The future of AI in Earth system modelling

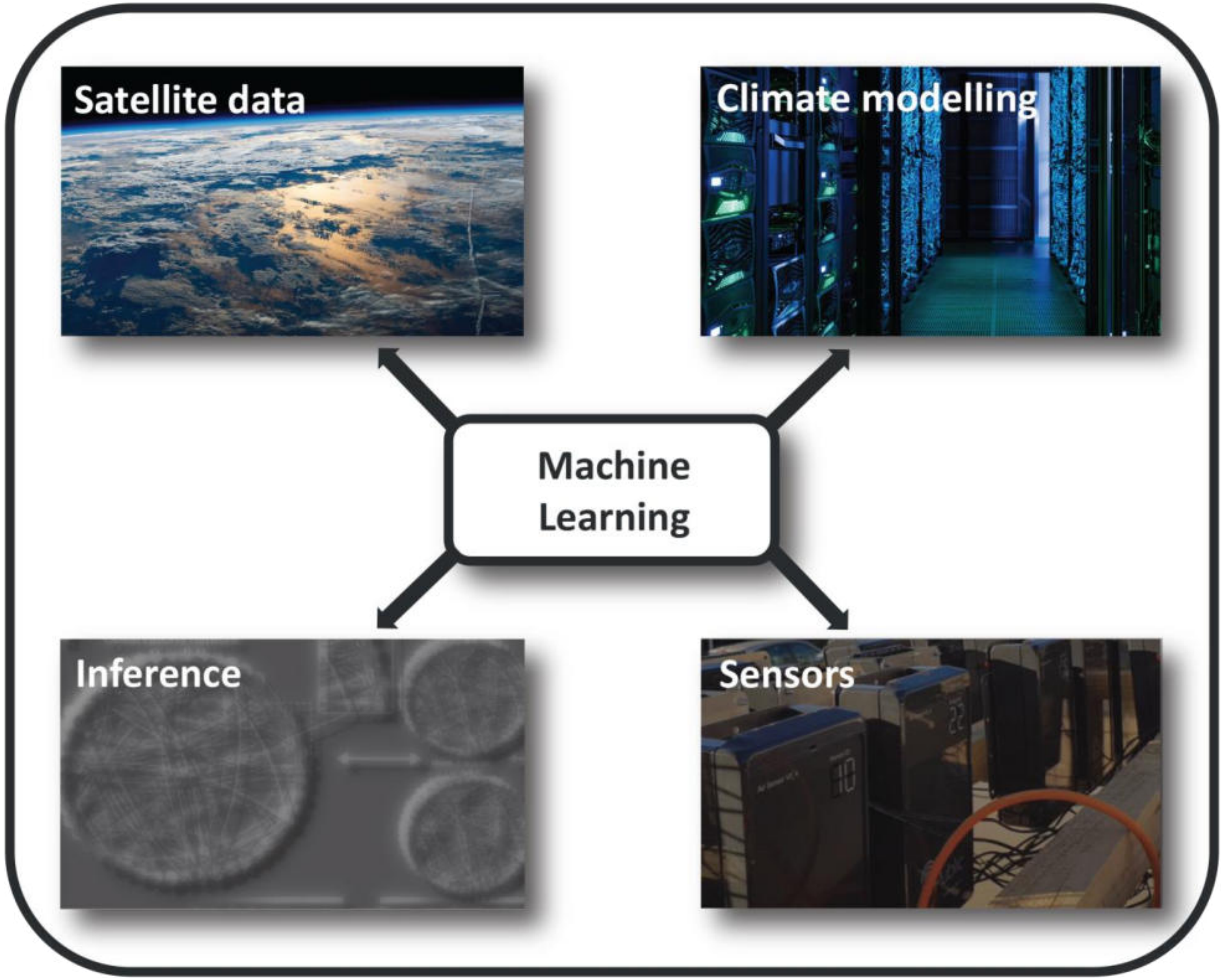
Fully data-driven or full of constraints?

Peer Nowack

Institute of Theoretical Informatics (ITI)
Institute of Meteorology and Climate Research (IMKASF)
Karlsruhe Institute of Technology
Germany

natESM Community Workshop, Leipzig, 25 February 2026

Our Chair for AI in Climate and Environmental Sciences



AI Climate

ki-klima.iti.kit.edu

What is machine learning?

The field of study that gives computers the ability to learn without being explicitly programmed.

Arthur Samuel, IBM, later Stanford, 1959

A set of methods that automatically detect patterns in data and then use uncovered patterns to predict future data.

Future data = data you have not seen before.

Kevin Murphy, Google, previously Uni. British Columbia, 2012

Machine learning vs. AI

Artificial intelligence (AI) is the broader concept of machines doing things that humans consider ‘intelligent’.

Machine learning is a subset of AI based on the idea that we just have to provide the machines (algorithms) with data and let them learn by themselves, without being explicitly programmed.

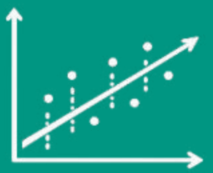
Careful: pending definition of ‘intelligent’…

Classes of machine learning algorithms + self-supervised learning

Supervised learning

Labelled data

Regression



Classification

Unsupervised learning

Unlabelled data

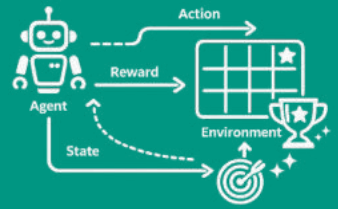
Find structure

Clustering

Dimension reduction

Reinforcement learning

Learn by trial-and-error



Actions trigger cumulative reward

Balance between exploration (*unchartered territory*) and exploitation (*existing knowledge*)

Self-supervised learning example (spatiotemporal data)

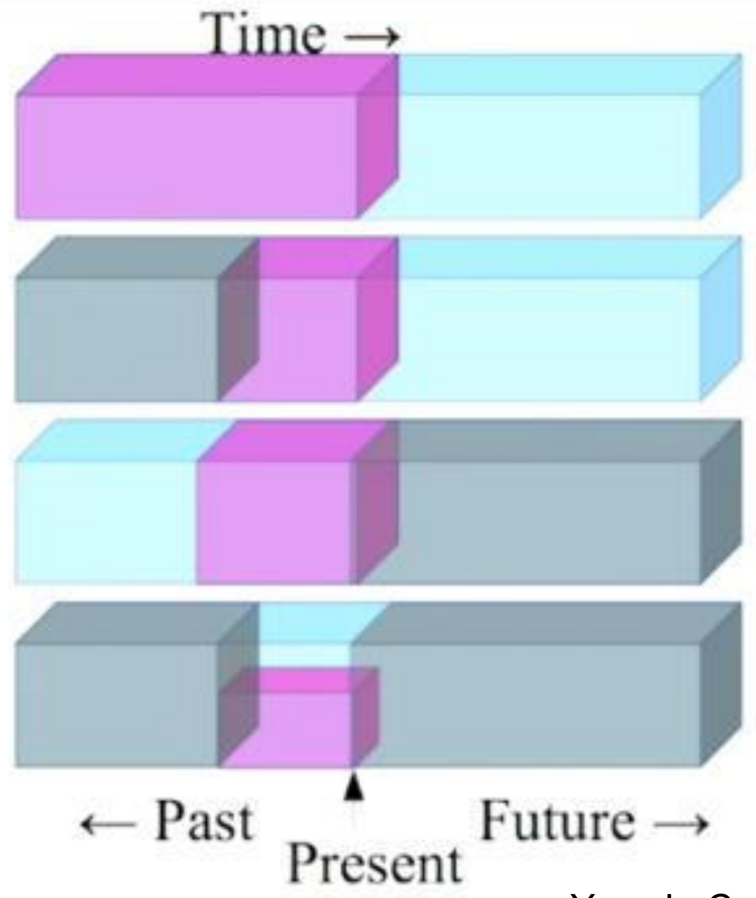
Pretend that you don't know **blue data** → predict from **pink data**.

Predict the **future** from the **past**.

Predict the **future** from the **recent past**.

Predict the **past** from the **present**.

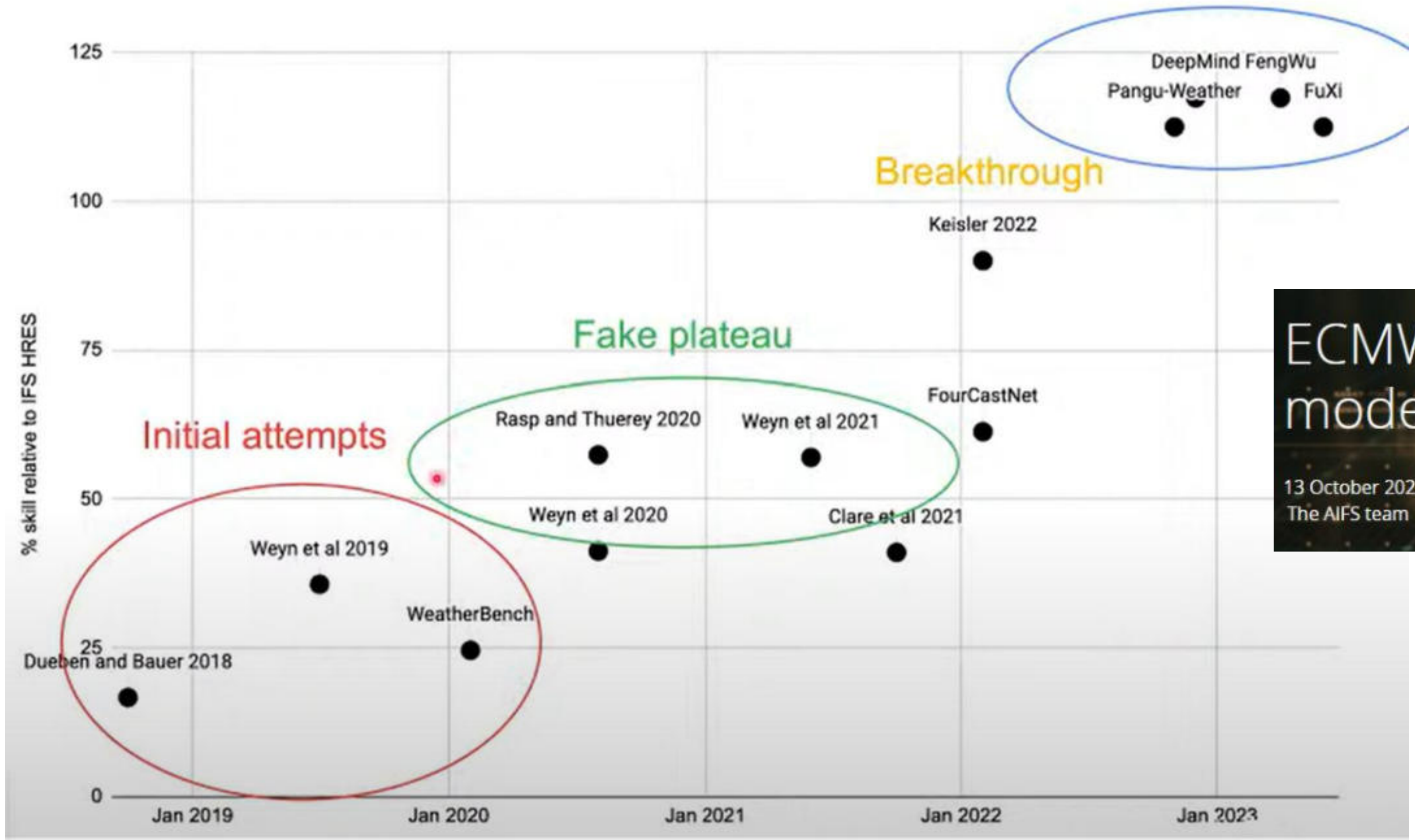
Predict **points in space** from **other points in space**.



Yann LeCun

Is the future of weather forecasting data-driven?

Machine learning weather forecasting → the AI revolution?!

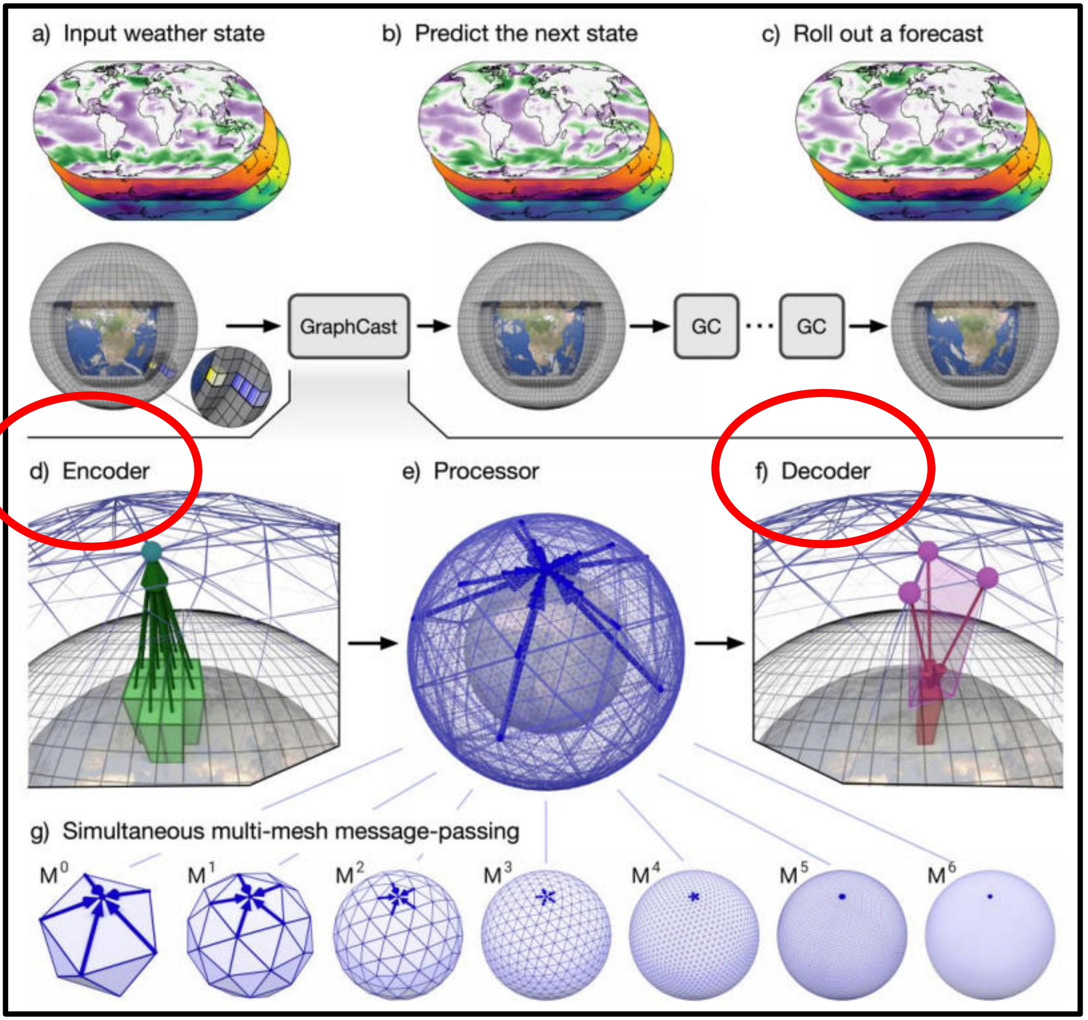


↑ **higher is better**

Stephan Rasp, Google, AI4Good talk

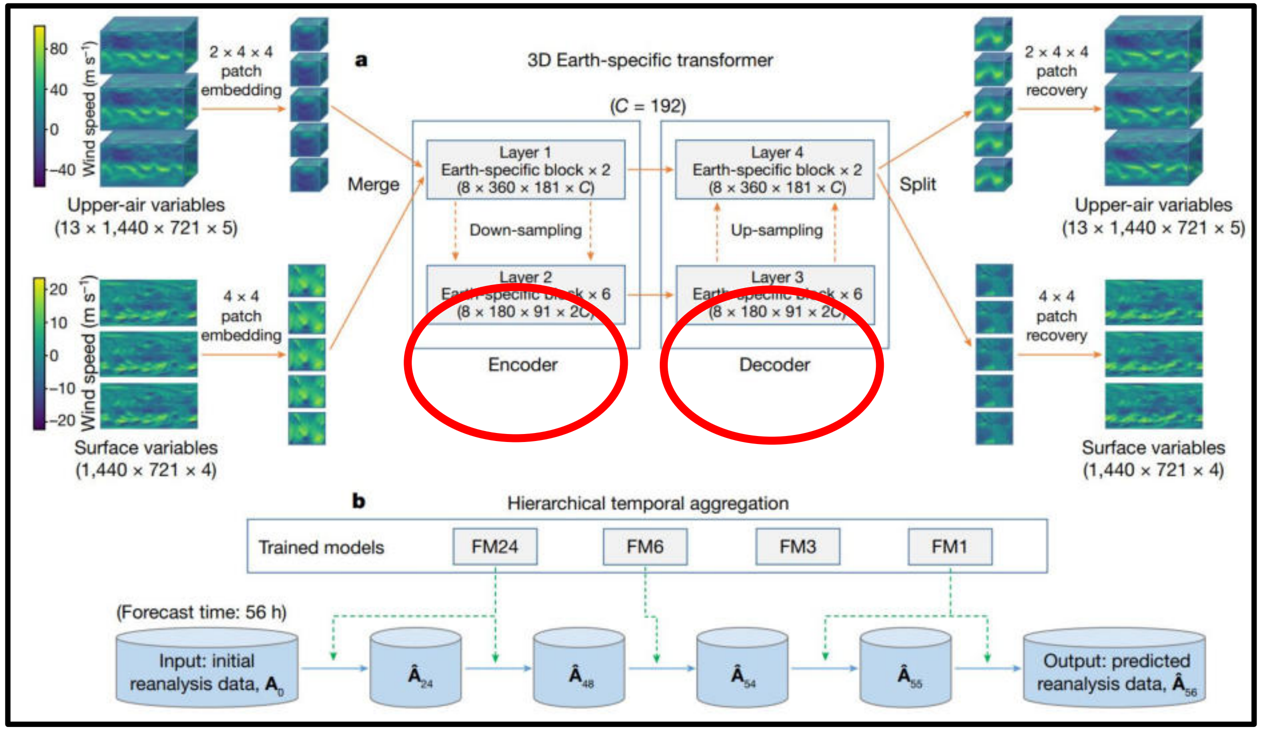
Neural architectures for data-driven weather forecasting

Graph neural networks



Lam et al. Learning skillful medium-range global weather forecasting, arXiv, 2022

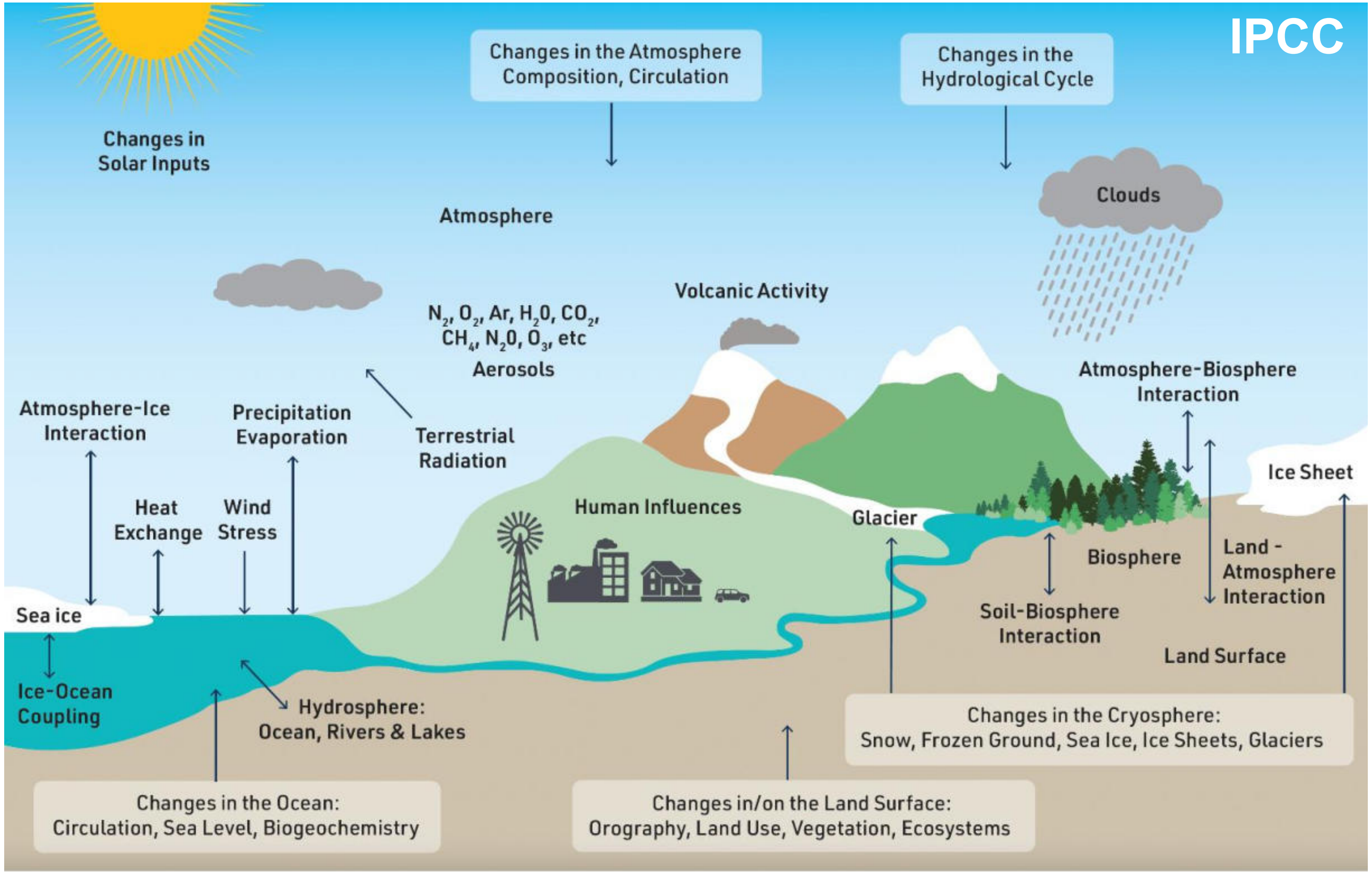
Transformers



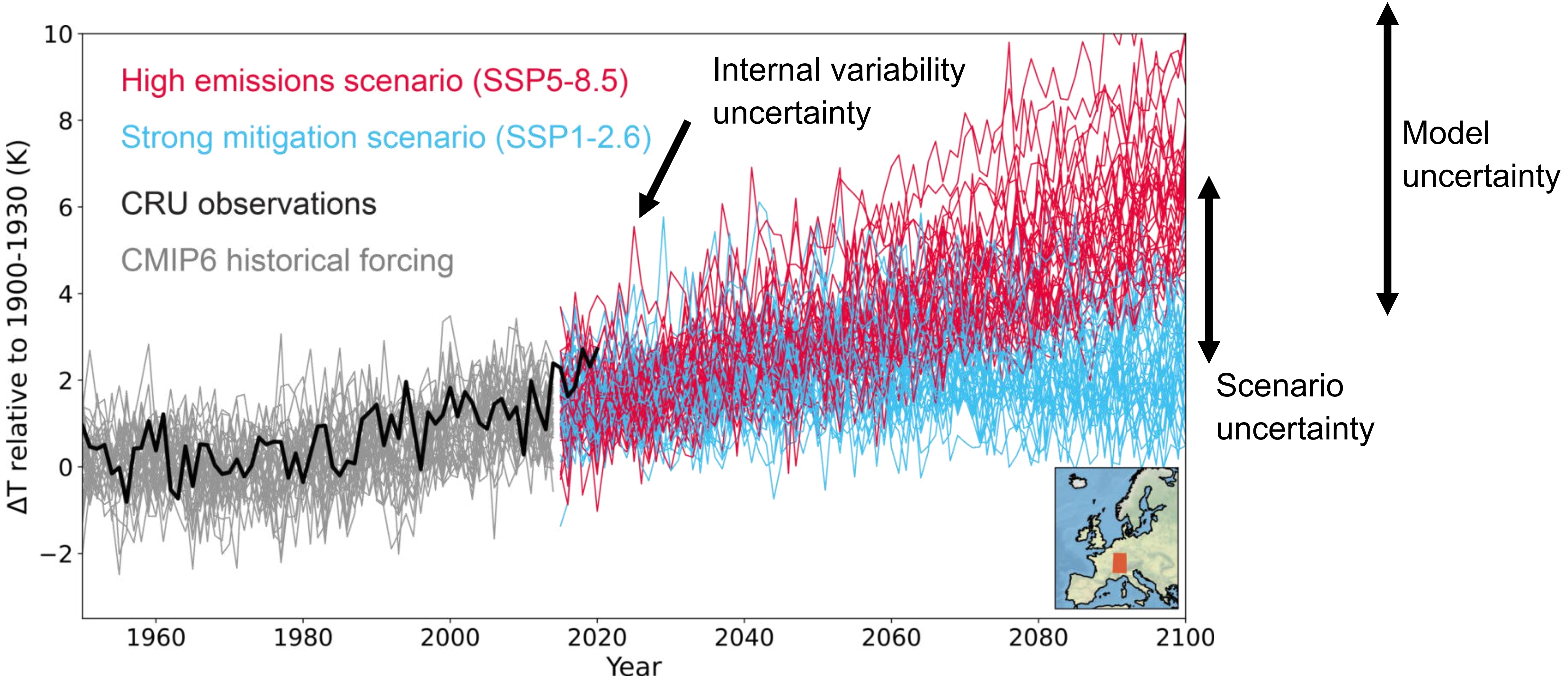
Bi et al. Accurate medium-range global weather forecasting with 3D neural networks, Nature, 2023

And how about Earth system modelling?

Earth system models and climate modelling



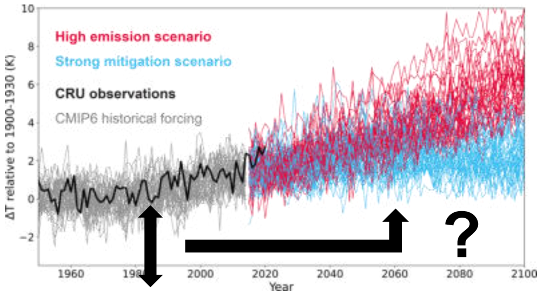
Our interest in climate change uncertainties



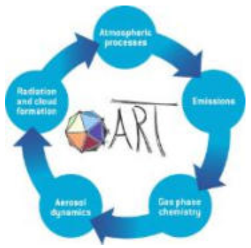
We tackle climate model uncertainty

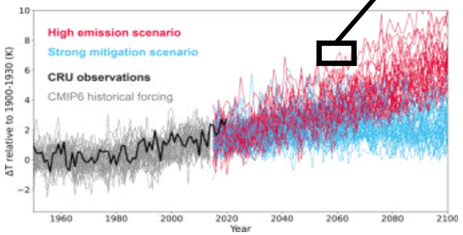
Fully data-driven? Causality? Physics-informed loss?

Strong constraints

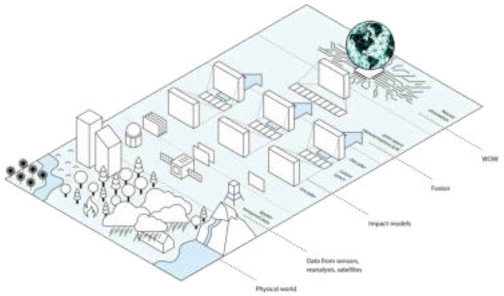


Constraint = ESM, combined with data-driven model





Init AI impact models



Climate data science

Focus on scientific problem definition / interpretable models

Neural climate models

Large-scale data / high AI model capacity

Controlling factor analyses
- Clouds
- Stratospheric water vapour
- Regional surface temperature
- Precipitation

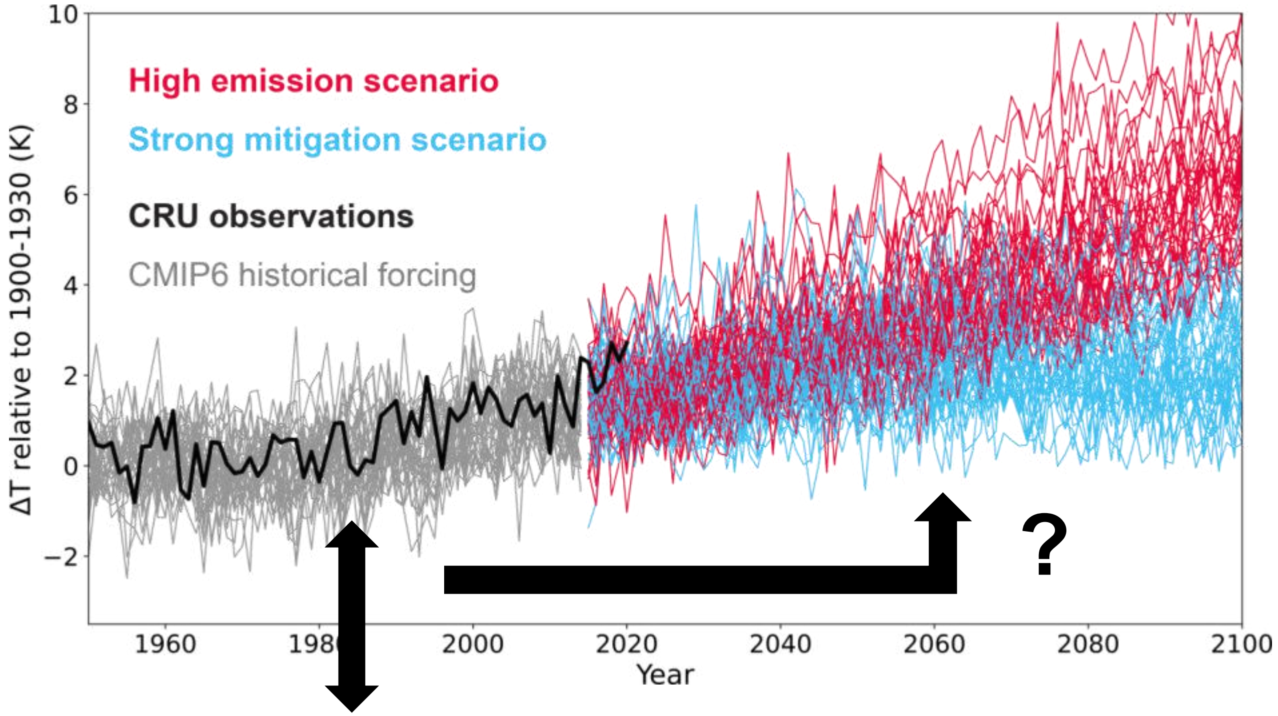
Hybrid climate models
- Model parameterizations
- Ozone
- ICON, UKESM

AI world models & emulation
- WOW world model
- Causal climate model emulation
- Transfer learning

Causal climate evaluation
- Teleconnections
- Precipitation dynamics
- Causal representation learning

Data-driven forecasting
- Air pollution
- Wildfire risks
- AI weather models & climate projections

Observational constraints on model uncertainties



Cloud feedback
Ceppi & Nowack PNAS (2021)
Wilson Kemsley et al. ACP (2024), GRL (2025, 2026)
Ceppi et al. GRL (2024), ACP (2026)

Stratospheric water vapour
Nowack et al. Nature Geoscience (2023)
Amiramjadi et al., in preparation.

Precipitation and surface temperature
Nowack et al. Nature Communications (2020)
Debeire et al. Earth System Dynamics (2025)
Wilkinson et al. JGR-Machine Learning (2025)

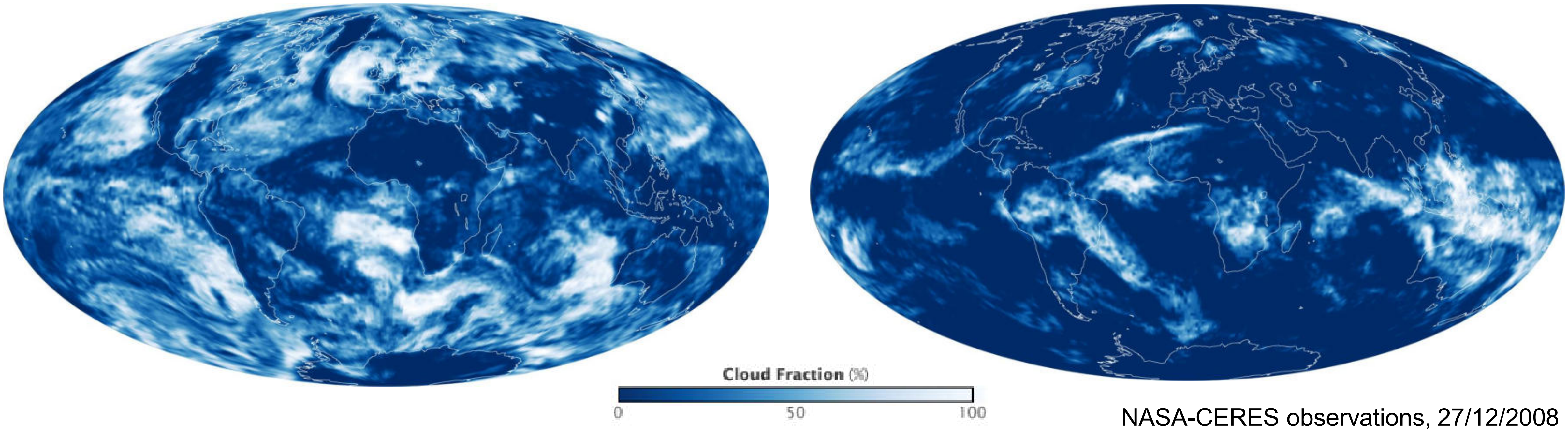
Overview article in:
Nowack & Watson-Parris. Opinion: Why all emergent constraints are wrong but some are useful – a machine learning perspective, ACP (2025)

Why are clouds so important for climate?

Clouds reflect shortwave = solar visible radiation (‘parasol’ ⛱) → a **cooling** effect

Clouds absorb longwave = terrestrial infrared radiation (‘blanket’ 🛏) → a **warming** effect

Low cloud fraction **High-altitude cloud fraction**



NASA-CERES observations, 27/12/2008

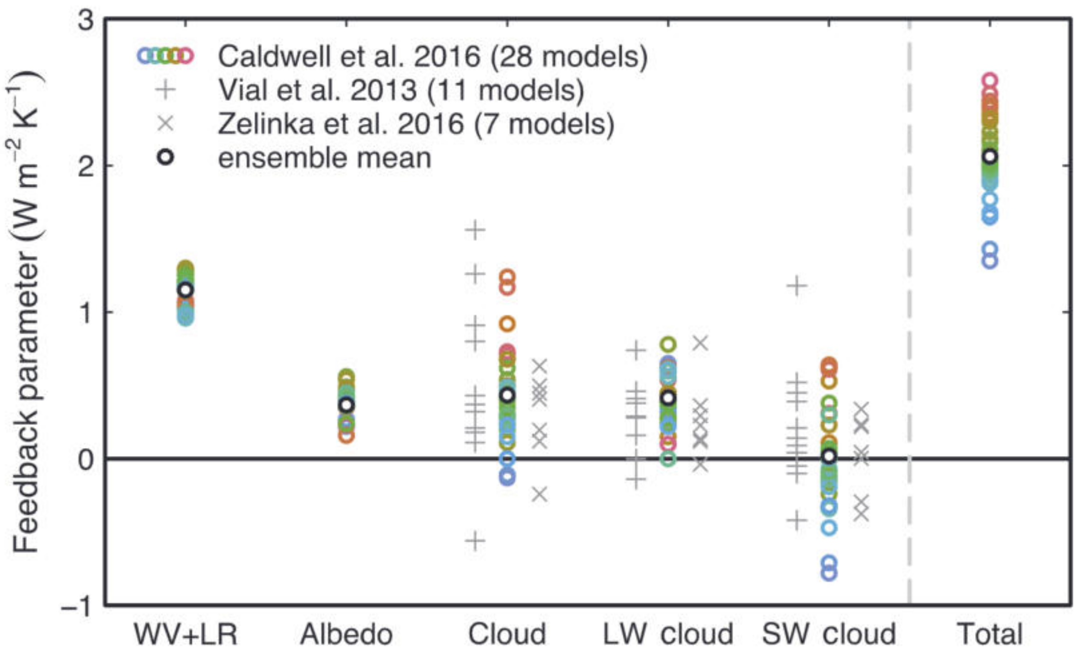
Cloud feedback and climate sensitivity

Changes in cloud properties (amount, optical thickness, altitude) can amplify or dampen global warming, leading to feedback effects.

= **main source of uncertainty for equilibrium climate sensitivity** (ECS)

ECS = global warming at equilibrium under $2xCO_2$

Urgent/sustained need to better **understand** and **constrain** cloud feedback!

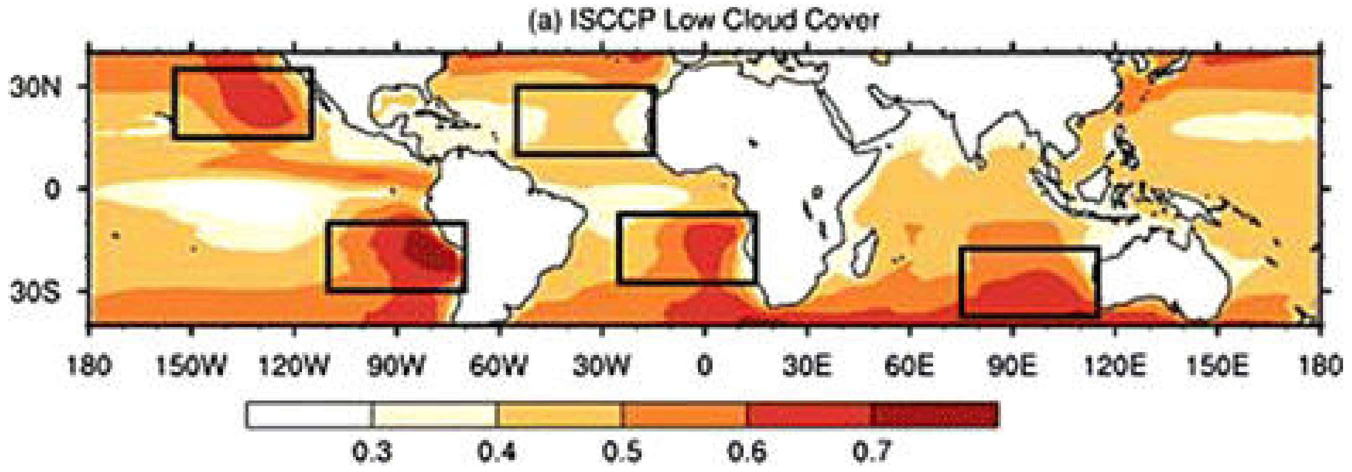


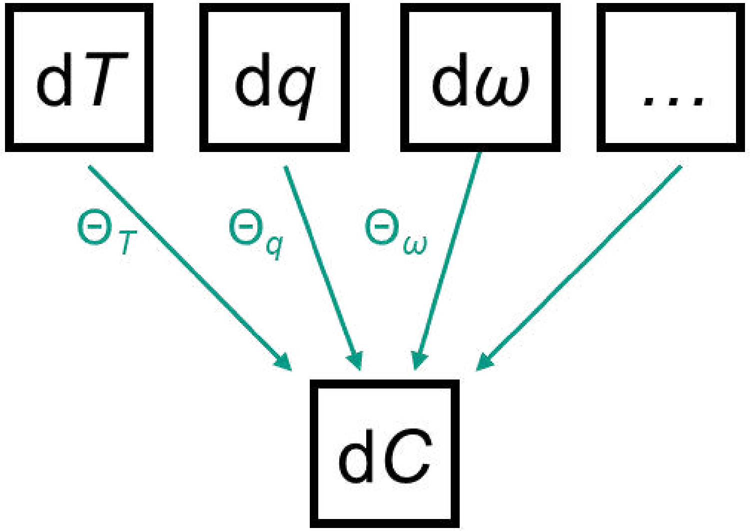
Ceppi et al. WIREs (2017)

Cloud controlling factor analysis (low clouds)

$$y = dC = \theta_T \cdot dT + \theta_q \cdot dq + \theta_\omega \cdot d\omega + \cdots$$

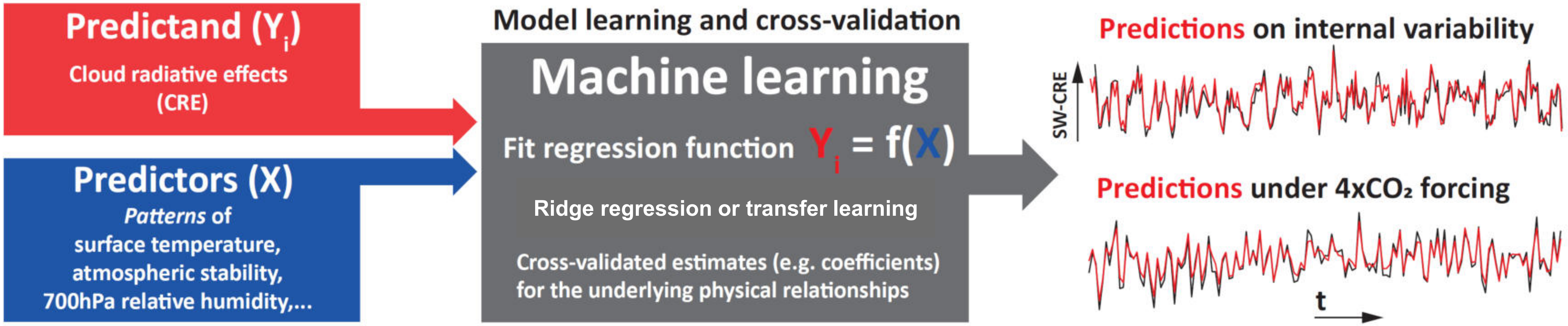
Estimate cloud radiative effect changes - dC - as a function of changes in large-scale meteorological *cloud-controlling factors,* e.g. surface temperature T, humidity q, vertical wind ω, etc.

