4th Summer School on Theory, Mechanisms and Hierarchical Modeling of Climate Dynamics: Atlantic Variability and Tropical Basin Interactions at Interannual to Multi-Decadal Time Scales
ICTP, Trieste, Italy

Climate prediction (Part 2):

Decadal Timescales

Stephen Yeager
National Center for Atmospheric Research (NCAR)
Boulder, Colorado

August 8, 2023

NCAR

NSF

This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

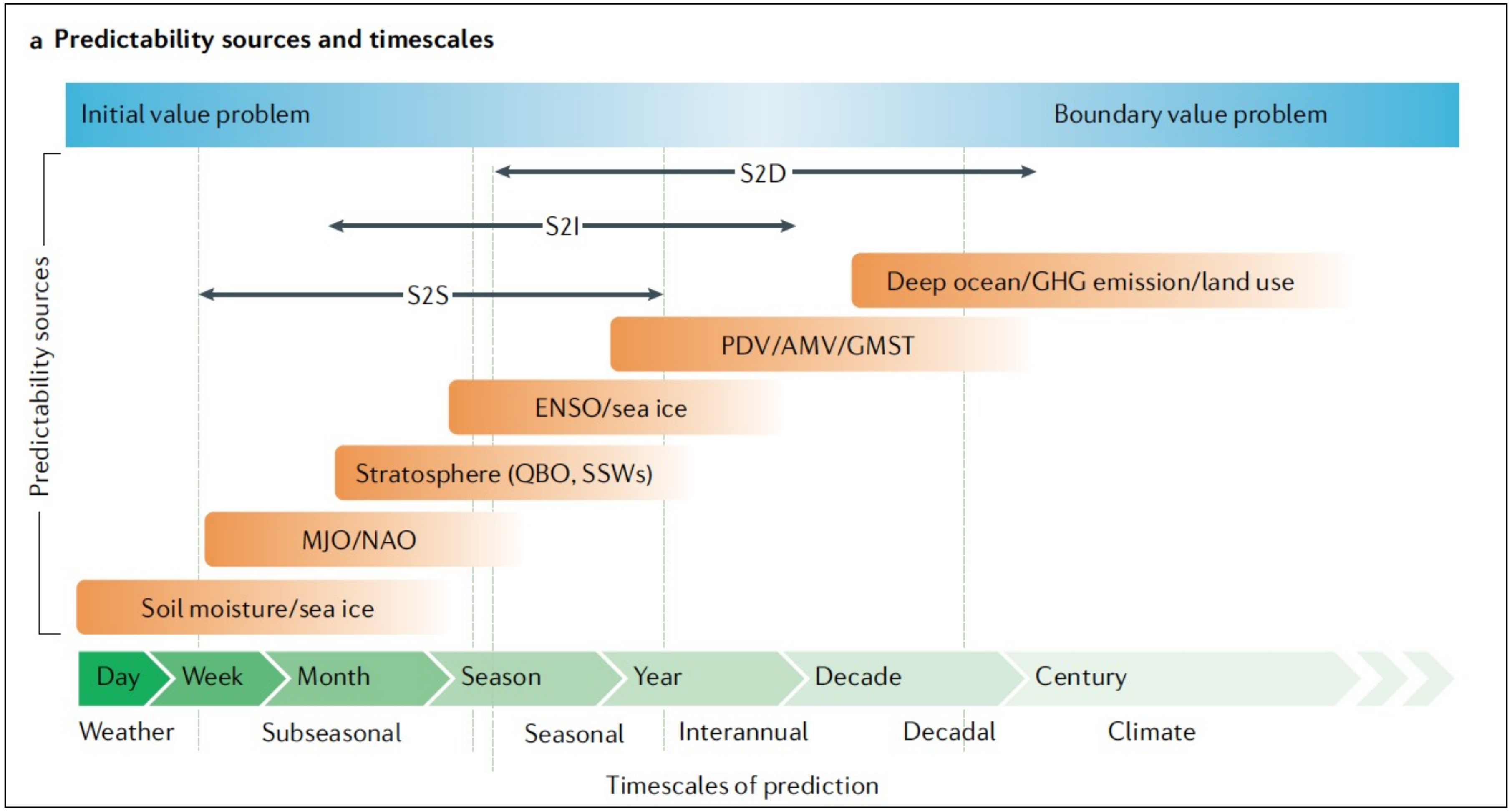
Outline

- Prediction System Theory & Design
- Predicting Atlantic Variability & Wider Impacts
- The role of AMOC

I. Prediction System Theory & Design

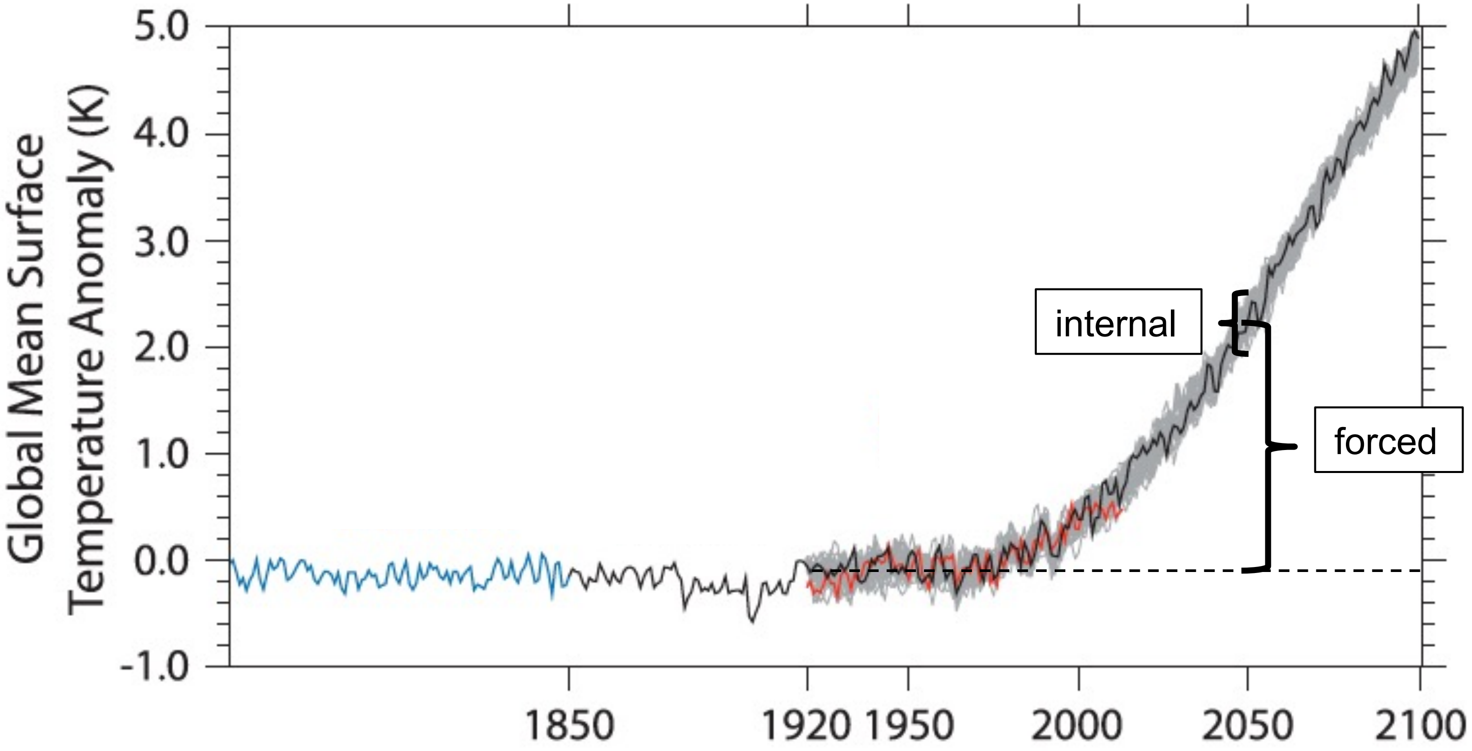
Climate Prediction vs. Climate Projection

