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CopERnIcus climate change Service Evolution - CERISE

HOW WELL DO DYNAMICAL SEASONAL FORECASTS CAPTURE SOIL-MOISTURE ATMOSPHERE COUPLING?

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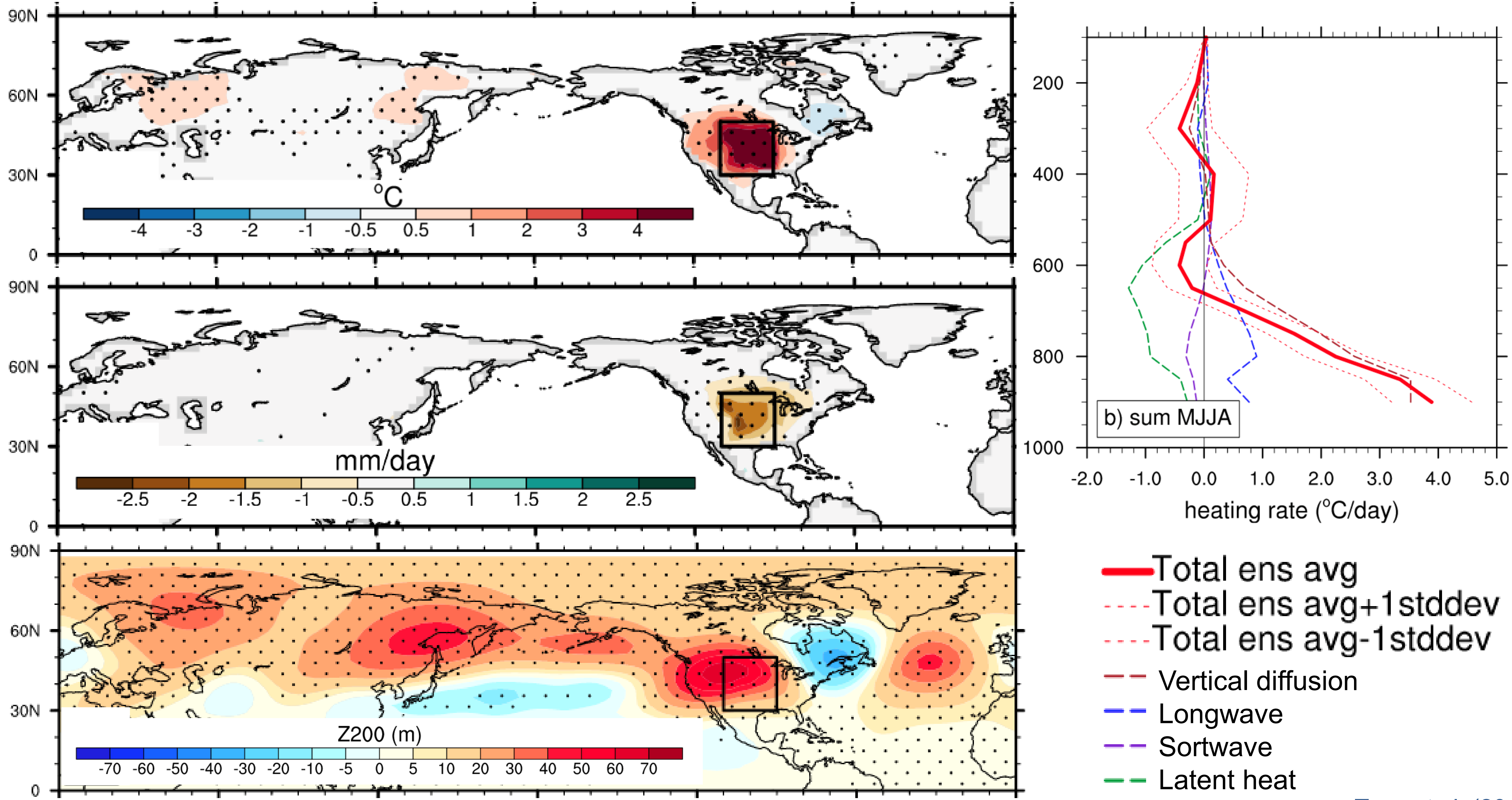
Thanks to Constantine Ardilouze (MF), Daniele Peano (CMCC), Kristina Fröhlich (DWD), Martin Andrews (UKMO)

Atmospheric response to soil-moisture depletion



Teng et al. (2019)

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Motivation

- Land-atmosphere coupling “hotspots” identified in idealised experiments (i.e. GLACE: Koster et al. 2004, Teng et al., 2019) and diagnostic analyses (e.g. Dirmeyer 2011).
- Prognostic approaches have been used to quantify sensitivity to land-initial conditions in seasonal forecasts (e.g. Materia et al. 2014; Prodhomme et al. 2016; Ardilouze et al. 2017)
- In this study we take a diagnostic approach to:
  1. Identify where we should expect skill in soil-moisture and related impact on the atmosphere
  2. Investigate links between soil-moisture atmosphere coupling and hindcast skill
  3. Investigate the causes of errors in land-atmosphere coupling strength.

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Datasets

- JJA Seasonal forecasts: 1st May forecasts for 7 (out of 9) systems contributing to the Copernicus Climate Change Service Multi-Model system (NCEP and JMA don't submit soil moisture).
- Observational data:
  - Berkeley Earth Surface Temperatures (BEST)
  - Global Precipitation Climatology Project (GPCP)
  - Global Land Evaporation Amsterdam Model (GLEAMv3.7) root-zone soil moisture and evaporation
  - ECWMF reanalysis (ERA5/ERA5-land) for everything else.

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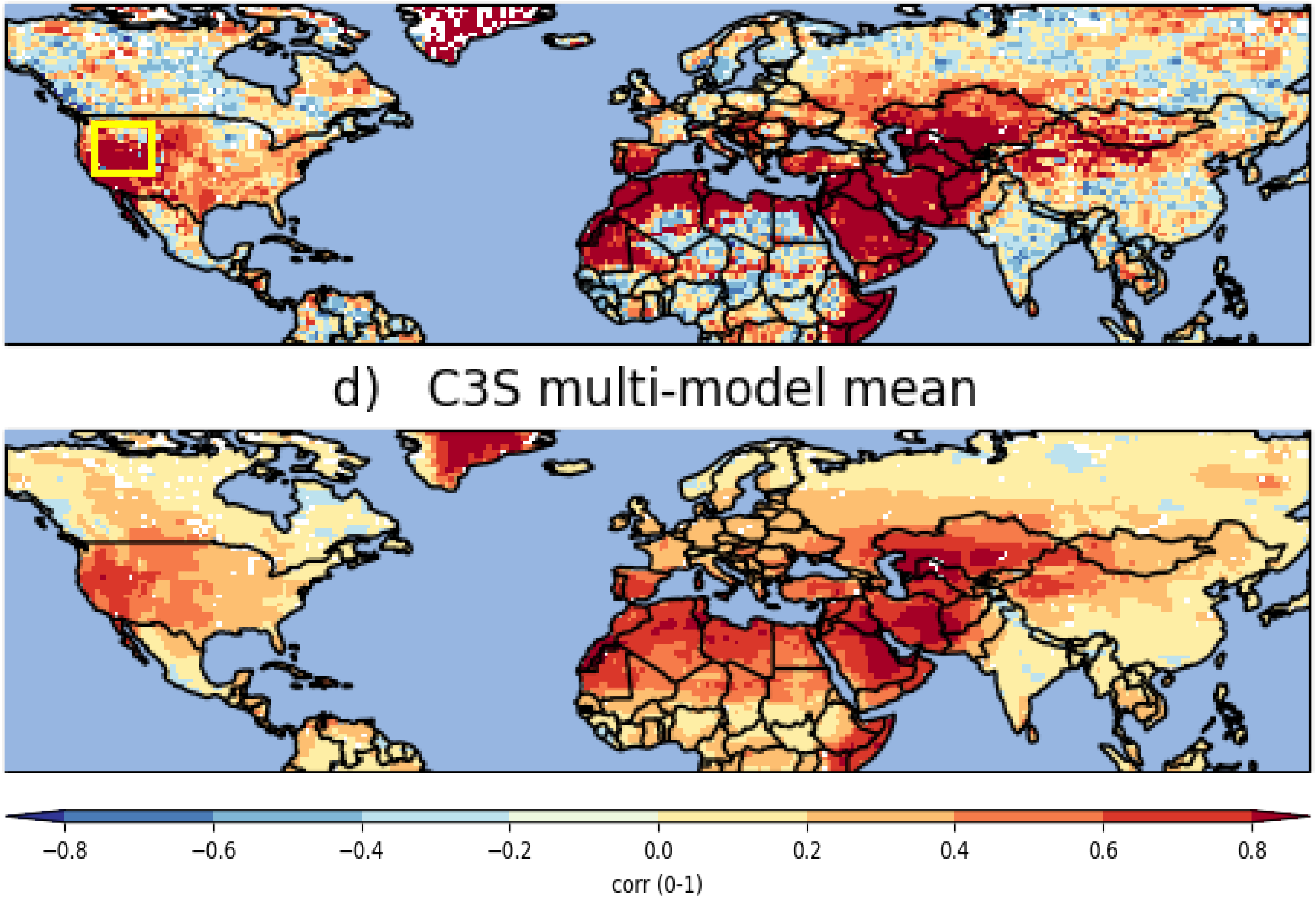
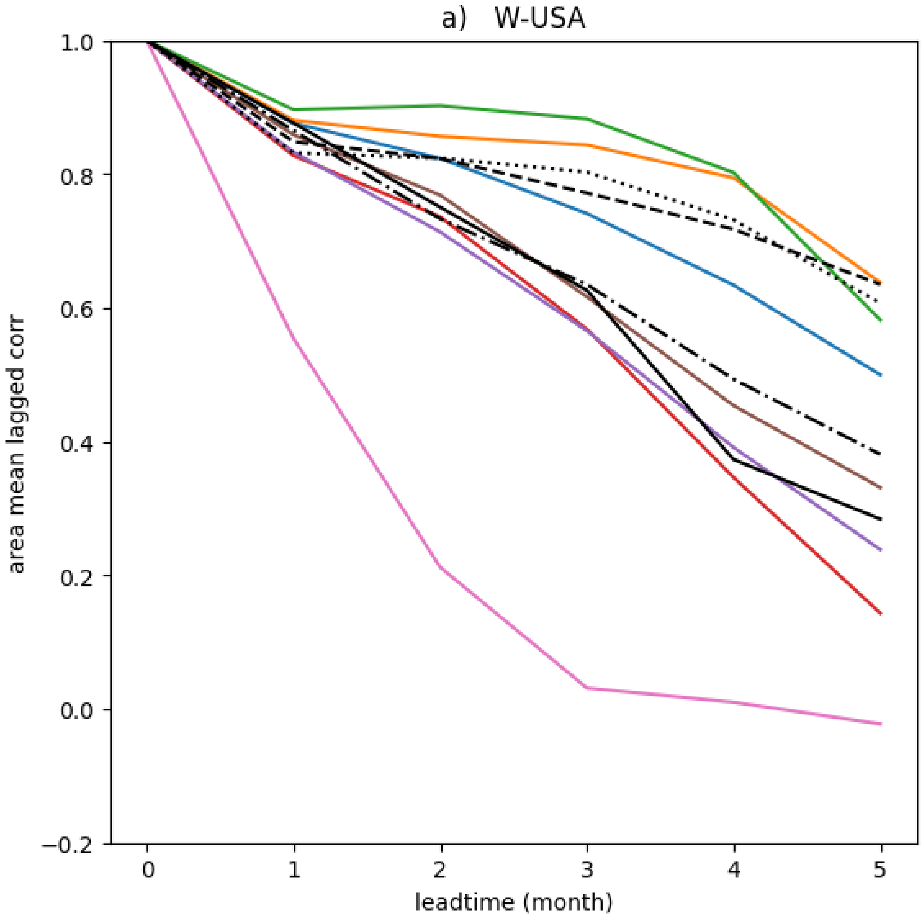
Soil-moisture lagged correlation

