

Geodemographic Analysis Using GIS Software

Data and Information Systems

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Abstract

This report covers a GIS based geodemographic analysis which investigates spatial patterns of socio-economic deprivation, health behaviours and access to primary care services across Wales. This case study used multiple datasets, which were all connected to an MSOA as the primary unit of analysis. The MSOA boundary layer was sourced from the Office for National Statistics Open Geography Portal and was projected into QGIS using the British National Grid coordinate reference system. Choropleth mapping and graduated symbology were applied to assist with the visualisation of the data for analysis, as well as spatial query techniques to identify clusters, overlaps and gaps of services/ across Wales. The thematic mapping reveals a clear concentration of lower income MSOAs in certain parts of Wales, which corresponded with higher BMI rates, greater physical inactivity, elevated disability figures and poorer self-rated health. This supports the primary research questions, that lower income is associated with a reduced adoption of healthy behaviours. The secondary research question was supported by the spatial distribution of GP services across Wales. Rural areas of Wales received less facilities, while urban and high-deprivation areas are well served. This analysis encountered several limitations, including temporal inconsistency, simulated MSOA-level data for BMI and physical activity as none was available at MSOA-level. Additionally, the absence of MSOA mental health service data. This study shows that GIS is an effective tool for identifying where health inequalities exist and recommends further research into other kinds of datasets to strengthen the research (e.g. public transport availability, mental health data etc).

Introduction

Geographical Information Systems (GIS) provide a framework for analysing spatial patterns and relationships between datasets [1]. These systems allow researchers to map out the data to visualise any correlations and relationships in a way that may not immediately be recognised through traditional analysis. This report presents the results of a GIS-based study investigating the spatial distribution of deprivation, health behaviours and access to primary care services across Wales. Using Middle Layer Super Output Areas (MSOA's) as the basis for this visualisation, a myriad of socio-economic and health related datasets have been implemented into QGIS to examine relationships between the variables that are relevant to the two research questions that the team selected.

The study utilises thematic mapping and spatial query techniques to explore whether lower income areas are associated with a reduced adoption of healthy behaviours and poorer health outcomes. The secondary objective that was investigated was if primary care and mental health services are adequately distributed in the areas that may need them more (e.g. lower income, higher BMI, unhealthier areas). By applying the established principles of thematic mapping and spatial data visualisation [2], this report evaluates the patterns of inequalities and accessibility across Wales in a geographical context.

Methodology

Data Processing

GIS Build

The GIS build process involved the integration of multiple spatial and non-spatial datasets to create a framework to examine the socio-economic and health inequalities across Wales. The primary unit of analysis was the MSOA, which provides a consistent boundary for comparing statistical data. The base layer consisted of an MSOA boundary polygon obtained from the Office for National Statistics Open Geography Portal in a 'shapefile' format. This was integrated into the GIS using the British National Grid coordinate reference system (EPSG:27700) [3]. All other datasets were with them joined onto this spatial framework.

Data Collection and Manipulation

Figure 1.1: Cleaned Data

Middle layer Super Output Areas Code	Middle layer Super Output Areas	Highest level of qualification (B categories) Code	Highest level of qualification (B categories)
W02000001	Isle of Anglessey 001	-8	Does not apply
W02000001	Isle of Anglessey 001	0	No qualifications
W02000001	Isle of Anglessey 001	1	Level 1 and entry level qualifications: 1 to 4 GCSEs grade A* to C, Any GCSEs at other grades, O levels or CSEs (any grades), 1 AS level, NVQ
W02000001	Isle of Anglessey 001	2	Level 2 qualifications: 5 or more GCSEs (A* to C or 9 to 4), O levels (passes), CSEs (grade 1), School Certification, 1 A level, 2 to 3 AS levels,
W02000001	Isle of Anglessey 001	3	Apprenticeship
W02000001	Isle of Anglessey 001	4	Level 3 qualifications: 2 or more A levels or VCEs, 4 or more AS levels, Higher School Certificate, Progression or Advanced Diploma, Welsh
W02000001	Isle of Anglessey 001	5	Level 4 qualifications or above: degree (BA, BSc), higher degree (MA, PhD, PGCE), NVQ level 4 to 5, HNC, HND, RSA Higher Diploma, BTEC
W02000001	Isle of Anglessey 001	6	Other: vocational or work-related qualifications, other qualifications achieved in England or Wales, qualifications achieved outside England
W02000002	Isle of Anglessey 002	-8	Does not apply
W02000002	Isle of Anglessey 002	0	No qualifications
W02000002	Isle of Anglessey 002	1	Level 1 and entry level qualifications: 1 to 4 GCSEs grade A* to C, Any GCSEs at other grades, O levels or CSEs (any grades), 1 AS level, NVQ
W02000002	Isle of Anglessey 002	2	Level 2 qualifications: 5 or more GCSEs (A* to C or 9 to 4), O levels (passes), CSEs (grade 1), School Certification, 1 A level, 2 to 3 AS levels,
W02000002	Isle of Anglessey 002	3	Apprenticeship
W02000002	Isle of Anglessey 002	4	Level 3 qualifications: 2 or more A levels or VCEs, 4 or more AS levels, Higher School Certificate, Progression or Advanced Diploma, Welsh
W02000002	Isle of Anglessey 002	5	Level 4 qualifications or above: degree (BA, BSc), higher degree (MA, PhD, PGCE), NVQ level 4 to 5, HNC, HND, RSA Higher Diploma, BTEC
W02000002	Isle of Anglessey 002	6	Other: vocational or work-related qualifications, other qualifications achieved in England or Wales, qualifications achieved outside England
W02000003	Isle of Anglessey 003	-8	Does not apply
W02000003	Isle of Anglessey 003	0	No qualifications
W02000003	Isle of Anglessey 003	1	Level 1 and entry level qualifications: 1 to 4 GCSEs grade A* to C, Any GCSEs at other grades, O levels or CSEs (any grades), 1 AS level, NVQ
W02000003	Isle of Anglessey 003	2	Level 2 qualifications: 5 or more GCSEs (A* to C or 9 to 4), O levels (passes), CSEs (grade 1), School Certification, 1 A level, 2 to 3 AS levels,
W02000003	Isle of Anglessey 003	3	Apprenticeship
W02000003	Isle of Anglessey 003	4	Level 3 qualifications: 2 or more A levels or VCEs, 4 or more AS levels, Higher School Certificate, Progression or Advanced Diploma, Welsh
W02000003	Isle of Anglessey 003	5	Level 4 qualifications or above: degree (BA, BSc), higher degree (MA, PhD, PGCE), NVQ level 4 to 5, HNC, HND, RSA Higher Diploma, BTEC
W02000003	Isle of Anglessey 003	6	Other: vocational or work-related qualifications, other qualifications achieved in England or Wales, qualifications achieved outside England
W02000004	Isle of Anglessey 004	-8	Does not apply

