CO2 PLUME DETECTION AND INVERSION USING NEURAL NETWORKS: APPLICATION TO SYNTHETIC IMAGES

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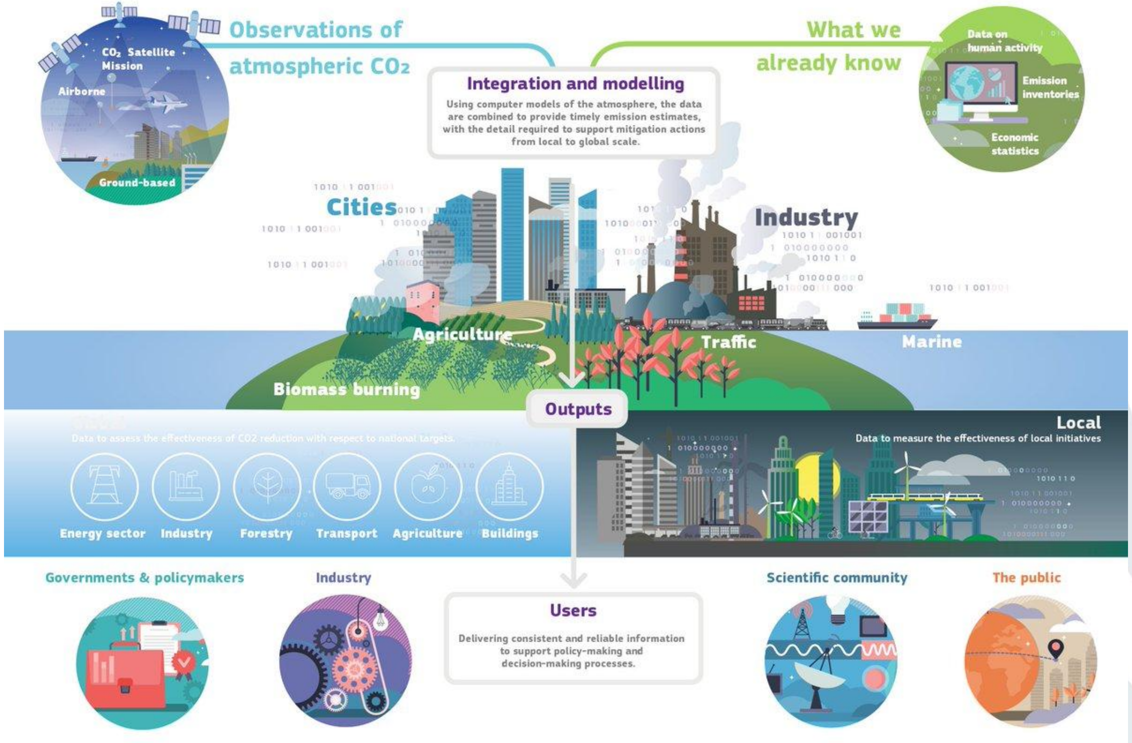
CoCO2, prototype system for a CO2MVS



CO2MVS concept

Copernicus CoCO2 project

Build a prototype system for a CO2 emission monitoring service exploiting atmospheric CO2 measurements

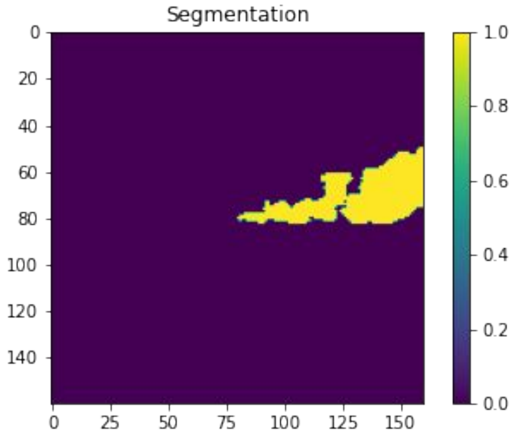
Our Task:

Build an inverse system to improve the quantification of CO2 sources

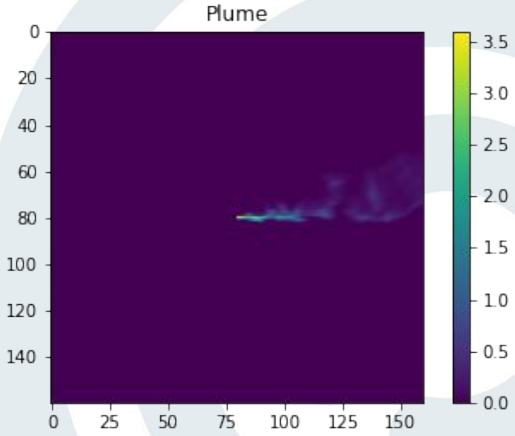
- of large magnitude
- at urban scale

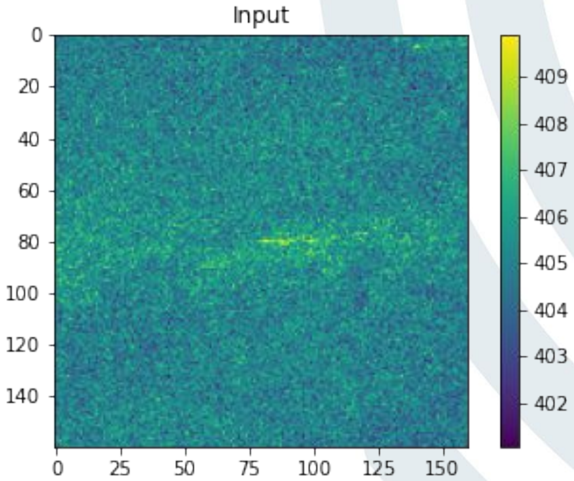
based on the spaceborne imagery of the CO2 atmospheric plumes from these sources.

Three objectives



Inversion:
-> retrieve emission rates on the hours preceding the image





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

Concentration map retrieval:
-> find map of values (all >0 pixel values) describing pixel concentrations of the anthropogenic plume

Detectability factors[1]

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

Simulate satellite observations (OSSE)

based on 1-year simulation of the hourly XCO2 fields in the

- Paris (LSCE/Suez-Origins)
- Berlin, and three power plants (EMPA)

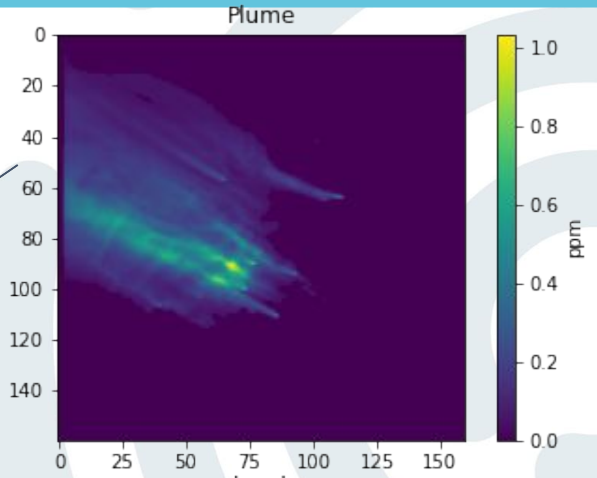
areas, tracing the anthropogenic plume and other bio and anthropogenic components.

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

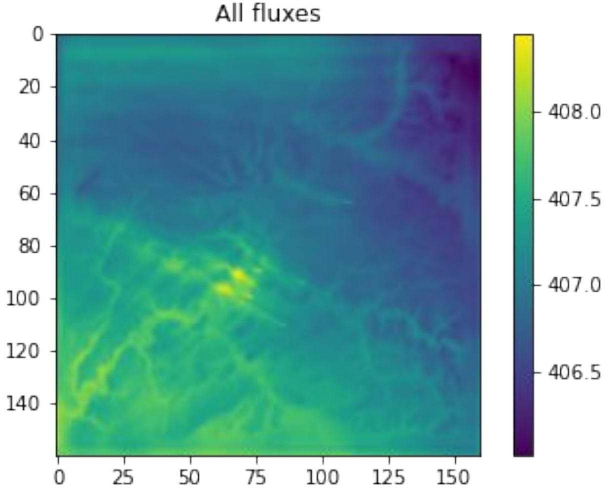
Creation of an input

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

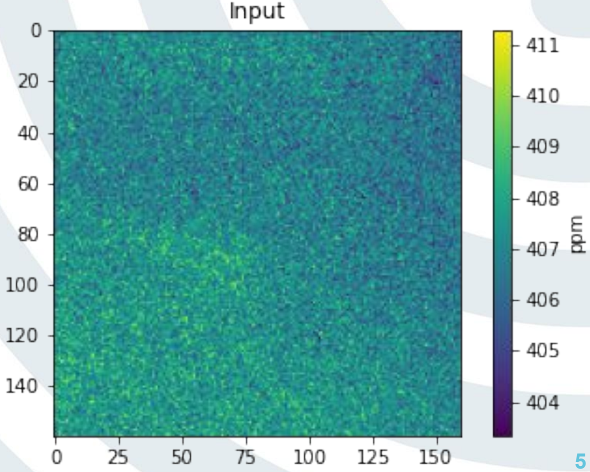
Simulated atmospheric dispersion of the plume only



Addition of the simulated background

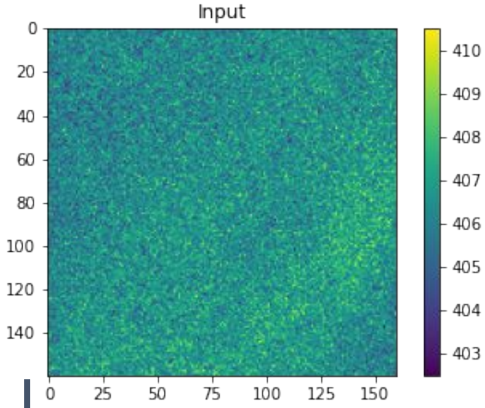


Addition of the satellite noise (1ppm)



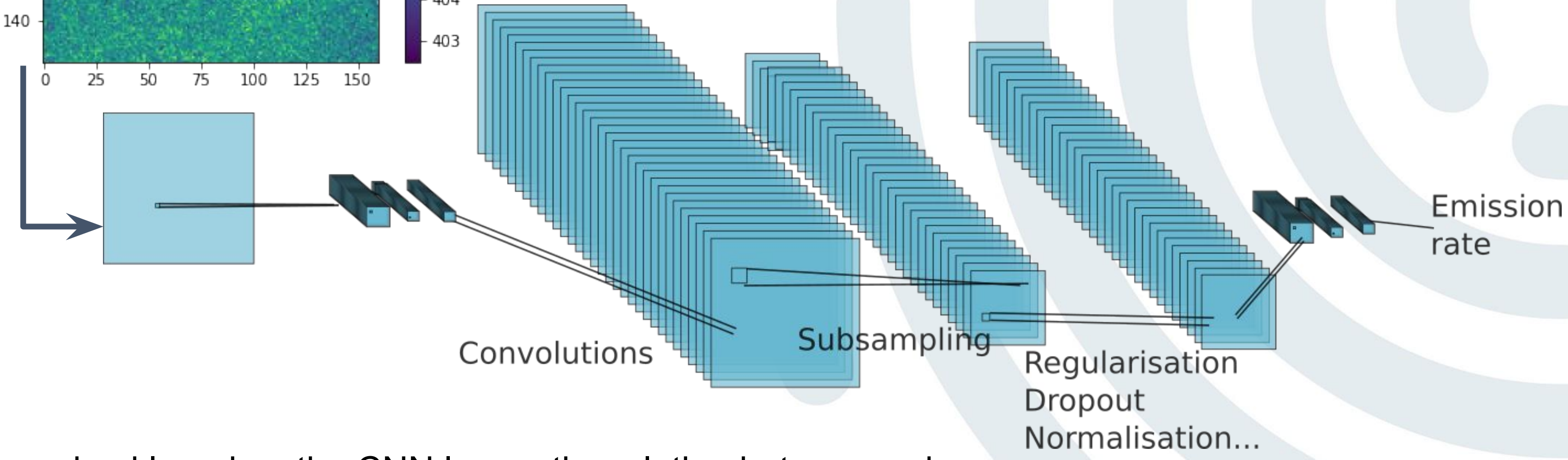
Signal of CO2 plumes induced by emissions = intrinsically difficult to detect

Convolutional Neural Networks



CNN:

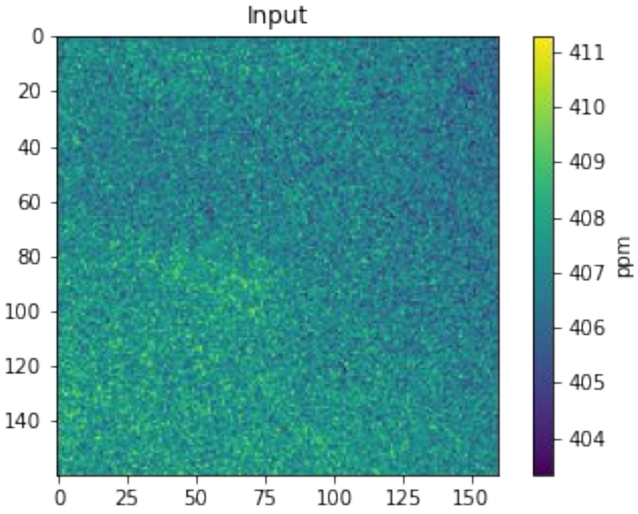
- ❑ capture spatial features of the image through application of successive filters
- ❑ i.e., transform image into relevant features maps
- ➢ used to recognise spatial features that belong to an anthropogenic plume

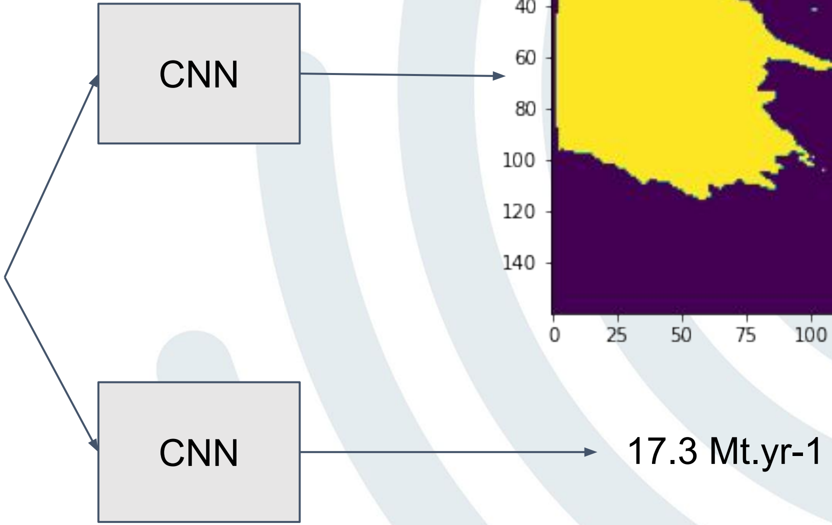


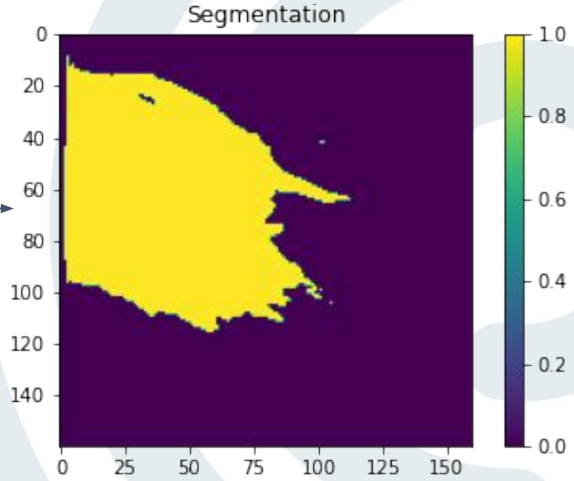
Supervised learning: the CNN learns the relation between pairs of provided inputs (simulated satellite image) and outputs (plume - emissions)

Segmentation and Inversion: Training

- Model = Slightly customised U-net (~1.5 million parameters)
- Loss = pixel-concentration-weighted binary cross entropy loss function

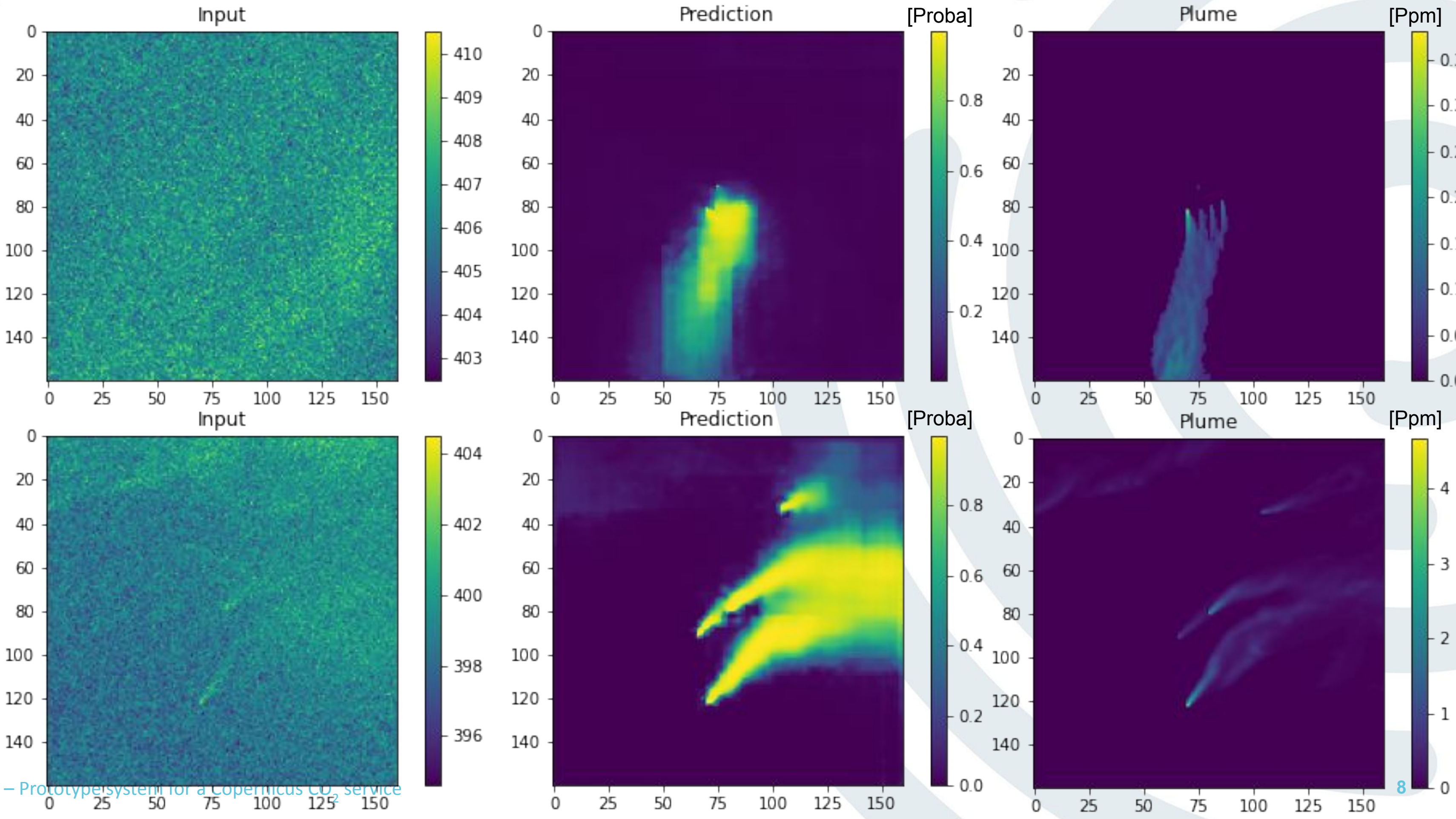




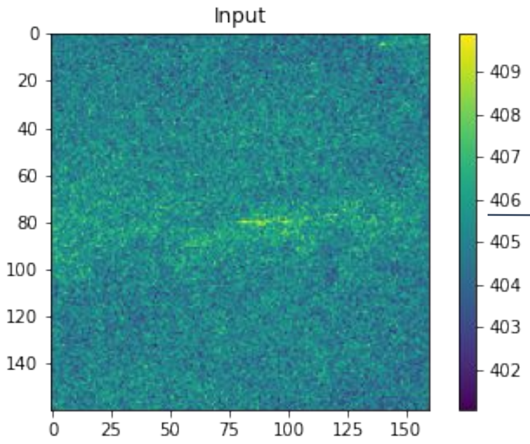


- Model = Slightly customised EfficientNetB0 (~4 million parameters)
- Loss = Mean Squared Logarithmic Error

Segmentation: results



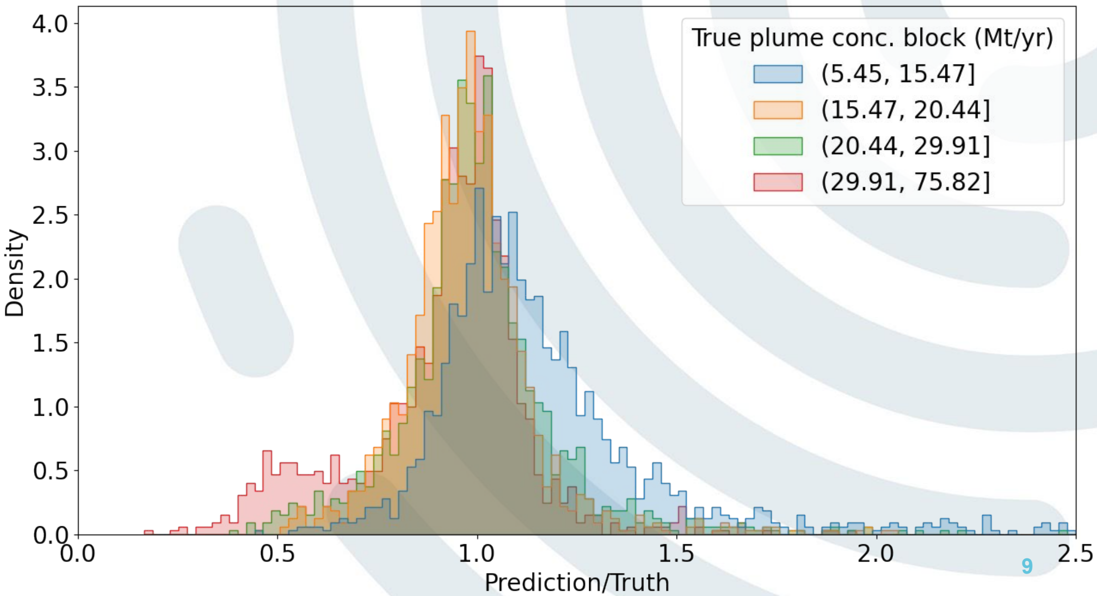
Inversion: results



True emissions rate:
22.47 Mt.yr-1

Trained CNN

Predicted emissions rate: 25.82 Mt.yr-1



Emissions reconstructed tend to get close to the mean:

- ➢ high emissions are slightly underestimated
- ➢ low emissions are slightly overestimated

CoCO2
Prototype system for a Copernicus CO_2 service

THANK YOU

coco2-project.eu

@CoCO2_project

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