ETH zürich

Institute for Atmospheric and Climate Sciences

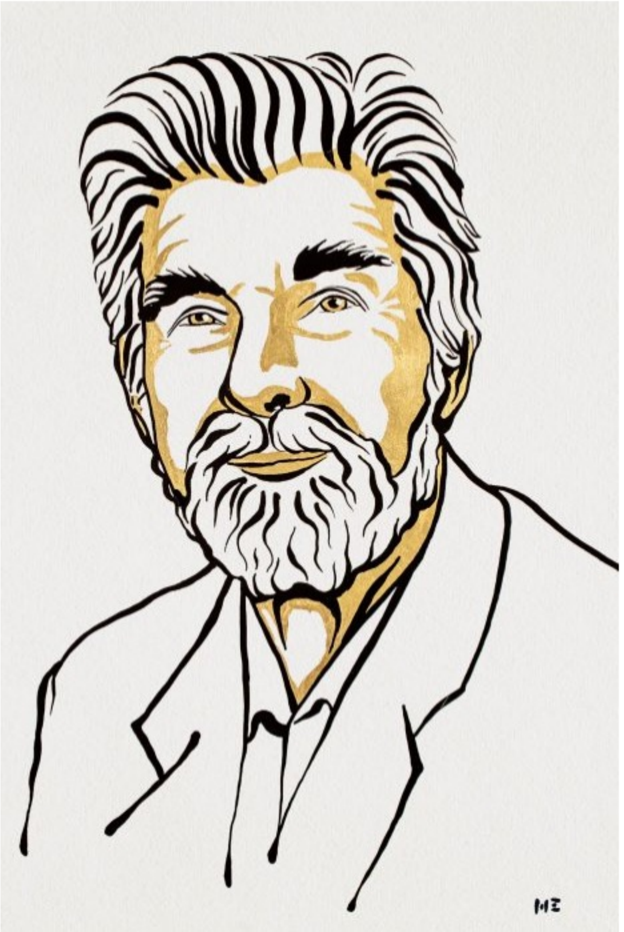
MPE-CDT Virtual Summer School Trend Attribution 2

Sebastian Sippel

Topics:

1. Introduction
2. Forced Signal vs. internal variability
3. Concepts and logic of detection & attribution
4. Fingerprinting [~25min]
   (1) Non-optimal fingerprinting
   (2) Optimal fingerprinting
5. Non-standard approaches
   (1) Dynamical adjustment: Dynamical vs. thermodynamical trends [10 min]
   (2) Signal/Noise maximizing pattern filtering [10 min]
   (3) Statistical and machine learning to extract the forced response [10 min]

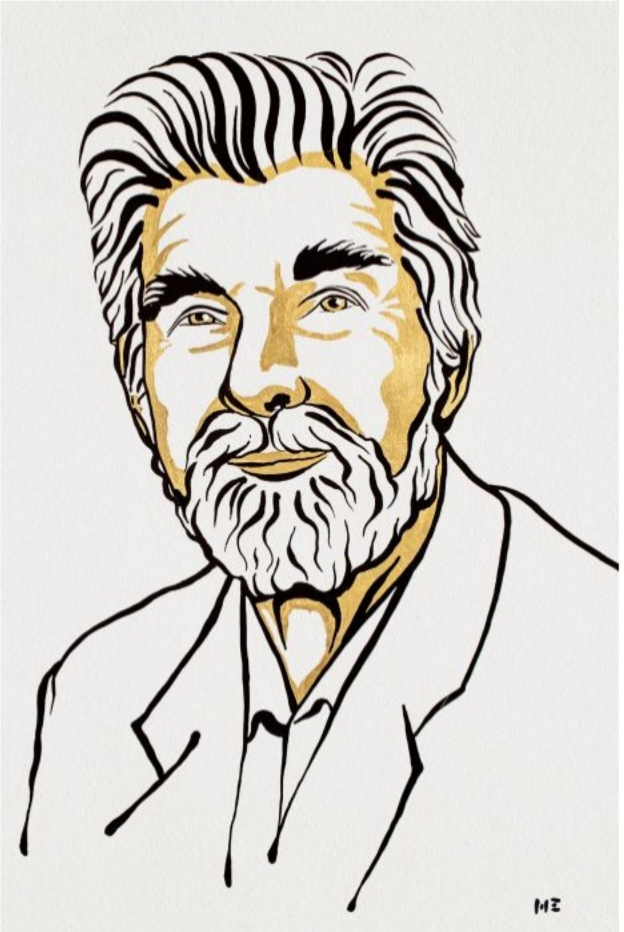
Beyond the global mean: Fingerprinting Detection



"it is necessary to regard the signal and noise fields as multi-dimensional vector quantities and the significance analysis should accordingly be carried out with respect to this multi-variate statistical field, rather than in terms of individual gridpoint statistics"

Klaus Hasselmann, 1979

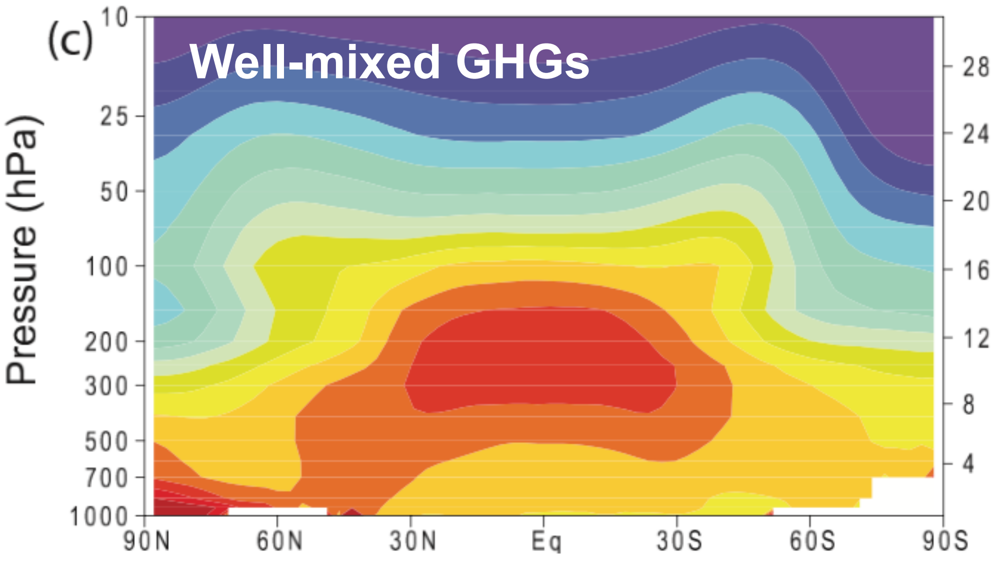
Beyond the global mean: Fingerprinting Attribution

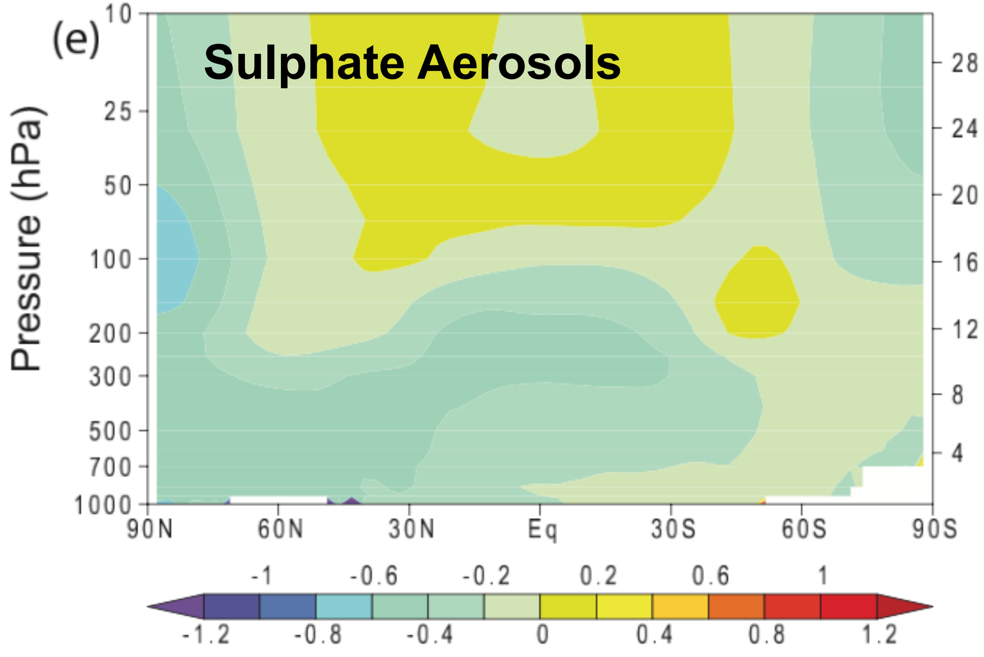


"Attribution analyses are necessarily limited to tests of consistency. Even if it has been shown that a detected climate change signal is consistent […] within a finite set of candidate mechanisms, it can never be ruled out that there exist other, overlooked forcing mechanisms, that could also produce the observed climate change signal."

Klaus Hasselmann, 1997

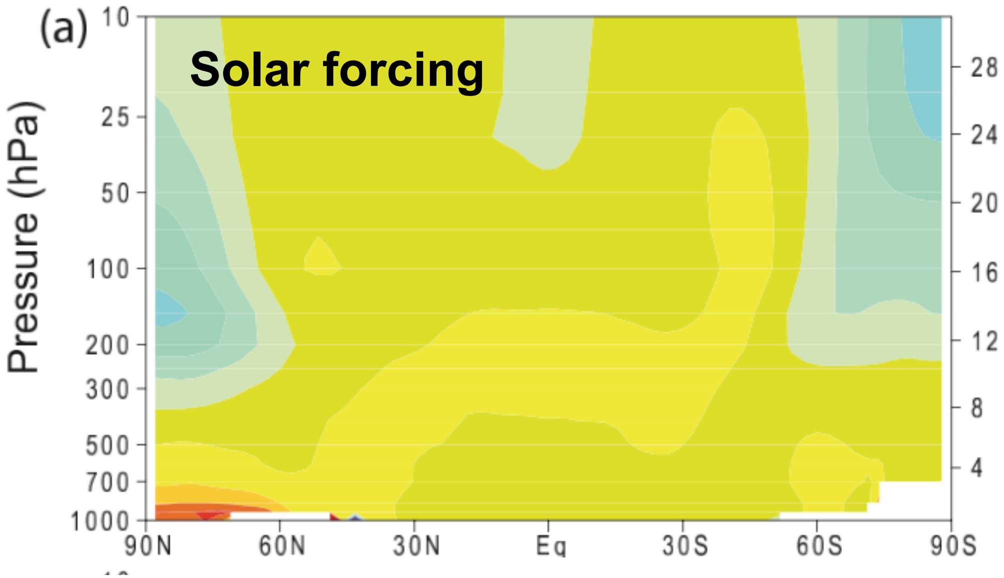
The “fingerprint” of external forcing agents





Total linear temperature change from 1890 to 1999 (°C per century)

IPCC 2007, AR4 WG1 Chapter 9, Based on Santer et al. (2003)



Fingerprinting D&A is based on the spatial, vertical, temporal or multivariate patterns of change, which are different for different forcings

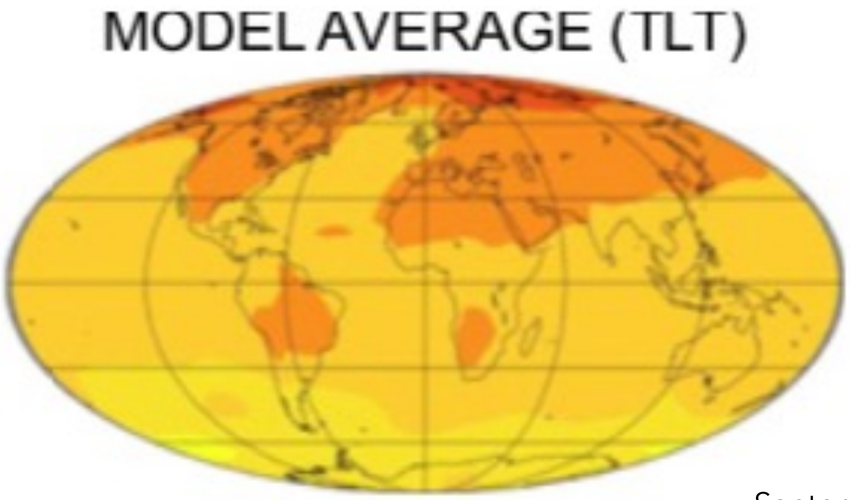
Fingerprinting: General assumptions

- Key forcings have been identified
- Signals are additive
- Noise is additive
- Large-scale patterns of response are correctly simulated by climate models
- Evaluation of internal variability as simulated by models is consistent with observations (i.e., with residual)

"Non-optimal" fingerprinting

1. "Fingerprints" to encapsulate physics-informed change signals from model simulations ("Forced response")
2. Observations and simulations of internal variability are projected onto "fingerprints":

$$S = \frac{(F \cdot X_{obs})}{||F||}$$



Santer et al., 2012, *PNAS*
Santer et al., 2019, *NClim*

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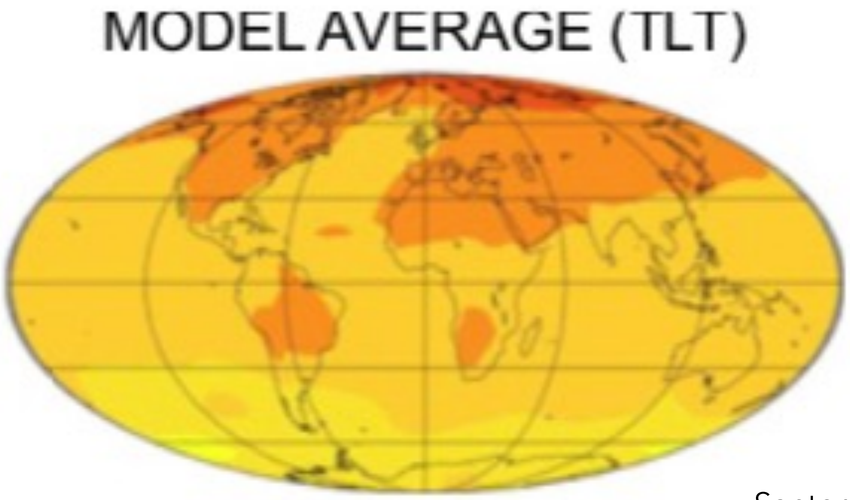
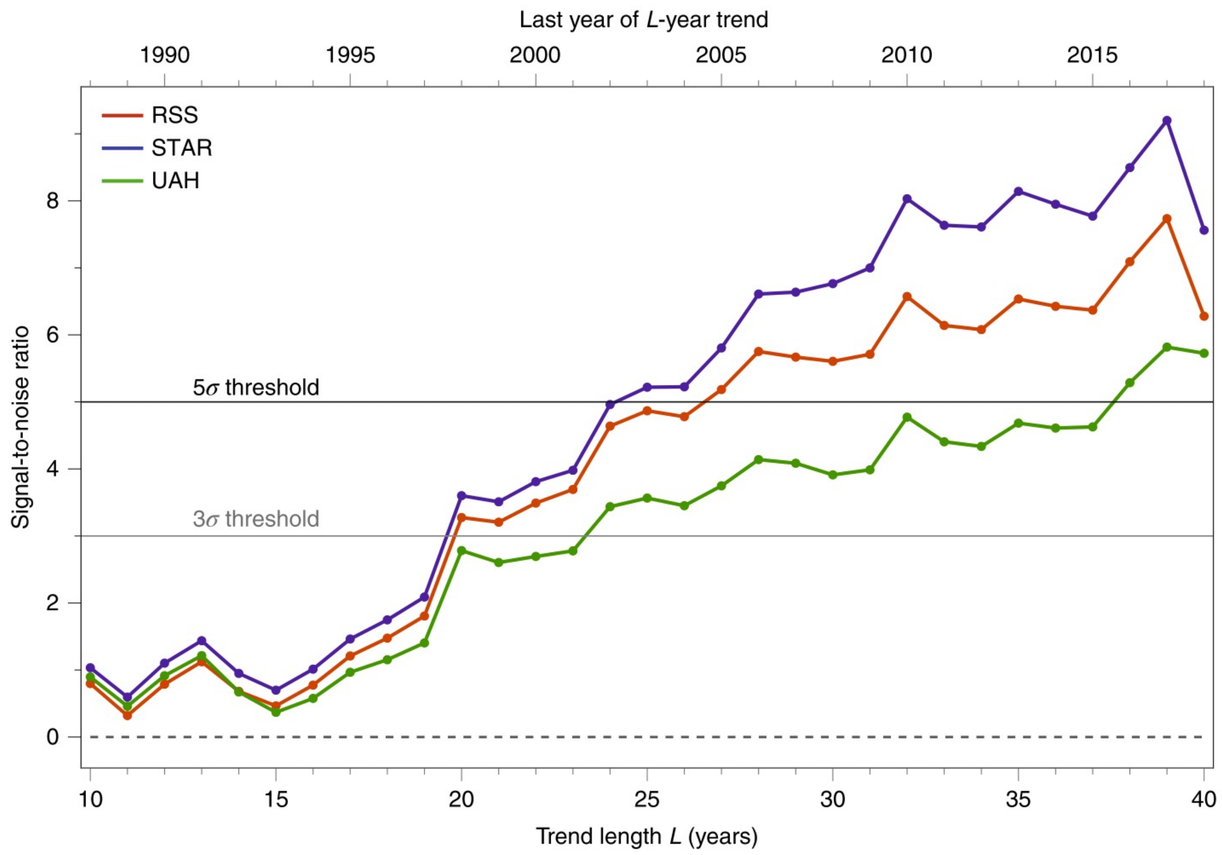


Santer et al., 2012, *PNAS*
Santer et al., 2019, *NClim*

Are observations becoming "more similar" to the fingerprint pattern?

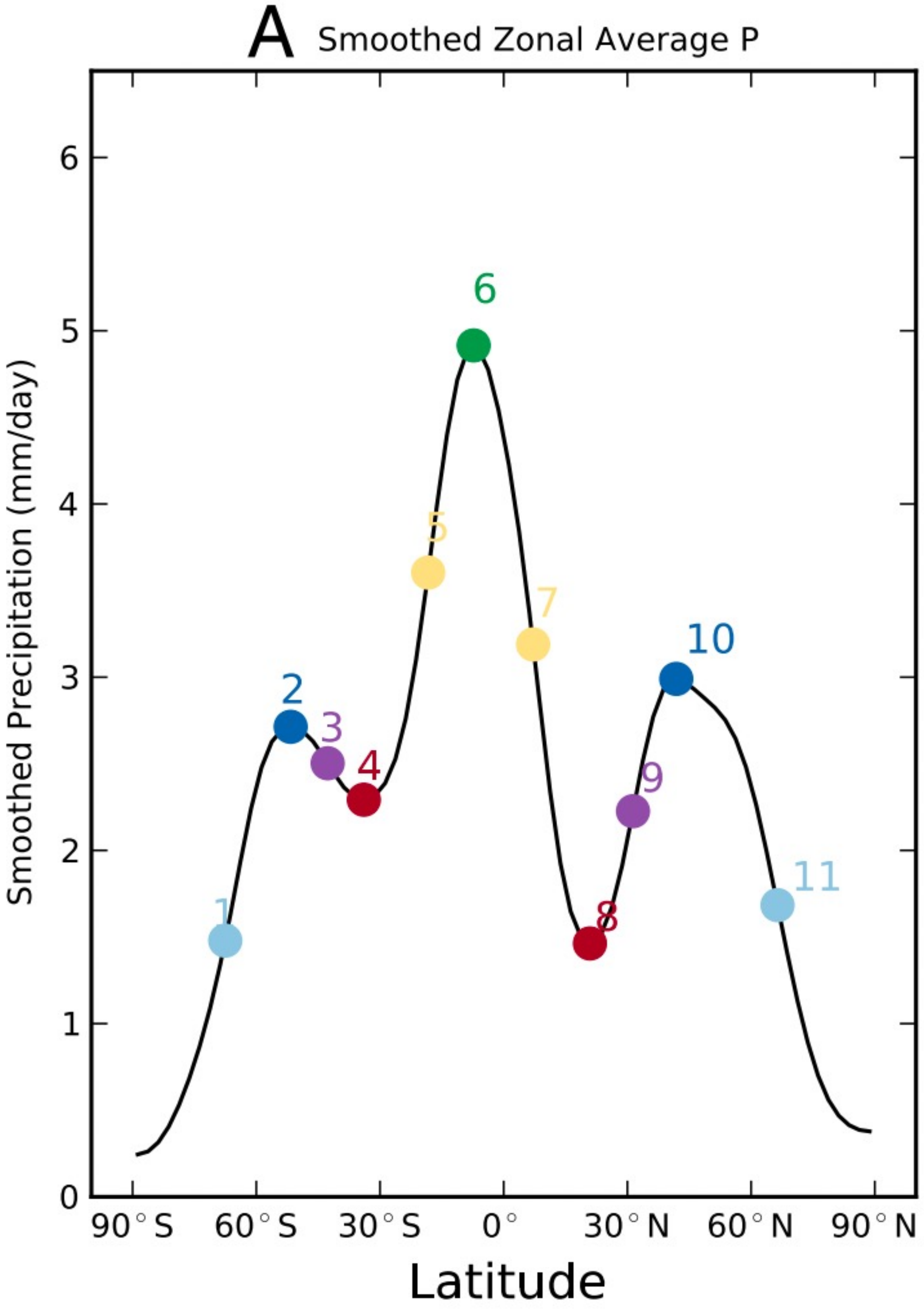


"Non-optimal" fingerprinting:

Water cycle example

"Fingerprint":

- precipitation intensity changes at local extrema
- Latitudinal shifts as "dynamic indicators"



Marvel et al., 2013, *PNAS*

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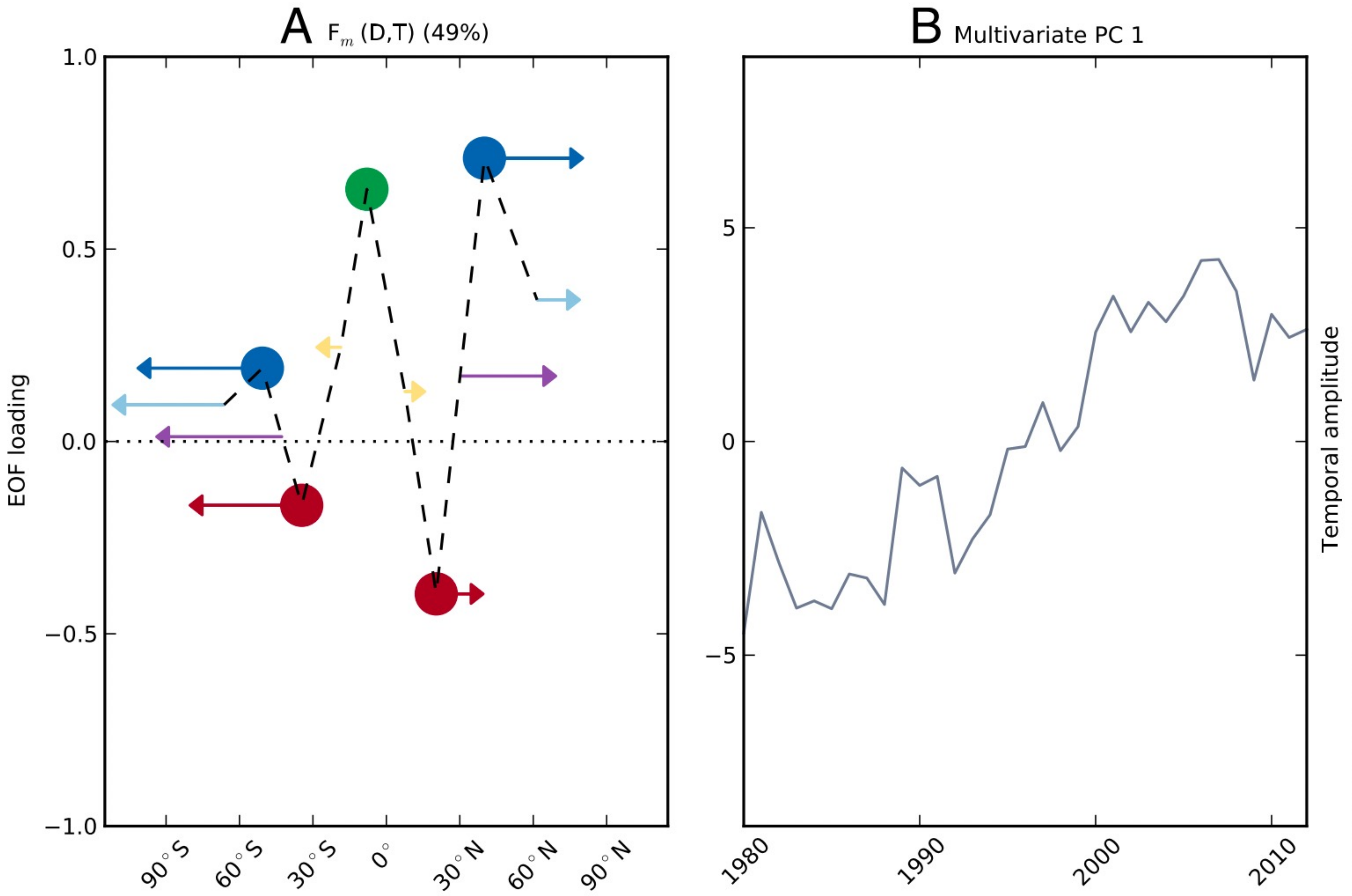
“Non-optimal” fingerprinting: Water cycle example



"Forced Pattern"

across models

Marvel et al., 2013, *PNAS*

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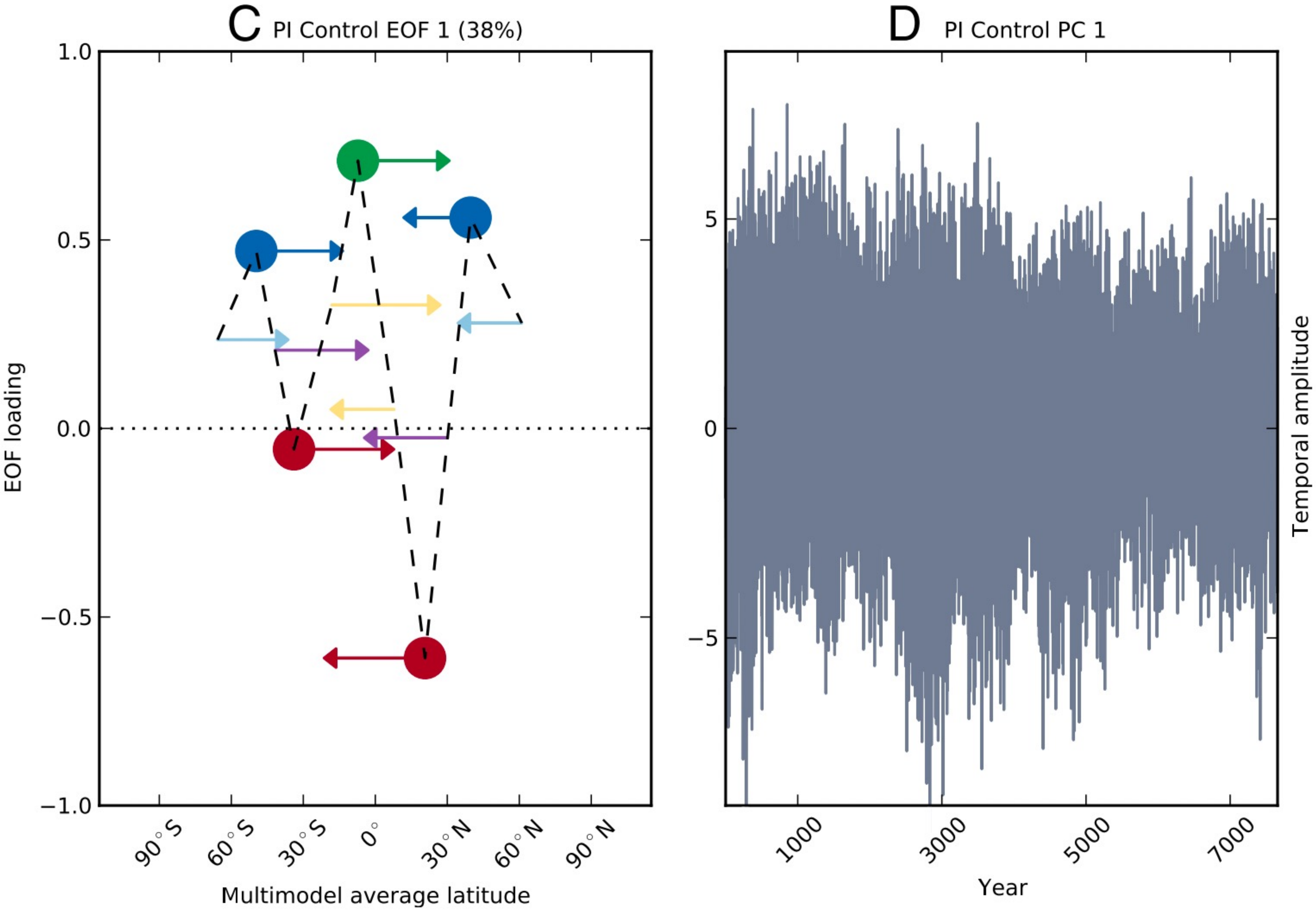
“Non-optimal” fingerprinting: Water cycle example



Leading “Noise” pattern

Marvel et al., 2013, *PNAS*

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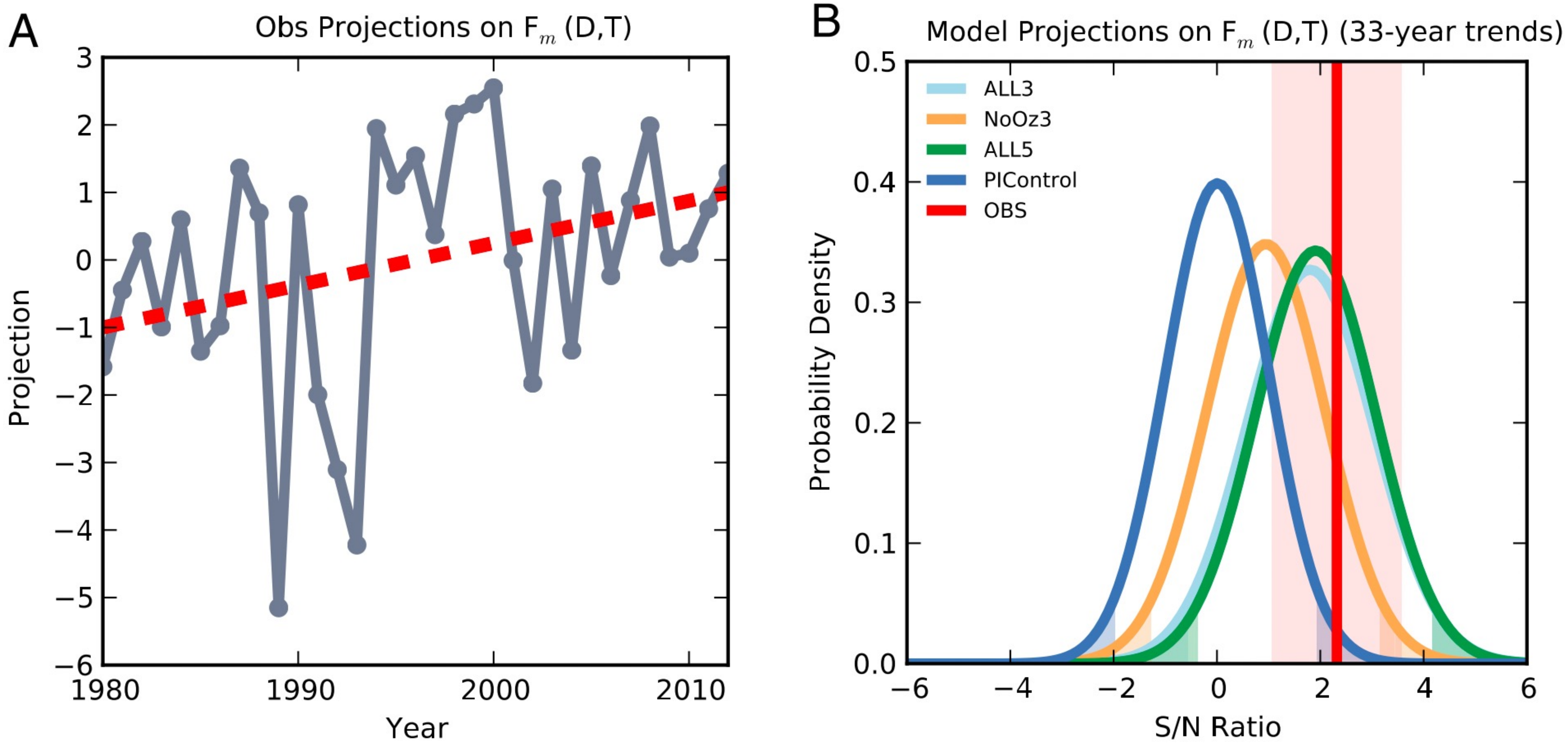
“Non-optimal” fingerprinting: Water cycle example



Projection of observations onto leading forced mode is not consistent with internal variability, but consistent with ANT forcing

Marvel et al., 2013, *PNAS*

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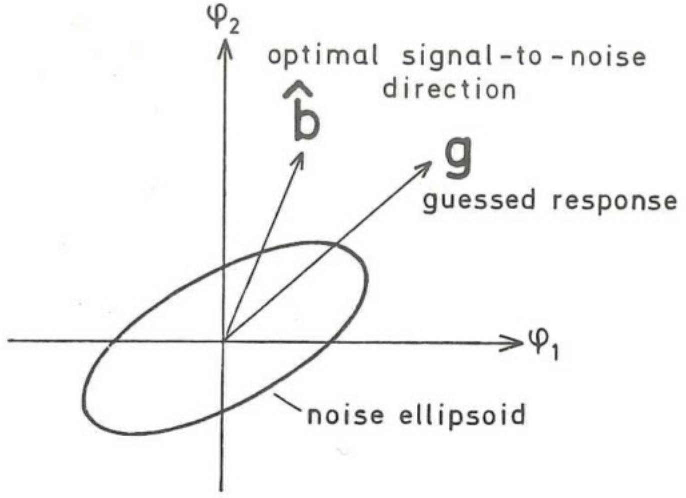
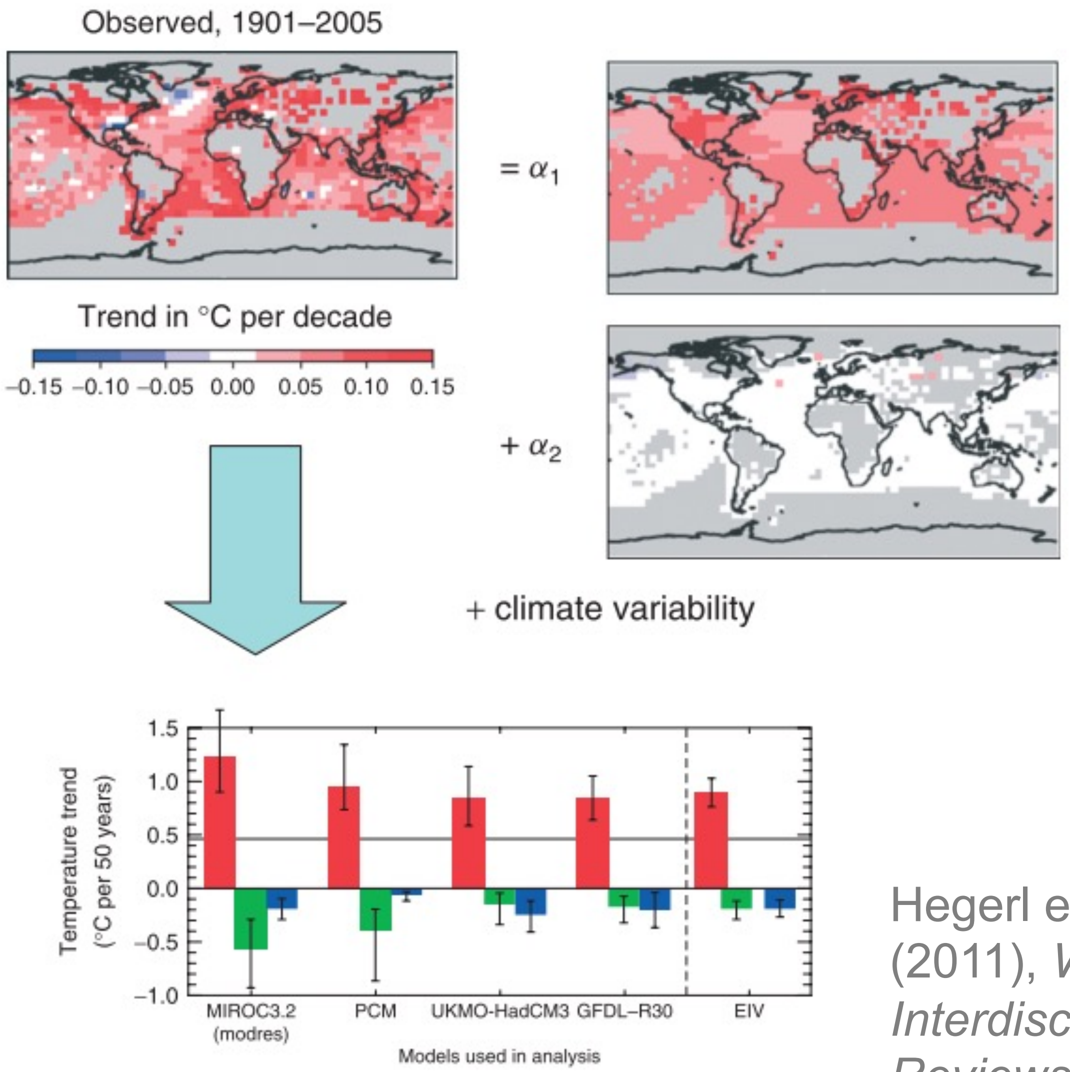
Optimal fingerprinting: Attribution recipe



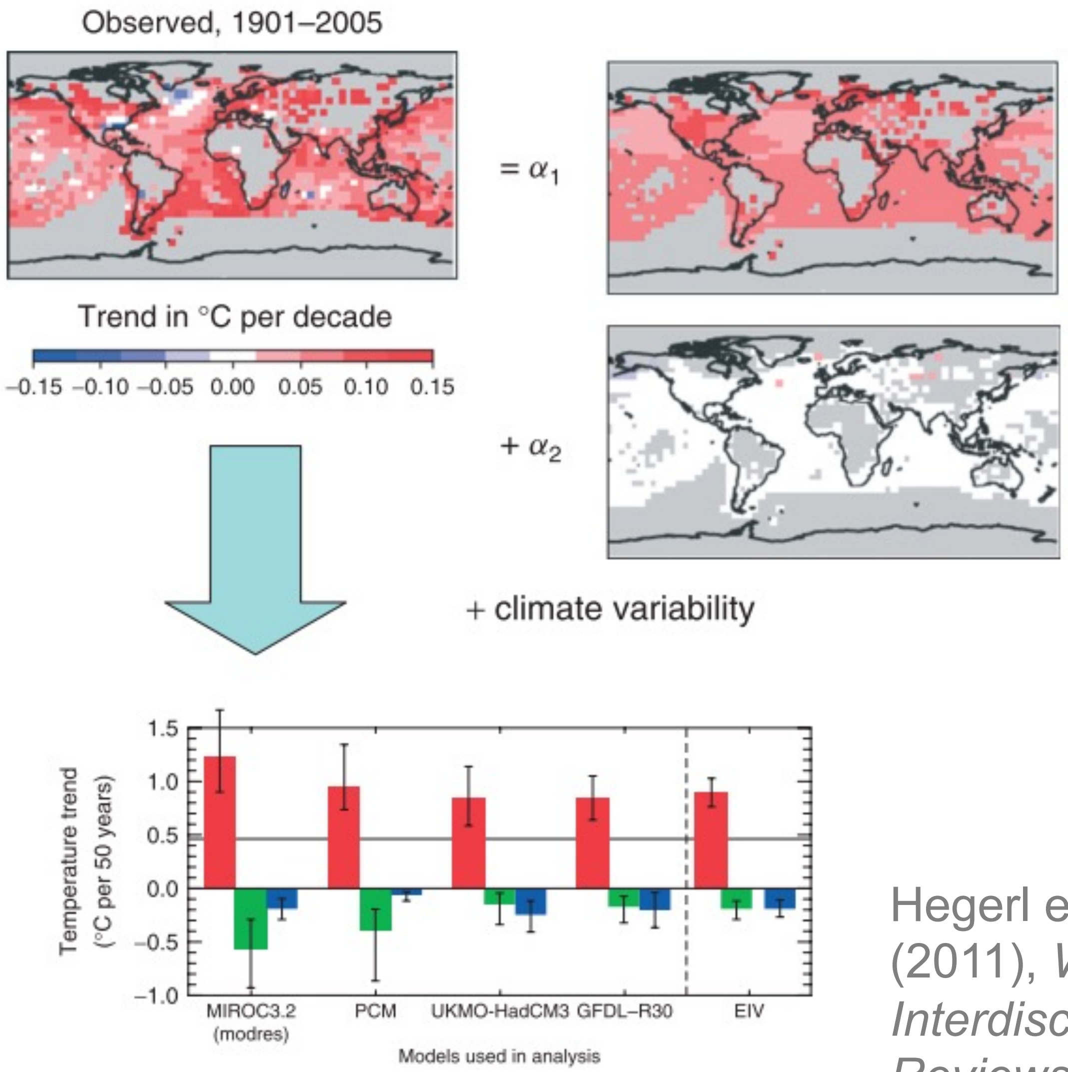
- Optimal fingerprinting "optimizes" (rotates) the direction in which the signal is detected/attributed against (an estimate of) internal variability
- Optimal fingerprinting is framed as a regression problem, in which model fingerprints (e.g., space-time) are taken to "interpret" the observations

Optimal fingerprinting: Attribution recipe



Hegerl et al. (2011), *Wiley Interdisciplinary Reviews Clim Change*

Optimal fingerprinting: Attribution recipe



Hegerl et al. (2011), *Wiley Interdisciplinary Reviews Clim Change*

- Optimal fingerprinting is framed as a regression problem, in which model fingerprints (e.g., space-time) are taken to "interpret" the observations:

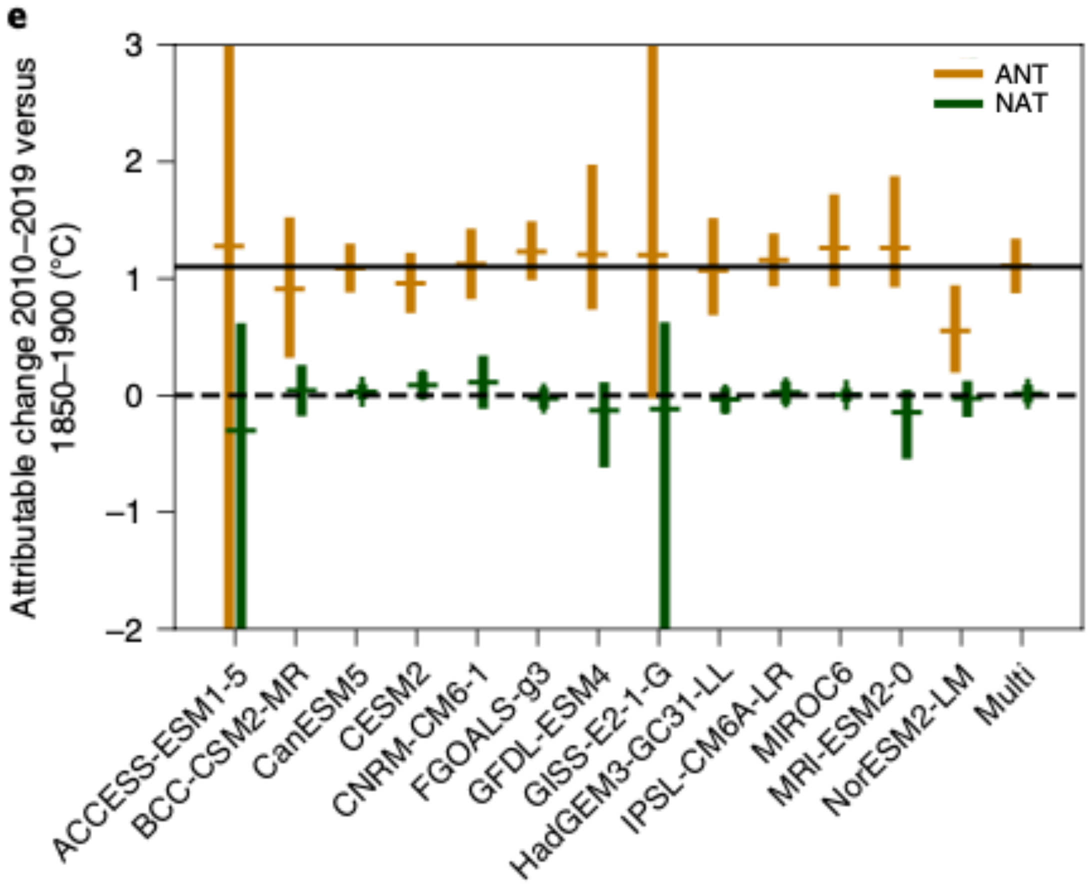
$$Y = \sum_{i=1}^{s} \beta_i X_i + \varepsilon$$

Y Observations,
X Expected changes ("space-time fingerprints"),
β_i Regression coefficients for factor i ("scaling factors"),
ϵ_i Internal variability.

- The goal is to estimate scaling factors and their confidence intervals

Optimal fingerprinting: Interpretation

- Detection is achieved when scaling factors do not include 0 in their confidence intervals (inconsistent with internal variability)
- Attribution is achieved when scaling factors include 1 in their confidence intervals
- Scaling factors reveal amplitude information about the respective forcing



Gillett et al. (2021), *Nature Climate Change*

Notes on optimal fingerprinting

- State-of-the-art algorithm for D&A
- "Small-sample" statistical problem and high spatio-temporal correlations require careful statistical application (questions on X, β and ε)
- "Optimal" means that regression is performed in a S/N maximized space, which is derived through estimating the covariance matrix C of internal variability (from models)
- Typically regression is performed in a dimension-reduced space (in EOF coordinates of internal variability, for example)
- Uncertainty in scaling factors must be assessed with a second, statistically independent estimate of the covariance matrix C
- Different algorithms to solve the regression problem are in frequent use with different estimates of error structures
- Residual variance in observations must be consistent with model estimated internal variability ("residual consistency test")

$$Y = \sum_{i=1}^{s} \beta_i X_i + \varepsilon$$

Y Observations,
X Expected changes ("space-time fingerprints"),
β_i Regression coefficients for factor i ("scaling factors"),
ϵ_i Internal variability

Further information (and references):
Hegerl and Zwiers 2011 *WIRE Clim Change*

Summary: Fingerprinting

- The goal of fingerprinting studies is to test whether a fingerprint (i.e., spatio-temporal, vertical, multivariate, etc.) of a given external forcing, usually given by a physics-based climate models, can be shown to have influenced the observations

- (“Non-optimal”) methods based on projections onto the signal vector, or based on pattern correlations

- Optimal fingerprinting aims to test for the difference external influences in a S/N maximized space

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Dynamical adjustment: Dynamical vs. thermodynamical trends

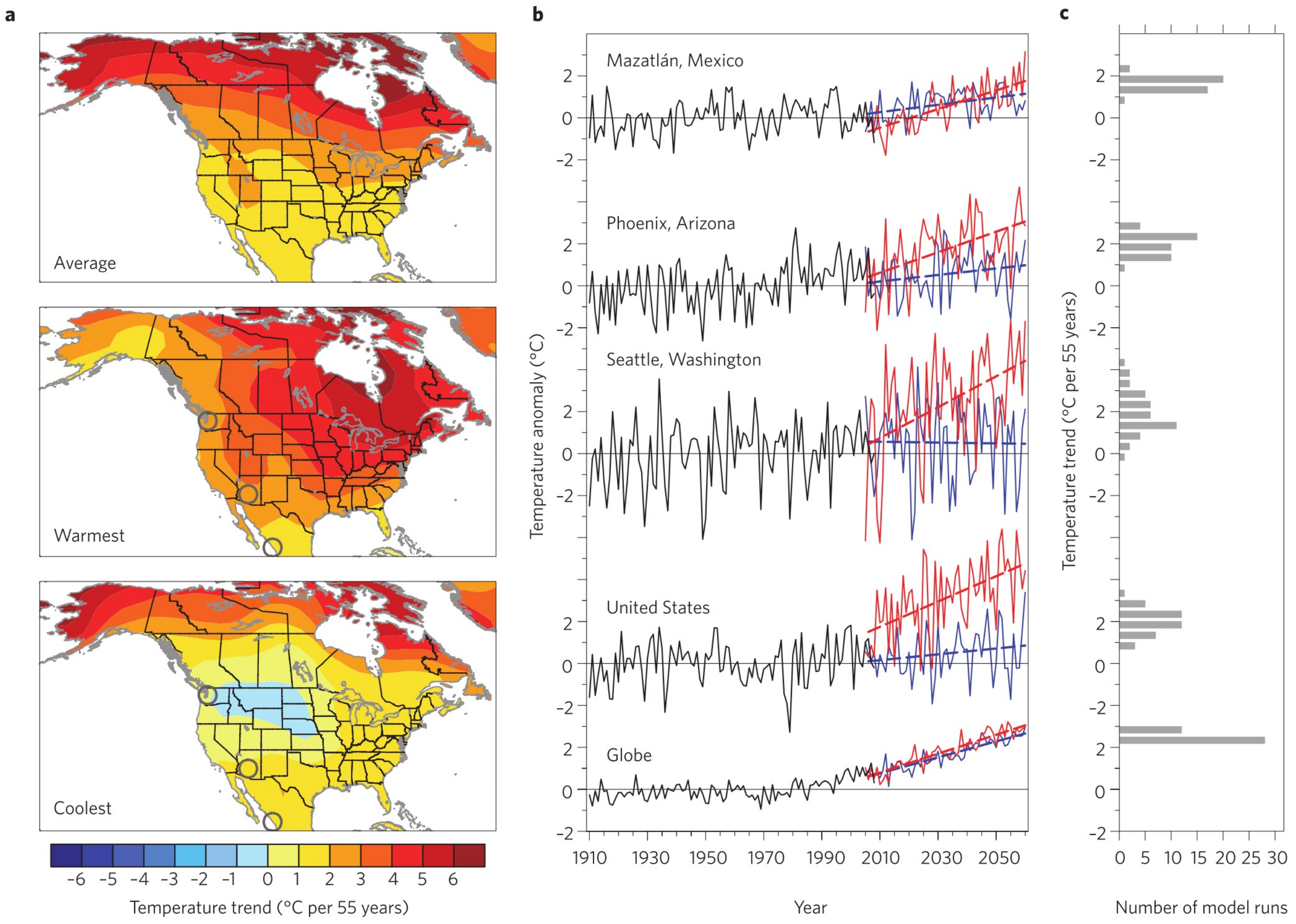


Figure 1 | Range of future climate outcomes. a, December–January–February (DJF) temperature trends during 2005–2060. Top panel shows the average

- Internal variability fundamentally limits climate projections
- Strong implications for interpretation of regional climate trends

- 45 model simulations with one **climate model** (=same physics)
- 55 year temperature trend maps, starting 2006

Deser et al., 2012, *Nat. Clim. Change*

Dynamical adjustment

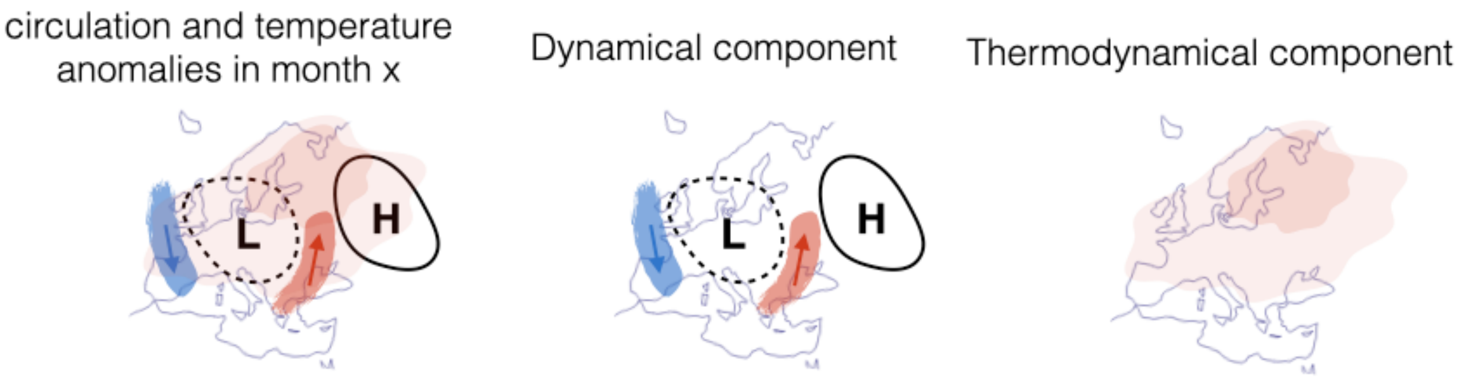


Figure Courtesy: Dr. Anna Merrifield

- Internal variability fundamentally limits climate projections
- Strong implications for interpretation of regional climate trends

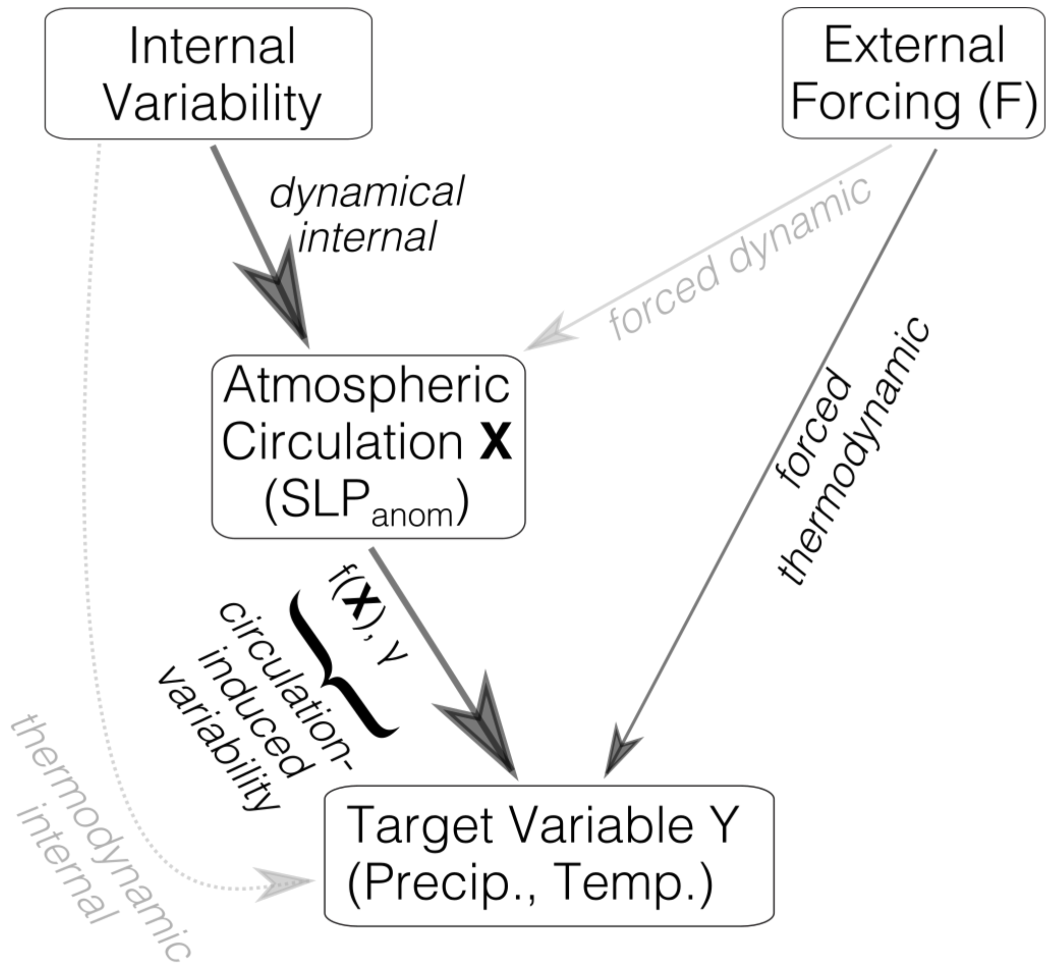
- Dynamical adjustment: extraction of regional climate signals using circulation information (a very established idea!)

In-depth introduction to dynamical adjustment:
Deser et al (2016) *Journal of Climate.*

Forced and Internal Components of Winter Air Temperature Trends over North America during the past 50 Years: Mechanisms and Implications*

CLARA DESER
Climate and Global Dynamics Division, National Center for Atmospheric Research,+ Boulder, Colorado
LAURENT TERRAY

Dynamical adjustment

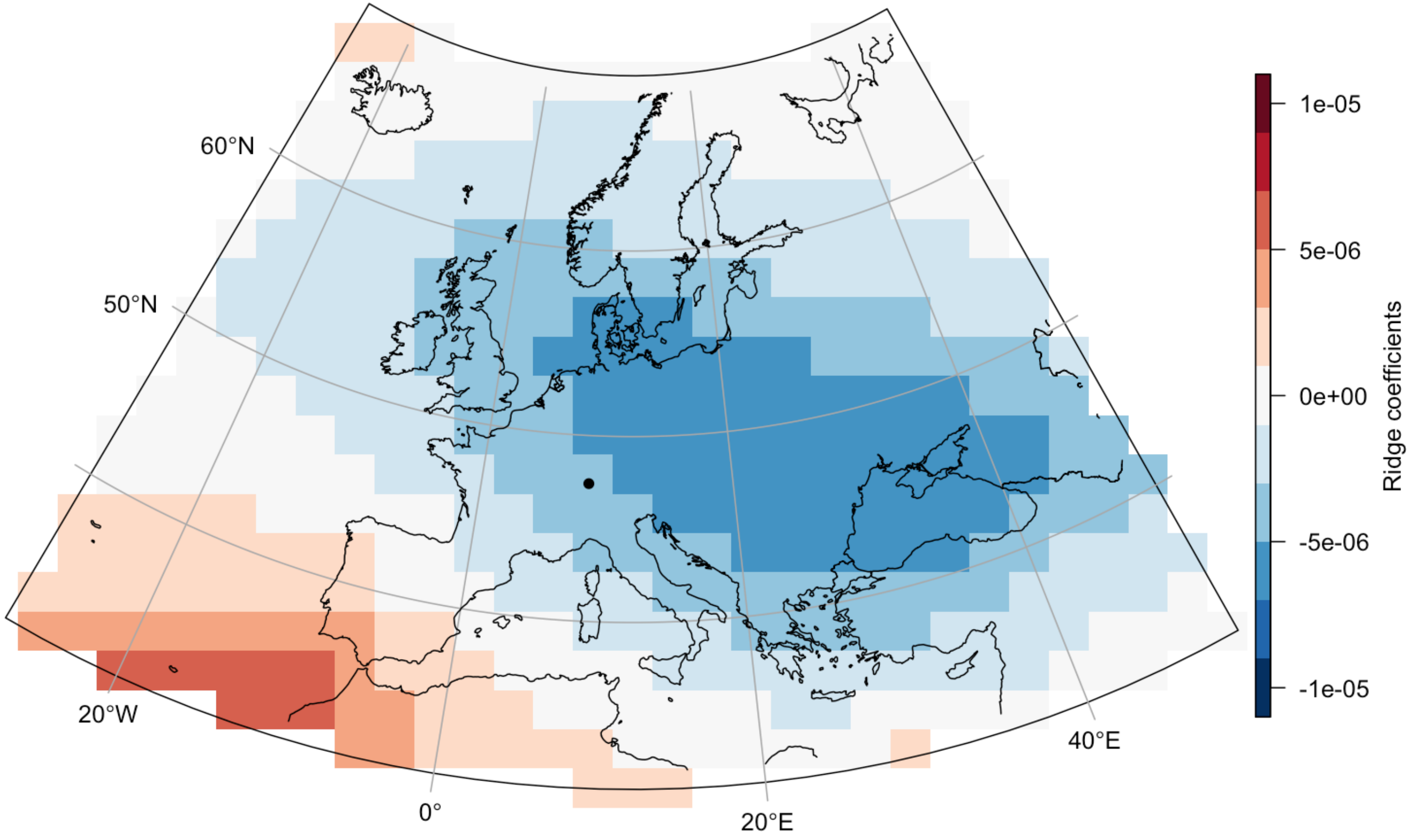


- Internal variability fundamentally limits climate projections
- Strong implications for interpretation of regional climate trends

- Dynamical adjustment: extraction of regional signals using circulation information
- Statistical learning method (ridge regression) to encapsulate the circulation information into a statistical model

Sippel et al., 2019, *Journal of Climate*, **32**, 5677-5699.

Dynamical adjustment



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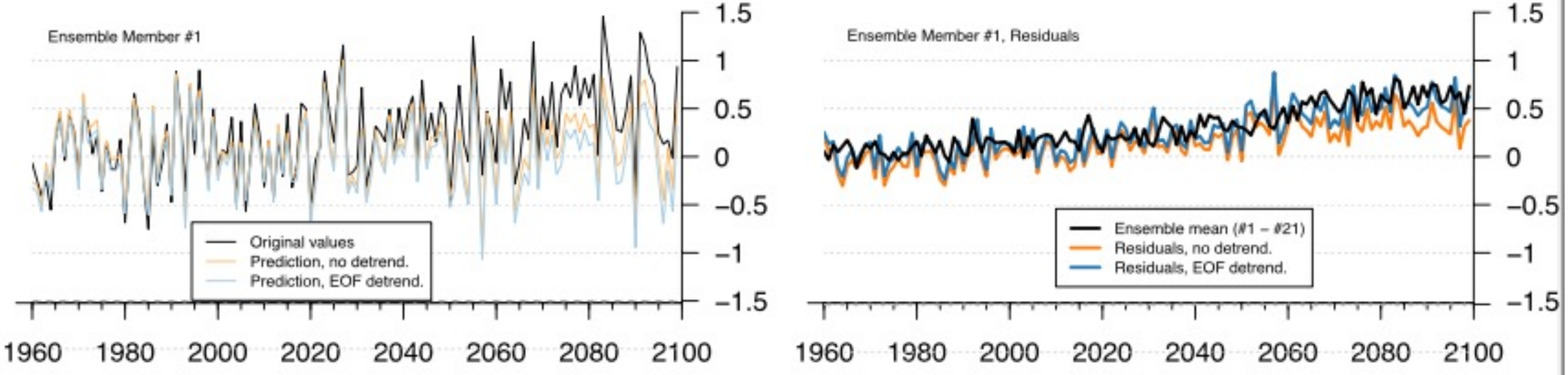
Sippel et al., 2019, *Journal of Climate*, **32**, 5677-5699.

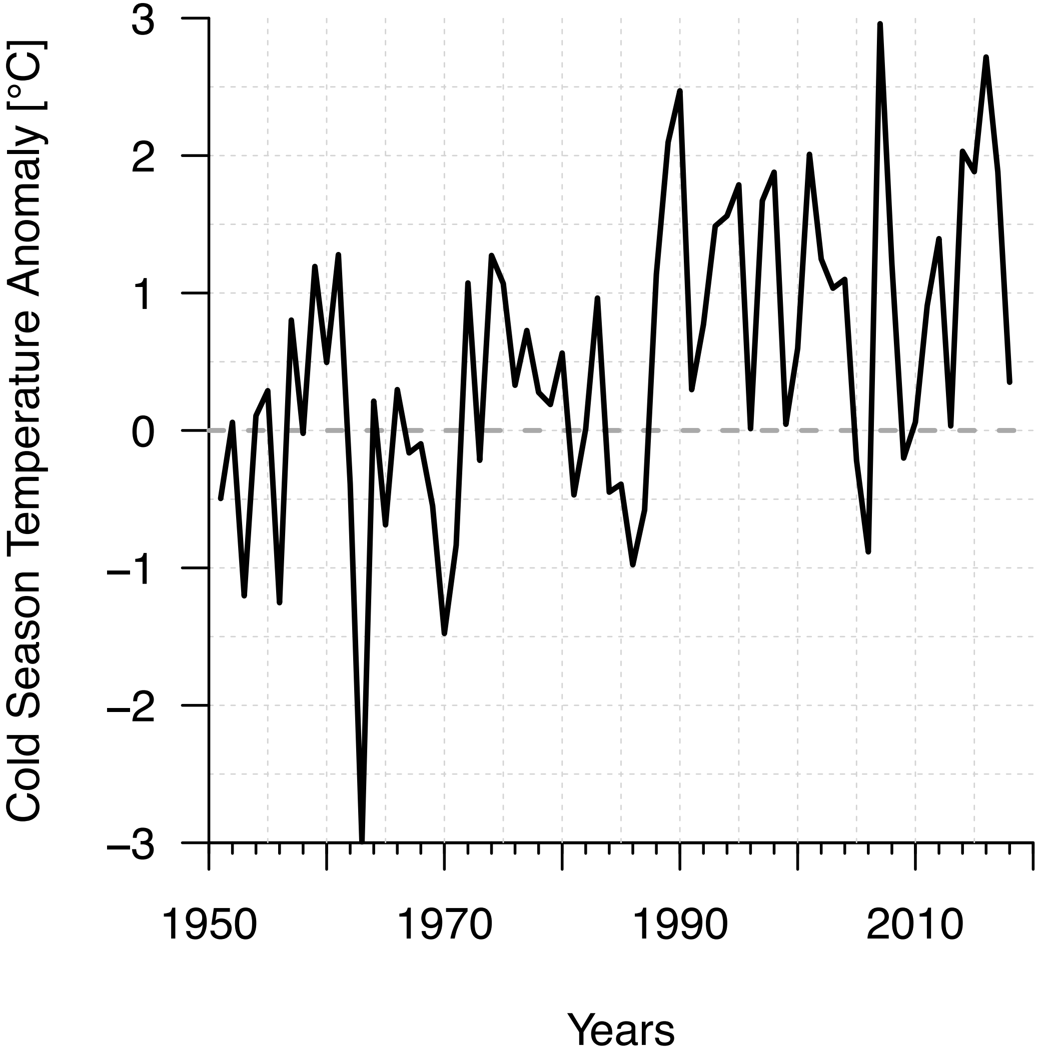
Dynamical adjustment: Illustration in a large ensemble



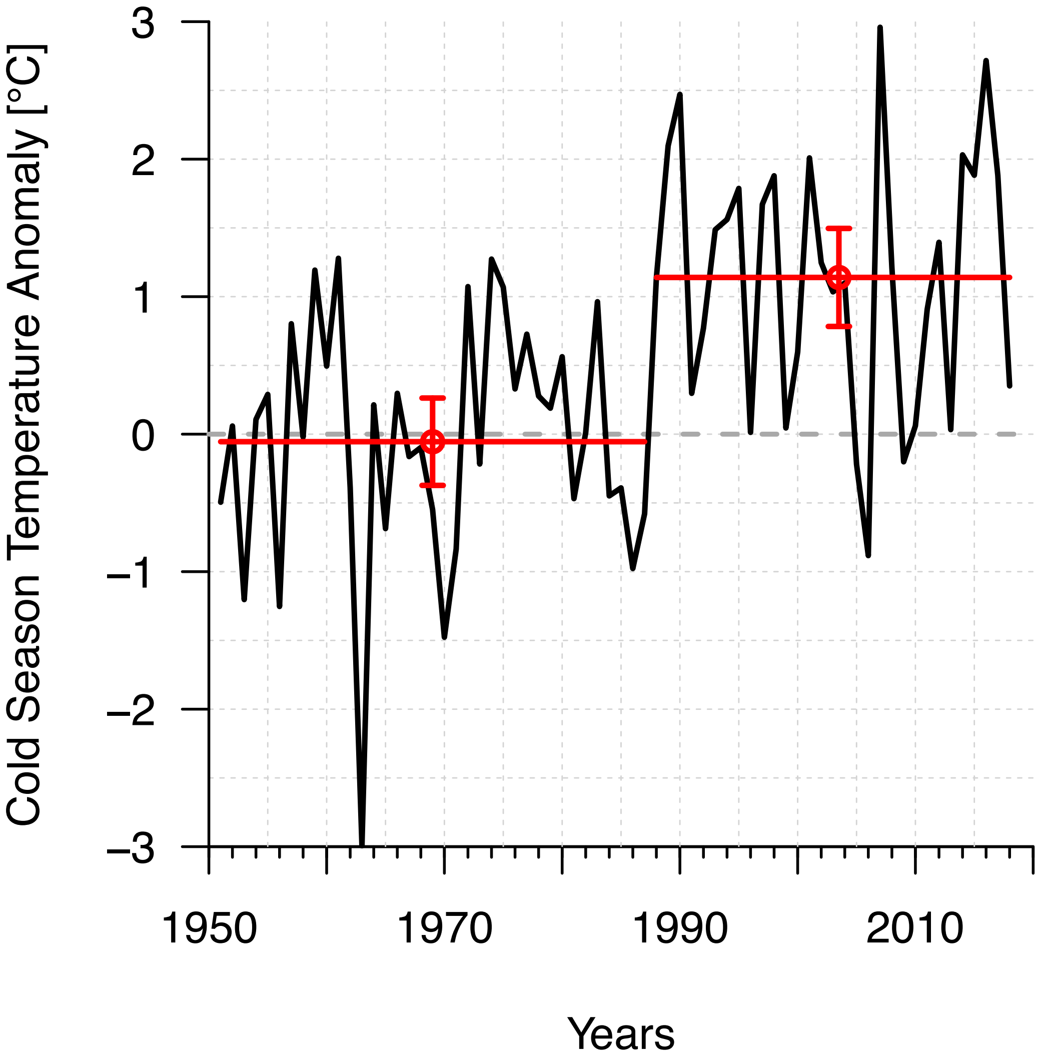
- *Winter precipitation, North Europe*
- Method application: CESM 1.2.2 21-member ensemble, HIST+RCP8.5

Sippel et al. (2019), *J. Clim.*, `doi:10.1175/JCLI-D-18-0882.s1`

Dynamical adjustment: Understanding abrupt winter climate change in Switzerland



An abrupt winter climate change in Switzerland?



Global Change Biology

Global Change Biology (2016) 22, 682–703, doi: 10.1111/gcb.13106

Global impacts of the 1980s regime shift

PHILIP C. REID[1,2,3], RENATA E. HARI[4], GRÉGORY BEAUGRAND[1,5], DAVID M. LIVINGSTONE[4], CHRISTOPH MARTY[6], DIETMAR STRAILE[7], JONATHAN

Regime shift of snow days in Switzerland

Christoph Marty[1]

Received 19 March 2008; revised 15 April 2008; accepted 7 May 2008; published 17 June 2008.

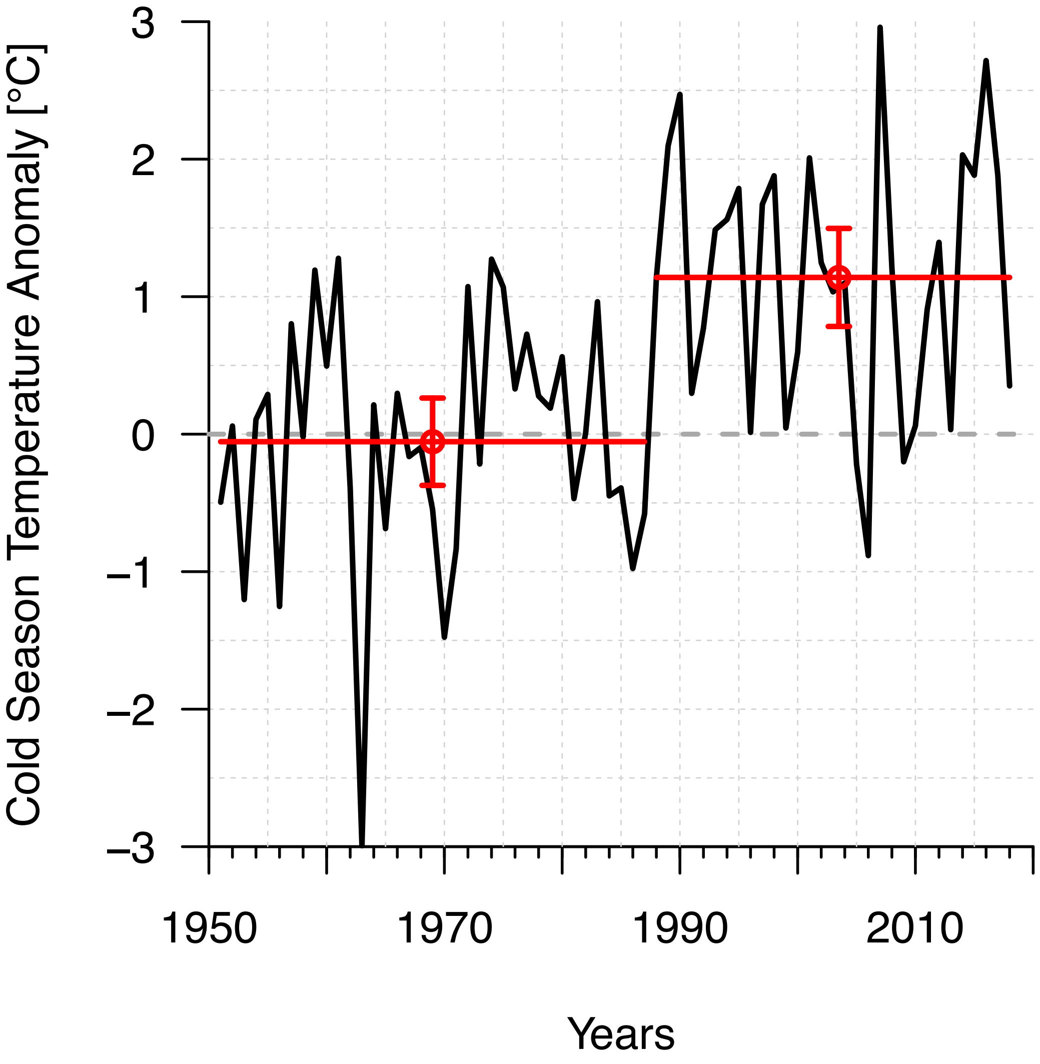
[1] The number of days with a snow depth above a [3] This work

ISSN: 2044-2041 (Print) 2044-205X (Online) Journal homepage: http://www.tandfonline.com/loi/tinw

The physical impact of the late 1980s climate regime shift on Swiss rivers and lakes

Ryan P. North, David M. Livingstone, Renata E. Hari, Oliver Köster, Pius Niederhauser & Rolf Kipfer

An abrupt winter climate change in Switzerland?



Tages-Anzeiger

Ade Schnee

Wo ist es noch schneesicher? Wie viele Schneetage 33 Schweizer Orte in den letzten 30 Jahren verloren haben.

Patrick Vögeli und Marc Brupbacher, Interaktiv-Team

ZEIT ONLINE

Günther Aigner

"Skisport wird zum Luxus"

Die Winter in den Alpen sind kälter geworden – dennoch haben manche Skigebiete keine Zukunft. Warum? Ein Gespräch mit dem Skitourismus-Experten Günther Aigner

Von **Uwe Jean Heuser**

19. Dezember 2013 / DIE ZEIT Nr. 52/2013

29. Dezember 2018, 00:00 Uhr Klima

Schnee war´s

Langzeitstudien zeigen, dass in den Alpen und auch im übrigen Europa immer weniger Schnee liegen bleibt. Das ist nicht nur für Wintersportler ein Problem.

Von Christoph von Eichhorn

Spektrum.de

19.01.2019

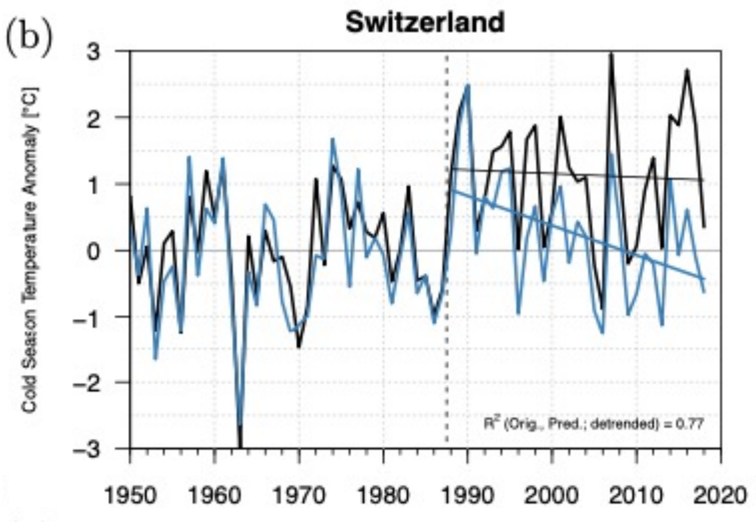
KLIMA

Bleiben die Alpen auch zukünftig weiß?

Schnee - und kein Ende in Sicht: Das legt eine Wintersportstudie nahe. Doch wird es in den Bergen tatsächlich gegen den Trend kälter?

Der Autor Andreas Frey ist Wissenschaftsjournalist in Freiburg.

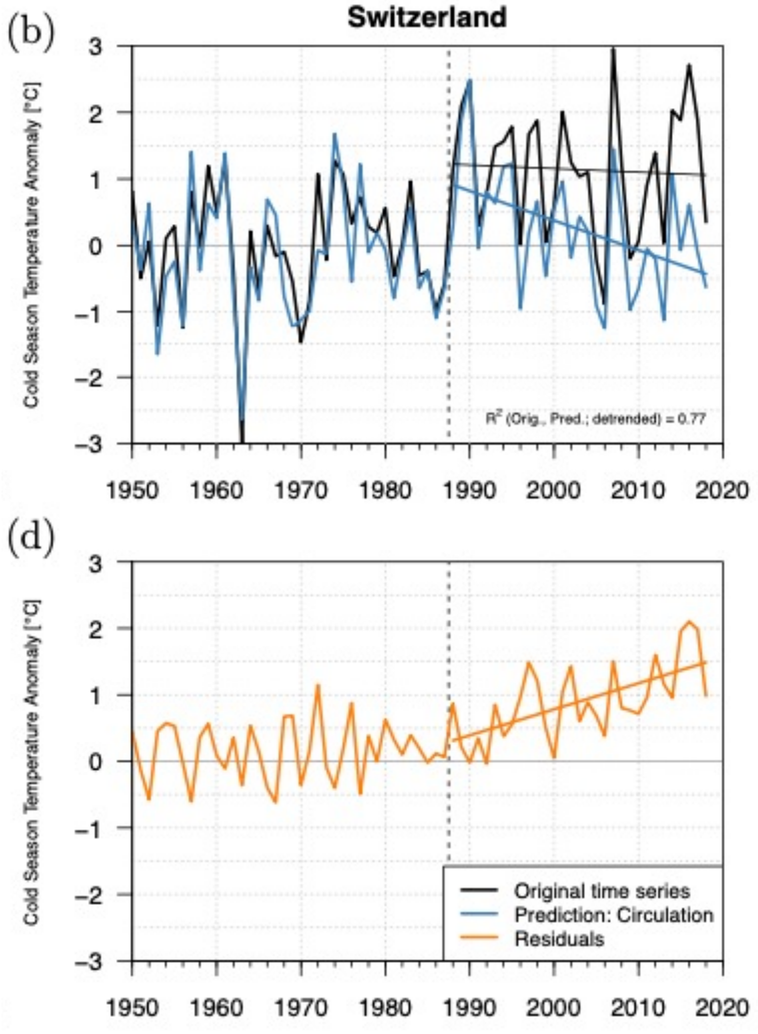
Dynamical adjustment: Understanding abrupt winter climate change in Switzerland



- At regional scales, circulation-induced variability explains a large fraction of temperature variability

Sippel et al., 2019, *Environmental Research Letters*, **15**, 094056.

Dynamical adjustment: Understanding abrupt winter climate change in Europe and Switzerland



- At regional scales, circulation-induced variability explains a large fraction of temperature variability
- Residuals of circulation-induced variability reveal a smooth (thermodynamical) signal of change

Sippel et al., 2019, *Environmental Research Letters*, **15**, 094056.

Summary Dynamical adjustment

- Dynamical adjustment is a technique to decompose observed or simulated trends into dynamical and residual (that contain thermodynamical) trends. This is not exactly a separation into forced and internal components, but it helps understanding

- Various methods exists, based on circulation analogues, EOF regression, statistical learning, etc.

- The apparent climate regime shift in Switzerland and in Europe can be explained as a combination of unusual atmospheric circulation combined with a smooth forced thermodynamical trend

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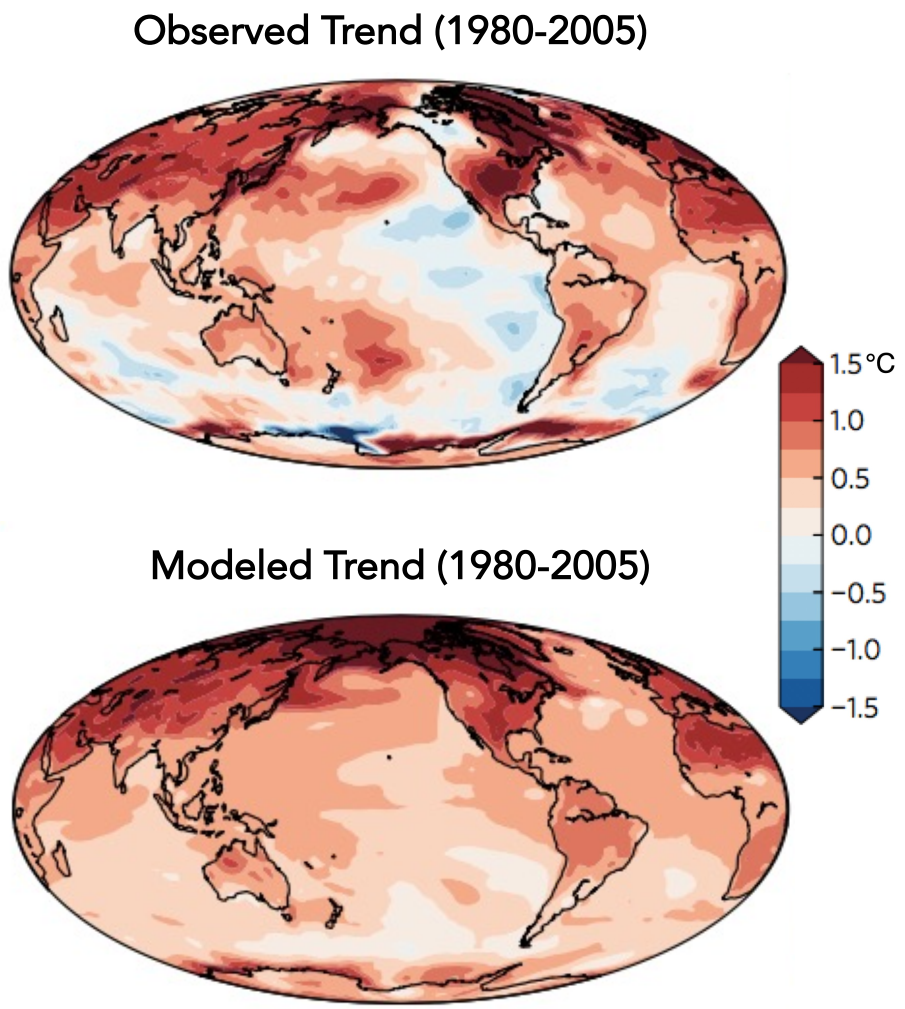
Pattern recognition to extract forced patterns

Slides adapted with permission from R. Wills



Zhou et al. 2016

Understanding differences across *forced patterns* across models and observations via isolating forced patterns:

- Model evaluation
- Predicting the future of warming (feedbacks, climate sensitivity)
- Understanding multi-decadal variability and differences across models

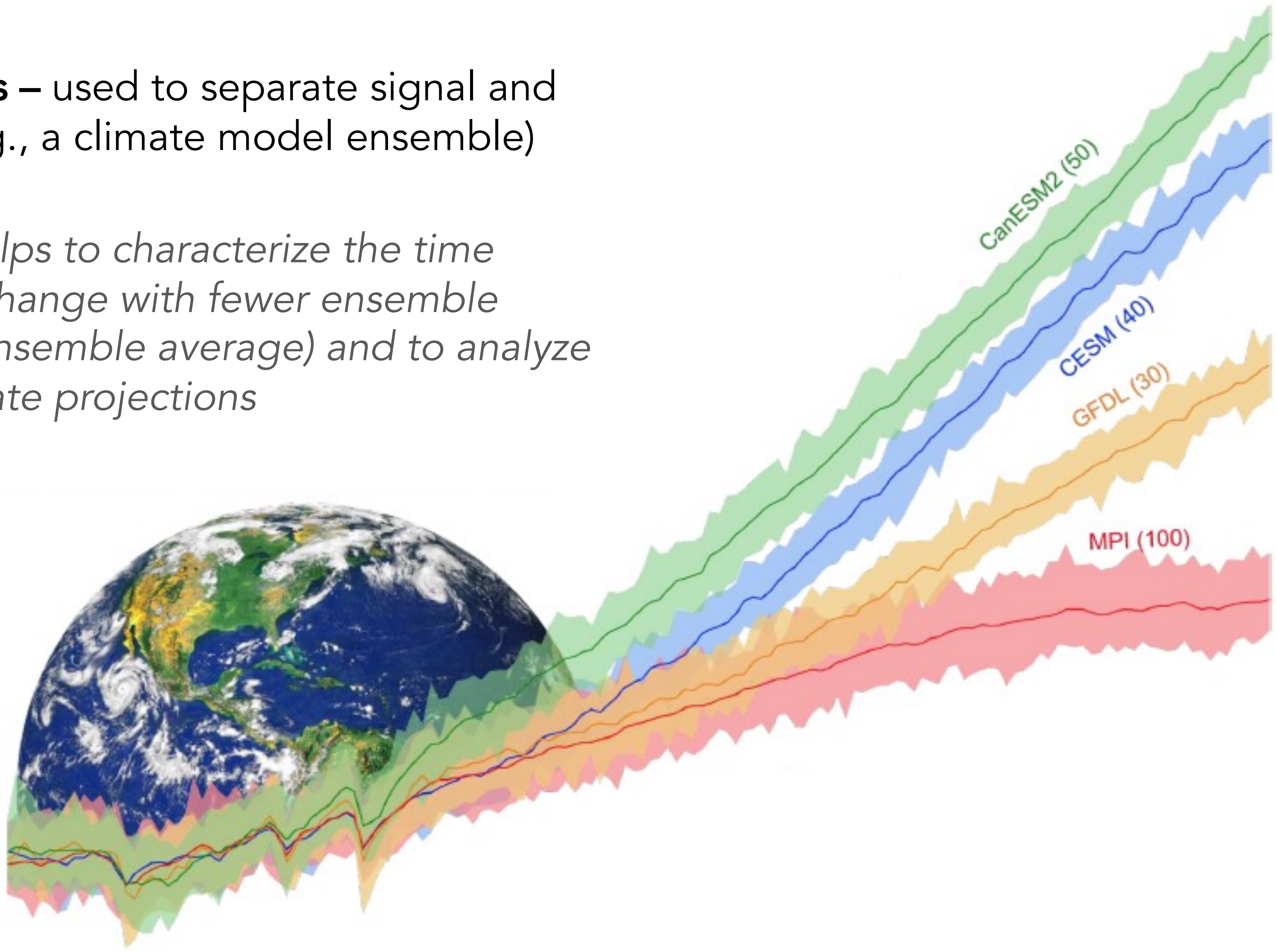
Pattern recognition to extract forced patterns

Slides adapted with permission from R. Wills

S/N-Maximizing Pattern Analysis – used to separate signal and noise within a single dataset (e.g., a climate model ensemble)

- *Using pattern information helps to characterize the time evolving pattern of climate change with fewer ensemble members (compared to an ensemble average) and to analyze structural uncertainty in climate projections*

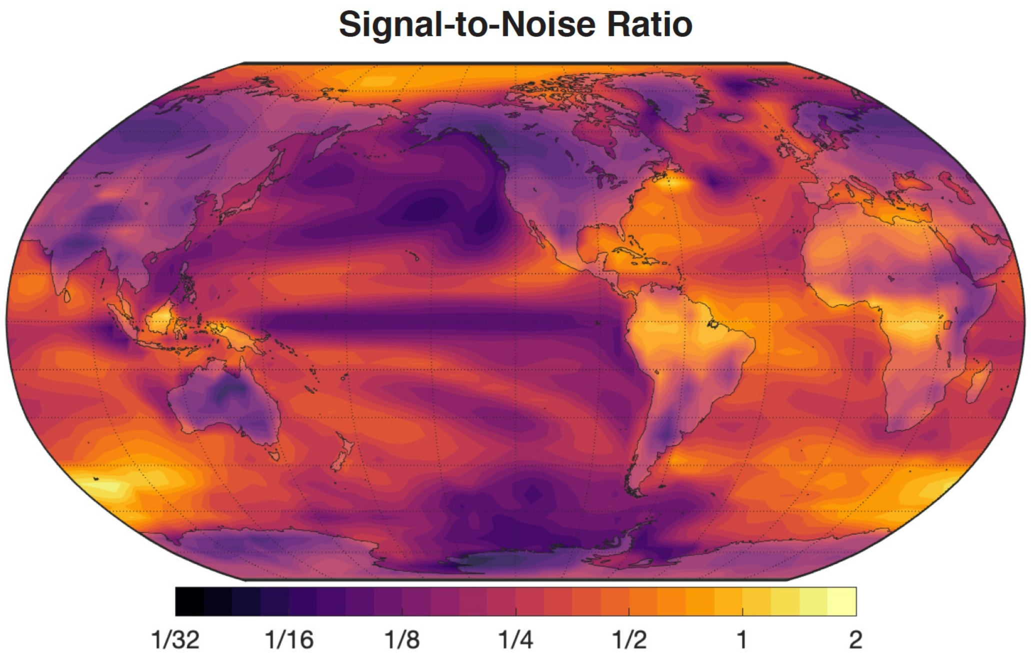
Can pattern information be used to reduce the ensemble size needed to separate signal from noise?

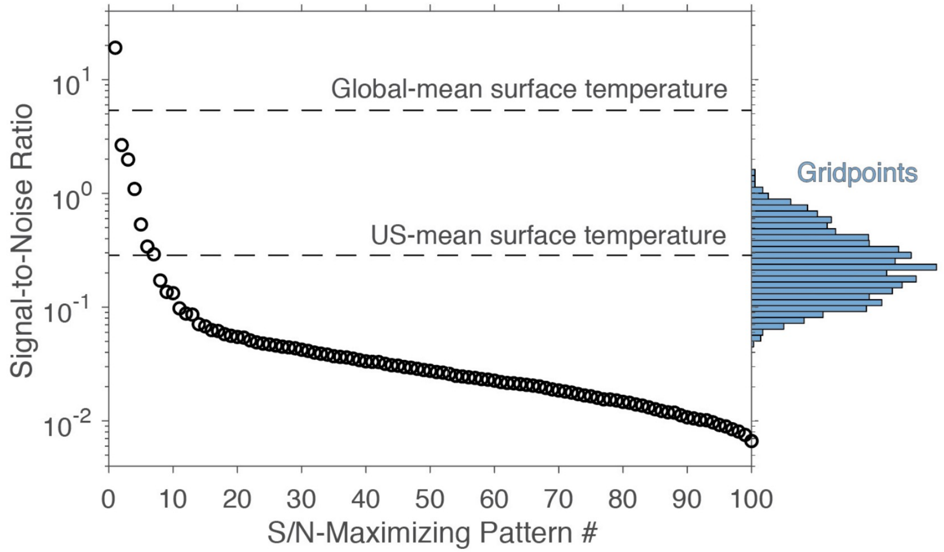


Graphic from usclivar.org, Flavio Lehner

Signal-to-noise ratio and the utility of pattern information

Slides adapted with permission from R. Wills





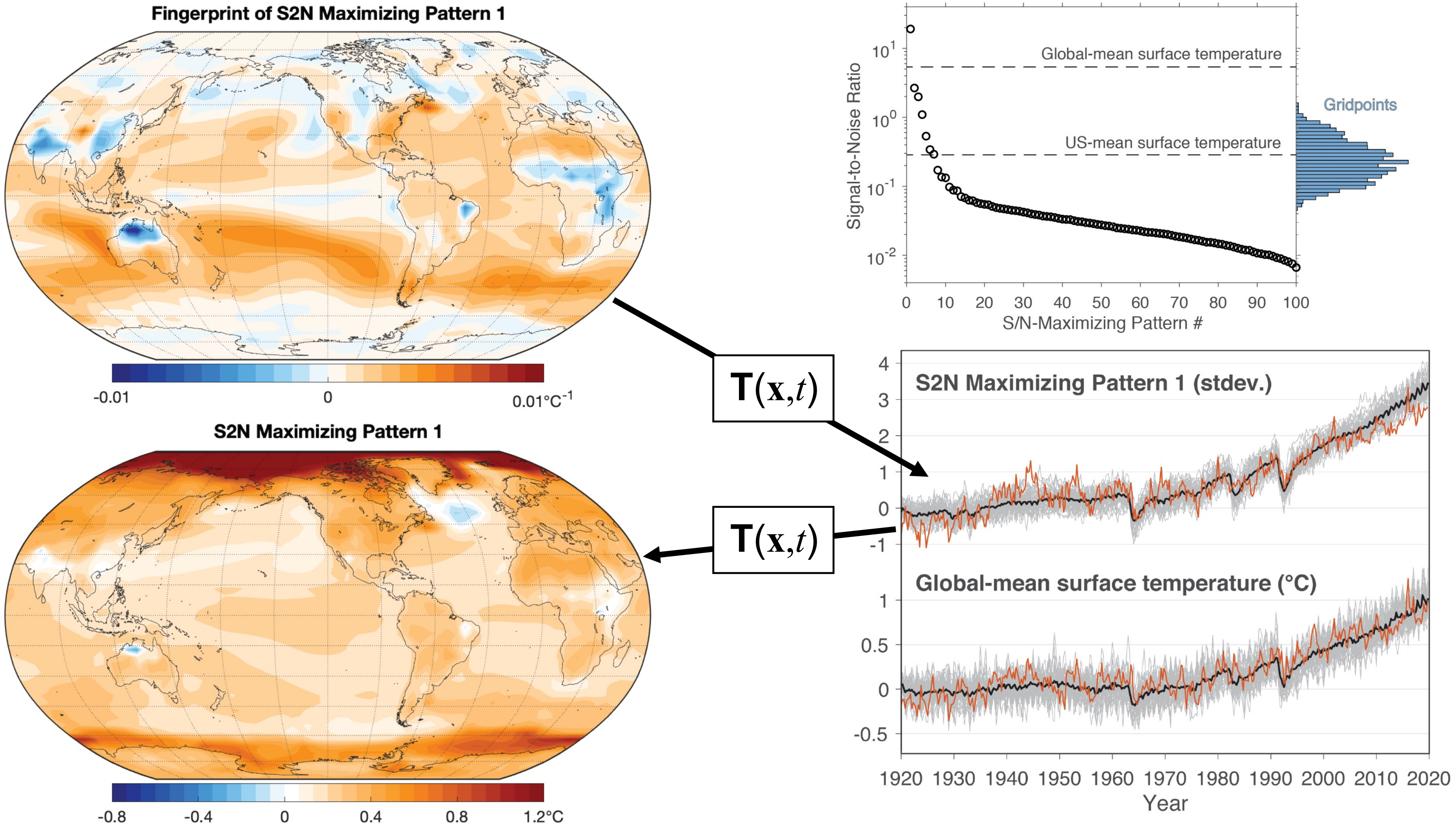
- Large ensembles (CESM-LE in this case) help to quantify the amplitude of the forced signal and of internal variability

