combo

July 23, 2024

0.1 NAIS data

[ ]:
```python
import xarray as xr
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

# Load the dataset
file_path = '/home/coliewo/Desktop/analysis/combined_test1.nc'
data = xr.open_dataset(file_path)

#To convert the diameter values to nm
dataset = data.assign_coords(diameter=data['diameter'] * 1e9)
```

[ ]:
```python
dataset
```

[ ]:
```
<xarray.Dataset>
Dimensions:              (diameter: 55, time: 1081, flag: 83)
Coordinates:
  * diameter             (diameter) float64 0.8029 0.8628 0.9273 … 38.46 41.55
  * time                 (time) datetime64[ns] 2024-05-16 … 2024-06-30
  * flag                 (flag) object '+ postfilter voltage may be too high' …
Data variables:
    neg_ions             (time, diameter) float64 …
    pos_ions             (time, diameter) float64 …
    neg_particles        (time, diameter) float64 …
    pos_particles        (time, diameter) float64 …
    neg_ion_flags        (time, flag) int64 …
    pos_ion_flags        (time, flag) int64 …
    neg_particle_flags   (time, flag) int64 …
    pos_particle_flags   (time, flag) int64 …
Attributes: (12/14)
    measurement_location:          ISAC
    description:                   Rooftop Industrial Area
    longitude:                     11.34
    latitude:                      44.52
    inlet_length:                  1.0
    do_inlet_loss_correction:      True
```

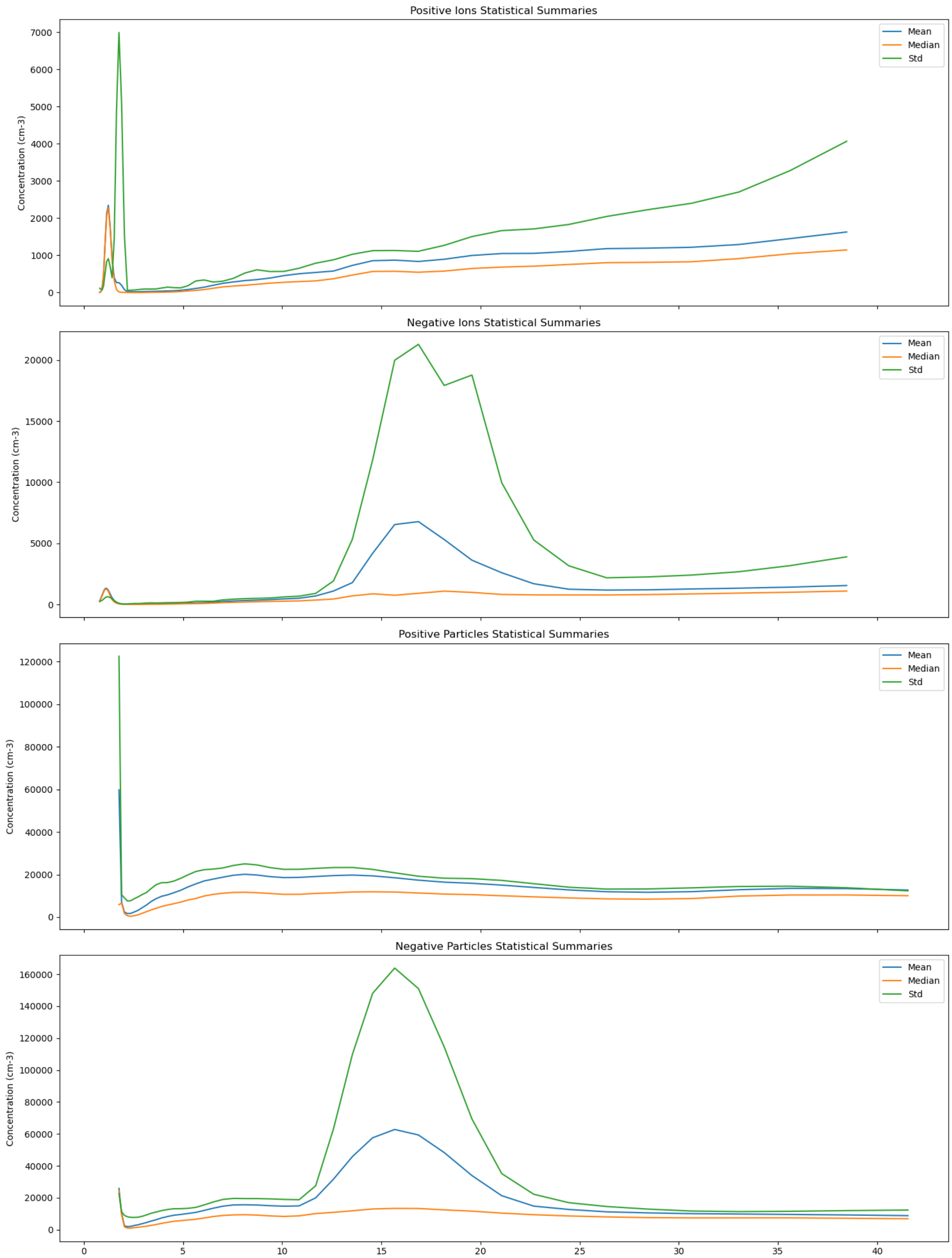
```
…                                    …
remove_corona_ions:                  True
fill_temperature:                    273.15
fill_pressure:                       101325.0
fill_flowrate:                       54.0
dilution_on:                         False
resolution:                          5min
```

[ ]:
```python
# Step 1: Visualize the Data

# 1.1 Time Series Plots
fig, axs = plt.subplots(4, 1, figsize=(15, 20), sharex=True)

# Positive ions
pos_ions = dataset['pos_ions'].mean(dim='diameter')
axs[0].plot(dataset['time'], pos_ions, label='Positive Ions', color='tab:blue')
axs[0].set_title('Positive Ions Time Series')
axs[0].set_ylabel('Concentration (cm-3)')
axs[0].legend()

# Negative ions
neg_ions = dataset['neg_ions'].mean(dim='diameter')
axs[1].plot(dataset['time'], neg_ions, label='Negative Ions', color='tab:
 ↪orange')
axs[1].set_title('Negative Ions Time Series')
axs[1].set_ylabel('Concentration (cm-3)')
axs[1].legend()

# Positive particles
pos_particles = dataset['pos_particles'].mean(dim='diameter')
axs[2].plot(dataset['time'], pos_particles, label='Positive Particles',␣
 ↪color='tab:green')
axs[2].set_title('Positive Particles Time Series')
axs[2].set_ylabel('Concentration (cm-3)')
axs[2].legend()

# Negative particles
neg_particles = dataset['neg_particles'].mean(dim='diameter')
axs[3].plot(dataset['time'], neg_particles, label='Negative Particles',␣
 ↪color='tab:red')
axs[3].set_title('Negative Particles Time Series')
axs[3].set_ylabel('Concentration (cm-3)')
axs[3].set_xlabel('Time')
axs[3].legend()

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


```
[ ]: # Step 2: Statistical Summaries
     def compute_statistics(data):
```

```
    mean = data.mean(dim='time')
    median = data.median(dim='time')
    std_dev = data.std(dim='time')
    return mean, median, std_dev

pos_ions_mean, pos_ions_median, pos_ions_std =␣
 ↪compute_statistics(dataset['pos_ions'])
neg_ions_mean, neg_ions_median, neg_ions_std =␣
 ↪compute_statistics(dataset['neg_ions'])
pos_particles_mean, pos_particles_median, pos_particles_std =␣
 ↪compute_statistics(dataset['pos_particles'])
neg_particles_mean, neg_particles_median, neg_particles_std =␣
 ↪compute_statistics(dataset['neg_particles'])


# 1.2 Statistical Summaries Plots
fig, axs = plt.subplots(4, 1, figsize=(15, 20), sharex=True)

# Positive ions
axs[0].plot(dataset['diameter'], pos_ions_mean, label='Mean', color='tab:blue')
axs[0].plot(dataset['diameter'], pos_ions_median, label='Median', color='tab:
 ↪orange')
axs[0].plot(dataset['diameter'], pos_ions_std, label='Std', color='tab:green')
axs[0].set_title('Positive Ions Statistical Summaries')
axs[0].set_ylabel('Concentration (cm-3)')
axs[0].legend()

# Negative ions
axs[1].plot(dataset['diameter'], neg_ions_mean, label='Mean', color='tab:blue')
axs[1].plot(dataset['diameter'], neg_ions_median, label='Median', color='tab:
 ↪orange')
axs[1].plot(dataset['diameter'], neg_ions_std, label='Std', color='tab:green')
axs[1].set_title('Negative Ions Statistical Summaries')
axs[1].set_ylabel('Concentration (cm-3)')
axs[1].legend()

# Positive particles
axs[2].plot(dataset['diameter'], pos_particles_mean, label='Mean', color='tab:
 ↪blue')
axs[2].plot(dataset['diameter'], pos_particles_median, label='Median',␣
 ↪color='tab:orange')
axs[2].plot(dataset['diameter'], pos_particles_std, label='Std', color='tab:
 ↪green')
axs[2].set_title('Positive Particles Statistical Summaries')
axs[2].set_ylabel('Concentration (cm-3)')
axs[2].legend()
```

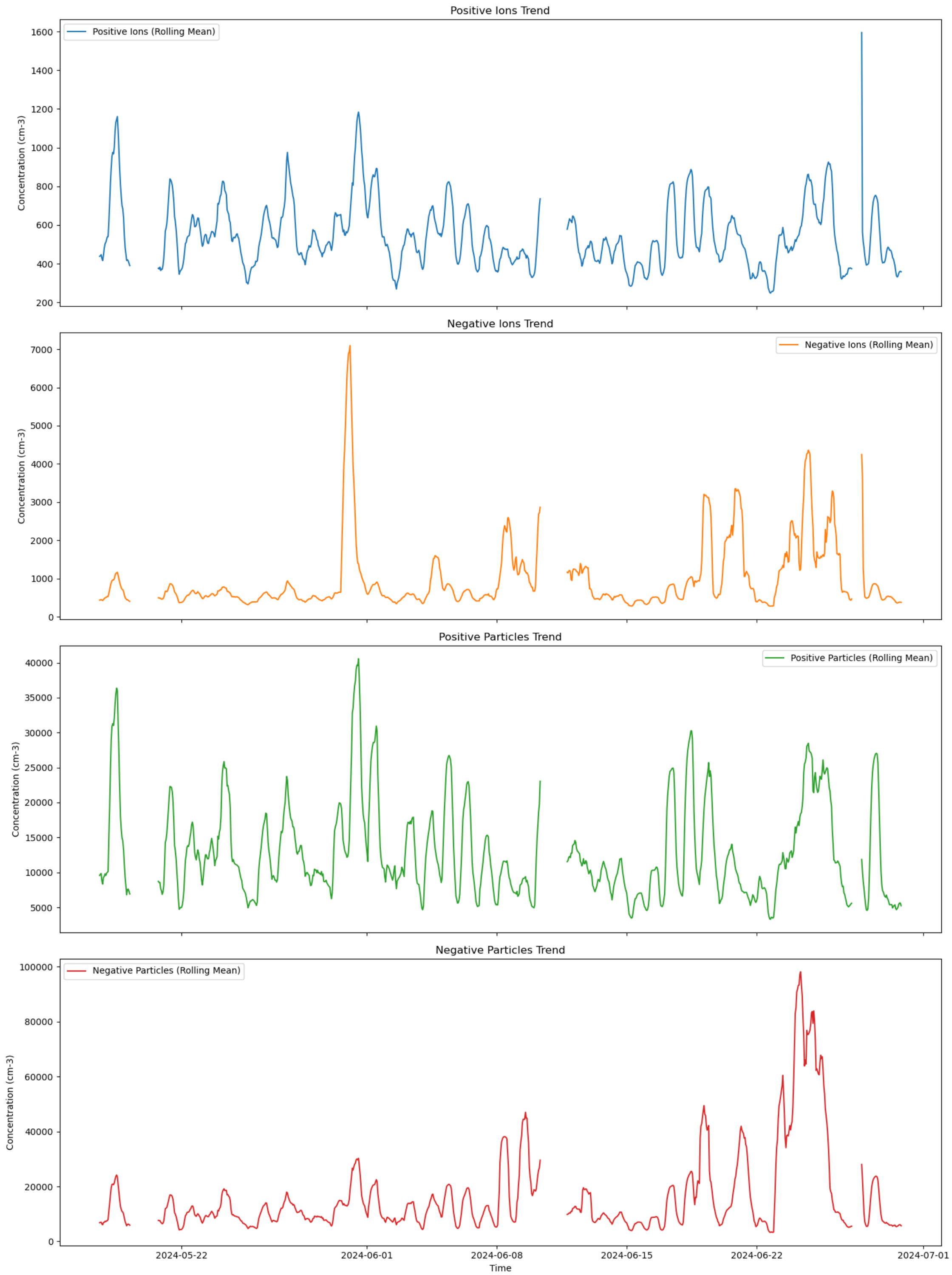
```
# Negative particles
axs[3].plot(dataset['diameter'], neg_particles_mean, label='Mean', color='tab:
 ↪blue')
axs[3].plot(dataset['diameter'], neg_particles_median, label='Median',␣
 ↪color='tab:orange')
axs[3].plot(dataset['diameter'], neg_particles_std, label='Std', color='tab:
 ↪green')
axs[3].set_title('Negative Particles Statistical Summaries')
axs[3].set_ylabel('Concentration (cm-3)')
axs[3].set_xlabel('Diameter_p')
axs[3].legend()

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



From the analysis above, the standard deviation values for the negative particles and ions alike is quite high between about 12nm and 22nm diameter range. The positive

ions and particles are more stable

```
[ ]: # Step 3: Trend Analysis
# Compute rolling mean to identify trends
# We are dealing with hourly data, what is the best window size to perform␣
↪rolling mean? Take 12 hours maybe (diurnal)?
window_size = 12
pos_ions_rolling_mean = pos_ions.rolling(time=window_size, center=True).mean()
neg_ions_rolling_mean = neg_ions.rolling(time=window_size, center=True).mean()
pos_particles_rolling_mean = pos_particles.rolling(time=window_size,␣
↪center=True).mean()
neg_particles_rolling_mean = neg_particles.rolling(time=window_size,␣
↪center=True).mean()

# 1.3 Plot rolling means
fig, axs = plt.subplots(4, 1, figsize=(15, 20), sharex=True)

axs[0].plot(dataset['time'], pos_ions_rolling_mean, label='Positive Ions␣
↪(Rolling Mean)', color='tab:blue')
axs[0].set_title('Positive Ions Trend')
axs[0].set_ylabel('Concentration (cm-3)')
axs[0].legend()

axs[1].plot(dataset['time'], neg_ions_rolling_mean, label='Negative Ions␣
↪(Rolling Mean)', color='tab:orange')
axs[1].set_title('Negative Ions Trend')
axs[1].set_ylabel('Concentration (cm-3)')
axs[1].legend()

axs[2].plot(dataset['time'], pos_particles_rolling_mean, label='Positive␣
↪Particles (Rolling Mean)', color='tab:green')
axs[2].set_title('Positive Particles Trend')
axs[2].set_ylabel('Concentration (cm-3)')
axs[2].legend()

axs[3].plot(dataset['time'], neg_particles_rolling_mean, label='Negative␣
↪Particles (Rolling Mean)', color='tab:red')
axs[3].set_title('Negative Particles Trend')
axs[3].set_ylabel('Concentration (cm-3)')
axs[3].set_xlabel('Time')
axs[3].legend()

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



The positive particles and ions vary more widely than the negative?

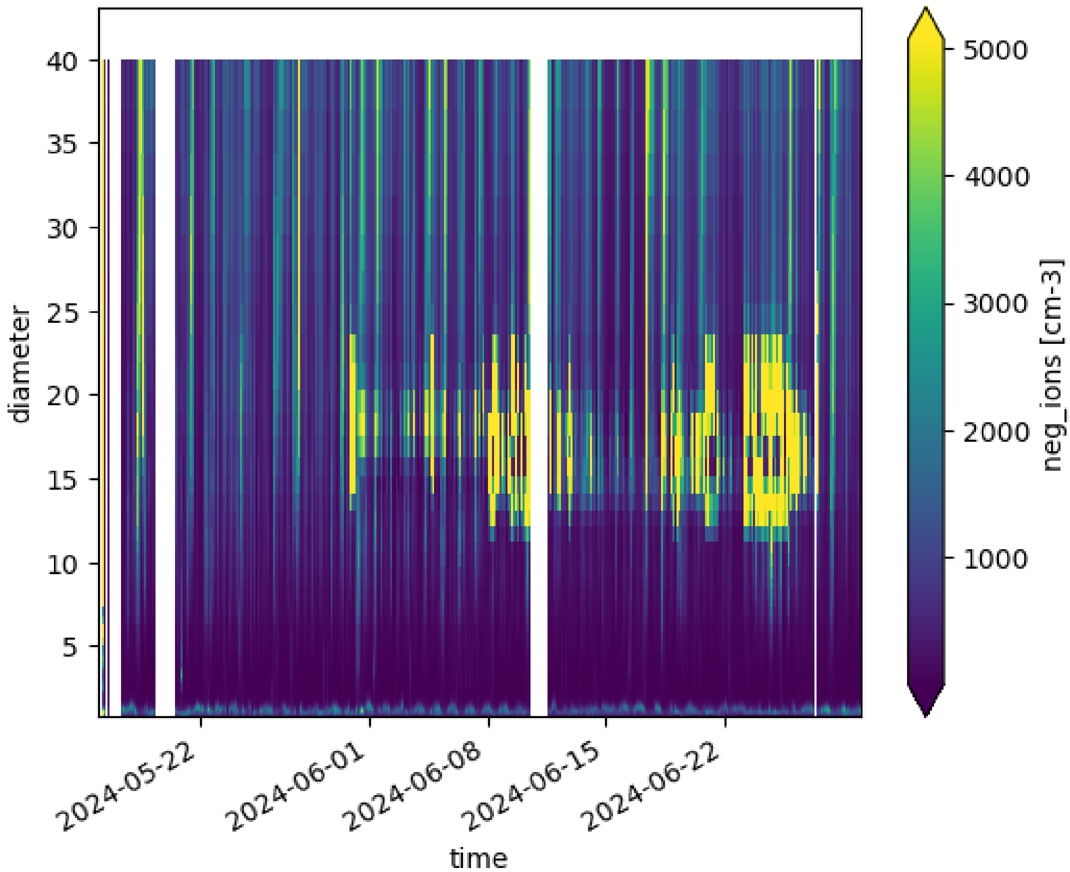
```
[ ]: # Step 4: Correlation Analysis
# Compute correlations
correlations = {
    "pos_ions_vs_neg_ions": xr.corr(dataset['pos_ions'].mean(dim='diameter'),␣
 ↪dataset['neg_ions'].mean(dim='diameter')),
    "pos_particles_vs_neg_particles": xr.corr(dataset['pos_particles'].
 ↪mean(dim='diameter'), dataset['neg_particles'].mean(dim='diameter')),
    "pos_ions_vs_pos_particles": xr.corr(dataset['pos_ions'].
 ↪mean(dim='diameter'), dataset['pos_particles'].mean(dim='diameter')),
    "neg_ions_vs_neg_particles": xr.corr(dataset['neg_ions'].
 ↪mean(dim='diameter'), dataset['neg_particles'].mean(dim='diameter')),
}

# Print correlations
print("Correlation between Positive Ions and Negative Ions:",␣
 ↪correlations["pos_ions_vs_neg_ions"].values)
print("Correlation between Positive Particles and Negative Particles:",␣
 ↪correlations["pos_particles_vs_neg_particles"].values)
print("Correlation between Positive Ions and Positive Particles:",␣
 ↪correlations["pos_ions_vs_pos_particles"].values)
print("Correlation between Negative Ions and Negative Particles:",␣
 ↪correlations["neg_ions_vs_neg_particles"].values)
```

```
Correlation between Positive Ions and Negative Ions: 0.4123625462599475
Correlation between Positive Particles and Negative Particles:
0.5848084469165065
Correlation between Positive Ions and Positive Particles: 0.6436830530619871
Correlation between Negative Ions and Negative Particles: 0.3243237136553278
```

0.1.1 Spectral plots

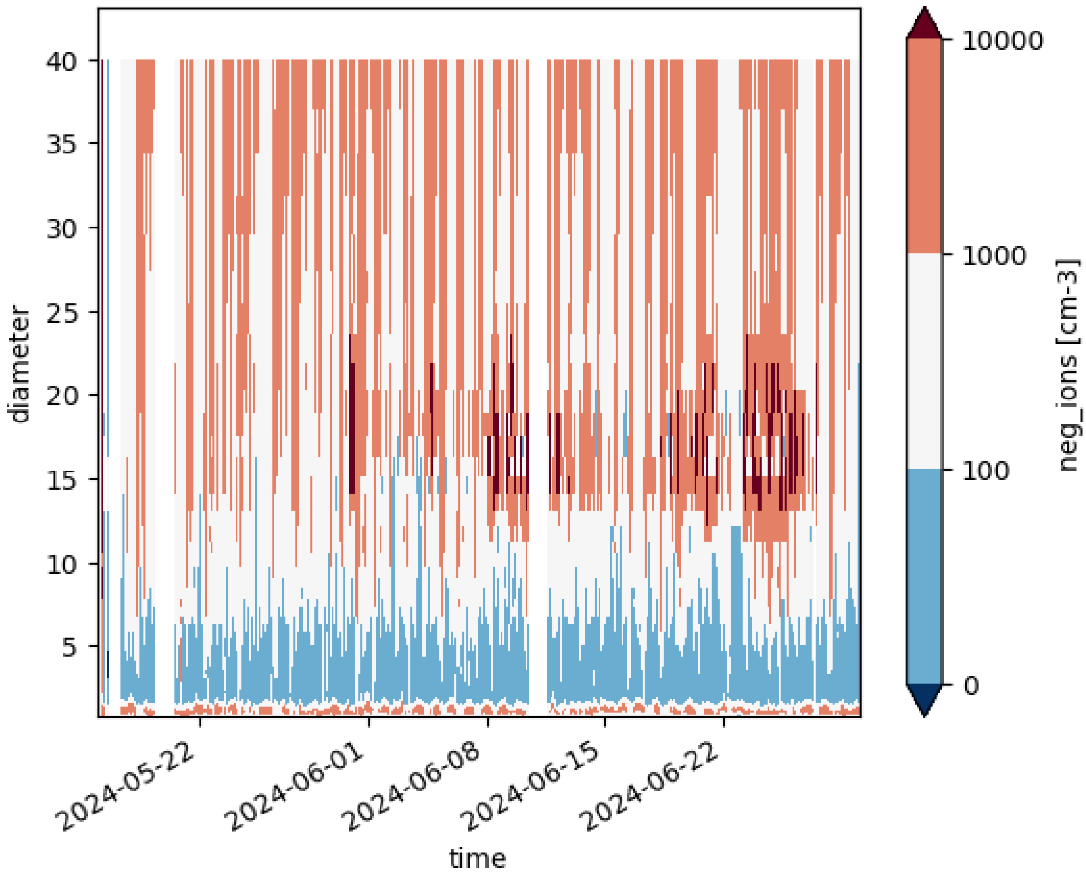
```
[ ]: dataset.neg_ions.T.plot(robust=True)
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a52ccc4d0>
```



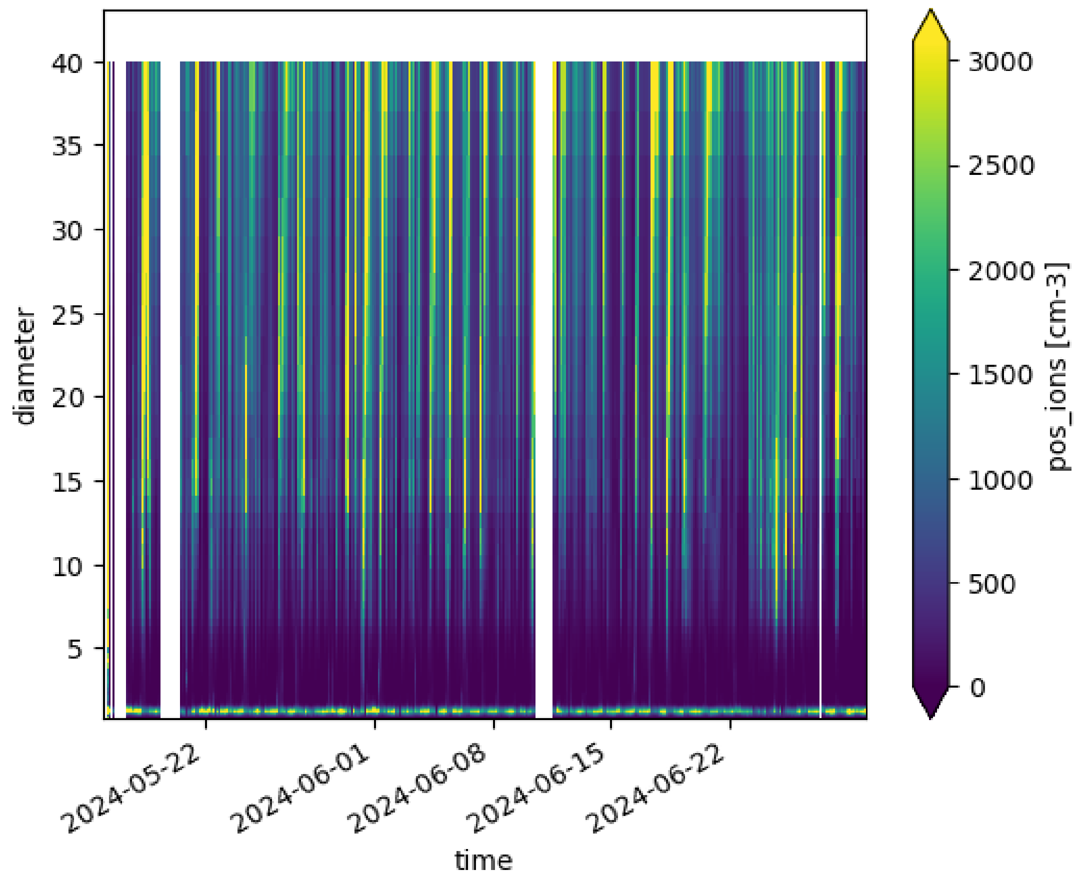

```
[ ]: dataset.neg_ions.T.plot(levels=[0,100,1000,10000])
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a52d74710>
```



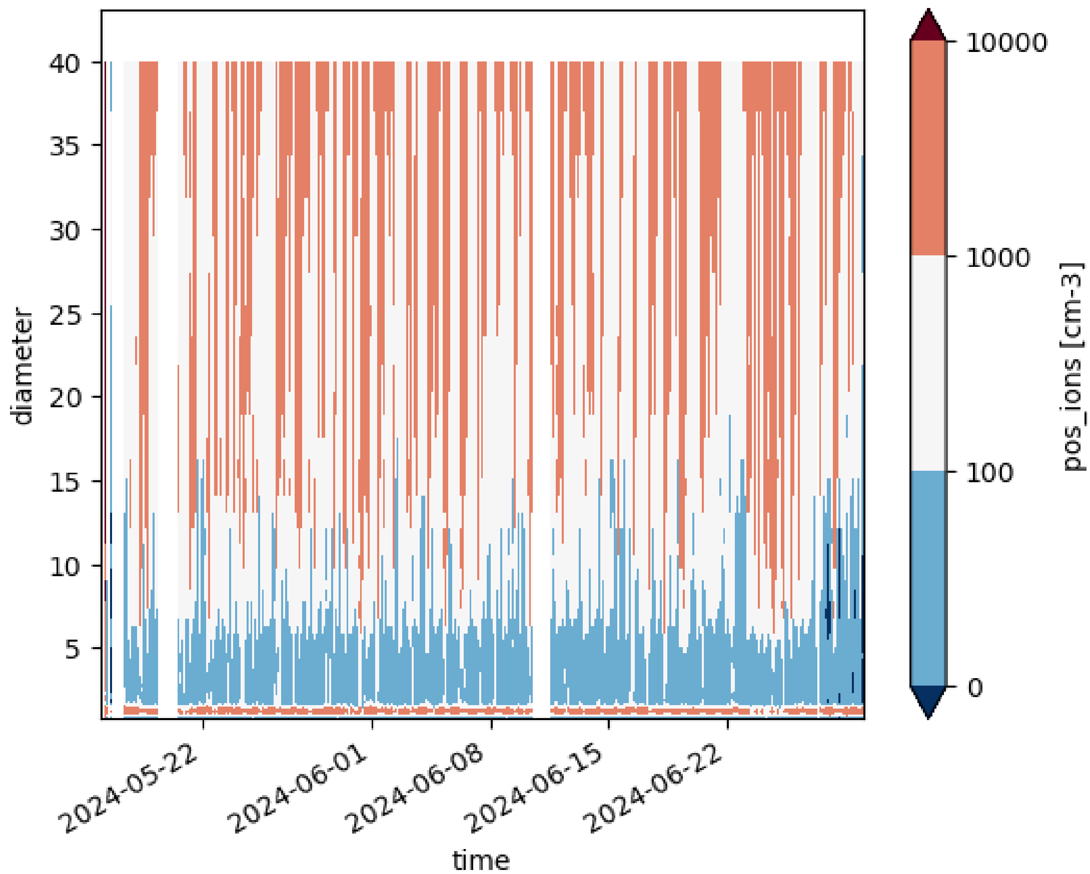
[ ]:
```
dataset.pos_ions.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a52c344d0>



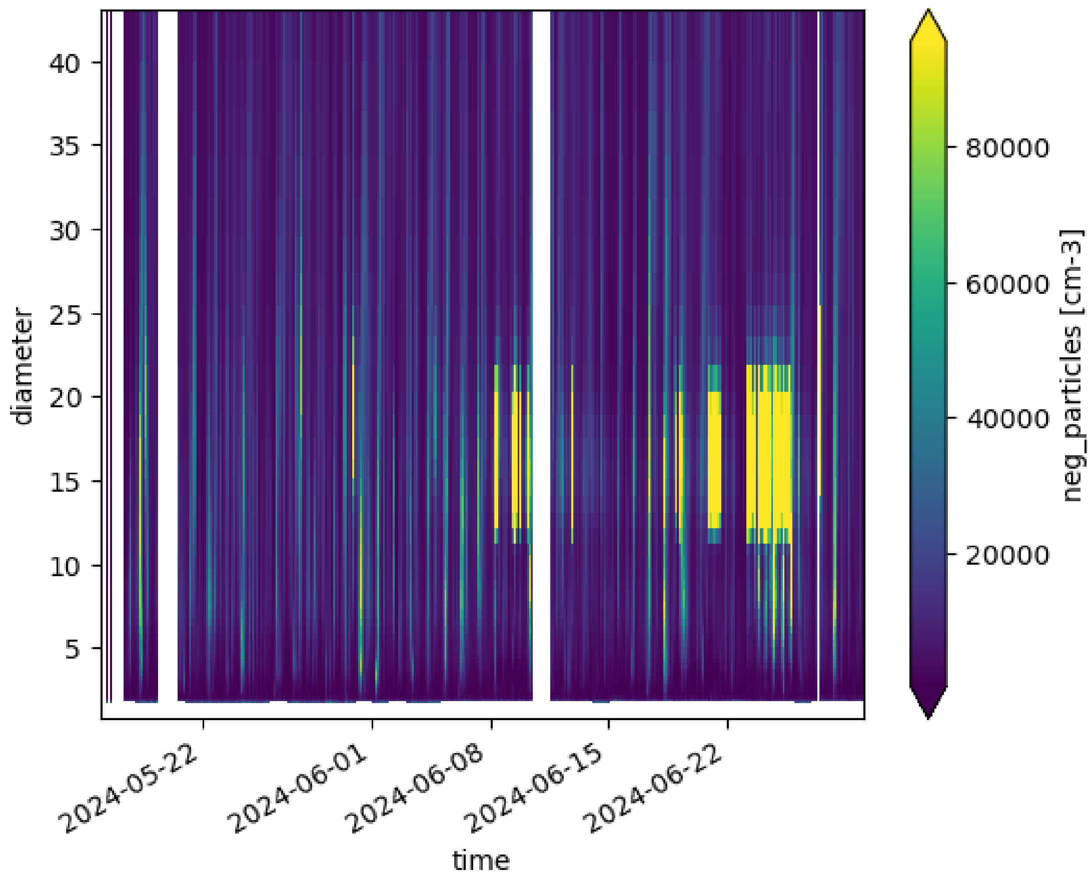
[ ]:
```
dataset.pos_ions.T.plot(levels=[0,100,1000,10000])
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a52b04b50>



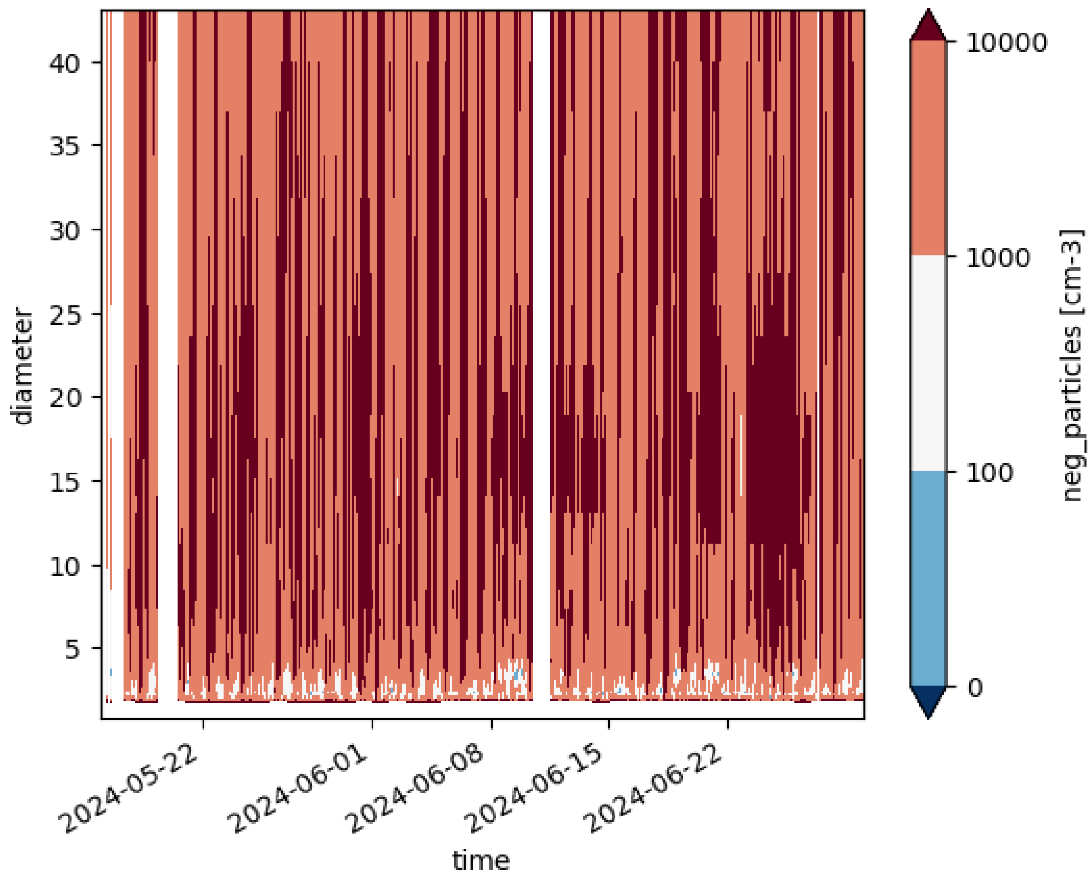

```
[ ]: dataset.neg_particles.T.plot(robust=True)
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a529ea4d0>
```



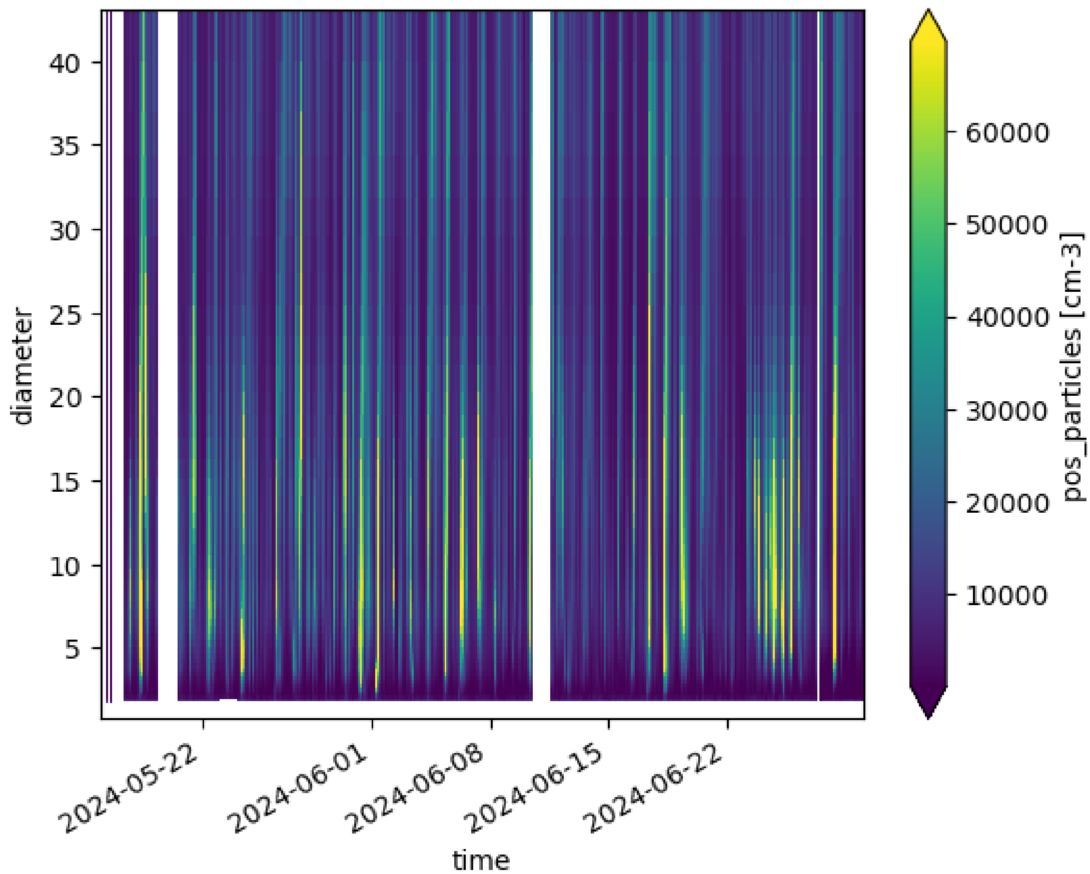

```
[ ]: dataset.neg_particles.T.plot(levels=[0,100,1000,10000])
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a52aac690>
```



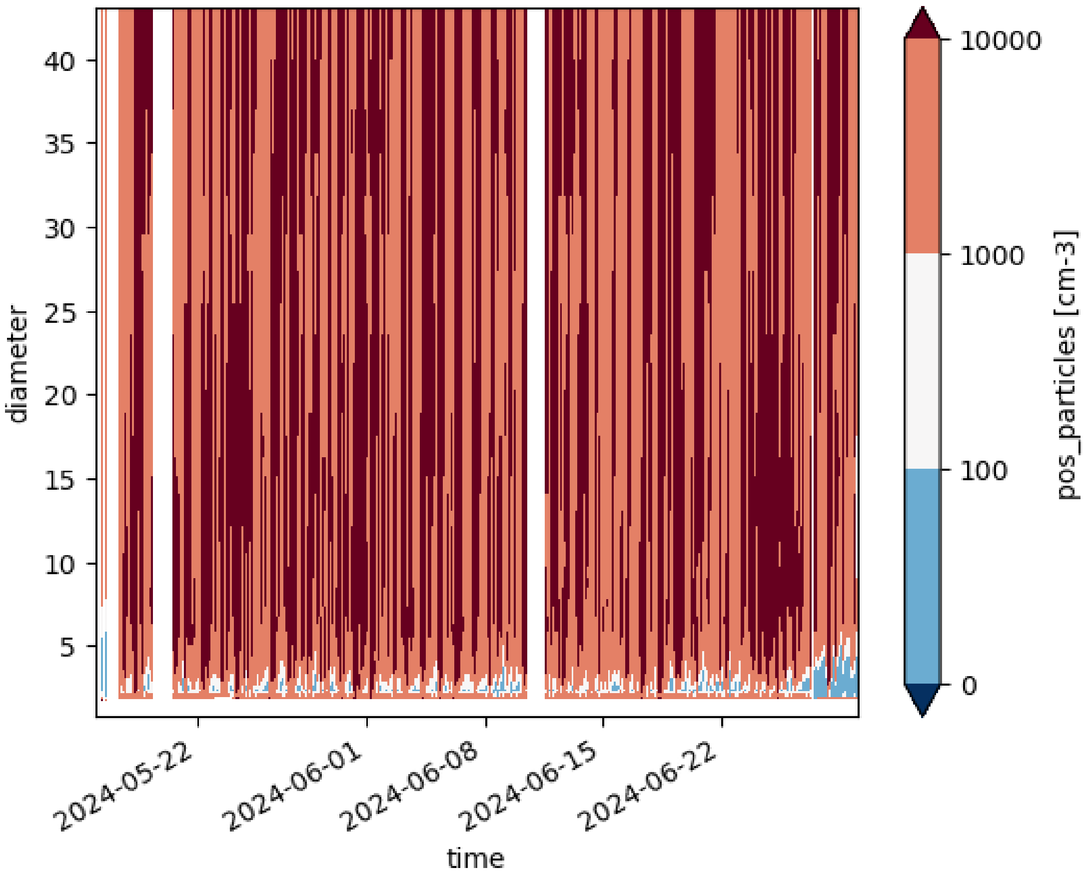
[ ]:
```
dataset.pos_particles.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a529648d0>



[ ]:
```
dataset.pos_particles.T.plot(levels=[0,100,1000,10000])
```

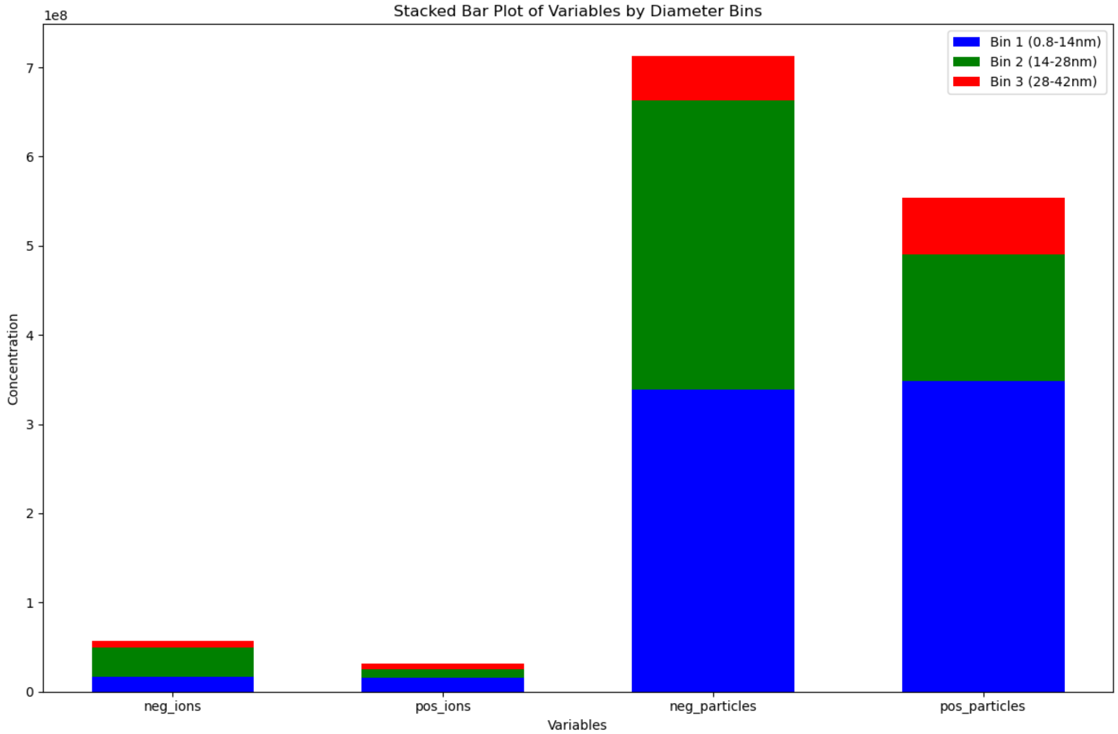
[ ]: <matplotlib.collections.QuadMesh at 0x790a5549ca90>



more plots….

[ ]:
```
# Define the number of bins
num_bins = 3

# Create bins for the diameter
# only gets to 42nm hence nothing in accumulation mode
diameter_bins = np.linspace(data['diameter'].min().item(), data['diameter'].
    ↪max().item(), num_bins + 1)
#diameter_bins = [1, 10, 100, 1000]
bin_labels = ['Bin 1 (0.8-14nm)', 'Bin 2 (14-28nm)', 'Bin 3 (28-42nm)']

# List of variables to plot
variables = ['neg_ions', 'pos_ions', 'neg_particles', 'pos_particles']

# Colors for each diameter bin in the stacked bar plot
colors = ['blue', 'green', 'red']

# Initialize lists to hold bin sums for each variable
```

```python
bin_sums = {var: [] for var in variables}

# Calculate the sum for each variable within each bin
for j in range(num_bins):
    bin_mask = (data['diameter'] >= diameter_bins[j]) & (data['diameter'] < diameter_bins[j+1])
    for var in variables:
        binned_data = data[var].where(bin_mask, drop=True)
        bin_sums[var].append(binned_data.sum().item())

# Create a stacked bar plot
fig, ax = plt.subplots(figsize=(12, 8))

# Bar positions
bar_width = 0.6
bar_positions = np.arange(len(variables))

# Bottoms for stacked bars
bottoms = np.zeros(len(variables))

# Plot each bin
for j in range(num_bins):
    bin_values = [bin_sums[var][j] for var in variables]
    ax.bar(bar_positions, bin_values, bar_width, bottom=bottoms, color=colors[j], label=bin_labels[j])
    bottoms += np.array(bin_values)

# Add labels and title
ax.set_xlabel('Variables')
ax.set_ylabel('Concentration')
ax.set_title('Stacked Bar Plot of Variables by Diameter Bins')
ax.set_xticks(bar_positions)
ax.set_xticklabels(variables)
ax.legend(loc='upper right')

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



[ ]:
```
diameter_bins
```

[ ]: array([8.02879995e-10, 1.43861530e-08, 2.79694261e-08, 4.15526991e-08])

0.1.2 Call in the other data - temp, RH, WD, WS, Rain, NO, NO2, NOx, O3

[ ]:
```
met = pd.read_csv('/home/coliewo/Desktop/data/meteo/met_may_jun24.txt')
no = pd.read_csv('/home/coliewo/Desktop/data/NOx/NO_may_june24.txt')
ozone = pd.read_csv('/home/coliewo/Desktop/data/ozone/ozone_may_june24.txt')
```

[ ]:
```
#new column for datetime
met['Date'] = pd.to_datetime(met['#date'] + ' ' + met['time'])
no['Date'] = pd.to_datetime(no['#date'] + ' ' + no['time'])
ozone['Date'] = pd.to_datetime(ozone['#date'] + ' ' + ozone['time'])
```

[ ]:
```
# Set datetime as index
met.set_index('Date', inplace=True)
no.set_index('Date', inplace=True)
ozone.set_index('Date', inplace=True)
```

[ ]:
```
# Descriptive Statistics to identify any outliers in the data??

print(met.describe())
```

```python
print(no.describe())
print(ozone.describe())
```

```
          day_dec   WD_min[Deg]   WD_ave[Deg]   WD_max[Deg]   WS_min[m/s]  \
count  87480.000000  87312.000000  87312.000000  87312.000000  87312.000000
mean     151.526396    185.820105    184.391158    185.135239      0.683900
std       17.622732     94.547636     89.372954     91.027029      0.507532
min      121.000000      0.000000      0.000000      0.000000      0.000000
25%      136.269271    105.000000     90.600000    100.000000      0.300000
50%      151.546180    197.000000    198.300000    202.000000      0.600000
75%      166.806423    252.000000    235.800000    239.000000      0.900000
max      181.999306    359.000000    360.000000    359.000000      4.800000

        WS_ave[m/s]   WS_max[m/s]     T_air[C]  T_internal[C]        RH[%%]  \
count  87312.000000  87312.000000  87312.000000   87312.000000  87312.000000
mean       1.745050      2.872162     21.439657      22.102361     55.095889
std        0.945312      1.495695      4.674831       5.077917     15.270463
min        0.100000      0.100000      9.300000       9.500000     23.000000
25%        1.000000      1.800000     17.900000      18.100000     42.800000
50%        1.600000      2.700000     21.000000      21.600000     53.800000
75%        2.300000      3.700000     24.600000      25.600000     67.400000
max        8.100000     15.700000     35.600000      37.300000     87.400000

       …  Rain_intensity[mm/h]  Hail_acc[hits/cm2]  Hail_duration[s]  \
count  …          87480.000000        87480.000000      87478.000000
mean   …              0.087490            0.000080          0.000457
std    …              1.104268            0.016735          0.067620
min    …              0.000000            0.000000          0.000000
25%    …              0.000000            0.000000          0.000000
50%    …              0.000000            0.000000          0.000000
75%    …              0.000000            0.000000          0.000000
max    …             94.300000            3.500000         10.000000

       Hail_intensity[hits/cm2]  Rain_peak_int[mm/h]  Hail_peak_int[hits/cm2]  \
count              87478.000000         87478.000000             87478.000000
mean                   0.000046            74.132740                 0.867430
std                    0.006762            29.859702                 0.991173
min                    0.000000            32.900000                 0.000000
25%                    0.000000            44.700000                 0.000000
50%                    0.000000            66.400000                 0.000000
75%                    0.000000           106.300000                 2.000000
max                    1.000000           106.300000                 2.000000

          T_heat[C]  V_heat[V]   Vsupply[V]   Vref3.5[V]
count  87478.000000    87478.0  87478.000000  87478.000000
mean      22.666536        0.0      9.654152      3.500886
std        6.201667        0.0      0.065663      0.004000
```

```
min       8.100000        0.0       9.400000       3.492000
25%      17.600000        0.0       9.600000       3.498000
50%      22.000000        0.0       9.700000       3.500000
75%      27.200000        0.0       9.700000       3.506000
max      40.500000        0.0       9.800000       3.511000

[8 rows x 23 columns]
            daydec       NO[ppb]      NO2[ppb]      NOx[ppb]      Pre  \
count  86495.000000  86495.000000  86495.000000  86495.000000  86495.0
mean     151.311520      0.873817      3.657212      4.531030   -999.0
std       17.542543     16.229638      3.409860     16.892126      0.0
min      121.000000     -0.714000    -14.010000     -1.795000   -999.0
25%      136.028819     -0.126000      1.628000      1.612000   -999.0
50%      151.306250      0.140000      2.728000      3.002000   -999.0
75%      166.322569      0.598000      4.672000      5.245000   -999.0
max      181.999306    910.705000    290.424000    919.508000   -999.0

       Pre_low  Pre_High         T_int  ReactCellT[C]     T_Cooler  \
count  86495.0   86495.0  86495.000000   86495.000000 86495.000000
mean    -999.0    -999.0     33.447324      39.991926    -1.243833
std        0.0       0.0      0.644272       0.003021     0.015314
min     -999.0    -999.0     29.682000      39.835000    -1.300000
25%     -999.0    -999.0     32.929500      39.990000    -1.255000
50%     -999.0    -999.0     33.379000      39.992000    -1.244000
75%     -999.0    -999.0     33.859000      39.994000    -1.235000
max     -999.0    -999.0     36.547000      40.010000    -1.086000

              PMT_V  T_NO2_conv  ReactCellP[incHg]  O3_flow[cc/m]  \
count  86495.000000     86495.0       86495.000000   86495.000000
mean     483.252613         0.0           1.377055      88.912742
std        0.061738         0.0           0.040600       0.289192
min      482.798000         0.0           1.356000      80.496000
25%      483.255000         0.0           1.374000      88.728000
50%      483.271000         0.0           1.377000      88.929000
75%      483.287000         0.0           1.380000      89.123000
max      483.342000         0.0          12.724000      90.153000

       SampleFlow[cc/m]       warning
count      86495.000000  8.649500e+04
mean        1119.111817  9.996650e+09
std            4.646726  1.830766e+08
min          701.748000  1.000100e+04
25%         1116.308000  1.000000e+10
50%         1119.528000  1.000000e+10
75%         1122.564000  1.000000e+10
max         1128.395000  1.001100e+10
            daydec            O3   Intensity_A   Intensity_B       T_bench  \
count  87484.000000  87484.000000  87484.000000  87484.000000  87484.000000
```

```
mean     151.552042     38.378055  71101.626560  75502.973835     33.564361
std       17.616044     95.432156    469.819646    313.192822      0.626420
min      121.000000 -27880.000000      0.000000  61087.000000     28.900000
25%      136.188020     29.540000  70733.000000  75209.000000     33.200000
50%      151.610764     39.170000  70977.000000  75452.000000     33.500000
75%      166.798785     47.690000  71502.000000  75782.000000     34.000000
max      181.999306     89.480000  71981.000000  76353.000000     36.100000

             T_lamp     T_03_lamp        Flow_A        Flow_B             P
count  87484.000000  8.748400e+04  87484.000000  87484.000000  87484.000000
mean      53.136916  4.240000e+01      0.633005      0.632367    746.247033
std        0.056387  6.215863e-11      0.005293      0.004811      4.929235
min       52.800000  4.240000e+01      0.615000      0.617000    733.800000
25%       53.100000  4.240000e+01      0.629000      0.629000    743.200000
50%       53.100000  4.240000e+01      0.633000      0.633000    746.800000
75%       53.200000  4.240000e+01      0.637000      0.636000    750.200000
max       53.500000  4.240000e+01      0.672000      0.685000    758.700000
```

Values in the met file look okay

NO file has some negative values, to remove??

O3 data has -27880 as min value (bad data)??

[ ]:
```python
# Start with NO data
# Replace values less than 0 with NaN in specific columns
columns = ['NO[ppb]', 'NO2[ppb]', 'NOx[ppb]']

no[columns] = no[columns].applymap(lambda x: np.nan if x < 0 else x)

# Replace values with NaN where 'status' is 'SPAN'
no.loc[no['status'] == 'SPAN', columns] = np.nan

print(no.describe())
```

```
/tmp/ipykernel_4839/1717307678.py:5: FutureWarning: DataFrame.applymap has been
deprecated. Use DataFrame.map instead.
  no[columns] = no[columns].applymap(lambda x: np.nan if x < 0 else x)

             daydec       NO[ppb]      NO2[ppb]      NOx[ppb]      Pre  \
count  86495.000000  51601.000000  85450.000000  84500.000000  86495.0
mean     151.311520      0.819622      3.658690      4.143939   -999.0
std       17.542543      1.533862      3.111466      3.936032      0.0
min      121.000000      0.000000      0.000000      0.000000   -999.0
25%      136.028819      0.224000      1.666000      1.700000   -999.0
50%      151.306250      0.492000      2.752000      3.049000   -999.0
75%      166.322569      0.892000      4.685000      5.278000   -999.0
max      181.999306     35.124000     29.509000     51.868000   -999.0
```

```
       Pre_low  Pre_High          T_int  ReactCellT[C]      T_Cooler  \
count  86495.0   86495.0   86495.000000   86495.000000  86495.000000
mean    -999.0    -999.0      33.447324      39.991926     -1.243833
std        0.0       0.0       0.644272       0.003021      0.015314
min     -999.0    -999.0      29.682000      39.835000     -1.300000
25%     -999.0    -999.0      32.929500      39.990000     -1.255000
50%     -999.0    -999.0      33.379000      39.992000     -1.244000
75%     -999.0    -999.0      33.859000      39.994000     -1.235000
max     -999.0    -999.0      36.547000      40.010000     -1.086000

              PMT_V  T_NO2_conv  ReactCellP[inchg]  O3_flow[cc/m]  \
count  86495.000000     86495.0       86495.000000   86495.000000
mean     483.252613         0.0           1.377055      88.912742
std        0.061738         0.0           0.040600       0.289192
min      482.798000         0.0           1.356000      80.496000
25%      483.255000         0.0           1.374000      88.728000
50%      483.271000         0.0           1.377000      88.929000
75%      483.287000         0.0           1.380000      89.123000
max      483.342000         0.0          12.724000      90.153000

       SampleFlow[cc/m]       warning
count      86495.000000  8.649500e+04
mean        1119.111817  9.996650e+09
std            4.646726  1.830766e+08
min          701.748000  1.000100e+04
25%         1116.308000  1.000000e+10
50%         1119.528000  1.000000e+10
75%         1122.564000  1.000000e+10
max         1128.395000  1.001100e+10
```

[ ]:
```python
# Now O3 data
# Replace values less than 0 with NaN in specific column
column = ['O3']

ozone[column] = ozone[column].applymap(lambda x: np.nan if x < 0 else x)

print(ozone.describe())
```

```
             daydec            O3   Intensity_A   Intensity_B       T_bench  \
count  87484.000000  87483.000000  87484.000000  87484.000000  87484.000000
mean     151.552042     38.697184  71101.626560  75502.973835     33.564361
std       17.616044     14.058013    469.819646    313.192822      0.626420
min      121.000000      0.790300      0.000000  61087.000000     28.900000
25%      136.188020     29.540000  70733.000000  75209.000000     33.200000
50%      151.610764     39.170000  70977.000000  75452.000000     33.500000
75%      166.798785     47.690000  71502.000000  75782.000000     34.000000
max      181.999306     89.480000  71981.000000  76353.000000     36.100000
```

```
          T_lamp     T_03_lamp        Flow_A        Flow_B             P
count  87484.000000  8.748400e+04  87484.000000  87484.000000  87484.000000
mean      53.136916  4.240000e+01      0.633005      0.632367    746.247033
std        0.056387  6.215863e-11      0.005293      0.004811      4.929235
min       52.800000  4.240000e+01      0.615000      0.617000    733.800000
25%       53.100000  4.240000e+01      0.629000      0.629000    743.200000
50%       53.100000  4.240000e+01      0.633000      0.633000    746.800000
75%       53.200000  4.240000e+01      0.637000      0.636000    750.200000
max       53.500000  4.240000e+01      0.672000      0.685000    758.700000
```

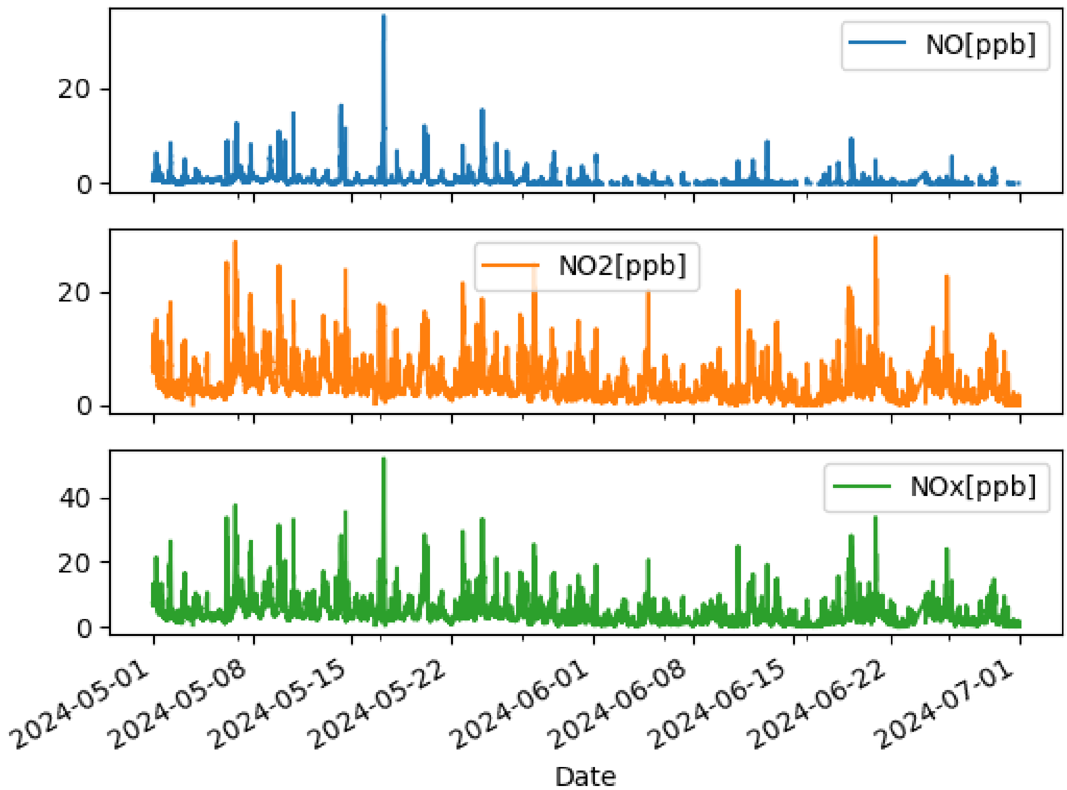
```
/tmp/ipykernel_4839/2177576757.py:5: FutureWarning: DataFrame.applymap has been
deprecated. Use DataFrame.map instead.
  ozone[column] = ozone[column].applymap(lambda x: np.nan if x < 0 else x)
```

[ ]:
```
#Keep only relevant data?
# Create a second DataFrame with fewer columns
columns_to_keep = ['T_air[C]', 'RH[%]', 'Rain_acc[mm]', 'WD_ave[Deg]',␣
↪'WS_ave[m/s]']
met2 = met[columns_to_keep]

no2 = no[columns]  # already described above

ozone2 = ozone[column]
```

0.1.3 Visualize the data

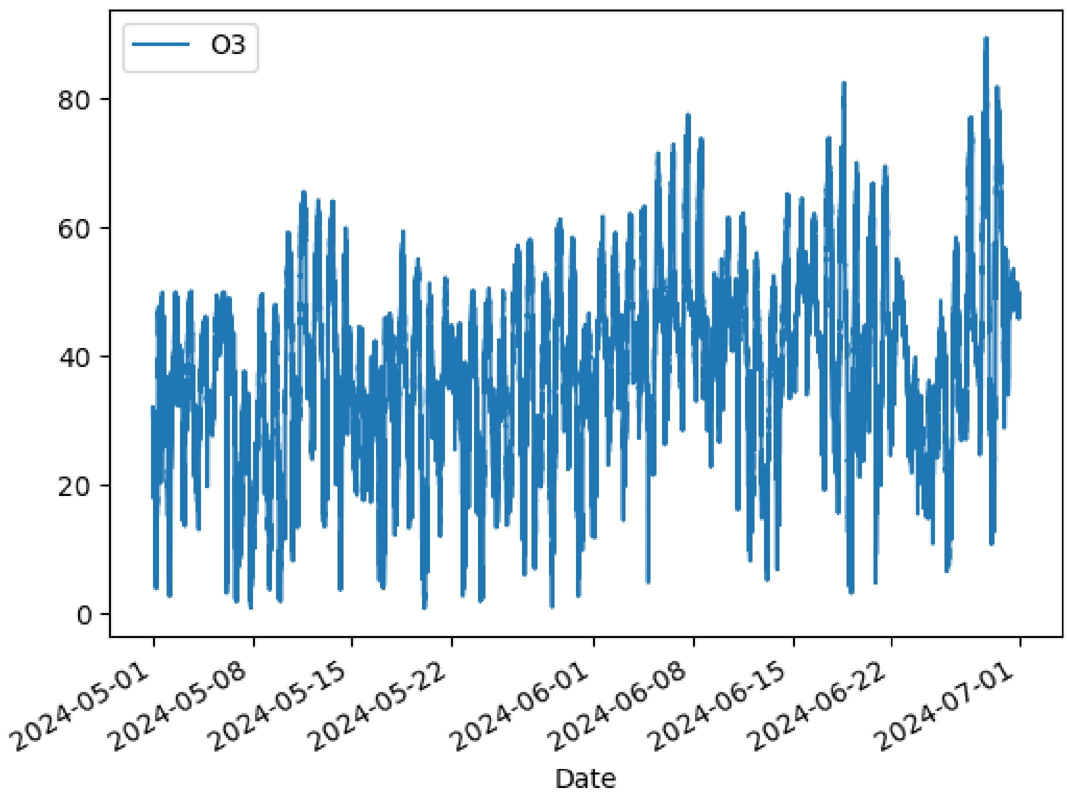
[ ]:
```
# Time Series Plots
#plt.figure(figsize=(15, 20))
no2[['NO[ppb]', 'NO2[ppb]', 'NOx[ppb]']].plot(subplots=True)
#plt.title("NO Time Series Plots")
#plt.show()
```

[ ]:
```
array([<Axes: xlabel='Date'>, <Axes: xlabel='Date'>,
       <Axes: xlabel='Date'>], dtype=object)
```



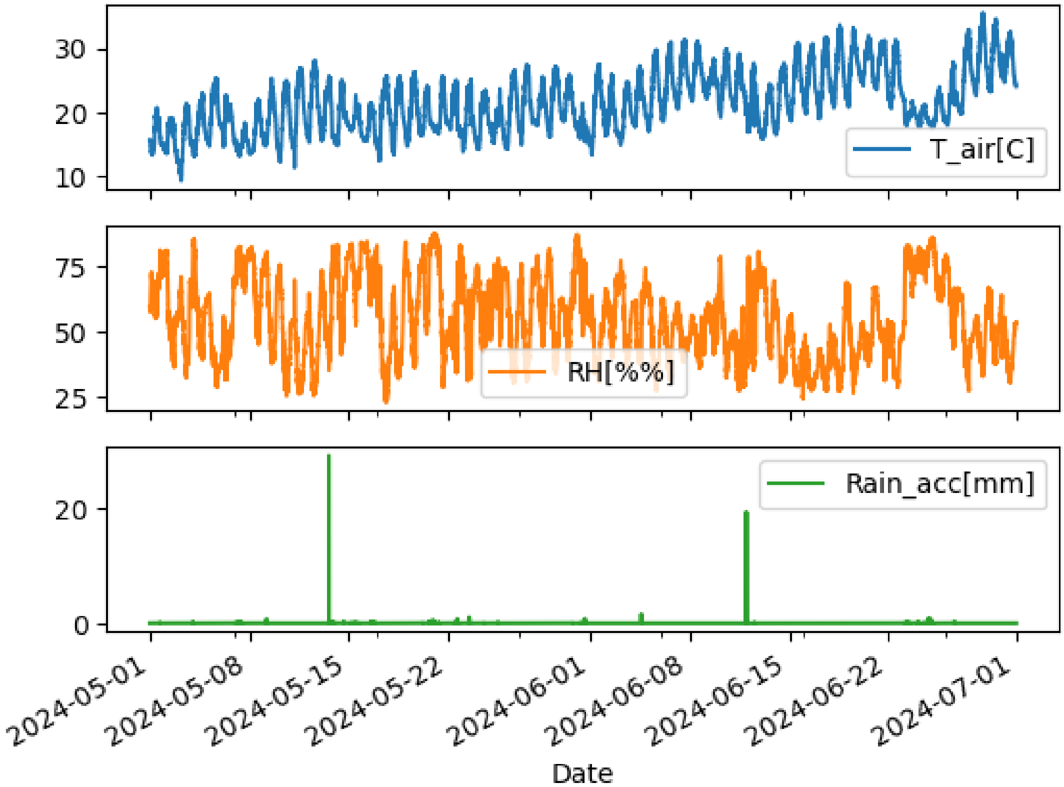
[ ]:
```
ozone2[['O3']].plot()
```

[ ]: <Axes: xlabel='Date'>

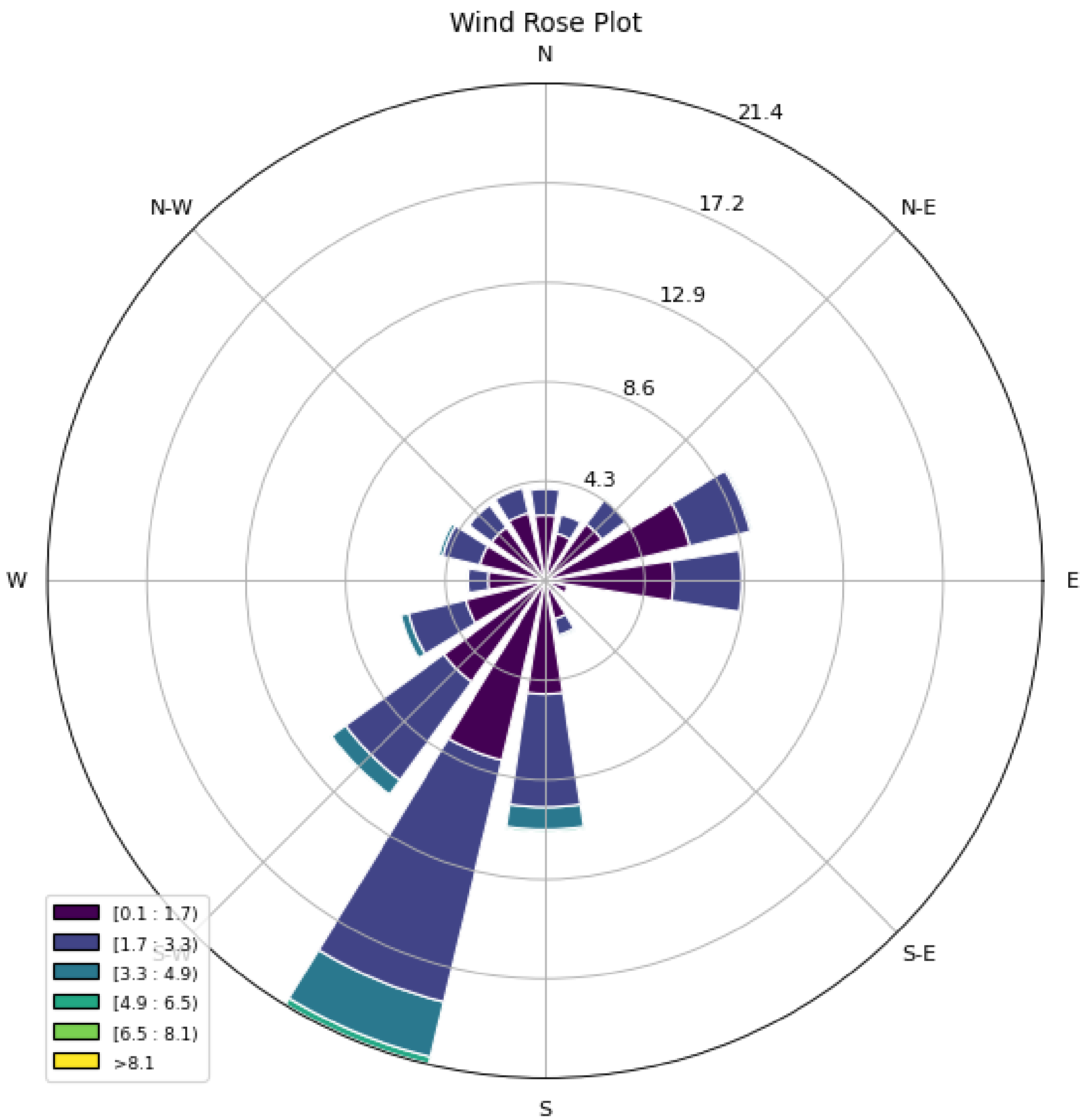


[ ]:
```
met2[['T_air[C]', 'RH[%%]', 'Rain_acc[mm]']].plot(subplots=True)
```

[ ]:
```
array([<Axes: xlabel='Date'>, <Axes: xlabel='Date'>,
       <Axes: xlabel='Date'>], dtype=object)
```



[ ]:
```python
# Wind Rose Plot for the WD, WS data

from windrose import WindroseAxes
ax = WindroseAxes.from_ax()
ax.bar(met2['WD_ave[Deg]'], met2['WS_ave[m/s]'], normed=True, opening=0.8,␣
 ↪edgecolor='white')
ax.set_legend()
plt.title("Wind Rose Plot")
plt.show()
```



0.1.4 Correlation Analysis between Negative particles and the different variables

[ ]:
```
# Average neg_particles over the diameter dimension and convert to a pandas␣
↪DataFrame
neg_particles = dataset['neg_particles'].mean(dim='diameter').to_dataframe().
↪reset_index()
neg_particles['time'] = pd.to_datetime(neg_particles['time'])
neg_particles_df = neg_particles.set_index('time')
```

[ ]:
```
# Merge the two datasets on the time index
```

```
merged_df = pd.merge(neg_particles_df, no2, left_index=True, right_index=True,␣
↪how='inner')

# Compute correlation
correlation = merged_df.corr()

# Extract the correlation value between neg_particles and NOx
neg_particles_no_correlation = correlation.loc['neg_particles', 'NO[ppb]']
neg_particles_no2_correlation = correlation.loc['neg_particles', 'NO2[ppb]']
neg_particles_nox_correlation = correlation.loc['neg_particles', 'NOx[ppb]']

print(f'Correlation between Negative Particles and NO:␣
↪{neg_particles_no_correlation}')
print(f'Correlation between Negative Particles and NO2:␣
↪{neg_particles_no2_correlation}')
print(f'Correlation between Negative Particles and NOx:␣
↪{neg_particles_nox_correlation}')
```

```
Correlation between Negative Particles and NO: 0.009855092996168423
Correlation between Negative Particles and NO2: 0.21471429754586296
Correlation between Negative Particles and NOx: 0.2035275195069866
```

[ ]:
```
# Merge the two datasets on the time index
merged2_df = pd.merge(neg_particles_df, met2, left_index=True,␣
↪right_index=True, how='inner')

# Compute correlation2
correlation2 = merged2_df.corr()

# Extract the correlation2 value between neg_particles and met values
neg_particles_temp_correlation = correlation2.loc['neg_particles', 'T_air[C]']
neg_particles_rh_correlation = correlation2.loc['neg_particles', 'RH[%]']
neg_particles_rain_correlation = correlation2.loc['neg_particles',␣
↪'Rain_acc[mm]']

print(f'Correlation between Negative Particles and Temp:␣
↪{neg_particles_temp_correlation}')
print(f'Correlation between Negative Particles and RH:␣
↪{neg_particles_rh_correlation}')
print(f'Correlation between Negative Particles and Rain:␣
↪{neg_particles_rain_correlation}')
```

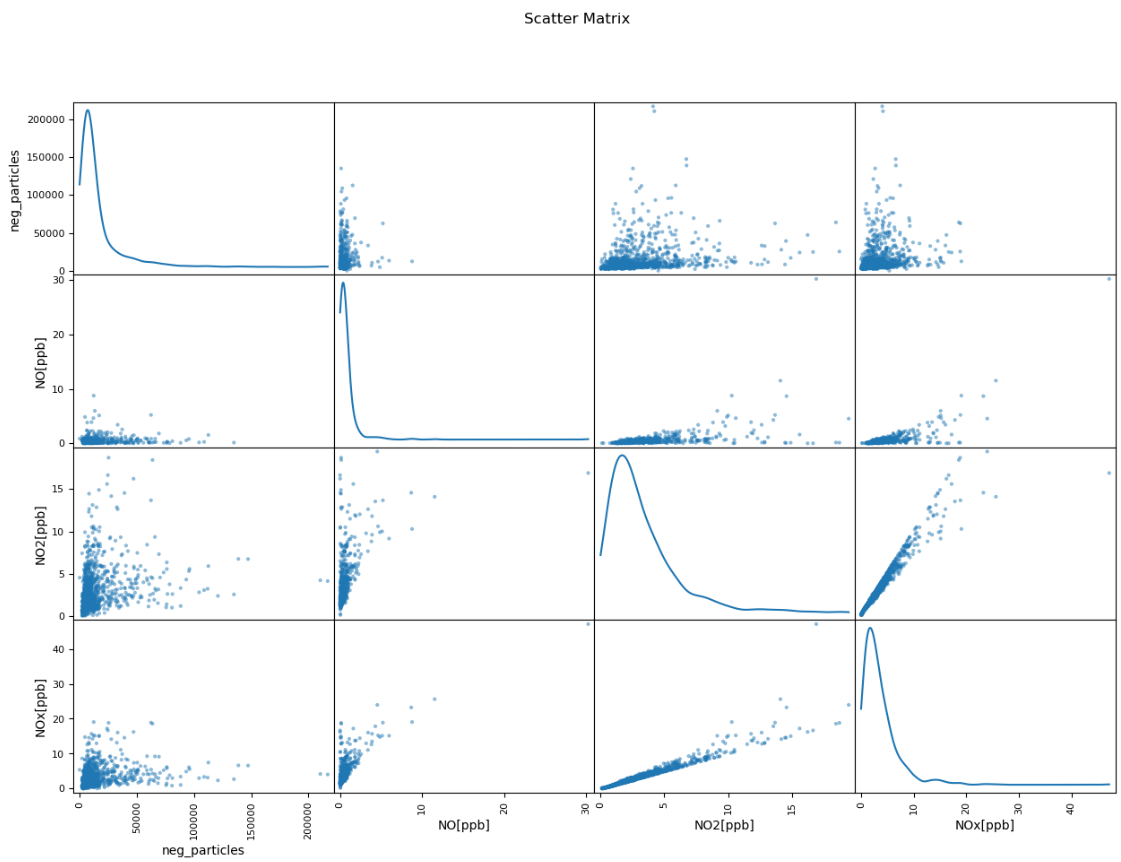
```
Correlation between Negative Particles and Temp: -0.028896533902825542
Correlation between Negative Particles and RH: 0.23985220442463615
Correlation between Negative Particles and Rain: 0.04604412222182278
```

```
[ ]: # Merge the two datasets on the time index
merged3_df = pd.merge(neg_particles_df, ozone2, left_index=True,␣
 ↪right_index=True, how='inner')

# Compute correlation3
correlation3 = merged3_df.corr()

# Extract the correlation3 value between neg_particles and met values
neg_particles_ozone_correlation = correlation3.loc['neg_particles', 'O3']

print(f'Correlation between Negative Particles and Ozone:␣
 ↪{neg_particles_ozone_correlation}')
```

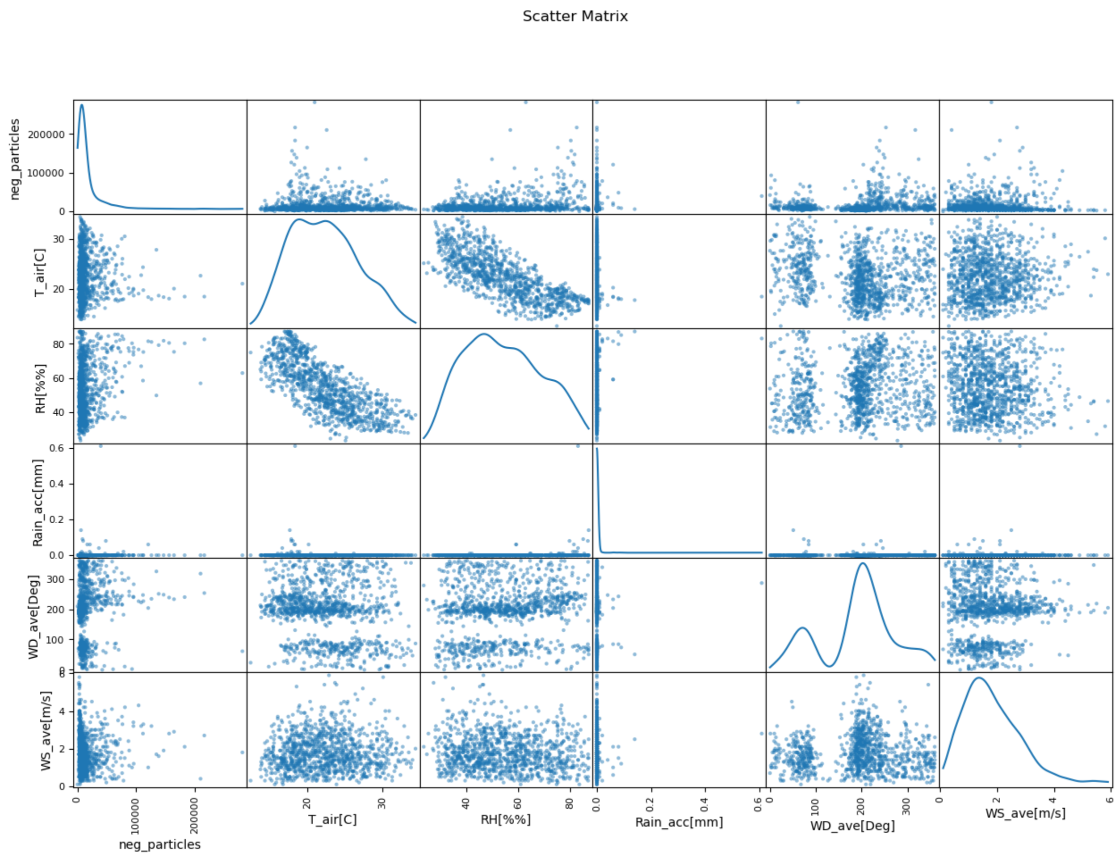
```
Correlation between Negative Particles and Ozone: -0.13785613177969216
```

0.1.5 Scatter Plots....

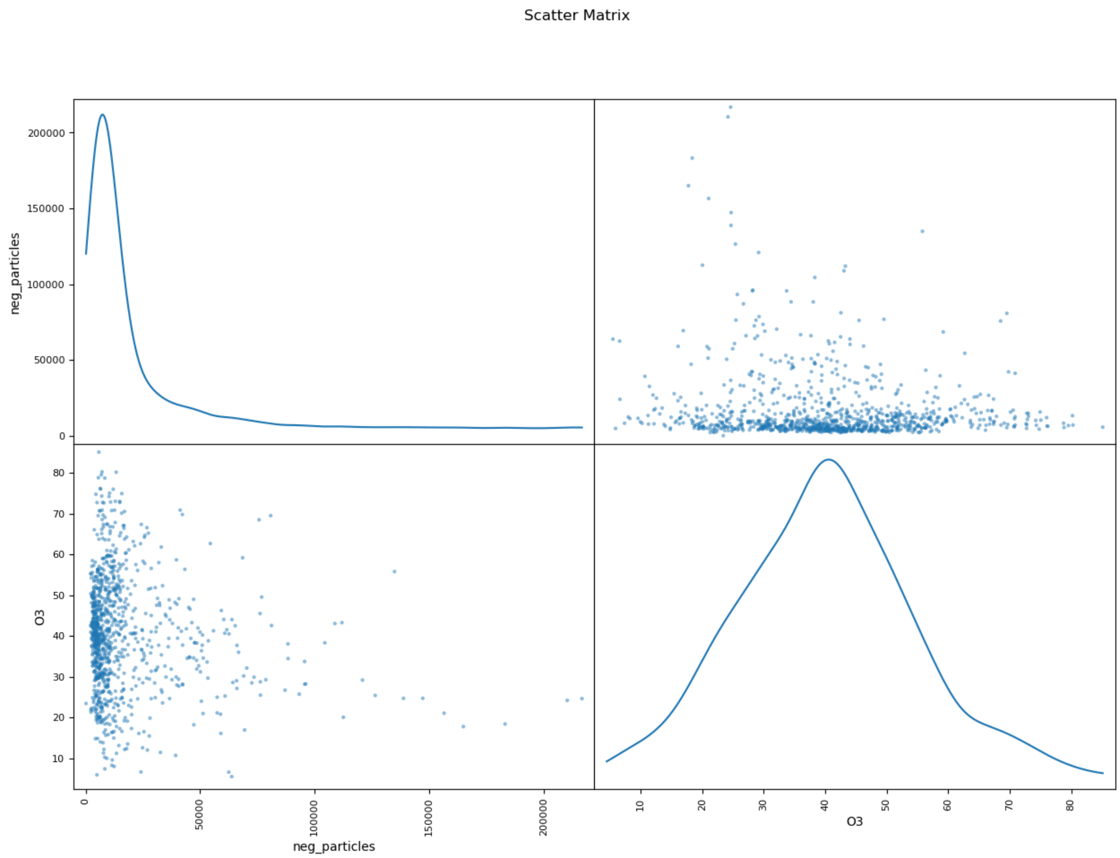
```
[ ]: # Scatter Matrix
pd.plotting.scatter_matrix(merged_df, figsize=(15, 10), diagonal='kde')
plt.suptitle("Scatter Matrix")
plt.show()
```



```
[ ]: # Scatter Matrix
pd.plotting.scatter_matrix(merged2_df, figsize=(15, 10), diagonal='kde')
plt.suptitle("Scatter Matrix")
plt.show()
```




```
[ ]: # Scatter Matrix
pd.plotting.scatter_matrix(merged3_df, figsize=(15, 10), diagonal='kde')
plt.suptitle("Scatter Matrix")
plt.show()
```



0.1.6 Nanoparticle ranking analysis: determining new particle formation (NPF) event occurrence and intensity based on the concentration spectrum of formed (sub-5 nm) particles

https://doi.org/10.5194/ar-1-81-2023

Subsequently, we employ a two-fold approach: #### firstly, the derived Δ N2.5—5 values are used to rank NPF events, and #### secondly, we scrutinize the logarithmic distribution of these values to discern any dominant modes

[ ]:
```
# Step 1: Extract data for the diameter range required 2.5-5nm
ds_2p5_5nm = dataset['neg_particles'].sel(diameter=slice(2.5, 5))
```

[ ]:
```
ds_2p5_5nm
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 1081, diameter: 10)>
array([[         nan,          nan,          nan, …,          nan,          nan,
                 nan],
       [         nan,          nan,          nan, …,          nan,          nan,
                 nan],
       [         nan,          nan,          nan, …,          nan,          nan,
```

```
               nan],
         …,
         [ 627.608706,  658.406955, 1047.195848, …, 3695.756149, 4314.862024,
          4575.879331],
         [ 252.848542,  494.867587,  404.279244, …, 1220.205738, 1611.609949,
          1944.126849],
         [ 510.434755,  471.272613,  484.89185 , …,  916.23926 , 1141.077917,
          1418.255486]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 … 2024-06-30
Attributes:
    units:        cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

[ ]:
```
# Step 2: Smooth out the time series, apply rolling median over 2hr intervals

ds_2p5_5nm_rolling_mean = ds_2p5_5nm.rolling(time=2, center=True).median()

# Drop NaN values resulting from the rolling operation
#ds_2p5_5nm_rolling_mean.dropna(dim='time', how='all')
rolling_median = ds_2p5_5nm_rolling_mean.dropna(dim='time')
rolling_median
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 1000, diameter: 10)>
array([[  396.94646147,   377.01711052,   398.15624596, …,
         -6125.03103572, -6299.80445959, -5845.05209916],
       [  519.97516952,   549.28915184,   628.70458783, …,
          297.00689848,   339.10285842,   359.33151333],
       [  853.8641654 ,   660.53425857,   588.68772669, …,
          666.2142384 ,   598.59907564,   506.73399953],
       …,
       [  496.91157498,   568.35477635,   940.37132861, …,
         3431.63740907,  4184.95024915,  4452.46556208],
       [  440.22862365,   576.63727095,   725.73754622, …,
         2457.98094354,  2963.23598628,  3260.00309014],
       [  381.64164853,   483.07009991,   444.58554692, …,
         1068.22249874,  1376.34393301,  1681.19116753]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16T08:00:00 … 2024-06-30
Attributes:
    units:        cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

[ ]:
```
np.min(rolling_median), np.max(rolling_median)   # we have negative values??
```

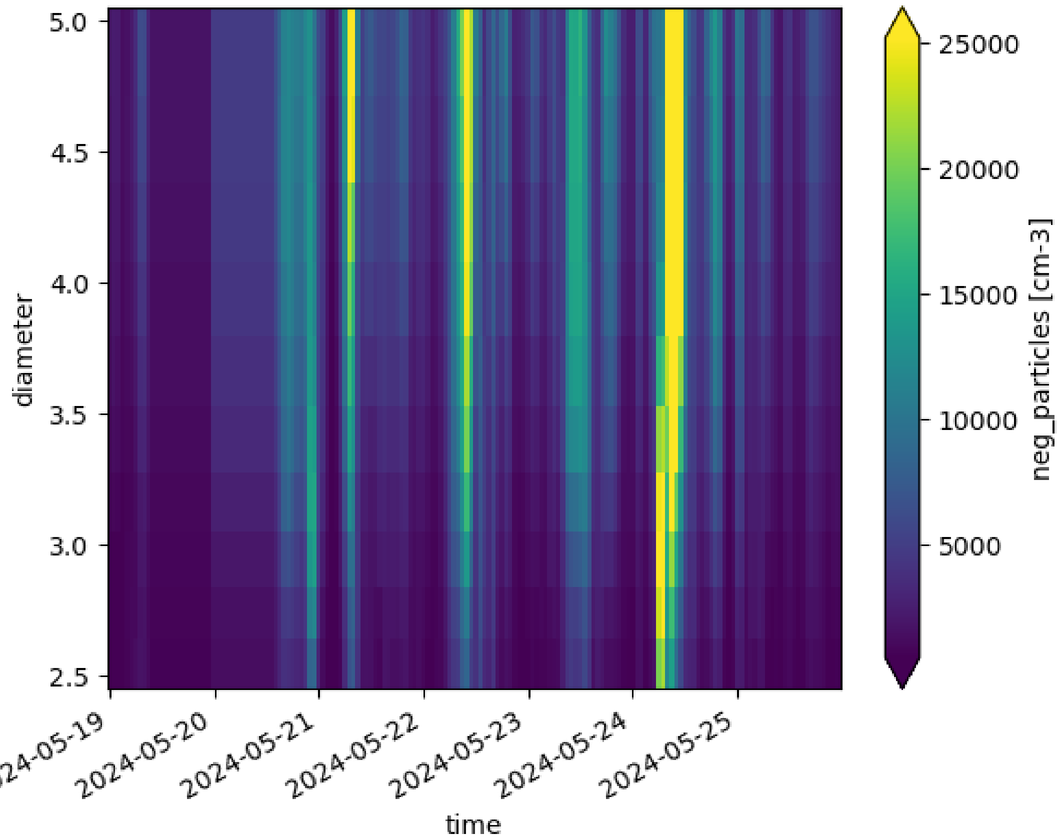
```
[ ]: (<xarray.DataArray 'neg_particles' ()>
      array(-6299.80445959),
      <xarray.DataArray 'neg_particles' ()>
      array(113768.96099142))
```

```
[ ]: #Step 3
     #Identify diurnal background and active regions. we recommend dividing the␣
      ↪dataset into seasons and examining the diurnal behaviour in each season␣
      ↪separately
     #Divide into weeks?

     week1 = rolling_median.sel(time=slice('2024-05-19','2024-05-25'))
     week2 = rolling_median.sel(time=slice('2024-05-26','2024-06-01'))
     week3 = rolling_median.sel(time=slice('2024-06-02','2024-06-08'))
     week4 = rolling_median.sel(time=slice('2024-06-09','2024-06-15'))
     week5 = rolling_median.sel(time=slice('2024-06-16','2024-06-22'))
     week6 = rolling_median.sel(time=slice('2024-06-23','2024-06-29'))
```

0.1.7 Spectral plots for each week?

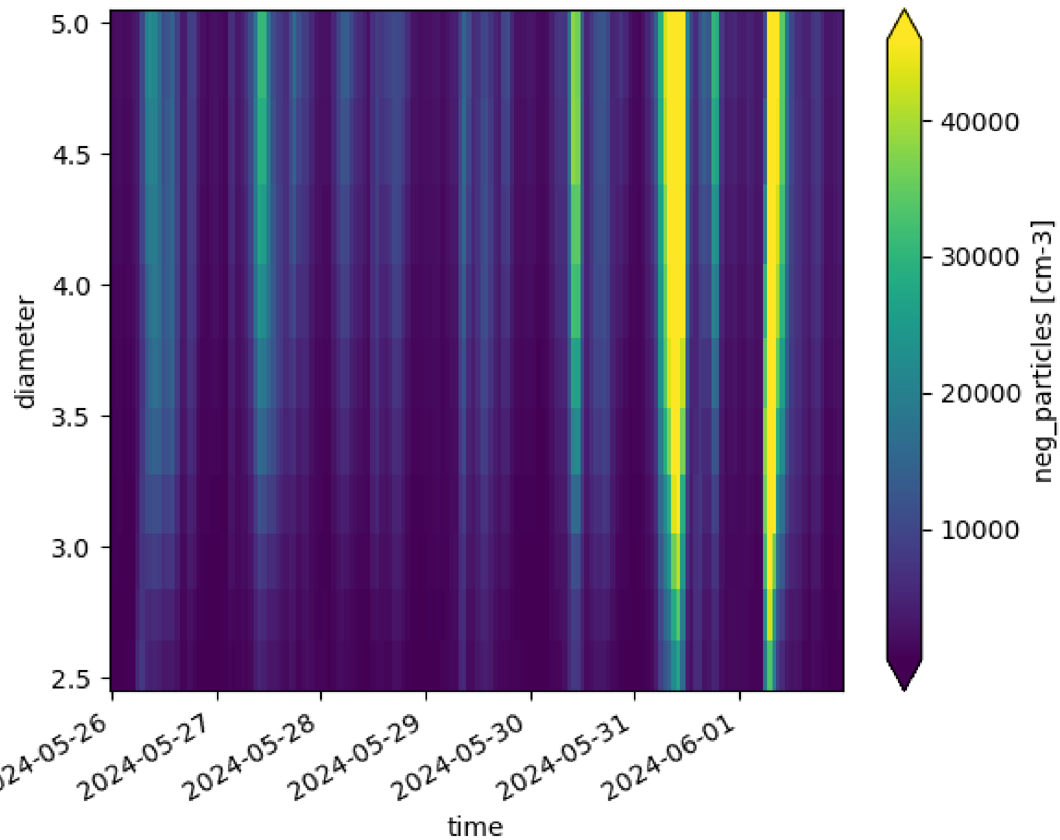
```
[ ]: week1.T.plot(robust=True)
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a40bd8fd0>
```



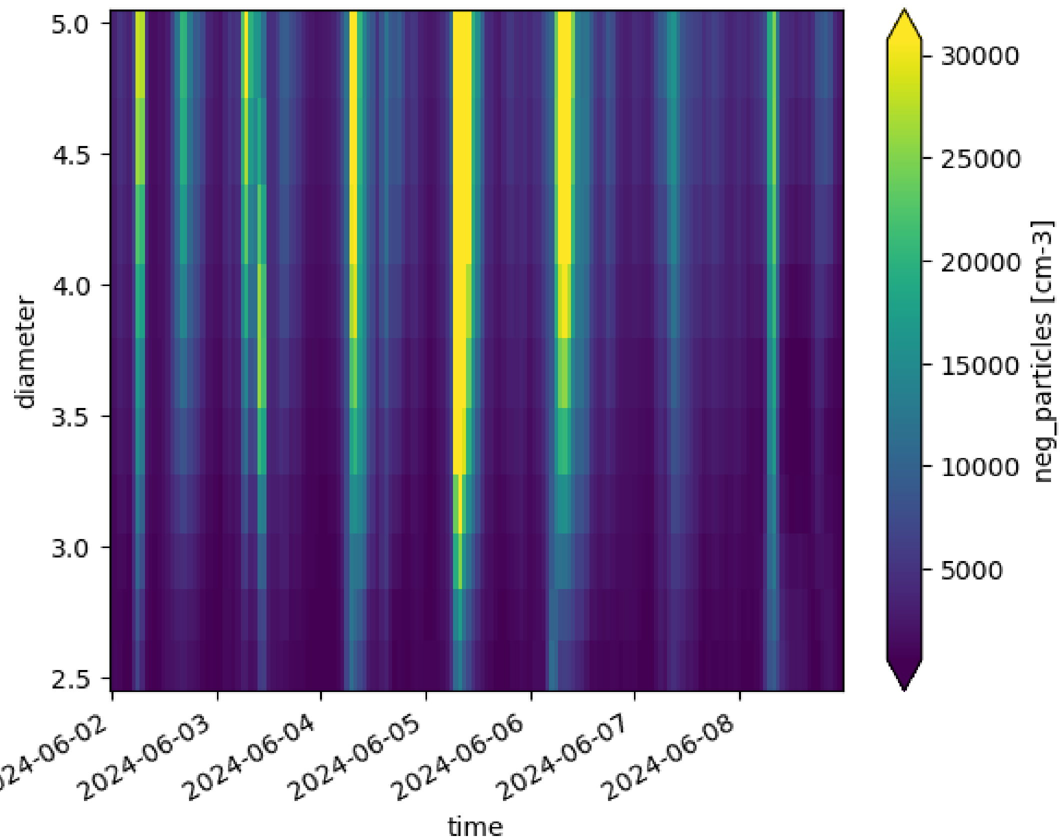

```
[ ]: week2.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a4093c650>



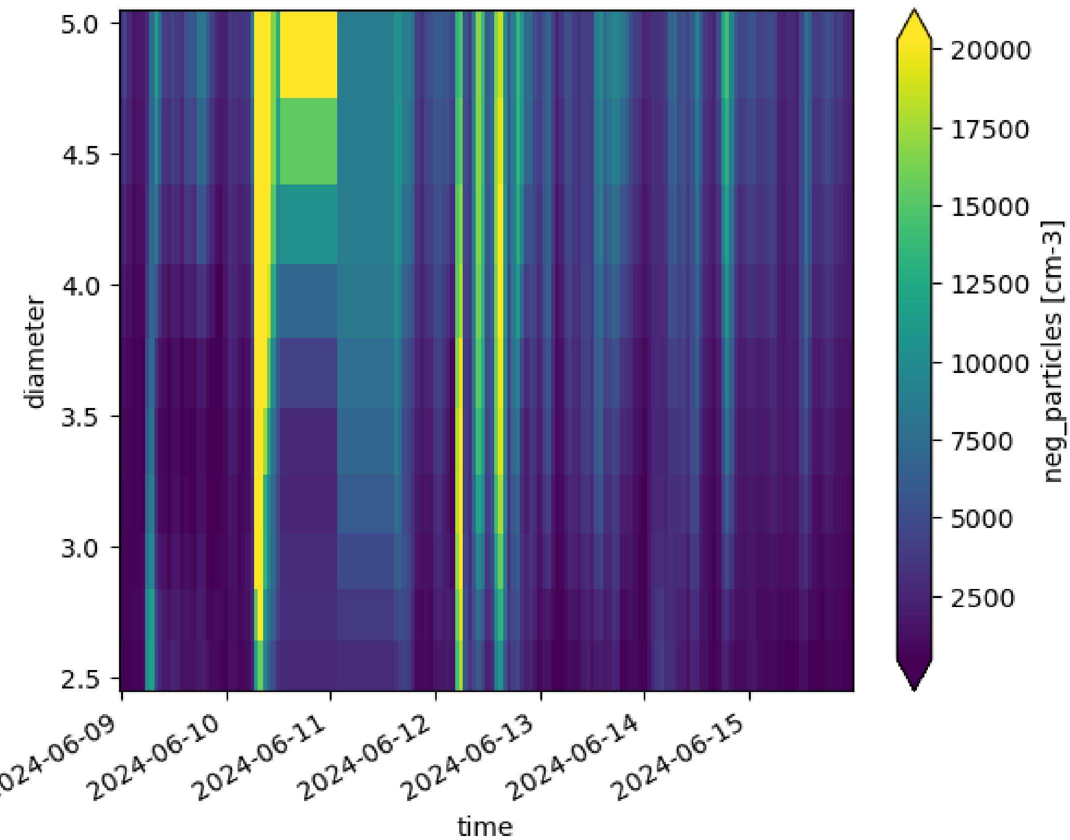
[ ]:
```
week3.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a4081c790>



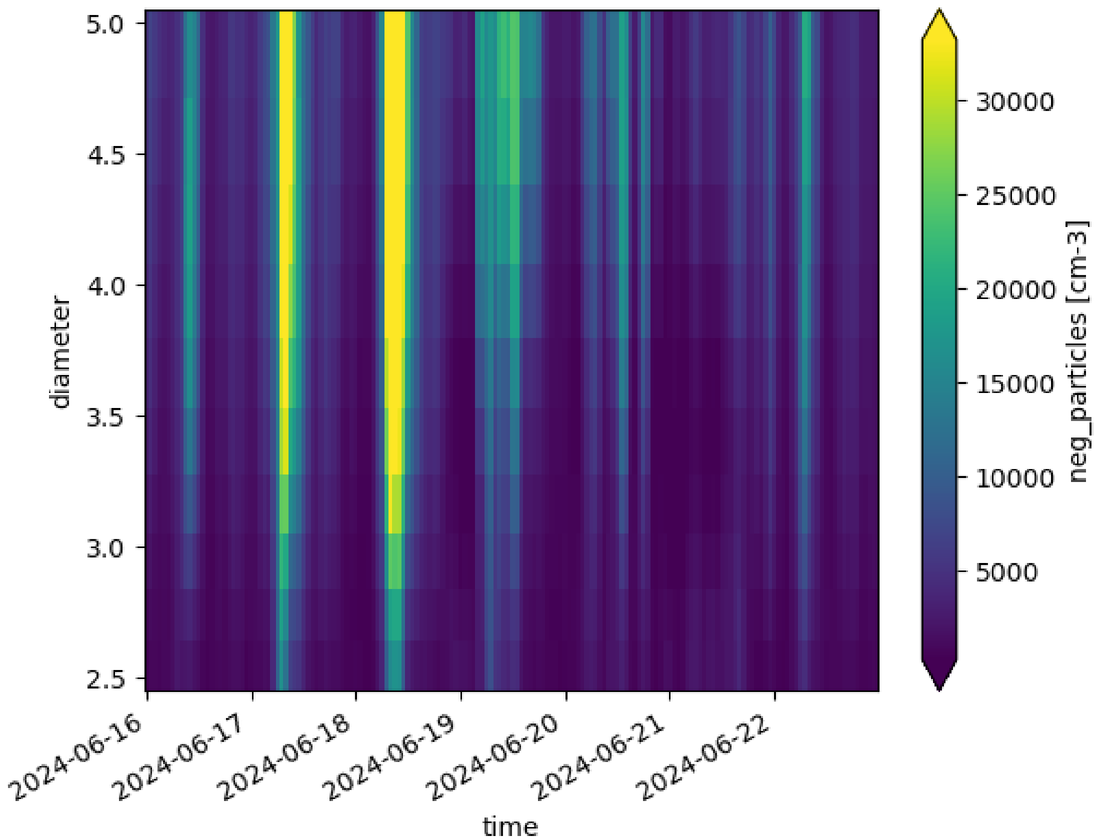
[ ]:
```
week4.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a406e4710>



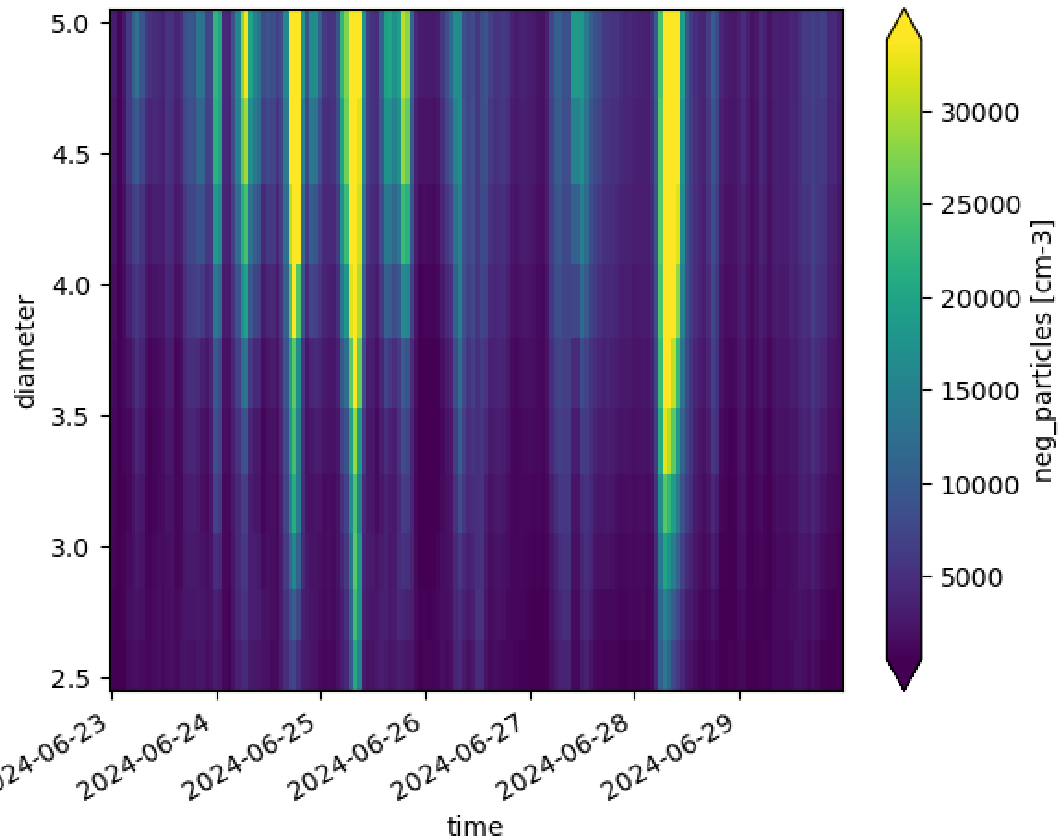
[ ]:
```
week5.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a407ac550>




```
[ ]: week6.T.plot(robust=True)
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a4066c690>
```

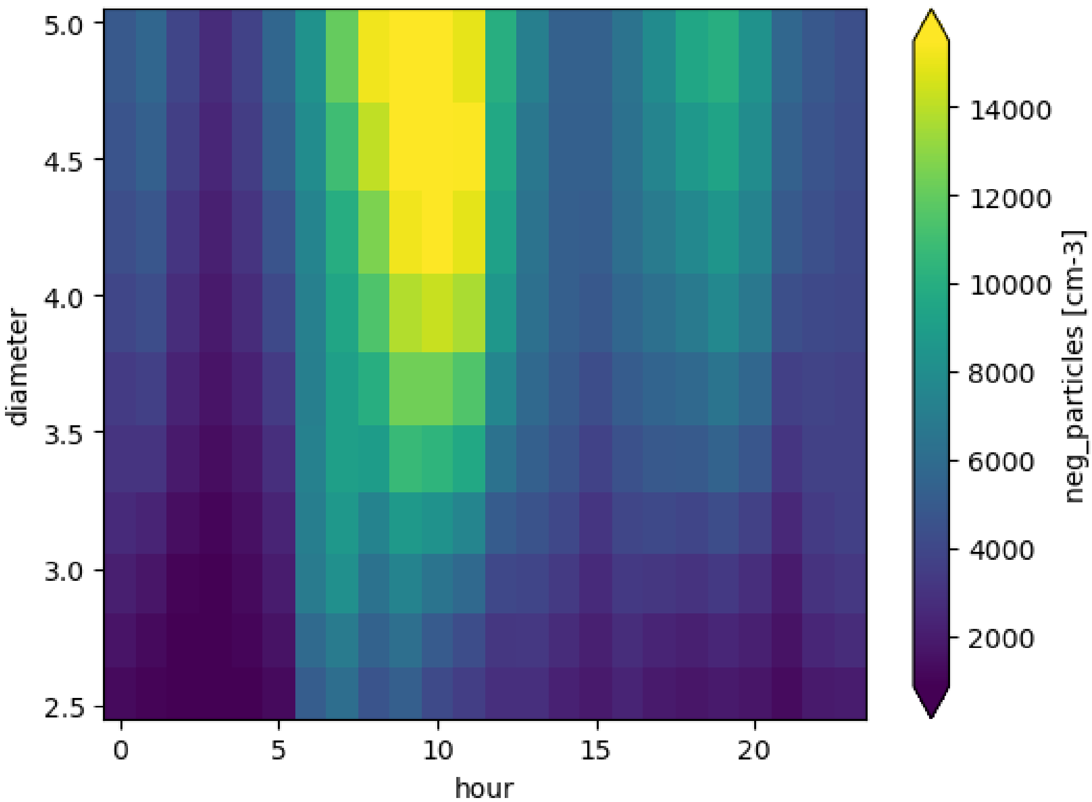


0.1.8 Diurnal variations

[ ]:
```
#  Calculate diurnal variations
week1_diurnal_variation = week1.groupby(week1.time.dt.hour).mean(dim='time')

week2_diurnal_variation = week2.groupby(week2.time.dt.hour).mean(dim='time')

week3_diurnal_variation = week3.groupby(week3.time.dt.hour).mean(dim='time')

week4_diurnal_variation = week4.groupby(week4.time.dt.hour).mean(dim='time')

week5_diurnal_variation = week5.groupby(week5.time.dt.hour).mean(dim='time')

week6_diurnal_variation = week6.groupby(week6.time.dt.hour).mean(dim='time')
```

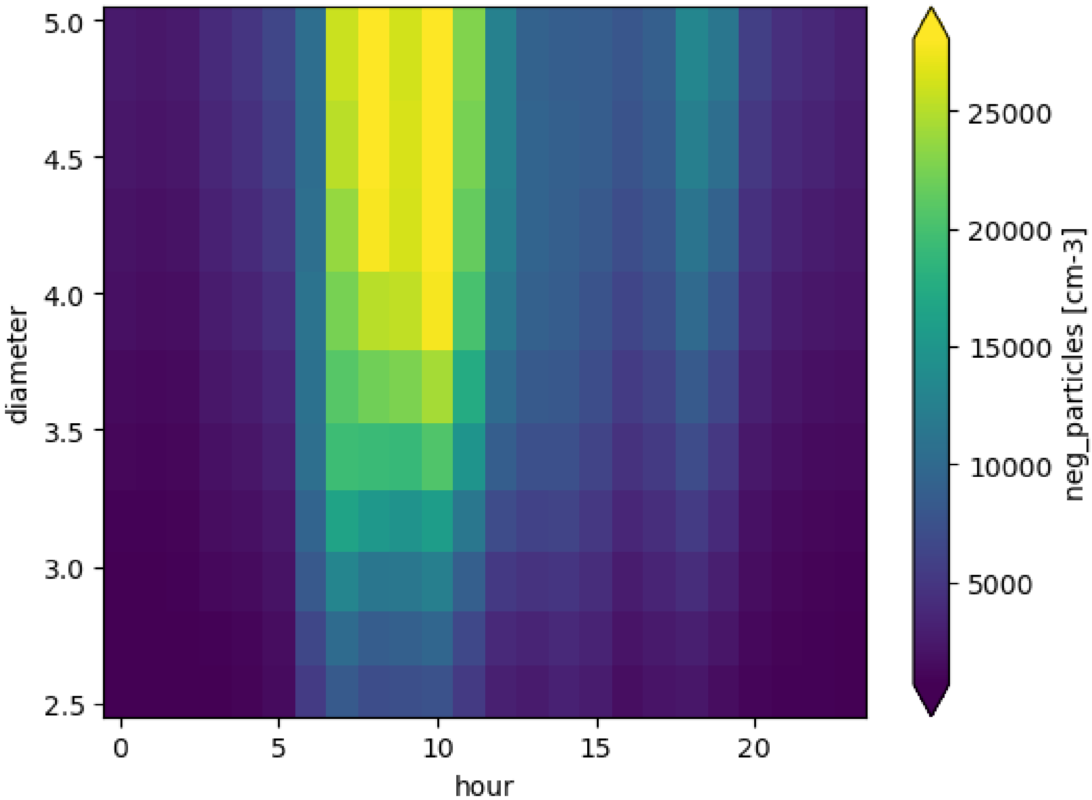
[ ]:
```
week1_diurnal_variation.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a4056c550>



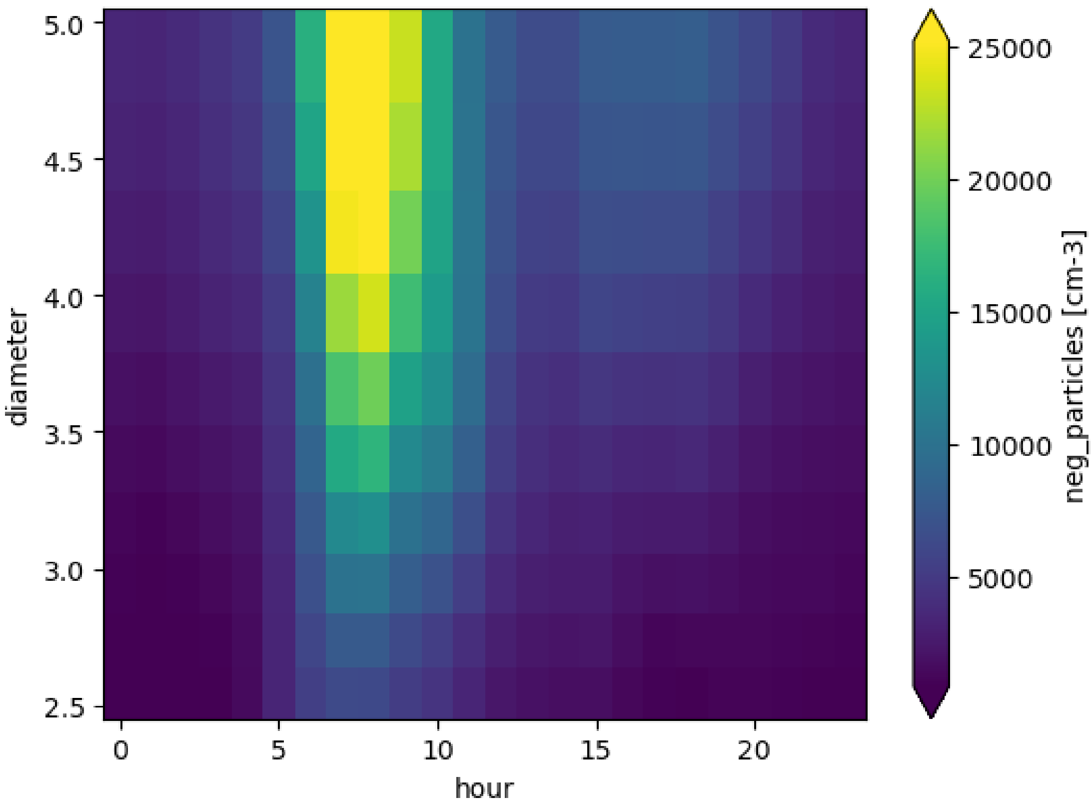
[ ]:
```
week2_diurnal_variation.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a40a04690>



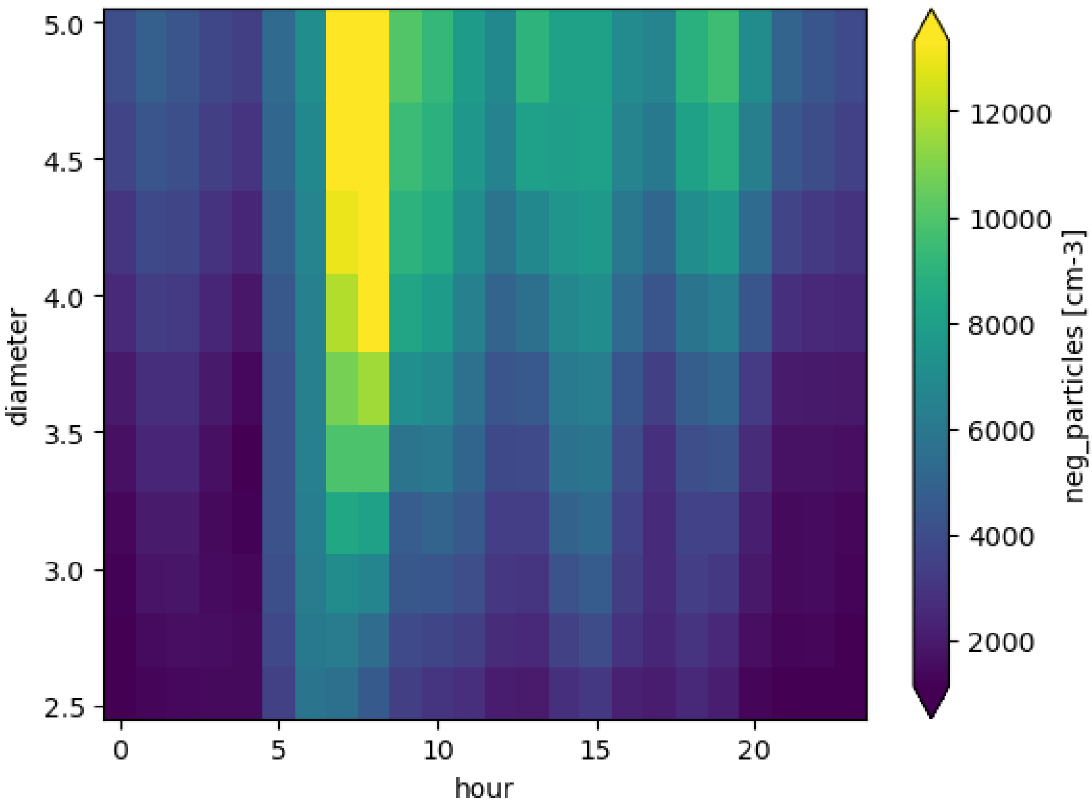
[ ]:
```
week3_diurnal_variation.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a40b7c690>



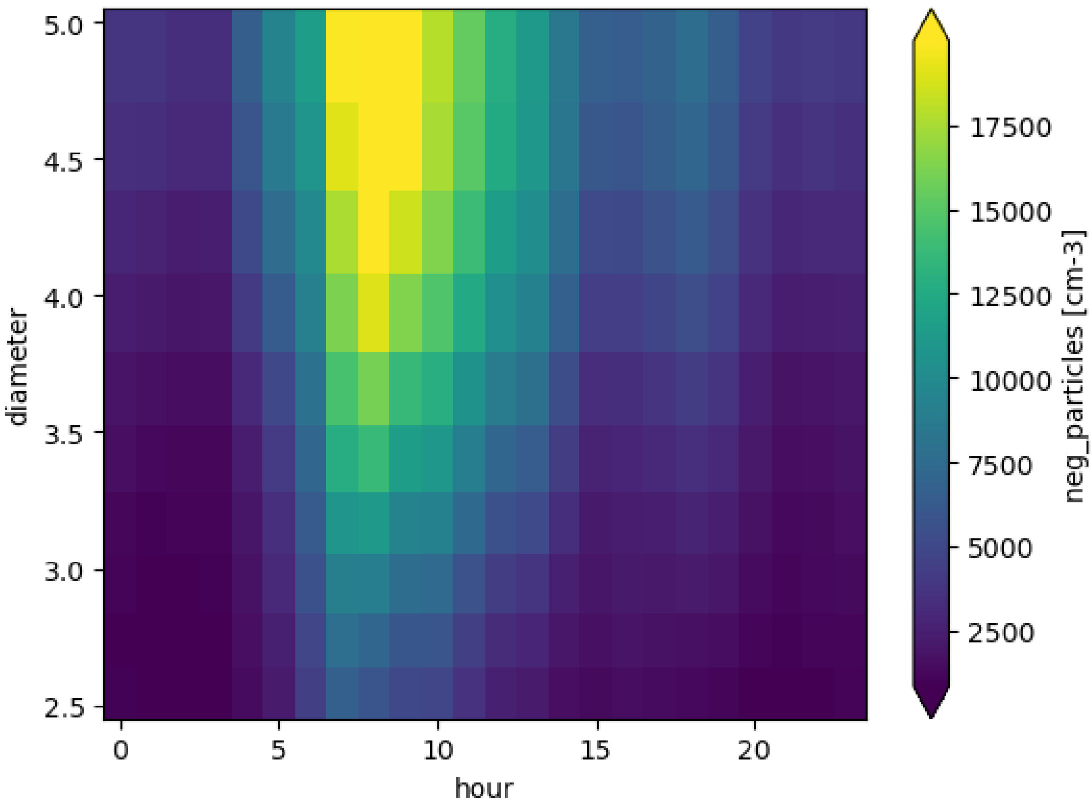

```
[ ]: week4_diurnal_variation.T.plot(robust=True)
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a40d4c690>
```



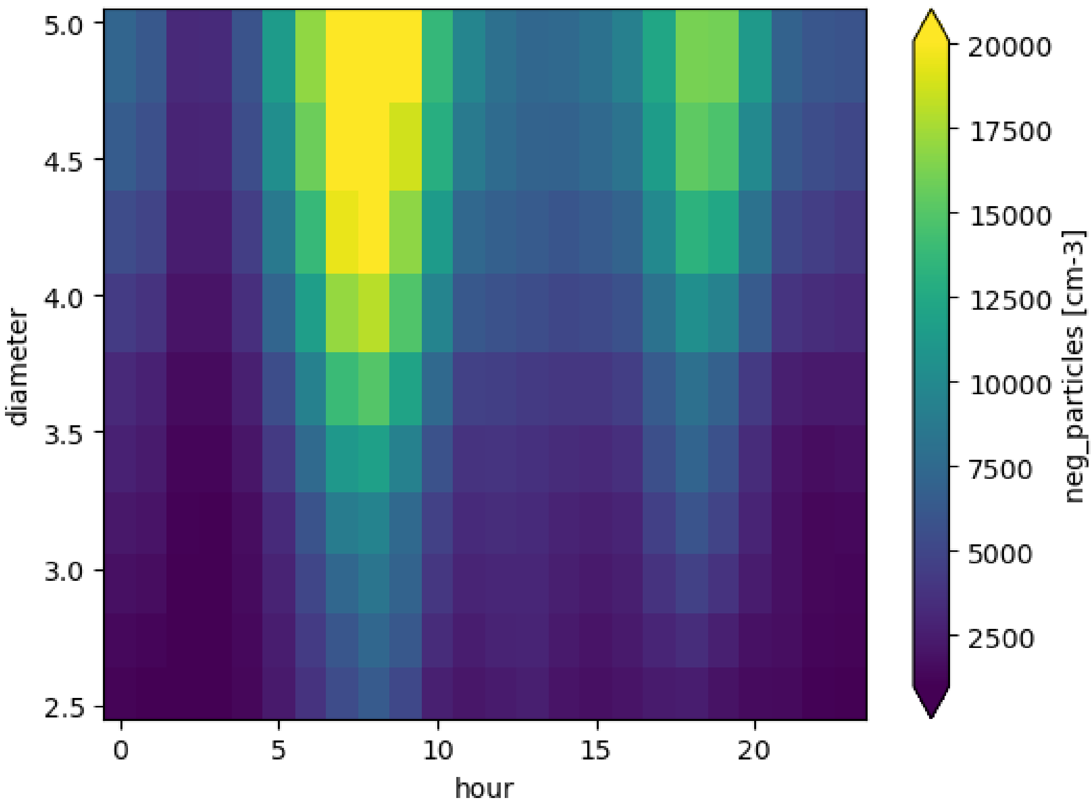

```
[ ]: week5_diurnal_variation.T.plot(robust=True)
```

```
[ ]: <matplotlib.collections.QuadMesh at 0x790a40e6bb50>
```



[ ]:
```
week6_diurnal_variation.T.plot(robust=True)
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a40abfb10>



0.1.9 Next

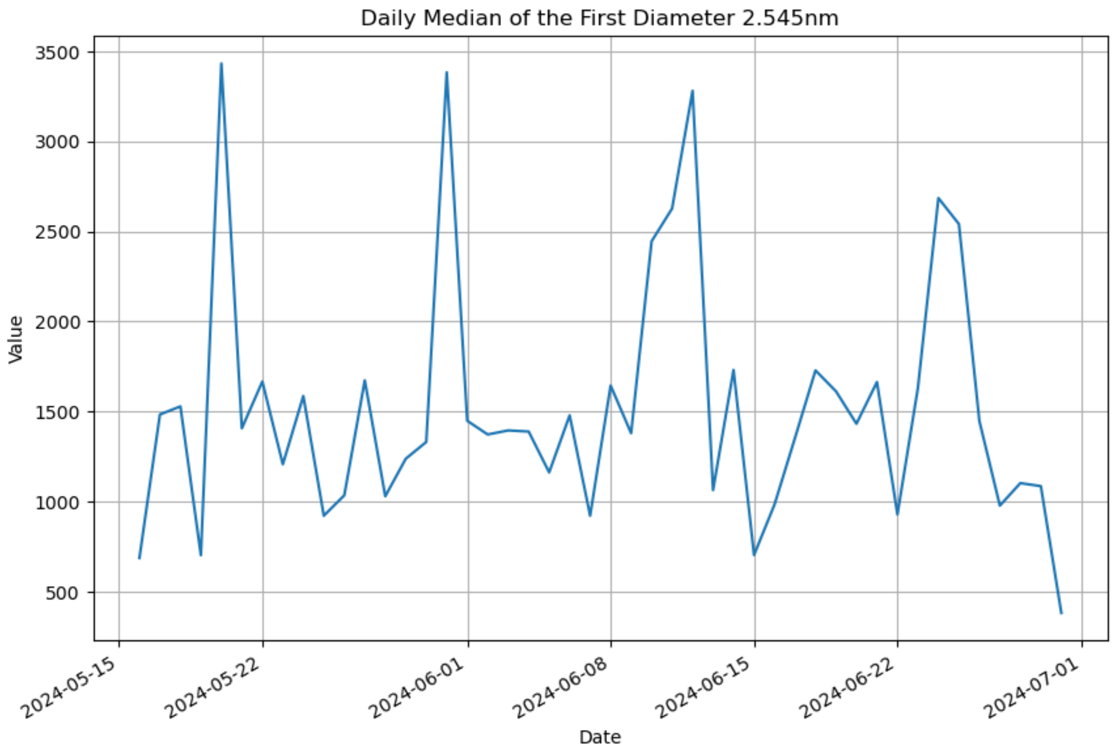
[ ]:
```python
#Step 4: Find the background number concentration for each day (N_B;2.5-5 ).
#The background concentration corresponding to a given day is determined based
↪on the median value of N2.5-5 in the so-called background region after
↪applying the 2 h rolling smoothing of the time series (step 2)

# using rolling median data, get the median for each day
# Resample the data to daily frequency and calculate the median for each day
daily_median = rolling_median.resample(time='1D').median()

print(daily_median)
```

```
<xarray.DataArray 'neg_particles' (time: 46, diameter: 10)>
array([[  686.91966746,   604.91170521,   608.69615726,   665.38855391,
          682.71464326,   635.76763437,   567.17595172,   481.61056844,
          468.85096703,   433.03275643],
        [ 1483.4177978 ,  1925.04445476,  2632.87509564,  3366.85119639,
         3758.6022508 ,  4319.14345328,  5002.67776478,  5968.35420296,
         6660.55476186,  6947.11684625],
        [ 1528.50666825,  1823.9253641 ,  2466.8958543 ,  2877.46780122,
```

```
          3505.40340732,  4093.72377098,  4863.62378263,  5341.33607703,
          5763.30398552,  6289.39053187],
        [ 702.48773343,   780.38027831,   749.19204185,   843.10130411,
          1216.5755096 ,  1410.76686782,  1736.02557686,  2016.29587286,
          2232.4661776 ,  2198.00018476],
        [ 3432.24876573,  4368.12506438,  5267.21563001,  6717.65920613,
          7941.38254343,  8816.67789183, 10144.28692454, 10871.2484283 ,
         10393.06687591, 10857.63740197],
        [ 1406.93465623,  1585.23296772,  2122.49828279,  2525.98537999,
          3298.52387241,  3959.56122154,  4545.06630708,  5057.85158735,
          5565.38132627,  5860.19054038],
        [ 1666.48884114,  1994.3739295 ,  2640.57896559,  3171.97760766,
          3655.91986961,  4256.08745814,  4814.9778736 ,  5723.15895117,
…
          3677.27036504,  4503.70769947,  7267.35680506, 10282.97372307,
         13920.8186743 , 15784.46712092],
        [ 2541.07404878,  3073.87595221,  3013.61645039,  2746.0611865 ,
          3436.44876793,  4630.2642841 ,  7557.80299906, 10342.59754736,
         12555.73575586, 14483.72292239],
        [ 1446.97866144,  1686.2319296 ,  1932.6134853 ,  2111.73213074,
          2650.4846149 ,  3513.48910763,  4271.12315108,  4940.31663829,
          5528.90234731,  5917.86316666],
        [  977.70572578,  1260.43279987,  1933.54595902,  2351.74838962,
          3062.18680961,  3742.33743562,  4303.95214474,  5028.40262916,
          5631.11483373,  5989.21527893],
        [ 1102.52871605,  1370.75018177,  2009.03238395,  2587.9443144 ,
          3305.98940073,  3916.67566046,  4646.04803679,  5103.73296215,
          5476.66795204,  5627.52327943],
        [ 1085.72617478,  1231.78687151,  1443.62196665,  1756.88282455,
          2061.95214411,  2547.92831609,  3151.68131856,  3490.1957767 ,
          3960.99535234,  3881.71303582],
        [  381.64164853,   483.07009991,   444.58554692,   629.08057473,
           761.34403231,   905.24270147,   848.32993839,  1068.22249874,
          1376.34393301,  1681.19116753]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-30
Attributes:
    units:        cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

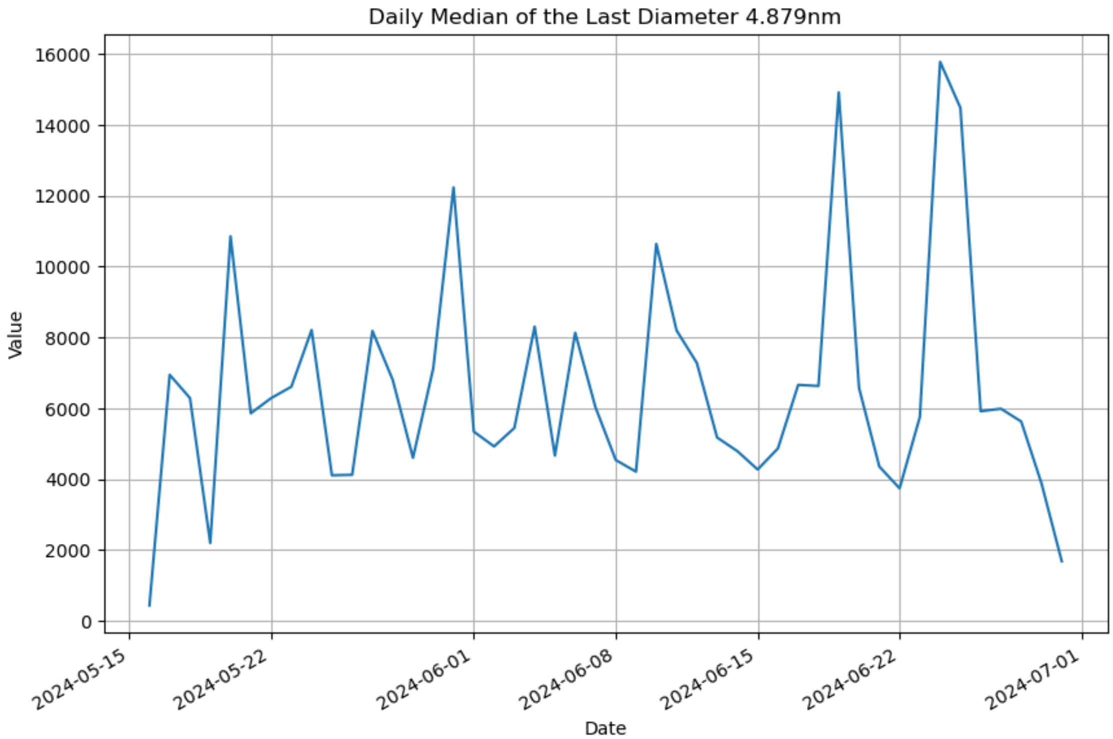
[ ]:
```python
# Example variable to plot (e.g., first diameter value 2.545nm)
daily_median_first_diameter = daily_median.isel(diameter=0)

plt.figure(figsize=(10, 6))
daily_median_first_diameter.plot()
plt.title('Daily Median of the First Diameter 2.545nm')
```

```
plt.xlabel('Date')
plt.ylabel('Value')
plt.grid(True)
plt.show()
```



[ ]:

```
# Example variable to plot (e.g., last diameter value 4.879nm)
daily_median_last_diameter = daily_median.isel(diameter=9)

plt.figure(figsize=(10, 6))
daily_median_last_diameter.plot()
plt.title('Daily Median of the Last Diameter 4.879nm')
plt.xlabel('Date')
plt.ylabel('Value')
plt.grid(True)
plt.show()
```

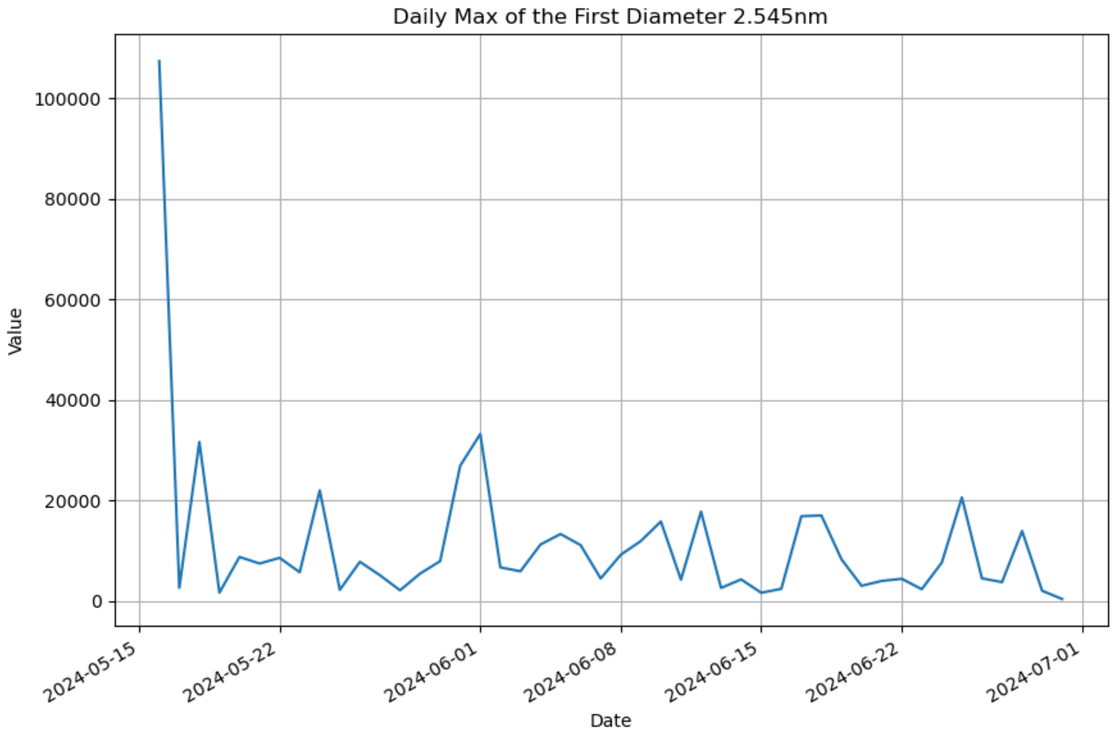


[ ]:
```
# Step 5: Find the active peak daytime number concentration (N_A;2.5-5 ) for␣
↪each day (based on the max value of N2.5-5 in the so-called active region)
# using rolling median data, get the max for each day
# Resample the data to daily frequency and calculate the max for each day
daily_max = rolling_median.resample(time='1D').max()

print(daily_max)
```

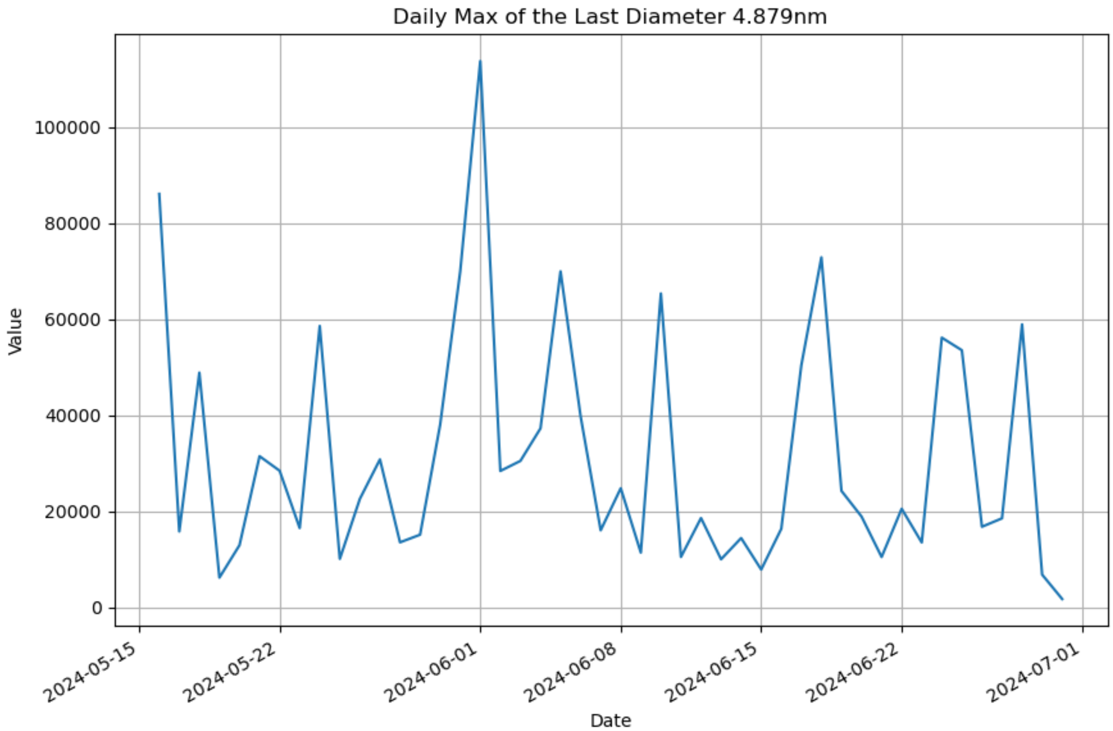
```
<xarray.DataArray 'neg_particles' (time: 46, diameter: 10)>
array([[107347.76161851, 102393.3837698 ,  98619.33117791,
         96660.98623261,  94520.43409171,  93137.04040408,
         93951.06388315,  94907.01970263,  91632.74324191,
         86099.85254766],
       [  2617.68795076,   3527.89778151,   4386.94569117,
          5291.7554388 ,   7422.21587326,   9941.12680775,
         11309.85842509,  12386.17717753,  14043.2435835 ,
         15766.25047702],
       [ 31628.67736228,  35780.38047848,  44314.4599852 ,
         52439.98865561,  57529.53880448,  59374.03026575,
         55778.25739885,  47566.2433213 ,  49683.70591689,
         48855.49620795],
       [  1659.60346548,   1624.49811721,   1971.51161391,
          2253.41938742,   2941.45222052,   3548.90070021,
```

```
            4115.12434605,   4866.4900328 ,   5572.0266704 ,
            6149.10488368],
         [  8748.64515359,  11922.7565337 ,  14318.8203885 ,
           15000.33179039,  14632.53465758,  13752.35623169,
           13516.19252365,  13638.204105   ,  13263.67863978,
           12898.07069629],
…
         [  4502.39568062,   5339.86318036,   5766.70155389,
            8381.26480348,  10571.49683646,  12570.59486254,
           14732.37433982,  15344.71817496,  16739.29869123,
           16743.15484695],
         [  3744.67060403,   4559.47229999,   5349.24497234,
            5743.42521004,   6661.07735961,   8259.79326764,
           11997.79467566,  14812.86178032,  17117.03178709,
           18499.95634731],
         [ 13914.19095233,  15556.77338991,  19907.81044265,
           24996.44640943,  32380.34076833,  38087.34590308,
           43394.53369289,  48800.01689691,  55059.12204755,
           58915.95390652],
         [  2031.8817536 ,   2264.39904386,   3001.07133961,
            3853.9371891 ,   4931.23915477,   5623.74511718,
            6451.92869989,   6763.69672664,   6728.96061366,
            6773.34901417],
         [   381.64164853,    483.07009991,    444.58554692,
             629.08057473,    761.34403231,    905.24270147,
             848.32993839,   1068.22249874,   1376.34393301,
            1681.19116753]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-30
Attributes:
    units:         cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

[ ]:
```python
# Example variable to plot (e.g., first diameter value 2.545nm)
daily_max_first_diameter = daily_max.isel(diameter=0)

plt.figure(figsize=(10, 6))
daily_max_first_diameter.plot()
plt.title('Daily Max of the First Diameter 2.545nm')
plt.xlabel('Date')
plt.ylabel('Value')
plt.grid(True)
plt.show()
```



[ ]:
```python
# Example variable to plot (e.g., last diameter value 4.879nm)
daily_max_last_diameter = daily_max.isel(diameter=9)

plt.figure(figsize=(10, 6))
daily_max_last_diameter.plot()
plt.title('Daily Max of the Last Diameter 4.879nm')
plt.xlabel('Date')
plt.ylabel('Value')
plt.grid(True)
plt.show()
```

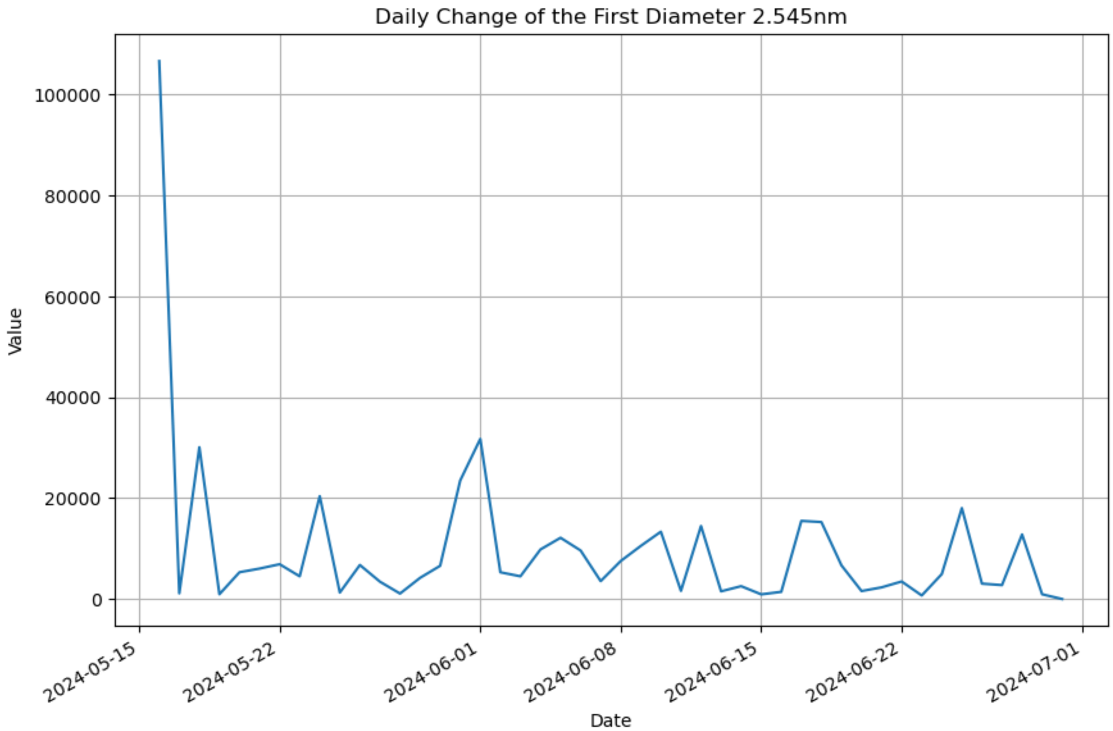



```
[ ]: # Step 6: Determine the change in number concentration ($\Delta$ N2.5-5 ) for
     ↪each day (step 5 - step 4).
     #Change for each day
     num_conc_change = daily_max - daily_median

     print(num_conc_change)
```

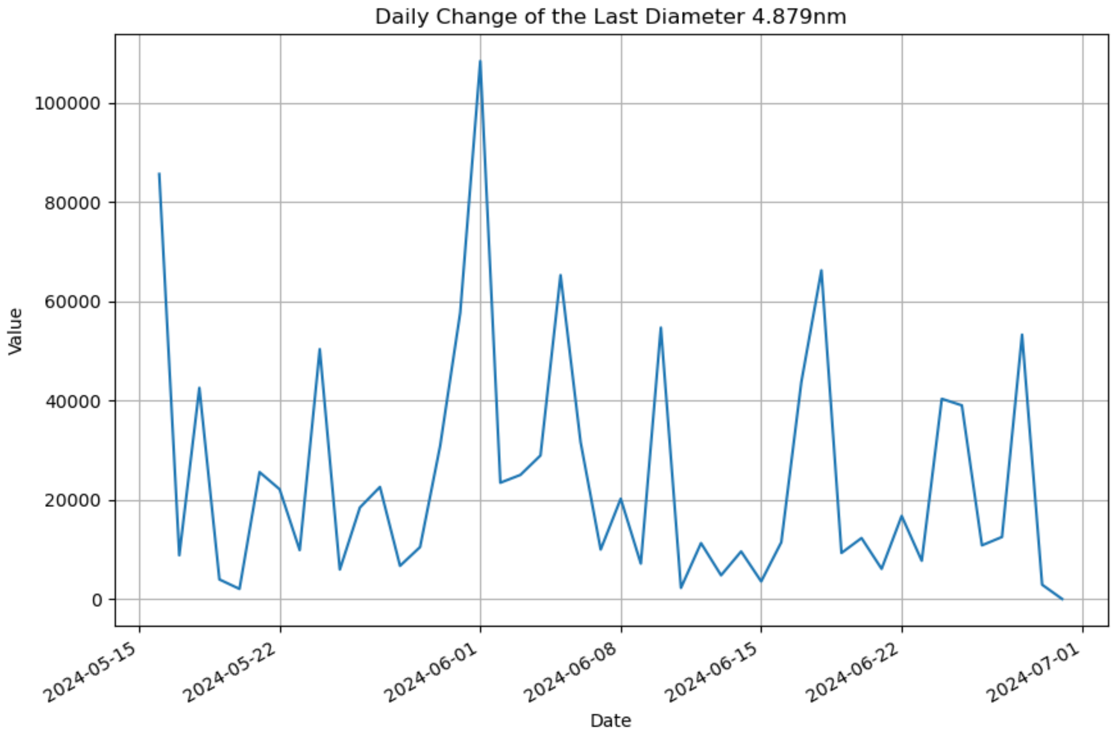
```
<xarray.DataArray 'neg_particles' (time: 46, diameter: 10)>
array([[106660.84195106, 101788.47206459,  98010.63502065,
         95995.5976787 ,  93837.71944845,  92501.27276971,
         93383.88793143,  94425.40913419,  91163.89227488,
         85666.81979123],
       [  1134.27015296,   1602.85332675,   1754.07059554,
          1924.90424241,   3663.61362246,   5621.98335447,
          6307.18066031,   6417.82297458,   7382.68882163,
          8819.13363077],
       [ 30100.17069403,  33956.45511438,  41847.5641309 ,
         49562.52085438,  54024.13539716,  55280.30649477,
         50914.63361623,  42224.90724427,  43920.40193137,
         42566.10567608],
       [   957.11573205,    844.11783889,   1222.31957206,
          1410.31808332,   1724.87671092,   2138.13383239,
          2379.09876919,   2850.19415994,   3339.56049279,
          3951.10469891],
```

```
        [  5316.39638785,   7554.63146933,   9051.6047585 ,
           8282.67258426,   6691.15211415,   4935.67833987,
           3371.90559912,   2766.9556767 ,   2870.61176388,
           2040.43329432],
…
        [  3055.41701919,   3653.63125077,   3834.0880686 ,
           6269.53267274,   7921.01222156,   9057.10575491,
          10461.25118874,  10404.40153667,  11210.39634392,
          10825.29168029],
        [  2766.96487825,   3299.03950012,   3415.69901331,
           3391.67682042,   3598.89055    ,   4517.45583202,
           7693.84253092,   9784.45915116,  11485.91695335,
          12510.74106837],
        [ 12811.66223628,  14186.02320813,  17898.7780587 ,
          22408.50209503,  29074.3513676 ,  34170.67024262,
          38748.48565609,  43696.28393476,  49582.45409551,
          53288.4306271 ],
        [   946.15557882,   1032.61217236,   1557.44937296,
           2097.05436455,   2869.28701066,   3075.81680109,
           3300.24738133,   3273.50094994,   2767.96526132,
           2891.63597835],
        [     0.        ,      0.        ,      0.        ,
              0.        ,      0.        ,      0.        ,
              0.        ,      0.        ,      0.        ,
              0.        ]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-30
```

[ ]:
```python
# Example variable to plot (e.g., first diameter value 2.545nm)
daily_change_first_diameter = num_conc_change.isel(diameter=0)

plt.figure(figsize=(10, 6))
daily_change_first_diameter.plot()
plt.title('Daily Change of the First Diameter 2.545nm')
plt.xlabel('Date')
plt.ylabel('Value')
plt.grid(True)
plt.show()
```




```
[ ]: # Example variable to plot (e.g., last diameter value 4.879nm)
daily_change_last_diameter = num_conc_change.isel(diameter=9)

plt.figure(figsize=(10, 6))
daily_change_last_diameter.plot()
plt.title('Daily Change of the Last Diameter 4.879nm')
plt.xlabel('Date')
plt.ylabel('Value')
plt.grid(True)
plt.show()
```




```
[ ]: # Step 7: Rank and group the days.
     # Calculate percentiles for daily_diff
     percentiles = num_conc_change.rank(dim='time', pct=True)
```

```
[ ]: percentiles
```

```
[ ]: <xarray.DataArray 'neg_particles' (time: 46, diameter: 10)>
     array([[1.        , 1.        , 1.        , 1.        , 1.        ,
              1.        , 1.        , 0.97826087, 0.97826087, 0.97826087],
            [0.15217391, 0.13043478, 0.10869565, 0.08695652, 0.19565217,
             0.2826087 , 0.2826087 , 0.2826087 , 0.2826087 , 0.2826087 ],
            [0.95652174, 0.95652174, 0.95652174, 0.95652174, 0.93478261,
             0.93478261, 0.89130435, 0.82608696, 0.82608696, 0.80434783],
            [0.10869565, 0.06521739, 0.06521739, 0.04347826, 0.04347826,
             0.04347826, 0.04347826, 0.06521739, 0.10869565, 0.13043478],
            [0.54347826, 0.63043478, 0.63043478, 0.47826087, 0.32608696,
             0.23913043, 0.10869565, 0.04347826, 0.06521739, 0.04347826],
            [0.56521739, 0.52173913, 0.5       , 0.56521739, 0.52173913,
             0.5       , 0.56521739, 0.56521739, 0.58695652, 0.67391304],
            [0.65217391, 0.67391304, 0.69565217, 0.7173913 , 0.65217391,
             0.65217391, 0.65217391, 0.67391304, 0.60869565, 0.58695652],
            [0.47826087, 0.45652174, 0.41304348, 0.41304348, 0.41304348,
             0.41304348, 0.36956522, 0.36956522, 0.34782609, 0.34782609],
```

```
        [0.91304348, 0.91304348, 0.91304348, 0.80434783, 0.80434783,
         0.80434783, 0.84782609, 0.86956522, 0.84782609, 0.84782609],
        [0.17391304, 0.17391304, 0.23913043, 0.19565217, 0.2173913 ,
         0.17391304, 0.2173913 , 0.23913043, 0.19565217, 0.17391304],
…
        [0.2826087 , 0.2826087 , 0.15217391, 0.2173913 , 0.23913043,
         0.26086957, 0.26086957, 0.26086957, 0.23913043, 0.19565217],
        [0.39130435, 0.43478261, 0.45652174, 0.5       , 0.47826087,
         0.47826087, 0.47826087, 0.47826087, 0.52173913, 0.52173913],
        [0.04347826, 0.04347826, 0.04347826, 0.06521739, 0.06521739,
         0.06521739, 0.13043478, 0.15217391, 0.2173913 , 0.26086957],
        [0.5       , 0.60869565, 0.73913043, 0.76086957, 0.76086957,
         0.7173913 , 0.76086957, 0.76086957, 0.7826087 , 0.7826087 ],
        [0.89130435, 0.89130435, 0.82608696, 0.7826087 , 0.7826087 ,
         0.84782609, 0.80434783, 0.7826087 , 0.76086957, 0.76086957],
        [0.34782609, 0.36956522, 0.30434783, 0.34782609, 0.39130435,
         0.39130435, 0.41304348, 0.39130435, 0.36956522, 0.41304348],
        [0.32608696, 0.32608696, 0.2826087 , 0.23913043, 0.17391304,
         0.19565217, 0.32608696, 0.34782609, 0.43478261, 0.5       ],
        [0.7826087 , 0.76086957, 0.7826087 , 0.84782609, 0.84782609,
         0.82608696, 0.82608696, 0.84782609, 0.86956522, 0.86956522],
        [0.08695652, 0.10869565, 0.08695652, 0.10869565, 0.08695652,
         0.08695652, 0.08695652, 0.08695652, 0.04347826, 0.08695652],
        [0.02173913, 0.02173913, 0.02173913, 0.02173913, 0.02173913,
         0.02173913, 0.02173913, 0.02173913, 0.02173913, 0.02173913]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-30
```

[ ]:

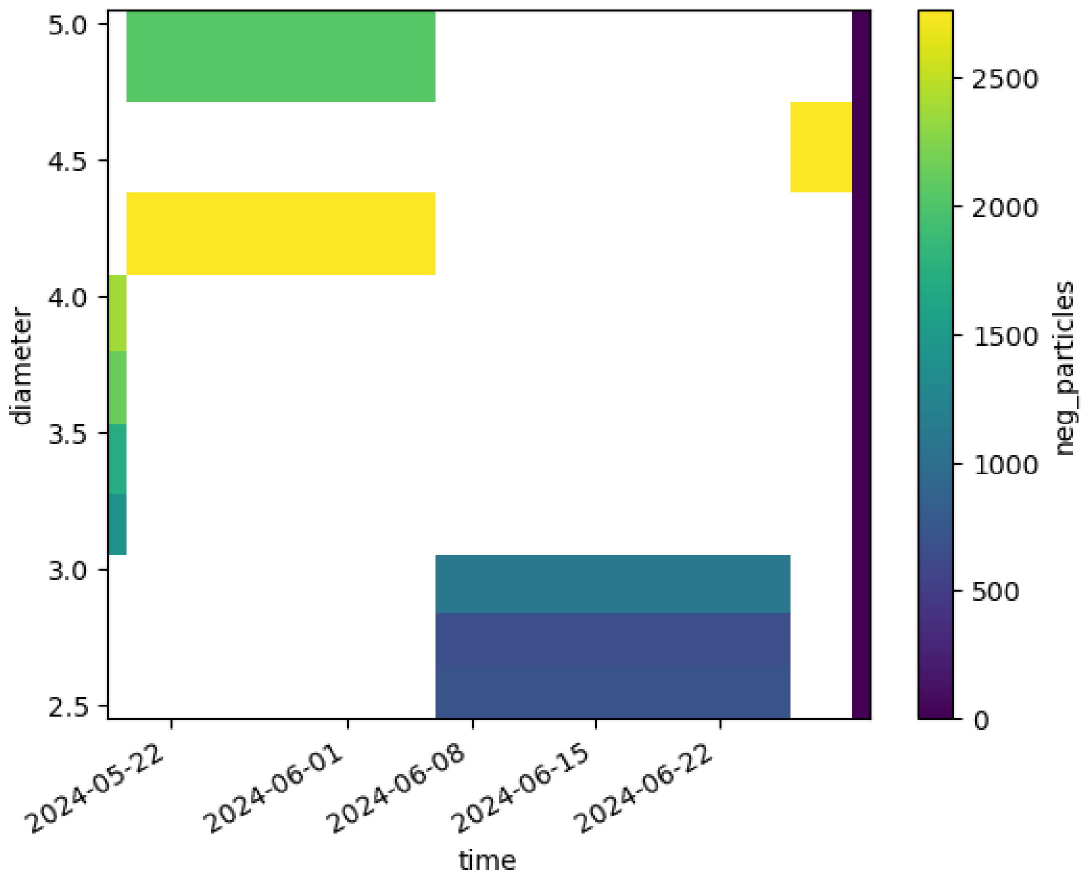
```python
# Group days based on 5% intervals
percentile_groups = (percentiles * 20).astype(int)  # Converts percentiles to␣
↪groups (0 to 19)

# Assess potential NPF pattern for each 5% interval group
grouped_patterns = {}

for i in range(20):
    group = num_conc_change.where(percentile_groups == i, drop=True)
    grouped_patterns[f'Group {i*5}-{(i+1)*5}%'] = group
```

[ ]:

```python
# the days in the first percentile group (0-5%)
grouped_patterns['Group 0-5%'].dropna(dim='time',how='all').T.plot()
```

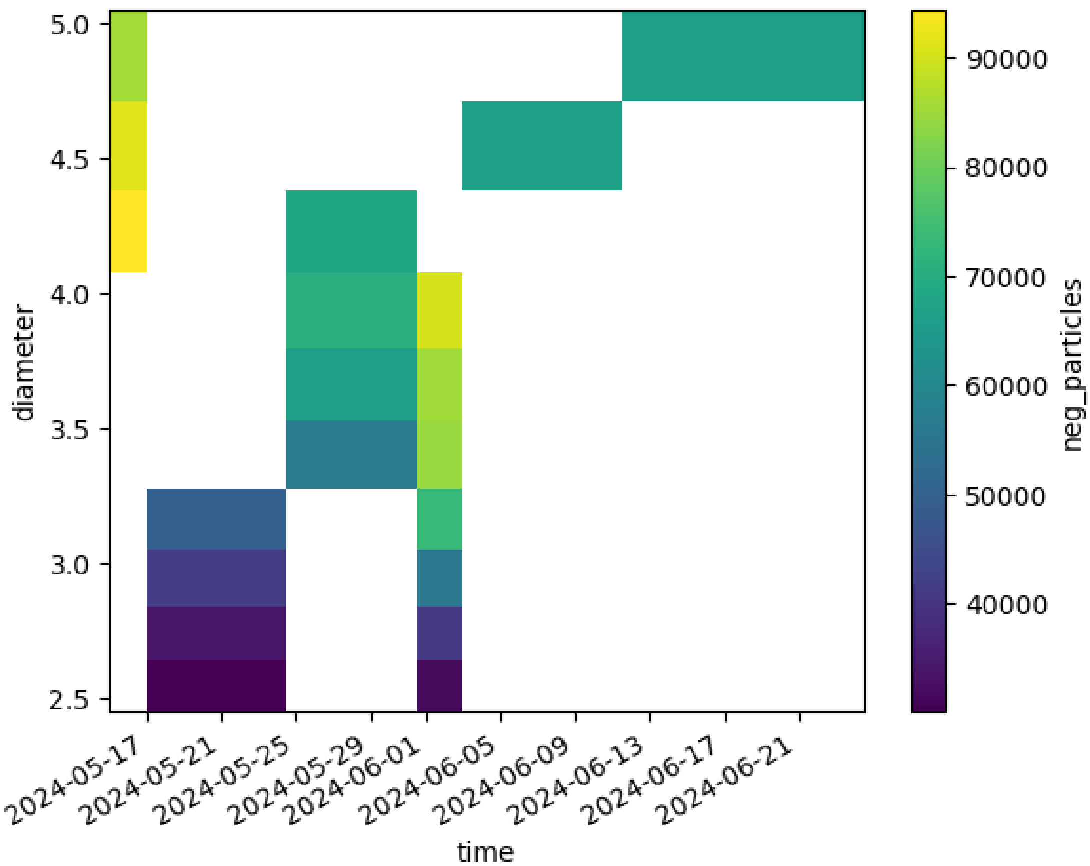
[ ]:

```
<matplotlib.collections.QuadMesh at 0x790a4116c550>
```



[ ]:
```
# the days in the last percentile group (95-100%)
grouped_patterns['Group 95-100%'].dropna(dim='time',how='all').T.plot()
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a5060c650>



[ ]:
```
# Example: the days in the first percentile group (0-5%) for the first and last␣
 ↪diameter values
grouped_patterns['Group 0-5%'].isel(diameter=0)  #23.06.2024 --> 707.82
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 5)>
array([         nan,          nan, 707.82383985,          nan,
         0.        ])
Coordinates:
    diameter  float64 2.545
  * time      (time) datetime64[ns] 2024-05-19 2024-05-20 … 2024-06-30
```

[ ]:
```
grouped_patterns['Group 95-100%'].isel(diameter=9) #16-05-2024 --> 85666.82 and␣
 ↪18.06.2024 --> 66249.65
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 6)>
array([85666.81979123,            nan,            nan,            nan,
                  nan, 66249.65367986])
Coordinates:
    diameter  float64 4.879
```

```
  * time      (time) datetime64[ns] 2024-05-16 2024-05-18 … 2024-06-18
```

0.2 NPF mode fitting

0.2.1 Step 1

The log ($\Delta N_{2.5-5}$) distribution is depicted, and a visual assessment is made to determine the number of Gaussian curves needed to describe the distribution – in our case, n curves

[ ]:
```
num_conc_change
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 46, diameter: 10)>
array([[106660.84195106, 101788.47206459,  98010.63502065,
         95995.5976787 ,  93837.71944845,  92501.27276971,
         93383.88793143,  94425.40913419,  91163.89227488,
         85666.81979123],
       [  1134.27015296,   1602.85332675,   1754.07059554,
          1924.90424241,   3663.61362246,   5621.98335447,
          6307.18066031,   6417.82297458,   7382.68882163,
          8819.13363077],
       [ 30100.17069403,  33956.45511438,  41847.5641309 ,
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         50914.63361623,  42224.90724427,  43920.40193137,
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       [   957.11573205,    844.11783889,   1222.31957206,
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          3951.10469891],
       [  5316.39638785,   7554.63146933,   9051.6047585 ,
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          3371.90559912,   2766.9556767 ,   2870.61176388,
          2040.43329432],
…
       [  3055.41701919,   3653.63125077,   3834.0880686 ,
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         10825.29168029],
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          7693.84253092,   9784.45915116,  11485.91695335,
         12510.74106837],
       [ 12811.66223628,  14186.02320813,  17898.7780587 ,
         22408.50209503,  29074.3513676 ,  34170.67024262,
         38748.48565609,  43696.28393476,  49582.45409551,
         53288.4306271 ],
       [   946.15557882,   1032.61217236,   1557.44937296,
          2097.05436455,   2869.28701066,   3075.81680109,
          3300.24738133,   3273.50094994,   2767.96526132,
```
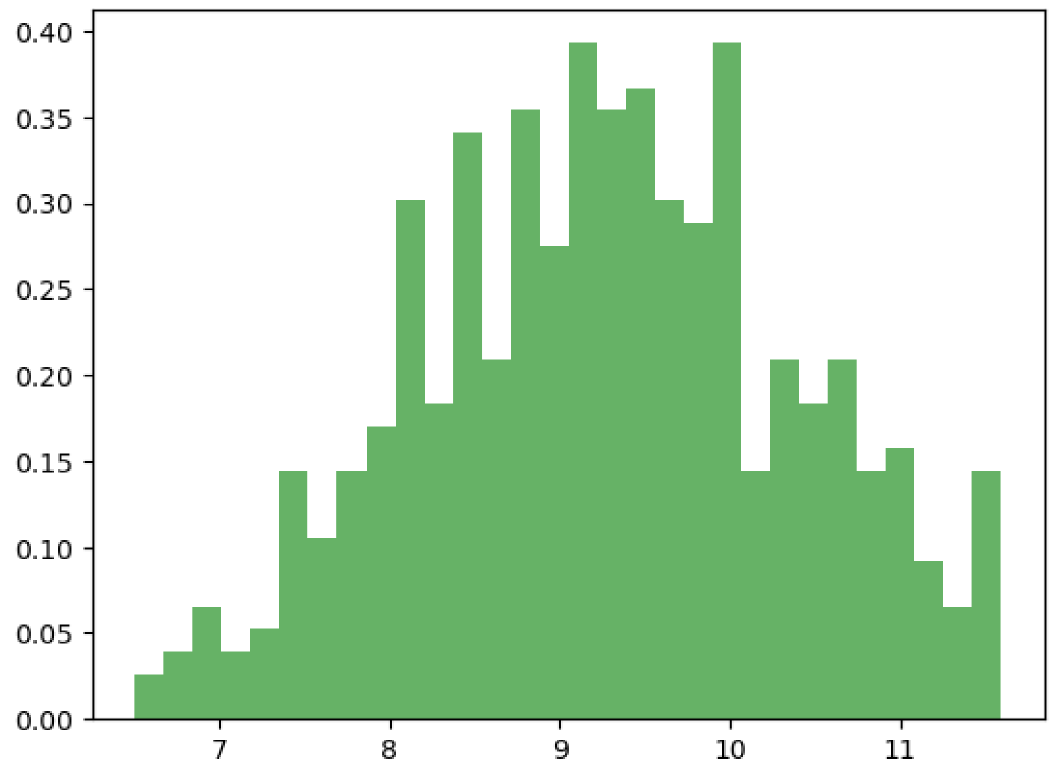
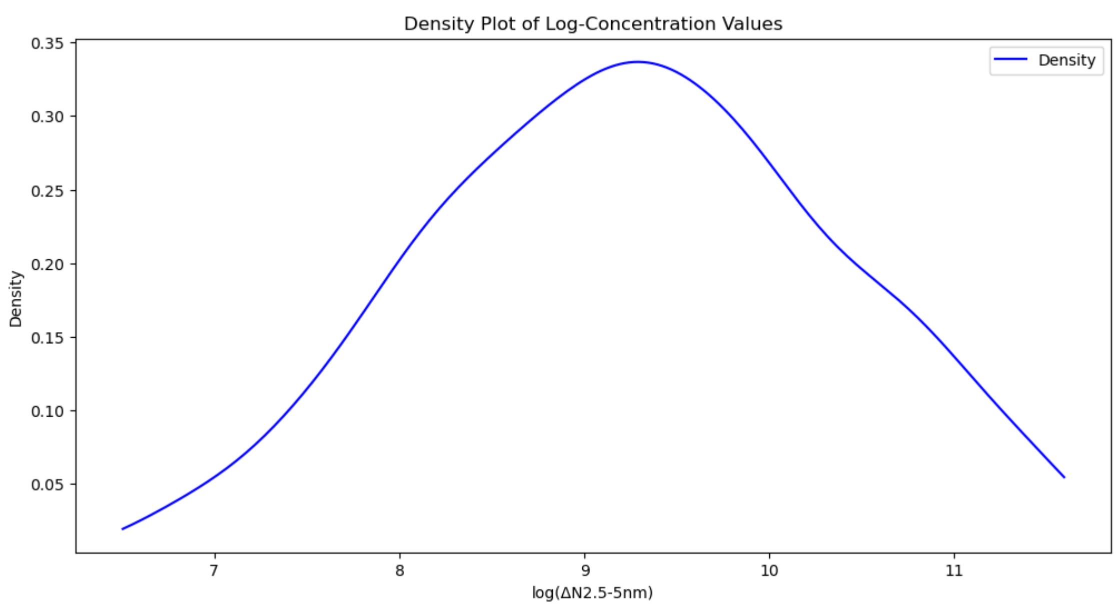

```
          2891.63597835],
       [    0.        ,     0.        ,     0.        ,
            0.        ,     0.        ,     0.        ,
            0.        ,     0.        ,     0.        ,
            0.        ]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-30
```

[ ]:
```
log_dist = np.log(num_conc_change)
```

```
/home/coliewo/anaconda3/lib/python3.11/site-
packages/xarray/core/computation.py:761: RuntimeWarning: divide by zero
encountered in log
  result_data = func(*input_data)
```

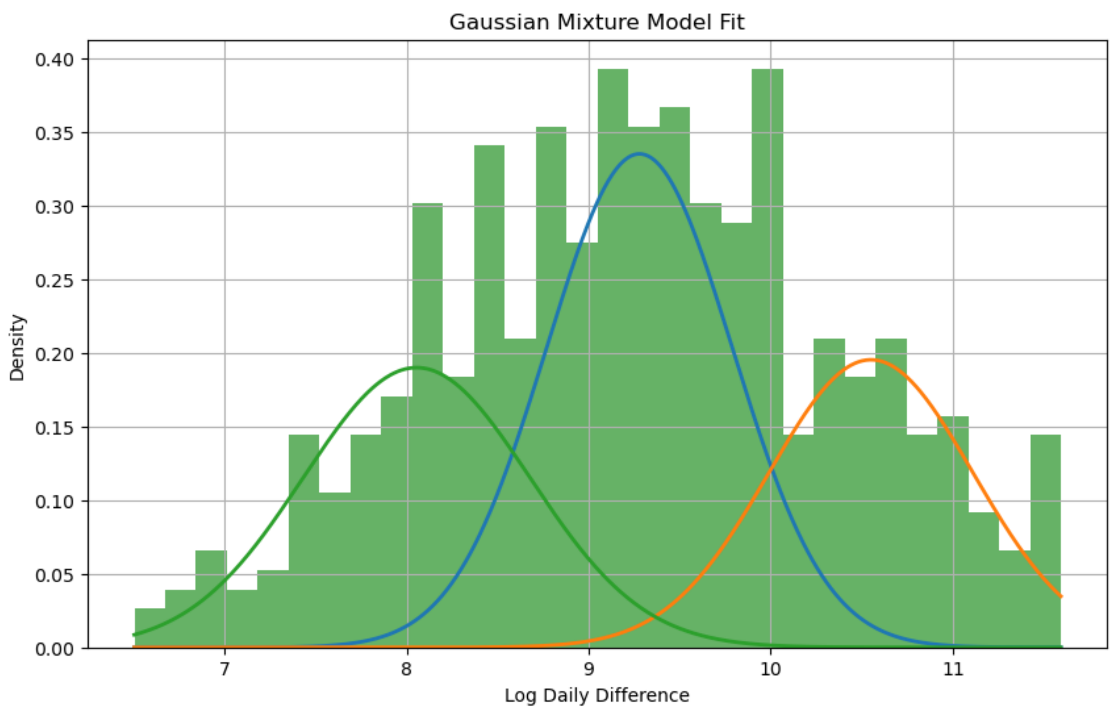
[ ]:
```
from scipy.stats import gaussian_kde

# Flatten the DataFrame to a 1D array
log_concentrations = log_dist.values.flatten()

# Remove NaN and infinite values from the flattened array
cleaned_log_concentrations = log_concentrations[np.isfinite(log_concentrations)]

plt.hist(cleaned_log_concentrations, bins=30, density=True, alpha=0.6,␣
 ↪color='g')

# Create the density plot
plt.figure(figsize=(12, 6))
density = gaussian_kde(cleaned_log_concentrations)
xs = np.linspace(min(cleaned_log_concentrations),␣
 ↪max(cleaned_log_concentrations), 200)
density_values = density(xs)

plt.plot(xs, density_values, label='Density', color='blue')
plt.xlabel('log(ΔN2.5-5nm)')
plt.ylabel('Density')
plt.title('Density Plot of Log-Concentration Values')
plt.legend()

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





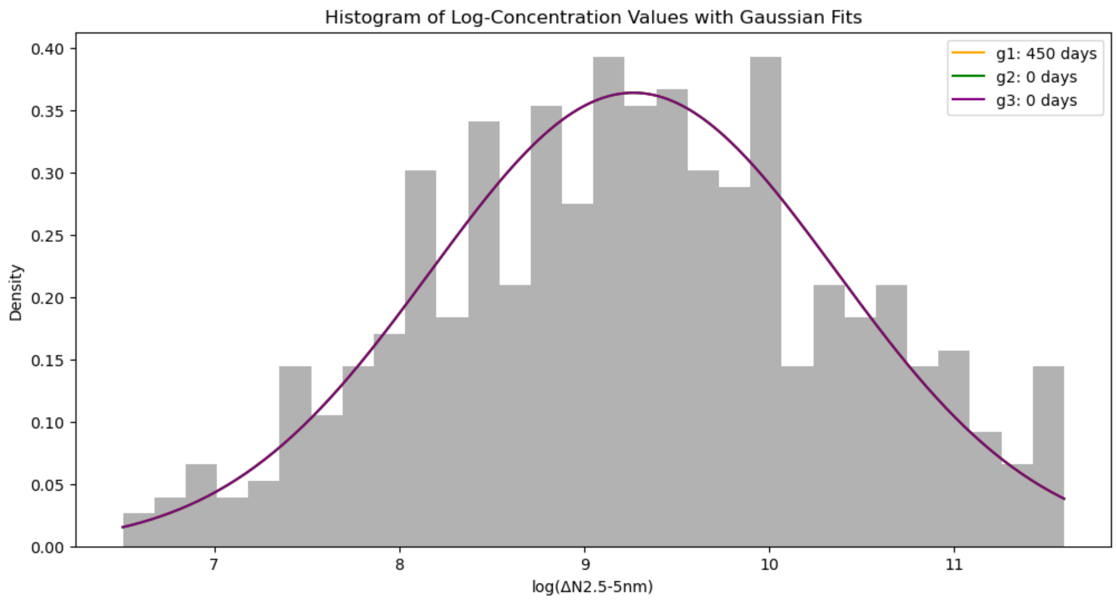
[ ]:
```
from scipy.stats import norm
from sklearn.mixture import GaussianMixture
```

```python
cleaned_values = cleaned_log_concentrations.reshape(-1, 1)

# Fit a Gaussian Mixture Model with 3 components
gmm = GaussianMixture(n_components=3)
gmm.fit(cleaned_values)

# Get the means and covariances of the fitted Gaussians
means = gmm.means_.flatten()
covariances = gmm.covariances_.flatten()
weights = gmm.weights_

# Plot the histogram and the fitted Gaussians
plt.figure(figsize=(10, 6))
plt.hist(cleaned_values, bins=30, density=True, alpha=0.6, color='g')

# Plot each Gaussian component
x = np.linspace(cleaned_values.min(), cleaned_values.max(), 1000)
for mean, covar, weight in zip(means, covariances, weights):
    plt.plot(x, weight * norm.pdf(x, mean, np.sqrt(covar)), linewidth=2)

plt.title('Gaussian Mixture Model Fit')
plt.xlabel('Log Daily Difference')
plt.ylabel('Density')
plt.grid(True)
plt.show()
```



[ ]:
```python
# Fit Gaussian distributions to the data
params1 = norm.fit(cleaned_values)
params2 = norm.fit(cleaned_values)
params3 = norm.fit(cleaned_values)

# Assign each data point to the closest Gaussian mode
def closest_gaussian(log_value, params_list):
    pdf_values = [norm.pdf(log_value, *params) for params in params_list]
    return np.argmax(pdf_values)

# Assign each data point to a Gaussian mode
gaussian_modes = [params1, params2, params3]
mode_assignments = [closest_gaussian(x, gaussian_modes) for x in cleaned_values]

# Count frequencies for each mode
unique, counts = np.unique(mode_assignments, return_counts=True)
mode_frequencies = dict(zip(unique, counts))

# Plot the histogram and Gaussian fits
plt.figure(figsize=(12, 6))
plt.hist(cleaned_values, bins=30, density=True, alpha=0.6, color='gray')

# Plot the Gaussian fits
xs = np.linspace(min(cleaned_values), max(cleaned_values), 200)
pdf1 = norm.pdf(xs, *params1)
pdf2 = norm.pdf(xs, *params2)
pdf3 = norm.pdf(xs, *params3)

plt.plot(xs, pdf1, label=f'g1: {mode_frequencies.get(0, 0)} days',␣
 ↪color='orange')
plt.plot(xs, pdf2, label=f'g2: {mode_frequencies.get(1, 0)} days',␣
 ↪color='green')
plt.plot(xs, pdf3, label=f'g3: {mode_frequencies.get(2, 0)} days',␣
 ↪color='purple')

plt.xlabel('log(ΔN2.5-5nm)')
plt.ylabel('Density')
plt.title('Histogram of Log-Concentration Values with Gaussian Fits')
plt.legend()

# Show the plot
plt.show()

# Print the number of data points assigned to each Gaussian mode
```

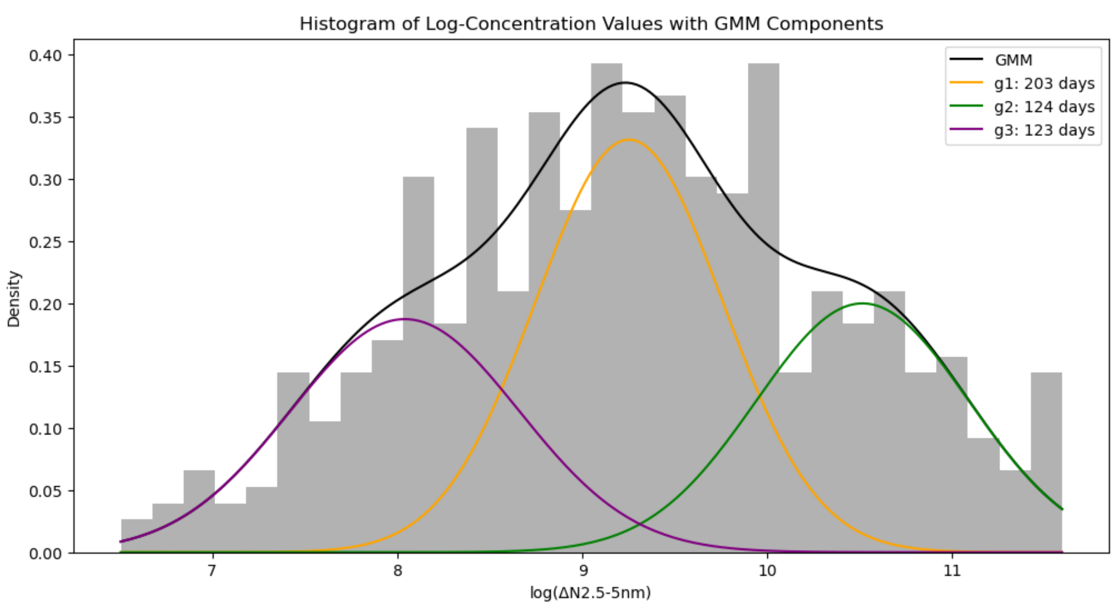
```
print(f'Number of data points in g1: {mode_frequencies.get(0, 0)}')
print(f'Number of data points in g2: {mode_frequencies.get(1, 0)}')
print(f'Number of data points in g3: {mode_frequencies.get(2, 0)}')
```




```
Number of data points in g1: 450
Number of data points in g2: 0
Number of data points in g3: 0
```

[ ]:
```
# Fit Gaussian distributions to the data

# Fit a Gaussian Mixture Model with 3 components
gmm = GaussianMixture(n_components=3, random_state=0)
gmm.fit(cleaned_values)

# Predict the component for each data point
gmm_labels = gmm.predict(cleaned_values)

# Count the number of data points in each component
unique, counts = np.unique(gmm_labels, return_counts=True)
component_frequencies = dict(zip(unique, counts))

# Plot the histogram and Gaussian Mixture Model fits
plt.figure(figsize=(12, 6))
plt.hist(cleaned_values, bins=30, density=True, alpha=0.6, color='gray')

# Plot the GMM components
xs = np.linspace(min(cleaned_values), max(cleaned_values), 200).reshape(-1, 1)
```

```
logprob = gmm.score_samples(xs)
responsibilities = gmm.predict_proba(xs)
pdf = np.exp(logprob)
pdf_individual = responsibilities * pdf[:, np.newaxis]

plt.plot(xs, pdf, label='GMM', color='black')
colors = ['orange', 'green', 'purple']
for i in range(3):
    plt.plot(xs, pdf_individual[:, i], label=f'g{i+1}: {component_frequencies.
 ↪get(i, 0)} days', color=colors[i])

plt.xlabel('log(ΔN2.5-5nm)')
plt.ylabel('Density')
plt.title('Histogram of Log-Concentration Values with GMM Components')
plt.legend()

# Show the plot
plt.show()

# Print the number of data points assigned to each GMM component
print(f'Number of data points in g1: {component_frequencies.get(0, 0)}')
print(f'Number of data points in g2: {component_frequencies.get(1, 0)}')
print(f'Number of data points in g3: {component_frequencies.get(2, 0)}')
```




```
Number of data points in g1: 203
Number of data points in g2: 124
Number of data points in g3: 123
```

[ ]:
```python
# Store the values in separate arrays based on their assigned components
component_1_values = cleaned_log_concentrations[gmm_labels == 0]
component_2_values = cleaned_log_concentrations[gmm_labels == 1]
component_3_values = cleaned_log_concentrations[gmm_labels == 2]

# Optionally, return the component values as arrays for further analysis
component_1_values, component_2_values, component_3_values
```

[ ]:
```
(array([8.63443979, 8.74944405, 8.76683424, 8.90689319, 9.08467892,
        8.57855098, 8.92991609, 9.11069734, 9.02192097, 8.80854135,
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        9.47865032, 9.63007783, 9.75821366, 8.84011738, 9.0574464 ,
        9.31868351, 9.54574423, 9.7094789 , 9.78183755, 9.8898115 ,
        9.92489859, 8.66756225, 8.89284697, 9.08360382, 9.1701003 ,
        9.22322941, 9.20883014, 9.17694054, 9.1962412 , 9.92322334,
        8.62356909, 8.68762952, 8.68992649, 8.81764658, 8.6547543 ,
        8.78358192, 9.07989423, 9.35468069, 9.500336  , 9.60114218,
        9.64177362, 9.74039772, 9.82246662, 8.68823573, 9.06740189,
        9.39003826, 9.56475395, 9.76646926, 9.91540035, 8.61253855,
        8.80880884, 8.72771331, 8.94240316, 9.06464781, 9.2281534 ,
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        9.05965546, 9.44687739, 9.80072691, 8.57748813, 8.82425371,
        9.08822335, 9.26850749, 9.43340965, 9.51865957, 9.68400145,
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        9.20810385, 8.92824747, 9.11259914, 9.3246638 , 9.46685499,
        9.65764528, 9.71432175, 9.7973214 , 9.87098839, 9.93977828,
        9.91471741, 9.26259219, 9.23044846, 9.08417894, 8.98224713,
        8.89431162, 8.76505169, 8.59785667, 8.78731879, 8.87381361,
        9.49978749, 9.76137931, 9.58069431, 9.63455796, 9.71360984,
        9.76169582, 9.73994081, 9.60583591, 9.57246927, 9.52126025,
        9.41588077, 9.33031438, 8.57896079, 8.76847648, 8.8866887 ,
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        8.73929978, 8.71402142, 8.77695746, 9.05316471, 9.25537963,
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        9.91009125, 9.95781992, 9.80038832, 9.92701723, 8.7434571 ,
        8.97727428, 9.11130489, 9.25543335, 9.24998422, 9.32459687,
```

```
       9.2896405 , 8.94817562, 9.18855061, 9.34887695, 9.43434284,
       9.45811115, 9.56001248, 9.79248772]),
array([11.57740938, 11.53065214, 11.49283127, 11.47205761, 11.44932218,
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       10.31228612, 10.43283425, 10.64178887, 10.8109902 , 10.89718618,
       10.920172  , 10.83790566, 10.65076554, 10.69013423, 10.65881357,
        9.95935129, 10.14976745,  9.96443135, 10.00451601, 10.0435037 ,
       10.1334536 ,  9.99688616, 10.18315553, 10.3962638 , 10.56839697,
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       11.10156741, 11.16831303, 11.13051443, 11.03558501, 10.9630984 ,
       10.3656057 , 10.62020339, 10.92637047, 11.20568454, 11.34335013,
       11.35333161, 11.40954304, 11.45814409, 11.56022485, 11.59382539,
        9.98393872, 10.06243796, 10.0068828 ,  9.99418151,  9.98227614,
       10.12749242, 10.05362318, 10.15267025, 10.25367642, 10.27293144,
       10.06052456, 10.36411454, 10.65188437, 10.82233823, 10.96307523,
       11.08367199, 11.11240237, 11.08657181, 10.1074528 , 10.22362274,
       10.30997549, 10.36115647, 10.10873522, 10.41287184, 10.67293569,
       10.8360595 , 10.92904555, 10.95961801, 10.94522411, 10.90976006,
       10.00471853, 10.20961595, 10.33916061, 10.44666323, 10.57657629,
       10.65046103, 10.68604137, 10.01153   , 10.28993671, 10.48767275,
       10.64768518, 10.83789792, 10.93224868, 11.04555242, 11.10118552,
       10.23767201, 10.50847826, 10.61863378, 10.60562808, 10.00443952,
        9.98370209, 10.12950149, 10.44421947, 10.54482321, 10.55477086,
       10.56665583, 10.57225997, 10.01719572, 10.27761167, 10.43912296,
       10.56484695, 10.68501834, 10.8113923 , 10.88347453]),
array([7.03374469, 7.37954065, 7.46969442, 7.5626315 , 8.20620527,
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       8.5042454 , 8.12323332, 7.92550296, 7.96228044, 7.62091746,
       8.41350512, 8.51847442, 7.1589342 , 7.4418142 , 7.81516896,
       8.05220186, 8.20666408, 8.37132699, 8.52659226, 8.14374154,
       8.39444835, 6.99116119, 7.5187262 , 7.71102229, 7.9738198 ,
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       7.36789136, 7.68537552, 8.30854096, 7.74793792, 7.7851036 ,
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       6.56219525, 6.50486074, 7.01009733, 7.50387937, 7.80281136,
```
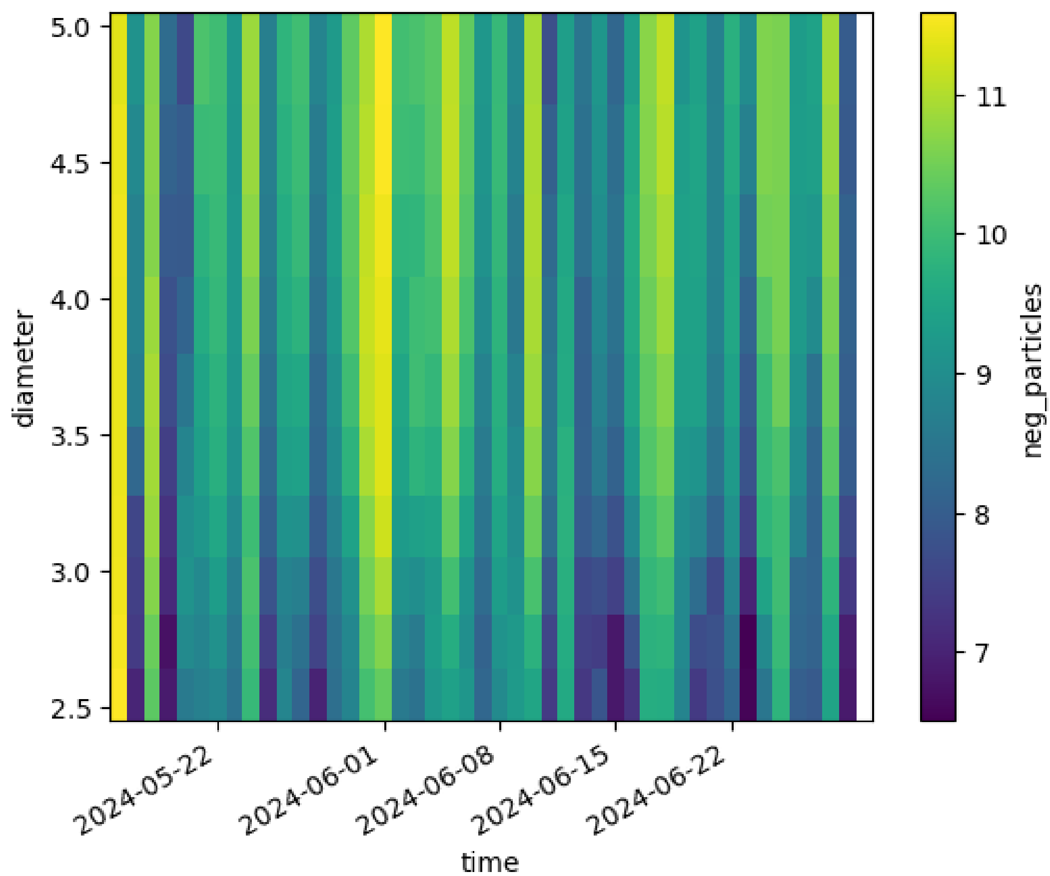

```
7.94100514, 8.14201884, 8.41703139, 8.50727461, 8.02467137,
8.20347682, 8.25168689, 7.92550629, 8.10138664, 8.13613744,
8.12907972, 8.1883809 , 8.41570425, 6.85240702, 6.93984696,
7.35080474, 7.64828896, 7.96181885, 8.03132577, 8.10175271,
8.09361532, 7.92586777, 7.9695777 ]))
```

[ ]:
```
log_dist.T.plot()
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a414744d0>



The intensity of NPF events is assessed within each group by plotting the diurnal median particle number size distribution so that both visual and statistical inspections of the diurnal variation of N2.5—5 can be performed for each group.

[ ]:
```
# we need to divide the N2.5-5 data into the 3 Gaussian curves
# the data is
ds_2p5_5nm.dropna(dim='time')
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 1006, diameter: 10)>
array([[     0.       ,      0.       ,      0.       , …, -12501.354266,
        -12938.894476, -12066.822736],
       [   793.892923,    754.034221,    796.312492, …,    251.292195,
           339.285557,    376.718538],
       [   246.057416,    344.544083,    461.096684, …,    342.721602,
           338.92016 ,    341.944488],
       …,
       [   627.608706,    658.406955,   1047.195848, …,   3695.756149,
          4314.862024,   4575.879331],
       [   252.848542,    494.867587,    404.279244, …,   1220.205738,
          1611.609949,   1944.126849],
       [   510.434755,    471.272613,    484.89185 , …,    916.23926 ,
          1141.077917,   1418.255486]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16T07:00:00 … 2024-06-30
Attributes:
    units:         cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

[ ]:
```
gmm_labels
```

[ ]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0,
       0, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       2, 2, 0, 0, 0, 0, 0, 0, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 2, 2,
       2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 2, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1,
       2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2,
       2, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 2, 2, 0, 0,
       0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 2, 0, 0, 0, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 0, 0, 0, 0, 0,
       0, 0, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

[ ]:
```
new = gmm_labels.reshape(45,10)
new
```

```
[ ]: array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
           [2, 2, 2, 2, 2, 0, 0, 0, 0, 0],
           [1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
           [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
           [0, 0, 0, 0, 0, 2, 2, 2, 2, 2],
           [0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
           [0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
           [2, 2, 0, 0, 0, 0, 0, 0, 0, 0],
           [0, 1, 1, 1, 1, 1, 1, 1, 1, 1],
           [2, 2, 2, 2, 2, 2, 2, 0, 0, 0],
           [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
           [2, 2, 0, 0, 0, 0, 0, 0, 1, 1],
           [2, 2, 2, 2, 2, 2, 2, 2, 0, 0],
           [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
           [0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
           [1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
           [1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
           [0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
           [2, 0, 0, 0, 0, 1, 1, 0, 1, 1],
           [0, 0, 0, 0, 0, 0, 1, 1, 1, 1],
           [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
           [0, 0, 0, 0, 0, 0, 1, 1, 1, 1],
           [2, 2, 2, 2, 0, 0, 0, 0, 0, 0],
           [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
           [0, 0, 0, 0, 0, 0, 2, 0, 0, 0],
           [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
           [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
           [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
           [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
           [2, 2, 2, 2, 0, 0, 0, 0, 0, 0],
           [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
           [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
           [0, 0, 0, 1, 1, 1, 1, 1, 1, 1],
           [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
           [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
           [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
           [2, 2, 2, 2, 2, 0, 0, 0, 0, 0],
           [2, 2, 0, 0, 0, 0, 0, 0, 0, 0],
           [2, 2, 2, 2, 2, 2, 2, 2, 0, 0],
           [2, 0, 0, 0, 0, 0, 1, 1, 1, 1],
           [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
           [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
           [2, 2, 2, 2, 2, 2, 0, 0, 0, 0],
           [0, 0, 0, 1, 1, 1, 1, 1, 1, 1],
           [2, 2, 2, 2, 2, 2, 2, 2, 2, 2]])
```

[ ]:
```
times = log_dist2.time
diameters = log_dist2.diameter

# Create the DataArray
data_array = xr.DataArray(new, coords=[times, diameters], dims=['time',␣
 ↪'diameter'])
data_array
```

[ ]:
```
<xarray.DataArray (time: 45, diameter: 10)>
array([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [2, 2, 2, 2, 2, 0, 0, 0, 0, 0],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
       [2, 2, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [2, 2, 2, 2, 2, 2, 2, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [2, 2, 0, 0, 0, 0, 0, 0, 1, 1],
       [2, 2, 2, 2, 2, 2, 2, 2, 0, 0],
       [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
       [2, 0, 0, 0, 0, 1, 1, 0, 1, 1],
       [0, 0, 0, 0, 0, 0, 1, 1, 1, 1],
…
       [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
       [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
       [2, 2, 2, 2, 0, 0, 0, 0, 0, 0],
       [2, 2, 2, 2, 2, 2, 2, 2, 2, 2],
       [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1],
       [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
       [2, 2, 2, 2, 2, 0, 0, 0, 0, 0],
       [2, 2, 0, 0, 0, 0, 0, 0, 0, 0],
       [2, 2, 2, 2, 2, 2, 2, 2, 0, 0],
       [2, 0, 0, 0, 0, 0, 1, 1, 1, 1],
       [0, 0, 1, 1, 1, 1, 1, 1, 1, 1],
       [2, 2, 2, 0, 0, 0, 0, 0, 0, 0],
```

```
       [2, 2, 2, 2, 2, 2, 0, 0, 0, 0],
       [0, 0, 0, 1, 1, 1, 1, 1, 1, 1],
       [2, 2, 2, 2, 2, 2, 2, 2, 2, 2]])
Coordinates:
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-29
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
```

[ ]:
```
# Add the components to the original DataArray for easier selection
#component_labels = xr.DataArray(components, coords=[log_daily_diff.time],␣
↪dims=['time'])
#neg_particles = neg_particles.sel(time=log_daily_diff.time)  # Filter the␣
↪DataArray to match the time coordinates of log_daily_diff
#neg_particles = neg_particles.assign_coords(component=component_labels)

test = ds_2p5_5nm.sel(time=log_dist2.time)
```

[ ]:
```
# Function to create subsets for each group
def get_group_subset(test, data_array, group_number):
    return test.where(data_array == group_number, drop=True)

# Create subsets for each group
group_0_data = get_group_subset(test, data_array, 0)
group_1_data = get_group_subset(test, data_array, 1)
group_2_data = get_group_subset(test, data_array, 2)
```

[ ]:
```
group_0_data.dropna(dim='time').T.plot()
```

[ ]:
```
<matplotlib.collections.QuadMesh at 0x790a3d227190>
```

```
Error in callback <function _draw_all_if_interactive at 0x790a587b5b20> (for
post_execute), with arguments args (),kwargs {}:
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
File ~/anaconda3/lib/python3.11/site-packages/matplotlib/pyplot.py:197, in␣
↪_draw_all_if_interactive()
    195 def _draw_all_if_interactive() -> None:
    196     if matplotlib.is_interactive():
--> 197         draw_all()

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/_pylab_helpers.py:132,␣
↪in Gcf.draw_all(cls, force)
    130 for manager in cls.get_all_fig_managers():
    131     if force or manager.canvas.figure.stale:
--> 132         manager.canvas.draw_idle()
```

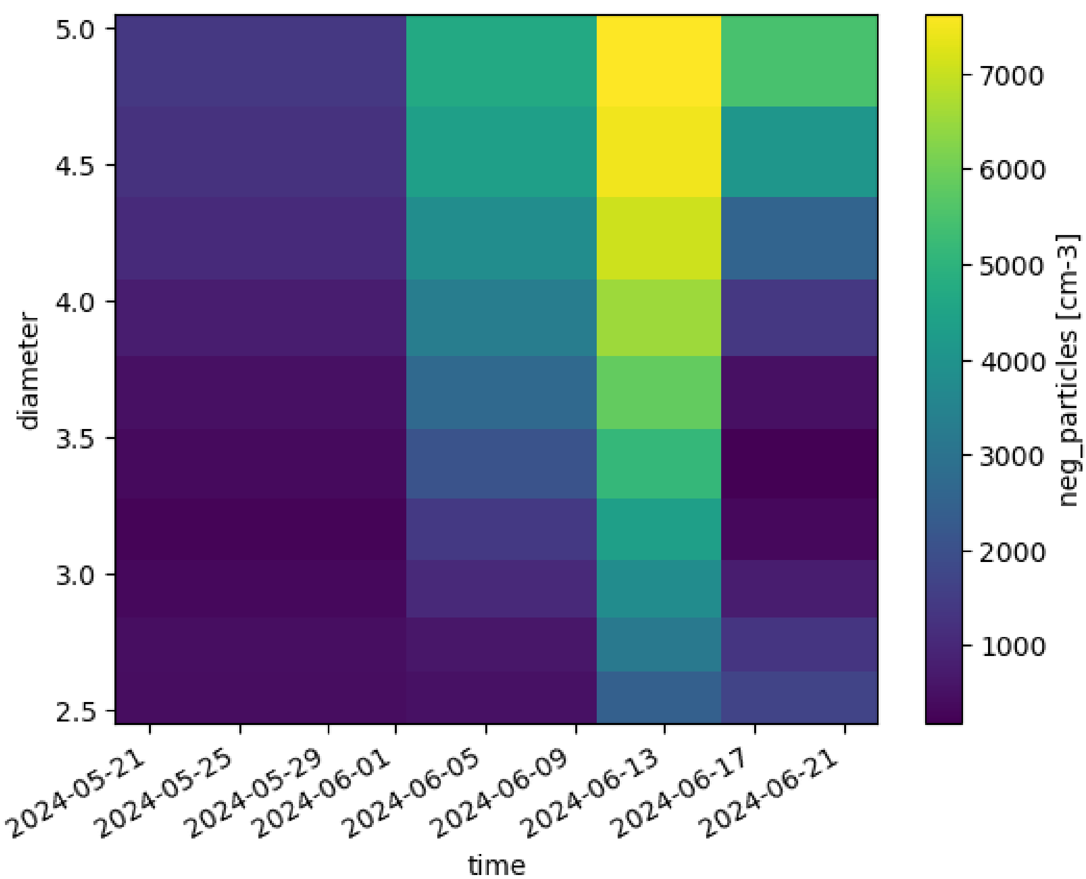
```
File ~/anaconda3/lib/python3.11/site-packages/matplotlib/backend_bases.py:1893, in FigureCanvasBase.draw_idle(self, *args, **kwargs)
   1891 if not self._is_idle_drawing:
   1892     with self._idle_draw_cntx():
-> 1893         self.draw(*args, **kwargs)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/backends/backend_agg.py:388, in FigureCanvasAgg.draw(self)
    385 # Acquire a lock on the shared font cache.
    386 with (self.toolbar._wait_cursor_for_draw_cm() if self.toolbar
    387       else nullcontext()):
--> 388     self.figure.draw(self.renderer)
    389     # A GUI class may be need to update a window using this draw, so
    390     # don't forget to call the superclass.
    391     super().draw()

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/artist.py:95, in _finalize_rasterization.<locals>.draw_wrapper(artist, renderer, *args, **kwargs)
     93 @wraps(draw)
     94 def draw_wrapper(artist, renderer, *args, **kwargs):
---> 95     result = draw(artist, renderer, *args, **kwargs)
     96     if renderer._rasterizing:
     97         renderer.stop_rasterizing()

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/artist.py:72, in allow_rasterization.<locals>.draw_wrapper(artist, renderer)
     69     if artist.get_agg_filter() is not None:
     70         renderer.start_filter()
---> 72     return draw(artist, renderer)
     73 finally:
     74     if artist.get_agg_filter() is not None:

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/figure.py:3154, in Figure.draw(self, renderer)
   3151         # ValueError can occur when resizing a window.
   3153 self.patch.draw(renderer)
-> 3154 mimage._draw_list_compositing_images(
   3155     renderer, self, artists, self.suppressComposite)
   3157 for sfig in self.subfigs:
   3158     sfig.draw(renderer)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/image.py:132, in _draw_list_compositing_images(renderer, parent, artists, suppress_composite)
    130 if not_composite or not has_images:
    131     for a in artists:
--> 132         a.draw(renderer)
    133 else:
```

```
    134     # Composite any adjacent images together
    135     image_group = []

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/artist.py:72, in␣
 ↪allow_rasterization.<locals>.draw_wrapper(artist, renderer)
     69     if artist.get_agg_filter() is not None:
     70         renderer.start_filter()
---> 72     return draw(artist, renderer)
     73 finally:
     74     if artist.get_agg_filter() is not None:

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axes/_base.py:3070, in␣
 ↪_AxesBase.draw(self, renderer)
   3067 if artists_rasterized:
   3068     _draw_rasterized(self.figure, artists_rasterized, renderer)
-> 3070 mimage._draw_list_compositing_images(
   3071     renderer, self, artists, self.figure.suppressComposite)
   3073 renderer.close_group('axes')
   3074 self.stale = False

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/image.py:132, in␣
 ↪_draw_list_compositing_images(renderer, parent, artists, suppress_composite)
    130 if not_composite or not has_images:
    131     for a in artists:
--> 132         a.draw(renderer)
    133 else:
    134     # Composite any adjacent images together
    135     image_group = []

