Spatial Segmentation and Drivers of Energy Consumption in England and Wales

Exploring Socioeconomic Influences and Consumption Patterns Among Energy Consumers in England and Wales

Word count: 1992

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 & Literature Review

After economic sanctions were imposed on Russian oil in 2022, energy prices in Europe surged. This sparked public discontent and prompted domestic relief payments. While these payments provided temporary relief, investigating domestic energy consumption could boost the UK's long-term resilience against price fluctuations and reduce costs for those most vulnerable through targeted policy. With this in mind, the objective of this study is to identify socioeconomic factors that are correlated with *High, Medium* and *Low* energy consumption.

This paper groups consumers based on similar energy usage and location through unsupervised clustering. Initially, clustering the population allows us to identify natural groupings based on energy use and geographical proximity (Jain & Ahuja, 2014). This approach provides an optimal level of specificity — neither too granular nor too broad - facilitating the development of targeted policies that effectively address the distinct needs of these well-defined groups (Balashankar et al., 2022; Soto et al., 2021).

We then classify these groups into four energy consumption *segments*: *High, Medium-High, Medium-Low,* and *Low*. Finally, we employ muliple linear regression to examine the socioeconomic factors correlated with each energy consumption category.

Developing targeted policy involves four steps, market segmentation, segment analysis, policy implementation and ongoing monitoring (Soto et al., 2021). This paper conducts the initial two steps, due to its analytical nature.

Segmentation is crucial for creating targeted policies by identifying distinct groups within a population (Soto et al., 2021). Clustering, particularly K-means, is a potent tool for effectively delineating target populations, as it groups based common characteristics, is suitable for spatial data and not computationally expensive (Balashankar et al., 2022; Jain & Ahuja, 2014).

The next step involves understanding the characteristics of these consumer segments. Multiple linear regression is commonly used to analyse the influence of multiple independent varibles on a dependent variable, such as the impact of socioeconomic factors on energy consumption (Balashankar et al., 2022).

The Office for National Statistics commonly reports three socioeconomic factors alongside energy consumption: 1. Central Heating Type—key for understanding energy consumption due to its direct impact on heating efficiency. 2. Income Level and 3. Dwelling Type—important for indicating the economic ability to invest in energy-efficient solutions and the physical characteristics of homes that affect energy needs. Thus, this study will investigate the influence of these three factors on energy consumption

With this in mind, this paper investigates 3 research questions.

```
    RQ1 | Can unsupervised clustering 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 *High, Medium-High, Medium-Low,*
and *Low* energy consumption in England and Wales?
```

2.0 Methodology

This study will use open data from the Office of National Statistics (ONS) and energy consumption records from the UK Department for Energy Security and Net Zero (DESNZ) from 2022. The energy data is provided at postcode level, while socioeconomic data are by Local Authority District (LAD). To address this, we'll cluster at the postcode level, then map these clusters to LADs. Where clusters span multiple LADs, we'll use a weighted average of energy consumption based on the number of postcodes per LAD, ensuring accurate geographical representation of the data.

The analysis consists of two main parts. Initially, consumer grouping will be conducted using unsupervised clustering based on geography and energy consumption, avoiding the initial influence of socio-economic factors. This approach, as Słupik et al. (2021) suggest, establishes baseline segments reflecting geographic and usage interactions and allows for the methodical addition of more variables if the study progresses.

We'll employ the elbow method, silhouette analysis and the Calinski-Harabasz index to determine the optimal number of clusters. Clusters will be divided into consumption quartiles: *High consumption, Medium-High consumption, Medium-Low consumption*, and *Low consumption*.

Following segmentation, the study will examine which characteristics correlate with different levels of energy consumption, focusing on factors like income, central heating type and dwelling type. This correlation analysis will utilise multiple linear regression to assess how these predictors affect energy consumption across segments, providing a statistically robust foundation for targeted policy recommendations (Forootan et al., 2022; Dou et al., 2023). This method not only quantifies relationship strengths but also accounts for variable interdependencies, enhancing the analysis's accuracy and relevance for policy-making.

3.0 Data Overview, Processing & Exploration

This section processes the data this study and provides an overview of the fields, the shape and distribution of the data. This includes checking for outliers and inconsistencies.

