Region segmentation for Electric Vehicles

In this assignment we are going to take in the infrastructural data in India which is relevant for electric vehicles. We are going to divide the states into regions or segments.We will then analyse which segment is proper for the electric vehicles.

In [36]:
```python
#importing the required packages
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

In [3]:
```python
# Load the datasets
evi = pd.read_excel('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Internships\\Feynn Labs\\Electric vehicle I
evi.head()
```

Out[3]:

	State Name	No. of Operational PCS	road density(m/km sqd.)	Road length state in KM	AQI	avg. temp	avg. humidity	Total\n(in MW)	% Renewable
0	Andhra Pradesh	587	16.50	13788	80	33	61	27442.32	0.3978
1	Arunachal Pradesh	9	23.79	10518	62	32	72	1259.34	1.0000
2	Assam	48	11.00	3134	74	29	84	1876.40	0.2819
3	Bihar	83	9.00	3766	72	31	76	8787.41	0.0441
4	Chhattisgarh	46	13.00	3419	58	28	75	24688.32	0.0405

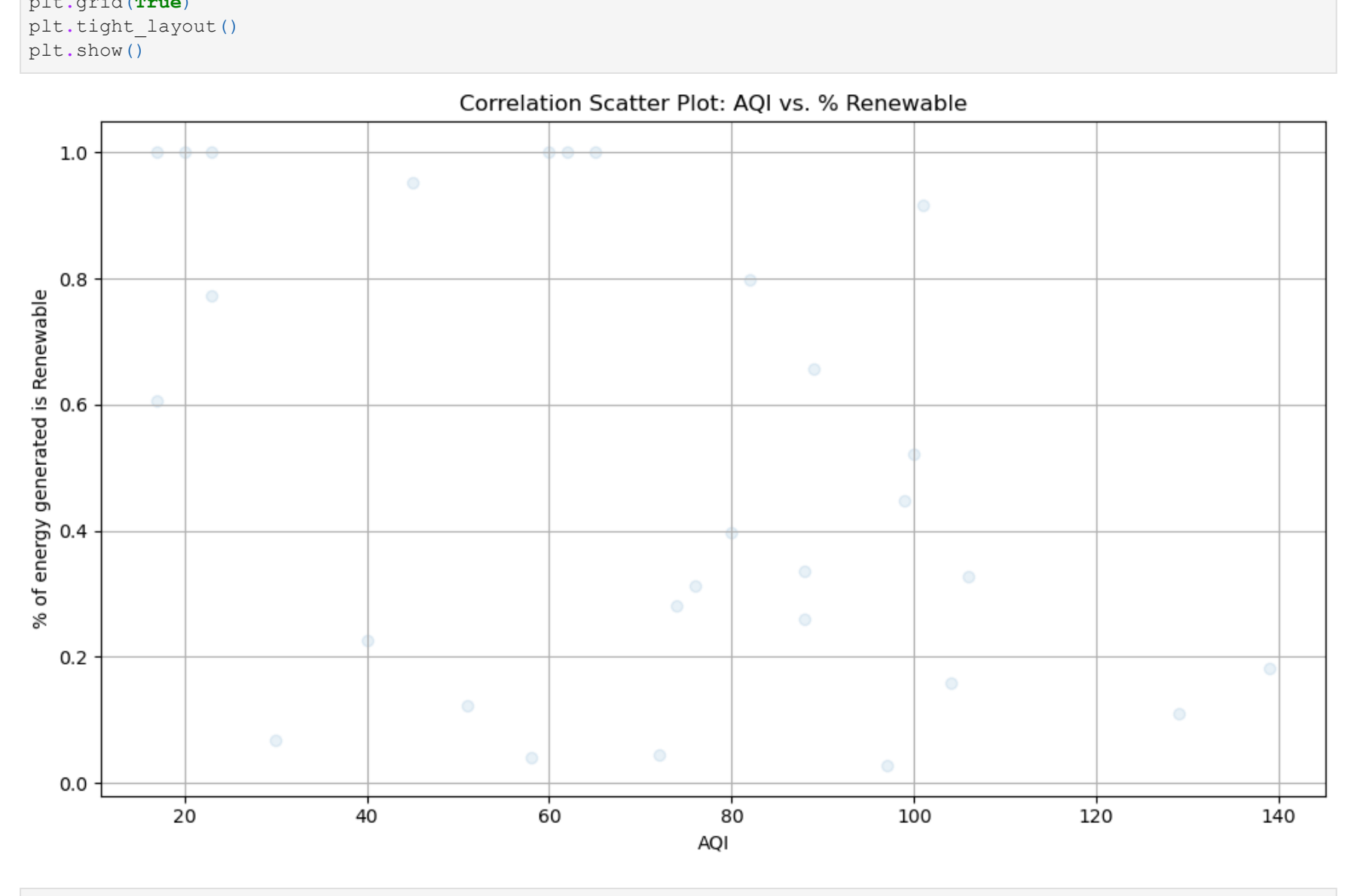
In [4]:
```python
#examining the dataset
evi.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29 entries, 0 to 28
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   State Name               29 non-null     object 
 1   No. of Operational PCS   29 non-null     int64  
 2   road density(m/km sqd.)  29 non-null     float64
 3   Road length state in KM  29 non-null     int64  
 4   AQI                      29 non-null     int64  
 5   avg. temp                29 non-null     int64  
 6   avg. humidity            29 non-null     int64  
 7   Total
(in MW)            29 non-null     float64
 8   % Renewable              29 non-null     float64
dtypes: float64(3), int64(5), object(1)
memory usage: 2.2+ KB
```

In [5]:
```python
# Trim extra spaces in column names
evi= pd.DataFrame(evi)


evi.columns = evi.columns.str.strip()


print(evi)
```

```
           State Name  No. of Operational PCS  road density(m/km sqd.)  \
0      Andhra Pradesh                     587                    16.50   
1   Arunachal Pradesh                       9                    23.79   
2               Assam                      48                    11.00   
3               Bihar                      83                     9.00   
4        Chhattisgarh                      46                    13.00   
5               Delhi                    1845                     0.00   
6                 Goa                      44                    27.00   
7             Gujarat                     195                    10.00   
8             Haryana                     232                    18.00   
9    Himachal Pradesh                      27                    20.00   
10    Jammu & Kashmir                      24                    21.00   
11          Jharkhand                      60                    16.00   
12          Karnataka                     704                     6.00   
13             Kerala                     192                    19.00   
14     Madhya Pradesh                     174                     4.00   
15        Maharashtra                     660                     7.00   
16            Manipur                      16                    22.00   
17          Meghalaya                      19                    24.00   
18            Mizoram                       0                    23.00   
19           Nagaland                       6                    25.00   
20             Odisha                     117                     8.00   
21             Punjab                     126                    17.00   
22          Rajasthan                     254                     2.00   
23             Sikkim                       1                    28.00   
24         Tamil Nadu                     441                     3.00   
25            Tripura                      18                    26.00   
26      Uttar Pradesh                     406                     1.00   
27        Uttarakhand                      48                    14.00   
28        West Bengal                     189                    12.00   

