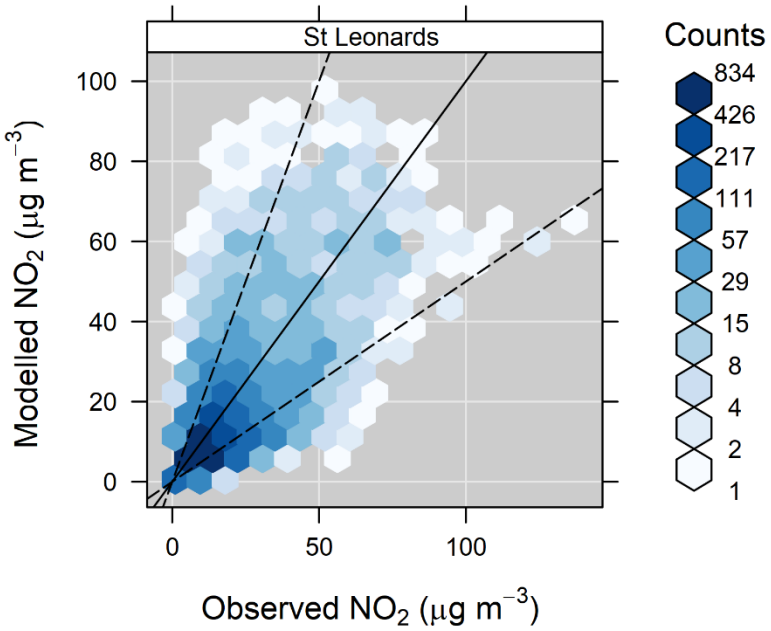

Figure 4.13 Scatter plot of modelled vs observed hourly NO_2 concentrations at St Leonards urban background station in 2016. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationships.

Table 4.4 Model evaluation statistics comparing the hourly ADMS-Urban model output against observations at automatic monitoring stations in the study area in 2015. n = number of observations, FAC2 = fraction of prediction within a factor of two, MB = mean bias, NMB = normalised mean bias, RMSE = root mean squared error, r = Spearman correlation coefficient.

Site	Site Type	Pollutant	*n*	Observed mean ($\mu g\ m^{-3}$)	FAC2	MB ($\mu g\ m^{-3}$)	NMB (%)	RMSE ($\mu g\ m^{-3}$)	*r*
St Leonards	Urban BG	NO_x	0	-	-	-	-	-	-
Currie	Suburban	NO_x	8360	8.3	0.54	4.7	56	18.4	0.60
Gorgie Rd	Roadside	NO_x	7778	68.8	0.80	1.0	1	52.2	0.64
Queen St	Roadside	NO_x	8587	56.5	0.70	6.9	12	53.5	0.59
Salamander St	Roadside	NO_x	8672	70.9	0.69	-10.2	-14	57.5	0.65
Queensferry Rd	Roadside	NO_x	8130	125.9	0.49	-69.9	-56	107.5	0.73
St John's Rd	Kerbside	NO_x	7827	181.2	0.50	-87.5	-48	144.2	0.68
St Leonards	Urban BG	NO_2	0	-	-	-	-	-	-
Currie	Suburban	NO_2	8360	6.0	0.53	3.2	52	9.3	0.73
Gorgie Rd	Roadside	NO_2	7778	31.4	0.82	0.0	0	17.1	0.68
Queen St	Roadside	NO_2	8587	26.9	0.75	6.1	23	20.3	0.64
Salamander St	Roadside	NO_2	8672	27.9	0.75	1.8	7	17.8	0.66
Queensferry Rd	Roadside	NO_2	8130	40.3	0.75	-11.7	-29	22.0	0.74
St John's Rd	Kerbside	NO_2	7827	64.5	0.59	-25.0	-39	41.9	0.57
St Leonards	Urban BG	O_3	8574	44.1	0.85	3.3	8	13.2	0.83
St Leonards	Urban BG	$PM_{2.5}$	7536	6.0	0.60	-1.0	-16	4.2	0.81

Table 4.5 Model evaluation statistics comparing the hourly ADMS-Urban model output against observations at automatic monitoring stations in the study area in 2016. n = number of observations, FAC2 = fraction of prediction within a factor of two, MB = mean bias, NMB = normalised mean bias, RMSE = root mean squared error, r = Spearman correlation coefficient.

Site	Site Type	Pollutant	*n*	Observed mean (µg m^{-3})	FAC2	MB (µg m^{-3})	NMB (%)	RMSE (µg m^{-3})	*r*
St Leonards	Urban BG	NO_x	5647	30.2	0.76	2.2	7	32.6	0.64
Currie	Suburban	NO_x	8494	9.3	0.56	5.5	59	21.7	0.55
Gorgie Rd	Roadside	NO_x	8738	69.1	0.78	7.2	10	55.4	0.64
Queen St [a]	Roadside	NO_x	4294	48.2	0.58	23.1	48	62.0	0.53
Salamander St	Roadside	NO_x	8074	70.0	0.72	-5.2	-7	59.1	0.68
Queensferry Rd	Roadside	NO_x	7284	130.4	0.50	-67.7	-52	104.3	0.74
St John's Rd	Kerbside	NO_x	8509	164.9	0.55	-72.3	-44	126.7	0.74
St Leonards	Urban BG	NO_2	5647	19.6	0.73	-1.1	-5	12.8	0.71
Currie	Suburban	NO_2	8494	6.6	0.58	3.5	53	10.3	0.69
Gorgie Rd	Roadside	NO_2	8738	32.4	0.83	1.6	5	17.4	0.69
Queen St [a]	Roadside	NO_2	4294	25.8	0.63	10.9	42	23.3	0.60
Salamander St	Roadside	NO_2	8074	26.1	0.78	4.6	18	17.5	0.72
Queensferry Rd	Roadside	NO_2	7284	41.8	0.75	-10.9	-26	22.1	0.74
St John's Rd	Kerbside	NO_2	8509	52.9	0.71	-14.0	-27	27.0	0.73
St Leonards	Urban BG	O_3	8534	44.7	0.83	-1.5	-3	13.6	0.82

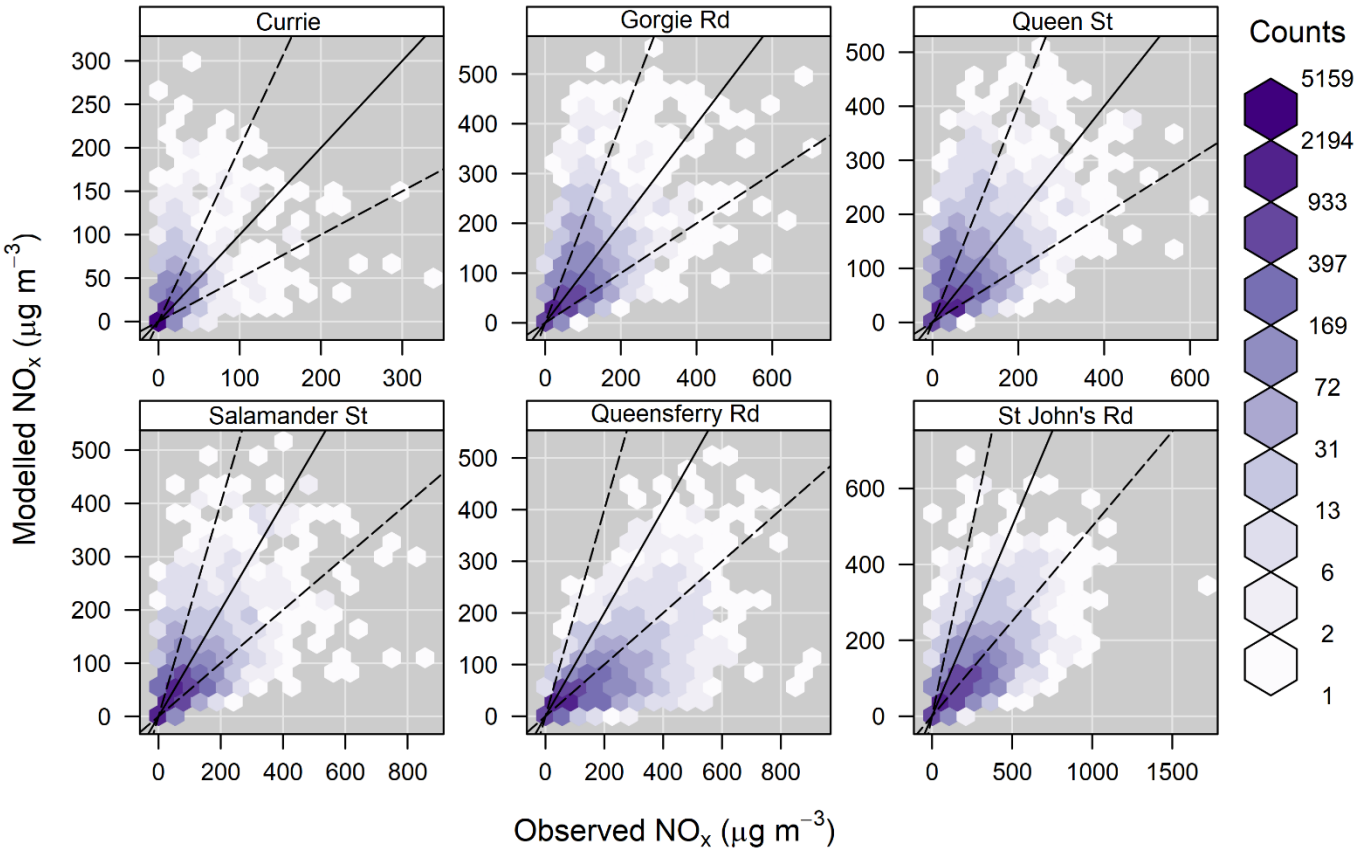

Figure 4.14 Scatter plots of modelled vs observed hourly NO_x concentrations at the automatic monitoring stations in the study area in 2015. Due to the large number of points, a colour scale is used to show the density of plotted points. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationships.

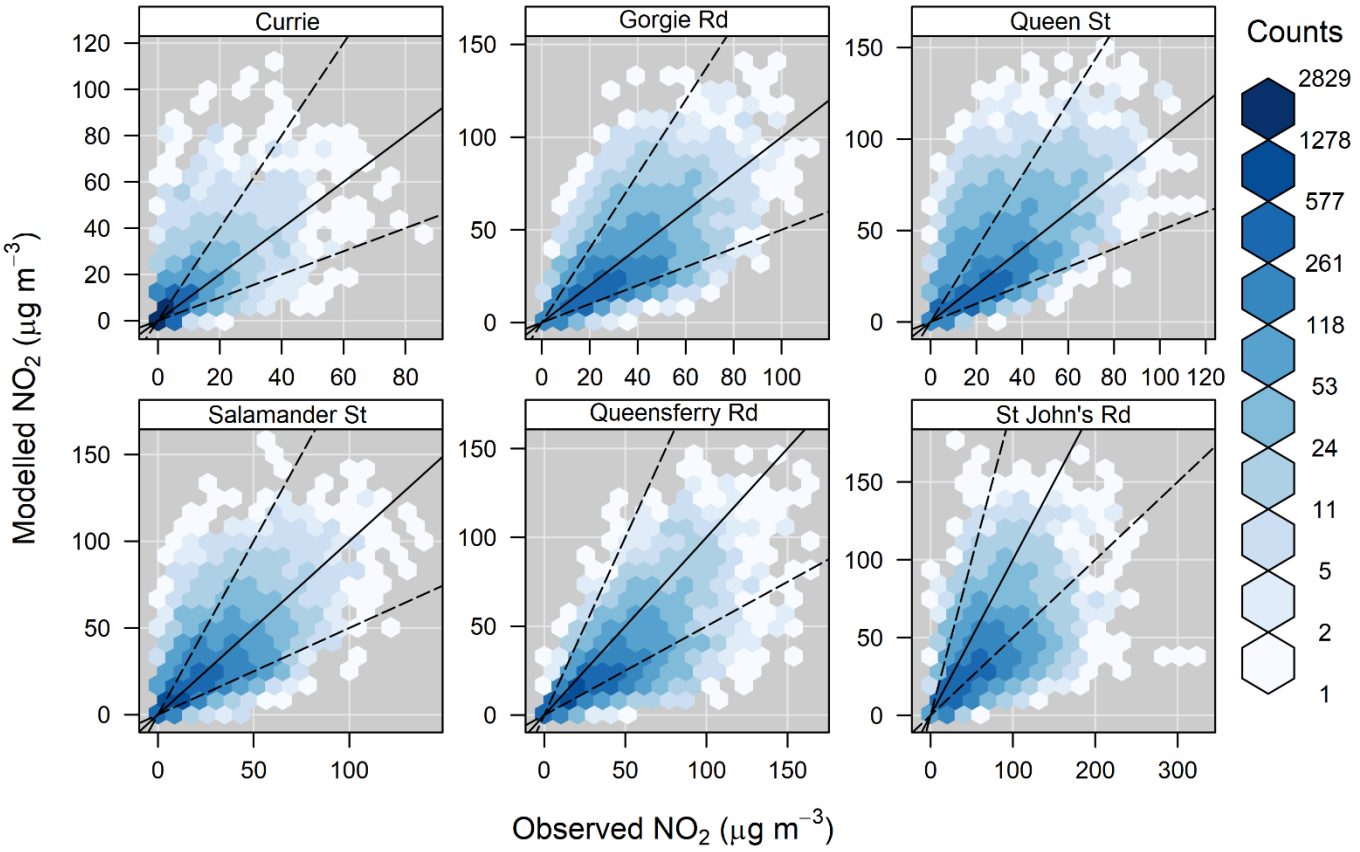

Figure 4.15 Scatter plots of modelled vs observed hourly NO_2 concentrations at the automatic monitoring stations in the study area in 2015. Due to the large number of points, a colour scale is used to show the density of plotted points. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationships.

Figures 4.14 and 4.15 show scatter plots of the 2015 modelled versus observed hourly NO_x and NO_2 concentrations, respectively, at the remaining monitoring stations in the study area. Tables 4.4 and 4.5, and Figures 4.14 and 4.15, show that the model performance at the other sites is mixed. The model overpredicts NO_x and NO_2 concentrations at the suburban site at Currie by approximately 50%; however, due to very low measured concentrations there, the mean bias in NO_x and NO_2 concentrations is only 4.7 µg m^{-3} and 3.2 µg m^{-3}, respectively, in 2015. In 2016, the overprediction is slightly larger. On the other hand, the model substantially underpredicts concentrations at the kerbside site at St John's Road where only 50% of the modelled NO_x concentrations in 2015 are within FAC2 and concentrations are on average 56% (or 69.9 µg m^{-3}) below observations. The results at the roadside sites range from a large underprediction of both NO_x and NO_2 at Queensferry Road to the northwest of the study area to an overprediction at Queen Street in the city centre.

It is worth noting that some model overprediction is expected due to the location of the Bush Estate monitoring station which provided the background concentration data for the model. As the station is situated to the south of Edinburgh and to the west of some built up areas, during winds from the north and east the station is not upwind of the modelling domain and some double-counting of emissions will have occurred. This impacts the suburban site at Currie the most as the NO_x and NO_2 concentrations are very low there. When winds are blowing from the 120º - 300º (south to southwesterly) direction the model MB for NO_2 at Currie is only 1.9 µg m^{-3} whereas for the other wind directions it is 7.2 µg m^{-3}. The issue cannot be avoided as there are no suitable background monitoring stations to the northeast of and sufficiently close to the modelling domain that could be utilised during north or northeasterly winds. The overall impact of this is likely to be small however, as winds from the 120º - 300º sector occurred most (78%) of the time.

Further investigation into the model performance was conducted at the monitoring stations where the model performed relatively poorly, namely at St

John's Road, Queensferry Road and Queen Street. The bottom left panel in Figure 4.16 shows a map of the area around St John's Road station including the locations of nearby diffusion tube monitoring sites which were also considered for model verification.

It can be seen in the figure that the large negative bias in modelled NO_2 concentrations at St John's Road only appears at the sites located on the southern side of the T-junction. In 2015, the observed annual mean NO_2 at the monitoring station was 64.5 µg m^{-3}. At the diffusion tube site 1d, located on a façade of a building 5 m to the west of the monitoring station and around 2.3 m from the kerb, annual mean NO_2 was 45.7 µg m^{-3}. The model underestimated the concentrations by 25.0 µg m^{-3} at the former and 10.6 µg m^{-3} at the latter. In contrast, the observed annual mean NO_2 at the diffusion tube site 1, on the north-eastern corner of the T-junction, and at diffusion tube site 1b, which is 40 m to the east of the junction, was 34.5 µg m^{-3} and 32.6 µg m^{-3}, respectively. At those two sites the model output was within 1.0 µg m^{-3} of the observations.

The contrast in measured concentrations by the diffusion tubes on either side of the junction suggests that the geometry of the street canyon may have created a very localised hotspot of air pollution near the monitoring station which the model was not able to replicate. The large underestimation of modelled concentrations at St John's Road site may also have been caused by underestimation of NO_x emissions in the area. The road where the automatic station is located is a well-known bottleneck for traffic with frequent traffic queues present. Queuing traffic was not considered in the modelling approach as there were no data on queuing frequency, duration and length available for the whole study area.

However, several sensitivity runs were conducted to examine the potential effect of lower traffic speeds and traffic queues on the modelled concentrations. These showed that queueing traffic would have had to be present near St John's Road station for most of the day throughout the year

for the modelled NO_2 concentrations to increase to within 10% of the observed concentrations by the automatic monitoring station. However, such a scenario also increased modelled NO_2 concentrations at the diffusion tube site 1 by 19.2 µg m^{-3} resulting in a substantial overestimation there. Detailed traffic data including accurate information on speed, traffic queue occurrence and duration together with detailed CFD model simulations would have been required to provide a better understanding of the contribution of each issue to the overall model bias at St John's Road.

The top left panel of Figure 4.16 shows a map of the area around Queensferry Road monitoring station. There are six diffusion tube monitoring sites located within 80 m of the automatic monitoring station, one of which is site 64 which observed the highest annual mean NO_2 concentration by a diffusion tube in the study domain and where there was the largest MB between observed and modelled concentrations in both 2015 and 2016. In the modelled years, the area surrounding the Queensferry Road monitoring station was a relatively open suburban environment where the street canyon geometry would likely have had a much smaller effect on pollution build-up than at St John's Road monitoring station.

It is likely that underestimated emissions was the factor contributing most to the negative model bias there. The carriageway by which the site is located is a major route out of Edinburgh with a major junction about 100 m to the west of the automatic monitoring station which results in frequent traffic congestion, particularly during the rush hour. Moreover, there is a bus stop adjacent to the monitoring station with a pedestrian crossing nearby. Similarly to traffic queues, the acceleration of buses and general traffic away from bus stops and pedestrian crossings were not considered in the model setup. It is worth noting however that whilst the model agreement in the area near the automatic monitoring station is generally poor, the agreement with the data from diffusion tube site 62 located approximately 200 m to the east of the junction and set back about 17 m from the kerb is very good.

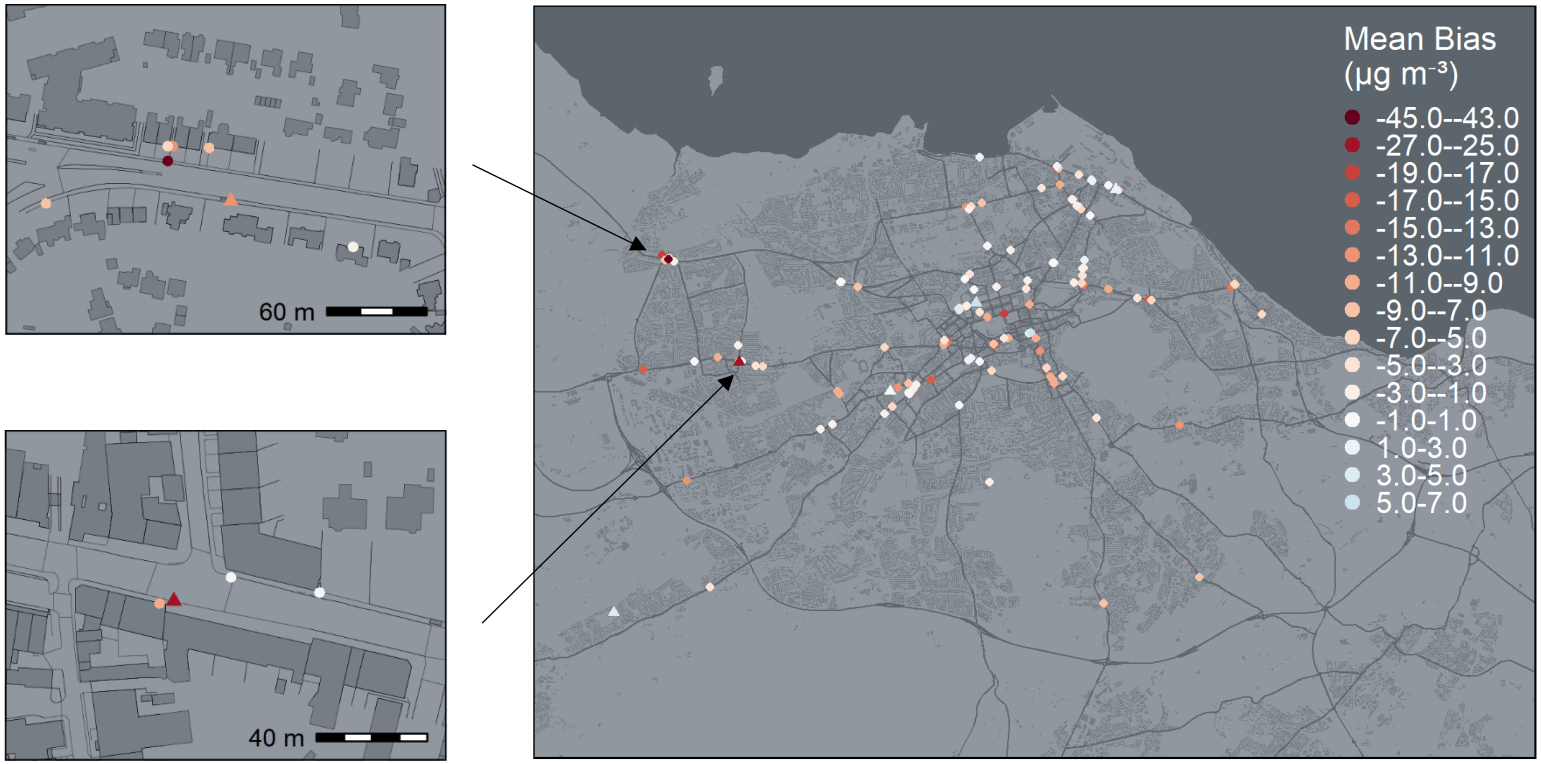

Figure 4.16 Mean bias of modelled NO_2 concentrations in the study area in 2015. Upper left panel shows in greater detail the area around Queensferry Road automatic monitoring station, bottom left panel shows the area around St John's Road automatic monitoring station. Triangles represent automatic monitoring stations, circles represent diffusion tube sites. ©Crown copyright/MasterMap 2021. Ordnance Survey/Edina supplied service.

The positive model bias at Queen Street station was also investigated, particularly the effect of the modelled street canyon on predicted concentrations. A map of the area is shown in the bottom right panel of Figure 4.17

There were no diffusion tube sites near the automatic monitoring station in the modelled years. The station (before being decommissioned in summer 2016) was located in an asymmetric street canyon where part of the street immediately to the west of the station was a two-sided canyon, whereas the station itself and the section of the road to the east of it were in a one-sided canyon with no obstacles behind the station. Whilst the Advanced Street Canyon Module within the modelling system accounts for canyon porosity based on the ratio of building face length and the road length (25:58 in this case), it is unable to simulate the exact location of the gaps between buildings unless the modelled road link is divided into shorter links, each with more homogeneous canyon geometry. Furthermore, when the modelled street canyon is asymmetric and the wind direction is parallel or near parallel with the canyon, the Advanced Street Canyon Specification document states that:

> Average (canyon) height and porosity values are used for all calculations, as upstream and downstream edges cannot be defined with confidence (CERC, 2015a).

The consequences of those limitations on modelled concentrations at Queen Street station are large, as demonstrated by two modelling simulations presented in Figure 4.17. Figure 4.17 shows the 2015 mean modelled NO_2 concentrations along a transect perpendicular to the centre line of the nearest modelled road and going through the monitoring station. Results for four wind direction sectors are shown. Two wind sectors are parallel or near parallel (<= ±30º) to the modelled road centre line, the other two sectors represent all the other wind directions and are considered perpendicular or near perpendicular. The blue triangle in Figure 4.17 represents the location of the monitoring station along the transect (all panels) and the mean observed NO_2 concentrations at the station (concentration panels). In the ‘main’ street canyon

simulation the road link was simulated as one link whereas in the 'alternative' simulation the road link is divided into two separate links at the point where the two-sided canyon transitions into a one-sided one. All other model input parameters were kept the same.

Figure 4.17 clearly shows that there are substantial differences in modelled NO_2 concentrations between the two simulations. At the monitoring site the main simulation always results in higher mean NO_2 concentrations than the alternative simulation. The difference is approximately 8-13 µg m^{-3} except for the 100º-220º winds sector where the results are comparable. The main simulation agrees well with observations when the wind direction is parallel with the road centre line. However it substantially overestimates concentrations during cross winds. The cross winds only occur 23.1% of the time; therefore despite the approximate 23 µg m^{-3} model bias, the overall mean bias equals 6.1 µg m^{-3}. In comparison, the alternative simulation overestimates concentrations during cross winds by ~13 µg m^{-3} but underestimates them during the prevailing south-westerly winds. Overall, these biases per wind sector almost cancel each other out and the alternative simulation results in a substantially better agreement with the observed concentrations (MB = -0.5 µg m^{-3}, NMB = 2.0%) at the monitoring station than the main simulation.

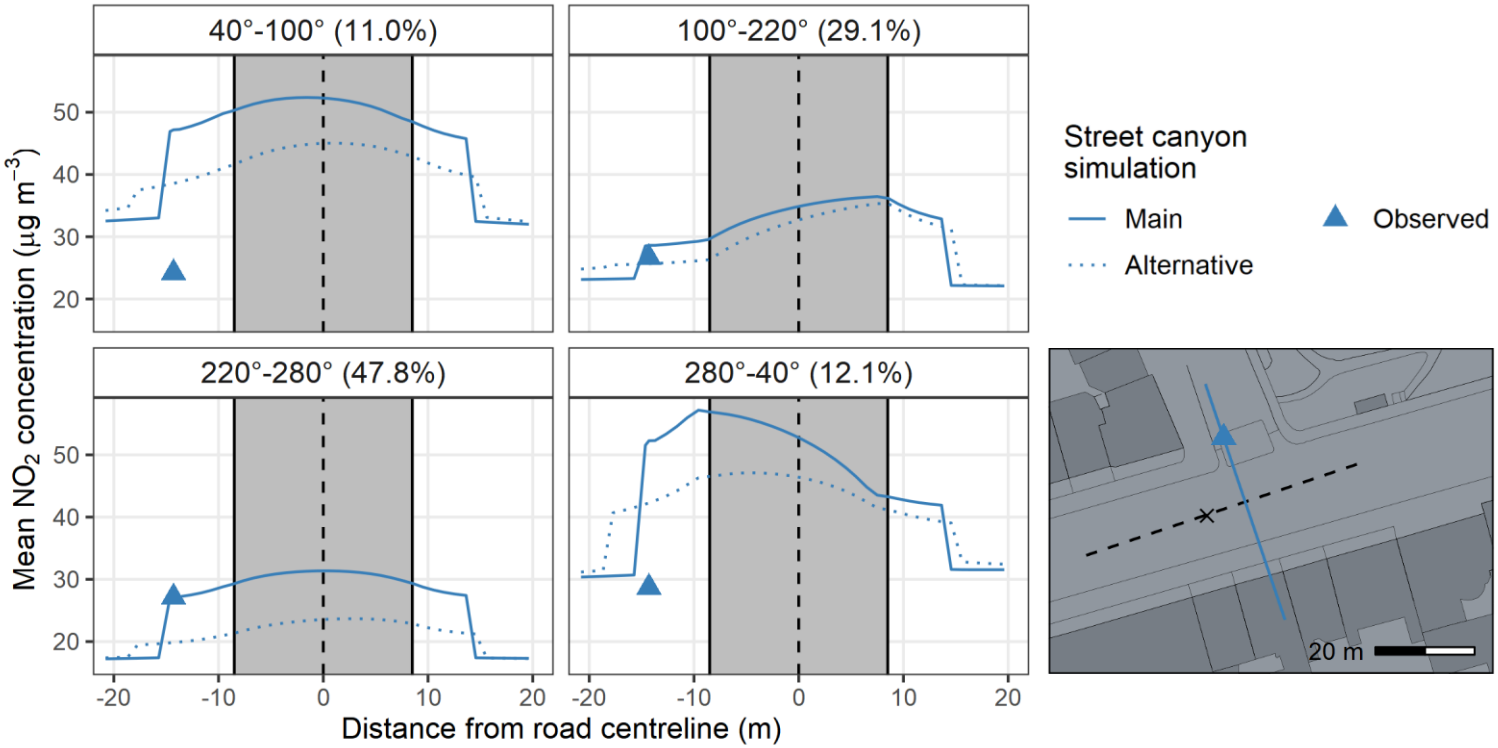

Figure 4.17 Modelled mean NO_2 concentrations on a transect through Queen Street monitoring station (Δ) per wind direction sector. Left panels – wind parallel or near parallel to the road centre line. Middle panels – wind perpendicular or near perpendicular to the road centre line. Bottom right panel shows a map of the area where dark grey polygons represent buildings. The solid blue line in the concentration panels represents the main simulation where the road link shown as a black dashed line on the map is modelled as one. The dotted line represents an alternative simulation where the road link is split into two at the vertex (×). Frequency of the wind from a presented sector is given as a percentage at the top of each panel. ©Crown copyright/MasterMap 2021. Ordnance Survey/Edina supplied service.

Passive NO_2 diffusion tube sites

The model evaluation statistics using annual data from passive NO_2 diffusion tubes are presented in Tables 4.6 and 4.7. A scatter plot of the annual mean modelled versus observed NO_2 concentrations in 2015 is shown in Figure 4.15. The model generally tends to underpredict NO_2 concentrations at the diffusion tube sites but overall performs well with nearly all modelled monthly mean concentrations within FAC2. At the four urban background sites in the study area the NMB is -11% in 2015 and -8% in 2016. At the sites in the vicinity of roads the model tends to underestimate NO_2 concentrations by a larger margin; however on average the magnitude of the NMB is never more than 19%. One exception is diffusion tube site 64 where the MB equals -43.9 µg m^{-3}. The potential reasons for the model underestimation at site 64 have already been discussed.

Table 4.6 Model evaluation statistics comparing the annual averaged NO_2 ADMS-Urban model output against data obtained from passive diffusion tubes in the study area in 2015. n = number of observations, FAC2 = fraction of prediction within a factor of two, MB = mean bias, NMB = normalised mean bias, RMSE = root mean squared error, r = Spearman correlation coefficient.

Site Type	*n*	Observed (µg m^{-3})	Modelled (µg m^{-3})	FAC2	MB (µg m^{-3})	NMB (%)	RMSE (µg m^{-3})	*r*
Urban BG	4	20.1	18.0	1.00	-2.1	-11	2.5	0.95
Roadside	115	34.2	27.8	0.96	-6.5	-19	9.0	0.56
Kerbside	12	36.2	30.6	1.00	-5.7	-16	7.5	0.80

Table 4.7 Model evaluation statistics comparing the annual averaged NO_2 ADMS-Urban model output against data obtained from passive diffusion tubes in the study area in 2016. n = number of observations, FAC2 = fraction of prediction within a factor of two, MB = mean bias, NMB = normalised mean bias, RMSE = root mean squared error, r = Spearman correlation coefficient.

Site Type	*n*	Observed (µg m^{-3})	Modelled (µg m^{-3})	FAC2	MB (µg m^{-3})	NMB (%)	RMSE (µg m^{-3})	*r*
Urban BG	4	21.4	19.6	1.00	-1.8	-8	2.3	0.94
Roadside	109	37.1	30.4	0.99	-6.6	-18	9.3	0.56
Kerbside	11	39.6	33.2	1.00	-6.4	-16	8.4	0.83

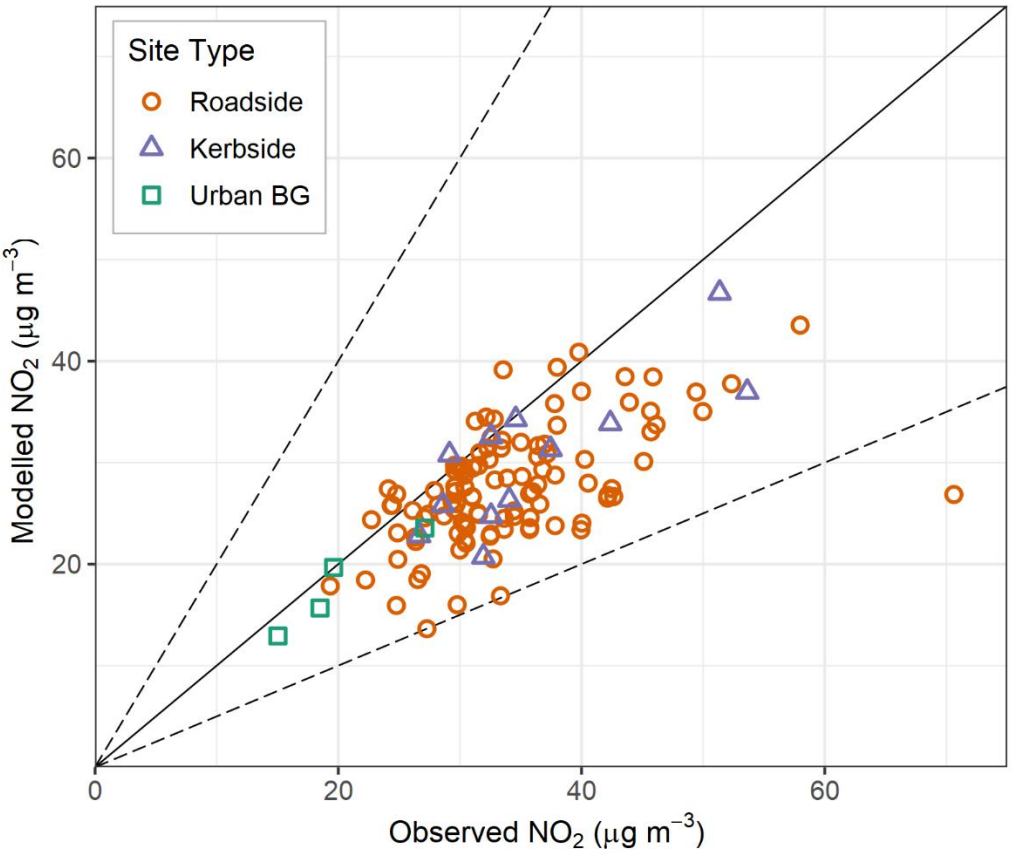

Figure 4.18 Scatter plot of modelled vs observed annual NO_2 concentrations by passive diffusion tubes in 2015. The solid line represents 1:1 relationship, the dashed lines 2:1 and 1:2 relationships.