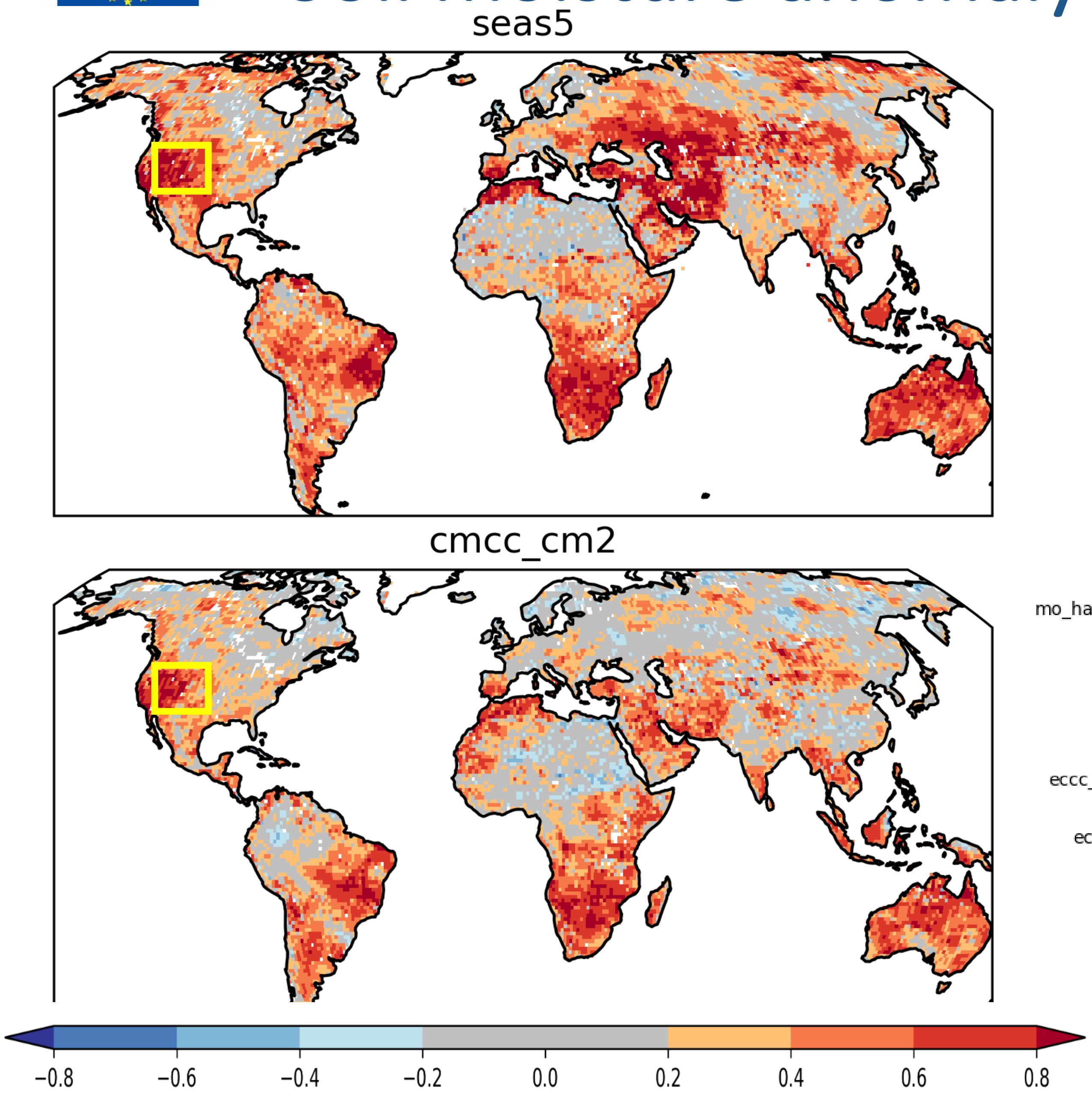
ERA5-land: $\rho(SM_{May}, SM_{Aug})$



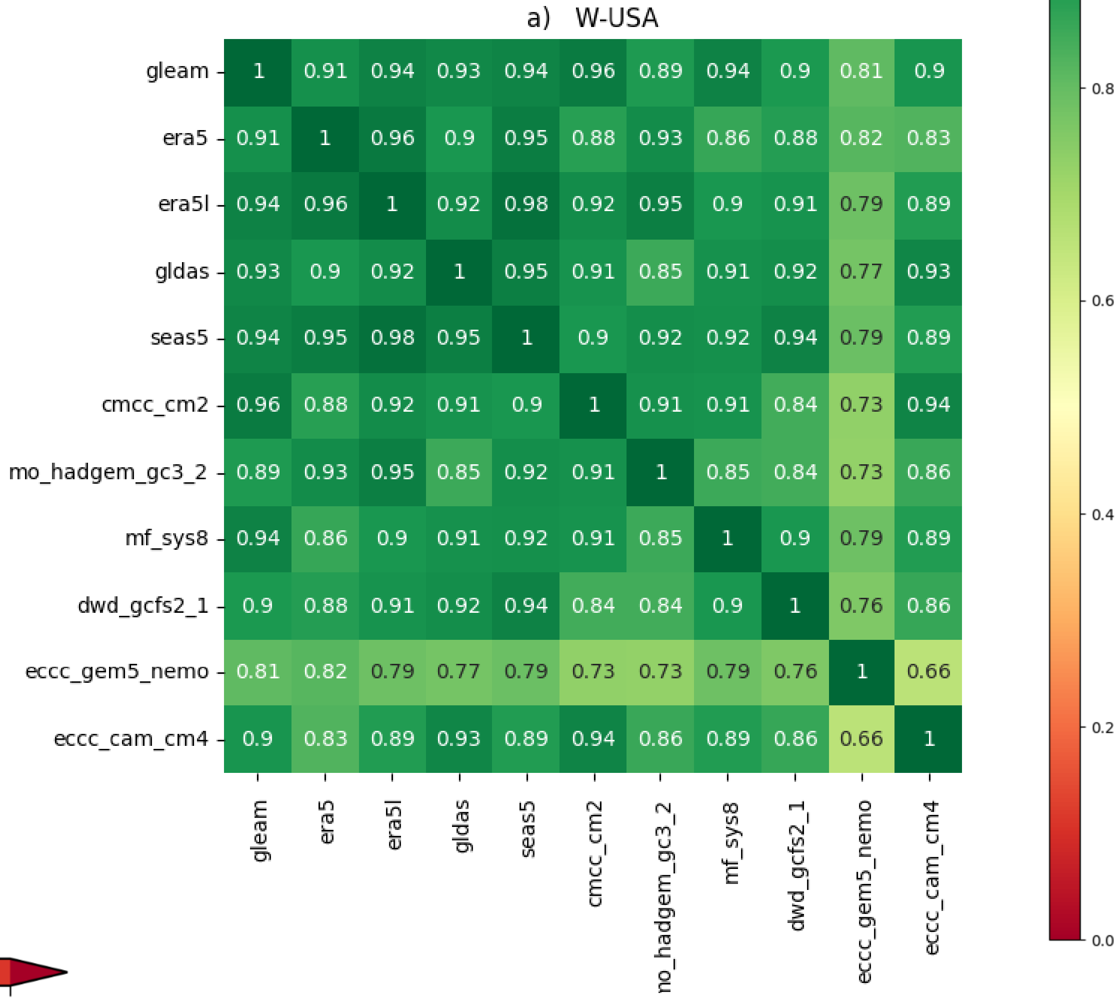


Similar to regions identified by Seneviratne et al. 2006

Soil moisture anomaly correlation

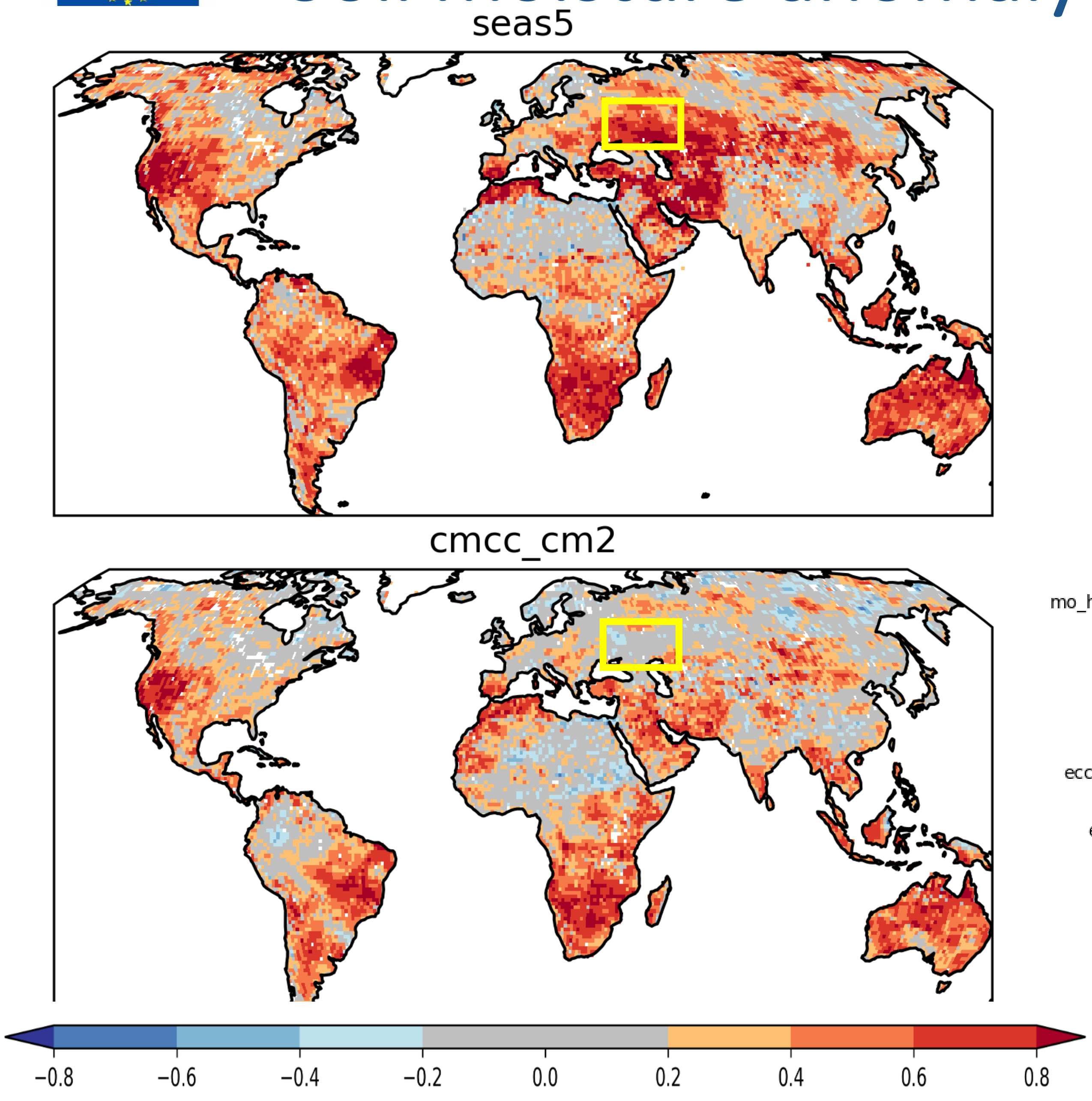


Cross correlation between initial conditions



	gleam	era5	era5l	gldas	seas5	cmcc_cm2	mo_hadgem_gc3_2	mf_sys8	dwd_gcfs2_1	eccc_gem5_nemo	eccc_cam_cm4
gleam	1	0.91	0.94	0.93	0.94	0.96	0.89	0.94	0.9	0.81	0.9
era5	0.91	1	0.96	0.9	0.95	0.88	0.93	0.86	0.88	0.82	0.83
era5l	0.94	0.96	1	0.92	0.98	0.92	0.95	0.9	0.91	0.79	0.89
gldas	0.93	0.9	0.92	1	0.95	0.91	0.85	0.91	0.92	0.77	0.93
seas5	0.94	0.95	0.98	0.95	1	0.9	0.92	0.92	0.94	0.79	0.89
cmcc_cm2	0.96	0.88	0.92	0.91	0.9	1	0.91	0.91	0.84	0.73	0.94
mo_hadgem_gc3_2	0.89	0.93	0.95	0.85	0.92	0.91	1	0.85	0.84	0.73	0.86
mf_sys8	0.94	0.86	0.9	0.91	0.92	0.91	0.85	1	0.9	0.79	0.89
dwd_gcfs2_1	0.9	0.88	0.91	0.92	0.94	0.84	0.84	0.9	1	0.76	0.86
eccc_gem5_nemo	0.81	0.82	0.79	0.77	0.79	0.73	0.73	0.79	0.76	1	0.66
eccc_cam_cm4	0.9	0.83	0.89	0.93	0.89	0.94	0.86	0.89	0.86	0.66	1