Figure 1.1: Cleaned Data

Figure 1.2: Cleaned Data

MSOA code	MSOA name	Local authority code	Local authority name	Region code	Region name	Total annual income (£)	Upper confidence limit (£)	Lower confidence interval (£)	Confidence interval (£)
E02002483	Hartlepool 001	E06000001	Hartlepool	E12000001	North East	50,689	58,296	43,332	15,964
E02002484	Hartlepool 002	E06000001	Hartlepool	E12000001	North East	32,399	37,948	27,661	10,287
E02002485	Hartlepool 003	E06000001	Hartlepool	E12000001	North East	38,135	44,530	32,659	11,871
E02002489	Hartlepool 007	E06000001	Hartlepool	E12000001	North East	34,225	40,057	29,242	10,815
E02002490	Hartlepool 008	E06000001	Hartlepool	E12000001	North East	37,845	44,326	32,311	12,015
E02002491	Hartlepool 009	E06000001	Hartlepool	E12000001	North East	38,139	44,540	32,658	11,882
E02002492	Hartlepool 010	E06000001	Hartlepool	E12000001	North East	41,049	47,917	35,165	12,752
E02002493	Hartlepool 011	E06000001	Hartlepool	E12000001	North East	50,394	59,033	43,019	16,014
E02002494	Hartlepool 012	E06000001	Hartlepool	E12000001	North East	33,764	39,507	28,856	10,651
E02006909	Hartlepool 014	E06000001	Hartlepool	E12000001	North East	52,774	61,746	45,106	16,640
E02007059	Hartlepool 015	E06000001	Hartlepool	E12000001	North East	42,105	49,164	36,059	13,105
E02002496	Middlesbrough 001	E06000002	Middlesbrough	E12000001	North East	33,579	39,525	28,527	10,998
E02002497	Middlesbrough 002	E06000002	Middlesbrough	E12000001	North East	33,520	39,236	28,636	10,602
E02002498	Middlesbrough 003	E06000002	Middlesbrough	E12000001	North East	29,830	35,124	25,333	9,791
E02002499	Middlesbrough 004	E06000002	Middlesbrough	E12000001	North East	37,121	43,597	31,607	11,990
E02002500	Middlesbrough 005	E06000002	Middlesbrough	E12000001	North East	45,021	52,892	38,467	14,225
E02002501	Middlesbrough 006	E06000002	Middlesbrough	E12000001	North East	41,313	48,258	35,367	12,891
E02002502	Middlesbrough 007	E06000002	Middlesbrough	E12000001	North East	33,569	39,307	28,669	10,638
E02002503	Middlesbrough 008	E06000002	Middlesbrough	E12000001	North East	43,272	50,673	36,951	13,722
E02002504	Middlesbrough 009	E06000002	Middlesbrough	E12000001	North East	49,001	57,489	41,766	15,723
E02002505	Middlesbrough 010	E06000002	Middlesbrough	E12000001	North East	36,110	42,443	30,721	11,722
E02002506	Middlesbrough 011	E06000002	Middlesbrough	E12000001	North East	36,362	42,475	31,128	11,347
E02002507	Middlesbrough 012	E06000002	Middlesbrough	E12000001	North East	57,525	67,300	49,171	18,129
E02002508	Middlesbrough 013	E06000002	Middlesbrough	E12000001	North East	50,247	58,889	42,874	16,015
E02002509	Middlesbrough 014	E06000002	Middlesbrough	E12000001	North East	43,997	51,634	37,489	14,145