Initialized Prediction **Forced Projection**



Meehl et al. (2021, 10.1038/s43017-021-00155- x)

Climate Projection Large Ensembles



https://esgf-data.dkrz.de/projects/mpi-ge/

Ensemble spread develops from slight differences in initial conditions

Predictions depend solely on future emissions scenarios

Permits decomposition into forced vs. internal variability

Kay et al. (2015, 10.1175/BAMS-D-13-00255.1)

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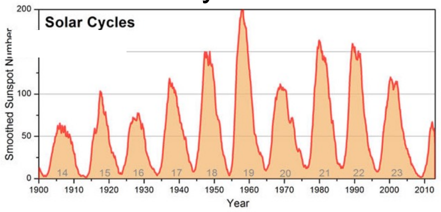
Forced Variability & Change

Greenhouse Gases

Biomass Emissions

Volcanic Eruptions

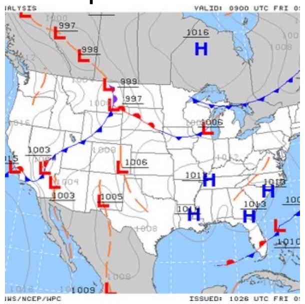
Solar Cycles



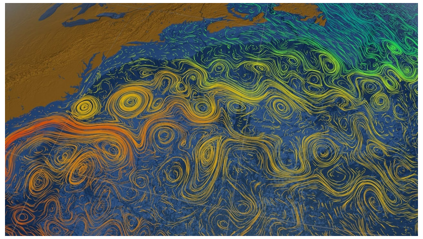
Regional Environmental Change

Internal Variability

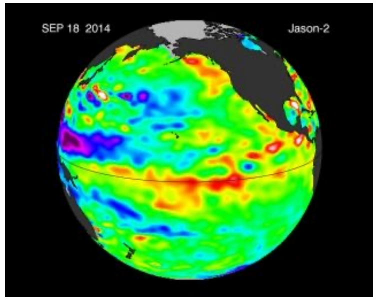
Atmospheric Turbulence



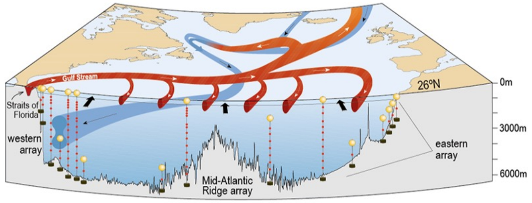
Oceanic Turbulence



El Niño/La Niña



Atlantic Meridional Overturning Circulation (AMOC)



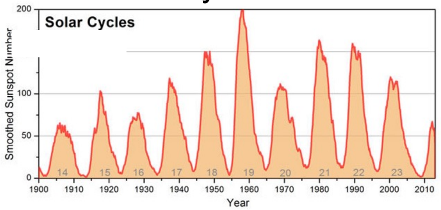
Forced Variability & Change

Greenhouse Gases

Biomass Emissions

Volcanic Eruptions

Solar Cycles



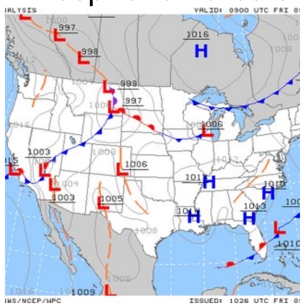
Ensemble mean (signal) =
forced variability/change

Regional Environmental Change

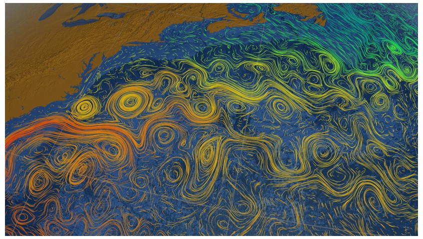
Uninitialized Large Ensembles

Internal Variability

Atmospheric Turbulence



Oceanic Turbulence



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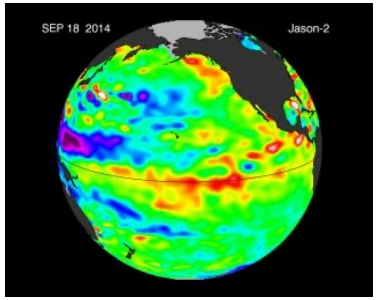

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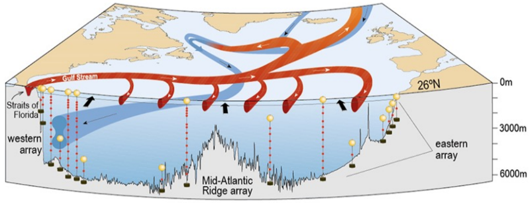


Ensemble spread (noise) =
internal variability
("irreducible uncertainty")

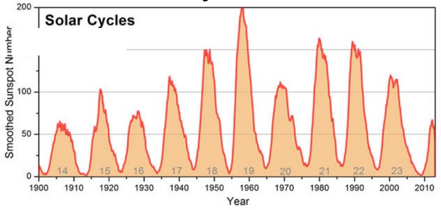
Forced Variability & Change

Greenhouse Gases

Biomass Emissions

Volcanic Eruptions

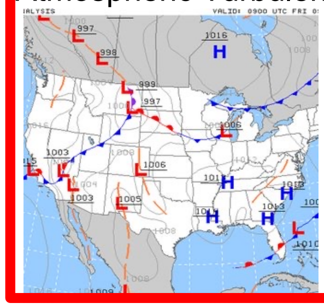
Solar Cycles



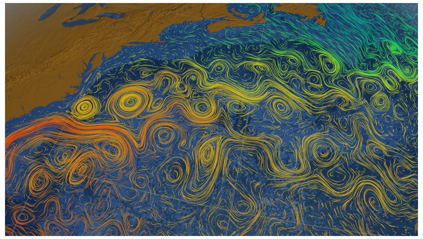
Regional Environmental Change

Internal Variability

Atmospheric Turbulence



Oceanic Turbulence



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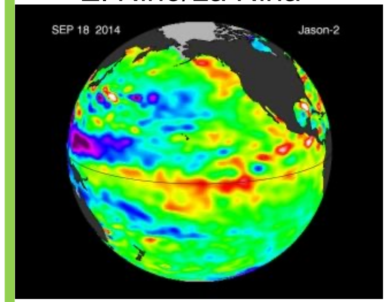

