Part II: AMOC predictability in CMIP6 models

Dylan Oldenburg

Postdoctoral Fellow
NSF National Center for Atmospheric Research

Supervisors:
Stephen Yeager
Gokhan Danabasoglu
Isla Simpson
Who Kim

Motivation

- AMOC predictive skill in CESM-DPLE has been linked to Labrador Sea water thickness (Yeager, 2020), propagating at depth towards the mid-Atlantic ridge, where these anomalies accumulate and drive predictable decadal changes in the gyre circulation, SSH gradient and near-surface surface circulation, accounting for skilful prediction of SPNA upper ocean heat content

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- Does this mechanism hold in other CMIP6 decadal prediction systems?
- Do models with high AMOC predictability show high SPNA upper ocean heat content prediction skill?

Goals

- Determine subpolar North Atlantic upper ocean heat content (SPNA UOHC) predictive skill in CMIP6 decadal prediction systems

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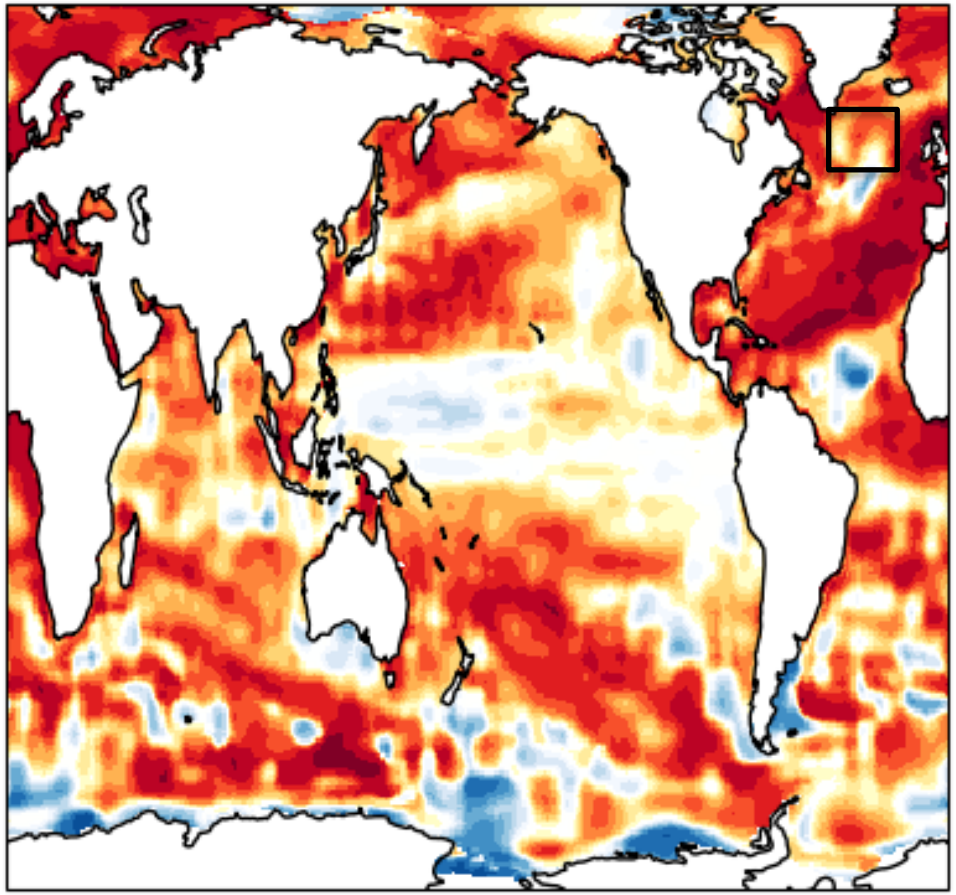
- Use all models with available data

CanESM5	HadGEM3-GC31-MM	MIROC6	MRI-ESM2-0	NorCPM1	CMCC-CM2-SR5	EC-Earth3
EC-Earth3-CC	IPSL-CM6A-LR	CESM1-LR DP	CESM2-LR DP	BCC-CSM2-MR	FGOALS-f3-L	

SPNA UOHC prediction skill varies greatly across models

CESM2-DP leads 5-9 years



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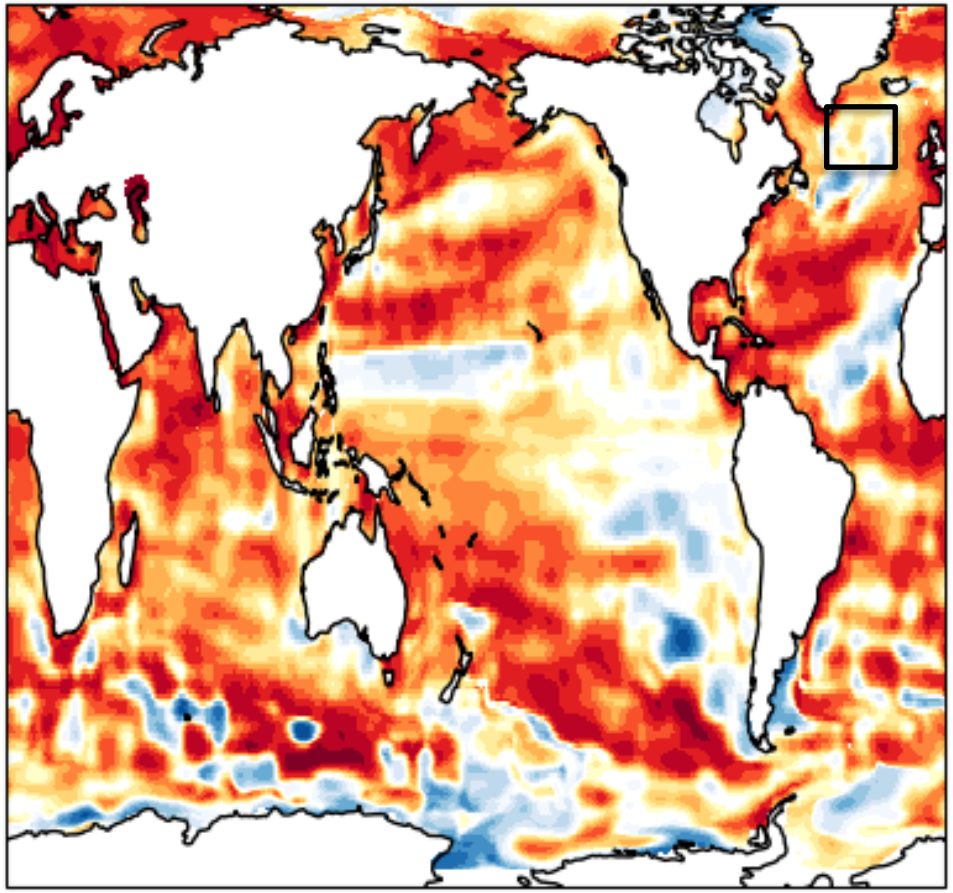
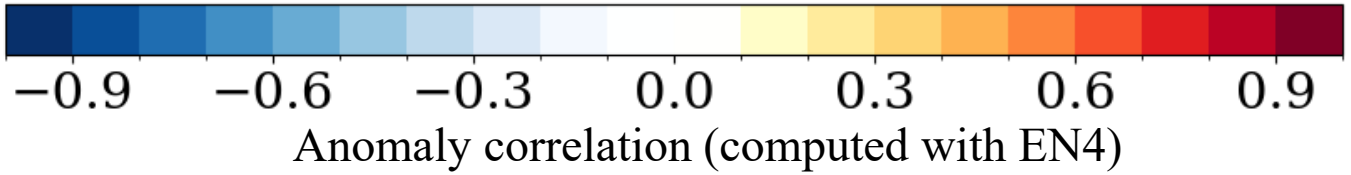
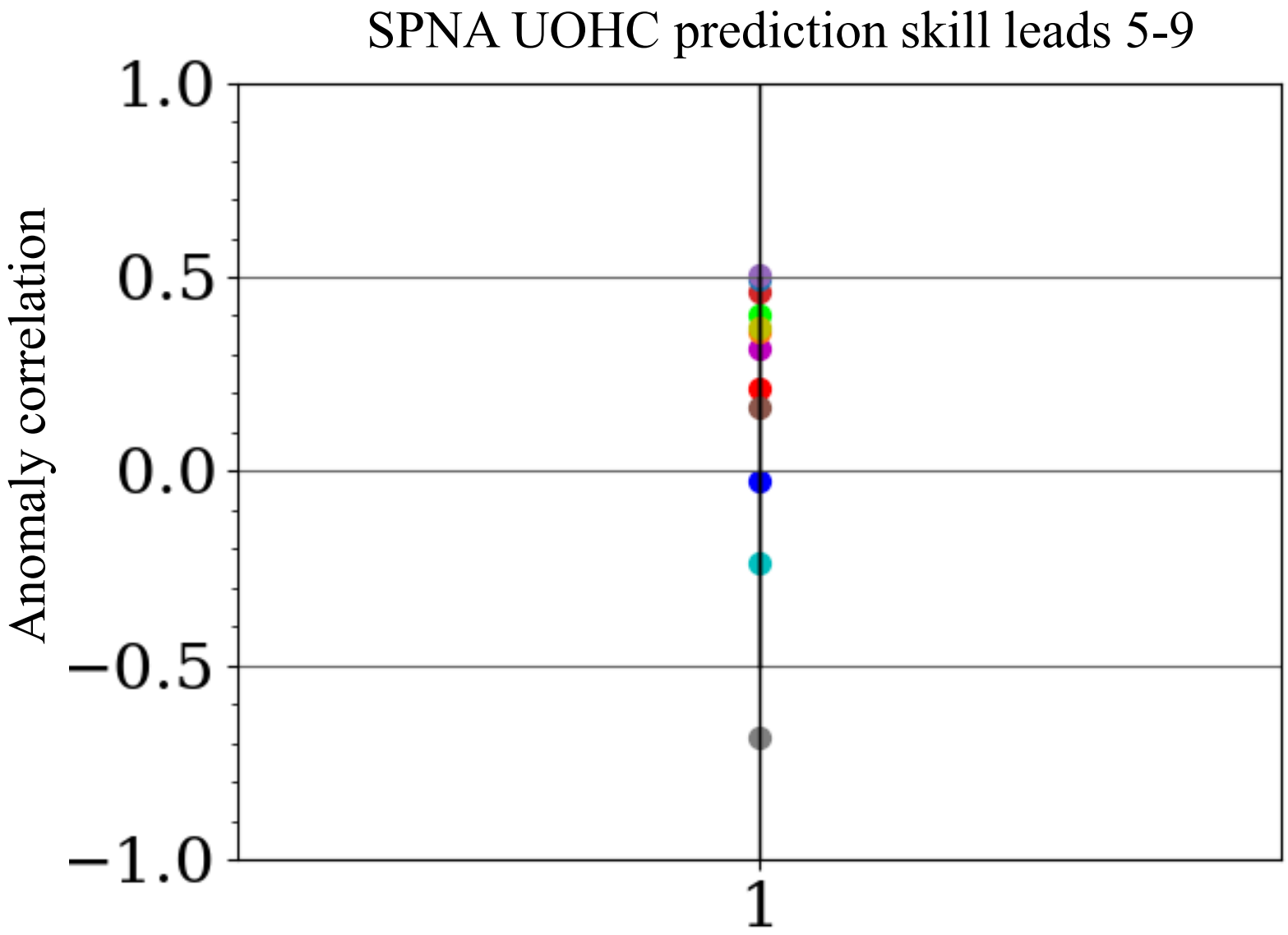