Inter-annual consistency and temporal agreement

Data presented in Tables 4.6 and 4.7 show that the modelling results are similar for a given pollutant and site in both modelled years even though there is a small shift in MB and NMB of the model in the positive direction (i.e. the negative values are less negative, and the positive values are more positive) from 2015 to 2016 at almost all stations. Two notable exceptions are St John's Road and Queen Street stations. At St John's Road in 2016 the model performance dramatically improved compared to 2015. This improvement was solely due to the station observing a large drop in NO_2 concentrations (see Tables 4.4 and 4.5) from the previous year whilst the modelled annual mean concentrations remained almost the same. The drop in measured concentrations was not observed at the diffusion tube locations nearby, however. There was only a very small decrease of 0.6 μm^{-3} in NO_2

concentrations at site 1d nearest to the monitoring station. Sites 1 and 1b saw a small increase in annual mean concentrations of approximately 3 µg m^3 which was well replicated by the model. It is unclear why only the monitoring station observed the large improvement in air quality in the area. There may have been issues with the performance or calibration of the analyser. At Queen Street the model performance is substantially worse in 2016 than it is in 2015. Measured NO_2 concentrations from January until June are comparable between the years, however the model output is over 5 µg m^{-3} higher in 2016 than in 2015. This is possibly due to NO_x emissions in the NAEI grid cells immediately to the west and northwest increasing by 3.7% and 12.4%, respectively from 2015 to 2016. This in turn changed the MB from -0.9 µg m^{-3} to 3.2 µg m^{-3} during westerly winds and from 15.9 µg m^{-3} to 27.6 µg m^{-3} during northwesterly winds.

Except for the two stations mentioned above, the inter-annual consistency described in the previous paragraph and shown in Tables 4.6 and 4.7 suggests that the NO_x and NO_2 model performance at St Leonards station in 2015 is likely comparable to that in 2016, albeit in terms of MB and NMB likely more negative and less positive, respectively. Since the modelled temporal distribution of emissions is the same in both modelled years, the hourly, daily and monthly variability is also likely to be similar between the years. Consequently, the 2016 modelled and observed data are considered appropriate to assess the temporal agreement between the model and observations for NO_x, NO_2 and O_3. $PM_{2.5}$ was only modelled in 2015 so data from that year are used.

The temporal agreement between the modelled and observed concentrations is demonstrated using the background monitoring station at St Leonards and shown in Figures 4.19-4.22. For NO_x, the model replicates all temporal profiles well except for overestimating the afternoon peak. The model simulates the monthly and diurnal profiles of NO_2 concentrations at St Leonards also well; however, it tends to underestimate the concentrations in the early morning between 00:00 and 04:00 and then again during the day between 07:00 and

15:00 by approximately 2-3 µg m^{-3}. On the other hand, the model tends to overpredict NO_2 concentrations by a similar amount between 17:00 and 00:00. As a result, there is a mean bias of -3.6 µg m^{-3} and -3.2 µg m^{-3} between the modelled and observed concentrations during working hours for the $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$ scenarios, respectively, whilst the mean bias outside working hours is -0.3 µg m^{-3} for the former and -0.1 µg m^{-3} for the latter. In comparison, at the suburban site at Currie (not shown) there is a mean bias of 3.8 µg m^{-3} during working hours for both $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$ scenarios. The mean bias outside working hours at Currie is 2.2 µg m^{-3} and 2.7 µg m^{-3} for $RWE_{9\text{-}17}$ and $RWE_{8\text{-}18}$, respectively. This means that if the model bias at the two sites were representative of the bias at the outer suburban and inner urban background areas, respectively, the model output would modify the difference between RWE and RE to NO_2 both spatially and temporally for those who live in the suburbs and commute to the city centre for work (and vice versa).

For example, a hypothetical person ‘A’ living at Currie and working at St Leonards would, after weighting for the number of hours spent in each place, be exposed on average to an additional 1.7 µg m^{-3} of NO_2 in the $RWE_{8\text{-}18}$ scenario compared to the base RE scenario than the modelled concentrations imply. Another person ‘B’ with the reverse commute pattern (i.e. living at St Leonards and working at Currie) would have their decrease in NO_2 exposure underestimated by the model by the same amount (Table 4.8). However, as Figure 2.3 shows, there are more persons ‘A’ than persons ‘B’ in the population and as such the overall change in population exposure due to exposure at workplace based on the modelled concentrations by ADMS-Urban is potentially underestimated. The example calculations of personal exposure above are based on concurrent observations at both monitoring sites and as such represent approximately 64% of the 8784 hours in 2016.

Table 4.8 Personal mean RE and RWE_{8-18} exposure to NO_2 based on observed and modelled data at Currie and St Leonards monitoring stations in 2016. Also shown is the modelled exposure mean bias. Person 'A' lives at Currie and works at St Leonards. Person 'B' lives at St Leonards and works at Currie. All units are µg m^{-3}. Calculations based on concurrent observations at both monitoring stations. MB = mean bias.

Person 'A'	Modelled	Observed	MB
RE	8.8	5.6	3.2
RWE_{8-18}	11.7	10.2	1.5
RWE_{8-18} - RE	2.9	4.6	-1.7

Person 'B'	Modelled	Observed	MB
RE	18.6	19.6	-1.0
RWE_{8-18}	15.7	15.0	0.7
RWE_{8-18} - RE	-2.9	-4.6	1.7

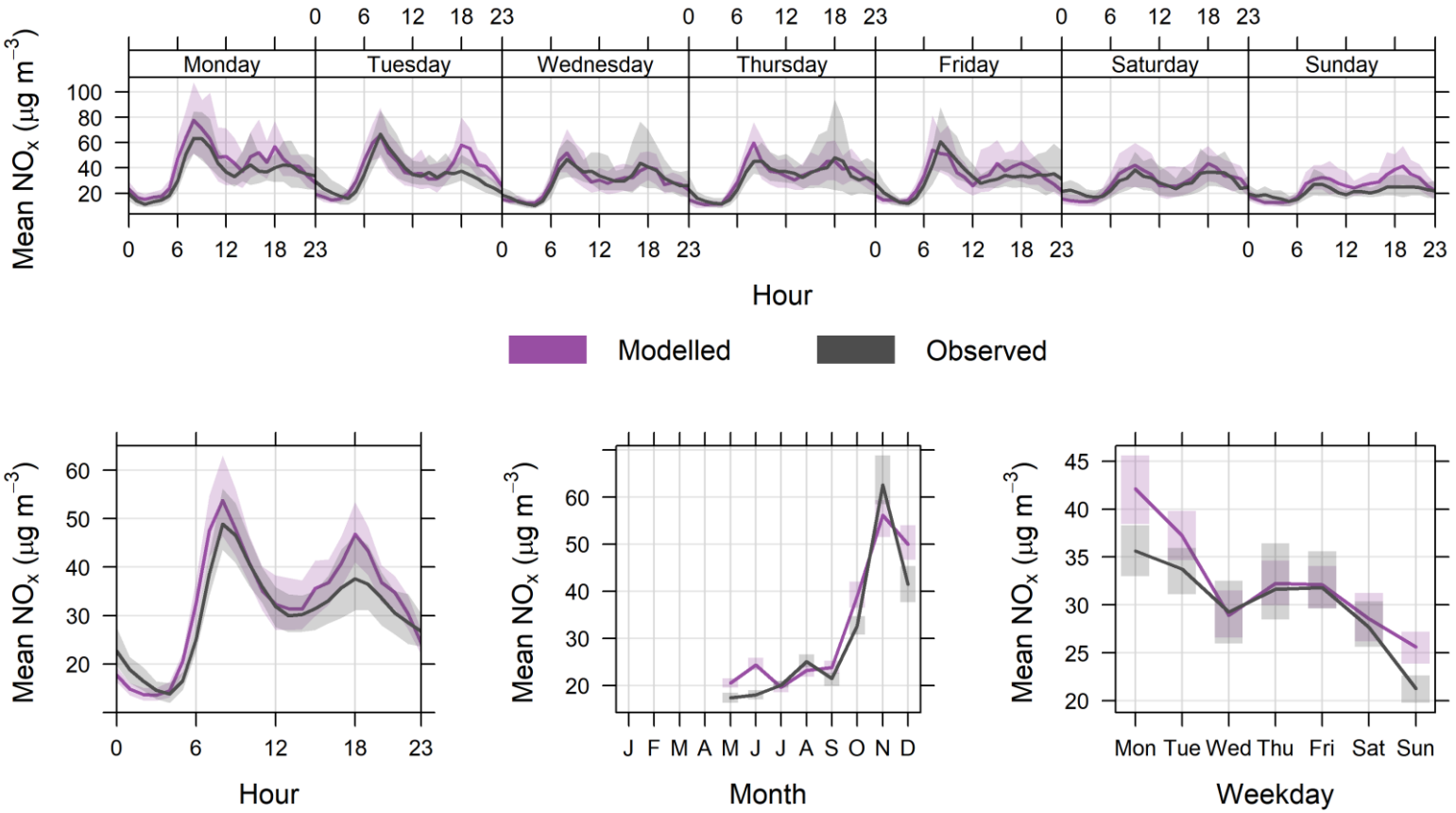

Figure 4.19 Observed and modelled hour-of-day, day-of-week and month-of-year mean NO_x concentration profiles at St Leonards station in 2016. Shaded areas represent the 95% confidence interval in the mean.

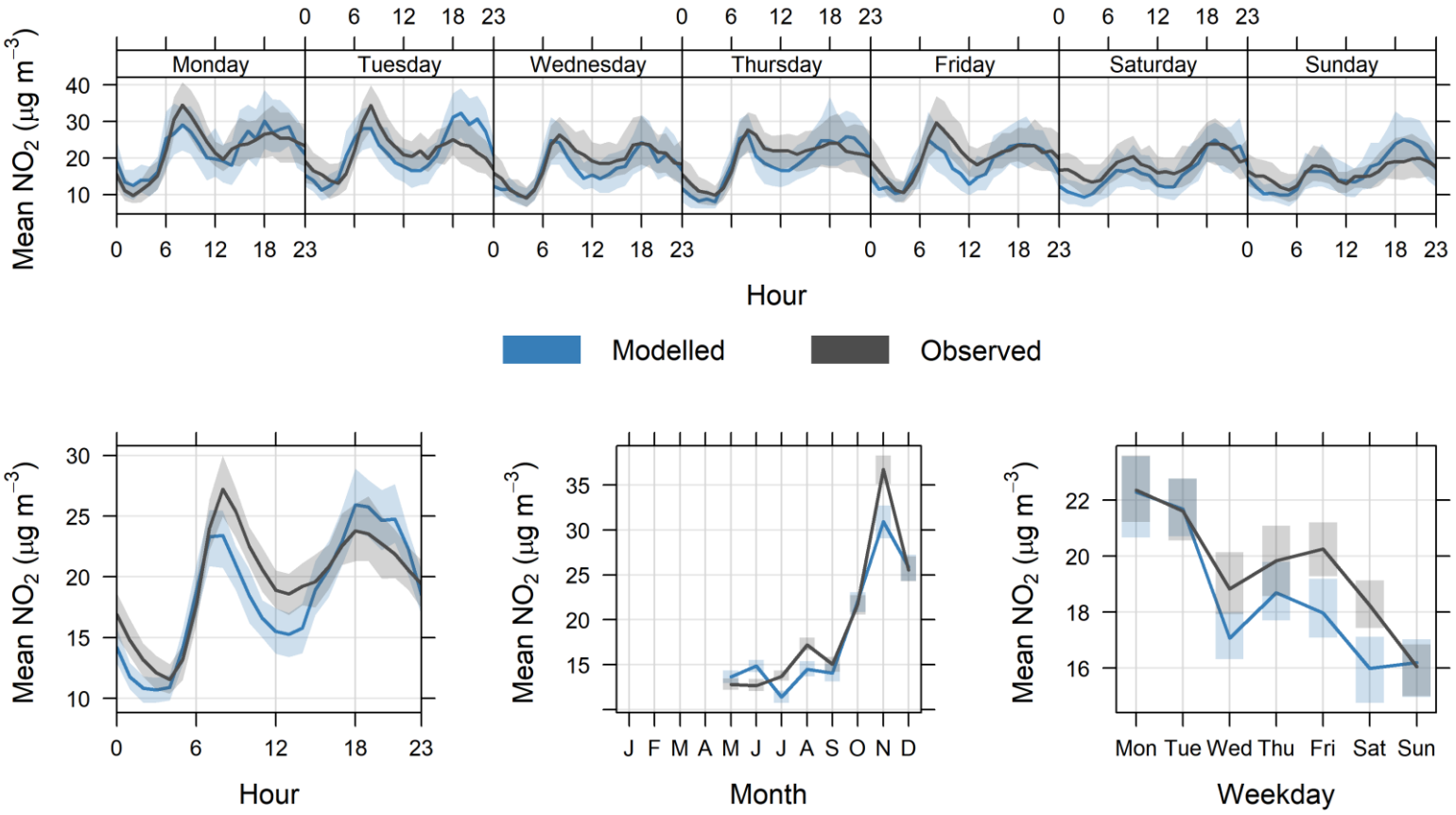

Figure 4.20 Observed and modelled hour-of-day, day-of-week and month-of-year mean NO_2 concentration profiles at St Leonards station in 2016. Shaded areas represent the 95% confidence interval in the mean.

Figures 4.21 and 4.22 show the temporal agreement between the ADMS-Urban model and observations for O_3 and $PM_{2.5}$, respectively. For O_3, the monthly profile is again very good. However, the model substantially underestimates O_3 concentrations in the evening and slightly overestimates the early afternoon concentration peak. In the case of $PM_{2.5}$ the model does reasonably well in capturing the monthly cycle, particularly in the first half of the year. The diurnal profile is less well captured; however, the range of daily $PM_{2.5}$ concentrations is much smaller than the range of the other pollutants.

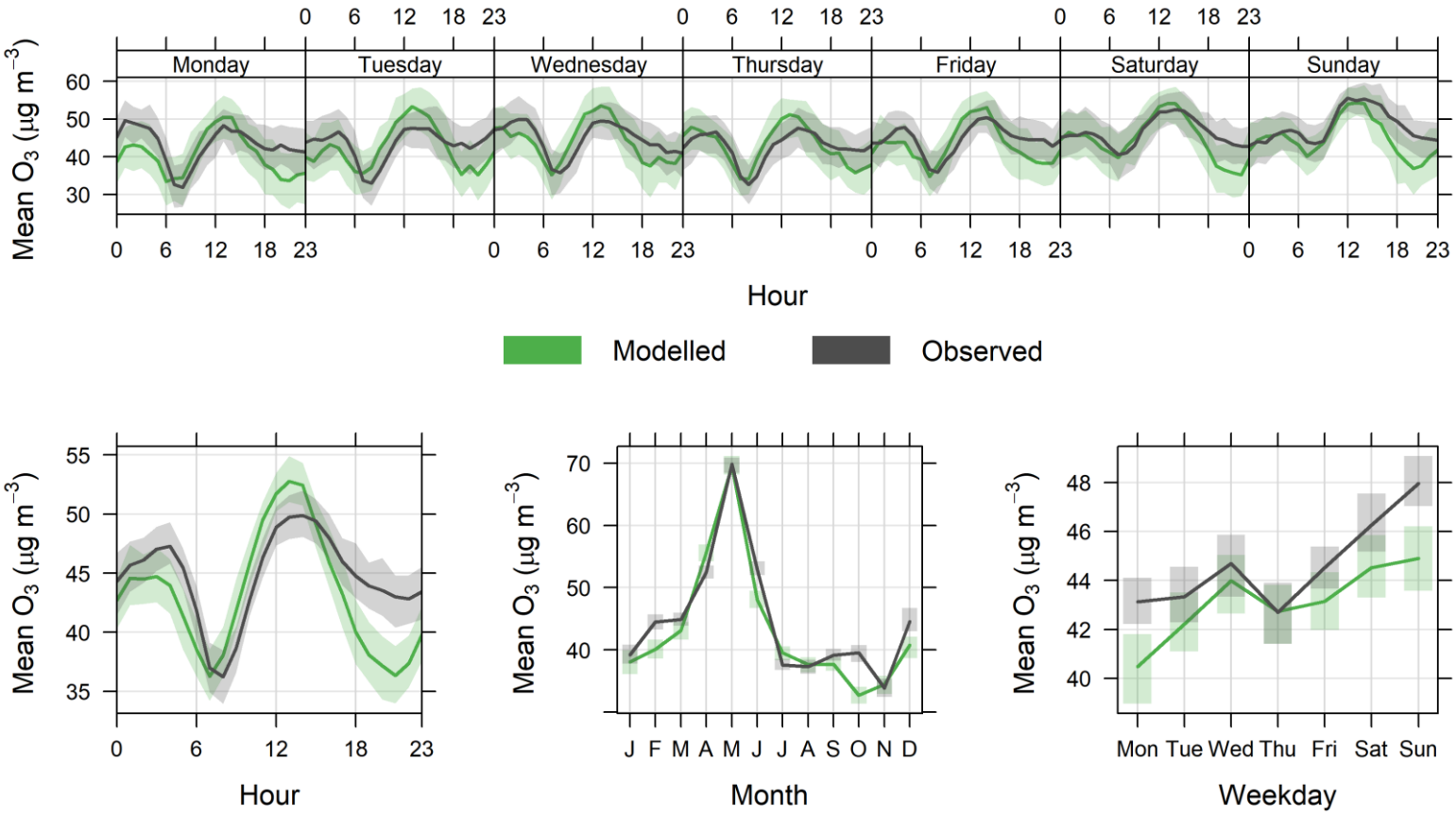

Figure 4.21 Observed and modelled hour-of-day, day-of-week and month-of-year mean O_3 concentration profiles at St Leonards station in 2016. Shaded areas represent the 95% confidence interval in the mean.

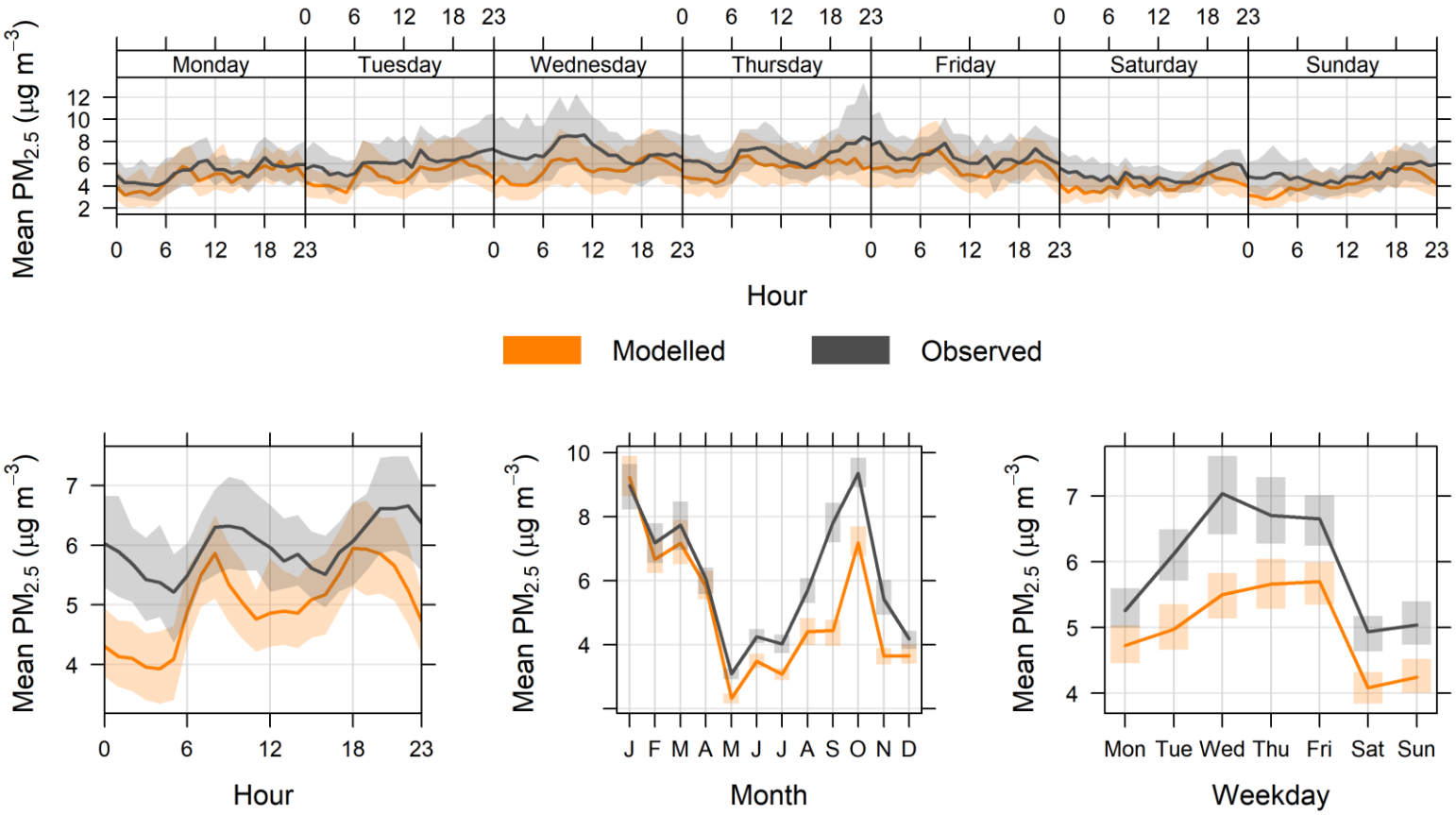

Figure 4.22 Observed and modelled hour-of-day, day-of-week and month-of-year mean $PM_{2.5}$ concentration profiles at St Leonards station in 2015. Shaded areas represent the 95% confidence interval in the mean.

To illustrate the model performance at a roadside site, the temporal profiles of NO_x and NO_2 at St John's Road station are shown in Figures 4.23 and 4.24, respectively. The figures show that despite the substantial underestimation of the concentrations the model simulates the intra-annual and day-of-week trends very well whilst the largest underestimates tend to occur between 07:00 and 18:00.

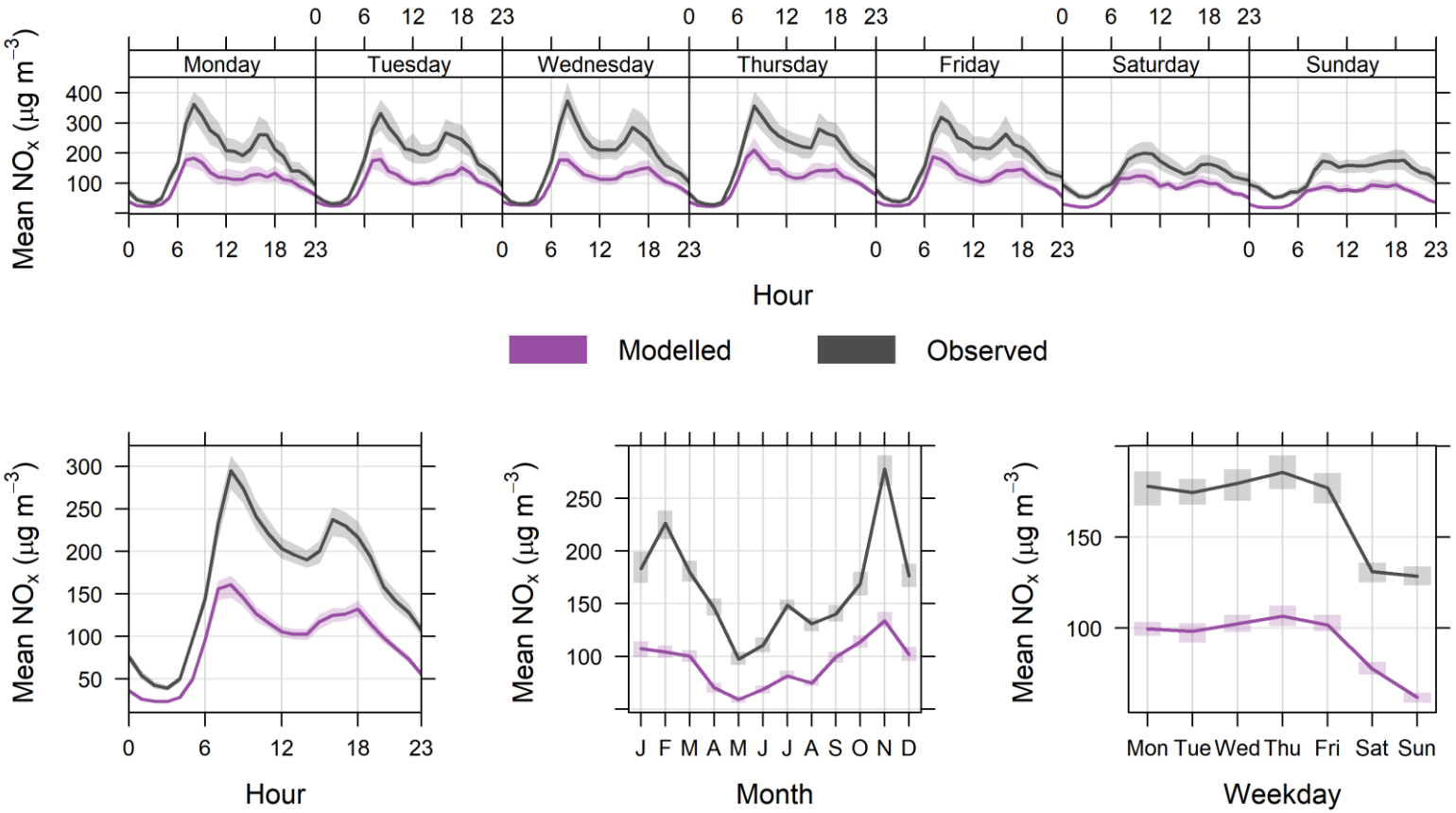

Figure 4.23 Observed and modelled hour-of-day, day-of-week and month-of-year mean NO_x concentration profiles at St John's Road station in 2016. Shaded areas represent the 95% confidence interval in the mean.

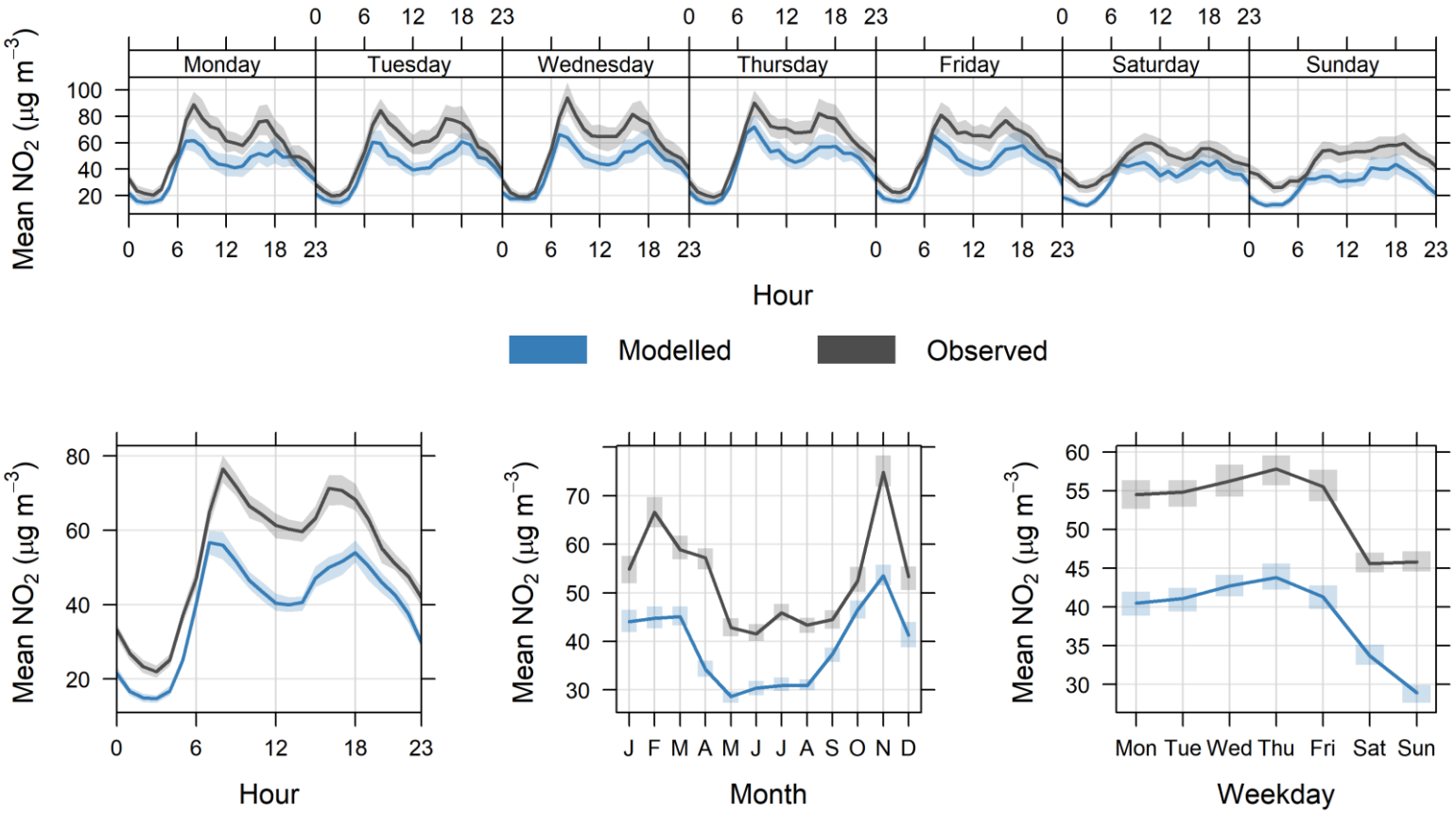

Figure 4.24 Observed and modelled hour-of-day, day-of-week and month-of-year mean NO_2 concentration profiles at St John's Road station in 2016. Shaded areas represent the 95% confidence interval in the mean.

The main panel in Figure 4.16 shows the spatial distribution of the mean bias of the modelled annual mean NO_2 concentrations in the study area at both automatic monitoring stations (triangles) and diffusion tube sites (circles) in 2015. There appear to be no clear spatial trends in model bias for NO_2 across the urban area albeit concentrations near roads are generally underestimated. Based on data from the automatic monitoring stations within the modelling domain, a similar conclusion can be made for NO_x. There are, however, some pollution hot spots where the model performs rather poorly. Nothing is known about the model performance for O_3 and $PM_{2.5}$ away from the urban background site at St Leonards due to the lack of measurements

A substantial amount of effort and time was spent trying to identify the drivers of the poor model performance in some locations within the study area, and on improvement of the modelling methods. However, detailed traffic data such as number and vehicle class, vehicle speed, and queuing traffic were not available throughout the modelling domain. Similarly, other sources such as industrial sources had to be modelled as part of the grid source, which has no plume rise in the model, due to the lack of information on volume flow rate and temperature of plumes from those sources. Furthermore, more detailed modelling of street canyons would have likely improved the modelled concentrations in many locations; however, it was not feasible to split the road network in the modelling domain into a very large number of small road segments. Despite the numerous limitations it is deemed that overall the model performs well.

4.3.2 Comparison of calculated air pollution concentrations by ADMS-Urban and EMEP4UK

The modelled annual mean concentrations of NO_2, O_3 and $PM_{2.5}$ generated by ADMS-Urban and EMEP4UK are summarized in Table 4.9. Maps of the ADMS-Urban modelled mean concentrations are shown in Figures 4.25, 4.27 and 4.29, and maps of EMEP4UK concentrations in the Edinburgh area are shown in Figures 3.2-3.4 in the previous chapter. For spatial comparison of the two models' outputs the differences in annual mean concentrations

(ADMS-Urban – EMEP4UK) at every postcode are shown in Figures 4.26, 4.28 and 4.30.

Table 4.9 Summary statistics of modelled annual mean NO_2, O_3 and $PM_{2.5}$ concentrations by ADMS-Urban and EMEP4UK in the study area in 2015. SD = standard deviation. All units are in µg m^{-3}.

Pollutant	Model	Mean	SD	Min	Q1	Median	Q3	Max
NO_2	ADMS-Urban	16.13	3.07	8.01	14.05	15.79	18.16	25.88
	EMEP4UK	13.08	3.11	4.26	11.02	13.58	15.19	18.75
O_3	ADMS-Urban	50.09	2.62	42.71	48.30	50.35	51.89	56.64
	EMEP4UK	58.52	2.96	52.76	56.54	57.94	59.86	67.82
$PM_{2.5}$	ADMS-Urban	4.80	0.31	3.61	4.63	4.82	5.01	5.55
	EMEP4UK	7.70	0.46	6.14	7.42	7.79	8.00	8.63

For NO_2, the modelled means from ADMS-Urban range from 8.01 µg m^{-3} to 25.88 µg m^{-3} with the mean value of all modelled postcode NO_2 concentrations equal to 16.13 µg m^{-3}. Figure 4.25 shows that the highest mean modelled concentrations occur in the central area of the city. The lowest concentrations occur in the south-westerly suburban section of the study area due to low local emissions and prevailing south-westerly wind which carries the comparatively high emissions from the city centre to the north and north-eastern parts of the study area. ADMS-Urban, being a local scale model, generates elevated NO_2 concentrations in the vicinity of the explicitly modelled roads.

Compared to EMEP4UK modelled concentrations the ADMS-Urban modelled mean is 3.05 µg m^{-3} higher and the range of values is larger by 3.38 µg m^{-3}, however the mean modelled concentrations correlate well (r = 0.89). Since EMEP4UK averages concentrations over the volume of each grid cell the largest differences in modelled NO_2 concentrations between the two models occur at postcodes near busy modelled roads. In particular, those which are the dominant local source in a particular EMEP4UK grid cell, for example around the Edinburgh Bypass section to the south-west of the urban area. There the difference in modelled NO_2 concentrations reaches 13.2 µg m^{-3}. Figure 4.26 also shows that away from modelled roads and some large industrial emitters the difference between ADMS-Urban and EMEP4UK is

generally larger to the south of the city centre compared with the north. EMEP4UK seems to perform better in the outer suburban areas as the model does not rely on background data from Bush Estate and does not suffer from double-counting of emissions. A comparison of the models' performances at the only automatic station in that area (Currie) shows that the MB of EMEP4UK at the station is only 0.3 µg m^{-3} for NO_2 compared to 3.2 µg m^{-3} of ADMS-Urban. Only in a few areas do EMEP4UK modelled concentrations exceed those by ADMS-Urban. The most notable of those is located in the north-western corner of the study area near the airport; however the magnitude of the difference is less than 1 µg m^{-3}.

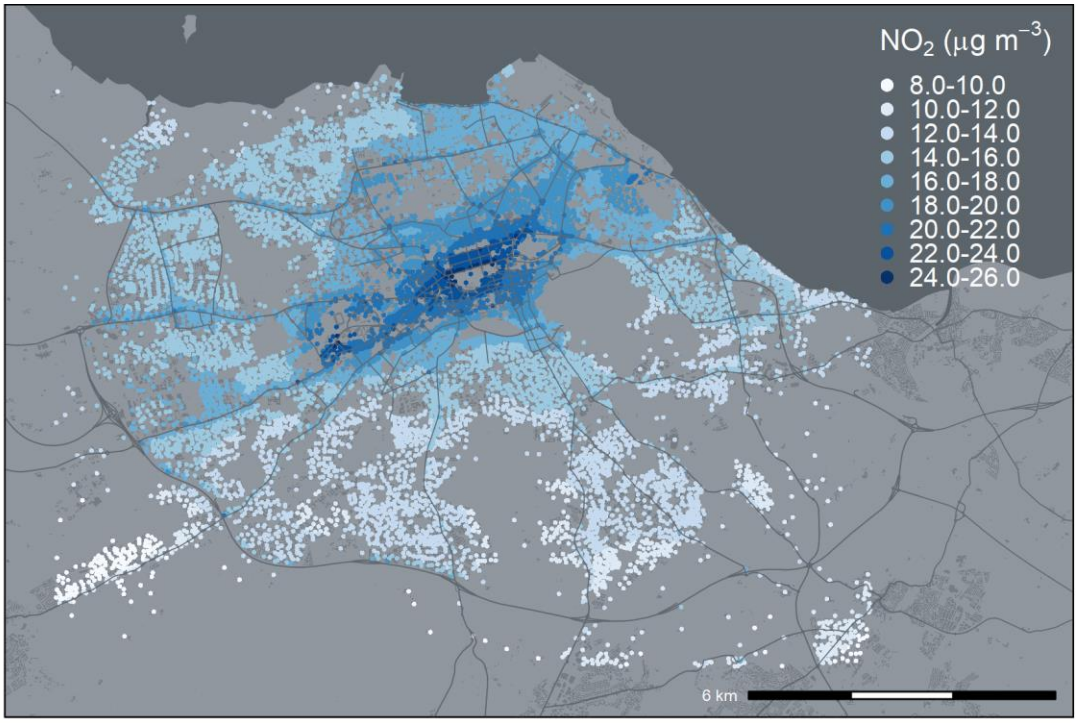

Figure 4.25 Modelled annual mean NO_2 concentrations (2015) by ADMS-Urban. Contains OS Data © Crown copyright and database right (2021).