Soil moisture anomaly correlation



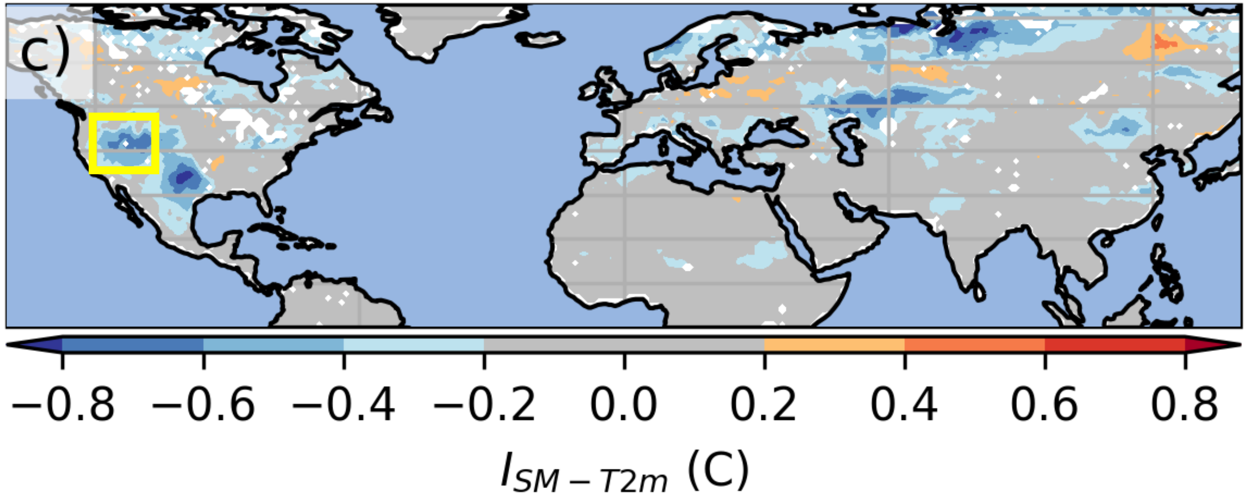
Cross correlation between initial conditions

c) EuPl

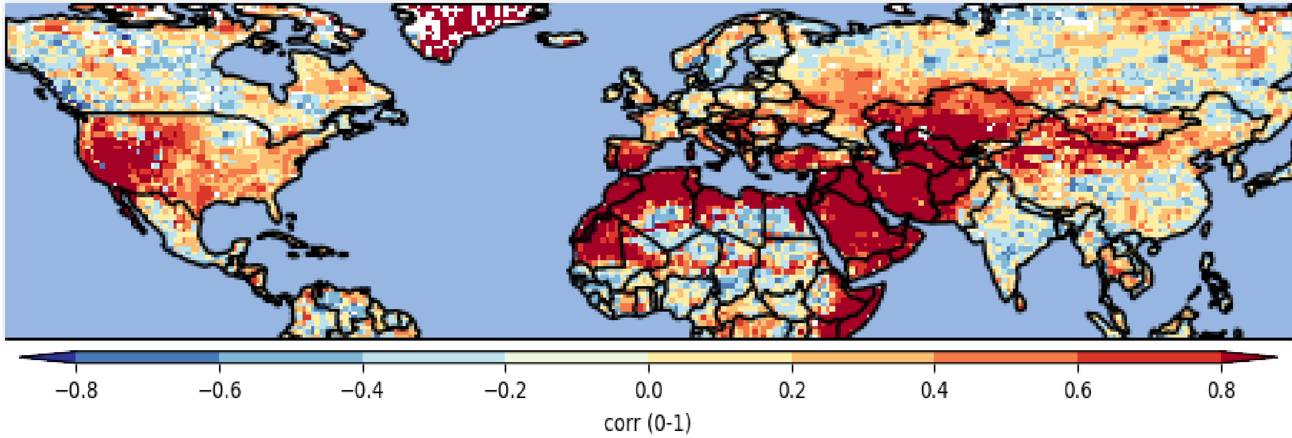
	gleam	era5	era5l	gldas	seas5	cmcc_cm2	mo_hadgem_gc3_2	mf_sys8	dwd_gcfs2_1	eccc_gem5_nemo	eccc_cam_cm4
gleam	1	0.9	0.92	0.69	0.95	0.021	0.73	0.75	0.43	0.94	0.73
era5	0.9	1	0.94	0.64	0.92	0.14	0.75	0.76	0.48	0.82	0.79
era5l	0.92	0.94	1	0.64	0.97	0.18	0.87	0.75	0.52	0.86	0.84
gldas	0.69	0.64	0.64	1	0.67	0.44	0.47	0.54	0.35	0.78	0.4
seas5	0.95	0.92	0.97	0.67	1	0.17	0.79	0.68	0.56	0.88	0.82
cmcc_cm2	0.021	0.14	0.18	0.44	0.17	1	0.26	0.015	0.21	0.092	0.13
mo_hadgem_gc3_2	0.73	0.75	0.87	0.47	0.79	0.26	1	0.63	0.38	0.68	0.81
mf_sys8	0.75	0.76	0.75	0.54	0.68	0.015	0.63	1	0.46	0.76	0.69
dwd_gcfs2_1	0.43	0.48	0.52	0.35	0.56	0.21	0.38	0.46	1	0.43	0.52
eccc_gem5_nemo	0.94	0.82	0.86	0.78	0.88	0.092	0.68	0.76	0.43	1	0.68
eccc_cam_cm4	0.73	0.79	0.84	0.4	0.82	0.13	0.81	0.69	0.52	0.68	1

Identifying predictable regions

GLEAM/BEST



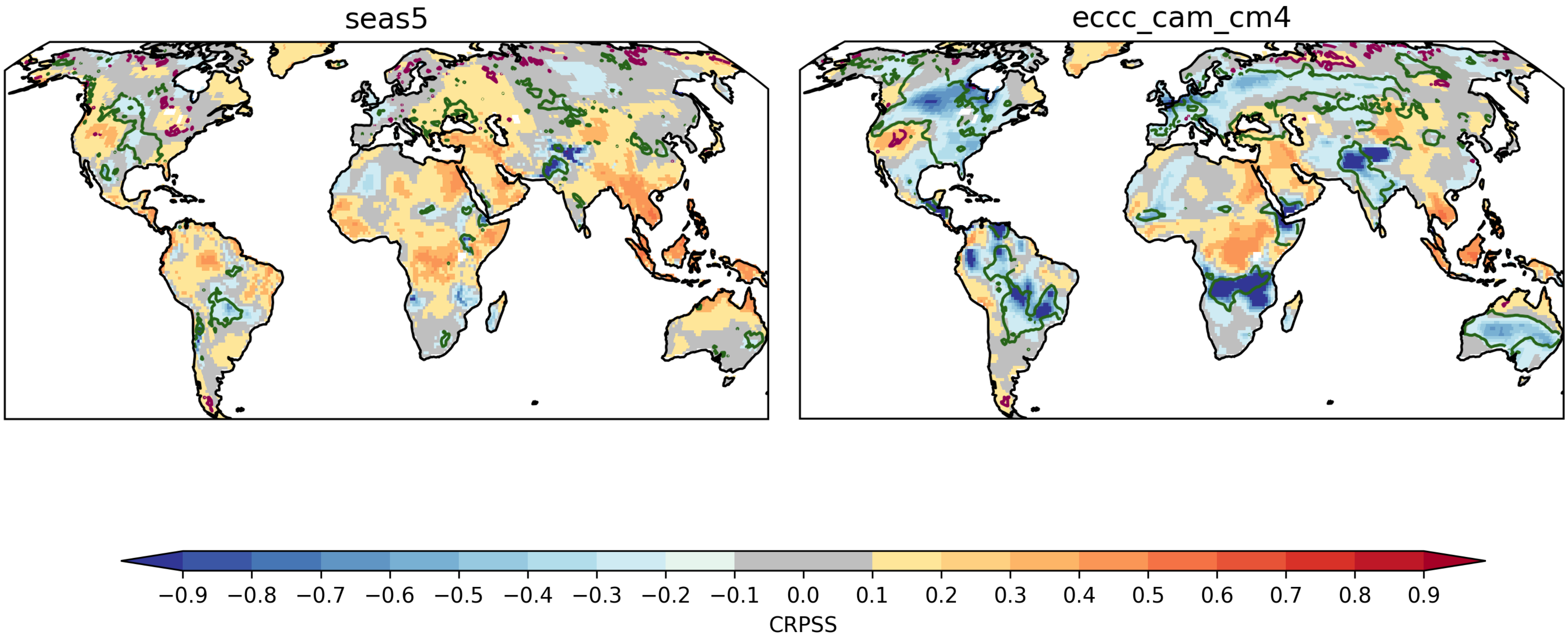
ERA5-land soil moisture persistence: $\rho(SM_{May}, SM_{Aug})$



