Using spatiotemporal infrastructure to manage and process air quality data for rapid responses

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Agenda

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5. Use cases
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   - 5.2. LA ship backlog AQ impact
   - 5.3. Ukraine war AQ impact
6. Take aways

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Why the research?

- Did COVID, ships, war impact environment and why we care?
- What **data** do we have for the impact analyses?
- How to analyze covid-19 **environment impact**?
- What are the **spatiotemporal** patterns of the impact?
- What impact have **COVID**, **LA ship backlog**, **Ukraine War** had on Air Quality?

Challenges

1) How different environmental factors are changed by the events?
   - Nighttime light
   - Air pollution
   - Atmospheric NO2
2) Do they have similar responses for different events?
   - COVID in Context of China, USA, Global
   - LA ship backlog
   - Ukraine War
3) How to explain the changes?
   - COVID-19 mitigation
   - Climate change
   - Regulation policies
   - Inter-annual variation

Motivation

1) The environmental factors are **essential indicators** of industrial production and global economic;
   - NO2 reflects the energy consumption;
   - Nighttime light shows the economic activities
2) Results can offer vital and practical basis for **loss assessment and economic impact**.
   - The regions with a decrease of economy can be shown from the results
   - The absolute and relative changes can be used to calculated the reduction of economy.

2. Objective

1) Generate the involved environmental **datasets in standardized formats and structures** for easy utilization and accessibility;
2) Examine the **spatiotemporal variations** of environmental factors;
3) Analyze the **correlation between the factors and the variations**;
4) Investigate the **COVID-19 impacts** in different regions and scales;
5) How the **Ukraine war** have impacted the air quality.

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3 Dataset

Data	Measuring method	Temporal scope	Re-gridded resolution	Reprocessed product	method	LA ship backlog	Ukraine conflict
TROPOMI NO2 TVCD	satellite	04/31/2018~present	5km	NO2 TVCD wit daily 5km resolution	Nearest neighbor	Jan. 1 2021-present, LA ports and Ukraine	Jan.1, 2022-present
TROPOMI SO2 TVCD	satellite	04/31/2018~present	5km	SO2 TVCD with 5km resolution	Nearest neighbor	Jan. 1 2021-present, LA ports and Ukraine	Jan.1, 2022-present
GOES 16/17 ABI aerosol	satellite	GOES-16: 07/25/2018~present GOES-17: 01/01/2019~present	2.5km	Gridded PM2.5 concentration with hourly 2.5 km resolution, no data under cloud coverage	Spatiotemporal weighted regression	Jan. 1 2021-present, LA ports and Ukraine	
Purple air	Ground base	10/2017~present	Down to 0.5x0.5km	PM2.5 matrix with a minute-by-minute granularity	Various methods	Jan. 1 2021-present, LA ports and Ukraine	Jan.1, 2022-present (only a few)
ACIQN	Ground base	1/2014~present	Down to 0.5X0.5km	Interoperation	Various methods		
AirNow	Ground base	1980~present	Down to 0.5X0.5km	Interoperation	Various methods		
VIIRS DNB-nighttime light	Satellite			Monthly and periodical mean over study region		Feb 14- Mar. 4, 2021/2022	Jan.1, 2022-present
Ship number data for LA port	record	2015-2022	N/A	Daily time series		Jan. 1 2021-Jan. 2022	

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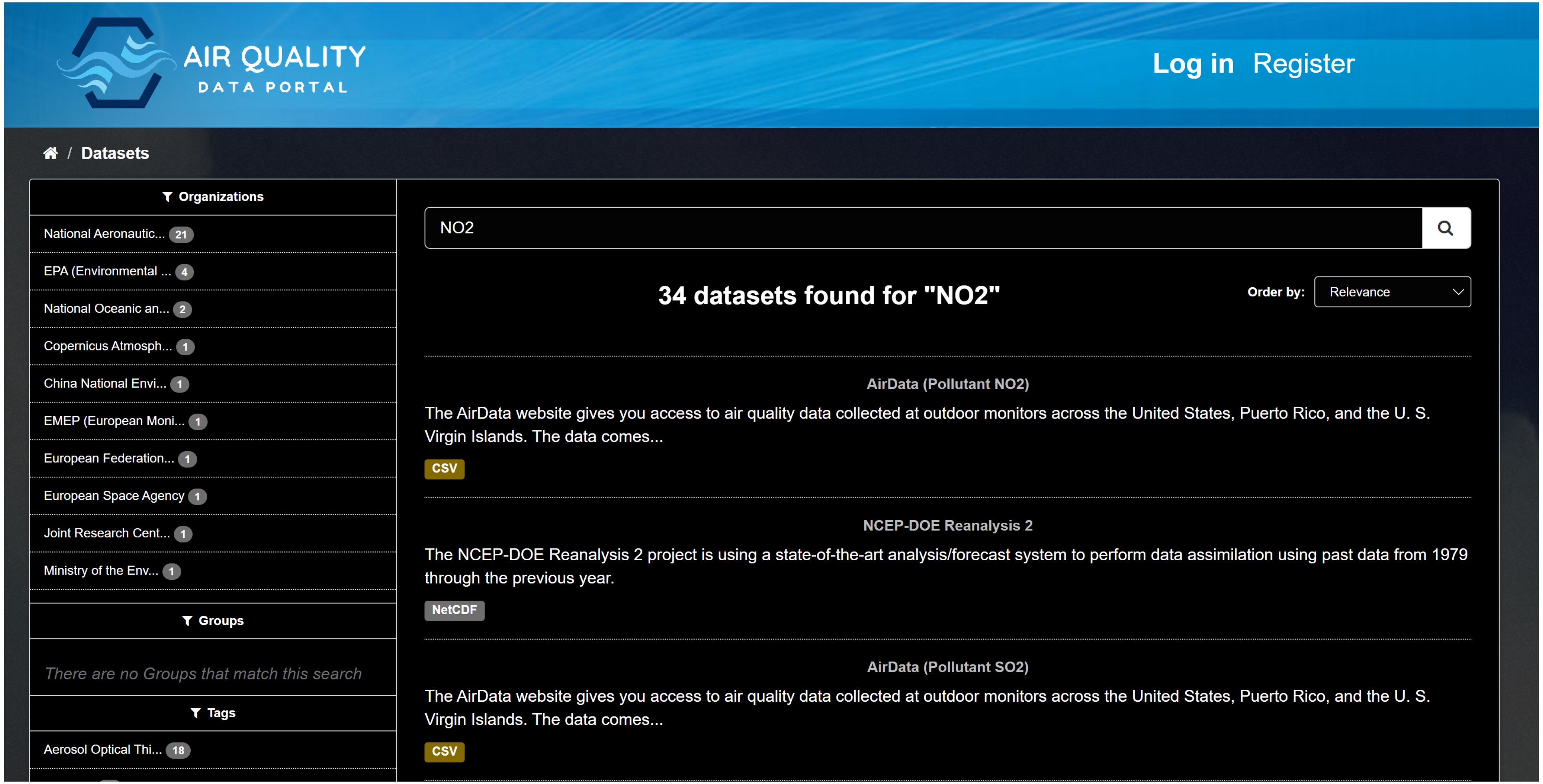
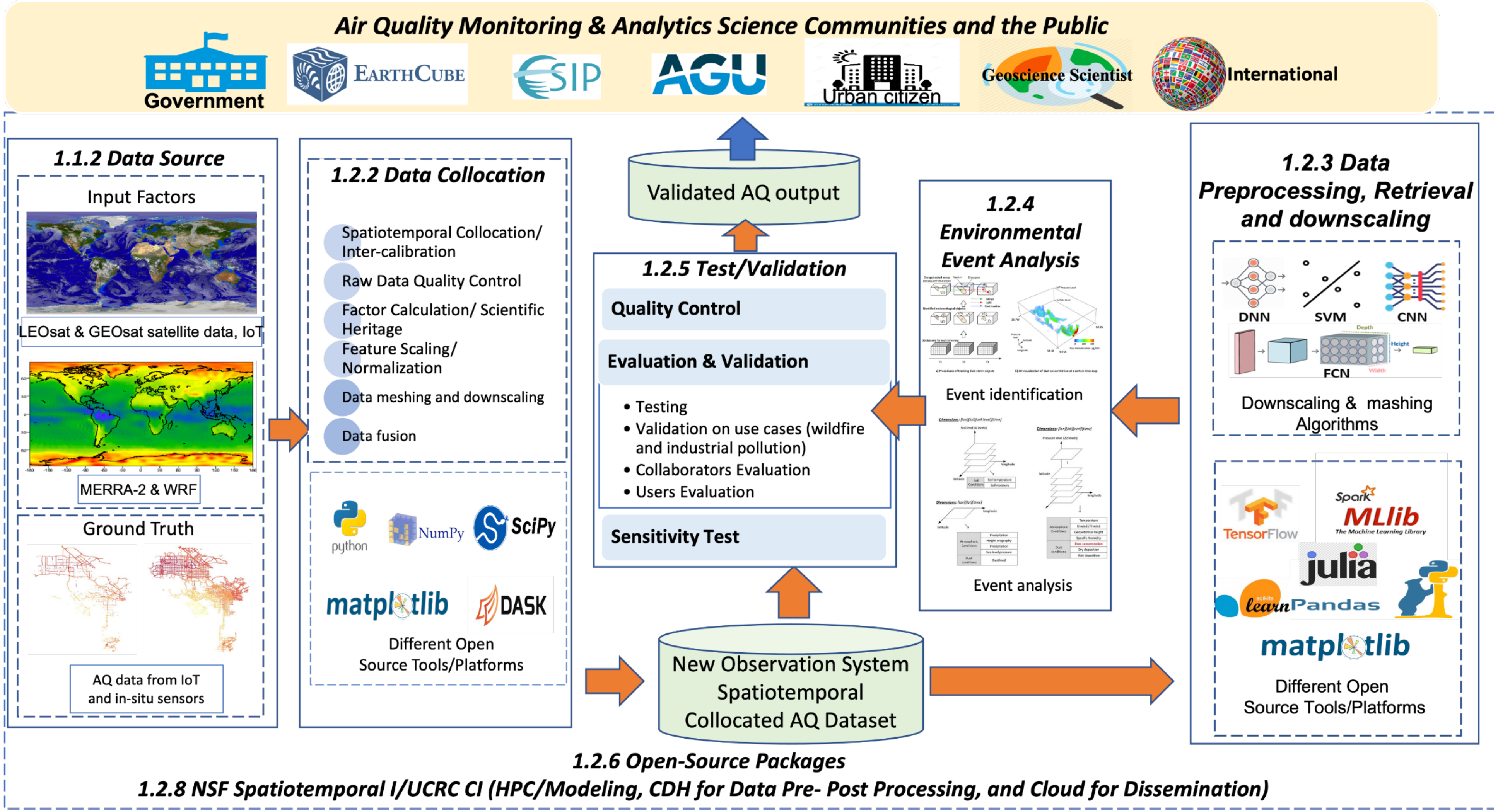
3. Data



