GEOG5415M_Final_Project_202018307

January 30, 2026

1 GEOG5415M Final Assignment

Student ID number:202018307

[1]:
```python
# import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import geopandas as gpd
```

2 Introduction & Data Sources

This project develops a spatial data analysis workflow to identify variations in energy vulnerability across Leeds. While national energy support policies in the UK are often income-based, they may overlook households that face high energy costs due to poor building efficiency rather than low income alone.

Previous research has shown significant spatial differences in residential energy efficiency across England, with Energy Performance Certificate (EPC) ratings closely correlated with local socioeconomic conditions (Buyuklieva et al., 2023[1]). To overcome the limitations of income-based approaches alone, recent research has shifted to multidimensional and comprehensive frameworks, such as the Low Income Low Energy Efficiency (LILEE) concept and spatiotemporal energy vulnerability indices, to better capture the complexity of energy vulnerability (Georgiadou et al., 2024[2]; Ward et al., 2025[5].)

Building on existing literature, this study applies a simplified, interpretable framework combining EPC-based energy efficiency and area-level poverty (IMD) to analyse cold-related vulnerability at the LSOA scale. Focusing on Leeds, selected for its diverse housing stock and well-defined LSOA geography, the analysis aims to generate clear, policy-relevant evidence to support targeted local energy interventions rather than replicating national indices.

Research questions

- How do economic deprivation and housing energy efficiency jointly shape cold-related vulnerability?
- Can policy-relevant neighbourhood types and statistically significant clusters be identified based on the cold index?

Data Sources:

- EPC Data: Domestic Energy Performance Certificates (DLUHC). https://epc.opendatacommunities.org/login
- IMD Data: English Indices of Deprivation 2019 (MHCLG), via ONS Nomis. https://assets.publishing.service.gov.uk/media/5dc407b440f0b6379a7acc8d/File_7_-_All_IoD2019_Scores___Ranks___Deciles_and_Population_Denominators_3.csv
- LSOA Boundaries: Boundaries: ONS Geoportal (2021 LSOA). https://geoportal.statistics.gov.uk/datasets/68515293204e43ca8ab56fa13ae8a547_0/explore?location=52.77 2.489483%2C7
- • Postcode–LSOA Lookup: ONS best-fit lookup for aggregating EPC postcodes to 2021 LSOAs https://open-geography-portalx-ons.hub.arcgis.com/datasets/ons::postcode-to-oa-2021-to-lsoa-to-msoa-to-lad-february-2025-best-fit-lookup-in-the-uk/about

3 Programming Workflow & Data preparation

The programming workflow comprises data preparation and visualisation; this chapter focuses on data preparation, including loading, cleaning, aggregation, and integration of multi-source data.

3.1 Data Loading

Multi-source data contain inconsistencies in structure, identifiers, and spatial reference systems, requiring standardized loading and verification prior to analysis.

[2]:
```
# load the data
epc  = pd.read_csv("epc_leeds_2025.csv")
imd  = pd.read_csv("imd_2019.csv")
lsoa = gpd.read_file("LSOA_2021_EW_BGC_V5.shp")
```

```
/tmp/ipython-input-46407388.py:2: DtypeWarning: Columns (15,37,39,40,83) have
mixed types. Specify dtype option on import or set low_memory=False.
  epc  = pd.read_csv("epc_leeds_2025.csv")
```

3.2 Spatial Linkage

[3]:
```
# after loading each dataset, basic data integrity checks (such as structure
↪and completeness) were performed.
# this demonstration shows the checks performed on the EPC dataset.

# check the key columns to confirm the existence of energy efficiency rating
↪variables
# required to be aggregated to the LSOA level later.
epc.head()
```

[3]:
```
                                             LMK_KEY             ADDRESS1  \
0  001dca82162cbdf798f746f53027c0cc82afda971d5e84…               Flat 2
1  18a413eb393a87aaccdcbbc35d75c519a13bf9713e5d8d…    8 Sackville Street
2  18ad988b1d1a739e5adfd04531c27c63e7ea810f40c31d…  20 Highfield Gardens
```

```
3  18bd4432597b334e2d8031b1ded0e4d713f2133e939b89…  17 Chestnut Gardens
4                 275687798052018050310193492080467   9, Foxwood Farm Way

         ADDRESS2 ADDRESS3  POSTCODE  BUILDING_REFERENCE_NUMBER  \
0  35a Town Street  Farsley  LS28 5HX                10003805692
1              NaN      NaN   LS7 2AS                10003489215
2              NaN      NaN  LS12 4DU                10003423919
3              NaN      NaN  LS12 4LP                10002989904
4              NaN      NaN   LS8 3EE                 4759821668

  CURRENT_ENERGY_RATING POTENTIAL_ENERGY_RATING  CURRENT_ENERGY_EFFICIENCY  \
0                     E                       C                         42
1                     D                       B                         61
2                     C                       B                         72
3                     B                       A                         88
4                     D                       B                         58

   POTENTIAL_ENERGY_EFFICIENCY  … CONSTITUENCY_LABEL POSTTOWN  \
0                           70  …             Pudsey   PUDSEY
1                           82  …   Leeds North East    LEEDS
2                           86  …         Leeds West    LEEDS
3                           92  …         Leeds West    Leeds
4                           87  …         Leeds East    LEEDS

           CONSTRUCTION_AGE_BAND   LODGEMENT_DATETIME           TENURE  \
0  England and Wales: before 1900  2022-12-06 16:54:30  Rented (private)
1    England and Wales: 1900-1929  2022-10-03 15:40:47  Rented (private)
2    England and Wales: 2007-2011  2022-10-25 07:49:22   Rented (social)
3    England and Wales: 1983-1990  2022-10-06 16:09:42    Owner-occupied
4    England and Wales: 1983-1990  2018-05-03 10:19:34    owner-occupied

  FIXED_LIGHTING_OUTLETS_COUNT LOW_ENERGY_FIXED_LIGHT_COUNT        UPRN  \
0                          9.0                          NaN  72736113.0
1                         12.0                          NaN  72658276.0
2                          6.0                          NaN  72683080.0
3                          7.0                          NaN  72266470.0
4                          NaN                          NaN  72269527.0

       UPRN_SOURCE  REPORT_TYPE
0  Energy Assessor          100
1  Energy Assessor          100
2  Energy Assessor          100
3  Address Matched          100
4  Address Matched          100

[5 rows x 93 columns]
```

A key issue is the absence of LSOA codes in the raw EPC data. This was addressed using a postcode-based linkage, mapping EPC postcodes to LSOAs via the ONSPD lookup table.

[4]:
```python
# load postcode-to-LSOA lookup (robust to malformed rows)
lookup = pd.read_csv("PCD_OA21_LSOA21.csv", usecols=["pcds",␣
↪"lsoa21cd"],dtype=str, engine="python",on_bad_lines="skip")

# standardise column names
lookup = lookup.rename(columns={"pcds": "postcode", "lsoa21cd": "lsoa_code"})

# clean postcode to match EPC format
lookup["postcode_clean"] = (lookup["postcode"].str.upper().str.replace(" ", "",␣
↪regex=False))

# keep only fields needed for joining
lookup = lookup[["postcode_clean", "lsoa_code"]]
```

[5]:
```python
# clean epc postcodes for reliable matching (uppercase + remove spaces)
epc["postcode_clean"]=(epc["POSTCODE"].astype(str).str.upper().str.replace(" ",␣
↪"", regex=False))

# add lsoa_code to epc dataset
epc=epc.merge(lookup,on="postcode_clean",how="left")

# check the match rate
print(epc['lsoa_code'].notna().mean())

# randomly select several samples
epc[['POSTCODE', 'postcode_clean', 'lsoa_code']].sample(10, random_state=42)
```

```
0.9988389184944723
```

[5]:

	POSTCODE	postcode_clean	lsoa_code
12561	LS7 2QE	LS72QE	E01011450
26108	LS7 3ER	LS73ER	E01011360
281043	LS28 5LW	LS285LW	E01011593
317456	LS18 4DH	LS184DH	E01011465
4183	LS4 2NG	LS42NG	E01011479
181626	LS12 1DH	LS121DH	E01033015
111460	LS16 7AT	LS167AT	E01011384
396899	LS20 9EY	LS209EY	E01011279
22246	LS10 3SQ	LS103SQ	E01032498
205074	LS3 1BX	LS31BX	E01035045

3.3 Data Aggregation

All attribute data are spatially joined to official LSOA boundaries.

[6]:
```
# convert the EPC energy efficiency column to numerical values (for calculating␣
↪the average)
for c in ["CURRENT_ENERGY_EFFICIENCY", "POTENTIAL_ENERGY_EFFICIENCY"]:
    if c in epc.columns:
        epc[c]=pd.to_numeric(epc[c], errors="coerce")
```

[7]:
```
# re-aggregate and analyze the scores of individual buildings according to LSOA␣
↪partitions
# aggregate EPC records by LSOA
# remove EPC records without LSOA code
epc_clean=epc.dropna(subset=["lsoa_code"])

# group EPC records by LSOA
epc_grouped=epc_clean.groupby("lsoa_code")

# summarise building-level EPC indicators at the LSOA level
epc_lsoa = epc_grouped.agg(mean_current_eff=("CURRENT_ENERGY_EFFICIENCY",␣
↪"mean"),mean_potential_eff=("POTENTIAL_ENERGY_EFFICIENCY",␣
↪"mean"),n_properties=("LMK_KEY", "count"))

# convert the group index (lsoa_code) back to a normal column
epc_lsoa = epc_lsoa.reset_index()
```

[8]:
```
# standardise LSOA identifiers to enable consistent joins across census tables
imd=imd.rename(columns={"LSOA code (2011)": "lsoa_code"})
```

[9]:
```
# define Leeds LSOA boundaries (baseline)
lsoa_leeds = lsoa[lsoa["LSOA21NM"].str.startswith("Leeds", na=False)].copy()
lsoa_leeds = lsoa_leeds.rename(columns={"LSOA21CD": "lsoa_code"})

leeds_codes = lsoa_leeds["lsoa_code"].unique()
print("Leeds LSOAs (baseline):", len(leeds_codes))  # expect 488
```

```
Leeds LSOAs (baseline): 488
```

[10]:
```
# keep EPC records within Leeds
epc_leeds = epc[epc["lsoa_code"].isin(leeds_codes)].copy()
print("EPC rows in Leeds:", len(epc_leeds))
```

```
EPC rows in Leeds: 416190
```

[11]:
```
# keep EPC records with a valid LSOA code
epc_leeds_clean = epc_leeds.dropna(subset=["lsoa_code"]).copy()

# aggregate EPC indicators to LSOA level
epc_grouped = epc_leeds_clean.groupby("lsoa_code", as_index=False)
```

```
epc_lsoa = epc_grouped.agg(mean_current_eff=("CURRENT_ENERGY_EFFICIENCY",
 ↪"mean"), mean_potential_eff=("POTENTIAL_ENERGY_EFFICIENCY",
 ↪"mean"),n_properties=("LMK_KEY", "count"))

print("Leeds LSOAs with EPC:", epc_lsoa["lsoa_code"].nunique())
```

```
Leeds LSOAs with EPC: 488
```

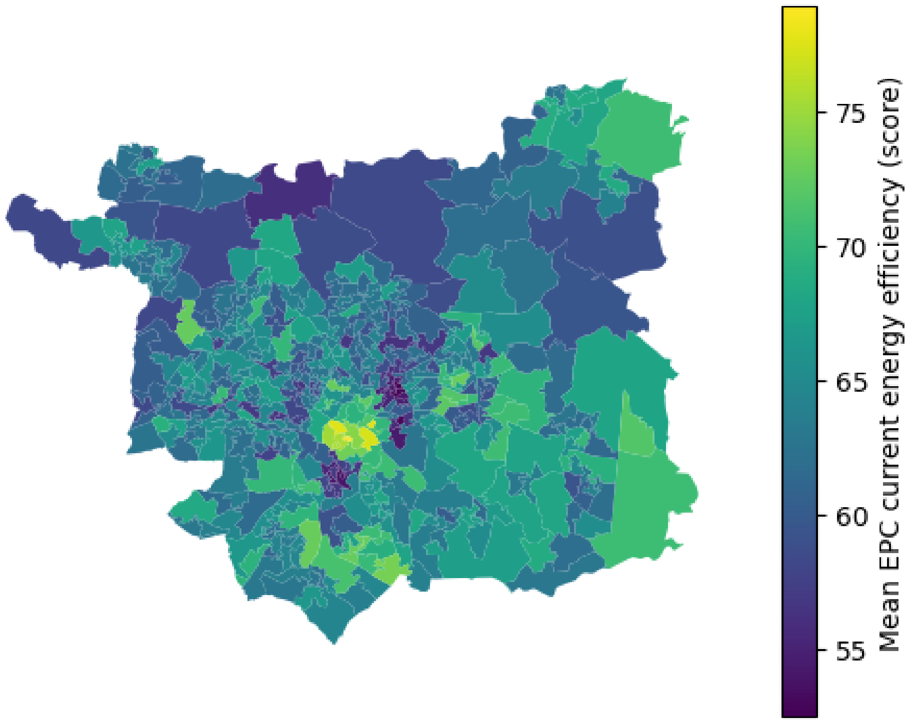
[12]:
```
# subset national IMD to Leeds LSOAs (based on the 2021 Leeds boundary codes)
imd_leeds = imd[imd["lsoa_code"].isin(leeds_codes)].copy()

# some LSOAs may not match due to 2011 vs 2021 boundary differences
print("Leeds LSOAs with IMD matched:", imd_leeds["lsoa_code"].nunique())
```

```
Leeds LSOAs with IMD matched: 473
```

The IMD index covers most of LSOAs in Leeds (473/488). Due to the difference between the 2011 and 2021 LSOA boundaries, a few regions could not be matched, and the relevant regions were preserved but their IMD values are missing.

[13]:
```
# merge IMD and EPC indicators onto the Leeds LSOA boundary (spatial unit = 488
 ↪LSOAs)
lsoa_geo = lsoa_leeds.copy()

# keep all Leeds LSOAs even if IMD cannot be matched for a small number of
 ↪areas (2011 vs 2021 boundaries)
lsoa_geo = lsoa_geo.merge(imd_leeds, on="lsoa_code", how="left")

# attach aggregated EPC indicators at LSOA level
lsoa_geo = lsoa_geo.merge(epc_lsoa, on="lsoa_code", how="left")

# quick sanity checks
print("Final LSOAs (geometry):", lsoa_geo["lsoa_code"].nunique())  # should be
 ↪488
print("Share with EPC:", lsoa_geo["mean_current_eff"].notna().mean())
# (optional) replace with your IMD column name
print("Share with IMD:", lsoa_geo["Income Score (rate)"].notna().mean())

ax = lsoa_geo.plot(column="mean_current_eff",legend=True,legend_kwds={"label":
 ↪"Mean EPC current energy efficiency (score)"})

# remove x/y axes for cleaner map output
ax.set_axis_off()
```

```
Final LSOAs (geometry): 488
Share with EPC: 1.0
Share with IMD: 0.9692622950819673
```



This map demonstrates the complete spatial coverage and alignment of all 488 LSOAs.

[14]:
```
# check missing EPC values after spatial merge
lsoa_geo[["mean_current_eff", "mean_potential_eff", "n_properties"]].isna().
 ↪sum()
```

[14]:
```
mean_current_eff      0
mean_potential_eff    0
n_properties          0
dtype: int64
```

[15]:
```
# check space merging status
lsoa_geo.geometry.is_valid.all()
```

[15]:
```
np.True_
```

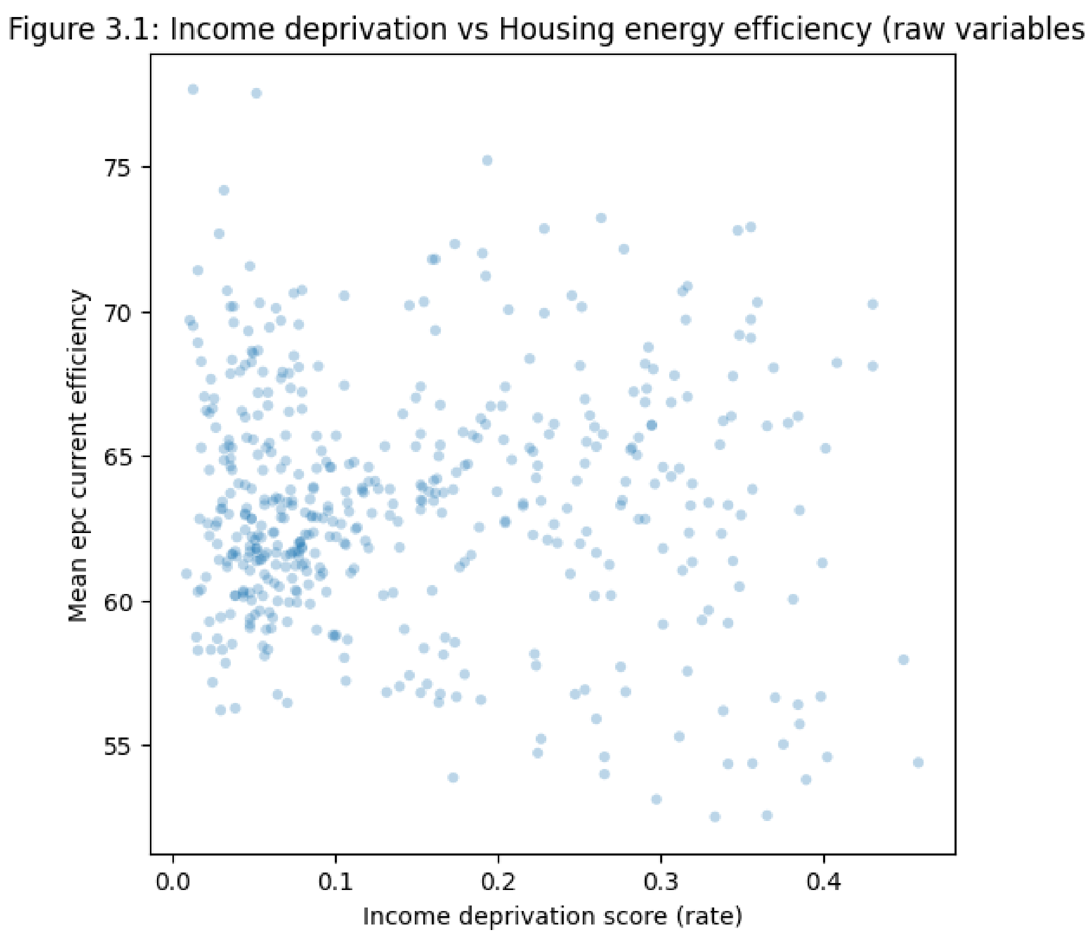
Final checks confirmed that spatial alignment remained consistent across the 488 Leeds Regional Small Area Statistical Units (LSOAs) covering the full EPC data.

3.4 Exploratory check of raw variables

To better understand the limitations of using a single indicator, an exploratory check was conducted to examine the relationship between income deprivation and housing energy efficiency at the LSOA level. The figure presents a scatter plot of the income deprivation score against mean EPC current efficiency.

[16]:

```
# create a scatter plot: income deprivation score vs mean epc current efficiency
# goal: visually check whether higher income deprivation tends to be associated
↪with poorer energy efficiency

fig, ax = plt.subplots(figsize=(6, 6))

# each point represents one lsoa
# x = income deprivation score (rate)
# y = mean epc current efficiency for the lsoa
ax.scatter(lsoa_geo["Income Score (rate)"],lsoa_geo["mean_current_eff"],alpha=0.
↪3,s=20,edgecolors="none")

ax.set_xlabel("Income deprivation score (rate)")
ax.set_ylabel("Mean epc current efficiency")

ax.set_title("Figure 3.1: Income deprivation vs Housing energy efficiency (raw
↪variables)")

plt.show()
```



The scatter shows substantial dispersion and no clear linear relationship, suggesting that income deprivation alone is insufficient to characterise variation in housing energy efficiency across areas.

4 Visualisation & Interpretation

4.1 Economic vs physical dimensions of cold-related risk

Recognising that income deprivation alone does not capture variation in building energy efficiency, this section adopts a multidimensional approach to cold-related vulnerability. Scatter plots of standardised (z-score) economic poverty and building inefficiency at the LSOA level are used, with zero reference lines dividing areas into four quadrants relative to the mean.

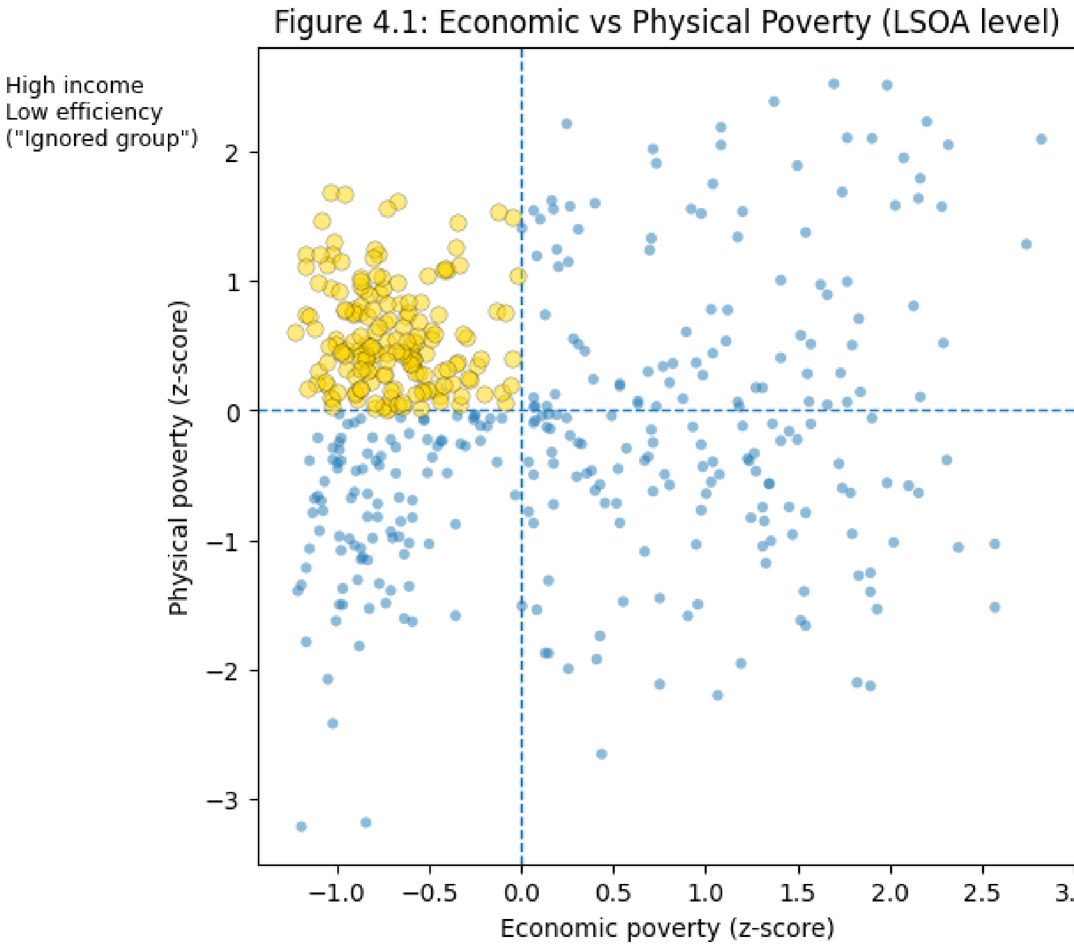
For ease of comparison, income poverty and housing energy efficiency are standardized using z-scores, where the energy efficiency values are inverted so that higher values represented greater physical vulnerability.

[17]:
```
# define column names used throughout the analysis
PHYSICAL_COL = "mean_current_eff"
ECON_COL     = "Income Score (rate)"
LSOA_NAME_COL = "LSOA21NM"
```

[18]:
```
# prepare a clean GeoDataFrame for analysis
# remove missing geometries
required_cols = [PHYSICAL_COL, ECON_COL, "geometry"]
missing = []
for c in required_cols:
    if c not in lsoa_geo.columns:
        missing.append(c)

if len(missing) > 0:
    raise KeyError(f"Missing columns: {missing}")

# keep only relevant fields
lsoa_risk_gdf = lsoa_geo.copy()
lsoa_risk_gdf = lsoa_risk_gdf[lsoa_risk_gdf.geometry.notnull()].copy()
lsoa_risk_gdf = lsoa_risk_gdf[[LSOA_NAME_COL, PHYSICAL_COL, ECON_COL,␣
 ↪"geometry"]].copy()
```

[19]:
```
# standardise indicators for comparability
# energy efficiency is reversed so higher values indicate higher vulnerability
def zscore(s):
    return (s - s.mean()) / s.std()

# standardise variables so they are comparable
lsoa_risk_gdf["phys_poverty_z"] = zscore(-lsoa_risk_gdf[PHYSICAL_COL])
lsoa_risk_gdf["econ_poverty_z"] = zscore(lsoa_risk_gdf[ECON_COL])
```

[20]:
```python
fig, ax = plt.subplots(figsize=(6, 6))

# define ignored group (upper-left quadrant)
ignored = lsoa_risk_gdf[(lsoa_risk_gdf["econ_poverty_z"] < 0) &␣
 ↪(lsoa_risk_gdf["phys_poverty_z"] > 0)]

# background points = everything except ignored
rest = lsoa_risk_gdf[~((lsoa_risk_gdf["econ_poverty_z"] < 0) &␣
 ↪(lsoa_risk_gdf["phys_poverty_z"] > 0))]

# plot background
ax.scatter(rest["econ_poverty_z"], rest["phys_poverty_z"],alpha=0.5,␣
 ↪s=20,edgecolors="none", linewidths=0,zorder=1)

# reference lines at mean (z=0)
ax.axhline(0, linestyle="--", linewidth=1)
ax.axvline(0, linestyle="--", linewidth=1)

# plot highlighted group
ax.scatter(ignored["econ_poverty_z"], ignored["phys_poverty_z"],color="gold",␣
 ↪alpha=0.5, s=45,edgecolors="black", linewidths=0.3,zorder=3)

ax.set_xlabel("Economic poverty (z-score)")
ax.set_ylabel("Physical poverty (z-score)")
ax.set_title("Figure 4.1: Economic vs Physical Poverty (LSOA level)")

ax.text(-2.8, 2.6, "High income\nLow efficiency\n(\"Ignored group\")",␣
 ↪fontsize=9, ha="left", va="top")

plt.show()
```



The figure reveals that economic and physical poverty are only weakly correlated overall. Notably, a distinct cluster of LSOAs appears in the upper-left quadrant, characterised by relatively high income levels but poor housing energy efficiency. These areas would be overlooked by income-based targeting alone, motivating the construction of a composite cold risk index that captures overlapping vulnerabilities more effectively.

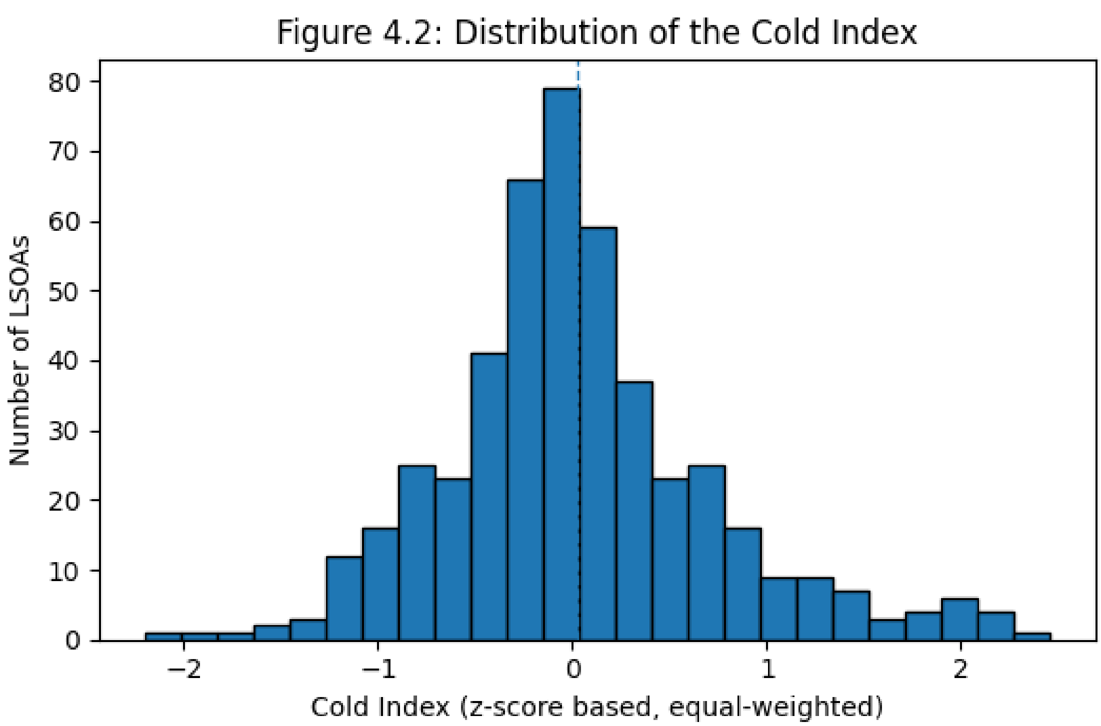
Previous research has shown that similar patterns are associated with rental-dominated communities where tenants have limited control over housing upgrades and landlords have little incentive to invest in energy efficiency improvements, especially in the absence of regulatory pressure (Häkkinen & Belloni, 2011[3]; Bouzarovski & Tirado Herrero, 2017[4]).

4.2 Construction of the Cold Index

The Cold Index is defined as the arithmetic mean of standardized economic and physical vulnerability indicators, with each dimension weighted equally. The formula reflects the combined impact of income constraints and housing conditions on cold-related risks and is consistent with the UK's definition of fuel poverty under the Low Income Low Energy Efficiency (LILEE) framework.

[21]:
```
# combine physical and economic poverty into a single index
lsoa_risk_gdf["cold_index"] = (lsoa_risk_gdf["phys_poverty_z"] +␣
↪lsoa_risk_gdf["econ_poverty_z"]) / 2
```

[22]:
```
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(6, 4))

# drop missing values to avoid plotting issues
cold_index_values = lsoa_risk_gdf["cold_index"].dropna()

ax.hist(cold_index_values, bins=25, edgecolor="black")
ax.axvline(cold_index_values.mean(), linestyle="--", linewidth=1)

ax.set_title("Figure 4.2: Distribution of the Cold Index")
ax.set_xlabel("Cold Index (z-score based, equal-weighted)")
ax.set_ylabel("Number of LSOAs")

plt.tight_layout()
plt.show()
```



The figure presents the distribution of the Cold Index across LSOAs, showing meaningful variation prior to spatial analysis in Section 3.3.

4.3 Spatial patterns of cold-related vulnerability

Building upon the coldness index, this section explores the spatial distribution of cold-related vulnerabilities in Leeds. First, a bivariate hierarchical statistical map is used to investigate the combined spatial structure of economic and physical poverty, highlighting different vulnerability combinations at the LSOA level. This descriptive mapping focuses on the structure and composition of risk rather than statistical significance. Subsequently, the Local Moran's I index is applied to the coldness index to assess whether there is significant spatial clustering of overall cold-related vulnerabilities.

4.3.1 Static Map: Bivariate Choropleth

While the Cold Index provides a continuous overview of joint vulnerability, this section employs bivariate contour plots to decompose its underlying dimensions and reveal the spatial distribution of different combinations of economic and physical poverty. Both indices are divided into three quantile-based groups (k = 3) to ensure balanced sample sizes across groups while avoiding excessive dispersion.

[23]:
```
econ_var = ECON_COL

# higher EPC efficiency = lower vulnerability
#  use -eff to make higher values = higher physical poverty
lsoa_risk_gdf["physical_poverty"] = -lsoa_risk_gdf[PHYSICAL_COL]
phys_var = "physical_poverty"
```

[24]:
```
# set the bivariate class resolution -- 3x3
# k = 3 divides each dimension into low / medium / high groups
# avoiding over-fragmentation
k = 3

# create quantile-based classes for each variable
# pd.qcut splits data into k quantiles (roughly equal counts)
# labels=False returns 0..(k-1); +1 converts them to 1..k
# duplicates="drop" avoids errors when tied values cause non-unique bin edges

lsoa_risk_gdf["ECON_q"] = ( pd.qcut(lsoa_risk_gdf[econ_var], q=k, labels=False,␣
↪duplicates="drop") + 1)
lsoa_risk_gdf["PHYSICAL_q"] = (pd.qcut(lsoa_risk_gdf[phys_var], q=k,␣
↪labels=False, duplicates="drop") + 1)
```

[25]:
```
# ensure class columns keep missing values properly
# using pandas "Int64" (capital I) keeps NA as <NA> instead of converting to␣
↪float
lsoa_risk_gdf["ECON_q"] = lsoa_risk_gdf["ECON_q"].astype("Int64")
lsoa_risk_gdf["PHYSICAL_q"] = lsoa_risk_gdf["PHYSICAL_q"].astype("Int64")
```

[26]:
```
# build bivariate code + define three headline risk types
# bivariate class code:
#   econ is the row (1..k), physical is the column (1..k)
```

```
#   results in 1..k^2 (e.g., for k=3 -> 1..9)
lsoa_risk_gdf["bi_class"] = (lsoa_risk_gdf["ECON_q"] - 1) * k +␣
↪lsoa_risk_gdf["PHYSICAL_q"]

# define headline risk types
# assumption: higher quantile = worse
# only three extreme combinations are explicitly labelled for interpretation;
# remaining combinations are grouped as "Other".
lsoa_risk_gdf["risk_type"] = "Other"
lsoa_risk_gdf.loc[(lsoa_risk_gdf["ECON_q"] == k) & (lsoa_risk_gdf["PHYSICAL_q"]␣
↪== k),"risk_type"] = "A: double poverty"
lsoa_risk_gdf.loc[(lsoa_risk_gdf["ECON_q"] == 1) & (lsoa_risk_gdf["PHYSICAL_q"]␣
↪== k),"risk_type"] = "B: physical only"
lsoa_risk_gdf.loc[(lsoa_risk_gdf["ECON_q"] == k) & (lsoa_risk_gdf["PHYSICAL_q"]␣
↪== 1), "risk_type"] = "C: economic only"
```

[27]:
```
# setup an manual matrices to avoid extra dependencies
# rows: economic poverty (low=1 -> high=k)
# cols: physical poverty (low=1 -> high=k)
palette = [ ["#e8e8e8", "#ace4e4", "#5ac8c8"],
        ["#dfb0d6", "#a5add3", "#5698b9"],
        ["#be64ac", "#8c62aa", "#3b4994"],]
```

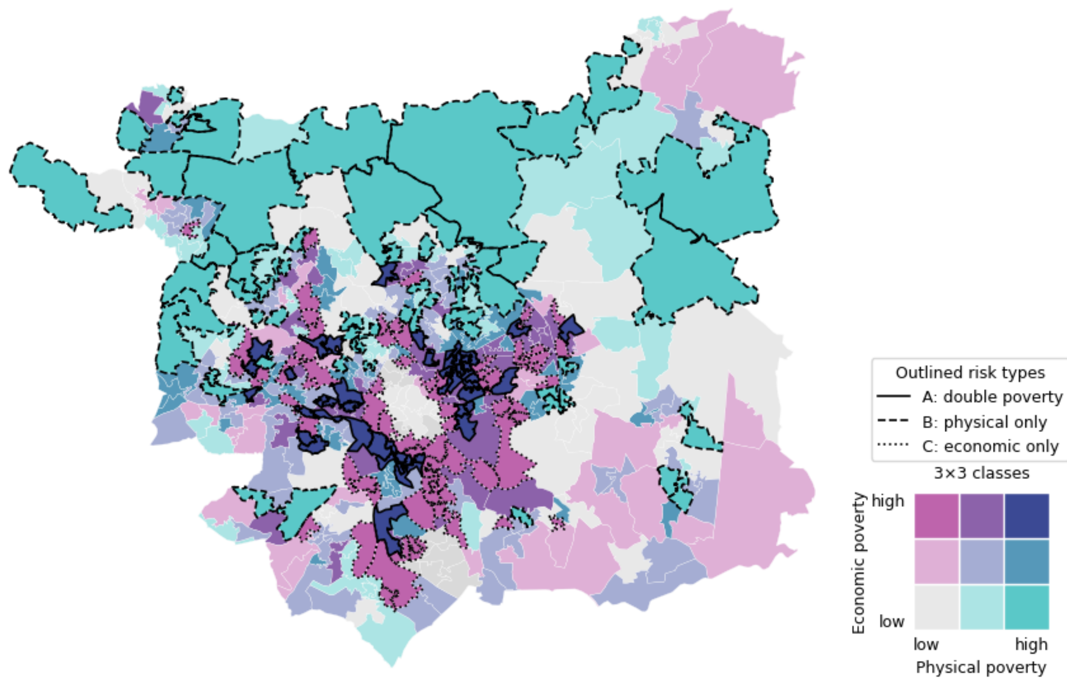
[28]:
```
# map (ECON_q, PHYSICAL_q) to a colour for each LSOA
# missing class values are assigned a neutral grey for plotting
na_color = "#d9d9d9"

def pick_colour(row):
    econ_q = row["ECON_q"]
    phys_q = row["PHYSICAL_q"]

    # if either dimension is missing, use the NA colour
    if pd.isna(econ_q) or pd.isna(phys_q):
        return na_color

    # convert class labels (1..k) to list indices (0..k-1) and pick colour
    return palette[int(econ_q) - 1][int(phys_q) - 1]

# apply the colour assignment row by row
lsoa_risk_gdf["bi_color"] = lsoa_risk_gdf.apply(pick_colour, axis=1)
```

[29]:
```
# create bivariate choropleth
fig, ax = plt.subplots(1, 1, figsize=(9, 9))

lsoa_risk_gdf.plot(ax=ax,color=lsoa_risk_gdf["bi_color"],␣
↪edgecolor="white",linewidth=0.2)
```

```python
ax.set_title("Figure 4.3: Bivariate choropleth (economic poverty × physical poverty)", fontsize=12)
ax.set_axis_off()

# highlight three headline risk types (outline only)
# A: solid, B: dashed, C: dotted
lsoa_risk_gdf.loc[lsoa_risk_gdf["risk_type"].str.startswith("A")].plot(ax=ax, facecolor="none", edgecolor="black", linewidth=1.2)
lsoa_risk_gdf.loc[lsoa_risk_gdf["risk_type"].str.startswith("B")].plot(ax=ax, facecolor="none", edgecolor="black", linewidth=1.2, linestyle="--")
lsoa_risk_gdf.loc[lsoa_risk_gdf["risk_type"].str.startswith("C")].plot(ax=ax, facecolor="none", edgecolor="black", linewidth=1.2, linestyle=":")

# add outline legend
outline_handles = [plt.Line2D([0], [0], color="black", lw=1.2, linestyle="-",  label="A: double poverty"),
    plt.Line2D([0], [0], color="black", lw=1.2, linestyle="--", label="B: physical only"),
    plt.Line2D([0], [0], color="black", lw=1.2, linestyle=":",  label="C: economic only"),]
ax.legend(handles=outline_handles,title="Outlined risk types",loc="lower right",bbox_to_anchor=(1.25, 0.32), frameon=True,fontsize=9,title_fontsize=9)

# turn off axes and draw the legend grid manually to avoid stray ticks/lines
# add a k×k bivariate legend (clean, no axis lines)
# move right + slightly smaller
legend_ax = fig.add_axes([0.95, 0.24, 0.12, 0.12])
legend_ax.set_xlim(0, k)
legend_ax.set_ylim(0, k)
# turn off all ticks/lines/frames
legend_ax.axis("off")

# draw legend squares
for econ_row in range(k):
    for phys_col in range(k):
        legend_ax.add_patch(plt.Rectangle((phys_col, econ_row), 1, 1,facecolor=palette[econ_row][phys_col],edgecolor="white"))

# add simple labels (placed just outside the grid)
legend_ax.text(k/2, -0.65, "Physical poverty", ha="center", va="top", fontsize=9)
legend_ax.text(-0.95, k/2, "Economic poverty", ha="right", va="center", rotation=90, fontsize=9)

legend_ax.text(0, -0.15, "low", ha="left", va="top", fontsize=9)
legend_ax.text(k, -0.15, "high", ha="right", va="top", fontsize=9)
```

```
legend_ax.text(-0.15, 0, "low", ha="right", va="bottom", fontsize=9)
legend_ax.text(-0.15, k, "high", ha="right", va="top", fontsize=9)

legend_ax.text(k/2, k + 0.25, f"{k}×{k} classes", ha="center", va="bottom", fontsize=9)

plt.show()
```

Figure 4.3: Bivariate choropleth (economic poverty × physical poverty)



This bivariate contour map jointly classifies Leeds' LSOAs based on both economic and material poverty, revealing significant spatial heterogeneity rather than a uniform poverty pattern. Areas of "double poverty" are primarily concentrated in central and eastern Leeds. This map aims to provide policymakers and planners with a reference by differentiating between different vulnerability types, enabling the rapid identification of priority areas and support for differentiated policy interventions.

4.3.2 Interactive Map: Local Moran's I clusters (and tooltips)

This section uses Local Moran's I (LSOA) analysis to analyze the composite risk score and identify statistically significant local poverty clusters. Queen adjacency spatial weights are used, and row standardization is applied, marking only clusters with $p < 0.05$; insignificant areas are retained for contextual reference.

[ ]:
```
# spatial weights and local spatial autocorrelation
from libpysal.weights import Queen
from esda.moran import Moran_Local
```

```
# keep lsoas with valid risk scores for lisa
lsoa_lisa_gdf = lsoa_risk_gdf.dropna(subset=["cold_index"]).copy()

# build queen contiguity weights and row-standardise
queen_weights = Queen.from_dataframe(lsoa_lisa_gdf)
queen_weights.transform = "r"

# run local moran's i and store quadrant + p-value
lisa_results = Moran_Local(lsoa_lisa_gdf["cold_index"].values, queen_weights,␣
↪permutations=999)
lsoa_lisa_gdf["lisa_q"] = lisa_results.q
lsoa_lisa_gdf["lisa_p"] = lisa_results.p_sim


# local moran’s i identifies spatial clustering of the risk score
# using queen contiguity weights (row-standardised);
# clusters are labelled only when p < 0.05, otherwise areas are treated as not␣
↪significant
alpha = 0.05
lsoa_lisa_gdf["lisa_label"] = "Not significant"
sig_mask = lsoa_lisa_gdf["lisa_p"] < alpha

# assign labels for significant lisa clusters (1=hh, 2=lh, 3=ll, 4=hl)
lsoa_lisa_gdf.loc[sig_mask & (lsoa_lisa_gdf["lisa_q"] == 1), "lisa_label"] =␣
↪"HH"
lsoa_lisa_gdf.loc[sig_mask & (lsoa_lisa_gdf["lisa_q"] == 2), "lisa_label"] =␣
↪"LH"
lsoa_lisa_gdf.loc[sig_mask & (lsoa_lisa_gdf["lisa_q"] == 3), "lisa_label"] =␣
↪"LL"
lsoa_lisa_gdf.loc[sig_mask & (lsoa_lisa_gdf["lisa_q"] == 4), "lisa_label"] =␣
↪"HL"

# quick checks
print(lsoa_lisa_gdf["lisa_label"].value_counts(dropna=False))
print((lsoa_lisa_gdf["lisa_p"] < alpha).mean())
```

```
/tmp/ipython-input-3528087696.py:9: FutureWarning: `use_index` defaults to False
but will default to True in future. Set True/False directly to control this
behavior and silence this warning
  queen_weights = Queen.from_dataframe(lsoa_lisa_gdf)
```

[ ]:

```
# interactive map to explore local moran's i clusters
# tooltips allow querying cluster label, p-value and component metrics for each␣
↪lsoa
import folium
```

```python
# compute centroid in a projected crs (epsg:27700), then convert to epsg:4326␣
↪for folium
cent_27700 = lsoa_lisa_gdf.to_crs(epsg=27700).geometry.centroid
cent_4326 = gpd.GeoSeries(cent_27700, crs=27700).to_crs(epsg=4326)

# colour mapping for lisa cluster labels
cluster_colors = {"HH": "#d7191c", "LL": "#2c7bb6","HL": "#fdae61","LH":␣
↪"#abd9e9","Not significant": "lightgrey"}

# fields shown when hovering over an lsoa
TOOLTIP_FIELDS = ["lisa_label", "lisa_p", "cold_index", "Income Score (rate)",␣
↪"mean_current_eff"]
TOOLTIP_ALIASES = [f"{c}:" for c in TOOLTIP_FIELDS]

# create the interactive basemap
lisa_map = folium.Map(location=[cent_4326.y.mean(), cent_4326.x.
↪mean()],zoom_start=9,tiles="CartoDB positron")

# style each polygon based on its lisa label
def style_func(feat):
    label = feat["properties"].get("lisa_label", "Not significant")
    col = cluster_colors.get(label, "lightgrey")
    return {"fillColor": col, "color": "white", "weight": 0.3, "fillOpacity": 0.
↪9}

# hover tooltip configuration
tooltip = folium.
↪GeoJsonTooltip(fields=TOOLTIP_FIELDS,aliases=TOOLTIP_ALIASES,localize=True,sticky=False)

# add lisa polygons to the folium map
folium.GeoJson(lsoa_lisa_gdf,name="local moran's i (p<0.
↪05)",style_function=style_func,tooltip=tooltip).add_to(lisa_map)

# layer toggle
folium.LayerControl().add_to(lisa_map)

lisa_map
```

The interactive LISA map visually presents different cluster types, with hover tips displaying cluster categories, significance levels, and key indicators that constitute the overall risk index. Designed specifically for local government analysts and researchers, the map provides statistically reliable community-scale evidence for identifying significant risk clusters and supports evidence-based target location and monitoring.

[ ]:
```python
# quick check: why some lsoas are excluded from lisa
econ_raw = "Income Score (rate)"
```

```python
print("total lsoas:", len(lsoa_risk_gdf))
print("missing income score:", lsoa_risk_gdf[econ_raw].isna().sum())
print("missing cold_index:", lsoa_risk_gdf["cold_index"].isna().sum())
```

A few regions (LSOAs) lack income scores, which makes it impossible to calculate the composite risk score; these regions are excluded from the LISA analysis and are therefore shown as unclassified on the map.

5 Limitations & Ethical Considerations

5.1 Simplification in Index Construction

The cold index assigns equal weight to economic poverty and housing energy efficiency for transparency, but this simplification may not fully capture their uneven influence on cold-related vulnerability across regions.

5.2 Data Coverage Bias

EPC data only cover properties involved in sale, rental, or refurbishment, potentially underrepresenting low-turnover dwellings. As a result, observed spatial patterns may partly reflect data availability rather than actual housing conditions.

5.3 Spatial Aggregation Effects

All indicators are aggregated at the LSOA level, masking within-area household differences. The findings therefore describe regional patterns rather than individual household vulnerability.

5.4 Temporal Misalignment

The analysis relies on pre-2021 data, including IMD 2019 and historical EPC assessments, and does not reflect recent UK energy price shocks. The results should thus be interpreted as a baseline of structural cold vulnerability rather than current energy poverty.

6 Conclusion

6.1 Summary of Key Findings

This study found significant spatial differences in cold-related vulnerabilities in Leeds, suggesting that different communities face different combinations of constraints and require localized policy responses.

6.2 Targeted Policy Implications by Area Type

Distinct cold-related vulnerability patterns, defined by combined housing energy efficiency and economic poverty, call for differentiated policy responses. High-poverty, low-efficiency areas require substantial financial support and public renovation programmes, while low-poverty but inefficient areas are better addressed through regulatory or incentive-based measures. Where poverty is high but energy efficiency is relatively good, targeted affordability interventions may be more appropriate.

6.3 Implications for Energy Justice and Urban Policy

From an energy justice perspective, spatial analysis of cold-related vulnerabilities, enabling targeted and phased interventions, can help develop more equitable policies. Identifying different regional patterns helps avoid a "one-size-fits-all" approach that could ignore local needs and inadvertently exacerbate inequalities.

6.4 Directions for Future Research

Future research could refine this framework by integrating more detailed building and demographic characteristics, thereby improving the accuracy of regional interpretations. Differentiating between student enclaves and private rental areas, and considering historical or conservation constraints on redevelopment, could provide more targeted policy insights while maintaining spatial comparability within the EPC-IMD framework.

7 References

[1] Buyuklieva, B., Dennett, A., Bailey, N. and Morley, J. 2023. Energy Efficient Homes: The Social and Spatial Patterns of Residential Energy Efficiency in England.

[2]Georgiadou, M.C., Greenwood, D., Schiano-Phan, R. and Russo, F. 2024. Assessing retrofit policies for fuel-poor homes in London. Buildings & cities. 5(1), pp.133–149.

[3]Häkkinen, T. and Belloni, K. 2011. Barriers and drivers for sustainable building. Building research and information : the international journal of research, development and demonstration. 39(3), pp.239–255.

[4]Palmer, J. and Cooper, I. 2013. United Kingdom housing energy fact file 2013. [Online]. London: Department of Energy & Climate Change (UK). [Accessed 4 September 2024]. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/345141/uk_

[5]Ward, C., Singleton, A., Robinson, C. and Rowe, F. 2025. Tracking spatio-temporal energy vulnerability: A composite indicator for England and Wales. Regional studies, regional science. 12(1), pp.319–337.

This project made limited use of generative artificial intelligence tools to support debugging and technical implementation, in accordance with the course guidelines.

[ ]:
```
# Declaration of Use of Generative Artificial Intelligence
# I acknowledge the use of ChatGPT-5.2 (OpenAI, https://chat.openai.com/)
# for assisting code testing and debugging, clarifying Python syntax,
# and supporting some simple visualization and interactive map formatting tasks.

# # Example tooltip used:
# "Help add tooltips to interactive maps so users can view
# LSOA level technical metrics."

# # All generated suggestions have been reviewed, adjusted, and independently
 ↪annotated,
# to ensure full understanding and accuracy.
```

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

[ ]:
```
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
↪texlive-plain-generic pandoc
```

[ ]:
```
!jupyter nbconvert --to pdf "/content/drive/MyDrive/Colab Notebooks/
↪GEOG5415M_Final_Project_202018307.ipynb"
```