Dataset of pm2.5 with lat and lon only

0. Load the modules

In [100…

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

In [101…

```python
# API Key and City Information
api_key = '[redacted]'
city_name = 'Bangkok,TH'
```

1. Get Dataset API and convert to dataframe

In [102…

```python
# Get coordinates from city name (Geocoding API)
geocode_url = f'http://api.openweathermap.org/geo/1.0/direct?q={city_name}&limit=1&appid={api_key}'
response = requests.get(geocode_url)
location_data = response.json()

if not location_data:
    raise ValueError("Invalid city name or no location data available.")

# List of monitoring stations with their coordinates
stations = [
    {'name': '3T', 'lat': 13.7563, 'lon': 100.5018},
    {'name': '5T', 'lat': 13.7367, 'lon': 100.5231},
    {'name': '10T', 'lat': 13.7291, 'lon': 100.7750},
    {'name': '11T', 'lat': 13.7898, 'lon': 100.4486},
    {'name': '12T', 'lat': 13.8225, 'lon': 100.5147},
    {'name': '15T', 'lat': 13.7083, 'lon': 100.3728},
    {'name': '61T', 'lat': 13.6796, 'lon': 100.6067},
    # {'name': '52T (Roadside, Bangkok)', 'lat': 13.7563, 'lon': 100.5018},
    # {'name': '54T (Roadside, Bangkok)', 'lat': 13.7367, 'lon': 100.5231}
]
```

In [103…
```python
# Fetch PM2.5 data for each station
start_date = int(pd.Timestamp("2023-01-01 00:00:00").timestamp())
end_date = int(pd.Timestamp.now().timestamp())

pm25_data = []
```

In [104…
```python
for station in stations:
    lat = station['lat']
    lon = station['lon']
    pollution_url = (
        f'http://api.openweathermap.org/data/2.5/air_pollution/history?'
        f'lat={lat}&lon={lon}&start={start_date}&end={end_date}&appid={api_key}'
    )

    response = requests.get(pollution_url)
    data = response.json()

    if 'list' in data:
        for entry in data['list']:
            dt = pd.to_datetime(entry['dt'], unit='s')
            pm2_5 = entry['components']['pm2_5']
            pm25_data.append({
                'datetime': dt,
                'station': station['name'],
                'lat': lat,
                'lon': lon,
                'pm2_5': pm2_5
            })
    else:
        print(f"No data available for station {station['name']} (lat={lat}, lon={lon})")

# Convert to DataFrame
pm25_df = pd.DataFrame(pm25_data)
print(pm25_df.head())
```

```
             datetime station      lat       lon   pm2_5
0 2023-01-01 00:00:00      3T  13.7563  100.5018  158.36
1 2023-01-01 01:00:00      3T  13.7563  100.5018  199.19
2 2023-01-01 02:00:00      3T  13.7563  100.5018  226.01
3 2023-01-01 03:00:00      3T  13.7563  100.5018  235.79
4 2023-01-01 04:00:00      3T  13.7563  100.5018  187.84
```

In [105…
```python
pm25_df.shape
```

Out[105... (132538, 5)

In [106...
```
pm25_df.head()
```

Out[106...

	datetime	station	lat	lon	pm2_5
0	2023-01-01 00:00:00	3T	13.7563	100.5018	158.36
1	2023-01-01 01:00:00	3T	13.7563	100.5018	199.19
2	2023-01-01 02:00:00	3T	13.7563	100.5018	226.01
3	2023-01-01 03:00:00	3T	13.7563	100.5018	235.79
4	2023-01-01 04:00:00	3T	13.7563	100.5018	187.84

In [107...
```
pm25_df
```

Out[107...

	datetime	station	lat	lon	pm2_5
0	2023-01-01 00:00:00	3T	13.7563	100.5018	158.36
1	2023-01-01 01:00:00	3T	13.7563	100.5018	199.19
2	2023-01-01 02:00:00	3T	13.7563	100.5018	226.01
3	2023-01-01 03:00:00	3T	13.7563	100.5018	235.79
4	2023-01-01 04:00:00	3T	13.7563	100.5018	187.84
...	...	...	...	...	...
132533	2025-03-13 17:00:00	61T	13.6796	100.6067	29.20
132534	2025-03-13 18:00:00	61T	13.6796	100.6067	29.09
132535	2025-03-13 19:00:00	61T	13.6796	100.6067	31.42
132536	2025-03-13 20:00:00	61T	13.6796	100.6067	33.79
132537	2025-03-13 21:00:00	61T	13.6796	100.6067	34.96

132538 rows × 5 columns

2. EDA

In [108…

```
pm25_df['datetime'].diff().value_counts()
```

Out[108…

```
datetime
0 days 01:00:00       132454
1 days 01:00:00           56
2 days 01:00:00           21
-803 days +03:00:00        6
Name: count, dtype: int64
```

Handling gaps

In [109…

```
actual_range = pd.date_range(start=pm25_df['datetime'].min(), end=pm25_df['datetime'].max(), freq='h')
actual_range
```

Out[109…

```
DatetimeIndex(['2023-01-01 00:00:00', '2023-01-01 01:00:00',
               '2023-01-01 02:00:00', '2023-01-01 03:00:00',
               '2023-01-01 04:00:00', '2023-01-01 05:00:00',
               '2023-01-01 06:00:00', '2023-01-01 07:00:00',
               '2023-01-01 08:00:00', '2023-01-01 09:00:00',
               ...
               '2025-03-13 12:00:00', '2025-03-13 13:00:00',
               '2025-03-13 14:00:00', '2025-03-13 15:00:00',
               '2025-03-13 16:00:00', '2025-03-13 17:00:00',
               '2025-03-13 18:00:00', '2025-03-13 19:00:00',
               '2025-03-13 20:00:00', '2025-03-13 21:00:00'],
              dtype='datetime64[ns]', length=19270, freq='h')
```

In [110…

```
# Create a new DataFrame with all datetime and station combinations
stations = pm25_df[['lat', 'lon']].drop_duplicates()

# Create full cartesian product of stations × timestamps
full_index = pd.MultiIndex.from_product([actual_range, stations.itertuples(index=False, name=None)],
                                        names=["datetime", "station_info"])
```

In [111…

```
# Convert station lat/lon to tuples for merging
pm25_df["station_info"] = list(zip(pm25_df["lat"], pm25_df["lon"]))

# Merge with full datetime-station grid to fill missing timestamps per station
full_df = pd.DataFrame(index=full_index).reset_index().merge(pm25_df, on=["datetime", "station_info"], how="left")

# Split 'station_info' back into separate lat/lon columns
full_df[["lat", "lon"]] = pd.DataFrame(full_df["station_info"].tolist(), index=full_df.index)
```

```python
# Drop redundant column
full_df.drop(columns=["station_info"], inplace=True)
```

In [112…

```python
# Check for missing timestamps
print(full_df["datetime"].diff().value_counts())

print('\n')
print('-'*50)
print('I can understand that there can be a duplicate timestamp due to many stations are being recorded at the same time')
```

```
datetime
0 days 00:00:00    115620
0 days 01:00:00     19269
Name: count, dtype: int64


--------------------------------------------------
I can understand that there can be a duplicate timestamp due to many stations are being recorded at the same time
```

Check missing values

In [113…

```python
full_df.isna().sum()
```

Out[113…

```
datetime       0
station     2352
lat            0
lon            0
pm2_5       2352
dtype: int64
```

Handling missing values

In [114…

```python
# # Handling missing values for station

# # Sort data for consistency
# full_df.sort_values(by=['lat', 'lon', 'datetime'], inplace=True)

# # Fill missing station names using mode per (lat, lon) group
# full_df['station'] = full_df.groupby(['lat', 'lon'])['station'].transform(lambda x: x.mode()[0] if not x.mode().empty else None)

# # Final check
# print(full_df.isna().sum())
```

In [115…
```
# # Handling missing PM2.5 values per station while keeping trends
# full_df.sort_values(by=['lat', 'lon', 'datetime'], inplace=True)

# # Reset index before interpolation
# full_df.reset_index(inplace=True)

# # Interpolate missing PM2.5 values per station
# full_df['pm2_5'] = full_df.groupby(['lat', 'lon'])['pm2_5'].transform(lambda group: group.interpolate(method='linear'))

# # Use backward fill for any remaining missing values
# full_df['pm2_5'].fillna(method='bfill', inplace=True)

# # Restore original index
# full_df.set_index('datetime', inplace=True)

# # Final check
# print(full_df.isna().sum())
```

Check unique values of lat and lon

In [116…
```
full_df['lat'].unique()
```

Out[116…
```
array([13.7563, 13.7367, 13.7291, 13.7898, 13.8225, 13.7083, 13.6796])
```

In [117…
```
full_df['lon'].unique()
```

Out[117…
```
array([100.5018, 100.5231, 100.775 , 100.4486, 100.5147, 100.3728,
       100.6067])
```

In [118…
```
full_df['station'].unique()
```

Out[118…
```
array(['3T', '5T', '10T', '11T', '12T', '15T', '61T', nan], dtype=object)
```

In [119…
```
full_df.isna().sum()
```

Out[119…
```
datetime       0
station     2352
lat            0
lon            0
pm2_5       2352
dtype: int64
```

In [120…
```
full_df.groupby(['lat', 'lon'])['station'].nunique()
```

Out[120…

```
lat      lon
13.6796  100.6067    1
13.7083  100.3728    1
13.7291  100.7750    1
13.7367  100.5231    1
13.7563  100.5018    1
13.7898  100.4486    1
13.8225  100.5147    1
Name: station, dtype: int64
```