AirData (Pollutant NO2) - Dataset - Air Quality Data Portal (stcenter.net)

3. Infrastructure



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4. Methodologies and relevant tools

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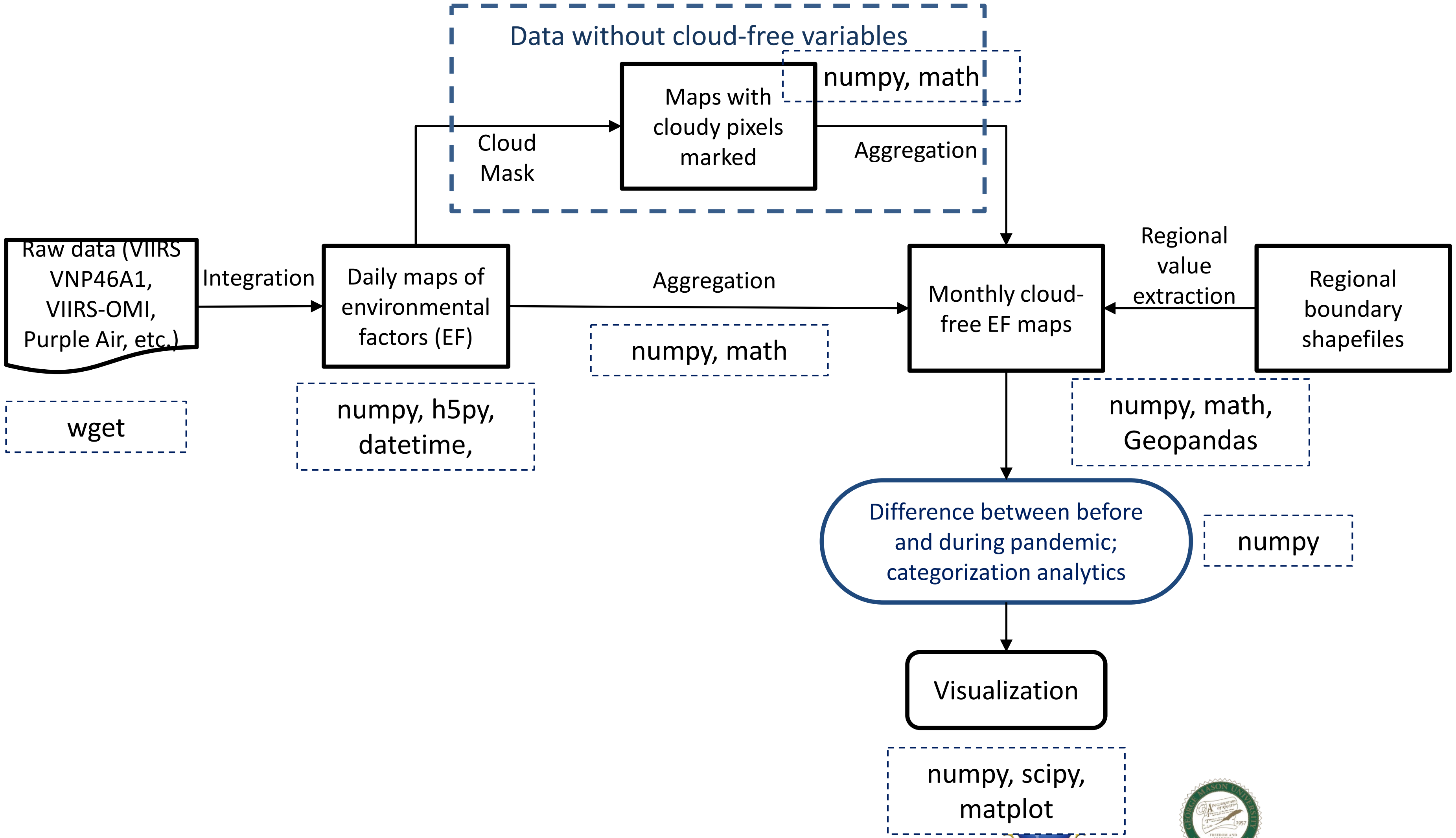
4.1 Workflow



