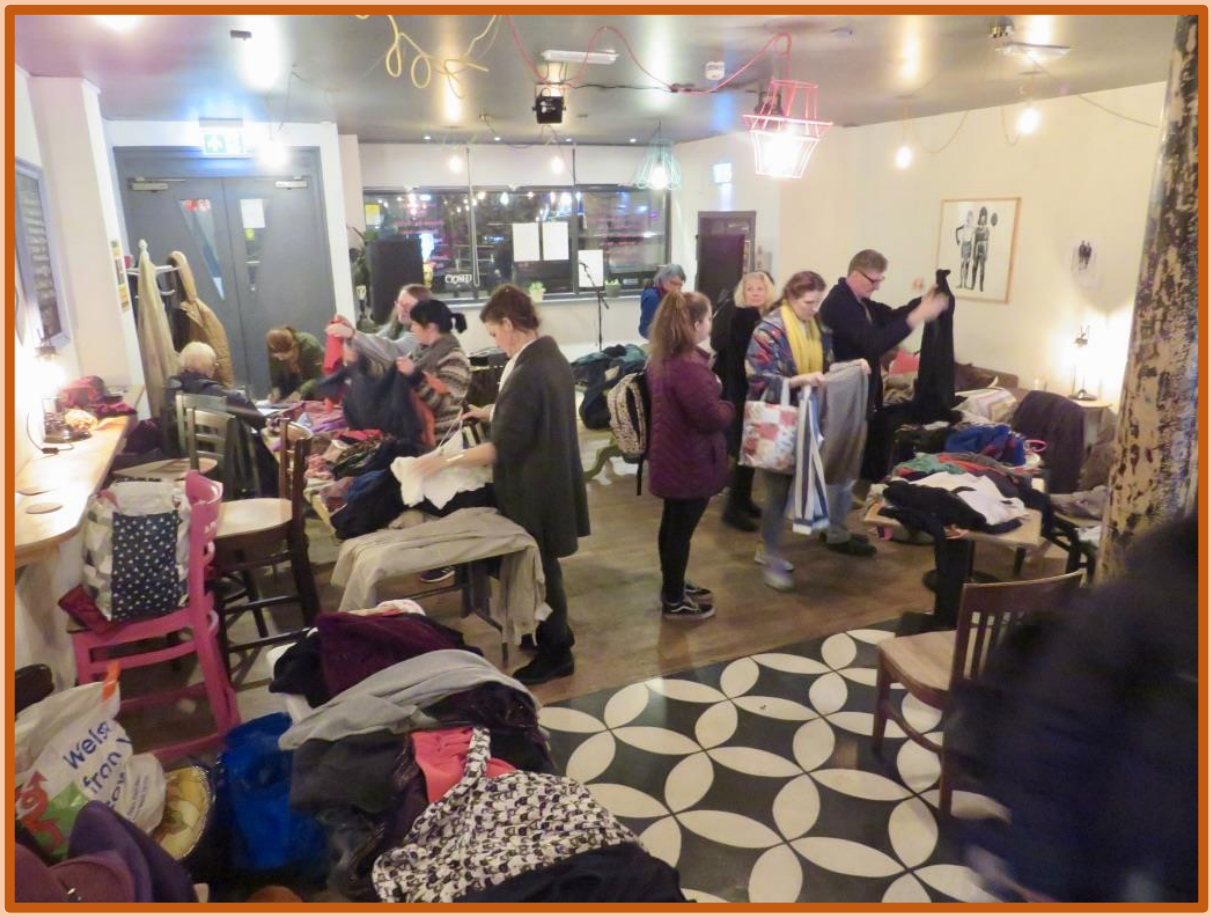
A GIS Analysis of shopping habits from varying socio-economic backgrounds

REACTIVATE



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GIS Reactivate

Introduction 1.0

Climate change is apparent in many sectors of life and as citizens of Earth, changes must be made regarding the way we utilise resources (Le Quéré *et al.*, 2015). Many industries are considering their Carbon emissions and currently the fashion industry is responsible for 10% of the global budget and uses 93 million cubic meters of water per year, causing 20% global water pollution (Ellen MacArthur Foundation, 2017) . This research aims to analyse data collected during an action case study on ways to reactivate fashion waste and lengthen the lifespan of a fashion garment. The workshops provided two platforms, one where participants could exchange clothing and one workshop where participants could learn ways to reuse garments and manipulate them into different items – upcycling. Using GIS this study considers the data from a socio-economic perspective, to understand further whether affluence and a variety of other socio economic factors affect participants shopping habits and whether there are any patterns to these habits which might be changed with the correct provision of skill learning.

Aims

- Understand whether socio-economic factors such as affluence affect shopping habits of 30 workshop participants
- Add literature to support of upscaling sustainable practices
- Understand whether the learning of sustainable practices can help people reactivate fashion waste

Objectives

- Utilise Digi maps
- Utilise MapInfo for analysis
- Create a GIS with data to compare patterns
- Use thematic maps for pattern analysis

Hypothesis

- Participants from more affluent areas will be keener to utilise clothing exchange more than participants from less affluent areas

Figure 1 - Two images of participants from Clothing Exchange at Reactivate event - Photo – Ndodds

Figure 2 Photo of upcycling participants – Ndodds

Figure 3 Photo of books available at event for Upcycling – Ndodds

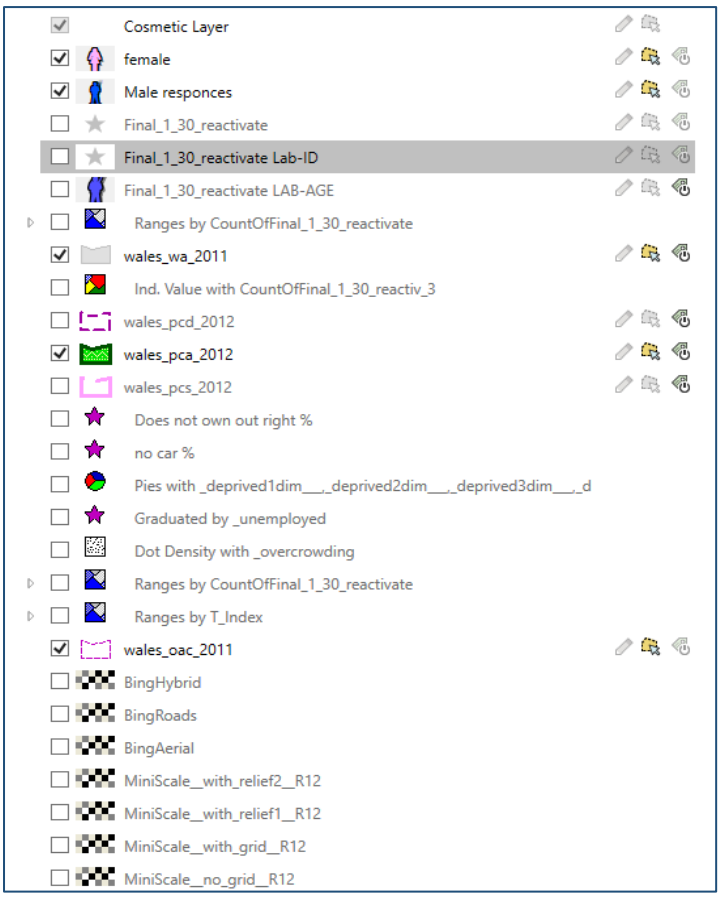
Discussion 2.0

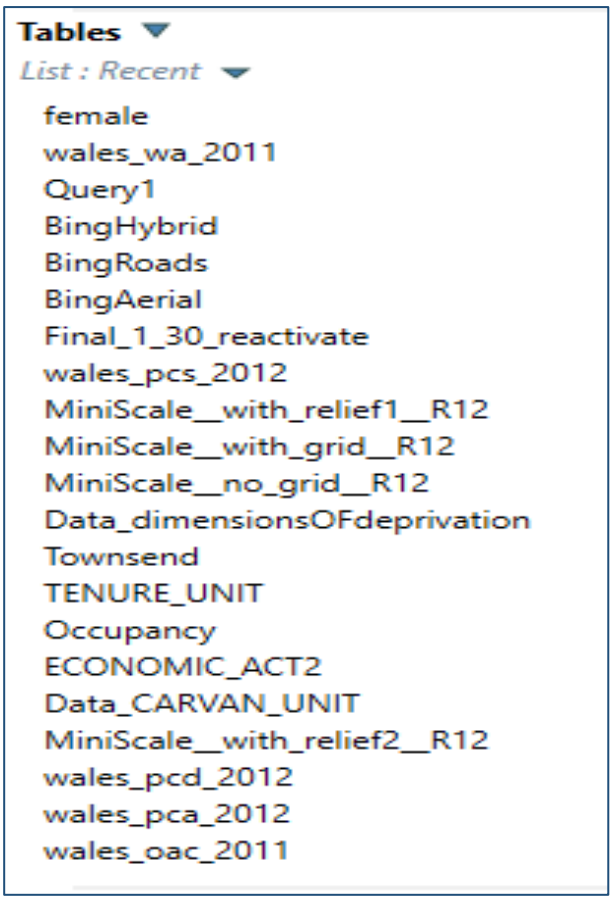
The GIS Model overview 2.1

In order to form conclusions as to whether socio economic status and affluence affected shopping habits, secondary data was used from a research dissertation. The data was collected at an action case study event testing ways to reactivate fashion waste such as Upcycling and Clothing Exchange. Data was first cleansed and base maps were obtained from Digi maps to show boundaries. A list of layers and tables are shown below in table 1 and 2 showing the full GIS model and all components before discussing each layer in further detail, to provide an overview of the model. Other layers involve Ordinance survey mini-scale maps, Bing Satellite images and census data. Further information being various queries and calculated data

The image below shows the varying layers by end of modelling which can be turned on and off to show different patterns and queries

Table 1 Table showing table and layers list on Mapinfo





Raster Layers 2.2

To create a GIS model that would allow analysis of the data, first background Rasta layers were created – OS miniscales and Bing Maps showing satellite, terrain and roads (fig4-6) which provides an overview of the study area in a variety of forms.

Figure 4 OS miniscale map

Figure 5 Os miniscale map

Figure 6 OS miniscale map

Bing Resources

Hybrid

Figure 7 Hybrid Map from Bing resources

Satellite.

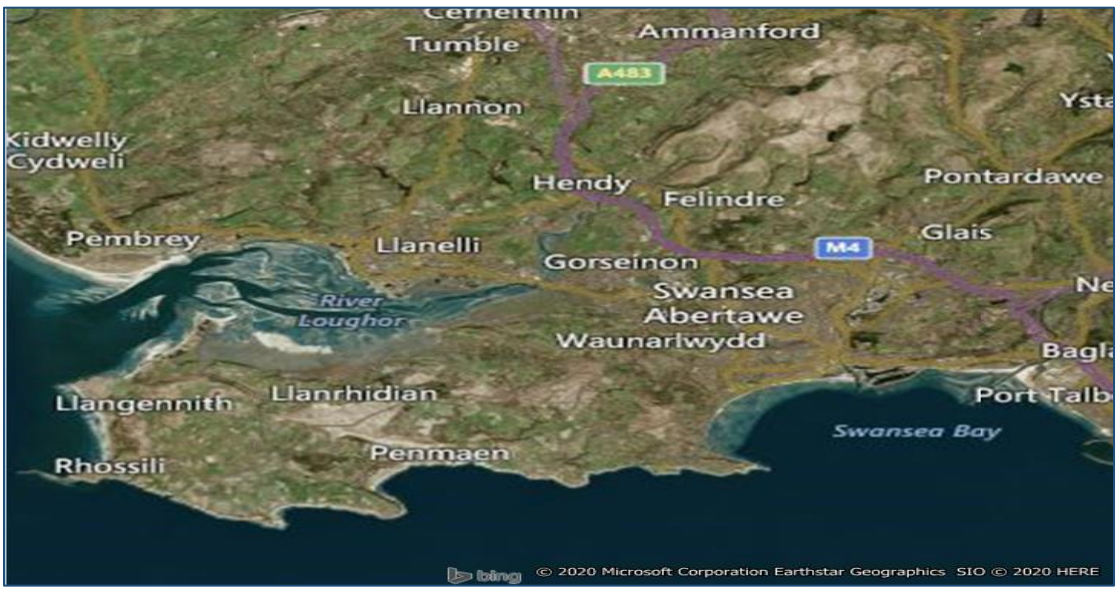


Figure 8 Satellite map from Bing resources

Roads

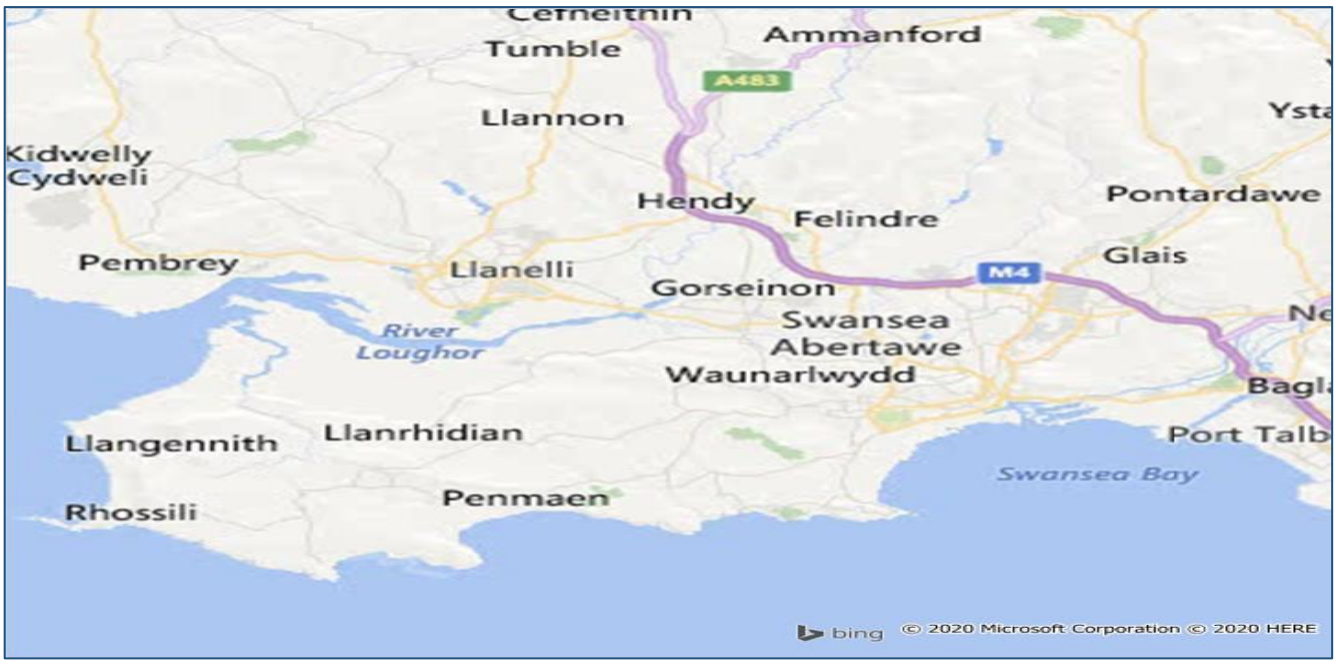


Figure 9 Map of Raods - Bing resources

Vector Layers 2.3

Vector layers were added next to show various boundaries including Lower output census boundaries, postal code sectors from UK borders, postal code district, Postal code SA and Electoral Ward census which provided useful as it showed different areas by name which were not shown on other boundary maps. Having the electoral and postal code boundaries at different levels allows data to be investigated on a more or less granular scope

