Towards CO2 plume detection and inversion from satellites using deep neural networks

Atmospheric Constituents Data Assimilation and Inverse Modeling- 23/03/22

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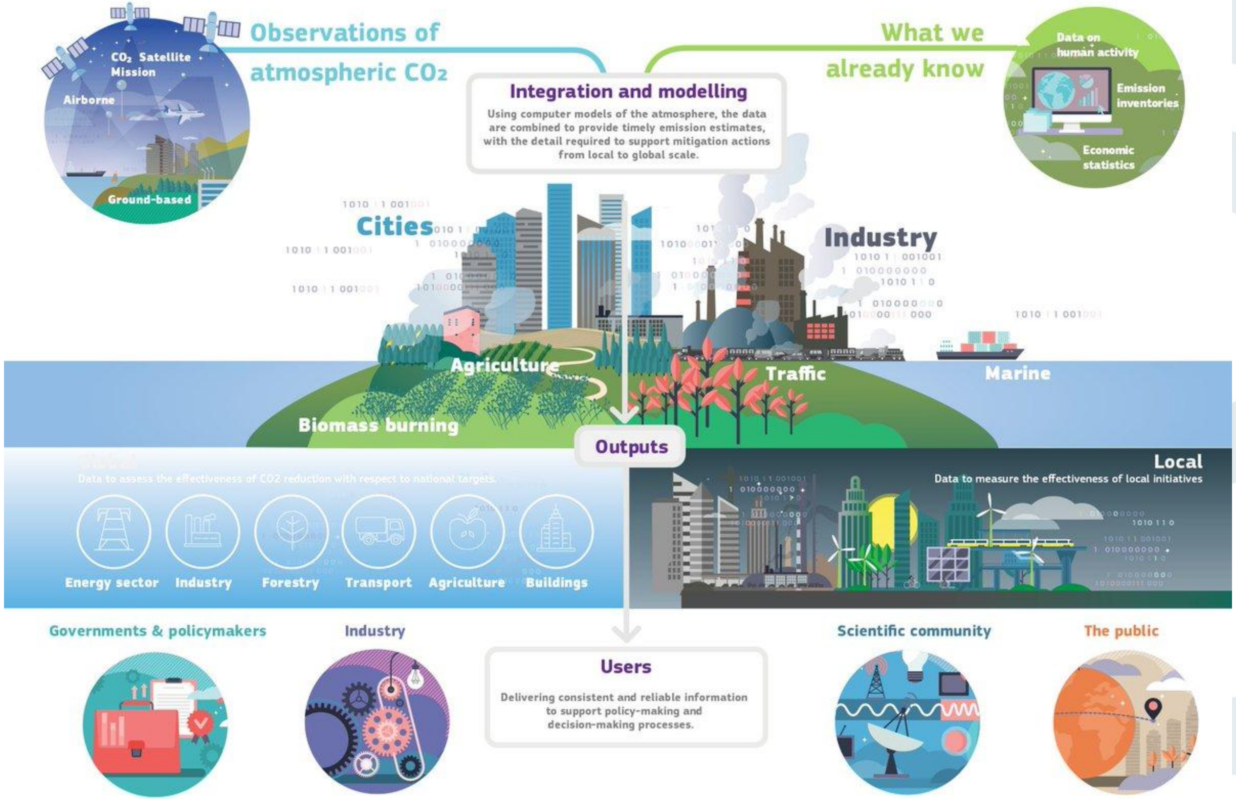
CoCO2, prototype system for a CO2 monitoring service

Our work = part of the **<u>Copernicus CoCO2 project</u>**, prototype of a CO_2 monitoring service which aims, in particular, to improve the estimation of CO_2 emissions from new satellites launched from 2025 onwards.



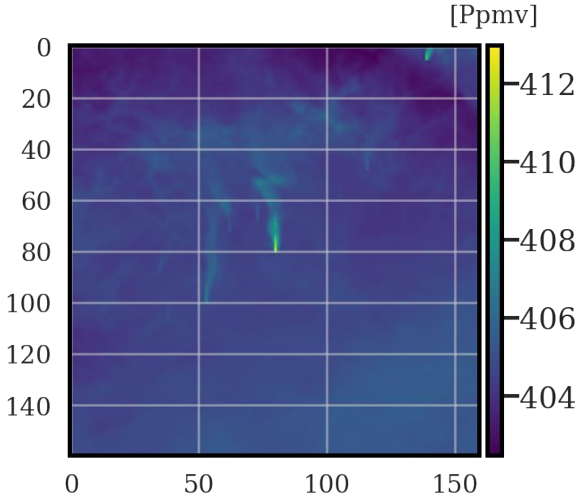
Our aim:

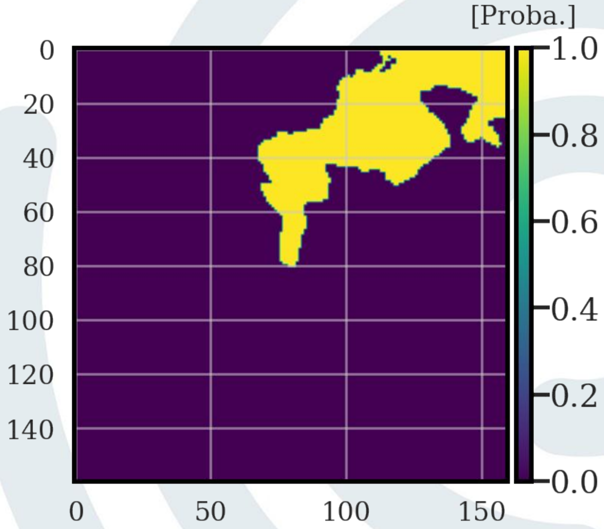
Focus on CO_2 emissions from point sources:

- ❑ large magnitude
- ❑ urban scale

based on the spaceborne imagery of the CO_2 atmospheric plumes from these sources.

