Part 3 Visualizing Time Series Data

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By visualizing time series data, we can detect patterns, identify its confidence, and spot potential problems like outliers and missing values. For this activity, in 250-500 words, answer the following:

1. Plot the time series data in a line chart using the plot() function. Use the date feature as your indexed column when plotting the data. Show the results.
2. Zoom into a particular range of time: pick a range of 2 months from your dataset and plot it into a line chart. Show the results and explain the difference between this step and step 1.
3. Add linear or polynomial trend lines to your time series dataset: plot a trend line using the regplot function from the seaborn library. Show the results and interpret the trend line.
4. Suppress Seasonality: aggregate your data using the mean function at the yearly level to remove seasonality from your dataset. Plot the data and interpret the graph.
5. Lag Scatter Plot: plot a scatter plot to test the correlation between lag values. Import the lag plot class from the pandas plotting library. Then, show and interpret the graph.
6. Autocorrelation Plots: plot correlations with all possible lag values in your time-series dataset. Import the autocorrelation plot class from pandas plotting library. Show and interpret the graph. Explain how an autocorrelation function (ACF) and partial autocorrelation function (PACF) can be useful in forecasting.

Dataset: Air Quality (UCI ML Repository) https://archive.ics.uci.edu/dataset/360/air+quality

Task 1

Plot the time series data in a line chart using the plot() function. Use the date feature as your indexed column when plotting the data. Show the results.

In [1]:
```
# Load libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import numpy as np
from pandas.plotting import lag_plot
from pandas.plotting import autocorrelation_plot
```

In [2]:
```
# Load data
df = pd.read_excel("AirQualityUCI.xlsx")

# Set "date" as index
df.set_index("date", inplace=True)

# View data
pd.options.display.max_columns = None
df.head(3)
```

Out[2]:

date	year	month	day	same_day_last_year	same_day_last_month	same_day_last_week	time	true_co	sensor_co	true_nmhc	true_benze
2004-03-10	2004	3	10	2003-03-10	2004-02-10	2004-03-03	18:00:00	2.6	1360.00	150.0	11.8817
2004-03-10	2004	3	10	2003-03-10	2004-02-10	2004-03-03	19:00:00	2.0	1292.25	112.0	9.3971
2004-03-10	2004	3	10	2003-03-10	2004-02-10	2004-03-03	20:00:00	2.2	1402.00	88.0	8.9978

In my view, it makes the most sense to simply plot the dataset's original numeric columns (the ones representing raw pollutant levels). These are the columns with "true" or "sensor" in their name, followed by the chemical only. Examples: `true_co`, `sensor_nmhc`. We will also plot temperature, relative humidity and absolute humidity.

We will assign different variables to different plots according to their units. For example, `true_nmhc`, `true_benzene` and `true_no2` will go together because they are all in $micrograms/m^3$.

In [3]:
```
# Rename "true_o3" to correct a mistake
df.rename(columns={"true_o3": "sensor_o3"}, inplace=True)
```

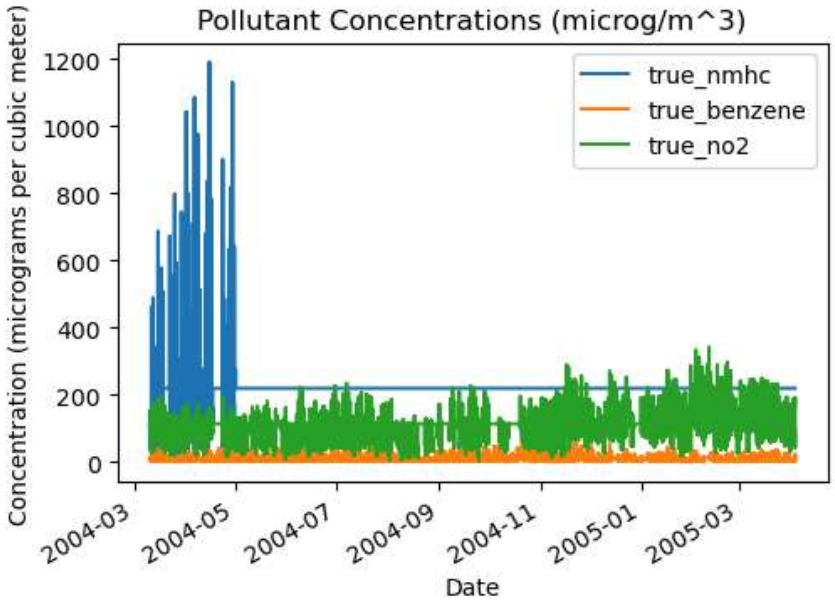
In [4]:
```
pollutant_columns = df[["true_co", "sensor_co", "true_nmhc", "sensor_nmhc", "true_benzene", "true_nox", "sensor_nox",
                        "true_no2", "sensor_no2", "sensor_o3"]]

# Select relevant column groups for graphing
microgram_per_cubicmeter_columns = df[["true_nmhc", "true_benzene", "true_no2"]]
```

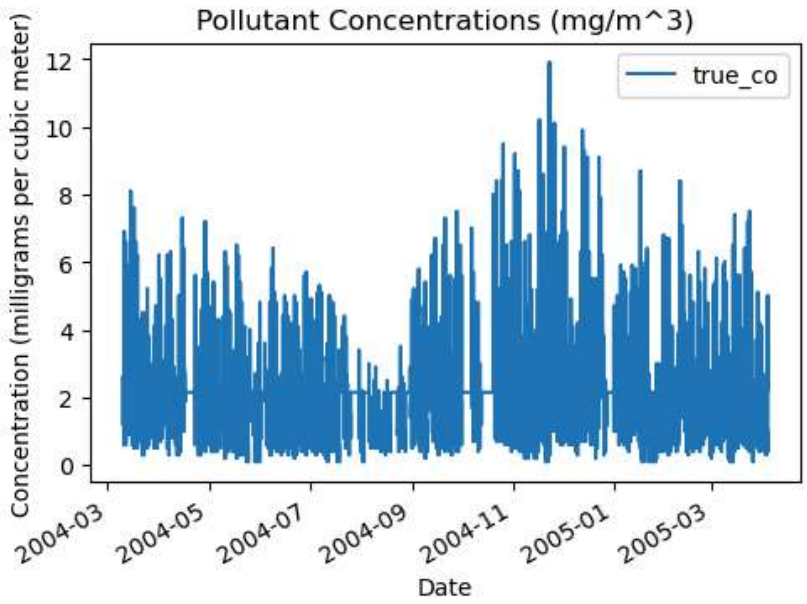
```
milligram_per_cubicmeter_columns = df[["true_co"]]
ppb_columns = df[["true_nox"]]
sensor_columns = df[["sensor_co", "sensor_nmhc", "sensor_nox", "sensor_no2", "sensor_o3"]]
# temp
# rel hum
# abs hum
```

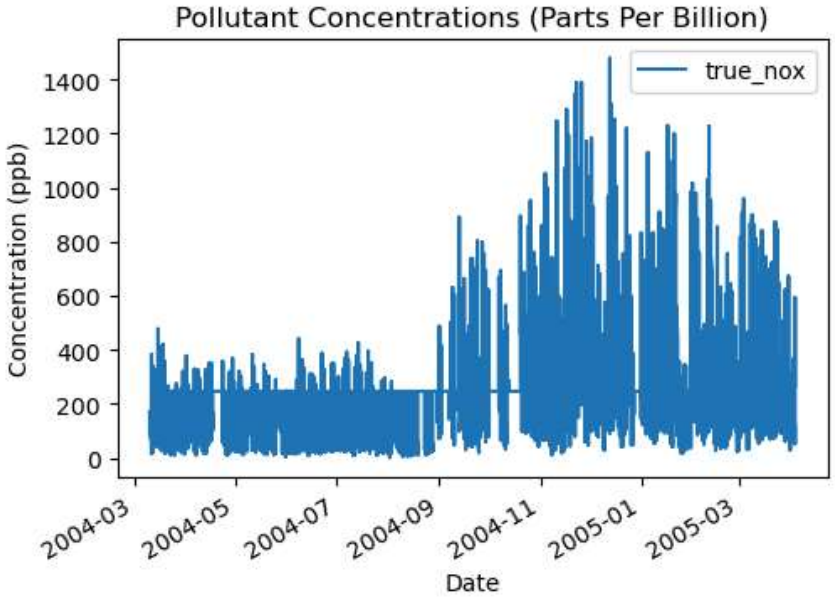
In [5]:

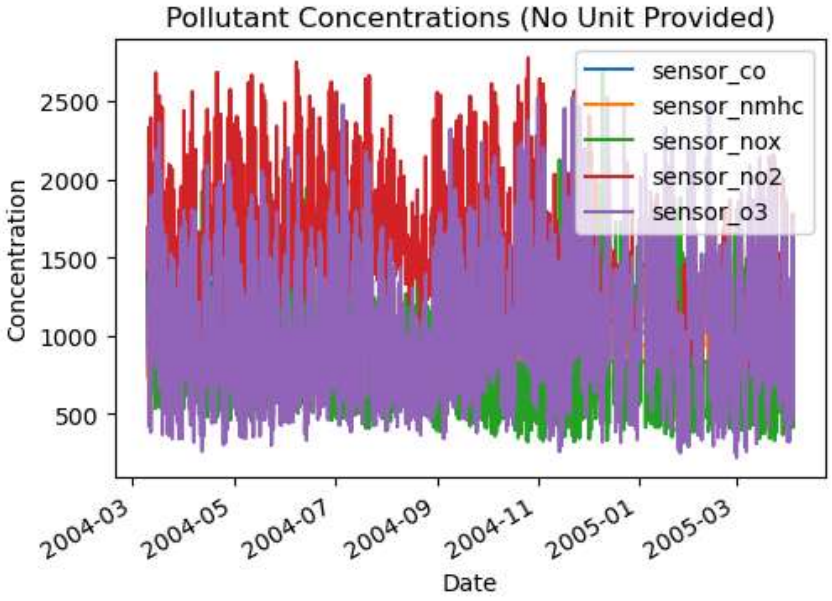
```
# Set up plot grid
fig, axes = plt.subplots(4, 2, figsize=(18, 10))
axes = axes.flatten()

# Graph levels of pollutants measured in microg/m^3 over time
microgram_per_cubicmeter_columns.plot(ax=axes[0], figsize=(12, 20))
axes[0].set_xlabel("Date")
axes[0].set_ylabel("Concentration (micrograms per cubic meter)")
axes[0].set_title("Pollutant Concentrations (microg/m^3)")

# Graph levels of carbon monoxide (CO) over time (measured in mg/m^3)
milligram_per_cubicmeter_columns.plot(ax=axes[1], figsize=(12, 20))
axes[1].set_xlabel("Date")
axes[1].set_ylabel("Concentration (milligrams per cubic meter)")
axes[1].set_title("Pollutant Concentrations (mg/m^3)")

# Graph levels of nitric oxide (NOx) over time (measured in parts per billion)
ppb_columns.plot(ax=axes[2], figsize=(12, 20))
axes[2].set_xlabel("Date")
axes[2].set_ylabel("Concentration (ppb)")
axes[2].set_title("Pollutant Concentrations (Parts Per Billion)")

# Graph sensor readings
sensor_columns.plot(ax=axes[3], figsize=(12, 20))
axes[3].set_xlabel("Date")
axes[3].set_ylabel("Concentration")
axes[3].set_title("Pollutant Concentrations (No Unit Provided)")

# Graph temperature
df["temp"].plot(ax=axes[4], figsize=(12, 20))
axes[4].set_xlabel("Date")
axes[4].set_ylabel("Temperature (°C)")
axes[4].set_title("Temperature")

# Graph relative humidity
df["rel_humidity"].plot(ax=axes[5], figsize=(12, 20))
axes[5].set_xlabel("Date")
axes[5].set_ylabel("Relative Humidity (%)")
```