Postal code sectors from UK borders

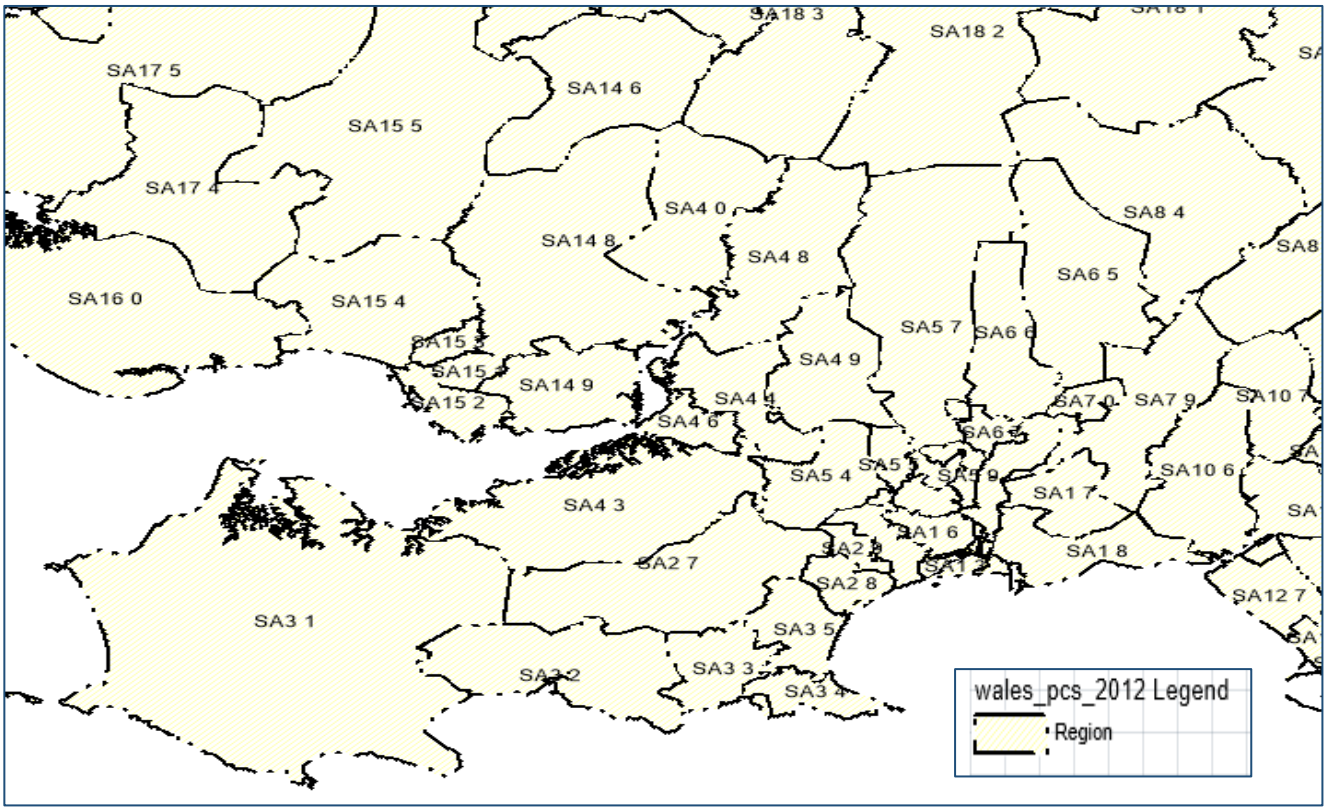


Figure 10 Postal code sectors from UK borders as vector layer

Postal code district

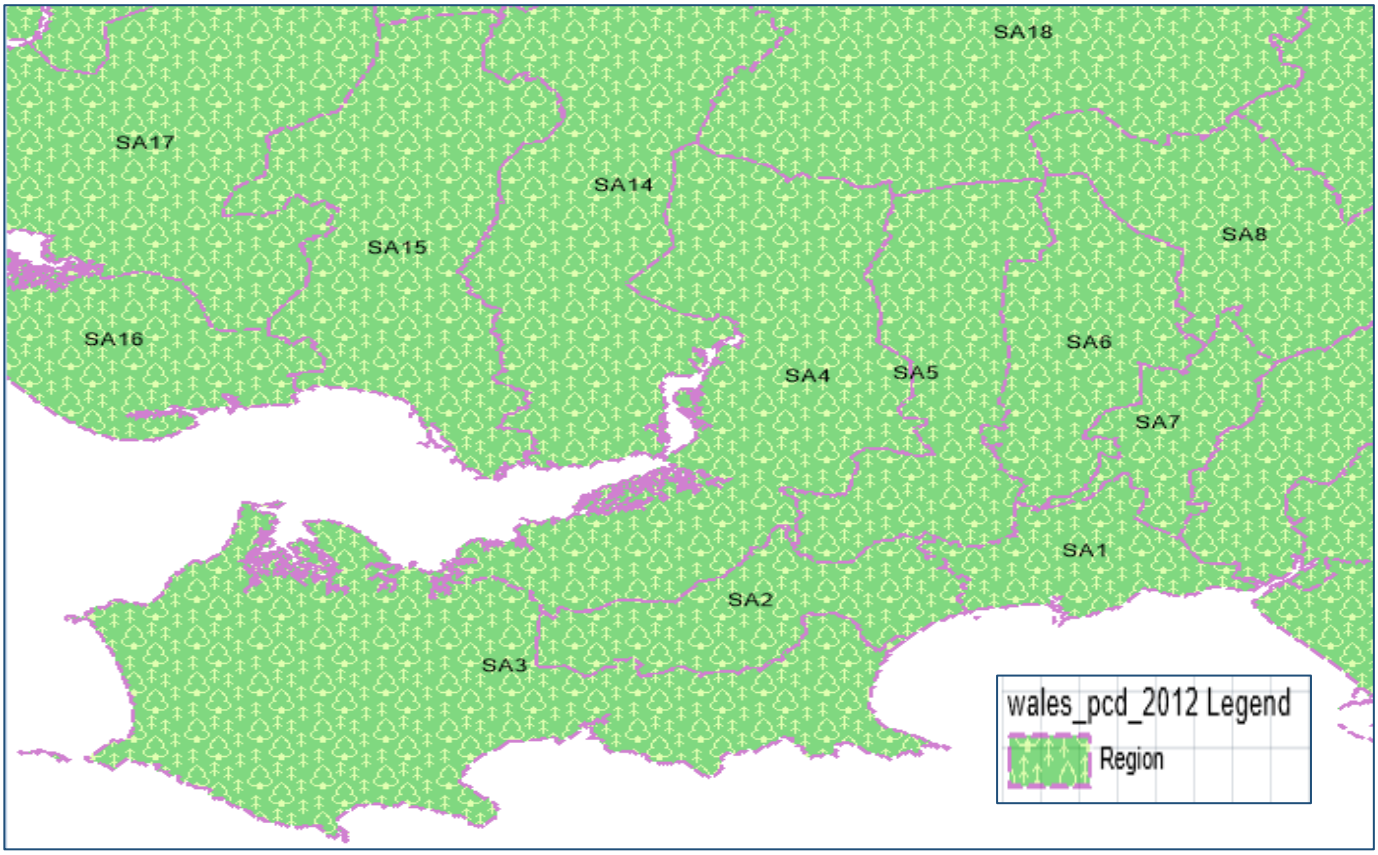


Figure 11 Postal code districts as vector layer

Postal Area 'SA'