Anomaly correlation (computed with EN4)

SPNA UOHC prediction skill varies greatly across models



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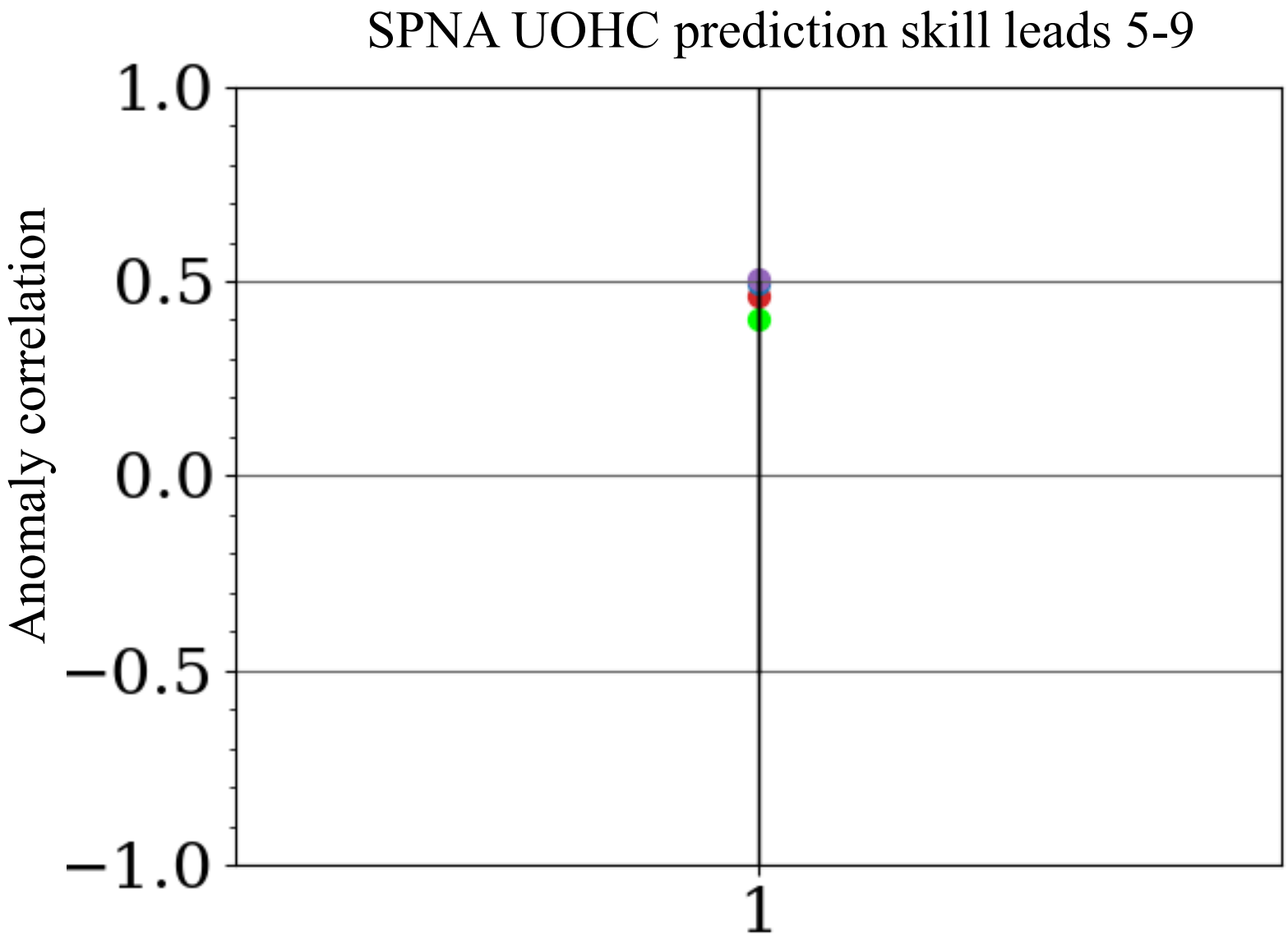

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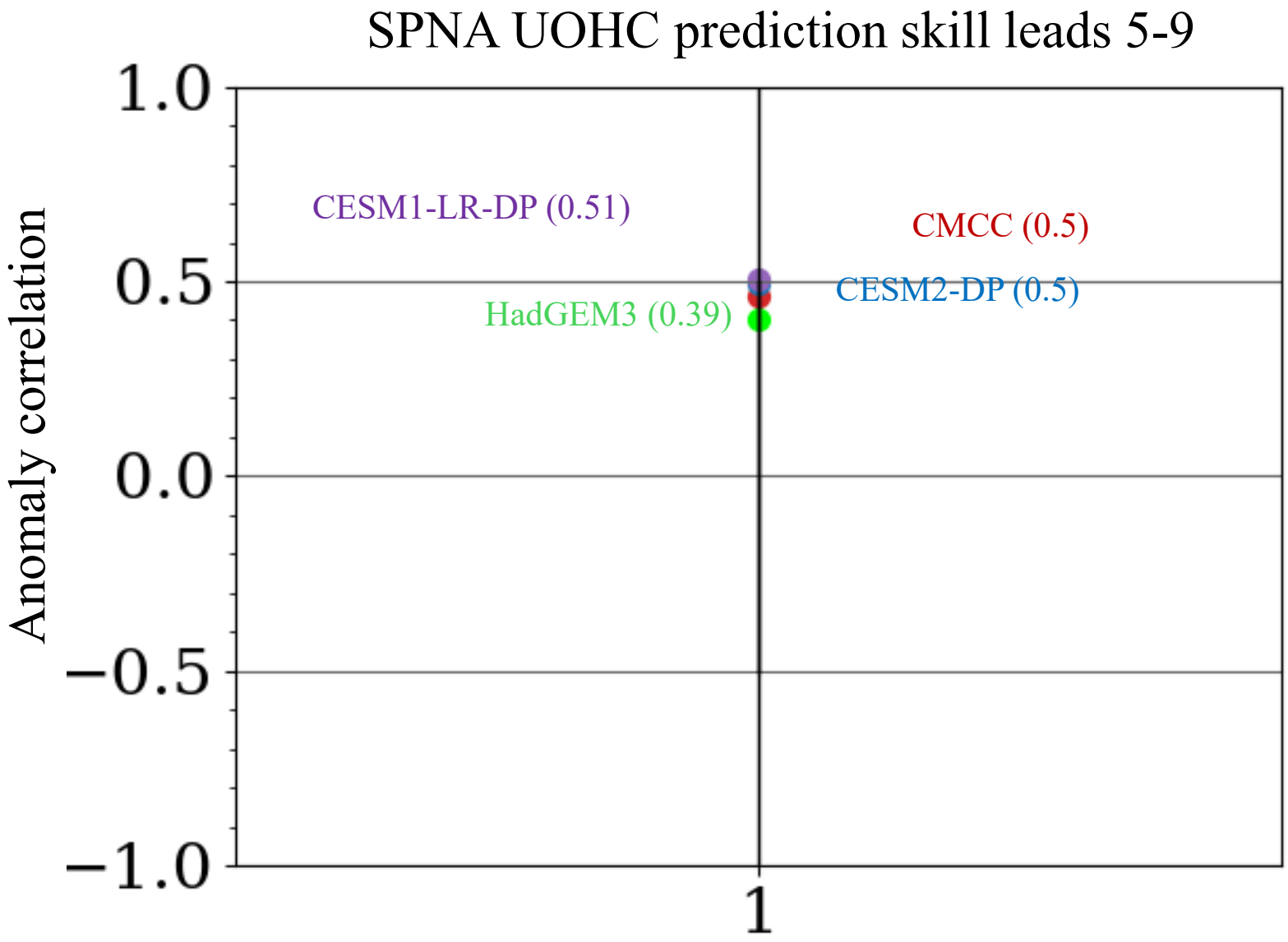

