Project Overview

Urban green spaces are very important in the daily lives of residents. However, the green spaces distribution may be affected by the economic situation. This may result in poorer groups having less access to green space resources. This study combines the Leeds 2021 deprived households, the public green space data and the administrative boundary data of Leeds for spatial data analysis. The aim is to explore the relationship between them and and provide support for a more equitable allocation of urban green space resources. This project is divided into three parts: data exploration and cleaning, K clustering modeling and results.

Data Exploration and Cleaning

Data Description

This study used three datasets which from public data platforms.

- Households_Deprivation_Leeds_2021Census_LSOA.xlsx This is a data on the deprivation dimension of family poverty for Leeds Lower Super Output Areas (LSOA) 2021 from the Office for National Statistics (Nomis) in Excel file format. The poverty dimension variable is a direct measure of poverty, while households in three or four dimensions of it can be considered to disadvantaged socioeconomic status (ONS, 2022). Link: https://www.nomisweb.co.uk/default.asp
- GB_GreenspaceSite.shp This is open green space data in shapefile format from Ordnance Survey data centres and contains all public green spaces in the UK. Link: https://osdatahub.os.uk/downloads/open/OpenGreenspace
- LSOA2021_Leeds.shp This is 2021 LSOA Leeds Boundary vector data in shapefile format from the ONS Open Geography Portal for spatial geographic analysis. Link: https://geoportal.statistics.gov.uk/datasets/2bbaef5230694f3abae4f9145a3a9800_0/explore?location=52.609880%2C-2.489483%2C6.90

Data Exploration

Work Environment Configuration

Access data files through the associated Google Drive to meet subsequent analysis needs. Then install necessary Python libraries and packages,and read the datasets.

```
# mount google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
# installing libraries for aggregation analysis
# install the mapclassify library, it is for spatial data classification
!pip install mapclassify

# it can be index points, lines and surfaces
!pip install rtree

# accelerating geometric calculations
!pip install pygeos

# it wiil be used to add a basemap
!pip install contextily

# it can be used to add a north arrow for spatial visualization results
!pip install git+https://github.com/pmdscully/geo_northarrow.git
```

```
Requirement already satisfied: mapclassify in /usr/local/lib/python3.11/dist-packages (2.8.1)
Requirement already satisfied: networkx>=2.7 in /usr/local/lib/python3.11/dist-packages (from mapclassify) (3.4.2)
Requirement already satisfied: numpy>=1.23 in /usr/local/lib/python3.11/dist-packages (from mapclassify) (2.0.2)
Requirement already satisfied: pandas!=1.5.0,>=1.4 in /usr/local/lib/python3.11/dist-packages (from mapclassify) (2.2.2)
Requirement already satisfied: scikit-learn>=1.0 in /usr/local/lib/python3.11/dist-packages (from mapclassify) (1.6.1)
Requirement already satisfied: scipy>=1.8 in /usr/local/lib/python3.11/dist-packages (from mapclassify) (1.15.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas!=1.5.0,>=1.4->mapclassify) (2.9
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas!=1.5.0,>=1.4->mapclassify) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas!=1.5.0,>=1.4->mapclassify) (2025.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.0->mapclassify) (1.5.0)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.0->mapclassify) (3.6.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas!=1.5.0,>=1.4->mapclas
Requirement already satisfied: rtree in /usr/local/lib/python3.11/dist-packages (1.4.0)
Requirement already satisfied: pygeos in /usr/local/lib/python3.11/dist-packages (0.14)
Requirement already satisfied: numpy>=1.13 in /usr/local/lib/python3.11/dist-packages (from pygeos) (2.0.2)
Requirement already satisfied: contextily in /usr/local/lib/python3.11/dist-packages (1.6.2)
```

```
Requirement already satisfied: geopy in /usr/local/lib/python3.11/dist-packages (from contextily) (2.4.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from contextily) (3.10.0)
Requirement already satisfied: mercantile in /usr/local/lib/python3.11/dist-packages (from contextily) (1.2.1)
Requirement already satisfied: pillow in /usr/local/lib/python3.11/dist-packages (from contextily) (11.2.1)
Requirement already satisfied: rasterio in /usr/local/lib/python3.11/dist-packages (from contextily) (1.4.3)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from contextily) (2.32.3)
Requirement already satisfied: joblib in /usr/local/lib/python3.11/dist-packages (from contextily) (1.5.0)
Requirement already satisfied: xyzservices in /usr/local/lib/python3.11/dist-packages (from contextily) (2025.4.0)
Requirement already satisfied: geographiclib<3,>=1.52 in /usr/local/lib/python3.11/dist-packages (from geopy->contextily) (2.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (1.4.8)
Requirement already satisfied: numpy>=1.23 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (2.0.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (24.2)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->contextily) (2.9.0.post0)
Requirement already satisfied: click>=3.0 in /usr/local/lib/python3.11/dist-packages (from mercantile->contextily) (8.1.8)
Requirement already satisfied: affine in /usr/local/lib/python3.11/dist-packages (from rasterio->contextily) (2.4.0)
Requirement already satisfied: attrs in /usr/local/lib/python3.11/dist-packages (from rasterio->contextily) (25.3.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.11/dist-packages (from rasterio->contextily) (2025.4.26)
Requirement already satisfied: cligj>=0.5 in /usr/local/lib/python3.11/dist-packages (from rasterio->contextily) (0.7.2)
Requirement already satisfied: click-plugins in /usr/local/lib/python3.11/dist-packages (from rasterio->contextily) (1.1.1)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->contextily) (3.4.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->contextily) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->contextily) (2.4.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib->contextily) (1.17.
Collecting git+https://github.com/pmdscully/geo_northarrow.git
  Cloning https://github.com/pmdscully/geo_northarrow.git to /tmp/pip-req-build-sp5vv3d1
  Running command git clone --filter=blob:none --quiet https://github.com/pmdscully/geo_northarrow.git /tmp/pip-req-build-sp5vv3d1
  Resolved https://github.com/pmdscully/geo_northarrow.git to commit 963bdd271707a3bcaa47b2d83d92b88ae0b10950
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
Requirement already satisfied: shapely in /usr/local/lib/python3.11/dist-packages (from geo_northarrow==0.2.0a0) (2.1.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from geo_northarrow==0.2.0a0) (2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from geo_northarrow==0.2.0a0) (2.0.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from geo_northarrow==0.2.0a0) (3.10.0)
Requirement already satisfied: geopandas in /usr/local/lib/python3.11/dist-packages (from geo_northarrow==0.2.0a0) (1.0.1)
Requirement already satisfied: pyogrio>=0.7.2 in /usr/local/lib/python3.11/dist-packages (from geopandas->geo_northarrow==0.2.0a0) (0.10.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from geopandas->geo_northarrow==0.2.0a0) (24.2)
```

```
# install required packages
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
import seaborn as sns
from geo_northarrow import add_north_arrow

# import the required machine learning packages
from sklearn import cluster
from sklearn.preprocessing import scale

# read data files
# it is a data on the deprivation dimension of family poverty for Leeds Lower Super Output Areas (LSOA) 2021 from the Office
# The access time is 6th may
# The access link: https://www.nomisweb.co.uk/default.asp
poverty_households = pd.read_excel('/content/drive/MyDrive/GEOG5990M_Assessment/Households_Deprivation_Leeds_2021Census_LSOA.xlsx')

# it is an open green space data in shapefile format from Ordnance Survey data centres and contains all public green spaces in
# The access time is 6th may
# The access link: https://osdatahub.os.uk/downloads/open/OpenGreenspace
greenspace = gpd.read_file('/content/drive/MyDrive/GEOG5990M_Assessment/OpenGreenSpace/GB_GreenspaceSite.shp')

# it is 2021 LSOA Leeds Boundary vector data in shapefile format from the ONS Open Geography Portal
# The access time is 6th may
# The access link: https://geoportal.statistics.gov.uk/datasets/2bbaef5230694f3abae4f9145a3a9800_0/explore?location=52.609880%2C-2.489483%2C6.90
leeds = gpd.read_file('/content/drive/MyDrive/GEOG5990M_Assessment/LSOA2021_Leeds/LSOA2021_Leeds.shp')
```

