Unsupervised Learning Project: Energy & Sustainability

Energy & Sustainability Patterns in Ohio

Project Overview

This notebook explores energy production, infrastructure, and sustainability-related patterns across Ohio using publicly available data. The goal is to understand how different energy characteristics cluster together and what structural patterns emerge across facilities and regions.

Rather than focusing on prediction, this analysis emphasizes exploratory data analysis and unsupervised learning to surface hidden structure in the data.

Analytical Goals

The primary objectives of this analysis are to:

- Explore the distribution and scale of key energy-related variables
- Identify similarities and differences across energy facilities
- Examine whether meaningful groupings emerge from the data
- Use dimensionality reduction techniques to support interpretation and visualization

Methods Used

The analysis follows a structured workflow including:

- Exploratory Data Analysis (EDA)
- Feature scaling and preprocessing
- Clustering (K-Means, K-Medoids, Hierarchical)
- Dimensionality Reduction (PCA, t-SNE)
- Cluster evaluation using internal metrics

Notes on Scope

This is an exploratory analysis. Findings are intended to highlight patterns and raise questions for further investigation rather than make causal or policy claims.

In [524…

```
!pip install numpy==1.26.0
```

```
Requirement already satisfied: numpy==1.26.0 in /usr/local/lib/python3.12/dist-packa
ges (1.26.0)
```

In [525…

```
!pip install scikit-learn-extra
```

```
Requirement already satisfied: scikit-learn-extra in /usr/local/lib/python3.12/dist-
packages (0.3.0)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.12/dist-packa
ges (from scikit-learn-extra) (1.26.0)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.12/dist-packa
ges (from scikit-learn-extra) (1.16.3)
Requirement already satisfied: scikit-learn>=0.23.0 in /usr/local/lib/python3.12/dis
t-packages (from scikit-learn-extra) (1.6.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-packa
ges (from scikit-learn>=0.23.0->scikit-learn-extra) (1.5.3)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.12/dis
t-packages (from scikit-learn>=0.23.0->scikit-learn-extra) (3.6.0)
```

In [526…

```
!pip -q install geopandas pyogrio shapely
```

Importing the necessary libraries and overview of the dataset

In [527…

```
# Core numerical & data handling
import numpy as np
import pandas as pd

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.colors import ListedColormap
import matplotlib.patches as mpatches

# Preprocessing & dimensionality reduction
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

# Clustering
from sklearn.cluster import KMeans
from sklearn_extra.cluster import KMedoids
from sklearn.metrics import silhouette_score

# Distance & hierarchical clustering
from scipy.spatial.distance import cdist, pdist
from scipy.cluster.hierarchy import dendrogram, linkage, cophenet, fcluster

# Utilities
from IPython.display import display, HTML
import pprint

# Colab / Drive (only keep if you are running in Colab)
```

```python
from google.colab import drive

# -------------------------------------------------------------------

sns.set_theme(style='darkgrid')

# Remove the limit for the number of displayed columns
pd.set_option("display.max_columns", None)

# Set the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)

import geopandas as gpd
```

In [528…

```python
url = "https://raw.githubusercontent.com/plotly/datasets/master/geojson-counties-fi
us_counties = gpd.read_file(url)

# Filter the US counties GeoDataFrame to Ohio
ohio_map = us_counties[us_counties["STATE"] == "39"].copy()
```

Data Loading & Initial Data Checks

Before merging or modeling, we inspect structure (rows/columns), column types, missing values, and potential duplicates to understand and verify the data loaded correctly.

In [529…

```python
drive.mount('/content/drive')
path_1 = '/content/drive/MyDrive/Colab Notebooks/Python for Data Science/Unsupervis
path_2 = '/content/drive/MyDrive/Colab Notebooks/Python for Data Science/Unsupervis

# read the data
df1 = pd.read_excel(path_1, sheet_name=0, header= 5)
df2 = pd.read_excel(path_2, sheet_name=0, header = 1)
```

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

In [530…

```python
# --- Quick Look ---
display(df1.head(3))
display(df2.head(3))

# --- Dimensions ---
print(f"df1: {df1.shape[0]:,} rows × {df1.shape[1]:,} columns")
print(f"df2: {df2.shape[0]:,} rows × {df2.shape[1]:,} columns")
```

	Plant Id	Combined Heat And\nPower Plant	Nuclear Unit Id	Plant Name	Operator Name	Operator Id	Plant State	Census Region	NERC Region	Re
0	1	Y	.	Sand Point	Sand Point Generating, LLC	63560	AK	PACN	NaN	
1	1	Y	.	Sand Point	Sand Point Generating, LLC	63560	AK	PACN	NaN	
2	2	N	.	Bankhead Dam	Alabama Power Co	195	AL	ESC	SERC	

	Utility ID	Utility Name	Plant Code	Plant Name	Street Address	City	State	Zip	County	Latit
0	63560	Sand Point Generating, LLC	1	Sand Point	100 Power Plant Way	Sand Point	AK	99661	Aleutians East	55.339
1	195	Alabama Power Co	2	Bankhead Dam	19001 Lock 17 Road	Northport	AL	35476	Tuscaloosa	33.458
2	195	Alabama Power Co	3	Barry	North Highway 43	Bucks	AL	36512	Mobile	31.0

```
df1: 17,964 rows × 97 columns
df2: 16,132 rows × 42 columns
```

In [531…

```
# --- Random samples ---
display(df1.sample(3, random_state=1))
display(df2.sample(3, random_state=1))
```

	Plant Id	Combined Heat And\nPower Plant	Nuclear Unit Id	Plant Name	Operator Name	Operator Id	Plant State	Census Region	NE Regi
3315	6484	N	.	Bend	PacifiCorp	14354	OR	PACC	WE
11001	60151	N	.	Building F	Golden Springs Development Company LLC	57104	CA	PACC	WE
6411	54780	Y	.	University of Illinois Abbott Power Plt	University of Illinois	19528	IL	ENC	SE

	Utility ID	Utility Name	Plant Code	Plant Name	Street Address	City	State	Zip	County	La
11968	64282	LeConte Energy Storage, LLC	64701	LeConte Energy Storage	1561 W. Highway 98	Calexico	CA	92231	Imperial	32.6
5816	67036	NW Stadium Solar Plant	57747	FedEx Field Solar Facility	1600 FedEx Way	Landover	MD	20785	Prince Georges	38.9
5657	17609	Southern California Edison Co	57543	Solar Photovoltaic Project #47	2211 E Carson Street	Carson	CA	90810	Los Angeles	33.7

In [532…

```
# --- Data types + non-null counts ---
print("\ndf1 info:")
df1.info()
```

```
df1 info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17964 entries, 0 to 17963
Data columns (total 97 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   Plant Id                            17964 non-null  int64  
 1   Combined Heat And 
Power Plant       17964 non-null  object 
 2   Nuclear Unit Id                     17964 non-null  object 
 3   Plant Name                          17963 non-null  object 
 4   Operator Name                       17963 non-null  object 
 5   Operator Id                         17964 non-null  object 
 6   Plant State                         17963 non-null  object 
 7   Census Region                       17964 non-null  object 
 8   NERC Region                         16942 non-null  object 
 9   Reserved                            0 non-null      float64
 10  NAICS Code                          17964 non-null  int64  
 11  EIA Sector Number                   17964 non-null  int64  
 12  Sector Name                         17964 non-null  object 
 13  Reported 
Prime Mover                 17964 non-null  object 
 14  Reported 
Fuel Type Code              17964 non-null  object 
 15  MER 
Fuel Type Code                   17964 non-null  object 
 16  Balancing 
Authority Code             17578 non-null  object 
 17  Respondent 
Frequency                 17696 non-null  object 
 18  Physical 
Unit Label                  8511 non-null   object 
 19  Quantity 
January                     17964 non-null  object 
 20  Quantity 
February                    17964 non-null  object 
 21  Quantity 
March                       17964 non-null  object 
 22  Quantity 
April                       17964 non-null  object 
 23  Quantity 
May                         17964 non-null  object 
 24  Quantity 
June                        17964 non-null  object 
 25  Quantity 
July                        17964 non-null  object 
 26  Quantity 
August                      17964 non-null  object 
 27  Quantity 
September                   17964 non-null  object 
 28  Quantity 
October                     17964 non-null  object 
 29  Quantity 
November                    17964 non-null  object 
 30  Quantity 
December                    17964 non-null  object 
```

```
 31  Elec_Quantity
January               17964 non-null  object
 32  Elec_Quantity
February              17964 non-null  object
 33  Elec_Quantity
March                 17964 non-null  object
 34  Elec_Quantity
April                 17964 non-null  object
 35  Elec_Quantity
May                   17964 non-null  object
 36  Elec_Quantity
June                  17964 non-null  object
 37  Elec_Quantity
July                  17964 non-null  object
 38  Elec_Quantity
August                17964 non-null  object
 39  Elec_Quantity
September             17964 non-null  object
 40  Elec_Quantity
October               17964 non-null  object
 41  Elec_Quantity
November              17964 non-null  object
 42  Elec_Quantity
December              17964 non-null  object
 43  MMBtuPer_Unit
January               17964 non-null  object
 44  MMBtuPer_Unit
February              17964 non-null  object
 45  MMBtuPer_Unit
March                 17964 non-null  object
 46  MMBtuPer_Unit
April                 17964 non-null  object
 47  MMBtuPer_Unit
May                   17964 non-null  object
 48  MMBtuPer_Unit
June                  17964 non-null  object
 49  MMBtuPer_Unit
July                  17964 non-null  object
 50  MMBtuPer_Unit
August                17964 non-null  object
 51  MMBtuPer_Unit
September             17964 non-null  object
 52  MMBtuPer_Unit
October               17964 non-null  object
 53  MMBtuPer_Unit
November              17964 non-null  object
 54  MMBtuPer_Unit
December              17964 non-null  object
 55  Tot_MMBtu
January                   17964 non-null  object
 56  Tot_MMBtu
February                  17964 non-null  object
 57  Tot_MMBtu
March                     17964 non-null  object
 58  Tot_MMBtu
April                     17964 non-null  object
```

```
 59  Tot_MMBtu
May                          17964 non-null  object
 60  Tot_MMBtu
June                         17964 non-null  object
 61  Tot_MMBtu
July                         17964 non-null  object
 62  Tot_MMBtu
August                       17964 non-null  object
 63  Tot_MMBtu
September                    17964 non-null  object
 64  Tot_MMBtu
October                      17964 non-null  object
 65  Tot_MMBtu
November                     17964 non-null  object
 66  Tot_MMBtu
December                     17964 non-null  object
 67  Elec_MMBtu
January                     17964 non-null  object
 68  Elec_MMBtu
February                    17964 non-null  object
 69  Elec_MMBtu
March                       17964 non-null  object
 70  Elec_MMBtu
April                       17964 non-null  object
 71  Elec_MMBtu
May                         17964 non-null  object
 72  Elec_MMBtu
June                        17964 non-null  object
 73  Elec_MMBtu
July                        17964 non-null  object
 74  Elec_MMBtu
August                      17964 non-null  object
 75  Elec_MMBtu
September                   17964 non-null  object
 76  Elec_MMBtu
October                     17964 non-null  object
 77  Elec_MMBtu
November                    17964 non-null  object
 78  Elec_MMBtu
December                    17964 non-null  object
 79  Netgen
January                         17964 non-null  object
 80  Netgen
February                        17964 non-null  object
 81  Netgen
March                           17964 non-null  object
 82  Netgen
April                           17964 non-null  object
 83  Netgen
May                             17964 non-null  object
 84  Netgen
June                            17964 non-null  object
 85  Netgen
July                            17964 non-null  object
 86  Netgen
August                          17964 non-null  object
```

```
 87  Netgen
September                     17964 non-null  object
 88  Netgen
October                       17964 non-null  object
 89  Netgen
November                      17964 non-null  object
 90  Netgen
December                      17964 non-null  object
 91  Total Fuel Consumption
Quantity     17964 non-null  int64
 92  Electric Fuel Consumption
Quantity  17964 non-null  int64
 93  Total Fuel Consumption
MMBtu        17964 non-null  int64
 94  Elec Fuel Consumption
MMBtu         17964 non-null  int64
 95  Net Generation
(Megawatthours)      17964 non-null  float64
 96  YEAR                                    17964 non-null  int64
dtypes: float64(2), int64(8), object(87)
memory usage: 13.3+ MB
```

In [533…

```
print("\ndf2 info:")
df2.info()
```

```
df2 info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16132 entries, 0 to 16131
Data columns (total 42 columns):
 #   Column                                           Non-Null Count  Dtype 
---  ------                                           --------------  ----- 
 0   Utility ID                                       16132 non-null  int64 
 1   Utility Name                                     16132 non-null  object
 2   Plant Code                                       16132 non-null  int64 
 3   Plant Name                                       16132 non-null  object
 4   Street Address                                   16011 non-null  object
 5   City                                             16096 non-null  object
 6   State                                            16132 non-null  object
 7   Zip                                              16132 non-null  object
 8   County                                           16108 non-null  object
 9   Latitude                                         16132 non-null  object
 10  Longitude                                        16132 non-null  object
 11  NERC Region                                      15886 non-null  object
 12  Balancing Authority Code                         15840 non-null  object
 13  Balancing Authority Name                         15861 non-null  object
 14  Name of Water Source                             4322 non-null   object
 15  Primary Purpose (NAICS Code)                     16132 non-null  int64 
 16  Regulatory Status                                16132 non-null  object
 17  Sector                                           16132 non-null  int64 
 18  Sector Name                                      16132 non-null  object
 19  FERC Cogeneration Status                         16132 non-null  object
 20  FERC Cogeneration Docket Number                  447 non-null    object
 21  FERC Small Power Producer Status                 16132 non-null  object
 22  FERC Small Power Producer Docket Number          4734 non-null   object
 23  FERC Exempt Wholesale Generator Status           16132 non-null  object
 24  FERC Exempt Wholesale Generator Docket Number    1520 non-null   object
 25  Ash Impoundment?                                 9628 non-null   object
 26  Ash Impoundment Lined?                           8586 non-null   object
 27  Ash Impoundment Status                           317 non-null    object
 28  Transmission or Distribution System Owner        16014 non-null  object
 29  Transmission or Distribution System Owner ID     16132 non-null  object
 30  Transmission or Distribution System Owner State  15235 non-null  object
 31  Grid Voltage (kV)                                16132 non-null  object
 32  Grid Voltage 2 (kV)                              16132 non-null  object
 33  Grid Voltage 3 (kV)                              16132 non-null  object
 34  Energy Storage                                   15927 non-null  object
 35  Natural Gas LDC Name                             1545 non-null   object
 36  Natural Gas Pipeline Name 1                      1438 non-null   object
 37  Natural Gas Pipeline Name 2                      225 non-null    object
 38  Natural Gas Pipeline Name 3                      55 non-null     object
 39  Pipeline Notes                                   253 non-null    object
 40  Natural Gas Storage                              8623 non-null   object
 41  Liquefied Natural Gas Storage                    7489 non-null   object
dtypes: int64(4), object(38)
memory usage: 5.2+ MB
```