$$I_{SM-t2m} = \sigma(t2m)\rho(SM, E)\rho(E, t2m)$$

from Dirmeyer et al., 2014

Link between 2m-temperature CRPSS and coupling strength bias



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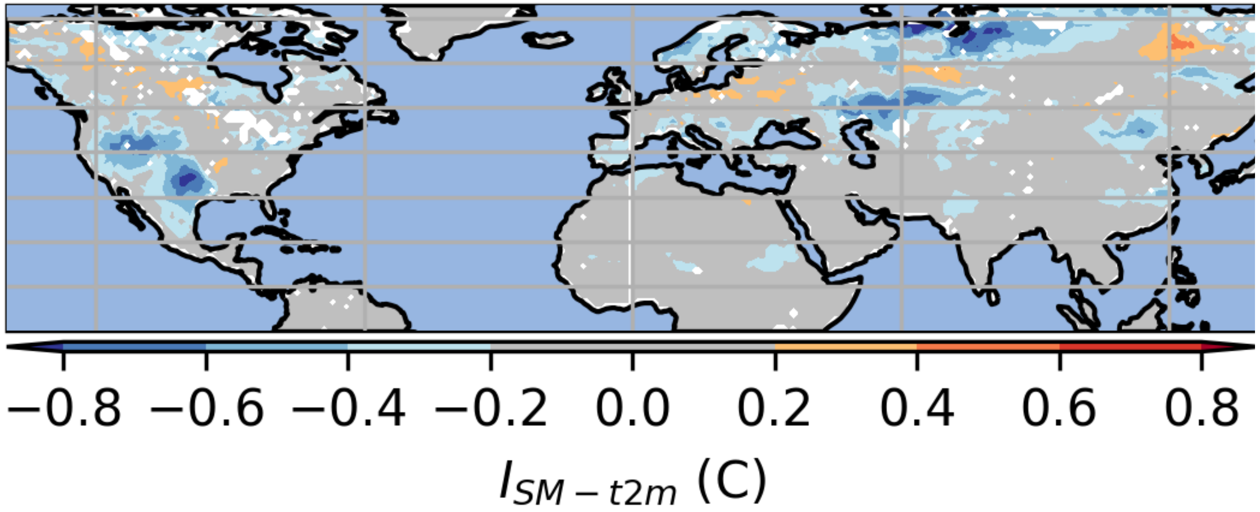
C3S models generally overestimate coupling

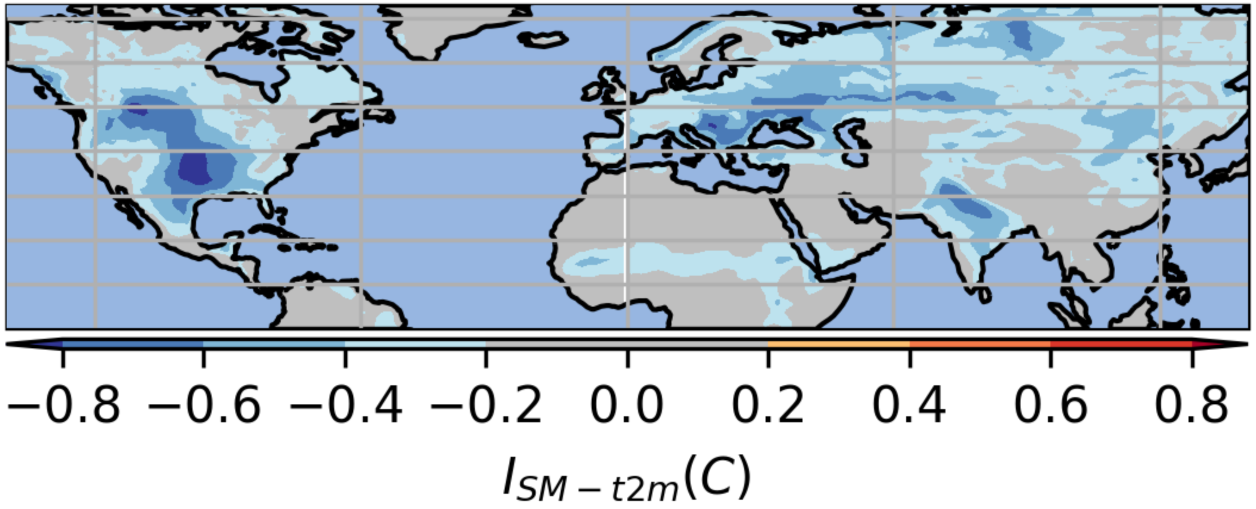
Metric from Lorenz et al., 2015/Dirmeyer et al. 2014 :

$$I_{SM-t2m} = \sigma(t2m)\rho(SM, E)\rho(E, t2m)$$

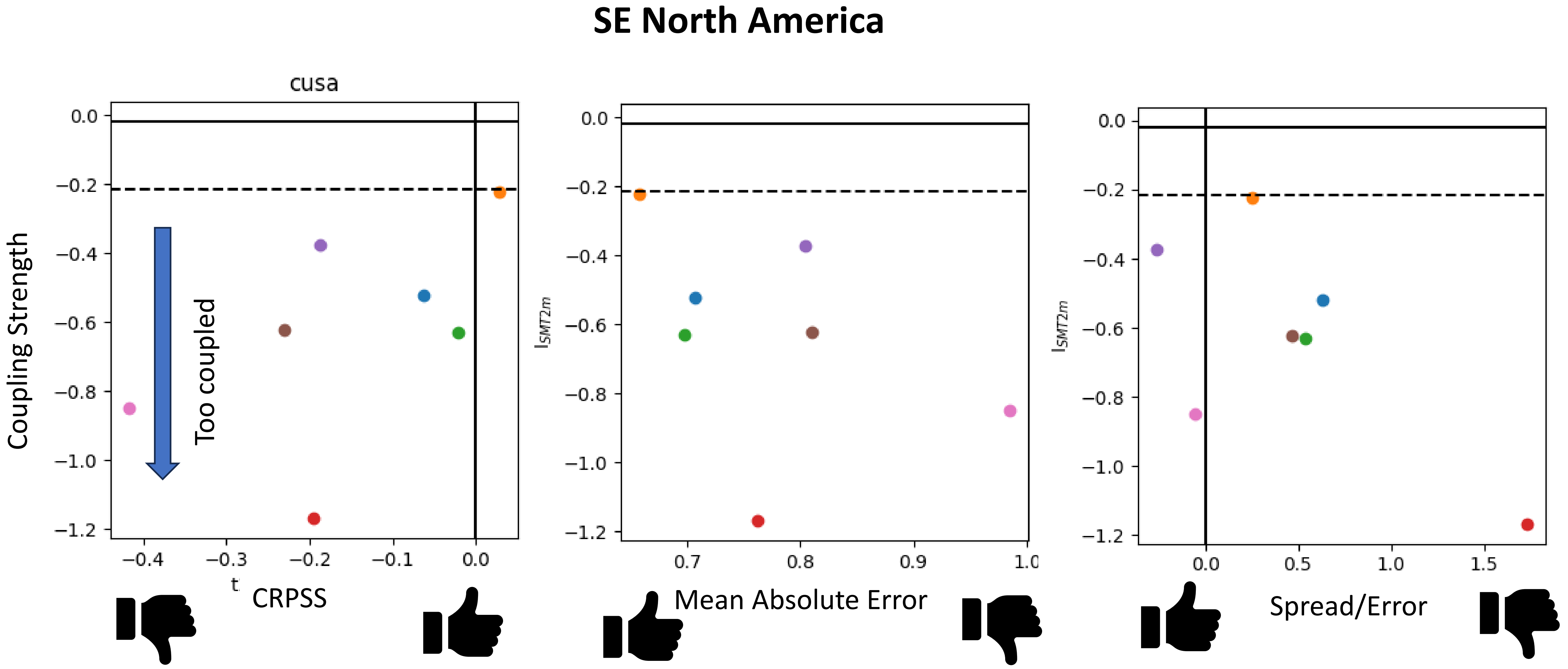
GLEAM/BEST



Average metric for C3S models

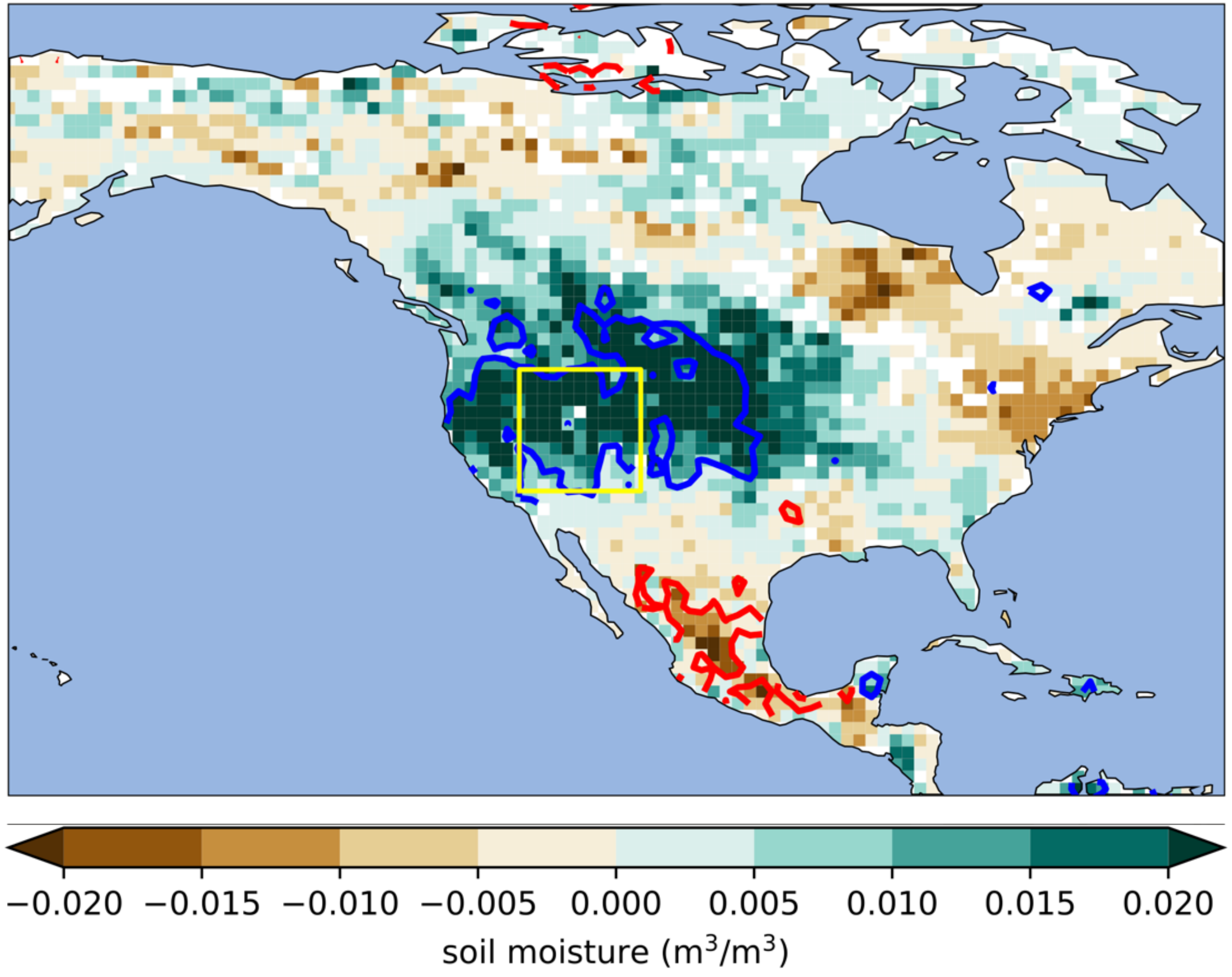


Models with better coupling-strength have better scores

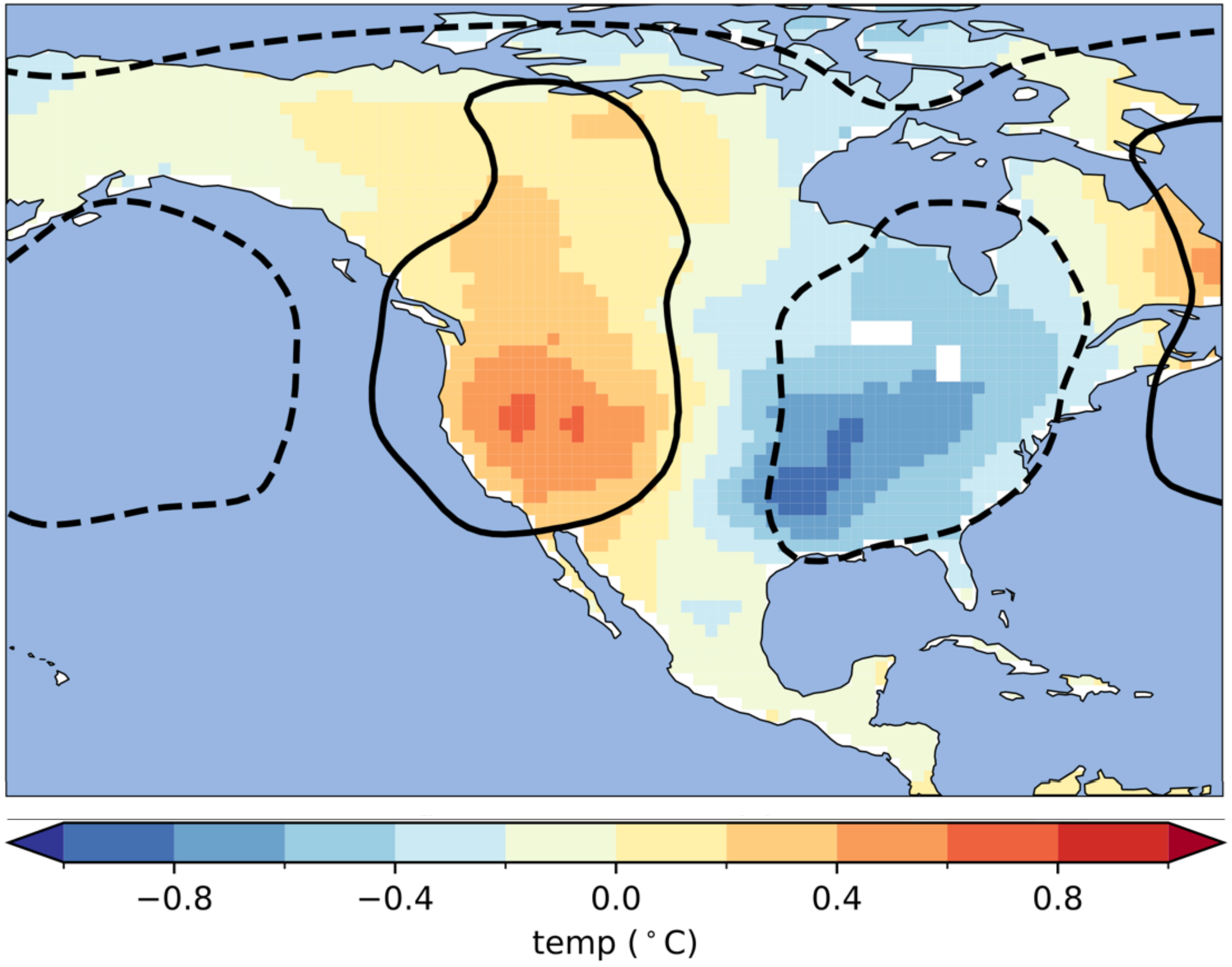


Example: wet summers in West USA

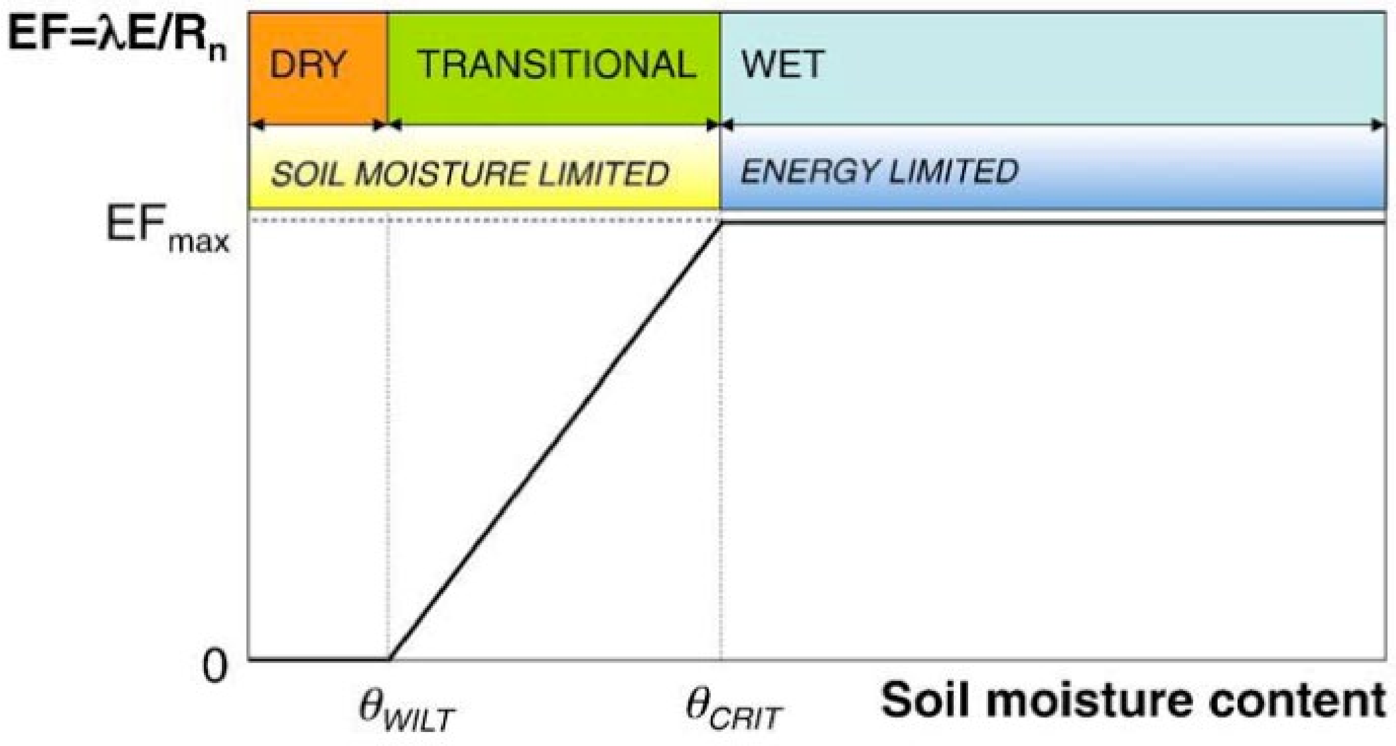
a) GLEAM anomaly



f) average C3S bias



Soil-moisture atmosphere coupling



$$E = \beta E_{POT} = \beta \rho_a \left[\frac{q_{sat}(T_s) - q_r}{r_a} \right]$$

with

$$\beta = \frac{\theta - \theta_{WILT}}{\theta_{CRIT} - \theta_{WILT}} \text{ for } \theta_{WILT} \leq \theta \leq \theta_{CRIT}$$

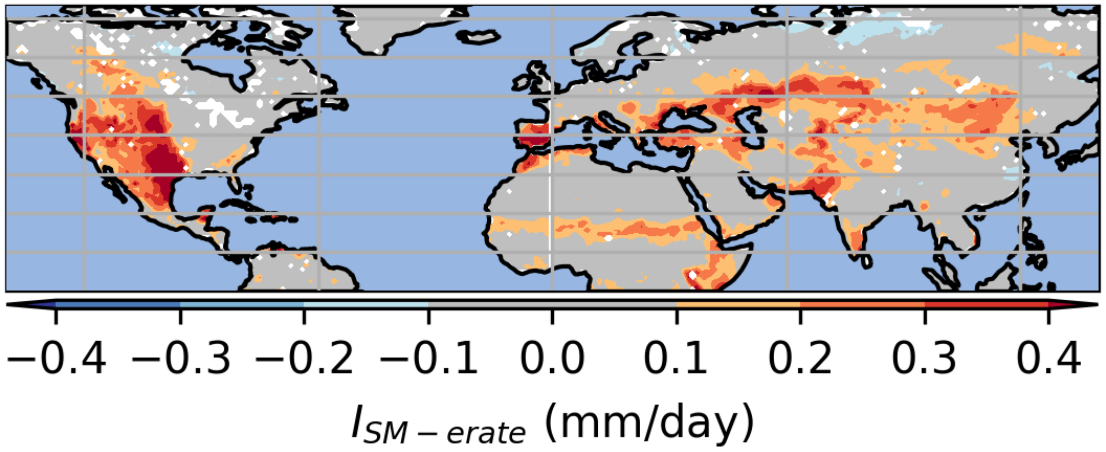
$$\beta = 1 \text{ for } \theta > \theta_{CRIT}$$
$$\beta = 0 \text{ for } \theta < \theta_{WILT}$$