Preliminary Exploration

Exploratory analyses can help identify data quality issues. It checks on the data are completed by using a range of data exploration functions. This provides an understanding of the distribution, completeness and potential outliers of the dataset. It can also inform subsequent data cleaning, modelling and visualisation decisions. The results are as follows: -

- Households_Deprivation_Leeds_2021Census_LSOA.xlsx contains 488 row;
- GB_GreenspaceSite.shp contains 16,1954 green polygons and rich geometric information;
- LSOA2021_Leeds.shp contains 524 row;
- All numerical poverty variables are of type `int64` and without null value, which provides a good basis for subsequent analyses. The `distName1-4` in greenfield has null values, but these are irrelevant for space. The boundary attributes are complete, except for `LSOA21MNW`,

whose 524 null values will be removed prior to merging. Only `LSOA21MNW` in LSOA2021_Leeds.shp has 524 null values but does not affect the analysis.

- The descriptive statistics show either no deprivation for the majority of households in Leeds. Severe multidimensional deprivation is rare but concentrated, which may be significant.

Overall, the datasets can support repeatable analyses due to the structure are clear and complete.

```
# view first 5 rows of the data to confirm whether the data has been loaded successfully
poverty_households.head()
```

	Row	Area_Name	Leeds_Code	Total Population	Total Households	Household is not deprived in any dimension	Household is deprived in one dimension	Household is deprived in two dimension	Household is deprived in three dimension	Household is deprived in four dimension
0	1	Leeds 001A	E01011698	1462	632	353	209	61	9	0
1	2	Leeds 001B	E01011699	1289	575	361	173	40	1	0
2	3	Leeds 001C	E01011701	1367	596	357	178	49	12	0
3	4	Leeds 001D	E01011702	1648	664	459	167	33	4	1

```
greenspace.head()
```

	id	function	distName1	distName2	distName3	distName4	geometry
0	2BE88E2E-6150-7FED-E063-AAEFA00A0EDD	Play Space	None	None	None	None	POLYGON Z ((462520.89 1190881.72 0, 462524.51 ...
1	2BE88E2E-6011-7FED-E063-AAEFA00A0EDD	Cemetery	None	None	None	None	MULTIPOLYGON Z (((451419.62 1190989.39 0, 4514...
2	2BE88DD0-F4E8-7FED-E063-AAEFA00A0EDD	Play Space	None	None	None	None	POLYGON Z ((451031.61 1191230.69 0, 451024.32 ...

```
leeds.head()
```

	FID_1	LSOA21CD	LSOA21NM	LSOA21NMW	BNG_E	BNG_N	LAT	LONG	Shape__Are	Shape__Len	GlobalID	Shape_Leng
0	11051	E01011623	Leeds 075B	None	432083	433331	53.79532	-1.51444	1.773643e+05	2857.411570	3c8ca484-e07d-46a3-80b7-2bcaa856569a	2857.411570
			Leeds								8f70eff1-7224-	

```
# view the columns of the data
poverty_households.columns
```

```
Index(['Row', 'Area_Name', 'Leeds_Code', 'Total Population',
       'Total Households', 'Household is not deprived in any dimension',
       'Household is deprived in one dimension',
       'Household is deprived in two dimension',
       'Household is deprived in three dimension',
       'Household is deprived in four dimension'],
      dtype='object')
```

```
greenspace.columns
```

```
Index(['id', 'function', 'distName1', 'distName2', 'distName3', 'distName4',
       'geometry'],
      dtype='object')
```

```
leeds.columns
```

```
Index(['FID_1', 'LSOA21CD', 'LSOA21NM', 'LSOA21NMW', 'BNG_E', 'BNG_N', 'LAT',
       'LONG', 'Shape__Are', 'Shape__Len', 'GlobalID', 'Shape_Leng',
       'Shape_Area', 'geometry'],
      dtype='object')
```

```
# view the type of the data
poverty_households.dtypes
```

	0
Row	int64
Area_Name	object
Leeds_Code	object
Total Population	int64
Total Households	int64
Household is not deprived in any dimension	int64
Household is deprived in one dimension	int64
Household is deprived in two dimension	int64
Household is deprived in three dimension	int64
Household is deprived in four dimension	int64

```
greenspace.dtypes
```

	0
id	object
function	object
distName1	object
distName2	object
distName3	object
distName4	object
geometry	geometry

```
leeds.dtypes
```

	0
FID_1	int64
LSOA21CD	object
LSOA21NM	object
LSOA21NMW	object
BNG_E	int64
BNG_N	int64
LAT	float64
LONG	float64
Shape__Are	float64
Shape__Len	float64
GlobalID	object
Shape_Leng	float64
Shape_Area	float64
geometry	geometry

```
# check the entire dataset structure and quality
poverty_households.info
```

```
pandas.core.frame.DataFrame.info
def info(verbose: bool | None=None, buf: WriteBuffer[str] | None=None, max_cols: int | None=None,
memory_usage: bool | str | None=None, show_counts: bool | None=None) -> None
```

```
Print a concise summary of a DataFrame.

This method prints information about a DataFrame including
the index dtype and columns, non-null values and memory usage.

Parameters
```

```
greenspace.info
```

```
pandas.core.frame.DataFrame.info
def info(verbose: bool | None=None, buf: WriteBuffer[str] | None=None, max_cols: int | None=None,
memory_usage: bool | str | None=None, show_counts: bool | None=None) -> None
```

```
Print a concise summary of a DataFrame.

This method prints information about a DataFrame including
the index dtype and columns, non-null values and memory usage.

Parameters
```

```
leeds.info
```

```
pandas.core.frame.DataFrame.info
def info(verbose: bool | None=None, buf: WriteBuffer[str] | None=None, max_cols: int | None=None,
memory_usage: bool | str | None=None, show_counts: bool | None=None) -> None
```

```
---  ------    --------------    -----
 0   column_1  1000000 non-null  object
 1   column_2  1000000 non-null  object
 2   column_3  1000000 non-null  object
dtypes: object(3)
memory usage: 165.9 MB
```

```
# check the value of each row is null or not and to know the total number of null rows
poverty_households.isnull().sum()
```

	0
Row	0
Area_Name	0
Leeds_Code	0
Total Population	0
Total Households	0
Household is not deprived in any dimension	0
Household is deprived in one dimension	0
Household is deprived in two dimension	0
Household is deprived in three dimension	0
Household is deprived in four dimension	0

```
greenspace.isnull().sum()
```

	0
id	0
function	0
distName1	116778
distName2	161602
distName3	161946
distName4	161953
geometry	0

```
leeds.isnull().sum()
```

	0
FID_1	0
LSOA21CD	0
LSOA21NM	0
LSOA21NMW	524
BNG_E	0
BNG_N	0
LAT	0
LONG	0
Shape__Are	0
Shape__Len	0
GlobalID	0
Shape_Leng	0
Shape_Area	0
geometry	0

```
# generate statistics summaries of numeric columns to determine the distribution, range, and presence of outliers of the variable
poverty_households.describe()
```

	Row	Total Population	Total Households	Household is not deprived in any dimension	Household is deprived in one dimension	Household is deprived in two dimension	Household is deprived in three dimension	Household is deprived in four dimension
count	488.000000	488.000000	488.000000	488.000000	488.000000	488.000000	488.000000	488.000000
mean	244.500000	1663.846311	699.729508	338.002049	230.235656	100.571721	28.940574	1.979508
std	141.017729	327.975901	136.456703	111.406585	49.711155	46.598320	22.774011	2.432580
min	1.000000	1042.000000	430.000000	105.000000	126.000000	19.000000	1.000000	0.000000
25%	122.750000	1461.750000	613.000000	256.750000	196.000000	63.000000	10.000000	0.000000
50%	244.500000	1607.500000	672.500000	326.000000	225.000000	92.000000	21.000000	1.000000

```
greenspace.describe()
```

	id	function	distName1	distName2	distName3	distName4	geometry
count	161954	161954	45176	352	8	1	161954
unique	161954	10	27660	345	8	1	161879
top	2BE88DCE-3340-7FED-E063-AAEFA00A0EDD	Play Space	St Mary's Church	Christ Church	The Old Golf Course	<Null>	POLYGON Z ((533044.36 194003.06 0, 533051.15 1...

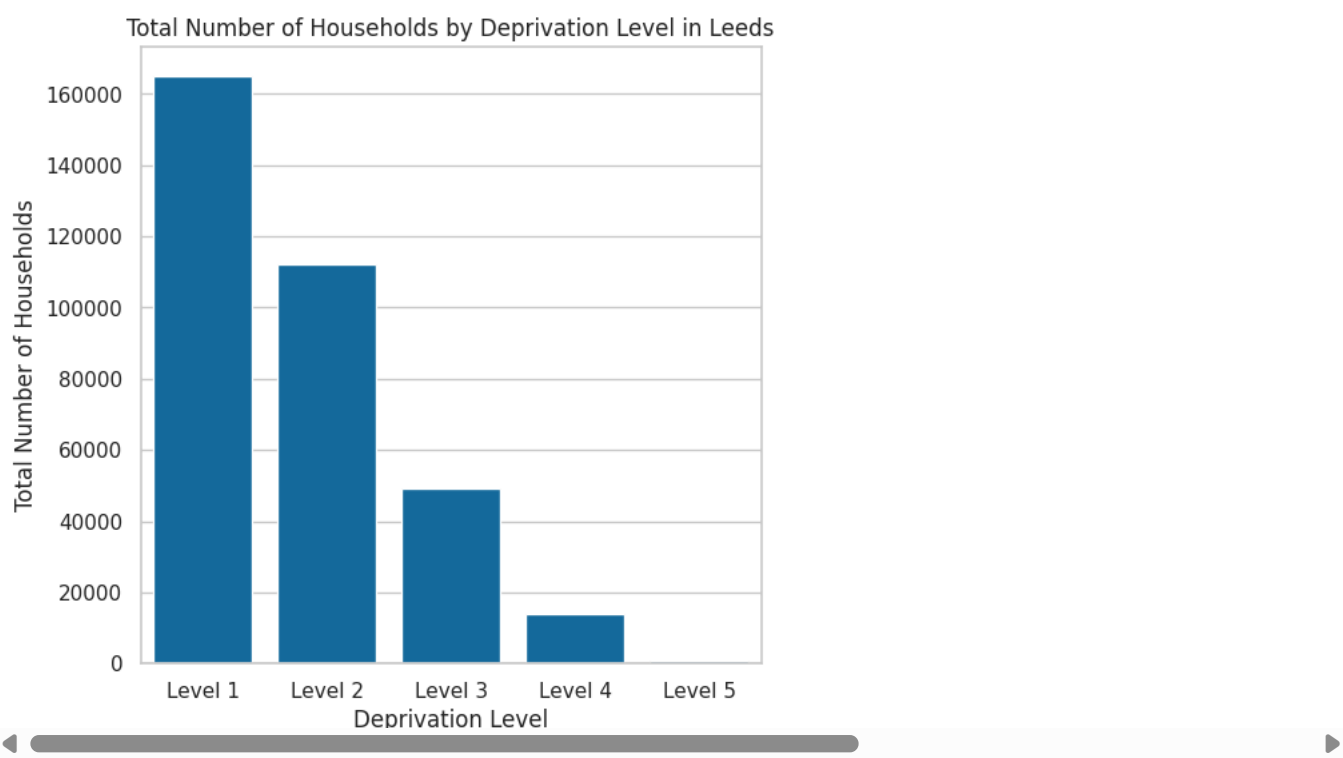
```
leeds.describe()
```

	FID_1	BNG_E	BNG_N	LAT	LONG	Shape__Are	Shape__Len	Shape_Leng	Shape_Area
count	524.000000	524.000000	524.000000	524.000000	524.000000	5.240000e+02	524.000000	524.000000	5.240000e+02
mean	13234.461832	429727.007634	434990.242366	53.810334	-1.550056	1.984000e+06	6750.446223	5403.841033	1.052910e+06
std	6424.022433	6377.441719	5361.622186	0.048215	0.096835	6.906137e+06	6883.089789	4202.562236	2.404922e+06
min	10045.000000	412764.000000	422102.000000	53.694600	-1.807350	6.841824e+04	1468.561952	0.834338	4.469999e-04
25%	10833.750000	425287.250000	431515.750000	53.779358	-1.617645	2.949397e+05	3683.473919	3355.389443	2.610911e+05
50%	10964.500000	429405.500000	434871.000000	53.809385	-1.554920	4.499067e+05	4787.265621	4489.536006	3.919106e+05
75%	11095.250000	433418.750000	437927.000000	53.836820	-1.494575	1.055203e+06	6710.294772	6110.942968	7.576408e+05
max	33049.000000	448566.000000	454669.000000	53.986360	-1.263410	9.239496e+07	64102.166609	30782.077776	2.551487e+07

Data Preprocessing

The histogram showing the distribution of data according to the level of poverty and the total number of families in Leeds presents a more extreme situation for multi-dimensional deprived families, suggesting that subsequent analysis should be converted to proportional indicators.

```
# count the total number of households in each poverty level
sums_levels = poverty_households[['Household is not deprived in any dimension',
                                  'Household is deprived in one dimension',
                                  'Household is deprived in two dimension',
                                  'Household is deprived in three dimension',
                                  'Household is deprived in four dimension']].sum()

# generate an index for each statistical number to support the production of a visual graph
sums_levels = sums_levels.reset_index()

# rename the columns
sums_levels.columns = ['Deprivation Level', 'Households']
sums_levels['Deprivation Level'] = ['Level 1', 'Level 2', 'Level 3', 'Level 4', 'Level 5']

# graph size and style
f, ax=plt.subplots(figsize=(6,6))
sns.set_theme(style="whitegrid", palette="colorblind")

# creat a barplot
sns.barplot(x='Deprivation Level',y='Households',data=sums_levels)

# add title and labels
plt.title('Total Number of Households by Deprivation Level in Leeds')
plt.xlabel('Deprivation Level')
plt.ylabel('Total Number of Households')

# show the
plt.show()
```




```
# merge LSOA2021_Leeds with the Census2021_Leeds data to produce a new data frame containing information on both leeds_census
leeds_poverty_households = leeds.merge(poverty_households, left_on='LSOA21CD', right_on='Leeds_Code', how='left')
print(leeds_poverty_households.shape)
```

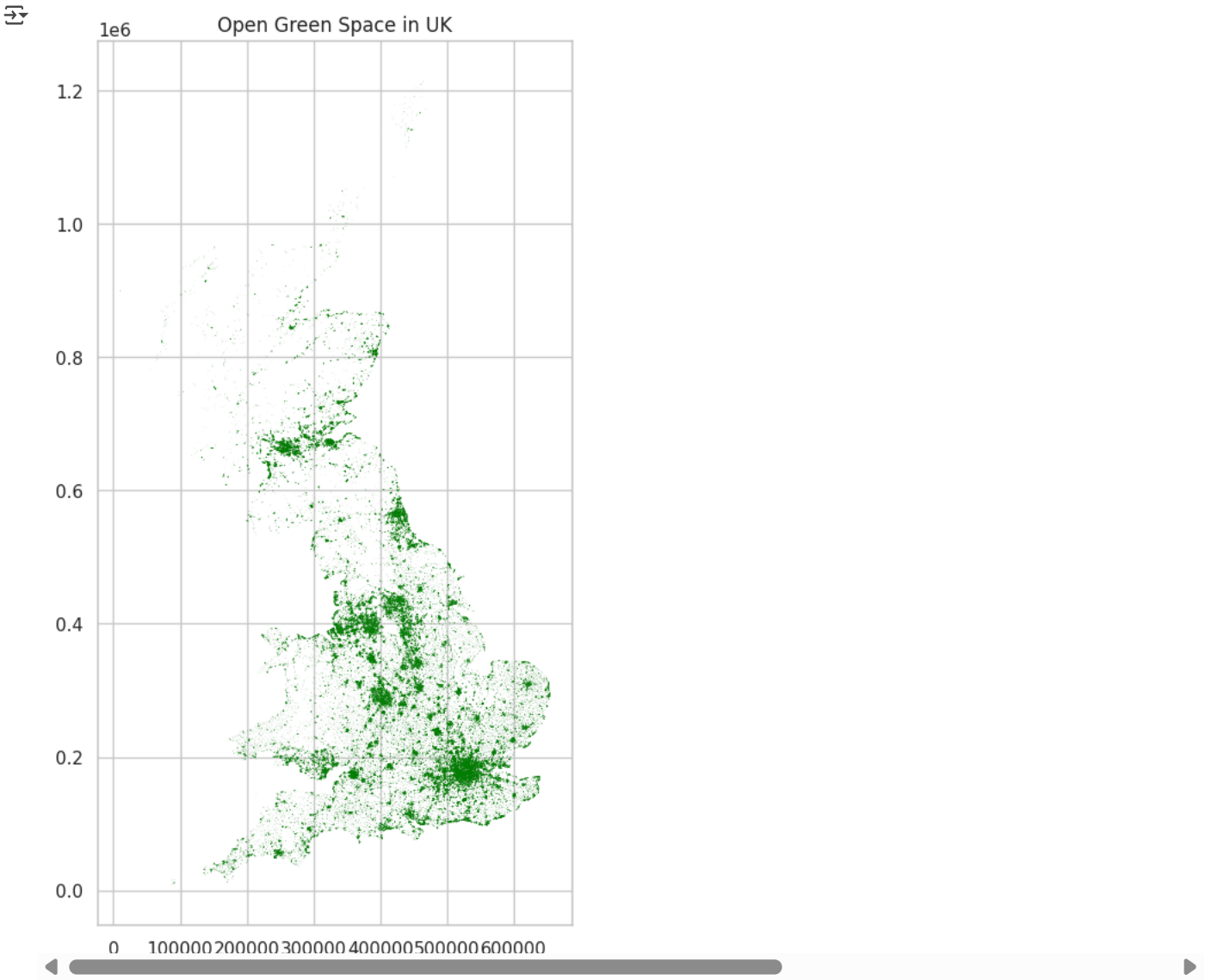
```
(524, 24)
```

双击（或按回车键）即可修改

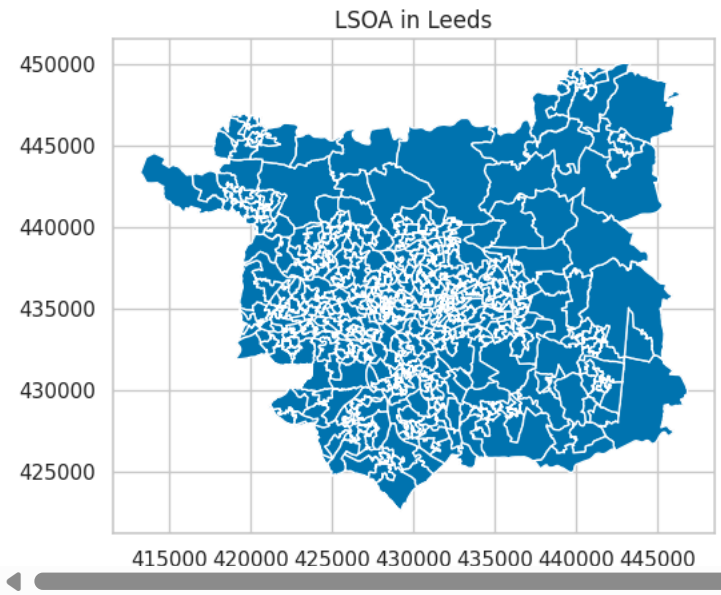
```
# Check the Coordinate Reference Systems (CRS)
print(greenspace.crs,leeds.crs)
```

```
EPSG:27700 EPSG:27700
```

```
# visualize green space data to provide evidence for the next step of clipping
# plot the image with size and style
greenspace.plot(figsize=(10, 10),color='green',edgecolor='green',linewidth=0.2)
plt.title("Open Green Space in UK")
plt.show()
```

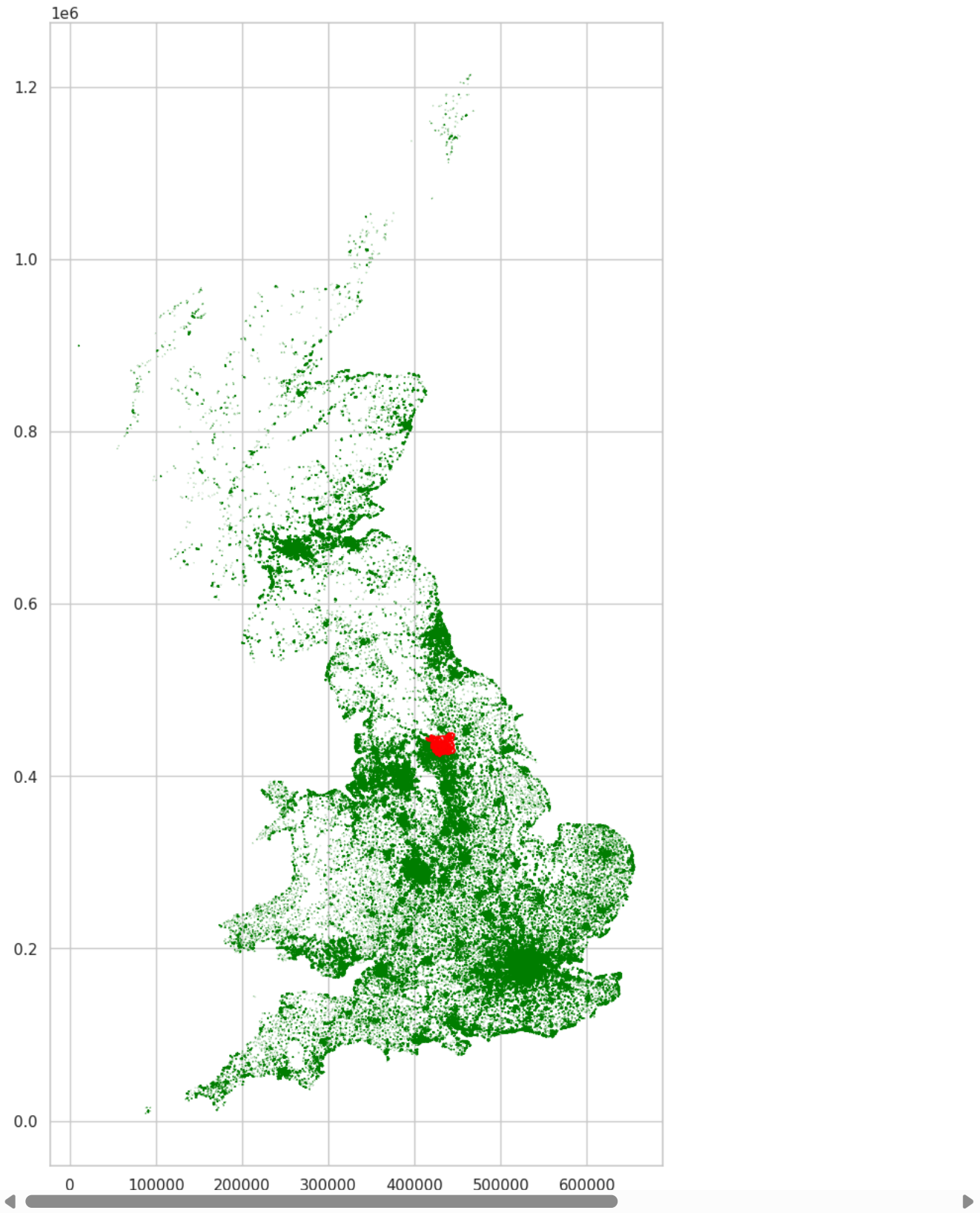



```
# visualize Leeds boundary data to provide evidence for the next step of clipping
# plot the image with size and style
leeds.plot()
plt.title("LSOA in Leeds")
plt.show()
```

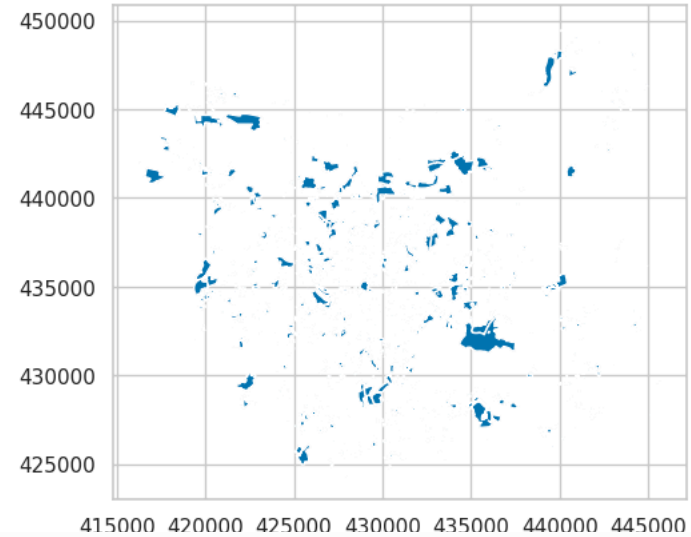


The spatial maps can be used to support data cleaning through visual comparison. First, the visualization and superposition of green space data and Leeds boundary data will intuitively compare the data range and support the rationality of cropping. Second, it verifies the CRS consistency.

```
# visualize and overlay Leeds boundary data and green space data to provide evidence for the next step of clipping
# plot a subplot with dimensions 15 X 15
f, ax = plt.subplots(1, figsize=(15, 15))

# define the basemap plot it on the sublot axis
base = greenspace.plot(ax=ax,color='green',edgecolor='green', alpha=1)

# Plot the bus stops on the basemap axis, colour the bus stops red
leeds.plot(ax=base,color='lightgrey',edgecolor='red')

# Show the map
plt.show()
```




```
# the extent of the grean space is larger than that of leeds
# leeds extent was used as a clipping criterion to clip the in-range data for grean space.
greenspace_leeds = gpd.clip(greenspace, leeds)
# show the range of green space in leeds
greenspace_leeds.plot()
plt.show()
```




```
# save the greensapce data to .geojson
greenspace_leeds.to_file('/content/drive/MyDrive/GEOG5990M_Assessment/greenspace_leeds.geojson', driver='GeoJSON')
```

```
# LSOA Leeds boundary data and greenspace data spatial join to assign LSOA information to greenspace
greenspace_with_leeds = gpd.sjoin(greenspace, leeds, how='inner', predicate='within')
```

```
# view the fields of leeds_poverty_households
leeds_poverty_households.columns
```

```
Index(['FID_1', 'LSOA21CD', 'LSOA21NM', 'LSOA21NMW', 'BNG_E', 'BNG_N', 'LAT',
       'LONG', 'Shape__Are', 'Shape__Len', 'GlobalID', 'Shape_Leng',
       'Shape_Area', 'geometry', 'Row', 'Area_Name', 'Leeds_Code',
       'Total Population', 'Total Households',
       'Household is not deprived in any dimension',
       'Household is deprived in one dimension',
       'Household is deprived in two dimension',
       'Household is deprived in three dimension',
       'Household is deprived in four dimension'],
      dtype='object')
```

```
# view the greenspace_leeds
greenspace_leeds.columns
```

```
Index(['id', 'function', 'distName1', 'distName2', 'distName3', 'distName4',
       'geometry'],
      dtype='object')
```

```
# view the greenspace_with_leeds
greenspace_with_leeds.columns
```

```
Index(['id', 'function', 'distName1', 'distName2', 'distName3', 'distName4',
       'geometry', 'index_right', 'FID_1', 'LSOA21CD', 'LSOA21NM', 'LSOA21NMW',
       'BNG_E', 'BNG_N', 'LAT', 'LONG', 'Shape__Are', 'Shape__Len', 'GlobalID',
       'Shape_Leng', 'Shape_Area'],
      dtype='object')
```

Variable selection and calculation Norman et al. (2024) shown that using standardized percentage variables for spatial analysis at the small area level can reveal spatial patterns of poverty. Four variables are created to build a link between social and environment:

- 'Severe_Deprivation_Households' is the sum of households deprived in three and four dimensions households. It reflects multi poverty(ONS, 2022).
- 'Deprivation_Percentage' expresses deprivation proportion, which can reflect accurately the degree of each regional economic vulnerability and can be used as a key variable to measure the spatial distribution of poverty.
- 'lsoa_area_m²'represents area of each LSOA polygon.
- 'greenspace_percentage'. The LSOA without green space is replaced by 0 to avoid NaNs and preserve analytical completeness (Pandas, 2024).

'Deprivation_Percentage' and 'greenspace_percentage' can eliminate the impacts in population and area, which is convenient for comparison (Buckley, 2013). These standardized percentage variables form the basis for subsequent clustering and visualization.

Besides, delete old area fields and validate dtypes before merging again to avoid duplicate fields and type errors and improve code stability and reproducibility.

```
# calculate the number of poor households in each region and the percentage of poor households in the total number of households
# severely deprived households are created by adding together the number of households with poverty deprivation dimensions 3 and 4
leeds_poverty_households['Severe_Deprivation_Households'] = (
        leeds_poverty_households['Household is deprived in three dimension'] +
        leeds_poverty_households['Household is deprived in four dimension'])

# calculate the proportion of households in severe poverty
leeds_poverty_households['Deprivation_Percentage'] = (
        leeds_poverty_households['Severe_Deprivation_Households'] /
        leeds_poverty_households['Total Households']) * 100

print(leeds_poverty_households['Deprivation_Percentage'])
```

```
0      10.271041
1       3.586801
2       3.466205
3       0.328407
4       3.291536
         ...
519     1.505017
520     4.454148
521     1.794454
522    10.000000
523     2.700000
Name: Deprivation_Percentage, Length: 524, dtype: float64
```

```
# calculate the area of each LSOA
leeds['lsoa_area_m2'] = leeds.geometry.area
print(leeds['lsoa_area_m2'].reset_index)
```

```
<bound method Series.reset_index of 0      1.773643e+05
1      2.098706e+05
2      6.373247e+05
3      1.285020e+07
4      4.079808e+05
          ...
519    4.566428e+05
520    6.588481e+06
521    3.540778e+05
522    1.408940e+05
523    8.712401e+05
Name: lsoa_area_m2, Length: 524, dtype: float64>
```

```
# calculate the area of green space of each LSOA in Leeds (m²)
greenspace_with_leeds['area_m²'] = greenspace_with_leeds.geometry.area
lsoa_greenspace_area = greenspace_with_leeds.groupby('LSOA21CD')['area_m²'].sum().reset_index()
print(lsoa_greenspace_area)
```

```
       LSOA21CD       area_m²
0     E01011264   11127.18615
1     E01011265   30976.96355
2     E01011266  163899.05260
3     E01011267   39214.99840
4     E01011268     275.66060
..          ...           ...
345   E01035049     810.09340
346   E01035051    7824.48705
347   E01035052   25877.63350
348   E01035053   23327.98890
349   E01035054    4912.67590

[350 rows x 2 columns]
```

```
# run it to avoid generating duplicate fields that cause operation failure
leeds = leeds.drop(columns=['area_m²', 'area_m²_x', 'area_m²_y','greenspace_percentage'], errors='ignore')
```

```
# merge the total green space area to the Leeds boundary data
leeds = leeds.merge(lsoa_greenspace_area, on='LSOA21CD', how='left')
leeds.head()
```

	FID_1	LSOA21CD	LSOA21NM	LSOA21NMW	BNG_E	BNG_N	LAT	LONG	Shape__Are	Shape__Len	GlobalID	Shape_Leng
0	11051	E01011623	Leeds 075B	None	432083	433331	53.79532	-1.51444	1.773643e+05	2857.411570	3c8ca484-e07d-46a3-80b7-2bcaa856569a	2857.411570
1	10960	E01011525	Leeds 095C	None	426267	428357	53.75094	-1.60315	2.098706e+05	3935.530790	8f70eff1-7224-4d29-a5db-a20a5d0c1f62	3935.530790

```
# for areas without green space, the green space area is assigned a value of 0.
# ##### ChatGPT 4o #####
# The following prompt was used in ChatGPT 4o to replace NaN:
# "Is there any formula in Python that can replace null values with data?"
# "In Python's pandas library, you can use the .fillna(), where() , apply(), interpolate() to replace missing values (NaN)."
# Then I check the pandas.DataFrame.dtypes(https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.dtypes.html) to learn it.

leeds['area_m²'] = leeds['area_m²'].fillna(0)
leeds.head()
```

	FID_1	LSOA21CD	LSOA21NM	LSOA21NMW	BNG_E	BNG_N	LAT	LONG	Shape__Are	Shape__Len	GlobalID	Shape_Leng
0	11051	E01011623	Leeds 075B	None	432083	433331	53.79532	-1.51444	1.773643e+05	2857.411570	3c8ca484-e07d-46a3-80b7-2bcaa856569a	2857.411570
1	10960	E01011525	Leeds 095C	None	426267	428357	53.75094	-1.60315	2.098706e+05	3935.530790	8f70eff1-7224-4d29-a5db-a20a5d0c1f62	3935.530790

```
# calculate the percentage of green space in each area
leeds['greenspace_percentage'] = leeds['area_m²']/leeds['lsoa_area_m2']*100
print(leeds['greenspace_percentage'])
```

```
0       9.298251
1       0.108320
2       1.745921
3       0.236086
4       0.000000
          ...
519     0.000000
520     2.792556
521     0.000000
522     1.562074
523     6.455484
Name: greenspace_percentage, Length: 524, dtype: float64
```

K-means Clustering

[ ] ↳ 已隐藏 7 个单元格

Result

Non-spatial Visualization

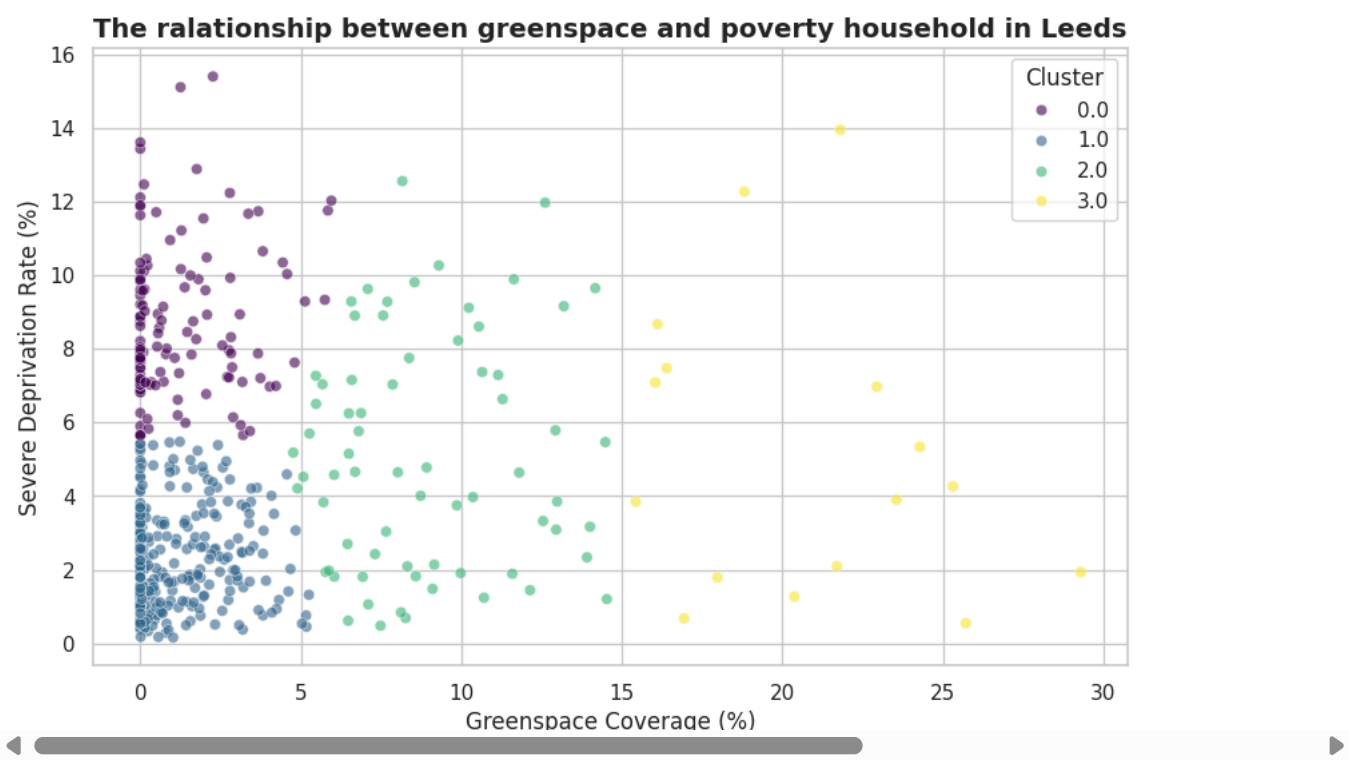
This scatter diagram uses Severe Deprivation Rate (%) as the vertical axis and Greenspace Coverage (%) as the horizontal axis. The different colors are used to represent K-means clustering results based on clustering labels. The distribution of points does not show a clear linear trend. The proportion of green space in most areas is concentrated in 0-5%, while the severe poverty rate fluctuates between 0% and 15%. Overall, the chart indicates that there may be a certain negative correlation between the proportion of green space and the degree of poverty, although the correlation is not strong. It needs to further analysis for validation.

It effectively show the correlation and distribution between variables. It helps reveal group characteristics and improve interpretability. The use of the viridis color palette also enhances the readability of images, especially for colorblind users (Nuñez et al., 2018). However, the

limitation of this map its cannot to reveal the geographical distribution of clusters in space. The evidence for research objectives is still not enough. Especially under the complex background, It is difficult to judge whether there is poverty and green space inequality only by the distribution of these values. Spatial and geographical presentation helps achieve research objectives (Bhatt and Wallgrün, 2014)

```
# run it to avoid generating duplicate fields that cause operation failure
leeds_merged = leeds_merged.drop(columns=['cluster'], errors='ignore')
```

```
# creat a new colum to add the clustering result to clustering_data
clustering_data['cluster'] = KM4cls.labels_

# add cluser result to leeds_merged as a new columns
leeds_merged = leeds_merged.merge(clustering_data[['LSOA21CD', 'cluster']],on='LSOA21CD',how='left')

# add Deprivation_Percentage value to leeds_merged as a new columns
leeds_merged['Deprivation_Percentage'] = leeds_poverty_households['Deprivation_Percentage'].values

# set size
plt.figure(figsize=(10, 6))

# plot a scatter
sns.scatterplot(x='greenspace_percentage',y='Deprivation_Percentage',hue='cluster',data=leeds_merged,palette='viridis',alpha=0.6)

# add tilte and labels
plt.title("The ralationship between greenspace and poverty household in Leeds", fontsize=14, weight='bold')
plt.xlabel('Greenspace Coverage (%)')
plt.ylabel('Severe Deprivation Rate (%)')
plt.legend(title='Cluster', loc='best')
plt.grid(True)

# show the scatter plot
plt.show()
```



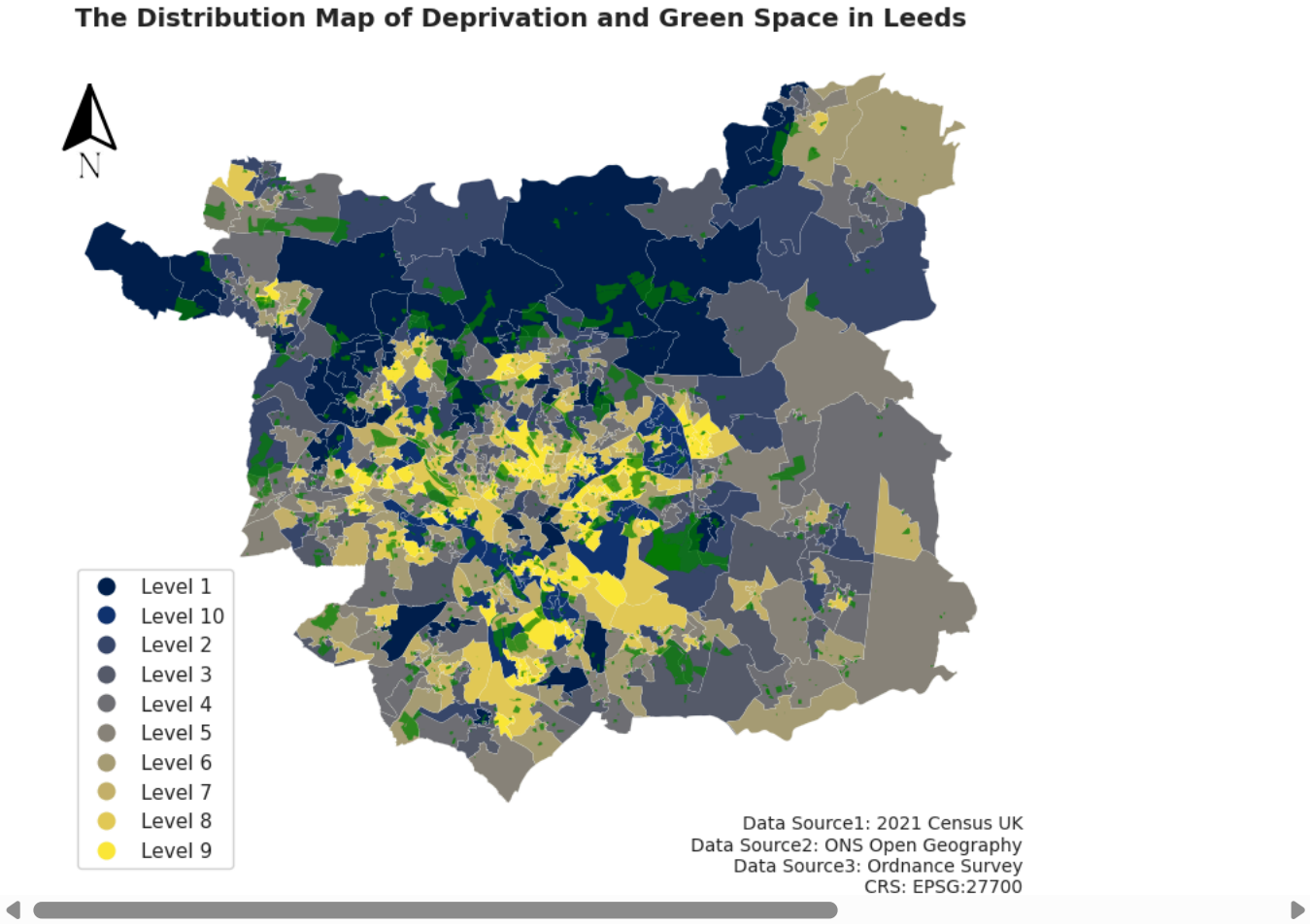
Spatial Visualization

This figure visually presents the spatial relationship between areas of different poverty levels and the distribution of green Spaces by means of spatial superposition. The spatial pattern can be observed effectively by overlaying the green space layer on the LSOA area, which is coded according to the ten equal parts. In addition, different color and legends are used in the map to distinguish each area level so that the map has strong interpretability and analytical value (Harrower and Brewer, 2003).

However, it still has limitations. First of all, the figure can not to show the proportion of green land corresponding to the poverty level. It limits the in-depth analysis of the correlation between them. Second, the judgment of the correlation is too dependent on vision. The results of spatial visualization itself cannot directly support the establishment of the relationship between the two (Goodchild, 1987). Although cluster analysis has been done in this study, it cannot be directly reflected on a graph, and the chaotic color will seriously reduce the explanatory power. This limitation makes it impossible to intuitively judge the geographical distribution characteristics of each cluster group. It limits the interpretation and analysis of spatial inequality.

```
# divide the data into 10 equal parts
leeds_poverty_households['Deprivation_Level'] = pd.qcut(leeds_poverty_households['Deprivation_Percentage'], q=10,
        labels=['Level 1', 'Level 2', 'Level 3', 'Level 4', 'Level 5', 'Level 6', 'Level 7', 'Level 8', 'Level 9', 'Level 10'])

# delete NaN
leeds_poverty_households = leeds_poverty_households.dropna(subset=['Deprivation_Level'])

# convert deprivation levels to strings to ease classification mapping
leeds_poverty_households['Deprivation_Level'] = leeds_poverty_households['Deprivation_Level'].astype(str)

# create a for loop for plotting a map of each area
leeds_poverty_households_cols = ['Deprivation_Level']

# for each item in a range from 0 to 7 (number of items in the deciles_cols list)
for i in range (0, len(leeds_poverty_households_cols)):

        # produce a plot
        fig, ax = plt.subplots(1, 1, figsize=(10, 10))

        # get the ith item in the decile column list and plot
        leeds_poverty_households.plot(column=leeds_poverty_households_cols[i],

        # reduce linewidth between polygons
        linewidth =0.1,
        # specify data is categorical (ordinal)
        categorical=True,
        # show the legend
        legend=True,
        # set the legend palette
        cmap='cividis',
        # use the axis
        ax=ax,
        # position the legend
        legend_kwds={'loc': 'center left','bbox_to_anchor':(1,0.5)})

        # overlay greenspace of Leeds
        greenspace_leeds.plot(ax=ax, color='green', alpha=0.7, linewidth=0)

        # add a title based on the column plotted, formatting the title to look better
        plt.title('The Distribution Map of Deprivation and Green Space in Leeds', fontsize=14, weight='bold')

        # add data source and CRS
        plt.text(1, -0.07, 'Data Source1: 2021 Census UK\nData Source2: ONS Open Geography\nData Source3: Ordnance Survey\nCRS: EPSG:27
                 transform=ax.transAxes, fontsize=10, verticalalignment='bottom', horizontalalignment='right')

        # add north arrow
        add_north_arrow(ax=ax, scale=0.65, xlim_pos=0.05, ylim_pos=0.86, color='black', text_scaler=3, text_yT=-1.25)

        # Position legend
        leg = ax.get_legend()
        leg.set_bbox_to_anchor((0.05, 0.15))


        # do not plot with the axis showing
        plt.axis('off')

        # save the figure as an image with name reflecting the domain plotted
        plt.savefig(str(leeds_poverty_households_cols[i])+'_'+'Leeds'+'.jpg',bbox_inches='tight');
```

```
/usr/local/lib/python3.11/dist-packages/geopandas/geodataframe.py:1819: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  super().__setitem__(key, value)
```



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Reference Bhatt, M. and Wallgrün, J. 2014. Geospatial Narratives and Their Spatio-Temporal Dynamics: Commonsense Reasoning for High-Level Analyses in Geographic Information Systems. ISPRS international journal of geo-information. [Online]. 3(1), pp.166-205. [Accessed 12 May 2025]. Available from: https://doi.org/10.3390/ijgi3010166

Bottou, L. and Bengio, Y. 1994. Convergence properties of the K-means algorithms. Advances in Neural Information Processing Systems. [Online]. pp.585-592. [Accessed 12 May 2025]. Available from: https://proceedings.neurips.cc/paper/1994/file/a1140a3d0df1c81e24ae954d935e8926-Paper.pdf

Buckley, A. 2013. Understanding statistical data for mapping purposes. ArcUser. [Online]. [Accessed 11 May 2025]. Available from: https://www.esri.com/about/newsroom/arcuser/understanding-statistical-data-for-mapping-purposes

Chrisman, N.R. 1987. The accuracy of map overlays: A reassessment. Landscape and urban planning. [Online]. 14(C), pp.427-439. [Accessed 11 May 2025]. Available from: https://doi.org/10.1016/0169-2046(87)90054-5

Goodchild, M.F. 1987. A spatial analytical perspective on geographical information systems. International journal of geographical information systems. [Online]. 1(4), pp.327-334. [Accessed 12 May 2025]. Available from: https://doi.org/10.1080/02693798708927820

Harrower, M. and Brewer, C.A. 2003. ColorBrewer.org: An Online Tool for Selecting Colour Schemes for Maps. Cartographic journal. [Online]. 40(1), pp.27-37. [Accessed 12 May 2025]. Available from: https://doi.org/10.1179/000870403235002042

Jain, A.K. 2010. Data clustering: 50 years beyond K-means. Pattern recognition letters. [Online]. 31(8), pp.651-666. [Accessed: 12 May 2025]. Available from: https://doi.org/10.1016/j.patrec.2009.09.011

Norman, P., Lloyd, C., McLennan, D., Ferguson, S. and Catney, G. 2024. 50-year Deprivation Trajectories: Local Area Change in England and Wales, 1971-2021. Applied spatial analysis and policy. [Online]. 17(3), pp.1183-1208. [Accessed 11 May 2025]. Available from: https://doi.org/10.1007/s12061-024-09583-w

Nuñez, J.R., Anderton, C.R. and Renslow, R.S. 2018. Optimizing colormaps with consideration for color vision deficiency to enable accurate interpretation of scientific data. PloS one. [Online]. 13(8), pp.e0199239-e0199239. [Accessed 12 May 2025]. Available from: https://doi.org/10.1371/journal.pone.0199239

Office for National Statistics (ONS), 2022. Household deprivation variable: Census 2021. [Online]. [Accessed 11 May 2025]. Available from: https://www.ons.gov.uk/census/census2021dictionary/variablesbytopic/demographyvariablescensus2021/householddeprivation

Pandas. 2024. pandas.DataFrame.fillna - pandas documentation. [Online]. [Accessed 8 May 2025]. Available from: https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.fillna.html

Spielman, S.E. and Thill, J.C. 2008. Social area analysis, data mining, and GIS. Computers, environment and urban systems. [Online]. 32(2), pp.110-122. [Accessed 11 May 2025]. Available from: https://doi.org/10.1016/j.compenvurbsys.2007.11.004

Xu, R. and Wunsch, D. 2005. Survey of clustering algorithms. IEEE transaction on neural networks and learning systems. [Online]. 16(3), pp.645-678. [Accessed 11 May 2025]. Available from: https://doi.org/10.1109/TNN.2005.845141

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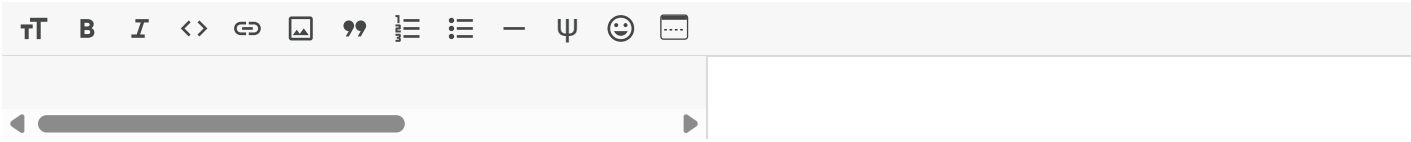

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