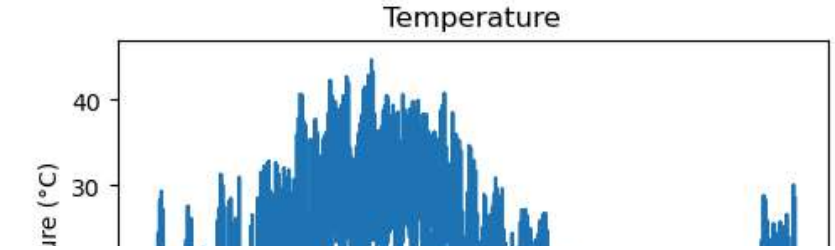
```
axes[5].set_title("Relative Humidity")

# Graph absolute humidity
df["abs_humidity"].plot(ax=axes[6], figsize=(12, 20))
axes[6].set_xlabel("Date")
axes[6].set_ylabel("Absolute Humidity (No Unit Provided)")
axes[6].set_title("Absolute Humidity")

# Show plot
plt.subplots_adjust(hspace=0.4)
plt.show()
```

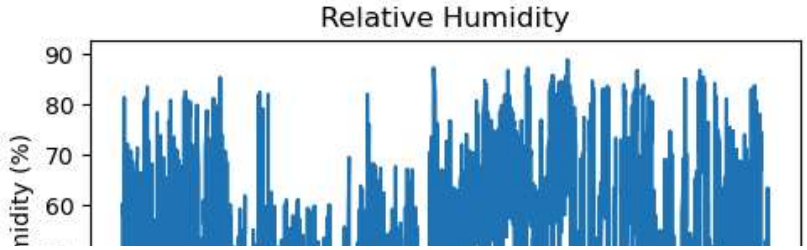

Pollutant Concentrations (microg/m^3)
Concentration (micrograms per cubic meter)
true_nmhc
true_benzene
true_no2
Date

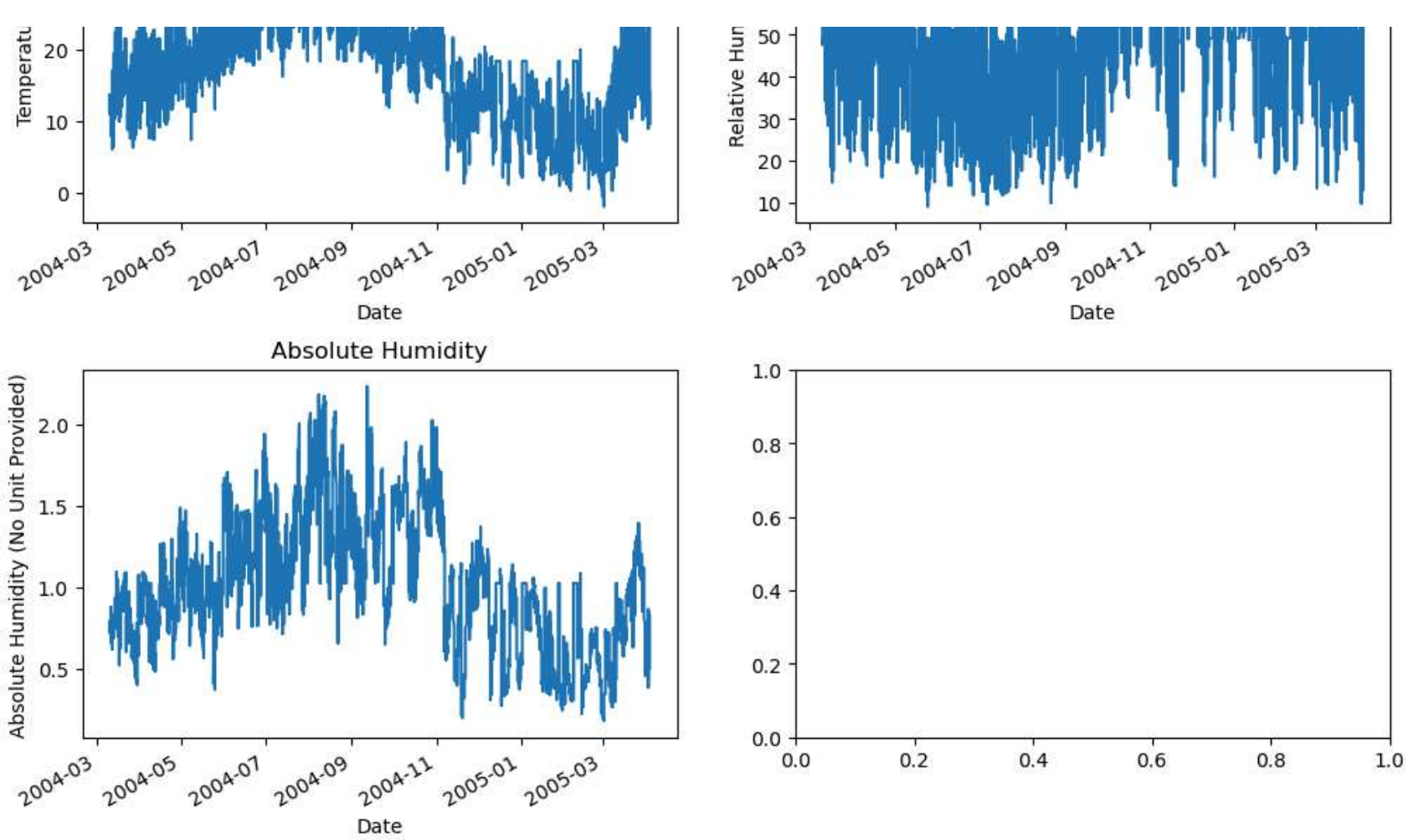

Pollutant Concentrations (mg/m^3)
Concentration (milligrams per cubic meter)
true_co
Date


Pollutant Concentrations (Parts Per Billion)
Concentration (ppb)
true_nox
Date


Pollutant Concentrations (No Unit Provided)
Concentration
sensor_co
sensor_nmhc
sensor_nox
sensor_no2
sensor_o3
Date


Temperature


Relative Humidity



As we've seen in previous explorations of the data, most pollutant levels are at their highest during the 2004-2005 winter, possibly because of holiday travel, certain industrial processes, or increased heating usage due to cold temperatures.

Task 2

Zoom into a particular range of time: pick a range of 2 months from your dataset and plot it into a line chart. Show the results and explain the difference between this step and step 1.

We will visualize pollutant concentrations between 11/2004 and 1/2005.

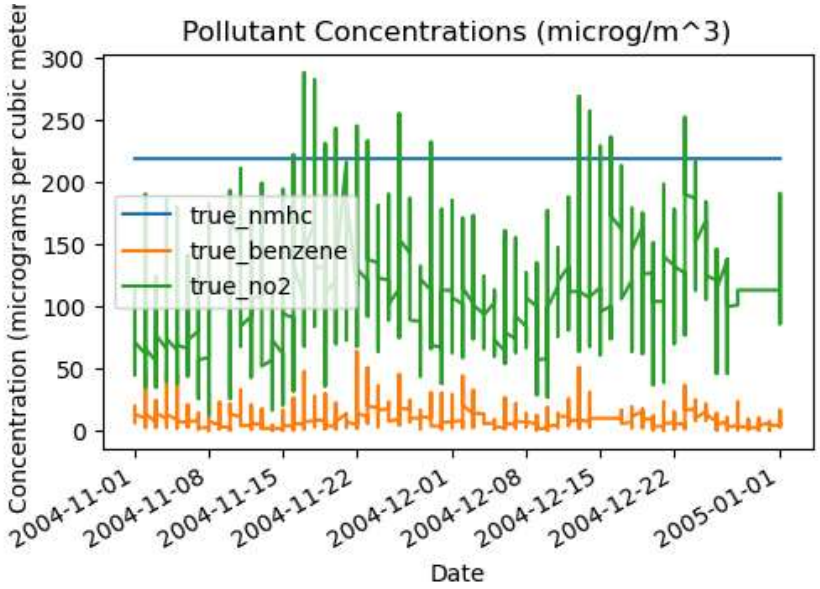
In [6]:
```
# Define start and end dates of 2-month period
start_date = pd.to_datetime("2004-11-01")
end_date = pd.to_datetime("2005-01-01")

# Filter data down to this 2-month period
filtered_df = df[(df.index >= start_date) & (df.index < end_date)]

filtered_df.head(3)
```

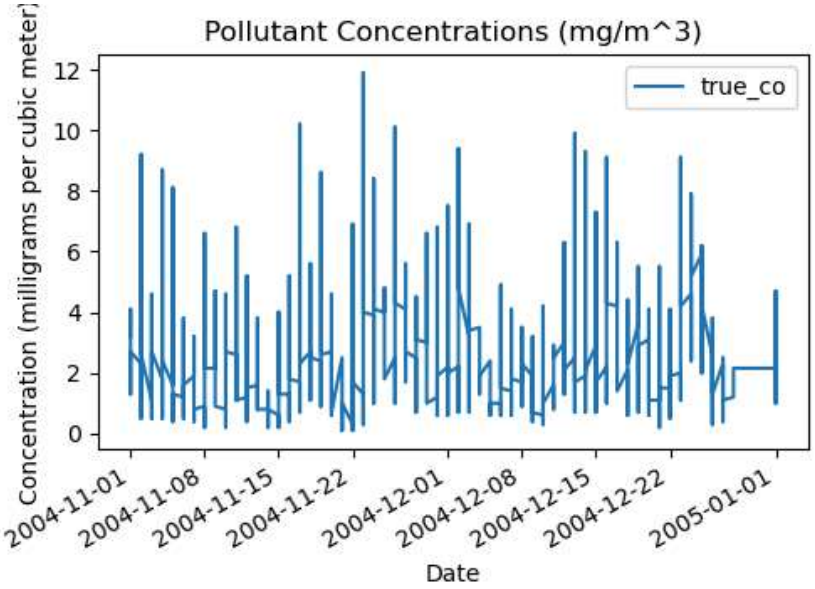
Out[6]:

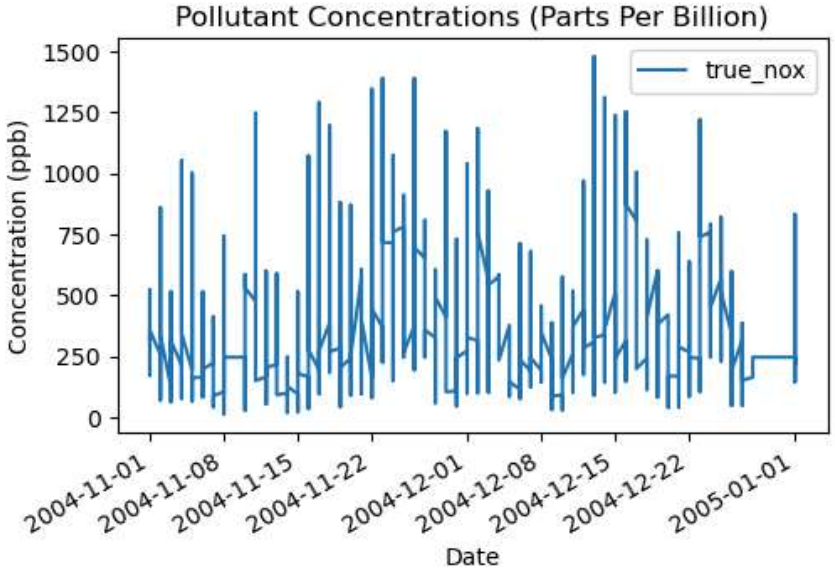
date	year	month	day	same_day_last_year	same_day_last_month	same_day_last_week	time	true_co	sensor_co	true_nmhc	true_benze
2004-11-01	2004	11	1	2003-11-01	2004-10-01	2004-10-25	00:00:00	3.2	1352.5	218.811816	15.8643
2004-11-01	2004	11	1	2003-11-01	2004-10-01	2004-10-25	01:00:00	3.7	1406.5	218.811816	17.8484
2004-11-01	2004	11	1	2003-11-01	2004-10-01	2004-10-25	02:00:00	3.5	1333.0	218.811816	16.6858

