



# MACHINE LEARNING FOR CLIMATE ACTION

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*CS-E407519 Lecture 1*



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# OUTLINE

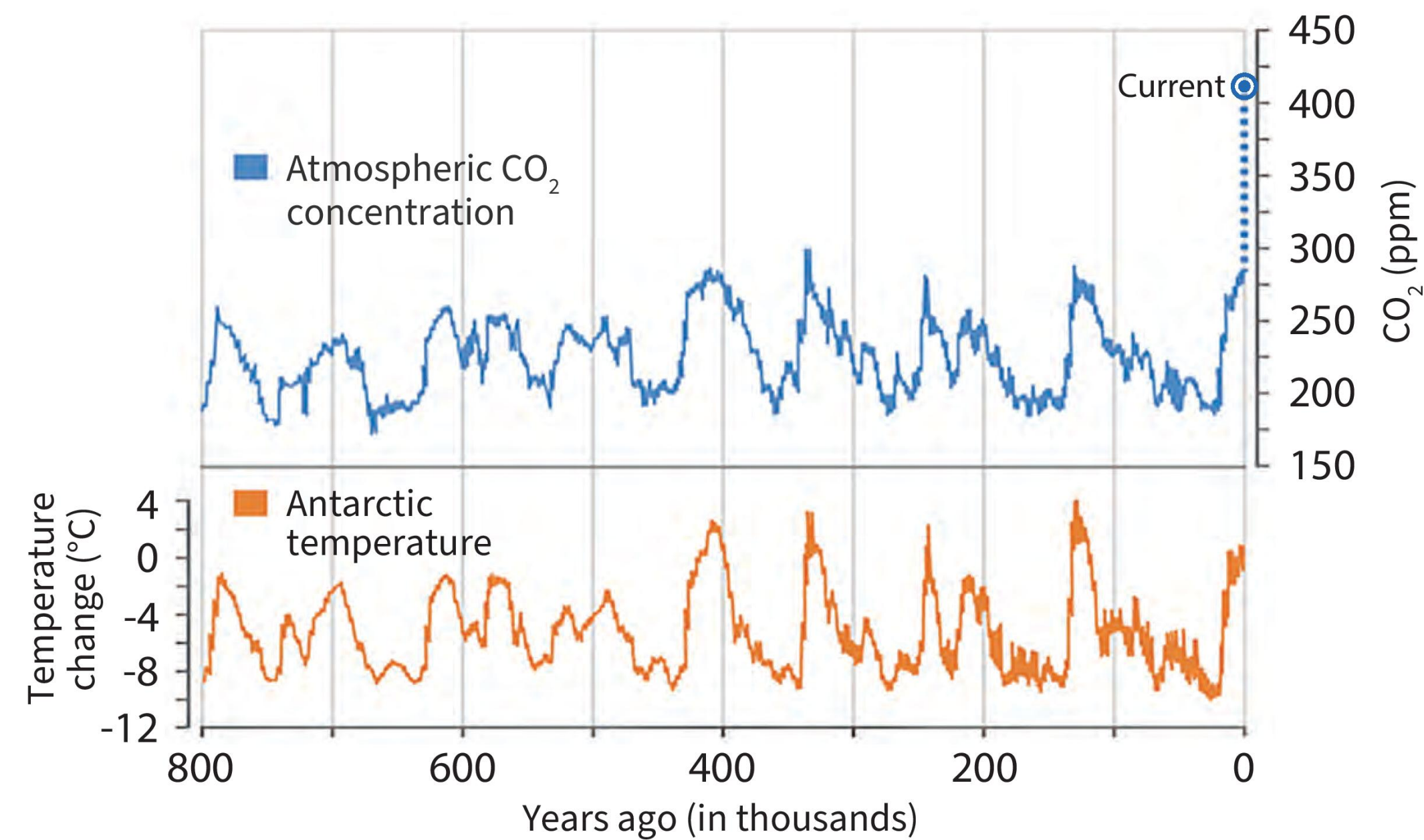
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- **Background for climate action**
  - Why are we here?
  - Macro picture for climate action
  - Challenges of measuring and modelling climate change
- **Role of ML in climate action**
  - Potential positive and negative impact of ML on climate action
  - ML methods covered in the course
- **Practicalities and expectations**

**WHY ARE WE HERE?**

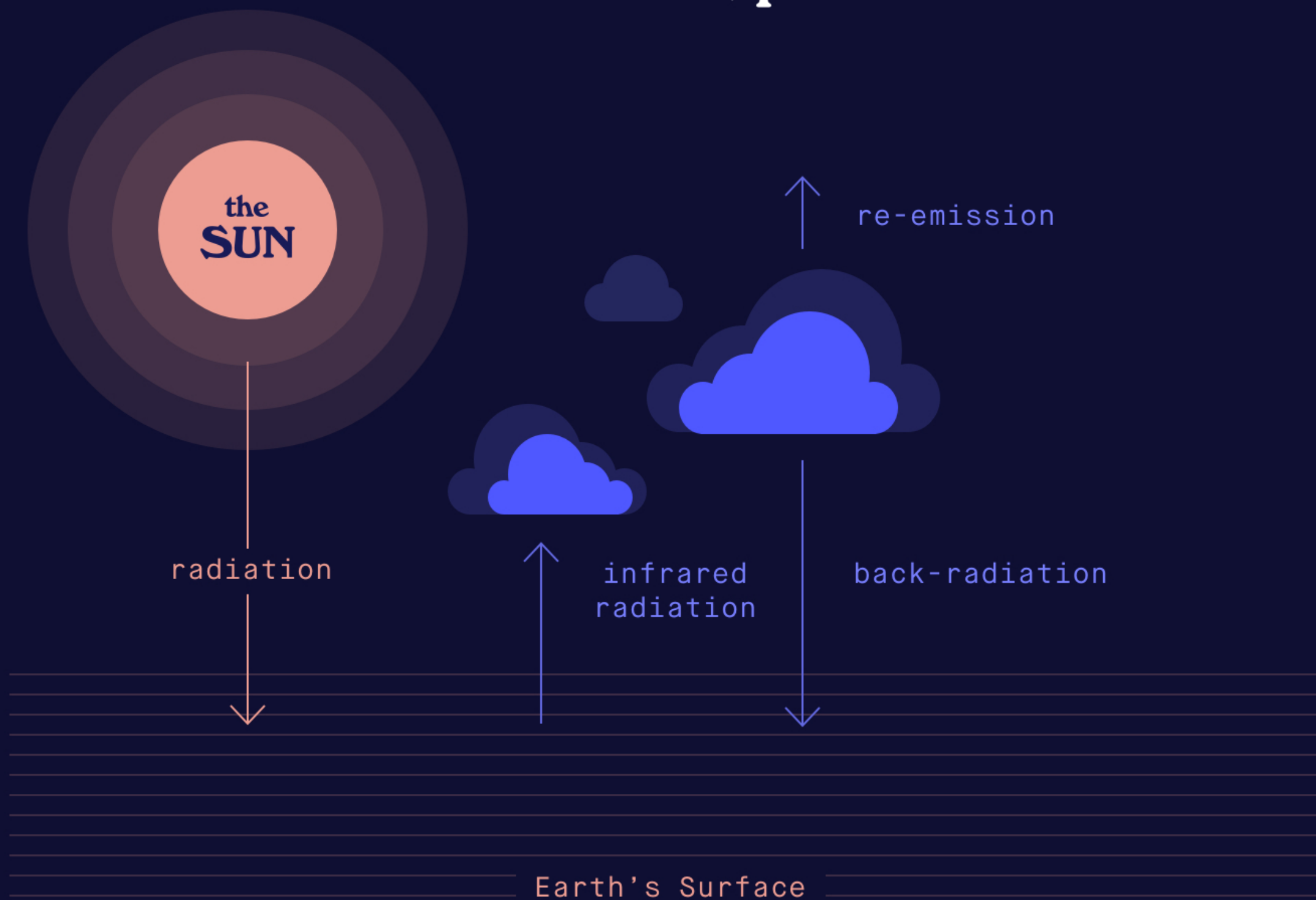
# UNPRECEDENTED INCREASE IN CO<sub>2</sub>