Estimating CO2 emissions from a satellite image





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

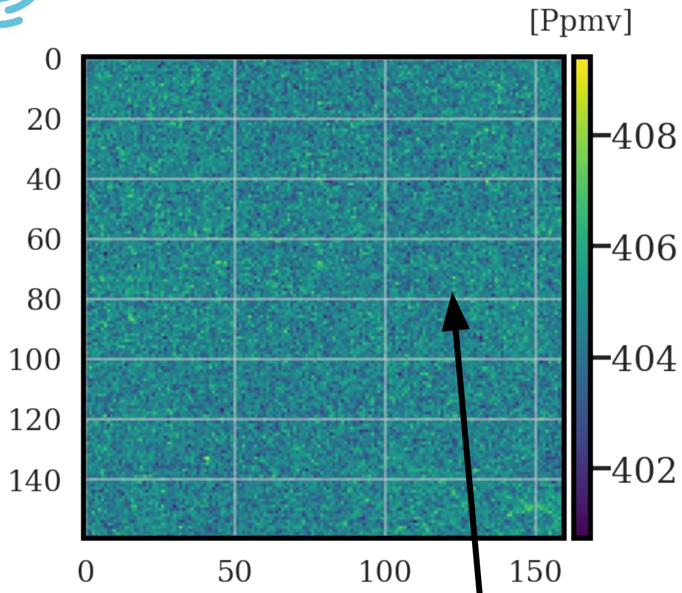
Inversion:
From a given satellite image: estimate emission rates from a point source

Segmentation:
-> find map of probabilities (pixel values between 0 and 1) describing potential positions of the plume

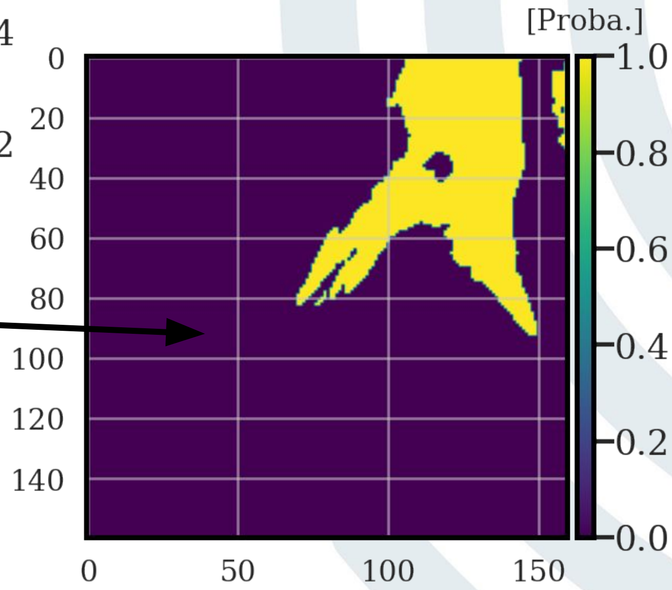
Where is the plume ?

Signal of CO2 plumes induced by cities emissions is intrinsically difficult to detect

- ➢ Rarely exceeds values of a few ppm
- ➢ Perturbed by variable regional CO2 background signals and satellite noise



Many plumes concealed under the background



Detectability factors[1]

- **Signal-to-noise ratio:**
  - "Background" noise:
    - Variability of the background
    - Instrument noise
  - Plume "definition" (signal):
    - Meteorological conditions, which determine dilution and dispersion
    - Intensity of the source emission
- Image integrity:
    - Clouds
    - Number of satellite overpasses

→ **Simulate satellite observations (OSSE)**

1. Detectability of CO2 emission plumes of cities and power plants with the Copernicus Anthropogenic CO2 Monitoring (CO2M) mission. Kuhlman et al.

Outline

To segment and inverse plumes in images with low SNR ratio: need of techniques that can learn specific characteristics of plumes, other than high signal, such as spatial patterns
-> deep learning methods