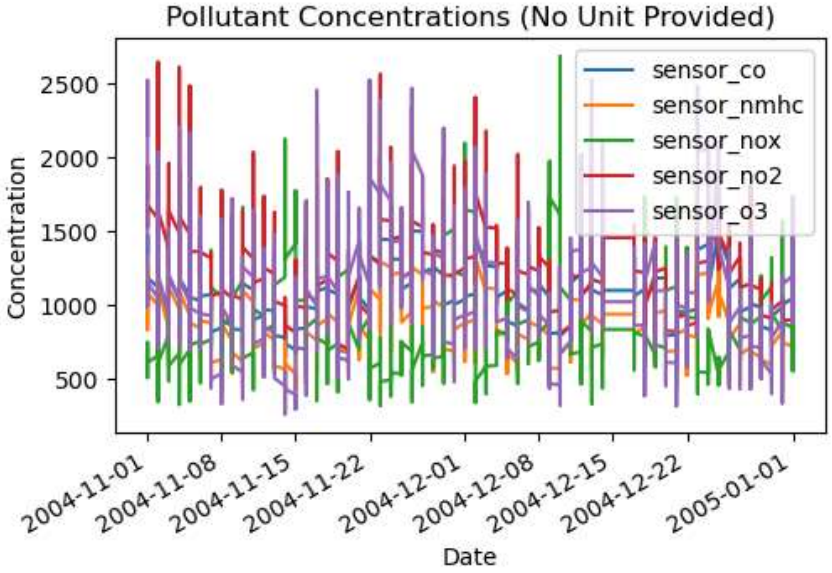
In [7]:
```
# Filter data down to the period between 2004-11-01 and 2005-01-01
start_date = pd.to_datetime("2004-11-01")
end_date = pd.to_datetime("2005-01-01")
filtered_df = df[(df.index >= start_date) & (df.index <= end_date)]

# Select relevant column groups for graphing
microgram_per_cubicmeter_columns = filtered_df[["true_nmhc", "true_benzene", "true_no2"]]
milligram_per_cubicmeter_columns = filtered_df[["true_co"]]
ppb_columns = filtered_df[["true_nox"]]
sensor_columns = filtered_df[["sensor_co", "sensor_nmhc", "sensor_nox", "sensor_no2", "sensor_o3"]]

# Set up plot grid
fig, axes = plt.subplots(4, 2, figsize=(18, 10))
axes = axes.flatten()

# Graph levels of pollutants measured in microg/m^3 over time
microgram_per_cubicmeter_columns.plot(ax=axes[0], figsize=(12, 20))
axes[0].set_xlabel("Date")
axes[0].set_ylabel("Concentration (micrograms per cubic meter)")
axes[0].set_title("Pollutant Concentrations (microg/m^3)")
```

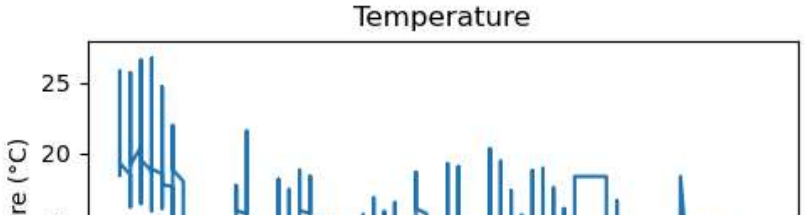
```
# Graph levels of carbon monoxide (CO) over time (measured in mg/m^3)
milligram_per_cubicmeter_columns.plot(ax=axes[1], figsize=(12, 20))
axes[1].set_xlabel("Date")
axes[1].set_ylabel("Concentration (milligrams per cubic meter)")
axes[1].set_title("Pollutant Concentrations (mg/m^3)")

# Graph levels of nitric oxide (NOx) over time (measured in parts per billion)
ppb_columns.plot(ax=axes[2], figsize=(12, 20))
axes[2].set_xlabel("Date")
axes[2].set_ylabel("Concentration (ppb)")
axes[2].set_title("Pollutant Concentrations (Parts Per Billion)")

# Graph sensor readings
sensor_columns.plot(ax=axes[3], figsize=(12, 20))
axes[3].set_xlabel("Date")
axes[3].set_ylabel("Concentration")
axes[3].set_title("Pollutant Concentrations (No Unit Provided)")

# Graph temperature
filtered_df["temp"].plot(ax=axes[4], figsize=(12, 20))
axes[4].set_xlabel("Date")
axes[4].set_ylabel("Temperature (°C)")
axes[4].set_title("Temperature")

# Graph relative humidity
filtered_df["rel_humidity"].plot(ax=axes[5], figsize=(12, 20))
axes[5].set_xlabel("Date")
axes[5].set_ylabel("Relative Humidity (%)")
axes[5].set_title("Relative Humidity")

# Graph absolute humidity
filtered_df["abs_humidity"].plot(ax=axes[6], figsize=(12, 20))
axes[6].set_xlabel("Date")
axes[6].set_ylabel("Absolute Humidity (No Unit Provided)")
axes[6].set_title("Absolute Humidity")

# Show plot
plt.subplots_adjust(hspace=0.6)
plt.show()
```

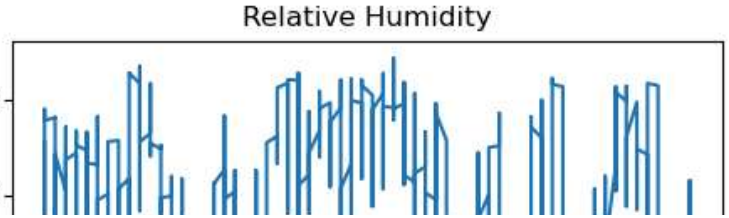

Pollutant Concentrations (microg/m^3)
Concentration (micrograms per cubic meter)
true_nmhc
true_benzene
true_no2
Date

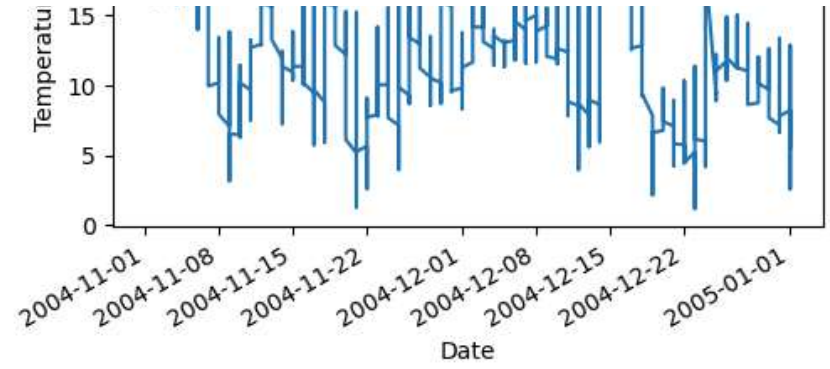

Pollutant Concentrations (mg/m^3)
Concentration (milligrams per cubic meter)
true_co
Date

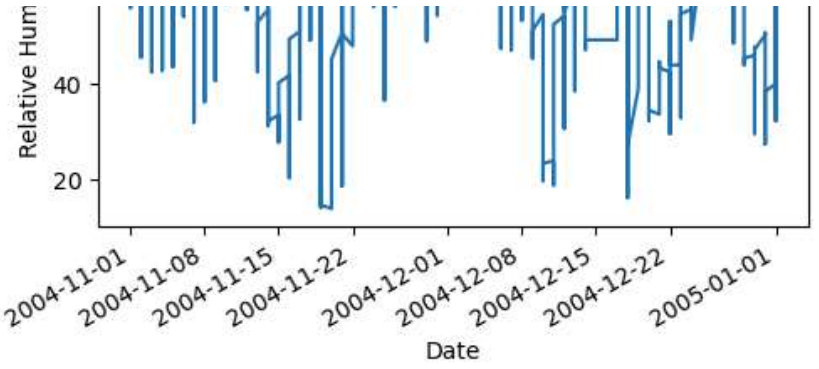

Pollutant Concentrations (Parts Per Billion)
Concentration (ppb)
true_nox
Date

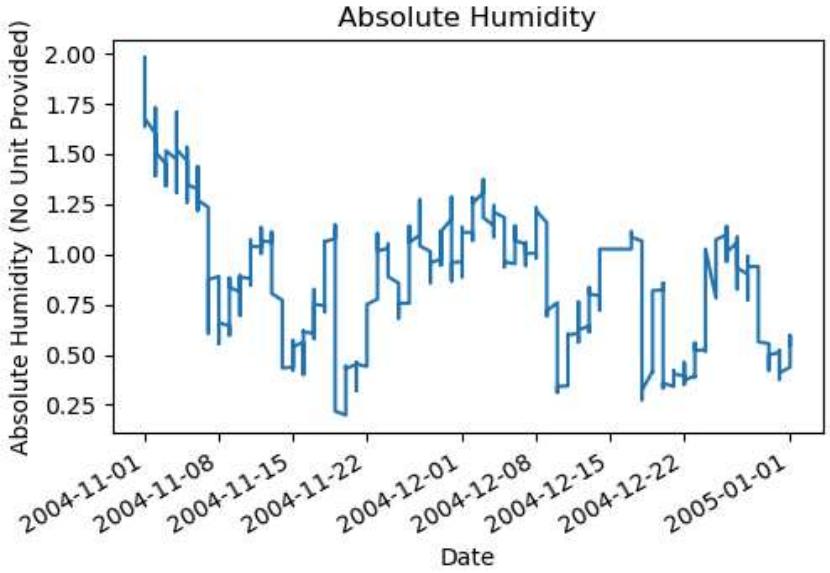

Pollutant Concentrations (No Unit Provided)
Concentration
sensor_co
sensor_nmhc
sensor_nox
sensor_no2
sensor_o3
Date

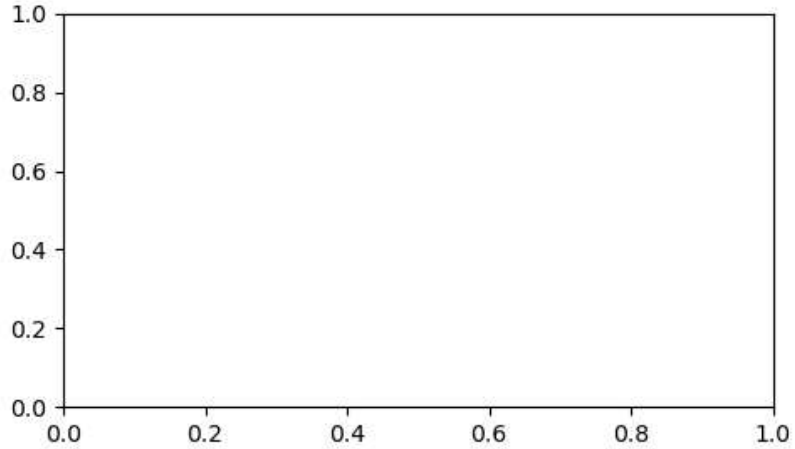

Temperature


Relative Humidity









Looking at a 2-month slice of time instead of the entire period gives us a finer-grained look at short-term trends in the data. With nitric oxide (NOx) in particular, we can see a huge spike in emissions in mid-to-late December, probably because of frequent holiday travel. Carbon monoxide (CO) levels seem to rise and fall frequently over this period, indicating some kind of cycle is present. We do also notice a problem with `true_nmhc` in the first plot, since it has a constant value over this 2-month window. This indicates a data quality issue in the original dataset, but this is difficult to resolve since the true values are not known.

