Investigating the association between air pollutant concentrations and temperature changes

Sahar Nazeri

10 July 2024

Agenda

1. Introduction

Air pollution is a global concern impacting human health, the environment, and climate change.

Black carbon (BC) is a significant contributor to air quality and climate issues, particularly global warming.

Particles from BC affect sunlight reaching and heating the planet, influencing weather patterns.

The effects of particles DMPS are most pronounced in heavily populated and industrialized regions like Europe.

Airborne particles indirectly affect climate by influencing cloud reflection of light.

Analyzing air pollution data helps identify trends in atmospheric composition and assess the impacts of emissions and rising temperatures.

In this study, black carbon and DMPS particle concentrations are chosen for analysis among all air pollutants.

Question: What is the correlation of the effect of air pollutant concentration with temperature change during 5 years in Ispra?

Used Data

Main Data Source

- Particulate matter data of equivalent Black Carbon Aethalometer, DMPS Measurements, and air temperature data

- Collected at two official monitoring stations namely Ispra Atmosphere Biosphere Climate Integrated monitoring Station of the JRC and Milano, Malpensa weather station.

- The Black Carbon column shows the measurements of equivalent black carbon [ng/m³]- EBC (880 nm) by Aethalometer

- DMPS_Total column interprets measurements of particle number concentration [cm3]. Particle number concentration was measured with a DMPS - Differential mobility particle spectrometer from 10 nm to 800 nm

- Between years of 2018 to 2022

- European Commission reuse License

- Creative Commons Attribution-Non-commercial 4.0 International Public License(CC BY-NC 4.0)

Used Data

Main Data Source

1. Atmospheric Particles-DMPS Particle Concentration 2022, 2021, 2020, 2019,2018 ,Metadata_DMPS_Particle_Concentration

2. Atmospheric Particles-Equivalent Black Carbon Aethalometer 2022, 2021, 2020, 2019,2018 ,Metadata_Equiv_BlackCarbon

3. Meteostat weather service: The Meteostat bulk data interface provides access to full data dumps of individual weather stations.

Metadata URL: Metadata weather data source, Data URL: Weather data source, subset full dataset , subset map dataset

Data Source 1:

RangeIndex: 230411 entries, 0 to 230410

Data columns (total 2 columns):

#	Column	Non-Null Count	Dtype
0	Date	230411 non-null	datetime64[ns]
1	DMPS_Total	230411 non-null	float64

dtypes: datetime64[ns](1), float64(1)

memory usage: 3.5 MB

	Date	DMPS_Total
0	2018-01-01 00:04:14	12629.411394
1	2018-01-01 00:16:01	12779.947706
2	2018-01-01 00:27:47	13376.037479

Main Data Source

Data Source 3:

RangeIndex: 1826 entries, 0 to 1825

Data columns (total 4 columns):

#	Column	Non-Null Count	Dtype
0	Date	1826 non-null	datetime64[ns]
1	tavg	1826 non-null	Float64
2	tmin	1826 non-null	Float64
3	tmax	1826 non-null	Float64

dtypes: datetime64[ns](1), float64(3)

memory usage: 57.2 MB

	Date	tavg	tmin	tmax
0	2018-01-01	3.2	2.6	4.2
1	2018-01-02	4.4	=1.0	13.0
2	2018-01-03	4.0	0.0	8.6

Data Source 2:

RangeIndex: 245474 entries, 0 to 245473

Data columns (total 2 columns):

#	Column	Non-Null Count	Dtype
0	Date	245474 non-null	datetime64[ns]
1	Black Carbon	245474 non-null	int64

dtypes: datetime64[ns](1), int64(1)

memory usage: 3.7 MB

	Date	Black Carbon
0	2018-01-01 00:05:00	6728
1	2018-01-01 00:15:00	6768
2	2018-01-01 00:45:00	7304

Analysis
Initial Inspection

BC_df.describe()

	Date	Black Carbon
count	245474	245474.000000
mean	2020-06-11 14:33:15.837522176	1347.680960
min	2018-01-01 00:05:00	-39259.000000
25%	2019-03-31 13:17:30	369.000000
50%	2020-06-11 11:10:00	728.000000
75%	2021-08-30 11:02:30	1592.000000
max	2022-11-18 09:05:00	52795.000000
std	NaN	1678.343174

- In the first step of the analysis, take a look at some statistical views for the columns to familiarize yourself with the data

- To demonstrate a basic inference, it is necessary to install a few dependencies.

