Towards CO2 plume inversion from satellites using deep neural networks

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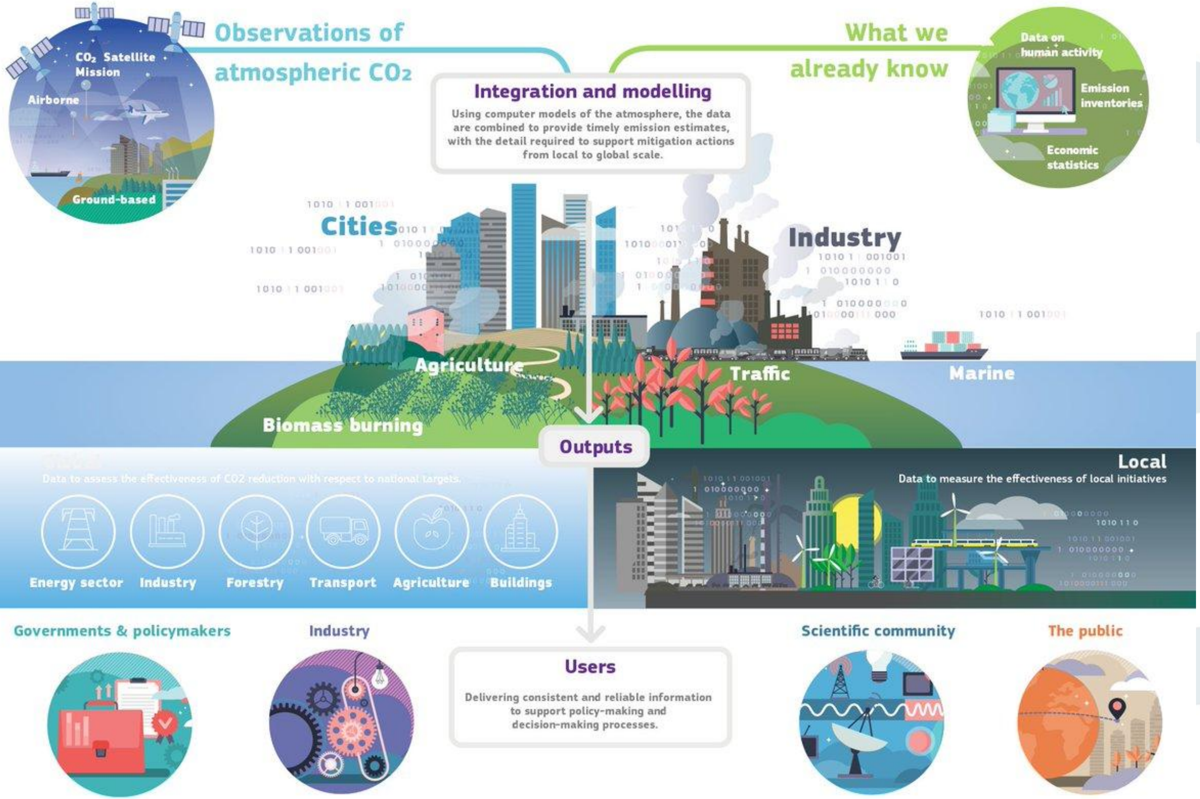
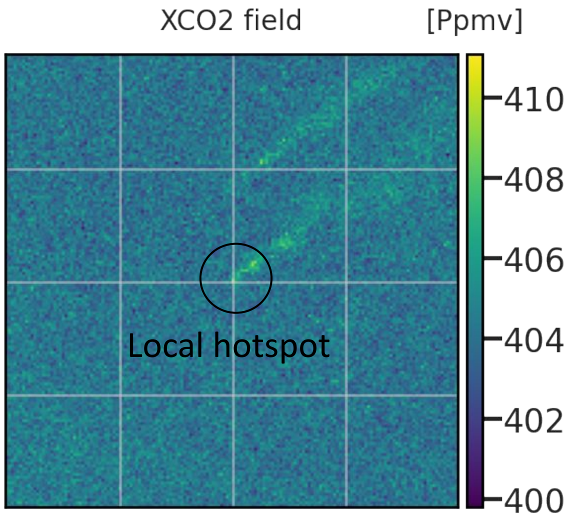
CoCO2, prototype system for a CO2 monitoring service

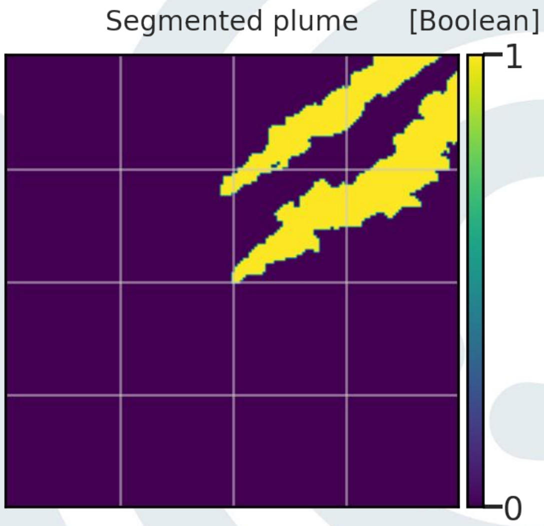
Our aim /
Quantify CO2 emissions from local hotspots based on the spaceborne imagery of the CO2 atmospheric plumes from these sources.

➢ Here, focus on power plants.