In [8]:
```
# Find value of horizontal line in plot of "true_nmhc"
df["true_nmhc"].mode()
```

Out[8]:
```
0    218.811816
Name: true_nmhc, dtype: float64
```

Task 3

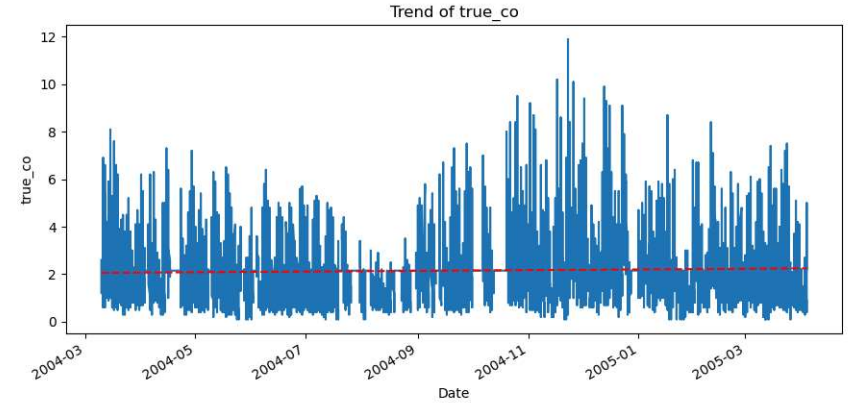
Add linear or polynomial trend lines to your time series dataset: plot a trend line using the regplot function from the seaborn library. Show the results and interpret the trend line.

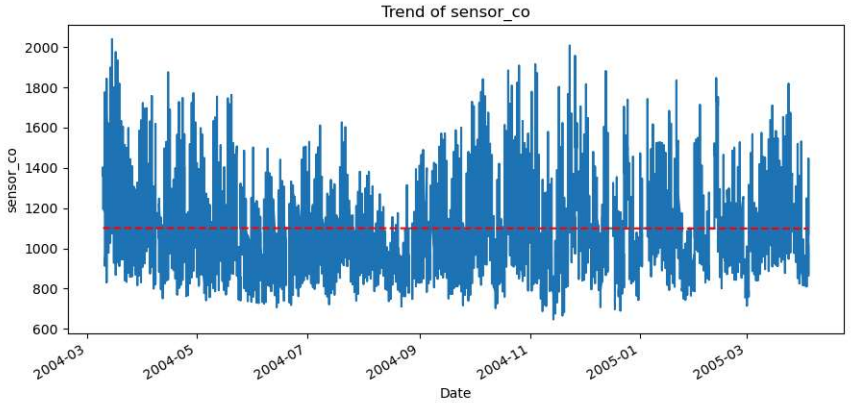
We will plot every original numeric column (`true_co` , `sensor_co` , `true_nmhc` , ...) with trend lines to give the clearest look into how each pollutant level, along with temperature and relative and absolute humidity, has changed over the given period.

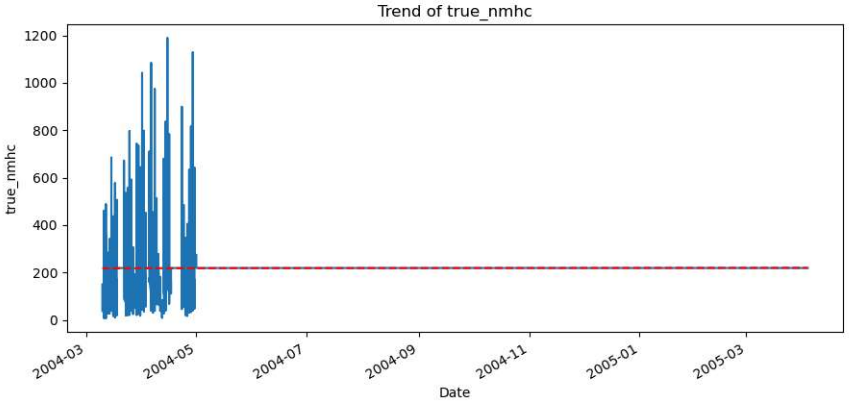
Because `sns.regplot()` is intended for creating scatterplots, I believe it makes more sense to continue plotting line plots in the way I have been doing them so far.

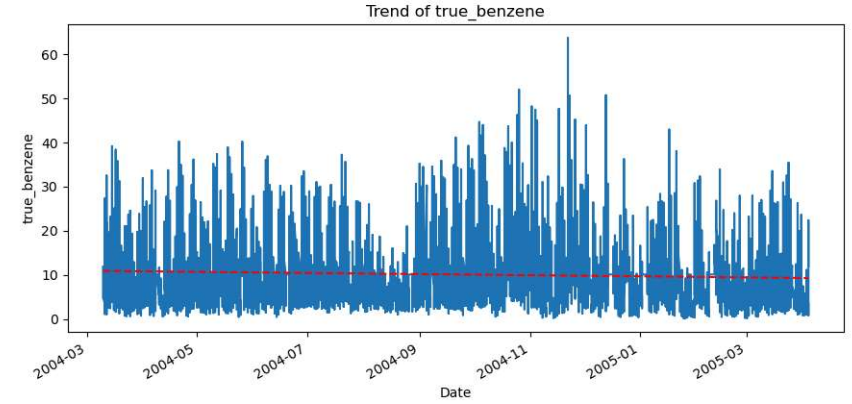
In [9]:
```
# Select original numeric columns for plotting
original_numeric_columns = df[["true_co", "sensor_co", "true_nmhc", "true_benzene", "sensor_nmhc", "true_nox", "sensor_
                               "true_no2", "sensor_no2", "sensor_o3", "temp", "rel_humidity", "abs_humidity"]]

# Create figure and grid
fig, axes = plt.subplots(7, 2, figsize=(18, 30))
axes = axes.flatten()

# Plot each column with trend lines
for i, column in enumerate(original_numeric_columns.columns):

    # Plot original data
    original_numeric_columns[column].plot(ax=axes[i])

    # Calculate trend line
    index_numeric = original_numeric_columns.index.astype(np.int64) // 10**9
    z = np.polyfit(index_numeric, original_numeric_columns[column], 1)
    trend_line = np.poly1d(z)

    # Plot trend line
    axes[i].plot(original_numeric_columns.index, trend_line(index_numeric), color="red", linestyle="--", label="Trend L

    # Set labels and title
    axes[i].set_xlabel("Date")
    axes[i].set_ylabel(column)
    axes[i].set_title(f"Trend of {column}")

# Show plots
```