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 electricity and gas consumption as it is least impacted by outliers. For this reason we do not normalise by population.

geopy can assign one postcode per second and is computationally intensive, thus, we run this on the gas consumption data and join electricity data later.

3.1 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…

```
# the following is a computational intense process and was run when this ana
# the new CSV file is read in below the following four code chunks.

# 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_lo
```

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

In [288…

```
gas_df = pd.read_csv('data/gas_df.csv')
```

In [288…

```
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 [288…

```
# 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

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

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

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

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

# join electricity 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 [289…

```
# 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_k
              (energycon_gdf[['n_gas_median_cons_kwh', 'n_elec_median_cons_k
energycon_gdf = energycon_gdf[~is_outlier]

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

In [289…

```
# 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 [289…

```
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
```

We infer the following conclusions about the 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 is 9,815 kWh.
- **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 population range from 55 to 170,304, suggesting diverse outcode sizes. 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. 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.

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

In [289…

```
# 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 [289…

```
# 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 annual
median_income.rename(columns={'Local authority code': 'Lower tier local auth
median_income.head(2)
```

Out[2896]:

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

In [289…

```
# 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 [289…

```
# merge 'dwpivot_df' and 'heatpivot_df' on 'Lower tier local authorities Co
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[2898]:

	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 [289…

```
# 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 [290…

```
# 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[2900]:

	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 [290…

```
# 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 [290…

```
# normalise all the necessary fields
# columns to normalise
columns_to_normalise = [
    'dwelling_type: mobile', 'dwelling_type: flat', 'dwelling_type: detached
    '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['population

# 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[2902]:

	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 [290…

```
# 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 [290…

```
# 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.

In [290…

```
# 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'].mec
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[2907]:

		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 [290…

```
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
```

4.0 Analysis: 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:

- 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 group consumers based on usage and location. The optimal number of groups was determined using the elbow method, silhouette analysis, and the Calinski-Harabasz index which identify the point where the increase in clusters ceases to significantly reduce the within-cluster sum of squares.

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 [291…

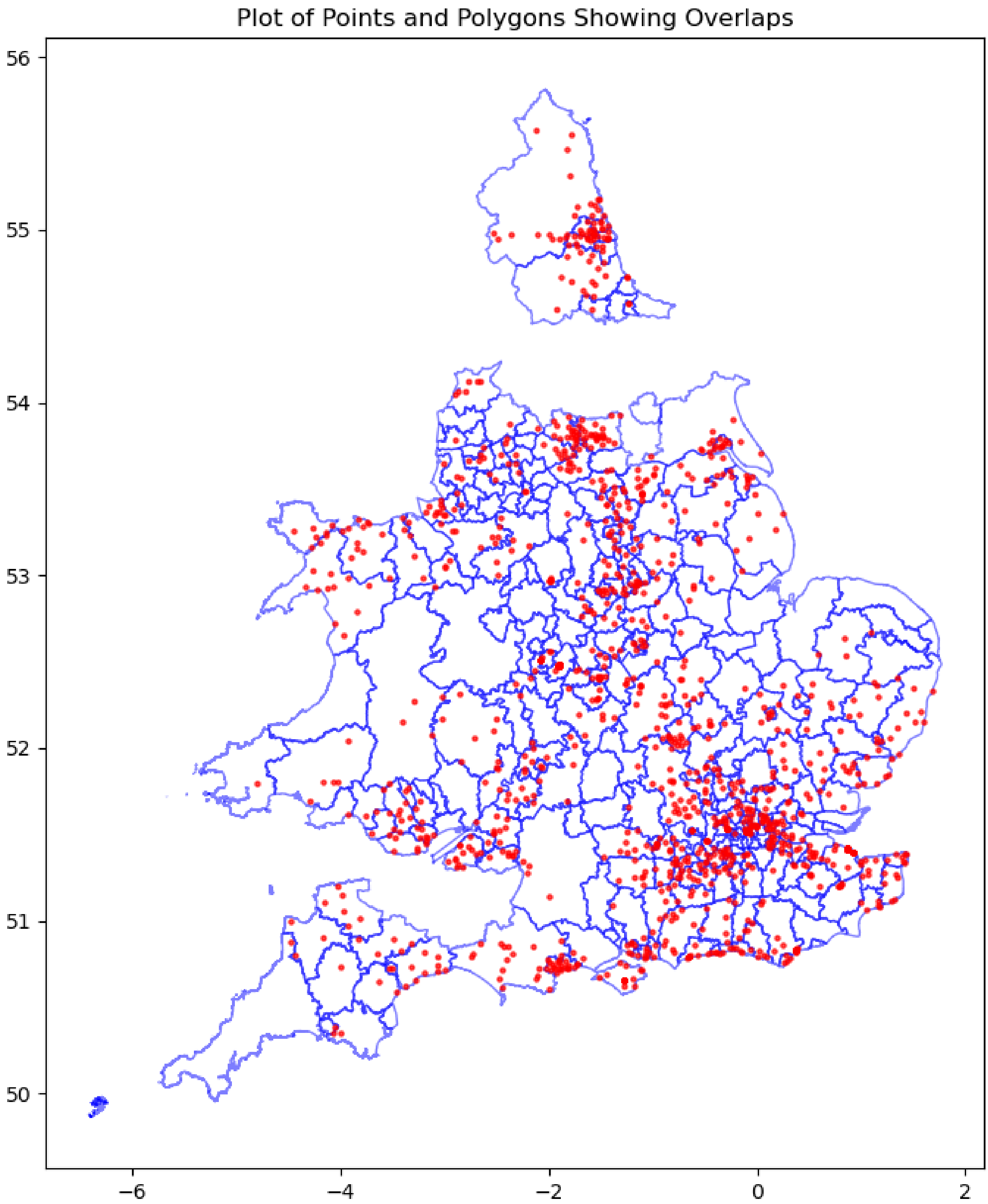
```
# read consumption data & view
gdf = gpd.read_file('energycon.gpkg')
gdf.info()
```

```
<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 [291…

```
# 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 [291…

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

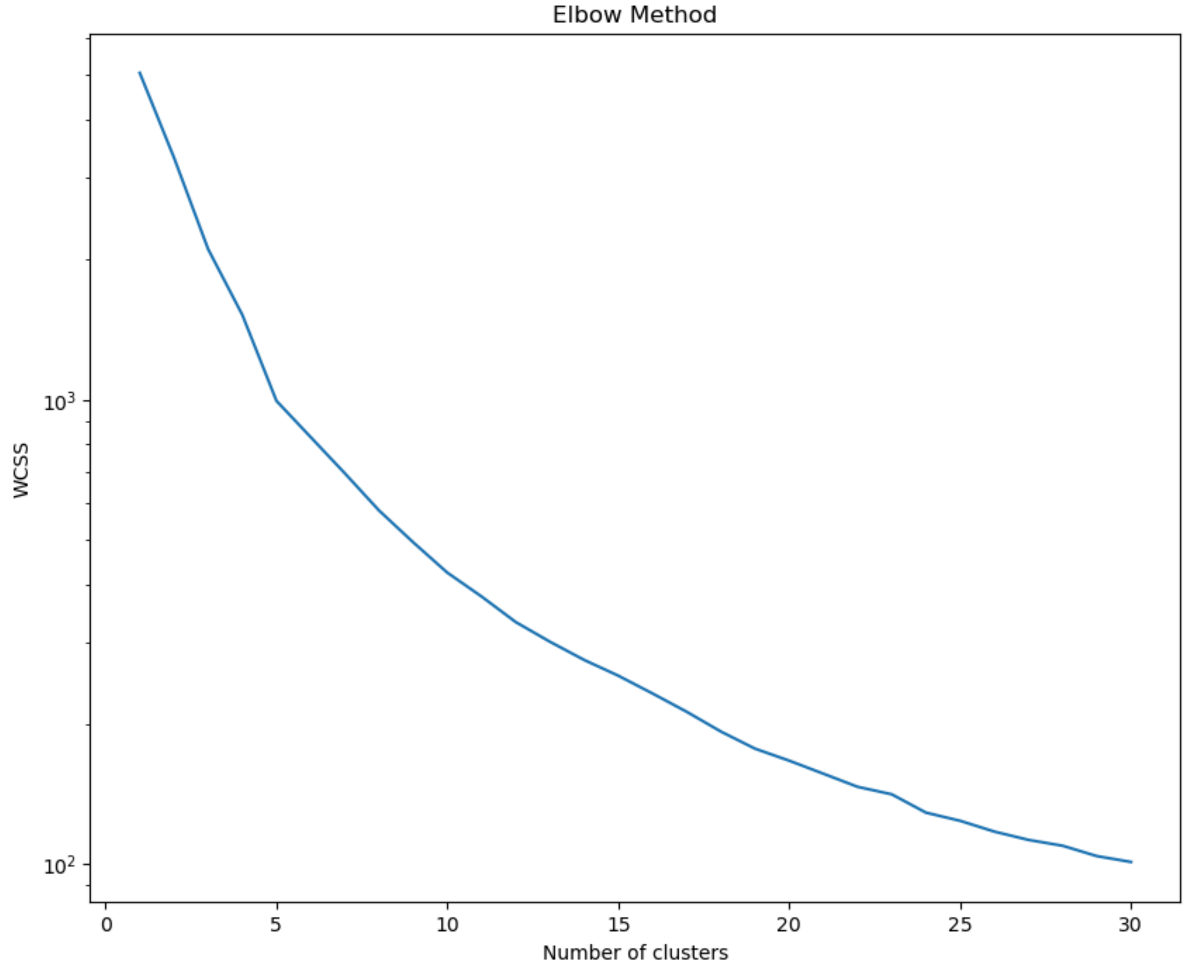
```
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 1264 entries, 0 to 1427
Data columns (total 18 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   outcode                             1264 non-null   object
 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 [291…

```python
#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)
```

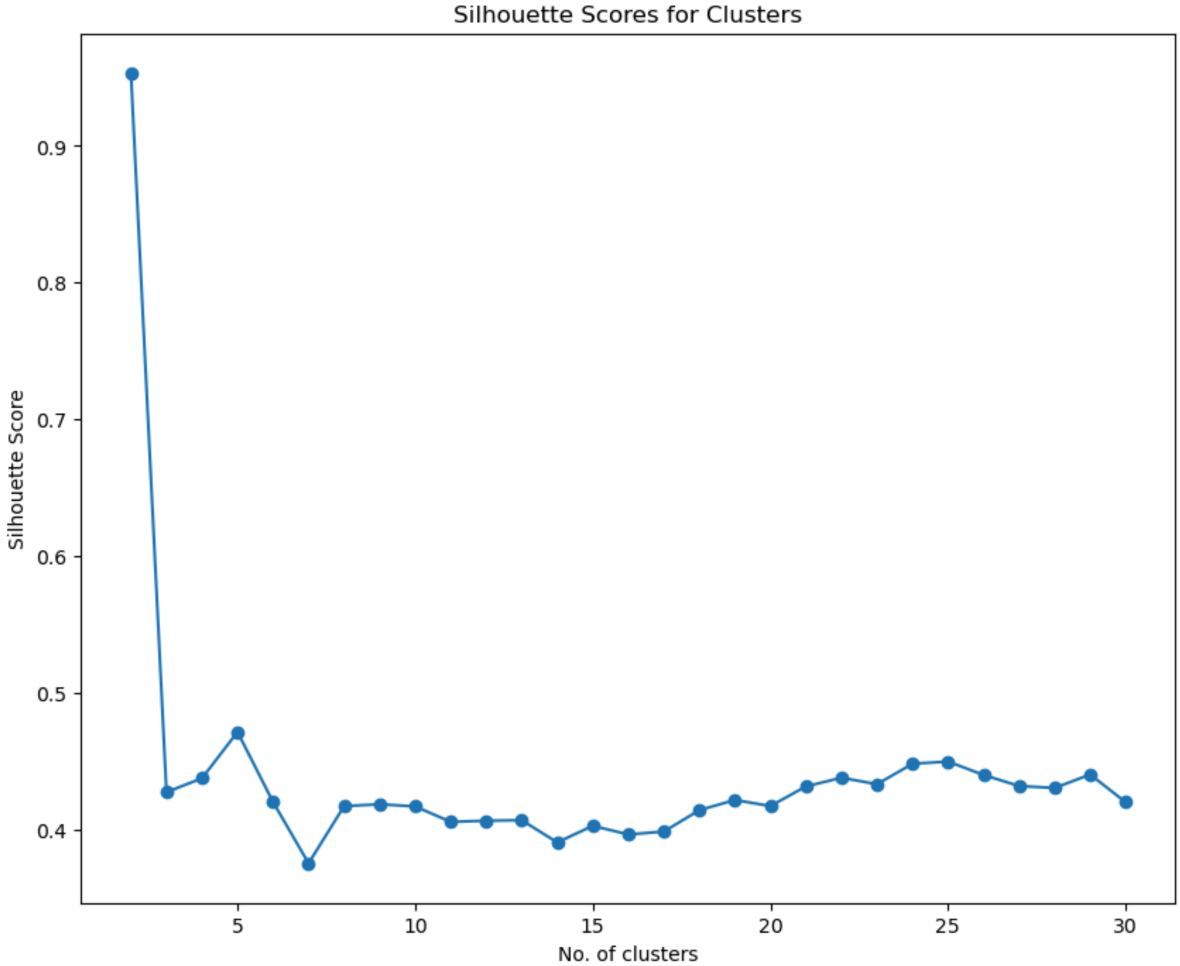
In [291…

```python
# 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()
```



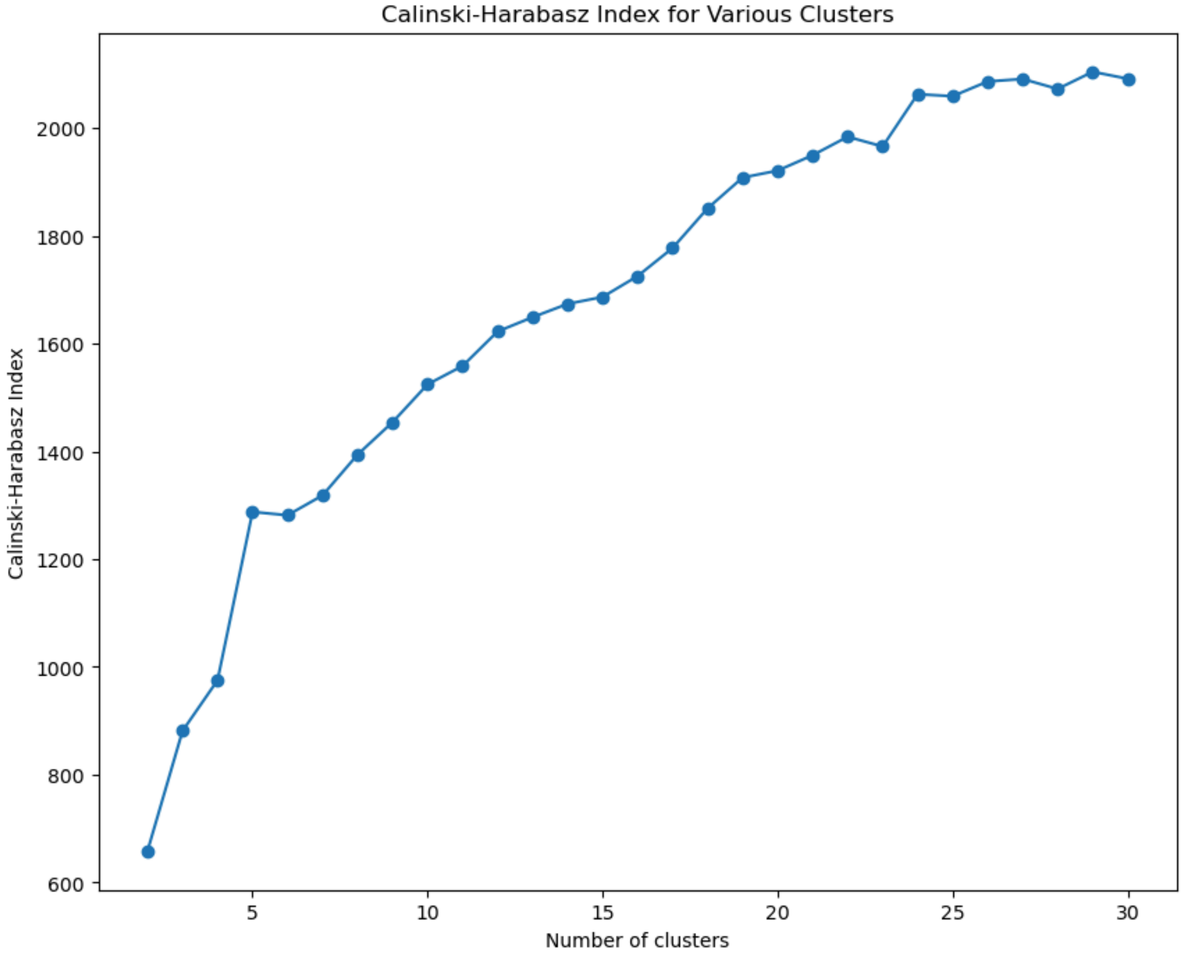
In [291…

```
# 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 Clusters')
plt.xlabel('No. of clusters')
plt.ylabel('Silhouette Score')
plt.show()
```



In [291…

```
# calinski-harabasz index
calinski_harabasz_scores = []
for i in range(2, 31):  # cannot compute with 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()
```



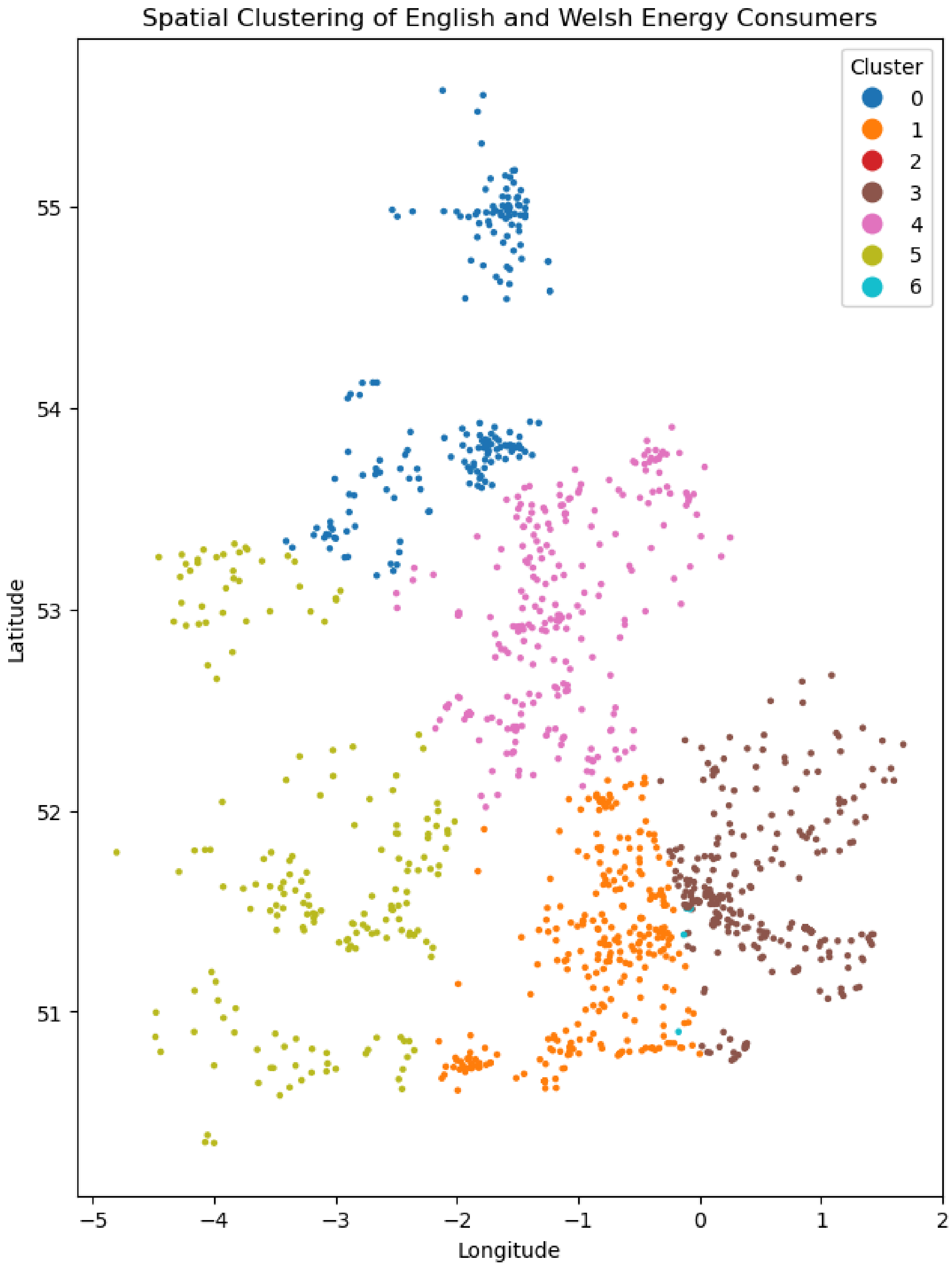
4.1.1 Number of Clusters

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 [291…

```
# 7 clusters chosen
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)
```



In [291…

```
# below are calculations of the silhouette score using 'postcode' and 'LAD'
# select relevant features for clustering
features = joined_df[['n_gas_median_cons_kwh', 'n_elec_median_cons_kwh']]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(features)

# apply K-means clustering, using 7 clusters
k = 7
kmeans = KMeans(n_clusters=k, random_state=42)
labels = kmeans.fit_predict(X_scaled)

# calc silhouette score to assess the quality of clustering
silhouette_avg = silhouette_score(X_scaled, labels)
print('average silhouette score for', k, 'clusters is:', silhouette_avg)
```

```
average silhouette score for 7 clusters is: 0.807069627829212
```

```
/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)
```

A silhouette score of 0.807, suggests that the clusters are well-separated and clearly defined. This indicates that the segmentation of the dataset into seven clusters is effective, with each cluster likely representing distinct patterns of energy consumption.

4.1.2 Segment Clusters by Quartile

Below we segment the 7 clusters into 1 of 4 consumption types outlined above.

In [292…

```python
# 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[2921]:

	outcode	gas_median_cons_kwh	elec_median_cons_kwh	Count	n_gas_median_co
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

4.3 Correlation between consumption segments and socioeconomic factors

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: Energy consumption is categorised into four segments (*Low, Medium-Low, Medium-High, High*) and coded numerically for regression. Socioeconomic factors are prepared as independent variables.
- Regression Analysis per Cluster: Multiple linear regressions are conducted for each of the 10 clusters, analysing the impact of socioeconomic factors on energy consumption levels.

- Results Compilation: Regression coefficients for each factor are compiled into a DataFrame, illustrating their correlations with energy consumption across clusters.

In [292…

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

# socioeconomic factors object
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']

# construct & print results df
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[2923]:

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

5.0 Results, Discussion & Conclusion

During the multilinear regression analysis, there was "Not enough data to fit a model for cluster 2". Thus, Cluster 2 was excluded from model fitting to preserve the statistical integrity of the analysis.

The multilinear regression analysis on English and Welsh energy consumption reveals varied impacts of socioeconomic factors across different clusters, highlighting how regional and housing characteristics influence energy usage. Higher income often correlates 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. 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 energy consumption in England and Wales shows clear patterns influenced by housing types, heating systems, and income levels. The High Consumption Segment is primarily affected by larger homes such as detached and semi-detached houses, which typically use more energy. Inefficiencies in advanced heating systems also contribute to higher consumption. Conversely, the Medium-Low Consumption Segment includes smaller residences like flats and mobile homes, which generally use less energy, with subtle impacts from income differences. The Low Consumption Segment benefits from traditional heating systems that tend to be more energy-efficient or involve better energy conservation measures.

5.1 Limitations

One limitation of this analysis is integrating data across different geographic levels, such as postcode-level energy consumption and Local Authority District-level socioeconomic data, which may introduce inaccuracies. Additionally, the lack of comprehensive data for all Local Authority Districts could lead to a biased analysis of energy consumption patterns.

Moreover, the use of unsupervised clustering might miss nuanced subgroups due to its sensitivity to outliers and data density variations. Also, the regression analysis may not include all relevant variables affecting energy consumption, potentially overlooking significant factors influencing energy use patterns.

5.2 Opportunities for further research

This study sets the stage for future research by facilitating the inclusion of additional variables at the clustering and socioeconomic stages, enhancing our understanding of energy consumption patterns. Subsequent studies could incorporate environmental factors such as weather conditions and renewable energy access to examine their impact alongside socioeconomic traits. Furthermore, employing time series analysis could provide forecasts of future consumption trends and policy impacts, aiding policymakers in proactive decision-making.

References

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