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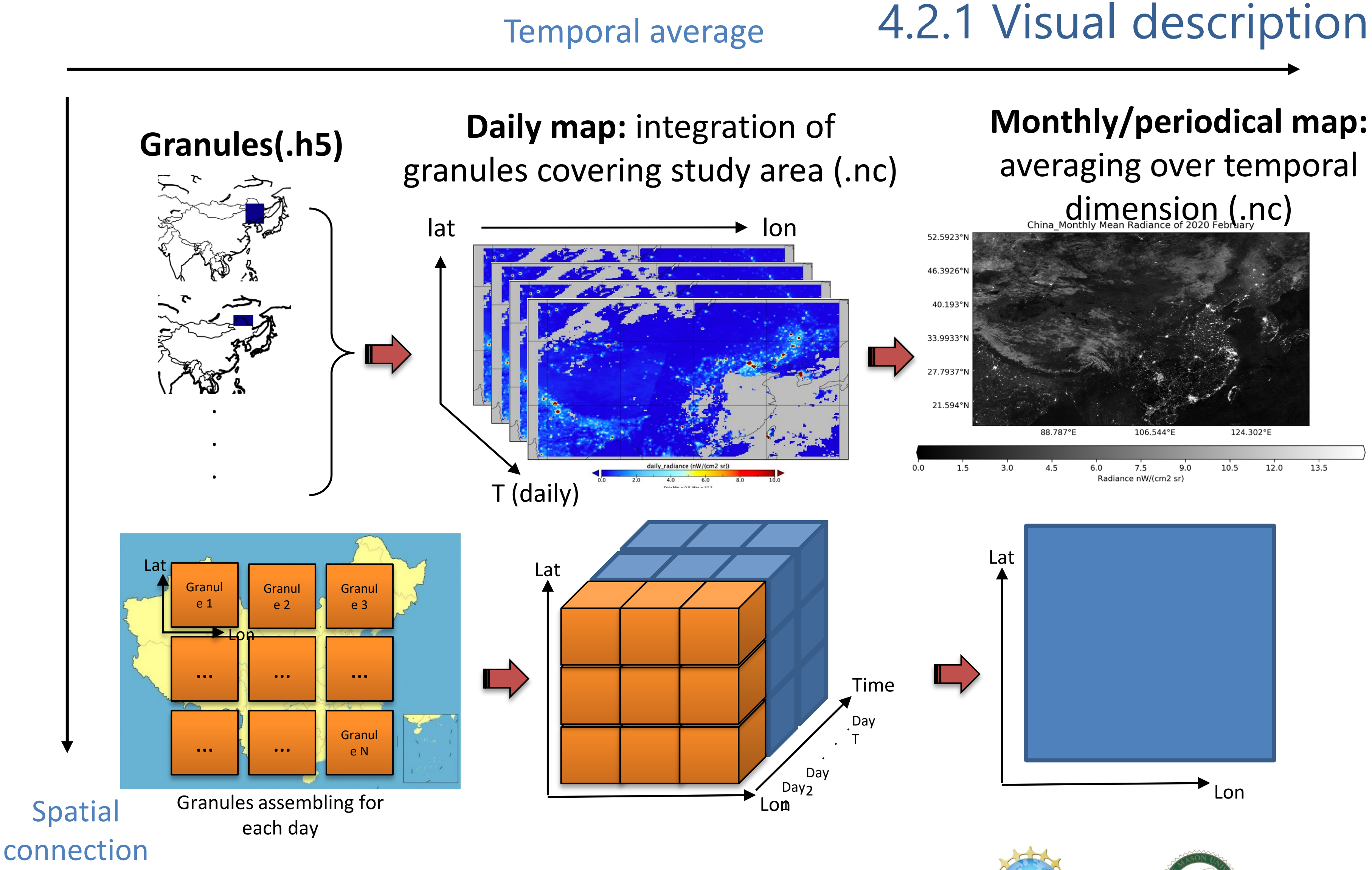
4.2 Data preprocessing and Spatiotemporal collocation

4.2.1 Visual description



4.3 Quantitative statistics of environmental factors (EF)

1) Daily mean value of study region

$$\overline{EF_t} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} EF_{i,j,t}}{m \times n}, t = 1,2,3,\ldots,T_{study} \quad \text{Eq (1)}$$

Where t is the day-of-year, $\overline{EF_t}$ is the mean EF value on day t; (i, j) are the coordinates of the pixels; $m \times n$ is the number of available observations over this target country; T_{study} is the last day-of-year in the study period.

Quantitative statistics: 2) Normalization of daily timeseries

To make the timeseries for different years comparable

$$NEF_t = \frac{\overline{\mathrm{EF}}_t}{\overline{EF_{pre}}} \qquad \text{Eq (2)}$$

where NEF_t is the normalized daily value of EF, $\overline{\mathrm{EF}}_{pre}$ is the mean EF values of before pandemic (pre-period)

$$\overline{EF_{pre}} = \frac{\sum_{t=1}^{n_{pre}} EF_t}{n_{pre}} \qquad \text{Eq (3)}$$

where n_{pre} is the number of days in the pre-period of study region.

Quantitative analyses: 3-4)

3). Calculate the 7-day moving average to smooth the variation.

4). Calculate the periodical (before, during and after the pandemic, here after regarded as pre-, peri- and post-period) mean EF value of each covered pixel (i,j):

$$\overline{\mathrm{EF}}_{i,j} = \frac{\sum_{t=T_{period\ start}}^{T_{period\ end}} EF_{\mathrm{i,j,t}}}{T_{period}}, i \in [0, m-1], j \in [0, n-1] \quad \text{Eq (4)}$$

Where t is the day-of-year, $\overline{\mathrm{EF}}_{i,j}$ is the mean EF values of the target period (pre-, peri- or post-period); (i, j) are the coordinates of the pixels; $m \times n$ is the number of available observations over this target country; $T_{period\ start}$ and $T_{period\ end}$ are the first and last day-of-year in the target period.