    Road length state in KM  AQI  avg. temp  avg. humidity  Total\n(in MW)  \
0                     13788   80         33             61        27442.32   
1                     10518   62         32             72         1259.34   
2                      3134   74         29             84         1876.40   
3                      3766   72         31             76         8787.41   
4                      3419   58         28             75        24688.32   
5                     28408  129         32             27         2478.52   
6                       279   76         28             59           69.93   
7                     19761   99         32             49        43588.37   
8                      2523  139         33             24         7036.70   
9                      1824   65         30             28        11309.49   
10                       67   45         28             27         3727.58   
11                     1886   30         28             79         4557.14   
12                    20738   89         30             58        30159.78   
13                     4341   82         30             73         3428.81   
14                     8728   88         32             41        29682.20   
15                    33705  106         30             66        42309.44   
16                     1137   23         27             83          158.71   
17                     1134   20         23             90          372.49   
18                      259   17         26             90          104.48   
19                      404   23         30             76          109.71   
20                     3806   40         29             82        12321.53   
21                     1393   88         34             23         8562.04   
22                    11716   17         31             60        32234.48   
23                      179   60         33             58         2341.80   
24                    26985  100         31             64        36317.00   
25                      689   97         30             78         1131.48   
26                     8432  104         31             41        31307.39   
27                     1576  101         33             29         5357.15   
28                     2991   51         28             83        15715.15   

    % Renewable  
0        0.3978  
1        1.0000  
2        0.2819  
3        0.0441  
4        0.0405  
5        0.1090  
6        0.3136  
7        0.4475  
8        0.1812  
9        1.0000  
10       0.9531  
11       0.0674  
12       0.6557  
13       0.7977  
14       0.2605  
15       0.3273  
16       0.7732  
17       1.0000  
18       1.0000  
19       1.0000  
20       0.2257  
21       0.3366  
22       0.6065  
23       1.0000  
24       0.5211  
25       0.0282  
26       0.1592  
27       0.9160  
28       0.1233  
```

In [6]:
```python
# Correlation between renewable energy percent and AQI
plt.figure(figsize=(10, 6))
plt.scatter(evi['AQI'], evi['% Renewable'], alpha=0.1)
plt.xlabel('AQI')
plt.ylabel('% of energy generated is Renewable')
plt.title('Correlation Scatter Plot: AQI vs. % Renewable')
plt.grid(True)
plt.tight_layout()
plt.show()
```

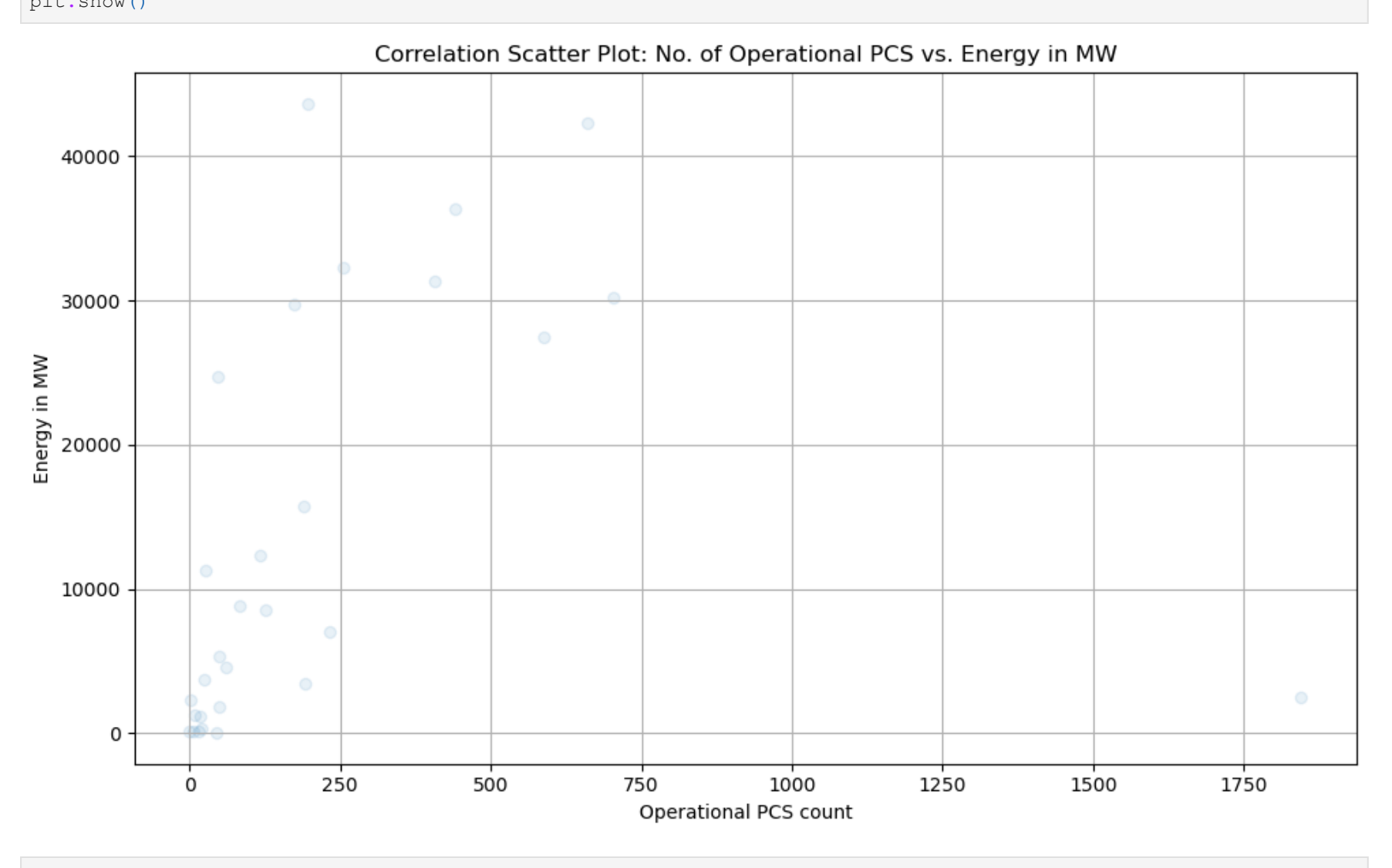


In [7]:
```python
# Calculate the correlation coefficient
correlation_coefficient = evi['AQI'].corr(evi['% Renewable'])

print(f"Correlation Coefficient between AQI and % Renewable: {correlation_coefficient}")
```

```
Correlation Coefficient between AQI and % Renewable: -0.42659288962921693
```

We can clearly see there is a moderate negative correlation between AQI and renewable energy percent which means a higher percentage of renewable energy will lead to lower Pollution

In [8]:
```python
# Correlation between Electricity generated and Number of PCS stations
plt.figure(figsize=(10, 6))
plt.scatter(evi['No. of Operational PCS'], evi['Total\n(in MW)'], alpha=0.1)
plt.xlabel('Operational PCS count')
plt.ylabel('Energy in MW')
plt.title('Correlation Scatter Plot: No. of Operational PCS vs. Energy in MW')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [9]:
```python
# Calculate the correlation coefficient
correlation_coefficient = evi['No. of Operational PCS'].corr(evi['Total\n(in MW)'])

print(f"Correlation Coefficient between No. of Operational PCS and Total energy (in MW): {correlation_coefficie
```

