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The determinants of double energy vulnerability: A geospatial analysis

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Abstract

This paper examines the spatial and social differences in people's lack of access to adequate energy and transport services in the UK. We respond to the need for developing a differentiated understanding of both the drivers and expressions of this 'double energy vulnerability' (DEV), while seeking to integrate and analyse relevant information from all four UK nations. Using a variety of statistically representative census and survey datasets, the paper develops a series of multi-dimensional indices to map transport- and energy-related injustices. This is followed by a cluster analysis to examine broad-level geographical patterns, and a Geographically Weighted Regression (GWR) model to explore the spatial variation of vulnerabilities related to contingencies such as income, ethnicity and housing. The paper corroborates the results of previous qualitative studies, and research within selected UK nations, while revealing several unexpected territorial clusters and underpinnings of infrastructural injustice. DEV is shown to disproportionately affect coastal, highland, peripheral and rural regions, with an internal granularity that exhibits high levels of variation within urban and peri-urban settings.

KEYWORDS

cluster analysis, energy poverty, Geographically Weighted Regression, spatial inequality, transport poverty, United Kingdom

1 | INTRODUCTION

The intersections among different types of infrastructure provision-related injustices in the Global North are gaining increasing scientific and policy attention. It is now increasingly recognised that some places and groups of people are

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adversely affected by overlapping transport- and energy-related injustices. The resultant 'double energy vulnerability' (DEV) (Simcock et al., 2021a) is underpinned by the inability to attain socially and materially needed levels of energy services (such as heating and cooling) and transport services (such as everyday mobility and access to essential amenities). Households who simultaneously experience energy and transport hardship are exposed to structurally embedded inequalities in the design and regulation of socio-technical systems aimed at enabling the consumption of energy and movement of people through the urban and regional fabric (Lowans et al., 2023). Therefore, DEV is the expression of interlocking policy choices and governance practices concerning the organisation of social and environmental systems as a whole (Middlemiss, 2022).

To date, research on the socio-spatial drivers, components and impacts of DEV—and other associated vulnerabilities—has been relatively limited. Relevant scholarship and policy initiatives have been primarily concentrated in a few countries in the Global North (Simcock et al., 2021a). Within this setting, there is a broad understanding of the types of social groups and spatial settings that may experience a higher combined incidence of energy poverty (EP) and transport poverty (TP). The existing body of scholarship, however, displays a relatively limited understanding of the sub-national spatial variations of EP and TP, particularly as they relate to existing and emergent socio-technical vulnerabilities (Sareen et al., 2020). It remains unclear how different types of housing structures, settlement typologies and regional inequalities jointly shape such socio-technical precarities (Martiskainen et al., 2023). Understanding the geographies of DEV is particularly relevant in the context of social inequalities that have received limited scientific and political recognition in both policy and practice—in terms of gender, ethnicity and housing tenure (Mashhoodi & Bouman, 2023).

This paper speaks to existing knowledge gaps in the EP, TP and DEV literature. Focusing on the entirety of the UK—where analyses including all four constituent nations have been rare due to divergent governance and monitoring frameworks (but see, e.g., Martiskainen et al., 2023)—our primary aim is to uncover the shared social and spatial tapestries of these two predicaments across different socio-demographic, urban and regional typologies. A second aim of the paper is to investigate the geographic clusters that can be observed when such infrastructural inequalities are cross-referenced with other forms of social injustice, in terms of specific demographic and housing characteristics. Thirdly—and underpinning the first two aims—we develop and test multi-dimensional indices that can capture infrastructural inequalities associated with the lack of access to adequate energy and transport services, and the resultant territorial variations that emerge. Here, and in line with the existing literature on the topic, 'adequate' is taken to mean an amount and quality of energy services that can enable 'participating in the lifestyles, customs and activities that define membership of society' (Bouzarovski & Petrova, 2015, p. 32) We seek to create a fine-grained and nuanced picture of DEV in the UK—based on statistically representative and comprehensive quantitative data—as a basis for developing broader scientific and policy recommendations aimed at tackling the underlying drivers of these conditions.

In articulating our analysis, we build on growing calls to unpack how different forms of energy and transport disadvantage are not the outcome of individual household behaviours and choices (Day et al., 2016). Rather, they are embedded in deeper and broader societal expectations and political decisions about how energy should be consumed, what housing should look like, and how people should move within and among settlements (Mattioli et al., 2020). In that sense, one of our key starting points is the intersectional nature of socio-geographical vulnerabilities—we posit that the injustices faced by households who struggle to attain adequate energy and mobility services are nested in, and enacted across, multiple layers of geographical, economic and demographic inequality (Middlemiss, 2022). The groups suffering from these forms of hardship are seldom heard and represented in mainstream debates (Simcock et al., 2021a) and there is limited recognition of the multiple trade-offs they face in negotiating energy-inefficient homes, high energy and fuel prices, low incomes, as well as the lack of public transport and active travel provision (Burlinson et al., 2022). Here, we speak to the emergent body of scholarship that has sought to untangle the spatial disaggregation of these challenges, developing context-sensitive typologies that unsettle conventional binaries (such as core–periphery, or urban–rural places) (Pelz et al., 2018). To that end, we extend research studies that have used multi-dimensional indices (Sokołowski et al., 2020) to determine the character and distribution of EP and TP across different social and spatial settings.