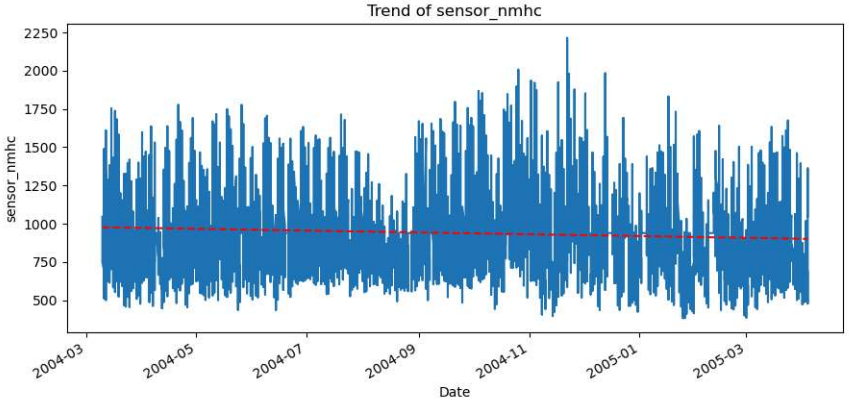
```
plt.tight_layout()
plt.show()
```

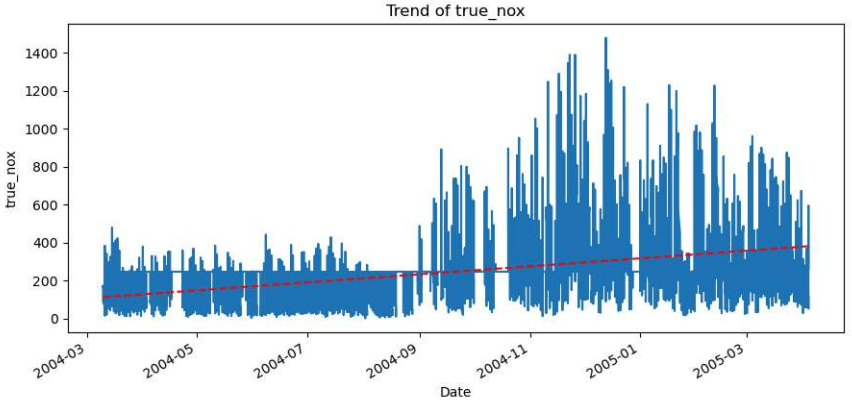

Trend of true_co
true_co
Date

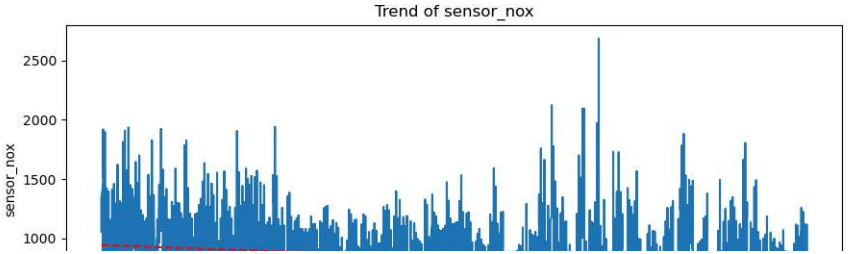

Trend of sensor_co
sensor_co
Date

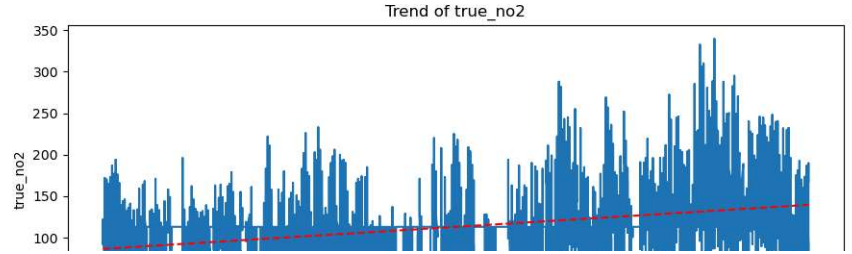

Trend of true_nmhc
true_nmhc
Date

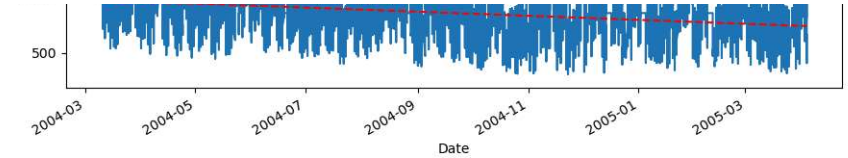

Trend of true_benzene
true_benzene
Date

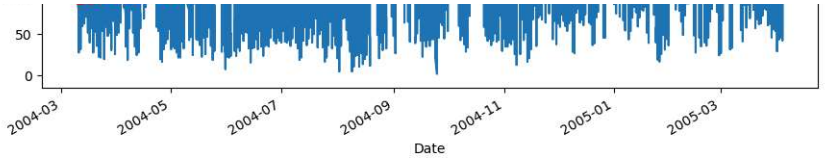

Trend of sensor_nmhc
sensor_nmhc
Date

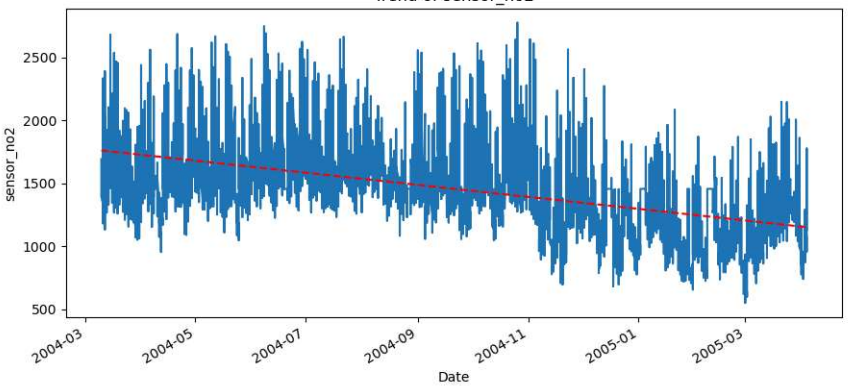

Trend of true_nox
true_nox
Date

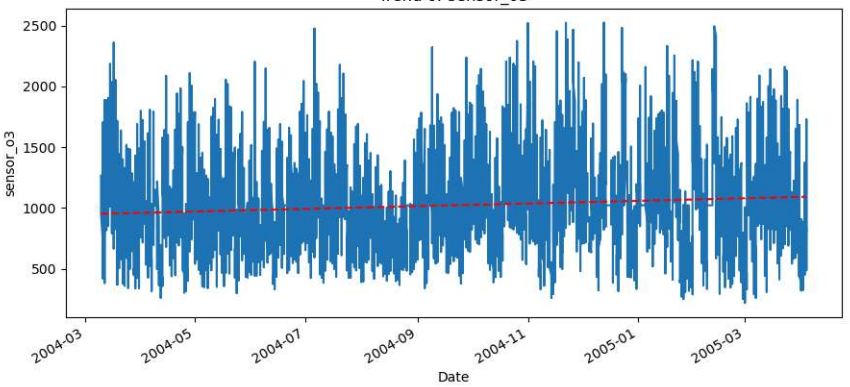

Trend of sensor_nox
sensor_nox

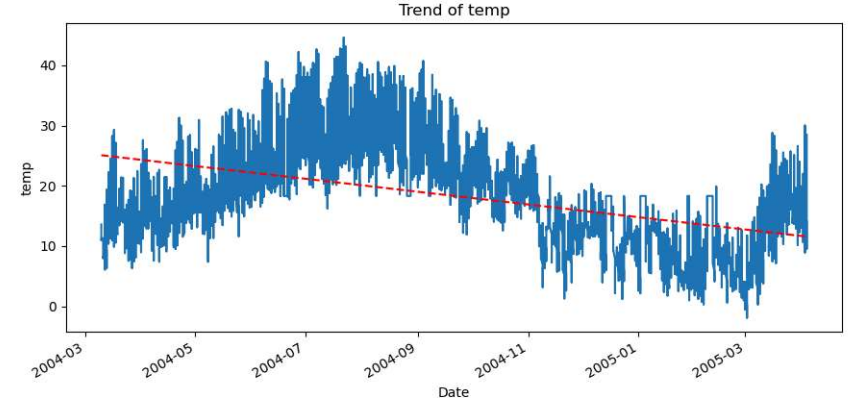

Trend of true_no2
true_no2

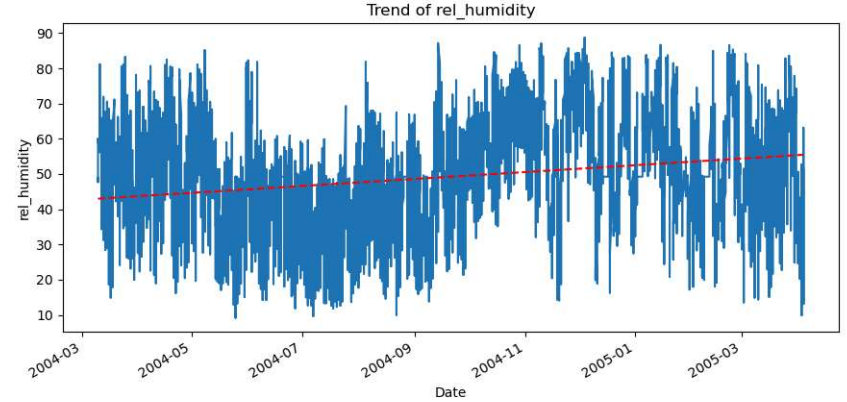

500
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date

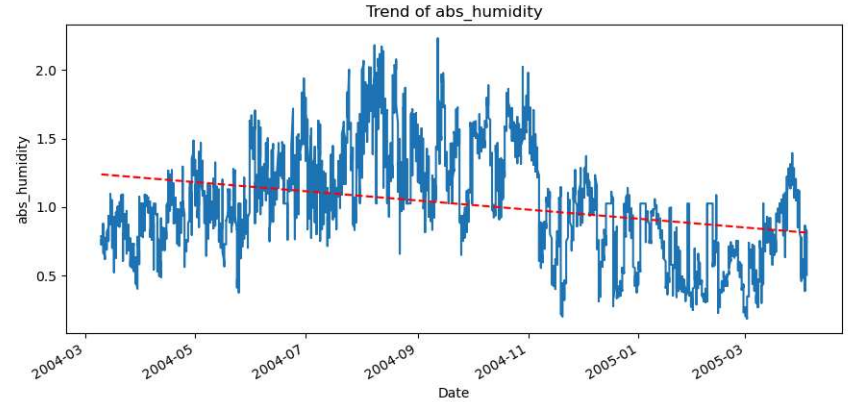

50
0
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date

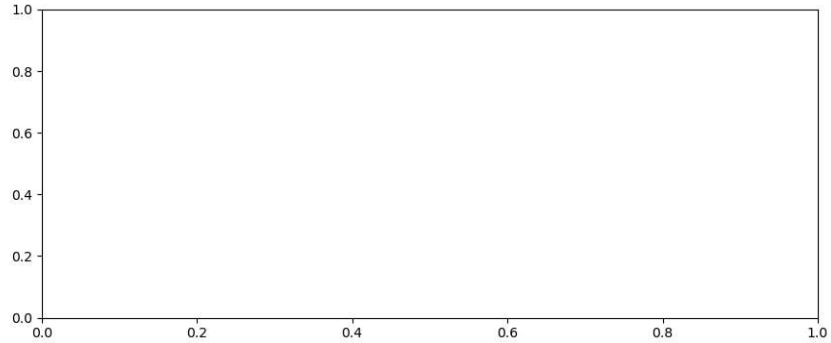

Trend of sensor_no2
sensor_no2
2500
2000
1500
1000
500
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date


Trend of sensor_o3
sensor_o3
2500
2000
1500
1000
500
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date


Trend of temp
temp
40
30
20
10
0
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date


Trend of rel_humidity
rel_humidity
90
80
70
60
50
40
30
20
10
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date


Trend of abs_humidity
abs_humidity
2.0
1.5
1.0
0.5
2004-03
2004-05
2004-07
2004-09
2004-11
2005-01
2005-03
Date

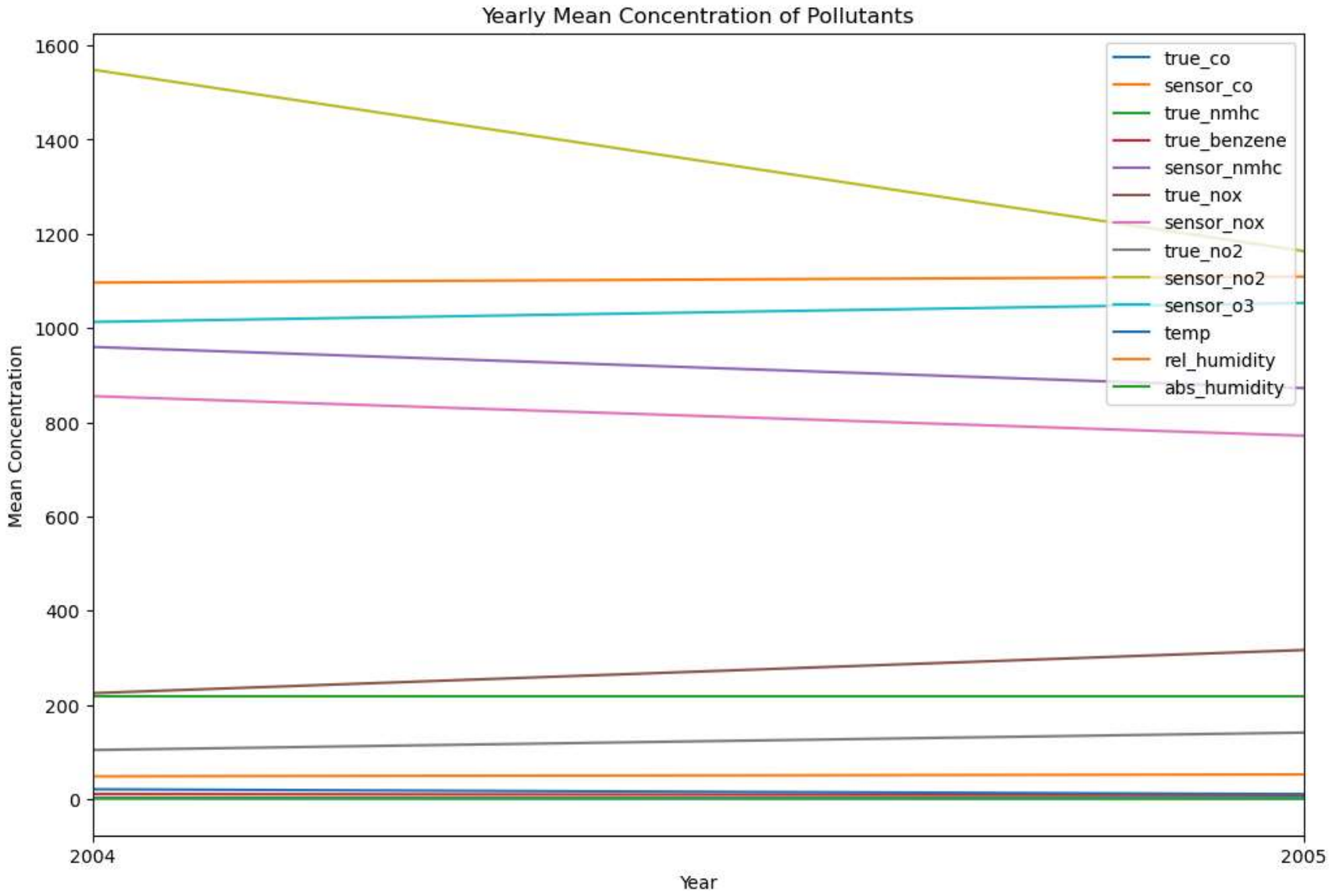

1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

We see that about half of the variables (`true_benzene` , `sensor_nmhc` , `sensor_nox` , `sensor_no2` , `temp` , and `abs_humidity`) show a negative trend, while four of them (`true_nox` , `true_no2` , `sensor_o3` , and `rel_humidity`) are increasing, and `true_co` and `true_nmhc` show no obvious trend. In the case of `true_nmhc` , the problem is caused by the abundance of values that are approximately 218.81 (as we saw earlier with the mode of the column).

Task 4

Suppress Seasonality: aggregate your data using the mean function at the yearly level to remove seasonality from your dataset. Plot the data and interpret the graph.

In [10]:
```
# Aggregate original numeric columns
yearly_mean = original_numeric_columns.resample("Y").mean()

# Plot aggregated data
yearly_mean.plot(figsize=(12, 8))
plt.xlabel("Year")
plt.ylabel("Mean Concentration")
plt.title("Yearly Mean Concentration of Pollutants")
plt.show()
```

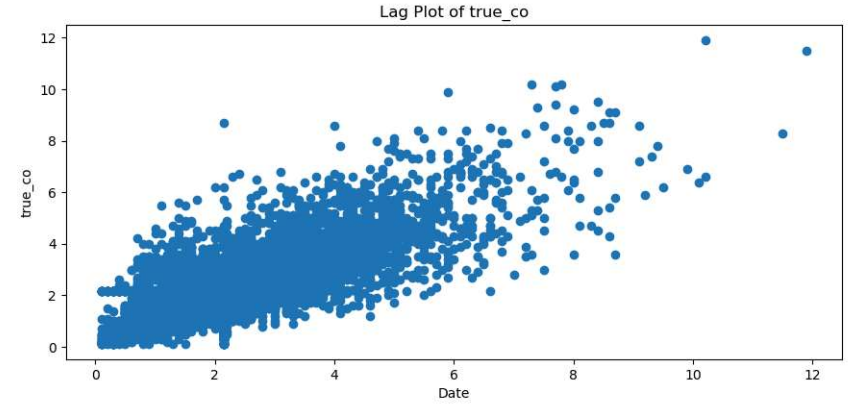


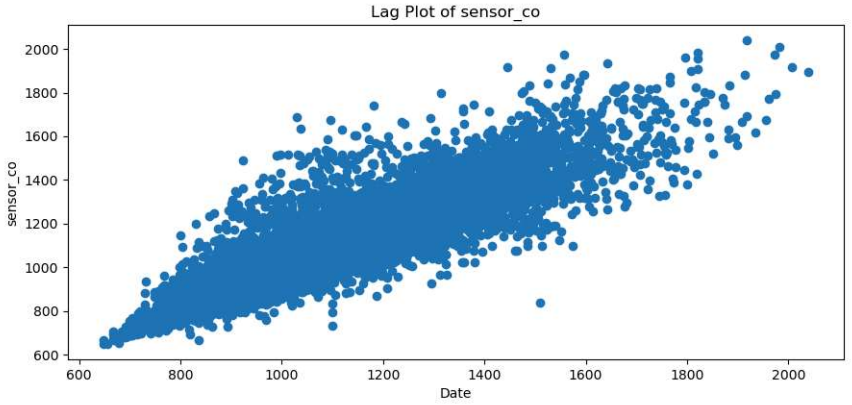
We see that `sensor_no2` has decreased drastically from 2004 to 2005, while most other readings have either stayed the same or increased slightly.