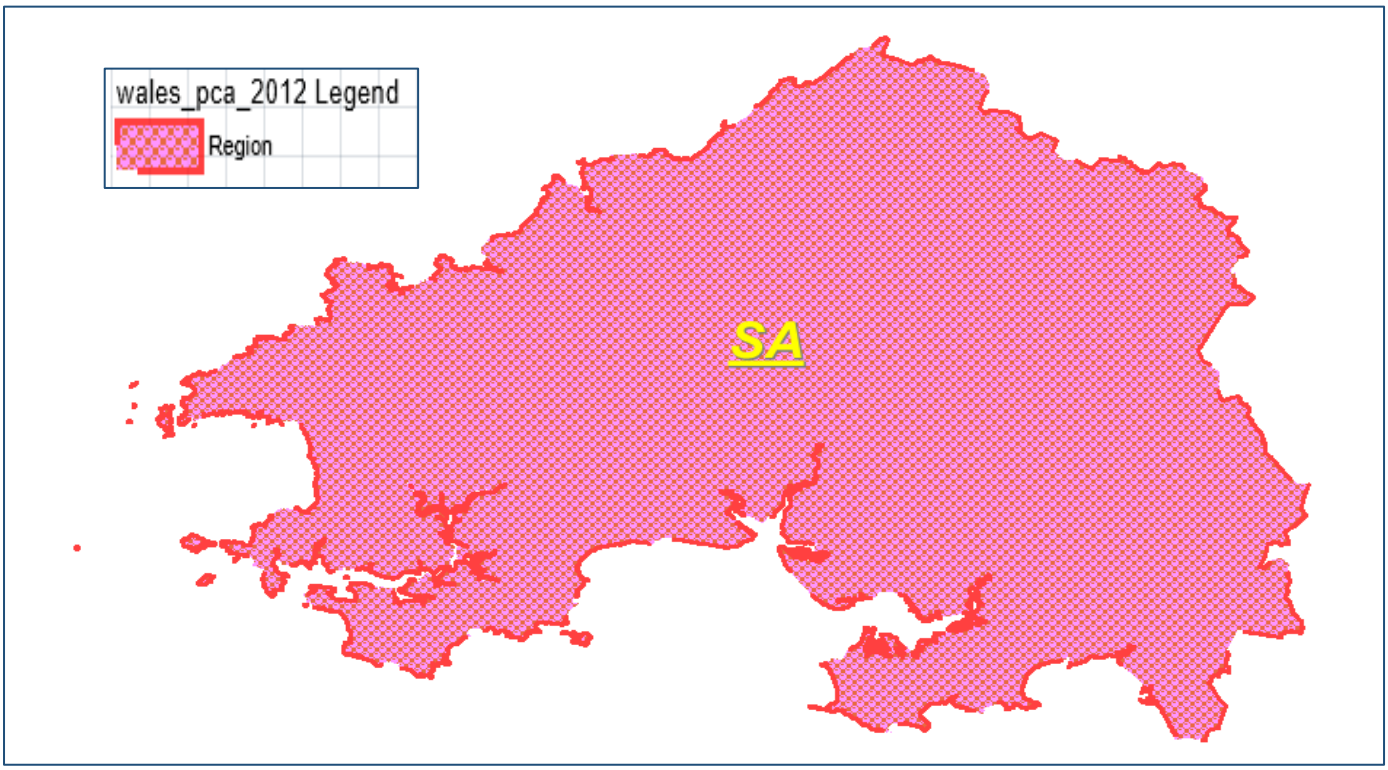


Figure 12 Vector showing Postal Area SA

Electoral wards- census boundaries

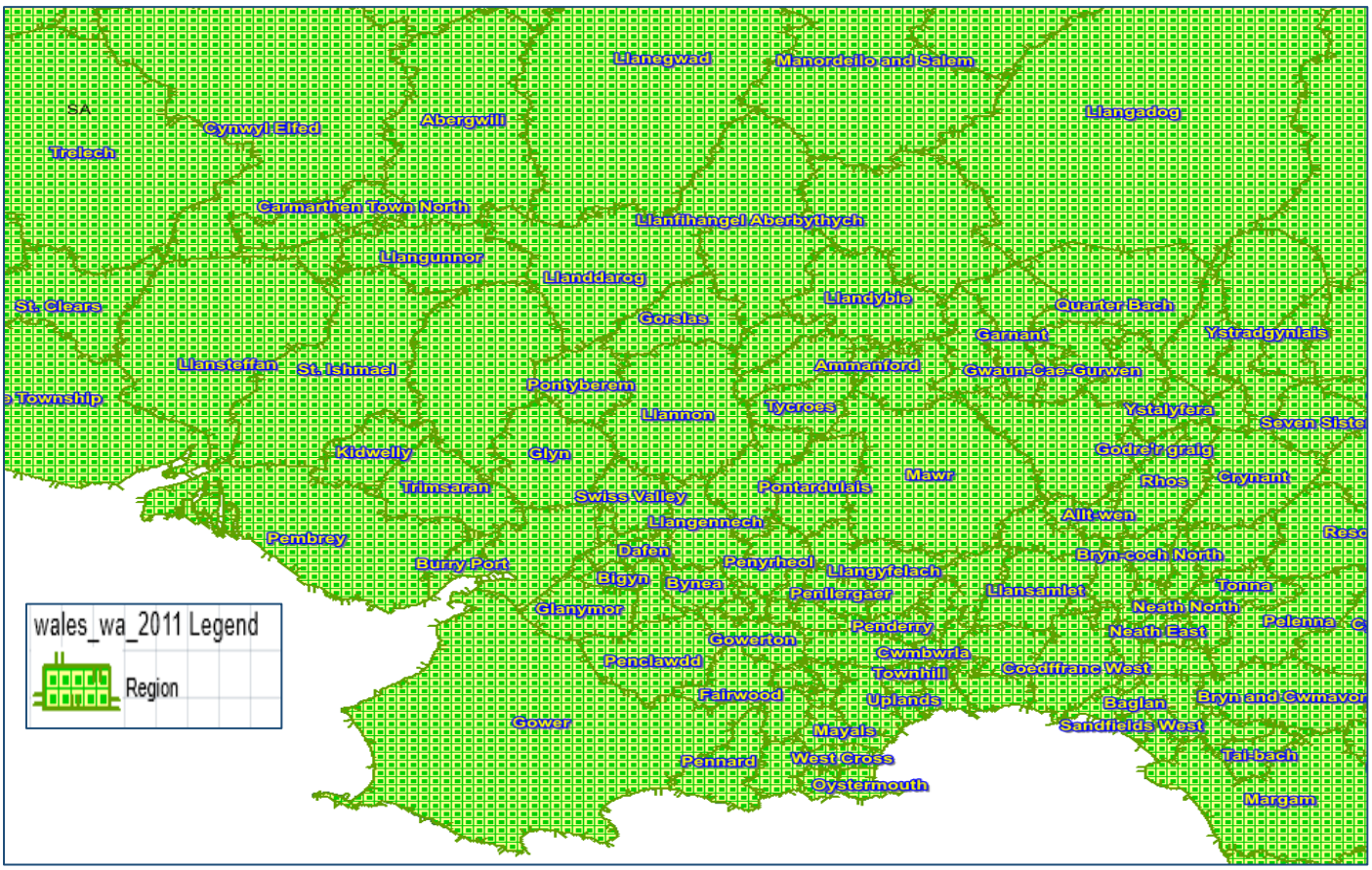


Figure 13 Vector showing Electoral wards- census boundaries

Lower output census boundaries

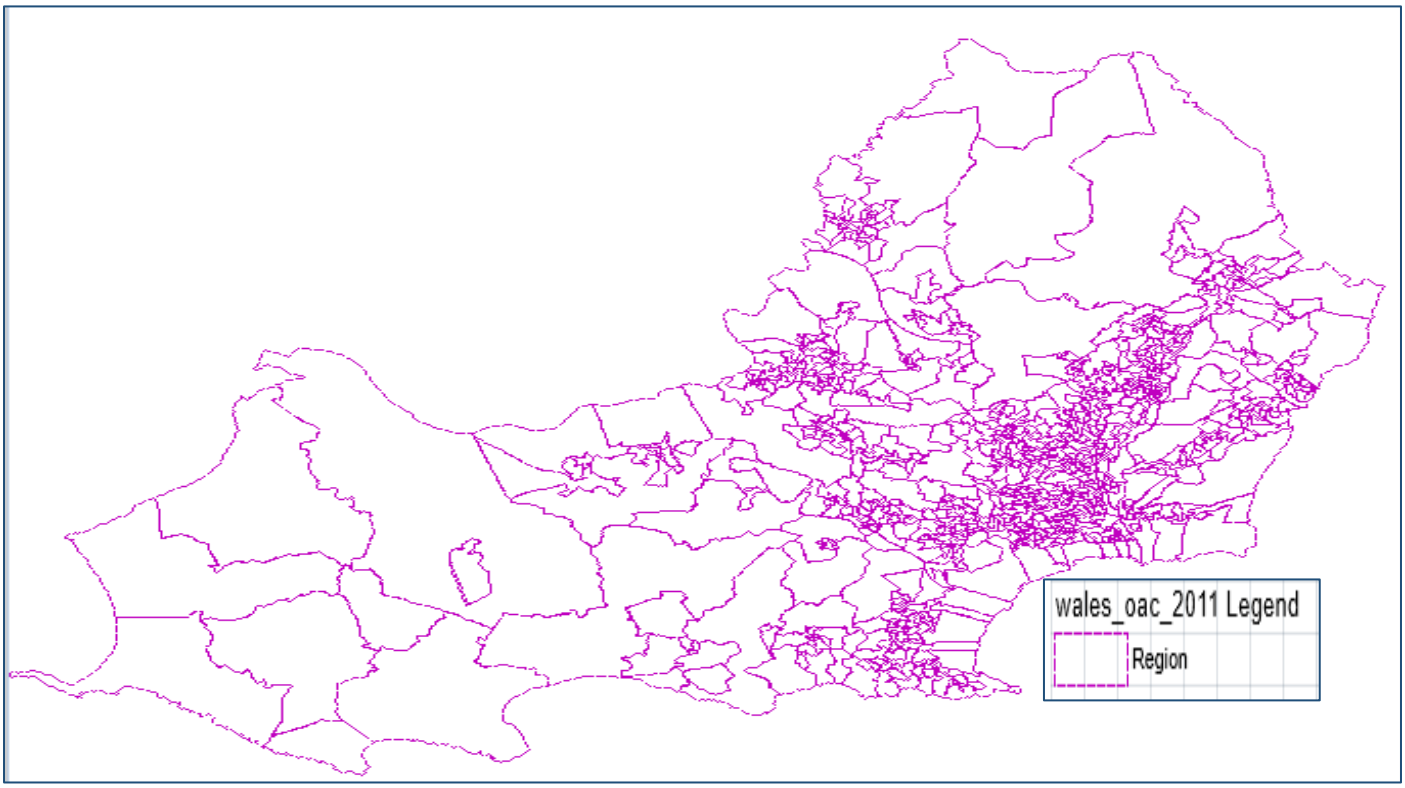


Figure 14 Lower output census boundaries

Point layers 2.4

The next layers added were point layers. The Respondents and are mapped as point data from excel spreadsheet with survey results, combined a selection by varying postcodes. SQL queries were performed such as- Age, Male/Female (fig 15) and by ID which participants were assigned numbers from 1-30.

More accurate postcodes in survey would have been beneficial as I would have had more accurate conclusions in my GIS. For example - sa18 - sa181ru - I would know exactly where they sat sector-wise as well as districts and area – there were a lot of results in SA1 for example so these points showed on top of each other, which didn't help form pattern analysis. This point data can show us various elements by simply changing the label in map info. The use of SQL queries allows user to filter datasets and there are other things that could have been investigated in this way should the data have been more comprehensive (Mark *et al.*, 2016)

The Respondents were mapped on SA postal area by ID

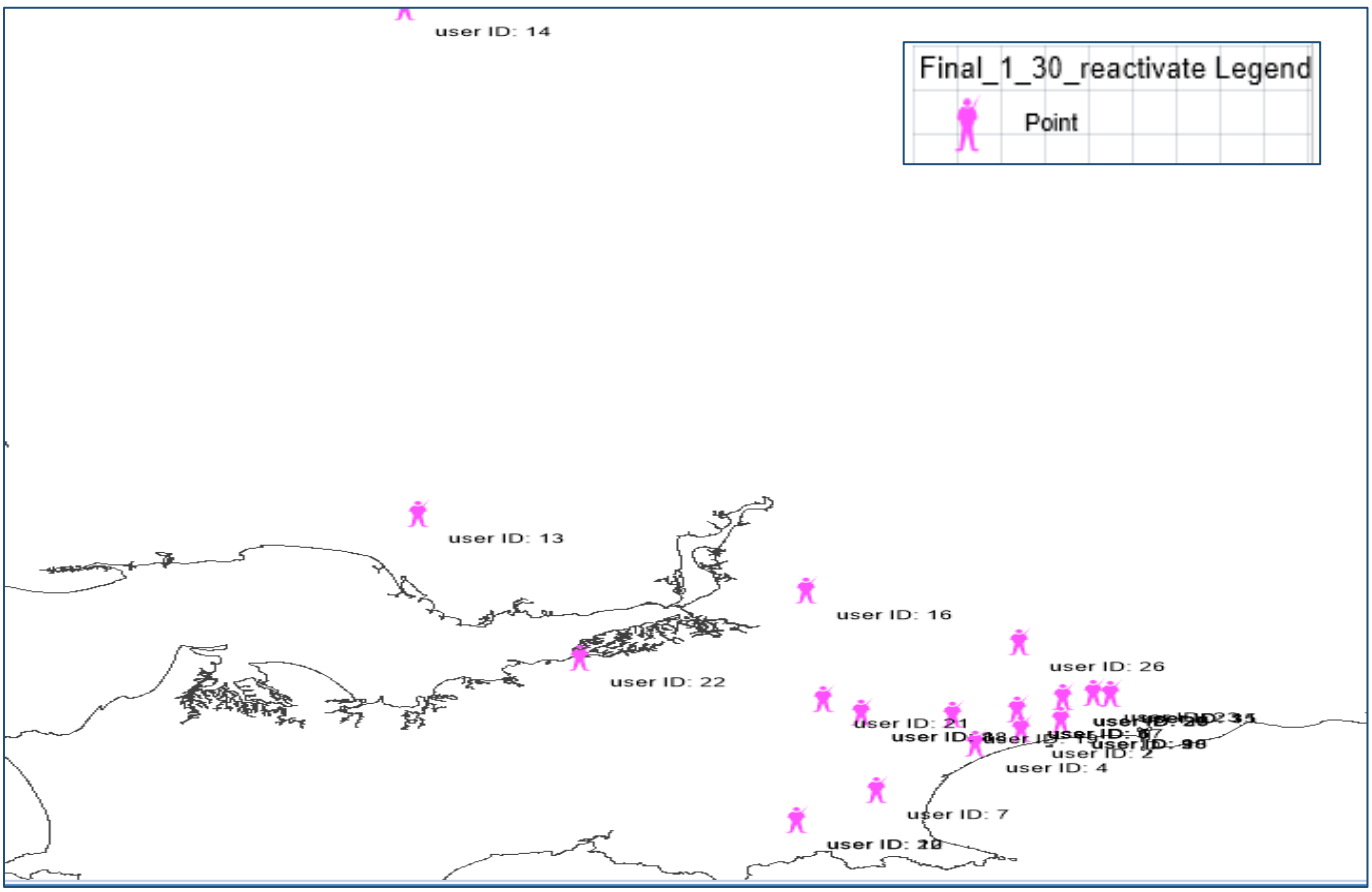


Figure 15 Point layer Respondents mapped on SA postal area by ID .

Respondents mapped on SA postal area by Age

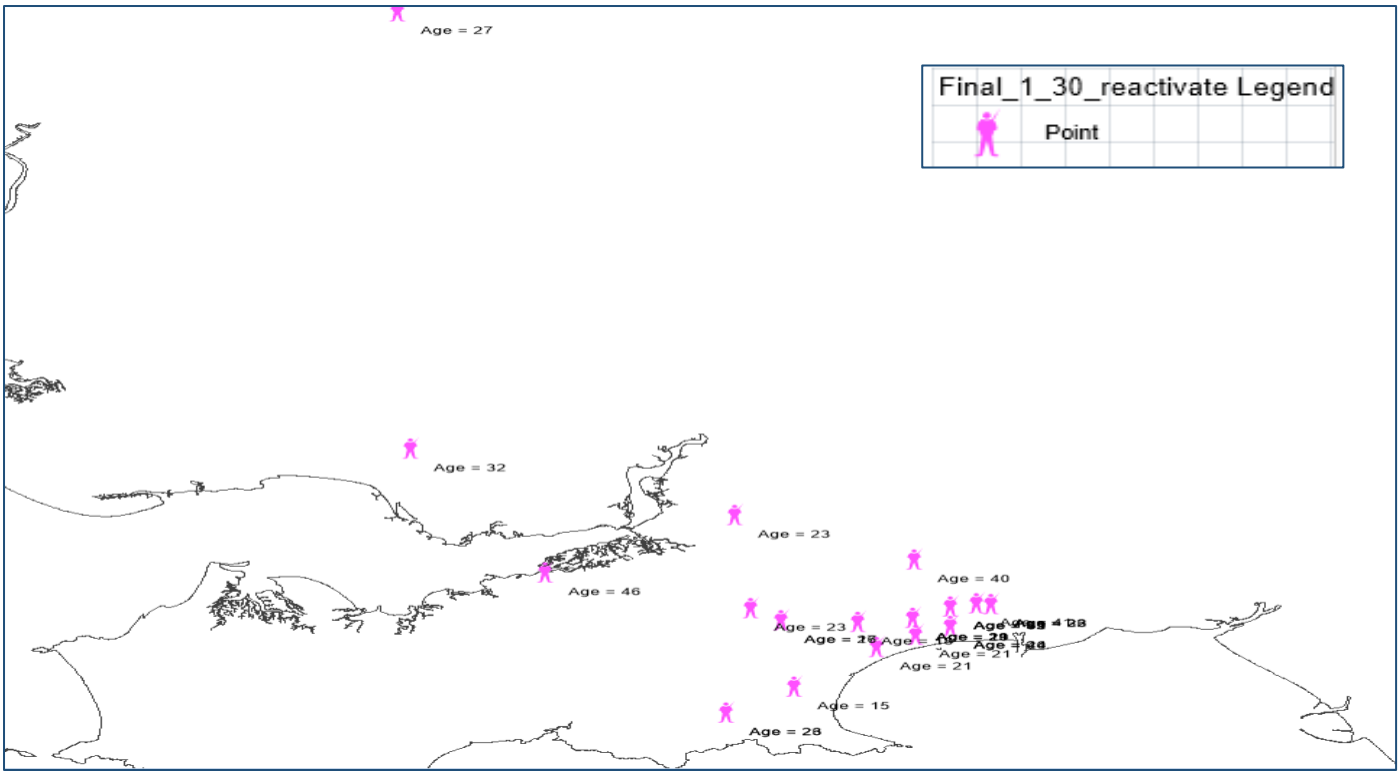


Figure 16 Respondents mapped on SA postal area by Age

Respondents mapped on SA postal area by Male female (SQL query)