Apart from this introduction and the conclusion, the paper consists of four sections. We first outline the methodology of the study, describing the data collection and analysis process, and the construction of two customised multi-dimensional indices. We then use the same indices to examine the multi-scalar geographies of energy and transport variabilities in the UK and its constituent nations of England, Northern Ireland (NI), Scotland and Wales. The third section delves deeper into the combined spatial patterns revealed by the indices, while exploring their broad-level distributions. Subsequently, we use a multivariate GWR model to investigate how different forms of social vulnerability underpin differences in the territorial expression of EP and TP. The conclusion returns to the aims of the paper, while identifying further areas for research and policy.

2 | METHODOLOGY

The quantification, modelling and mapping of vulnerabilities to EP and TP undertaken for the purposes of this study were all predicated upon the development of robust EP and TP measurement frameworks. As a first step, a combination of statistical data—including socio-demographics, housing, transport, energy use characteristics of households, and transport accessibility information—were compiled and processed to provide a comprehensive evidence base. We conducted an extensive audit of the UK's energy, transport and socio-demographic statistics available at the lower super output area (LSOA) scale in England and Wales, with data zones (DZs) being used for Scotland, and super output areas (SOAs) for NI. These are units of a comparatively similar size: on average, LSOAs, DZs and SOAs contain 1,614, 784 and 2,100 people, respectively (National Records of Scotland, 2013; Northern Ireland Statistics and Research Agency, 2019; Office for National Statistics, 2012). Here, it is worth noting that good quality disaggregated data at the neighbourhood scale are difficult to find, with some of the information being outdated, or—in most cases—inconsistent across the four nations of the UK. Moreover, LSOAs, DZs and SOAs themselves contain a great deal of internal variation that remains undetected when considering average values across each unit.

In the absence of consistent EP and TP indicators for the whole of the UK, we constructed two unique metrics covering England, Wales, Scotland and NI. The key constituent datasets for the composite indicators were shortlisted based on a review of previous work on EP and TP indicators in England and Wales (e.g., Robinson & Mattioli, 2020). We carefully considered the multiple drawbacks, challenges and advantages offered by multidimensional measures, with regard to interplays among intersectionality dimensions and index component weightings in particular (Everuss, 2019; Greco et al., 2019; Weintrob et al., 2021). This was accompanied by an extensive data audit, which revealed that the reliability, completeness and representativeness of relevant data in England and Wales were the greatest, although it was possible to obtain sufficient information for Scotland and NI too.

The EP metric included three dimensions: central heating coverage (sourced from the 2011 Census), energy efficiency (as the share of properties with an Energy Performance Certificate below band D, sourced from the Department of Business, Energy, and Industrial Strategy—BEIS, the Energy Savings Trust, and the Department for Communities in NI) as well as social vulnerability (including total equivalised household energy costs—from BEIS and customised surveys, and income—from the 2011 Experian Income dataset, one of the few relevant databases for the provision of detailed weekly and annual income information at the local scale). The complexity of our data requirements meant that the 2011 Census was the most recent complete dataset available.

The TP metric was constructed based on inadequate access to mobility services (by different travel modes) and social vulnerability. This pinpoints the areas that experience a combination of low car ownership, poor public transport provision and low population density (as a proxy for accessibility by active travel), as well as low incomes. The metric primarily captures the 'access' dimension of TP (i.e., the 'mobility capital' available to the residents of the area), as well as (indirectly, through the inclusion of income) the affordability dimension (Mattioli, 2021). In developing the measure, we combined Census data on car ownership and population density with a newly constructed metric of public transport access (PTA), based on the National Public Transport Access Nodes (NaPTAN) dataset—which includes all public transport stops in England, Scotland and Wales—alongside additional data from NI. NI's transport system is based on public bus stops and rail halts. In producing a consistent measure of access to public transport across the UK, NI was used as the lowest common denominator and all relevant locations selected across the UK.

Each public transport stop was mapped and used as a feature layer for Network Analysis Service Areas in ArcGIS Pro software. A walking time of 10 minutes from each public transport stop was calculated following accessibility measures used by Transport for London (TFL 2015). The number of 10-minute walking bands intersecting the population weighted centroid for each census zone was calculated to determine the density of public transport in each census zone. Population density was also calculated for all UK census zones as the number of people in each zone divided by the area (hectares) of the zone. Example cities with more than 150 public transport stops intersecting population-weighted census zones included Glasgow, Manchester, Cardiff and Belfast (Figure 1).

The weighting of the TP index was based on the assumption that in a highly motorised and car-dependent country like the UK access to cars has more bearing on access to services and opportunities than alternative modes such as public transport (captured by the PTA metric) and walking and cycling (captured by population density as a proxy). In line with previous work on multi-dimensional indices (Ulucak et al., 2021), we standardised the constituent elements of the composite measures to z scores and applied different weightings to them, based on theoretical considerations (Bouzarovski & Tirado Herrero, 2017).