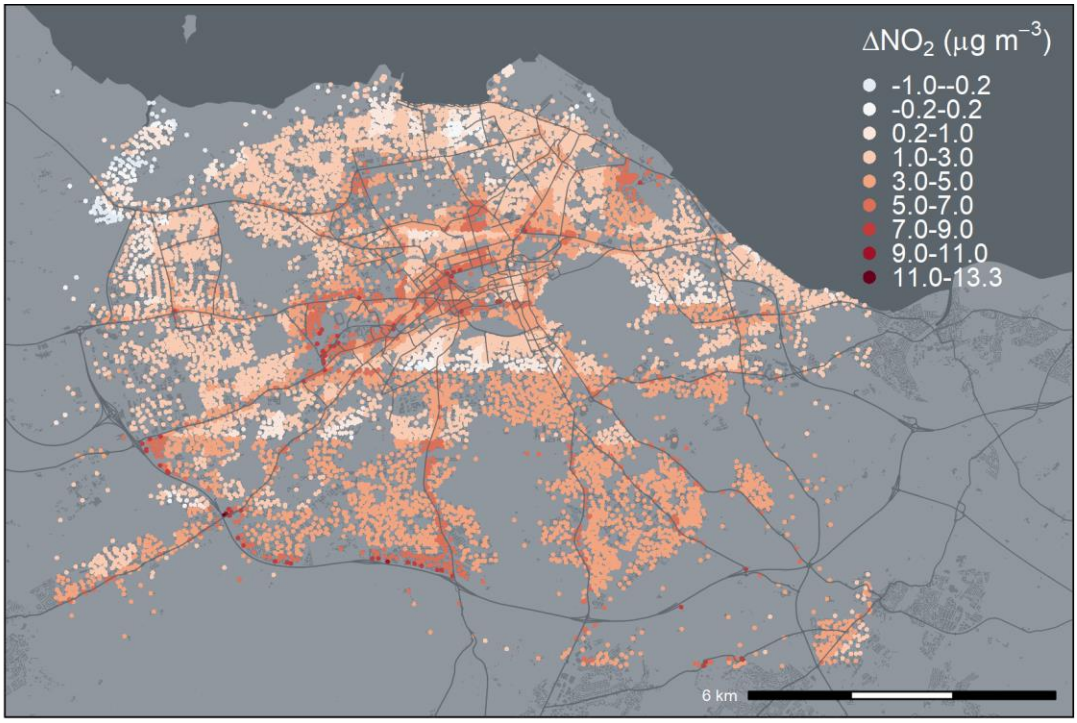

Figure 4.26 Difference in modelled annual mean NO_2 concentrations (ADMS-Urban - EMEP4UK). Contains OS Data © Crown copyright and database right (2021).

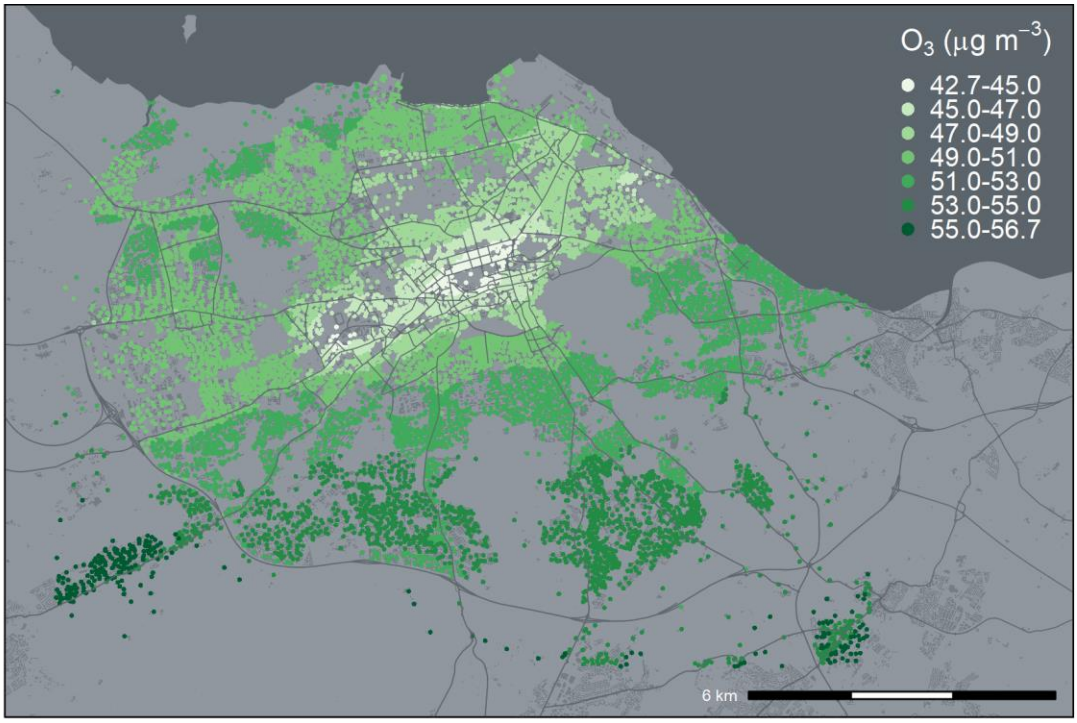

Figure 4.27 Modelled annual mean O_3 concentrations (2015) by ADMS-Urban. ontains OS Data © Crown copyright and database right (2021).

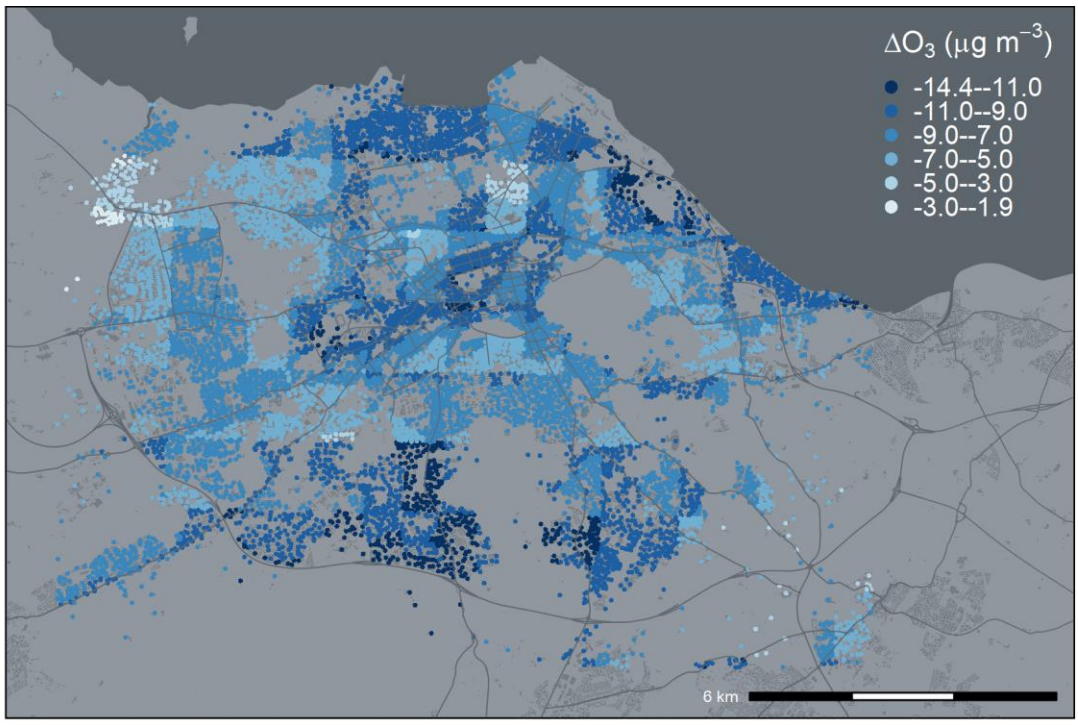

Figure 4.28 Difference in modelled annual mean O_3 concentrations (ADMS-Urban - EMEP4UK). Contains OS Data © Crown copyright and database right (2021).

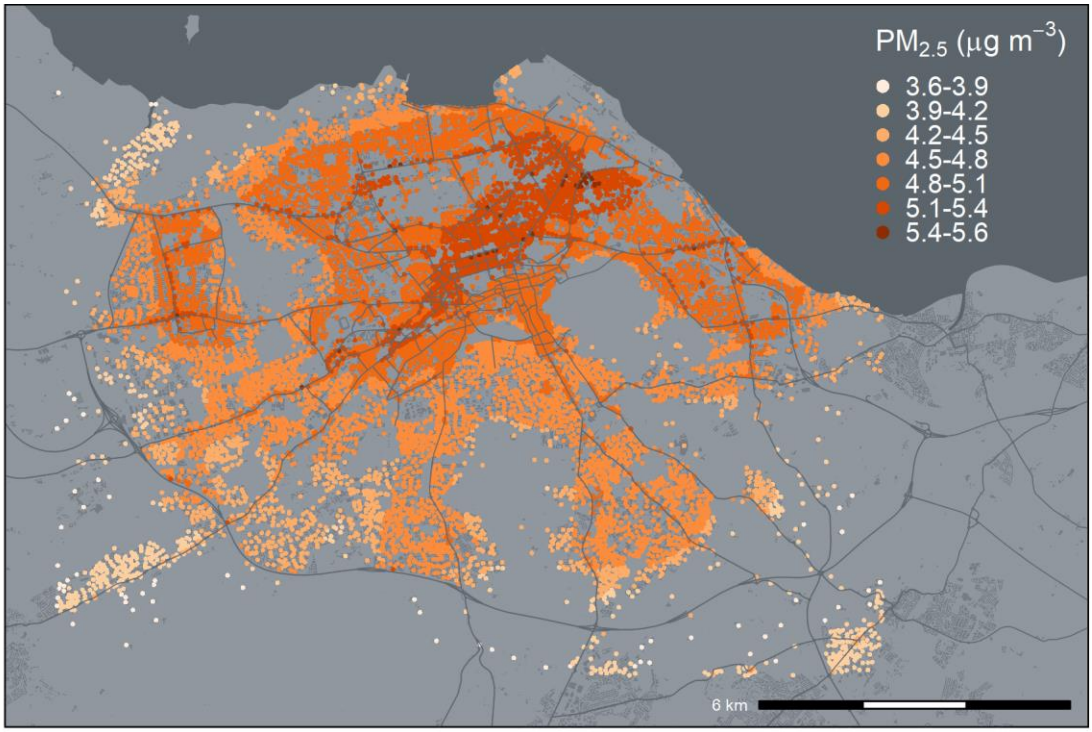

Figure 4.29 Modelled annual mean $PM_{2.5}$ concentrations (2015) by ADMS-Urban. Contains OS Data © Crown copyright and database right (2021).

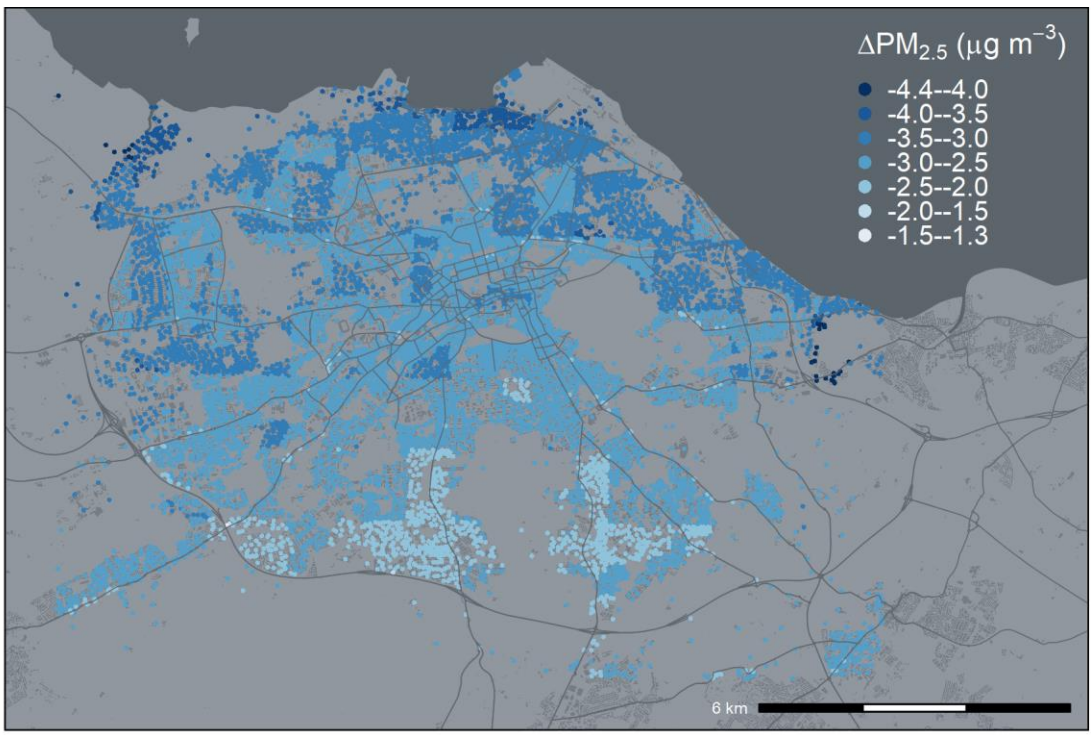

Figure 4.30 Difference in modelled annual mean $PM_{2.5}$ concentrations (ADMS-Urban - EMEP4UK). Contains OS Data © Crown copyright and database right (2021).

For O_3, ADMS-Urban modelled mean concentrations range from 42.7 µg m^{-3} in the city centre to 56.6 µg m^{-3} on the southern edges of the study area (Figure 4.27). The mean of all modelled postcode O_3 concentrations is 50.1 µg m^{-3}. That is 8.4 µg m^{-3} less than the equivalent mean O_3 modelled by EMEP4UK. EMEP4UK O_3 concentrations are larger across the whole domain with the smallest differences occurring near the airport (Figure 4.28). The largest differences are observed near some large NO_2 emitters, for example a wastewater treatment works to the northeast, and in the southern part of the domain near explicitly modelled roads. In contrast with NO_2 there is also a substantial difference between the models on the northern edge of the study area near the harbour. The correlation between the modelled means is also slightly worse at r = 0.82.

For $PM_{2.5}$, modelled mean concentrations by ADMS-Urban range from 3.6 µg m^{-3} to 5.6 µg m^{-3} with the mean equal to 4.8 µg m^{-3}. The spatial pattern of the concentrations is similar to NO_2 albeit with smaller gradients (Figure 4.29). Similarly to O_3, EMEP4UK modelled $PM_{2.5}$ mean concentrations are higher across the domain, on average by 60% (2.9 µg m^{-3}). The agreement between the models generally decreases from south to north and the correlation is the weakest out of all the investigated pollutants (r = 0.78).

4.3.3 Comparison of estimated population exposures by ADMS-Urban and EMEP4UK

There were 18,113 SLS participants that fulfilled the selection criteria. Since the Edinburgh study area here and in the Central Belt study in the previous chapter are nearly identical the distribution of social characteristics in the population sample is virtually the same as well (Table 3.1) and there are only minor differences in the exposure results from those presented for Edinburgh in Section 3.3. Here the focus is placed on the difference in estimated exposure between the local model ADMS-Urban and the regional model EMEP4UK which is considered as the benchmark.

Table 4.10 shows the summary statistics of exposure to NO_2, O_3 and $PM_{2.5}$ at the population level for both models. The differences in exposure means reflect the differences in modelled concentrations by the two models presented in Table 4.9. ADMS-Urban mean and median exposures to NO_2 are approximately 3 µg m^{-3} higher than EMEP4UK exposures, whilst for O_3 and $PM_{2.5}$ the difference is approximately -8 µg m^{-3} and -3 µg m^{-3}, respectively.

The choice of model has the largest impact on estimates of NO_2 exposure. This is as expected as NO_2 shows the highest spatial heterogeneity of the three pollutants and on a scale smaller than the EMEP4UK grid resolution. Additionally, the smoother NO_2 concentration fields generated by ADMS-Urban result in a substantial difference in personal exposure distributions compared with the gridded output from EMEP4UK. To illustrate the difference, distributions for the RE and $RWE_{8\text{-}18}$ scenarios and both models are shown in the left-hand panels in Figure 4.31. The ADMS-Urban NO_2 exposure distribution is much more normal than the EMEP4UK exposure distribution. Consequently, the difference between the means and medians of population exposure has been reduced in all NO_2 exposure scenarios from nearly 0.6 µg m^{-3} using EMEP4UK data to just over 0.1 µg m^{-3} when ADMS-Urban data are used. The difference between $RWE_{8\text{-}18}$ and RE when means are considered is 0.17 µg m^{-3} or 1.3% (EMEP4UK) and 0.25 µg m^{-3} or 1.6% (ADMS-Urban). However, it is 0.10 µg m^{-3} or 0.7% for the former when comparing medians while it is still 0.25 µg m^{-3} (1.6%) for the latter. Regardless of the model used there is a large overlap between the RE and $RWE_{8\text{-}18}$ scenario distributions and hence the small observed effect on mean or median exposure.

As shown in Figure 4.31, using ADMS-Urban data results in the number of individuals that work or study away from home and experience less than 0.1 µg m^{-3} change in exposure to NO_2 to decrease by approximately one third (~500 individuals). The vast majority of those are in the right-hand tail, i.e. they experience an increase in personal exposure. The largest difference between the distributions on the right occurs beyond about 1.7 µg m^{-3} difference in

exposure where the EMEP4UK-based exposures drop off much more sharply than the ADMS-Urban-based exposures. As a result, ~1600 individuals have their exposure increased by more than 1.7 µg m^{-3} due to exposure at workplace based on the ADMS-Urban data compared with ~1000 individuals based on EMEP4UK data. On the other hand, the left-hand tails are largely comparable in shape. A negative change in personal exposure exceeding 1.7 µg m^{-3} is experienced by ~380 and ~360 individuals for ADMS-Urban and EMEP4UK, respectively.

For O_3, the impact of workplace exposure on overall population exposure depends on both the model used and statistic considered. This is caused by the difference in median exposure being more than twice the size of the difference in mean exposure for the EMEP4UK model. However, in relative terms the observed decreases in population exposures are comparable (≤ 0.1%) between the models. As was the case with NO_2, ADMS-Urban-based personal exposures result in a more normal and smoother exposure distributions (Figure 4.32) without the secondary peaks on the extremes of the distributions seen in the EMEP4UK data. Due to larger spatial homogeneity of O_3 the number of commuters whose $RWE_{8\text{-}18}$ – RE difference is less than 0.1 µg m^{-3} decreases by only ~16%.

For $PM_{2.5}$, workplace population mobility has virtually zero effect on overall population exposure regardless of the model used or the RWE scenario considered. The exposure distributions in Figure 4.33 show that ADMS-Urban-based RE and $RWE_{8\text{-}18}$ distributions are narrower than those based on the EMEP4UK data; however, the magnitude of personal exposure changes is rarely more than 0.45 µg m^{-3}.

Table 4.10 Descriptive statistics of population exposure for each pollutant, model and exposure scenario. Also shown are the absolute and relative differences in the means and medians between each of the RWE scenarios and the RE scenario. SD = standard deviation, Q1 = 25th percentile, Q3 = 75th percentile. Units are µg m^{-3}. Source: Scottish Longitudinal Study.

Pollutant	Model	Exposure Scenario	Mean	SD	Q1	Median	Q3	RWE* - RE (means)	RWE* - RE (means) %	RWE* - RE (medians)	RWE* - RE (medians) %
NO_2	ADMS-Urban	RE	15.78	2.75	13.94	15.66	17.77	-	-	-	-
		RWE_{9-17}	15.97	2.64	14.20	15.84	17.87	0.19	1.2	0.18	1.1
		RWE_{8-18}	16.03	2.63	14.28	15.91	17.91	0.25	1.6	0.25	1.6
		RWE_{hw+}	15.96	2.62	14.21	15.84	17.83	0.18	1.1	0.18	1.1
	EMEP4UK	RE	12.85	2.95	11.02	13.49	15.02	-	-	-	-
		RWE_{9-17}	12.98	2.81	11.13	13.58	15.03	0.13	1.0	0.09	0.7
		RWE_{8-18}	13.02	2.78	11.15	13.59	15.02	0.17	1.3	0.10	0.7
		RWE_{hw+}	12.98	2.78	11.13	13.58	15.02	0.13	1.0	0.09	0.7
O_3	ADMS-Urban	RE	50.37	2.36	48.68	50.49	52.02	-	-	-	-
		RWE_{9-17}	50.23	2.26	48.59	50.30	51.78	-0.14	-0.3	-0.19	-0.4
		RWE_{8-18}	50.18	2.25	48.54	50.24	51.70	-0.19	-0.4	-0.25	-0.5
		RWE_{hw+}	50.22	2.24	48.62	50.29	51.75	-0.15	-0.3	-0.20	-0.4
	EMEP4UK	RE	58.72	2.87	56.68	58.40	60.32	-	-	-	-
		RWE_{9-17}	58.61	2.73	56.74	58.14	60.00	-0.11	-0.2	-0.26	-0.4
		RWE_{8-18}	58.57	2.69	56.71	58.09	59.86	-0.15	-0.3	-0.31	-0.5
		RWE_{hw+}	58.61	2.68	56.77	58.12	59.97	-0.11	-0.2	-0.28	-0.5
$PM_{2.5}$	ADMS-Urban	RE	4.79	0.30	4.62	4.81	4.99	-	-	-	-
		RWE_{9-17}	4.79	0.28	4.64	4.81	4.99	0.00	0.0	0.00	0.0
		RWE_{8-18}	4.79	0.28	4.64	4.81	4.99	0.00	0.0	0.00	0.0
		RWE_{hw+}	4.79	0.28	4.64	4.81	4.99	0.00	0.0	0.00	0.0
	EMEP4UK	RE	7.69	0.46	7.42	7.75	8.00	-	-	-	-
		RWE_{9-17}	7.69	0.43	7.43	7.75	7.96	0.00	0.0	0.00	0.0
		RWE_{8-18}	7.69	0.42	7.43	7.75	7.96	0.00	0.0	0.00	0.0
		RWE_{hw+}	7.69	0.43	7.43	7.74	7.96	0.00	0.0	-0.01	-0.1

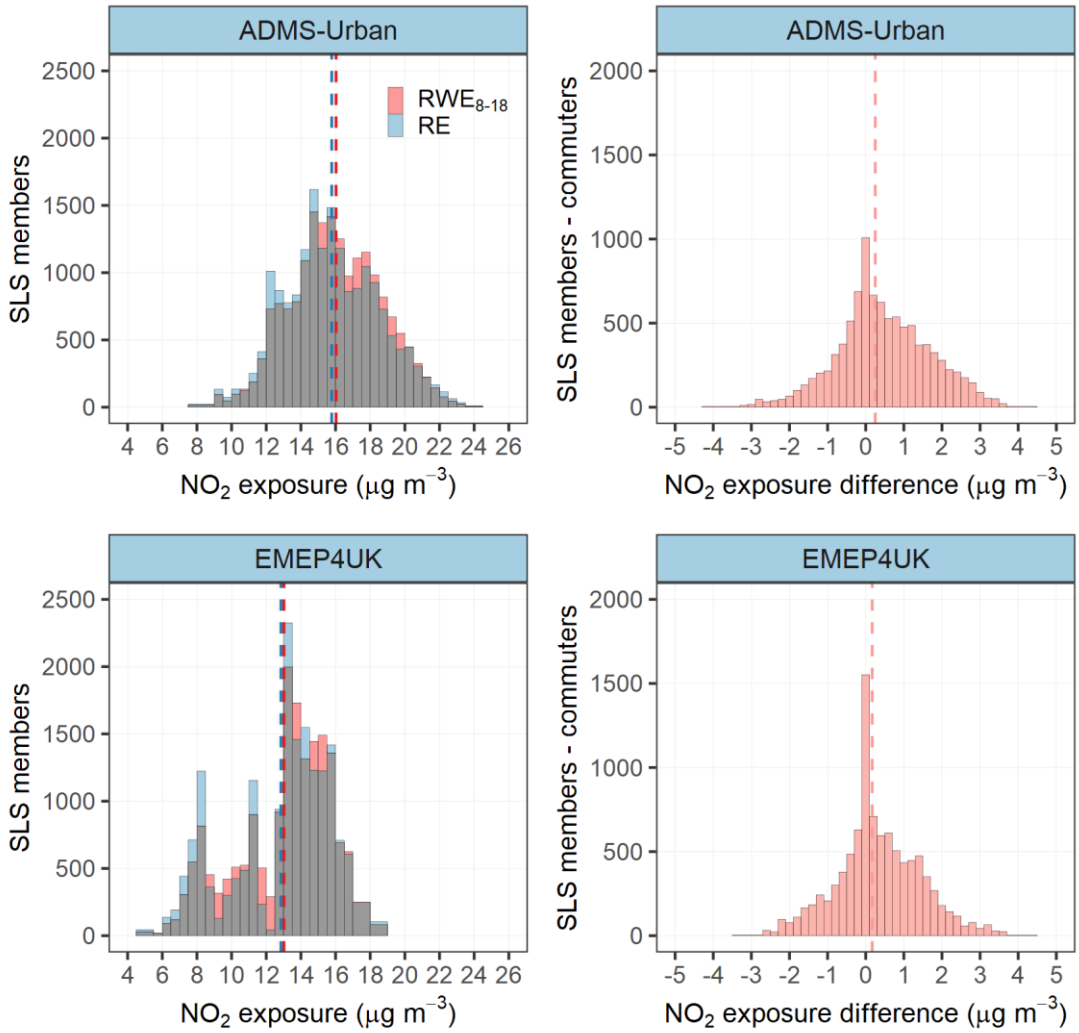

Figure 4.31 Distributions of NO_2 RE and $RWE_{8\text{-}18}$ of the SLS participants in the study area (left panels) and the NO_2 $RWE_{8\text{-}18}$ – RE exposure differences of the participants who commute to place of work and study (right panels). Grey shading in the left panels represents the distribution overlap. Dashed lines represent the means of the distributions. Bins with fewer than 10 SLS participants are aggregated with a neighbouring bin and the aggregated participant number is normalised by the aggregated bin width. Source: Scottish Longitudinal Study.

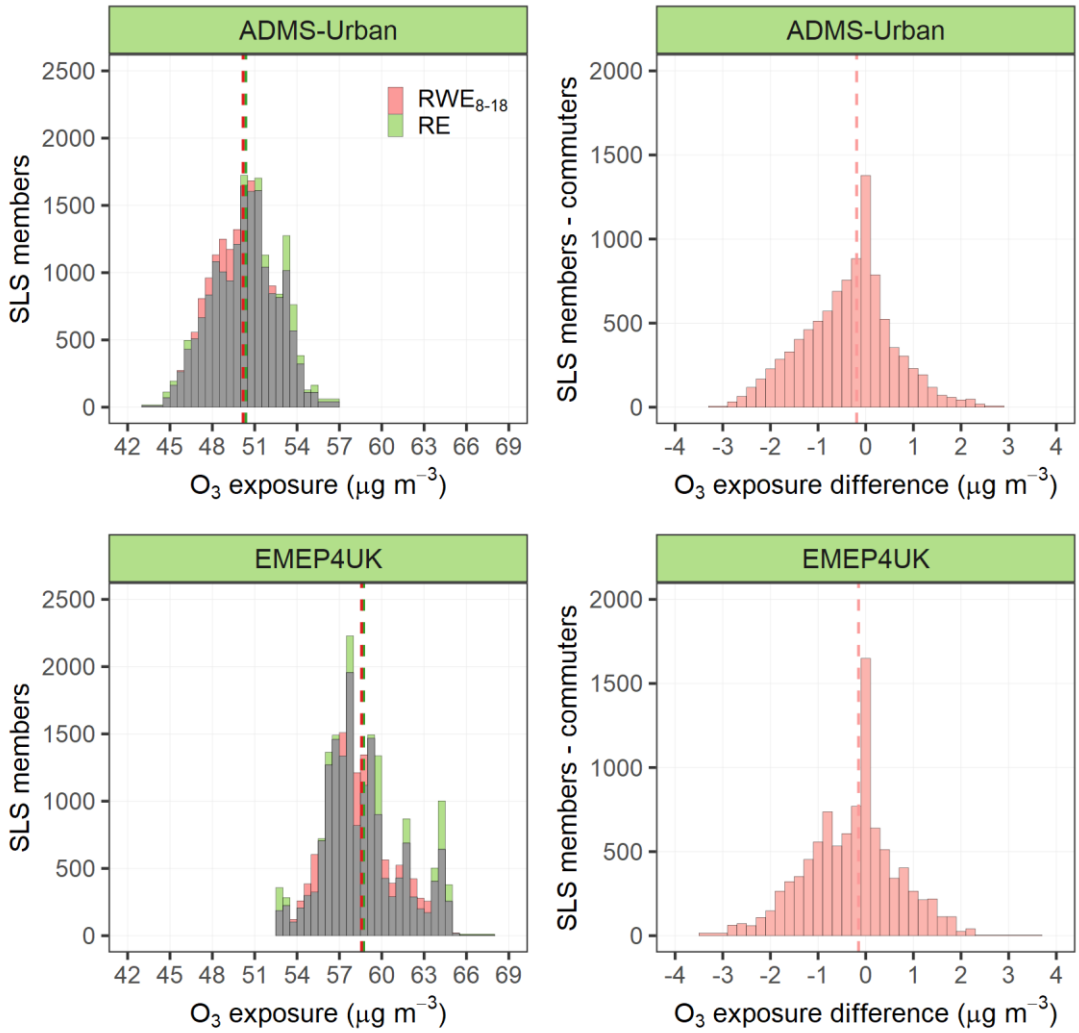

Figure 4.32 Distributions of O_3 RE and $RWE_{8\text{-}18}$ of the SLS participants in the study area (left panels) and the O_3 $RWE_{8\text{-}18}$ – RE exposure differences of the participants who commute to place of work and study (right panels). Grey shading in the left panels represents the distribution overlap. Dashed lines represent the means of the distributions. Bins with fewer than 10 SLS participants are aggregated with a neighbouring bin and the aggregated participant number is normalised by the aggregated bin width. Source: Scottish Longitudinal Study.

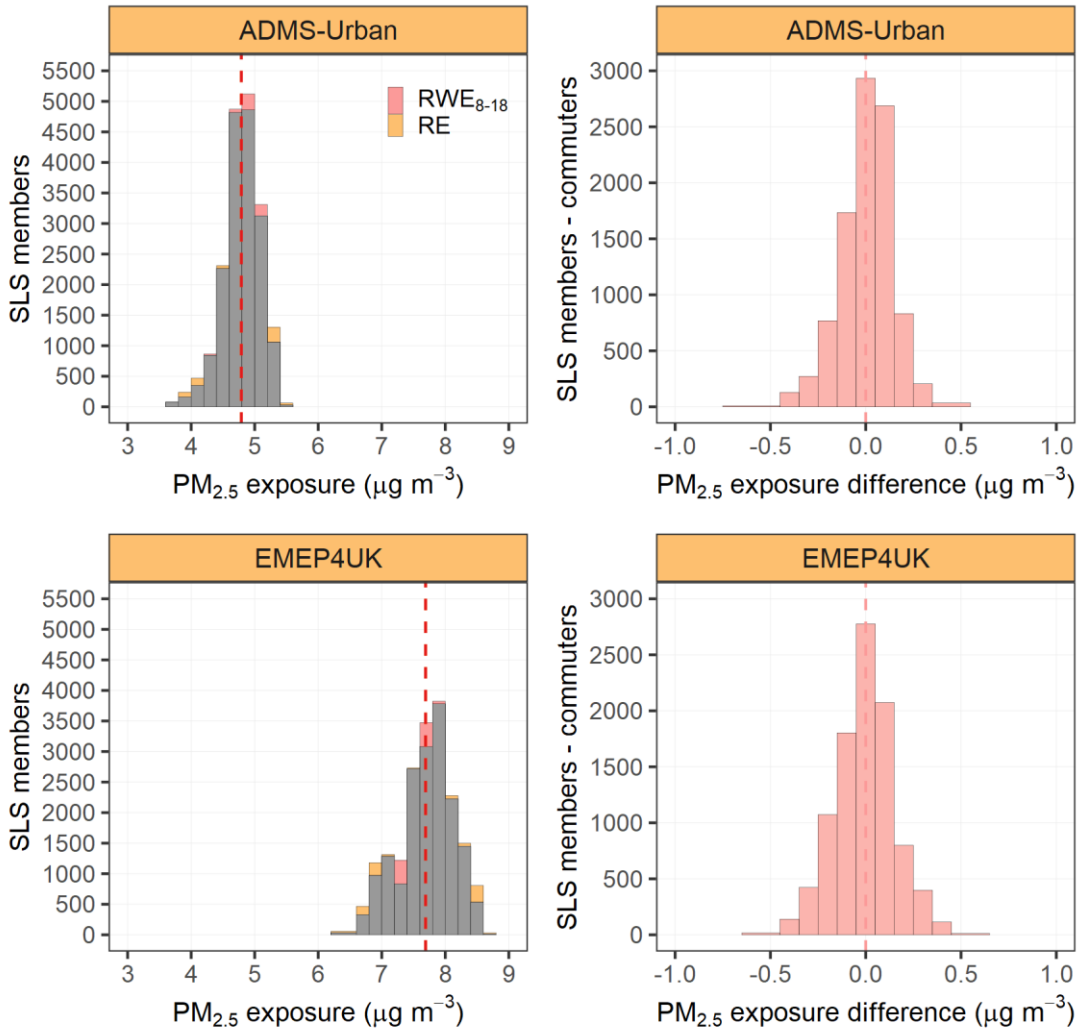

Figure 4.33 Distributions of $PM_{2.5}$ RE and $RWE_{8\text{-}18}$ of the SLS participants in the study areas (left panels) and the $PM_{2.5}$ $RWE_{8\text{-}18}$ – RE exposure differences of the participants who commute to place of work and study (right panels). Grey shading in the left panels represents the distribution overlap. Dashed lines represent the means of the distributions. Bins with fewer than 10 SLS participants are aggregated with a neighbouring bin and the aggregated participant number is normalised by the aggregated bin width. Source: Scottish Longitudinal Study.