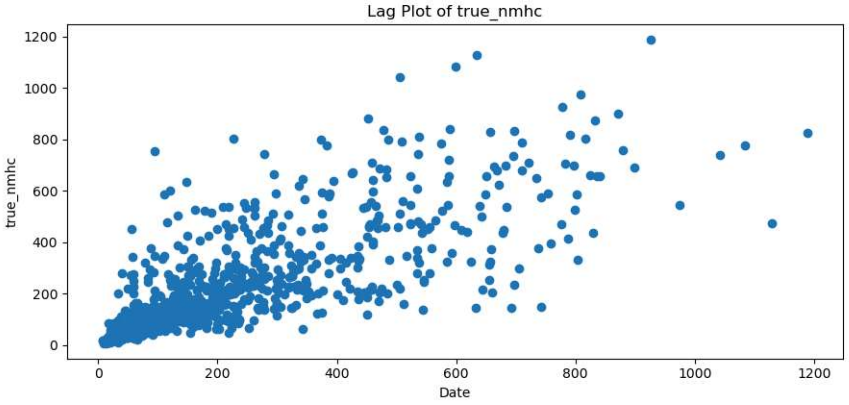
Task 5

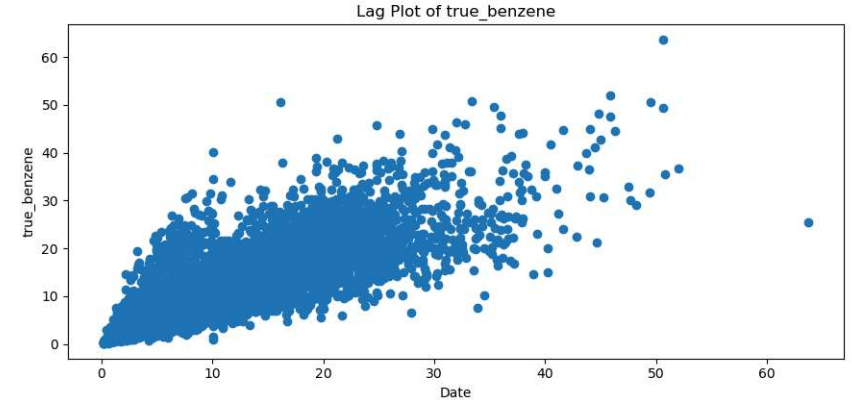
Lag Scatter Plot: plot a scatter plot to test the correlation between lag values. Import the lag plot class from the pandas plotting library. Then, show and interpret the graph.

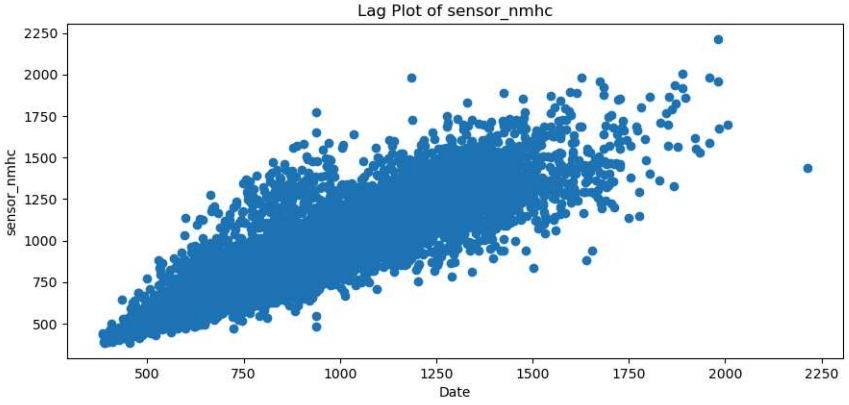
In [11]:
```
# Create figure and grid
fig, axes = plt.subplots(7, 2, figsize=(18, 30))
axes = axes.flatten()

# Create lag plot for each column
for i, column in enumerate(original_numeric_columns.columns):

    # Plot original data
    lag_plot(original_numeric_columns[column], lag=1, ax=axes[i])

    # Set labels and title
    axes[i].set_xlabel("Date")
    axes[i].set_ylabel(column)
    axes[i].set_title(f"Lag Plot of {column}")

# Show plots
plt.tight_layout()
plt.show()
```