FIGURE 1 Ten minutes' walking time with National Public Transport Access Node (NaPTAN) stops for a data zone in Glasgow (City Centre South—04).

$$\text{EP index (EPI)} = \text{lack of central heating } (25\%) + \text{energy cost } (25\%) + \text{inefficient housing } (25\%) - \text{income } (25\%)$$

$$\text{TP index (TPI)} = -\text{PTA } (16.6\%) - \text{population density } (16.6\%) - \text{car ownership } (33.3\%) - \text{income } (33.3\%)$$

$$\text{DEV index} = \text{EPI } (50\%) + \text{TPI } (50\%)$$

Income was assumed to impact the affordability of transport and energy as a whole—hence it was 'double counted' in the final DEV index. The DEV index was standardised using *z* scores. To test the robustness of our indicators, the composite measures were compared with established metrics that are available for some of the regions that they cover. At the LSOA level in England and Wales, a Pearson correlation indicated a moderate positive r value of 0.508 ($p < 0.001$) between the EPI and 10% EP indicator (whereby EP is defined through the need to spend more than 10% on energy services; see Hills, 2012), and a similar positive r value of 0.545 ($p < 0.001$) for the low income high cost indicator (or LIHC—which states that EP occurs if required fuel costs are above the national median, while residual income after the same falls below the official poverty line; ibid.). Similarly, a Pearson correlation between the TPI and Mattioli et al.'s (2019) fuel price vulnerability indicator indicated a moderate positive r value of 0.531 ($p < 0.001$) for English LSOAs.

3 | SPATIAL PATTERNS OF EP AND TP IN THE UK

Across the UK, the mean EPI values for each region were relatively consistent, though Wales had the highest average and England had the largest range of values (Table 1). There were clear spatial variations across the UK, even if rural areas had greater overall risk. At the same time, pockets of risk occurred in urban areas. Wales has the highest overall average

TABLE 1 Summary energy poverty index (EPI) and transport poverty index (TPI) statistics for each UK region (Count: England = 32,884; Scotland = 6976; Wales = 1909; NI = 890).

Indicator	UK country	Mean	Minimum	Maximum	Range
EPI	England	0.203	−0.056	0.461	0.517
	NI	0.203	0.000	0.382	0.382
	Scotland	0.206	−0.032	0.432	0.464
	Wales	0.220	0.000	0.386	0.387
TPI	NI	0.248	−0.93	1.03	1.96
	Wales	0.217	−1.54	1.1	2.64
	England	0.023	−2.85	1.47	4.32
	Scotland	−0.199	−4.11	1.4	5.51

in the UK, ranging from 0.38 to 0.03. Within Wales, rural areas registered the highest scores, though towns in rural locations were less at risk (e.g., Merthyr Tydfil). Within urban areas, such as the Swansea to Newport corridor along the south coast, a variation from high risk to low risk was observed.

Scotland recorded the highest EPI averages for all rural areas, though 'very remote small towns' had the highest mean EPI score (0.246). 'Large urban areas' and 'other urban areas' were characterised by the lowest mean EPI scores (0.197 and 0.199, respectively). Rural areas tended to have a lower range of EPI values than urban areas (e.g., Edinburgh, Glasgow and Aberdeen). Values were similar for NI, with the highest value noted in a rural area, while the major urban areas of Belfast and Derry had lower averages. As with the rest of the UK, there was significant variation of scores within urban areas such as Belfast. Numerous SOAs were affluent yet had high EPI values (e.g., Malone). This may be due to large, detached dwellings with low energy efficiency ratings.

England displayed the widest range of EPI values, ranging from 0.46 (Barrow in Furness) to −0.055 (North Somerset). Rural and northern regions registered higher EPI results while urban areas had lower values, though there was spatial variation across all settlement types. This distribution echoes the findings of previous studies (Robinson et al., 2018) whereby rural areas recorded higher mean EP scores for both the LIHC and 10% indicators. The only divergent result in our study was the North East. Its average of 0.198 is comparable with the South East, and lower than both the South West and East of England—areas that were found to experience a lower risk in both the 10% and LIHC indicators by Robinson et al. (2018).

The regional distribution of the TPI was not dissimilar to that of the EPI (Table 1). As with the energy metric, there was significant variation in values across different regions and settlement types. NI had the highest overall average in the UK. Within NI, urban areas tended to have higher average TPI scores (0.29) compared with rural areas (0.26). Derry City and medium-sized towns (such as Strabane and Limavady), with lower incomes and lower levels of car ownership, had higher scores.

Wales had the second-highest average TPI score. Within Wales, the highest value was found in Newport, with Cardiff recording the lowest score. At the regional level, Conwy experienced the highest risk within the whole of Wales. Small towns and villages in rural settings had the highest average TPI scores, displaying the lowest range of values. Larger conurbations and towns had the lowest average TPI scores, and the largest range of values. These results suggest that rural areas had a greater risk of TP than urban areas, though there were pockets of TP within all settlement types.

Scotland had by far the lowest average TPI score of all regions. The TPI in Scotland established a distinct group of settlement types with lower average scores in urban areas, and higher average scores in the most remote areas. The highest TPI value (1.4) occurred in Toryglen and Oatlands, Glasgow, while the lowest score occurred in Whitburn, Croftmalloch and Greenrigg, between Motherwell and Edinburgh. The highest rural TPI score was found in Doon Valley South—a remote rural area with a low population density and limited provision of public transport.