5) Climatological anomalies calculation

$$A_{i,j} = \overline{EF(i,j)}_{p,y} - \overline{EF(i,j)}_{p,2010-2019},$$

p ∈ {pre-m peri- and post-period}, y ∈ {2020,2021}

Eq (5)

- where $\overline{EF(i,j)}_{p,2010-2019}$ is the 10-year climatology of the EF, from 2010 to 2019:

$$\overline{EF(i,j)}_{p,2010-2019} = \text{Average}(\overline{EF}_{t0}, \overline{EF}_{t2}, \dots, \overline{EF}_{tn})_{2010\text{-}2019}$$

- $\overline{EF(i,j)}_{p,y}$ is the mean value of the study year (2020,2021):

$$\overline{EF(i,j)}_{p,y} = \text{Average}(\overline{EF}_{t0}, \overline{EF}_{t2}, \dots, \overline{EF}_{tn})_{y}$$

- EF_t is calculated from Eq. (1)

4.4 Python open source tools and packages:

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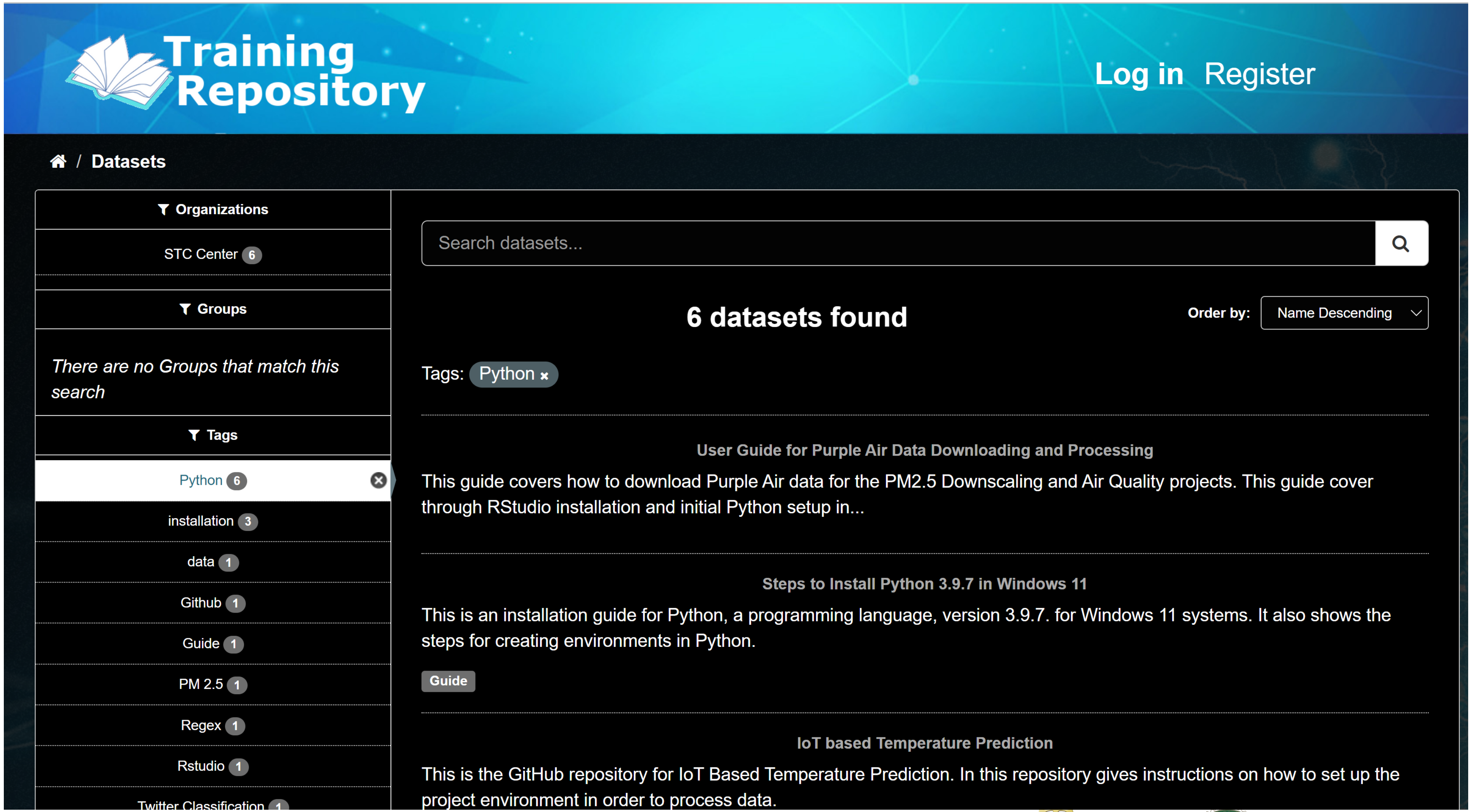

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4.5 Climatological analytics/interpretation

1). Comparison between anomalies of before, during and after pandemic period.

- Through the statistical methods mentioned in section 4.2, anomalies from 10-year climatology are derived for 2020 and 2019 over the study regions.
- Compare the anomalies in 2020 and 2019, find the abnormal pixels in 2020.
- Try to explain the abnormal changes considering climate change, wildfires and the pandemic.

2). Comparison between normalized trends of timeseries of long-term means, pandemic year and adjacent year.

- Visualize the three timeseries together;
- Find the abnormal in 2020 especially during the lockdown period of the target region.

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4.6 Results extraction and visualization

```
outfile = output_dir + region + '_'+ str(year) + str('{0:02}'.format(month)) + 'China.png'
y_min = lats.min()
y_max = lats.max()
x_min = lons.min()
x_max = lons.max()

ratio = (x_max - x_min) / (y_max - y_min)
idx_nan = np.where(all_radiance_mean==np.nan)
#all_radiance_mean[idx_nan] = 0
all_radiance_mean = np.array(all_radiance_mean)
mindata = all_radiance_mean[~np.isnan(all_radiance_mean)].min()
maxdata = all_radiance_mean[~np.isnan(all_radiance_mean)].max()
```

claim output path and read data (results calculated form daily, monthly mean and differences)

```
fig = plt.figure(figsize=(16, 12))  # Create a new figure window
rect = [0.125, 0.25, 0.5, 0.5 / ratio]  # [left, bottom, width, height] (ratio 0~1)0.256
ax = plt.axes(rect)

# create a basemap
map = Basemap(projection='cyl', llcrnrlat=y_min, urcrnrlat=y_max, \
              llcrnrlon=x_min, urcrnrlon=x_max, ax=ax)  # lon_0=0.0,
plt.title('China' + '_' + 'Monthly Mean Night Light Radiance of '+ str(year) + ' ' + month_name)
# convert lat and lon to map projection coordinates
lons, lats = map(lons, lats)

# create render
cmap = mpl.cm.jet # seismic
#cmap = mpl.cm.gist_gray
maxdata = 60
mindata = 0
ticker_width = maxdata - mindata
nticks = 10
ticker_interval = ticker_width / nticks
nticks += 1
normticks = np.arange(mindata, maxdata, ticker_interval)
norm = mpl.colors.Normalize(vmin=mindata, vmax=maxdata, clip=True)
```

set up the maximum and minimum value of the figure

set up the interval of the legend

setup base map, color map, etc.

```
cs = map.scatter(lons, lats, s=5, marker='s', c=all_radiance_mean, cmap=cmap, norm=norm, edgecolors='none')
```

plot data and geospatial locations

```
# create color bar
cbaxes = fig.add_axes([rect[0], rect[1] - 0.05, rect[2], 0.02])
# divider = make_axes_locatable(ax)
# cbaxes = divider.append_axes("bottom", size="5%", pad=0.05)
cbar = fig.colorbar(cs, cmap=cmap, ax=ax, cax=cbaxes, orientation='horizontal',
                    ticks=normticks, fraction=0.046, pad=0.05, extend='both', extendfrac='auto')
# cbar.set_label('Some Units')
tick_locator = mpl.ticker.MaxNLocator(nbins=nticks)
cbar.locator = tick_locator
cbar.ax.xaxis.set_ticks_position('bottom')
```

