World Bank Research with GHG Data

Global Analyses with Satellite Readings

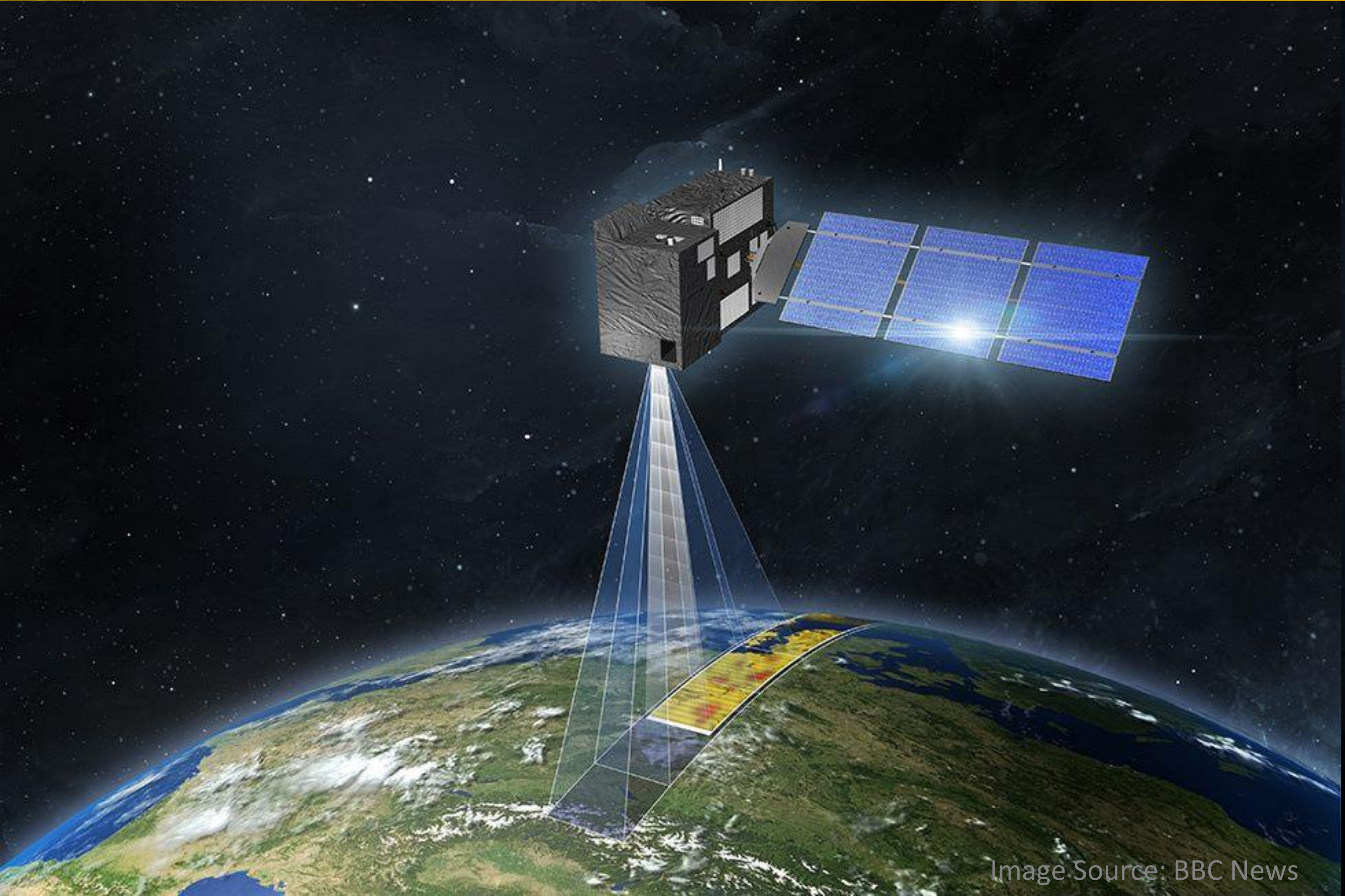

Image Source: BBC News

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World Bank

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World Bank Publications

1. Urban CO_2 Emissions: A Global Analysis with New Satellite Data. WPS 9845.
2. Subways and CO2 Emissions: A Globak Analysis with Satellite Data
3. Scalable Tracking of CO2 Emissions: A Global Analysis with Satellite Data, WPS 10297.
4. Tracking Methane Emissions by Satellite: A New World Bank Database and Case Study for Irrigated Rice Production, WPS 10224.
5. Identifying and Monitoring Priority Areas for Methane Emissions Reduction, WPS 10391.

Presentation Outline

1. Motivation for the Use of Satellite Data in Research
2. World Bank Research To Date
   - Scalable Tracking of CO_2 Emissions
   - Global CO_2 Emissions: Impacts of Subways
   - Identifying and Monitoring Priority Areas for CH_4 Emissions Reductions
3. Processing of Satellite Data
4. WBG Research and Other Global Initiatives
5. Potential for Using Satellite Data for Incentive-based Mitigation Policies
6. Learning about Satellite Data from Applications
7. GHG local anomalies data at your fingertips

Global Warming in a Changing Climate

Climate change already affects every global region, at an unprecedented level on a millennial time scale.

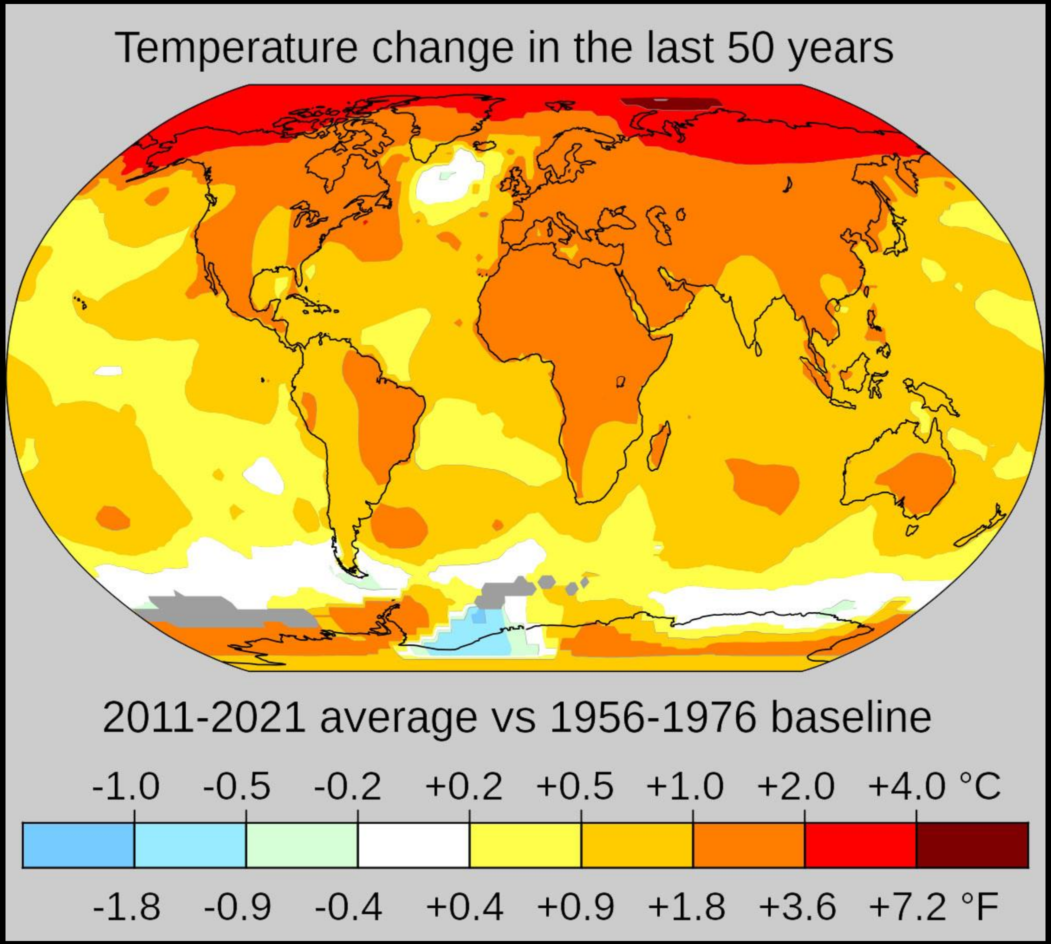
- IPCC AR6

"Global temperatures are on course for a 3°-5°C rise this century, far overshooting a global target of limiting the increase to 2°C or less."

