World Bank Research with GHG Data
Global Analyses with Satellite Readings

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World Bank
April 2023

Image Source: BBC News

2. **Subways and CO₂ Emissions: A Global Analysis with Satellite Data.**


5. **Identifying and Monitoring Priority Areas for Methane Emissions Reduction,** WPS 10391.
1. Motivation for the Use of Satellite Data in Research

2. World Bank Research To Date
   - Scalable Tracking of CO₂ Emissions
   - Global CO₂ Emissions: Impacts of Subways
   - Identifying and Monitoring Priority Areas for CH₄ 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
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.
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.
CO₂ and CH₄ emissions monitoring via satellites provide direct, independent, low-cost and objective measurements of GHG concentrations.
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

- 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
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:  
   \[ CO2_{ijI} = \gamma_{0I} + \gamma_{1jI} t + \varepsilon_{itjI} \]

   Outside Regression:  
   \[ CO2_{ijO} = \gamma_{0O} + \gamma_{1jO} t + \varepsilon_{itjO} \]
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
  \[ \text{sign}(\gamma_{1jI}) \neq \text{sign}(\gamma_{1jO}) \]

  and/or

- the inside parameter is significant while the outside parameter is not
  \[ p(\gamma_{1ji}) \leq p(.05); \quad p(\gamma_{1jO}) > p(.05) \]
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)

Vila Velha, Brazil
Dhaka, Bangladesh
Nice, France

Naples, Italy
Osaka, Japan
Jinzhou, China

Negatives trends

1 < p ≤ .05
Not Significant (t ≈ 1.0)
p ≤ .001
### FUAs, 2021 Deviation from 5-year means, 2017-2021

Dependent variable: Local CO2 Anomaly (ppm)

<table>
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<th>Significance Level</th>
<th>Negative</th>
<th>Positive</th>
<th>Total</th>
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<tr>
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<td>107</td>
<td>235</td>
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<tr>
<td>Total</td>
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<tr>
<td>Not Significant</td>
<td>546</td>
<td>538</td>
<td>1,084</td>
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</table>
2. Global CO$_2$ Emission Impacts of Subways

Source CO$_2$ data: OCO-2
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)
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 CO₂ 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

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

For grid cell ‘i’ in period ‘t’:

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>( C_{it} )</td>
<td>Satellite-measured mean CO(_2) anomaly</td>
</tr>
<tr>
<td>( I_{it} )</td>
<td>CO(_2) emissions from industrial sources</td>
</tr>
<tr>
<td>( DI_{it} )</td>
<td>Wind-displaced industrial CO(_2) emissions from other cells</td>
</tr>
<tr>
<td>( F_{it} )</td>
<td>CO(_2) emissions from agricultural and forest fires</td>
</tr>
<tr>
<td>( DF_{it} )</td>
<td>Wind-displaced fire CO(_2) emissions from other cells</td>
</tr>
<tr>
<td>( P_{it} )</td>
<td>Population</td>
</tr>
<tr>
<td>( H_{it} )</td>
<td>Heating degree days</td>
</tr>
<tr>
<td>( C_{it} )</td>
<td>Cooling degree days</td>
</tr>
<tr>
<td>( Y_{it} )</td>
<td>Income per capita</td>
</tr>
<tr>
<td>( S_{it} )</td>
<td>Subway impact index, a function of system scale (L) and age (A)</td>
</tr>
<tr>
<td>( \epsilon )</td>
<td>Random error term</td>
</tr>
</tbody>
</table>
Source Data: CO₂ Measures from NASA’s OCO-2

- 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 CO₂ concentrations were computed for a terrestrial grid (25 km resolution) from the georeferenced column-averaged dry air mole fraction of CO₂.
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.
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

- Sentinel-5P’s L2 Offline georeferenced measure of \(X\text{CH}_4\), 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 \(\text{CH}_4\) concentrations were computed for each 5 km grid cell from the georeferenced column-averaged dry air mole fraction of \(\text{CO}_2\).
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.
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:

- **Enteric Fermentation**: 108.4 mt (28.9%)
- **Waste Water Handling**: 44.4 mt (11.8%)
- **Fuel Exploitation - Gas**: 44.4 mt (11.6%)
- **Agricultural Soils**: 37.9 mt (10.1%)
- **Fuel Exploitation - Coal**: 36.7 mt (9.8%)
- **Solid Waste Landfills**: 34.9 mt (9.3%)
- **Fuel Exploitation - Oil**: 32.2 mt (8.6%)
- **Other**: 47.3 mt (9.9%)

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

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

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)
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)
Econometric trend models

(1) \[ CH4_{ijt} = \gamma_0 i + \gamma_1 t + \epsilon_{ijt} \]

(2) \[ CH4_{ijt} = \gamma_0 i + \delta_1 D_F + \epsilon_{ijt} \]

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)
- \( \epsilon_{ijt} \) = Random error term
CH4 Emissions Changes
Top 4 EDGAR Deciles - Europe, Africa, Asia
# Methane Emissions Changes by EDGAR Decile

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<th>Country</th>
<th>Province</th>
<th>District</th>
<th>Sector</th>
<th>Model_1</th>
<th>Model_2</th>
<th>Overall</th>
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<td>Increasing</td>
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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

This research is funded by the Knowledge for Change Trust Fund administered by the World Bank