- Installing visualization libraries matplotlib and seaborn as well as a required text file in your project repository

- Use the describe function to obtain a summary descriptive statistic of the numeric columns in the dataset

- This summary includes the mean, count, standard deviation, percentiles, and minimum and maximum values for all columns.

DMPS_df.describe()

	Date	DMPS_Total
count	230411	230411.000000
mean	2020-07-16 20:29:34.095416064	5876.551670
min	2018-01-01 00:04:14	-3535.039706
25%	2019-04-25 23:53:06.500000	3361.173864
50%	2020-07-15 01:19:21	4900.345953
75%	2021-10-12 23:54:12	7340.669689
max	2022-12-31 23:52:49	214203.718795
std	NaN	4060.013642

I

temp_df.describe()

	Date	tavg	tmin	tmax
count	1826	1826.000000	1826.000000	1826.000000
mean	2020-07-01 12:00:00	13.893538	8.580778	19.253122
min	2018-01-01 00:00:00	-3.800000	-10.600000	0.000000
25%	2019-04-02 06:00:00	6.700000	1.225000	12.000000
50%	2020-07-01 12:00:00	13.550000	9.000000	19.000000
75%	2021-09-30 18:00:00	21.500000	16.000000	27.000000
max	2022-12-31 00:00:00	30.600000	25.500000	37.000000
std	NaN	8.138400	7.967887	8.495913

Visualize concentrations data with the aid of a boxplot for annual Maximum Black Carbon concentrations(ng/m³)