- World Meteorological Organization

Overshooting the 2°C limit pledged by the 2015 Paris climate accord (COP 21) might have a catastrophic impact

- Steffen et al. 2018; World Bank 2012



Source: Google Image

GHG Emissions

- More than 150 nations have outlined their ambition to reduce carbon emissions in their NDCs.
- Global Methane Pledge joins 122 countries in a collective effort to reduce global CH_4 emissions by at least 30% from 2020 levels by 2030.

➢ Need for accurate data on GHG emissions for defining the baseline and monitoring changes.

Source: Google Image

Limited Information on GHG Emissions

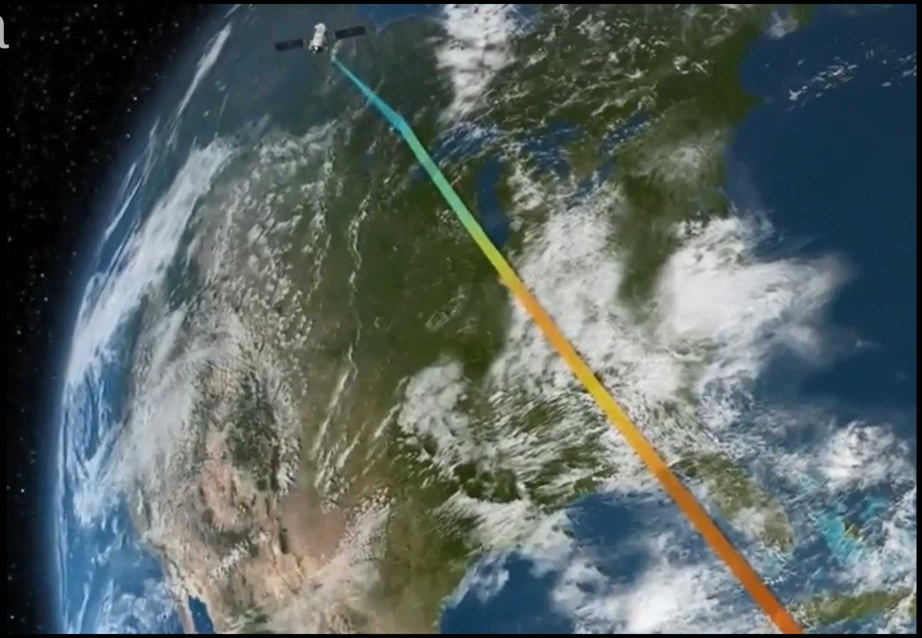
Near-total absence of local & regional GHG emissions data for problem diagnosis, program design & performance assessment.

- Only a few of the available estimates are based on actual GHG emissions.
- Conventional practice: Rely on emissions parameters from engineering studies, often conducted in developed countries, that are applied to survey-based activity measures for energy production, manufacturing, transport and agriculture

➡ Limited information has hindered monitoring & decision making

Changing Global Practice

- CO_2 and CH_4 emissions monitoring via satellites provide direct, independent, low-cost and objective measurements of GHG concentrations.



Source: Google Image

Extraction of GHG “Concentration Anomaly”

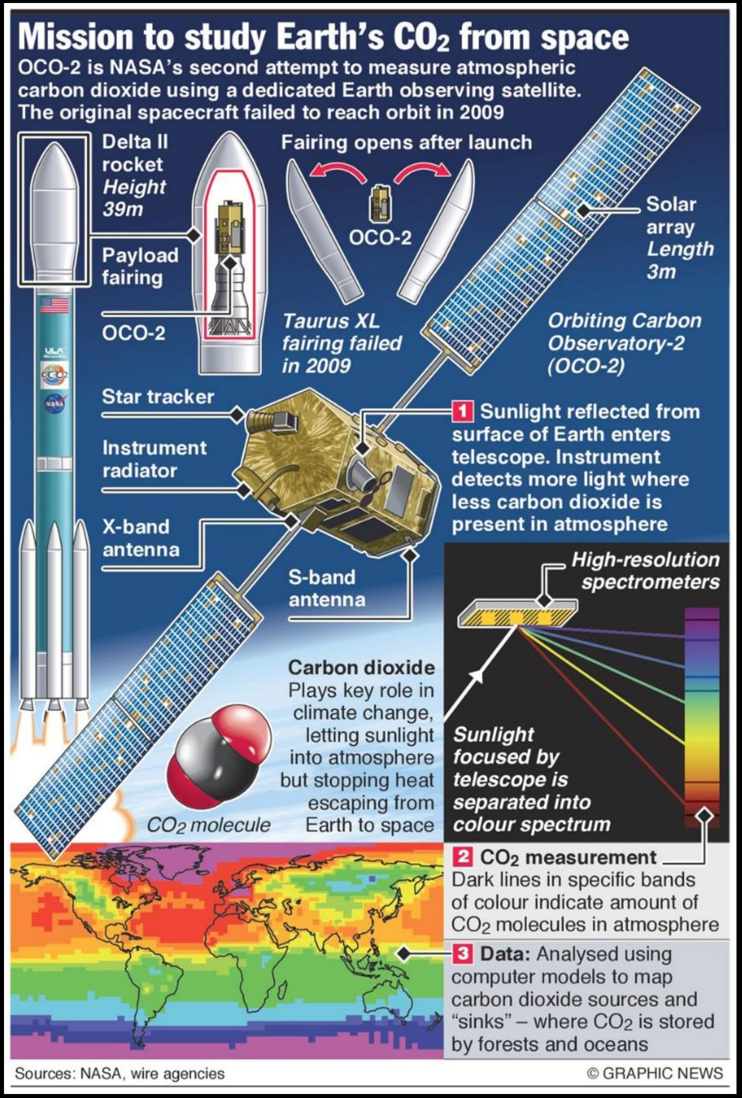
Location-specific atmospheric GHG concentration

- Global stock of GHG accumulated since Industrial Revolution
- Seasonal Component: Differential GHG absorption & release by vegetation over the annual cycle
- “Concentration anomaly”: local deviation from the global background GHG concentration

1. Scalable Tracking of CO_2 Emissions

Source CO_2 data: OCO-2

Source Data: CO_2 Measures from NASA's OCO-2



Source: Google Image

- Open access
- Long panel of consistently-measured daily observations (Sept. 6, 2014 - present)
- Highest spatial resolution among the available sources (1.29 x 2.25 km)
- For this study, daily CO_2 concentrations were computed for a terrestrial grid (25 km resolution) from the georeferenced column-averaged dry air mole fraction of CO_2.

Estimation of Local CO_2 "Concentration Anomaly"

- The bias-corrected XCO2 data was downloaded from the NASA's repository.
- The data is filtered to isolate "local anomalies" using the methodology of Hakkarainen et al. (2019).

1. Computation of "Background" Value: Daily median XCO2 for each 10-degree latitude band is computed and the result is linearly interpolated to each observation with 1-degree resolution. The median represents the representative "Background" value because it is not skewed by extreme observations.
2. The "Background" value is subtracted to compute the local anomaly for each observation.

Monthly mean values of concentration anomalies are computed for each 25 km grid cell in the database.

Urban Areas: Trends in Local Concentration Anomalies, 2014-2021

Testing for Atmospheric Circulation: Methodology

Some UA trend results may reflect regional atmospheric circulation effects rather than changes in local emissions, as region-scale changes in atmospheric circulation can alter measurements by several parts per million, even if local emissions remain constant (Weir et al. 2021).