setup color bar

5. Application and Use cases

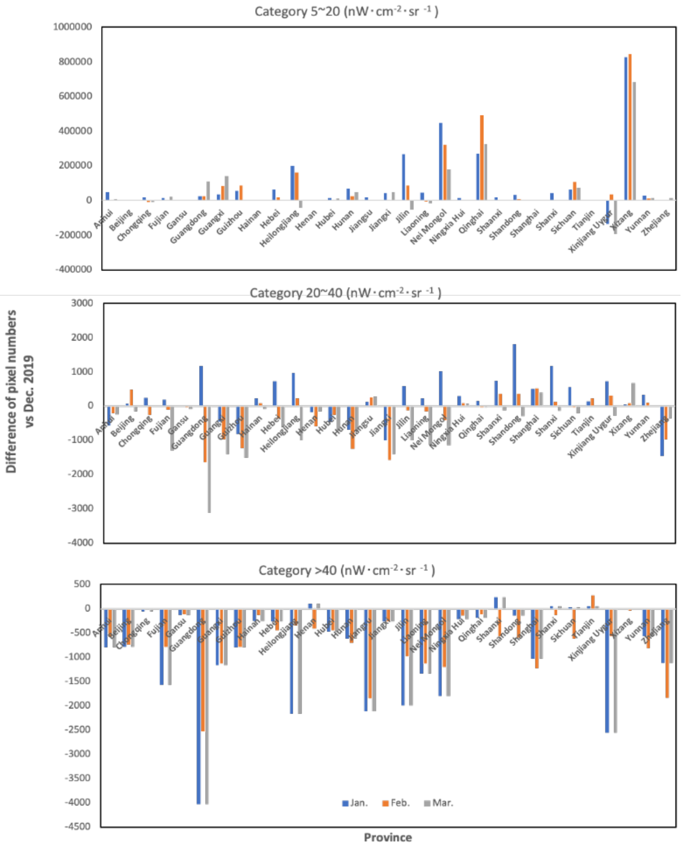
5.1 Impact on nighttime light in China

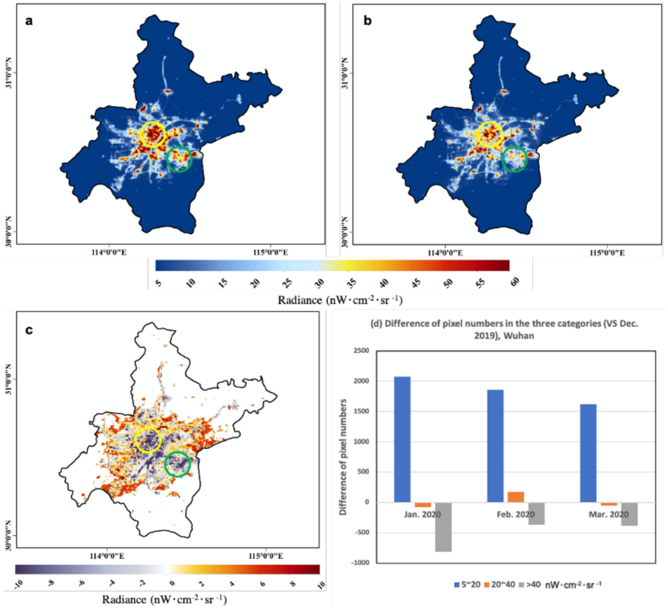
5.2 Impact on air pollution in California

5.3 Impact in Global NO2

- 5.3.1 Workflow
- 5.3.2 Temporal variation analyses
- 5.3.3 Spatiotemporal dynamics

5.1.3 Results visualization: Night light categorization

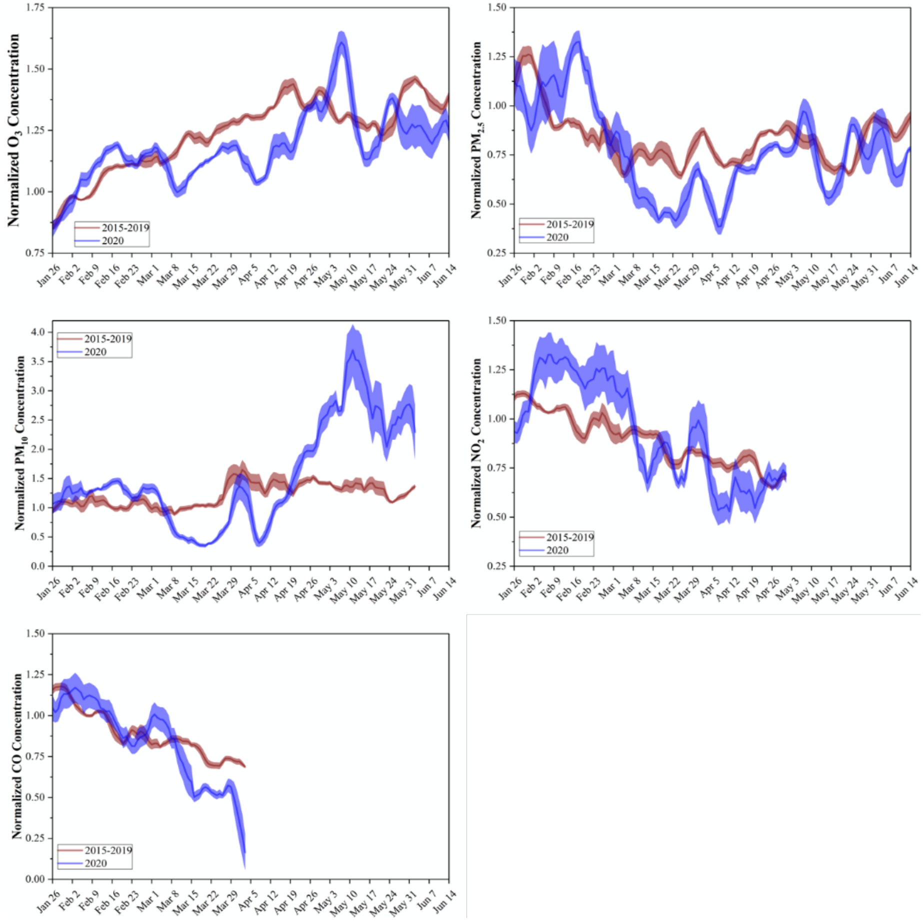




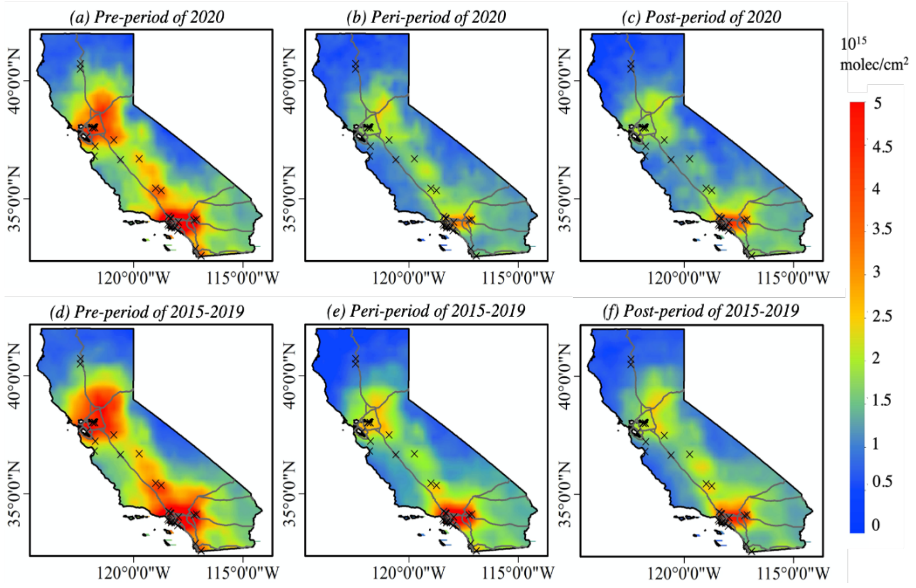
- The number of detected NTL pixels increases in the residential areas
- It decreases in the commercial center regions;
- NTL stays the same in the transportation and public facilities during the studied pandemic time period.