Figure 1.2: Cleaned Data

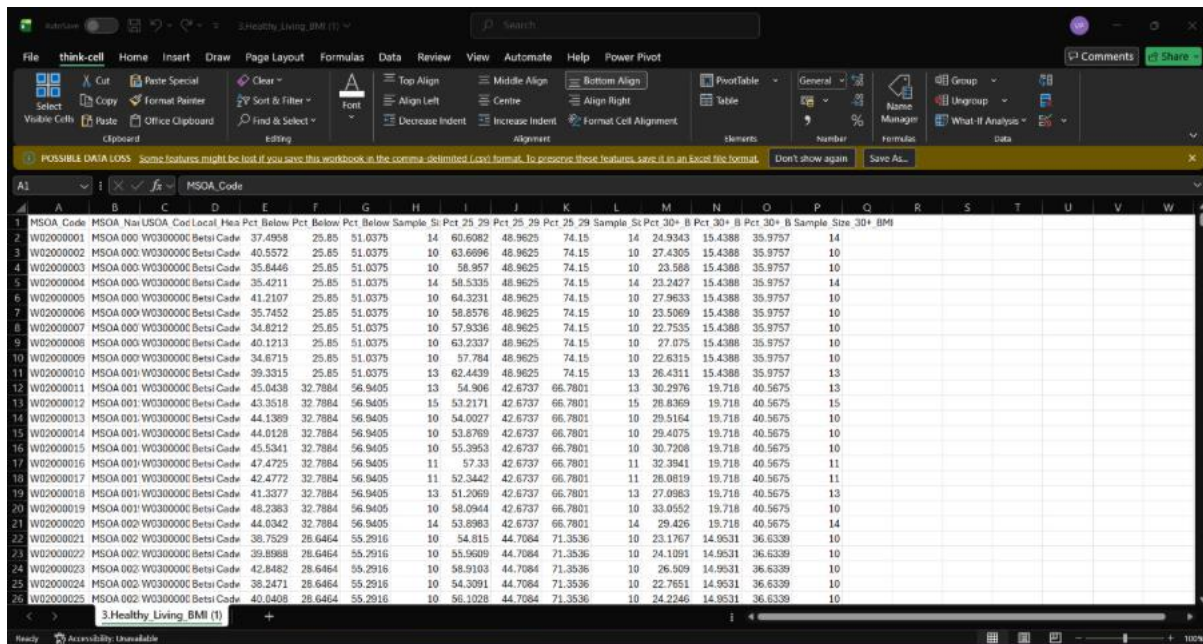


Figure 1.3: Cleaned Data

A range of health-related datasets were sourced from a multitude of reputable sources, including The Office for National Statistics, StatsWales and DataMap Wales. These datasets included income estimates across Wales, educational attainment levels, rates of physical activity, body mass index (BMI), disability statistics, primary care services and suicide rates. Most datasets were initially provided in a Microsoft Excel sheet (.xlsx) or an OpenDocument (.ods) and were subsequently converted into the correct format; Comma-Separated Values (.csv) to ensure compatibility with QGIS software [4]. This conversion process also ensures that the attribute tables were standardised before being integrated.

Using QGIS

One of the most important stages in the GIS build was implementing attribute joins. This is where each dataset is linked to the main MSOA boundary layer using a common identifier (MSOA code e.g. MSOA21CD) [5]. Data cleaning was also required to ensure that there was consistency in field names and formatting. More specifically, when datasets used different names for the same geographic identifiers. If these fields were not standardised, this would have resulted in unsuccessful joins and incomplete representation on the GIS build.

The environment used for this project was QGIS, an open-source platform that supports spatial analysis and visualisation. Within QGIS, datasets were imported in as separate layers and were styled and joined using thematic mapping techniques. Choropleth maps were created for variables such as income, education and health [6]. On the other hand, primary care service locations were shown on the map as a point vector layer using latitude and longitude. This means the map can show both area patterns and specific locations at the same time.

As well as data integration, several spatial analysis techniques were used to explore the relationships between the datasets. Certain tools, including ‘Select by Attribute’ and ‘Select by Location’ were used to identify clusters, overlaps and gaps in services provided across Wales. These outcomes assisted in supporting the overall research questions and objectives.

Limitations with GIS Build Process

There were several limitations that were encountered while building the GIS map. Certain datasets had data that were collected from different time periods, ranging from 2011 to 2024, which may affect the temporal consistency of the analysis. Additionally, some datasets (particularly those relating to the BMI and physical activity) required a simulated MSOA as there was an absence of directly compatible geographic identifiers [7]. While this assisted with the continuation of the analysis, it introduced some uncertainty regarding the accuracy. Furthermore, the lack of MSOA-level data available for mental health services limited the ability to fully address all aspects of the secondary research question.

Overall, the GIS build process was very successful. The map includes fully integrated datasets into one coherent spatial framework and enables a detailed thematic mapping and analysis.

Thematic Maps

Principles of Thematic Mapping

Thematic mapping is a fundamental technique within GIS which enables the visual representation of spatial variation across defined geographic areas [8]. Unlike general reference maps, which prioritise location and orientation, thematic maps are designed to communicate patterns, relationships and trends easily. In this study, thematic mapping was used to represent socio-economic and health indicators across Wales, allowing for the identification of spatial inequalities and potential correlations.

A primary method in this project was choropleth mapping, where geographic areas are shaded according to the value of a particular variable. Choropleth maps are suitable for standardised or rate-based data, such as income levels, health outcomes or proportions of populations exhibiting certain behaviours [9]. By aggregating data at MSOA level, the maps provide a clear visual representation of how variables are distributed. It is important to note that choropleth maps can obscure intra-area variation, which introduces the risk of generalisation.