I. In the framework of CoCO2: creation of a synthetic dataset, i.e., of pairs of XCO2 field/plume or emission

II. Segmentation

III. Inversion

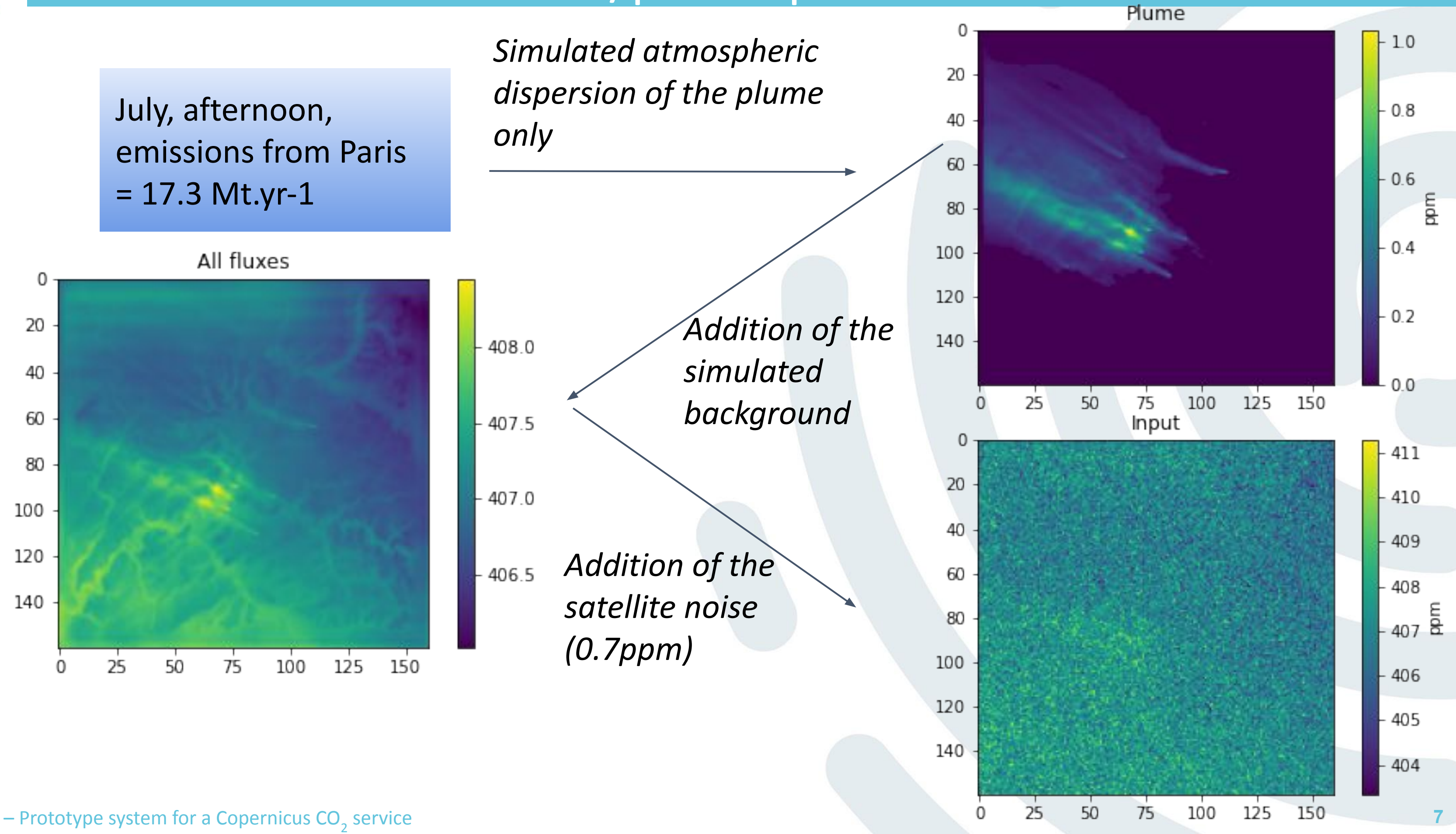
Creation of an XCO2 field/plume pair

July, afternoon, emissions from Paris = 17.3 Mt.yr-1

Simulated atmospheric dispersion of the plume only

Addition of the simulated background

Addition of the satellite noise (0.7ppm)



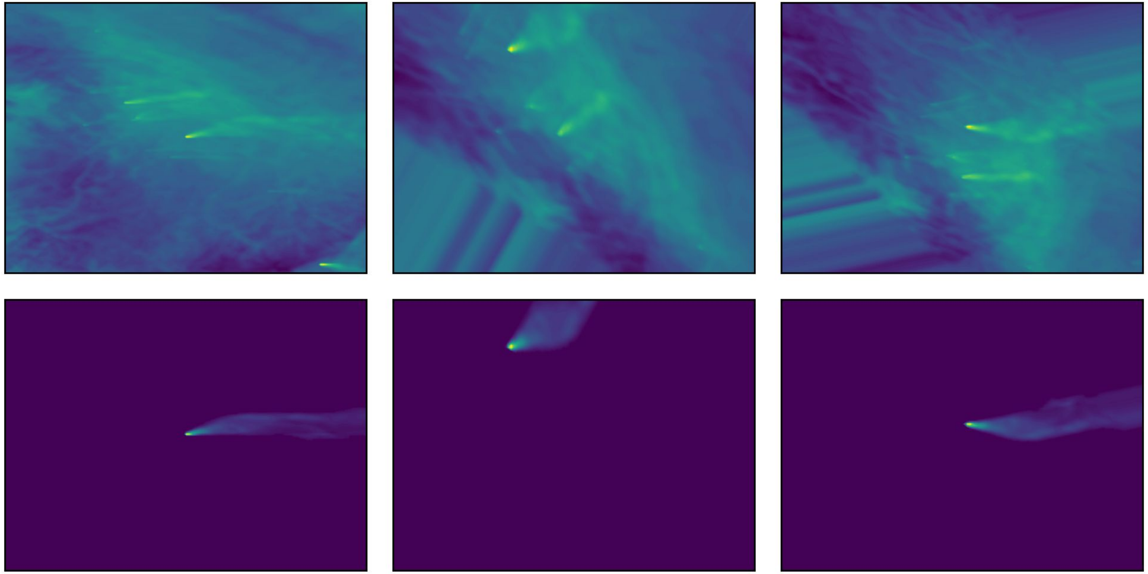
Get the widest possible diversity of plumes

Variety of point sources, geographical areas, plume types, plumes number …

1-year simulation (~2km, 1hr) of the XCO2 fields in the

- ❖ Paris (LSCE/Suez-Origins) with CHIMERE model
- ❖ Berlin, and ~15 power plants (EMPA) with COSMO-GHG model

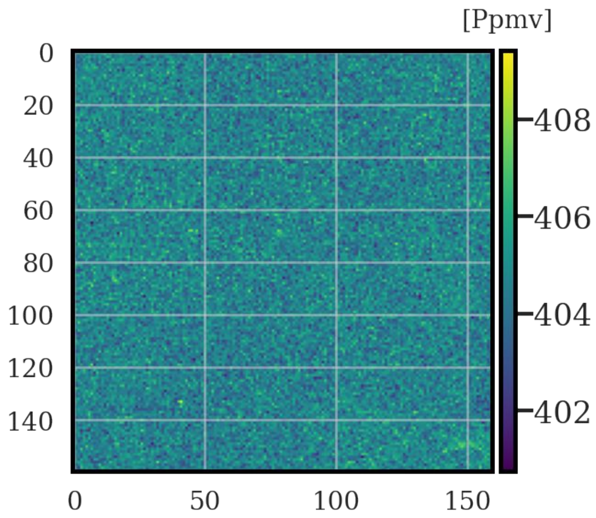
areas, tracing the anthropogenic plume and other bio and anthropogenic components.

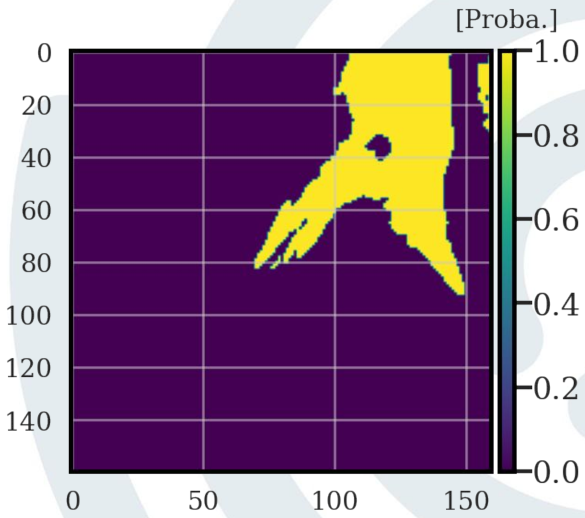


Dataset must be as diverse as possible:

- ➢ use of data augmentation techniques to artifically “create” more plumes

Segmentation: Supervised learning

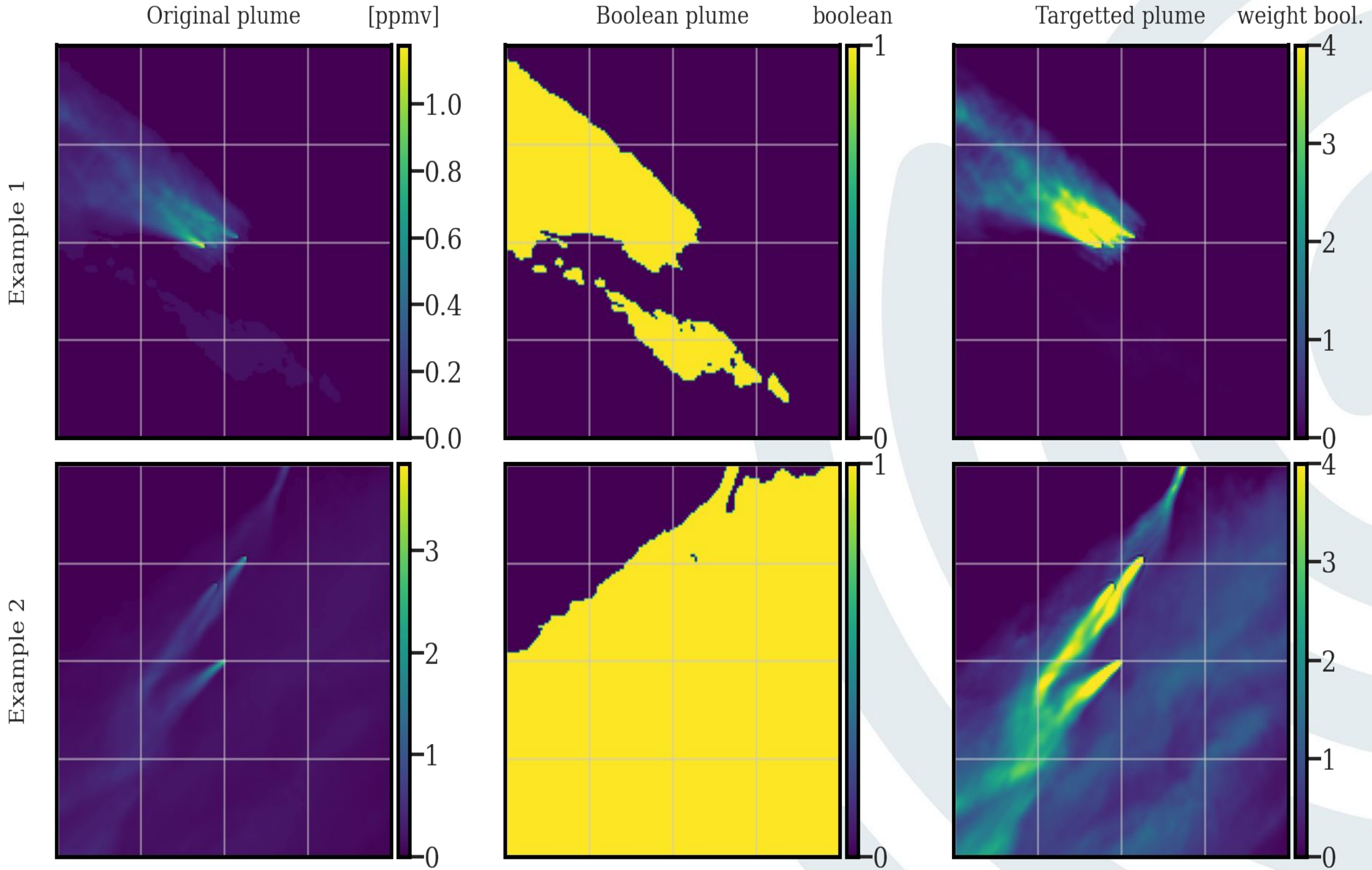




Statistical model

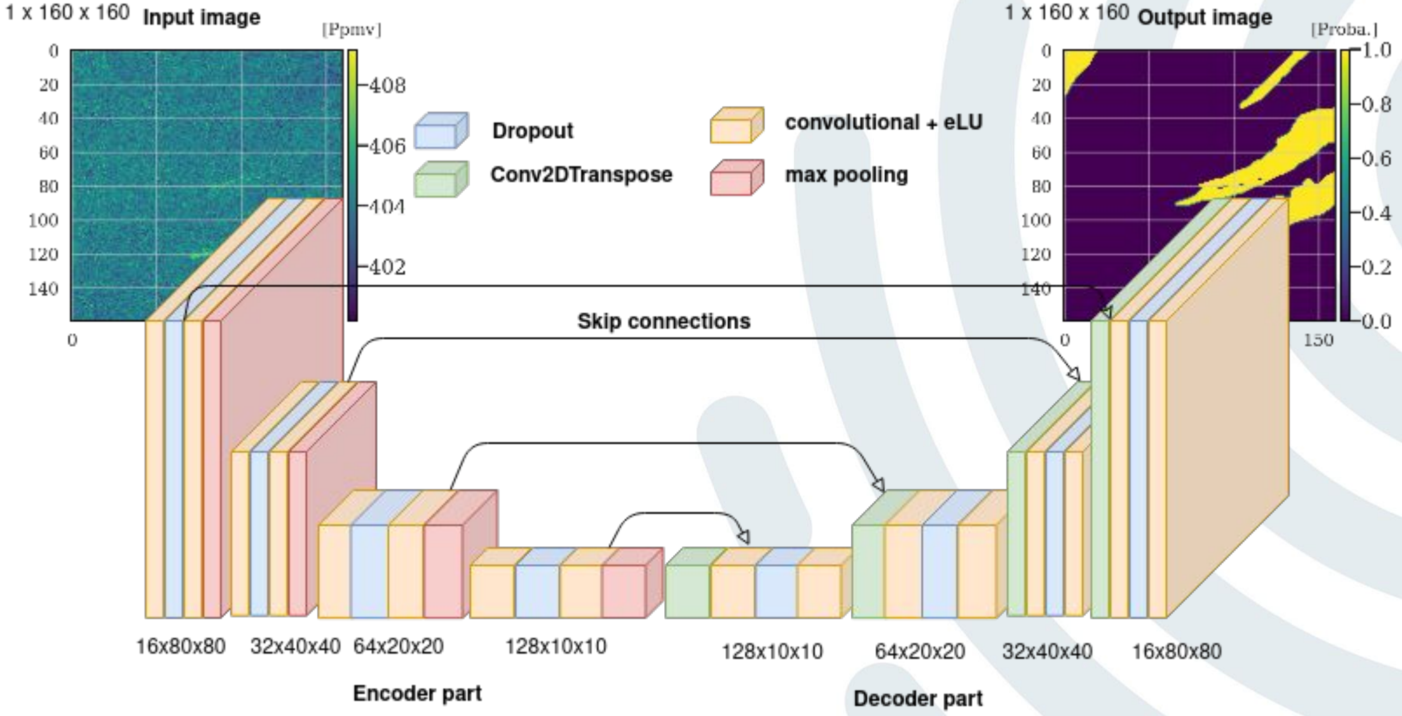
The model learns the relation between pairs of a provided input (simulated satellite image) and an output (here, segmented plume)