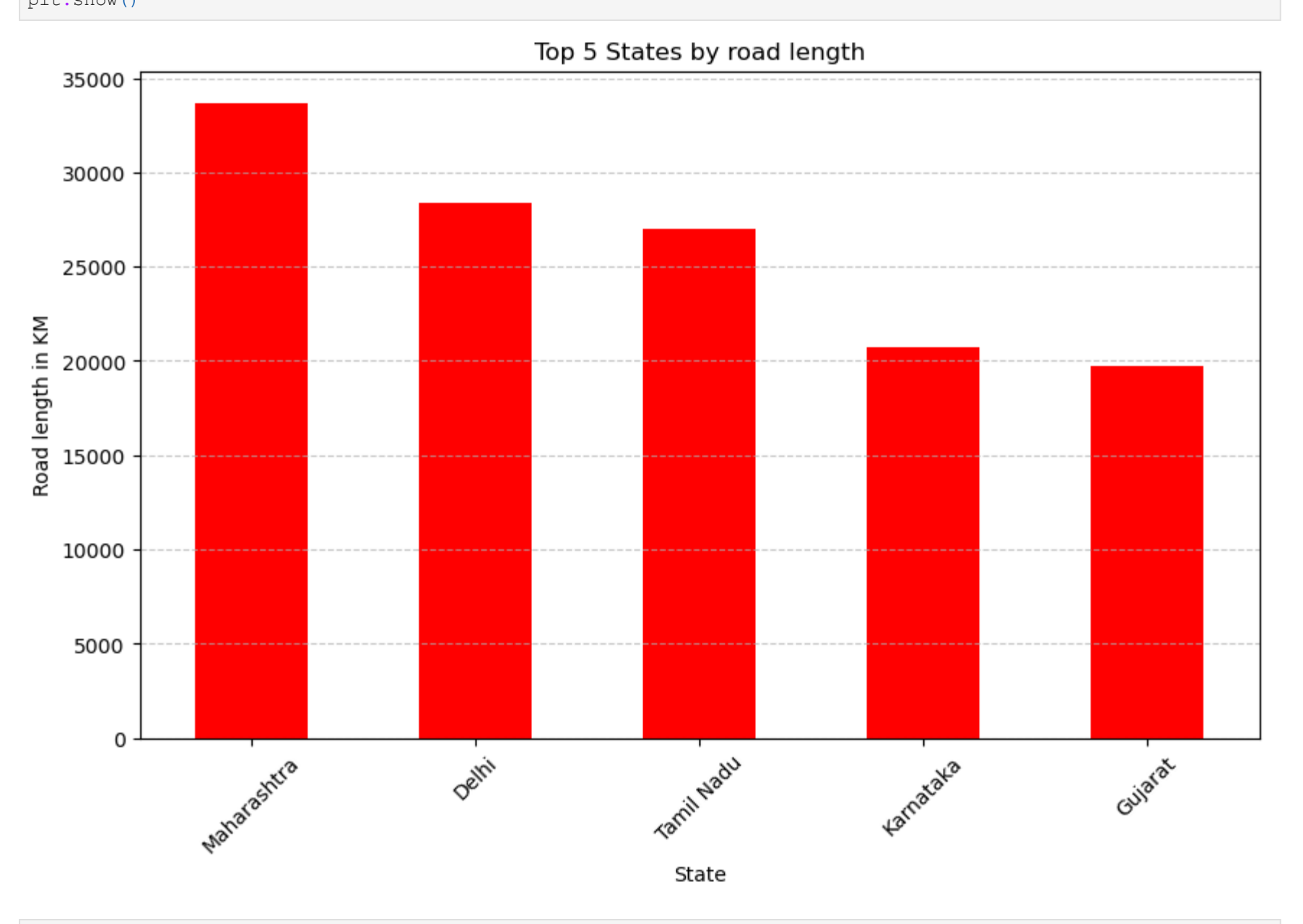
```
Correlation Coefficient between No. of Operational PCS and Total energy (in MW): 0.2881456275037449
```

Remarks: There is a moderate positive correlation between number of PCS and the Energy produced in MW.

In [10]:
```python
#top 5 states by longest roads
road_length = evi.groupby('State Name')['Road length state in KM'].sum()

top_states_road = road_length.sort_values(ascending=False).head(5)
top_states_road
```

Out[10]:
```
State Name
Maharashtra    33705
Delhi          28408
Tamil Nadu     26985
Karnataka      20738
Gujarat        19761
Name: Road length state in KM, dtype: int64
```