Seneviratne et al., 2010

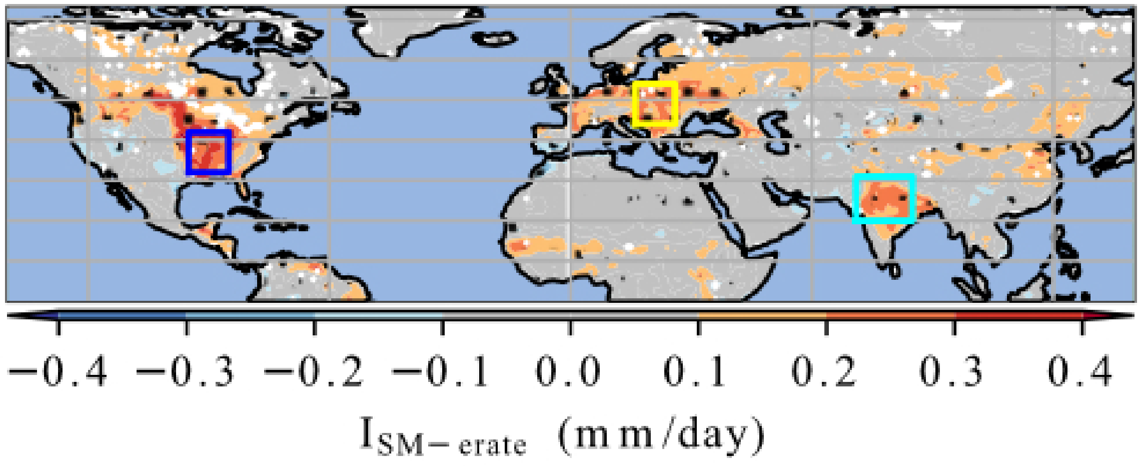
The areal extent of the SM limited regime is too large

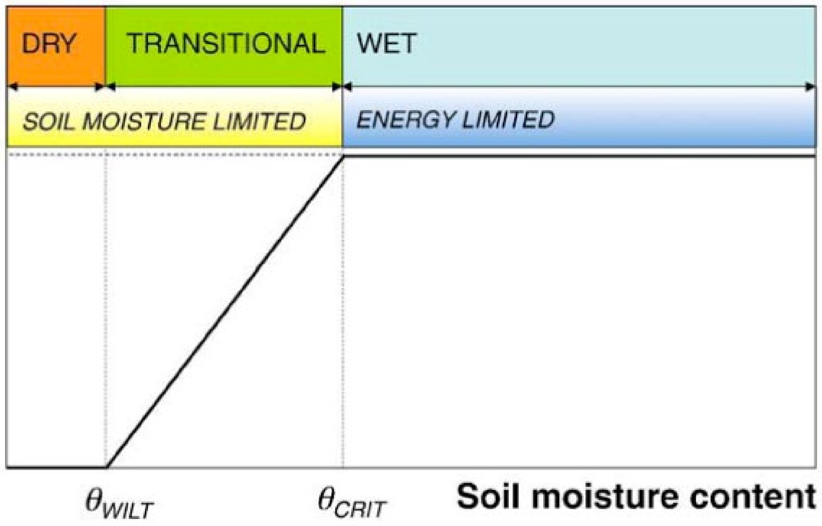
$$I_{SM-E} = \sigma(E)\rho(SM, E)$$

e) observed $I_{SM-erate}$

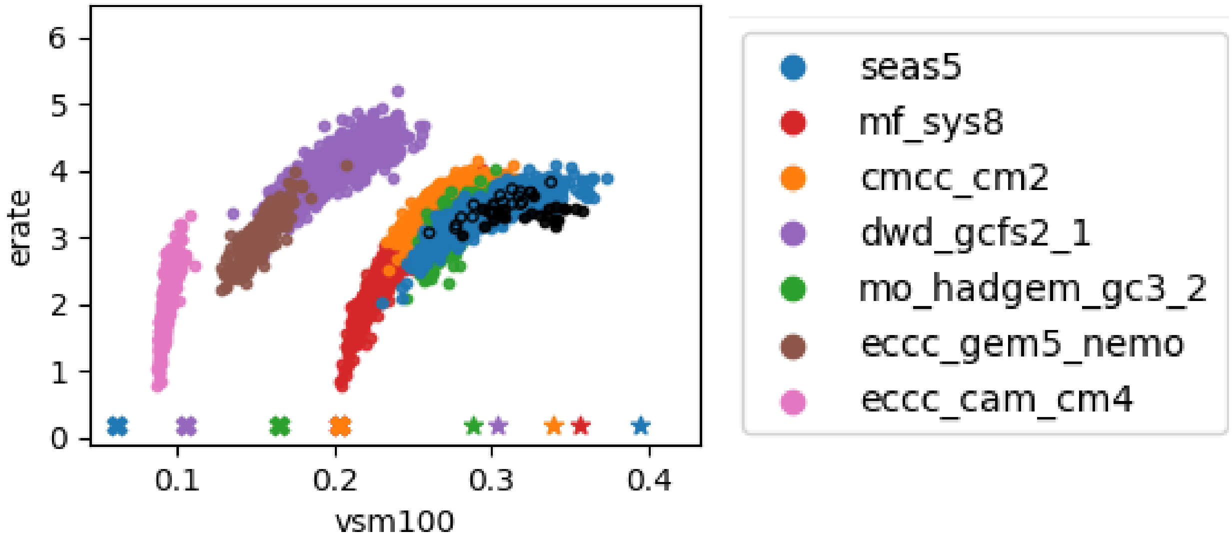


c) multi-model bias in $I_{SM-erate}$





Central US (Aug)



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Coupling errors linked to model bias

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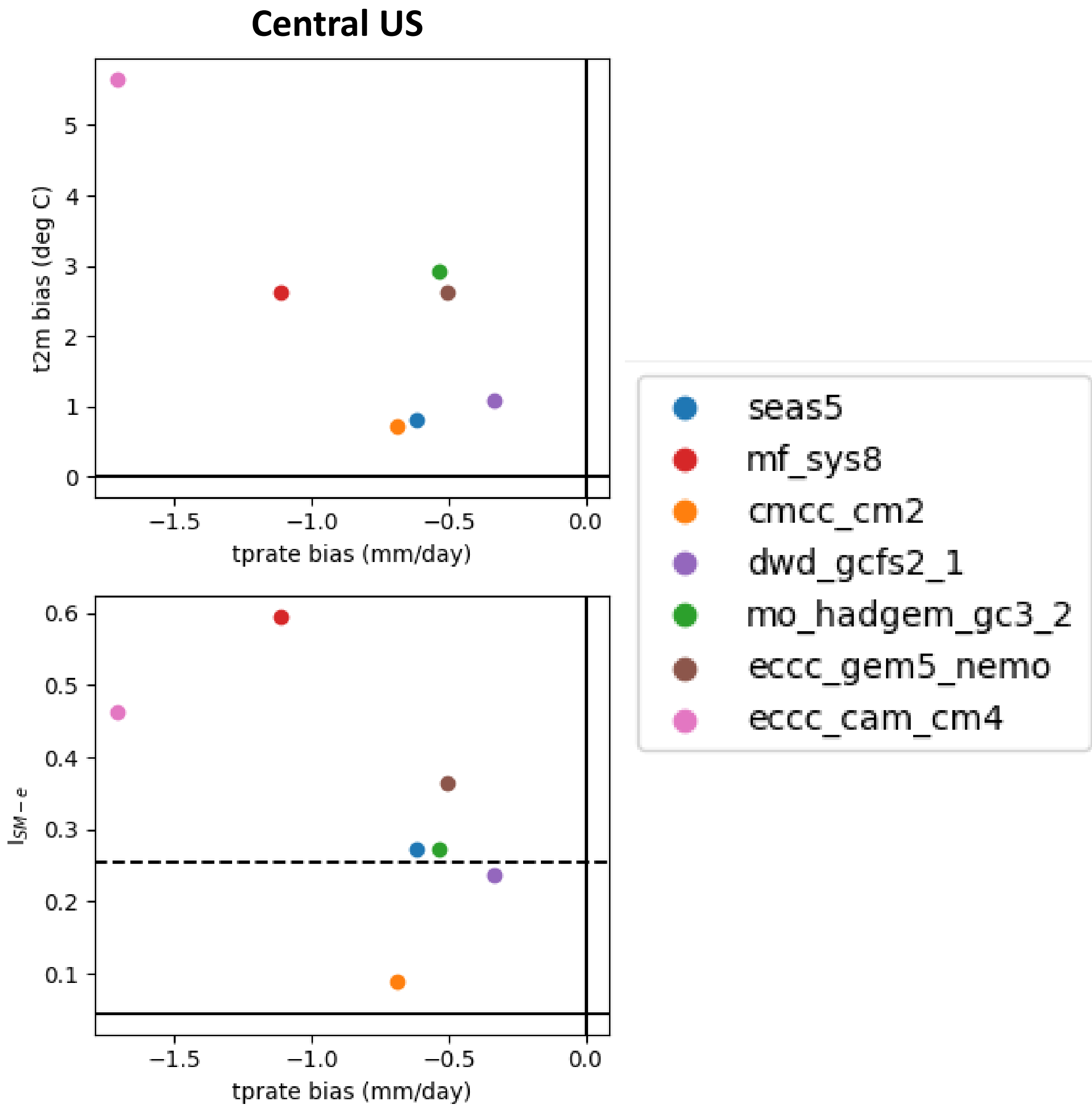
C3S multi-model mean bias



See also Ardilouze et al., (2019; WAF) and Lin et al., (2017; Nat Comms.)

Conclusions and Implications

1. We have identified Western USA and Eurasian Plain as a regions of high potential predictability (of T2m) over land in JJA based on 2-legged coupling diagnostics of Dirmeyer 2011 and soil-moisture persistence.
2. Models show relatively high T2m skill in these regions, but models exhibit land-atmosphere coupling in regions not supported by reanalyses (particularly Eastern half of the USA, Eastern Europe and Northern India).
3. Biases in the coupling strength in these regions go hand in hand with negative CRPSS values (worse than climatology).
4. Improved soil-moisture atmosphere coupling can significantly improve the skill of seasonal forecasts.
5. We need to know the causes: climate, vegetation, soil type,...
6. Is this an issue in medium-range or sub-seasonal forecasts too?

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Thank you!

ECMWF | Norwegian Meteorological Institute | SMHI | Deutscher Wetterdienst – Wetter und Klima aus einer Hand | CMCC – Centro Euro-Mediterraneo sui Cambiamenti Climatici | Barcelona Supercomputing Center – Centro Nacional de Supercomputación

Météo France | The Danish Meteorological Institute | Estellus | IPMA | NILU | Met Office

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Impact of spring soil-moisture on summer (JJA) anomalies (dry-wet years)

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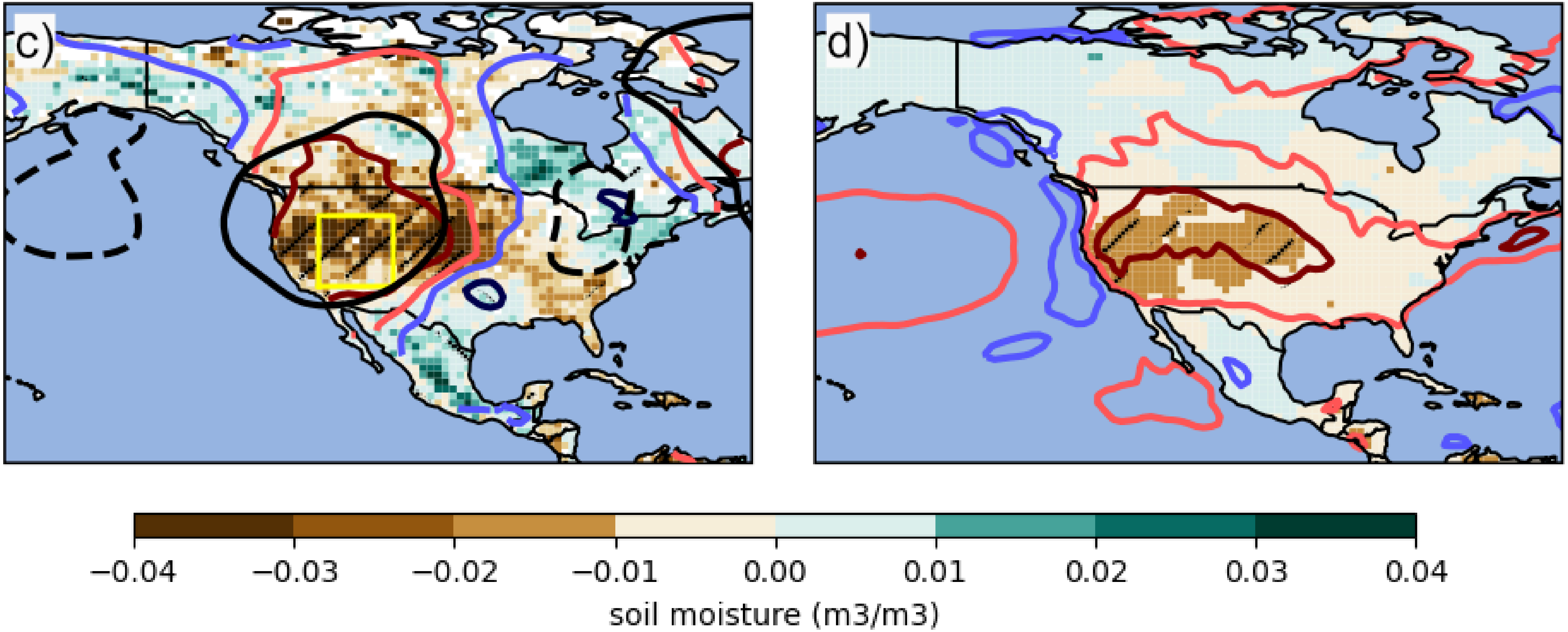
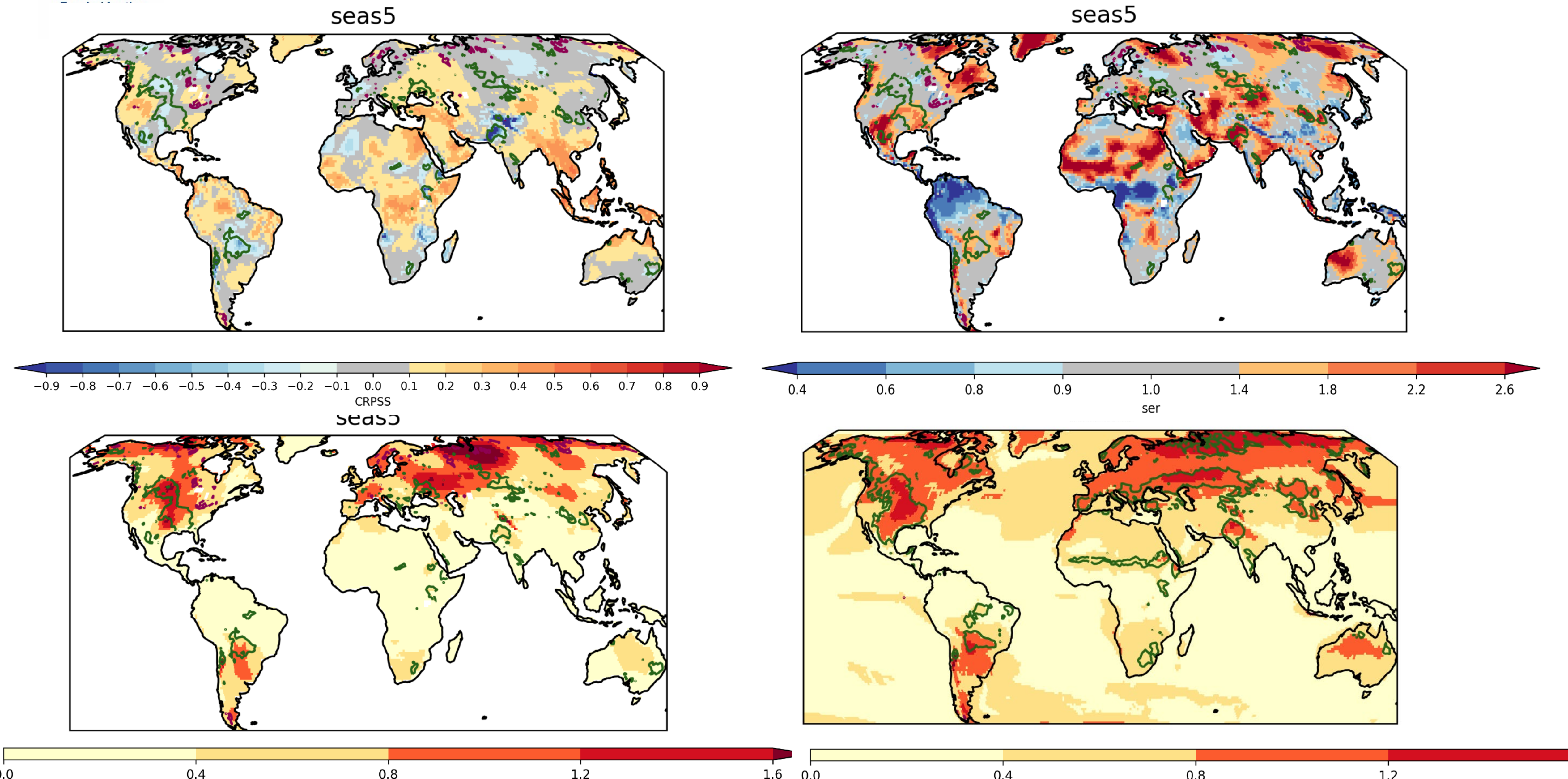


Decomposition of the CRPS



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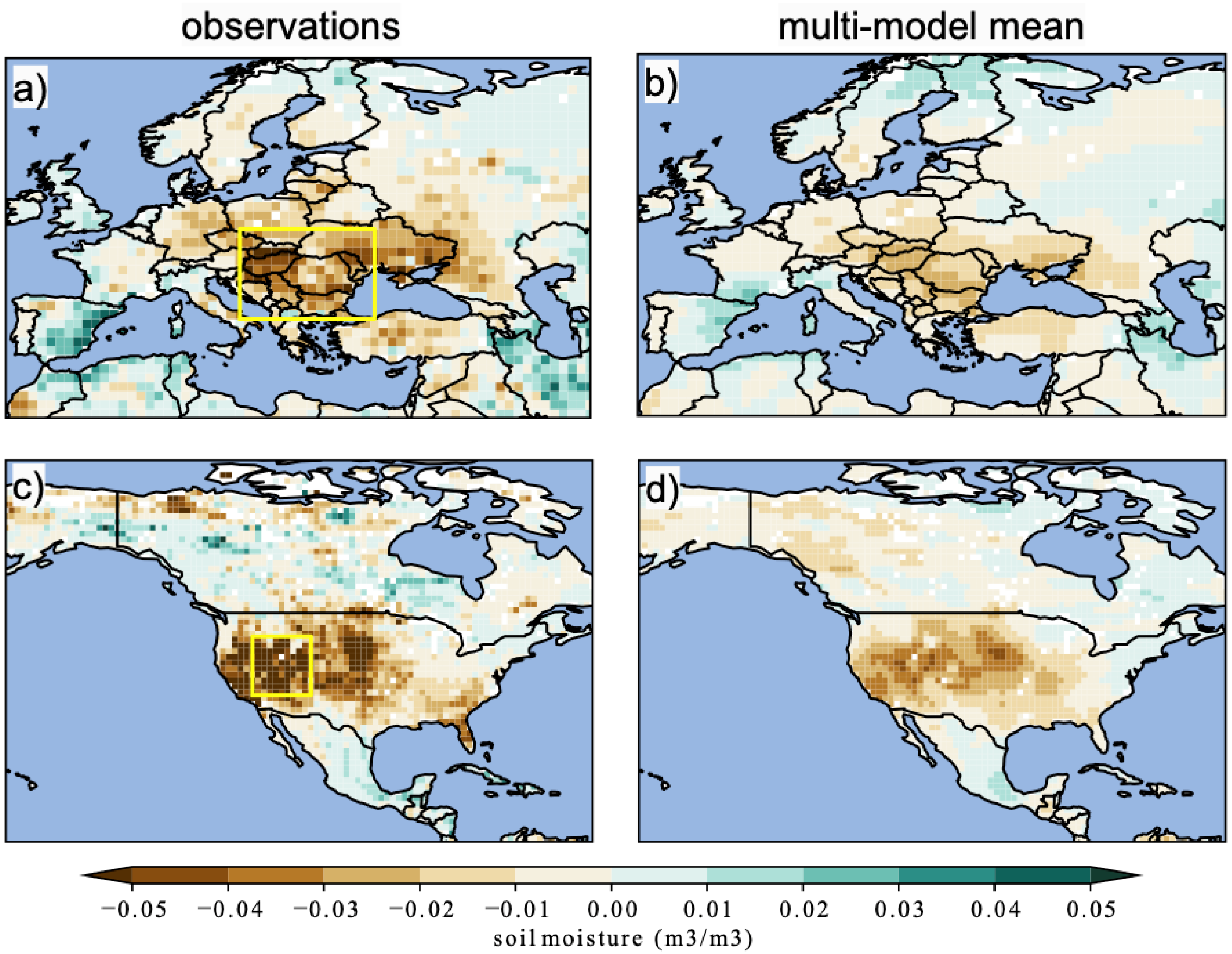
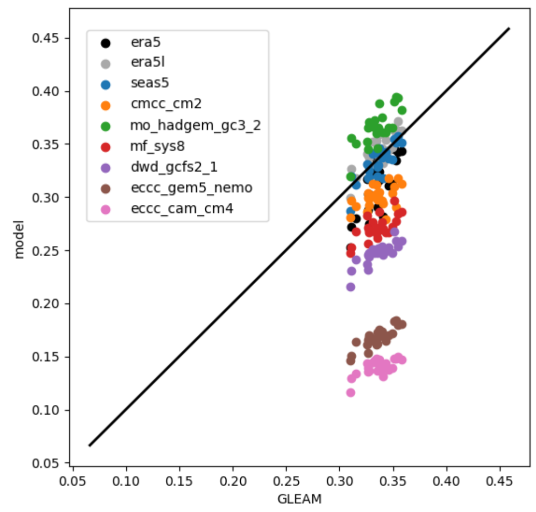
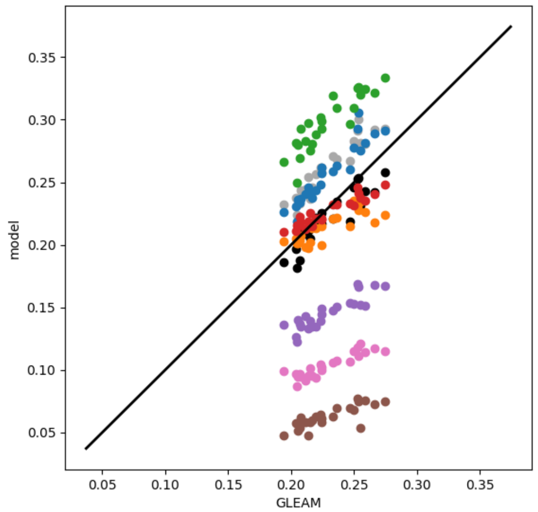
Soil-moisture initial conditions (Dry-Wet years)







Consistent with Koster et al., 2009

Impact of time varying land properties on seasonal reforecasts

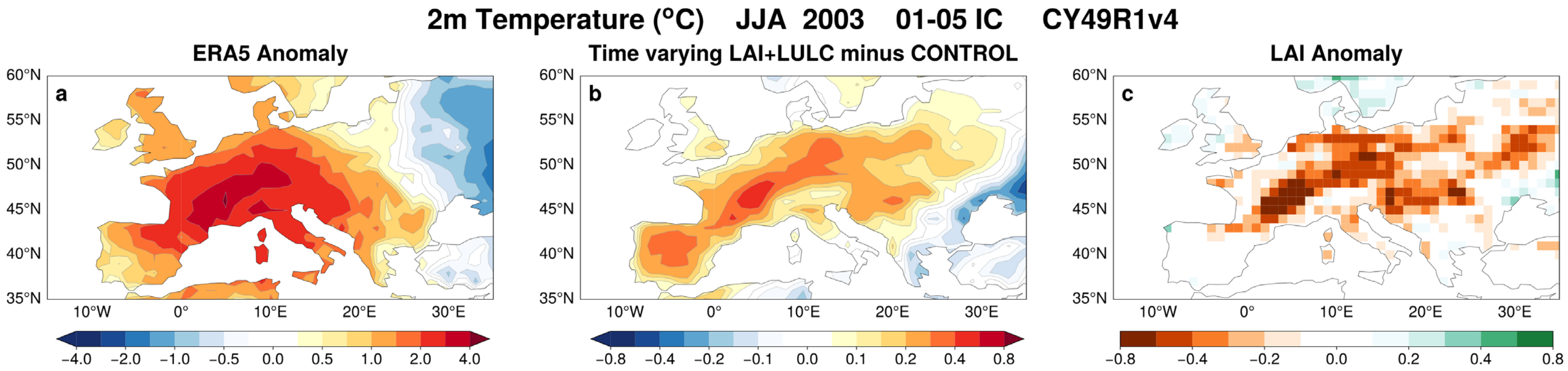


Figure: June-to-August 2003 seasonal mean 2m temperature over Europe: (a) ERA5 anomaly and (b) difference between LAI+LULC and CONTROL experiments. Also plotted in (c) is the Leaf Area Index anomaly.

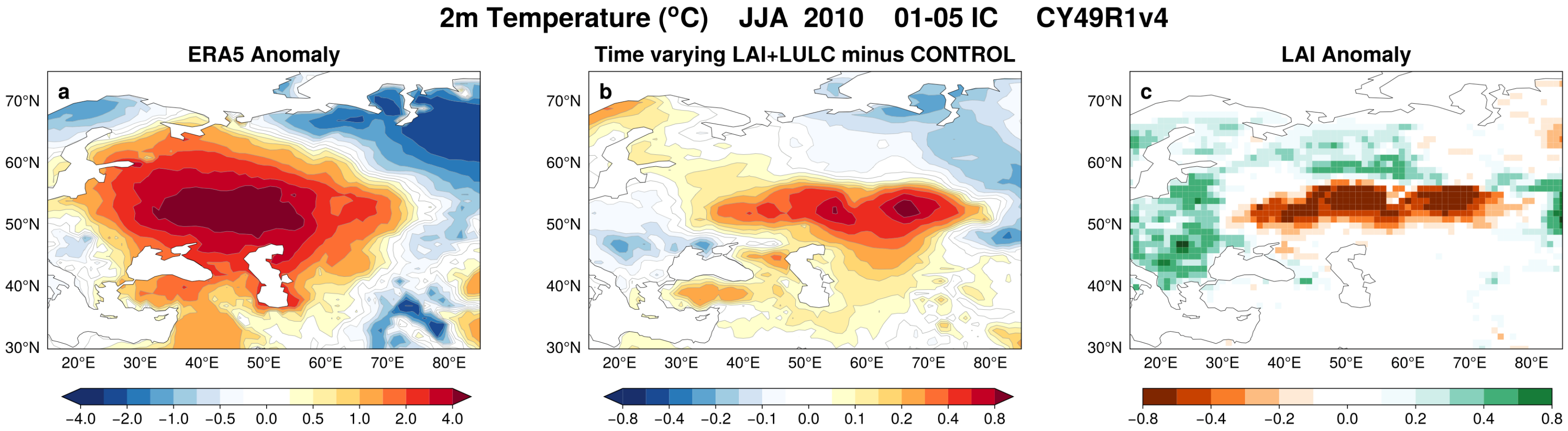


Figure: Same as above, but for 2010.

Slide from Retish Senan

Lagged Maximum covariance

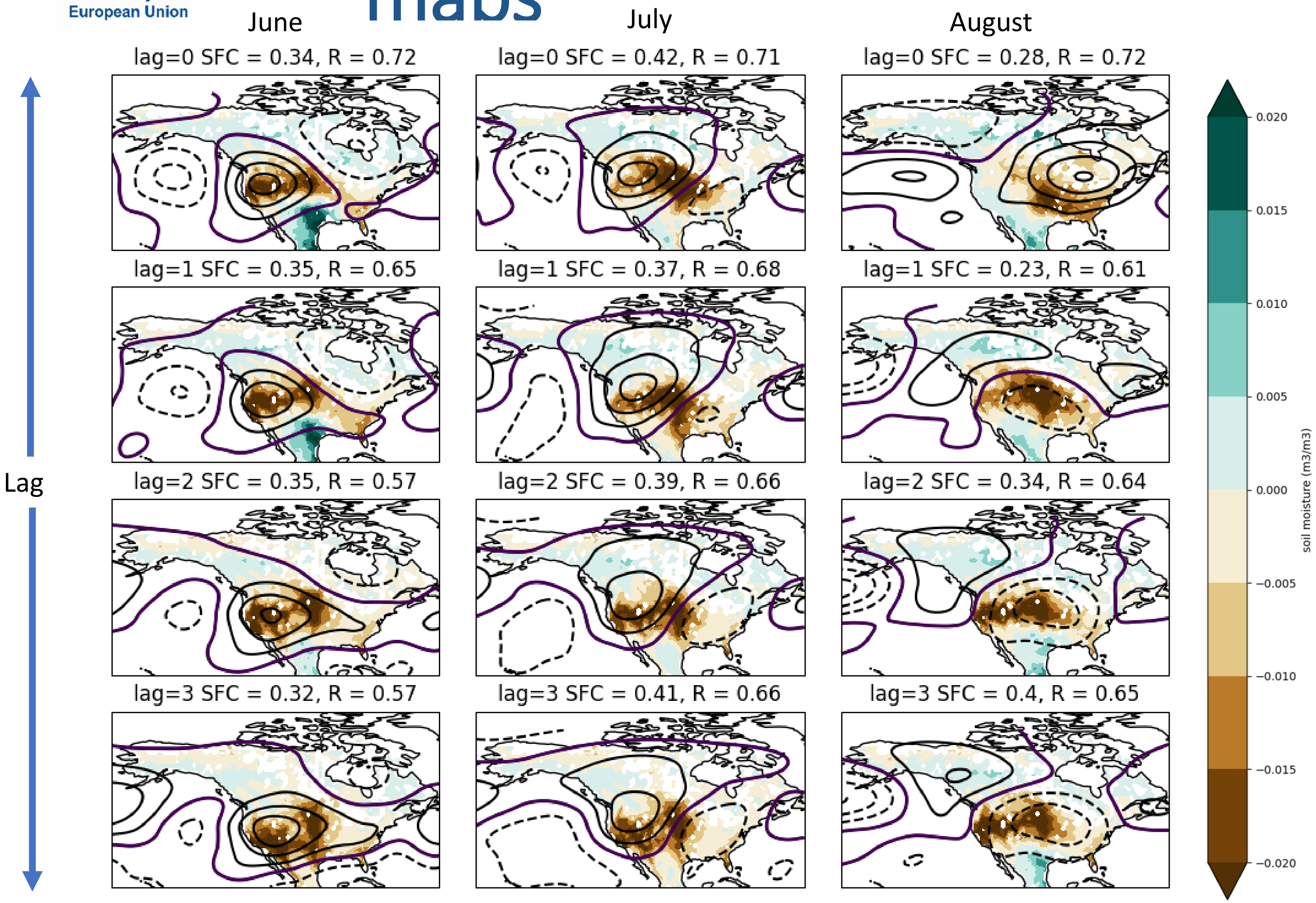
Z_{200} at time t and 1m soil moisture, SM_{1m} at time t+$\boldsymbol{\tau}$ and t are expanded into K orthogonal signals:

$$Z_{200}(x,t) = \sum_{k=1}^{K} \mathbf{U}_k(x)\mathbf{a}_k(t)$$

$$SM_{1m}(x,t+\tau) = \sum_{k=1}^{K} \mathbf{V}_k \mathbf{b}_k(t+\tau)$$

where the covariance between $a_k(t)$ and $b_k(t\ 1\ t)$ is the kth singular value of the covariance matrix between SM and Z200, decreasing for increasing k

Obs Lagged maximum-covariance maps



The April SM pattern of the leading coupled MCA mode is the first SM EOF. Correlation between the principal component and the (April-June) MCA expansion coefficient is 0.98, April-July is 0.88

The June z200 pattern of the leading (April-June) MCA mode is the second EOF. Correlation between pc and expansion coeff is 0.86

The July z200 pattern of the leading (April-July) MCA mode is the first EOF. Correlation between pc and expansion coeff is -0.85