Test for regional atmospheric circulation effects:

1. Two groups within 100 km of each UA centroid: grid squares inside the UA and those lying outside were created.
2. Separate regressions for 100-km-radius grid squares inside (I) and outside (O) of UA j were estimated:

Inside Regression: $$CO2_{ijtI} = \gamma_{0I} + \gamma_{1jI}t + \varepsilon_{itjI}$$

Outside Regression: $$CO2_{ijtO} = \gamma_{0O} + \gamma_{1jO}t + \varepsilon_{itjO}$$

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Testing for Atmospheric Circulation: Methodology

Continued

Regional atmospheric circulation as the source of a significant change in an UA concentration anomaly is rejected if :

- the outside change parameter has the opposite sign from the inside parameter

  $\mathrm{sign}(\gamma_{1jI}) \neq \mathrm{sign}(\gamma_{1jO})$

  and/or

- the inside parameter is significant while the outside parameter is not

  $p(\gamma_{1jI}) \leq p(.05)$; $p(\gamma_{1jO}) > p(.05)$

Long Period (2014 – 2021) Changes for Urban Areas : Results

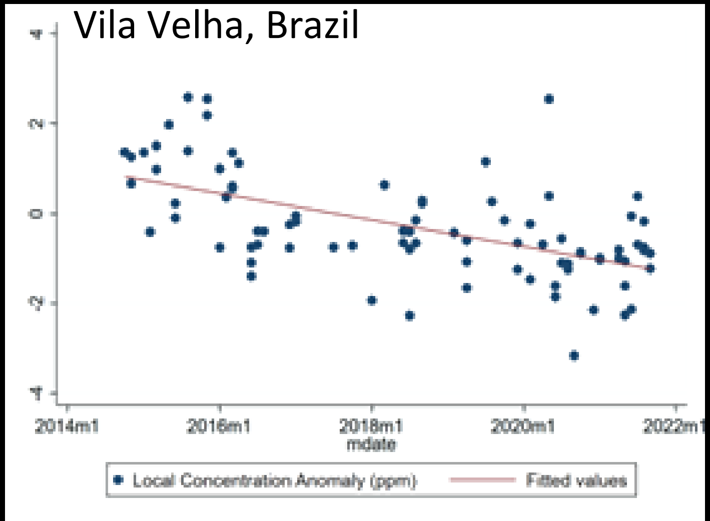
- Overall, 380 of 1,799 urban areas (21.1%) have significant changes during the 8-year period.
- Of these, 272 have significant decreases in local concentration anomalies and 108 have significant increases.

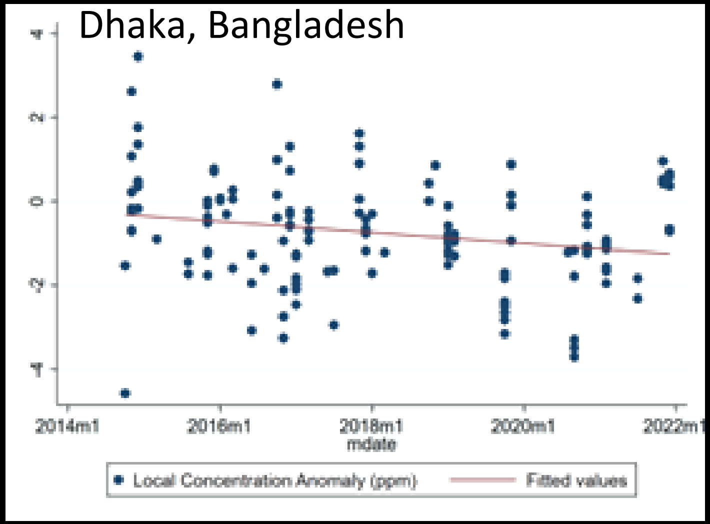
Regional Distributions of Urban Area CO_2 Anomaly Trends, 2014-2021

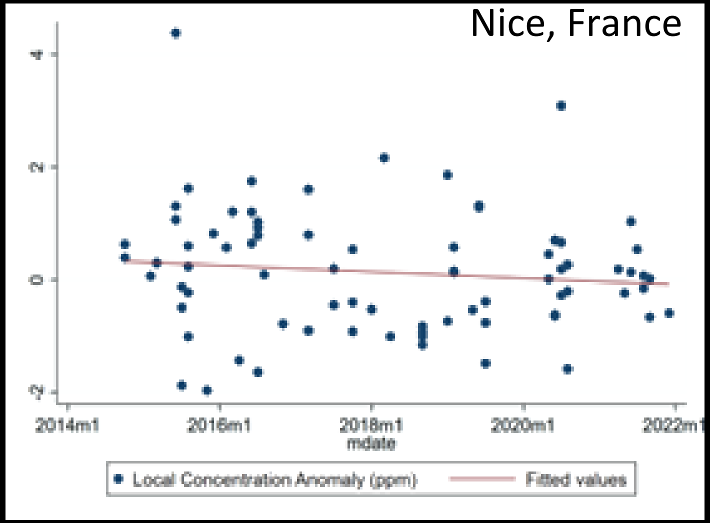
- disproportionate share of increases in Asia
- disproportionate shares of decreases in other regions.

Trends in Monthly Concentration Anomalies, 2014-2021 (ppm)

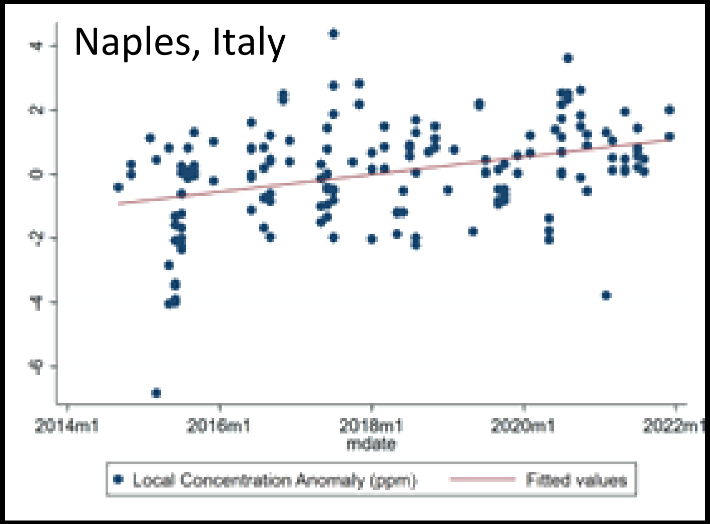
Negativ
e
trends

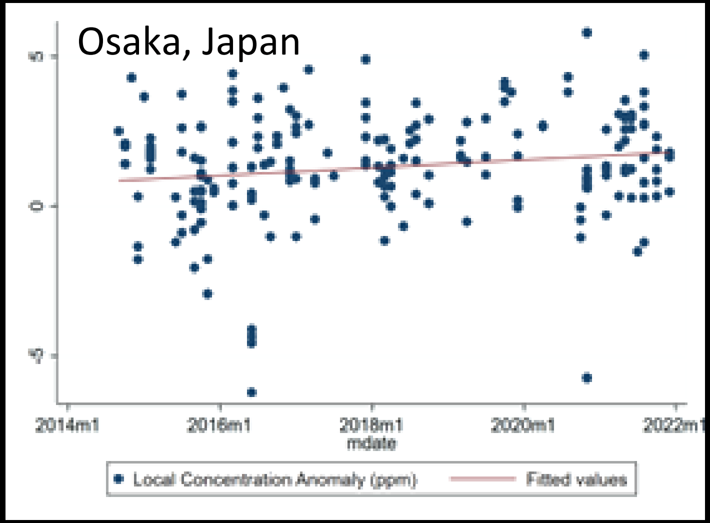


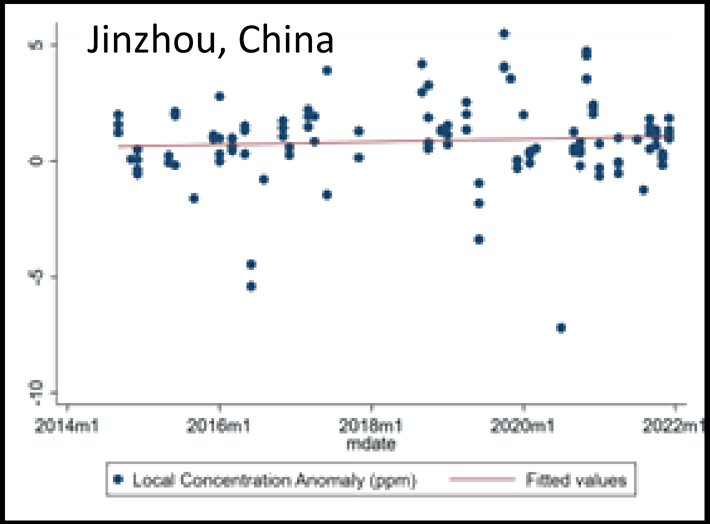




Positive
trends







FUAs, 2021 Deviation from 5-year means, 2017-2021

Dependent variable: Local CO2 Anomaly (ppm)

Significance Level	Negative	Positive	Total
Not Significant	418	431	849
.05	76	70	146
.01	37	25	62
.001	15	12	27
Total Significant	128	107	235
Total			
Not Significant	546	538	1,084

2. Global CO_2 Emission Impacts of Subways

Source CO_2 data: OCO-2

Climate Policy Instruments

Alternative Policy Instruments for CO_2 Emissions Reduction

1. Incentive-Based: (Carbon Pricing or Tradable Emissions Permits)
2. Directed Infrastructure Investment: (Public Investment in Low-Carbon Land Development, Energy, and Transport)

Research Question of Interest

Effectiveness of Directed Infrastructure Investment for CO_2 Emissions Reduction:

- Can large-scale public investments in mass transit (subways) reduce Carbon emissions significantly by promoting low-carbon urban development?

