Identifying areas of poor health outcome risk due to food insecurity – A Geographically Weighted Regression approach

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Summary

Food insecurity is a growing issue in the UK. However, local drivers of food insecurity risk and the impact on health is poorly understood. This paper applies geographically weighted regression to open data to quantify the spatial association between food insecurity risk, as captured by the Priority Places for Food Index - PPFI (Consumer Data Research Center, 2022), and health outcomes in England, focusing on Oxfordshire as an area with high inequalities in health. These findings are used to identify ‘priority areas’, displayed on a dashboard that enables local government, charities, and policymakers to identify areas where food insecurity is straining NHS resources the most.

KEYWORDS: Food insecurity – Health outcomes – Priority Places for Food Index - Geographically Weighted Regression – Interactive Dashboard

1. Introduction

Financial austerity, the recent pandemic, and soaring living costs have increased the UK's food insecurity levels (Rai & Blane, 2023). Based on survey results, the Food Foundation (2023) estimated that 9 million adults in the UK (17% of households) experienced food insecurity in June 2023. Food insecurity can lead to under and over-nutrition (Tanumihardjo et al., 2007), thus increasing the risks of various non-communicable diseases, including diabetes, hypertension, stroke, cardiovascular disease, and several cancers (Rai & Blane, 2023). Food-insecure individuals also report feelings of depression and anxiety due to restricted food choices and limited access (Myers, 2020). According to a report released by the NHS Confederation (2023), the adverse effect of rising food insecurity levels on individuals' mental and physical health is ramping up the pressure on the already exhausted NHS services. The report estimates that by 2050, malnutrition will cost the NHS £19.6 billion per year, while annual spending on obesity is forecast to hit £9.7 (NHS Confederation, 2022).

Food insecurity in the UK is dynamic and directly relates to local-level characteristics (deprivation levels, child count, prevalence of long-term health conditions, and overall health quality). Thus, no single intervention will address nation-wide food insecurity (Blake & Cromwell, 2022). A limitation of food insecurity data in the UK has always been its absence at the local area level (Smith, et al., 2022). Previous studies investigating the association between food insecurity and health in the UK have relied on data from cross-sectional surveys conducted on relatively small sample sizes.

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Investigating the local-level association between food insecurity risk and health outcomes in the UK would empower policymakers to allocate the local government's resources to the areas and communities facing the highest food insecurity risks and suffering from the greatest health inequalities (Smith, et al., 2022).

In this study, we have partnered with Good Food Oxfordshire (GFO) to investigate the spatial association between food insecurity risk and adverse health outcomes in Oxfordshire using open data. GFO is a network of 150+ of Oxfordshire's local producers and food businesses, farmers and growers, community groups and garden owners, cooks, and other charities/businesses that thrive to secure the county's healthy, sustainable, and fair food system.

Oxfordshire has stark inequalities, where life expectancy can vary by up to 13 years between the most and least deprived areas. Besides, the county exhibits pockets of high food insecurity risk. Stroke admissions were identified as a health outcome of interest through engagement with Oxfordshire County Council and GFO in their health strategy priorities. In this paper, we take emergency stroke admissions as an example of health outcomes related to malnutrition and food insecurity (Venci & Lee, 2018; Ejebu et al., 2019). However, multiple health outcomes have been explored. This research will be made available to GFO via an interactive dashboard that provides evidence on local food insecurity risk and a wide range of health outcomes, informing ongoing policy development and targeted interventions and funding for a fairer, healthier, and more sustainable food system in Oxfordshire (Good Food Oxfordshire, 2024).

2. Methods

2.1 Data

LSOA-level data from the Priority Places for Food Index domains, which was used as a measure of food insecurity risk, was spatially joined with physical and mental health data.

2.1.1. Priority Places for Food Index (PPFI)

The PPFI is a composite index developed by the Consumer Data Research Centre (CDRC) as a measure of food insecurity risk across the UK. The PPFI combines open-source data from seven domains (Table 1) to rank UK areas (LSOAs or equivalent) by food insecurity risk using deciles. For access to the full methodology and data, see Consumer Data Research Center (2022) and Pontin, et al. (2023).

Table 1 Priority Places for Food Index Domain Weightings

Weighting	Domain
12.5%	Proximity to supermarket retail facilities
12.5%	Accessibility to supermarket retail facilities
12.5%	Proximity to non-supermarket retail facilities
12.5%	E-commerce Access
16.7%	Socio-demographic barriers
16.7%	Food support for families
16.7%	Fuel poverty

2.1.2 Health Data – Emergency Stroke Admissions

Ward-level Emergency stroke admissions data (Standard Admissions Rate) for 2018 were obtained from Oxfordshire County Council (2019). The health data, which showed the ward names and codes, Oxfordshire district name, and the emergency admissions rates (with the confidence intervals), were transformed into a form readable by Python. An LSOA-Ward lookup table was then used to match the LSOA-level PPFI data with the ward-level health data ahead of conducting the LSOA-level analysis.