Estimating CO2 emissions from a satellite image



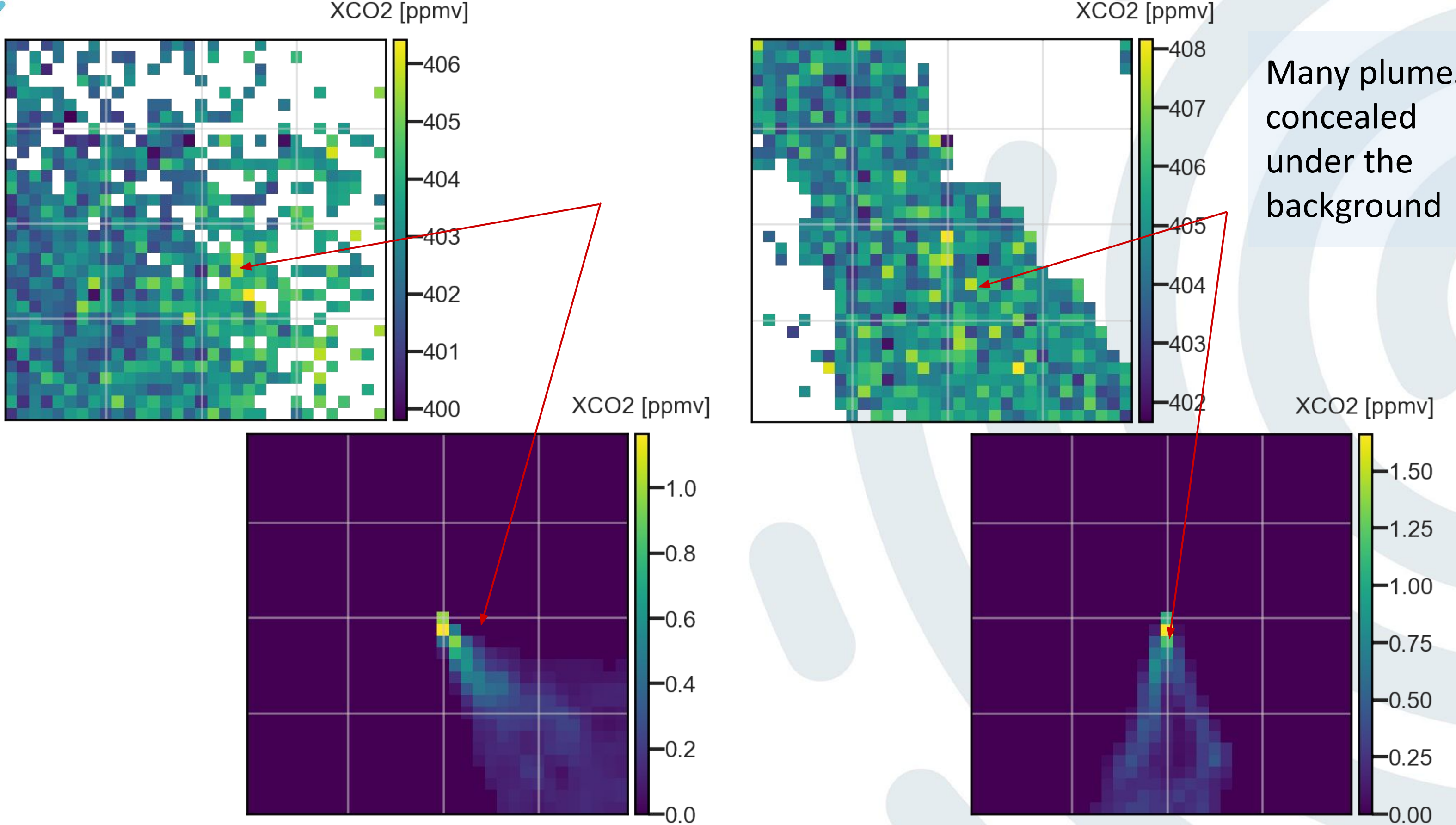


Emissions and "consequences" of the emissions: the plume, are directly related

Inversion:
From a given satellite image: estimate emission fluxes from the power plant

Detection:
Find contour of the plume

Where is the plume ?



Many plumes concealed under the background

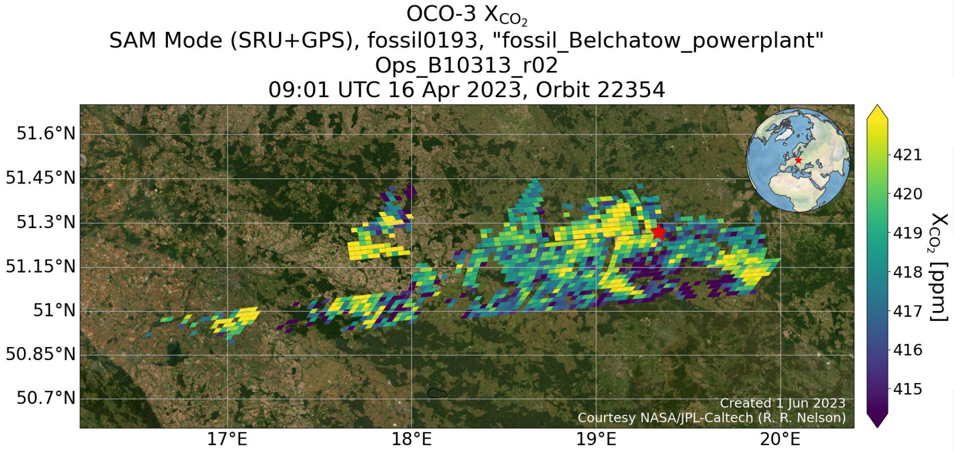
Why is CO2 plume inversion difficult ?

