Exploring the Relationship and Impact of Spatial Social Inequality on Childhood Obesity Prevalence in London

Preparation

- Github link
- Number of words: 1497
- Runtime: 0.6 minutes (*Hardware: 16.0GB RAM, 4.06GHz CPU (psutil-detected) OS: Darwin 24.4.0*)
- Coding environment: Local Python 3.9.6 environment (macOS 15.4 ARM processor)
-
- Additional library *[libraries not included in common python environment]*:
  - **libpysal**: Core library of the PySAL project used for spatial weights and spatial econometrics.
  - **spopt**: Spatial optimization library used for region-building algorithms such as SKATER.
  - **rfpimp**: A utility for calculating and plotting permutation-based feature importance for tree-based models.

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Introduction

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Child obesity has become one of the global public health challenges (World Health Organization, 2018). According to the report released by the Office for Health Improvement & Disparities, from 2023 to 2024, 24% of children in Year 6 were considered obese in London. As Gupta et al. (2012) observe, the diseases caused by childhood obesity might cause psychosocial consequences like discrimination, social stigmatization, and bullying, which experiences not only diminish children's immediate quality of life but also exacerbate existing social inequalities.

There are strong links between socioeconomic status(SES) with childhood obesity, indicators like household income and parental education, influence children's diet habits. White, Rehkopf & Mortensen (2016) found that children in England showed significant social inequalities in obesity prevalence, with children in low SES being more likely to be obese. Zhou, Harris & Tranos (2023) found that not only do traditional SES variables play a significant role in obesity risk in the UK, but also living location influences greatly in obesity prevalence, so the interaction between spatial factors and socioeconomic status cannot be ignored. Using spatial autocorrelation and clustering methods, Sun et al. (2020) reveal a significant geographical clustering of childhood obesity prevalence in different regions in England, which are often closely related to factors such as SES, educational resources, and the quality of public services within the region.

Although research on childhood obesity prevalences in the UK now addresses socioeconomic inequalities, not much consideration has been given to their spatial dependence. London, as a representative metropolis with large internal disparities and significant socio-spatial inequalities, examining the clustering of childhood obesity rates and socio-economic characteristics in the London region could help us to better understand regional child health and target child health interventions.

In [1]:
```
# for running the analysis
import numpy as np
import pandas as pd
import geopandas as gpd
import libpysal as ps
import matplotlib.pyplot as plt
import seaborn as sns

import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV, valid
from sklearn import metrics
from sklearn.metrics import root_mean_squared_error, mean_squared_error,

import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_facto
from statsmodels.tools.tools import add_constant

# Linear regression
from sklearn.linear_model import LinearRegression

# CART
```

```
from sklearn.tree import DecisionTreeRegressor

# random forest
from sklearn.ensemble import RandomForestRegressor

# feature importance
import rfpimp

# Skater clustering
from spopt.region import Skater
```

Research questions

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1. Is the association between childhood obesity and socioeconomic and social environmental factors primarily linear, or do non-linear models capture further nuances?
2. How do spatial clusters of ward-level childhood obesity and key socioeconomic factors manifest in London, and what do they reveal about regional social inequalities affecting childhood health?

Data

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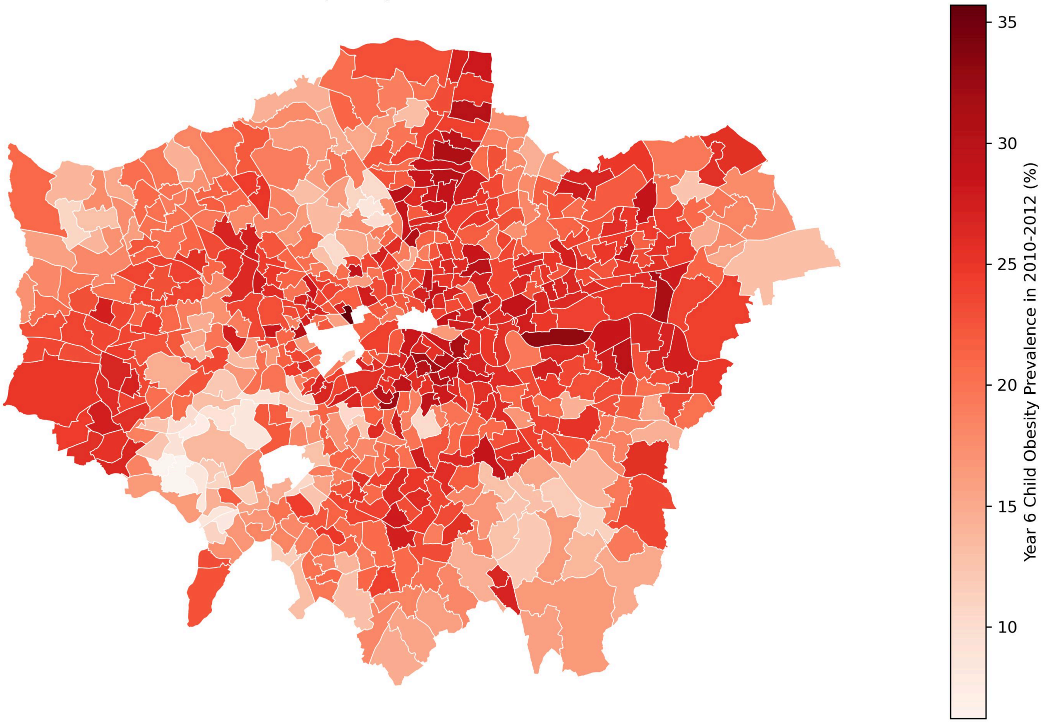
The Year 6 childhood obesity prevalence data (2010/11–2012/13) at the ward level (**Figure 1**) is used as the dependent variable. This period provides consistent data based on pre-2014 ward boundaries, ensuring uniform standards. Additionally, ward-level statistics are representative given children's limited activity ranges. It is also notable that in the NCMP dataset, wards with ≤5 obese children have suppressed values (recorded as zero).

Figure 1: The distribution of Year6 Children Obesity Prevalence in London for each ward (except City of London) from 2010 to 2012



Nine selected ward-level socioeconomic and social environmental factors (**Table 1**) were selected from various official sources such as Census 2011; Department for Education; Greenspace Information for Greater London. They are associated with household income, family status, parental education, lifestyle habits, resources accessibility and public security, which in turn affects childhood obesity prevalence (Cutler & Lleras-Muney, 2010; Goisis, Sacker & Kelly, 2016; Wang & Lim, 2012).

Table 1 Variable Selection and Description

Variable	Type	Description
Year 6 (age 10-11) child obesity prevalence (%)	Numeric	The year 6 (age 10-11) children's obesity prevalence for wards. Used as dependent variable in regression.
Children in poverty rate (%)	Numeric	The percentages of children in poverty for wards.
Median household income	Numeric	The median of household income for wards.
Unemployed rate (%)	Numeric	The percentage of unemployed people for wards.
Qualifications – Level 4 and above rate (%)	Numeric	The percentage of people with Level 4 and above level qualifications for wards.
Average GCSE score	Numeric	The student's average GCSE score for wards.
Unauthorised absence in all schools rate (%)	Numeric	The percentage of pupils absent unauthorisedly in all schools for wards.
Crime rate (%)	Numeric	The total crime rate for wards.
People with bad or very bad health rate (%)	Numeric	The percentage of people with bad or very bad health for wards.

Variable	Type	Description
Households with access to open space (%)	Numeric	The percentage of households with access to open space for wards.

In [2]:
```
# load in the dataset
obesity_ward = pd.read_csv('https://github.com/YUJIA-MA-UCL/Casa0006_chil
obesity_ward.info()

# The prevalence of childhood obesity that is less than 5 is
# being suppressed, so there are some 'na' value in
# 'Childhood_Obesity_Year6' column
obesity_ward_clean = obesity_ward.dropna()
obesity_ward_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 625 entries, 0 to 624
Data columns (total 13 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   ward_code                           625 non-null    object 
 1   Ward                                625 non-null    object 
 2   Borough                             625 non-null    object 
 3   Childhood_Obesity_Year6             613 non-null    float64
 4   Children_in_poverty                 625 non-null    float64
 5   Crime_rate                          625 non-null    float64
 6   Unauthorised_Absence_in_All_Schools 625 non-null    float64
 7   Median_Household_income             625 non-null    int64  
 8   Qualifications_Level4_and_above     625 non-null    float64
 9   Households_with_access_to_openspace 625 non-null    float64
 10  People_with_Bad_or_Very_Bad_Health  625 non-null    float64
 11  Average_GCSE                        625 non-null    float64
 12  Unemployed                          625 non-null    float64
dtypes: float64(9), int64(1), object(3)
memory usage: 63.6+ KB
<class 'pandas.core.frame.DataFrame'>
Index: 613 entries, 1 to 624
Data columns (total 13 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   ward_code                           613 non-null    object 
 1   Ward                                613 non-null    object 
 2   Borough                             613 non-null    object 
 3   Childhood_Obesity_Year6             613 non-null    float64
 4   Children_in_poverty                 613 non-null    float64
 5   Crime_rate                          613 non-null    float64
 6   Unauthorised_Absence_in_All_Schools 613 non-null    float64
 7   Median_Household_income             613 non-null    int64  
 8   Qualifications_Level4_and_above     613 non-null    float64
 9   Households_with_access_to_openspace 613 non-null    float64
 10  People_with_Bad_or_Very_Bad_Health  613 non-null    float64
 11  Average_GCSE                        613 non-null    float64
 12  Unemployed                          613 non-null    float64
dtypes: float64(9), int64(1), object(3)
memory usage: 67.0+ KB
```