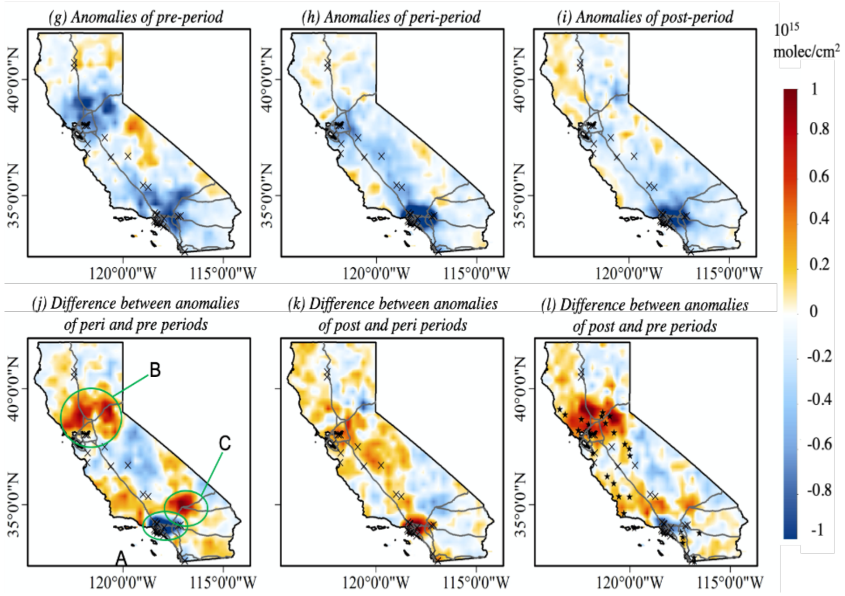
5.2.1 Results visualization: Temporal variations in air pollutants

- The lockdown policy generally reduced the concentration of air pollutants in CA;
- The reopening increased the emissions of air pollution back to a normal trend, as compared to previous years.
- The concentration of CO has a sharper decline than that of NO_2 and $PM_{2.5}$ during the pandemic.
- For visualization method, please refer to slide 43.



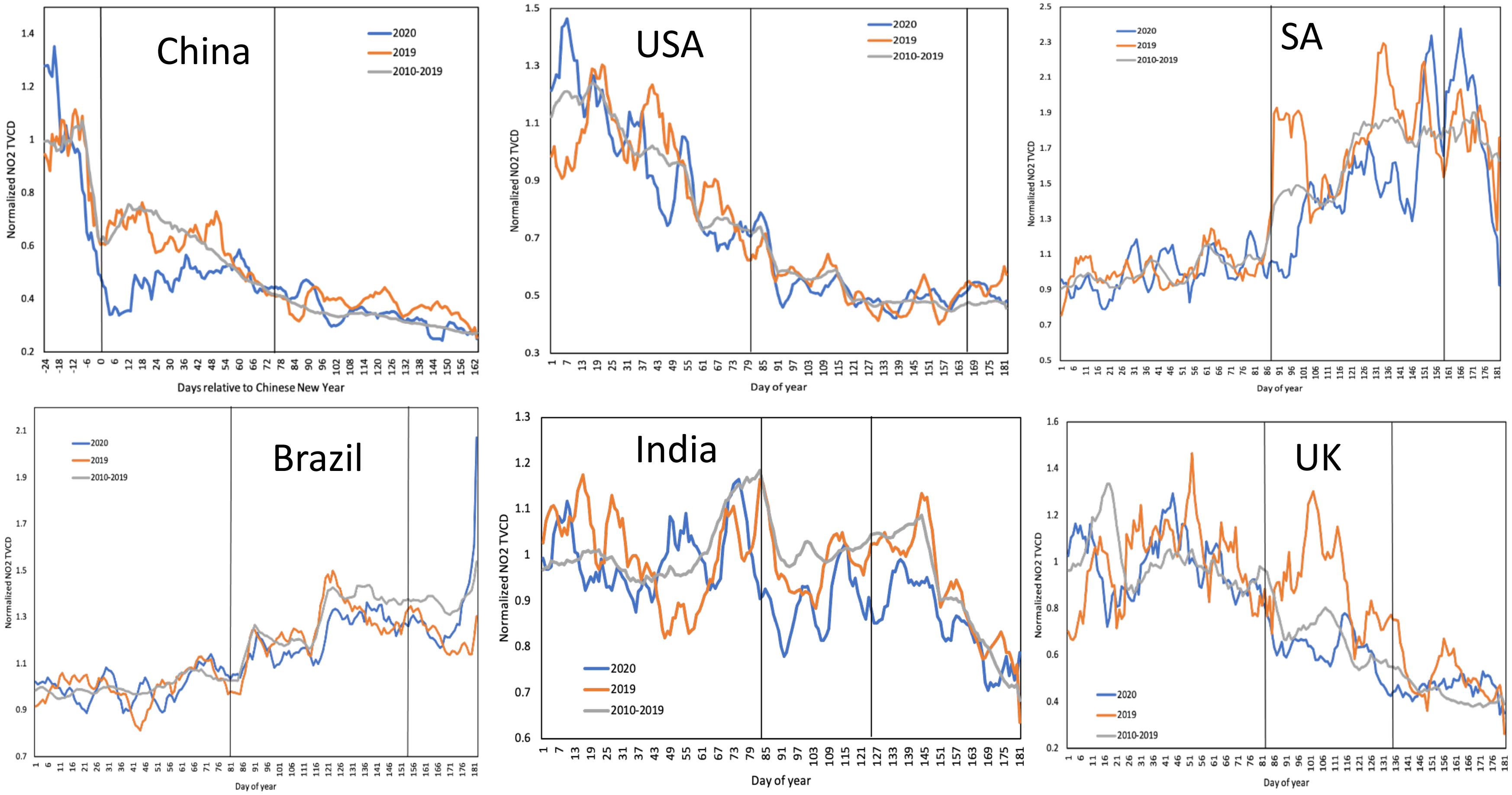
5.2.3 Spatial patterns in Atmospheric NO2





- NO_2 emissions decreased over locations of major power plants;
- NO_2 increased over populous residential areas, especially those serving as transportation hubs at the intersections of national highways.

5.3.3 Results visualization: timeseries analysis



- After the reopening, the NO_2 emissions rebounded to similar levels as the pre-period in most target countries except India.
- The NO_2 columns in India stay at a lower level compared to previous years, indicating that industrial production has not yet recovered from the pandemic.
- Please refer to slide 43 for visualization method.