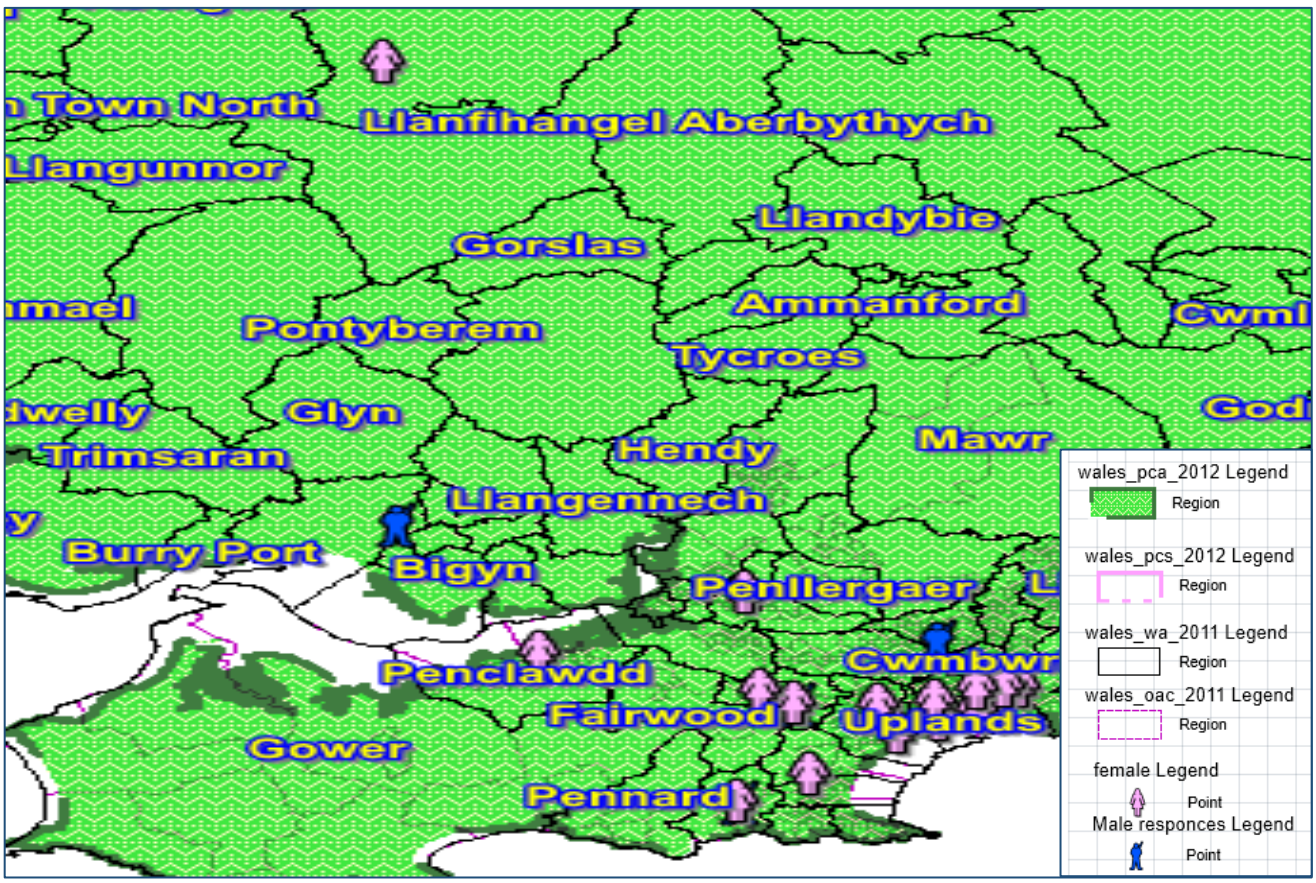


Figure 17 Respondents mapped on SA postal area by Male female

Thematic Layers 2.4

The next layers added were thematic layers which enabled a further understand of participants and their shopping habits in relation to affluence and socio economic status . In order to obtain this data both electoral census data was needed. The Townsend calculation allowed a further investigation into these socio-economic differences between participants as did the depravation data from Infuse showing 4 dimensions by lower output.

Varying SQL queries were performed showing range counts of respondents in electoral census wards (fig) by postcode district (fig) and thought this did not show any patterns, it was useful to understand the spread of data geographically. The range count of respondents in post code district shows where the respondents were focused, most accurate lever that can be achieved to incomplete postcodes. This could be compared to areas of deprivation or one of the Townsend sub calculations

Range: Count of respondents in Electoral census wards

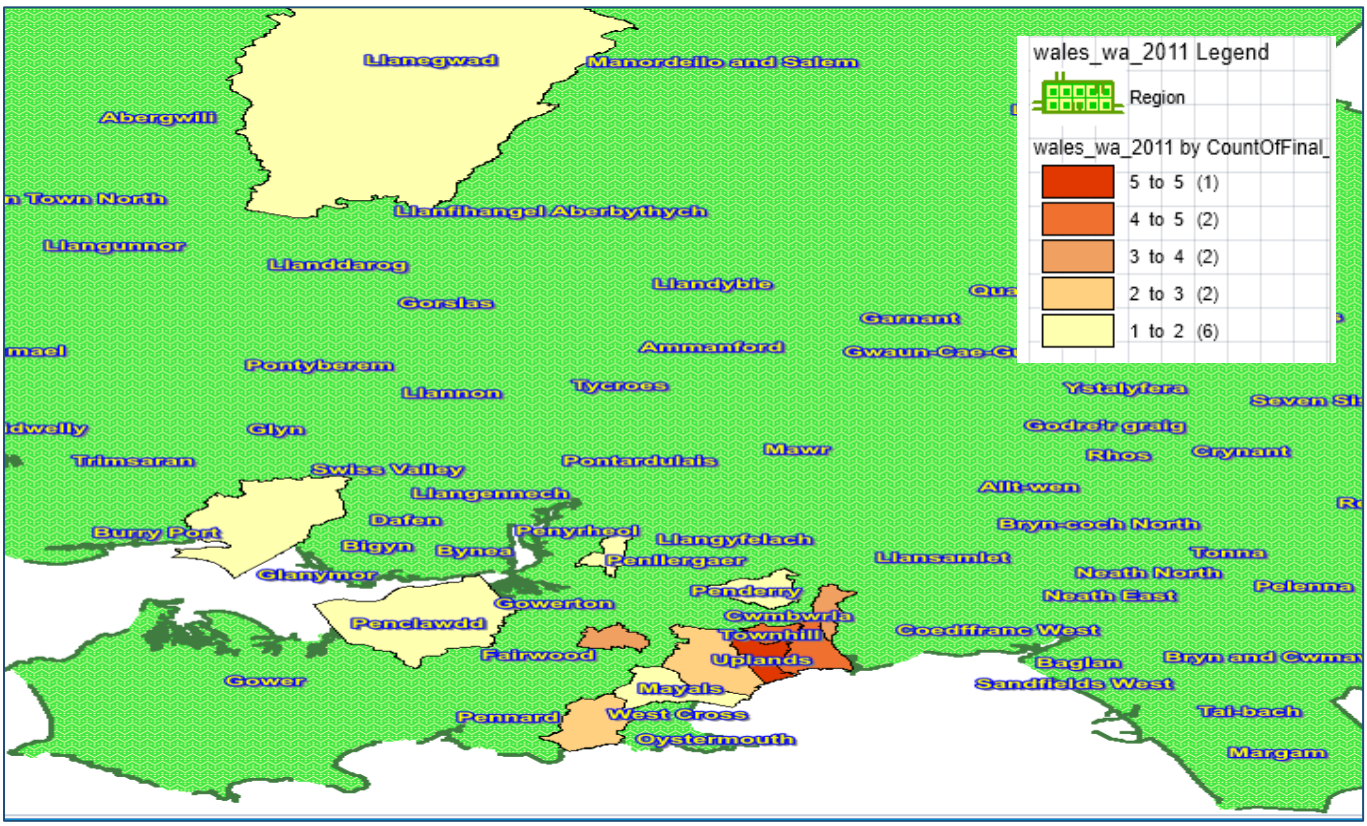


Figure 18 Range: Count of respondents in Electoral census wards

Range: Count of respondents in post code district

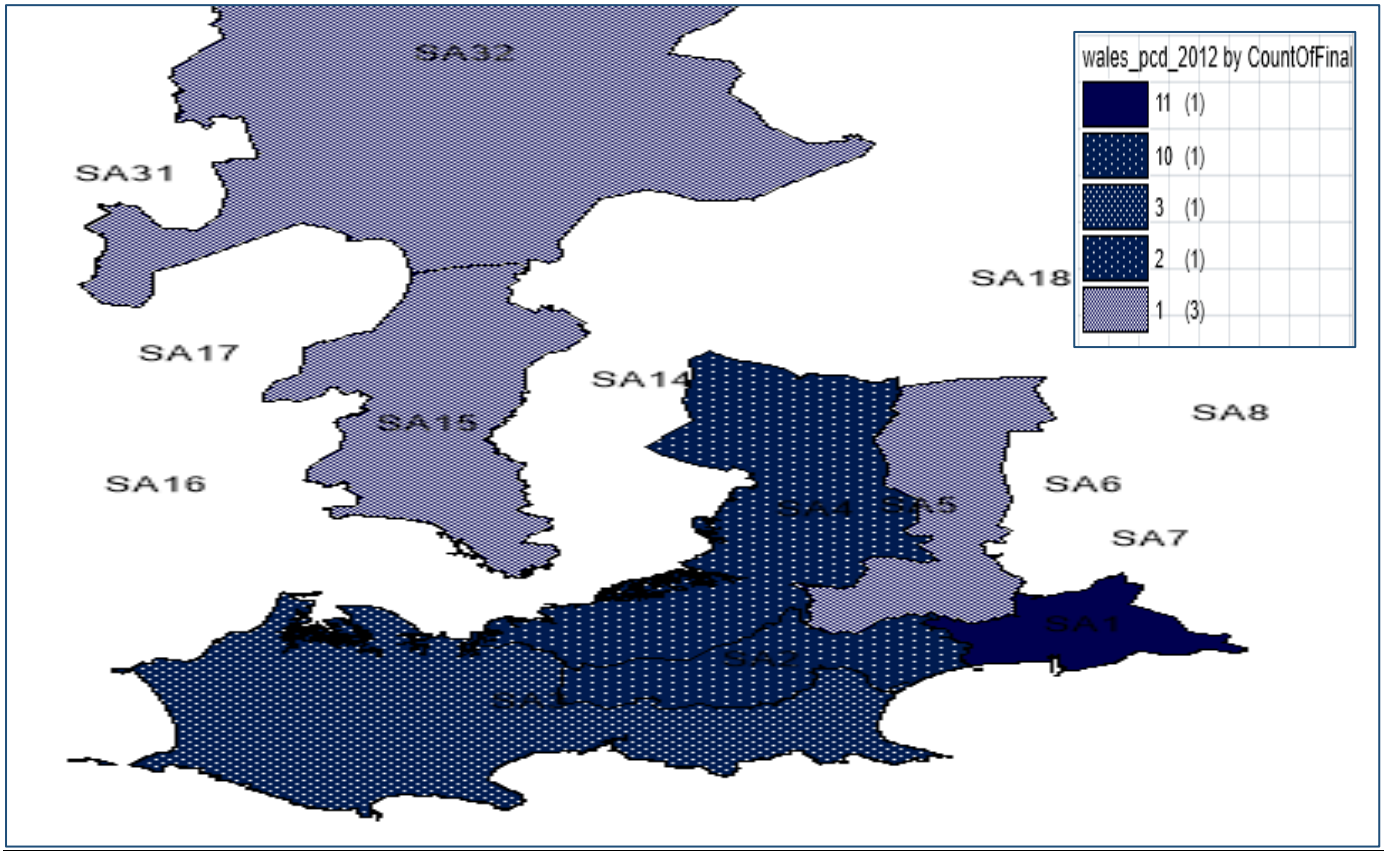


Figure 19 Range: Count of respondents in post code district

Individual Value: Count of respondents in Lower census wards shows where the respondents were focused, but would be thrown at this level due to vague postcodes

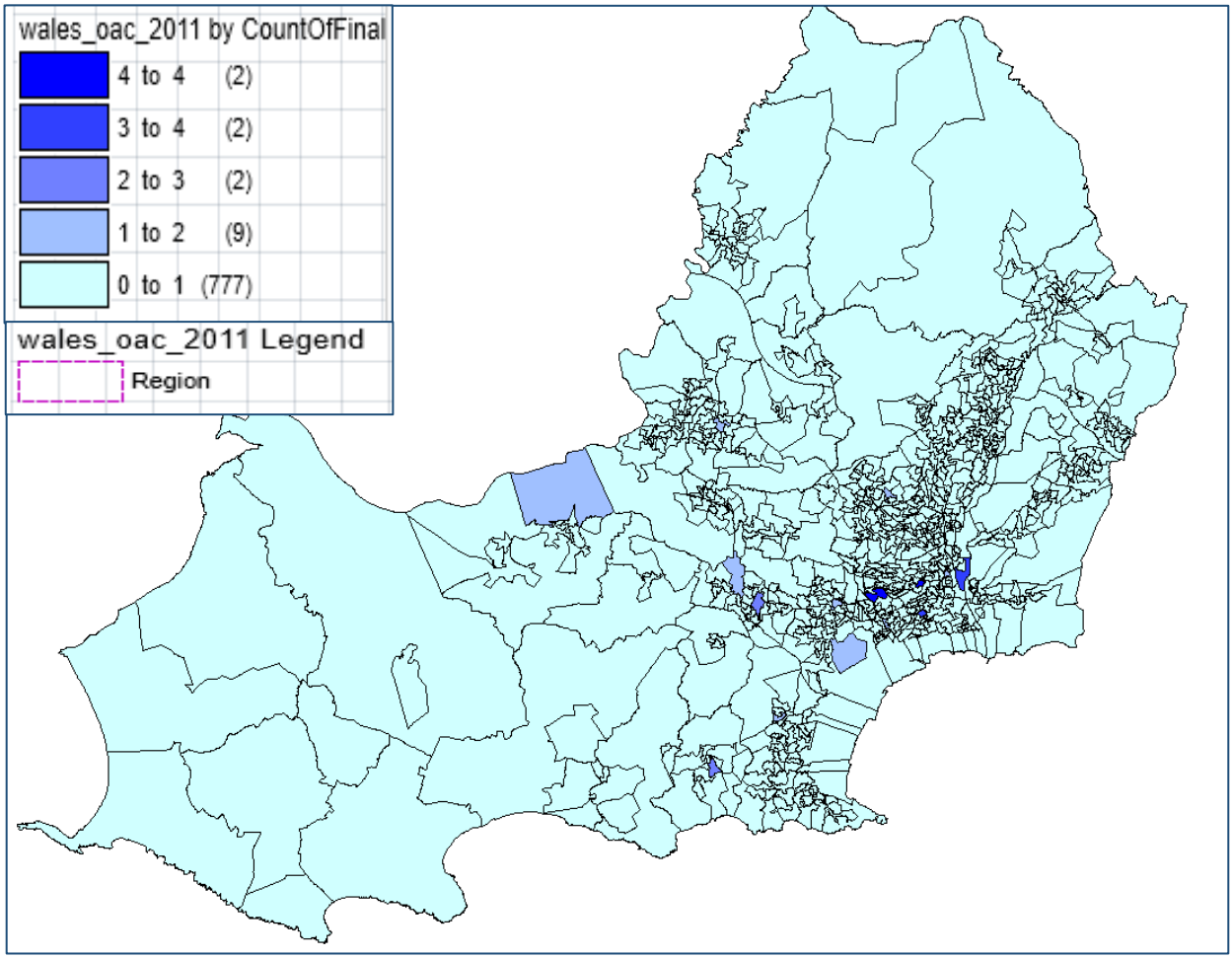


Figure 20 Count of respondents in Lower census wards

Deprivation

Infuse 4 dimensions pie chart by lower output this is an alternative to using a Townsend which shows dimensions of depravation as a pie chart set over the lower output using census and boundary data. Could be compared to Townsend to see if there are differences between the two calculation types