In [3]:
```
# download the shapefile and read in
import requests
import zipfile
import io
```

```
url = "https://github.com/YUJIA-MA-UCL/Casa0006_childhood_obesity/raw/ref
response = requests.get(url)

# unzip the package
with zipfile.ZipFile(io.BytesIO(response.content)) as z:
    z.extractall("Ward_boundary_shapefile")

# load in the boudary shapefile data
gdf = gpd.read_file("statistical-gis-boundaries-london/London_Ward_CityMe

# merge the data with gdf
gdf_obesity = pd.merge(gdf,obesity_ward_clean,
                       left_on='GSS_CODE',
                       right_on='ward_code',
                       how='left')
gdf_obesity.info()

gdf_obesity_clean = gdf_obesity.dropna()
gdf_obesity_clean.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 625 entries, 0 to 624
Data columns (total 21 columns):
 #   Column                               Non-Null Count  Dtype   
---  ------                               --------------  -----   
 0   NAME                                 625 non-null    object  
 1   GSS_CODE                             625 non-null    object  
 2   HECTARES                             625 non-null    float64 
 3   NONLD_AREA                           625 non-null    float64 
 4   LB_GSS_CD                            625 non-null    object  
 5   BOROUGH                              625 non-null    object  
 6   POLY_ID                              625 non-null    int64   
 7   geometry                             625 non-null    geometry
 8   ward_code                            613 non-null    object  
 9   Ward                                 613 non-null    object  
 10  Borough                              613 non-null    object  
 11  Childhood_Obesity_Year6              613 non-null    float64 
 12  Children_in_poverty                  613 non-null    float64 
 13  Crime_rate                           613 non-null    float64 
 14  Unauthorised_Absence_in_All_Schools  613 non-null    float64 
 15  Median_Household_income              613 non-null    float64 
 16  Qualifications_Level4_and_above      613 non-null    float64 
 17  Households_with_access_to_openspace  613 non-null    float64 
 18  People_with_Bad_or_Very_Bad_Health   613 non-null    float64 
 19  Average_GCSE                         613 non-null    float64 
 20  Unemployed                           613 non-null    float64 
dtypes: float64(12), geometry(1), int64(1), object(7)
memory usage: 102.7+ KB
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 613 entries, 0 to 623
Data columns (total 21 columns):
 #   Column                               Non-Null Count  Dtype   
---  ------                               --------------  -----   
 0   NAME                                 613 non-null    object  
 1   GSS_CODE                             613 non-null    object  
 2   HECTARES                             613 non-null    float64 
 3   NONLD_AREA                           613 non-null    float64 
 4   LB_GSS_CD                            613 non-null    object  
 5   BOROUGH                              613 non-null    object  
 6   POLY_ID                              613 non-null    int64   
 7   geometry                             613 non-null    geometry
 8   ward_code                            613 non-null    object  
 9   Ward                                 613 non-null    object  
 10  Borough                              613 non-null    object  
 11  Childhood_Obesity_Year6              613 non-null    float64 
 12  Children_in_poverty                  613 non-null    float64 
 13  Crime_rate                           613 non-null    float64 
 14  Unauthorised_Absence_in_All_Schools  613 non-null    float64 
 15  Median_Household_income              613 non-null    float64 
 16  Qualifications_Level4_and_above      613 non-null    float64 
 17  Households_with_access_to_openspace  613 non-null    float64 
 18  People_with_Bad_or_Very_Bad_Health   613 non-null    float64 
 19  Average_GCSE                         613 non-null    float64 
 20  Unemployed                           613 non-null    float64 
dtypes: float64(12), geometry(1), int64(1), object(7)
memory usage: 105.4+ KB
```

In [4]:

```
# define a function to plot the obesity distribution map
def obesityPlot():
    fig, ax = plt.subplots(1, 1, figsize=(15,8))
```

```
    gdf_obesity_clean.plot(edgecolor=(1, 1, 1, 1),linewidth=0.5,
                           column='Childhood_Obesity_Year6',
                           cmap='Reds',
                           legend=True,
                           legend_kwds={'label': "Year 6 Child Obesity Pr
                           ax=ax)

    ax.set_title("Figure 1: The distribution of Year6 Children Obesity Pr
    ax.axis('off')
    #plt.savefig("obesity_map.jpg", dpi=300, bbox_inches='tight')
    plt.show()

#obesityPlot()
```

In [5]:

```
# subset the obesity_ward with only numeric variables to prepare
# for data handling, as ML models can't deal with strings
df = obesity_ward_clean[['Childhood_Obesity_Year6',
                        'Children_in_poverty',
                        'Median_Household_income',
                        'Unemployed',
                        'Qualifications_Level4_and_above',
                        'Average_GCSE',
                        'Unauthorised_Absence_in_All_Schools',
                        'Crime_rate',
                        'People_with_Bad_or_Very_Bad_Health',
                        'Households_with_access_to_openspace']]
```

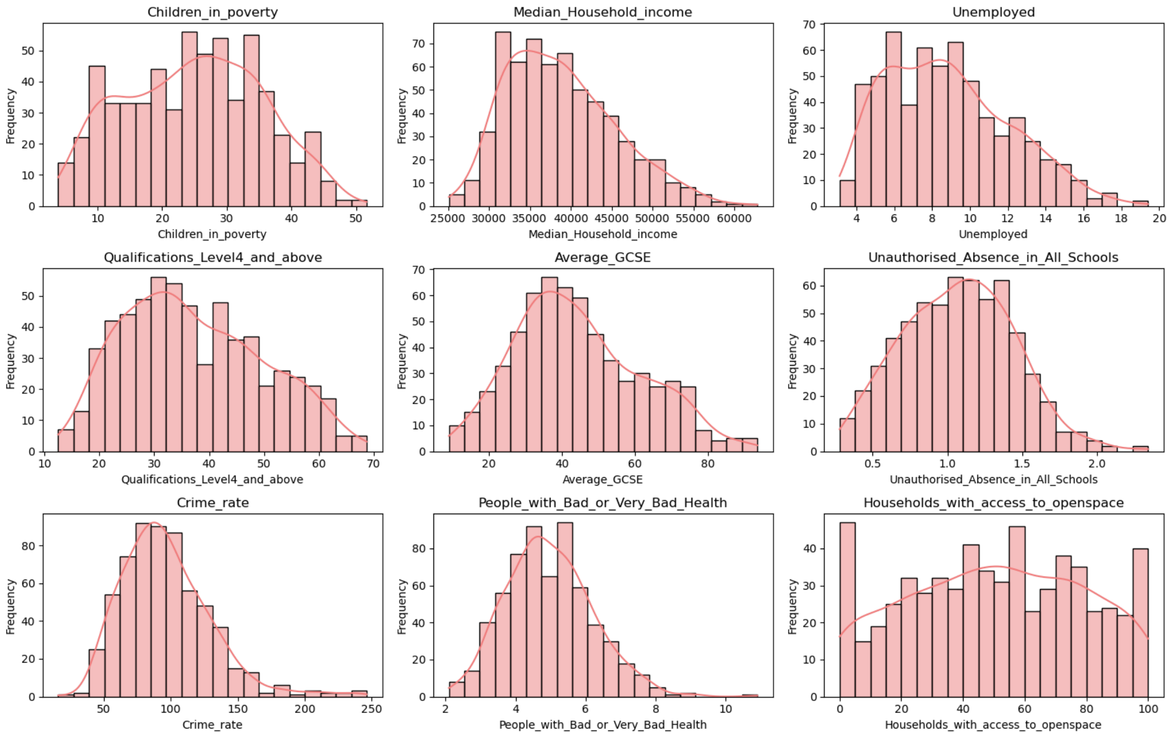
Figure 2 and the table below show histograms and descriptive statistics for the selected variables, and it can be learnt that: there are differences in the scale of the variables; and “Crime_rate”, “Median_household_income” and “Unemployed” are skewed. So, log transformation and z-score standardisation can be used here to reduce the impact of different scales and skewed distributions on the results.

In [6]:

```
# descriptive analysis
fig, axes = plt.subplots(3, 3, figsize=(15, 10))
axes = axes.flatten()
variables = df.columns[1:10]
# Histgram of each variable
for i, var in enumerate(variables):
    sns.histplot(df[var].dropna(), bins=20,
                 kde=True, ax=axes[i], color='lightcoral')
    axes[i].set_title(var)
    axes[i].set_xlabel(var)
    axes[i].set_ylabel("Frequency")
for j in range(len(variables), len(axes)):
    fig.delaxes(axes[j])

fig.suptitle("Figure 2: The histogram of SES and social environmental fac

plt.tight_layout(rect=[0, 0, 1, 0.98])
plt.show()

# generate summary statistics for the DataFrame
# the result is transposed so that variables are shown as rows
summary = df.describe().T
# the skewness of each variable (measure of asymmetry)
summary['Skewness'] = df.skew()
# the kurtosis of each variable (measure of tail heaviness)
```

```
summary['Kurtosis'] = df.kurtosis()
print(summary.round(3))
```

Figure 2: The histogram of SES and social environmental factors for each ward



```
                                    count       mean       std        min  \
Childhood_Obesity_Year6             613.0     21.539     5.062      6.220
Children_in_poverty                 613.0     24.808    10.540      3.900
Median_Household_income             613.0  38808.630  6657.753  25090.000
Unemployed                          613.0      8.812     3.247      3.115
Qualifications_Level4_and_above     613.0     37.217    12.570     12.500
Average_GCSE                        613.0     44.557    17.302      9.077
Unauthorised_Absence_in_All_Schools 613.0      1.074     0.370      0.280
Crime_rate                          613.0     96.599    33.500     15.950
People_with_Bad_or_Very_Bad_Health  613.0      4.966     1.232      2.100
Households_with_access_to_openspace 613.0     50.494    28.569      0.000

                                          25%        50%        75%  \
Childhood_Obesity_Year6                18.500     22.220     25.380
Children_in_poverty                    16.170     25.070     33.100
Median_Household_income             33570.000  38090.000  43160.000
Unemployed                              6.096      8.549     10.966
Qualifications_Level4_and_above        27.200     35.200     46.300
Average_GCSE                           31.858     42.157     55.979
Unauthorised_Absence_in_All_Schools     0.800      1.080      1.330
Crime_rate                             73.250     91.210    115.860
People_with_Bad_or_Very_Bad_Health      4.100      4.800      5.700
Households_with_access_to_openspace    27.980     51.760     73.820

                                          max  Skewness  Kurtosis
Childhood_Obesity_Year6                35.710    -0.500    -0.058
Children_in_poverty                    51.670     0.029    -0.851
Median_Household_income             62840.000     0.610    -0.014
Unemployed                             19.410     0.519    -0.380
Qualifications_Level4_and_above        68.700     0.347    -0.737
Average_GCSE                           93.619     0.429    -0.367
Unauthorised_Absence_in_All_Schools     2.340     0.164    -0.220
Crime_rate                            246.410     1.084     2.204
People_with_Bad_or_Very_Bad_Health     10.900     0.475     0.673
Households_with_access_to_openspace   100.000    -0.057    -1.030
```

In [30]:

```python
# do the log-transformation on the data
# and add the transformed data columns to the df
df['Median_Household_income_log']= np.log1p(df['Median_Household_income']
df['Crime_rate_log']= np.log1p(df['Crime_rate'])
df['Unemployed_log']= np.log1p(df['Unemployed'])

# subset the dataframe with transformed data
df1 = df[['Childhood_Obesity_Year6',
         'Children_in_poverty',
         'Median_Household_income_log',
         'Unemployed_log',
         'Qualifications_Level4_and_above',
         'Average_GCSE',
         'Unauthorised_Absence_in_All_Schools',
         'Crime_rate_log',
         'People_with_Bad_or_Very_Bad_Health',
         'Households_with_access_to_openspace']]

# do the z-score normalisation
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df2 = scaler.fit_transform(df1)
```

```
df2 = pd.DataFrame(df2, columns=df1.columns)
```

After data handling, all variables tend to be normally distributed and are in similar ranges (**Figure 3**).

In [8]:
```
# show the new histogram and summary after data processing
fig, axes = plt.subplots(3, 3, figsize=(15, 10))
axes = axes.flatten()
variables = df2.columns[1:10]
# Histgram of each variable
for i, var in enumerate(variables):
    sns.histplot(df2[var].dropna(), bins=20, kde=True, ax=axes[i], color=
    axes[i].set_title(var)
    axes[i].set_xlabel(var)
    axes[i].set_ylabel("Frequency")

for j in range(len(variables), len(axes)):
    fig.delaxes(axes[j])

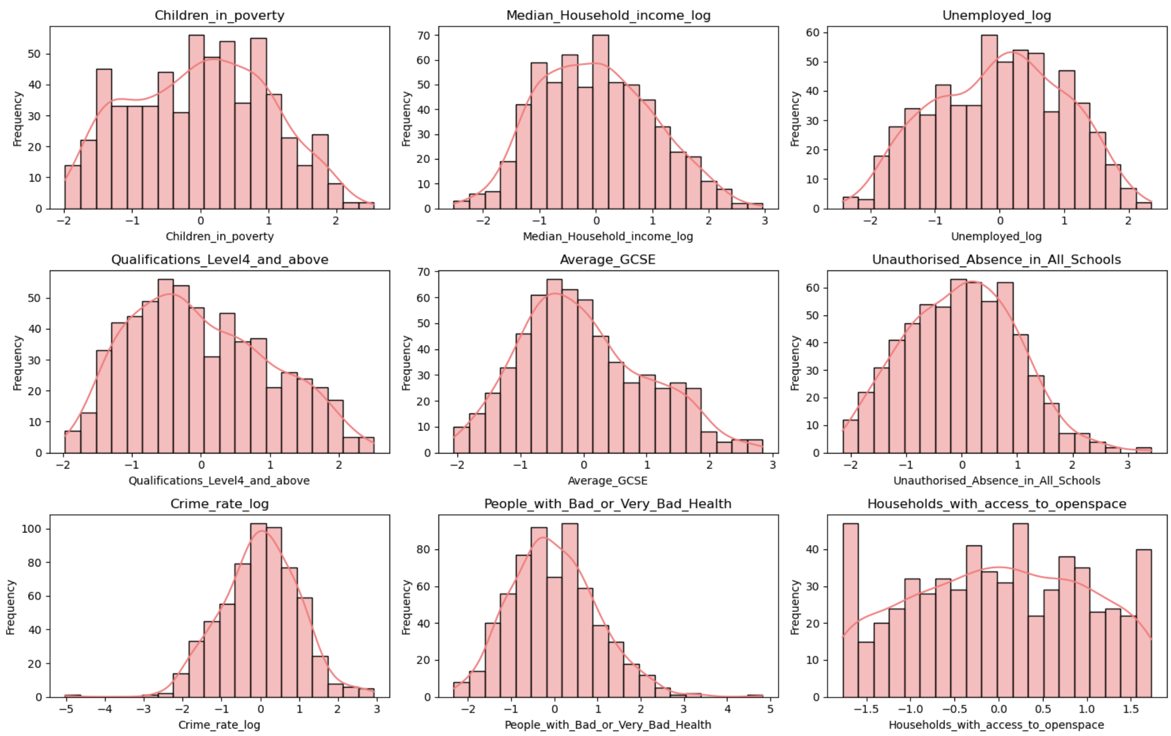
fig.suptitle("Figure 3: The histogram of transformed SES and social envir

plt.tight_layout(rect=[0, 0, 1, 0.98])
plt.show()

newsummary = df2.describe().T
newsummary['Skewness'] = df2.skew()
newsummary['Kurtosis'] = df2.kurtosis()
print(newsummary.round(3))

# show the results of normalisation
print("\nThe range of data:")
for c in df2.columns.values:
    print("The range of {} is [{}, {}]".format(c, df2[c].min(), df2[c].ma
```

Figure 3: The histogram of transformed SES and social environmental factors for each ward



```
                                     count  mean    std    min    25%    5
0%  \
Childhood_Obesity_Year6              613.0   0.0  1.001 -3.029 -0.601  0.1
35
Children_in_poverty                  613.0  -0.0  1.001 -1.985 -0.820  0.0
25
Median_Household_income_log          613.0  -0.0  1.001 -2.516 -0.780 -0.0
27
Unemployed_log                       613.0   0.0  1.001 -2.431 -0.803  0.0
83
Qualifications_Level4_and_above      613.0  -0.0  1.001 -1.968 -0.798 -0.1
61
Average_GCSE                         613.0   0.0  1.001 -2.052 -0.735 -0.1
39
Unauthorised_Absence_in_All_Schools  613.0  -0.0  1.001 -2.146 -0.741  0.0
16
Crime_rate_log                       613.0   0.0  1.001 -5.023 -0.644 -0.0
02
People_with_Bad_or_Very_Bad_Health   613.0  -0.0  1.001 -2.329 -0.703 -0.1
35
Households_with_access_to_openspace  613.0   0.0  1.001 -1.769 -0.789  0.0
44

                                       75%    max  Skewness  Kurtosis
Childhood_Obesity_Year6              0.759  2.802    -0.500    -0.058
Children_in_poverty                  0.787  2.551     0.029    -0.851
Median_Household_income_log          0.719  2.959     0.230    -0.464
Unemployed_log                       0.757  2.351    -0.090    -0.797
Qualifications_Level4_and_above      0.723  2.507     0.347    -0.737
Average_GCSE                         0.661  2.838     0.429    -0.367
Unauthorised_Absence_in_All_Schools  0.692  3.422     0.164    -0.220
Crime_rate_log                       0.700  2.924    -0.163     0.760
People_with_Bad_or_Very_Bad_Health   0.597  4.822     0.475     0.673
Households_with_access_to_openspace  0.817  1.734    -0.057    -1.030

The range of data:
The range of Childhood_Obesity_Year6 is [-3.0287899198672394, 2.8017123567
135984]
The range of Children_in_poverty is [-1.9852229783198796, 2.5506652520095
3]
The range of Median_Household_income_log is [-2.5162230150111773, 2.958873
0966871957]
The range of Unemployed_log is [-2.4305594852498373, 2.35137464889191]
The range of Qualifications_Level4_and_above is [-1.9679827532707768, 2.50
6731572786896]
The range of Average_GCSE is [-2.0523511988518606, 2.8379508174938883]
The range of Unauthorised_Absence_in_All_Schools is [-2.145890998910234,
3.421556888178575]
The range of Crime_rate_log is [-5.022784012727783, 2.9238792812576664]
The range of People_with_Bad_or_Very_Bad_Health is [-2.3285503206716616,
4.821863437984461]
The range of Households_with_access_to_openspace is [-1.7688995846791957,
1.7343041618408053]
```

Figure 4 shows the relationship between childhood obesity prevalence and nine selected variables. Most of the scatterplots show a more linear positive or negative relationship. While some variables, like “Crime_rate_log”, implicitly show some trend — a more dispersed distribution of point clouds, suggesting that the association may be weaker or exhibit non-linearity.

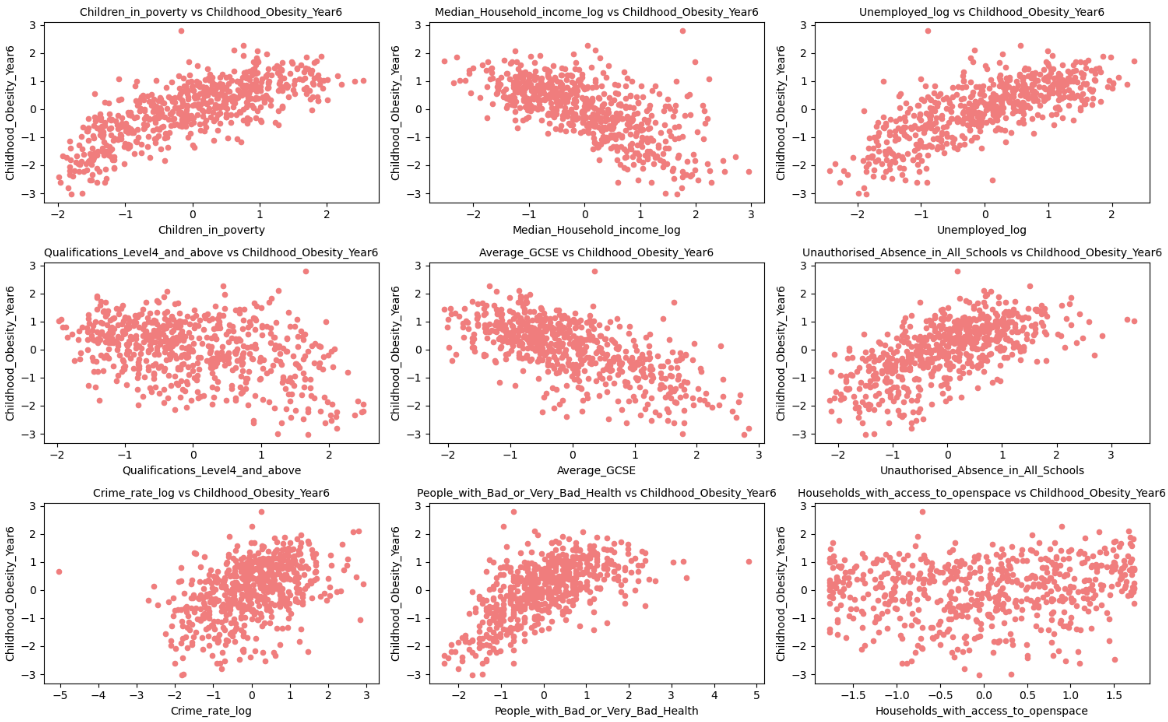
In [9]:

```
# show the scatterplots of
# Year6 childhood obesity prevalences vs selected variables
fig, axes = plt.subplots(3, 3, figsize=(15, 10))
axes = axes.flatten()

for i, col in enumerate(df2.columns[1:10]):
    df2.plot.scatter(x=col, y='Childhood_Obesity_Year6', ax=axes[i], colo
    axes[i].set_title(f"{col} vs Childhood_Obesity_Year6", fontsize=10)
fig.suptitle("Figure 4: Year6 Childhood obesity prevalence VS selected va

plt.tight_layout(rect=[0, 0, 1, 0.98])
plt.show()
```

Figure 4: Year6 Childhood obesity prevalence VS selected variables



Subsequently, we examined the variable correlations (**Figure 5**), which revealed potential multicollinearity. We calculated the Variance Inflation Factor for each predictor. Since no variable exceeded threshold of 10, all variables were retained for the regression analysis.

In [10]:

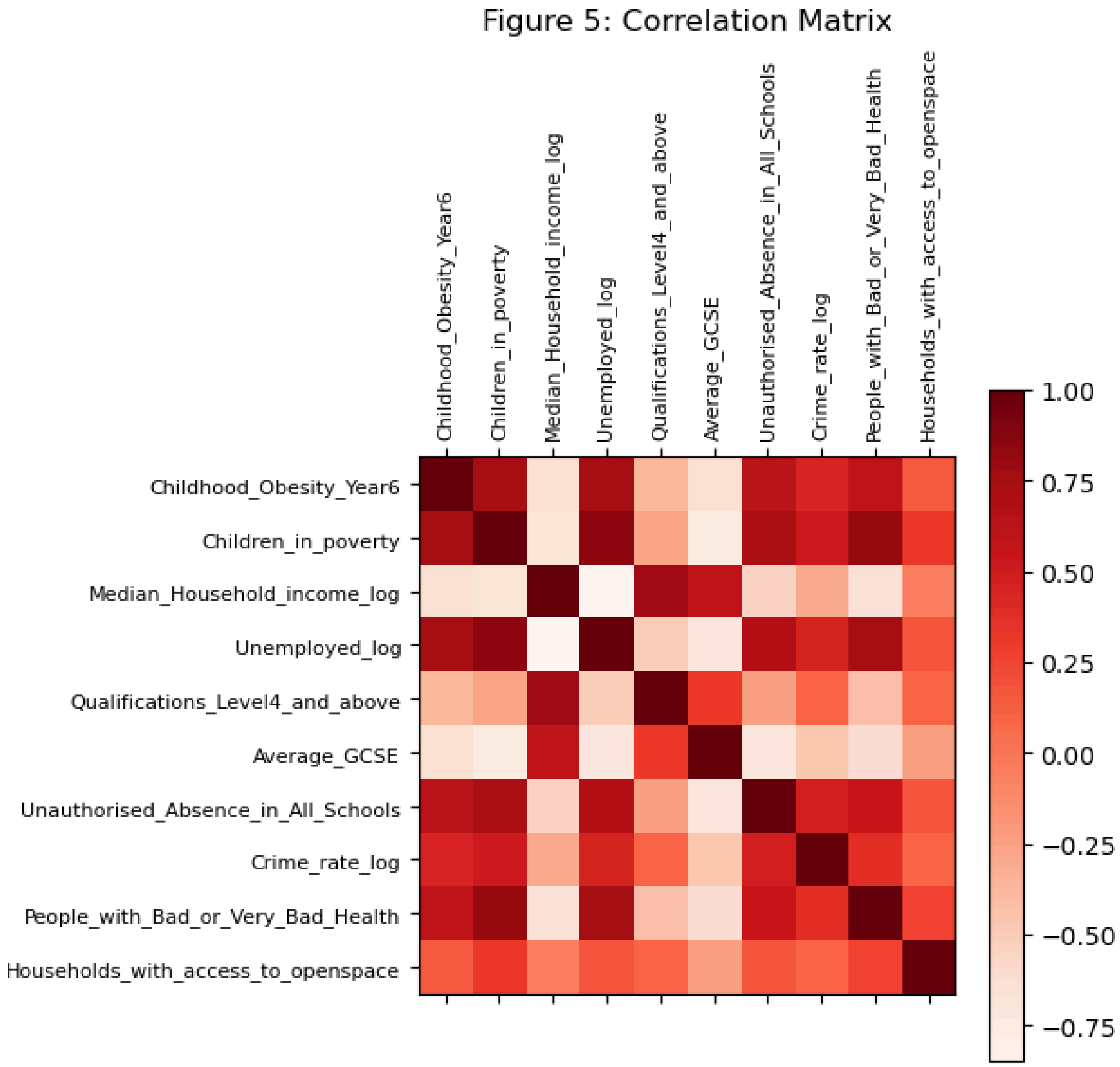
```
# define a correlation matrix calculation function
def CorrelationMatrix(df):
    corr_matrix = df.corr()
    #corr_matrix.to_csv("correlation_matrix.csv")

    f = plt.figure(figsize=(15, 10))
    plt.matshow(df.corr(), fignum=None, cmap='Reds')
    num_cols = corr_matrix.shape[1]
    plt.xticks(range(num_cols), corr_matrix.columns, fontsize=8, rotation
    plt.yticks(range(num_cols), corr_matrix.columns, fontsize=8)
    plt.title('Figure 5: Correlation Matrix', fontsize=12)
    plt.colorbar()

    #plt.savefig("Correlation Matrix.jpg", dpi=300, bbox_inches='tight')
    plt.show()
```

```
# compute the correlation between nine variables
CorrelationMatrix(df2)
```

<Figure size 1500x1000 with 0 Axes>



In [11]:
```
# define a VIF test function
def drop_column_using_vif_(df, thresh=5):
    while True:
        # adding a constatnt item to the data
        df_with_const = add_constant(df)

        vif_df = pd.Series([variance_inflation_factor(df_with_const.value
              for i in range(df_with_const.shape[1])], name= "VIF",index

        # drop the const
        vif_df = vif_df.drop('const')

        # if the largest VIF is above the thresh,
        # remove a variable with the largest VIF
        # If there are multiple variabels with VIF>thresh,
        # only one of them is removed.
        # Because we want to keep as many variables as possible.
        if vif_df.VIF.max() > thresh:
            # If there are multiple variables with the maximum VIF,
            # choose the first one
            index_to_drop = vif_df.index[vif_df.VIF == vif_df.VIF.max()].
            print('Dropping: {}'.format(index_to_drop))
```

```
            print(vif_df.VIF.max())
            df = df.drop(columns = index_to_drop)
        else:
            # No VIF is above threshold. Exit the loop.
            break
    return df.columns, vif_df
```

In [12]:
```
# calculate the VIF, and show the dataset columns
# after dropping the variable with the VIF higher than 10
drop_column_using_vif_(df2.drop('Childhood_Obesity_Year6',axis=1), thresh
```

Out[12]:
```
(Index(['Children_in_poverty', 'Median_Household_income_log', 'Unemployed_log',
        'Qualifications_Level4_and_above', 'Average_GCSE',
        'Unauthorised_Absence_in_All_Schools', 'Crime_rate_log',
        'People_with_Bad_or_Very_Bad_Health',
        'Households_with_access_to_openspace'],
       dtype='object'),
                                            VIF
 Children_in_poverty                   8.071529
 Median_Household_income_log           9.774373
 Unemployed_log                        7.083408
 Qualifications_Level4_and_above       5.000526
 Average_GCSE                          2.960171
 Unauthorised_Absence_in_All_Schools   2.595122
 Crime_rate_log                        1.767667
 People_with_Bad_or_Very_Bad_Health    3.629832
 Households_with_access_to_openspace   1.232980)
```

Overall, we still have nine variables as the independent variable.

In [13]:
```
# final variables
X = df2[['Children_in_poverty', 'Median_Household_income_log', 'Unemploye
       'Qualifications_Level4_and_above', 'Average_GCSE',
       'Unauthorised_Absence_in_All_Schools', 'Crime_rate_log',
       'People_with_Bad_or_Very_Bad_Health',
       'Households_with_access_to_openspace']]
y = df2['Childhood_Obesity_Year6']
```

Methodology

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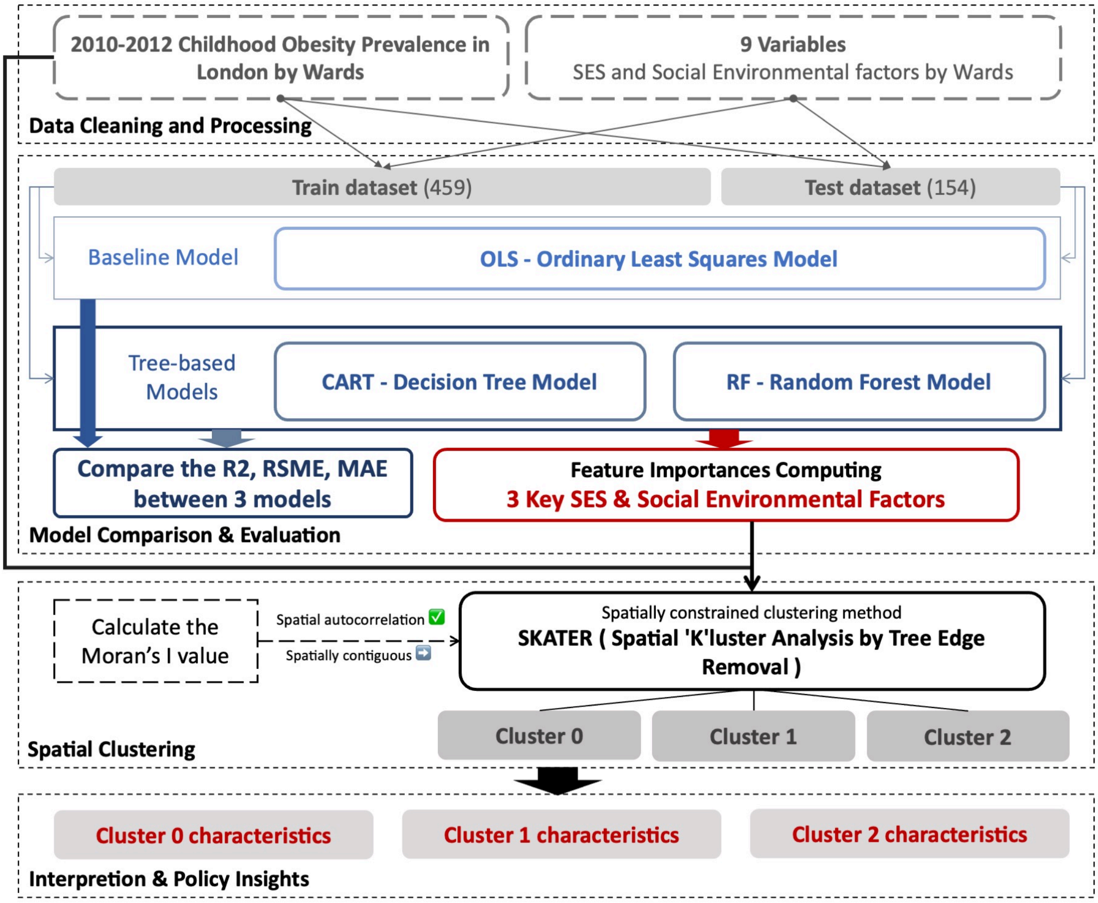
Figure 6: Methodology Flow Chart



The Ordinary Least Squares (OLS) model is the baseline model to compare with two tree-based models: Classification and Regression Tree (CART) and Random Forest. The dataset is split according to a 75:25 split into training and test sets to ensure unbiased evaluation.

The baseline model is specified as:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_9 X_9 + \beta_0$$

where Y is the childhood obesity prevalence and X_1–X_9 are nine indicators. The OLS model estimates the linear relationships between these variables. CART and Random Forest will capture the potential non-linear effects. And hyperparameter tuning is conducted via K-fold cross-validation.

We compare R^2, RMSE, and MAE across models on the same test set, to see which model shows the best performance, and the tree-based models also provide feature importance, which identifies the key factors driving childhood obesity.

To evaluate spatial dependences, we compute Moran's I, which equals 0.51, indicating a significant spatial autocorrelation. Consequently, we use SKATER—a spatially constrained clustering algorithm—to partition London wards into coherent clusters. For clustering, we focus on the three most influential variables alongside obesity prevalence to reduce noise and enhance interpretability. This approach simplifies the model and yields robust, actionable insights into regional disparities in childhood obesity, thereby better informing targeted public health interventions.

In [14]:
```
train_x, test_x, train_y, test_y = train_test_split(
    X, y, random_state=100)

print(train_x.shape)
print(train_y.shape)
print(test_x.shape)
print(test_y.shape)

# check the index of train_x and train_y - they should be identical.
# the index indicates which rows from the original data.
print(train_x.index.identical(train_y.index))
print(test_x.index.identical(test_y.index))
```

```
(459, 9)
(459,)
(154, 9)
(154,)
True
True
```

In [15]:
```
# constructing weight matrices using Queen neighbours
w = ps.weights.contiguity.Queen.from_dataframe(gdf_obesity_clean, use_ind
# normalisation of the weight matrix (row normalisation)
w.transform = 'r'

# calculate Moran's I value and the p-value
from esda import Moran
y = gdf_obesity_clean['Childhood_Obesity_Year6']
mi = Moran(y, w)

print("Moran's I:", mi.I)
print("p-value:", mi.p_sim)
```

```
Moran's I: 0.5168189268424859
p-value: 0.001
```

Results and discussion

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In [16]:
```
# build a OLS - linear regression model
lm = LinearRegression()
lm.fit(train_x, train_y)
```

Out[16]:
```
▾ LinearRegression
LinearRegression()
```

In [17]:
```
# build a CART using default settings
cart_default = DecisionTreeRegressor(random_state=0)
cart_default.fit(train_x, train_y)
# print the tree depth
print("Tree depth: {}".format(cart_default.get_depth()))
```

```
Tree depth: 23
```

In [18]:
```
# 1. values of max_depth
# smaller values (e.g., 2, 3) help prevent overfitting
# and encourage generalization
# larger values (e.g., 15, 20, 30) allow the model to capture
# more complex patterns

# 2. values of min_samples_split
# smaller values (e.g., 2, 4) allow more frequent splitting and
# may lead to overfitting
# larger values (e.g., 50, 80, 100) create more conservative splits
# and may reduce model complexity

# This range allows testing both highly flexible and
# more regularized models

hyperparameters = {'max_depth':[2,3,5,10,15,20,30],
                   'min_samples_split':[2,4,6,8,10,20,50,80,100]}
randomState_dt = 10000
dt = DecisionTreeRegressor(random_state=randomState_dt)

# K-fold cross-validation to tuning the hyperparameters:
# cv=5 by default, which means 5-fold cross-validation
clf_dt = GridSearchCV(dt, hyperparameters)
clf_dt.fit(train_x, train_y)

# we can query the best parameter value and its accuracy score
print ("The best parameter value is: ")
print (clf_dt.best_params_)
print ("The best score is: ")
print (clf_dt.best_score_)
```

```
The best parameter value is:
{'max_depth': 3, 'min_samples_split': 80}
The best score is:
0.6302288007578204
```

In [19]:
```
# build a Decision Tree Regressor using the best hyperparameters
dt_final = DecisionTreeRegressor(
    max_depth = clf_dt.best_params_['max_depth'],
    min_samples_split = clf_dt.best_params_['min_samples_split'],
    random_state = randomState_dt)
# train the final Decision Tree model using the training data
dt_final.fit(train_x, train_y)
```

Out[19]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(max_depth=3, min_samples_split=80, random_s
tate=10000)
```

In [20]:
```
# build a Random Forest using default settings
rf_default = RandomForestRegressor(random_state=0)
rf_default.fit(train_x, train_y)

# view the depth of all trees in a random forest
tree_depths = [estimator.get_depth() for estimator in rf_default.estimato

print("Number of trees:", len(tree_depths))
print("Average tree depth:", sum(tree_depths)/len(tree_depths))
```

```
print("Maximum tree depth:", max(tree_depths))
print("Minimum tree depth:", min(tree_depths))
```

```
Number of trees: 100
Average tree depth: 18.7
Maximum tree depth: 26
Minimum tree depth: 14
```

In [21]:
```
hyperparameters = {'max_depth':[2,3,5,10,15,20,30,40,50],
                   'min_samples_split':[2,4,6,8,10,20,40,50]}

randomState_rf = 10000
rf = RandomForestRegressor(random_state=randomState_rf)

# K-fold cross-validation to tuning the hyperparameters:
# cv=5 by default, which means 5-fold cross-validation
clf_rf = GridSearchCV(rf, hyperparameters)
clf_rf.fit(train_x, train_y)

# we can query the best parameter value and its accuracy score
print ("The best parameter value is: ")
print (clf_rf.best_params_)
print ("The best score is: ")
print (clf_rf.best_score_)
```

```
The best parameter value is:
{'max_depth': 10, 'min_samples_split': 6}
The best score is:
0.6439488031833459
```

In [22]:
```
# build a Random Forest Regressor using the best hyperparameters
rf_final = RandomForestRegressor(
    max_depth = clf_rf.best_params_['max_depth'],
    min_samples_split = clf_rf.best_params_['min_samples_split'],
    random_state = randomState_rf)
# train the final Random Forest model using the training data
rf_final.fit(train_x, train_y)
```

Out[22]:

RandomForestRegressor

```
RandomForestRegressor(max_depth=10, min_samples_split=6, random_state=10000)
```

In [23]:
```
# create a dataframe for comparison
# evaluate the performance of the OLS (Linear Regression) model
ols_results = {
    'Training R²':lm.score(X=train_x, y=train_y),
    'Testing R²':lm.score(X=test_x, y=test_y),
    'Training RMSE':root_mean_squared_error(train_y,
                                            lm.predict(train_x)),
    'Testing RMSE':root_mean_squared_error(test_y,
                                           lm.predict(test_x)),
    'Training MAE':mean_absolute_error(train_y,
                                       lm.predict(train_x)),
    'Testing MAE':mean_absolute_error(test_y,
                                      lm.predict(test_x))
}
# evaluate the performance of the CART (Decision Tree Regressor) model
cart_results = {
```

```
    'Training R²': dt_final.score(X=train_x, y=train_y),
    'Testing R²': dt_final.score(X=test_x, y=test_y),
    'Training RMSE':root_mean_squared_error(train_y,
                                           dt_final.predict(train_x)),
    'Testing RMSE': root_mean_squared_error(test_y,
                                           dt_final.predict(test_x)),
    'Training MAE':mean_absolute_error(train_y,
                                      dt_final.predict(train_x)),
    'Testing MAE': mean_absolute_error(test_y,
                                      dt_final.predict(test_x))
}
# evaluate the performance of the Random Forest model
rf_results = {
    'Training R²': rf_final.score(X=train_x, y=train_y),
    'Testing R²': rf_final.score(X=test_x, y=test_y),
    'Training RMSE':root_mean_squared_error(train_y,
                                           rf_final.predict(train_x)),
    'Testing RMSE': root_mean_squared_error(test_y,
                                           rf_final.predict(test_x)),
    'Training MAE':mean_absolute_error(train_y,
                                      rf_final.predict(train_x)),
    'Testing MAE': mean_absolute_error(test_y,
                                      rf_final.predict(test_x))
}

# combine the results
compare_results = pd.DataFrame({
    'OLS': ols_results,
    'CART': cart_results,
    'Random Forest': rf_results
})
compare_results = compare_results.T
```

In [24]:

```
def compare_result(df_results):
    fig, axes = plt.subplots(1, 3, figsize=(15, 6))

    # Plot R²
    df_results[['Training R²', 'Testing R²']].plot(kind='bar', ax=axes[0]
    axes[0].set_title('Model R² Comparison')
    axes[0].set_ylabel('R² Score')

    # Plot RMSE
    df_results[['Training RMSE', 'Testing RMSE']].plot(kind='bar', ax=axe
    axes[1].set_title('Model RMSE Comparison')
    axes[1].set_ylabel('RMSE')

    # Plot MAE
    df_results[['Training MAE', 'Testing MAE']].plot(kind='bar', ax=axes[
    axes[2].set_title('Model MAE Comparison')
    axes[2].set_ylabel('MAE')

    plt.suptitle("Figure 7: Model Performance Comparison", fontsize=14)
    plt.tight_layout(rect=[0, 0, 1, 0.95])
    #plt.savefig("Model Performance Comparison.jpg", dpi=300, bbox_inches
    plt.show()
    return df_results
```

After building and training three models, we evaluate their performances: the OLS model yielded a training R^2 of 0.651 and a testing R^2 of 0.568, with RMSE values of

0.602 (training) and 0.613 (testing), and MAE values of 0.475 on both sets, indicating moderate linear predictive power and similar performance on both sets, confirming the linear relationships in the predictors.

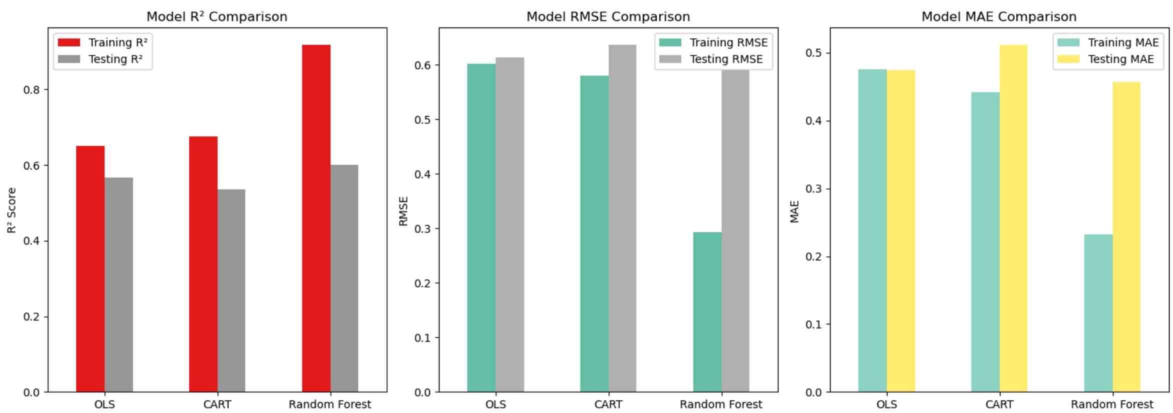
In contrast, the CART model achieved a slightly higher training R^2 (0.677) but a lower testing R^2 (0.535), along with higher testing RMSE (0.636) and MAE (0.511), suggesting poorer generalizability.

The Random Forest model achieved an exceptionally high training R^2 of 0.917 with low training errors. Although the Random Forest shows overfitting, it successfully captures complex and nonlinear relationships to slightly improve test performance compared to OLS.

In summary, the baseline OLS model exhibits robust and interpretable performance, while the Random Forest provides marginal improvements on unseen data. This suggests that although the relationship between socioeconomic factors and childhood obesity is predominantly linear, the ensemble approach captures subtle nuances that slightly enhance prediction in a complex urban context.

In [25]:
```
compare_result(compare_results)
```

Figure 7: Model Performance Comparison



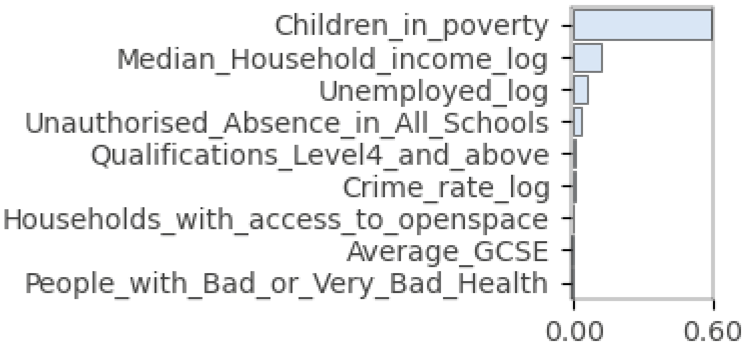
Out[25]:

	Training R^2	Testing R^2	Training RMSE	Testing RMSE	Training MAE	Testing MAE
OLS	0.651381	0.567782	0.602136	0.613267	0.474992	0.474573
CART	0.676508	0.534580	0.580030	0.636385	0.441490	0.511137
Random Forest	0.917447	0.599828	0.293013	0.590093	0.232283	0.456595

Feature importance from the Random Forest reveals that “Children_in_poverty” is the dominant predictor, followed by “Median_Household_income_log” and “Unemployed_log,” while other variables contribute little. Therefore, we focus our spatial clustering on these three key variables in addition to childhood obesity prevalence. This targeted variable selection improves cluster interpretability and provides valuable insights into the spatial patterns of social inequality affecting childhood obesity across London wards.

In [26]:
```
# as RF model shows the best prediction performance,
# we use the RF model to calculate the importances of each predictors
imp_rf = rfpimp.importances(rf_final, test_x, test_y)
print(imp_rf)
rfpimp.plot_importances(imp_rf).view()
```

```
                                    Importance
Feature
Children_in_poverty                   0.600453
Median_Household_income_log           0.116150
Unemployed_log                        0.057850
Unauthorised_Absence_in_All_Schools   0.034779
Qualifications_Level4_and_above       0.003000
Crime_rate_log                        0.001550
Households_with_access_to_openspace  -0.002654
Average_GCSE                         -0.008193
People_with_Bad_or_Very_Bad_Health   -0.014068
```



Using the SKATER algorithm, we partitioned wards into three clusters(**Figure 7**). Cluster 1 (473 wards) represents high children in poverty rate, high unemployment, low household income and higher obesity prevalences. Cluster 0 (105 wards) comprises wards with better socioeconomic conditions and lower obesity, while Cluster 2 (35 wards) shows a mixed profile with intermediate obesity.

In [31]:
```
# subset the key features for clustering from gdf_obesity_clean
attrs = ['Childhood_Obesity_Year6',
         'Children_in_poverty',
         'Median_Household_income',
         'Unemployed']
attributes = gdf_obesity_clean[attrs]

# define the number of clusters after trying 'n_clusters' value
# from 2 to 4, we find that when the value is 3,
# the silhouette score is the highest
n_clusters = 3

# build a SKATER clustering model
Skat = Skater(gdf_obesity_clean, w=w, n_clusters=n_clusters, attrs_name=a
# solve the spatial clustering model
Skat.solve()

# add the cluster label column to the gdf
gdf_obesity_clean.loc[:, 'clusters'] = Skat.labels_

print(gdf_obesity_clean[['clusters']].value_counts())
```

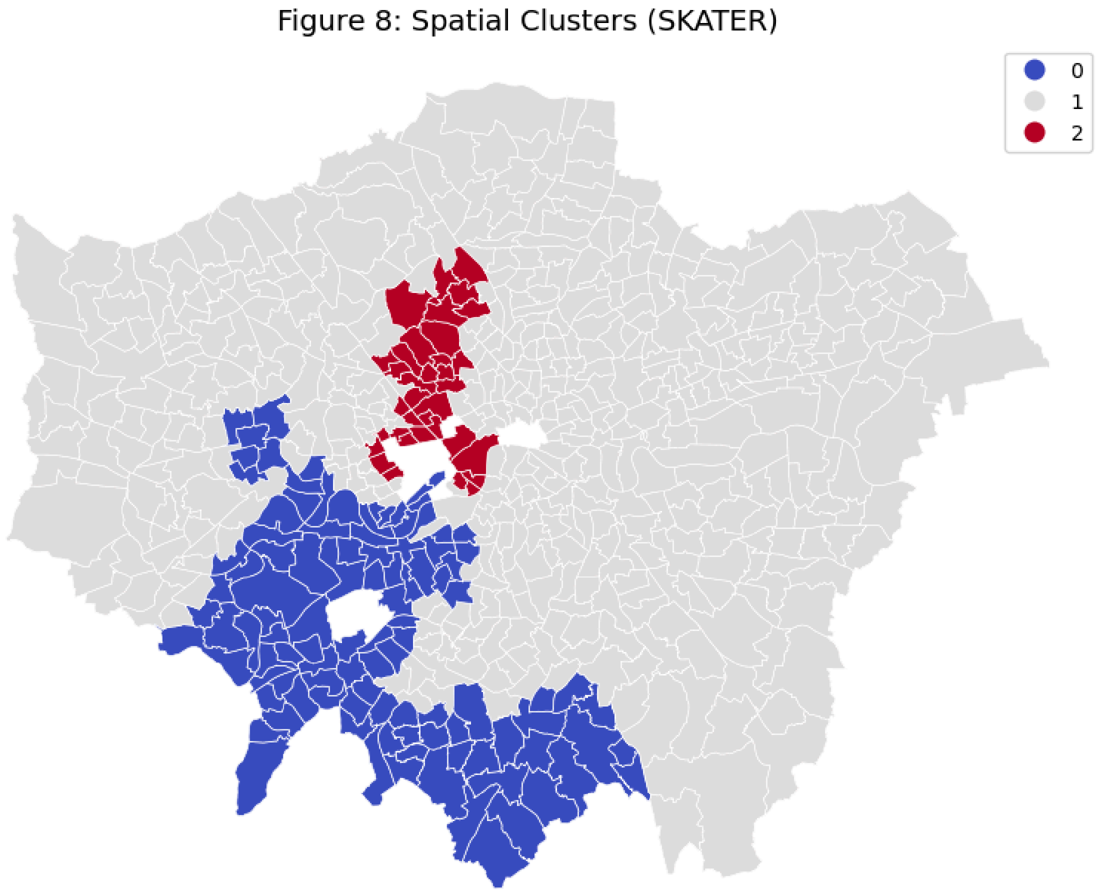
```
# to estimate the quality of clustering results
print(f"The silhouette score is:{metrics.silhouette_score(attributes, Ska
```

```
clusters
1      473
0      105
2       35
Name: count, dtype: int64
The silhouette score is:0.24239121462746716
```

In [28]:
```
# define a function to show the plot and information of clusters
def cluster_plot():
    fig, ax = plt.subplots(1, 1, figsize=(10, 8))
    gdf_obesity_clean.plot(edgecolor=(1, 1, 1, 1),linewidth=0.5,
                           column='clusters',
                           categorical=True, legend=True,
                           cmap='coolwarm', ax=ax)
    ax.set_title("Figure 8: Spatial Clusters (SKATER)", fontsize=14)
    ax.axis('off')
    plt.savefig("Spatial Clusters(SKATER).jpg", dpi=300, bbox_inches='tig
    plt.show()

    # show the information of each clusters
    cluster_info = gdf_obesity_clean.groupby('clusters')[attrs].mean()
    print(cluster_info)

cluster_plot()
```



```
          Childhood_Obesity_Year6  Children_in_poverty  \
clusters
0                       16.954381            14.881619
1                       22.659281            27.128605
2                       20.157714            23.217143

          Median_Household_income  Unemployed
clusters
0                    44956.571429    5.747431
1                    36681.120507    9.652661
2                    49116.571429    6.653094
```

In [29]:

```
# the specific wards and their boroughs contained within each cluster
for cluster_label, group in gdf_obesity_clean.groupby('clusters'):
    ward_names = group['NAME'].unique()
    borough_names = group['BOROUGH'].unique()

    print("  Cluster {} contains wards:".format(cluster_label))
    print(ward_names)
    print("  Cluster {} contains boroughs:".format(cluster_label))
    print(borough_names)
    print("\n")
```

```
 Cluster 0 contains wards:
['Chessington South' 'Tolworth and Hook Rise' 'Berrylands' 'Alexandra'
 'Beverley' 'Coombe Hill' 'Chessington North and Hook' 'Surbiton Hill'
 'Old Malden' "St. Mark's" 'Grove' 'Canbury' 'Norbiton' 'Coombe Vale'
 'St. James' 'Tudor' 'Coulsdon East' 'Selsdon and Ballards'
 'Coulsdon West' 'Waddon' 'Kenley' 'Purley' 'Sanderstead' 'Heathfield'
 'Fairfield' 'New Addington' 'Croham' 'Fieldway' 'Shirley' 'Ashburton'
 'Addiscombe' 'Chiswick Homefields' 'Chiswick Riverside' 'Turnham Green'
 'Northfield' 'Walpole' 'Cleveland' 'Ealing Common' 'Ealing Broadway'
 'Southfield' 'Hanger Hill' 'Clapham Common' 'Clapham Town'
 'Carshalton South and Clockhouse' 'Cheam' 'Beddington South' 'Belmont'
 'Nonsuch' 'Worcester Park' 'Sutton South' 'Sutton West' 'Sutton Central'
 'Carshalton Central' 'Sutton North' 'Stonecot' 'The Wrythe'
 'Wallington South' 'Wallington North' 'Beddington North' 'Hampton'
 'Teddington' 'Hampton Wick' 'Twickenham Riverside'
 'Ham, Petersham and Richmond Riverside' 'North Richmond' 'Kew'
 'East Sheen' 'Mortlake and Barnes Common' 'Fulwell and Hampton Hill'
 'South Twickenham' 'St. Margarets and North Twickenham' 'South Richmond'
 'Barnes' 'Cannon Hill' 'Wimbledon Park' 'Lower Morden' 'West Barnes'
 'Raynes Park' 'Dundonald' 'Merton Park' 'Abbey' 'Trinity'
 'Roehampton and Putney Heath' 'Thamesfield' 'Wandsworth Common'
 'West Hill' 'West Putney' 'East Putney' 'Southfields' 'Earlsfield'
 'Nightingale' 'Bedford' 'Balham' 'Northcote' "St. Mary's Park"
 'Shaftesbury' 'Palace Riverside' 'Munster' 'Sands End'
 'Parsons Green and Walham' 'Town' 'Cremorne' 'Stanley' 'Hans Town']
 Cluster 0 contains boroughs:
['Kingston upon Thames' 'Croydon' 'Hounslow' 'Ealing' 'Lambeth' 'Sutton'
 'Richmond upon Thames' 'Merton' 'Wandsworth' 'Hammersmith and Fulham'
 'Kensington and Chelsea']


 Cluster 1 contains wards:
['Broad Green' 'West Thornton' 'Bensham Manor' 'Norbury' 'Selhurst'
 'Woodside' 'Thornton Heath' 'Upper Norwood' 'South Norwood' 'Darwin'
 'Hayes and Coney Hall' 'Bromley Common and Keston'
 'Chelsfield and Pratts Bottom' 'Biggin Hill' 'West Wickham' 'Clock House'
 'Kelsey and Eden Park' 'Farnborough and Crofton' 'Shortlands'
 'Bromley Town' 'Bickley' 'Petts Wood and Knoll' 'Crystal Palace'
 'Penge and Cator' 'Copers Cope' 'Plaistow and Sundridge' 'Chislehurst'
 'Mottingham and Chislehurst North' 'Orpington' 'Cray Valley West'
 'Cray Valley East' 'Bedfont' 'Hanworth' 'Cranford' 'Syon' 'Heston West'
 'Heston East' 'Osterley and Spring Grove' 'Brentford' 'Feltham West'
 'Hanworth Park' 'Feltham North' 'Hounslow Heath' 'Hounslow West'
 'Heston Central' 'Hounslow South' 'Isleworth' 'Hounslow Central'
 'Norwood Green' 'Southall Green' 'Northolt West End' 'Dormers Wells'
 'Greenford Broadway' 'North Greenford' 'East Acton' 'Southall Broadway'
 'Elthorne' 'Lady Margaret' 'Northolt Mandeville' 'Hobbayne'
 'Greenford Green' 'Perivale' 'South Acton' 'Acton Central' 'Upminster'
 'Rainham and Wennington' 'South Hornchurch' 'Elm Park' 'Brooklands'
 'Romford Town' 'Mawneys' 'Pettits' 'Hacton' "St. Andrew's" 'Emerson Park'
 "Squirrel's Heath" 'Harold Wood' 'Cranham' 'Havering Park' 'Heaton'
 'Gooshays' 'Hylands' 'Heathrow Villages' 'Harefield' 'West Drayton'
 'Yiewsley' 'Uxbridge South' 'Brunel' 'Uxbridge North' 'Hillingdon East'
 'Ickenham' 'West Ruislip' 'Northwood' 'South Ruislip' 'Manor'
 'Eastcote and East Ruislip' 'Northwood Hills' 'Pinkwell' 'Botwell'
 'Charville' 'Townfield' 'Barnhill' 'Yeading' 'Cavendish' 'Roxeth'
 'Harrow on the Hill' 'Pinner' 'Pinner South' 'Greenhill'
 'Headstone North' 'Marlborough' 'Harrow Weald' 'Stanmore Park' 'Canons'
 'Rayners Lane' 'Roxbourne' 'West Harrow' 'Hatch End' 'Headstone South'
 'Kenton West' 'Wealdstone' 'Belmont' 'Kenton East' 'Queensbury' 'Edgware'
```

```
'Northwick Park' 'Wembley Central' 'Preston' 'Stonebridge' 'Welsh Harp'
'Fryent' 'Sudbury' 'Alperton' 'Kensal Green' 'Harlesden'
'Willesden Green' 'Queens Park' 'Brondesbury Park' 'Kilburn' 'Tokyngton'
'Kenton' 'Dudden Hill' 'Dollis Hill' 'Mapesbury' 'Underhill'
'High Barnet' 'West Hendon' 'Golders Green' 'Colindale' 'Childs Hill'
'Finchley Church End' 'East Finchley' 'Mill Hill' 'Hale' 'Totteridge'
'Oakleigh' 'Woodhouse' 'Coppetts' 'Brunswick Park' 'East Barnet'
'Burnt Oak' 'Hendon' 'West Finchley' 'Streatham South' "St. Leonard's"
'Streatham Wells' "Knight's Hill" 'Thornton' 'Streatham Hill'
'Brixton Hill' 'Tulse Hill' 'Coldharbour' 'Ferndale' 'Larkhall' 'Oval'
'Vassall' 'Gipsy Hill' 'Thurlow Park' 'Herne Hill' "Bishop's" 'Stockwell'
"Prince's" 'College' 'Riverside' 'Village' 'South Camberwell'
'East Dulwich' 'Peckham Rye' 'Camberwell Green' 'The Lane' 'Nunhead'
'Peckham' 'Newington' 'Faraday' 'East Walworth' 'Livesey'
'South Bermondsey' 'Cathedrals' 'Grange' 'Rotherhithe' 'Surrey Docks'
'Chaucer' 'Bellingham' 'Telegraph Hill' 'Downham' 'Whitefoot'
'Blackheath' 'Sydenham' 'Forest Hill' 'Perry Vale' 'Rushey Green'
'Catford South' 'Crofton Park' 'Ladywell' 'Lewisham Central' 'Brockley'
'New Cross' 'Grove Park' 'Lee Green' 'Evelyn' 'Middle Park and Sutcliffe'
'Coldharbour and New Eltham' 'Eltham South' 'Shooters Hill' 'Peninsula'
'Woolwich Riverside' 'Greenwich West' 'Eltham West'
'Blackheath Westcombe' 'Kidbrooke with Hornfair' 'Eltham North'
'Charlton' 'Woolwich Common' 'Plumstead' 'Glyndon' 'Thamesmead Moorings'
'Abbey Wood' 'Longlands' 'Blackfen and Lamorbey' 'Cray Meadows' 'Sidcup'
"St. Mary's" 'Crayford' 'North End' 'Erith' 'Belvedere' 'Thamesmead East'
'Falconwood and Welling' 'East Wickham' 'Blendon and Penhill'
'Danson Park' 'Christchurch' "St. Michael's" 'Brampton'
'Northumberland Heath' 'Barnehurst' 'Colyers' 'Lesnes Abbey' 'Chase'
'Winchmore Hill' 'Cockfosters' 'Highlands' 'Upper Edmonton'
'Palmers Green' 'Edmonton Green' 'Lower Edmonton' 'Jubilee' 'Ponders End'
'Enfield Highway' 'Bowes' 'Southgate Green' 'Southgate' 'Haselbury'
'Bush Hill Park' 'Town' 'Southbury' 'Turkey Street' 'Enfield Lock'
'Leyton' 'High Street' 'Higham Hill' 'Valley' 'Chingford Green' 'Cathall'
'Lea Bridge' 'Markhouse' 'Grove Green' 'Forest' 'William Morris'
'Hoe Street' 'Wood Street' 'Chapel End' 'Hale End and Highams Park'
'Cann Hall' 'Larkswood' 'Endlebury' 'Hatch Lane' 'Leytonstone' 'Wanstead'
'Cranbrook' 'Newbury' 'Roding' 'Fairlop' 'Goodmayes' 'Aldborough'
'Bridge' 'Hainault' 'Loxford' 'Clementswood' 'Mayfield' 'Valentines'
'Seven Kings' 'Snaresbrook' 'Clayhall' 'Church End' 'Barkingside'
'Fullwell' 'Chadwell' 'Monkhams' 'St. Helier' 'Wandle Valley'
'Heathfield' 'Hampton North' 'West Twickenham' 'Whitton' 'Cricket Green'
'Ravensbury' "Figge's Marsh" 'Pollards Hill' 'Graveney' 'Longthornton'
'Lavender Fields' 'Colliers Wood' 'Tooting' 'Furzedown' 'Latchmere'
'Queenstown' 'Fulham Broadway' 'Ravenscourt Park' 'Hammersmith Broadway'
'Avonmore and Brook Green' 'Askew' 'Wormholt and White City'
"Shepherd's Bush Green" 'College Park and Old Oak' 'Fulham Reach'
'Addison' 'Golborne' 'Notting Barns' 'St. Charles' "Earl's Court"
'Churchill' 'Harrow Road' "Queen's Park" 'Westbourne' 'Bloomsbury'
'Holborn and Covent Garden' 'St. Pancras and Somers Town' 'Cantelowes'
"King's Cross" "Regent's Park" 'Millwall' 'Blackwall and Cubitt Town'
'Shadwell' "St. Katharine's and Wapping" 'Limehouse'
'Bethnal Green South' 'Mile End and Globe Town' 'Bethnal Green North'
"St. Dunstan's and Stepney Green" 'Mile End East'
'East India and Lansbury' 'Bromley-by-Bow' 'Bow West' 'Bow East'
'Whitechapel' 'Spitalfields and Banglatown' 'Weavers' 'Clerkenwell'
'Caledonian' 'Holloway' 'Highbury East' 'Highbury West' 'Tollington'
'Bunhill' "St. Peter's" 'Canonbury' 'Barnsbury' "St. George's" 'Junction'
'Finsbury Park' 'Hillrise' 'Mildmay' 'Haggerston' 'Brownswood'
'De Beauvoir' 'Queensbridge' 'Wick' 'Dalston' 'Stoke Newington Central'
'Hackney Downs' 'Leabridge' 'New River' 'Cazenove' "King's Park" 'Hoxton'
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 'Victoria' 'Hackney Central' 'Chatham' 'Clissold' 'Lordship'
 'Springfield' 'Harringay' 'Bounds Green' 'Stroud Green' 'Hornsey'
 'Noel Park' "St. Ann's" 'Seven Sisters' 'Tottenham Green' 'West Green'
 'Tottenham Hale' 'White Hart Lane' 'Bruce Grove' 'Northumberland Park'
 'Royal Docks' 'Canning Town North' 'Beckton' 'East Ham South'
 'Stratford and New Town' 'Canning Town South' 'Custom House'
 'Plaistow South' 'West Ham' 'Plaistow North' 'Forest Gate South' 'Boleyn'
 'East Ham Central' 'Green Street West' 'Green Street East'
 'East Ham North' 'Wall End' 'Forest Gate North' 'Manor Park'
 'Little Ilford' 'Gascoigne' 'Thames' 'River' 'Abbey' 'Longbridge'
 'Eastbury' 'Goresbrook' 'Mayesbrook' 'Becontree' 'Alibon' 'Valence'
 'Heath' 'Whalebone' 'Eastbrook' 'Chadwell Heath' 'Parsloes']
  Cluster 1 contains boroughs:
['Croydon' 'Bromley' 'Hounslow' 'Ealing' 'Havering' 'Hillingdon' 'Harrow'
 'Brent' 'Barnet' 'Lambeth' 'Southwark' 'Lewisham' 'Greenwich' 'Bexley'
 'Enfield' 'Waltham Forest' 'Redbridge' 'Sutton' 'Richmond upon Thames'
 'Merton' 'Wandsworth' 'Hammersmith and Fulham' 'Kensington and Chelsea'
 'Westminster' 'Camden' 'Tower Hamlets' 'Islington' 'Hackney' 'Haringey'
 'Newham' 'Barking and Dagenham']


  Cluster 2 contains wards:
['Garden Suburb' 'Holland' 'Norland' 'Abingdon' 'Colville' "St. James's"
 'Lancaster Gate' 'Hyde Park' 'Vincent Square' 'West End'
 'Bryanston and Dorset Square' "Regent's Park" 'Abbey Road' 'Bayswater'
 'Warwick' 'Tachbrook' 'Little Venice' 'Maida Vale' 'Church Street'
 'Swiss Cottage' 'Highgate' 'Camden Town with Primrose Hill'
 'Fortune Green' 'Frognal and Fitzjohns' 'Gospel Oak' 'Hampstead Town'
 'Kentish Town' 'West Hampstead' 'Belsize' 'Haverstock' 'Fortis Green'
 'Crouch End' 'Muswell Hill' 'Alexandra']
  Cluster 2 contains boroughs:
['Barnet' 'Kensington and Chelsea' 'Westminster' 'Camden' 'Haringey']
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Conclusion

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In conclusion, OLS exhibits robust, interpretable performance, while Random Forest yields marginal improvements. This suggests that the relationship is primarily linear, though non-linear methods capture subtle nuances.

To address spatial inequalities in childhood obesity, policymakers should tailor interventions by cluster:

- **Cluster 1** (high childhood obesity control area): Provide free healthy meals in schools and community centers, raise public awareness of the consequences of obesity among parents and children, and expand safe and open spaces to encourage physical activity.
- **Cluster 2** (mixed childhood obesity control area): Investigate the dietary and activity patterns of children at the bottom of the ladder, enhance access to health and social services, and consider the redistribution of health resources within the region.

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