eda_01

July 2, 2025

[1]:
```python
# CONFIG CELL
from notebook_utils import set_root_directory

set_root_directory()
```

[2]:
```python
# IMPORTS
import pandas as pd
import os
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from app.measurement_ingestor import MeasurementIngestor
from app.constants import TARGET_VARIABLES
import dask.dataframe as dd
import dask.dataframe as dd
from dask.diagnostics import ProgressBar
import contextily as ctx
```

[3]:
```python
# PATH DEFINE
INPUT_DIR = "input_files"
SENSOR_METADATA_PATH = "input_files/sensor_metadata.parquet"

sensor_metadata = pd.read_parquet(SENSOR_METADATA_PATH)
```

[4]:
```python
class FlatMeasurementIngestor(MeasurementIngestor):
    def transform(self):
        from collections import defaultdict
        import pandas as pd

        time_1h = defaultdict(list)
        time_24h = defaultdict(list)

        # Get all files in directory
        files = [
            os.path.join(self.input_dir, f)
            for f in os.listdir(self.input_dir)
```

```
            if f.endswith((".xlsx", ".xls", ".parquet")) and "sensor_metadata"␣
 ↪not in f
        ]

        for file in files:
            file_name = os.path.basename(file)

            try:
                # Handle different file types
                if file.endswith(".parquet"):
                    df = pd.read_parquet(file)
                elif file.endswith((".xlsx", ".xls")):
                    # Explicitly specify engine for Excel files
                    df = pd.read_excel(file, engine="openpyxl")  # or 'xlrd'

                # Add your processing logic here
                if "1h" in file_name.lower():
                    time_1h[file_name].append(df)
                elif "24h" in file_name.lower():
                    time_24h[file_name].append(df)

            except Exception as e:
                print(f"Error processing {file_name}: {str(e)}")
                continue

        # Convert dictionaries to DataFrames
        def concat_dict(d):
            if not d:
                return pd.DataFrame()
            return pd.concat([pd.concat(df_list) for df_list in d.values()])

        return concat_dict(time_1h), concat_dict(time_24h)
```

[5]:

```
# LOADING DATA

ingestor = FlatMeasurementIngestor(
    input_dir=INPUT_DIR,
    sensor_metadata=sensor_metadata,
    exclude_depoyzcja=True,
    target_variables=TARGET_VARIABLES,
)


time_1h_df, time_24h_df = ingestor.transform()

# Now these will be DataFrames with proper columns
print("Columns in time_1h_df:", time_1h_df.columns.tolist())
```

```python
print("Columns in time_24h_df:", time_24h_df.columns.tolist())
```

```
Columns in time_1h_df: ['ds', 'unique_id', 'NO2', 'NOx', 'O3', 'SO2', 'C6H6',
'CO', 'PM10', 'PM2.5', 'NO']
Columns in time_24h_df: ['ds', 'unique_id', 'PM10', 'NO2', 'SO2', 'C6H6',
'PM2.5', 'prediction', 'prediction-lo-68', 'prediction-hi-68']
```

[6]:
```python
time_1h_df
```

[6]:
```
                          ds  unique_id  NO2  NOx    O3  SO2  C6H6   CO  PM10  \
0        2000-01-01 01:00:00         10  NaN  NaN   NaN  NaN   NaN  NaN   NaN
1        2000-01-01 02:00:00         10  6.0  7.0  35.0  NaN   NaN  NaN   NaN
2        2000-01-01 03:00:00         10  3.0  3.0  42.0  NaN   NaN  NaN   NaN
3        2000-01-01 04:00:00         10  4.0  4.0  39.0  NaN   NaN  NaN   NaN
4        2000-01-01 05:00:00         10  3.0  3.0  44.0  NaN   NaN  NaN   NaN
…                          …          …  …  …  …   …  …  …   ..   …
97197403 2023-12-31 20:00:00       1098  NaN  NaN   NaN  NaN   NaN  NaN   NaN
97197404 2023-12-31 21:00:00       1098  NaN  NaN   NaN  NaN   NaN  NaN   NaN
97197405 2023-12-31 22:00:00       1098  NaN  NaN   NaN  NaN   NaN  NaN   NaN
97197406 2023-12-31 23:00:00       1098  NaN  NaN   NaN  NaN   NaN  NaN   NaN
97197407 2024-01-01 00:00:00       1098  NaN  NaN   NaN  NaN   NaN  NaN   NaN

          PM2.5   NO
0           NaN NaN
1           NaN NaN
2           NaN NaN
3           NaN NaN
4           NaN NaN
…           …   ..
97197403    NaN NaN
97197404    NaN NaN
97197405    NaN NaN
97197406    NaN NaN
97197407    NaN NaN

[97197408 rows x 11 columns]
```

[7]:
```python
# BASIC STATISTICS


def basic_stats(df, name):
    print(f"\n=== BASIC STATISTICS - {name} ===")
    print(f"Number of rows: {len(df)}")

    # Handle datetime column
    if "ds" in df.columns:
        print(f"Date range: {df['ds'].min()} - {df['ds'].max()}")
    elif "timestamp" in df.columns:
```

```
        print(f"Date range: {df['timestamp'].min()} - {df['timestamp'].max()}")

    # Handle ID column
    if "unique_id" in df.columns:
        print(f"Unique sensors count: {df['unique_id'].nunique()}")

    # Numeric statistics
    numeric_cols = df.select_dtypes(include=["number"]).columns
    if not numeric_cols.empty:
        print("\nDescriptive statistics for numeric columns:")
        print(df[numeric_cols].describe())
    else:
        print("\nNo numeric columns found")

    # Categorical statistics (only if such columns exist)
    categorical_cols = df.select_dtypes(include=["object", "category"]).columns
    if not categorical_cols.empty:
        print("\nDescriptive statistics for categorical columns:")
        print(df[categorical_cols].describe())

    # Column types summary
    print("\nColumn types summary:")
    print(df.dtypes.value_counts())
```