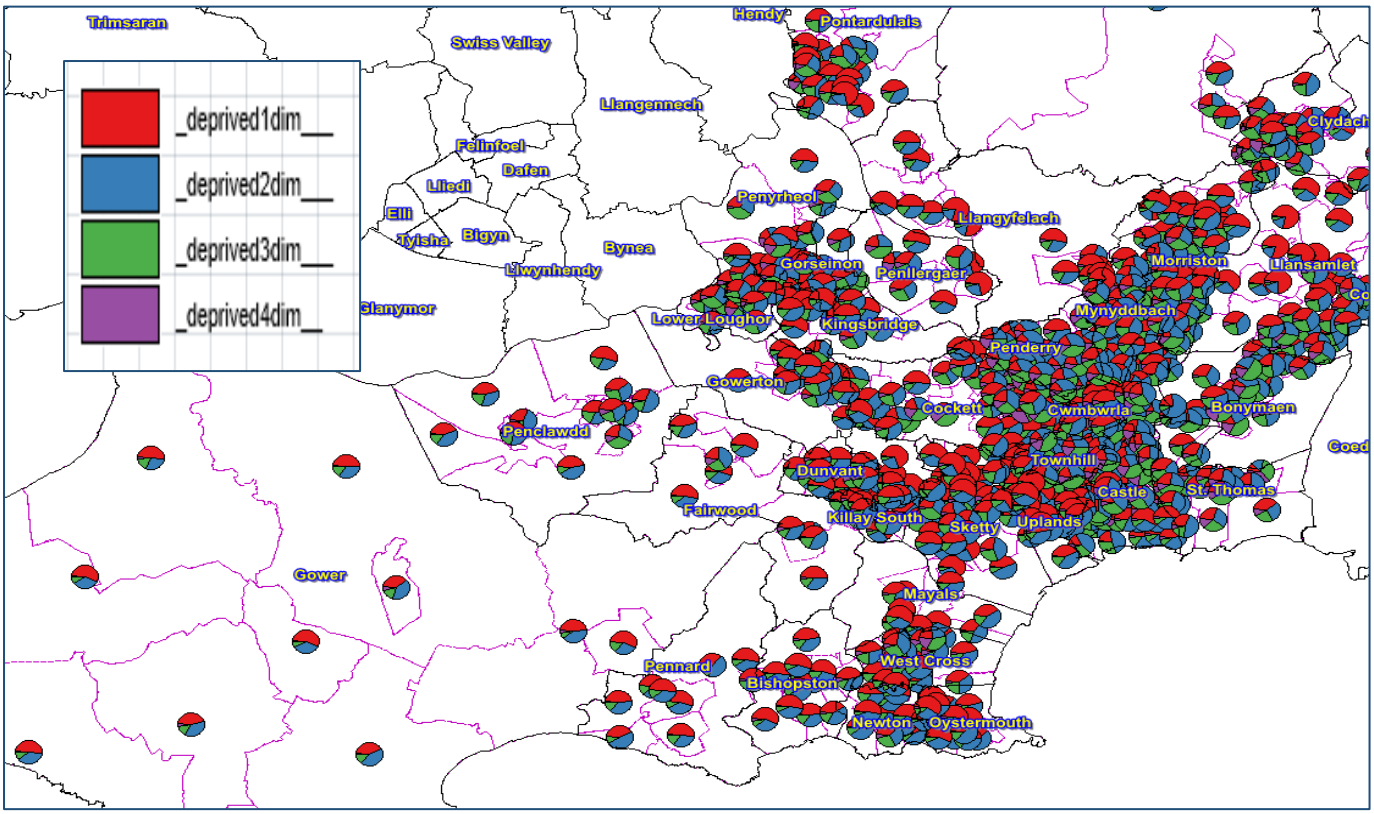


Figure 21 Infuse 4 dimensions pie chart by lower output

The Townsend Index 2.5

The Townsend index was created from census data showing lower output, these numbers were calculated in order to create the Townsend calculation- all data is infuse census data such as the percentage of graduates with no car in central Swansea (fig the larger the icon the higher the percentage of people with no car) and the amount of graduates owing homes in the area (fig23), the amount of graduates unemployed (fig24) and the dot density of overcrowding (fig 25)

Each sub part of the calculation can be used for comparative analysis against elements of the data gathered

Such as question responses etc Gender split or Age group (Esri, 2015). The larger the icon the higher the percentage of people with no car (fig22)

Townsend calculation by lower output: graduated percentage no car Central Swansea

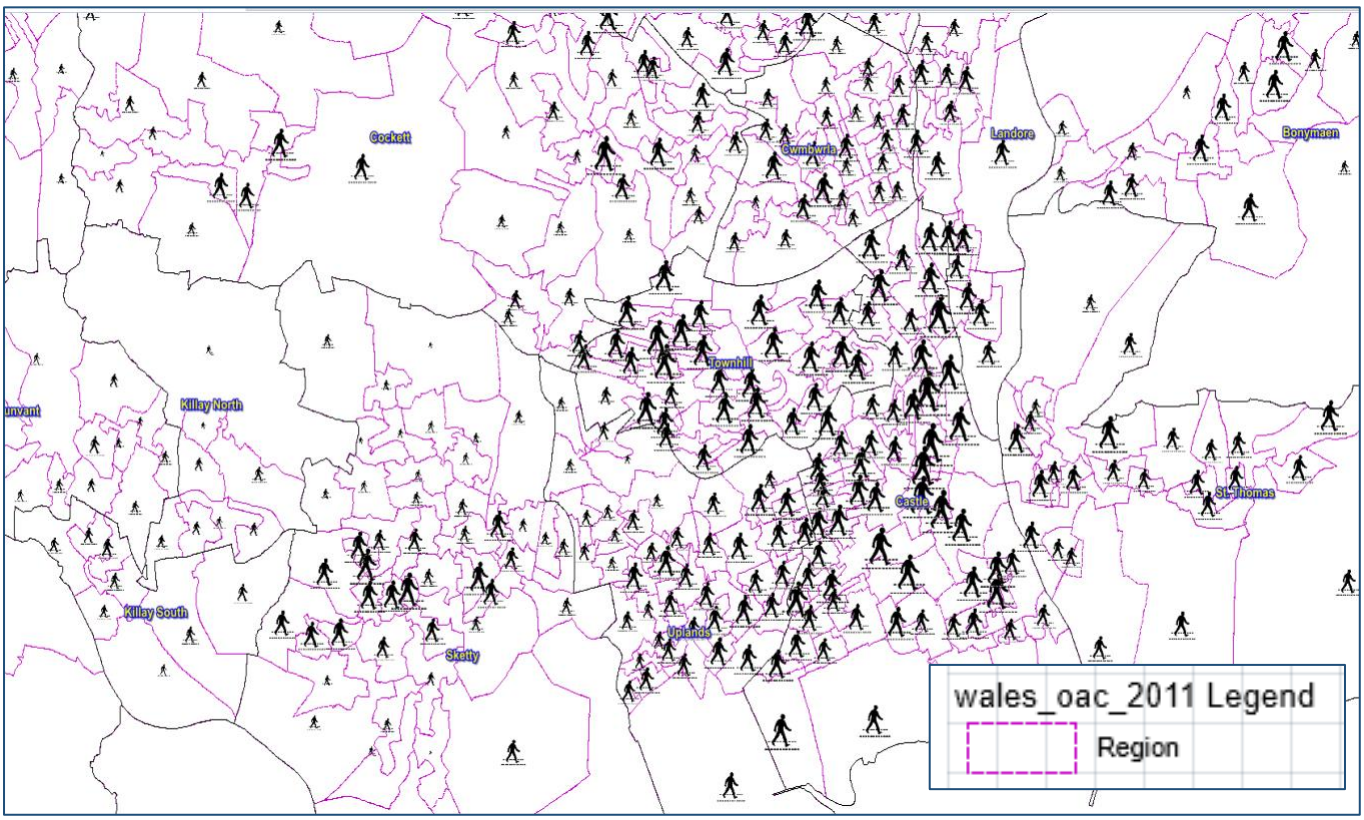


Figure 22 Townsend calculation by lower output: graduated percentage no car Central Swansea

Townsend calculation by lower output: graduated home ownership – The larger the icon the higher the percentage of people who do not own their own home

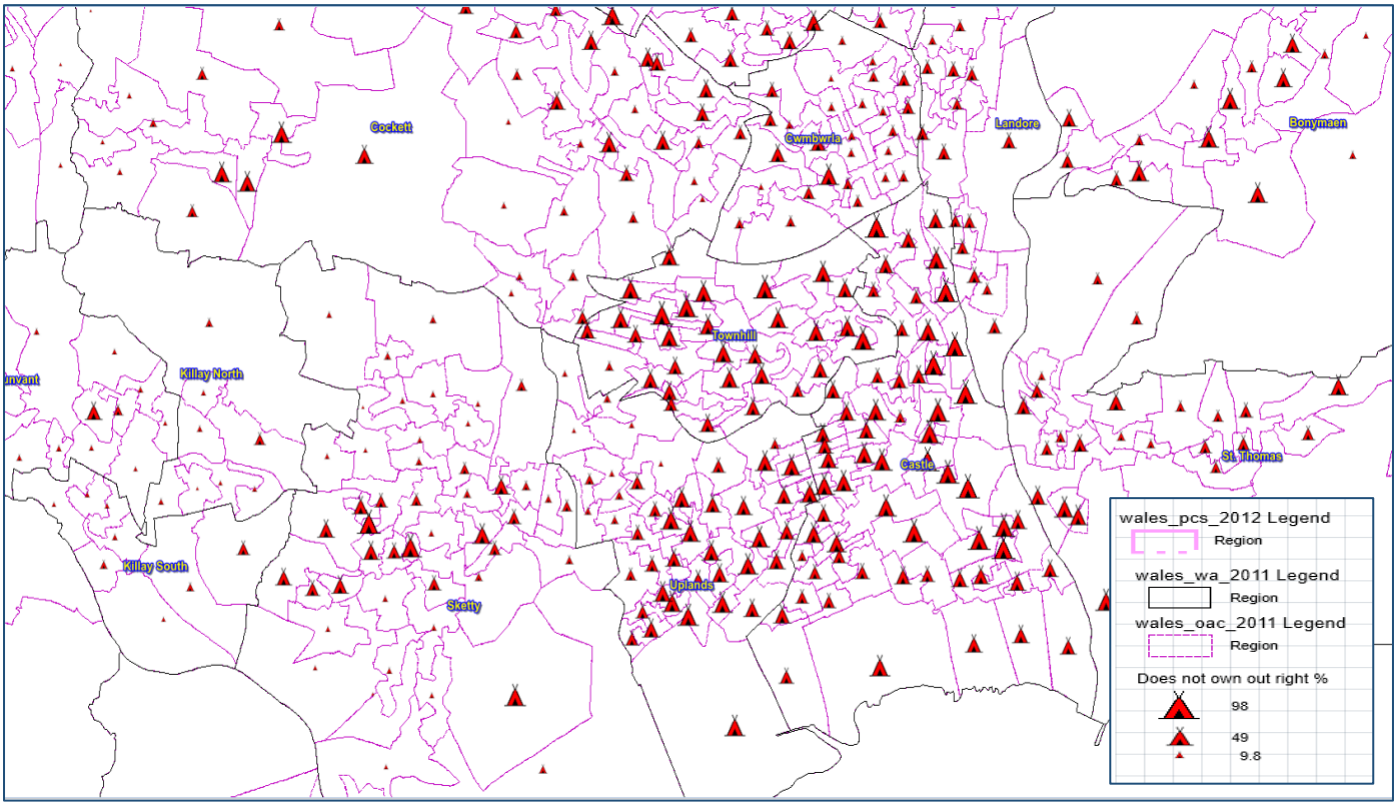


Figure 23 Townsend calculation by lower output: graduated home ownership

Townsend calculation by lower output: graduated unemployment – The larger the icon the higher the percentage of people are unemployed