An essential consideration in thematic mapping is the classification method used to group data values into categories. Common approaches include equal intervals, quantiles and natural breaks (Jenks). In this project, classification plays a critical role in shaping how patterns are perceived. For example, quantile classification ensures an equal number of areas in each class, which can be useful for comparison but may exaggerate differences between similar values. On the other hand, natural breaks aim to minimise variance within classes and maximise differences between them, often producing a more natural representation of data distribution. The choice of classification method therefore directly influences the interpretation of spatial patterns and must be selected with consideration of the underlying data distribution [10].

Data Symbolology

Colour selection is another key principle of effective visualisation. Sequential colour schemes, typically progressing from light to dark, are appropriate for ordered data such as income or health indicators where darker shades often represent higher intensity or severity. Consistency in colour usage across maps is important to avoid confusion and to support comparative analysis between variables. Poor colour choices can mislead interpretation and reduce the clarity of the map [11].

The principle of visual hierarchy is also central to effective thematic mapping. Maps should be designed so that the most important information is immediately visible, while less critical elements (such as base layers or boundaries) remain subtle. In this project, the MSOA boundary layer serves as a reference framework, while thematic layers (e.g. income deprivation or health outcomes) are emphasised through colour and symbology. The inclusion of clear legends, titles, and scale bars further enhances map readability and ensures that outputs are interpretable to a wider audience [12].

Data Normalisation

A further critical concept is data normalisation, particularly when dealing with variables such as health outcomes or service provision. Raw counts (e.g. number of suicides) can be misleading when mapped directly, as they do not account for differences in population size between areas. Normalising data, such as expressing values per 1,000 or 100,000 people, allows for fairer comparisons and more accurate representation of spatial patterns. Without normalisation, areas with larger populations may appear to have disproportionately higher values, distorting the analysis.

Thematic Mapping in QGIS

The software environment used to implement these visualisation techniques was QGIS. QGIS provides a range of tools for styling layers, applying classification methods, and

customising symbology. Features such as graduated colour rendering, layer transparency, and labelling allow users to refine map outputs to effectively communicate spatial patterns. Additionally, QGIS supports the integration of multiple data types, enabling both polygon-based choropleth maps and point-based visualisations (e.g. primary care locations) to be analysed within the same environment.

Finally, it is important to acknowledge potential limitations in thematic mapping. Issues such as the modifiable areal unit problem (MAUP) and the ecological fallacy can affect interpretation. MAUP refers to the way results can vary depending on the spatial unit of analysis (e.g. MSOA vs LSOA), while the ecological fallacy occurs when assumptions about individuals are made based on aggregated data. Recognising these limitations is essential for ensuring that conclusions drawn from thematic maps remain appropriately cautious and analytically robust.

Outcomes

This section of the report presents the findings derived from the GIS build, using thematic maps and spatial queries to examine relationships between income deprivation, health behaviours, health outcomes and access to primary care services across Wales. The analysis is structured around the key variables introduced in the dataset, with each subsection supported by map outputs generated in QGIS.

Income Deprivation Patterns

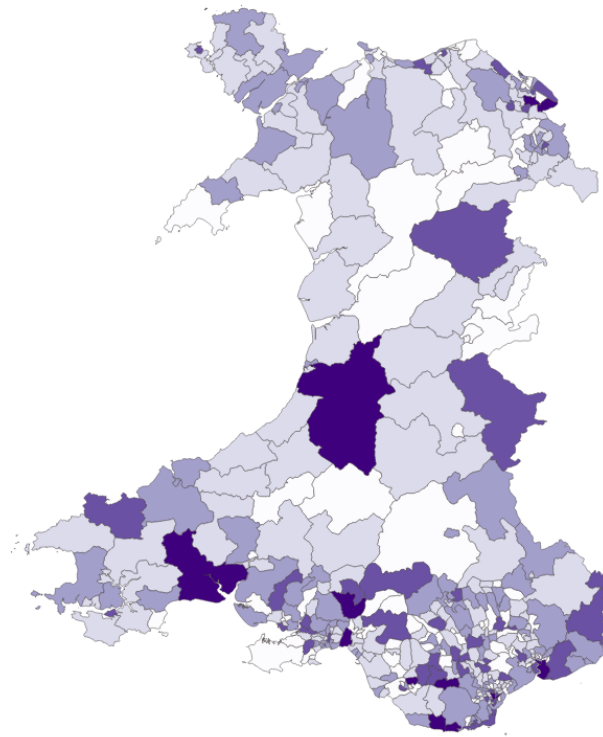


Figure 2: Income Data Map

The choropleth map of income deprivation reveals a clear spatial clustering of lower-income MSOA's, particularly concentrated in parts of South Wales. These areas exhibit consistently darker shading, indicating lower average household income levels compared to other regions. In contrast, more rural and less densely populated areas tend to display higher income levels, although there is evidence of some isolated pockets of deprivation.

This spatial clustering suggests that income deprivation is not randomly distributed but is instead geographically concentrated, reflecting a broader structural inequality. The identification of these clusters provides a foundational layer for subsequent analysis, as income is treated as the primary independent variable influencing health behaviours and outcomes throughout the study.