Number of black carbon
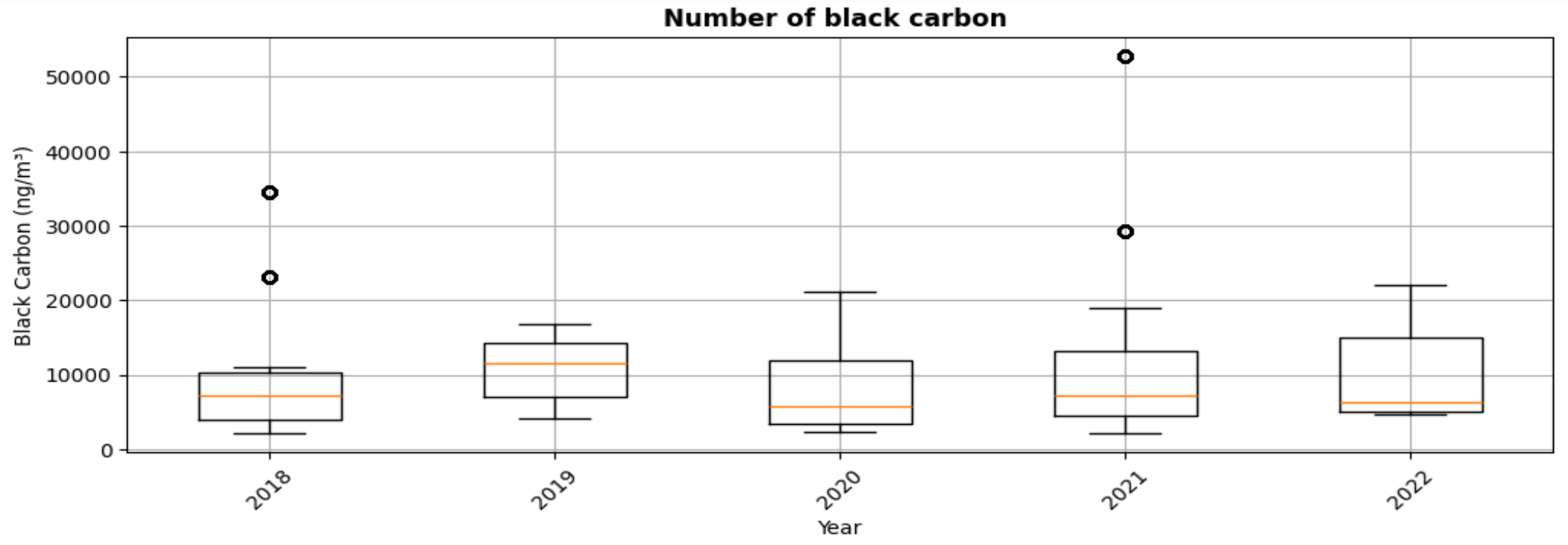
The following plot displays the box-whisker plots of the annual Maximum total of DMPS Particle concentrations(particles/cm³).
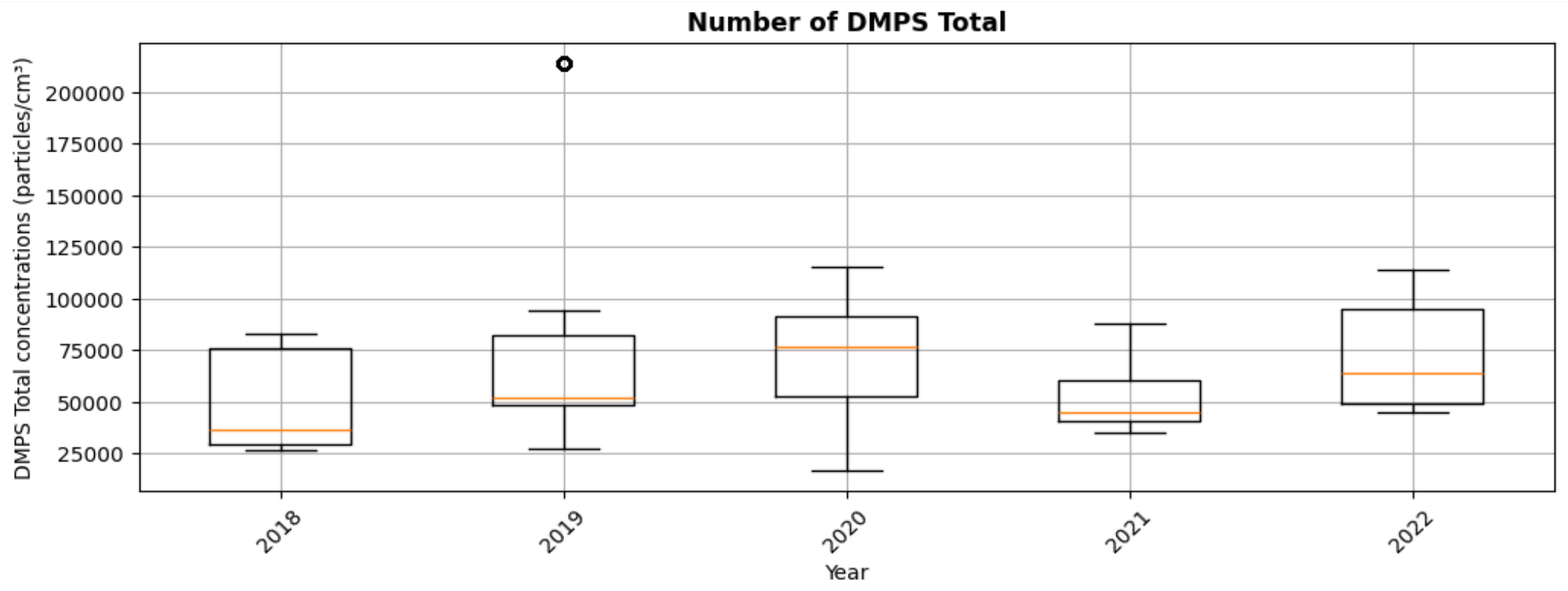
The below bar chart displays the mean value of air pollutant concentrations in seasons from 2018 to 2022

