Climate Modelling and Current Research Topics in Climate Science

Peter Kuma

Researcher

Department of Meteorology (MISU) and Bolin Centre for Climate Research
Stockholm University, Stockholm, Sweden

Web: peterkuma.net
E-mail: peter.kuma@misu.su.se

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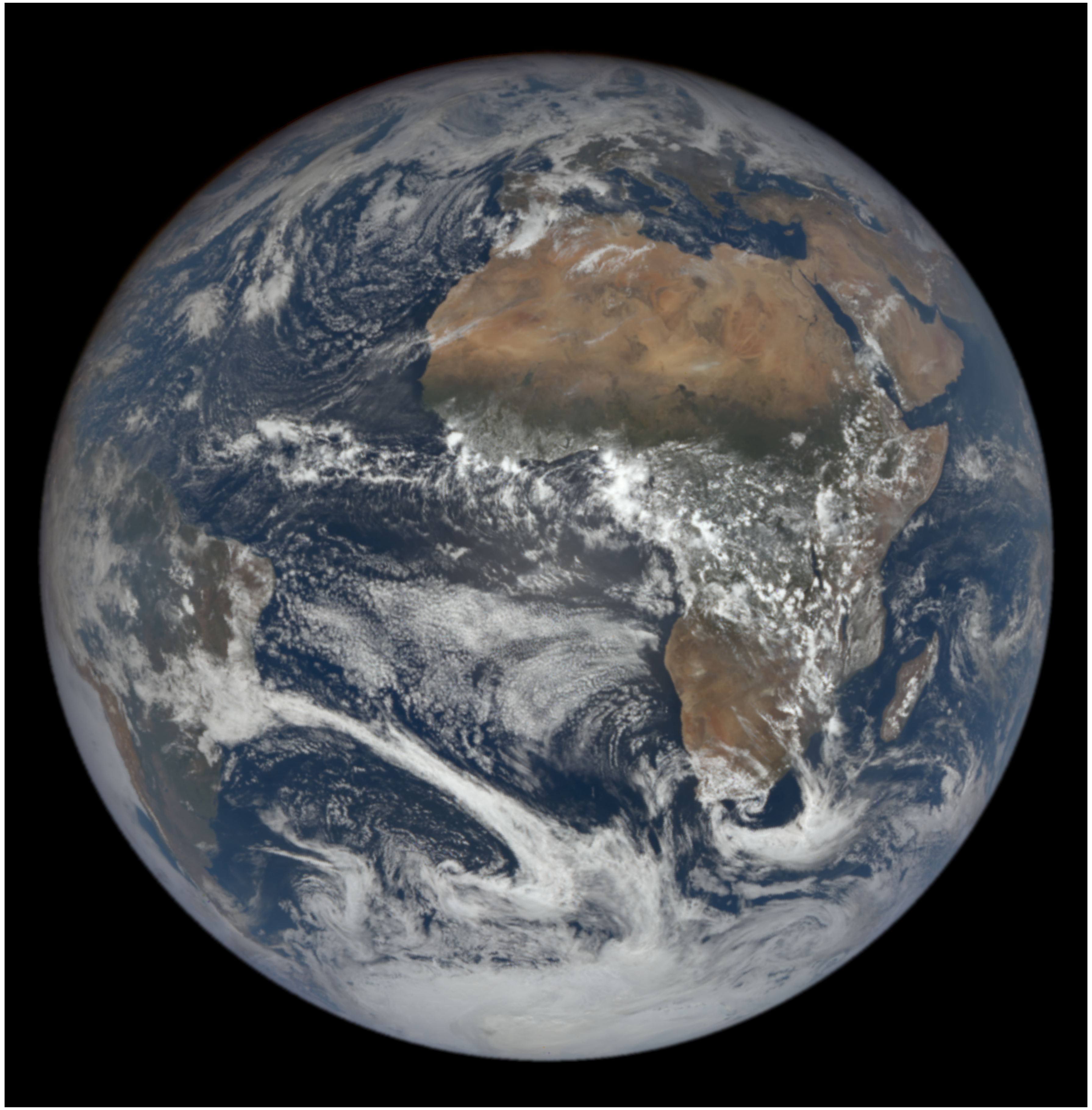
The Climate System

Components:
– Atmosphere
– Ocean
– Cryosphere
– Biosphere
– Humans

Forcing:
– Solar radiation
– Greenhouse gases (GHG)
– Aerosols
– Land use change



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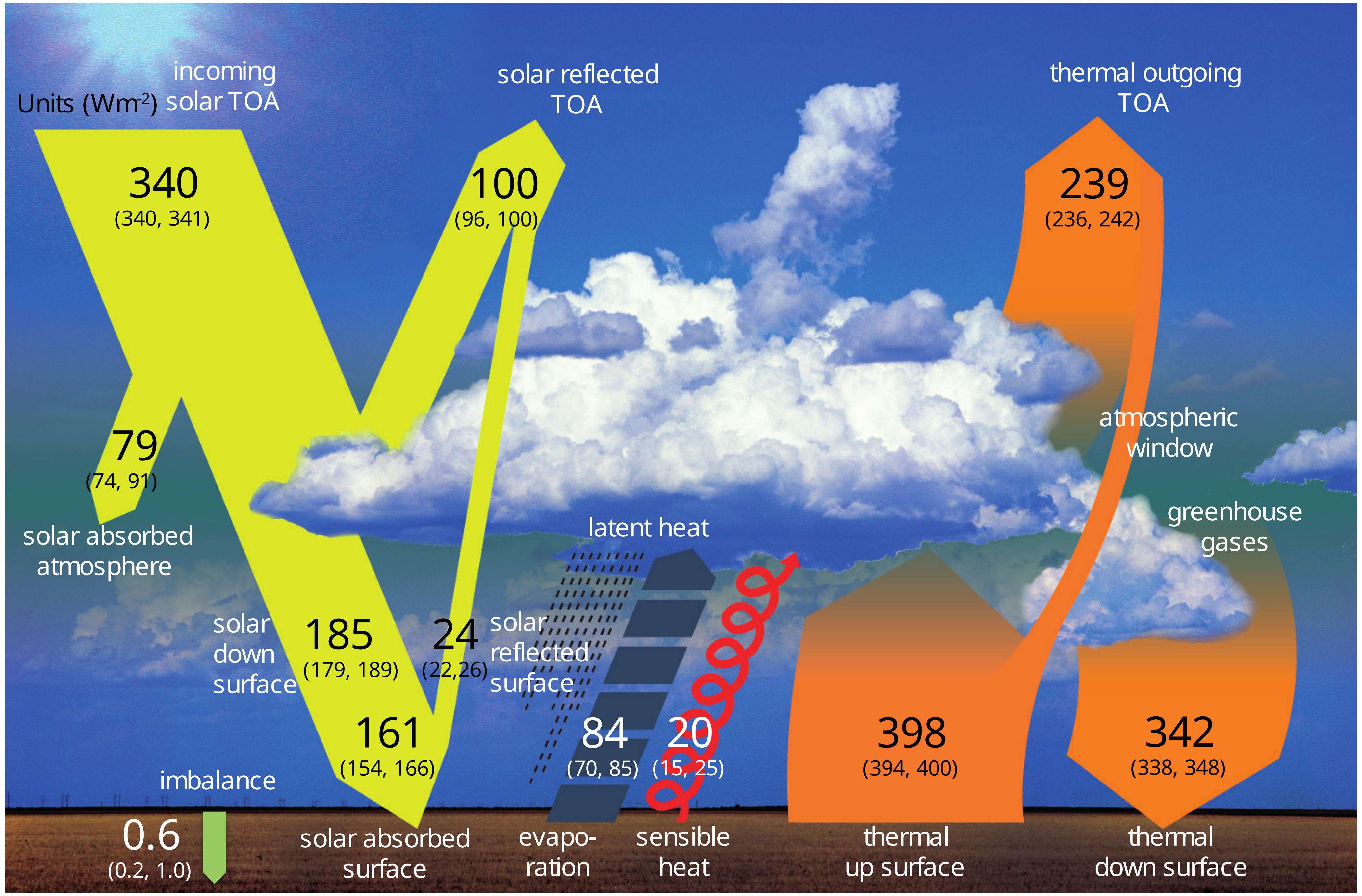
Radiation Balance

The radiation balance determines the rate of warming or cooling of the planet.

The only* way the climate system can warm or cool is by exchanging radiation with space:
– incoming solar radiation from the Sun
– outgoing terrestrial radiation due to Planck's law

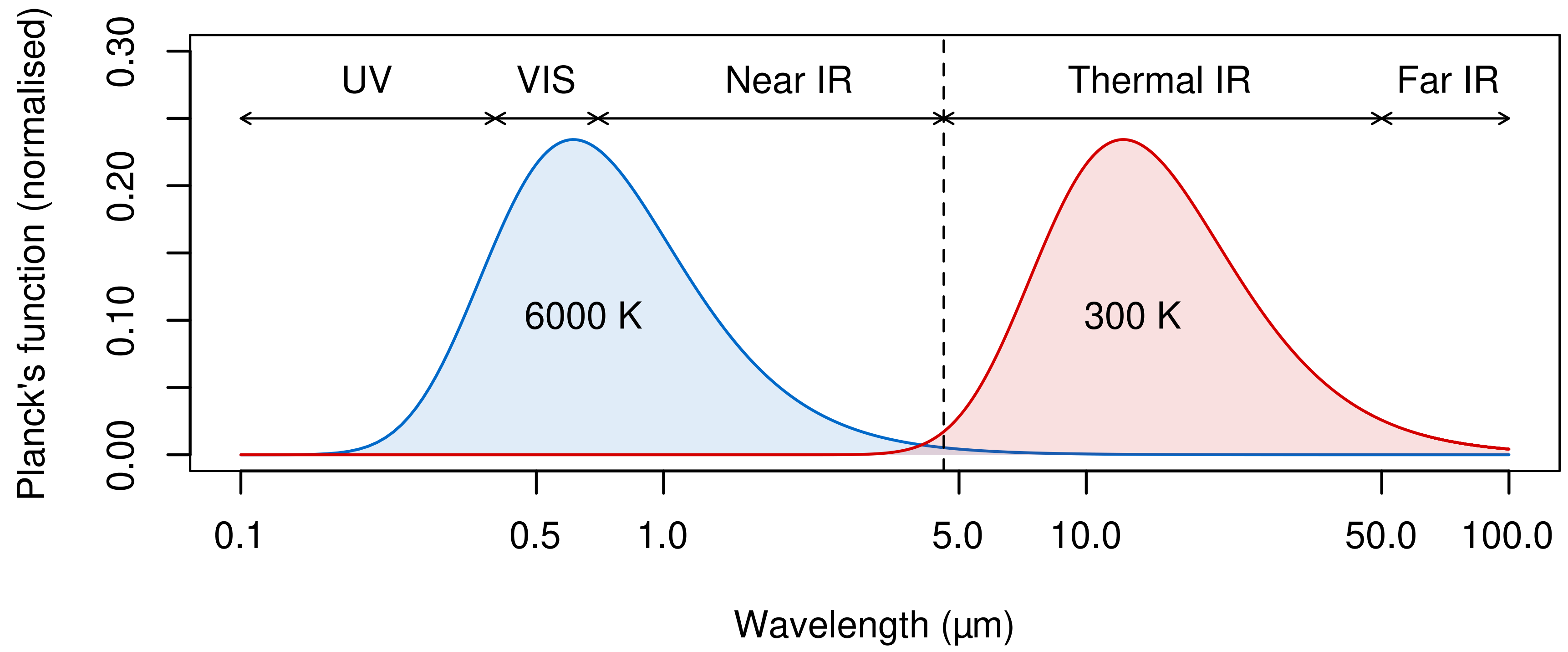
The surface albedo and emissivity, and stuff in the atmosphere affects the radiation balance:
– greenhouse gases
– clouds
– aerosols

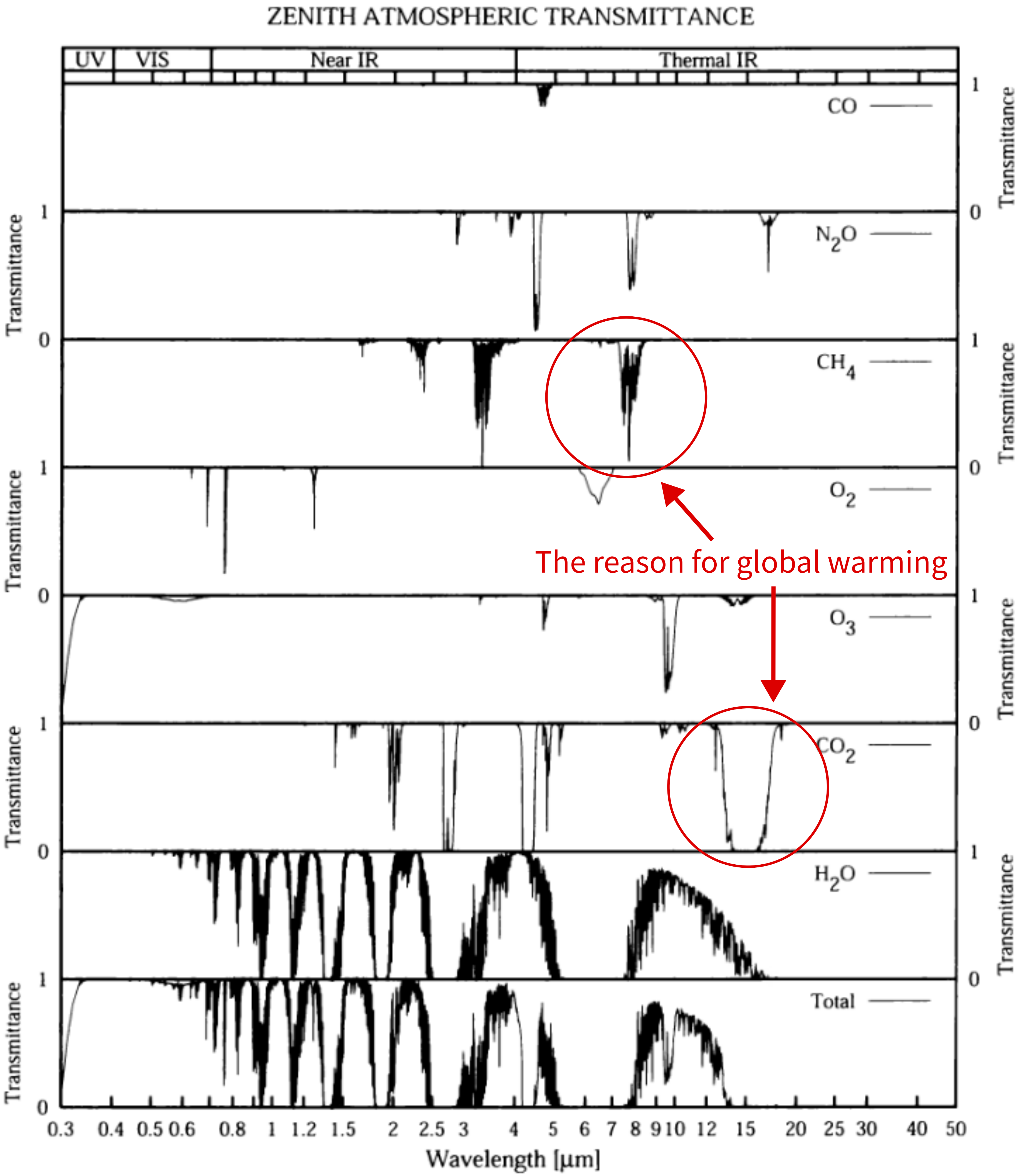


Adopted from IPCC 4th Assessment Report.

Radiation Balance

GHGs absorb and emit radiation at different wavelengths according to allowed quantum transitions in their molecules.





Adopted from Petty (2006): *A first course in atmospheric radiation.*

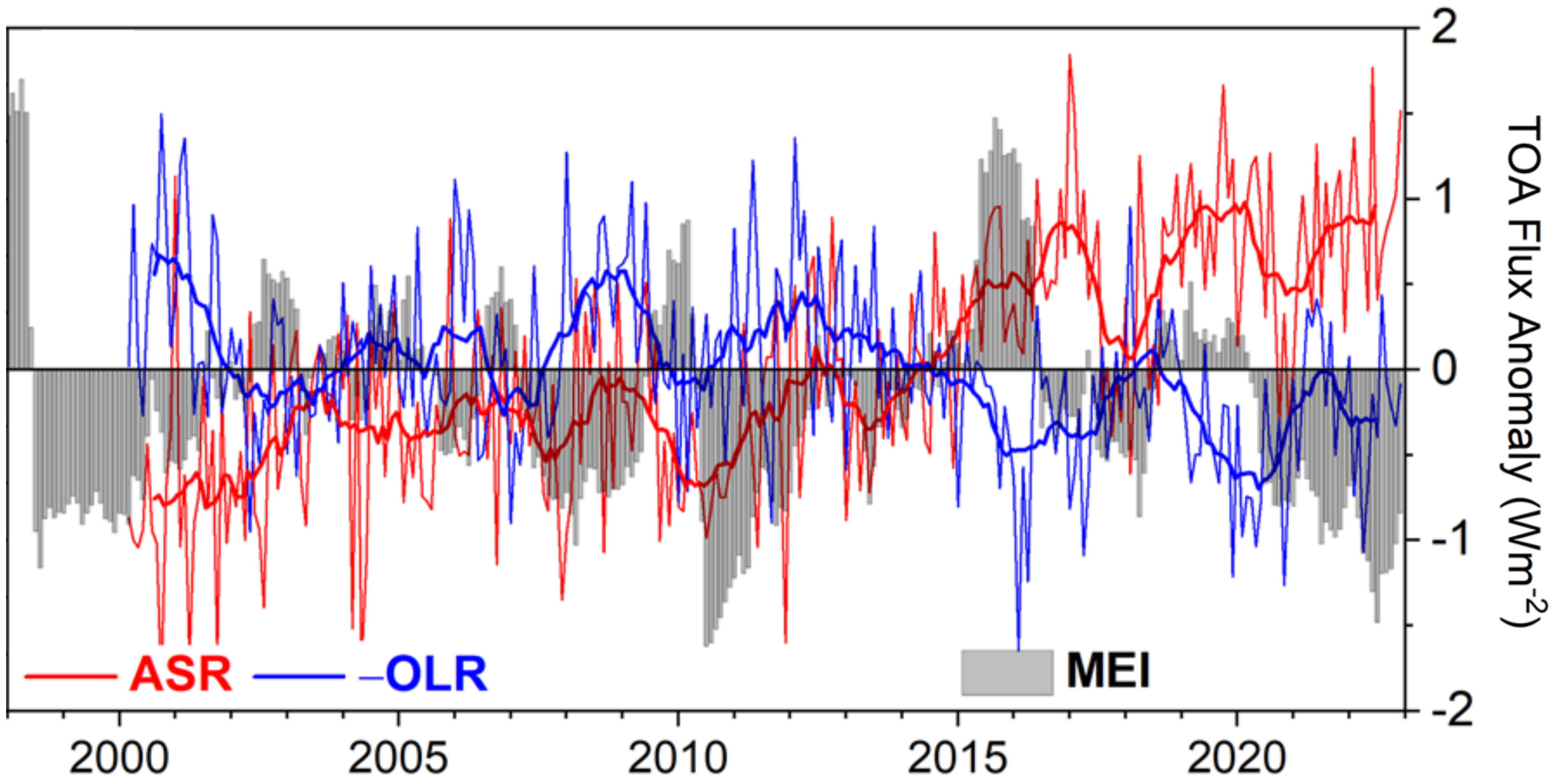
Radiation Balance

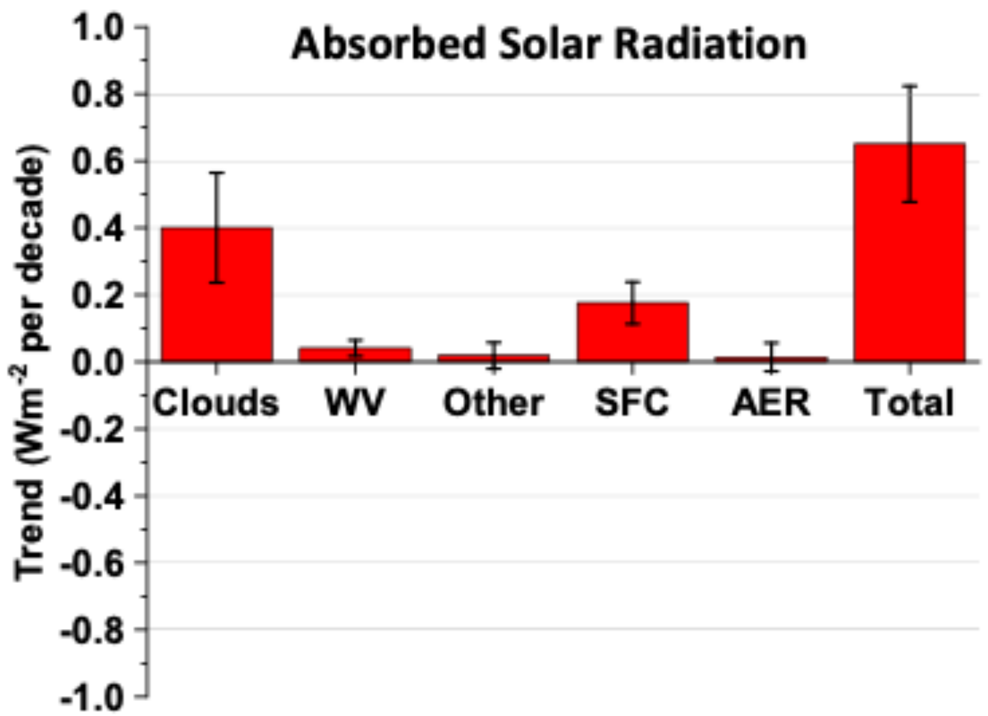
At the "top of atmosphere" (TOA), measured by the satellite instruments CERES.

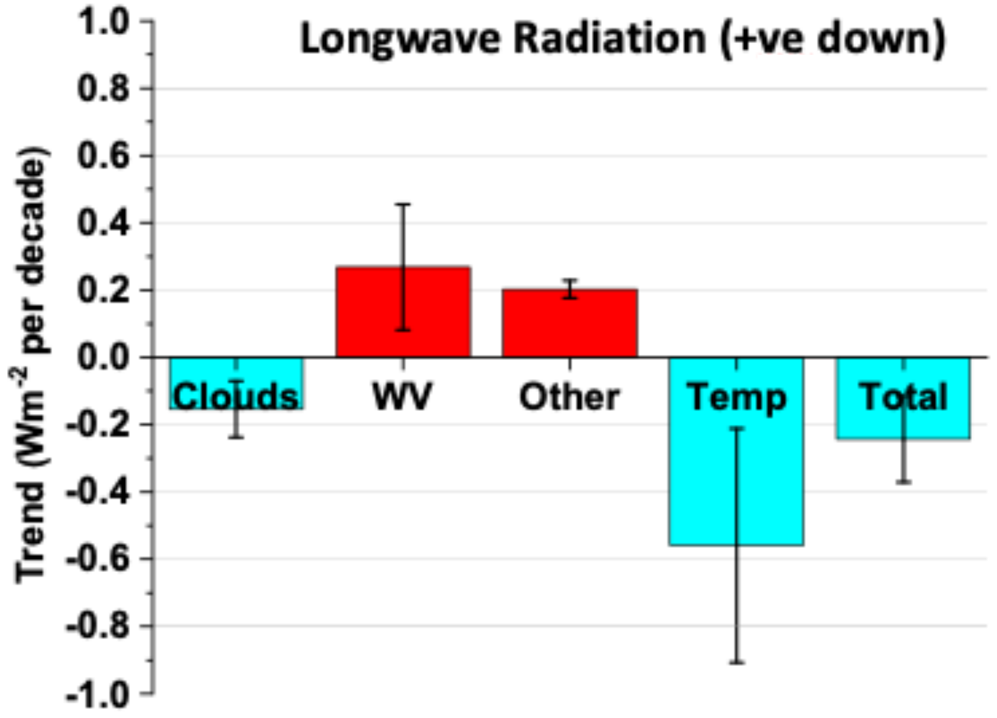
Absorbed longwave radiation:
– increased by GHGs
– decreased by more thermal cooling
– decreased slightly by clouds

Absorbed shortwave radiation:
– increased by lower cloud reflectivity
– increased by lower surface albedo

End effect: increased radiative warming.







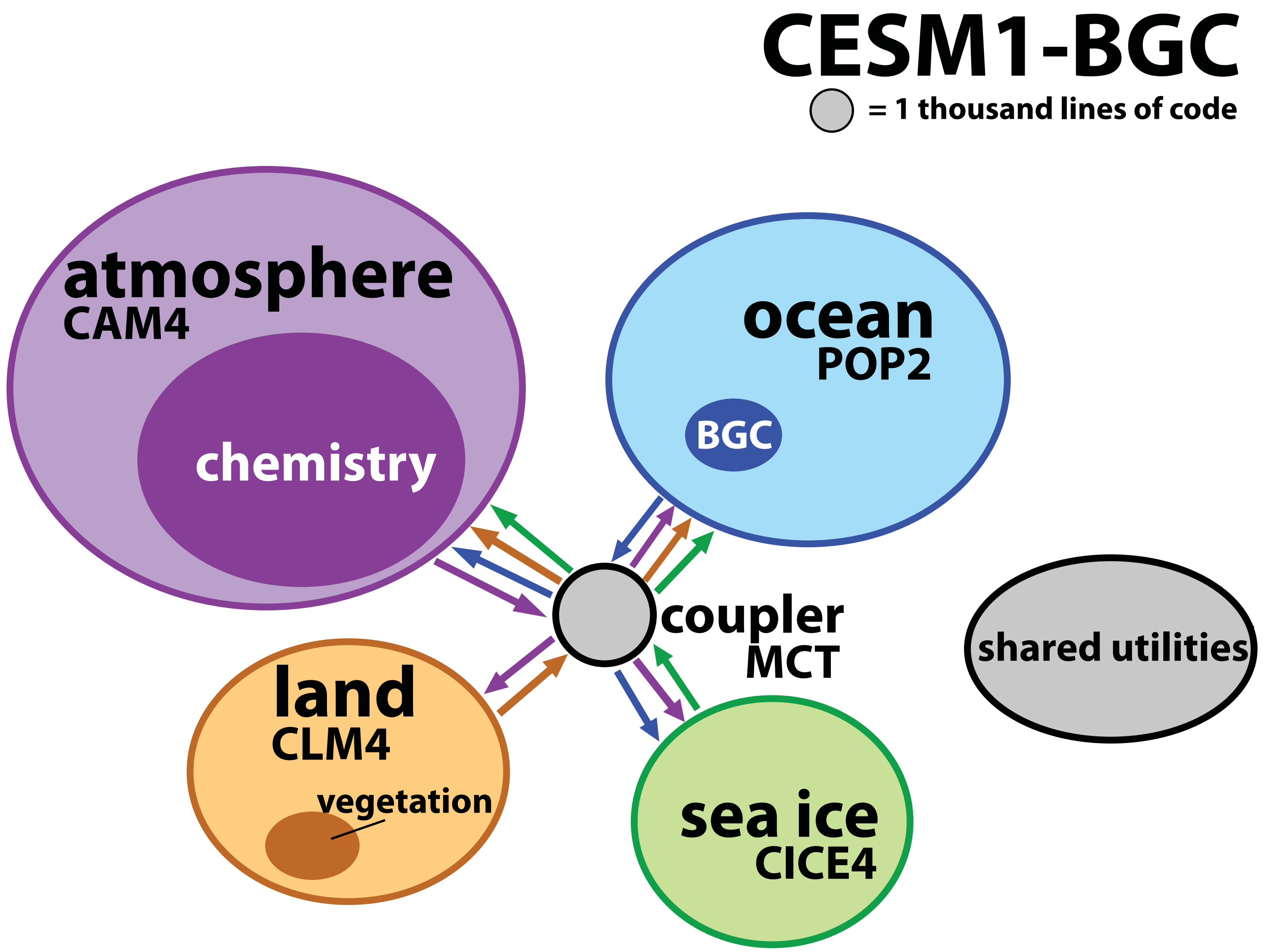
Adopted from Loeb et al. (2024): *Observational Assessment of Changes in Earth's Energy Imbalance Since 2000* [paper and slides].

Climate Models

Computer programs that simulate some or all components of the climate system.
Work by integrating various physical and statistical equations over time steps.

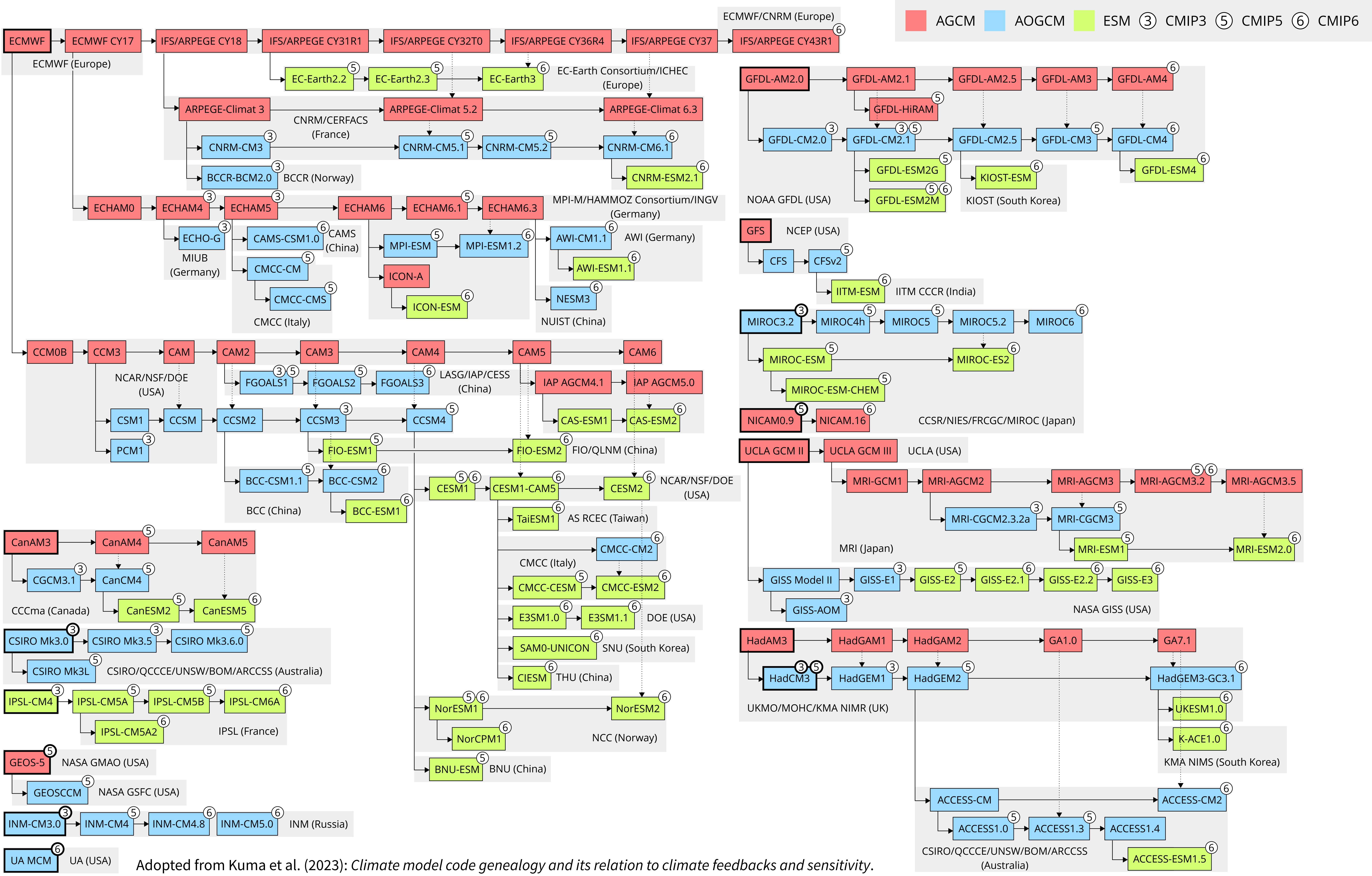
Primarily asking questions about:
– global temperature
– weather extremes
– circulation in the atmosphere and ocean
– sea ice and ice sheet reduction or growth
– clouds
– precipitation

Adopted from Hohenegger et al. (2023): *ICON-Sapphire: simulating the components of the Earth system and their interactions at kilometer and subkilometer scales.*



Adopted from Alexander and Easterbrook (2015): *The software architecture of climate models: a graphical comparison of CMIP5 and EMICAR5 configurations.*

Climate Model Genealogy

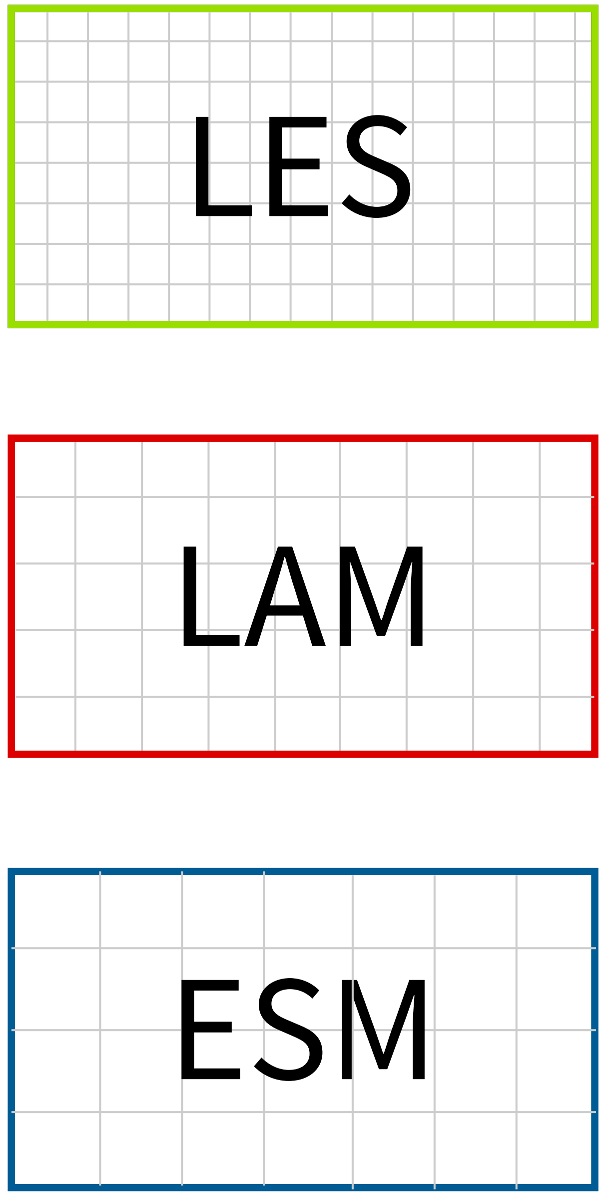


Adopted from Kuma et al. (2023): *Climate model code genealogy and its relation to climate feedbacks and sensitivity.*

Climate Supercomputing

Climate models have varying complexity:
- components included
- spatial and temporal resolution
- processes parametrised
- local, regional, or global

Computing requirements:
1. personal computer (low-res models and emulators)
2. workstation/server/single supercomputer node
3. cluster of supercomputing nodes or servers
(4. globally distributed clusters)



Large-eddy simulation
~ 100 m resolution
~ 10 km domain

Limited-area model
~ 10 km resolution
~ 1000 km domain

Earth system model
~ 100 km resolution
global domain

Climate Supercomputing

Technically (almost) normal computer programs.
Programming languages:
– Fortran and C/C++
– Julia (niche)
– Python (niche)
– GPU special purpose languages
Operating system usually some Linux distribution.
Multi-threading (OpenMP) and clustering (MPI)

Typical supercomputer node:
– ~256 GB RAM
– Dual Intel Xeon or AMD EPYC CPUs
– ~64 cores
– some "GPU nodes"

Examples: Levante (Atos) at DKRZ, Germany: 2832 nodes (14 PFLOPS);
Māui (Cray XC50) at NIWA, New Zealand: 464 nodes (1.425 PFLOPS)

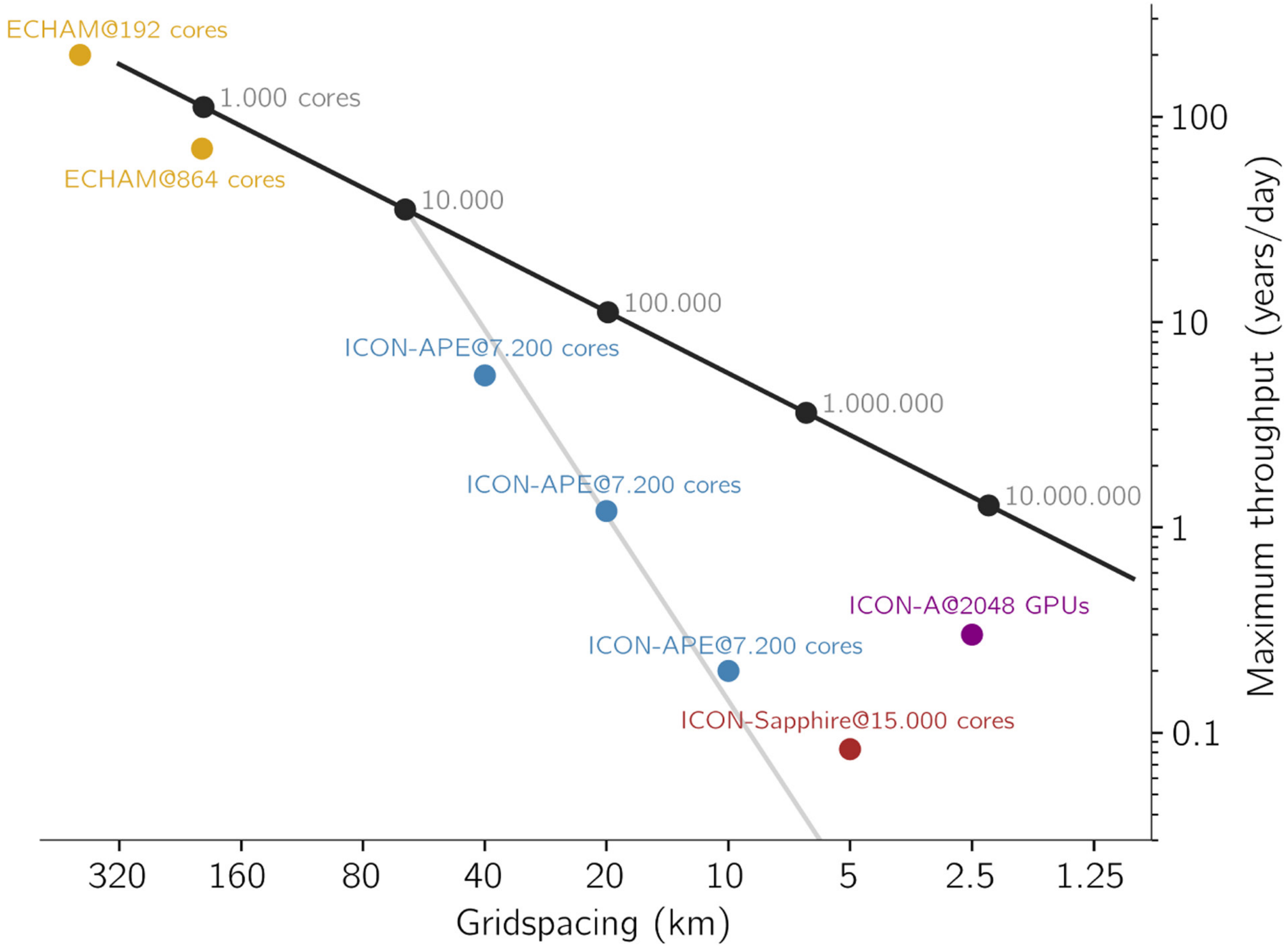
Resolution vs. Performance

We want to use all available resources (RAM, CPU, GPU, and disk space):
– maximise resolution
– minimise time steps
– maximise number of climate components
– maximise number of physical processes

Over time CPU and GPU performance increases ~exponentially.

Resolution increases demands with the fourth power (x × y × z × t).

Aim: compromise between all of the above.



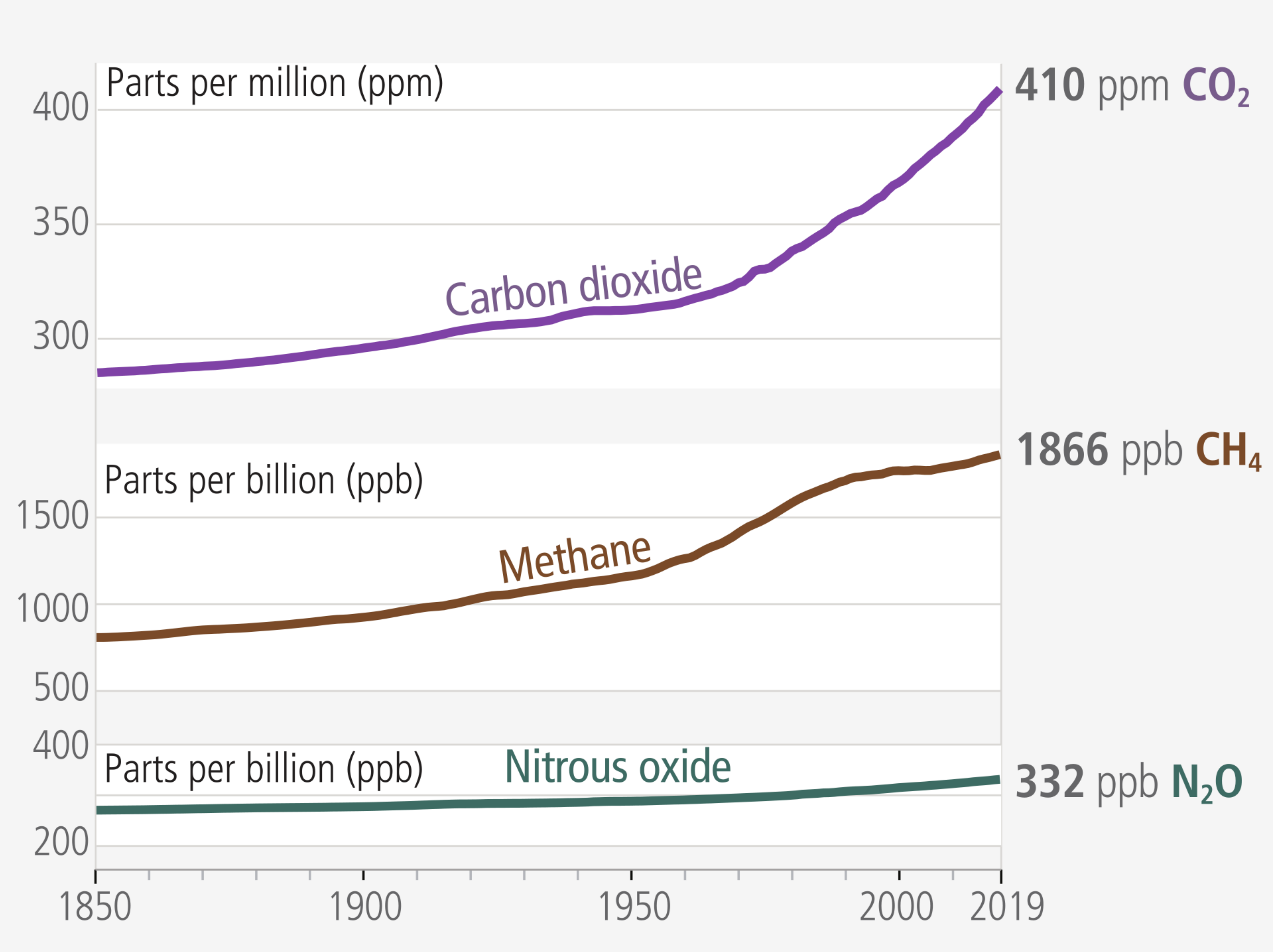
Adopted from Mauritsen et al. (2022): *Early Development and Tuning of a Global Coupled Cloud Resolving Model, and its Fast Response to Increasing CO2*

Climate Change

Greenhouse gases in the atmosphere absorb and emit thermal (terrestrial) radiation.

This is a normal state of the atmosphere, but:
– carbon dioxide increasing
– methane increasing
– water vapour increasing with temperature
– aerosols increasing, now slowly decreasing
– land use change limits carbon uptake, or releases carbon

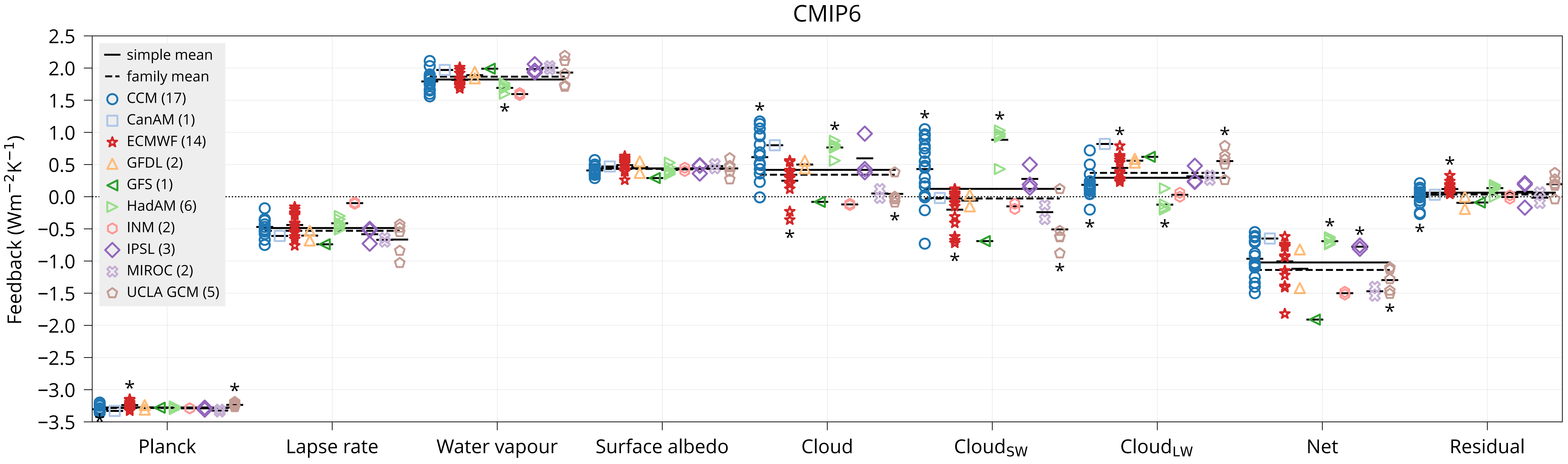
Blocking terrestrial radiation → less escapes into space.
Climate feedbacks mostly accelerate warming.
Ocean acidification due to CO_2 uptake into carbonic acid (H_2CO_3).



Adopted from the IPCC 6th Assessment report.

Climate Feedbacks

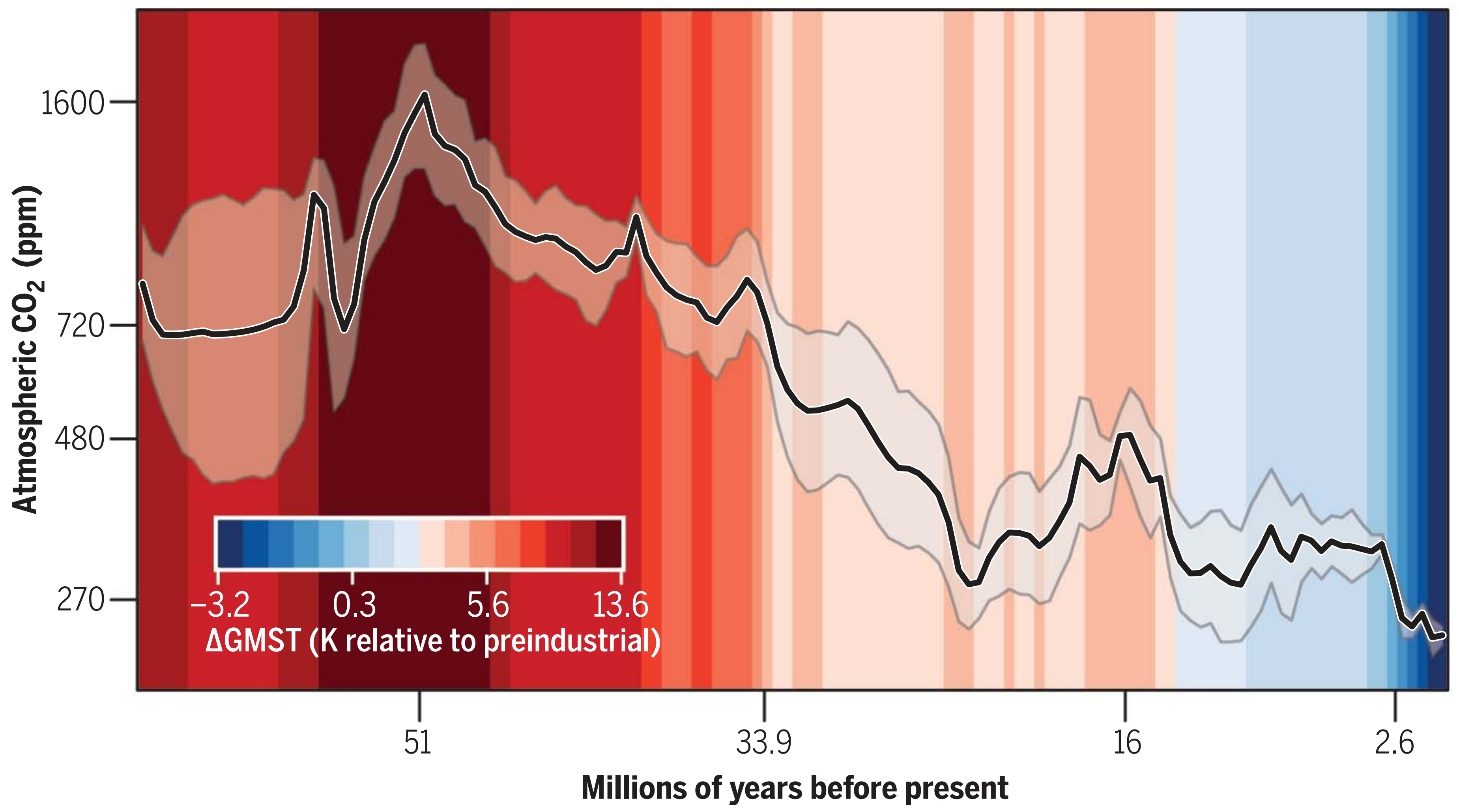
Temperature change triggers processes with increase/decrease radiative warming/cooling of the planet. Initial push by GHGs, amplified by feedbacks.



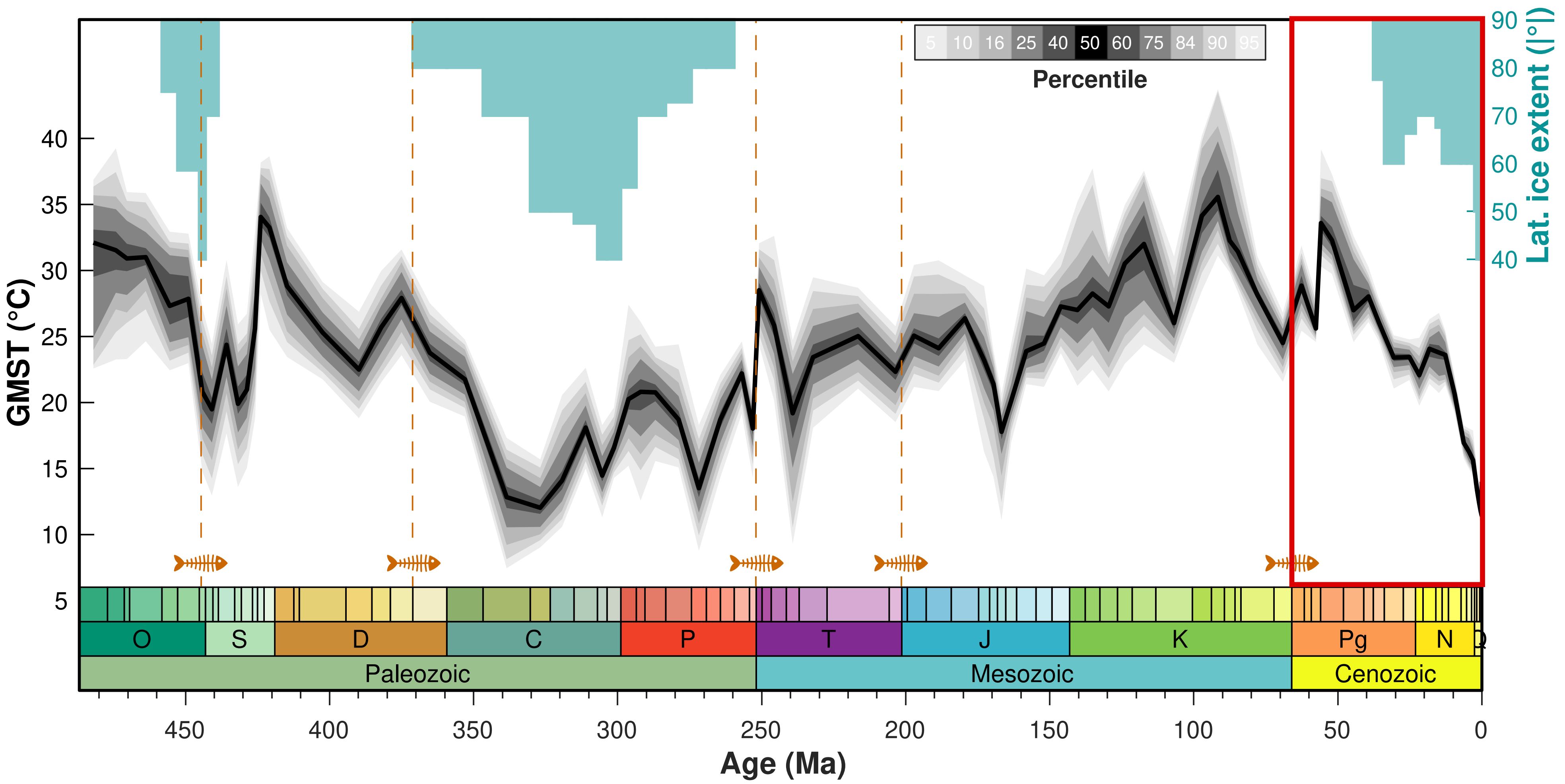
Adopted from Kuma et al. (2023): *Climate model code genealogy and its relation to climate feedbacks and sensitivity.*

Paleo Greenhouse Gas and Temperature Change

CO_2 evolution over the last 66 mil. years.



Temperature evolution over the last 500 mil. years.

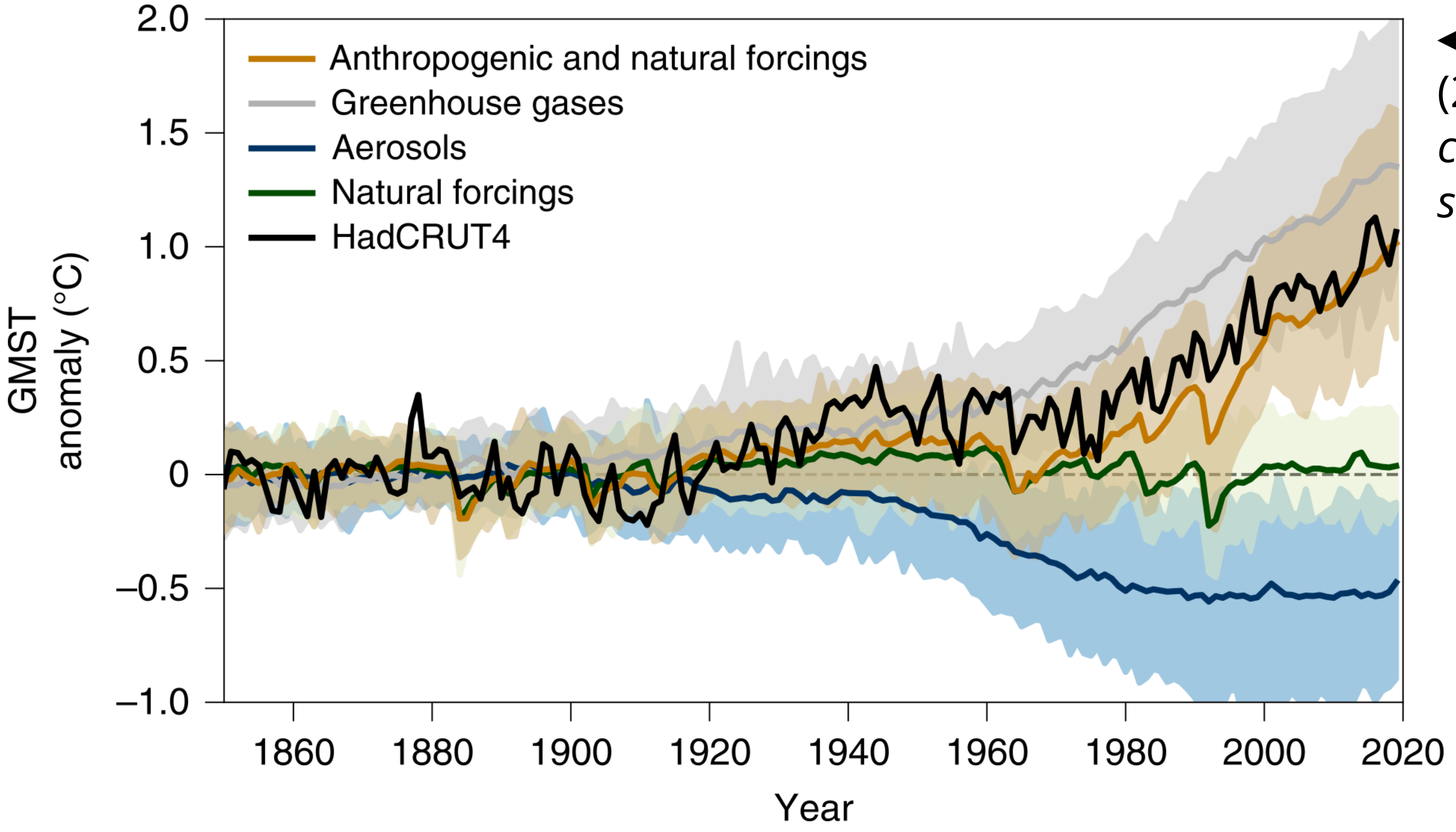


▲ Adopted from CenCO2PIP (2024): *Toward a Cenozoic history of atmospheric CO2.*

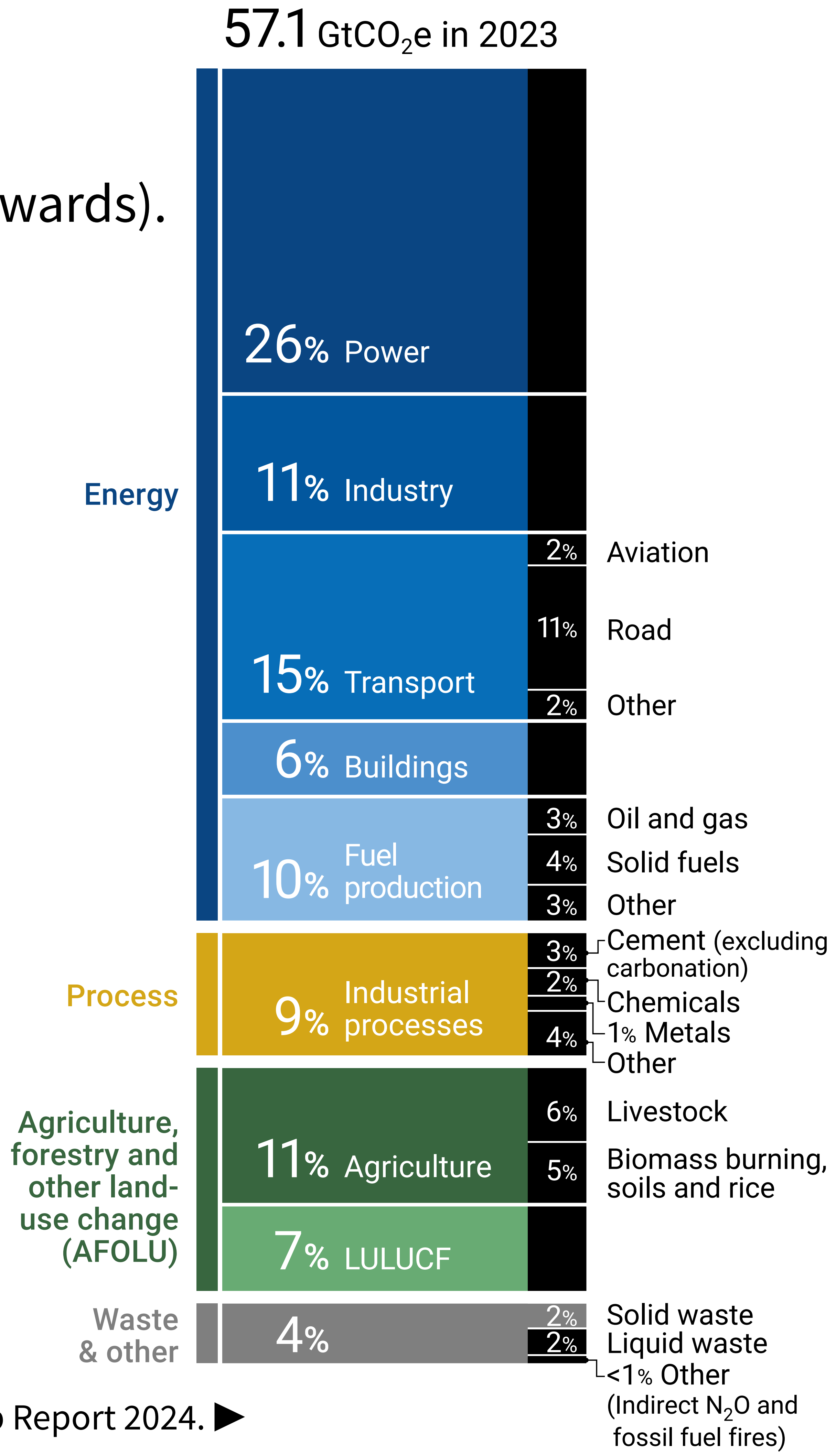
Adopted from Judd et al. (2024): *A 485-million-year history of Earth's surface temperature.* ▲

GHG Emissions in the Past and Future

(Substantial) GHG emissions started with the industrial revolution (~1750 onwards).
Aerosol emissions mostly from 1950 onwards.
Peak GHG emissions still not reached.
Main GHG sources:
– fossil fuel burning (power generation, transport, industires, agriculture, ...)
– fossil fuel production
– livestock, rice growing (methane), and land use change
Main aerosol source: fossil fuel and biomass burning



◀ Adopted from Gillett et al. (2021): *Constraining human contributions to observed warming since the pre-industrial period.*



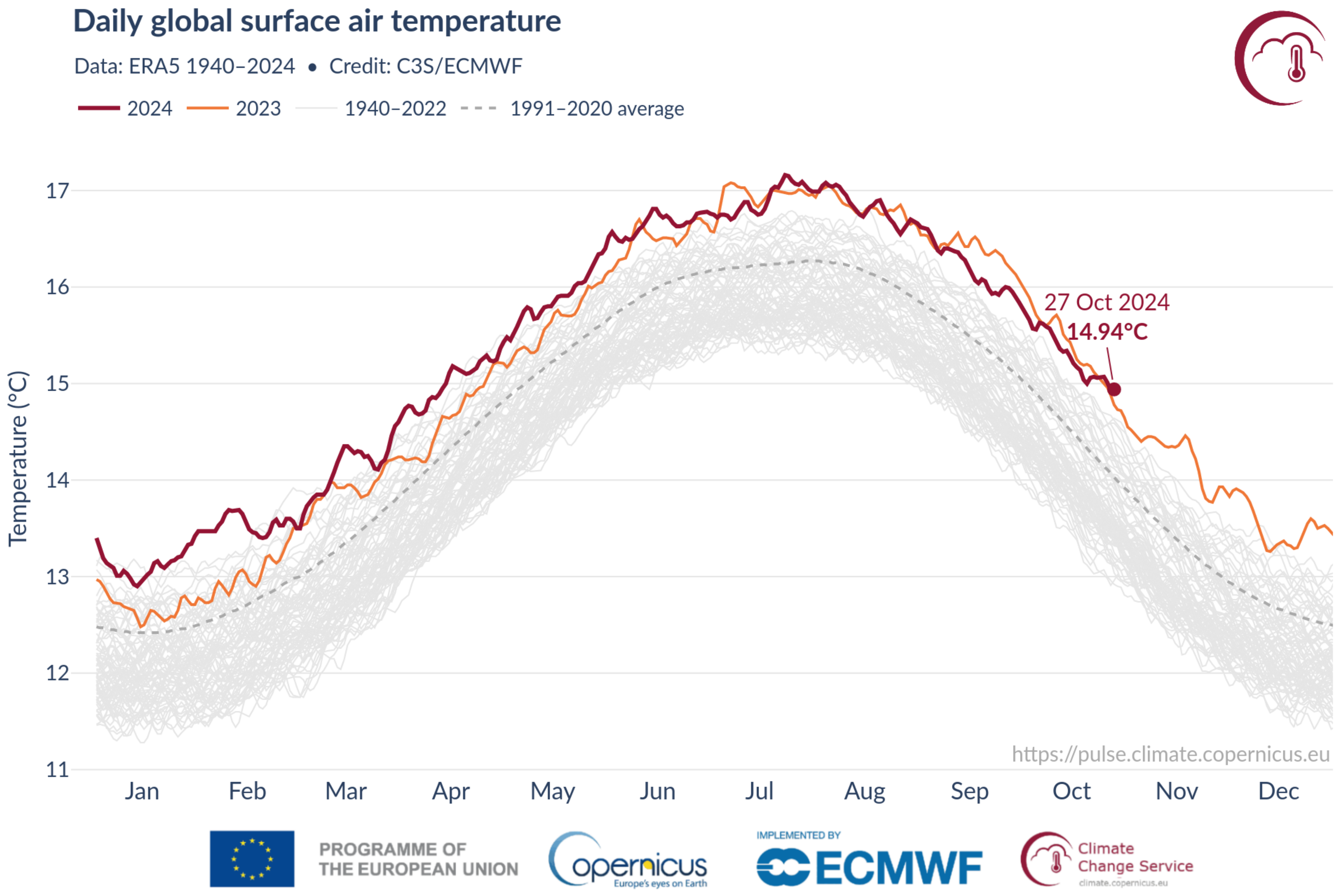
Adopted from UNEP Emissions Gap Report 2024. ▶

Recent Temperature Change

Strong global temperature jump observed in the last two years.

Now at about 1.5°C warmer than pre-industrial.

Probable reasons:
– El Niño
– Preceding years with La Niña suppressing warming
– changes in aerosols
– other unknown reasons



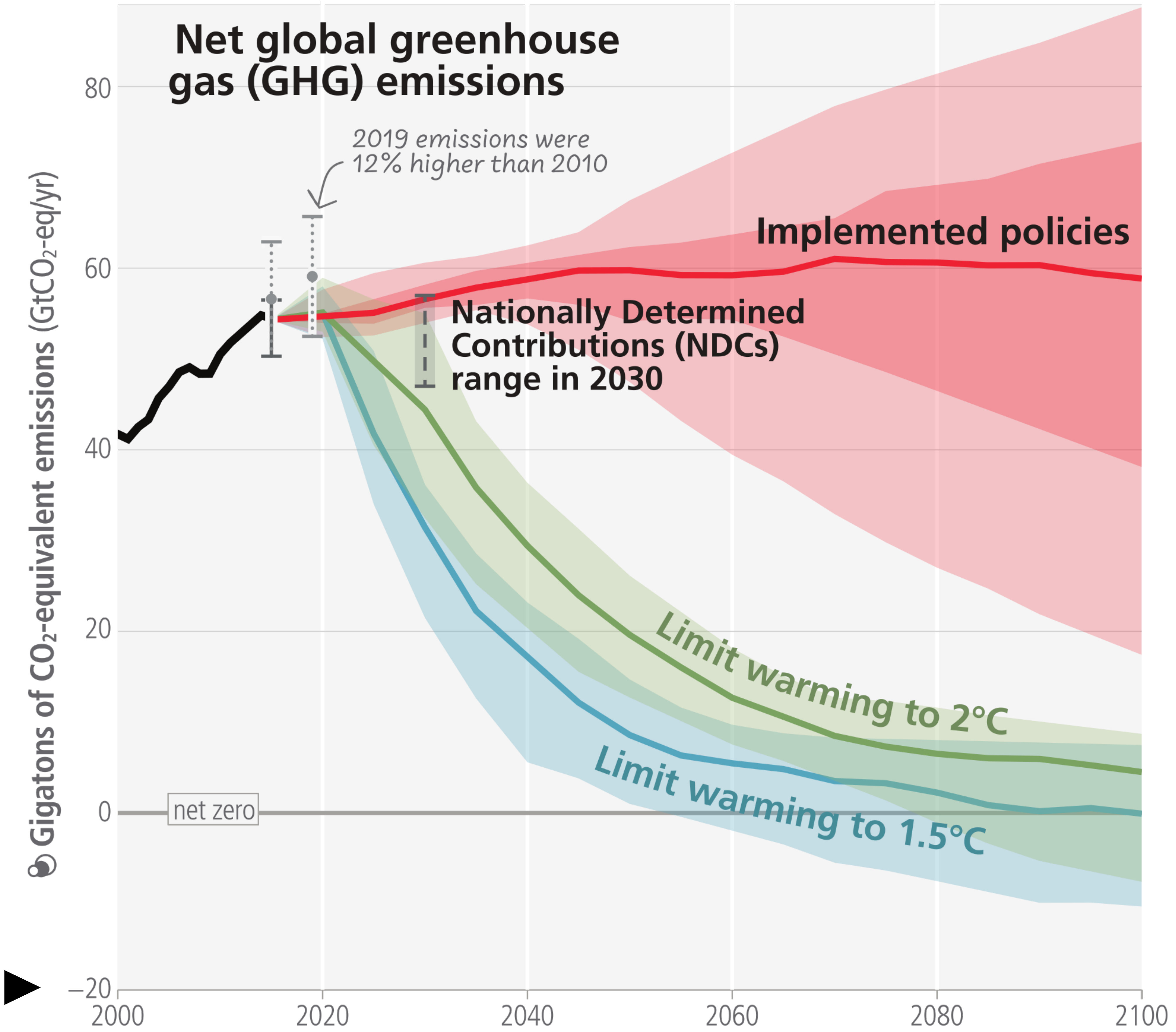
Adopted from https://pulse.climate.copernicus.eu.

Reducing Emissions

A mix of:
– renewables (solar, wind, ...) and nuclear energy, and less energy consumption
– electrified transport (EVs, ...), public transport, and less transport
– land use change and methane reduction:
  – reduce use of wood and paper
  – less land and methane intensive food

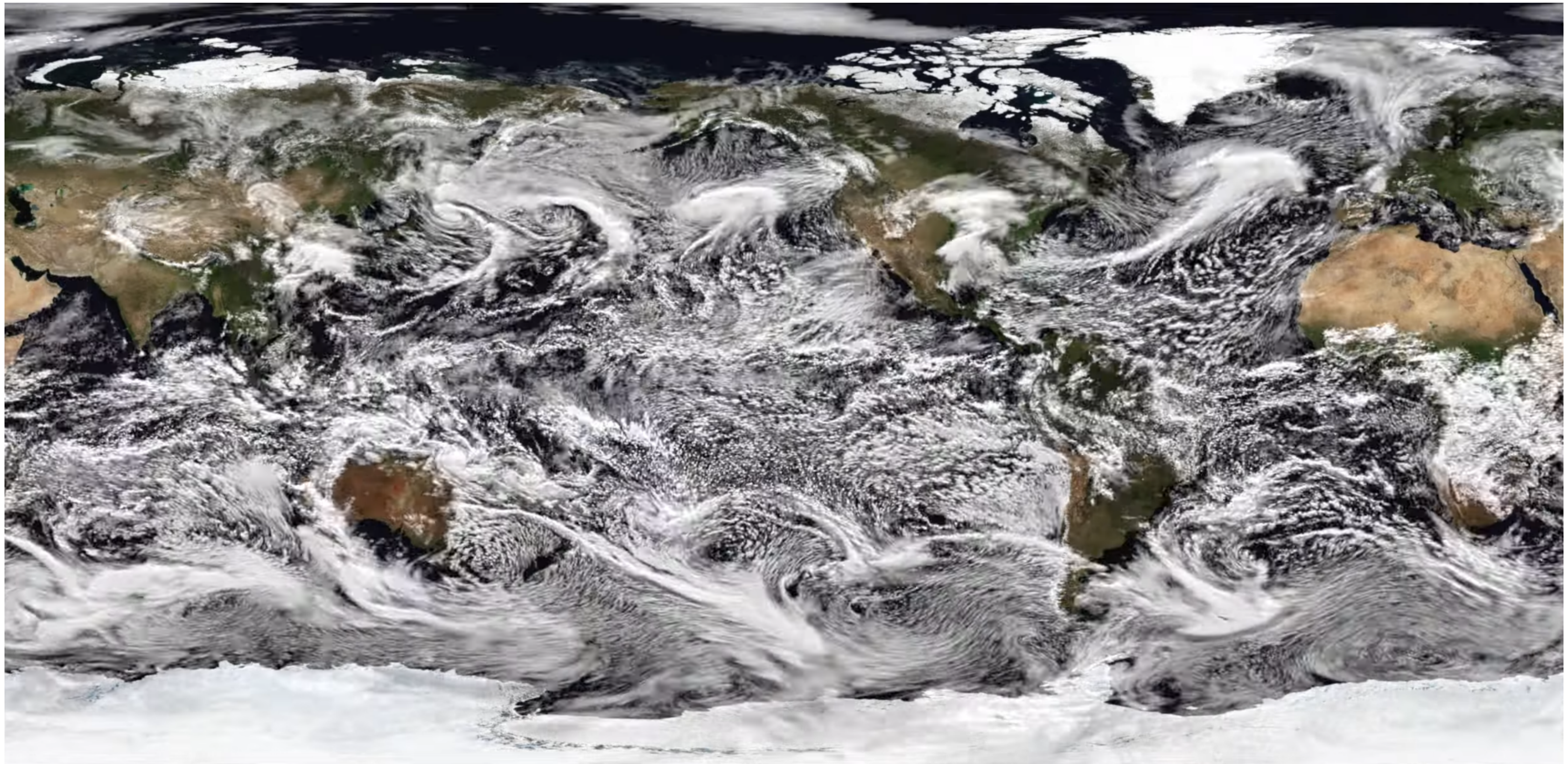
Geoengineering possible but very risky, we have options to reduce emissions now and quickly.

Adopted from IPCC 6th Assessment Report. ▶



km-scale Climate Modelling

Recent generation of Earth system models have about ~100 km resolution.
To be replaced by ~1-10 km models in a few years.
Moving from parametrisation to explicitly resolving processes (convection, clouds, ocean eddies, ...).



From animation by René Redler (MPI-M), Helmuth Haak (MPI-M), and Felicia Brisc (CEN/UHH).

km-scale Climate Modelling

Video 1

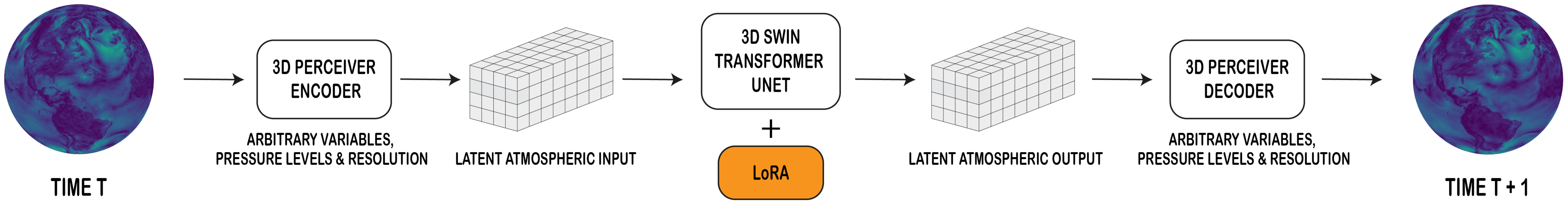
https://files.peterkuma.net/media/e3i2xmqkw5/icon.mp4

AI-based Climate Modelling

Concept: Train a deep neural network (NN) on climate model or reanalysis output and using it to make projections.
Advantage: Deep NN are much faster than physical models.
Hybrid approach: Combine physics-based model with a deep neural network.

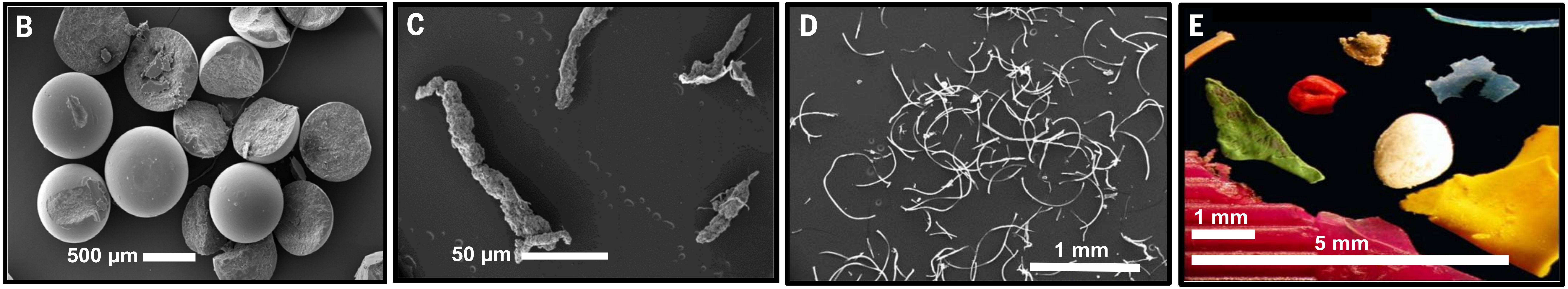
Currently most progress in AI-based weather forecasting:
– FourCastNet (NVIDIA)
– Pangu-Weather (HUAWEI CLOUD)
– GraphCast (Google)
– Aurora (Microsoft)
– AIFS (ECMWF)
– ...

▼ Adopted from Bodnar et al. (2024): *Aurora: A Foundation Model of the Atmosphere*.



Microplastics

Plastics degrade into smaller pieces, or are produced as small pieces.
Over time, they mix in the environment: atmosphere, ocean, and the cryosphere.
Microplastics: ~1µm–5mm
Nanoplastics: < 1µm
Primary (manufactured as microplastics) and secondary (from larger plastics).



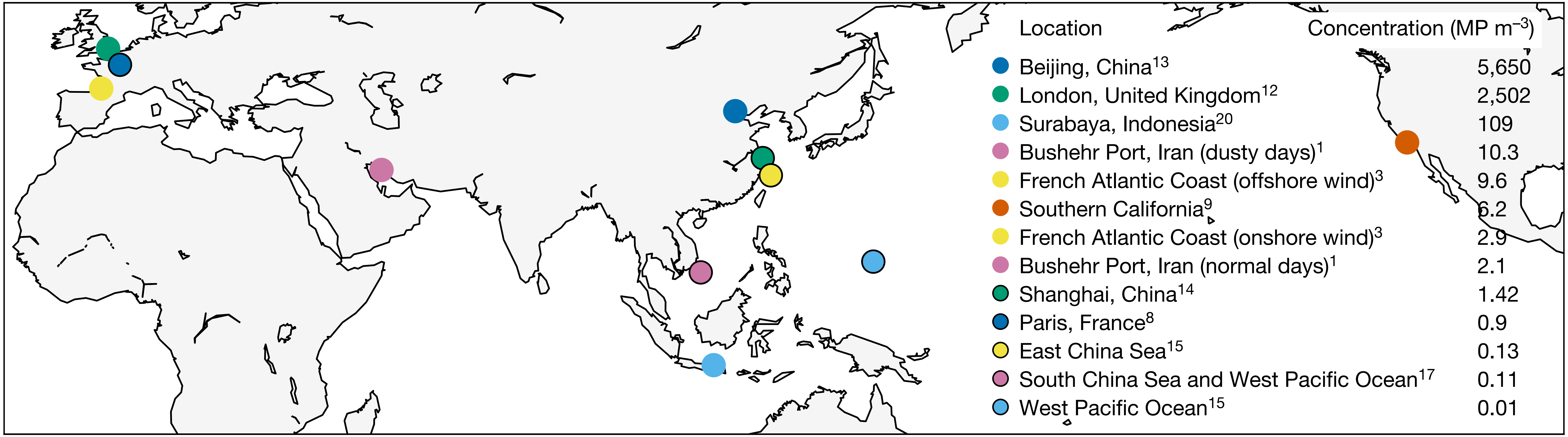
Adopted from Thompson et al. (2024): *Twenty years of microplastic pollution research—what have we learned?*

Sources of Microsplastics and Distribution

Sources: macroplastics, textiles, tire and brake wear, paint, ...

Globally distributed including remote locations (the Arctic and Antarctic).

High concentrations in cities and over land. Low concentration over the ocean.



Adopted from Revell et al. (2021): *Direct radiative effects of airborne microplastics*.

Radiative Effects of Microplastics

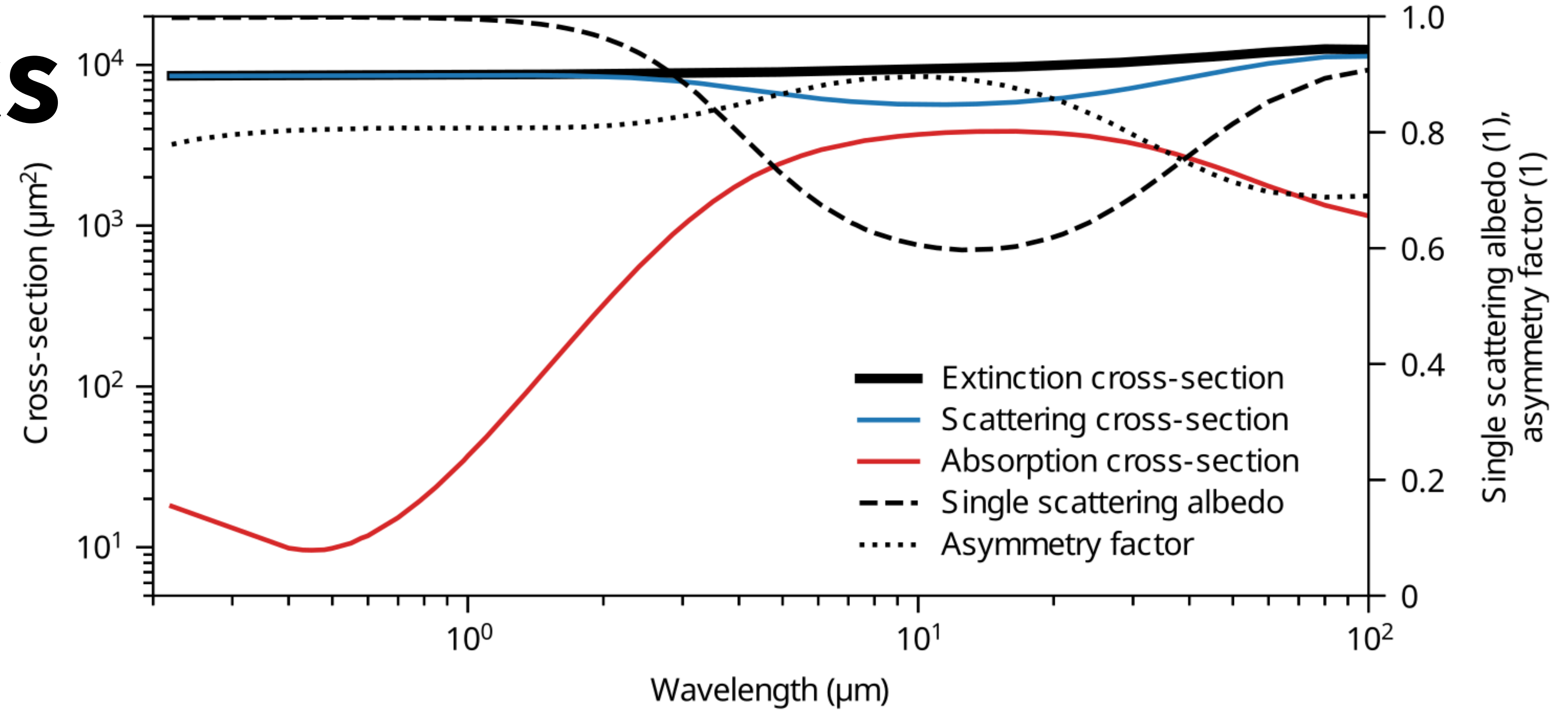
Microplastics in the atmosphere can scatter and absorb solar and terrestrial radiation.

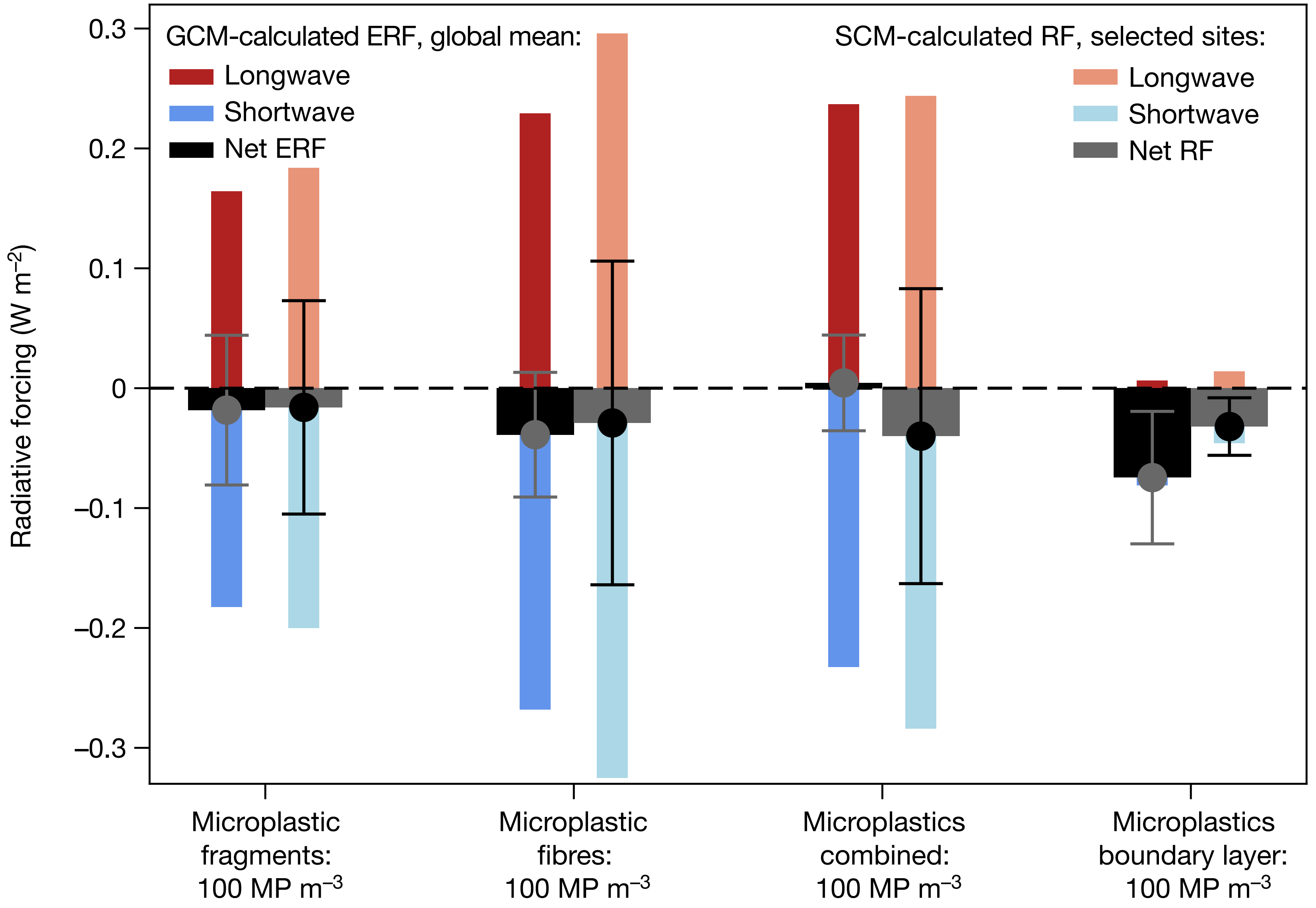
Input:
– a mix of fragments and fibres
– size distribution
– aspect ratio distribution
– index of refraction

Optical properties: from Mie theory and special computations (fibres)

Model: global climate model HadGEM3

Outcome: longwave warming and shortwave cooling



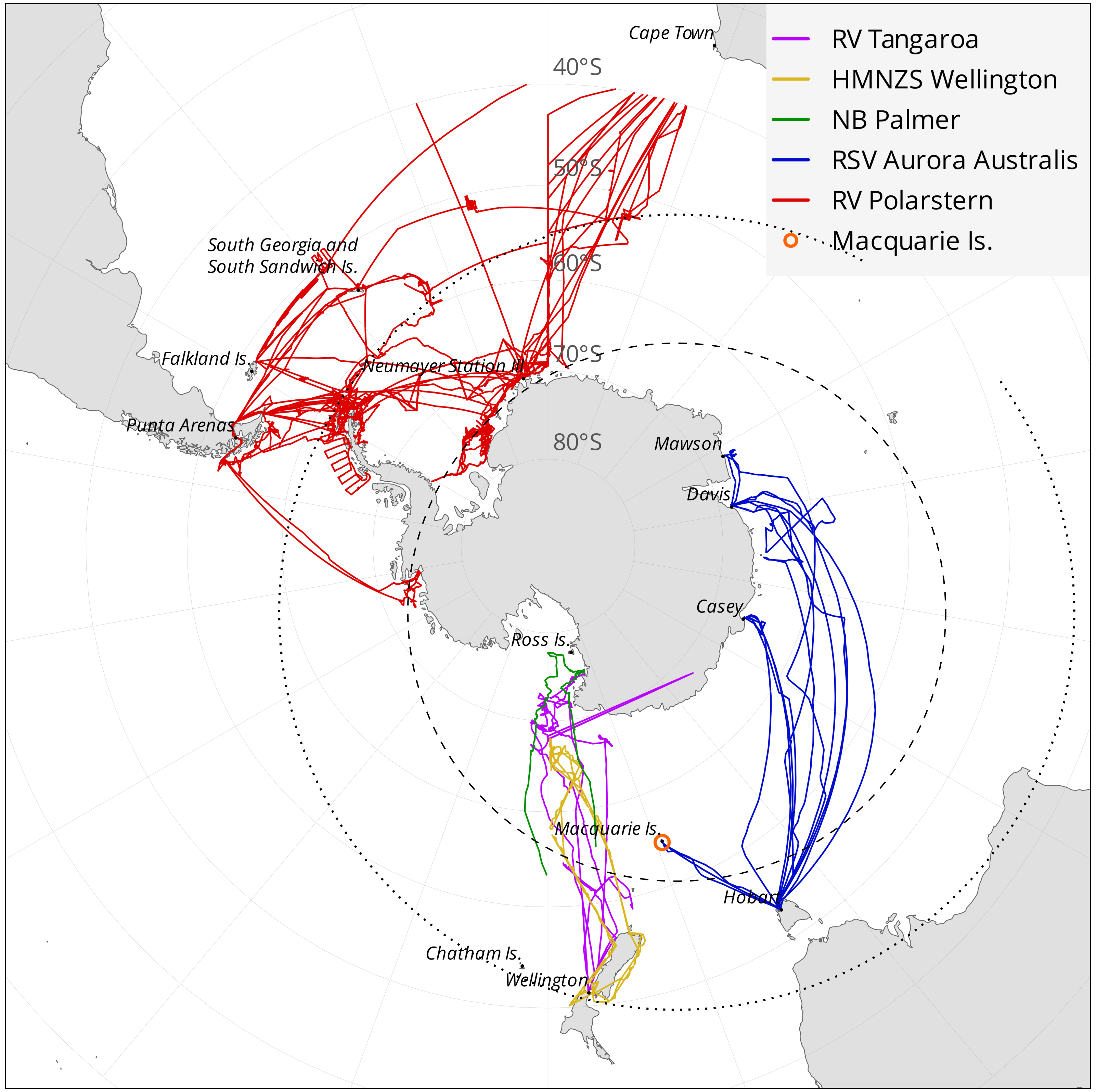


Adopted from Revell et al. (2021): *Direct radiative effects of airborne microplastics*.

Ship-based Observations over the Southern Ocean

Atmospheric measurements over the Southern Ocean are complementary to satellites.

Measurements of clouds, aerosols, and atmospheric thermodynamic profile using various methods.



Adopted from Kuma et al. (2024): *Ship-based lidar evaluation of Southern Ocean clouds in the storm-resolving general circulation model ICON and the ERA5 and MERRA-2 reanalyses* [manuscript in preparation].

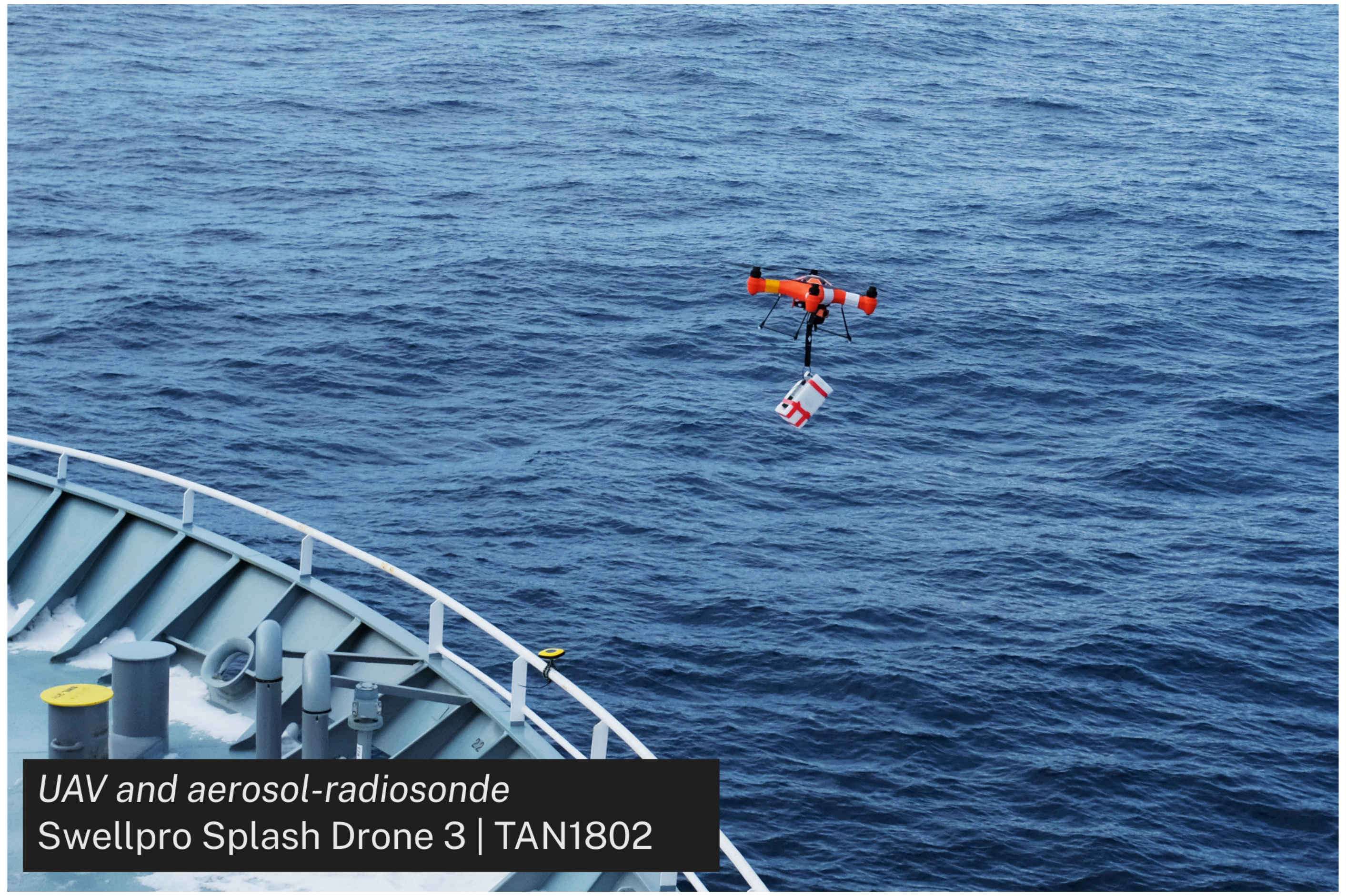
Ship-based Observations over the Southern Ocean

Ceilometer © Jeff Aquilina
Vaisala CL51 | Macquarie Is.

Ceilometer
Lufft CHM 15k | TAN1702

Micro rain radar
Meter MRR-2 | TAN1802

Helikite | TAN1802



UAV and aerosol-radiosonde
Swellpro Splash Drone 3 | TAN1802

Radiosonde release
iMet-1 ABx | TAN1802

Ship-based Observations over the Southern Ocean

Video 2 and 3

https://files.peterkuma.net/media/svxde2yho3/radiosonde.webm

https://files.peterkuma.net/media/3k146je3bn/uav.webm

Evaluation of Climate Models using Lidar Observations

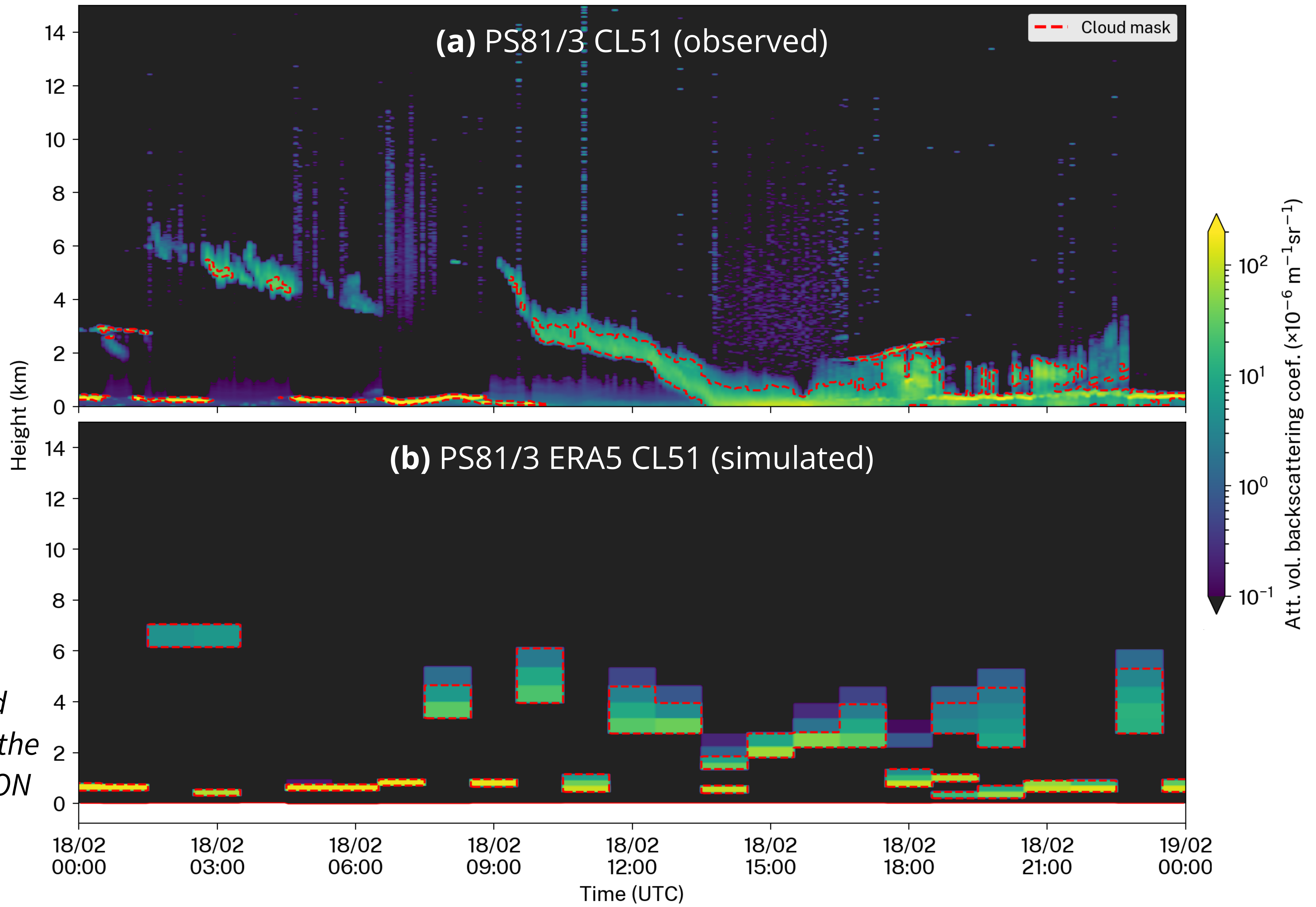
Lidars can measure backscattered laser radiation.

Clouds are aerosols are sampled vertically and over time.

Cloud fraction by height can be calculated from a cloud mask.

Using a lidar simulator, we can calculate the same for a climate model or a reanalysis.

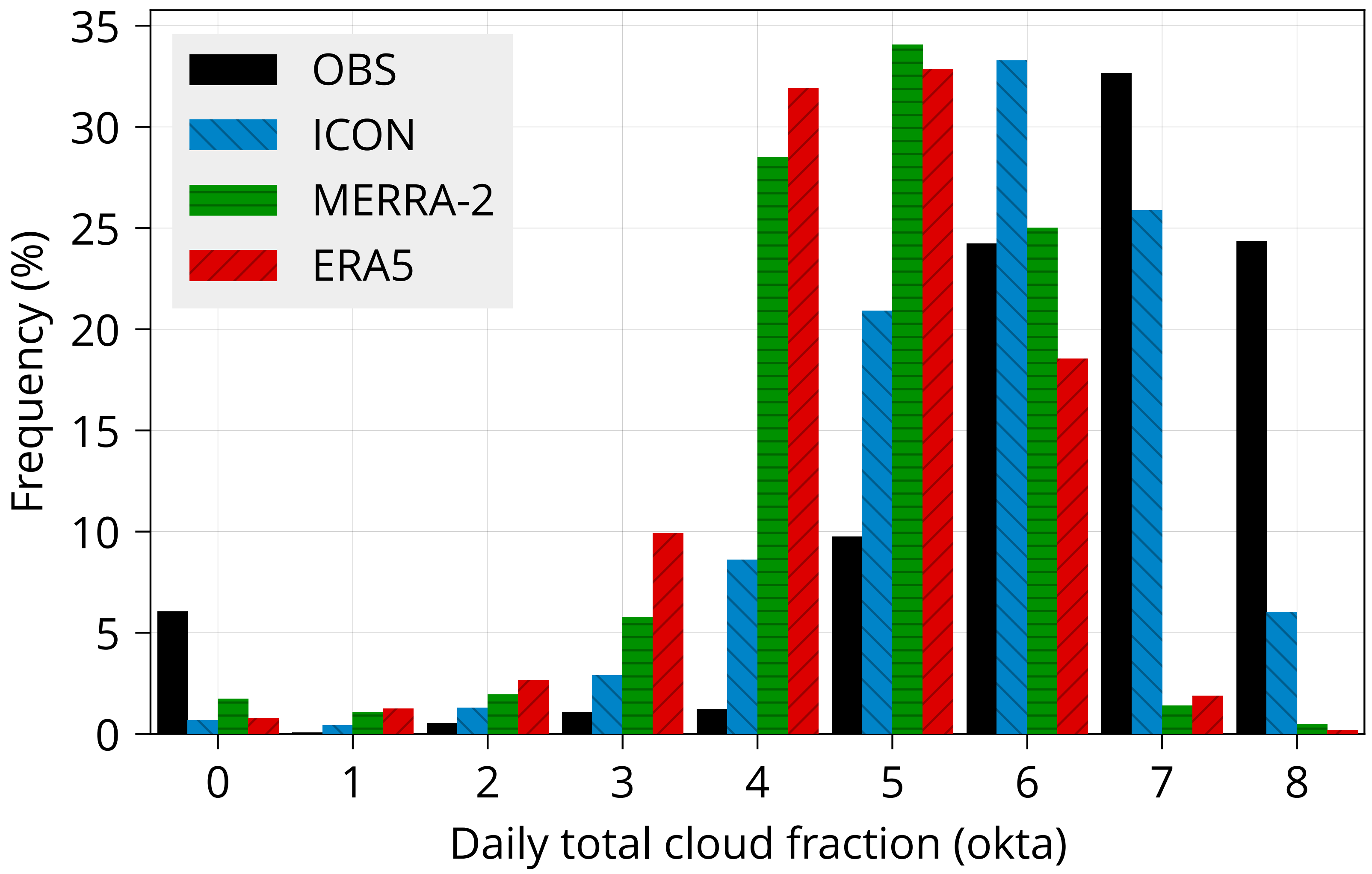
Adopted from Kuma et al. (2024): *Ship-based lidar evaluation of Southern Ocean clouds in the storm-resolving general circulation model ICON and the ERA5 and MERRA-2 reanalyses* [manuscript in preparation].

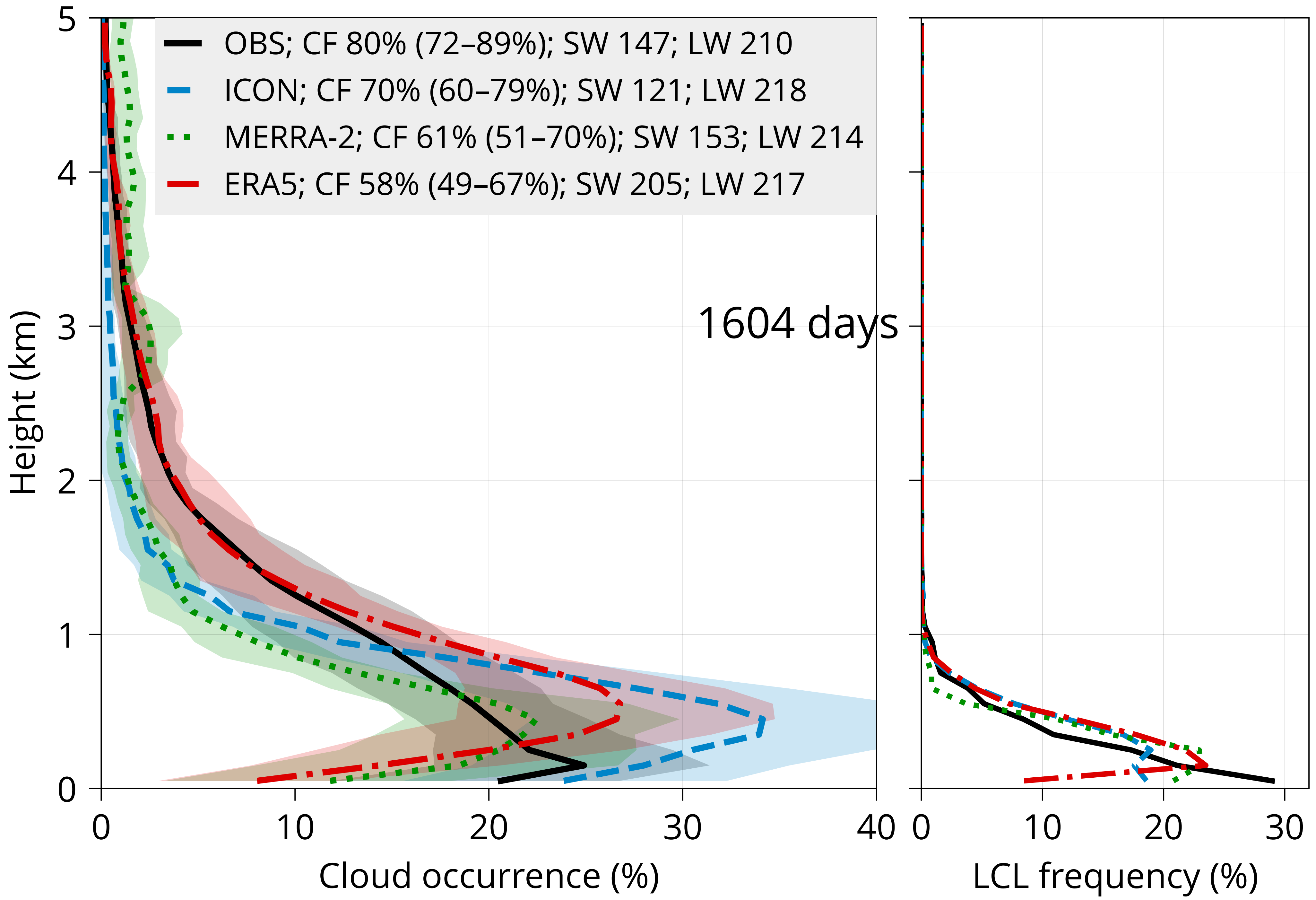


Evaluation of Climate Models using Lidar Observations

Cloud fraction by height can be compared between the observations (OBS) and models.

Models tend to underestimate cloud fraction, but overestimate reflected solar radiation.





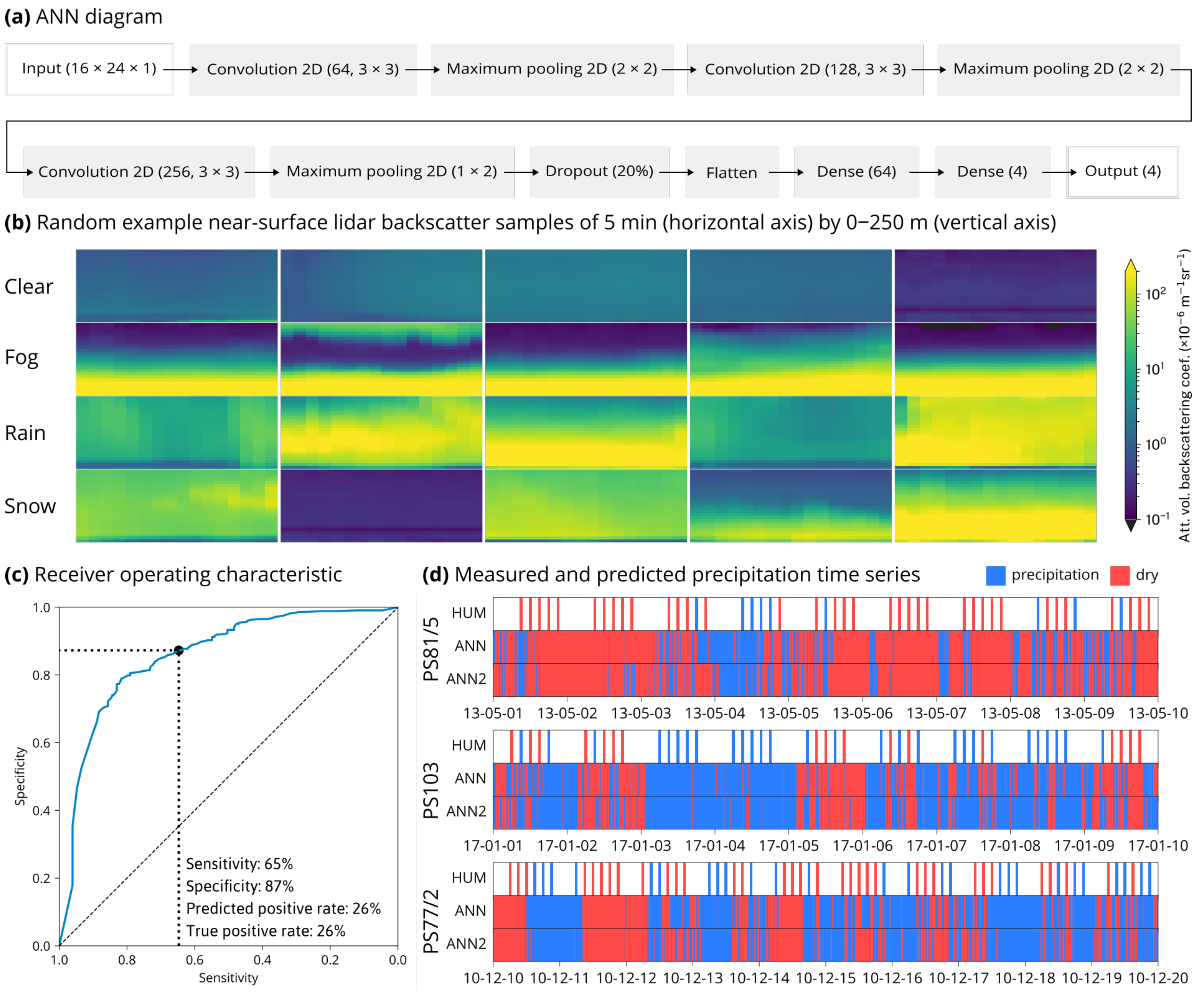
Adopted from Kuma et al. (2024): *Ship-based lidar evaluation of Southern Ocean clouds in the storm-resolving general circulation model ICON and the ERA5 and MERRA-2 reanalyses* [manuscript in preparation].

Precipitation Detection from Lidar Backscatter Using ML

Profiles with precipitation are unwanted in the comparison.

We can train a U-Net neural network to identify samples with different conditions, based on limited human-performed observations.

Sensitivity about 65%, which is good enough for the filtering step.



Adopted from Kuma et al. (2024): *Ship-based lidar evaluation of Southern Ocean clouds in the storm-resolving general circulation model ICON and the ERA5 and MERRA-2 reanalyses* [manuscript in preparation].

Using Meachine Learning to Identify Clouds

Identify cloud types using a neural network.

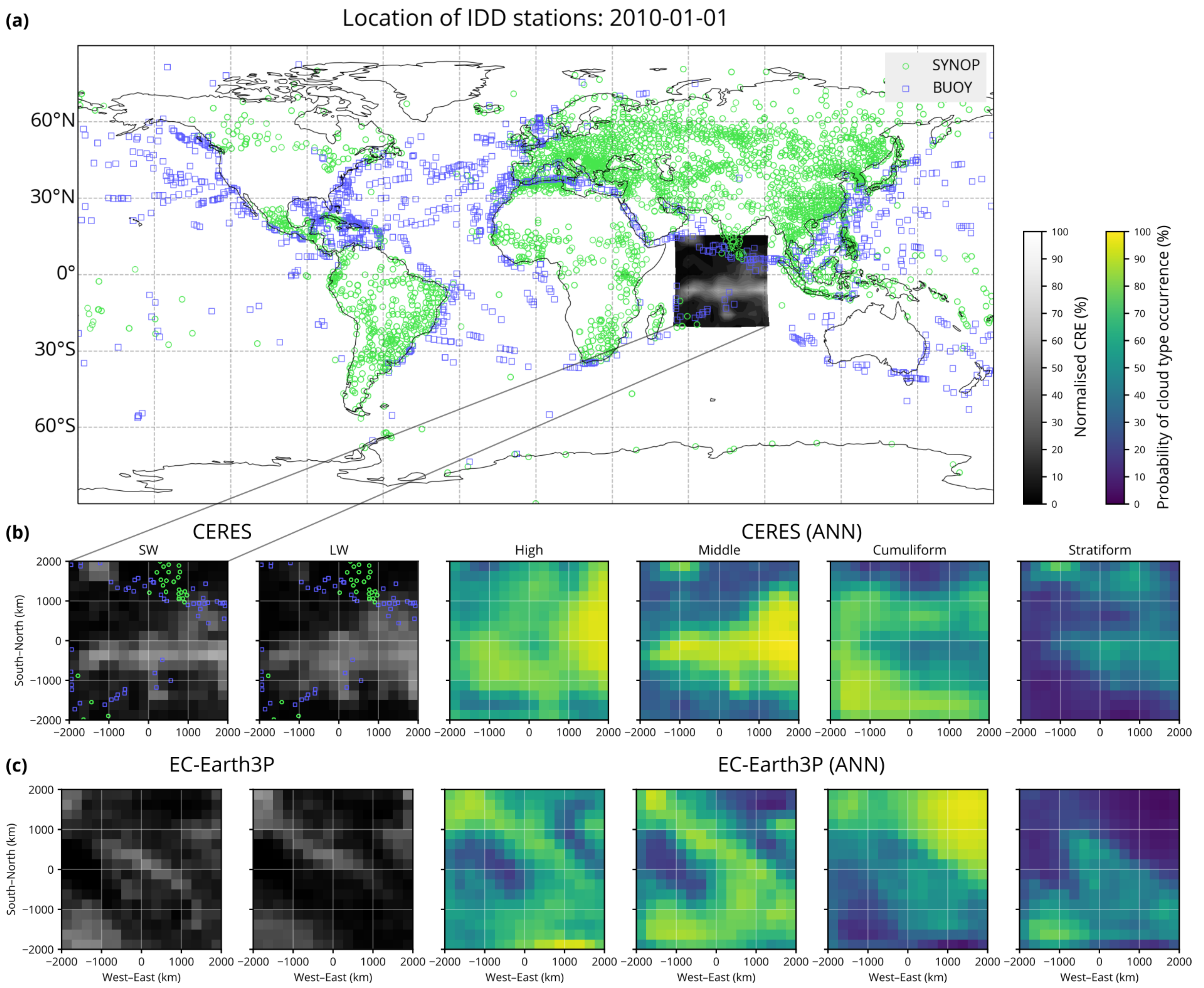
Training:
– global station observations
– satellite images (shortwave and longwave)

Prediction:
– satellite images
– equivalent climate model images

What is the distribution of clouds types in the reality and in the models?

