POWER

CS-E407519 Lecture 2

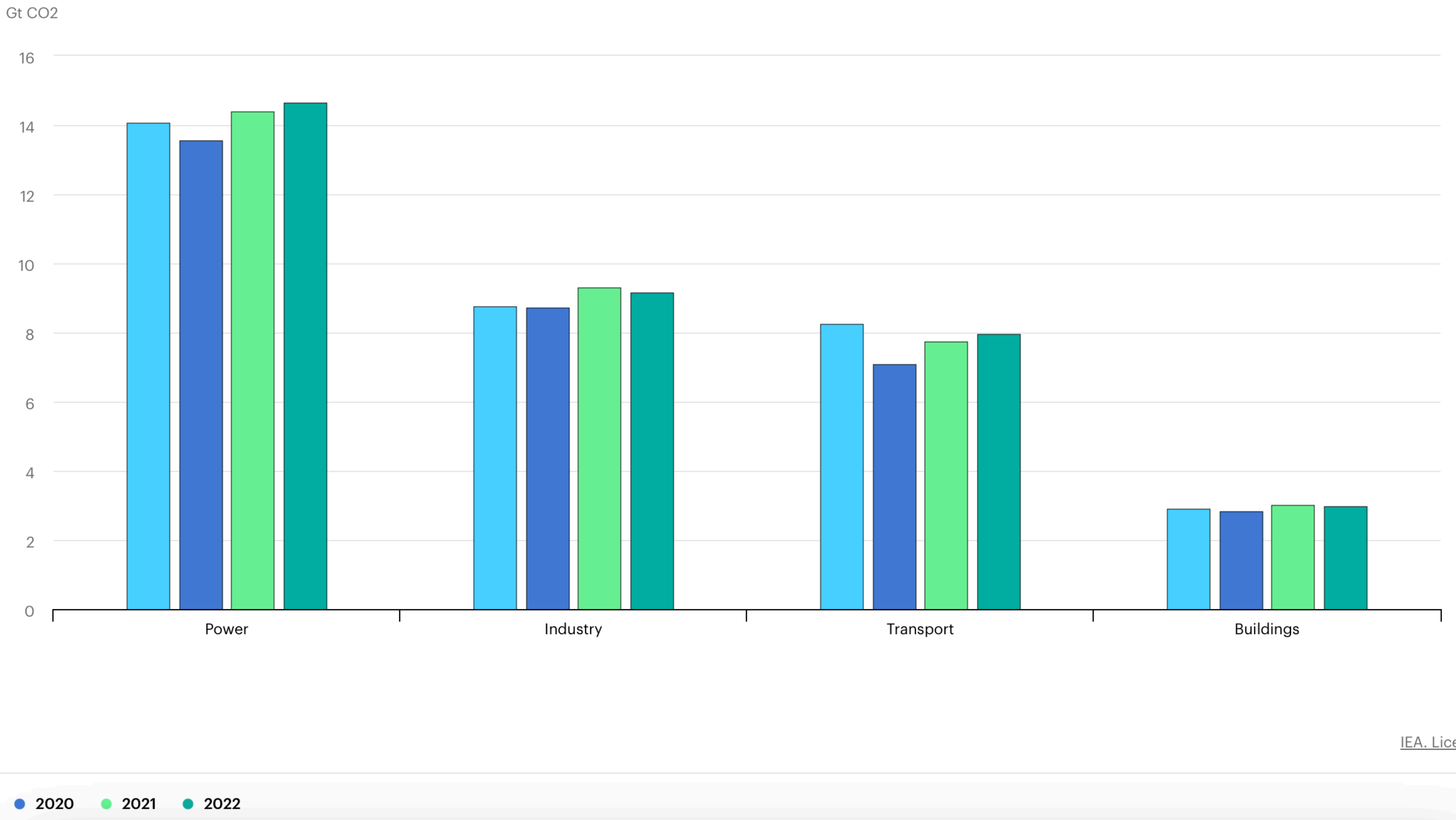
Photo by American Public Power Association on Unsplash

OUTLINE

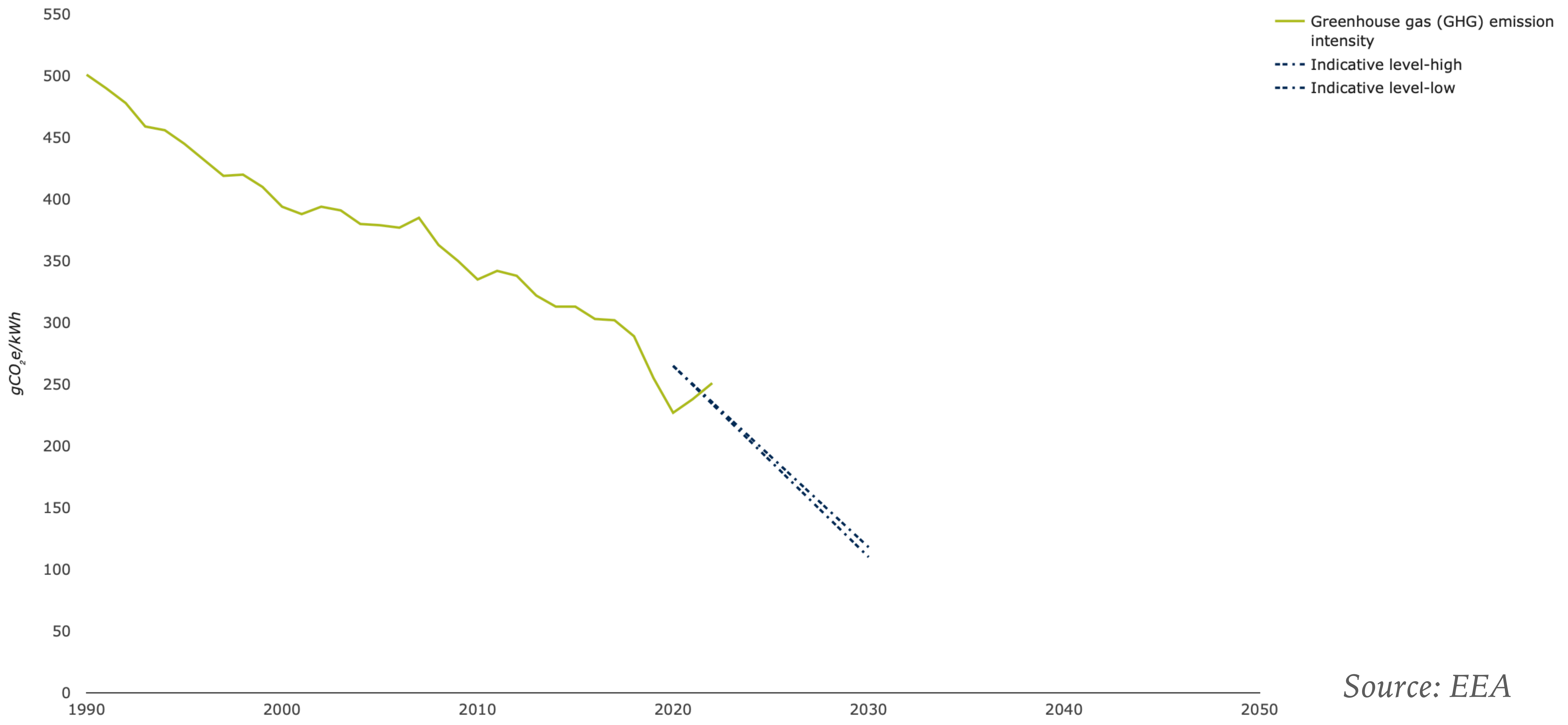
- Emissions and climate action potential of power sector
- Role of NO_2 in detecting CO_2 emissions
- Automated detection of atmospheric NO2 plumes from satellite data (paper)
- Convolution Neural Networks (CNN)

POWER

GLOBAL CO2 EMISSIONS BY SECTOR



GREENHOUSE GAS EMISSION INTENSITY OF ELECTRICITY GENERATION IN THE EU



Source: EEA

POLL: DOES WIND POWER GENERATION EMIT GREENHOUSE GASES IN ITS LIFECYCLE?