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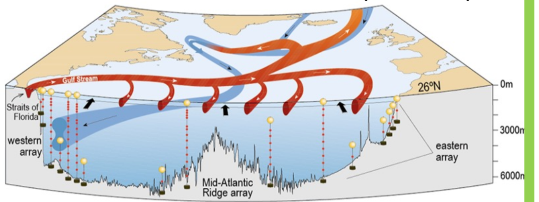

Initialized Decadal Prediction Ensembles

Ensemble mean (signal) = forced variability/change + predictable internal variability

Ensemble spread (noise) = unpredictable internal variability

Prediction in the Large Ensemble Limit

Boer et al. (2013, 10.1007/s00382-013-1705-0)

- Observations: $\boldsymbol{X} = \chi + \boldsymbol{x} = \chi_f + \chi_i + \boldsymbol{x}$
- Uninitialized Projections: $\boldsymbol{U} = \phi + \boldsymbol{u} = \phi_f + \phi_i + \boldsymbol{u}$
- Initialized Hindcasts: $\boldsymbol{Y} = \psi + \boldsymbol{y} = \psi_f + \psi_i + \boldsymbol{y}$

Potentially Predictable
Noise

- Ensemble Average: $\sigma_{U_a}^2 = \sigma_{\phi_f}^2 + \frac{1}{n}\sigma_{\phi_i}^2 + \frac{1}{n}\sigma_u^2 \rightarrow \sigma_{\phi_f}^2$ Uninitialized

$\sigma_{Y_a}^2 = \sigma_{\psi_f}^2 + \sigma_{\psi_i}^2 + \frac{1}{m}\sigma_y^2 \rightarrow \sigma_{\psi_f}^2 + \sigma_{\psi_i}^2 = \sigma_\psi^2$ Initialized

➔ Initialized systems are better suited for exploring real-world predictability because they allow quantification of the full potentially predictable component

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Potentially Predictable

Noise

What is the predictability of the real-world?

- Predictable Variance Fraction (PVF): $\mathrm{p} = {\sigma_\chi^2}/{\sigma_X^2}$
- Implies an inherent prediction skill limit: $r_{max} = \sqrt{\mathrm{p}} \leq 1$

Prediction in the Large Ensemble Limit

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Potentially Predictable

Noise

What is the predictability of model-world?

- PVF (aka signal-to-total or S2T): $\mathrm{q} = \sigma^2_{Y_a} / \sigma^2_Y \quad \rightarrow \quad \mathrm{q}_{truth} = \sigma^2_\psi / \sigma^2_Y$

- Note that $\mathrm{q} \geq \mathrm{q}_{truth}$ for a finite ensemble size, so $\mathrm{q}_{ratio} = \mathrm{q}_{truth} / \mathrm{q} \rightarrow 1$

Prediction in the Large Ensemble Limit

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Potentially Predictable

Noise

Some implications:

- Correlation Skill: $r = \sqrt{\mathrm{pq}_{ratio}}\mathcal{R}_{\chi\psi} \rightarrow \sqrt{\mathrm{p}}\mathcal{R}_{\chi\psi} \leq r_{max}$

Prediction in the Large Ensemble Limit

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Potentially Predictable
Noise

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Reducible skill limitation associated with finite ensemble size

Prediction in the Large Ensemble Limit

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Potentially Predictable
Noise

Some implications:

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Reducible skill limitation associated with system fidelity (initialization, physics, etc)

Prediction in the Large Ensemble Limit

Boer et al. (2013, 10.1007/s00382-013-1705-0)

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Potentially Predictable
Noise

Some implications:

- Correlation Skill: $r = \sqrt{\mathrm{pq}_{ratio}}\mathcal{R}_{\chi\psi} \rightarrow \sqrt{\mathrm{p}}\mathcal{R}_{\chi\psi} \leq r_{max}$

Inherent predictability limit

Prediction in the Large Ensemble Limit

- Instructive to consider the ratio of predictable components (RPC):

$$RPC_{truth} = \frac{\sqrt{\mathrm{p}}}{\sqrt{\mathrm{q}_{truth}}} \geq RPC = \frac{r}{\sqrt{\mathrm{q}}}$$

- RPC=1 (well-behaved system)
- RPC<1 (overconfident system; achieved skill is less than implied by ensemble spread)
- RPC>1 (underconfident system: achieved skill is greater than implied by ensemble spread)

Scaife et al. (2014, 10.1002/2014GL059637)
Eade et al. (2014, 10.1002/2014GL061146)
Dunstone et al. (2016, 10.1038/ngeo2824)
Scaife & Smith (2018, 10.1038/s41612-018-0038-4)
Strommen & Palmer (2019, 10.1002/qj.3414)
Smith et al. (2020, 10.1038/s41586-020-2525-0)

Prediction in the Large Ensemble Limit

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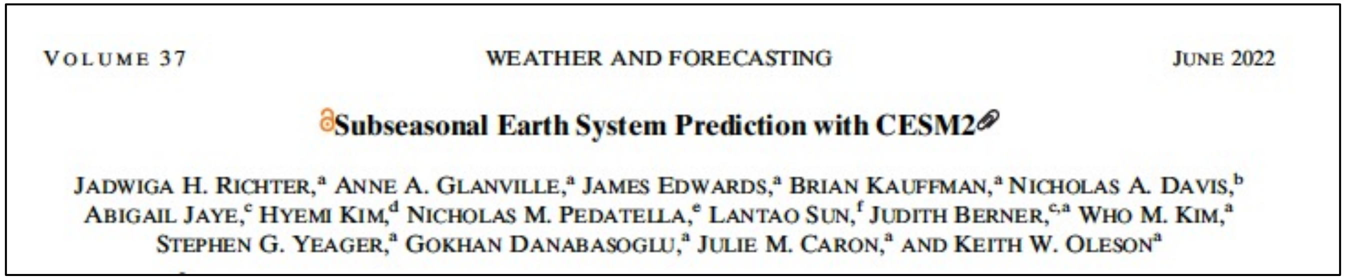
- RPC=1 (well-behaved system)
- RPC<1 (overconfident system; achieved skill is less than implied by ensemble spread)
- RPC>1 (underconfident system: achieved skill is greater than implied by ensemble spread)

"signal-to-noise paradox": model is able to predict the real-world better than it can predict itself

Scaife et al. (2014, 10.1002/2014GL059637)
Eade et al. (2014, 10.1002/2014GL061146)
Dunstone et al. (2016, 10.1038/ngeo2824)
Scaife & Smith (2018, 10.1038/s41612-018-0038-4)
Strommen & Palmer (2019, 10.1002/qj.3414)
Smith et al. (2020, 10.1038/s41586-020-2525-0)

S2S Prediction with CESM



VOLUME 37 WEATHER AND FORECASTING JUNE 2022

Subseasonal Earth System Prediction with CESM2

JADWIGA H. RICHTER,[a] ANNE A. GLANVILLE,[a] JAMES EDWARDS,[a] BRIAN KAUFFMAN,[a] NICHOLAS A. DAVIS,[b] ABIGAIL JAYE,[c] HYEMI KIM,[d] NICHOLAS M. PEDATELLA,[e] LANTAO SUN,[f] JUDITH BERNER,[c,a] WHO M. KIM,[a] STEPHEN G. YEAGER,[a] GOKHAN DANABASOGLU,[a] JULIE M. CARON,[a] AND KEITH W. OLESON[a]