In [121…

```
full_df[full_df['station'].isna()]
```

Out[121…

	datetime	station	lat	lon	pm2_5
8911	2023-02-23 01:00:00	NaN	13.7563	100.5018	NaN
8912	2023-02-23 01:00:00	NaN	13.7367	100.5231	NaN
8913	2023-02-23 01:00:00	NaN	13.7291	100.7750	NaN
8914	2023-02-23 01:00:00	NaN	13.7898	100.4486	NaN
8915	2023-02-23 01:00:00	NaN	13.8225	100.5147	NaN
...	...	...	...	...	...
133730	2025-03-07 00:00:00	NaN	13.7291	100.7750	NaN
133731	2025-03-07 00:00:00	NaN	13.7898	100.4486	NaN
133732	2025-03-07 00:00:00	NaN	13.8225	100.5147	NaN
133733	2025-03-07 00:00:00	NaN	13.7083	100.3728	NaN
133734	2025-03-07 00:00:00	NaN	13.6796	100.6067	NaN

2352 rows × 5 columns

In [122…

```
full_df['station'].value_counts()
```

Out[122...

```
station
3T     18934
5T     18934
10T    18934
11T    18934
12T    18934
15T    18934
61T    18934
Name: count, dtype: int64
```

In [123...

```
isna = full_df['station'].isna().value_counts()
```

In [124...

```
missing_stations = full_df[full_df['station'].isna()]
missing_stations
```

Out[124...

	datetime	station	lat	lon	pm2_5
8911	2023-02-23 01:00:00	NaN	13.7563	100.5018	NaN
8912	2023-02-23 01:00:00	NaN	13.7367	100.5231	NaN
8913	2023-02-23 01:00:00	NaN	13.7291	100.7750	NaN
8914	2023-02-23 01:00:00	NaN	13.7898	100.4486	NaN
8915	2023-02-23 01:00:00	NaN	13.8225	100.5147	NaN
...	...	...	...	...	...
133730	2025-03-07 00:00:00	NaN	13.7291	100.7750	NaN
133731	2025-03-07 00:00:00	NaN	13.7898	100.4486	NaN
133732	2025-03-07 00:00:00	NaN	13.8225	100.5147	NaN
133733	2025-03-07 00:00:00	NaN	13.7083	100.3728	NaN
133734	2025-03-07 00:00:00	NaN	13.6796	100.6067	NaN

2352 rows × 5 columns

In [125...

```
full_df['lat'].unique()
```

Out[125...

```
array([13.7563, 13.7367, 13.7291, 13.7898, 13.8225, 13.7083, 13.6796])
```

In [126…

```python
full_df['lon'].unique()
```

Out[126…

```
array([100.5018, 100.5231, 100.775 , 100.4486, 100.5147, 100.3728,
       100.6067])
```

In [127…

```python
full_df.isna().sum()
```

Out[127…

```
datetime       0
station     2352
lat            0
lon            0
pm2_5       2352
dtype: int64
```

In [128…

```python
full_df.groupby('station')[['lat', 'lon']].nunique()
```

Out[128…

station	lat	lon
10T	1	1
11T	1	1
12T	1	1
15T	1	1
3T	1	1
5T	1	1
61T	1	1

In [129…

```python
full_df.groupby(['lat', 'lon'])['station'].nunique()
```

Out[129…

```
lat      lon
13.6796  100.6067    1
13.7083  100.3728    1
13.7291  100.7750    1
13.7367  100.5231    1
13.7563  100.5018    1
13.7898  100.4486    1
13.8225  100.5147    1
Name: station, dtype: int64
```

`Remove the (Roadside, Bangkok) emtries that shared the same lat, lon`

In [130…
```
full_df.groupby(['lat', 'lon'])['station'].unique()
```

Out[130…
```
lat      lon
13.6796  100.6067    [61T, nan]
13.7083  100.3728    [15T, nan]
13.7291  100.7750    [10T, nan]
13.7367  100.5231     [5T, nan]
13.7563  100.5018     [3T, nan]
13.7898  100.4486    [11T, nan]
13.8225  100.5147    [12T, nan]
Name: station, dtype: object
```

In [131…
```
full_df.head()
```

Out[131…

	datetime	station	lat	lon	pm2_5
0	2023-01-01	3T	13.7563	100.5018	158.36
1	2023-01-01	5T	13.7367	100.5231	158.36
2	2023-01-01	10T	13.7291	100.7750	63.83
3	2023-01-01	11T	13.7898	100.4486	71.83
4	2023-01-01	12T	13.8225	100.5147	158.36

In [132…
```
full_df.index.diff().value_counts()
```

Out[132…
```
1.0    134889
Name: count, dtype: int64
```

In [133…
```
full_df.isna().sum()
```

Out[133…
```
datetime       0
station     2352
lat            0
lon            0
pm2_5       2352
dtype: int64
```

3. Save the dataframe

In [134…

```
full_df.to_csv('pm25_bangkok_2025_lat_lon.csv', index=True)
```

In [135…

```
full_df
```

Out[135…

	datetime	station	lat	lon	pm2_5
0	2023-01-01 00:00:00	3T	13.7563	100.5018	158.36
1	2023-01-01 00:00:00	5T	13.7367	100.5231	158.36
2	2023-01-01 00:00:00	10T	13.7291	100.7750	63.83
3	2023-01-01 00:00:00	11T	13.7898	100.4486	71.83
4	2023-01-01 00:00:00	12T	13.8225	100.5147	158.36
...	...	...	...	...	...
134885	2025-03-13 21:00:00	10T	13.7291	100.7750	34.96
134886	2025-03-13 21:00:00	11T	13.7898	100.4486	21.47
134887	2025-03-13 21:00:00	12T	13.8225	100.5147	33.04
134888	2025-03-13 21:00:00	15T	13.7083	100.3728	5.86
134889	2025-03-13 21:00:00	61T	13.6796	100.6067	34.96

134890 rows × 5 columns

In [136…

```
full_df.index.diff().value_counts()
```

Out[136…

```
1.0    134889
Name: count, dtype: int64
```

4. Try loading the saved dataset and start analysis

In [137…

```
df = pd.read_csv('pm25_bangkok_2025_lat_lon.csv', parse_dates=['datetime'])
df.head()
```

Out[137...

	Unnamed: 0	datetime	station	lat	lon	pm2_5
0	0	2023-01-01	3T	13.7563	100.5018	158.36
1	1	2023-01-01	5T	13.7367	100.5231	158.36
2	2	2023-01-01	10T	13.7291	100.7750	63.83
3	3	2023-01-01	11T	13.7898	100.4486	71.83
4	4	2023-01-01	12T	13.8225	100.5147	158.36

Validate the loaded dataframe

In [138...

```
df.isna().sum()
```

Out[138...

```
Unnamed: 0       0
datetime         0
station       2352
lat              0
lon              0
pm2_5         2352
dtype: int64
```

In [139...

```
df.set_index('datetime', inplace=True)
```

In [140...

```
df.index.diff().value_counts()
```

Out[140...

```
datetime
0 days 00:00:00    115620
0 days 01:00:00     19269
Name: count, dtype: int64
```

In [141...

```
df.head()
```

Out[141…

	Unnamed: 0	station	lat	lon	pm2_5
datetime					
2023-01-01	0	3T	13.7563	100.5018	158.36
2023-01-01	1	5T	13.7367	100.5231	158.36
2023-01-01	2	10T	13.7291	100.7750	63.83
2023-01-01	3	11T	13.7898	100.4486	71.83
2023-01-01	4	12T	13.8225	100.5147	158.36

In [142…

```
df.reset_index(inplace=True)
df
```

Out[142…

	datetime	Unnamed: 0	station	lat	lon	pm2_5
0	2023-01-01 00:00:00	0	3T	13.7563	100.5018	158.36
1	2023-01-01 00:00:00	1	5T	13.7367	100.5231	158.36
2	2023-01-01 00:00:00	2	10T	13.7291	100.7750	63.83
3	2023-01-01 00:00:00	3	11T	13.7898	100.4486	71.83
4	2023-01-01 00:00:00	4	12T	13.8225	100.5147	158.36
...	...	...	...	...	...	...
134885	2025-03-13 21:00:00	134885	10T	13.7291	100.7750	34.96
134886	2025-03-13 21:00:00	134886	11T	13.7898	100.4486	21.47
134887	2025-03-13 21:00:00	134887	12T	13.8225	100.5147	33.04
134888	2025-03-13 21:00:00	134888	15T	13.7083	100.3728	5.86
134889	2025-03-13 21:00:00	134889	61T	13.6796	100.6067	34.96

134890 rows × 6 columns

In [143…

```
df
```

Out[143…

	datetime	Unnamed: 0	station	lat	lon	pm2_5
0	2023-01-01 00:00:00	0	3T	13.7563	100.5018	158.36
1	2023-01-01 00:00:00	1	5T	13.7367	100.5231	158.36
2	2023-01-01 00:00:00	2	10T	13.7291	100.7750	63.83
3	2023-01-01 00:00:00	3	11T	13.7898	100.4486	71.83
4	2023-01-01 00:00:00	4	12T	13.8225	100.5147	158.36
...	...	...	...	...	...	...
134885	2025-03-13 21:00:00	134885	10T	13.7291	100.7750	34.96
134886	2025-03-13 21:00:00	134886	11T	13.7898	100.4486	21.47
134887	2025-03-13 21:00:00	134887	12T	13.8225	100.5147	33.04
134888	2025-03-13 21:00:00	134888	15T	13.7083	100.3728	5.86
134889	2025-03-13 21:00:00	134889	61T	13.6796	100.6067	34.96

