

Article

Fuel Poverty in Liverpool: The Deprivation-Pollution-Housing Loop

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Abstract

Fuel poverty is shaped by interacting social, environmental and housing conditions, yet these links remain underexplored at city scale. The analysis is framed as an ecological, cross-sectional assessment of spatial associations rather than as a causal proof of a closed feedback mechanism. This study examines the relationship between fuel poverty, deprivation, particulate air pollution and housing typology across 54 wards in Liverpool, UK. Ward-level fuel poverty and Index of Multiple Deprivation (IMD) data were integrated with 2023–2024 annual mean particulate matter (PM_{2.5} and PM₁₀) from 58 low-cost air-quality sensors and classified housing types. Regression models were used to compare individual, additive and interaction effects. Fuel poverty ranged from 12.4% to 25.29%, while PM_{2.5} and PM₁₀ frequently exceeded World Health Organization guideline values. IMD was the strongest individual predictor of fuel poverty ($R^2 = 0.281$, $p < 0.001$). The preferred additive model including IMD, PM_{2.5}, PM₁₀ and housing type explained 43.5% of the variance, with Victorian Terraces emerging as a significant risk factor. Although interaction models suggested pollution-deprivation coupling, model selection and uncertainty diagnostics favoured the simpler additive specification. The findings support targeted retrofit, fuel-poverty and emissions-control policies in deprived urban neighbourhoods where inefficient housing and environmental stressors compound energy insecurity and where local action can contribute to more equitable urban sustainability.

Keywords: fuel poverty; energy security; socio-economic deprivation; air pollution; housing type; Liverpool; environmental justice; urban sustainability



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1. Introduction

Fuel poverty, defined as the inability of households to afford adequate energy services, represents a critical public health and environmental justice challenge, particularly in urban settings where socio-economic deprivation and air pollution converge to exacerbate energy insecurity [1]. As a proxy for energy security, fuel poverty encapsulates the broader struggle to ensure equitable access to essential energy resources, a cornerstone of sustainable urban development [1]. In the United Kingdom, over 3 million households were in fuel poverty in 2023, a crisis intricately linked to socio-economic inequalities [2]. Deprived communities face disproportionate burdens due to limited resources, substandard housing conditions, and heightened exposure to environmental stressors such as air pollution, which

can increase energy demands through health-related needs (e.g., heating for respiratory conditions) [3,4].

This framing links fuel poverty directly to sustainability because household energy insecurity sits at the intersection of poverty reduction, health protection, affordable and clean energy, reduced inequalities, sustainable cities and climate action. In practical terms, retrofit programmes that reduce heat loss can lower household energy demand and carbon emissions, but their sustainability value depends on whether investment reaches the neighbourhoods where deprivation, poor housing and environmental exposure overlap [5].

Liverpool, a major urban centre in North West England, with a population of approximately 486,000, provides a compelling context for examining these dynamics [6]. The city's industrial legacy as a port and manufacturing hub has left a lasting imprint on its environmental and socio-economic landscape, with Liverpool ranking as one of the most deprived local authorities in England [7]. The Indices of Multiple Deprivation (IMD) 2019 reveal that over half of Liverpool's Lower Layer Super Output Areas (LSOAs) are among the most deprived 10% nationally. This deprivation is spatially heterogeneous, with northern wards such as Kirkdale East and Linacre exhibiting high IMD scores (28.41 and 31.78, respectively), while central wards like City Centre South show lower deprivation (IMD score of 14.21). High deprivation correlates strongly with fuel poverty, as limited income and poor housing conditions, particularly in older, less energy-efficient homes like Victorian Terraces, drive up energy costs [8,9]. In 2022, ward-level fuel poverty proportions in Liverpool ranged from 12.4% to 25.29%, with the highest rates in northern wards where deprivation is acute [10]. Air pollution further compounds these challenges, driven by traffic emissions, domestic combustion, and industrial activity around the Mersey Estuary [11]. Recent Liverpool work using dense low-cost sensor networks has demonstrated strong ward-scale and LSOA-scale variation in PM exposure across the city, including deprivation-linked exposure gradients, paediatric respiratory-health applications and spatiotemporal modal structure in the Liverpool particulate-matter record [12–15]. In 2023, the 58-sensor network used here recorded annual mean PM_{2.5} concentrations ranging from 5.09 to 13.07 µg/m³ and PM₁₀ from 10.67 to 30.46 µg/m³, frequently exceeding World Health Organization (WHO) guidelines of 5 µg/m³ for PM_{2.5} and 15 µg/m³ for PM₁₀ [16,17]. These elevated levels are pronounced in densely populated northern wards, where high building density and limited vegetation constrain pollutant dispersion [18]. The health implications are stark, with the Liverpool City Region experiencing substantial premature mortality attributed to poor air quality and significant economic costs [19]. Children in Liverpool face elevated respiratory hospital admission rates relative to national averages, reinforcing the importance of integrating household, health and environmental evidence [7,13,15].

The combined impact of air pollution and deprivation on health outcomes is well-documented, with socio-economic disadvantage acting as both a confounder and mediator in the pollution-health relationship [18,20,21]. Despite extensive evidence linking air pollution to respiratory morbidity [3] and deprivation to health inequalities [22], the specific role of these factors in driving fuel poverty remains underexplored in urban contexts. This paper extends Liverpool-specific sensor-network evidence on pollution, deprivation, spatial exposure structure and child-health burden into the connected domain of household energy insecurity and housing typology [12–15]. To address these gaps, this study systematically examines the associations among socio-economic deprivation, PM_{2.5} and PM₁₀ exposure, and housing type on fuel poverty in Liverpool. We aim to quantify the individual and combined effects of deprivation, air pollution, and housing type on fuel poverty, and identify the most predictive model to highlight key levers for mitigating energy insecurity. The paper is structured to achieve these goals: the methods section outlines the data sources, including high-resolution air quality measurements and ward-level fuel poverty data, and

describes the systematic regression approach used to model these relationships; the results section presents the spatial distribution of fuel poverty, deprivation, and pollution, followed by the regression findings; the discussion integrates these findings, comparing them with prior research and proposing policy interventions; and the conclusions summarize the key insights and their implications for urban energy security.

The term “Deprivation-Pollution-Housing Loop” is therefore used as a conceptual organising frame rather than as a claim that the present regression models establish a closed causal cycle. The proposed logic is that deprivation can constrain household resources and housing quality; older and less thermally efficient housing can increase heating costs and exposure to cold; and air pollution can add a health-related burden that may increase vulnerability to energy insecurity. The empirical analysis tests whether these components co-occur spatially and whether their combined associations help identify priority areas for sustainable retrofit and public-health intervention. This conceptual framing is summarised in Figure 1.