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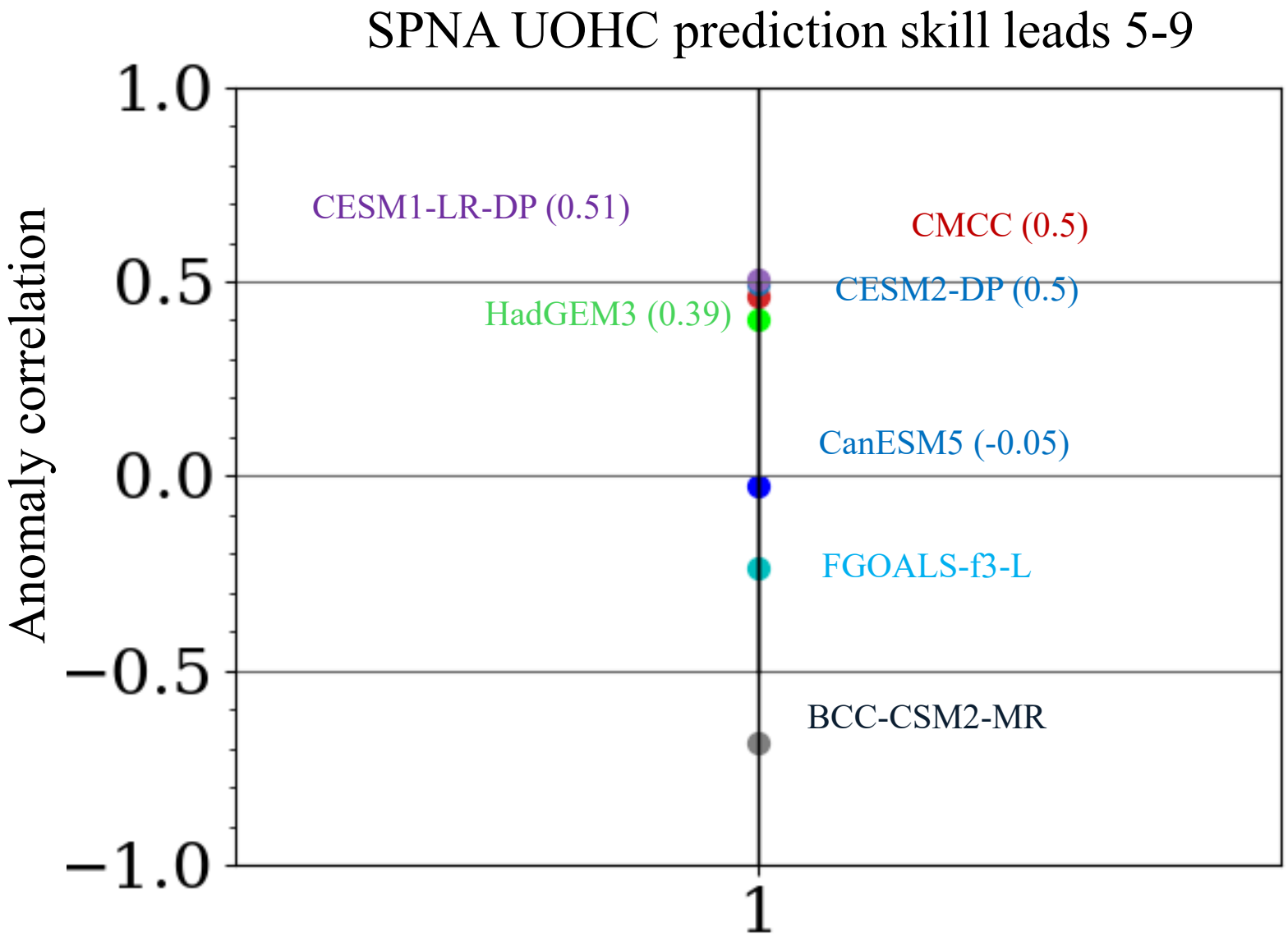

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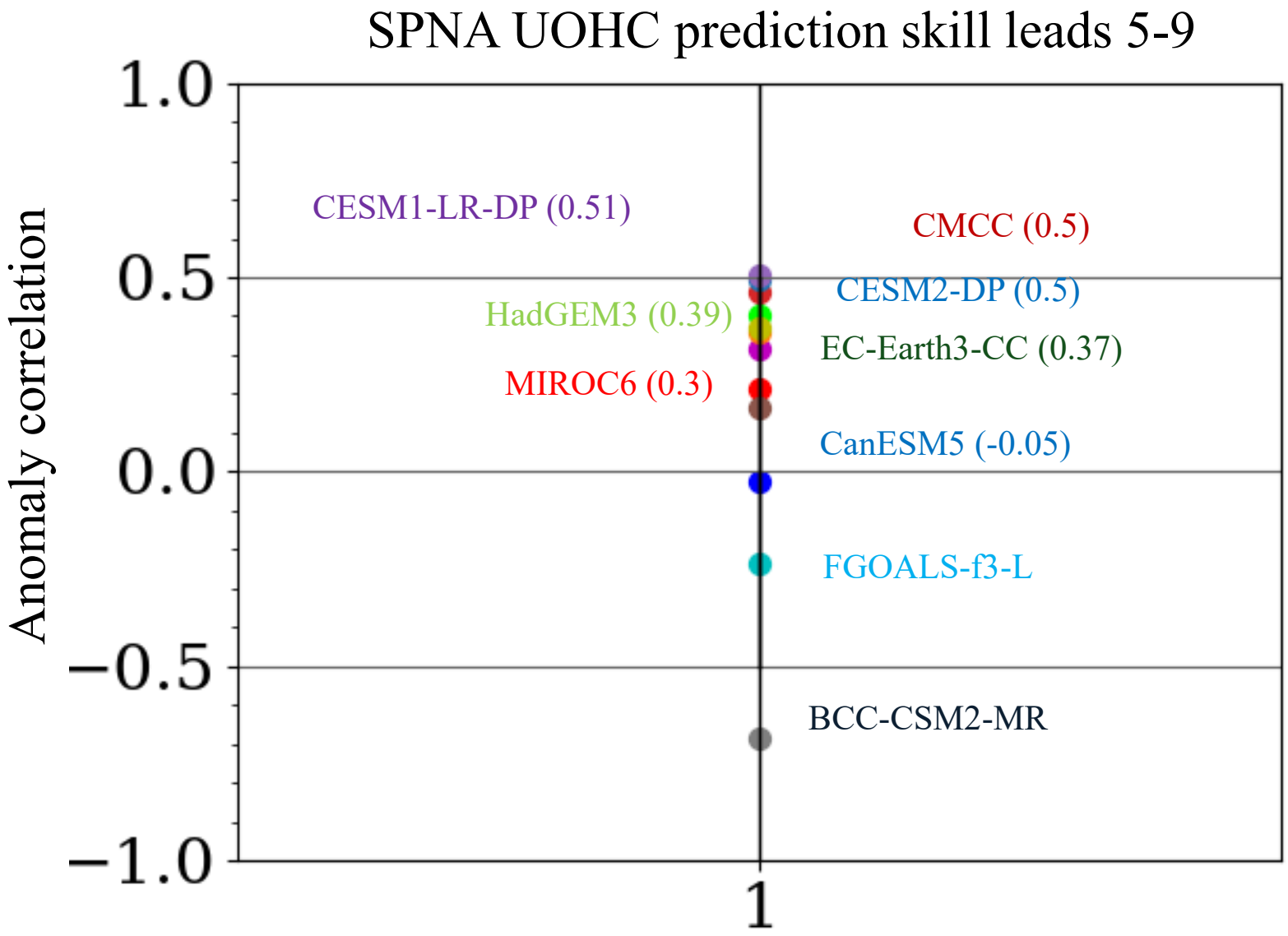

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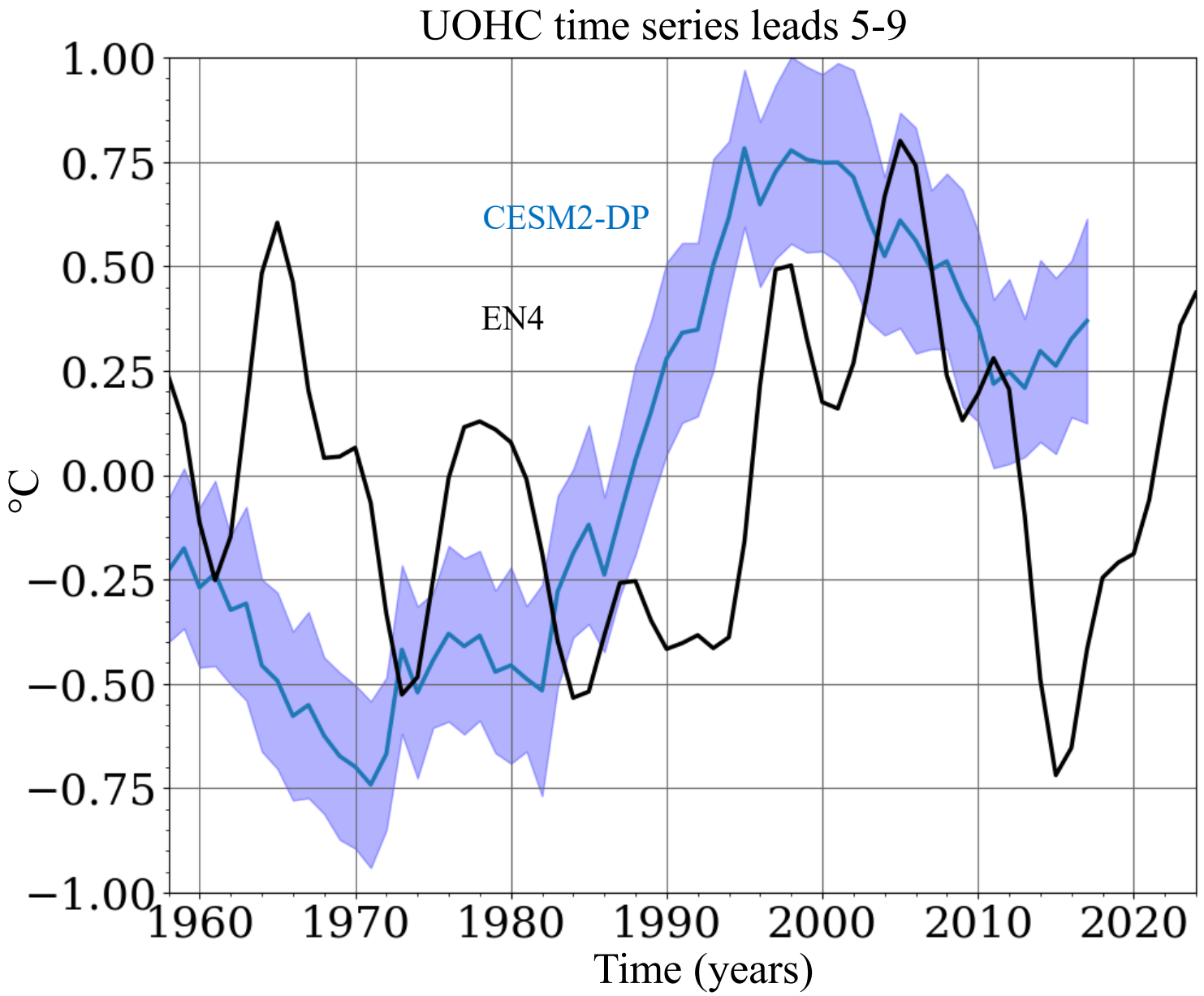

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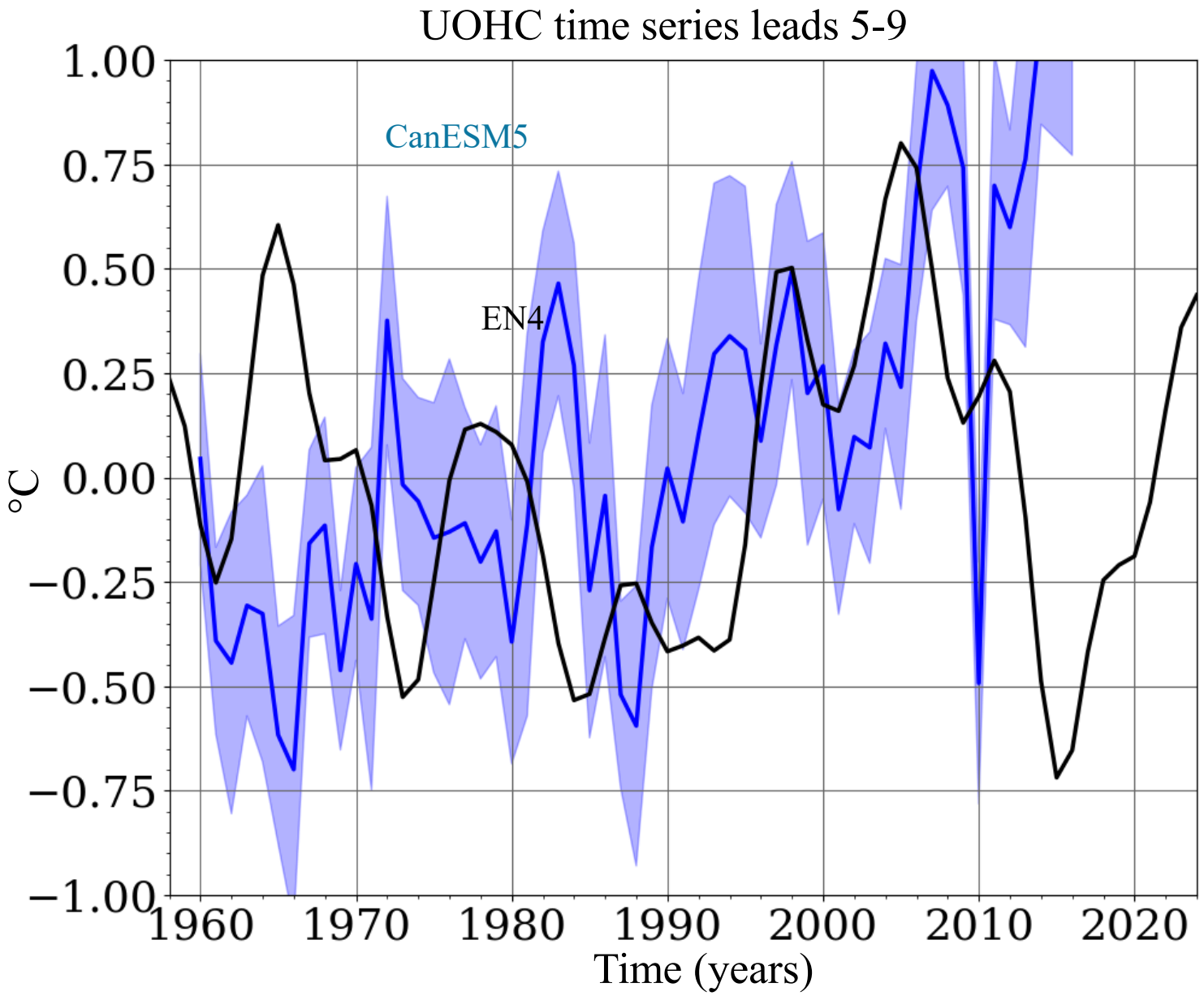
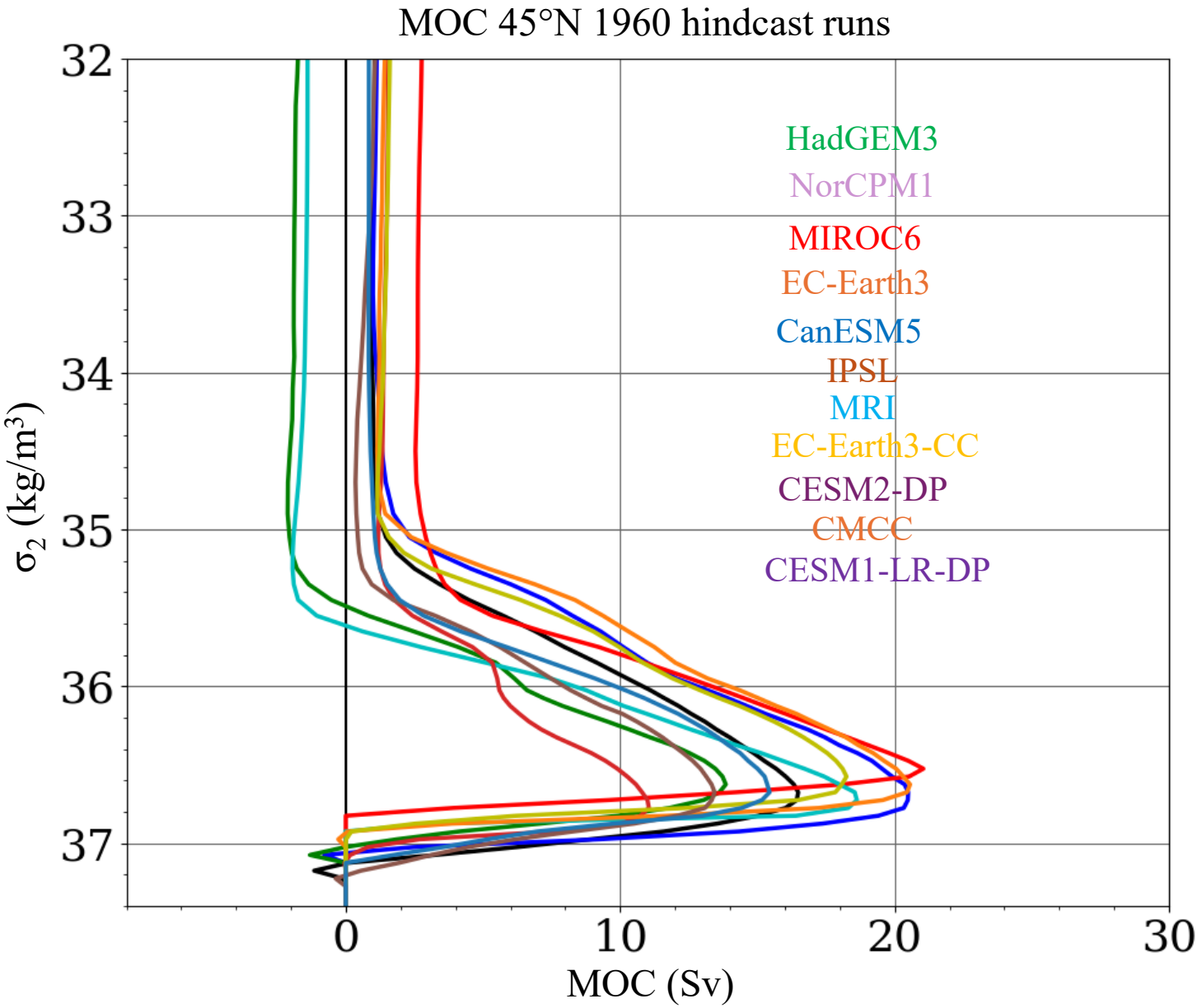
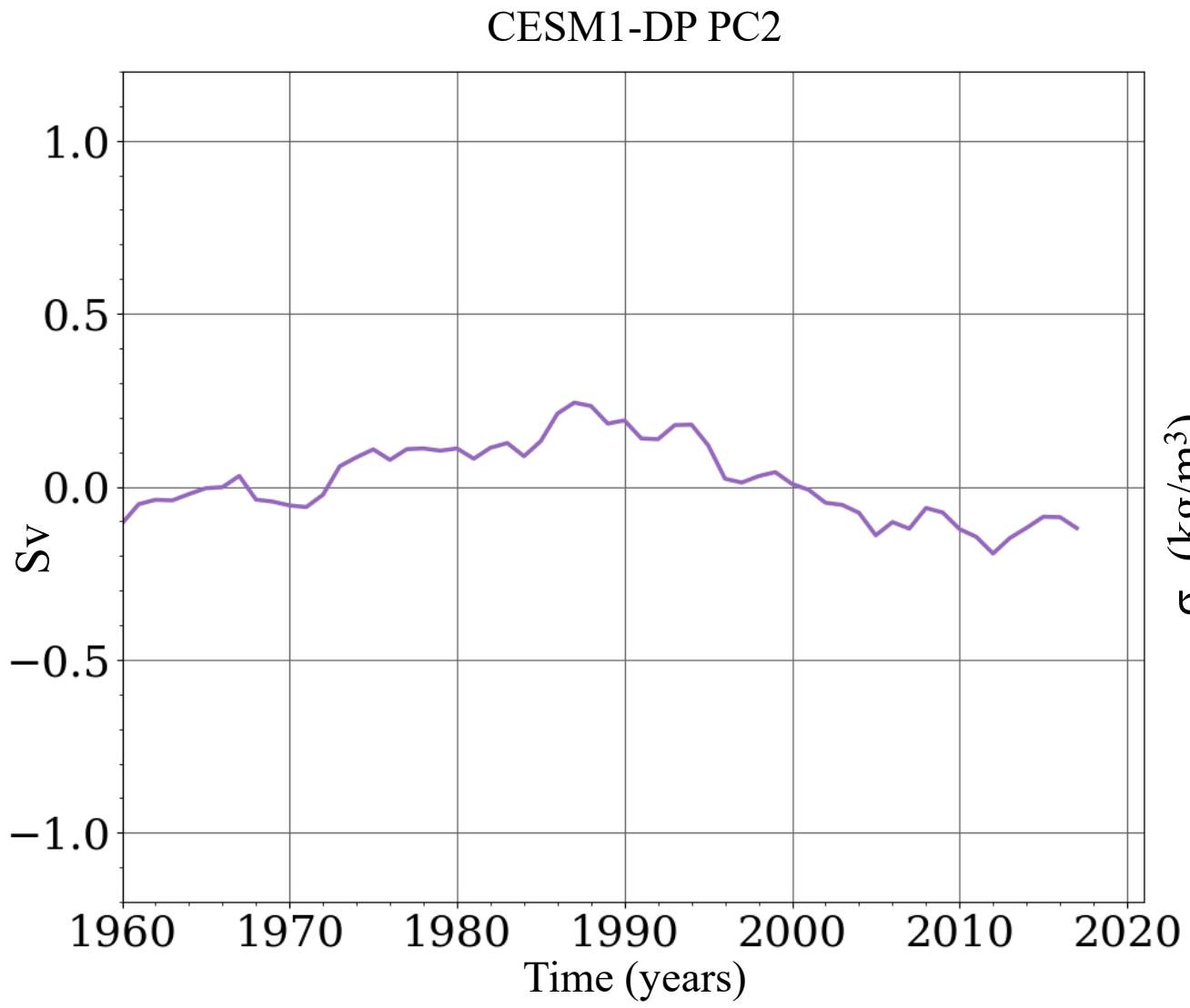
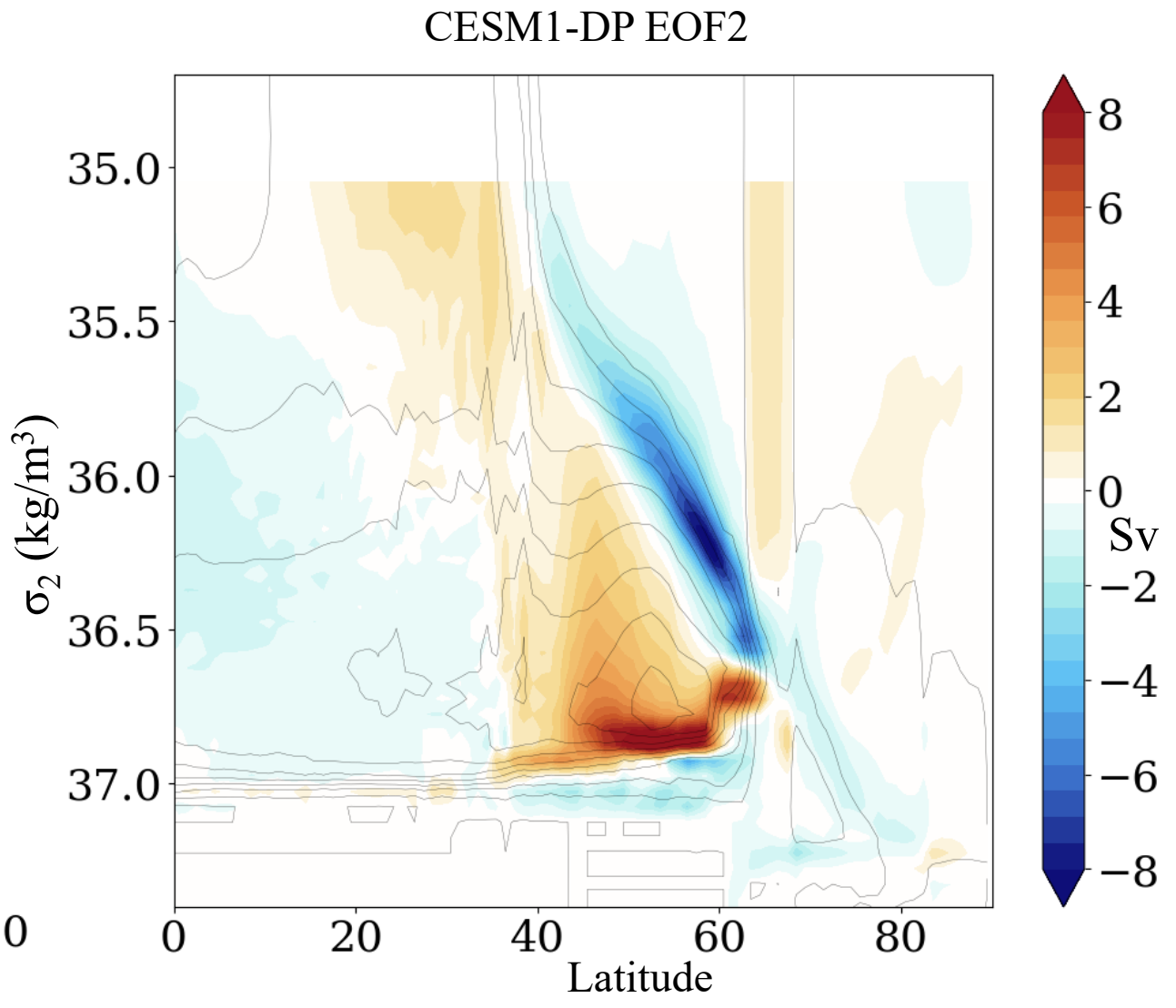