134890 rows × 6 columns

5. Feature engineering

In [144…

```
#Add more feature about time
df['datetime'] = pd.to_datetime(df['datetime'])

# Extract hour as 'time'
df['hour'] = df['datetime'].dt.hour

# Extract month
df['month'] = df['datetime'].dt.month

# Extract day of the week as a number (0 as Monday to 6 as Sunday)
df['day_of_week'] = df['datetime'].dt.dayofweek

# Display the updated DataFrame
print(df.head())
```

```
     datetime  Unnamed: 0 station      lat       lon   pm2_5  hour  month  \
0 2023-01-01           0      3T  13.7563  100.5018  158.36     0      1
1 2023-01-01           1      5T  13.7367  100.5231  158.36     0      1
2 2023-01-01           2     10T  13.7291  100.7750   63.83     0      1
3 2023-01-01           3     11T  13.7898  100.4486   71.83     0      1
4 2023-01-01           4     12T  13.8225  100.5147  158.36     0      1

   day_of_week
0            6
1            6
2            6
3            6
4            6
```

In [145…
```
df2 = pd.read_csv(r'df2.csv',header=0)
```

In [146…
```
df = df.merge(df2, on=['station'])
```

In [147…
```
df.head()
```

Out[147…

	datetime	Unnamed: 0	station	lat	lon	pm2_5	hour	month	day_of_week	sea_level	population	population_density	household
0	2023-01-01	0	3T	13.7563	100.5018	158.36	0	1	6	23	64468	9046.87	58039
1	2023-01-01	1	5T	13.7367	100.5231	158.36	0	1	6	10	40077	4788.74	32138
2	2023-01-01	2	10T	13.7291	100.7750	63.83	0	1	6	20	179899	1452.45	105461
3	2023-01-01	3	11T	13.7898	100.4486	71.83	0	1	6	26	101330	3437.36	44465
4	2023-01-01	4	12T	13.8225	100.5147	158.36	0	1	6	3	118634	10275.79	78240

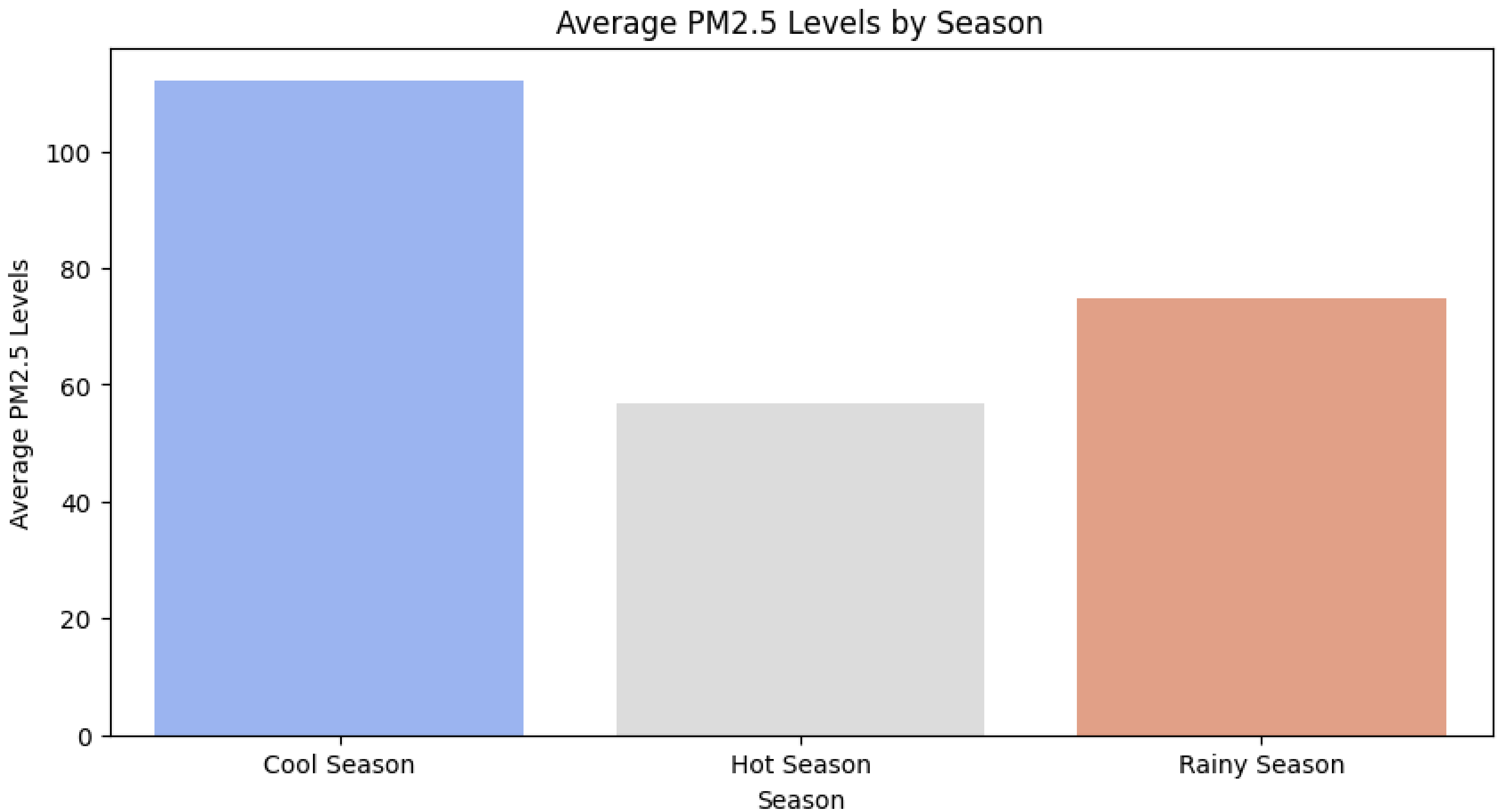
In [148…
```
def map_season(month):
    if 3 <= month <= 4:
        return 'Hot Season'
    elif 5 <= month <= 10:
        return 'Rainy Season'
    else:
```

```python
        return 'Cool Season'

# Apply the function to create a new 'season' column
df['season'] = df['month'].apply(map_season)
```

In [149…

```python
seasonal_pm25 = df.groupby('season')['pm2_5'].mean().reset_index()

# Create a bar plot
plt.figure(figsize=(10, 5))
sns.barplot(data=seasonal_pm25, x='season', y='pm2_5', palette='coolwarm')
plt.title('Average PM2.5 Levels by Season')
plt.xlabel('Season')
plt.ylabel('Average PM2.5 Levels')
plt.show()
```

```
C:\Users\Aimmy\AppData\Local\Temp\ipykernel_30320\2605075261.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `l
egend=False` for the same effect.

  sns.barplot(data=seasonal_pm25, x='season', y='pm2_5', palette='coolwarm')
```



In [150…

```
df=pd.get_dummies(df, columns=['season'], drop_first=True)
```

In [151…

```
# Add time step column
# df['time_step'] = df.index.to_list()
```

In [152…

```
# df['time_step']
```

In [153…

```
# df.set_index('datetime', inplace=True)
```

In [154…

```
df.dtypes
```

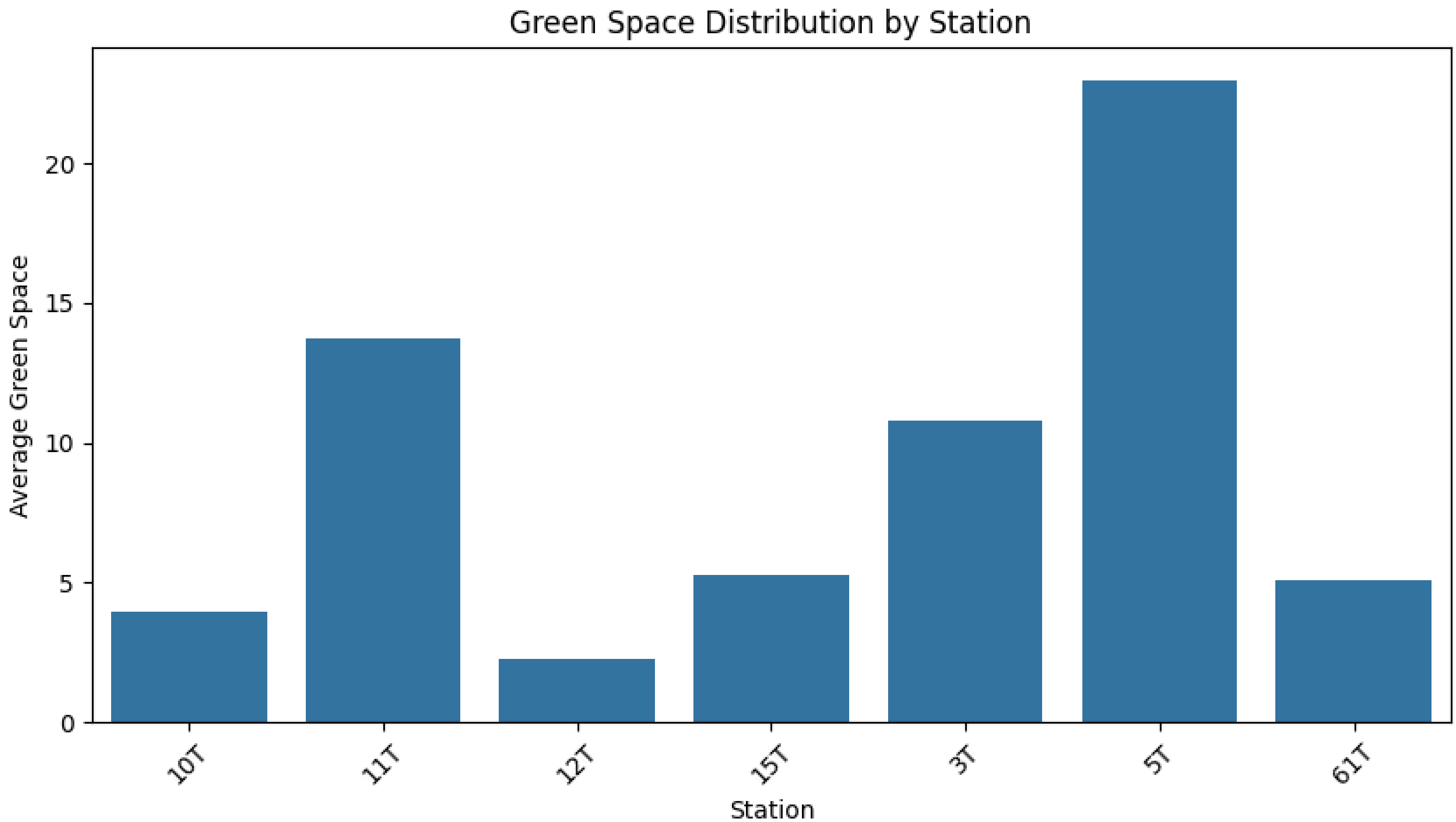
Out[154…
```
datetime                 datetime64[ns]
Unnamed: 0                        int64
station                          object
lat                             float64
lon                             float64
pm2_5                           float64
hour                              int32
month                             int32
day_of_week                       int32
sea_level                         int64
population                        int64
population_density              float64
household                         int64
household_density               float64
green_space                     float64
green_space_area                float64
factory_num                       int64
factory_area                      int64
season_Hot Season                  bool
season_Rainy Season                bool
dtype: object
```