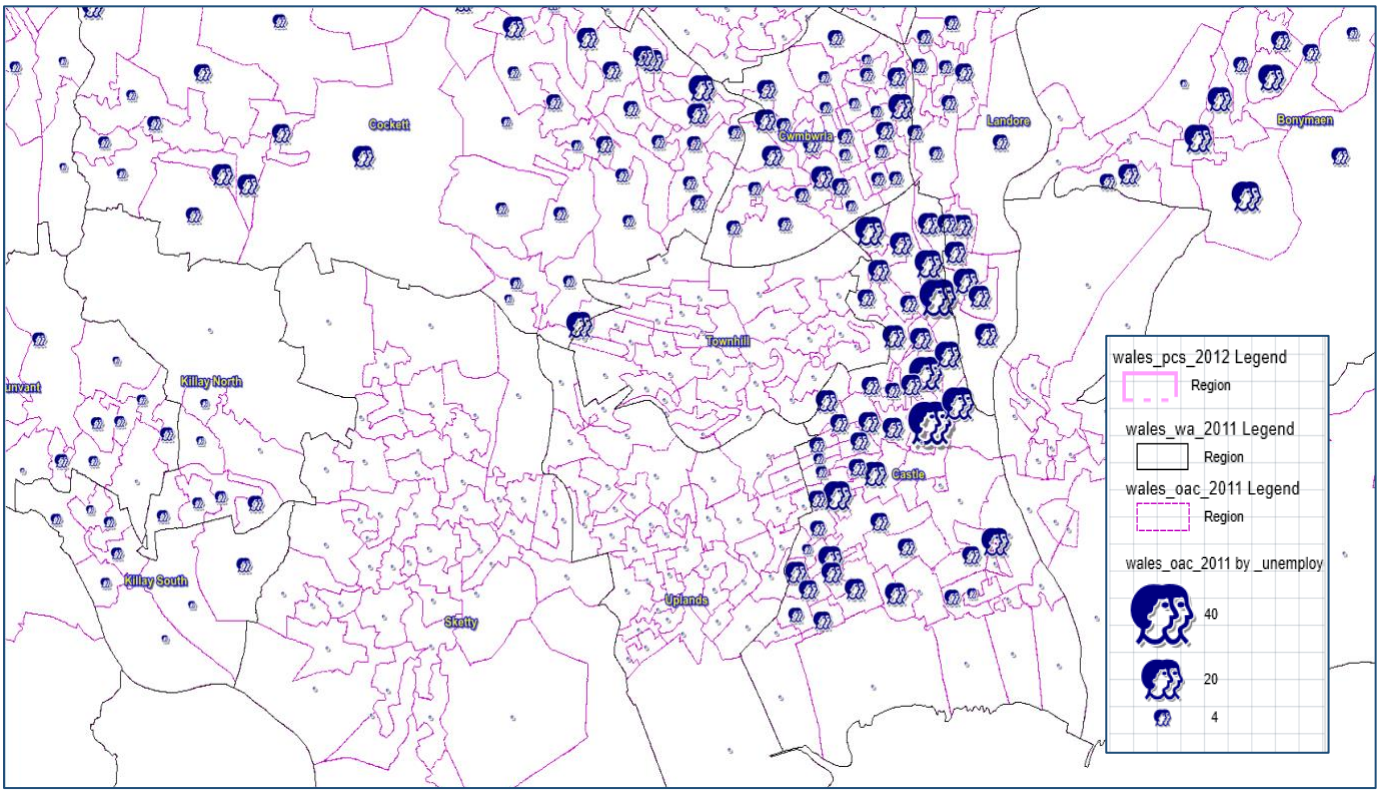


Figure 24 Townsend calculation by lower output: graduated unemployment

Townsend calculation by lower output: dot density overcrowding - Unemployment map over lower output, the closer the dots the greater the percentage of unemployment

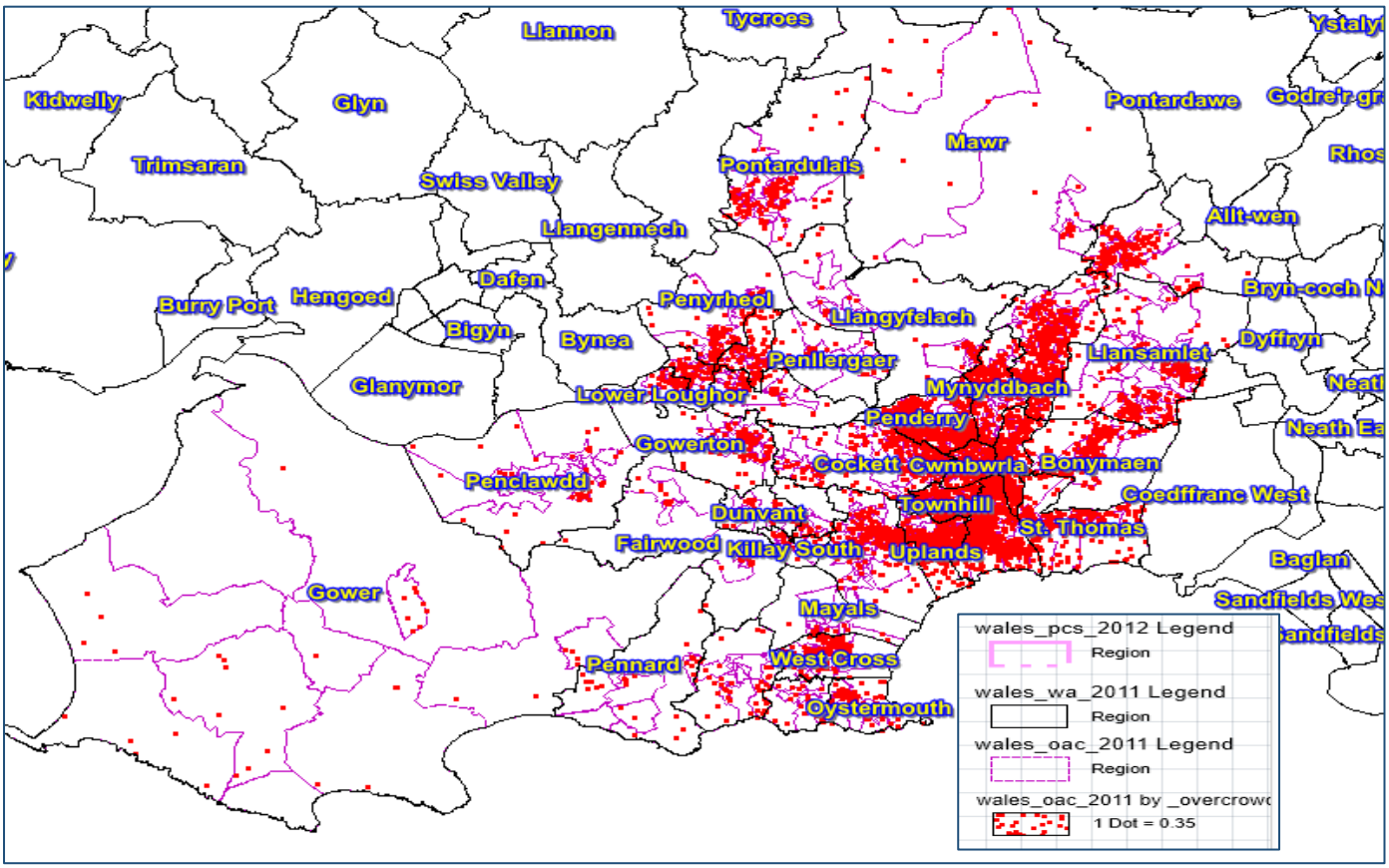


Figure 25Townsend calculation by lower output: dot density overcrowding -

Townsend calculation by lower output: Townsend index- Ranged Townsend index formed from the previous %calculation layers can be used to compare elements of the gathered data against poverty

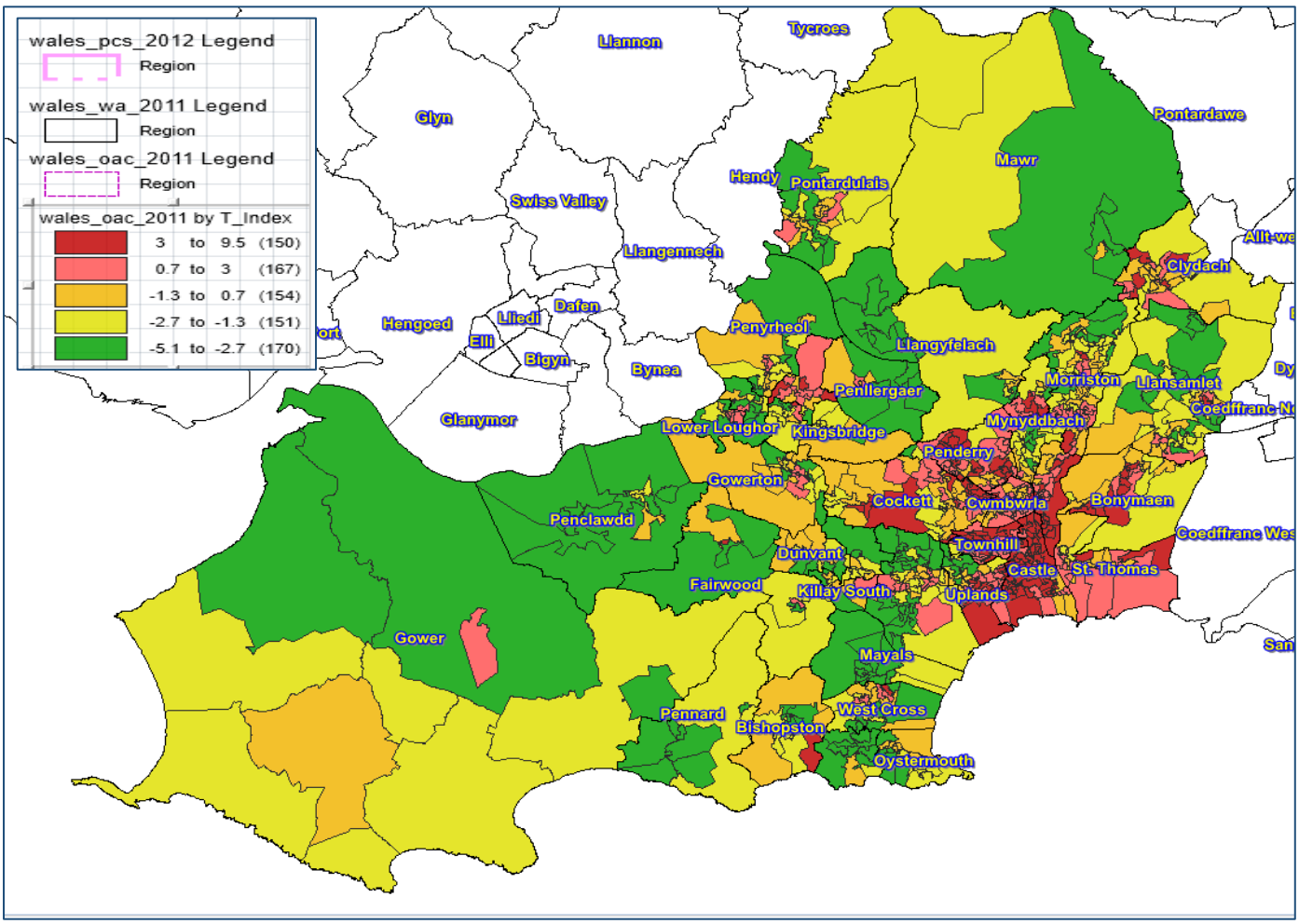


Figure 26 Townsend calculation by lower output: Townsend index-

Combined layers 2.6

Lower output census boundaries over Bing hybrid - Shows context, how lower output fits into the satellite image. Further investigation could have been useful into different queries surrounding the individual questions as point data on the map, however owing to the accuracy issue this would have been impractical with the data as it stands. All the data from census was from 2011 which was the most recent data available.

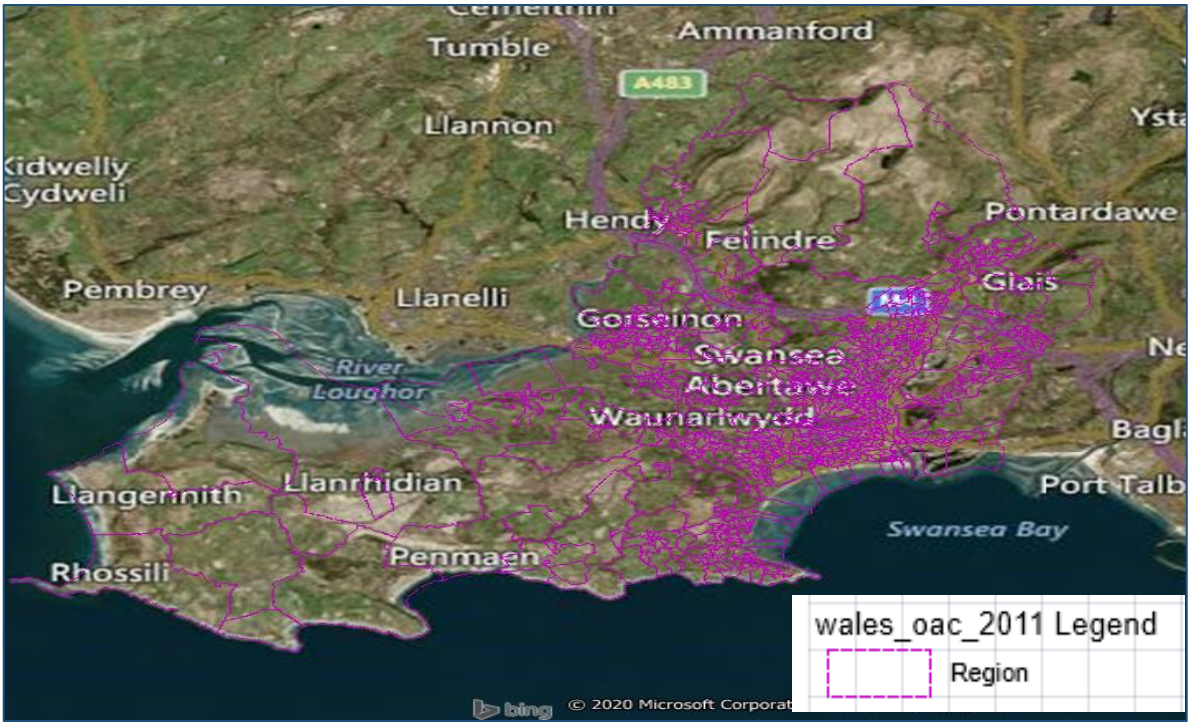


Figure 27 Lower output census boundaries over Bing hybrid

Lower output census boundaries over OS mini-scale with relief which Shows context, how lower output fits into the OS road map

