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Assessing $PM_{2.5}$ exposure bias towards deprived areas in England using a new indicator

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ABSTRACT

In many countries higher concentrations of harmful air pollutants coincide with more deprived areas of society, where prevalence of health impacts associated with air pollution are greater. However, the impact of policies aimed at mitigating air pollution on the bias in exposure across deprivation groups rarely feature in policy development.

We introduce the Indicator of Exposure Bias (IoEB) to the UK Integrated Assessment Model to quantify this bias, providing a method for comparing different scenarios and sectors. We analyse the bias in exposure to $PM_{2.5}$ concentrations across deprivation levels within England currently and for future scenarios, and by sectors. While England's Index of Multiple Deprivation (IMD) and the Health domain are used as measures of deprivation here, the indicator can be applied to any pair of spatial socio-economic status and environmental exposure metrics.

An IoEB of 0.88 $\mu g.m^{-3}$ was calculated for the 2018 baseline, indicating a bias in exposures towards more deprived areas ranked using the IMD. All future scenarios considered here lead to reductions in population exposure and a reduction in the bias towards more deprived areas, with the greatest reduction of 59 % achieved by focusing on urban sources of primary $PM_{2.5}$. The total bias in exposure towards more deprived areas is mitigated by an opposite bias for the transboundary contribution, therefore the bias in exposure of total $PM_{2.5}$ does not accurately reflect that associated to UK anthropogenic emissions. The bias varies significantly between sectors, with non-industrial combustion and road transport the greatest contributors.

Reaching England's 2040 $PM_{2.5}$ exposure target is likely to deliver substantially greater health benefits for the more deprived members of society than the less deprived, reducing health inequality. The bias is sensitive to the measure of deprivation used, demonstrated using the Health domain.

1. Background

Deprived communities in many countries and cities tend to be exposed to higher levels of ambient air pollution, (Fairburn et al., 2019; Bell and Ebisu, 2012; Bramble et al., 2023; European Environment Agency 2019; Ganzleben and Kazmierczak, 2020) exacerbating the inequality between more and less deprived groups which otherwise exists due to differences in income, employment and health status, among other factors. This bias in exposure exists for both $PM_{2.5}$ and NO_2 concentrations across many European cities, (Samoli et al., 2019) including London, (Young et al., 2023; Brook and King, 2017; Tonne et al., 2018; Ferguson et al., 2021; Brook et al., 2023) in addition to countries within the UK. (Chalabi et al., 2017; Defra 2019; Milojevic et al., 2017; Brunt et al., 2017) In the UK, it is estimated that health inequalities add an extra cost of £4.8 billion a year to the National Health Service (NHS) due to the additional use of hospitals by people in deprived areas. (Asaria et al., 2016) Health inequalities also reduce employment rates and productivity in more deprived areas, which has an economic cost, estimated at £31-33 billion for England in 2010. (Marmot et al., 2010; Marmot et al., 2020) These inequalities have a

Abbreviations: CORINAIR, Core Inventory of Air Emissions; IMD, Index of Multiple Deprivation; IoEB, Indicator of exposure Bias; LSOA, Lower-layer Super Output Area; PERT, Population Exposure Reduction Target; PWMC, Population-weighted Mean Concentration; NAEI, National Atmospheric Emission Inventory; NHS, National Health Service; NZ, Net Zero; SIA, Secondary Inorganic Aerosol; SNAP, Selected Nomenclature for Air Pollution; TNZ, Towards Net Zero; UKIAM, UK Integrated Assessment Model; WAM, With Additional Measures.

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profound impact on quality of life; from 2015 to 2017 the gap in healthy-life expectancy between the least and most deprived areas was 19 years, (ONS 2019) and is increasing. (Bennett et al., 2018) Air pollution is recognised (e.g. in the NHS Long Term Plan (NHS 2019)) as one of a mix of environmental and social factors, requiring action across many policy areas, that generates inequalities. Despite this, there is no target for the reduction of the bias in air pollution exposure towards more deprived communities in the UK, neither is this bias typically considered in analyses supporting policy development (an exception being a short qualitative analysis in ApSimon et al. (ApSimon et al. (2022), ApSimon et al. (2023)).

Air quality in the UK has improved dramatically since the first Clean Air Act in 1956 targeted smoke emissions from coal burning. A wide range of actions were taken to reduce harmful emissions, such as the burning of cleaner fuels, the use of post-combustion treatment technologies, smoke control zones and congestion-charging zones, with additional improvements due to the decline in heavy industry and the transition from coal power to less polluting energy generation. Since the UK's Air Quality Strategy was first published in 1997, targets have been set for the concentration of harmful pollutants in the air and have been used to drive policy. These air quality targets have, in the most part, consisted of setting limit values for mean concentrations averaged over different time periods, e.g. hourly, daily, annual, often driven by the desire to meet recommended limits such as those of the World Health Organisation. (WHO 2022) While these targets have proven effective at driving further reductions in concentrations for the most polluted areas, they are not necessarily the most effective way of reducing the overall exposure of the population. In recognition of this, as part of England's Environment Act (Environment Act 2021) a target was set to reduce the mean population exposure to $PM_{2.5}$, the Population Exposure Reduction Target (PERT), with the aim of driving down overall exposure as well as the maximum allowable concentration. (Oxley et al., 2013; ApSimon et al., 2021) The target set was for a 35 % reduction in the population weighted mean concentration by 2040 relative to 2018.

The UK Integrated Assessment Model (UKIAM) was a central tool in the development of the air quality targets set in the Environment Act. UKIAM is a model framework, consisting of a family of reduced-form models, used to investigate the impact of future emissions scenarios on UK air quality and impacts on natural ecosystems such as eutrophication. (ApSimon et al., 2022; ApSimon et al., 2023; Oxley et al., 2013; ApSimon et al., 2021; Woodward et al., 2022; Oxley et al., 2023) This paper describes the latest development to the UKIAM framework which provides an analysis of the inequality in exposure to $PM_{2.5}$ concentrations. We derive a new metric, the Indicator of Exposure Bias (IoEB), a quantitative measure of the bias in exposure to poor air quality across the scale of deprivation within a population. The metric is designed to be used by policy makers to track the progress towards reducing this bias, and to explore the relative contributions of different sectors to this bias, utilising the UKIAM's source-apportionment capabilities.

In a detailed study of the ways in which inequality in England varies in relation to different environmental factors, including atmospheric concentrations of harmful pollutants, Briggs et al. (2008) highlighted the complexity of these relations, reflected in the non-linearity of fitted exposure-deprivation curves. The IoEB aims to reduce this complexity to a single metric of the bias in exposure towards either more or less deprived areas, allowing policy makers to measure progress towards reducing this bias, and if appropriate, as a means to set a quantitative target for exposure bias. Unlike previous indicators of exposure bias, such as variations of the Gini index (Pye et al., 2006; Walker et al., 2003; Walker et al., 2003; Pisoni et al., 2022) or Pearson correlation (Briggs et al., 2008), the IoEB is not dimensionless. This allows the magnitude of the bias to be easily compared between scenarios or between sectors.

While we focus on $PM_{2.5}$ exposure in England, the methodology can be used to characterise the bias in the exposure of any spatially varying environmental hazard across any spatially varying socio-economic metric provided that the required data is available at a suitable spatial resolution.

The methodology is applied to population exposure in the England only using the current UKIAM baseline of 2018, and future scenarios predicting exposure reductions by 2040 as a result of existing measures and of additional policies towards Net Zero (NZ), in addition to measures specifically targeting the emissions of air pollutants. We model two scenarios that meet the 2040 PERT target in order to assess what achieving this target could mean for the bias in $PM_{2.5}$ exposure. The IoEB is used to assess the impact of each scenario on the bias in exposure and the sectors which contribute the most to this bias are identified.

