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Impact of net zero policy scenarios on air pollution inequalities in England and Wales

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ABSTRACT

Background: The UK is committed to achieve net zero greenhouse gas emissions by 2050. The suite of policies needed to reach net zero will lead to improvements in air quality and, consequently, could lessen air pollution inequalities. We assessed air pollution inequalities across different sociodemographic groups in England and Wales and explored how these might be differentially impacted by future air pollution projections in 2030 and 2040 under net zero policies.

Methods: We employed a geodemographic classification approach to categorise neighbourhoods into five distinct clusters based on 2021 UK Census sociodemographic variables. We modelled fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) concentrations for the year 2019, and predicted concentrations in 2030 and 2040. We compared a business-as-usual (BAU) scenario and two policy pathways to achieve net zero currently considered by the UK government. We aggregated air pollution concentrations to the neighbourhood level and assessed differential neighbourhood-level concentrations across the geodemographic groups using descriptive statistics and box plots.

Results: The *Urban Central Professionals* group experienced 14 μg/m^3 higher average NO_2 concentrations compared with the *Rural Elderly* group in 2019. Despite substantial improvements to air quality in 2030 and 2040 of up to 6.3 μg/m^3 for NO_2 based on BAU, and further reductions of up to 2.4 μg/m^3 NO_2 under net zero policies, the overall pattern of inequality persists, but is predicted to be less pronounced.

Conclusions: Our findings demonstrate the effectiveness of targeted policies and innovations in reducing both air quality and greenhouse gas emissions and in bridging the environmental inequality gap. Our findings are essential to develop targeted communication campaigns to secure acceptance and willingness across the sociodemographic spectrum to support the significant behavioural changes needed to achieve net zero, by highlighting the wider co-benefits to the environment and health of such policies.

1. Introduction

Outdoor air pollution is the leading environmental health risk and has a burden on mortality equivalent to 4.2 million deaths globally in 2019 (World Health Organization, 2022). In the UK, the burden on mortality due to anthropogenic particulate matter is equivalent to 29,000 premature deaths per year (Committee on the Medical Effects of Air Pollutnats, 2018), with associated economic costs of up to £18.6 billion by 2035 (Pimpin et al., 2018). Air pollutants such as nitrogen dioxide (NO_2) and particulate matter (for example, particles with diameters 2.5 μm or less [$PM_{2.5}$]) have been associated with adverse health effects across the life course, including birth outcomes,

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cardiovascular and respiratory disease and brain health (Cohen et al., 2017; de Bont et al., 2022; Huangfu & Atkinson, 2020; Song et al., 2023).

The impact of climate change on air quality in the coming decades is anticipated to be significant. Changing weather patterns will influence formation, dispersion, and deposition of pollutants (Graham et al., 2020). The release of anthropogenic greenhouse gas emissions, a major driver of climate change, often coincides with the release of other air pollutants, for example, from road traffic or heating systems in buildings. Mitigation measures to reduce greenhouse gas emissions to net zero in the coming decades to prevent the most severe consequences of climate change (Intergovernmental Panel on Climate Change, 2022), will, therefore, have important co-benefits relating to air quality improvements (The Royal Society, 2021). This presents a unique opportunity to formulate integrated policy approaches addressing both poor air quality and climate change, as part of a comprehensive suite of climate and public health strategies. The UK has committed to achieving net zero emissions by 2050 (Department for Business Energy & Industrial Strategy, 2019a), which demands ambitious policies to significantly reduce carbon dioxide equivalent emissions. This requires both technological and societal shifts, transitioning from reliance on fossil fuels to embracing low carbon energy sources, thereby altering energy consumption patterns (Climate Change Committee, 2020). Such fundamental changes will have differential impacts and benefits across different parts of society.

Environmental inequality, the uneven distribution of pollution burden across society, is a significant public health and social justice concern. Lower-income and certain demographic groups, particularly in urban areas, often face higher air pollution levels (Fairburn et al., 2019; Fecht et al., 2015; Goforth & Nock, 2022; Hajat et al., 2015; Jbaily et al., 2022; Samoli et al., 2019). This can lead to increased health risks and economic challenges, as marginalised communities, especially those from deprived or ethnic backgrounds, might be more susceptible to the adverse health effects from air pollution and climate change (Brunt et al., 2017; Richardson et al., 2013; Stieb et al., 2023). Previous studies have highlighted air pollution inequalities for various demographic and socioeconomic factors, for example, age, gender, ethnicity, and educational attainment (Fecht et al., 2015; Tonne et al., 2018). Most existing research, however, fails to treat socioeconomic, demographic, and living environment factors as interconnected elements. Yet these factors are deeply interwoven, influencing, and being influenced by each other in complex ways that single-variable analyses cannot fully capture. There is, therefore, a need for studies that more comprehensively represent the intricate urban contexts shaping the unequal distribution of neighbourhood-level air pollution.

Our study assesses air pollution inequalities among sociodemographic groups in England and Wales and explores how these might be differentially impacted by future air pollution projections under different net zero policies. By focusing on detailed profiling of population groups our approach can inform targeted policy interventions more effectively to reduce air pollution and inequalities in the future.

2. Methods

We estimated neighbourhood level air pollution concentrations in 2019 using a hybrid model and predicted concentrations for 2030 and 2040 under different net zero policy scenarios. We combined these estimates and predictions with geodemographic profiles of the neighbourhoods to assess the differential air pollution levels across the geodemographic spectrum.

2.1. Study area

We conducted our analysis at the neighbourhood level which we defined using Middle Layer Super Output Areas (MSOA) ($n = 7{,}264$) in England and Wales. MSOAs are small areas of the Census 2021 output geography and contain between 2,000 and 6,000 households (5,000 and 15,000 usual residents) with an average population of 8,204 according to the 2021 Census. MSOAs are designed to contain relatively consistent population counts which means they tend to cover smaller geographic areas in urban areas and larger geographic areas in rural areas due to low population density. Their small area size with relatively homogeneous population characteristics provides sufficient geographic granularity to assess air pollutants of high spatial variability in relation to detailed socioeconomic and demographic information.

2.2. Geodemographic classification of neighbourhoods

We used geodemographics as a multidimensional approach that systematically captures the intricate socio and demographic contexts of neighbourhoods. Defined as ’an analysis of people by where they live’ (Sleight, 1997, p.16), geodemographic analysis serves as a refined analytical framework for categorising small geographic areas. It effectively integrates a wide array of socioeconomic, demographic, and environmental attributes into a cohesive geodemographic multidimensional classification by utilising clustering techniques (Harris et al., 2005; Webber & Burrows, 2018). This classification approach and its extensive benefits are well-established (Harris et al., 2005; Leventhal, 2016; Liu et al., 2019; Singleton et al., 2017), with its applications acknowledged globally across both private and public sectors (Gale et al., 2016; Liu et al., 2020, 2021; Singleton & Longley, 2015; Singleton & Spielman, 2014).

Drawing from the variable selection methodologies used in well-established classifications, such as the 2011 London Output Area Classification (LOAC) and the 2011 Output Area Classification (OAC) (Gale et al., 2016; Singleton & Longley, 2015), a set of 54 variables was chosen from the 2021 UK Census at MOSA level (Table 1, the variable correlation structure is shown in Supplementary Material Appendix 1). These variables span 16 domains, encapsulating key concepts of demography, housing, and socioeconomic conditions.

To enhance data normality, we applied an inverse hyperbolic sine transformation and used range standardisation on all variables. The inverse hyperbolic sine transformation is particularly useful for handling data that includes both very small and very large values, effectively stabilising and normalising the distribution without the need to remove or cap outliers (Gale et al., 2016; Pence, 2006). This method, which also aligns with practices observed in prior classifications such as the 2011 LOAC and OCA, helps maintain the integrity of original data ranges while maximising skewness. Range standardisation further complements this by scaling the data to a consistent range, typically 0 to 1, ensuring that each variable contributes equally to the analysis and is not dominated by those with larger ranges. Although normalising data is not a strict prerequisite for constructing the geodemographic classification (Harris et al., 2005), it enhances the quality of the clustering outcomes by ensuring that the clusters are more statistically robust and representative of the underlying population structures (Liu et al., 2019). Together, these techniques ensure uniform measurability across all variables, facilitating more reliable comparisons and enhancing the overall quality of the clustering process.

The hierarchical *k*-means (h-*k*-means) algorithm was then used to categorise the 7,264 MSOAs across England and Wales. This method effectively combines hierarchical clustering to identify preliminary groupings, with *k*-means clustering refining these groups using optimised centroidal means. Such a dual approach counters the limitations of random seed placement found in standard *k*-means clustering (Arai & Ridho Barakbah, 2007), and has proven effective in urban studies for discerning neighbourhood differences based on attributes such as socioeconomic factors and land use (Liu et al., 2020, 2021). We adapted the h-*k*-means to the pre-processed census data to develop a geodemographic classification that reflects the multifaceted characteristics of neighbourhoods in England and Wales.

To determine the optimal quantity of clusters, denoted as *k*, we

Table 1
2021 UK Census variables used in the construction of geodemographic classification of MSAOs in England and Wales.

Concept	Domain	Variable Description
Demographic	Age	0–4 years old
		5–14 years old
		15–24 years old
		25–44 years old
		45–64 years old
		65–84 years old
		85 years old and over
	Population density	Number of usual residents per km^2
	Ethnic background	White
		Mixed/Multiple
		Asian: Indian, Pakistani, Bangladeshi
		Asian: Chinese
		Black
		Arab or other groups
	Proficiency in English	Cannot speak English well or not at all
	Marital status	Single
		Married or civil partnership
		Separated or divorced
	Household composition	One-person household
		Families with no children
		Families with dependent children
Housing	Tenure	Owned or shared property ownership
		Social rented housing
		Private rented housing
	Housing type	Detached housing
		Terraced housing
		Flats
		Semi-detached housing
	Overcrowding	Fewer bedrooms than required (rate −1 or less)
Socioeconomic	Education	No qualification
		Entry or standard qualification (level 1 and 2)
		University entry qualification (level 3)
		University or equivalent professional qualification (level 4 +)
	Employment status	Unemployment
		Full-time employment
		Part-time employment
		Student
	Occupation	Managers, directors and senior officials
		Professional occupations
		Associate professional and technical occupations
		Administrative and secretarial occupations
		Skilled trades occupations
		Caring, leisure and other service occupations
		Sales and customer service occupations
		Process, plant and machine operatives
		Elementary occupations
	Car ownership	Households without a car
		Households with two or more cars
	Unpaid care	Provide unpaid care
	Health condition	Bad or very bad self-rated health
	Means of travel to work	Public transport
		Private transport
		Active travel

employed the elbow method. This approach involves generating a scree plot that displays the total within-cluster sum of squares (WSS) for various values of k. The aim is to identify the 'elbow point', where the reduction rate of the WSS begins to level off. This point indicates the value of k where adding more clusters does not significantly improve the clustering solution, suggesting the most appropriate value for k. The elbow method is widely used in geodemographic studies to determine the optimal number of clusters, as it balances the trade-off between cluster compactness and the number of clusters, ensuring that the selected k is both practical and interpretable (Alexiou and Singleton, 2019; Liu et al., 2019; Singleton and Longley, 2015). However, as noted by Singleton and Longley (2009), when dealing with high-dimensional geodemographic data, the elbow point may not be distinctly prominent. Therefore, the selection of k often incorporates qualitative considerations, such as the utility of the classification for end users and its comparability with existing classifications. A detailed description of the method including the scree plot is provided in Supplementary Material Appendix 2.

To enhance the interpretability of the clustering results, we conducted an index score analysis. This analysis involved calculating index scores for each variable within each geodemographic cluster as ratios against the average values across England and Wales. The regional average for each variable was set to 100. The index score for each variable in a cluster was calculated as follows:

$$IndexScore = \left(\frac{ClusterMean}{RegionalMean}\right) \times 100$$

This approach allowed us to quantify the extent to which certain characteristics are overrepresented or underrepresented in each cluster compared to the regional average. To further facilitate interpretation, we also mapped the spatial distribution of the MSOA-level geodemographic classification across England and Wales. Together, these tools enabled us to assign descriptive names or 'pen portraits' for each cluster, providing a clear characterisation of each cluster, key for assessing 'who' or 'what type of neighbourhoods' face higher air pollution concentrations, both now, and projected for 2030 and 2040.

2.3. *Air pollution predictions*

We modelled annual average ambient air pollution concentrations for $PM_{2.5}$ and NO_2 in 2019 and predicted concentrations for 2030 and 2040 under future policy scenarios. The Business as Usual (BAU) scenario reflected existing and agreed air pollution policies such as the Industrial Emissions Directive and European vehicle exhaust emission standards as well as energy projections from the Department for Business, Energy and Industrial Strategy (Department for Business Energy Industrial Strategy, 2019b). We compared the BAU scenario to two policy pathways which aim to achieve net zero by 2050, developed by the UK's Climate Change Committee (CCC). The CCC is an independent statutory body which advises the UK government on emissions targets to reduce greenhouse gas emissions. We used two policy pathways developed by the CCC as part of the 6th Carbon Budget (Climate Change Committee, 2020) focusing on building heating and vehicles. The Balanced Net Zero Pathway (BNZP) aims to reduce greenhouse gas emissions by 78 % compared to 1990 by 2035 and focuses on energy efficiency measures, heat pumps, solar and hydrogen technologies, transition to electric vehicles and behavioural change. The Widespread Innovation (WI) pathway is similar to the BNZP in its emission reduction strategy but assumes a lower cost in low-carbon technologies resulting in a more widespread and swifter transition to electrification of the vehicle fleet via accelerated battery technology and better affordability of electric vehicles and a large uptake of e-bikes.

We predicted air pollution concentrations using a hybrid model which enabled us to combine a meteorological model with a dispersion and chemical transport model, accounting for changes in meteorology and hemispheric anthropogenic and biogenic emissions. Briefly, we used the CMAQ-Urban model (Dajnak et al., 2023), a combination of the Weather Researching and Forecasting (WRF v4.1) meteorological model (Skamarock et al., 2021), the US EPA CMAQ model (v5.4) (Byun & Ching, 1999) and the ADMS-Roads model (Cambridge Environmental Research Consultants (CERC), 2018) to predict 20 m x 20 m concentrations. To model concentrations in 2019 and BAU predictions in 2030 and 2040, we used non-road anthropogenic emissions from the National Atmospheric Emissions Inventory (v2020) and the London Atmospheric Emissions Inventory (LAEI). To predict concentrations for 2030 and 2040 under the BNZP pathway, we used building data (residential, commercial and public) from the CCC's 6th Carbon Budget. Additionally, for both BNZP and WI pathways, we processed vehicle emissions data from the 6th Carbon Budget using a road emissions model (Beevers et al., 2012). In evaluation of the 2019 model, CMAQ-Urban performed well with a *r*-value of 0.79 (root mean square error [RMSE] of 9.7 $\mu g/m^3$) for NO_2 and 0.71 (RMSE of 1.7 $\mu g/m^3$) for $PM_{2.5}$. For more information on the validation process see Supplementary Material Appendix 3.

We averaged 20 m × 20 m concentrations within each MSOA to map air pollution concentrations at MSOA level. To compare the two net zero pathways (BNZP and WI) to the BAU scenario, we subtracted MSOA-level concentrations under BAU from BNZP- and WI-derived concentrations.

2.4. *Statistical analysis*

We used descriptive statistics and box plots to assess the distribution of air pollution concentrations across the geodemographic profiles in England and Wales. We compared differential exposures in 2019 and under future scenarios in 2030 and 2040 using the BAU scenario as

Demographic

	A	B	C	D	E
Families with dependent children	81	126	110	90	77
Families with no children	109	64	100	120	93
One-person household	124	92	89	97	107
Separated or divorced	71	87	89	104	120
Married or civil partnership	62	88	111	118	91
Single	153	117	89	77	107
Cannot speak English well or not at all	175	342	64	17	67
Arab or other groups	272	264	106	21	45
Black	274	318	76	13	45
Asian: Chinese	251	219	127	28	54
Asian: Indian, Pakistani, Bangladeshi	131	362	114	16	41
Mixed/Multiple	213	161	125	49	74
White	78	61	98	121	110
Number of usual residents per km²	292	190	81	26	87
85 years old and over	50	54	107	204	96
65-84 years old	50	58	95	208	99
45-64 years old	77	86	102	111	100
25-44 years old	141	119	101	79	77
15-24 years old	171	122	90	80	79
5-14 years old	74	123	106	90	104
0-4 years old	85	130	104	80	106

Socioeconomic

	A	B	C	D	E
Active travel	210	105	92	70	101
Private transport	45	80	102	123	106
Public transport	288	208	95	30	66
Bad or very bad self-rated health	77	122	67	90	132
Provide unpaid care	71	121	95	100	108
Households with two or more cars	33	62	119	201	87
Households without a car	219	155	64	50	112
Elementary occupations	81	115	63	77	126
Process, plant and machine operatives	50	143	62	84	135
Sales and customer service occupations	84	123	78	88	121
Caring, leisure and other service occupations	73	113	77	93	124
Skilled trades occupations	49	93	78	117	115
Administrative and secretarial occupations	75	92	107	106	101
Associate professional and technical occupations	132	80	117	103	87
Professional occupations	157	82	133	99	72
Managers, directors and senior officials	114	66	129	120	73
Student	241	161	86	60	77
Part-time employment	93	116	97	97	99
Full-time employment	121	99	108	91	102
Unemployment	148	174	78	60	105
University or equivalent professional qualification (level 4)	173	89	125	101	73
University entry qualification (level 3)	103	87	94	105	103
Entry or standard qualification (level 1 and 2)	53	100	91	104	116
No qualification	61	133	71	89	126

Housing

	A	B	C	D	E
Private rented housing	198	119	85	67	94
Social rented housing	141	162	59	54	132
Owned or shared property ownership	58	71	116	123	93
Fewer bedrooms than required (Rate -1 or less)	273	247	61	31	71
Semi-detached housing	34	89	126	136	115
Flats	335	151	90	32	81
Terraced housing	111	145	81	63	200
Detached housing	18	31	118	179	63

Index Score
Regional Average = 100

- 🟥 < 50
- 🟥 50 - 79
- ⬜ 80 - 119
- 🟦 120 - 199
- 🟦 > 200

Fig. 1. Index scores for variables in each cluster (grouped by concepts), where a score of 100 represents the England and Wales average, 50 indicates half the national average and 200 twice the national average.

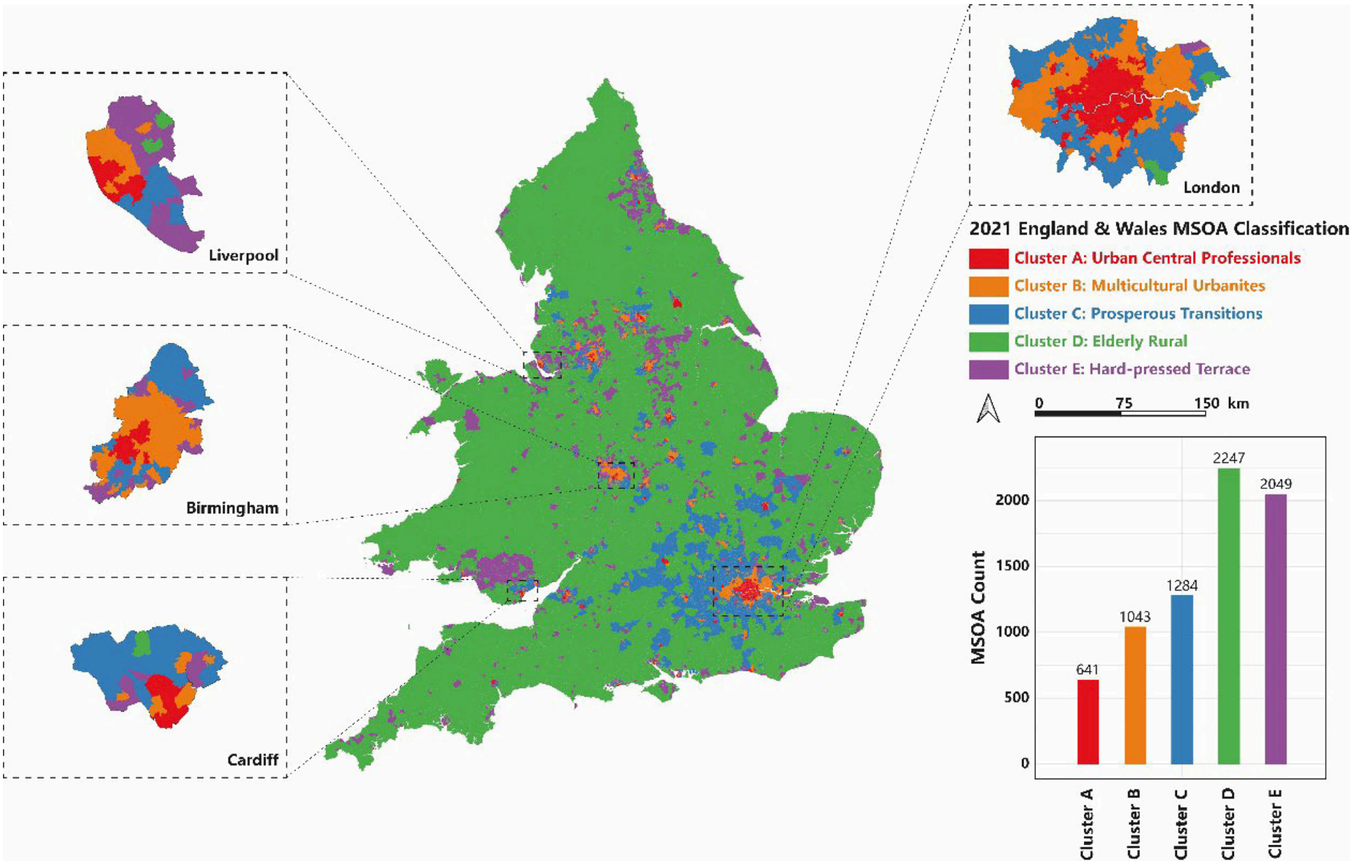

Fig. 2. Spatial distribution of geodemographic classification of MSOAs in England and Wales using 2021 Census variables and histogram showing number of MSOAs in each category.

benchmark for comparison with more ambitious net zero policies such as the BNZP and WI pathways.

3. Results

3.1. Geodemographic classification of MSOAs in England and Wales

Fig. 1 depicts the index scores for variables within each geodemographic cluster, calculated as ratios against the average values across England and Wales. These scores help quantify the extent to which certain characteristics are overrepresented or underrepresented compared with the national average, where a score of 100 represents the average, 50 indicates half the average, and 200 signifies twice the average. Fig. 2 illustrates the spatial distribution of the MSOA-level geodemographic classification across England and Wales which categorises the 7,264 MSOAs into five unique clusters. These clusters capture the diverse and distinct contextual characteristics of various neighbourhoods. The combination of these index scores and the spatial distribution of categories played a crucial role in developing descriptive profiles for each geodemographic cluster. Clusters are described below with index scores underpinning these profiles provided in Supplementary Material Appendix 4.

Cluster A: Urban Central Professionals (641 MSOAs)

Residents of communities classified as *Urban Central Professionals* are predominantly aged between 15–44 years old, representing a youthful and active demographic, largely engaged in full-time professional or associate professional occupations. A notable portion are students at universities. These communities are typically single and tend to live alone in privately rented flats located in high-density, urban central areas, with some experiencing overcrowded living conditions. They are from a diverse range of ethnic backgrounds, including a significant presence of individuals of Chinese ethnicity. Educationally, residents are typically well-qualified, with many holding university or equivalent qualifications. A defining characteristic of this cluster is their minimal reliance on car ownership, coupled with a preference for using public transport or engaging in active travel.

Cluster B: Multicultural Urbanites (1,043 MSOAs)

Communities classified as *Multicultural Urbanities* are characterised by a diverse ethnic tapestry, predominantly comprising Asian, Black, Mixed, and other non-White ethnic groups. A significant proportion of residents of these communities face challenges with English proficiency, reflecting the areas' multicultural essence. The age distribution is notably skewed towards the 0–24-year age range, indicative of the presence of young families. Residents of these communities typically inhabit high-density urban areas, often residing in overcrowded terraced houses and flats, primarily accessed through social renting. Educational attainment in this cluster tends to be below the national average, with many engaged in elementary occupations or facing unemployment. The limited car ownership in these communities underscores a significant reliance on public transport.

Cluster C: Prosperous Transitions (1,284 MSOAs)

Communities classified as *Prosperous Transitions* accommodate a diverse age range and feature an average ethnic mix with a lower-than-average representation of Black ethnicity. Predominantly located in southern England, these communities are often located in transitional zones between urban centres and suburbia. Homeownership and private renting are common, with semi-detached houses as the prevalent housing type. Residents of these communities are generally well-educated, with many holding university qualifications, and

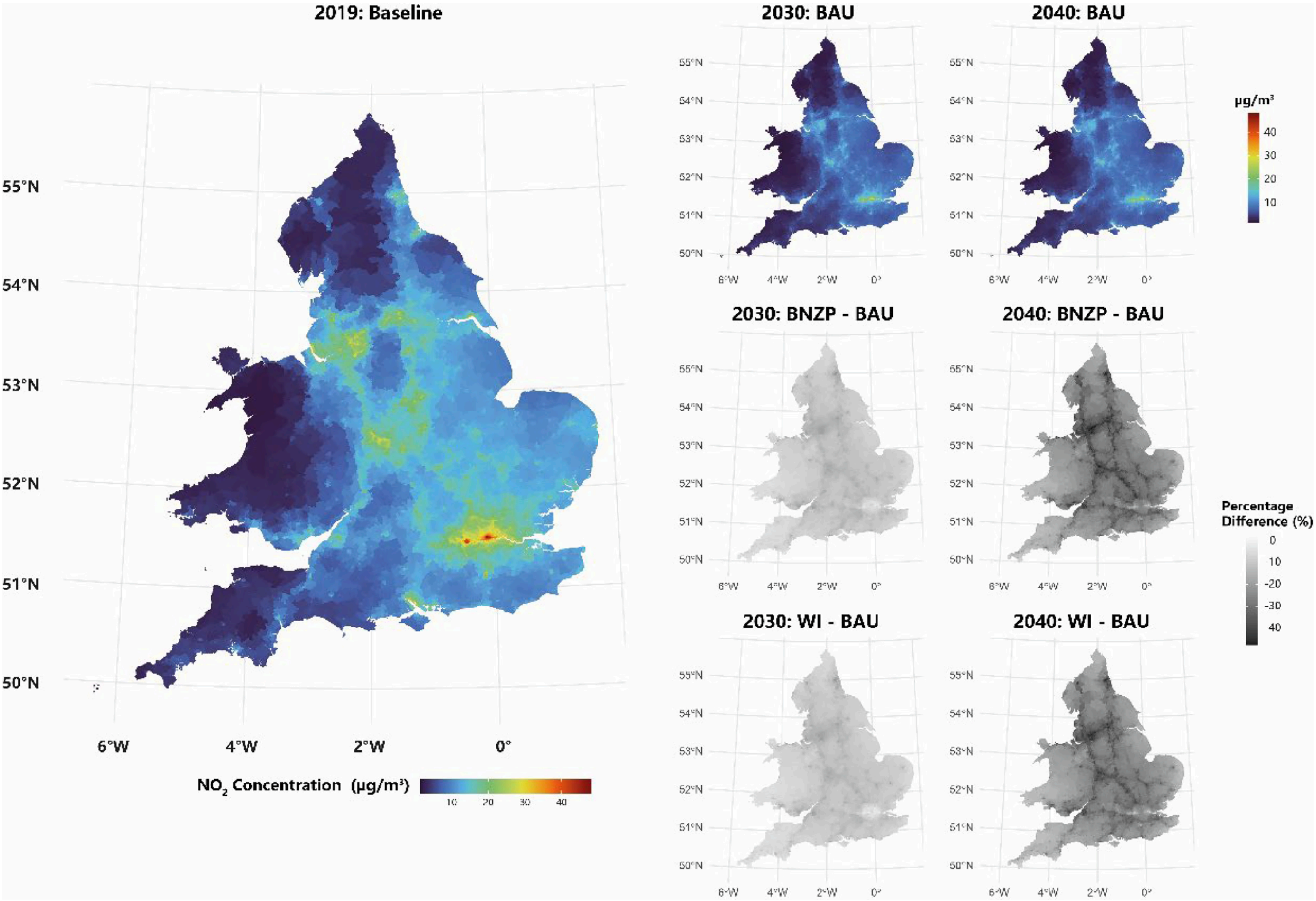

Fig. 3. Nitrogen dioxide (NO_2) concentrations across MSOAs in England and Wales in 2019, prediction for 2030 and 2040 under the business-as-usual (BAU) scenario, and reductions in concentrations under the Balanced Net Zero pathway (BNZP) and Widespread Innovation pathway (WI) compared to BAU.

employment rates are high, particularly in full-time professional or associate professional roles. The overall self-rated health is better than the national average.

Cluster D: Elderly Rural (2,247 MSOAs)

Residents of the communities classified as *Elderly Rural* are predominantly older, with the age distribution heavily skewed towards middle-aged and elderly individuals. A significant portion of the population is aged 65 and above, including many who are 85 and older. Ethnic diversity is low, with the majority being of White ethnicity. Homeownership is common, with most residents living in privately owned detached or semi-detached houses, often located in rural areas or on the outskirts of major cities in England and Wales. These communities typically feature lower residential densities compared to the national average, and households often have spare rooms. These communities are marked by a high reliance on cars, with many households owning two or more vehicles, indicating a preference for private transport as the primary means of commuting.

Cluster E: Hard-pressed Terrace (2,049 MSOAs)

Situated predominantly in suburban areas of northern England and southern Wales, communities classified as *Hard-pressed Terrace* are characterised by terraced housing that are less overcrowded than the national average. These communities predominantly consist of White residents, with lower ethnic diversity. A distinctive feature is the, compared to other clusters, smaller proportion of young adults aged 15–44 years with non-dependent children, coupled with rates of divorce and separation that exceed the national average. Housing here is primarily social-rented terraced or semi-detached properties. The educational attainment of residents is generally slightly below the national average, and they are employed in a variety of occupations, such as skilled trades, service industries, sales, and construction. The overall self-rated health in these communities is below the national average, yet the level of unpaid care provision is consistent with national figures.

3.2. Air pollution concentrations at MSOA-level between 2019 and 2040

Figs. 3 and 4 show MSOA-level NO_2 and $PM_{2.5}$ concentrations, respectively, in 2019 and predictions under the BAU scenario and the BNZP and WI pathways for 2030 and 2040. In 2019, large parts of the country, mainly in urban areas, had average MSOA-level NO_2 concentrations above 20 µg/m^3 (24 % of MSOAs, $n = 1{,}719$) and $PM_{2.5}$ concentrations above 10 µg/m^3 (40 % of MSOAs, $n = 2{,}932$).

Emission reduction policies focusing on stricter emission standards and advanced vehicle technologies under the BAU scenario resulted in significant decreases in average MSOA-level concentrations in 2030 (average decrease compared with 2019 for NO_2: 6.1 µg/m^3 (37 % reduction) and $PM_{2.5}$: 2.3 µg/m^3 (25 % reduction)) which remain relatively stable in 2040 (average decrease compared to 2019 for NO_2: 6.3 µg/m^3 (38 % reduction) and $PM_{2.5}$: 2.2 µg/m^3 (23 % reduction)) (Table 2). Reductions were most pronounced in urban areas compared with rural areas. We predicted additional average concentration reductions under the BNZP pathway compared with BAU (Figs. 3 and 4) of 2.4 µg/m^3 (24 % reduction) for NO_2 and 0.7 µg/m^3 (10 % reduction) for $PM_{2.5}$ which were most pronounced along major roads and in city centres. In particular, cities in the North of England such as Liverpool, Manchester and Birmingham benefitted most from the additional emission reductions from road traffic and buildings. Under the WI

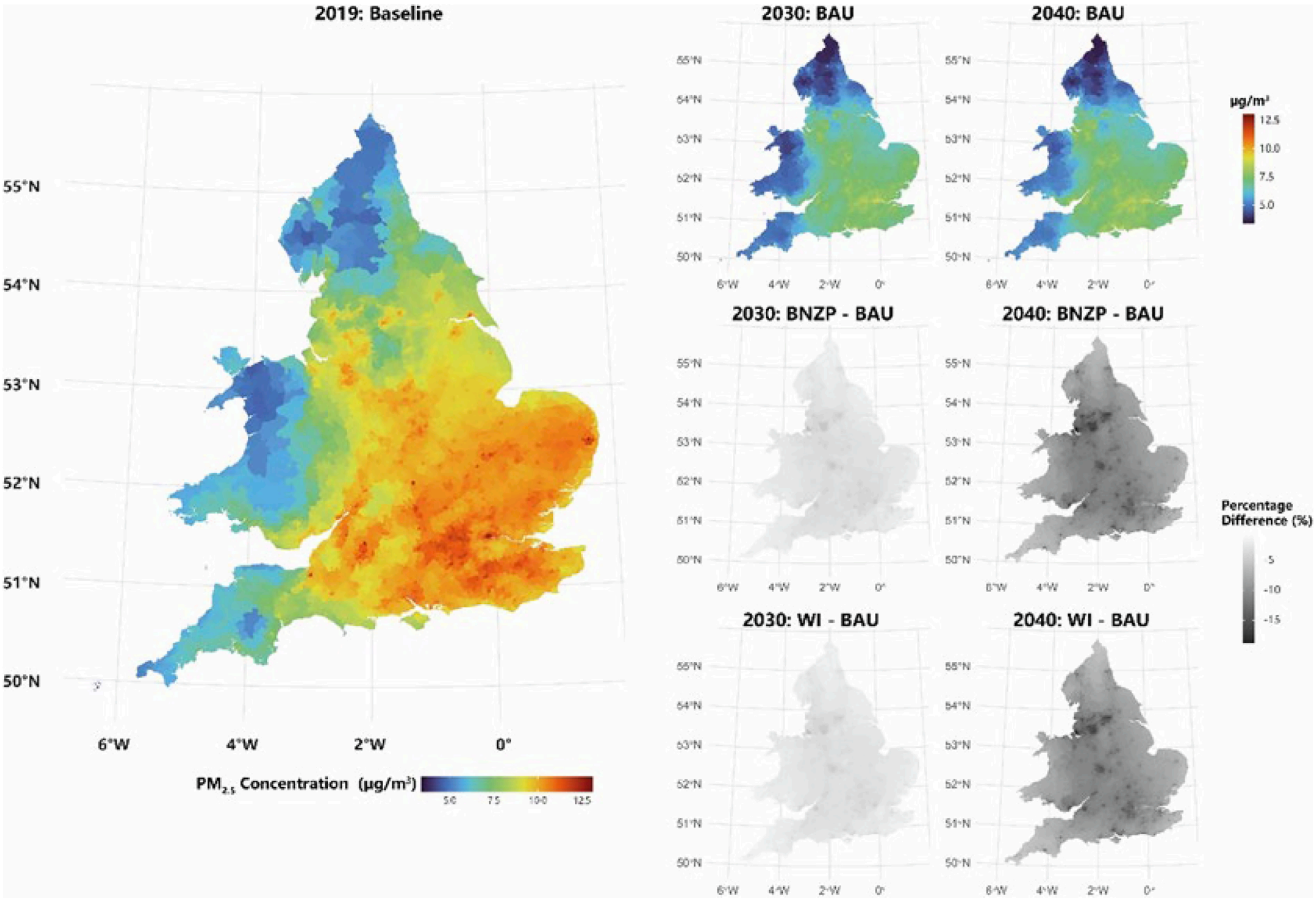

Fig. 4. Fine particulate matter ($PM_{2.5}$) concentrations across MSOAs in England and Wales in 2019, prediction for 2030 and 2040 under the business-as-usual (BAU) scenario, and reductions in concentrations under the Balanced Net Zero pathway (BNZP) and Widespread Innovation pathway (WI) compared to BAU.

Table 2
Summary statistics for MSOA-level concentrations for nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$) at 2019 baseline and for 2030 and 2040 under business as usual (BAU) scenario and Balanced Net Zero pathway (BNZP) and Widespread Innovation pathway (WI).

		5th PCT	25th PCT	Median	75th PCT	95th PCT	Mean	Standard deviation
NO_2 (µg/m^3)	2019	6.3	12.0	15.7	19.9	28.6	16.3	6.6
	BAU 2030	4.2	7.5	9.6	12.1	18.2	10.2	4.2
	BAU 2040	4.4	7.5	9.5	11.9	17.6	10.0	4.0
	BNZP 2030	3.9	6.8	8.7	10.9	17.7	9.4	4.1
	BNZP 2040	3.6	5.7	7.0	8.6	14.7	7.6	3.3
	WI 2030	3.9	6.8	8.7	11.0	17.8	9.4	4.1
	WI 2040	3.6	5.8	7.2	8.8	14.8	7.8	3.1
$PM_{2.5}$ (µg/m^3)	2019	6.5	8.8	9.7	10.4	11.2	9.4	1.4
	BAU 2030	4.9	6.7	7.3	7.6	8.3	7.1	1.0
	BAU 2040	5.0	6.8	7.4	7.8	8.3	7.2	1.0
	BNZP 2030	4.8	6.5	7.1	7.4	8.0	6.9	0.9
	BNZP 2040	4.6	6.1	6.7	7.0	7.5	6.5	0.8
	WI 2030	4.8	6.5	7.1	7.4	8.0	6.9	0.9
	WI 2040	4.6	6.1	6.7	7.0	7.6	6.5	0.9

PCT: percentile.

pathway, MSOA-level concentration reductions compared with BAU were of similar magnitude (2.2 µg/m^3 (22 % reduction) for NO_2 and 0.7 µg/m^3 (10 % reduction) for $PM_{2.5}$ by 2040).