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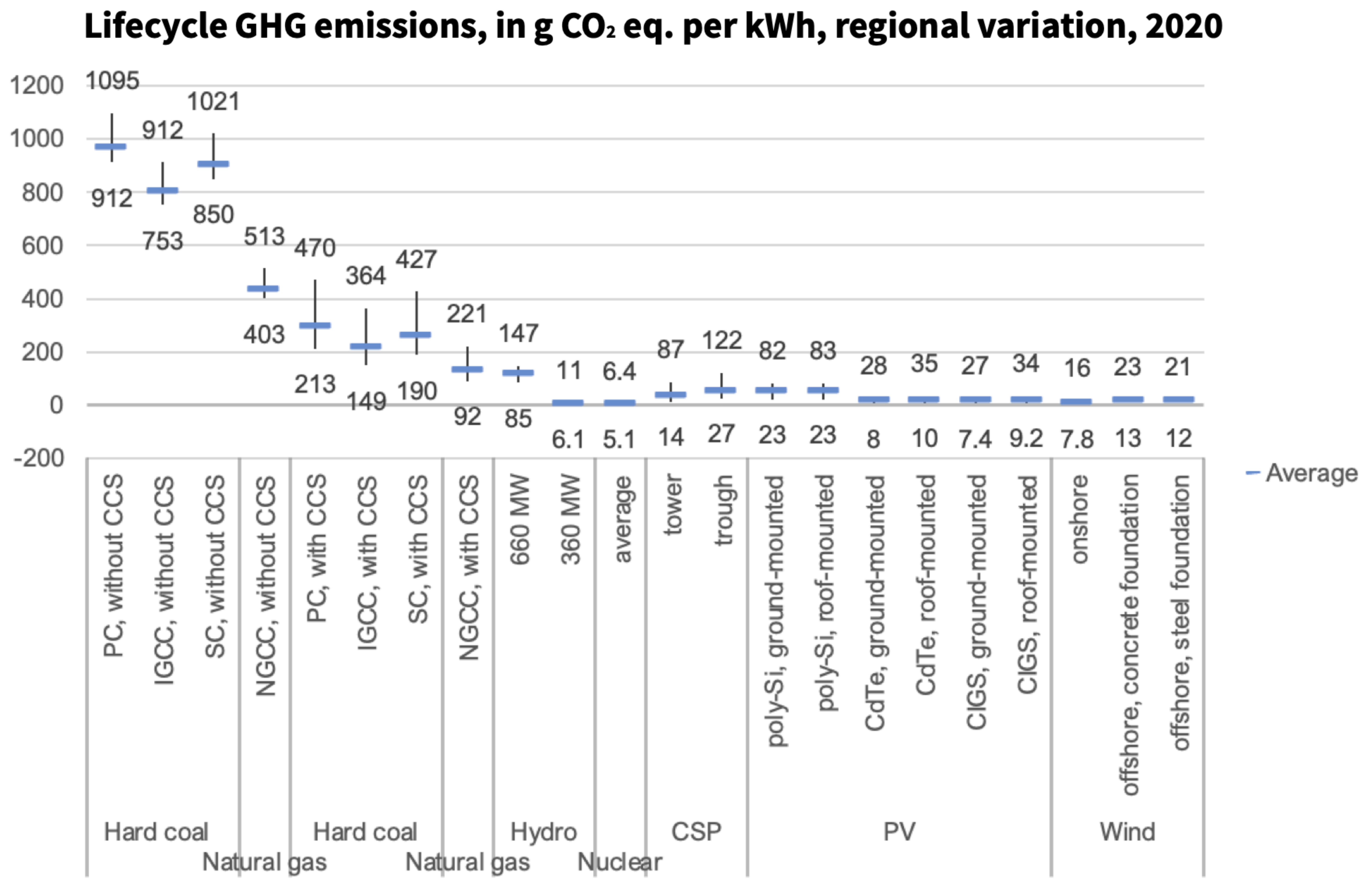
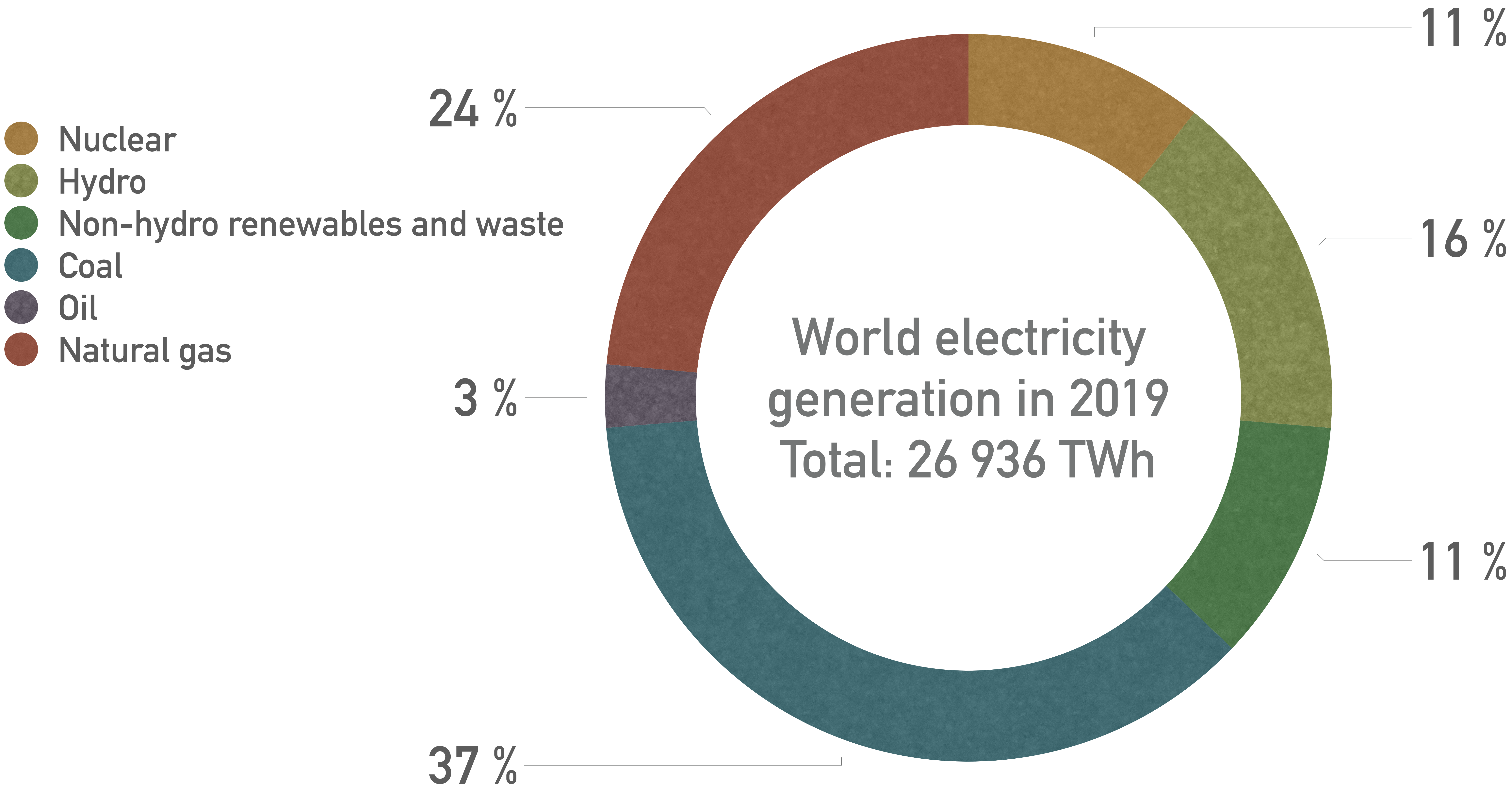
ALL ELECTRICITY GENERATION TECHNOLOGIES PRODUCE GHG



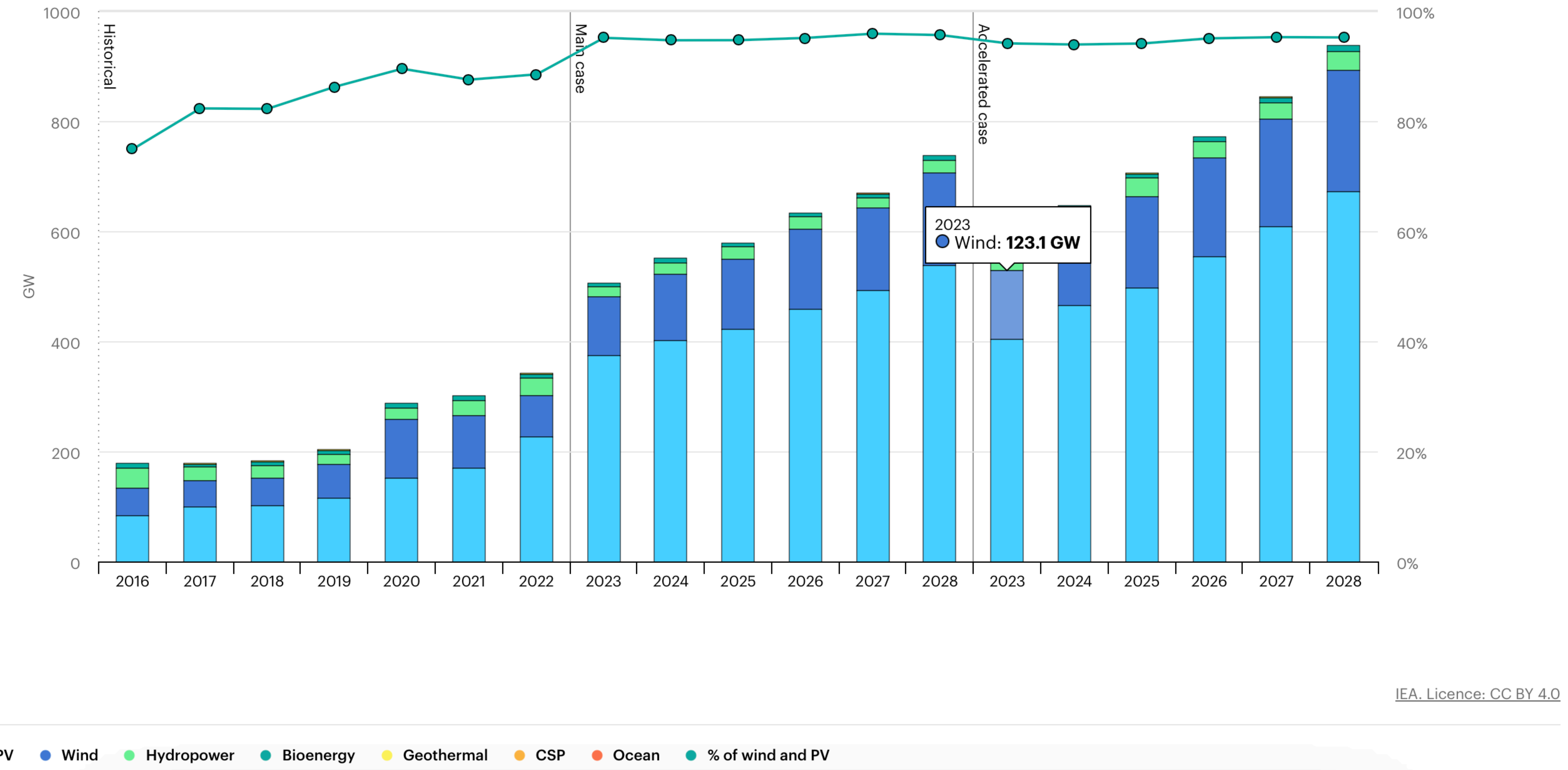
Source: UNECE (2021)

COAL POWER REMAINS THE LEADING GENERATION TECHNOLOGY



Source: IEA (2020)

RENEWABLE ELECTRICITY GENERATION



Renewable electricity capacity additions by technology and segment, 2016-2028

POLL: RANK SOURCES OF GHG EMISSIONS IN ELECTRICITY TRANSMISSION IN FINLAND?

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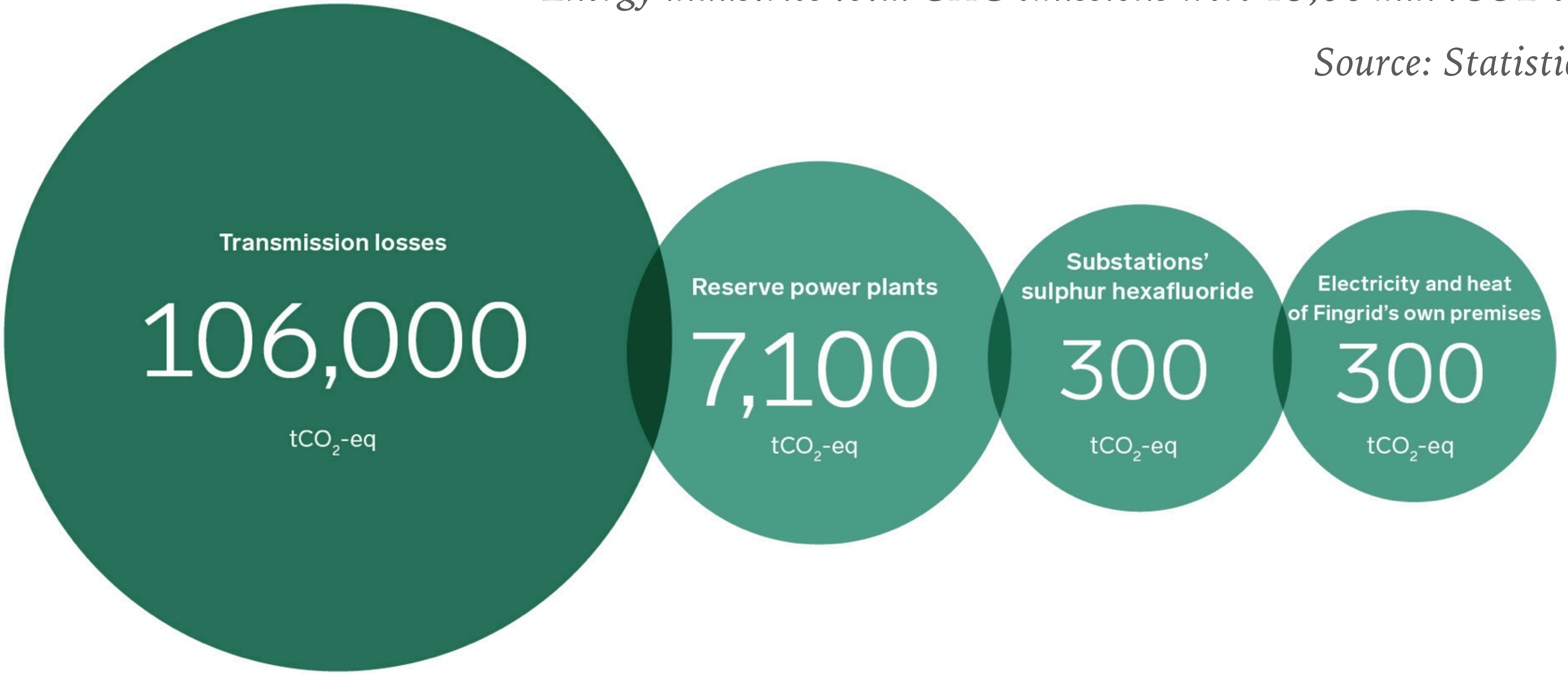
CARBON FOOTPRINT OF ENERGY TRANSMISSION

Energy industries total GHG emissions were 13,06 mln tCO2-eq in 2020

Source: Statistics Finland



Greenhouse gas emissions of Fingrid in 2020 Source: Fingrid

MAIN STRATEGIES

- De-carbonize power generation
  - Direct limits on emissions: EU Large Combustion Plant Directive (LCPD, 2001/80/EC)
  - Nuclear energy
  - Green energy
- Smart grids
- Grid-scale storage
- Electrification
- Policies affecting demand: EU Emissions Trading Scheme (from 2005)

Photo by Daniel Zacatenco on Unsplash

NITROGEN DIOXIDE (NO_2)

NITROGEN DIOXIDE (NO_2) POLLUTION

- NO_2 and NO_x are highly reactive pollutants
- Harmful to humans (respiratory system) and the environment (acid rains, air quality, water nutrient pollution)
- Primarily produced during combustion (transport, coal- and gas power, forest fires)
- Short-lived in the atmosphere (few hours), converts to other pollutants through photochemical reactions

Source: EPA, NOAA

Photo by Marcin Jozwiak on Unsplash

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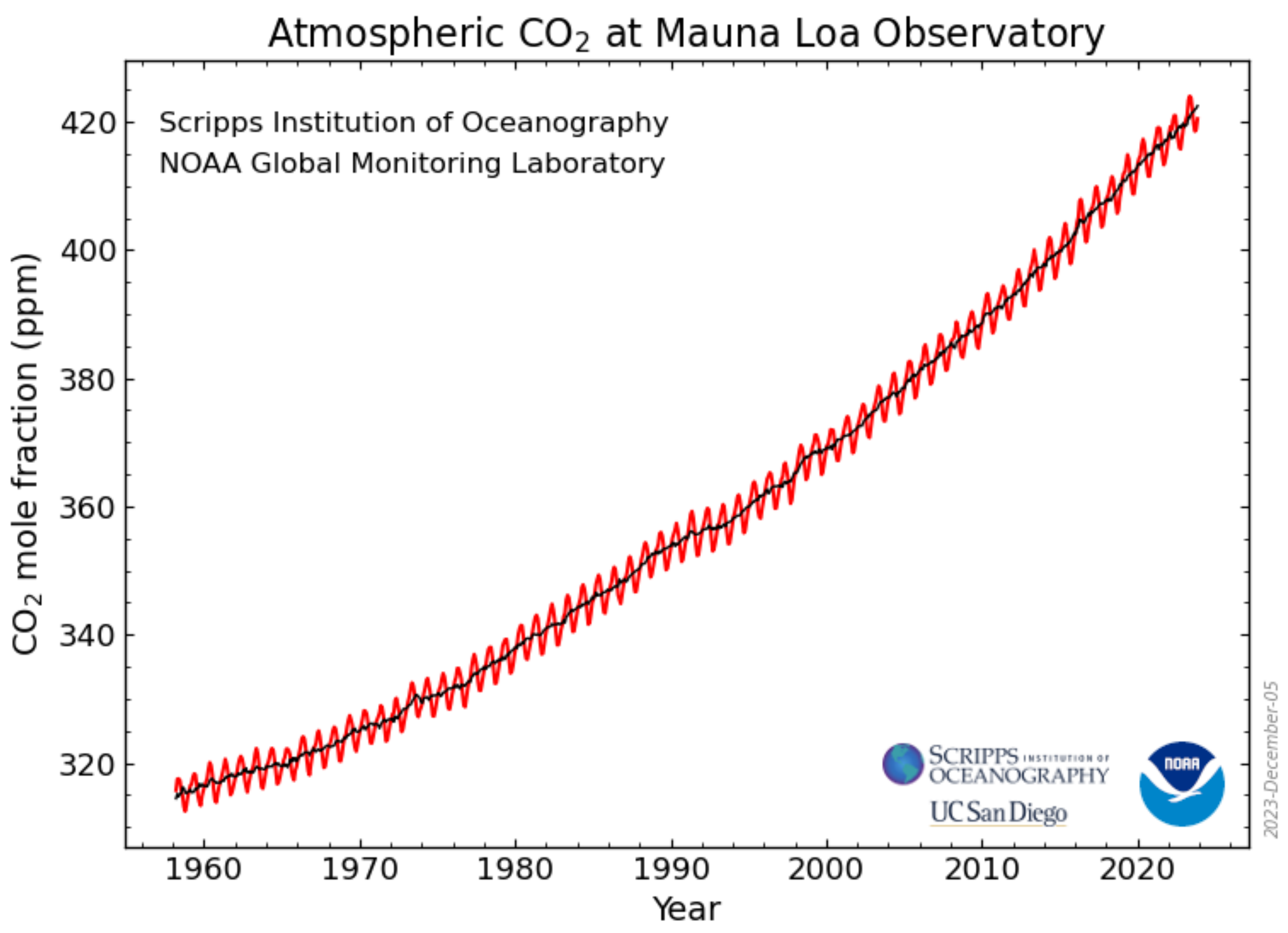
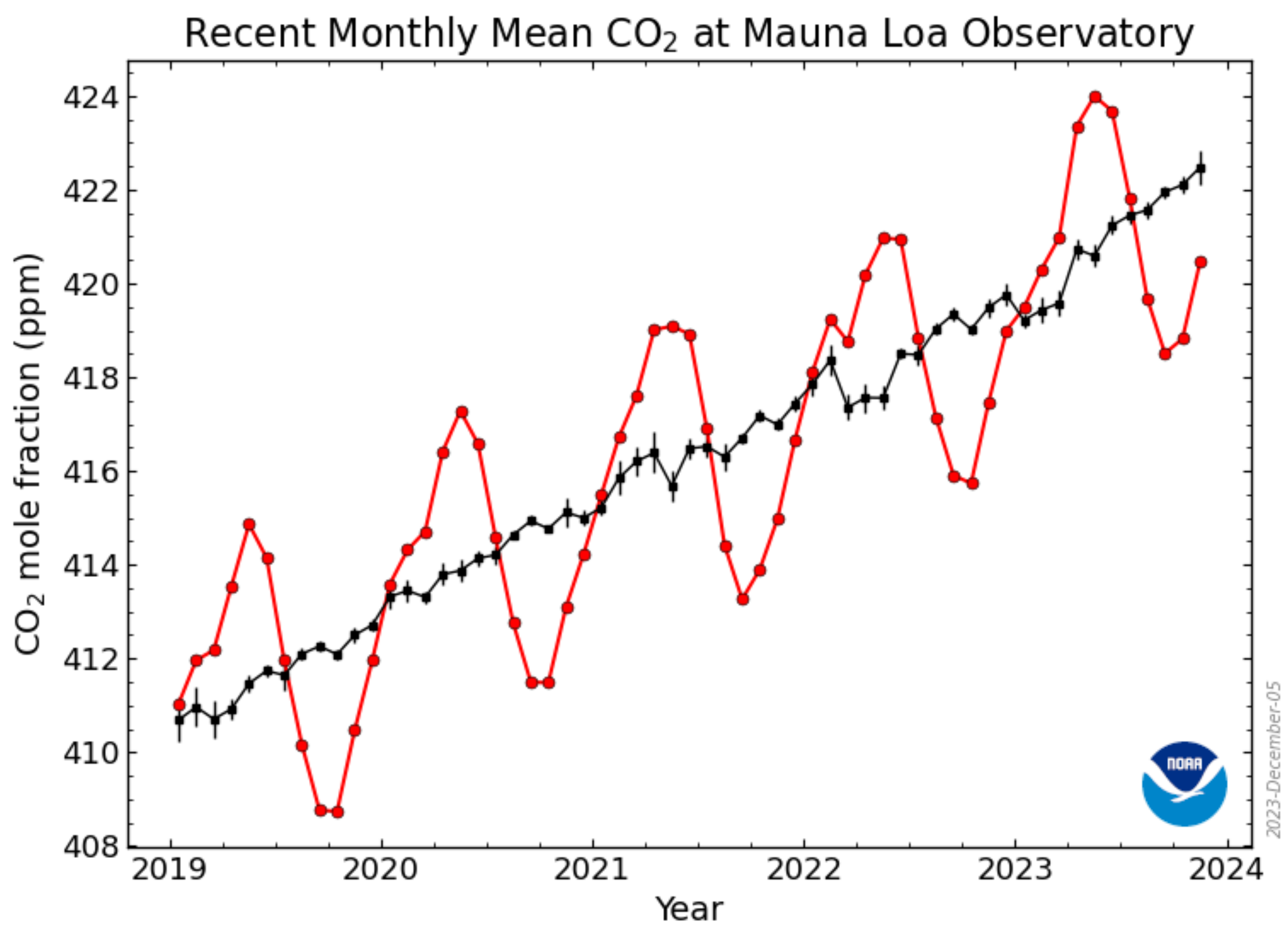
NO_2 is widely assumed to be a robust proxy for combustion CO_2

-D. P. Finch, P. I. Palmer, and T. Zhang (2022)

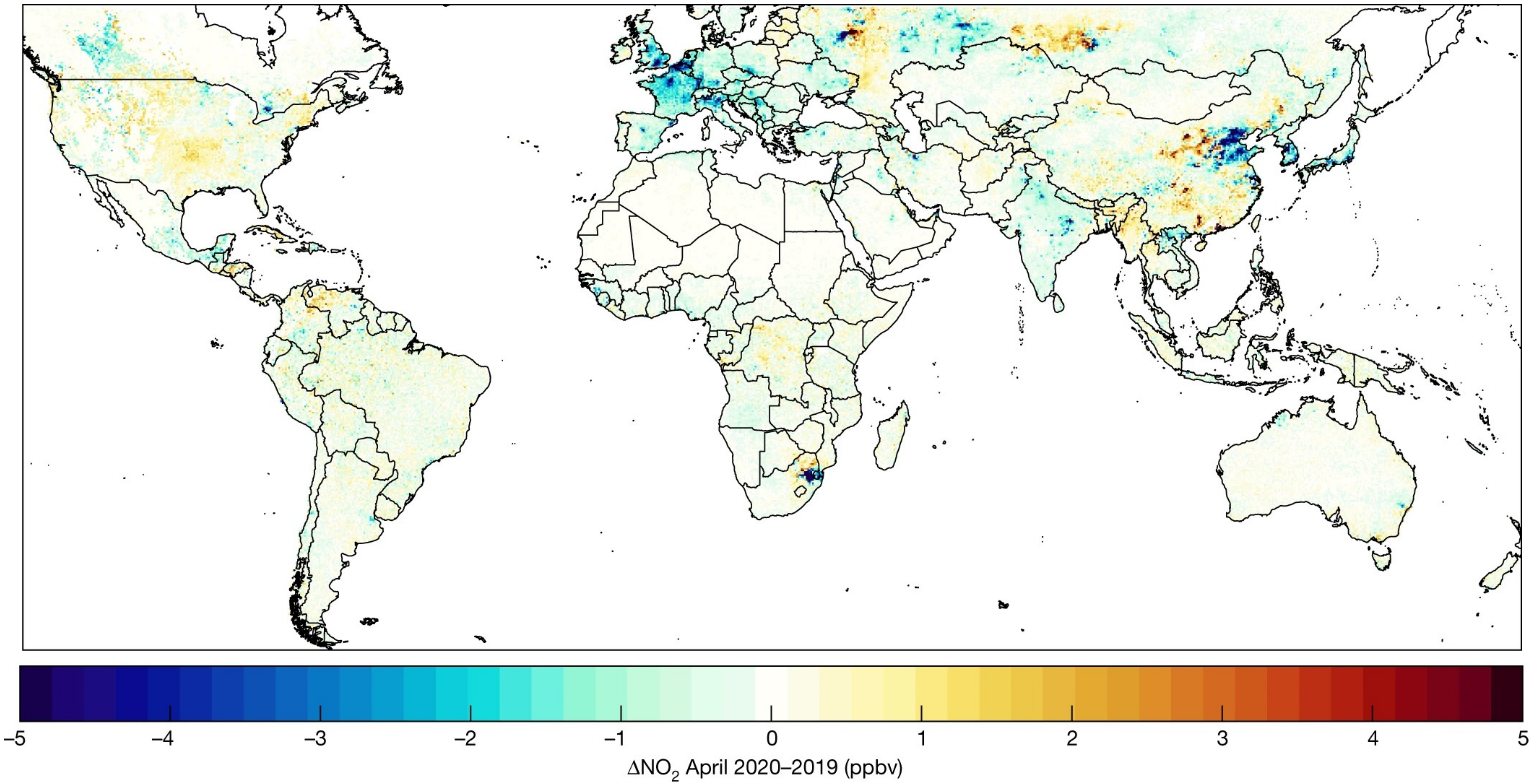
ATMOSPHERIC CONCENTRATION OF CO_2 DID NOT DECREASE DURING COVID





The carbon dioxide data on Mauna Loa constitute the longest record of direct measurements of CO2 in the atmosphere.

ATMOSPHERIC CONCENTRATION OF NO_2 DETECTABLE USING SENTINEL 5 DATA



Differences in April mean ground-level NO_2 from 2020 to 2019 at 1x1 km2 resolution

Source: Cooper et al. (2022)

DIFFERENCE IN SATELLITE OBSERVATIONS

- NO_2 (ESA Sentinel 5) - 2600 km swath, 7x3.5 km2 per pixel
- CO_2 (NASA OCO-2) - 10 km swath, 1.29x2.25 km2 per pixel

AUTOMATIC DETECTION OF NO_2 PLUMES

D. P. Finch, P. I. Palmer, and T. Zhang. *Automated detection of atmospheric NO2 plumes from satellite data: a tool to help infer anthropogenic combustion emissions*. Atmospheric Measurement Techniques, 15(3):721–733, 2022.

MOTIVATION

- Objective CO_2 monitoring is needed to limit long-term temperature rise
  - Accuracy of self-reported emissions is questionable
  - Disproportionate role of few super-emitters
  - New emission sources appear
- Satellite observations are used to study point sources of CO2 and methane emissions but not straightforward
- Idea: study traces of co-emitted gases, in particular, NO_2
- *Comment: this traces anthropogenic CO2 emissions but not the lifecycle of CO2 (oceans, forests, esp. tropics, poles)*