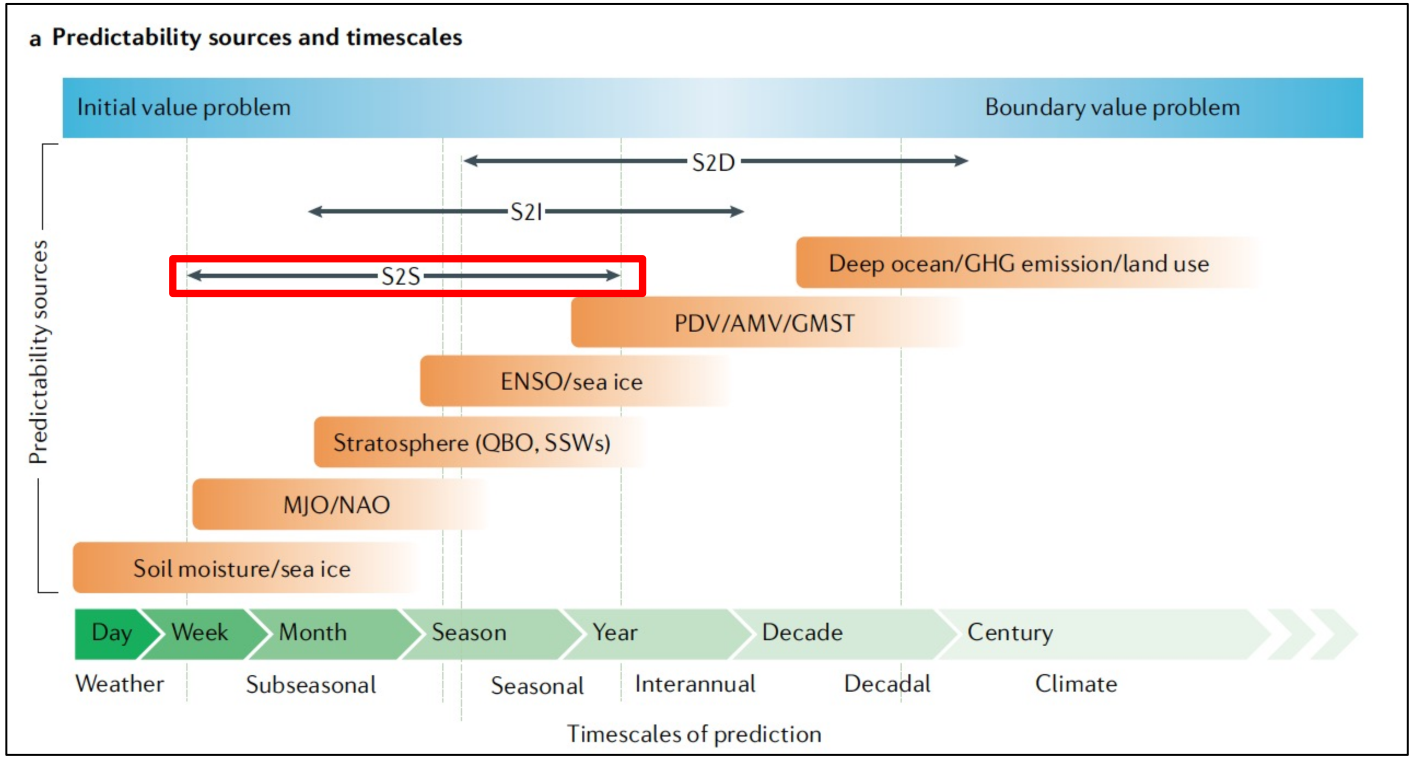
Richter et al. (2022, 10.1175/WAF-D-21-0163.1)

CESM Earth System Prediction Working Group
www.cesm.ucar.edu/working-groups/earth-system

S2S system design:

- Weekly initializations (1999-2020)
- 45-day simulations
- 10-member ensembles

➔ ~1,600 sim-years



S2I Prediction with CESM

Geosci. Model Dev., 15, 6451–6493, 2022
https://doi.org/10.5194/gmd-15-6451-2022

Geoscientific Model Development
Open Access
EGU

The Seasonal-to-Multiyear Large Ensemble (SMYLE) prediction system using the Community Earth System Model version 2

Stephen G. Yeager[1], Nan Rosenbloom[1], Anne A. Glanville[1], Xian Wu[1], Isla Simpson[1], Hui Li[1], Maria J. Molina[1], Kristen Krumhardt[1], Samuel Mogen[2], Keith Lindsay[1], Danica Lombardozzi[1], Will Wieder[1], Who M. Kim[1], Jadwiga H. Richter[1], Matthew Long[1], Gokhan Danabasoglu[1], David Bailey[1], Marika Holland[1], Nicole Lovenduski[2], Warren G. Strand[1], and Teagan King[1]

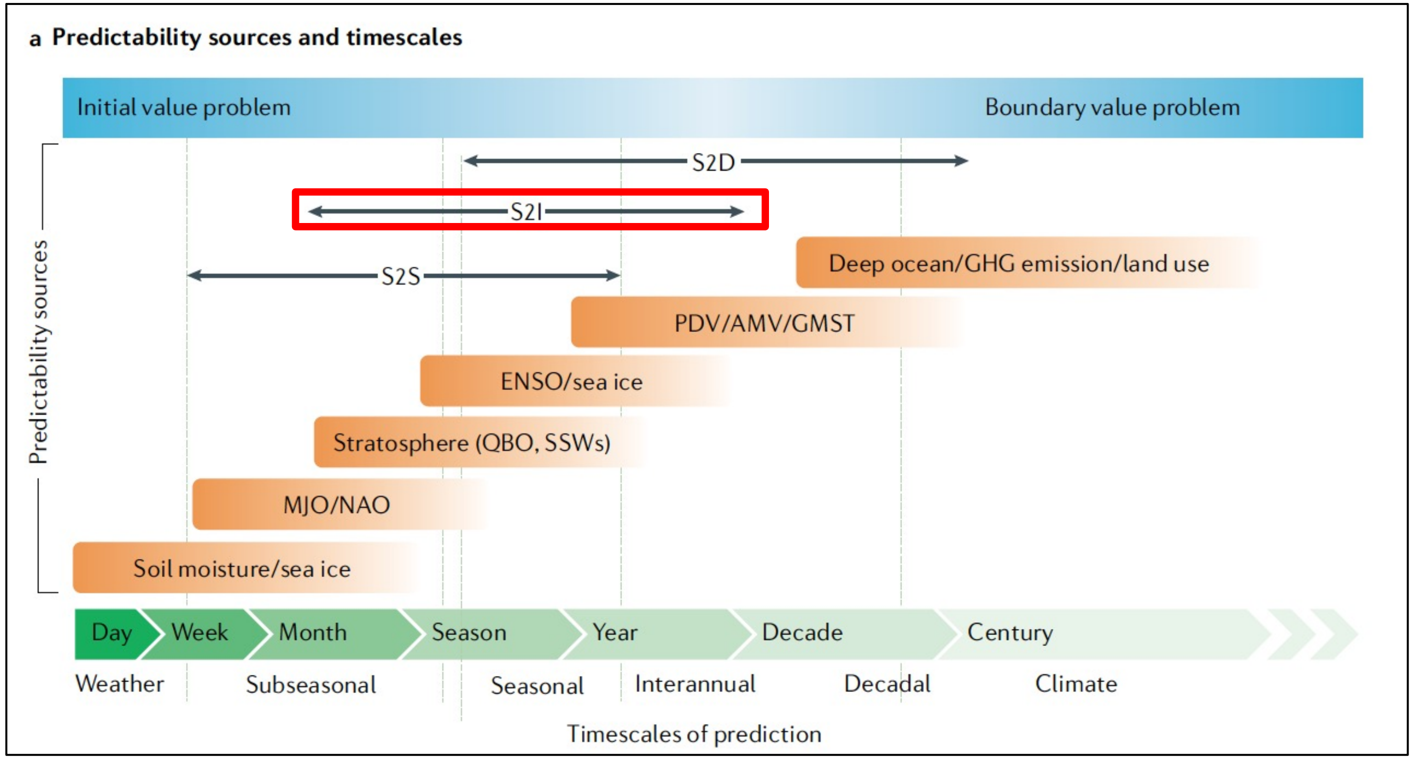
Yeager et al. (2022, 10.5194/gmd-15-6451-2022)