In [11]:
```python
# Creating a bar graph
plt.figure(figsize=(10, 6))
top_states_road.plot(kind='bar', color='red')
plt.xlabel('State')
plt.ylabel('Road length in KM')
plt.title('Top 5 States by road length')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



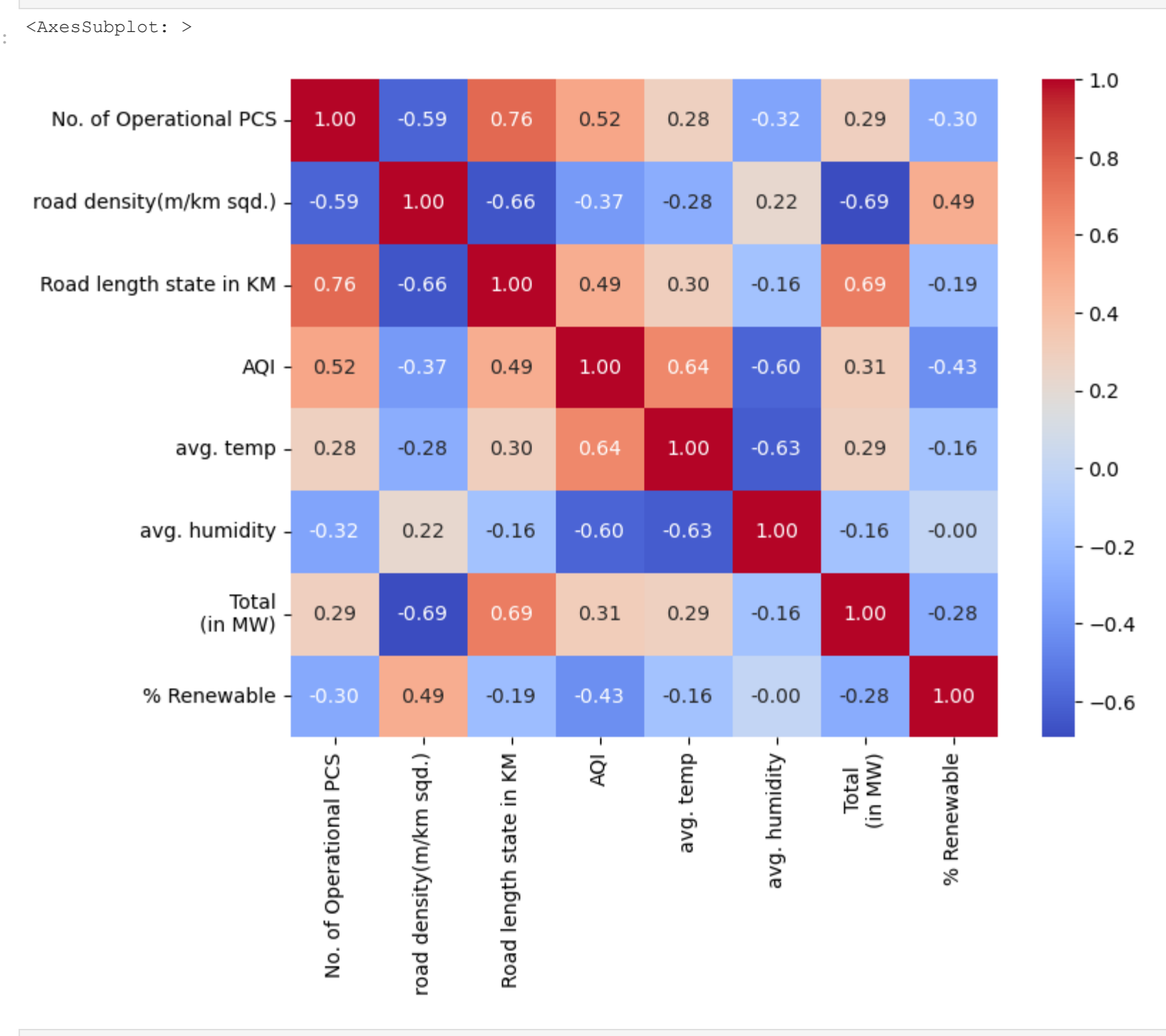
In [12]:
```python
# correlation matrix
correlation_matrix = evi.corr()
correlation_matrix
```

Out[12]:

	No. of Operational PCS	road density(m/km sqd.)	Road length state in KM	AQI	avg. temp	avg. humidity	Total\n(in MW)	% Renewable
No. of Operational PCS	1.000000	-0.593356	0.760366	0.523558	0.283339	-0.324678	0.288146	-0.301876
road density(m/km sqd.)	-0.593356	1.000000	-0.657142	-0.374633	-0.281083	0.223579	-0.692280	0.489199
Road length state in KM	0.760366	-0.657142	1.000000	0.489625	0.296718	-0.158800	0.688153	-0.192832
AQI	0.523558	-0.374633	0.489625	1.000000	0.644877	-0.598740	0.311552	-0.426593
avg. temp	0.283339	-0.281083	0.296718	0.644877	1.000000	-0.630697	0.285264	-0.161685
avg. humidity	-0.324678	0.223579	-0.158800	-0.598740	-0.630697	1.000000	-0.161132	-0.003206
Total\n(in MW)	0.288146	-0.692280	0.688153	0.311552	0.285264	-0.161132	1.000000	-0.284154
% Renewable	-0.301876	0.489199	-0.192832	-0.426593	-0.161685	-0.003206	-0.284154	1.000000

In [13]:
```python
# correlation plot
plt.figure(figsize=(8, 6))
sb.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
```

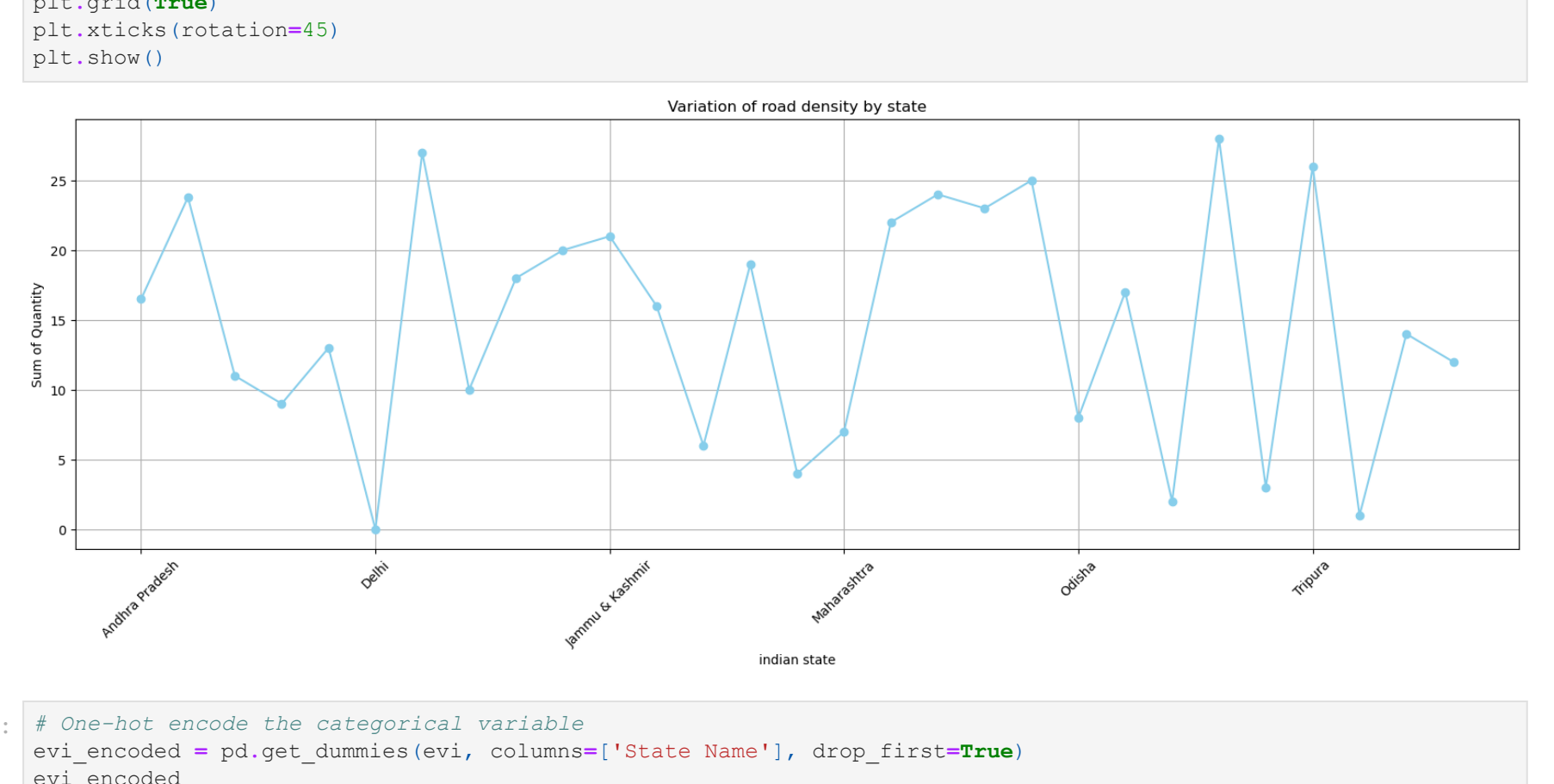
Out[13]:
```
<AxesSubplot: >
```



In [14]:
```python
# Group the data by state and seeing road density
statewiseroaddensity = evi.groupby('State Name')['road density(m/km sqd.)'].sum()
statewiseroaddensity
```

Out[14]:
```
State Name
Andhra Pradesh       16.50
Arunachal Pradesh    23.79
Assam                11.00
Bihar                 9.00
Chhattisgarh         13.00
Delhi                 0.00
Goa                  27.00
Gujarat              10.00
Haryana              18.00
Himachal Pradesh     20.00
Jammu & Kashmir      21.00
Jharkhand            16.00
Karnataka             6.00
Kerala               19.00
Madhya Pradesh        4.00
Maharashtra           7.00
Manipur              22.00
Meghalaya            24.00
Mizoram              23.00
Nagaland             25.00
Odisha                8.00
Punjab               17.00
Rajasthan             2.00
Sikkim               28.00
Tamil Nadu            3.00
Tripura              26.00
Uttar Pradesh         1.00
Uttarakhand          14.00
West Bengal          12.00
Name: road density(m/km sqd.), dtype: float64
```

In [15]:
```python
# Create a line chart to see road density per state
state_names = evi['State Name'].unique()


plt.figure(figsize=(20, 6))
statewiseroaddensity.index = state_names
statewiseroaddensity.plot(kind='line', marker='o', color='skyblue')
plt.xlabel('indian state')
plt.ylabel('Sum of Quantity')
plt.title('Variation of road density by state')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```



In [16]:
```python
# One-hot encode the categorical variable
evi_encoded = pd.get_dummies(evi, columns=['State Name'], drop_first=True)
evi_encoded
```

Out[16]:

	No. of Operational PCS	road density(m/km sqd.)	Road length state in KM	AQI	avg. temp	avg. humidity	Total\n(in MW)	% Renewable	State Name_Arunachal Pradesh	State Name_Assam	...	State Name_Nagaland
0	587	16.50	13788	80	33	61	27442.32	0.3978	0	0	...	0
1	9	23.79	10518	62	32	72	1259.34	1.0000	1	0	...	0
2	48	11.00	3134	74	29	84	1876.40	0.2819	0	1	...	0
3	83	9.00	3766	72	31	76	8787.41	0.0441	0	0	...	0
4	46	13.00	3419	58	28	75	24688.32	0.0405	0	0	...	0
5	1845	0.00	28408	129	32	27	2478.52	0.1090	0	0	...	0
6	44	27.00	279	76	28	59	69.93	0.3136	0	0	...	0
7	195	10.00	19761	99	32	49	43588.37	0.4475	0	0	...	0
8	232	18.00	2523	139	33	24	7036.70	0.1812	0	0	...	0
9	27	20.00	1824	65	30	28	11309.49	1.0000	0	0	...	0
10	24	21.00	67	45	28	27	3727.58	0.9531	0	0	...	0
11	60	16.00	1886	30	28	79	4557.14	0.0674	0	0	...	0
12	704	6.00	20738	89	30	58	30159.78	0.6557	0	0	...	0
13	192	19.00	4341	82	30	73	3428.81	0.7977	0	0	...	0
14	174	4.00	8728	88	32	41	29682.20	0.2605	0	0	...	0
15	660	7.00	33705	106	30	66	42309.44	0.3273	0	0	...	0
16	16	22.00	1137	23	27	83	158.71	0.7732	0	0	...	0
17	19	24.00	1134	20	23	90	372.49	1.0000	0	0	...	0
18	0	23.00	259	17	26	90	104.48	1.0000	0	0	...	0
19	6	25.00	404	23	30	76	109.71	1.0000	0	0	...	1
20	117	8.00	3806	40	29	82	12321.53	0.2257	0	0	...	0
21	126	17.00	1393	88	34	23	8562.04	0.3366	0	0	...	0
22	254	2.00	11716	17	31	60	32234.48	0.6065	0	0	...	0
23	1	28.00	179	60	33	58	2341.80	1.0000	0	0	...	0
24	441	3.00	26985	100	31	64	36317.00	0.5211	0	0	...	0
25	18	26.00	689	97	30	78	1131.48	0.0282	0	0	...	0
26	406	1.00	8432	104	31	41	31307.39	0.1592	0	0	...	0
27	48	14.00	1576	101	33	29	5357.15	0.9160	0	0	...	0
28	189	12.00	2991	51	28	83	15715.15	0.1233	0	0	...	0

29 rows × 36 columns

In [17]:
```python
# Standardizing the numerical features
scaler = StandardScaler()
numerical_cols = ['No. of Operational PCS', 'road density(m/km sqd.)', 'Road length state in KM', 'AQI', 'avg.
evi_encoded[numerical_cols] = scaler.fit_transform(evi_encoded[numerical_cols])

evi_encoded[numerical_cols]
```

Out[17]:

	No. of Operational PCS	road density(m/km sqd.)	Road length state in KM	AQI	avg. temp	avg. humidity	Total\n(in MW)	% Renewable
0	0.987818	0.214870	0.671096	0.296834	1.218270	0.020872	0.993460	-0.292463
1	-0.596358	1.084929	0.321936	-0.246841	0.802625	0.533036	-0.858172	1.392686
2	-0.489467	-0.441552	-0.466504	0.115609	-0.444310	1.091761	-0.814535	-0.616789
3	-0.393539	-0.680252	-0.399021	0.055201	0.386980	0.719278	-0.325795	-1.282230
4	-0.494948	-0.202853	-0.436073	-0.367657	-0.859955	0.672718	0.798700	-1.292304
5	4.435728	-1.754398	2.232172	1.776837	0.802625	-1.562182	-0.771953	-1.100618
6	-0.500430	1.468041	-0.771352	0.176017	-0.859955	-0.072249	-0.942286	-0.528082
7	-0.086571	-0.560902	1.308873	0.870712	0.802625	-0.537853	2.135291	-0.153387
8	0.014838	0.393895	-0.531745	2.078878	1.218270	-1.701863	-0.449604	-0.898580
9	-0.547023	0.632594	-0.606382	-0.156228	-0.028665	-1.515622	-0.147437	1.392686
10	-0.555246	0.751944	-0.793988	-0.760311	-0.859955	-1.562182	-0.683621	1.261445
11	-0.456577	0.155196	-0.599761	-1.213373	-0.859955	0.858959	-0.624956	-1.217029
12	1.308490	-1.038300	1.413194	0.568671	-0.028665	-0.118809	1.185636	0.429224
13	-0.094793	0.513244	-0.337624	0.357242	-0.028665	0.579597	-0.704750	0.826586
14	-0.144128	-1.277000	0.130805	0.538467	0.802625	-0.910336	1.151862	-0.676673
15	1.187895	-0.918951	2.797769	1.082141	-0.028665	0.253674	2.044847	-0.489745
16	-0.577172	0.871293	-0.679737	-1.424802	-1.275601	1.045201	-0.936008	0.758027
17	-0.568950	1.109992	-0.680058	-1.515415	-2.938181	1.371124	-0.920890	1.392686
18	-0.621025	0.990643	-0.773487	-1.606027	-1.691246	1.371124	-0.939843	1.392686
19	-0.604580	1.229342	-0.758005	-1.424802	-0.028665	0.719278	-0.939473	1.392686
20	-0.300353	-0.799601	-0.394750	-0.911332	-0.444310	0.998641	-0.075866	-0.774054
21	-0.275685	0.274545	-0.652402	0.538467	1.633915	-1.748424	-0.341733	-0.463720
22	0.075135	-1.515699	0.449854	-1.606027	0.386980	-0.025689	1.332356	0.291547
23	-0.618284	1.587391	-0.782029	-0.307249	1.218270	-0.118809	-0.781622	1.392686
24	0.587663	-1.396349	2.080229	0.900917	0.386980	0.160553	1.621068	0.052570
25	-0.571690	1.348692	-0.727573	0.810304	-0.028665	0.812399	-0.867215	-1.326723
26	0.491735	-1.635048	0.099199	1.021733	0.386980	-0.910336	1.266793	-0.960143
27	-0.489467	-0.083504	-0.632862	0.931121	1.218270	-1.469061	-0.568380	1.157627
28	-0.103016	-0.322203	-0.481773	-0.579086	-0.859955	1.045201	0.164127	-1.060602