RESULT: CNN WITH 90% SUCCESS RATE CAPTURING 92% OF TOTAL CO_2 EMISSIONS

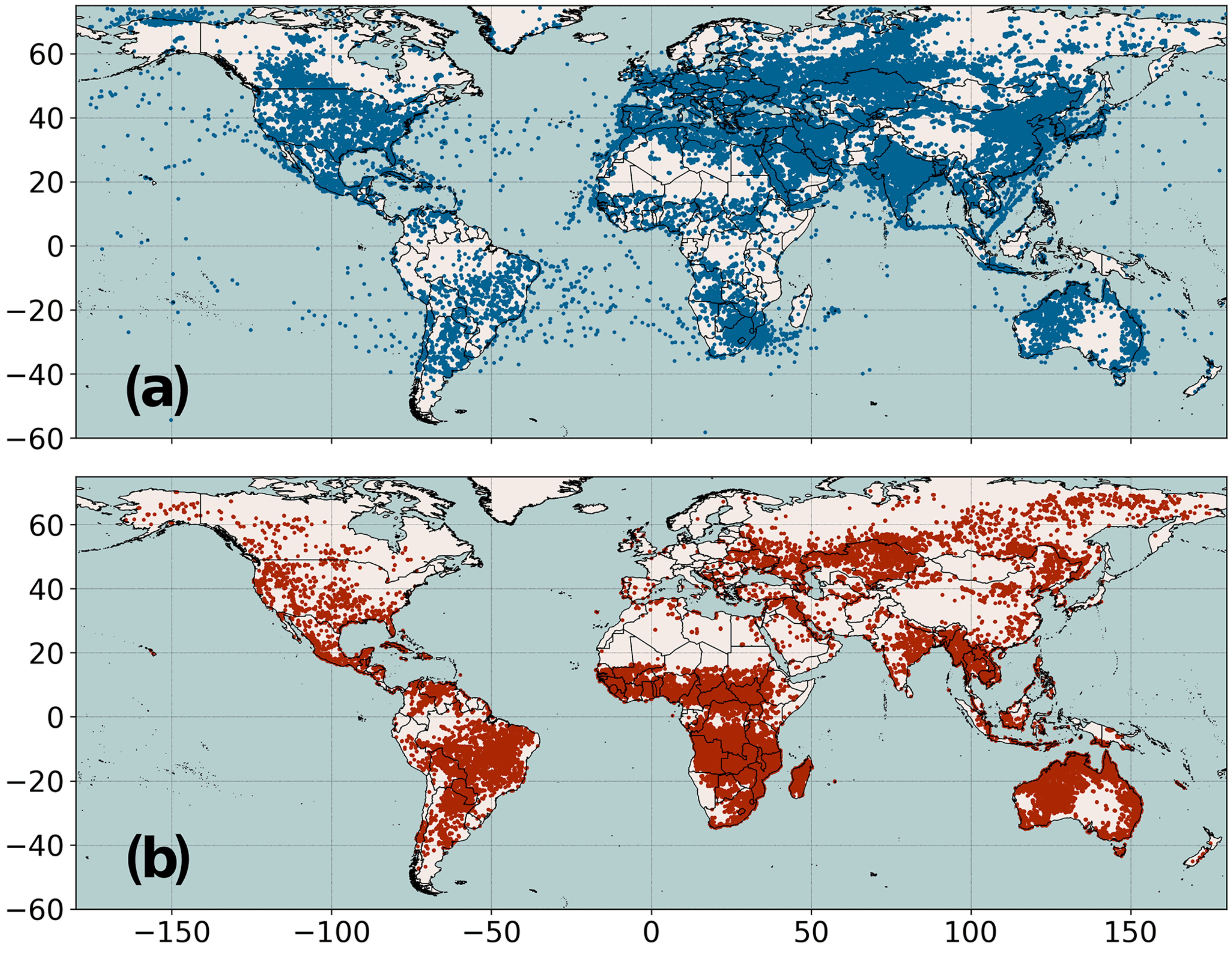
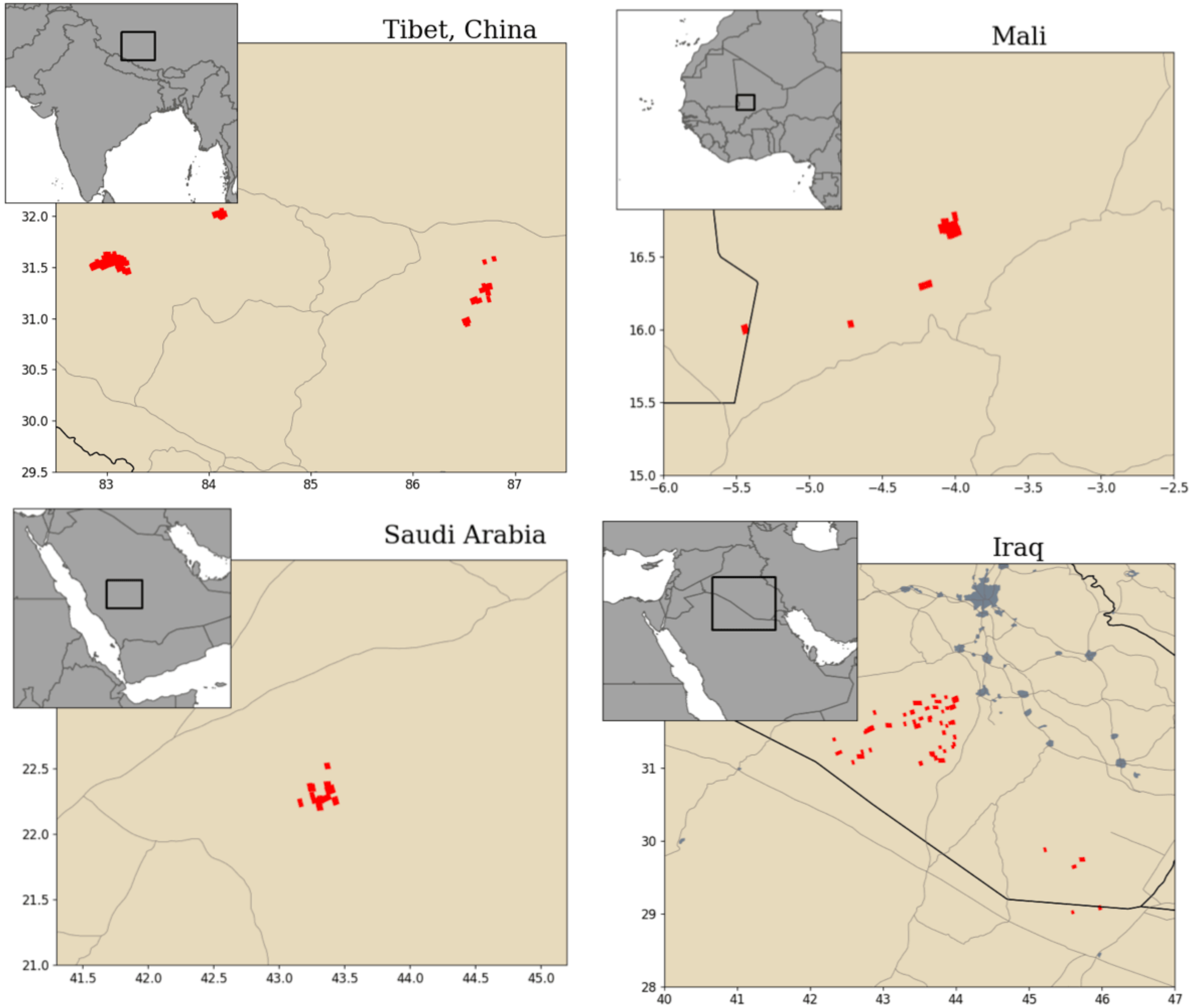


Figure: Geographical locations of individual TROPOMI NO2 plumes identified using a CNN model, July 2018–June 2020. We attribute these plumes to (a) anthropogenic combustion or (b) biomass burning, depending on whether the plume falls within 15 km of the nearest VIIRS thermal anomaly measurement.

Source: Finch et al. (2022)

IDENTIFIED 4 CLUSTERS OF NO_2 EMISSION SOURCES NOT VISIBLE IN THE CO_2 DATASET

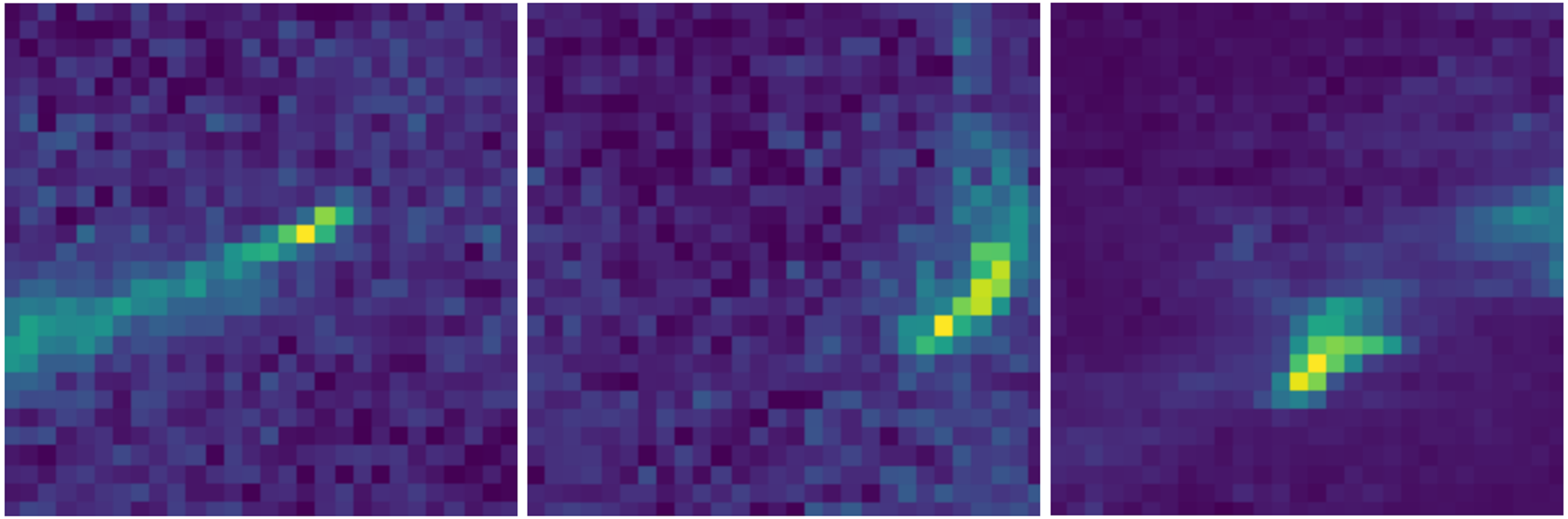


- Locations with plume clusters that are not associated with ODIAC CO_2 emissions
- The light-grey lines show major roads, and urban areas are shown by grey patches.
- Conjecture: true identification of otherwise unknown fossil fuel extraction and processing sites

Source: Finch et al. (2022)

DATA

- Sentinel 5 (TROPOMI) 6 000 images (28 × 28 pixel, approx. 266km×133km) from July 2018 and June 2020, 310 000 individual NO_2 plumes
- VIIRS to separate sources of burning biomass (as proxy for fires)
- ODIAC Fossil Fuel CO_2 Emissions Dataset to verify sources of CO_2 emissions



Examples of individually normalised NO_2 plumes (Source: Finch et al., 2022)

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For the full chemistry simulations, the NO_2 and NO concentrations became almost null 40 km away from the point source due to the formation of O_3, whereas for the passive tracers simulation, the NO_2 concentrations remain significant even 57 km away from the source leading to a 200 % mismatch between the two configurations.

-I. Cheliotis et al.(2023)

IDEAS: HOW WOULD YOU RESOLVE THE ISSUE OF IDENTIFYING NO2 PLUMES?

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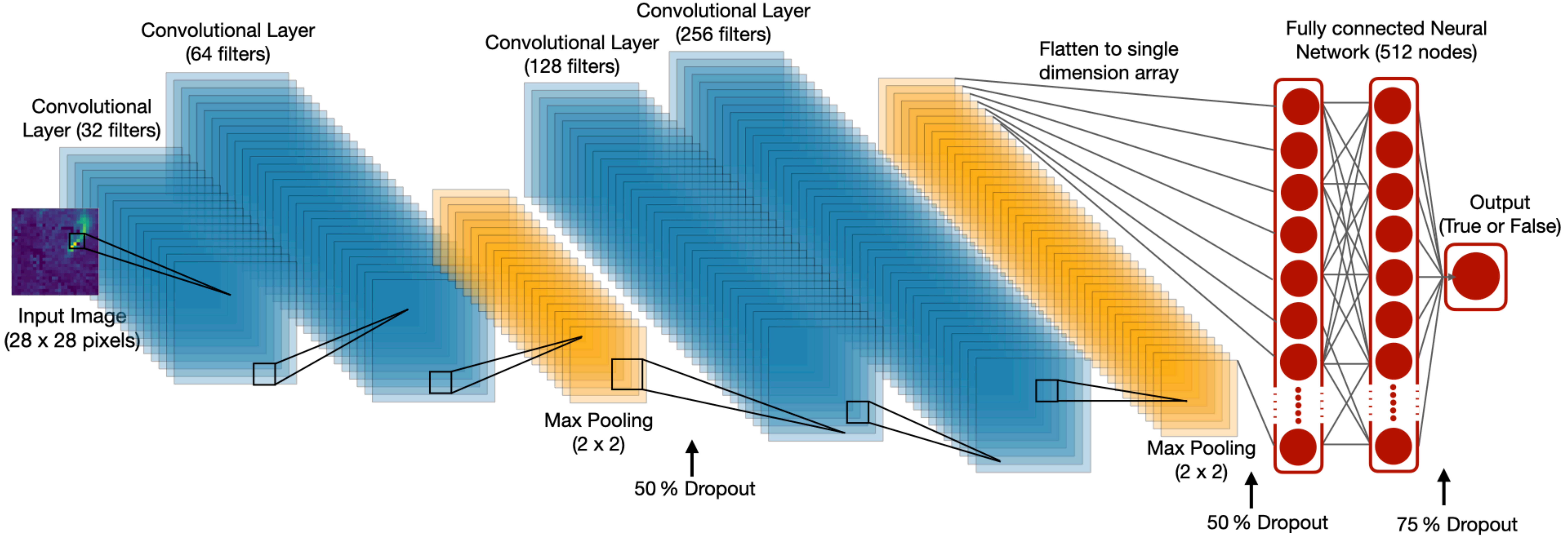
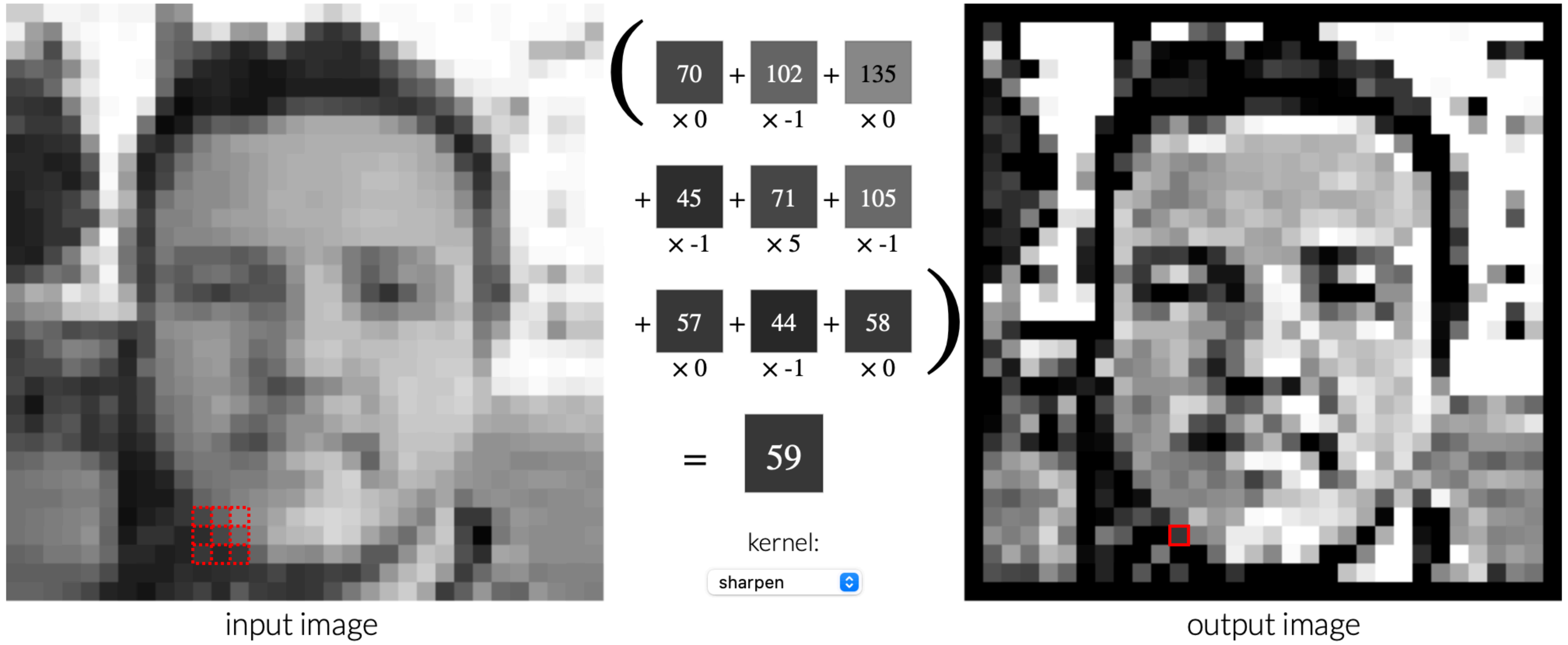
- Data sources
- Data collection methods
- Other learning algorithms