2.2 Geographically Weighted Regression (GWR)

GWR is a spatial statistical technique that uses a group of location-specific linear models to compute a set of parameter estimates that capture the relationship between the dependent and independent variables whilst allowing the effects to vary over space (Oshan et al., 2019). We apply the methodology adopted by the same paper, which uses the Python's MGWR package, to calculate the LSOA-level parameter estimates of the relationship between food insecurity risk and stroke admissions (dependent variable).

Model 1 used the combined PPFI decile as the predictor variable while Model 2 used the index's seven dimensions as the set of independent variables. Both models help identify where reduction in overall food insecurity risk or specific food insecurity risk factors (e.g., fuel poverty) could also have a positive impact on stroke admissions. We do not attempt to outline the full causal relationship between this association as we expect it to be multifaceted. For example, reducing food insecurity risk factors will lead to improved nutritional quality of diet, better access to services, as well as better social care, all of which can also contribute to reduced stroke risk.

An adaptive bi-square kernel function was used for both models to reduce the effect of faraway observations on model estimates while addressing the issue of spatial heteroscedasticity, which can lead to biased parameter estimates, (Oshan et al. 2019). The bandwidth was determined via optimal selection using the corrected Akaike information criterion (AICc) as the model fit criterion before calibrating the GWR model using the fit method. After calibration, a t-test was used to check the statistical significance of the LSOA-level parameter estimates.

3. Results & Discussion

3.1 Geographically Weighted Regression (GWR)

Table 2 shows the parameter estimates for Models 1 & 2. Referring to the lower AICc and higher R^2/adjusted R^2 values for both models compared to their baseline counterparts, we can infer that the GWR models fit the data better and their predictors explain a significantly larger proportion of the variance in stroke admissions.

Table 2. GWR Models Parameters and Performance

Model Parameters		
	Model 1	Model 2
Kernel Function	Bi-Square	Bi-Square
Kernel Type	Adaptive	Adaptive
Bandwidth (Optimized)	45	133
Model Performance		
	Model 1 (Baseline)	Model 2 (Baseline)
AICc	3442 (3626)	3366 (3510)
R^2	0.546 (0.106)	0.653 (0.338)
Adjusted R^2	0.488 (0.104)	0.593 (0.327)

Tables 3 and 4 provide summaries of the GWR models' coefficient estimates. It is worth noting the model coefficients' high standard deviation values, which reflects the high level of spatial heterogeneity. The negative mean and median values of the model coefficient associated with the PPFI combined decile (Table 3) reflect that an improvement in Oxfordshire's food security levels could contribute towards reducing the cases of stroke. Specifically, according to Table 4, reducing fuel poverty and deprivation as well as enhancing e-commerce access could be focus points for policymaking. Nonetheless, to ensure reliable inferences, the spatial distribution and statistical significance of the parameter estimates was investigated.

Table 3 Statistical Summary of Model 1 Coefficients

Variable	Mean	STD	Min	Median	Max
Intercept	94.13	15.07	65.35	91.51	124.18
Combined Decile	-1.50	1.70	-8.55	-0.96	1.70

Table 4 Statistical Summary of Model 2 Coefficients

Variable	Mean	STD	Min	Median	Max
Intercept	107.03	22.78	66.94	100.57	147.05
Supermarket Proximity	0.84	1.83	-1.91	0.87	4.58
Supermarket Accessibility	-0.08	1.09	-2.71	-0.24	2.39
Non-Supermarket Proximity	-0.79	1.50	-3.39	-0.73	3.51
Fuel Poverty	-0.38	0.69	-1.71	-0.22	1.70
Socio-Demographic Barriers	-0.82	1.61	-4.43	-0.44	2.13
Family Food Support	-1.11	1.28	-3.93	-0.96	1.69
E-Commerce Access	-1.36	0.90	-3.50	-1.33	1.15

Figure 1 highlights the statistically significant Model 1 coefficients (grey being insignificant) while Table 5 presents a statistical summary of these coefficients. We can infer that tackling food insecurity risk factors in Cherwell followed by parts of Oxford and South Oxfordshire could also be highly beneficial to reducing the cases of stroke (a decrease of 3-9 SAR units for every decile change)