England had a relatively low average TPI value, with a relatively wide range—the lowest risk occurred in Kensington and Chelsea, London. Regional urban centres with better transport connectivities, along with major urban areas, had low average TPI scores. However, corresponding values were high in major urban conurbations. As a whole, values were low in London and the South East (>14), while other regions—particularly in the North of England—experienced higher vulnerabilities. Our results for England correspond, broadly, to Mattioli et al.'s (2019), who identified large inter-regional inequalities in vulnerability to fuel price increases. They detected lower values in the South East and London, versus higher ones in the South West, East Midlands and the West Midlands.

4 | THE (UN)EXPECTED GEOGRAPHIES OF DEV

Combining the TPI and EPI measures allowed for generating a DEV index for the entire UK (Table 2). Values ranged from a maximum of 3.466 (Newcastle upon Tyne, England) to −0.583 (Whitburn, Croftmalloch and Greenrigg, Scotland). The geographies of DEV displayed a distinct broad-level pattern—economically peripheral, low-income and physically remote areas are characterised by higher values, while the outskirts of prosperous urban areas are among the least vulnerable. This general spatial distribution, however, conceals a great deal of internal, fine-grained variation.

NI recorded the highest overall average of DEV in the UK, ranging from −2.391 (Jordanstown) to 2.433 (Colin Glen), but also the smallest range, suggesting fewer outliers of risk. Within NI, rural areas displayed greater DEV risk than urban areas, even if the latter—including medium and large towns—contained pockets of higher-risk areas. This pattern of increased DEV in rural areas is consistent with the one found by Robinson and Mattioli (2020) within England.

Wales had the second-highest DEV values. Within Wales, towns and villages in low population density settings exhibited the highest scores, though urban centres in similar areas (Carmarthen, Aberystwyth, Milford and Holyhead) also had a high average. A number of distinct rural and suburban areas, however, had lower DEV scores—they tended to be concentrated along the north and south coasts, in relatively close proximity to larger cities such as Cardiff, Newport, Swansea, Wrexham and Bangor. Internally, cities and towns manifested the greatest range of values, while rural areas in low-density settings expressed the lowest range, suggesting risk was relatively uniform in these settlement types.

England had middle-average DEV scores compared with other countries, with values ranging from −6.840 (Kensington and Chelsea) to 3.466 (Newcastle upon Tyne). England's highest average DEV score was found in urban centres located amidst otherwise relatively thinly populated areas: Minehead (Somerset), Penrith (Cumbria), Berwick-on-Tweed (Northumberland) and Whitby (North Yorkshire). Larger towns and villages in rural locations had lower average DEV scores, along with major urban areas. The greatest range of DEV values occurred in urban areas.

Scotland had the lowest overall average DEV score in the UK, ranging from −9.583 (Whitburn, Croftmalloch and Greenrigg) to 2.916 (Toryglen and Oatlands). We attribute this somewhat surprising finding to particularly low TPI values. Scotland's highest DEV averages were recorded in rural areas, with remote regions exhibiting the highest mean DEV scores. Urban areas experienced the lowest average DEV values, although we found a high range of values in larger cities. Rural regions exhibited a lower range of DEV values compared with metropolitan centres such as Edinburgh, Glasgow, Dundee and Aberdeen.

To test these results further, we estimated Ordinary Least Square (OLS) and GWR models. OLS uses a single regression equation for the total dataset, whereas GWR allows for local spatial variation by fitting a regression equation to each LSOA. This can be articulated using the equation:

$$y_i = a_0 u_i, v_i + \sum_k a_k u_i, v_i x_{ik} + \varepsilon_i$$

where y_i is the DEV score, and u_i, v_i represents the coordinates of the ith point in space (each census zone population-weighted centroid), $a_k\ (u_i, v_i)$ is a continuous function $a_k\ (u, v)$ at each point i and ε_i is the error term (Charlton & Fotheringham, 2009; Fotheringham et al., 2002).

Model performance was evaluated by comparing three indicators: adjusted R^2, Akaike information criterion (AIC) and the spatial distribution of the residuals (Global Moran's I). Robinson et al. (2018) and Mashhoodi and Bouman (2023) found that GWR models better explained variations in EP and energy consumption than traditional OLS models.

TABLE 2 Summary double energy vulnerability (DEV) statistics for each UK country.

Region	Mean	Minimum	Maximum	Range
NI	0.561	−2.391	2.433	4.824
Wales	0.531	−3.4639	2.525	5.9889
England	0.049	−6.84	3.466	10.306
Scotland	−0.451	−9.583	2.916	12.499

TABLE 3 OLS and GWR models.

Variable	OLS model Coefficient est	SE	*t*-statistic	VIF	GWR model Coefficient est. Mean	Coefficient est. SD
Intercept	−2.3873	0.02	−105.80	–	−2.2207	1.0677
Age > 60	1.8631*	0.07	25.52	4.05	0.5242	2.2578
Disability	3.4988*	0.06	55.81	3.21	4.1987	2.1872
Private rentals	0.8165*	0.03	23.59	1.56	1.1015	1.4298
Unemployment	1.6508*	0.06	29.12	3.56	1.9487	1.3218
Lone parent	2.3781*	0.07	35.83	2.93	1.7493	1.8241
Ethnic minority	−0.1210*	0.03	−4.60	1.50	−1.0803	4.3585
N	42,453				42,453	
AIC	98,016.74				71,983.85	
Adjusted R^2	0.4109				0.7045	
Moran's I	0.4335*				−0.0224*	
Joint Wald statistic	21,323.24*					
Koenker (BP) statistic	1214.96*					
Jarque-Bera statistic	38,507.26					

*OLS coefficients significant at $p < 0.001$.

Of the statistics output by the OLS model, the variance inflation factor (VIF) was <7.5 for each independent variable, suggesting low collinearly (Song et al. 2021). Both the Koenker (BP) and joint Wald statistics were significant (p <0.001), suggesting statistically significant heteroscedasticity and/or non-stationarity, and a statistically significant model, warranting further analysis using GWR. The Jarque-Bera was also statistically significant, indicating that the residuals were not normally distributed. All estimated coefficients were significant.

Given variations in the density of census zone distribution, an adaptive (Gaussian) kernel was used for GWR, with the corrected AIC method to predict the optimal bandwidth, generating a parameter of 31. The GWR model outperformed the OLS model with an increased adjusted R^2 (GWR = 70.4%; OLS = 41.1%), a lower AIC value (GWR = 71,983.85; OLS = 98,016.74), implying a better model fit, and a Global Moran's I value closer to zero (GWR = −0.022; OLS = 0.434), indicating much reduced spatial autocorrelation in the residuals. The GWR models suggested significant spatial variation in DEV across the UK (Table 3).

5 | SOCIO-SPATIAL INEQUALITIES UNDERPINNING DEV

A Global Moran's I value of 0.422 (z = 361.88, p = 0.001) indicated moderate autocorrelation in the distribution of DEV. Local Moran's I was carried out to investigate local spatial clustering of DEV across the four UK regions. This process identified four distinct spatial clusters, showing, comparatively, how areas of high or low concentration of the index compared with regions around them (Figure 2).

We found that the majority of ‘high-high’ clusters were in major urban areas (62%), possibly due to the fact the vast majority of LSOAs across the UK are classed as urban. However, many smaller towns and villages (approximately one fifth of all the settlements within this settlement type) were also classed as ‘high-high’. While rural areas had high concentrations of DEV, they were generally small and occupied fewer than 10% of all ‘high-high’ clusters. The majority of ‘low-low’ clusters (approximately 86%) were also in urban areas, with a small number of rural areas also belonging to this category. A similar trend was observed for the ‘high-low’ outliers—80% of them occurred in major urban areas. Smaller towns and villages in rural regions were mainly characterised as ‘Low-High’ outliers, even though, once again, the vast majority occurred in major urban areas. As a whole, Wales and NI had the largest number of census zones (63%) classified as high-high risk. In England, 29% of LSOAs were categorised as ‘high-high’ clusters, across all regions. Scotland had the greatest proportion of outliers, with 14% of DZs categorised as ‘high-low’ clusters.

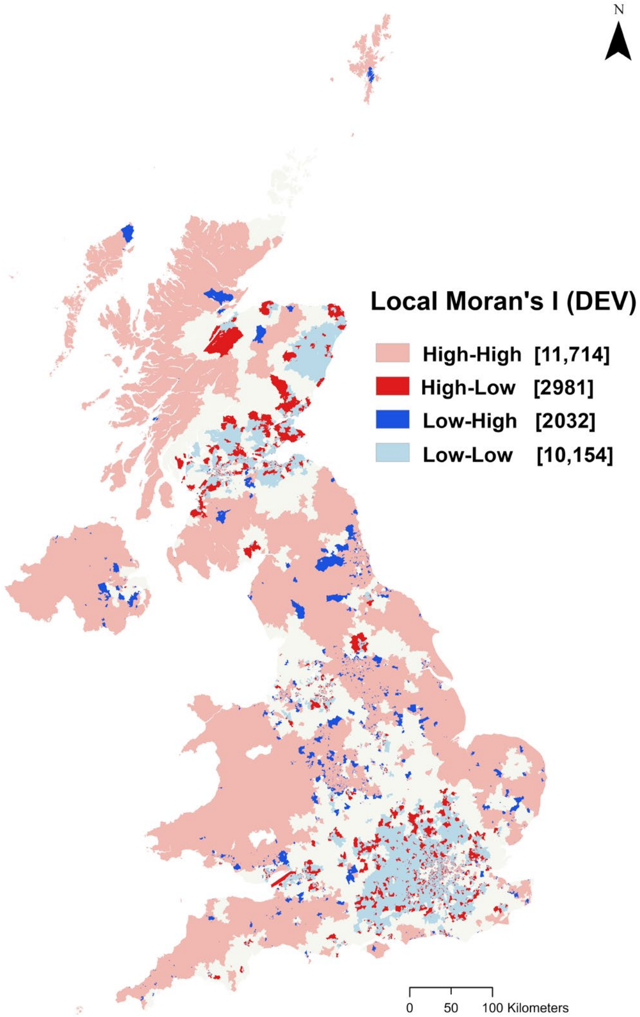

FIGURE 2 Clusters of double energy vulnerability (DEV) across the UK. Only statistically significant coefficients ($p < 0.05$) are shown.

The GWR model allowed us to generate multiple cartographic representations of the relationship between the DEV index and various socio-demographic determinants. Due to constraints on space, we show here only one set of maps depicting the full range of DEV coefficients (Figure 3).