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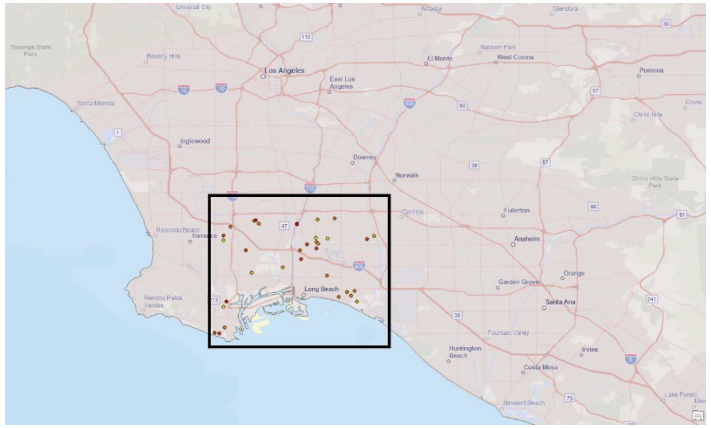
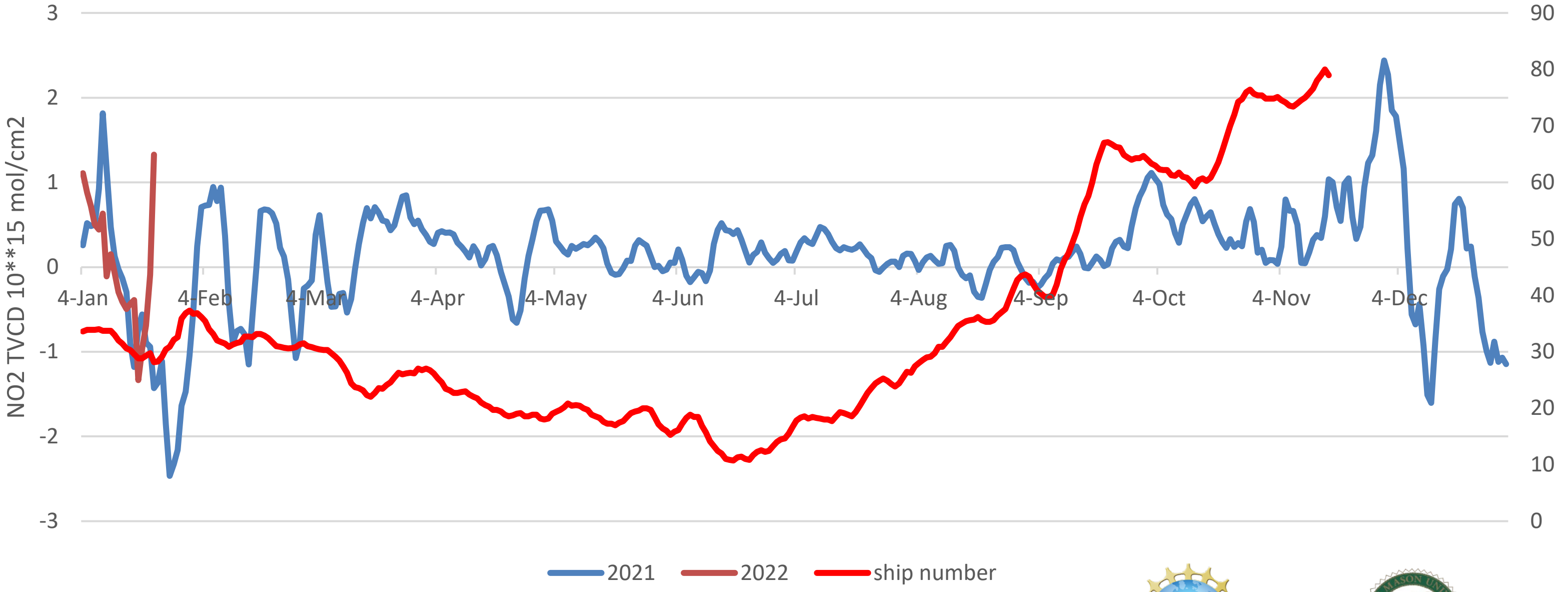
LA port influence on AQ