The Index of Multiple Deprivation (IMD) (English Indices of deprivation (English Indices of deprivation 2019)) is used as the primary measure of deprivation for the analysis. The IMD captures the impact of seven different components used as measures of deprivation, as described in Section 2.2. One of these components is Health Deprivation and Disability. This sub-domain of the IMD is also used both to illustrate the sensitivity of the analysis to the choice of deprivation index, and because we are concerned with the health impacts of exposure. Equivalent spatial indices are available for many other regions and countries, some examples of which are provided here. (Métropole - Indice de défavorisation sociale (FDep) à l'échelle de l'IRIS – Inserm 11th September 2023; The Canadian Index of Multiple Deprivation: Database and User Guide 11th September 2023; Landscape of Area-Level Deprivation 11th September 2023; Wang et al., 2021; Dhongde et al., 2023)

2. Methods

2.1. UKIAM

The UK Integrated Assessment Model (UKIAM), developed at Imperial College London with support from the UK Centre for Ecology and Hydrology is able to model atmospheric concentrations and population exposure, and can also evaluate the impact of air pollutants on sensitive habitats. (Woodward et al., 2022) The model combines local, primary contributions to $PM_{2.5}$ concentrations with long-range contributions from secondary inorganic aerosol formed from precursor emissions of SO_2, NO_x and NH_3. The model also includes other "irreducible" components such as sea salt and natural dust, and secondary organic aerosol, in addition to other urban sources not included in the National Atmospheric Emission Inventory (NAEI), such as cooking, which may be significant in densely populated metropolitan areas like London. (Shah et al., 2023) A fixed secondary inorganic aerosol (SIA) adjustment is included in order to correct for non-linearities in the chemistry. (Oxley et al., 2023) Imported contributions from other countries and from shipping are also included in the model. Emissions of other countries reflect scenarios for the EU's 2nd Clean Air Outlook, with additional measures (WAM). (Amann et al., 2020) Emissions from shipping have been modelled using Automatic Identification System, AIS, tracking data provided by Ricardo for the domestic and international fleets around the coast of the UK and in the North and Irish Seas. ApSimon et al. (2021) A detailed description of the UKIAM is provided by ApSimon et al. (2021) and Oxley et al. (2013), Oxley et al. (2023) while the application of the model in support of the UK's Environment Act targets is described in ApSimon et al. (2022), ApSimon et al. (2023)

The UKIAM is a reduced-form model and therefore a complex Atmospheric Chemistry Transport Model (EMEP4UK) is used to check and validate the results for core scenarios. Oxley et al. (2023) Generally we find that the UKIAM model generates results that are in good agreement with the complex model and therefore provide a suitable set of $PM_{2.5}$ concentration maps for our analysis.

For the scenarios modelled in ApSimon et al. (2022) the model was linked to Defra's Scenario Modelling Tool (https://smt.ricardo-aea.com/) which was used to make future emission projections for the UK, using the NAEI 2020 emissions (Richmond et al., 2020) as a starting point. For the analysis presented here, new independently developed scenarios are used to explore the implications of reaching the PERT target on exposure inequality. These scenarios use updated emission estimates for domestic wood combustion reflecting the latest NAEI2022. Churchill et al. (2022) These latest primary $PM_{2.5}$ domestic wood burning emissions are a significant reduction (roughly a half) compared to previous NAEI versions and remains a highly uncertain source in terms of the magnitude and spatial distribution of emissions.

Six scenarios are considered for analysis and the emissions are given in Table 1:

- B2018 – 2018 emissions based on NAEI2020 submission with some adjustments including the revision of domestic wood burning emissions to reflect the latest NAEI2022.
- B2040 – 2040 emissions assuming existing interventions and policies with a natural technology turnover.
- TNZ2040 – 2040 emissions assuming a NZ pathway which includes the electrification of power sector and the road transport fleet, in addition to some mitigation of NH_3 emissions from agriculture as a result of GHG mitigation measures.
- PERT2040 – scenario that meets the Environment Act's 2040 PERT target of 35 % reduction in population exposure relative to 2018 levels. This scenario meets the target by assuming the NZ pathway in the TNZ2040 scenario and adding ambitious technological measures and significant levels of behaviour change, leading to emission reductions across all sectors including power generation, industrial processes, agriculture, road transport and domestic and commercial combustion. A reduction of roughly a quarter is assumed for imported emissions from shipping and other countries.
- PERTUrban2040 – scenario that meets the Environment Act's 2040 PERT target of 35 % reduction in population exposure relative to 2018 levels. This scenario meets the target beginning with the TNZ2040 scenario and then targeting emission reductions in urban sources. A ban on domestic wood burning achieves a 78 % reduction in emissions (assuming that 100 % compliance is not achieved). Road transport emissions are reduced by a further 25 % beyond the NZ2040 scenario emissions assuming a reduction in vehicle-kilometres driven, and NRMM emissions are reduced by 57 % using technological measures. A reduction of roughly a quarter is assumed for imported emissions from shipping and other countries.

2.2. The index of multiple deprivation

The index of multiple deprivation is derived for England from statistical data as a weighted average of seven different domains, as summarised below (English Indices of deprivation (English Indices of deprivation 2019)):

- Income Deprivation (22.5 %)
- Employment Deprivation (22.5 %)
- Education, Skills and Training Deprivation (13.5 %)
- Health Deprivation and Disability (13.5 %)
- Crime (9.3 %)
- Barriers to Housing and Services (9.3 %)
- Living Environment Deprivation (9.3 %)

The Living Environment Deprivation domain contains an indicator for air quality; there is therefore a degree of statistical bias when looking at the relation between the IMD and exposure. However, this bias was investigated by Pye et al. (2006) and was found to be of little significance, largely due to the very small proportion allocated to the air quality indicator in the overall calculation of the IMD. Similarly, Milojevic et al. (2017) excluded both the Health and Disability and the Living Environment domains and found a high correlation with the original index, suggesting that the adjustment had little impact on the results. The weight given to the Living Environment domain has not changed since Pye et al.'s analysis, we therefore use the IMD without adjusting for this bias.

Fig. 1 shows the Index of Multiple Deprivation produced in 2019 at Lower-layer Super Output Area (LSOA) level across England. The areas have been ranked and divided into 10 equal groups (deciles) by population. Areas shaded dark blue are the most deprived 10 % of LSOAs in England, while areas shaded bright yellow are the least deprived 10 %. As was the case in earlier versions of the index, there is a greater proportion of deprivation in large cities and towns, including areas that have historically had large heavy industry, manufacturing and/or mining sectors, coastal towns, and parts of London (see smaller inset map).

Fig. 2 shows the breakdown of the population located in urban (excluding London) and rural areas, and in London for each decile. Decile 1 (most deprived) has the greatest proportion of people in urban areas (excluding London). This proportion reduces from the first decile to the fifth and then is fairly constant across the remaining deciles. Despite decile 1 having the greatest urban proportion, it has a much smaller proportion of people in London than the other deciles, particularly when compared with other deprived deciles. This is likely due to London-specific factors such as higher wages, more expensive property and rent values. A greater proportion of the less deprived deciles belong to rural areas.

2.3. Relationship with $PM_{2.5}$ concentrations

The relationship of deprivation with $PM_{2.5}$ concentrations can be investigated by overlaying the map of the IMD on the 1×1 km^2 grid of pollutant concentrations calculated by UKIAM, used for deriving population exposure and health impacts. Fig. 3 shows the $PM_{2.5}$ concentrations in England in 2018 as modelled by UKIAM. IMD values for each LSOA area were projected onto the UKIAM grid. Using the mapped IMD values, concentrations from UKIAM, and population densities enabled the population weighted mean concentration (PWMC) of each LSOA to be calculated before being sorted by IMD deciles. The PWMC is a measure of the mean exposure of the population in the area considered and is calculated as follows:

$$PWMC = \frac{\sum_{i,j}(P_{ij} \times C_{ij})}{\sum_{i,j} P_{ij}}$$

where the summation is over each grid cell (i,j) with population P_{ij} and concentration C_{ij} within a predefined region. This region can be the UK as a whole, or any sub-region of the UK, for example England, or the region consisting of all LSOAs of a certain deprivation score.

The distribution of exposures for each decile can then be plotted as in Fig. 4, ranging from the most deprived in decile 1 on the left, to the least deprived decile 10 on the right. Note that across England as a whole, the highest mean decile exposure (black line) does not coincide with the most deprived sector, but with deciles 2 and 3. Deciles 2, 3 and 4 show a bimodal distribution, with a second, smaller mode above 12 μg.m^{-3}.

These high concentrations are predominantly found in London, where deciles 2, 3 and 4 have a higher proportion of people than other deciles (Fig. 2). Meanwhile, decile 1 has only a very small proportion of its population in London and therefore is missing this second mode. This smaller proportion in London is one factor contributing towards the lower mean exposure for decile 1, despite a greater overall proportion in urban areas. A second factor is the interplay between the north-south divide that exists within England for the most deprived decile 1 areas

Table 1
Annual UK emissions assumed for each scenario.

Scenario	NH_3 (kt)	SO_2 (kt)	NO_x (kt)	$PM_{2.5}$ (kt)
B2018	274	157	788	87
B2040	274	73	461	64
TNZ2040	264	59	381	59
PERT2040	196	33	220	43
PERTUrban2040	261	55	329	42

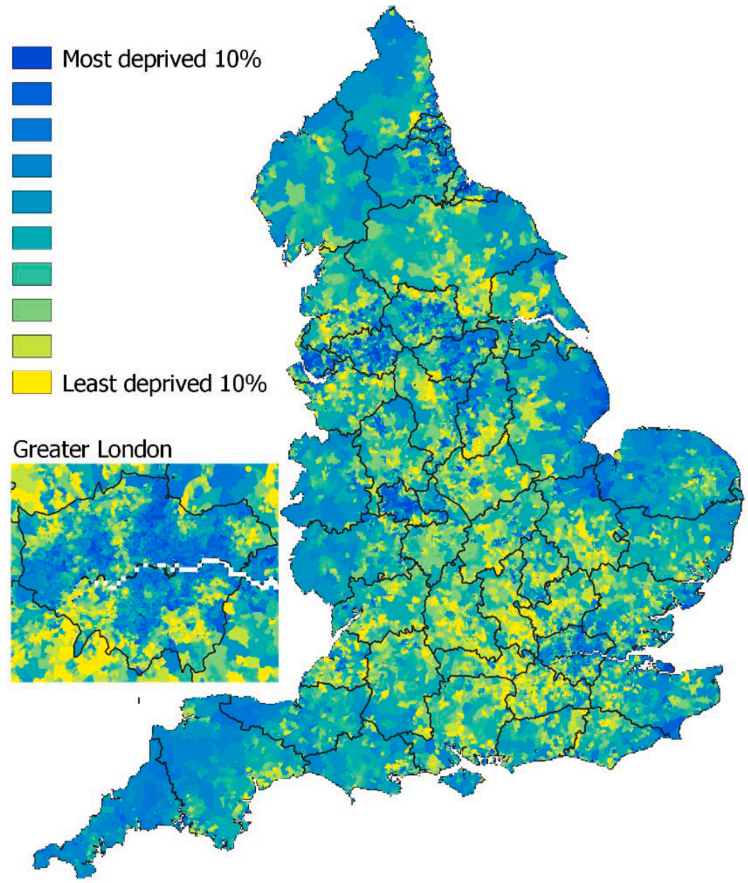

Fig. 1. Map of the Index of Multiple Deprivation 2019 at LSOA level (English Indices of deprivation (English Indices of deprivation 2019)).

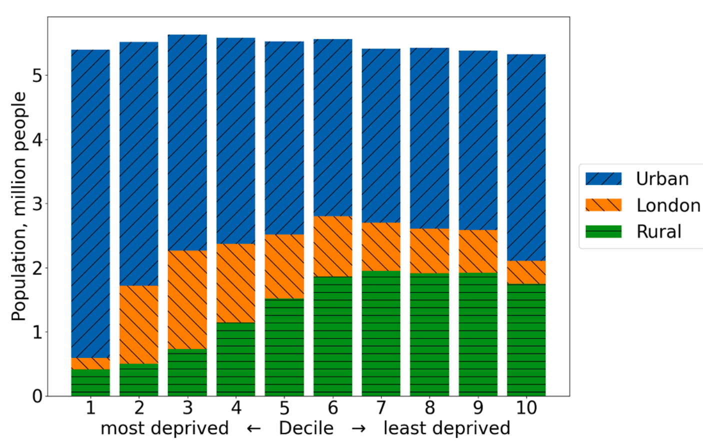

Fig. 2. Proportion of population belonging to each IMD decile located in urban areas excluding London, rural areas, and in London, from most deprived (decile 1) to least deprived (decile 10).

(see Figure S9), and the greater concentrations in the south east of England resulting from imported emissions, such as those from international shipping and mainland Europe (see Figure S7).

The northern regions of England have a significantly greater proportion of decile 1 LSOAs than southern regions. For example, in the north of England the proportion of LSOAs assigned to decile 1 is 20 %, while for the south of England the proportion is only 3 %. The north south divide is much less significant for deciles 2, 3 and 4 with the proportion of LSOAs in the north of England in these deciles is 12 %, 10 % and 9 %, respectively, compared with 8 %, 10 % and 11 % in the south. Meanwhile the contribution to $PM_{2.5}$ concentrations from imported sources (international shipping and other countries) is approximately twice as high in the south east of England as it is in the north of England. These factors combine to introduce a bias in the exposure to total $PM_{2.5}$ beyond the direct control of UK policy makers. The contribution of imported sources, in addition to individual UK sectors, is explored further in Section 3.1.1.

This raises the question as to what spatial breakdown is appropriate when considering the bias in exposure, the choice of which will impact the distribution of exposures across deciles. Here we consider rural areas, urban areas outside of London, and then London, separately. This recognises that some measures are applied specifically in urban areas

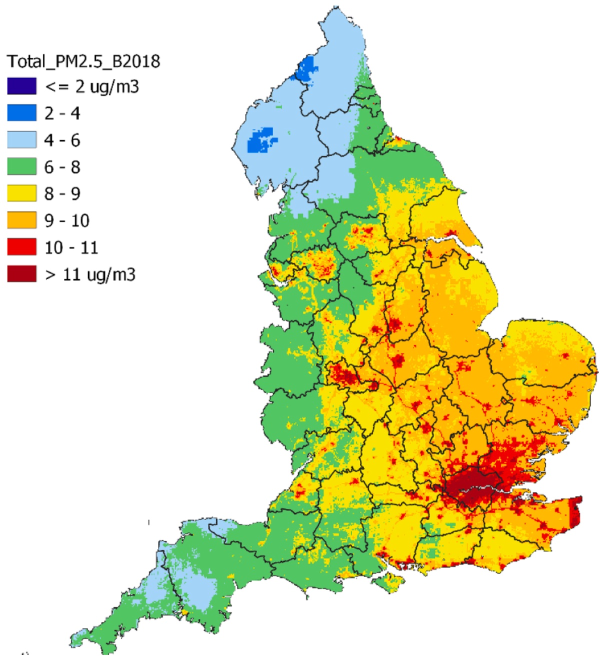

Fig. 3. Map of $PM_{2.5}$ concentrations in 2018 as predicted by UKIAM.

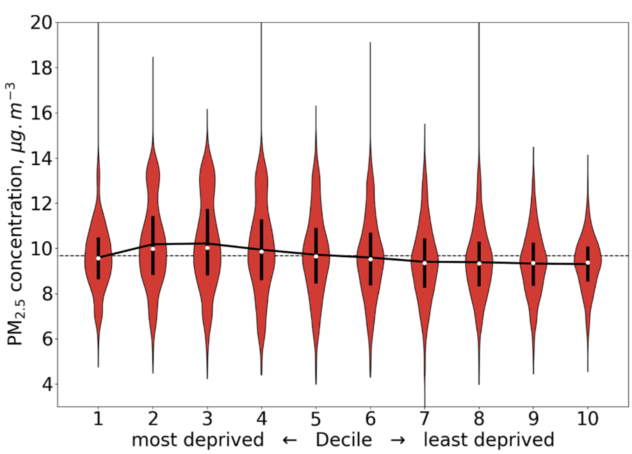

Fig. 4. Distribution of England LSOA $PM_{2.5}$ exposures for each decile, given in red. The black line across deciles shows the mean exposure for each decile, the white circle shows the median, the vertical black lines show the interquartile range. The dashed line indicates the mean exposure across all deciles from most deprived (decile 1) to least deprived (decile 10).

and the unique position of London as a pollution hotpot in England.

We also consider UK anthropogenic sources only in Section 3 in order to evaluate the bias due to these emissions from that due to imported and other sources. Concentrations of $PM_{2.5}$ in the UK are relatively low compared to many other countries, and are projected to decrease as policies are introduced to meet the targets set in the Environment Act. As concentrations decrease the natural and imported fractions will become increasingly important. These fractions can vary significantly from year to year, for example due to variations in meteorology. By separating the contribution of these fractions to the bias their relative importance could be tracked from year to year.

While considering the distribution of LSOA exposures for each decile can be informative, for the purpose of comparing multiple scenarios we consider the mean exposure only. The left-hand plot in Fig. 5 shows the mean exposure across deciles for each scenario. A large decrease in overall exposure is seen for the baseline across all deciles by 2040. There is then an additional reduction for the TNZ scenario and a further, larger reduction for the two PERT scenarios. The shape of the mean line is similar for each scenario, suggesting that the relative spatial distribution of concentrations is similar for each. This is the case in Figures S1 which shows the TNZ2040 and PERT scenarios maps of concentrations. London remains a hotspot in each case.

While the mean PWMC plot is helpful in showing the degree of improvement for each decile, it is difficult to see the change in bias between deciles. The middle plot in Fig. 5 shows the mean exposure for each decile, d, ($PWMC_d$) subtracted by the England-wide mean population exposure ($PWMC_{pop}$)

$$\Delta\ PWMC_d = PWMC_d - PWMC_{pop}.$$

In this case, the greater the deviation from zero for $\Delta\ PWMC_d$, the greater the deviation from the mean PWMC for that decile. It is now clear to see that the absolute bias in exposure has decreased by 2040, but with only a small improvement for the TNZ scenario beyond that achieved by the baseline. The PERT2040 scenario achieves only a small additional improvement beyond the TNZ scenario, however the PERTUrban2040 scenario achieves a significant improvement.

It is also informative to consider the relative bias in exposure. The right-hand plot in Fig. 5 shows the exposure delta normalised by the mean population exposure:

$$\overline{\Delta\ PWMC_d} = \Delta\ PWMC_d / PWMC_{pop}.$$

We now see that while the absolute bias in exposure has decreased by 2040 for the Baseline, TNZ and PERT scenarios (central plot), the bias relative to the mean population exposure has not changed significantly (right hand plot). The PERTUrban2040 scenario however does achieve a visible reduction in the relative bias, driven by the removal of domestic wood burning and significantly lower traffic emissions, both of which are large urban sources of primary $PM_{2.5}$ and contribute significantly to both the overall exposure and the bias in exposure, as shown in Section 3.1.1.

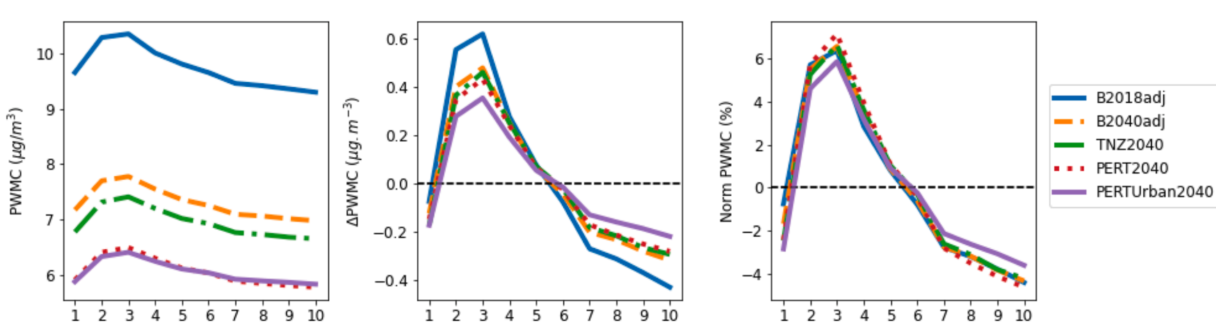

Fig. 5. Mean PWMC distributions across IMD deciles for each scenario from most deprived (decile 1) to least deprived (decile 10).

2.4. Index of exposure bias

2.4.1. Calculation of index

Fig. 5 provides a helpful qualitative view of the bias in exposures for each scenario, and how this bias changes with varying levels of ambition. However, in order to measure progress towards the reduction of this bias in exposure, a quantitative evaluation of the bias is required.

We derive a new indicator, called the Indicator of Exposure Bias (IoEB), by taking the co-variance of $\Delta\ PWMC_d$ and the deprivation decile, d, such that

$$\begin{aligned} IoEI &= cov(\Delta\ PWMC_d, d) \\ &= \frac{1}{10}\sum_{i=1}^{10}(\Delta\ PWMC_d - E[\Delta\ PWMC_d])\ (d - E[d]) \\ &= \frac{1}{10}\sum_{i=1}^{10}(\Delta\ PWMC_d)\ (d - E[d]), \end{aligned} \quad (1)$$

where $E[]$ denotes the expected, or mean, value, which for $\Delta\ PWMC_d$ is equal to zero.

2.4.2. Comparison with other indices

Previous studies (e.g. Pye et al. (2006) and Walker et al. (2003), Walker et al. (2003)) have used an indicator based on the Gini index, as a recognised statistical technique (e.g. Giorgi and Gigliarano (2017)), to quantify any bias in the number of people in exceedance of a chosen limit value across deciles. This variation of the Gini index can vary from −1 to +1, with negative values indicating a greater proportion of the population in exceedance belonging to less deprived areas, and positive values indicating a greater proportion belonging to more deprived areas. A limitation of the this approach is that it can only be used to quantify bias in the exceedances of a limit value; rather than to quantify the bias in total exposures. We have also found that population in exceedance can be subject to large step changes in response to very small reductions in concentrations, making it an unreliable indicator for progress. ApSimon et al. (2021), Pisoni et al. (2022) use the Gini index (varying between 0 and 1) to quantify the inequality in exposure across a population, but don't relate this to inequality in any socio-economic indicator.

Other studies have used Pearson's coefficient of correlation (e.g. Briggs et al. (2008)) to quantify the relationship between exposure and deprivation decile. This again varies between −1 and +1 and can therefore only evaluate the relative change from one scenario to another.

A common approach is to report the difference, or ratio, between the most and least deprived deciles or quintiles (Tonne et al., 2018; Brook et al., 2023; Brunt et al., 2017), or the 5th and 9th decile (Chalabi et al., 2017). While this approach provides a method to compare both relative and absolute values of the bias between different scenarios, it can also lead to a misrepresentation of the inequality. For example, comparing 1st and 10th decile PWMC values shown in Fig. 5 would undervalue the bias in exposure towards more deprived areas due to the non-linear shape of the curve.

The IoEB is analogous to the variation of the Gini index used by Pye et al. (2006) and Walker et al. (2003), Walker et al. (2003) in that negative values indicate a bias towards less deprived areas and positive values indicate a bias towards more deprived areas. It can also be derived in a similar way to their index by calculating the area under the curve of cumulative concentrations. However, rather than quantify the bias in the population exceeding a limit value, the indicator quantifies the bias in total population exposure in relation to the mean. Another key difference is that the indicator is not limited to vary between −1 and +1 and is not dimensionless, rather it can be expressed with a unit of μg.m^{-3} indicating the magnitude towards the more or less deprived areas. This makes the IoEB more intuitive in its meaning and also allows the magnitude of the contribution of different sources to the total bias in exposure to be compared with ease. It can also be expressed as a percentage relative to the mean population exposure by substituting $\overline{\Delta\ PWMC}$ into Eq. (1).

3. Results

3.1. Index of multiple deprivation and $PM_{2.5}$ exposure

3.1.1. SNAP sector analysis

Using UKIAM's source-apportionment capability we can look at the contribution of different sectors to the bias in exposure. We consider SNAP (Selected Nomenclature for Air Pollution) sectors as defined by the European Environment Agency's CORINAIR (Core Inventory of Air Emissions). These define emissions in eleven categories, covering power generation, domestic and industrial combustion, industrial processes, solvents, transport and agricultural emissions. We separate out the contribution to total concentrations from UK anthropogenic sources (the sum of all SNAP sectors within the UK), imported sources (from other countries and international shipping) and other sources (natural sources such as soil dust, secondary organic aerosols, a non-linear correction for the SIA (see Oxley et al. 2023) and sources not included in the NAEI such as cooking). Fig. 6 shows the curve for the $\Delta\ PWMC$ across all deciles for each SNAP sector, the total UK anthropogenic sources, imported and other sources. Table 2 gives the Absolute IoEB values associated with each line shown in Fig. 6.

By separating out the sources we can see that the lower concentration values for decile 1 seen in Fig. 5 for the total $PM_{2.5}$ is mainly due to road transport (SNAP7), imported and other sources. For road transport the mean concentration across all decile 1 areas is lower due to the small proportion of decile 1 areas in London where road transport emissions are greatest. We see the same effect for "other" sources which also contributes high concentrations in London due to the presence of urban sources not included in the NAEI such as domestic and commercial cooking. In the case of the imported contribution, the lower concentrations for the more deprived deciles is due to these concentrations being lower in the north (see Figure S7), where there is a large proportion of decile 1 areas, and higher in the south of England, where there is only a small proportion of decile 1 areas (see Figure S9). Because the imported fraction has a bias towards less deprived areas, any decrease in this fraction leads to an increase in the bias towards more deprived areas for the total $PM_{2.5}$.

In England, the greatest contributor to the bias in $PM_{2.5}$ exposure is non-industrial combustion (SNAP2) with an Absolute IoEB value of 0.34 μg.m^{-3}. The outlier amongst the SNAP sectors is agriculture (SNAP10) as the only SNAP sector which has a bias towards less deprived areas. This is primarily due to the greater proportion of less deprived communities in rural areas (Fig. 2).

The vast majority of PM emissions from non-industrial combustion is due to domestic wood burning, which is generally associated with wealthier households. Kantar (2020) This raises the question of why the exposure due to this sector is biased towards more deprived areas rather than less deprived areas. For England as a whole this can again be explained by Fig. 2 – there is a greater proportion of deprived LSOAs in urban areas where concentrations due to wood burning are highest. Therefore, while wealthier households may be the predominant users of wood burning stoves, it is the least wealthy households who are most affected due to their greater density in urban areas.

However, we also see a bias for non-industrial combustion when considering urban areas only, and for London only, which cannot be explained by this imbalance in more and less deprived LSOAs between urban and rural areas. To explain the bias within urban areas we must consider the method used to derive the spatial emissions map for domestic wood burning. These non-industrial combustion emission maps are generated using the population density as a proxy for activity, i.e. a

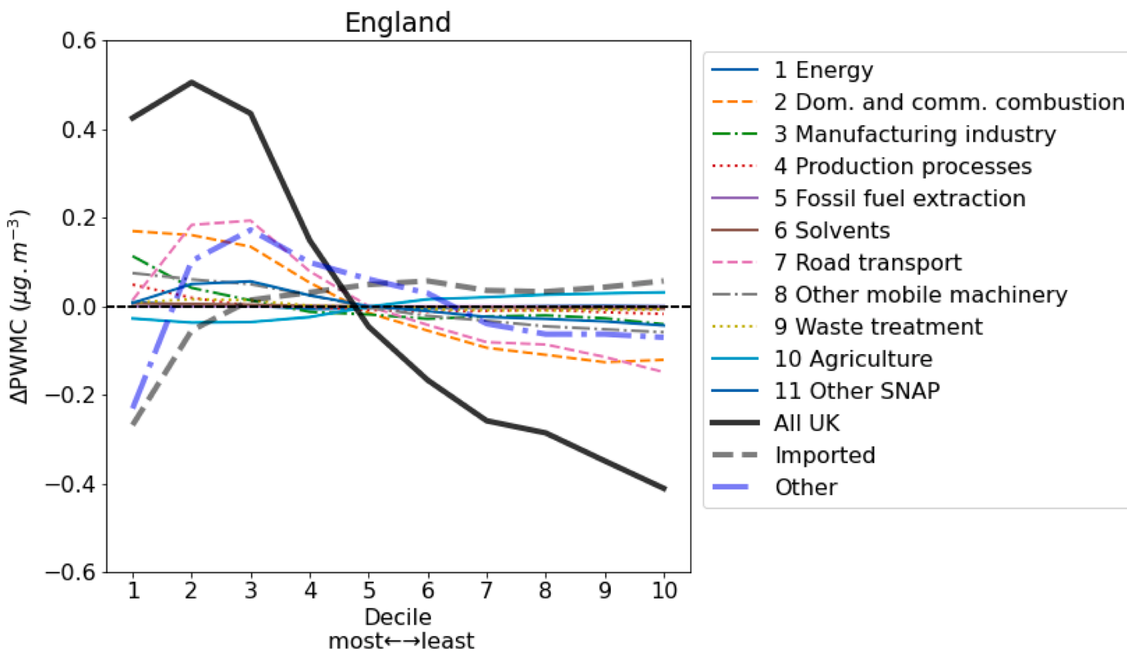

Fig. 6. Absolute IoEB (IoEB(Δ *PWMC*)) distributions across IMD deciles by SNAP sector from most deprived (decile 1) to least deprived (decile 10). "All UK" denotes all UK anthropogenic sources.

Table 2
Absolute IoEB (IoEB(Δ *PWMC*)) values for B2018 by SNAP sector. All UK indicates the total for all UK sources.

Unit = $\mu g.m^{-3}$	B2018			
	England	Urban excl Lon	Rural	London
1. Energy	0.00	0.00	0.01	0.01
2. Non-industrial comb.	0.34	0.24	0.05	0.25
3. Manufacturing	0.11	0.12	0.11	0.05
4. Production processes,	0.05	0.05	0.05	0.01
5. Fossil fuel extraction and distribution	0.00	0.00	0.00	0.00
6. Solvents	0.01	0.01	0.01	0.01
7. Road transport	0.29	0.14	0.03	0.49
8. Other mobile machinery	0.13	0.11	0.07	0.13
9. Waste	0.03	0.01	0.01	−0.01
10. Agriculture	−0.07	−0.04	−0.07	−0.01
11. Other SNAP	0.09	0.04	0.01	0.16
All UK Anthropogenic Sources	0.92	0.62	0.19	1.12
Imported	−0.19	−0.24	−0.21	0.05
Other	0.07	−0.08	−0.20	0.51

proxy for the amount of wood burning occurring within a grid square, and do not consider social or economic factors which may affect this spatial distribution. More deprived areas tend to have higher populations, for example dwellings are more likely to be small flats in multistorey buildings in these areas than in less deprived areas such as suburban neighbourhoods. Therefore, using the population density as a proxy for the amount of wood burning activity introduces a model bias resulting in greater exposures for more deprived areas. The bias evaluated for this sector, non-industrial combustion, is therefore likely to be an overestimate.

Note that the map of $PM_{2.5}$ concentrations used for this study, at 1 km x 1 km resolution, is not able to resolve hyper-local hotspots that may occur near buildings which are burning solid fuel, such as those observed by Casey et al. (2021) Were these hotspots to be resolved then the bias of the non-industrial combustion sector towards more deprived areas may be smaller.

3.1.2. *Scenario analysis*

Table 3 shows the PWMC and IoEB calculated for each scenario for England, urban areas excluding London, rural areas and London. The reduction in the PWMC relative to 2018 is also provided. The baseline achieves significant progress towards the 35 % target, achieving 25 %. The TNZ2040 scenario achieves only an additional 2 % beyond the baseline. The two PERT scenarios exceed the reduction required for the target, both achieving a 37 % reduction relative to 2018.

Looking at the Absolute IoEB values for England, the rate of improvement between scenarios seen in Fig. 5 is reflected in the reduction in these numbers with increasing scenario ambition. Further, for the Relative IoEB, a much smaller reduction reflects the right-hand plot in Fig. 5.

The TNZ scenario is predicted to reduce the absolute bias in exposure towards more deprived areas in England by 43 % (0.88 $\mu g.m^{-3}$ to 0.51 $\mu g.m^{-3}$), despite only achieving a 27 % reduction for the mean population exposure. Only a very small additional reduction in the Absolute IoEB beyond that achieved by the TNZ2040 scenario is seen for the PERT2040 scenario, despite the population exposure being lower by nearly 1 $\mu g.m^{-3}$. The PERT scenarios assume a reduction in the imported contribution from other countries and international shipping, which as discussed in section 3.1.1 and shown in Fig. 6, is biased towards less deprived areas in 2018, i.e. the imported fraction has higher mean concentrations for less deprived areas than more deprived areas. By reducing the imported contribution for the PERT scenarios, this bias towards *less* deprived areas is reduced and therefore counteracts, at least partially, the reduction in bias towards *more* deprived areas resulting from reduced UK emissions. When considering the bias due to UK sources only, the far right column in Table 3, a greater reduction in the bias is seen for the PERT2040 scenario (0.49 $\mu g.m^{-3}$) relative to TNZ2040 (0.60 $\mu g.m^{-3}$).

The PERTUrban2040 scenario achieves the greatest reduction of IoEB bias for both the total $PM_{2.5}$ (0.36 $\mu g.m^{-3}$), a 59 % reduction relative to 2018, and for UK sources only (0.40 $\mu g.m^{-3}$), a 60 % reduction relative to 2018.

The relative IoEB also decreases, indicating that the reduction in the bias is not only due to a reduction in the total population average exposure – the change in spatial distribution of total emissions is also contributing to the decrease in bias.

Table 3
Population-weighted mean concentration (PWMC), absolute Index of Exposure Bias (IoEB(Δ *PWMC*)), absolute standard deviation (STD(Δ *PWMC*)) and relative Index of Exposure Bias IoEB($\overline{\Delta\ PWMC}$) values for each scenario. Statistics calculated using the Index of Multiple Deprivation.

	Total PM2.5 (including natural and imported)					All UK anthropogenic
England	**PWMC (μg.m^{-3})**	**Reduction rel. 2018**	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	9.68		0.88	0.38	9.08	0.92
B2040	7.26	25 %	0.64	0.29	8.78	0.65
TNZ2040	7.05	27 %	0.51	0.26	7.30	0.60
PERT2040	6.06	37 %	0.50	0.25	8.21	0.49
PERTUrban2040	6.06	37 %	0.36	0.20	6.02	0.40
Urban excl London	**PWMC (μg.m^{-3})**	**Reduction rel. 2018**	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	9.51		0.38	0.14	3.98	0.62
B2040	7.11	25 %	0.24	0.10	3.35	0.45
TNZ2040	6.90	27 %	0.16	0.09	2.36	0.42
PERT2040	5.90	38 %	0.16	0.08	2.73	0.33
PERTUrban2040	5.89	38 %	0.09	0.06	1.56	0.29
Rural	**PWMC (μg.m^{-3})**	**Reduction rel. 2018**	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	8.48		−0.15	0.17	−1.74	0.19
B2040	6.34	25 %	−0.18	0.11	−2.78	0.14
TNZ2040	6.16	27 %	−0.22	0.11	−3.49	0.13
PERT2040	5.21	39 %	−0.20	0.10	−3.88	0.09
PERTUrban2040	5.39	36 %	−0.20	0.09	−3.70	0.10
London	**PWMC (μg.m^{-3})**	**Reduction rel. 2018**	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	12.31		1.67	0.59	13.55	1.12
B2040	9.35	24 %	1.30	0.46	13.89	0.77
TNZ2040	8.98	27 %	1.19	0.42	13.27	0.67
PERT2040	7.92	36 %	1.13	0.40	14.22	0.59
PERTUrban2040	7.64	38 %	0.98	0.35	12.83	0.48

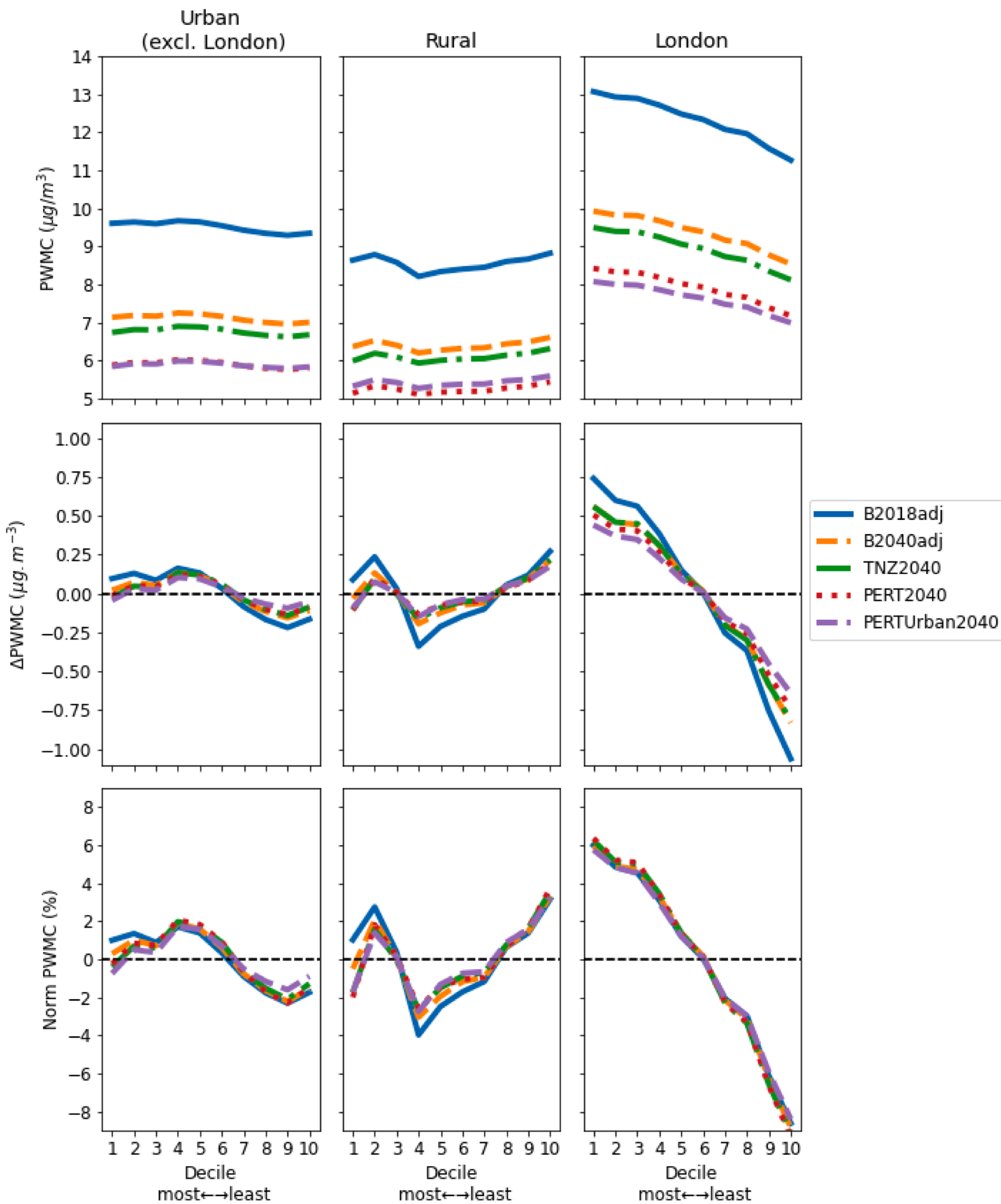

Fig. 7. Mean PWMC distributions across IMD deciles for each scenario from most deprived (decile 1) to least deprived (decile 10).

For the urban excluding London case, both the relative and absolute IoEB values are significantly smaller than those for all of England. However, there is a similar trend in terms of the reduction relative to 2018. Fig. 7 shows the PWMC, Δ *PWMC* and $\overline{\Delta\ PWMC}$ curves for each scenario for urban excluding London (left-hand panels), and also for rural and London-only.

For rural areas both the absolute and relative IoEB are negative across all scenarios. This means that for rural areas there is a bias in higher exposures towards less deprived areas. As seen in Fig. 7 (central panels), the shape of the curve is particularly complex in this case, with a V, or even N, shape, with the lowest exposure for decile 4 and an above average exposure for deciles 1 and 2. Road transport and non-industrial combustion are responsible for this V-shape of the curve for rural areas (see Figure S3). These are urban sources which suggests that both the most deprived and least deprived rural areas tend to be located in small towns or villages, too small to meet our criteria for "urban" but still with higher concentrations than the surrounding countryside.

Not only are the IoEB values negative for rural areas, but their magnitudes increase relative to 2018 for the B2040 and TNZ2040 scenarios. This means that the measures included in these scenarios which reduce exposure to harmful air pollution actually *increase* the bias in exposure towards less deprived rural areas as compared to more deprived rural areas. However, this information must be taken within the context of significant decreases in mean exposures for *all* rural

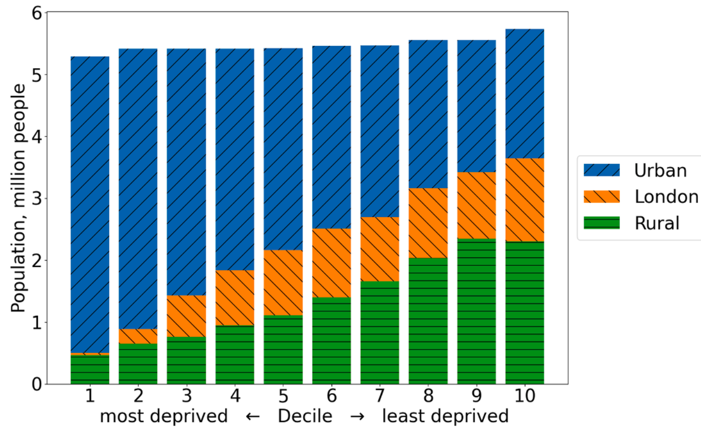

Fig. 8. Proportion of population belonging to each health domain decile located in urban or rural areas (excluding London), or in London.

deciles, including the least deprived (top central panel in Fig. 6). It is also worth considering the standard deviation of the Δ *PWMC* across deciles as a measure of the variation regardless of bias towards either more or less deprived groups, the values of which are included in Table 3. The standard deviation across rural deciles decreases from B2018 to B2040 and TNZ2040. Similar values are seen for the two PERT scenarios.

Finally, for London, the absolute IoEB values are significantly greater than those for urban and rural areas outside of London, and for England as a whole. This is in part due to the higher concentrations seen in London (see Fig. 3). However, the relative IoEB values are greater in London, indicating that the bias relative to the mean exposure is also greater. A significant reduction in the bias towards more deprived areas is seen for the baseline by 2040, with a small additional improvement for the TNZ2040 and PERT2040 scenarios. The PERTUrban2040 scenario achieves a further significant improvement with a 59 % decrease relative to 2018 (1.67 μg.m^{-3} to 0.98 μg.m^{-3}), compared with 32 % for PERT2040 (1.67 μg.m^{-3} to 1.13 μg.m^{-3}). Next to no improvement is seen in relative IoEB which remains more or less constant across all scenarios for London, and actually increases slightly for PERT2040.

3.2. Health deprivation and $PM_{2.5}$ exposure

The spatial distribution of deciles differs depending on the overall IMD or its components. A map of the health domain deciles is shown in Figure S2. There is a clearer divide between urban and rural areas than that seen for the IMD (Fig. 1). This is reflected in Fig. 8 showing the proportion of each decile belonging to urban areas outside of London, rural areas or London. The vast majority of areas considered deprived regarding to health and disability are in urban areas outside of London, with very few in London itself. Meanwhile there is a steady increase in the proportion belonging to rural areas and to London as deprivation decreases. There is a stronger north-south divide for the health index (see Figure S8 and S10), with the urban areas of the north west, north east and Yorkshire particularly standing out as containing many deprived areas.

Table 4
Population-weighted mean concentration (PWMC), absolute Index of Exposure Bias (IoEB(Δ *PWMC*)), absolute standard deviation (STD(Δ *PWMC*)) and relative Index of Exposure Bias IoEB($\overline{\Delta\ PWMC}$) values for each scenario. Statistics calculated using the Health deprivation and disability sub-domain.

	Total PM2.5 (including natural and imported)			All UK anthropogenic
England	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	−0.33	0.22	−3.35	0.56
B2040	−0.36	0.20	−4.89	0.35
TNZ2040	−0.43	0.22	−6.18	0.34
PERT2040	−0.36	0.19	−5.91	0.25
PERTUrban2040	−0.39	0.19	−6.51	0.24
Urban excl London	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	−0.33	0.14	−3.45	0.59
B2040	−0.35	0.14	−4.83	0.39
TNZ2040	−0.43	0.17	−6.28	0.35
PERT2040	−0.36	0.14	−6.02	0.26
PERTUrban2040	−0.38	0.14	−6.37	0.27
Rural	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	−0.36	0.17	−4.23	0.47
B2040	−0.41	0.16	−6.50	0.29
TNZ2040	−0.50	0.19	−8.36	0.25
PERT2040	−0.43	0.16	−8.27	0.17
PERTUrban2040	−0.41	0.15	−7.69	0.20
London	**IoEB(Δ *PWMC*) (μg.m^{-3})**	**STD(Δ *PWMC*) (μg.m^{-3})**	**IoEB($\overline{\Delta\ PWMC}$) (%)**	**IoEB(Δ *PWMC*) (μg.m^{-3})**
B2018	1.20	0.43	9.49	0.73
B2040	0.91	0.33	9.49	0.51
TNZ2040	0.92	0.34	10.06	0.44
PERT2040	0.85	0.31	10.45	0.42
PERTUrban2040	0.73	0.27	9.32	0.35

Table 5
Absolute IoEB (IoEB(Δ *PWMC*)) values for B2018 and High2040 by SNAP sector. All UK indicates the total for all UK sources.

Unit = μg.m^{-3}	B2018			
	England	Urban excl Lon	Rural	London
1. Energy	0.01	0.01	0.02	0.00
2. Non-industrial comb.	0.23	0.16	0.09	0.16
3. Manufacturing	0.17	0.18	0.18	0.02
4. Production processes,	0.06	0.07	0.06	0.01
5. Fossil fuel extraction and distribution	0.00	0.00	0.00	0.00
6. Solvents	0.01	0.01	0.01	0.01
7. Road transport	0.01	0.08	0.09	0.38
8. Other mobile machinery	0.09	0.10	0.10	0.04
9. Waste	0.01	0.00	0.01	−0.03
10. Agriculture	−0.05	−0.05	−0.09	−0.02
11. Other SNAP	0.02	0.03	0.02	0.16
All UK Anthropogenic Sources	0.41	0.44	0.32	0.76
Imported	−0.45	−0.47	−0.43	0.06
Other	−0.43	−0.45	−0.41	0.40

Table 4 gives the IoEB values for 2018 derived using the health domain index (see Figure S4 for the PWMC distribution curves). Perhaps surprisingly, the IoEB values for total $PM_{2.5}$ are negative for England for each scenario, indicating higher exposures for less deprived areas. This is also true when considering urban areas outside of London and rural areas. However, in London itself the values are positive, indicating a bias towards more deprived areas. The reason for the negative values for England, urban and rural areas is the north-south divide seen for health deprivation, which is more significant than that for the IMD. As discussed in section 3.1.1, the imported contribution to the total $PM_{2.5}$ concentrations has a strong gradient with higher values towards the south east and lower values to the north west (see Figure S7). As England's wealthiest regions are also in the south east, this introduces a bias that is particularly strong when considering the health domain index. A similar bias exists for the other sources which also has higher concentrations towards the south east.

The bias in total $PM_{2.5}$ towards more deprived areas increases in magnitude for the TNZ2040 scenario, despite the overall reduction in concentrations, due to the reduction in UK anthropogenic emissions which tend to have a bias towards more deprived areas. This bias towards more deprived areas then decreases in magnitude for the PERT scenarios, despite further decreases in UK emissions, due to decreases in the transboundary contribution.

When considering the bias due to UK anthropogenic sources only (far right column), a steady reduction in the Absolute IoEB is seen in England from B2018 to B2040, and then to TNZ2040 and the two PERT scenarios. The PERTUrban2040 scenario again has the lowest bias in exposures in England and in London. However, the difference in the Absolute IoEB for England between the PERT2040 and PERTUrban2040 scenarios is much smaller than that when evaluating using the IMD (Table 3). The reason for this is the greater proportion of less deprived areas in London where contributions from urban sources are high.

This bias in the imported and other sources contributions to the total $PM_{2.5}$ towards less deprived areas is reflected in the negative values for these fractions in Table 5 for England, urban excluding London and rural areas (the PWMC distributions curves for each SNAP sector can be found in Figures S5 and S6). The IoEB values for each SNAP sector for the B2018 scenario is also given. For all UK anthropogenic sources the value is positive for the health domain index for each region considered, although lower than those for the IMD in Table 2. Therefore, when considering UK anthropogenic sources only, the bias towards more deprived areas is lower for the health domain than for the IMD.

Non-industrial combustion remains a major source of exposure inequality when considering the health domain. However, this evaluation is subject to the same model limitations and inherent model bias discussed in section 3.1.1. Road transport is not one of the major contributors when evaluated using the health index, other than in London where it is the greatest. The reason for the small bias for road transport in England is the increasing proportion of people in London with increasing decile number (Fig. 8), i.e. there is a greater proportion of people deemed less deprived relating to health and disability in London, where road transport emissions are particularly high. This London trend counteracts the trend in the rest of the country where more deprived LSOAs tend to be in urban areas.