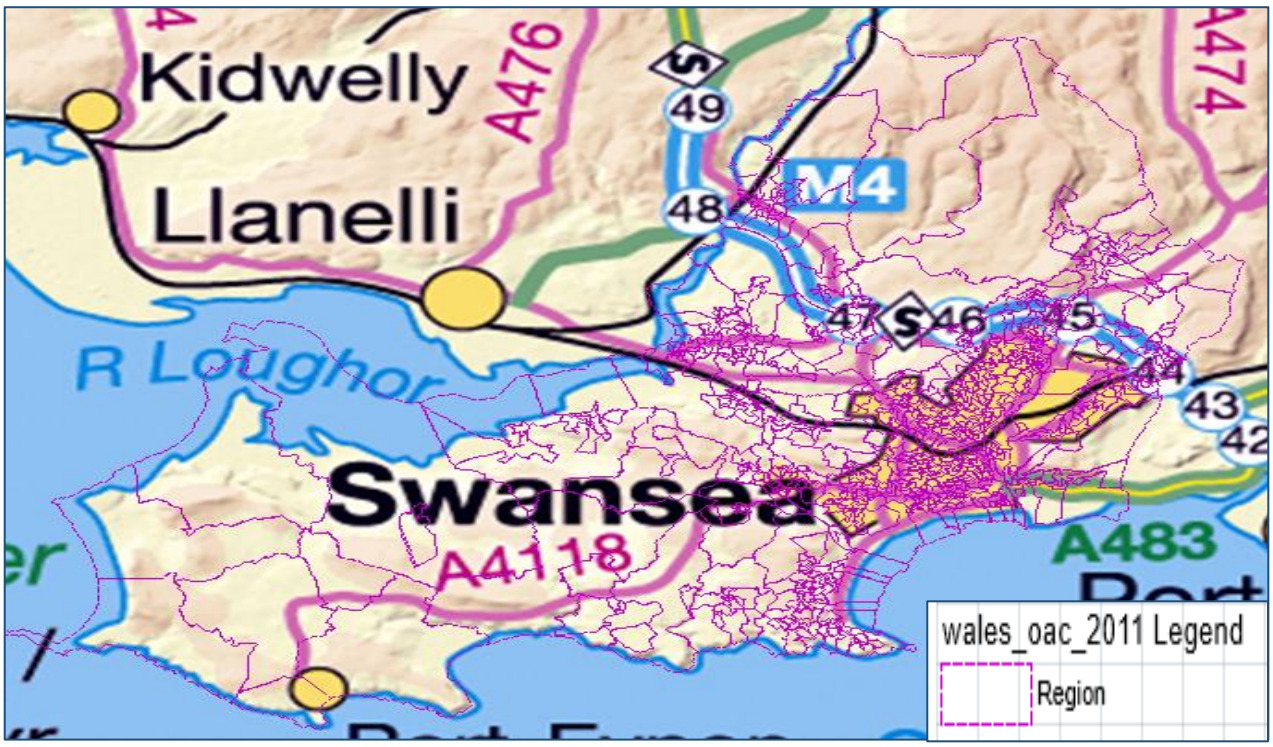


Figure 28 Lower output census boundaries over OS mini-scale

Postal code sectors on mini scale with no grid which is a Post code over road map

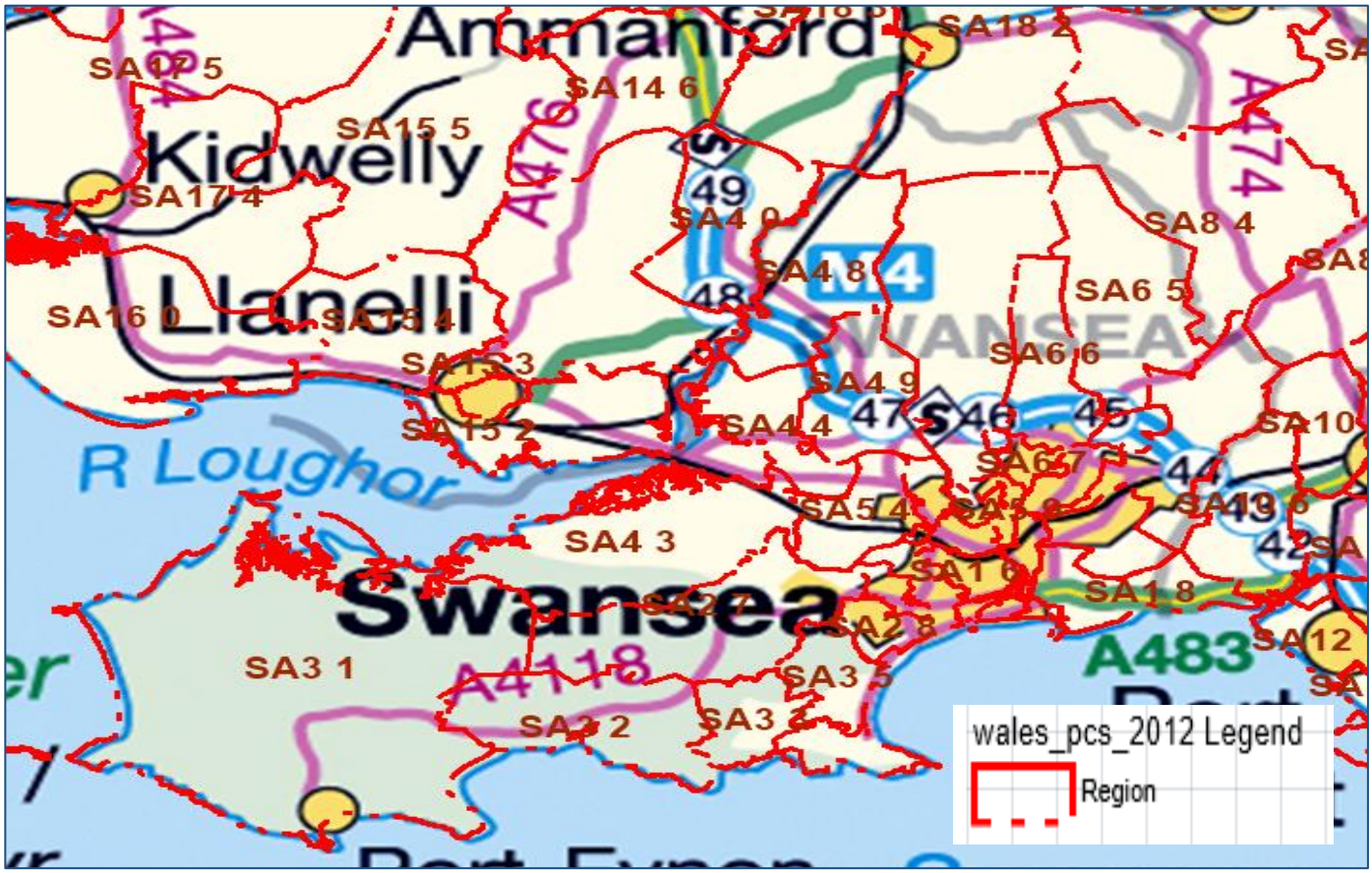


Figure 29 Postal code sectors on mini scale with no grid

Postal code sectors over a Bing Hybrid map

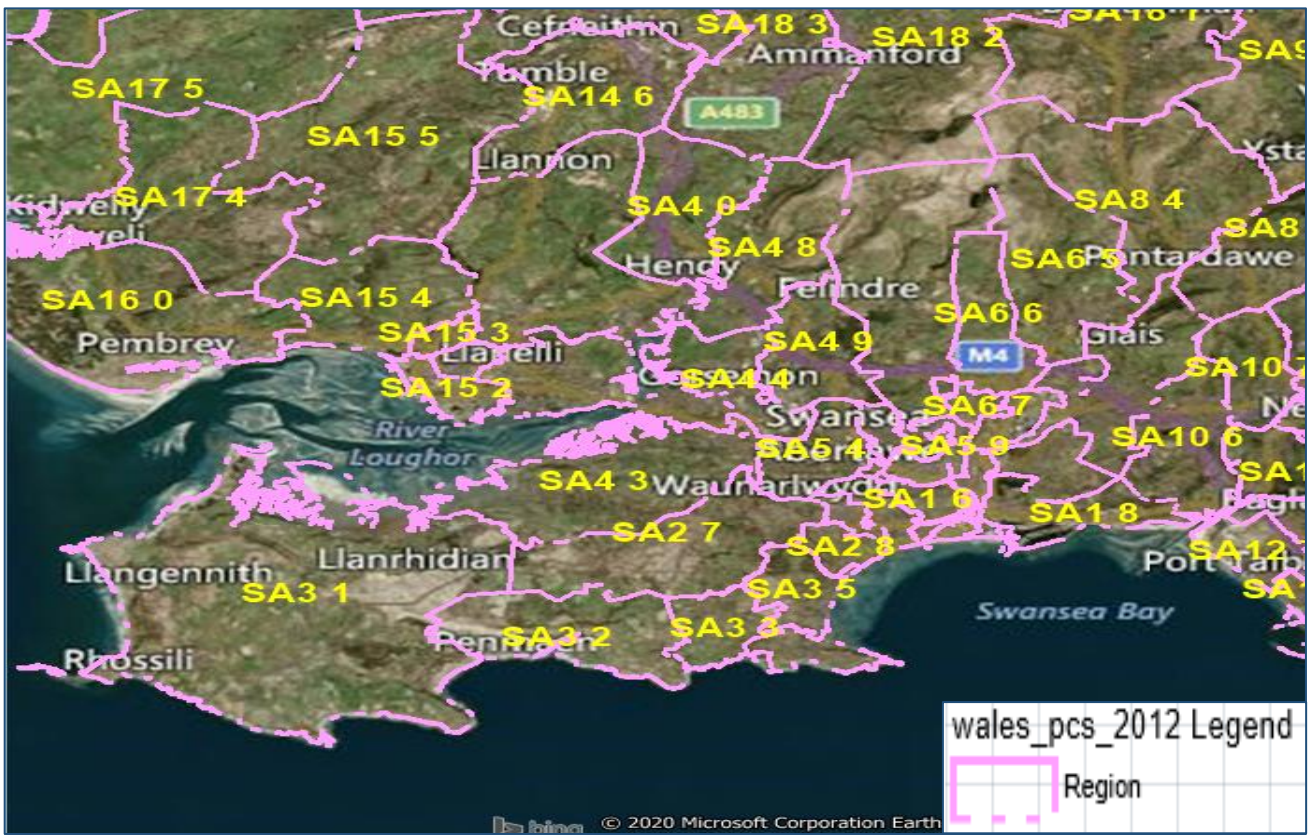


Figure 30 Postal code sectors over a Bing Hybrid map

Responders over Townsend index which Shows the distribution of the responders plotted over the poverty map, this could be queried to find specifics within the data

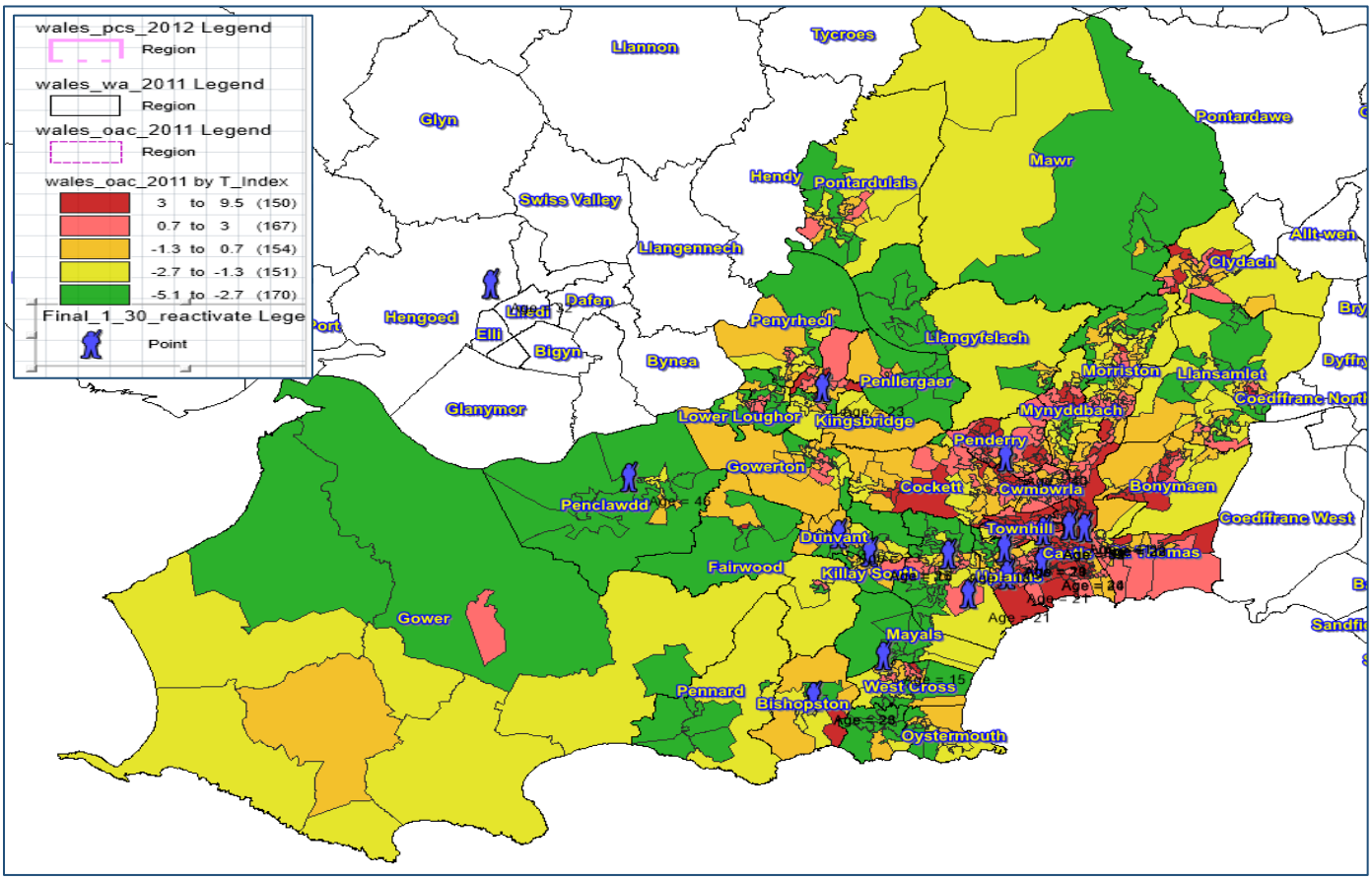


Figure 31 Responders over Townsend index

Townsend index compared to 4 dimensions which Shows four dimensions over Townsend, could be used as a test to see if we are getting a similar view of the data from both sets