[8]:

```
basic_stats(time_1h_df, "Dane 1-godzinne")
basic_stats(time_24h_df, "Dane 24-godzinne")
```

```
=== BASIC STATISTICS - Dane 1-godzinne ===
Number of rows: 97197408
Date range: 2000-01-01 01:00:00 - 2024-01-01 00:00:00
Unique sensors count: 462

Descriptive statistics for numeric columns:
          unique_id           NO2           NOx            O3           SO2  \
count  9.719741e+07  2.146812e+07  2.085802e+07  1.380542e+07  1.911445e+07
mean   5.458874e+02  1.773697e+01  2.972659e+01  5.019842e+01  7.623290e+00
std    3.235175e+02  1.647957e+01  4.905571e+01  2.944795e+01  1.174727e+01
min    1.000000e+00 -2.404340e+00 -1.600000e+00 -1.057220e+00 -5.000000e+00
25%    2.420000e+02  6.900000e+00  8.200000e+00  2.800000e+01  2.000660e+00
50%    5.355000e+02  1.271820e+01  1.550000e+01  4.830000e+01  4.115750e+00
75%    8.350000e+02  2.300000e+01  3.050000e+01  6.939440e+01  8.500000e+00
max    1.116000e+03  5.340000e+02  1.877000e+03  5.330000e+02  1.294000e+03

               C6H6            CO          PM10         PM2.5            NO
count  5.456655e+06  1.111020e+07  1.839411e+07  4.222026e+06  5.940571e+06
mean   1.544551e+00  4.529910e-01  2.984016e+01  1.837393e+01  6.580557e+00
std    4.938870e+00  3.882657e-01  3.130964e+01  1.892202e+01  1.916376e+01
```

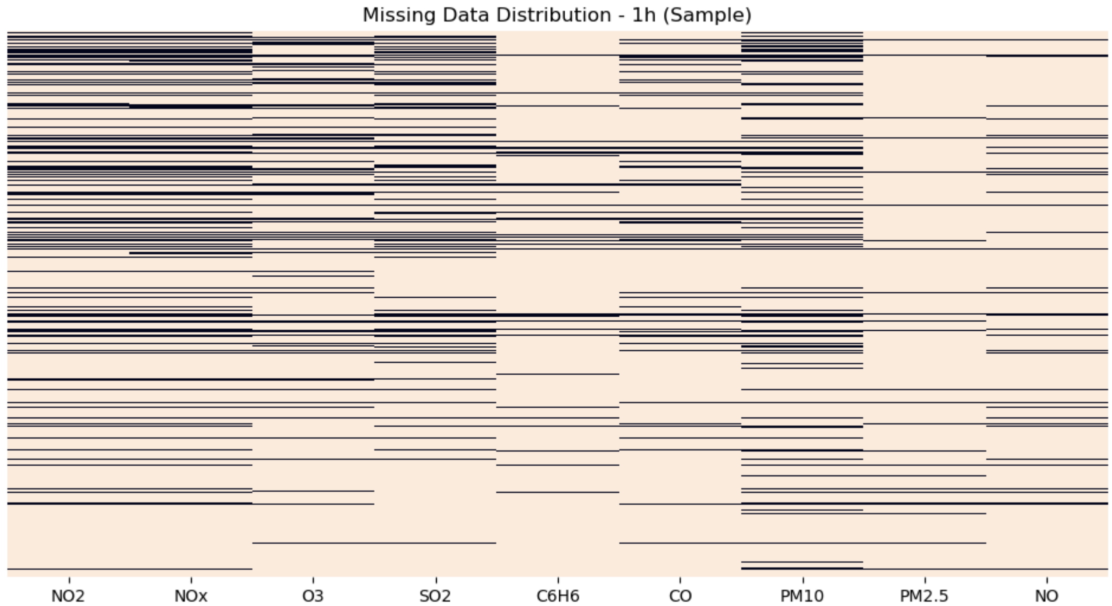
```
min   -5.000000e-02 -1.078600e-01 -6.000000e+00 -3.352276e+00 -9.564340e+00
25%    2.984100e-01  2.467100e-01  1.300000e+01  7.668610e+00  6.808050e-01
50%    7.300000e-01  3.471300e-01  2.140000e+01  1.293211e+01  1.400000e+00
75%    1.665240e+00  5.236900e-01  3.560000e+01  2.218647e+01  3.900000e+00
max    7.980000e+02  1.686000e+01  2.047000e+03  6.442000e+02  9.551610e+02

Column types summary:
float64           9
datetime64[ns]    1
int64             1
Name: count, dtype: int64

=== BASIC STATISTICS - Dane 24-godzinne ===
Number of rows: 8956384
Date range: 2000-01-01 00:00:00 - 2023-12-31 00:00:00
Unique sensors count: 897

Descriptive statistics for numeric columns:
               PM10            NO2            SO2          C6H6  \
count  2.263036e+06  401410.000000  412672.000000  37655.000000
mean   2.857056e+01      19.925634       5.193946      2.413461
std    2.315706e+01      14.132106       9.492338      3.260340
min    0.000000e+00       0.000000       0.000000      0.000000
25%    1.510000e+01      10.200000       1.000000      0.760000
50%    2.200000e+01      17.000000       2.000000      1.500000
75%    3.400000e+01      26.000000       5.800000      3.000000
max    1.098000e+03     293.000000     369.000000     84.940000

               PM2.5  prediction  prediction-lo-68  prediction-hi-68
count  175457.000000   70.000000         70.000000         70.000000
mean       19.264772   23.032094         11.294694         34.769494
std        16.528266    7.948186          7.723040          8.795446
min         0.000000   12.518574          5.638255         19.398894
25%         9.600000   18.763286          6.415980         29.312061
50%        14.300000   20.773875          8.179441         32.751679
75%        22.800000   25.402400         12.653046         40.007629
max       292.000000   53.478715         45.209154         61.748277

Descriptive statistics for categorical columns:
        unique_id
count     8956384
unique        897
top            23
freq        13878

Column types summary:
float64           8
datetime64[ns]    1
```

```
object            1
Name: count, dtype: int64
```