Segmentation: But what *exactly* is a plume ?



Segmentation: U-net CNN with EfficientNetB0 encoder

- ❑ capture spatial features of the image through application of successive filters
- ❑ i.e., transform image into relevant features maps
- ➢ used to recognise spatial features that belong to an anthropogenic plume



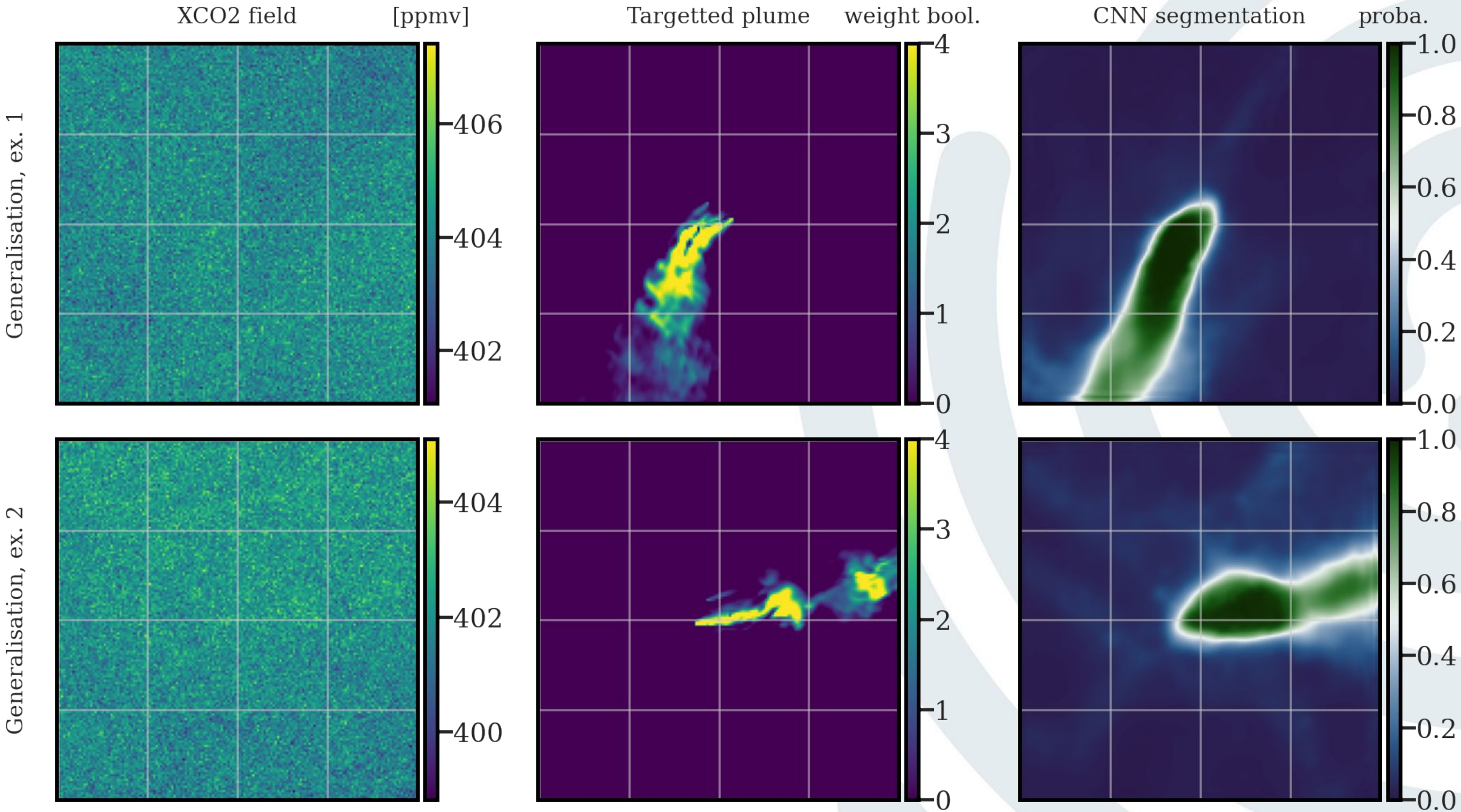
Generalising or extrapolating geographically

Two ways of training !

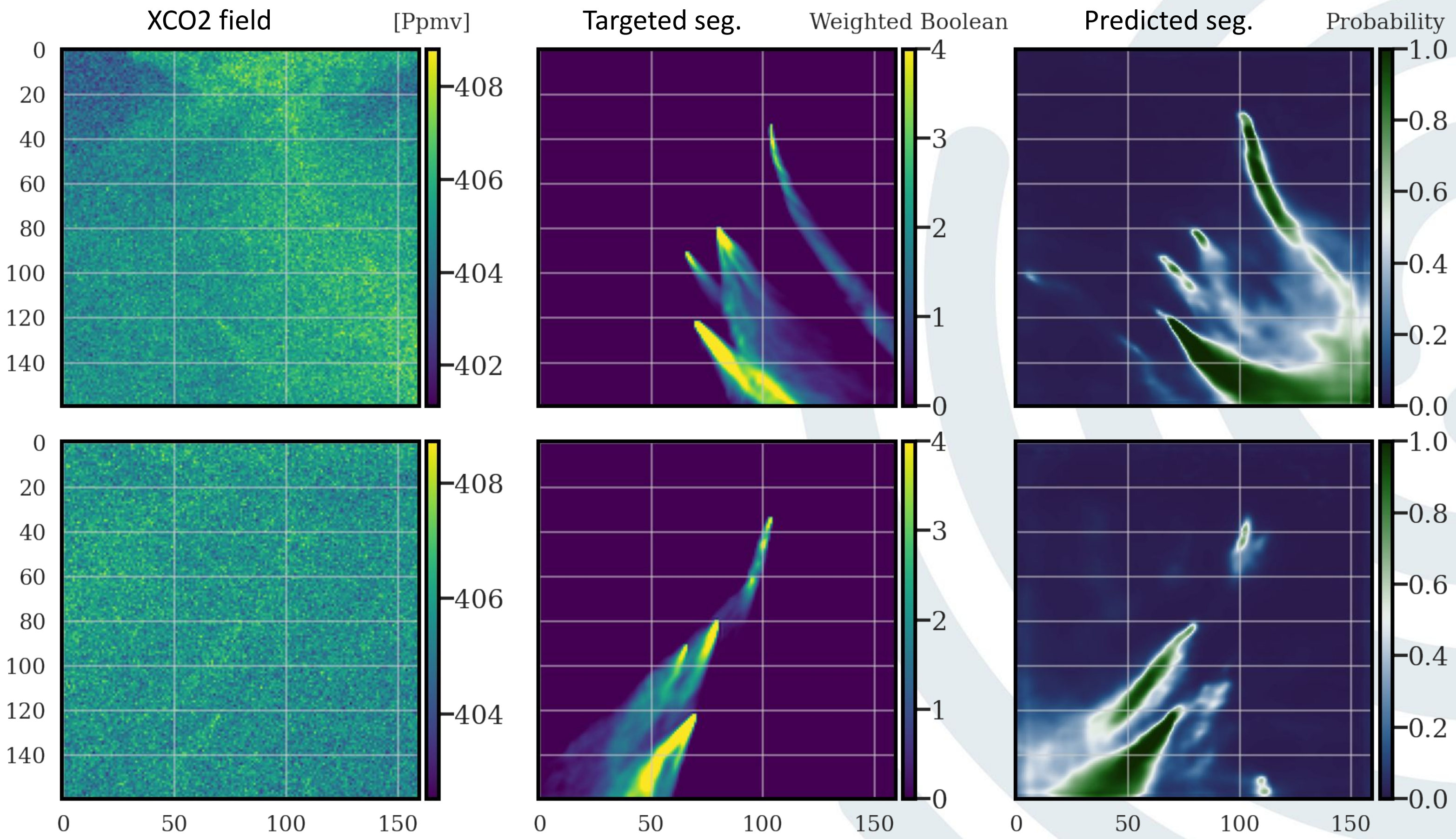
- **Generalising**
  - Training on pairs of Berlin fields/plumes
  - Testing on Berlin fields
- **Extrapolating**
  - Training on pairs of Paris and power plant fields/plumes
  - Testing on Berlin fields

A universal model (=extrapolation) is harder but preferable:
it limits the amount of data needed to segment all future plumes