In [155…
```
df.columns
```

Out[155…
```
Index(['datetime', 'Unnamed: 0', 'station', 'lat', 'lon', 'pm2_5', 'hour',
       'month', 'day_of_week', 'sea_level', 'population', 'population_density',
       'household', 'household_density', 'green_space', 'green_space_area',
       'factory_num', 'factory_area', 'season_Hot Season',
       'season_Rainy Season'],
      dtype='object')
```

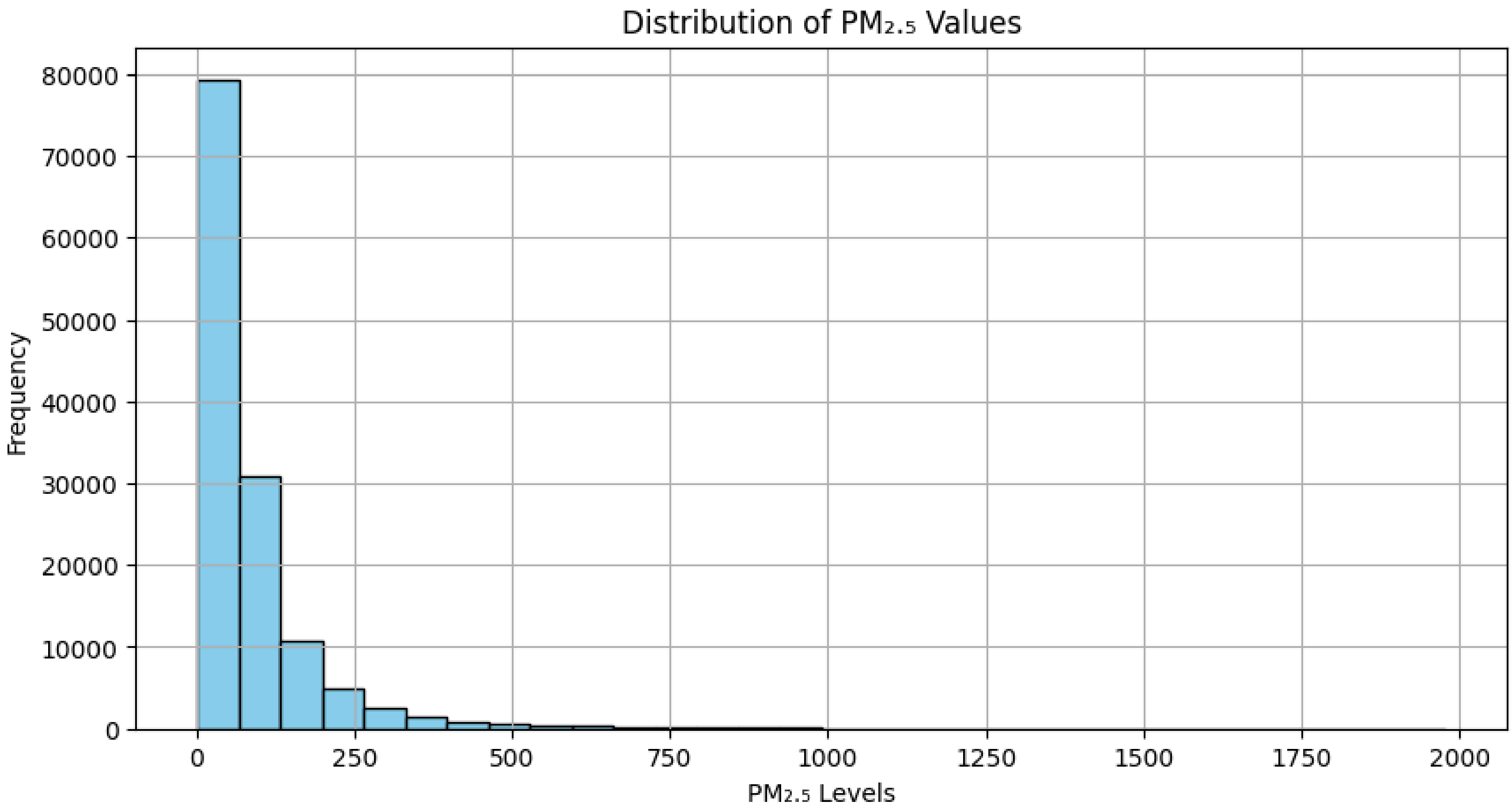
Visualize

In [156…
```
green_space_per_station = df.groupby('station')['green_space'].mean().reset_index()

# Create the bar graph
plt.figure(figsize=(10, 5))
sns.barplot(x='station', y='green_space', data=green_space_per_station)
plt.title('Green Space Distribution by Station')
plt.xlabel('Station')
plt.ylabel('Average Green Space')
plt.xticks(rotation=45)  # Rotate station names for better readability
plt.show()
```



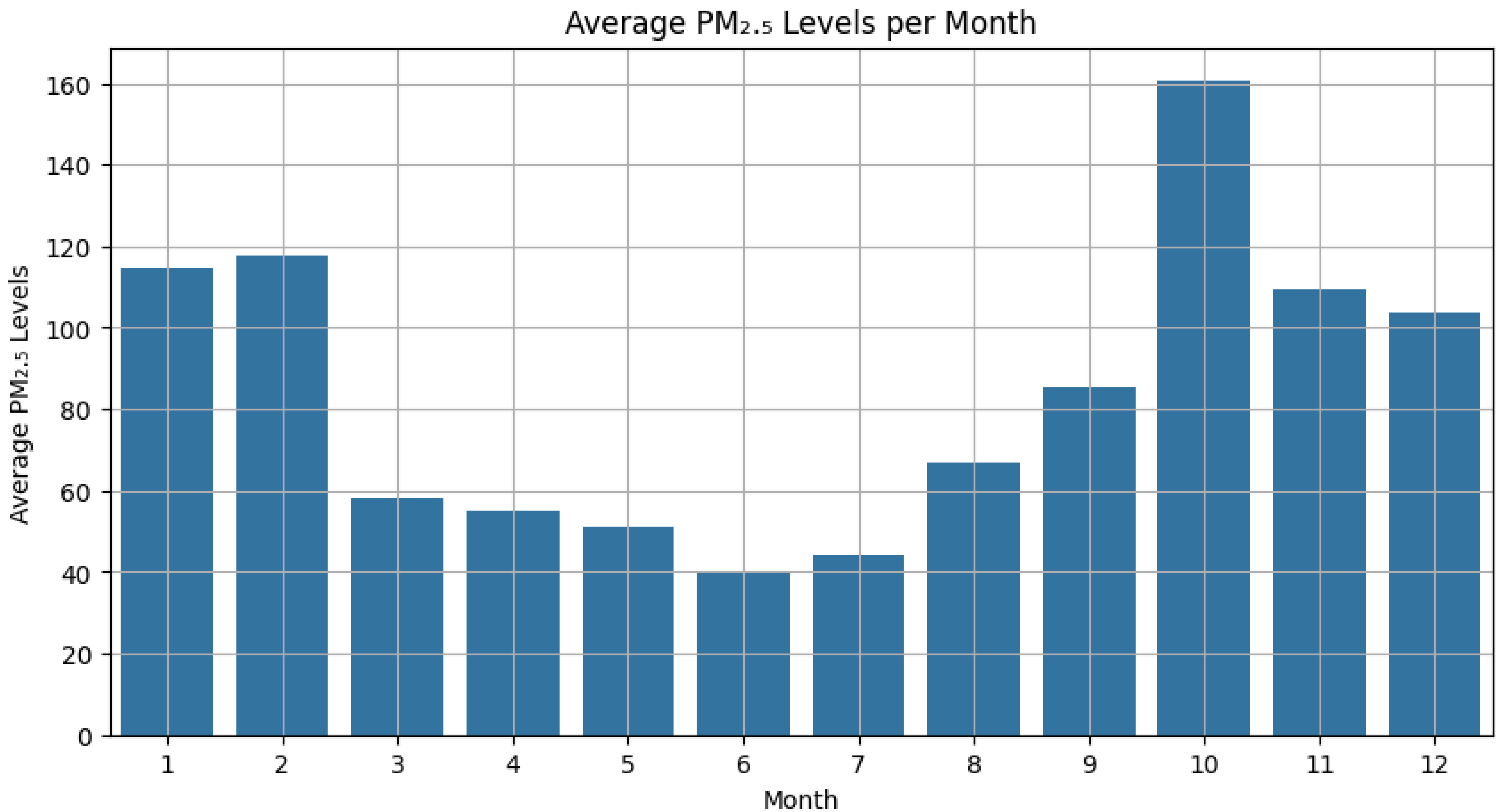
In [157…

```
# Create histogram for PM2.5 distribution
plt.figure(figsize=(10, 5))
plt.hist(df['pm2_5'], bins=30, color='skyblue', edgecolor='black')
plt.title('Distribution of PM₂.₅ Values')
plt.xlabel('PM₂.₅ Levels')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



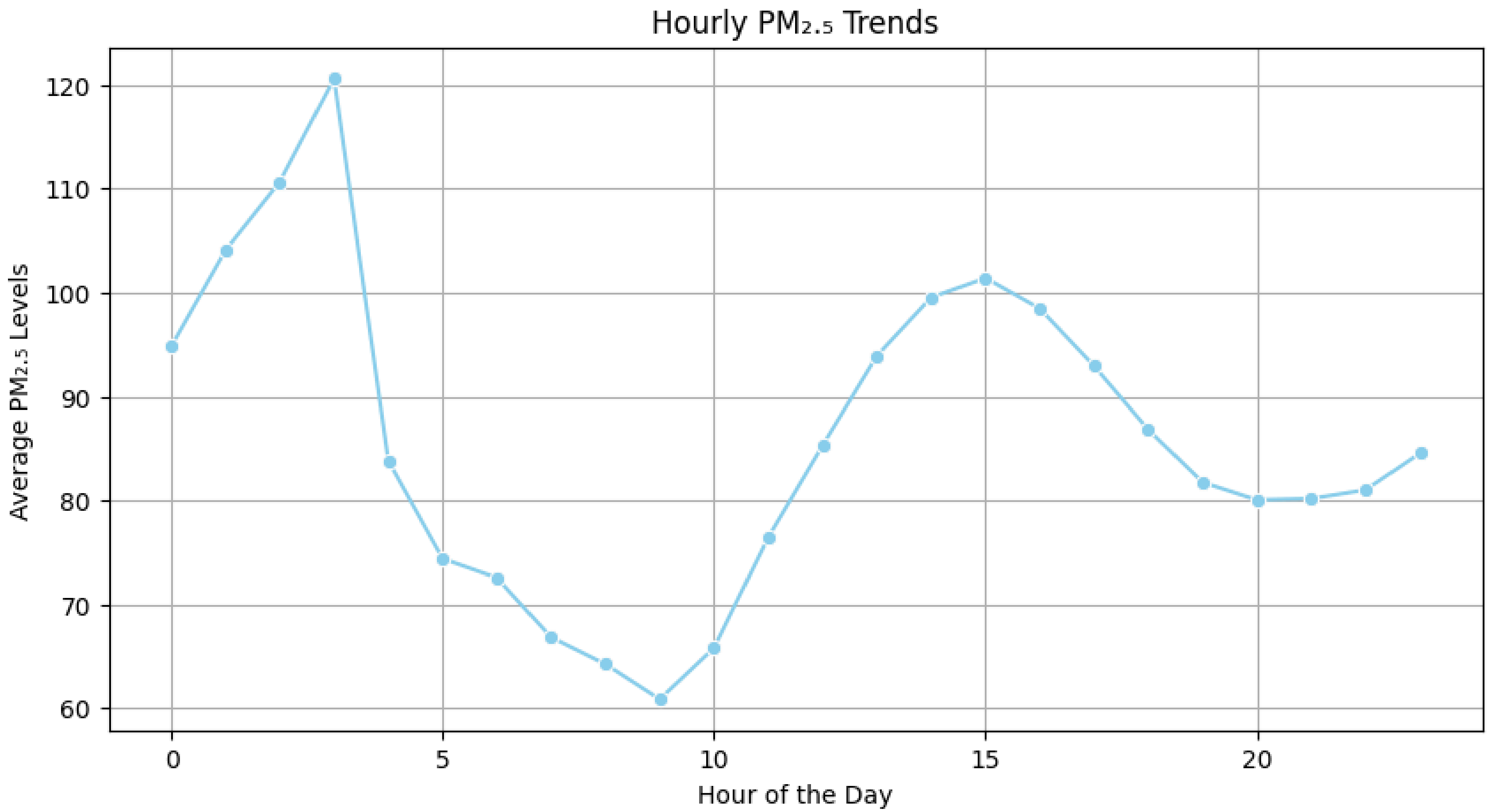
In [158…

```
# Calculate average PM2.5 per month
average_pm25_per_month = df.groupby('month')['pm2_5'].mean().reset_index()

# Create bar chart
plt.figure(figsize=(10, 5))
sns.barplot(data=average_pm25_per_month, x='month', y='pm2_5')
plt.title('Average PM₂.₅ Levels per Month')
plt.xlabel('Month')
plt.ylabel('Average PM₂.₅ Levels')
plt.grid(True)
plt.show()
```



In [159…

```
hourly_pm25_trends = df.groupby('hour')['pm2_5'].mean().reset_index()

# Create line plot for hourly trends
plt.figure(figsize=(10, 5))
sns.lineplot(data=hourly_pm25_trends, x='hour', y='pm2_5', marker='o', color='skyblue')
plt.title('Hourly PM₂.₅ Trends')
plt.xlabel('Hour of the Day')
plt.ylabel('Average PM₂.₅ Levels')
plt.grid(True)
plt.show()
```



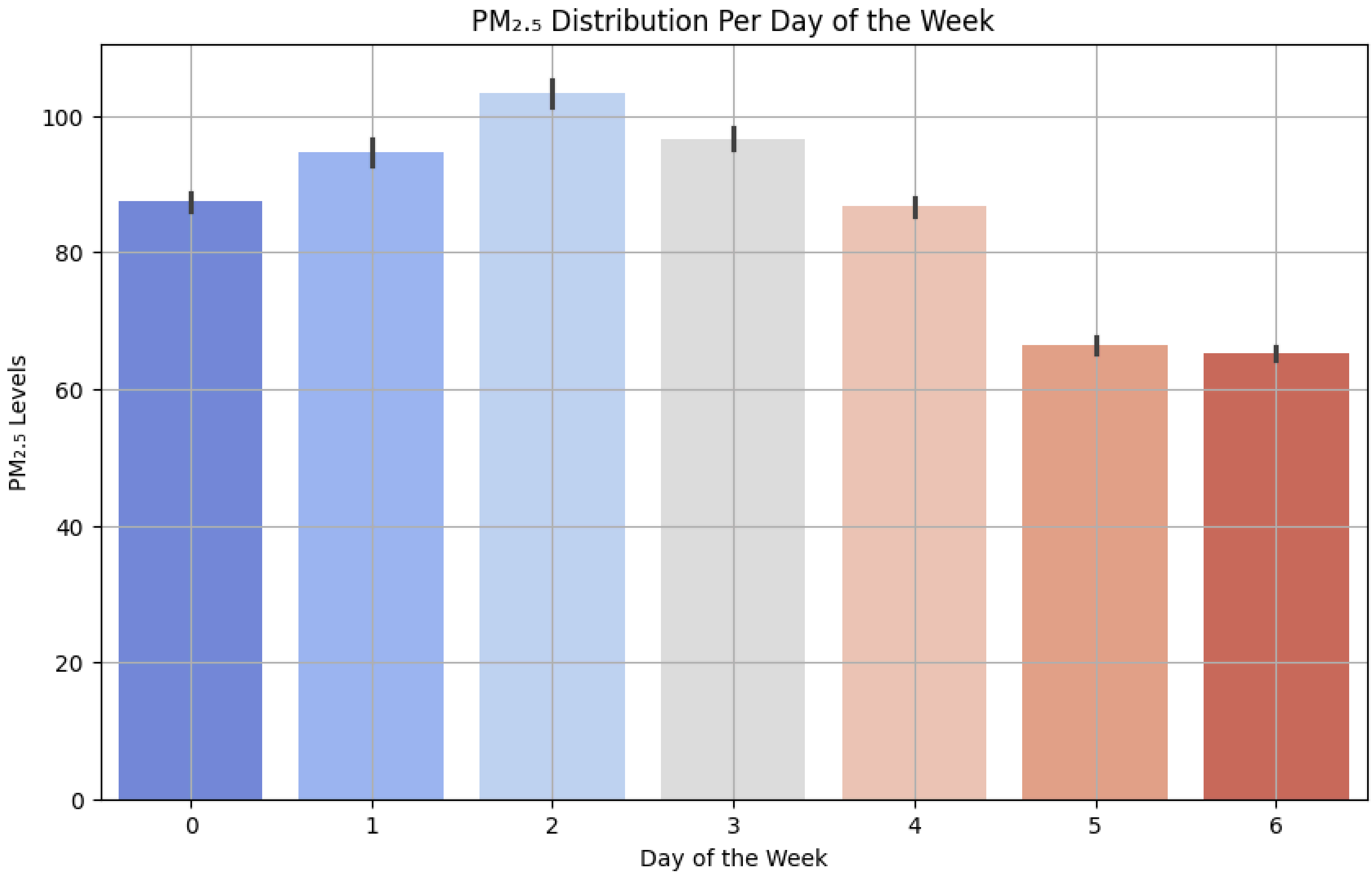
In [160…