What are the model errors?

How do they imact climate sensitivity?



Adopted from Kuma et al. (2023): *Machine learning of cloud types in satellite observations and climate models*.

Using Meachine Learning to Identify Clouds

Neural network of type U-Net.

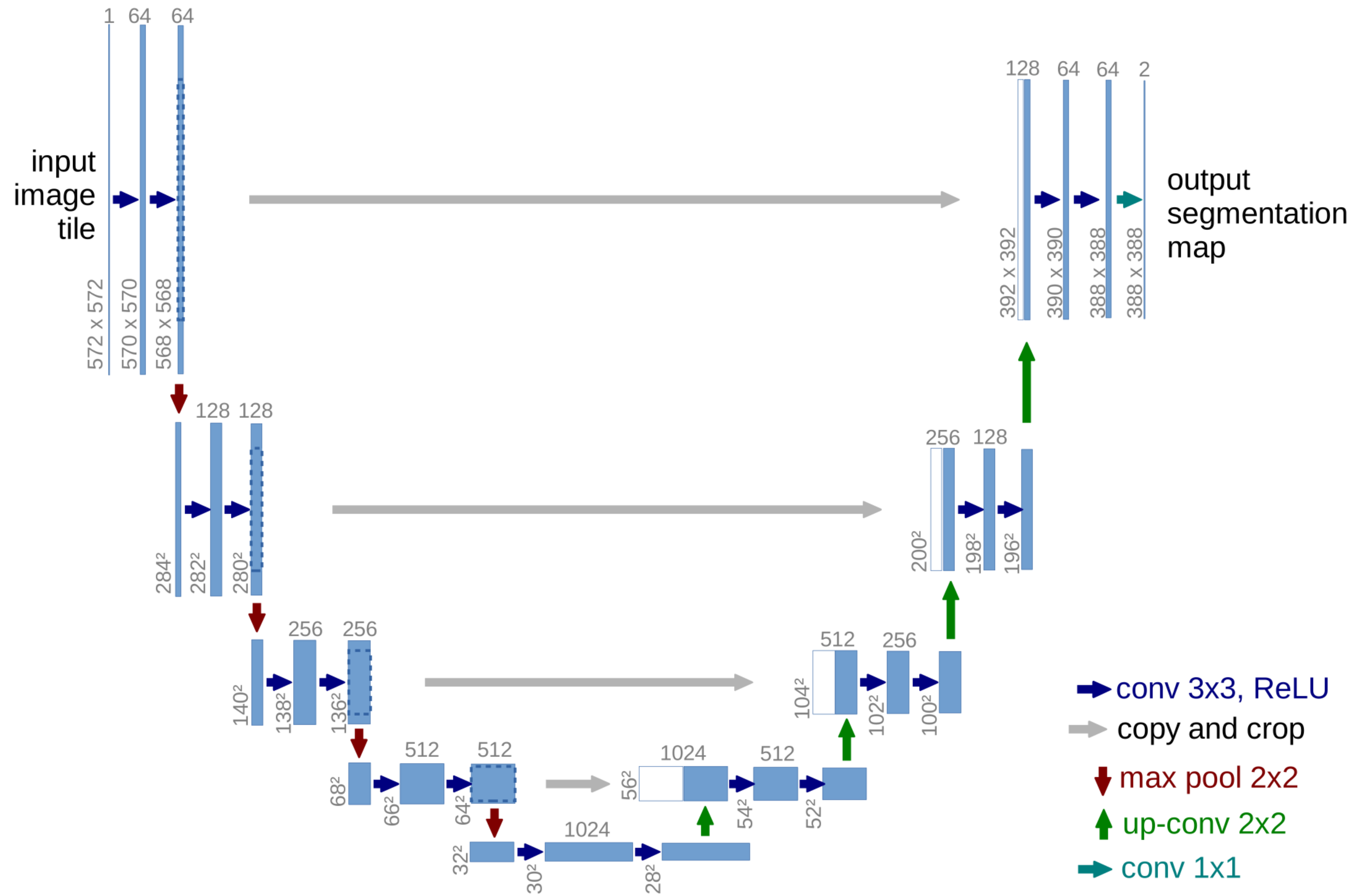
encoder–decoder design

Input: 2D image with multiple channels (colour, etc.)

Output: 2D image with multiple channels.

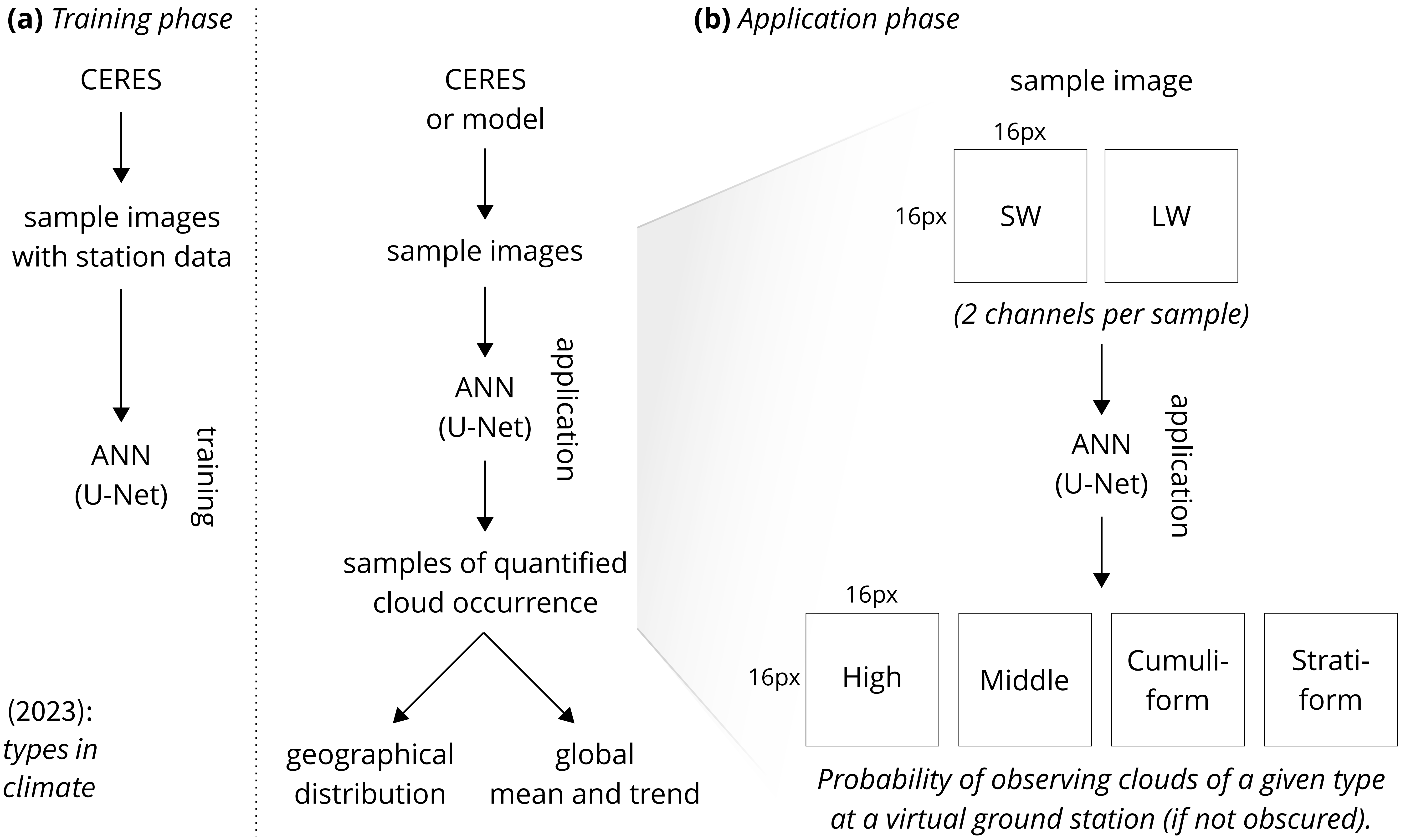
Layers of downscaling, followed by layers of upscaling.

Useful for classifying all pixels.



Adopted from Ronneberger et al. (2015): *U-Net: Convolutional Networks for Biomedical Image Segmentation*.

Using Meachine Learning to Identify Clouds



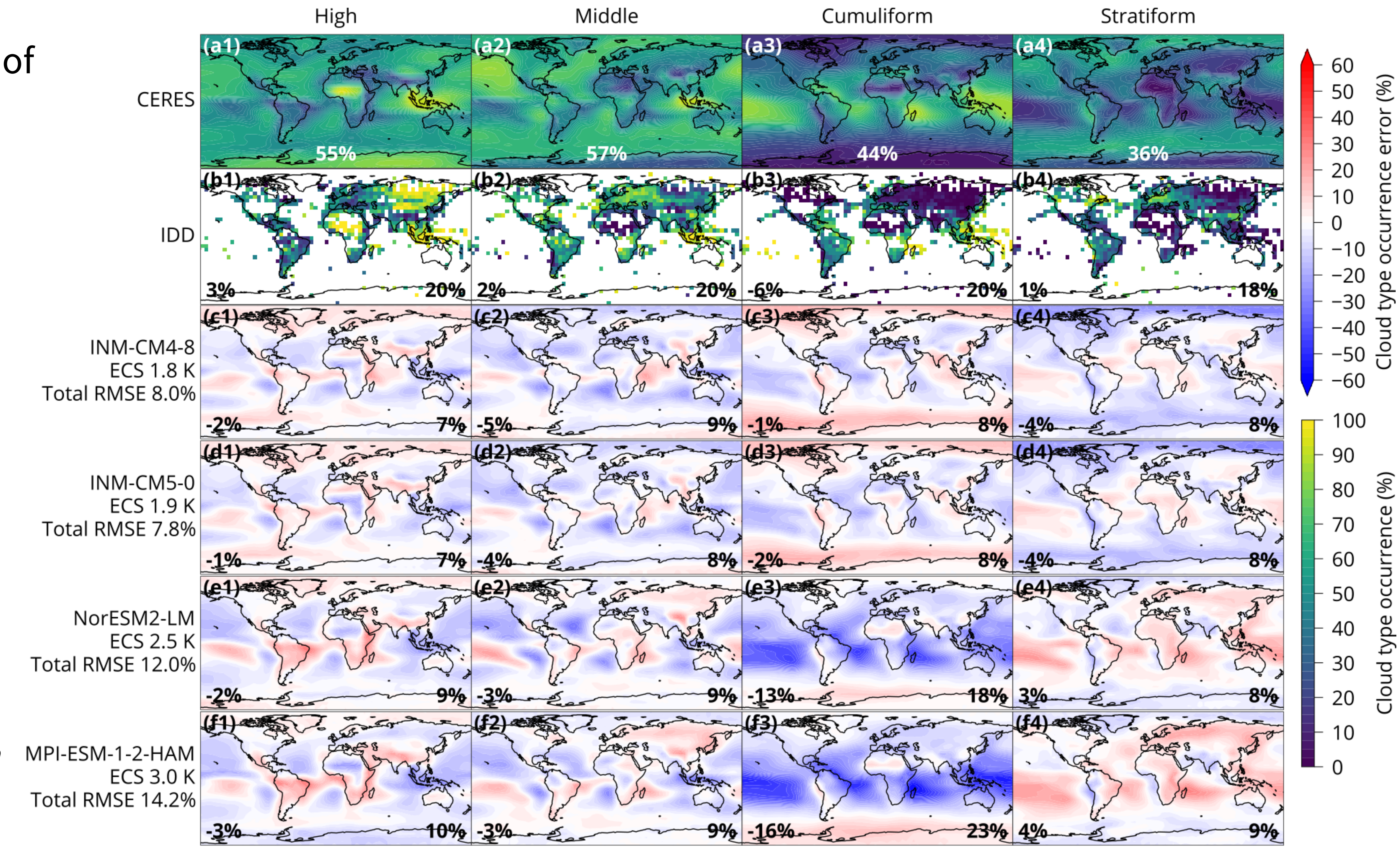
Adopted from Kuma et al. (2023):
Machine learning of cloud types in satellite observations and climate models.

Using Meachine Learning to Identify Clouds

Geographical distribution of cloud types.

IDD (station reference).

Climate model errors.



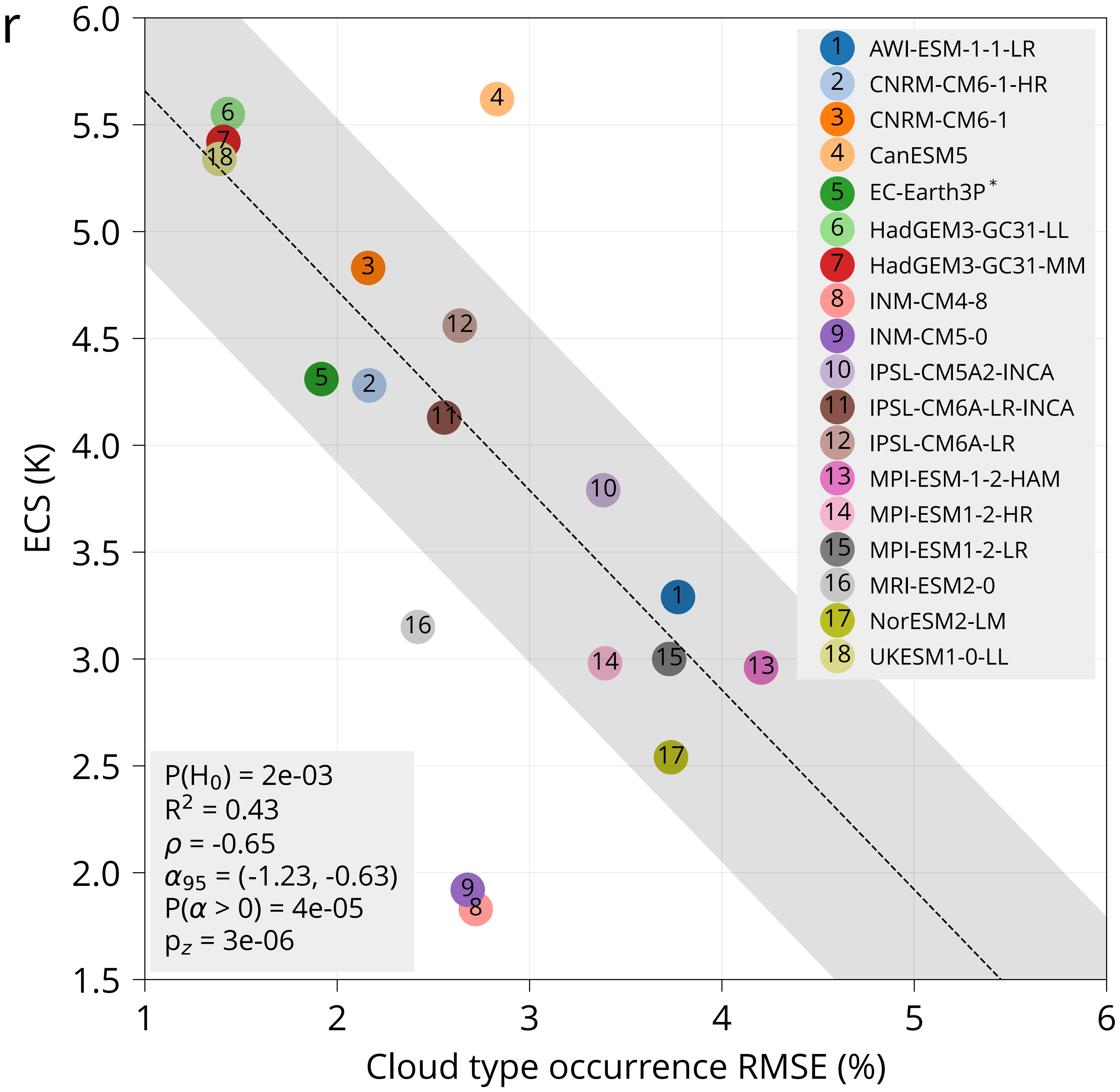
Adopted from Kuma et al. (2023): *Machine learning of cloud types in satellite observations and climate models.*

Using Meachine Learning to Identify Clouds

Models with greater error in the cloud types have a greater climate sensitivity.

It could imply that warmer models are more correct.

[But, correlation does not imply causation.]



Adopted from Kuma et al. (2023): *Machine learning of cloud types in satellite observations and climate models*.

Thank you for your attention. Questions?

Photos © Glen Walker, NIWA (TAN1802 voyage)