Education and Income Relationships

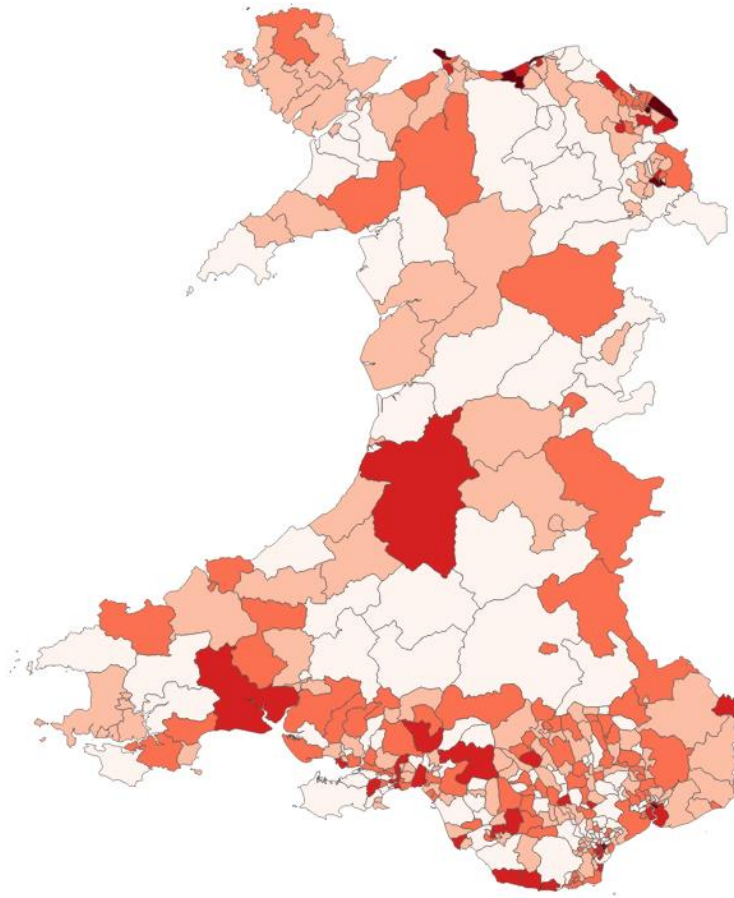


Figure 3: Education Data Map

A comparative analysis between income deprivation and educational attainment demonstrates a noticeable spatial correlation. MSOA's characterised by lower income levels frequently correspond with lower levels of educational attainment, as indicated by higher proportions of residents with minimal or no formal qualifications.

Using spatial query functions such as "Select by Attribute," areas meeting both low-income and low-education criteria were identified. These overlapping areas reinforce the relationship between socio-economic deprivation and limited access to education, suggesting a cyclical pattern in which reduced educational opportunities may contribute to continued economic disadvantage. However, some exceptions were observed, indicating that the relationship is not uniform across all regions.