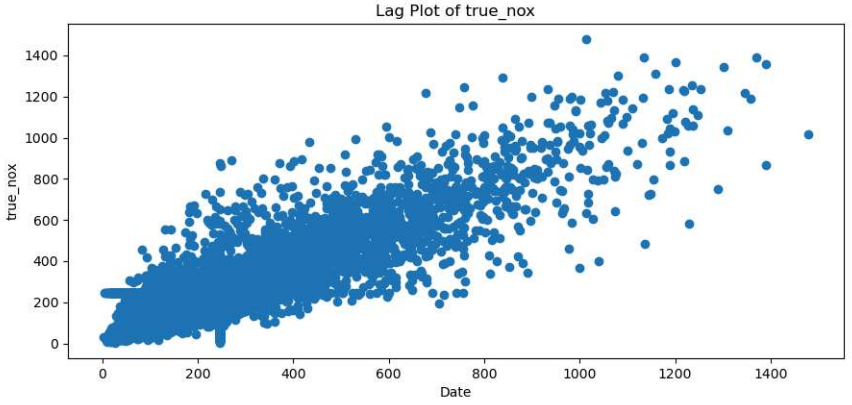

Lag Plot of true_co
true_co
Date

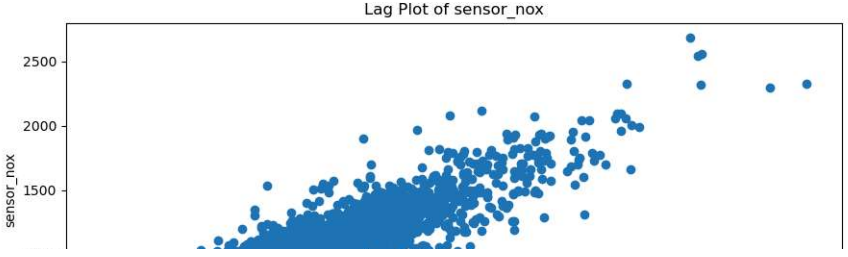

Lag Plot of sensor_co
sensor_co
Date

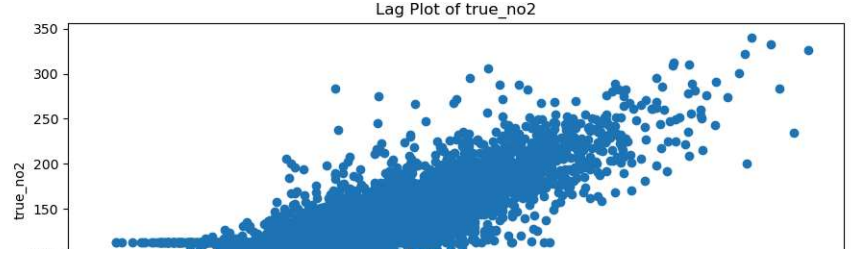

Lag Plot of true_nmhc
true_nmhc
Date

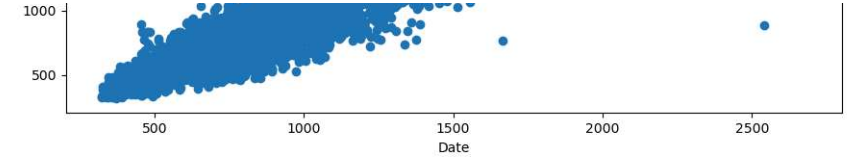

Lag Plot of true_benzene
true_benzene
Date

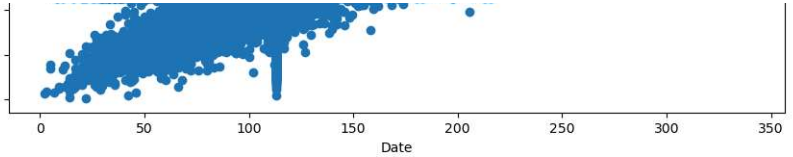

Lag Plot of sensor_nmhc
sensor_nmhc
Date

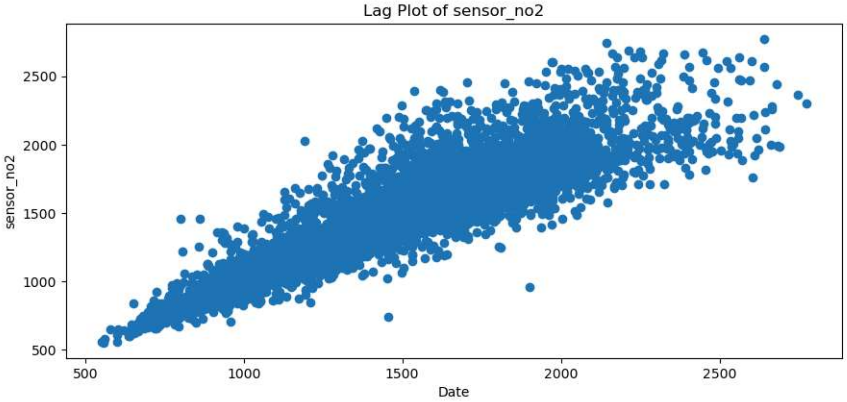

Lag Plot of true_nox
true_nox
Date

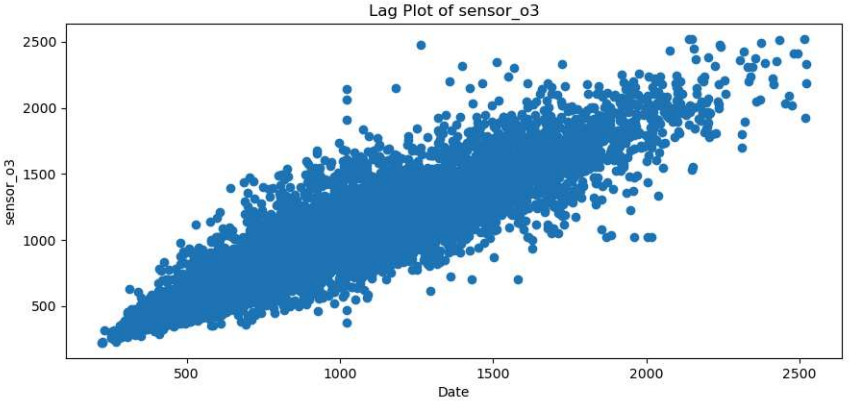

Lag Plot of sensor_nox
sensor_nox

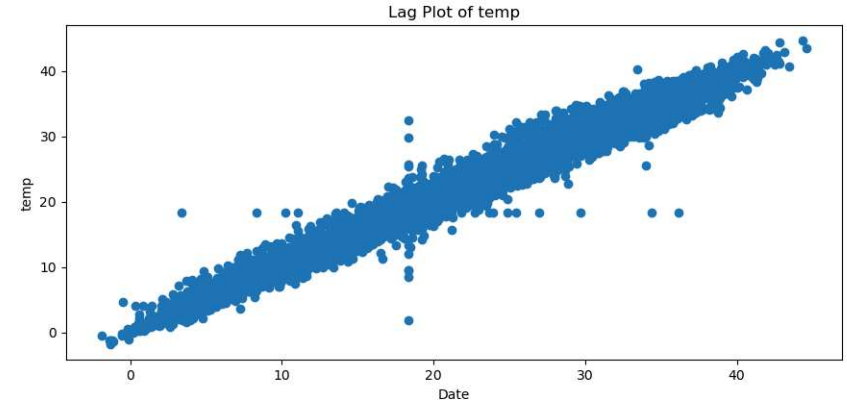

Lag Plot of true_no2
true_no2

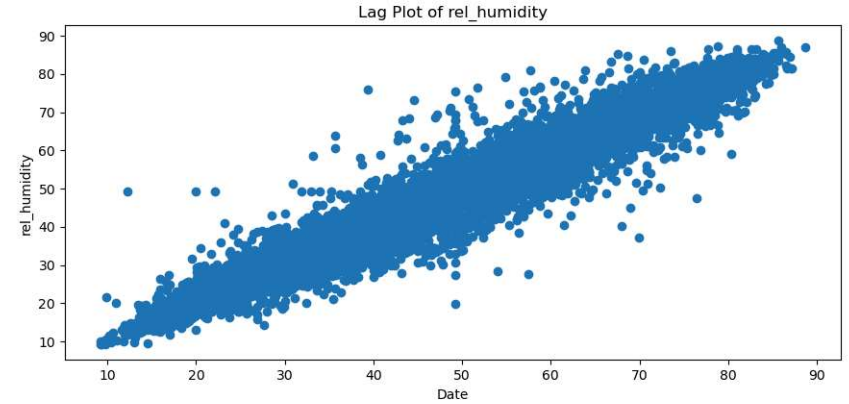

1000
500
500
1000
1500
2000
2500
Date

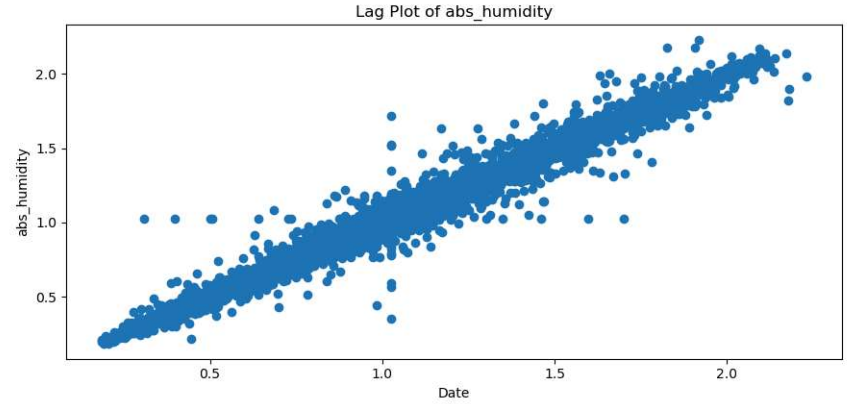

100
50
0
0
50
100
150
200
250
300
350
Date

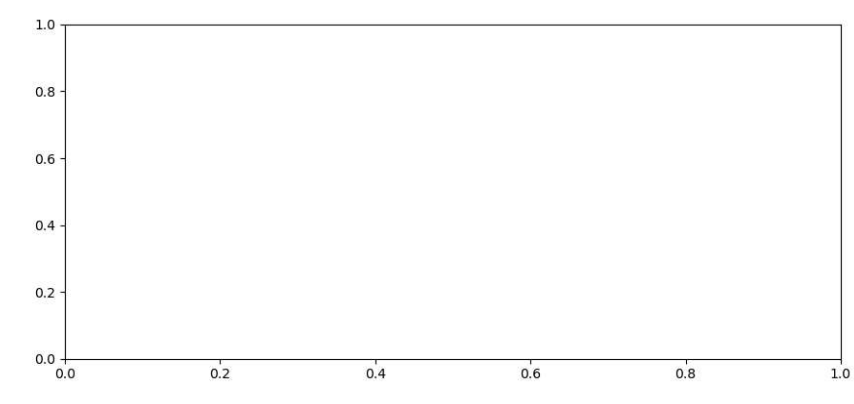

Lag Plot of sensor_no2
sensor_no2
2500
2000
1500
1000
500
500
1000
1500
2000
2500
Date


Lag Plot of sensor_o3
sensor_o3
2500
2000
1500
1000
500
500
1000
1500
2000
2500
Date


Lag Plot of temp
temp
40
30
20
10
0
0
10
20
30
40
Date


Lag Plot of rel_humidity
rel_humidity
90
80
70
60
50
40
30
20
10
10
20
30
40
50
60
70
80
90
Date


Lag Plot of abs_humidity
abs_humidity
2.0
1.5
1.0
0.5
0.5
1.0
1.5
2.0
Date

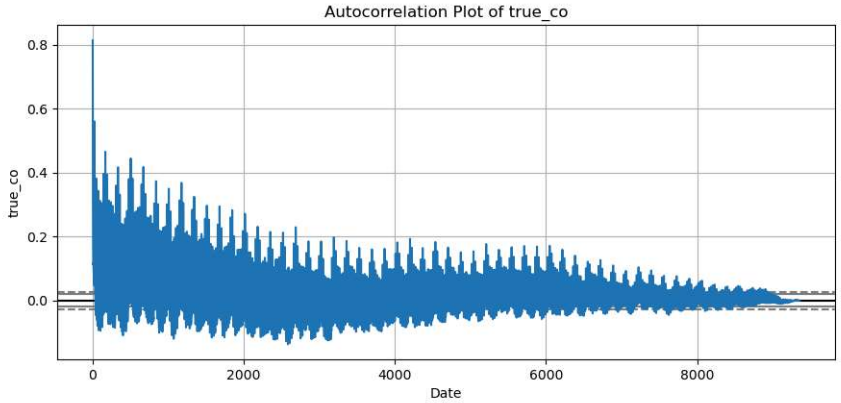

1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

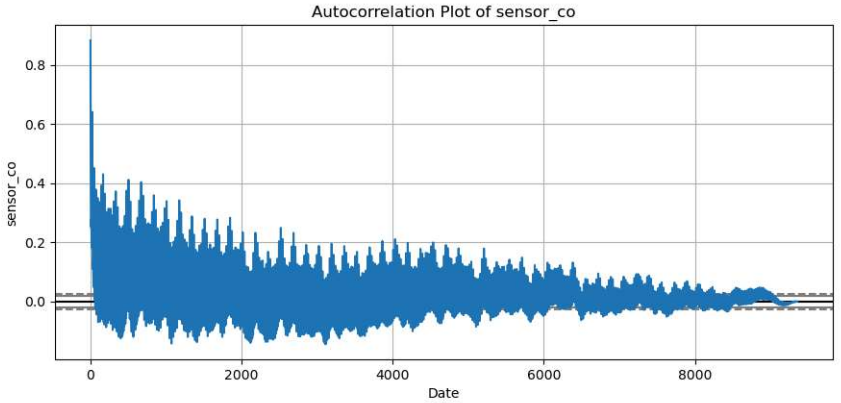
We see a positive relationship between current observations and lagged values for every original variable, suggesting that the current values all depend on the previous values, IE autocorrelation is present.

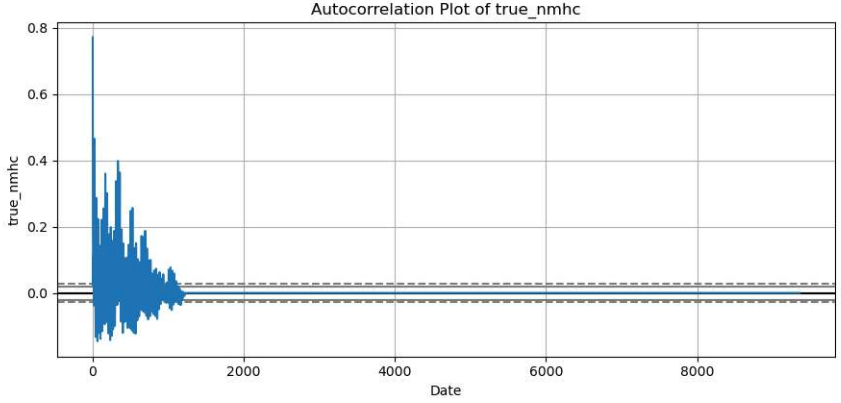
Task 6

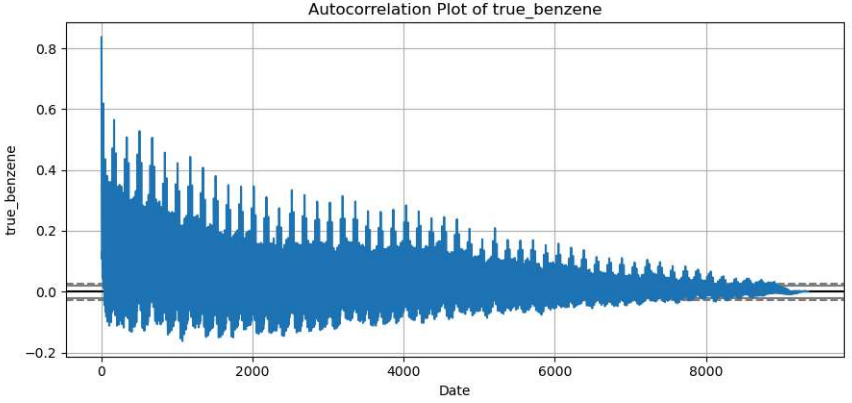
Autocorrelation Plots: plot correlations with all possible lag values in your time-series dataset. Import the autocorrelation plot class from pandas plotting library. Show and interpret the graph. Explain how an autocorrelation function (ACF) and partial autocorrelation function (PACF) can be useful in forecasting.

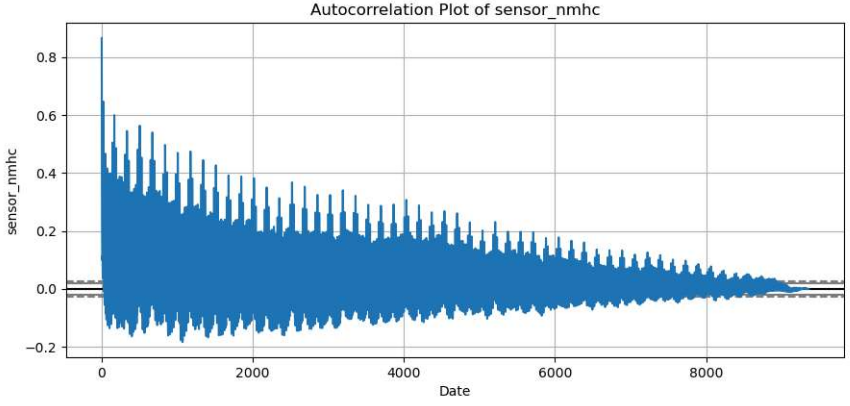
In [13]:
```
# Create figure and grid
fig, axes = plt.subplots(7, 2, figsize=(18, 30))
axes = axes.flatten()

# Create autocorrelation plot for each column
for i, column in enumerate(original_numeric_columns.columns):

    # Plot original data
    autocorrelation_plot(original_numeric_columns[column], ax=axes[i])

    # Set labels and title
    axes[i].set_xlabel("Date")
    axes[i].set_ylabel(column)
    axes[i].set_title(f"Autocorrelation Plot of {column}")

# Show plots
plt.tight_layout()
plt.show()
```

