SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

20PAIE51J- MACHINE LEARNING (UNSUPERVISED MODEL)

Hiearchial Clustering

a. Import required Library (2 marks)

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage, cophenet
from scipy.spatial.distance import pdist

# For supressing all sorts of warnings
import warnings
warnings.filterwarnings("ignore")
```

b. Read the dataset (tab, csv, xls, txt, inbuilt dataset). (1 mark)

In [2]:
```
df = pd.read_csv(r"C:\Users\priya\SRM PYTHON\ML-unsupervised\MP1\MPA-1_forestfires.csv")
df.head(5)
```

Out[2]:

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
0	7	5	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0
1	7	4	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0
2	7	4	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0
3	8	6	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0
4	8	6	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0

In [3]:
```
# pip install --user --upgrade pandas
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 13 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   X       517 non-null    int64  
 1   Y       517 non-null    int64  
 2   month   517 non-null    object 
 3   day     517 non-null    object 
 4   FFMC    517 non-null    float64
 5   DMC     517 non-null    float64
 6   DC      517 non-null    float64
 7   ISI     517 non-null    float64
 8   temp    517 non-null    float64
 9   RH      517 non-null    int64  
 10  wind    517 non-null    float64
 11  rain    517 non-null    float64
 12  area    517 non-null    float64
dtypes: float64(8), int64(3), object(2)
memory usage: 52.6+ KB
```

c. Perform explanatory data analysis on the dataset. (3 marks)

In [5]:
```
df.describe()
```

Out[5]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
count	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000
mean	4.669246	4.299807	90.644681	110.872340	547.940039	9.021663	18.889168	44.288201	4.017602	0.021663	12.847292
std	2.313778	1.229900	5.520111	64.046482	248.066192	4.559477	5.806625	16.317469	1.791653	0.295959	63.655818
min	1.000000	2.000000	18.700000	1.100000	7.900000	0.000000	2.200000	15.000000	0.400000	0.000000	0.000000
25%	3.000000	4.000000	90.200000	68.600000	437.700000	6.500000	15.500000	33.000000	2.700000	0.000000	0.000000
50%	4.000000	4.000000	91.600000	108.300000	664.200000	8.400000	19.300000	42.000000	4.000000	0.000000	0.520000
75%	7.000000	5.000000	92.900000	142.400000	713.900000	10.800000	22.800000	53.000000	4.900000	0.000000	6.570000
max	9.000000	9.000000	96.200000	291.300000	860.600000	56.100000	33.300000	100.000000	9.400000	6.400000	1090.840000

In [6]:
```
# to check missing values
df.isnull().sum()
```

Out[6]:
```
X         0
Y         0
month     0
day       0
FFMC      0
DMC       0
DC        0
ISI       0
temp      0
RH        0
wind      0
rain      0
area      0
dtype: int64
```

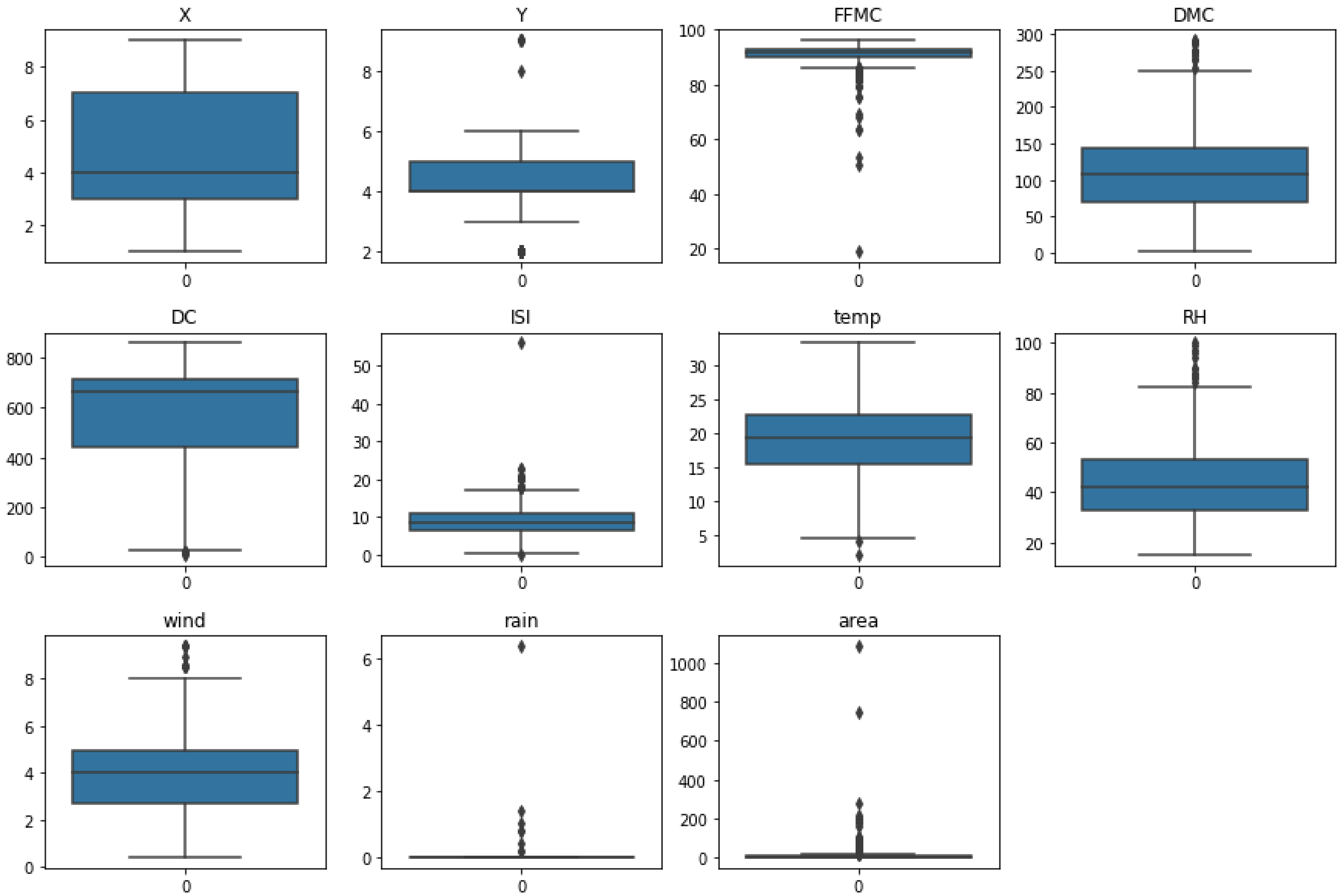
In [7]:

```
# to check outlier spread
num_c = df.select_dtypes(include=np.number).columns.tolist()
print("Number of numeric var:" ,len(num_c))
print(num_c)
```

```
Number of numeric var: 11
['X', 'Y', 'FFMC', 'DMC', 'DC', 'ISI', 'temp', 'RH', 'wind', 'rain', 'area']
```

In [8]:

```
plt.figure(figsize=(15,10))
plt.subplots_adjust(wspace=0.2, hspace=0.3)
for i in range(0,len(num_c)):
    plt.subplot(3,4,i+1)
    sns.boxplot(df[num_c[i]])
    plt.title(num_c[i])
```


X
Y
FFMC
DMC
DC
ISI
temp
RH
wind
rain
area

d. Plot the datapoints using Scatter Plot. (3 marks)

In [9]:

```
df1=df.copy()
df1['month_num']=df1['month'].replace(['jan','feb','mar','apr','may','jun','jul','aug','sep','oct','nov','dec'],
                                      [1,2,3,4,5,6,7,8,9,10,11,12])
```

In [10]:

```
df1.head()
```

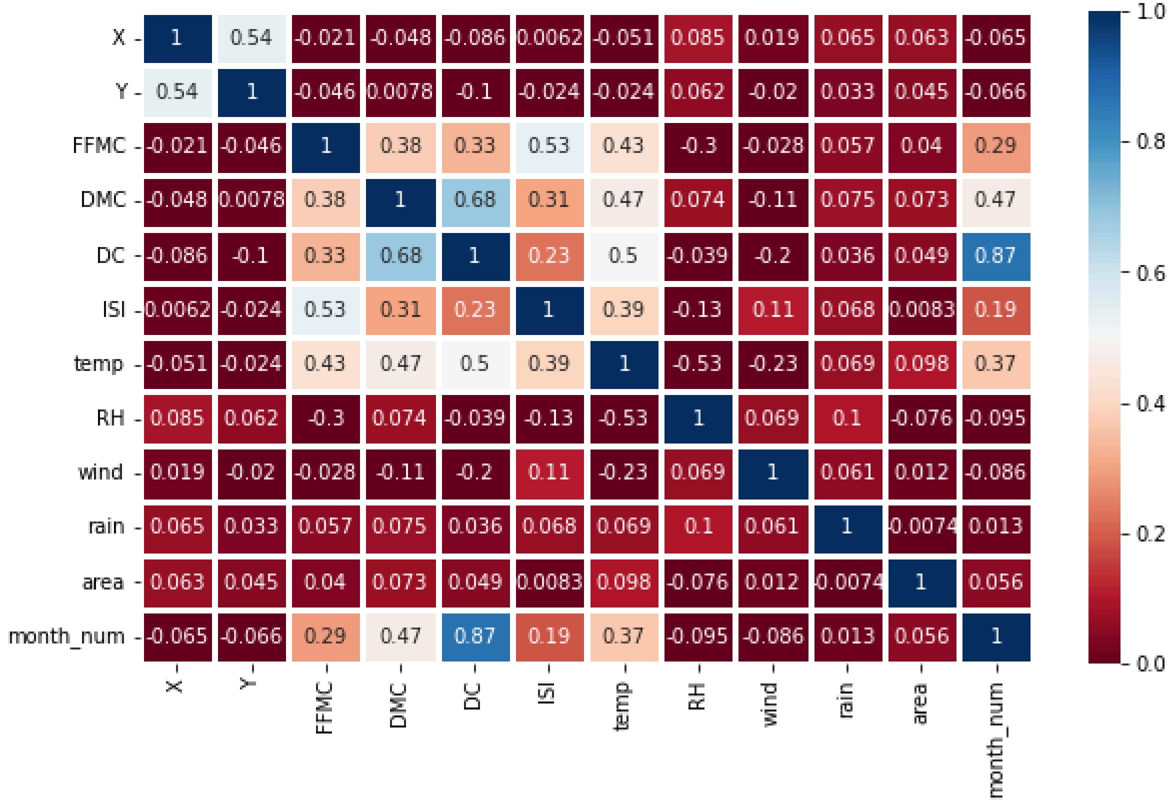
Out[10]:

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num
0	7	5	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3
1	7	4	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10
2	7	4	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10
3	8	6	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	3
4	8	6	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	3

In [11]:

```python
plt.figure(figsize=(10, 6))
sns.heatmap(df1.corr(),annot = True,linewidths=3,cmap='RdBu',vmin=0,vmax=1)
```

Out[11]: <AxesSubplot:>



FFMC (Fine Fuel Moisture Code), DMC (Duff Moisture Code), DC (Drought Code), ISI (Initial Spread Index)

In [12]:

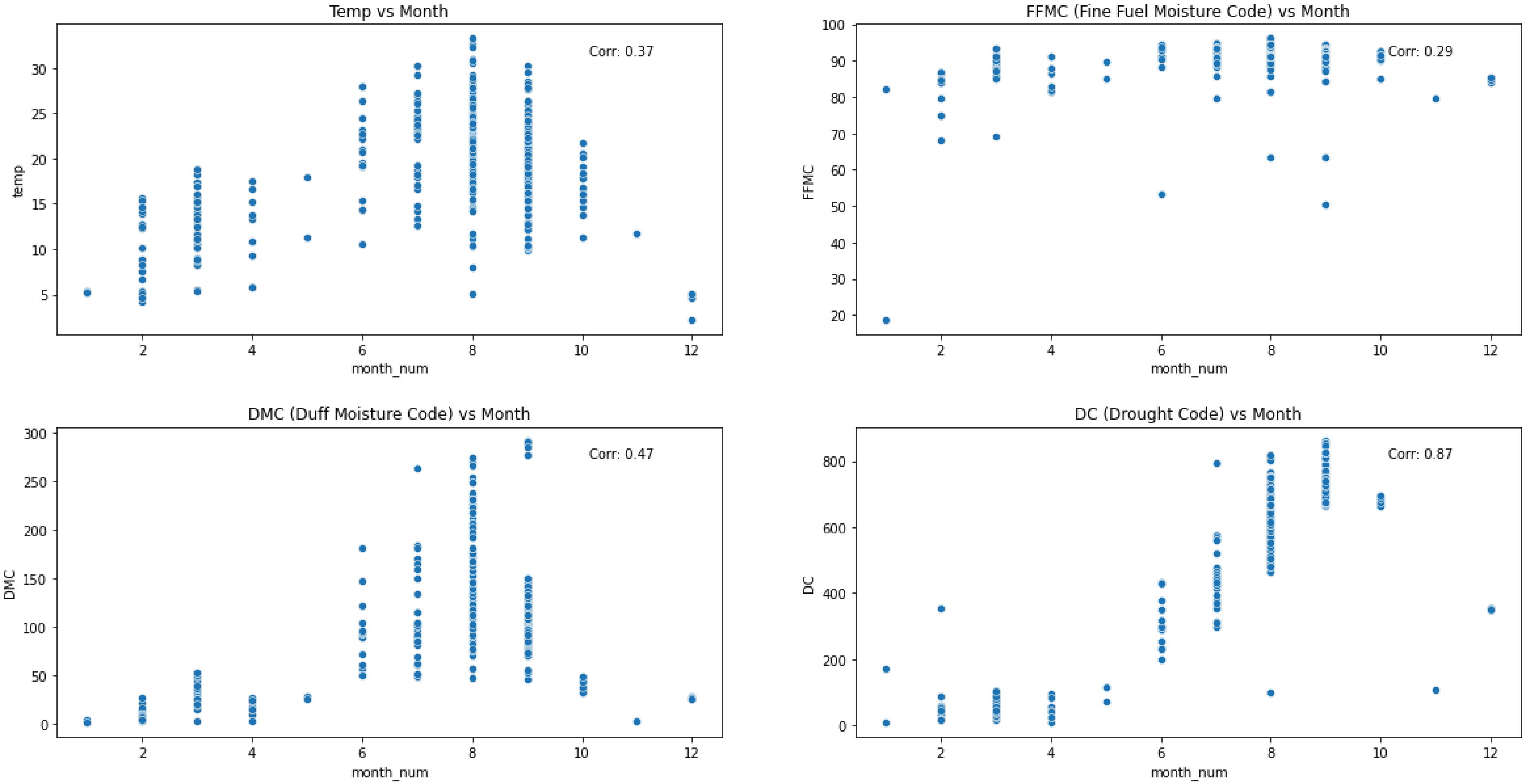
```
fig, axes = plt.subplots(2, 2, figsize=(20,10))
plt.subplots_adjust(wspace=0.2, hspace=0.3)

sns.scatterplot(x=df1['month_num'], y=df1['temp'],legend='auto', ax=axes[0][0])
axes[0, 0].set_title('Temp vs Month')
corr2 = np.corrcoef(df1['month_num'],df1['temp'])[0, 1]
axes[0, 0].annotate(f'Corr: {corr2:.2f}', xy=(0.8, 0.9), xycoords='axes fraction')

sns.scatterplot(x=df1['month_num'], y=df1['FFMC'],legend='auto', ax=axes[0][1])
axes[0, 1].set_title('FFMC (Fine Fuel Moisture Code) vs Month')
corr3 = np.corrcoef(df1['month_num'],df1['FFMC'])[0, 1]
axes[0, 1].annotate(f'Corr: {corr3:.2f}', xy=(0.8, 0.9), xycoords='axes fraction')

sns.scatterplot(x=df1['month_num'],y=df1['DMC'],legend='auto', ax=axes[1][0])
axes[1, 0].set_title('DMC (Duff Moisture Code) vs Month')
corr1 = np.corrcoef(df1['month_num'], df1['DMC'])[0, 1]
axes[1, 0].annotate(f'Corr: {corr1:.2f}', xy=(0.8, 0.9), xycoords='axes fraction')

sns.scatterplot(x=df1['month_num'],y=df1['DC'],legend='auto', ax=axes[1][1])
plt.title('DC (Drought Code) vs Month')
corr4 = np.corrcoef(df1['month_num'],df1['DC'])[0, 1]
axes[1, 1].annotate(f'Corr: {corr4:.2f}', xy=(0.8, 0.9), xycoords='axes fraction')
plt.show()
```



Temp vs Month
Corr: 0.37
temp
month_num
FFMC (Fine Fuel Moisture Code) vs Month
Corr: 0.29
FFMC
month_num
DMC (Duff Moisture Code) vs Month
Corr: 0.47
DMC
month_num
DC (Drought Code) vs Month
Corr: 0.87
DC
month_num

e. Apply five methods of agglomerative hierachial clustering. [Single, complete, average, centroid and ward's linkage method] (2 marks)

In [13]:

```
df1.drop(columns=['month','day'],inplace= True)
df1.head(3)
```

Out[13]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10

In [14]:

```
# to standardize data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df1)
df_scaled
```

Out[14]:

```
array([[ 1.00831277,  0.56986043, -0.80595947, ..., -0.07326831,
        -0.20201979, -1.96844301],
       [ 1.00831277, -0.24400101, -0.00810203, ..., -0.07326831,
        -0.20201979,  1.1101202 ],
       [ 1.00831277, -0.24400101, -0.00810203, ..., -0.07326831,
        -0.20201979,  1.1101202 ],
       ...,
       [ 1.00831277, -0.24400101, -1.64008316, ..., -0.07326831,
        -0.02653216,  0.23053071],
       [-1.58736044, -0.24400101,  0.68095666, ..., -0.07326831,
        -0.20201979,  0.23053071],
       [ 0.57570057, -1.05786246, -2.02087875, ..., -0.07326831,
        -0.20201979,  1.54991494]])
```

Single linkage method

In [15]:

```
from sklearn.cluster import AgglomerativeClustering

# creating a copy from original dataframe
df_single = df1.copy()

single = AgglomerativeClustering(n_clusters=5, affinity='euclidean',  linkage='single')
s_label = single.fit_predict(df_scaled)
df_single['labels'] = s_label
df_single.head()
```

Out[15]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num	labels
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3	1
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10	1
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10	1
3	8	6	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	3	1
4	8	6	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	3	1

Complete linkage method

In [16]:

```
# creating a copy from original dataframe
df_complete = df1.copy()

complete = AgglomerativeClustering(n_clusters=5, affinity='euclidean',  linkage='complete')
c_label = complete.fit_predict(df_scaled)
df_complete['labels'] = c_label
df_complete.head()
```

Out[16]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num	labels
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3	0
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10	0
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10	0
3	8	6	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	3	0
4	8	6	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	3	0

Average linkage method

In [17]:

```
# creating a copy from original dataframe
df_avg = df1.copy()

average = AgglomerativeClustering(n_clusters=5, affinity='euclidean',  linkage='average')
a_label = average.fit_predict(df_scaled)
df_avg['labels'] = a_label
df_avg.head()
```

Out[17]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num	labels
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3	0
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10	0
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10	0
3	8	6	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	3	0
4	8	6	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	3	0

Ward's linkage method

In [18]:
```
# creating a copy from original dataframe
df_ward = df1.copy()