3.3. *Differential air pollution concentrations by geodemographic classification*

Fig. 5 shows the distribution of MSOA-level NO_2 and $PM_{2.5}$ concentrations across the five geodemographic categories in England and Wales for the years 2019, 2030, and 2040. The year 2019 serves as the baseline, with 2030 and 2040 projections under the BAU scenario and BNZP and WI pathways.

There were notable differences in average MSOA-level NO_2 concentration in 2019 across the geodemographic categories, with the *Urban Central Professionals* category experiencing the highest NO_2 levels (mean: 25.8 µg/m^3, 95th percentile: 38.8 µg/m^3) compared with the *Elderly Rural* category with the lowest average MSOA-level concentrations (mean: 11.7 µg/m^3, 95th percentile: 18.4 µg/m^3) (Table 3). In comparison, differences in $PM_{2.5}$ concentrations were not as pronounced with means ranging from 8.9 µg/m^3 (95 % percentile: 10.8 µg/m^3) for

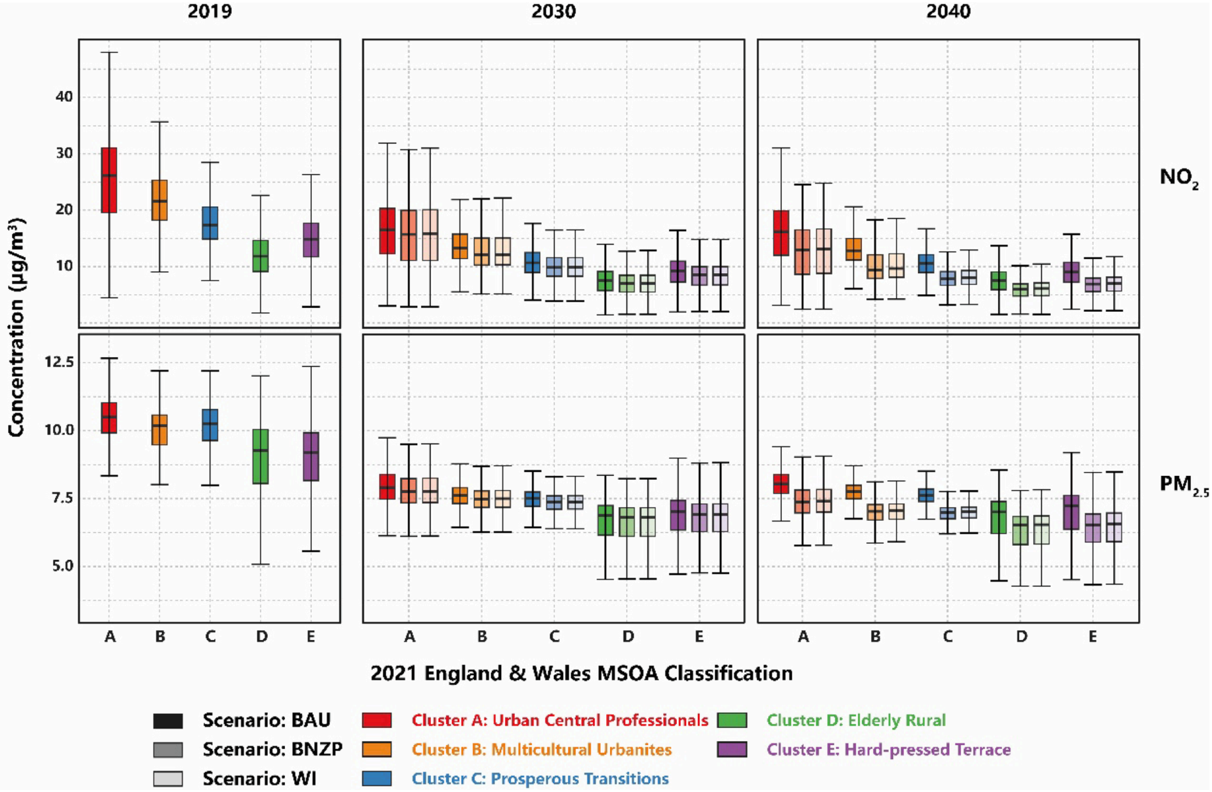

Fig. 5. NO_2 and $PM_{2.5}$ MSOA-level concentrations in 2019 and for business-as-usual (BAU) scenario and Balanced Net Zero pathway (BNZP) and Widespread Innovation pathway (WI) in 2030 and 2040 (distinguished by varying levels of transparency relative to the BAU scenario) stratified by the five geodemographic categories in England and Wales. The boxplots display the median (Q2), first quartile (Q1), third quartile (Q3), and whiskers extend to the smallest and largest values within 1.5 times the interquartile range (IQR) from Q1 and Q3, respectively. Outliers are not shown due to the large number of MSOAs.

Table 3
Mean and 95th percentile MSOA-level concentrations for nitrogen dioxide (NO2) and fine particulate matter (PM2.5) at 2019 baseline and for 2030 and 2040 under business as usual (BAU) scenario and Balanced Net Zero pathway (BNZP) and Widespread Innovation pathway (WI), stratified by the five geodemographic categories in England and Wales.

		Urban Central Professionals		Multicultural Urbanities		Prosperous Transitions		Elderly Rural		Hard-pressed Terrace	
		Mean	95th PCT	Mean	95th PCT	Mean	95th PCT	Mean	95th PCT	Mean	95th PCT
NO_2 (μg/m^3)	2019	25.8	38.8	21.9	29.7	17.8	24.8	11.7	18.4	14.6	21.5
	BAU 2030	16.6	26.7	13.7	19.3	10.9	15.4	7.4	11.3	9.0	13.3
	BAU 2040	16.3	25.8	13.2	18.5	10.7	14.7	7.4	11.2	9.0	13.0
	BNZP 2030	15.7	25.4	12.7	18.9	9.9	14.5	6.8	10.2	8.2	12.0
	BNZP 2040	12.7	20.7	10.0	15.8	8.0	11.7	5.7	8.2	6.6	9.4
	WI 2030	15.8	25.6	12.7	19.0	10.0	14.5	6.8	10.2	8.2	12.0
	WI 2040	12.9	20.9	10.2	16.0	8.1	12.0	5.8	8.4	6.8	9.6
$PM_{2.5}$ (μg/m^3)	2019	10.4	11.9	10.0	11.1	10.1	11.5	8.9	10.8	9.0	10.9
	BAU 2030	7.9	9.2	7.6	8.4	7.4	8.1	6.6	7.7	6.8	7.9
	BAU 2040	8.0	9.1	7.7	8.4	7.6	8.3	6.7	7.9	6.9	8.1
	BNZP 2030	7.7	8.9	7.4	8.2	7.2	7.9	6.4	7.5	6.6	7.6
	BNZP 2040	7.3	8.5	6.9	7.6	6.8	7.4	6.2	7.1	6.2	7.3
	WI 2030	7.7	9.0	7.4	8.2	7.2	7.9	6.4	7.5	6.6	7.7
	WI 2040	7.3	8.5	6.9	7.7	6.8	7.4	6.2	7.2	6.3	7.3

the *Elderly Rural* category to 10.4 μg/m^3 (95 % percentile: 11.9 μg/m^3) for the *Urban Central Professionals* category.

