Spatial Segmentation and Key Drivers of Energy Consumption in England and Wales

An analysis of consumer groups within the English and Welsh energy market and investigating socio-economic factors that influence the consumption patterns of different segments

In [169…

```
# load relevant packages for analysis
import geopandas as gpd
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import statsmodels.api as sm

from geopy.geocoders import Nominatim
from geopy.extra.rate_limiter import RateLimiter
from shapely.geometry import Point
from sklearn.cluster import KMeans
from sklearn.linear_model import LinearRegression
from sklearn.metrics import silhouette_score
from sklearn.metrics import calinski_harabasz_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
```

1.0 Introduction

The purpose of this paper is to segment English and Welsh consumers based on energy usage quartiles and investigate factors which are correlated to each segment.

After economic sanctions were imposed on Russian oil in 2022, energy prices in Europe surged. This sparked public dissatisfaction and prompted immediate relief payments from the public sector. While these payments offered short-term alleviation investigating consumption patterns can guide more precise policies, enhancing the UK's long-term resilience against price fluctuations and identifying factors influencing energy usage.

This paper uses unsupervised clustering to group and segment energy consumers based on their energy consumption level, then investigates socioeconomic factors that are highly correlated with these different energy consumption quartiles.

2.0 Literature Review

Developing targetted policy involves market segmentation, segment analysis, implementation and ongoing monitoring (Soto et al., 2021). This paper, due to its analytical nature, will conduct the first two steps.

Segmentation plays a crucial role in developing targeted policies by identifying distinct groups within a population. This enables the creation of finely tuned interventions that are more likely to be effective and meet the needs of different segments (Soto et al., 2021).

Clustering has emerged as a powerful tool to delineate target populations more effectively for policy implementation. Balashankar et al. illustrate how clustering methods can help segment populations and identify distinct groups crucial for developing effective and targeted policies. There are many clustering strategies including Hierarchal clustering, DBSCAN and K-means (2022).

K-means clustering is suitable for analysing the energy market in England and Wales because it effectively segments consumers based on their usage patterns, which can enhance targeted marketing strategies and policy development. Additionally, this approach allows for the efficient allocation of resources by grouping consumers with similar characteristics and behaviors, thereby improving service delivery and customer satisfaction (Jain & Ahuja, 2014).

From here, Soto et al., 2021 suggest investigating consumer segments to understand their characteritics. Multiple linear regression is frequently used to evaluate the influence of socio-economic and environmental factors on distinct population segments. This approach controls for multiple variables simultaneously, pinpointing the impacts of each factor. By applying this method, researchers can provide precise insights essential for targeted policy formulation. This tailored approach improves the effectiveness and fairness of interventions, addressing the unique needs of different consumer groups (Balashankar et al., 2022).

There are three socioeconomic fields the ONS commonly reports alongside energy consumption. 1. **Central Heating Type** is crucial for understanding energy consumption as it directly influences the efficiency and amount of energy required to heat homes, making it a pivotal variable for targeted energy-saving interventions. 2. **Income Level** and 3. **Dwelling Type** are similarly important; they reflect the economic capacity to invest in energy-efficient solutions and the physical characteristics of a home that affect energy needs, which can guide the formulation of policies tailored to specific economic and housing conditions.

With this in mind, this paper investgates 2 research questions.

```
        RQ1 | Can we use spatial clustering to effectively
segment the English and Welsh population based on electricity
and gas consumption behaviour?
        RQ2 | How do central heating type, income level and
dwelling type correlate with the energy consumption patterns
of different consumer segments?
```

3.0 Methodology

This study will leverage open data from the *Office of National Statistics (ONS)* and energy consumption data from the *UK Department for Energy Security and Net Zero (DESNZ)*. All datasets are from the 2022.

The energy consumption data provided by DESNZ is at the postcode level, while other fields are provided by Local Authority District (LAD). To overcome this issue we proceed with clustering at a postcode level, then determine which LADs these clusters geographically sit within. If clusters sit within 2 or more LADs, we simply aggregate the energy consumption data from these clusters for each LAD using a weighted average based on the number of postcodes from the cluster falling within each LAD. This method ensures that our analysis accurately reflects the geographical distribution of consumption data while aligning it with the socio-economic data at the LAD level.

As outlined above, this analysis will be conducted in two parts. First, consumer segmentation will done using unsupervised clustering. This will done purely based on variables geography and electricity and gas consumption for several reasons (Rehmatulla et al., 2017).

Starting with geography and energy consumption keeps the analysis clear and focused, allowing for an understanding of core consumption patterns without the distraction of socio-economic factors. Słupik et al. suggests that this method establishes baseline segments that reflect the interaction between geographic characteristics and energy usage, providing a reference for further analysis (2021). Adopting this phased approach enhances methodological rigour, enabling systematic integration of additional variables and ensuring the analysis remains robust as complexity increases.

Each cluster will be categorised into 4 segments based on quartiles, 1. High, 2. Medium-High, 3. Medium-Low and 4. Low Consumption.

Unsupervised clustering is selected over supervised methods because it effectively identifies natural groupings within the data without prior labelling, crucial for discovering inherent patterns in energy consumption that are not predefined. To determine the optimal number of clusters for K-means clustering, the elbow method, silhouette analysis and the Calinski-Harabasz index are employed. These methods provide quantitative metrics to evaluate the variance within clusters and the separation between them, ensuring that the chosen number of clusters best captures the underlying patterns in the data.

Next, we will determine what characteristics are highly correlated with *High*, *Medium-High*, *Medium-Low* and *Low* energy consumption. Since this analysis aims to inform domestic policy, we select variables that are commonly assciated with previous domestic energy relief, these are income, central heating type and dwelling type. This correlation analysis will be based heavily on multiple linear regression. Given the goal of informing targeted domestic energy policies, multiple linear regression allows for the simultaneous examination of how various predictors influence energy consumption across different segments(Forootan et al., 2022).

This method not only quantifies the strength of these relationships but also adjusts for the interdependencies among variables, providing a comprehensive and statistically robust basis for policy recommendations (Dou et al., 2023).

4.0 Data Overview, Processing & Exploration

This section reads in and processes the data for RQ1 and RQ2. Before moving into our analysis we provide an overview of the fields, explore the shape and distribution of our data and check for outliers and incosistencies which could lead to issues in this study. This will all be conducted in the following section after the cleaning phase of each dataset.

The energy consumption from the DESNZ is provided at outcode level without geometry. The geopy library automatically finds and builds a geometry column based on outcode. DESNEZ provide mean, median and total electricity and gas consumption data by Kilowatt-hour (kWh). Below we drop both the *Mean* and *Total* consumption column and use *Median* annual electrity and gas consumption as it is least impacted by outliers. For this reason we do not normlise by population.

The geopy library can only assign one postcode per second and is computationally intensive. As a result, we only run this on the gas consumption data and join electricity data later.

As highlighted, the following is a computational intense process and was run when this analysis was originally conducted. The new CSV file is read in below the following four code chunks.