Method and Result
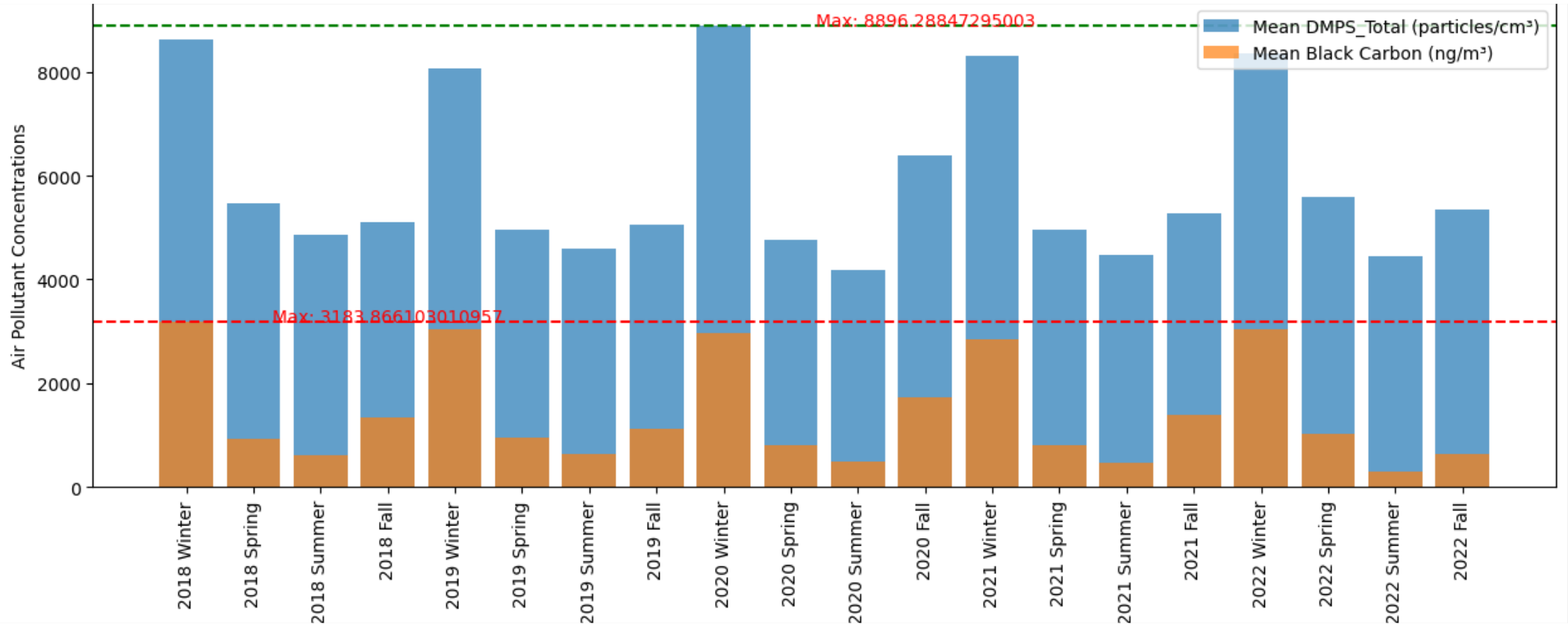
The temperature variations in Ispra show moderate changes over the five-year period,

Monthly Temperature (tavg, tmin, tmax) Variation in Ispra
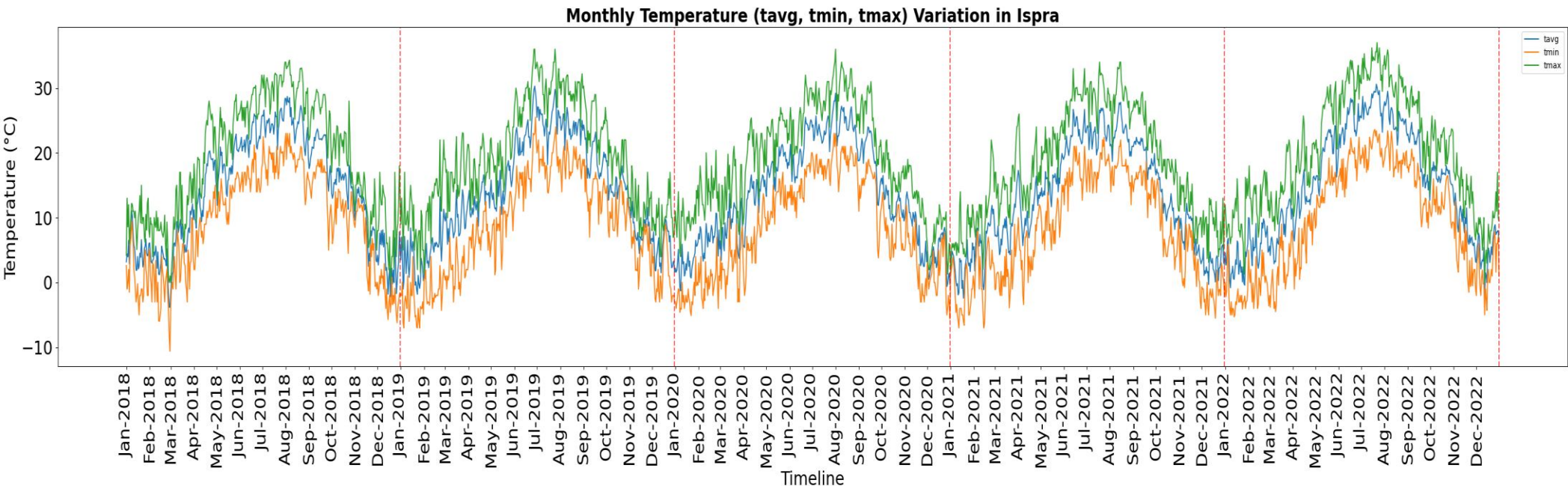
Histograms of the weather table help to identify common ranges and general patterns in temperature changes.
(These histograms provide a visual representation of the frequency distribution)