In [18]:
```python
# Apply PCA to the combined numerical features
pca = PCA(n_components=2)
pca_result = pca.fit_transform(evi_encoded[numerical_cols])
pca_result
```

Out[18]:
```
array([[ 1.49234652,  0.09452699],
       [-1.17211336,  0.87445116],
       [-0.72505322, -0.65422492],
       [ 0.11404599, -0.44942768],
       [-0.2895768 , -1.34178792],
       [ 4.73795957,  0.27512918],
       [-1.48897087,  0.58667083],
       [ 2.26330864, -0.23344137],
       [ 1.36498014,  2.46826524],
       [-0.77794004,  1.57240015],
       [-1.55284624,  1.22825813],
       [-1.38962509, -1.11389211],
       [ 2.06715141, -0.87931645],
       [-0.85990298,  0.42140198],
       [ 1.80115611,  0.16658299],
       [ 3.17407769, -1.71367947],
       [-2.6258659 , -0.71908934],
       [-3.52446463, -1.53949986],
       [-3.18107399, -0.96580771],
       [-2.48853724,  0.34668885],
       [-0.56162405, -1.34600128],
       [ 0.7141388 ,  2.27965567],
       [ 0.71503332, -1.27845977],
       [-1.52765349,  1.87189365],
       [ 2.64128592, -1.16916198],
       [-0.94861293,  0.44829715],
       [ 2.35045175, -0.14161378],
       [ 0.24985381,  2.35693003],
       [-0.57192886, -1.44574834]])
```

In [19]:
```python
# seeing the weightage  of variables in each principal component
loadings = pca.components_
loadings_df = pd.DataFrame(loadings, columns=numerical_cols, index=['PC1', 'PC2'])
print("Variable Loadings in Principal Components:")
print(loadings_df)
```

```
Variable Loadings in Principal Components:
     No. of Operational PCS  road density(m/km sqd.)  Road length state in KM  \
PC1                0.388348                -0.405200                 0.411657   
PC2               -0.099059                 0.317386                -0.271375   

          AQI  avg. temp  avg. humidity  Total\n(in MW)  % Renewable  
PC1  0.396619   0.317806      -0.270177        0.349815    -0.248723  
PC2  0.323934   0.484835      -0.579738       -0.308865     0.210516  
```

Interpretation The first component has more to do with Technology and infrastructure and second one has more to do with environmental factors and climate.

In [20]:
```python
# Creating a new DataFrame with PCA components
pca_evi = pd.DataFrame(data=pca_result, columns=['Infrastructure component', 'Environmental component'])
pca_evi
```

Out[20]:

	Infrastructure component	Environmental component
0	1.492347	0.094527
1	-1.172113	0.874451
2	-0.725053	-0.654225
3	0.114046	-0.449428
4	-0.289577	-1.341788
5	4.737960	0.275129
6	-1.488971	0.586671
7	2.263309	-0.233441
8	1.364980	2.468265
9	-0.777940	1.572400
10	-1.552846	1.228258
11	-1.389625	-1.113892
12	2.067151	-0.879316
13	-0.859903	0.421402
14	1.801156	0.166583
15	3.174078	-1.713679
16	-2.625866	-0.719089
17	-3.524465	-1.539500
18	-3.181074	-0.965808
19	-2.488537	0.346689
20	-0.561624	-1.346001
21	0.714139	2.279656
22	0.715033	-1.278460
23	-1.527653	1.871894
24	2.641286	-1.169162
25	-0.948613	0.448297
26	2.350452	-0.141614
27	0.249854	2.356930
28	-0.571929	-1.445748