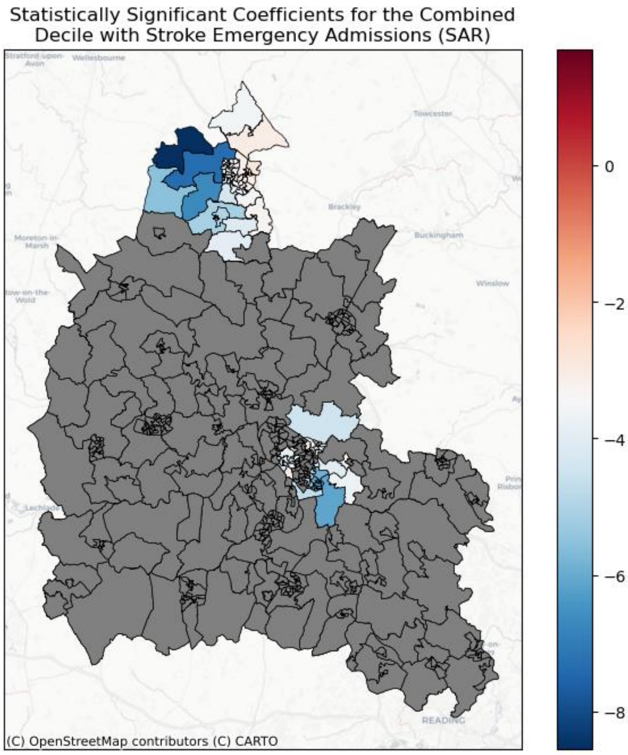

Figure 1. Significant Coefficients for the Combined PPFI Decile (Model 1)

Table 5. District-Level Summary of Significant Model 1 Coefficients

District	LSOA Count	Average	Median	Absolute Minimum	Absolute Maximum
Cherwell	47	-3.942	-3.539	(-) 2.86	(-) 8.549
Oxford	34	-4.445	-4.070	(-) 2.976	(-) 6.419
South Oxfordshire	6	-4.403	-4.259	(-) 3.398	(-) 6.129

In what follows, we examine the coefficients computed by Model 2, which uses the seven PPFI dimensions as independent variables.

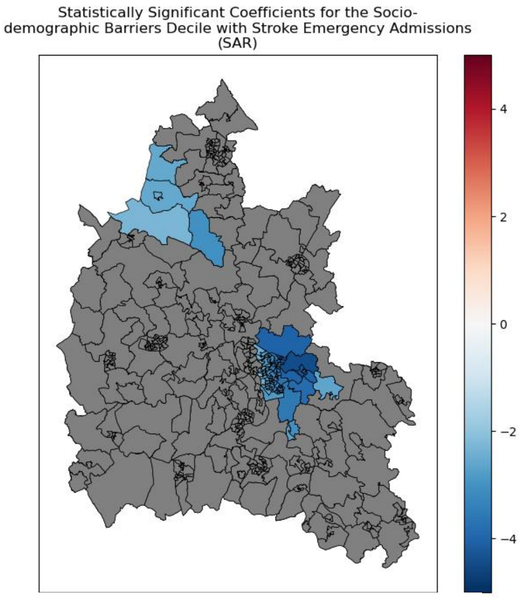

Figure 2. Significant Coefficients for the SD Barriers Dimension (Model 2)

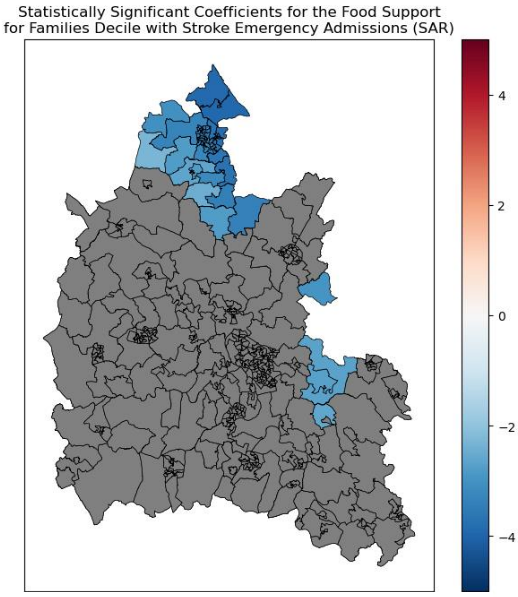

Figure 3. Significant Coefficients for the SD Barriers Dimension (Model 2)