Histograms for temperature changes dataset

Method and Result
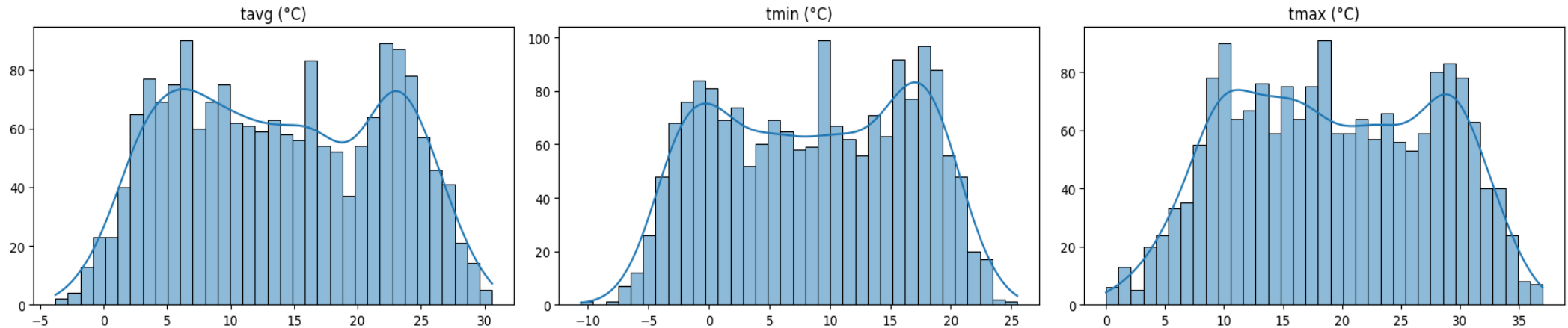
RangeIndex: 59 entries, 0 to 58

Data columns (total 12 columns):

dtypes: datetime64[ns](1), float64(4), int32(4),

int64(1), object(2)

memory usage: 4.7+ KB

<Figure size 1400x400 with 0 Axes>

#	Column	Non-Null Count	Dtype
0	Year_x	59 non-null	int32
1	Month_x	59 non-null	int32
2	Max Black Carbon	59 non-null	int64
3	Join Date	59 non-null	Object
4	Season	59 non-null	object
5	Max DMPS_Total	59 non-null	float64
6	Date	59 non-null	datetime64[ns]
7	tavg	59 non-null	float64
8	tmin	59 non-null	float64
9	tmax	59 non-null	float64
10	Month_y	59 non-null	int32
11	Year_y	59 non-null	int32

	Year_x	Month_x	Max Black Carbon	Join Date	Season	Max DMPS_Total	Date	tavg	tmin	tmax	Month_y	Year_y
0	2018	1	10997	2018-01-01	Winter	26522.440646	2018-01-01	3.2	2.6	4.2	1	2018
1	2018	2	23051	2018-02-01	Winter	82883.127327	2018-02-01	6.1	5.0	7.0	2	2018
2	2018	3	7495	2018-03-01	Spring	29714.849725	2018-03-01	-1.7	-3.6	0.0	3	2018