4.1 Read in Energy Consumption Data, Process and add Geometry

In [723…
```
# read in desnez data
gas_df = pd.read_csv('data/gas_consumption.csv')
elec_df = pd.read_csv('data/electricity_consumption.csv')
outpop_df = pd.read_csv('data/outcode_population.csv') # pop. by outcode to
```

In [725…
```
# init geolocator
geolocator = Nominatim(user_agent="geoapiExercises")

# function to get lat / long
def get_lat_lon(outcode):
    try:
        location = geolocator.geocode(f"{outcode}, United Kingdom")
        return (location.latitude, location.longitude)
    except:
        return (None, None)

# avoid hitting rate limits
geocode = RateLimiter(geolocator.geocode, min_delay_seconds=1)

# apply to outcode column
gas_df['Latitude_Longitude'] = gas_df['outcode'].apply(lambda x: get_lat_lor

gas_df.to_csv('data/gas_df.csv', index=False)
```

In [275…
```
gas_df = pd.read_csv('data/gas_df.csv')
```

In [275…
```
gas_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2410 entries, 0 to 2409
Data columns (total 5 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   outcode               2410 non-null   object 
 1   gas_total_cons_kwh    2410 non-null   float64
 2   gas_mean_cons_kwh     2410 non-null   float64
 3   gas_median_cons_kwh   2410 non-null   float64
 4   Latitude_Longitude    2410 non-null   object 
dtypes: float64(3), object(2)
memory usage: 94.3+ KB
```

In [275…

```
# convert string coordinates to a point object
def parse_coordinates(coord_str):
    if coord_str == "None, None":
        return None
    try:
        lat, lon = coord_str.strip('()').split(',')
        return Point(float(lon.strip()), float(lat.strip()))
    except (ValueError, TypeError):
        return None

# Apply to 'Latitude_Longitude'
gas_df['geometry'] = gas_df['Latitude_Longitude'].apply(parse_coordinates)

# Remove 'None' rows
gas_df = gas_df[gas_df['geometry'].notna()]

# DataFrame to GeoDataFrame
gas_gdf = gpd.GeoDataFrame(gas_df, geometry='geometry')

# Set WGS 84 CRS
gas_gdf.set_crs(epsg=4326, inplace=True)

# Join electricity consumption data by outcode
energycon_gdf = pd.merge(gas_gdf, elec_df, on='outcode', how='inner')

# Drop total & mean consumption columns
columns_to_drop = ['gas_total_cons_kwh', 'gas_mean_cons_kwh', 'elec_total_co
energycon_gdf = energycon_gdf.drop(columns=columns_to_drop)
```

In [275…

```
# normalise our energy consumption data by outcode population
# perform inner join
energycon_gdf = pd.merge(
    energycon_gdf,
    outpop_df[['Postcode Districts', 'Count']],
    left_on='outcode',
    right_on='Postcode Districts',
    how='inner'
)

# normalise x population count
energycon_gdf['n_gas_median_cons_kwh'] = energycon_gdf['gas_median_cons_kwh
energycon_gdf['n_elec_median_cons_kwh'] = energycon_gdf['elec_median_cons_kw

# drop 'Postcode Districts'
energycon_gdf.drop(columns=['Postcode Districts'], inplace=True)

# calc mean and standard deviation
mean_values = energycon_gdf[['n_gas_median_cons_kwh', 'n_elec_median_cons_kw
std_dev = energycon_gdf[['n_gas_median_cons_kwh', 'n_elec_median_cons_kwh']]

# detect and remove outliers more than 2 StD. from the mean
```

```
is_outlier = ((energycon_gdf[['n_gas_median_cons_kwh', 'n_elec_median_cons_l
              (energycon_gdf[['n_gas_median_cons_kwh', 'n_elec_median_cons_l
energycon_gdf = energycon_gdf[~is_outlier]

# save
energycon_gdf.to_file('energycon.gpkg', driver='GPKG')
```

In [276…

```
# read in processed 'energy consumption data' & check
energycon_gdf = gpd.read_file('energycon.gpkg')
energycon_gdf.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 1429 entries, 0 to 1428
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   outcode                1429 non-null   object
 1   gas_median_cons_kwh    1429 non-null   float64
 2   elec_median_cons_kwh   1429 non-null   float64
 3   Count                  1429 non-null   int64
 4   n_gas_median_cons_kwh  1429 non-null   float64
 5   n_elec_median_cons_kwh 1429 non-null   float64
 6   geometry               1429 non-null   geometry
dtypes: float64(4), geometry(1), int64(1), object(1)
memory usage: 78.3+ KB
```

In [276…

```
numeric_cols = energycon_gdf.select_dtypes(include=[np.number])

# descriptive stats
basic_stats = numeric_cols.describe()

# count of non-null entries
nonnull_counts = energycon_gdf.count()

# data types
data_types = energycon_gdf.dtypes

# quantiles
quantiles = numeric_cols.quantile([0.25, 0.5, 0.75])

# correlation matrix
correlation_matrix = numeric_cols.corr()

# display
print("Descriptive Statistics:\n", basic_stats)
print("\nCount of Non-Null Entries:\n", nonnull_counts)
print("\nData Types:\n", data_types)
print("\nQuantiles:\n", quantiles)
print("\nCorrelation Matrix:\n", correlation_matrix)
```

```
Descriptive Statistics:
        gas_median_cons_kwh  elec_median_cons_kwh          Count  \
count           1429.000000           1429.000000    1429.000000   
mean           10095.291839           2611.974050   27664.167950   
std             1998.934236            352.451779   17787.980163   
min             3728.318537           1577.100000      55.000000   
25%             8926.833145           2392.400000   14852.000000   
50%             9815.550000           2542.000000   25310.000000   
75%            10889.086886           2772.200000   36906.000000   
max            28575.457630           5444.500000  170304.000000   

       n_gas_median_cons_kwh  n_elec_median_cons_kwh  
count            1429.000000             1429.000000  
mean                1.340411                0.339435  
std                 8.360627                2.049145  
min                 0.059852                0.014346  
25%                 0.256299                0.066603  
50%                 0.386284                0.100337  
75%                 0.691026                0.184862  
max               193.217824               50.412037  

Count of Non-Null Entries:
 outcode                   1429
gas_median_cons_kwh       1429
elec_median_cons_kwh      1429
Count                     1429
n_gas_median_cons_kwh     1429
n_elec_median_cons_kwh    1429
geometry                  1429
dtype: int64

Data Types:
 outcode                     object
gas_median_cons_kwh        float64
elec_median_cons_kwh       float64
Count                        int64
n_gas_median_cons_kwh      float64
n_elec_median_cons_kwh     float64
geometry                  geometry
dtype: object

Quantiles:
       gas_median_cons_kwh  elec_median_cons_kwh    Count  \
0.25           8926.833145                2392.4  14852.0   
0.50           9815.550000                2542.0  25310.0   
0.75          10889.086886                2772.2  36906.0   

      n_gas_median_cons_kwh  n_elec_median_cons_kwh  
0.25               0.256299                0.066603  
0.50               0.386284                0.100337  
0.75               0.691026                0.184862  

Correlation Matrix:
                         gas_median_cons_kwh  elec_median_cons_kwh     Coun
t  \
gas_median_cons_kwh                 1.000000              0.462543 -0.099420   
elec_median_cons_kwh                0.462543              1.000000 -0.293575   
Count                              -0.099420             -0.293575  1.000000   
n_gas_median_cons_kwh               0.231040              0.209652 -0.181584   
n_elec_median_cons_kwh              0.169004              0.244621 -0.186089   

                        n_gas_median_cons_kwh  n_elec_median_cons_kwh  
gas_median_cons_kwh                  0.231040                0.169004  
elec_median_cons_kwh                 0.209652                0.244621  
```

```
Count                          -0.181584              -0.186089
n_gas_median_cons_kwh           1.000000               0.977005
n_elec_median_cons_kwh          0.977005               1.000000
```

Given the following summary statistics we can infer the following conclusions about our data:

- **Consumption Variability:** The dataset from 1,429 outcodes shows a median gas consumption range of 3,728 to 28,575 kWh, with electricity consumption being less variable, ranging from 1,577 to 5,444 kWh. Median gas consumption typically around 9,815 kWh reflects substantial regional differences.
- **Correlation and Efficiency:** There's a moderate correlation (about 0.46) between gas and electricity consumption, suggesting that higher gas usage often aligns with higher electricity usage. Normalised consumption values reveal efficiencies of about 1.34 kWh for gas and 0.34 kWh for electricity per unit count, with some regions showing exceptionally high usage.
- **Statistical Overview:** The dataset exhibits a broad count range from 55 to 170,304, suggesting diverse outcode sizes. All key columns are fully populated, ensuring comprehensive data analysis. The strong correlation (0.977) between normalised gas and electricity values underscores consistent regional energy usage patterns.