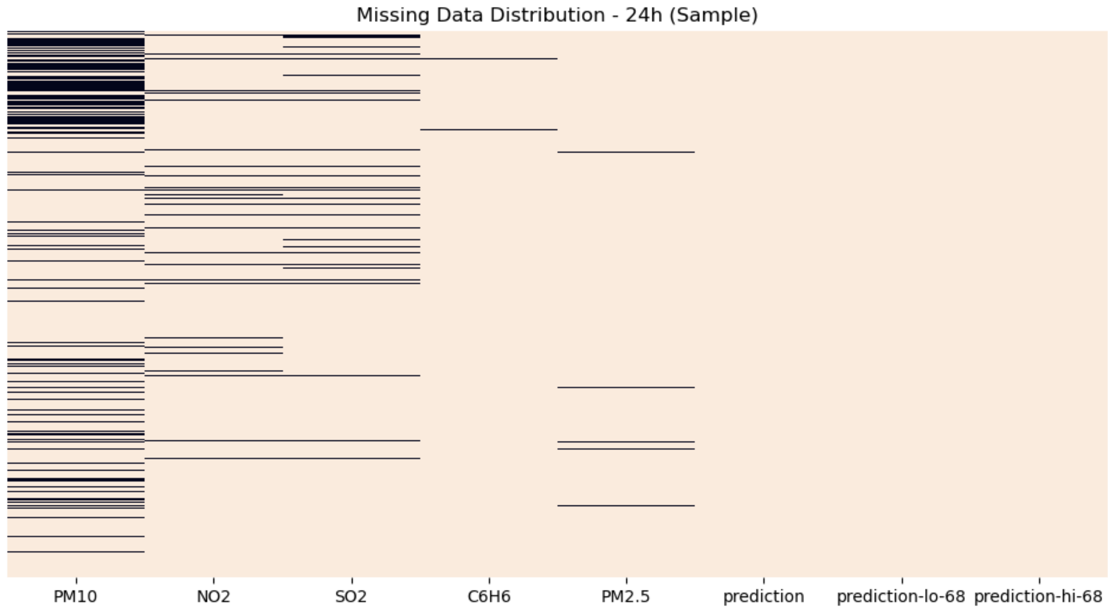
[9]:
```
def missing_data_analysis_dask(dask_df, name, sample_size=100000):
    """
    Optimized missing data analysis for large datasets using Dask
    Skips 'ds' and 'unique_id' columns in analysis

    Parameters:
    - dask_df: Dask DataFrame
    - name: Analysis name for display
    - sample_size: Number of rows to sample for visualization
    """
    print(f"\n=== MISSING DATA ANALYSIS - {name} ===")

    # 1. Exclude timestamp and ID columns from analysis
    cols_to_analyze = [col for col in dask_df.columns if col not in ["ds",␣
↪"unique_id"]]
    analysis_df = dask_df[cols_to_analyze]

    # 2. Calculate missing values statistics
    missing = analysis_df.isnull().sum().compute()
    missing_percent = (missing / len(analysis_df)) * 100

    # Create and display results
    missing_df = pd.DataFrame(
        {"Missing Values": missing, "% of Total": missing_percent.round(2)}
    ).sort_values("Missing Values", ascending=False)

    print(missing_df)

    # 3. Visualization using a sample
    print(f"\nVisualizing missing data pattern (sample of {sample_size} rows)...
↪")

    # Take a sample for visualization (excluding timestamp/id columns)
    sample_df = analysis_df.sample(frac=sample_size / len(analysis_df)).
↪compute()

    plt.figure(figsize=(12, 6))
    sns.heatmap(sample_df.isnull(), cbar=False, yticklabels=False)
    plt.title(f"Missing Data Distribution - {name} (Sample)")
    plt.show()

    # 4. Additional metrics
    print("\nAdditional Metrics:")
    print(f"Total rows analyzed: {len(analysis_df):,}")
```

```
    print(f"Columns with >50% missing: {sum(missing_percent > 50)}")
    print(
        f"Most complete column: {missing_percent.idxmin()} ({missing_percent.
 ↪min():.2f}% missing)"
    )
    print(
        f"Least complete column: {missing_percent.idxmax()} ({missing_percent.
 ↪max():.2f}% missing)"
    )


# Usage example:
dask_time_1h = dd.from_pandas(time_1h_df, npartitions=10)
dask_time_24h = dd.from_pandas(time_24h_df, npartitions=10)

missing_data_analysis_dask(dask_time_1h, "1h")
missing_data_analysis_dask(dask_time_24h, "24h")
```

```
=== MISSING DATA ANALYSIS - 1h ===
       Missing Values  % of Total
PM2.5        92975382       95.66
C6H6         91740753       94.39
NO           91256837       93.89
CO           86087211       88.57
O3           83391985       85.80
PM10         78803295       81.08
SO2          78082958       80.33
NOx          76339392       78.54
NO2          75729292       77.91

Visualizing missing data pattern (sample of 100000 rows)…
```




```
Additional Metrics:
Total rows analyzed: 97,197,408
Columns with >50% missing: 9
Most complete column: NO2 (77.91% missing)
Least complete column: PM2.5 (95.66% missing)

=== MISSING DATA ANALYSIS - 24h ===
                  Missing Values  % of Total
prediction               8956314      100.00
prediction-lo-68         8956314      100.00
prediction-hi-68         8956314      100.00
C6H6                     8918729       99.58
PM2.5                    8780927       98.04
NO2                      8554974       95.52
SO2                      8543712       95.39
PM10                     6693348       74.73

Visualizing missing data pattern (sample of 100000 rows)…
```



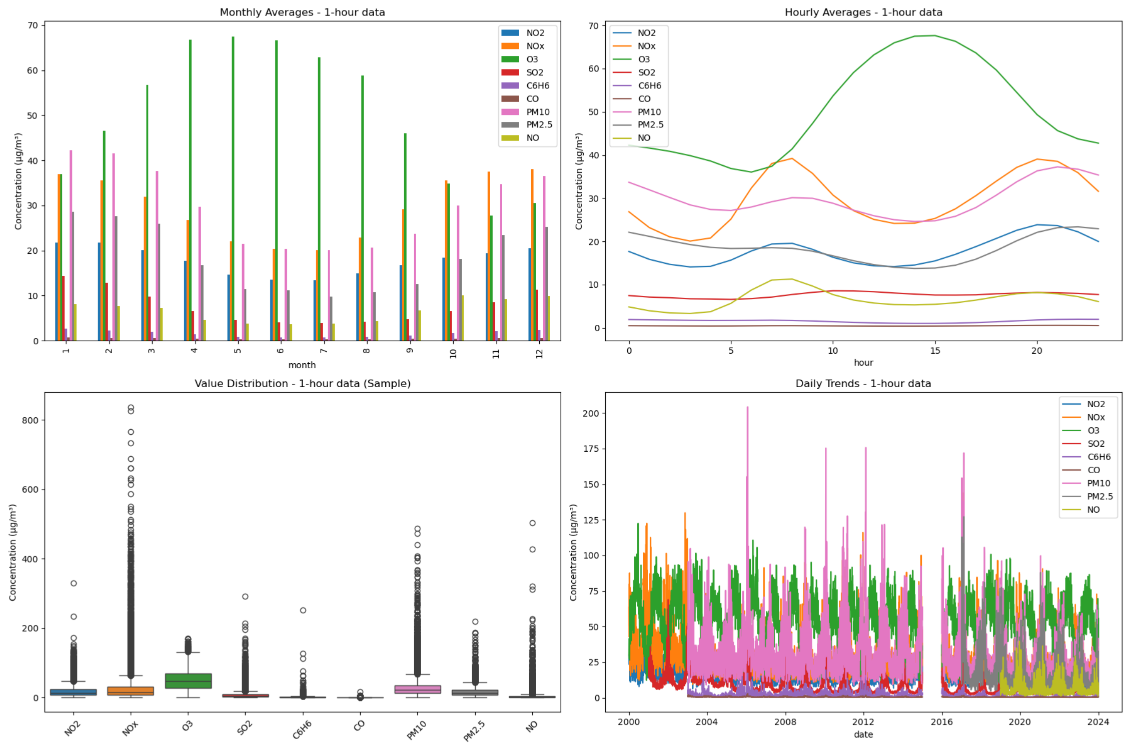

```
Additional Metrics:
Total rows analyzed: 8,956,384
Columns with >50% missing: 8
Most complete column: PM10 (74.73% missing)
Least complete column: prediction (100.00% missing)
```