CESM Earth System Prediction Working Group
www.cesm.ucar.edu/working-groups/earth-system

S2I system design:

- Quarterly initializations (1st of Nov/Feb/May/Aug 1958-2020)
- 24-month simulations
- 20-member ensembles

➔ ~10,000 sim-years



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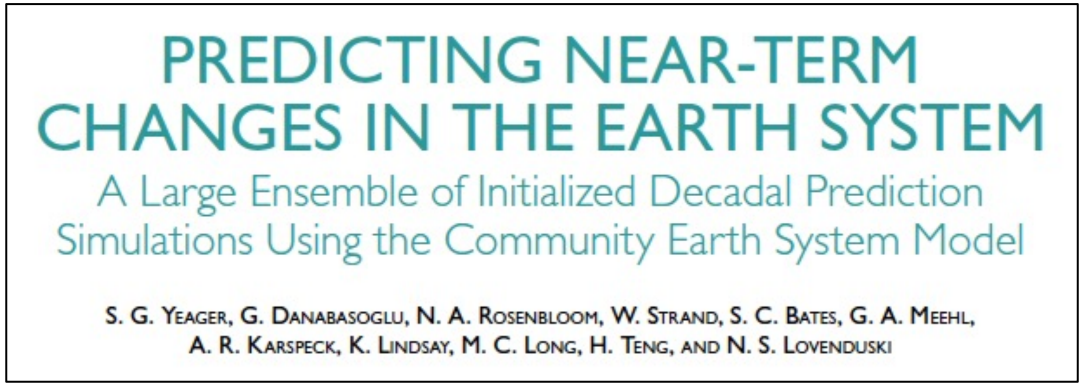
S2D Prediction with CESM



PREDICTING NEAR-TERM CHANGES IN THE EARTH SYSTEM

A Large Ensemble of Initialized Decadal Prediction Simulations Using the Community Earth System Model

S. G. Yeager, G. Danabasoglu, N. A. Rosenbloom, W. Strand, S. C. Bates, G. A. Meehl, A. R. Karspeck, K. Lindsay, M. C. Long, H. Teng, and N. S. Lovenduski

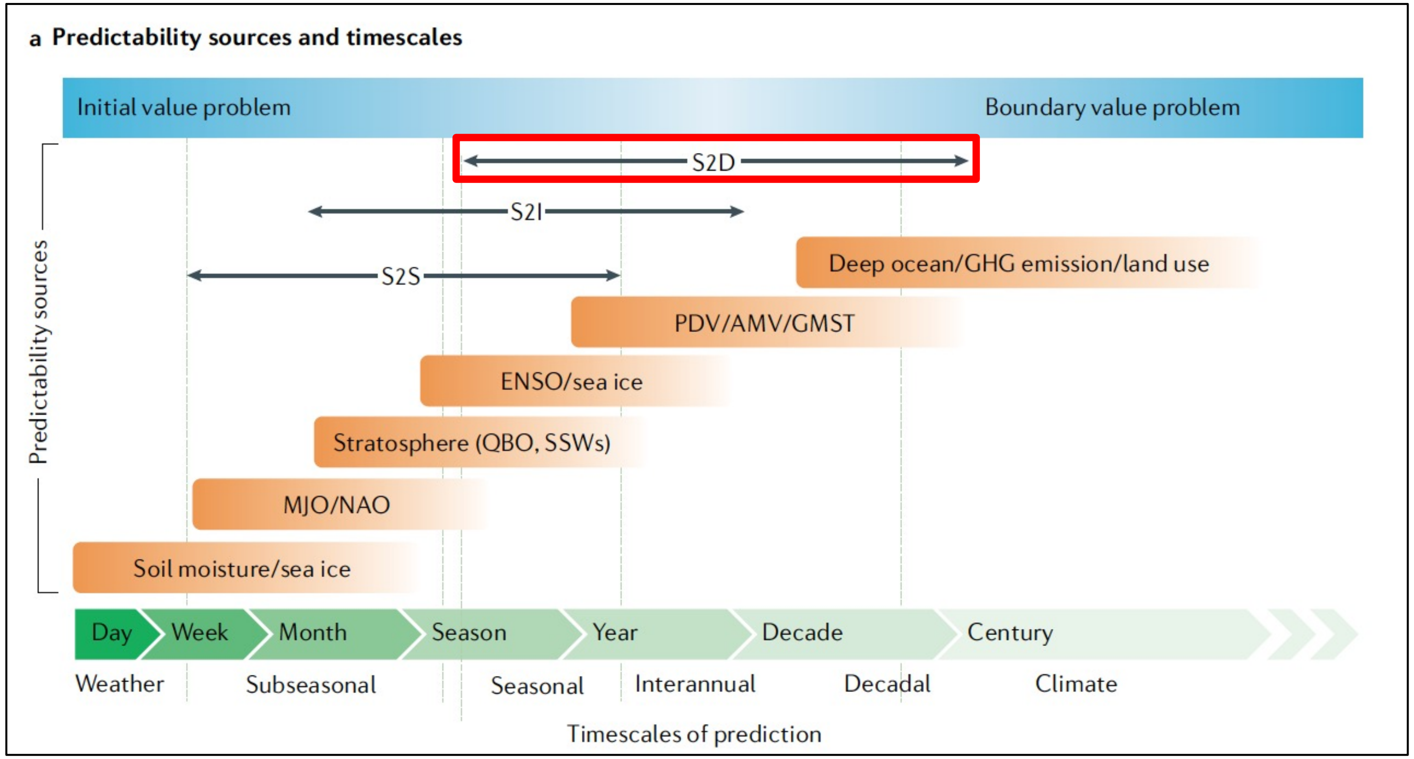
Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