Below, we read and process the socio-economic data for the clustering and segmentation analysis. There are five fields taken from four datasets recorded by LAD. The population, dwelling type, central heating type and income data all comes from the ONS. This data is merged with LAD polygon data, also provided by the ONS.

The socio-economic data is provided as raw counts, thus, we conduct per capita normalisation to ensure our analysis is accurate. During the normalisation process we deal with NaN and 0 values.

4.2 Read in Socio-Economic Data, Process and add Geometry column

In [276…

```python
# read in ONS socioeconomic & LAD geometry data
income = pd.read_csv('data/annual_income.csv') # annual income
heat_type = pd.read_csv('data/heating_type.csv') # central heating type
dw_type = pd.read_csv('data/accomodation_type.csv') # dwelling type
lad = gpd.read_file("data/Local_Authority_Districts/LAD_MAY_2022_UK_BFE_V3.s
pop = pd.read_excel("data/population.xlsx") # pop
```

In [276…

```python
# process and clean income data
median_income = income.groupby('Local authority code')['Total annual income

# rename 'med average annual income' & print
median_income.rename(columns={'Total annual income (£)': 'Med average annua
median_income.rename(columns={'Local authority code': 'Lower tier local auth
median_income.head(2)
```

Out[2765]:

	Lower tier local authorities Code	Med average annual income (£)
0	E06000001	31050.0
1	E06000002	35500.0

In [276…

```
# process heating & dwelling type data
# pivot heating type
heatpivot_df = heat_type.pivot(
    index='Lower tier local authorities Code',
    columns='Type of central heating in household (5 categories)',
    values='Observation'
)

# 'LAD Code' as index
heatpivot_df.reset_index(inplace=True)

# pivot 'dw type'
dwpivot_df = dw_type.pivot(index='Lower tier local authorities Code',
                           columns='Accommodation type (5 categories)',
                           values='Observation')

# 'LAD Code' as index
dwpivot_df.reset_index(inplace=True)
```

In [276…

```
# merge 'dwpivot_df' and 'heatpivot_df' on 'Lower tier local authorities Coc
merged_df = pd.merge(dwpivot_df, heatpivot_df, on='Lower tier local authori

# merge with 'income' on 'Lower tier local authorities Code'
socec_df = pd.merge(merged_df, median_income, on='Lower tier local authorit:

# display
socec_df.head(2)
```

Out[2767]:

	Lower tier local authorities Code	A caravan or other mobile or temporary structure	Flat, maisonette or apartment	Whole house or bungalow: Detached	Whole house or bungalow: Semi-detached	Whole house or bungalow: Terraced	Does not apply	Does not have central heating
0	E06000001	115.0	4725.0	8086.0	14537.0	13469.0	0.0	342.0
1	E06000002	51.0	7569.0	10389.0	25485.0	16768.0	0.0	752.0

In [276…

```
# merge 'LAD' and 'socec_df' geographic data
lad_filtered = lad[['LAD22CD', 'geometry']]

# keep all 'socec_df' columns and only 'geometry' from 'lad'
socec_df = pd.merge(socec_df, lad_filtered, how='left', left_on='Lower tier

# drop 'LAD22CD' & display
socec_df.drop(columns=['LAD22CD'], inplace=True)
```

In [276…

```
# final cleaning
# drop
socec_df.drop(columns=['Does not apply'], inplace=True)

# rename index as 'LAD'
socec_df.rename(columns={'Lower tier local authorities Code': 'LAD'}, inplac

# geometry as last column
geometry = socec_df.pop('geometry')
socec_df['geometry'] = geometry

# rename
```

```
column_rename_map = {
    'A caravan or other mobile or temporary structure': 'dwelling_type: mob
    'Flat, maisonette or apartment': 'dwelling_type: flat',
    'Whole house or bungalow: Detached': 'dwelling_type: detached house',
    'Whole house or bungalow: Semi-detached': 'dwelling_type: semi-detached
    'Whole house or bungalow: Terraced': 'dwelling_type: terraced',
    'Does not have central heating': 'no central heating',
    'Has one type of central heating': '1 central heating',
    'Two or more types of central heating (including renewable energy)': '2-
    'Two or more types of central heating (not including renewable energy)'
    'Med average annual income (£)': 'mean annual income'
}
socec_df.rename(columns=column_rename_map, inplace=True)

# print
socec_df.head(2)
```

Out[2769]:

	LAD	dwelling_type: mobile	dwelling_type: flat	dwelling_type: detached house	dwelling_type: semi-detached	dwelling_ty terrac
0	E06000001	115.0	4725.0	8086.0	14537.0	1346
1	E06000002	51.0	7569.0	10389.0	25485.0	1676

In [277…

```
# normalise these values by the population of each LAD
# start by adding population to df:
# left join data using 'socec_df' as master
pop_filtered = pop[['Code', 'All ages']]
socec_df = pd.merge(socec_df, pop_filtered, how='left', left_on='LAD', righ

# rename 'All ages' column to 'population' and drop redundant 'Code' column
socec_df.rename(columns={'All ages': 'population'}, inplace=True)
socec_df.drop(columns=['Code'], inplace=True)
```

In [277…

```
# normalise all the necessary fields
# columns to normalise
columns_to_normalise = [
    'dwelling_type: mobile', 'dwelling_type: flat', 'dwelling_type: detache
    'dwelling_type: semi-detached', 'dwelling_type: terraced',
    'no central heating', '1 central heating',
    '2+ central heating (renewable)', '2+ central heating (non-renewable)'
]

# remove rows where pop is NaN / 0
cleaned_df = socec_df[socec_df['population'].notna() & (socec_df['populatio

# new df for normalised data
nsocec_df = cleaned_df[['LAD', 'geometry', 'mean annual income']].copy()

# normalise each column by population & display
for column in columns_to_normalise:
    nsocec_df[column] = cleaned_df[column] / cleaned_df['population']
nsocec_df.head(2)
```

Out[2771]:

	LAD	geometry	mean annual income	dwelling_type: mobile	dwelling_type: flat	dwelling_type: detached house	dwe
0	E06000001	POLYGON ((447213.900 537036.104, 447228.798 53...	31050.0	0.001225	0.050340	0.086149	
1	E06000002	POLYGON ((448489.897 522071.798, 448592.597 52...	35500.0	0.000344	0.051044	0.070061	

In [277…

```
# convert to gdf using epsg:4326
nsocec_gdf = gpd.GeoDataFrame(nsocec_df, geometry='geometry')
nsocec_gdf.set_crs("epsg:4326", inplace=True, allow_override=True)
nsocec_gdf.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 314 entries, 0 to 330
Data columns (total 12 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   LAD                                  314 non-null    object
 1   geometry                             314 non-null    geometry
 2   mean annual income                   301 non-null    float64
 3   dwelling_type: mobile                314 non-null    float64
 4   dwelling_type: flat                  314 non-null    float64
 5   dwelling_type: detached house        314 non-null    float64
 6   dwelling_type: semi-detached         314 non-null    float64
 7   dwelling_type: terraced              314 non-null    float64
 8   no central heating                   314 non-null    float64
 9   1 central heating                    314 non-null    float64
 10  2+ central heating (renewable)       314 non-null    float64
 11  2+ central heating (non-renewable)   314 non-null    float64
dtypes: float64(10), geometry(1), object(1)
memory usage: 31.9+ KB
```

The socioeconomic data is merged and formatted. Below we produce the summary statistics for each field.