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/artist.py:72, in␣
 ↪allow_rasterization.<locals>.draw_wrapper(artist, renderer)
     69     if artist.get_agg_filter() is not None:
     70         renderer.start_filter()
---> 72     return draw(artist, renderer)
     73 finally:
     74     if artist.get_agg_filter() is not None:

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:1387, in Axis.
 ↪draw(self, renderer, *args, **kwargs)
   1384     return
   1385 renderer.open_group(__name__, gid=self.get_gid())
-> 1387 ticks_to_draw = self._update_ticks()
   1388 tlb1, tlb2 = self._get_ticklabel_bboxes(ticks_to_draw, renderer)
   1390 for tick in ticks_to_draw:

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:1277, in Axis.
 ↪_update_ticks(self)
   1275 major_locs = self.get_majorticklocs()
```

```
   1276 major_labels = self.major.formatter.format_ticks(major_locs)
-> 1277 major_ticks = self.get_major_ticks(len(major_locs))
   1278 for tick, loc, label in zip(major_ticks, major_locs, major_labels):
   1279     tick.update_position(loc)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:1626, in Axis.
↪get_major_ticks(self, numticks)
   1622     numticks = len(self.get_majorticklocs())
   1624 while len(self.majorTicks) < numticks:
   1625     # Update the new tick label properties from the old.
-> 1626     tick = self._get_tick(major=True)
   1627     self.majorTicks.append(tick)
   1628     self._copy_tick_props(self.majorTicks[0], tick)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:1562, in Axis.
↪_get_tick(self, major)
   1558     raise NotImplementedError(
   1559         f"The Axis subclass {self.__class__.__name__} must define "
   1560         "_tick_class or reimplement _get_tick()")
   1561 tick_kw = self._major_tick_kw if major else self._minor_tick_kw
-> 1562 return self._tick_class(self.axes, 0, major=major, **tick_kw)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:470, in YTick.
↪__init__(self, *args, **kwargs)
    469 def __init__(self, *args, **kwargs):
--> 470     super().__init__(*args, **kwargs)
    471     # x in axes coords, y in data coords
    472     ax = self.axes

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:187, in Tick.
↪__init__(self, axes, loc, size, width, color, tickdir, pad, labelsize,␣
↪labelcolor, labelfontfamily, zorder, gridOn, tick1On, tick2On, label1On,␣
↪label2On, major, labelrotation, grid_color, grid_linestyle, grid_linewidth,␣
↪grid_alpha, **kwargs)
    178 self.label1 = mtext.Text(
    179     np.nan, np.nan,
    180     fontsize=labelsize, color=labelcolor, visible=label1On,
    181     fontfamily=labelfontfamily, rotation=self._labelrotation[1])
    182 self.label2 = mtext.Text(
    183     np.nan, np.nan,
    184     fontsize=labelsize, color=labelcolor, visible=label2On,
    185     fontfamily=labelfontfamily, rotation=self._labelrotation[1])
--> 187 self._apply_tickdir(tickdir)
    189 for artist in [self.tick1line, self.tick2line, self.gridline,
    190                self.label1, self.label2]:
    191     self._set_artist_props(artist)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/axis.py:505, in YTick.
↪_apply_tickdir(self, tickdir)
```

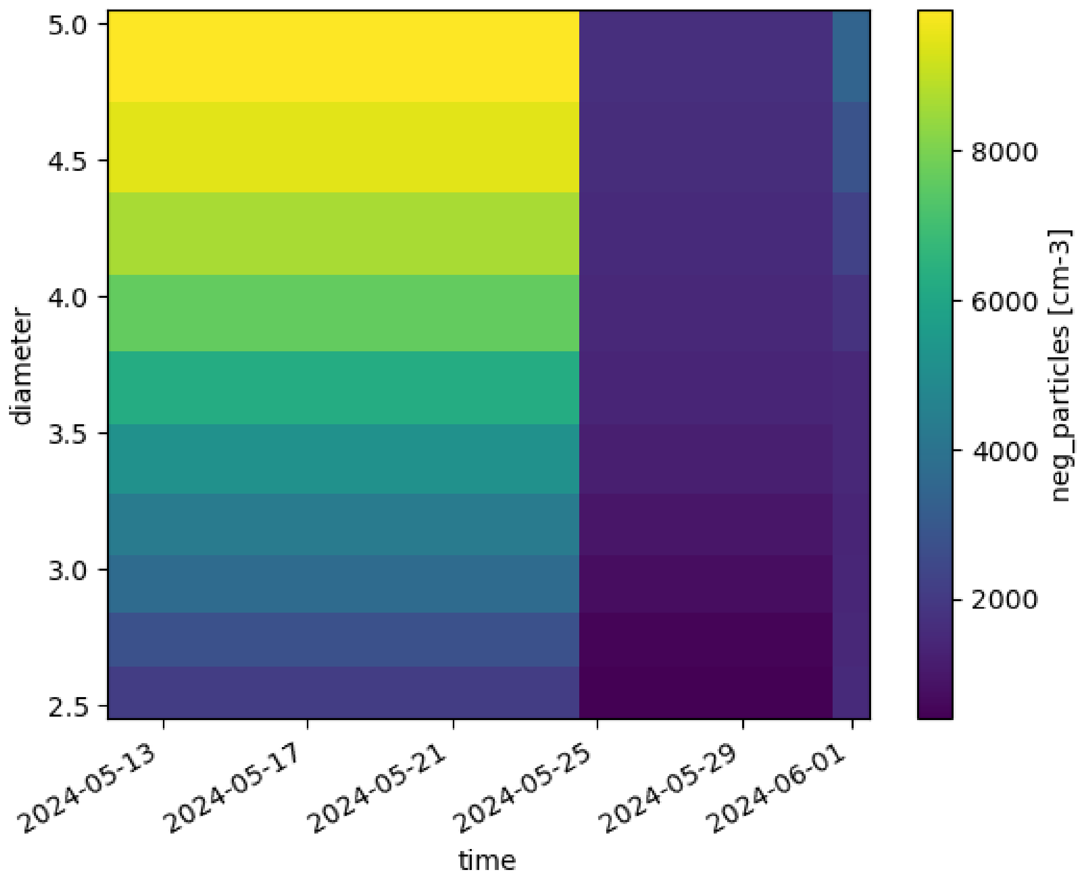
```
    499 super()._apply_tickdir(tickdir)
    500 mark1, mark2 = {
    501     'out': (mlines.TICKLEFT, mlines.TICKRIGHT),
    502     'in': (mlines.TICKRIGHT, mlines.TICKLEFT),
    503     'inout': ('_', '_'),
    504 }[self._tickdir]
--> 505 self.tick1line.set_marker(mark1)
    506 self.tick2line.set_marker(mark2)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/lines.py:1194, in Line2D.set_marker(self, marker)
   1183 @_docstring.interpd
   1184 def set_marker(self, marker):
   1185     """
   1186     Set the line marker.
   1187
   (…)
   1192         arguments.
   1193     """
-> 1194     self._marker = MarkerStyle(marker, self._marker.get_fillstyle())
   1195     self.stale = True

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/markers.py:255, in MarkerStyle.__init__(self, marker, fillstyle, transform, capstyle, joinstyle)
    253 self._user_joinstyle = JoinStyle(joinstyle) if joinstyle is not None else None
    254 self._set_fillstyle(fillstyle)
--> 255 self._set_marker(marker)

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/markers.py:343, in MarkerStyle._set_marker(self, marker)
    341 if not isinstance(marker, MarkerStyle):
    342     self._marker = marker
--> 343     self._recache()

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/markers.py:271, in MarkerStyle._recache(self)
    267 # Initial guess: Assume the marker is filled unless the fillstyle is
    268 # set to 'none'. The marker function will override this for unfilled
    269 # markers.
    270 self._filled = self._fillstyle != 'none'
--> 271 self._marker_function()

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/markers.py:766, in MarkerStyle._set_tickleft(self)
    765 def _set_tickleft(self):
--> 766     self._transform = Affine2D().scale(-1.0, 1.0)
    767     self._snap_threshold = 1.0
```

```
    768     self._filled = False

File ~/anaconda3/lib/python3.11/site-packages/matplotlib/transforms.py:1903, in
 ↪Affine2D.__init__(self, matrix, **kwargs)
   1900 if matrix is None:
   1901     # A bit faster than np.identity(3).
   1902     matrix = IdentityTransform._mtx
-> 1903 self._mtx = matrix.copy()
   1904 self._invalid = 0

KeyboardInterrupt:
```



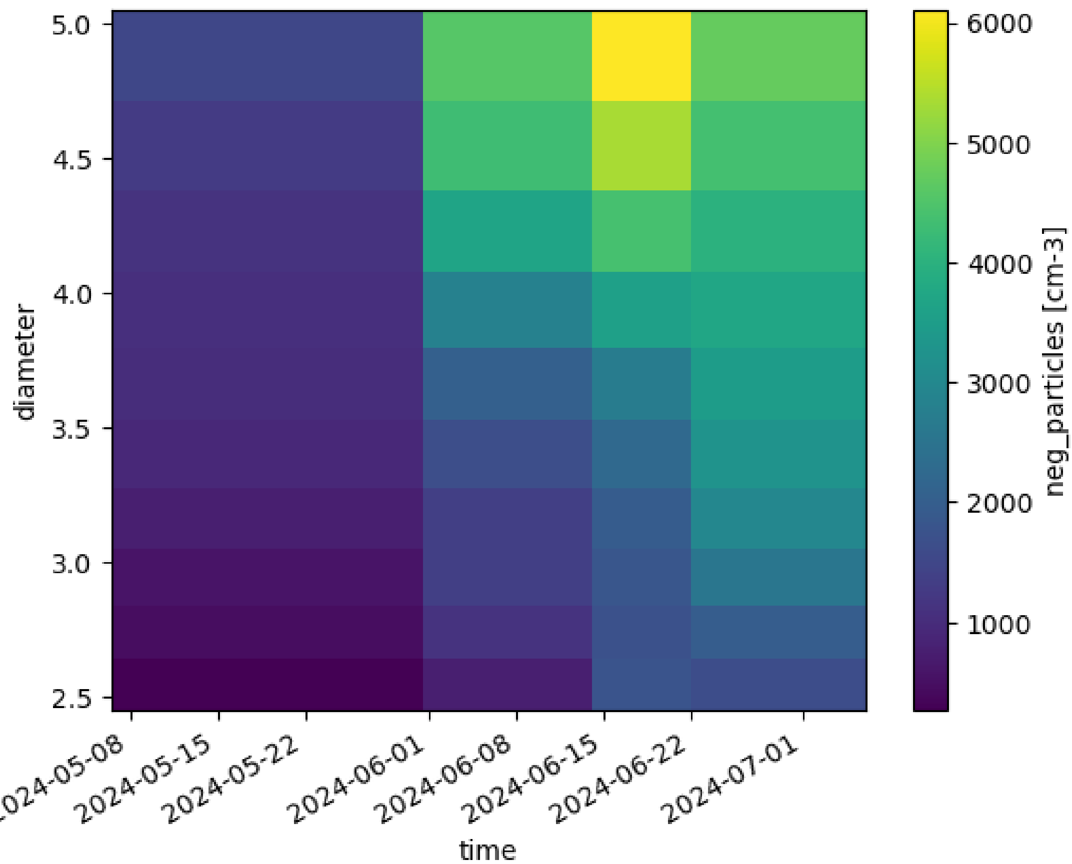
[ ]:
```
group_1_data.dropna(dim='time').T.plot()
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a3d280fd0>



[ ]:
```
group_2_data.dropna(dim='time').T.plot()
```

[ ]: <matplotlib.collections.QuadMesh at 0x790a2a007b10>




```
[ ]: group_0_data
```

```
[ ]: <xarray.DataArray 'time' (time: 24)>
array(['2024-05-17T00:00:00.000000000', '2024-05-19T00:00:00.000000000',
       '2024-05-20T00:00:00.000000000', '2024-05-23T00:00:00.000000000',
       '2024-05-25T00:00:00.000000000', '2024-05-27T00:00:00.000000000',
       '2024-05-28T00:00:00.000000000', '2024-05-29T00:00:00.000000000',
       '2024-06-03T00:00:00.000000000', '2024-06-07T00:00:00.000000000',
       '2024-06-09T00:00:00.000000000', '2024-06-11T00:00:00.000000000',
       '2024-06-13T00:00:00.000000000', '2024-06-14T00:00:00.000000000',
       '2024-06-15T00:00:00.000000000', '2024-06-16T00:00:00.000000000',
       '2024-06-20T00:00:00.000000000', '2024-06-21T00:00:00.000000000',
       '2024-06-22T00:00:00.000000000', '2024-06-23T00:00:00.000000000',
       '2024-06-24T00:00:00.000000000', '2024-06-26T00:00:00.000000000',
       '2024-06-27T00:00:00.000000000', '2024-06-29T00:00:00.000000000'],
      dtype='datetime64[ns]')
Coordinates:
  * time     (time) datetime64[ns] 2024-05-17 2024-05-19 … 2024-06-29
Attributes:
```

```
timezone:  utc
```

[ ]:
```python
import xarray as xr
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Create sample DataArrays for demonstration
times = pd.date_range('2020-01-01', periods=46, freq='D')
diameters = np.linspace(1e-9, 10e-9, 10)
neg_particles_data = np.random.rand(46, 10)
group_values = np.random.choice([0, 1, 2], size=(46, 10))

# Create DataArrays
neg_particles = xr.DataArray(neg_particles_data, coords=[times, diameters],␣
↪dims=['time', 'diameter'])
group_array = xr.DataArray(group_values, coords=[times, diameters],␣
↪dims=['time', 'diameter'])

# Function to create subsets for each group
def get_group_subset(neg_particles, group_array, group_number):
    return neg_particles.where(group_array == group_number, drop=True)

# Create subsets for each group
group_0_data = get_group_subset(neg_particles, group_array, 0)
group_1_data = get_group_subset(neg_particles, group_array, 1)
group_2_data = get_group_subset(neg_particles, group_array, 2)
```

[ ]:
```python
# Function to calculate daily median and IQR
def calculate_daily_statistics(data_array):
    daily_median = data_array.resample(time='1D').median(dim=['time',␣
↪'diameter'])
    daily_q25 = data_array.resample(time='1D').quantile(0.25, dim=['time',␣
↪'diameter'])
    daily_q75 = data_array.resample(time='1D').quantile(0.75, dim=['time',␣
↪'diameter'])
    return daily_median, daily_q25, daily_q75

# Calculate daily statistics for each group
group_0_median, group_0_q25, group_0_q75 =␣
↪calculate_daily_statistics(group_0_data)
group_1_median, group_1_q25, group_1_q75 =␣
↪calculate_daily_statistics(group_1_data)
group_2_median, group_2_q25, group_2_q75 =␣
↪calculate_daily_statistics(group_2_data)
```

```python
# Plotting function
def plot_daily_statistics(time, median, q25, q75, group_number):
    plt.fill_between(time, q25, q75, alpha=0.3, label=f'Group {group_number}␣
↪IQR')
    plt.plot(time, median, label=f'Group {group_number} Median')
    plt.xlabel('Time')
    plt.ylabel('Concentration')
    plt.title(f'Daily Median and IQR for Group {group_number}')
    plt.legend()

# Plot the results
plt.figure(figsize=(12, 8))

plt.subplot(3, 1, 1)
plot_daily_statistics(group_0_median.time, group_0_median, group_0_q25,␣
↪group_0_q75, 0)

plt.subplot(3, 1, 2)
plot_daily_statistics(group_1_median.time, group_1_median, group_1_q25,␣
↪group_1_q75, 1)

plt.subplot(3, 1, 3)
plot_daily_statistics(group_2_median.time, group_2_median, group_2_q25,␣
↪group_2_q75, 2)

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

```
/home/coliewo/anaconda3/lib/python3.11/site-
packages/numpy/lib/nanfunctions.py:1545: RuntimeWarning: All-NaN slice
encountered
  return _nanquantile_unchecked(
/home/coliewo/anaconda3/lib/python3.11/site-
packages/numpy/lib/nanfunctions.py:1545: RuntimeWarning: All-NaN slice
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/home/coliewo/anaconda3/lib/python3.11/site-
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/home/coliewo/anaconda3/lib/python3.11/site-
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encountered
  return _nanquantile_unchecked(
/home/coliewo/anaconda3/lib/python3.11/site-
packages/numpy/lib/nanfunctions.py:1545: RuntimeWarning: All-NaN slice
encountered
```
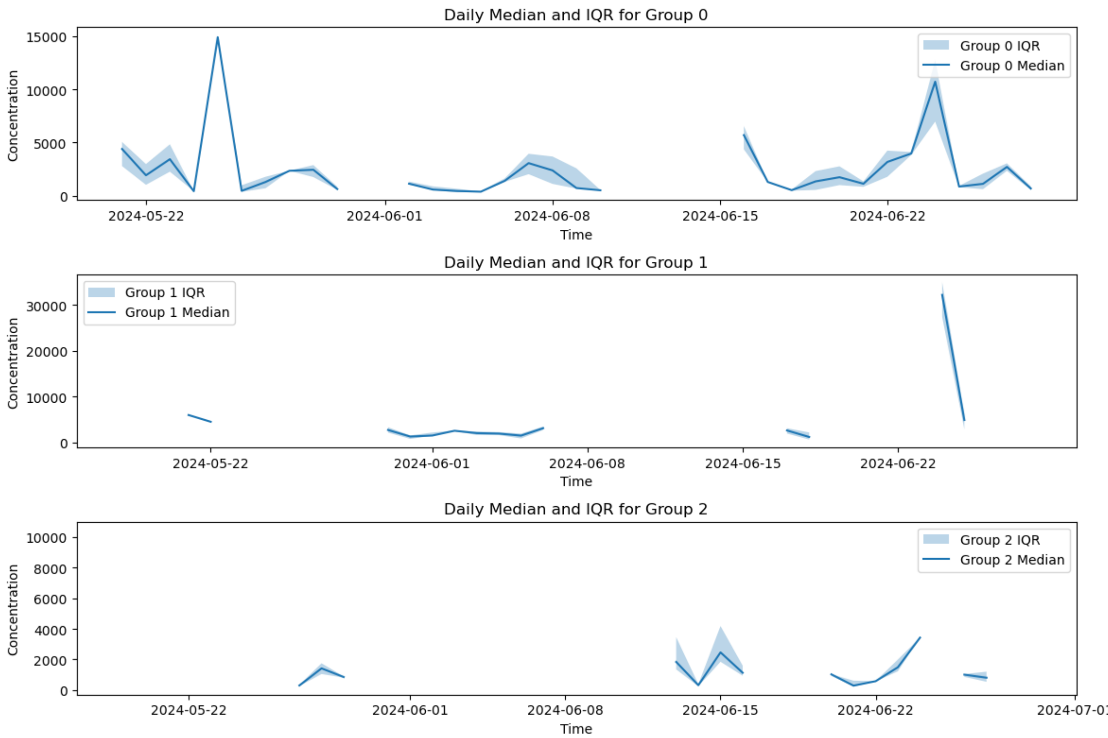
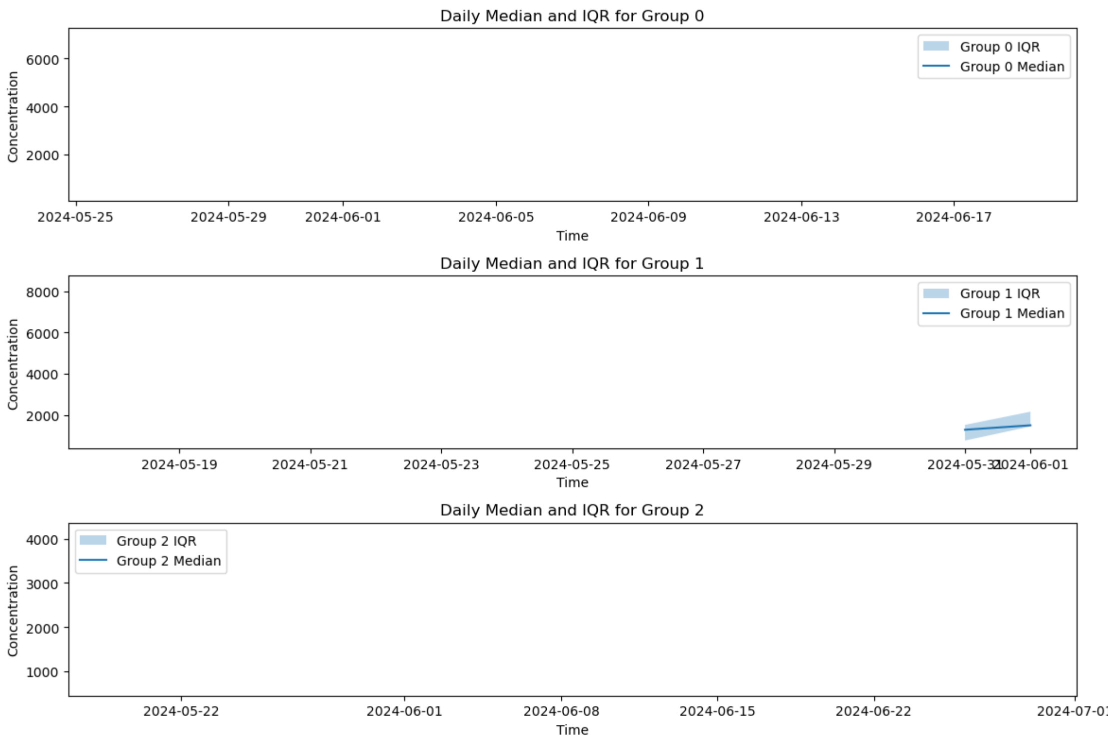

```
  return _nanquantile_unchecked(
/home/coliewo/anaconda3/lib/python3.11/site-
packages/numpy/lib/nanfunctions.py:1545: RuntimeWarning: All-NaN slice
encountered
  return _nanquantile_unchecked(
```



[ ]:
```
# Function to calculate daily median and IQR
def calculate_daily_statistics(data_array):
    daily_median = data_array.resample(time='1D').median(dim=['time',␣
 ↪'diameter'])
    daily_q25 = data_array.resample(time='1D').quantile(0.25, dim=['time',␣
 ↪'diameter'])
    daily_q75 = data_array.resample(time='1D').quantile(0.75, dim=['time',␣
 ↪'diameter'])
    return daily_median, daily_q25, daily_q75

# Calculate daily statistics for each group
group_0_median, group_0_q25, group_0_q75 =␣
 ↪calculate_daily_statistics(group_0_data.dropna(dim='time'))
group_1_median, group_1_q25, group_1_q75 =␣
 ↪calculate_daily_statistics(group_1_data.dropna(dim='time'))
group_2_median, group_2_q25, group_2_q75 =␣
 ↪calculate_daily_statistics(group_2_data.dropna(dim='time'))
```

```python
# Plotting function
def plot_daily_statistics(time, median, q25, q75, group_number):
    plt.fill_between(time, q25, q75, alpha=0.3, label=f'Group {group_number}␣
↪IQR')
    plt.plot(time, median, label=f'Group {group_number} Median')
    plt.xlabel('Time')
    plt.ylabel('Concentration')
    plt.title(f'Daily Median and IQR for Group {group_number}')
    plt.legend()

# Plot the results
plt.figure(figsize=(12, 8))

plt.subplot(3, 1, 1)
plot_daily_statistics(group_0_median.time, group_0_median, group_0_q25,␣
↪group_0_q75, 0)

plt.subplot(3, 1, 2)
plot_daily_statistics(group_1_median.time, group_1_median, group_1_q25,␣
↪group_1_q75, 1)

plt.subplot(3, 1, 3)
plot_daily_statistics(group_2_median.time, group_2_median, group_2_q25,␣
↪group_2_q75, 2)

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



Did I use the wrong data?

[ ]:

[ ]:

[ ]:
```
group_0_data.groupby(group_0_data.time.dt.hour).mean(dim='time')
```

[ ]:
```
<xarray.DataArray 'neg_particles' (hour: 1, diameter: 10)>
array([[ 824.64007643, 1124.34384621, 1502.21692618, 1837.71150063,
        2176.97800833, 2646.7564621 , 2763.65711856, 3693.76607837,
        4314.86541007, 4720.48374776]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * hour      (hour) int64 0
Attributes:
    units:        cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

[ ]:
```
group_1_data.groupby(group_1_data.time.dt.hour).mean(dim='time')
```

[ ]:
```
<xarray.DataArray 'neg_particles' (hour: 1, diameter: 10)>
array([[1335.08044667, 1318.91588724, 1221.32720432, 1501.49550309,
        1931.0699438 , 2221.35022628, 3867.82191218, 5017.48989424,
```

```
        5186.72529912, 5530.23813639]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * hour      (hour) int64 0
Attributes:
    units:         cm-3
    description:  Negative particle number-size distribution (dN/dlogDp)
```

[ ]:
```
#  Calculate diurnal variations
group_0_data_diurnal_variation = group_0_data.groupby(group_0_data.time.dt.
 ↪hour).mean(dim='time')
```

[ ]:
```

```

[ ]:
```
log_dist2
```

[ ]:
```
<xarray.DataArray 'neg_particles' (time: 45, diameter: 10)>
array([[11.57740938, 11.53065214, 11.49283127, 11.47205761, 11.44932218,
        11.43497768, 11.4444741 , 11.45556548, 11.42041418, 11.35822086],
       [ 7.03374469,  7.37954065,  7.46969442,  7.5626315 ,  8.20620527,
         8.63443979,  8.74944405,  8.76683424,  8.90689319,  9.08467892],
       [10.31228612, 10.43283425, 10.64178887, 10.8109902 , 10.89718618,
        10.920172  , 10.83790566, 10.65076554, 10.69013423, 10.65881357],
       [ 6.86392432,  6.7382921 ,  7.10850562,  7.25157055,  7.45291085,
         7.66768869,  7.77447703,  7.9551424 ,  8.11359449,  8.28175049],
       [ 8.57855098,  8.92991609,  9.11069734,  9.02192097,  8.80854135,
         8.5042454 ,  8.12323332,  7.92550296,  7.96228044,  7.62091746],
       [ 8.7061146 ,  8.80317424,  8.89693838,  9.18897128,  9.35363325,
         9.47865032,  9.63007783,  9.75821366,  9.95935129, 10.14976745],
       [ 8.84011738,  9.0574464 ,  9.31868351,  9.54574423,  9.7094789 ,
         9.78183755,  9.8898115 ,  9.92489859,  9.96443135, 10.00451601],
       [ 8.41350512,  8.51847442,  8.66756225,  8.89284697,  9.08360382,
         9.1701003 ,  9.22322941,  9.20883014,  9.17694054,  9.1962412 ],
       [ 9.92322334, 10.0435037 , 10.1334536 ,  9.99688616, 10.18315553,
        10.3962638 , 10.56839697, 10.70790065, 10.79903725, 10.82706451],
       [ 7.1589342 ,  7.4418142 ,  7.81516896,  8.05220186,  8.20666408,
         8.37132699,  8.52659226,  8.62356909,  8.68762952,  8.68992649],
…
       [ 7.36789136,  7.68537552,  8.30854096,  8.82108255,  9.13816448,
         9.37132479,  9.41968244,  9.46364999,  9.47081309,  9.4167032 ],
       [ 7.74793792,  7.7851036 ,  7.63009921,  8.11759771,  8.45152536,
         8.59438824,  8.72039714,  8.73622173,  8.73929978,  8.71402142],
       [ 8.15570147,  8.46708298,  8.77695746,  9.05316471,  9.25537963,
         9.44175556,  9.53070389,  9.51923701,  9.62010956,  9.7261399 ],
       [ 6.56219525,  6.50486074,  7.01009733,  7.50387937,  7.80281136,
         7.94100514,  8.14201884,  8.41703139,  8.71646296,  8.9504097 ],
       [ 8.50727461,  8.92911332,  9.46456295,  9.8149873 ,  9.91009125,
```

```
         9.95781992, 10.23767201, 10.50847826, 10.61863378, 10.60562808],
       [ 9.80038832,  9.92701723, 10.00443952,  9.98370209, 10.12950149,
        10.44421947, 10.54482321, 10.55477086, 10.56665583, 10.57225997],
       [ 8.02467137,  8.20347682,  8.25168689,  8.7434571 ,  8.97727428,
         9.11130489,  9.25543335,  9.24998422,  9.32459687,  9.2896405 ],
       [ 7.92550629,  8.10138664,  8.13613744,  8.12907972,  8.1883809 ,
         8.41570425,  8.94817562,  9.18855061,  9.34887695,  9.43434284],
       [ 9.45811115,  9.56001248,  9.79248772, 10.01719572, 10.27761167,
        10.43912296, 10.56484695, 10.68501834, 10.8113923 , 10.88347453],
       [ 6.85240702,  6.93984696,  7.35080474,  7.64828896,  7.96181885,
         8.03132577,  8.10175271,  8.09361532,  7.92586777,  7.9695777 ]])
Coordinates:
  * diameter  (diameter) float64 2.545 2.736 2.941 3.16 … 4.224 4.538 4.879
  * time      (time) datetime64[ns] 2024-05-16 2024-05-17 … 2024-06-29
```