21st International Conference on
Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes
27-30 September 2022, Aveiro, Portugal

CO2 plume detection and inversion using convolutional neural networks: application to synthetic images of XCO2 fields over urban areas

Joffrey Dumont Le Brazidec[1], *Pierre Vanderbecken*[1], *Alban Farchi*[1], *Marc Bocquet*[1], *Jinghui Lian*[2,3], *Grégoire Broquet*[2], *Thomas Lauvaux*[2], *and Alexandre Danjou*[2]

[1] CEREA, École des Ponts and EDF R&D, Île-de-France, France
[2] Laboratoire des Sciences du Climat et de l'Environnement, LSCE/IPSL, CEA-CNRS-UVSQ, Université Paris-Saclay, 91198 Gif-sur-Yvette, France
[3] Origins.S.A.S, Suez Group, Île-de-France, France

Abstract:
Carbon dioxide emissions, accounting for more than 70% of global anthropogenic greenhouse gas releases, are the main driver of climate change. Current emissions estimates, which are needed to guide reduction policies, rely on statistical data of energy consumption including self-reporting from emitters and are subject to important uncertainties. In order to assess these emissions in an independent, timely and accurate manner, the Copernicus CoCO2 project aims to build a prototype system for a CO2 emission monitoring service exploiting atmospheric CO2 measurements. As part of this project, our goal is to build an atmospheric transport modelling 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. The reconstruction of such sources depends on the detection of the associated plumes in the satellite images of the vertically averaged CO2 column concentrations (XCO2), which represents a significant challenge. Indeed, the signal of CO2 plumes induced by point-source emissions is intrinsically difficult to detect since it rarely exceeds values of a few ppm and is perturbed by variable regional CO2 background signals and noise or error patterns in XCO2 images due to instrument and retrieval algorithms.

To tackle the problem of CO2 plume detection and inversion, we investigate the potential of deep learning methods. Neural networks are trained on hourly simulated XCO2 fields in the regions of Paris, Berlin, and several power plants, consisting of the plume from the city or the power plant and of other biogenic and anthropogenic fluxes. Convolutional neural networks are trained to evaluate the presence and the contour of the CO2 plume in an image and to reconstruct the corresponding emissions. In 75% of the estimates, the relative error between predictions and actual emissions is less than 0.2.

Key words: *CO2 plumes, Satellite CO2 images, Inverse modelling, Convolutional Neural Networks, Segmentation, Emissions assessment*

Introduction

Currently, countries' progress in reducing their greenhouse gas (GHG) emissions is monitored through regular national inventories, based on self-reported energy consumption statistics. Independent assessment of countries' emissions would support these inventories: estimates based on spaceborne measurements can enable this verification and monitoring of countries' GHG releases. Within the Copernicus programme, the CO2 Monitoring and Verification Service (CO2MVS) aims to develop an operational emission monitoring system (Janssens-Maenhout et al., 2020) with the help of the CO2M satellite mission. Satellites can provide images of vertical integrated CO2 (XCO2) characterising the CO2 plumes from point-sources: cities or power plants. These signals can be used to estimate the associated emissions. As part of the CoCO2 project, which aims to elaborate a prototype CO2MVS, we develop supervised deep learning methods able to detect anthropogenic plumes and estimate the associated emissions. The neural networks receive pairs of inputs (simulated satellite images) and labels (the target to be learned, e.g. emissions) and learn the features of the inputs that correspond to the associated targets. We use convolutional neural networks (CNN) which are able to extract spatial features from the image by applying successive convolution filters, with the aim of recognising characteristics associated with anthropogenic plumes. Our models are trained with simulated fields of average CO2 column concentrations (XCO2) consisting of plumes of various cities and power plants, as well as other biogenic and anthropogenic fluxes.

Simulation of the satellite XCO2 images

The detection and inversion of CO2 plumes in satellite images is a challenge with many obstacles (Kuhlmann et al., 2019):

- the integrity of the image which may be affected due to insufficient coverage of the plume by the satellite or the presence of clouds preventing the satellite from observing a large part of the plume;
- a low ratio between:
  - the plume signal, dependent on the intensity of the emission source and on the meteorological conditions determining its dilution and dispersion,
  - and the background interference, whose variability depends on the single sounding precision of the satellite instrument and the anthropogenic and biospheric fluxes in the vicinity of the target, affected by the meteorology.

  The plume signal is often lower than the observation error and the background variability.

In this study, we focus on the second problem, assuming that the integrity of the image is intact. The XCO2 fields used for this study consist of simulations by atmospheric transport models, composed of the anthropogenic plume from the point-source emitter (city or power plant) and other biogenic and anthropogenic fluxes (the background). Two different atmospheric dispersion models are used to compute the fields: simulations in the region of Paris by WRF-Chem V3.9.1 are based on the configuration of Lian et al. (2021) while simulations in the region of Berlin and the power plants are based on COSMO-GHG and issued from the SMARTCARB project (Kuhlmann et al., 2019). Paris data consist of 3-months simulations on a nested domain of various resolutions (the innermost domain covering the Île-de-France being at 1 km resolution), while SMARTCARB simulations consist of 1-year data with a resolution of $0.01°$. The full SMARTCARB domain covers $\sim 700\,\mathrm{km}^2$ and is centered around Berlin. A random gaussian noise of 1 ppm is added to the simulated XCO2 fields to represent the satellite instrument noise. The construction of a XCO2 field is shown on Fig. 1.

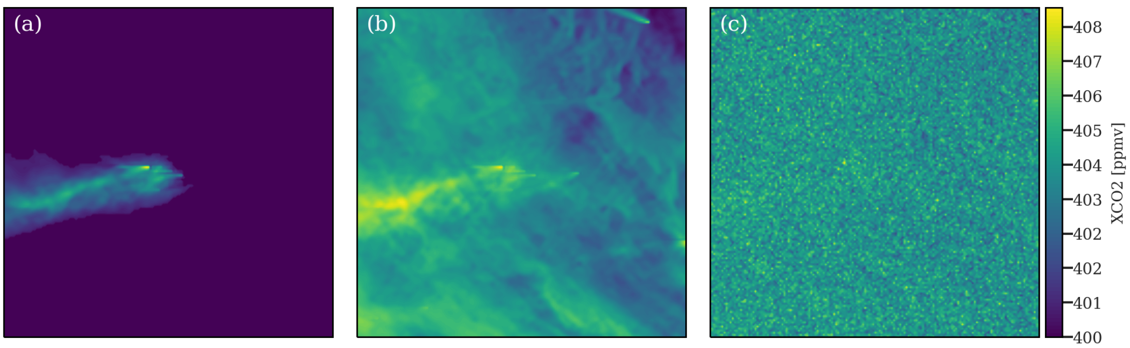

Figure 1: Construction of a simulated XCO2 field observed by the satellite with a) the anthropogenic XCO2 plume, b) the plume added to the background noise (biogenic + other anthropogenic fluxes), and c) the addition of the satellite instrument noise.

Detection: segmentation of a plume

Plume detection, or segmentation, is the detection of the outline of a plume in a given image, or, equivalently, the detection of the pixels compounding the plume. To perform this task, a convolutional neural network is used which takes as input a given XCO2 field and gives a probability map as output. The shape of the input and output are equal and each pixel in the output represents the probability that the concentration of the pixel partially originates from the plume. To tackle this image-to-image problem, we use a model based on the U-net architecture (Ronneberger et al., 2015), an encoder-decoder composed of a contracting phase (increasing feature information) and an expansive phase (increasing the resolution back to its original shape). This type of architecture allows the network to learn from information captured on the entire image.

On Fig. 2, two applications of the U-net are provided on an satellite image of a city (left) and a power plant (right), unseen by the model during the training phase. The segmented probability maps represent typical results obtained by the model. For both of these very dissimilar plumes, a good fit can be observed between the segmented probability maps and the true concentration fields: for a threshold equal to 0.5 (pixels with probabilities higher than 0.5 are considered as pixels compounding the plume), the IoU scores are higher than 0.9 in both cases.

Inversion: emissions estimation

The inversion problem is the problem of retrieving the emissions associated to a plume in a given XCO2 field image. A convolutional neural network is used, processing as input a given XCO2 field and resulting in a scalar output representing the emission rate of CO2 in Mt.year^{-1} on the last hour. We thus assume that a plume observed on the image depends only on the emissions of the last few hours and that the emissions vary little in time. On the power plants and cities considered, typical emission rates range between 10 and 70 Mt.year^{-1}. The neural network used for this regression problem is built on the EfficientNetB0 (Tan and Le, 2020), a classification neural network made of inverted residual blocks. The loss function chosen is a mean squared logarithmic loss, to address proportional errors between the predicted and true emission rates. Fig. 3 presents two applications of the trained EfficientNetB0 on XCO2 fields, unseen during the training phase. A histogram of the relative error between true and predicted emission rates by the CNN is provided in Fig. 4. For 75% of the estimations, relative error is below 0.2. However, a typical regression problem is encountered: high emissions are slightly underestimated and low emissions are slightly overestimated. The worst estimations are the result of this problem.

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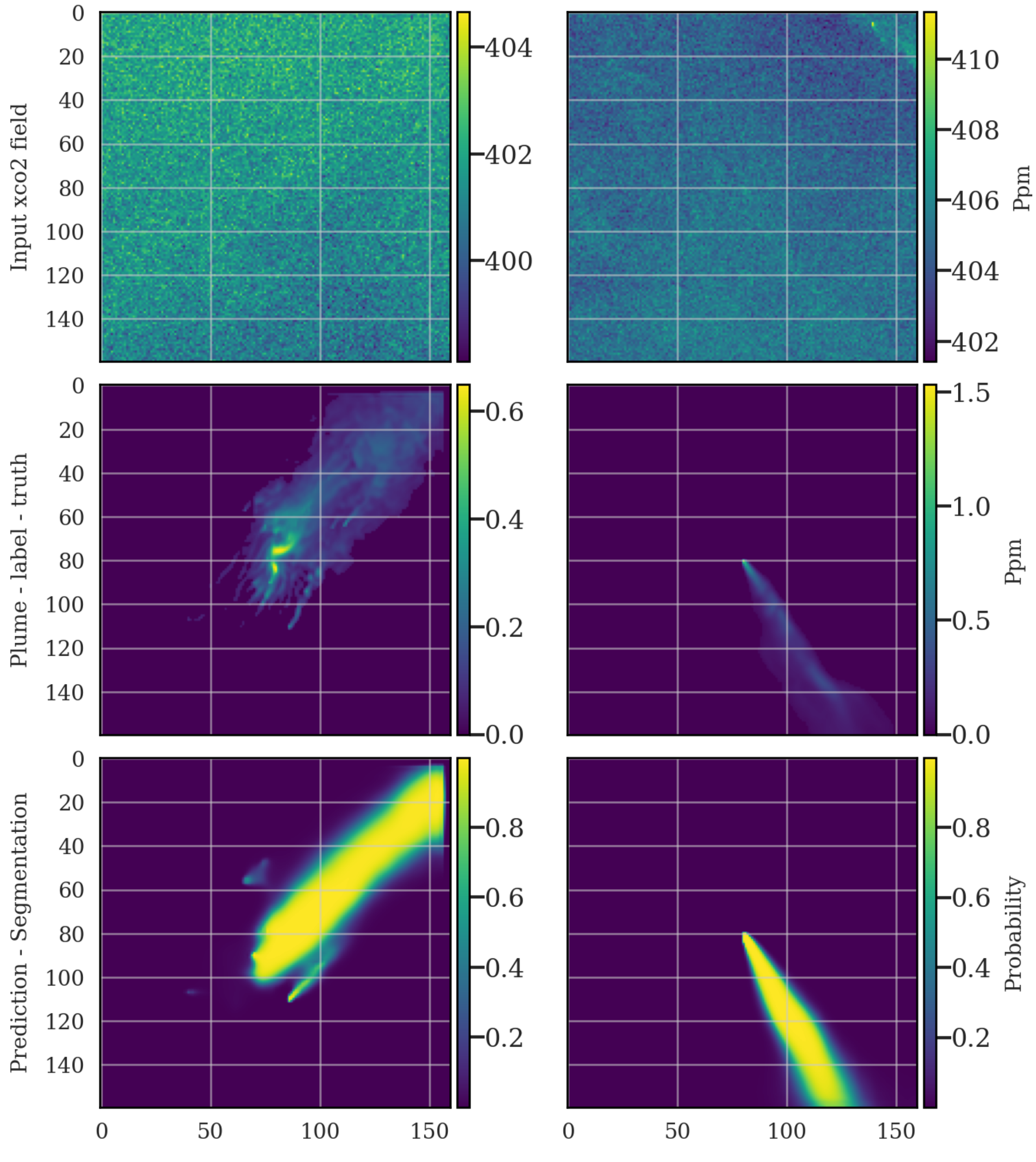

Figure 2: Two examples of the U-net application. The first row corresponds to two independent (and unseen by the model during the training phase) XCO2 simulated satellite image inputs in ppmv, the second row corresponds to the corresponding plumes, or truths, targets of the U-net in ppmv, and the third row corresponds to the predictions of the U-net as maps of probability. These two examples are representative of the average results of the model: the pixel-weighted binary cross entropy errors of the left and right example are equal to 0.25 and 0.04, respectively, while the average error on all unseen data is 0.12.

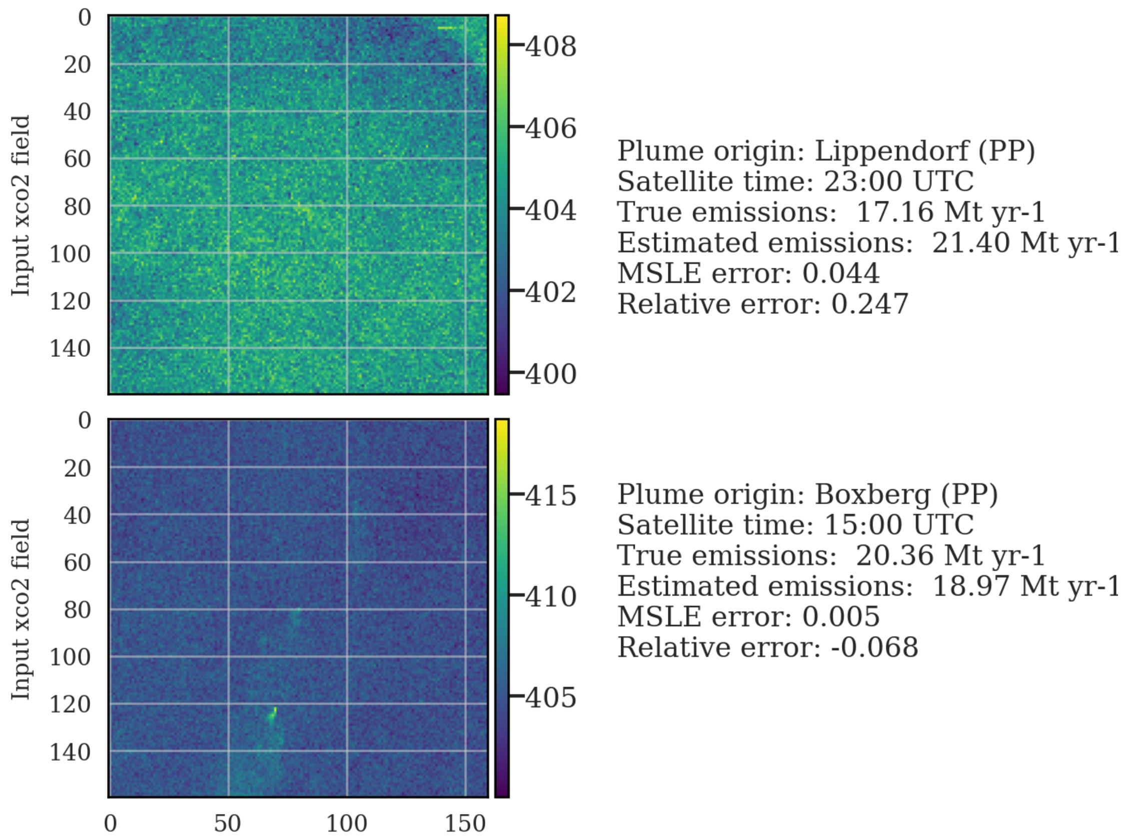

Figure 3: Two examples of the inversion EfficientNetB0 application. The left images correspond to two independent (and unseen by the model during the training phase) XCO2 simulated satellite image inputs in ppmv. The estimated and real emissions are given on the right of the images.

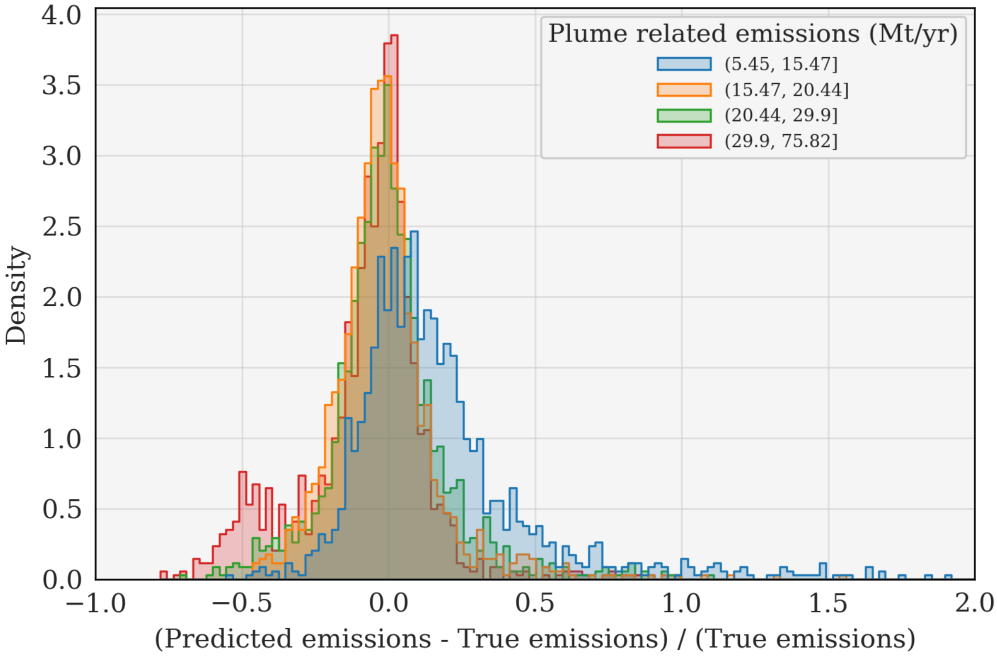

Figure 4: Histogram of the relative error between true emission rates and predictions by the EfficientNetB0 model.