In [277…

```
# summary statistics for numeric fields
numeric_stats = nsocec_gdf.describe()

# statistics for 'geometry'
if 'geometry' in nsocec_gdf.columns:
    geometry_types = nsocec_gdf['geometry'].geom_type.value_counts()

# numeric statistics
print("Numeric Fields Summary Statistics:\n", numeric_stats)

# print the geometry statistics
if 'geometry' in nsocec_gdf.columns:
    print("\nGeometry Types:\n", geometry_types)
```

```
Numeric Fields Summary Statistics:
        mean annual income  dwelling_type: mobile  dwelling_type: flat  \
count           301.000000             314.000000           314.000000
mean          46630.232558               0.002067             0.082017
std            9870.109740               0.002098             0.065401
min           31050.000000               0.000000             0.017910
25%           39000.000000               0.000503             0.044090
50%           44600.000000               0.001333             0.063788
75%           53350.000000               0.002957             0.094242
max          101800.000000               0.013217             0.443809

       dwelling_type: detached house  dwelling_type: semi-detached  \
count                     314.000000                    314.000000
mean                        0.108347                      0.130504
std                         0.055624                      0.037655
min                         0.000645                      0.001383
25%                         0.061627                      0.113079
50%                         0.108352                      0.129826
75%                         0.154927                      0.153265
max                         0.230133                      0.208866

       dwelling_type: terraced  no central heating  1 central heating  \
count               314.000000          314.000000         314.000000
mean                  0.092400            0.005939           0.371254
std                   0.034206            0.004523           0.023074
min                   0.007191            0.002067           0.259097
25%                   0.070083            0.004013           0.359787
50%                   0.087103            0.004991           0.372924
75%                   0.107266            0.006824           0.388052
max                   0.226177            0.072337           0.420104

       2+ central heating (renewable)  2+ central heating (non-renewable)
count                      314.000000                          314.000000
mean                         0.002470                            0.035671
std                          0.001553                            0.006680
min                          0.000777                            0.023665
25%                          0.001545                            0.031555
50%                          0.002032                            0.034285
75%                          0.003090                            0.038071
max                          0.017536                            0.064007

Geometry Types:
 Polygon         296
MultiPolygon     18
Name: count, dtype: int64
```

The average mean annual income across the 301 entries is approximately £46,630, but the range is quite broad, with a maximum income reported as £101,800. The normalised dwelling data reveals a predominance of flats and semi-detached houses, with relatively minor variations in central heating systems, suggesting a general uniformity in dwelling types and heating across the sampled regions.

The presence of missing data in 'mean annual income' alongside its lack of normalisation may skew comparative analyses, especially when compared to other per capita normalised metrics. The mix of Polygon and MultiPolygon geometries in the dataset necessitates careful handling to ensure accuracy in spatial operations and consistency in geographic analyses.

In [277…

```
# address missing data in 'mean annual income'
print(f"Missing data in 'mean annual income' before cleanup: {nsocec_gdf['me
```

```
nsocec_gdf['mean annual income'].fillna(nsocec_gdf['mean annual income'].med
print(f"After imputing missing values with median: {nsocec_gdf['mean annual 

# ensure geometry consistency
nsocec_gdf['geometry'] = nsocec_gdf['geometry'].apply(lambda x: x if x.is_va
nsocec_gdf = nsocec_gdf.explode('geometry', index_parts=True)

# correct data type inconsistencies
nsocec_gdf['mean annual income'] = pd.to_numeric(nsocec_gdf['mean annual inc

# status report
print("\nData Types in DataFrame:")
nsocec_gdf.head()
```

```
Missing data in 'mean annual income' before cleanup: 13
After imputing missing values with median: 0

Data Types in DataFrame:
```

Out[2776]:

		LAD	mean annual income	dwelling_type: mobile	dwelling_type: flat	dwelling_type: detached house	dwelling_type: semi-detached
0	**0**	E06000001	31050.0	0.001225	0.050340	0.086149	0.154878
1	**0**	E06000002	35500.0	0.000344	0.051044	0.070061	0.171865
2	**0**	E06000003	34000.0	0.000612	0.040066	0.090753	0.203696
3	**0**	E06000004	35850.0	0.000395	0.038392	0.111064	0.177500
4	**0**	E06000005	36100.0	0.000713	0.058683	0.085239	0.174917

In [277…

```
nsocec_gdf.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
MultiIndex: 446 entries, (0, 0) to (330, 0)
Data columns (total 12 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   LAD                               446 non-null    object
 1   mean annual income                446 non-null    float64
 2   dwelling_type: mobile             446 non-null    float64
 3   dwelling_type: flat               446 non-null    float64
 4   dwelling_type: detached house     446 non-null    float64
 5   dwelling_type: semi-detached      446 non-null    float64
 6   dwelling_type: terraced           446 non-null    float64
 7   no central heating                446 non-null    float64
 8   1 central heating                 446 non-null    float64
 9   2+ central heating (renewable)    446 non-null    float64
 10  2+ central heating (non-renewable) 446 non-null    float64
 11  geometry                          446 non-null    geometry
dtypes: float64(10), geometry(1), object(1)
memory usage: 56.2+ KB
```

5.0 Analysis

After cleaning and conducting an inner join on the energy consumption data, there are 1429 data points remaining. We now proceed with the analysis. First, this entails segmentation and secondly a socioeconomic analysis of those consumers segments.

5.1 Segmentation of English and Welsh Energy Consumers: Unsupervised Clustering

Below, we leverage unsupervised spatial clustering to group consumers based on energy consumption and geography. These groups will then be categorised into four segments we will use in the second part of our analysis. These segments are:

- High: Top 25% of consumption
- Medium-High: 50-75% of consumption
- Medium-Low: 25-50% of consumption
- Low: Bottom 25% of consumption

In our study of English and Welsh energy consumption, we applied the K-Means clustering algorithm to segment consumers based on usage and location. The optimal number of clusters was determined using the Elbow Method, which identifies the point where the increase in clusters ceases to significantly reduce the within-cluster sum of squares. This approach helps in choosing an appropriate cluster count that maximises both cluster compactness and separation.

The effectiveness of the clusters was evaluated using the Silhouette Score, a measure of how well-separated the clusters are relative to their proximity. High Silhouette Scores indicate well-defined clusters, supporting the robustness of our clustering approach, which is crucial for informed energy policy development.

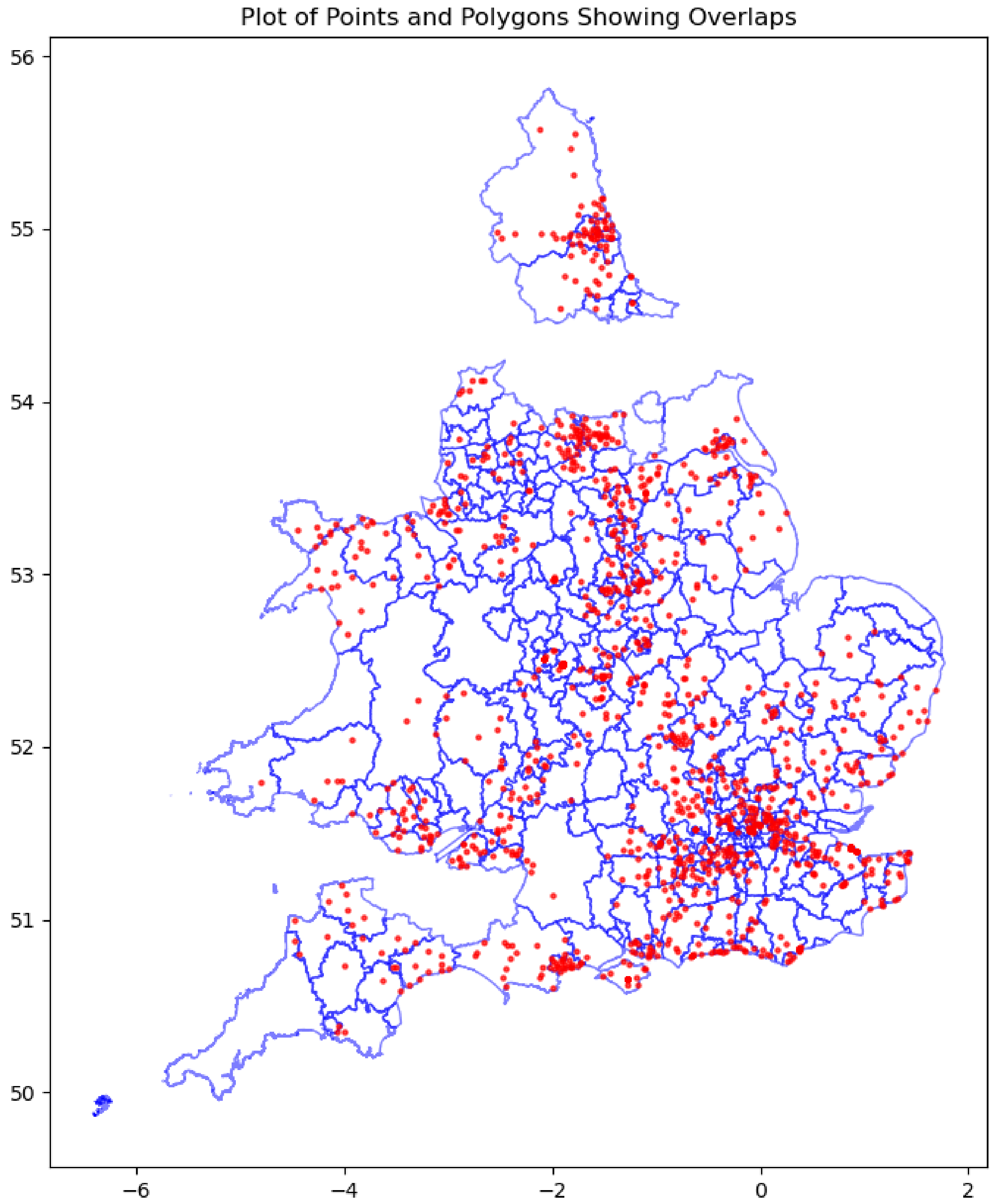
In [278…

```
# read consumption data & view
gdf = gpd.read_file('energycon.gpkg')
gdf.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 1429 entries, 0 to 1428
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   outcode                1429 non-null   object
 1   gas_median_cons_kwh    1429 non-null   float64
 2   elec_median_cons_kwh   1429 non-null   float64
 3   Count                  1429 non-null   int64
 4   n_gas_median_cons_kwh  1429 non-null   float64
 5   n_elec_median_cons_kwh 1429 non-null   float64
 6   geometry               1429 non-null   geometry
dtypes: float64(4), geometry(1), int64(1), object(1)
memory usage: 78.3+ KB
```

In [278…

```
# here we conduct a spatial join and remove all energy consumption point dat
# convert CRS to EPSG:4326
nsocec_gdf = nsocec_gdf.set_crs("EPSG:27700", allow_override=True)
nsocec_gdf = nsocec_gdf.to_crs("EPSG:4326")

# inner spatial join to keep only overlapping geometries
joined_df = gpd.sjoin(gdf, nsocec_gdf, how='inner', predicate='intersects')

# drop 'index_right0' & 'index_right1'
joined_df.drop(columns=['index_right0', 'index_right1'], inplace=True)

# head
joined_df.head()

# overlap
points_filtered = joined_df[['geometry']].copy()
fig, ax = plt.subplots(figsize=(10, 10))
nsocec_gdf.plot(ax=ax, color='none', edgecolor='blue', alpha=0.5)  # polygon
points_filtered.plot(ax=ax, color='red', markersize=5, alpha=0.7)  # points
plt.title('Plot of Points and Polygons Showing Overlaps')
plt.show()
```



In [278…

```
joined_df.info()
# the this joined eliminates about 160 points
```

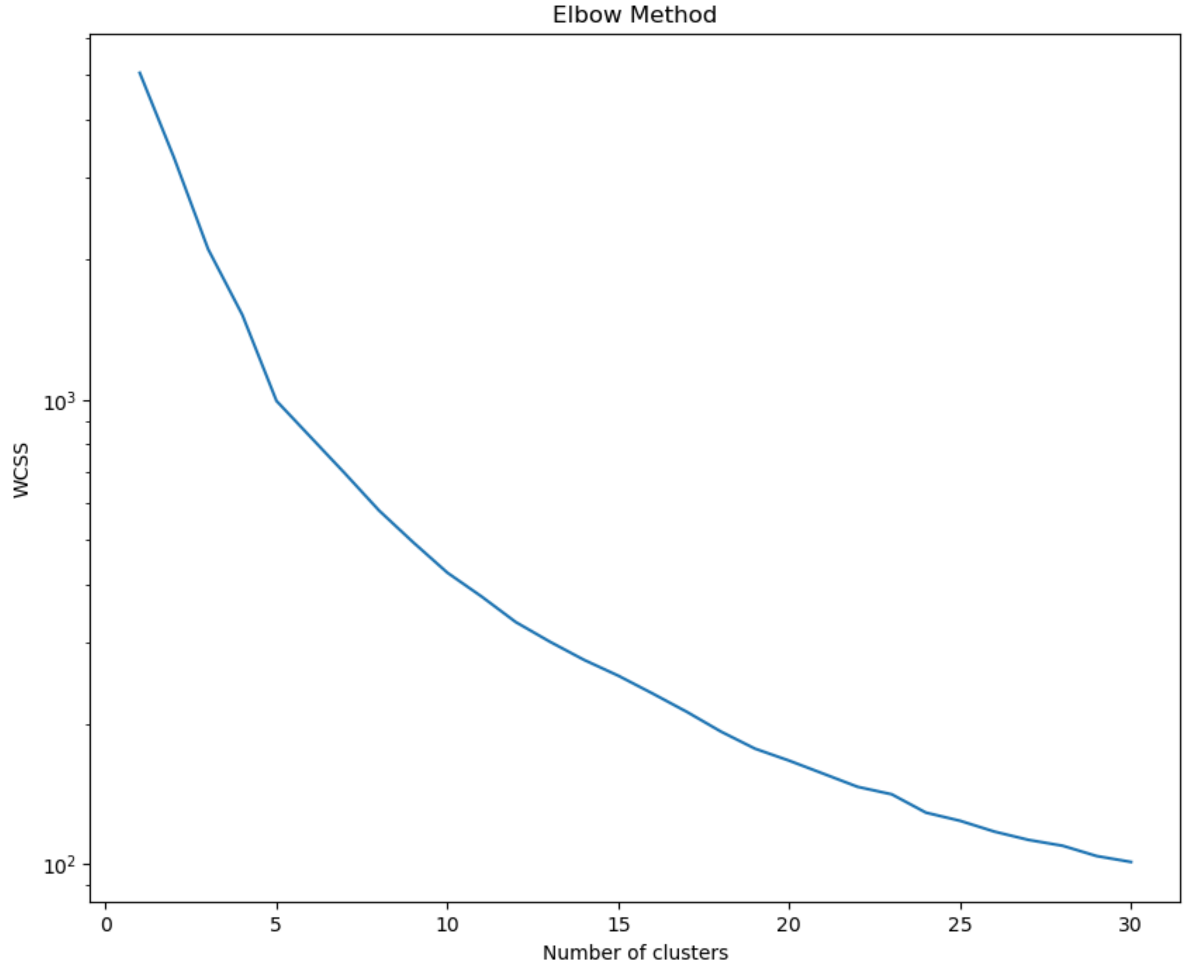
```
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 1264 entries, 0 to 1427
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   outcode                           1264 non-null   object
 1   gas_median_cons_kwh               1264 non-null   float64
 2   elec_median_cons_kwh              1264 non-null   float64
 3   Count                             1264 non-null   int64
 4   n_gas_median_cons_kwh             1264 non-null   float64
 5   n_elec_median_cons_kwh            1264 non-null   float64
 6   geometry                          1264 non-null   geometry
 7   LAD                               1264 non-null   object
 8   mean annual income                1264 non-null   float64
 9   dwelling_type: mobile             1264 non-null   float64
 10  dwelling_type: flat               1264 non-null   float64
 11  dwelling_type: detached house     1264 non-null   float64
 12  dwelling_type: semi-detached      1264 non-null   float64
 13  dwelling_type: terraced           1264 non-null   float64
 14  no central heating                1264 non-null   float64
 15  1 central heating                 1264 non-null   float64
 16  2+ central heating (renewable)    1264 non-null   float64
 17  2+ central heating (non-renewable)  1264 non-null   float64
dtypes: float64(14), geometry(1), int64(1), object(2)
memory usage: 187.6+ KB
```