- Global-mean surface temperature has a factor of three higher ***signal-to-noise ratio (S/N)*** than any single grid point
- The leading ***S/N-maximizing pattern*** has a S/N ratio that is higher still; an order of magnitude higher than any grid point
- Patterns thus help to separate signal and noise

Wills, Sippel, Barnes (2020, US CLIVAR Variations)

Signal-to-noise maximizing patterns

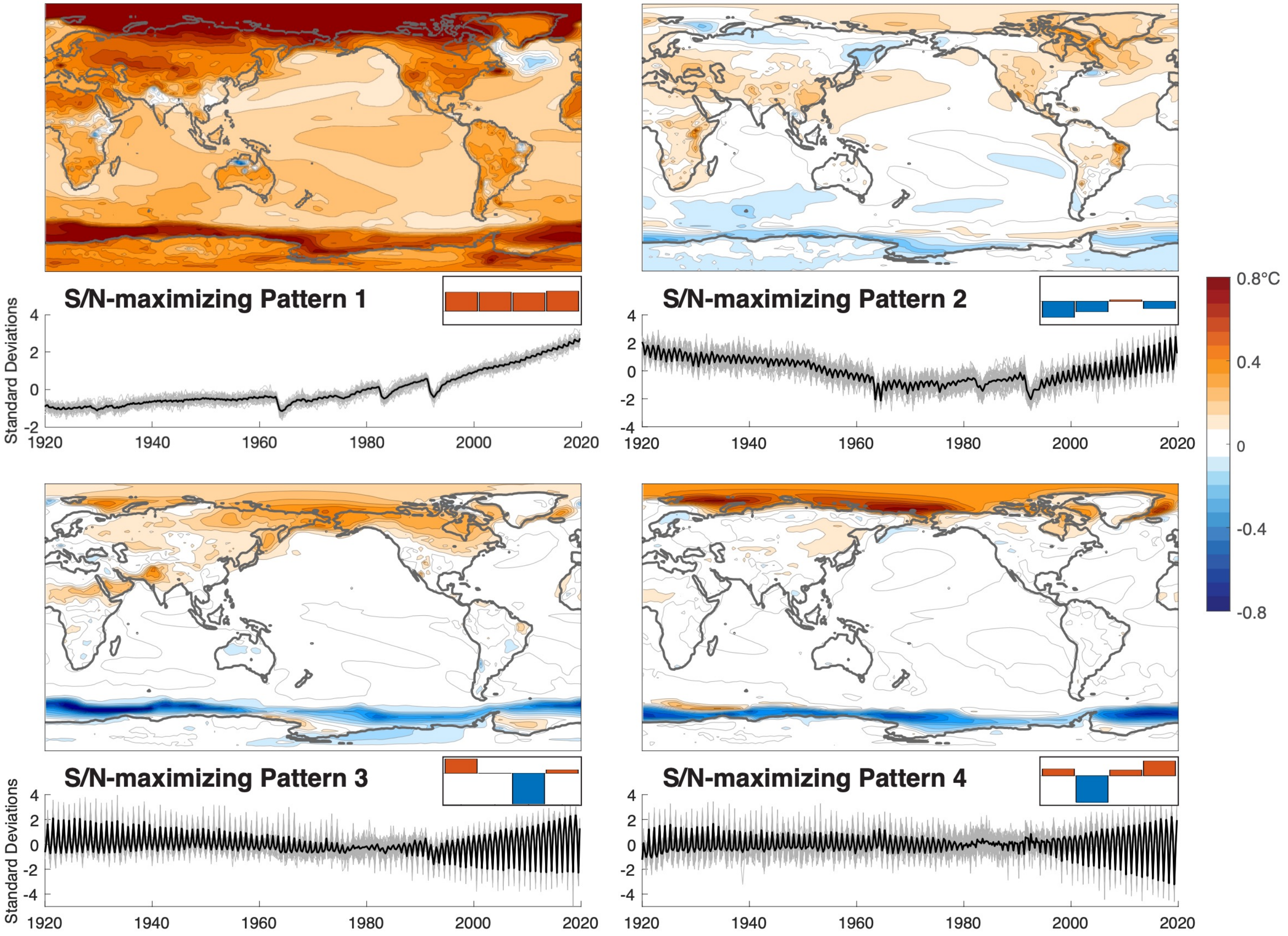
Slides adapted with permission from R. Wills



Wills, Sippel, Barnes (2020, US CLIVAR Variations); Wills et al. (2020; J. Climate); Ting et al. (2009)

Slides adapted with permission from R. Wills

Isolating the forced response with S/N-maximizing pattern filtering

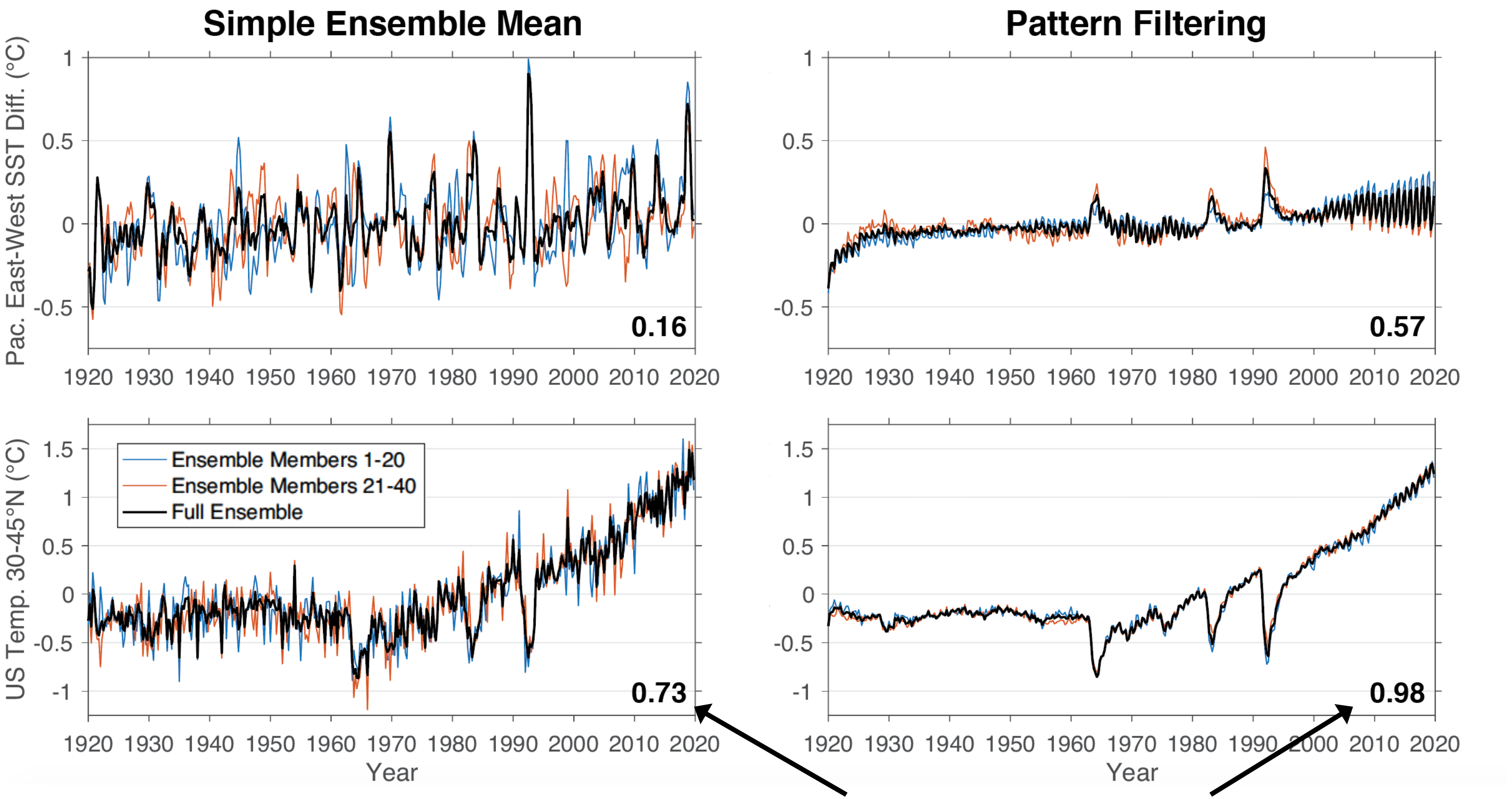


- Construct the spatiotemporally varying forced response by combining all of the S/N-maximizing patterns that are significant (could not have occurred due to random chance)

Wills et al. (2020, J. Climate) – Analysis of CESM Large Ensemble

Testing within large ensembles: S/N-maximizing pattern filtering improves estimate of the forced response estimate

Slides adapted with permission from R. Wills



Correlation² between half ensembles

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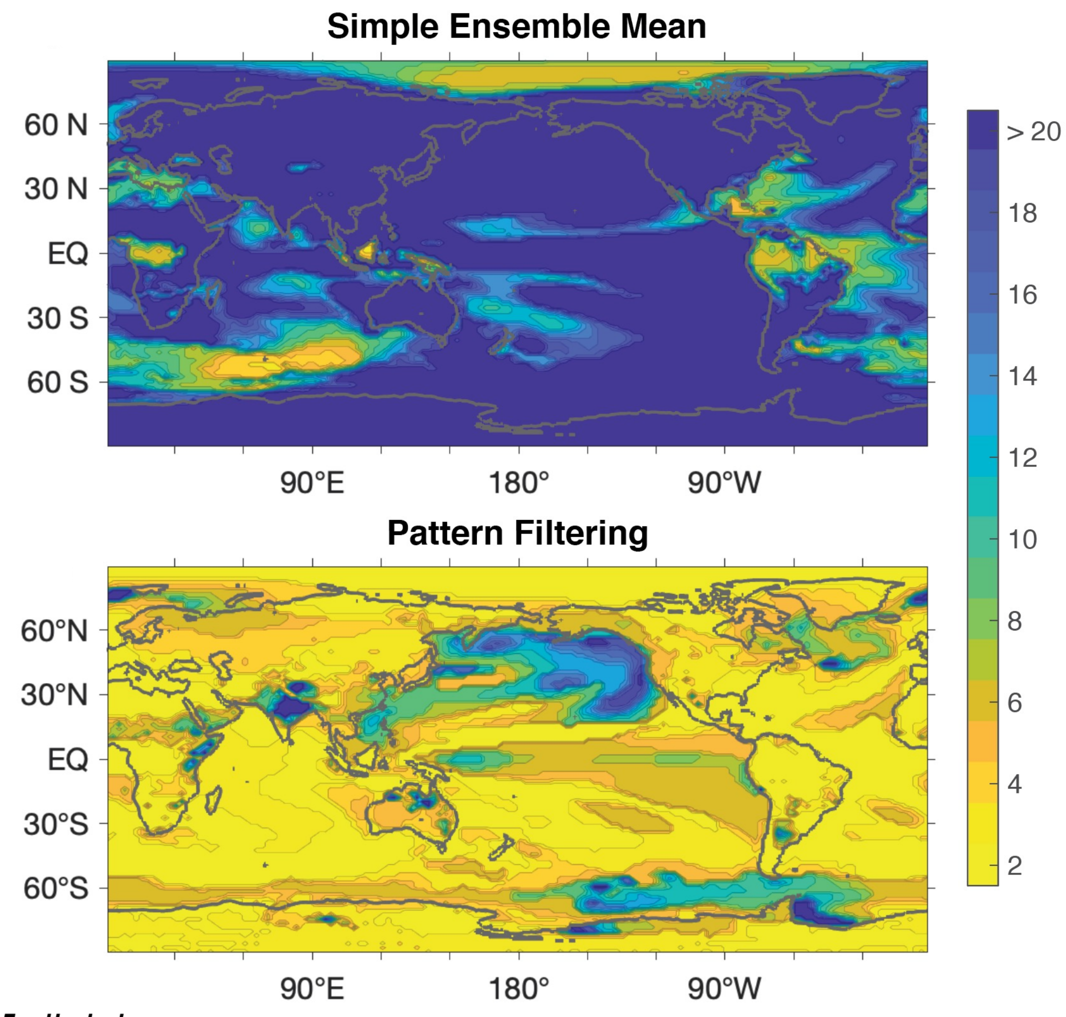
Wills et al. (2020, J. Climate) – Analysis of CESM Large Ensemble

Filtering with S/N-maximizing patterns identifies forced response with fewer ensemble members

Slides adapted with permission from R. Wills

Ensemble members needed to identify forced temperature response (based on 80% correlation²)



Average grid point: 4 (>20)

Pattern Filtering (Simple Ensemble Mean)

Large-Scale Indices:

Global mean: 2 (4)

Based on 95% correlation²

North Atlantic SST: 3 (9)

Pacific SST gradient: 9 (>20)

Based on 30% correlation²

US temperature: 2 (>20)

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Wills et al. (2020, J. Climate) – Analysis of CESM Large Ensemble

Summary: Pattern recognition to extract forced patterns

- S/N maximizing pattern filtering is a technique to extract patterns of the forced response in large ensembles, using pattern recognition techniques.

- Can be very helpful to understand structural uncertainties across models.

- Extensions exist to apply a similar technique, "low-frequency component analysis" to observations (with the criterion to filter for low-frequency patterns). See *Schneider & Held* (2001) *and* Wills et al. (2020) *Journal of Climate*.

- Pattern filtering techniques and dynamical adjustment aim both to extract different forced/unforced or dynamical/thermodynamical components, and thus differ in the assumptions (time scale separation, relative influence of atmopheric circulation).

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Statistical and machine learning to extract the forced response

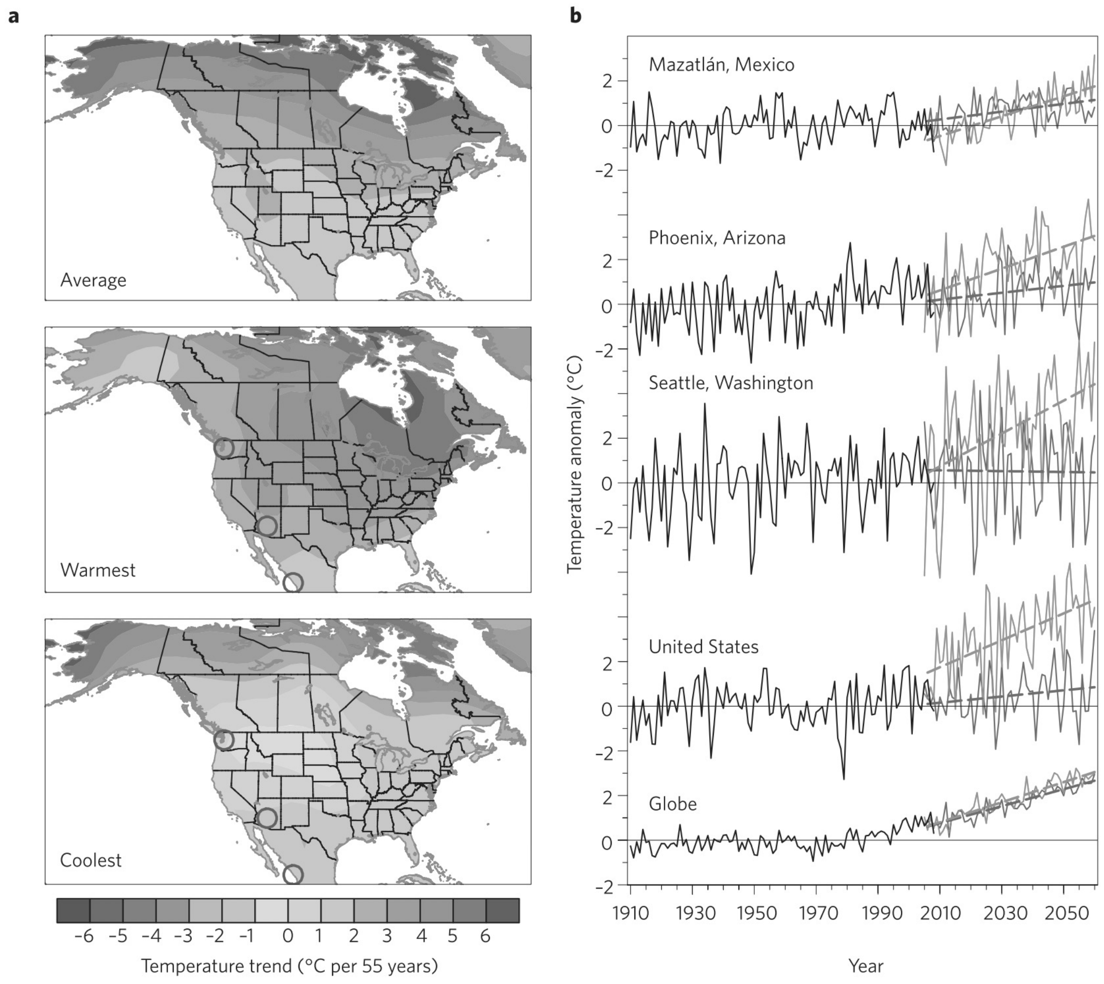


Figure 1 | Range of future climate outcomes. a, December–January–February (DJF) temperature trends during 2005–2060.

Deser et al., 2012, *Nat. Clim. Change*

Statistical and machine learning to extract the forced response

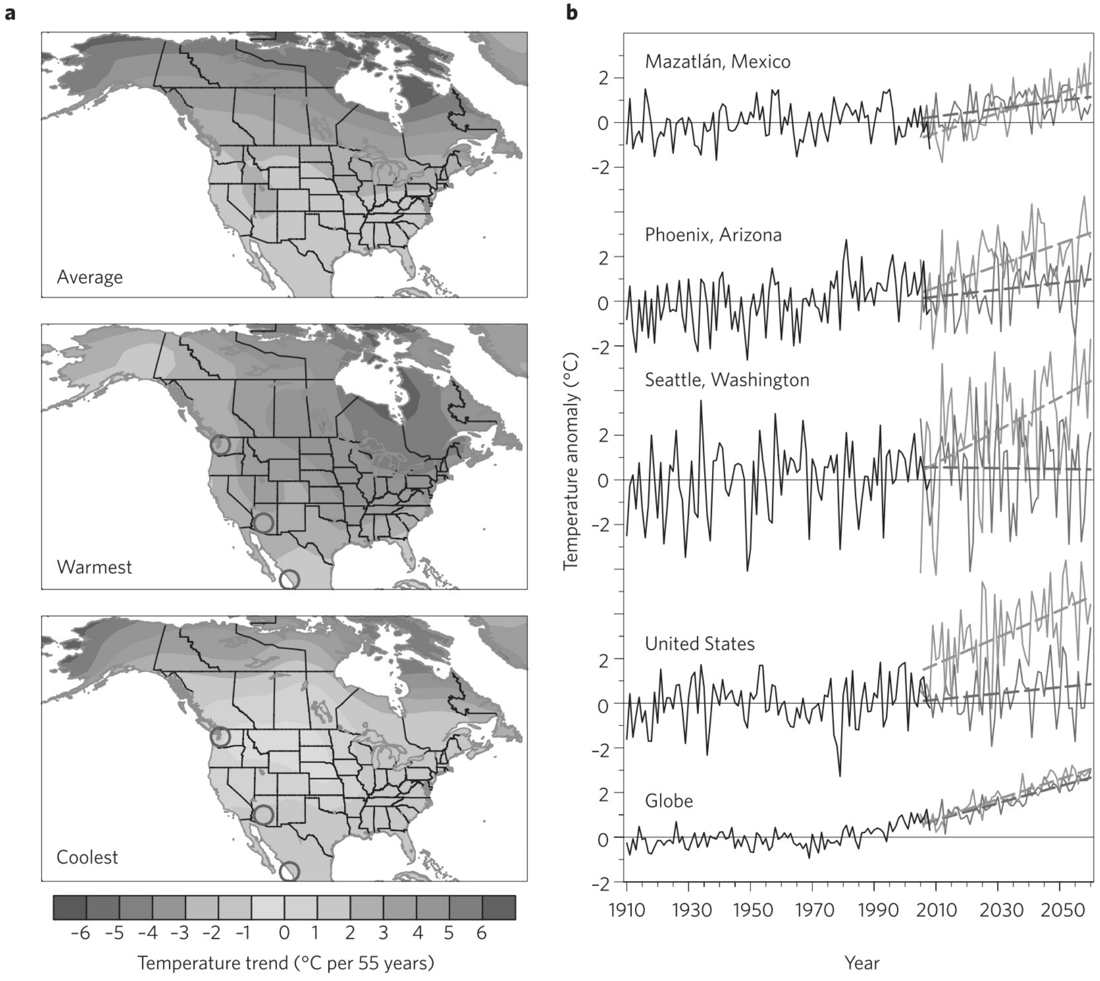
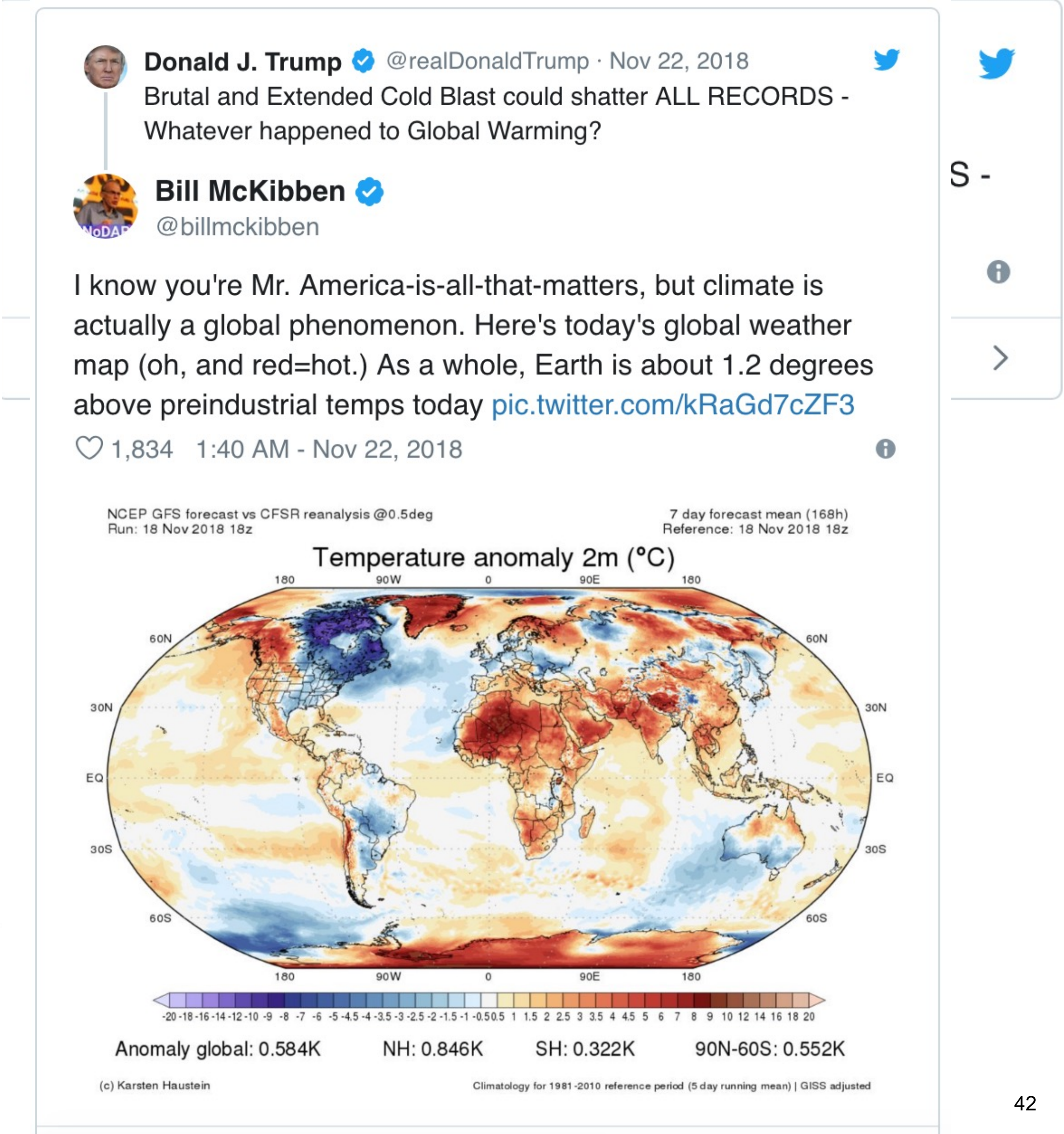
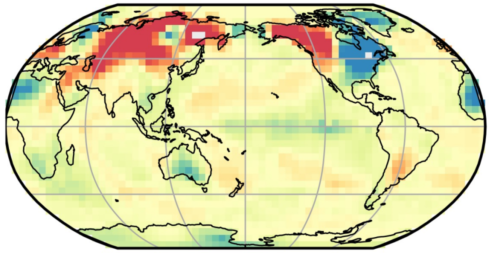


Figure 1 | Range of future climate outcomes. a, December–January–February (DJF) temperature trends during 2005–2060.

Deser et al., 2012, *Nat. Clim. Change*

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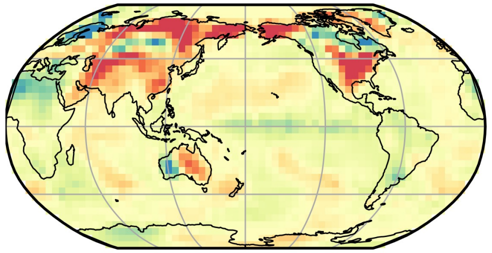
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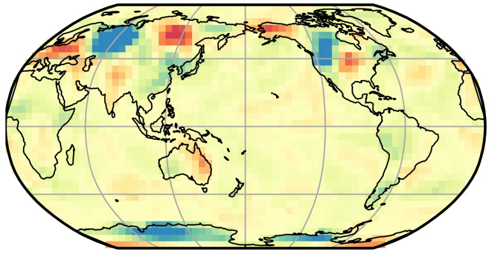
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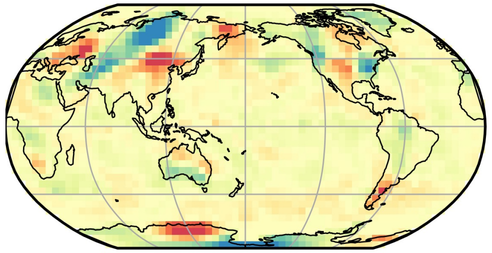
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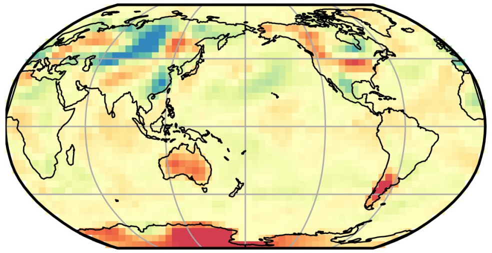
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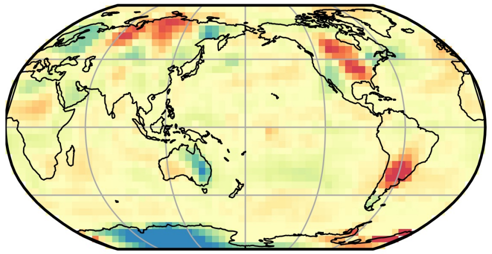
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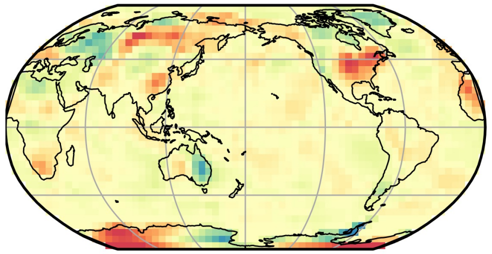
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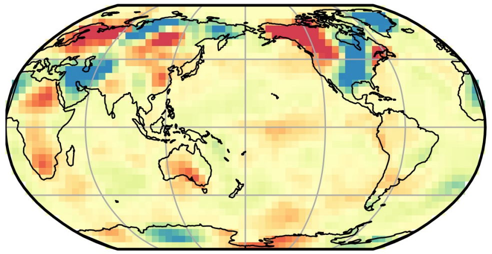
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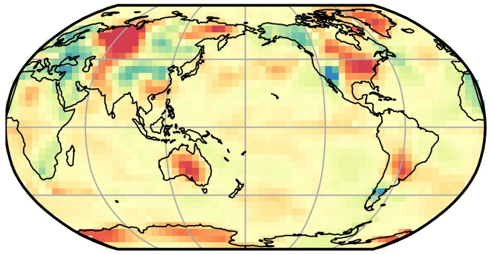
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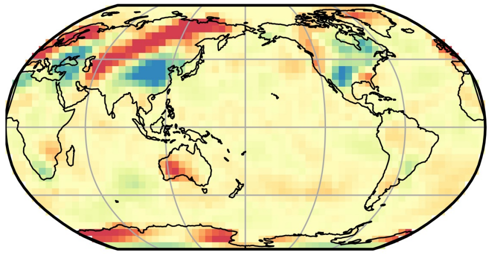
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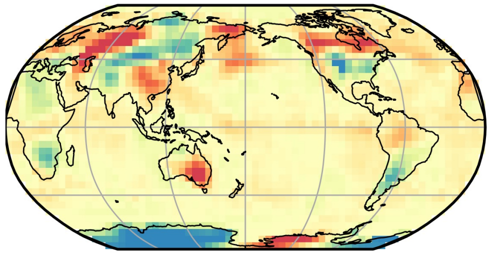
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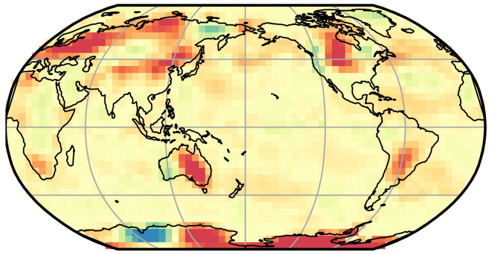
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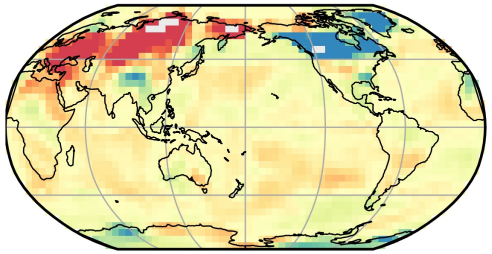
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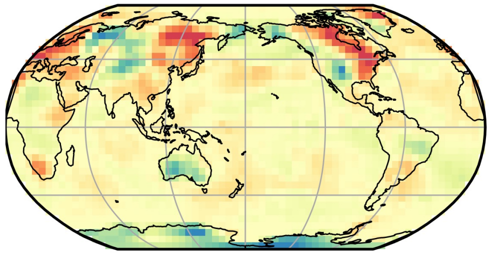
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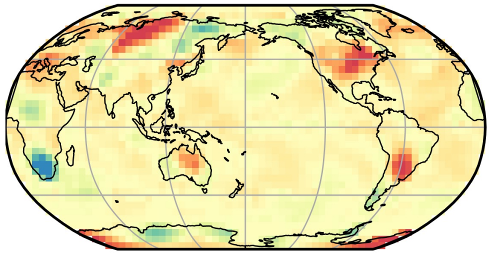
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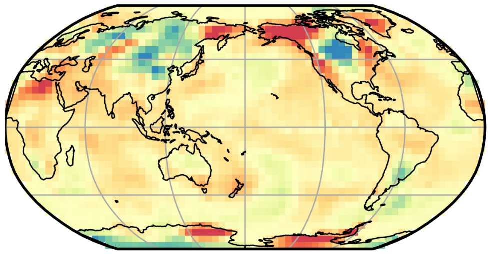
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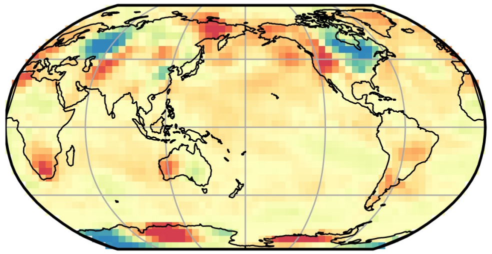
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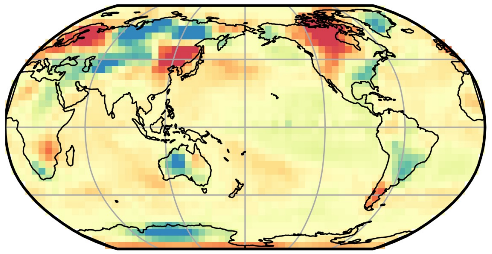
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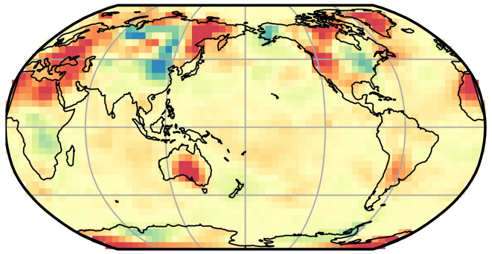
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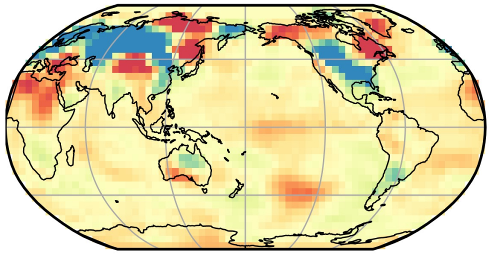
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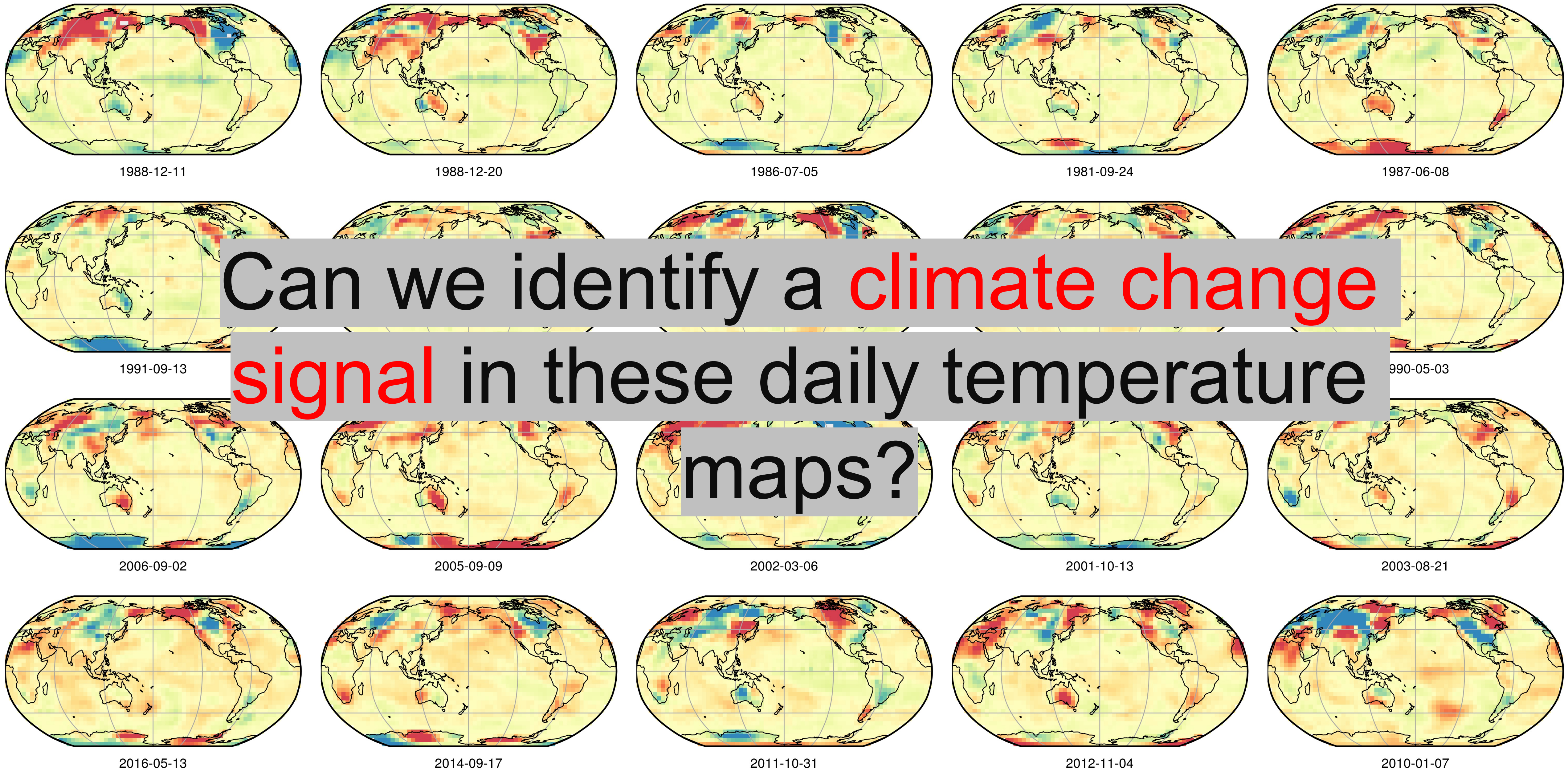

Can we identify a climate change signal in these daily temperature maps?

Detection method

1. Learn „fingerprint“ (β) from climate model simulations

X = daily pattern of temperature

Y = climate change proxy (annual global mean temperature)

Regularized linear model: $Y = X\beta + \varepsilon$

$$\hat{\beta} = \mathrm{argmin}_\beta\ \mathbb{E}_{(x,y)\sim P}[l(y, f_\beta(x))]$$
$$= \mathrm{argmin}_\beta\ \| Y - X\beta \|_2^2 + \lambda \| \beta \|_2^2$$
$$\hat{y} = f_\beta(x)$$

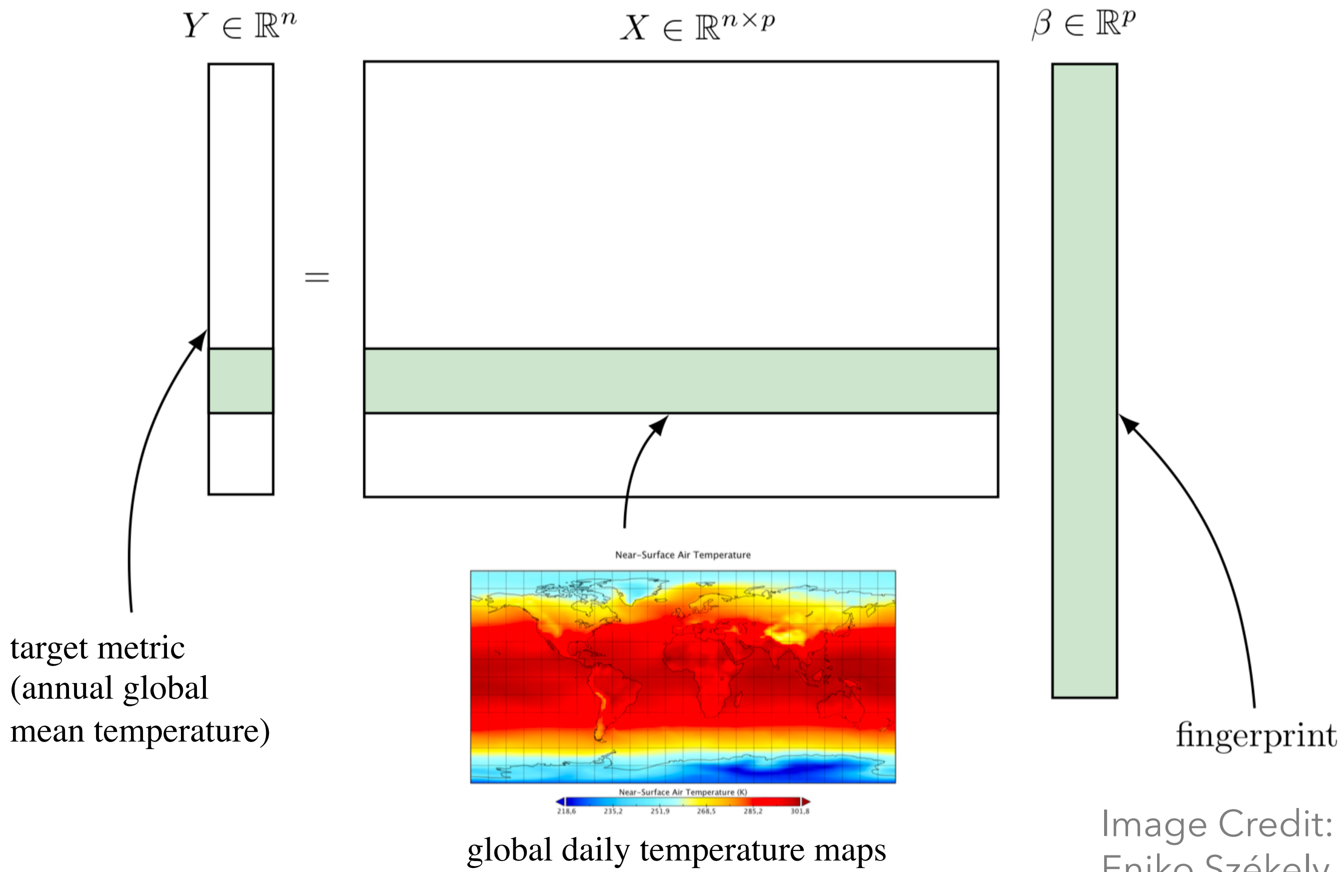

Image Credit: Eniko Székely

Szekely et al., 2019, *Climate Informatics*. `doi:10.5065/y82j-f154`

Sippel et al., 2020, *Nature Climate Change*. `doi:10.1038/s41558-019-0666-7`

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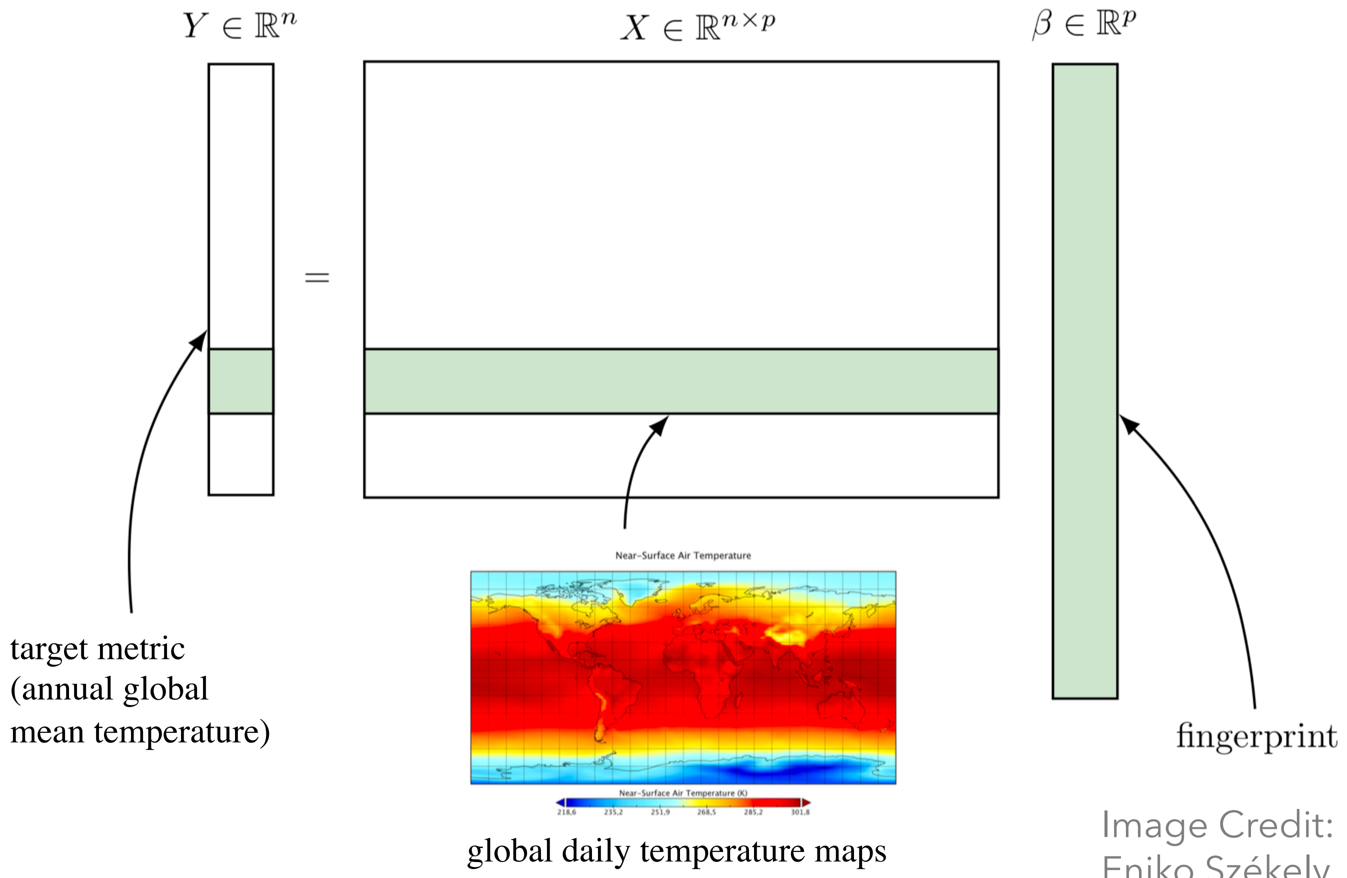
2. Project observations onto fingerprint to obtain climate change test statistic



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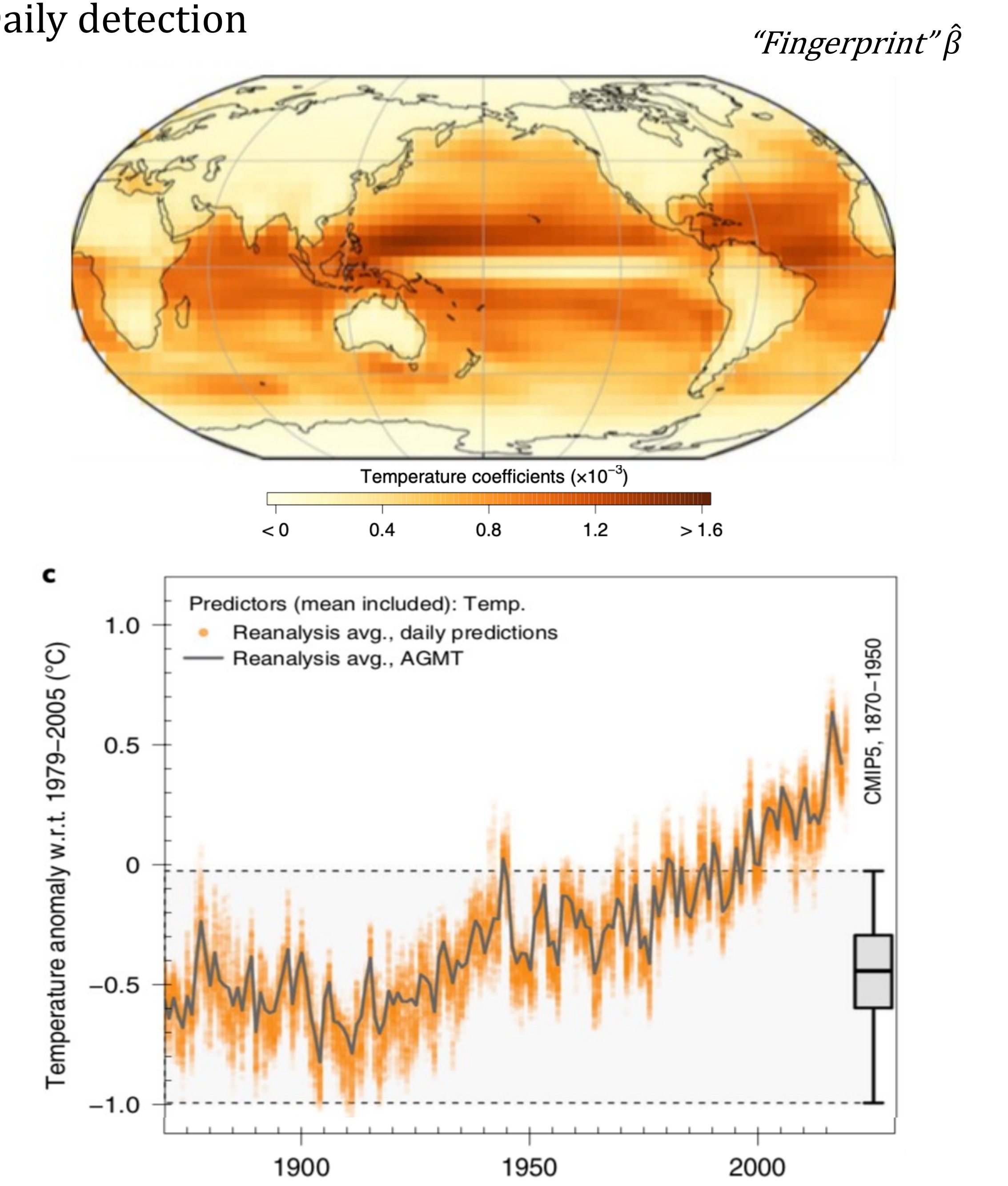
Daily detection



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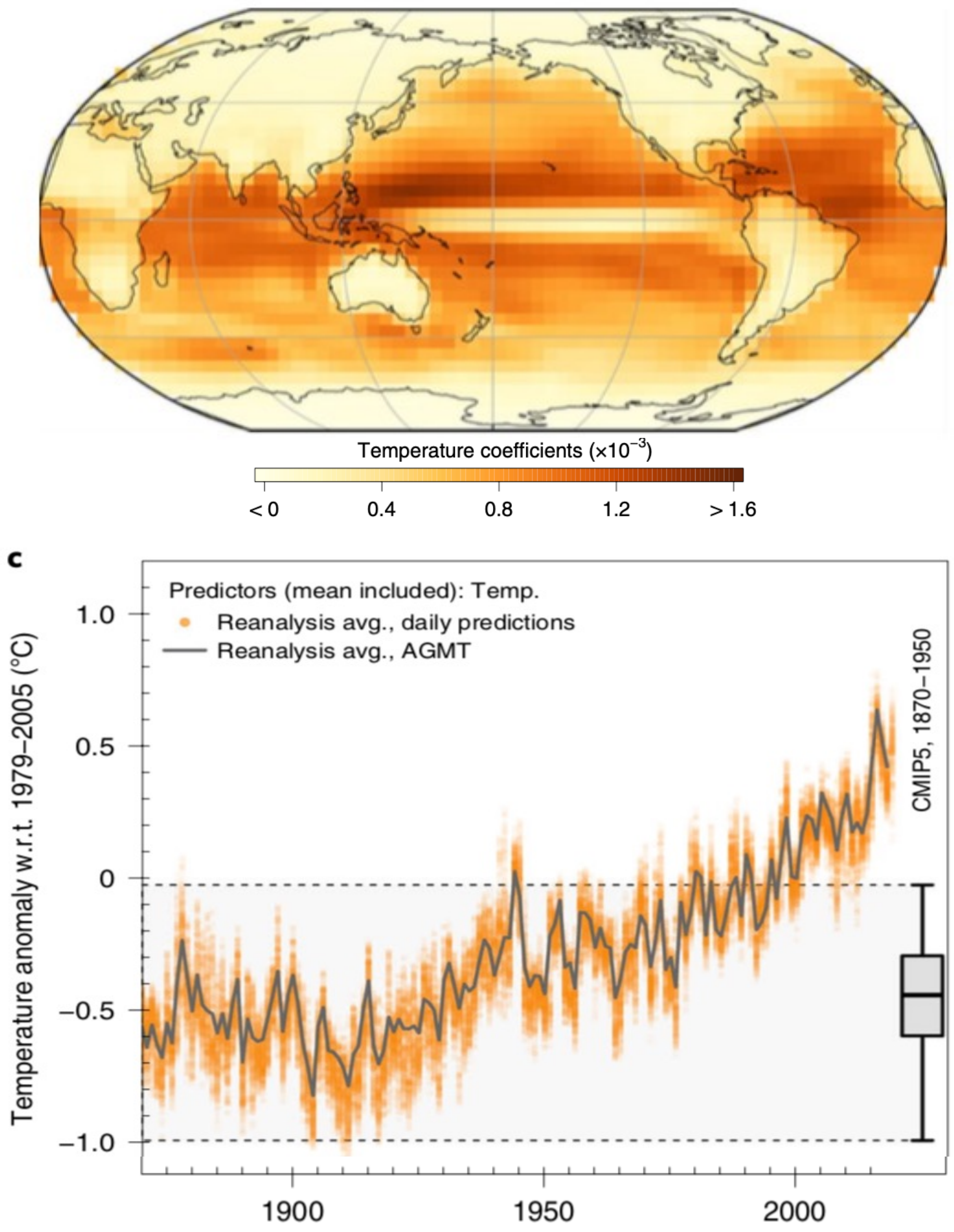
Daily detection

“Fingerprint” $\hat{\beta}$



Summary: Statistical and machine learning to extract the forced response

- Statistical learning based detection and attribution of global climate change reveals the fingerprint of change
- Approach allows interpretation of short-term climate signals. Provides a link between "traditional" attribution and event attribution

Summary: Statistical and machine learning to extract the forced response

- Statistical learning based detection and attribution of global climate change reveals the fingerprint of change
- Approach allows interpretation of short-term climate signals. Provides a link between "traditional" attribution and event attribution
- Neural networks are being used in addition to linear pattern recognition/stat. learning methods to identify estimates/proxies of the forced response (Barnes et al. 2019, 2020)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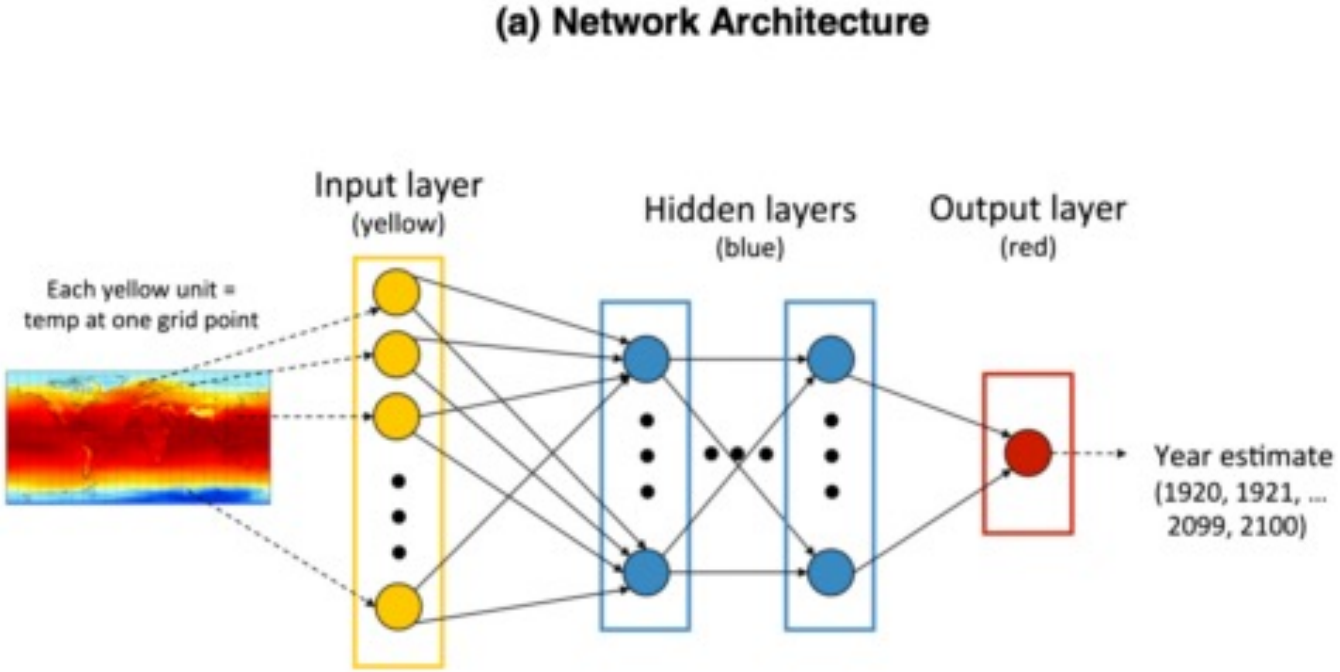
Viewing Forced Climate Patterns Through an AI Lens

Elizabeth A. Barnes[1], James W. Hurrell[1], Imme Ebert-Uphoff[2,3], Chuck Anderson[4,5], and David Anderson[5]

[1]Department of Atmospheric Science, Colorado State University, Fort Collins, CO, USA, [2]Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, CO, USA, [3]Department of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO, USA, [4]Department of Computer Science, Colorado State University, Fort Collins, CO, USA, [5]Pattern Exploration LLC, Fort Collins, CO, USA

Key Points:
- Neural networks can identify forced patterns of surface temperature and precipitation amidst climate noise and model disagreement
- These "indicator patterns" of forced change are present in the



Topics Covered in “Trend attribution” – Overview lecture

1. Introduction
   (1) Large-scale changes in the Earth system and IPCC statements
   (2) The issue of cause and effect (and why correlation is *not* attribution)
   (3) Earth’s energy budget and imbalance
2. Forced Signal vs. internal variability
3. Concepts and logic of detection & attribution
4. Fingerprinting
   (1) Non-optimal fingerprinting
   (2) Optimal fingerprinting
5. Non-standard approaches
   (1) Dynamical adjustment: Dynamical vs. thermodynamical trends
   (2) Signal/Noise maximizing pattern filtering
   (3) Statistical and machine learning to extract the forced response

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Thank you very much for the attention!!