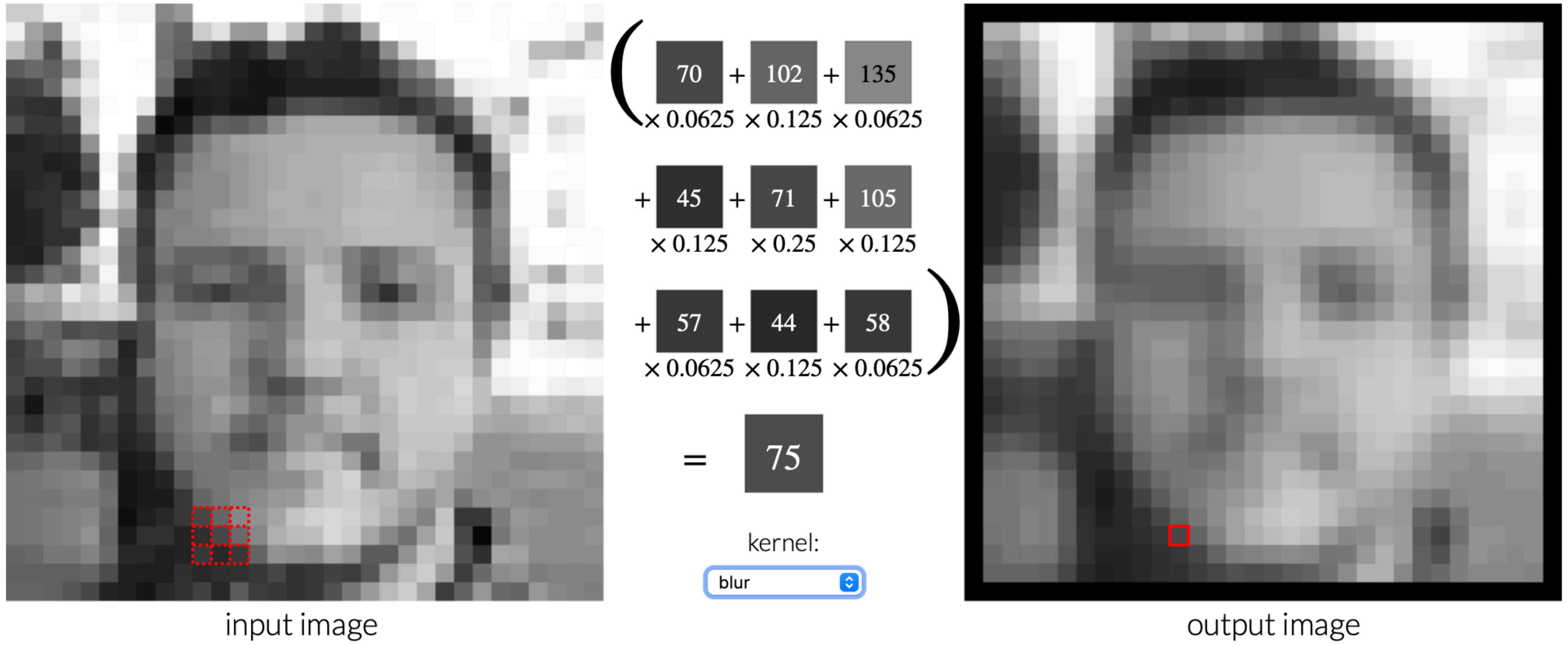
METHODOLOGY



Simplified scheme of the CNN for identifying NO_2 plumes. Source: Finch et al. (2022)

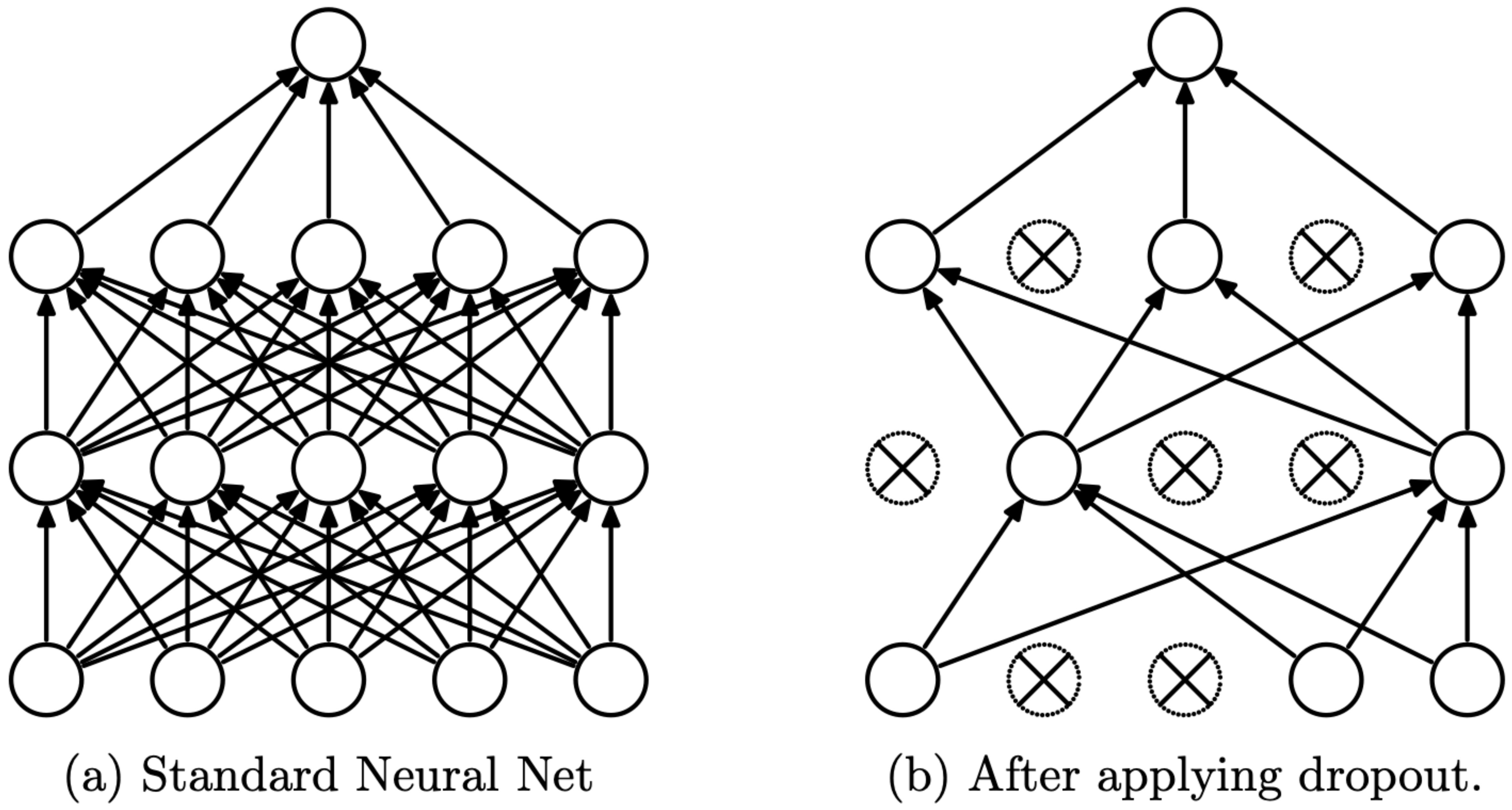
IMAGE KERNELS FOR FEATURE EXTRACTION





Source: https://setosa.io/ev/image-kernels/

DROP-OUT



Left: A standard neural net with 2 hidden layers. Right: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped. Source: Srivastava et al. (2014)

- Reduce overfitting by randomly dropping units during the training of a neural network

PAIRS: WHAT OTHER RESEARCH QUESTIONS COULD YOU STUDY USING SATELLITE NO_2 DATA?

- Climate action
- Your domain

LEARNING MATERIALS FOR CNNS

- CS-EJ3311 - Deep learning with Python (2023)
  - Online lecture available on MyCourses
  - Detailed Jupyter Notebook on the course's JupyterHub
- Basic tutorial: https://www.tensorflow.org/tutorials/images/cnn (also loaded on Aalto JupyterHub)
- Free access to books via O'Reilly: F. Chollet, "Deep Learning with Python" or A. Géron, "Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow"
- Mathematical intro: Higham, Catherine F., and Desmond J. Higham. "Deep learning: An introduction for applied mathematicians." *SIAM Review* 61.4 (2019): 860-891.

BEFORE EXERCISE SESSION 2

- Try CNN tutorial (JupyterHub/Assignment List/cnn-tutorial)
- Make sure plumes have random identifiers and the images are not corrupted
- If possible, upload one plume image today

https://spaceworkshop.fi/