Future projections for 2030 and 2040 under the BAU scenario and BNZP and WI pathways indicate a persistence of the disparities observed in 2019, albeit to a decreasing extent, with similar patterns across the different geodemographic categories (Table 3). The largest reductions in MSOA-level NO_2 and $PM_{2.5}$ levels between 2019 and 2030 predictions under the BAU scenario were observed for the *Urban Central Professionals* category (−9.2 μg/m^3 and −2.7 μg/m^3, respectively), the lowest for the *Elderly Rural* category for NO_2 (−4.3 μg/m^3) and *Hard-pressed Terrace* category for $PM_{2.5}$ (−2.2 μg/m^3). For both pollutants, there were only marginal reductions under the BAU scenario from 2030 to 2040, reflecting the early effectiveness of existing and agreed air pollution policies, with little impact on reducing air pollution levels beyond 2030 across all geodemographic categories. For the two net zero pathways, BNZP and WI, however, we predicted early benefits in 2030 and additional benefits by 2040 resulting in average reductions of −13.1 μg/m^3 NO_2 and −3.1 μg/m^3 $PM_{2.5}$ in 2040 compared to 2019 for the *Urban Central Professionals* category (Table 3). Differences between the BAU scenario and the two net zero pathways in 2030 were small for both pollutants and varied little across the geodemographic groups (Fig. 6). We saw, however, larger reductions in MSOA-level

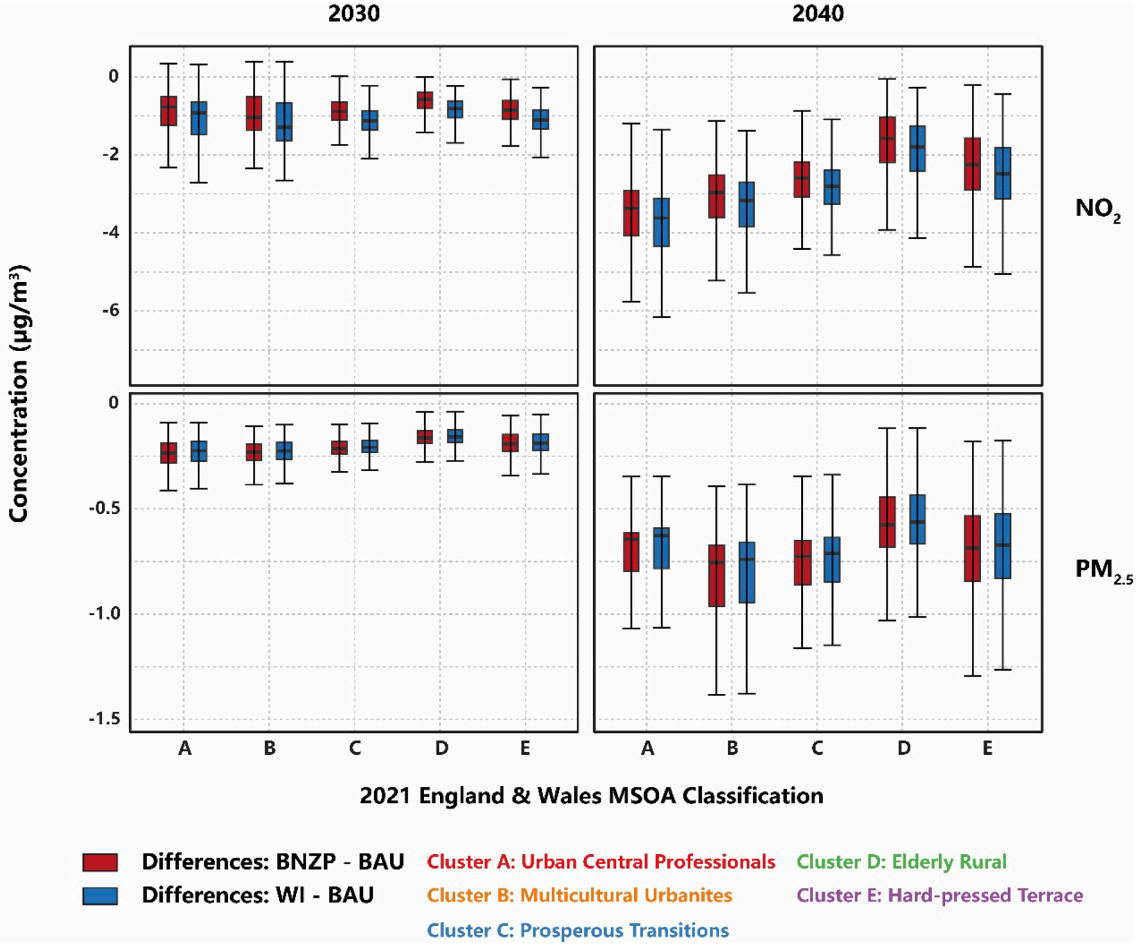

Fig. 6. Differences in NO_2 and $PM_{2.5}$ MSOA-level concentrations between the business-as-usual (BAU) scenario and the two net zero pathways – Balanced Net Zero pathway (BNZP) and Widespread Innovation pathway (WI) – in 2030 and 2040, stratified by the five geodemographic categories in England and Wales.

concentrations between BAU and both BNZP and WI pathways by 2040 which varied substantially by geodemographic group (Fig. 6). Patterns for NO_2 and $PM_{2.5}$ were similar, with largest reductions observed for the *Urban Central Professionals* category, followed by the *Multicultural Urbanities* category. The *Elderly Rural* and *Hard-pressed Terrace* categories had the smallest benefits in terms of additional air pollution reductions from net zero pathways compared to BAU scenario.

4. Discussion

Our study aimed to explore air pollution inequalities across different geodemographic groups in England and Wales and assessed how these might be differentially impacted by future air pollution projections in 2030 and 2040 under net zero policies. We found clear environmental inequalities, with *Urban Central Professionals* experiencing 14 $\mu g/m^3$ higher average NO_2 concentrations compared to *Rural Elderly* in 2019. $PM_{2.5}$ concentration varied significantly less across geodemographic groups (max difference 1.5 $\mu g/m^3$). Despite substantial improvements to air quality in 2030 and 2040 of up to 6.3 $\mu g/m^3$ for NO_2 based on BAU, and further reductions of up to 2.4 $\mu g/m^3$ NO_2 under net zero policies, the overall pattern of inequality persists, but is predicted to be less pronounced.

The more pronounced disparities observed for NO_2 can be attributed to the steeper exposure contrast with higher localised concentrations close to sources such as roads. In contrast, the disparities in $PM_{2.5}$ concentrations are less severe, suggesting a more uniform distribution of concentrations across the five geodemographic categories. $PM_{2.5}$ concentrations are due to a mix of sources including residential heating, industrial combustion and road transport, and, therefore, affect a broader and more diverse demographic. Gradients of secondary aerosols (formed in the atmosphere from reactions involving gaseous pollutants) are especially gradual across the country.