[10]:
```
def time_analysis_dask(dask_df, name, target_variables, sample_size=100000):
    """
    Optimized time series analysis using Dask for large datasets

    Parameters:
    - dask_df: Dask DataFrame
    - name: Analysis name
    - target_variables: List of columns to analyze
    - sample_size: Sample size for visualizations
    """
    print(f"\n=== TIME SERIES ANALYSIS - {name} (Dask) ===")

    # Create temporary columns for analysis
    dask_df = dask_df.copy()
    if "ds" in dask_df.columns:
        dask_df["date"] = dask_df["ds"].dt.date
        dask_df["hour"] = dask_df["ds"].dt.hour
        dask_df["month"] = dask_df["ds"].dt.month

    # Take a sample for visualization
```

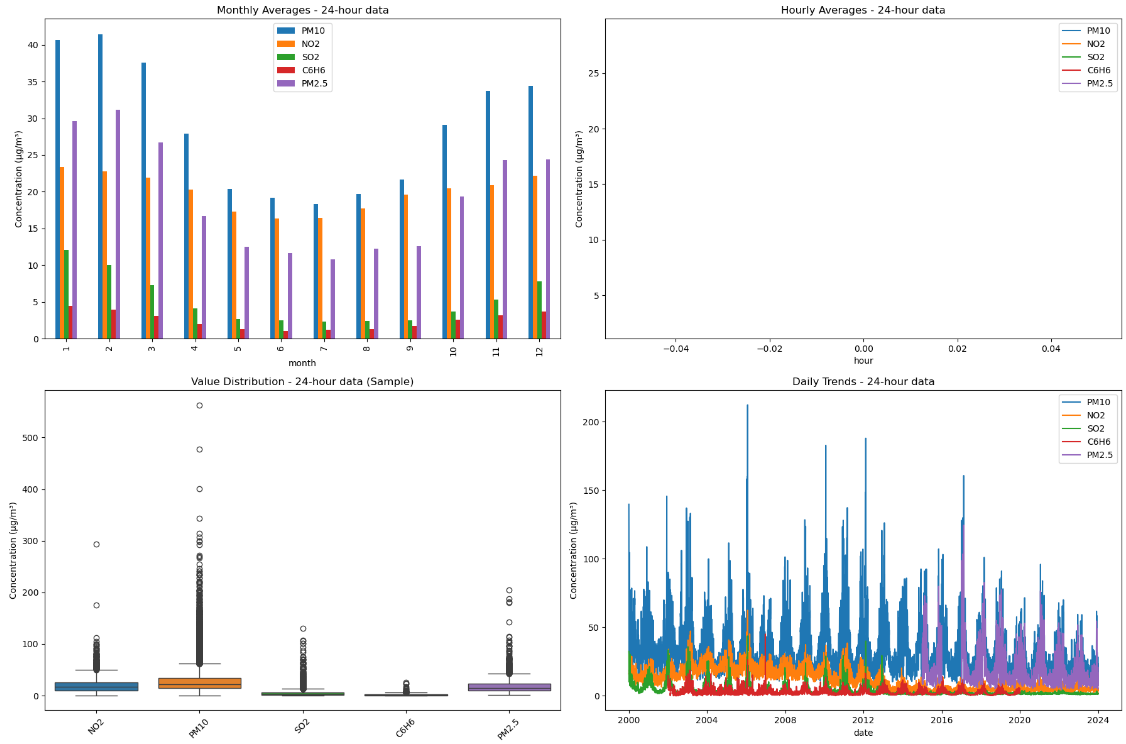
```python
with ProgressBar():
    print(f"\nSampling {sample_size} rows for visualization...")
    df_sample = dask_df.sample(frac=sample_size / len(dask_df)).compute()

# Visualization
plt.figure(figsize=(18, 12))

# 1. Monthly trends (computed in parallel)
with ProgressBar():
    print("\nCalculating monthly averages...")
    monthly = dask_df.groupby("month")[target_variables].mean().compute()

plt.subplot(2, 2, 1)
monthly.plot(kind="bar", ax=plt.gca())
plt.title(f"Monthly Averages - {name}")
plt.ylabel("Concentration (µg/m³)")

# 2. Hourly trends (computed in parallel)
with ProgressBar():
    print("\nCalculating hourly averages...")
    hourly = dask_df.groupby("hour")[target_variables].mean().compute()

plt.subplot(2, 2, 2)
hourly.plot(kind="line", ax=plt.gca())
plt.title(f"Hourly Averages - {name}")
plt.ylabel("Concentration (µg/m³)")

# 3. Boxplots (on sample)
plt.subplot(2, 2, 3)
sns.boxplot(data=df_sample[target_variables])
plt.title(f"Value Distribution - {name} (Sample)")
plt.xticks(rotation=45)
plt.ylabel("Concentration (µg/m³)")

# 4. Daily trends (computed in parallel)
with ProgressBar():
    print("\nCalculating daily trends...")
    daily = dask_df.groupby("date")[target_variables].mean().compute()

plt.subplot(2, 2, 4)
daily.plot(ax=plt.gca())
plt.title(f"Daily Trends - {name}")
plt.ylabel("Concentration (µg/m³)")

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

```python
    return dask_df.drop(["date", "hour", "month"], axis=1)


# Convert to Dask DataFrames
dask_time_1h = dd.from_pandas(time_1h_df, npartitions=10)
dask_time_24h = dd.from_pandas(time_24h_df, npartitions=10)

# Define target variables
TARGET_1H = ["NO2", "NOx", "O3", "SO2", "C6H6", "CO", "PM10", "PM2.5", "NO"]
TARGET_24H = ["NO2", "PM10", "SO2", "C6H6", "PM2.5"]

# Execute analysis
print("\nStarting analysis for 1-hour data...")
dask_time_1h = time_analysis_dask(dask_time_1h, "1-hour data", TARGET_1H)

print("\nStarting analysis for 24-hour data...")
dask_time_24h = time_analysis_dask(dask_time_24h, "24-hour data", TARGET_24H)
```

```
Starting analysis for 1-hour data…

=== TIME SERIES ANALYSIS - 1-hour data (Dask) ===

Sampling 100000 rows for visualization…
[########################################] | 100% Completed | 101.72 ms
[########################################] | 100% Completed | 12.05 s

Calculating monthly averages…
[########################################] | 100% Completed | 3.53 sms