Method and Result

the relationship between temperature changes and air pollutant concentrations, using both line plots and Pearson's correlation coefficient (r).
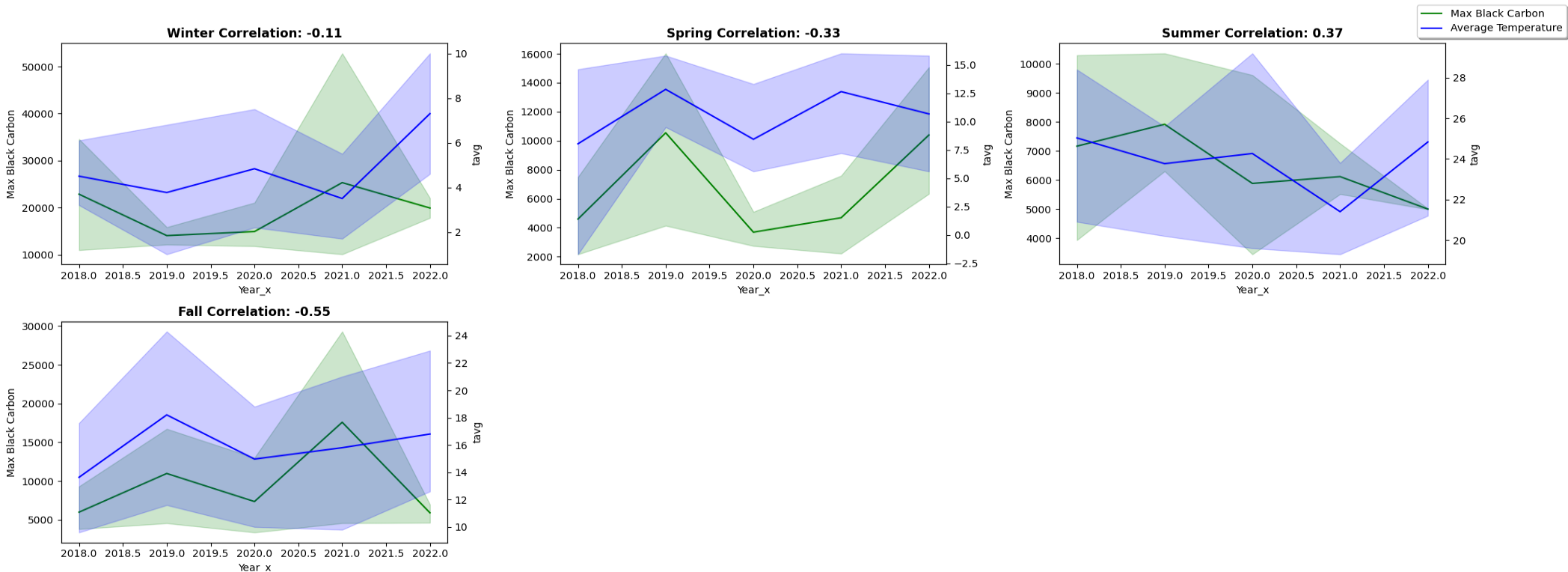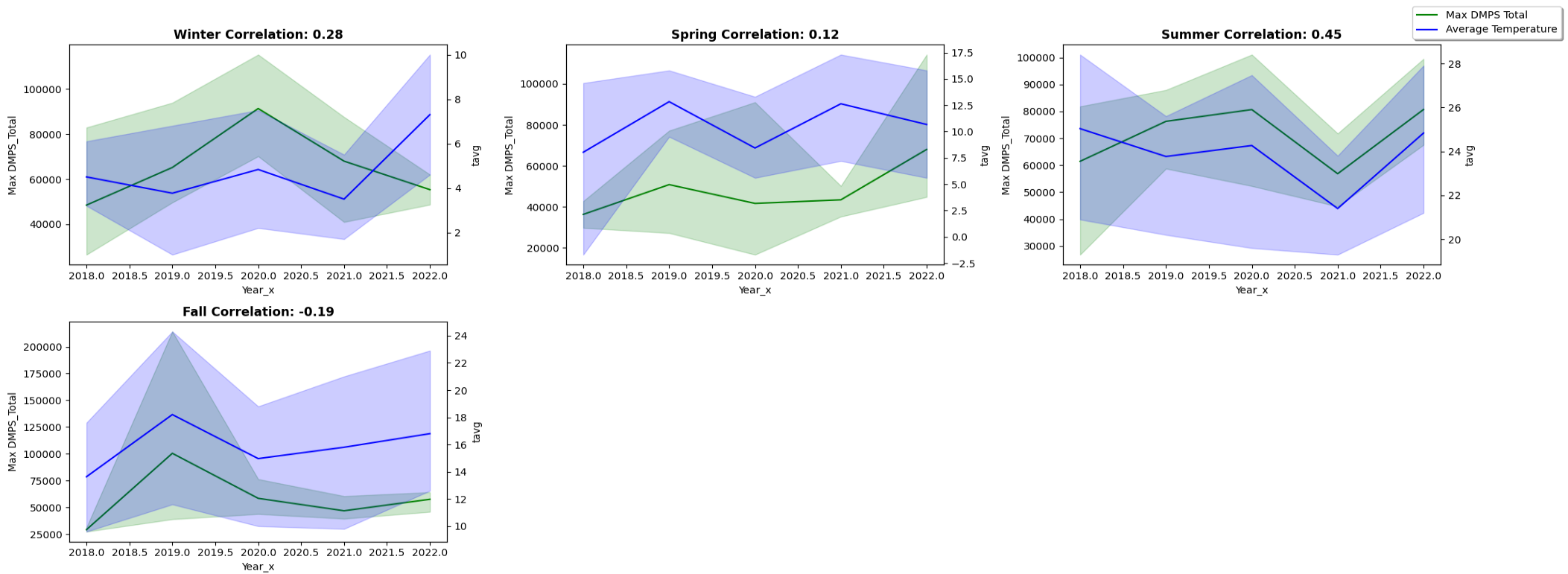
Correlations of Max Black Carbon and Max DMPS Total with respect to Temperatures:
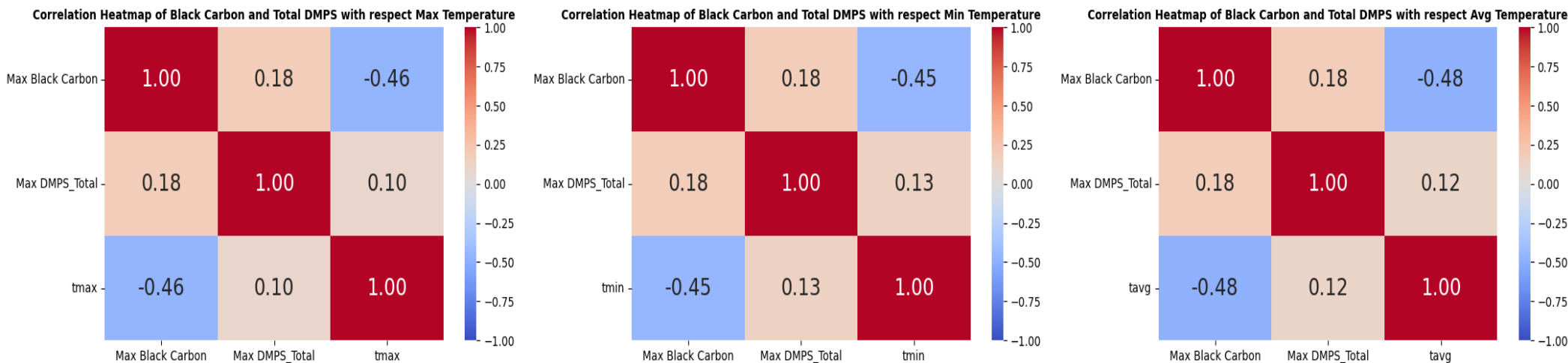
Max DMPS_Total 0.096488

Max Black Carbon -0.461225

Name: tmax, dtype: float64

Max DMPS_Total 0.133284

Max Black Carbon -0.447234

Name: tmin, dtype: float64

Max DMPS_Total 0.115889

Max Black Carbon -0.478773

Name: tavg, dtype: float64

Conclusions

Analysis of Trends and Correlations in Black Carbon, DMPS Atmospheric Particles, and Temperature Changes Over a 5-Year Period

- Despite relatively unchanged individual trends in the aggregate, there is a seasonal correlation rather than an annual correlation.

- The study shows that black carbon emissions contribute to cooler temperatures and air pollutant DMPS concentrations contribute to warmer annual temperatures.

- In 2020, there were changes in trends that were not directly related to temperature changes

- black carbon and DMPS particles play a role in global warming

- The importance of data engineering methods in understanding the relationships between these variables

Conclusions

- **Missing data**

    To maintain and keep links and information updated

    Depends on the assumption that trends observed at long-term sites accurately

- **Geographical limitation**

    Changes across the entire country of Italy over more years to have more data

- **Influencing other factors**

    Such as additional particulate matter, geographical conditions, and greenhouse gas emissions.

Reference

1. *Improving the current air quality index with new particulate indicators using a robust statistical approach*

2. *Air & Environment2023 Swedish Environmental Protection Agency*

3. *Atmospheric black carbon concentrations Nov 1, 2022*

Thanks for your attention!