```
# You can reuse average_pm25_per_month calculated previously
average_pm25_per_month = df.groupby('month')['pm2_5'].mean().reset_index()

plt.figure(figsize=(10, 5))
sns.lineplot(data=average_pm25_per_month, x='month', y='pm2_5', marker='o', color='green')
plt.title('Monthly PM₂.₅ Trends')
plt.xlabel('Month')
plt.ylabel('Average PM₂.₅ Levels')
plt.grid(True)
plt.show()
```

In [161…

```
# Box plot for PM2.5 distribution per day of the week
plt.figure(figsize=(10, 6))
sns.barplot(data=df, x='day_of_week', y='pm2_5', palette='coolwarm')
plt.title('PM₂.₅ Distribution Per Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('PM₂.₅ Levels')
plt.grid(True)
plt.show()
```

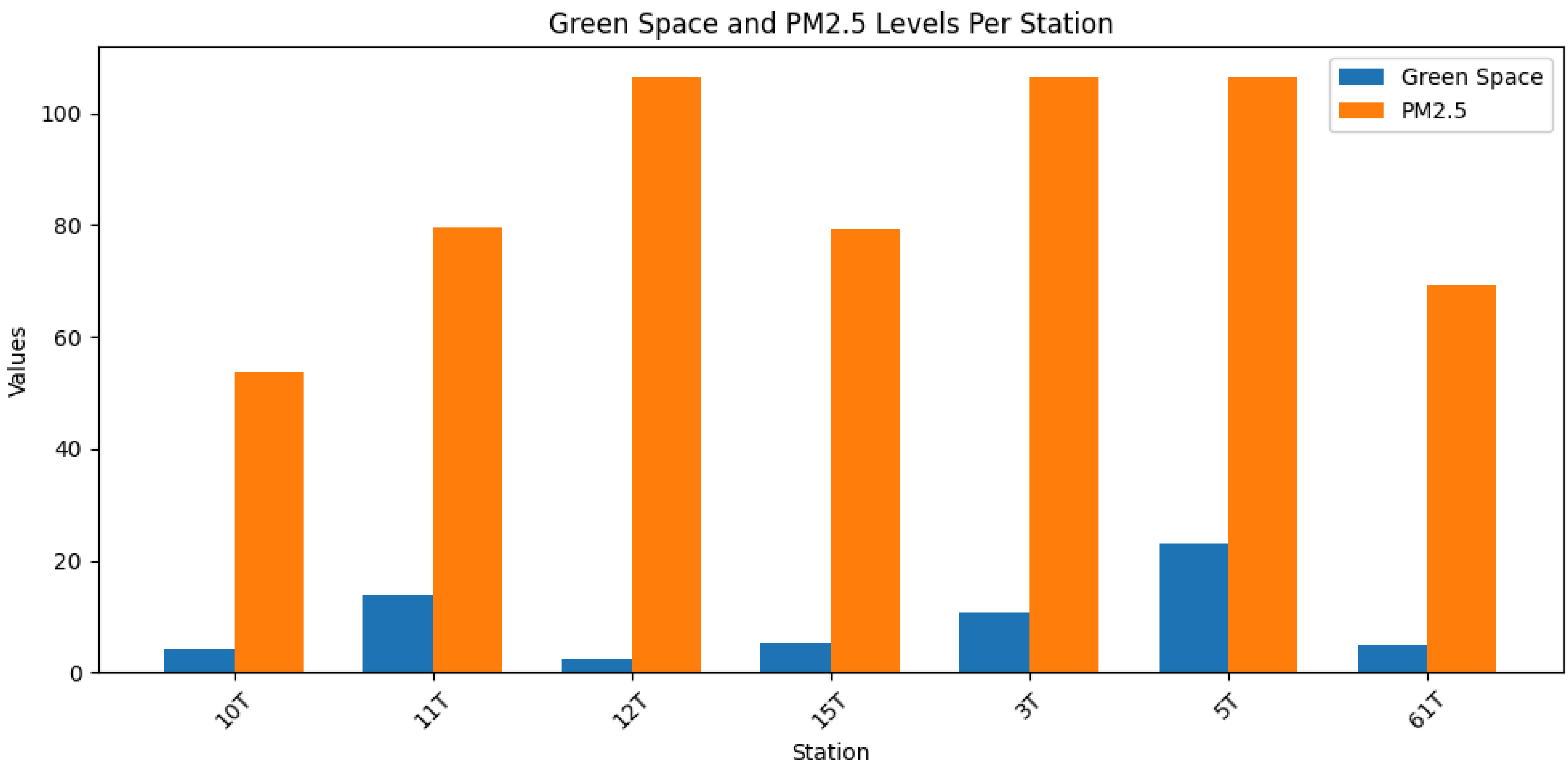
```
C:\Users\Aimmy\AppData\Local\Temp\ipykernel_30320\2316793127.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `l
egend=False` for the same effect.

  sns.barplot(data=df, x='day_of_week', y='pm2_5', palette='coolwarm')
```



In [162…

```
station_stats = df.groupby('station').agg({
    'green_space': 'mean',  # Average or sum of green space per station
    'pm2_5': 'mean'        # Average PM2.5 levels per station
}).reset_index()

# Create a grouped bar chart
plt.figure(figsize=(10, 5))
# Setting the positions for the bars
bar_width = 0.35
index = range(len(station_stats['station']))

# Plotting both 'green_space' and 'pm2_5' data
```

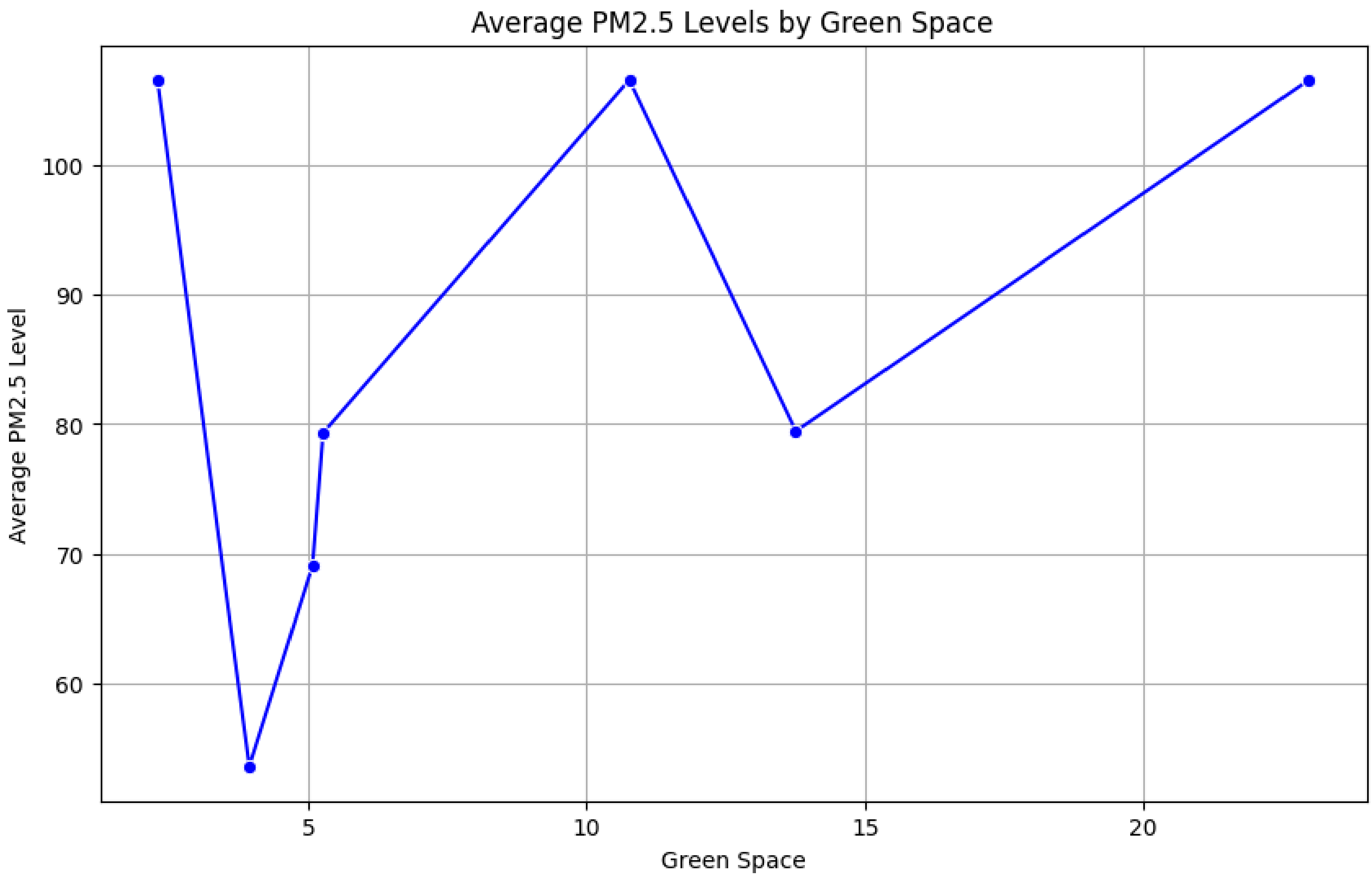
```python
bars1 = plt.bar(index, station_stats['green_space'], bar_width, label='Green Space')
bars2 = plt.bar([p + bar_width for p in index], station_stats['pm2_5'], bar_width, label='PM2.5')

# Adding labels, title, and legend
plt.xlabel('Station')
plt.ylabel('Values')
plt.title('Green Space and PM2.5 Levels Per Station')
plt.xticks([p + bar_width / 2 for p in index], station_stats['station'], rotation=45)
plt.legend()