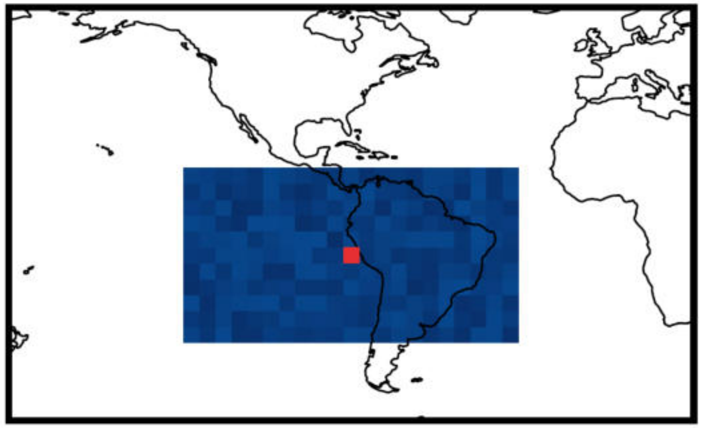




Klein et al. Low-cloud feedbacks from cloud controlling factors: a review. Surveys in Geophysics (2017).

Cloud controlling factor analysis (Ceppi & Nowack PNAS 2021)





1. Learn function f_{obs} from Earth observations (2000-2019).
2. Learn functions f_{CMIP} from 52 CMIP5/6 models (2000-2019).
3. Compare $4xCO_2$ projections using f_{obs} and f_{CMIP}
$\rightarrow$ observational constraint.

5°× 5°, monthly-mean

Statistical learning framework

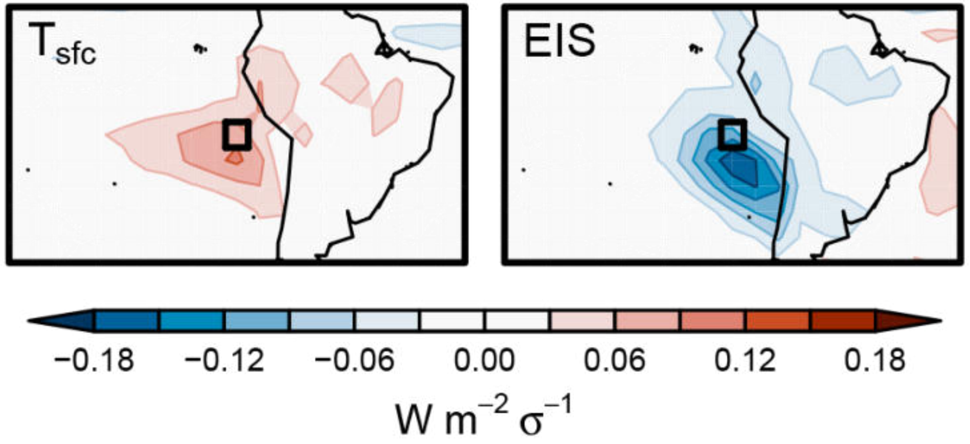
Karlsruhe Institute of Technology

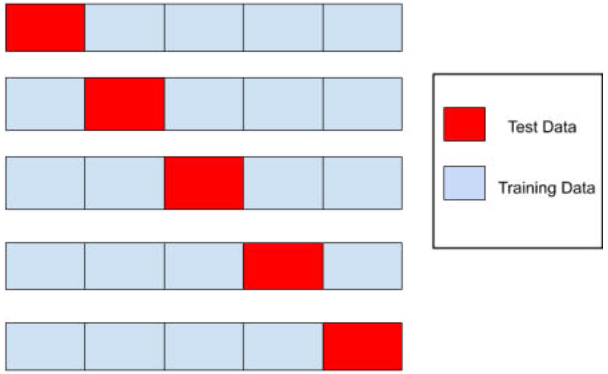
Ridge regression

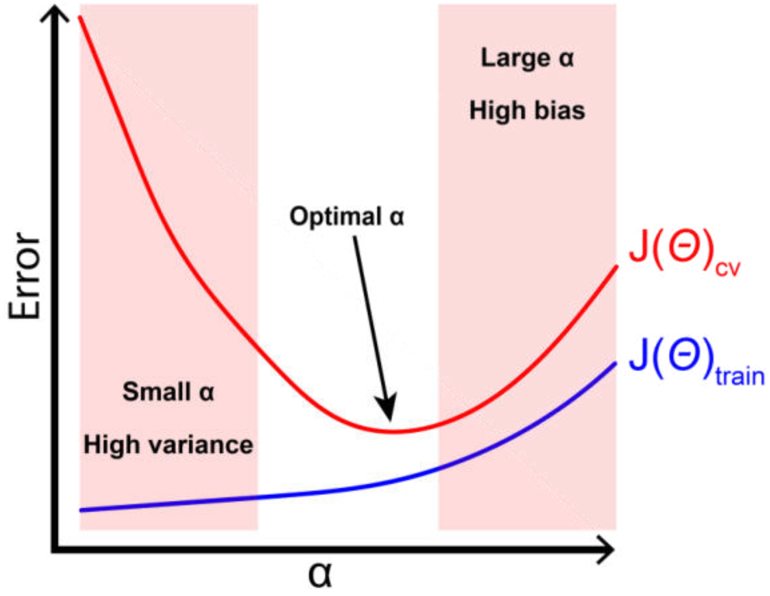
Minimises the cost function at grid point *r*

$$J_{\text{ridge}}(r, \boldsymbol{\Theta}) = \underbrace{\sum_{t=1}^{n} \left(Y_t(r) - \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \boldsymbol{X}_{i,t}(r) \right)^2}_{\text{Least squares}} + \underbrace{\alpha(r) \sum_{i=1}^{M} \|\boldsymbol{\Theta}_i(r)\|^2}_{\textbf{Ridge penalty term}}$$

Maps of Ridge coefficients θ_i

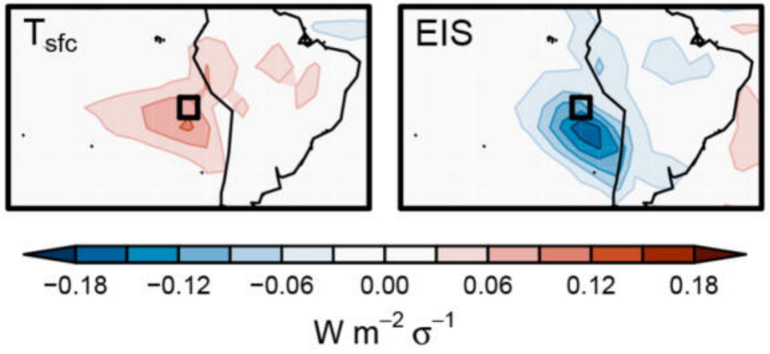






Linear framework – why?

1. Interpretable



$$dY_i \approx \sum_{j=1}^{M} \frac{\partial Y_i}{\partial \boldsymbol{X}_{ij}} \cdot d\boldsymbol{X}_{ij} \overset{\text{ridge}}{=} \sum_{j=1}^{M} \boldsymbol{\Theta}_{ij} \cdot d\boldsymbol{X}_{ij}$$

2. Small sample size

19 years of observations = 228 monthly samples.

3. Extrapolation

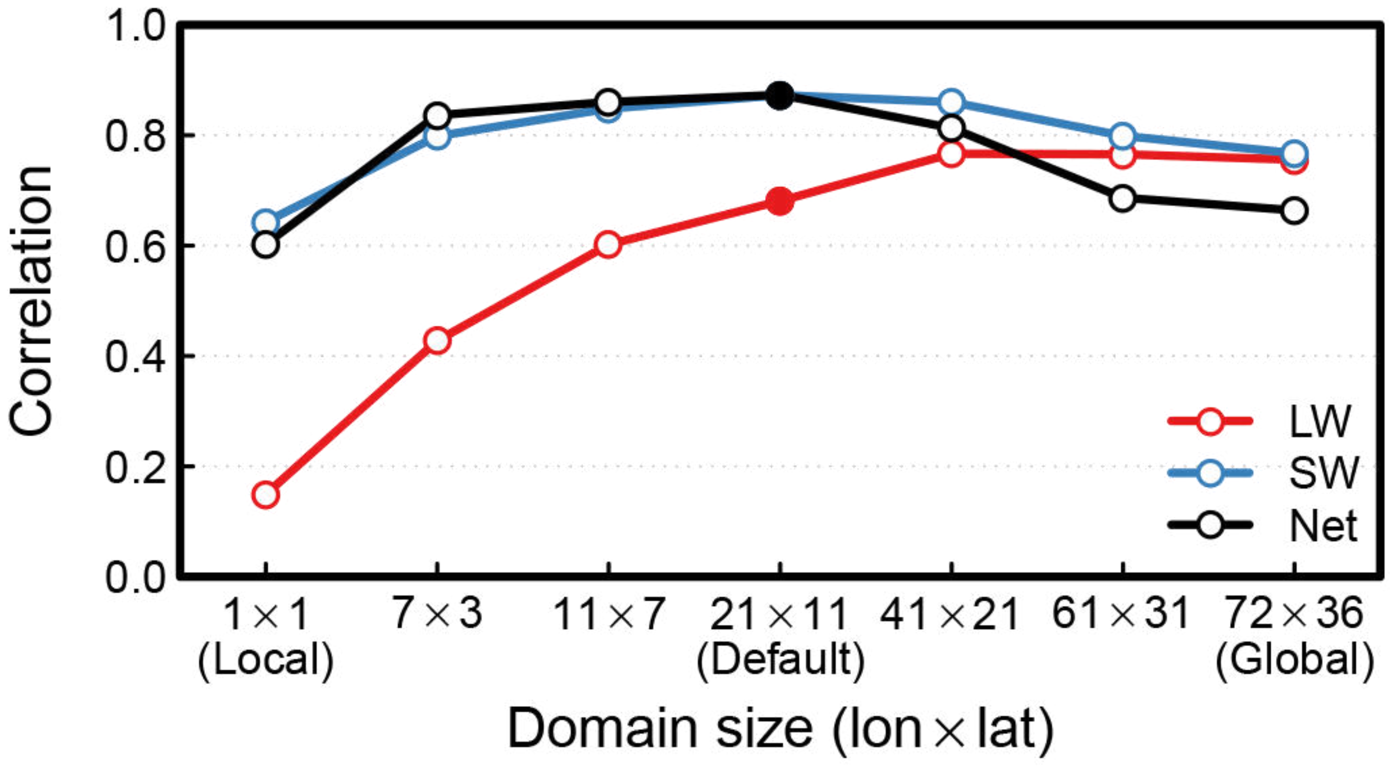
Learn from years 2000-2019 to predict Δ under $4xCO_2$.

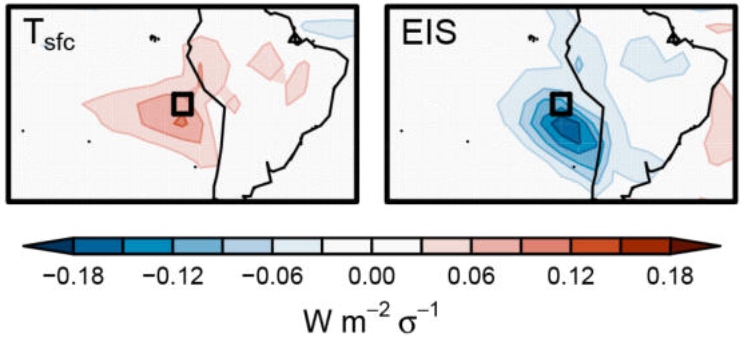
Non-linear frameworks possible?
Yes - transfer learning!

Lina Rennstich

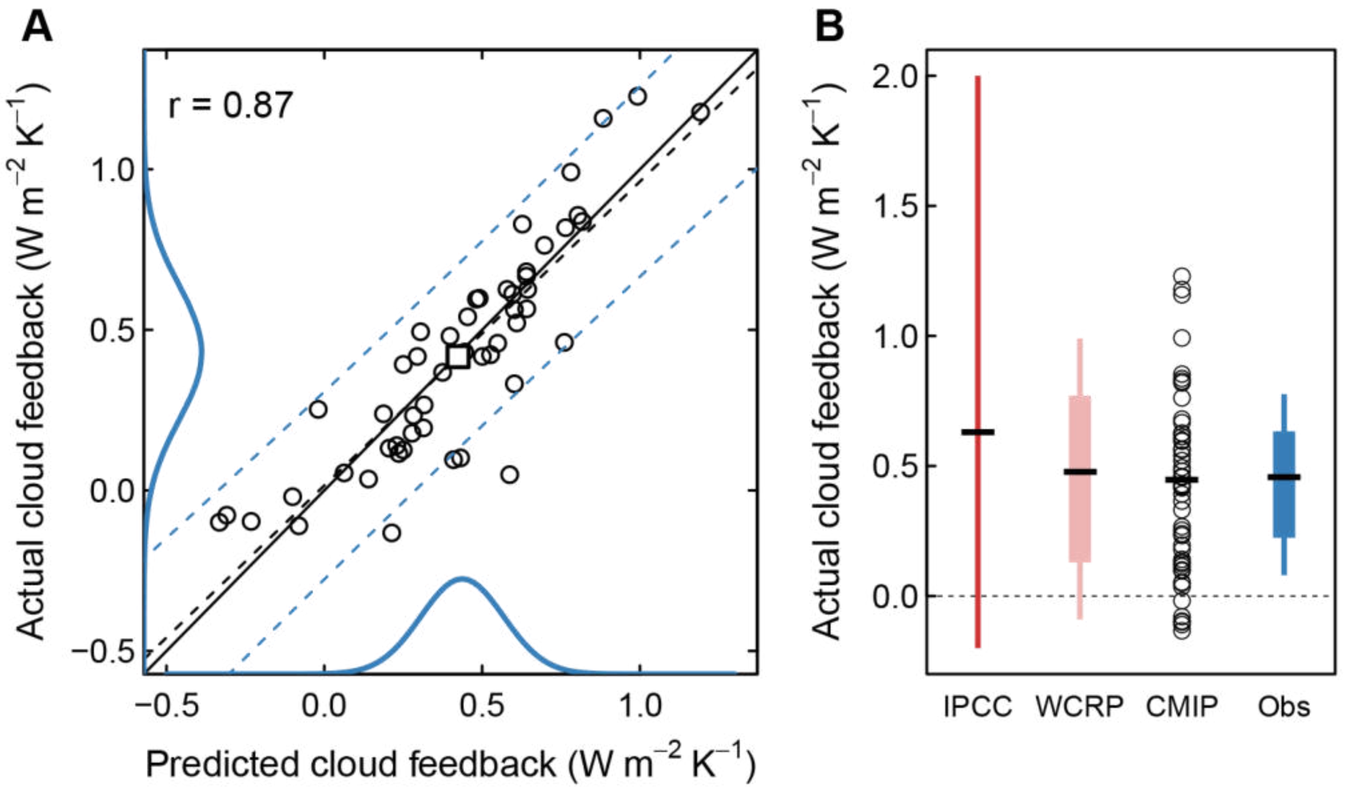
Does statistical learning help?

Skill depending on predictor pattern size





Final constraint on global cloud feedback



PNAS (2021)

Observational evidence that cloud feedback amplifies global warming

Paulo Ceppi[a,b,1,2] and Peer Nowack[a,b,c,d,1]

[a]Grantham Institute, Imperial College London, London SW7 2AZ, United Kingdom; [b]Department of Physics, Imperial College London, London SW7 2AZ, United Kingdom; [c]Data Science Institute, Imperial College London, London SW7 2AZ, United Kingdom; and [d]Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich NR4 7TJ, United Kingdom

Edited by Isaac M. Held, Princeton University, Princeton, NJ, and approved June 10, 2021 (received for review December 21, 2020)

Global warming drives changes in Earth's cloud cover, which, in turn, may amplify or dampen climate change. This "cloud feedback" is the single most important cause of uncertainty in Equilibrium Climate Sensitivity (ECS)—the equilibrium global warming following a doubling of atmospheric carbon dioxide. Using data from Earth observations and climate model simulations, we here develop a statistical learning analysis of how clouds respond to changes in the environment. We show that global cloud feedback is dominated by the sensitivity of clouds to surface temperature and tropospheric stability. Considering changes in just these two factors, we are able to constrain global cloud feedback to 0.43 ± 0.35 W·m^{-2}·K^{-1} (90% confidence), implying a robustly amplifying effect of clouds on global warming and only a 0.5% chance of ECS below 2 K. We thus anticipate that our approach will enable tighter constraints on climate change projections, including its manifold socioeconomic and ecological impacts.

climate change | clouds | climate feedbacks | climate modeling | climate sensitivity

Clouds have long been recognized as the leading source of uncertainty in Earth's climate response to anthropogenic forcing through their key role in modulating the global energy balance. While a combined assessment of all available lines of evidence—theory, modeling, and Earth observations—suggests that cloud feedback is likely positive, i.e., amplifies global warming (1–3), so far, a narrow constraint on this feedback has remained elusive. This is reflected in the broad 90% CI for cloud feedback (−0.09 to +0.99 W·m^{-2}·K^{-1}) estimated in a recent assessment under the auspices of the World Climate Research Program [WCRP (3)], which relied both on a review of existing studies and expert judgment. Part of the challenge stems from the variety of physical processes contributing to the net cloud feedback, involving the interaction of clouds with both solar (shortwave [SW]) and terrestrial (longwave [LW]) radiative fluxes (4).

Uncertainty in cloud feedback has persisted because each line of evidence comes with its limitations and challenges. Theory cannot provide precise projections. Global climate models (GCMs) are unable to explicitly represent small-scale cloud processes on their coarse spatial grids, resulting in large spread in their simulation of cloud feedback (4, 5). High-resolution models may better represent such cloud processes, but limitations in computational power prevent climate change experiments on global grids (6). Most of the available observational estimates high-resolution simulations or observations. The method is based on cloud-controlling factor analysis (7, 8, 10, 11, 14–16), where we assume that cloud-radiative anomalies at grid point r, $\mathrm{d}C(r)$, can be approximated as a linear function of anomalies in a set of M relevant meteorological cloud-controlling factors $\mathrm{d}\boldsymbol{X}_i(r)$:

$$\mathrm{d}C(r) \approx \sum_{i=1}^{M} \frac{\partial C(r)}{\partial \boldsymbol{X}_i(r)} \cdot \mathrm{d}\boldsymbol{X}_i(r) = \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \mathrm{d}\boldsymbol{X}_i(r). \quad [1]$$

$\boldsymbol{\Theta}_i(r)$ represents the sensitivities of $C(r)$ to the controlling factors. As a key difference to previous studies (7, 8, 10, 11, 14) focused on grid-point-wise relationships—e.g., between surface temperature at point r and $C(r)$—we here model cloud-radiative anomalies at grid point r as a function of the controlling factor variables within a 105° × 55° (longitude × latitude) domain centered on r (see Fig. 1 and *SI Appendix*, Fig. S1 for an example). The contribution of each controlling factor to $\mathrm{d}C(r)$ is then obtained by the scalar product of the spatial vectors $\boldsymbol{\Theta}_i(r)$ and $\mathrm{d}\boldsymbol{X}_i(r)$.

Different from previous work, we use ridge regression (17) to avoid overfitting when including this large number of predictors in the regressions (*Materials and Methods*). Importantly, this statistical learning approach allows us to robustly estimate sensitivities $\boldsymbol{\Theta}_i(r)$, despite the presence of many collinear predictors and the limited sample size available from the short record of satellite observations (18–20).

We include five controlling factors $\boldsymbol{X}_i$ quantifying surface temperature, estimated boundary-layer inversion strength

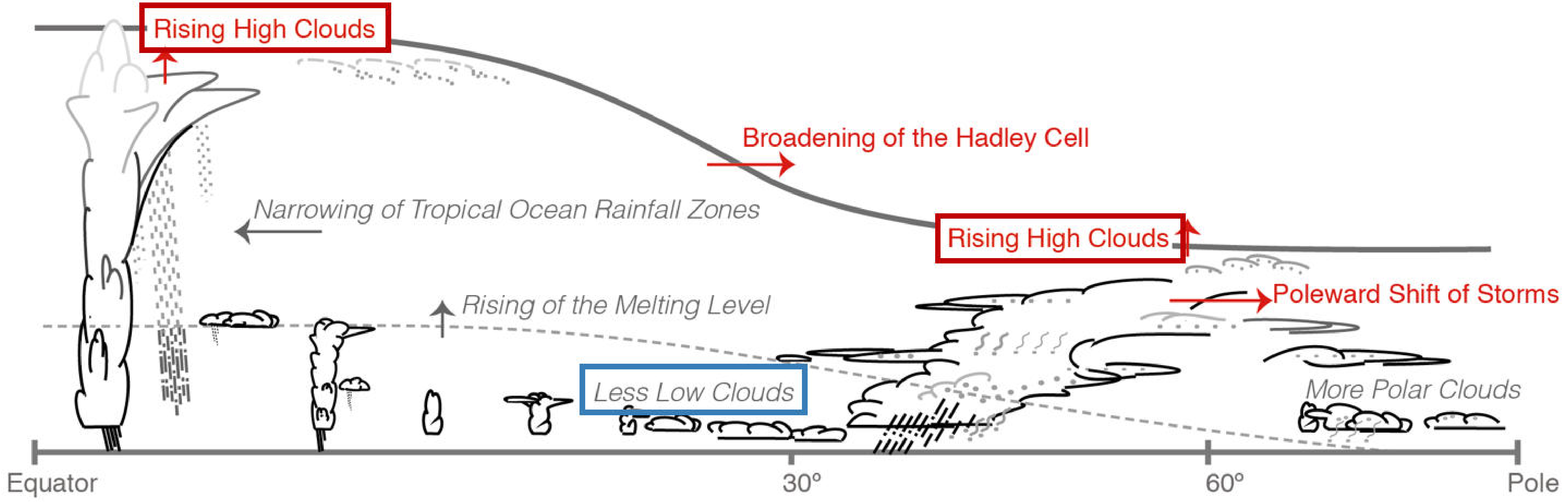
Significance

A key challenge of our time is to accurately estimate future global warming in response to a doubling of atmospheric carbon dioxide—a number known as the *climate sensitivity*. This number is highly uncertain, mainly because it remains unclear how clouds will change with warming. Such changes in clouds could strongly amplify or dampen global warming, providing a climate feedback. Here, we perform a statistical learning analysis that provides a global observational constraint on the future cloud response. This constraint supports that cloud feedback will amplify global warming, making it very unlikely that climate sensitivity is smaller than 2 °C.

Cloud feedback = net effect of many mechanisms

Changes in cloud properties (amount, optical thickness, altitude) can amplify or dampen global warming

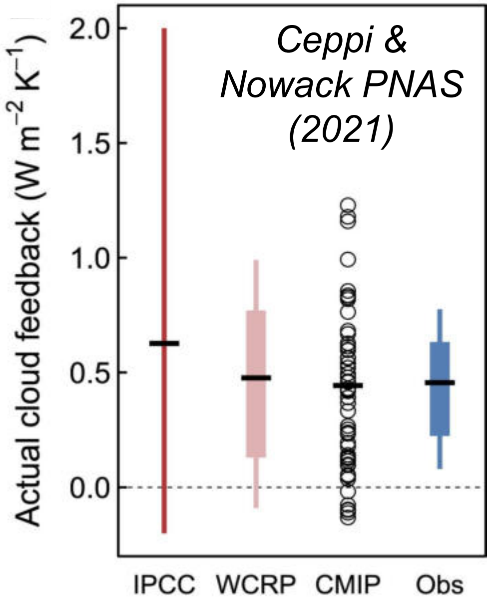
→ the main source of model uncertainty in global warming projections under ↑ CO_2



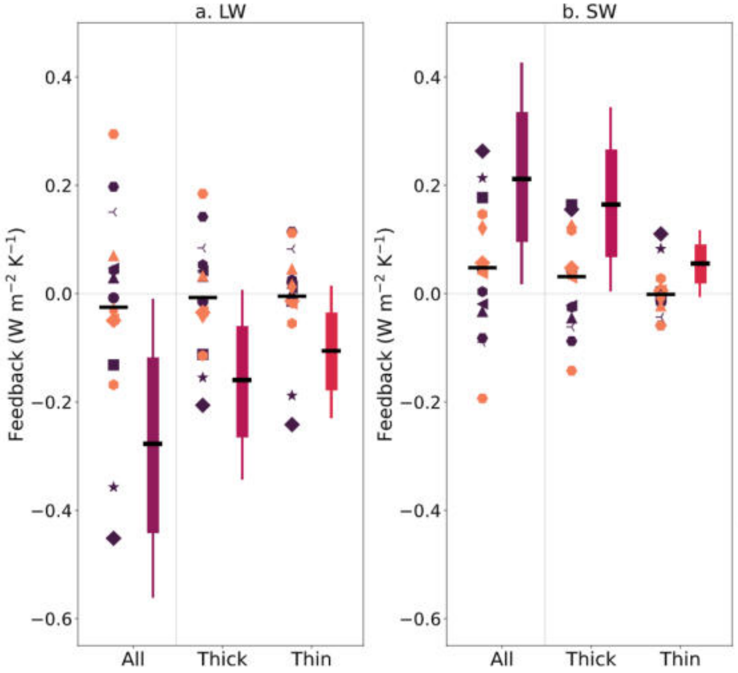
IPCC AR5 WG1 Chapter 7

ML4CLOUDS project (2022-2025)

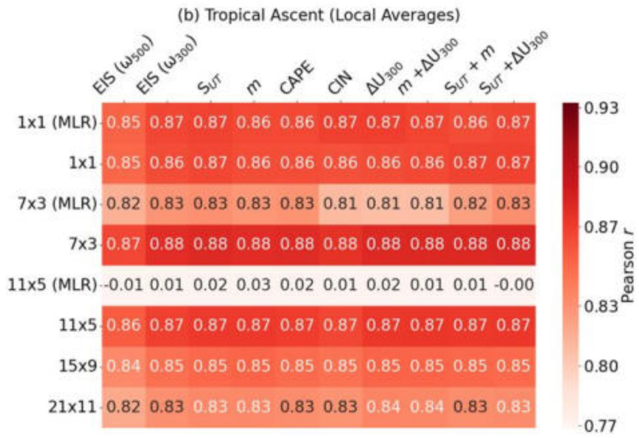
Dr. Sarah Wilson Kemsley (UEA), now at University of Oxford



Ceppi & Nowack PNAS (2021)

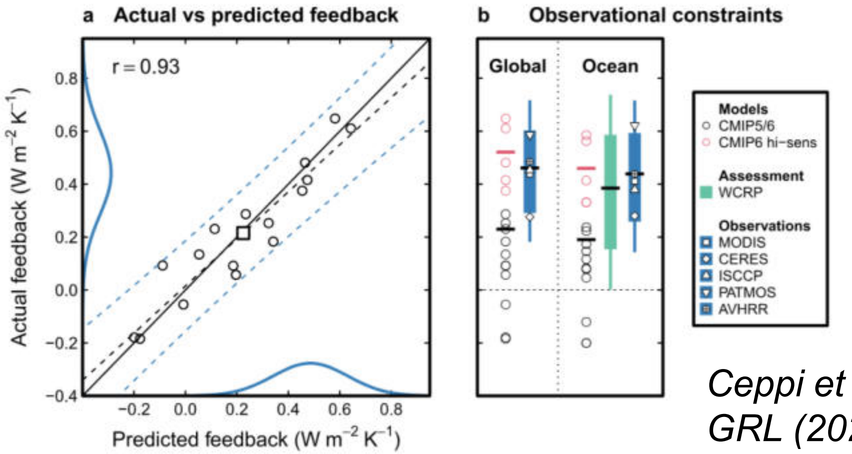


Wilson-Kemsley et al. GRL (2025)

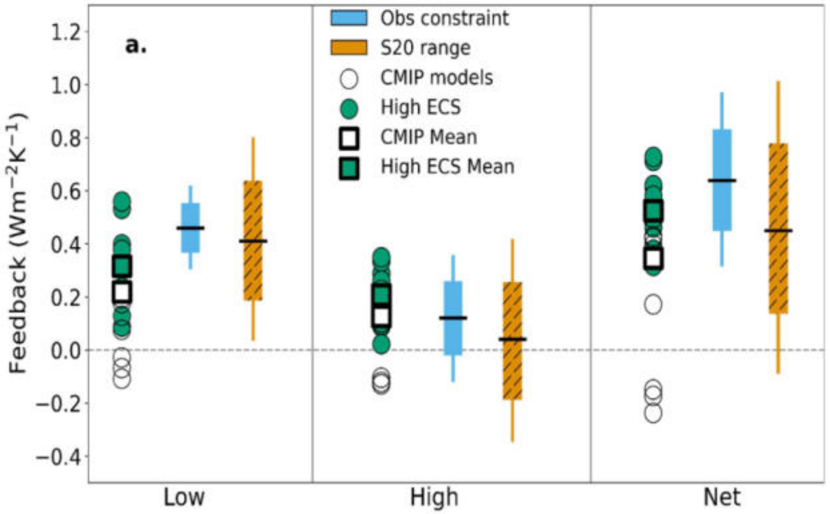


Wilson-Kemsley et al. ACP (2024)

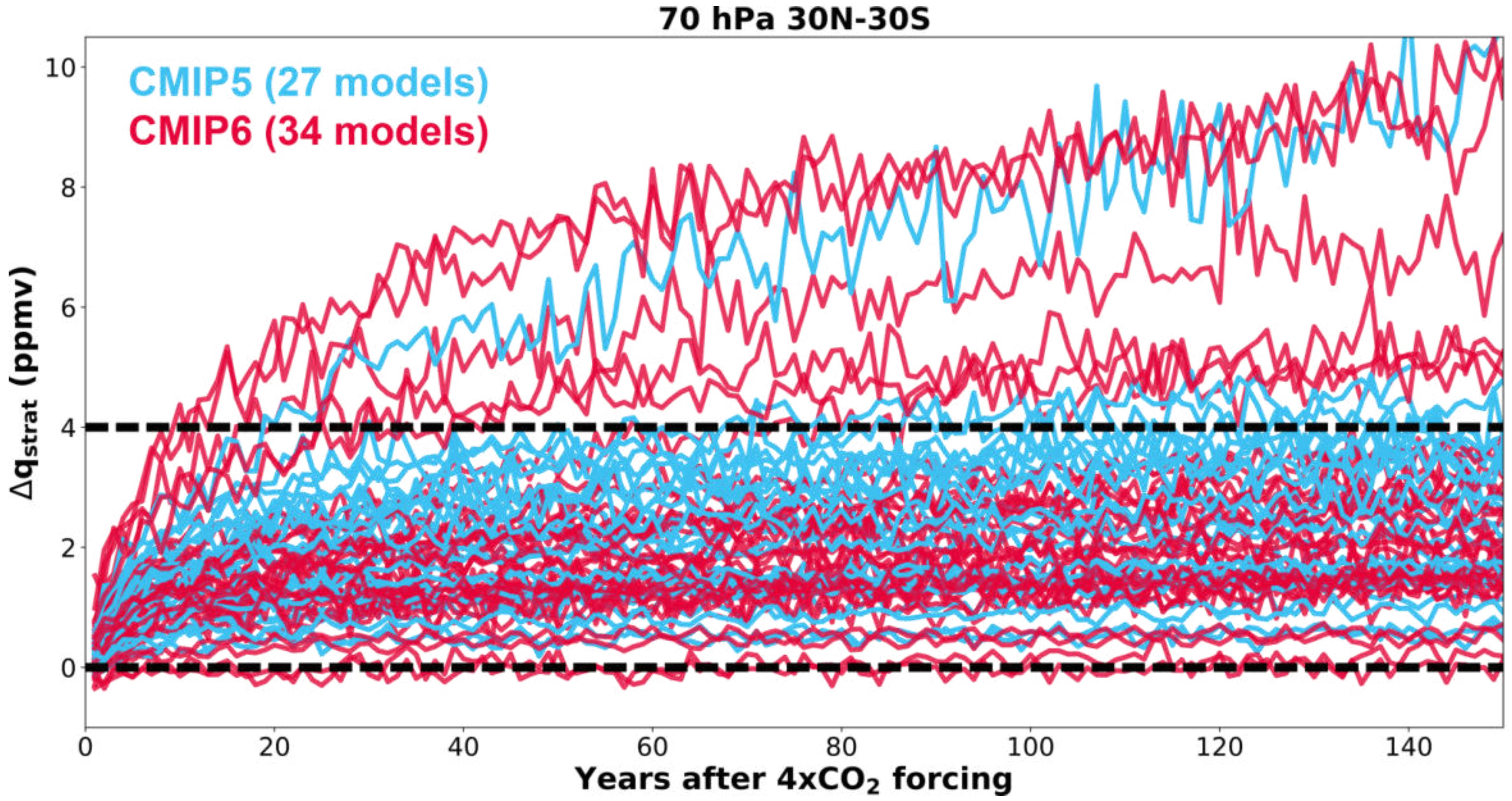
Wilson-Kemsley et al. GRL (2026)

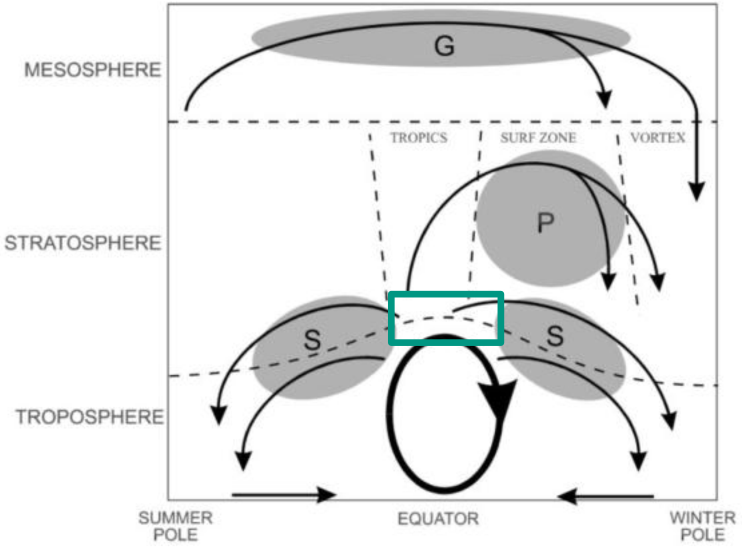


Ceppi et al. GRL (2024)



Large uncertainty in stratospheric water vapour projections

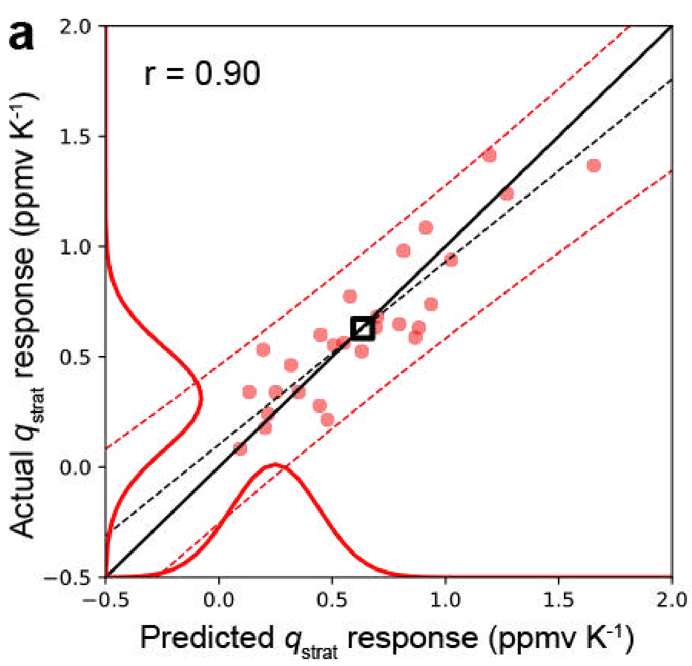


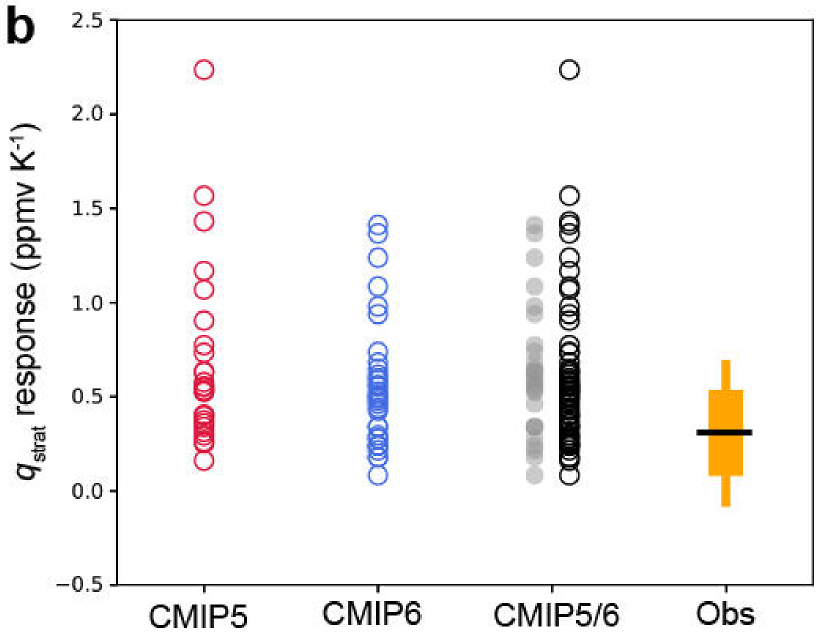


4 ppmv
≈ 100% present-day

abrupt-4xCO_2 relative to pre-industrial

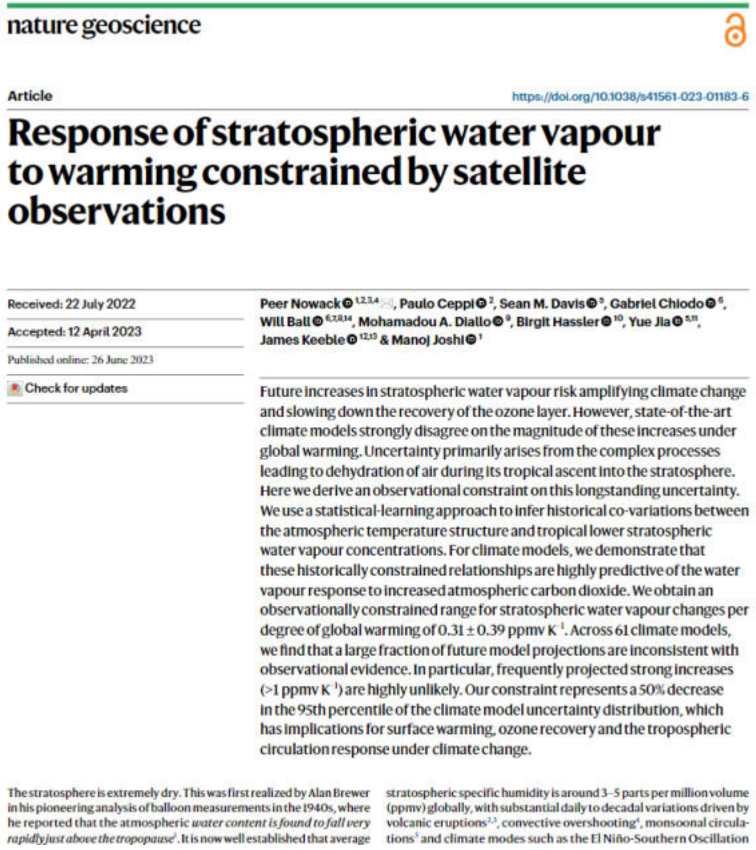
Constraint on the stratospheric water vapour feedback





1 in 2 models exceeds the 83rd percentile

1 in 5 CMIP models exceeds the 97.5th percentile



nature geoscience

Article

https://doi.org/10.1038/s41561-023-01183-6

Response of stratospheric water vapour to warming constrained by satellite observations

Received: 22 July 2022

Accepted: 12 April 2023

Published online: 26 June 2023

Check for updates

Peer Nowack [1,2,3,4], Paulo Ceppi [2], Sean M. Davis [3], Gabriel Chiodo [6], Will Ball [6,7,8,14], Mohamadou A. Diallo [9], Birgit Hassler [10], Yue Jia [5,11], James Keeble [12,13] & Manoj Joshi [1]

Future increases in stratospheric water vapour risk amplifying climate change and slowing down the recovery of the ozone layer. However, state-of-the-art climate models strongly disagree on the magnitude of these increases under global warming. Uncertainty primarily arises from the complex processes leading to dehydration of air during its tropical ascent into the stratosphere. Here we derive an observational constraint on this longstanding uncertainty. We use a statistical-learning approach to infer historical co-variations between the atmospheric temperature structure and tropical lower stratospheric water vapour concentrations. For climate models, we demonstrate that these historically constrained relationships are highly predictive of the water vapour response to increased atmospheric carbon dioxide. We obtain an observationally constrained range for stratospheric water vapour changes per degree of global warming of 0.31 ± 0.39 ppmv K^{-1}. Across 61 climate models, we find that a large fraction of future model projections are inconsistent with observational evidence. In particular, frequently projected strong increases (>1 ppmv K^{-1}) are highly unlikely. Our constraint represents a 50% decrease in the 95th percentile of the climate model uncertainty distribution, which has implications for surface warming, ozone recovery and the tropospheric circulation response under climate change.

The stratosphere is extremely dry. This was first realized by Alan Brewer in his pioneering analysis of balloon measurements in the 1940s, where he reported that the atmospheric *water content is found to fall very rapidly just above the tropopause*[1]. It is now well established that average stratospheric specific humidity is around 3–5 parts per million volume (ppmv) globally, with substantial daily to decadal variations driven by volcanic eruptions[2,3], convective overshooting[4], monsoonal circulations[5] and climate modes such as the El Niño-Southern Oscillation

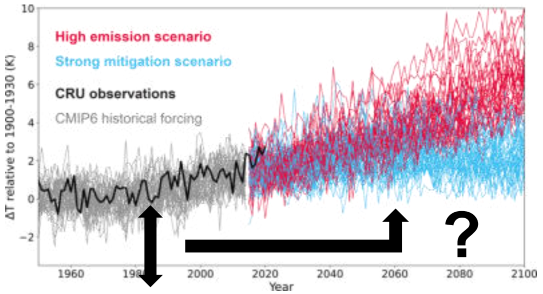
Nowack et al. Nature Geoscience (2023)

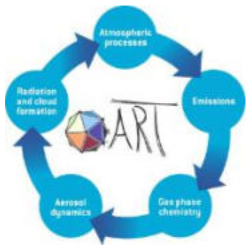
Fully data-driven? Causality? Physics-informed loss?

We tackle climate model uncertainty

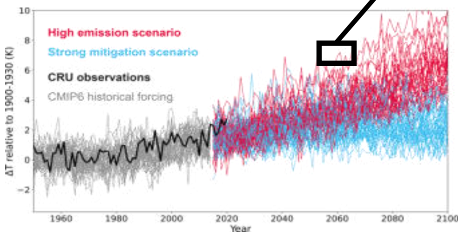
Strong constraints

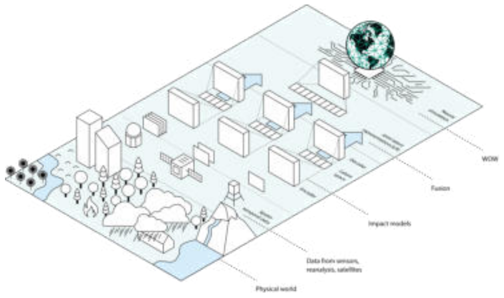
Constraint = ESM, combined with data-driven model





Init AI impact models





Climate data science

Focus on scientific problem definition / interpretable models

Neural climate models

Large-scale data / high AI model capacity

Controlling factor analyses
- Clouds
- Stratospheric water vapour
- Regional surface temperature
- Precipitation

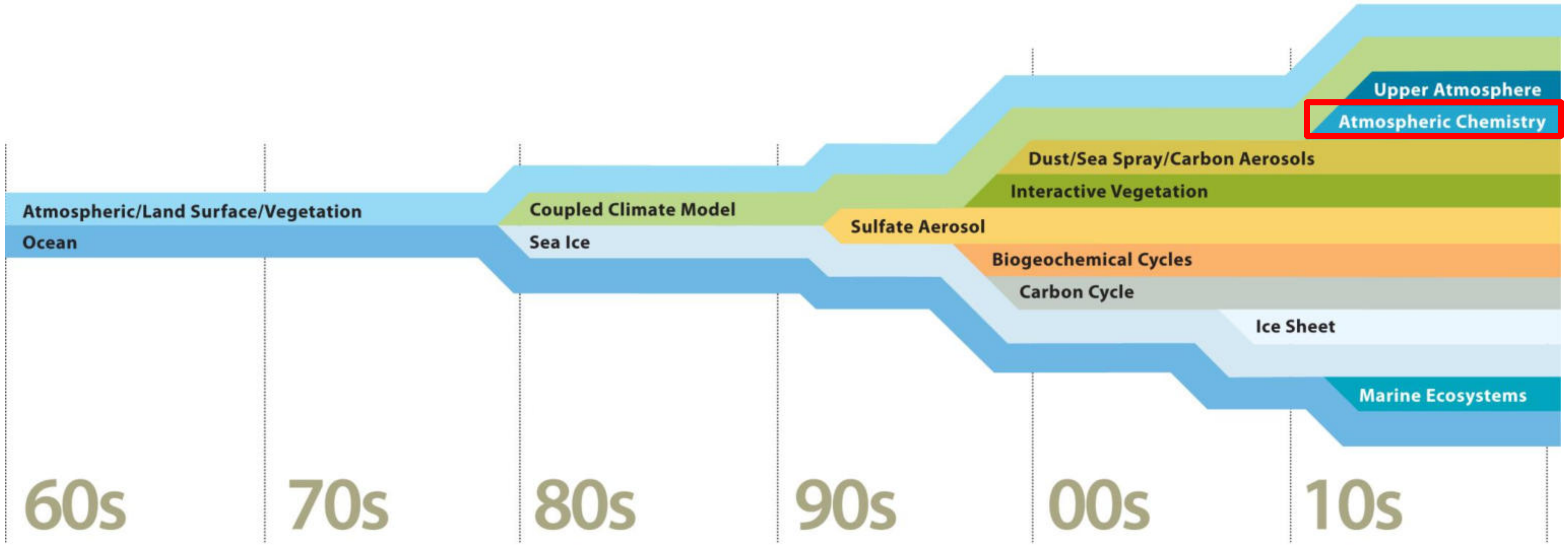
Causal climate evaluation
- Teleconnections
- Precipitation dynamics
- Causal representation learning

Hybrid climate models
- Model parameterizations
- Ozone
- ICON, UKESM

Data-driven forecasting
- Air pollution
- Wildfire risks
- AI weather models & climate projections

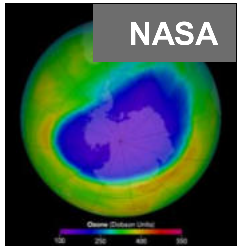
AI world models & emulation
- WOW world model
- Causal climate model emulation
- Transfer learning

The evolution of climate modelling



ucar.edu

- A key chemical species for climate is ozone.
- Greenhouse gas and shortwave absorber.
- Air pollutant in the troposphere.



Modelling atmospheric chemistry – a dilemma?

Karlsruhe Institute of Technology

Important, but slows down climate models run on supercomputers by factor 2-3

→ Transport of chemical tracers.

→ Large system of coupled chemical rate equations.

Table 1. Table of Gas-Phase Chemical Reactions[a]

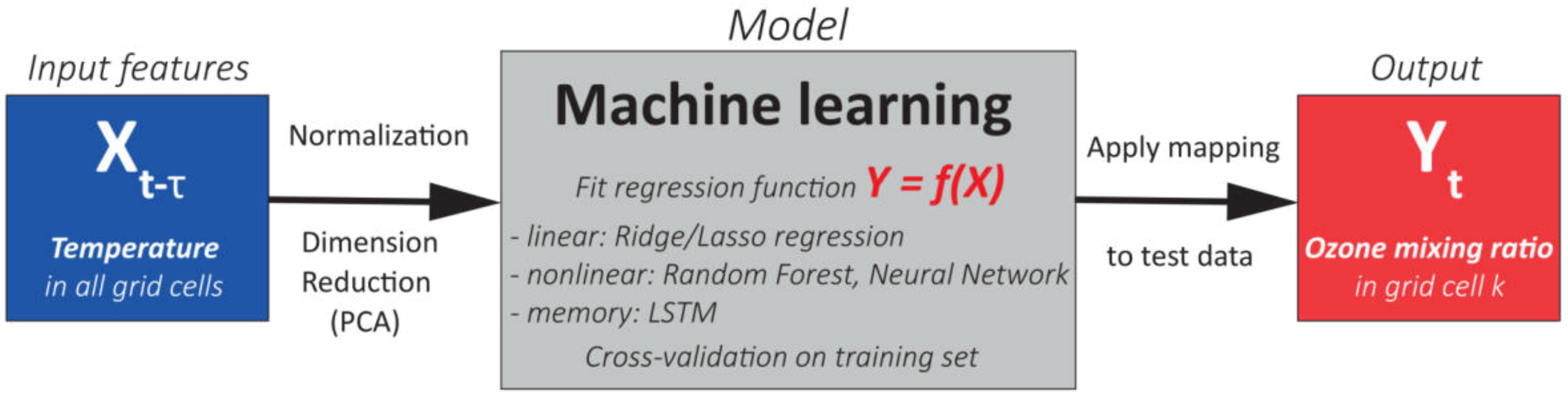
Reaction No.	Reaction		
R1	$O + O_2 + M$	$\longrightarrow$	$O_3 + M$
R2	$O + O_3$	$\longrightarrow$	$2\,O_2$
R3	$O + O + M$	$\longrightarrow$	$O_2 + M$
R4	$O(^1D) + M$	$\longrightarrow$	$O + M$
R5	$O(^1D) + O_3$	$\longrightarrow$	$2\,O_2$
R6	$O(^1D) + H_2O$	$\longrightarrow$	$2\,OH$
R7	$O(^1D) + H_2$	$\longrightarrow$	$OH + H$
R8	$O(^1D) + N_2O$	$\longrightarrow$	$2\,NO$
R9	$O(^1D) + N_2O$	$\longrightarrow$	$N_2 + O_2$
R10	$O(^1D) + CH_3Br$	$\longrightarrow$	$BrO + OH + CO + H_2O$
R11	$O(^1D) + CH_4$	$\longrightarrow$	$OH + CH_3O_2$
R12	$O + OH$	$\longrightarrow$	$O_2 + H$
R13	$O + HO_2$	$\longrightarrow$	$OH + O_2$
R14	$O + H_2O_2$	$\longrightarrow$	$OH + HO_2$

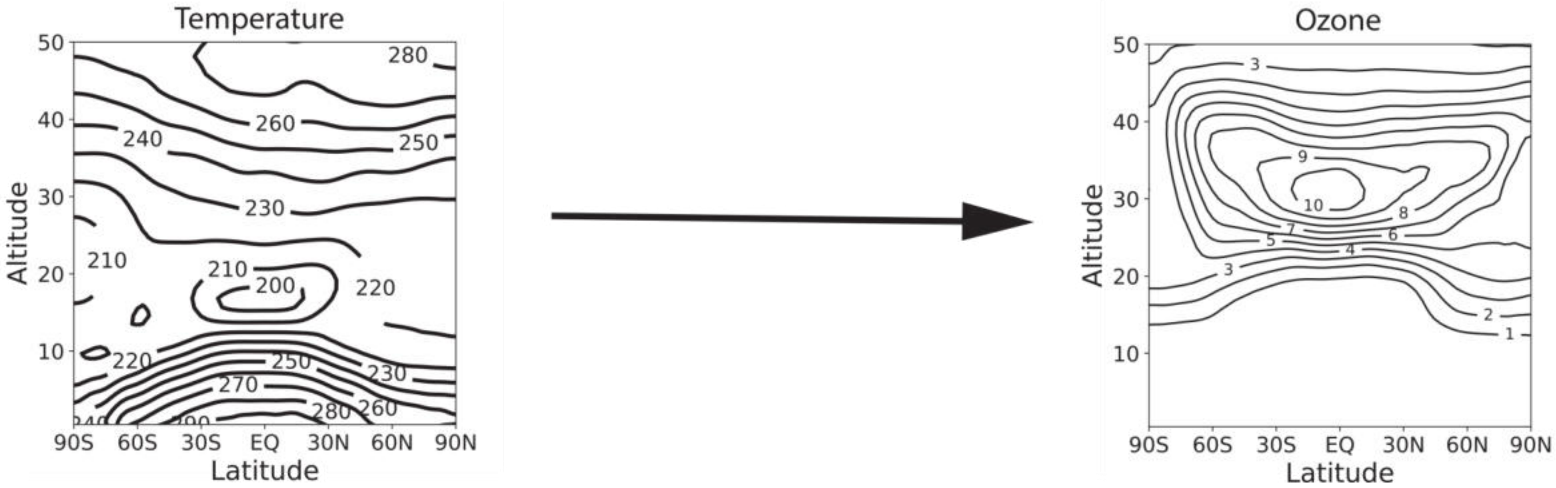
Table 1. (continued)

Reaction No.	Reaction		
R74	$Br + O_3$	$\longrightarrow$	$BrO + O_2$
R75	$Br + HO_2$	$\longrightarrow$	$HBr + O_2$
R76	$Br + OClO$	$\longrightarrow$	$BrO + ClO$
R77	$BrO + O$	$\longrightarrow$	$Br + O_2$
R78	$BrO + OH$	$\longrightarrow$	$Br + HO_2$
R79	$BrO + OH$	$\longrightarrow$	$HBr + O_2$
R80	$BrO + HO_2$	$\longrightarrow$	$HOBr + O_2$
R81	$BrO + NO$	$\longrightarrow$	$Br + NO_2$
R82	$BrO + NO_2 + M$	$\longrightarrow$	$BrONO_2 + M$
R83	$BrO + ClO$	$\longrightarrow$	$Br + OClO$
R84	$BrO + ClO$	$\longrightarrow$	$Br + Cl + O_2$
R85	$BrO + ClO$	$\longrightarrow$	$BrCl + O_2$
R86	$BrO + BrO$	$\longrightarrow$	$2\,Br + O_2$
R87	$HBr + OH$	$\longrightarrow$	$Br + H_2O$

Jonsson et al.
JGR (2004)

Fast machine learning parameterization for ozone



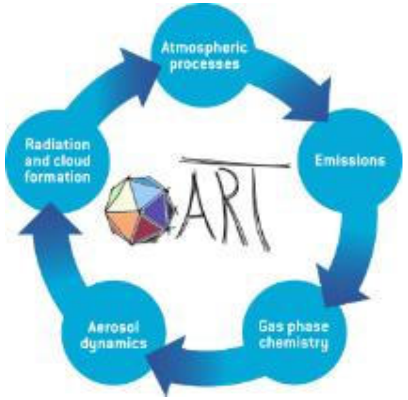


Nowack et al. ERL (2018), CICP (2019)

Implemented in UKESM

Transferred to ICON

UKESM



PhD project Yiling Ma
Stefan Versick, Peter Braesicke, Roland Ruhnke

More on arXiv…

Cornell University

We gratefully acknowledge support member in

arXiv > cs > arXiv:2509.20422

Search...

Help | Adv

Computer Science > Machine Learning

[Submitted on 24 Sep 2025]

mloz: A Highly Efficient Machine Learning-Based Ozone Parameterization for Climate Sensitivity Simulations

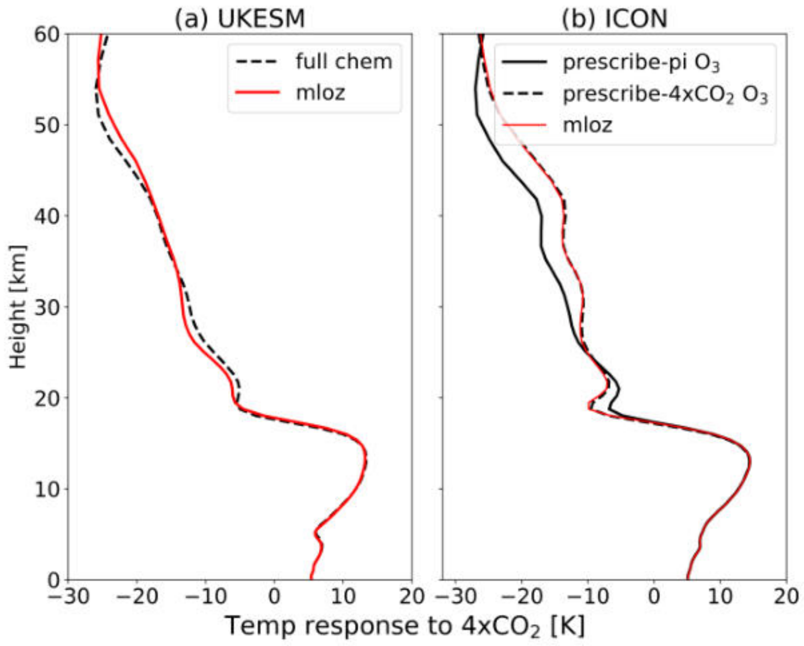
Yiling Ma, Nathan Luke Abraham, Stefan Versick, Roland Ruhnke, Andrea Schneidereit, Ulrike Niemeier, Felix Back, Peter Braesicke, Peer Nowack

Atmospheric ozone is a crucial absorber of solar radiation and an important greenhouse gas. However, most climate models participating in the Coupled Model Intercomparison Project (CMIP) still lack an interactive representation of ozone due to the high computational costs of atmospheric chemistry schemes. Here, we introduce a machine learning parameterization (mloz) to interactively model daily ozone variability and trends across the troposphere and stratosphere in standard climate sensitivity simulations, including two-way interactions of ozone with the Quasi-Biennial Oscillation. We demonstrate its high fidelity on decadal timescales and its flexible use online across two different climate models -- the UK Earth System Model (UKESM) and the German ICOsahedral Nonhydrostatic (ICON) model. With atmospheric temperature profile information as the only input, mloz produces stable ozone predictions around 31 times faster than the chemistry scheme in UKESM, contributing less than 4 percent of the respective total climate model runtimes. In particular, we also demonstrate its transferability to different climate models without chemistry schemes by transferring the parameterization from UKESM to ICON. This highlights the potential for widespread adoption in CMIP-level climate models that lack interactive chemistry for future climate change assessments, particularly when focusing on climate sensitivity simulations, where ozone trends and variability are known to significantly modulate atmospheric feedback processes.

Subjects: **Machine Learning (cs.LG)**; Atmospheric and Oceanic Physics (physics.ao-ph)
Cite as: arXiv:2509.20422 **[cs.LG]**
(or arXiv:2509.20422v1 **[cs.LG]** for this version)
https://doi.org/10.48550/arXiv.2509.20422

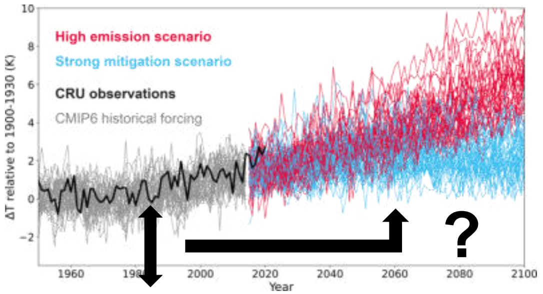
Table 2. Average wall-clock time across all processors for different chemistry schemes.

Model / Chemistry scheme	UKESM mloz	UKESM chemistry module	ICON mloz	ICON Linoz
Cores	720		912	
Length	3 months		1.5 years	
Time cost	1.75%	54.45% (Esentürk et al., 2018)	947s	2603s



We tackle climate model uncertainty

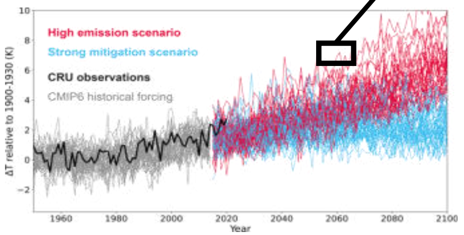
Strong constraints

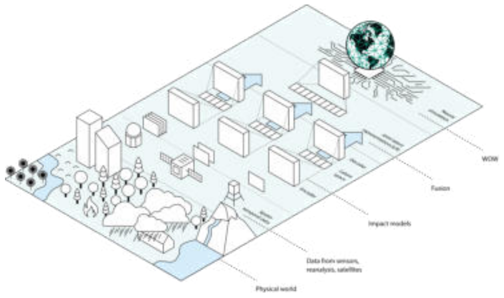


Constraint = ESM, combined with data-driven model

Fully data-driven? Causality? Physics-informed loss?

Init AI impact models





Climate data science

Focus on scientific problem definition / interpretable models

Neural climate models

Large-scale data / high AI model capacity

Controlling factor analyses
- Clouds
- Stratospheric water vapour
- Regional surface temperature
- Precipitation

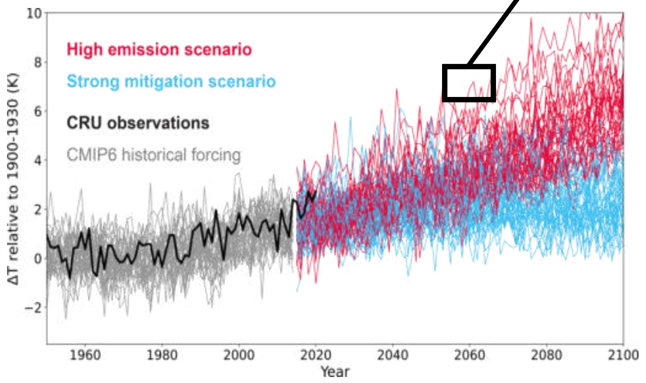
Causal climate evaluation
- Teleconnections
- Precipitation dynamics
- Causal representation learning

Hybrid climate models
- Model parameterizations
- Ozone
- ICON, UKESM

Data-driven forecasting
- Air pollution
- Wildfire risks
- AI weather models & climate projections

AI world models & emulation
- WOW world model
- Causal climate model emulation
- Transfer learning

Init AI weather ensembles



Robustness of AI-based weather forecasts in a changing climate

Rackow et al. arXiv (2024)

A Preprint

Thomas Rackow
European Centre for Medium-Range Weather Forecasts (ECMWF)
thomas.rackow@ecmwf.int

Nikolay Koldunov
Alfred Wegener Institute Helmholtz Centre for Polar and Marine Research (AWI)
nikolay.koldunov@awi.de

Christian Lessig
European Centre for Medium-Range Weather Forecasts (ECMWF)
christian.lessig@ecmwf.int

Irina Sandu
European Centre for Medium-Range Weather Forecasts (ECMWF)

Mihai Alexe
European Centre for Medium-Range Weather Forecasts (ECMWF)

Matthew Chantry
European Centre for Medium-Range Weather Forecasts (ECMWF)

Mariana Clare
European Centre for Medium-Range Weather Forecasts (ECMWF)

Jesper Dramsch
European Centre for Medium-Range Weather Forecasts (ECMWF)

Florian Pappenberger
European Centre for Medium-Range Weather Forecasts (ECMWF)

Xabier Pedruzo-Bagazgoitia
European Centre for Medium-Range Weather Forecasts (ECMWF)

Steffen Tietsche
European Centre for Medium-Range Weather Forecasts (ECMWF)

Thomas Jung
Alfred Wegener Institute (AWI)
University of Bremen

Rackow et al. arXiv (2024)

ERA5 1955
"colder"

ECMWF operational analysis 2023
"present-day"

IFS-FESOM 2049
"+ 2.9 K"

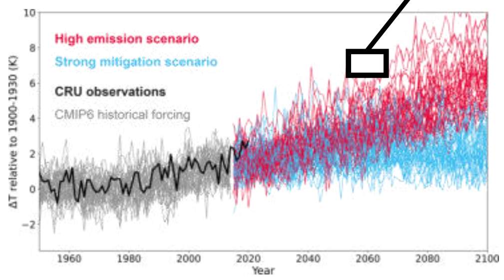
+

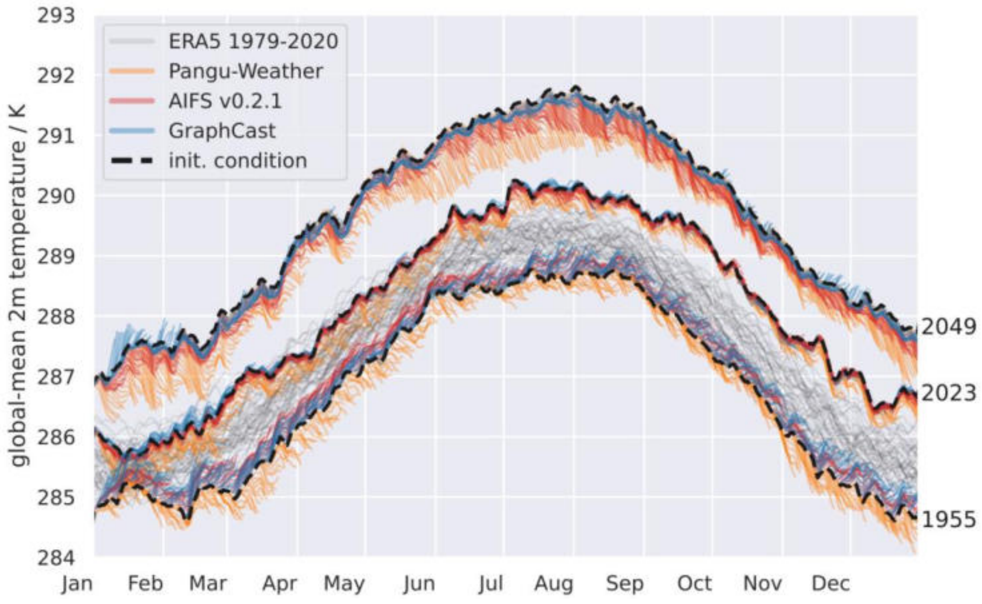
- AIFS
- GraphCast
- Pangu-Weather

(trained on ERA5, ~1979-2018)

Daily 10-day forecasts

Init AI weather ensembles

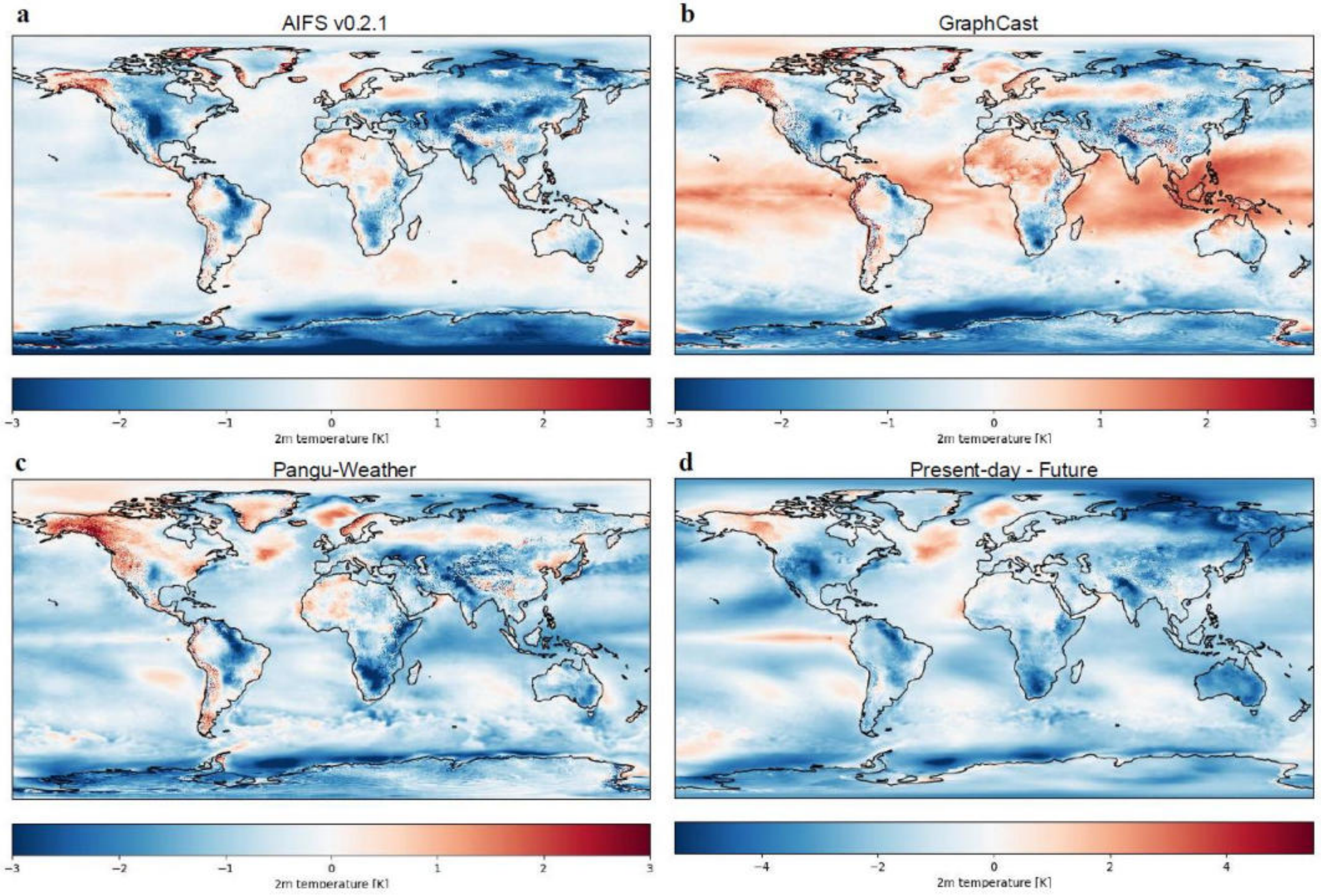


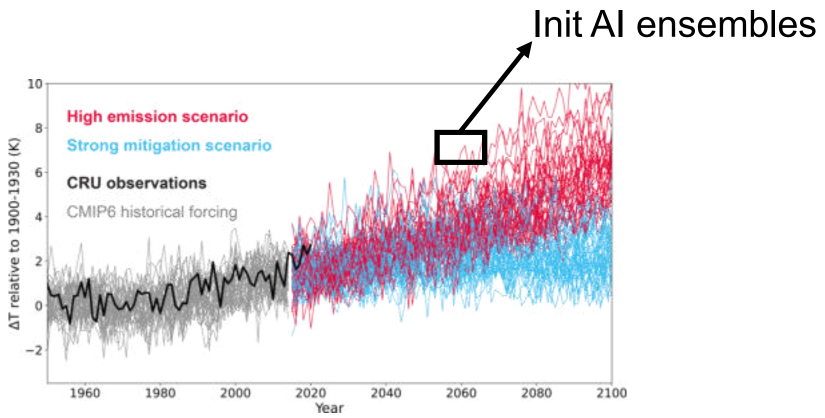


Potential for high-resolution (spatial + temporal), low-bias, large weather ensembles under future climate states?!

Rackow et al. arXiv (2024)

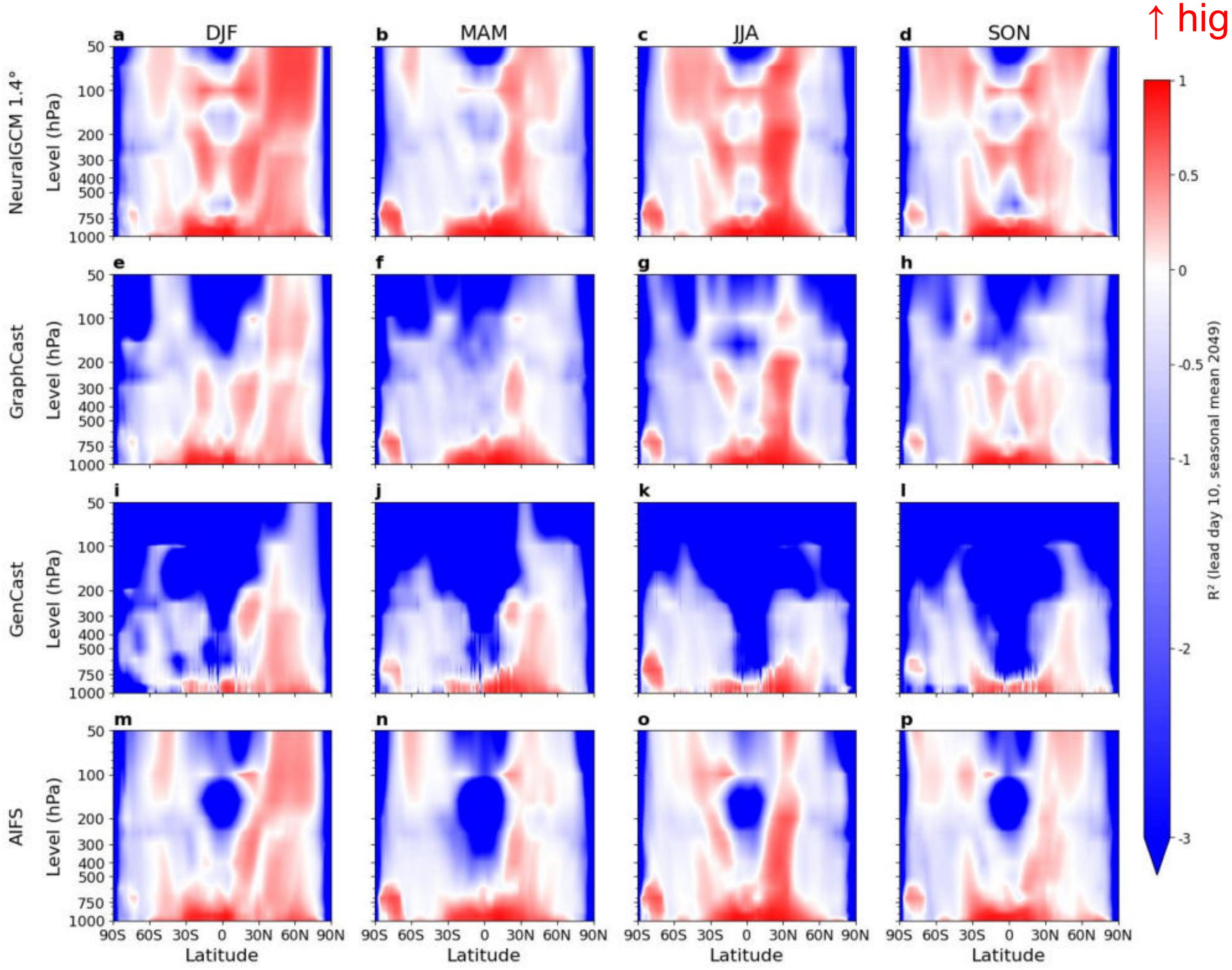
Of course, not everything is perfect…





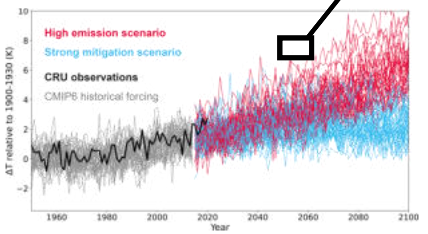
Mean 2m temperature drift over 10 days in 2049…

Amiramjadi, Roth et al., in preparation



↑ higher is better

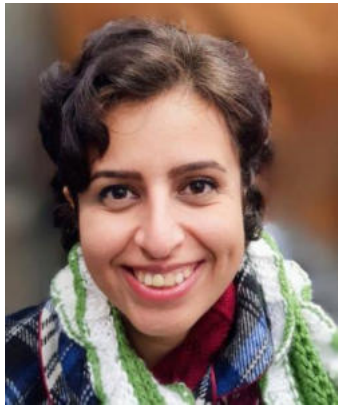
Init AI ensembles



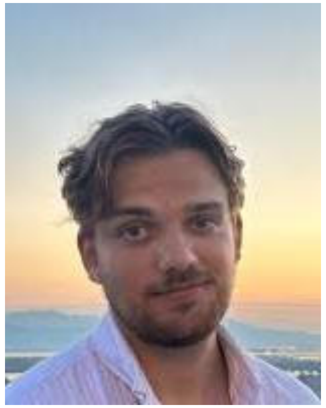
More data-driven models + variables

Full vertical extent

General tendencies?



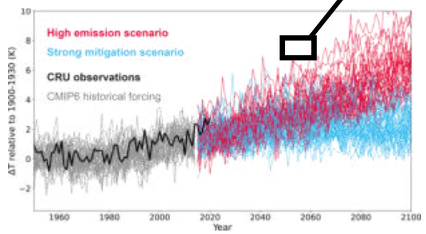
Dr. Mozhgan Amiramjadi



Christopher Roth

Init AI impact model

Data-driven impact models: surface urban heat island



PNAS | RESEARCH ARTICLE | EARTH, ATMOSPHERIC, AND PLANETARY SCIENCES | OPEN ACCESS

Amplified warming in tropical and subtropical cities under 2 °C climate change

S. Berk[a,1,2], M. M. Joshi[a], C. M. Goodess[a], and P. Nowack[b]

Edited by Karen Seto, Yale University, New Haven, CT; received February 6, 2025; accepted December 11, 2025

Cities are often warmer than rural surroundings due to a phenomenon known as the urban heat island, which can be influenced by various factors, such as regional climate and land surface types. Under climate change, cities face not only the challenge of increasing temperatures in their surrounding hinterland but also the challenge of potential changes in their heat islands. However, even high-resolution global Earth system models (ESMs) with "urban tiles" can only properly resolve the largest urban areas or megacities. Here, we address these limitations by applying a process-based statistical learning model to ESM outputs to provide projections of changes in land surface temperature (LST) for 104 medium-sized cities of population 300 K to 1 M in the subtropics and tropics. Under a 2 °C global warming scenario, annual mean LST in 81% of these cities is projected to increase faster than the surrounding area. In 16% of these cities, mostly in India and China, mean LST is projected to increase by an additional 50-112% above ESM projections of the surrounding area. Our findings underscore the importance of investigating the specific effects of climate change on urban heat exposure.

urban heat island | climate change | machine learning | urban climate

Significance

Urban heat stress under climate change is an increasing concern, as most cities are already warmer than their rural surroundings, heightening their vulnerability to rising temperatures and exposing a large share of the global population. While Global Climate Models are essential for projecting future temperature changes, their relatively coarse scale limits their ability to capture the trends of smaller cities. To bridge this gap, projected changes in land surface temperature in medium-sized cities are created and compared to surrounding regions, identifying areas where the urban warming rate is faster than rural surroundings. Our analysis shows low-resolution projections likely underestimate future urban warming in most cities, highlighting the need for deeper study.

The urban heat island (UHI) is a phenomenon whereby the temperature in a city differs from the surrounding rural area, typically being warmer. This leads to increased heat-related health risks for urban inhabitants in comparison to their rural counterparts (1). In 2018, it was estimated that over half the world's population resided in cities and this proportion is projected to increase to 68% by 2050 (2). Climate change results in rising global temperatures and increased frequency of extreme heat events (3), which can have severe human health impacts including increased mortality (4–6).

UHIs are influenced by both climate and city attributes (e.g., city area, rural aridity, and landcover) (7), all of which can change over time. A deeper understanding of climate change related shifts in UHI intensities will inform city planners as they design cities aiming to optimize human comfort and health, and enable evidence based adaptation planning. However, modeling and projecting changes in UHI on a global scale remains a challenge. ESM or Global Climate Model (GCM) outputs have spatial resolutions larger than the scale of most cities due to limitations in computational power. As urban landcover only represents a small fraction of the earth's surface, its inclusion is not essential for projecting mean global temperature changes and is often not represented, although studies utilizing more complex urban schemes exist (8). Even in such cases however, ESMs can

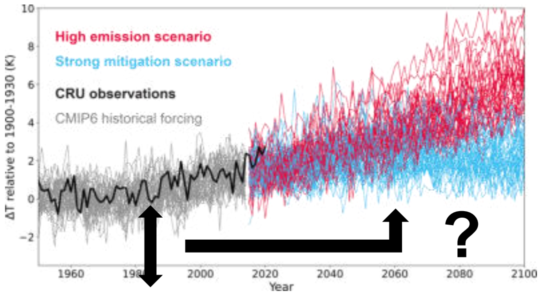
Author affiliations: [a]Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich, Norfolk NR4 7TJ, United Kingdom; and [b]Institute of Theoretical Informatics, Institute of Meteorology and Climate Research Atmospheric Trace Gases and Remote Sensing, Karlsruhe Institute of Technology, Karlsruhe

- Combine CMIP6 projections at 2˚C global warming with machine learning (ML) function to estimate changes in urban heat islands.
- Focus on understudied tropical and subtropical medium-size cities (104 in total).
- Common technical challenge: ensure approx. generalization of ML function to future climates.

Dr. Sarah Berk (UEA), now at University of North Carolina Chapel Hill, USA

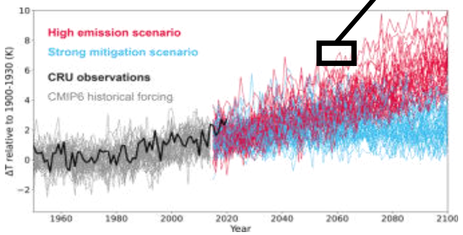
We tackle climate model uncertainty

Strong constraints

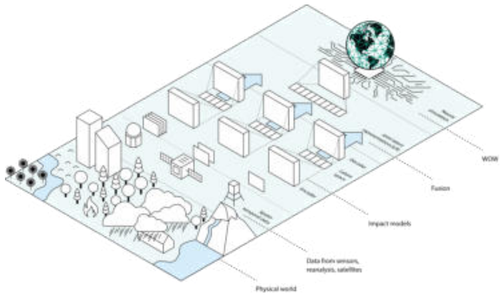


Constraint = ESM, combined with data-driven model

Init AI impact models



Fully data-driven? Causality? Physics-informed loss?



Climate data science

Focus on scientific problem definition / interpretable models

Neural climate models

Large-scale data / high AI model capacity

Controlling factor analyses
- Clouds
- Stratospheric water vapour
- Regional surface temperature
- Precipitation

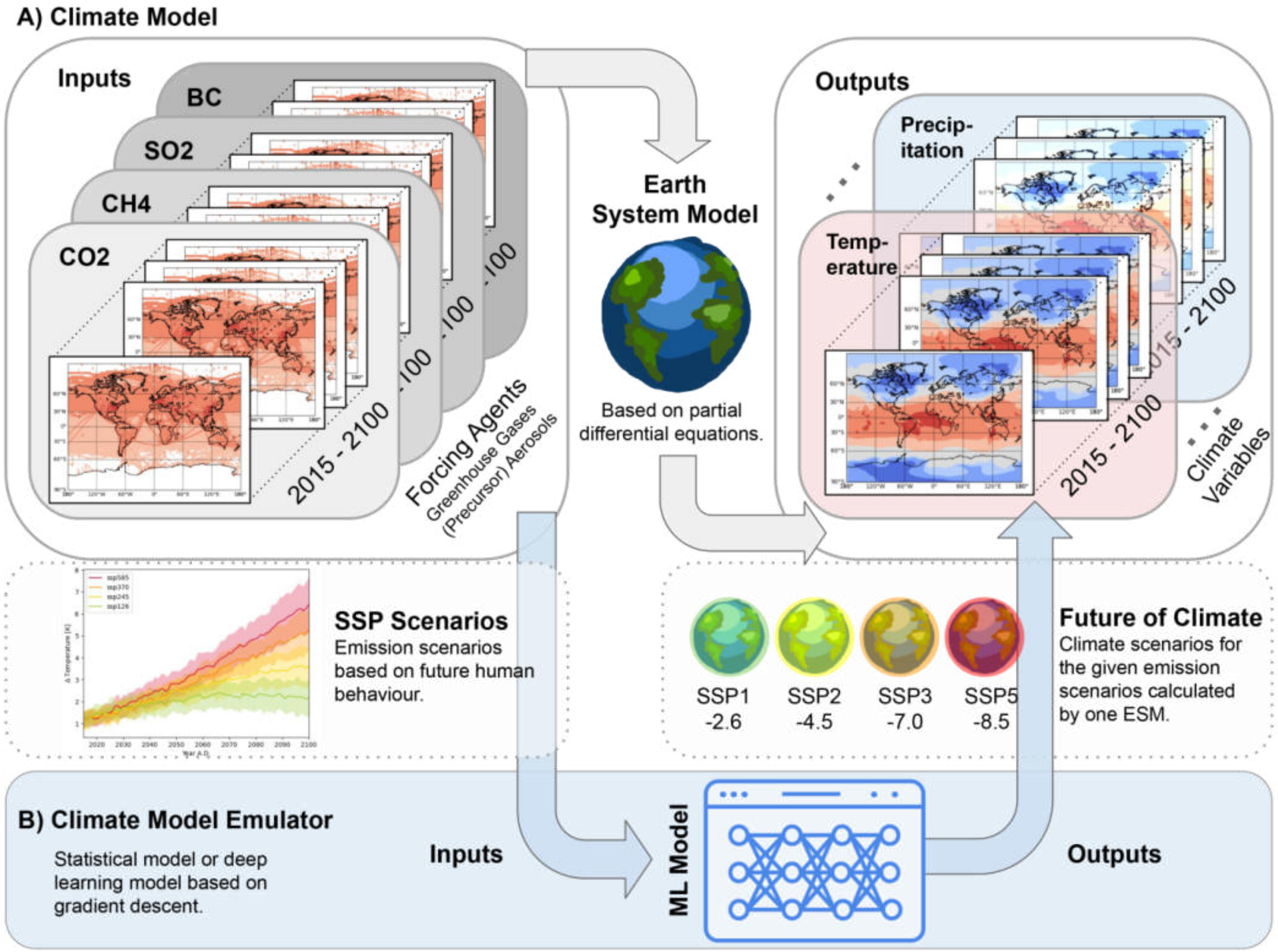
Causal climate evaluation
- Teleconnections
- Precipitation dynamics
- Causal representation learning

Hybrid climate models
- Model parameterizations
- Ozone
- ICON, UKESM

Data-driven forecasting
- Air pollution
- Wildfire risks
- AI weather models & climate projections

AI world models & emulation
- WOW world model
- Causal climate model emulation
- Transfer learning

Machine learning for climate model emulation



Mansfield et al. npj Clim. and Atm. Sci. (2020), GMDD (2026)

Watson-Parris et al. JAMES (2022)

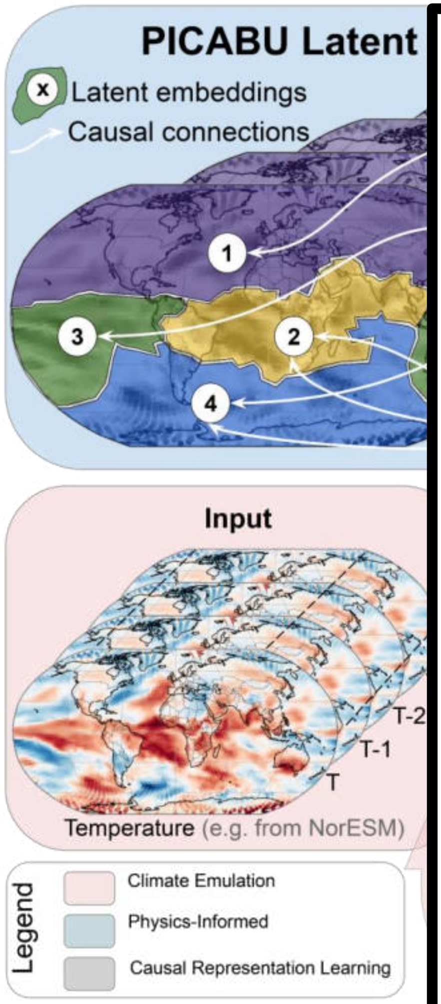
Kaltenborn et al. NeurIPS (2023)

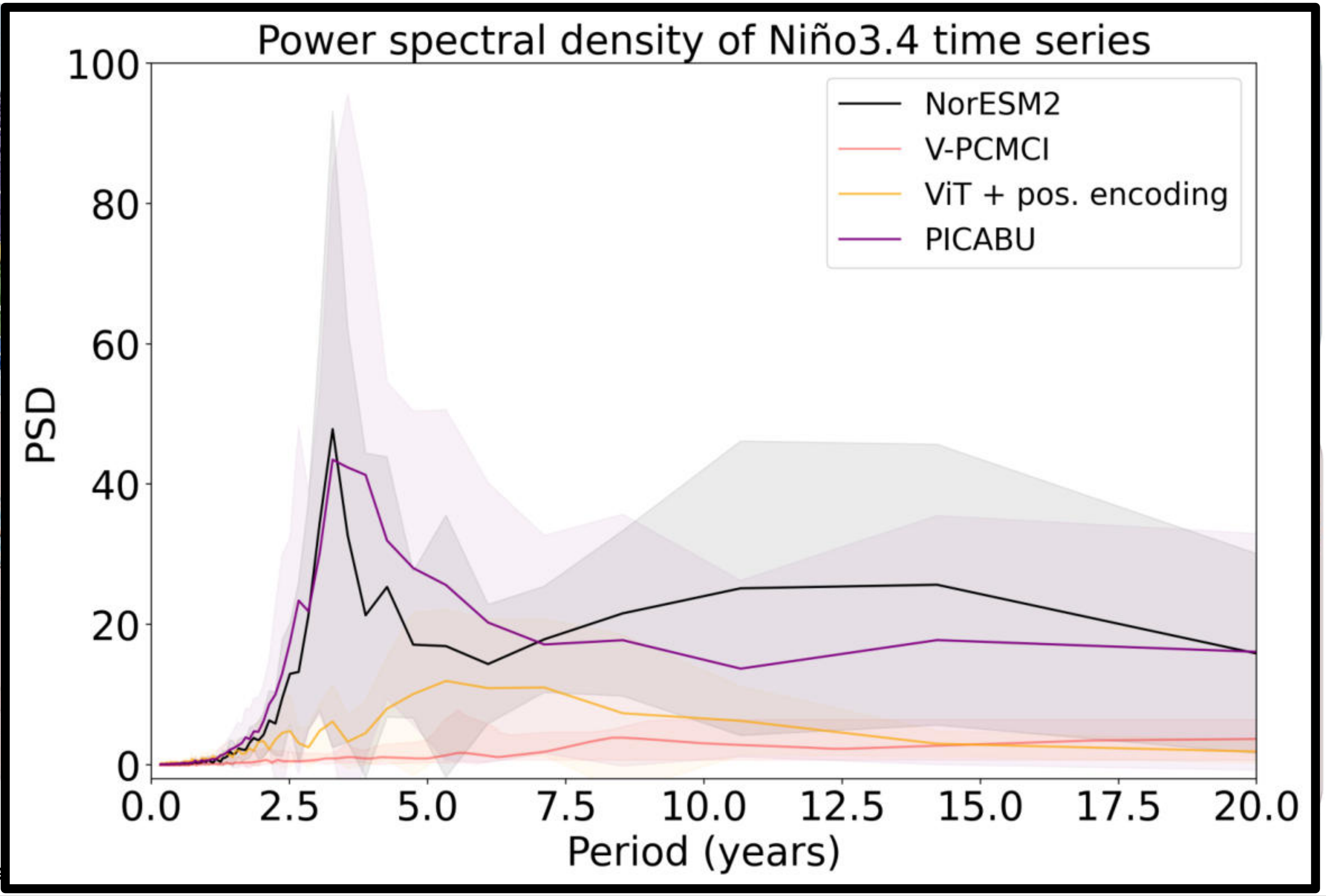
Fully data-driven?

Constraint = data we train on

Could be CMIP, observations…

Machine learning for climate model emulation: PICABU





Hickman et al. Causal climate

Sebastian Hickman

Ilija Trajkovic

Julien Boussard (Mila)

Autoregressive long-term prediction

However, we do need additional constraints…

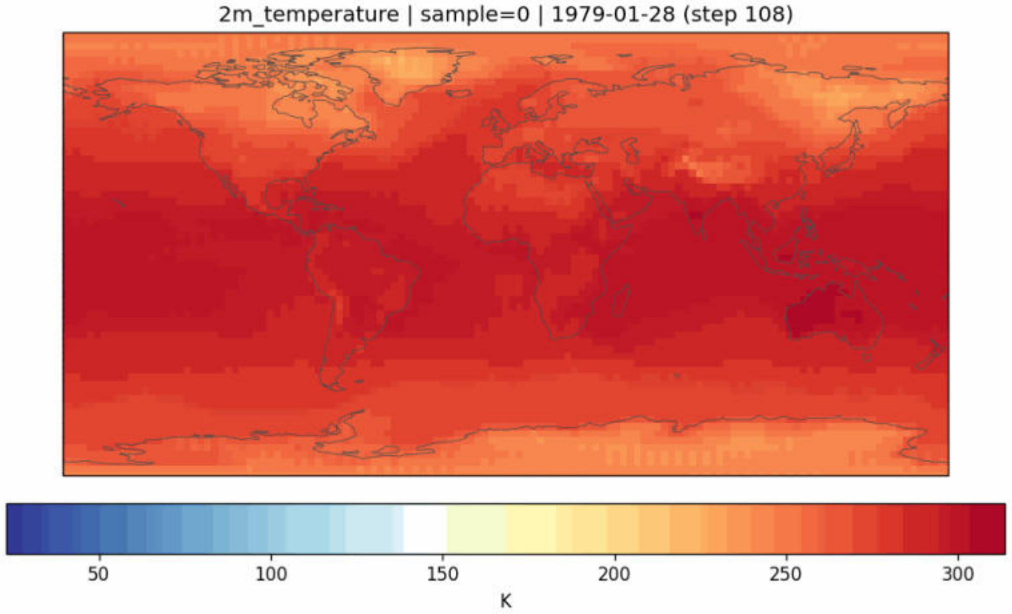
- Autoregressive predictions are often unstable.
- **Bayesian filter:** at each step

  → get multiple samples from the posterior distribution
  → reject "bad" samples

- Output: collection of trajectories each associated with a probability

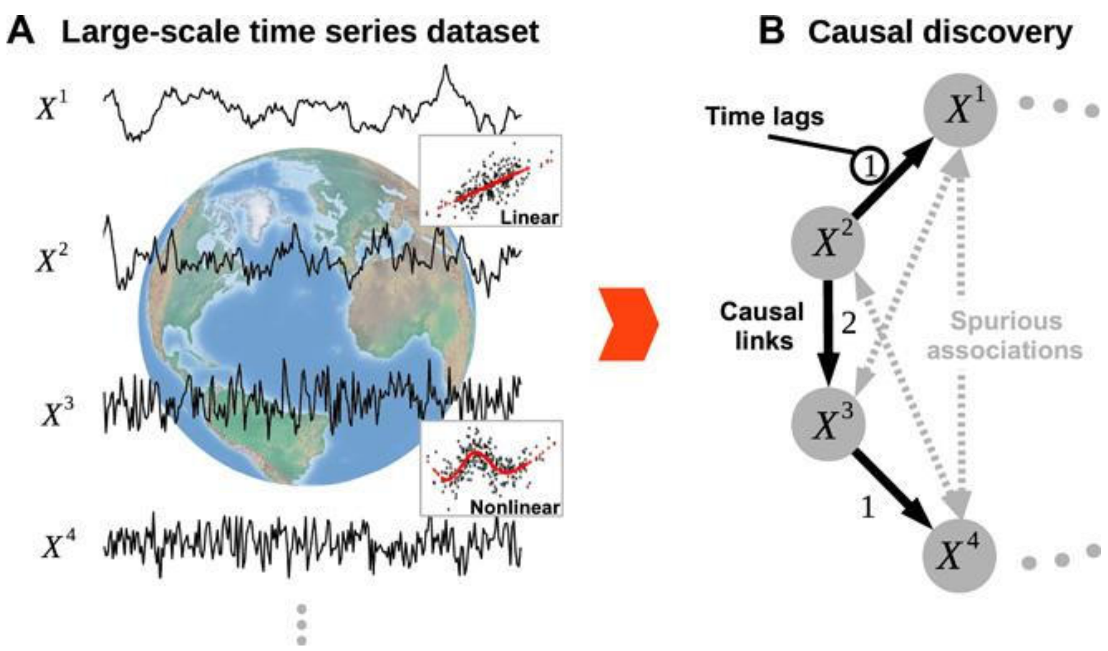
  → stable autoregressive rollouts
  → propagate uncertainty through the prediction

- Important: should also create realistic multi-annual frequency spectra in long roll-outs!



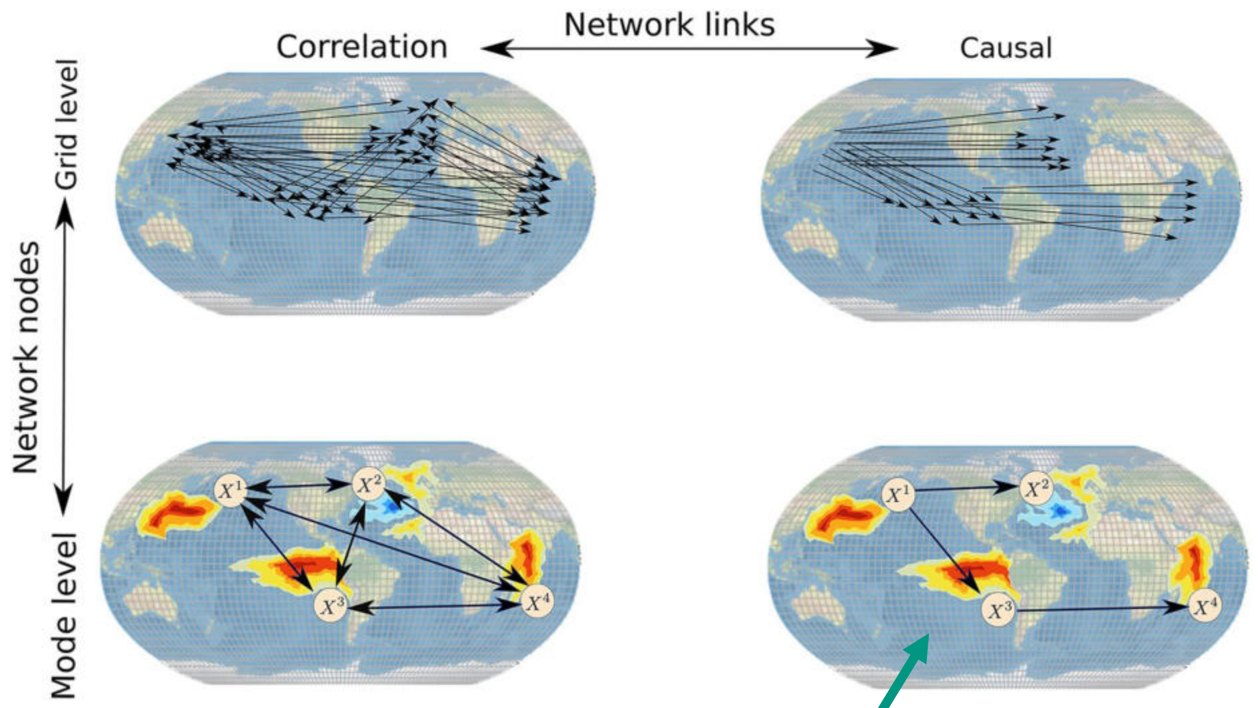
Christopher Roth

Another constraint: causality



Runge et al. Science Advances (2019);

Nowack et al. Nature Communications (2020)



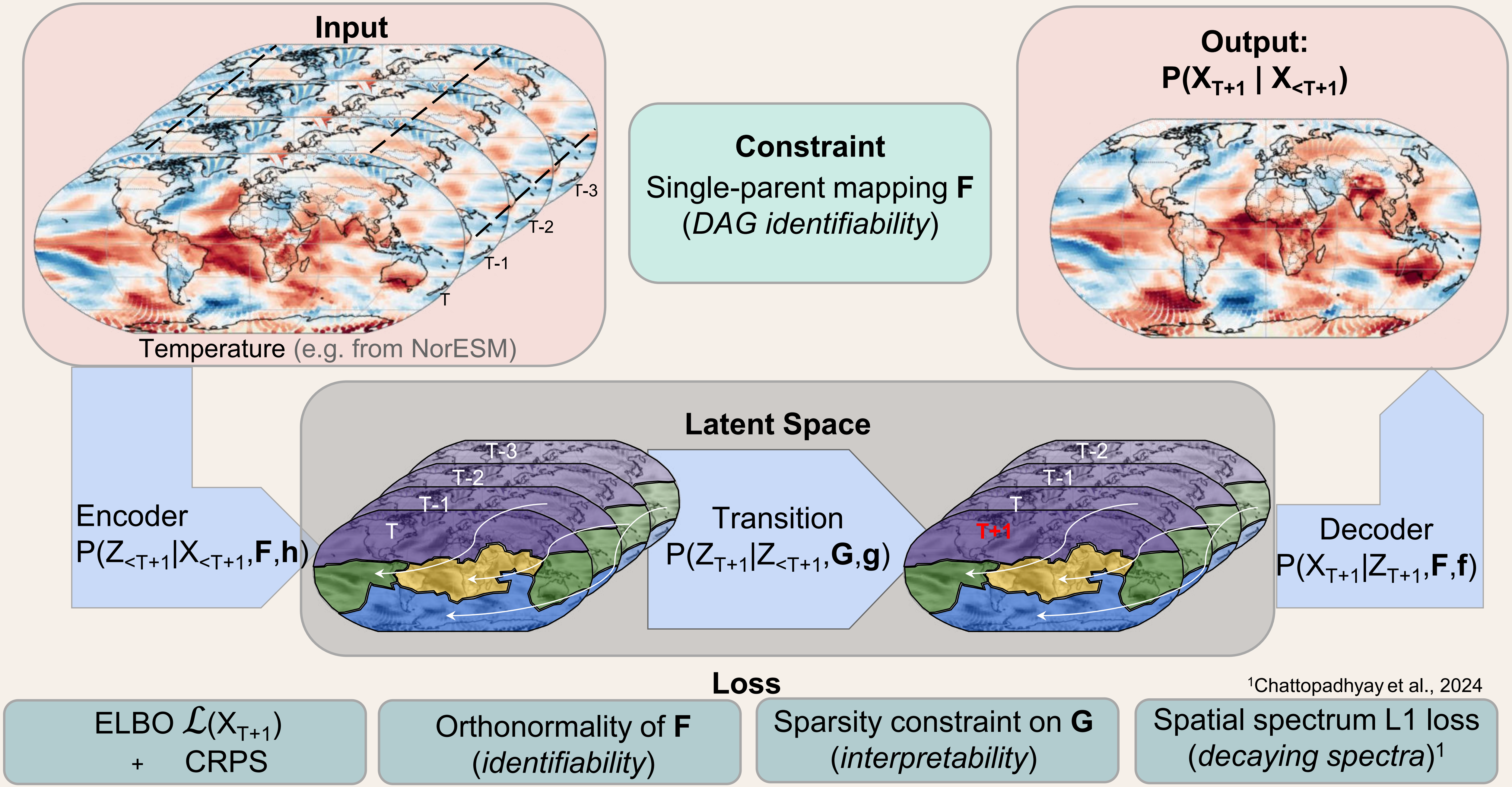
Tibau et al. Environmental Data Science (2024)

Causal representation learning

Latent variables = modes of variability

Causal graph = dynamics

Model training and next step prediction (Dr. Julien Boussard)



WOW – a World model of Our World

Peer Nowack, Almut Arneth, Jan Cermak, **Charlotte Debus, Markus Götz,** Peter Knippertz, Jan Stühmer, Erwin Zehe

Carl-Zeiss Foundation Breakthroughs Grants 2025 – AI and Environment

The team behind WOW

Ecology	Clouds	Efficient AI	AI Energy	Weather	AI Climate	AI Theory	Hydrology

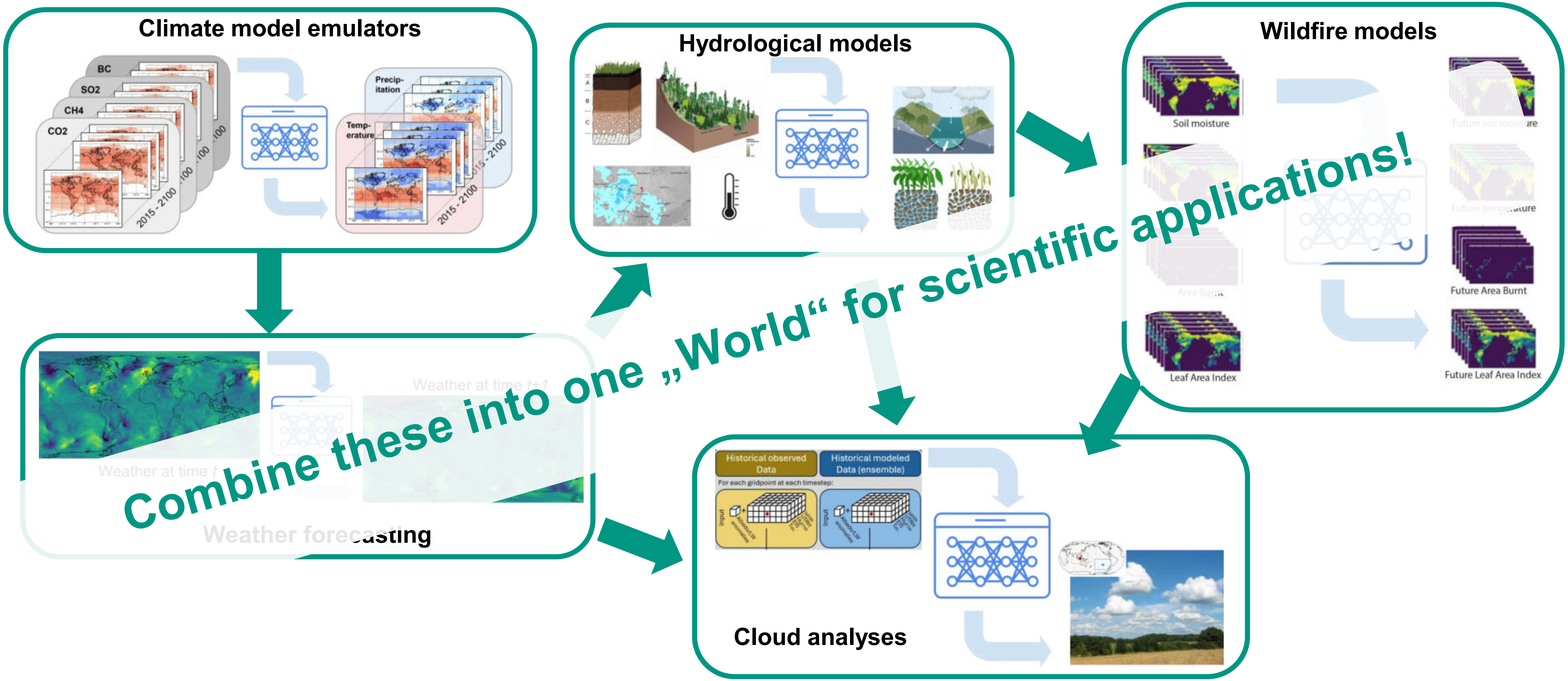
Almut Arneth	Jan Cermak	Charlotte Debus	Markus Götz	Peter Knippertz	Peer Nowack	Jan Stühmer	Erwin Zehe

- 8 PIs, 7 Postdocs, 2 PhDs, plus multiple associated Postdocs
- 6 Mio. Euro funding (Carl-Zeiss-Foundation) from 1 March 2026
- Five partners for transfer → **Project Advisory Board**

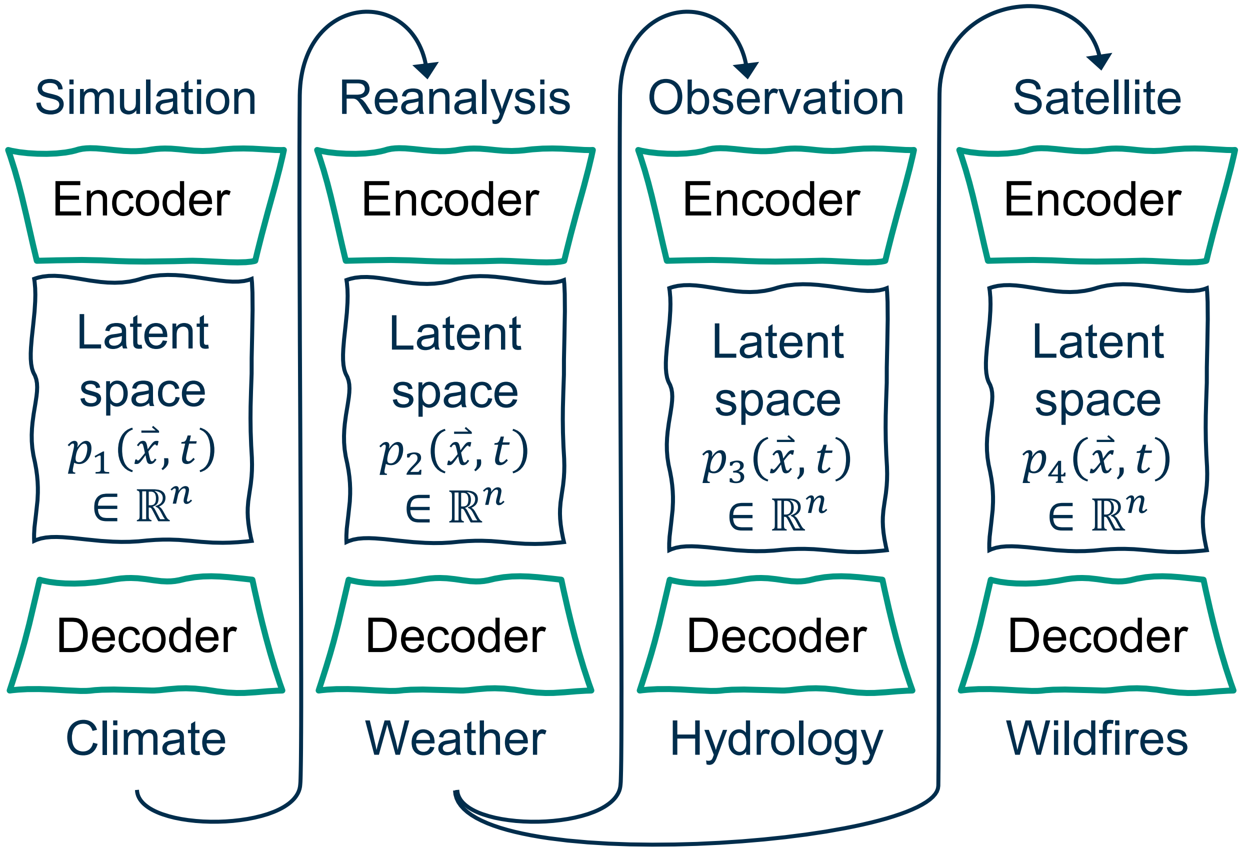
Carl Zeiss Stiftung

AMD SIEMENS LUBW BfG Bundesanstalt für Gewässerkunde DWD Deutscher Wetterdienst Wetter und Klima aus einer Hand

AI models in Earth system modelling



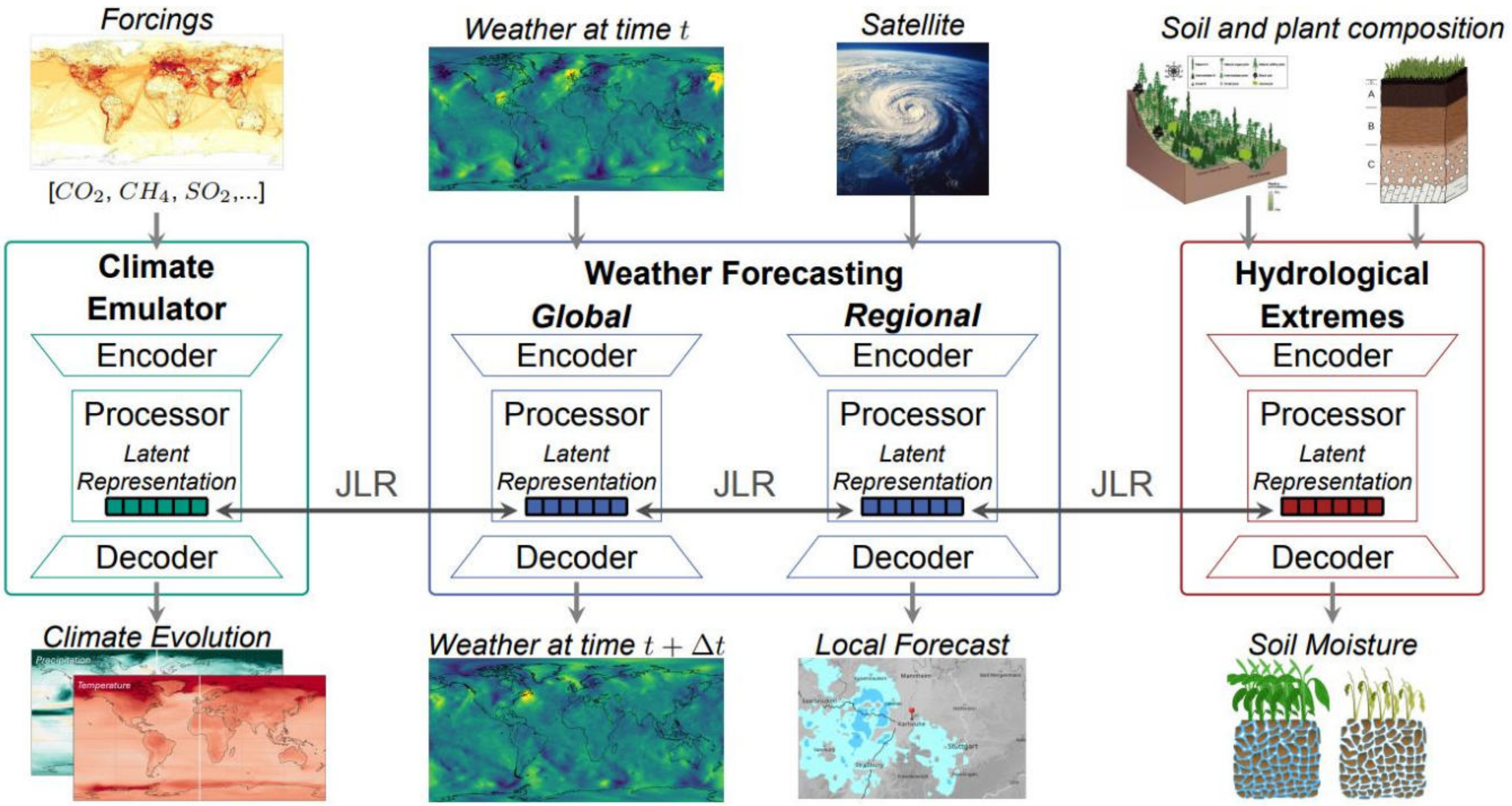
Foundation Models vs. World Models



- Large-scale neural network model
- Pre-trained on large, heterogeneous datasets; self-supervised learning
- Can be adapted (fine-tuned) for different downstream tasks
- All modalities/tasks → same latent space
  - Latent space needs to be very large
- But what if we want to
  - Predict several tasks simultaneously?
  - “Chain” events?
    E.g. Climate → Weather → Water/Wildfire

How do they “know about each other”? → **World Models**

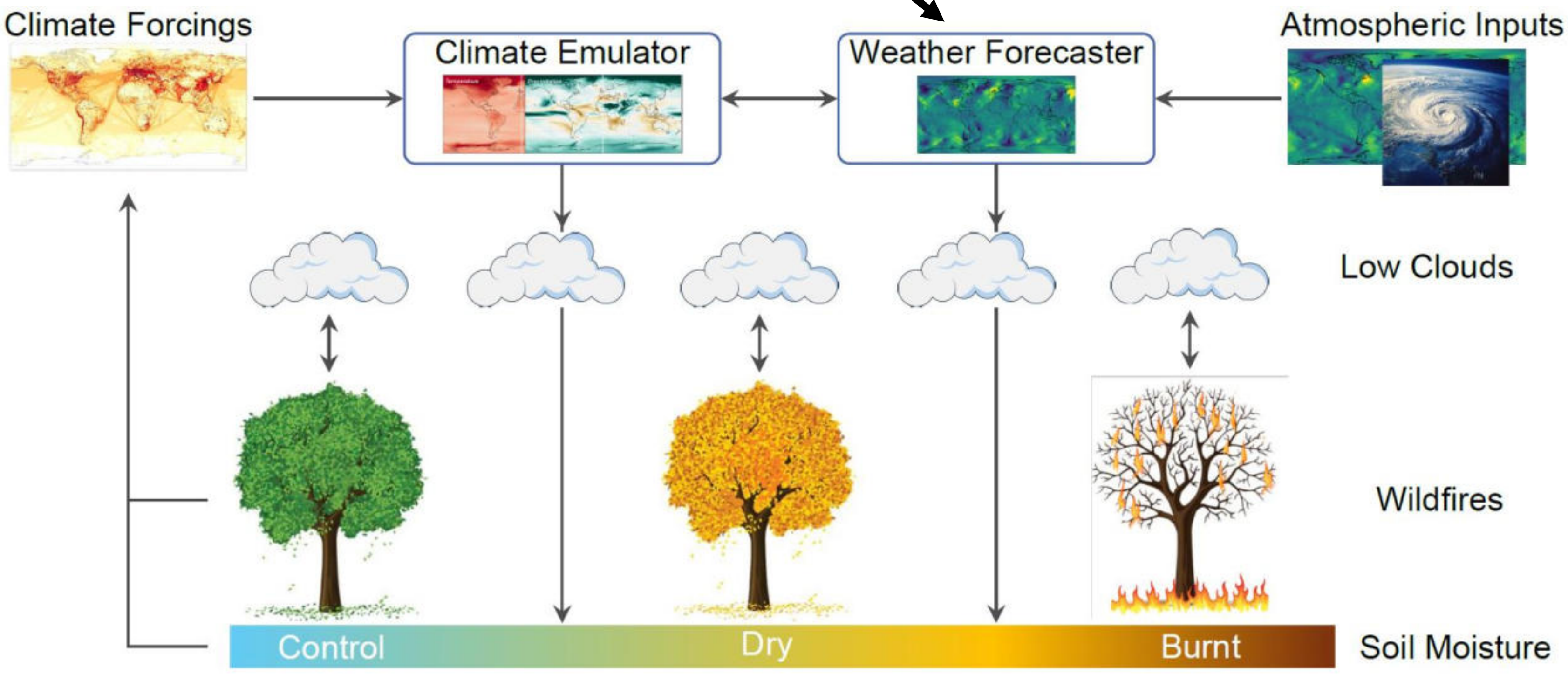
An illustration of the WOW world model



WOW - The environmental sciences focus

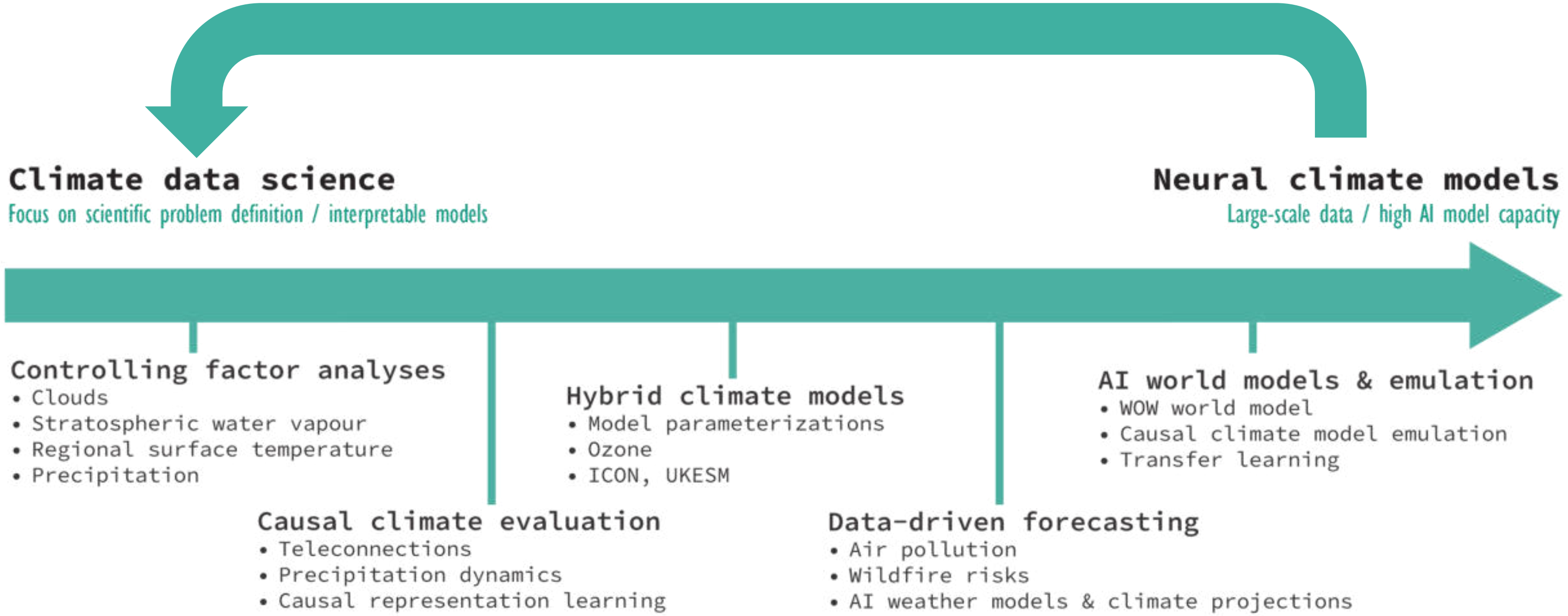
First applications of WOW to interactions between the atmosphere, hydrological cycle, and land surface

Fast high-resolution AI weather ensembles under climate change



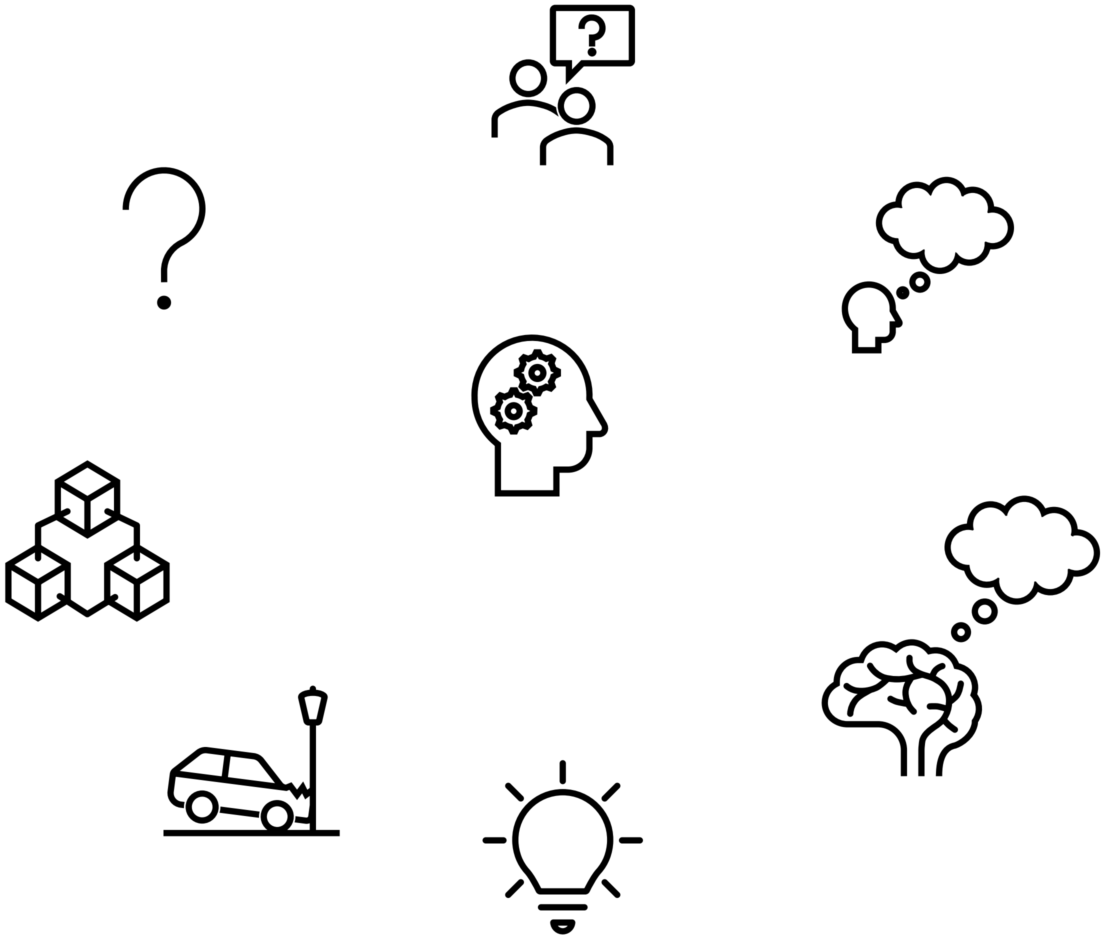
Summary

- There are **many exciting opportunities** for machine learning in earth system modelling.
- For example, it could help us **tackle longstanding issues** such as uncertainties in global climate change projections.
- Key challenge under climate change: extrapolation relative to historical Earth observations → data-driven models **need constraints + a robust evaluation** (closing the circle)!



Thank you!

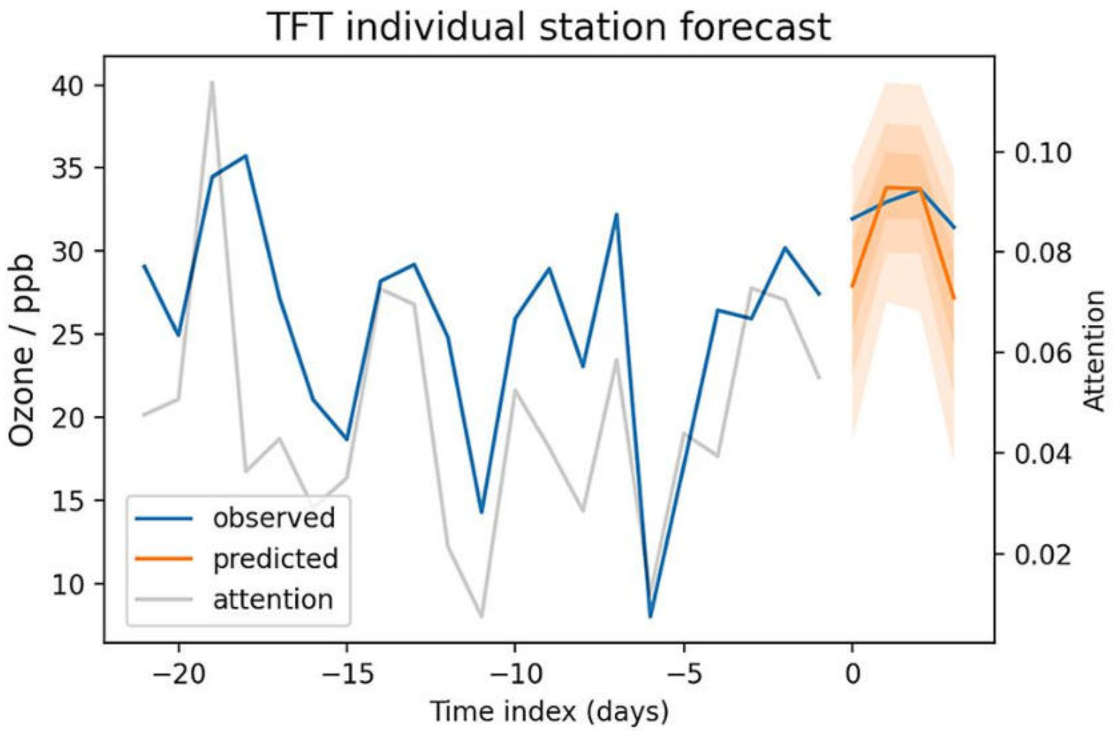
Questions?



Back-up slides

Example of a data-driven single task model

Temporal Fusion Transformers (TFT) to forecast surface ozone pollution in Europe up to four days in advance.



Method (paper)	r (Pearson)	RMSE/ppb	Stations
Chemical transport models			
GEOS-Chem (Ivatt and Evans, 2020)	0.48	16.2	2,200
AQUM (Neal et al., 2014)	0.64	20.9	61
Bias-corrected AQUM (Neal et al., 2014)	0.76	16.4	61
Bias-corrected GEOS-Chem (Ivatt and Evans, 2020)	0.84	7.5	2,200
ML methods			
DRR (Debry and Mallet, 2014)	0.70	6.3	729
CNN (Sayeed et al., 2020)	0.77	8.8	21
CNN (Eslami et al., 2020),	0.79	12.0	25
RNN (Biancofiore et al., 2015)	0.86	12.5	1
CNN-transformer (Chen et al., 2022)	*NA*	7.8	14
Our dataset			1,012
Persistence	0.67	10.9	
Ridge regression	0.69	10.8	
Random forest	0.80	9.0	
LSTM	0.84	8.3	
TFT	**0.91**	**6.6**	

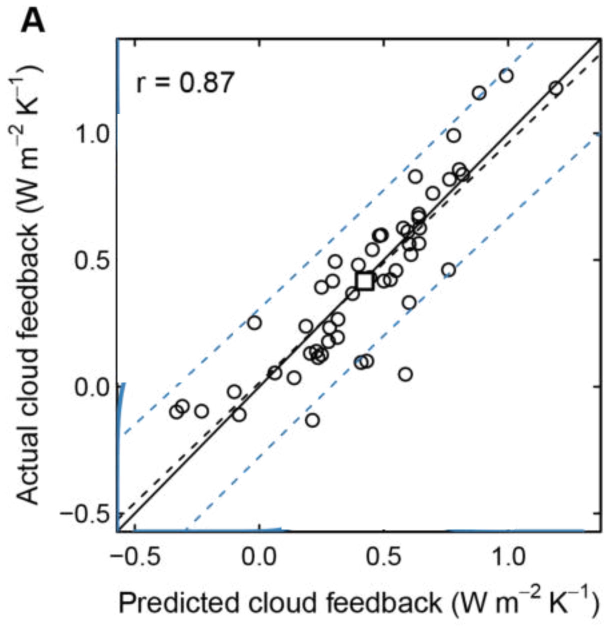
Sebastian Hickman et al. Environmental Data Science (2023)

Observational constraint on cloud feedback
Ceppi & Nowack PNAS (2021)

$$\frac{\mathrm{d}C(r)}{\mathrm{d}T} \approx \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \frac{\mathrm{d}\boldsymbol{X}_i(r)}{\mathrm{d}T}$$

observed cloud-radiative sensitivities

from climate models

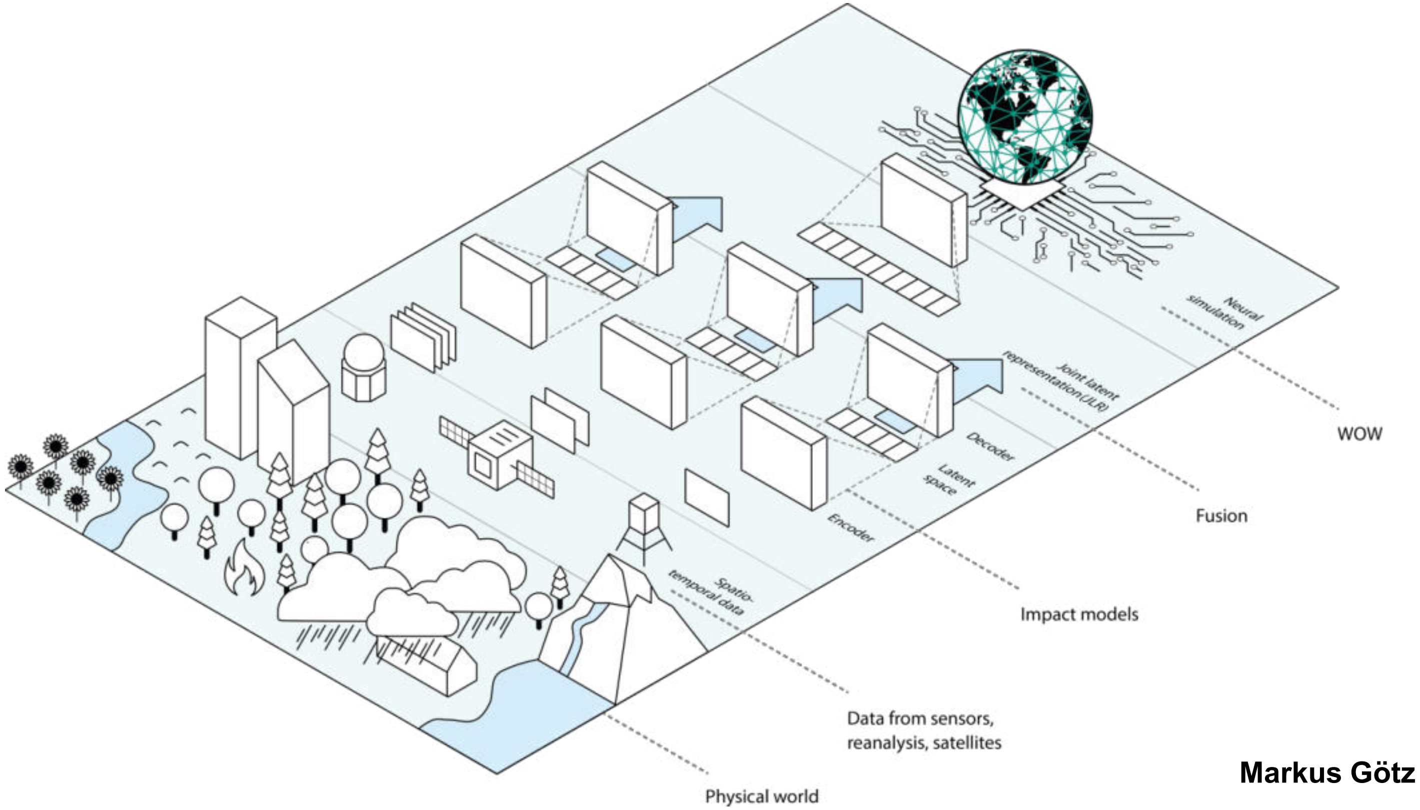


PDF includes observational uncertainty & other error sources

Observations indicate positive cloud feedback (0.43 ± 0.35 W m^{-2} K^{-1})

WOW

- **Adaptable, extendable architecture** → inclusive to future AI developments.
- **Efficiencies in latent space modelling** + explore **(causal) explainability**, without the need to “chain” models via their decoded outputs.
- Intrinsic **separation of spatial and temporal scales.**

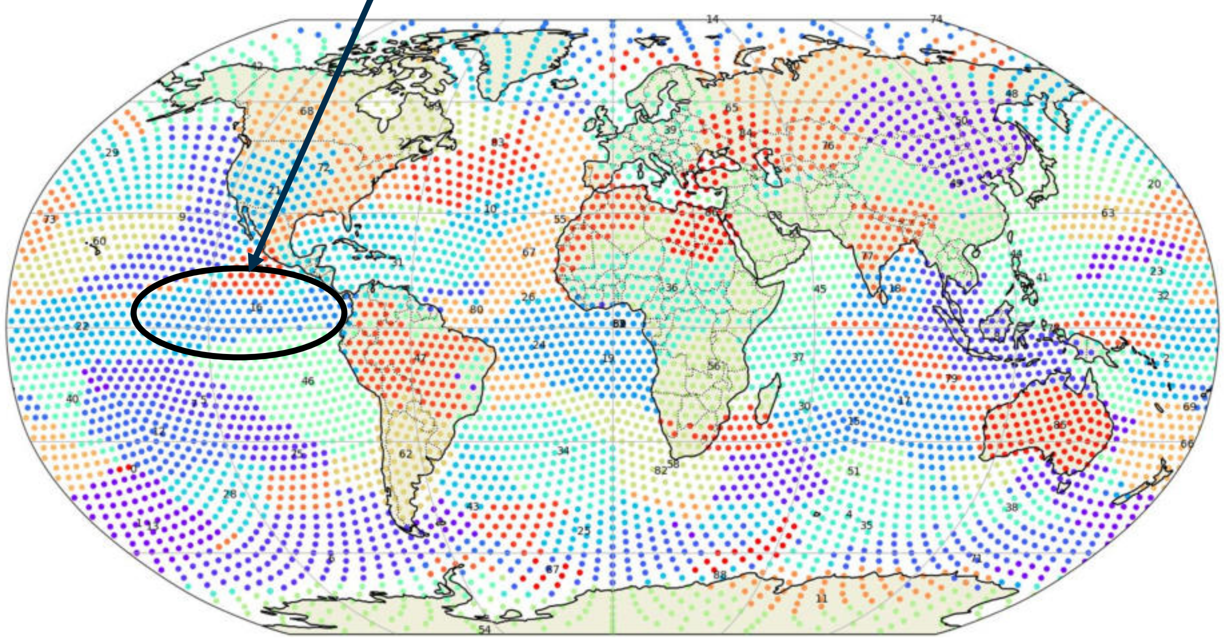


Markus Götz

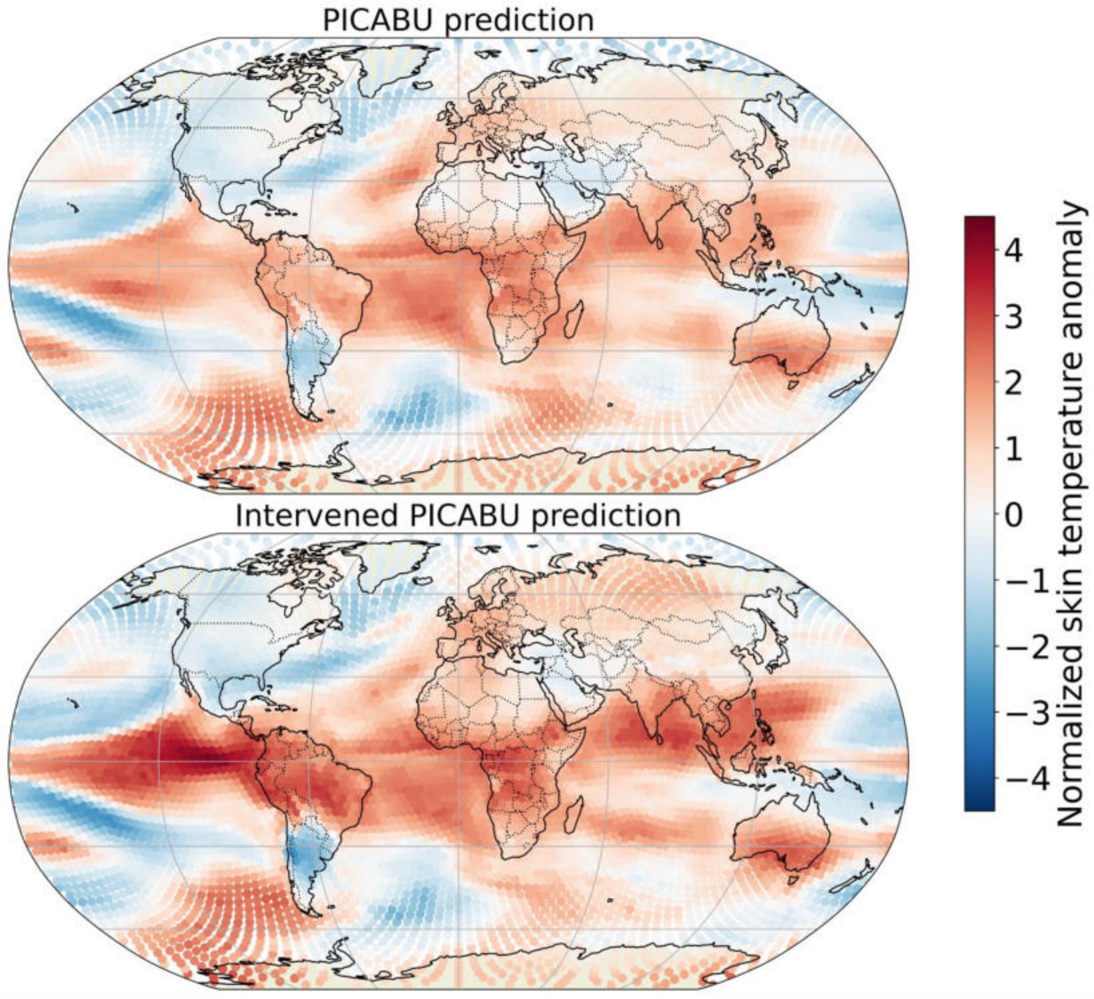
Counterfactual experiments

What if ENSO was stronger?

Intervention (set temperature of ENSO index to a predefined value)



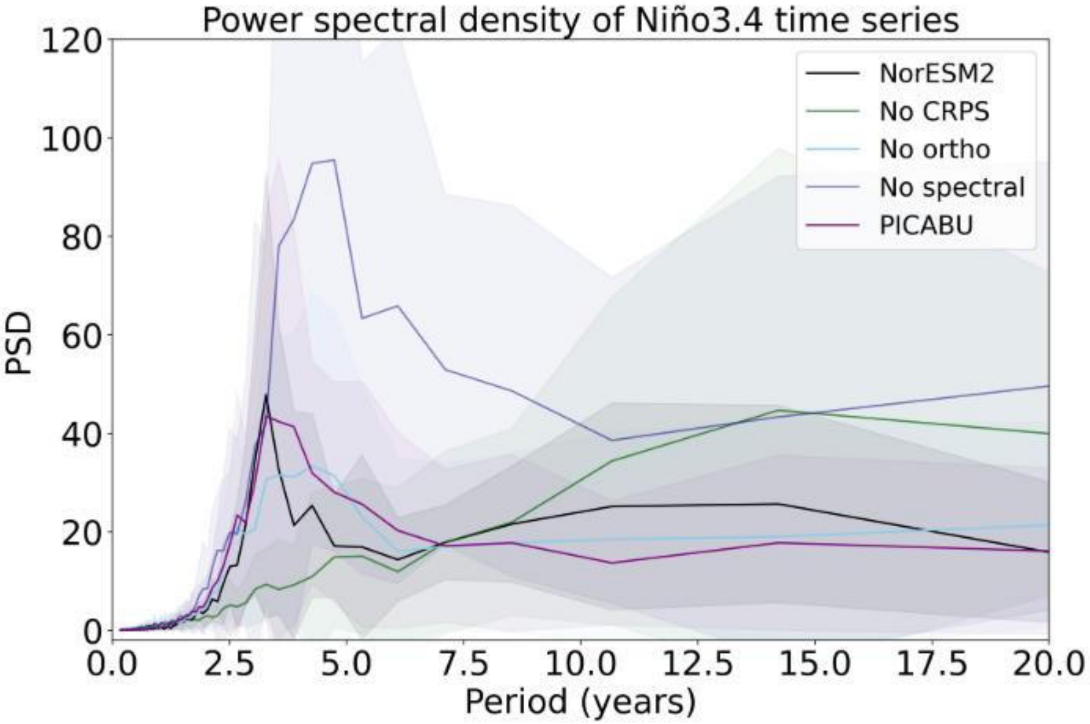
Colors represent single-parent mapping between latents and observations



Effect: the global temperatures rise

Constraints on the loss function help!

Hickman et al. Causal climate emulation with Bayesian filtering, NeurIPS (2025)



Similar results for Indian Ocean Dipole and Atlantic Multidecadal Oscillation, and CESM

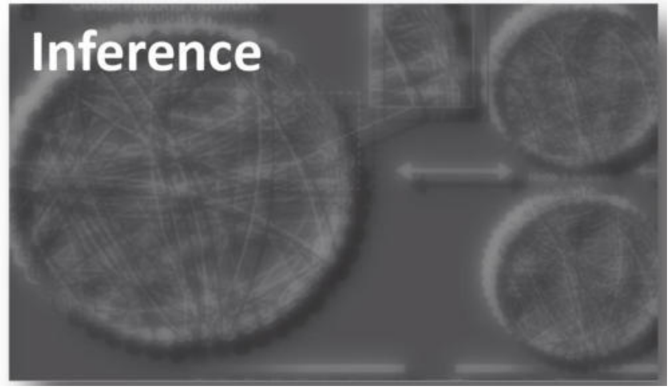
ELBO $\mathcal{L}(X_{T+1})$
\+ CRPS

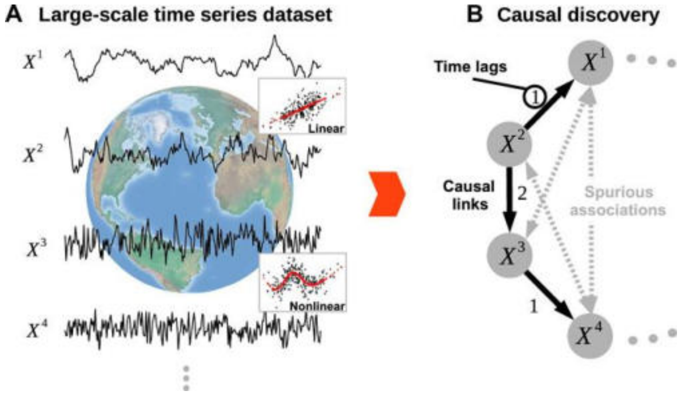
Orthonormality of **F**
(*identifiability*)

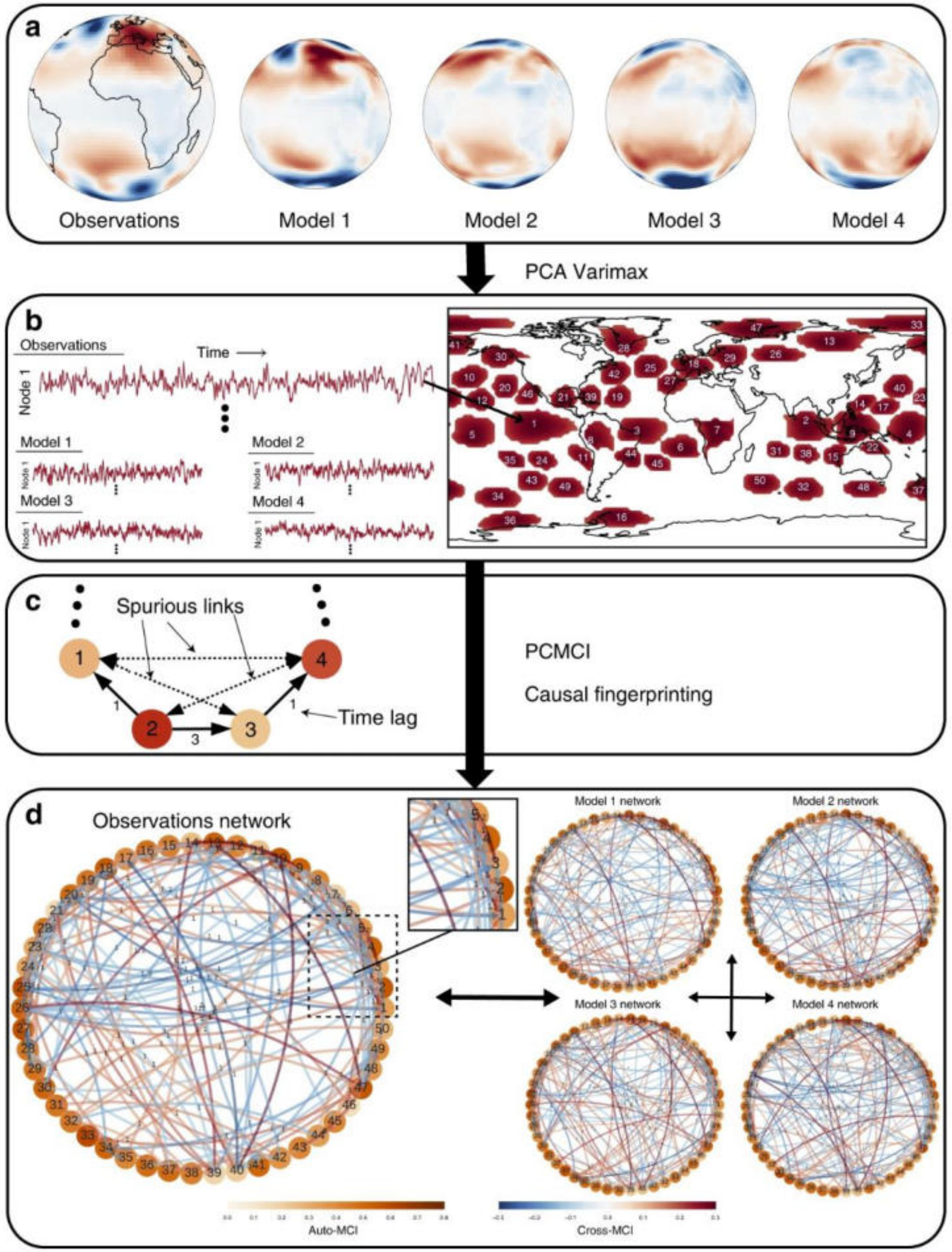
Sparsity constraint on **G**
(*interpretability*)

Spatial spectrum L1 loss
(*decaying spectra*)[1]

Causal model evaluation







Causal discovery algorithms

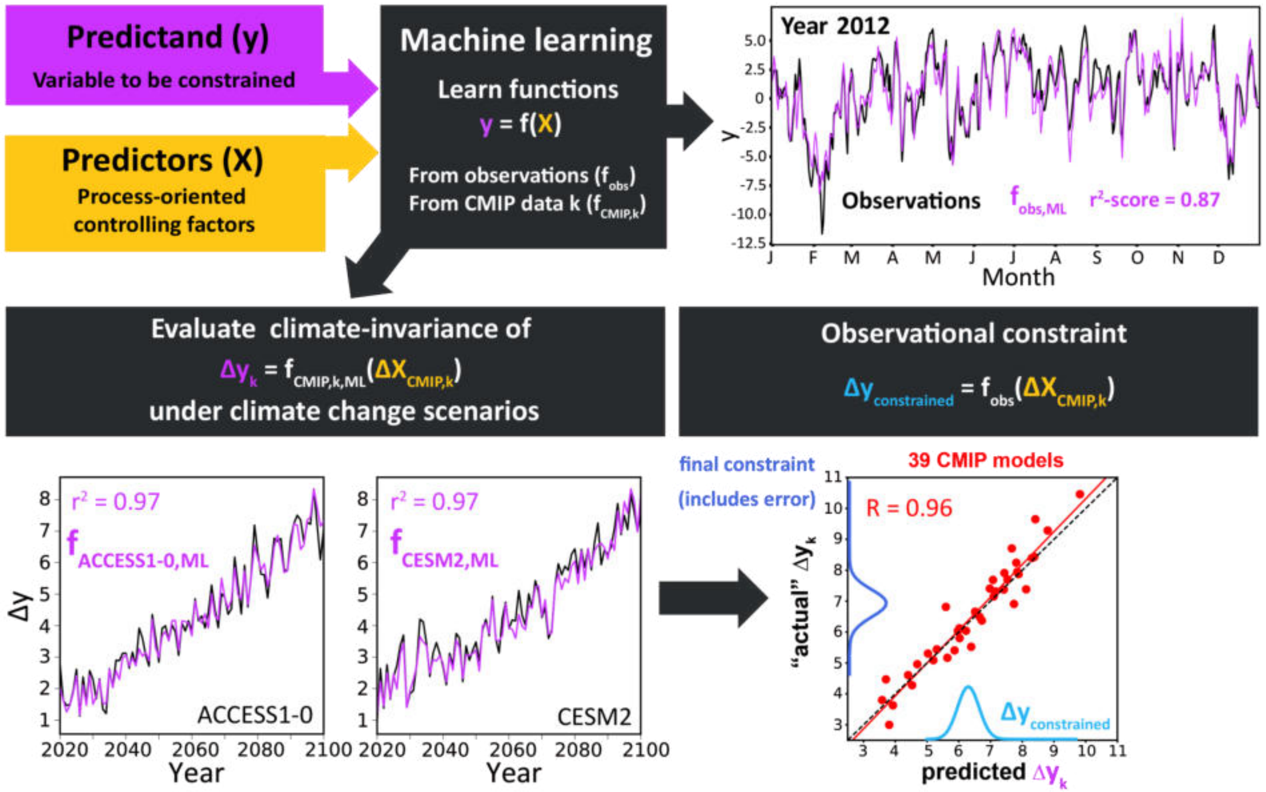
- Go beyond mere correlations
- Time series method PCMCI
- Constraints on precipitation projections

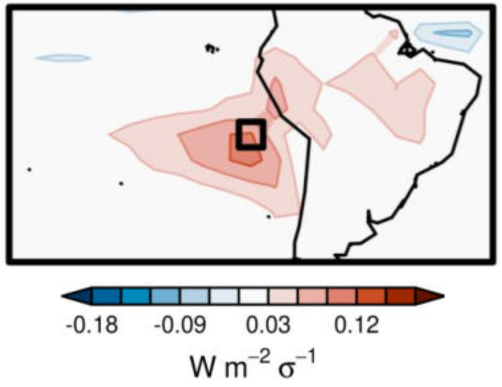
Nowack et al. Nature Communications (2020); Runge et al. Science Advances (2019)

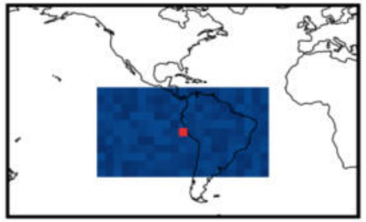
Cloud controlling factor analysis with machine learning

Cloud-radiative effects (shortwave and longwave)

Patterns of surface temperature, relative humidity,…



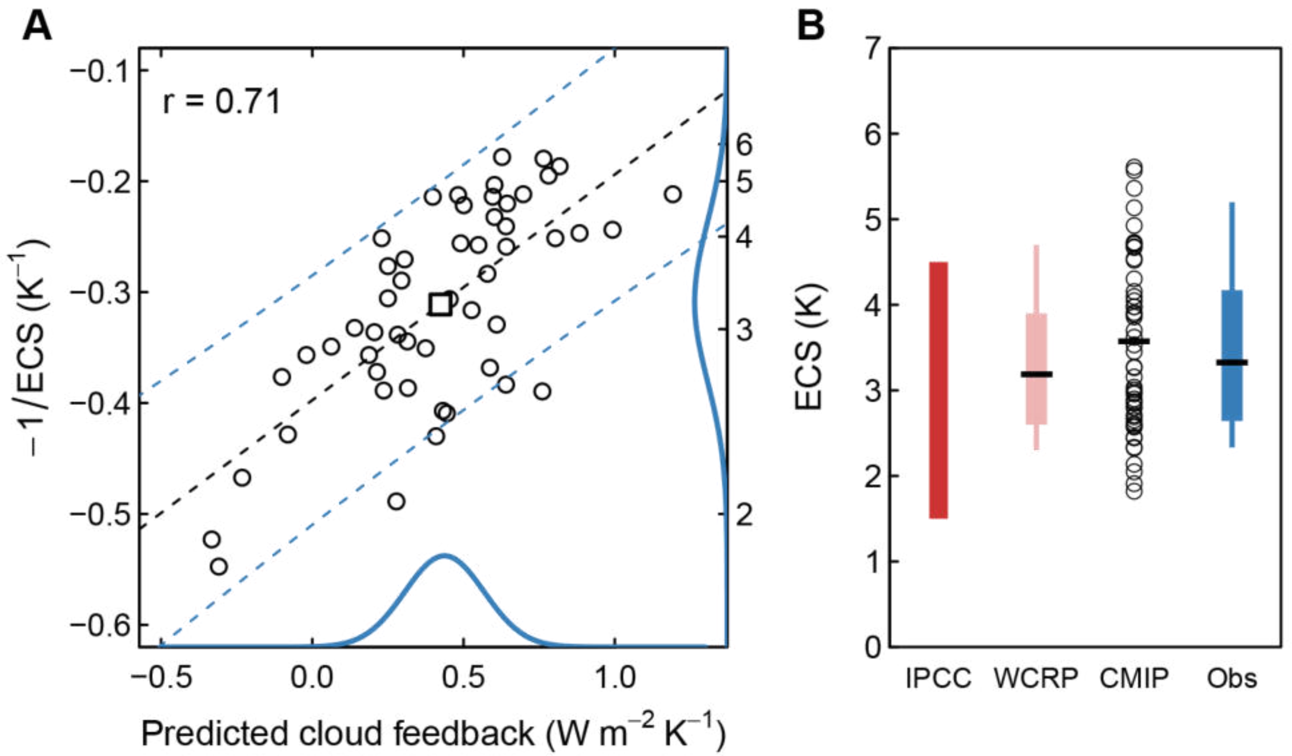




Key novelty aspects

- ✓ Shortwave and longwave, globally.
- ✓ Better predictive skill/narrower constraint, due to consideration of predictor patterns.

What does the new cloud feedback constraint imply for climate sensitivity?



Best estimate = 3.2 K

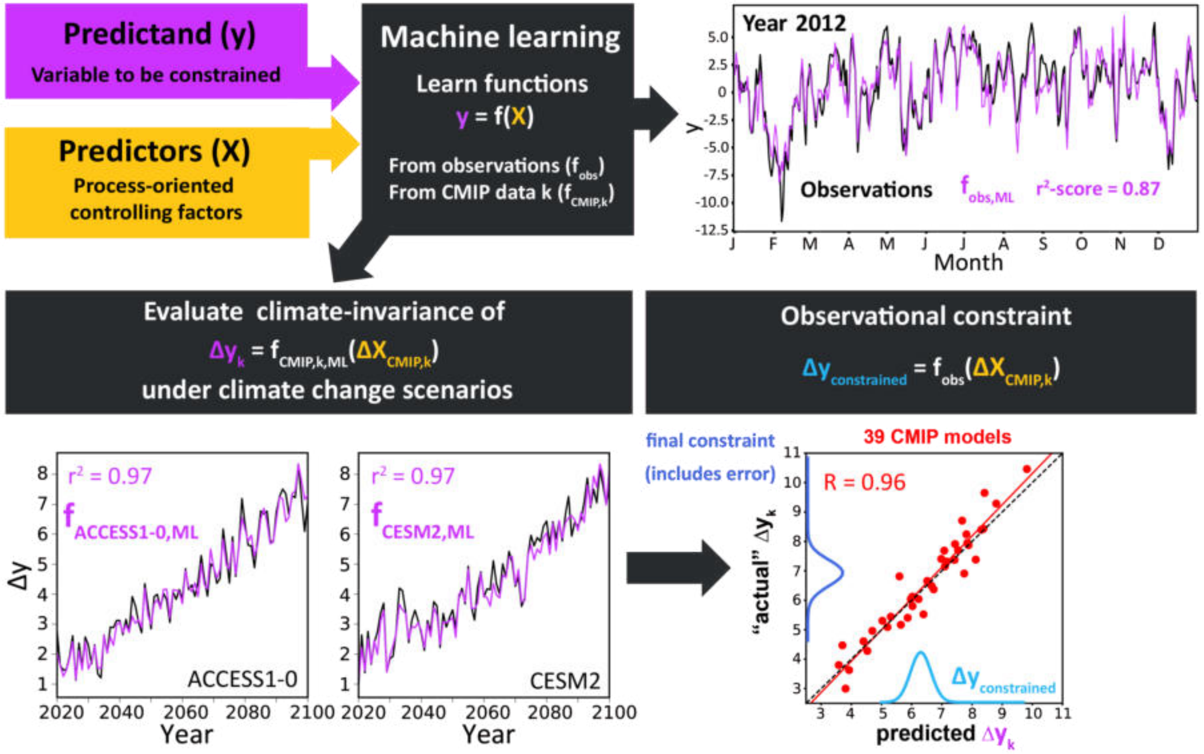
ECS almost certainly higher than 2 K (p > 99.5%)

Carbon Brief: Clouds study finds that low climate sensitivity is 'extremely unlikely'

Ceppi & Nowack *PNAS* (2021)

New observational constraint supports ECS best estimate ~3 K.
Low ECS (< 2 K) highly unlikely.

Alternative! Controlling factor analyses with machine learning

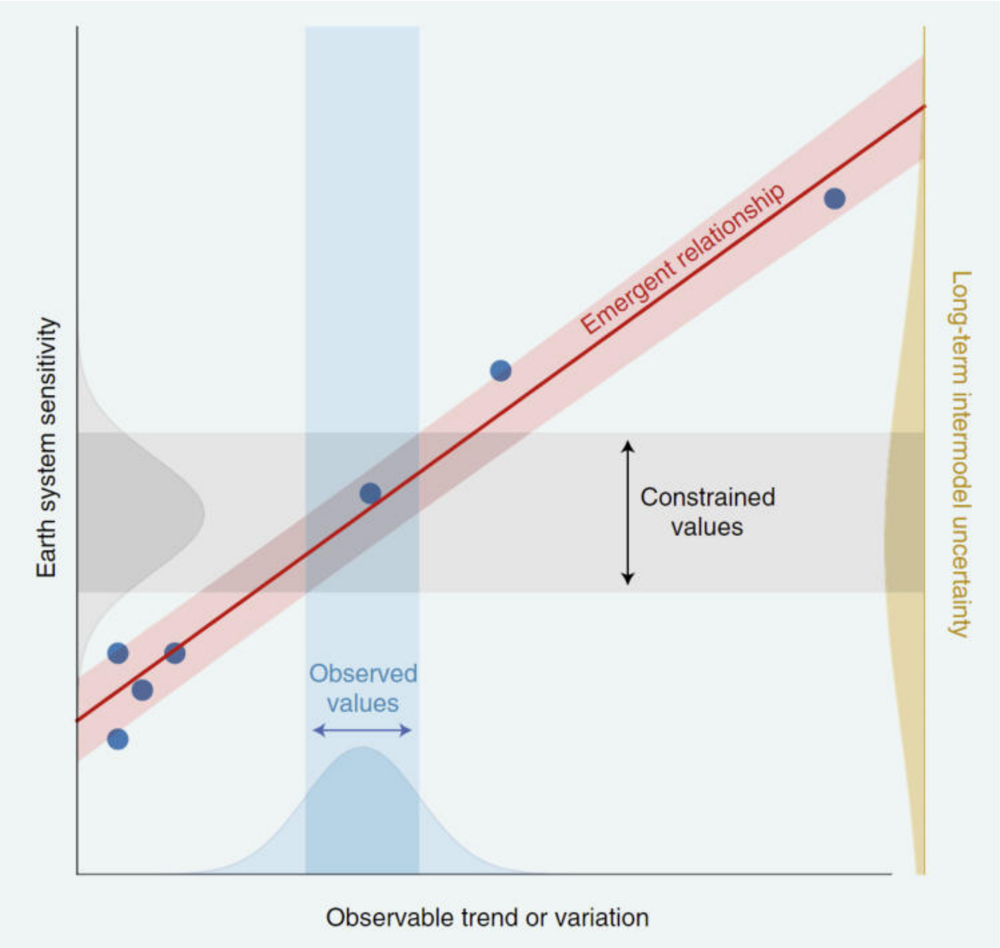


Why is this better?

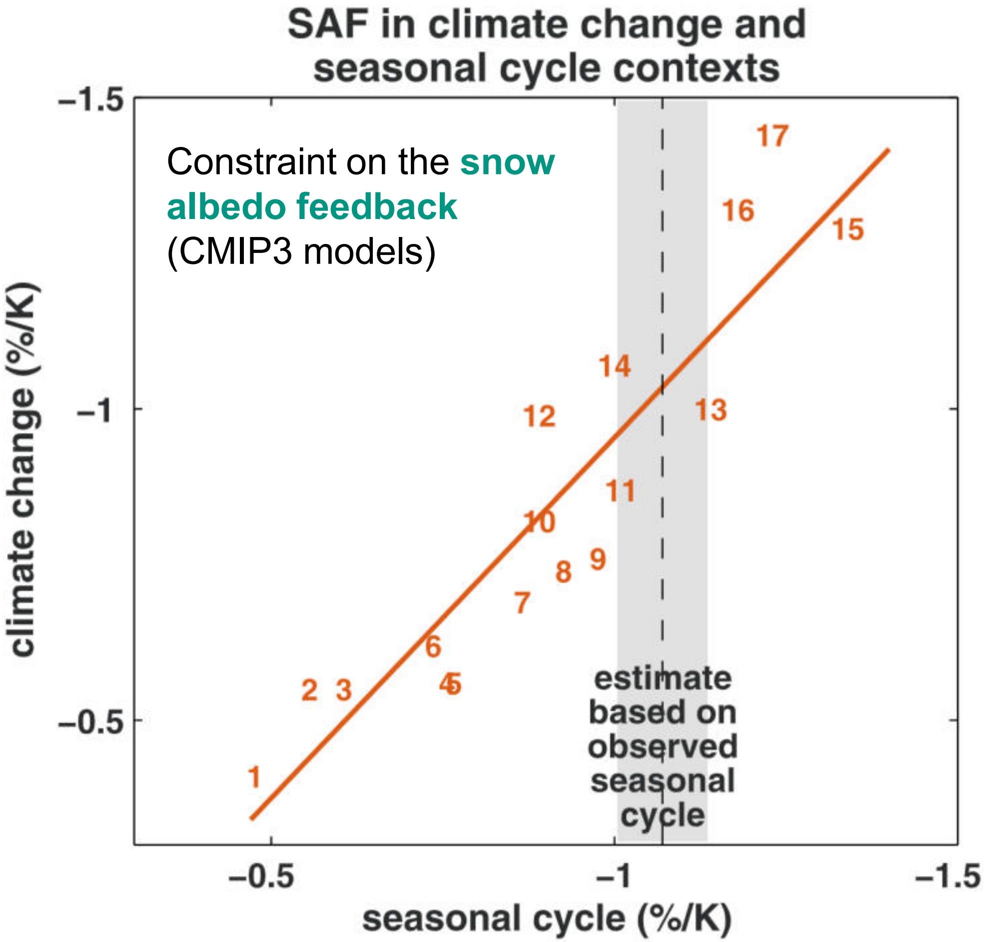
- Climate invariance = **direct link** between present-day and future.
- Evaluation on both historical and future simulations → **robust!**
- **Process-oriented:** the choice of controlling factors is by design motivated by physical principles.

Suggested constraints on: cloud feedback, equilibrium climate sensitivity, responses of the hydrological cycle, responses of the carbon cycle, wintertime Arctic amplification, marine primary production, ocean acidification, permafrost melting, the atm. circulation responses, mid-latitude heat extremes, …

„Traditional“ approach: emergent constraints

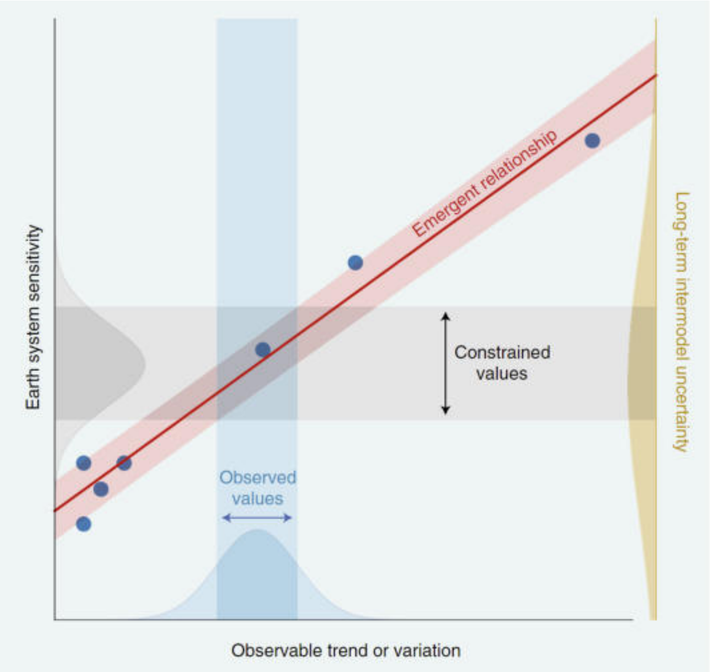


Eyring et al. *Nature Climate Change* (2019)



Hall & Qu. *Geophysical Research Letters* (2006)

„Traditional approach“: emergent constraints



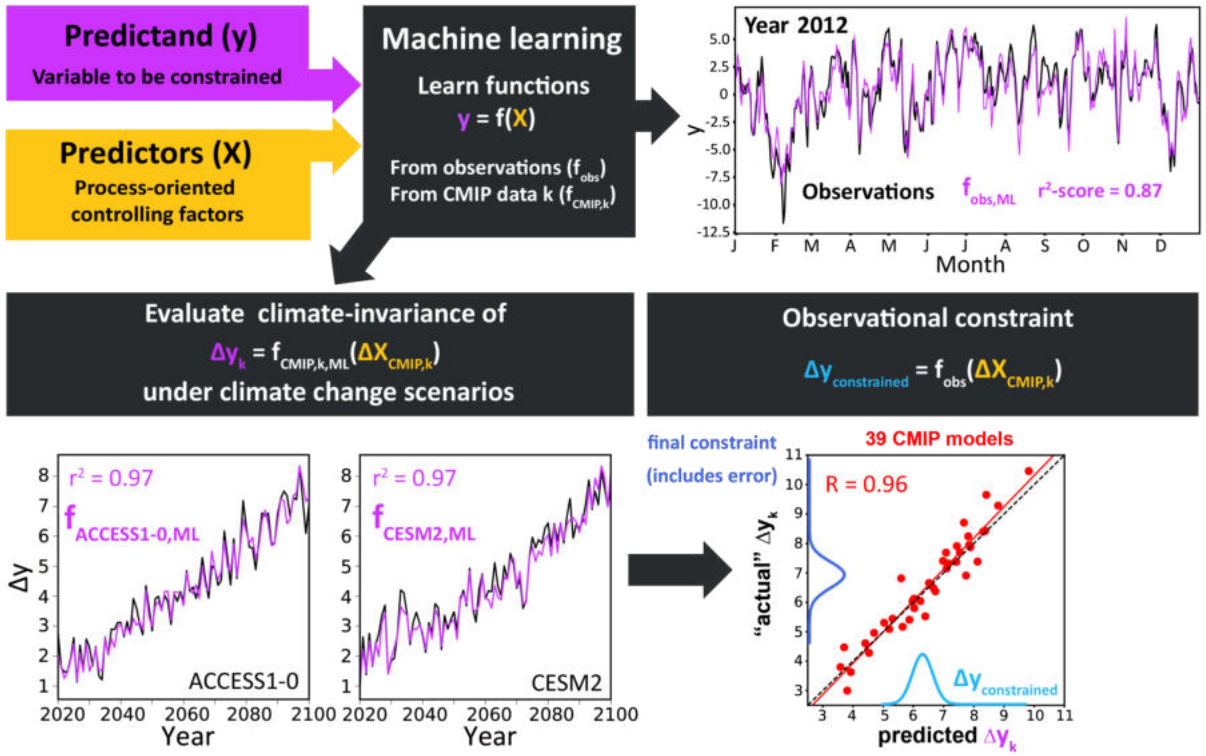
Over-confident constraints?

- Is this just data mining for linear correlations? (Caldwell et al. GRL 2014)
- Often not robust (CMIP5→CMIP6).
- Simple relationship y = f(x) to constrain very complex response?

In machine learning, we:

- Want correlations that are robust across training and test data.
- Could use more complex functions to relate observable to future response.

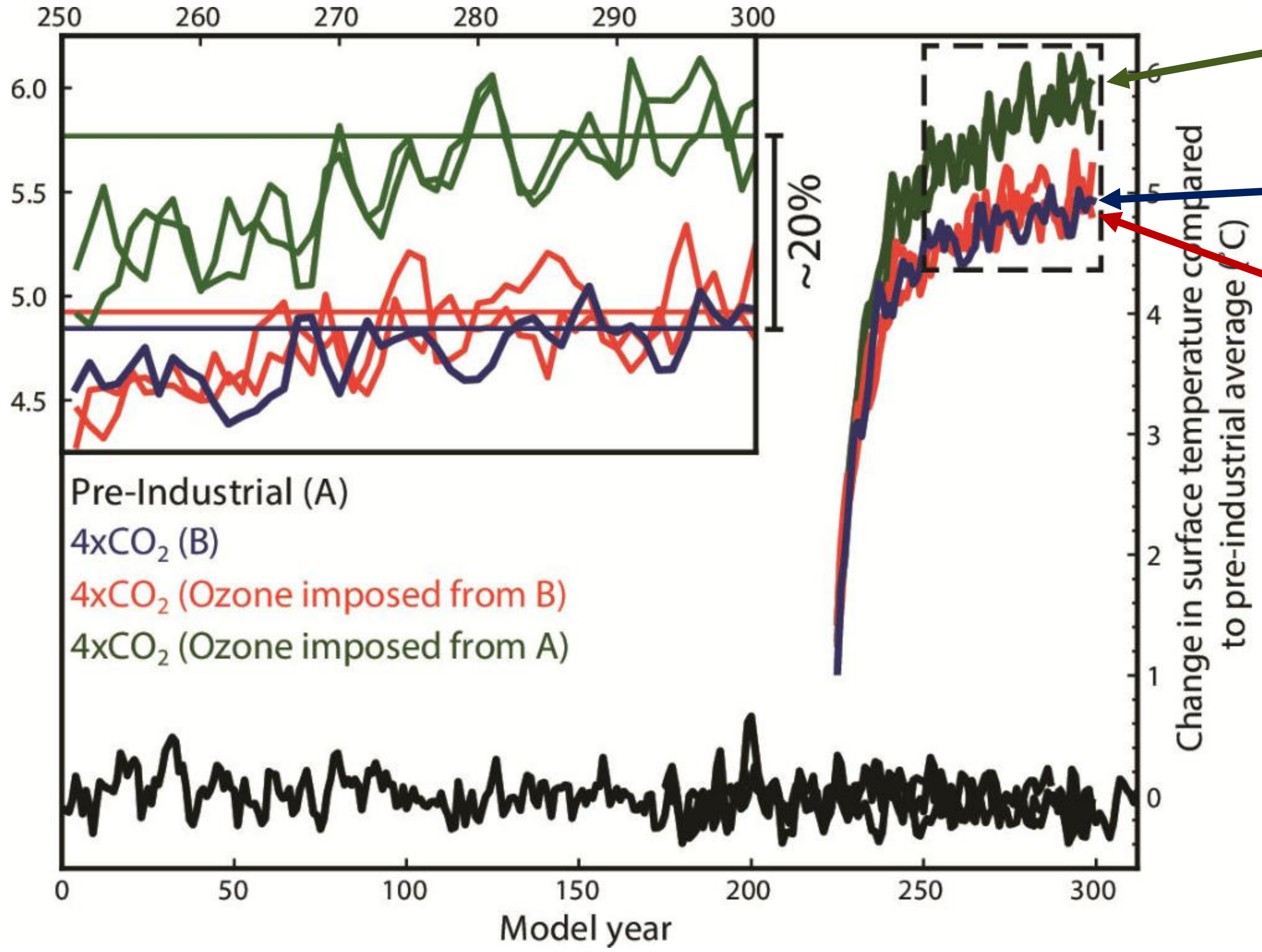
Alternative! Controlling factor analyses with machine learning



Steps:

- Learn function from observations $y = f_{obs}(\mathbf{X})$.
- Learn the corresponding $f_{CMIP,k}$ from historical simulations.
- Evaluate the **climate-invariance** of the relationships learned in a perfect-model framework.
- Combine f_{obs} with the CMIP5/6 set of controlling factor responses $\Delta\mathbf{X}_{CMIP,k}$ to obtain observationally constained $\Delta y_{constrained}$.

Global warming depending on atmospheric chemistry



No chemical feedback included

Interactive chemistry (B)

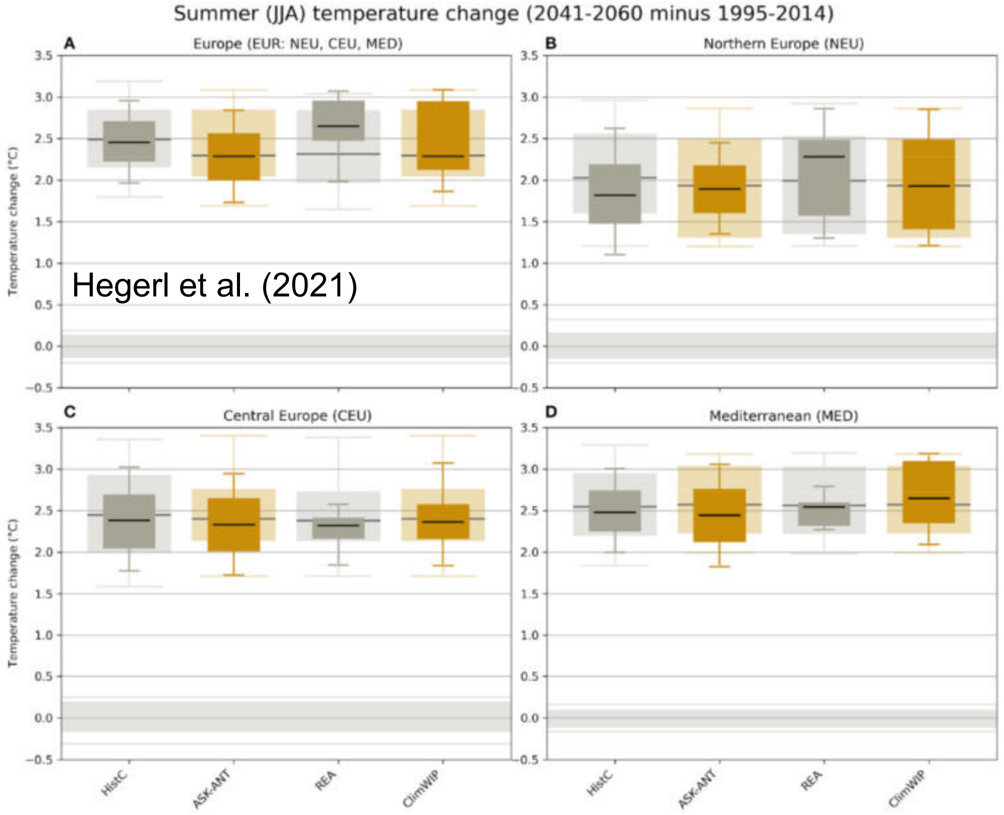
Chemical fields imposed from B (mean over years 250-300)

Pre-industrial control runs (A)

Nowack et al. Nature Climate Change (2015), UK Met Office model

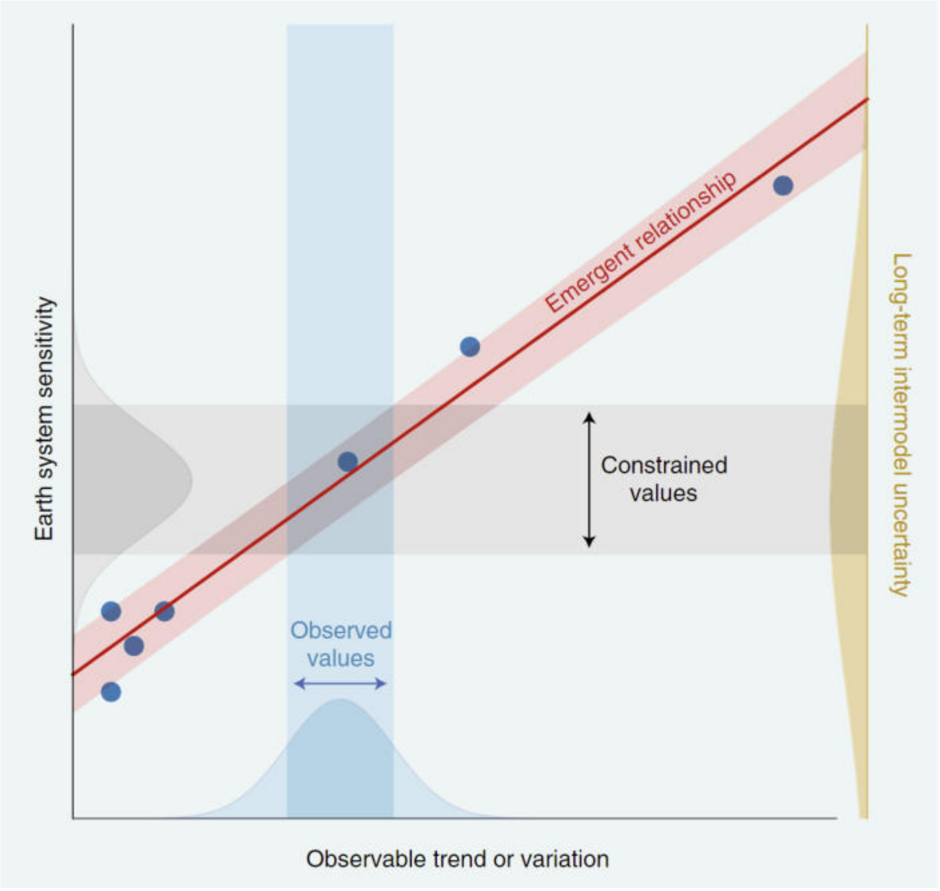
„Traditional“ approaches to constrain model uncertainty

Model evaluation metrics



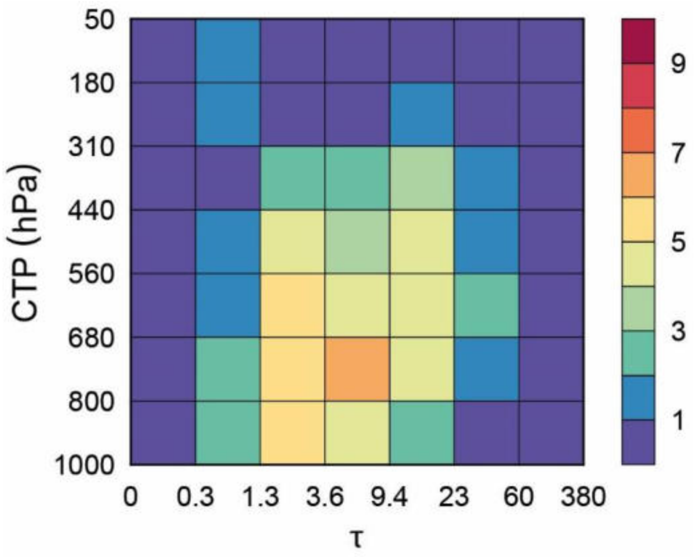
Hegerl et al. (2021)

Emergent constraints

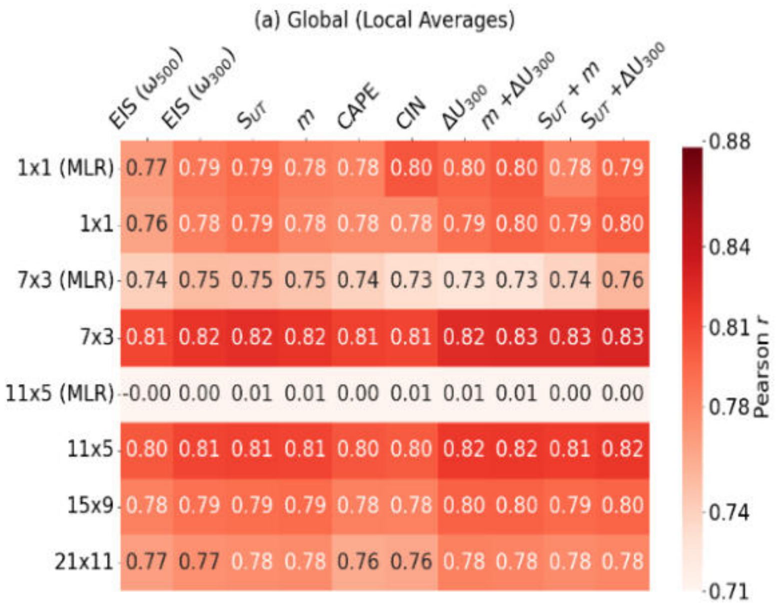


Current work

- Statistical learning method. Exploration of non-linearity + multivariate regression.
- Constraints on more specific cloud feedback components. Decomposition into cloud histograms for low and high clouds, optical depth and cloud amount, etc.
- Design of new controlling factors. Sarah Wilson Kemsley et al. ACP (2024).



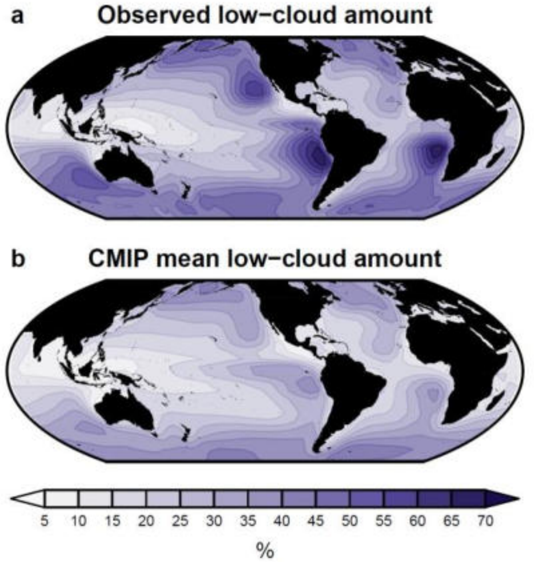
45°-60°S ISCCP cloud fraction (in %), binned by 7x7 cloud top pressure (CTP) and cloud optical depth (τ) boxes.

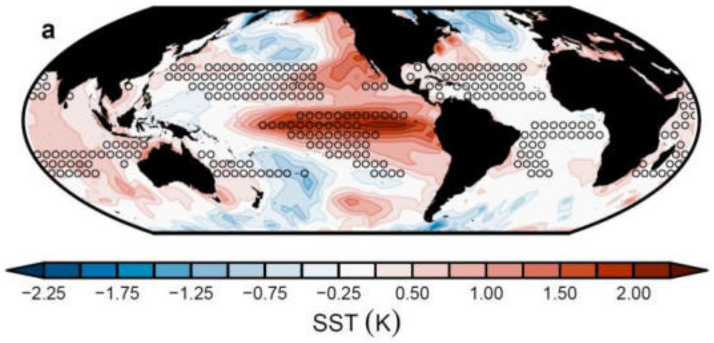


Focus on low-cloud feedback - link to model biases?

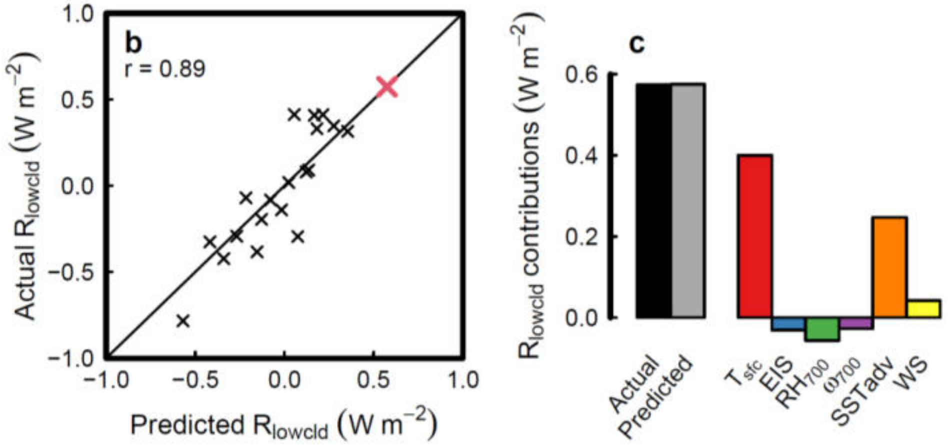
Ceppi et al., in review

- Low-cloud amount is systematically underestimated by CMIP models, but in turn too reflective („too few, too bright“ problem). (CMIP satellite simulator data)
- Comparison of satellite products (MODIS, CERES, ISCCP, PATMOS-x, AVHRR-PM); cloud amount binned by cloud top pressure and cloud optical depth.

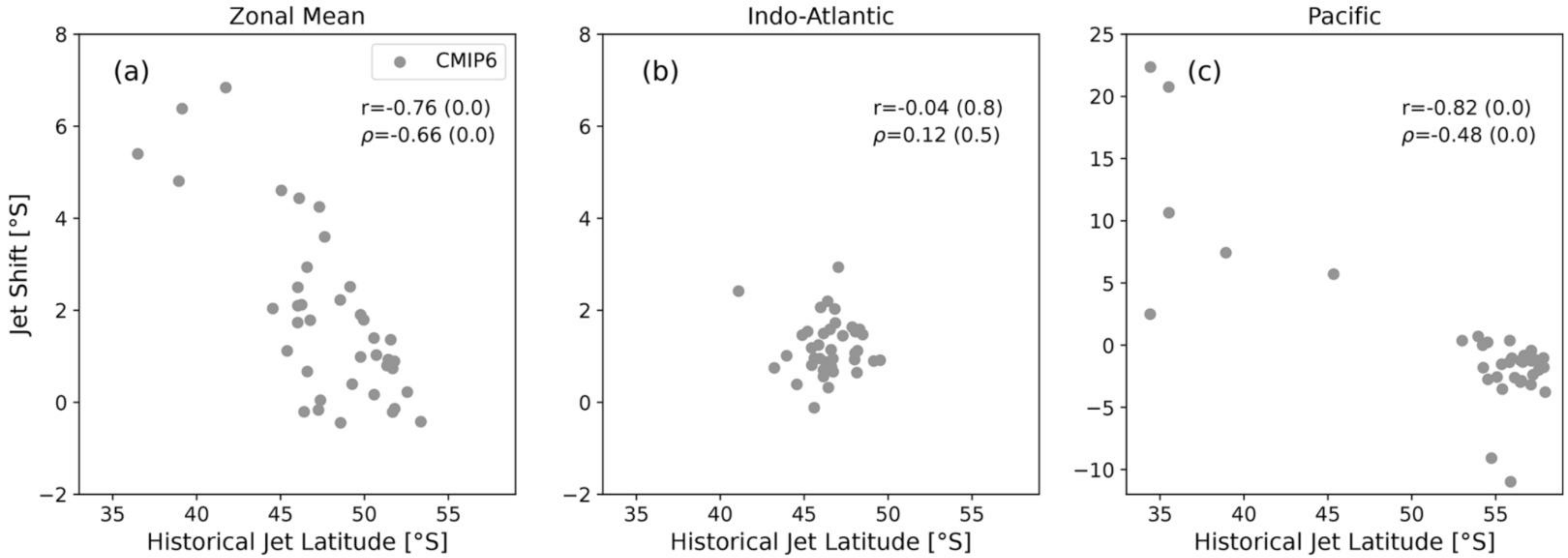




Circles = tropical trade cumulus grid points

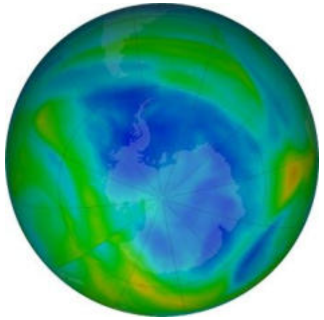


Emergent constraint on the Southern Hemisphere zonal mean jet response (austral winter)?



Breul et al. *Weather and Climate Dynamics* (2023)

Why is this uncertainty important?



Ozone hole building up,
22 August 2022, NASA.

Stratospheric water vapour (SWV)

- is a greenhouse gas

  lead to a positive radiative forcing (CMIP5/6: 0.09-0.26 W m^{-2} K^{-1}, 90% CI)

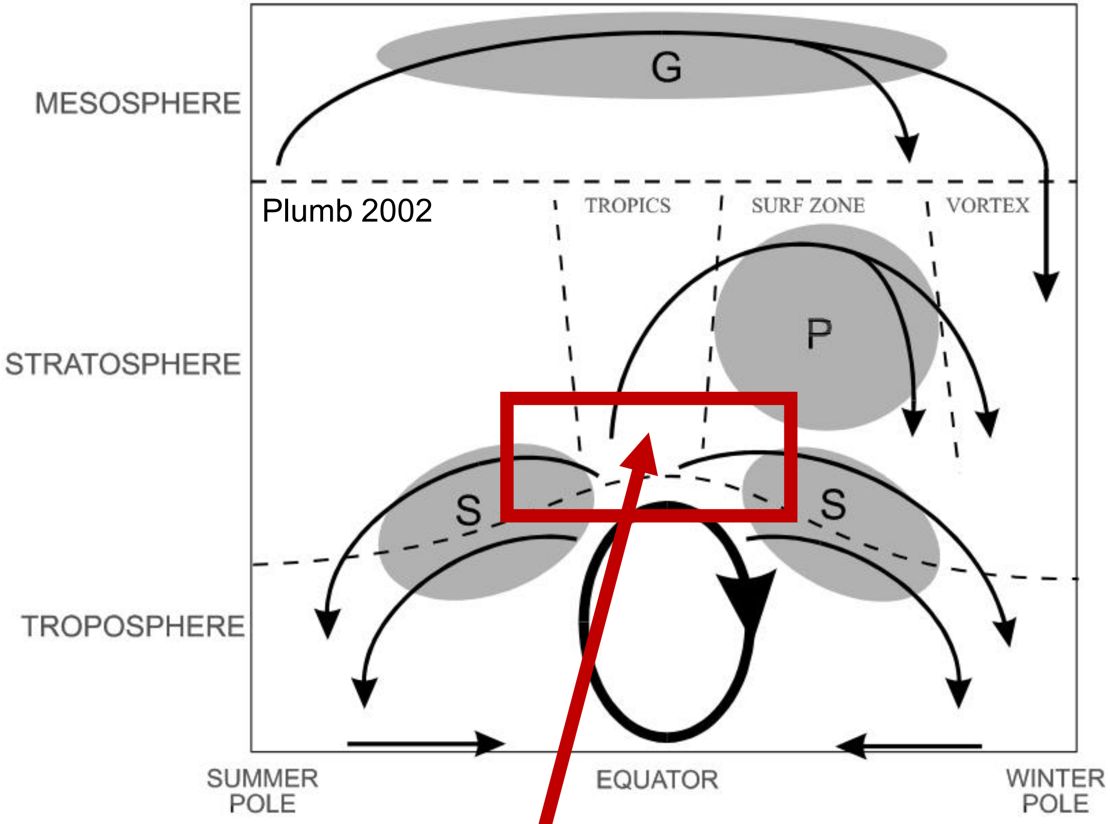
- is a key radiative cooling agent of the lower stratosphere

⟶ affects the tropospheric/stratospheric circulation (e.g. NAO; Joshi et al. *GRL* 2006)

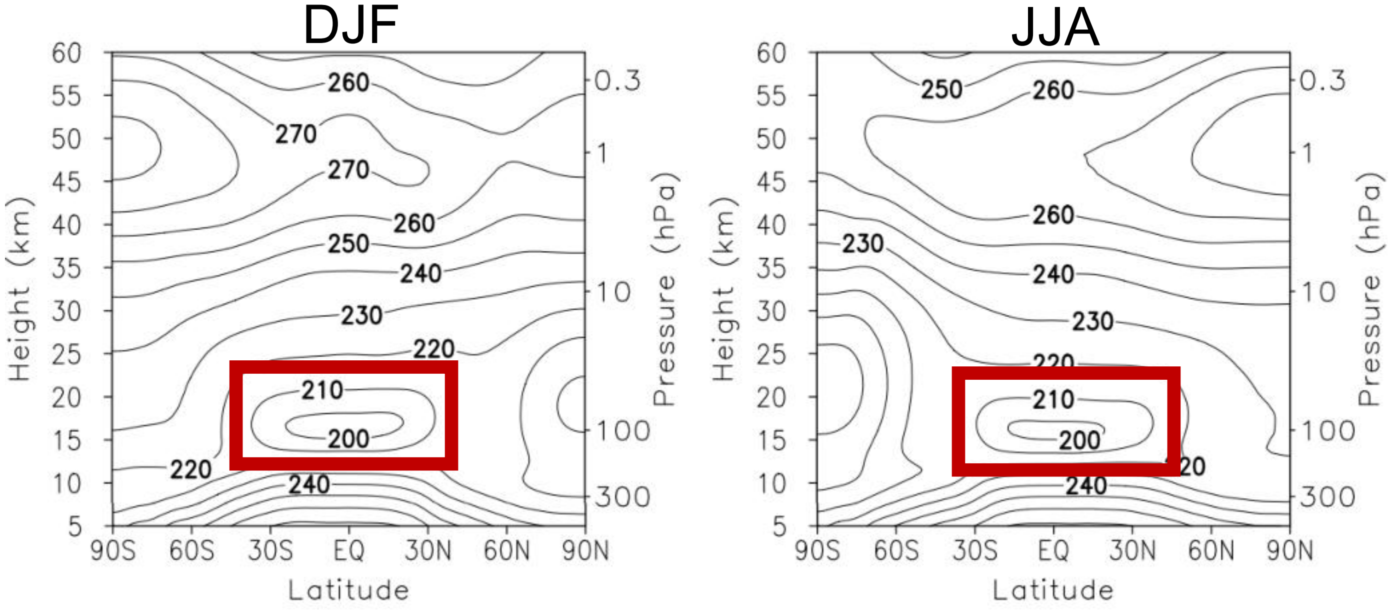
- is a major factor for the ozone layer (Dvortsov & Solomon *JGR* 2001, Stenke & Grewe *ACP* 2005)

⟶ HOx radicals ⟶ effects on catalytic ozone depletion⟶ UV exposure, air pollution

What controls SWV? (dry stratosphere)



Slow ascent of tropospheric air into the stratosphere (Brewer-Dobson circulation)

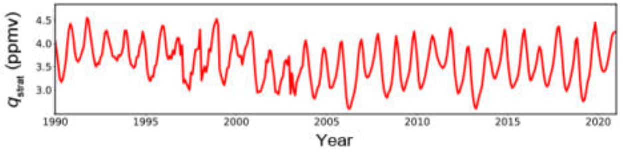


Freeze-drying

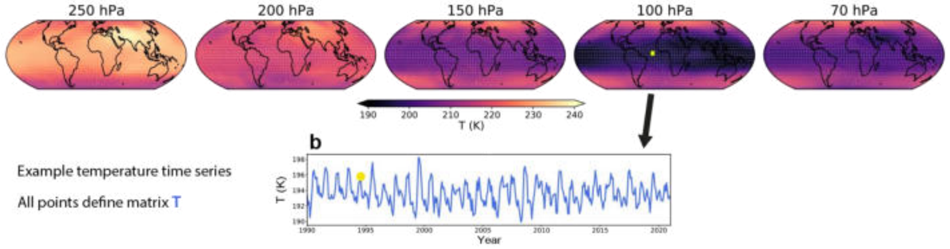
During its slow ascent, air traverses the very cold tropical upper troposphere and lower stratosphere (UTLS) and is dehydrated to its very low stratospheric concentrations.

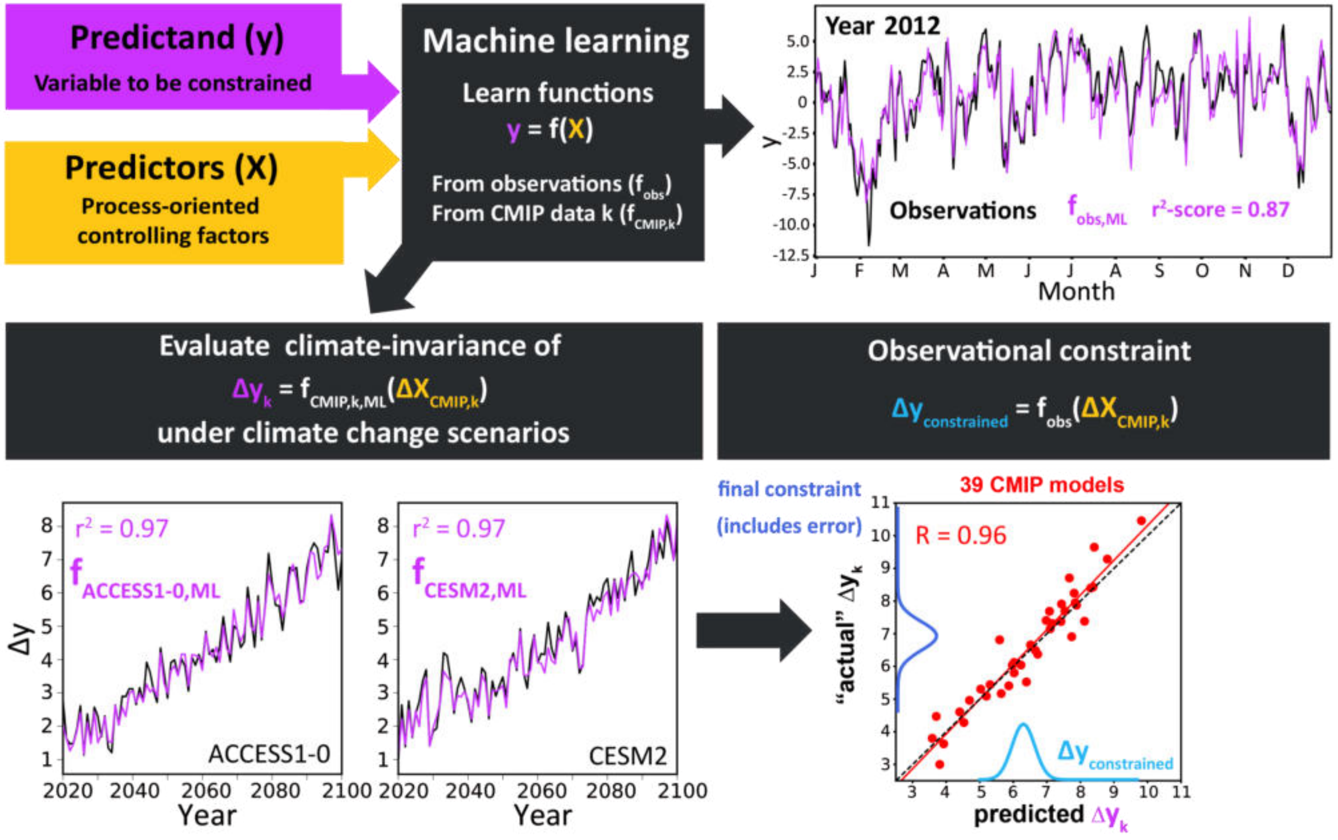
SWV controlling factor analysis with machine learning

Stratospheric humidity



Tropical upper tropospheric to lower stratospheric temperatures (τ_{max} = 2 months)

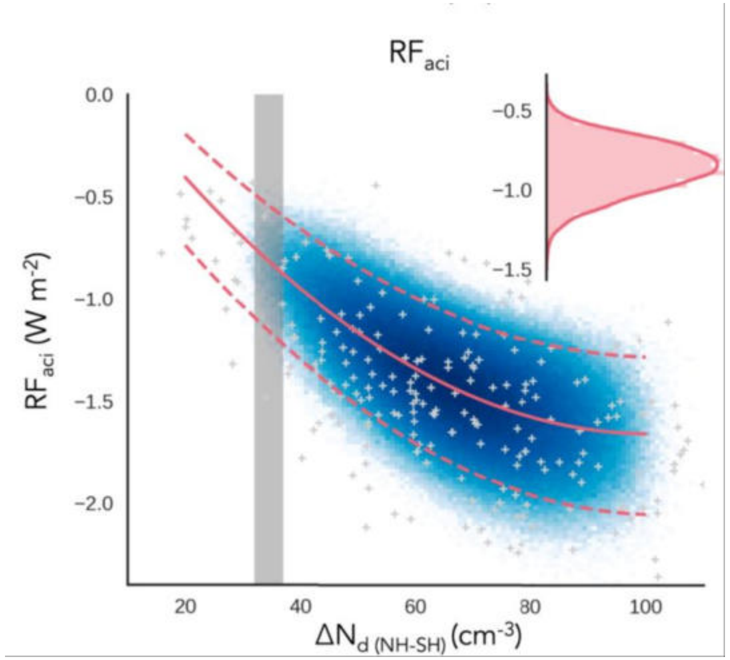




New concept for the stratosphere (climate-invariance)

✓ First observational constraint on the SWV feedback.

What about non-linearity? → ACP Opinion Article



McCoy et al. *PNAS* (2020)

Many processes of interest are non-linear such as **aerosol forcing** and **stratospheric water vapour feedback.**

Machine learning offers many tools to model these relationships, such as:

- Random Forests
- Gaussian Proceses

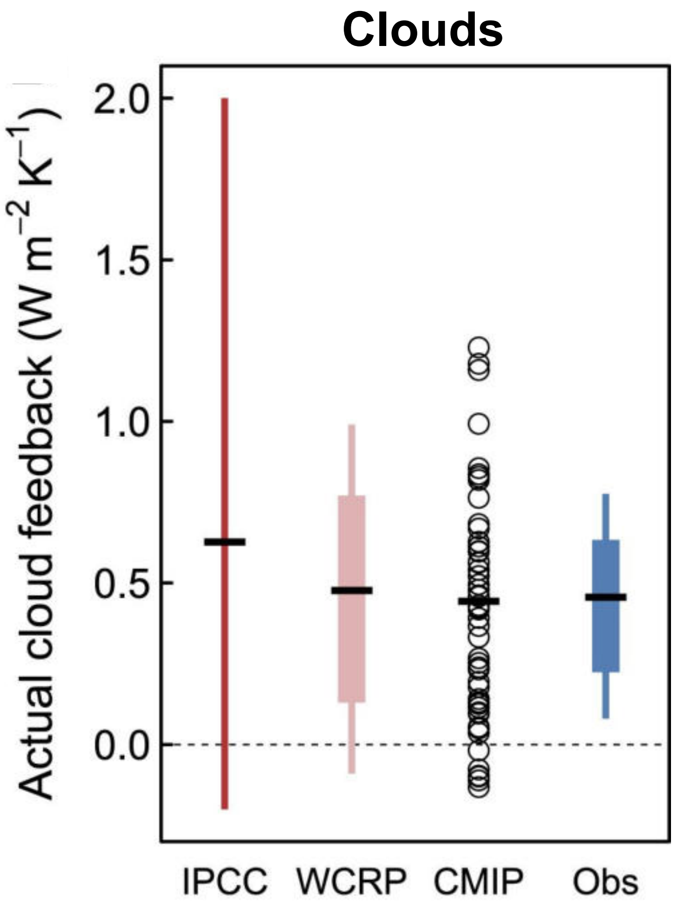
BUT, we have to be even more careful:

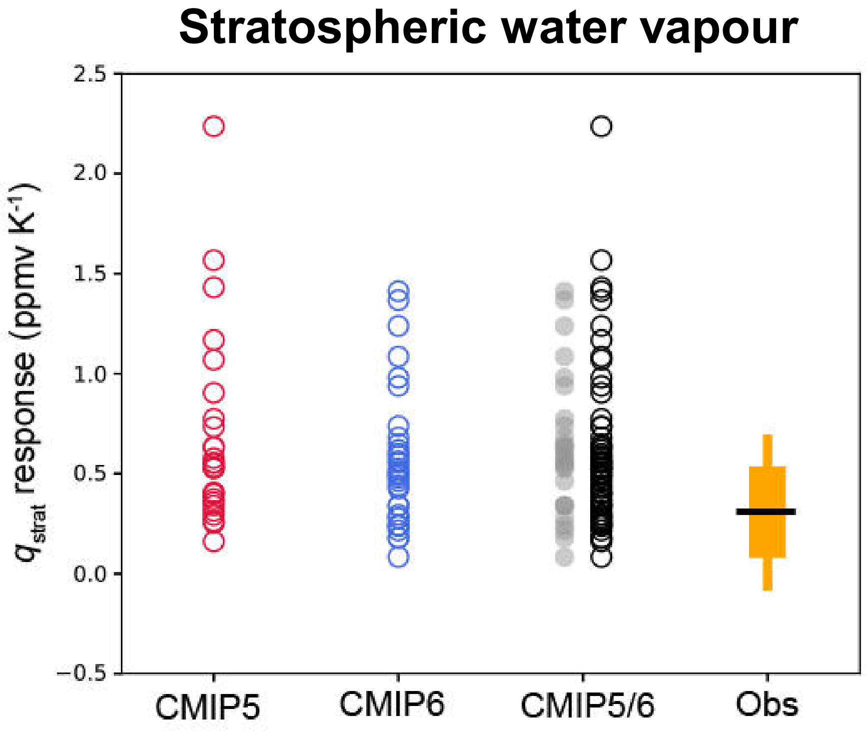
- We must ensure the model data fully encapsulates the response (cf. **extrapolation**)
- Model uncertainties must be well quantified to allow robust inferences

Two examples of controlling factor analyses

Ceppi & Nowack PNAS (2021)
ML4CLOUDS project

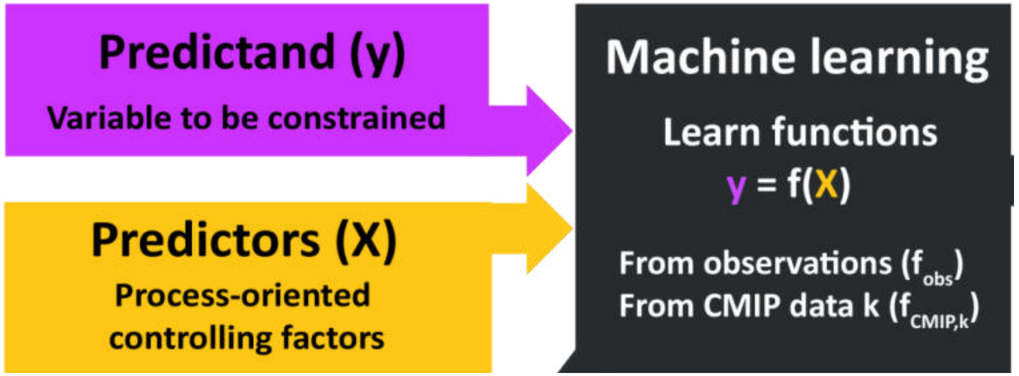
Two examples



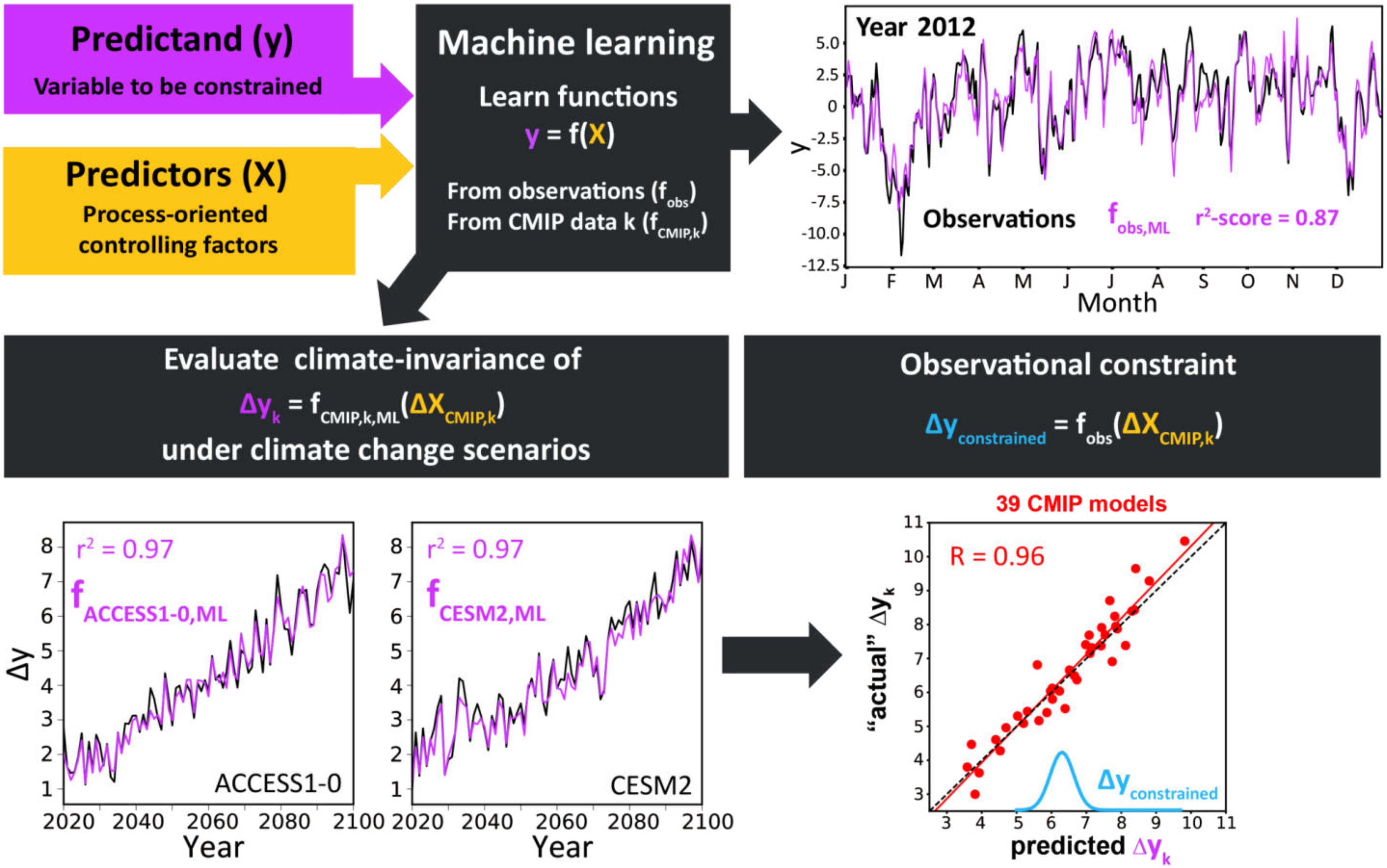


Nowack et al. Nature Geoscience (2023)

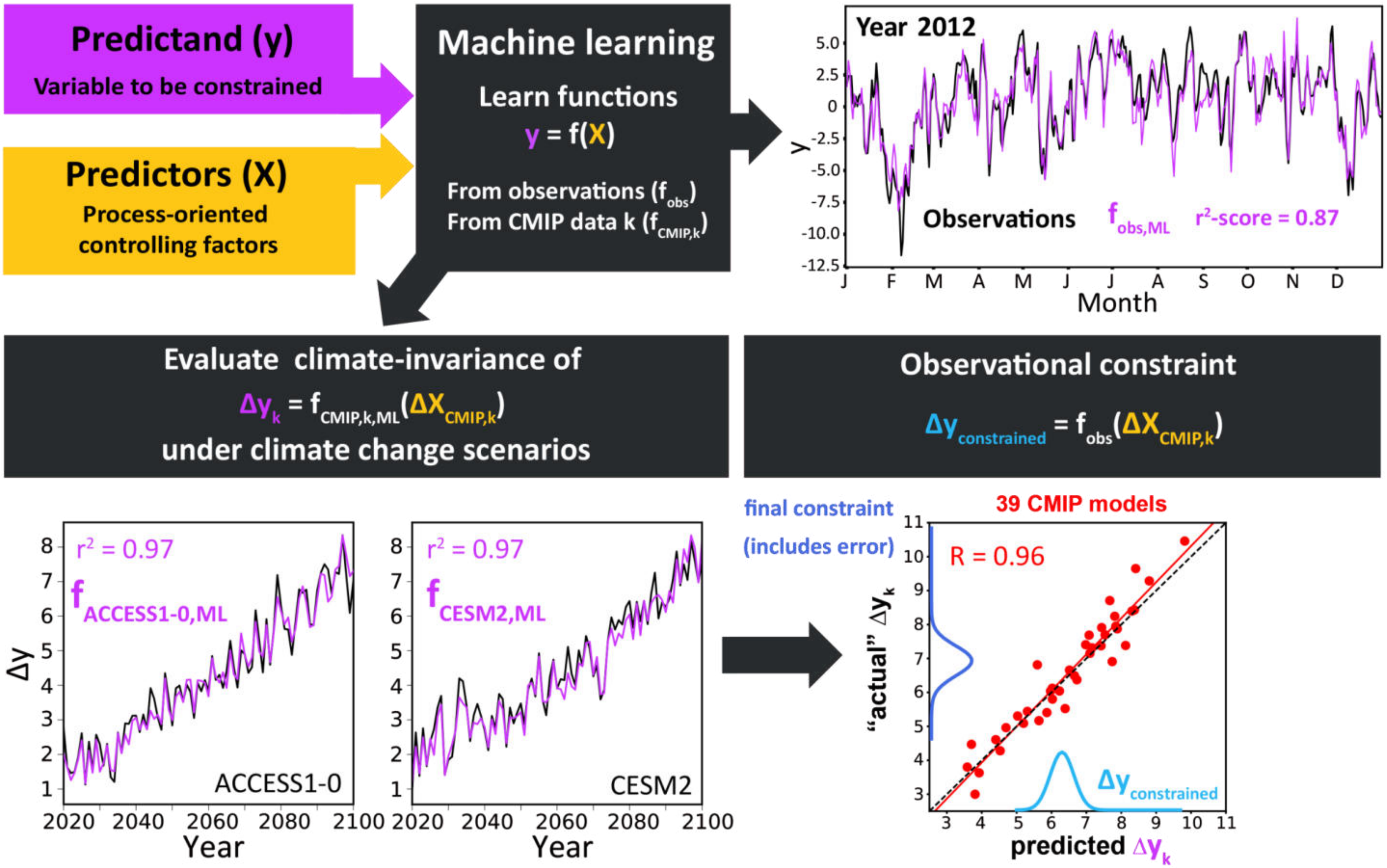
Alternative! Controlling factor analyses with machine learning



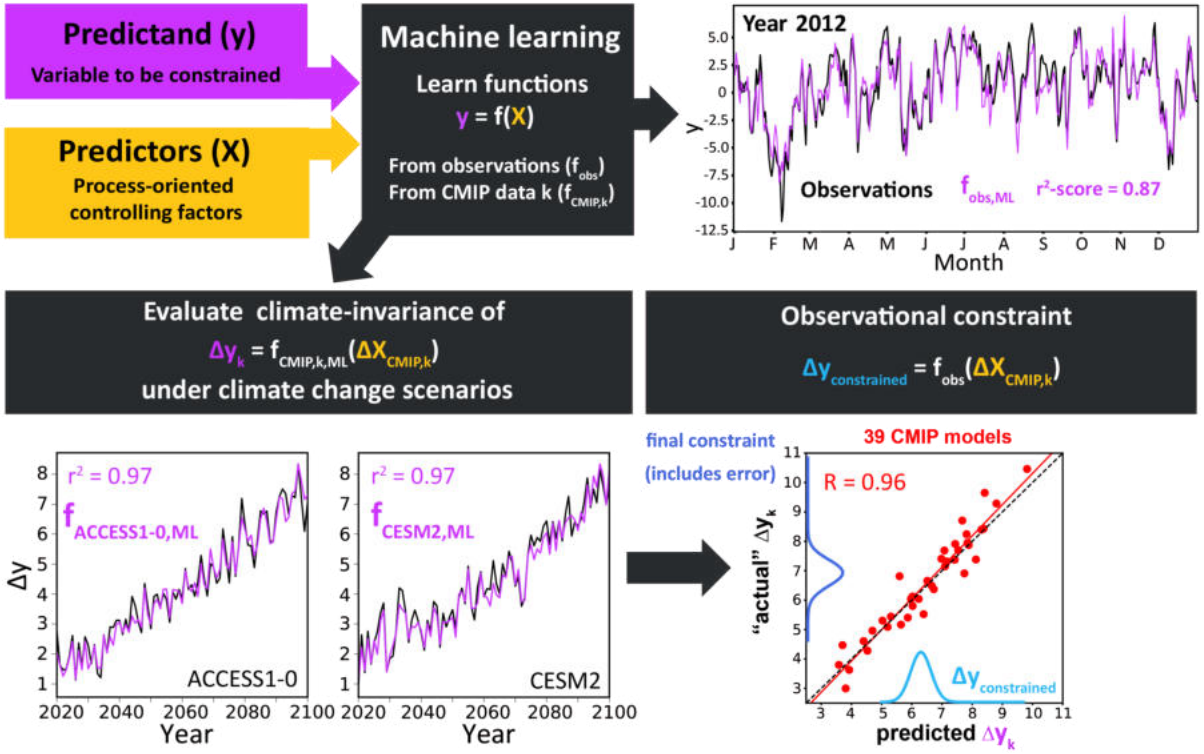
Alternative! Controlling factor analyses with machine learning



Alternative! Controlling factor analyses with machine learning

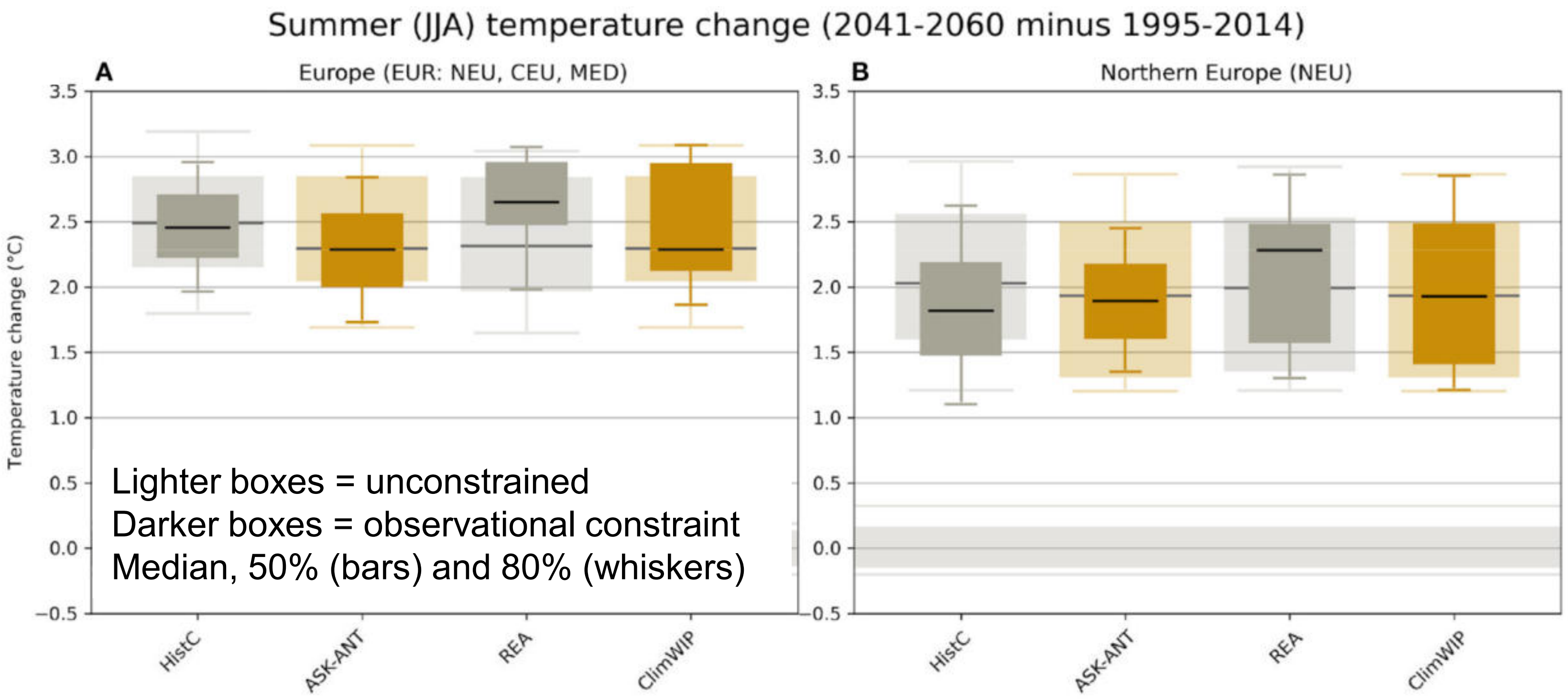


Alternative! Controlling factor analyses with machine learning



Model evaluation metrics to constrain projections?

Karlsruhe Institute of



ClimWIP	CMIP5	Weighted based on historical performance of six diagnostics
REA	CMIP5	Weighted based on historical performance of the target variable
ASK	CMIP5	Scaled based on observed time–space change over the historical period.

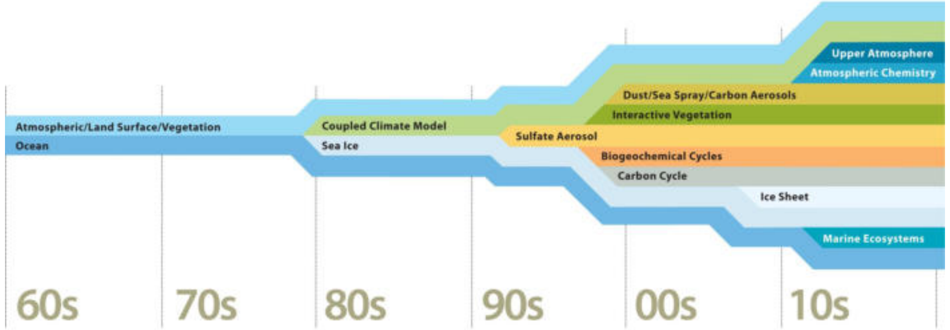
Performance e.g. measured through average biases, σ

- Can be right for the wrong reasons (e.g. model tuning).
- Which method to choose?
- No clear mechanistic link between past and future.

Three ways in which AI can advance climate modelling

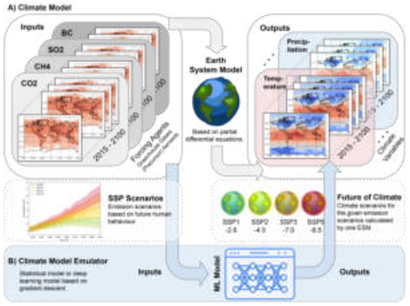
(1) Add otherwise too expensive processes

→ „parameterizations“ (*faster / better*)



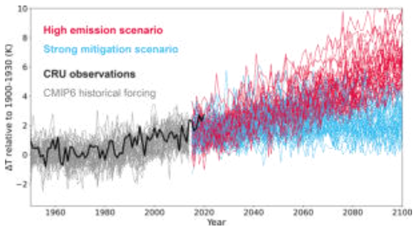
(2) Replace entire numerical climate model

→ „emulation“ (*faster*)

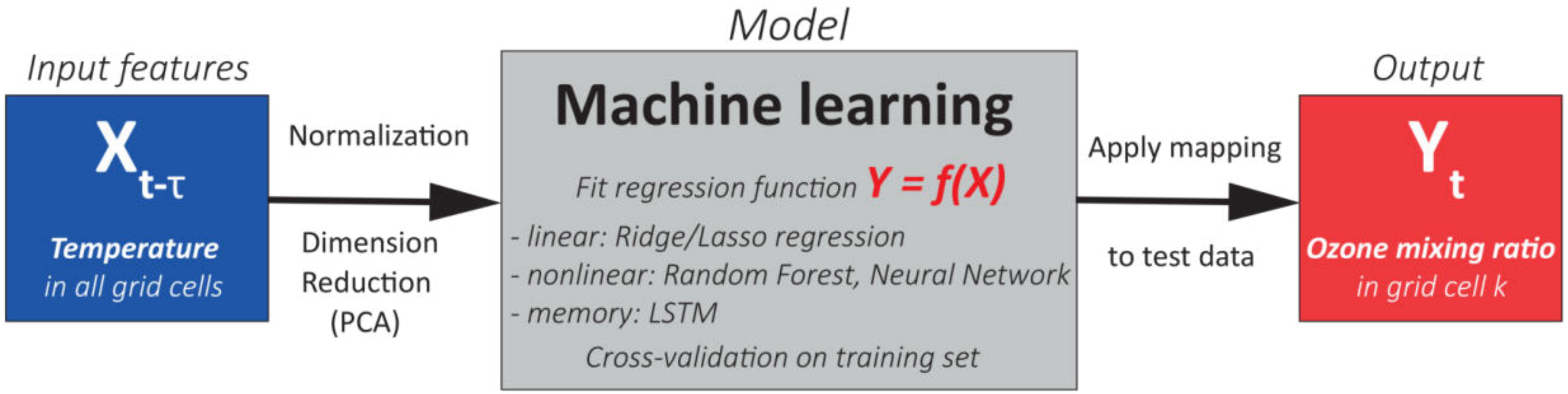


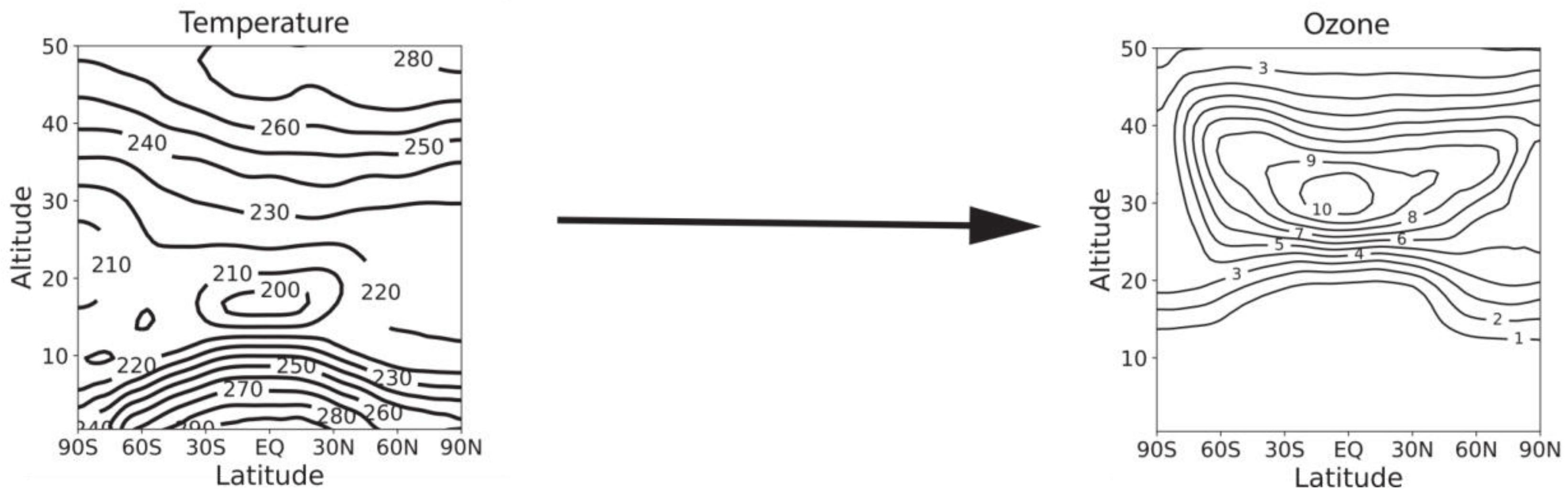
(3) Combine Earth observations + model projections

→ reduce uncertainty (*better*)



(1) Fast machine learning parameterizations





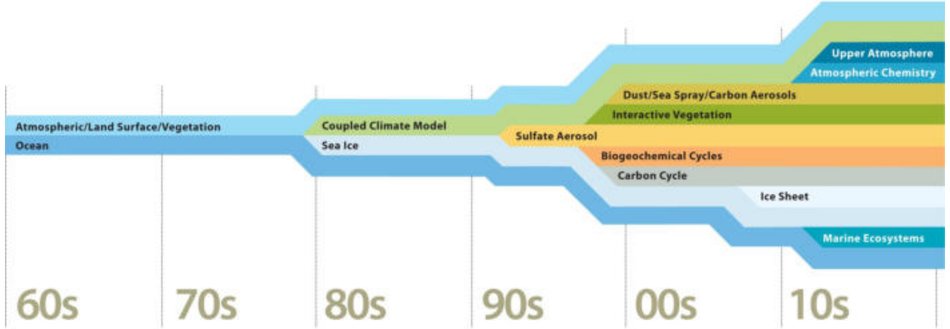
Nowack et al. Nature Climate Change (2015)
ERL (2018), CICP (2019)

Three ways in which AI can advance climate modelling

Karlsruhe Institute of Technology

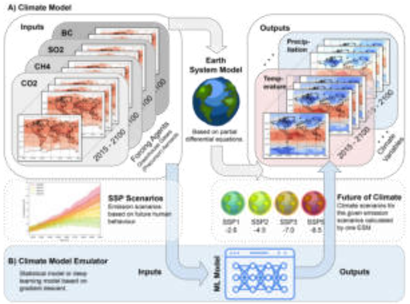
(1) Add otherwise too expensive processes

→ „parameterizations“ (*faster / better*)



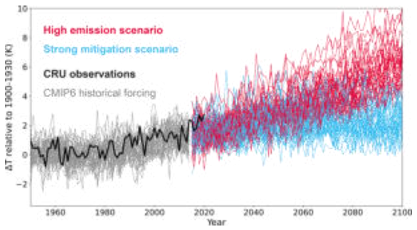
(2) Replace entire numerical climate model

→ „emulation“ (*faster*)



(3) Combine Earth observations + model projections

→ reduce uncertainty (*better*)



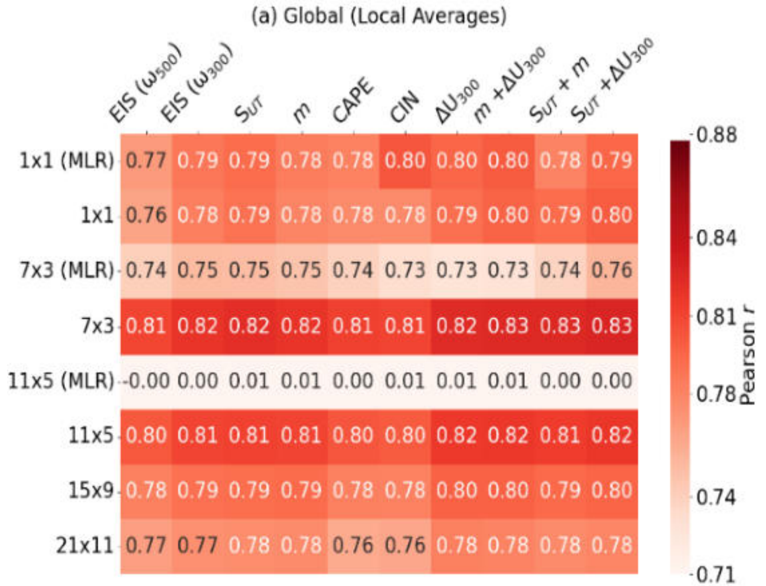
A systematic evaluation of high-cloud controlling factors

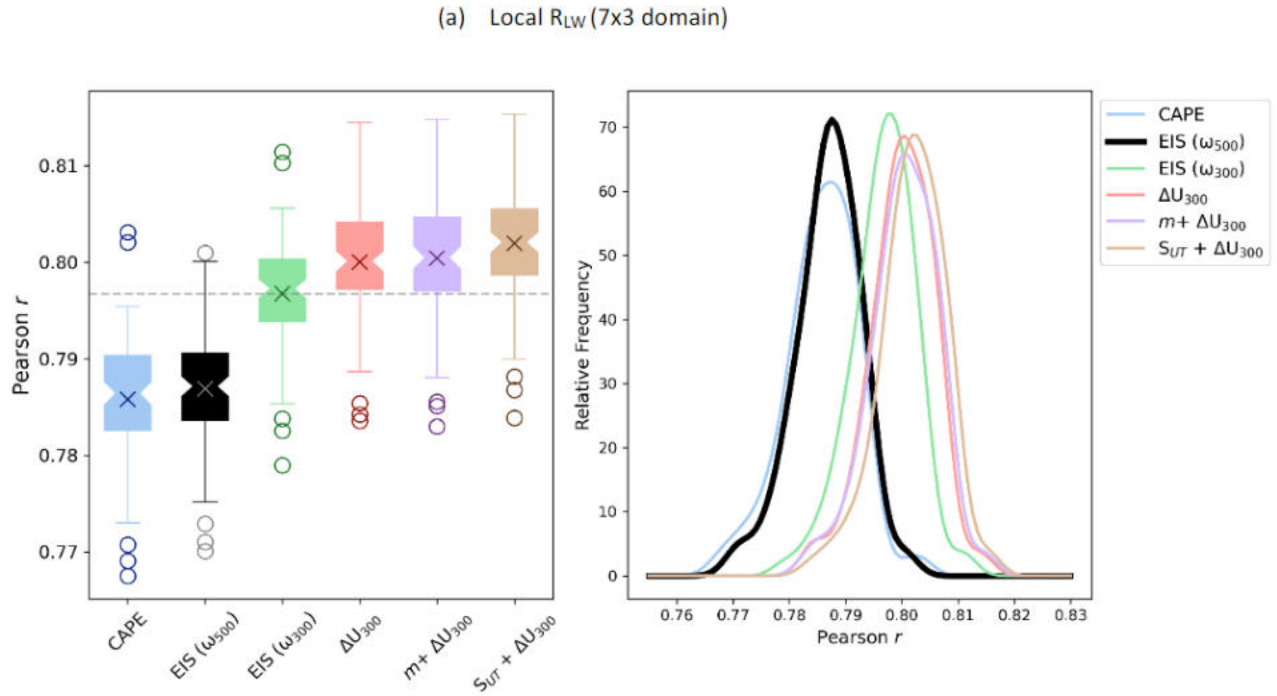
Sarah Wilson-Kemsley et al., Atmospheric Chemistry and Physics, 2024

Comparison of five additional factors on historical predictions:

upper-tropospheric static stability, sub-cloud moist static energy, CAPE, convective inhibition, upper tropospheric wind shear.

All depending on domain size.

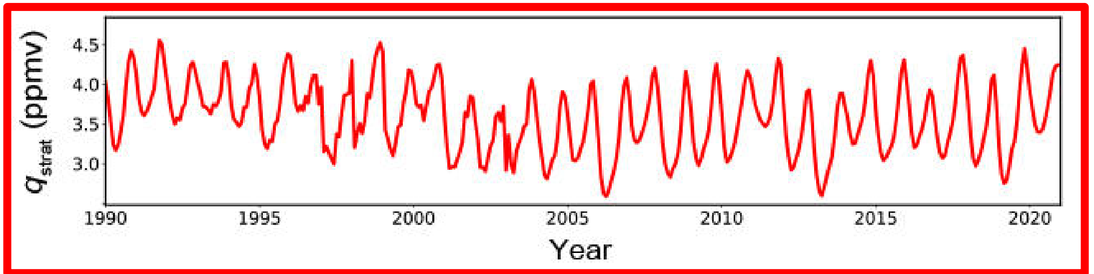




Nowack et al. Nature Geoscience (2023)

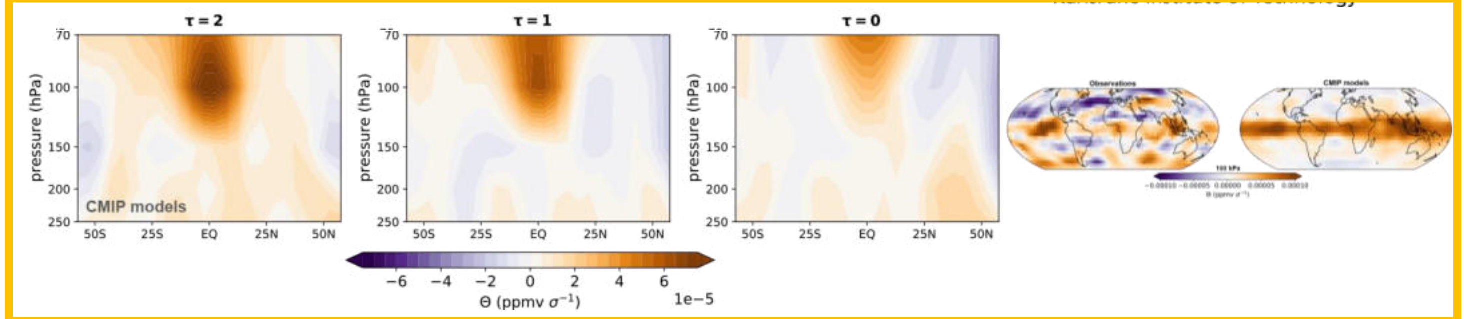
Observational constraint with statistical learning

SWOOSH



Water vapour time series

30N - 30S, 70 hPa



$$\log\left(\boxed{q_{\mathrm{strat}}(t)}\right) = f(\Theta, \mathbf{T}; t, \tau_{\max}) = \sum_{i}^{\mathrm{lat}}\sum_{j}^{\mathrm{lon}}\sum_{k}^{p}\sum_{\tau}^{\tau_{\max}} \boxed{\Theta_{\mathrm{ijk},\tau}}\,\boxed{\mathrm{d}T_{\mathrm{ijk}}(t-\tau)}$$

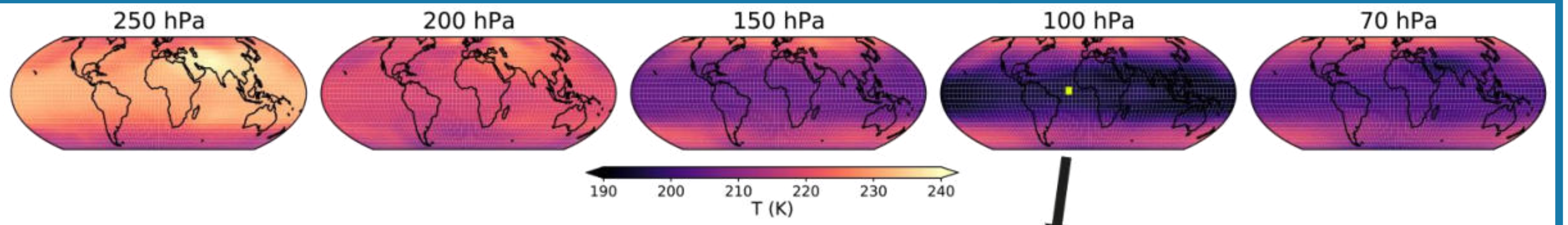
Ridge regression

Learn *f* from 1990-2020

Observations: f_{obs}

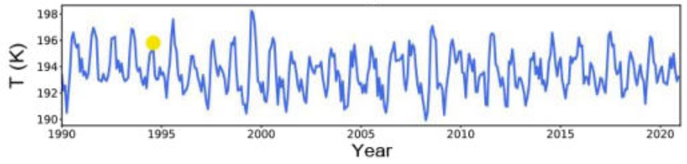
CMIP5/6: f_{CMIP}

ERA5, MERRA-2, JRA-55



Example temperature time series

All points define matrix **T**

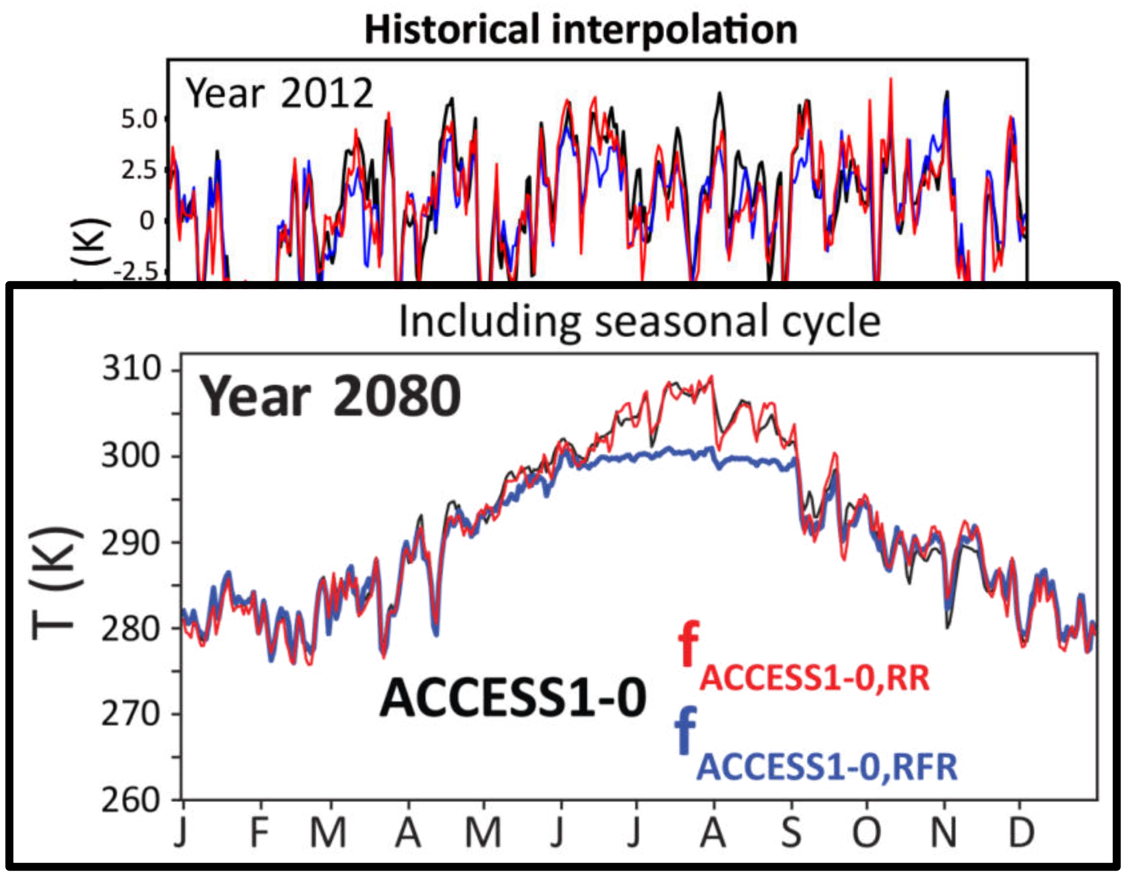


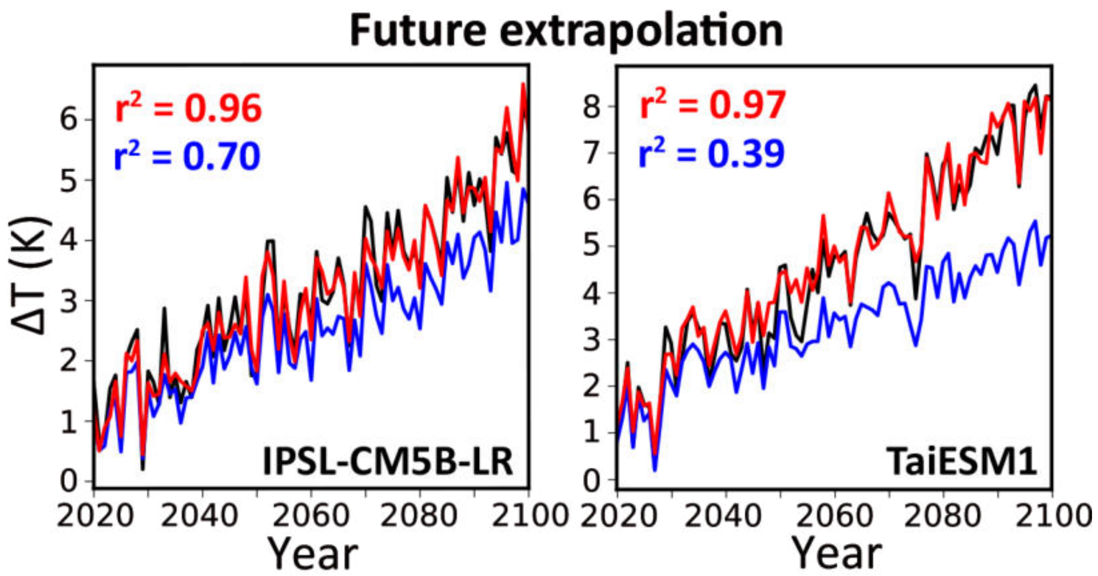
T_{max} = 2 months

60°N – 60°S

Standard ML cannot extrapolate

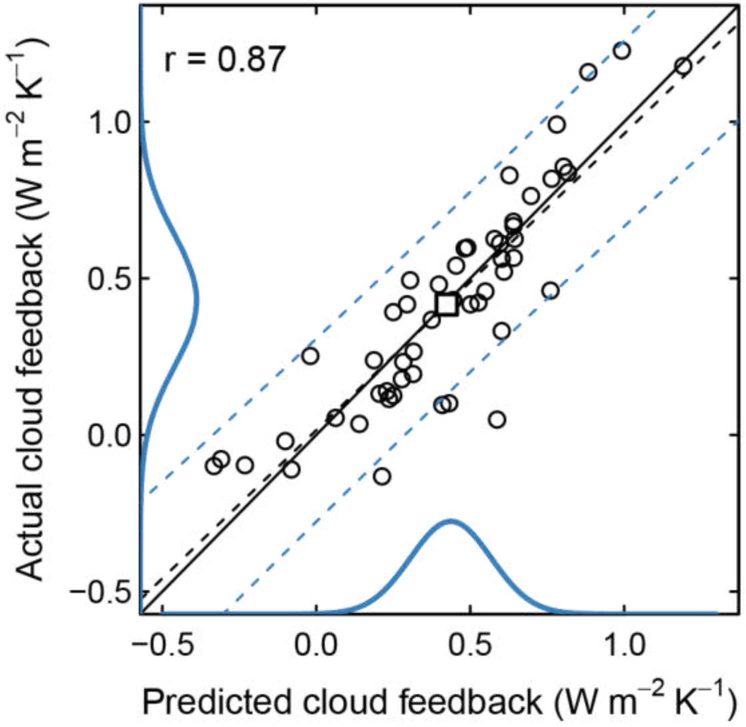
Specific case: I learned a random forest model to predict surface temperature anomalies on climate model data from 1979-2020, excluding the year 2012…



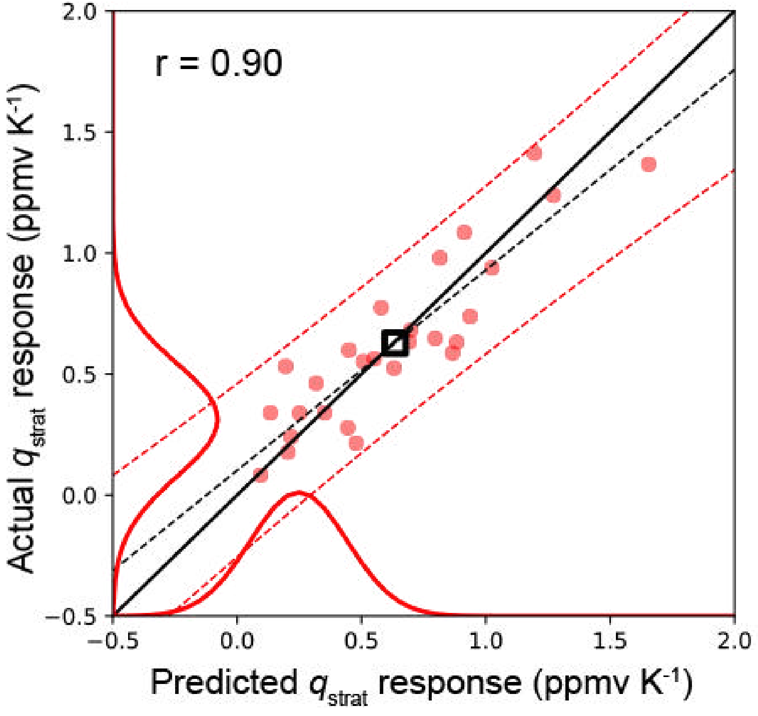


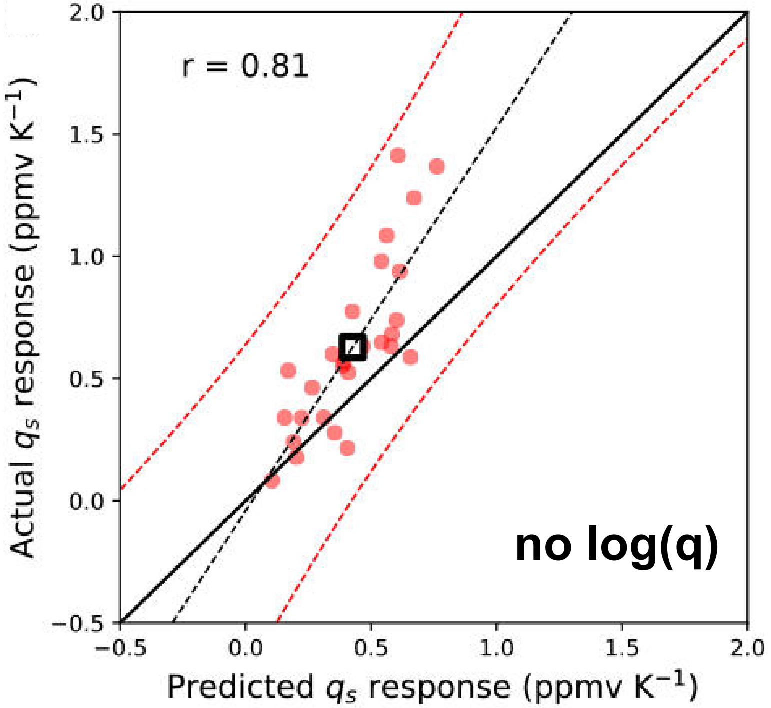
Key challenge: how can we use ML to learn from the past, to better predict the future in a non-stationary system?

Example observational constraints



Clouds





Stratospheric water vapour

Advantages of controlling factor analyses

- Process-based and direkt links between past + future.
- Objective out-of-sample cross-validation possible on both historical and future scenarios, also abrupt-4xCO2 (within models).
- Can be high-dimensional, can benefit from machine learning.
- Since process-based, might be possible to linearize and therefore to extrapolate (cf. 4xCO2) → turning relationships approx. *climate-invariant*.

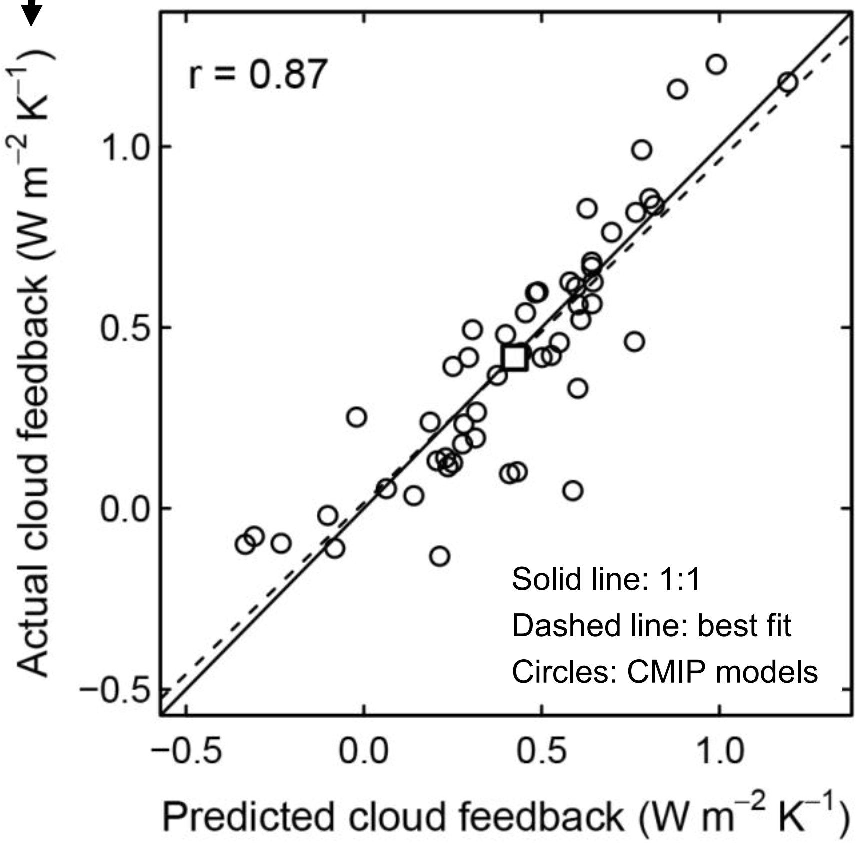
Key question shifts to: smart choices for **θ?**

$$\frac{\mathrm{d}C(r)}{\mathrm{d}T} \approx \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \frac{\mathrm{d}\boldsymbol{X}_i(r)}{\mathrm{d}T}$$

So far: dynamical variables helpful for prediction, but not useful to constrain.

Step 1: test CMIP model-consistent predictions

Cloud feedback diagnosed directly from $4xCO_2$ simulations

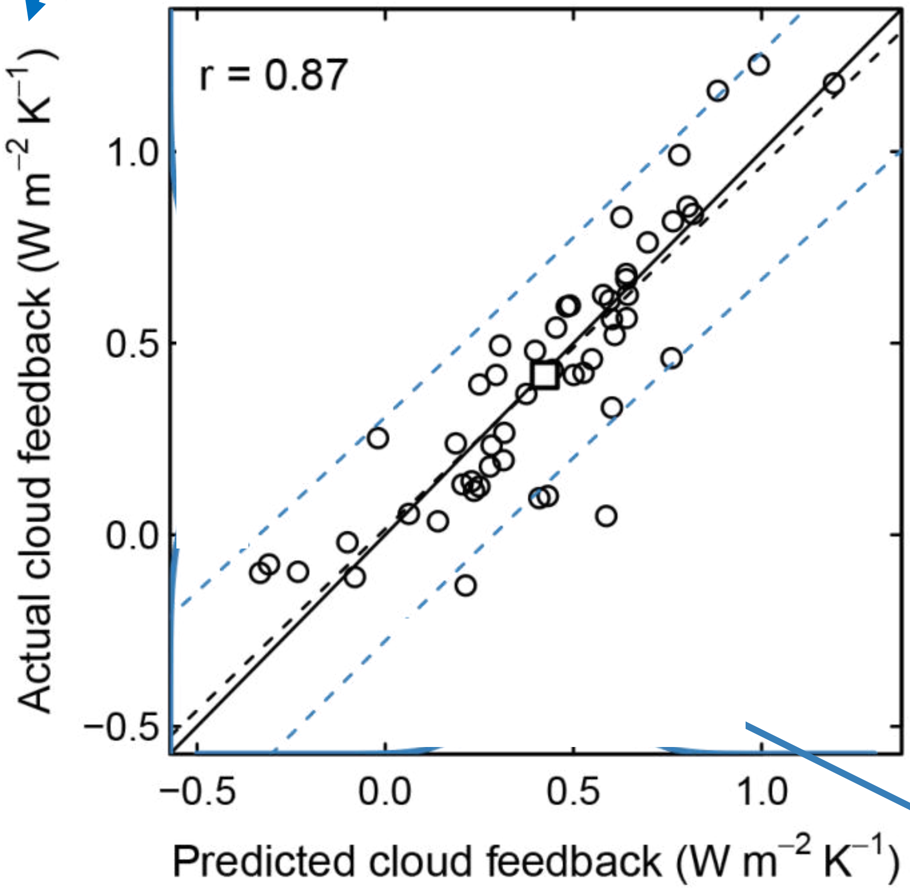


For CMIP models, we can predict the long-term cloud feedback from just 20 years of historical data!

Model consistent predictions using $f_{CMIP}(\mathbf{X}_{CMIP,4xCO2})$

Step 2: combining models and observations

$f_{obs}(\mathbf{X}_{CMIP,4xCO2})$ + error method



$f_{obs}(\mathbf{X}_{CMIP,4xCO2})$

Observations indicate positive cloud feedback (0.43 ± 0.35 W m^{-2} K^{-1})

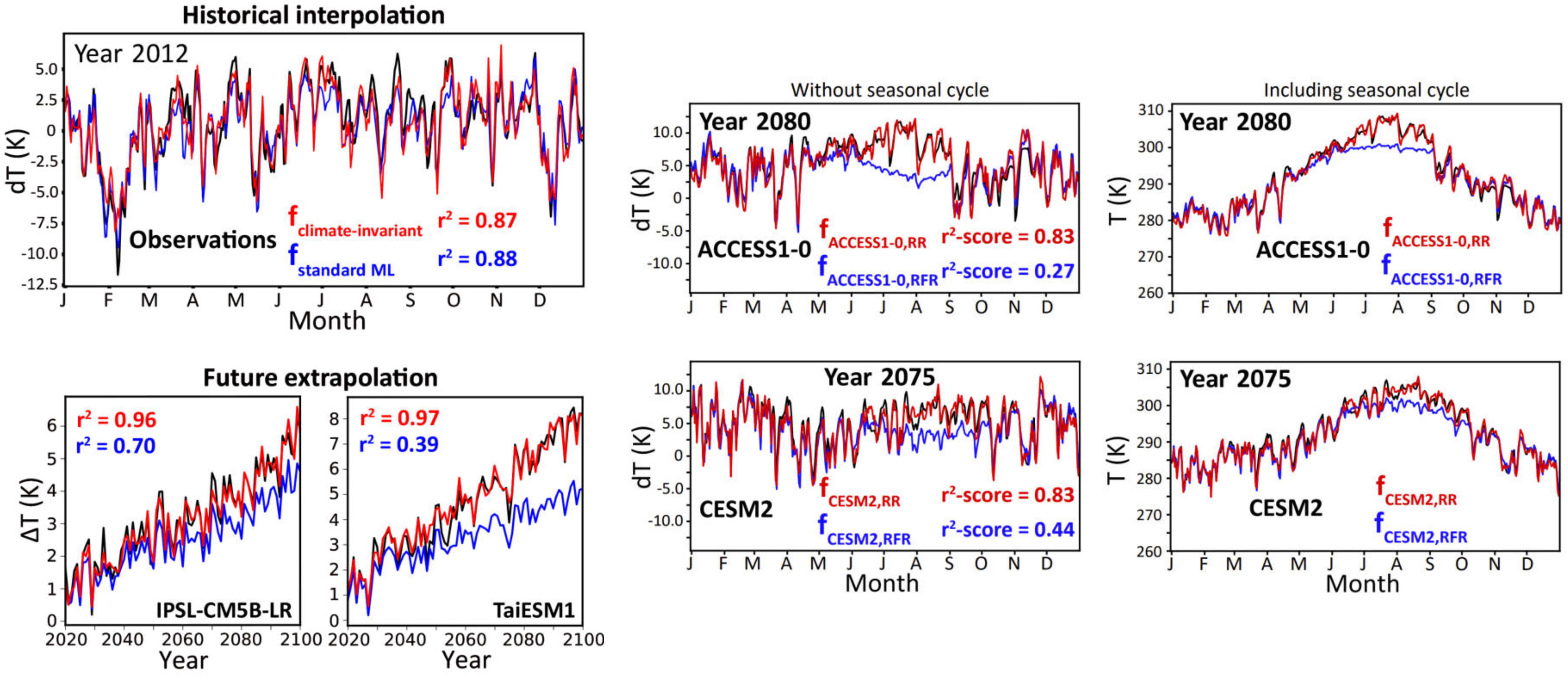
Advantages of controlling factor analyses

- **Process-oriented** and **direkt links** between past + future.
- Objective out-of-sample **cross-validation** possible on both historical and future scenarios, also abrupt-4xCO_2 (within models).
- Can be **high-dimensional**, can benefit from machine learning.

<u>Key question:</u>

Are similar ideas applicable to other highly uncertain Earth system feedbacks?

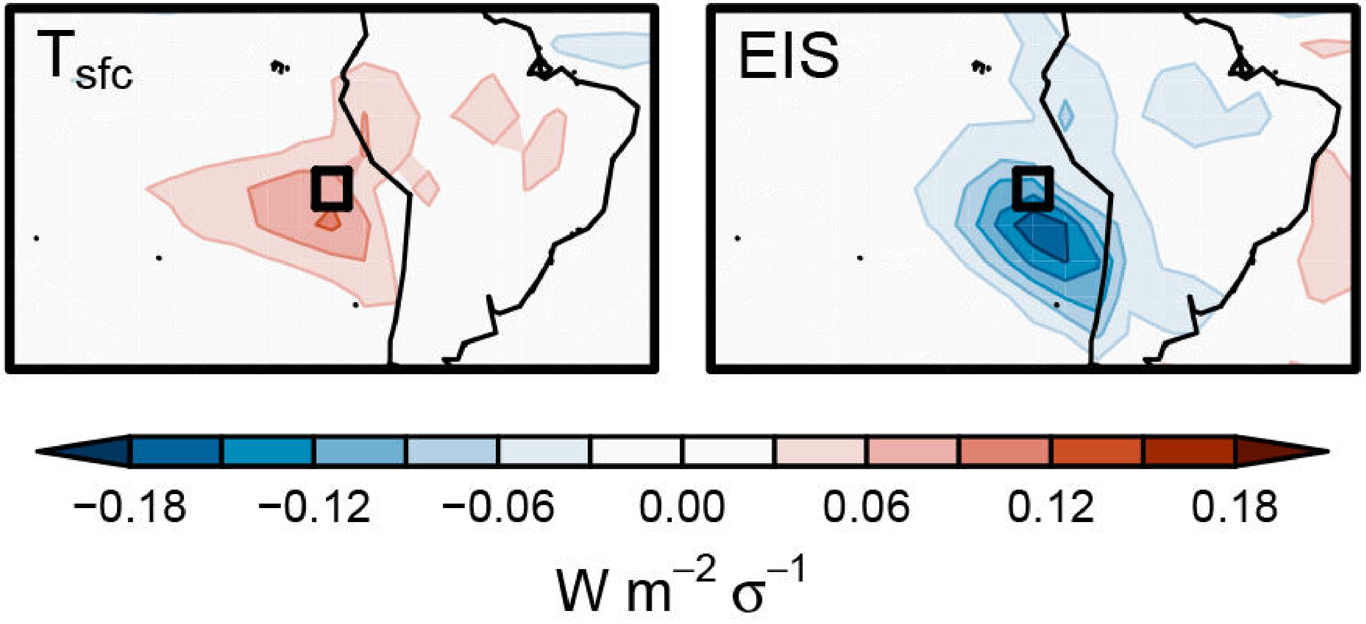
Standard machine learning (ML) cannot extrapolate!



Non-local regressions for each grid point (5°× 5°) globally; shortwave and longwave

$$\mathrm{d}C(r) \approx \sum_{i=1}^{M} \frac{\partial C(r)}{\partial \boldsymbol{X}_i(r)} \cdot \mathrm{d}\boldsymbol{X}_i(r) = \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \mathrm{d}\boldsymbol{X}_i(r)$$

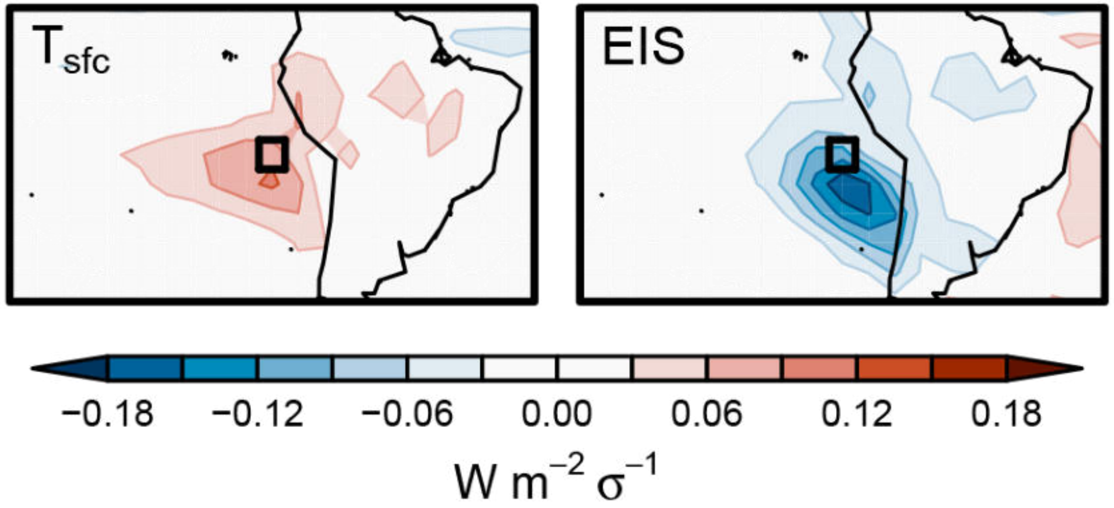
Maps of Ridge coefficients θ_i



We have a regression function to „learn"…

- Machine learning can shine…especially if we want to consider high-dimensional predictors such as patterns of controlling factors.
- Key question: are similar ideas applicable to other highly uncertain Earth system feedbacks?

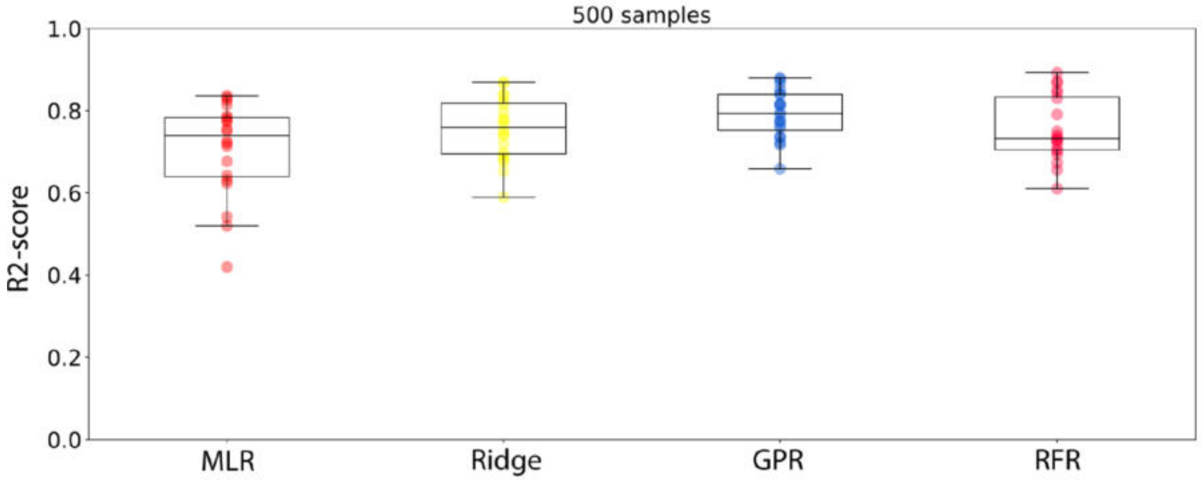
Maps of Ridge coefficients θ_i



Machine learning for measurements

Better, cheaper, and denser measurements

- Calibration
- Empirical air pollution models
- Filling in measurement gaps

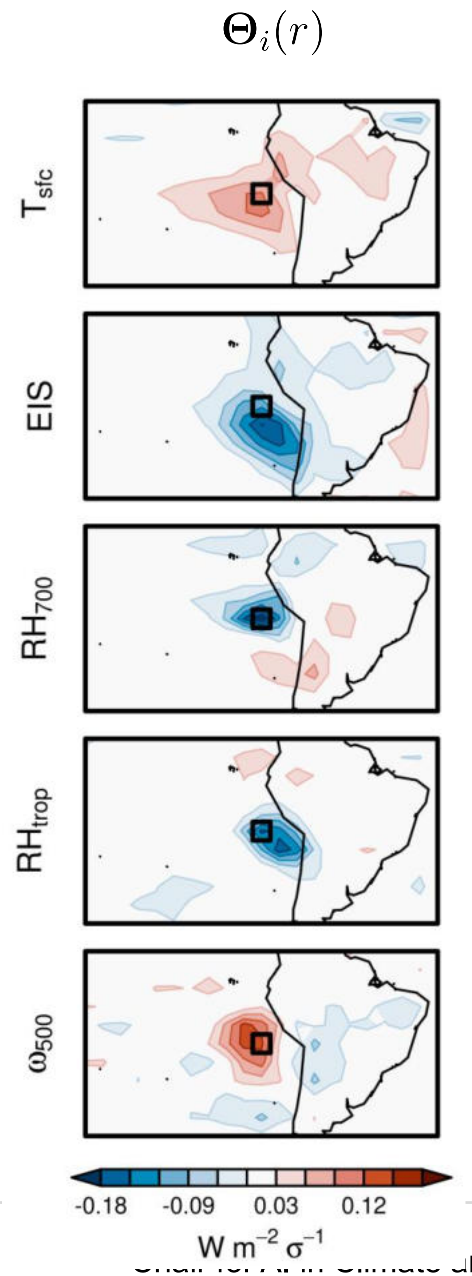


Nowack et al. Atm. Measurement Techniques (2021), Weng et al. ACP (2022), Hickman et al. NeurIPS (2022)

Statistical learning framework

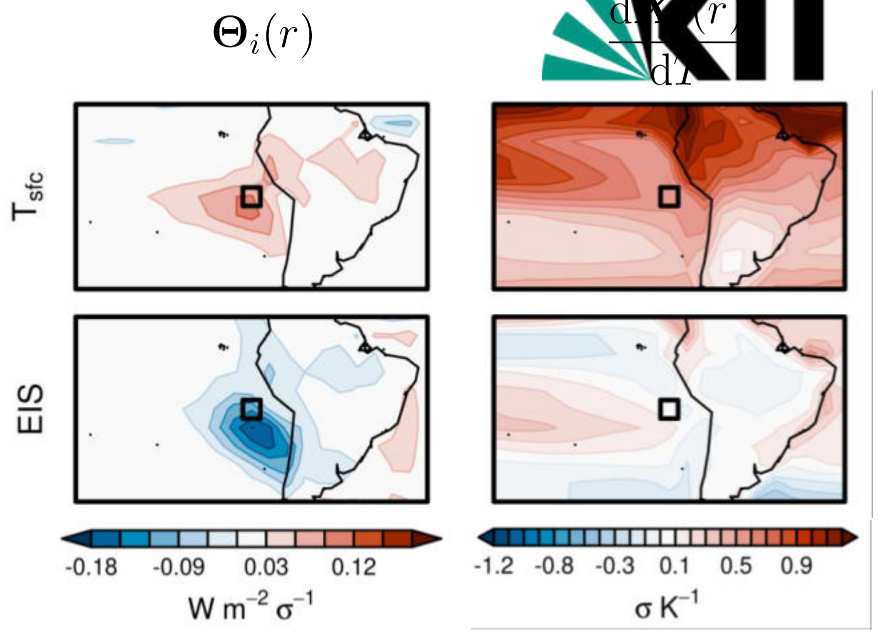
$$\mathrm{d}C(r) \approx \sum_{i=1}^{M} \frac{\partial C(r)}{\partial \boldsymbol{X}_i(r)} \cdot \mathrm{d}\boldsymbol{X}_i(r) = \sum_{i=1}^{M} \underbrace{\boldsymbol{\Theta}_i(r)}_{\text{cloud-radiative sensitivities}} \cdot \underbrace{\mathrm{d}\boldsymbol{X}_i(r)}_{\text{anomalies in cloud-controlling factors}}$$

- For each gridpoint *r*, we learn the cloud-radiative sensitivities Θ_i over a **regional domain** of size 21×11 gridpoints
  - Allows us to understand how clouds depend not just on local conditions, but also on the larger-scale patterns
- Hence $\boldsymbol{\Theta}_i(r)$ is a spatial vector

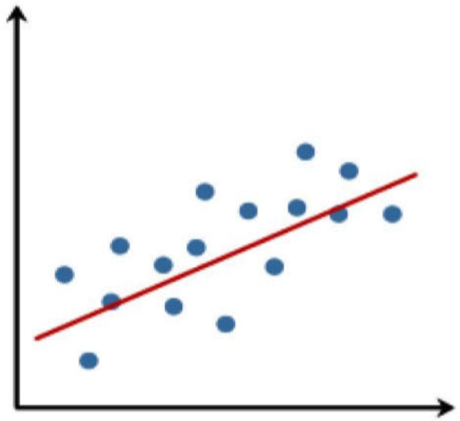


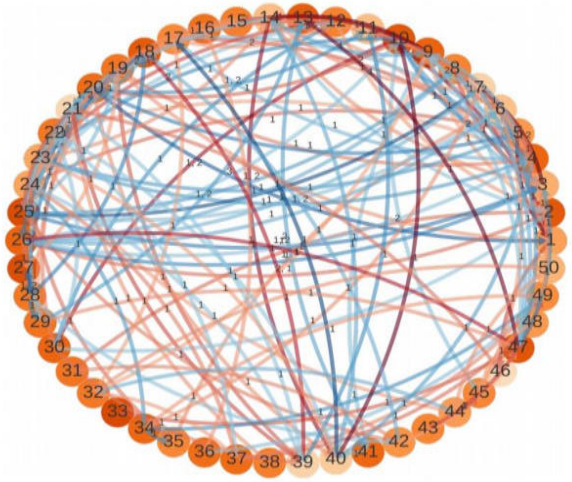
Prediction model

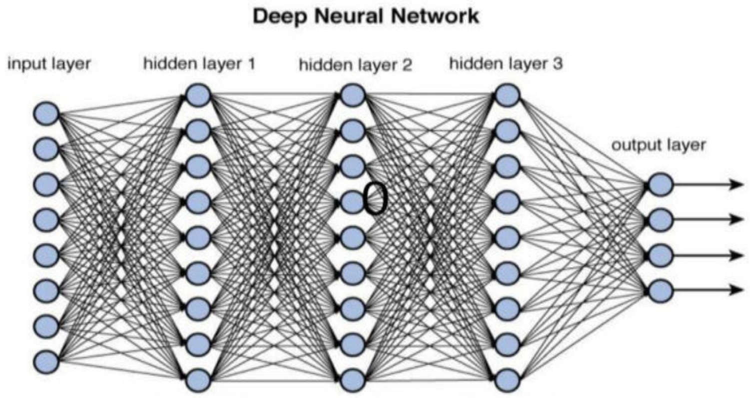
$$\lambda_C(r) = \frac{\mathrm{d}C(r)}{\mathrm{d}T} \approx \boldsymbol{\Theta}_{T_{\mathrm{sfc}}}(r) \cdot \frac{\mathrm{d}\boldsymbol{T}_{\mathbf{sfc}}(r)}{\mathrm{d}T} + \boldsymbol{\Theta}_{\mathrm{EIS}}(r) \cdot \frac{\mathrm{d}\mathbf{EIS}(r)}{\mathrm{d}T}$$



Statistical learning



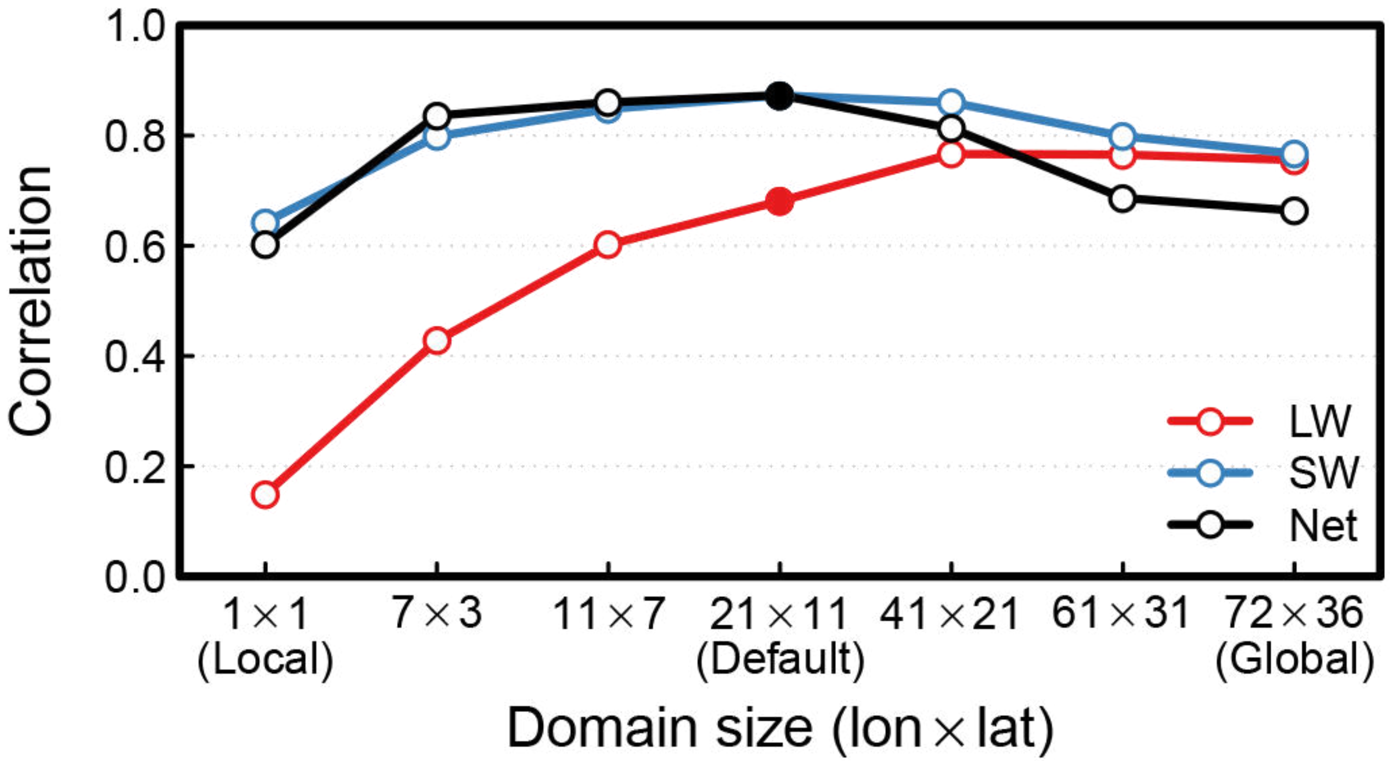


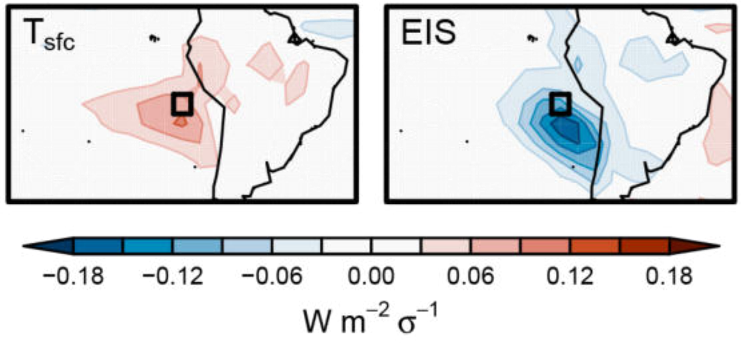


Classic statistics	**Statistical learning**	**Machine learning**
Linear regression	Regularized (linear) regression	Non-linear regression
Few predictors (<10)	Many predictors	Many predictors
(low-dimensional)	(high-dimensional)	(high-dimensional)
	Interpretable	Complex algorithm structures

Does statistical learning help?

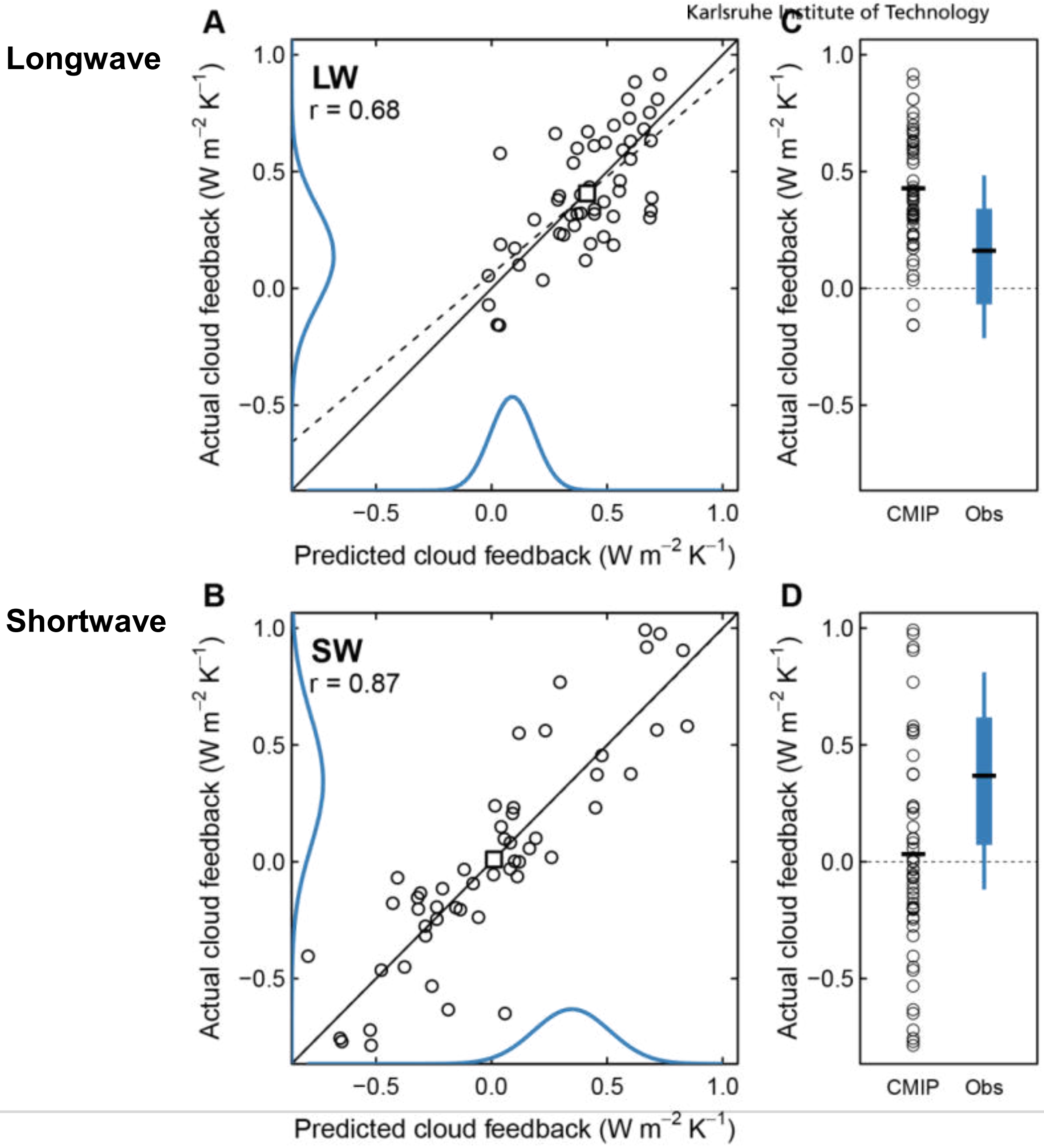
Skill depending on predictor pattern size





Cloud feedback – longwave and shortwave

- Observations suggest positive longwave and shortwave cloud feedbacks
- Longwave less positive than in models; shortwave more positive than in models



Summary

- We use ~20 years of global satellite observations of clouds and radiation to infer the sensitivity of clouds to environmental changes
- These sensitivities are good predictors of the actual cloud feedbacks in climate models
- Observations point to moderately positive cloud feedback, agreeing with multi-model mean
- This supports ECS ≈ 3 K; ECS < 2 K very unlikely

Constraining cloud feedback

<u>Step 1:</u> can we use learned θ_i to predict model-consistent cloud responses to strong CO_2 forcing?

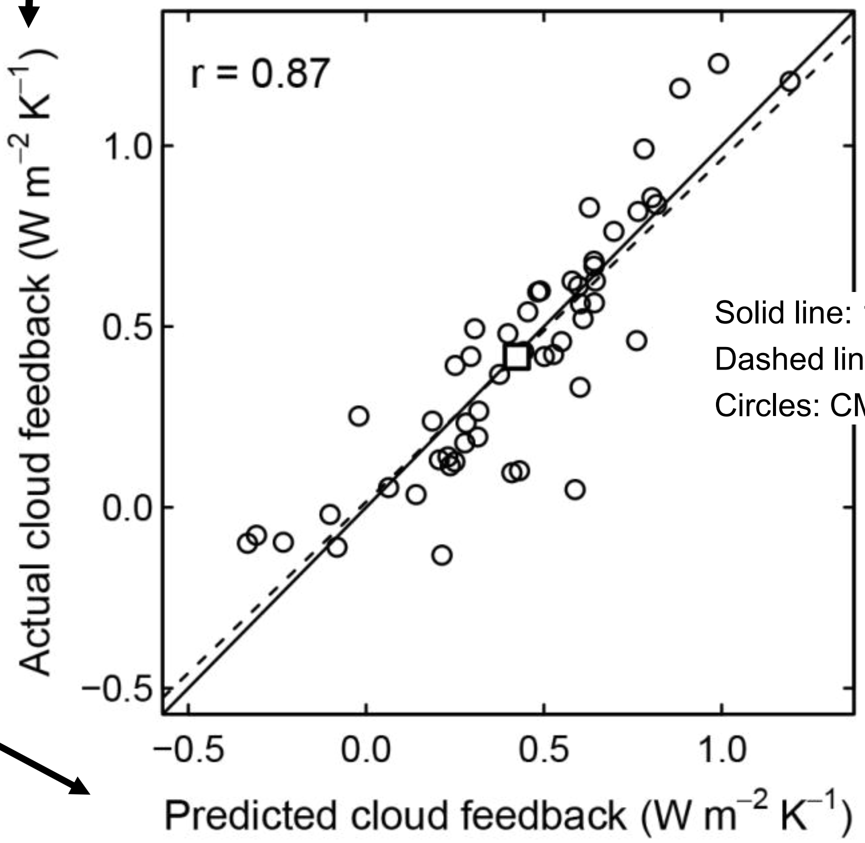
Cloud feedback $\mathrm{d}C/\mathrm{d}T$

shortwave + longwave, average globally

$$\frac{\mathrm{d}C(r)}{\mathrm{d}T} \approx \sum_{i=1}^{M} \mathbf{\Theta}_i(r) \cdot \frac{\mathrm{d}\boldsymbol{X}_i(r)}{\mathrm{d}T}$$

$\mathrm{d}\boldsymbol{X}_i / \mathrm{d}T$: cloud-controlling factor responses
→ estimated from 4×CO_2 simulations

Cloud feedback diagnosed directly from 4xCO_2 simulations



Solid line: 1:1
Dashed line: best fit
Circles: CMIP models

For CMIP models, we can predict the long-term cloud feedback from just 20 years of historical data!

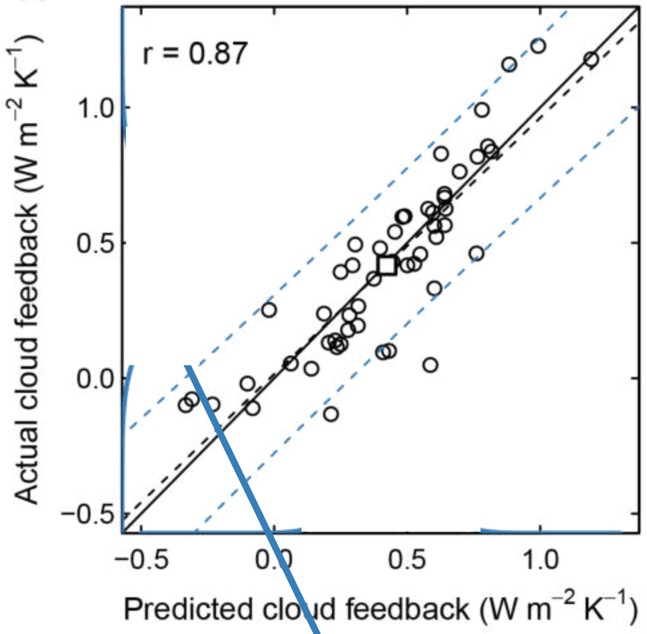
Constraining cloud feedback

<u>Step 2:</u> add observations:

$$\frac{\mathrm{d}C(r)}{\mathrm{d}T} \approx \sum_{i=1}^{M} \boldsymbol{\Theta}_i(r) \cdot \frac{\mathrm{d}\boldsymbol{X}_i(r)}{\mathrm{d}T}$$

from climate models

observed cloud-radiative sensitivities



PDF includes observational uncertainty & other error sources

Observations indicate positive cloud feedback (0.43 ± 0.35 W m^{-2} K^{-1})