Collaborative Innovation Center for Western Ecological Safety (CIEWS)

4th Atmospheric Oxygen Workshop

‘Urban Respiration’: Insights from O_2 Measurements

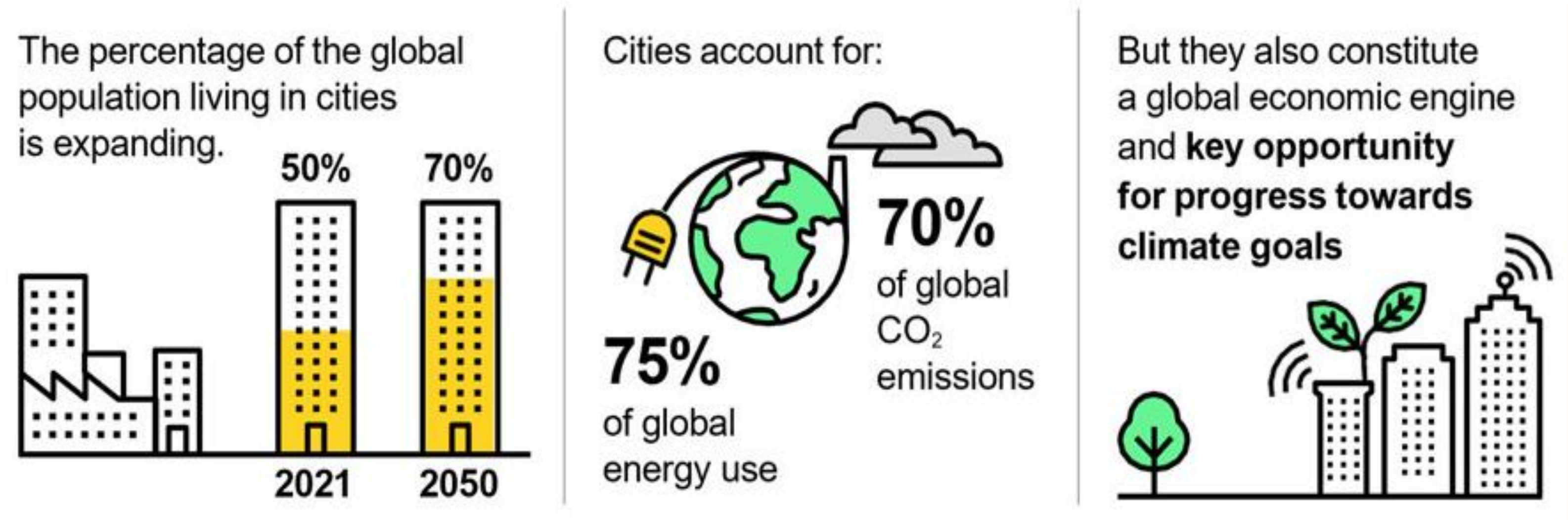
Xiaoyue Liu, Jianping Huang*, Li Wang, Changyu Li

Collaborative Innovation Center for Western Ecological Safety, Lanzhou University

Aug. 25th 2023

CONTENTS

Urban regions: the largest CO_2 sources and O_2 sinks



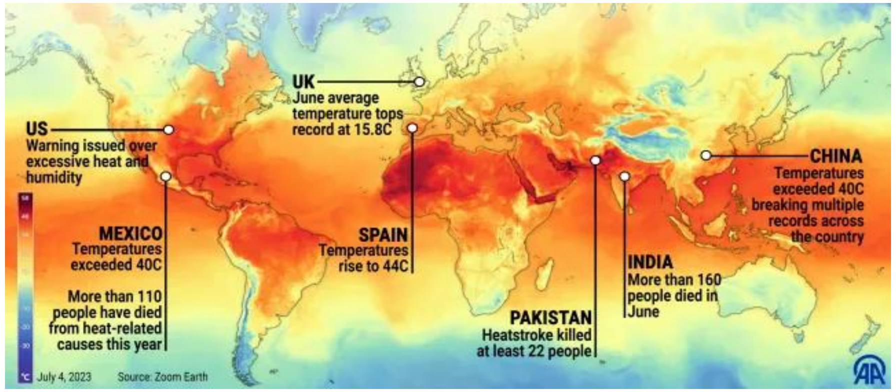
0.37% of the Earth's land

More than half of population

70% CO_2 emissions

Higher risk of pollutant exposure

- **Jul. 2023 the hottest month on record**



Global warming
&
Air pollution

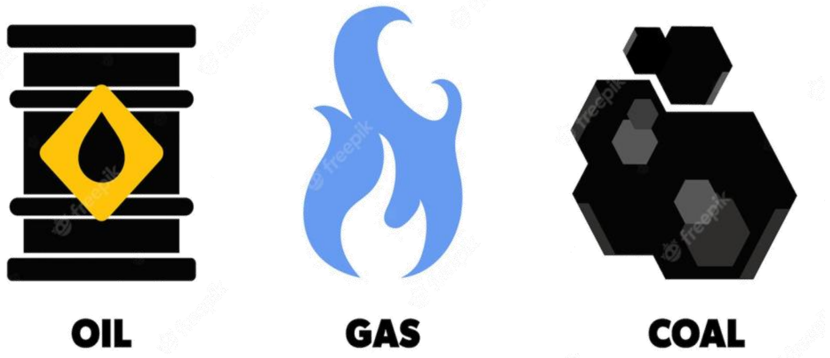
- **Air pollution kill ~7 million people/yr**

(International Energy Agency, 2021; NASA, 2023; WHO, 2022)

Anthropogenic O_2 consumption in urban regions

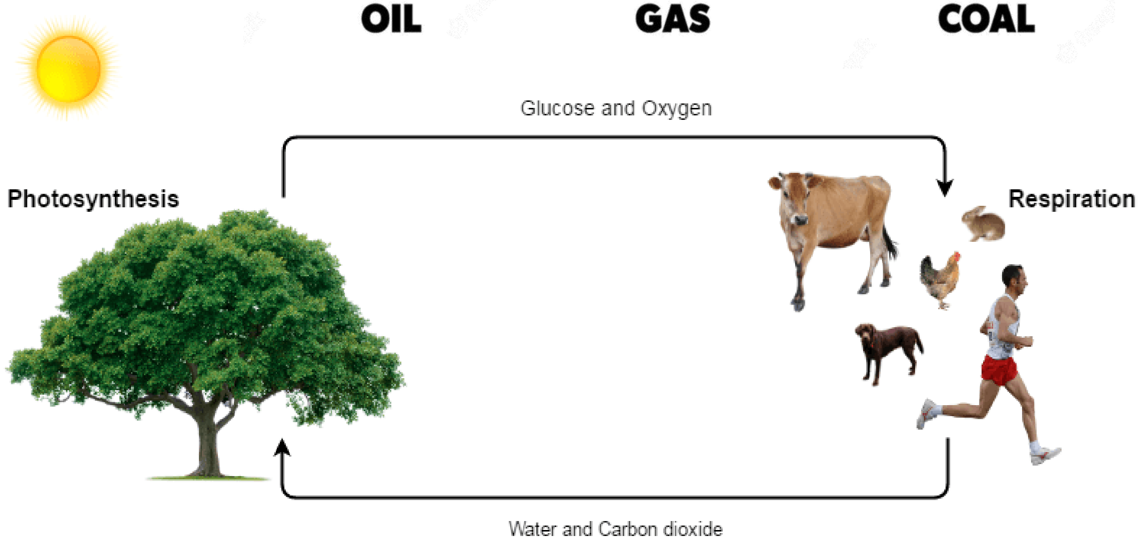
✓ Fossil Fuel Combustion

$$\text{fossil fuel} + O_2 \rightarrow CO_2 + H_2O + \text{pollutants}$$



✓ Respiration

$$C_6H_{12}O_6 + O_2 \rightarrow CO_2 + H_2O$$

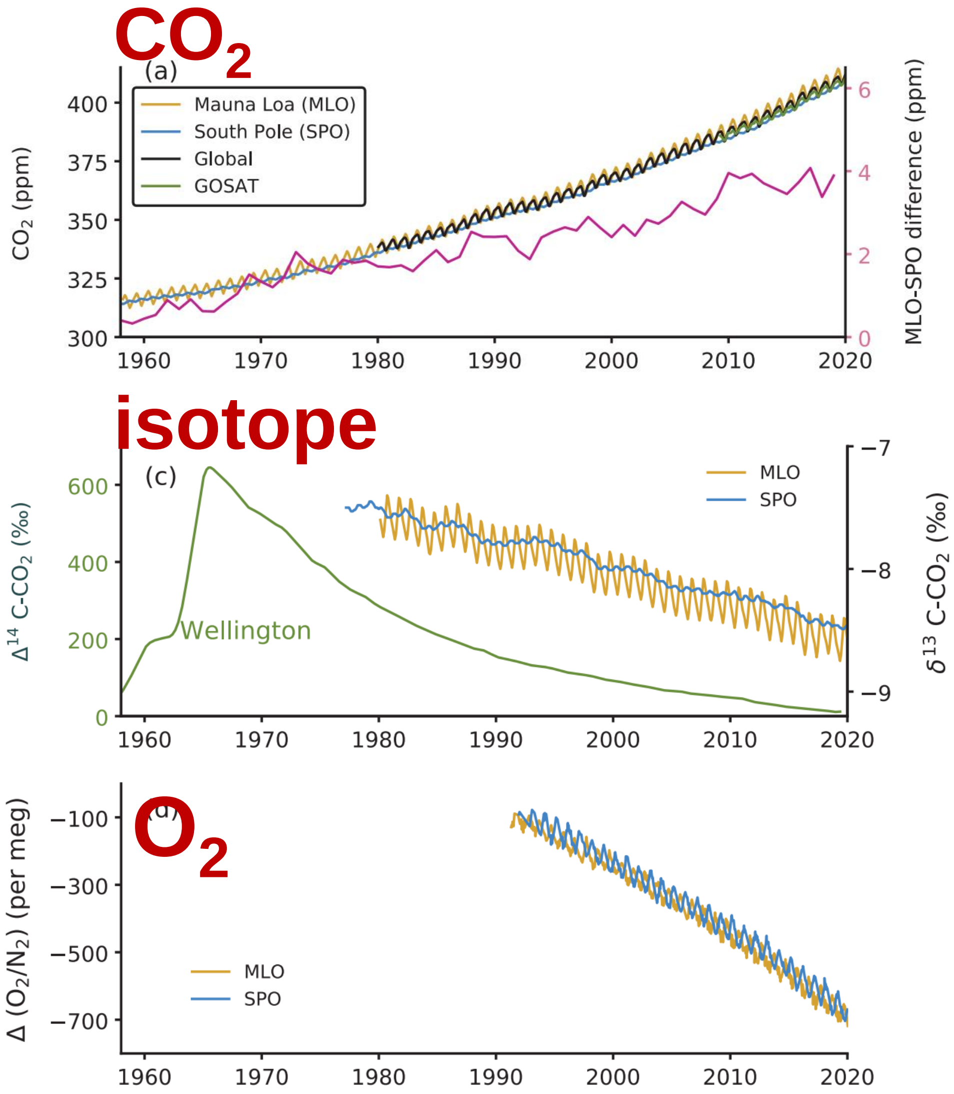


✓ Others

Industrial use of O_2, refining of metals

(Battle et al., 2023)

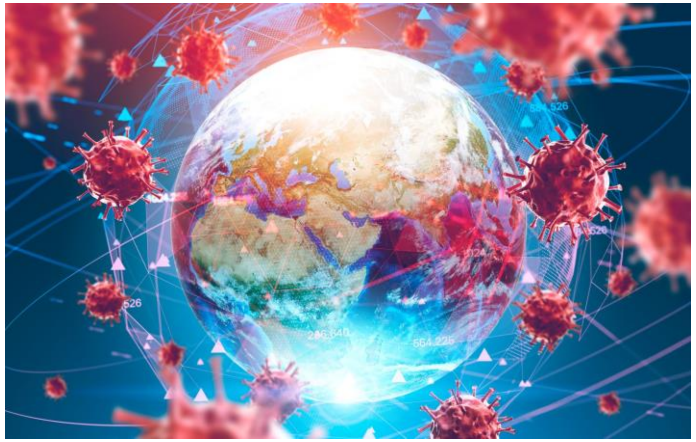
Long-term Fossil Fuel Impact on O_2 and CO_2



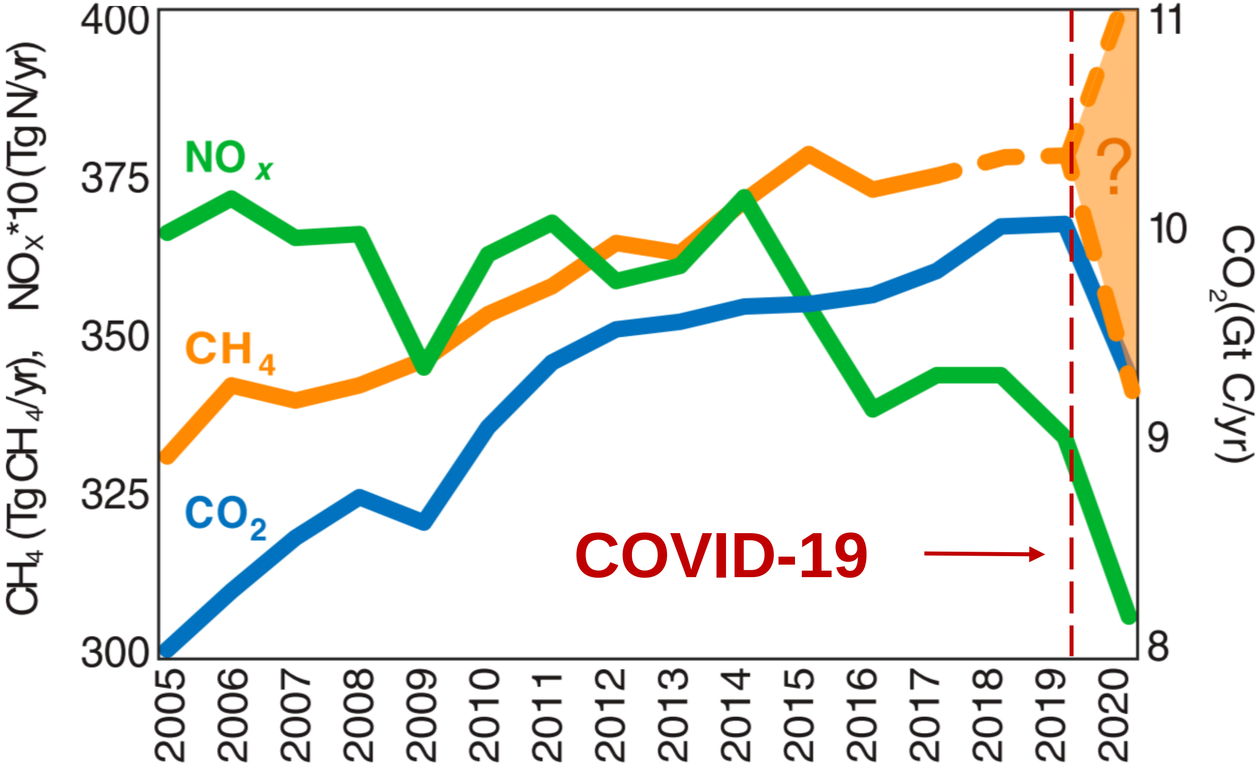
(IPCC AR6, 2021)

Short-term Changes in Fossil Fuel Emission

COVID-19 lockdown



Impact on emission changes

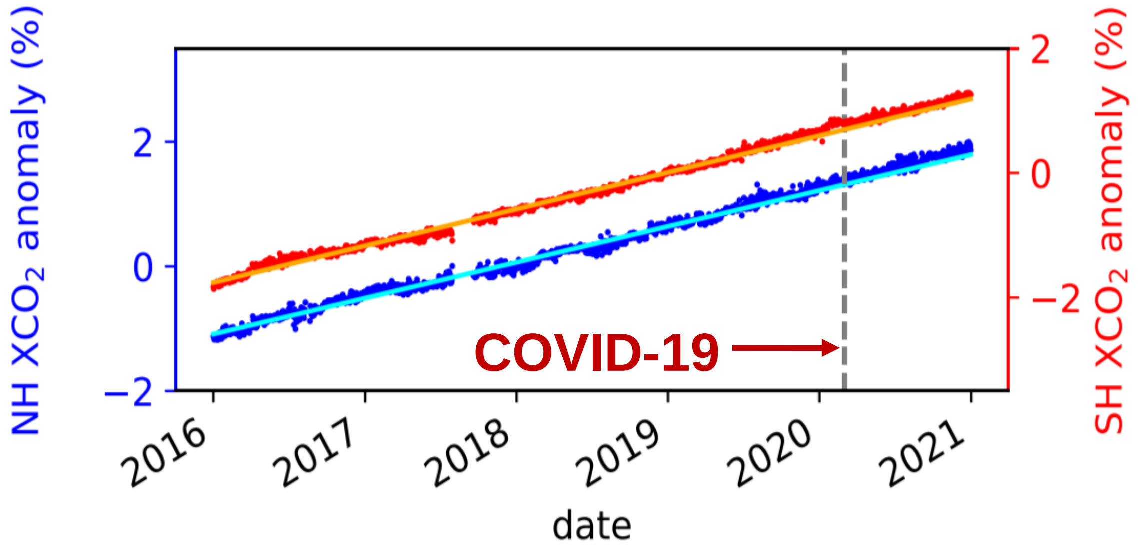


- Comparable reductions (10%~20%) in CO_2 and NO_x emission in 2020 (COVID-19 lockdown).
- Can this emission decline be detected in short-term observations?