Calculating hourly averages…
[########################################] | 100% Completed | 1.93 sms

Calculating daily trends…
[########################################] | 100% Completed | 16.96 s
```




```
Starting analysis for 24-hour data…

=== TIME SERIES ANALYSIS - 24-hour data (Dask) ===

Sampling 100000 rows for visualization…
[########################################] | 100% Completed | 105.12 ms
[########################################] | 100% Completed | 1.24 sms

Calculating monthly averages…
[########################################] | 100% Completed | 205.72 ms

Calculating hourly averages…
[########################################] | 100% Completed | 204.48 ms

Calculating daily trends…
[########################################] | 100% Completed | 1.74 sms
```



[22]:
```python
# SPATIAL ANALYSIS
def spatial_analysis_dask(dask_df, sensor_metadata, target_var="PM2.5", sample_size=1000):
    """
    Spatial analysis with Dask optimization and Poland map background

    Parameters:
    - dask_df: Dask DataFrame with measurement data
    - sensor_metadata: Pandas DataFrame with sensor locations
    - target_var: Variable to visualize (default: PM2.5)
    - sample_size: Number of points to sample for visualization
    """
    sensor_metadata = sensor_metadata.copy()
    dask_df = dask_df.copy()

    if not all(col in sensor_metadata.columns for col in ["latitude", "longitude"]):
        print("Skipping spatial analysis - missing coordinates")
        return

    print("\n=== SPATIAL ANALYSIS WITH POLAND MAP (Dask) ===")

    with ProgressBar():
```

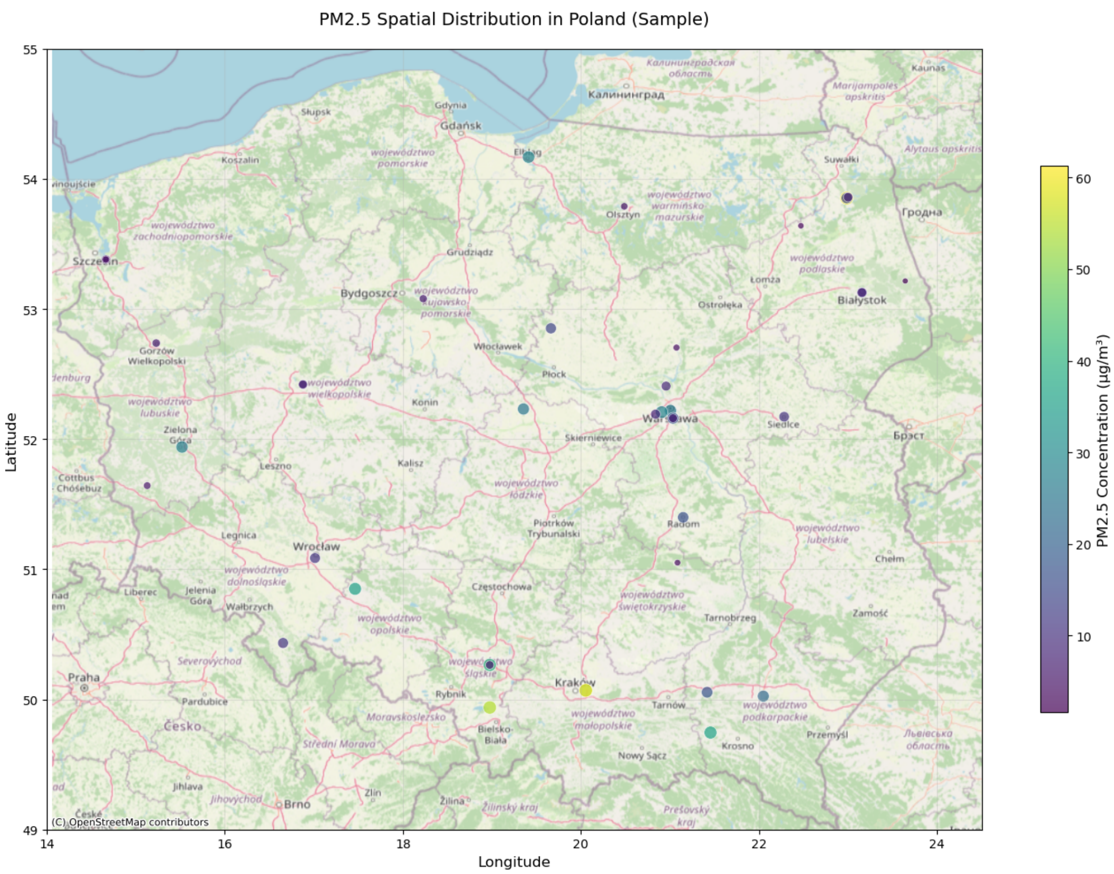
```
    # Merge with metadata
    sensor_metadata["sensor_id"] = sensor_metadata["sensor_id"].astype(str)
    dask_df["unique_id"] = dask_df["unique_id"].astype(str)
    merged = dd.merge(
        dask_df[["unique_id", target_var]],
        sensor_metadata[["sensor_id", "latitude", "longitude"]],
        left_on="unique_id",
        right_on="sensor_id",
    ).compute()

    sample = merged.sample(min(sample_size, len(merged)))

# Create figure and axis
plt.figure(figsize=(14, 10))
ax = plt.gca()

# Calculate plot boundaries (Poland approximate coordinates)
min_lon, max_lon = 14.0, 24.5
min_lat, max_lat = 49.0, 55.0

# Filter points within Poland boundaries
sample = sample[
    (sample["longitude"].between(min_lon, max_lon))
    & (sample["latitude"].between(min_lat, max_lat))
]

# Create scatter plot
scatter = ax.scatter(
    x=sample["longitude"],
    y=sample["latitude"],
    c=sample[target_var],
    s=sample[target_var].rank(pct=True) * 100 + 20,
    alpha=0.7,
    cmap="viridis",
    edgecolors="w",
    linewidths=0.5,
)

# Add map background
ctx.add_basemap(
    ax,
    crs="EPSG:4326",  # WGS84 coordinate system
    source=ctx.providers.OpenStreetMap.Mapnik,
    zoom=7,
)

# Customize plot
```

```python
    plt.title(f"{target_var} Spatial Distribution in Poland (Sample)",␣
 ↪fontsize=14, pad=20)
    cbar = plt.colorbar(scatter, ax=ax, shrink=0.7)
    cbar.set_label(f"{target_var} Concentration (µg/m³)", fontsize=12)

    ax.set_xlabel("Longitude", fontsize=12)
    ax.set_ylabel("Latitude", fontsize=12)
    ax.set_xlim(min_lon, max_lon)
    ax.set_ylim(min_lat, max_lat)