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*Source: The Royal Society, based on figure by Jeremy Shakun, data from Lüthi et al., 2008 and Jouzel et al., 2007.*

**Earth's surface receives radiation from both the Sun, and the greenhouse gases and clouds in the atmosphere.**



## GREENHOUSE GASES

- Natural greenhouse affect maintains the average Earth temperature of 15° C
- If carbon dioxide was removed completely, the temperature would drop by 33° C
- Main greenhouse gases - total of 53.8 Gt CO<sub>2</sub> eq (CO<sub>2</sub> eq is the amount of heat an equal amount of CO<sub>2</sub> would be expected to trap over the next 100 years):
  - Carbon dioxide (CO<sub>2</sub>) - 71.6%
  - Methane (CH<sub>4</sub>) - 21%
  - Nitrous oxide (N<sub>2</sub>O) - 4.8%
  - Fluorinated gases - 2.6%

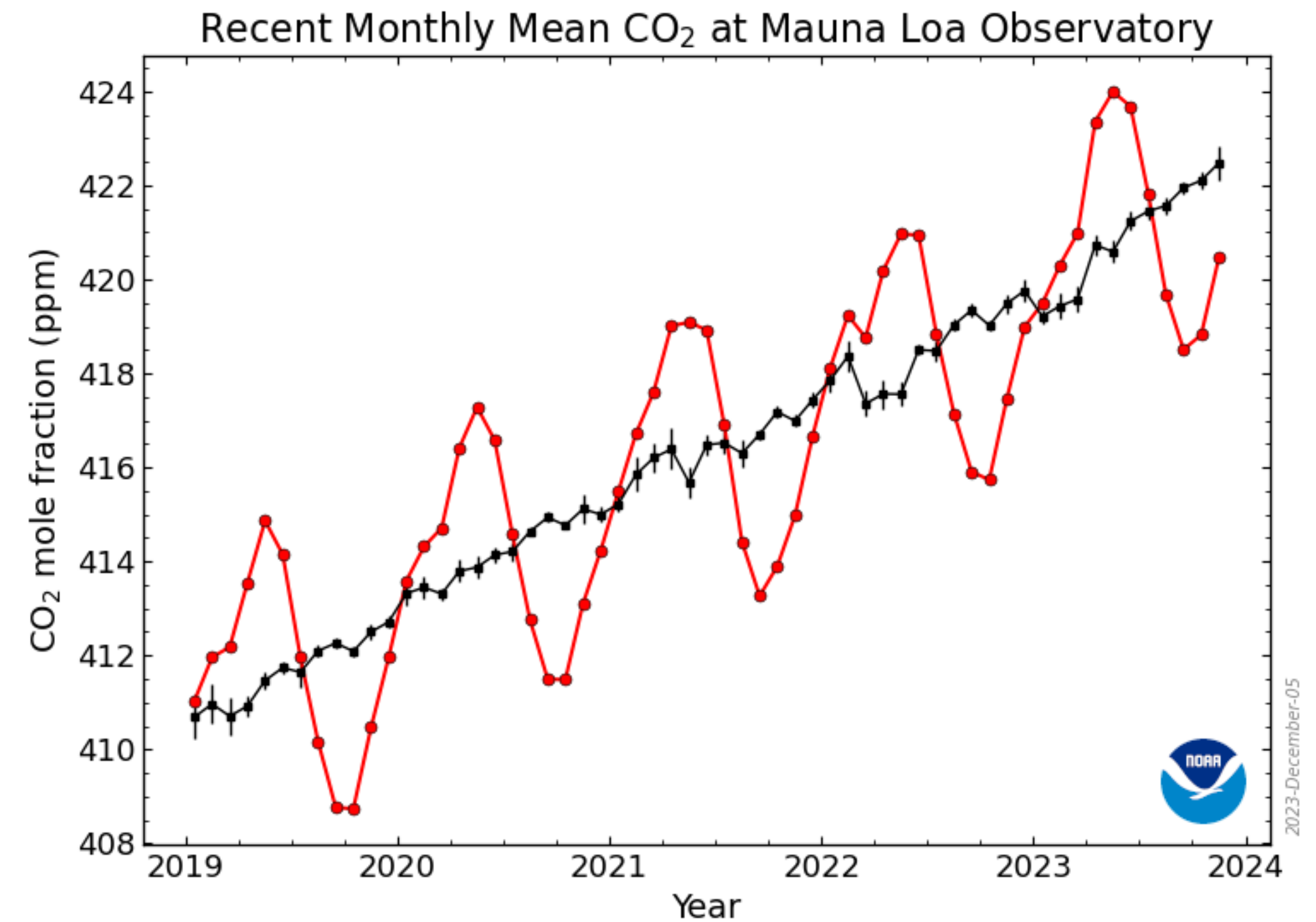
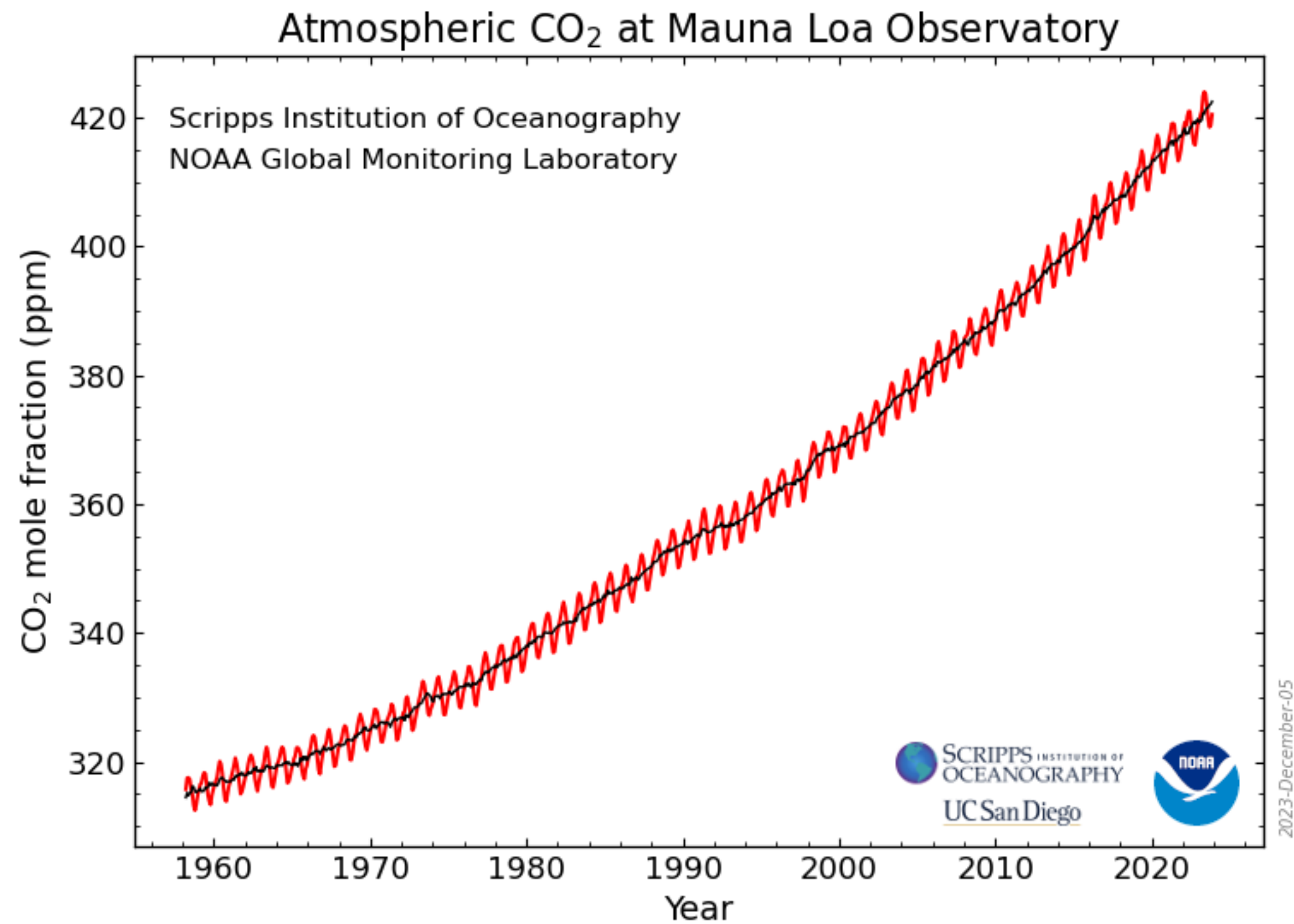
# POLL: DID THE LEVEL OF ATMOSPHERIC CO<sub>2</sub> GO DOWN DURING THE PANDEMIC?

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# NO PHOTOCHEMICAL DESTRUCTION OF ATMOSPHERIC CO<sub>2</sub>



*The carbon dioxide data on Mauna Loa constitute the longest record of direct measurements of CO<sub>2</sub> in the atmosphere.*



# CARBON DIOXIDE (CO<sub>2</sub>)

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- In 2022: 38.5 Gt emissions in 2022 (71.6% of all GHG emissions) and 3236.4 Gt in the atmosphere
- Long lifetime in the atmosphere:
  - 40% remains after 100s of years
  - 20% after 1000s of years
  - 10% after 10000s of years
- Industries rely on carbon-rich fuels
- Difficult to monitor: annual anthropogenic emissions about 1.2% of atmospheric concentration, seasonality

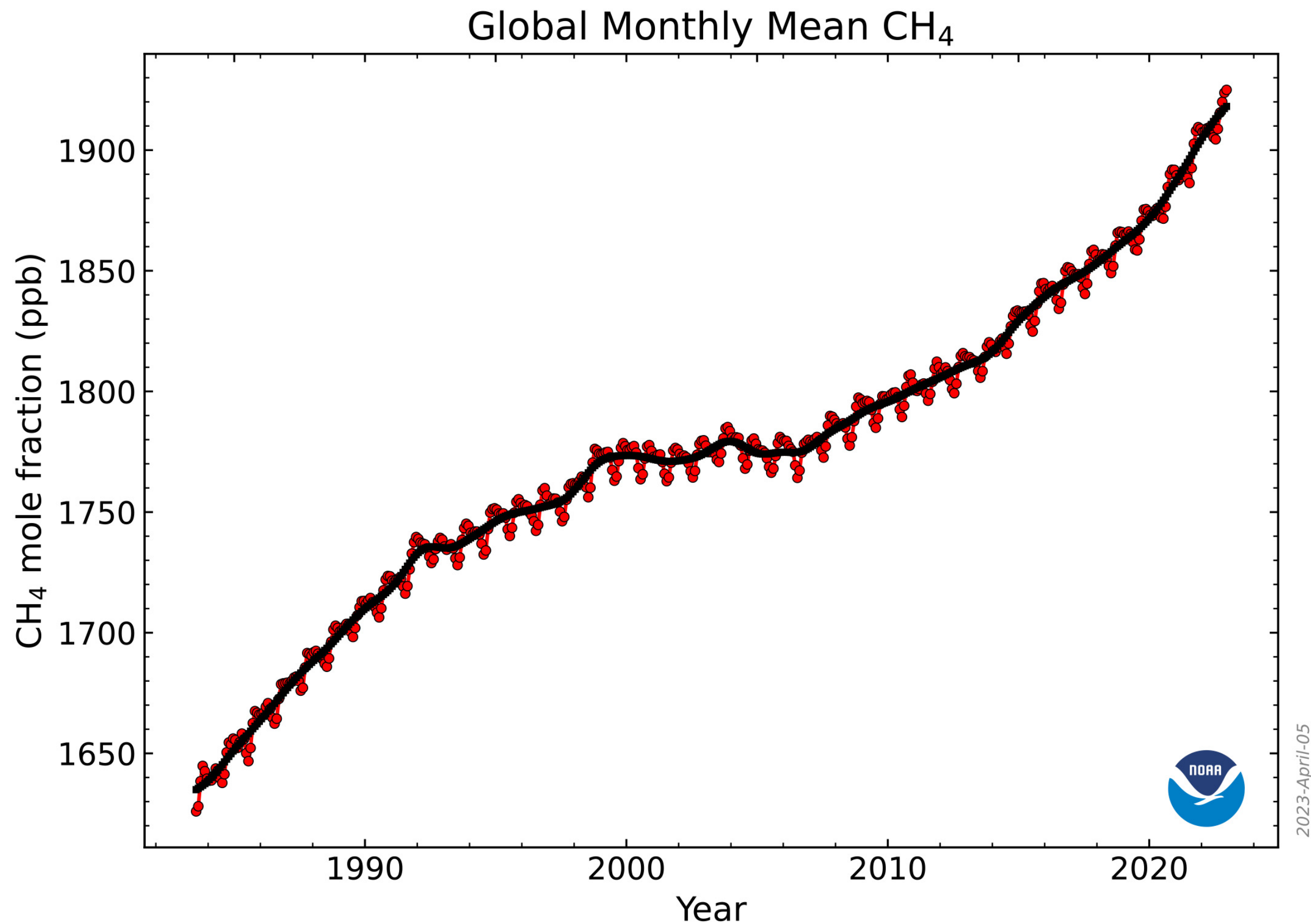


*Sources: NRDC 2023, Crippa et al. 2023, NOAA 2023*

*Photo by Jas Min on Unsplash*

# METHANE (CH<sub>4</sub>)

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This graph shows the globally-averaged, monthly mean atmospheric methane abundance determined from marine surface sites since the inception of NOAA measurements starting in 1983. (Image credit: NOAA Global Monitoring Laboratory)

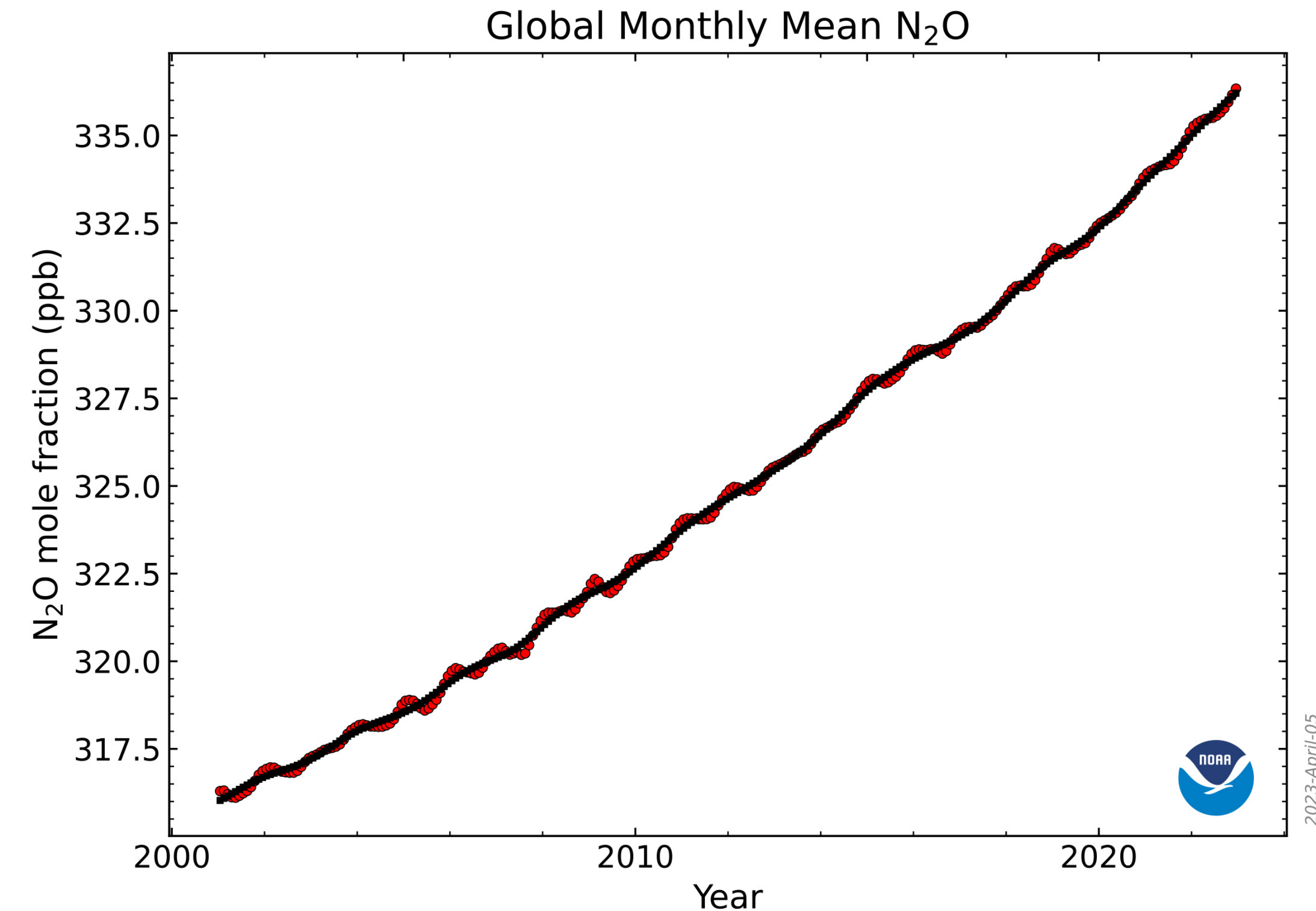
Sources: NOAA 2023, MIT Climate Portal

- 28 CO<sub>2</sub> eq: reflects 100x more heat than CO<sub>2</sub> but lifetime 10 years
- Cause of increase from 2006 is not fully known:
  - 85% is attributed to livestock, agriculture, waste, wetlands and aquatic sources.
  - Rest attributed to fossil fuel emissions (leaks from gas wells and pipes)
  - Possibly a feedback loop? (Warmer climate causes more methane emissions which in turn warms the climate)

# NITROUS OXIDE (N<sub>2</sub>O)

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- 273 CO<sub>2</sub> eq: stays in the atmosphere for 100s of years
- Main source: nitrogen-based fertilizers in agriculture. Other sources: industrial activities, combustion of fossil fuels and solid waste, treatment of wastewater



This graph shows the globally-averaged, monthly mean atmospheric nitrous oxide abundance determined from marine surface sites since 2001. (Image credit: NOAA Global Monitoring Laboratory)

*Sources: NOAA 2023, MIT Climate Portal*



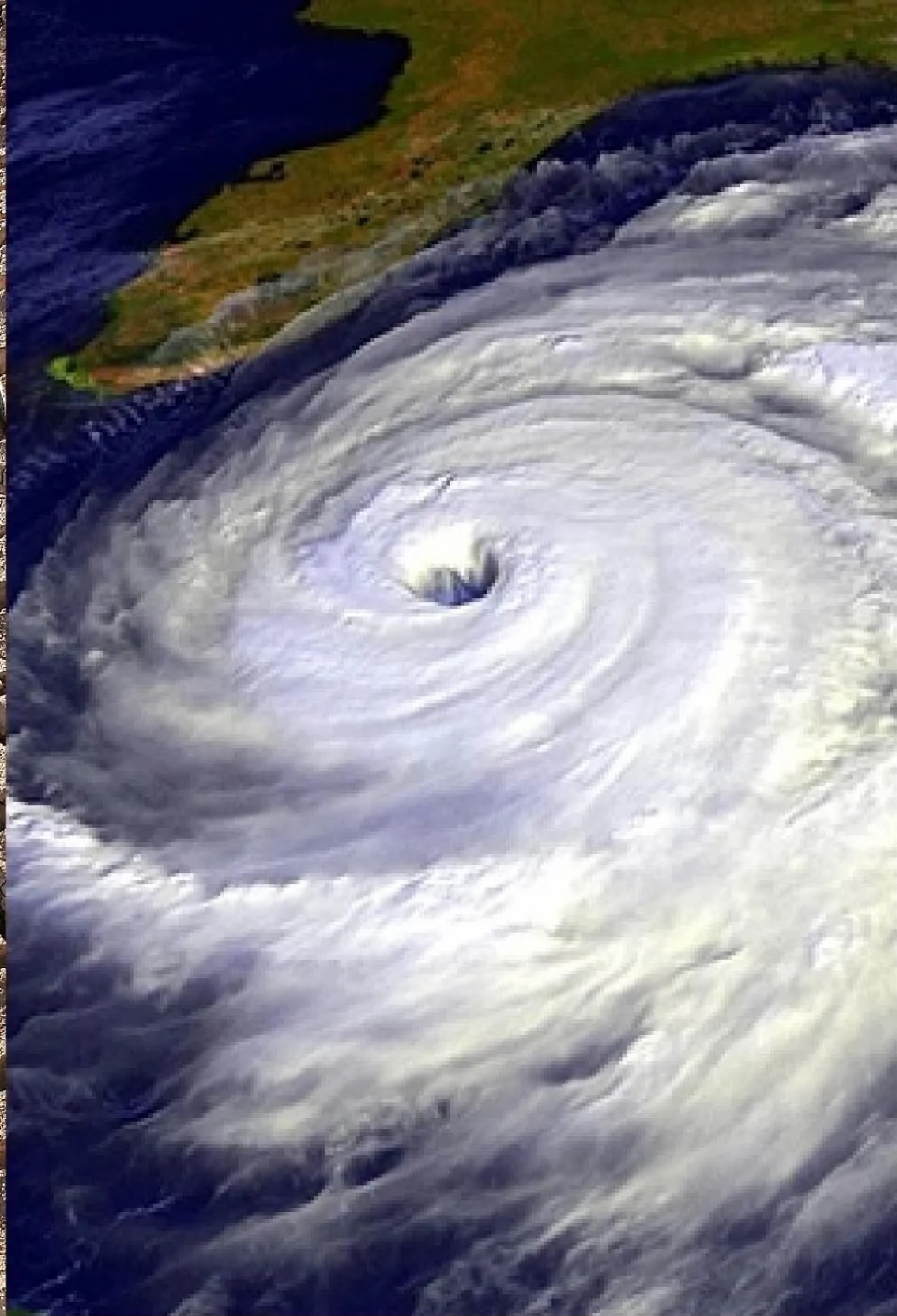
# FLUORINATED GASES ('F-GASES')

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- Many gases: hydrofluorocarbons (HFCs) - 90%, perfluorocarbons (PFCs), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3).
- Up to 14,600 CO<sub>2</sub> eq
- Used in refrigerators, air conditioners and other industrial processes

*Sources: MIT Climate Portal*

*Photo by Eduardo Soares on Unsplash*



*Photo: NASA (left - Mike McMillan/USFS, center - Tomas Castelazo / Wikimedia Commons / CC BY-SA 4.0, right - NASA)*

	Climate Driver	Exposure	Health Outcome	Impact
 <b>Extreme Heat</b>	More frequent, severe, prolonged heat events	Elevated temperatures	Heat-related death and illness	Rising temperatures will lead to an increase in heat-related deaths and illnesses.
 <b>Outdoor Air Quality</b>	Increasing temperatures and changing precipitation patterns	Worsened air quality (ozone, particulate matter, and higher pollen counts)	Premature death, acute and chronic cardiovascular and respiratory illnesses	Rising temperatures and wildfires and decreasing precipitation will lead to increases in ozone and particulate matter, elevating the risks of cardiovascular and respiratory illnesses and death.
 <b>Flooding</b>	Rising sea level and more frequent or intense extreme precipitation, hurricanes, and storm surge events	Contaminated water, debris, and disruptions to essential infrastructure	Drowning, injuries, mental health consequences, gastrointestinal and other illness	Increased coastal and inland flooding exposes populations to a range of negative health impacts before, during, and after events.
 <b>Vector-Borne Infection</b> (Lyme Disease)	Changes in temperature extremes and seasonal weather patterns	Earlier and geographically expanded tick activity	Lyme disease	Ticks will show earlier seasonal activity and a generally northward range expansion, increasing risk of human exposure to Lyme disease-causing bacteria.
 <b>Water-Related Infection</b> ( <i>Vibrio vulnificus</i> )	Rising sea surface temperature, changes in precipitation and runoff affecting coastal salinity	Recreational water or shellfish contaminated with <i>Vibrio vulnificus</i>	<i>Vibrio vulnificus</i> induced diarrhea & intestinal illness, wound and bloodstream infections, death	Increases in water temperatures will alter timing and location of <i>Vibrio vulnificus</i> growth, increasing exposure and risk of water-borne illness.
 <b>Food-Related Infection</b> ( <i>Salmonella</i> )	Increases in temperature, humidity, and season length	Increased growth of pathogens, seasonal shifts in incidence of <i>Salmonella</i> exposure	<i>Salmonella</i> infection, gastrointestinal outbreaks	Rising temperatures increase <i>Salmonella</i> prevalence in food; longer seasons and warming winters increase risk of exposure and infection.
 <b>Mental Health and Well-Being</b>	Climate change impacts, especially extreme weather	Level of exposure to traumatic events, like disasters	Distress, grief, behavioral health disorders, social impacts, resilience	Changes in exposure to climate- or weather-related disasters cause or exacerbate stress and mental health consequences, with greater risk for certain populations.

# IMPACT OF CLIMATE CHANGE

- Weather
- Environment
- Agriculture
- Animals
- Humans

Figure by Crimmins et al. (2016)

# POLL: WHAT IS THE CURRENT TEMPERATURE GOAL FOR GLOBAL WARMING?

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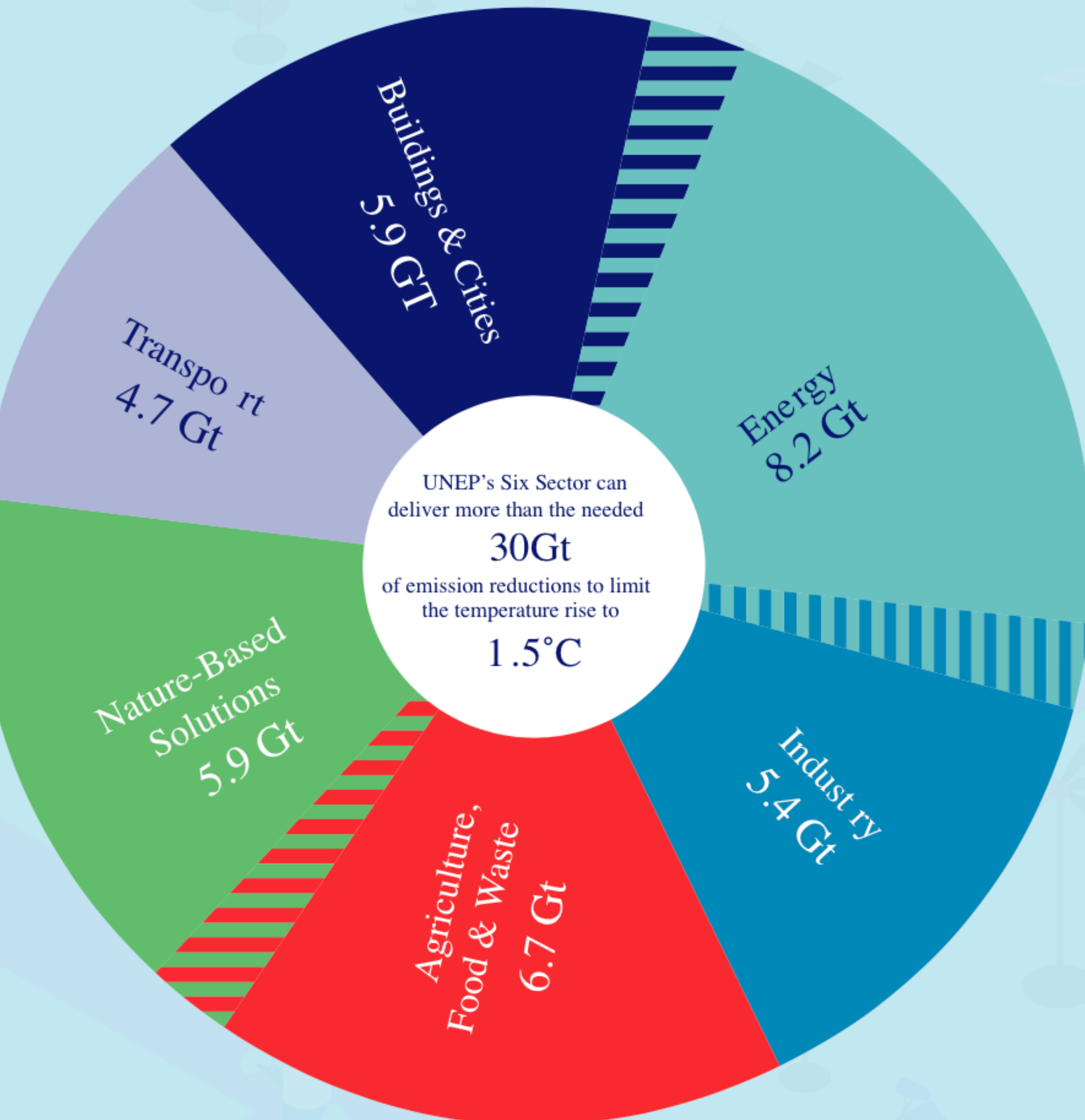


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# **MACRO PICTURE: INTRODUCE POLICIES AND MONITOR THEIR IMPACT**



# MAIN AGREEMENTS



- ▶ United Nations Framework Convention on Climate Change - UNFCCC (1992):
  - ▶ Multilateral treaty to stabilise anthropogenic GHG emissions, in force since 1994
  - ▶ Currently 198 parties
- ▶ Kyoto Protocol (1997):
  - ▶ Operationalises UNFCCC, binding for developed countries
  - ▶ 192 parties, in force since 2005
- ▶ Paris Agreement (2015):
  - ▶ Legally binding (196 parties, in force since 2016)
  - ▶ Hold the increase of global average temperature to well below 2°C above pre-industrial levels and limit the temperature increase to 1.5°C above pre-industrial levels (1°C was reached in 2017)
  - ▶ For 1.5°C: GHG emissions need to peak by 2015 and need to cut 30 Gt GHG emissions/year by 2030
  - ▶ Nationally determined contributions

Sources: UNEP, UNFCCC

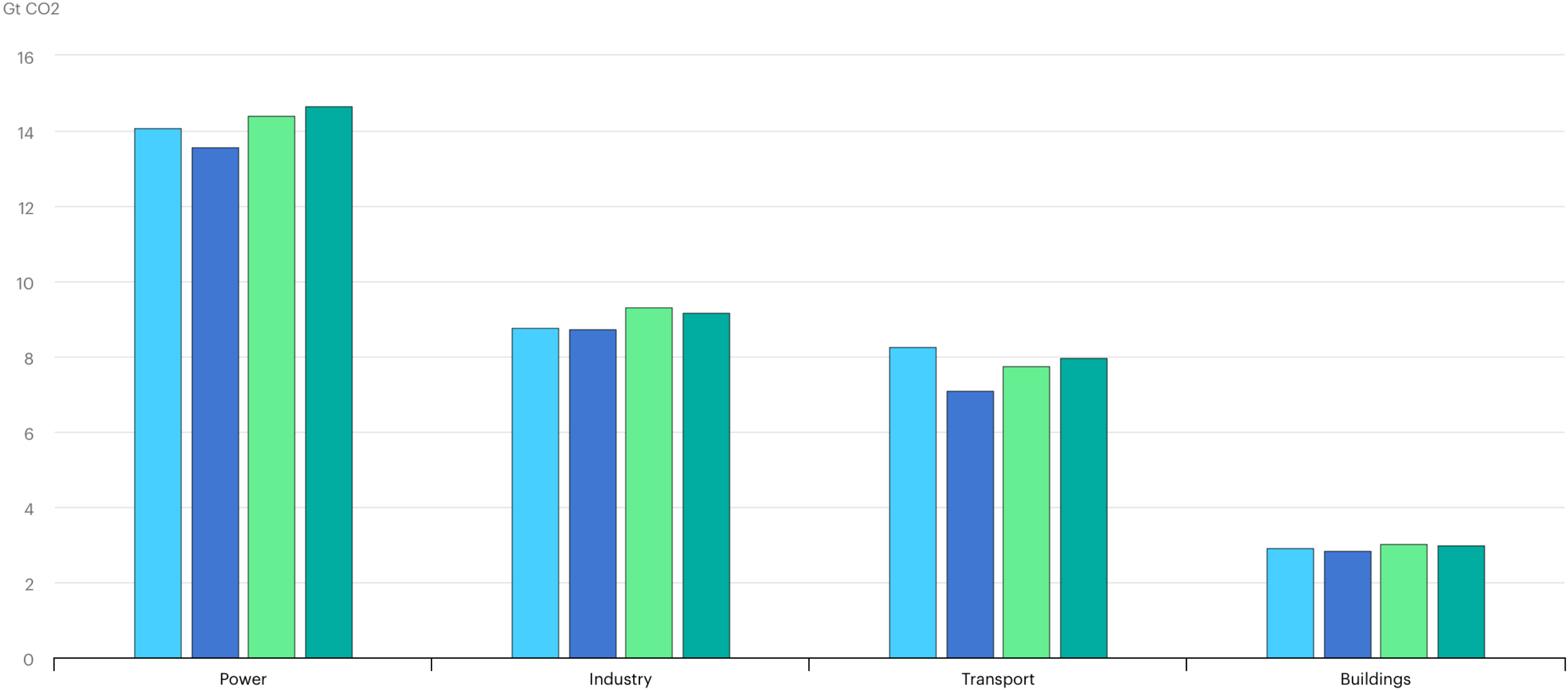
# POLL: WHICH SECTOR IS THE BIGGEST CONTRIBUTOR OF CO2 EMISSIONS GLOBALLY

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# GLOBAL CO2 EMISSIONS BY SECTOR



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● 2019 ● 2020 ● 2021 ● 2022

# CHALLENGES OF MEASURING AND MODELLING CLIMATE CHANGE

# MAIN CHALLENGES

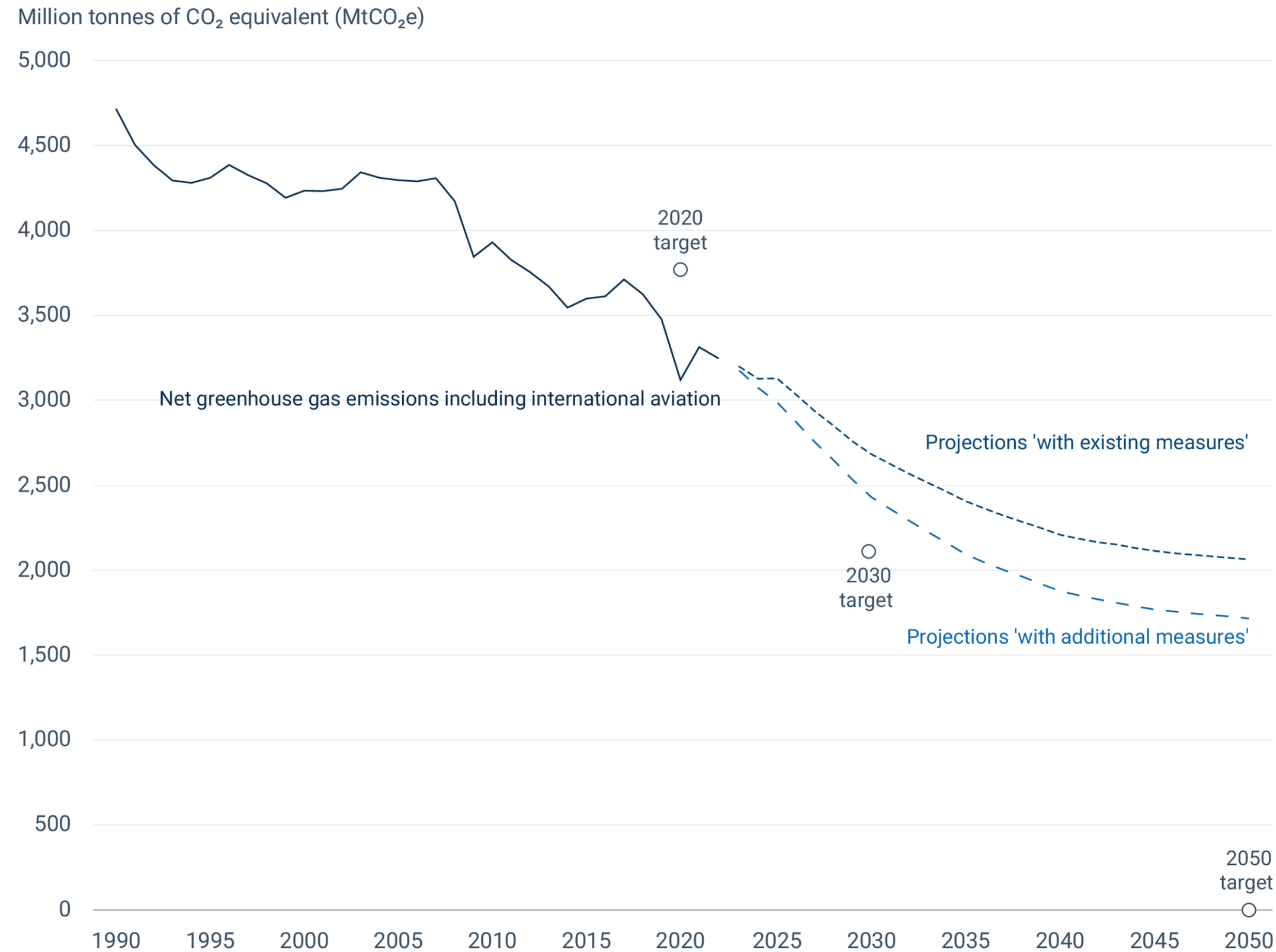


Figure: EEA - Progress towards achieving climate targets in the EU-27

- Modelling assumptions and interactions between variables
- Reliability and availability of data
- Conflicts of interest and maladaptation



# REMOTE SENSING

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- Objective
- Global
- Still: coverage, clouds, high background concentration, natural variation, noise

*Photo by NASA on Unsplash*

# THE COPERNICUS PROGRAMME

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The Copernicus Sentinel missions offer Earth observation data for applications such as climate change monitoring and natural disaster response.

