Organisationseinheit verbal
optional auf 2 Zeilen

Dynamical adjustment and distributional robustness for D&A

Sebastian Sippel
XAIDA summer school
ICTP, Trieste

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement 101003469.

Agenda

1. Introduction: Internal variability vs. forced response
2. Understanding circulation-induced components or recent change
3. Robust detection of forced warming in the presence of potentially large climate variability
4. Conclusions

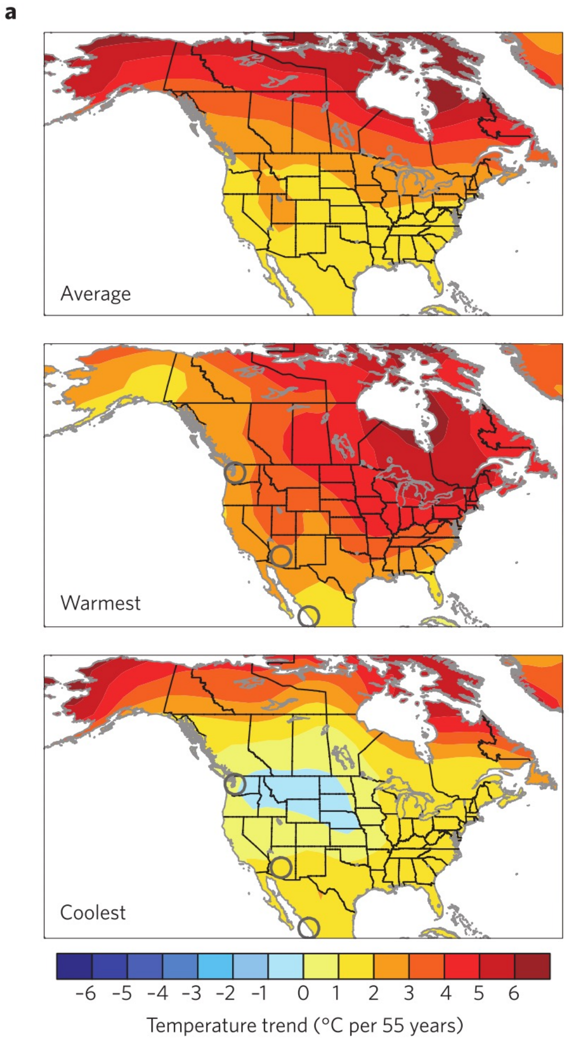

Figure 1 | Range of future climate outcomes. a, December–Jan

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

- Internal variability fundamentally limits climate projections

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

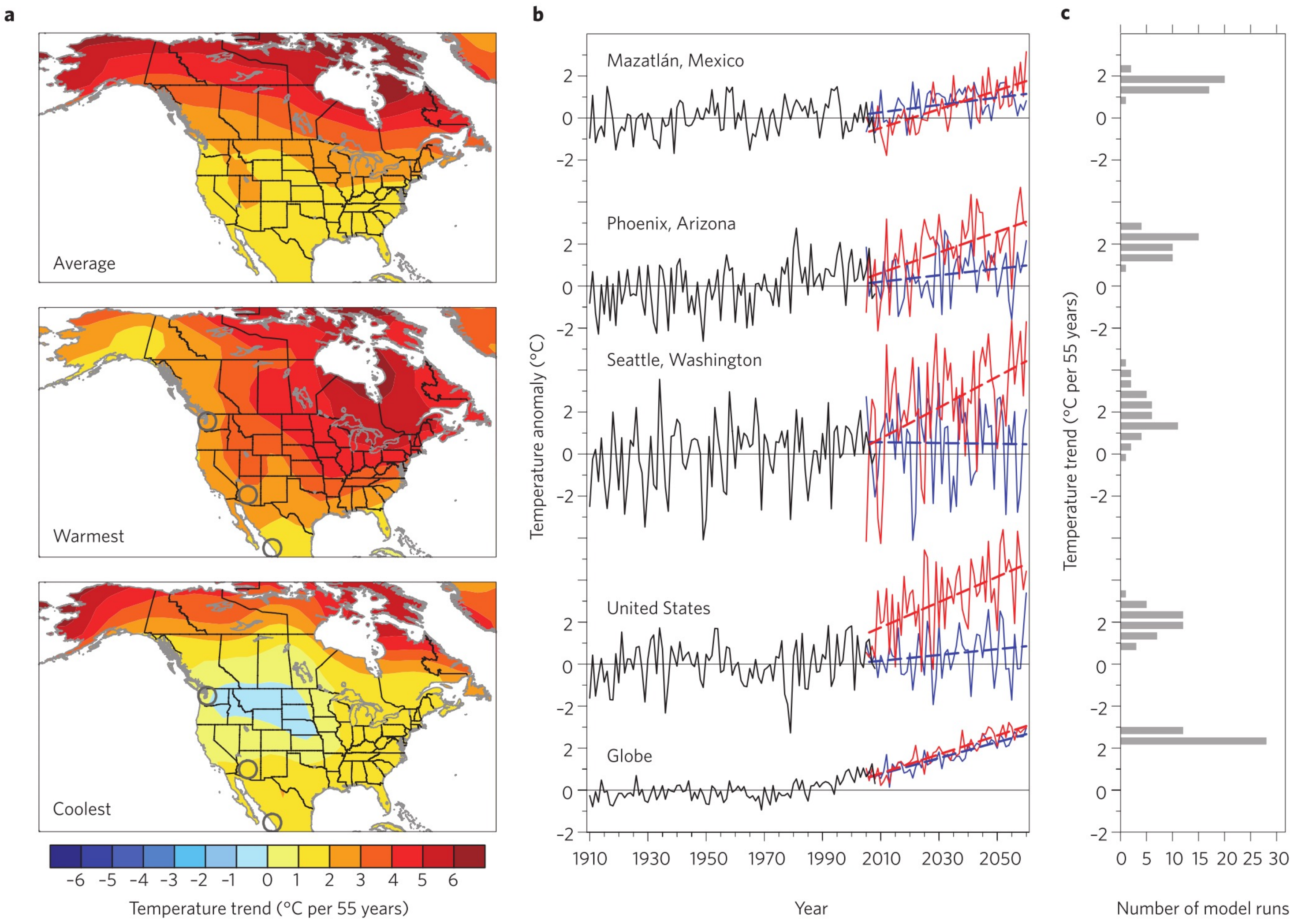

Figure 1 | Range of future climate outcomes. a, December–January–February (DJF) temperature trends during 2005–2060. Top panel shows the average

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

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- Strong implications for interpretation of regional climate trends

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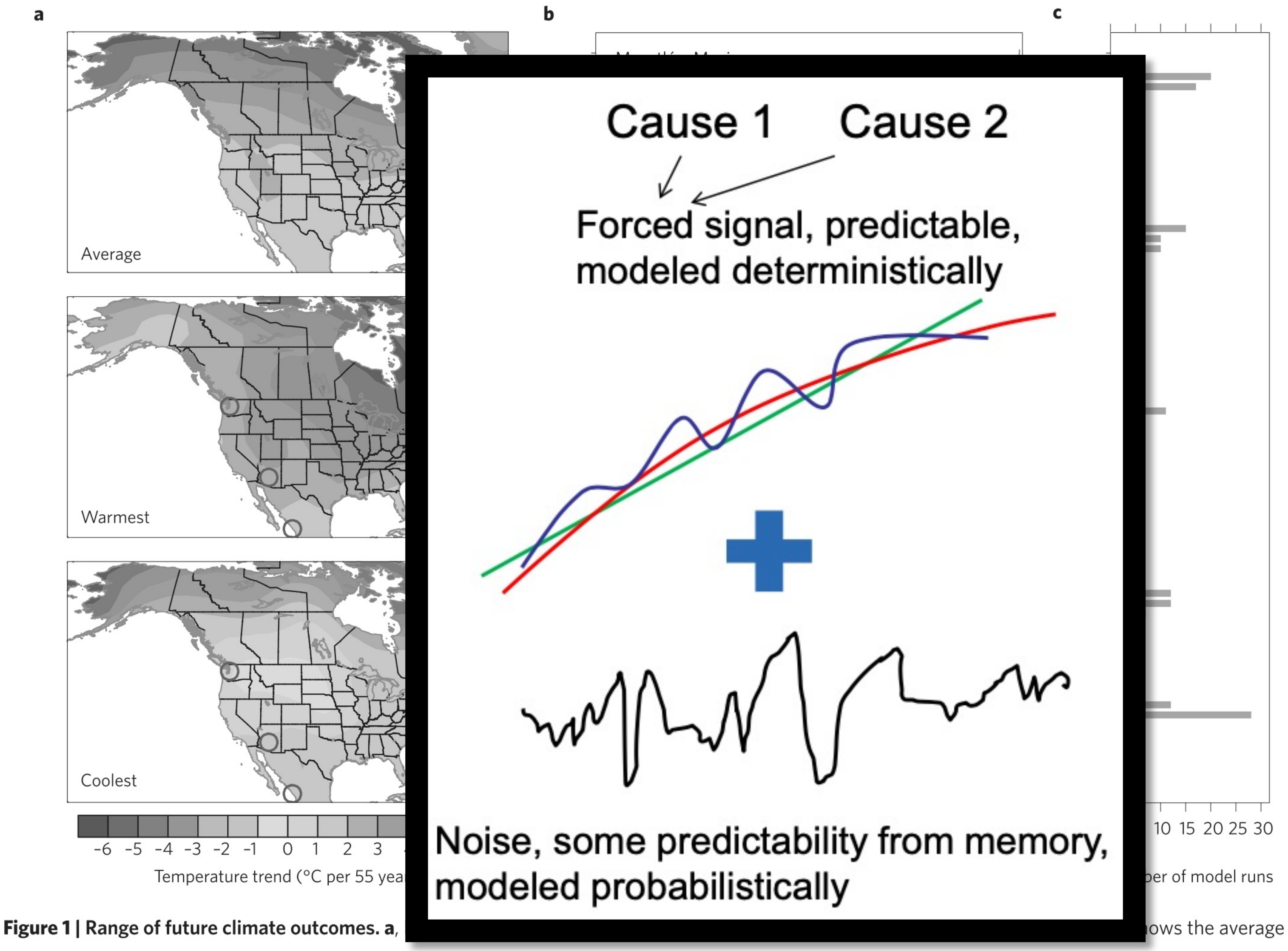

Figure 1 | Range of future climate outcomes. a, ... ows the average

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

Figure Credit: Reto Knutti.

- Internal variability: internal climate variation over time and space
- Forced response: Component that is externally forced (e.g. Solar forcing, Aerosols, GHGs)

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

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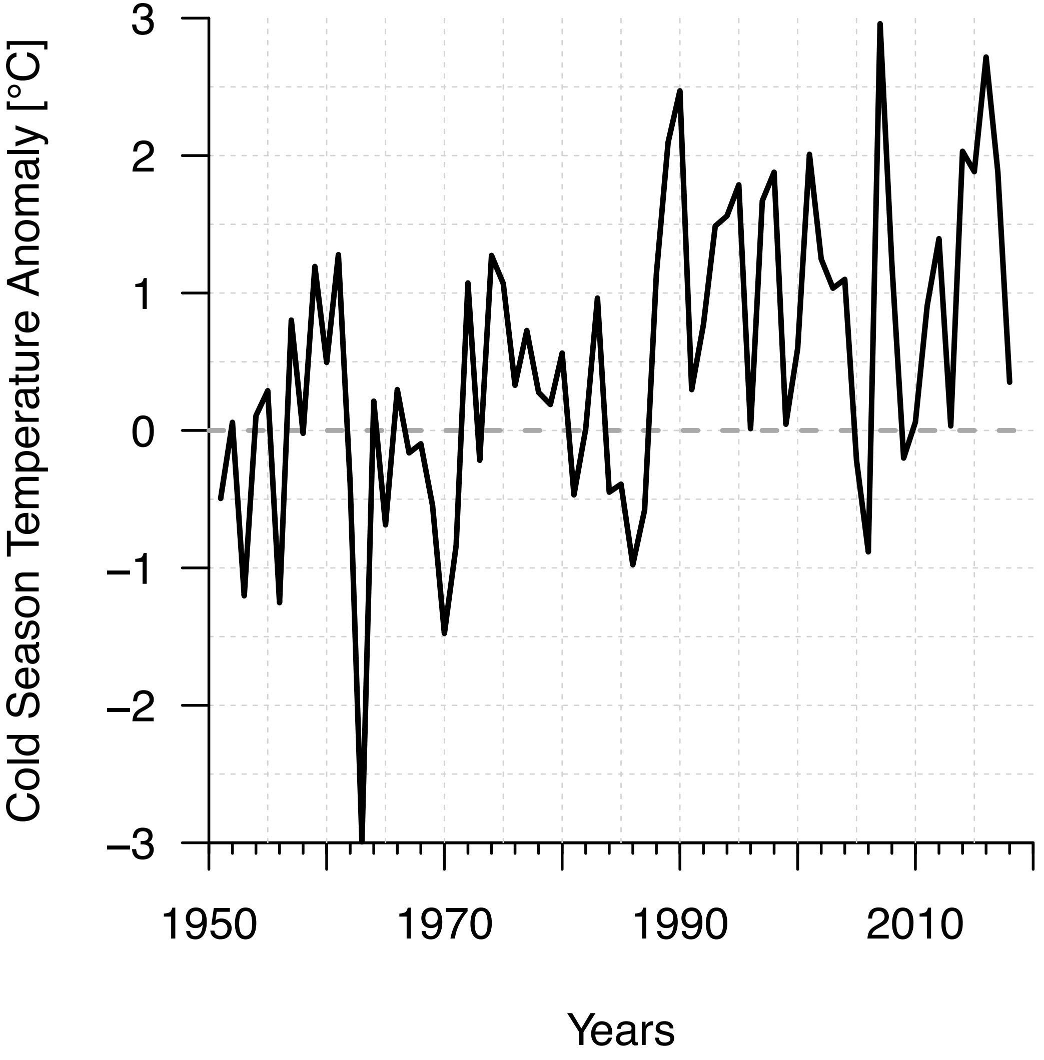
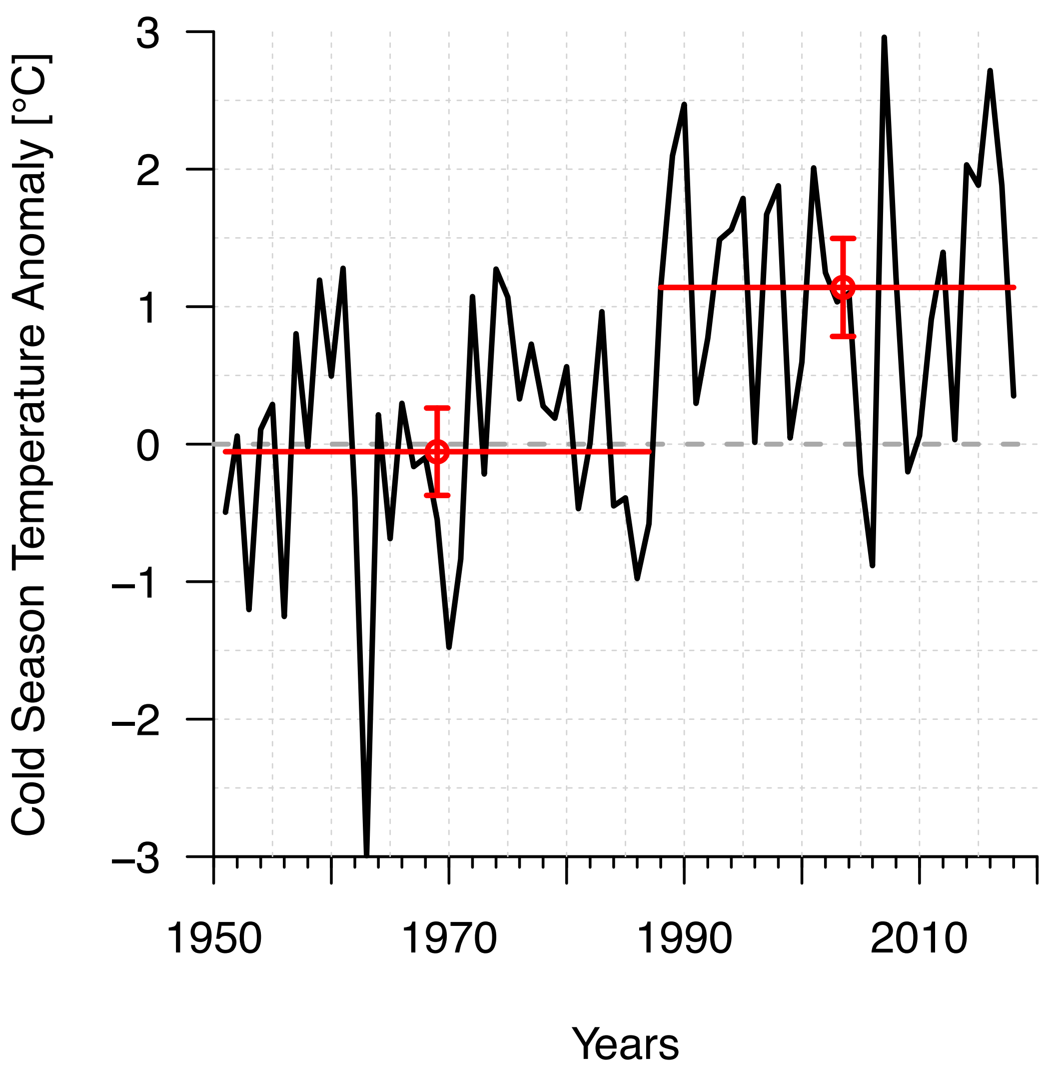
Understanding abrupt winter climate change in Switzerland



