# Satellite monitoring of urban CO<sub>2</sub> emissions: an extensive analysis of the OCO-3 SAMs database

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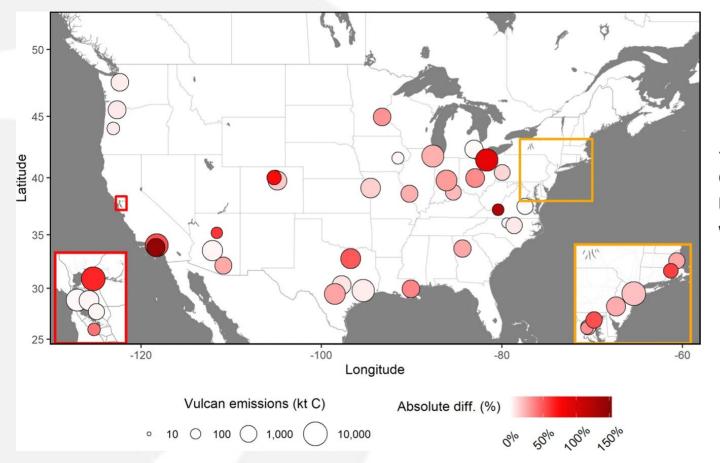








# Reporting urban CO2 emissions



→ **systematic underestimation** of CO2 emissions across US cities in the Self Reported Inventories when compared to Vulcan.

Fig. 1: Total individual city (N = 48) FFCO2 emissions and absolute difference (AD = positive RD) between the Vulcan version 3.0 data product and self-reported inventories (SRIs). (Gurney et al. 2021)











# PhD goal

PhD goal: Develop **methods** to estimate **urban CO2 emission** with **satellite** data

 $\rightarrow$  assess emissions where there is a lack of reporting.

Study of **computationally-light** methods to estimate urban CO2 emissions that can be **applied automatically**:

- **selection of the methods** with synthetic data (test-case over Paris);
- identification of **criteria to select targets** and associate typical error bars (synthetic data with 31 cities simulated);
- application to **OCO-3 data**.

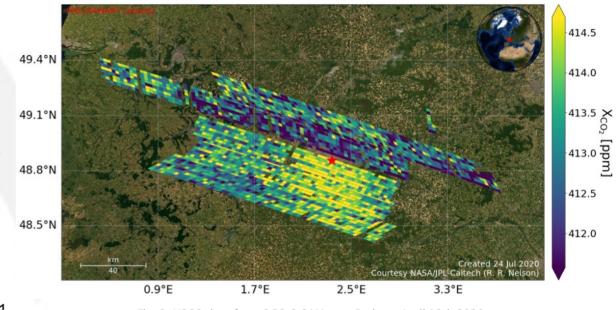


Fig. 2: XCO2 data from OCO-3 SAM over Paris on April 13th 2020.

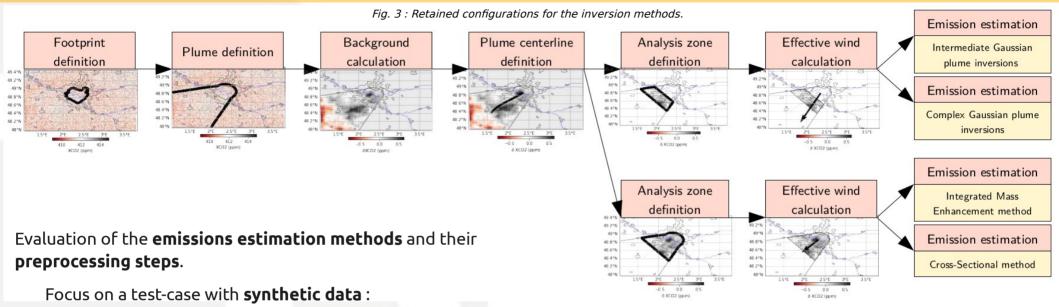








# 1 - Inversion process



High-resolution simulations of hourly atmospheric CO2 concentrations (WRF-Chem V3.9.1);

Using Origins.Earth inventory.

Aim: (i) **parametrization** of the inversions methods, (ii) **analysis of the sensitivity** of the error.