(Laughnera et al., 2021)

Short-term Changes in Fossil Fuel Emission

- CO_2 (O_2): anthropogenic & biological

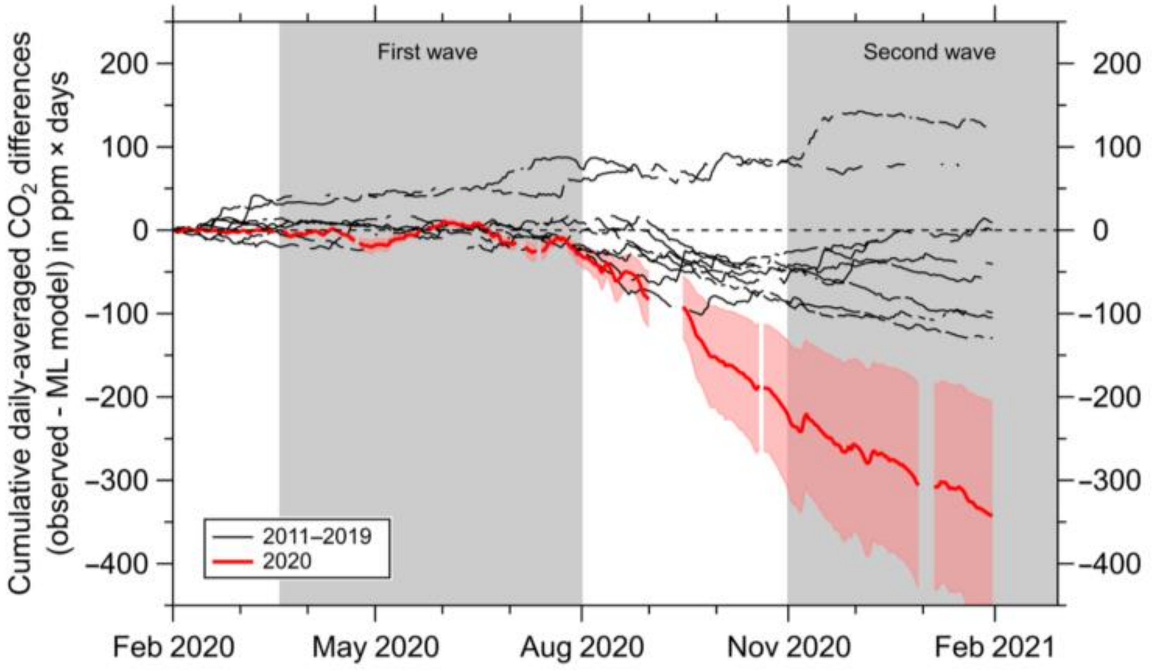


- Almost no change in the observed XCO_2
- longer atmospheric lifetime
- impact from biological and oceanic fluxes

(Laughnera et al., 2021)

- ffCO2 from APO

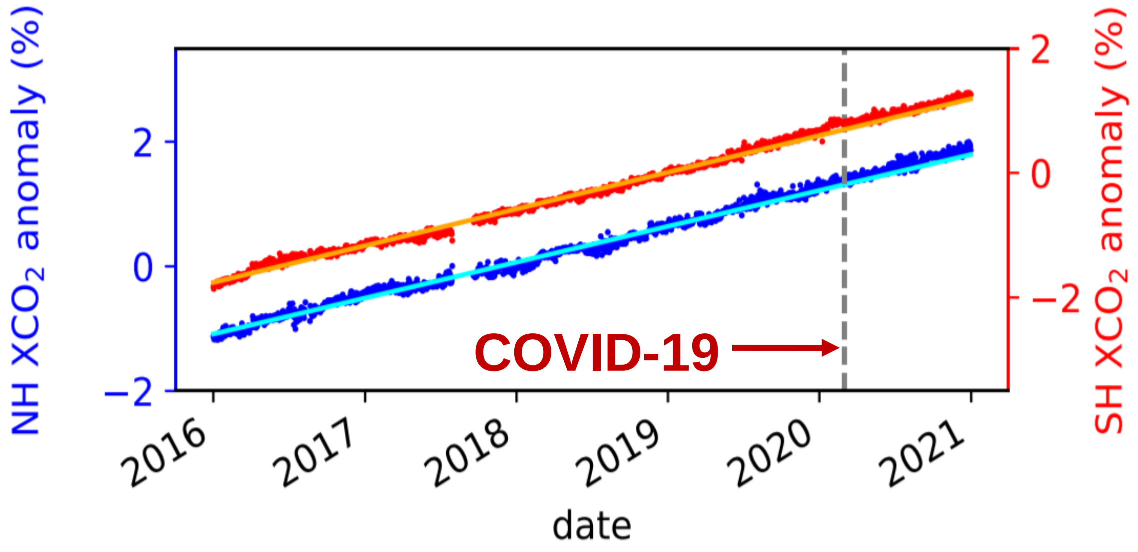
$$ffCO_2[APO] = \frac{APO - APO_{BL}}{R_{APO}}$$



(Pickers et al., 2022)

Short-term Changes in Fossil Fuel Emission

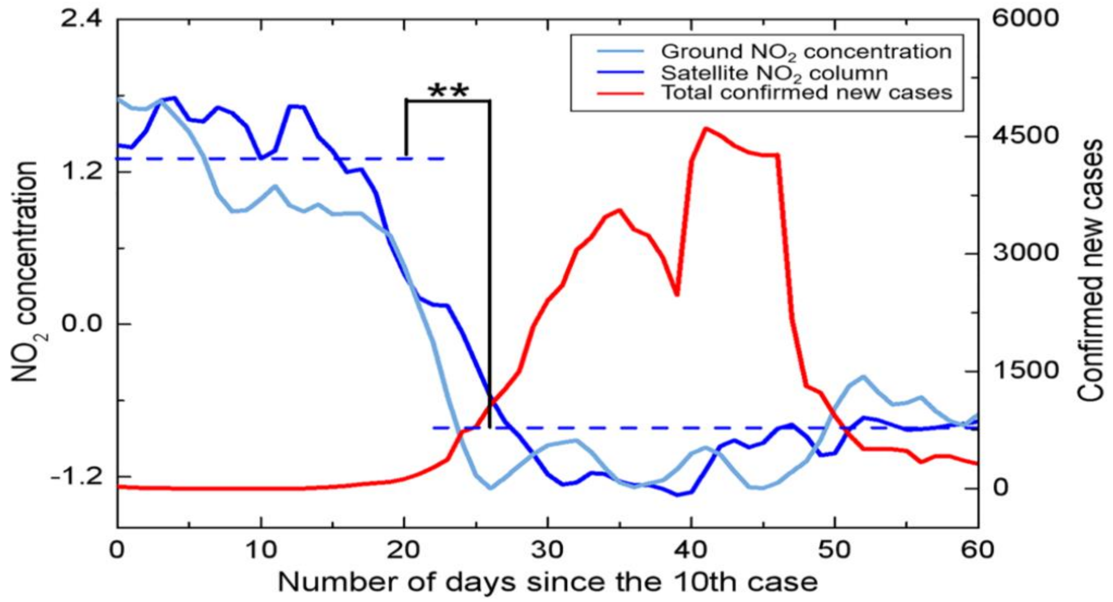
➢ CO_2 (O_2):
anthropogenic & biological



- Almost no change in the observed XCO_2
- longer atmospheric lifetime
- impact from biological and oceanic fluxes

(Laughnera et al., 2021)

➢ Pollutants:
alternative tracer?

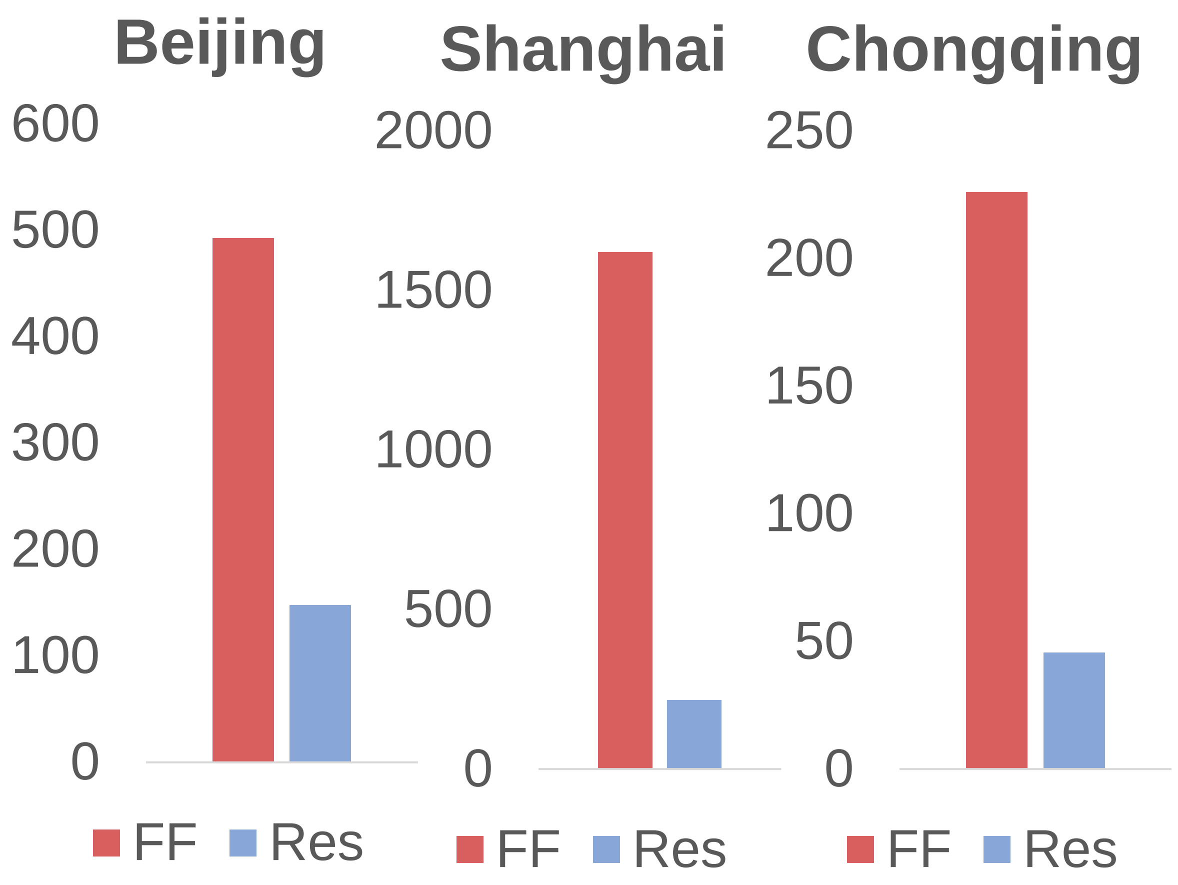


- Effective indicator for lockdown
- shorter atmospheric lifetime
- co-emitted during FF combustion
- Tracer of human activities

(Lian et al., 2020)

Respiration Impact on Atmospheric O_2 and CO_2

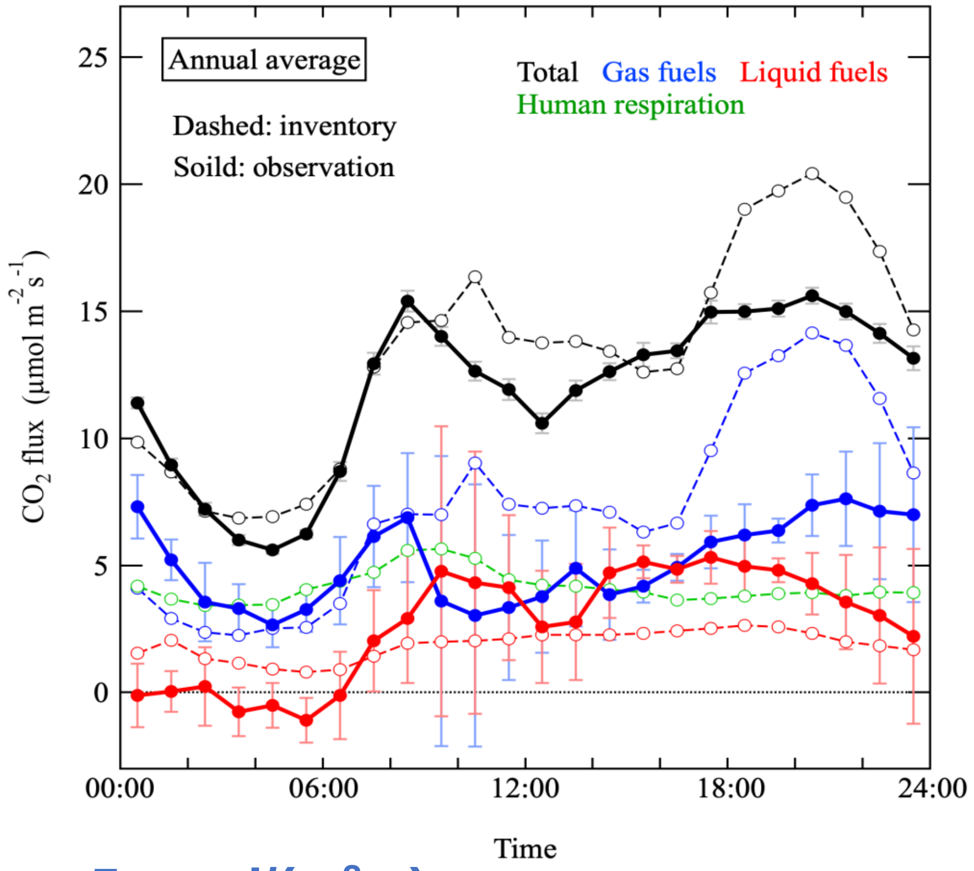
➢ Based on food consumption



~30% **~13%** **~20%**

(Ciais et al., 2007)

➢ Based on O_2 and CO_2 measurements



- **~ 5 μmol/(m^2·s)**
- **with pop density 16 600 persons / km^2**

(Ishidoya et al., 2020)

CONTENTS

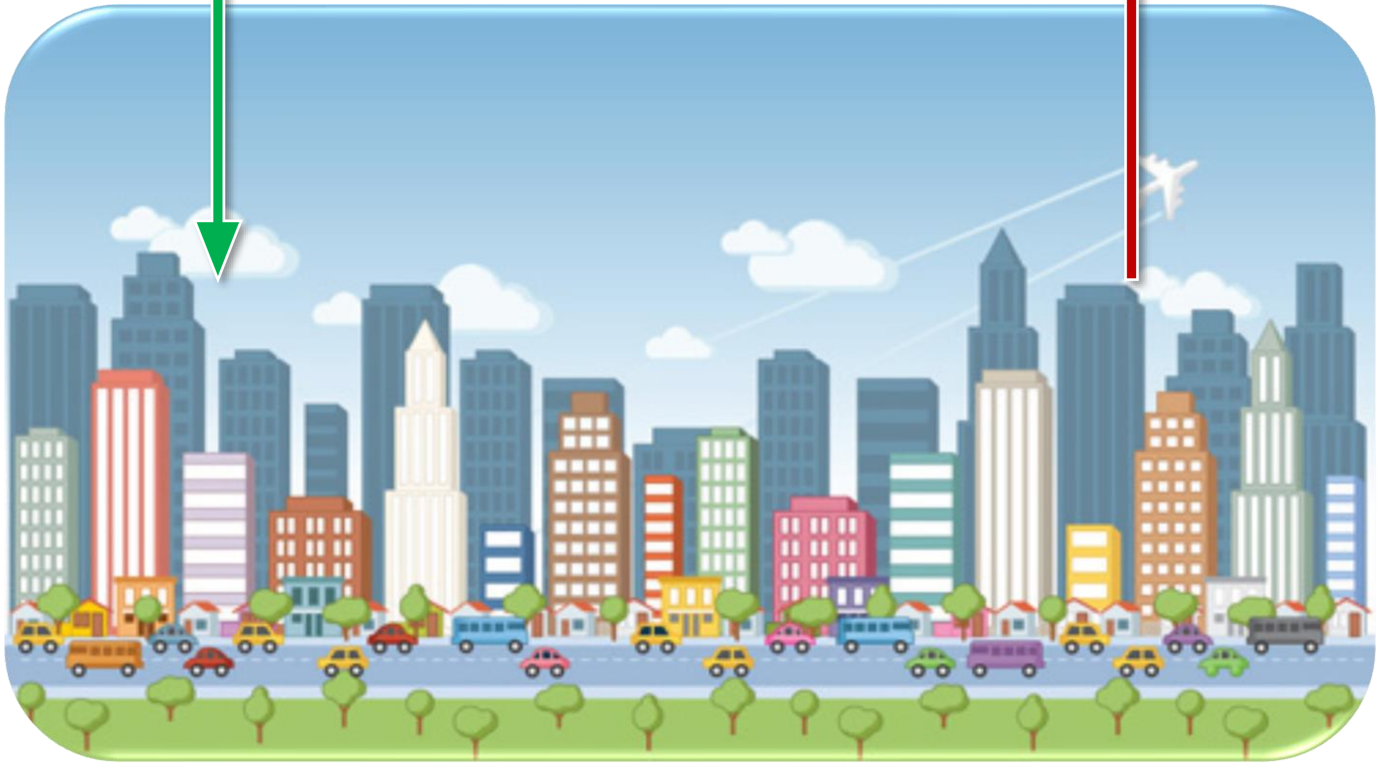
Introducing "Urban Respiration"

Inhale

O_2

exhale

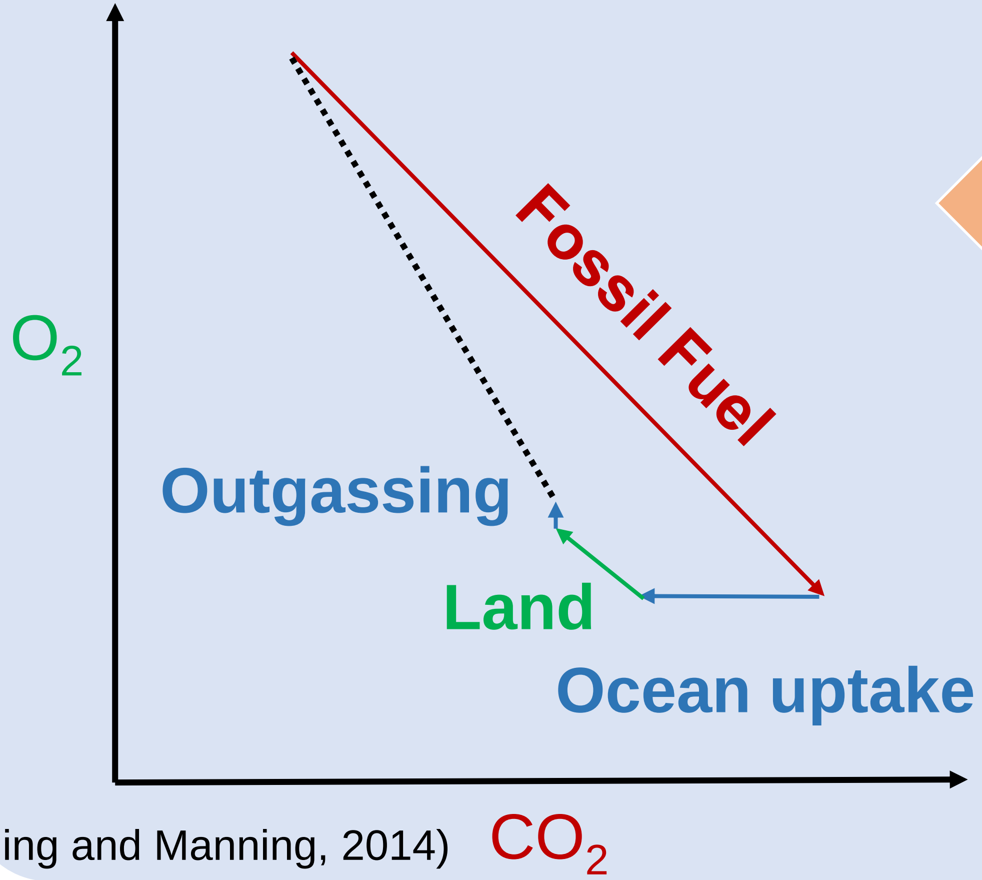
CO_2 & pollutants



Introducing "Urban Respiration"

Global Scale

$$\Delta CO_2 = FF - O - B$$
$$\Delta O_2 = -OR_{FF}(FF) + OR_B(B) + ZO_2$$

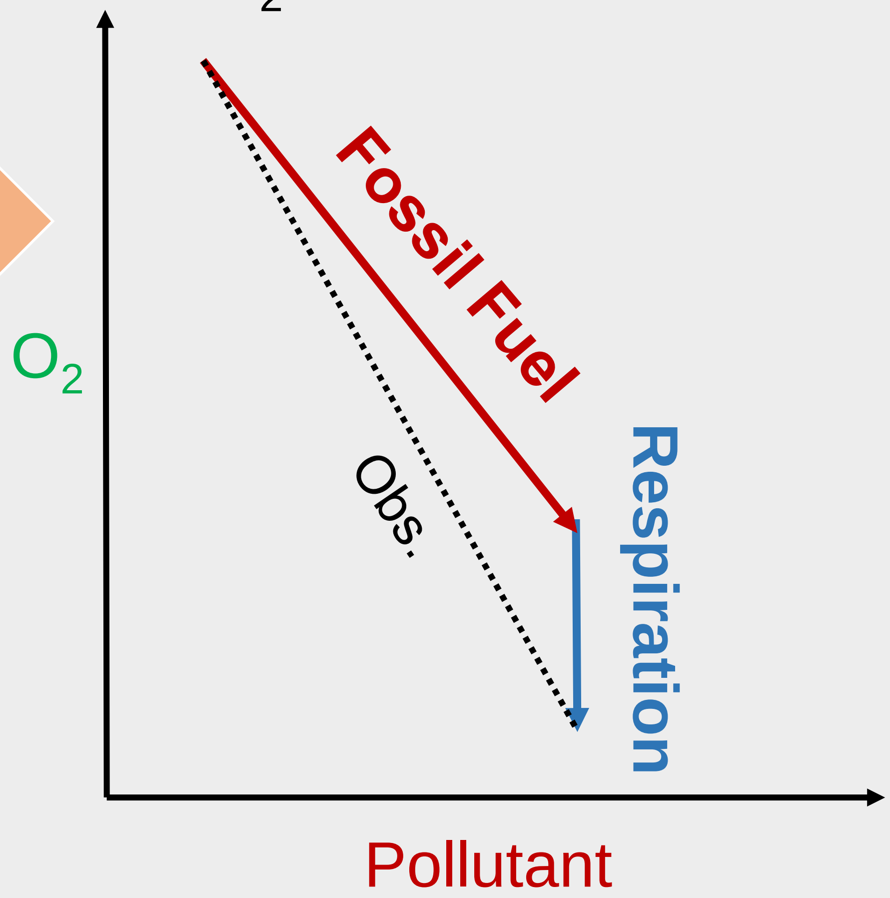


(Keeling and Manning, 2014)

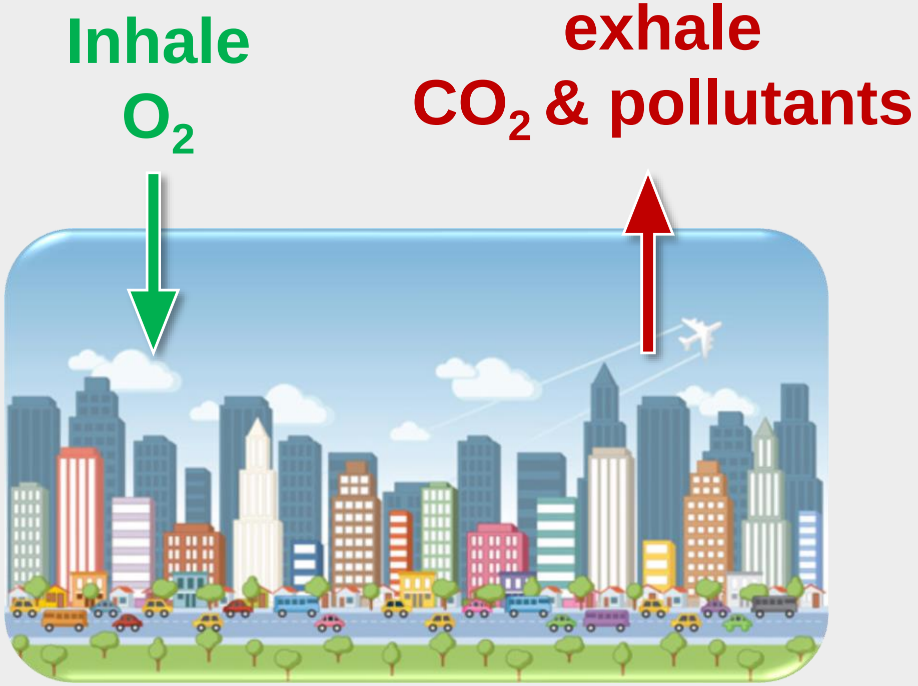
Constrain

Urban Scale

$$\Delta Poll \sim FF$$
$$\Delta O_2 = -FF - Res$$



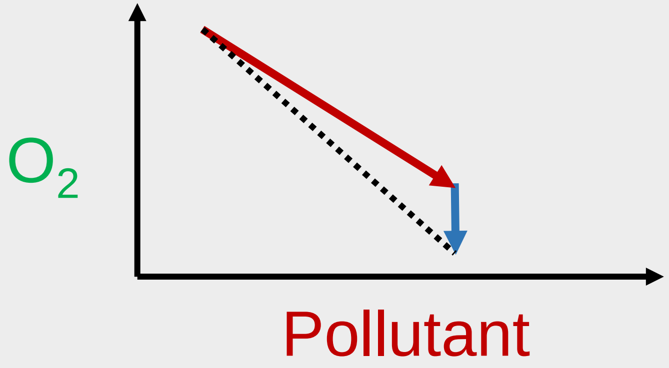
Introducing "Urban Respiration"



Urban Scale

ΔPoll ~ FF

ΔO_2 = – FF– Res

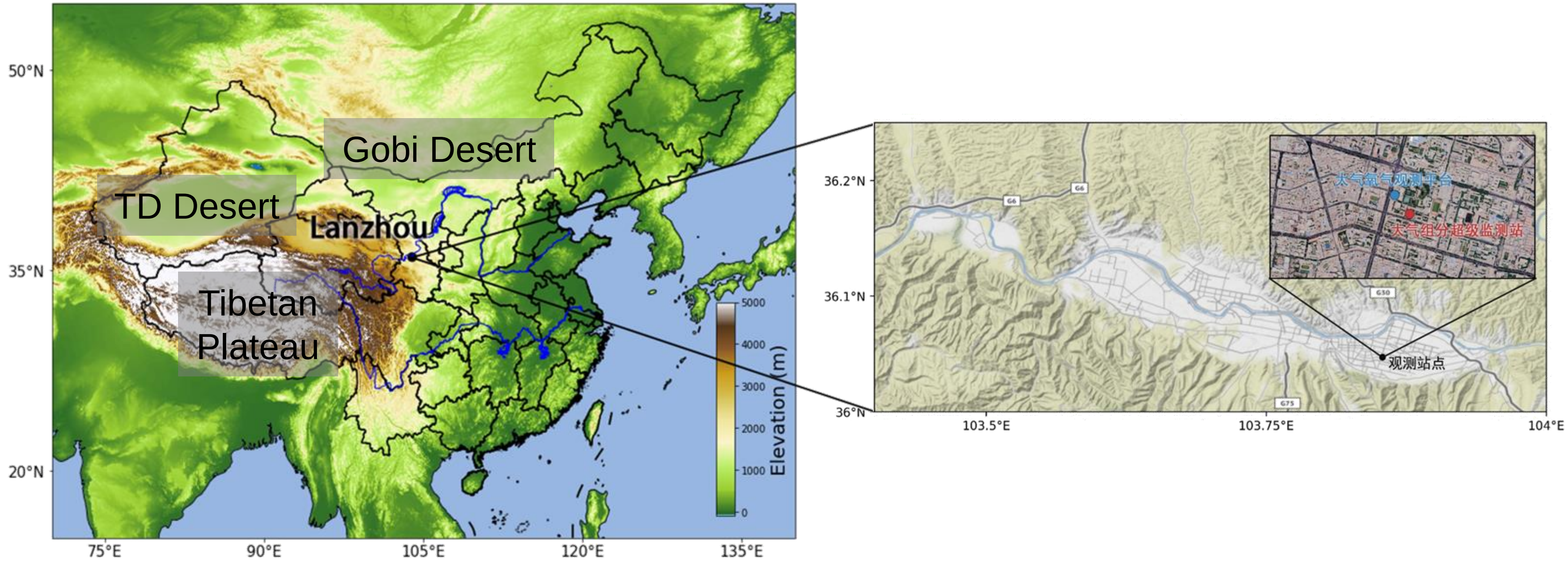


- What insights can urban measurements of O_2 and pollutants provide?
- Can pollutant measurements help us distinguish between **fossil fuel combustion** and **resident respiration** in urban atmosphere?

CONTENTS

Site location: Downtown Lanzhou

✓ Capital City of Gansu Province in Northwestern China



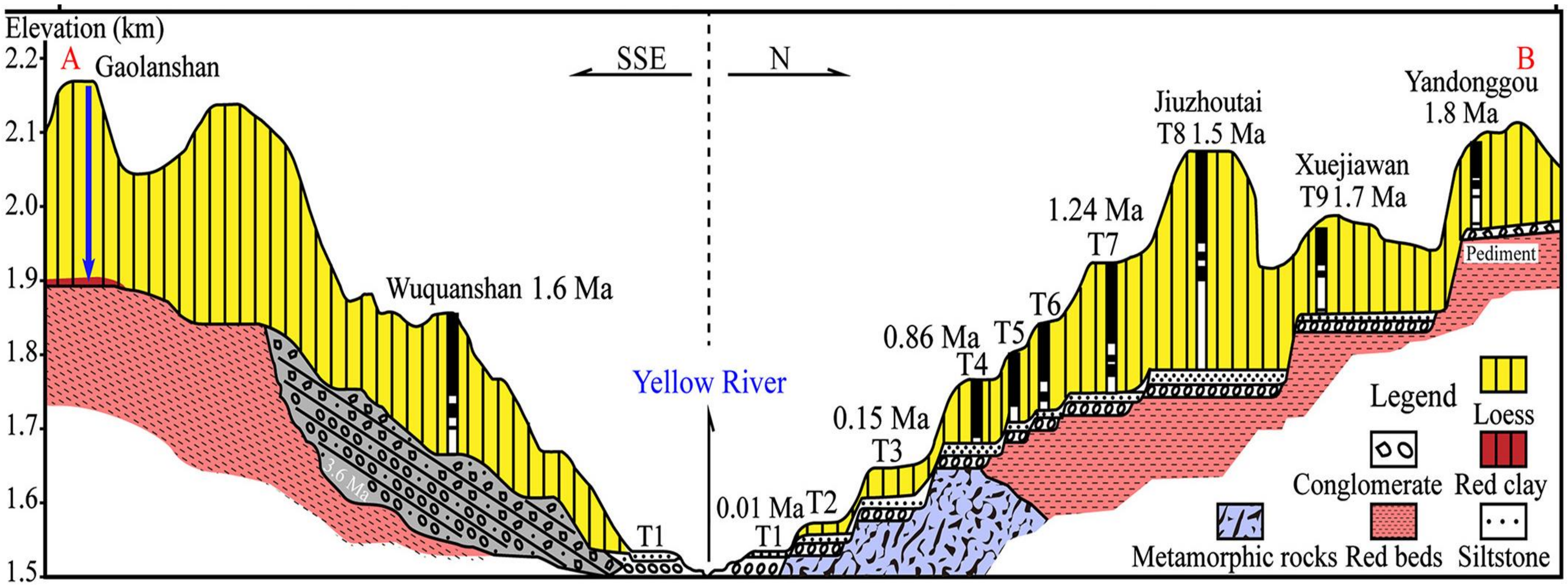
2000s

2020s

- semi-arid climate, south of Gobi desert, with sparse vegetation
- ~ 4 million population, nestled in a narrow river valley
- used to be one of the most polluted city in China

Site location: Downtown Lanzhou

✓ Capital City of Gansu Province in Northwestern China



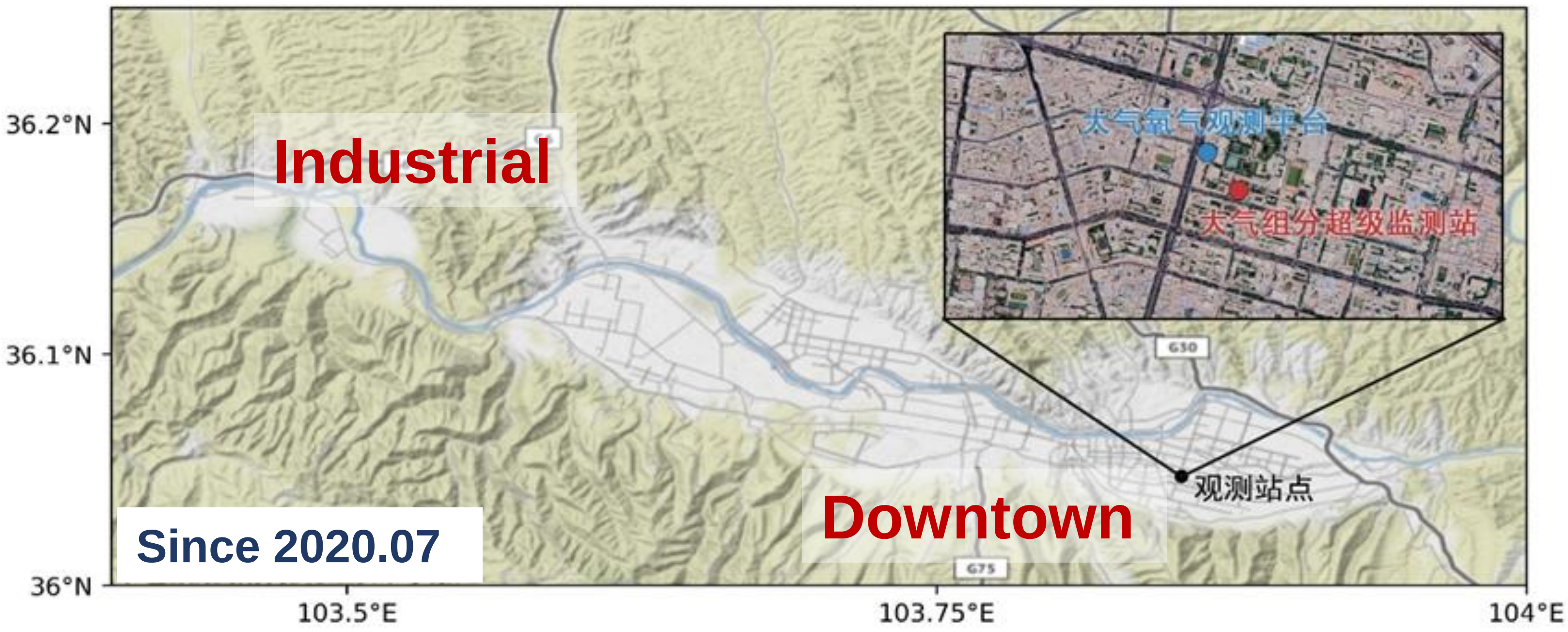
(Guo et al., 2020)

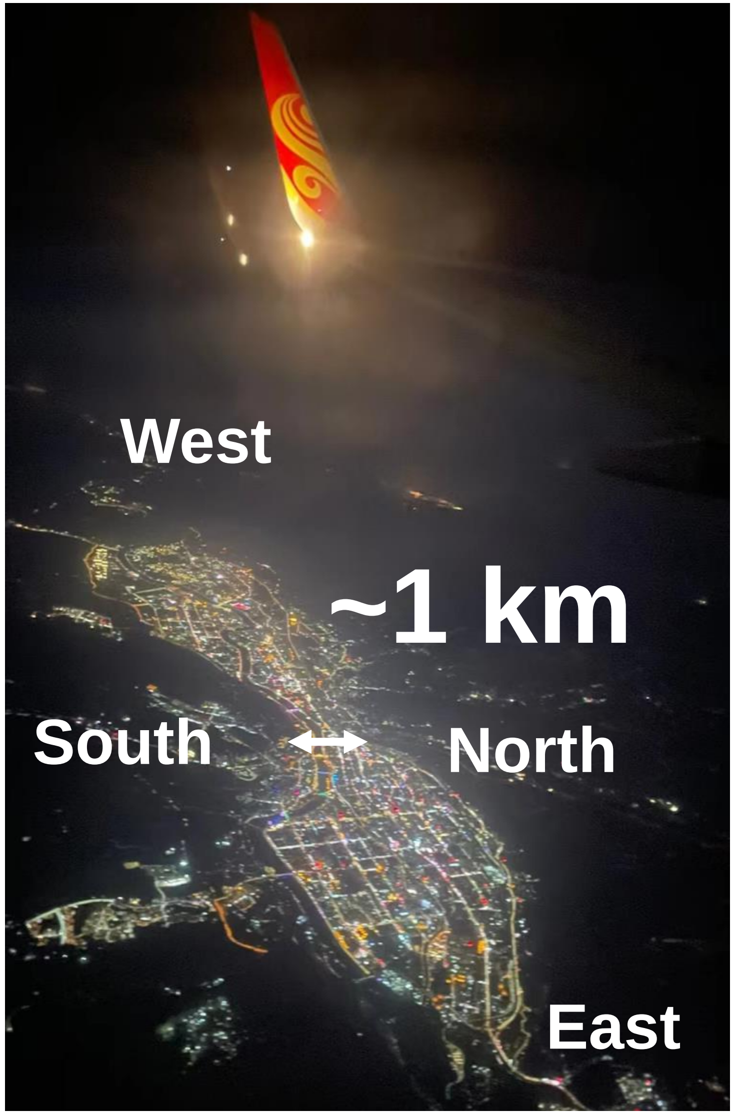
2000s

2020s

- semi-arid climate, south of Gobi desert, with sparse vegetation
- ~ 4 million population, nestled in a narrow river valley
- used to be one of the most polluted city in China

Site location: Downtown Lanzhou





O_2/N_2 ratio

Agilent 7890B

4.77 per meg

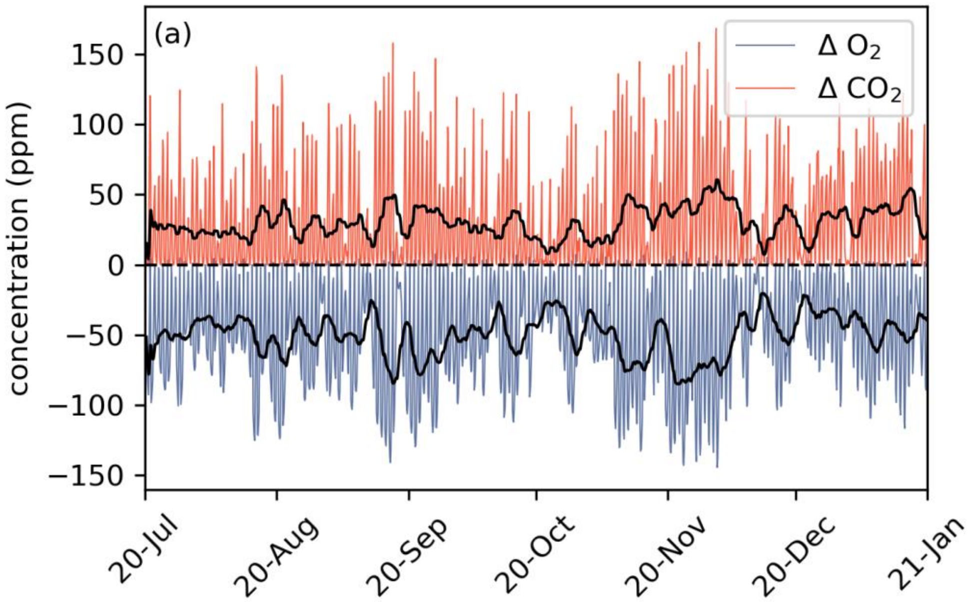
~

1 ppm

O_2 volume fraction

Picarro G2207-i

Site location: Downtown Lanzhou

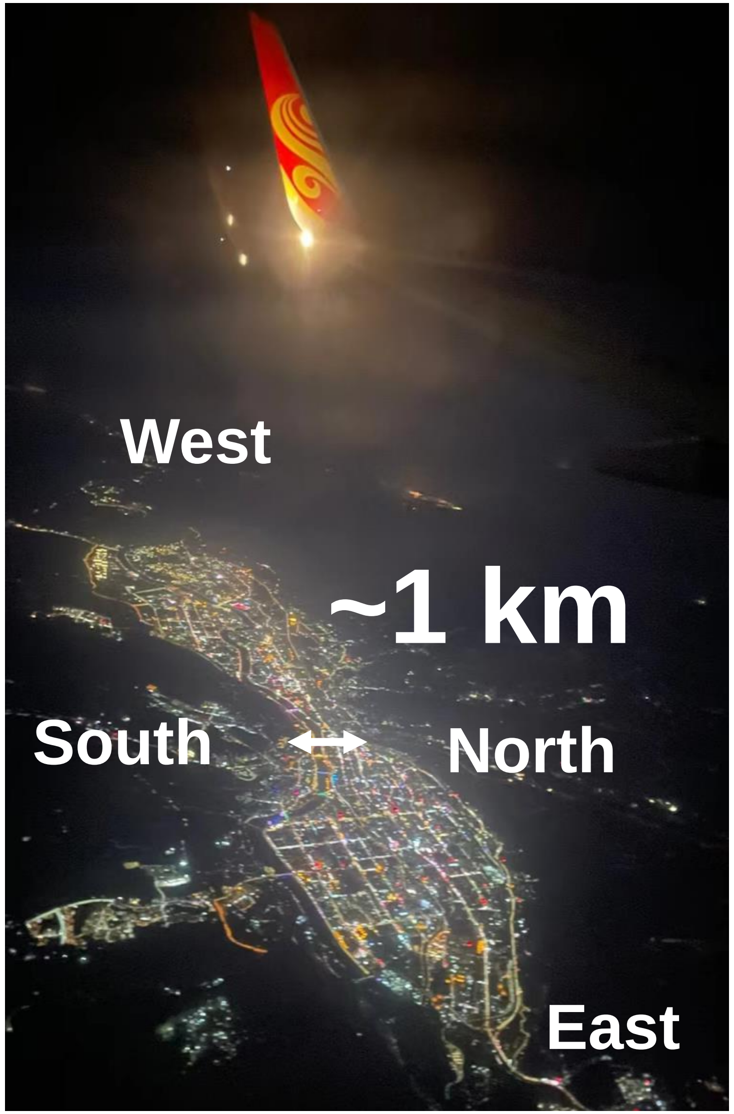


OR_gas ~ 1.96

OR_oil ~ 1.44

OR_obs ~ 1.33 ± 0.017

OR_coal ~ 1.17



O_2/N_2 ratio

Agilent 7890B

4.8 per meg ~ 1 ppm

O_2 volume fraction

Picarro G2207-i

Site location: Downtown Lanzhou

With population density > 50,000 persons/km^2, resident respiration could contribute significantly to local O_2 variability.

Atmospheric Pollutants Measurements

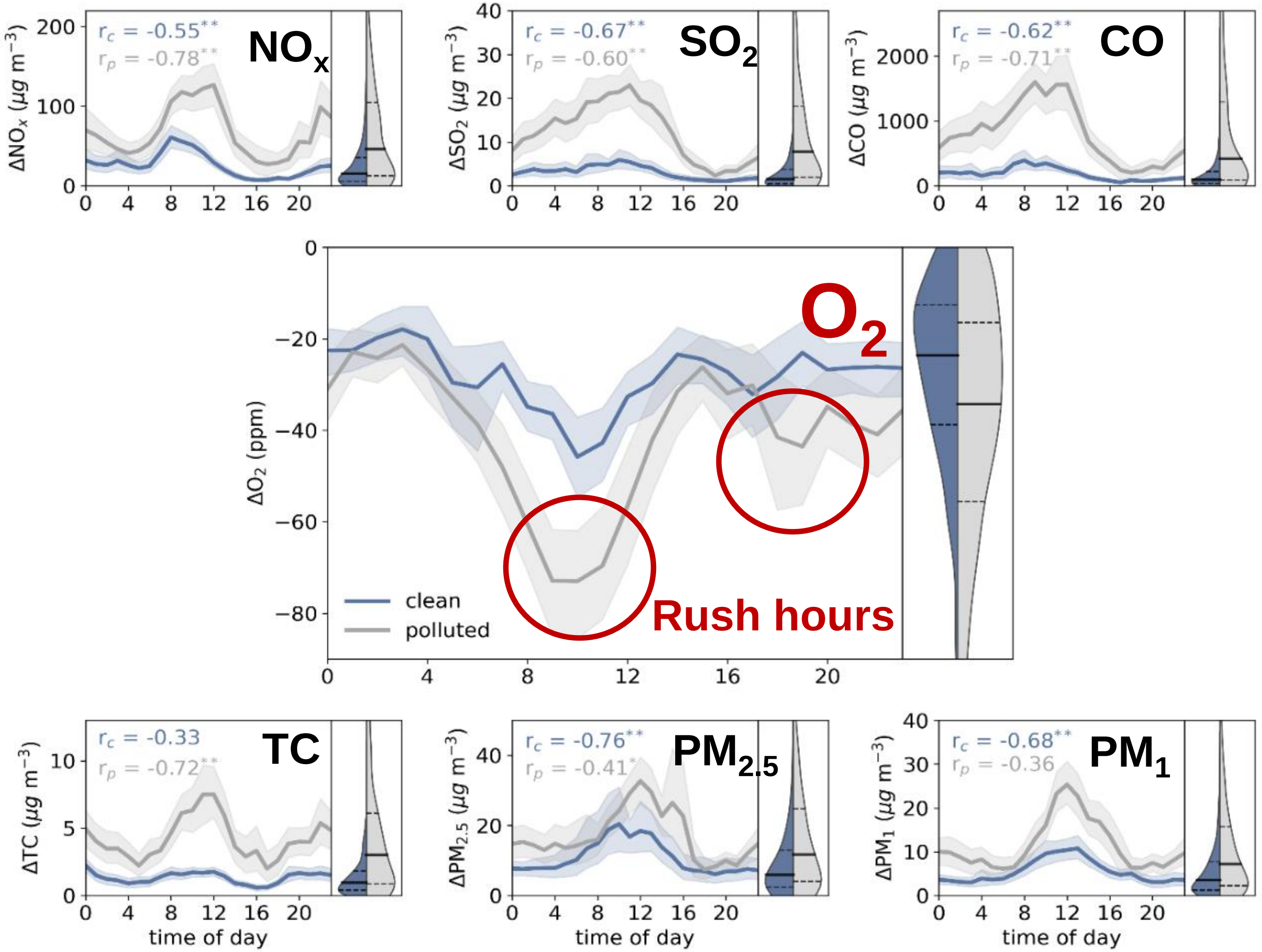
Emitted with fossil fuel combustion from broad sources

- **Oxides**: CO, NO, NO_2, SO_2
- **Particulate matter**: TSP, PM_{10}, $PM_{2.5}$, PM_1
- **Carbon in Particulate Matter**: OC, EC

$$\text{Fossil Fuel} + O_2 \rightarrow H_2O + CO_2 + CO + NO_x + SO_2 + \text{others}$$

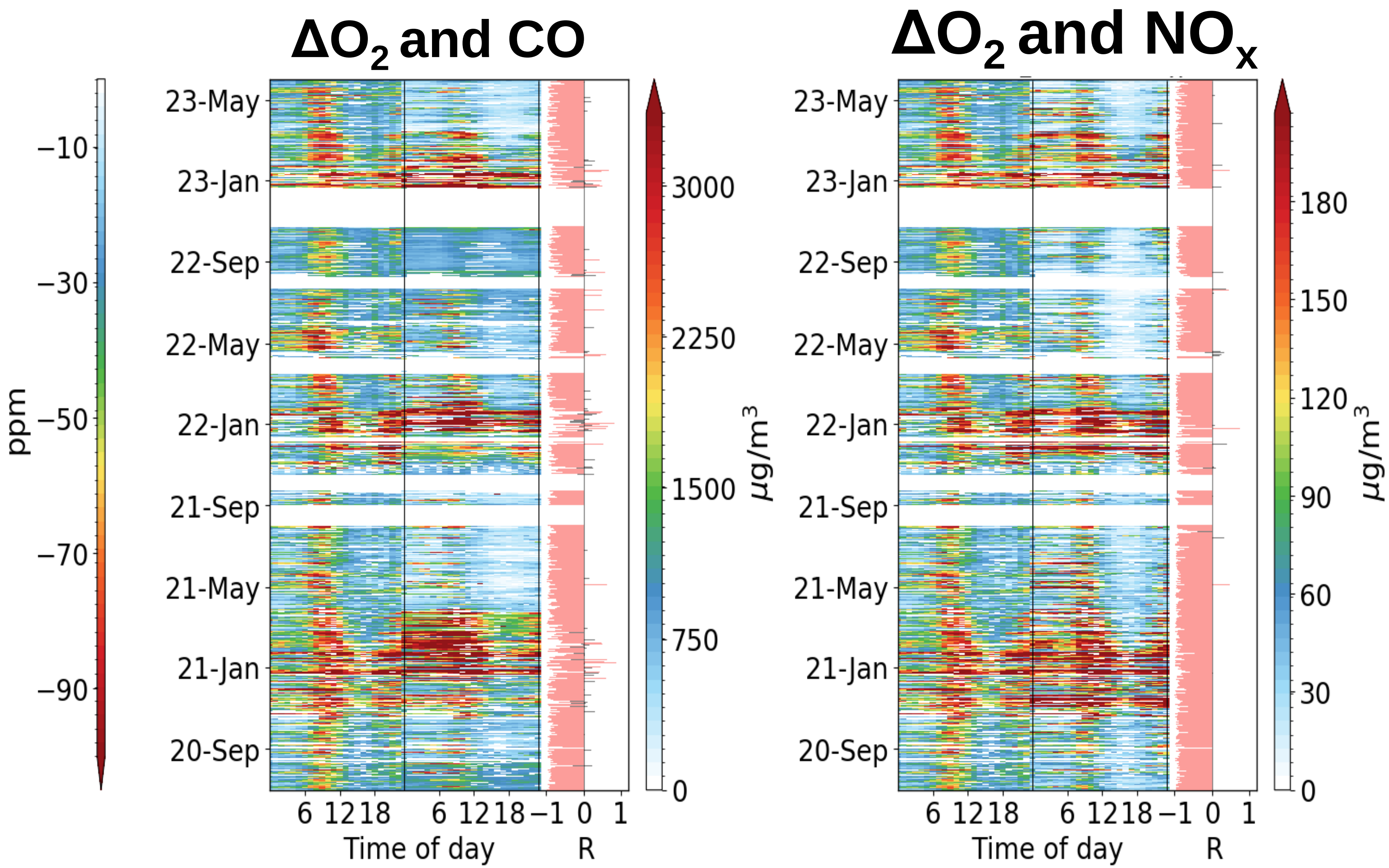
$$\mathbf{FF \sim k_1 \times CO + k_2 \times NO_x + k_3 \times SO_2 + \ldots + k_n \times Poll}$$

Correlation between O_2 and Pollutants



- Strong anti-correlations;
- Obvious diurnal and seasonal cycles;
- Low O_2 and high pollutants during cold seasons
- Lowest O_2 in the morning

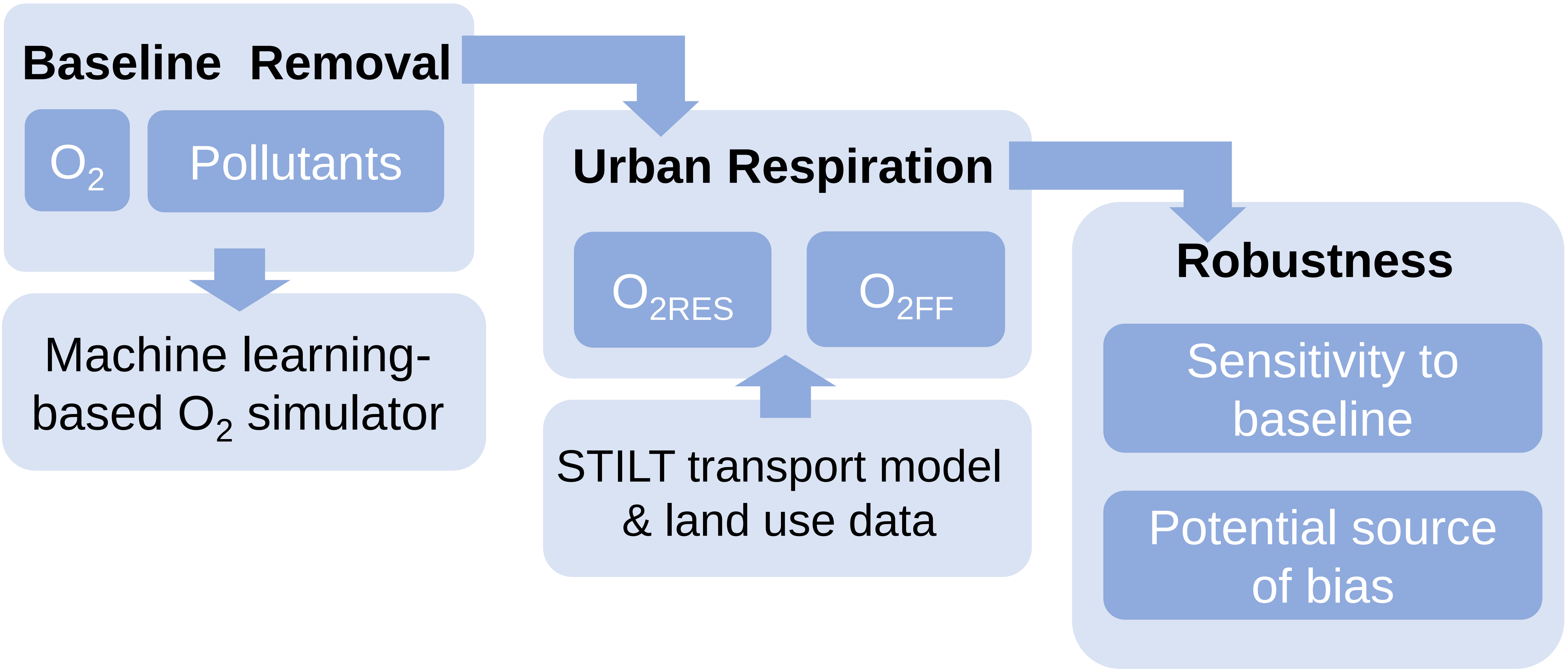
Correlation between O_2 and Pollutants



- Strong anti-correlations;
- Obvious diurnal and seasonal cycles;
- Low O_2 and high pollutants during cold seasons
- Lowest O_2 in the morning

CONTENTS

Quantifying “Urban Respiration”



Quantifying "Urban Respiration"

➢ Baseline removal: highlight excess decline (growth) in O_2 (pollutants)

- Pollutant: the ***1st*** percentile in each 24 hour

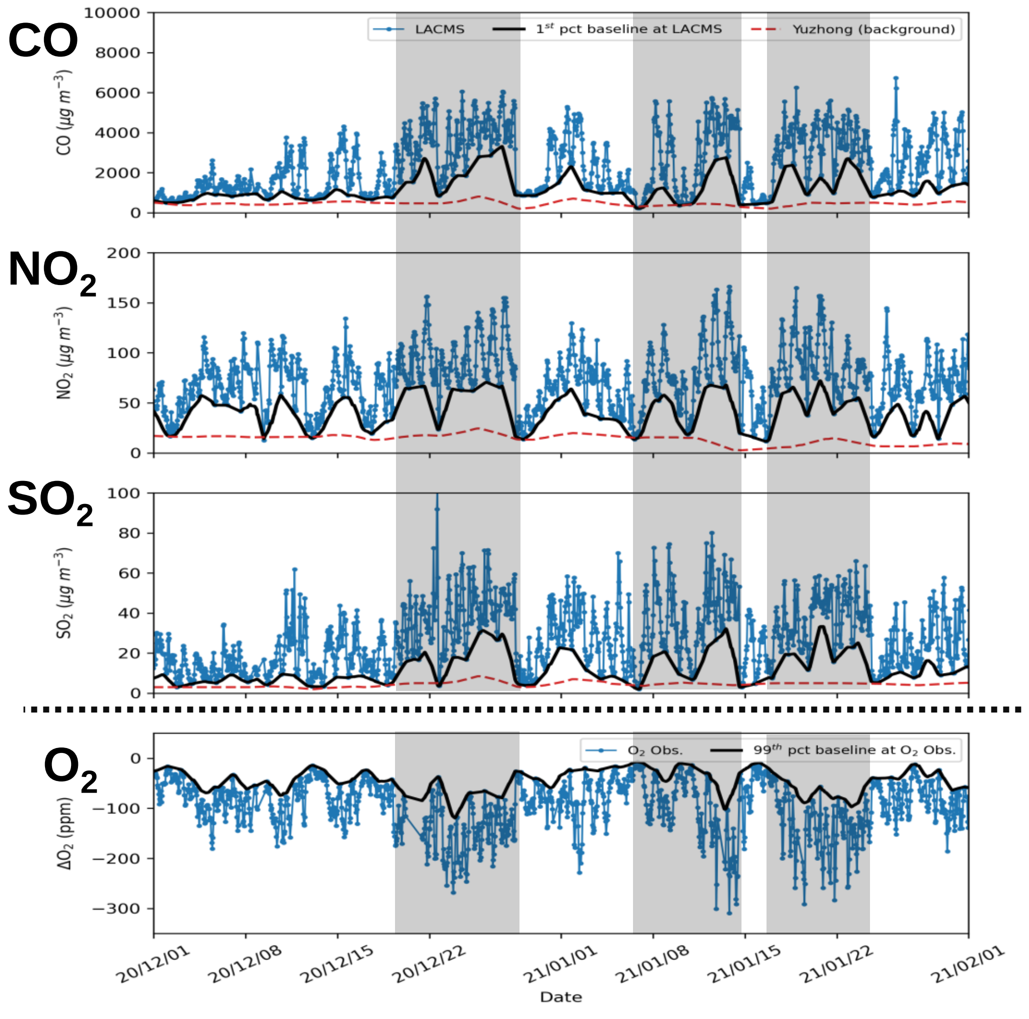
$$Poll_{baseline} = \text{24h rolling avg [Poll.quantile(0.01)]}$$

- O_2: the ***99th*** percentile in each 24 hour

$$\Delta O_{2baseline} = \text{24h rolling avg } [\Delta O_2\text{.quantile(0.99)}]$$

- isolate the recent anthropogenic signals
- minimize impact of vegetation

$$\mathbf{Con_{URB} = Con - Con_{baseline}}$$



(Liu et al., 2023)

Quantifying "Urban Respiration"

➢ **Baseline removal: highlight excess decline (growth) in O_2 (pollutants)**

- Pollutant: the ***1st*** percentile in each 24 hour

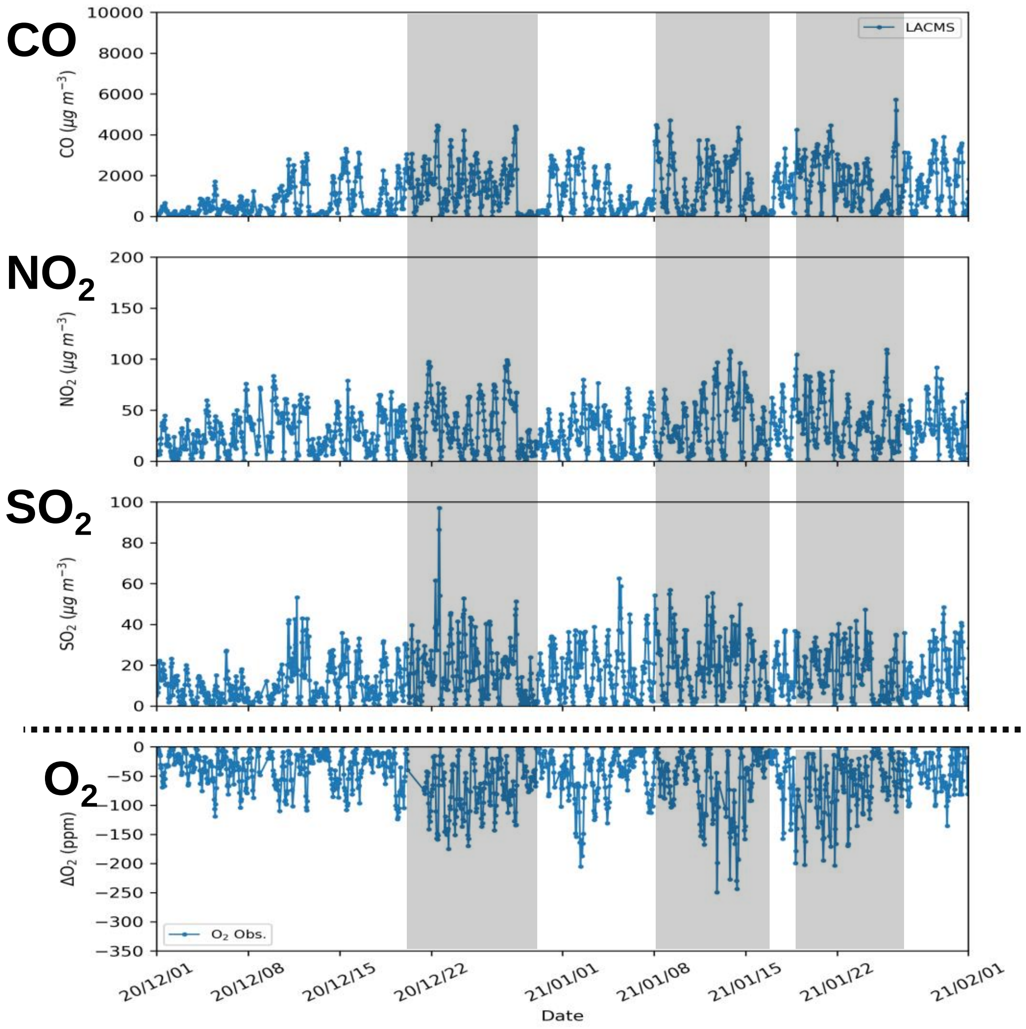
$$Poll_{baseline} = 24h\ rolling\ avg\ [Poll.quantile(0.01)]$$

- O_2: the ***99th*** percentile in each 24 hour

$$\Delta O_{2baseline} = 24h\ rolling\ avg\ [\Delta O_2.quantile(0.99)]$$

- isolate the recent anthropogenic signals
- minimize impact of vegetation

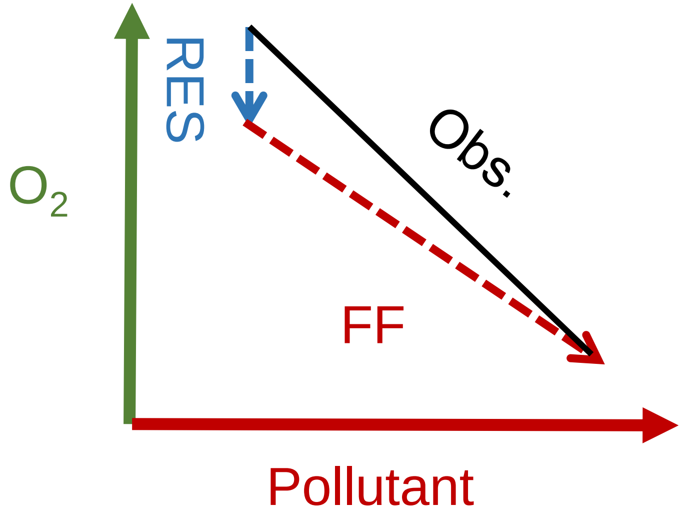
$$\mathbf{Con_{URB} = Con - Con_{baseline}}$$



(Liu et al., 2023)

Quantifying "Urban Respiration"

✓ Statistical model



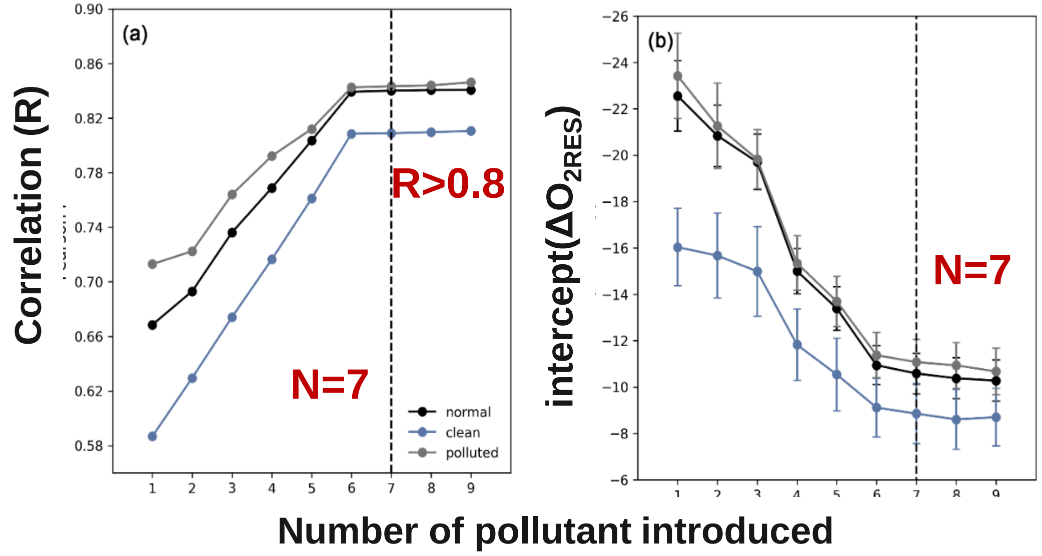
FF RES

$$\Delta O_{2URB} = \Delta O_{2FF} + \Delta O_{2RES}$$

$$= -\sum_{i=0}^{n} k_i \times \Delta Poll_i + \text{intercept}$$

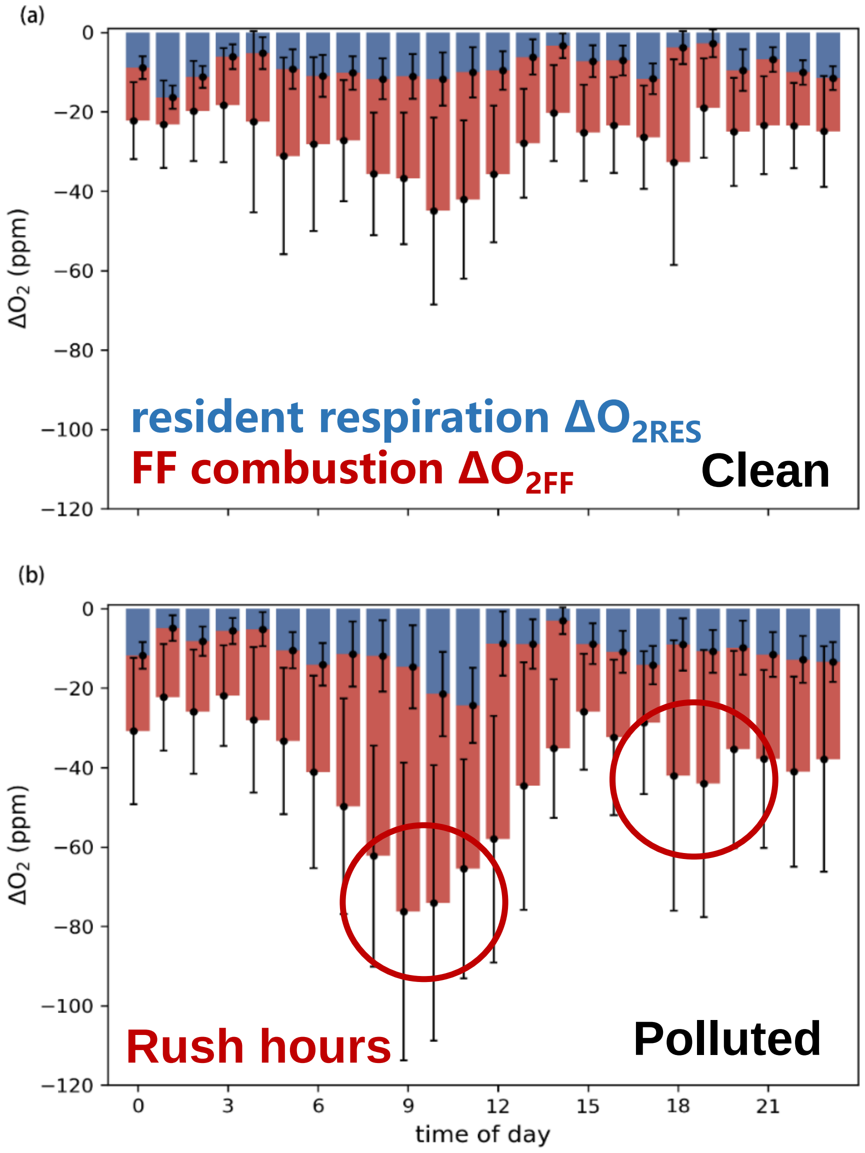
✓ Feature (pollutant) selection

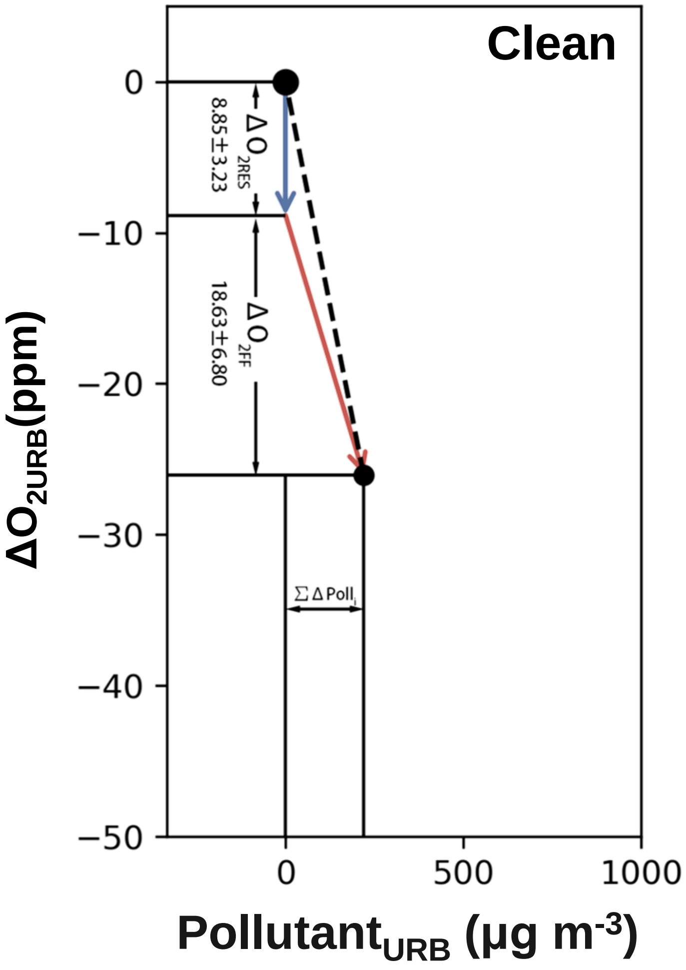
- Recursive feature elimination:
  - Input： CO, NO, NO_2, SO_2, EC, OC, PM_1
  - Excluded (natural dust)： PM_{10}, $PM_{2.5}$

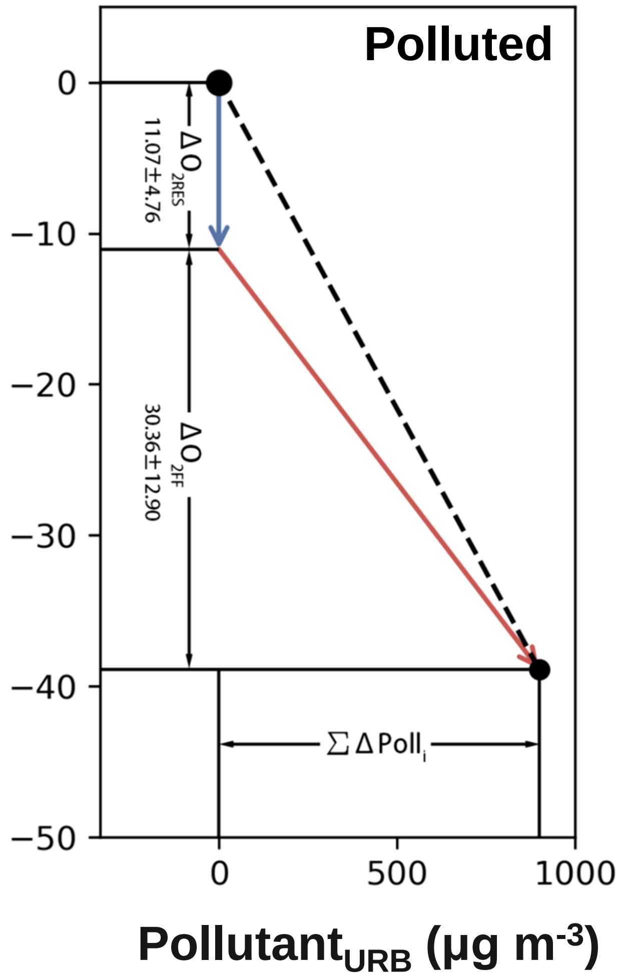


(Liu et al., 2023)

Quantifying "Urban Respiration"







ΔO_{2RES} = 8.85 ± 3.23 ppm

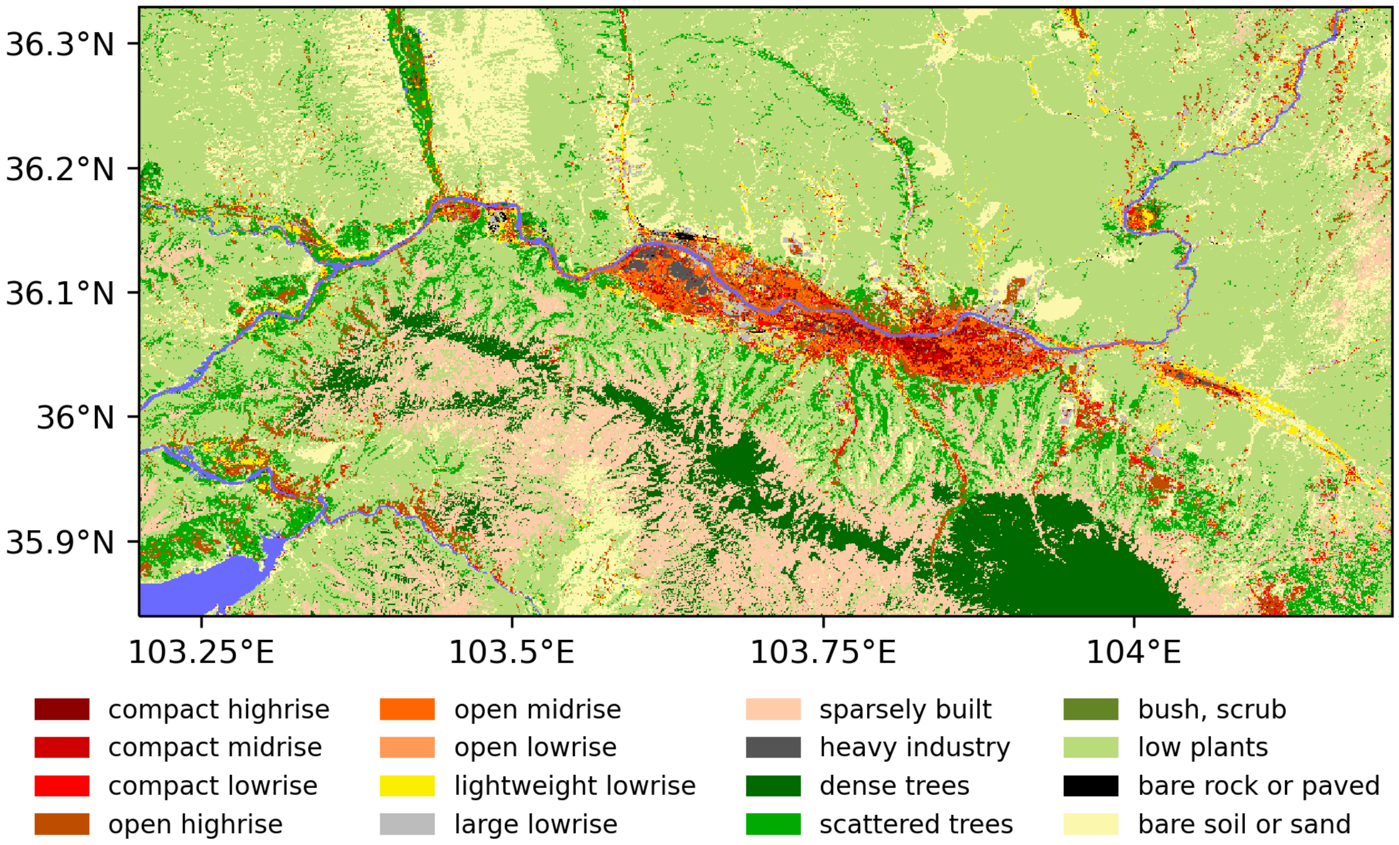
ΔO_{2FF} = 18.63 ± 6.80 ppm

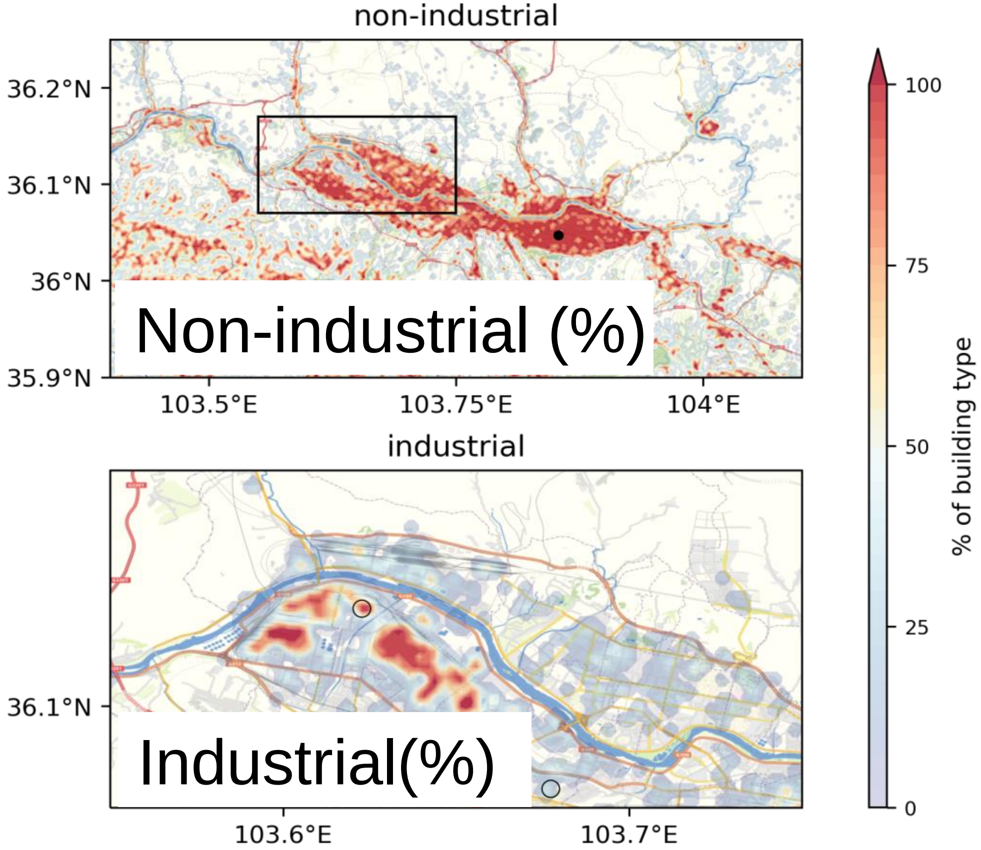
ΔO_{2RES} = 11.07 ± 4.76 ppm

ΔO_{2FF} = 30.36 ± 12.90 ppm

Quantifying "Urban Respiration"

✓STILT simulation coupled with high-res land use data (~120 m)



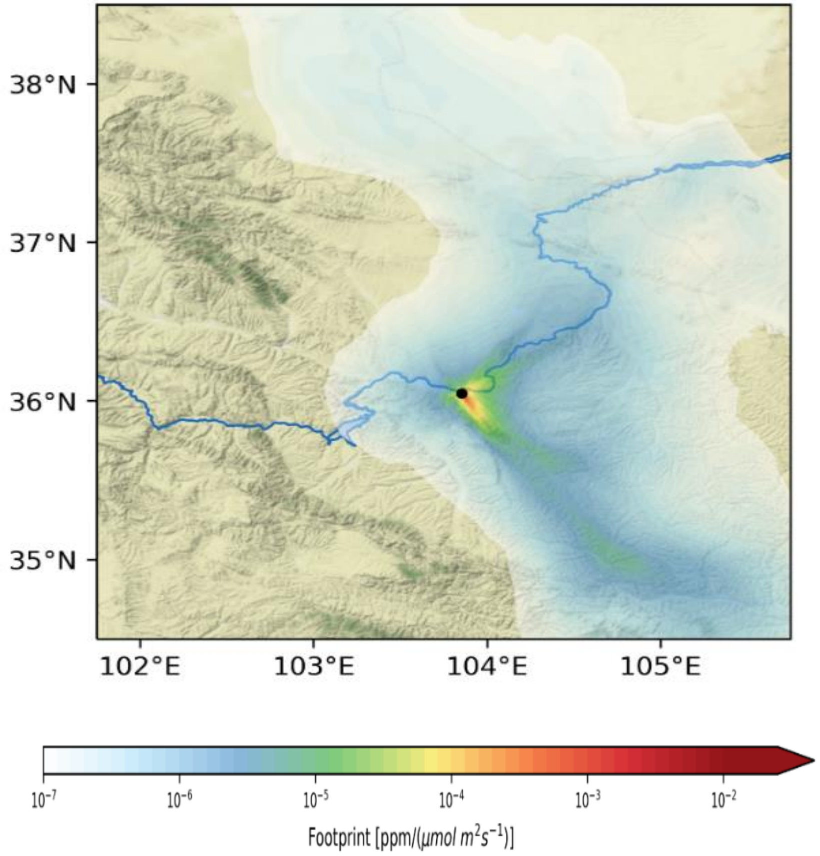


(Ching et al,. 2018; Liu et al., 2023)

Quantifying “Urban Respiration”

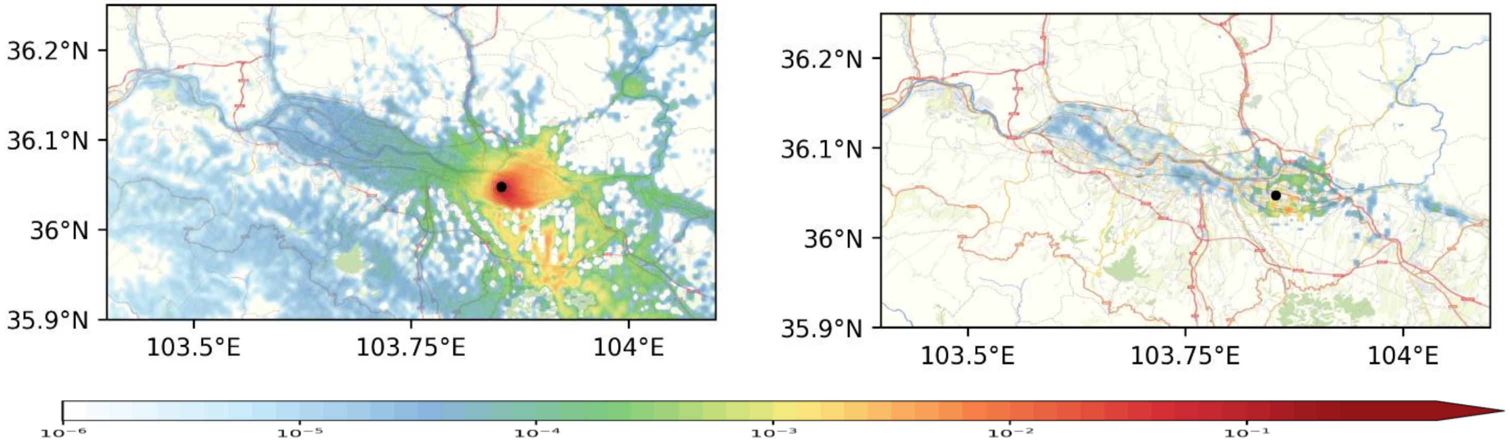
✓ **STILT simulation coupled with high-res land use data**

STILT Footprint



Avoid reliance on prior emission estimates

Non-industrial (%) Industrial(%)

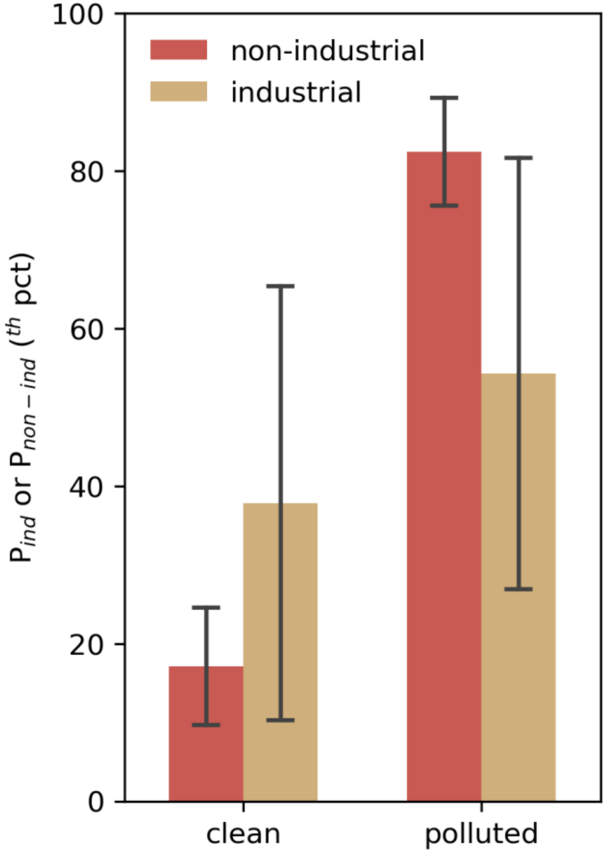


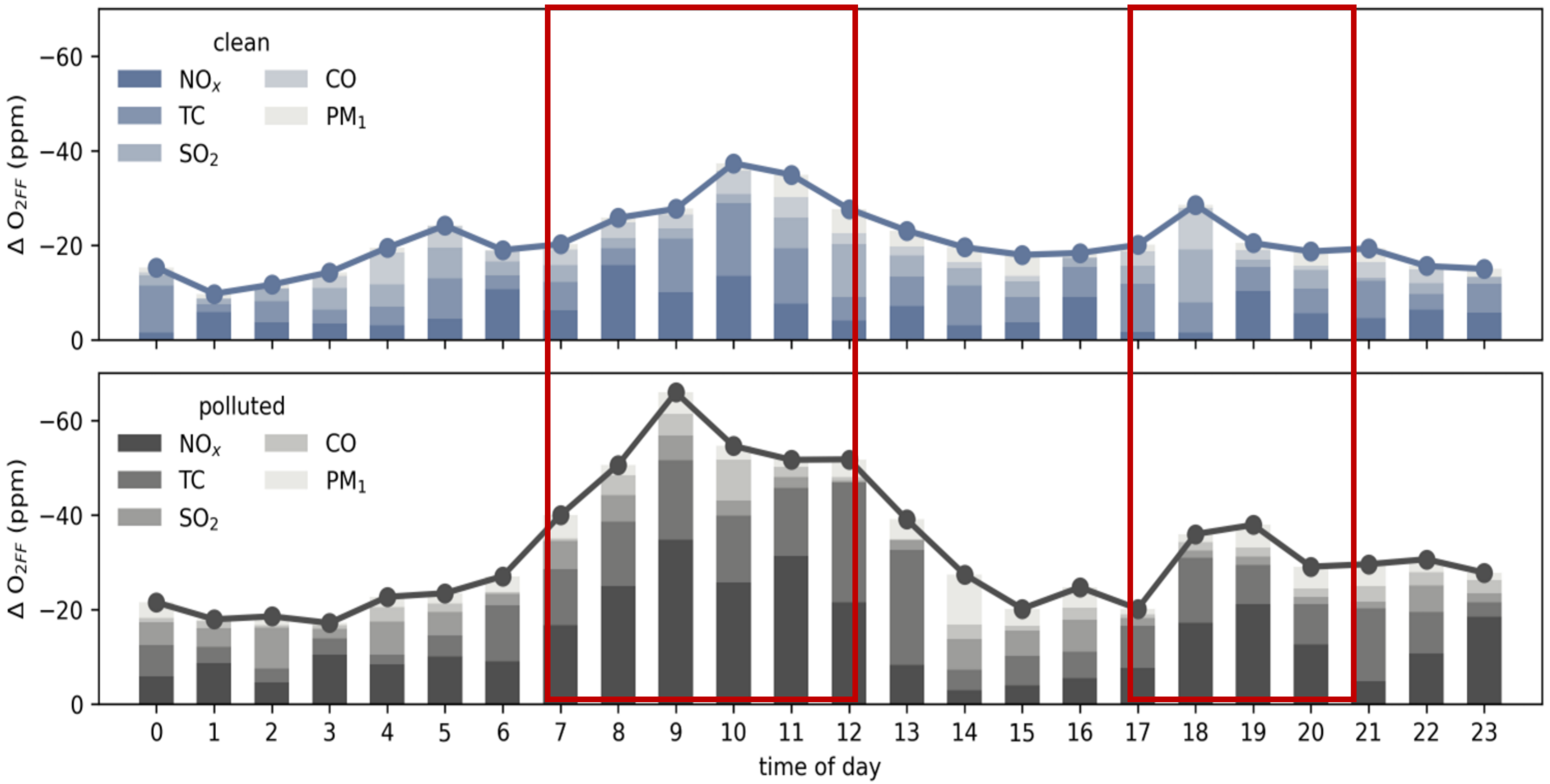
footprint-normalized fraction

$$P(x, y) = P_{STILT}(x, y) \cdot BF(x, y) / \sum P_{STILT}(x, y)$$

(Loughner et al., 2021; Wu et al,. 2022; Liu et al., 2023)

Quantifying “Urban Respiration”





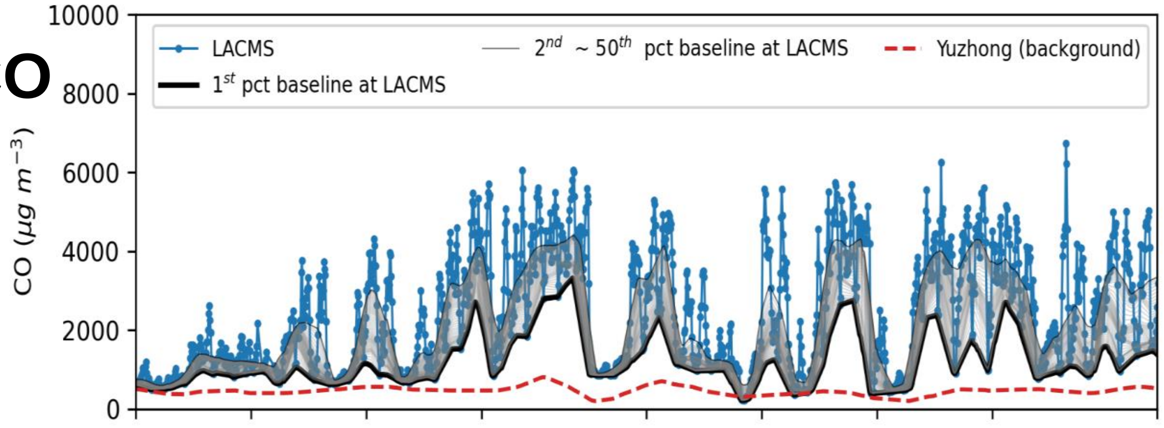
- Increased industrial impact in a relatively cleaner atmosphere.
- ΔO_{2URB} decline during rush hours is associated with emission of NO_x from non-industrial sources, pointing to transportation sectors.

Sensitivity to baseline determination

✓ The robustness of the result could be influenced by the **selection of percentiles** for baseline removal.

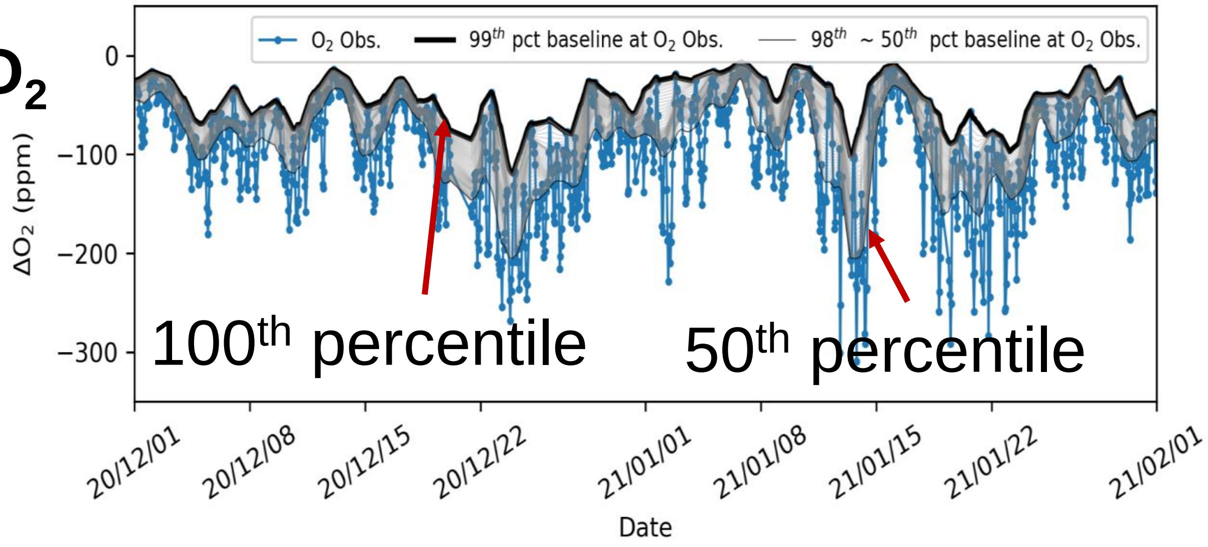
- Pollutant baseline
  the ***0th ~ 50th*** percentile

CO



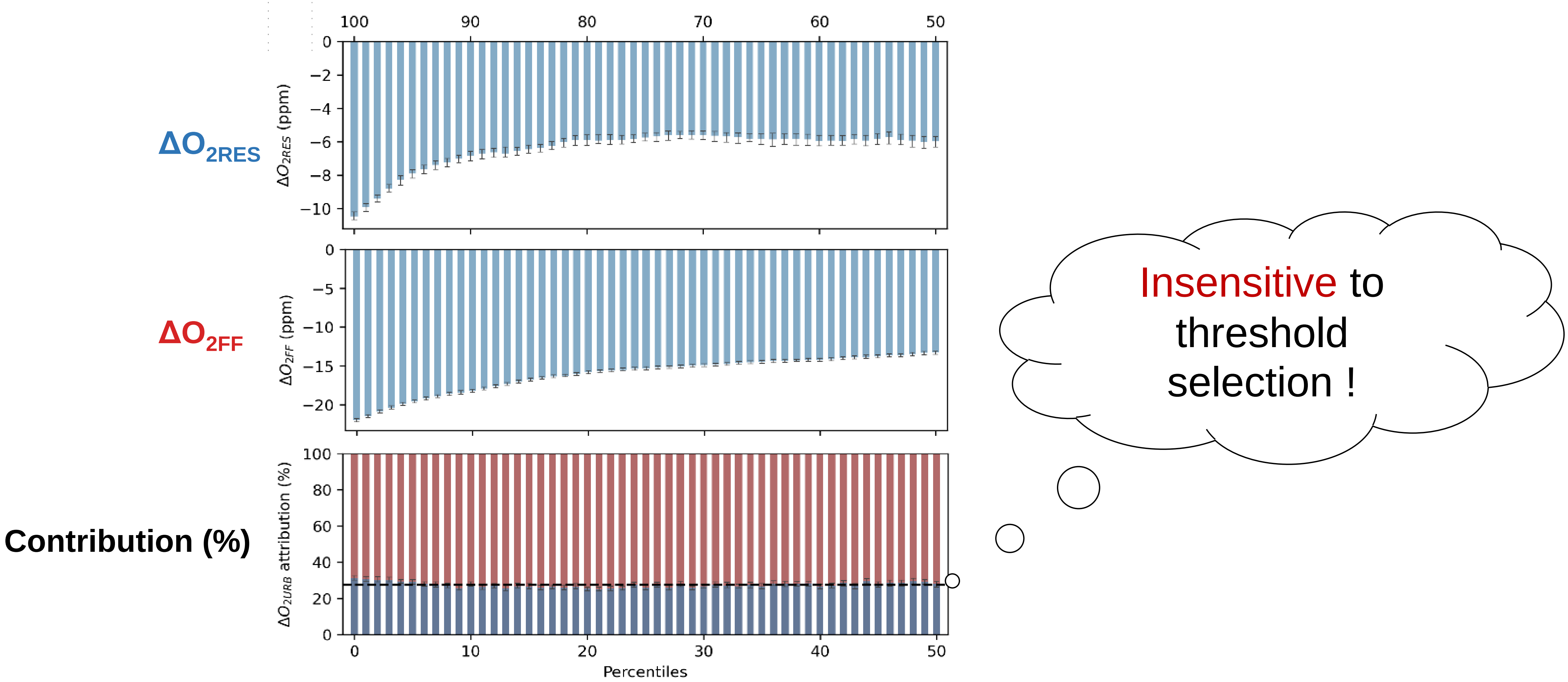
- O_2 baseline:
  the ***50th ~ 100th*** percentile

O_2



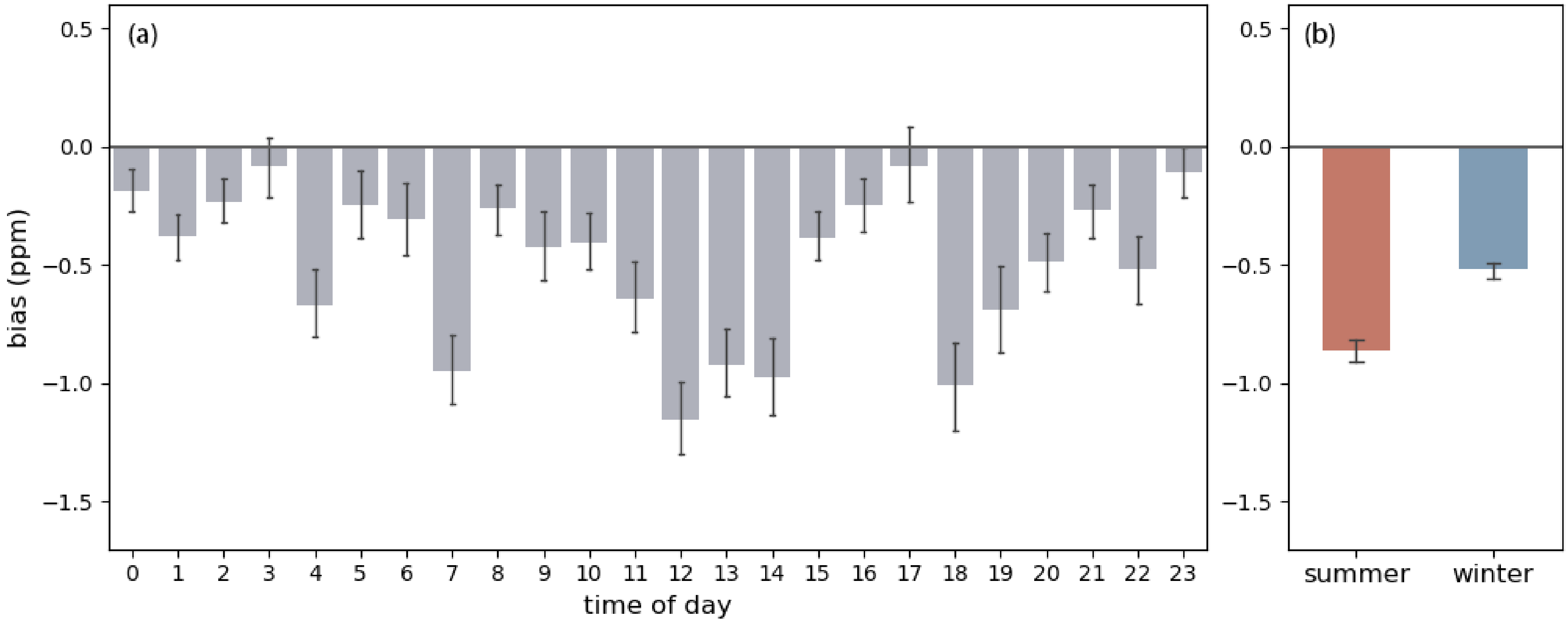
Sensitivity to baseline determination

✓ The robustness of the result could be influenced by the **selection of percentiles** for baseline removal.



Missing O_2 source?

bias = ΔO_{2URB_sim} - ΔO_{2URB_obs} ~ **-1 ppm**



- Amplified bias in the afternoon, and summertime;
- Possibly due to **vegetation**; could also be caused by other unknown sources.

Quantifying "Urban Respiration"

O_{2URB} in Lanzhou

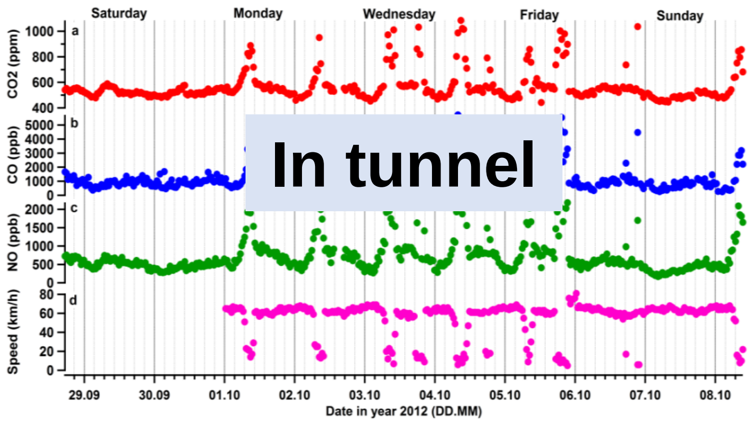
Population density > 50,000 people/km^2

ΔO_{2FF} (66.92~72.50%)

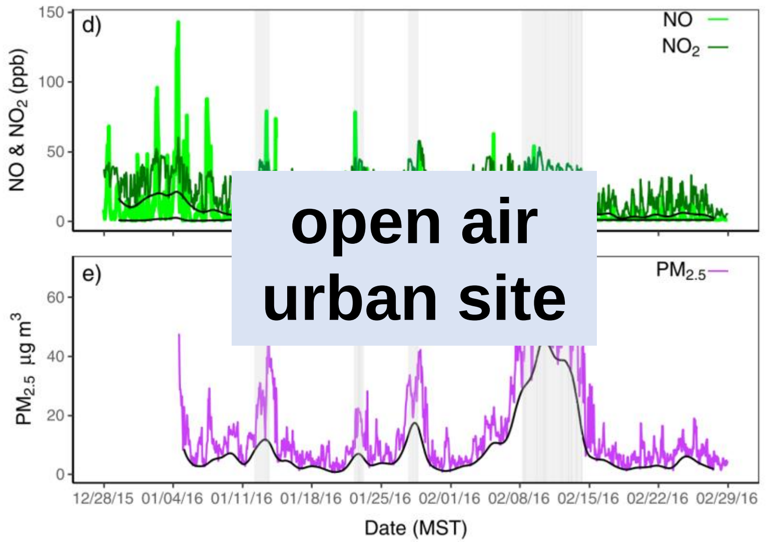
ΔO_{2RES} (27.50~33.08%)

Why respiration matters?

Observations



In tunnel



open air urban site

Validation

Emission ratio:

CO/CO_2 NO_x/CO_2 etc.

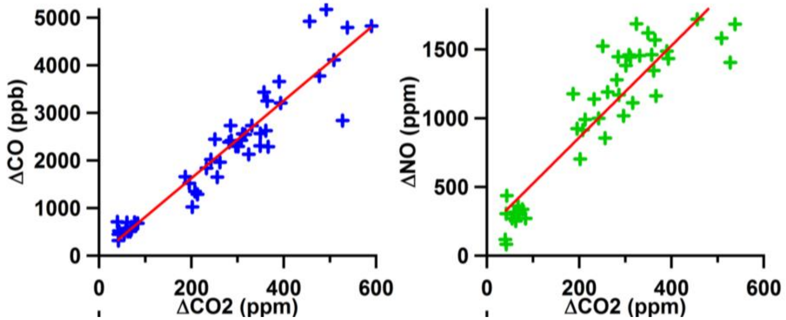
$$\left(\frac{POLL}{CO_2}\right)_{obs} < \left(\frac{POLL}{CO_2}\right)_{inv}$$

Overestimated POLL emission factor?

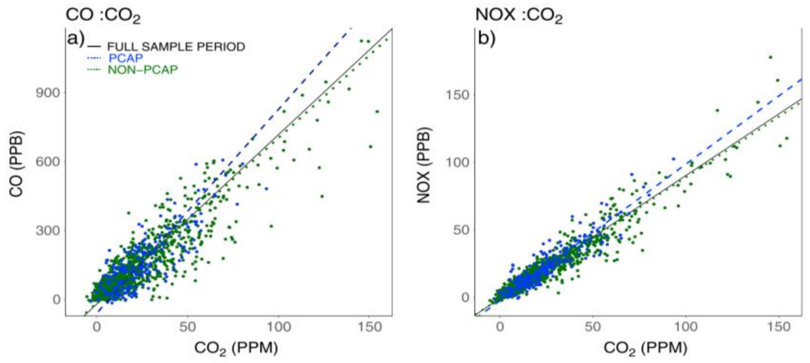
Overestimated $FFCO_2$ due to ignore of RES?

Emission inventory

Good consistency



Lower observed poll/CO_2 ratios



(Bares et al., 2018, Ammoura et al., 2014)

Why respiration matters?

As increasing populations streams into cities, do we need to consider the impact of resident respiration when interpreting urban CO_2 and O_2 variabilities?

Urban green space

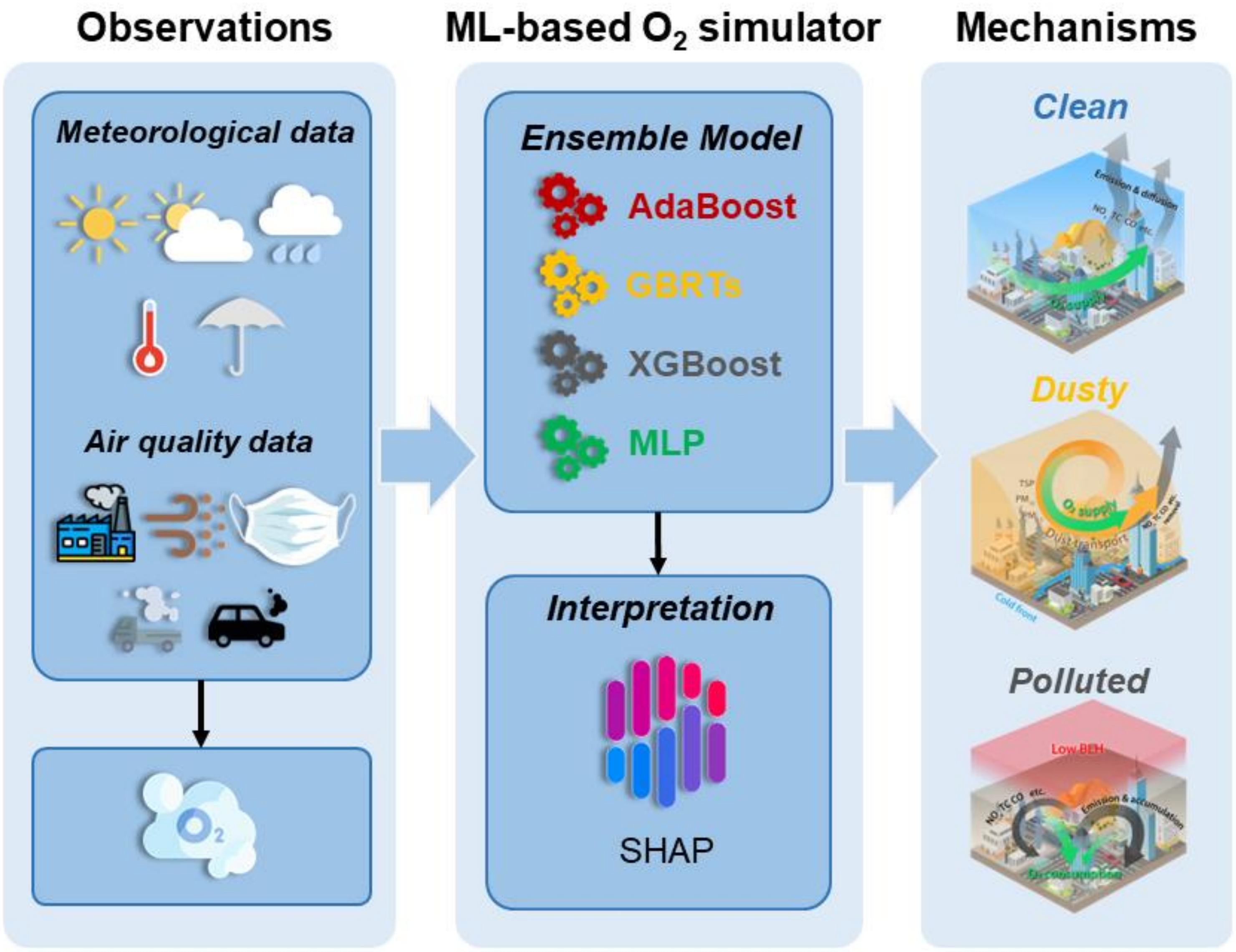
Urban traffic emission

Urban resident respiration

Limitation & Future work

- **Secondary reactions with/between O_2 and pollutants**
  - Pollutants: ppb
  - O_2/CO_2: ppm
  - NO_x & $SO_2 \rightarrow$ PMs, O_3
- **Combining O_2, CO_2, and pollutants measurements to constrain OR**
  - e.g. diesel & gasoline (CO & NO_x)

Machine Learning Based O_2 simulator

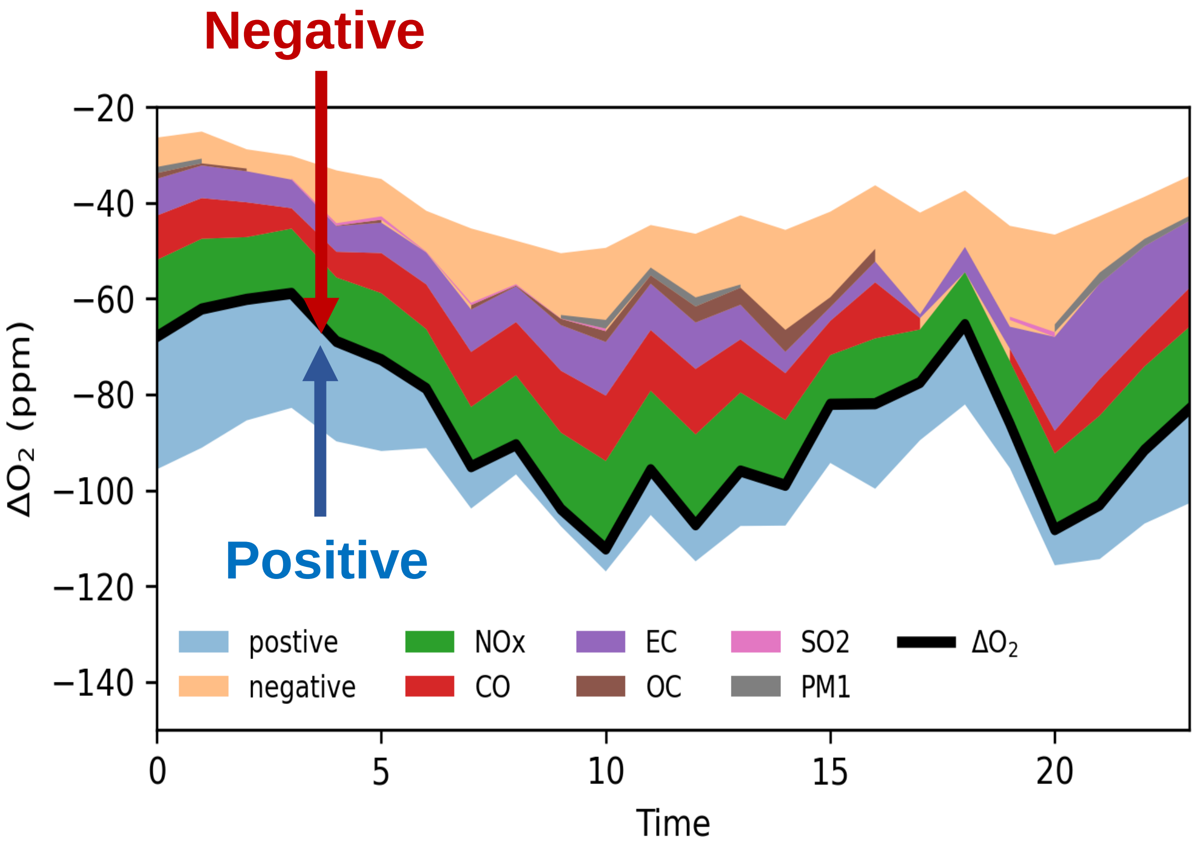


(Liu et al., 2023, under review)

Machine Learning Based O_2 simulator

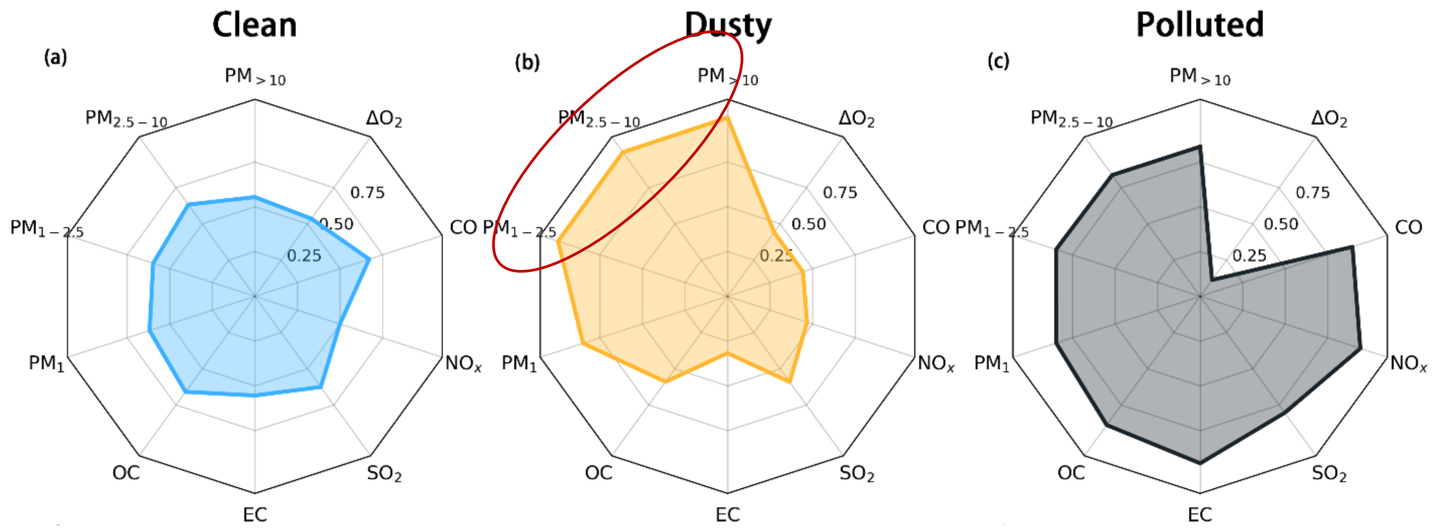
➢ **Model interpretability tool: SHapley Additive exPlanations (SHAP)**

$$\psi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(N - [S] - 1)!}{|N|!} \left(f(S \cup \{i\}) - f(S) \right)$$



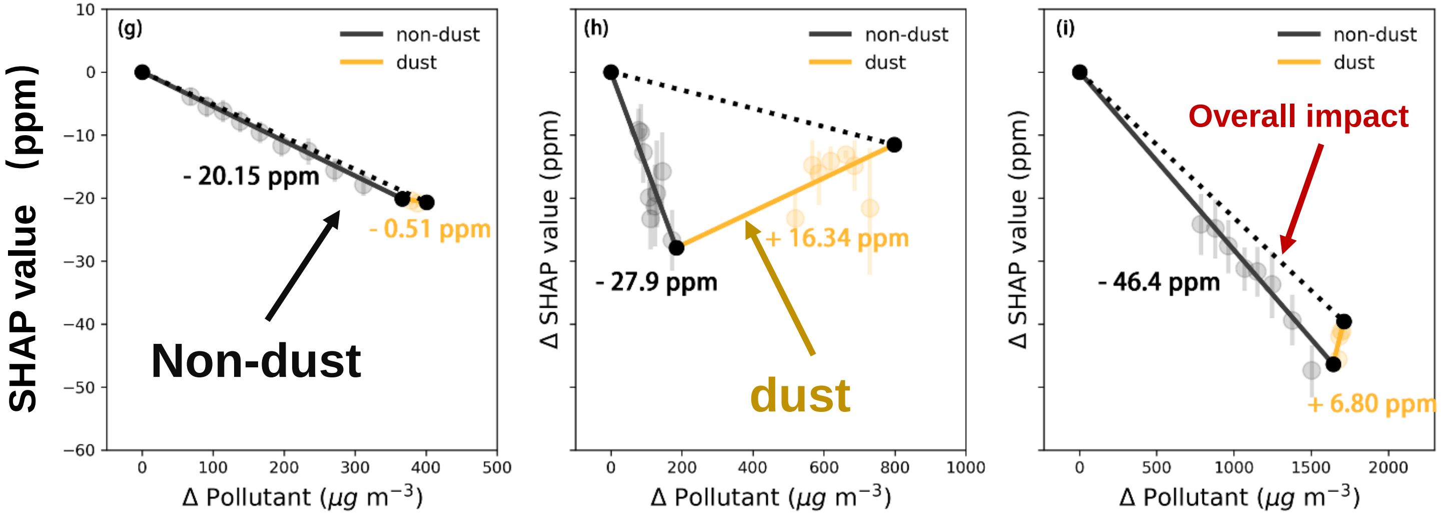
(Liu et al., 2023, under review)

Machine Learning Based O_2 simulator



Dust pollutants: $PM_{1\sim2.5}$, $PM_{2.5\sim10}$, $PM_{>10}$

Non-dust pollutants: $PM_{<1}$, OC, EC, SO_2, NO_x, SO_2, CO



Dust pollution

Non-dust pollutants

- **Urban O_2 variabilities associated with pollutants:**
  - **Local O_2 consumption**
  - **Long-range transport**

(Liu et al., 2023, under review)

CONTENTS

Summary

Front Cover of ES&T

- The novel framework integrating O2 with pollutants, enables quantification of ΔO_{2FF} and ΔO_{2RES} in cities.
- In Lanzhou's high density settings, resident respiration contributes 27.50~33.08% to urban O_2 variability.
- Rush hour traffic dominates O_2 uptake, pointing to transportation sources.
- Machine learning techniques shed light on pollutant impacts on urban O_2.

Thanks

Website

Xiaoyue Liu

PhD Candidate, Lanzhou University

Email: liuxiaoyue14@lzu.edu.cn

Website: silence-lxy.github.io