# Show the plot
plt.tight_layout()
plt.show()
```



In [163…

```python
average_pm25_by_greenspace = df.groupby('green_space')['pm2_5'].mean().reset_index()
average_pm25_by_greenspace = average_pm25_by_greenspace.sort_values('green_space')
```

```python
# Create a line plot for the average PM2.5 levels by green space
plt.figure(figsize=(10, 6))
sns.lineplot(x='green_space', y='pm2_5', data=average_pm25_by_greenspace, marker='o', color='blue')
plt.title('Average PM2.5 Levels by Green Space')
plt.xlabel('Green Space')
plt.ylabel('Average PM2.5 Level')
plt.grid(True)  # Optional: Adds a grid for better readability
plt.show()
```



We need to use these analysis

- Trend analysis

- Cyclicity analysis
- Seasonal analysis

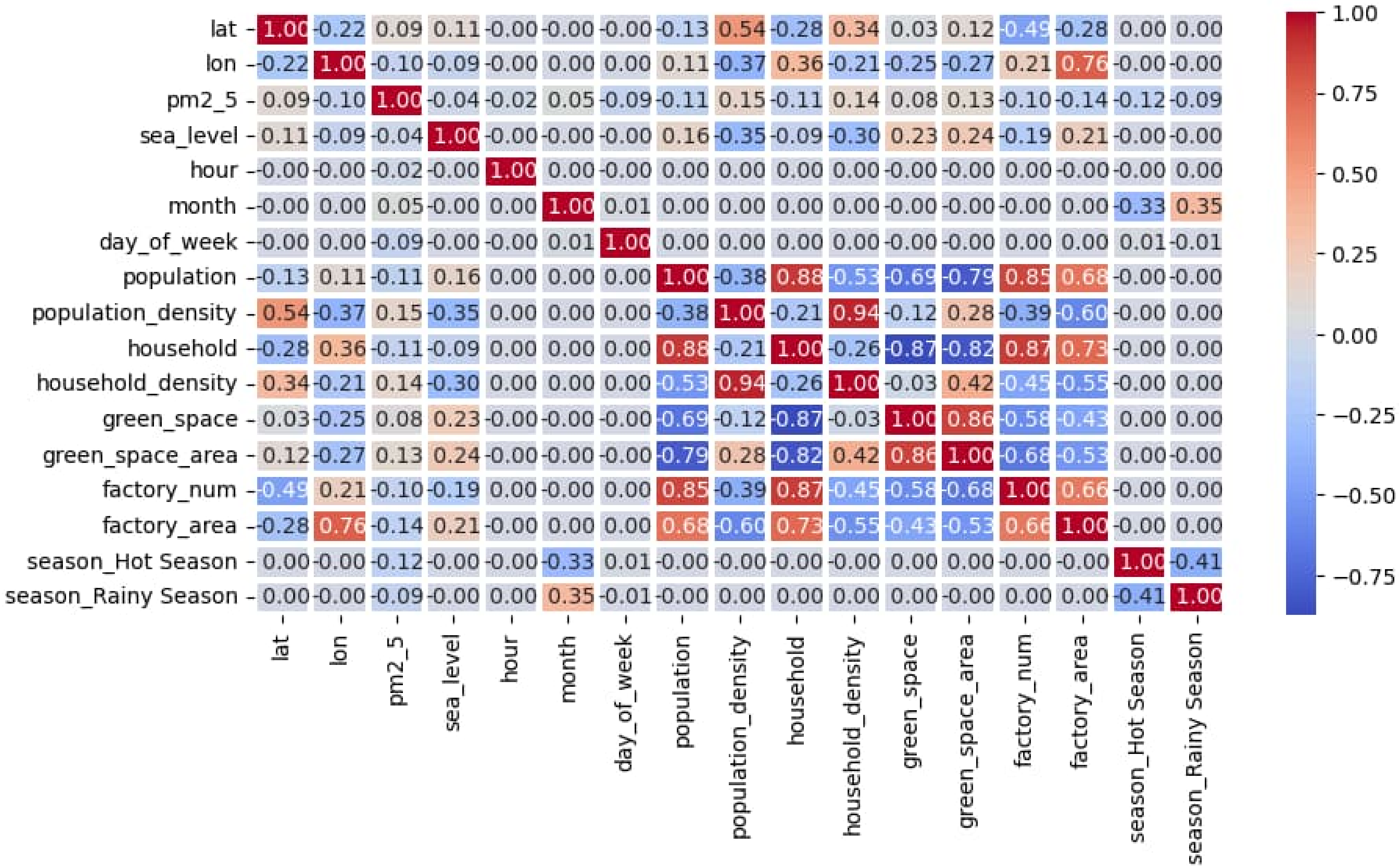
In [184…

```
# Selected features for heatmap correlation analysis
selected_cols = ['lat', 'lon','pm2_5','sea_level', 'hour','month','day_of_week', 'population', 'population_density', 'household',
```

Heatmap with `pearson` method: Good for linear relationship

In [185…

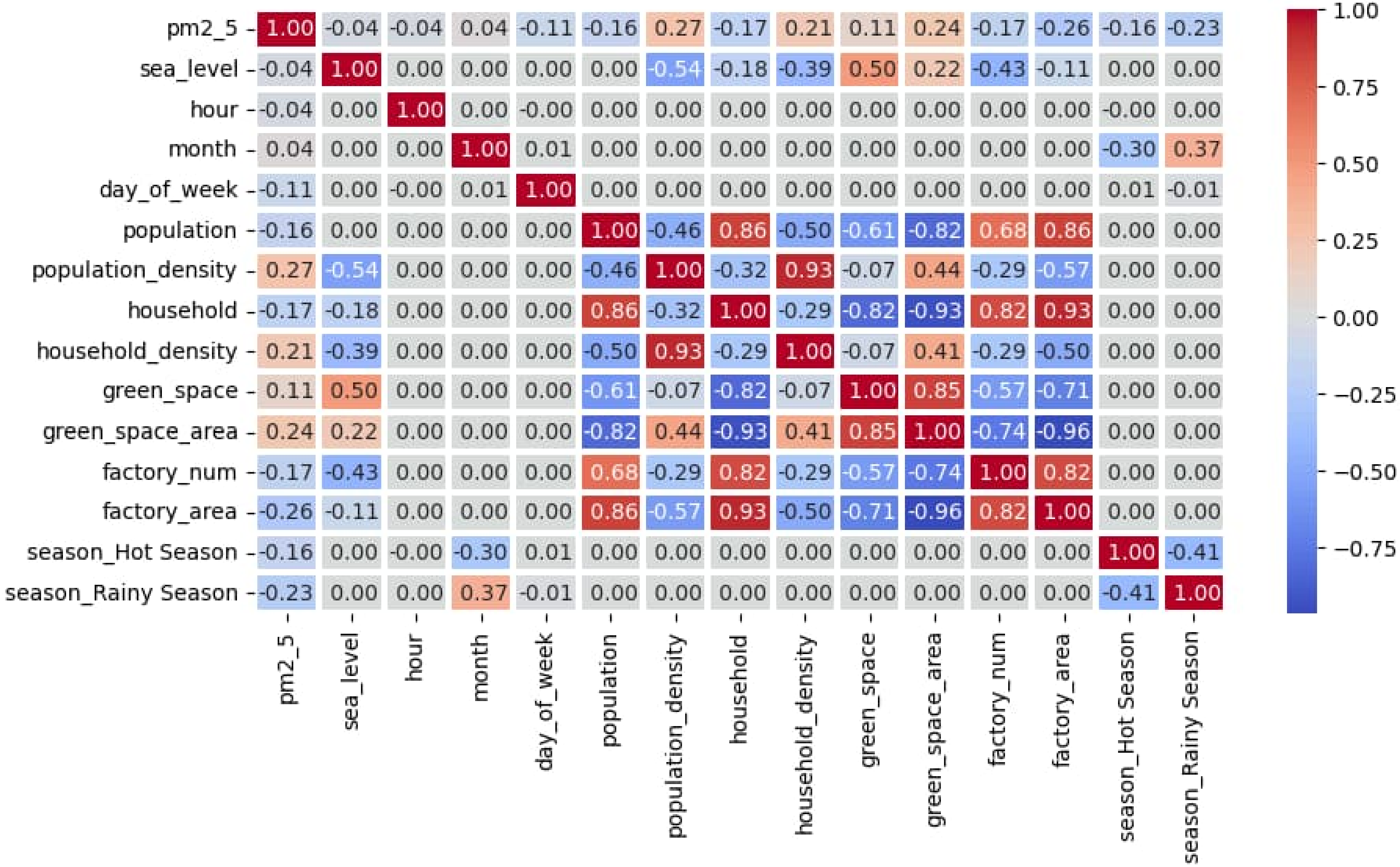
```
corr_matrix = df[selected_cols].corr(method='pearson')
corr_matrix

# Plotting the heatmap for numerical columns
plt.figure(figsize=(10,5))
sns.heatmap(data=corr_matrix, cmap='coolwarm', fmt=' .2f', annot=True, linewidths=1.5)
plt.show()
```



Heatmap with `spearman` method: Good for non-linear relationship

In [166…