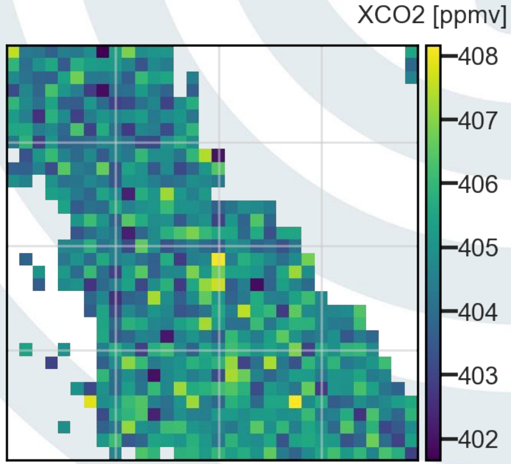
- **Image integrity**
  - Clouds
  - Number of satellite overpasses

- **Distinguish plume from background**

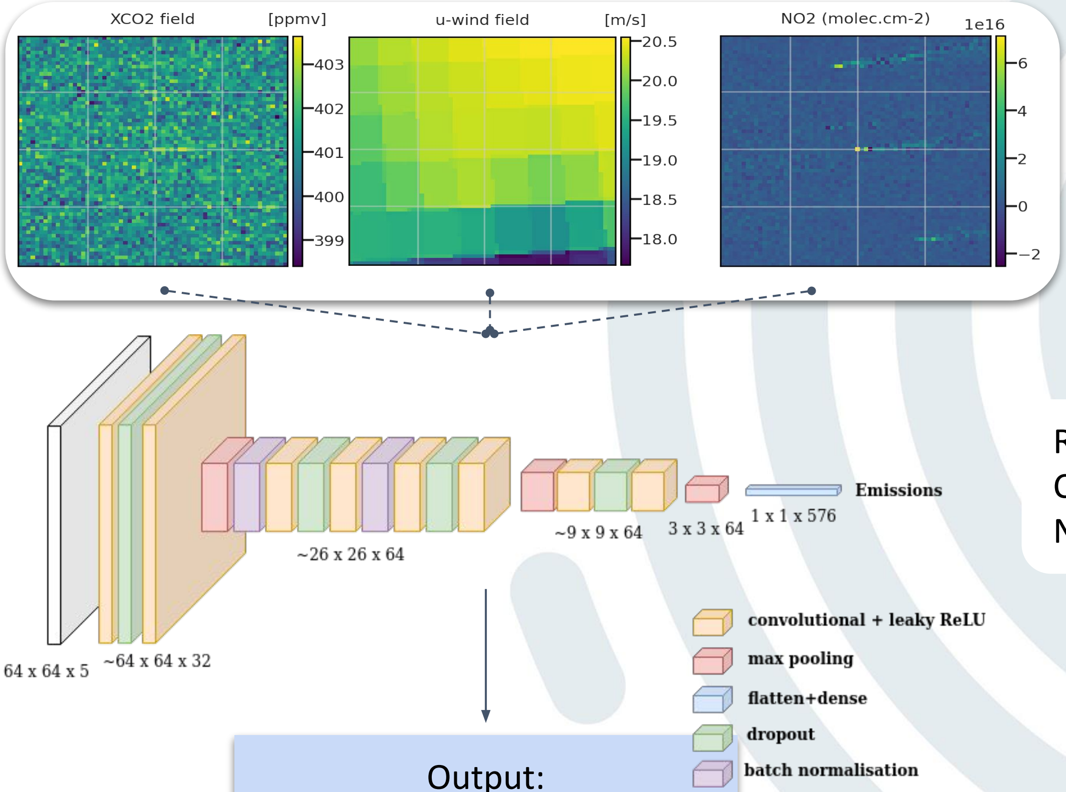
  Low signal-to-noise ratio:
  - "Background" noise:
    - Variability of the background
    - Instrument noise
  - Plume "definition" (signal):
    - Intensity of the source emission

- **From well-determined plume, estimate emissions**
  - Uncertainties in meteorological conditions (winds) which determine dilution and dispersion