    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()
```

[23]:
```python
# CORRELATION ANALYSIS


def correlation_analysis_dask(dask_df, name, target_variables):
    """
    Correlation analysis with Dask optimization

    Parameters:
    - dask_df: Dask DataFrame
    - name: Analysis name
    - target_variables: List of columns for correlation
    """
    print(f"\n=== CORRELATION ANALYSIS - {name} (Dask) ===")

    with ProgressBar():
        # Compute correlation matrix in parallel
        corr_matrix = dask_df[target_variables].corr().compute()

    plt.figure(figsize=(12, 8))
    sns.heatmap(
        corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", center=0, vmin=-1,␣
 ↪vmax=1, square=True
    )
    plt.title(f"Correlation Matrix - {name}")
    plt.tight_layout()
    plt.show()
```

[24]:
```python
spatial_analysis_dask(dask_time_1h, sensor_metadata, "PM2.5")
spatial_analysis_dask(dask_time_24h, sensor_metadata, "PM2.5")

correlation_analysis_dask(dask_time_1h, "1h", TARGET_1H)
correlation_analysis_dask(dask_time_24h, "24h", TARGET_24H)
```

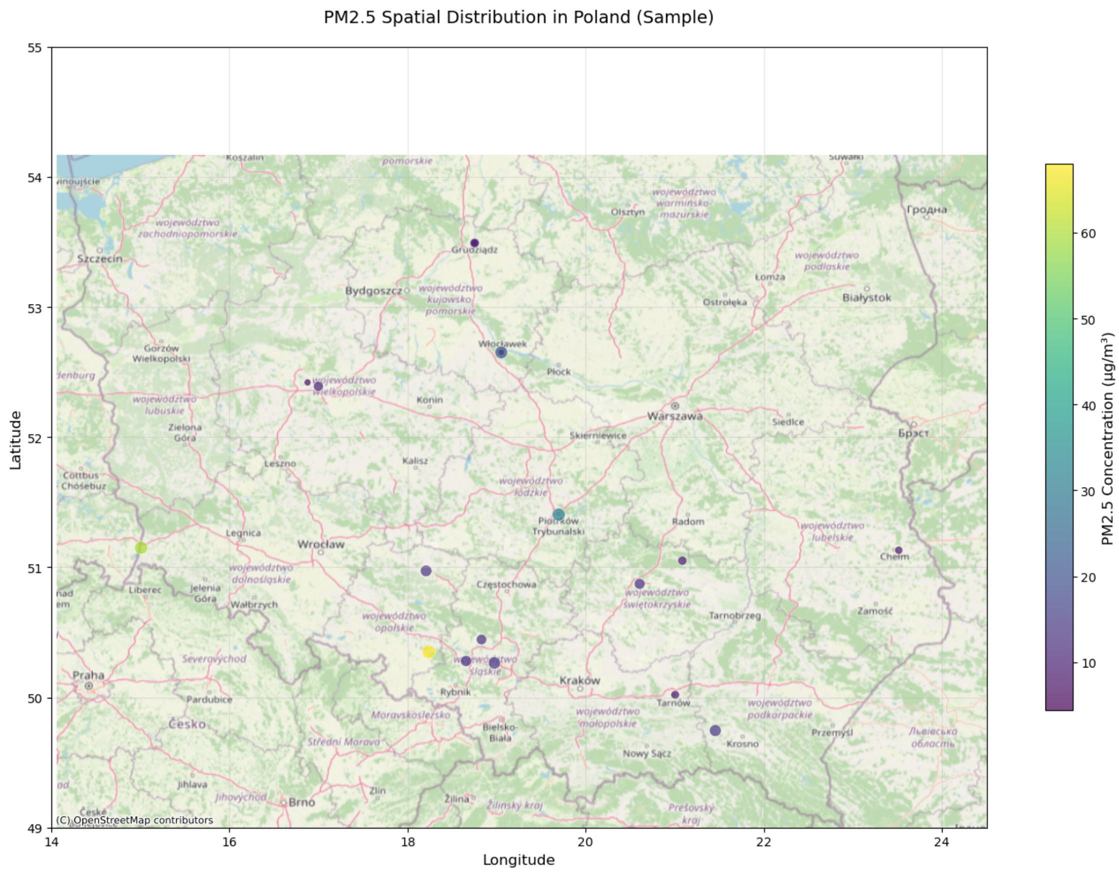
```
=== SPATIAL ANALYSIS WITH POLAND MAP (Dask) ===

c:\Users\Mambo\.conda\envs\ispies\Lib\site-packages\dask\dataframe\multi.py:169:
UserWarning: Merging dataframes with merge column data type mismatches:
+----------------------------+------------+-------------+
| Merge columns              | left dtype | right dtype |
+----------------------------+------------+-------------+
| ('unique_id', 'sensor_id') | object     | string      |
+----------------------------+------------+-------------+
Cast dtypes explicitly to avoid unexpected results.
  warnings.warn(

[########################################] | 100% Completed | 21.19 s
```



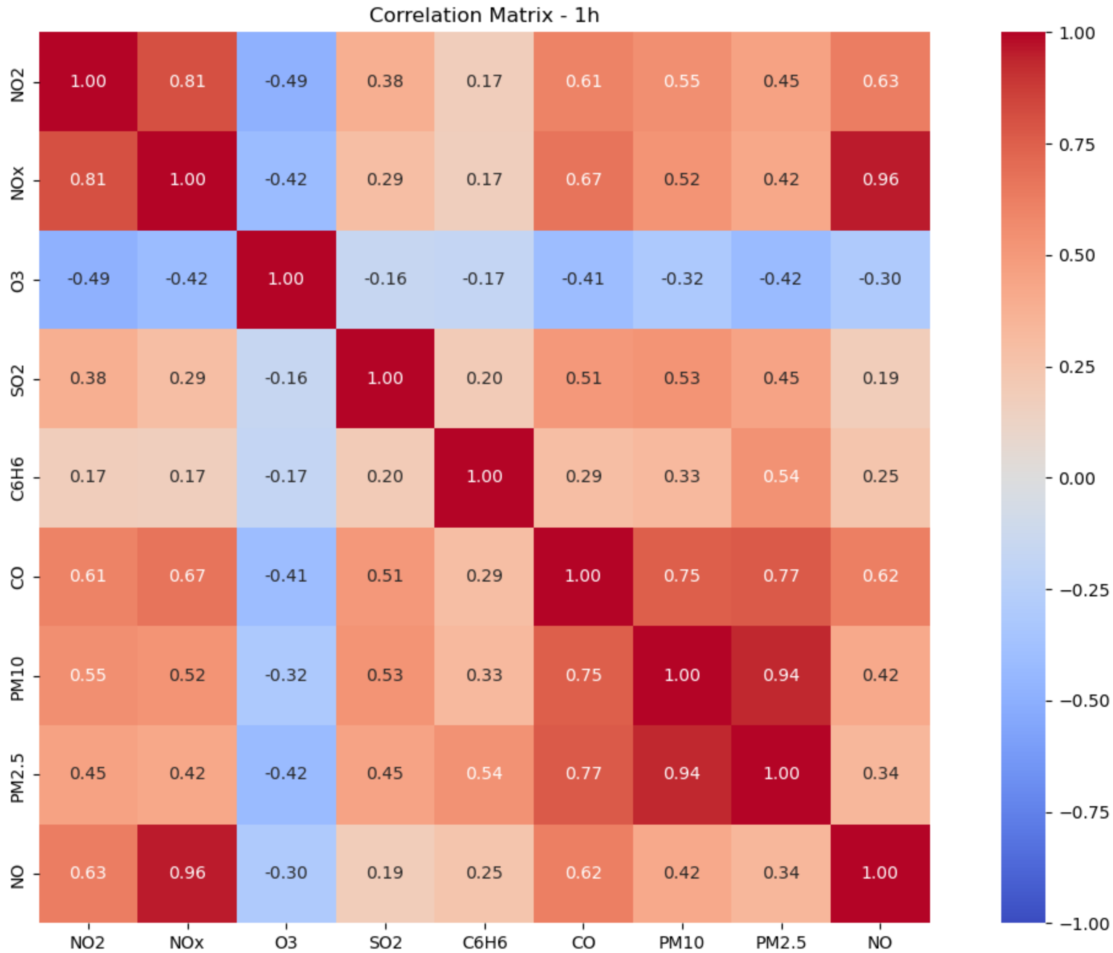

```
=== SPATIAL ANALYSIS WITH POLAND MAP (Dask) ===

c:\Users\Mambo\.conda\envs\ispies\Lib\site-packages\dask\dataframe\multi.py:169:
UserWarning: Merging dataframes with merge column data type mismatches:
+----------------------------+------------+-------------+
| Merge columns              | left dtype | right dtype |
+----------------------------+------------+-------------+
```

```
| ('unique_id', 'sensor_id') | object     | string      |
+---------------------------+------------+-------------+
Cast dtypes explicitly to avoid unexpected results.
  warnings.warn(
```

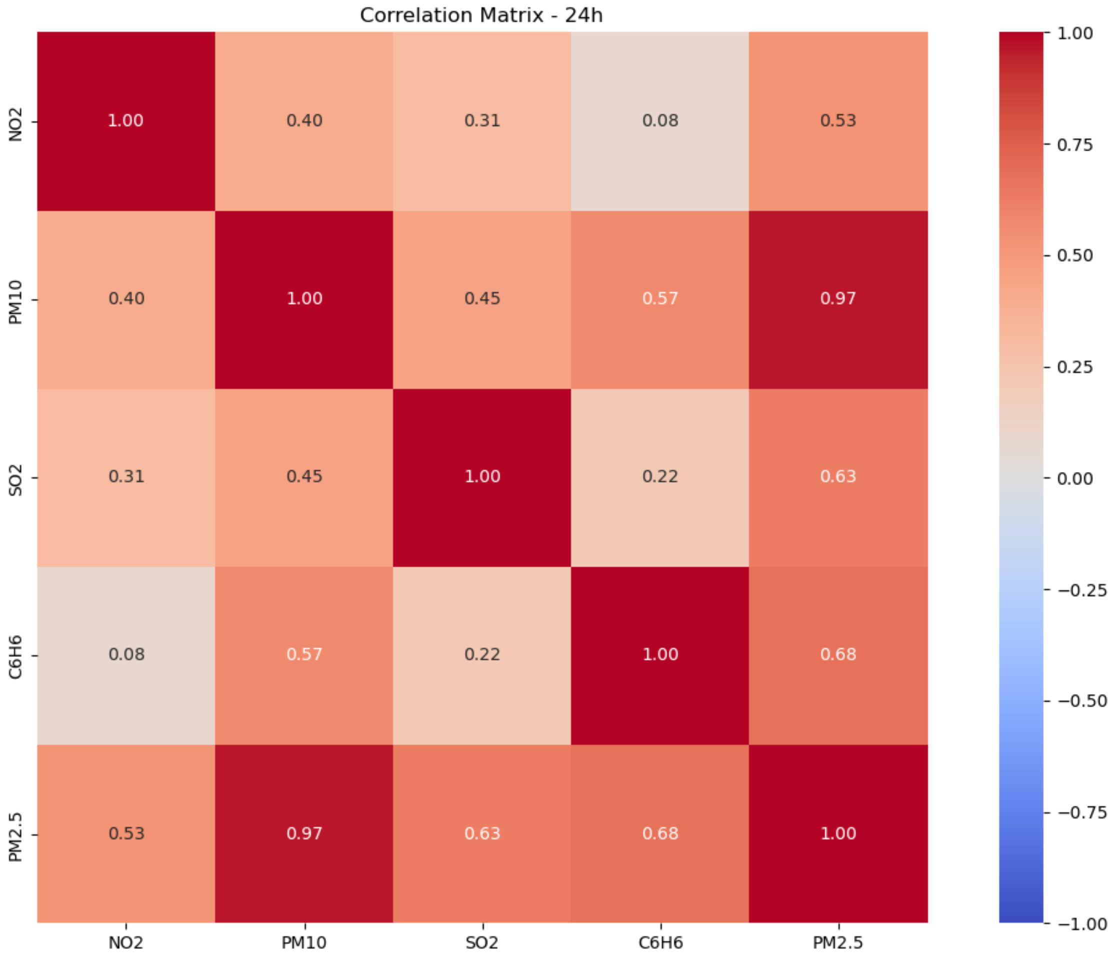
```
[########################################] | 100% Completed | 2.17 sms
```




```
=== CORRELATION ANALYSIS - 1h (Dask) ===
[########################################] | 100% Completed | 22.90 s
```