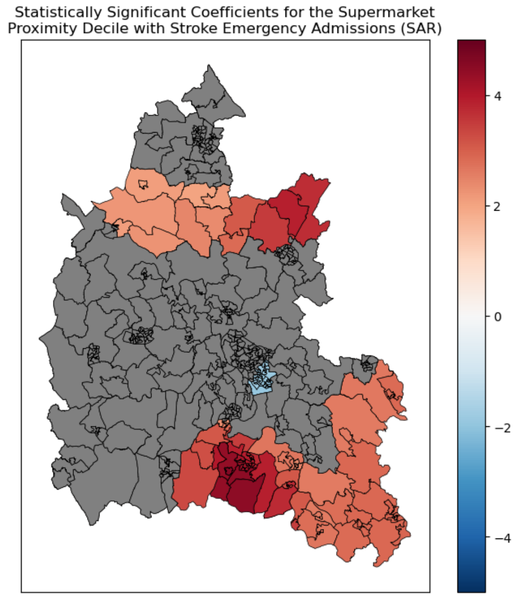

Figure 4. Significant Coefficients for the SD Barriers Dimension (Model 2)

Table 6. Statistical Summary of the Significant Model 2 Coefficients for Selected PPFI Dimensions

District	LSOA Count	Average	Median	Absolute Minimum	Absolute Maximum
Food Support for Families (FFF)					
Cherwell	51	-3.406	-3.476	(-) 2.285	(-) 3.925
South Oxfordshire	3	-2.662	-2.695	(-) 2.587	(-) 2.706
Socio-demographic Barriers					
Cherwell	3	-2.532	-2.539	(-) 2.498	(-) 2.539
Oxford	61	-3.114	-3.094	(-) 2.237	(-) 4.212
South Oxfordshire	12	-3.641	-3.925	(-) 2.647	(-) 4.432
West Oxfordshire	2	-2.662	-2.662	(-) 2.281	(-) 3.044
Supermarket Proximity					
Cherwell	11	2.761	2.841	1.999	3.899
Oxford	26	-1.832	-1.83	(-) 1.728	(-) 1.908
South Oxfordshire	64	3.183	2.904	(-) 1.884	4.468
Vale of White Horse	18	3.499	3.384	2.171	4.58
West Oxfordshire	4	2.241	2.226	2.087	2.426

Figures 2 and 3 show that addressing the factors driving the demand for family food support (e.g., food banks) and tackling deprivation could address the risks of food insecurity and stroke in Cherwell and parts of Oxfordshire. Based on Table 6, each decile shift (decrease in priority) in the FFF dimension is associated with a reduction in the admissions rate by up to 4 SAR units. This could be explained by the fact that stroke is more common among 65+ year-old adults (National Center for Chronic Disease Prevention and Health Promotion, 2023), who constitute 18.3% and 21.1% of the population in Cherwell and South Oxfordshire (Oxford City Council and District Data Service, 2021)

At the same time, tackling deprivation is estimated to reduce stroke admissions in all Oxfordshire districts except Vale of White Horse (no significance). Each decile shift in the socio-demographic barriers dimension is estimated to reduce stroke admissions by anywhere between 2 and 5 SAR units. The statistical insignificance in the Vale of White Horse could be due to other risk factors of stroke which are not controlled for by the model (e.g., smoking and drinking habits, physical inactivity and drug abuse).

Figure 4 shows that improving access to supermarkets (e.g., through making public transport more reliable, affordable, and attractive) could contribute to improving health outcomes in Oxford city centre through reducing emergency admissions for stroke by around 2 SAR units. Still, the association is of the opposite sign in the other districts. This discrepancy in the coefficient estimates could be justified by the fact that 8.3% of Oxford's population is in IMD's top two deciles for health deprivation while 0% of the population in South Oxfordshire, Vale of White Horse and West Oxfordshire is. Furthermore, only 5.3% of Cherwell's population live in health deprivation hotspots (Oxford City Council and District Data Service, 2021). However, health deprivation in Cherwell could be driven by other health outcomes and associated risk factors.

4. Conclusion

This paper presents work that not only allows the identification of areas facing high food insecurity levels but also those where the latter may impact health outcomes. By being able to quantify food insecurity risk and potential impact on health outcomes, we can provide local government, charities, and the organizations with local-level evidence on where funding and support is most needed. The development of a dashboard alongside the GWR analysis allows these insights to be communicated in a quick, digestible format to policy makers. Whilst we recognise many confounding factors in the relationship between food insecurity risk and poor health outcomes, being able to highlight areas where there is a strong relationship can focus interventions and further qualitative local investigation. Furthermore, we can also identify areas where the potential negative impacts captured in our measure of food insecurity risk are not related to poor health outcomes and what may be mitigating this relationship - these insights may apply to other areas.

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Biographies

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Dr Fran Pontin is a Senior Research Data Scientist at the Consumer Data Research Centre, University of Leeds. Her research looks at health inequalities and place-based behaviour, including Food Insecurity, dietary and physical activity behaviour, to inform policy.

Alex Hambley is a Research Software Engineer at the Consumer Data Research Centre, University of Leeds. He works to make consumer data insights accessible to wide ranging audiences through the development of web applications, dashboards, data products and reproducible code repositories.