Disability exhibited the strongest positive association with DEV in the model, indicating a close relationship between households with a member with a disability, on the one hand, and combined EP and TP, on the other. Areas of highest coefficients were predominantly urban (95%) and peri-urban. Our findings confirm earlier results reported by Robinson et al. (2018) who identified strong correlations between areas with greater disability rates and EP in urban areas, particularly across the North of England, the Midlands, London and Southampton. These patterns were mirrored in our analysis, with high coefficients in the North West, West Midlands, South West and the Greater London area. The GWR model also exhibited high disability-related coefficients in coastal communities. These findings also reflect broader—but poorly understood—patterns that have been identified in the relevant literature (Bouzarovski & Cauvain, 2016).

A second axis of vulnerability—unemployment—had a coefficient estimate that was lower than that of disability. There were high values across the UK, with distinct hotspots in Scotland (Lewis and Harris, North East and South of Scotland), NI (Omagh, Ards), Wales (Wrexham, Caerphilly, Caernarfon and Llandudno) and England (South West, East Midlands, Yorkshire and North West). While urban areas had the highest proportion of vulnerable households, some rural areas throughout the UK also exhibited high coefficients. Within cities (e.g., Glasgow, Birmingham, Cardiff, Newtownabbey), high coefficients appeared in the inner urban cores, and then decreased towards suburban areas.

The GWR model showed that areas of high unemployment do not exhibit a uniform spatial relationship with DEV, with both rural and urban areas indicating variations in coefficients. This echoes findings by Simcock et al. (2021b), who established that unemployment exhibits a strong relationship with both transport and EP. Within NI, high coefficients

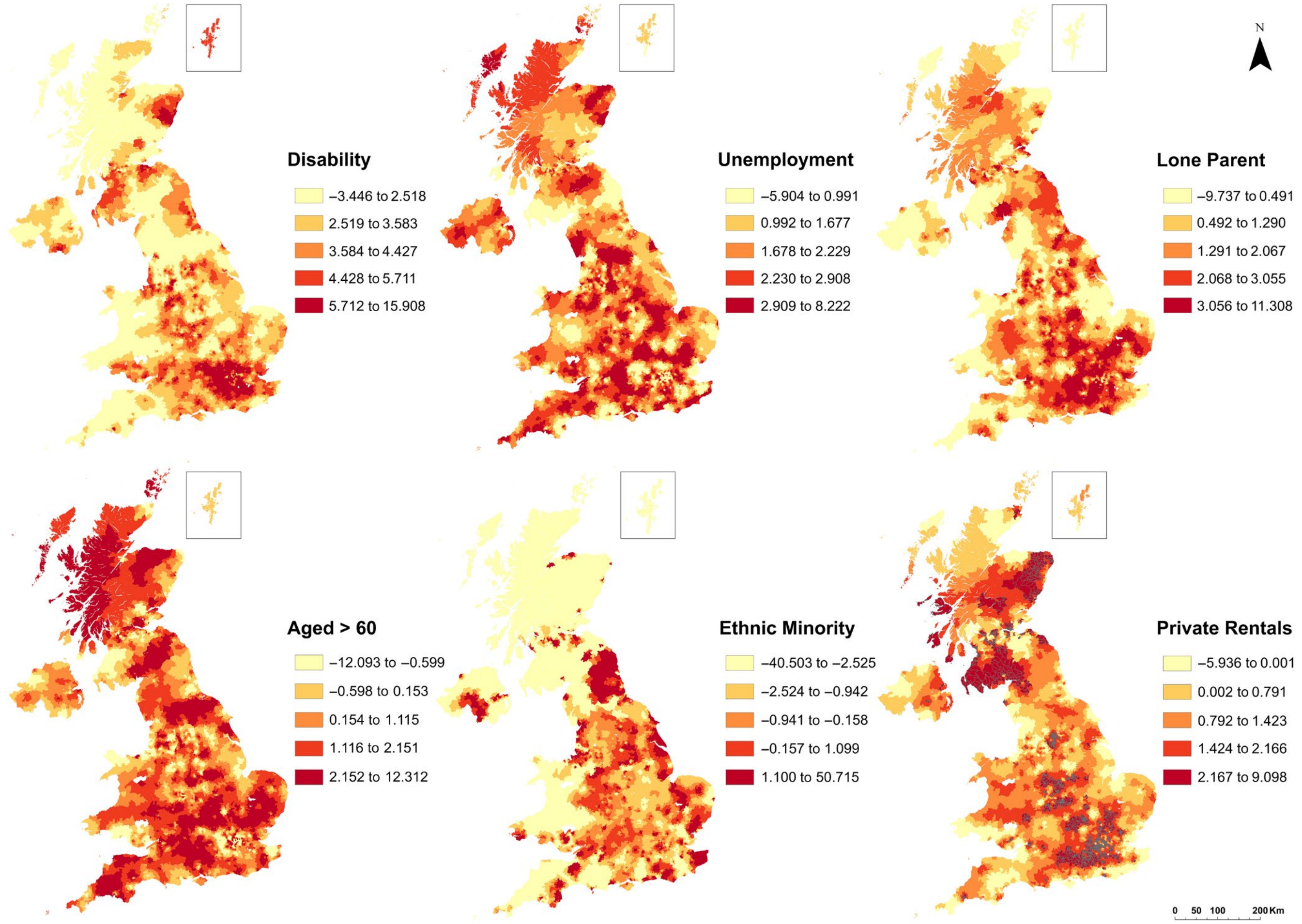

FIGURE 3 Spatial variation of double energy vulnerability (DEV) in relation to various socio-demographic determinants across the UK (local values of GWR coefficients).

occurred in southwestern areas that were overly reliant on home heating oil (due to being off the main gas grid). A similar pattern emerged in the South West of England (e.g., Cornwall), West Wales (e.g., Ceredigion) and Northern Scotland (Highlands and Orkney) where homes are not served by the gas grid (https://www.nongasmap.org.uk/).