```
corr_matrix = df[selected_cols].corr(method='spearman')
corr_matrix

# Plotting the heatmap for numerical columns
plt.figure(figsize=(10,5))
sns.heatmap(data=corr_matrix, cmap='coolwarm', fmt=' .2f', annot=True, linewidths=1.5)
plt.show()
```



pm2_5
sea_level
hour
month
day_of_week
population
population_density
household
household_density
green_space
green_space_area
factory_num
factory_area
season_Hot Season
season_Rainy Season

We use `spearman` method of correlation

- Because we are relying on rendom forest, XGBoost, Decision Tree!
- This is the non-parametric method!
- And we will compare performance for these 3 models (non-parametric method) to Linear models like Linear Regression, Ridge, Lasso Regression (Parametric method), and non-machine-learning method such as moving average to make sure that our assumption of non-parametric method is the best suited for PM2.5 prediction
- Additionally, spearman (non-linear relation) captures relationship better than pearson (Linear relation)

6. Feature selection

Choose the most salient X

- Rule of thumb: Good features MUST NOT BE correlated, i.e., independent
- Rule of thumb: Correlation is not causation; don't pick features using correlation only; it should make sense!
- Rule of thumb: For ML, less features are usually better (but NOT necessarily for DL)

Specify the y

Split train / test

In [167…

```
features = df[['population_density','factory_area','season_Hot Season', 'season_Rainy Season']]
target = df['pm2_5']
```

In [168…

```
# Selecting X and y features
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.1, random_state=42)
```

In [169…

```
X_train
```

Out[169…

	population_density	factory_area	season_Hot Season	season_Rainy Season
82890	3437.36	144736	False	True
16340	1452.45	4770457	True	False
126622	4542.29	631723	False	False
101661	9046.87	123059	False	True
30376	3437.36	144736	False	True
...	...	...	...	...
110268	10275.79	297638	False	True
119879	10275.79	297638	False	False
103694	3437.36	144736	False	True
131932	3437.36	144736	True	False
121958	10275.79	297638	False	False

119284 rows × 4 columns

In [170…

```
X_test
```

Out[170...

	population_density	factory_area	season_Hot Season	season_Rainy Season
30811	10275.79	297638	False	True
24784	10275.79	297638	False	True
46354	9046.87	123059	False	True
48040	4542.29	631723	False	True
13770	4788.74	54185	True	False
...	...	...	...	...
111203	4788.74	54185	False	False
54600	9046.87	123059	False	False
3377	3437.36	144736	False	False
72664	10275.79	297638	True	False
93206	4788.74	54185	False	True

13254 rows × 4 columns

In [171...

```
y_train
```

Out[171...

```
82890      19.77
16340      22.66
126622     99.46
101661     43.06
30376      16.07
           ...
110268    550.57
119879     61.50
103694      8.01
131932     83.88
121958    213.60
Name: pm2_5, Length: 119284, dtype: float64
```

In [172...

```
y_test
```

Out[172...

```
30811      92.66
24784      90.74
46354      61.78
48040      92.88
13770      39.16
           ...
111203    192.50
54600     110.26
3377       88.48
72664      25.59
93206      32.59
Name: pm2_5, Length: 13254, dtype: float64
```

In [173...

```
X_train
```

Out[173...

	population_density	factory_area	season_Hot Season	season_Rainy Season
82890	3437.36	144736	False	True
16340	1452.45	4770457	True	False
126622	4542.29	631723	False	False
101661	9046.87	123059	False	True
30376	3437.36	144736	False	True
...	...	...	...	...
110268	10275.79	297638	False	True
119879	10275.79	297638	False	False
103694	3437.36	144736	False	True
131932	3437.36	144736	True	False
121958	10275.79	297638	False	False

119284 rows × 4 columns

In [174...

```
X_train.isna().sum()
```

Out[174...
```
population_density     0
factory_area           0
season_Hot Season      0
season_Rainy Season    0
dtype: int64
```

In [175...
```
X_test.isna().sum()
```

Out[175...
```
population_density     0
factory_area           0
season_Hot Season      0
season_Rainy Season    0
dtype: int64
```

In [176...
```
y_train.shape
```

Out[176...
```
(119284,)
```

In [177...
```
y_train.isna().sum()
```

Out[177...
```
np.int64(0)
```

In [178...
```
y_test.shape
```

Out[178...
```
(13254,)
```

In [179...
```
y_test.isna().sum()
```

Out[179...
```
np.int64(0)
```

Handling Missing Values After Spliting

In [180...
```
# Drop missing values in y_train and y_test
X_train = X_train[~y_train.isna()]
y_train = y_train.dropna()

X_test = X_test[~y_test.isna()]
y_test = y_test.dropna()
```

7. Modeling

Modeling using non-parametric method (`XGBoost`, `RandomForest`, `DecisionTree`)

Scaling for `XGBoost` model

- We will use these scaled X features for `XGBoost` model only

In [181…
```
# Try StandardScaler
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()


X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [182…
```
# Checking XGBoost Scaling
pd.DataFrame(X_train_scaled).describe()
```

Out[182…

	0	1	2	3
count	1.192840e+05	1.192840e+05	1.192840e+05	1.192840e+05
mean	1.854926e-16	-1.346221e-17	1.191346e-18	5.833129e-17
std	1.000004e+00	1.000004e+00	1.000004e+00	1.000004e+00
min	-1.365095e+00	-6.180545e-01	-4.464621e-01	-9.178206e-01
25%	-6.799969e-01	-5.742038e-01	-4.464621e-01	-9.178206e-01
50%	-2.986269e-01	-4.630527e-01	-4.464621e-01	-9.178206e-01
75%	1.256143e+00	7.886486e-02	-4.464621e-01	1.089538e+00
max	1.680309e+00	2.384704e+00	2.239832e+00	1.089538e+00

In [183…
```
# Import modules for modeling
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
```

```python
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[183], line 3
      1 # Import modules for modeling
      2 from sklearn.ensemble import RandomForestRegressor
----> 3 from xgboost import XGBRegressor
      4 from sklearn.tree import DecisionTreeRegressor
      5 from sklearn.model_selection import GridSearchCV

ModuleNotFoundError: No module named 'xgboost'
```

In [ ]:

```python
# Double-Check Time Splits (Data Leakage Check)
print("Train Date Range:", X_train.index.min(), "to", X_train.index.max())
print("Test Date Range:", X_test.index.min(), "to", X_test.index.max())
```

In [ ]:

```python
# Define the models
models = {
    "RandomForest": RandomForestRegressor(random_state=42),
    "XGBoost": XGBRegressor(objective="reg:squarederror", random_state=42),
    "DecisionTree": DecisionTreeRegressor(random_state=42)
}

# Define hyperparameter grids
param_grids = {
    "RandomForest": {
        "n_estimators": [1000, 1500, 2000],
        "max_depth": [25, 30, 35],
        "min_samples_split": [10, 15, 20]
    },
    "XGBoost": {
        "n_estimators": [1000, 1500, 2000],
        "learning_rate": [0.1, 0.01, 0.001],
        "max_depth": [25, 30, 35],
        "subsample": [0.7, 0.9],
        "colsample_bytree": [0.7, 1],
    },
    "DecisionTree": {
        "max_depth": [25, 30, 35],
        "min_samples_split": [10, 15, 20]
    }
}
```

In [ ]:

```python
# Perform Cross-Validation and GridSearchCV

from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split, cross_val_score

best_models = {}

for model_name, model in models.items():
    print(f"Training {model_name}...")

    # Use scaled data for XGBoost, but original data for RF and DT
    X_train_used = X_train_scaled if model_name == "XGBoost" else X_train
    X_test_used = X_test_scaled if model_name == "XGBoost" else X_test

    # GridSearchCV
    grid_search = GridSearchCV(model, param_grids[model_name], cv=5, scoring="neg_mean_squared_error", n_jobs=-1)
    grid_search.fit(X_train_used, y_train)

    # Best model
    best_model = grid_search.best_estimator_
    best_models[model_name] = best_model

    # Cross-validation RMSE
    scores = cross_val_score(best_model, X_train_used, y_train, cv=5, scoring="neg_mean_squared_error")
    mean_cv_rmse = np.sqrt(-scores.mean())

    # Cross-validation R² Score
    cv_r2_scores = cross_val_score(best_model, X_train_used, y_train, cv=5, scoring="r2")
    mean_cv_r2 = cv_r2_scores.mean()

    # Evaluate on test set
    y_pred = best_model.predict(X_test_used)
    test_rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    test_r2 = r2_score(y_test, y_pred)  # Compute R² score

    # Print RMSE & R² scores
    print(f"{model_name} Mean CV Score (RMSE): {mean_cv_rmse}")
    print(f"{model_name} Mean CV R² Score: {mean_cv_r2}")
    print(f"{model_name} Test RMSE: {test_rmse}")
    print(f"{model_name} Test R² Score: {test_r2}\n")
```

In [ ]:

```python
# # Perform Cross-Validation and GridSearchCV

# from sklearn.metrics import mean_squared_error
```

```
# from sklearn.model_selection import train_test_split

# best_models = {}

# for model_name, model in models.items():
#     print(f"Training {model_name}...")

#     # Use scaled data for XGBoost, but original data for RF and DT
#     X_train_used = X_train_scaled if model_name == "XGBoost" else X_train
#     X_test_used = X_test_scaled if model_name == "XGBoost" else X_test

#     # GridSearchCV
#     grid_search = GridSearchCV(model, param_grids[model_name], cv=5, scoring="neg_mean_squared_error", n_jobs=-1)
#     grid_search.fit(X_train_used, y_train)

#     # Best model
#     best_model = grid_search.best_estimator_
#     best_models[model_name] = best_model

#     # Cross-validation
#     scores = cross_val_score(best_model, X_train_used, y_train, cv=5, scoring="neg_mean_squared_error")
#     print(f"{model_name} Mean CV Score (RMSE): {np.sqrt(-scores.mean())}")

#     # Evaluate on test set
#     y_pred = best_model.predict(X_test_used)
#     test_rmse = np.sqrt(mean_squared_error(y_test, y_pred))
#     print(f"{model_name} Test RMSE: {test_rmse}\n")
```