ward = AgglomerativeClustering(n_clusters=5, affinity='euclidean',  linkage='ward')
w_label = ward.fit_predict(df_scaled)
df_ward['labels'] = w_label
df_ward.head()
```

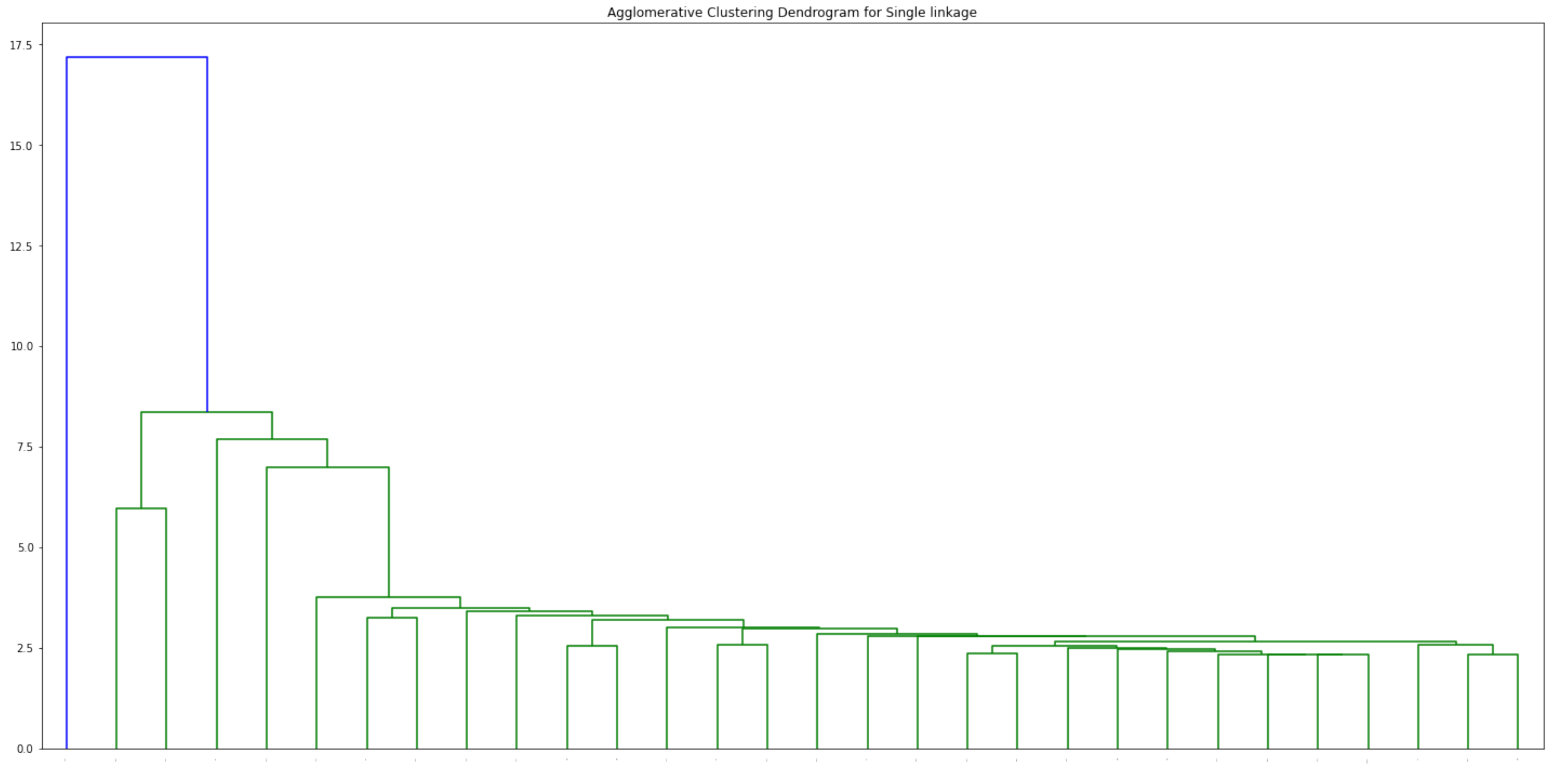
Out[18]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num	labels
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3	0
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10	1
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10	1
3	8	6	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	3	0
4	8	6	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	3	0

f. Draw dendrogram for the above five clustering methods. (2 marks)

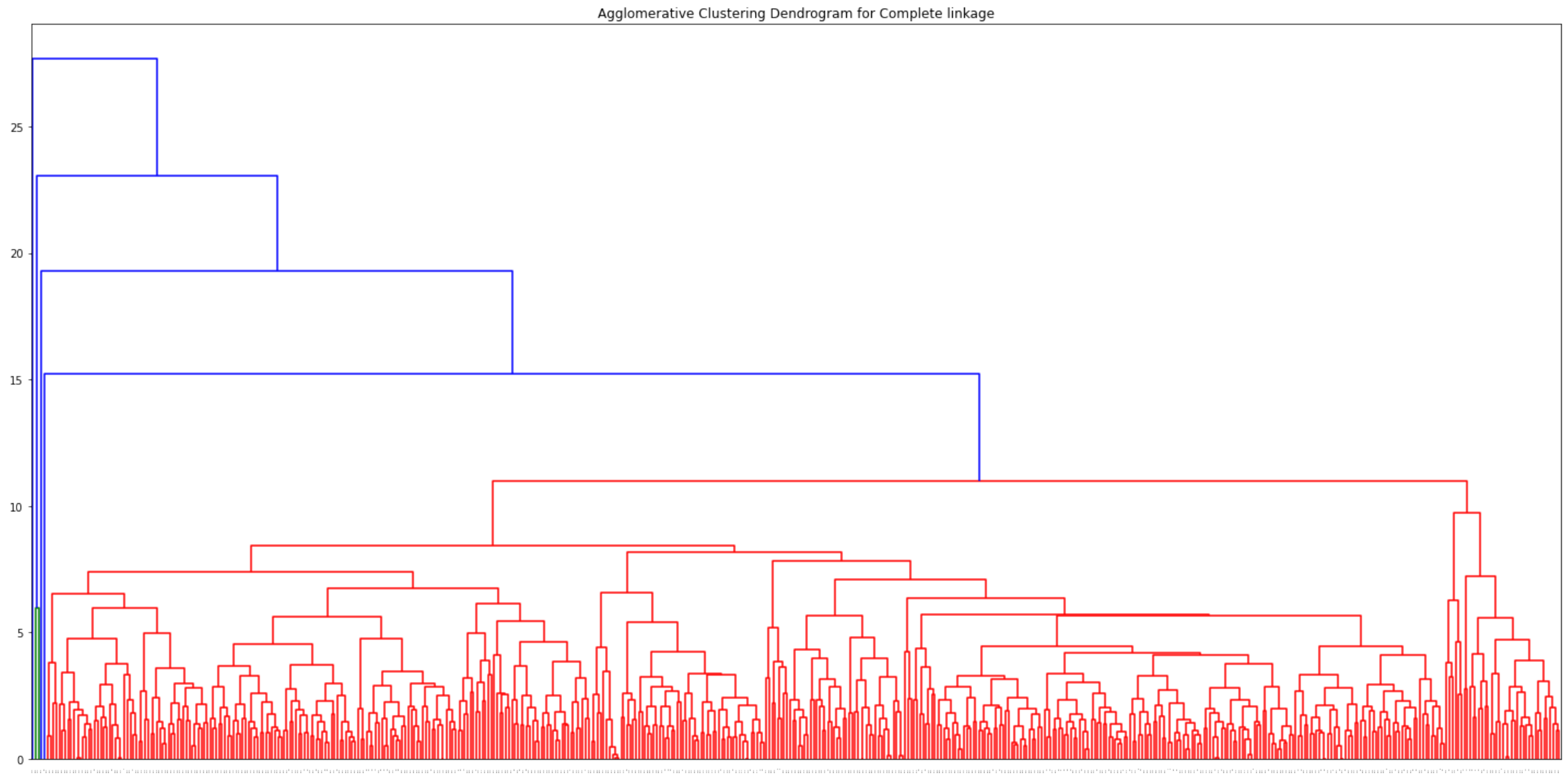
Single

In [19]:
```
l_single = linkage(df_scaled,'single')
plt.figure(figsize=(20,10))
plt.title('Agglomerative Clustering Dendrogram for Single linkage')
dendrogram(l_single,leaf_rotation=90.,color_threshold = 12, leaf_font_size=2,truncate_mode='lastp')
plt.tight_layout()
```



Complete

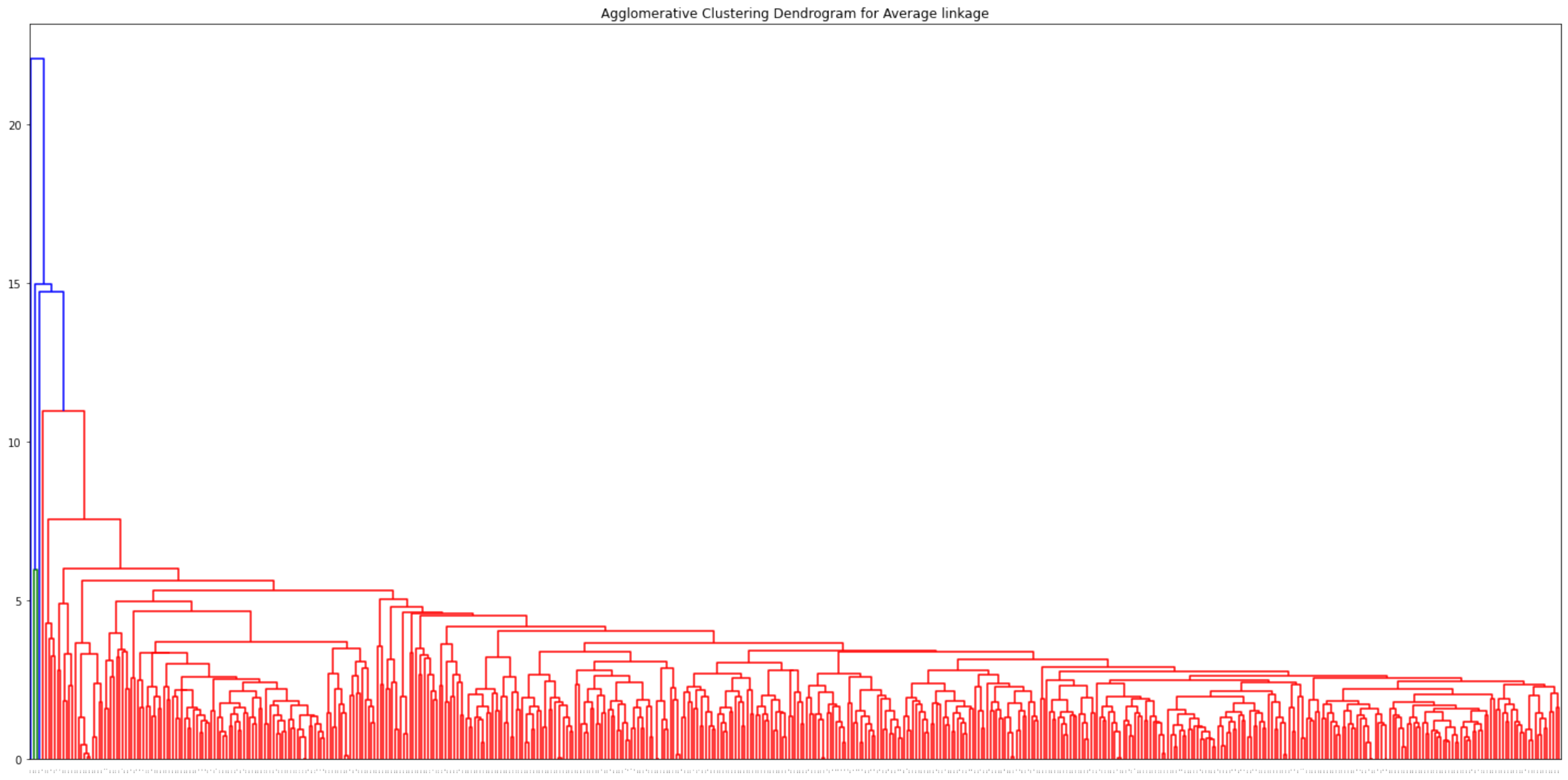
In [40]:
```
l_comp = linkage(df_scaled,'complete')
plt.figure(figsize=(20,10))
plt.title('Agglomerative Clustering Dendrogram for Complete linkage')
dendrogram(l_comp,leaf_rotation=90.,color_threshold = 12, leaf_font_size=2)