Research Design

1. Modeling CO_2 emissions
2. Testing the effectiveness of public investment in subway systems for reducing CO_2 emissions in a large sample of cities worldwide
3. Estimating CO_2 emissions reductions from future subways

Major Sources of CO_2 Emissions

Fossil-Fired Power Plants

Refineries

Steel Mills

Cement Plants

Motor Vehicles

Agricultural and Forest Fires

Heating

Trash Burning

Source: Google Image

Major Sources of CO_2 Emissions

Major Industrial Sources

- Power Plants
  - Coal Fired
  - Gas Fired
  - Oil Fired
- Steel & Iron Plants
  - Non-Electric
- Cement Plants
- Oil Refineries

Agricultural & Forest Fires

Population-Related Determinants

- Population
- Household Heating & Cooling
- Income Per Capita
- Emissions from Transport

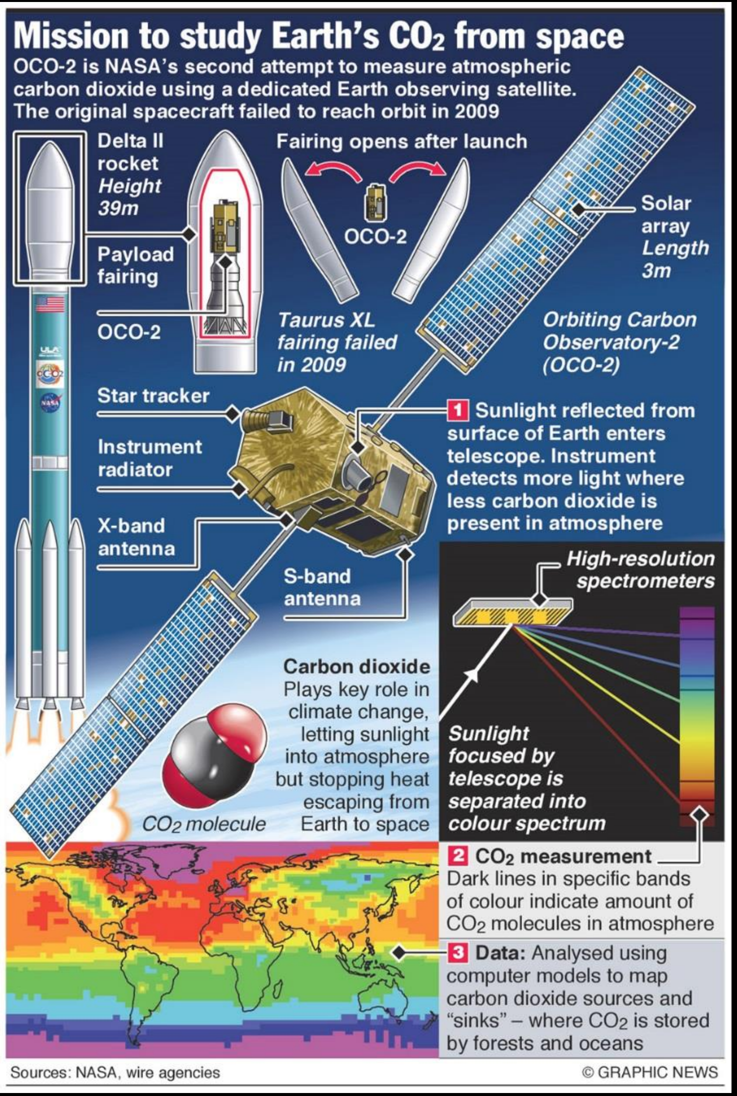
Regression Model

$$CO2_{it} = \beta_0 + \beta_1 I_{it} + \beta_2 DI_{it} + \beta_3 F_{it} + \beta_4 DF_{it} +$$
$$(\beta_5 P_{it} H_{it} + \beta_6 P_{it} C_{it} + \beta_7 P_{it} Y_{it})\, e^{\beta_8 S_{it}(L_{it} A_{it})} + \varepsilon_{it}$$

For grid cell 'i' in period 't':

C_{it}	=	Satellite-measured mean CO_2 anomaly
I_{it}	=	CO_2 emissions from industrial sources
Di_{it}	=	Wind-displaced industrial CO_2 emissions from other cells
F_{it}	=	CO_2 emissions from agricultural and forest fires
Df_{it}	=	Wind-displaced fire CO_2 emissions from other cells
P_{it}	=	Population
H_{it}	=	Heating degree days
C_{it}	=	Cooling degree days
Y_{it}	=	Income per capita
S_{it}	=	Subway impact index, a function of system scale (L) and age (A)
ε	=	Random error term

Source Data: CO_2 Measures from NASA's OCO-2



Source: Google Image

- Open access
- Long panel of consistently-measured daily observations (Sept. 6, 2014 - present)
- Highest spatial resolution among the available sources (1.29 x 2.25 km)
- For this study, daily CO_2 concentrations were computed for a terrestrial grid (25 km resolution) from the georeferenced column-averaged dry air mole fraction of CO_2.

Estimation of Local CO_2 "Concentration Anomaly"

- The bias-corrected XCO2 data was downloaded from the NASA's repository.
- The data is filtered to isolate "local anomalies" using the methodology of Hakkarainen et al. (2019).
  1. Computation of "Background" Value: Daily median XCO2 for each 10-degree latitude band is computed and the result is linearly interpolated to each observation with 1-degree resolution. The median represents the representative "Background" value because it is not skewed by extreme observations.
  2. The "Background" value is subtracted to compute the local anomaly for each observation.

Monthly mean values of concentration anomalies are computed for each 25 km grid cell in the database.

Wind Displacement of CO_2 Emissions

- As the prevailing winds displace emissions from their sources, deviations from background concentrations persist for some time along wind paths.
- Wind effects are modeled with historical ERA5 monthly wind direction data for all grid cells in the database.
- Grid cells as origins: CO2 emissions along monthly wind paths from each grid cell across other grid cells, with distance-determined persistence of local anomalies.
- Grid cells as destinations: For each grid cell, summation over distance-weighted emissions from all origin cells.

Source: Google Image

Main Messages on Subways and CO_2 Emissions

- Regression results suggest that subways have significantly reduced CO_2 emissions in the cities where they operate, with impacts affected by both the scale of the systems and the time elapsed since their installation.
- In a counterfactual exercise covering 192 FUAs, estimates suggest subway systems have cut CO_2 emissions by about half in those FUAs and 11 percent globally.
- Projective analyses for future subway installations in other cities indicate that, in hundreds of cities, the climate benefits alone warrant construction.

Implications for Climate Policies

- Most climate economists have argued for carbon pricing via emissions taxation or permit trading.
- Many policy analysts who support Carbon pricing also argue for a supplement: Coordinated public investment in low-carbon land development, energy, and transport that will accelerate the transition to low-carbon economies.

To highlight one illustration, subway investments, our results indicate:

- In 192 subway cities, large reductions in carbon emissions.
- In hundreds of additional cities, carbon emissions reductions large enough to warrant future subway investments on climate grounds alone.

3. Identifying and Monitoring Priority Areas for Methane Emissions Reduction

Source data: Sentinel-5P

Source Data from Sentinel-5P

Source: Google Image

- Sentinel-5P's L2 Offline georeferenced measure of XCH_4, the column average dry-air mixing ratio of methane, corrected for bias associated with surface albedo is used.
- Per the ESA's recommendations, only pixels with quality values greater than 0.5 are used.

➡ For this study, daily CH_4 concentrations were computed for each 5 km grid cell from the georeferenced column-averaged dry air mole fraction of CO_2.

Estimation of Local CH_4 "Concentration Anomaly" (S5P CH_4 Anomalies)

- The bias-corrected XCH4 data was downloaded from the ESA's repository managed by MEEO (Meteorological Environmental Earth Observation).
- The data is filtered to isolate "local anomalies" using the methodology of Hakkarainen et al. (2019).

1. Computation of "Background" Value: Daily median XCH4 for each 10-degree latitude band is computed and the result is linearly interpolated to each S5P observation with 1-degree resolution. The median represents the representative "Background" value because it is not skewed by extreme observations.
2. The "background" value is subtracted to compute the local anomaly for each observation.

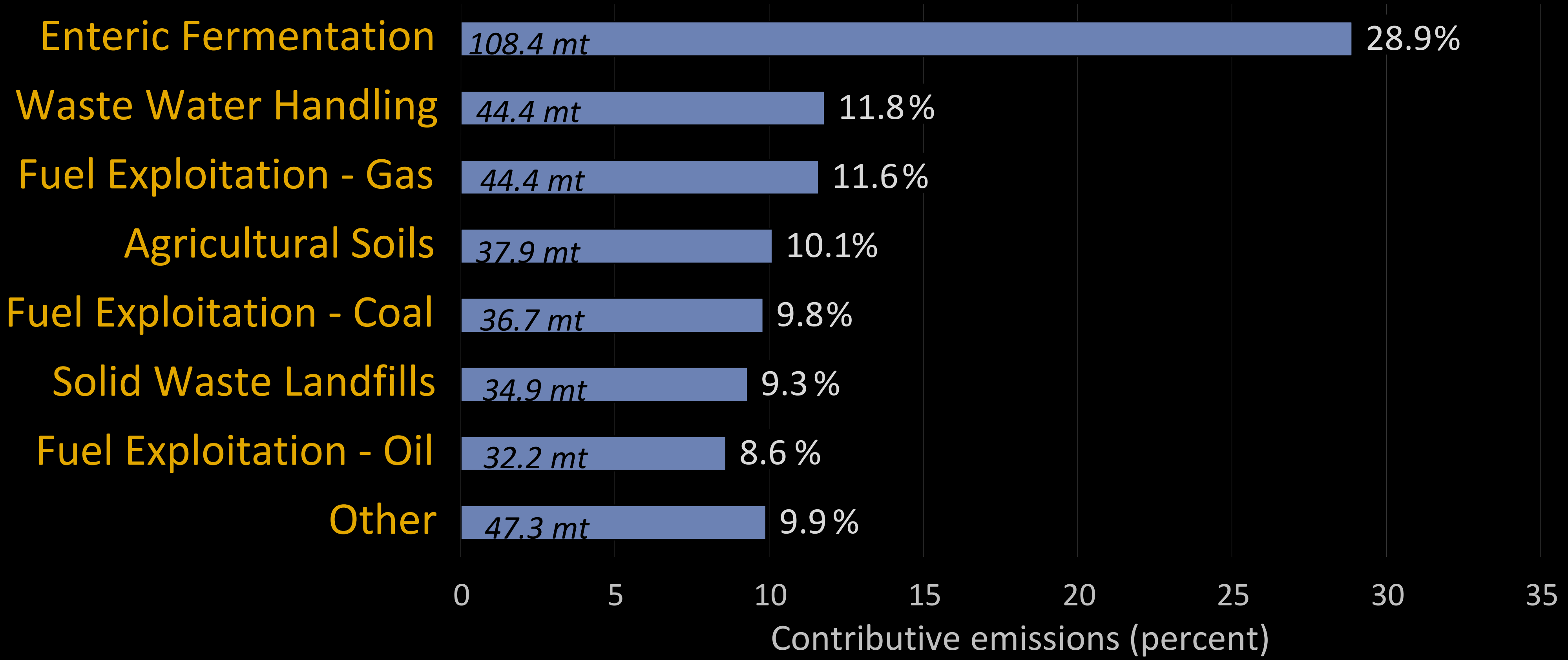
Monthly mean values of concentration anomalies are computed for each 5 km grid cell in the database.

Algorithm

1. Identification of the global distribution of CH4 emissions from EDGARS (2022).
2. Identification of 775 high-priority sites accounting for 50% of global CH4 emissions, where rapid reduction of methane emissions would accelerate the global transition.
3. Understanding actual emission in the high-priority areas with Sentinel-5P CH4 concentration anomalies.
4. Analysis of the distribution of emissions trends in each high-priority areas by source sector.

Global Methane Emissions, 2018

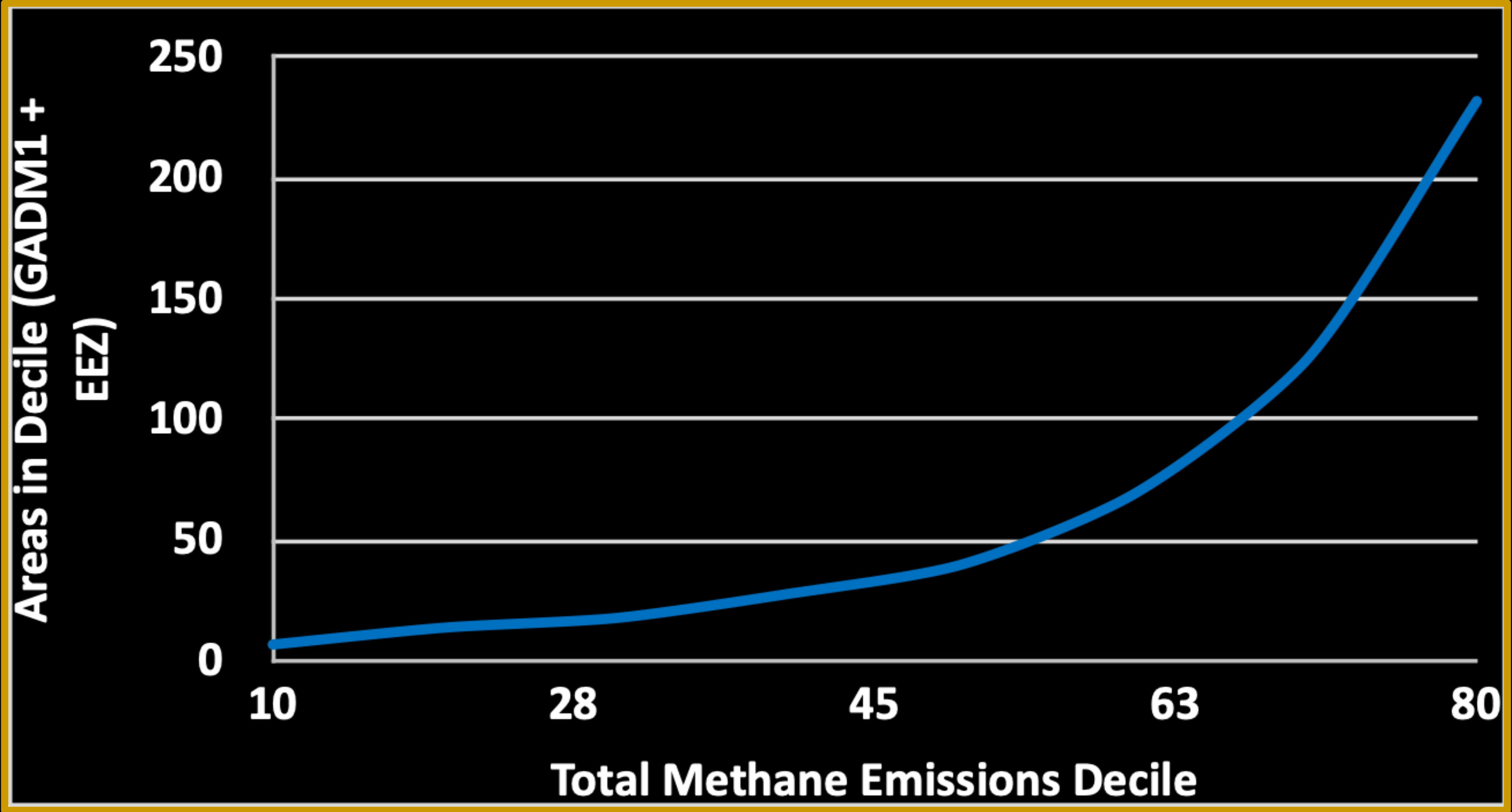
EDGAR sectors:



Source: EDGAR (2022)

Other includes manure management, energy for buildings, oil refining and transformation industry, agricultural waste burning, solid waste incineration, road transportation (no resuspension), combustion for manufacturing, power industry, chemical processes, iron and steel production, fossil fuel fires, and railways, pipelines, and off-road transport.

Global CH4 Emissions



Highly-skewed spatial distribution: Only 2.8% (107) of the 3,812 areas account for 50% of global methane emissions.

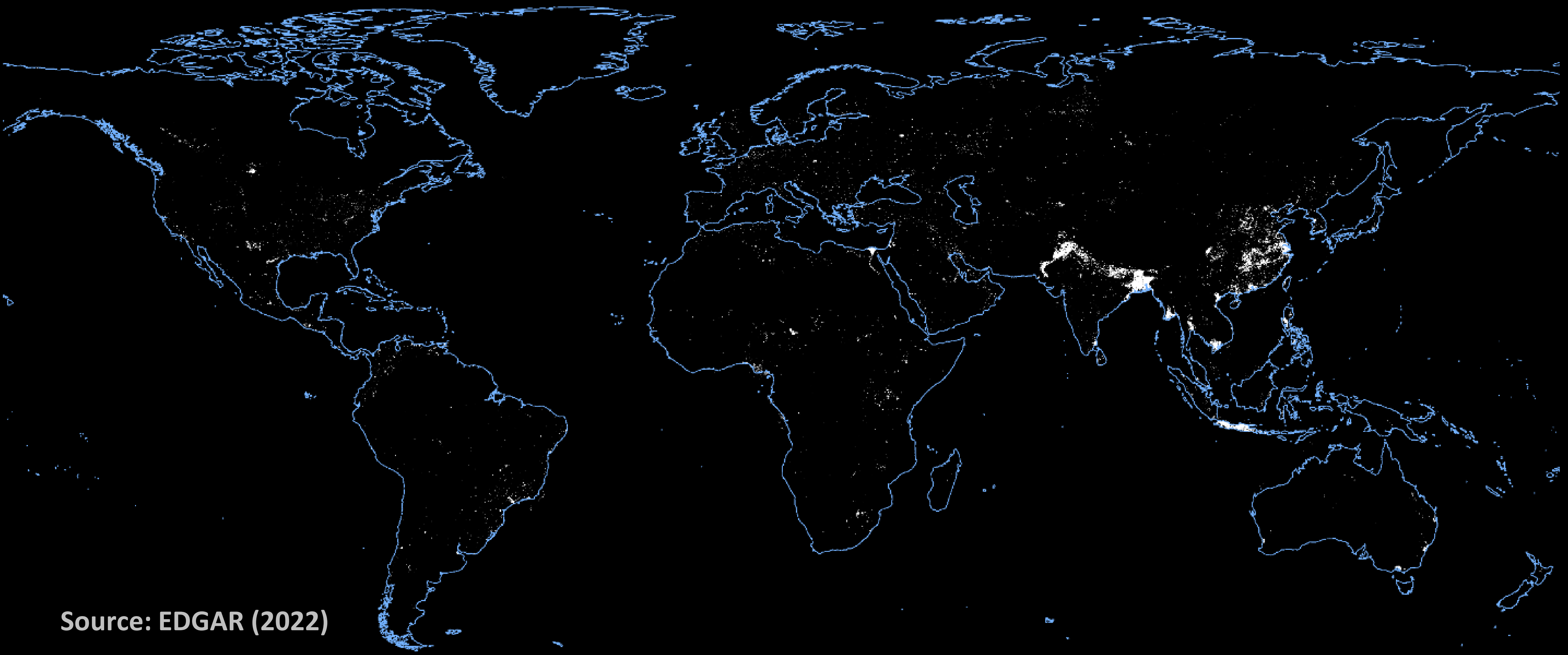
Spatial Clustering of Global Methane Emissions

EDGAR Decile	Cells	Cum. Cells	Cum. %
1	142	142	0.002
2	578	720	0.011
3	1,775	2,495	0.039
4	5,817	8,312	0.128
5	12,745	21,057	0.325
6	22,364	43,421	0.670
7	37,919	81,340	1.255
8	64,334	145,674	2.248
9	124,529	270,203	4.170
10	6,209,797	6,480,000	100.000

Out of 6.5 million cells in the EDGAR 10 km global raster:

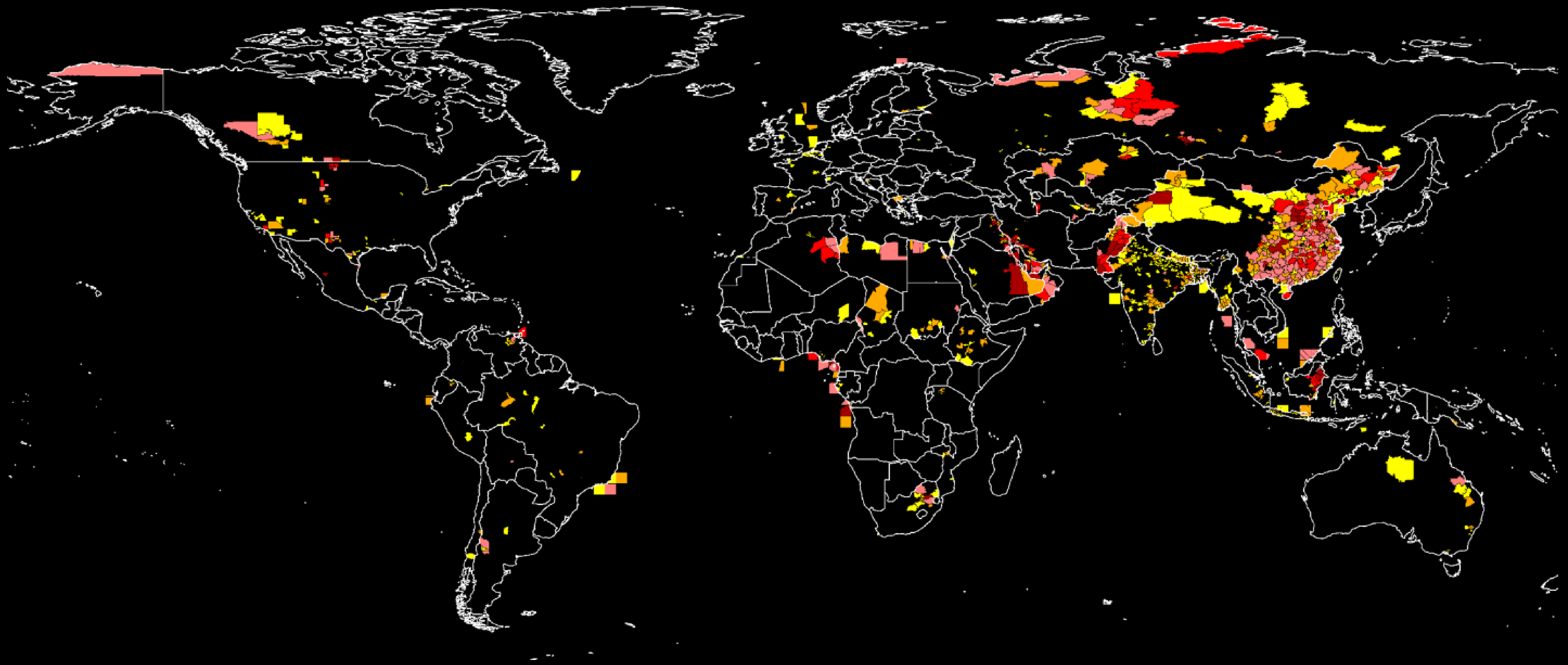
- Only 142 (0.002% of total cells) account for 10% of global methane emissions, and
- 21,057 (0.325%) account for 50%

Areas that account for 50% of Global Methane Emissions



Source: EDGAR (2022)

Global Geographic Units, EDGARS Top 5 Deciles

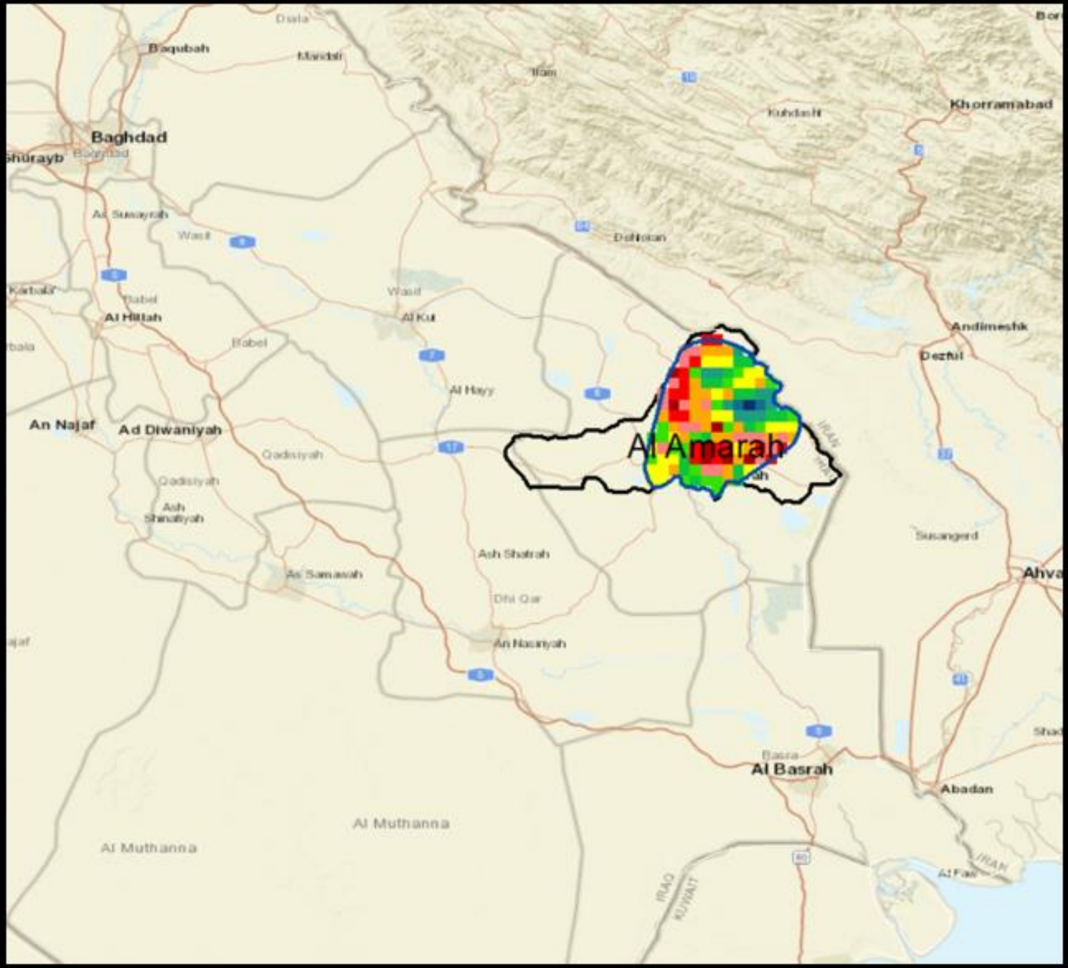


Understanding actual emission in the high-priority areas with Sentinel-5P CH4 concentration anomalies

Al Amarah District
Maysan Governorate
Iraq

Sentinel-5P
Mean CH4 Anomalies
2019 -2022 (5 KM)

-31.04 - -24.03
-24.02 - -8.11
-8.1 - 1.93
1.94 - 4.78
4.79 - 6.86
6.87 - 8.19
8.2 - 9.32
9.33 - 10.46
10.47 - 12.17
12.18 - 17.28



Econometric trend models

$$(1) \quad CH4_{ijt} = \gamma_{0i} + \gamma_1 t + \varepsilon_{ijt}$$

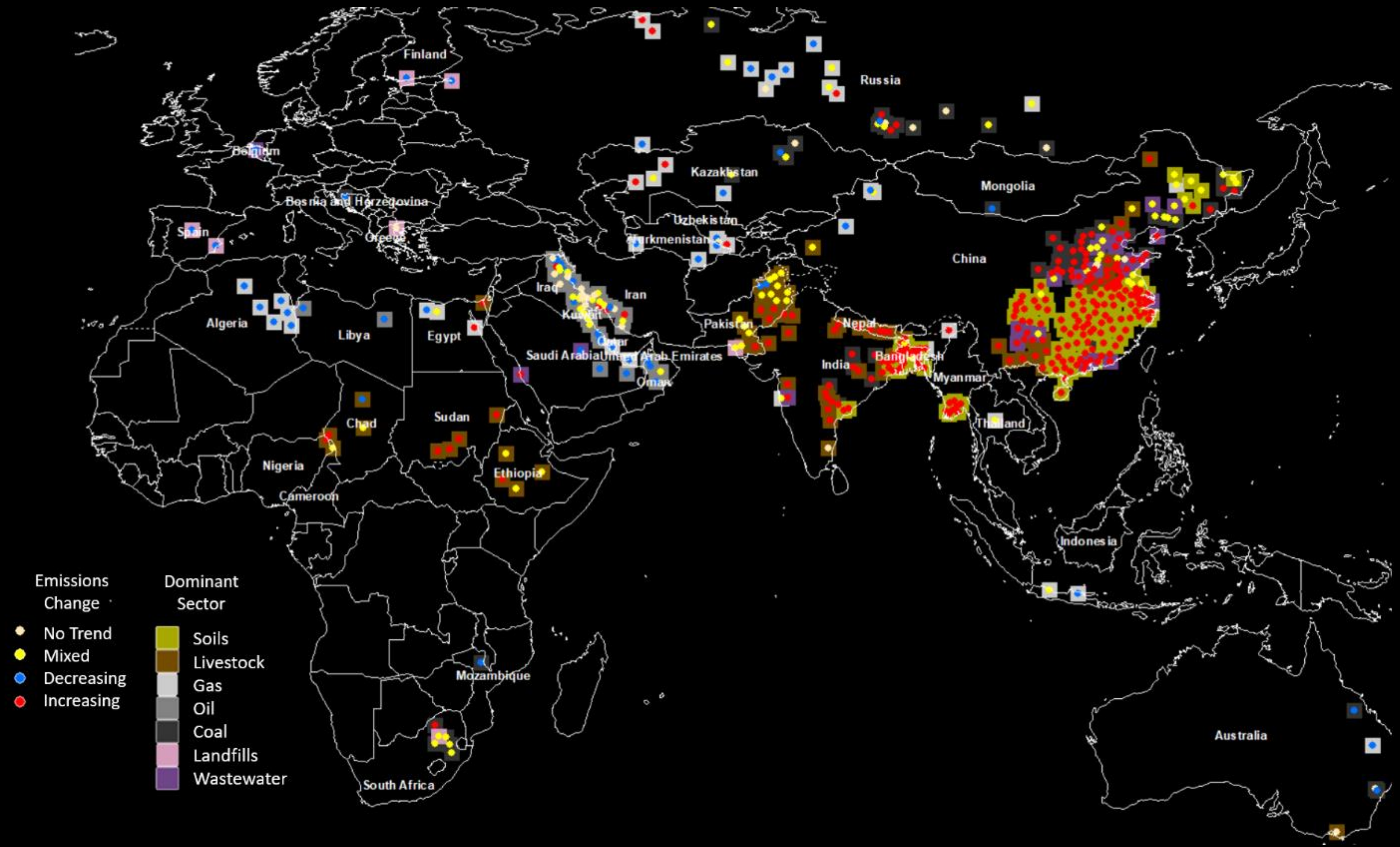
$$(2) \quad CH4_{ijt} = \gamma_{0i} + \delta_1 D_F + \varepsilon_{ijt}$$

Where, for GGU (global geographic unit) *i* in month *t* :

- $CH4_{ijt}$ = Mean CH4 anomaly (ppb) in 5-km sampling cell *j*
- t = Time from initial period in months
- D_F = Dummy variable for the final observation year (2022)
- ε_{ijt} = Random error term

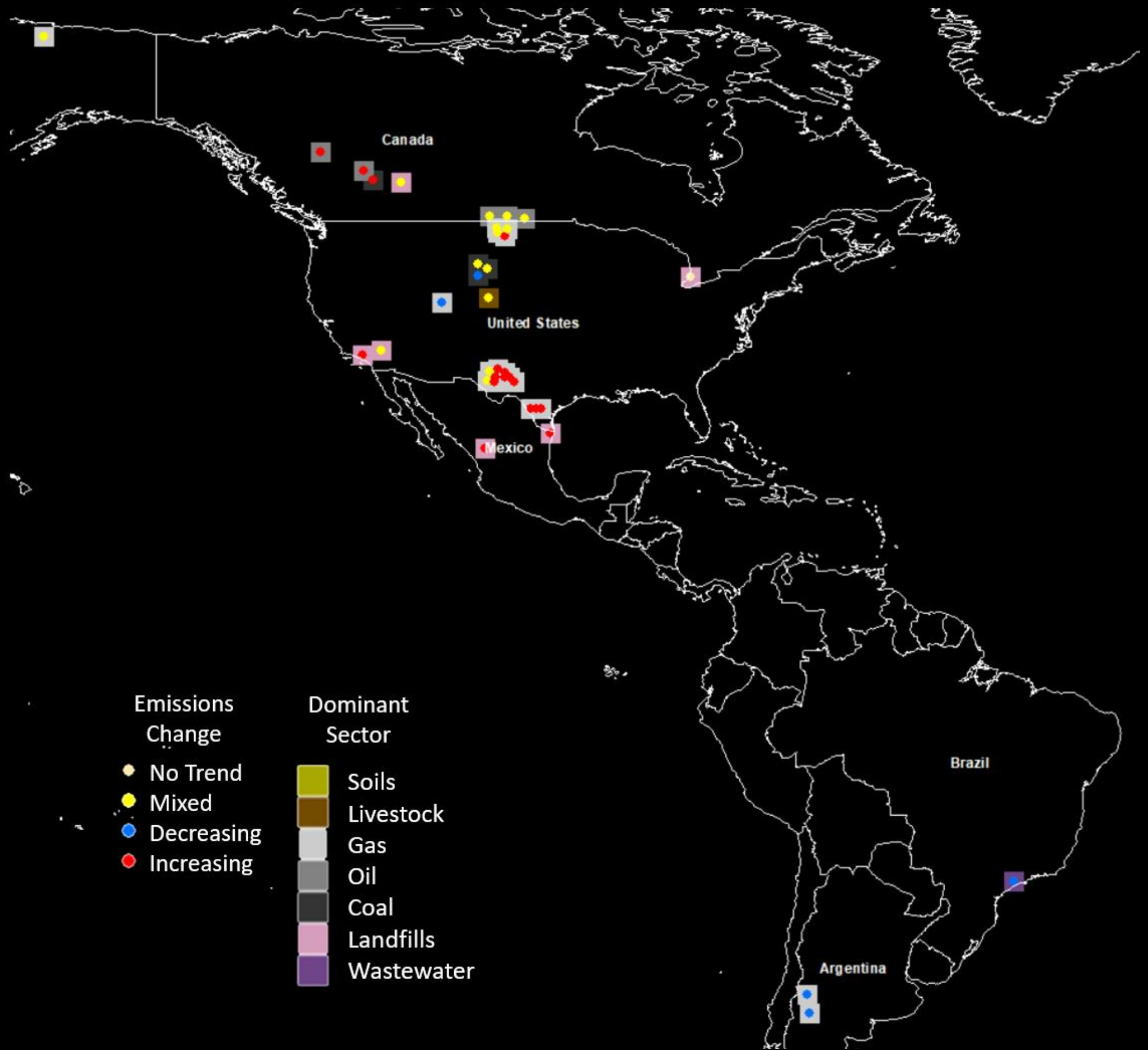
CH4 Emissions Changes

Top 4 EDGAR Deciles - Europe, Africa, Asia



CH4 Emissions Changes

Top 4 EDGAR Deciles - North, Central, South America



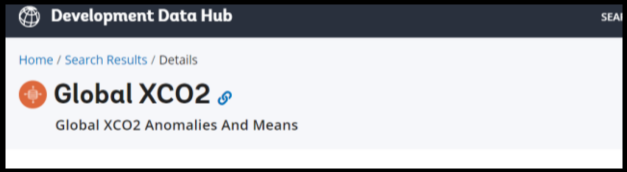
Methane Emissions Changes by EDGAR Decile

ISO3	Country	Province	District	Sector	Model_1	Model_2	Overall
CAN	Canada	Saskatchewan	Division No. 1	Oil	Decreasing	Increasing	Mixed
CHN	China	Beijing	Beijing	Livestock	Increasing	Increasing	Increasing
CHN	China	Chongqing	Chongqing	Soils	Increasing	Increasing	Increasing
CHN	China	Henan	Zhengzhou	Coal	Increasing	Increasing	Increasing
CHN	China	Shandong	Jining	Coal	Increasing	Increasing	Increasing
CHN	China	Shandong	Tai'an	Coal	Increasing	Increasing	Increasing
CHN	China	Shanxi	Yangquan	Coal	Increasing	No Trend	Mixed
CHN	China	Shanxi	Changzhi	Coal	Increasing	Increasing	Increasing
CHN	China	Shanxi	Shuozhou	Coal	Increasing	Increasing	Increasing
CHN	China	Shanxi	Linfen	Coal	Increasing	Increasing	Increasing
CHN	China	Shanxi	Taiyuan	Coal	Increasing	Increasing	Increasing
CHN	China	Shanxi	Jincheng	Coal	Increasing	Increasing	Increasing
CHN	China	Shanxi	Luliang	Coal	Increasing	Increasing	Increasing
CHN	China	Xinjiang Uygur	Aksu	Gas	Decreasing	Decreasing	Decreasing
IRN	Iran	Ilam	Dehloran	Oil	No Trend	No Trend	No Trend
IRN	Iran	Khuzestan	Ahvaz	Oil	No Trend	Increasing	Mixed
IRQ	Iraq	Diyala	Khanaqin	Oil	No Trend	No Trend	No Trend
MEX	Mexico	Durango	Durango	Landfills	Increasing	Increasing	Increasing
PAK	Pakistan	Punjab	Dera Ghazi Khan	Livestock	Increasing	Increasing	Increasing
PAK	Pakistan	Punjab	Bahawalpur	Livestock	Increasing	Increasing	Increasing
PAK	Pakistan	Punjab	Multan	Livestock	Increasing	Increasing	Increasing
PAK	Pakistan	Sind	Hyderabad	Livestock	Increasing	Decreasing	Mixed
RUS	Russia	Kemerovo	Novokuznetskiy	Coal	Increasing	Increasing	Increasing
ZAF	South Africa	Mpumalanga	Nkangala	Coal	Decreasing	No Trend	Mixed
ARE	United Arab Emirates	Abu Dhabi	Al Gharbia	Gas	Decreasing	Decreasing	Decreasing
USA	United States	North Dakota	McKenzie	Gas	Decreasing	Increasing	Mixed

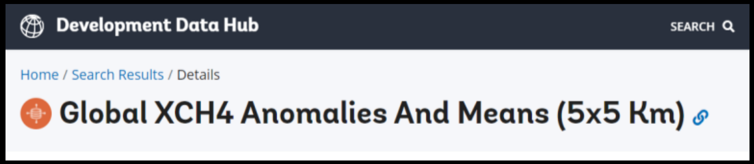
GHG local anomalies data at your fingertips

Development Data Hub is the World Bank data depository
http://datacatalog.worldbank.org

- CO2 local anomalies



- XCH4 local anomalies



- Methane Emissions Changes By EDGAR Decile

Thank You

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