Health Behaviours – BMI and Physical Activity

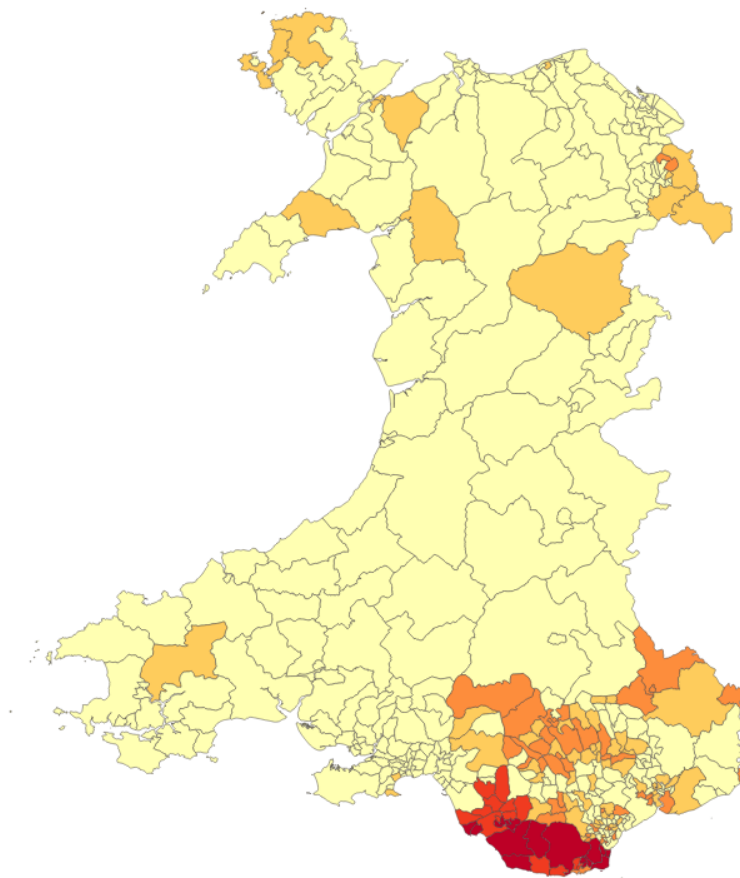


Figure 4: BMI Data Map

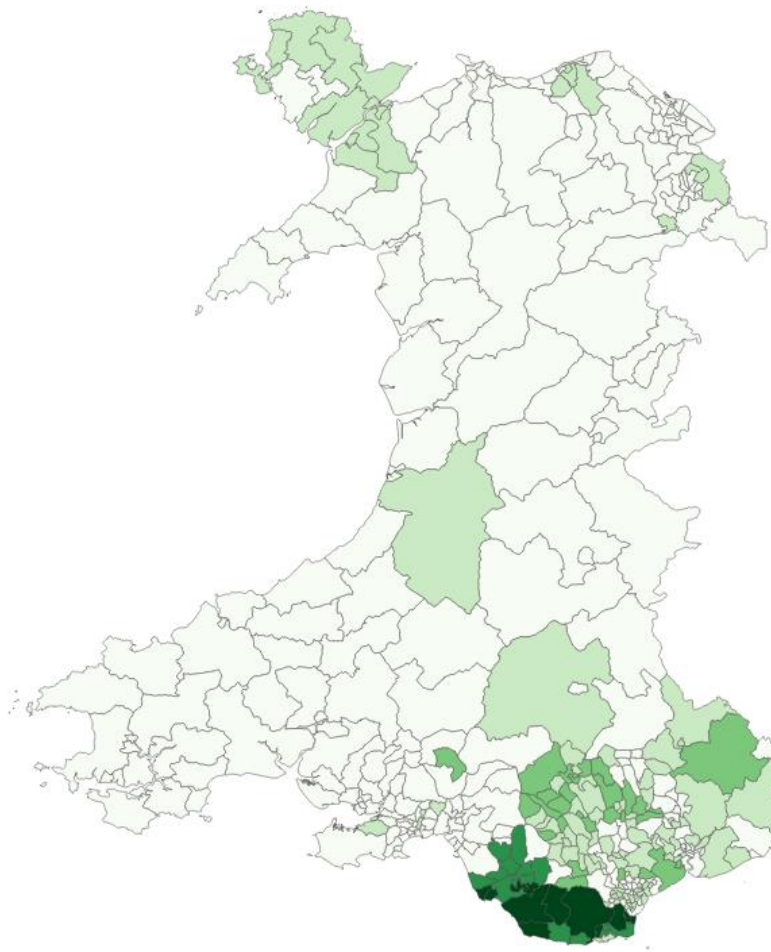


Figure 5: Physical Activity Data Map

The thematic maps representing Body Mass Index (BMI) and physical activity levels highlight further spatial disparities. Areas with higher levels of income deprivation generally correspond to higher average BMI values and lower levels of physical activity. This pattern supports the hypothesis that socio-economic conditions influence lifestyle behaviours, potentially due to factors such as access to recreational facilities, availability of healthy food options, and broader environmental constraints.

However, it is important to note that the BMI and physical activity datasets were partially simulated to align with MSOA geography. While this allowed for spatial analysis to be conducted, the reliability of these findings should be interpreted with caution. Despite this limitation, the overall pattern remains consistent with established research on health inequalities.