In [278…

```
#init. values for the spatial clustering
joined_df['x'] = joined_df.geometry.x
joined_df['y'] = joined_df.geometry.y

# prep data for clustering
X = joined_df[['n_gas_median_cons_kwh', 'n_elec_median_cons_kwh', 'x', 'y']]

# scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

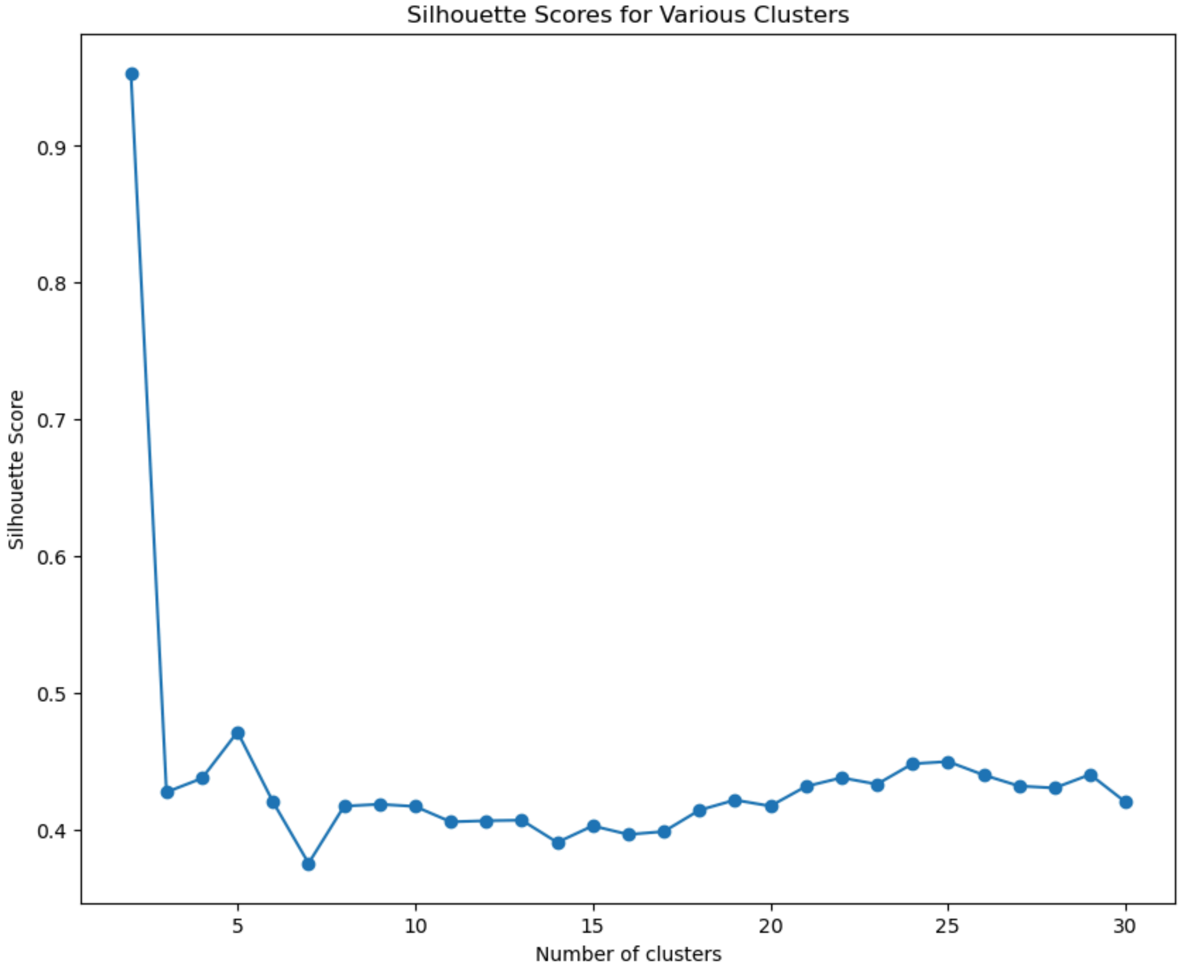
In [278…

```
# elbow analysis
wcss = []
for i in range(1, 31):  # 1 to 30
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=20,
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