In [534…

```
# --- Missing values (top contributors) ---
missing_df1 = df1.isna().mean().sort_values(ascending=False)
missing_df2 = df2.isna().mean().sort_values(ascending=False)

print("\nTop missing (df1):")
```

```
display((missing_df1[missing_df1 > 0] * 100).head(15).to_frame("% missing"))

print("\nTop missing (df2):")
display((missing_df2[missing_df2 > 0] * 100).head(15).to_frame("% missing"))

# --- Duplicate rows ---
print("\nDuplicate rows:")
print("df1 duplicates:", df1.duplicated().sum())
print("df2 duplicates:", df2.duplicated().sum())
```

```
Top missing (df1):
```

	% missing
Reserved	100.000000
Physical\nUnit Label	52.621910
NERC Region	5.689156
Balancing\nAuthority Code	2.148742
Respondent\nFrequency	1.491873
Operator Name	0.005567
Plant State	0.005567
Plant Name	0.005567

```
Top missing (df2):
```

	% missing
Natural Gas Pipeline Name 3	99.659063
Natural Gas Pipeline Name 2	98.605257
Pipeline Notes	98.431689
Ash Impoundment Status	98.034962
FERC Cogeneration Docket Number	97.229110
Natural Gas Pipeline Name 1	91.086040
FERC Exempt Wholesale Generator Docket Number	90.577734
Natural Gas LDC Name	90.422762
Name of Water Source	73.208530
FERC Small Power Producer Docket Number	70.654600
Liquefied Natural Gas Storage	53.576742
Ash Impoundment Lined?	46.776593
Natural Gas Storage	46.547235
Ash Impoundment?	40.317382
Transmission or Distribution System Owner State	5.560377

```
Duplicate rows:
df1 duplicates: 0
df2 duplicates: 0
```

Data Preparation & Merge Strategy

We combine:

- **EIA-923 generation data (df1)**: plant-level generation values by fuel type
- **EIA-860 plant metadata (df2)**: plant location fields (State, County)

Merge key:

- `df1['Plant Id']` ↔ `df2['Plant Code']`

Before merging, we standardize key formats and verify whether `Plant Code` is unique in the metadata table.

We keep only the columns needed for:

- Joining generation records to plant metadata (Plant Id ↔ Plant Code)
- Filtering to Ohio (Plant State)
- Quantifying output (Net Generation)

- Stratifying by fuel type (MER Fuel Type Code)

This keeps the workflow focused and reduces noise during checks and merging.

In [535...

```
display(df1[['Plant Id', 'Plant Name']].head())
display(df2[['Plant Code', 'Plant Name', 'State', 'County']].head())
```

	Plant Id	Plant Name
0	1	Sand Point
1	1	Sand Point
2	2	Bankhead Dam
3	3	Barry
4	3	Barry

	Plant Code	Plant Name	State	County
0	1	Sand Point	AK	Aleutians East
1	2	Bankhead Dam	AL	Tuscaloosa
2	3	Barry	AL	Mobile
3	4	Walter Bouldin Dam	AL	Elmore
4	7	Gadsden	AL	Etowah

In [536...

```
# Keeping only the columns we need
df1_sub = df1[['Plant Id', 'Plant State', 'MER\nFuel Type Code', 'Net Generation\n(
df2_sub = df2[['Plant Code', 'State', 'County']].copy()

df1_sub.info(), df2_sub.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17964 entries, 0 to 17963
Data columns (total 4 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Plant Id                          17964 non-null  int64
 1   Plant State                       17963 non-null  object
 2   MER
Fuel Type Code                17964 non-null  object
 3   Net Generation
(Megawatthours)  17964 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 561.5+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16132 entries, 0 to 16131
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Plant Code  16132 non-null  int64
 1   State       16132 non-null  object
 2   County      16108 non-null  object
dtypes: int64(1), object(2)
memory usage: 378.2+ KB
```

Out[536…

```
(None, None)
```

In [537…

```
print("Missing Plant Id in df1_sub:", df1_sub['Plant Id'].isna().sum())
print("Missing Plant Code in df2_sub:", df2_sub['Plant Code'].isna().sum())
```

```
Missing Plant Id in df1_sub: 0
Missing Plant Code in df2_sub: 0
```

Validate metadata uniqueness

Plant metadata should ideally be one row per plant (`Plant Code`). If duplicates exist in the metadata table, a merge can unintentionally become many-to-many and inflate the dataset. We check this explicitly before merging.

In [538…

```
dup_codes = df2_sub['Plant Code'].duplicated().sum()
print("Duplicate Plant Codes in df2_sub:", dup_codes)

if dup_codes > 0:
    display(df2_sub[df2_sub['Plant Code'].duplicated(keep=False)].sort_values('Plan
```

```
Duplicate Plant Codes in df2_sub: 0
```

Merge generation data with plant metadata

We perform a left join so that all generation records remain in the dataset.

In [539…

```
# Merging generation data with county information

merged = pd.merge(
    df1_sub,
```

```
    df2_sub,
    left_on='Plant Id',
    right_on='Plant Code',
    how='left',
    validate='m:1',
    indicator=True
)

print("Rows before merge:", len(df1_sub))
print("Rows after merge:", len(merged))
print("Merge indicator counts:")
print(merged['_merge'].value_counts())

print("Missing County:", merged['County'].isna().sum())
```

```
Rows before merge: 17964
Rows after merge: 17964
Merge indicator counts:
_merge
both          17626
left_only       338
right_only        0
Name: count, dtype: int64
Missing County: 338
```

Merge check summary

The merge preserves all generation records and does not introduce duplicate rows. A total of 338 generation rows do not match plant metadata, which corresponds exactly to the number of missing county values. These unmatched records will be reassessed after filtering to Ohio.

In [540…

```
merged = merged.rename(columns={
    'Plant Id': 'plant_id',
    'Plant State': 'plant_state',
    'MER\nFuel Type Code': 'fuel_code',
    'Net Generation\n(Megawatthours)': 'net_generation_mwh',
    'Plant Code': 'plant_code',
    'State': 'state',
    'County': 'county'
})

display(merged.sample(3, random_state=1))
```

	plant_id	plant_state	fuel_code	net_generation_mwh	plant_code	state	county
3315	6484	OR	HYC	1101.000	6484.0	OR	Deschutes
11001	60151	CA	SUN	2302.000	60151.0	CA	Los Angeles
6411	54780	IL	NG	67553.463	54780.0	IL	Champaign

Ohio Subset

The focus of this analysis is Ohio.
We therefore restrict the merged dataset to plants reported in Ohio before proceeding with exploratory analysis.

In [541…

```
oh = merged[merged['plant_state'] == 'OH'].copy()

print("Total Ohio rows:", len(oh))
print("Unique Ohio plants:", oh['plant_id'].nunique())
print("Missing county values in Ohio:", oh['county'].isna().sum())
print("\nFuel codes in Ohio (top 15):")
display(oh['fuel_code'].value_counts().head(5))
display(oh['fuel_code'].value_counts().tail(5))
```

```
Total Ohio rows: 304
Unique Ohio plants: 198
Missing county values in Ohio: 13

Fuel codes in Ohio (top 15):
```

fuel_code	count
NG	80
DFO	72
SUN	60
COL	27
WND	23

dtype: int64

fuel_code	count
ORW	5
PC	2
NUC	2
WOO	1
WOC	1

dtype: int64

Ohio contains multiple generation records per plant, reflecting different fuel types or reporting entries.

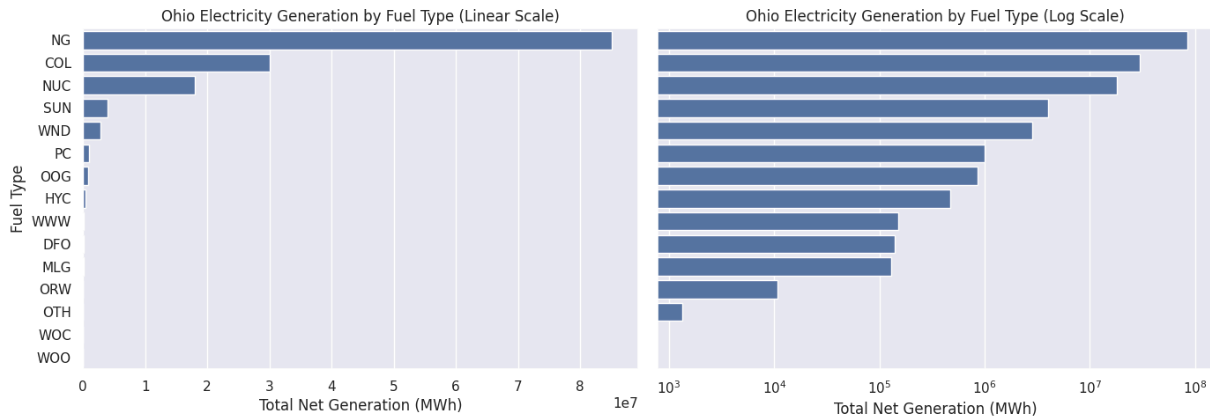
A small number of Ohio records lack county information, which will be handled explicitly during aggregation.

Fuel Mix in Ohio

We begin by examining total net generation by fuel type to understand Ohio's energy composition.

In [542…

```
fuel_mix = (
    oh.groupby('fuel_code')['net_generation_mwh']
      .sum()
      .sort_values(ascending=False)
)

fig, axes = plt.subplots(1, 2, figsize=(14, 5), sharey=True)

# Linear scale
sns.barplot(
    x=fuel_mix.values,
    y=fuel_mix.index,
    orient='h',
    ax=axes[0]
)
axes[0].set_xlabel("Total Net Generation (MWh)")
axes[0].set_ylabel("Fuel Type")
axes[0].set_title("Ohio Electricity Generation by Fuel Type (Linear Scale)")

# Log scale
sns.barplot(
    x=fuel_mix.values,
    y=fuel_mix.index,
    orient='h',
    ax=axes[1]
)
axes[1].set_xscale('log')
axes[1].set_xlabel("Total Net Generation (MWh)")
axes[1].set_title("Ohio Electricity Generation by Fuel Type (Log Scale)")

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



Ohio electricity generation spans multiple orders of magnitude across fuel types.

Natural gas is the dominant source of electricity, followed by coal and nuclear generation at lower but still substantial levels.

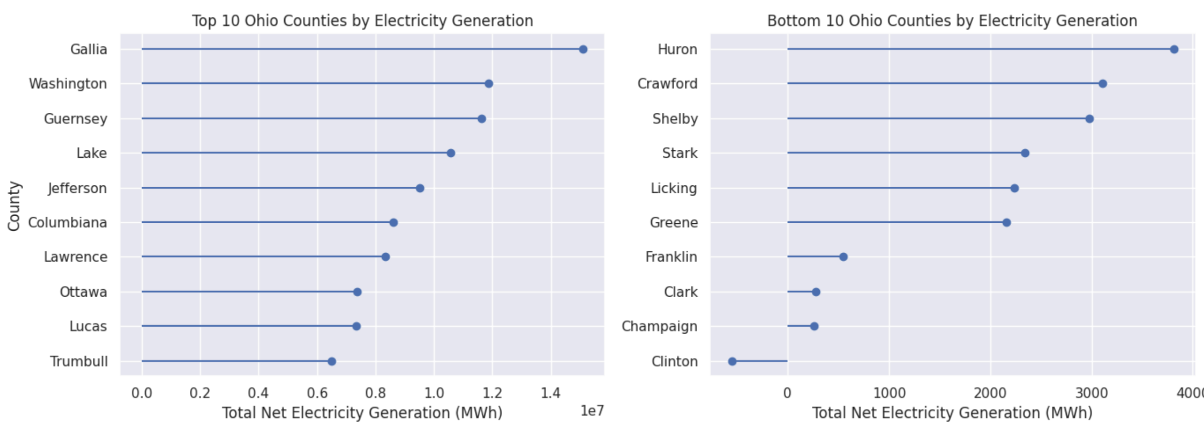
Smaller fuel categories contribute electricity at much lower scales, which becomes visible when using a logarithmic scale.

This distribution indicates a fuel mix that is heavily concentrated in a few dominant sources rather than evenly spread across fuel types.

In [543…

```
county_gen = (
    oh.dropna(subset=['county'])
      .groupby('county')['net_generation_mwh']
      .sum()
      .sort_values(ascending=False)
)

n = 10

top_counties = county_gen.sort_values(ascending=False).head(n)
bottom_counties = county_gen.sort_values(ascending=True).head(n)


fig, axes = plt.subplots(1, 2, figsize=(14, 5), sharex=False)

# -------- Top N counties --------
axes[0].hlines(
    y=top_counties.index,
    xmin=0,
    xmax=top_counties.values
)
axes[0].plot(
    top_counties.values,
    top_counties.index,
    'o'
)
axes[0].invert_yaxis()

axes[0].set_title(f"Top {n} Ohio Counties by Electricity Generation")
axes[0].set_xlabel("Total Net Electricity Generation (MWh)")
```

```python
axes[0].set_ylabel("County")

# -------- Bottom N counties --------
axes[1].hlines(
    y=bottom_counties.index,
    xmin=0,
    xmax=bottom_counties.values
)
axes[1].plot(
    bottom_counties.values,
    bottom_counties.index,
    'o'
)

axes[1].set_title(f"Bottom {n} Ohio Counties by Electricity Generation")
axes[1].set_xlabel("Total Net Electricity Generation (MWh)")

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



Electricity generation in Ohio is highly uneven across counties. The left panel shows that a small group of counties produces very large amounts of electricity, with the top counties contributing on the order of tens of millions of megawatt-hours.

In contrast, the right panel highlights counties whose electricity generation is several orders of magnitude smaller, in some cases only a few thousand megawatt-hours.

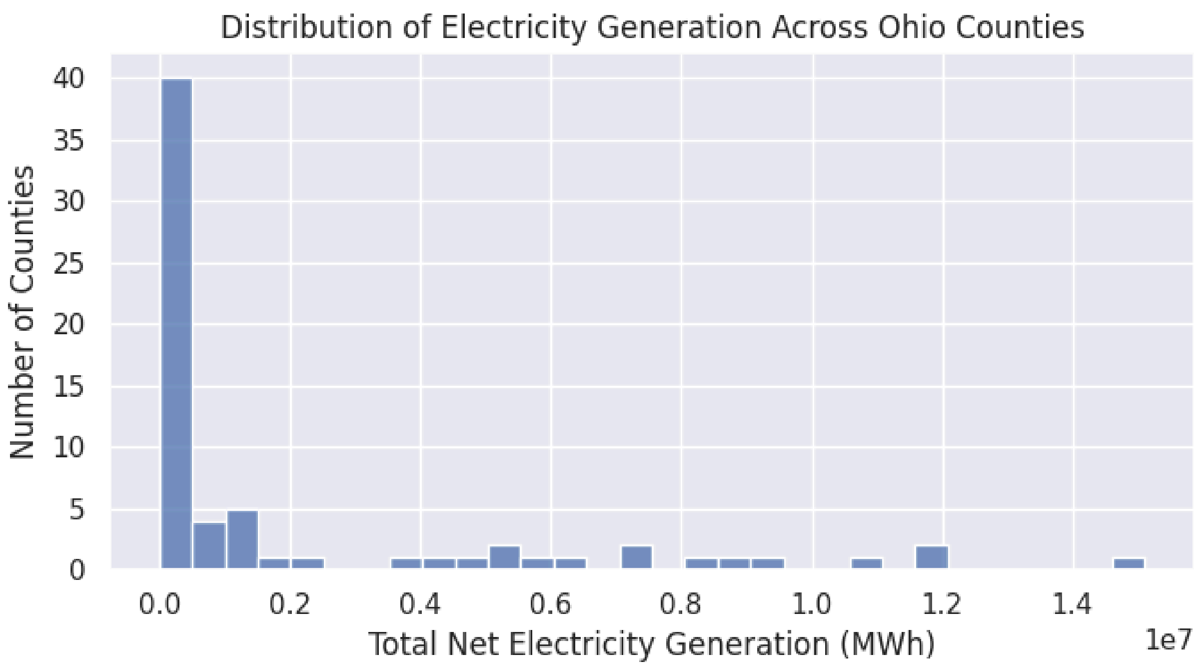
Clinton county exhibits negative total net electricity generation, as shown in the lower tail of the distribution. This arises from how net generation is reported, reflecting plant-level consumption and accounting adjustments rather than physical “negative production.”

Together, these panels demonstrate a strong disparity between the highest- and lowest-producing counties, indicating substantial geographic concentration of electricity generation rather than uniform distribution across the state.

In [544…

```python
plt.figure(figsize=(7, 4))
sns.histplot(county_gen.values, bins=30)

plt.xlabel("Total Net Electricity Generation (MWh)")
plt.ylabel("Number of Counties")
```

```python
plt.title("Distribution of Electricity Generation Across Ohio Counties")

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



The distribution of county-level electricity generation is strongly right-skewed.

Most counties generate relatively small amounts of electricity, while a small number of counties account for very large generation levels.

Together with the top–bottom comparison, this confirms a pronounced head–tail structure and highlights strong geographic concentration of electricity generation infrastructure across Ohio.

In [545…

```python
county_gen.describe()
```

Out[545...

	net_generation_mwh
count	6.700000e+01
mean	2.118240e+06
std	3.611296e+06
min	-5.520000e+02
25%	1.707650e+04
50%	1.821090e+05
75%	1.953597e+06
max	1.510928e+07

dtype: float64

Handling Missing County Information

A small number of Ohio records were missing county information.

In [546...

```
oh.head(3)
```

Out[546...

	plant_id	plant_state	fuel_code	net_generation_mwh	plant_code	state	county	_
2141	2828	OH	COL	9461214.000	2828.0	OH	Jefferson	
2142	2828	OH	DFO	35910.984	2828.0	OH	Jefferson	
2143	2830	OH	OTH	-522.000	2830.0	OH	Clermont	

In [547...

```
oh[oh['county'].isna()]['plant_id'].unique()
```

Out[547...

```
array([ 8867, 99999])
```

In [548...

```
display(df1[df1['Plant Id'] ==99999]['Plant Name'].unique())
display(df1[df1['Plant Id'] ==8867]['Plant Name'].unique())
```

```
array(['State-Fuel Level Increment'], dtype=object)
array(['Warrenton Terminal'], dtype=object)
```

In [549...

```
# Removing non-physical state-level adjustment record
oh = oh[oh['plant_id'] != 99999]
```

In [550...

```
oh = oh[oh['plant_id'] != 8867]
```

In [551...

```
oh.isna().sum()
```

Out[551…

	0
plant_id	0
plant_state	0
fuel_code	0
net_generation_mwh	0
plant_code	0
state	0
county	0
_merge	0

dtype: int64

Inspection of the plant names associated with missing county records confirms that some of these entries do not correspond to physical electricity generation facilities.

Plant Id 99999 represents a State-Fuel Level Increment, which is an accounting-level adjustment rather than a plant located in a specific county. Plant Id 8867 corresponds to Warrenton Terminal, does not appear with county-level plant metadata. Because it does not map to a physical plant location, it is treated as a non-plant reporting entry and excluded from county-based analysis.

Because these entries do not represent county-based electricity generation, they are excluded from the Ohio dataset.

After their removal, all remaining Ohio records have valid county information.

Duplicate Record Checks

Before constructing features for clustering, we check whether any rows are exact duplicates across key fields.

Exact duplicates in this case would indicate redundant records rather than legitimate multiple observations.

In [552…

```
dup_rows = oh[
    oh.duplicated(
        subset=['plant_id', 'fuel_code', 'net_generation_mwh', 'county'],
        keep=False
    )
]

dup_rows
```

Out[552...

	plant_id	plant_state	fuel_code	net_generation_mwh	plant_code	state	county	_
8964	57929	OH	COL	0.0	57929.0	OH	Hamilton	
8966	57929	OH	NG	0.0	57929.0	OH	Hamilton	
8968	57929	OH	COL	0.0	57929.0	OH	Hamilton	
8970	57929	OH	NG	0.0	57929.0	OH	Hamilton	

In [553...

```
oh = oh.drop_duplicates(
    subset=['plant_id', 'fuel_code', 'net_generation_mwh', 'county']
)
```

The duplicate records are identical across plant ID, fuel type, net generation, and county.

These rows represent redundant entries rather than distinct observations.

The duplicate records are therefore removed to avoid redundancy in subsequent analysis.

Feature Preparation for Unsupervised Analysis

To explore structural patterns across energy facilities, we construct a plant-level feature representation based on generation characteristics. This representation will be used for clustering and dimensionality reduction.

In [554...

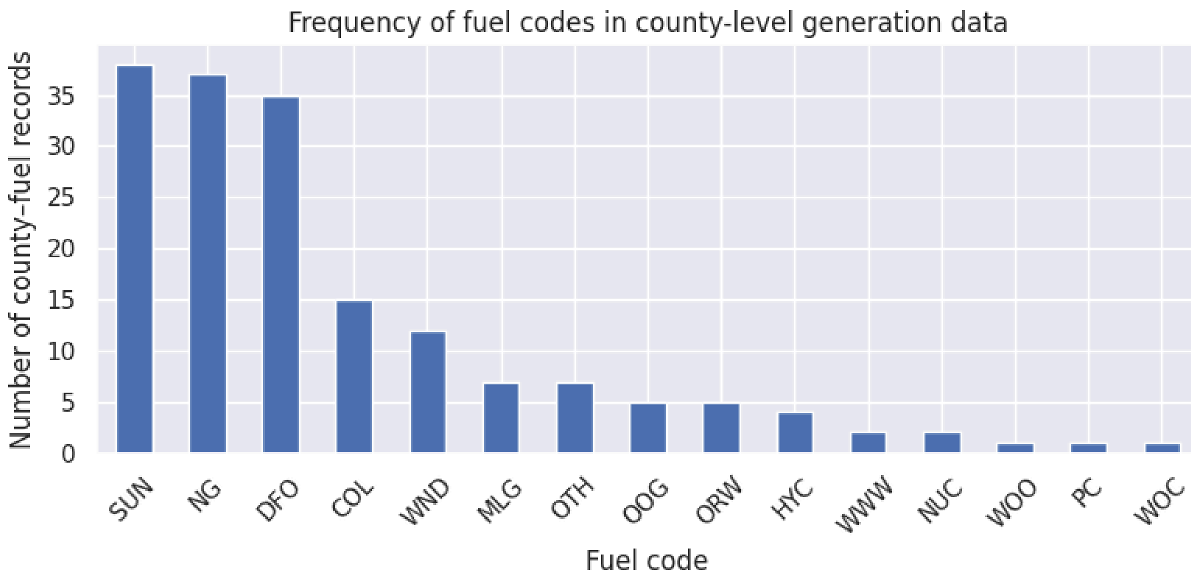
```
county_fuel = (
    oh
    .groupby(['county', 'fuel_code'], as_index=False)
    .agg(
        total_generation_mwh=('net_generation_mwh', 'sum'),
        n_records=('net_generation_mwh', 'count')
    )
)

county_fuel.head(5)
```

Out[554...

	county	fuel_code	total_generation_mwh	n_records
0	Ashtabula	MLG	16144.000	1
1	Ashtabula	NG	165965.000	2
2	Auglaize	COL	0.000	1
3	Auglaize	DFO	218.391	1
4	Auglaize	NG	131.609	1

In [555…

```
plt.figure(figsize=(8,4))
county_fuel['fuel_code'].value_counts().plot(kind='bar')
plt.title('Frequency of fuel codes in county-level generation data')
plt.xlabel('Fuel code')
plt.ylabel('Number of county-fuel records')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



The distribution of fuel codes across county-level generation records highlights clear differences in how energy sources are represented spatially across Ohio.

Solar (SUN), natural gas (NG), and distillate fuel oil (DFO) appear most frequently, indicating that these fuel types are present across a large number of counties. This reflects widespread geographic coverage rather than total energy contribution.

Coal (COL) and wind (WND) appear in a moderate number of counties, suggesting more spatial concentration. These fuel types may therefore play an important role in distinguishing counties with specific energy profiles in downstream clustering analyses.

Several fuel codes occur only rarely, forming a long tail in the distribution. Treating each of these fuels as a separate feature would introduce sparsity and potentially destabilize unsupervised learning methods. To address this, individual fuel codes are grouped into broader fuel categories, reducing dimensionality while preserving meaningful distinctions in energy composition.

In [556…

```
# Defining fuel group mapping
fuel_map = {
    # Core fuels
    'COL': 'Coal',
    'NG': 'Natural Gas',
    'NUC': 'Nuclear',
```

```python
    # Renewables
    'SUN': 'Renewables',
    'WND': 'Renewables',
    'HYC': 'Renewables',
    'MLG': 'Renewables',
    'WWW': 'Renewables',
    'WOO': 'Renewables',
    'WOC': 'Renewables',
    'ORW': 'Renewables',
    'OOG': 'Renewables',

    # Other fuels
    'DFO': 'Other fuels',
    'PC':  'Other fuels',
    'OTH': 'Other fuels'
}

county_fuel['fuel_group'] = county_fuel['fuel_code'].map(fuel_map)

# Keep only rows that mapped to a fuel group
county_fuel_grouped = county_fuel.dropna(subset=['fuel_group']).copy()

county_fuel_grouped.head()
```

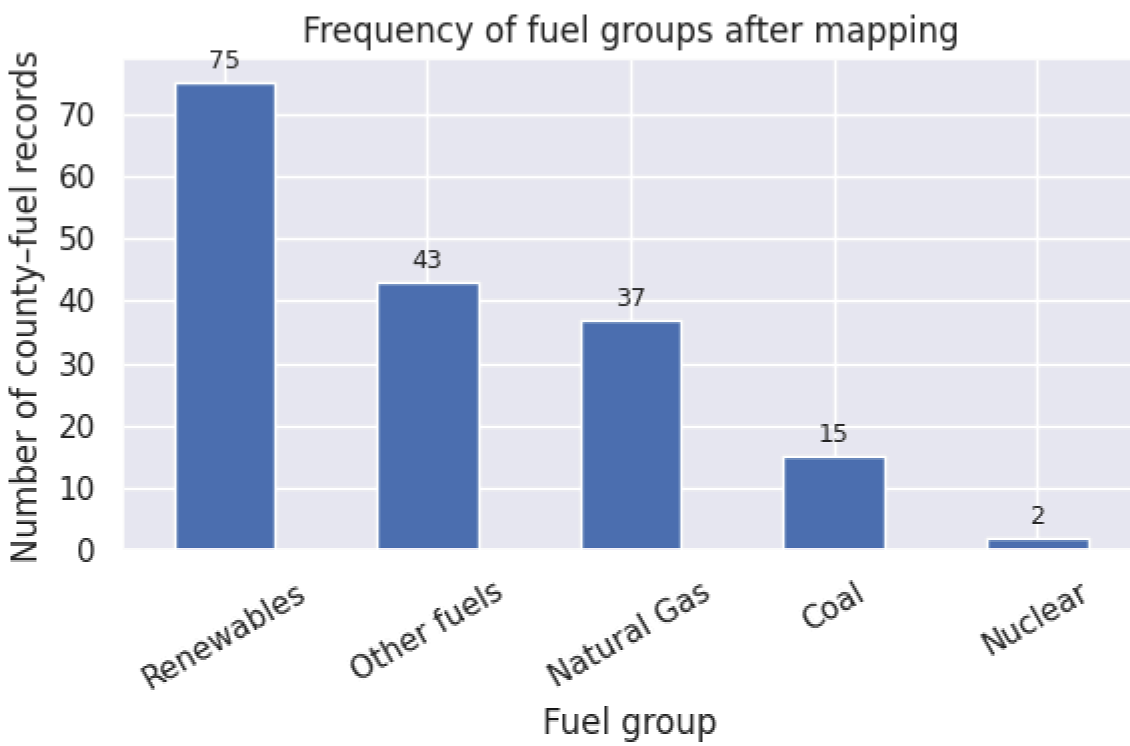
Out[556…

	county	fuel_code	total_generation_mwh	n_records	fuel_group
0	Ashtabula	MLG	16144.000	1	Renewables
1	Ashtabula	NG	165965.000	2	Natural Gas
2	Auglaize	COL	0.000	1	Coal
3	Auglaize	DFO	218.391	1	Other fuels
4	Auglaize	NG	131.609	1	Natural Gas

In [557…

```python
plt.figure(figsize=(6,4))
ax = county_fuel_grouped['fuel_group'].value_counts().plot(kind='bar')

plt.title('Frequency of fuel groups after mapping')
plt.xlabel('Fuel group')
plt.ylabel('Number of county-fuel records')
plt.xticks(rotation=30)

# Add value annotations on bars
for p in ax.patches:
    ax.annotate(
        f'{int(p.get_height())}',
        (p.get_x() + p.get_width() / 2, p.get_height()),
        ha='center',
        va='bottom',
        fontsize=9,
        xytext=(0, 3),
        textcoords='offset points'
    )
```

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



These grouped fuel categories form the basis for constructing county-level feature vectors used in unsupervised analyses.

In [558…

```
# Dropping raw fuel code column
df = county_fuel_grouped.drop(columns=['fuel_code']).copy()
df.head(5)
```

Out[558…

	county	total_generation_mwh	n_records	fuel_group
0	Ashtabula	16144.000	1	Renewables
1	Ashtabula	165965.000	2	Natural Gas
2	Auglaize	0.000	1	Coal
3	Auglaize	218.391	1	Other fuels
4	Auglaize	131.609	1	Natural Gas

Constructing County-Level Fuel Share Features

To compare counties based on their energy composition rather than absolute generation size, total generation is normalized at the county level. For each county, the share of electricity generation attributable to each fuel group is computed.

These fuel shares provide scale-invariant features that capture the relative energy mix of each county and are well suited for unsupervised learning methods.

In [559...

```
display(df[df['county'] == 'Clermont'])
display(df[df['county'] == 'Wood'])
```

	county	total_generation_mwh	n_records	fuel_group
18	Clermont	0.0	1	Coal
19	Clermont	0.0	1	Other fuels
20	Clermont	-522.0	1	Other fuels
21	Clermont	140212.0	1	Renewables

	county	total_generation_mwh	n_records	fuel_group
165	Wood	2457.854	2	Other fuels
166	Wood	991601.151	3	Natural Gas
167	Wood	-2591.000	1	Other fuels
168	Wood	42356.000	3	Renewables
169	Wood	3588.000	1	Renewables

Because fuel shares are intended to represent compositional contributions of energy sources, negative net generation values are not meaningful in this context.

To ensure interpretability and stability of fuel-share features, negative generation values are clipped to zero prior to normalization.

In [560...

```
# Remove negative net generation for composition analysis
df['generation_nonneg'] = df['total_generation_mwh'].clip(lower=0)

df['county_total_mwh'] = (
    df.groupby('county')['generation_nonneg']
      .transform('sum')
)

df['fuel_share'] = df['generation_nonneg'] / df['county_total_mwh']
```

In [561...

```
df.head()
```

Out[561…

	county	total_generation_mwh	n_records	fuel_group	generation_nonneg	county_tot…
0	Ashtabula	16144.000	1	Renewables	16144.000	1…
1	Ashtabula	165965.000	2	Natural Gas	165965.000	1…
2	Auglaize	0.000	1	Coal	0.000	…
3	Auglaize	218.391	1	Other fuels	218.391	…
4	Auglaize	131.609	1	Natural Gas	131.609	…

In [562…

```
# Sanity check: fuel shares should sum to 1 per county
fuel_share_check = (
    df.groupby('county')['fuel_share']
      .sum()
)

fuel_share_check.describe()
```

Out[562…

	fuel_share
count	67.000000
mean	0.985075
std	0.122169
min	0.000000
25%	1.000000
50%	1.000000
75%	1.000000
max	1.000000

dtype: float64

The fuel share values sum to approximately one for each county, confirming that the normalization step was applied correctly.

Creating the County–Fuel Feature Matrix

To prepare the data for unsupervised learning, the normalized fuel shares are reshaped into a county-level feature matrix. Each row represents a county, and each column corresponds to the share of electricity generation from a given fuel group.

Counties with no generation from a particular fuel group are assigned a value of zero.

This matrix forms the core input for subsequent scaling, dimensionality reduction, and clustering analyses.

In [563…

```
# Pivot to county × fuel group matrix
X = (
    df.pivot_table(
        index='county',
        columns='fuel_group',
        values='fuel_share',
        aggfunc='sum'   # collapse duplicates
    )
    .fillna(0)
)

X.head()
```

Out[563…

fuel_group	Coal	Natural Gas	Nuclear	Other fuels	Renewables
county					
Ashtabula	0.0	0.911350	0.0	0.000000	0.088650
Auglaize	0.0	0.003880	0.0	0.006438	0.989683
Brown	0.0	0.000000	0.0	0.000000	1.000000
Butler	0.0	0.935122	0.0	0.001020	0.063858
Carroll	0.0	1.000000	0.0	0.000000	0.000000

In [564…

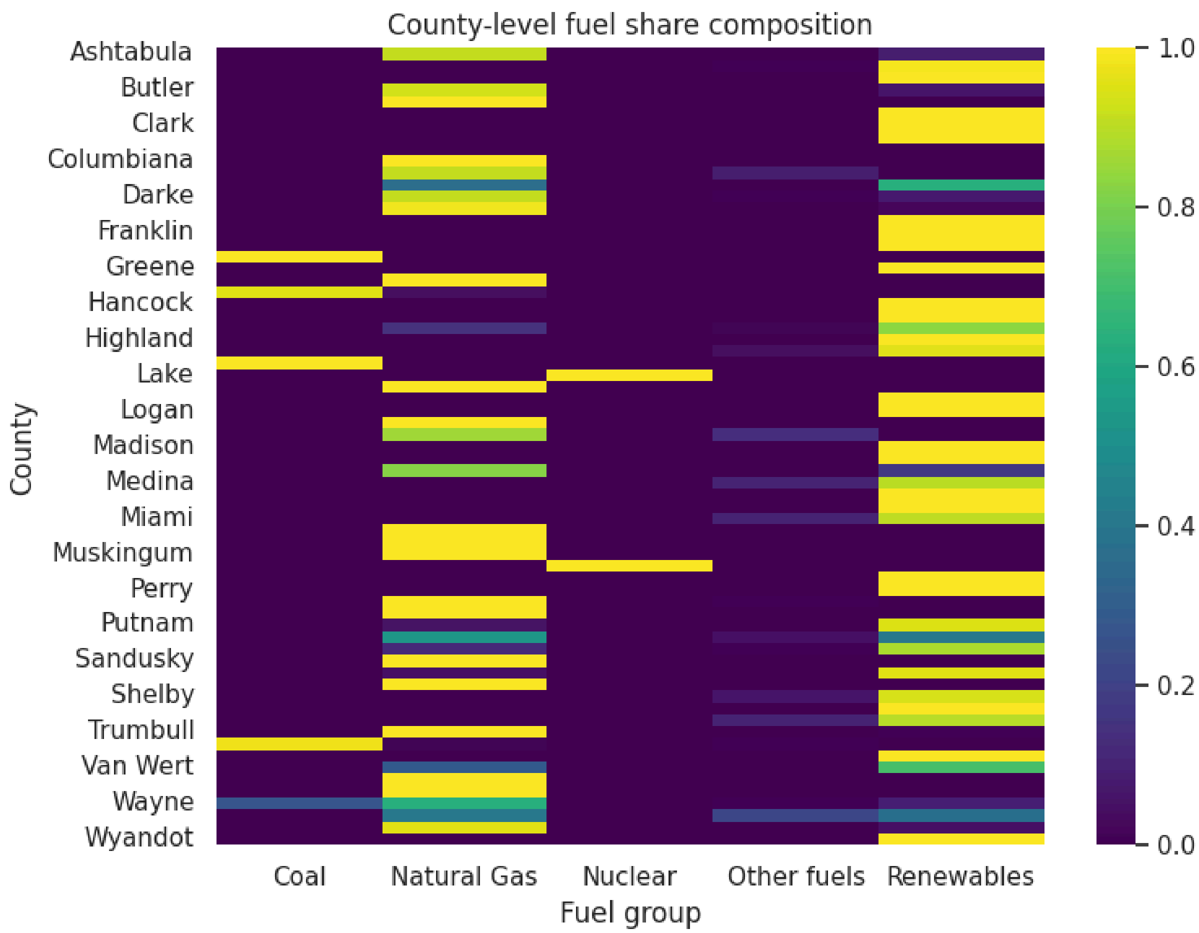
```
X.shape, X.columns
```

Out[564…

```
((67, 5),
 Index(['Coal', 'Natural Gas', 'Nuclear', 'Other fuels', 'Renewables'], dtype='obj
ect', name='fuel_group'))
```

In [565…

```
plt.figure(figsize=(8,6))
sns.heatmap(X, cmap='viridis')
plt.title('County-level fuel share composition')
plt.xlabel('Fuel group')
plt.ylabel('County')
plt.tight_layout()
plt.show()
```



The heatmap reveals strong heterogeneity in county-level energy composition. Many counties exhibit near-complete reliance on a single fuel group, reflecting the localized nature of energy infrastructure and generation assets.

Natural gas and renewables dominate the energy mix across most counties, while coal and nuclear generation are highly concentrated in a small number of locations.

The resulting feature matrix is sparse by design, with zero values indicating the absence of specific fuel types.

These patterns suggest that counties are likely to cluster according to dominant fuel sources. To ensure that no single fuel group disproportionately influences distance-based methods, feature scaling is applied in the next step prior to dimensionality reduction and clustering.

For readability, only a subset of county labels is shown on the heatmap.

In [566…

```
X.describe(include='all')
```

Out[566...

fuel_group	Coal	Natural Gas	Nuclear	Other fuels	Renewables
count	67.000000	67.000000	67.000000	67.000000	67.000000
mean	0.062702	0.371903	0.029849	0.014512	0.506108
std	0.235787	0.451754	0.171449	0.038802	0.470504
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.012740	0.000000	0.000000	0.639938
75%	0.000000	0.944291	0.000000	0.003781	1.000000
max	0.996219	1.000000	0.999969	0.222626	1.000000

Summary statistics of the county-level fuel share features further highlight the heterogeneity in Ohio’s energy composition.

Most fuel groups exhibit a median share of zero, indicating that many counties do not generate electricity from these sources at all.

In contrast, renewables show a high median value, reflecting their widespread presence across counties.

Natural gas and renewables display large variability, as indicated by their high standard deviations, suggesting substantial differences in reliance on these fuel sources across counties.

Coal and nuclear generation are highly concentrated, with near-unity maximum values but low mean shares.

In [567...

```
(X == 0).mean().sort_values()
```

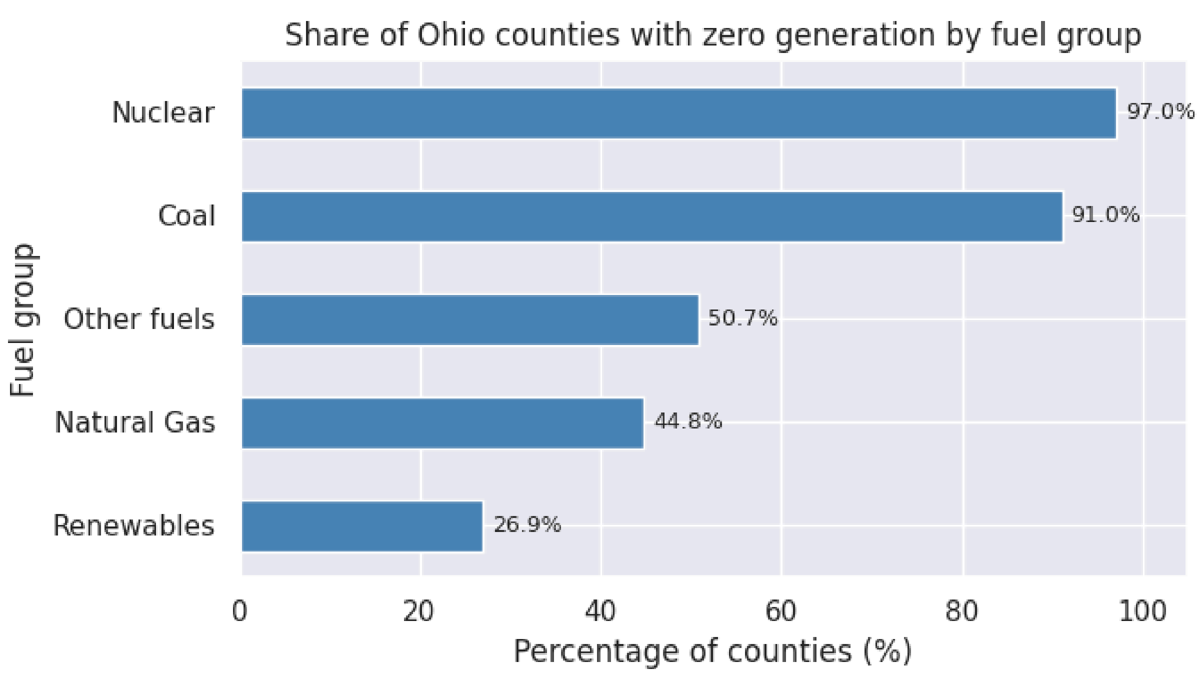
Out[567...

fuel_group	0
Renewables	0.268657
Natural Gas	0.447761
Other fuels	0.507463
Coal	0.910448
Nuclear	0.970149

dtype: float64

In [568…

```python
zero_share = (X == 0).mean().sort_values()

plt.figure(figsize=(7,4))
ax = zero_share.mul(100).plot(
    kind='barh',
    color='steelblue'
)

plt.title('Share of Ohio counties with zero generation by fuel group')
plt.xlabel('Percentage of counties (%)')
plt.ylabel('Fuel group')

# Add annotations
for i, v in enumerate(zero_share.mul(100)):
    ax.text(
        v + 1,
        i,
        f'{v:.1f}%',
        va='center',
        fontsize=9
    )

plt.xlim(0, 105)
plt.tight_layout()
plt.show()
```



- Nuclear energy is not present in approximately 97% of Ohio counties, indicating extreme spatial concentration of nuclear generation.
- Coal generation is absent in about 91% of counties, reflecting the limited number of coal-based generation sites.
- Natural gas generation is not present in roughly 45% of counties.

- Renewable generation is the most widespread, with fewer than 27% of counties exhibiting zero renewable generation.

In [569…

```
X.var().sort_values()
```

Out[569…

fuel_group	0
Other fuels	0.001506
Nuclear	0.029395
Coal	0.055595
Natural Gas	0.204082
Renewables	0.221374

dtype: float64

Feature Scaling

The county-level fuel share features exhibit substantial differences in sparsity and variance across fuel groups. Some fuel groups (e.g., renewables) are widespread with high variability, while others (e.g., coal and nuclear) are highly concentrated and mostly zero.

Because distance-based methods such as PCA, K-means, and t-SNE are sensitive to feature scale and variance, the feature matrix is standardized prior to dimensionality reduction and clustering. Standardization ensures that each fuel group contributes comparably to distance computations.

In [570…

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled = pd.DataFrame(X_scaled, index=X.index, columns=X.columns)
X_scaled.head(2)
```

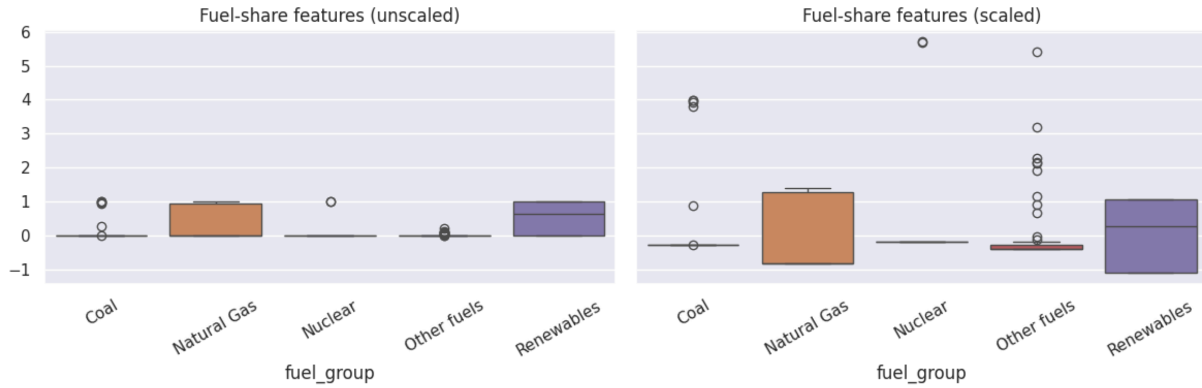
Out[570…

fuel_group	Coal	Natural Gas	Nuclear	Other fuels	Renewables
county					
Ashtabula	-0.267935	1.203127	-0.175412	-0.376831	-0.893953
Auglaize	-0.267935	-0.820804	-0.175412	-0.209669	1.035539

In [571…

```
fig, axes = plt.subplots(1, 2, figsize=(12,4), sharey=True)

# Before scaling
sns.boxplot(data=X, ax=axes[0])
axes[0].set_title('Fuel-share features (unscaled)')
axes[0].tick_params(axis='x', rotation=30)
```

```python
# After scaling
sns.boxplot(data=pd.DataFrame(X_scaled, columns=X.columns), ax=axes[1])
axes[1].set_title('Fuel-share features (scaled)')
axes[1].tick_params(axis='x', rotation=30)

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



The comparison between unscaled and scaled fuel-share features illustrates the impact of standardization. Prior to scaling, fuel groups differ substantially in spread and concentration, with renewables and natural gas exhibiting much larger variability than coal or nuclear.

After standardization, all features are centered and scaled to comparable variance. This prevents any single fuel group from disproportionately influencing distance-based methods, while preserving the relative structure of the data.

Principal Component Analysis (PCA)

Principal Component Analysis is applied to the scaled fuel-share feature matrix to reduce dimensionality while preserving the dominant patterns of variation across counties. PCA identifies orthogonal directions (principal components) that capture the largest sources of variance in the data.

This step serves two purposes:

1. To assess the intrinsic dimensionality of county-level energy composition.
2. To provide a lower-dimensional representation for visualization and clustering.

In [572...

```python
pca = PCA()
X_pca = pd.DataFrame(pca.fit_transform(X_scaled))

explained_variance = pca.explained_variance_ratio_
explained_variance
```

Out[572...

```
array([0.35848021, 0.23426807, 0.20956847, 0.19186611, 0.00581714])
```

In [573...

```python
# Explained variance
explained_var = pd.Series(
```

```
    pca.explained_variance_ratio_,
    index=[f'PC{i+1}' for i in range(len(pca.explained_variance_ratio_))]
)

explained_var.cumsum()
```

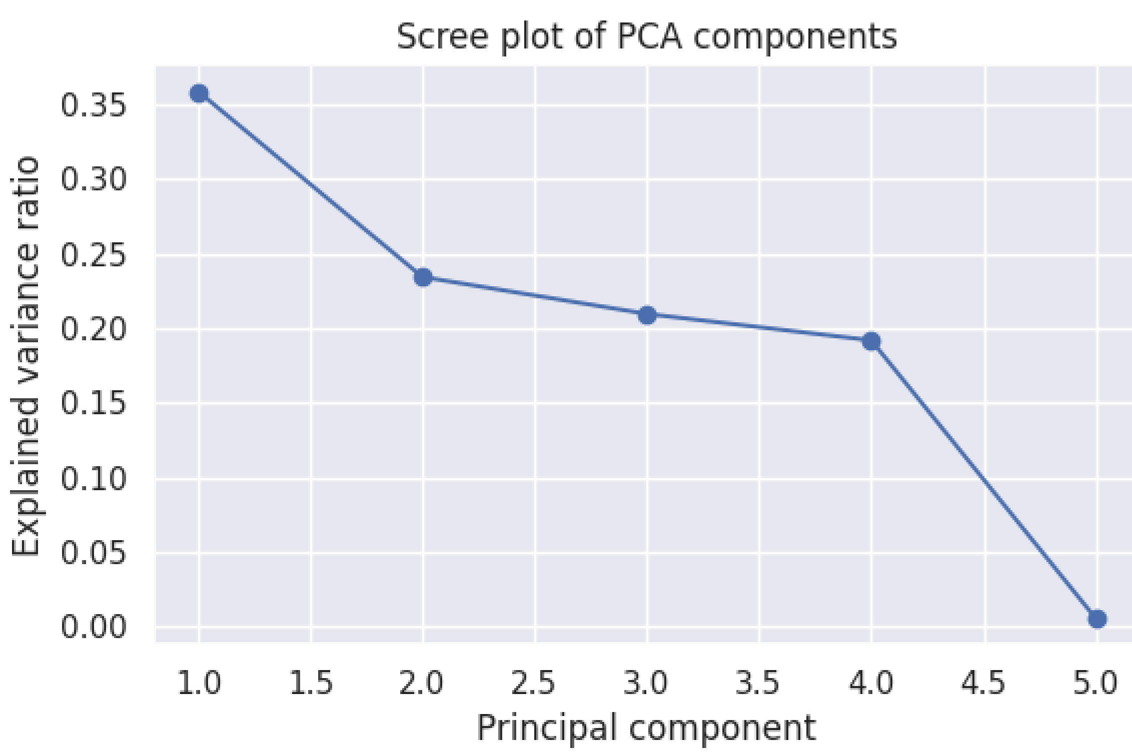
Out[573…

	0
PC1	0.358480
PC2	0.592748
PC3	0.802317
PC4	0.994183
PC5	1.000000

dtype: float64

In [574…

```
plt.figure(figsize=(6,4))
plt.plot(
    range(1, len(explained_variance) + 1),
    explained_variance,
    marker='o'
)
plt.xlabel('Principal component')
plt.ylabel('Explained variance ratio')
plt.title('Scree plot of PCA components')
plt.tight_layout()
plt.show()
```

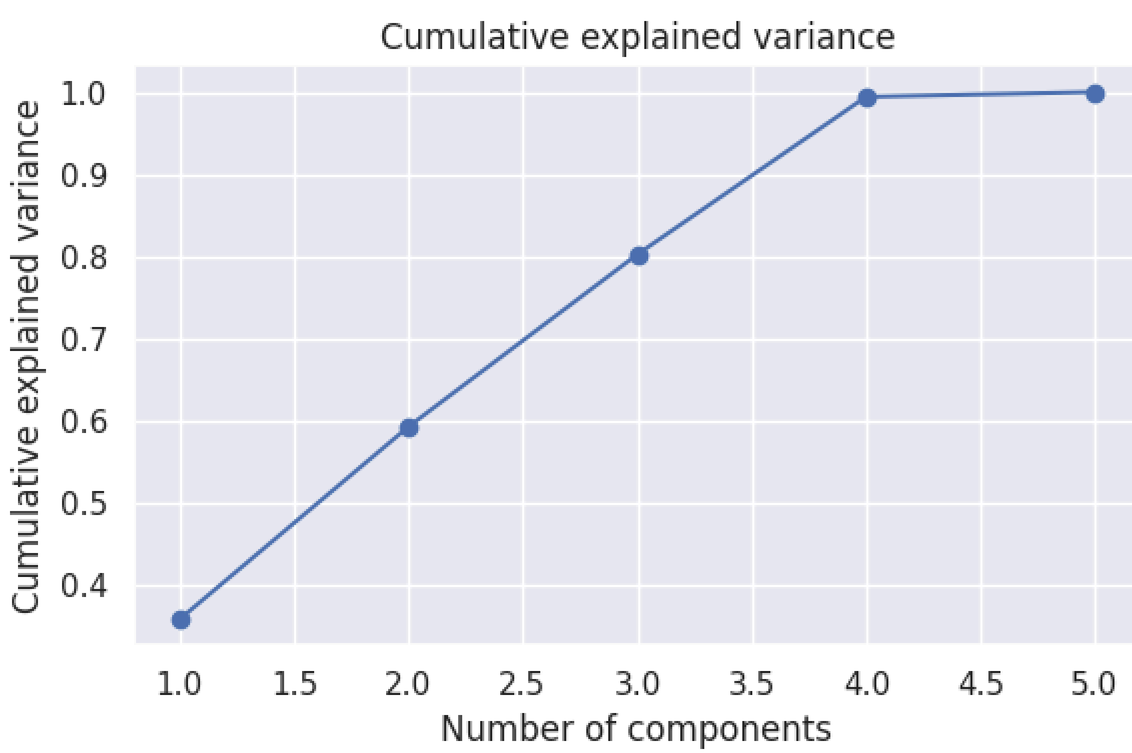


The scree plot shows that the first principal component accounts for approximately 35% of the total variance in county-level fuel composition, indicating a strong dominant axis of variation. Subsequent components explain progressively smaller, but still meaningful, proportions of variance, with no sharp elbow point.

This gradual decay suggests that multiple dimensions contribute to differences in county energy profiles.

In [575…

```
plt.figure(figsize=(6,4))
plt.plot(
    range(1, len(explained_variance) + 1),
    explained_variance.cumsum(),
    marker='o'
)

plt.xlabel('Number of components')
plt.ylabel('Cumulative explained variance')
plt.title('Cumulative explained variance')
plt.tight_layout()
plt.show()
```



Because fuel shares sum to one, the county-level energy mix lies in a four-dimensional subspace. Accordingly, PCA captures 100% of the variance using four components.

In [576…

```
loadings = pd.DataFrame(
    pca.components_.T,
    index=X.columns,
    columns=[f'PC{i+1}' for i in range(X.shape[1])]
)
```

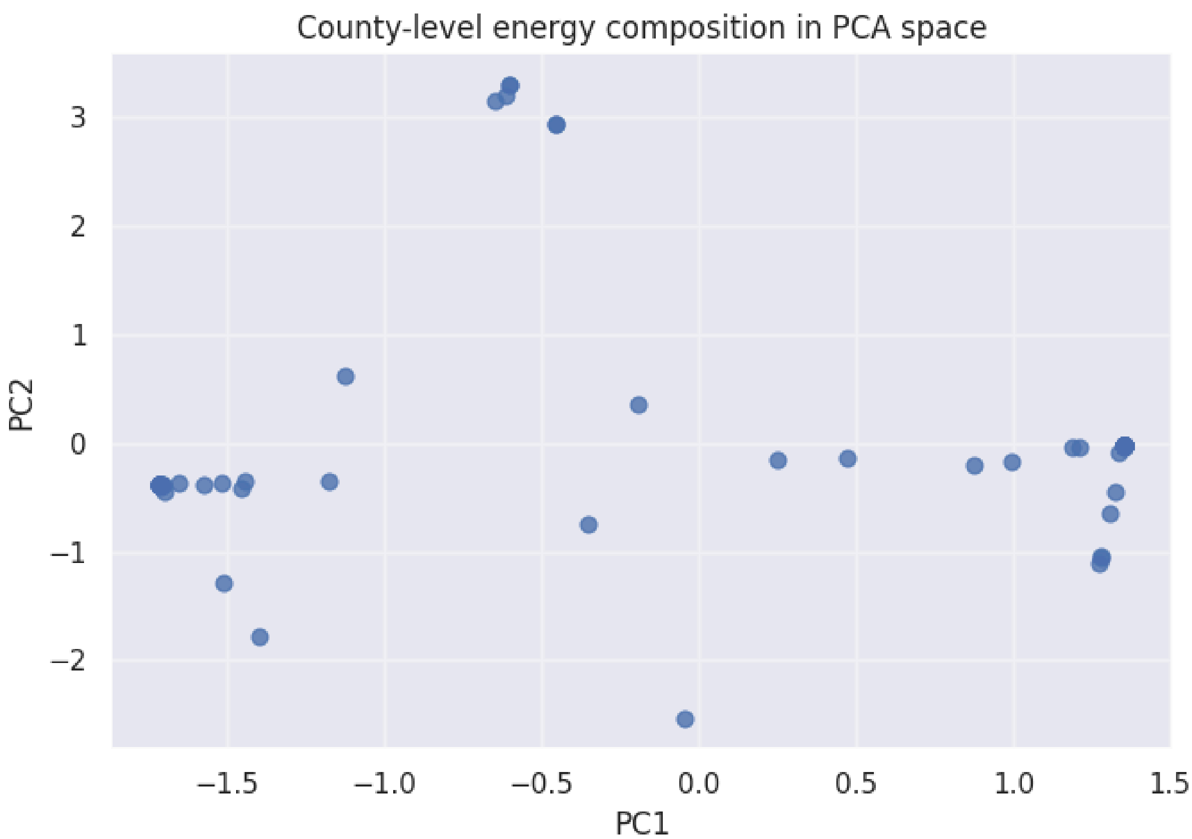
```
loadings
```

Out[576...

fuel_group	PC1	PC2	PC3	PC4	PC5
Coal	-0.097300	0.700721	-0.597861	0.177233	0.332677
Natural Gas	-0.683103	-0.327943	0.030257	-0.161693	0.631477
Nuclear	-0.044508	0.439242	0.771907	0.387976	0.242321
Other fuels	0.030323	-0.423390	-0.213973	0.878477	0.048115
Renewables	0.721805	-0.171031	0.004629	-0.142113	0.655384

In [577...

```
pca_df = X_pca.iloc[:, :2].copy()
pca_df.columns = ['PC1', 'PC2']
pca_df.index = X.index

plt.figure(figsize=(7,5))
plt.scatter(pca_df['PC1'], pca_df['PC2'], s=40, marker='o', alpha=0.8)

plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('County-level energy composition in PCA space')
plt.grid(True, alpha=0.3)

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



This visualization is intended as a diagnostic view of the dominant axes of variation.

t-SNE Visualization of County-Level Energy Composition

While PCA captures global variance structure, it is a linear method and may not fully reveal local similarities between counties. To better visualize neighborhood-level structure in the data, t-distributed Stochastic Neighbor Embedding (t-SNE) is applied to the scaled fuel-share features.

t-SNE is used here as a visualization tool to explore local grouping patterns among counties.

In [578…

```
X_pca_4 = X_pca.iloc[:, :4].copy()
X_pca_4.columns = ['PC1', 'PC2', 'PC3', 'PC4']
X_pca_4.head(2)
```

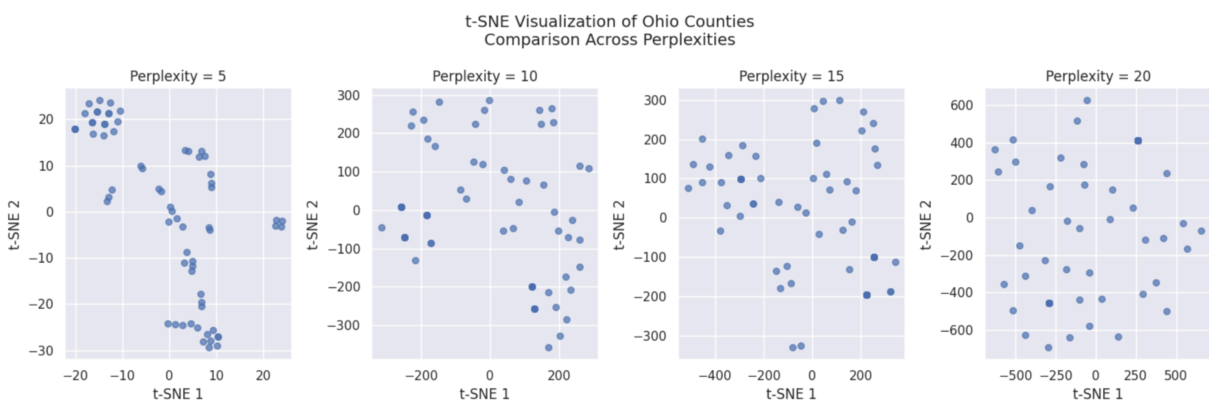
Out[578…

	PC1	PC2	PC3	PC4
0	-1.444669	-0.346914	0.137683	-0.514075
1	1.335670	-0.083956	0.049609	-0.314177

In [579…

```
# Trying a few perplexity values
perplexities = [5, 10, 15, 20]

tsne_results = {}
```

```python
for p in perplexities:
    tsne = TSNE(
        n_components = 2, perplexity = p, random_state =1, init = 'pca', learning_r
    tsne_results[p] = tsne.fit_transform(X_pca_4)


tsne_dfs = {}

for p, coords in tsne_results.items():
    tsne_dfs[p] = pd.DataFrame(coords, index = X_pca_4.index, columns = ['tSNE1', '


# visualization
fig, axes = plt.subplots(1, 4, figsize=(15, 5), sharex=False, sharey=False)

for ax, p in zip(axes, perplexities):
    ax.scatter(
        tsne_dfs[p]['tSNE1'],
        tsne_dfs[p]['tSNE2'],
        s=30,
        alpha=0.7
    )
    ax.set_title(f"Perplexity = {p}")
    ax.set_xlabel("t-SNE 1")
    ax.set_ylabel("t-SNE 2")

fig.suptitle("t-SNE Visualization of Ohio Counties\nComparison Across Perplexities"
plt.tight_layout()
plt.show()
```



To assess the robustness of the t-SNE visualization, multiple perplexity values were explored. Lower perplexities emphasize very local structure and result in tightly packed clusters, while higher perplexities produce more diffuse layouts that emphasize broader relationships.

A perplexity of 15 provides a balanced representation, preserving local similarity while maintaining a coherent global layout. This value is used for subsequent visual analysis.

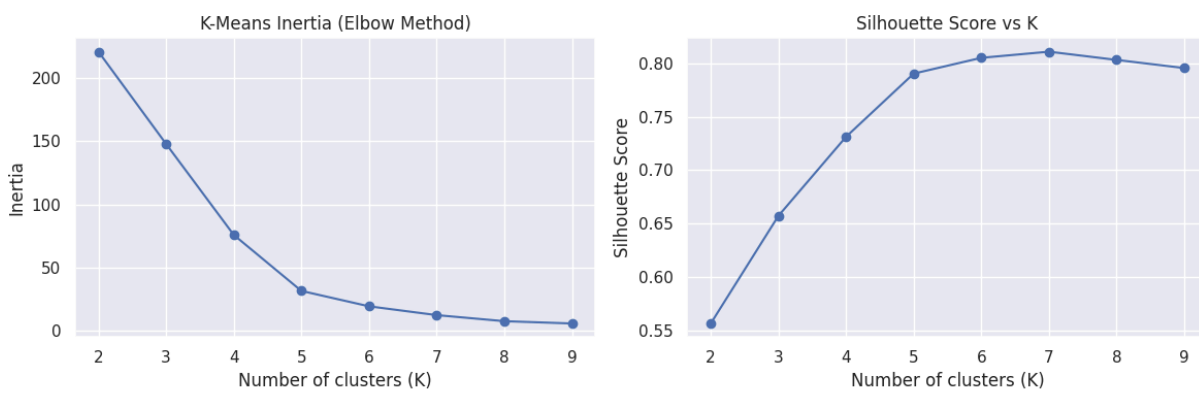
K-Means Clustering

In [580…

```
inertia = []
silhouette = []
K = range(2, 10)

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=1, n_init=20)
    labels = kmeans.fit_predict(X_pca_4)

    inertia.append(kmeans.inertia_)
    silhouette.append(silhouette_score(X_pca_4, labels))
```

In [581…

```
fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# Inertia (Elbow Method)
axes[0].plot(K, inertia, marker='o')
axes[0].set_title("K-Means Inertia (Elbow Method)")
axes[0].set_xlabel("Number of clusters (K)")
axes[0].set_ylabel("Inertia")
axes[0].grid(True)

# Silhouette Score
axes[1].plot(K, silhouette, marker='o')
axes[1].set_title("Silhouette Score vs K")
axes[1].set_xlabel("Number of clusters (K)")
axes[1].set_ylabel("Silhouette Score")
axes[1].grid(True)

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



Selecting the number of clusters

The elbow method is used as the primary criterion for selecting the number of clusters, as it highlights diminishing returns in within-cluster variance reduction as (K) increases. In this case, a clear elbow is observed around (K = 5), beyond which reductions in inertia become marginal.

The silhouette score is included as a secondary diagnostic to verify that the chosen value of (K) yields well-separated clusters. While the silhouette score continues to increase slightly for larger values of (K), this behavior reflects improved separation with additional clusters rather than a fundamentally better clustering structure.

Based on the elbow method and supported by the silhouette scores, (K = 5) is selected for the final K-means model.

Using $K = 5$, we fit the K-means model on the PCA-reduced feature space and assign each county to a cluster.

In [582…

```
# Fit final K-Means model (K = 5)
kmeans_final = KMeans(n_clusters=5, random_state=1, n_init=20)
kmeans_labels = kmeans_final.fit_predict(X_pca_4)

# Attach labels
km_df = X.copy()
km_df["KMeans_Cluster"] = kmeans_labels

# Quick check: cluster counts
km_df["KMeans_Cluster"].value_counts().sort_index()
```

Out[582…

	count
KMeans_Cluster	
0	32
1	24
2	4
3	5
4	2

dtype: int64

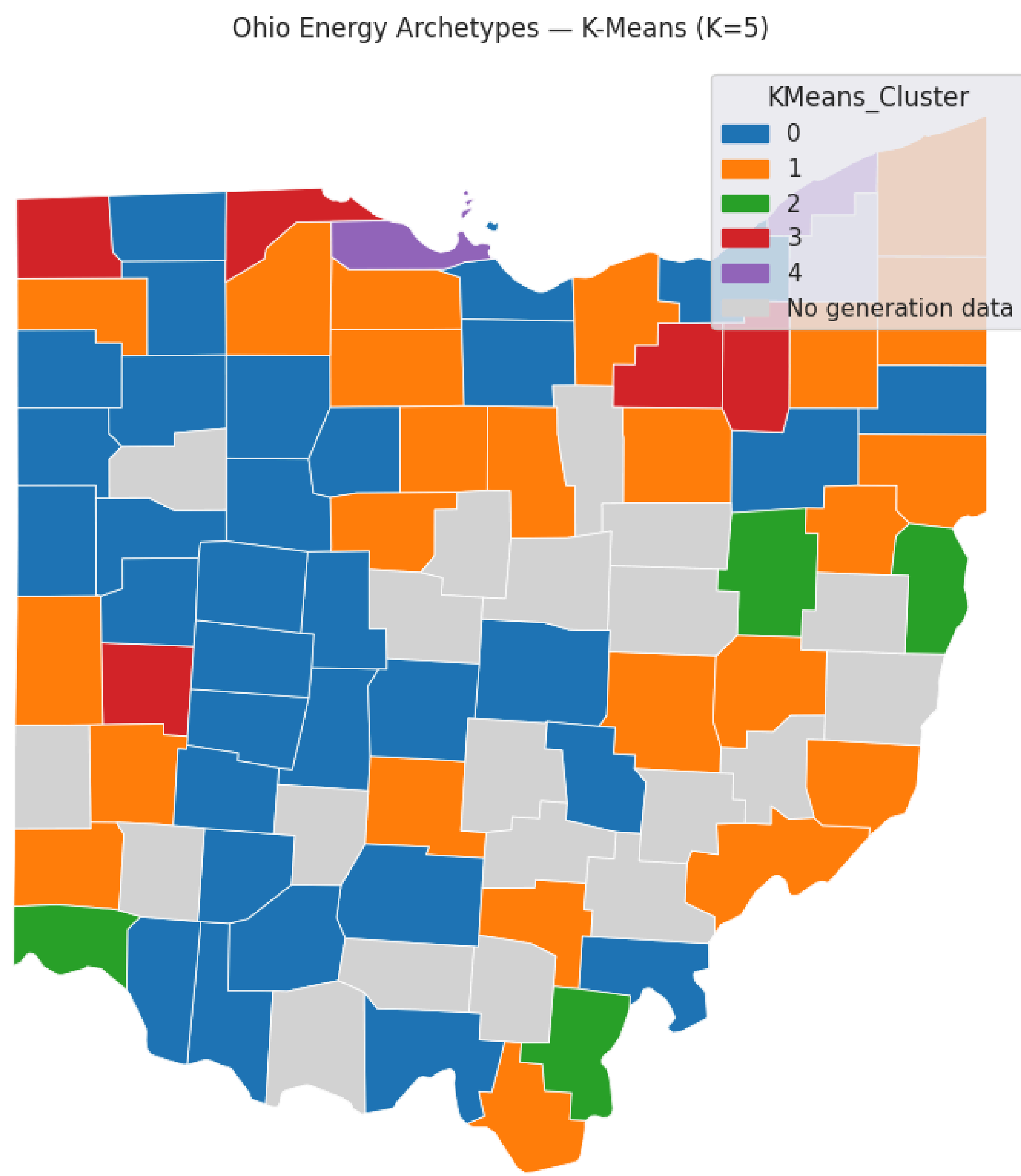
In [583…

```
def clean_name(s):
    return str(s).strip().lower()

base_map = ohio_map.copy()
base_map["county_clean"] = base_map["NAME"].apply(clean_name)

cluster_colors = {
    0: "#1f77b4",  # blue
    1: "#ff7f0e",  # orange
    2: "#2ca02c",  # green
    3: "#d62728",  # red
    4: "#9467bd"   # purple
}

def plot_cluster_map(cluster_df, cluster_col, title):
    # Build county->cluster table
    tmp = cluster_df[[cluster_col]].copy()
```

```
    tmp.index.name = "county"
    tmp = tmp.reset_index()
    tmp["county_clean"] = tmp["county"].apply(clean_name)

    # Merge onto geometry
    gdf = base_map.merge(
        tmp[["county_clean", cluster_col]],
        on="county_clean",
        how="left"
    )

    # Keep NaNs for missing counties
    gdf[cluster_col] = gdf[cluster_col].astype("Float64")

    # Discrete colormap in order 0..4
    cmap = ListedColormap([cluster_colors[i] for i in range(5)])

    fig, ax = plt.subplots(1, 1, figsize=(9, 10))

    gdf.plot(
        column=cluster_col,
        cmap=cmap,
        vmin=0, vmax=4,
        legend=False,
        edgecolor="white",
        linewidth=0.6,
        ax=ax,
        missing_kwds={"color": "lightgrey"}
    )

    # Legend
    handles = [mpatches.Patch(color=cluster_colors[i], label=str(i)) for i in range
    handles.append(mpatches.Patch(color="lightgrey", label="No generation data"))

    ax.legend(handles=handles, title=cluster_col, loc="upper right", frameon=True)

    ax.set_title(title, pad=12)
    ax.axis("off")
    plt.show()
```

In [584…

```
plot_cluster_map(
    km_df,
    "KMeans_Cluster",
    "Ohio Energy Archetypes — K-Means (K=5)"
)
```



Counties are grouped primarily according to dominant fuel composition, resulting in large regional patterns corresponding to renewables-dominant, natural-gas–dominant, coal-dominant, nuclear-dominant, and mixed-profile energy systems.

This representation emphasizes large-scale structural similarities in county-level energy composition and serves as a spatial visualization for the analysis.

In [585…

```
km_cluster_profile = km_df.groupby('KMeans_Cluster').mean()

km_cluster_profile.style.highlight_max(color = "lightgreen", axis = 0)
```

Out[585…

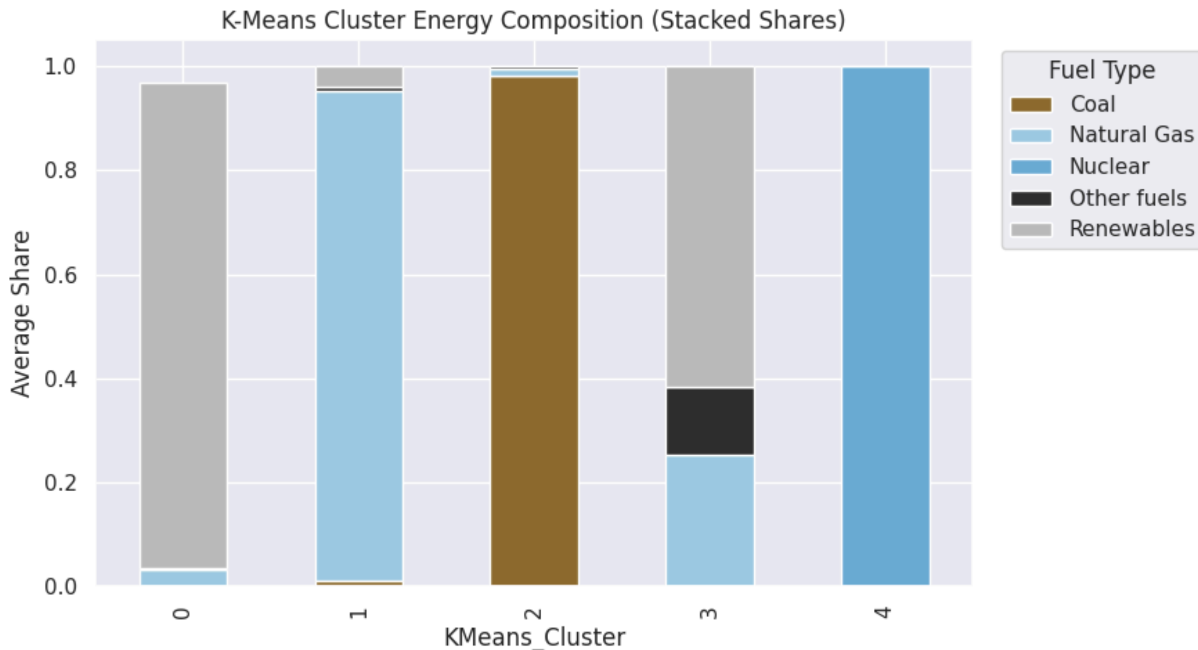
fuel_group	Coal	Natural Gas	Nuclear	Other fuels	Renewables
KMeans_Cluster					
0	0.000000	0.031715	0.000000	0.004169	0.932865
1	0.011381	0.941095	0.000000	0.006860	0.040664
2	0.981963	0.013442	0.000000	0.004523	0.000072
3	0.000000	0.252512	0.000000	0.131228	0.616260
4	0.000029	0.000016	0.999937	0.000018	0.000000

In [586…

```
fuel_colors = {
    "Coal":         "#8c6d31",
    "Natural Gas": "#9ecae1",
    "Nuclear":      "#6baed6",
    "Other fuels": "#2f2f2f",
    "Renewables":  "#bdbdbd"
}
```

In [587…

```
plot_df = km_cluster_profile.copy()

ax = plot_df.plot(
    kind="bar",
    stacked=True,
    figsize=(9, 5),
    color=[fuel_colors[c] for c in plot_df.columns]
)

ax.set_title("K-Means Cluster Energy Composition (Stacked Shares)")
ax.set_xlabel("KMeans_Cluster")
ax.set_ylabel("Average Share")
ax.legend(title="Fuel Type", bbox_to_anchor=(1.02, 1), loc="upper left")

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



The table above shows the mean energy composition for each cluster, allowing clusters to be interpreted as distinct energy-generation archetypes:

- **Cluster 0** is dominated by renewables, with negligible contributions from other fuel types.
- **Cluster 1** is strongly natural-gas–dominated, with minimal presence of other sources.
- **Cluster 2** represents coal-dominant counties, with coal accounting for nearly all generation.
- **Cluster 3** shows a mixed profile, combining renewables with a moderate share of natural gas and other fuels.
- **Cluster 4** corresponds to nuclear-dominant counties, with nuclear accounting for nearly all generation.

These profiles indicate that K-means successfully separates counties according to their dominant energy-generation patterns.

In [588…

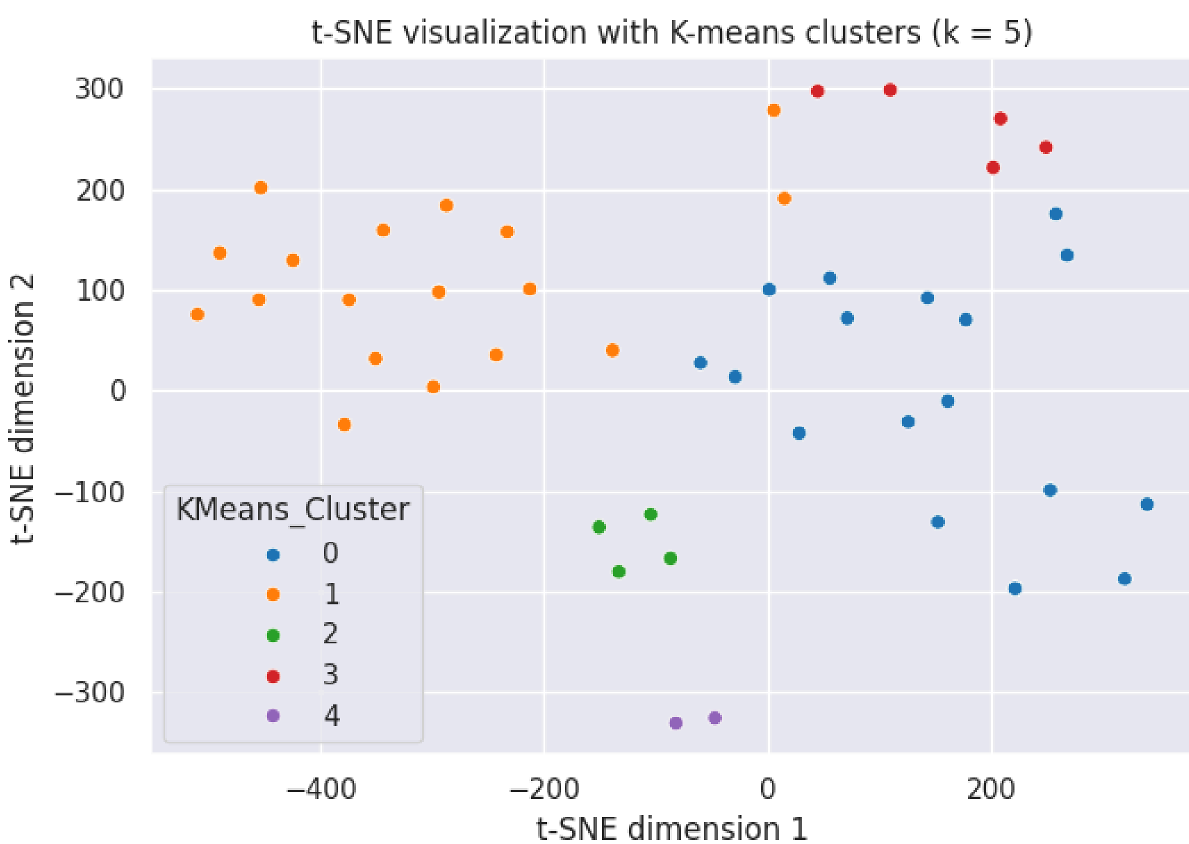
```
tsne_dfs[15].head()
```

Out[588…

	tSNE1	tSNE2
0	-489.627045	136.665329
1	28.520191	-42.466743
2	221.438126	-196.859604
3	-454.546173	90.260284
4	-293.622650	97.759186

In [589…

```
tsne_df = tsne_dfs[15].copy()

# Attach actual KMeans cluster labels
tsne_df["KMeans_Cluster"] = km_df["KMeans_Cluster"].values

plt.figure(figsize=(7, 5))
sns.scatterplot(
    data=tsne_df,
    x="tSNE1",
    y="tSNE2",
    hue="KMeans_Cluster",
    palette="tab10"
)

plt.title("t-SNE visualization with K-means clusters (k = 5)")
plt.xlabel("t-SNE dimension 1")
plt.ylabel("t-SNE dimension 2")
plt.legend(title="KMeans_Cluster")
plt.tight_layout()
plt.show()
```



K-Medoids Clustering (K = 5)

In [590…

```
# K-Medoids on scaled original features (consistent with K-Means)
kmedoids = KMedoids(n_clusters=5, metric="euclidean", random_state=1)
kmed_labels = kmedoids.fit_predict(X_pca_4)

kmed_df = X.copy()
```

```
kmed_df["KMedoids_Cluster"] = kmed_labels

kmed_df["KMedoids_Cluster"].value_counts().sort_index()
```

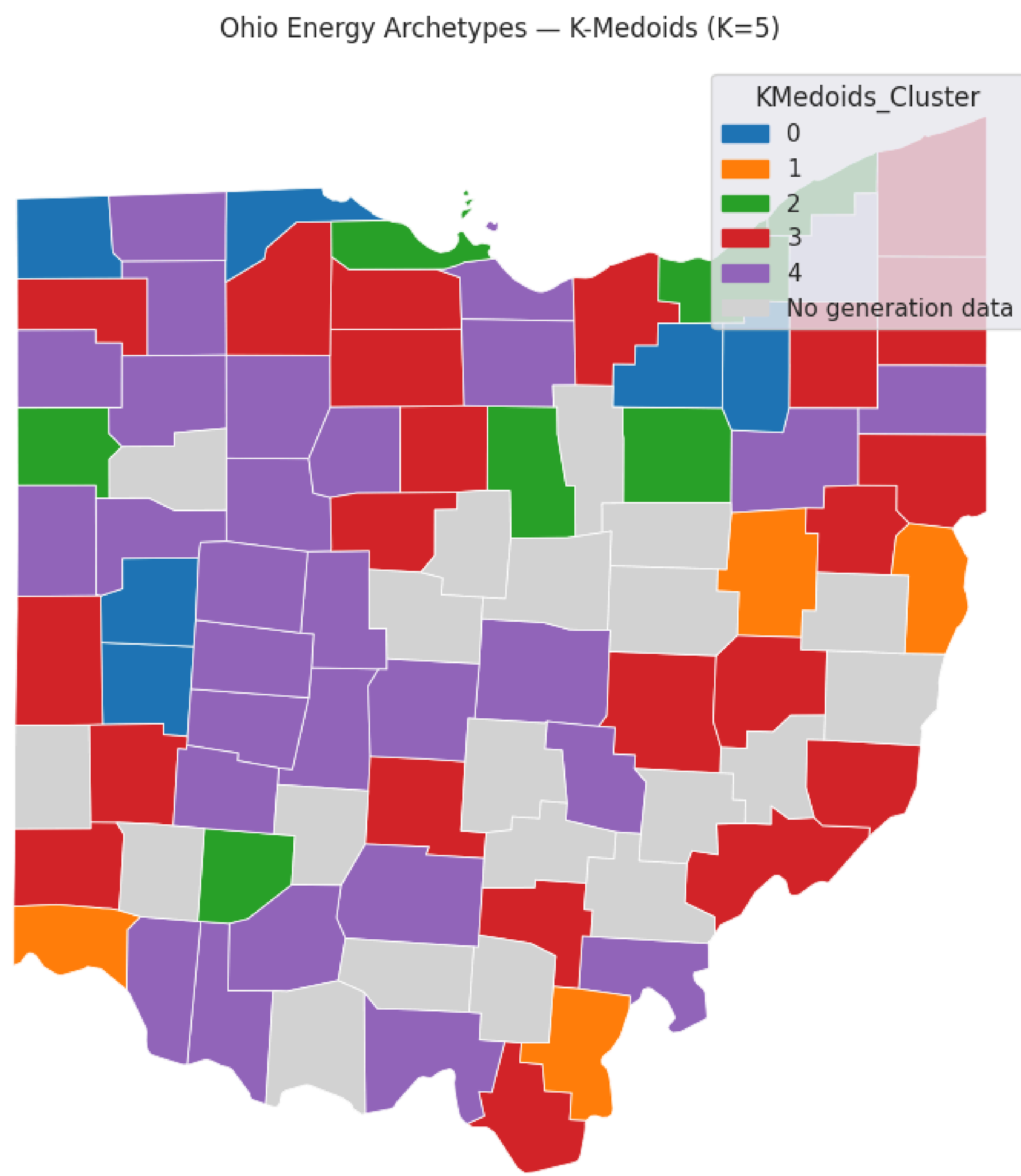
Out[590…

KMedoids_Cluster	count
0	6
1	4
2	7
3	22
4	28

dtype: int64

In [591…

```
plot_cluster_map(
    kmed_df,
    "KMedoids_Cluster",
    "Ohio Energy Archetypes — K-Medoids (K=5)"
)
```



Despite increased local variability, the same dominant energy archetypes identified by K-Means are clearly present, indicating robustness of the underlying structure.

In [592…

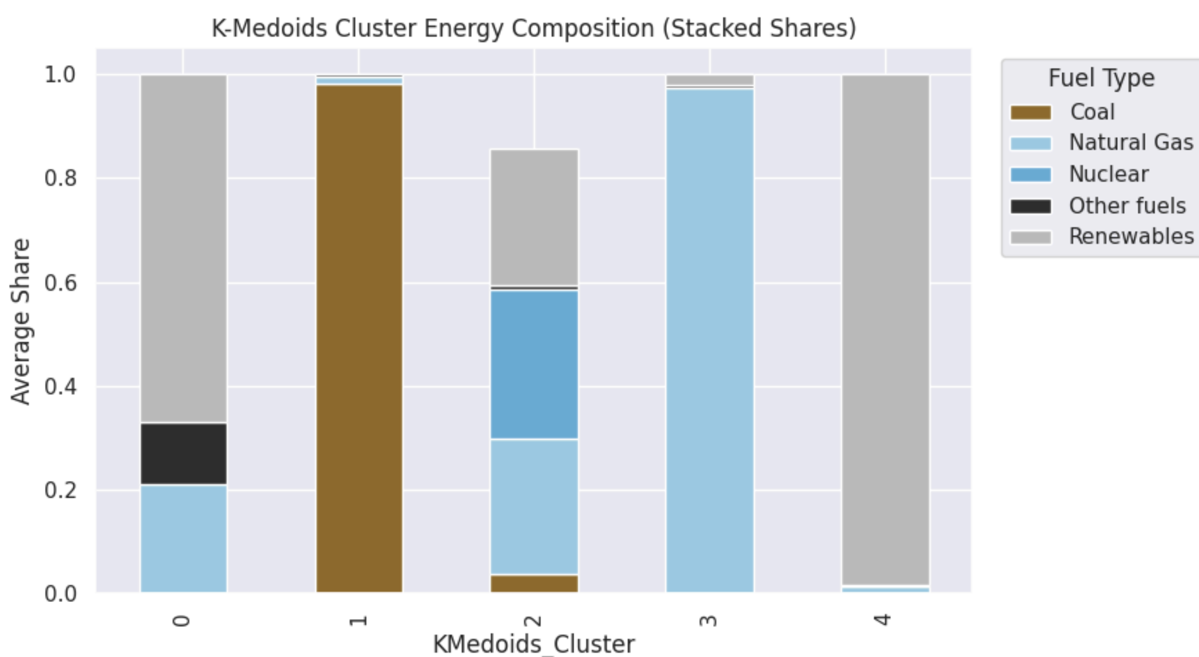
```
kmed_cluster_profile = kmed_df.groupby('KMedoids_Cluster').mean()
kmed_cluster_profile.style.highlight_max(color = "lightgreen", axis = 0)
```

Out[592...

fuel_group KMedoids_Cluster	Coal	Natural Gas	Nuclear	Other fuels	Renewables
0	0.000000	0.210427	0.000000	0.119167	0.670406
1	0.981963	0.013442	0.000000	0.004523	0.000072
2	0.039029	0.259825	0.285696	0.008306	0.264288
3	0.000000	0.973309	0.000000	0.004968	0.021723
4	0.000000	0.013201	0.000000	0.002564	0.984235

In [593...

```
plot_df = kmed_cluster_profile.copy()

ax = plot_df.plot(
    kind="bar",
    stacked=True,
    figsize=(9, 5),
    color=[fuel_colors[c] for c in plot_df.columns]
)

ax.set_title("K-Medoids Cluster Energy Composition (Stacked Shares)")
ax.set_xlabel("KMedoids_Cluster")
ax.set_ylabel("Average Share")
ax.legend(title="Fuel Type", bbox_to_anchor=(1.02, 1), loc="upper left")

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



The K-Medoids cluster profiles indicate strong stability in the underlying energy-generation patterns.

Coal-dominant, natural-gas–dominant, renewables-dominant, and mixed-profile clusters are clearly identified.

The presence of a mixed cluster containing non-negligible shares of nuclear, renewables, and natural gas reflects counties with more diversified energy portfolios.

Overall, the similarities between K-Means and K-Medoids results suggests that the observed clustering structure is robust to the choice of clustering algorithm.

Hierarchical clustering (Ward linkage, K = 5)

In [594…

```
# Hierarchical clustering on scaled original features
Z = linkage(X_pca_4, method="ward")

# Cut dendrogram at K = 5
hc_labels = fcluster(Z, t=5, criterion="maxclust") - 1

# Attach labels
hc_df = X.copy()
hc_df["HC_Cluster"] = hc_labels

hc_df["HC_Cluster"].value_counts().sort_index()
```

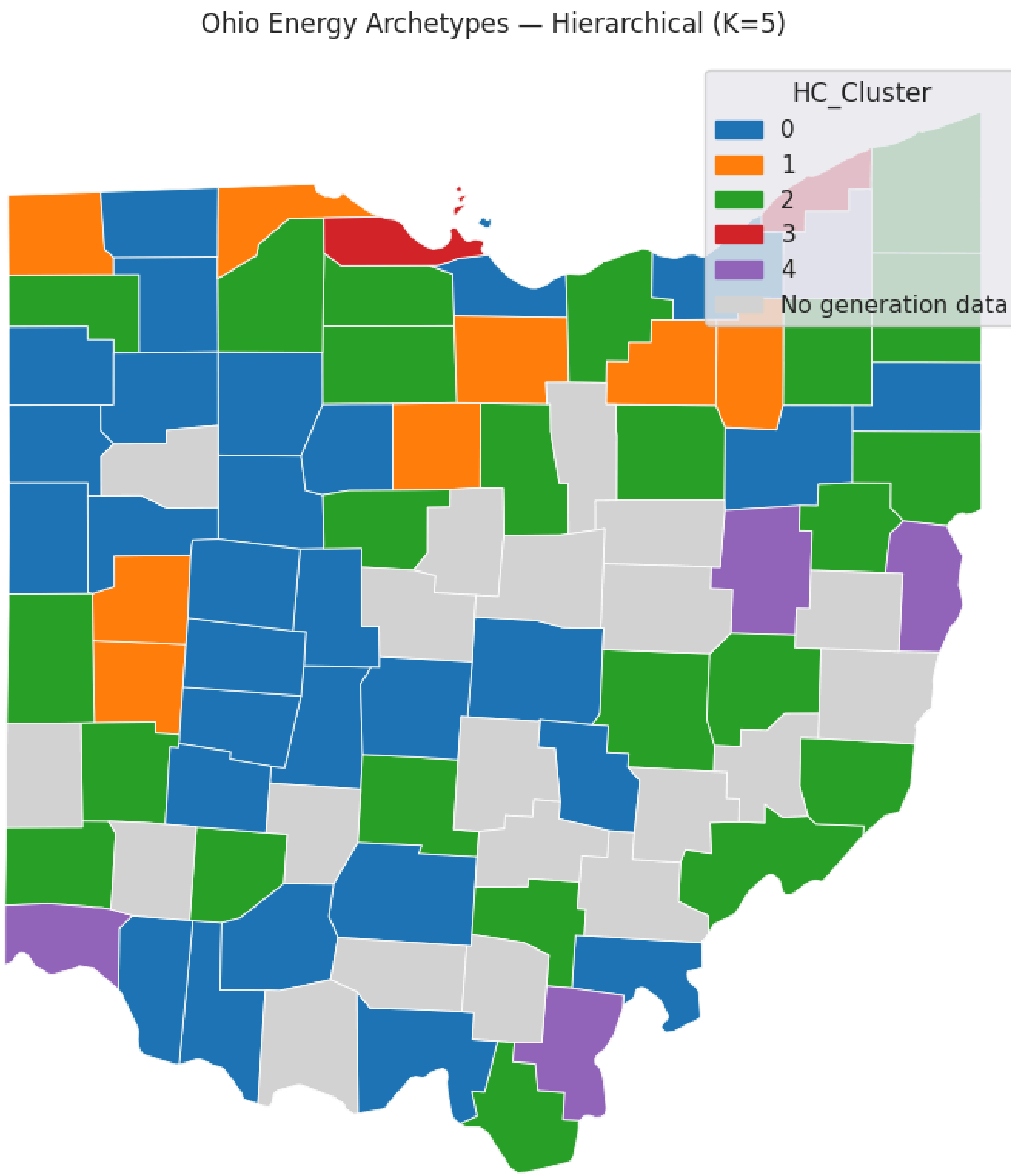
Out[594…

HC_Cluster	count
0	29
1	8
2	24
3	2
4	4

dtype: int64

In [595…

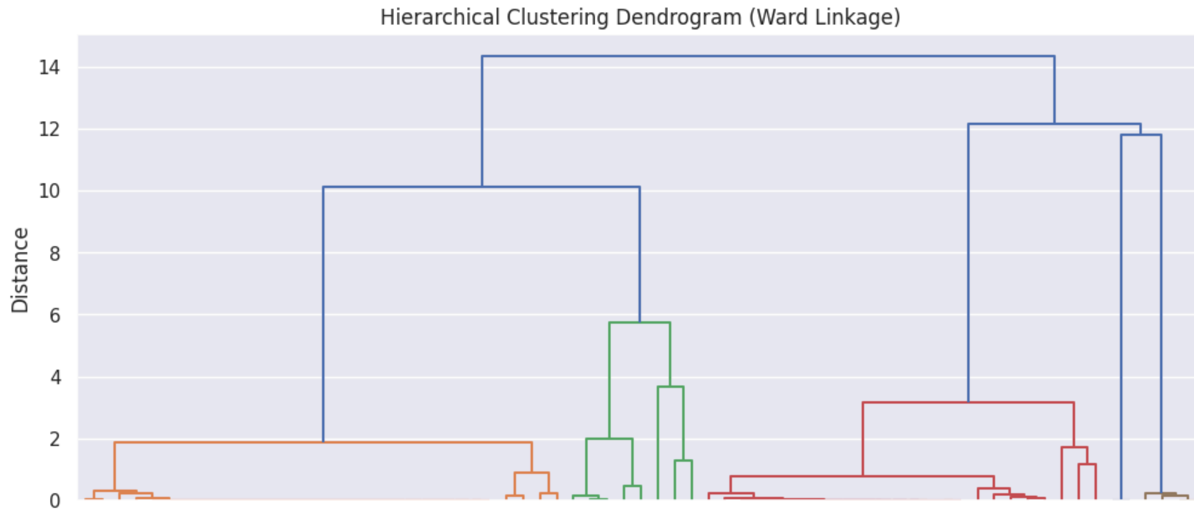
```
plot_cluster_map(
    hc_df,
    "HC_Cluster",
    "Ohio Energy Archetypes — Hierarchical (K=5)"
)
```



The map shows a close agreement between hierarchical clustering and the other methods.

In [596…

```
plt.figure(figsize=(12, 5))
dendrogram(Z, no_labels=True)
plt.title("Hierarchical Clustering Dendrogram (Ward Linkage)")
plt.ylabel("Distance")
plt.show()
```



The dendrogram produced using Ward linkage shows clear separation between groups, with large increases in linkage distance prior to the final merges.

Cutting the dendrogram to obtain five clusters is consistent with the structure suggested by the hierarchy and aligns with the number of clusters used in K-means and K-Medoids.

This agreement across methods supports the presence of stable and well-defined energy-generation archetypes among Ohio counties.

In [597…

```
# Pairwise distances in PCA space
pairwise_dist = pdist(X_pca_4, metric="euclidean")

# Cophenetic correlation
coph_corr, coph_dist = cophenet(Z, pairwise_dist)

coph_corr
```

Out[597…

```
0.7792025486944671
```

The cophenetic correlation coefficient quantifies how well the hierarchical clustering preserves pairwise distances from the underlying feature space.

The obtained value (approximately 0.78) indicates that the dendrogram provides a reasonably faithful representation of the data's distance structure, offering additional support for the hierarchical clustering results.

In [598…

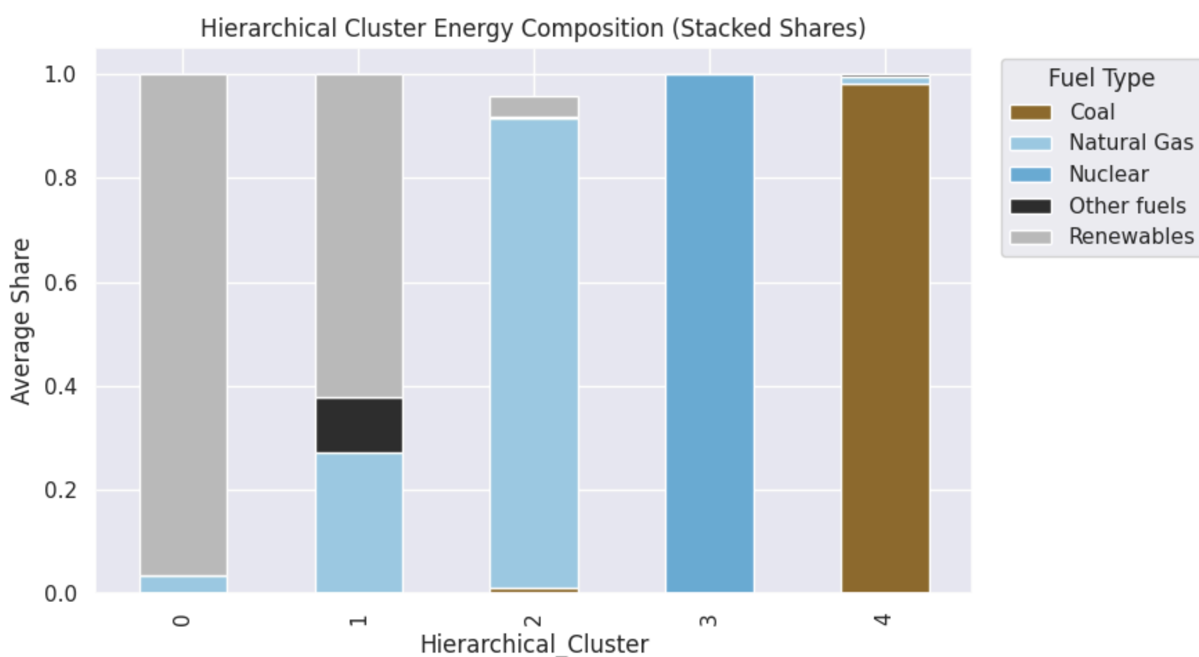
```
hc_cluster_profile = hc_df.groupby('HC_Cluster').mean()
hc_cluster_profile.style.highlight_max(color = "lightgreen", axis = 0)
```

Out[598...

fuel_group HC_Cluster	Coal	Natural Gas	Nuclear	Other fuels	Renewables
0	0.000000	0.034996	0.000000	0.001186	0.963818
1	0.000000	0.271833	0.000000	0.105383	0.622783
2	0.011381	0.903091	0.000000	0.003197	0.040664
3	0.000029	0.000016	0.999937	0.000018	0.000000
4	0.981963	0.013442	0.000000	0.004523	0.000072

In [599...

```
plot_df = hc_cluster_profile.copy()

ax = plot_df.plot(
    kind="bar",
    stacked=True,
    figsize=(9, 5),
    color=[fuel_colors[c] for c in plot_df.columns]
)

ax.set_title("Hierarchical Cluster Energy Composition (Stacked Shares)")
ax.set_xlabel("Hierarchical_Cluster")
ax.set_ylabel("Average Share")
ax.legend(title="Fuel Type", bbox_to_anchor=(1.02, 1), loc="upper left")

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



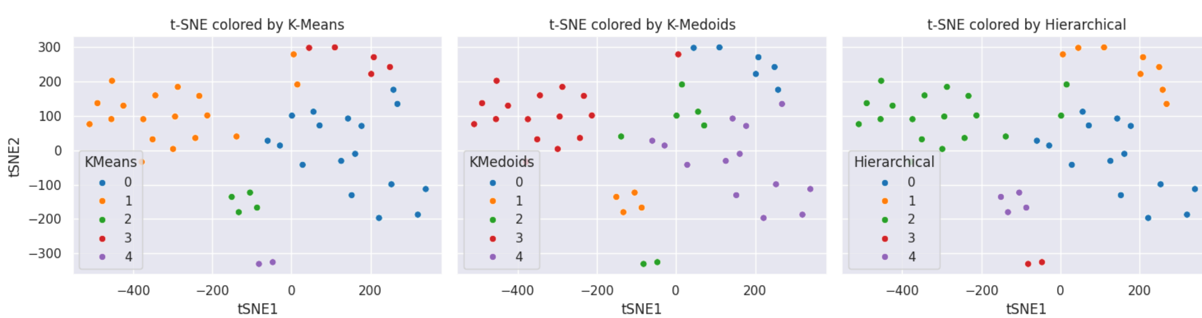
The hierarchical clustering results closely match the cluster structures identified using K-means.

The same dominant energy-generation archetypes are recovered, including renewables-dominant, natural-gas–dominant, coal-dominant, nuclear-dominant, and mixed-profile counties.

The consistency of these profiles across clustering approaches provides strong evidence that the identified clusters reflect stable and meaningful structure in the data.

In [600…

```python
tsne_vis = tsne_df.copy()

tsne_vis["KMeans"] = kmeans_labels
tsne_vis["KMedoids"] = kmed_labels
tsne_vis["Hierarchical"] = hc_labels


fig, axes = plt.subplots(1, 3, figsize=(15, 4), sharex=True, sharey=True)

sns.scatterplot(
    data=tsne_vis, x="tSNE1", y="tSNE2",
    hue="KMeans", ax=axes[0], palette="tab10"
)
axes[0].set_title("t-SNE colored by K-Means")

sns.scatterplot(
    data=tsne_vis, x="tSNE1", y="tSNE2",
    hue="KMedoids", ax=axes[1], palette="tab10"
)
axes[1].set_title("t-SNE colored by K-Medoids")

sns.scatterplot(
    data=tsne_vis, x="tSNE1", y="tSNE2",
    hue="Hierarchical", ax=axes[2], palette="tab10"
)
axes[2].set_title("t-SNE colored by Hierarchical")

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



The side-by-side t-SNE visualizations color the same low-dimensional embedding using cluster assignments from each method.

The similar separation patterns across all three panels provide qualitative confirmation that K-means, K-medoids, and hierarchical clustering recover consistent structure in the data.

Conclusion

This unsupervised analysis explored county-level energy composition patterns in Ohio using multiple clustering approaches; K-means, K-medoids, and hierarchical clustering.

Across all methods, a consistent set of energy-generation archetypes emerged, corresponding to coal-dominant, natural-gas–dominant, nuclear-dominant, renewables-dominant, and mixed-profile counties.

The agreement observed across clustering algorithms, supported by dendrogram structure, and cophenetic correlation, indicates that the identified patterns reflect stable structure in the data rather than artifacts of a particular method.

Overall, the results suggest that Ohio counties can be meaningfully segmented based on dominant energy-generation profiles, providing a compact and interpretable representation of heterogeneity in the state’s energy landscape.

These findings establish a foundation for further analysis, such as geographic interpretation, temporal dynamics, or policy-relevant comparisons across energy transition pathways.