4. Discussion

4.1. Relevance to population health impacts

Description of the effects of air pollution on inequality based on population exposure only provides a partial impression of health inequalities linked to air pollution exposure. It is recognised that the prevalence and incidence of health impacts associated with air pollution are substantially greater amongst deprived populations in the UK than for those that are less deprived. With respect to mortality there is a factor between 2 and 3 difference in stillbirth rates (Kingdon et al., 2019) and a difference in life expectancy of 9.4 years for males and 7.6 years for females. (ONS 2021) There is a similar pattern for healthy life expectancy with a difference of 19.0 years for males and 19.3 years for females. (ONS 2021) Similar patterns are seen for stroke, (Weir et al., 2021) dementia, (Baker, 2016) emergency respiratory hospitalisations, (Collins et al., 2018) diabetes (Unwin) and asthma. (Lung, 2022)

Quantification of health impacts typically combines air pollution data with response functions and national data on mortality or disease incidence without accounting for this variation with deprivation. The overall estimate of health burden in the population may then be broadly correct, but will fail to recognise greater damage in more deprived communities per person per unit of exposure than for the less deprived. This has important consequences for the development of policy. First, targeting air pollution controls on areas with the highest exposures may not generate the highest health benefit per unit expenditure, leading to policy inefficiencies. Second, it underplays the importance of air pollution as a driver for poor health amongst deprived communities.

4.2. Limitations of study

It is important to recognise the limitations of the approach used here. We have based our analysis on the residential exposure of the population, i.e. by overlaying the $PM_{2.5}$ concentration map with a population density map. This is equivalent to assuming that the concentration experienced by people at their homes is representative of their actual personal exposure. Tonne et al. (2018) showed that this assumption can lead to a misclassification of exposure at a population level, with indoor air quality an area of increasing concern relating to its impact on poorer households. Ferguson et al. (2021)

Briggs et al. (2008) also highlight the limitation of deriving a relation between environmental hazards and a single characterisation of socio-economic status, and show how environmental associations between different domains of the IMD, as well as the IMD itself, vary substantially. We have limited our analysis to the overall IMD and health domain only, but our methodology could be extended to consider other domains, or other measures of deprivation. The challenge when considering this approach for policy development and target setting is to determine which measure or measures of deprivation are most suitable. Despite this, our analysis shows that reducing UK emissions of harmful air pollutants leads to a reduction in the bias towards more deprived areas both when using the IMD or the Health domain as measures of deprivation.

It should be noted that poor households are often found near major roads, where concentrations are higher due to traffic emissions. The approach used here will not pick up on these instances as the LSOAs are ordered by the *average* deprivation in each area, and the resolution of the concentration map used (1 km x 1 km) is not sufficient to resolve elevated concentrations near busy roads. This is likely to be a bigger problem for NO_2, which is highly local to roads, than for $PM_{2.5}$ which tends to vary less across urban areas. However, Goodman et al. (2011) reported only weak associations between NO_x (modelled at 20 m x 20 m resolution) and individual-level socio-economic position statistics once adjusted at LSOA level, suggesting that this level is sufficient to capture most of the variation in exposure between deprivation deciles.

A similar limitation may apply for domestic wood burning, where the current modelling is unable to resolve hyper-local hotspots near buildings which are burning biomass. There is likely model bias within the evaluation of the bias in exposure for non-industrial combustion for which the spatial distribution of emission sources uses the population density as a proxy for activity, without considering social or economic factors, as discussed in section 3.1.1. Further, domestic wood burning is a particularly uncertain source, with NAEI estimates of $PM_{2.5}$ emissions for this source varying considerably over the last few years, and likely to change again in upcoming versions.

Further work is required to address some of the modelling limitations highlighted and to expand this approach to other harmful air pollutants or components such as NO_2, ozone and black carbon (Oxley et al., 2015) in order to fully evaluate the inequality in exposure to poor air quality within England. Consideration of variation in exposure to indoor air pollutants would also be beneficial.

5. Conclusions

The Indicator of Exposure Bias (IoEB) developed here allows a quantitative analysis of the bias in exposure to harmful air pollutants towards more or less deprived communities which can be applied to different scenarios, across different regions and broken down to consider individual sources or sectors. The analysis showed that there is a bias in the exposure of $PM_{2.5}$ concentrations towards more deprived areas in England (0.88 $\mu g.m^{-3}$) when evaluated using the IMD as a measure of deprivation (i.e. greater exposures for more deprived areas), in addition to within London (1.67 $\mu g.m^{-3}$). The bias towards more deprived areas in England for total $PM_{2.5}$ is less than that when considering $PM_{2.5}$ from UK anthropogenic sources only (0.92 $\mu g.m^{-3}$). The reason for this is the north south wealth divide that exists within England, combined with greater contributions to $PM_{2.5}$ concentrations from imported sources (i.e. other countries and international shipping) in the south of England, resulting in a bias towards *less* deprived areas for this transboundary contribution. This reduces the bias towards more deprived areas for total $PM_{2.5}$, as compared to UK anthropogenic sources only, when evaluated using the IMD.

The north south divide is more significant for the health domain of the IMD. This results in an overall bias towards less deprived areas for total $PM_{2.5}$ in England (-0.33 $\mu g.m^{-3}$) (i.e. greater exposures for less deprived areas) when evaluated using the health domain as a measure of deprivation. This highlights both the sensitivity of the analysis to the choice of deprivation indicator and the important role that transboundary pollution and regional wealth gaps play in determining the overall bias in exposure. It also demonstrates that evaluating the bias in exposure across deprivation deciles using total $PM_{2.5}$, without considering source-apportionment, does not provide an accurate assessment of the impact of UK emissions on the bias in exposure.

When considering UK anthropogenic sources only, both the IMD and health domain showed a bias towards more deprived areas. Road transport and non-industrial combustion (which is mainly due to domestic wood burning) were identified as the two UK sectors contributing the most to $PM_{2.5}$ exposure bias in England when evaluated using the Index of Multiple Deprivation (IMD), both having greater contributions in more deprived areas. When using the health domain to evaluate the IoEB, non-industrial combustion and manufacturing were identified as the two sectors contributing the most to the bias towards more deprived areas in England, with road transport the greatest in London.

There is likely model bias in the evaluation of non-industrial combustion leading to an overestimation of the concentrations in deprived areas and an underestimation of concentrations in wealthy areas. However, it is clear that urban sources of primary $PM_{2.5}$ contribute disproportionately to the bias in exposure in England due to the greater proportion of poorer households in towns and cities as compared to rural areas.

A scenario including measures towards achieving Net Zero, TNZ2040, mainly consisting of the electrification of the fleet, resulted in a decrease in the absolute bias in exposures towards more deprived areas in England of 43 % relative to 2018 when evaluated using the IMD as an indicator for exposure. This was a greater reduction than the baseline 2040 scenario which achieved a 27 % reduction. Reaching the 2040 target for population exposure to $PM_{2.5}$ recently passed in England as part of the Environment Act 2021 will likely lead to further reductions in the bias in exposure towards more deprived areas when evaluated using the IMD as a measure of deprivation. Two scenarios were modelled which reach this target, the PERT2040 assumed emission reductions across all sectors in addition to measures towards reaching NZ, while the PERTUrban2040 assumed a greater focus on reducing urban sources of primary $PM_{2.5}$. Both PERT scenarios exceeded the 35 % target, achieving a 37 % reduction in population exposure. The PERT2040 scenario achieved a 43 % reduction in the absolute bias in exposure towards less deprived area in England relative to 2018, while the PERTUrban2040 achieved a 59 % reduction. Reductions in the bias were also seen in London at 32 % and 59 % relative to 2018 for PERT2040 and PERTUrban2040, respectively. Reaching England's $PM_{2.5}$ exposure target is therefore likely to deliver substantially greater health benefits for the more deprived members of society than the less deprived, reducing health inequality. These benefits can be maximised by targeting urban sources of primary $PM_{2.5}$.

The IoEB can easily be applied to different countries or regions using any model that estimates spatial estimates of population exposure and spatial metrics of socio-economic status, to identify the sectors which contribute disproportionately to the bias in exposure and to identify effective strategies for reducing this bias.

CRediT authorship contribution statement

Huw Woodward: Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Data curation, Formal analysis, Writing – review & editing. **Tim Oxley:** Conceptualization, Data curation, Methodology, Software, Writing – review & editing. **Mike Holland:** Investigation, Writing – original draft, Writing – review & editing. **Daniel Mehlig:** Conceptualization, Software, Writing – review & editing. **Helen ApSimon:** Conceptualization, Funding acquisition, Project administration, Resources, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Supplementary materials

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