# plot WCSS values
plt.figure(figsize=(10, 8))
plt.plot(range(1, 31), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.yscale('log')
plt.show()
```



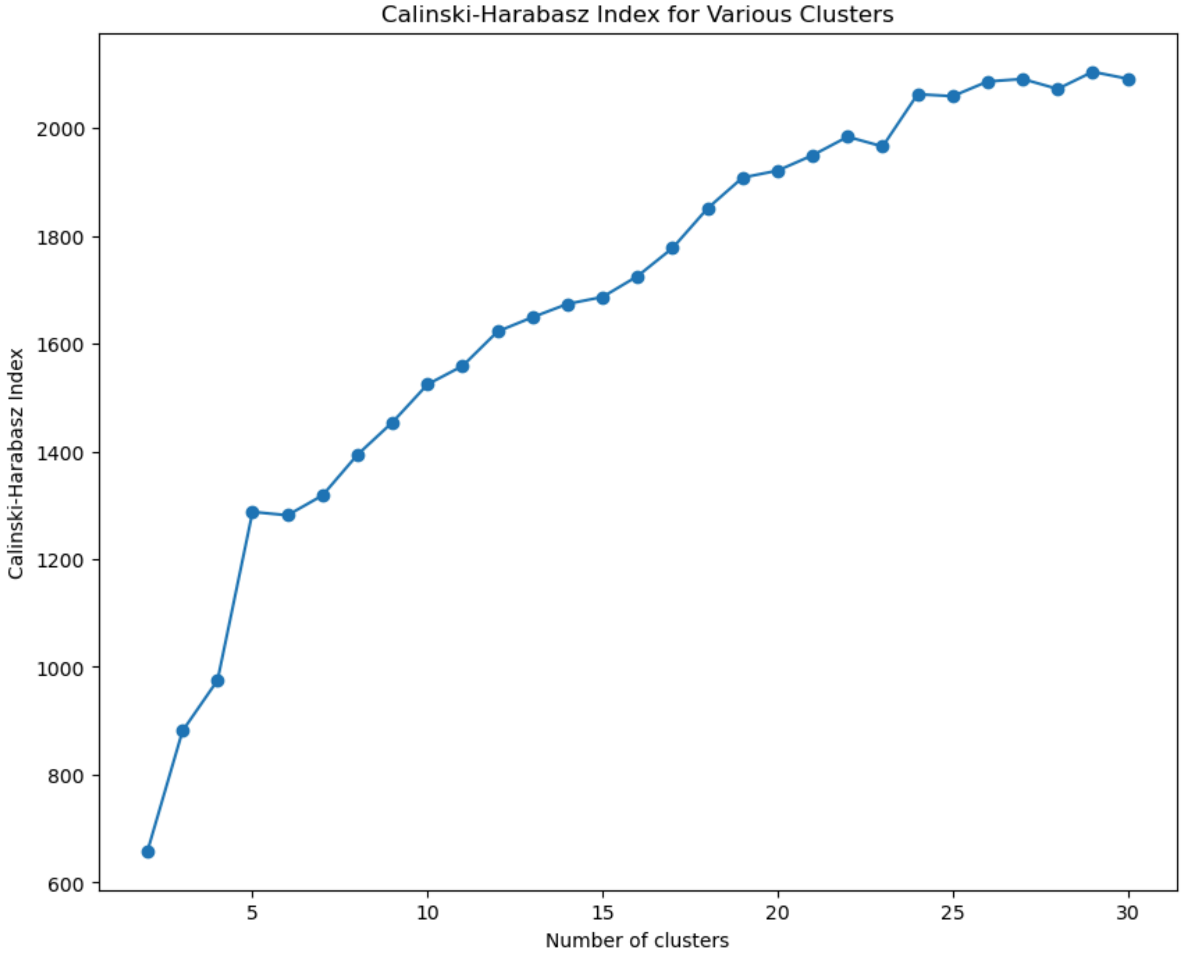
In [278…

```
# init and create loop
silhouette_scores = []
for i in range(2, 31):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=20,
    labels = kmeans.fit_predict(X_scaled)
    score = silhouette_score(X_scaled, labels)
    silhouette_scores.append(score)

# plot silhouette scores
plt.figure(figsize=(10, 8))
plt.plot(range(2, 31), silhouette_scores, marker='o')
plt.title('Silhouette Scores for Various Clusters')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.show()
```



In [278…

```
# calinski-harabasz index
calinski_harabasz_scores = []
for i in range(2, 31):  # Cannot compute with only one cluster
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=20,
    labels = kmeans.fit_predict(X_scaled)
    score = calinski_harabasz_score(X_scaled, labels)
    calinski_harabasz_scores.append(score)

# plot CH index
plt.figure(figsize=(10, 8))
plt.plot(range(2, 31), calinski_harabasz_scores, marker='o')
plt.title('Calinski-Harabasz Index for Various Clusters')
plt.xlabel('Number of clusters')
plt.ylabel('Calinski-Harabasz Index')
plt.show()
```



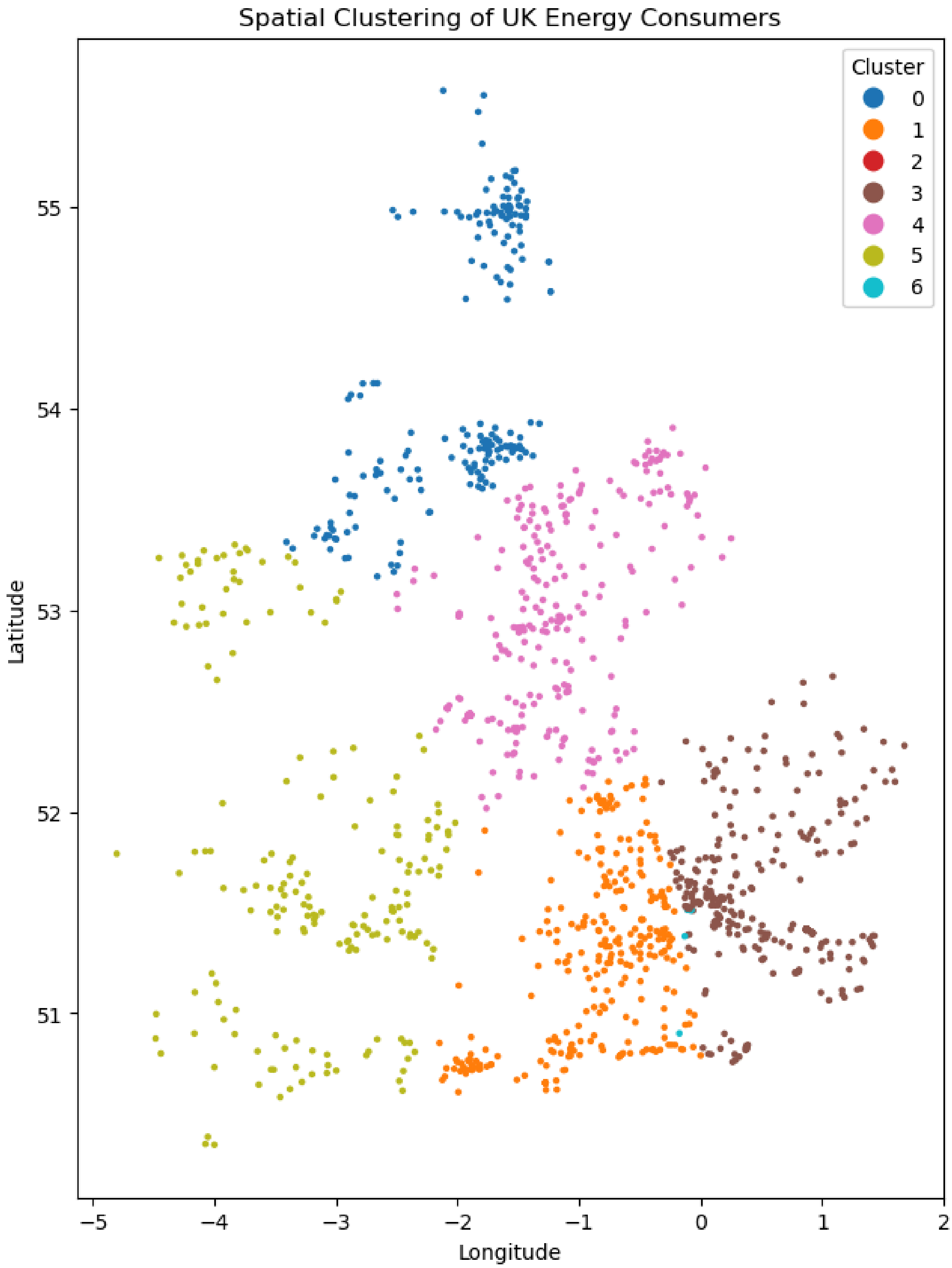
5.1.1 Number of Clusters

The Elbow Method suggests a more gradual WCSS decrease from 6 clusters, while the Silhouette Score plateaus after 7, indicating stable cluster definition. The Calinski-Harabasz Index increases with more clusters and shows no clear plateau. Between 6 - 7 the gradient becomes more stable. Combining these insights, starting with 7 clusters would balance distinctness and model complexity, aligning with the goal of identifying meaningful English and Welsh energy consumption segments.

In [278…

```
# 7 clusters
optimal_clusters = 7
kmeans = KMeans(n_clusters=optimal_clusters, random_state=0)
cluster_labels = kmeans.fit_predict(X_scaled)

# cluster labels
joined_df['cluster'] = cluster_labels

fig, ax = plt.subplots(1, 1, figsize=(15, 10))
joined_df.plot(column='cluster', ax=ax, categorical=True, markersize=5, lege

plt.title('Spatial Clustering of English and Welsh Energy Consumers')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

```
/Users/nikhildesai/anaconda3/lib/python3.11/site-packages/sklearn/cluster/_
kmeans.py:1412: FutureWarning: The default value of `n_init` will change fr
om 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress th
e warning
  super()._check_params_vs_input(X, default_n_init=10)
```



5.1.2 Segment Clusters by Quartile

K-means has grouped English and Welsh energy consumers into 10 clusters. Below we segment clusters into 1 of 4 consumption types outlined above.