plt.tight_layout()
```



Average

In [30]:

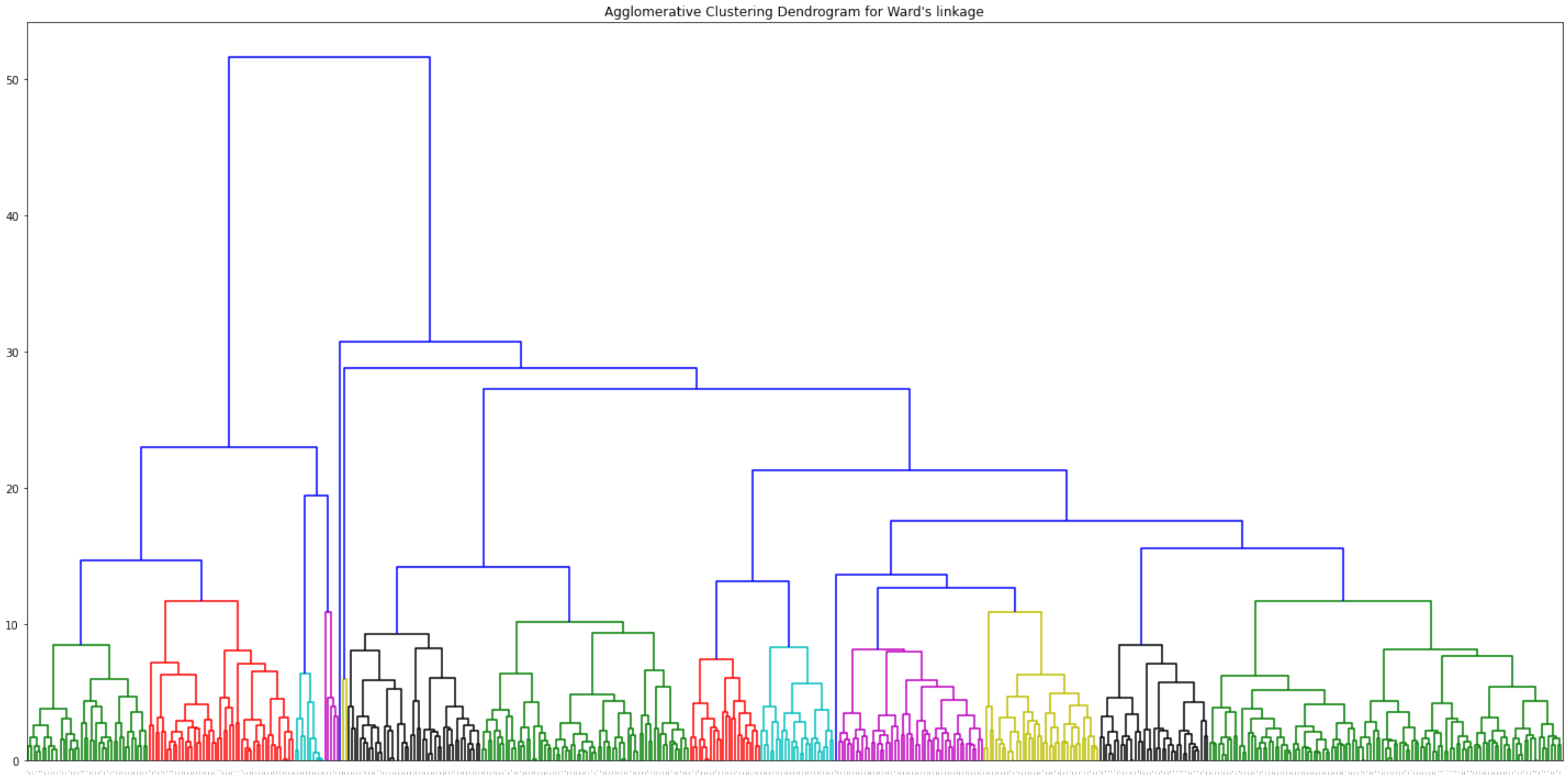
```
l_avg = linkage(df_scaled,'average')
plt.figure(figsize=(20,10))
plt.title('Agglomerative Clustering Dendrogram for Average linkage')
dendrogram(l_avg,leaf_rotation=90.,color_threshold = 12, leaf_font_size=2)
plt.tight_layout()
```



Ward

In [31]:

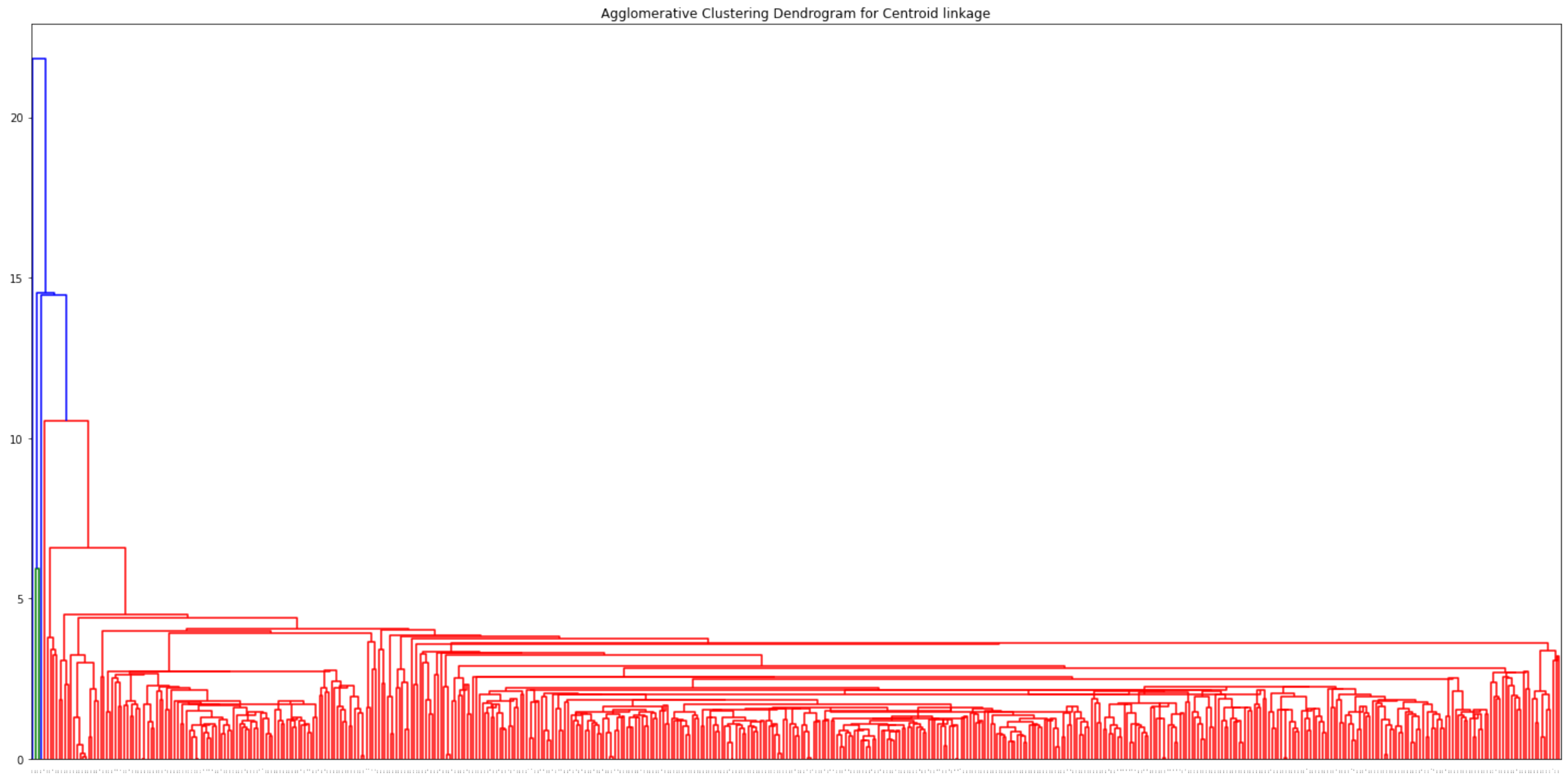
```
l_ward = linkage(df_scaled,'ward')
plt.figure(figsize=(20,10))
plt.title("Agglomerative Clustering Dendrogram for Ward's linkage")
dendrogram(l_ward,leaf_rotation=90.,color_threshold = 12, leaf_font_size=2)
plt.tight_layout()
```



Centroid

In [32]:

```
l_cen = linkage(df_scaled,'centroid')
plt.figure(figsize=(20,10))
plt.title('Agglomerative Clustering Dendrogram for Centroid linkage')
dendrogram(l_cen,leaf_rotation=90.,color_threshold = 12, leaf_font_size=2)
plt.tight_layout()
```



g. Calculate Cophenet Coorelation coefficient for the above five methods. (4 marks)

In [33]:

```
print("Cophenetic coefficient of correlation")

c_single , coph_dist = cophenet(l_single,pdist(df_scaled))
print("Single Linkage =",c_single)

c_comp , coph_dist = cophenet(l_comp,pdist(df_scaled))
print("Complete Linkage =",c_comp)

c_avg , coph_dist = cophenet(l_avg,pdist(df_scaled))
print("Average Linkage =",c_avg)

c_ward , coph_dist = cophenet(l_ward,pdist(df_scaled))
print("Ward's Linkage =",c_ward)

c_cent , coph_dist = cophenet(l_cen,pdist(df_scaled))
print("Centroid Linkage =",c_cent)
```

```
Cophenetic coefficient of correlation
Single Linkage = 0.854591654994345
Complete Linkage = 0.802948520905804
Average Linkage = 0.9130134898604785
Ward's Linkage = 0.4766781285005207
Centroid Linkage = 0.9047435200805628
```

h. Plot the best method labels using the scatter plot. (3 marks)

In [34]:

```
df_avg.head()
```

Out[34]:

	X	Y	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	month_num	labels
0	7	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	3	0
1	7	4	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	10	0
2	7	4	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	10	0
3	8	6	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	3	0
4	8	6	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	3	0

In [35]:

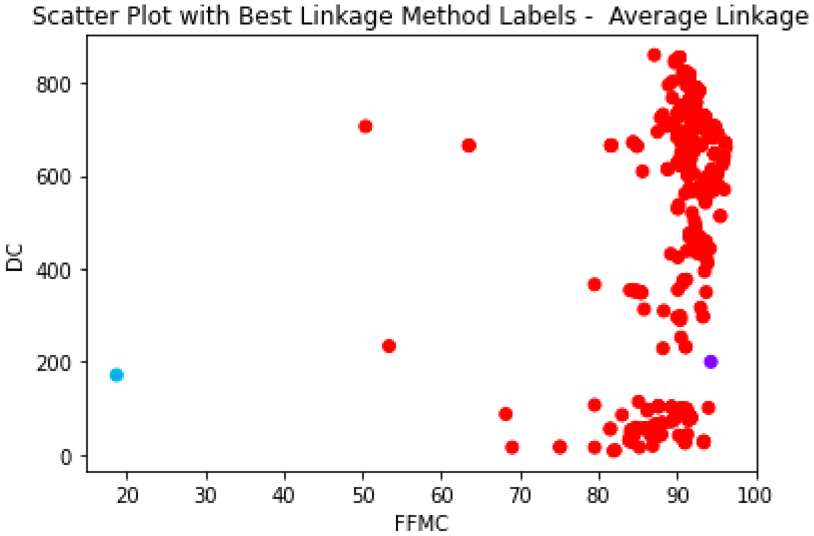
```
np.unique(a_label)
```

Out[35]:

```
array([0, 1, 2, 3, 4], dtype=int64)
```

In [43]:

```
# Plot the scatter plot with the best method labels
plt.scatter(df_avg['FFMC'], df_avg['DC'], c= a_label, cmap='rainbow_r')
plt.xlabel('FFMC')
plt.ylabel('DC')
plt.title('Scatter Plot with Best Linkage Method Labels -  Average Linkage')
plt.show()
```



In [ ]: