CO2 PLUME DETECTION USING NEURAL NETWORKS: APPLICATION TO SYNTHETIC IMAGES OF THE XCO2 FIELD OVER THE PARIS AREA

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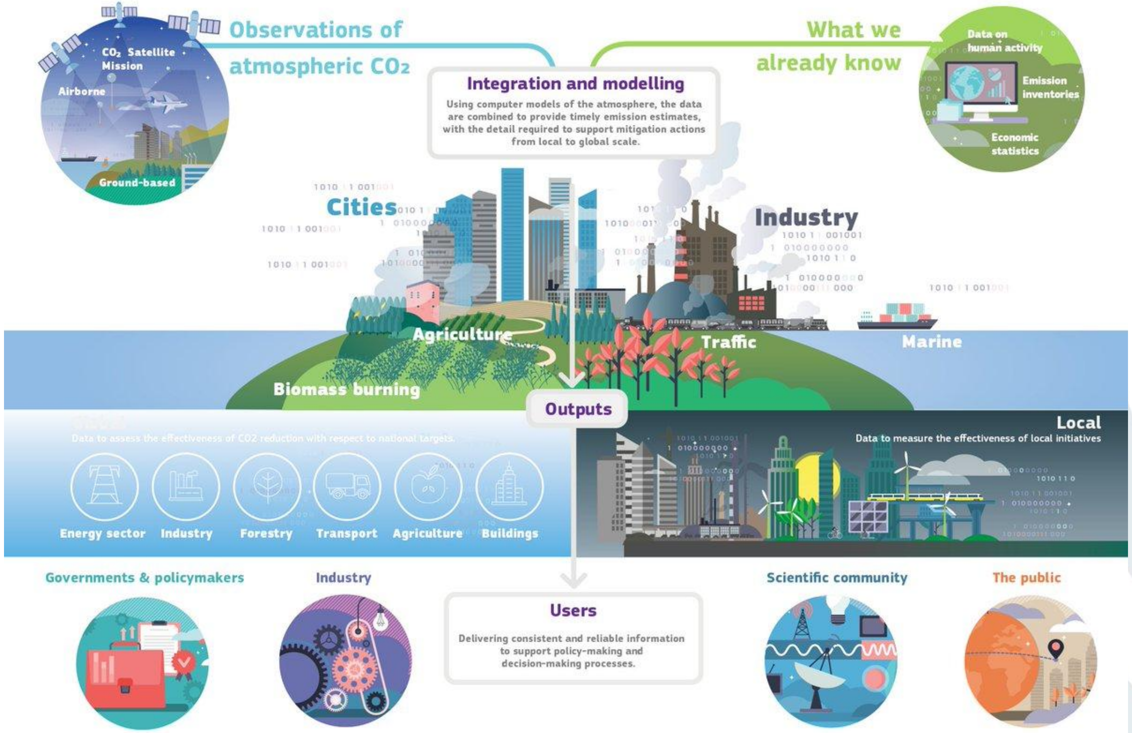
CoCO2, prototype system for a CO2MVS



CO2MVS concept

Copernicus CoCO2 project

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

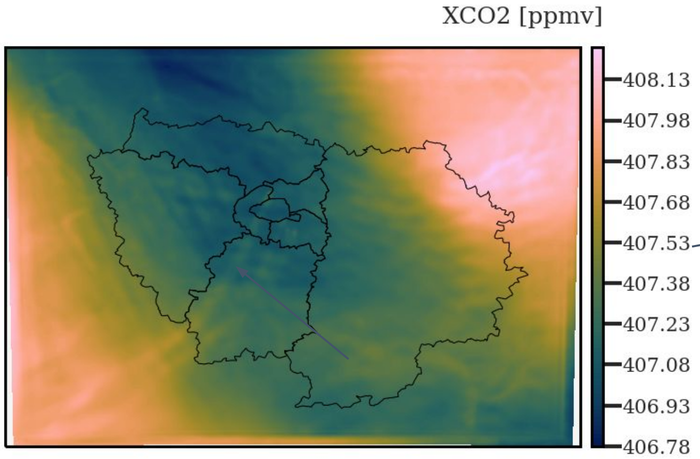
Our Task:

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.

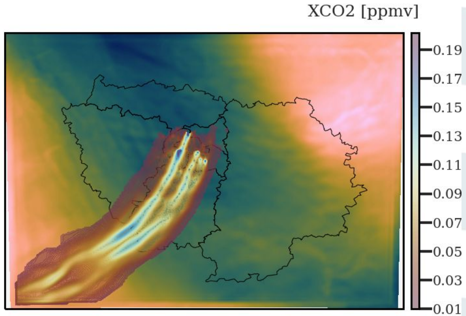
THREE OBJECTIVES



Plume inverse modelling
- ➢ find the source of the plume (=corresponding anthropogenic emissions)

Plume presence
- ➢ guess if an image contains a plume

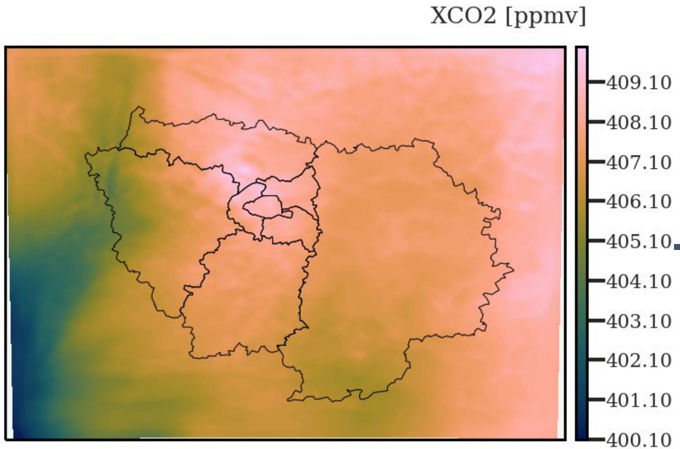
Plume Segmentation



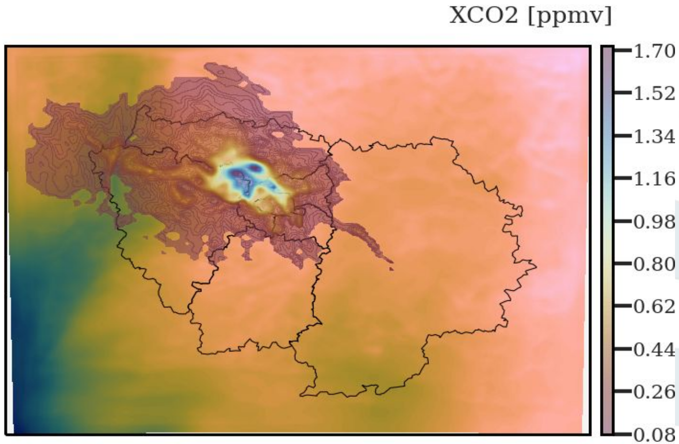
XCO2 plumes dataset

- ❖ Tests (training and evaluation) with a 1-year simulation of the hourly XCO2 fields in the Paris area, tracing the plume from Paris and other bio and anthropogenic components.

- ❖ Simulations by LSCE/Suez-Origins (Lian et al., 2021)

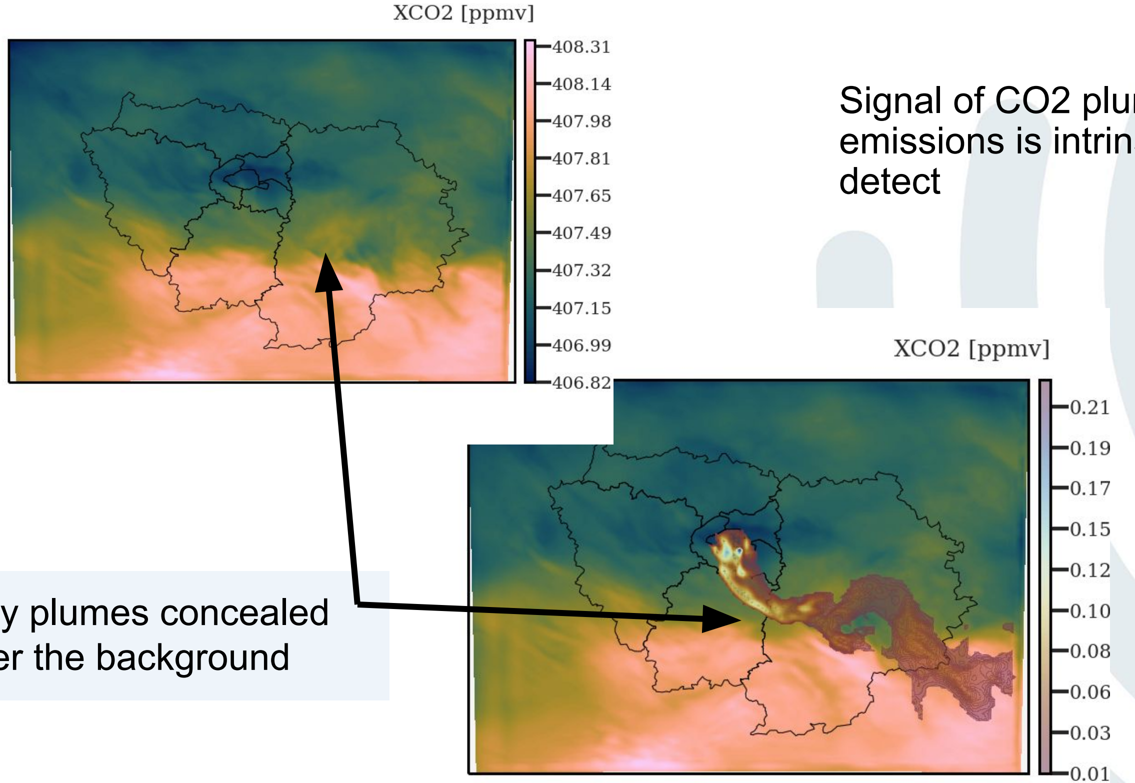


XCO2 field



Anthropogenic plume enhanced

Where is the plume ?

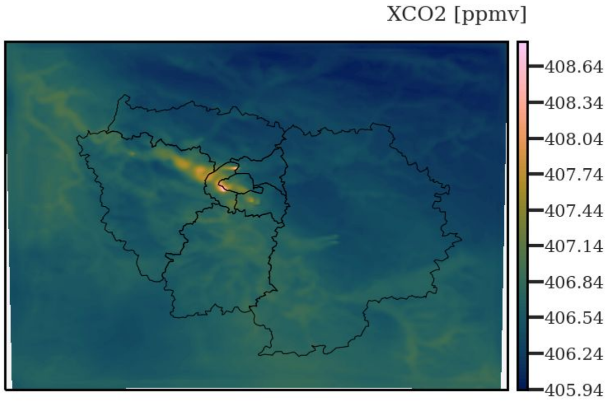


Many plumes concealed under the background

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

Supervised learning



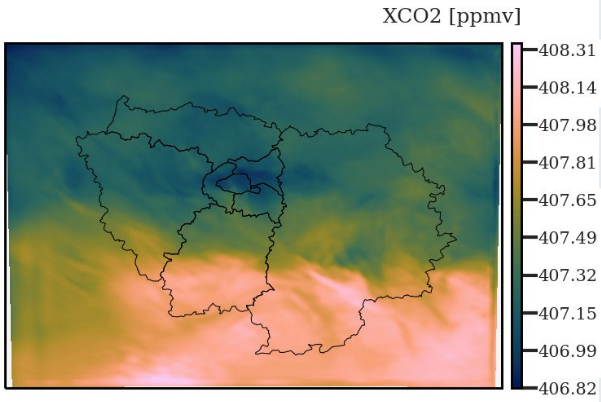


Image containing
- Paris anthropogenic signal (=plume)
- background components (=noise)

labelled as a 1

Statistical model

Image containing
- only background components

labelled as a 0

Learn which characteristics distinguish an image with a Paris signal from pure noise

Detectability factors[1]

1. **Noise:**
   a. **Variability of the background**
   b. Instrument noise

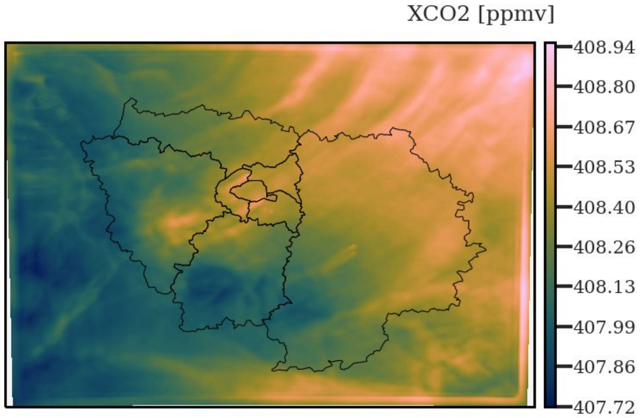
2. **Plume "definition":**
   a. **Meteorological conditions, which determine dilution and dispersion**
   b. **Intensity of the emission source**

3. Image quality:
   a. Clouds
   b. Number of satellite overpasses

Simulate satellite observations (OSSE) ?

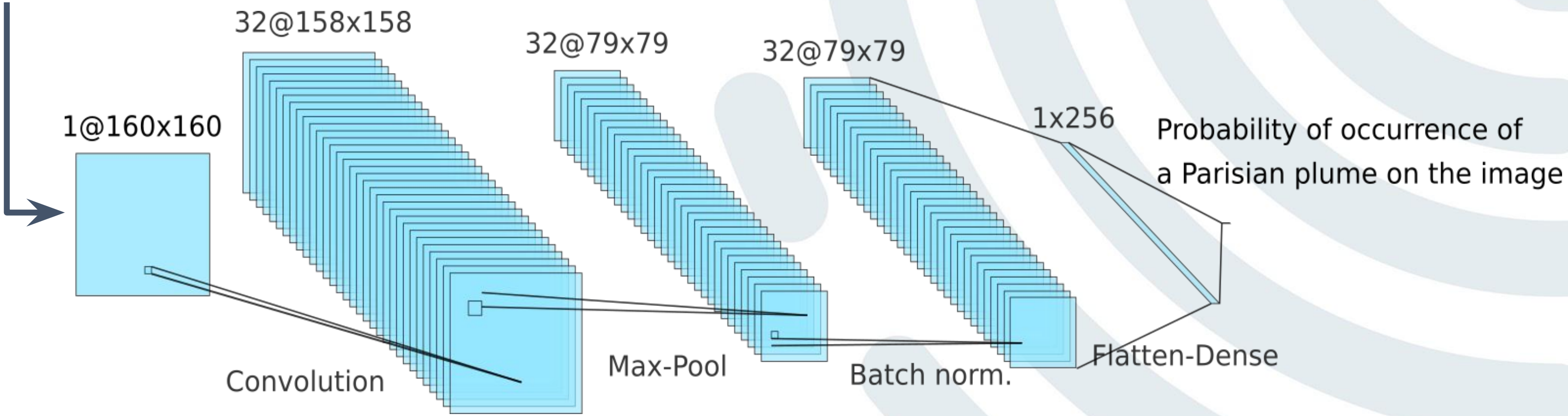
1. Detectability of CO2 emission plumes of cities and power plants with the Copernicus Anthropogenic CO2 Monitoring (CO2M) mission. Kuhlman et al.

Convolutional Neural Networks for plume presence

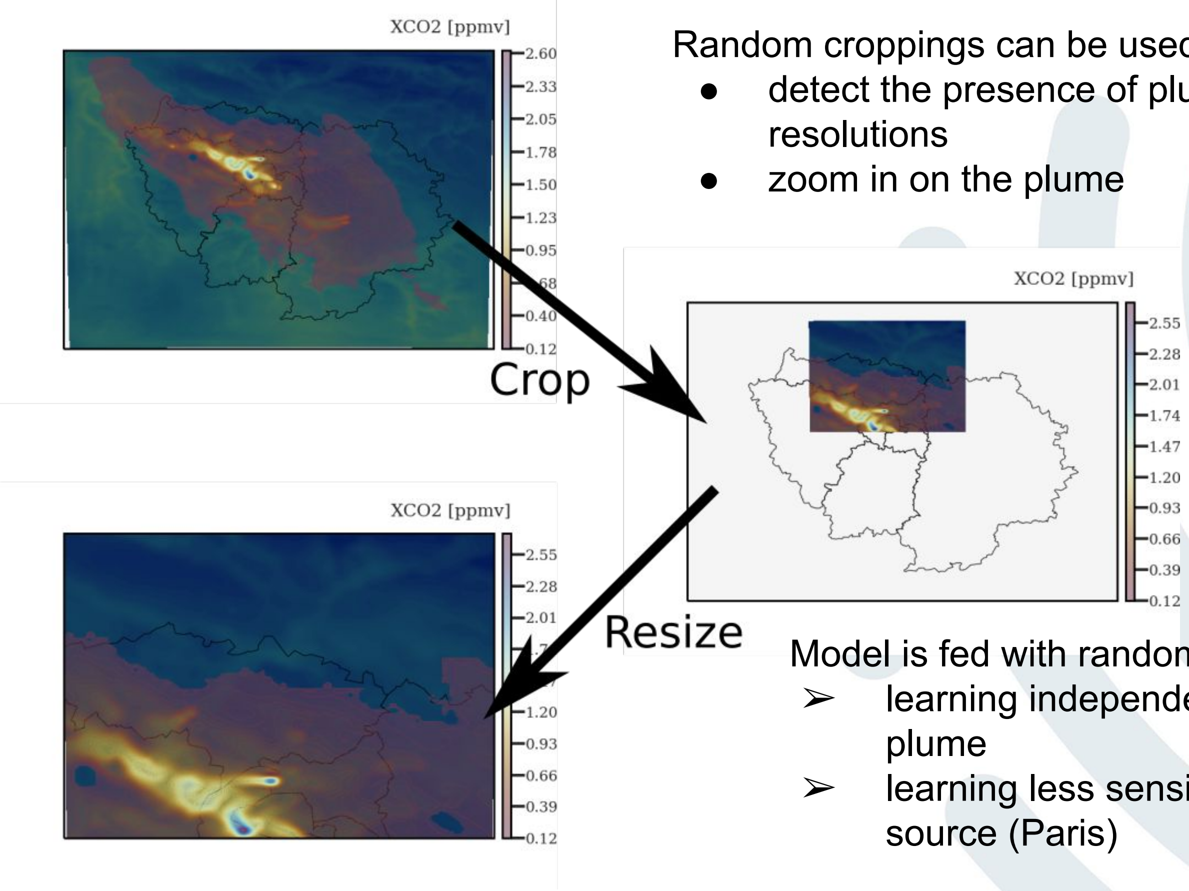


Convolutional Neural Networks:

- ❑ 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



Random croppings



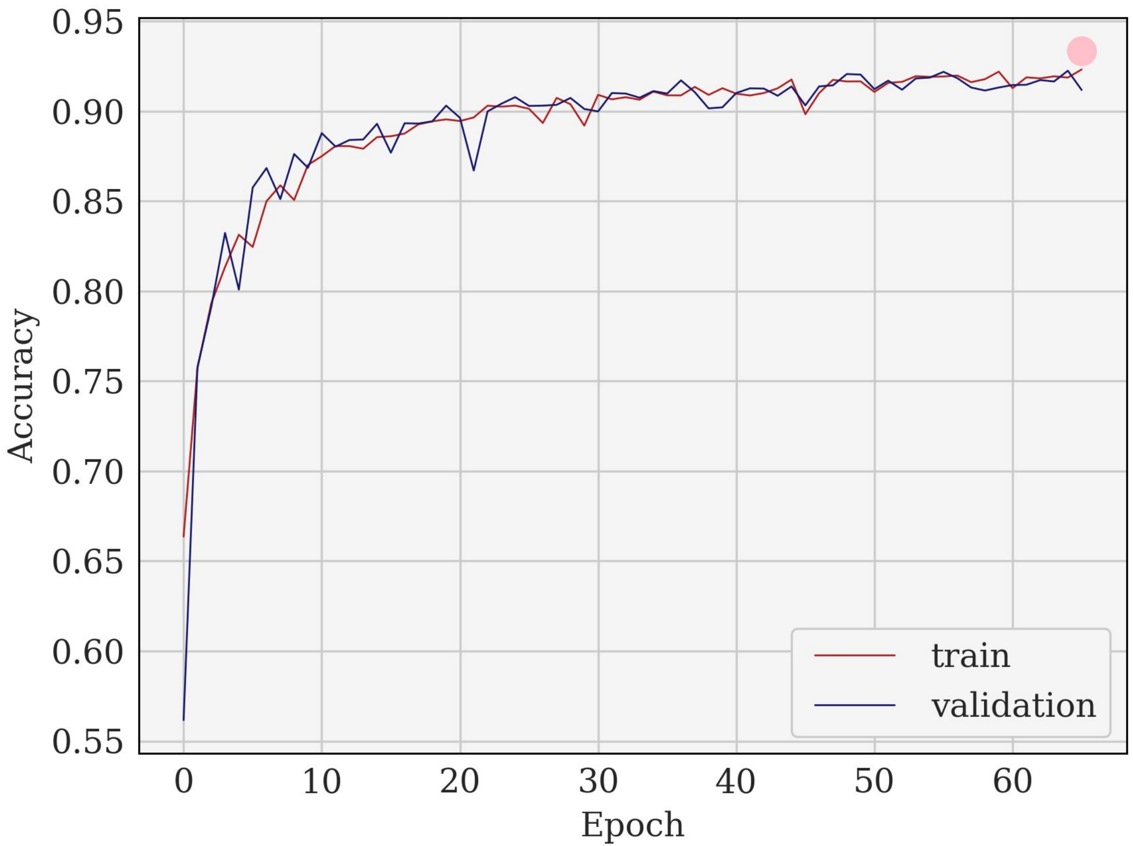
Random croppings can be used to:

- detect the presence of plumes in images of various resolutions
- zoom in on the plume

Model is fed with randomly cropped images

- ➢ learning independent from the resolution of the plume
- ➢ learning less sensitive to the position of the source (Paris)

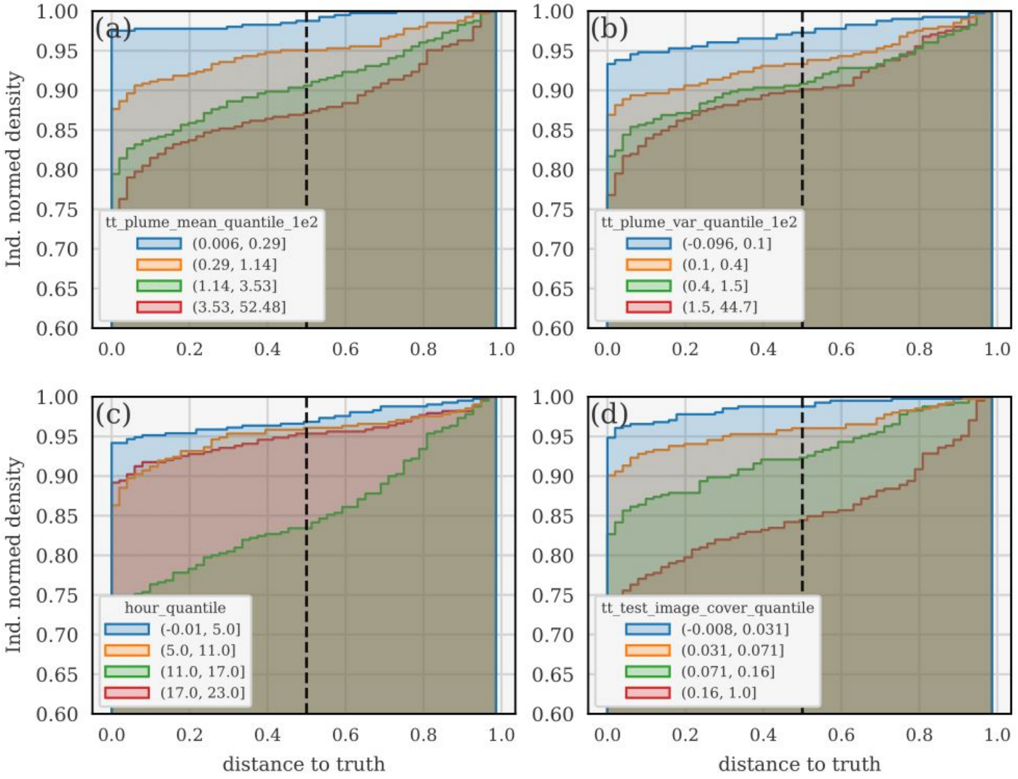
Neural network performances



- ❑ Network is trained from scratch
- ❑ Overfitting is avoided thanks to:
  - use of dropout layers
  - various data augmentations using Keras API tools
- ❑ Training time ~ 20mn on GPU (Nvidia Quadro RTX 5000 16Go)

➢ Accuracy performance ~ 93%

Model evaluation: which data are poorly predicted?

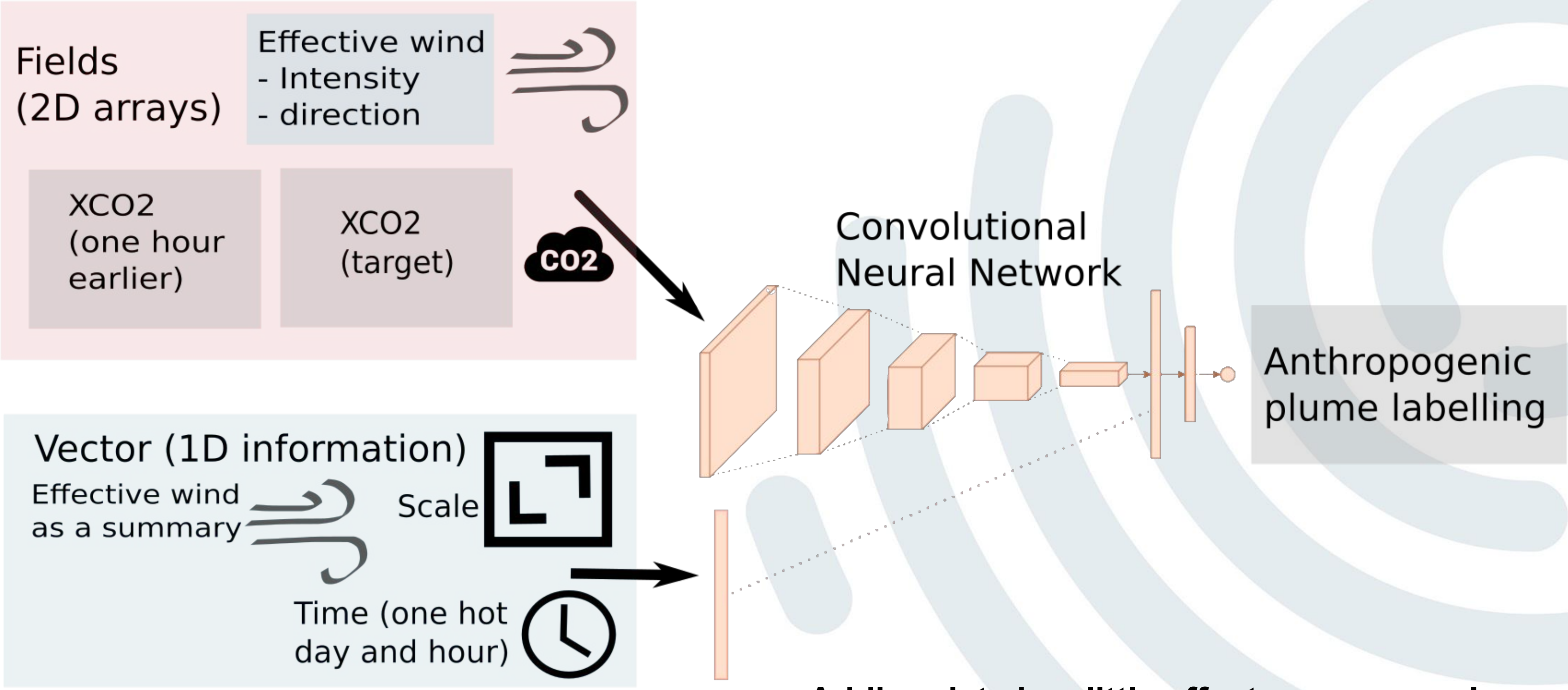


Many false negatives: images with a plume, evaluated as images with no plume.

Images with plumes poorly predicted are:

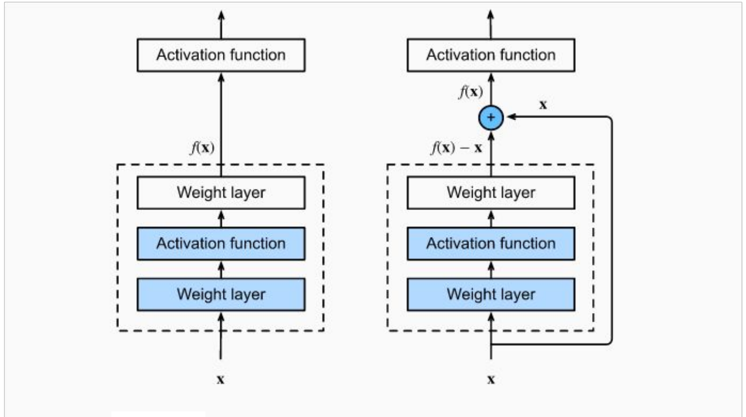
- ➔ full-day plumes (between 11h and 18h)
- ➔ high mean plumes
- ➔ high variance plumes
- ➔ large (=extending over a large area)

Feed more data to improve plume detection accuracy ?



Adding data has little effect on accuracy!

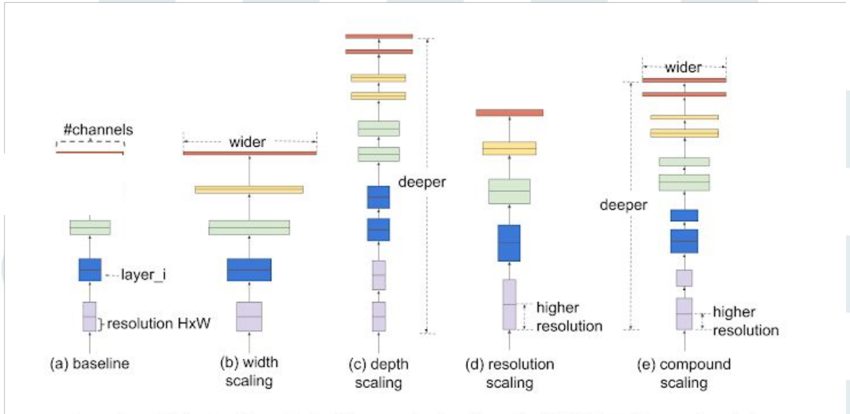
Using more complex models



A regular block (left) and a residual block (right).

Dive into deep learning, Zhang et al.

ResNet: idea, learn residual mapping instead of full mapping

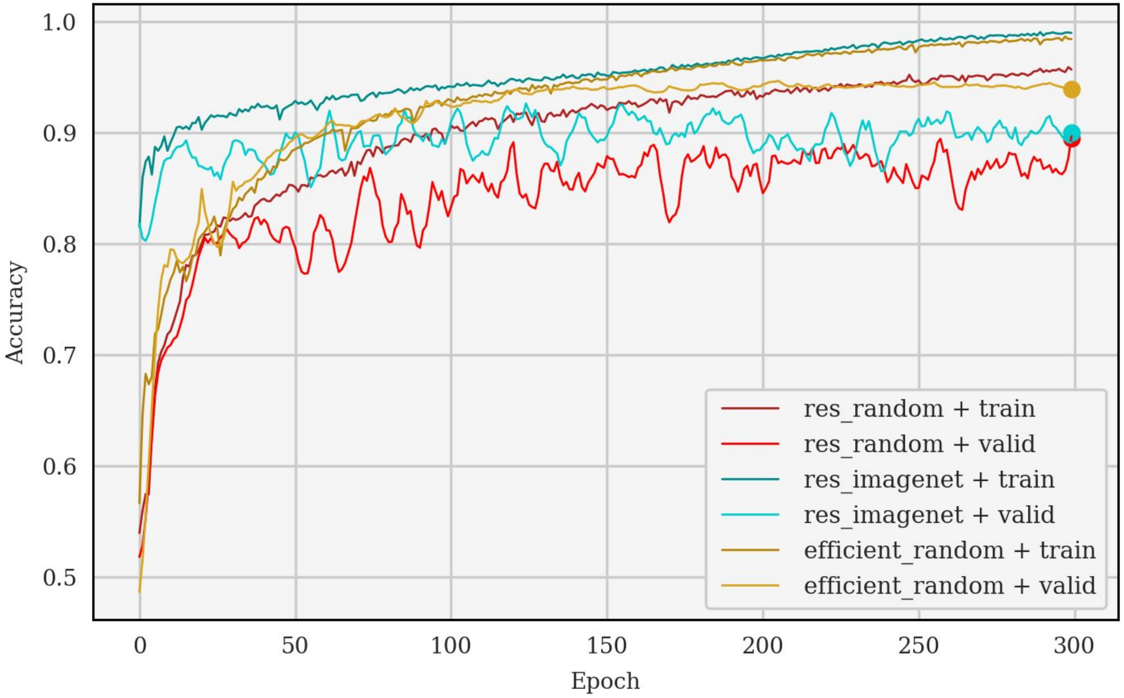


Comparison of different scaling methods. Unlike conventional scaling methods (b)-(d) that arbitrary scale a single dimension of the network, our compound scaling method uniformly scales up all dimensions in a principled way.

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. Mingxing Tan, Quoc V. Le

EfficientNet: based on MobileNet and the use of a width-depth-resolution compound scaling to optimise accuracy

Using more complex models: results



Weights initialised

- randomly
- using pre-trained weights on ImageNet

Performance ~ 95% validation accuracy with EfficientNet

Huge overfitting!

Conclusions

Next steps

Progress on presence assessment:

- reduce overfitting and improve ability to generalise:
  - add data
  - diminish model complexity
  - tune model (batch size, regularisation)

Progress on the next tasks:

- plume segmentation task using
  - cropped plume presence assessment models
  - sophisticated image to image deep learning algorithms
- plume inverse modelling task
  - use as additional input segmented plumes

CoCO2

Prototype system for a Copernicus CO_2 service

THANK YOU

This presentation reflects the views only of the author, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

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