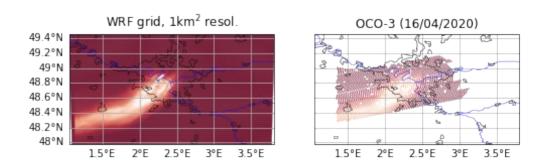


Fig. 4 : Illustration of the samplings used.



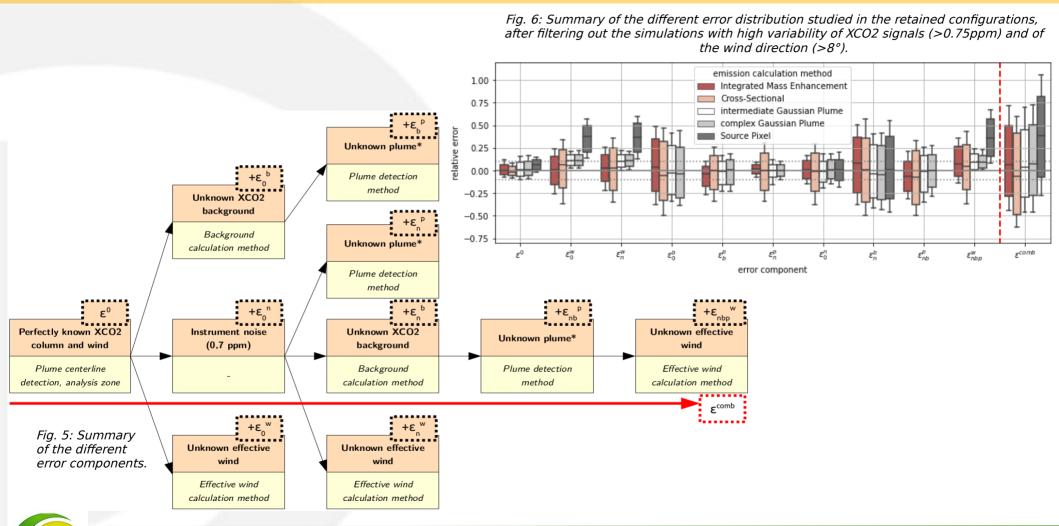








## 1 - Decomposition of the error







## 1 - Sensitivity of the combined error

Paris test-case	without filtering (100% of data)	with Paris filtering (57% of data)
WRF-grid sampling	6% [-38%,+56%]	4% [-29%,+45%]
OCO-3 like sampling	3% [-43%;+60%]	5% [-37%;+53%]

Table 1 : Total error in percentage of the true emissions.(median [1st quartile, 3rd quartile]). Results are obtained without and with filtering the data, following criteria defined over Paris test-case. Results are shown for the Intermediate Gaussian plume method.

#### Main conclusions:

- Small bias when rightly configured, but significant spread;
- Main error sources come from the **background** and **effective wind** estimations.

#### Two main factors for the precision of the results:

- spatial variability of the wind direction in the PBL;
- variability of the XCO2 signal outside of the plume.

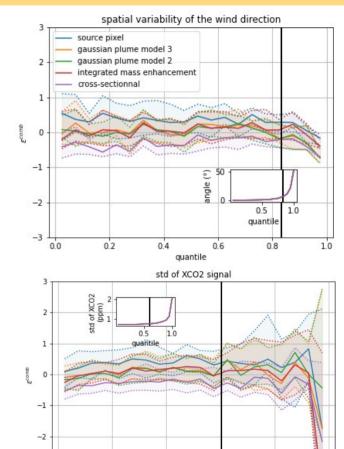


Fig. 7: Error sensitivity to the spatial variability of the wind in the PBL and to std of the XCO2 signal

0.4

0.6

quantile





0.2

-3





0.8

## 2 - Analysis of the sensitivity of the error with synthetic data (31 cities)

Influence of the different characteristics of a city (size, compacity,..) and of the meteorological conditions on the error on the emission estimation.

- model OLAM ([Schuh et al. 2021]);
- spatial resolution: octahedral variable resolution grid, reprojected on 100x100km² images at 3x3km resolution for **31 cities worldwide**;
  - → **optimistic sampling** compared to real satellite data (no clouds)
- temporal coverage: August 2015,
- $\mathrm{CO_2}$  data : ODIAC for anthropogenic emissions, CarbonTracker2017 for biogenic emissions.
- → Analysis of the **sensitivity** of the error distribution to **define objective selection criteria**.

Paris test-case	without filtering (100% of data)	with Paris filtering (57% of data)
WRF-grid sampling (165x200km, 1x1km)	6% [-38%,+56%]	4% [-29%,+45%]
OCO-3 like sampling (~80x80km,~1,7x2km)	3% [-43%;+60%]	5% [-37%;+53%]
31 cities	without filtering (100% of data)	with Paris filtering (53% of data)
OLAM sampling (100x100km, 3x3km)	-16% [-53%,+35%]	-5% [-34%,+30%]

Table 2: Total error obtained without and with filtering of the data, following criteria defined over Paris test-case. Results are obtained with Intermediate Gaussian plume method.

Criteria found in with Paris test-case relevant.

 $\rightarrow$  can we find **better ones**?







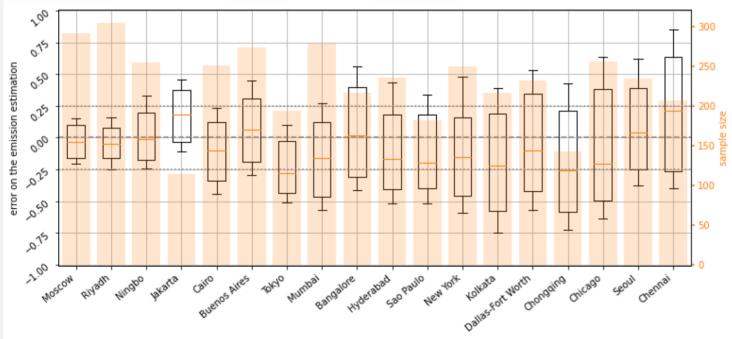
# 2 - Analysis of the sensitivity of the error with synthetic data (31 cities)

	without filtering	with Paris filtering	with DT filtering
	(100% of data)	(53% of data)	(47% of the data)
OLAM sampling	-16% [-53%,+35%]	-5% [-34%,+30%]	-6% [-33%,22%]

Table 3: Total error obtained with the different filtering strategies.

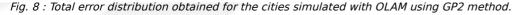
Application of a **Decision Tree algortihm** to define **criteria of selection** of the pseudo-image :

→ emission levels in the city, spatial variability of the wind direction.



Only 17 cities left (out of 31) after application of the criteria.

→ some cities and atmospheric conditions are more pertinent to target than others for satellite inversion with light methods.













#### 3 - Evaluation of urban emissions with OCO-3 SAMs

Application of our methods to SAM database:

- August 2019 to April 2022
- SAMs with more than 1000 points (before L2 quality flag)
- $\rightarrow$  **2536 images** (SAMs) : 171 cities and 45 powerplants targeted.

Assess the potential of automatic processing of the SAMs database with our light methods and objective filtering criteria.

- re-assessing the criteria for favorable plume inversion conditions derived from the analysis of pseudo images,
- evaluating emission estimates for sources relatively well known,
- providing insight on emissions for sources for which emissions are more uncertain.
- → ongoing, will only display some examples today.







# 3 - Performance of our inversion process on the OCO-3 SAMs

	Inve	rsion meth	nods	Commentaires
	GP2	IME	CS	Commencanes
# success	1551	1977	1632	The calculation performed to the end, we have an emission estimation.
# fail	985	559	904	Not enough pixels, patterns that prevent the method to converge,

Table 4: Number of fail and success of the different inversion methods when applied to the OCO-3 SAMs. GP dente the inversion methods based on a gaussian plume model, IME the one using the Integrated Mass Enhancement Method and CS to one using the Cross-Sectional method.

Important proportion of fail, for various reason mainly due to the SAM configuration:

→ not enough « good quality » flagged pixels, too few pixels downwind of the plume, spurious patterns that affect the convergence of the optimization, ...

Success does not mean a credible estimate..









# 3 - Examples of inversions : « good » estimation

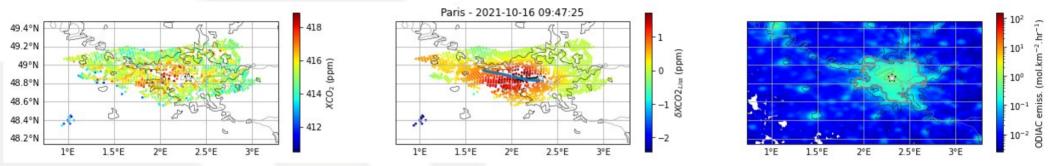


Fig. 8: SAM taken over Paris on October 16th 2021 with XCO, data (right panel), smoothed background removed data (middle panel) and emissions from ODAC (left panel).

	GP2	IME	CS	ODIAC
Emission (ktCO <sub>2</sub> /hr)	5,5	5,5	7,7	2,9

Visible plume, coherence between the plume direction and the wind direction.

→ Coherent estimations between the GP2 and IME inversion methods (not CS).











# 3 - Examples of inversions: «erroneous» estimation

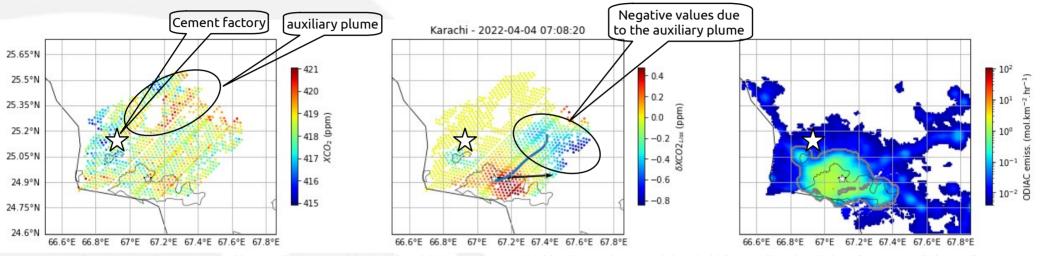


Fig. 9: SAM taken over Karachi on April 4th 2022 with XCO<sub>2</sub> data (right panel), smoothed background removed data (middle panel) and emissions from ODAC (left panel).

	GP2	IME	CS	ODIAC
Emission (ktCO <sub>2</sub> /hr)	-1,4	1,3	1,1	3,5

Cement factory at 25.1°N, 66.9°E.

Overestimated background in the vicinity of the auxiliary plume :

→ negative values in the plume from Karachi.



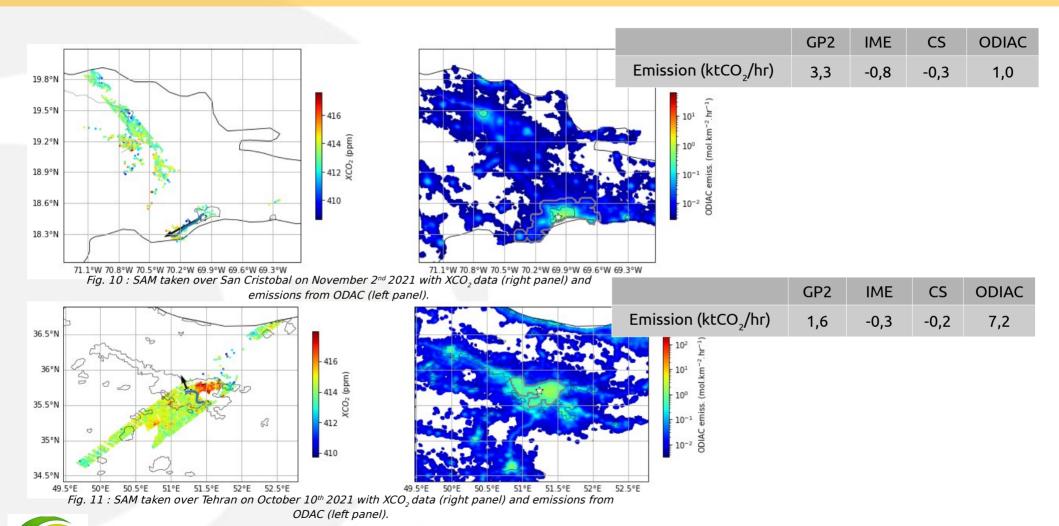








# 3 - Examples of inversions : other typical SAMs











#### **Conclusions**

Studies with synthetic data show interesting results for our light methods, but not for every cities.

- → our capacity to provide trustful estimations **depend** mainly on:
  - meteorological conditions (wind field homogeneity, cloud coverage)
  - and the level of emissions.

Still work to do to understand the problems we face with real data and define objective selection criteria:

→ we still **need a visual check** to select the SAMs..

Not enough understanding and not enough data yet to provide statistically relevant emission estimation.