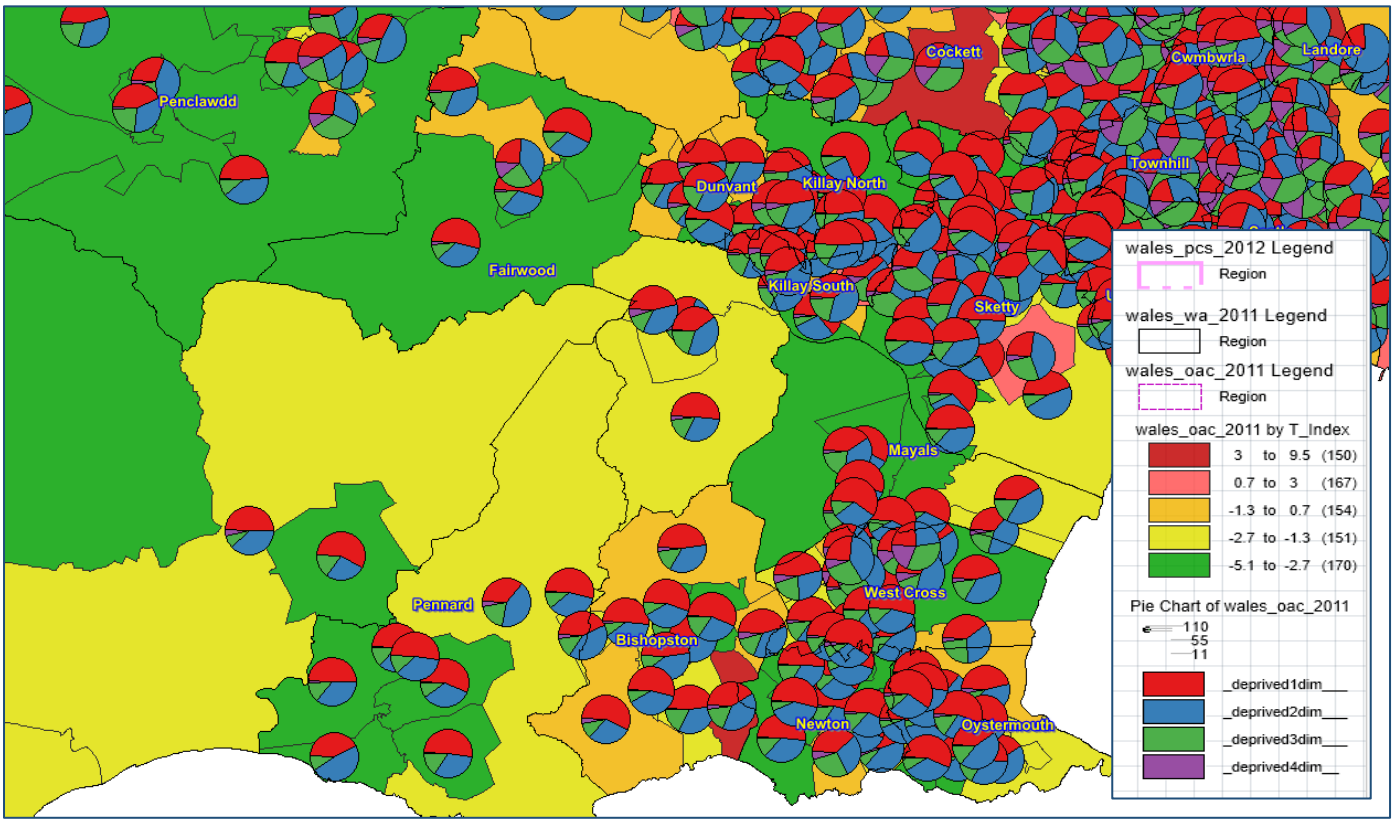


Figure 32 Townsend index compared to 4 dimensions

The combined layer combines Reactivate point data with unemployed after graduation and shows some minor correlation with a cluster around the north SA1 area but nothing highly conclusive as some points are on top of each other due to restricted postcode data.

Unemployed point data layers over a Thematic map showing depravation again brings no solid conclusion but some correlation where arrow points to more deprived in red and clusters of both reactivate participant data and unemployed after graduation data. There is an even spread which indicates between this type of sustainable practice appeals to all socio economic backgrounds

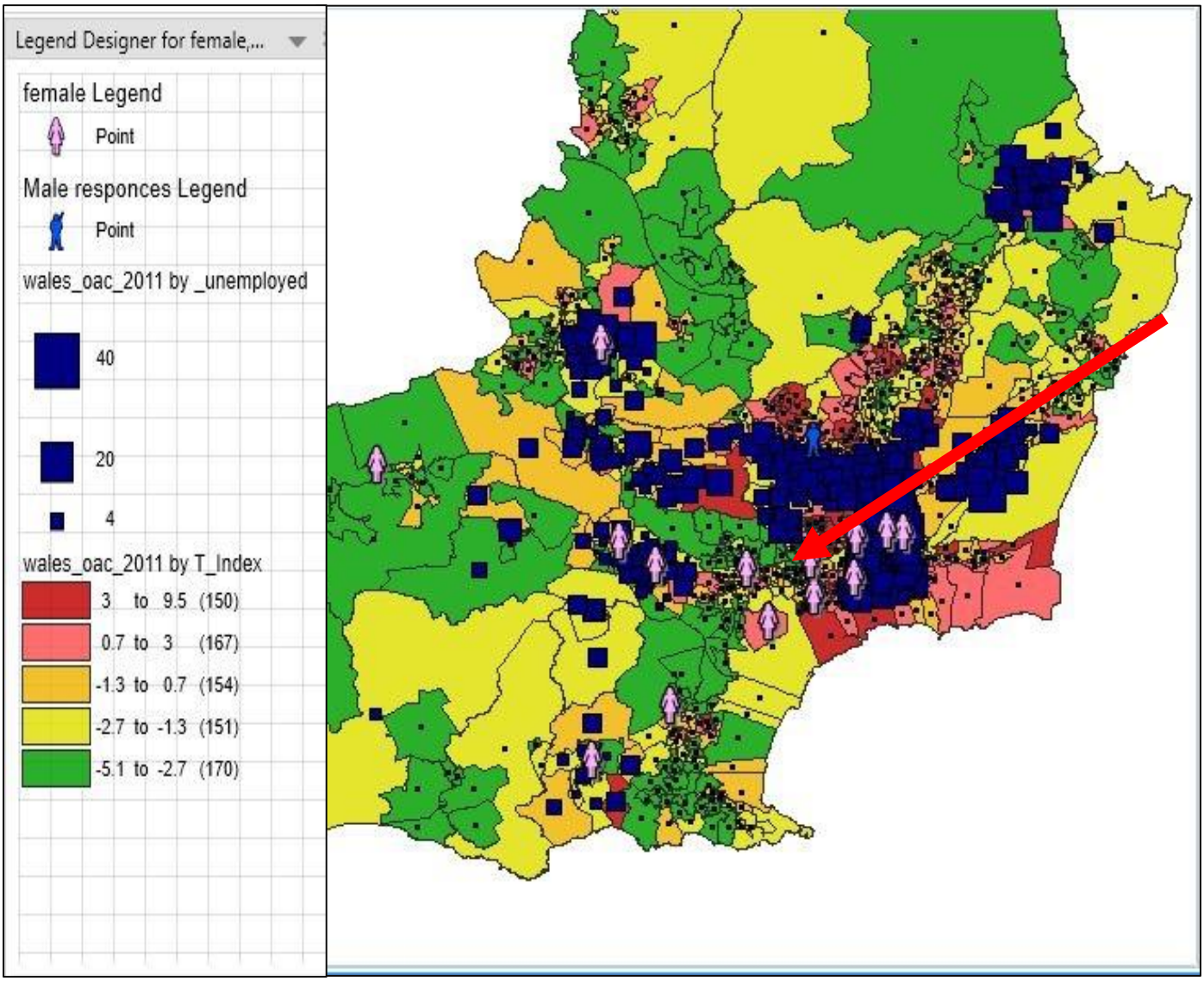
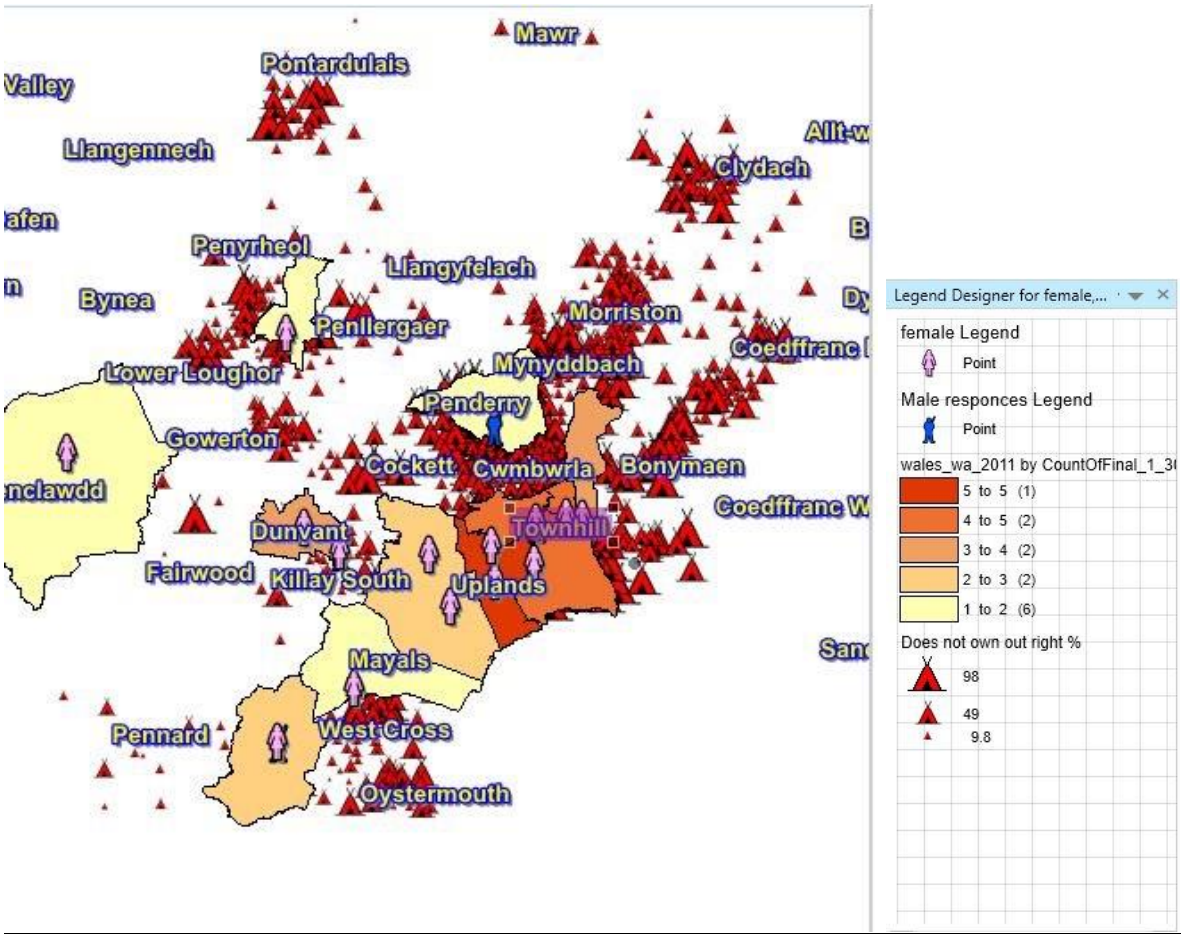


Figure 33 Unemployed point data layers over a Thematic map showing depravation

The combined map below shows final count in thematic colours with house owners who do not own outright as an overlay, the larger icons indicate the. higher the amount of people who do not own outright and there is some correlation with participants but not definingly so.



Conclusions 3.0

In Conclusion the data was limited due to the lack of full postcodes. There were no obvious trends regarding affluence a due to the lack of accurate location of each participant but although the hypothesis was not proven, it did show that in fact people from all socio economic backgrounds are just as keen to partake in sustainable practices, as opposed to more affluent people being less keen and more socially deprived people being more likely to use second hand stores and recycle due to the need for saving money. This was shown not to be the case as participants from varying backgrounds attended indicating this type of shopping is not just for the socially deprived and perhaps can be used to slow more affluent peoples fast fashion shopping habits. The majority were from SA1 which is the city centre which makes sense considering many were students attending university in the city centre.

The software has allowed a full overview of the data in the sense it has allowed visual analysis and understanding of data from a different perspective (Esri, 2018). The use of Townsend and infuse data helps provide an understanding of different areas and their socio economic status in relation to the point data but due to the aforementioned issues, it was hard to draw any notable conclusions.

A full data set would have provided more scope to work with and form conclusions. The use of GIS modelling allows a visual perspective of the data which allows the finding of patterns and similarities which could have been missed without visualisation (Larsen, 1999).

References 4.0

Ellen MacArthur Foundation (2017) ‘A new textiles economy: Redesigning fashion’s future’. Available at: https://www.ellenmacarthurfoundation.org/assets/downloads/publications/A-New-Textiles-Economy_Full-Report_Updated_1-12-17.pdf (Accessed: 9 March 2019).

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