CESM Earth System Prediction Working Group
www.cesm.ucar.edu/working-groups/earth-system

S2D system design:

- Annual initializations (Nov. 1st 1954-2020)
- 122-month simulations
- 40-member ensembles

➔ ~27,000 sim-years



Decadal Prediction System Design: Choices & Challenges

- **How best to initialize a (biased) coupled climate/earth-system model?**
  - brute force, native data assimilation (uncoupled vs. coupled), forced single-component state reconstructions
  - “full field” vs. “anomaly”

- **Include unpredictable external forcings (e.g., volcanic aerosols) in hindcasts?**
  - CMIP6 protocols say yes, to facilitate direct comparison with uninitialized projections

- **How many {start dates, ensemble members} are needed?**

- **How best to generate ensemble spread? Does it matter?**

★ **How to explore design choice impacts without having to replicate full experiment?**

Model Drift & Drift Correction

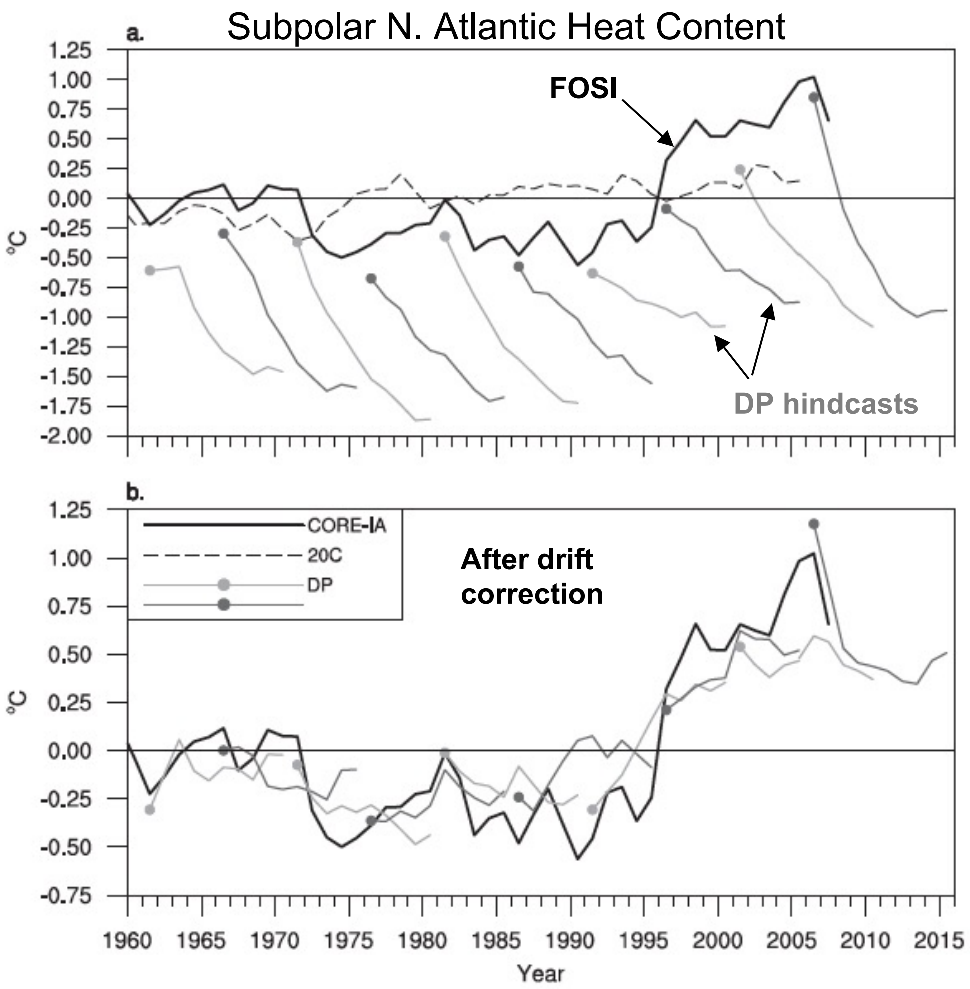
- Standard post-processing to remove hindcast drift:

$$\acute{f}_{i\tau} = f_{i\tau} - \overline{f_\tau} = f_{i\tau} - \frac{1}{N}\sum_{1}^{N} f_{i\tau}$$

for hindcast samples $i = 1 \ldots N$ and forecast lead time τ

- Other more sophisticated methods have been explored

Kharin et al. (2012, *GRL*, https://doi.org/10.1029/2012GL052647)
Meehl et al. (2022, *CLI DYN*, https://doi.org/10.1007/s00382-022-06272-7)



Yeager et al. (2012, https://doi.org/10.1175/JCLI-D-11-00595.1)