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.

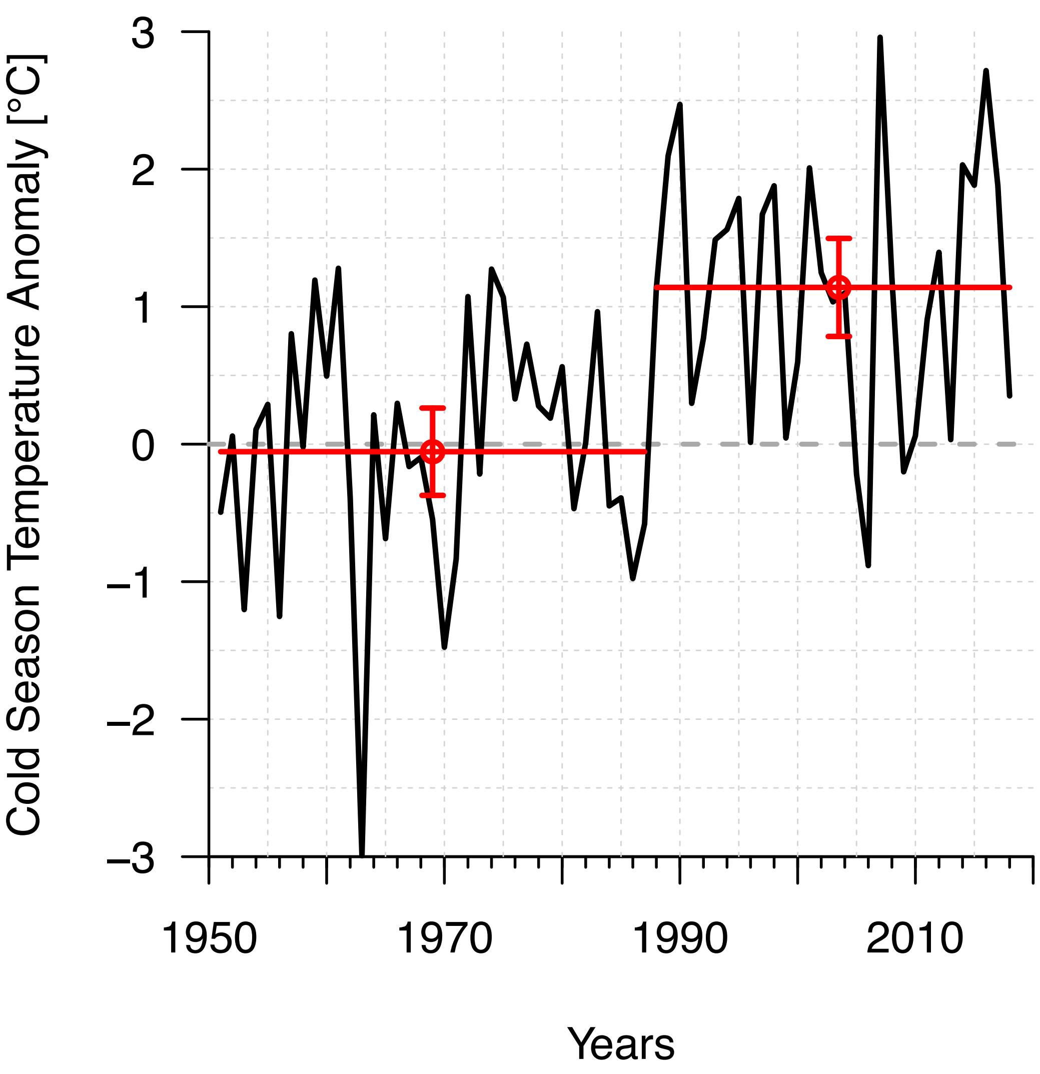
[1] The number of days with a snow depth above a [3] This work

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

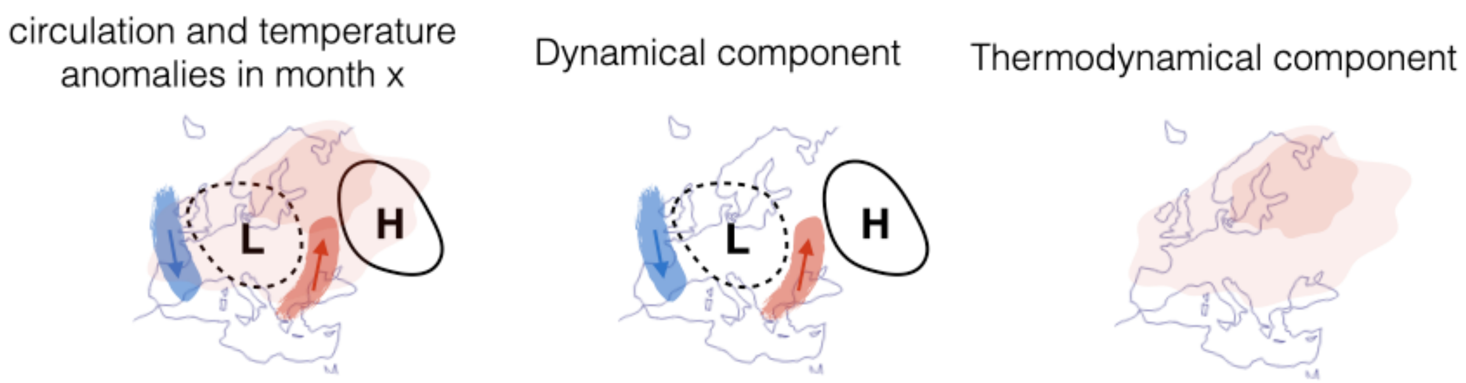


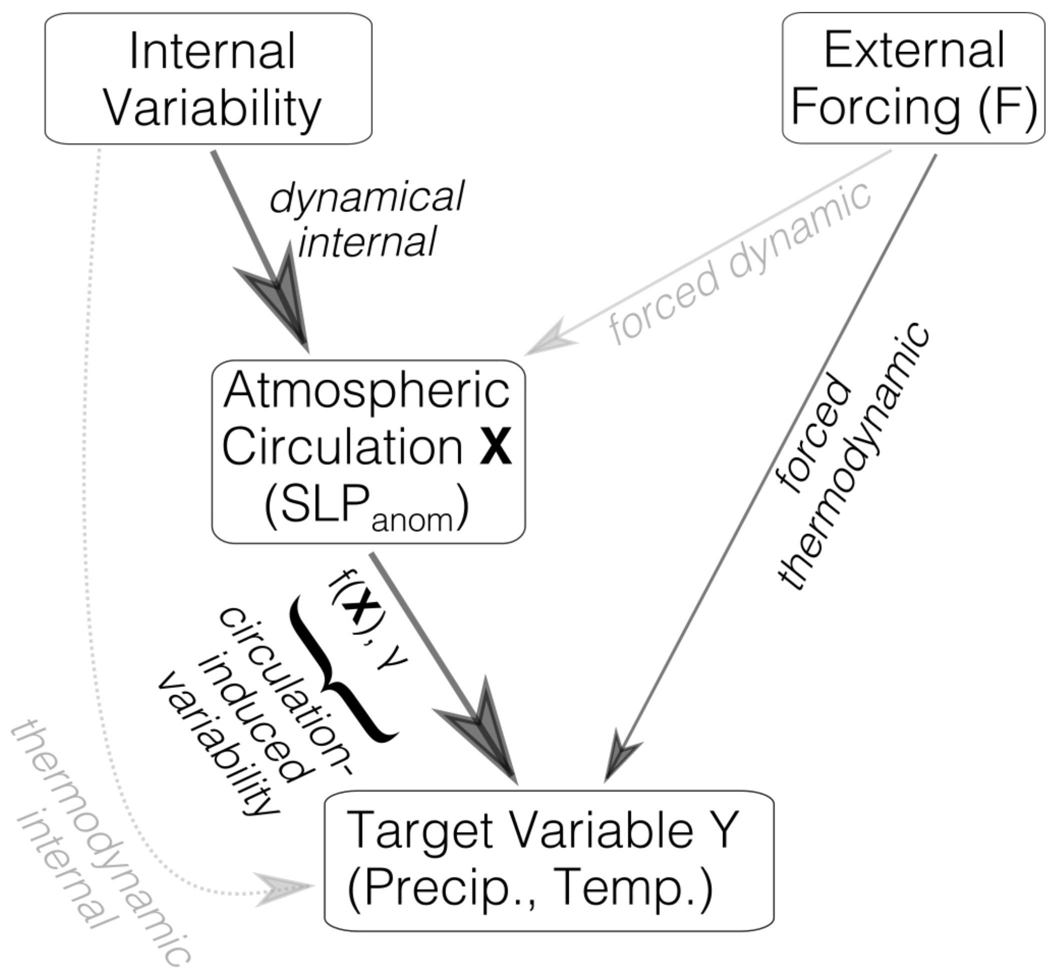
Figure Courtesy: Dr. Anna Merrifield

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

- Dynamical adjustment: extraction of regional climate signals using circulation information

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

Dynamical adjustment



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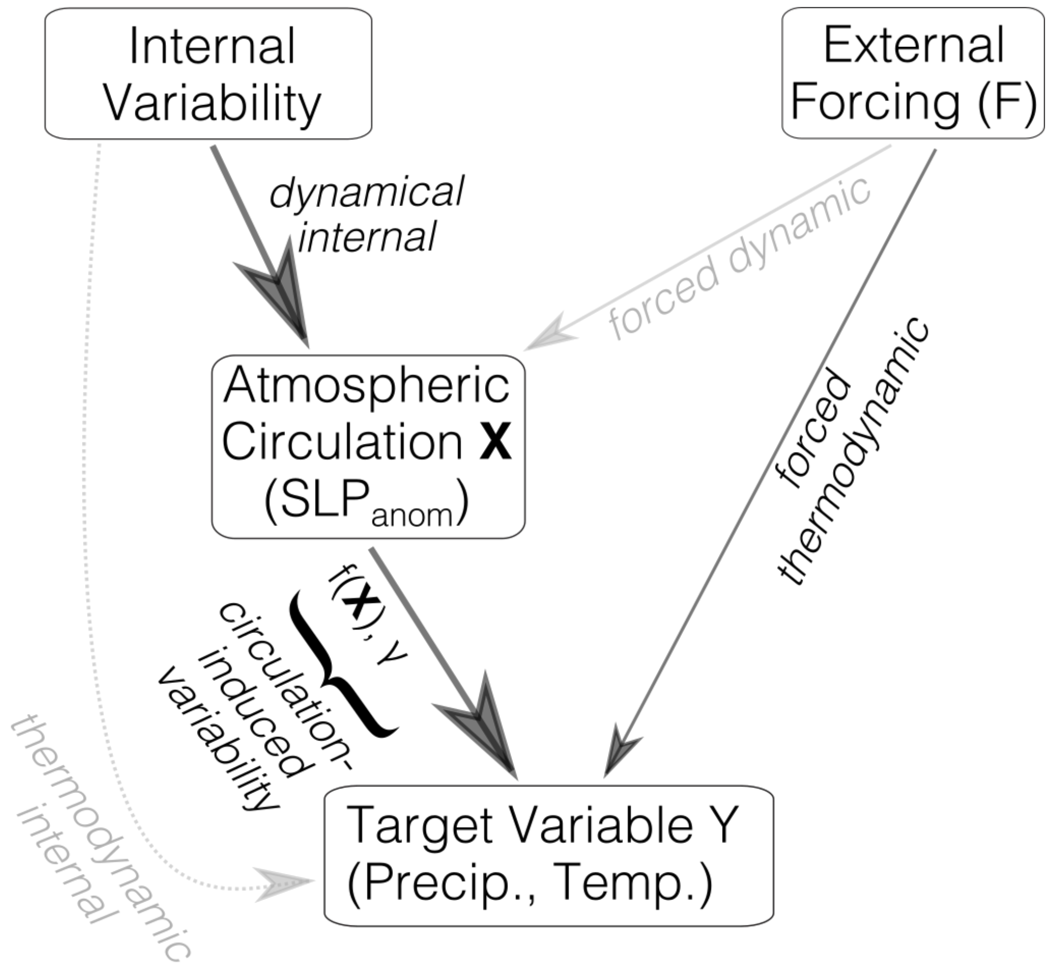


Statistical model: Regularized linear regression

$$\hat{Y}_{\mathbf{X}} = \hat{f}(\mathbf{X}) \quad \underbrace{\approx \mathbf{X}\hat{\gamma}}_{\text{linear approximation}}$$

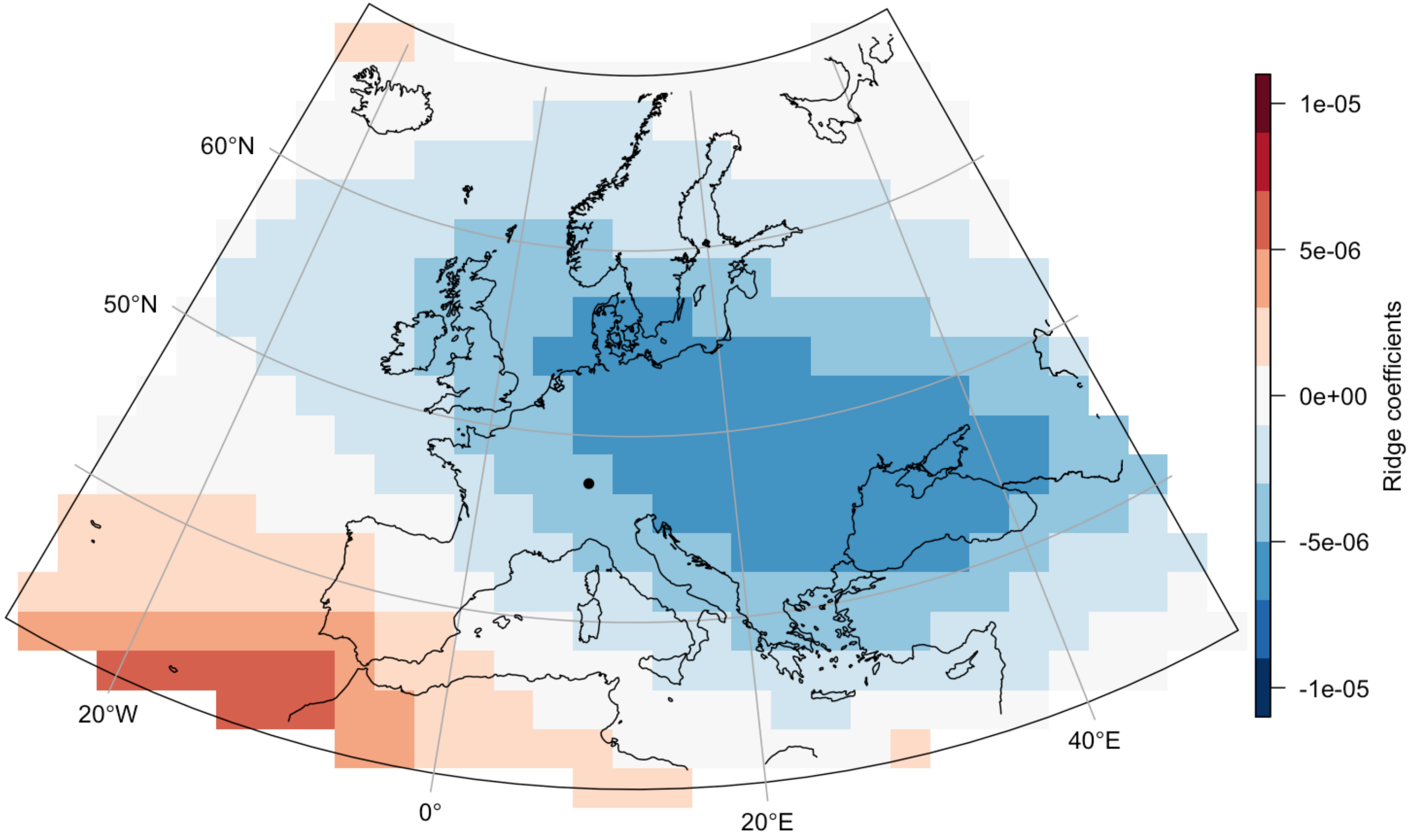
$$\underbrace{\hat{R} = Y - \hat{Y}_{\mathbf{X}}}_{\text{Stat. Inference}}$$

$$\hat{\gamma}^{OLS} = \underset{\gamma}{\text{argmin}}\{RSS\}$$

$$\hat{\gamma}^{\text{elastic-net}} = \underset{\gamma}{\text{argmin}}\{RSS + \lambda \sum_{j=1}^{p}((1-\alpha)\gamma_j^2 + \alpha|\gamma_j|)\}$$

Hastie et al. (2009) Elements of statistical learning.

Dynamical adjustment

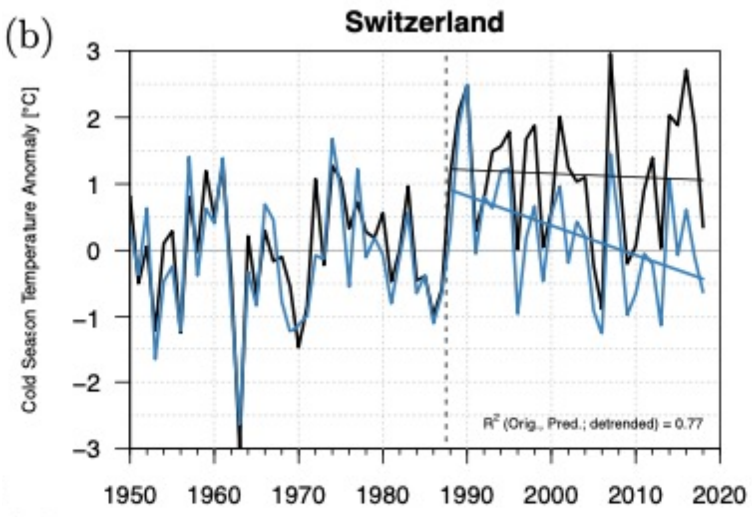


- Internal variability fundamentally limits climate projections
- Strong implications for interpretation of regional climate trends

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

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

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.

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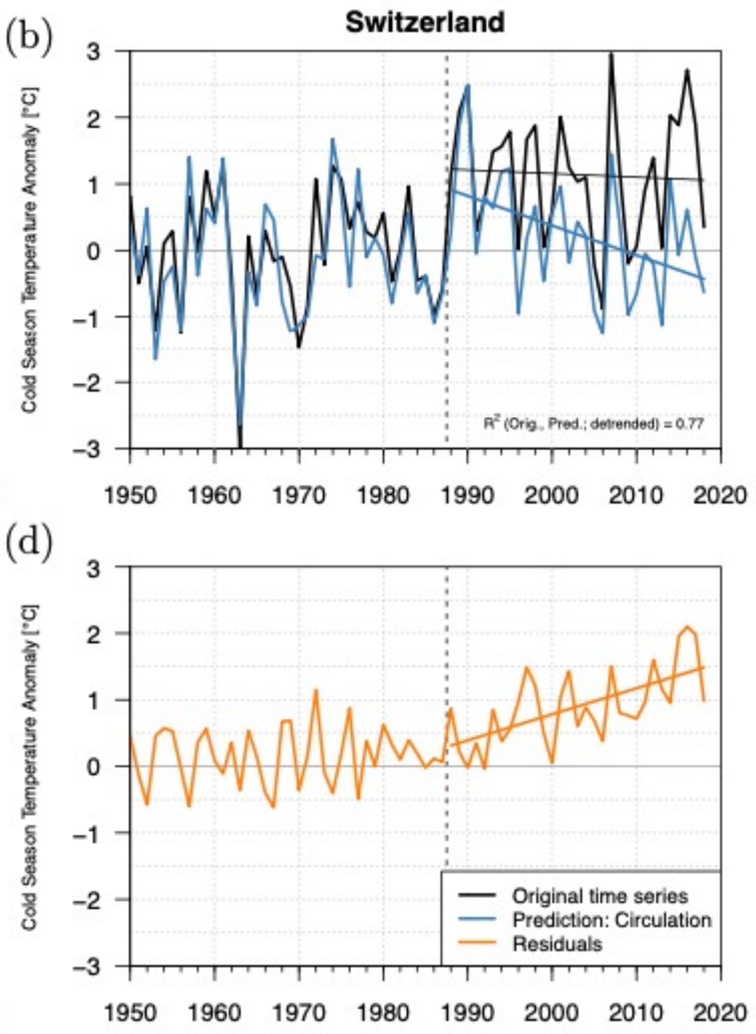
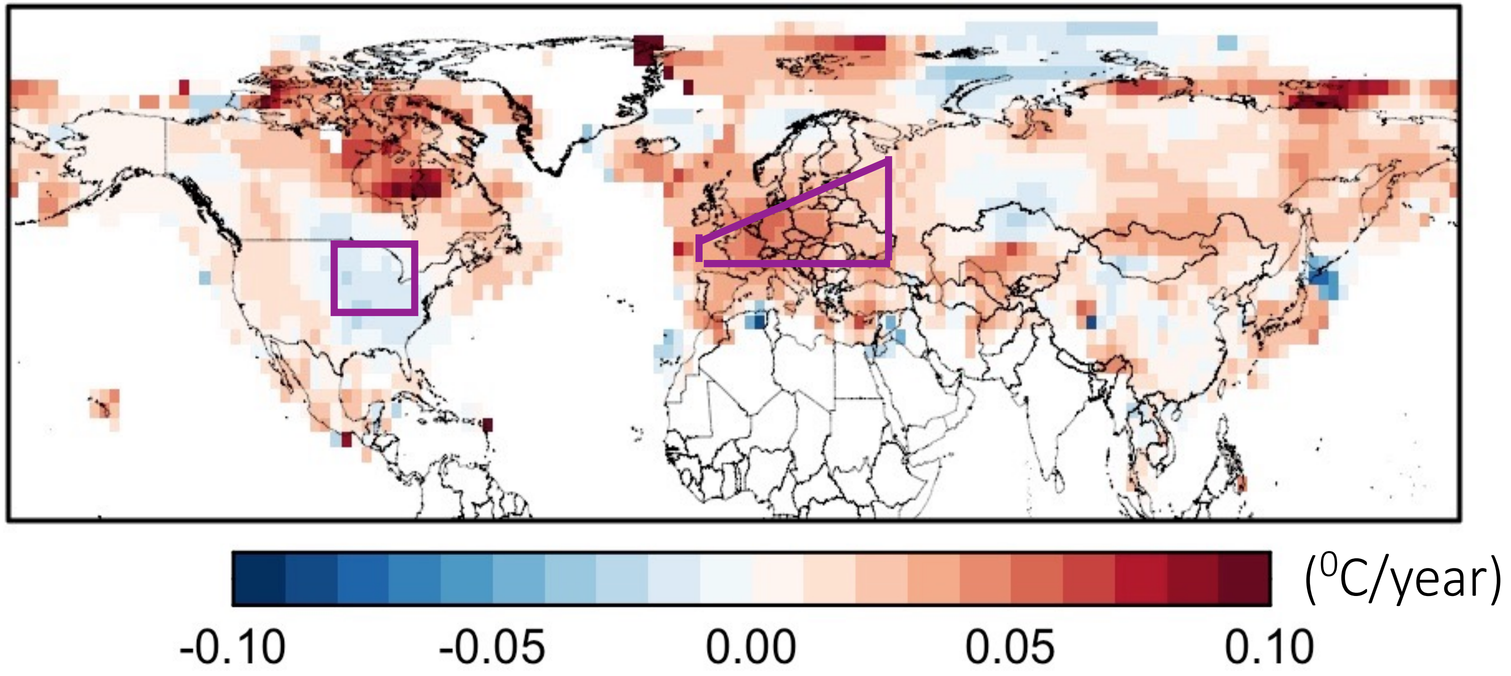


- At regional scales, circulation-induced variability explains a large fraction of temperature variability
- Residuals of circulation-induced variability reveal a smooth (thermodynamical) signal of change

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

Understanding dynamical and thermodynamical drivers of extreme event trends

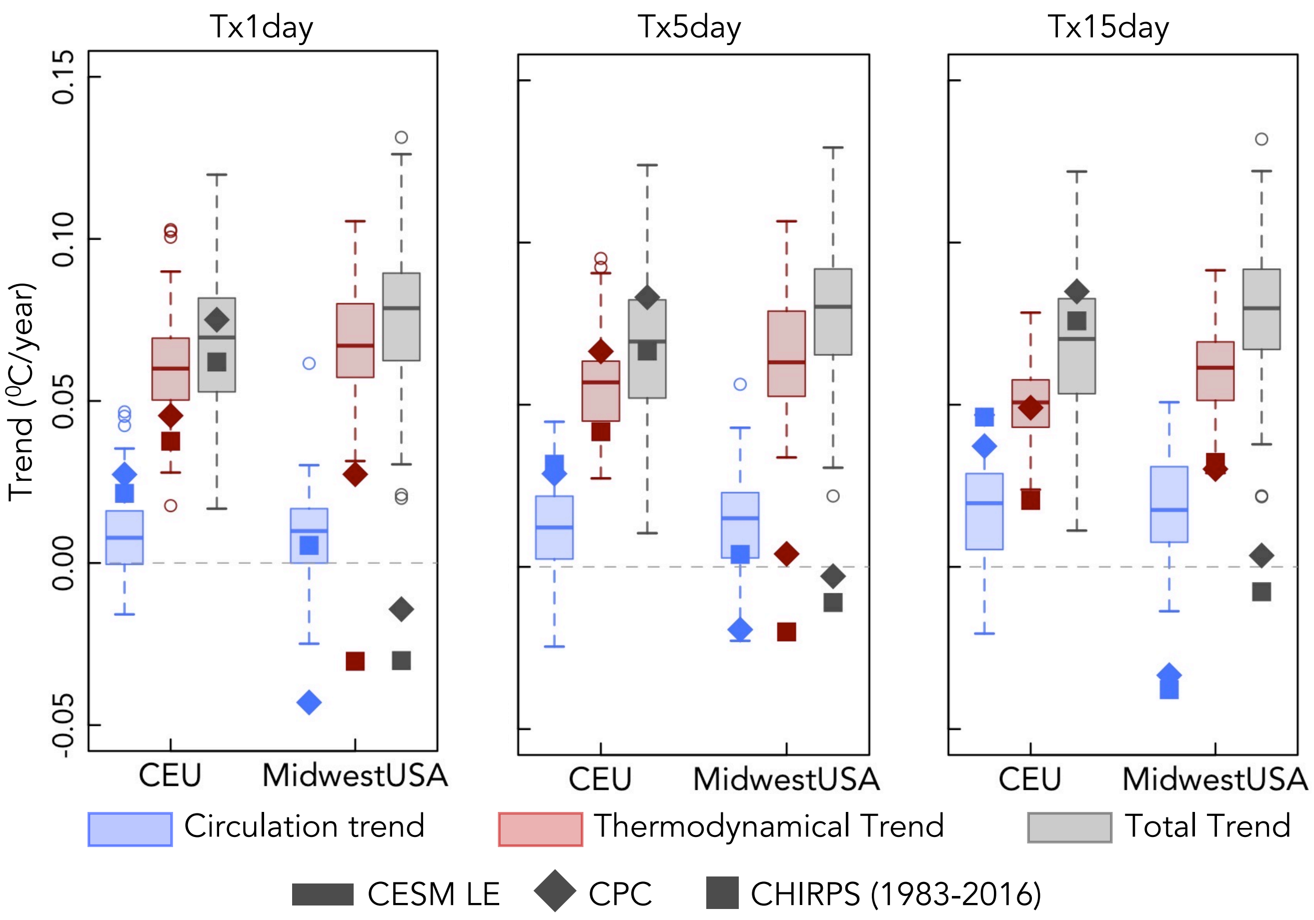
Tx1day trend (1951-2021; GHCNDEX)



- Strongly contrasting trends in temperature extremes between CEU and the Midwest US
- Dynamical adjustment with detrended z500 geopotential height predictors

XAIDA work by Jitendra Singh (see Poster).

Understanding dynamical and thermodynamical drivers of extreme event trends



- Strongly contrasting trends in temperature extremes between CEU and the Midwest US
- Dynamical adjustment with detrended z500 geopotential height predictors
- Circulation has contributed to CEU temperature extremes – but dampened in Midwest US
- Thermodynamical trends are better aligned

XAIDA

XAIDA work by Jitendra Singh (see Poster).

Summary Part 1

- 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
- Trends in temperature extremes contrast strongly between Central Europe and Midwest US. At least part of the discrepancy can be reconciled by different influences of atmospheric circulation

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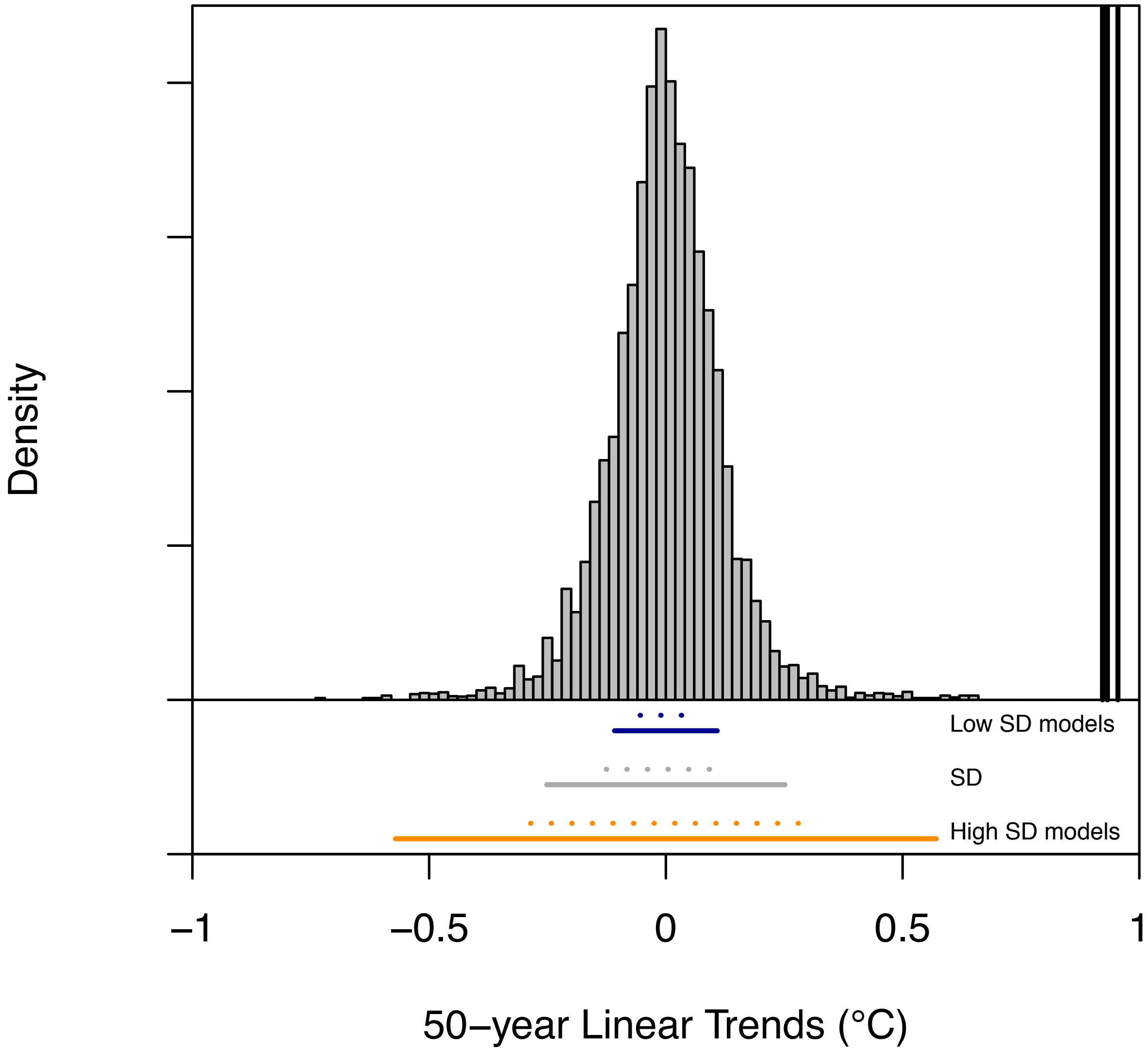
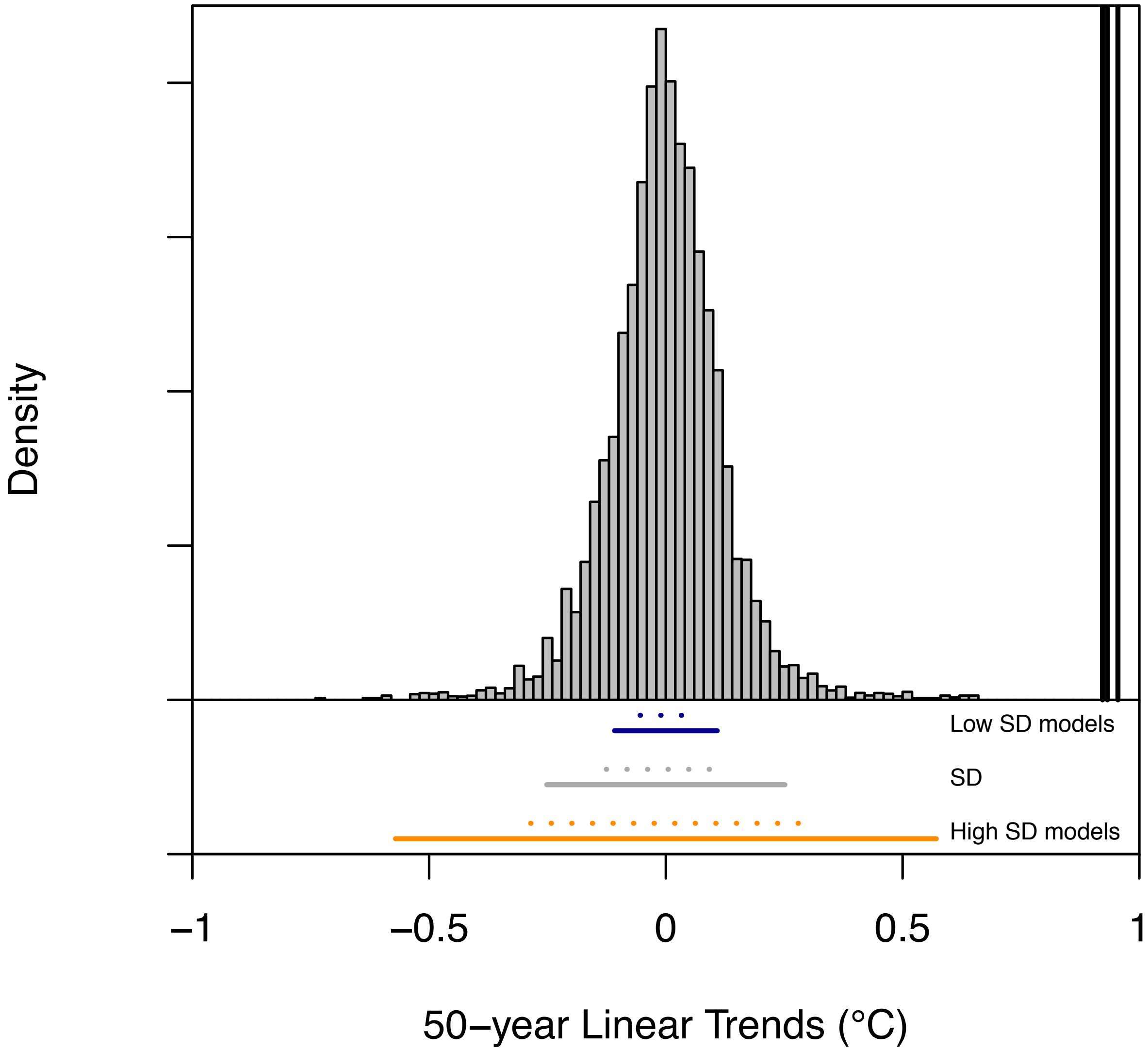


- Are external causal factors at play in the climate system?



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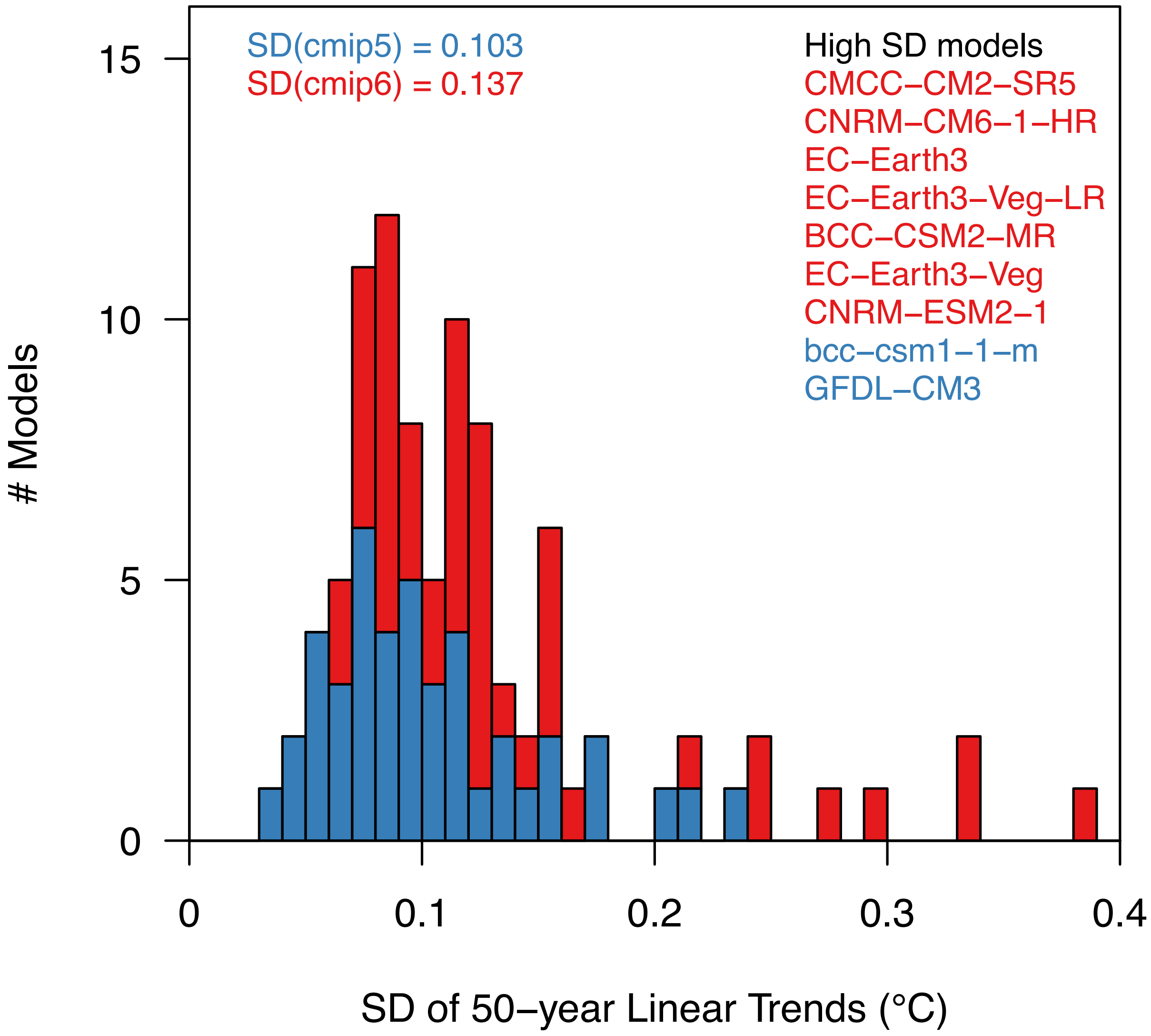

