# Decoupling the Effects of Anthropogenic Emission Reductions from the Meteorology and Natural Emissions in TROPOMI $NO_2$ Retrievals During the 2020 COVID-19 Lockdowns

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Many published studies reported unprecedented reductions in $NO_2$ tropospheric vertical column densities over the world's most populated cities during the 2020 COVID-19 lockdowns due to lower $NO_2$ emissions from anthropogenic sources.

In estimating how much of the decline was due to a reduction in anthropogenic sources, there emerged two important sources of uncertainty in the satellite retrievals that were difficult to account for early on:

1) *A priori $NO_2$ profiles used in the satellite retrievals were not adjusted for the lower anthropogenic emissions observed during the lockdowns, which affects the AMF*
2) *Meteorological variability in some cases reduced the apparent decline in anthropogenic emissions and in other cases augmented it*

Geophysical Research Letters

RESEARCH LETTER
10.1029/2020GL089269

Special Section:
The COVID-19 pandemic:
Linking health, society and

**Disentangling the Impact of the COVID-19 Lockdowns on Urban $NO_2$ From Natural Variability**

Daniel L. Goldberg[1,2], Susan C. Anenberg[1], Debora Griffin[3], Chris A. McLinden[3], Zifeng Lu[2], and David G. Streets[2]

Geophysical Research Letters

RESEARCH LETTER
10.1029/2020GL087978

Special Section:
The COVID-19 pandemic:
linking health, society and

**Impact of Coronavirus Outbreak on $NO_2$ Pollution Assessed Using TROPOMI and OMI Observations**

M. Bauwens[1], S. Compernolle[1], T. Stavrakou[1], J.-F. Müller[1], J. van Gent[1], H. Eskes[2], P. F. Levelt[2,3], R. van der A[2], J. P. Veefkind[2], J. Vlietinck[1], H. Yu[1], and C. Zehner[4]

JGR Atmospheres

RESEARCH ARTICLE
10.1029/2021JD035440

**Tropospheric $NO_2$ and $O_3$ Response to COVID-19 Lockdown Restrictions at the National and Urban Scales in Germany**

Vigneshkumar Balamurugan[1], Jia Chen[1], Zhen Qu[2], Xiao Bi[1], Johannes Gensheimer[1], Ankit Shekhar[3], Shrutilipi Bhattacharjee[4], and Frank N. Keutsch[2,5]

Key Points:

- During the COVID-19 lockdown period, $NO_2$ concentrations decreased and $O_3$ concentrations increased in eight German cities
- The degree of $NO_x$ saturation of

**Quantifying urban, industrial, and background changes in $NO_2$ during the COVID-19 lockdown period based on TROPOMI satellite observations**

Vitali Fioletov[1], Chris A. McLinden[1], Debora Griffin[1], Nickolay Krotkov[2], Fei Liu[2], and Henk Eskes[3]

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SCIENCE ADVANCES | RESEARCH ARTICLE

CORONAVIRUS

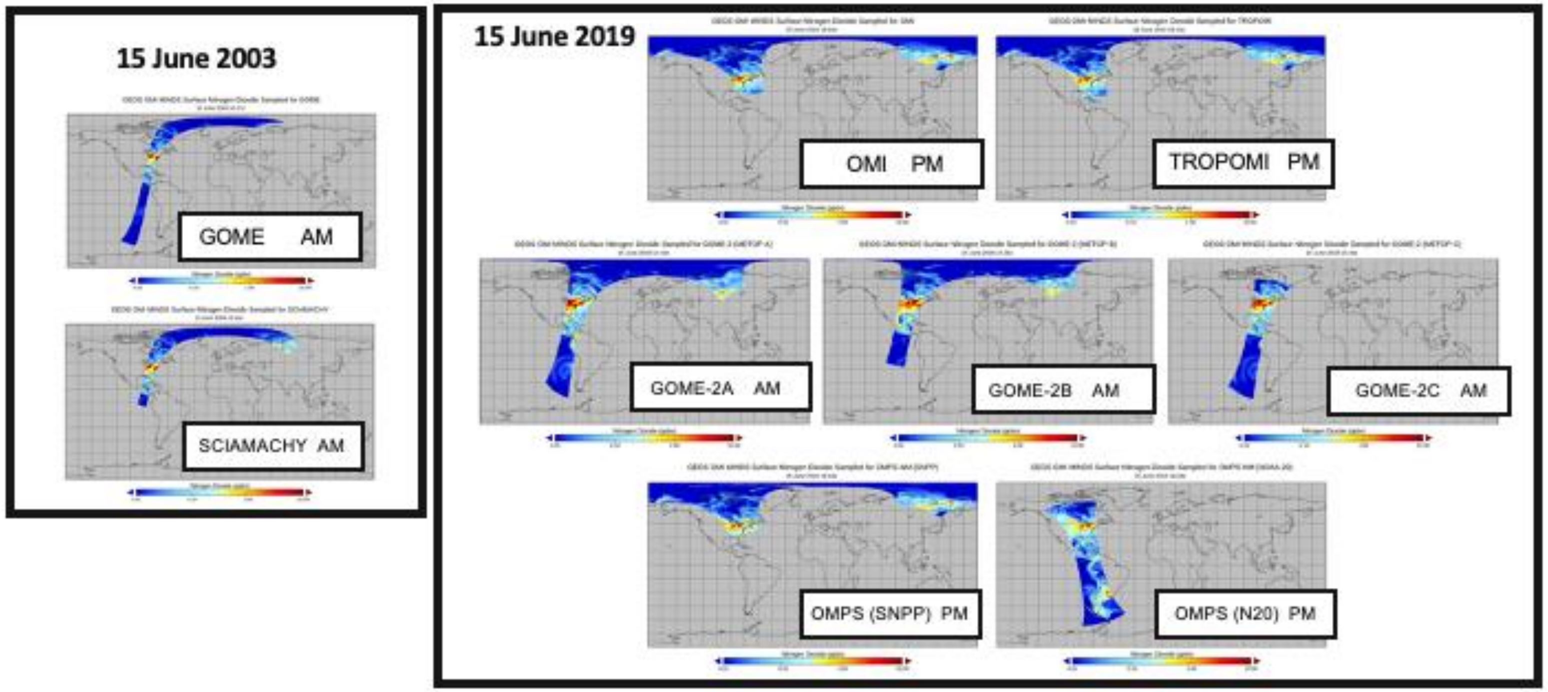
**Abrupt decline in tropospheric nitrogen dioxide over China after the outbreak of COVID-19**

Fei Liu[1,2]*, Aaron Page[3], Sarah A. Strode[1,2], Yasuko Yoshida[2,4], Sungyeon Choi[2,4], Bo Zheng[5], Lok N. Lamsal[1,2], Can Li[2,6], Nickolay A. Krotkov[2], Henk Eskes[7], Ronald van der A[7,8], Pepijn Veefkind[7,9], Pieternel F. Levelt[7,9], Oliver P. Hauser[10†], Joanna Joiner[2†]

# GEOS Global Modeling Initiative (GMI)

GEOS GMI is a full chemistry CTM run in replay mode that is constrained by assimilated 3-hour, averaged meteorological fields from MERRA-2 [*Orbe et al.*, 2017].

- Full stratospheric and tropospheric chemistry
- 0.25º longitude x 0.25º latitude geospatial resolution
- 72-layer a priori profiles ($NO_2$ and temperature)
- Swath simulator: samples the same longitude, latitude, and time as the measurement.



# Our Approach

We estimated the mean reductions in TROPOMI Tropospheric $NO_2$ columns during the 2020 lockdowns by comparing satellite retrievals in 2020 to the same period in 2019. For this study, we selected 36 megacities from around the world and for each city we considered a 1º x 1º region for two lockdown periods:

1) January 23 to April 1: All seven selected megacities in China
2) March 17 to June 1: All other cities

We generated three GMI data sets to account for the 1) changes in the $NO_2$ anthropogenic emission profiles during the 2020 lockdowns and 2) the effects meteorological variability:

- Simulation 1: **2019** with 2019 emissions and 2019 meteorology
- Simulation 2: **2020** with COVID-19 adjusted emissions (Forster, et al., *Nature Climate Change*, 2020)
- Simulation 3: **2020BAU** with business-as-usual 2019 emissions and 2020 meteorology

# Methodology

- Use the GMI model to disentangle the meteorological and natural emission variability from the anthropogenic emissions in Tropospheric VCDs;
  - ❖ Anthropogenic Emissions: $\overline{\Delta NO2}_{GMI,emis} = \overline{TVCD}_{GMI}[2020] - \overline{TVCD}_{GMI}\ [2020BAU]$
  - ❖ Meteorological Variability: $\overline{\Delta NO2}_{GMI,met} = \overline{TVCD}_{GMI}[2020BAU] - \overline{TVCD}_{GMI}[2019]$

- Estimate the total reduction (%) in mean TROPOMI tropospheric VCDs during the study period using GMI a priori $NO_2$ profiles adjusted for the lockdowns and corrected for meteorological variability
  - ❖ Change in $NO_2$ emissions, including meteorological and natural emission variability:

$$\overline{\Delta NO2}_{Tot} = \overline{TVCD}_{Sat}[2020] - \overline{TVCD}_{Sat}[2019]$$

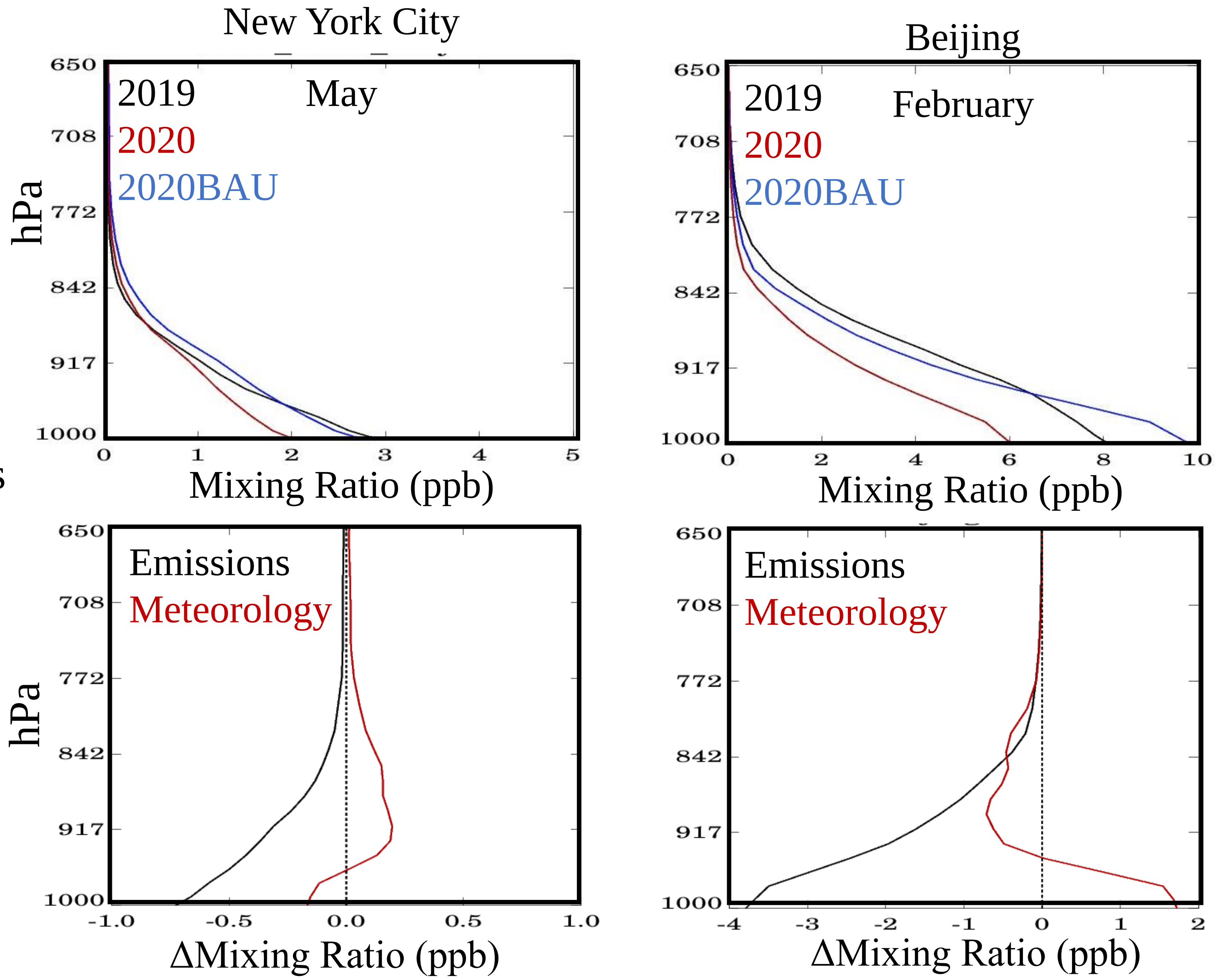
  - ❖ Inferred change in TROPOMI tropospheric $NO_2$ columns due to anthropogenic $NO_2$ emissions only (accounting for meteorology):

$$\overline{\Delta NO2}_{Net} = \overline{TVCD}_{Sat}[2020] - \overline{TVCD}_{Sat}[2019] - \overline{\Delta NO2}_{GMI,met}$$

# GMI a Priori $NO_2$ and $dNO_2$ profiles for 2019, 2020 and 2020BAU

How do profile shape changes due reduced $NO_2$ emissions and meteorology affect the AMF calculated in the satellite retrieval?

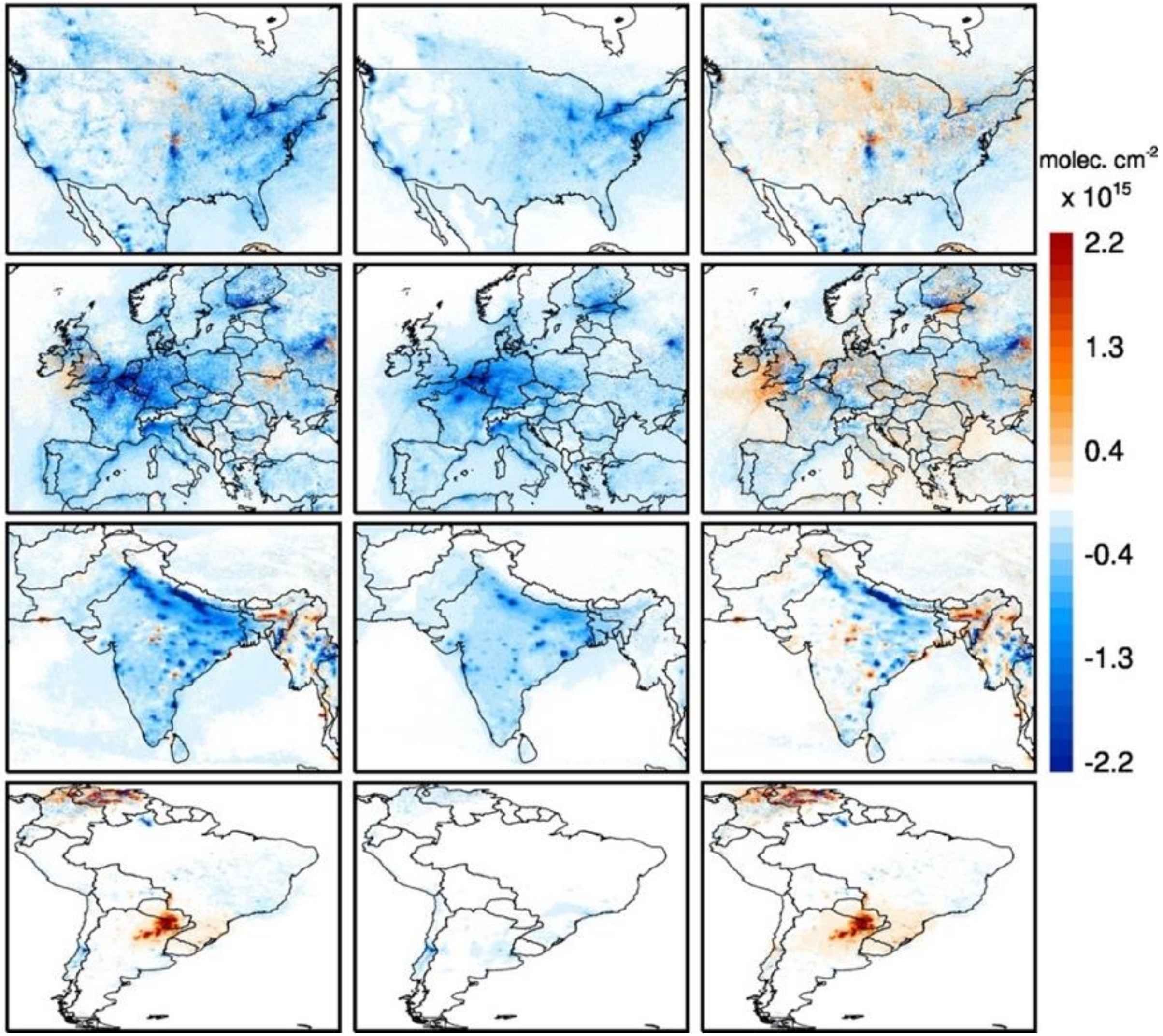
- In the upper two panels, the 2020 $NO_2$ profile (red) shows reduced lockdown emissions relative to 2019 (black). The 2020BAU(blue) profile is affected by the 2020 meteorology and the 2019 emissions
- In the lower two panels, the effects of anthropogenic emissions and meteorological variability are displayed with respect to the profile differences
  - ❖ Anthropogenic emissions display a monotonic decline through the lower troposphere
  - ❖ Meteorological variability changes sign in the lower boundary layer near the surface




- ❖ Emissions: $\overline{\Delta NO2}_{GMI,emis} = \overline{TVCD}_{GMI}[2020] - \overline{TVCD}_{GMI}\,[2020BAU]$
- ❖ Meteorology: $\overline{\Delta NO2}_{GMI,met} = \overline{TVCD}_{GMI}[\text{2020BAU}] - \overline{TVCD}_{GMI}[2019]$

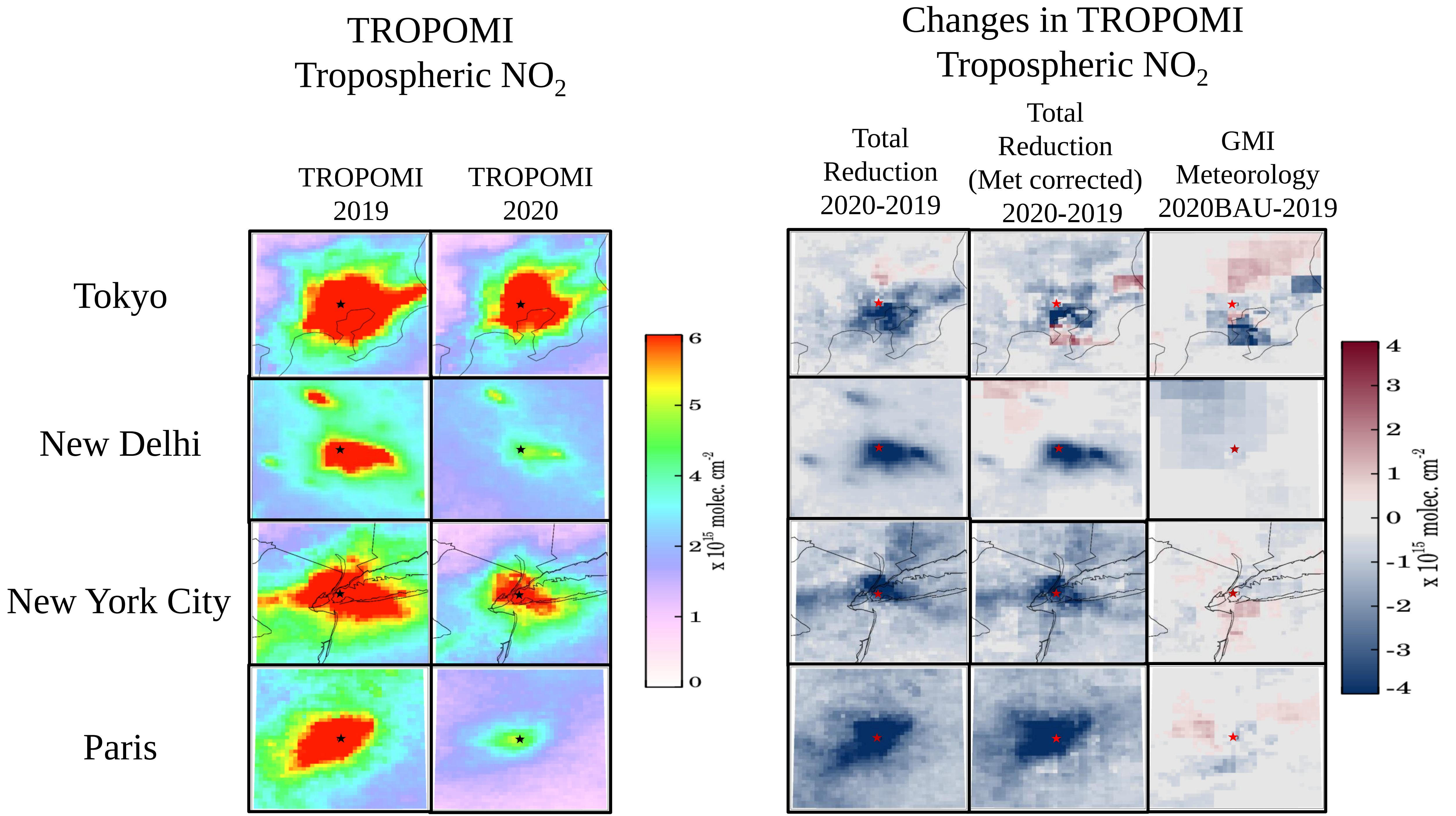
# 2020-2019 $\Delta NO_2$ in GMI Tropospheric Columns

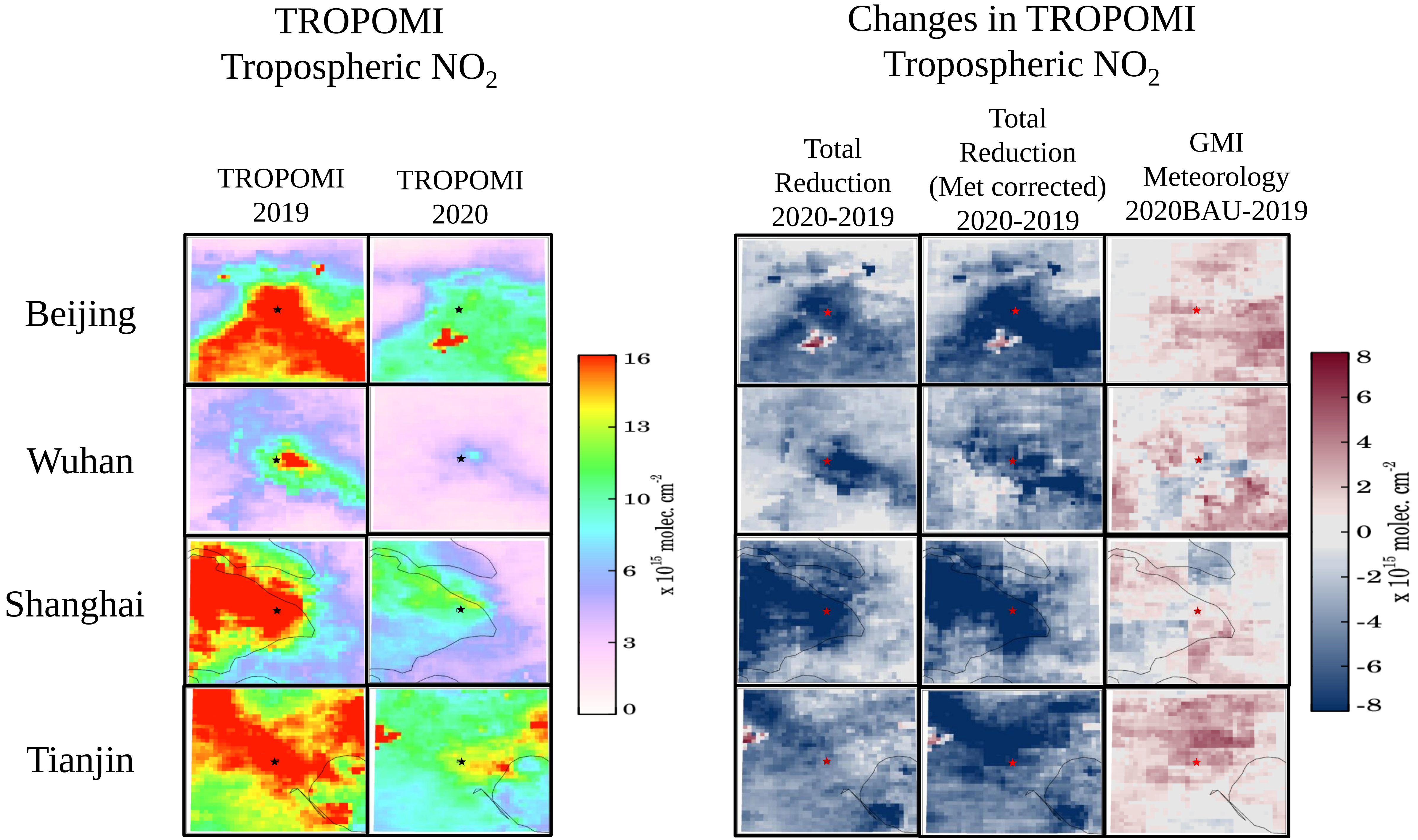
- Large reductions in anthropogenic emissions around urban areas (blue)
- In the GMI total change, there are some positive $\Delta NO_2$ regions (red). These regions were affected by meteorological and natural emission variability
  - ❖ Biomass burning in South America
  - ❖ Natural emission variability in the central US
  - ❖ Meteorological variability in Europe and India



# The NASA $NO_2$ Algorithm Adapted for TROPOMI

- Used $NO_2$ slant column densities (SCD) in Version 2.3.1 (S5P_PAL )
- Air mass factors (AMF) were calculated using v. 4.0 of the NASA $NO_2$ algorithm:
  - GLER – derived from MODIS data (MODIS BRDF/Albedo Product MCD43), accounts for anisotropic variations caused by bidirectional reflectance distribution function (BRDF) effects that vary with sun-satellite geometry and surface characteristics (see Wenhan Qin's poster)
  - FRESCO – re-calculate FRESCO cloud parameters using GLER data for $NO_2$ spectral window (440 nm) to correct for the effect of surface reflectivity
  - Daily GMI: $NO_2$ profiles, temperature profiles, surface and tropopause pressures
- Stratosphere-Troposphere separation — data driven approach (Buscela et al., 2013)
- Re-gridded data at 0.05º longitude x 0.05º latitude for the satellite and GMI (qa_value > 0.75)


TROPOMI
Tropospheric $NO_2$
TROPOMI 2019
TROPOMI 2020
Tokyo
New Delhi
New York City
Paris
6
5
4
3
2
1
0
x $10^{15}$ molec. $cm^{-2}$
Changes in TROPOMI
Tropospheric $NO_2$
Total Reduction 2020-2019
Total Reduction (Met corrected) 2020-2019
GMI Meteorology 2020BAU-2019
4
3
2
1
0
-1
-2
-3
-4
x $10^{15}$ molec. $cm^{-2}$



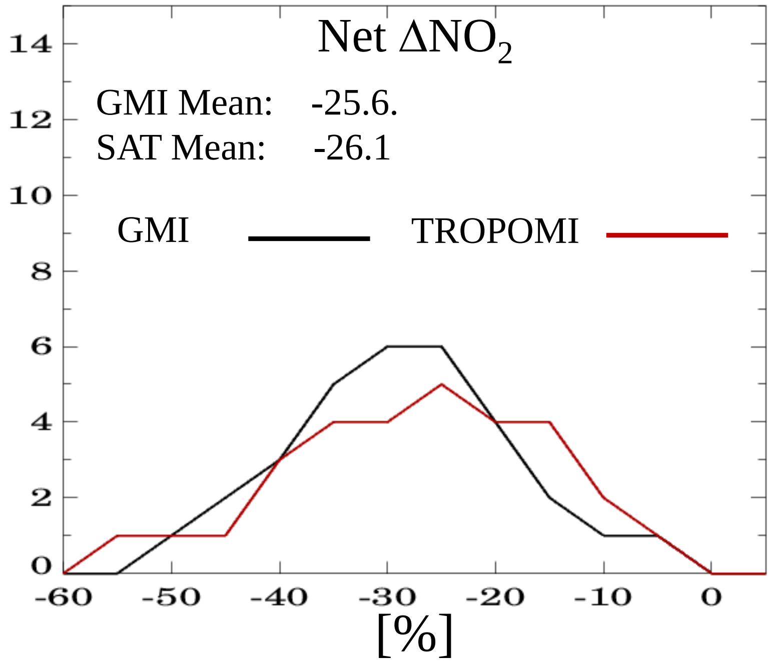
TROPOMI
Tropospheric NO2
Changes in TROPOMI
Tropospheric NO2
TROPOMI 2019
TROPOMI 2020
Total Reduction 2020-2019
Total Reduction (Met corrected) 2020-2019
GMI Meteorology 2020BAU-2019
Beijing
Wuhan
Shanghai
Tianjin
16
13
10
6
3
0
x 10^15 molec. cm^-2
8
6
4
2
0
-2
-4
-6
-8
x 10^15 molec. cm^-2

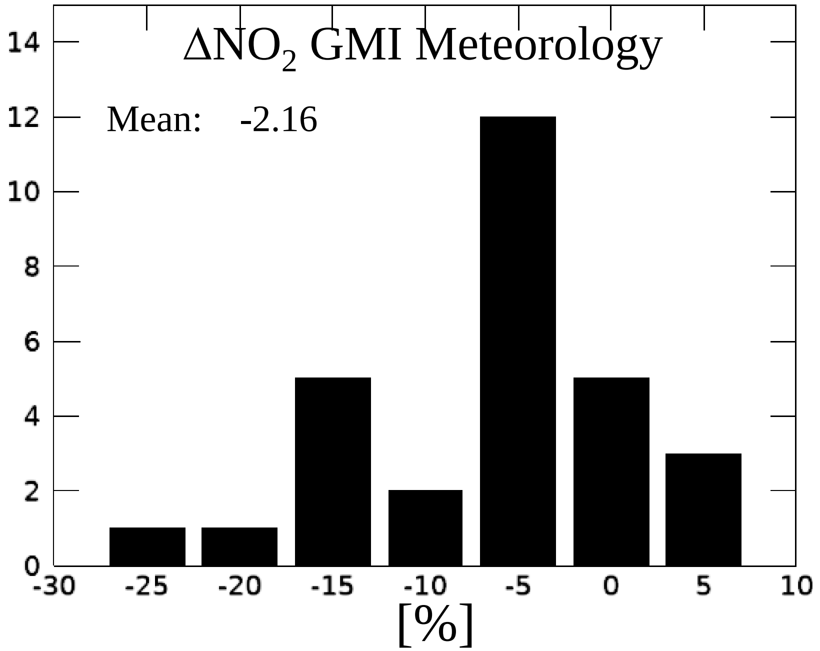
# Summary of TROPOMI and GMI $NO_2$ Reductions for Selected Cities

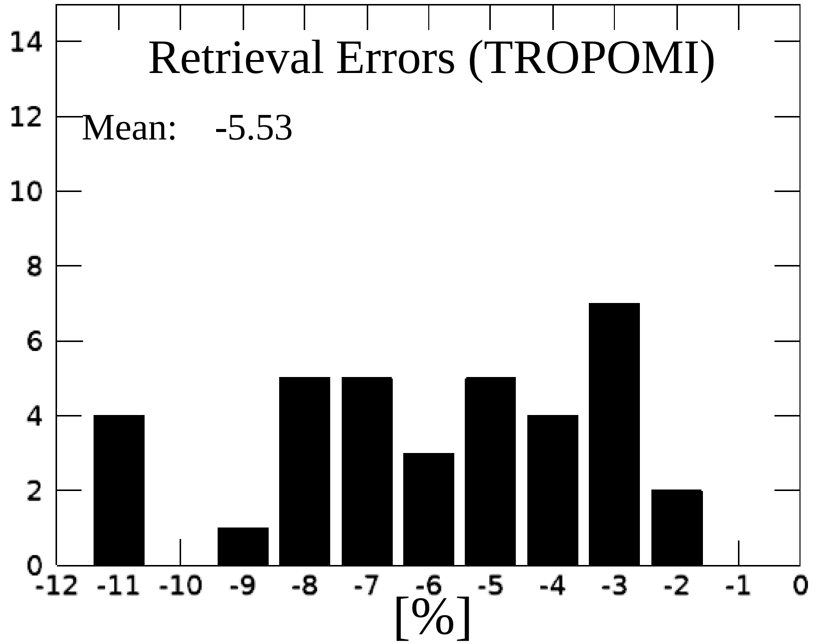
- TROPOMI and GMI yield consistent results with respect to the change in Tropospheric VCDs but some larger differences exist
- Meteorological variability was significant for many cities
  - The change in anthropogenic $NO_2$ for five of the Chinese cities in the study was much lower than originally thought (Hua J., et al., 2020)
  - In other cases, the reductions were notably higher due to meteorology
- Retrieval errors (RE) incurred in using BAU a priori files were systematically negative and contributed as much as ~10% error
  - RE: $\overline{\mathrm{RE}}_{Sat} = \overline{TVCD}_{Sat}[2020] - \overline{TVCD}_{Sat}[2020BAU]$
- Sampling biases (SB) incurred as a result of selective sampling (qa_value > 0.7) accounted for up to 10% error
  - SB: $\overline{SB}_{GMI} = \overline{TVCD}_{GMI,T_{All}} - \overline{TVCD}_{GMI,T_{Sub}}$

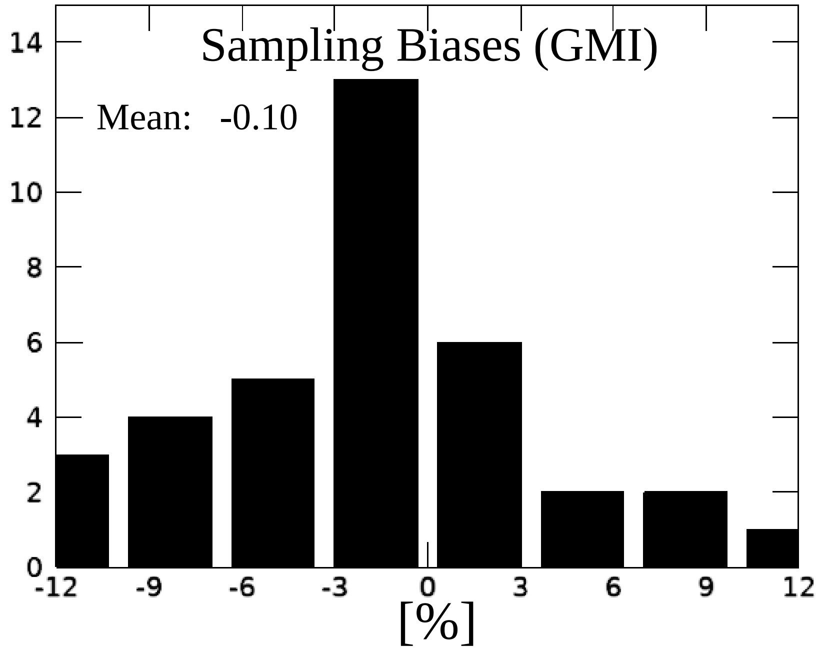
| City | Total Change in TropVCD | | Change in Anthropogenic TropVCD | | GMI Met | TROP RE | GMI SB |
|---|---|---|---|---|---|---|---|
| | TROP | GMI | TROP | GMI | | | |
| Tokyo | -18.2 | -25.9 | -15.1 | -22.8 | -3.1 | -3.5 | -3.9 |
| New York City | -31.5 | -32.8 | -30.2 | -31.5 | -1.3 | -7.5 | 1.0 |
| New Delhi | -28.2 | -36.9 | -14.7 | -23.4 | -13.5 | -4.7 | 1.6 |
| Istanbul | -37.9 | -27.2 | -37.4 | -26.7 | -0.5 | -6.9 | -1.8 |
| Manila | -34.5 | -27.6 | -27.0 | -20.1 | -7.5 | -10.3 | 5.1 |
| Seoul | -26.6 | -21.4 | -17.3 | -12.1 | -9.3 | -1.4 | 2.7 |
| Mexico City | -25.7 | -35.0 | -13.8 | -23.1 | -11.9 | -7.0 | 1.1 |
| Kinshasa | 6.9 | 13.8 | -7.6 | -0.7 | 14.5 | -1.6 | -6.3 |
| Cairo | -11.6 | -28.5 | -11.8 | -28.7 | 0.2 | -6.3 | 0.6 |
| Karachi | -26.7 | -17.9 | -22.4 | -13.6 | -4.3 | -5.0 | 0.6 |
| Wuhan | -53.1 | -29.0 | -64.1 | -40.0 | 11.0 | -2.6 | -2.3 |
| Lima | -52.0 | -29.4 | -49.9 | -27.3 | -2.1 | -4.5 | 1.4 |
| Jakarta | -29.9 | -38.9 | -16.2 | -25.2 | -13.7 | -6.6 | 4.7 |
| Chennai | -43.0 | -51.9 | -2.5 | -11.4 | -40.5 | -8.8 | 0.1 |
| Moscow | -20.6 | -32.7 | -6.7 | -18.8 | -13.9 | -2.9 | 1.0 |
| Wuhan | -53.1 | -29.0 | -64.1 | -40.0 | 11.0 | -2.6 | -2.3 |
| Shanghai | -44.4 | -27.5 | -51.5 | -34.6 | 7.1 | -1.7 | 4.7 |
| Beijing | -32.1 | -21.5 | -46.5 | -35.9 | 14.4 | -3.5 | -8.2 |
| Tianjin | -28.0 | -21.6 | -41.5 | -35.1 | 13.5 | -2.2 | -10.9 |
| Guangzhou | -44.0 | -36.5 | -32.6 | -25.1 | -11.4 | -2.1 | 10.1 |
| Shenzhen | -35.5 | -26.0 | -33.6 | -24.1 | -1.9 | -2.4 | 2.0 |

# Statistical Summary



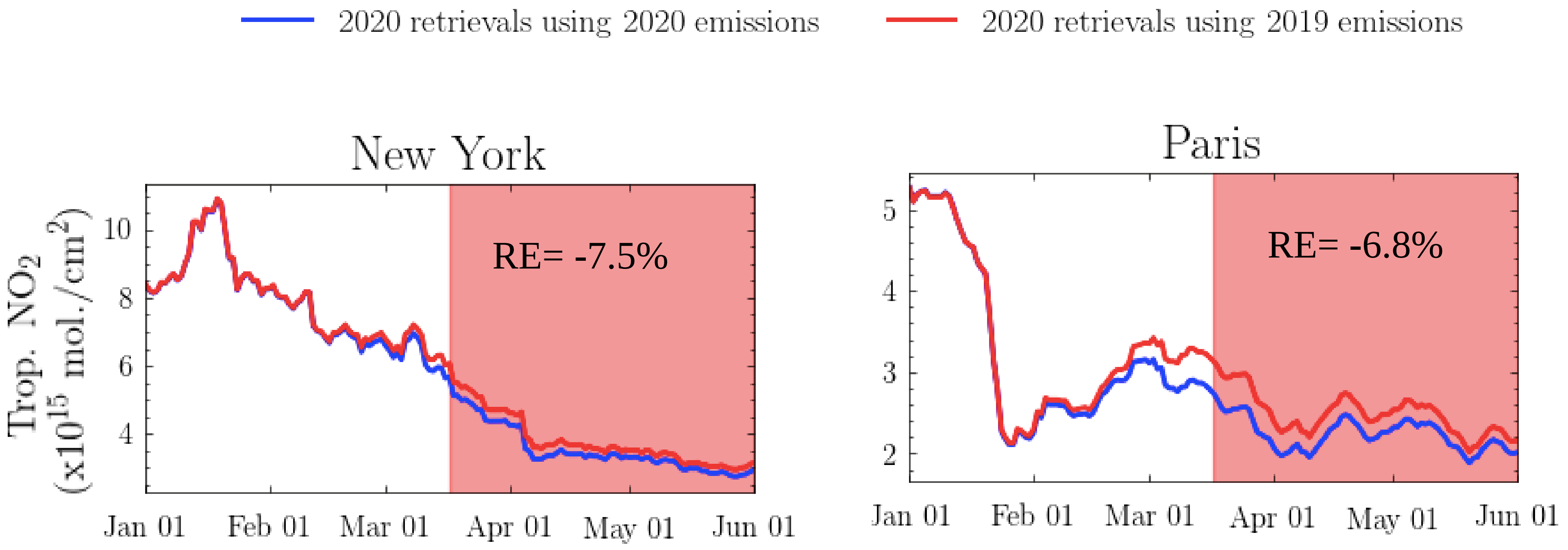



# Conclusions

- We characterized the $NO_2$ reductions in VCD Trop for TROPOMI during the COVID-19 lockdown periods using GEOS GMI run on a on a global scale to decouple the effects of anthropogenic $NO_2$ emissions from the meteorological and natural emission variability
  - Used lockdown adjusted and “business as usual” a priori $NO_2$ Profiles in 2020 to account for the effect of meteorological variability and the retrieval errors incurred in using unadjusted emissions
  - For the 36 cities in the study, net $NO_2$ reductions during the lockdowns ranged from -64.1% (Wuhan) to 2.6% (Lahore).
- The effects of meteorological variability significantly impacted the mean VCD Trop for many of the selected cities:
  - Meteorological effects on VCD Trop were non-uniformly distributed within the study region and ranged between -40.5 % (Chennai) and 15% (Beijing)
- Retrieval errors incurred from using BAU $NO_2$ profile shapes instead of lockdown-corrected emissions were systematically negative and ranged from -1.4% (Seoul) to -11.0% (Mumbai)
- Sampling Biases were randomly distributed and ranged from about ±10%

# Backup Slides

# Satellite Retrieval Errors




- Retrieval error: $\overline{\mathrm{RE}}_{Sat} = \overline{TVCD}_{Sat}[2020] - \overline{TVCD}_{Sat}[BAU]$

Satellite retrieval error represents the differences in the two time series plots