Health Outcomes – Disability and Suicide Rates

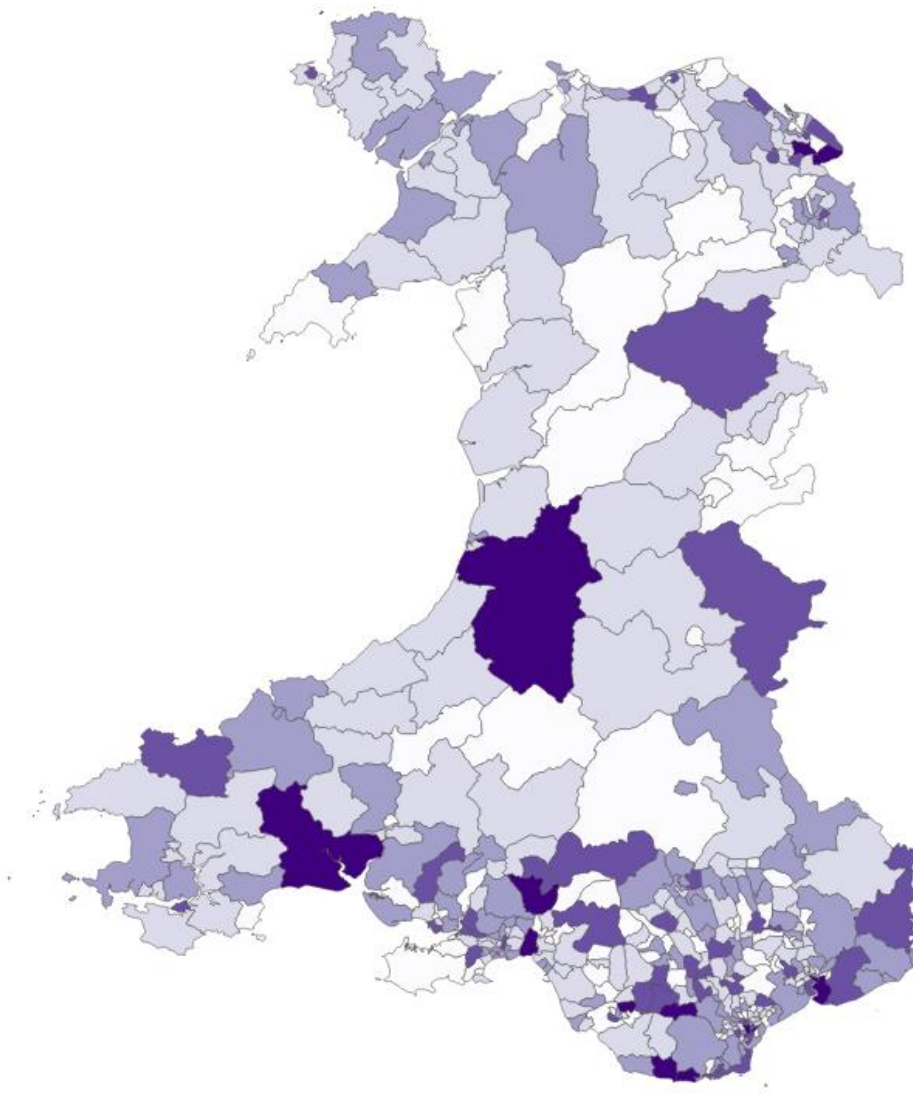


Figure 6: Disability Data Map

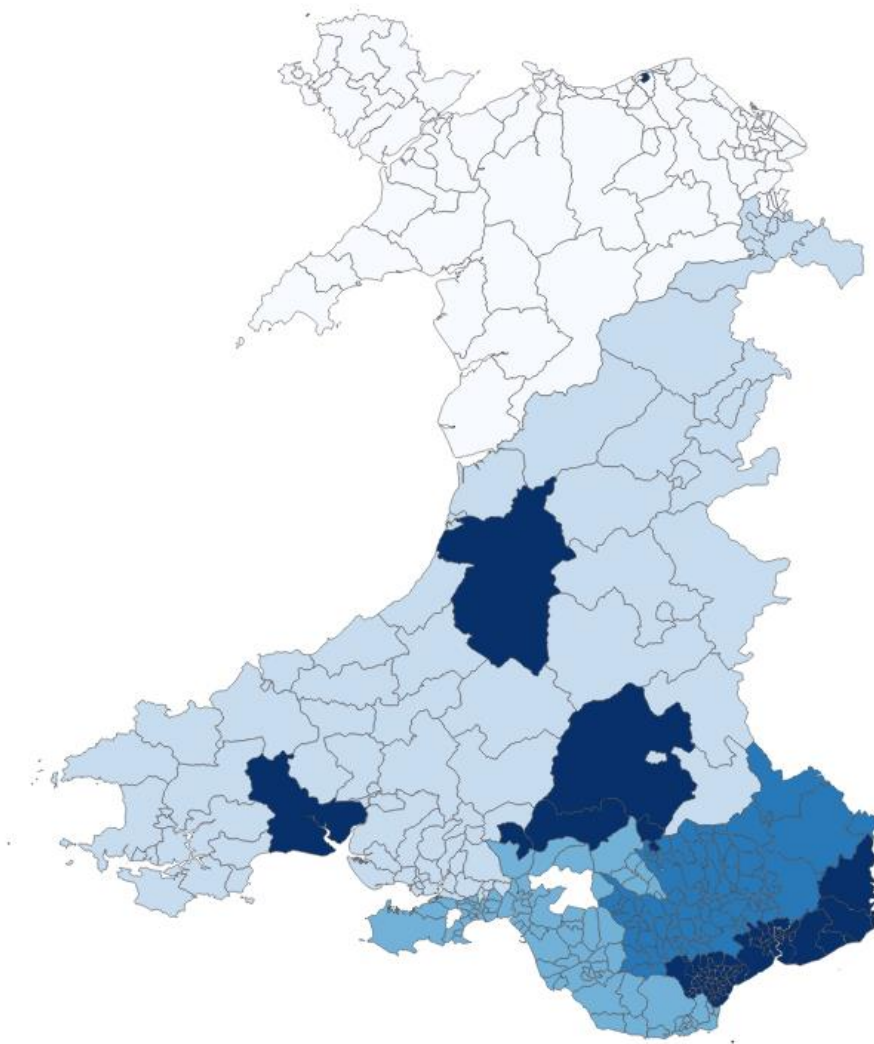


Figure 7: General Health Data Map

Spatial analysis of health outcomes, including disability prevalence and suicide rates, reveals additional layers of complexity. Areas with higher levels of deprivation tend to show increased rates of reported long-term disability and poorer general health classifications. This reinforces the association between socio-economic disadvantage and negative health outcomes.

The distribution of suicide rates, however, presents a less uniform pattern. While some deprived areas exhibit higher rates, other regions with relatively higher income levels also display elevated values. This suggests that suicide is influenced by a broader set of factors beyond income alone, including mental health service accessibility, social isolation, and demographic characteristics. These findings highlight the importance of avoiding overly simplistic interpretations of spatial data.