The DEV-related vulnerabilities experienced by single parents (a statistic that has a strong gendered dimension, see e.g., Robinson, 2019) displayed a similar GWR coefficient to unemployment, despite differences in geographical patterns. Across the UK, there were 23 census zones where the percentage of single parents exceeded 30%, with the highest shares found in NI (44.9%, Belfast). Other areas with high values included Cardiff, Birmingham, Leeds, Wolverhampton, London, Dundee and Glasgow. While NI's GWR coefficients for unemployment and disabilities were high, the equivalent values for single parents were substantially lower. Higher coefficients in NI tended to occur in urban areas in the east. In England, the South East, the East and the Midlands displayed high coefficients, along with metropolitan centres in the North and South West. Wales' highest coefficients were found in large urban centres: Cardiff, Newport and Rhyl. In Scotland, we observed a mixture of both rural and urban typologies, ranging from Dumfries and surrounding areas in the south west, to Aberdeen in the north east. There were also pockets in Glasgow, Edinburgh and North East Fife. Within NI and Wales, higher coefficients tended to be concentrated in urban areas, while Scotland and England also experienced high coefficients in rural regions.

Our results are consistent with findings by Robinson et al. (2018), who identified high coefficients in the Midlands, the East of England, and urban areas such as Newcastle. The same authors established negative coefficients between both the 10% and LIHC indicators in urban areas with high concentrations of lone parent households. At the same time, Simcock et al. (2021b) contend that households with children are vulnerable to both transport and EP, though this may be exacerbated in single-parent households. Furthermore, caring responsibilities often force parents to stay at home, heating more rooms over longer periods of time to facilitate family routines (Lane et al., 2020). While this issue appears predominantly urban, we also found rural areas with high coefficients, particularly in the South East—within a 50-mile radius of London.

The vulnerabilities faced by people aged 60 or above tended to be located in rural areas, although high percentages also occurred in urban centres such as Belfast, Glasgow, Swansea and Sunderland. Many of the cities and towns with high GWR coefficients were also coastal, with high values recorded in Bangor (NI), Aberdeen, Rhyl and Brighton. The highest positive coefficients were concentrated in the Highlands and Islands of Scotland, Yorkshire and the Humber, the South West, South West and East of England. In broad terms, similar patterns have been observed by Robinson et al. (2018) who identified strong negative coefficients in urban areas, and positive coefficients in rural and coastal areas. The same group of authors also note that the bandwidth employed in GWR regression equations may smooth results, and hide urban areas that are positively correlated. In our model, there were strong negative coefficients in rural areas across the UK: the western parts of NI, North East Highlands, North West Wales and the North East of England. In some city regions, the spatial pattern broadly represented the distribution of the population over 60 (e.g., Edinburgh), though in other cities (such as Liverpool), GWR coefficients were negative, and their distribution did not reflect the older population more broadly.

In terms of ethnic minorities, 63.4% of our units of analysis recorded negative coefficients across all four regions of the UK (meaning that the two variables are moving in opposite directions). The highest positive coefficients were concentrated in urban Scotland along the Central Belt, the south west of NI, the south coast of Wales, the South West (e.g., Exeter), the South East (e.g., Brighton and Hove), East of England (e.g., Norwich) and Yorkshire and the Humber (e.g., York). London also had strong positive coefficients, particularly in western boroughs such as Brent and Wandsworth. Areas with high percentages of ethnic minorities—Edinburgh, Glasgow, Cardiff, Newport, Dungannon and Craigavon—were also characterised by strong positive coefficients. However, regions with the highest percentages of ethnic minorities did not always coincide with positive coefficients in the GWR model. For instance, while North East England recorded the lowest proportion of ethnic minorities in the 2011 UK Census, the GWR model identified strong positive coefficients throughout the region, particularly in rural Northumberland and urban County Durham. The main urban centres in the North East (Newcastle-upon-Tyne, South Shields, Sunderland and Middleborough) also saw positive coefficients, while negative coefficients were recorded in LSOAs with higher percentages of ethnic minorities. Beyond this region, some areas with high concentrations of ethnic minorities—such as Newham and Slough—had negative coefficients. We note that the bandwidth used in the GWR could be influencing the coefficients for ethnic minority groups—an issue detected in other studies (Robinson et al., 2018), even though these communities are heavily disadvantaged in the energy market (Bouzarovski et al., 2022).

Tenants in the private rented sector have been pinpointed as one of the most vulnerable groups to EP, due to poor quality housing, low energy efficiency rates and an increased likelihood of relying on pre-payment meters (Papantonis et al., 2022). Robinson et al. (2018) identified strong correlations between both the 10% and LIHC indicators, on the one hand, and households living in the private rented sector across England, on the other. The highest GWR coefficients for private renters and DEV occurred in the east of NI, North East and Southern Scotland, South East and East England and the Midlands. Wales has a band of high coefficients to the North West of Cardiff, ranging from peri-urban (Caerphilly) to villages (Beddau) and rural areas. We also found elevated coefficient values within remote rural areas of Scotland (Wick, Mull, Islay, East Cairngorms) and England (Herefordshire, Cornwall, Staffordshire, Hampshire), though urban areas also exhibit high coefficients, including multiple areas within London (Figure 4).