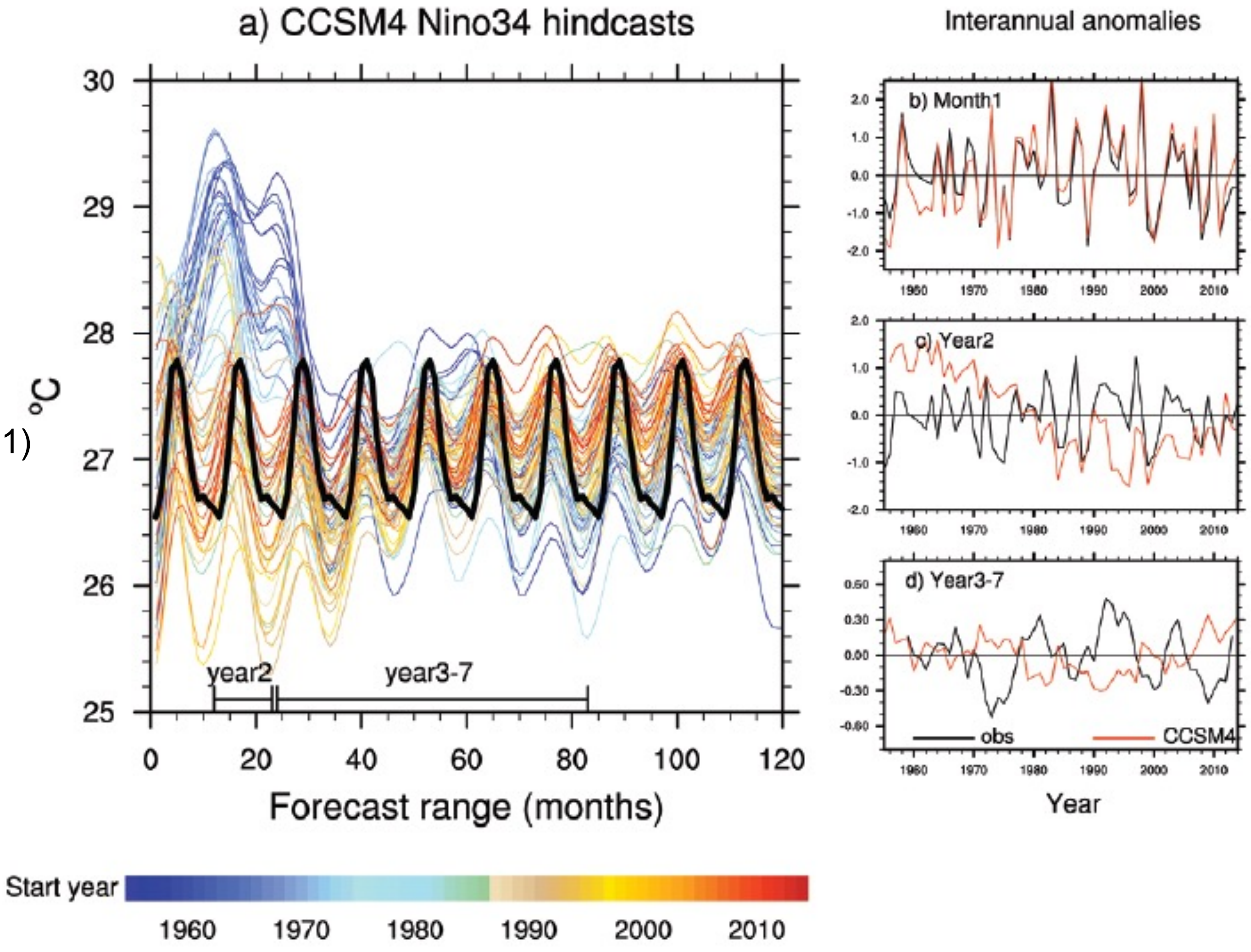
Initialization Shock

- Skill degradation resulting from imbalanced initial conditions
- Large initialization shock in CCSM4-DP was traced to a biased tropical Pacific zonal SST gradient in ocean initial conditions

Yeager et al. (2018, *BAMS*, https://doi.org/10.1175/BAMS-D-17-0098.1)

- Long Range Forecast Transient Intercomparison Project (LRFTIP) dataset was developed by WGSIP to facilitate study of drift/shock in S2D systems

Saurral et al. (2021, *JAMES*, https://doi.org/10.1029/2021MS002570)



Teng et al. (2017, https://doi.org/10.22498/pages.25.1.41)

The CESM Decadal Prediction Large Ensemble (CESM-DPLE)

Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

Model	**CESM1.1**
atm	**CAM5** (FV 1°, **30 levels**)
ocn	POP2 (1°, 60 levels) **with BGC**
ice	CICE4 (1°)
lnd	CLM4
UI ensemble	**40-member CESM twentieth-century Large Ensemble** (Kay et al. 2015)
Forcing	
through 2005	CMIP5 historical
from 2006 onward	CMIP5 **RCP 8.5**
Initialization	
method	Full field
atm	UI
ocn	**CORE*-forced FOSI**
ice	**CORE*-forced FOSI**
lnd	UI
Ensembles	
Ensemble size	**40**
Start dates	Annual; **1 Nov 1954–2015 (*N* = 62)**
Ensemble generation	Round-off perturbation of atm initial conditions
Simulation length	122 months

40-member uninitialized projection ensemble

40-member initialized prediction ensemble

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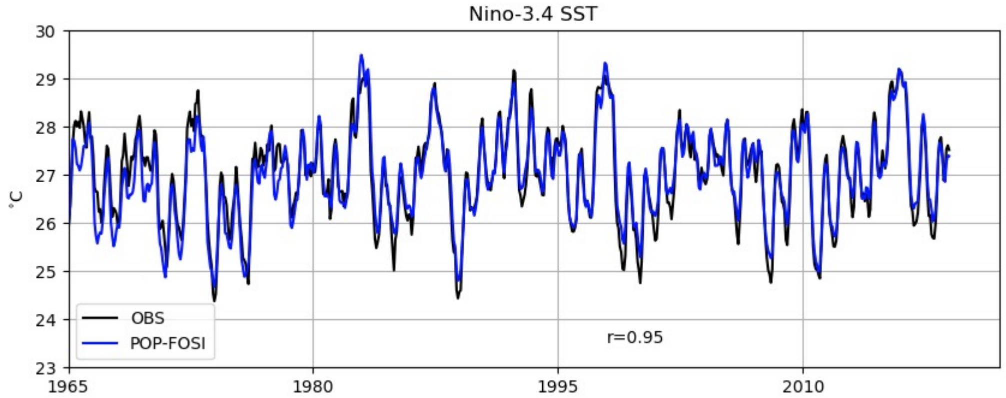

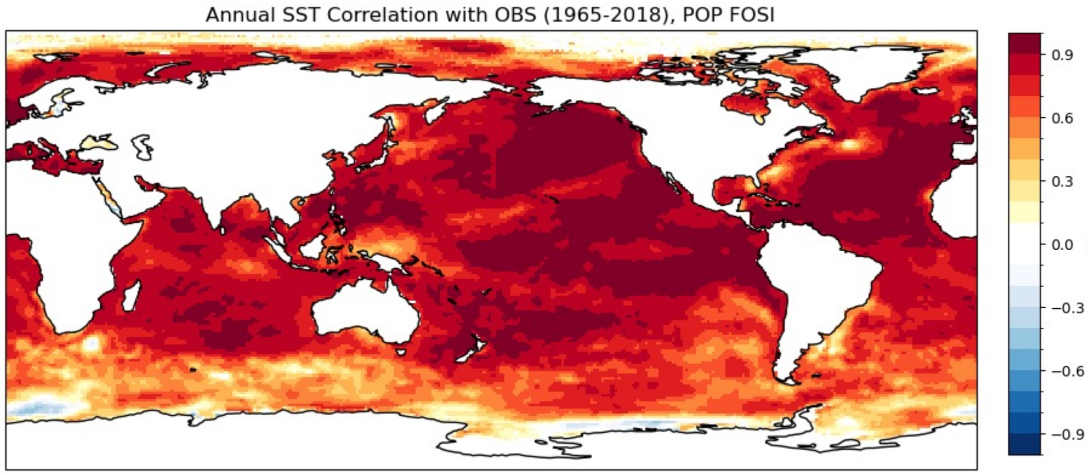

Ocean & sea-ice initial conditions come from a forced ocean/sea-ice (**FOSI**) simulation following the OMIP1 protocol (includes ocean biogeochemical fields).

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Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

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Atmosphere and land initial conditions are not accurate historical states (they come from the uninitialized ensemble).