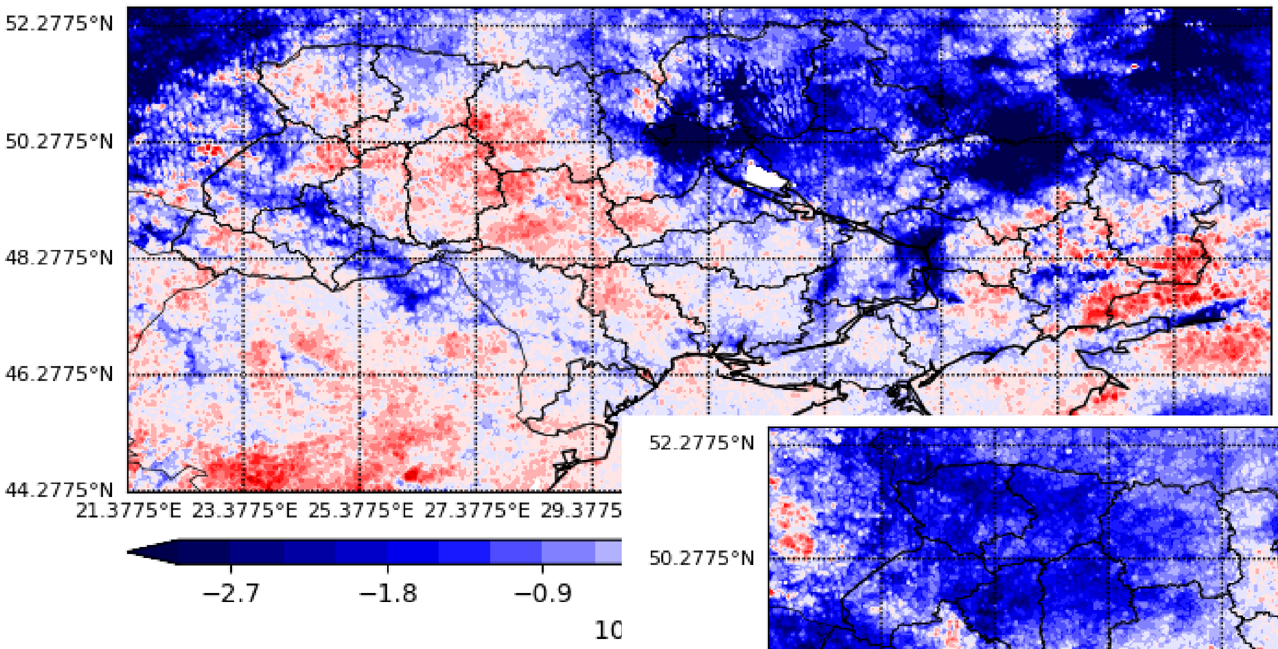


NO2 anomalies from 3-year mean (7-day moving average) over LA

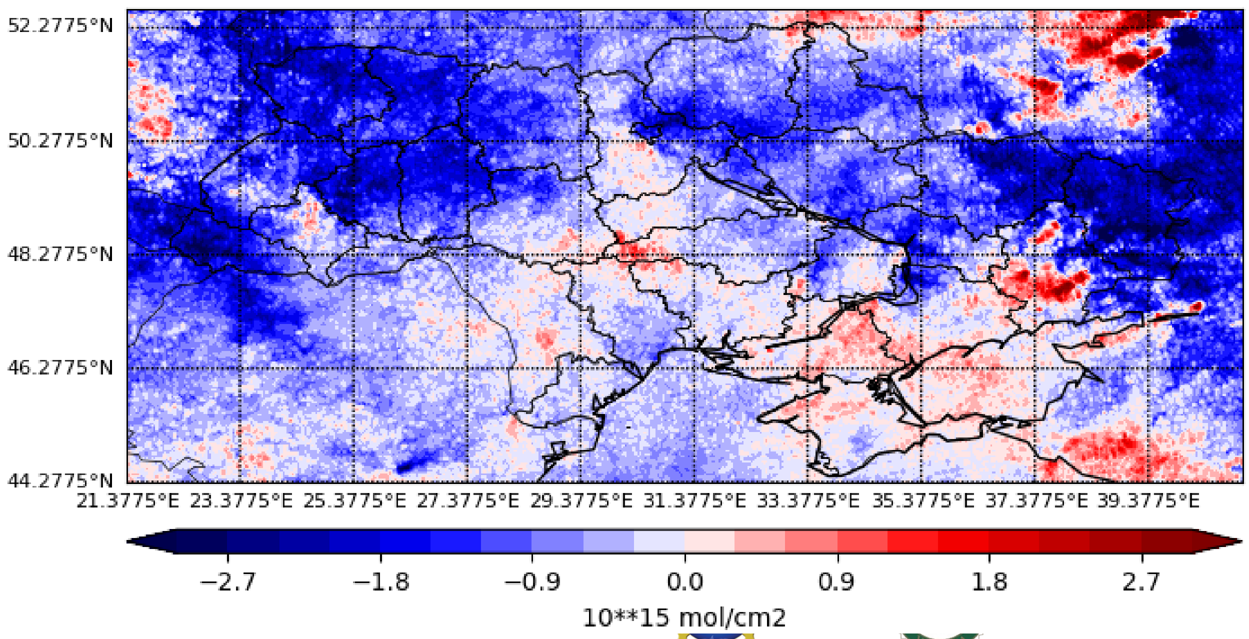


Ukraine conflict influence on AQ

2021



2022



NO2 TVCD differences between after and before the conflict started on Feb 24, in 2021 and 2022

Results: Ukraine conflict influence on NTL

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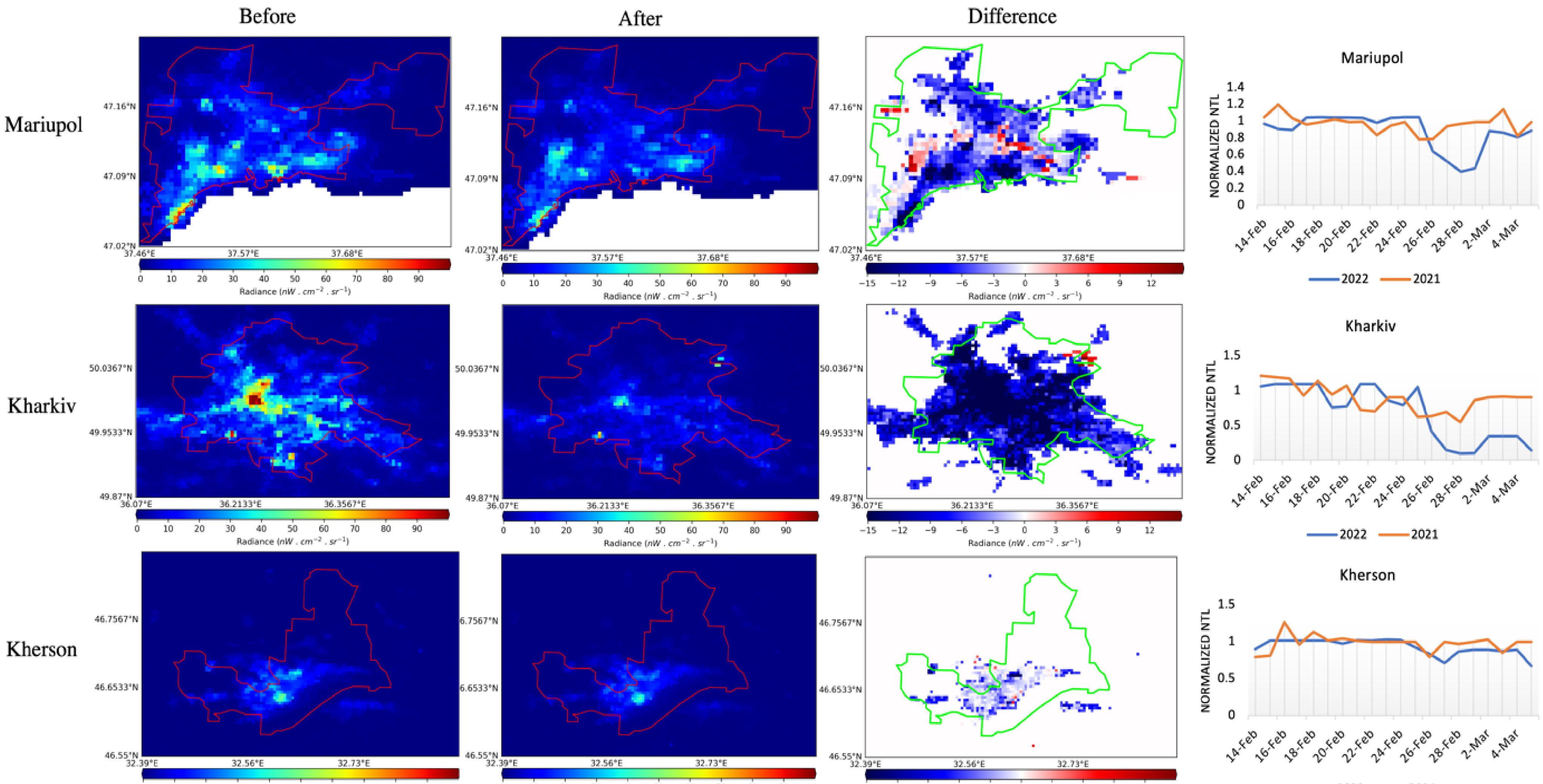

6. Conclusions and Future Research

1) The COVID-19 lockdown and reopening policies have had crucial influences on the air pollution emissions and night light radiances;
2) The impacts vary in different countries, regions and communities;
3) The lockdown policy generally reduced the concentration of air pollutants and night light radiances;
4) The reopening increased the air pollution and night light back to a normal trend;
5) The ship backlog in LA ports increased air pollution;
6) The Ukraine war decreased air pollution at no-ground battle areas but increased where ground battle taken place.

Future work

1) Investigate other affected environmental factors, such as aerosol.
2) Conduct more comprehensive error analysis.
3) Quantitative analysis of other parameters' impacts on the results, such as transportation and wind.
4) Further estimation on the economy based on the derived results.
5) Derive the factors that may be helpful to mitigate air pollution for other use cases.
6) Investigate the public health impact by the air quality change.

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Thank you!

Any questions, comments, suggestions, please email to

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