The reduction in the degree of inequality over time, particularly under the BNZP scenario, reflects the positive influence of net zero policy initiatives and technological advancements geared towards air pollution control. These findings demonstrate the effectiveness of targeted environmental policies and innovations in not only reducing overall pollution levels but also in bridging the environmental inequality gap. Areas which are predicted to have smaller reductions in air pollution concentration relative to other areas do not necessarily fall behind in their policy efforts. Emissions could have been low already and additional policies could not further reduce these (e.g. in very rural areas). Some areas could have implemented additional policies earlier than the timescale of our scenarios, which means these changes might not be reflected here (e.g. London has implemented low emission zones ahead of the rest of the country).

The inequalities in exposure to air pollutants reveal a distinct urban–rural dimension. *Urban Central Professionals* have consistently the highest exposure to NO_2 and $PM_{2.5}$, in 2019 and under all assessed future policy scenarios. Despite their higher socio-economic status, higher education and better resource availability and accessibility, these urban residents, living in high-density, traffic-congested areas, remain the highest exposed geodemographic group. Their preference for public transport and active commuting, though reducing some emissions, does not significantly lessen their exposure to air pollution sources, such as vehicle exhaust and residential gas emissions, which presents a clear case of environmental injustice.

Elderly Rural communities, on the other hand, consistently experience the lowest exposure, a pattern that persists into future projections. Despite their reliance on private transport, the low residential density and rural setting of their communities result in significantly cleaner air. This demographic, often residing on the urban periphery or in rural areas, thus enjoys the benefits of reduced exposure to air pollution sources that predominantly affect high-density urban areas. The marked contrast in pollution levels between *Urban Central Professionals* and the *Elderly Rural* clearly illustrates the pronounced division in environmental quality and air pollution exposure between urban and rural settings.

The exploration of air quality disparities in England and Wales underscores the intricate role of socio-economic and locational factors in environmental inequality. The juxtaposition of *Prosperous Transitions* and *Multicultural Urbanites* underscores this point, as the wealthier *Prosperous Transitions*, positioned in transitional urban–rural areas, enjoy cleaner air than their less affluent counterparts. These findings echo established research that links lower deprivation to better environmental conditions (Brunt et al., 2017; Fairburn et al., 2019; Fecht et al., 2015; Hajat et al., 2015; Jbaily et al., 2022; Samoli et al., 2019). Similarly, *Hard-pressed Terraced*, despite its economic challenges, benefits from its rural setting, facing less pollution than its urban counterparts.

The trend towards reducing disparities in air pollution exposure, while encouraging, also emphasises the need for sustained and multifaceted efforts to comprehensively tackle the myriad factors that contribute to air quality issues. In particular, the importance of air pollution inequalities on health inequalities can only be partially addressed based on population exposure. There is significant evidence that the prevalence and incidence of health impacts associated with air pollution (for example, stroke, dementia and diabetes) is greater amongst certain geodemographic groups, in particular more deprived and older communities (Baker, 2016; NICE, 2014; Weir et al., 2005). This is evident throughout the life course, including 2–3-fold increased still birth rates (Kingdon et al., 2019), reduced life expectancy by up to 9 years and healthy life expectancy by up to 18 years in more deprived areas (Office for National Statistics, 2021). Although *Urban Central Professionals* experience highest air pollution levels, other geodemographic groups, such as the *Elderly Rural* or *Hard-pressed Terraced* might carry the higher disease burden associated with air pollution exposure.

The significant societal and behavioural changes needed to achieve net zero, therefore, provide a unique opportunity to reduce air pollution concentrations and reduce the inequality gap.

Our study deviates from previous studies on air pollution inequalities (Fairburn et al., 2019) in that it makes the move away from single factors such as age, sex or socioeconomic status to a more comprehensive assessment of geodemographic groups. This allows to assess inequalities in more detail but also brings limitations. We assessed air pollution inequalities at the MSOA level, which facilitates a broader regional analysis. This coarse geographic level, however, might mask the steep gradients in air pollution for pollutants such as NO_2 and obscure finer local details that are crucial for understanding the nuances of air pollution exposure and its impacts on smaller demographic groups. Studies that aim to capture these finer details might consider employing a more granular geographical scale, which could offer deeper insights into localised environmental disparities and inequalities. Our focus on neighbourhood-level air pollution neglects indoor air pollution and personal exposure and results might not be directly transferable to individuals. We aligned our variable selection process with methodologies from earlier classifications such as the 2011 OAC and LOAC (Gale et al., 2016; Singleton & Longley, 2015). This traditional approach ensures continuity and comparability, providing a solid theoretical foundation for our classifications. However, the relevance of the 2011 variables selected in previous studies to the socio-economic and environmental contexts of 2021 remains uncertain, as the dynamics of populations and environments evolve rapidly. Different variable inputs and clustering methods might have resulted in different geodemographic clusters. We also make the assumption that geodemographic classification based on 2021 census data is valid into the future. Although there is evidence that deprivation patterns are consistent over time (Norman, 2010), this has not been assessed yet for geodemographic groups. Air pollution inequalities captured in this study are, therefore, due to geographic differences in emissions in the future and not due to changes in the geographic pattern of geodemographic groups.

To address these uncertainties and enhance the relevance and accuracy of future classifications, a systematic literature review is recommended. Such a review would help identify new demographic and environmental factors that have emerged since the last census. Additionally, employing advanced machine learning algorithms could dynamically adapt the variable selection process, allowing for an analysis of large datasets to determine which variables most effectively predict current geodemographic patterns. Implementing these strategies would ensure that geodemographic classifications not only retain their theoretical roots but also stay robust and applicable to current and future socio-economic and environmental conditions.

Moreover, the clustering method employed, hierarchical *k*-means, faced challenges due to the high dimensionality and potential multicollinearity among the over 50 variables used. This could affect the stability and interpretability of the resulting classifications (Alelyani et al., 2019). To mitigate these issues, future research could implement dimension reduction techniques like Principal Component Analysis (PCA) (Liu et al., 2019) or feature importance assessment through methods such as Random Forest (Chen et al., 2022). Additionally, considering more sophisticated clustering techniques, such as Self-Organizing Maps (Liu et al., 2021; Miljkovic, 2017) or other modern algorithms, might improve the delineation of geodemographic groups by better handling the complexities of large data sets.

5. Conclusions

Our findings demonstrate the effectiveness of targeted policies and innovations in reducing both air quality and greenhouse gas emissions and in bridging the environmental inequality gap. Our findings are also essential to develop targeted communication campaigns to secure acceptance and willingness across the sociodemographic spectrum to support the significant behavioural changes needed to achieve net zero, by highlighting the wider co-benefits to the environment and health of such policies.

CRediT authorship contribution statement

Yunzhe Liu: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **David Dajnak:** Writing – review & editing, Methodology, Funding acquisition, Data curation. **Nosha Assareh:** Writing – review & editing, Methodology, Data curation. **Andrew Beddows:** Writing – review & editing, Data curation. **Gregor Stewart:** Writing – review & editing, Data curation. **Mike Holland:** Writing – review & editing, Funding acquisition, Conceptualization. **Dimitris Evangelopoulos:** Writing – review & editing, Funding acquisition, Conceptualization. **Dylan Wood:** Writing – review & editing, Methodology, Data curation. **Tuan Vu:** Writing – review & editing, Methodology, Data curation. **Heather Walton:** Writing – review & editing, Funding acquisition, Conceptualization. **Christian Brand:** Writing – review & editing, Funding acquisition, Conceptualization. **Sean Beevers:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Daniela Fecht:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Co-authors Heather Walton and Mike Holland declare membership of the Committee on the Medical Effects of Air Pollutants reporting to the UK Department for Health and Social Care. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper].

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2024.109065.

Data availability

Data will be made available on request.

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