```
=== CORRELATION ANALYSIS - 24h (Dask) ===
[########################################] | 100% Completed | 814.69 ms
```



[25]:

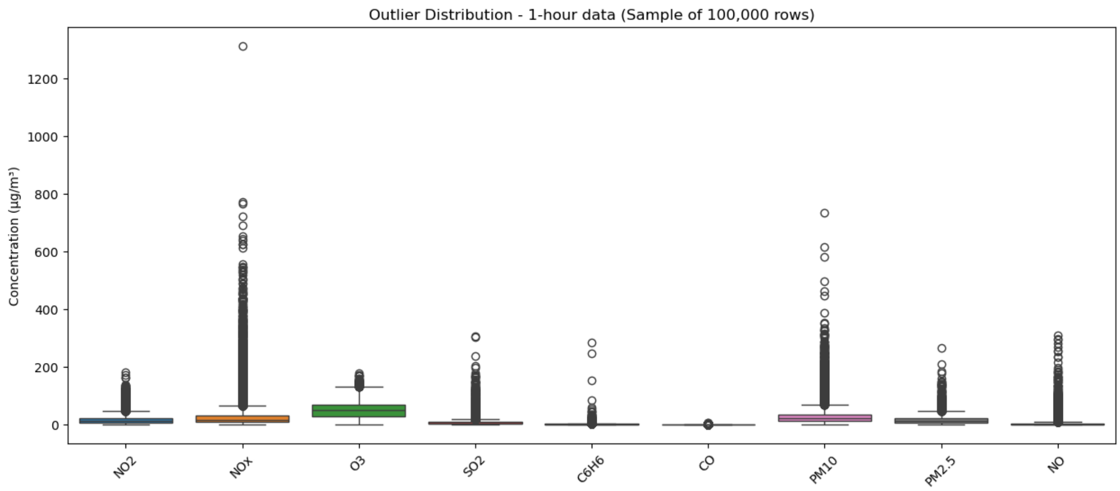
```
# OUTLIER ANALYSIS
def outlier_analysis_dask(dask_df, name, target_variables, n_partitions=10):
    """
    Outlier analysis using Dask with boxplots and statistical summary

    Parameters:
    - dask_df: Dask DataFrame
    - name: Analysis name
    - target_variables: List of columns to analyze
    - n_partitions: Number of partitions for Dask
    """
    print(f"\n=== OUTLIER ANALYSIS - {name} (Dask) ===")

    # Convert to Dask if not already
    if not isinstance(dask_df, dd.DataFrame):
        dask_df = dd.from_pandas(dask_df, npartitions=n_partitions)
```

```
    # Calculate basic statistics in parallel
    with ProgressBar():
        stats = dask_df[target_variables].describe(percentiles=[0.01, 0.99]).compute()

    print("\nExtreme Value Statistics:")
    display(stats.loc[["min", "1%", "99%", "max"]])

    # Calculate IQR-based outliers in parallel
    with ProgressBar():
        q1 = dask_df[target_variables].quantile(0.25).compute()
        q3 = dask_df[target_variables].quantile(0.75).compute()
        iqr = q3 - q1

        lower_bound = q1 - 1.5 * iqr
        upper_bound = q3 + 1.5 * iqr

        outlier_counts = {}
        for col in target_variables:
            outliers = (
                dask_df[(dask_df[col] < lower_bound[col]) | (dask_df[col] > upper_bound[col])][col]
                .count()
                .compute()
            )
            outlier_counts[col] = outliers

    print("\nIQR-based Outlier Counts (1.5*IQR rule):")
    outlier_df = pd.DataFrame.from_dict(outlier_counts, orient="index", columns=["Outlier Count"])
    outlier_df["% of Total"] = (outlier_df["Outlier Count"] / len(dask_df)) * 100
    display(outlier_df.round(2))

    # Sample data for visualization
    sample_size = min(100000, len(dask_df) // 10)
    sample_df = dask_df.sample(frac=sample_size / len(dask_df)).compute()

    # Visualization
    plt.figure(figsize=(15, 6))
    sns.boxplot(data=sample_df[target_variables])
    plt.title(f"Outlier Distribution - {name} (Sample of {sample_size:,} rows)")
    plt.xticks(rotation=45)
    plt.ylabel("Concentration (µg/m³)")
    plt.show()

    return {
```

```
        "stats": stats,
        "outlier_counts": outlier_df,
        "iqr_bounds": pd.DataFrame({"lower": lower_bound, "upper":␣
↪upper_bound}),
    }


outlier_results_1h = outlier_analysis_dask(dask_time_1h, "1-hour data",␣
↪TARGET_1H)


outlier_results_24h = outlier_analysis_dask(dask_time_24h, "24-hour data",␣
↪TARGET_24H)
```

```
=== OUTLIER ANALYSIS - 1-hour data (Dask) ===
[########################################] | 100% Completed | 6.13 sms

Extreme Value Statistics:
            NO2     NOx        O3     SO2      C6H6        CO        PM10  \
min   -2.404340    -1.6  -1.05722    -5.0  -0.05000  -0.107860   -6.000000
1%     1.586367     2.2   2.10000     0.5   0.07072   0.157688    3.380894
99%   88.500000   325.0 131.00000    65.6  23.80000   2.173000  188.760000
max  534.000000  1877.0 533.00000  1294.0 798.00000  16.860000 2047.000000

          PM2.5          NO
min   -3.352276   -9.564340
1%     2.471120    0.110269
99%  119.086260  134.209580
max  644.200000  955.161000
[########################################] | 100% Completed | 655.87 ms
[########################################] | 100% Completed | 698.82 ms
[########################################] | 100% Completed | 102.69 ms
[########################################] | 100% Completed | 102.32 ms
[########################################] | 100% Completed | 102.47 ms
[########################################] | 100% Completed | 102.32 ms
[########################################] | 100% Completed | 102.99 ms
[########################################] | 100% Completed | 102.34 ms
[########################################] | 100% Completed | 102.91 ms
[########################################] | 100% Completed | 102.29 ms
[########################################] | 100% Completed | 102.24 ms

IQR-based Outlier Counts (1.5*IQR rule):

       Outlier Count  % of Total
NO2          1002567        1.03
NOx          1698707        1.75
```

O3	54763	0.06
SO2	1097371	1.13
C6H6	309497	0.32
CO	552334	0.57
PM10	1062389	1.09
PM2.5	232513	0.24
NO	679708	0.70




```
=== OUTLIER ANALYSIS - 24-hour data (Dask) ===
[########################################] | 100% Completed | 413.62 ms

Extreme Value Statistics:
```

	NO2	PM10	SO2	C6H6	PM2.5
min	0.0	0.000	0.0	0.00	0.000
1%	3.0	6.400	0.4	1.00	6.148
99%	87.0	164.189	51.0	20.00	105.450
max	293.0	1098.000	369.0	84.94	292.000

```
[########################################] | 100% Completed | 104.03 ms
[########################################] | 100% Completed | 103.40 ms
[########################################] | 100% Completed | 102.94 ms
[########################################] | 100% Completed | 102.67 ms
[########################################] | 100% Completed | 102.49 ms
[########################################] | 100% Completed | 102.64 ms
[########################################] | 100% Completed | 102.54 ms

IQR-based Outlier Counts (1.5*IQR rule):
```

	Outlier Count	% of Total
NO2	8461	0.09

```
PM10            81704         0.91
SO2             29130         0.33
C6H6             2053         0.02
PM2.5            6863         0.08
```