Broad range of MOC structures



AMOC EOF Decomposition





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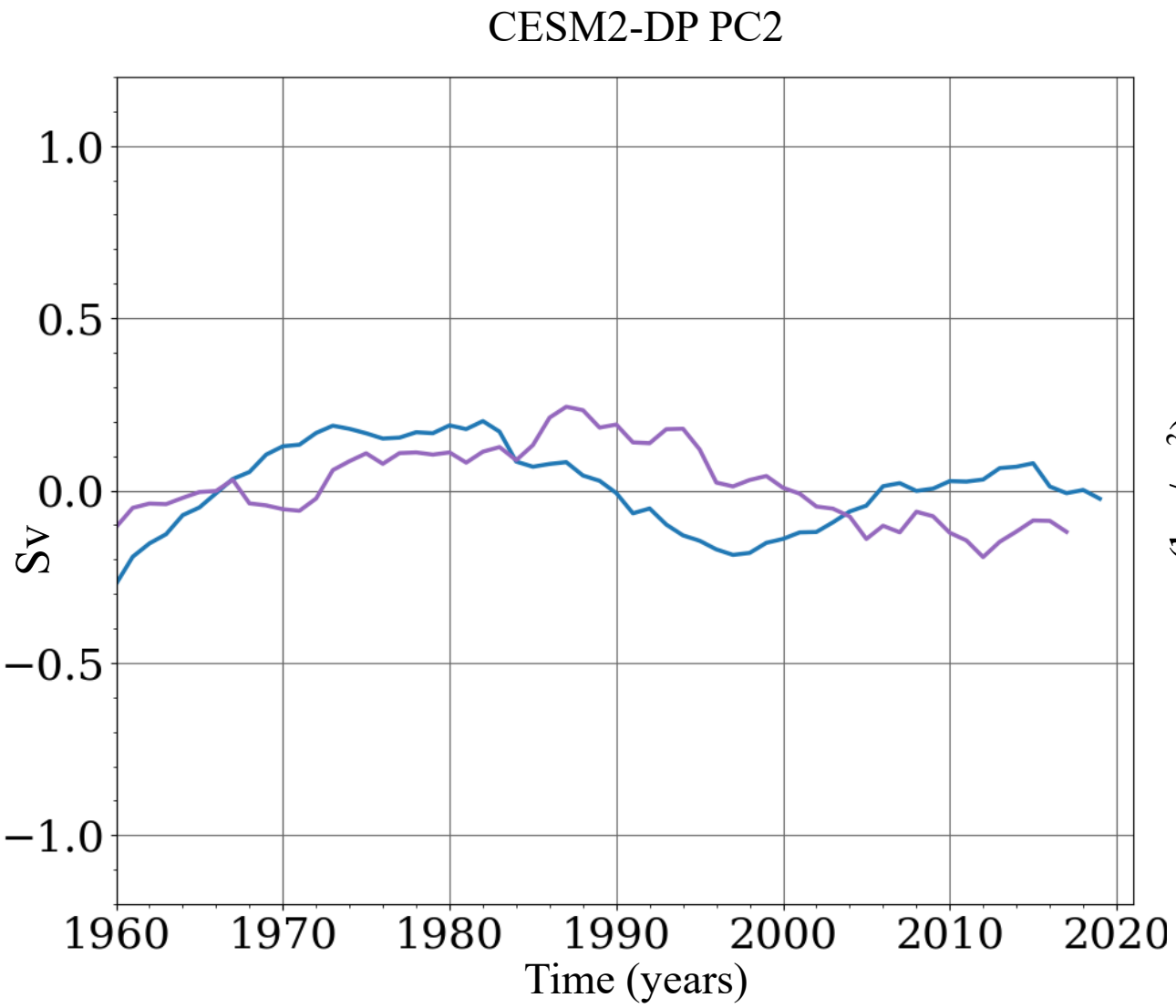