- Sentinel-1: images Earth's surface through rain and cloud regardless of whether it is day or night.
- Sentinel-2: carries a high-resolution multispectral optical imager to monitor changes in vegetation.
- Sentinel-3: supplies data related mainly to the marine environment.
- Sentinel-4: is an ultraviolet, visible and near-infrared spectrometer.
- Sentinel-5P: carries the Tropomi imaging spectrometer to provide information on trace gases (NO<sub>2</sub>, CO, CH<sub>4</sub>, ...) and aerosols affecting air quality and climate.



# MONITORING CO<sub>2</sub> EMISSIONS

- OCO-2 (Orbiting Carbon Observatory-2): was launched in 2014 by NASA. It monitors global CO<sub>2</sub> concentrations.
- OCO-3 was launched in 2019, mounted on the International Space Station (ISS). It is a follow-up mission to OCO-2. Being at ISS, it allows for more targeted observations, measuring specific cities or regions



*OCO-2 and OCO-3 overpass on April 17, 2020*



# METHANE HOTSPOTS DETECTED WITH COPERNICUS SENTINEL-5P (TROPOMI)

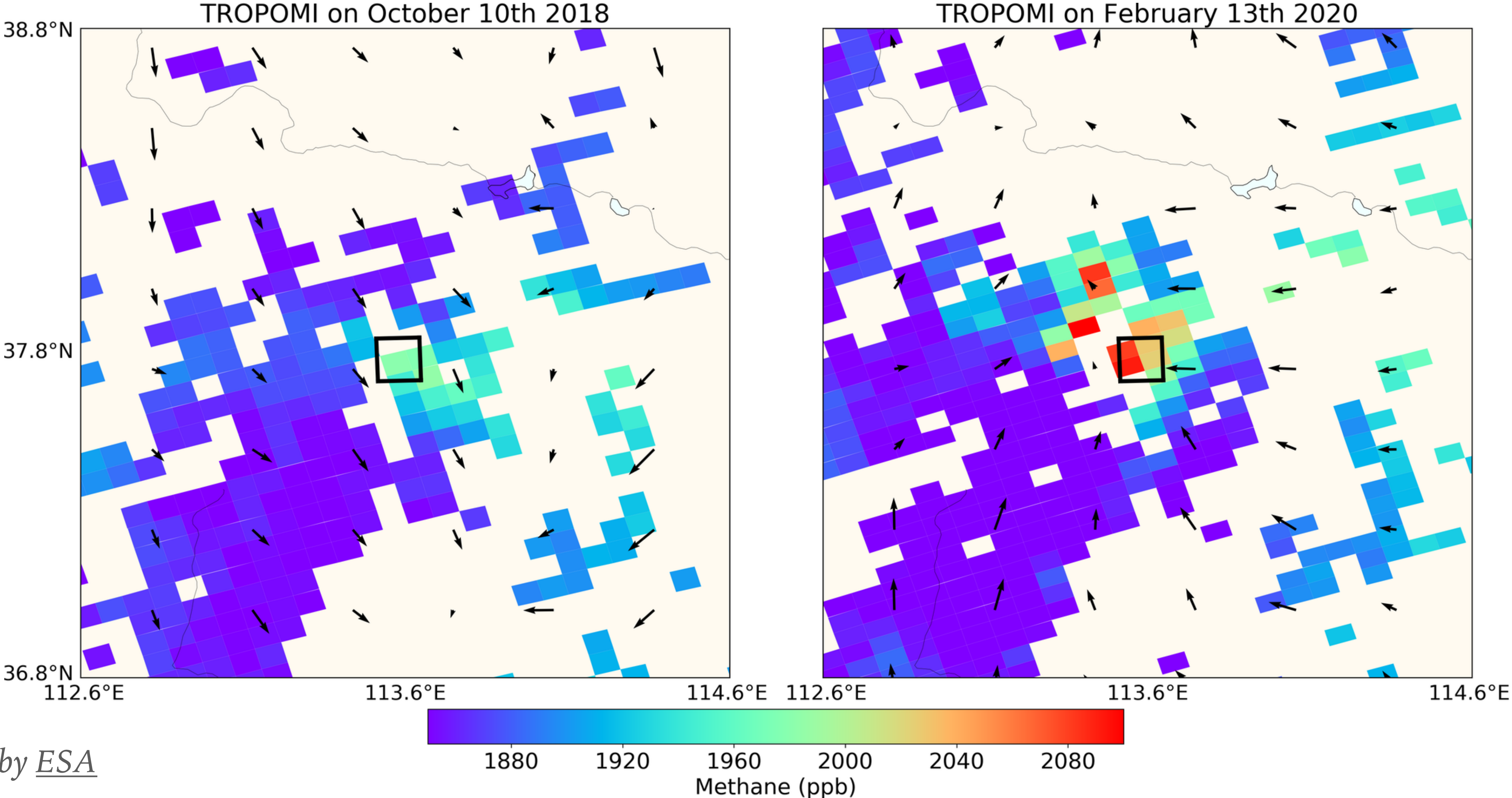


Image by ESA

# ROLE OF ML IN CLIMATE ACTION

# MACHINE LEARNING

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➤ Components:

- ◆ Data: features and labels
- ◆ Hypothesis space
- ◆ Loss function

➤ Let  $\{(\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(m)}, y^{(m)})\} \subseteq \mathbb{R}^d \times \mathbb{R}$  be the *data*. In the ML problem

$$\min_{\mathbf{w} \in \mathbb{R}^d} \frac{1}{m} \sum_{i=1}^m (y^{(i)} - \mathbf{w}^T \mathbf{x}^{(i)})^2$$

the loss function is the **mean squared error** and the hypothesis space is  $\mathbb{R}^d$ .



# ML AND CLIMATE ACTION

- 13.1 Strengthen resilience and adaptive capacity
- 13.2 National policies, strategies and planning
- 13.3 Improve education, awareness-raising and human and institutional capacity
- 13.A Developed countries mobilizing jointly \$100 billion annually by 2020
- 13.B Effective climate change-related planning and management in least developed countries and small island developing states

## Environment



Table from Vinuesa et al. (2020)

# DISCUSSION: HOW ML CAN BE USED TO ENABLE AND INHIBIT CLIMATE ACTION

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# AI ETHICS

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- **Beneficence:** promoting well-being, preserving dignity, and sustaining the planet
- **Non-maleficence:** privacy, security and ‘capability caution.’
- **Autonomy:** the power to decide (whether to decide)
- **Justice:** promoting prosperity and preserving solidarity
- **Explicability:** enabling the other principles through intelligibility and accountability

*Source: Morley et al. (2021), adapted from The Digital Catapult AI Ethics Framework*

<https://www.digicatatapult.org.uk/>

# PUBLICATIONS THAT WILL BE COVERED IN THIS COURSE

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- **Power** D. P. Finch, P. I. Palmer, and T. Zhang (2022). *Automated detection of atmospheric NO<sub>2</sub> plumes from satellite data: a tool to help infer anthropogenic combustion emissions*. *Atmospheric Measurement Techniques*, 15(3):721–733, 2022.
- **Industry** Schuit, B. J., Maasakkers, J. D., Bijl, P., Mahapatra, G., Van den Berg, A. W., Pandey, S., Aben, I. (2023). *Automated detection and monitoring of methane super-emitters using satellite data*. *Atmospheric Chemistry and Physics Discussions*, 1-47.
- **Transport** Paolo, F., Kroodsma, D., Raynor, J. *et al.* *Satellite mapping reveals extensive industrial activity at sea*. *Nature* 625, 85–91 (2024). <https://doi.org/10.1038/s41586-023-06825-8>
- **Buildings** TBD
- **Uncertainty quantification** TBD



# PRACTICALITIES

# SCHEDULE

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- Lectures - Mondays, 12:15 - 14:00, R001/Y313
- Exercises
  - Thu 11.01.2024 10:15 - 12:00, R037/1521-1522 AS6
  - Thu 18.01.2024 10:15 - 12:00, R030/A136 T6
  - Thu 25.01.2024 10:15 - 12:00, R037/1521-1522 AS6
  - Thu 01.02.2024 10:15 - 12:00, R030/A136 T6
  - Thu 08.02.2024 10:15 - 12:00, R030/A136 T6
  - Thu 15.02.2024 10:15 - 12:00, R030/A136 T6

*Bring your laptop to the exercise sessions.*

# CONTACT US

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- Primary channel: Zulip
- Email: [cs-e407519@aalto.fi](mailto:cs-e407519@aalto.fi)
- Office hours: upon request
- Pre-course poll

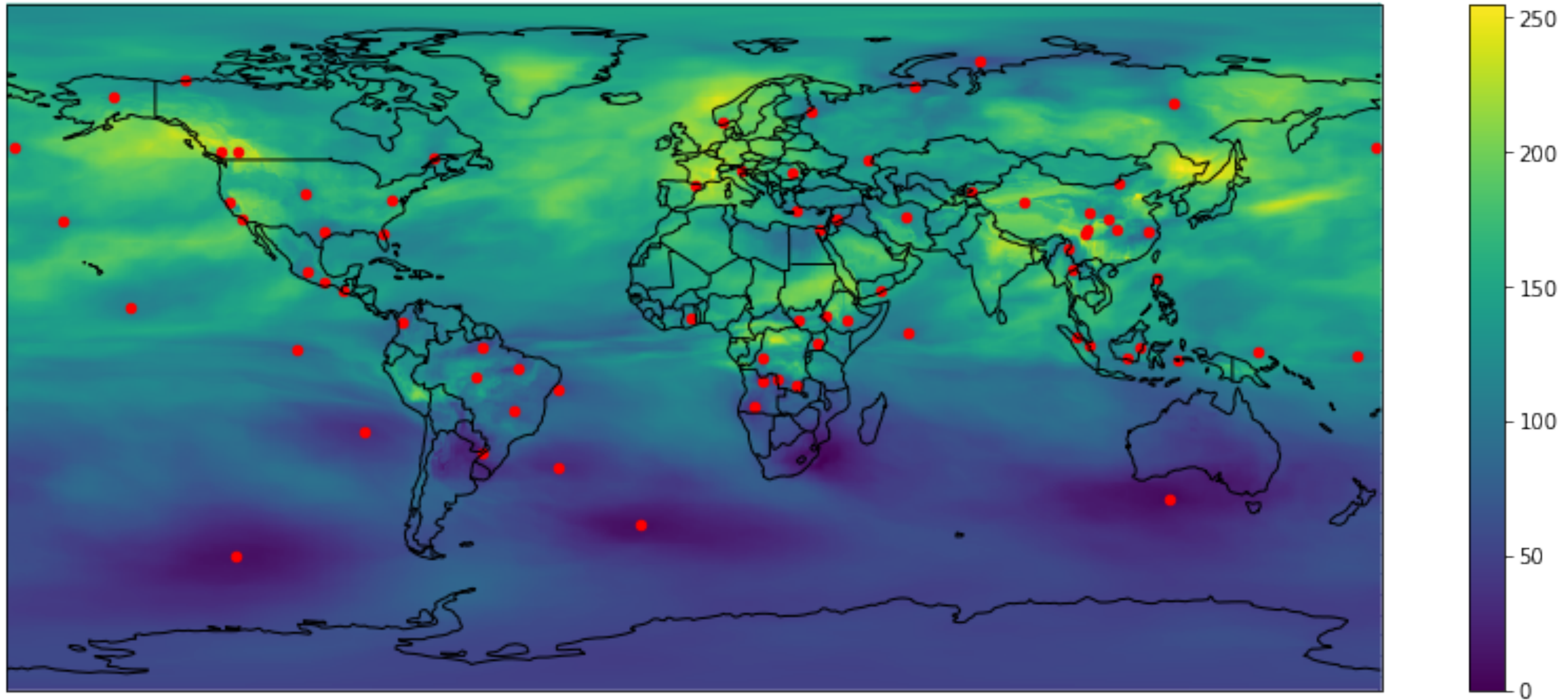
# EXPECTATIONS

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- How to pre-read a paper
  - Read abstract, figures, tables, discussion and results
  - Skim through introduction, methodology and data
- Exercises - think of it as a first rough experiment for a Master's thesis project
  - What worked?
  - What didn't work?
  - What would be a good next step/analysis/improvement of the algorithm?
- ChatGPT - use at your own risk + disclose how it was used in your submission

# EXAMPLE: DETECTING CO<sub>2</sub> ANOMALIES USING TOPOLOGICAL DATA ANALYSIS

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*Normalised change in yearly mean CO<sub>2</sub> levels in from 2015 to 2021*

# ANALYSIS

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- What worked:
  - Methodology seems to identify anomalies
  - Identifies relative anomalies not just the largest anomalies
  - Fast
  - Can be used to identify regions that whose CO<sub>2</sub> dynamics is consistently different from its neighbours
- What did not work:
  - Seems better at identifying concentrations of blue than of yellow
  - Some big regions are missing
- What to do next
  - Interpretation of anomalies?
  - Recover complete contour of anomalies?
  - Related analyses: instantaneous identification, comparison of tiles, dynamics over time, identify spurious anomalies, etc
  - Optimal algorithm?
  - Other topological properties?

# REFERENCES

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- Crimmins, A., Balbus, J., Gamble, J. L., Beard, C. B., Bell, J. E., Dodgen, D., Eisen, R. J., Fann, N., Hawkins, M. D., Herring, S. C., Jantarasami, L., Mills, D. M., Saha, S., Sarofim, M. C., Trtanj, J., & Ziska, L. (2016). Executive Summary. In *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment* (pp. 1–24). U.S. Global Change Research Program. <https://doi.org/10.7930/J00POWXS>
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- NOAA, Greenhouse gases continued to increase rapidly in 2022 <https://www.noaa.gov/news-release/greenhouse-gases-continued-to-increase-rapidly-in-2022> (Accessed Dec 2023)
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- Federica Zennaro, Elisa Furlan, Christian Simeoni, Silvia Torresan, Sinem Aslan, Andrea Critto, Antonio Marcomini (2021) Exploring machine learning potential for climate change risk assessment, *Earth-Science Reviews*, 220, <https://doi.org/10.1016/j.earscirev.2021.103752>.