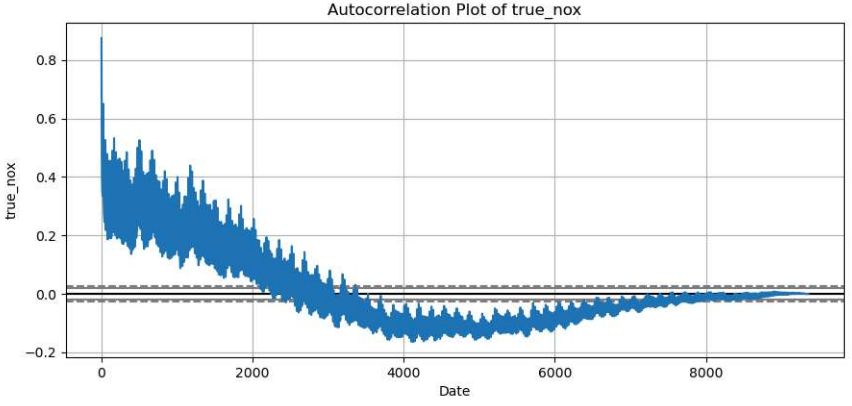

Autocorrelation Plot of true_co
true_co
Date

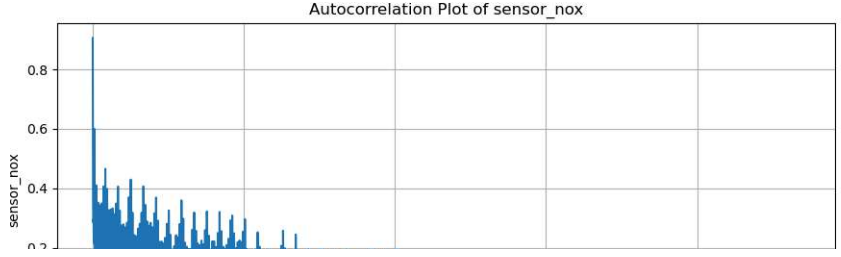

Autocorrelation Plot of sensor_co
sensor_co
Date

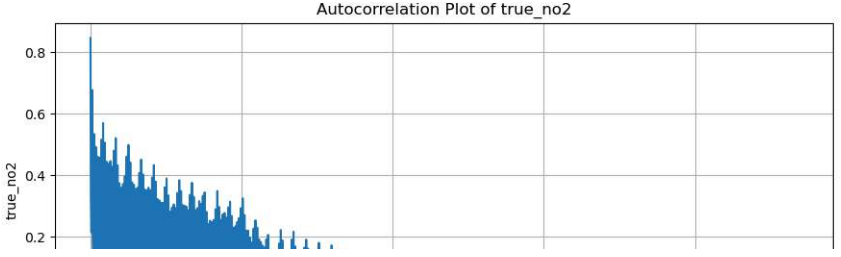

Autocorrelation Plot of true_nmhc
true_nmhc
Date

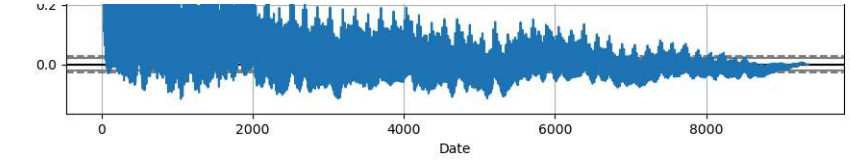

Autocorrelation Plot of true_benzene
true_benzene
Date

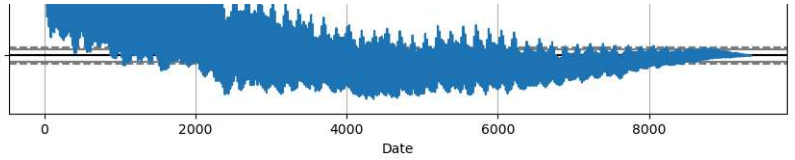

Autocorrelation Plot of sensor_nmhc
sensor_nmhc
Date

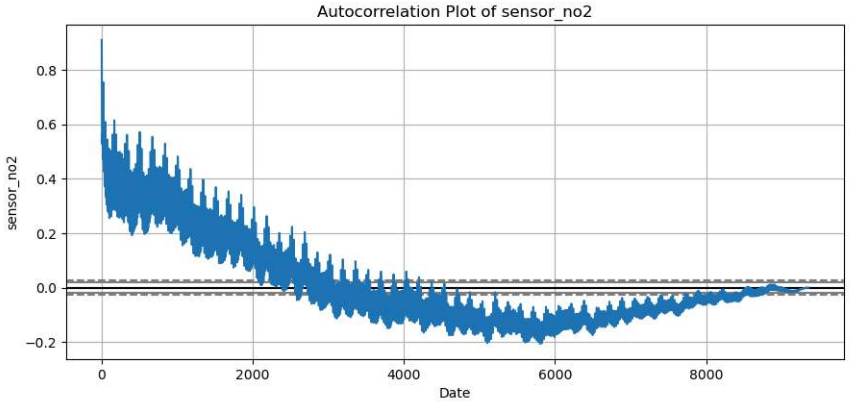

Autocorrelation Plot of true_nox
true_nox
Date

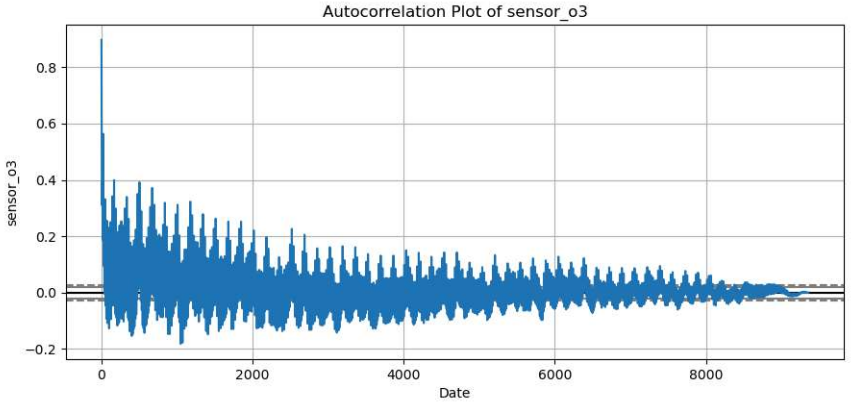

Autocorrelation Plot of sensor_nox
sensor_nox

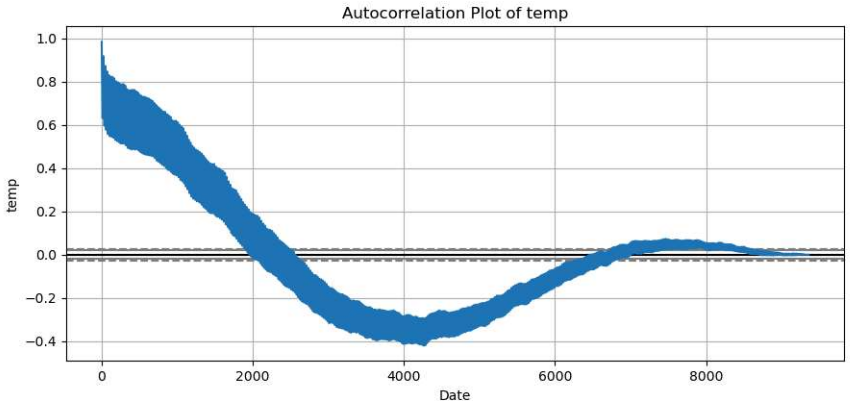

Autocorrelation Plot of true_no2
true_no2

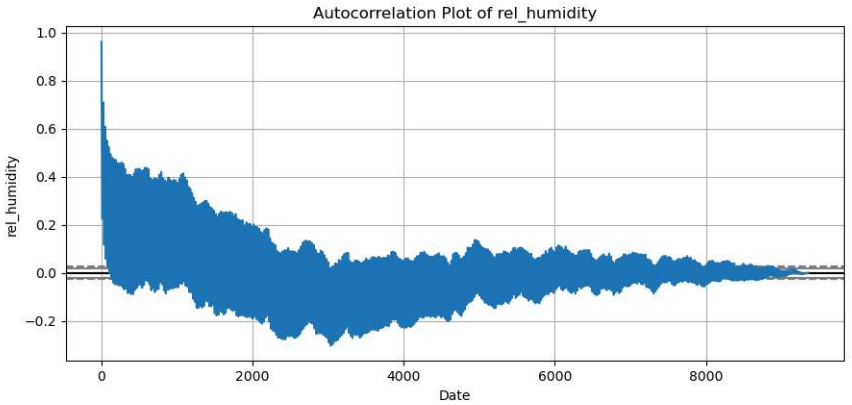

0.2
0.0
0
2000
4000
6000
8000
Date

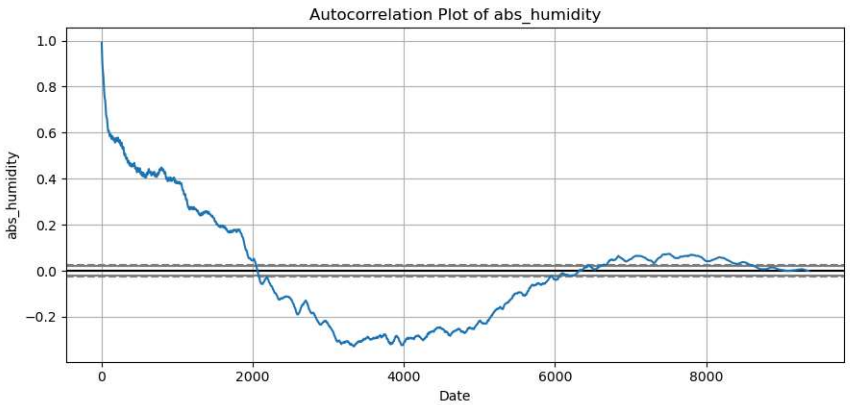

0.0
0
2000
4000
6000
8000
Date

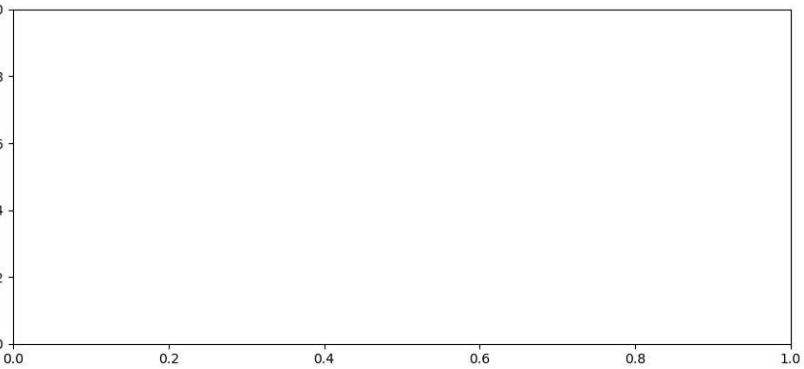

Autocorrelation Plot of sensor_no2
sensor_no2
0.8
0.6
0.4
0.2
0.0
−0.2
0
2000
4000
6000
8000
Date


Autocorrelation Plot of sensor_o3
sensor_o3
0.8
0.6
0.4
0.2
0.0
−0.2
0
2000
4000
6000
8000
Date


Autocorrelation Plot of temp
temp
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0
2000
4000
6000
8000
Date


Autocorrelation Plot of rel_humidity
rel_humidity
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
2000
4000
6000
8000
Date


Autocorrelation Plot of abs_humidity
abs_humidity
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
2000
4000
6000
8000
Date


1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

We see that every autocorrelation plot stabilizes near 0 on the vertical axis by the end of the time interval, suggesting that autocorrelation between current and lagged observations steadily decreases with time for every original variable in the dataset.

Explain how an autocorrelation function (ACF) and partial autocorrelation function (PACF) can be useful in forecasting. Autocorrelation functions are very useful for detecting autocorrelation between a time series and its lagged values at various time lags, helping us understand the degree to which past observations influence current ones. On the other hand, partial autocorrelation functions measure the correlation between two variables while accounting for the effects of intermediate lag values, making it useful for understanding how the current observation is related to the previous one without the influence of other lags getting in the way.

References

ChatGPT. (n.d.). https://chat.openai.com/

GfG. (2023, November 22). Autocorrelation and partial autocorrelation. GeeksforGeeks. https://www.geeksforgeeks.org/autocorrelation-and-partial-autocorrelation/