In [21]:
```python
# Finding the optimal number of clusters using the Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=42)
    kmeans.fit(pca_evi[['Infrastructure component', 'Environmental component']])
    wcss.append(kmeans.inertia_)
```

```
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known t
o have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it b
y setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known t
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  warnings.warn(
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known t
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  warnings.warn(
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known t
o have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it b
y setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```
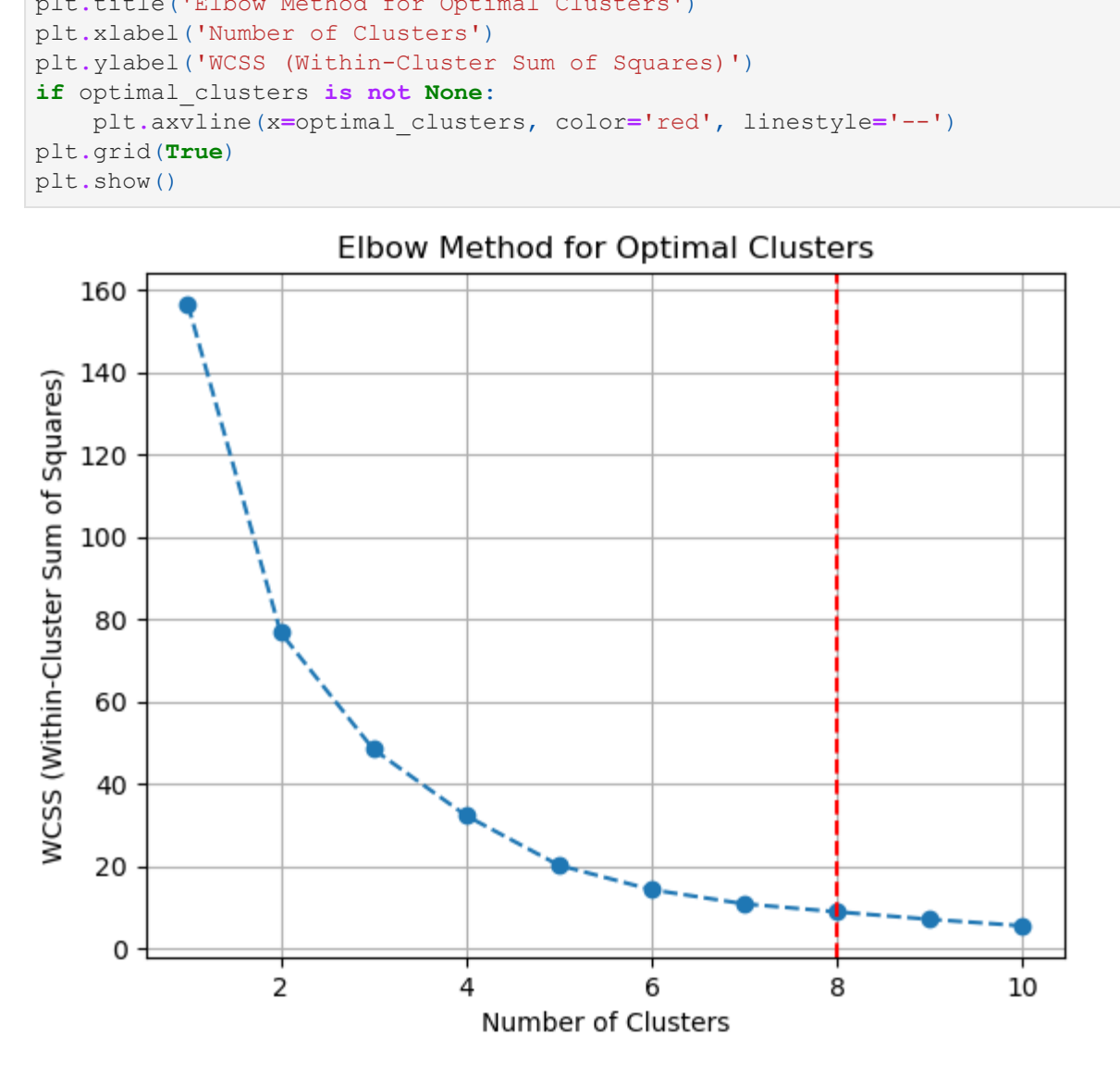

In [22]:
```python
# Determine the optimal number of clusters using the "Elbow Method"
optimal_clusters = None
for i in range(1, len(wcss) - 1):
    reduction_ratio = (wcss[i] - wcss[i + 1]) / (wcss[i - 1] - wcss[i])
    if reduction_ratio > 0.9:
        optimal_clusters = i + 1
        break
```

In [23]:
```python
# Plotting the Elbow Method graph and highlight the optimal cluster count
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
if optimal_clusters is not None:
    plt.axvline(x=optimal_clusters, color='red', linestyle='--')
plt.grid(True)
plt.show()
```



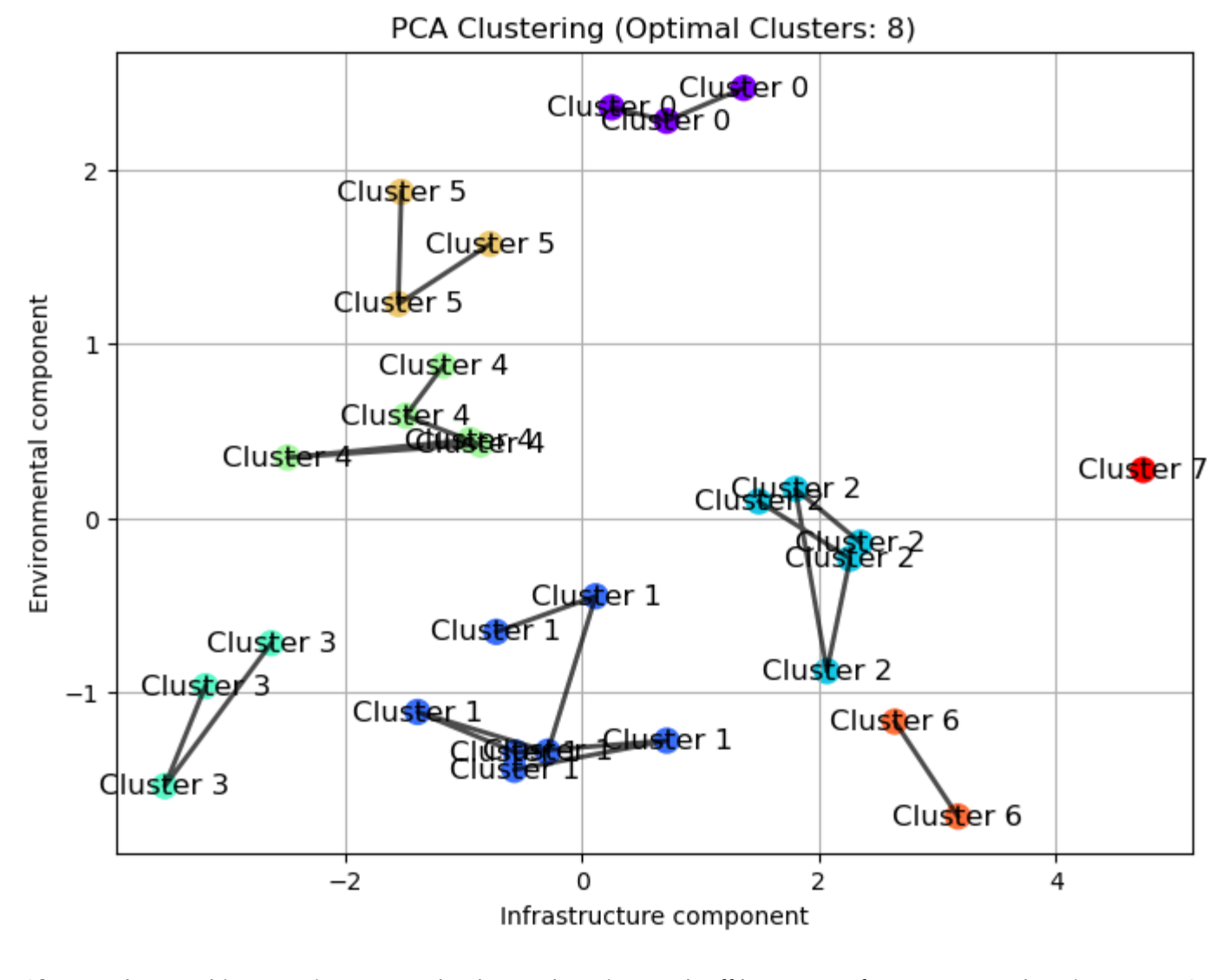
Conclusion:We need to make 8 number of clusters

In [24]:
```python
# Apply K-means clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=optimal_clusters, init='k-means++', max_iter=300, n_init=10, random_state=42)
pca_evi['Cluster'] = kmeans.fit_predict(pca_evi[['Infrastructure component', 'Environmental component']])
pca_evi['Cluster']
```

```
C:\Users\sujoydutta\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1334: UserWarning: KMeans is known t
o have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it b
y setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

Out[24]:
```
0     2
1     4
2     1
3     1
4     1
5     7
6     4
7     2
8     0
9     5
10    5
11    1
12    2
13    4
14    2
15    6
16    3
17    3
18    3
19    4
20    1
21    0
22    1
23    5
24    6
25    4
26    2
27    0
28    1
Name: Cluster, dtype: int32
```