The impacts of workplace exposure on overall exposure of the population stratified by ethnic group, age and SES per model, pollutant and exposure scenario are summarized in Figures 4.34-4.42. The exposure means, medians and interquartile ranges are shown in the top panels. As there are relatively large differences in concentrations generated by the models the y axes in the top panels are not the same scale. Also, due to the skewed exposure distributions in the EMEP4UK data the absolute differences in median rather than mean exposure are shown in the bottom panels. The summary statistics for each exposure distribution shown in Figures 4.34-4.42 are presented in Tables A37-A60 in Appendix A.2.

Possible explanations for the observed discrepancies between the models are also discussed below. It is important to note that while they are plausible, they cannot be confirmed since there is no access to the actual postcodes.

Ethnicity

As Figures 4.34-4.36 show, the ranking of ethnic groups in median exposure is largely similar for both models and exposure scenarios as is the effect of workplace mobility on exposures. There are some exceptions, however. ADMS-Urban suggests a larger (and above the population median) impact of workplace mobility on African and Other ethnic groups' exposure to NO_2 than EMEP4UK by approximately 0.4 µg m^{-3}. Similarly, the impact is larger for O_3 exposure of the Caribbean and Black group for ADMS-Urban (~ -0.6 µg m^{-3}) than for EMEP4UK (~ 0.0 µg m^{-3}). For $PM_{2.5}$, the models show similar and marginal effect of workplace mobility on exposure, albeit the magnitude of change is larger for EMEP4UK.

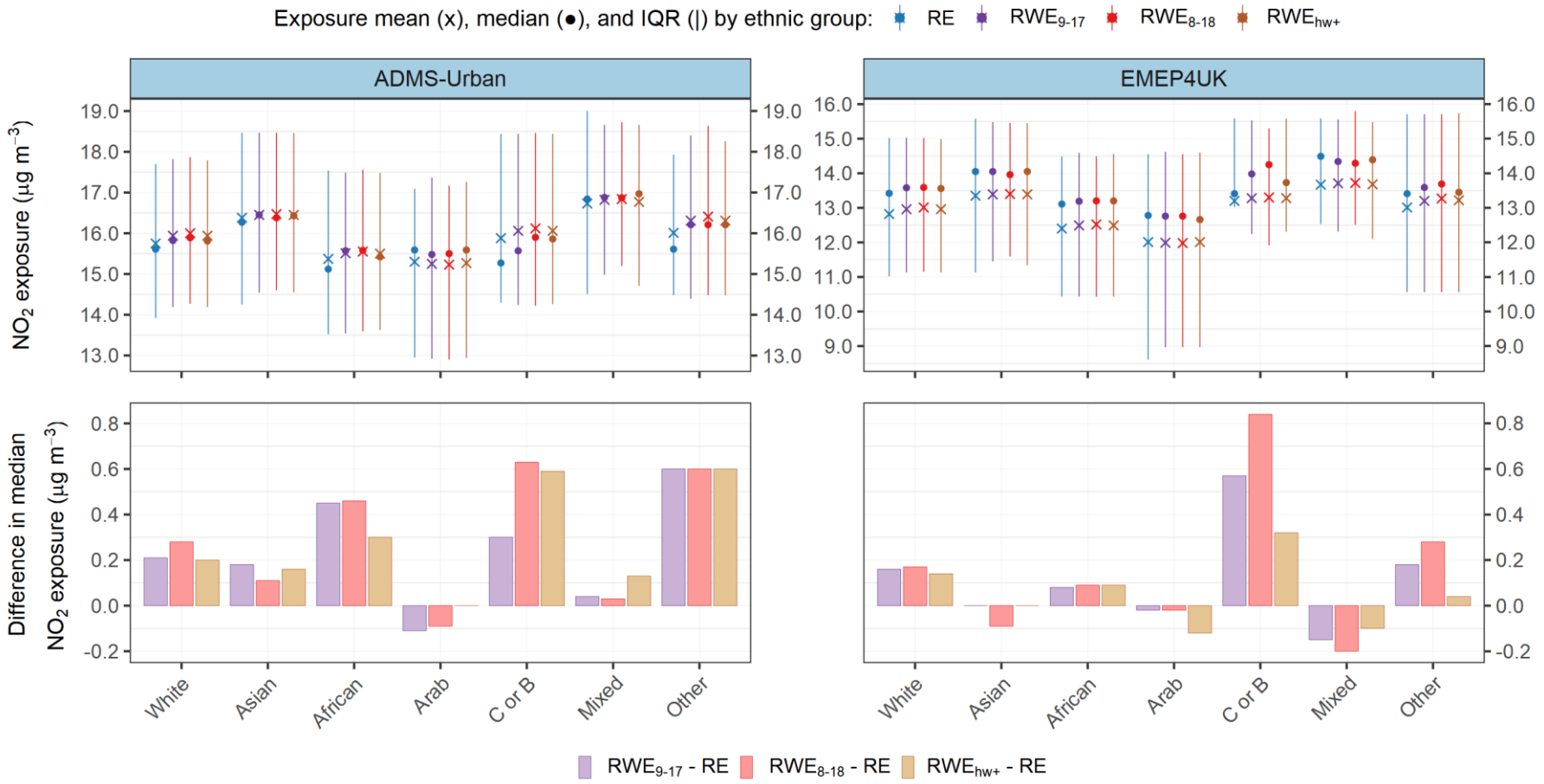

Figure 4.34 NO_2 exposure means, medians and interquartile ranges by ethnic group, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). C or B = Caribbean or Black. Source: Scottish Longitudinal Study.

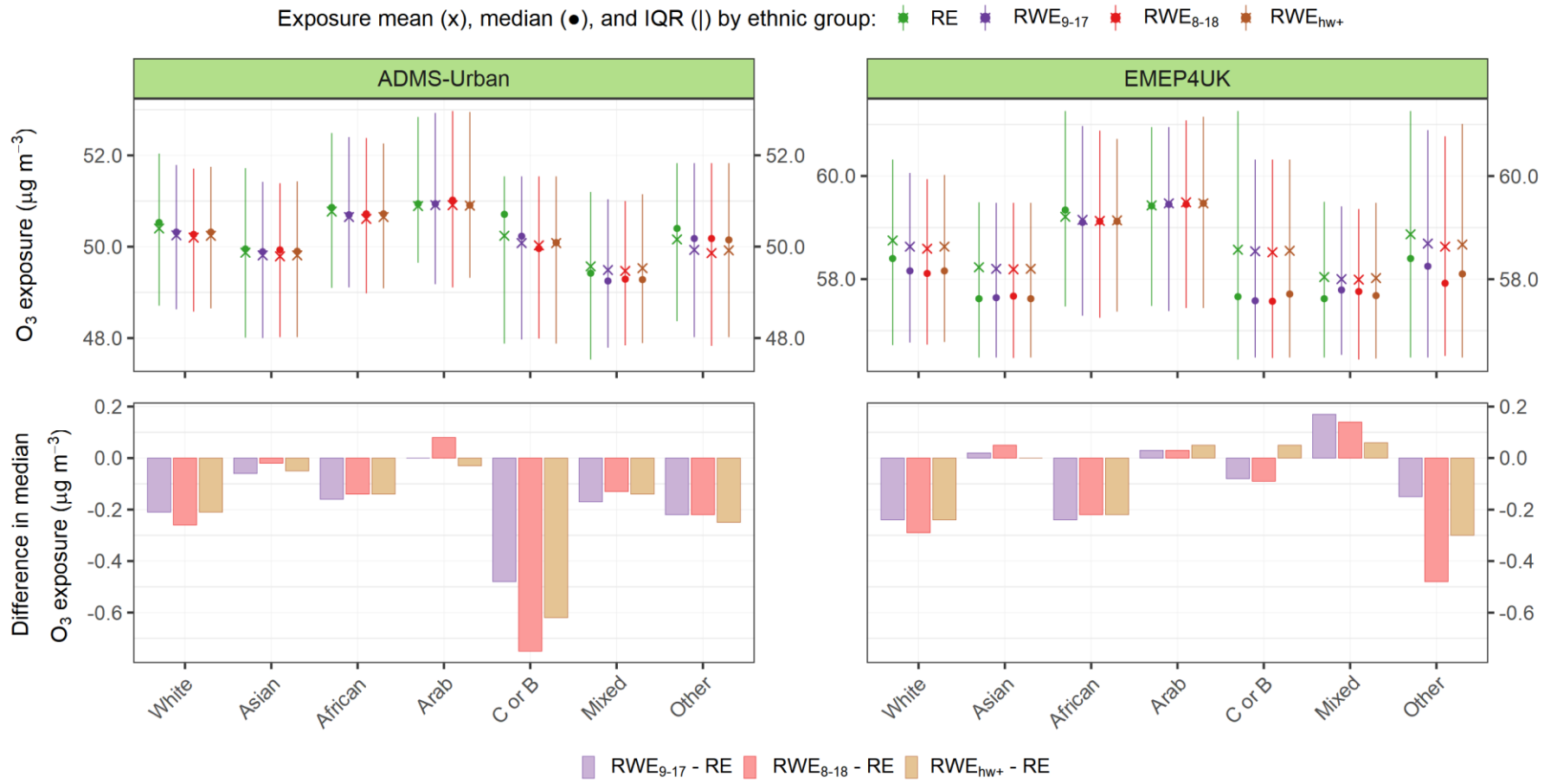

Figure 4.35 O_3 exposure means, medians and interquartile ranges by ethnic group, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). C or B = Caribbean or Black. Source: Scottish Longitudinal Study.

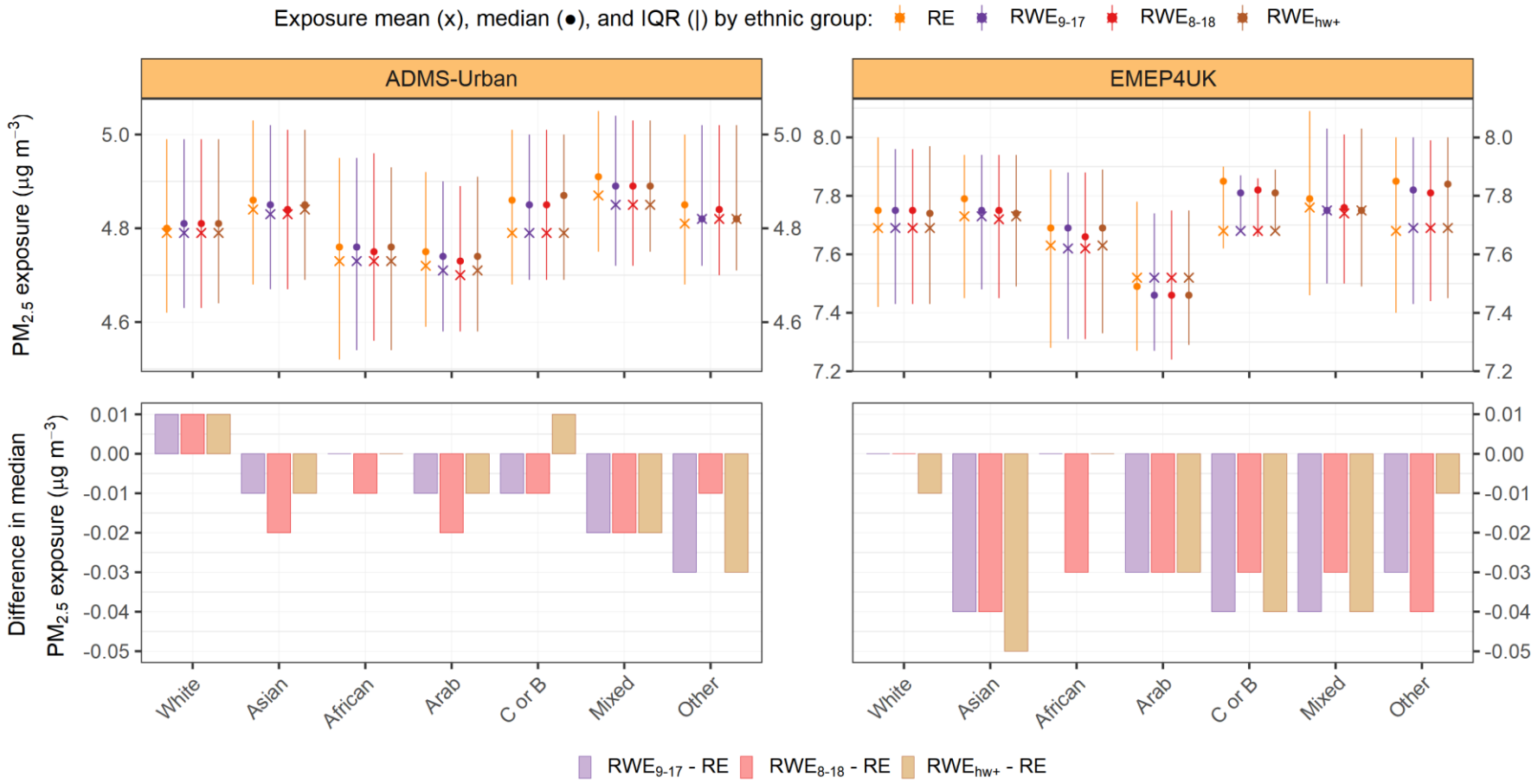

Figure 4.36 $PM_{2.5}$ exposure means, medians and interquartile ranges by ethnic group, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). C or B = Caribbean or Black. Source: Scottish Longitudinal Study.

Age

Both models show similar distributions of exposures to all three pollutants for the population stratified by age (Figures 4.37-4.39). However the peak in median residential exposure observed in the young adult age groups (21-30 years old) is more pronounced for ADMS-Urban than EMEP4UK. Both models also agree that the observed increase in NO_2 and decrease in O_3 exposures is largely driven by working age population from around the age of 30 and this impact diminishes from around the age of 65 when people tend to retire. However, some of the most striking differences between the models in terms of the impact of workplace mobility are seen for the 16-20 and 21-25 age groups, where a large proportion of the population is made of college and university students. Whereas EMEP4UK suggests a decrease in overall NO_2 exposure as a result of workplace (school) exposure and a corresponding increase in O_3 exposure for those and only those age groups, ADMS-Urban data suggest a pattern more in line with the other age groups. It's likely that the disparity is caused by siting of educational institutions in the study area. Several universities and colleges are located on the fringes of the city where EMEP4UK NO_2 and O_3 concentrations tend to be the lowest and the highest, respectively. Some of those institutions are, however, also located near major roads where ADMS-Urban is able to capture the elevated (or depressed) concentrations but EMEP4UK is not. Interestingly, ADMS-Urban also suggest a larger impact of exposure at school on the 6-10 and 11-15 years old age groups. It is expected that the majority of schoolchildren attend their local school and that their commute is relatively short and possibly within the same (or neighbouring) EMEP4UK grid cell as their home. Hence this analysis shows that using a gridded model output may lead to an underestimation of NO_2 exposure of a particularly susceptible population subgroup whose lungs are still developing. This finding also has implications for the Central Belt study in the previous chapter. Figure 3.11 shows that in Glasgow the impact of NO_2 exposure at school for the 6-10 year-old group is also negligible whilst the impact of workplace mobility on exposure of the vast majority of the other age groups is twice of more larger than in Edinburgh. It is therefore likely that using

a local dispersion model to estimate NO_2 exposure in Glasgow would lead to a substantially larger impact on exposure estimates of schoolchildren in the city. On the other hand, in all the RWE scenarios the time spent at school is overestimated since school children spent less time at school than the working population at work. Moreover, school holidays were not accounted for in the assessment.

The impact of workplace exposure on $PM_{2.5}$ exposure is marginal.

Socio-economic status

Figures 4.40-4.42 show similar patterns in exposures of the population stratified by Carstairs Index decile for both models. The lowest NO_2 and $PM_{2.5}$ exposures, and highest O_3 exposures are seen in the two least (1 and 2) and the most deprived (10) deciles with exposure maxima (NO_2 and $PM_{2.5}$) and minima (O_3) observed in decile 7. Compared with EMEP4UK the impact of workplace mobility on NO_2 exposure is much more uniformly distributed across the deciles even though deciles 1 and 2 still show the largest increase in NO_2 exposure. The top panels of Figure 4.40 show that the residential NO_2 exposure difference observed between deciles 2 and 3 for ADMS-Urban is about half the magnitude of EMEP4UK. This suggests that at least part of the decreased influence of workplace mobility for those subgroups is probably caused by ADMS-Urban overestimating NO_2 concentrations in the suburban southwestern section of the study area which is predominantly very affluent. For the most vulnerable deciles 9 and 10, ADMS-Urban suggests a slightly larger increase in exposure than EMEP4UK (~ <0.2 µg m^{-3}). For O_3, ADMS-Urban data suggest a decrease in exposure across all deciles due to workplace exposure whereas EMEP4UK only effectively shows decrease in deciles 1, 2 and 3, and an increase in exposure for deciles 7 and 8, albeit the magnitude of those increases are marginal. Both models show a similar impact of workplace mobility on the vulnerable deciles 9 and 10.

As in all previous cases exposure to $PM_{2.5}$ has a similar pattern to that of NO_2 but smaller in magnitude and the impact of workplace mobility on exposure to $PM_{2.5}$ is effectively negligible.

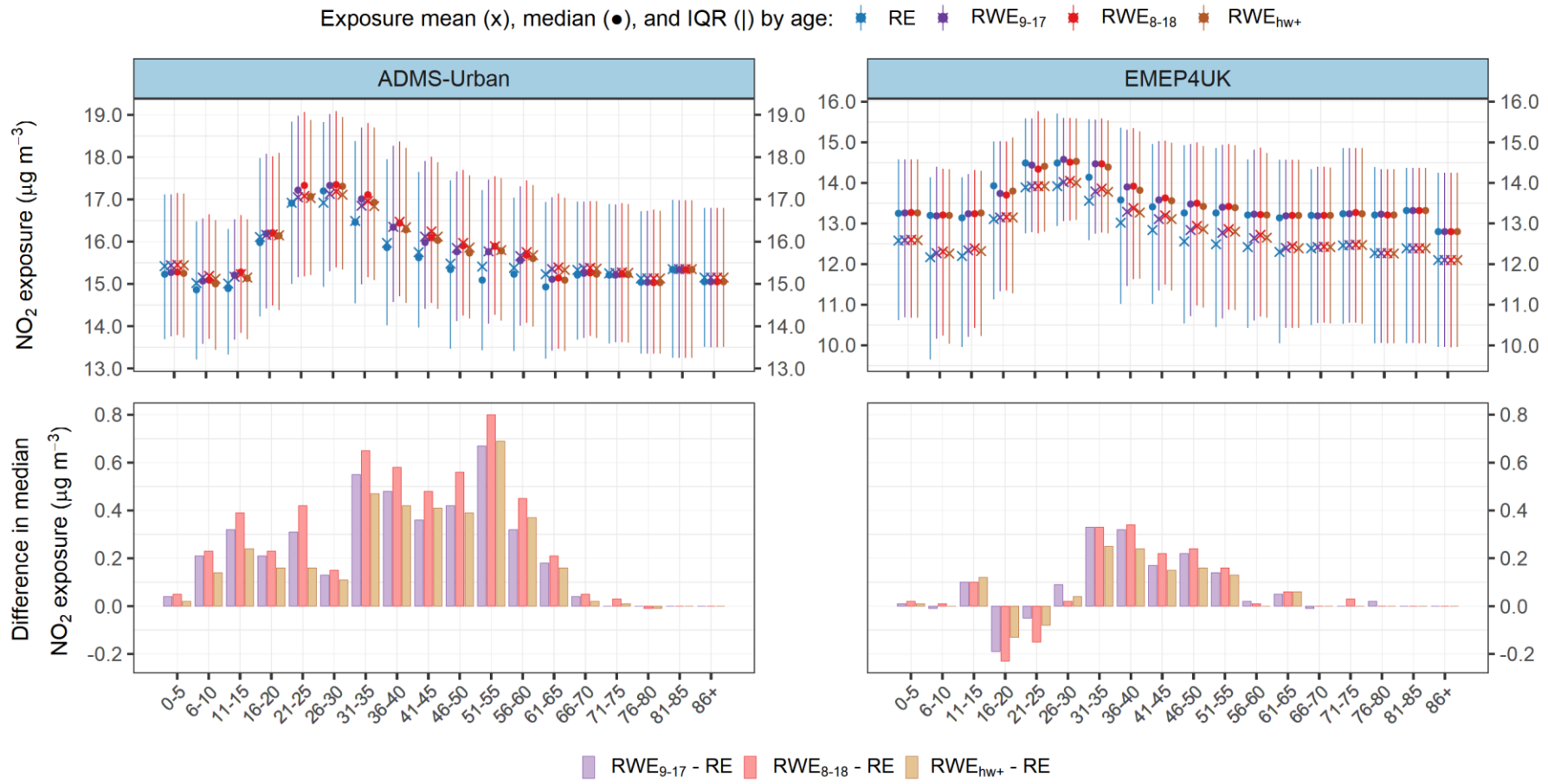

Figure 4.37 NO_2 exposure means, medians and interquartile ranges by age group, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Source: Scottish Longitudinal Study.

Figure 4.38 O_3 exposure means, medians and interquartile ranges by age group, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Source: Scottish Longitudinal Study.

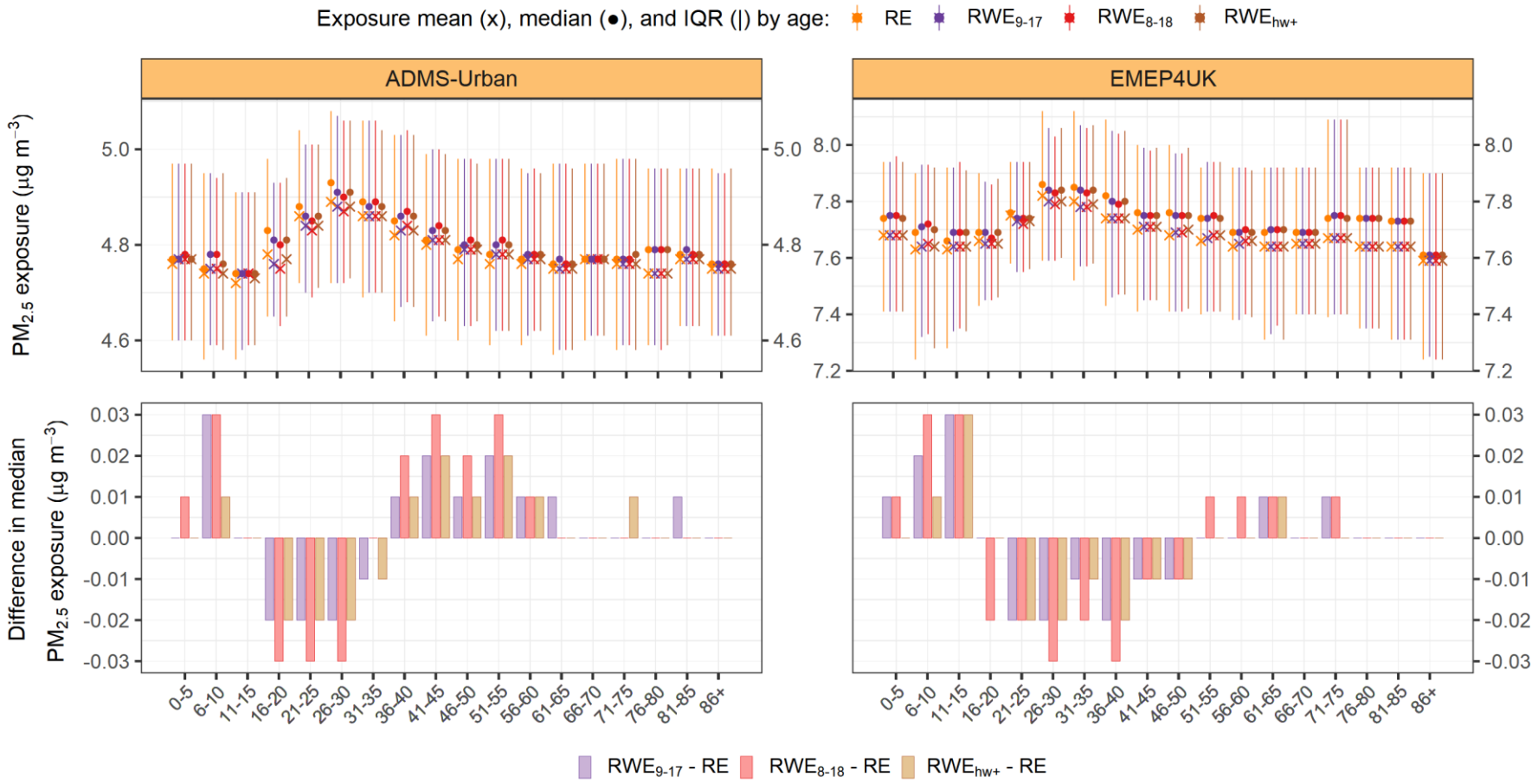

Figure 4.39 $PM_{2.5}$ exposure means, medians and interquartile ranges by age group, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Source: Scottish Longitudinal Study.

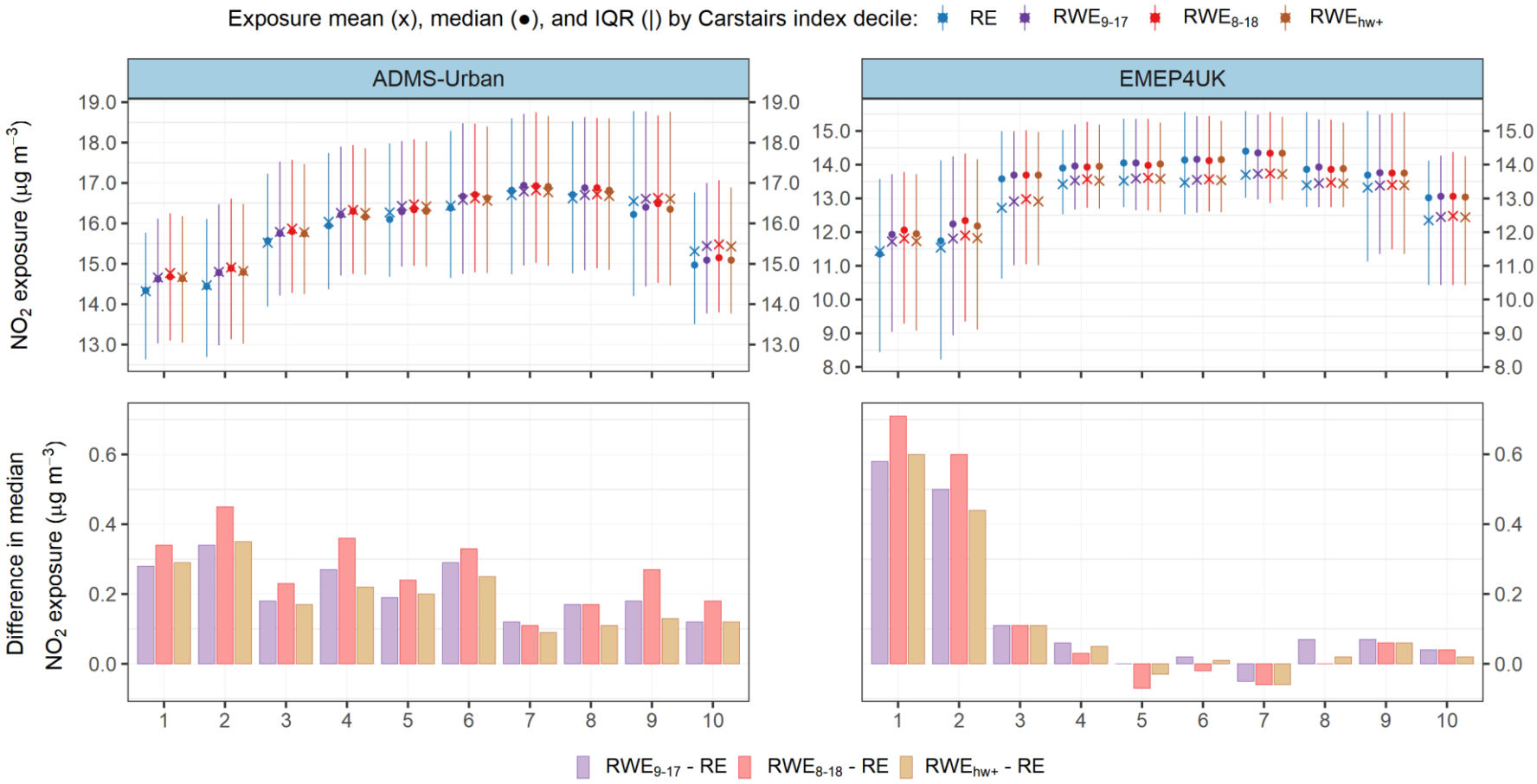

Figure 4.40 NO_2 exposure means, medians and interquartile ranges by Carstairs index decile, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Decile 1 = least deprived, decile 10 = most deprived. Source: Scottish

Longitudinal ***Study.***

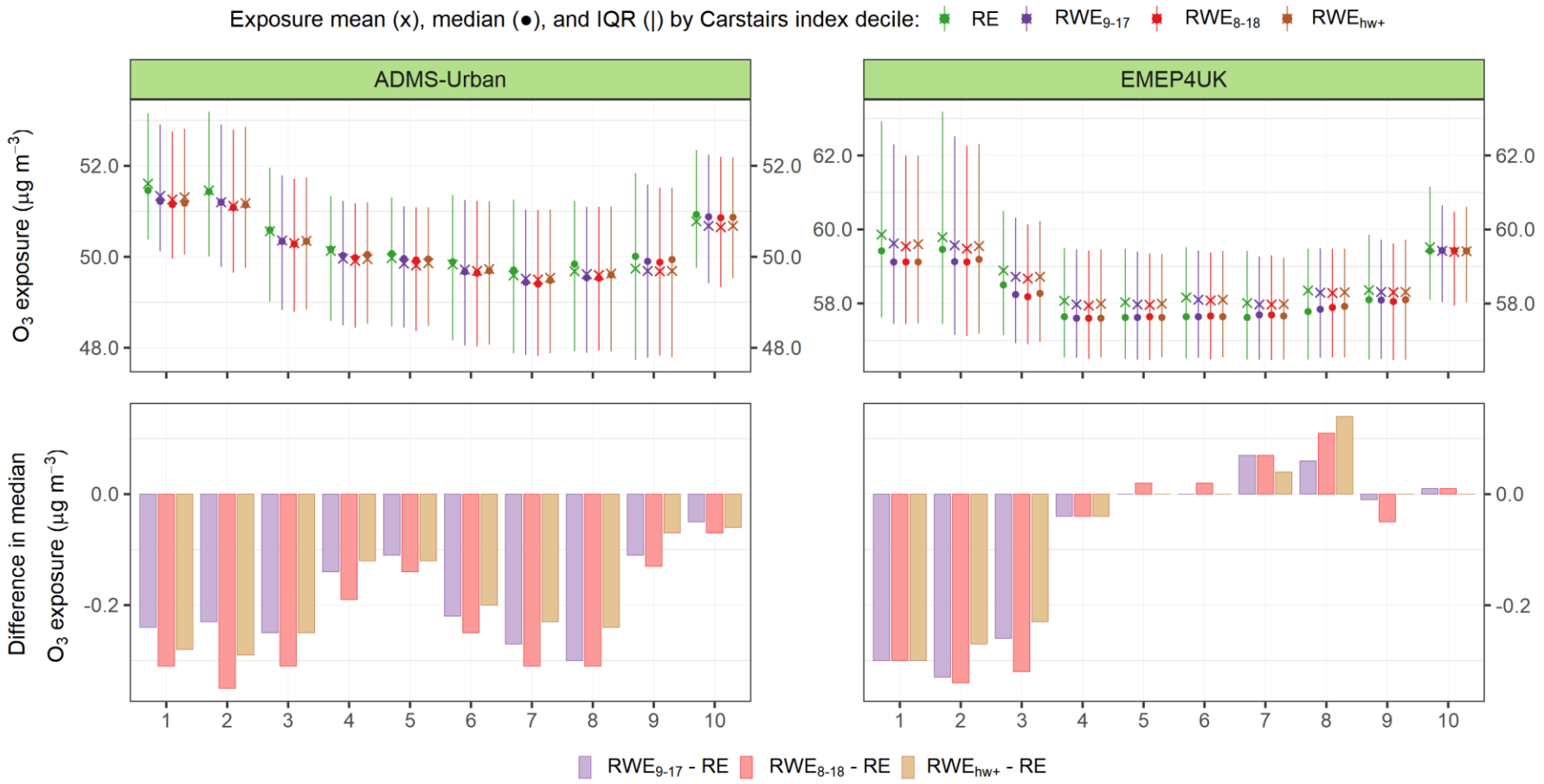

Figure 4.41 O_3 exposure means, medians and interquartile ranges by Carstairs index decile, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Decile 1 = least deprived, decile 10 = most deprived. Source: Scottish

Longitudinal ***Study.***

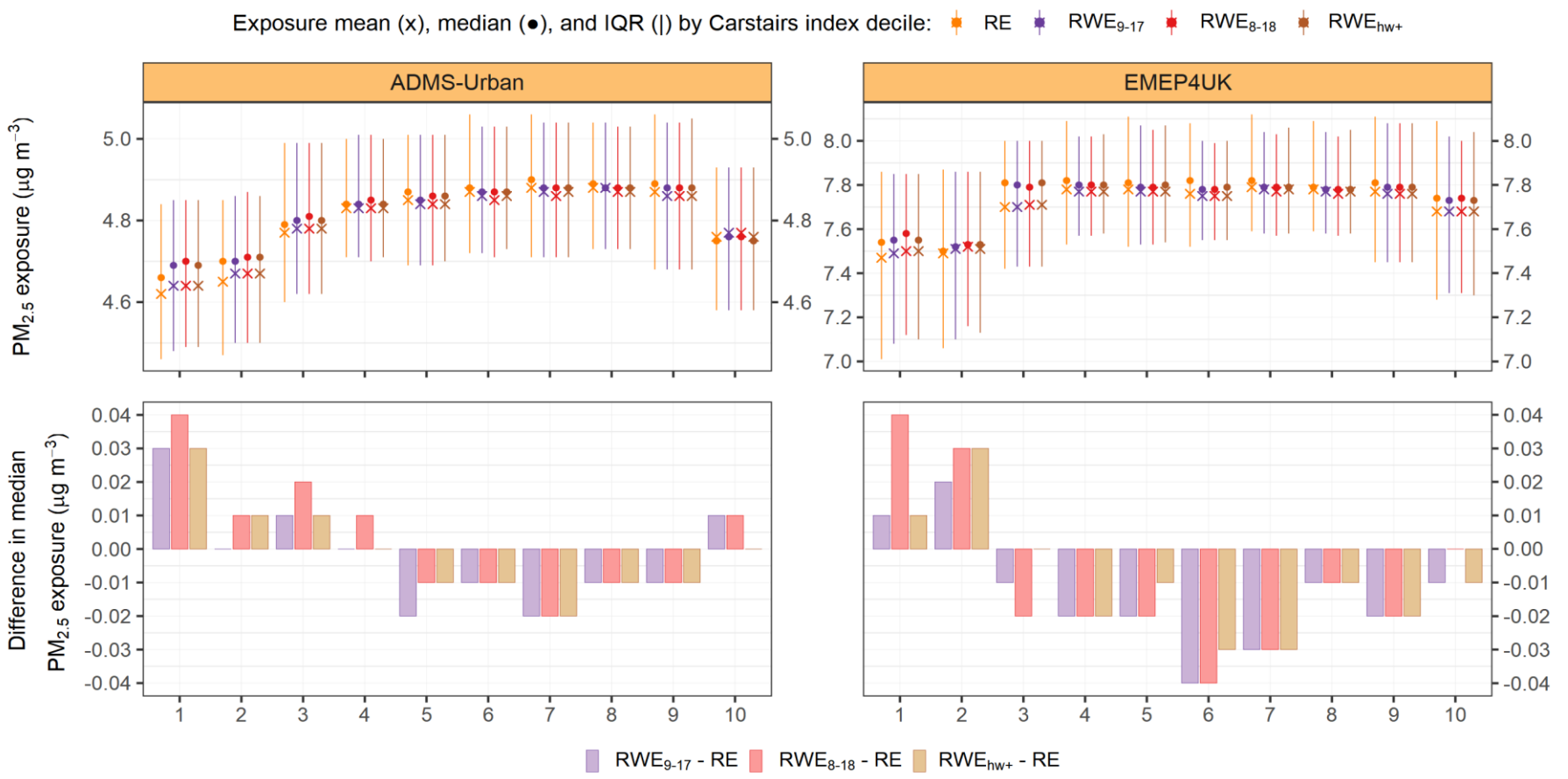

Figure 4.42 $PM_{2.5}$ exposure means, medians and interquartile ranges by Carstairs index decile, model and exposure scenario (top panels), and the differences in medians of each RWE and RE (bottom panels). Decile 1 = least deprived, decile 10 = most deprived. Source: Scottish Longitudinal Study.

The effect of using a particular model on estimates of population exposure to air pollution has not been extensively studied. This is particularly the case for a comparison of an ACTM and a Gaussian dispersion model and considering a dynamic population. Therefore whilst the following studies and this study have some methods in common the results are not directly comparable.

Shafran-Nathan *et al.* (2017) compared the differences between ambient concentrations at the place of work or study and home using data from a LUR model (NO_x concentrations at 50 m × 50 m spatial resolution) and a dispersion model (NO_2 concentrations at 500 m × 500 m spatial resolution) in the central coast area of Israel which covered approximately 40% of the Israeli population. Both models showed generally symmetric distributions of the differences, however in the LUR model 54% of adults and 75% of school children experienced concentration differences ≤ 5 ppb compared with 88% and 98%, respectively, using the dispersion model. The authors argued that some of the differences were attributable to the type of model and their spatial resolution. Their results, which suggest a smaller impact of the lower spatial resolution model on the estimated exposure differences, are in agreement with this study. In Basel, Switzerland, Ragettli *et al.* (2014) used three models with different spatial resolution (25 m, 50 m and 100 m) to estimate exposure to NO_2 during the commute between home and the place of work. They observed that annual mean exposure to NO_2 was similar for all models, however the highest resolution model also had the highest within-city and within-subject variability in annual mean NO_2 exposure. Whilst it was not possible to estimate exposure during commuting in this work this works has also observed a higher variability in mean NO_2 exposure associated with a higher spatial resolution model.

The agreement between LUR and dispersion models (including two ACTMs) in estimates of residential exposure only to NO_2, PM_{10} and $PM_{2.5}$ was investigated by de Hoogh *et al.* (2014) in several European study areas. The correlation between the LUR and dispersion models was generally good for NO_2 but less so for PM_{10} and $PM_{2.5}$. The agreement between the LUR and ACTM models (1 km × 1 km spatial resolution) was weaker (< 0.43) than the

agreement between LUR and Gaussian plume dispersion models which tend to have a comparable spatial resolution. In contrast, in this study the correlation between EMEP4UK and ADMS-Urban concentrations was high for all pollutants (≥ 0.78). This may have been caused by differences in dispersion modelling methods or by the relatively low air pollution concentrations in the Edinburgh study area.

In London, Walton *et al.* (2018) investigated the impact of using a higher resolution model (LAQT, 20 m × 20 m spatial resolution) on NO_2 exposure burden calculations compared with the traditionally used Pollution Climate Mapping (PCM) model (1 km × 1 km spatial resolution). Walton *et al.* (2018) aggregated the LAQT modelled concentrations on the PCM model grid and found the LAQT mean NO_2 concentrations were 4.3 µg m^{-3} higher than the PCM concentrations and the difference was spatially variable across the study area. The higher mean NO_2 concentrations in turn led to an 11.8% or 14% increase in attributable deaths (depending on the choice of counterfactual). The health burden calculations were not conducted in this study, therefore it is not clear what impact the observed 3.01 µg m^{-3} difference in mean NO_2 exposure ($RWE_{8\text{-}18}$) between ADMS-Urban and EMEP4UK would have on mortality in the study area.

4.3.4 Limitations

There are a number of considerations in this study which had no impact on EMEP4UK modelled concentrations but impacted on ADMS-Urban modelling. Firstly, traffic data were available for all major roads in the study area and for roads in and near Air Quality Management Areas that were mainly located in the central and northern parts of the study area. However, there were no traffic data for several other relatively busy roads primarily to the south and southwest of the city centre which were therefore not modelled. It is uncertain what impact modelling those roads explicitly would have on exposure estimates as both residential properties and places of work and school are located along those roads. Secondly, receptor points in ADMS-Urban are very sensitive to their distance from modelled sources. The modelled receptor

points were located inside a building polygon and had the coordinates of the postal delivery address nearest to the mean position of all delivery points in the postcode unit. In other words, the distance to the edge of the building varied between the receptor points which may have introduced a bias in the exposure estimates. As a consequence of the above, and more importantly however, a majority of the receptor points were modelled behind the modelled street canyon wall where air pollution rapidly decreases towards background levels, particularly in canyons with zero porosity. This limitation led to an underestimation of air pollution concentrations on highly polluted streets which tend to be located in the city centre where many people work.

4.4 Conclusion

In this study, a local Gaussian plume dispersion model ADMS-Urban was used to assess a potential underestimation of the effects of workplace mobility on population exposure to air pollution previously estimated from a coarser, regional ACTM EMEP4UK. The ADMS-Urban output was evaluated against observations from automatic monitoring stations and passive diffusion tube sites (NO_2 only) and was shown to capture air pollution gradients near road emission sources well.

On average, across the study area ADMS-Urban NO_2 concentrations were higher and had a higher range of values than those by EMEP4UK. The opposite was true for O_3 and $PM_{2.5}$. The exposure analysis at the population level revealed that the local model suggests a slightly larger impact of workplace mobility on population exposure than the regional model does for NO_2 (difference in median exposure 1.1% - 1.6% vs 0.7%) and similar impact for O_3 (-0.5% - -0.4% vs -0.5% - -0.4%). Neither model showed any impact of workplace mobility on population exposure for $PM_{2.5}$. The observed differences between the models in terms of modelled concentrations and exposures are relatively modest, likely a consequence of comparatively low levels of pollution in the Edinburgh urban area, and also a relatively high resolution of the EMEP4UK model.

At the population subgroup level, both models showed largely similar patterns in both exposure inequality and the influence of workplace mobility on it with some notable exceptions. Those include 16-25 year old age group where the models disagree on the direction of change in exposure to NO_2 and O_3 due to exposure at the place of work or study.

Overall, the study suggests that any change in estimates of exposure to air pollution by accounting for exposure at the place of work or study is small for NO_2 and O_3 and negligible for $PM_{2.5}$ regardless of the model used.

Chapter 5 Conclusions and future work

5.1 Overview of the thesis

The aim of this work was to investigate and improve estimates of population exposure, and the exposure of population subgroups, to the key air pollutants of NO_2, $PM_{2.5}$ and O_3 in the UK.

Substantial improvements in air pollution modelling capabilities achieved in the last few decades have resulted in detailed and generally accurate predictions of air pollution concentrations across the country. Unfortunately, until recently, the lack of consistent individual mobility data at a national scale had largely prevented exposure studies to progress beyond the traditional approach of using residential exposure as a surrogate of overall exposure. However, data collected in the latest UK Census (2011) include, for the first time, mobility elements and make it possible to consider exposure at the place of work (or study) in exposure assessments using this particular source of population data.

As a result, in Chapter 2 pollution fields generated by the EMEP4UK high-resolution atmospheric chemistry transport model (ACTM) were combined with publicly available population density datasets to estimate at the national level (the whole of the UK, and Scotland separately) population exposure to the key air pollutants whilst accounting for time spent at home and work – the two generally most important exposure microenvironments (e.g. de Nazelle *et al.*, 2013; Ragettli *et al.*, 2015; Shafran-Nathan *et al.*, 2018).

In Chapter 3, a similar methodology was applied on regional and urban scales in the case study of the Central Belt of Scotland. Unlike in Chapter 2, the population dataset used in Chapter 3 was anonymised personal data of the participants in the Scottish Longitudinal Study (Boyle *et al.*, 2009) – a representative 5.3% sample of the Scottish population. This restricted-access population dataset enabled the investigation of exposures at an individual level and across the population stratified by age, ethnic group and socio-economic

status. The combined home and place of work (or study) exposure estimates were used to further investigate the air pollution exposure inequalities reported in numerous studies (Mitchell and Dorling, 2003; Fairburn *et al.*, 2005, 2019; Fecht *et al.*, 2015; Milojevic *et al.*, 2017; Barnes *et al.*, 2019).

Finally, the choice of model type (ACTM, Gaussian dispersion model, land-use regression (LUR)), and of a specific model within a model type, can have a substantial impact on estimates of pollution concentrations (Carslaw, 2011; Hennig *et al.*, 2016; Hood *et al.*, 2018) and exposures (Ragettli *et al.*, 2014; Walton *et al.*, 2018). Therefore, the effect of model choice on estimated concentrations and exposures in the Edinburgh urban area was investigated in Chapter 4. For this part of the study, the Gaussian plume dispersion model ADMS-Urban was used alongside the EMEP4UK model.

5.2 Summary of findings

This work has demonstrated that accounting for time spent at the place of work or study has only a small effect on overall exposure to air pollution at the population level and across all spatial scales (national, regional and urban). The effect is largest for NO_2 - the most spatially heterogeneous of the three investigated pollutants.

Based on concentration data from EMEP4UK the following was observed. At the national level, annual mean population exposure to NO_2 in the UK was estimated to be larger by 2.0% (increase from 14.28 µg m^{-3} to 14.56 µg m^{-3}) under the assumption that workers and students (≥16 years old) spend 40 hours during the working week at the place of work or study. In Scotland the estimated increase was 3.1% (from 9.09 µg m^{-3} to 9.38 µg m^{-3}), in the Central Belt region 3.0% (from 10.92 µg m^{-3} to 11.25 µg m^{-3}) and in the Greater Glasgow urban area the increase in mean NO_2 exposure was the highest of all investigated areas in both relative and absolute terms at 3.3% (from 13.39 µg m^{-3} to 13.83 µg m^{-3}). The smallest relative and absolute increase was observed in Edinburgh urban area at 1.5% (from 12.71 µg m^{-3} to 12.90 µg m^{-3}).

For O_3, accounting for exposure at the place of work or study led to a reduction in modelled exposure compared with traditional calculations. The reduction was in relative terms an order of magnitude smaller than for NO_2. As for NO_2, the magnitude of both relative and absolute change in exposure to O_3 was largest in the Greater Glasgow urban area at -0.6% (from 55.72 µg m^{-3} to 58.24 µg m^{-3}) and the smallest in Edinburgh at -0.3% (from 58.78 µg m^{-3} to 58.62 µg m^{-3}).

For $PM_{2.5}$, the pollutant most strongly associated with adverse health effects, the difference in exposure was positive virtually everywhere but also an order of magnitude smaller than for NO_2. The maximum relative increase in $PM_{2.5}$ exposure was observed for Scotland (0.5%); however in the Edinburgh urban area, accounting for exposure at the place of work or study had no impact on estimated exposure.

However, the estimated differences in mean population exposure were shown to mask some much larger differences on an individual level. For example, whilst in the Central Belt region the mean increase in NO_2 exposure was 0.33 µg m^{-3}, nearly 3,500 individuals in the SLS sample experienced an increase in overall exposure of 3.50 µg m^{-3} or more when including exposure to NO_2 at their workplace location. If scaled up to the whole population of the Central Belt, just over 65,000 individuals were impacted in that way. In contrast, only approximately 130 individuals in the SLS sample (and correspondingly just over 3,700 Central Belt residents) had an overall NO_2 exposure that decreased by 3.50 µg m^{-3} or more when accounting for exposure at their workplace location.

When investigating exposure inequality among population subgroups, in the Central Belt the white ethnic group, children and people over 60 years of age, and the least deprived groups in the society were on average least exposed to NO_2 and $PM_{2.5}$. The opposite was true for exposure to O_3. However, the white ethnic and the least deprived groups were also most affected by changes in magnitude by exposure at the place of work. Accounting for exposure at the

place of work or study therefore seems to attenuate, but not cancel, exposure gradients between subgroups of different ethnicity or socio-economic status. Whilst this conclusion was applicable to both investigated urban areas within the Central Belt as well, large contrasts in exposure patterns across population subgroups were found between Greater Glasgow and Edinburgh. This is in agreement with other studies that investigated exposure inequality in the society both in the UK and elsewhere (e.g. Fecht *et al.*, 2015; Temam *et al.*, 2017).

One of the strengths of the analysis here lies in the fact that individual level data on ethnicity and age (but not SES) were used and as such the results were not affected by the modifiable area unit problem, in contrast to most other similar studies.

The choice of air pollution model appeared to have only a modest influence on the estimate of the impact of workplace exposure on overall population exposure. Whilst the distributions of individual exposures were dissimilar between the models, at the population level ADMS-Urban showed a slightly larger impact of workplace mobility on population exposure than the EMEP4UK model for NO_2 and similar impacts for O_3. Neither model showed any impact of workplace mobility on population exposure for $PM_{2.5}$. Except for certain population demographics, such as the 16-25 years of age group, both models showed largely similar patterns across population subgroups. The rather close agreement between the models may have been caused by the relatively highly spatially resolved output of EMEP4UK and also the fact the most of the modelled postcode locations lie away from busy roads modelled explicitly by ADMS-Urban. This suggests that any biases between models are spatially fairly consistent.

5.3 Implications for future exposure assessments

The findings of this work point to only small or even negligible errors in estimates of exposures to NO_2, O_3 and $PM_{2.5}$ at the population level when exposure at the place of work or study is not considered. The findings are

broadly in agreement with other recent studies in this research area conducted in other parts of the world (e.g. the Netherlands, Israel, Belgium, the USA and Switzerland).

This work shows that considering the exposure at the place of work or study would only marginally decrease exposure misclassification in large, population-scale epidemiological studies and health impact assessments. Therefore, the inclusion of this microenvironment in such studies in the future may increase confidence in the studies, however it is not crucial, as it will not substantially affect their outcomes. This is a useful observation, since obtaining mobility data on a large scale is at present time-consuming and costly.

5.4 Limitations and future work

Many exposure studies, including this work, only consider exposure to outdoor air pollution despite the fact that the majority of the population in Europe spend much more time indoors than outdoors. This limitation has largely been caused by the lack of reliable data on pollutants originating from indoor air pollution as well as the uncertainty in the magnitude of the modifying effect of building characteristics and occupant behaviours on outdoor pollution infiltrating indoors. Considering infiltration of outdoor pollution indoors alone, the filtration effect of buildings together with deposition of pollutants on indoor surfaces can substantially reduce the concentrations of pollutants of outdoor origin indoors (Taylor *et al.*, 2014) and have a much larger effect on overall exposure than does accounting for exposure at the place of work or study (Smith *et al.*, 2016).

The limitations associated with the restricted access to personal data prevented accounting for exposure during commuting between home and place of work or study of the study subjects. Had it been possible to account for commuting in the assessment the estimated difference between the dynamic and static population exposures would likely not have changed substantially. For example, Ragettli *et al.* (2015) and Shafran-Nathan *et al.* (2018) argued that at the population level the impact of commuting on overall

exposure is negligible. Moreover, emissions from traffic in Europe have been falling (European Environmental Agency, 2019) and if the trend continues, the importance of exposure during commuting will likely further diminish.

The impact of exposure both during commuting and at the place of work may decrease even further and faster if work from home arrangements, in place due to the Covid-19 pandemic for most of 2020 and the start of 2021, remain to some extent beyond the pandemic. Such a transformation from the current common practice of working at one's workplace (Table 3.1 suggests that only 10.5% of the working/studying population worked or studied at home in the Central Belt area in 2011) would however only affect those who can work from home, e.g. 'office' workers. In turn that may affect inequalities in exposure between those who do stay at home and those who do not. It is unclear whether the inequalities would be exacerbated or attenuated, which suggests an area of further research. For illustration, the least deprived members of the society often live either in the countryside or in the prestigious and affluent inner urban areas such as Mayfair in London or the New Town in Edinburgh. In terms of exposure to NO_2 in particular, those living in the countryside would almost certainly benefit from working at home whereas those living in city centres would likely see little change (e.g. Figure 2.10).

Due to data availability this work was also not able to address exposure of those without a fixed place of work. They were either considered to be at home all the time (Chapter 2), or completely excluded from the analysis unless they reported to a depot within the study areas (Chapters 3 and 4). However, many of those workers would have been drivers (bus, taxi, delivery, emergency services) who spend most of their working hours in some of the most polluted environments – urban streets. Exclusion of such workers from the analyses here has almost certainly decreased the magnitude of the estimated impact of exposure at the place of work. Furthermore, the Covid-19 pandemic has increased the popularity of online shopping and therefore the number of people working as delivery drivers, who may have previously worked in less polluted environment, has also increased. An exposure assessment of workers in this

occupation to understand the current and potential future impacts on their health would be desirable.

Appendix

A.1 Summary statistics of population exposure per study area, pollutant, exposure scenario and population subgroup in the Central Belt

Table A1 Residential exposure (RE) to NO_2 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	10.81	3.90	7.55	10.51	13.69
	Asian	13.35	4.36	10.18	13.58	15.73
	African	13.75	4.56	10.43	13.56	16.80
	Arab	13.98	4.93	9.48	13.80	17.29
	C or B	13.04	4.62	9.09	13.26	15.72
	Mixed	12.38	4.20	8.73	12.93	15.21
	Other	12.85	4.37	9.25	13.26	15.76
Age group	0-5	10.66	3.74	7.54	10.4	13.44
	6-10	10.27	3.59	7.39	10.01	13.13
	11-15	10.31	3.60	7.38	10.05	13.17
	16-20	11.18	4.31	7.64	10.75	14.19
	21-25	12.21	4.53	8.42	12.13	15.25
	26-30	12.02	4.23	8.51	12.12	15.02
	31-35	11.49	4.12	8.04	11.3	14.57
	36-40	10.96	3.91	7.76	10.68	13.71
	41-45	10.78	3.83	7.60	10.56	13.58
	46-50	10.76	3.84	7.59	10.46	13.65
	51-55	10.80	3.86	7.61	10.57	13.70
	56-60	10.60	3.81	7.46	10.36	13.55
	61-65	10.55	3.78	7.44	10.3	13.41
	66-70	10.45	3.76	7.39	10.25	13.32
	71-75	10.59	3.75	7.47	10.35	13.44
	76+	10.79	3.77	7.65	10.57	13.58
Carstairs index decile	1	9.51	3.25	7.02	9.15	11.83
	2	9.81	3.37	7.14	9.39	12.24
	3	10.31	3.53	7.44	10.09	13.21
	4	10.76	3.76	7.56	10.62	13.71
	5	10.96	3.86	7.96	10.90	13.82
	6	11.02	4.03	7.72	10.80	13.86
	7	10.94	4.16	7.47	10.42	13.91
	8	11.26	4.05	7.86	11.08	14.13
	9	11.64	4.18	8.23	11.56	14.53
	10	12.73	4.14	9.52	12.95	15.36

Table A2 Combined exposure ($RWE_{9\text{-}17}$) to NO_2 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	11.05	3.80	7.98	10.81	13.78
	Asian	13.51	4.21	10.43	13.70	15.76
	African	13.87	4.46	10.43	13.70	16.94
	Arab	14.06	4.79	9.80	13.86	17.34
	C or B	13.09	4.52	9.12	13.46	15.73
	Mixed	12.57	4.08	9.08	13.02	15.43
	Other	13.03	4.15	9.93	13.22	16.22
Age group	0-5	10.67	3.74	7.60	10.42	13.44
	6-10	10.33	3.52	7.44	10.06	13.11
	11-15	10.39	3.49	7.45	10.12	13.16
	16-20	11.51	4.15	8.23	11.13	14.31
	21-25	12.55	4.35	8.96	12.56	15.45
	26-30	12.39	4.02	9.11	12.51	15.19
	31-35	11.92	3.92	8.71	11.79	14.82
	36-40	11.42	3.72	8.43	11.15	14.14
	41-45	11.21	3.67	8.27	11.02	13.86
	46-50	11.15	3.69	8.21	10.94	13.83
	51-55	11.15	3.72	8.10	10.97	13.90
	56-60	10.88	3.70	7.89	10.67	13.59
	61-65	10.66	3.74	7.59	10.42	13.43
	66-70	10.49	3.76	7.42	10.29	13.34
	71-75	10.60	3.74	7.48	10.36	13.48
	76+	10.79	3.77	7.65	10.57	13.58
Carstairs index decile	1	9.93	3.17	7.41	9.66	12.13
	2	10.20	3.31	7.55	9.97	12.61
	3	10.64	3.45	7.81	10.47	13.40
	4	11.05	3.68	7.97	10.86	13.86
	5	11.20	3.78	8.14	11.10	14.03
	6	11.22	3.94	7.98	11.02	14.03
	7	11.12	4.05	7.77	10.72	14.05
	8	11.42	3.97	8.11	11.29	14.17
	9	11.77	4.10	8.42	11.73	14.61
	10	12.82	4.09	9.69	13.02	15.42

Table A3 Combined exposure (RWE_{8-18}) to NO_2 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	11.14	3.81	8.05	10.95	13.85
	Asian	13.57	4.19	10.54	13.70	15.89
	African	13.91	4.45	10.56	13.70	17.14
	Arab	14.08	4.76	9.99	13.86	17.36
	C or B	13.10	4.50	9.39	13.28	15.84
	Mixed	12.64	4.08	9.27	13.00	15.48
	Other	13.10	4.11	10.00	13.23	16.16
Age group	0-5	10.67	3.73	7.61	10.42	13.44
	6-10	10.35	3.51	7.45	10.09	13.12
	11-15	10.42	3.47	7.50	10.19	13.14
	16-20	11.63	4.14	8.36	11.34	14.38
	21-25	12.68	4.34	9.09	12.71	15.67
	26-30	12.52	4.00	9.32	12.59	15.31
	31-35	12.07	3.91	8.92	12.00	14.94
	36-40	11.58	3.72	8.62	11.41	14.27
	41-45	11.37	3.66	8.45	11.19	13.99
	46-50	11.30	3.69	8.38	11.13	13.97
	51-55	11.28	3.71	8.26	11.13	14.00
	56-60	10.98	3.70	8.00	10.83	13.65
	61-65	10.71	3.74	7.62	10.45	13.48
	66-70	10.50	3.76	7.42	10.29	13.37
	71-75	10.60	3.74	7.49	10.36	13.48
	76+	10.79	3.77	7.65	10.57	13.59
Carstairs index decile	1	10.09	3.21	7.52	9.93	12.36
	2	10.35	3.35	7.70	10.15	12.74
	3	10.76	3.48	7.95	10.62	13.49
	4	11.15	3.70	8.05	11.02	13.92
	5	11.28	3.79	8.26	11.17	14.06
	6	11.30	3.94	8.03	11.13	14.04
	7	11.19	4.05	7.89	10.83	14.06
	8	11.47	3.97	8.22	11.32	14.20
	9	11.81	4.10	8.44	11.77	14.66
	10	12.85	4.08	9.74	13.04	15.43

Table A4 Combined exposure (RWE_{hw+}) to NO_2 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	11.06	3.79	8.00	10.84	13.78
	Asian	13.52	4.20	10.45	13.70	15.73
	African	13.87	4.44	10.56	13.70	16.80
	Arab	14.05	4.76	9.91	13.91	17.29
	C or B	13.07	4.49	9.61	13.22	15.78
	Mixed	12.56	4.10	9.06	13.00	15.40
	Other	12.98	4.14	9.82	13.15	15.93
Age group	0-5	10.67	3.74	7.60	10.40	13.44
	6-10	10.31	3.53	7.43	10.07	13.11
	11-15	10.37	3.50	7.45	10.10	13.15
	16-20	11.45	4.14	8.20	11.08	14.30
	21-25	12.54	4.33	8.97	12.53	15.37
	26-30	12.39	3.99	9.14	12.49	15.17
	31-35	11.93	3.89	8.84	11.81	14.78
	36-40	11.44	3.70	8.50	11.22	14.13
	41-45	11.25	3.65	8.38	11.08	13.88
	46-50	11.19	3.66	8.31	11.02	13.84
	51-55	11.20	3.70	8.20	11.03	13.93
	56-60	10.90	3.69	7.98	10.72	13.58
	61-65	10.67	3.73	7.59	10.43	13.44
	66-70	10.48	3.76	7.41	10.29	13.34
	71-75	10.60	3.74	7.48	10.36	13.48
	76+	10.79	3.77	7.65	10.57	13.58
Carstairs index decile	1	9.96	3.18	7.42	9.74	12.17
	2	10.22	3.30	7.58	10.01	12.61
	3	10.65	3.44	7.86	10.50	13.42
	4	11.05	3.67	7.99	10.90	13.86
	5	11.20	3.76	8.22	11.13	14.02
	6	11.23	3.92	8.00	11.04	13.99
	7	11.12	4.04	7.81	10.77	14.05
	8	11.42	3.97	8.13	11.28	14.17
	9	11.77	4.10	8.43	11.73	14.61
	10	12.82	4.08	9.69	13.02	15.41

Table A5 Residential exposure (RE) to NO_2 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	13.24	3.88	10.36	13.51	15.47
	Asian	14.97	4.26	12.01	15.14	17.50
	African	16.05	4.11	13.25	15.52	19.57
	Arab	16.88	4.53	14.05	17.26	20.56
	C or B	16.21	4.02	13.71	16.58	20.20
	Mixed	14.71	3.95	12.04	15.09	17.24
	Other	15.27	4.00	12.77	15.25	17.94
Age group	0-5	13.02	3.69	10.30	13.21	15.27
	6-10	12.36	3.64	9.39	12.42	15.07
	11-15	12.65	3.60	10.07	12.95	15.07
	16-20	14.06	4.44	10.60	14.05	17.24
	21-25	15.02	4.49	11.12	15.07	17.99
	26-30	14.58	4.11	11.36	14.69	17.49
	31-35	14.10	4.08	10.91	14.30	17.16
	36-40	13.43	3.88	10.47	13.56	15.55
	41-45	13.22	3.85	10.34	13.56	15.47
	46-50	13.17	3.73	10.35	13.55	15.39
	51-55	13.21	3.70	10.45	13.56	15.36
	56-60	13.06	3.68	10.36	13.44	15.28
	61-65	13.00	3.76	10.29	13.37	15.27
	66-70	12.83	3.73	10.29	13.16	15.14
	71-75	12.76	3.69	10.25	13.05	15.14
	76+	12.98	3.68	10.36	13.37	15.27
Carstairs index decile	1	10.57	3.05	7.98	10.34	12.42
	2	11.57	3.35	8.68	11.02	14.19
	3	12.04	3.46	9.18	12.04	14.79
	4	12.93	3.64	10.36	13.19	15.12
	5	13.36	3.64	10.61	13.55	15.41
	6	13.62	4.14	10.36	13.70	15.86
	7	13.94	4.16	10.80	13.75	16.06
	8	13.97	3.99	10.97	13.79	16.33
	9	14.24	3.90	11.12	14.41	17.23
	10	14.64	3.74	11.40	15.07	17.20

Table A6 Combined exposure ($RWE_{9\text{-}17}$) to NO_2 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	13.57	3.77	10.65	13.70	15.88
	Asian	15.21	4.08	12.30	15.14	17.50
	African	16.23	3.94	13.47	16.05	19.42
	Arab	17.08	4.30	14.71	17.34	20.70
	C or B	16.25	3.97	13.56	17.15	19.59
	Mixed	14.99	3.88	12.37	15.21	17.26
	Other	15.62	3.68	12.88	16.35	17.94
Age group	0-5	13.02	3.68	10.30	13.20	15.29
	6-10	12.38	3.56	9.44	12.42	15.05
	11-15	12.73	3.43	10.20	13.02	15.11
	16-20	14.51	4.15	11.16	14.39	17.26
	21-25	15.53	4.21	12.43	15.55	18.59
	26-30	15.14	3.86	12.47	15.16	17.81
	31-35	14.74	3.80	12.01	15.00	17.25
	36-40	14.05	3.62	11.17	14.17	16.45
	41-45	13.76	3.64	10.92	14.03	16.08
	46-50	13.69	3.54	10.90	13.95	15.89
	51-55	13.64	3.54	10.95	13.84	15.78
	56-60	13.44	3.51	10.72	13.56	15.70
	61-65	13.15	3.71	10.36	13.51	15.40
	66-70	12.88	3.72	10.30	13.19	15.25
	71-75	12.77	3.69	10.25	13.12	15.14
	76+	12.98	3.67	10.36	13.37	15.28
Carstairs index decile	1	11.16	3.05	8.84	10.73	13.23
	2	12.11	3.33	9.47	12.00	14.63
	3	12.53	3.41	9.98	12.57	15.12
	4	13.39	3.57	10.69	13.62	15.63
	5	13.76	3.57	10.97	13.81	16.04
	6	13.97	4.03	10.72	14.03	16.62
	7	14.21	4.02	11.11	14.23	16.90
	8	14.19	3.89	11.31	14.17	16.85
	9	14.44	3.81	11.52	14.56	17.22
	10	14.76	3.67	11.89	15.10	17.22

Table A7 Combined exposure ($RWE_{8\text{-}18}$) to NO_2 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	13.69	3.78	10.70	13.79	16.06
	Asian	15.29	4.05	12.42	15.25	17.78
	African	16.29	3.91	13.57	16.06	19.34
	Arab	17.15	4.25	14.74	17.36	20.56
	C or B	16.25	3.99	13.54	17.12	19.47
	Mixed	15.09	3.89	12.48	15.25	17.51
	Other	15.75	3.63	13.11	16.27	17.98
Age group	0-5	13.03	3.68	10.31	13.20	15.29
	6-10	12.40	3.55	9.54	12.40	15.06
	11-15	12.76	3.39	10.28	13.02	15.12
	16-20	14.68	4.09	11.61	14.61	17.26
	21-25	15.71	4.15	12.71	15.82	18.74
	26-30	15.34	3.83	12.75	15.35	17.94
	31-35	14.97	3.77	12.47	15.14	17.50
	36-40	14.28	3.60	11.65	14.49	16.88
	41-45	13.96	3.63	11.12	14.21	16.50
	46-50	13.88	3.54	11.13	14.17	16.13
	51-55	13.79	3.53	11.03	14.06	15.97
	56-60	13.58	3.50	10.91	13.70	15.82
	61-65	13.20	3.72	10.45	13.56	15.44
	66-70	12.90	3.72	10.30	13.19	15.25
	71-75	12.77	3.69	10.24	13.12	15.14
	76+	12.98	3.67	10.36	13.37	15.28
Carstairs index decile	1	11.39	3.14	9.08	11.00	13.61
	2	12.31	3.39	9.72	12.13	14.81
	3	12.70	3.46	10.08	12.79	15.14
	4	13.56	3.60	10.77	13.75	15.91
	5	13.90	3.60	11.02	14.04	16.37
	6	14.10	4.04	10.81	14.13	17.06
	7	14.32	4.01	11.35	14.41	17.16
	8	14.27	3.89	11.43	14.26	17.16
	9	14.51	3.81	11.65	14.69	17.25
	10	14.81	3.67	12.22	15.10	17.34

Table A8 Combined exposure (RWE_{hw+}) to NO_2 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	13.57	3.76	10.66	13.70	15.86
	Asian	15.22	4.08	12.32	15.20	17.50
	African	16.20	3.95	13.53	15.97	19.21
	Arab	17.04	4.29	14.61	17.31	20.60
	C or B	16.18	3.98	13.57	16.86	19.60
	Mixed	15.00	3.85	12.47	15.25	17.26
	Other	15.52	3.75	12.82	15.92	17.98
Age group	0-5	13.02	3.68	10.30	13.20	15.28
	6-10	12.38	3.57	9.50	12.42	15.06
	11-15	12.71	3.45	10.20	12.98	15.10
	16-20	14.43	4.16	11.12	14.32	17.24
	21-25	15.49	4.19	12.47	15.49	18.34
	26-30	15.14	3.82	12.48	15.19	17.73
	31-35	14.75	3.77	12.15	15.01	17.24
	36-40	14.09	3.60	11.36	14.23	16.44
	41-45	13.79	3.62	11.02	14.07	16.04
	46-50	13.73	3.51	10.98	14.04	15.90
	51-55	13.67	3.52	11.02	13.90	15.80
	56-60	13.48	3.48	10.79	13.58	15.67
	61-65	13.16	3.71	10.36	13.52	15.41
	66-70	12.88	3.72	10.30	13.19	15.24
	71-75	12.77	3.69	10.25	13.12	15.14
	76+	12.98	3.67	10.35	13.37	15.27
Carstairs index decile	1	11.21	3.07	8.86	10.80	13.30
	2	12.12	3.31	9.45	12.04	14.60
	3	12.54	3.39	9.98	12.59	15.10
	4	13.39	3.56	10.69	13.65	15.64
	5	13.76	3.55	10.97	13.88	15.99
	6	13.97	4.01	10.75	14.06	16.60
	7	14.22	4.01	11.13	14.24	16.75
	8	14.18	3.89	11.40	14.17	16.82
	9	14.43	3.81	11.57	14.54	17.23
	10	14.75	3.67	11.96	15.10	17.23

Table A9 Residential exposure (RE) to NO_2 in Edinburgh per population subgroup. Source: All units µg m^{-3}. Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.67	3.01	10.62	13.41	14.96
	Asian	13.29	2.97	11.02	14.05	15.56
	African	12.36	2.75	10.43	13.11	14.49
	Arab	12.00	3.02	8.69	12.76	14.71
	C or B	12.90	3.30	12.07	13.41	15.26
	Mixed	13.56	3.15	11.40	14.49	15.58
	Other	13.01	3.27	10.56	13.41	15.71
Age group	0-5	12.42	2.91	10.43	13.20	14.57
	6-10	11.88	3.05	8.88	13.00	14.11
	11-15	11.94	2.94	9.28	13.02	13.91
	16-20	12.86	3.09	10.62	13.75	15.02
	21-25	13.78	2.85	12.74	14.49	15.59
	26-30	13.78	2.71	12.76	14.49	15.59
	31-35	13.49	2.83	11.74	14.14	15.56
	36-40	12.86	3.06	10.68	13.42	15.03
	41-45	12.73	2.89	10.88	13.34	14.93
	46-50	12.48	3.00	10.43	13.21	14.86
	51-55	12.34	3.10	9.96	13.20	14.74
	56-60	12.34	2.95	10.13	13.14	14.57
	61-65	12.15	3.08	9.96	13.05	14.40
	66-70	12.25	2.95	10.43	13.14	14.34
	71-75	12.34	3.05	10.13	13.20	14.74
	76+	12.20	2.96	9.96	13.11	14.34
Carstairs index decile	1	11.27	3.15	8.44	11.34	13.58
	2	11.46	3.18	8.27	11.35	14.12
	3	12.45	3.22	10.45	13.41	14.93
	4	13.31	2.67	11.97	13.88	15.02
	5	13.33	2.77	11.35	13.90	15.03
	6	13.45	2.78	11.75	14.14	15.56
	7	13.45	2.76	11.35	14.05	15.56
	8	13.24	2.77	11.35	13.72	15.56
	9	13.18	2.88	10.88	13.49	15.59
	10	12.28	2.62	10.43	13.02	14.05

Table A10 Combined exposure (RWE_{9-17}) to NO_2 in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.82	2.86	10.88	13.48	14.96
	Asian	13.34	2.79	11.29	14.04	15.45
	African	12.44	2.69	10.37	13.19	14.57
	Arab	12.00	2.91	8.97	12.76	14.73
	C or B	13.06	3.05	11.69	13.98	15.50
	Mixed	13.58	3.01	12.08	14.29	15.54
	Other	13.20	3.15	10.56	13.59	15.71
Age group	0-5	12.43	2.89	10.43	13.19	14.57
	6-10	11.97	2.94	9.43	13.00	14.26
	11-15	12.08	2.79	9.71	13.03	14.05
	16-20	12.90	2.83	10.77	13.60	14.96
	21-25	13.83	2.62	12.53	14.40	15.56
	26-30	13.92	2.47	12.89	14.57	15.59
	31-35	13.74	2.58	12.53	14.40	15.52
	36-40	13.17	2.81	11.13	13.82	15.26
	41-45	13.03	2.66	11.18	13.54	14.99
	46-50	12.77	2.76	10.69	13.39	14.92
	51-55	12.65	2.86	10.50	13.27	14.91
	56-60	12.56	2.78	10.56	13.19	14.74
	61-65	12.27	3.00	10.06	13.08	14.49
	66-70	12.28	2.93	10.43	13.14	14.34
	71-75	12.36	3.05	10.39	13.19	14.74
	76+	12.20	2.96	9.96	13.11	14.15
Carstairs index decile	1	11.56	3.01	8.97	11.83	13.72
	2	11.74	3.02	9.04	11.97	14.15
	3	12.65	3.05	10.61	13.48	14.94
	4	13.44	2.54	12.53	13.90	15.19
	5	13.43	2.62	12.17	13.93	15.27
	6	13.52	2.63	12.33	14.14	15.41
	7	13.50	2.63	11.98	14.05	15.41
	8	13.31	2.63	11.75	13.81	15.23
	9	13.25	2.74	11.13	13.69	15.45
	10	12.38	2.55	10.43	13.02	14.19

Table A11 Combined exposure ($RWE_{8\text{-}18}$) to NO_2 in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.87	2.83	11.02	13.47	15.00
	Asian	13.35	2.75	11.35	13.90	15.45
	African	12.47	2.69	10.43	13.17	14.47
	Arab	12.00	2.90	8.97	12.76	14.66
	C or B	13.11	2.98	11.53	14.04	15.29
	Mixed	13.57	2.99	12.17	14.14	15.60
	Other	13.27	3.12	10.56	13.69	15.71
Age group	0-5	12.44	2.88	10.44	13.20	14.57
	6-10	12.01	2.92	9.54	12.90	14.30
	11-15	12.13	2.75	10.07	13.01	14.13
	16-20	12.91	2.78	10.87	13.57	14.96
	21-25	13.84	2.59	12.57	14.26	15.71
	26-30	13.95	2.43	12.95	14.48	15.60
	31-35	13.81	2.53	12.63	14.43	15.58
	36-40	13.27	2.75	11.34	13.84	15.32
	41-45	13.13	2.60	11.32	13.55	15.02
	46-50	12.87	2.70	10.93	13.41	14.96
	51-55	12.76	2.80	10.73	13.37	14.93
	56-60	12.64	2.74	10.68	13.20	14.83
	61-65	12.31	2.98	10.13	13.13	14.57
	66-70	12.29	2.93	10.43	13.14	14.34
	71-75	12.36	3.05	10.43	13.20	14.74
	76+	12.20	2.96	9.95	13.12	14.15
Carstairs index decile	1	11.66	2.99	9.13	11.90	13.71
	2	11.84	3.00	9.41	12.05	14.15
	3	12.72	3.02	10.75	13.51	14.96
	4	13.48	2.53	12.53	13.90	15.25
	5	13.46	2.59	12.20	13.90	15.28
	6	13.54	2.61	12.44	14.04	15.40
	7	13.51	2.61	11.99	14.00	15.44
	8	13.33	2.61	11.81	13.75	15.23
	9	13.27	2.72	11.17	13.69	15.36
	10	12.42	2.54	10.43	13.02	14.30

Table A12 Combined exposure (RWE_{hw+}) to NO_2 in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.82	2.84	10.90	13.45	14.96
	Asian	13.34	2.78	11.27	13.96	15.44
	African	12.44	2.65	10.43	13.20	14.54
	Arab	12.01	2.93	8.97	12.57	14.73
	C or B	13.04	3.04	11.72	13.73	15.50
	Mixed	13.55	3.03	11.81	14.36	15.48
	Other	13.22	3.13	10.56	13.45	15.74
Age group	0-5	12.43	2.89	10.43	13.20	14.57
	6-10	11.96	2.95	9.38	12.93	14.16
	11-15	12.06	2.79	9.61	13.03	14.00
	16-20	12.90	2.84	10.88	13.70	15.02
	21-25	13.83	2.61	12.47	14.39	15.56
	26-30	13.90	2.44	12.91	14.47	15.58
	31-35	13.73	2.54	12.57	14.34	15.51
	36-40	13.15	2.77	11.23	13.75	15.17
	41-45	13.03	2.61	11.17	13.49	14.96
	46-50	12.79	2.69	10.84	13.34	14.79
	51-55	12.68	2.81	10.62	13.26	14.85
	56-60	12.57	2.75	10.62	13.15	14.73
	61-65	12.26	2.99	10.05	13.09	14.49
	66-70	12.27	2.93	10.43	13.14	14.34
	71-75	12.36	3.05	10.41	13.20	14.74
	76+	12.20	2.96	9.96	13.11	14.15
Carstairs index decile	1	11.57	3.00	8.97	11.83	13.72
	2	11.75	2.99	9.23	11.95	14.14
	3	12.65	3.03	10.65	13.48	14.91
	4	13.44	2.52	12.53	13.90	15.16
	5	13.42	2.60	12.12	13.90	15.19
	6	13.52	2.62	12.29	14.14	15.28
	7	13.49	2.61	12.06	14.05	15.34
	8	13.30	2.62	11.75	13.80	15.19
	9	13.25	2.74	11.13	13.68	15.42
	10	12.38	2.53	10.43	13.02	14.16

Table A13 Residential exposure (RE) to O_3 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.59	3.90	55.78	58.70	61.54
	Asian	56.38	4.36	53.26	56.48	59.46
	African	56.11	4.63	52.90	56.54	59.74
	Arab	56.08	5.01	52.22	57.00	59.72
	C or B	56.92	4.71	53.70	56.54	60.24
	Mixed	57.52	4.06	54.35	57.62	60.29
	Other	57.31	4.42	54.27	57.39	60.23
Age group	0-5	58.69	3.79	55.90	58.82	61.54
	6-10	59.01	3.69	56.28	59.12	61.86
	11-15	58.96	3.71	56.22	59.06	61.76
	16-20	58.25	4.20	55.48	58.44	61.48
	21-25	57.44	4.36	54.62	57.62	60.58
	26-30	57.66	4.12	55.16	57.66	60.64
	31-35	58.09	4.04	55.50	58.14	61.08
	36-40	58.50	3.91	55.72	58.56	61.40
	41-45	58.59	3.84	55.74	58.66	61.48
	46-50	58.60	3.89	55.66	58.72	61.60
	51-55	58.56	3.93	55.58	58.58	61.54
	56-60	58.78	3.90	55.92	58.84	61.70
	61-65	58.78	3.84	55.98	58.86	61.72
	66-70	58.90	3.85	56.08	58.94	61.86
	71-75	58.76	3.81	55.98	58.84	61.64
	76+	58.66	3.85	55.84	58.70	61.60
Carstairs index decile	1	59.76	3.47	57.30	59.72	62.46
	2	59.41	3.60	56.90	59.50	62.16
	3	59.02	3.56	56.54	59.16	61.66
	4	58.57	3.74	55.84	58.68	61.48
	5	58.54	3.78	56.12	58.50	61.24
	6	58.50	3.96	55.84	58.58	61.38
	7	58.54	4.08	55.80	58.72	61.60
	8	58.22	3.99	55.52	58.34	61.18
	9	57.86	4.12	55.02	57.98	61.06
	10	56.79	4.21	53.84	56.50	59.86

Table A14 Combined exposure (RWE_{9-17}) to O_3 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.41	3.82	55.70	58.51	61.25
	Asian	56.25	4.24	53.25	56.48	59.25
	African	56.02	4.55	52.49	56.48	59.60
	Arab	56.03	4.93	52.16	56.86	59.86
	C or B	56.87	4.61	53.81	56.60	60.20
	Mixed	57.37	3.99	54.25	57.59	60.17
	Other	57.13	4.23	53.79	57.34	60.03
Age group	0-5	58.68	3.78	55.94	58.80	61.51
	6-10	58.97	3.62	56.28	59.05	61.70
	11-15	58.92	3.60	56.28	59.03	61.64
	16-20	58.01	4.07	55.38	58.21	61.09
	21-25	57.17	4.22	54.43	57.44	60.26
	26-30	57.36	3.95	54.83	57.47	60.18
	31-35	57.76	3.87	55.23	57.85	60.55
	36-40	58.14	3.74	55.59	58.27	60.90
	41-45	58.26	3.69	55.64	58.36	61.01
	46-50	58.30	3.75	55.56	58.44	61.08
	51-55	58.28	3.79	55.52	58.38	61.13
	56-60	58.56	3.78	55.81	58.68	61.39
	61-65	58.69	3.80	55.93	58.81	61.59
	66-70	58.87	3.85	56.09	58.93	61.74
	71-75	58.76	3.80	55.98	58.84	61.63
	76+	58.66	3.85	55.84	58.70	61.60
Carstairs index decile	1	59.45	3.36	57.14	59.48	62.01
	2	59.11	3.51	56.58	59.30	61.71
	3	58.78	3.47	56.41	58.84	61.30
	4	58.35	3.66	55.74	58.42	61.09
	5	58.35	3.71	55.91	58.38	61.01
	6	58.35	3.88	55.78	58.44	61.16
	7	58.40	3.99	55.73	58.56	61.40
	8	58.10	3.92	55.48	58.19	61.03
	9	57.76	4.06	54.92	57.86	60.86
	10	56.71	4.16	53.75	56.51	59.78

Table A15 Combined exposure ($RWE_{8\text{-}18}$) to O_3 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.34	3.81	55.64	58.45	61.16
	Asian	56.20	4.22	53.25	56.46	59.15
	African	55.99	4.54	52.45	56.38	59.56
	Arab	56.01	4.92	52.17	56.61	59.86
	C or B	56.86	4.59	53.80	56.76	60.22
	Mixed	57.32	3.99	54.29	57.55	60.21
	Other	57.07	4.18	54.00	57.23	59.85
Age group	0-5	58.68	3.78	55.94	58.78	61.50
	6-10	58.95	3.60	56.28	59.00	61.68
	11-15	58.90	3.57	56.30	58.99	61.60
	16-20	57.91	4.06	55.34	58.14	61.02
	21-25	57.07	4.21	54.34	57.41	60.18
	26-30	57.25	3.93	54.72	57.43	60.02
	31-35	57.63	3.85	55.13	57.74	60.39
	36-40	58.00	3.71	55.52	58.14	60.70
	41-45	58.13	3.67	55.56	58.24	60.85
	46-50	58.19	3.73	55.51	58.34	61.01
	51-55	58.18	3.77	55.49	58.28	61.03
	56-60	58.48	3.77	55.75	58.57	61.30
	61-65	58.66	3.79	55.88	58.76	61.55
	66-70	58.86	3.85	56.08	58.92	61.72
	71-75	58.75	3.80	55.98	58.84	61.63
	76+	58.66	3.85	55.84	58.70	61.60
Carstairs index decile	1	59.32	3.36	57.00	59.35	61.91
	2	59.00	3.51	56.46	59.14	61.60
	3	58.68	3.47	56.37	58.74	61.19
	4	58.27	3.66	55.69	58.35	61.01
	5	58.29	3.71	55.83	58.34	60.94
	6	58.29	3.87	55.71	58.39	61.08
	7	58.35	3.98	55.72	58.51	61.35
	8	58.05	3.92	55.46	58.17	60.97
	9	57.72	4.06	54.87	57.82	60.82
	10	56.69	4.16	53.75	56.51	59.76

Table A16 Combined exposure (RWE_{hw+}) to O_3 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.38	3.79	55.71	58.49	61.19
	Asian	56.23	4.22	53.26	56.48	59.16
	African	56.02	4.52	52.58	56.48	59.60
	Arab	56.04	4.91	52.21	56.87	59.86
	C or B	56.87	4.56	53.71	56.54	60.23
	Mixed	57.36	3.99	54.18	57.48	60.14
	Other	57.16	4.17	54.09	57.30	59.92
Age group	0-5	58.68	3.78	55.91	58.80	61.53
	6-10	58.97	3.62	56.28	59.03	61.73
	11-15	58.92	3.59	56.28	59.06	61.62
	16-20	58.03	4.05	55.43	58.20	61.12
	21-25	57.16	4.18	54.42	57.45	60.21
	26-30	57.33	3.90	54.79	57.47	60.09
	31-35	57.72	3.82	55.26	57.82	60.46
	36-40	58.09	3.69	55.56	58.22	60.79
	41-45	58.20	3.65	55.63	58.28	60.90
	46-50	58.24	3.70	55.56	58.39	61.02
	51-55	58.22	3.75	55.52	58.31	61.02
	56-60	58.52	3.75	55.82	58.56	61.30
	61-65	58.68	3.79	55.88	58.80	61.58
	66-70	58.87	3.84	56.08	58.94	61.74
	71-75	58.76	3.80	55.98	58.84	61.64
	76+	58.66	3.84	55.84	58.70	61.60
Carstairs index decile	1	59.39	3.35	57.10	59.42	61.98
	2	59.07	3.48	56.58	59.19	61.64
	3	58.75	3.44	56.42	58.80	61.23
	4	58.33	3.64	55.74	58.40	61.02
	5	58.34	3.69	55.90	58.36	60.96
	6	58.33	3.85	55.77	58.40	61.08
	7	58.39	3.97	55.77	58.50	61.37
	8	58.09	3.91	55.48	58.18	60.98
	9	57.75	4.05	54.91	57.86	60.84
	10	56.71	4.15	53.79	56.50	59.76

Table A17 Residential exposure (RE) to O_3 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	55.86	3.78	53.34	55.48	58.72
	Asian	54.27	4.06	52.06	53.84	57.10
	African	53.32	3.73	50.42	53.26	55.66
	Arab	52.53	4.10	49.30	52.21	54.78
	C or B	53.13	3.62	49.50	53.12	55.31
	Mixed	54.52	3.75	52.22	54.18	56.90
	Other	54.07	3.83	51.74	53.26	56.12
Age group	0-5	56.07	3.63	53.60	55.56	58.88
	6-10	56.72	3.63	54.02	56.38	59.84
	11-15	56.40	3.57	53.88	55.80	59.24
	16-20	55.12	4.21	52.22	55.00	58.40
	21-25	54.23	4.21	51.42	54.02	57.67
	26-30	54.62	3.91	52.06	54.34	57.56
	31-35	55.08	3.94	52.52	54.66	58.00
	36-40	55.72	3.81	53.26	55.46	58.50
	41-45	55.89	3.76	53.34	55.46	58.88
	46-50	55.92	3.64	53.46	55.48	58.70
	51-55	55.84	3.61	53.42	55.46	58.50
	56-60	56.02	3.63	53.66	55.56	58.72
	61-65	56.06	3.69	53.63	55.56	58.82
	66-70	56.26	3.68	53.80	55.66	58.94
	71-75	56.29	3.63	53.76	55.84	58.94
	76+	56.10	3.58	53.74	55.62	58.72
Carstairs index decile	1	58.27	3.42	55.40	58.36	61.00
	2	57.38	3.57	54.68	57.56	60.38
	3	56.91	3.63	54.04	56.90	60.00
	4	56.07	3.69	53.66	55.56	58.88
	5	55.75	3.58	53.26	55.66	58.50
	6	55.52	3.97	52.78	55.26	58.82
	7	55.24	3.96	52.76	55.06	58.40
	8	55.23	3.78	52.66	55.00	58.12
	9	54.98	3.69	52.52	54.66	57.78
	10	54.60	3.48	52.54	54.18	57.28

Table A18 Combined exposure (RWE_{9-17}) to O_3 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	55.6	3.7	53.1	55.3	58.4
	Asian	54.1	3.9	51.9	53.7	56.9
	African	53.2	3.6	50.5	53.2	55.4
	Arab	52.4	3.9	49.2	52.2	54.8
	C or B	53.1	3.6	50.0	52.6	55.4
	Mixed	54.3	3.7	52.2	54.0	56.8
	Other	53.8	3.6	51.4	53.1	56.5
Age group	0-5	56.1	3.6	53.6	55.6	58.9
	6-10	56.7	3.6	54.0	56.4	59.6
	11-15	56.3	3.4	53.9	55.9	59.0
	16-20	54.8	3.9	52.2	54.6	57.7
	21-25	53.8	4.0	50.8	53.5	56.8
	26-30	54.2	3.7	51.5	54.0	56.8
	31-35	54.6	3.7	52.1	54.2	57.3
	36-40	55.2	3.6	52.7	54.8	57.8
	41-45	55.5	3.6	53.0	55.0	58.3
	46-50	55.5	3.5	53.2	55.1	58.2
	51-55	55.5	3.5	53.2	55.2	58.2
	56-60	55.7	3.5	53.3	55.5	58.4
	61-65	55.9	3.6	53.4	55.6	58.7
	66-70	56.2	3.7	53.8	55.7	58.9
	71-75	56.3	3.6	53.8	55.8	58.9
	76+	56.1	3.6	53.8	55.6	58.7
Carstairs index decile	1	57.8	3.3	55.4	58.0	60.3
	2	57.0	3.5	54.2	57.0	59.8
	3	56.5	3.5	53.8	56.4	59.4
	4	55.7	3.6	53.2	55.4	58.4
	5	55.4	3.5	52.9	55.3	58.2
	6	55.2	3.9	52.6	54.8	58.5
	7	55.0	3.8	52.5	54.8	57.8
	8	55.0	3.7	52.5	54.8	57.7
	9	54.8	3.6	52.3	54.4	57.6
	10	54.5	3.4	52.3	54.2	57.1

Table A19 Combined exposure ($RWE_{8\text{-}18}$) to O_3 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	55.5	3.7	53.0	55.2	58.4
	Asian	54.0	3.9	51.7	53.6	56.8
	African	53.1	3.6	50.5	53.1	55.4
	Arab	52.3	3.8	49.4	52.2	54.5
	C or B	53.1	3.6	50.2	52.8	55.4
	Mixed	54.2	3.7	51.8	54.0	56.6
	Other	53.7	3.5	51.4	53.0	56.2
Age group	0-5	56.1	3.6	53.6	55.6	58.9
	6-10	56.7	3.5	54.0	56.4	59.6
	11-15	56.3	3.4	53.9	55.9	58.9
	16-20	54.6	3.9	52.2	54.5	57.6
	21-25	53.7	3.9	50.7	53.3	56.4
	26-30	54.0	3.6	51.4	53.8	56.4
	31-35	54.4	3.6	51.9	54.0	56.9
	36-40	55.0	3.5	52.5	54.7	57.6
	41-45	55.3	3.5	52.8	54.8	58.0
	46-50	55.4	3.4	53.0	54.9	58.0
	51-55	55.4	3.4	53.0	55.1	58.0
	56-60	55.6	3.4	53.2	55.4	58.2
	61-65	55.9	3.6	53.4	55.5	58.7
	66-70	56.2	3.7	53.8	55.7	58.9
	71-75	56.3	3.6	53.8	55.8	58.9
	76+	56.1	3.6	53.8	55.6	58.7
Carstairs index decile	1	57.6	3.4	55.2	58.0	60.2
	2	56.8	3.5	54.1	56.7	59.5
	3	56.4	3.5	53.7	56.2	59.1
	4	55.6	3.6	53.1	55.2	58.3
	5	55.3	3.5	52.8	55.1	58.1
	6	55.1	3.9	52.3	54.8	58.4
	7	54.9	3.8	52.3	54.7	57.7
	8	55.0	3.7	52.5	54.8	57.7
	9	54.8	3.6	52.2	54.4	57.4
	10	54.5	3.4	52.2	54.2	56.9

Table A20 Combined exposure (RWE_{hw+}) to O_3 in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	55.57	3.64	53.12	55.25	58.38
	Asian	54.05	3.88	51.89	53.59	56.90
	African	53.19	3.57	50.52	53.12	55.63
	Arab	52.39	3.87	49.29	52.20	54.78
	C or B	53.18	3.59	50.07	52.77	55.28
	Mixed	54.27	3.66	52.06	54.04	56.57
	Other	53.84	3.60	51.49	53.14	56.64
Age group	0-5	56.07	3.62	53.60	55.56	58.88
	6-10	56.69	3.54	54.02	56.38	59.58
	11-15	56.34	3.41	53.91	55.94	58.98
	16-20	54.80	3.93	52.21	54.64	57.76
	21-25	53.82	3.91	50.84	53.54	56.63
	26-30	54.13	3.61	51.63	53.91	56.50
	31-35	54.51	3.61	52.09	54.14	56.94
	36-40	55.13	3.50	52.76	54.78	57.65
	41-45	55.39	3.51	52.97	54.94	58.02
	46-50	55.44	3.40	53.14	55.00	57.98
	51-55	55.44	3.40	53.18	55.10	58.00
	56-60	55.64	3.41	53.34	55.39	58.25
	61-65	55.92	3.63	53.42	55.56	58.71
	66-70	56.22	3.66	53.74	55.66	58.94
	71-75	56.29	3.62	53.76	55.83	58.94
	76+	56.10	3.58	53.74	55.62	58.72
Carstairs index decile	1	57.69	3.33	55.20	58.00	60.28
	2	56.89	3.46	54.24	56.84	59.60
	3	56.48	3.49	53.78	56.26	59.26
	4	55.67	3.56	53.21	55.27	58.36
	5	55.39	3.46	52.93	55.16	58.20
	6	55.21	3.83	52.56	54.84	58.40
	7	55.00	3.81	52.54	54.76	57.72
	8	55.03	3.67	52.52	54.76	57.72
	9	54.82	3.60	52.33	54.40	57.45
	10	54.50	3.41	52.39	54.16	56.98

Table A21 Residential exposure (RE) to O_3 in Edinburgh per population subgroup. Source: All units µg m^{-3}. Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.81	2.87	56.78	58.40	60.46
	Asian	58.24	2.78	56.48	57.62	59.50
	African	59.22	2.56	57.50	59.23	61.26
	Arab	59.47	2.60	57.52	59.42	61.54
	C or B	58.64	3.09	56.32	57.66	61.28
	Mixed	58.13	2.91	56.49	57.62	59.62
	Other	58.87	3.12	56.48	58.40	61.26
Age group	0-5	59.04	2.76	57.44	58.58	60.60
	6-10	59.53	2.90	57.58	59.12	61.74
	11-15	59.38	2.94	57.44	59.06	61.30
	16-20	58.61	2.73	56.68	57.74	60.30
	21-25	57.83	2.67	56.47	57.44	59.46
	26-30	57.88	2.57	56.48	57.62	59.46
	31-35	58.16	2.68	56.48	57.72	59.52
	36-40	58.71	2.98	56.54	58.10	60.46
	41-45	58.78	2.80	56.90	58.44	60.22
	46-50	59.06	2.89	57.14	58.56	61.02
	51-55	59.05	2.99	56.96	58.56	61.02
	56-60	59.14	2.90	57.24	58.56	61.02
	61-65	59.20	2.99	57.24	58.86	61.30
	66-70	59.13	2.85	57.26	58.58	61.02
	71-75	59.06	2.94	57.24	58.56	60.82
	76+	59.14	2.85	57.24	58.56	61.02
Carstairs index decile	1	59.93	3.19	57.60	59.46	63.44
	2	59.78	3.27	57.44	59.46	63.18
	3	59.10	3.02	57.24	58.90	61.02
	4	58.08	2.62	56.56	57.64	59.48
	5	58.14	2.75	56.54	57.64	59.50
	6	58.15	2.54	56.54	57.64	59.52
	7	58.17	2.59	56.48	57.74	59.48
	8	58.35	2.49	56.54	57.85	59.48
	9	58.39	2.56	56.48	58.14	59.86
	10	59.49	2.30	58.10	59.42	61.16

Table A22 Combined exposure ($RWE_{9\text{-}17}$) to O_3 in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.68	2.73	56.82	58.20	60.24
	Asian	58.21	2.62	56.48	57.65	59.48
	African	59.16	2.49	57.31	59.05	61.00
	Arab	59.49	2.52	57.30	59.46	61.16
	C or B	58.54	2.95	56.46	57.58	60.48
	Mixed	58.11	2.77	56.54	57.83	59.47
	Other	58.69	3.05	56.48	58.25	60.89
Age group	0-5	59.03	2.74	57.34	58.59	60.60
	6-10	59.46	2.76	57.51	58.91	61.46
	11-15	59.27	2.76	57.31	58.79	61.04
	16-20	58.59	2.51	56.82	58.04	60.10
	21-25	57.78	2.45	56.32	57.51	59.05
	26-30	57.76	2.34	56.38	57.48	59.06
	31-35	57.95	2.47	56.44	57.61	59.41
	36-40	58.44	2.74	56.57	57.93	59.92
	41-45	58.53	2.59	56.76	58.25	59.86
	46-50	58.81	2.67	56.90	58.41	60.57
	51-55	58.80	2.77	56.90	58.36	60.45
	56-60	58.94	2.73	57.15	58.50	60.65
	61-65	59.11	2.91	57.15	58.59	61.04
	66-70	59.10	2.83	57.25	58.59	60.81
	71-75	59.05	2.94	57.25	58.56	60.81
	76+	59.14	2.85	57.25	58.56	61.01
Carstairs index decile	1	59.69	3.05	57.45	59.12	62.39
	2	59.55	3.11	57.15	59.12	62.45
	3	58.92	2.87	57.08	58.58	60.89
	4	57.97	2.49	56.53	57.60	59.43
	5	58.05	2.60	56.53	57.64	59.45
	6	58.09	2.40	56.53	57.64	59.43
	7	58.12	2.46	56.53	57.79	59.44
	8	58.29	2.39	56.63	57.92	59.43
	9	58.34	2.44	56.53	58.09	59.75
	10	59.40	2.23	58.01	59.40	60.64

Table A23 Combined exposure ($RWE_{8\text{-}18}$) to O_3 in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.63	2.69	56.77	58.15	60.15
	Asian	58.20	2.58	56.47	57.69	59.48
	African	59.14	2.48	57.25	59.05	61.01
	Arab	59.50	2.51	57.40	59.47	61.28
	C or B	58.50	2.91	56.45	57.57	60.34
	Mixed	58.10	2.75	56.45	57.80	59.45
	Other	58.63	3.03	56.51	57.92	60.77
Age group	0-5	59.03	2.73	57.36	58.58	60.61
	6-10	59.43	2.73	57.51	58.83	61.30
	11-15	59.23	2.70	57.37	58.66	61.06
	16-20	58.58	2.45	56.87	58.13	60.14
	21-25	57.77	2.41	56.23	57.60	59.01
	26-30	57.73	2.28	56.36	57.48	58.95
	31-35	57.88	2.42	56.42	57.61	59.36
	36-40	58.35	2.66	56.48	57.89	59.78
	41-45	58.45	2.53	56.70	58.13	59.72
	46-50	58.72	2.60	56.89	58.41	60.45
	51-55	58.71	2.71	56.81	58.32	60.44
	56-60	58.87	2.69	57.10	58.44	60.51
	61-65	59.07	2.89	57.15	58.58	61.01
	66-70	59.09	2.83	57.24	58.58	60.81
	71-75	59.04	2.94	57.24	58.57	60.81
	76+	59.14	2.85	57.24	58.57	61.01
Carstairs index decile	1	59.60	3.01	57.44	59.12	62.02
	2	59.47	3.07	57.15	59.12	62.03
	3	58.86	2.82	57.04	58.55	60.81
	4	57.94	2.46	56.50	57.60	59.39
	5	58.03	2.56	56.50	57.69	59.43
	6	58.07	2.37	56.51	57.69	59.38
	7	58.10	2.43	56.51	57.80	59.41
	8	58.28	2.37	56.59	57.92	59.41
	9	58.32	2.42	56.54	58.09	59.68
	10	59.36	2.22	57.93	59.39	60.48

Table A24 Combined exposure (RWE_{hw+}) to O_3 in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.67	2.68	56.89	58.20	60.21
	Asian	58.21	2.59	56.50	57.64	59.48
	African	59.15	2.43	57.37	59.05	60.75
	Arab	59.49	2.52	57.35	59.48	61.30
	C or B	58.55	2.94	56.46	57.71	60.48
	Mixed	58.12	2.78	56.46	57.78	59.48
	Other	58.67	3.03	56.48	58.10	61.01
Age group	0-5	59.03	2.74	57.41	58.58	60.60
	6-10	59.45	2.76	57.50	58.99	61.51
	11-15	59.27	2.74	57.32	58.87	61.01
	16-20	58.58	2.49	56.97	58.03	60.04
	21-25	57.79	2.40	56.32	57.45	59.06
	26-30	57.78	2.26	56.40	57.50	59.04
	31-35	57.96	2.40	56.48	57.62	59.35
	36-40	58.44	2.64	56.59	58.00	59.86
	41-45	58.52	2.51	56.89	58.19	59.84
	46-50	58.78	2.56	56.99	58.47	60.46
	51-55	58.77	2.67	56.90	58.40	60.43
	56-60	58.93	2.67	57.14	58.50	60.65
	61-65	59.11	2.88	57.24	58.67	61.08
	66-70	59.10	2.83	57.26	58.58	60.82
	71-75	59.05	2.94	57.24	58.56	60.82
	76+	59.14	2.85	57.24	58.56	61.02
Carstairs index decile	1	59.67	2.99	57.46	59.15	62.21
	2	59.53	3.04	57.20	59.15	62.19
	3	58.91	2.82	57.08	58.60	60.84
	4	57.99	2.43	56.57	57.61	59.42
	5	58.07	2.55	56.55	57.64	59.46
	6	58.10	2.36	56.59	57.64	59.42
	7	58.12	2.42	56.54	57.78	59.42
	8	58.30	2.36	56.64	57.94	59.42
	9	58.33	2.43	56.50	58.10	59.76
	10	59.39	2.21	58.01	59.41	60.60

Table A25 Residential exposure (RE) to $PM_{2.5}$ in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.62	0.66	7.16	7.65	8.07
	Asian	7.89	0.56	7.55	7.94	8.27
	African	7.91	0.57	7.49	8.00	8.32
	Arab	7.89	0.61	7.45	7.91	8.37
	C or B	7.85	0.96	7.47	7.85	8.29
	Mixed	7.76	0.59	7.40	7.85	8.20
	Other	7.78	0.61	7.40	7.90	8.21
Age group	0-5	7.61	0.63	7.17	7.65	8.05
	6-10	7.55	0.60	7.13	7.58	8.00
	11-15	7.57	0.64	7.13	7.58	8.01
	16-20	7.63	0.66	7.17	7.66	8.09
	21-25	7.74	0.65	7.31	7.80	8.19
	26-30	7.75	0.65	7.34	7.82	8.18
	31-35	7.69	0.63	7.24	7.76	8.13
	36-40	7.64	0.65	7.19	7.68	8.08
	41-45	7.62	0.67	7.16	7.65	8.07
	46-50	7.63	0.69	7.16	7.65	8.08
	51-55	7.62	0.62	7.16	7.65	8.08
	56-60	7.60	0.66	7.14	7.63	8.06
	61-65	7.58	0.63	7.14	7.60	8.03
	66-70	7.59	0.72	7.13	7.60	8.03
	71-75	7.61	0.70	7.15	7.64	8.07
	76+	7.64	0.71	7.17	7.66	8.08
Carstairs index decile	1	7.42	0.58	6.98	7.43	7.87
	2	7.49	0.59	7.06	7.51	7.92
	3	7.56	0.59	7.15	7.58	7.99
	4	7.62	0.61	7.20	7.65	8.04
	5	7.63	0.60	7.20	7.66	8.07
	6	7.65	0.70	7.20	7.67	8.08
	7	7.62	0.65	7.14	7.64	8.08
	8	7.69	0.71	7.21	7.74	8.12
	9	7.74	0.76	7.28	7.79	8.17
	10	7.87	0.66	7.50	8.00	8.23

Table A26 Combined exposure ($RWE_{9\text{-}17}$) to PM2.5 in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.64	0.63	7.21	7.67	8.07
	Asian	7.90	0.54	7.56	7.96	8.28
	African	7.91	0.55	7.51	8.01	8.31
	Arab	7.88	0.56	7.43	7.92	8.38
	C or B	7.82	0.74	7.45	7.85	8.24
	Mixed	7.77	0.57	7.39	7.81	8.21
	Other	7.78	0.58	7.39	7.88	8.23
Age group	0-5	7.61	0.63	7.18	7.65	8.05
	6-10	7.56	0.58	7.15	7.60	8.00
	11-15	7.58	0.61	7.14	7.60	8.00
	16-20	7.66	0.61	7.23	7.69	8.10
	21-25	7.76	0.61	7.35	7.79	8.19
	26-30	7.77	0.59	7.39	7.83	8.16
	31-35	7.72	0.58	7.31	7.77	8.12
	36-40	7.67	0.60	7.25	7.71	8.08
	41-45	7.65	0.62	7.24	7.69	8.07
	46-50	7.66	0.64	7.23	7.70	8.08
	51-55	7.65	0.59	7.23	7.70	8.08
	56-60	7.62	0.64	7.19	7.64	8.06
	61-65	7.59	0.62	7.16	7.62	8.04
	66-70	7.59	0.72	7.13	7.61	8.04
	71-75	7.61	0.70	7.15	7.64	8.07
	76+	7.64	0.71	7.16	7.66	8.08
Carstairs index decile	1	7.46	0.56	7.06	7.46	7.88
	2	7.52	0.57	7.13	7.53	7.93
	3	7.59	0.56	7.20	7.61	8.00
	4	7.64	0.59	7.24	7.67	8.06
	5	7.65	0.58	7.23	7.69	8.07
	6	7.66	0.65	7.23	7.69	8.08
	7	7.63	0.63	7.17	7.65	8.08
	8	7.70	0.68	7.24	7.75	8.12
	9	7.74	0.72	7.30	7.80	8.16
	10	7.87	0.64	7.51	7.98	8.24

Table A27 Combined exposure ($RWE_{8\text{-}18}$) to $PM_{2.5}$ in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.65	0.63	7.22	7.68	8.07
	Asian	7.90	0.53	7.57	7.97	8.28
	African	7.91	0.55	7.52	8.01	8.32
	Arab	7.89	0.56	7.44	7.94	8.38
	C or B	7.82	0.69	7.44	7.85	8.23
	Mixed	7.77	0.56	7.41	7.81	8.21
	Other	7.78	0.58	7.38	7.90	8.23
Age group	0-5	7.61	0.63	7.18	7.65	8.04
	6-10	7.57	0.57	7.16	7.60	7.99
	11-15	7.59	0.61	7.16	7.61	8.00
	16-20	7.67	0.61	7.25	7.71	8.11
	21-25	7.77	0.60	7.37	7.80	8.20
	26-30	7.78	0.58	7.41	7.82	8.17
	31-35	7.73	0.58	7.34	7.77	8.13
	36-40	7.69	0.59	7.28	7.72	8.09
	41-45	7.67	0.61	7.26	7.70	8.08
	46-50	7.67	0.64	7.26	7.71	8.09
	51-55	7.66	0.59	7.25	7.71	8.09
	56-60	7.63	0.64	7.20	7.66	8.07
	61-65	7.60	0.63	7.16	7.62	8.04
	66-70	7.59	0.72	7.14	7.61	8.04
	71-75	7.61	0.70	7.15	7.64	8.07
	76+	7.64	0.71	7.16	7.66	8.08
Carstairs index decile	1	7.48	0.56	7.08	7.48	7.88
	2	7.54	0.57	7.15	7.55	7.94
	3	7.60	0.56	7.20	7.62	8.00
	4	7.65	0.60	7.24	7.68	8.06
	5	7.66	0.58	7.24	7.69	8.07
	6	7.67	0.65	7.24	7.70	8.08
	7	7.64	0.63	7.19	7.65	8.08
	8	7.70	0.68	7.25	7.75	8.12
	9	7.75	0.71	7.31	7.80	8.17
	10	7.87	0.64	7.52	7.99	8.25

Table A28 Combined exposure (RWE_{hw+}) to $PM_{2.5}$ in Central Belt per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.64	0.63	7.21	7.67	8.07
	Asian	7.90	0.54	7.57	7.96	8.28
	African	7.91	0.55	7.50	8.01	8.31
	Arab	7.89	0.57	7.45	7.91	8.38
	C or B	7.82	0.76	7.45	7.85	8.23
	Mixed	7.77	0.57	7.40	7.83	8.21
	Other	7.78	0.58	7.40	7.89	8.23
Age group	0-5	7.61	0.63	7.18	7.65	8.05
	6-10	7.56	0.59	7.14	7.60	8.00
	11-15	7.58	0.62	7.14	7.60	8.01
	16-20	7.65	0.62	7.23	7.69	8.09
	21-25	7.76	0.61	7.35	7.79	8.19
	26-30	7.77	0.60	7.40	7.82	8.16
	31-35	7.72	0.58	7.32	7.77	8.12
	36-40	7.67	0.60	7.26	7.71	8.09
	41-45	7.66	0.62	7.25	7.69	8.07
	46-50	7.66	0.64	7.24	7.70	8.08
	51-55	7.65	0.59	7.24	7.70	8.09
	56-60	7.63	0.63	7.19	7.65	8.06
	61-65	7.59	0.62	7.16	7.63	8.04
	66-70	7.59	0.72	7.13	7.61	8.04
	71-75	7.61	0.70	7.15	7.64	8.07
	76+	7.64	0.71	7.17	7.66	8.08
Carstairs index decile	1	7.46	0.56	7.06	7.47	7.88
	2	7.52	0.56	7.13	7.54	7.93
	3	7.59	0.56	7.20	7.61	8.00
	4	7.64	0.59	7.24	7.67	8.06
	5	7.65	0.58	7.23	7.69	8.07
	6	7.66	0.66	7.23	7.69	8.08
	7	7.63	0.63	7.17	7.65	8.07
	8	7.70	0.69	7.24	7.74	8.12
	9	7.75	0.73	7.30	7.80	8.17
	10	7.87	0.64	7.51	7.99	8.24

Table A29 Residential exposure (RE) to $PM_{2.5}$ in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	8.01	0.44	7.74	8.07	8.31
	Asian	8.14	0.42	7.92	8.19	8.43
	African	8.22	0.40	8.02	8.27	8.47
	Arab	8.26	0.37	8.14	8.37	8.47
	C or B	8.24	0.35	8.10	8.30	8.47
	Mixed	8.16	0.45	7.93	8.20	8.43
	Other	8.15	0.38	7.83	8.18	8.45
Age group	0-5	7.99	0.43	7.71	8.06	8.26
	6-10	7.93	0.44	7.66	7.98	8.22
	11-15	7.96	0.44	7.69	8.03	8.25
	16-20	8.07	0.46	7.78	8.16	8.43
	21-25	8.15	0.44	7.85	8.23	8.46
	26-30	8.13	0.44	7.87	8.18	8.43
	31-35	8.08	0.44	7.81	8.14	8.37
	36-40	8.02	0.44	7.75	8.07	8.32
	41-45	8.00	0.44	7.74	8.07	8.30
	46-50	8.01	0.43	7.74	8.09	8.30
	51-55	8.02	0.44	7.75	8.09	8.31
	56-60	8.01	0.43	7.74	8.07	8.30
	61-65	7.99	0.44	7.71	8.07	8.29
	66-70	7.97	0.43	7.71	8.04	8.26
	71-75	7.97	0.43	7.67	8.04	8.27
	76+	8.00	0.43	7.74	8.07	8.28
Carstairs index decile	1	7.77	0.50	7.37	7.86	8.09
	2	7.89	0.47	7.56	7.91	8.22
	3	7.93	0.46	7.60	7.98	8.25
	4	8.02	0.42	7.75	8.06	8.35
	5	8.04	0.41	7.81	8.07	8.35
	6	8.05	0.45	7.74	8.11	8.37
	7	8.06	0.43	7.81	8.12	8.37
	8	8.07	0.42	7.81	8.16	8.37
	9	8.08	0.41	7.82	8.14	8.36
	10	8.11	0.39	7.84	8.17	8.31

Table A30 Combined exposure ($RWE_{9\text{-}17}$) to $PM_{2.5}$ in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	8.03	0.42	7.76	8.09	8.31
	Asian	8.16	0.40	7.93	8.20	8.43
	African	8.23	0.38	8.04	8.29	8.45
	Arab	8.27	0.34	8.14	8.37	8.50
	C or B	8.24	0.35	8.15	8.29	8.48
	Mixed	8.17	0.43	7.95	8.23	8.44
	Other	8.16	0.34	7.86	8.19	8.45
Age group	0-5	7.99	0.43	7.71	8.06	8.26
	6-10	7.93	0.42	7.65	7.97	8.22
	11-15	7.97	0.40	7.71	8.03	8.25
	16-20	8.10	0.42	7.83	8.16	8.42
	21-25	8.18	0.40	7.92	8.28	8.47
	26-30	8.16	0.40	7.92	8.20	8.44
	31-35	8.12	0.40	7.87	8.18	8.38
	36-40	8.07	0.40	7.82	8.12	8.33
	41-45	8.04	0.41	7.79	8.11	8.31
	46-50	8.04	0.39	7.78	8.11	8.31
	51-55	8.05	0.41	7.81	8.12	8.31
	56-60	8.03	0.40	7.78	8.10	8.30
	61-65	8.00	0.43	7.72	8.08	8.30
	66-70	7.98	0.43	7.71	8.05	8.25
	71-75	7.97	0.43	7.67	8.04	8.27
	76+	8.00	0.43	7.74	8.08	8.28
Carstairs index decile	1	7.82	0.46	7.50	7.88	8.12
	2	7.93	0.44	7.60	7.95	8.25
	3	7.96	0.43	7.65	8.02	8.28
	4	8.04	0.40	7.82	8.09	8.35
	5	8.07	0.40	7.84	8.11	8.36
	6	8.07	0.43	7.77	8.13	8.38
	7	8.08	0.41	7.83	8.14	8.38
	8	8.09	0.41	7.83	8.16	8.37
	9	8.10	0.40	7.83	8.16	8.36
	10	8.12	0.38	7.85	8.18	8.33

Table A31 Combined exposure (RWE_{8-18}) to $PM_{2.5}$ in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	8.04	0.41	7.77	8.10	8.33
	Asian	8.17	0.39	7.94	8.20	8.43
	African	8.23	0.37	8.04	8.28	8.45
	Arab	8.28	0.33	8.14	8.37	8.48
	C or B	8.24	0.35	8.16	8.28	8.48
	Mixed	8.18	0.43	7.96	8.27	8.45
	Other	8.17	0.34	7.92	8.23	8.45
Age group	0-5	7.99	0.43	7.71	8.05	8.27
	6-10	7.93	0.41	7.65	7.98	8.22
	11-15	7.97	0.40	7.72	8.03	8.25
	16-20	8.11	0.40	7.84	8.18	8.43
	21-25	8.20	0.39	7.94	8.28	8.47
	26-30	8.18	0.39	7.95	8.22	8.44
	31-35	8.14	0.39	7.89	8.19	8.40
	36-40	8.09	0.39	7.84	8.14	8.35
	41-45	8.06	0.40	7.82	8.13	8.32
	46-50	8.06	0.39	7.82	8.13	8.32
	51-55	8.06	0.40	7.83	8.13	8.32
	56-60	8.05	0.40	7.80	8.10	8.31
	61-65	8.00	0.43	7.74	8.07	8.30
	66-70	7.98	0.43	7.71	8.05	8.27
	71-75	7.97	0.43	7.67	8.04	8.27
	76+	8.00	0.43	7.74	8.07	8.28
Carstairs index decile	1	7.84	0.45	7.53	7.88	8.15
	2	7.95	0.44	7.64	7.97	8.26
	3	7.97	0.43	7.67	8.03	8.28
	4	8.06	0.40	7.84	8.11	8.35
	5	8.08	0.39	7.86	8.13	8.35
	6	8.08	0.42	7.80	8.15	8.38
	7	8.09	0.41	7.84	8.16	8.38
	8	8.09	0.40	7.84	8.16	8.37
	9	8.10	0.39	7.84	8.16	8.37
	10	8.12	0.38	7.86	8.18	8.35

Table A32 Combined exposure (RWE_{hw+}) to $PM_{2.5}$ in Greater Glasgow per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	8.03	0.42	7.77	8.10	8.31
	Asian	8.16	0.40	7.93	8.20	8.43
	African	8.22	0.38	8.03	8.28	8.44
	Arab	8.27	0.34	8.14	8.37	8.48
	C or B	8.24	0.35	8.14	8.29	8.49
	Mixed	8.18	0.43	7.98	8.25	8.44
	Other	8.16	0.36	7.86	8.23	8.46
Age group	0-5	7.99	0.43	7.71	8.06	8.26
	6-10	7.93	0.43	7.65	7.98	8.22
	11-15	7.97	0.41	7.72	8.03	8.25
	16-20	8.09	0.42	7.82	8.16	8.42
	21-25	8.18	0.41	7.92	8.27	8.46
	26-30	8.16	0.40	7.92	8.20	8.43
	31-35	8.12	0.40	7.88	8.18	8.39
	36-40	8.07	0.40	7.82	8.13	8.34
	41-45	8.04	0.41	7.80	8.11	8.31
	46-50	8.05	0.39	7.79	8.12	8.31
	51-55	8.06	0.41	7.81	8.12	8.31
	56-60	8.04	0.40	7.80	8.10	8.30
	61-65	8.00	0.43	7.72	8.07	8.30
	66-70	7.98	0.43	7.71	8.05	8.26
	71-75	7.97	0.43	7.67	8.04	8.27
	76+	8.00	0.43	7.74	8.07	8.28
Carstairs index decile	1	7.82	0.47	7.50	7.88	8.14
	2	7.93	0.44	7.61	7.95	8.25
	3	7.96	0.43	7.65	8.01	8.28
	4	8.04	0.40	7.82	8.09	8.35
	5	8.07	0.39	7.85	8.11	8.35
	6	8.07	0.43	7.78	8.13	8.37
	7	8.08	0.41	7.84	8.14	8.38
	8	8.09	0.41	7.84	8.16	8.37
	9	8.10	0.40	7.84	8.16	8.36
	10	8.12	0.38	7.85	8.18	8.32

Table A33 Residential exposure (RE) to $PM_{2.5}$ in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.70	0.48	7.41	7.75	8.00
	Asian	7.73	0.43	7.45	7.79	7.94
	African	7.62	0.46	7.28	7.69	7.89
	Arab	7.52	0.40	7.25	7.49	7.79
	C or B	7.63	0.47	7.47	7.84	7.90
	Mixed	7.75	0.46	7.45	7.75	8.09
	Other	7.68	0.48	7.40	7.85	8.00
Age group	0-5	7.68	0.47	7.41	7.74	7.98
	6-10	7.62	0.51	7.24	7.69	7.90
	11-15	7.62	0.50	7.28	7.63	7.92
	16-20	7.65	0.46	7.42	7.69	7.90
	21-25	7.76	0.42	7.58	7.79	8.00
	26-30	7.82	0.42	7.59	7.87	8.12
	31-35	7.80	0.44	7.52	7.85	8.12
	36-40	7.73	0.49	7.42	7.82	8.09
	41-45	7.71	0.47	7.41	7.76	8.08
	46-50	7.70	0.49	7.41	7.76	8.08
	51-55	7.66	0.49	7.40	7.74	7.92
	56-60	7.66	0.48	7.40	7.69	7.92
	61-65	7.64	0.50	7.38	7.69	7.94
	66-70	7.66	0.50	7.40	7.69	8.00
	71-75	7.68	0.52	7.40	7.74	8.09
	76+	7.65	0.48	7.38	7.71	7.92
Carstairs index decile	1	7.45	0.52	7.01	7.49	7.86
	2	7.51	0.52	7.07	7.50	7.87
	3	7.69	0.53	7.42	7.81	8.08
	4	7.78	0.43	7.53	7.81	8.08
	5	7.79	0.45	7.50	7.82	8.12
	6	7.78	0.41	7.52	7.85	8.08
	7	7.81	0.40	7.58	7.85	8.12
	8	7.79	0.41	7.58	7.79	8.11
	9	7.76	0.41	7.45	7.79	8.09
	10	7.68	0.45	7.28	7.74	8.09

Table A34 Combined exposure ($RWE_{9\text{-}17}$) to $PM_{2.5}$ in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.70	0.44	7.43	7.75	7.98
	Asian	7.73	0.40	7.47	7.75	7.94
	African	7.62	0.44	7.30	7.67	7.88
	Arab	7.52	0.38	7.27	7.45	7.75
	C or B	7.63	0.44	7.47	7.79	7.87
	Mixed	7.73	0.44	7.49	7.75	8.03
	Other	7.69	0.46	7.43	7.82	8.00
Age group	0-5	7.68	0.47	7.41	7.74	7.98
	6-10	7.63	0.49	7.32	7.69	7.93
	11-15	7.63	0.46	7.35	7.67	7.93
	16-20	7.64	0.42	7.43	7.69	7.88
	21-25	7.74	0.37	7.56	7.75	7.94
	26-30	7.80	0.37	7.59	7.84	8.07
	31-35	7.79	0.39	7.57	7.85	8.07
	36-40	7.74	0.43	7.45	7.80	8.05
	41-45	7.72	0.41	7.45	7.75	8.00
	46-50	7.70	0.43	7.42	7.76	7.98
	51-55	7.67	0.44	7.41	7.74	7.95
	56-60	7.67	0.44	7.41	7.71	7.92
	61-65	7.64	0.48	7.38	7.70	7.94
	66-70	7.66	0.49	7.40	7.69	8.00
	71-75	7.68	0.52	7.40	7.75	8.09
	76+	7.65	0.48	7.38	7.71	7.92
Carstairs index decile	1	7.47	0.49	7.07	7.54	7.85
	2	7.52	0.48	7.15	7.53	7.86
	3	7.69	0.49	7.42	7.80	8.01
	4	7.77	0.40	7.55	7.79	8.02
	5	7.78	0.42	7.53	7.81	8.08
	6	7.77	0.38	7.55	7.79	8.00
	7	7.79	0.37	7.58	7.81	8.06
	8	7.78	0.39	7.57	7.78	8.05
	9	7.76	0.39	7.45	7.78	8.08
	10	7.68	0.43	7.32	7.73	8.02

Table A35 Combined exposure ($RWE_{8\text{-}18}$) to $PM_{2.5}$ in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.70	0.44	7.43	7.75	7.98
	Asian	7.72	0.40	7.46	7.75	7.94
	African	7.62	0.44	7.30	7.66	7.88
	Arab	7.52	0.38	7.24	7.45	7.75
	C or B	7.63	0.43	7.47	7.79	7.86
	Mixed	7.73	0.43	7.49	7.75	8.01
	Other	7.69	0.45	7.44	7.81	7.99
Age group	0-5	7.68	0.47	7.41	7.74	7.98
	6-10	7.63	0.48	7.34	7.70	7.93
	11-15	7.64	0.46	7.35	7.68	7.94
	16-20	7.64	0.40	7.43	7.66	7.87
	21-25	7.73	0.36	7.56	7.75	7.94
	26-30	7.79	0.36	7.59	7.84	8.04
	31-35	7.79	0.38	7.58	7.84	8.06
	36-40	7.74	0.41	7.47	7.80	8.04
	41-45	7.72	0.40	7.47	7.76	8.00
	46-50	7.71	0.42	7.43	7.76	7.98
	51-55	7.68	0.43	7.41	7.74	7.95
	56-60	7.67	0.43	7.41	7.70	7.92
	61-65	7.64	0.48	7.38	7.70	7.95
	66-70	7.66	0.49	7.40	7.69	8.00
	71-75	7.68	0.52	7.40	7.75	8.09
	76+	7.65	0.48	7.38	7.70	7.92
Carstairs index decile	1	7.48	0.48	7.10	7.57	7.84
	2	7.53	0.47	7.18	7.56	7.87
	3	7.69	0.48	7.41	7.79	8.00
	4	7.77	0.39	7.56	7.79	8.01
	5	7.78	0.41	7.54	7.80	8.07
	6	7.77	0.37	7.56	7.78	8.00
	7	7.79	0.36	7.58	7.80	8.04
	8	7.78	0.38	7.57	7.78	8.03
	9	7.76	0.38	7.45	7.79	8.06
	10	7.68	0.43	7.32	7.74	8.00

Table A36 Combined exposure (RWE_{hw+}) to $PM_{2.5}$ in Edinburgh per population subgroup. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.70	0.44	7.43	7.74	7.98
	Asian	7.73	0.40	7.47	7.74	7.94
	African	7.62	0.44	7.32	7.69	7.89
	Arab	7.52	0.39	7.28	7.45	7.75
	C or B	7.63	0.44	7.47	7.79	7.89
	Mixed	7.73	0.44	7.48	7.75	8.03
	Other	7.69	0.45	7.45	7.84	8.00
Age group	0-5	7.68	0.47	7.41	7.74	7.98
	6-10	7.63	0.49	7.28	7.69	7.92
	11-15	7.63	0.47	7.33	7.66	7.92
	16-20	7.65	0.42	7.43	7.69	7.89
	21-25	7.74	0.37	7.57	7.74	7.95
	26-30	7.80	0.37	7.59	7.84	8.06
	31-35	7.80	0.39	7.58	7.85	8.08
	36-40	7.74	0.43	7.46	7.80	8.05
	41-45	7.72	0.41	7.45	7.75	8.00
	46-50	7.71	0.43	7.43	7.76	8.00
	51-55	7.68	0.44	7.41	7.74	7.94
	56-60	7.67	0.44	7.41	7.70	7.92
	61-65	7.64	0.48	7.36	7.70	7.94
	66-70	7.66	0.49	7.40	7.69	8.00
	71-75	7.68	0.52	7.40	7.74	8.09
	76+	7.65	0.48	7.38	7.71	7.92
Carstairs index decile	1	7.48	0.49	7.08	7.54	7.85
	2	7.53	0.48	7.16	7.54	7.87
	3	7.70	0.49	7.42	7.81	8.01
	4	7.77	0.39	7.55	7.79	8.01
	5	7.78	0.42	7.54	7.81	8.08
	6	7.77	0.38	7.56	7.79	8.00
	7	7.80	0.37	7.58	7.81	8.07
	8	7.78	0.39	7.57	7.78	8.07
	9	7.76	0.39	7.45	7.79	8.08
	10	7.69	0.43	7.31	7.73	8.04

A.2 Summary statistics of population exposure per model, pollutant, exposure scenario and population subgroup in Edinburgh

Table A37 Residential exposure (RE) to NO_2 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	15.75	2.74	13.92	15.61	17.70
	Asian	16.38	2.87	14.25	16.27	18.47
	African	15.37	2.55	13.52	15.12	17.54
	Arab	15.30	2.69	12.95	15.59	17.09
	C or B	15.88	2.92	14.30	15.27	18.44
	Mixed	16.73	2.85	14.51	16.84	19.00
	Other	16.01	2.95	14.48	15.61	17.93
Age group	0-5	15.42	2.52	13.69	15.23	17.12
	6-10	15.02	2.40	13.21	14.86	16.48
	11-15	15.01	2.31	13.33	14.89	16.30
	16-20	16.11	2.99	14.23	15.98	17.98
	21-25	16.92	2.91	15.00	16.91	18.84
	26-30	16.92	2.74	14.93	17.20	18.83
	31-35	16.49	2.78	14.54	16.46	18.38
	36-40	15.97	2.80	14.02	15.86	17.95
	41-45	15.75	2.60	13.97	15.62	17.65
	46-50	15.48	2.69	13.47	15.34	17.45
	51-55	15.41	2.71	13.43	15.09	17.22
	56-60	15.38	2.61	13.41	15.23	17.04
	61-65	15.23	2.69	13.23	14.93	16.94
	66-70	15.33	2.48	13.68	15.21	16.95
	71-75	15.25	2.54	13.59	15.21	16.89
	76-80	15.13	2.66	13.35	15.04	16.72
	81-85	15.35	2.51	13.25	15.34	16.99
	86+	15.15	2.56	13.51	15.05	16.80
Carstairs index decile	1	14.32	2.37	12.63	14.34	15.77
	2	14.47	2.53	12.69	14.44	16.11
	3	15.52	2.63	13.94	15.57	17.23
	4	16.04	2.44	14.37	15.94	17.74
	5	16.27	2.55	14.68	16.10	17.98
	6	16.44	2.81	14.65	16.38	18.29
	7	16.70	2.80	14.74	16.82	18.60
	8	16.62	2.78	14.76	16.71	18.53
	9	16.55	2.86	14.20	16.22	18.78
	10	15.31	2.35	13.51	14.97	16.77

Table A38 Combined exposure ($RWE_{9\text{-}17}$) to NO_2 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	15.94	2.63	14.19	15.82	17.82
	Asian	16.45	2.70	14.54	16.45	18.47
	African	15.51	2.53	13.54	15.57	17.49
	Arab	15.25	2.55	12.92	15.48	17.37
	C or B	16.06	2.90	14.24	15.57	18.44
	Mixed	16.82	2.66	14.98	16.88	18.66
	Other	16.31	2.84	14.39	16.21	18.40
Age group	0-5	15.44	2.50	13.76	15.27	17.12
	6-10	15.15	2.29	13.58	15.07	16.55
	11-15	15.17	2.18	13.68	15.21	16.53
	16-20	16.16	2.74	14.42	16.19	18.08
	21-25	17.05	2.72	15.16	17.22	18.98
	26-30	17.13	2.55	15.30	17.33	19.02
	31-35	16.85	2.58	14.99	17.01	18.70
	36-40	16.35	2.60	14.57	16.34	18.27
	41-45	16.12	2.45	14.41	15.98	17.91
	46-50	15.85	2.52	14.12	15.76	17.66
	51-55	15.77	2.52	14.06	15.76	17.47
	56-60	15.66	2.46	14.01	15.55	17.31
	61-65	15.35	2.64	13.42	15.11	17.05
	66-70	15.37	2.47	13.72	15.25	16.95
	71-75	15.26	2.54	13.62	15.21	16.88
	76-80	15.13	2.66	13.35	15.04	16.73
	81-85	15.35	2.51	13.25	15.34	16.98
	86+	15.15	2.56	13.50	15.05	16.80
Carstairs index decile	1	14.66	2.35	13.03	14.62	16.12
	2	14.80	2.51	12.98	14.78	16.47
	3	15.79	2.54	14.21	15.75	17.53
	4	16.26	2.39	14.71	16.21	17.90
	5	16.43	2.43	14.93	16.29	18.04
	6	16.58	2.67	14.75	16.67	18.48
	7	16.79	2.66	14.96	16.94	18.71
	8	16.70	2.63	14.84	16.88	18.63
	9	16.61	2.71	14.44	16.40	18.77
	10	15.44	2.29	13.77	15.09	17.00

Table A39 Combined exposure ($RWE_{8\text{-}18}$) to NO_2 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	16.00	2.62	14.27	15.89	17.87
	Asian	16.47	2.68	14.60	16.38	18.47
	African	15.55	2.55	13.59	15.58	17.56
	Arab	15.23	2.54	12.90	15.50	17.17
	C or B	16.12	2.90	14.22	15.90	18.46
	Mixed	16.84	2.64	15.20	16.87	18.73
	Other	16.41	2.83	14.48	16.21	18.64
Age group	0-5	15.45	2.49	13.79	15.28	17.15
	6-10	15.19	2.27	13.70	15.09	16.65
	11-15	15.23	2.17	13.84	15.28	16.63
	16-20	16.17	2.71	14.49	16.21	18.02
	21-25	17.08	2.71	15.18	17.33	19.07
	26-30	17.19	2.54	15.39	17.35	19.09
	31-35	16.96	2.57	15.16	17.11	18.81
	36-40	16.47	2.58	14.71	16.44	18.37
	41-45	16.24	2.45	14.55	16.10	18.01
	46-50	15.97	2.50	14.25	15.90	17.70
	51-55	15.89	2.50	14.27	15.89	17.55
	56-60	15.75	2.45	14.08	15.68	17.45
	61-65	15.39	2.64	13.47	15.14	17.14
	66-70	15.38	2.47	13.77	15.26	16.96
	71-75	15.27	2.54	13.62	15.24	16.91
	76-80	15.13	2.66	13.35	15.03	16.76
	81-85	15.35	2.52	13.25	15.34	16.98
	86+	15.15	2.56	13.50	15.05	16.80
Carstairs index decile	1	14.77	2.38	13.10	14.68	16.25
	2	14.91	2.53	13.13	14.89	16.61
	3	15.87	2.55	14.28	15.80	17.57
	4	16.33	2.40	14.75	16.30	17.94
	5	16.47	2.43	14.95	16.34	18.08
	6	16.62	2.66	14.79	16.71	18.47
	7	16.82	2.65	15.02	16.93	18.75
	8	16.72	2.62	14.89	16.88	18.61
	9	16.63	2.69	14.53	16.49	18.67
	10	15.48	2.30	13.80	15.15	17.07

Table A40 Combined exposure (RWE_{hw+}) to NO_2 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	15.94	2.61	14.19	15.81	17.79
	Asian	16.45	2.69	14.55	16.43	18.46
	African	15.50	2.51	13.63	15.42	17.48
	Arab	15.27	2.56	12.94	15.59	17.26
	C or B	16.06	2.87	14.26	15.86	18.44
	Mixed	16.77	2.67	14.71	16.97	18.66
	Other	16.31	2.83	14.48	16.21	18.26
Age group	0-5	15.44	2.50	13.73	15.25	17.14
	6-10	15.12	2.29	13.44	15.00	16.51
	11-15	15.15	2.18	13.69	15.13	16.53
	16-20	16.15	2.76	14.38	16.14	18.10
	21-25	17.03	2.71	15.21	17.07	18.88
	26-30	17.11	2.53	15.34	17.31	18.95
	31-35	16.84	2.55	15.09	16.93	18.70
	36-40	16.34	2.57	14.55	16.28	18.22
	41-45	16.12	2.43	14.41	16.03	17.88
	46-50	15.86	2.47	14.18	15.73	17.57
	51-55	15.80	2.50	14.13	15.78	17.50
	56-60	15.68	2.44	13.99	15.60	17.34
	61-65	15.33	2.62	13.41	15.09	17.04
	66-70	15.36	2.46	13.72	15.23	16.96
	71-75	15.26	2.54	13.61	15.22	16.89
	76-80	15.13	2.66	13.35	15.03	16.73
	81-85	15.35	2.51	13.25	15.34	16.98
	86+	15.15	2.56	13.51	15.05	16.80
Carstairs index decile	1	14.67	2.35	13.05	14.63	16.18
	2	14.82	2.49	13.02	14.79	16.48
	3	15.78	2.51	14.25	15.74	17.47
	4	16.26	2.36	14.73	16.16	17.86
	5	16.42	2.42	14.93	16.30	18.03
	6	16.56	2.65	14.77	16.63	18.40
	7	16.77	2.65	14.95	16.91	18.66
	8	16.68	2.64	14.85	16.82	18.60
	9	16.61	2.71	14.46	16.35	18.76
	10	15.43	2.29	13.77	15.09	16.89

Table A41 Residential exposure (RE) to NO_2 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.82	2.95	11.02	13.42	15.02
	Asian	13.35	2.94	11.13	14.05	15.58
	African	12.40	2.70	10.43	13.11	14.49
	Arab	12.01	3.01	8.61	12.78	14.55
	C or B	13.20	2.90	13.02	13.41	15.59
	Mixed	13.67	2.97	12.53	14.49	15.59
	Other	13.01	3.27	10.56	13.41	15.71
Age group	0-5	12.58	2.84	10.62	13.25	14.58
	6-10	12.17	2.90	9.65	13.20	14.14
	11-15	12.20	2.85	9.96	13.14	14.14
	16-20	13.11	2.92	11.13	13.93	15.02
	21-25	13.89	2.79	12.76	14.49	15.59
	26-30	13.92	2.61	12.94	14.49	15.71
	31-35	13.56	2.81	12.59	14.14	15.57
	36-40	13.02	2.96	11.02	13.58	15.36
	41-45	12.84	2.85	11.02	13.41	14.96
	46-50	12.56	3.01	10.54	13.26	14.93
	51-55	12.49	3.04	10.45	13.26	14.86
	56-60	12.42	2.94	10.43	13.21	14.58
	61-65	12.30	3.02	10.05	13.14	14.57
	66-70	12.39	2.87	10.50	13.20	14.34
	71-75	12.46	3.00	10.53	13.24	14.86
	76-80	12.27	3.07	10.05	13.21	14.39
	81-85	12.39	2.89	10.05	13.32	14.37
	86+	12.10	2.98	9.96	12.80	14.25
Carstairs index decile	1	11.44	2.98	8.44	11.35	13.58
	2	11.54	3.14	8.22	11.74	14.13
	3	12.72	3.05	10.62	13.58	14.99
	4	13.42	2.61	12.53	13.90	15.03
	5	13.52	2.68	12.74	14.05	15.36
	6	13.47	2.85	12.53	14.14	15.56
	7	13.70	2.71	13.02	14.40	15.59
	8	13.39	2.75	12.74	13.86	15.56
	9	13.32	2.83	11.13	13.69	15.59
	10	12.35	2.61	10.43	13.02	14.12

Table A42 Combined exposure ($RWE_{9\text{-}17}$) to NO_2 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.96	2.80	11.13	13.58	15.03
	Asian	13.39	2.76	11.45	14.05	15.48
	African	12.49	2.63	10.43	13.19	14.59
	Arab	11.99	2.89	8.97	12.76	14.62
	C or B	13.28	2.86	12.24	13.98	15.53
	Mixed	13.71	2.83	12.31	14.34	15.56
	Other	13.20	3.15	10.56	13.59	15.71
Age group	0-5	12.59	2.81	10.69	13.26	14.58
	6-10	12.27	2.77	10.16	13.19	14.40
	11-15	12.34	2.68	10.21	13.24	14.22
	16-20	13.15	2.69	11.33	13.74	15.03
	21-25	13.92	2.59	12.79	14.44	15.59
	26-30	14.02	2.40	13.06	14.58	15.60
	31-35	13.79	2.57	12.75	14.47	15.56
	36-40	13.29	2.73	11.46	13.90	15.31
	41-45	13.11	2.63	11.35	13.58	15.03
	46-50	12.84	2.77	10.72	13.48	14.96
	51-55	12.77	2.82	10.66	13.40	14.94
	56-60	12.64	2.75	10.61	13.23	14.82
	61-65	12.40	2.94	10.43	13.19	14.57
	66-70	12.42	2.85	10.55	13.19	14.40
	71-75	12.47	2.99	10.56	13.24	14.86
	76-80	12.27	3.07	10.06	13.23	14.34
	81-85	12.39	2.89	10.06	13.32	14.37
	86+	12.10	2.98	9.96	12.80	14.25
Carstairs index decile	1	11.72	2.85	9.04	11.93	13.72
	2	11.81	3.00	8.94	12.24	14.25
	3	12.91	2.88	11.02	13.69	14.99
	4	13.53	2.51	12.67	13.96	15.20
	5	13.59	2.54	12.65	14.05	15.36
	6	13.55	2.70	12.58	14.16	15.44
	7	13.73	2.59	12.97	14.35	15.48
	8	13.45	2.62	12.74	13.93	15.34
	9	13.38	2.69	11.35	13.76	15.48
	10	12.45	2.54	10.43	13.06	14.27

Table A43 Combined exposure (RWE_{8-18}) to NO_2 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	13.01	2.78	11.15	13.59	15.02
	Asian	13.40	2.72	11.59	13.96	15.46
	African	12.52	2.62	10.43	13.20	14.49
	Arab	11.98	2.87	8.97	12.76	14.55
	C or B	13.30	2.86	11.91	14.25	15.30
	Mixed	13.72	2.81	12.51	14.29	15.80
	Other	13.27	3.12	10.56	13.69	15.71
Age group	0-5	12.60	2.81	10.68	13.27	14.58
	6-10	12.31	2.73	10.24	13.21	14.35
	11-15	12.39	2.64	10.43	13.24	14.32
	16-20	13.16	2.65	11.35	13.70	15.02
	21-25	13.92	2.56	12.76	14.34	15.77
	26-30	14.05	2.37	13.07	14.51	15.60
	31-35	13.86	2.53	12.78	14.47	15.59
	36-40	13.38	2.68	11.63	13.92	15.35
	41-45	13.20	2.58	11.50	13.63	15.04
	46-50	12.94	2.71	10.98	13.50	15.00
	51-55	12.86	2.76	10.88	13.42	14.96
	56-60	12.72	2.72	10.71	13.22	14.87
	61-65	12.44	2.93	10.43	13.20	14.57
	66-70	12.43	2.85	10.56	13.20	14.40
	71-75	12.48	2.99	10.56	13.27	14.86
	76-80	12.27	3.07	10.05	13.21	14.34
	81-85	12.39	2.89	10.05	13.32	14.37
	86+	12.10	2.98	9.95	12.80	14.25
Carstairs index decile	1	11.81	2.83	9.29	12.06	13.78
	2	11.90	2.98	9.35	12.34	14.33
	3	12.98	2.85	11.05	13.69	15.02
	4	13.57	2.49	12.72	13.93	15.27
	5	13.61	2.52	12.64	13.98	15.36
	6	13.57	2.67	12.61	14.12	15.45
	7	13.74	2.58	12.86	14.34	15.56
	8	13.47	2.60	12.74	13.86	15.33
	9	13.40	2.67	11.49	13.75	15.53
	10	12.48	2.53	10.43	13.06	14.38

Table A44 Combined exposure (RWE_{hw+}) to NO_2 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	12.96	2.78	11.13	13.56	14.99
	Asian	13.39	2.75	11.34	14.05	15.45
	African	12.49	2.59	10.43	13.20	14.56
	Arab	12.01	2.91	8.97	12.66	14.60
	C or B	13.28	2.81	12.31	13.73	15.58
	Mixed	13.68	2.85	12.10	14.39	15.48
	Other	13.22	3.13	10.56	13.45	15.74
Age group	0-5	12.59	2.82	10.68	13.26	14.58
	6-10	12.26	2.78	10.04	13.20	14.34
	11-15	12.32	2.68	10.23	13.26	14.30
	16-20	13.15	2.69	11.28	13.80	15.12
	21-25	13.92	2.57	12.80	14.41	15.59
	26-30	14.00	2.37	13.09	14.53	15.59
	31-35	13.78	2.54	12.76	14.39	15.54
	36-40	13.27	2.68	11.64	13.82	15.27
	41-45	13.11	2.58	11.35	13.56	14.99
	46-50	12.86	2.70	10.93	13.42	14.91
	51-55	12.80	2.76	10.87	13.39	14.93
	56-60	12.65	2.72	10.68	13.21	14.74
	61-65	12.39	2.93	10.43	13.20	14.57
	66-70	12.42	2.85	10.54	13.20	14.38
	71-75	12.47	2.99	10.53	13.24	14.86
	76-80	12.26	3.07	10.05	13.21	14.34
	81-85	12.39	2.89	10.05	13.32	14.37
	86+	12.10	2.98	9.96	12.80	14.25
Carstairs index decile	1	11.73	2.83	9.08	11.95	13.72
	2	11.82	2.97	9.11	12.18	14.16
	3	12.91	2.85	11.02	13.69	14.97
	4	13.52	2.48	12.70	13.95	15.19
	5	13.58	2.52	12.59	14.02	15.25
	6	13.54	2.69	12.59	14.15	15.30
	7	13.72	2.57	12.95	14.34	15.42
	8	13.44	2.60	12.74	13.88	15.25
	9	13.39	2.69	11.35	13.75	15.56
	10	12.44	2.52	10.43	13.04	14.25

Table A45 Residential exposure (RE) to O_3 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	50.40	2.35	48.71	50.53	52.04
	Asian	49.87	2.46	48.01	49.95	51.72
	African	50.77	2.17	49.10	50.86	52.49
	Arab	50.89	2.26	49.65	50.94	52.84
	C or B	50.24	2.46	47.88	50.71	51.54
	Mixed	49.57	2.43	47.53	49.42	51.20
	Other	50.16	2.53	48.37	50.40	51.83
Age group	0-5	50.66	2.17	49.23	50.82	52.12
	6-10	51.00	2.08	49.72	51.00	52.73
	11-15	51.02	2.03	49.93	51.06	52.64
	16-20	50.14	2.51	48.52	50.19	51.78
	21-25	49.42	2.47	47.62	49.54	51.05
	26-30	49.40	2.33	47.68	49.21	51.08
	31-35	49.75	2.39	48.08	49.78	51.35
	36-40	50.20	2.40	48.41	50.27	51.84
	41-45	50.40	2.25	48.72	50.52	52.05
	46-50	50.63	2.32	48.94	50.76	52.49
	51-55	50.68	2.33	49.17	50.86	52.47
	56-60	50.71	2.25	49.24	50.84	52.42
	61-65	50.84	2.32	49.34	50.98	52.63
	66-70	50.78	2.13	49.49	50.92	52.26
	71-75	50.81	2.20	49.41	50.83	52.38
	76-80	50.92	2.27	49.56	50.95	52.52
	81-85	50.75	2.15	49.36	50.81	52.50
	86+	50.94	2.17	49.59	51.00	52.52
Carstairs index decile	1	51.61	2.02	50.38	51.46	53.16
	2	51.46	2.21	50.01	51.43	53.19
	3	50.56	2.29	49.02	50.59	51.96
	4	50.13	2.11	48.59	50.17	51.34
	5	49.97	2.18	48.47	50.07	51.31
	6	49.83	2.39	48.16	49.89	51.36
	7	49.59	2.39	47.88	49.71	51.26
	8	49.68	2.38	47.92	49.84	51.23
	9	49.74	2.45	47.73	50.01	51.84
	10	50.78	2.04	49.76	50.93	52.35

Table A46 Combined exposure ($RWE_{9\text{-}17}$) to O_3 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	50.25	2.25	48.63	50.32	51.79
	Asian	49.81	2.32	48.00	49.89	51.42
	African	50.65	2.15	49.11	50.70	52.40
	Arab	50.91	2.14	49.18	50.94	52.93
	C or B	50.08	2.42	47.97	50.23	51.54
	Mixed	49.49	2.29	47.79	49.25	51.04
	Other	49.93	2.47	48.02	50.18	51.83
Age group	0-5	50.65	2.15	49.21	50.80	52.13
	6-10	50.92	1.99	49.67	50.94	52.52
	11-15	50.88	1.92	49.75	50.89	52.32
	16-20	50.08	2.31	48.51	50.06	51.51
	21-25	49.32	2.30	47.65	49.21	50.90
	26-30	49.24	2.17	47.59	49.02	50.78
	31-35	49.47	2.22	47.84	49.33	51.00
	36-40	49.91	2.23	48.25	49.98	51.47
	41-45	50.11	2.12	48.53	50.20	51.58
	46-50	50.35	2.17	48.74	50.41	51.92
	51-55	50.40	2.17	48.92	50.47	51.96
	56-60	50.49	2.13	49.04	50.60	52.00
	61-65	50.74	2.28	49.24	50.88	52.53
	66-70	50.75	2.12	49.46	50.87	52.20
	71-75	50.80	2.20	49.41	50.79	52.29
	76-80	50.92	2.28	49.55	50.94	52.51
	81-85	50.75	2.15	49.36	50.80	52.50
	86+	50.94	2.17	49.59	51.00	52.52
Carstairs index decile	1	51.34	2.00	50.12	51.22	52.91
	2	51.20	2.17	49.78	51.20	52.91
	3	50.36	2.21	48.83	50.34	51.79
	4	49.96	2.05	48.49	50.03	51.23
	5	49.85	2.08	48.44	49.96	51.11
	6	49.72	2.27	48.05	49.67	51.25
	7	49.52	2.27	47.84	49.44	51.04
	8	49.62	2.26	47.89	49.54	51.10
	9	49.69	2.32	47.78	49.90	51.59
	10	50.68	1.99	49.42	50.88	52.25

Table A47 Combined exposure ($RWE_{8\text{-}18}$) to O_3 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	50.20	2.24	48.58	50.27	51.71
	Asian	49.79	2.29	48.02	49.93	51.39
	African	50.61	2.17	48.98	50.72	52.38
	Arab	50.91	2.13	49.11	51.02	52.97
	C or B	50.03	2.42	47.99	49.96	51.54
	Mixed	49.47	2.28	47.84	49.29	51.00
	Other	49.86	2.46	47.83	50.18	51.83
Age group	0-5	50.64	2.15	49.18	50.78	52.12
	6-10	50.89	1.97	49.61	50.94	52.42
	11-15	50.84	1.90	49.64	50.86	52.17
	16-20	50.06	2.28	48.45	50.00	51.46
	21-25	49.30	2.29	47.65	49.13	50.88
	26-30	49.20	2.16	47.55	49.01	50.74
	31-35	49.39	2.20	47.79	49.25	50.91
	36-40	49.82	2.20	48.19	49.85	51.31
	41-45	50.02	2.11	48.42	50.11	51.48
	46-50	50.26	2.15	48.70	50.33	51.81
	51-55	50.32	2.15	48.84	50.36	51.82
	56-60	50.43	2.11	48.98	50.50	51.88
	61-65	50.71	2.27	49.19	50.85	52.47
	66-70	50.74	2.12	49.42	50.86	52.16
	71-75	50.79	2.20	49.38	50.80	52.29
	76-80	50.91	2.28	49.54	50.94	52.52
	81-85	50.75	2.15	49.36	50.80	52.50
	86+	50.94	2.17	49.59	51.00	52.52
Carstairs index decile	1	51.26	2.02	49.96	51.15	52.76
	2	51.12	2.18	49.65	51.08	52.80
	3	50.30	2.21	48.79	50.28	51.72
	4	49.91	2.06	48.44	49.98	51.18
	5	49.81	2.07	48.37	49.93	51.09
	6	49.69	2.26	48.03	49.64	51.23
	7	49.50	2.26	47.82	49.40	51.03
	8	49.60	2.24	47.94	49.53	51.10
	9	49.68	2.30	47.83	49.88	51.52
	10	50.65	1.99	49.33	50.86	52.20

Table A48 Combined exposure (RWE_{hw+}) to O_3 in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	50.24	2.24	48.65	50.32	51.75
	Asian	49.81	2.30	48.02	49.90	51.43
	African	50.65	2.14	49.09	50.72	52.26
	Arab	50.90	2.15	49.32	50.91	52.95
	C or B	50.08	2.40	47.88	50.09	51.54
	Mixed	49.53	2.30	47.89	49.28	51.15
	Other	49.92	2.45	48.02	50.15	51.83
Age group	0-5	50.65	2.16	49.21	50.81	52.12
	6-10	50.93	1.99	49.65	50.96	52.51
	11-15	50.90	1.91	49.79	50.91	52.31
	16-20	50.10	2.31	48.53	50.13	51.58
	21-25	49.34	2.29	47.67	49.31	50.91
	26-30	49.25	2.15	47.62	49.06	50.75
	31-35	49.46	2.19	47.84	49.39	50.95
	36-40	49.90	2.20	48.25	49.97	51.46
	41-45	50.09	2.10	48.54	50.17	51.53
	46-50	50.32	2.13	48.78	50.46	51.85
	51-55	50.36	2.15	48.91	50.44	51.83
	56-60	50.47	2.10	49.08	50.53	51.94
	61-65	50.75	2.26	49.27	50.87	52.48
	66-70	50.76	2.11	49.48	50.90	52.23
	71-75	50.80	2.20	49.41	50.80	52.29
	76-80	50.92	2.27	49.55	50.95	52.52
	81-85	50.75	2.15	49.36	50.81	52.50
	86+	50.94	2.17	49.59	51.00	52.52
Carstairs index decile	1	51.31	2.00	50.05	51.18	52.82
	2	51.18	2.15	49.75	51.14	52.86
	3	50.35	2.18	48.84	50.34	51.75
	4	49.95	2.03	48.53	50.05	51.20
	5	49.86	2.06	48.48	49.95	51.09
	6	49.73	2.26	48.07	49.69	51.22
	7	49.54	2.26	47.88	49.48	51.04
	8	49.63	2.26	47.92	49.60	51.11
	9	49.69	2.32	47.79	49.94	51.52
	10	50.68	1.99	49.53	50.87	52.19

Table A49 Residential exposure (RE) to O_3 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.75	2.87	56.72	58.40	60.32
	Asian	58.23	2.78	56.48	57.62	59.49
	African	59.21	2.57	57.47	59.34	61.26
	Arab	59.43	2.58	57.48	59.42	60.95
	C or B	58.57	2.87	56.44	57.66	61.26
	Mixed	58.04	2.83	56.48	57.62	59.50
	Other	58.87	3.12	56.48	58.40	61.26
Age group	0-5	59.00	2.76	57.26	58.86	60.46
	6-10	59.41	2.87	57.50	59.12	61.62
	11-15	59.29	2.96	57.24	58.90	61.30
	16-20	58.54	2.68	56.68	57.66	59.72
	21-25	57.77	2.65	56.44	57.26	59.40
	26-30	57.79	2.54	56.44	57.60	59.42
	31-35	58.15	2.71	56.48	57.66	59.52
	36-40	58.66	2.97	56.54	58.10	60.32
	41-45	58.75	2.79	56.90	58.44	59.86
	46-50	59.03	2.91	56.90	58.56	61.13
	51-55	59.02	3.01	56.90	58.56	61.12
	56-60	59.13	2.91	57.14	58.58	61.30
	61-65	59.15	2.98	57.14	58.86	61.30
	66-70	59.05	2.84	57.24	58.58	60.50
	71-75	59.02	2.93	57.14	58.56	60.60
	76-80	59.15	2.94	57.24	58.56	61.26
	81-85	59.03	2.86	56.90	58.50	61.12
	86+	59.13	2.78	57.24	59.12	61.06
Carstairs index decile	1	59.86	3.14	57.62	59.42	62.92
	2	59.79	3.27	57.44	59.46	63.18
	3	58.89	2.97	57.14	58.50	60.50
	4	58.07	2.63	56.54	57.64	59.50
	5	58.03	2.75	56.50	57.62	59.48
	6	58.16	2.59	56.51	57.64	59.52
	7	58.01	2.54	56.48	57.62	59.42
	8	58.35	2.54	56.48	57.78	59.48
	9	58.36	2.57	56.48	58.10	59.86
	10	59.52	2.31	58.10	59.42	61.16

Table A50 Combined exposure ($RWE_{9\text{-}17}$) to O_3 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.63	2.73	56.77	58.16	60.06
	Asian	58.20	2.62	56.48	57.64	59.48
	African	59.15	2.49	57.29	59.10	60.97
	Arab	59.47	2.49	57.38	59.45	60.95
	C or B	58.54	2.80	56.48	57.58	60.32
	Mixed	58.00	2.69	56.53	57.79	59.41
	Other	58.69	3.05	56.48	58.25	60.89
Age group	0-5	58.99	2.74	57.25	58.59	60.45
	6-10	59.32	2.73	57.42	58.90	61.28
	11-15	59.16	2.77	57.22	58.69	60.91
	16-20	58.51	2.48	56.82	57.97	59.76
	21-25	57.74	2.45	56.22	57.45	58.91
	26-30	57.70	2.33	56.32	57.40	58.95
	31-35	57.94	2.49	56.44	57.61	59.42
	36-40	58.42	2.73	56.55	57.92	59.88
	41-45	58.52	2.59	56.74	58.27	59.86
	46-50	58.79	2.69	56.85	58.41	60.60
	51-55	58.78	2.79	56.84	58.38	60.45
	56-60	58.94	2.74	57.08	58.51	60.60
	61-65	59.06	2.90	57.15	58.59	61.14
	66-70	59.03	2.83	57.25	58.59	60.50
	71-75	59.01	2.93	57.15	58.56	60.60
	76-80	59.15	2.94	57.25	58.56	61.26
	81-85	59.03	2.86	56.90	58.51	61.13
	86+	59.13	2.78	57.25	59.11	61.06
Carstairs index decile	1	59.62	3.00	57.45	59.12	62.30
	2	59.57	3.12	57.15	59.13	62.52
	3	58.72	2.81	56.93	58.24	60.32
	4	57.97	2.51	56.53	57.60	59.46
	5	57.97	2.60	56.48	57.62	59.40
	6	58.10	2.46	56.53	57.64	59.43
	7	57.97	2.42	56.48	57.69	59.27
	8	58.29	2.44	56.53	57.84	59.49
	9	58.31	2.46	56.50	58.09	59.72
	10	59.42	2.25	58.03	59.43	60.65

Table A51 Combined exposure ($RWE_{8\text{-}18}$) to O_3 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.59	2.69	56.73	58.11	59.94
	Asian	58.19	2.58	56.47	57.67	59.48
	African	59.13	2.47	57.25	59.12	60.88
	Arab	59.49	2.47	57.44	59.45	61.08
	C or B	58.52	2.79	56.47	57.57	60.32
	Mixed	57.99	2.67	56.44	57.76	59.36
	Other	58.63	3.03	56.51	57.92	60.77
Age group	0-5	58.99	2.74	57.25	58.58	60.45
	6-10	59.29	2.68	57.44	58.82	61.17
	11-15	59.11	2.71	57.23	58.59	61.01
	16-20	58.50	2.44	56.76	58.05	59.76
	21-25	57.73	2.41	56.20	57.54	58.91
	26-30	57.67	2.28	56.30	57.44	58.91
	31-35	57.88	2.44	56.39	57.60	59.36
	36-40	58.34	2.66	56.47	57.89	59.78
	41-45	58.44	2.54	56.67	58.12	59.73
	46-50	58.71	2.63	56.81	58.39	60.45
	51-55	58.70	2.73	56.74	58.36	60.45
	56-60	58.88	2.70	57.05	58.50	60.51
	61-65	59.03	2.88	57.15	58.58	60.95
	66-70	59.02	2.82	57.24	58.58	60.51
	71-75	59.00	2.93	57.15	58.57	60.61
	76-80	59.15	2.94	57.24	58.57	61.27
	81-85	59.03	2.86	56.90	58.50	61.12
	86+	59.13	2.78	57.24	59.12	61.06
Carstairs index decile	1	59.54	2.96	57.44	59.12	62.00
	2	59.48	3.08	57.12	59.12	62.26
	3	58.67	2.76	56.90	58.18	60.14
	4	57.94	2.49	56.50	57.60	59.43
	5	57.96	2.56	56.47	57.64	59.35
	6	58.08	2.42	56.49	57.66	59.38
	7	57.97	2.40	56.47	57.69	59.30
	8	58.28	2.41	56.54	57.89	59.48
	9	58.30	2.44	56.47	58.05	59.62
	10	59.39	2.23	57.94	59.43	60.48

Table A52 Combined exposure (RWE_{hw+}) to O_3 in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	58.63	2.68	56.78	58.16	60.02
	Asian	58.20	2.59	56.48	57.62	59.48
	African	59.14	2.42	57.37	59.12	60.72
	Arab	59.47	2.49	57.44	59.47	61.15
	C or B	58.55	2.77	56.48	57.71	60.32
	Mixed	58.02	2.70	56.46	57.68	59.48
	Other	58.67	3.03	56.48	58.10	61.01
Age group	0-5	58.99	2.74	57.26	58.58	60.46
	6-10	59.32	2.72	57.42	58.96	61.21
	11-15	59.16	2.75	57.23	58.77	61.01
	16-20	58.50	2.46	56.91	57.95	59.82
	21-25	57.75	2.40	56.29	57.45	58.98
	26-30	57.72	2.25	56.31	57.45	58.95
	31-35	57.96	2.41	56.47	57.62	59.39
	36-40	58.42	2.63	56.56	57.97	59.86
	41-45	58.51	2.51	56.81	58.19	59.84
	46-50	58.76	2.58	56.92	58.44	60.46
	51-55	58.75	2.69	56.82	58.41	60.44
	56-60	58.93	2.68	57.10	58.53	60.58
	61-65	59.07	2.87	57.14	58.67	61.24
	66-70	59.03	2.82	57.24	58.58	60.50
	71-75	59.01	2.93	57.14	58.56	60.60
	76-80	59.16	2.94	57.24	58.56	61.26
	81-85	59.04	2.86	56.90	58.50	61.12
	86+	59.13	2.78	57.24	59.12	61.06
Carstairs index decile	1	59.60	2.94	57.46	59.12	62.00
	2	59.55	3.05	57.18	59.19	62.31
	3	58.72	2.75	56.96	58.27	60.23
	4	57.99	2.45	56.54	57.60	59.46
	5	57.99	2.54	56.54	57.62	59.34
	6	58.10	2.42	56.54	57.64	59.42
	7	57.98	2.38	56.48	57.66	59.24
	8	58.30	2.41	56.54	57.92	59.48
	9	58.31	2.45	56.48	58.10	59.72
	10	59.41	2.23	58.03	59.42	60.61

Table A53 Residential exposure (RE) to $PM_{2.5}$ in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	4.79	0.30	4.62	4.80	4.99
	Asian	4.84	0.28	4.68	4.86	5.03
	African	4.73	0.34	4.52	4.76	4.95
	Arab	4.72	0.30	4.59	4.75	4.92
	C or B	4.79	0.35	4.68	4.86	5.01
	Mixed	4.87	0.29	4.75	4.91	5.05
	Other	4.81	0.28	4.68	4.85	5.00
Age group	0-5	4.76	0.29	4.60	4.77	4.97
	6-10	4.74	0.29	4.56	4.75	4.95
	11-15	4.72	0.27	4.56	4.74	4.91
	16-20	4.78	0.32	4.65	4.83	4.98
	21-25	4.86	0.28	4.72	4.88	5.04
	26-30	4.89	0.28	4.72	4.93	5.08
	31-35	4.86	0.29	4.69	4.89	5.06
	36-40	4.82	0.29	4.64	4.85	5.03
	41-45	4.80	0.29	4.61	4.81	4.99
	46-50	4.77	0.30	4.60	4.79	4.98
	51-55	4.76	0.30	4.59	4.78	4.98
	56-60	4.76	0.28	4.59	4.77	4.96
	61-65	4.75	0.30	4.57	4.76	4.97
	66-70	4.77	0.29	4.60	4.77	4.97
	71-75	4.76	0.31	4.58	4.77	4.98
	76-80	4.74	0.32	4.59	4.79	4.96
	81-85	4.77	0.27	4.63	4.78	4.96
	86+	4.75	0.29	4.61	4.76	4.96
Carstairs index decile	1	4.62	0.33	4.46	4.66	4.84
	2	4.65	0.31	4.47	4.70	4.85
	3	4.77	0.30	4.60	4.79	4.99
	4	4.83	0.28	4.71	4.84	5.00
	5	4.85	0.27	4.69	4.87	5.01
	6	4.87	0.28	4.72	4.88	5.06
	7	4.88	0.26	4.71	4.90	5.06
	8	4.88	0.25	4.73	4.89	5.04
	9	4.87	0.25	4.68	4.89	5.06
	10	4.76	0.25	4.58	4.75	4.93

Table A54 Combined exposure ($RWE_{9\text{-}17}$) to $PM_{2.5}$ in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	4.79	0.28	4.63	4.81	4.99
	Asian	4.83	0.27	4.67	4.85	5.02
	African	4.73	0.34	4.54	4.76	4.95
	Arab	4.71	0.30	4.58	4.74	4.90
	C or B	4.79	0.35	4.69	4.85	5.00
	Mixed	4.85	0.26	4.72	4.89	5.04
	Other	4.82	0.27	4.72	4.82	5.02
Age group	0-5	4.77	0.29	4.60	4.77	4.97
	6-10	4.75	0.28	4.59	4.78	4.95
	11-15	4.74	0.26	4.58	4.74	4.91
	16-20	4.76	0.30	4.65	4.81	4.93
	21-25	4.84	0.27	4.70	4.86	5.01
	26-30	4.88	0.26	4.72	4.91	5.07
	31-35	4.86	0.26	4.70	4.88	5.06
	36-40	4.83	0.27	4.67	4.86	5.03
	41-45	4.81	0.26	4.64	4.83	5.00
	46-50	4.79	0.27	4.63	4.80	4.98
	51-55	4.78	0.28	4.62	4.80	4.98
	56-60	4.77	0.26	4.61	4.78	4.95
	61-65	4.75	0.30	4.58	4.77	4.97
	66-70	4.77	0.29	4.61	4.77	4.97
	71-75	4.76	0.31	4.59	4.77	4.98
	76-80	4.74	0.32	4.59	4.79	4.96
	81-85	4.77	0.27	4.63	4.79	4.96
	86+	4.75	0.29	4.61	4.76	4.95
Carstairs index decile	1	4.64	0.32	4.48	4.69	4.85
	2	4.67	0.30	4.50	4.70	4.86
	3	4.78	0.28	4.62	4.80	4.99
	4	4.83	0.27	4.71	4.84	5.01
	5	4.84	0.25	4.69	4.85	5.01
	6	4.86	0.26	4.72	4.87	5.03
	7	4.87	0.24	4.71	4.88	5.04
	8	4.88	0.23	4.73	4.88	5.04
	9	4.86	0.24	4.68	4.88	5.04
	10	4.77	0.24	4.58	4.76	4.93

Table A55 Combined exposure ($RWE_{8\text{-}18}$) to $PM_{2.5}$ in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	4.79	0.28	4.63	4.81	4.99
	Asian	4.83	0.28	4.67	4.84	5.01
	African	4.73	0.34	4.56	4.75	4.96
	Arab	4.70	0.30	4.58	4.73	4.89
	C or B	4.79	0.35	4.69	4.85	5.01
	Mixed	4.85	0.26	4.72	4.89	5.03
	Other	4.82	0.27	4.70	4.84	5.02
Age group	0-5	4.77	0.29	4.60	4.78	4.97
	6-10	4.75	0.27	4.59	4.78	4.94
	11-15	4.74	0.26	4.59	4.74	4.91
	16-20	4.75	0.29	4.63	4.80	4.93
	21-25	4.83	0.27	4.69	4.85	5.01
	26-30	4.87	0.26	4.72	4.90	5.06
	31-35	4.86	0.26	4.70	4.89	5.06
	36-40	4.84	0.27	4.68	4.87	5.04
	41-45	4.81	0.26	4.65	4.84	5.00
	46-50	4.79	0.27	4.63	4.81	4.98
	51-55	4.78	0.27	4.62	4.81	4.98
	56-60	4.77	0.26	4.62	4.78	4.96
	61-65	4.75	0.30	4.58	4.76	4.97
	66-70	4.77	0.29	4.61	4.77	4.97
	71-75	4.76	0.31	4.59	4.77	4.98
	76-80	4.74	0.32	4.58	4.79	4.96
	81-85	4.77	0.27	4.63	4.78	4.96
	86+	4.75	0.29	4.61	4.76	4.95
Carstairs index decile	1	4.64	0.31	4.49	4.70	4.85
	2	4.67	0.30	4.50	4.71	4.87
	3	4.78	0.28	4.62	4.81	4.99
	4	4.83	0.27	4.70	4.85	5.01
	5	4.84	0.25	4.69	4.86	5.01
	6	4.85	0.26	4.71	4.87	5.03
	7	4.86	0.24	4.71	4.88	5.04
	8	4.87	0.23	4.73	4.88	5.03
	9	4.86	0.24	4.68	4.88	5.04
	10	4.77	0.24	4.58	4.76	4.93

Table A56 Combined exposure (RWE_{hw+}) to $PM_{2.5}$ in Edinburgh per population subgroup – ADMS-Urban. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	4.79	0.28	4.64	4.81	4.99
	Asian	4.84	0.27	4.69	4.85	5.01
	African	4.73	0.34	4.54	4.76	4.93
	Arab	4.71	0.29	4.58	4.74	4.91
	C or B	4.79	0.35	4.69	4.87	5.00
	Mixed	4.85	0.26	4.75	4.89	5.03
	Other	4.82	0.27	4.71	4.82	5.02
Age group	0-5	4.77	0.29	4.60	4.77	4.97
	6-10	4.74	0.28	4.58	4.76	4.95
	11-15	4.73	0.26	4.59	4.74	4.91
	16-20	4.77	0.30	4.65	4.81	4.94
	21-25	4.84	0.26	4.71	4.86	5.01
	26-30	4.88	0.26	4.73	4.91	5.06
	31-35	4.86	0.26	4.70	4.88	5.04
	36-40	4.83	0.27	4.67	4.86	5.03
	41-45	4.81	0.26	4.64	4.83	4.99
	46-50	4.79	0.27	4.64	4.80	4.97
	51-55	4.78	0.27	4.62	4.80	4.98
	56-60	4.77	0.26	4.62	4.78	4.95
	61-65	4.75	0.30	4.58	4.76	4.96
	66-70	4.77	0.29	4.61	4.77	4.97
	71-75	4.76	0.31	4.58	4.78	4.98
	76-80	4.74	0.32	4.59	4.79	4.96
	81-85	4.77	0.27	4.63	4.78	4.96
	86+	4.75	0.29	4.61	4.76	4.96
Carstairs index decile	1	4.64	0.32	4.49	4.69	4.85
	2	4.67	0.30	4.50	4.71	4.86
	3	4.78	0.28	4.62	4.80	4.99
	4	4.83	0.27	4.71	4.84	5.00
	5	4.84	0.25	4.70	4.86	5.01
	6	4.86	0.26	4.73	4.87	5.03
	7	4.87	0.24	4.71	4.88	5.04
	8	4.87	0.23	4.73	4.88	5.03
	9	4.86	0.24	4.68	4.88	5.05
	10	4.76	0.24	4.58	4.75	4.93

Table A57 Residential exposure (RE) to $PM_{2.5}$ in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.69	0.46	7.42	7.75	8.00
	Asian	7.73	0.42	7.45	7.79	7.94
	African	7.63	0.45	7.28	7.69	7.89
	Arab	7.52	0.39	7.27	7.49	7.78
	C or B	7.68	0.41	7.62	7.85	7.90
	Mixed	7.76	0.44	7.46	7.79	8.09
	Other	7.68	0.48	7.40	7.85	8.00
Age group	0-5	7.68	0.46	7.41	7.74	7.94
	6-10	7.63	0.48	7.24	7.69	7.90
	11-15	7.63	0.47	7.28	7.66	7.92
	16-20	7.66	0.42	7.43	7.69	7.90
	21-25	7.75	0.40	7.58	7.76	7.94
	26-30	7.82	0.41	7.59	7.86	8.12
	31-35	7.80	0.44	7.52	7.85	8.12
	36-40	7.74	0.47	7.43	7.82	8.09
	41-45	7.70	0.46	7.41	7.76	8.00
	46-50	7.68	0.48	7.41	7.76	8.00
	51-55	7.66	0.48	7.40	7.74	7.92
	56-60	7.64	0.47	7.38	7.69	7.92
	61-65	7.64	0.48	7.31	7.69	7.92
	66-70	7.65	0.47	7.40	7.69	7.92
	71-75	7.67	0.51	7.39	7.74	8.09
	76-80	7.64	0.50	7.35	7.74	7.92
	81-85	7.64	0.46	7.31	7.73	7.92
	86+	7.59	0.46	7.24	7.61	7.90
Carstairs index decile	1	7.47	0.49	7.01	7.54	7.86
	2	7.49	0.50	7.06	7.50	7.87
	3	7.70	0.49	7.42	7.81	8.00
	4	7.78	0.43	7.53	7.82	8.09
	5	7.78	0.44	7.52	7.81	8.11
	6	7.76	0.42	7.52	7.82	8.08
	7	7.79	0.40	7.59	7.82	8.12
	8	7.78	0.41	7.59	7.79	8.09
	9	7.77	0.41	7.45	7.81	8.11
	10	7.68	0.45	7.28	7.74	8.09

Table A58 Combined exposure ($RWE_{9\text{-}17}$) to $PM_{2.5}$ in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.69	0.43	7.43	7.75	7.96
	Asian	7.73	0.40	7.48	7.75	7.94
	African	7.62	0.43	7.31	7.69	7.88
	Arab	7.52	0.38	7.27	7.46	7.74
	C or B	7.68	0.40	7.68	7.81	7.87
	Mixed	7.75	0.41	7.50	7.75	8.03
	Other	7.69	0.46	7.43	7.82	8.00
Age group	0-5	7.68	0.46	7.41	7.75	7.94
	6-10	7.64	0.46	7.32	7.71	7.93
	11-15	7.64	0.45	7.34	7.69	7.92
	16-20	7.65	0.39	7.45	7.69	7.87
	21-25	7.73	0.36	7.55	7.74	7.94
	26-30	7.80	0.36	7.59	7.84	8.06
	31-35	7.78	0.39	7.57	7.84	8.07
	36-40	7.74	0.42	7.46	7.80	8.05
	41-45	7.71	0.41	7.45	7.75	7.99
	46-50	7.69	0.43	7.41	7.75	7.97
	51-55	7.67	0.43	7.41	7.74	7.94
	56-60	7.65	0.43	7.38	7.69	7.92
	61-65	7.64	0.46	7.33	7.70	7.92
	66-70	7.65	0.47	7.40	7.69	7.92
	71-75	7.67	0.50	7.40	7.75	8.09
	76-80	7.64	0.50	7.35	7.74	7.92
	81-85	7.64	0.46	7.31	7.73	7.92
	86+	7.59	0.46	7.25	7.61	7.90
Carstairs index decile	1	7.49	0.46	7.08	7.55	7.85
	2	7.51	0.46	7.10	7.52	7.86
	3	7.70	0.45	7.43	7.80	8.00
	4	7.77	0.40	7.57	7.80	8.02
	5	7.77	0.41	7.53	7.79	8.07
	6	7.75	0.38	7.55	7.78	8.00
	7	7.78	0.37	7.58	7.79	8.04
	8	7.77	0.38	7.58	7.78	8.04
	9	7.76	0.39	7.45	7.79	8.08
	10	7.68	0.43	7.31	7.73	8.02

Table A59 Combined exposure ($RWE_{8\text{-}18}$) to $PM_{2.5}$ in Edinburgh per population subgroup – EMEP4UK. All units µg m^{-3}. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.69	0.42	7.43	7.75	7.96
	Asian	7.72	0.39	7.45	7.75	7.94
	African	7.62	0.42	7.31	7.66	7.88
	Arab	7.52	0.38	7.24	7.46	7.75
	C or B	7.68	0.40	7.66	7.82	7.86
	Mixed	7.74	0.40	7.50	7.76	8.01
	Other	7.69	0.45	7.44	7.81	7.99
Age group	0-5	7.68	0.46	7.41	7.75	7.96
	6-10	7.65	0.45	7.33	7.72	7.93
	11-15	7.64	0.44	7.35	7.69	7.94
	16-20	7.65	0.38	7.45	7.67	7.86
	21-25	7.72	0.35	7.55	7.74	7.94
	26-30	7.79	0.35	7.59	7.83	8.03
	31-35	7.78	0.38	7.57	7.83	8.06
	36-40	7.74	0.41	7.47	7.79	8.04
	41-45	7.71	0.40	7.45	7.75	7.98
	46-50	7.69	0.42	7.41	7.75	7.97
	51-55	7.68	0.42	7.41	7.75	7.94
	56-60	7.66	0.42	7.40	7.70	7.92
	61-65	7.64	0.46	7.36	7.70	7.92
	66-70	7.65	0.46	7.40	7.69	7.92
	71-75	7.67	0.50	7.40	7.75	8.09
	76-80	7.64	0.50	7.35	7.74	7.92
	81-85	7.64	0.46	7.31	7.73	7.92
	86+	7.59	0.46	7.24	7.61	7.90
Carstairs index decile	1	7.50	0.45	7.12	7.58	7.85
	2	7.52	0.46	7.16	7.53	7.86
	3	7.71	0.44	7.43	7.79	8.00
	4	7.77	0.40	7.57	7.80	8.02
	5	7.77	0.40	7.53	7.79	8.05
	6	7.75	0.38	7.55	7.78	7.99
	7	7.77	0.36	7.57	7.79	8.03
	8	7.76	0.38	7.57	7.78	8.02
	9	7.76	0.39	7.45	7.79	8.08
	10	7.68	0.43	7.31	7.74	8.00

Table A60 Combined exposure (RWE_{hw+}) to $PM_{2.5}$ in Edinburgh per population subgroup – EMEP4UK. Source: Scottish Longitudinal Study.

Variable	Subgroup	Mean	SD	Q1	Median	Q3
Ethnic group	White	7.69	0.43	7.43	7.74	7.97
	Asian	7.73	0.40	7.49	7.74	7.94
	African	7.63	0.43	7.33	7.69	7.89
	Arab	7.52	0.38	7.29	7.46	7.75
	C or B	7.68	0.40	7.68	7.81	7.89
	Mixed	7.75	0.41	7.49	7.75	8.03
	Other	7.69	0.45	7.45	7.84	8.00
Age group	0-5	7.68	0.46	7.41	7.74	7.94
	6-10	7.64	0.46	7.28	7.70	7.92
	11-15	7.64	0.45	7.34	7.69	7.91
	16-20	7.65	0.39	7.46	7.69	7.88
	21-25	7.73	0.36	7.56	7.74	7.94
	26-30	7.80	0.36	7.60	7.84	8.06
	31-35	7.79	0.39	7.58	7.84	8.07
	36-40	7.74	0.42	7.47	7.80	8.05
	41-45	7.71	0.41	7.45	7.75	7.99
	46-50	7.70	0.43	7.42	7.75	7.99
	51-55	7.68	0.43	7.41	7.74	7.94
	56-60	7.66	0.43	7.39	7.69	7.91
	61-65	7.64	0.46	7.31	7.70	7.92
	66-70	7.65	0.47	7.40	7.69	7.92
	71-75	7.67	0.50	7.40	7.74	8.09
	76-80	7.64	0.50	7.35	7.74	7.92
	81-85	7.64	0.46	7.31	7.73	7.92
	86+	7.59	0.46	7.24	7.61	7.90
Carstairs index decile	1	7.50	0.46	7.10	7.55	7.85
	2	7.51	0.46	7.13	7.53	7.86
	3	7.71	0.45	7.43	7.81	8.00
	4	7.77	0.40	7.58	7.80	8.03
	5	7.77	0.40	7.54	7.80	8.07
	6	7.75	0.38	7.55	7.79	8.00
	7	7.78	0.37	7.58	7.79	8.06
	8	7.77	0.38	7.58	7.78	8.05
	9	7.76	0.39	7.45	7.79	8.08
	10	7.68	0.43	7.30	7.73	8.04

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