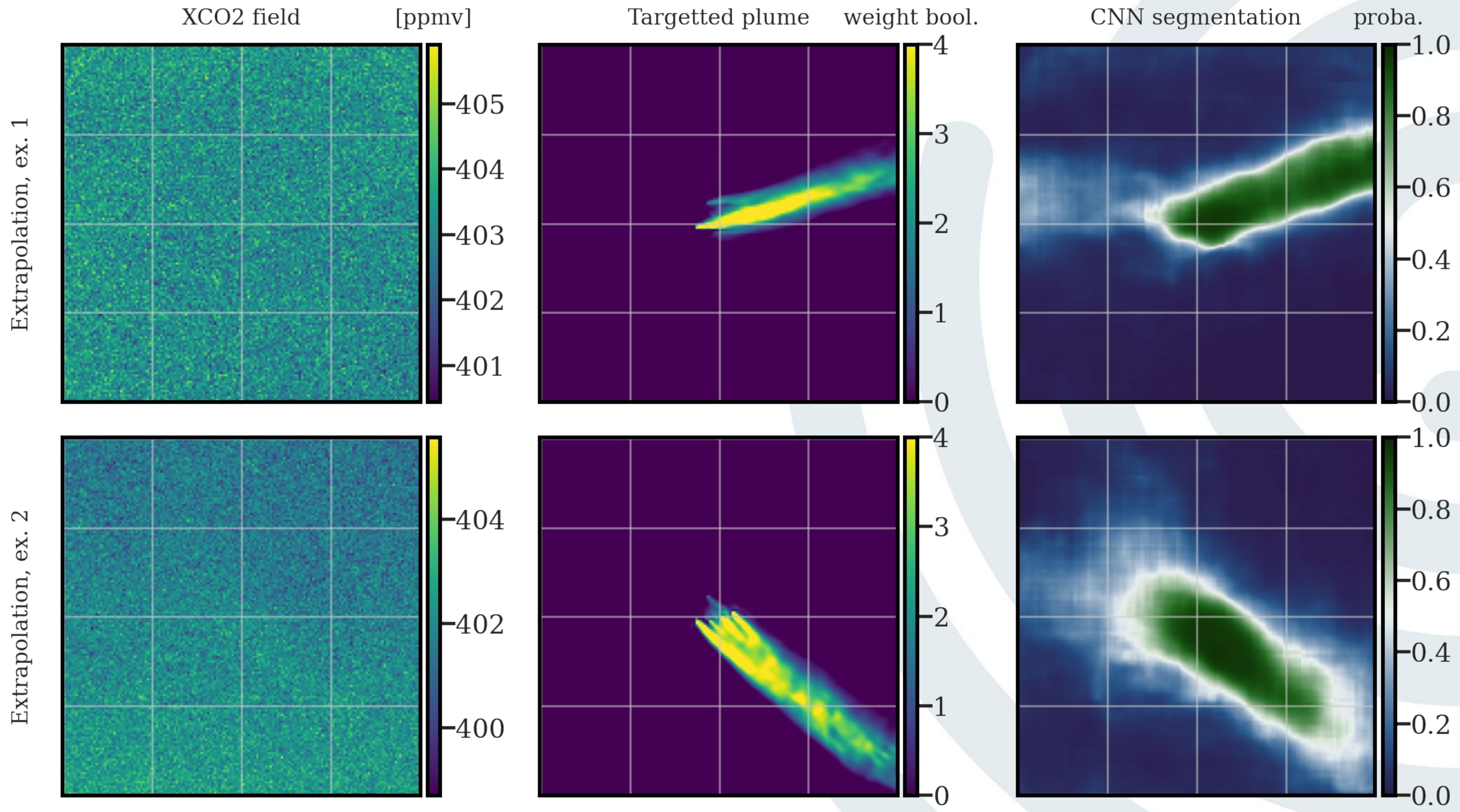
Segmentation: Generalisation on Berlin



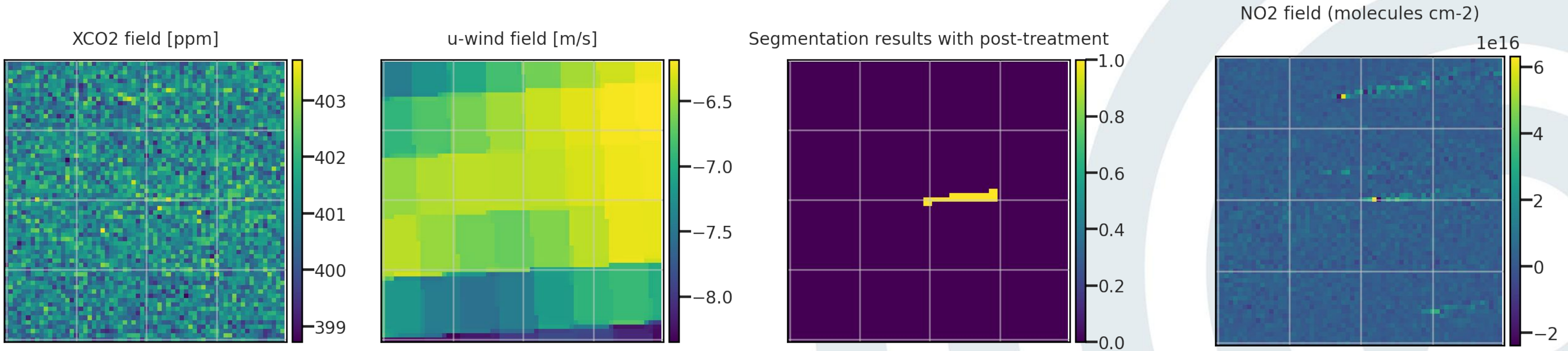
Segmentation as generalisation: multi-plume PP area



Segmentation as extrapolation: Berlin



Inversion: Set-up

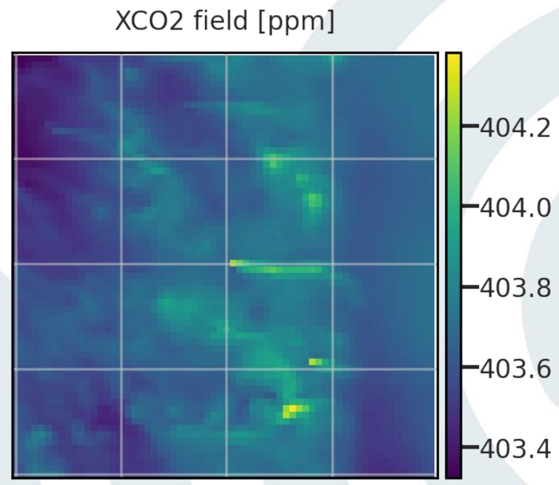


Regression CNN model
([images] to [emission flux rate])

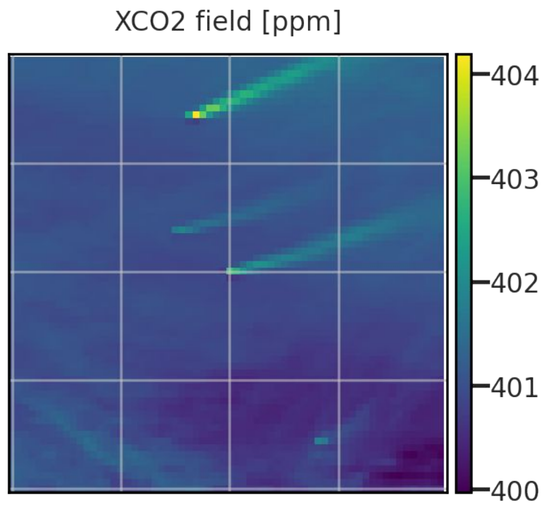
Output: Emission flux rate in Mt/yr

- xco2 field at time t
- xco2 field at time t-2
- wind fields at time t (u and v)
- segmentation predictions (with post-treatment)
- no2 field

Inversion: About the data



Patnow - emissions flux: 7.0 Mt/yr

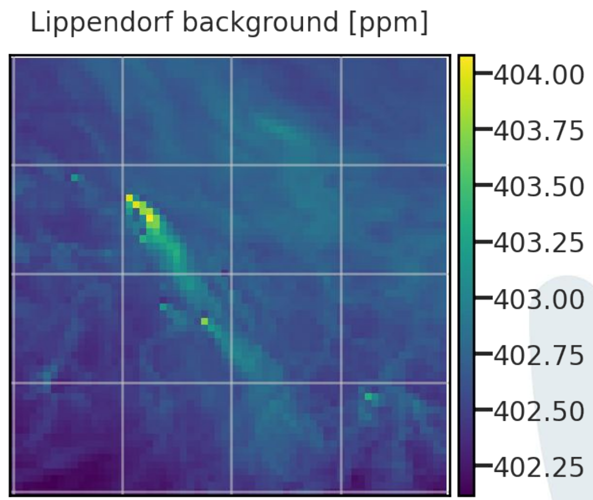


Boxberg - emissions flux: 23.5 Mt/yr

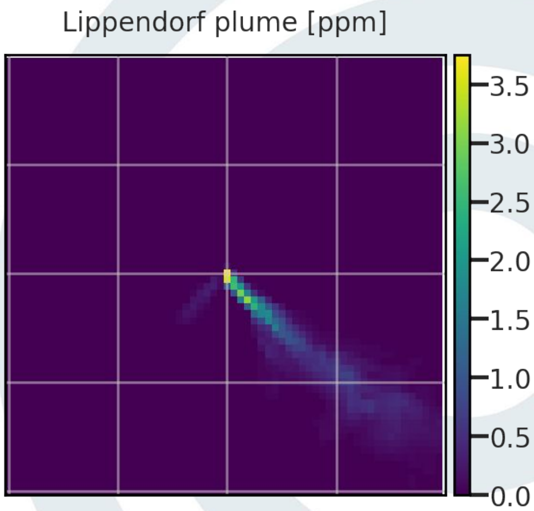
Power plants for test considered are various:

- ➢ power plant above background noise / of high emission rate (e.g. Boxberg)
- ➢ power plant below background noise / of low emission rate (e.g. Patnow)
- ➢ power plant with multiple “high” plumes (e.g. Boxberg)

Inversion: data augmentation ?



+ scaling ×



scaling × emission flux

Key is to generate new data at training time:

- each image used to train the CNN has new random gaussian noise
- each {plume, emission} of an image used to train the CNN is scaled by a random scaling factor

Inversion: About the model

Model:

Inversion is a less complicate problem than segmentation.

For ~ the same base set of images

- ★ for segmentation, good performance is achieved with encoders such as EfficientNetB0 (~5M parameters)
- ★ for inversion, good performance is achieved with much simpler regression models (~100k parameters)

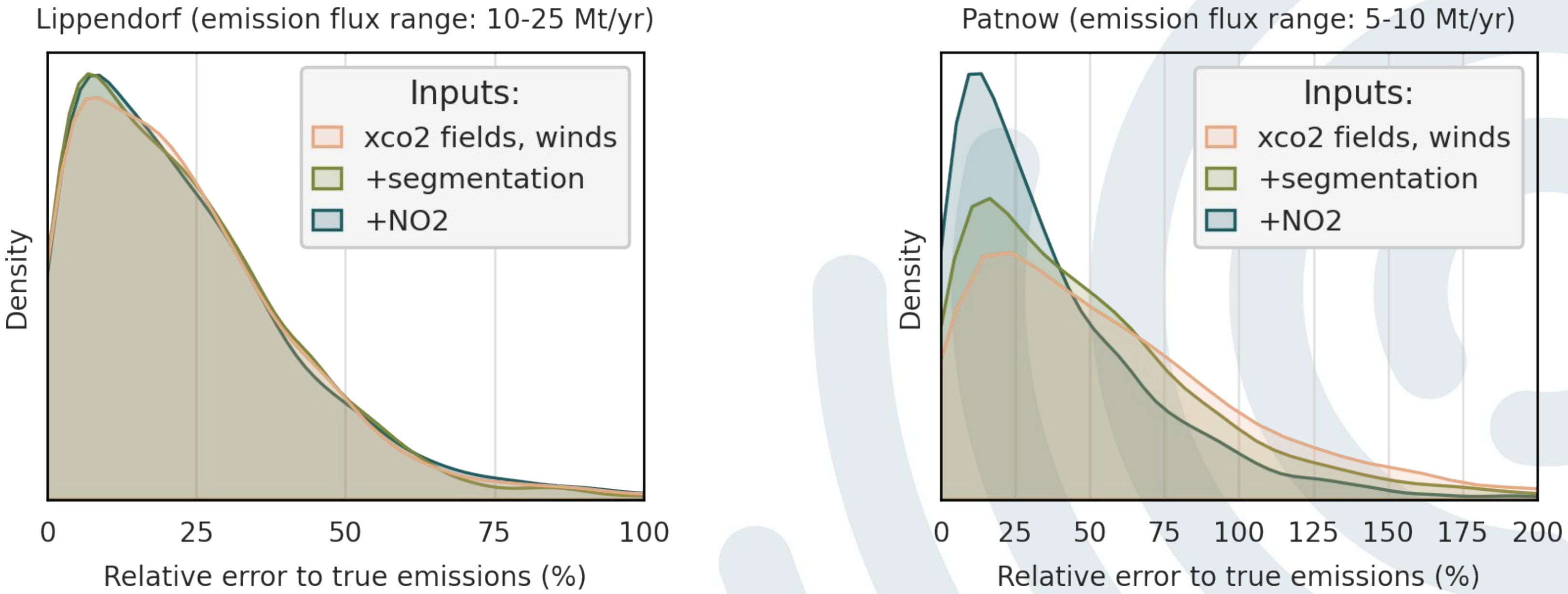
Several “small” state-of-the-art models (with descaling) have been considered (squeezenet, shufflenet) but less good performances than simple model only consisting of convolutions, maxpooling, dropout, …

Training

Model only trained only in “geographical extrapolation” mode. For example:

- ❖ *Train*: on a subset of power plants excluding Boxberg
- ❖ *Test*: on Boxberg power plant.

Inversion: preliminary results



	Mass-balance, Cross-sectional	CNN model
Lippendorf (high SNR)	median > 35% (when applicable)	median ~ 19%
Patnow (low SNR)	non-applicable	median ~ 28%

Conclusions - next steps

Inversion conclusions

CNN models for XCO2 plume inversion:

I. Ability to perform inversion on low SNR plumes with the help of a segmentation pre-step or NO2 fields
II. CNN models outperform standard plume inversion methods with or without the help of NO2 fields
III. Performance is not degraded by the presence of multiple plumes on the same image

Next steps

- ❖ Inversion of city plumes. But few data available …
- ❖ Consideration of clouds on images.
- ❖ Dealing with real CO2 satellite observations (coming in 2027)

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CoCO2

Prototype system for a Copernicus CO_2 service

THANK YOU

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