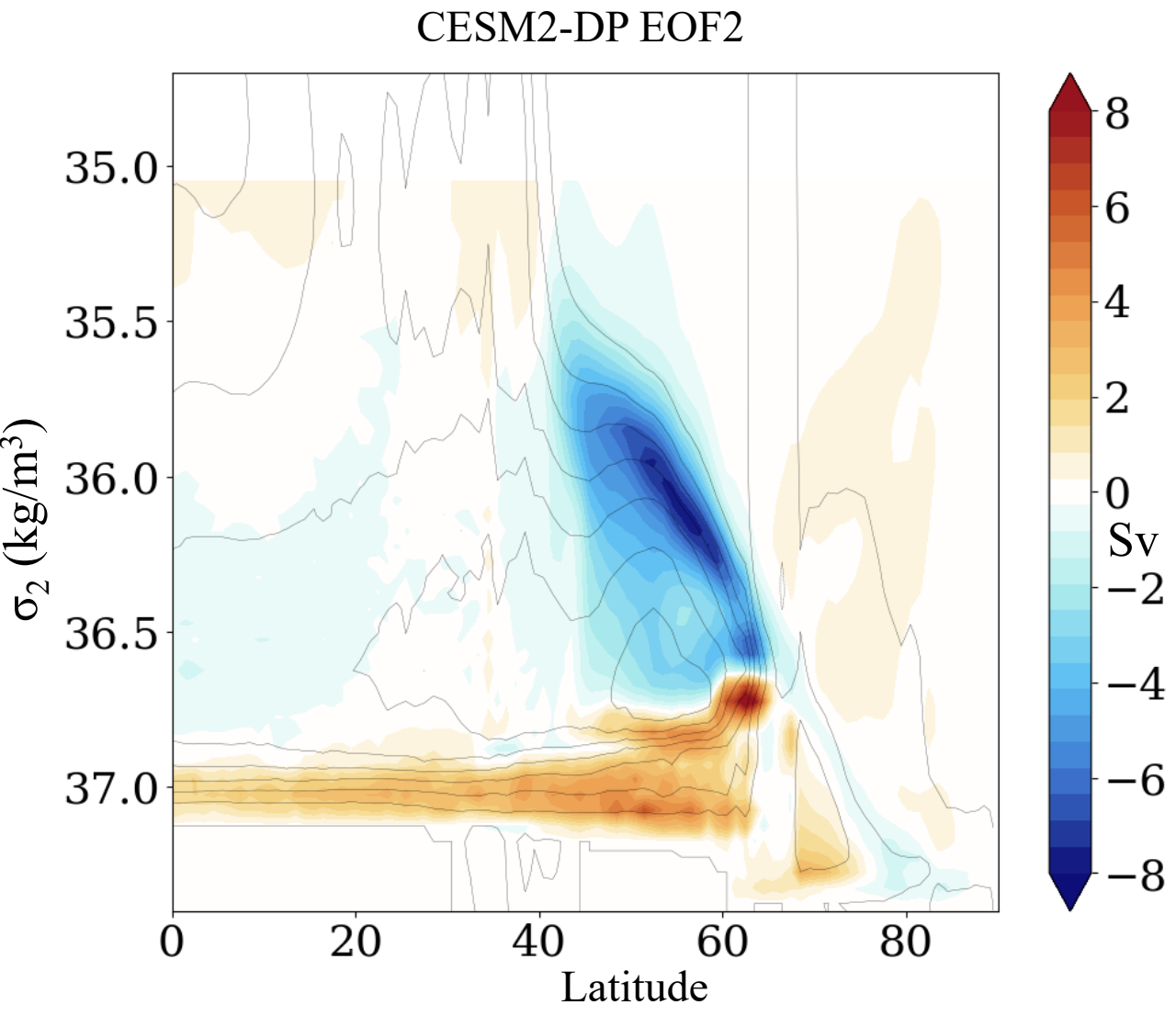

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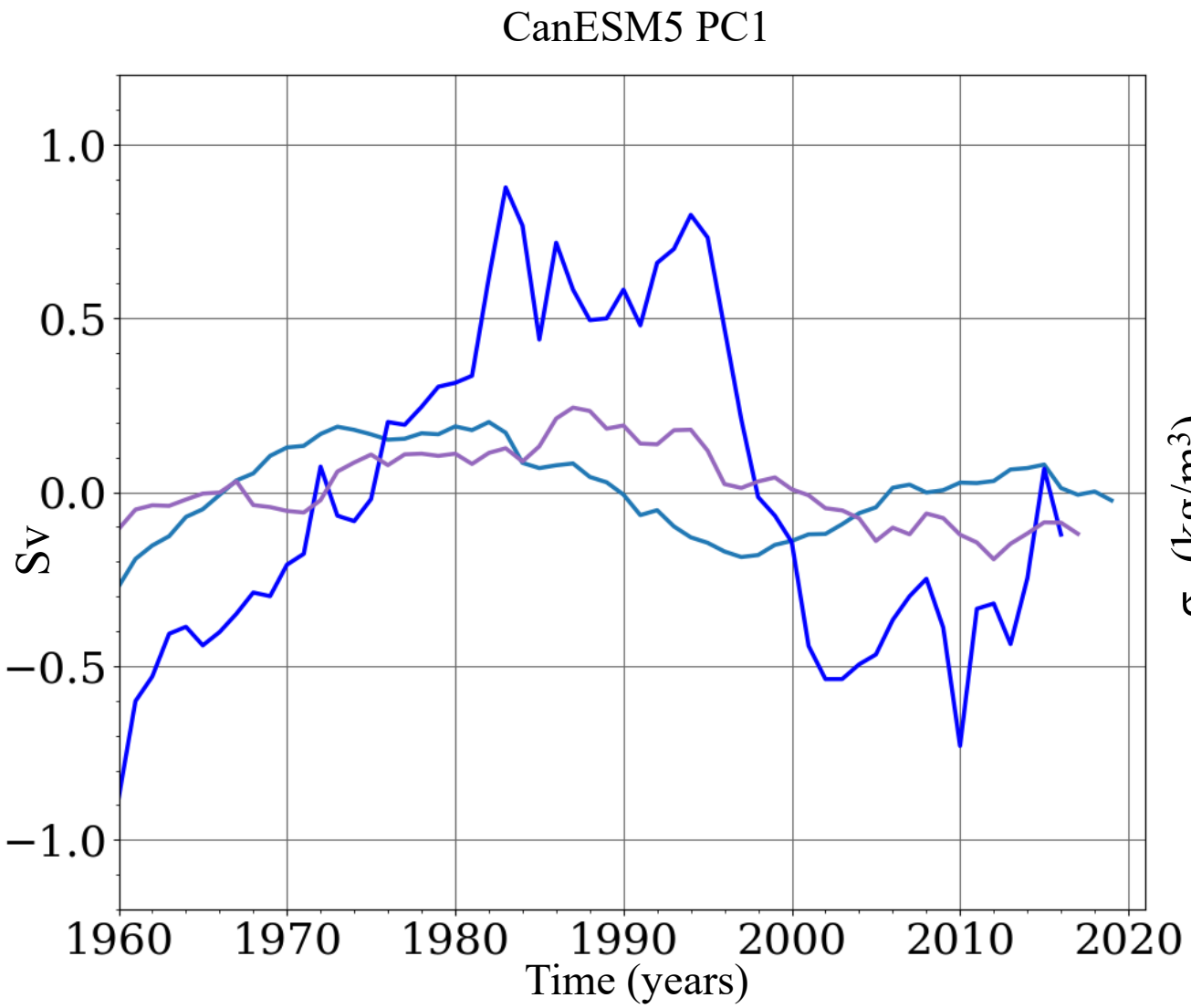
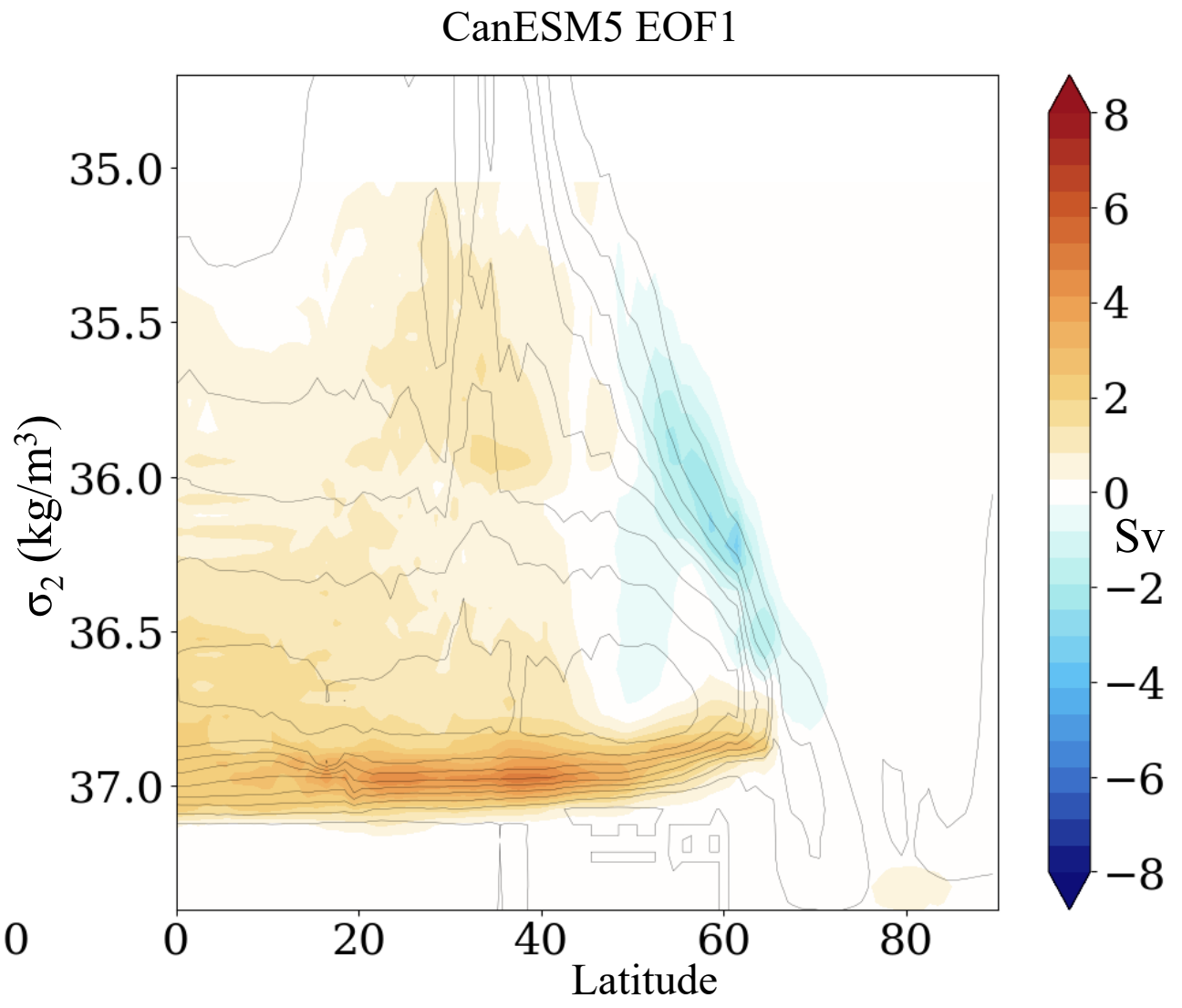
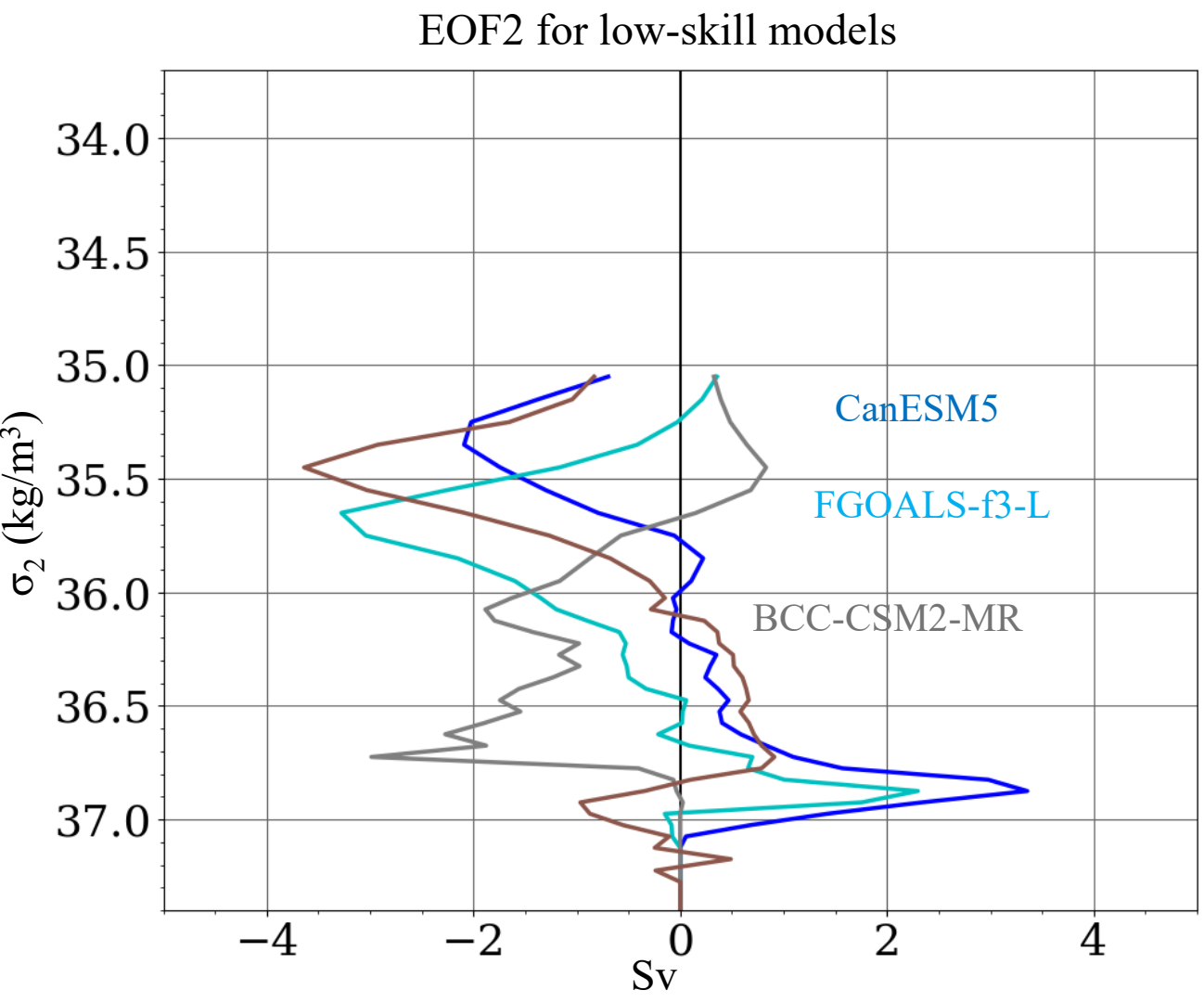
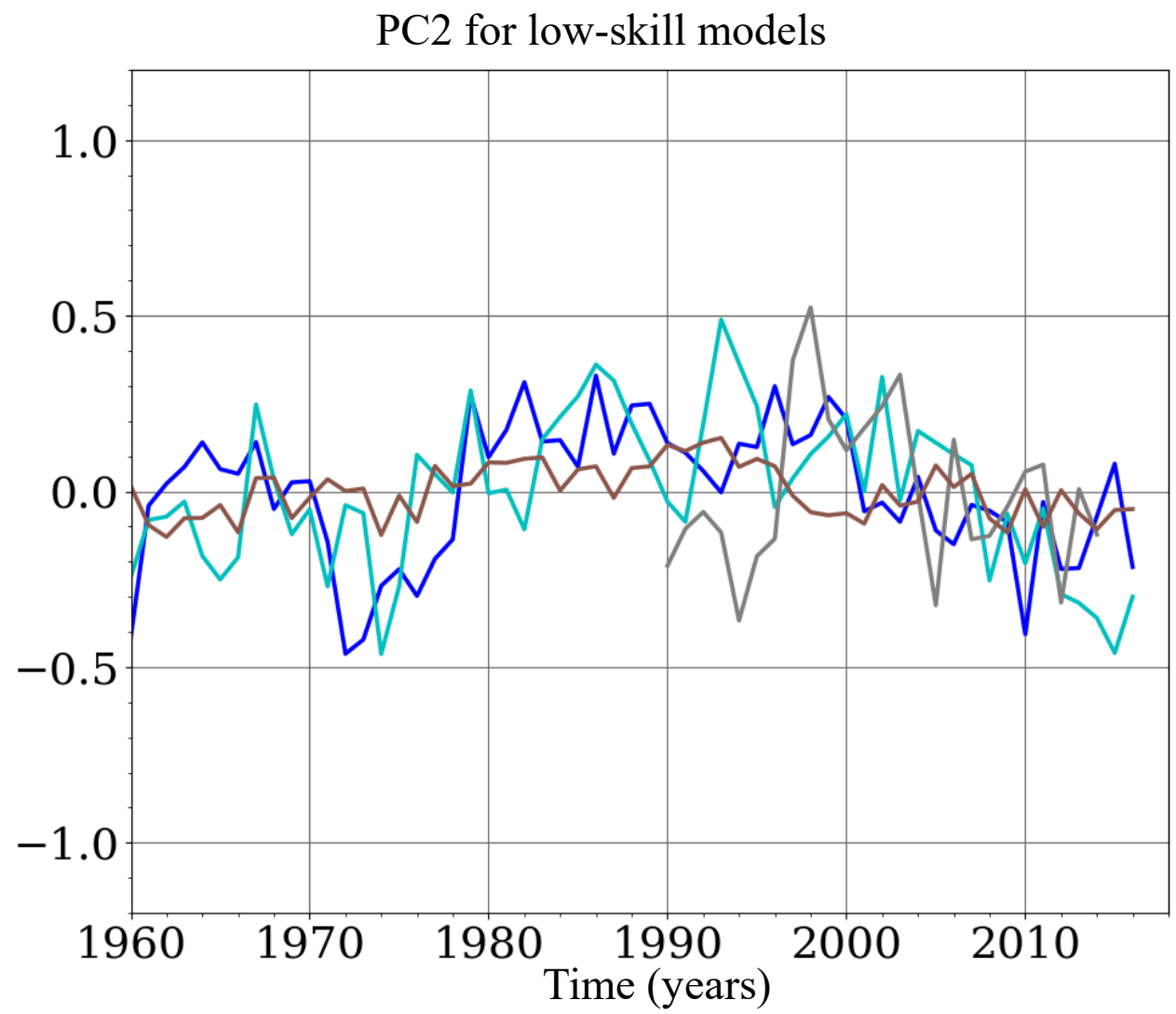
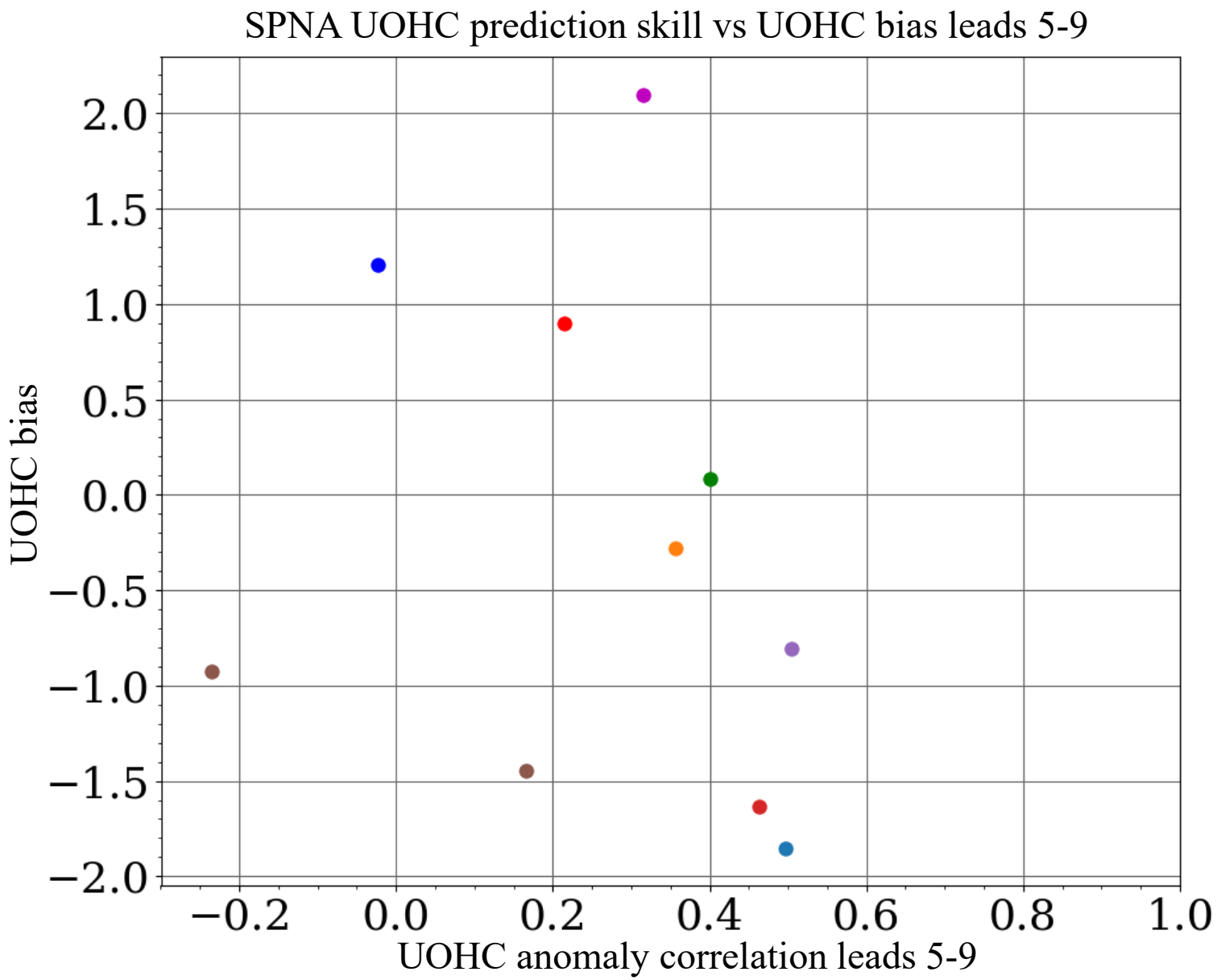
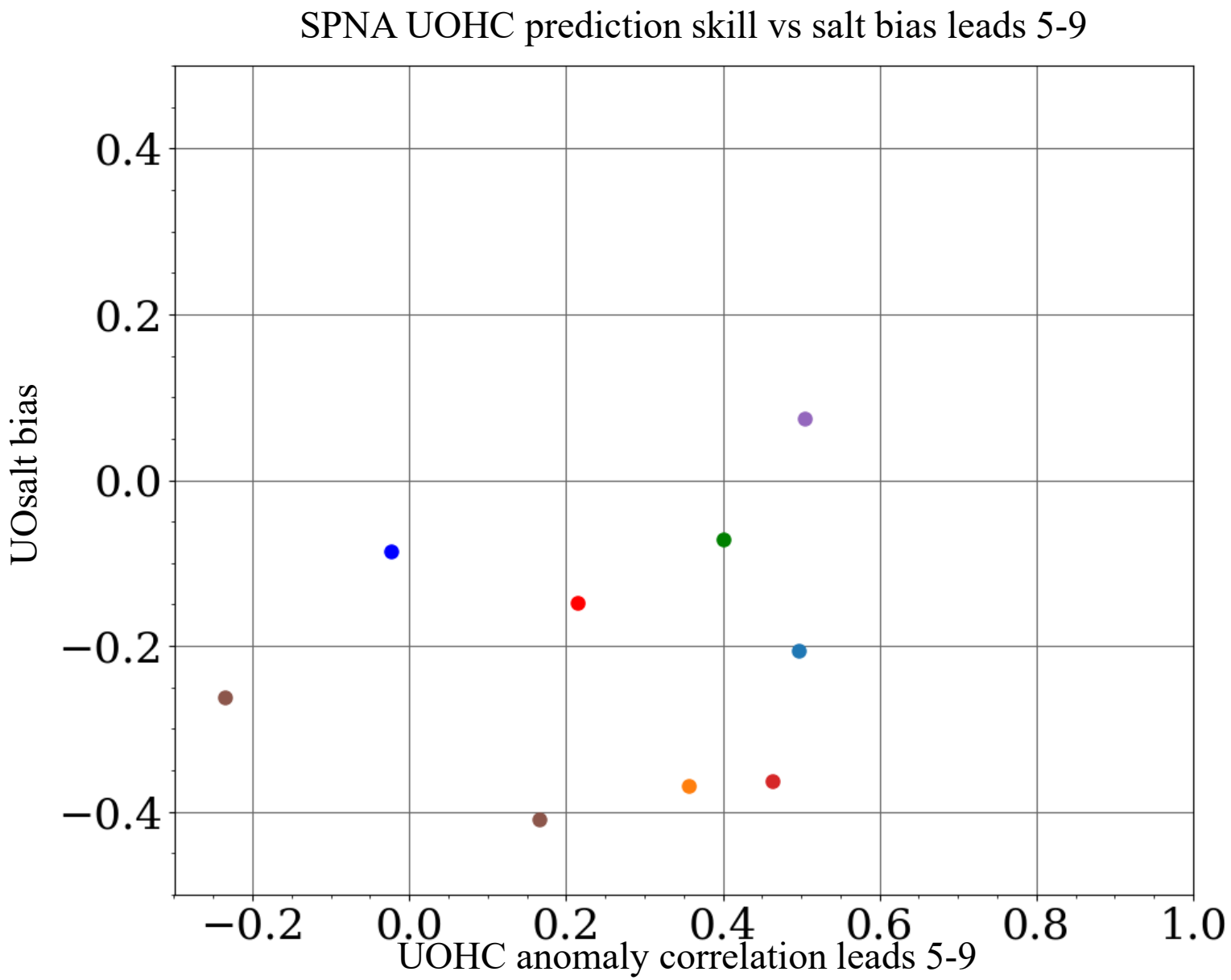





EOF2 for low-skill models
34.0
34.5
35.0
35.5
36.0
36.5
37.0
σ2 (kg/m3)
−4
−2
0
2
4
Sv
CanESM5
FGOALS-f3-L
BCC-CSM2-MR


PC2 for low-skill models
1.0
0.5
0.0
−0.5
−1.0
1960
1970
1980
1990
2000
2010
Time (years)


SPNA UOHC prediction skill vs UOHC bias leads 5-9
UOHC bias
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
UOHC anomaly correlation leads 5-9


SPNA UOHC prediction skill vs salt bias leads 5-9
UOsalt bias
0.4
0.2
0.0
−0.2
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
UOHC anomaly correlation leads 5-9

Next Steps

- Determine link between leading EOFs and SPNA UOHC
- Conclusively determine whether large biases in some models outside of SPNA control SPNA UOHC predictability