In [35]:
```python
# Plotting the clusters
plt.figure(figsize=(8, 6))
scatter = plt.scatter(pca_evi['Infrastructure component'], pca_evi['Environmental component'], c=pca_evi['Clust


for i, txt in enumerate(pca_evi['Cluster']):
    plt.annotate(f'Cluster {txt}', (pca_evi['Infrastructure component'][i], pca_evi['Environmental component'][

for cluster_num in set(pca_evi['Cluster']):
    cluster_points = pca_evi[pca_evi['Cluster'] == cluster_num]
    plt.plot(cluster_points['Infrastructure component'], cluster_points['Environmental component'], linestyle='


plt.xlabel('Infrastructure component')
plt.ylabel('Environmental component')
plt.title(f'PCA Clustering (Optimal Clusters: {optimal_clusters})')

plt.grid(True)
plt.show()
```



Observation: In this scenario, we can clearly see there is a tradeoff between Infrastructure and Environment. Our goal is to find the best of both worlds so that we can launch our Electric Vehicles. As we can see in this graph that Cluster 7 has the best Infrastructure but performs poor in terms of environmental factors. Hence we can say the state in Cluster 7 will do the best for launching the Electric Vehicles as it is known that the people living in the place with high quality of infrastructure have higher literacy and higher purchasing power. Then we would gradually moves to states in Cluster 2 and Cluster 6 as they have a less better infrastructural quality and poor environmental factors. Launching Electric Vehicles in such areas and marketing them as a solution to pollution could help skyrocket sales of Electric Vehicles in such areas. They would have a bit less purchasing power than cluster 7 and segmentation of customers could be needed. Clusters 4, 5 and 0 dont have good infrastructure and have amazing environmental factors, so marketing here would need extra resources and manpower. In my opinion these clusters along with clusters 3 and 1 are not feasible for Electric Vehicle launch.

In [26]:

```
# Concatenating the dataframes side by side
evi_combined = pd.concat([evi, pca_evi], axis=1)

evi_combined
```

Out[26]:

	State Name	No. of Operational PCS	road density(m/km sqd.)	Road length state in KM	AQI	avg. temp	avg. humidity	Total\n(in MW)	% Renewable	Infrastructure component	Environmental component	Cluster
0	Andhra Pradesh	587	16.50	13788	80	33	61	27442.32	0.3978	1.492347	0.094527	2
1	Arunachal Pradesh	9	23.79	10518	62	32	72	1259.34	1.0000	-1.172113	0.874451	4
2	Assam	48	11.00	3134	74	29	84	1876.40	0.2819	-0.725053	-0.654225	1
3	Bihar	83	9.00	3766	72	31	76	8787.41	0.0441	0.114046	-0.449428	1
4	Chhattisgarh	46	13.00	3419	58	28	75	24688.32	0.0405	-0.289577	-1.341788	1
5	Delhi	1845	0.00	28408	129	32	27	2478.52	0.1090	4.737960	0.275129	7
6	Goa	44	27.00	279	76	28	59	69.93	0.3136	-1.488971	0.586671	4
7	Gujarat	195	10.00	19761	99	32	49	43588.37	0.4475	2.263309	-0.233441	2
8	Haryana	232	18.00	2523	139	33	24	7036.70	0.1812	1.364980	2.468265	0
9	Himachal Pradesh	27	20.00	1824	65	30	28	11309.49	1.0000	-0.777940	1.572400	5
10	Jammu & Kashmir	24	21.00	67	45	28	27	3727.58	0.9531	-1.552846	1.228258	5
11	Jharkhand	60	16.00	1886	30	28	79	4557.14	0.0674	-1.389625	-1.113892	1
12	Karnataka	704	6.00	20738	89	30	58	30159.78	0.6557	2.067151	-0.879316	2
13	Kerala	192	19.00	4341	82	30	73	3428.81	0.7977	-0.859903	0.421402	4
14	Madhya Pradesh	174	4.00	8728	88	32	41	29682.20	0.2605	1.801156	0.166583	2
15	Maharashtra	660	7.00	33705	106	30	66	42309.44	0.3273	3.174078	-1.713679	6
16	Manipur	16	22.00	1137	23	27	83	158.71	0.7732	-2.625866	-0.719089	3
17	Meghalaya	19	24.00	1134	20	23	90	372.49	1.0000	-3.524465	-1.539500	3
18	Mizoram	0	23.00	259	17	26	90	104.48	1.0000	-3.181074	-0.965808	3
19	Nagaland	6	25.00	404	23	30	76	109.71	1.0000	-2.488537	0.346689	4
20	Odisha	117	8.00	3806	40	29	82	12321.53	0.2257	-0.561624	-1.346001	1
21	Punjab	126	17.00	1393	88	34	23	8562.04	0.3366	0.714139	2.279656	0
22	Rajasthan	254	2.00	11716	17	31	60	32234.48	0.6065	0.715033	-1.278460	1
23	Sikkim	1	28.00	179	60	33	58	2341.80	1.0000	-1.527653	1.871894	5
24	Tamil Nadu	441	3.00	26985	100	31	64	36317.00	0.5211	2.641286	-1.169162	6
25	Tripura	18	26.00	689	97	30	78	1131.48	0.0282	-0.948613	0.448297	4
26	Uttar Pradesh	406	1.00	8432	104	31	41	31307.39	0.1592	2.350452	-0.141614	2
27	Uttarakhand	48	14.00	1576	101	33	29	5357.15	0.9160	0.249854	2.356930	0
28	West Bengal	189	12.00	2991	51	28	83	15715.15	0.1233	-0.571929	-1.445748	1

In [27]:

```
#seeing the states by segment
evi_subset = evi_combined.iloc[:, [0, -1]]
evi_subset
```

Out[27]:

	State Name	Cluster
0	Andhra Pradesh	2
1	Arunachal Pradesh	4
2	Assam	1
3	Bihar	1
4	Chhattisgarh	1
5	Delhi	7
6	Goa	4
7	Gujarat	2
8	Haryana	0
9	Himachal Pradesh	5
10	Jammu & Kashmir	5
11	Jharkhand	1
12	Karnataka	2
13	Kerala	4
14	Madhya Pradesh	2
15	Maharashtra	6
16	Manipur	3
17	Meghalaya	3
18	Mizoram	3
19	Nagaland	4
20	Odisha	1
21	Punjab	0
22	Rajasthan	1
23	Sikkim	5
24	Tamil Nadu	6
25	Tripura	4
26	Uttar Pradesh	2
27	Uttarakhand	0
28	West Bengal	1

In [32]:

```
# Grouping the dataframe by cluster and displaying the respective state names by their cluster
result = evi_subset.groupby('Cluster')['State Name'].agg(', '.join).reset_index()
pd.set_option('display.max_colwidth', None)
result
```

Out[32]:

	Cluster	State Name
0	0	Haryana, Punjab, Uttarakhand
1	1	Assam, Bihar, Chhattisgarh, Jharkhand, Odisha, Rajasthan, West Bengal
2	2	Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh, Uttar Pradesh
3	3	Manipur, Meghalaya, Mizoram
4	4	Arunachal Pradesh, Goa, Kerala, Nagaland, Tripura
5	5	Himachal Pradesh, Jammu & Kashmir, Sikkim
6	6	Maharashtra, Tamil Nadu
7	7	Delhi

In [ ]: