Is Western Europe warming much faster than expected ?

L. Terray *and* **C. Deser**

CERFACS & NCAR/CGD/CAS.

Motivation

Climate of the Past

Western Europe is warming much faster than expected

G. J. van Oldenborgh[1], S. Drijfhout[1], A. van Ulden[1], R. Haarsma[1], A. Sterl[1], C. Severijns[1], W. Hazeleger[1], and H. Dijkstra[2]

[1]KNMI (Koninklijk Nederlands Meteorologisch Instituut), De Bilt, The Netherlands
[2]Institute for Marine and Atmospheric Research, Utrecht University, The Netherlands

- 2m-temperature (SAT) *trends* 1950 – 2007

- Compare Observations with CMIP3

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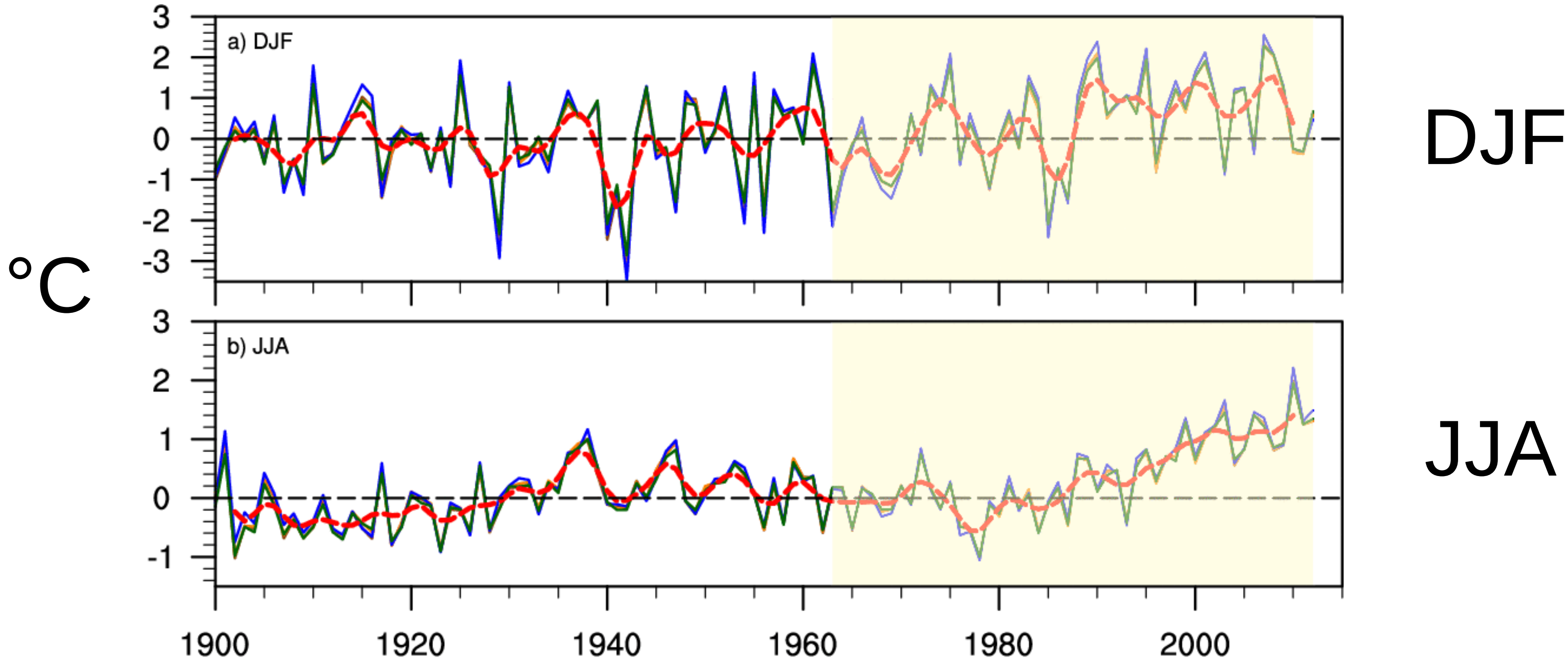
- 2m-temperature (SAT) *trends* 1950 – 2007
- Compare Observations with CMIP3
- **Discrepancy between models and observations**
- **Model and forcing biases rather than internal variability**

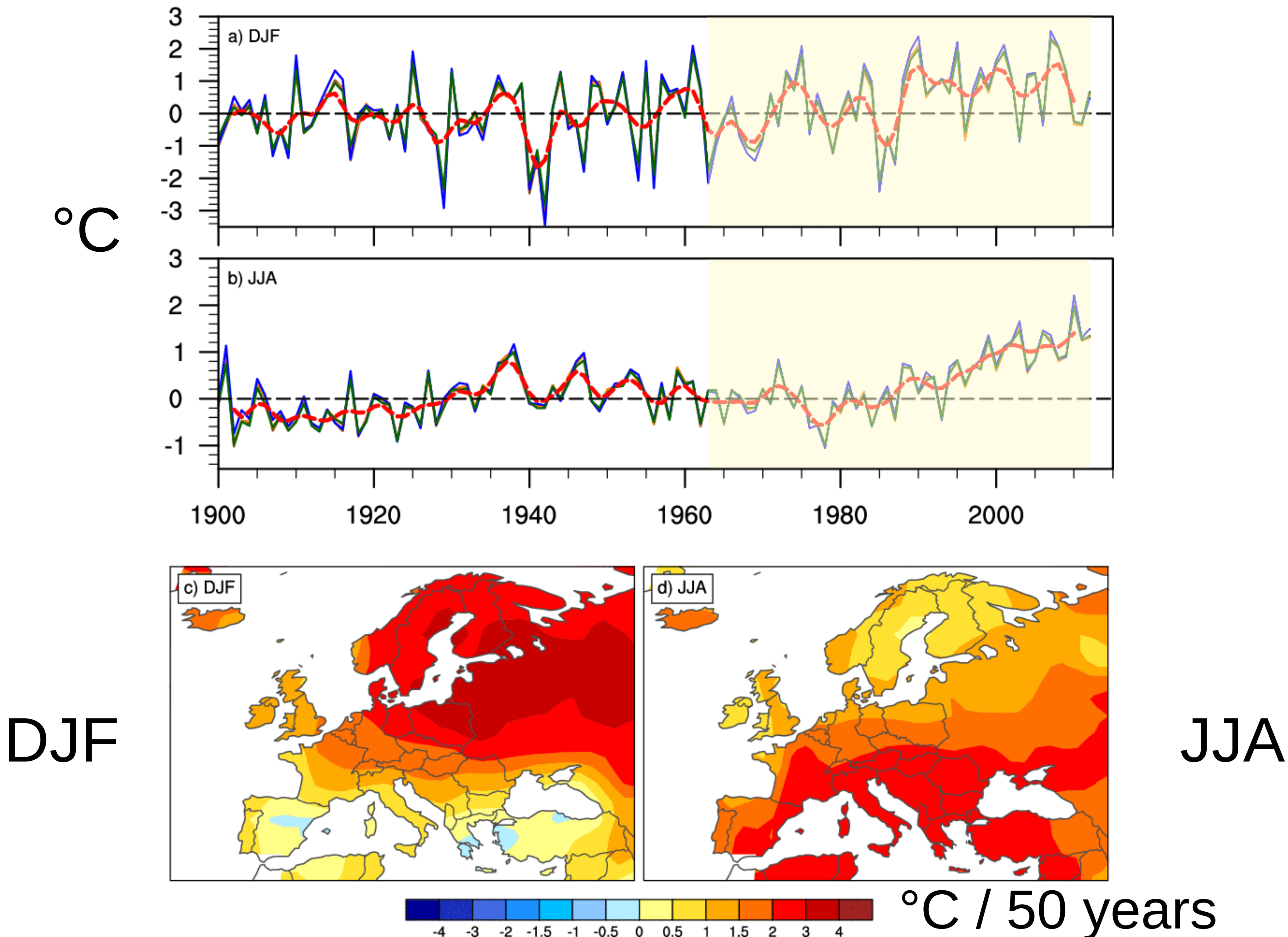
Outline

- Observations
- A climate variability paradigm for attribution
- A simple approach to estimate variability related to a change in atmospheric circulation
- Use the CESM1 large ensemble (Kay, Deser et al. 2015) to estimate the possible influence of internal variability on past temperature trends over Europe
- Summary

Observed temperature time series



Observed temperature trends: 1963-2012



Climate variability paradigm

4 components of variability

Forced	Free
Thermodynamical	Dynamical

Dynamical / thermodynamical SAT components

- Dynamical component : due to a change in atmospheric circulation
- The thermodynamical component is simply defined as the residual (Total – Dynamical)
- Intrinsically linked to a certain extent
- **How to estimate the dynamical component ?**

Get the dynamical component using analogues

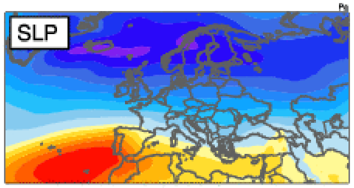
☞ World with constant external forcing

➔ CESM1 2000-years PiCntrl simulation

☞ Use large-scale circulation analogues

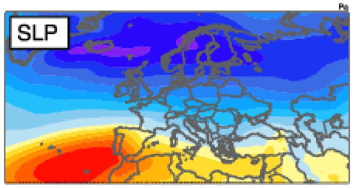
☞ SLP monthly means

January SLP
Year 576

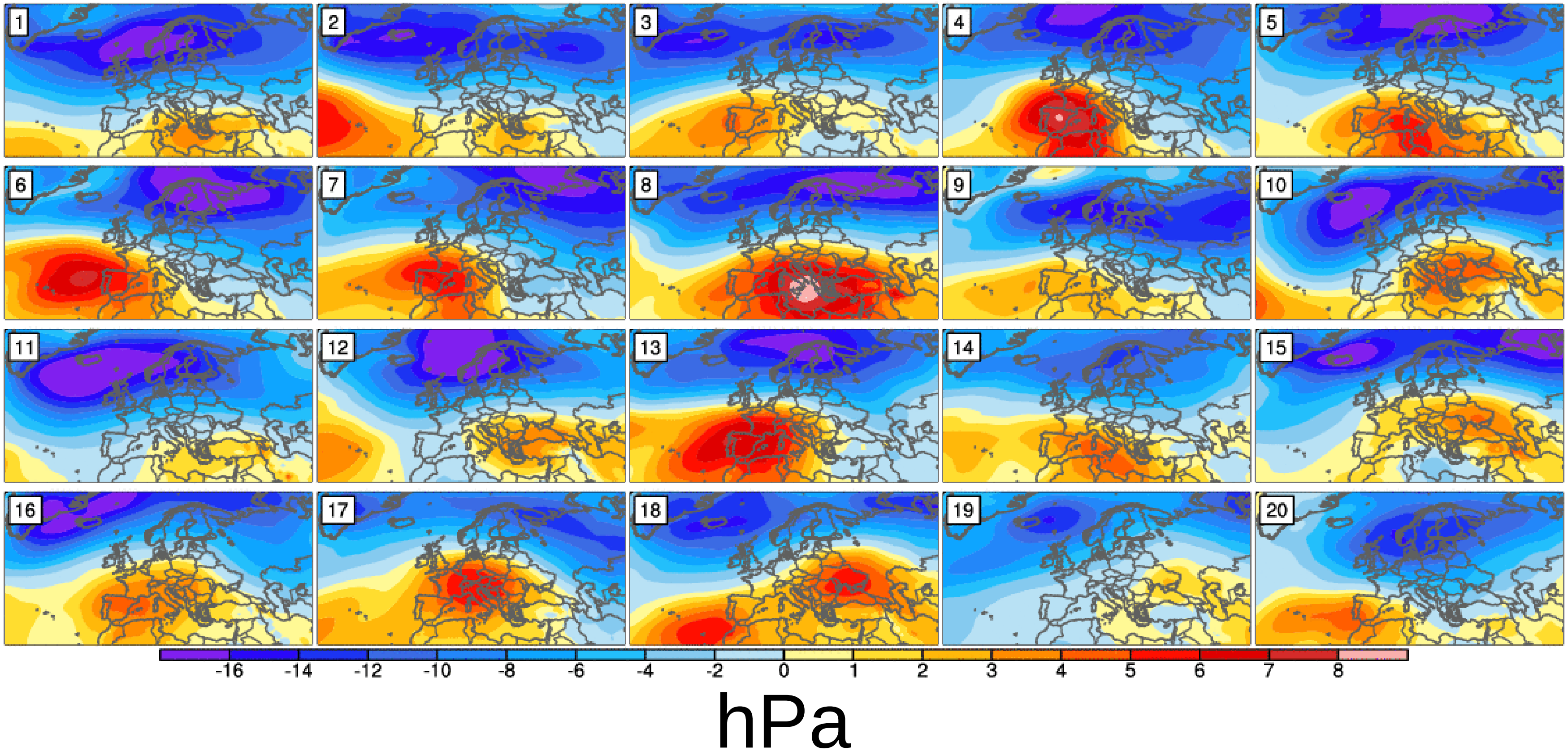


Dynamical component using analogues

January SLP
Year 576

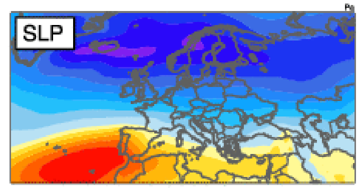


Step 1: *Select N closest analogues among all Jan.*

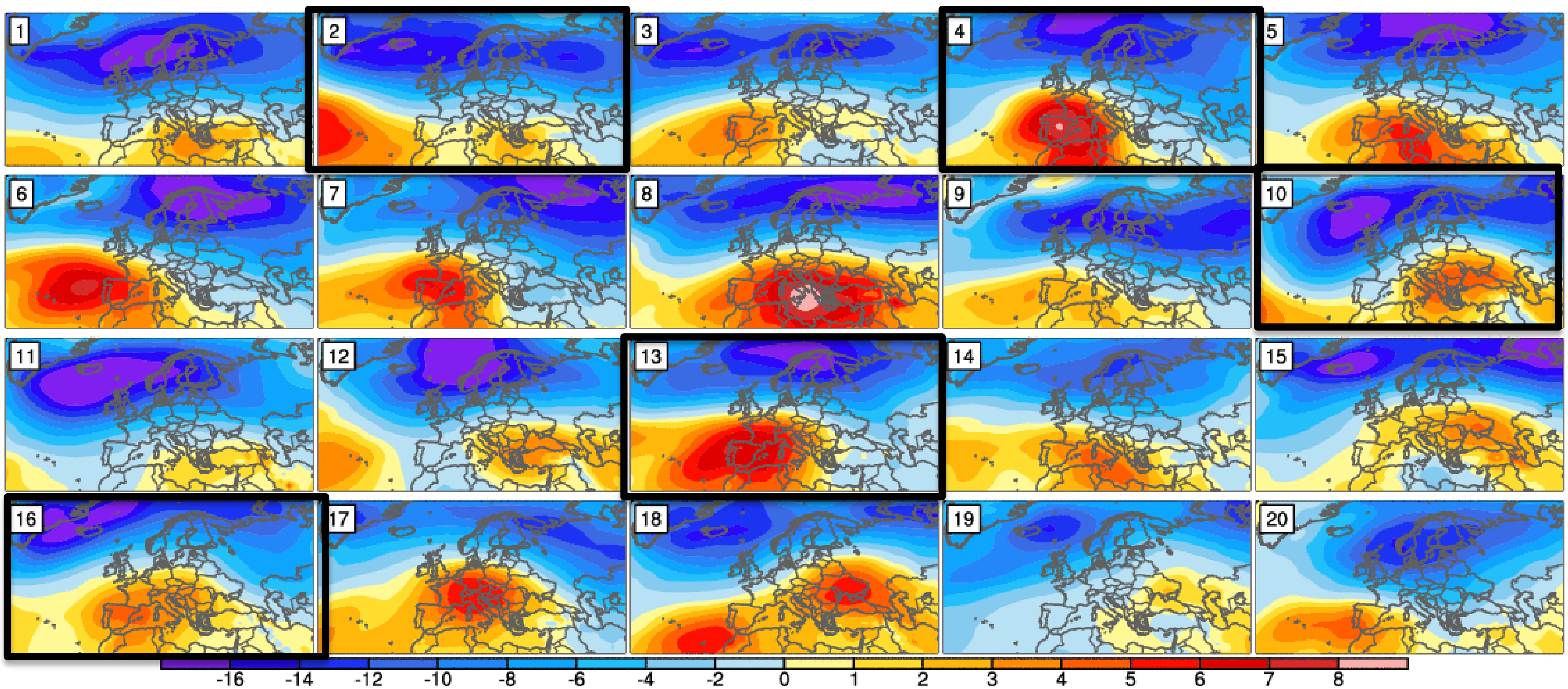


Dynamical component using analogues

January SLP
Year 576



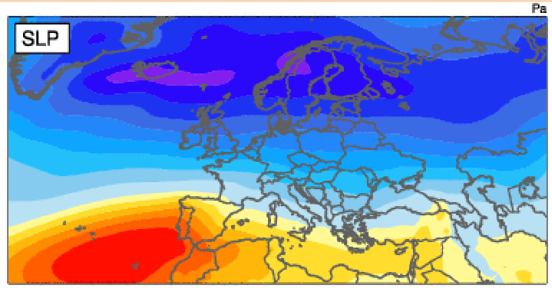
Step 2: *Randomly draw M out of N*



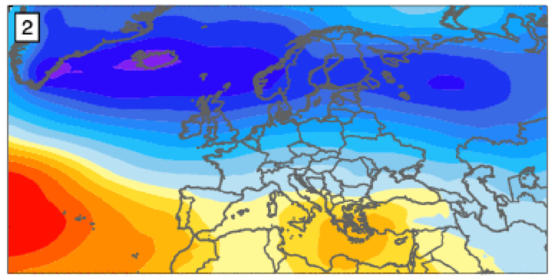
hPa

Step 3: Find best linear fit coefficients

January SLP
Year 576

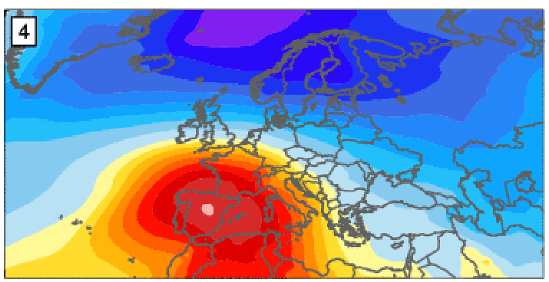


$\cong a_1$

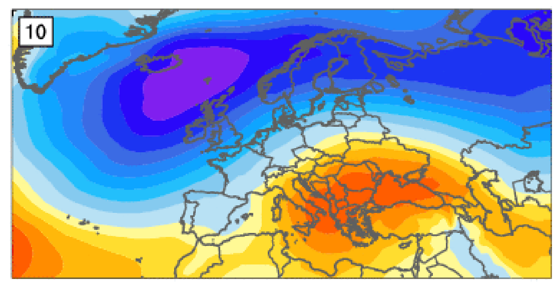


$+$

a_2

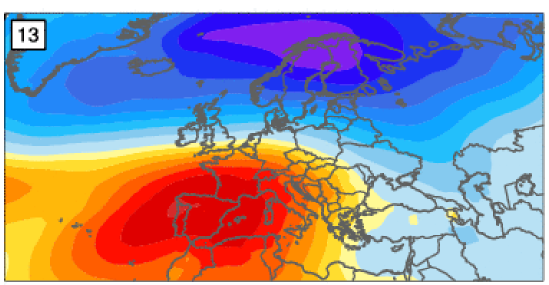


$+a_3$

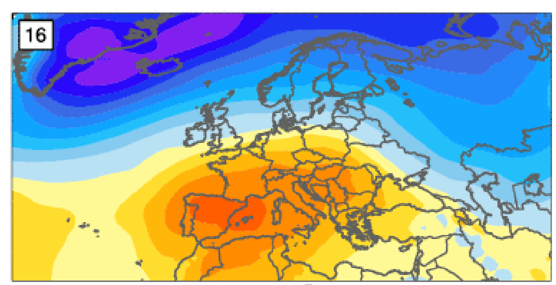


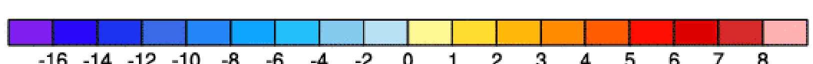
$+$

a_4

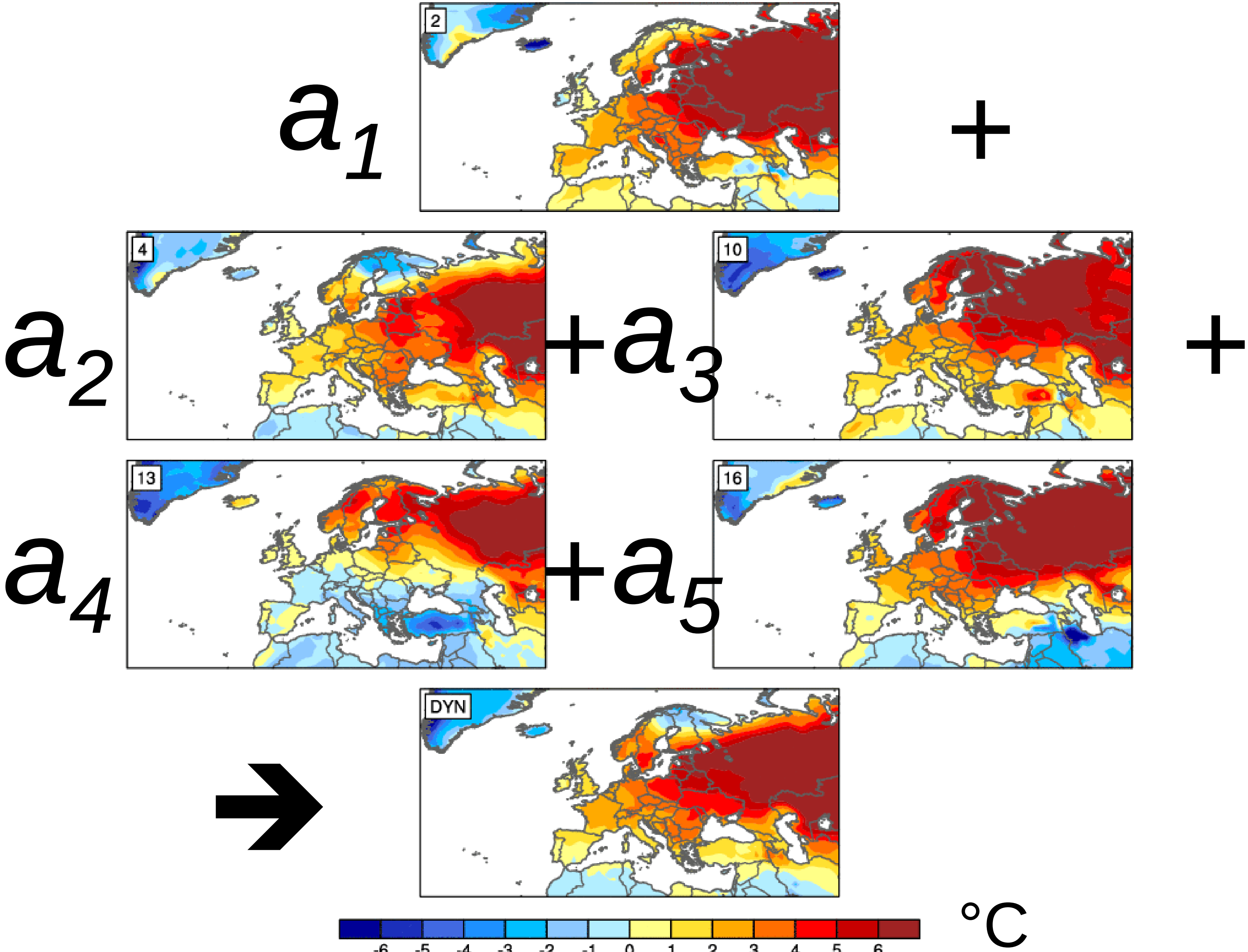


$+a_5$





Step 4: SAT linear combination using the a_i

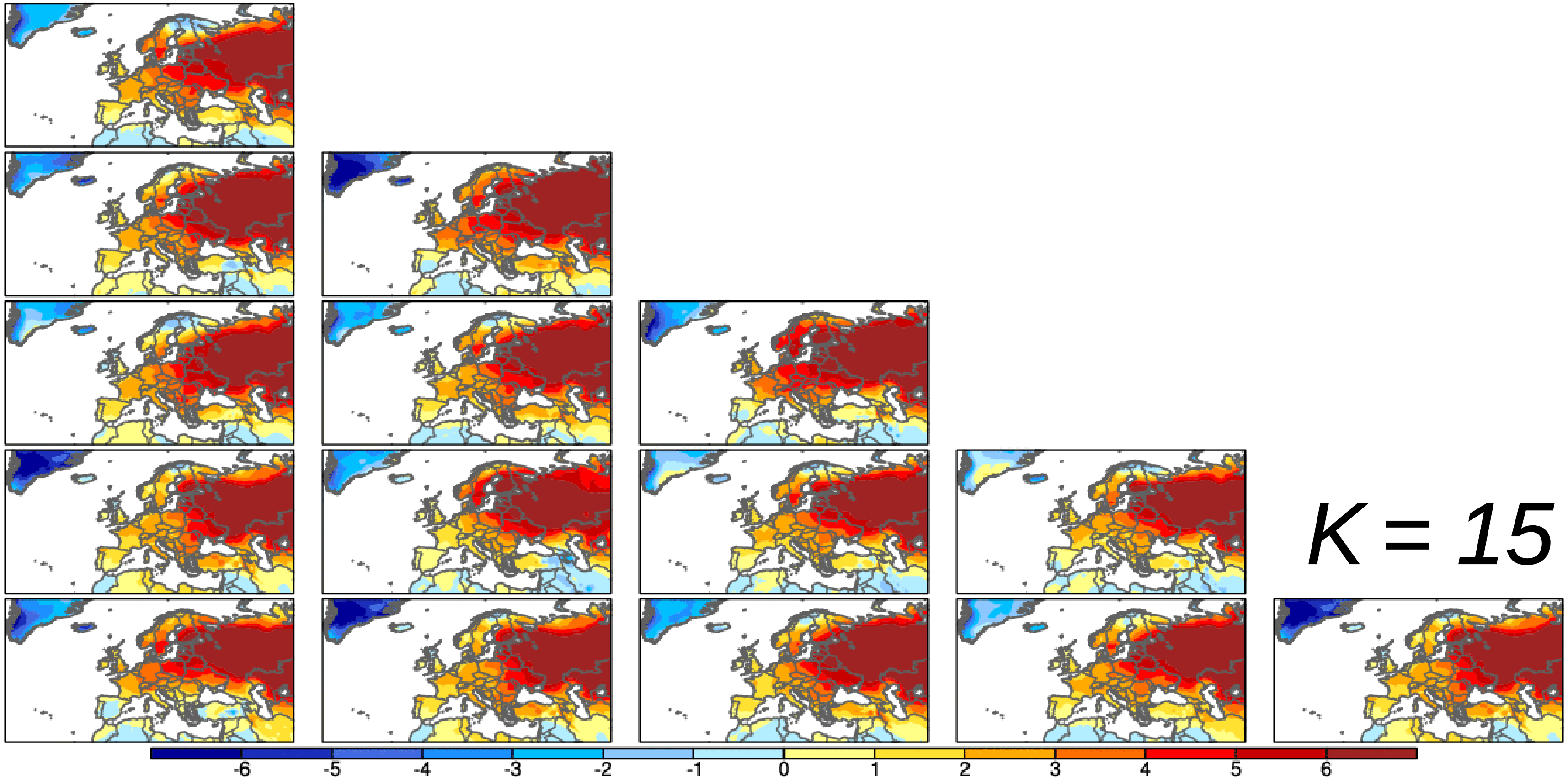


Step 5: Iterate steps 2,3,4

$K = 1,\ldots\ldots,N_{iter}\ (=15)$

$K = 1$

$K = 15$



°C

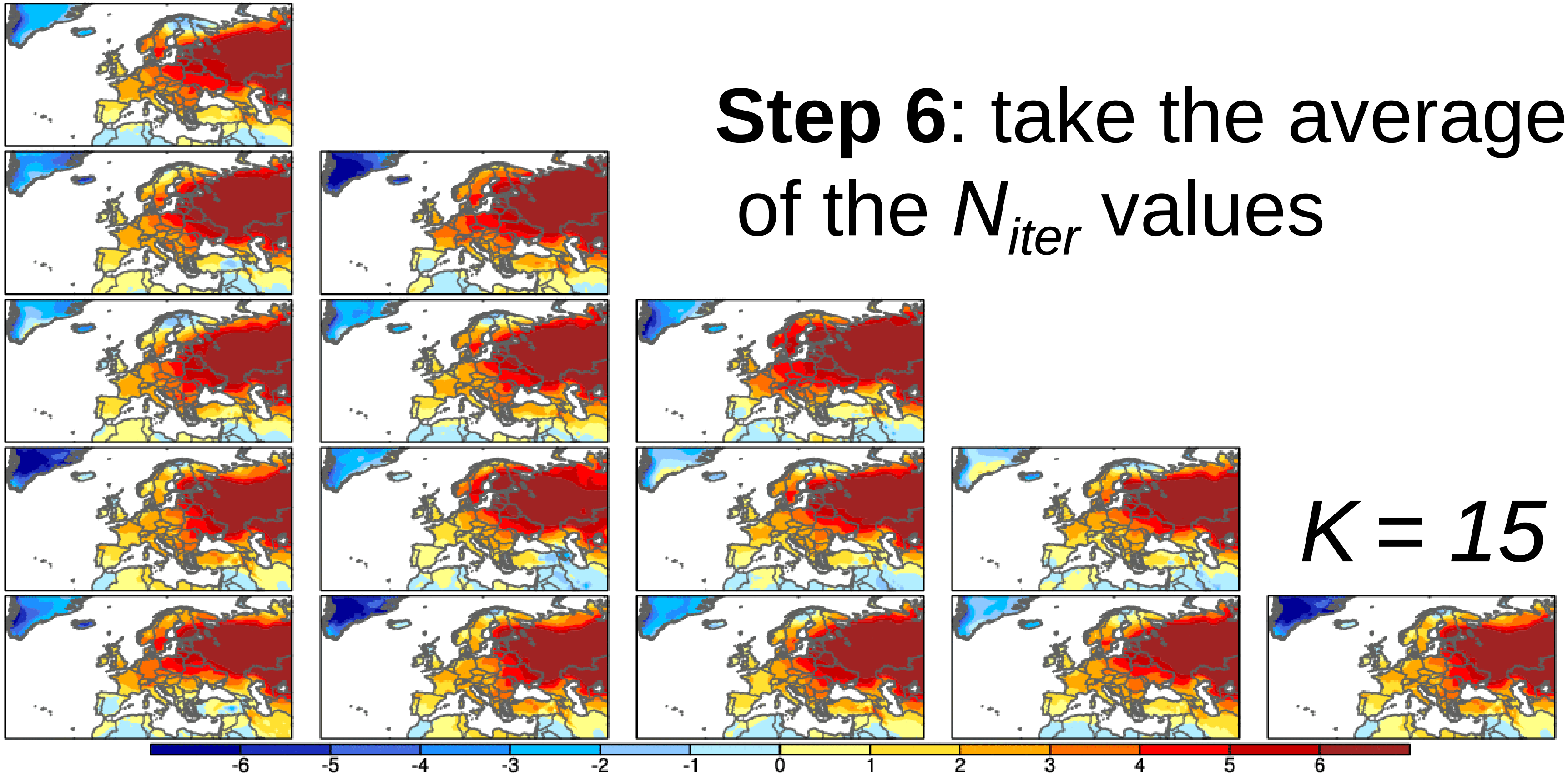
Step 5: Iterate steps 2,3,4

$K = 1, \ldots\ldots, N_{iter}$ (=15)

$K = 1$

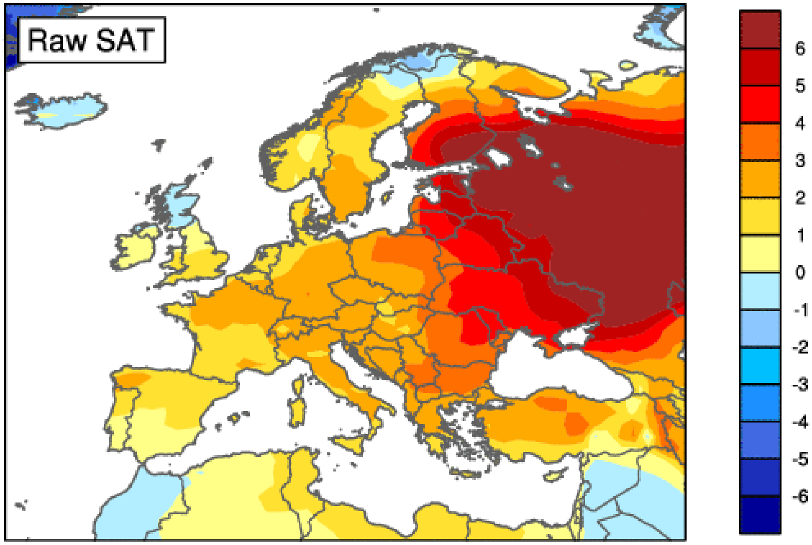
Step 6: take the average of the N_{iter} values

$K = 15$

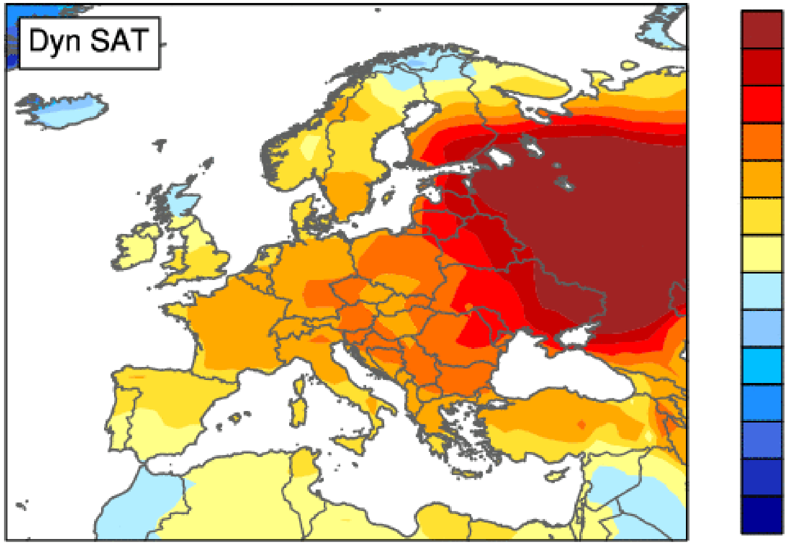


°C

SAT dynamical component

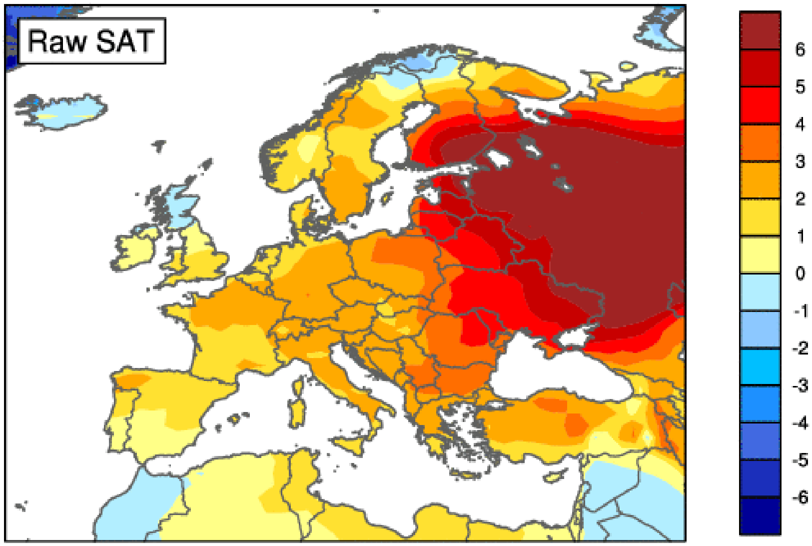


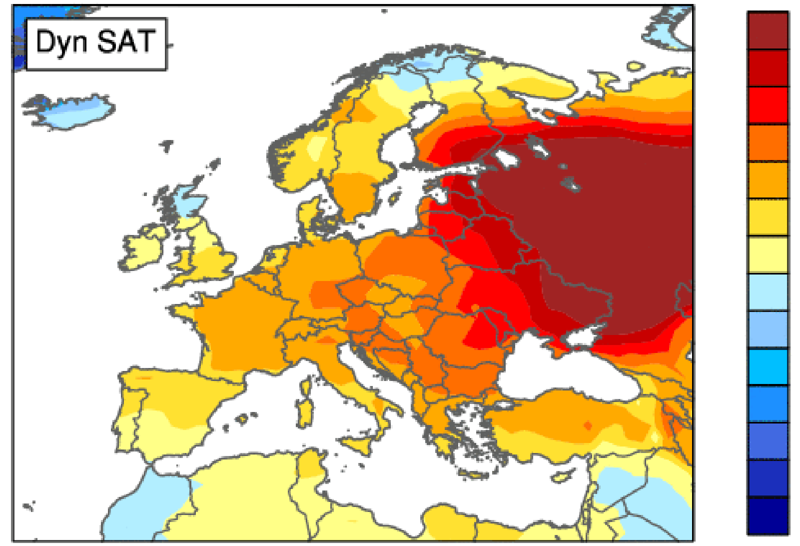
Total anomaly °C

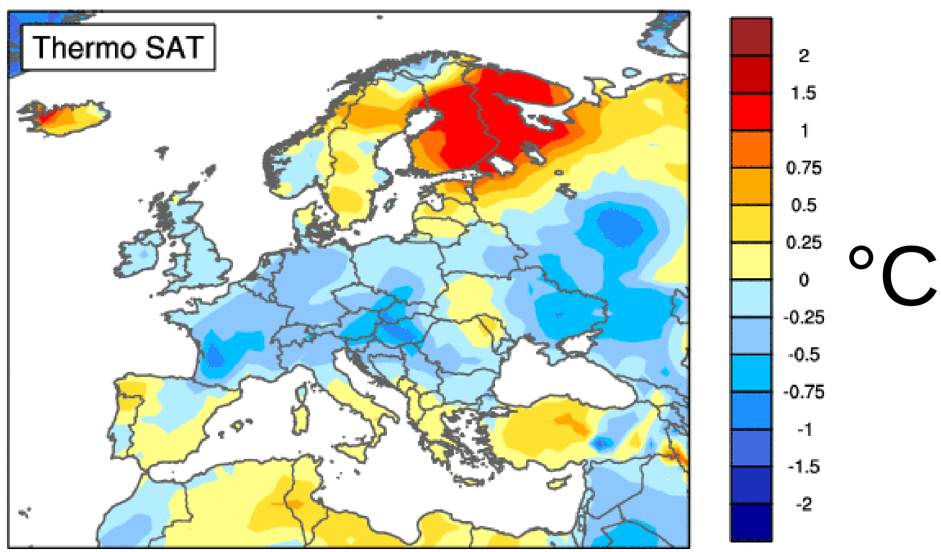


Dynamical component

SAT thermodynamical component







Thermodynamical component

Influence of internal variability on SAT trends

Model framework: use the CESM1 large ensemble (30 members, HISTorical 1920-2012)

$\Rightarrow$ **1.** Focus on the 1963-2012 period

$\Rightarrow$ **2.** Focus on winter season (DJF)

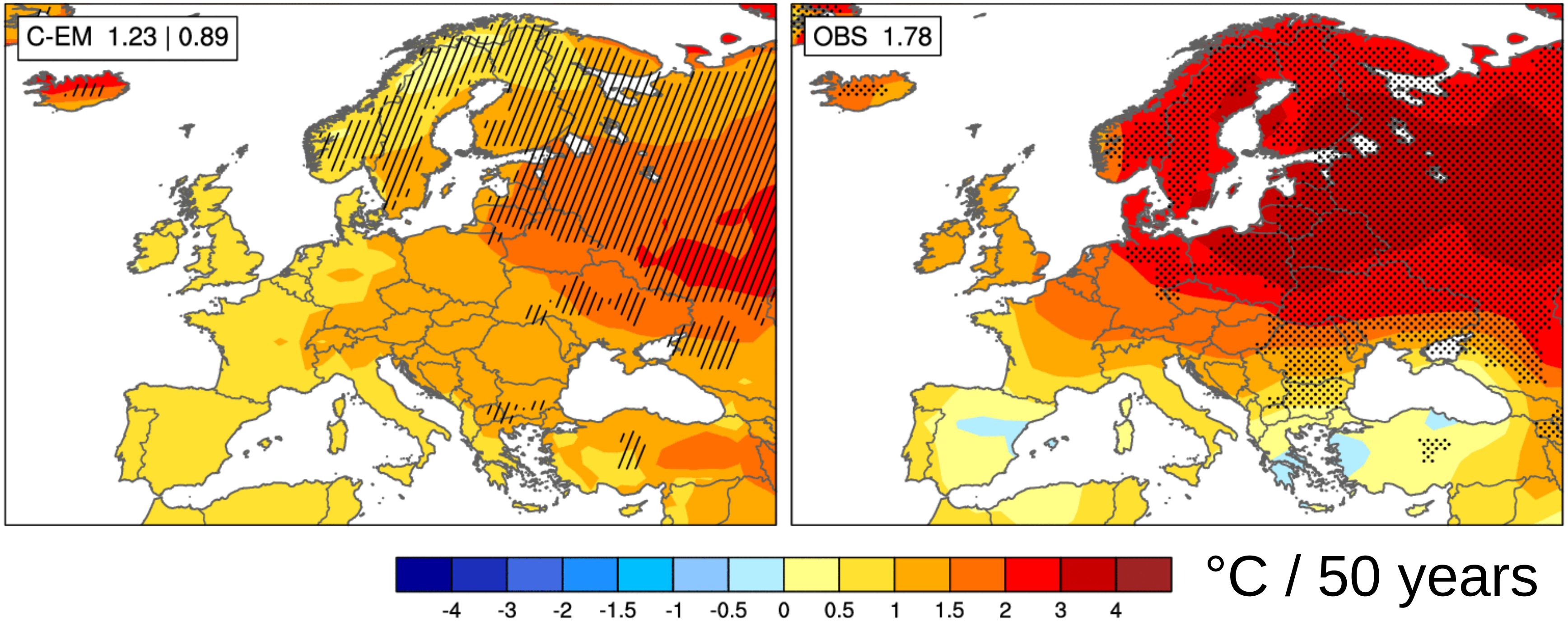
$\Rightarrow$ **3.** Reconstruct HIST monthly SLP from PiCntrl closest analogues

$\Rightarrow$ **4.** Derive monthly SAT dynamical component for all months of all HIST members

$\Rightarrow$ **5.** Use paradigm to partition 50-yr trends

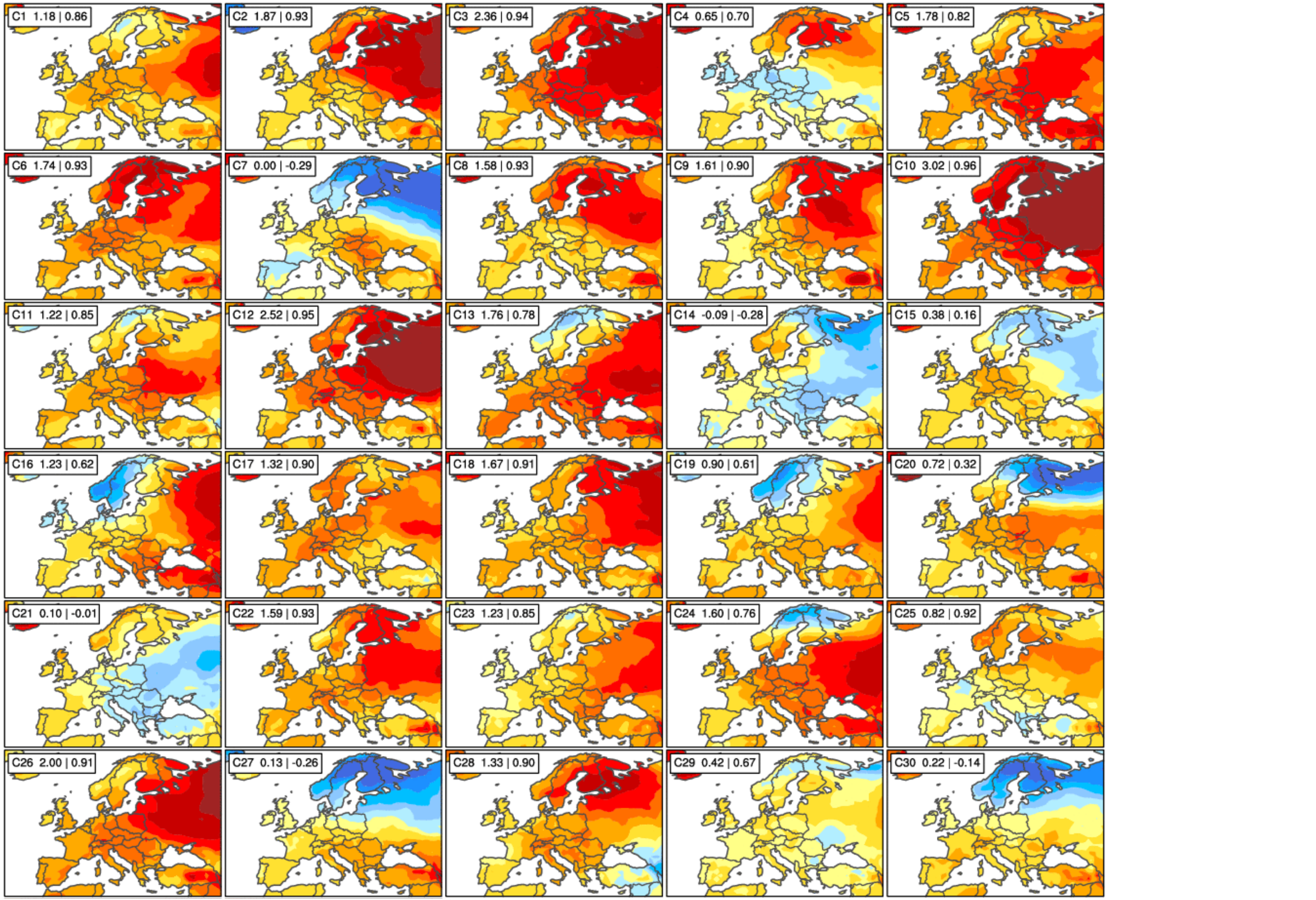
Winter SAT 1963-2012 trends

CESM1 Ens.Mean | Obs

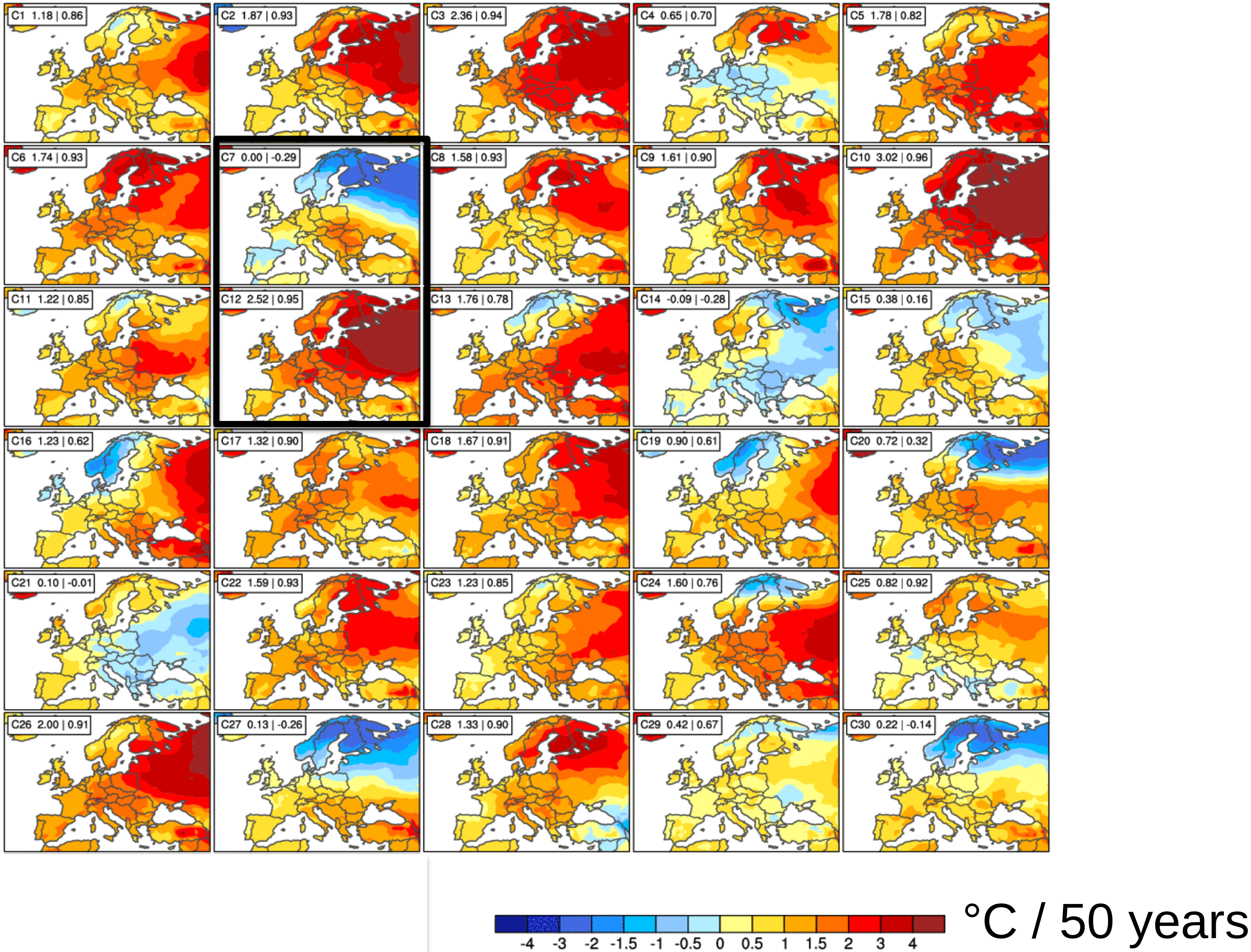


1.2 °C / 50 years | 1.8 °C / 50 years

All CESM1 trends

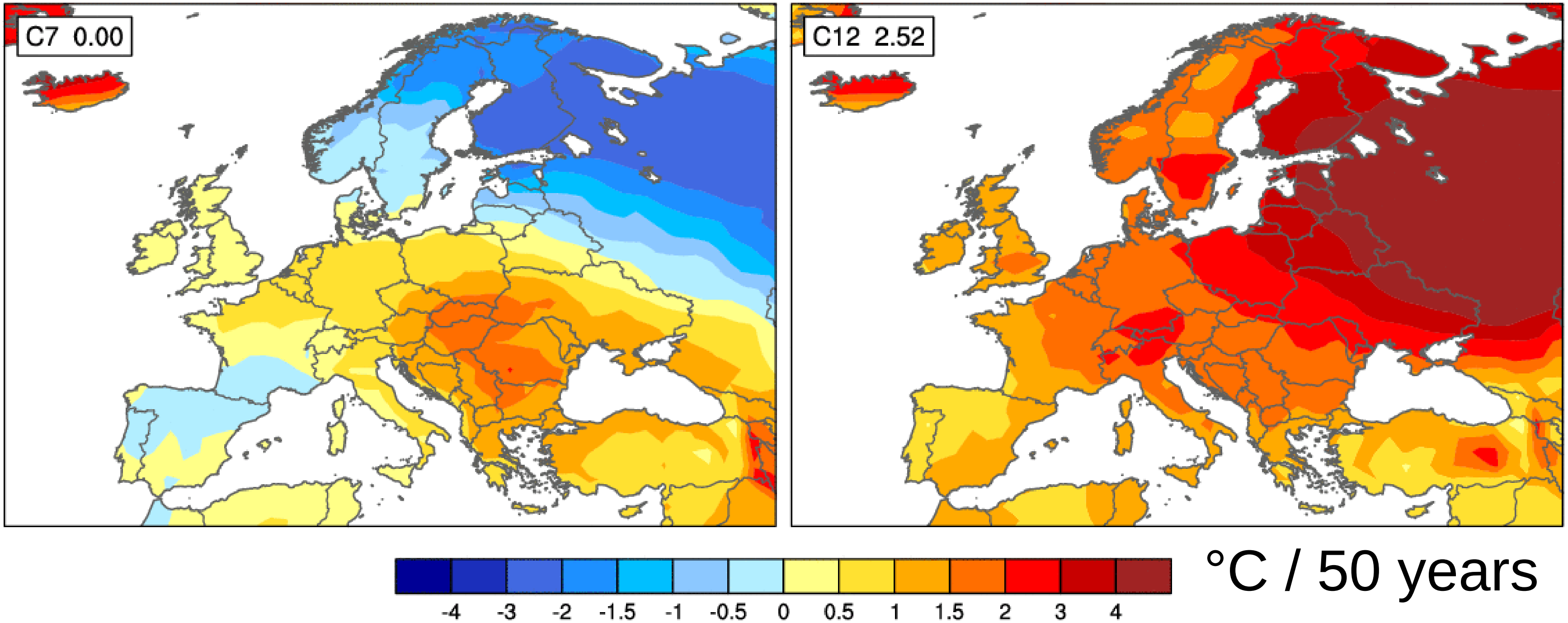


All CESM1 trends



Total trends

Member 7 | Member 12

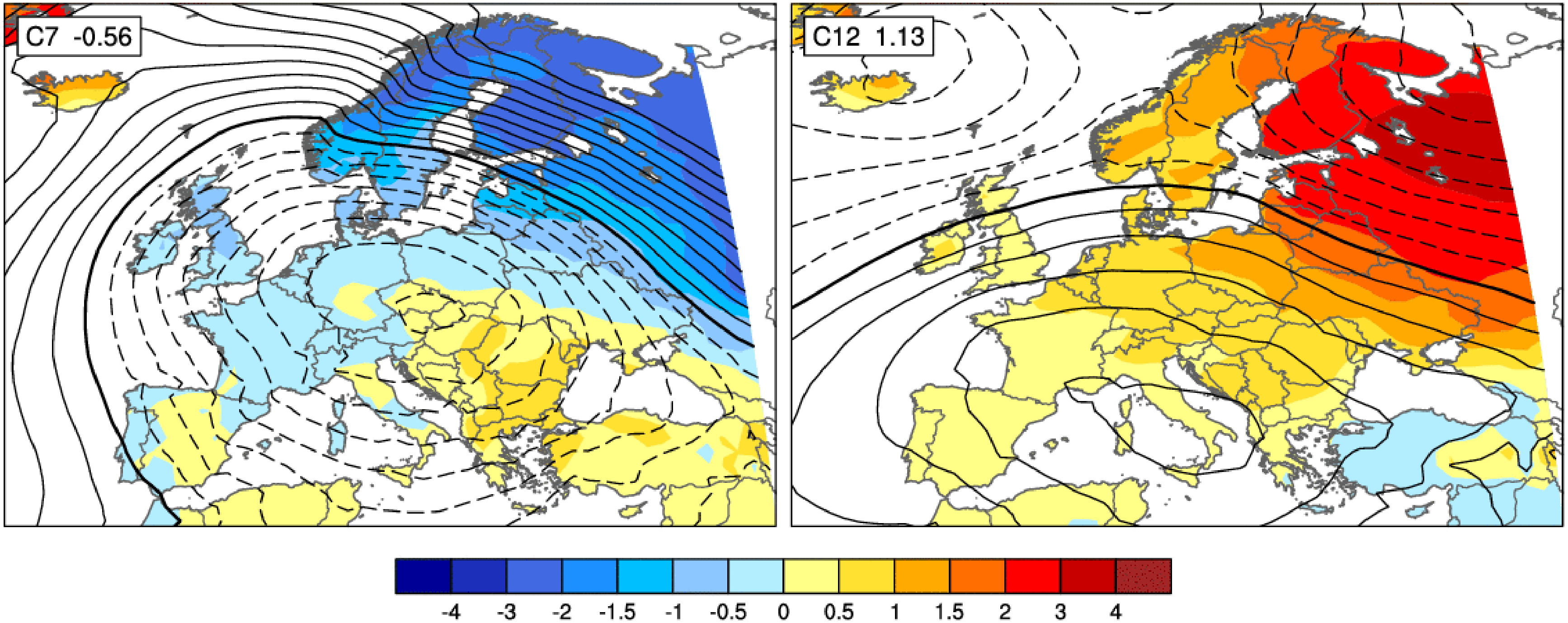


0 °C / 50 years

2.5 °C / 50 years

Dynamical component

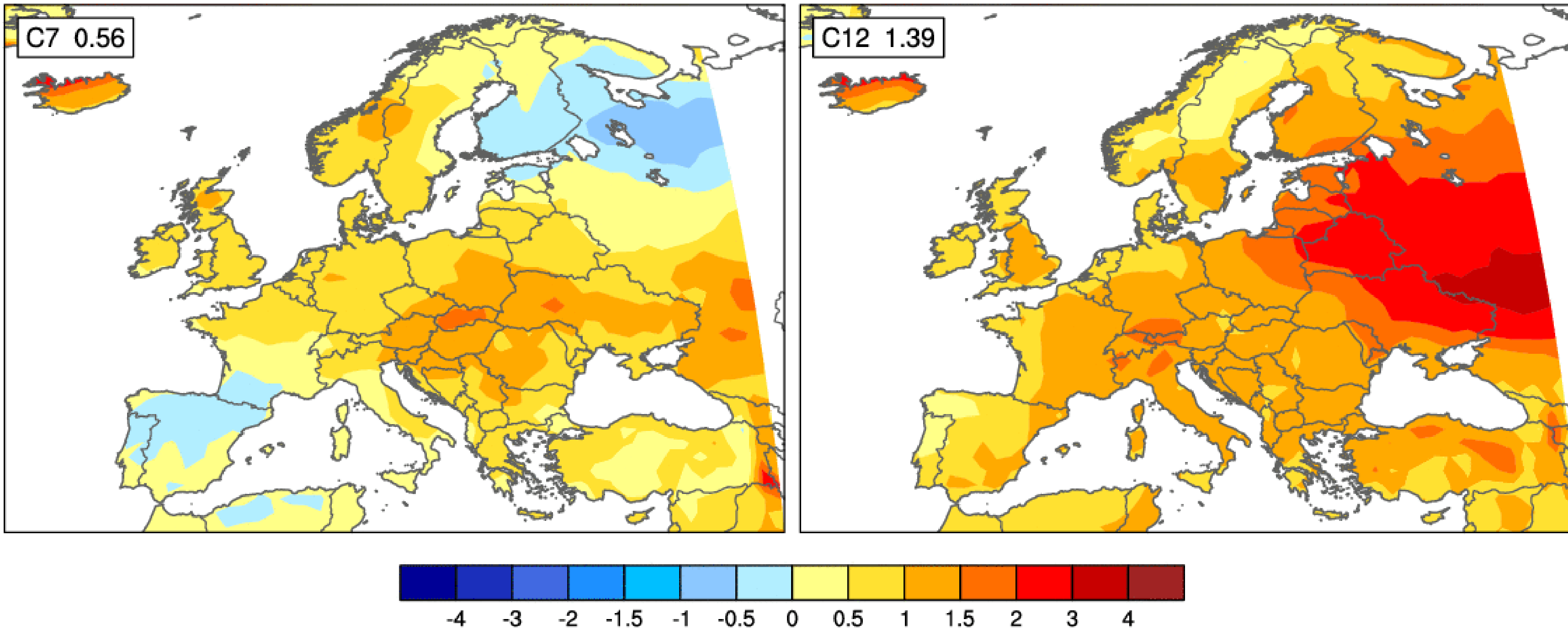
Member 7 | Member 12



-0.56 °C / 50 years | 1.1 °C / 50 years

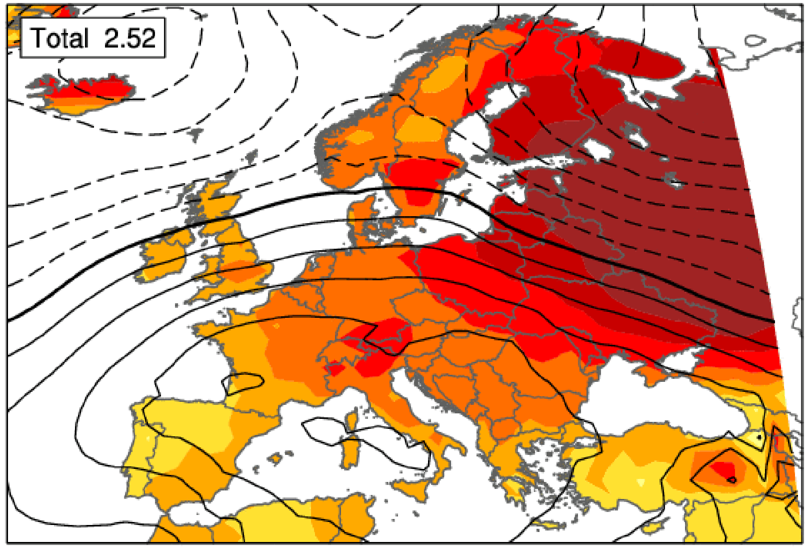
Thermodynamical component

Member 7 | Member 12



0.56 °C / 50 years | 1.4 °C / 50 years

Member 12: free and forced components

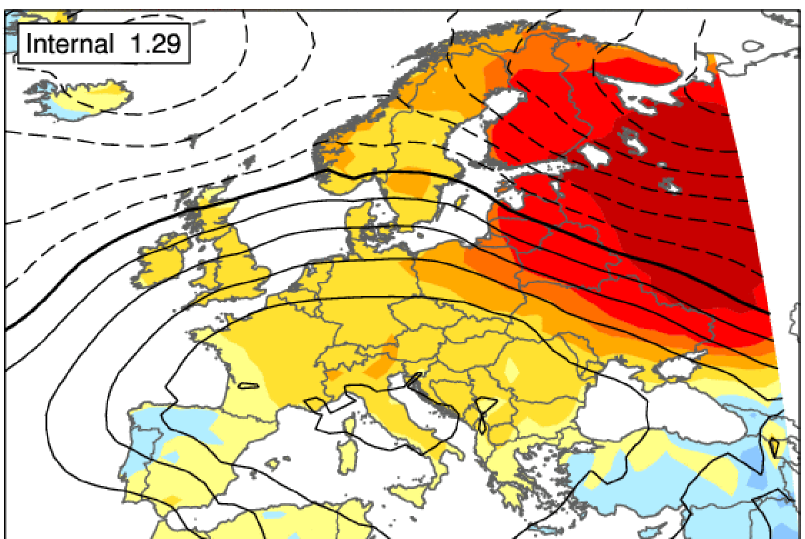


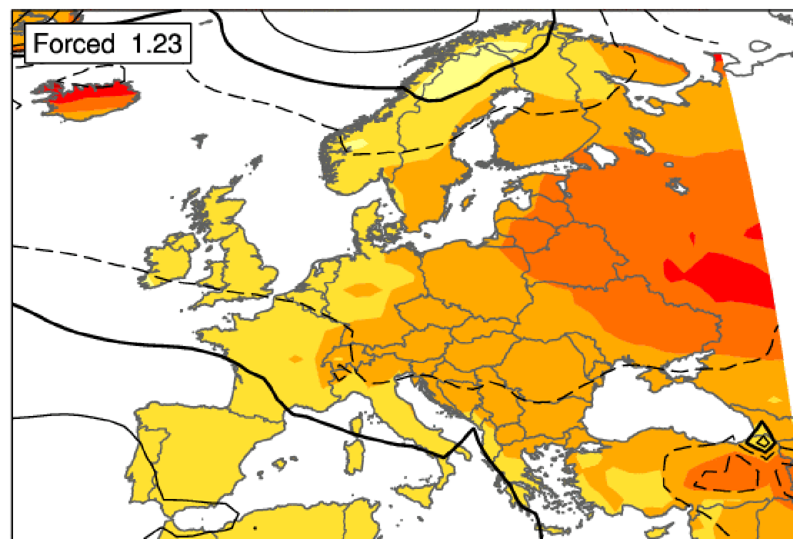
Total

2.5 °C/50yr

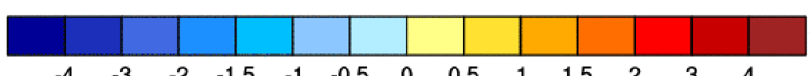
Free

Forced





1.3 °C/50yr

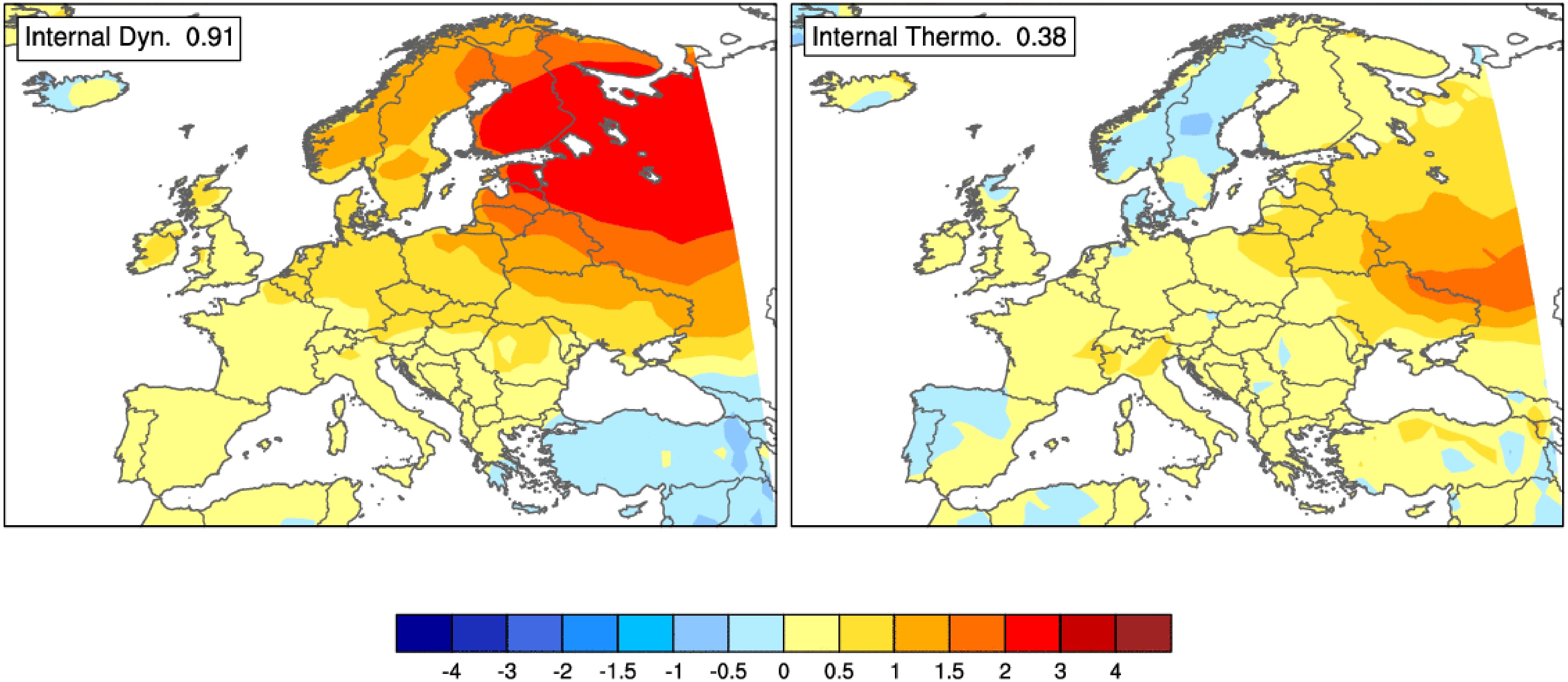


1.2 °C/50yr

Dynamical and thermodynamical free components

Dynamical

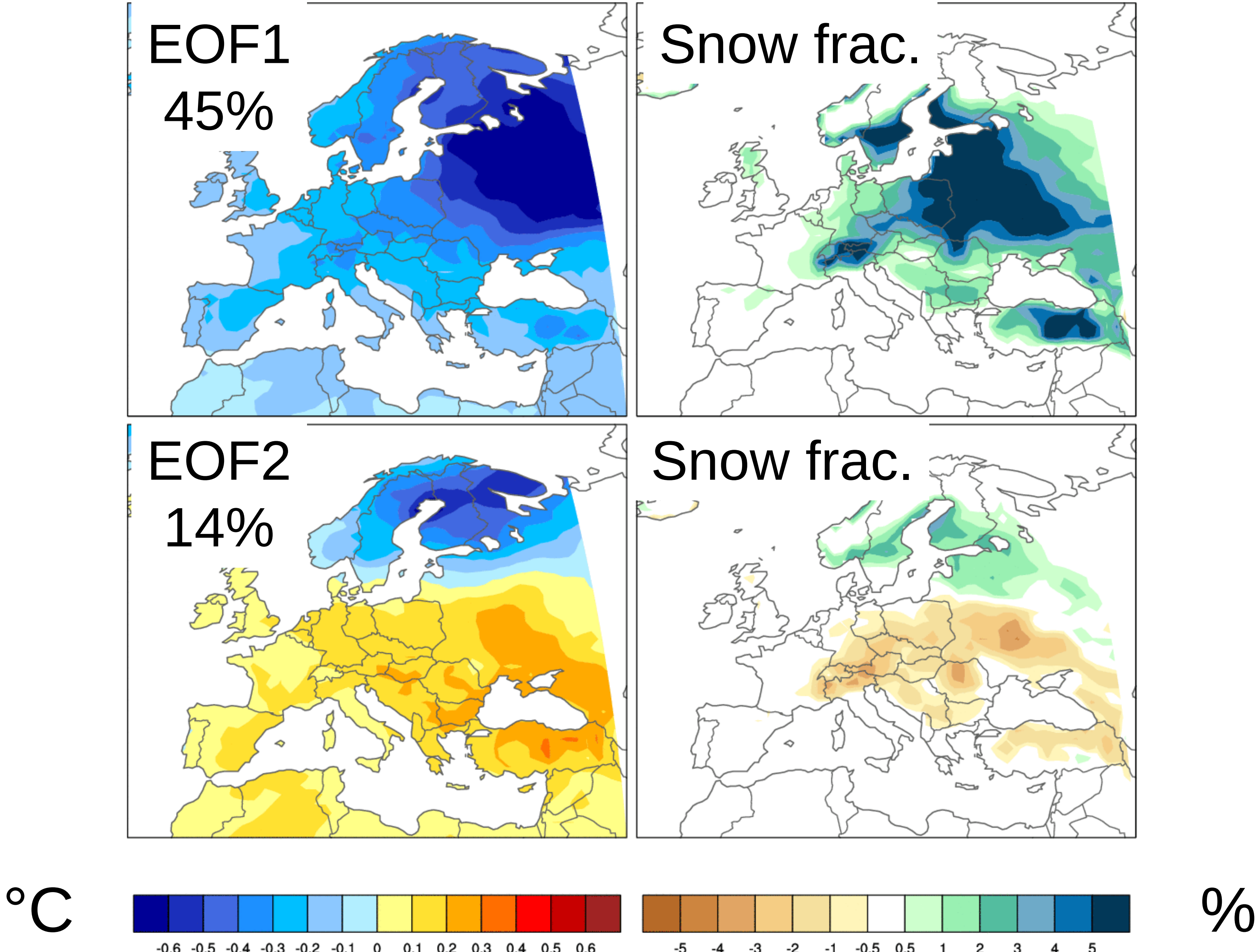
Thermodynamical



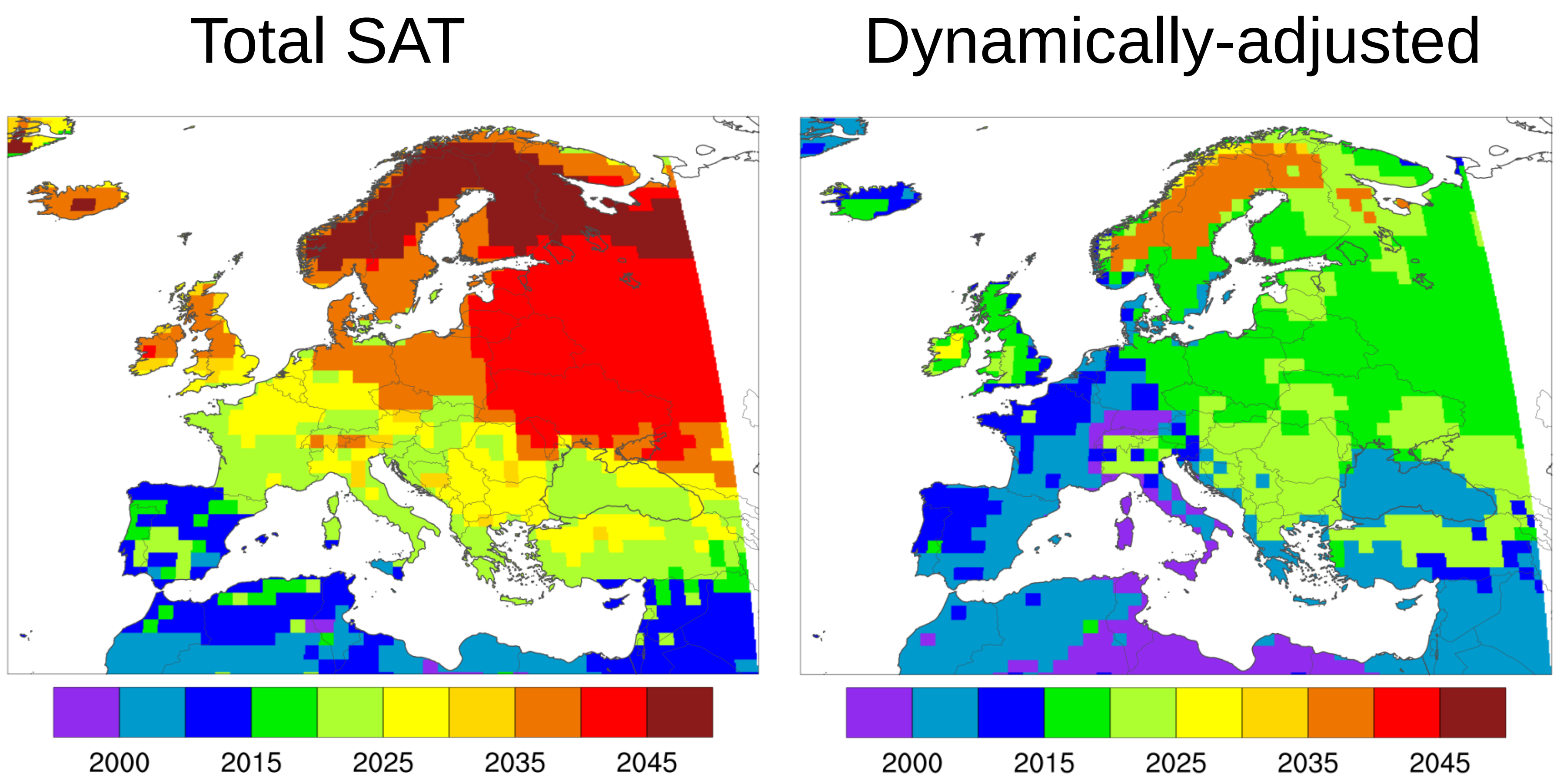
0.9 °C / 50 years

0.4 °C / 50 years

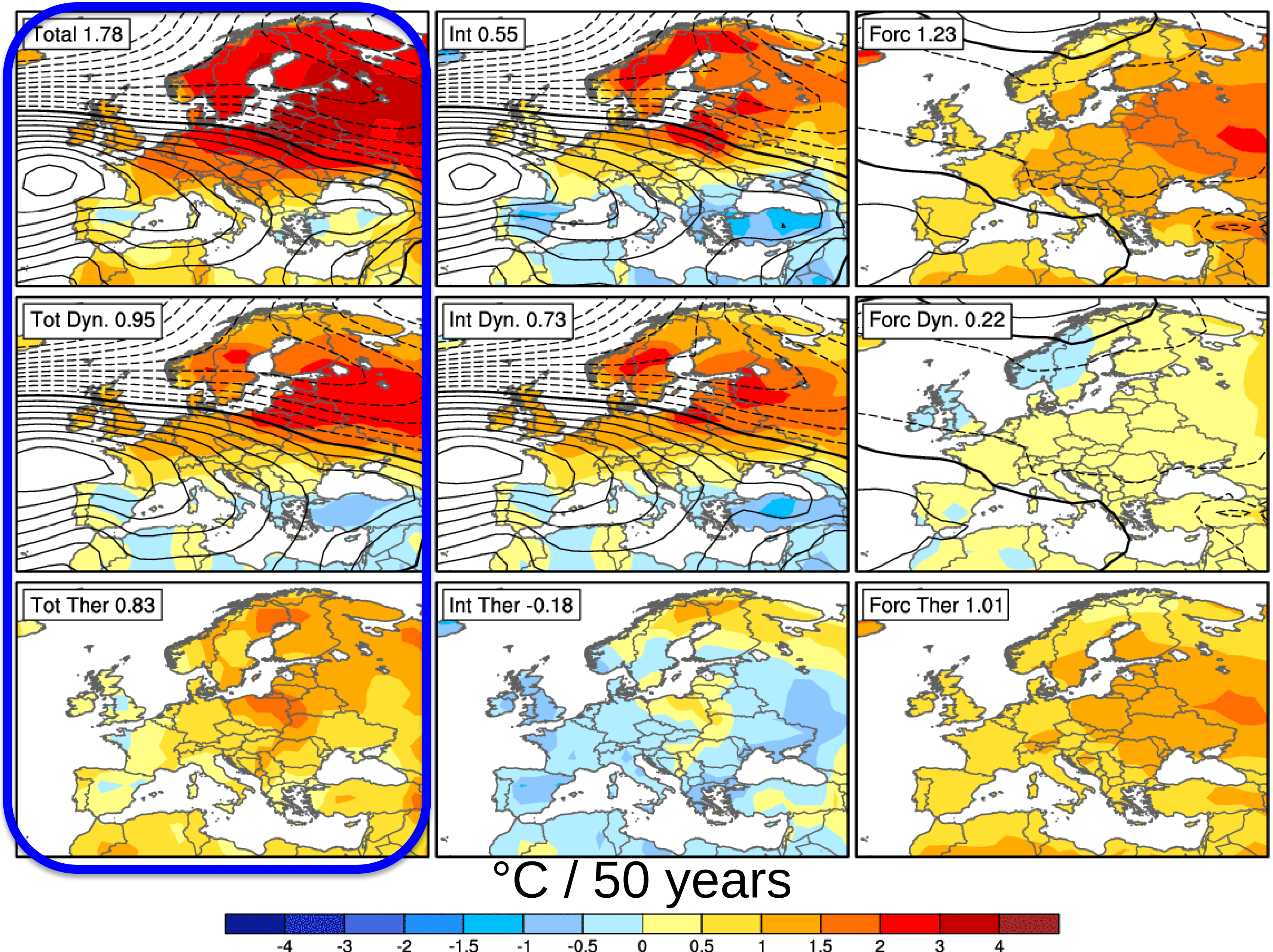
EOFs of the trends thermodynamical component



Dynamical adjustment and time of emergence



Observations: trend attribution



Summary

⇒ Western Europe is warming (1.8 K / 50 years in winter)

⇒ Analysis of CESM1 LE suggests a possible large contribution from internal variability (same magnitude as the forced response)

⇒ Main contribution comes from the dynamical component

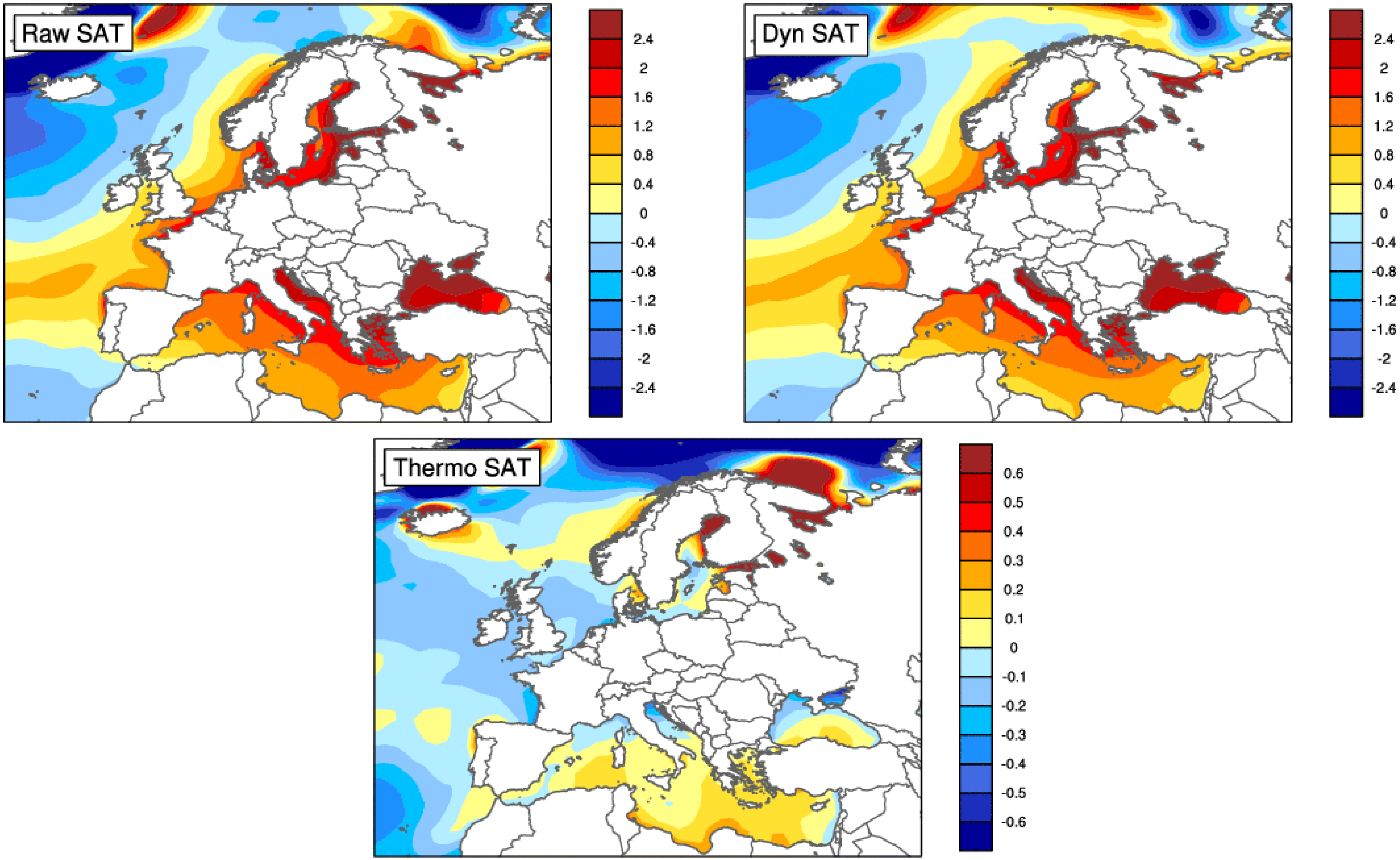
⇒ Dynamical adjustment increases signal to noise ratio (more in winter than summer) and advances time of emergence

⇒ Spread in internal thermodynamical component related to the ocean state and land-atmosphere interactions (snow effect dominant in winter)

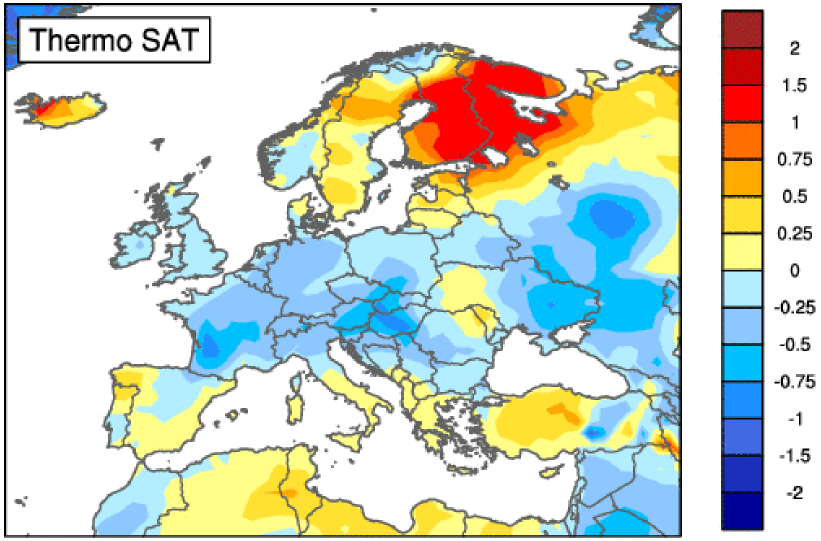
⇒ No discrepancy between CESM1 and observations

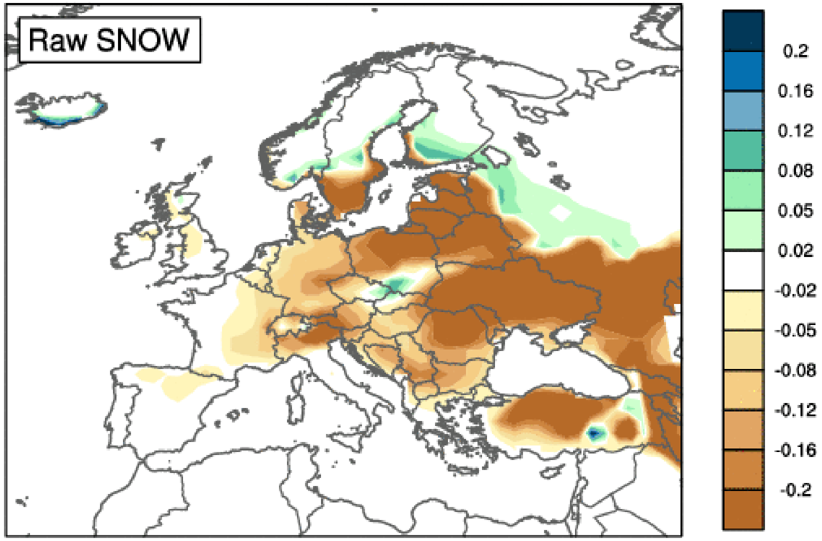
⇒ Dynamically adjusting observations suggests that half of the observed trend could be due to unpredictable decadal changes in atmospheric circulation

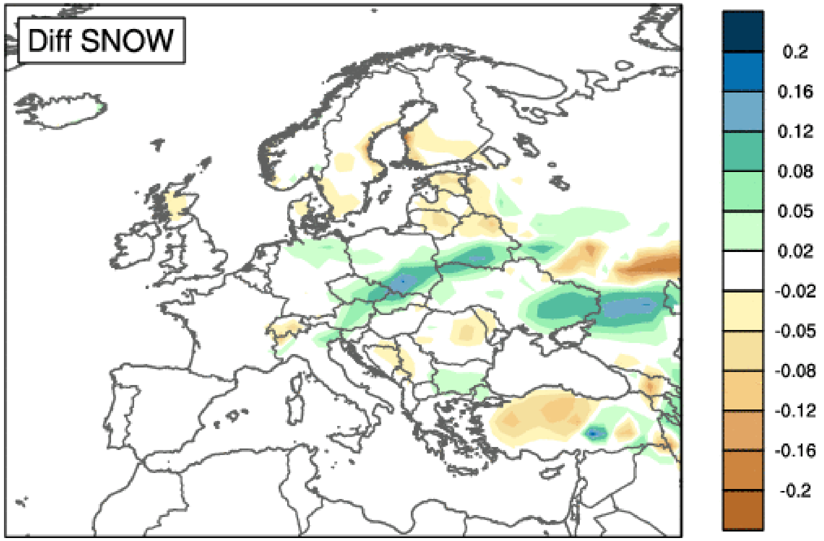
Thermodynamical component: ocean



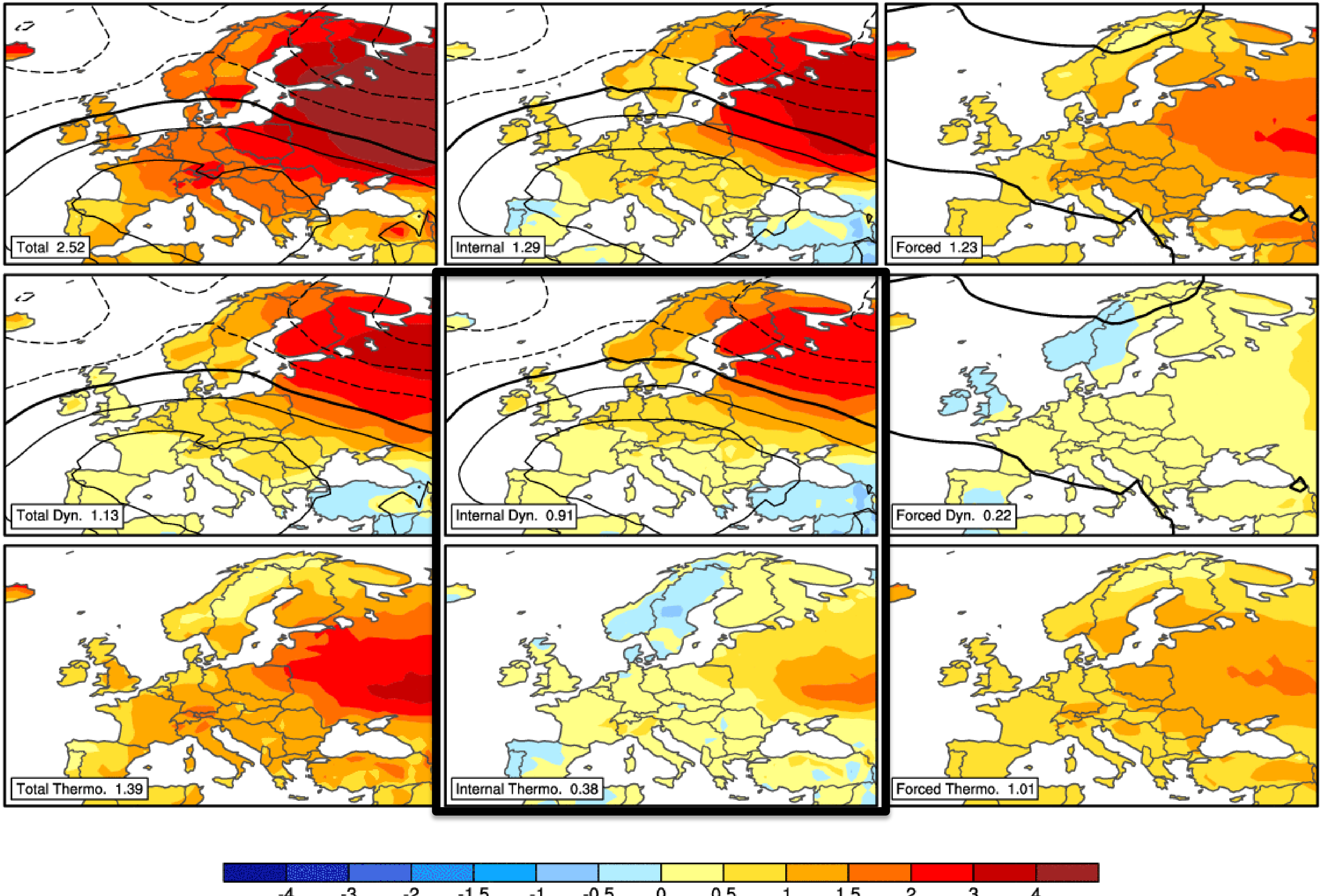
Thermodynamical component: snow



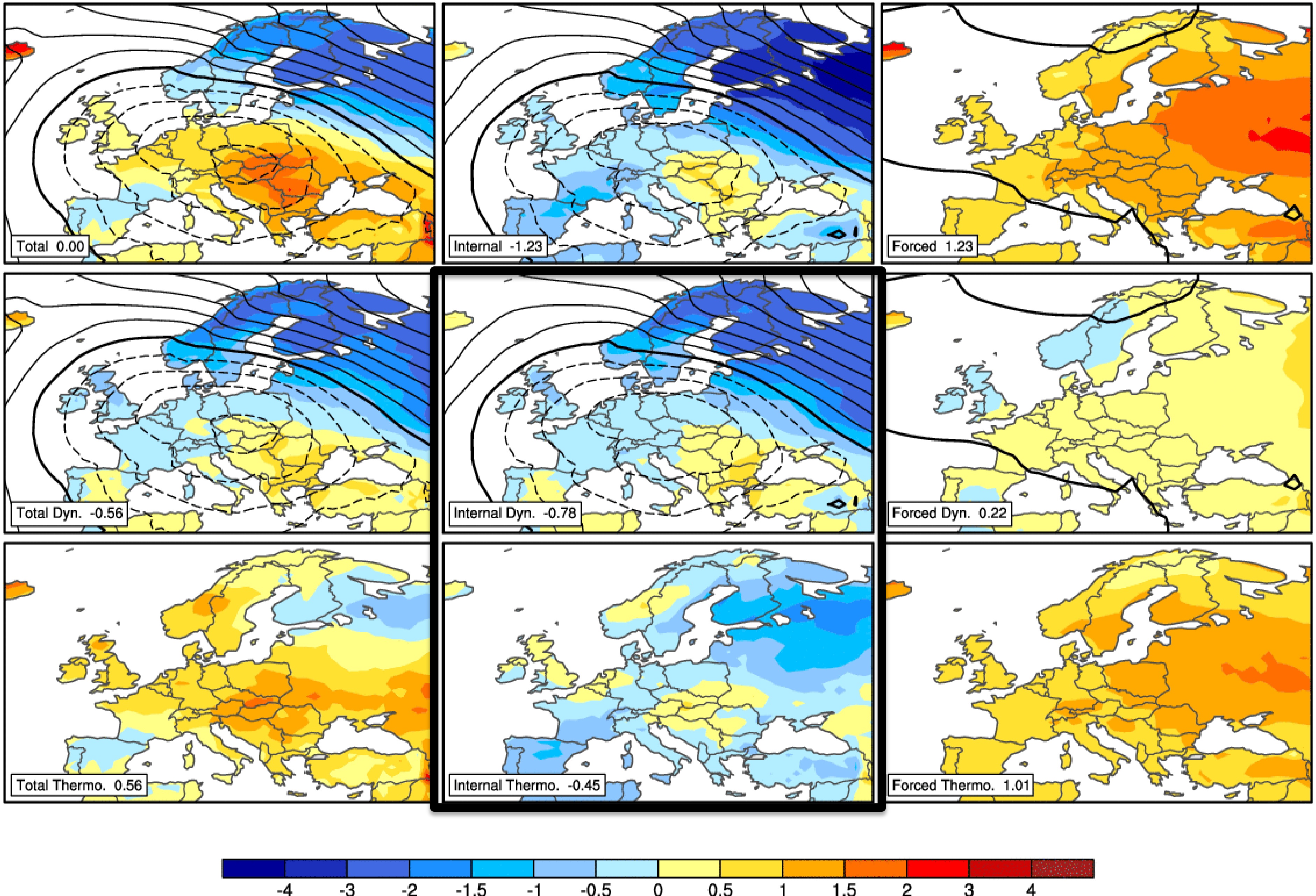




Trend attribution: member 12



Trend attribution: member 7



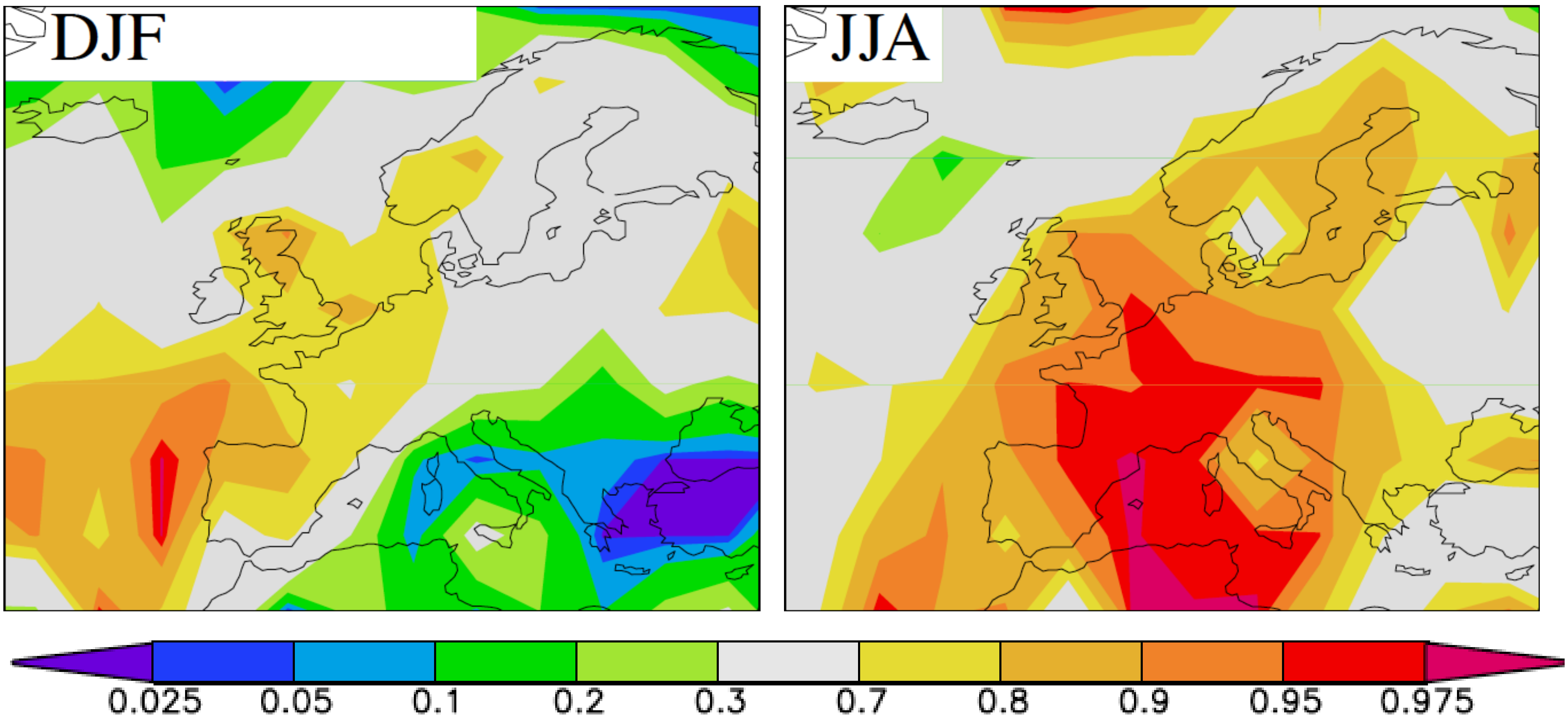
Reliability in space

Period 1950-2007: Observations SAT (GISS)

⇒ Use SAT regression on global mean temperature

$$SAT(x,y,t) = B(x,y)\ .\ SAT_{glob.mean} + \varepsilon\ (x,y,t)$$

⇒ Percentile of observed B in model CMIP3 values



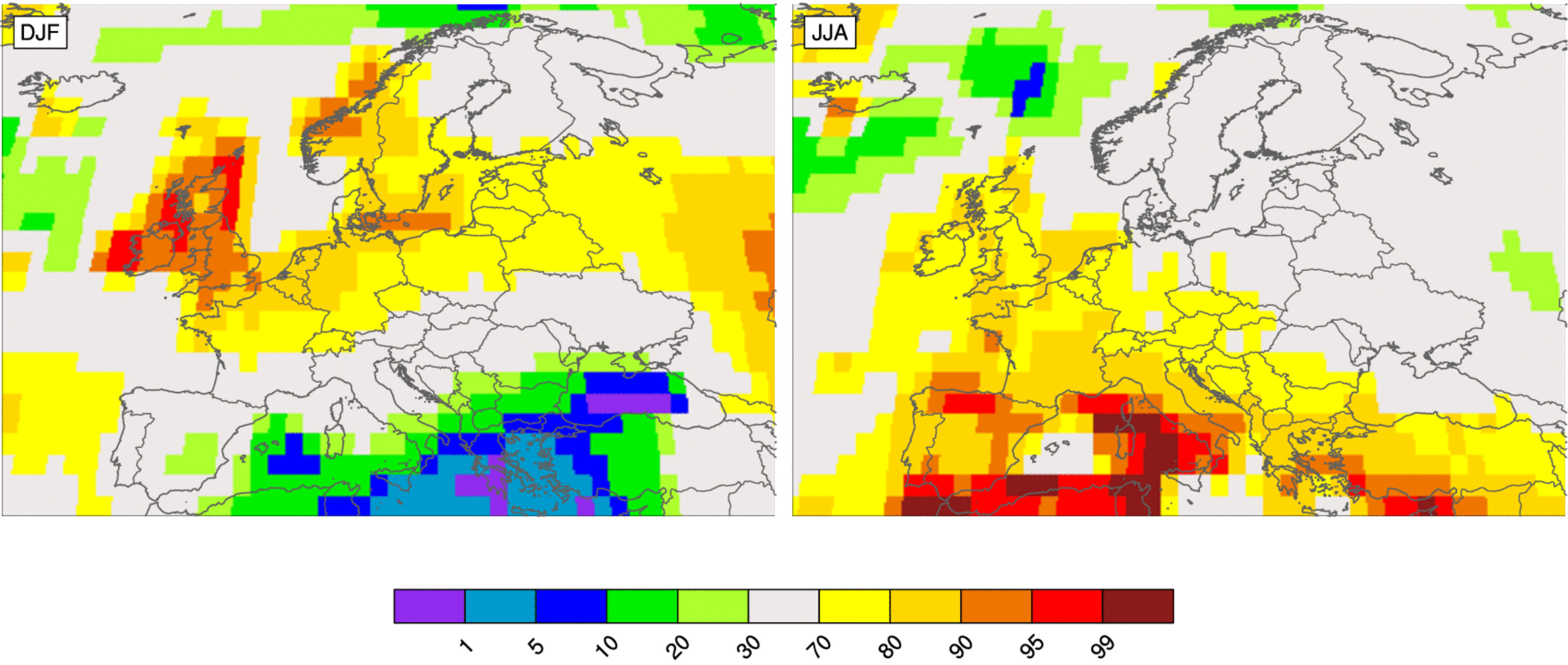
Reliability: CMIP5

Period 1950-2007: Observations SAT (GISS)

⇒ Use SAT regression on global mean temperature

$$SAT(x,y,t) = B(x,y) \, . \, SAT_{glob.mean} + \varepsilon\,(x,y,t)$$

⇒ Percentile of observed B in CMIP5



Algorithm

- Use monthly data
- Use a large regional domain (e.g North America), m grid points
- **Algorithm**

=> Start with SLP of Jan. 1920 of the first HIST member and look for the N_a closest SLP analogues among all (1200) PICNTRL January

⇒ Even a 1200-year period is not enough to get good enough analogues.

⇒ Use the Constructed Flow Analogue (CFA) method (Van den Dool 1994)

⇒ Draw randomly N_b analogs among the N_a

⇒ Let X_h be the Jan. 1920 monthly SLP from HIST, $X_{c,i=1,Nb}$ the N_b analogues from PICNTRL. We estimate β such as : $X_h \approx X_{ca} = X_c \, . \, \beta$

⇒ X_{ca} constructed analogue as a linear combination of the N_b closest analogues (dims of X_c : m x N_b , X_{ca} : m x 1 and β : N_b x 1)

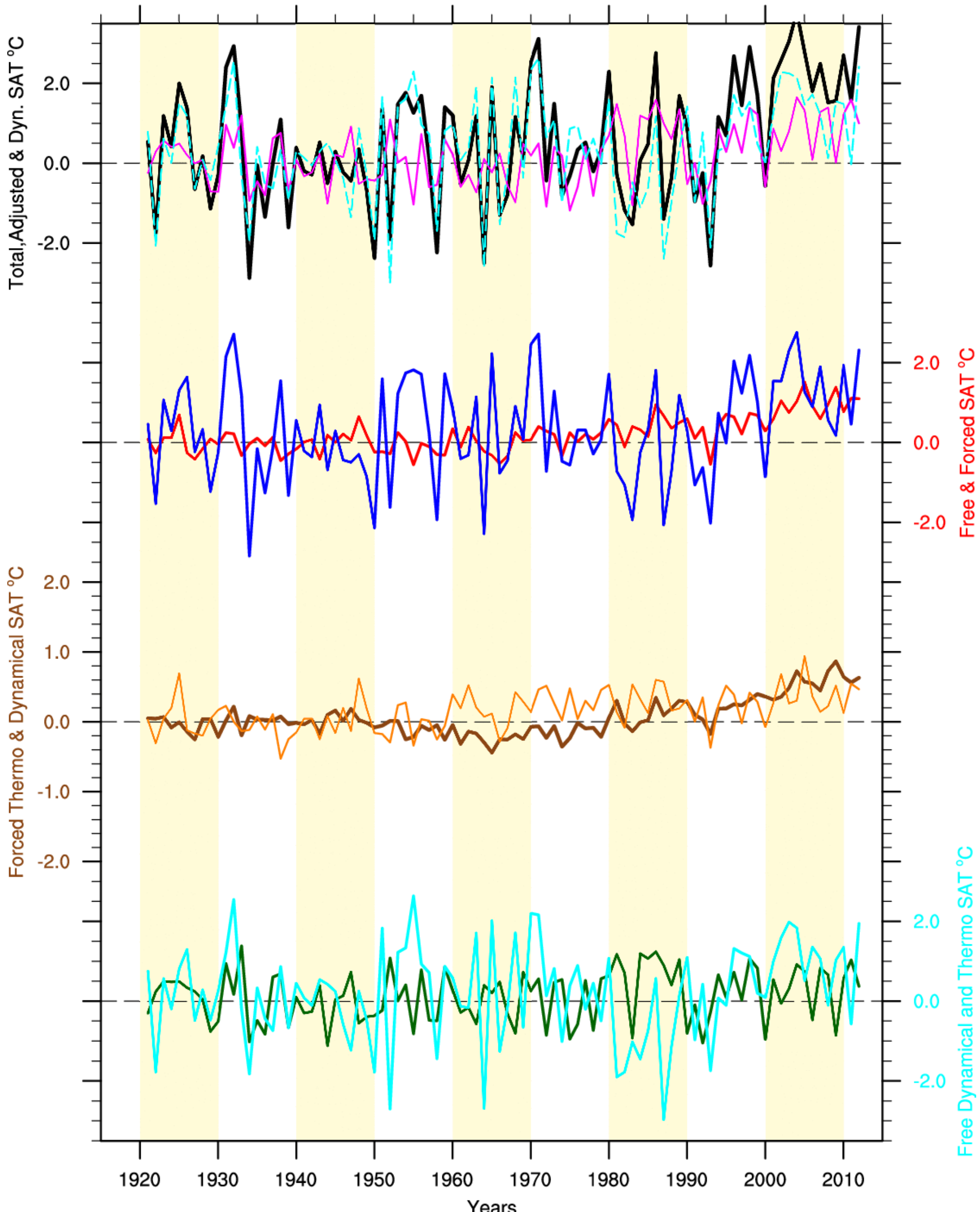
⇒ Estimate β as $[\, (\boldsymbol{X_c}^{\boldsymbol{T}} . \boldsymbol{X_c})^{-1} . \ \boldsymbol{X_c}^{\boldsymbol{T}} \,] . X_h$ (Moore-Penrose pseudo_inv)

⇒ Reconstruct any other monthly variable (SAT, PR) using β

⇒ Repeat previous steps N_i times

⇒ Do that for all months and all members from HIST

Europe DJF temperature: member 12



Sensitivity to number of analogues