In [279…

```
# calc total energy cons.
joined_df['total_energy'] = joined_df['n_gas_median_cons_kwh'] + joined_df[

# calc median total energy consumption for each cluster
cluster_median = joined_df.groupby('cluster')['total_energy'].median().sort_

# quartile cutoffs for total energy consumption among clusters
quantiles = cluster_median.quantile([0.25, 0.5, 0.75])
```

```
# to determine category based on quartiles
def consumption_category(value):
    if value <= quantiles.iloc[0]:
        return 'Low'
    elif value <= quantiles.iloc[1]:
        return 'Medium-Low'
    elif value <= quantiles.iloc[2]:
        return 'Medium-High'
    else:
        return 'High'

# map clusters to category
cluster_to_category = cluster_median.map(consumption_category).to_dict()
joined_df['consumption_section'] = joined_df['cluster'].map(cluster_to_cate

joined_df
```

Out[2790]:

	outcode	gas_median_cons_kwh	elec_median_cons_kwh	Count	n_gas_median_coı
0	AL1	11212.445815	2704.2	39038	0.
2	AL2	12388.751514	2917.6	24211	0
1	AL10	9859.944538	2522.9	38933	0.
7	AL7	8830.802190	2439.4	36930	0.
8	AL8	11826.127001	2851.3	13596	0.
...	...	...	...	...	
1423	SA14	8921.626667	2535.6	35356	0.
1424	SA15	8822.299817	2280.1	37743	0.
1425	SA16	8842.560518	2241.8	8291	1.
1426	SA18	10453.039155	2522.4	30428	0.
1427	SA19	10196.568331	2832.1	9446	1.

1264 rows × 23 columns

5.3 Factors Contributing to Segment Energy Consumption: Multiple Linear Regression Analysis

Energy consumers and now clustered and segmented. Below, each segment is assessed against socio-economic data to understand which socioeconomic factors are correlated with each segment. There are three steps conducted in this analysis:

- **Data Preparation:** The dataset is prepared by categorising energy consumption into four segments ("Low," "Medium-Low," "Medium-High," "High") and mapping these to numerical codes for regression analysis. Socioeconomic factors are identified and organised for inclusion as independent variables.
- **Regression Analysis per Cluster:** For each of the 10 clusters, a multiple linear regression is performed using socioeconomic factors as independent variables against the energy consumption segment. This helps identify how these factors correlate with different levels of energy consumption within each cluster.
- **Results Compilation:** The regression coefficients for each socioeconomic factor are compiled into a DataFrame, providing a clear view of the positive or negative correlations between these factors and energy consumption segments across clusters.

In [279…

```
# init results dict.
cluster_results = {}

# socioeconomic factors
socioeconomic_cols = [
    "mean annual income", "dwelling_type: mobile", "dwelling_type: flat",
    "dwelling_type: detached house", "dwelling_type: semi-detached",
    "dwelling_type: terraced", "no central heating", "1 central heating",
    "2+ central heating (renewable)", "2+ central heating (non-renewable)"
]

# perform regression for each cluster using weighted averages
for cluster in joined_df['cluster'].unique():
    cluster_data = joined_df[joined_df['cluster'] == cluster]
    # ensure sufficient data
    if len(cluster_data) < 2:
        print(f"Not enough data to fit a model for cluster {cluster}")
        continue
    X = cluster_data[socioeconomic_cols]
    y = cluster_data['total_energy']
    model = LinearRegression()
    model.fit(X, y)
    # regression coefficients & intercept stored in dict above
    cluster_results[cluster] = {
        'coefficients': model.coef_,
        'intercept': model.intercept_
    }

# create df to hold coefficients
# prepare data for df construction
data_for_df = {}
for cluster, data in cluster_results.items():
    # coefficients + intercept
    data_for_df[cluster] = np.append(data['coefficients'], data['intercept']

# columns: socioeconomic factors + 'Intercept'
columns_for_df = socioeconomic_cols + ['Intercept']
```

```
# cinstruct & print
regression_results_df = pd.DataFrame(data_for_df, index=columns_for_df).T
regression_results_df.index.name = 'Cluster'

regression_results_df
```

```
Not enough data to fit a model for cluster 2
```

Out[2792]:

Cluster	mean annual income	dwelling_type: mobile	dwelling_type: flat	dwelling_type: detached house	dwelling_type: semi-detached	dwellin t
0	0.000110	-10157.925694	-9997.684611	-9996.470178	-9995.438998	-1000
3	0.000084	6020.854609	6061.076509	6070.339503	6061.229644	6064
1	0.000012	4695.866007	4670.908607	4689.236629	4671.505440	4677
4	-0.000012	782.846380	744.338980	737.792328	739.266682	736
6	-0.002327	19.917984	248.227614	-155.255492	-148.506991	97
5	0.000026	13537.333626	13686.014293	13688.455072	13684.251562	13679

6.0 Discussion & Analysis

During the multilinear regression analysis, the statement "Not enough data to fit a model for cluster 2" indicated an insufficient number of observations to reliably estimate the relationships between socioeconomic factors and energy consumption for this cluster. Consequently, Cluster 2 was excluded from the model fitting to maintain the statistical validity of the analysis

The multilinear regression analysis on English and Welsh energy consumption reveals varied impacts of socioeconomic factors across different clusters, illuminating how regional and housing characteristics influence energy usage. Income sensitivity is marked by the varying coefficients for 'mean annual income', with higher income often correlating with increased energy consumption, potentially due to larger homes and greater appliance use. Housing types such as mobile homes and flats frequently exhibit negative coefficients, indicating lower energy use, whereas other types display positive coefficients, suggesting regional disparities in consumption patterns. Heating systems also play a crucial role, with certain clusters showing that advanced heating technologies may lead to higher energy use, likely due to inefficiencies in older systems. Notably, Cluster 6 demonstrates significant variance in how socioeconomic factors converge, with its high consumption section influenced by a mix of dwelling types and heating efficiencies, underscoring the nuanced interplay of factors that dictate energy consumption within specific clusters.

The analysis of English and Welsh energy consumption segments reveals distinct trends influenced by housing types, heating systems, and income levels. The High Consumption Segment is significantly impacted by larger living spaces such as detached and semi-detached houses, which correlate with higher energy use, while inefficiencies in advanced heating systems can further increase consumption. In contrast, the Medium-Low Consumption Segment demonstrates that smaller dwellings like flats and mobile homes tend to use less energy, with income variations subtly affecting energy consumption patterns. The Low Consumption Segment distinctly benefits from traditional heating systems, which are associated with reduced energy use, likely due to more efficient energy management or the implementation of conservation measures. These findings highlight how specific characteristics and living conditions drive energy consumption in different segments of the population.

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