Accessibility of Primary Care Services

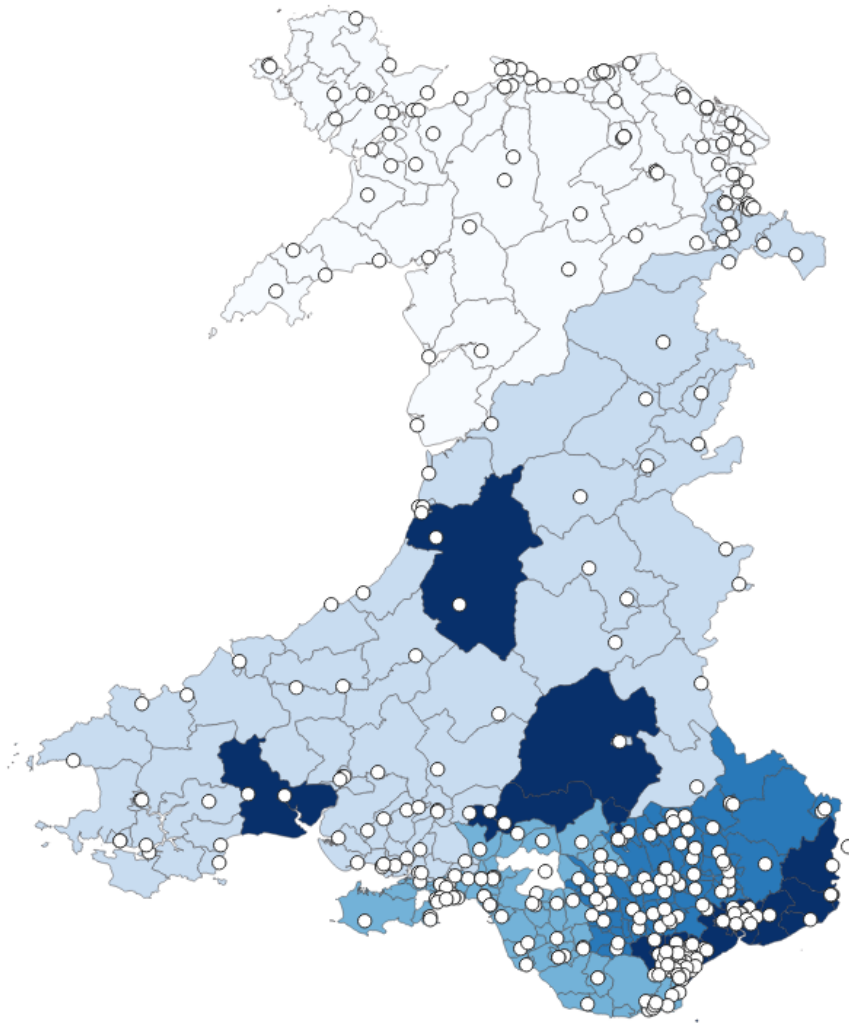


Figure 8: GP Services Data Map

The spatial distribution of primary care services was analysed using a point layer representing GP locations. When overlaid with income deprivation data, the results indicate that many urban areas with higher population density, and often higher deprivation, have relatively good access to primary care services. This is reflected in the clustering of GP locations within and around these areas.

However, disparities become more apparent in rural regions, where GP locations are more sparsely distributed. Although these areas may not always correspond to the highest levels of deprivation, the increased distance to services suggests potential accessibility challenges. Spatial analysis techniques, such as proximity assessment and visual inspection of service distribution, indicate that while services are generally present in high-need areas, accessibility is not uniform across all regions.

Analysis

The findings from the spatial analysis provide strong evidence of a relationship between socio-economic deprivation and health-related outcomes across Wales. The thematic maps consistently demonstrate that areas characterised by lower income levels tend to exhibit poorer health behaviours, including higher average Body Mass Index (BMI) and lower levels of physical activity. This aligns with broader theoretical frameworks surrounding the social determinants of health, which suggest that economic conditions significantly influence lifestyle choices, access to resources, and overall wellbeing.

In addressing the secondary research question, the analysis indicates a clear spatial correlation between income deprivation and negative health indicators. Areas with lower income not only show reduced educational attainment but also poorer general health outcomes and higher levels of long-term disability. This suggests areas with low income also tend to have worse health outcomes, suggesting these factors feed into each other. However, the relationship is not entirely uniform, as some areas deviate from this trend, highlighting the influence of additional contextual factors such as local infrastructure, community support, and environmental conditions.

Regarding the primary research question, the distribution of primary care services presents a more complex picture. The spatial overlay of GP locations with deprivation data suggests that, in many urban areas, services are relatively well-positioned in relation to population need. This may reflect strategic placement of healthcare facilities in densely populated regions. However, rural areas demonstrate reduced accessibility due to the dispersed nature of settlements and greater distances to services. While these areas may not always correspond to the highest levels of deprivation, the physical accessibility of healthcare remains a significant concern.

Overall, the analysis suggests that while there is some alignment between service provision and areas of need, inequalities persist, particularly in terms of accessibility rather than absolute presence. These findings emphasise the importance of considering both spatial distribution and service reach when evaluating healthcare provision. GIS has proven to be an effective tool in uncovering these patterns, allowing for a more nuanced understanding of how socio-economic factors and service accessibility interact.

Limitations

Some limitations included temporal inconsistency within the data, having to use simulated MSOA-level data and the absence of specific types of data.

Realistically, I would've ensured to include data relating to Mental Health and Therapy Services in Wales to dive deeper into if that has any correlation to a higher BMI/poorer physical activity levels. For future research, I would encourage for additional data to be included. Suggestions for additional data include:

- Public Transport Availability
- Mental Health Service Wait Times (if available in the correct format)
- Food Environment Data

All the above data sets could be added for additional insight into how accessible Primary Care services are, additional effects that mental health may have on health and types of food that are available in certain areas (fast food, restaurants, market, farms etc.).

Conclusion

This report has demonstrated the value of Geographic Information Systems in analysing and visualising spatial patterns of socio-economic deprivation, health behaviours, and healthcare accessibility across Wales. By integrating multiple datasets within a GIS environment, it has been possible to identify clear spatial relationships between income deprivation and negative health outcomes, supporting the hypothesis that lower-income areas are associated with poorer health behaviours and reduced wellbeing.

The analysis also highlights that, while primary care services are often located within or near areas of higher need, accessibility remains uneven, particularly in rural regions. This suggests that service provision cannot be evaluated solely based on location, but must also consider factors such as distance, connectivity, and population distribution.

Overall, the study reinforces the importance of spatial analysis in understanding complex social and health inequalities. GIS-based approaches provide valuable insights that can inform policy decisions, resource allocation, and targeted interventions aimed at reducing disparities. Future research would benefit from more consistent and granular datasets, as well as the integration of additional analytical techniques, to make future findings more reliable.

Citations

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