6 | CONCLUSION

In this study, we used a series of quantitative methodologies to examine the patterns and drivers of transport and EP across the UK. We sought to uncover DEV-inducing processes and dynamics that have received limited conceptual attention to date, while corroborating the outcomes of previous studies by providing comprehensive and detailed insights covering the whole of the UK. Thus, and returning to the first aim of the paper—to examine the geographical underpinnings of DEV—we established that this condition is present throughout the UK, with particularly pronounced distributions in Cornwall, Wales, coastal, highland and rural regions of England and Scotland, and the entirety of western NI. DEV is underpinned by distinct geographies of EP and TP, primarily within rural, low-income areas that lack adequate networked infrastructure provision and are car dependent. On average, NI recorded the highest rate of DEV across the UK, even if the maximum values were observed in parts of England.

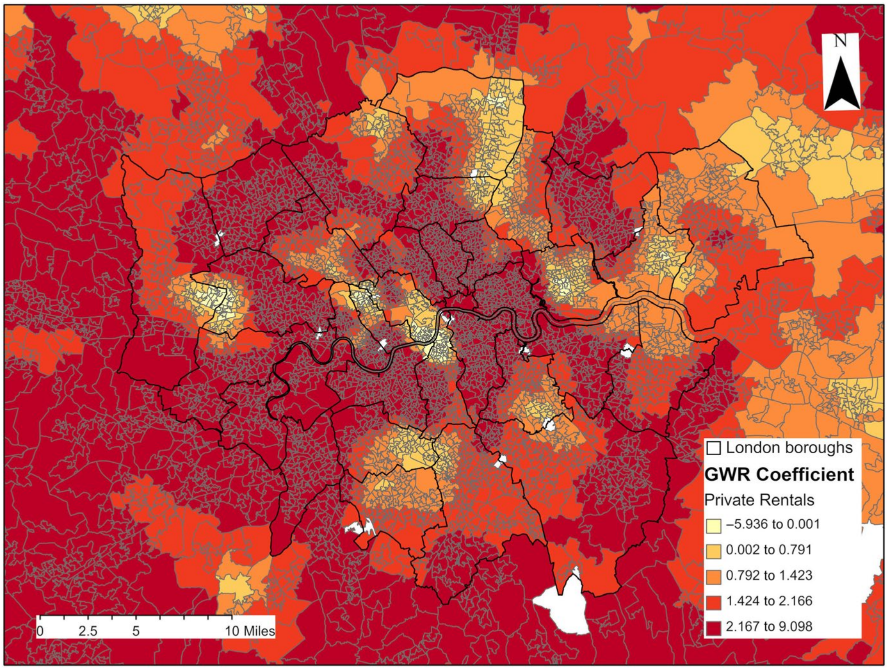

FIGURE 4 Spatial variation of double energy vulnerability (DEV) in London in relation to the private rented sector.

However, and this relates to our second aim—to delve into the granularity of DEV clusters and drivers—we also observed a number of unexpected trends and idiosyncratic geographies. EP and TP varied less within rural areas, as opposed to urban and peri-urban settings. The relatively low EP rates in the North East of England bucked other inequality patterns present in that region, as did the high TP score recorded by England as a whole. At the same time, Scotland's DEV score was one of the lowest in the UK—an unexpected finding given high EP rates in some Scottish regions. In our multivariate GWR, we found that the vulnerabilities associated with variables such as disability and ethnicity did not necessarily coincide with the broader spatial distributions of these axes of difference. Areas where their concentrations were higher tended to exhibit lower associations with DEV.

Throughout our analyses, we found that the identification of particular forms of socio-spatial inequality was closely influenced by the manner in which we had constructed the EP and TP indices, as well as the regression models. One of the main challenges we encountered related to the different settlement classifications that exist in the four constituent countries of the UK: our analysis was calibrated in a manner that allowed for a consistent approach in relation to settlement sizes and typologies. This connects to our third aim—on the development and testing of multi-dimensional indices. While the creation of composite measures allowed us to capture several axes of disadvantage, the process also revealed numerous issues that require further investigation. One of these is the role of urban density as a mediating factor in DEV—it is not entirely clear how this variable interacts with car dependency and some aspects of domestic energy use—as well as the bandwidth employed in GWR equations. If anything, such issues highlight the need for improving the standardisation and availability of data while developing multiple measures of energy deprivation. The highly differentiated and fragmented landscape of DEV in the UK necessitates the development of improved mechanisms for place-based detection and targeting. Undertaking further in-depth research that will identify vulnerable socio-demographics will remain of paramount importance in the period to come, given the continued challenges of high energy prices, growing income inequalities, as well as slow progress on housing decarbonisation and reducing car dependence more broadly.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available with the UK Data Service at https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=857062.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.
Figure S1. Box plots comparing the local coefficients of the GWR model.
Figure S2. Spatial variation of DEV in relation to various socio-demographic determinants across the UK (only significant coefficients at $p < 0.001$) reported by the GWR model.

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