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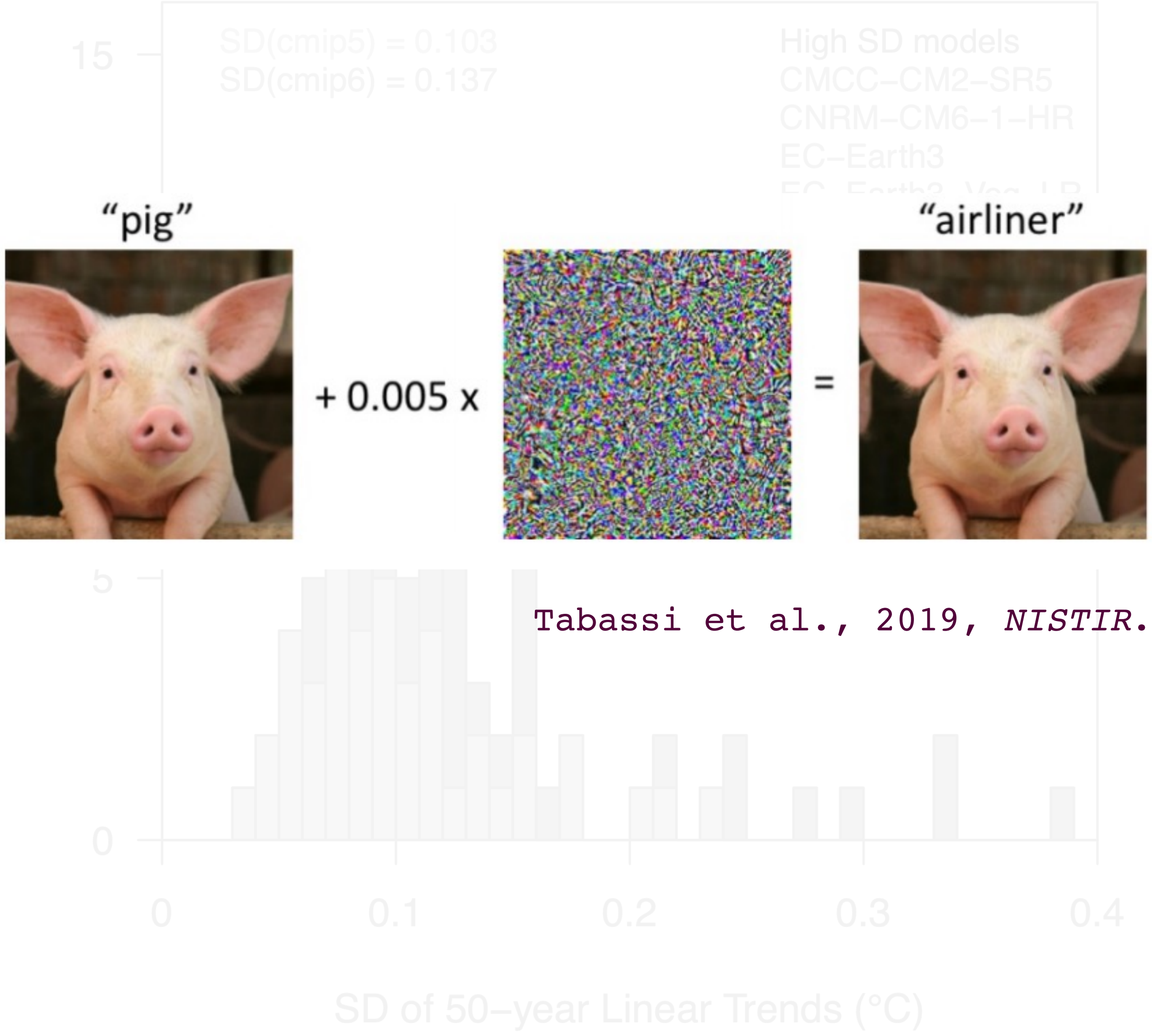

Tabassi et al., 2019, *NISTIR*.

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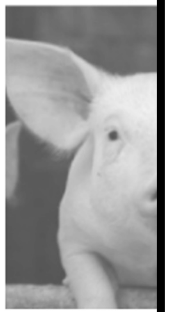
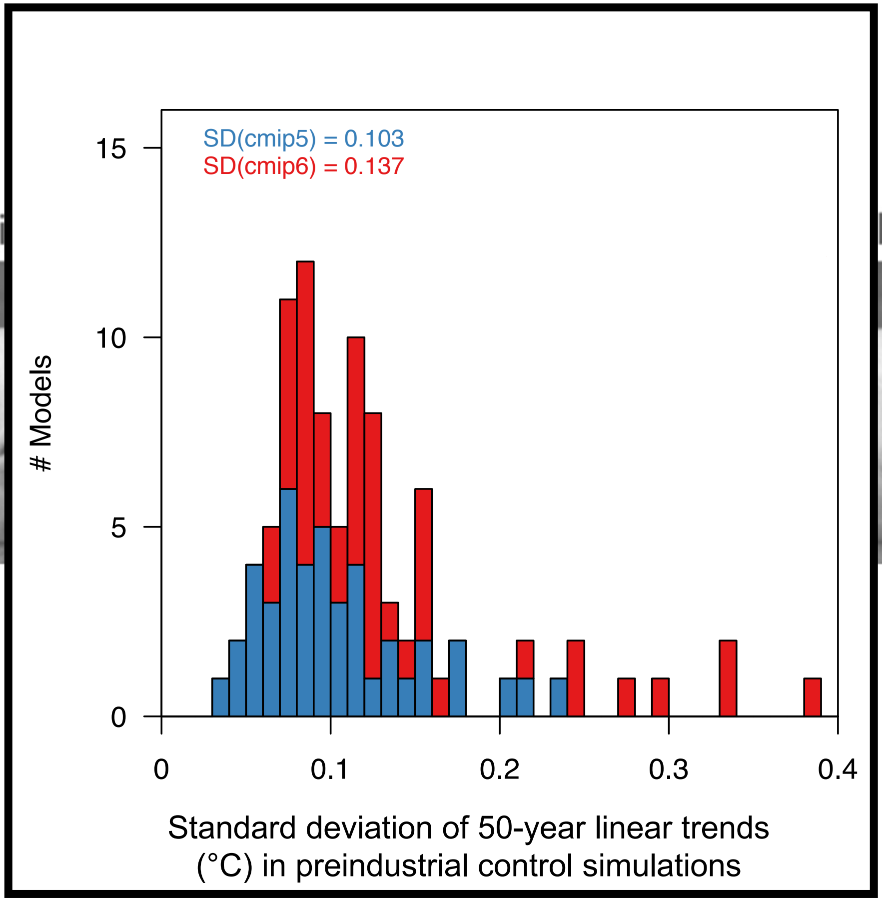
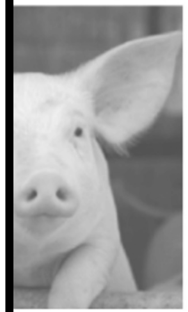
“pi





liner”



NISTIR.

Example: climate model structural uncertainty.

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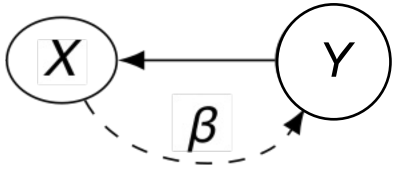
Detection of climate change using statistical learning



X = temperature map (e.g., annual)
Y = forced response metric
β = set of regression coefficients ("fingerprint")

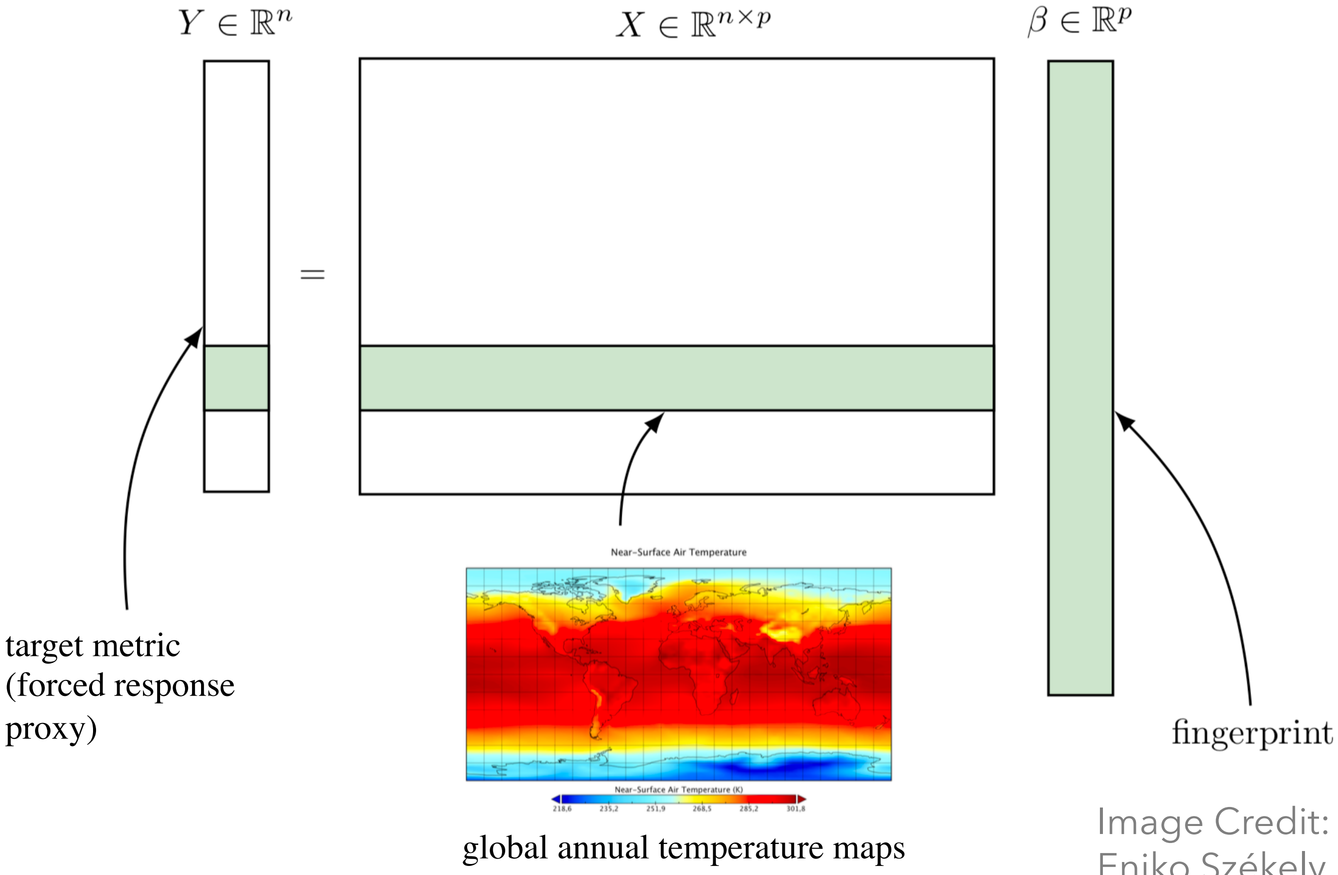
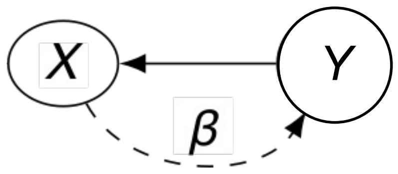


Image Credit: Eniko Székely

Detection of climate change using statistical learning



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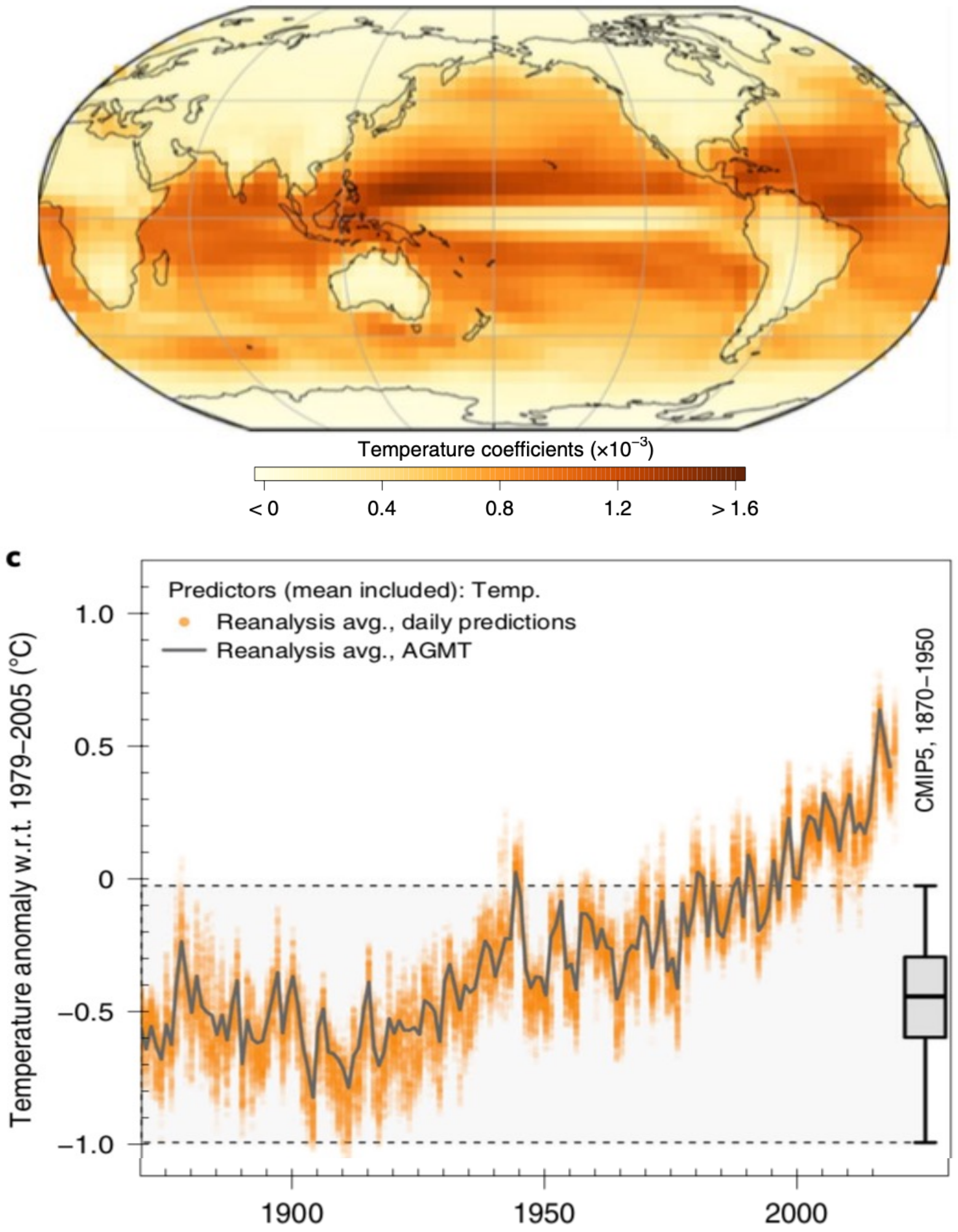
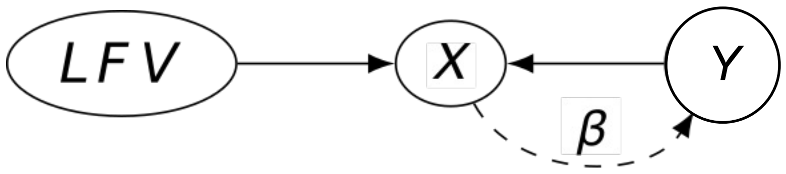
Sippel et al., 2020, *Nat Clim Change*. doi:10.1038/s41558-019-0666-7

"Fingerprint" $\hat{\beta}$



Detection of climate change using statistical learning



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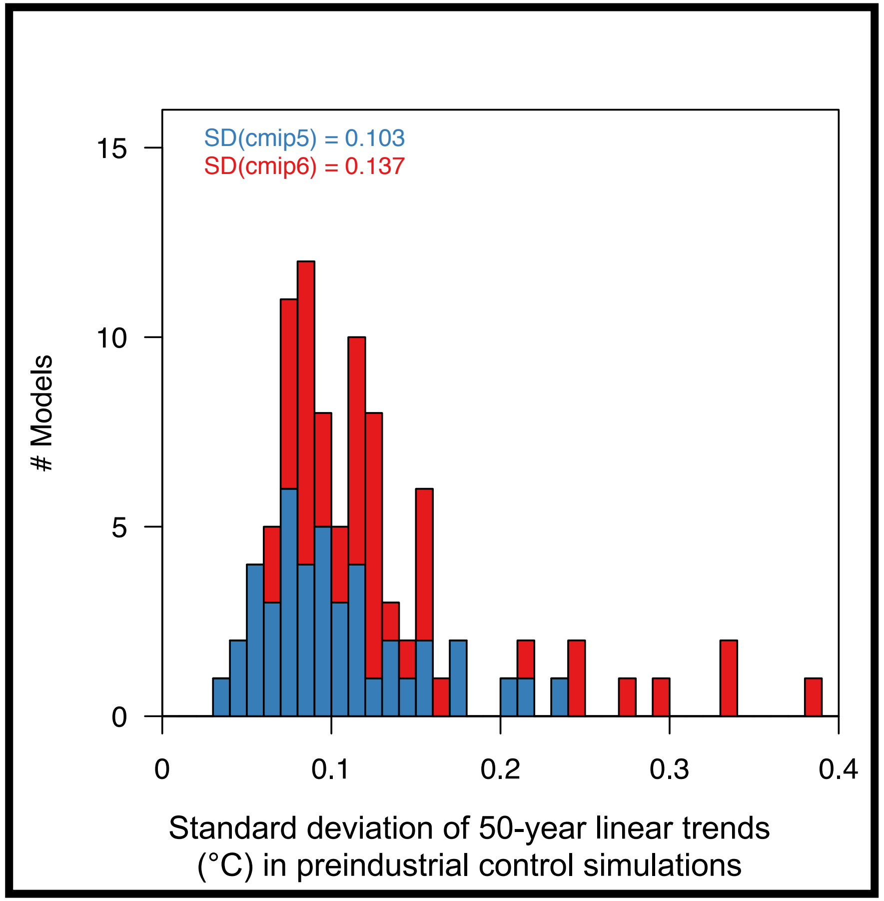
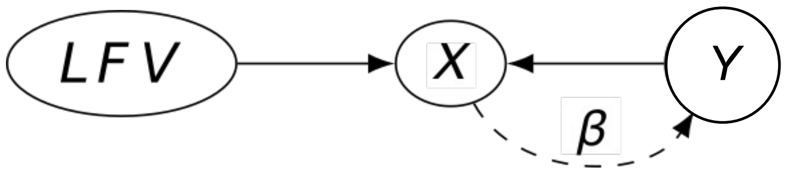
LFV = Low-frequency internal variability



Example: climate model structural uncertainty.

Robust detection under potentially large variability



X = temperature map (e.g., annual)
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Goal: Good prediction accuracy even under changed distributions (of multi-decadal internal variability) ("distributional robustness").

Observational Distribution $(x, y) \sim P$ ("Standard regression"):

$$\hat{\beta} = \operatorname{argmin}_\beta \mathbb{E}_{(x,y)\sim P}[l(y, f_\beta(x))]$$

Class of distributions $(x, y) \sim Q$ where $Q \in \mathcal{Q}$:

$$\hat{\beta} = \operatorname{argmin}_\beta \sup_{Q\in\mathcal{Q}} \mathbb{E}_{(x,y)\sim Q}[l(y, f_\beta(x))]$$

Meinshausen, N., 2018, *IEEE Data Science Workshop*.

Analogy "Distributional robustness": Which bike should I take on holiday?

Training @ home

Road bike on road ✓

Mountain bike in forest ✓

Analogy "Distributional robustness": Which bike should I take on holiday?

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Road bike in forest ✗

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Analogy "Distributional robustness": Which bike should I take on holiday?

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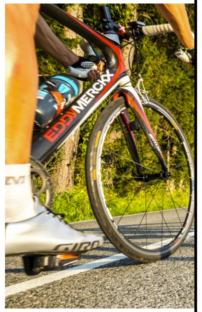
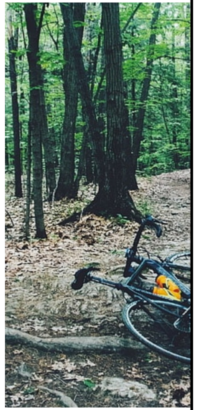


Road bi

lountain bike in forest

Solution: Optimize bike characteristics to perform well under many different circumstances…

Cross bike on snow…



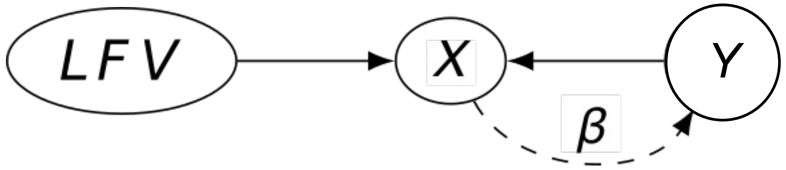
Road bi

lountain bike on road

Robust detection under potentially large variability

Anchor regression estimator*:

$$\hat{\beta}^{\gamma} = \text{argmin}_{\beta} \parallel \underbrace{(I_n - \Pi_A)}_{\text{Minimize Error}}(Y - X\beta) \parallel_2^2 + {\color{red}\gamma} \parallel \underbrace{\Pi_A}_{\text{Robustness w.r.t. Anchor}} (Y - X\beta) \parallel_2^2$$



${\color{red}\gamma}$ = "causal" regularization parameter that gives the strength of the intervention on the anchor variable (encouraging orthogonality with residuals)

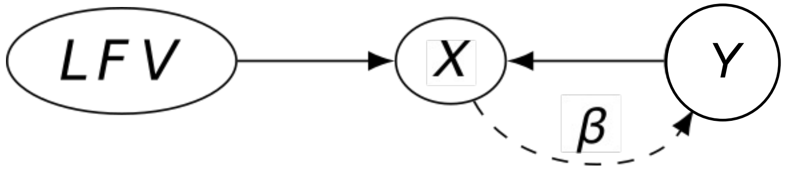
X = temperature map (e.g., annual)
Y = forced response metric
β = set of regression coefficients ("fingerprint")
LFV = Low-frequency internal variability (= Anchor)

* Rothenhäusler et al. (2021), Anchor regression: heterogeneous data meets Causality. *Journal of the Royal Statistical Society, Series B.*

Robust detection under potentially large variability

Anchor regression estimator*:

$$\hat{\beta}^{\gamma} = \operatorname{argmin}_{\beta} \underbrace{\| (I_n - \Pi_A)(Y - X\beta) \|_2^2}_{\text{Minimize Error}} + \color{red}{\gamma} \underbrace{\| \Pi_A (Y - X\beta) \|_2^2}_{\text{Robustness w.r.t. Anchor}}$$



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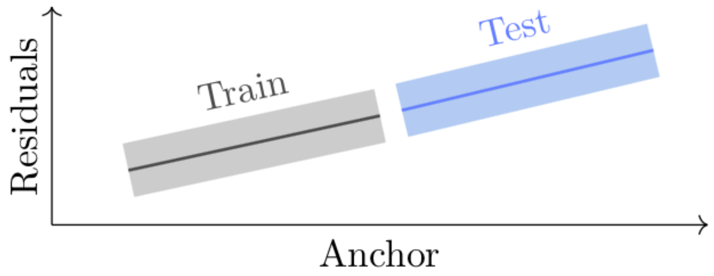
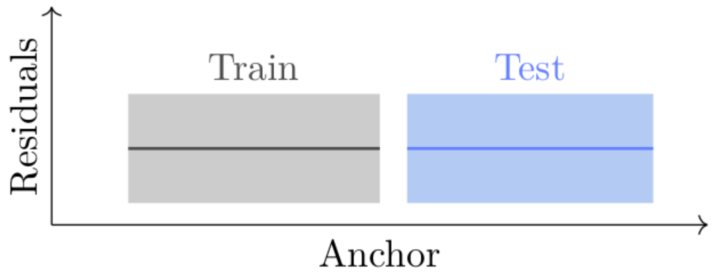
(= Anchor)

Standard regression (γ = 1):



$\Longrightarrow$

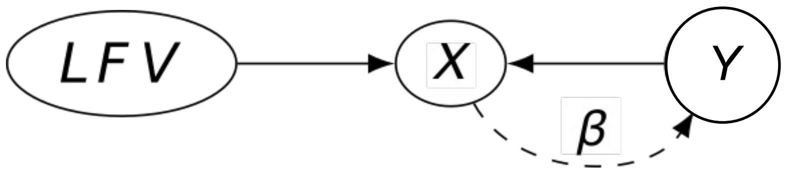
Anchor regression ($\gamma \gg 1$):



Robust detection under potentially large variability

Anchor regression estimator combined with L2 penalty:

$$\hat{\beta}^{\gamma} = \text{argmin}_{\beta} \underbrace{\| (I_n - \Pi_A)(Y - X\beta) \|_2^2}_{\text{Minimize Error}} + \gamma \underbrace{\| \Pi_A (Y - X\beta) \|_2^2}_{\text{Robustness w.r.t. Anchor}} + \lambda \underbrace{\| \beta \|_2^2}_{\text{Avoiding Overfitting}}$$



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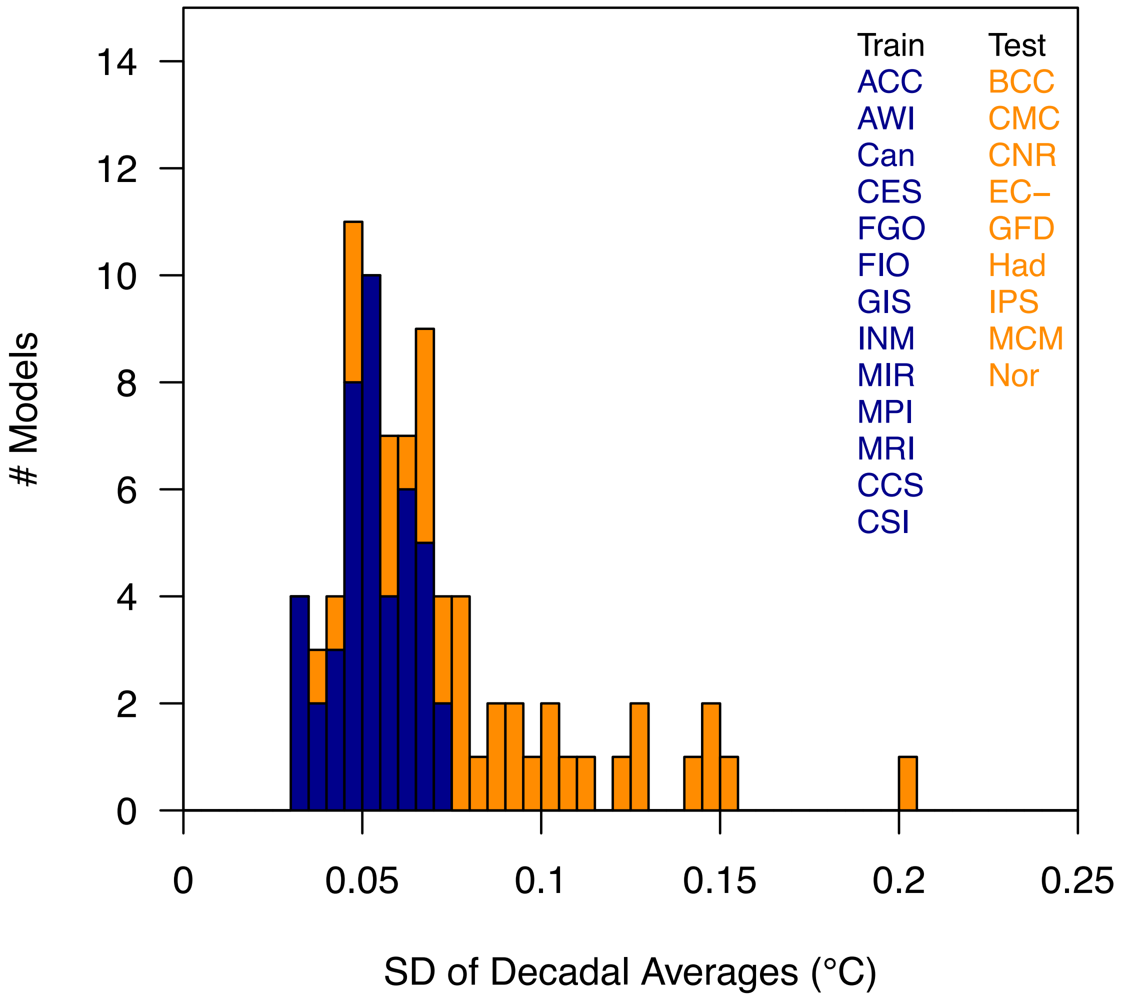
β = set of regression coefficients ("fingerprint")
LFV = Low-frequency internal variability (= Anchor)

γ = "causal" regularization parameter that gives the strength of the intervention on the anchor variable (encouraging orthogonality with residuals)

λ = L2 regularization to handle multicollinearity and ensure smoothness

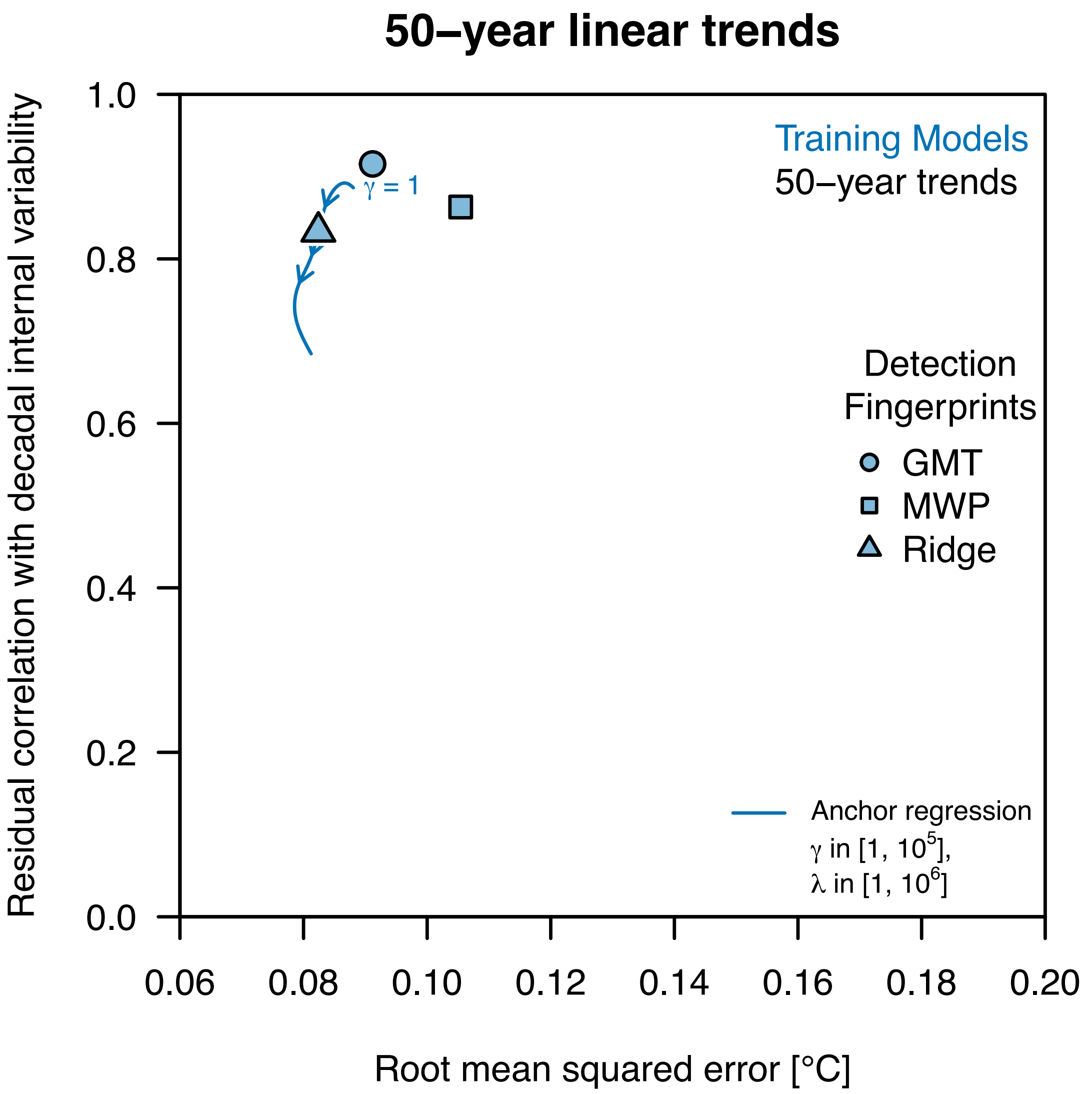
A train-test split of CMIP simulations: Experiment Design



- We split the CMIP archive into "low-variability" (=training) and "high-variability" (=test) models

Sippel et al., 2021, *Science Advances* **7**, eabh4429, doi:10.1126/sciadv.abh4429.

A train-test split of CMIP simulations: Results



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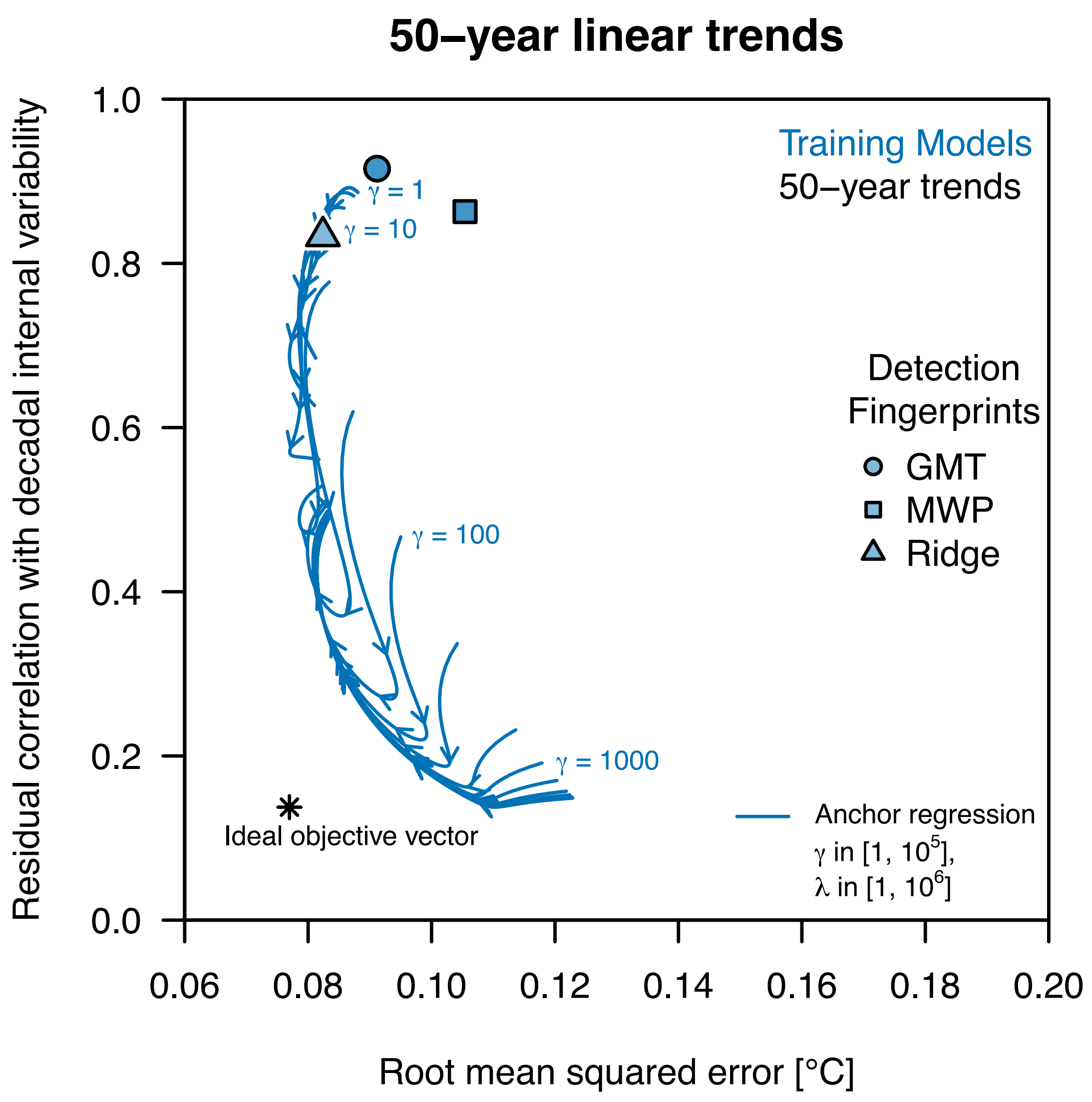

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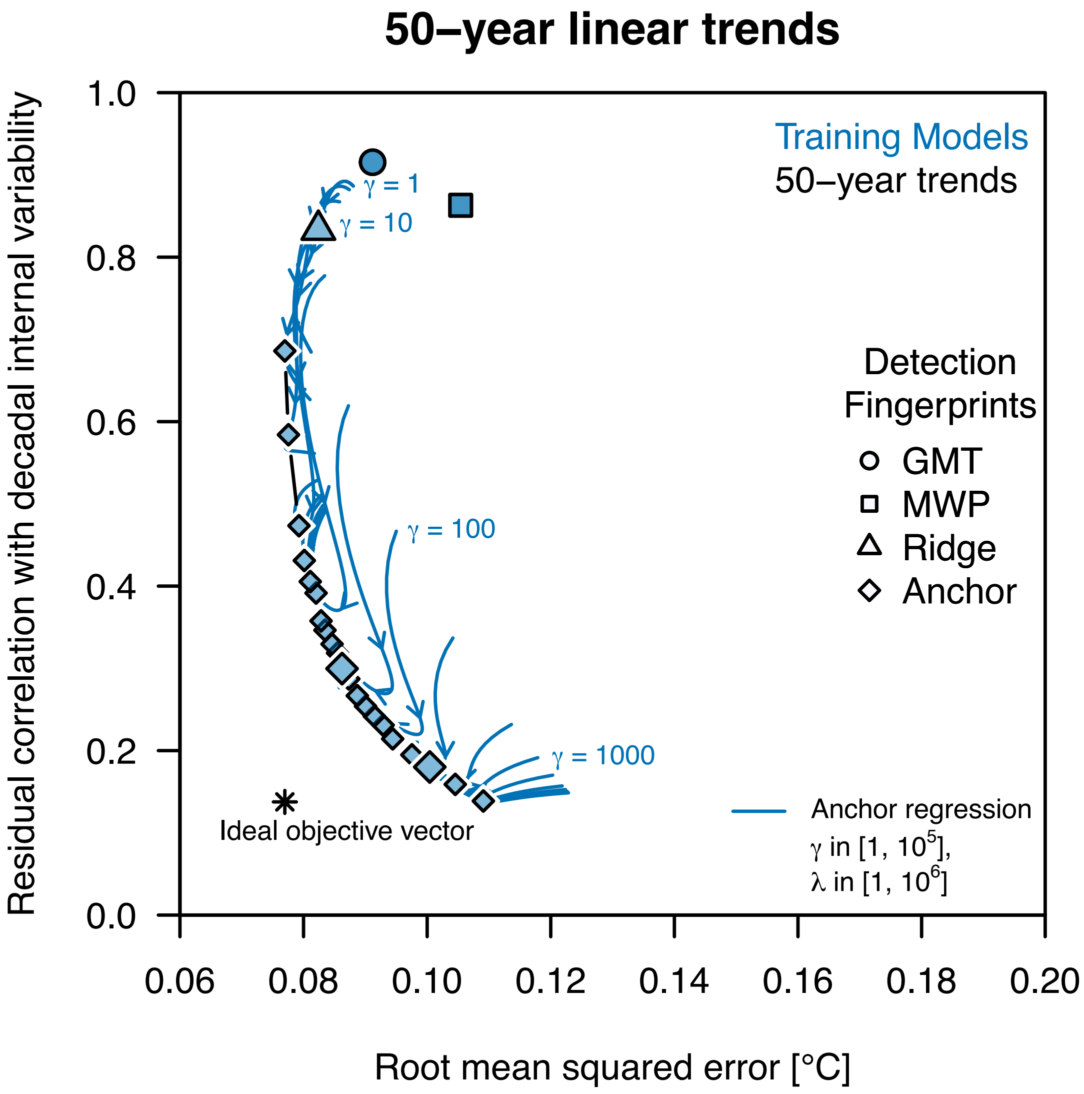

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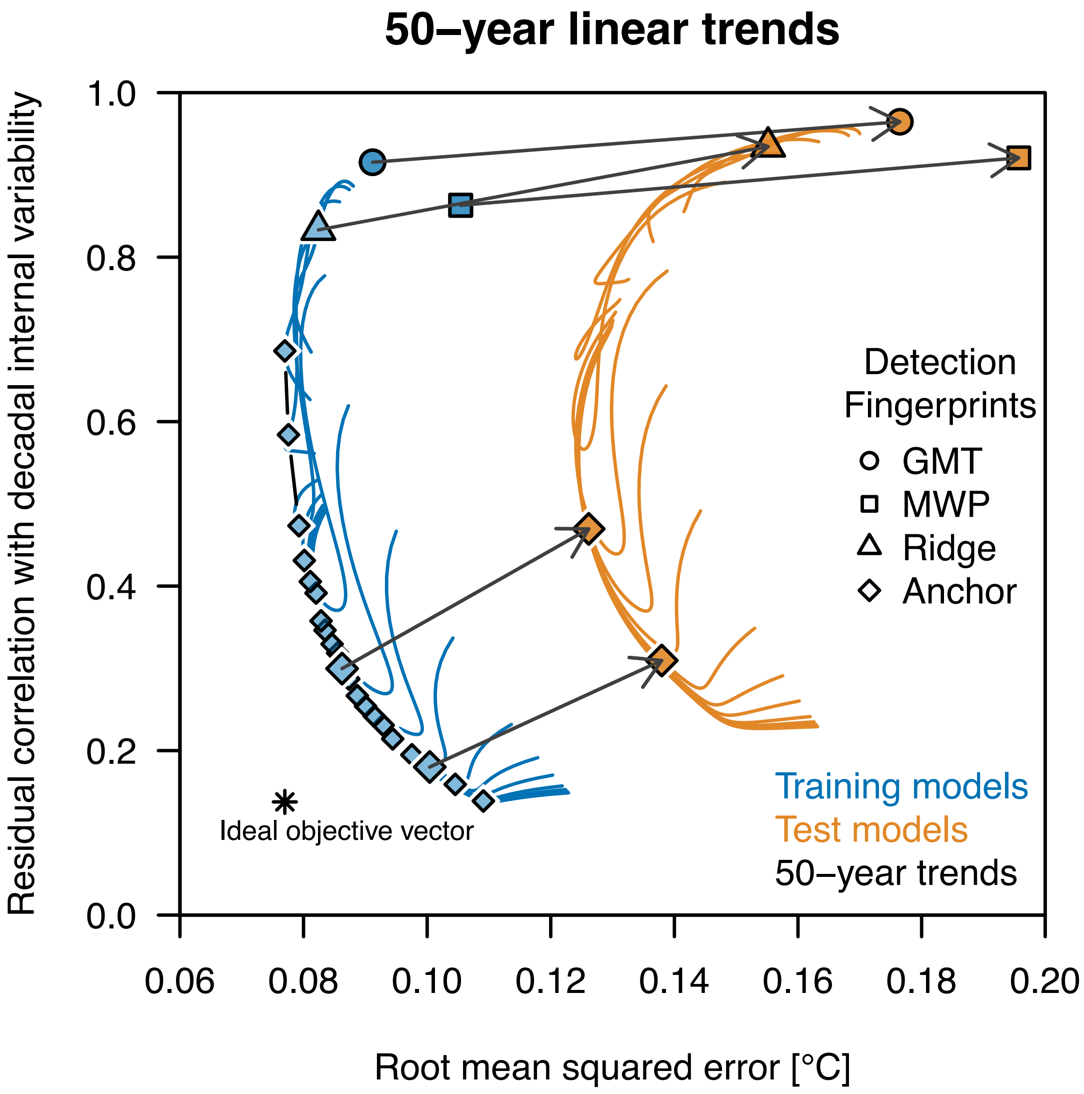
Sippel et al., 2021, *Science Advances* **7**, eabh4429, doi:10.1126/sciadv.abh4429.

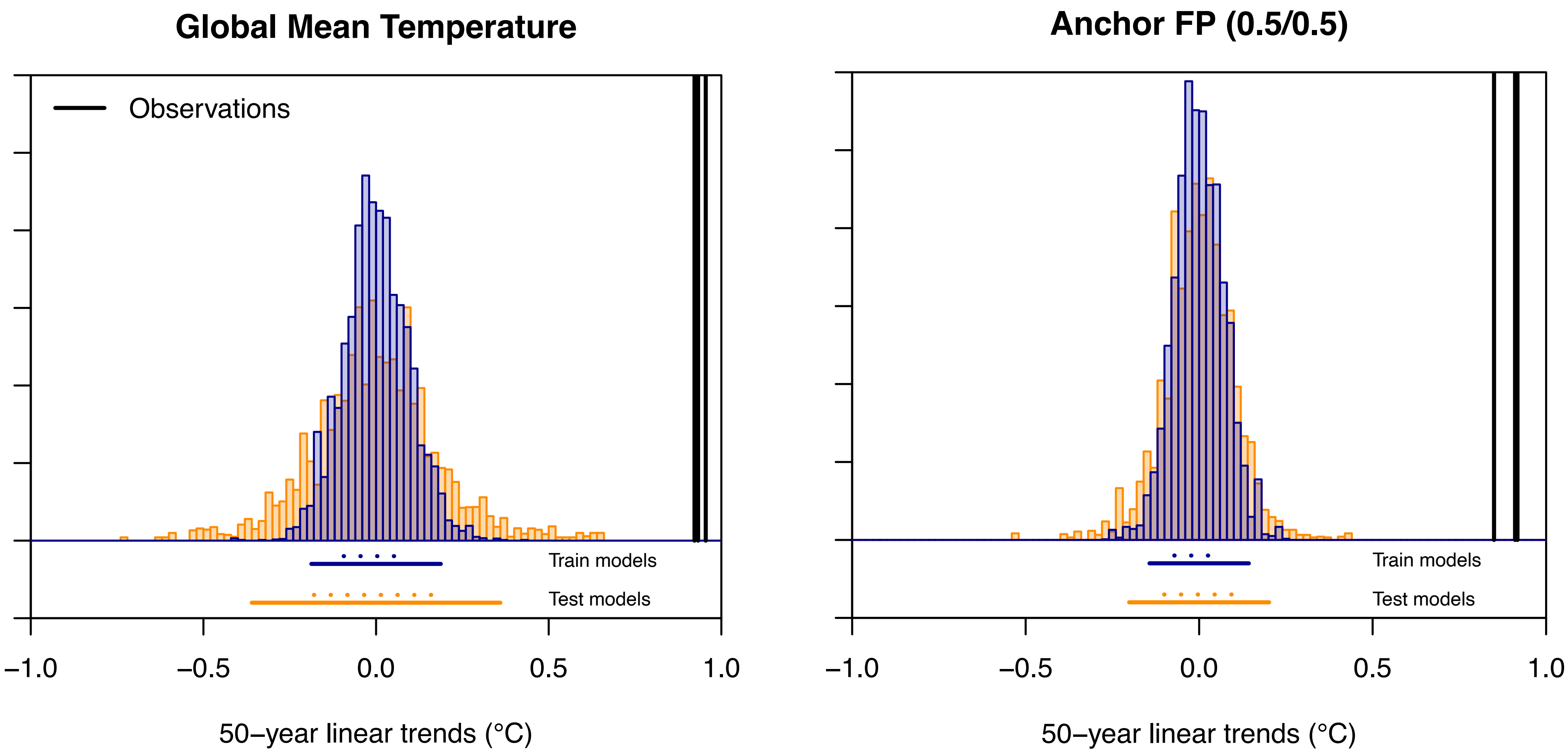
A train-test split of CMIP simulations: Results



- We split the CMIP archive into "low-variability" (=training) and "high-variability" (=test) models
- Traditional detection metrics such as global mean temperature ("GMT") show a reasonable RMSE but high residual correlation (training models)
- A trade-off arises for Anchor solutions that aim to jointly minimize RMSE and res. Correlation (training mod.)
- Distributional shift to high-variability (test) models almost doubles RMSE for traditional detection metrics, but RMSE increases more moderately for anchor regression solutions

Sippel et al., 2021, *Science Advances* **7**, eabh4429, doi:10.1126/sciadv.abh4429.

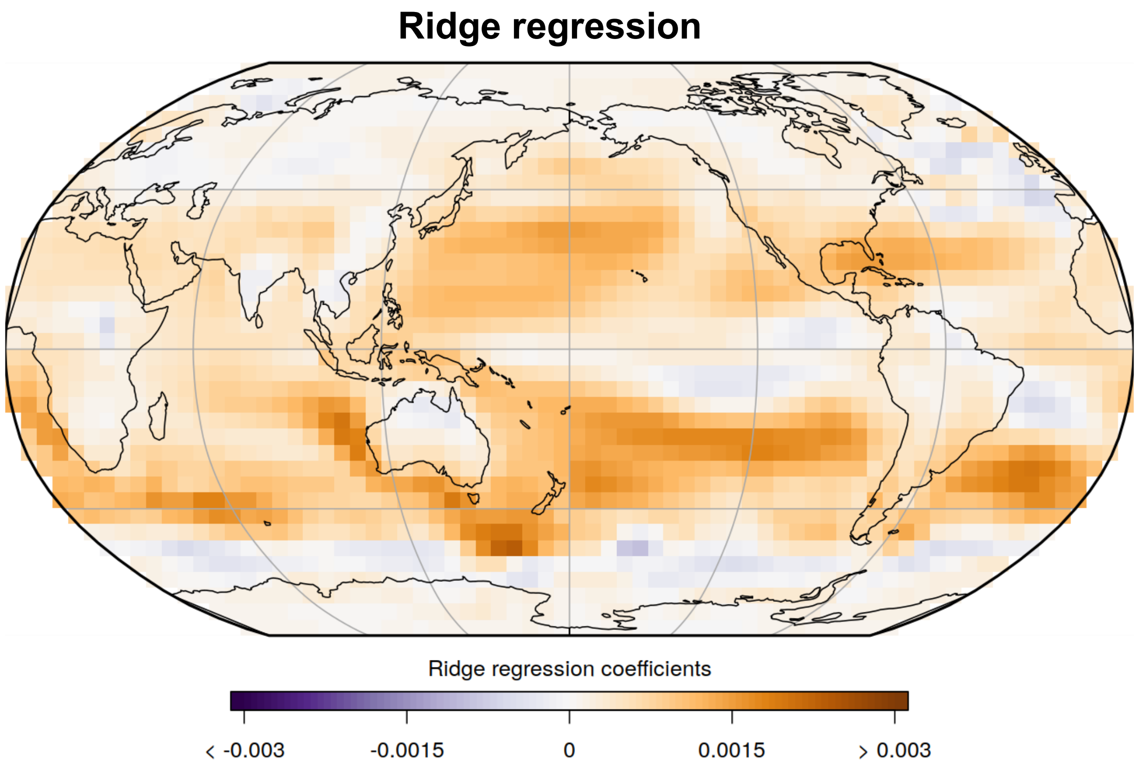
A train-test split of CMIP simulations: Results (2)

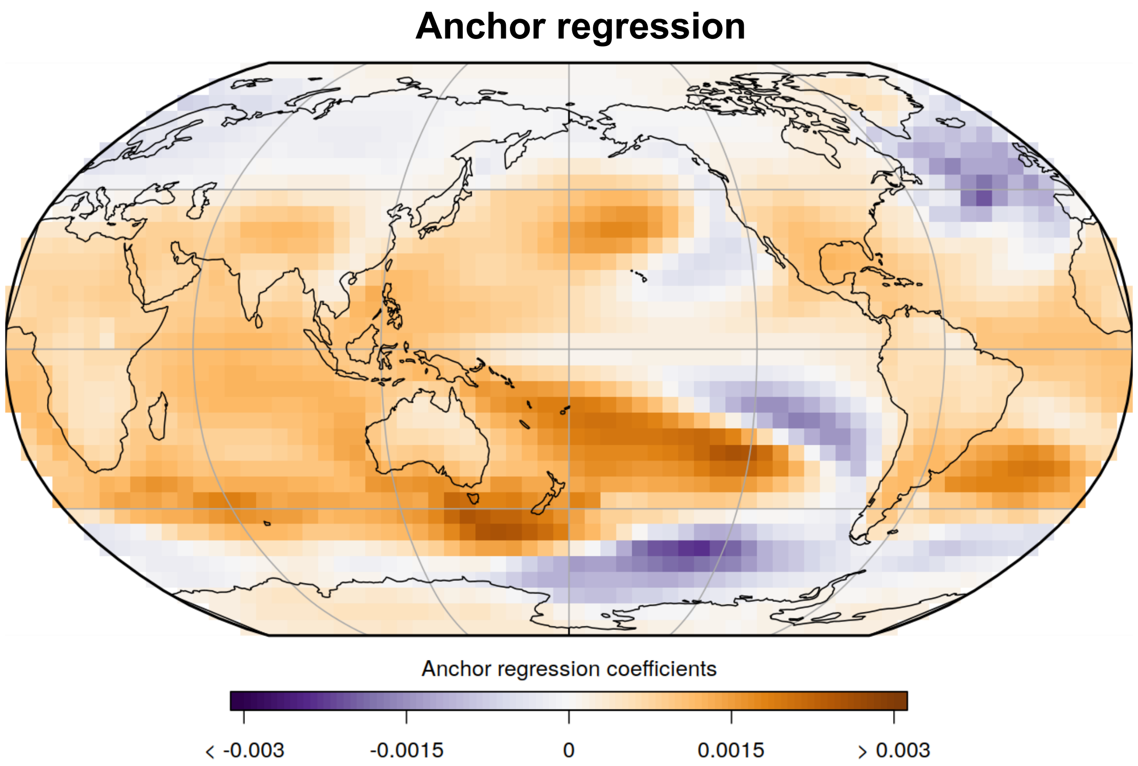


Sippel et al., 2021, *Science Advances* **7**, eabh4429, doi:10.1126/sciadv.abh4429.

Climate change detection with anchor detection metric is much more robust to multi-decadal variability.

How does the "fingerprint" differ in anchor regression?

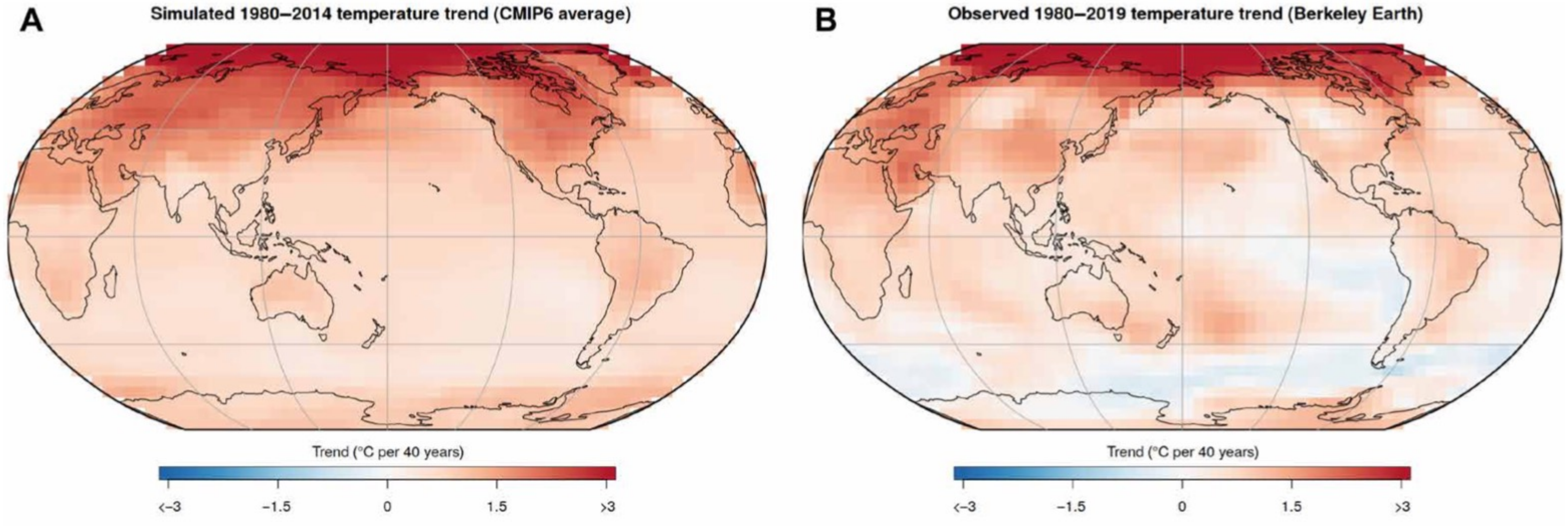




Anchor constraint-based fingerprint puts more negative weights on regions of multi-decadal internal variability (PDO, AMO, etc.), to "counterbalance" positive weights.

Sippel et al., 2021, *Science Advances* **7**, eabh4429, doi:10.1126/sciadv.abh4429.

How does the anchor fingerprint differ?



Anchor constraint-based fingerprint puts more negative weights on regions of multi-decadal internal variability (PDO, AMO, etc.), to “counterbalance” positive weights

Sippel et al., 2021, *Science Advances* **7**, eabh4429, doi:10.1126/sciadv.abh4429.

Summary Part 2

- Fingerprints to estimate the forced response using statistical learning techniques in daily global temperature patterns since approx. 2012

- A key limitation of D&A is that confidence estimates rely on a realistic simulation of unforced multi-decadal variability. Robustness constraints (anchors) allow to build D&A estimates that are robust also against potentially large multi-decadal internal variability

- Encouraging robustness against possible uncertainties/distributional shifts using anchor regression may prove useful for climate science more broadly (Extremes? Distributional shifts across climate models and/or towards observations?)

Thank you for the attention!

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