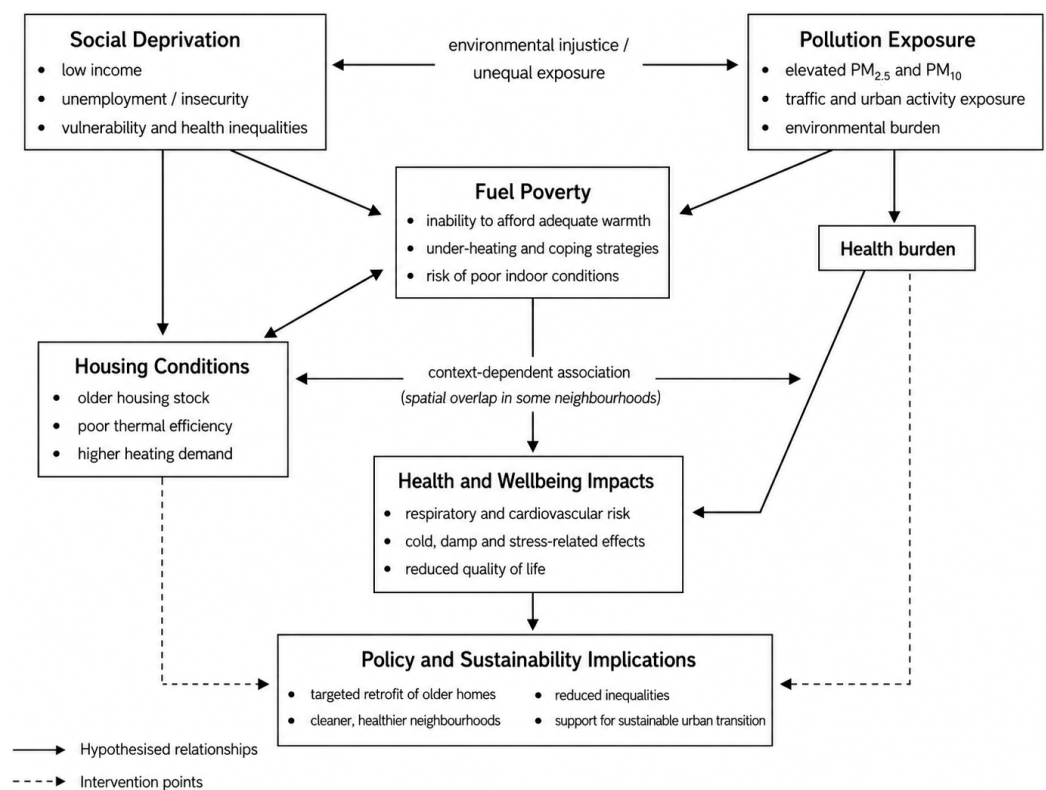


Figure 1. Conceptual framework presented in a directed-acyclic-graph style to clarify the hypothesised relationships among social deprivation, pollution exposure, housing conditions, fuel poverty, health and wellbeing impacts, and policy intervention points. The figure is intended as an organising framework for the study and does not imply that the regression analysis proves a closed causal loop.

2. Materials and Methods

2.1. Study Setting and Data Sources

This study was conducted in Liverpool, a major urban centre in northwest England characterised by significant socio-economic deprivation and a legacy of industrial and maritime activity that continues to shape its environmental landscape [6,7]. The dataset comprised 54 electoral urban wards (of Liverpool’s 64 wards; inclusion was limited by sensor-location coverage), each characterized by ward-level data on the proportion of households in fuel poverty, IMD scores, annual average concentrations of PM_{2.5} and PM₁₀, and housing type. Fuel poverty data were sourced from the UK Government’s Sub-Regional Fuel Poverty dataset for 2024 (based on 2022 data), providing a robust measure of energy

insecurity at the ward level [10]. The PM dataset was therefore not treated as temporally prior to the fuel-poverty outcome; rather, the 2023 sensor record was used as the nearest measured contextual indicator of contemporary ward-level air-quality conditions. This means that the analysis supports spatial association and targeting, not causal sequencing. IMD scores reflect multiple dimensions of deprivation including income, employment, education, health, crime, barriers to housing, and living environment. The complete IMD score was used, rather than a domain-excluded recalculation, because harmonised ward-level IMD components excluding the housing and living-environment domains were not available for this analysis. This creates a possible overlap with fuel poverty and housing conditions, so IMD is interpreted here as a broad contextual deprivation measure rather than as a fully independent causal variable. Air pollution data were collected using a network of 58 fixed-location air quality sensors (Aeternum, equipped with AlphaSense N Series Optical Particle Counters) deployed across Liverpool in 2023, building on the city-scale monitoring framework and open sensor dataset described in prior Liverpool air-quality work [12,14,16]. These sensors measured PM_{2.5} (particles < 2.5 µm) and PM₁₀ (particles 2.5–10 µm), along with temperature and humidity, at hourly intervals throughout the year, with seasonal variations in sampling frequency (shorter intervals in summer, longer in winter) due to solar gain effects. Sensors were strategically distributed, with higher density in the city centre and densely populated areas, and annual mean values were calculated and aggregated to the ward level to align with deprivation and fuel poverty datasets. Housing types were pre-classified into six clusters based on architectural and spatial characteristics—Central Business District (CBD), High Street and Promenades (HSP), Suburban Landscapes (SL), The Old Town (OT), Victorian Terraces (VT), and Waterside Settings (WS)—derived from prior spatial analysis of ward-level housing data [23]. Low-frequency housing types were combined into ‘Other’ to enhance statistical robustness. Data limitations prevented access to deeper IMD details, EPC scores, or income at ward level, with aggregation reflecting availability. Future research could leverage building-level or sensor-proximity data for greater precision.

2.2. Model Selection and Analytical Approach

Fuel poverty is a complex socio-environmental issue influenced by interconnected factors including economic disadvantage, environmental exposures, and the built environment, necessitating a comprehensive analytical approach to disentangle these relationships. We selected socio-economic deprivation, as captured by the Index of Multiple Deprivation (IMD), because it encompasses multiple dimensions such as income, employment, and housing quality, which are known to correlate with energy affordability challenges [22]. Air pollution, specifically PM_{2.5} and PM₁₀, was included due to its prevalence in urban environments like Liverpool and its potential to exacerbate health conditions that increase energy demands (e.g., respiratory illnesses requiring heating) [3]. Housing type, categorized into clusters such as CBD, HSP, SL, OT, VT, and WS, was incorporated to account for variations in building characteristics (e.g., insulation, age, and density) that influence energy efficiency and heating costs [8].

To explore these relationships, we adopted a systematic, cross-sectional regression approach, generating a series of linear models that progressively incorporate the predictors of interest. Linear regression was chosen for its interpretability and suitability for continuous outcomes like the proportion of households in fuel poverty, allowing us to quantify the individual and combined effects of each factor. We generated 15 models in total, starting with simple bivariate models to establish baseline relationships, followed by additive models to evaluate combined effects, and concluding with an interaction model to explore whether there was evidence consistent with synergistic effects between deprivation and

pollution. This hierarchical structure was designed to provide a thorough understanding of both main effects and interactions, offering an interpretable framework for identifying the most influential drivers of fuel poverty. All analyses were conducted in MATLAB R2022a (MathWorks, Natick, MA, USA), with model performance evaluated using R^2 , adjusted R^2 , F-statistics, and Akaike Information Criterion (AIC) to identify the best-fitting model. The models are summarized in Table 1, with their equations and purposes clearly outlined to provide a comprehensive overview of the analytical framework.

Table 1. Summary of linear regression models used to explore the relationships between fuel poverty and socio-economic deprivation, air pollution, and housing type.

Model	Equation	Purpose
1	Prop. Fuel Pov. IMD Score	Assessed the direct effect of socio-economic deprivation on fuel poverty, establishing a baseline relationship.
2	Prop. Fuel Pov. $PM_{2.5}$	Examined the effect of $PM_{2.5}$ on fuel poverty, testing the hypothesis that air pollution may influence energy demands.
3	Prop. Fuel Pov. PM_{10}	Tested the effect of PM_{10} , providing a comparison with $PM_{2.5}$.
4	Prop. Fuel Pov. IMD Score + $PM_{2.5}$	Evaluated the additive effects of deprivation and fine particulate matter.
5	Prop. Fuel Pov. IMD Score + PM_{10}	Assessed the combined effects of deprivation and larger particulate matter.
6	Prop. Fuel Pov. $PM_{2.5}$ + PM_{10}	Tested the joint effect of both pollutants, accounting for potential collinearity.
7	Prop. Fuel Pov. IMD Score + $PM_{2.5}$ + PM_{10}	Included all continuous predictors to assess their combined influence.
8	Prop. Fuel Pov. IMD Score + Cluster	Introduced housing type as a categorical predictor alongside deprivation, evaluating the role of the built environment.
9	Prop. Fuel Pov. $PM_{2.5}$ + Cluster	Explored the joint effects of $PM_{2.5}$ and housing characteristics.
10	Prop. Fuel Pov. PM_{10} + Cluster	Tested the combined effects of PM_{10} and housing type.
11	Prop. Fuel Pov. IMD Score + $PM_{2.5}$ + Cluster	Assessed the additive effects of deprivation, $PM_{2.5}$, and housing type.
12	Prop. Fuel Pov. IMD Score + PM_{10} + Cluster	Evaluated the combined effects of deprivation, PM_{10} , and housing type.
13	Prop. Fuel Pov. $PM_{2.5}$ + PM_{10} + Cluster	Examined the joint impact of both pollutants and housing type.
14	Prop. Fuel Pov. IMD Score + $PM_{2.5}$ + PM_{10} + Cluster	Included all predictors to assess their combined effects.
15	Prop. Fuel Pov. Cluster + $PM_{2.5}$ + PM_{10} + IMD Score + $PM_{2.5}$: IMD Score + PM_{10} : IMD Score	Tested whether the effects of $PM_{2.5}$ and PM_{10} on fuel poverty vary with levels of deprivation, alongside main effects of all predictors.

2.3. Data Preparation and Model Validation

Continuous predictors (IMD score, $PM_{2.5}$ and PM_{10}) were z-score normalised to standardise scales and aid coefficient comparison. No train/test split was used due to the small sample size ($n = 54$); leave-one-out cross-validation (LOOCV) was employed for validation instead. Housing type was dummy-encoded with CBD as the reference category. Multicollinearity was assessed using variance inflation factors (VIFs), with values below 5 interpreted as below conventional concern thresholds. Model assumptions were assessed using residual-versus-fitted plots for linearity and homoscedasticity, QQ plots for normality, and the Durbin–Watson test for residual independence. Bootstrapped confidence intervals (1000 resamples) were computed for coefficient stability, and residual diagnostics were inspected to check for remaining unexplained structure. Model selection relied on AIC and BIC, favoring the additive model (AIC = 396.10, BIC = 412.02) over the interaction model (AIC = 397.38, BIC = 417.27) for its balance of fit and simplicity. Ridge regression was

retained only as a sensitivity analysis for coefficient stability in a small-sample setting, not as evidence that severe multicollinearity was present, since the VIF diagnostics were below conventional concern thresholds. Post-hoc power diagnostics were not used as confirmatory evidence of detection. Instead, the low value reported for key coefficients is interpreted as further evidence that the ward-level sample has limited inferential precision. Prediction intervals, with a LOOCV MSE of 85.38 and a 157.64% width, revealed high uncertainty, suggesting the need for larger datasets. Spatial econometric models were not fitted because the available manuscript dataset did not include a validated ward adjacency or spatial-weights matrix; possible spatial autocorrelation is therefore treated as a limitation of the present OLS-based analysis.

3. Results

3.1. Spatial Distribution of Environmental Variables, Housing Type, IMD Score, and Fuel Poverty

The spatial analysis of environmental variables, housing type, Index of Multiple Deprivation (IMD) scores, and fuel poverty across the 54 wards of Liverpool revealed distinct geographical patterns, providing a foundation for understanding the contextual factors influencing energy security. Figure 2 illustrates the spatial distribution of annual average PM_{2.5} and PM₁₀ concentrations across Liverpool wards. PM_{2.5} ranged from 5.09 to 13.07 $\mu\text{g}/\text{m}^3$, with higher levels in Kirkdale East (12.15 $\mu\text{g}/\text{m}^3$), City Centre South (11.33 $\mu\text{g}/\text{m}^3$), and City Centre North (11.41 $\mu\text{g}/\text{m}^3$), reflecting urban density and traffic emissions. Lower levels were observed in peripheral wards like Aigburth (5.09 $\mu\text{g}/\text{m}^3$) and Mossley Hill (5.09 $\mu\text{g}/\text{m}^3$). PM₁₀ ranged from 10.67 to 30.46 $\mu\text{g}/\text{m}^3$, with peaks in Speke (30.46 $\mu\text{g}/\text{m}^3$), County (25.73 $\mu\text{g}/\text{m}^3$), and Clubmoor West (24.15 $\mu\text{g}/\text{m}^3$), likely due to industrial activity, and lows in Aigburth (10.67 $\mu\text{g}/\text{m}^3$) and Grassendale & Cressington (10.67 $\mu\text{g}/\text{m}^3$).

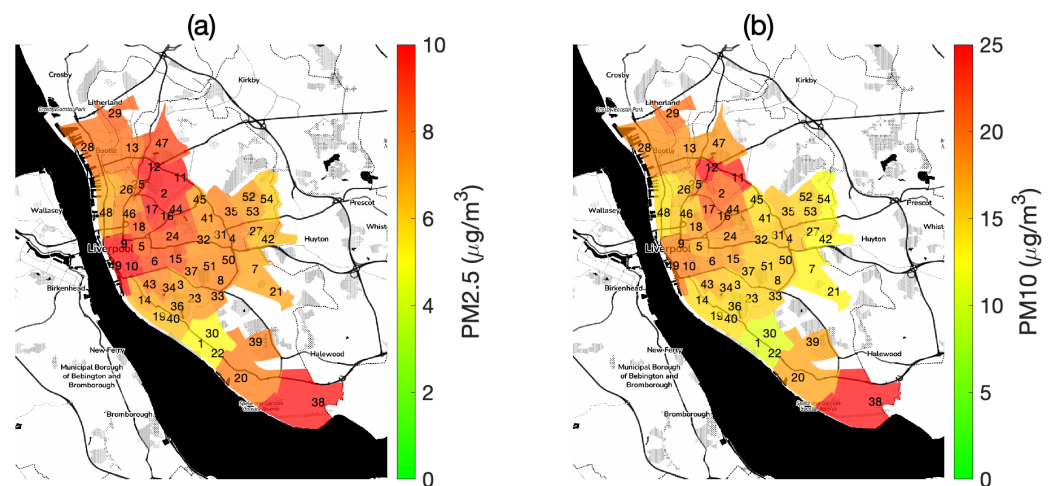


Figure 2. Spatial distribution of annual average environmental variables across Liverpool wards: (a) PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$), ranging from 5.09 to 13.07 $\mu\text{g}/\text{m}^3$; (b) PM₁₀ concentrations ($\mu\text{g}/\text{m}^3$), ranging from 10.67 to 30.46 $\mu\text{g}/\text{m}^3$. Darker colours indicate higher annual mean concentrations.

Figure 3 maps housing types across wards, categorized into Central Business District (CBD), High Street and Promenades (HSP), Suburban Landscapes (SL), The Old Town (OT), Victorian Terraces (VT), and Waterside Settings (WS). CBD includes City Centre North and Waterfront South, HSP includes Brownlow Hill and Kirkdale West, SL totals 14 wards like Aigburth and Childwall, OT is limited to City Centre South, VT covers 29 wards like Anfield and Arundel, and WS is represented by Waterfront North. This highlights the prevalence of Victorian Terraces, influencing energy efficiency.

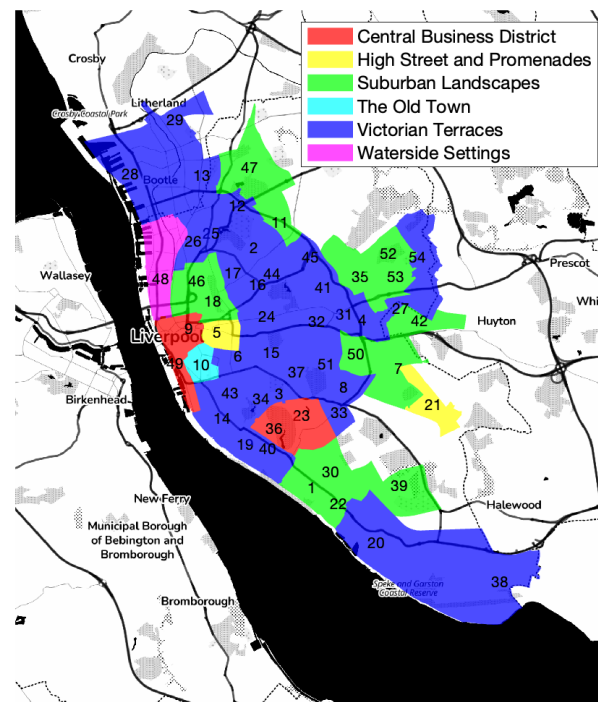


Figure 3. Spatial distribution of housing types across Liverpool wards, categorised into Central Business District (CBD), High Street and Promenades (HSP), Suburban Landscapes (SL), The Old Town (OT), Victorian Terraces (VT), and Waterside Settings (WS). Each colour denotes a different housing-type cluster; red denotes Victorian Terraces where used in the legend.

Figure 4 presents IMD scores, ranging from 13.21 to 35.32, with highs in Grassendale & Cressington (35.25), Knotty Ash & Dovecot Park (35.32), and Wavertree Garden Suburb (34.26), and lows in Springwood (13.21) and City Centre South (14.21), indicating varied deprivation patterns.

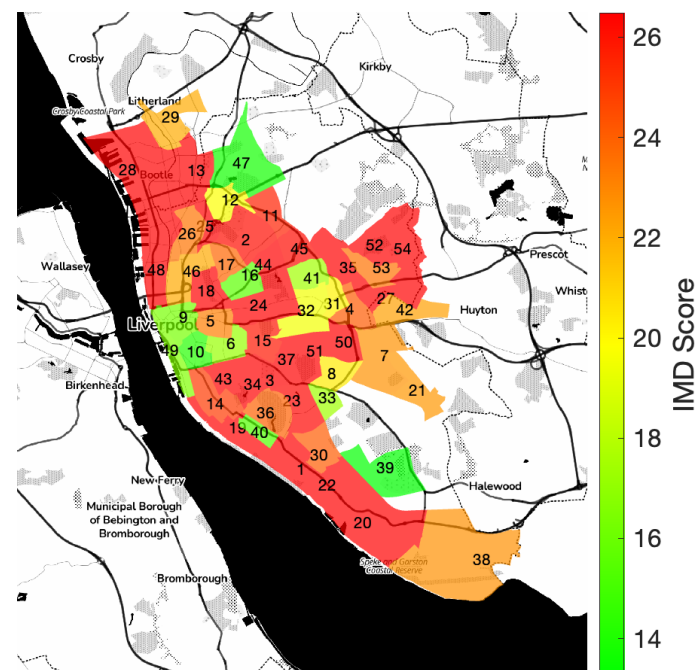


Figure 4. Spatial distribution of Index of Multiple Deprivation (IMD) scores across Liverpool wards, ranging from 13.21 to 35.32. Higher numeric values and darker colours indicate greater deprivation.

Figure 5 maps fuel poverty proportions, ranging from 12.4% to 25.29%, with peaks in Princes Park (25.29%), Knotty Ash & Dovecot Park (24.81%), and Aigburth (24.38%), and lows in Waterfront South (12.4%) and City Centre North (13.24%). These patterns suggest that older housing and high deprivation drive fuel poverty, while modern infrastructure mitigates it.

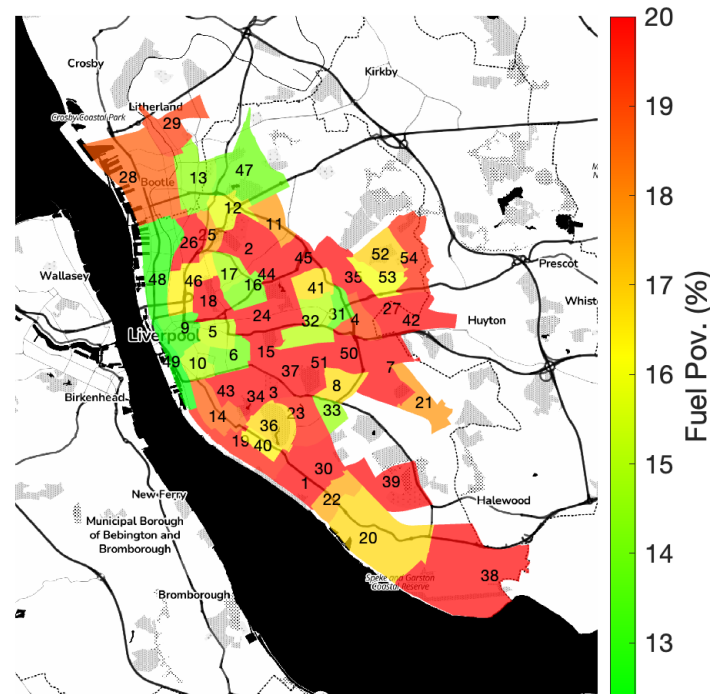


Figure 5. Spatial distribution of the proportion of households in fuel poverty across Liverpool wards, ranging from 12.4% to 25.29%. Higher numeric values and darker colours indicate a larger proportion of households in fuel poverty.

3.2. Regression Analysis of Fuel Poverty Drivers

The regression analysis systematically explored the contributions of socio-economic deprivation, air pollution, and housing type to fuel poverty across Liverpool's 54 wards, aiming to uncover the key drivers of energy insecurity. A total of 15 linear models were developed to progressively build understanding, starting with individual predictors, combining them additively, and finally examining interactions, with full results provided in Appendix B. We began with bivariate models to establish baseline relationships. Model 1 examined the effect of the IMD score, revealing that deprivation alone explained 28.1% of the variance in fuel poverty ($R^2 = 0.281$, $p = 3.81 \times 10^{-5}$), with a significant positive coefficient (0.31656, $p < 0.001$), indicating that a 1-unit increase in IMD score corresponds to a 0.32% increase in fuel poverty proportion. This underscores deprivation as a primary spatial correlate of energy insecurity. Models 2 and 3 assessed the individual effects of air pollution, with Model 2 showing that $PM_{2.5}$ explained 12.6% of the variance ($R^2 = 0.126$, $p = 0.00845$) and a significant negative coefficient (-0.69937 , $p = 0.008$), suggesting that higher $PM_{2.5}$ levels are associated with lower fuel poverty. This counter-intuitive result is not interpreted as a protective effect of pollution; it is more plausibly a contextual association arising because some higher-pollution central wards also contain newer or denser housing stock and different socio-economic profiles. Model 3, focusing on PM_{10} , explained only 6.3% of the variance ($R^2 = 0.063$, $p = 0.0671$), with a non-significant negative coefficient (-0.2437 , $p = 0.067$), indicating a weaker influence of PM_{10} on fuel poverty.

To explore combined effects, Models 4 through 7 examined additive relationships between continuous predictors. Model 4, combining IMD score and $PM_{2.5}$, explained

30.9% of the variance ($R^2 = 0.309$, $p = 8.19 \times 10^{-5}$), with IMD score remaining significant (0.27579, $p < 0.001$) but $PM_{2.5}$'s effect weakening (-0.35602 , $p = 0.157$), suggesting potential collinearity. Model 5, using IMD score and PM_{10} , explained 29.4% of the variance ($R^2 = 0.294$, $p = 0.000137$), with IMD score significant (0.29767, $p < 0.001$) but PM_{10} not (-0.11848 , $p = 0.321$). Model 6, combining $PM_{2.5}$ and PM_{10} , explained 15.7% of the variance ($R^2 = 0.157$, $p = 0.013$), with $PM_{2.5}$ significant (-1.4622 , $p = 0.021$) but PM_{10} not (0.41248, $p = 0.179$), indicating $PM_{2.5}$'s stronger influence. Model 7, including all continuous predictors (IMD score, $PM_{2.5}$, and PM_{10}), explained 31.5% of the variance ($R^2 = 0.315$, $p = 0.000258$), with the IMD score significant (0.26368, $p = 0.001$) but neither $PM_{2.5}$ (-0.73824 , $p = 0.223$) nor PM_{10} (0.19851, $p = 0.486$) showing significance.

Models 8 through 14 incorporated housing type to assess its role alongside continuous predictors. Model 8, combining IMD score and housing type, increased the explained variance to 41.6% ($R^2 = 0.416$, $p = 0.000197$), with IMD score significant (0.30827, $p < 0.001$) and housing type showing varying effects, including a marginally significant positive effect for Suburban Landscapes (SL) (2.9814, $p = 0.075$) and a negative effect for Waterside Settings (WS) (-5.3096 , $p = 0.106$). Models 9 and 10, combining $PM_{2.5}$ and PM_{10} with housing type, explained 25.7% ($R^2 = 0.257$, $p = 0.0245$) and 23.7% ($R^2 = 0.237$, $p = 0.0391$) of the variance, respectively, with $PM_{2.5}$ significant in Model 9 (-0.59647 , $p = 0.034$) and SL significant in Model 10 (3.9263, $p = 0.039$). Models 11 and 12, adding $PM_{2.5}$ and PM_{10} to IMD score and housing type, explained 43.4% ($R^2 = 0.434$, $p = 0.000266$) and 43.1% ($R^2 = 0.431$, $p = 0.000299$) of the variance, respectively, with IMD score consistently significant (0.28122, $p < 0.001$ in Model 11; 0.28868, $p < 0.001$ in Model 12). Model 13, combining $PM_{2.5}$, PM_{10} , and housing type, explained 26.0% of the variance ($R^2 = 0.260$, $p = 0.0415$). Model 14, including all predictors, explained 43.5% of the variance ($R^2 = 0.435$, $p = 0.000639$), with IMD score significant (0.28022, $p < 0.001$).

Finally, Model 15 tested interactions between predictors, providing the best fit with 53.5% of the variance explained ($R^2 = 0.535$, $p = 9.5 \times 10^{-5}$). It revealed significant interactions between $PM_{2.5}$ and IMD (0.40861, $p = 0.005$) and PM_{10} and IMD (-0.17724 , $p = 0.016$), indicating that the effect of air pollution on fuel poverty varies by deprivation level in the fitted model, alongside a significant negative effect for Waterside Settings (WS) (-7.8987 , $p = 0.018$). Ridge regression with an optimal lambda of 0.0100 was used as a sensitivity analysis, yielding coefficients of 6.042 ($PM_{2.5}$ Norm), -4.6022 (PM_{10} Norm), -5.1147 (IMD Score Norm), 19.304 (HSP), 19.523 (SL), 28.534 (VT), and 11.829 (Other), with Victorian Terraces' high value consistent with a housing-type signal but not direct evidence of measured energy efficiency. The previously reported power diagnostic has been reinterpreted: its low value indicates limited sample-level detection capability rather than confirmation of strong predictive power. Prediction intervals showed a LOOCV MSE of 85.38 with a 157.64% width, indicating high uncertainty. The coefficients and confidence intervals for the preferred additive specification are summarised in Table 2. The VIF, bootstrapped coefficient and residual diagnostic outputs are presented in Figure 6, Figure 7 and Figure 8, respectively.

Table 2. Regression results for the additive Model 14.

Predictor	Coefficient	p-Value	95% Lower CI	95% Upper CI
(Intercept)	16.2243	0.0023	6.3590	22.6287
High Street and Promenades	9.0606	0.2768	0.0000	19.0787
Suburban Landscapes	5.4575	0.3013	-1.6082	13.9881
Victorian Terraces	12.4505	0.0308	4.9817	21.6945
Other	-0.0300	0.9796	-9.0648	9.2958
$PM_{2.5}$ Norm	-4.1838	0.0608	-8.2807	0.0358
PM_{10} Norm	-1.2345	0.1089	-2.7890	0.5678
IMD Score Norm	2.7431	0.0183	0.4879	4.9983

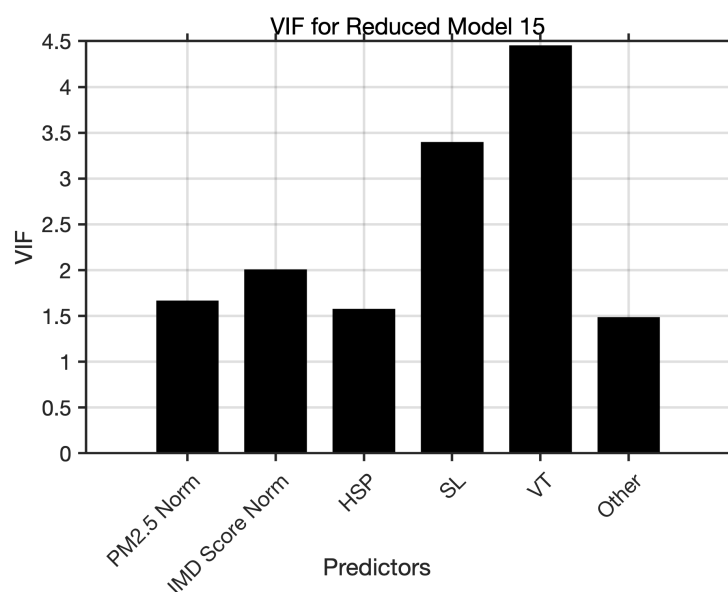


Figure 6. Variance inflation factors for additive Model 14 predictors.

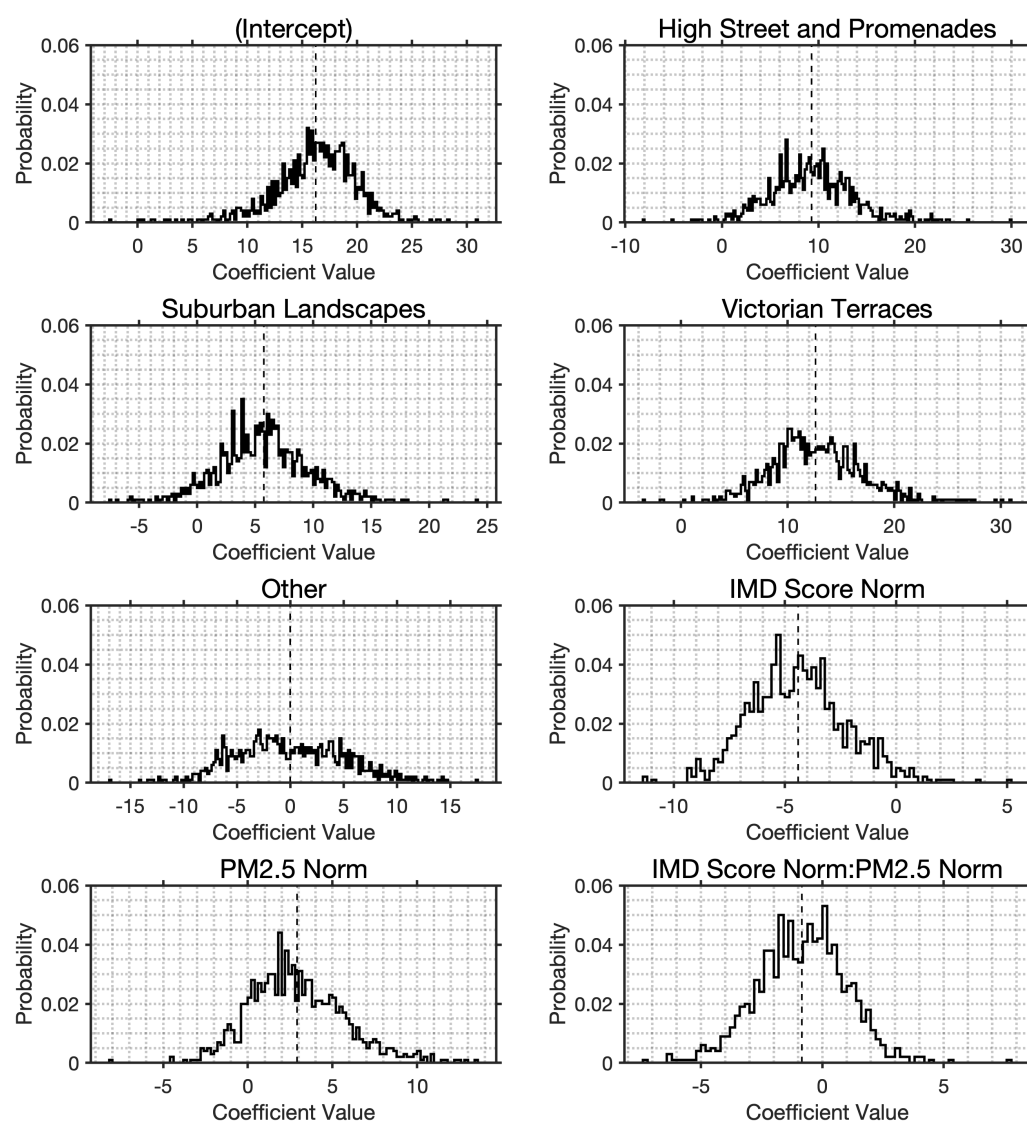


Figure 7. Bootstrapped coefficient distributions for additive Model 14.

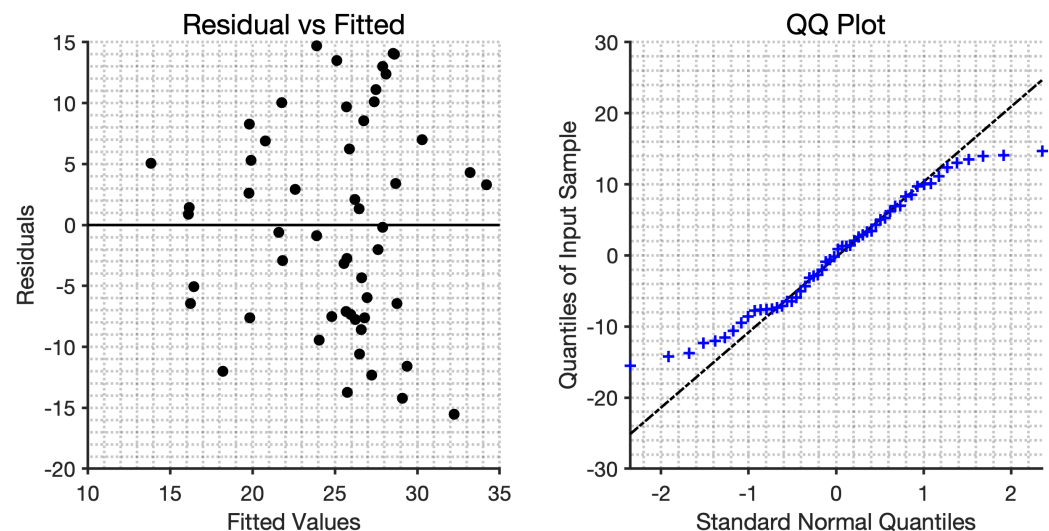


Figure 8. Residual diagnostics for additive Model 14: **(left)** Residual vs. Fitted; **(right)** QQ Plot.

3.3. Physical Interpretations of Local Areas

The spatial and regression analyses provide a comprehensive understanding of local variations in fuel poverty across Liverpool's 54 wards, revealing how socio-economic deprivation, air pollution, and housing type co-occur to shape energy insecurity. In central wards like City Centre North (13.24% fuel poverty) and City Centre South (15.08% fuel poverty), characterized by CBD and OT housing, lower IMD scores (16.30 and 14.21) mitigate fuel poverty despite high $PM_{2.5}$ (11.41 and 11.33 $\mu g/m^3$), consistent with the negative $PM_{2.5}$ coefficient (-4.1838 , $p = 0.0608$). Conversely, northern wards like Princes Park (25.29% fuel poverty) and Knotty Ash & Dovecot Park (24.81% fuel poverty), dominated by VT and high IMD (32.35 and 35.32), show elevated rates, amplified by the IMD effect ($p = 0.0183$). Suburban wards like Grassendale & Cressington (17.53% fuel poverty) and Wavertree Garden Suburb (22.9% fuel poverty), with lower pollution (5.09 $\mu g/m^3$ $PM_{2.5}$), face challenges from SL housing, which may be consistent with higher heating demand, although EPC or insulation data would be needed to verify this mechanism directly. Speke (20.08% fuel poverty), with high PM_{10} (30.46 $\mu g/m^3$), reflects industrial impacts, while Waterfront North (12.9% fuel poverty) may benefit from newer housing stock ($p = 0.018$). Ridge regression's 28.534 coefficient for Victorian Terraces and the 157.64% prediction interval width support the case for prioritising retrofit assessment in high-deprivation zones.

4. Discussion

The findings expose a stark environmental injustice in Liverpool, where wards like Princes Park and Knotty Ash & Dovecot Park endure fuel poverty rates up to 25.29%, associated with high deprivation (IMD up to 35.32), pollution ($PM_{2.5}$ up to 12.15 $\mu g/m^3$), and older terraced housing typologies that may be vulnerable to heat loss, although EPC ratings and insulation data were not available in this study. This aligns with wider evidence showing that particulate exposure and socio-economic disadvantage can cluster spatially rather than acting as isolated risks, including recent Liverpool-specific evidence linking particulate exposure, deprivation and child-health burden [12,13,15,18,20,21]. This crisis is associated with substantial health burdens and economic impacts [7,19]. The additive model, preferred for its lower AIC (396.10) and BIC (412.02) over the interaction model (397.38, 417.27), explains 43.5% of variance ($p = 0.000639$), with IMD as the dominant correlate ($p < 0.001$) and Victorian Terraces significant ($p = 0.0308$, coefficient = 12.4505). Ridge regression (lambda = 0.0100) aligns with this, showing a 28.534 coefficient for VT, but is interpreted only as a stability check rather than as additional causal evidence. However,

the low post-hoc power diagnostic and a 157.64% prediction interval width ($MSE = 85.38$) highlight data constraints, suggesting precision could improve with larger samples.

Targeted building retrofits, especially for Victorian Terraces in high-IMD wards, can reduce energy costs and health burdens, aligning with the UK Fuel Poverty Strategy and Liverpool's retrofit programmes; comparable schemes indicate that a 5000 investment per home can yield around £300–£500 in annual energy bill savings [24]. In Liverpool, this means that the results should be used to support area-based retrofit planning, housing-association investment cases and external wall insulation or fabric-first interventions in older terraced neighbourhoods, rather than as a stand-alone prediction tool for individual buildings. Emission controls in industrial areas like Speke ($PM_{10} = 30.46 \mu g/m^3$) are critical, while newer and better-performing housing stock, as seen in Waterfront North (12.9% fuel poverty), offers a useful comparison for policy learning. This sustainability framing is important because well-targeted retrofit can simultaneously address energy affordability, health protection, neighbourhood inequality and reduced energy demand. The stability from ridge regression and significant IMD effect support these priorities, though the wide prediction interval calls for refined data collection to enhance accuracy. Future research should leverage building-level data (e.g., EPCs, heating systems), denser sensor networks and spatial modelling approaches using explicit ward adjacency or distance-weight matrices to address the uncertainty, ensuring precise interventions.

While the findings provide valuable insight into the socio-environmental drivers of fuel poverty in Liverpool, several limitations must be acknowledged. First, the analysis is constrained by the ward-level aggregation of data ($n = 54$), which inevitably limits statistical power and the granularity of inference. The models should therefore be read as explanatory and prioritisation tools, not as high-precision prediction models. Although consistent effect directions across models, ridge regression stability, and bootstrapped confidence intervals lend robustness, larger samples or building-level data would enhance reliability. Second, the use of the overall IMD score may introduce overlap with fuel poverty and housing conditions because IMD includes income, housing-related barriers and living-environment components. This limitation does not invalidate IMD as a contextual deprivation measure, but it means that the estimated coefficient should not be interpreted as a fully independent causal effect. Third, the temporal alignment is imperfect: fuel poverty reflects 2022 data, whereas PM exposure is measured from the 2023 sensor record. The analysis therefore represents a near-contemporary spatial comparison rather than a longitudinal causal test. Fourth, possible spatial autocorrelation remains a limitation because a spatial weights matrix was not available for robust spatial econometric modelling. Fifth, some counter-intuitive results, such as negative coefficients for $PM_{2.5}$, likely reflect the spatial co-location of higher pollution with newer urban housing typologies, rather than a protective effect of pollution itself. These relationships warrant careful interpretation and confirmatory analysis in other contexts. Finally, while the study identifies priority housing clusters (e.g., Victorian Terraces) for retrofit investment, the absence of building-level performance indicators (e.g., EPC ratings, insulation type, heating systems) prevents detailed technical prescription. Despite these constraints, the results highlight clear, actionable levers: deprivation, housing typology, and localised emissions. These levers can inform targeted energy retrofit and pollution control strategies in line with UK fuel poverty and energy efficiency policy frameworks and with wider urban sustainability objectives.

5. Conclusions

Fuel poverty in Liverpool reveals a pressing environmental injustice, with wards such as Princes Park (25.29%) and Knotty Ash & Dovecot Park (24.81%) showing elevated fuel poverty alongside high deprivation, pollution, and Victorian Terraces. The additive model,

avored by lower AIC (396.10) and BIC (412.02), explains 43.5% of variance ($p = 0.000639$), with IMD as a key correlate and Victorian Terraces significant ($p = 0.0308$). Ridge regression ($\lambda = 0.0100$) supports the stability of the housing-type signal, motivating targeted retrofit assessment rather than untargeted intervention. Low power and wide prediction intervals signal the need for larger datasets, but current evidence supports spatially targeted policy action under national policy and local programmes to enhance energy security and deliver more equitable urban sustainability outcomes.

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Appendix A. Wards

The following is a comprehensive list of the 54 electoral wards of Liverpool included in this study, based on data availability from sensor locations and ward-level aggregations:

1. Aigburth
2. Allerton
3. Anfield
4. Arundel
5. Belle Vale
6. Broadgreen
7. Brownlow Hill
8. Childwall
9. Church
10. City Centre North
11. City Centre South
12. Clubmoor East
13. Clubmoor West
14. County
15. Croxteth
16. Croxteth Park
17. Dingle
18. Edge Hill
19. Everton East
20. Everton North
21. Everton West

22. Fazakerley East
23. Fazakerley North
24. Fazakerley West
25. Festival Gardens
26. Garston
27. Grassendale & Cressington
28. Kensington & Fairfield
29. Kirkdale East
30. Kirkdale West
31. Knotty Ash & Dovecot Park
32. Linacre
33. Litherland
34. Mossley Hill
35. Netherley
36. Norris Green
37. Old Swan
38. Orrell Park
39. Picton
40. Princes Park
41. St. Michaels
42. Seaforth
43. Sefton Park
44. Speke
45. Springwood
46. Stoneycroft
47. Toxteth
48. Vauxhall
49. Walton
50. Waterfront North
51. Waterfront South
52. Wavertree Garden Suburb
53. West Derby
54. Woolton

Appendix B. Regression Model Outputs

Table A1. Updated summary of regression model outputs (normalized predictors). Significant coefficients include boot CIs.

Model	Equation	R ²	Adj. R ²	F	<i>p</i> -Value	AIC	Significant Coefficients (SE, <i>p</i> -Value)
1	Prop. Fuel Pov. 1 + IMD Score	0.281	0.267	20.3	3.81×10^{-5}	285.0	IMD: 0.31656 (0.0703, <0.001)
2	Prop. Fuel Pov. 1 + PM _{2.5}	0.126	0.109	7.49	0.00845	295.0	PM _{2.5} : −0.69937 (0.2552, 0.008)
3	Prop. Fuel Pov. 1 + PM ₁₀	0.063	0.045	3.5	0.0671	300.0	PM ₁₀ : −0.2437 (0.1302, 0.067)
4	Prop. Fuel Pov. 1 + IMD Score + PM _{2.5}	0.309	0.281	11.4	8.19×10^{-5}	282.0	IMD: 0.27579 (0.0712, <0.001)
5	Prop. Fuel Pov. 1 + IMD Score + PM ₁₀	0.294	0.265	10.6	0.000137	283.5	IMD: 0.29767 (0.0715, <0.001)
6	Prop. Fuel Pov. 1 + PM _{2.5} + PM ₁₀	0.157	0.123	4.74	0.013	292.0	PM _{2.5} : −1.4622 (0.6182, 0.021)

Table A1. Cont.

Model	Equation	R ²	Adj. R ²	F	p-Value	AIC	Significant Coefficients (SE, p-Value)
7	Prop. Fuel Pov. 1 + IMD Score + PM _{2.5} + PM ₁₀	0.315	0.272	7.68	0.000258	281.0	IMD: 0.26368 (0.0772, 0.001)
8	Prop. Fuel Pov. 1 + IMD Score + Cluster	0.416	0.344	5.58	0.000197	275.0	IMD: 0.30827 (0.0710, <0.001)
9	Prop. Fuel Pov. 1 + PM _{2.5} + Cluster	0.257	0.164	2.7	0.0245	288.0	PM _{2.5} : −0.59647 (0.2735, 0.034)
10	Prop. Fuel Pov. 1 + PM ₁₀ + Cluster	0.237	0.142	2.44	0.0391	289.5	PM ₁₀ : −0.24212 (0.1305, 0.069)
11	Prop. Fuel Pov. 1 + IMD Score + PM _{2.5} + Cluster	0.434	0.347	5.05	0.000266	273.0	IMD: 0.28122 (0.0718, <0.001)
12	Prop. Fuel Pov. 1 + IMD Score + PM ₁₀ + Cluster	0.431	0.343	4.98	0.000299	273.5	IMD: 0.28868 (0.0715, <0.001)
13	Prop. Fuel Pov. 1 + PM _{2.5} + PM ₁₀ + Cluster	0.260	0.155	2.31	0.0415	287.0	None significant
14	Prop. Fuel Pov. 1 + IMD Score + PM _{2.5} + PM ₁₀ + Cluster	0.435	0.333	4.32	0.000639	272.5	IMD: 0.28022 (0.0720, <0.001)
15	Prop. Fuel Pov. 1 + Cluster + PM _{2.5} + PM ₁₀ + IMD Score + PM _{2.5} : IMD Score + PM ₁₀ : IMD Score	0.535	0.413	4.94	9.5×10^{-5}	267.91	PM _{2.5} : IMD: 0.40861 (0.1412, 0.005), PM ₁₀ : IMD: −0.17724 (0.0715, 0.016), Cluster_WS: −7.8987 (3.250, 0.018)

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