Inversion: Supervised learning with CNNs



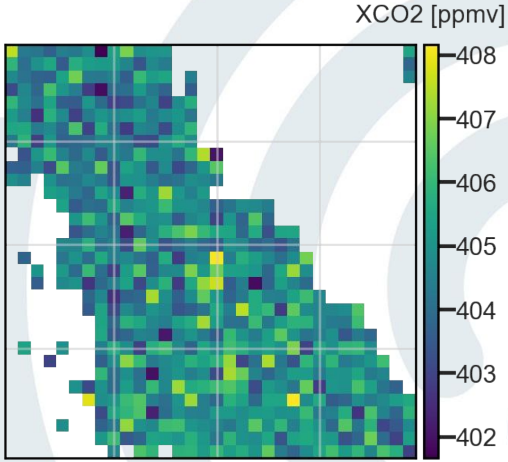
Output:
Emission flux rate in Mt.yr-1

Regression Convolutional Neural Network

Dataset

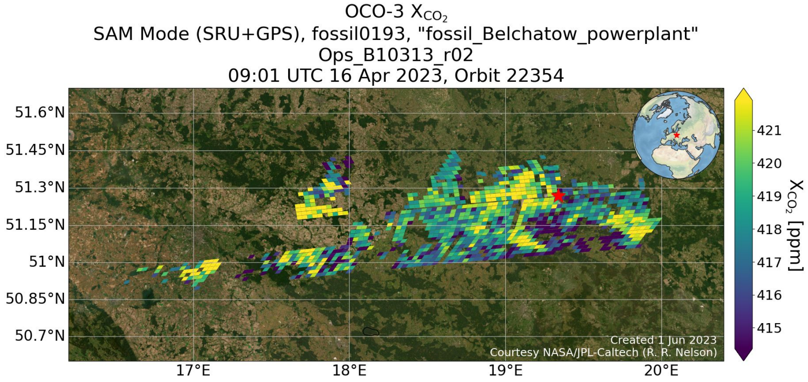
Dataset used to train

- SMARTCARB COSMO-GHG simulated fields (resolution CO2M)
  - with NO2 simulated fields
  - with ERA5 wind fields (not those used to simulate the fields)

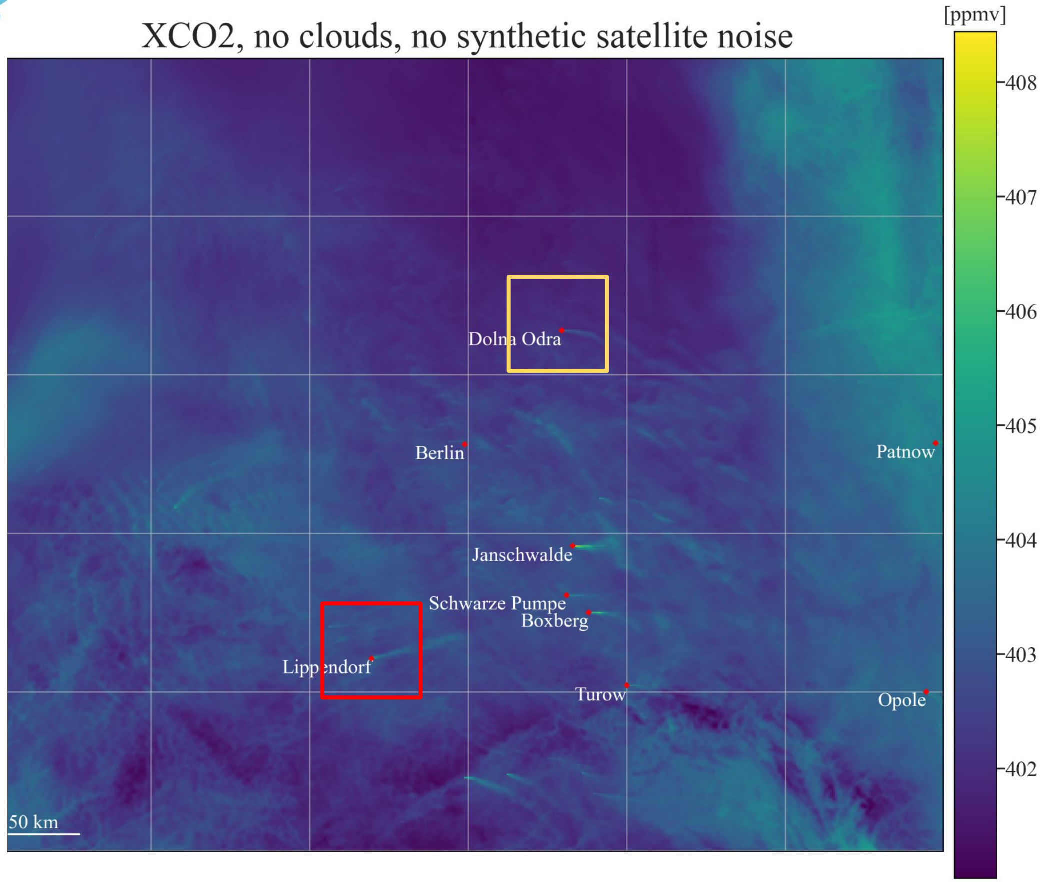


Datasets used to evaluate

- SMARTCARB simulated fields
- OCO-3 Snapshot Area Maps (SAMs) data with ERA5 fields and no NO2



Geographical extrapolation only



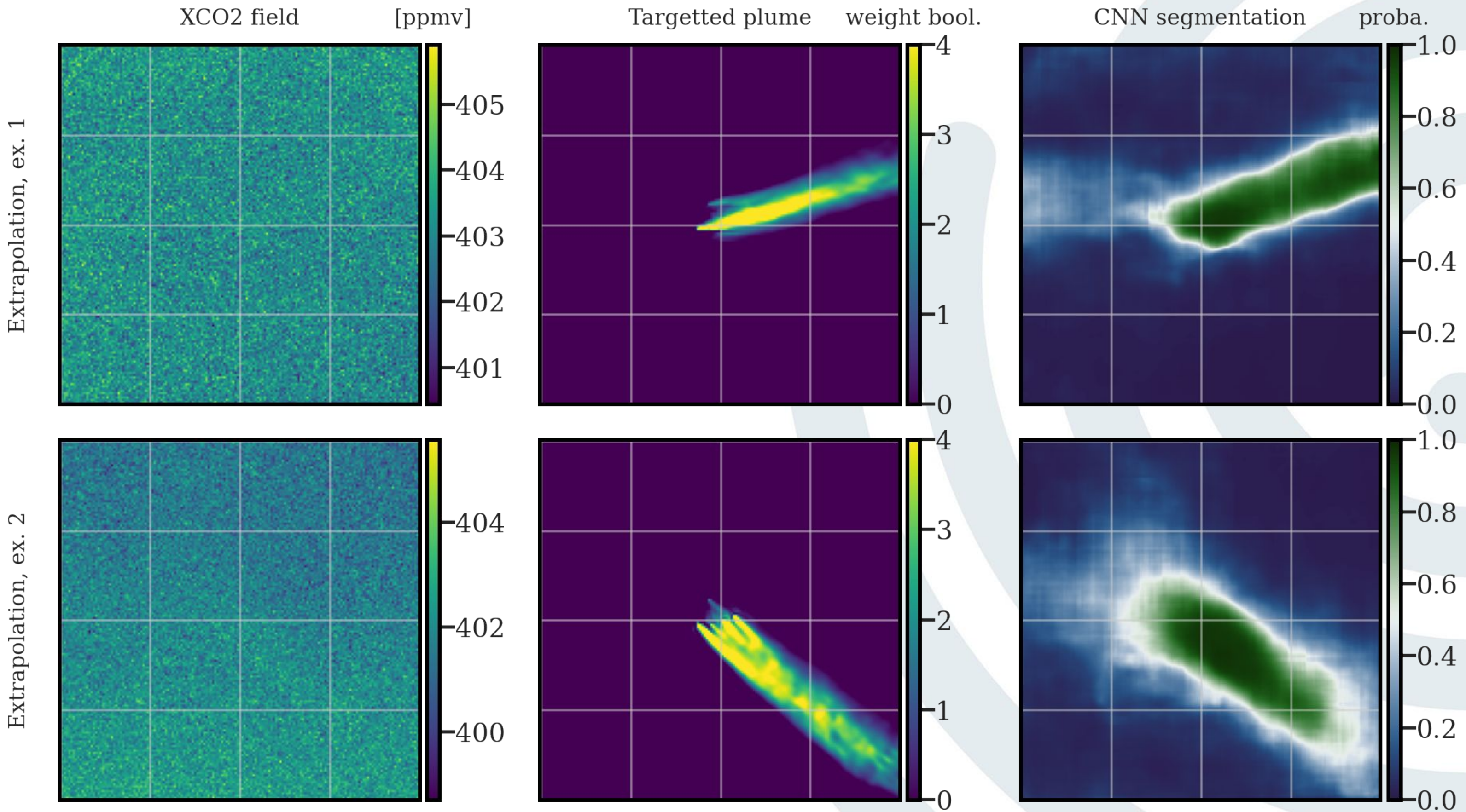
Simulations used to train and evaluate the model:

- **Geographical extrapolation**
  - Training on plumes of Dolna Odra power plant
  - Testing on Lippendorf

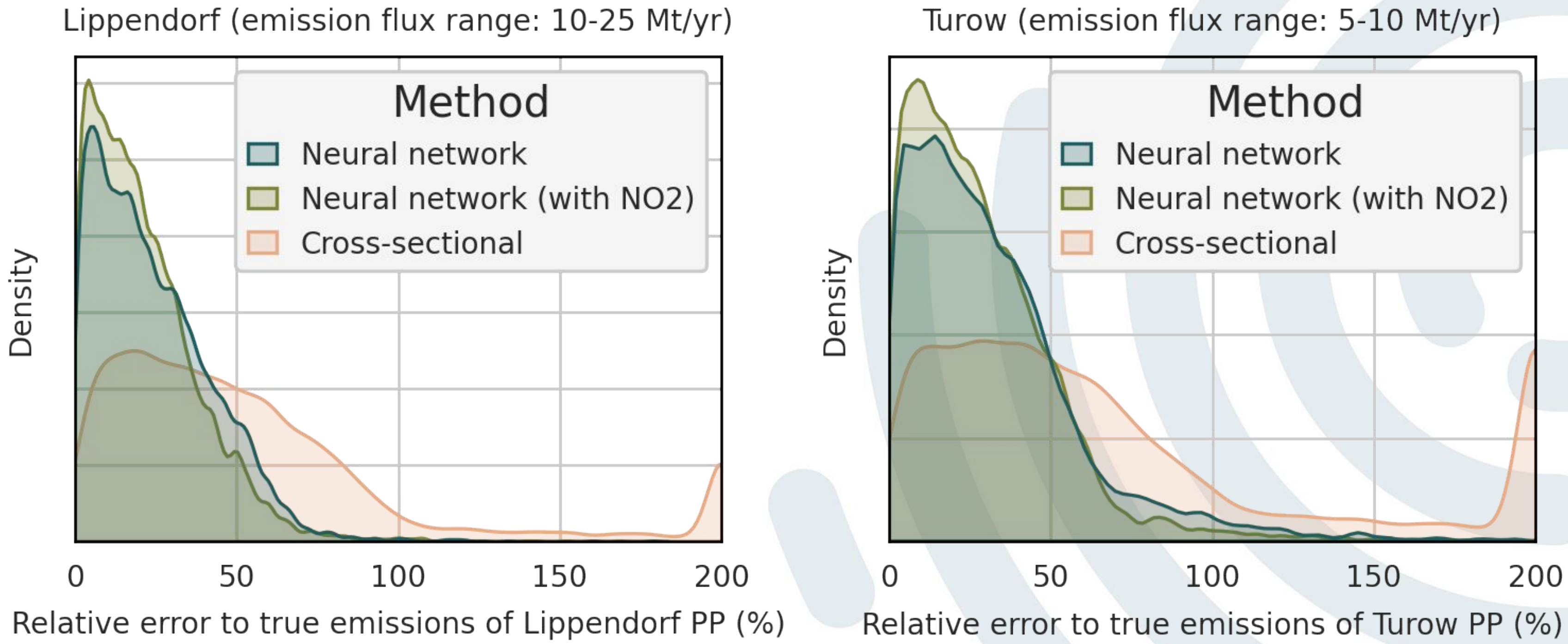
→ economic: trained on a limited number of plumes

→ universal: able to inverse all future plumes

Segmentation of SMARTCARB plumes (no NO2, no winds)

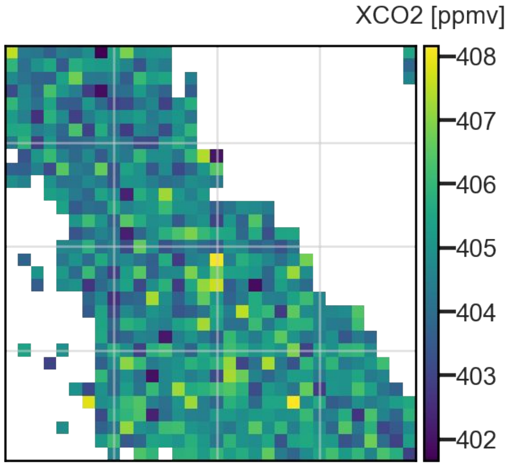


Inversion of power plants (simulated) plumes

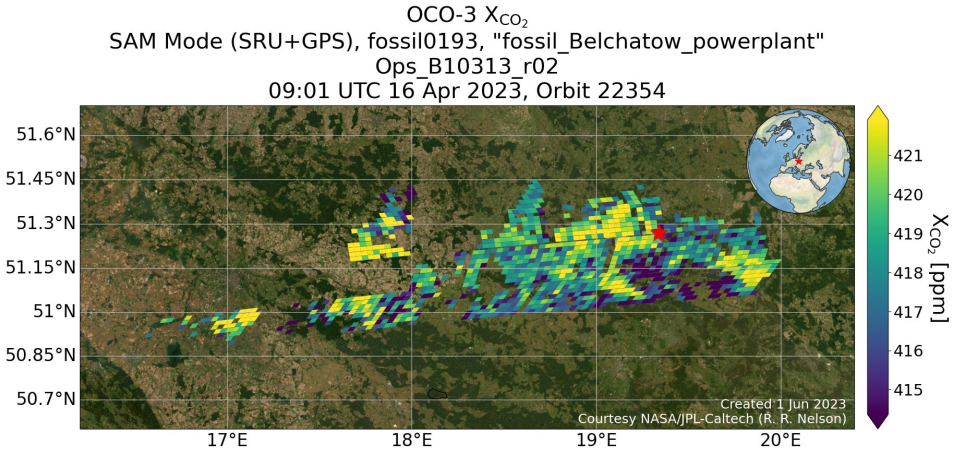


Absolute error of the CNN = half the absolute error of the cross-sectional fluxes method

From CO2 simulations to OCO3-SAM data

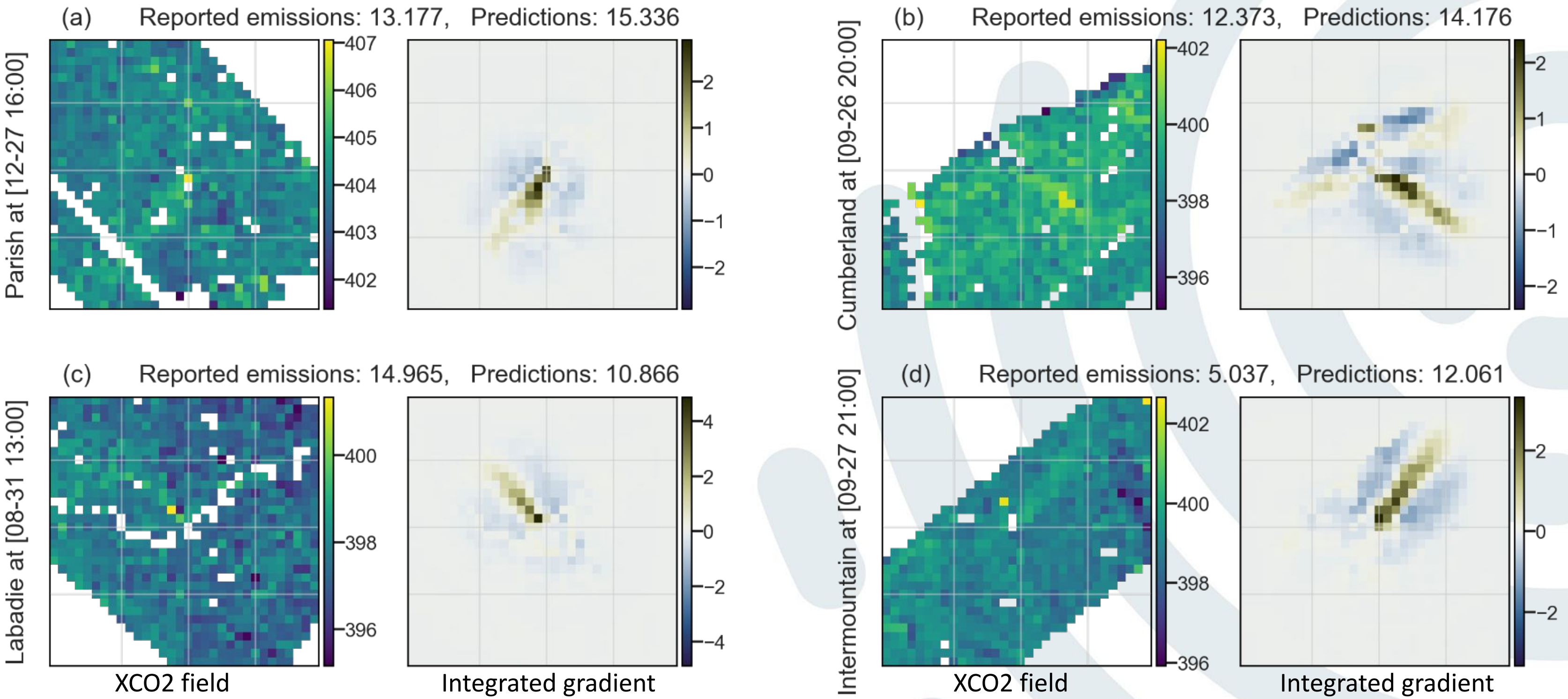


SMARTCARB or OCO3-SAM data after cleaning/processing

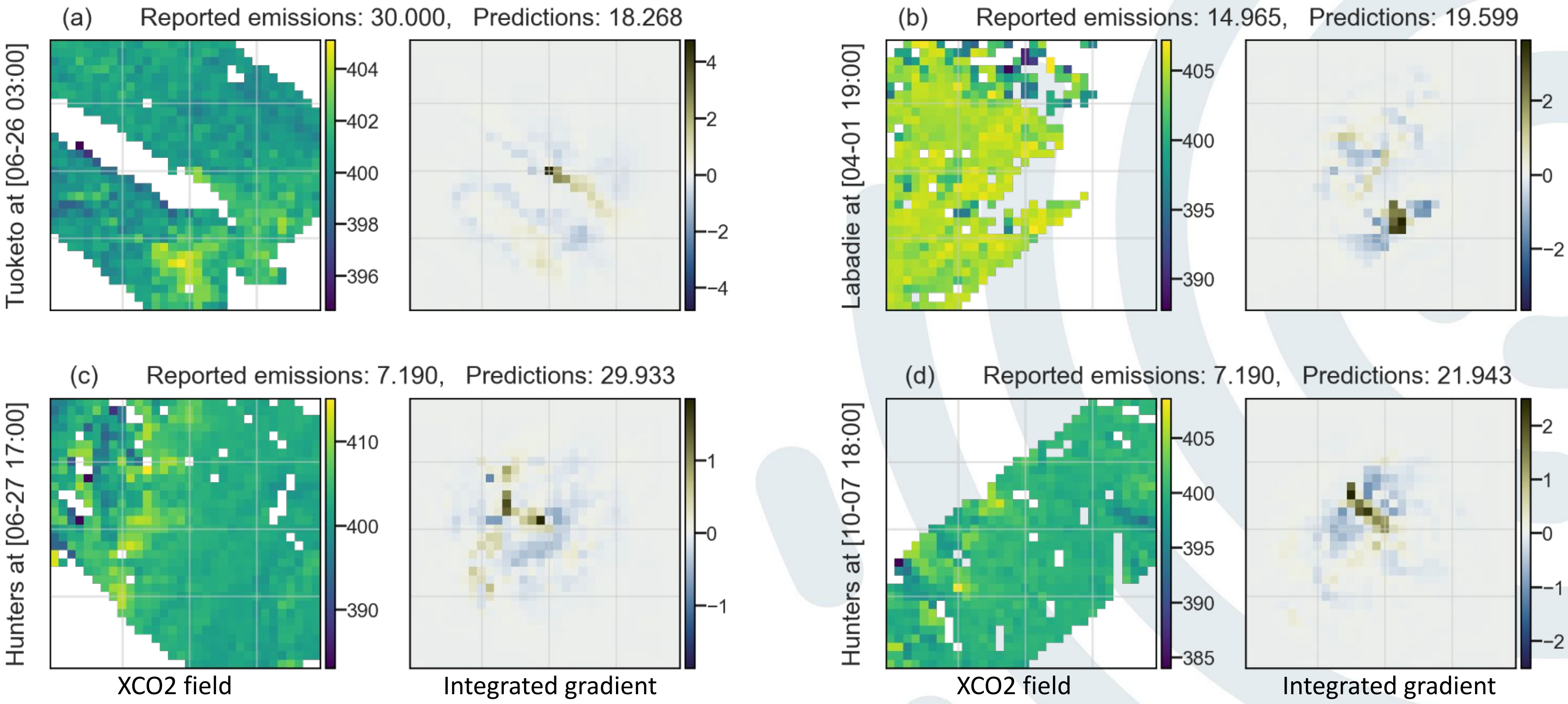


OCO3-SAM observation before cleaning/processing

Inversion of OCO3-SAM observed plumes - 1



Inversion of OCO3-SAM observed plumes - 2



Data-centric approach

Relative difference OCO3-SAM obs. reported emissions/predictions only slightly higher than relative error on SMARTCARB simulations Method works nicely on both simulations and observations.

Brute force approach was not working, to improve the results, various approaches have been tried.

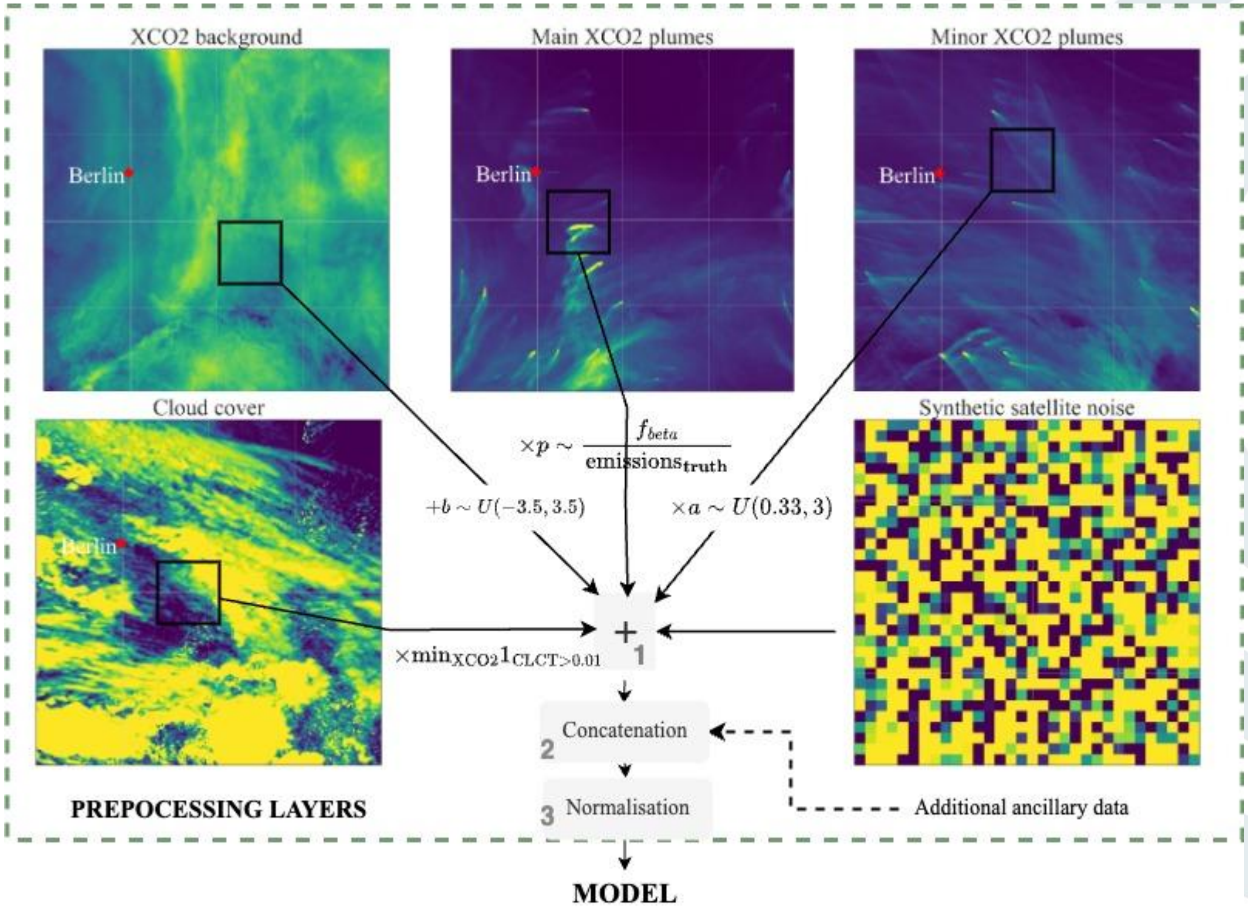
Some relying on improving the model
-> 1-5% relative error variations

When focusing on improving the data:
-> 20-30% relative error variations

Good Data >> Good model

How to improve the data ?
The model learns because the only invariant thing in the data is that the output (= the emission) is proportional to some input pixels (the plume) -> create model behaviour invariance to all other changes

Training works because of heavy data generation



Conclusions - Next steps

Main messages

- Our model, trained on CO2 simulations, can be directly applied to invert OCO3-SAM CO2 plumes (with some caveats - systematic noise)
- Deep learning performs better than alternative methods for CO2 plume inversion
- Models trained on power plants from Germany generalise to US / China power plants
- Improving data yielded better results than improving the model.

Next steps /

- Inversion of city plumes. But few data available …
- Addressing discrepancy between simulated CO2 fields and OCO3-SAM satellite data -> mix both in training
- Dealing with future CO2M satellite observations, coming in 2027 (?)

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CoCO2
Prototype system for a Copernicus CO_2 service

THANK YOU

« Segmentation of XCO_2 images with deep learning: application to synthetic plumes from cities and power plants », Geosci. Model Dev., 16, 3997–4016, https://doi.org/10.5194/gmd-16-3997-2023, 2023

« Deep learning applied to CO2 power plant emissions quantification using simulated satellite images », *Geoscientific Model Development Discussions* **https://doi.org/10.5194/gmd-2023-142**

OCO3-SAM data application paper in preparation …

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