II. Predicting Atlantic Variability & Wider Impacts

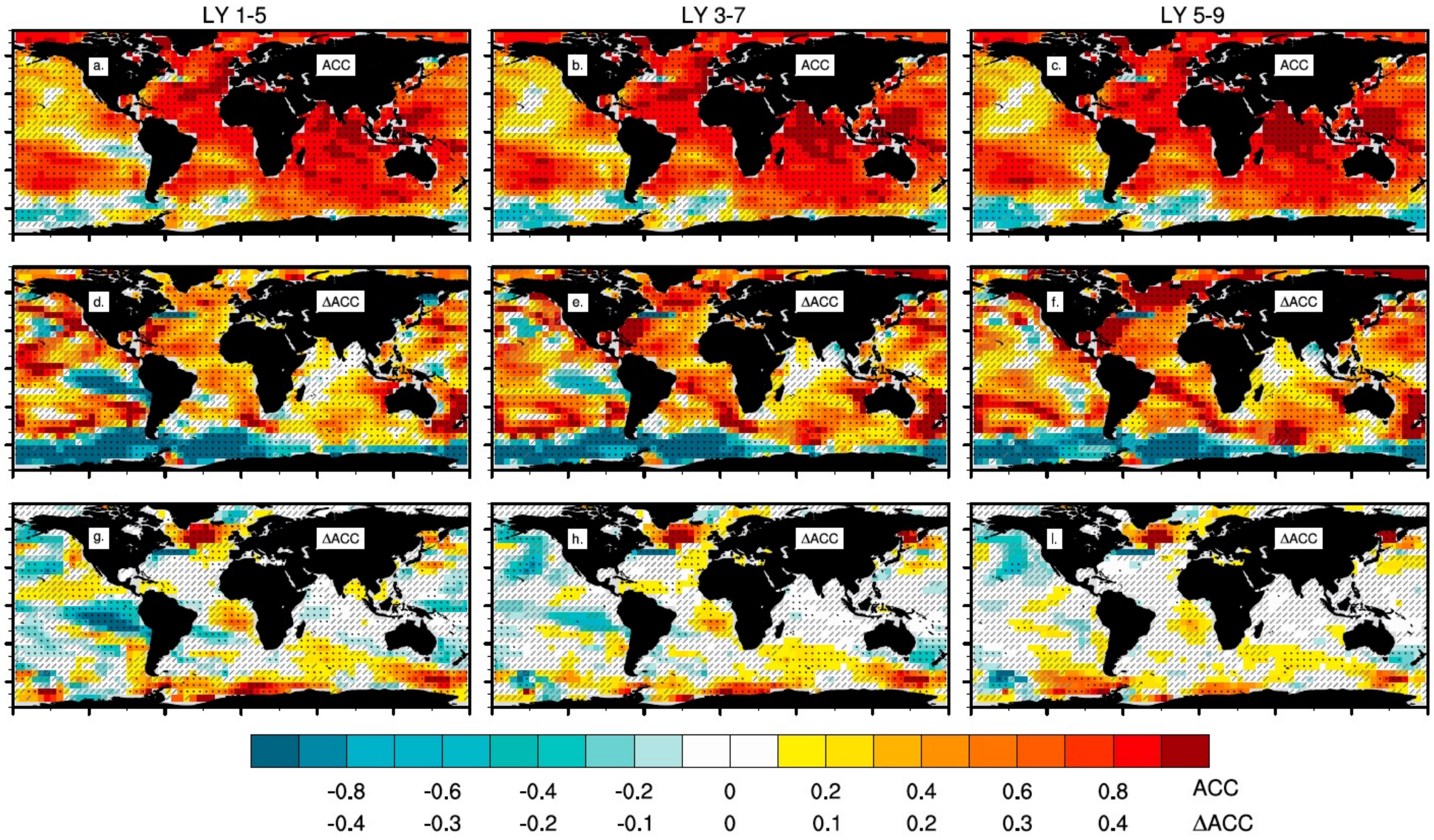
CESM-DPLE

Annual Sea Surface Temperature

Correlation Skill

Skill improvement over persistence

Skill improvement due to initialization

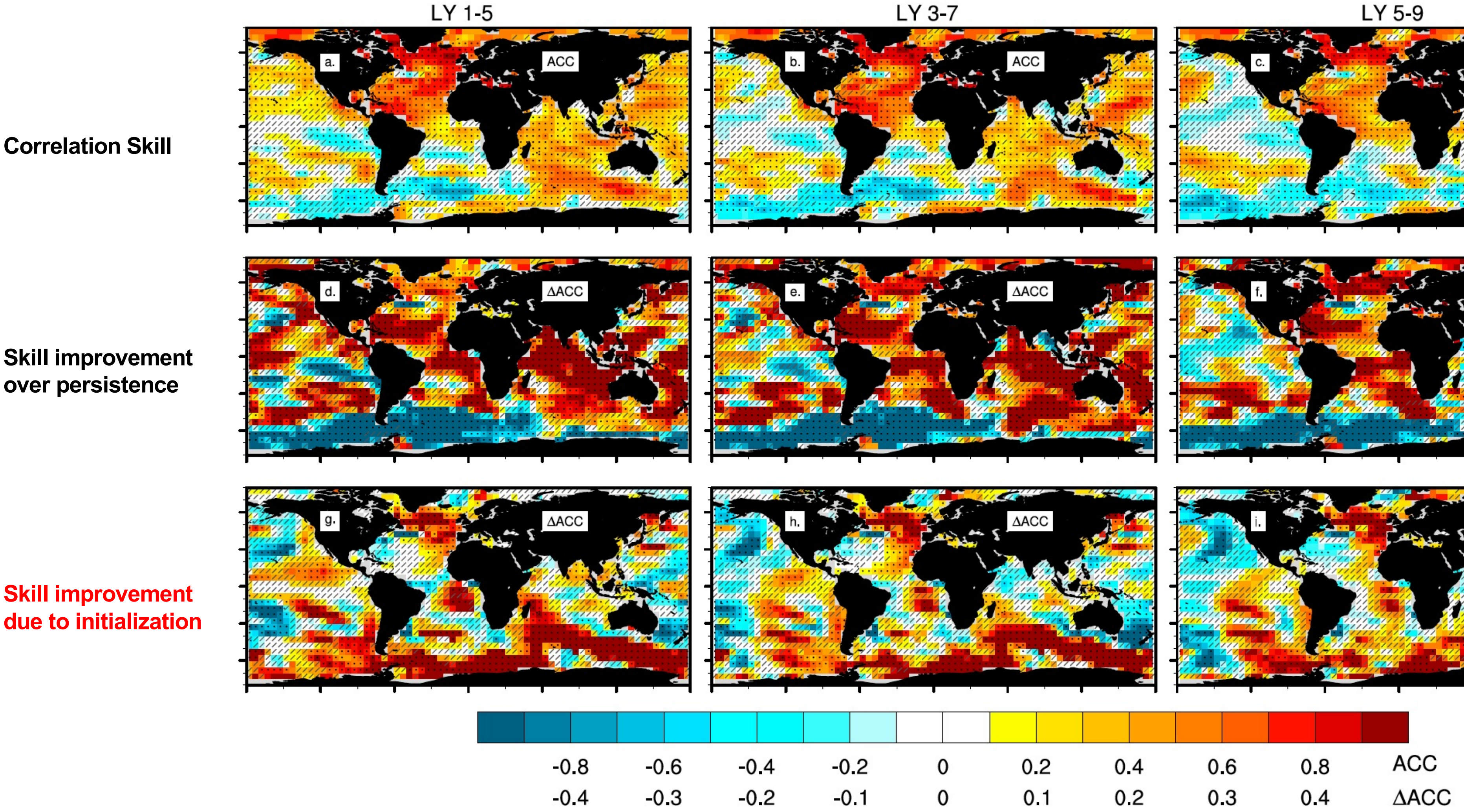


Largest impact of initialization in SPNA, generally interpreted as coming from AMOC initialization.

Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

CESM-DPLE

Detrended Annual Sea Surface Temperature



Detrended skill reveals more AMV-like improvement with initialization. Some improvement for PDV, but eastern Pacific skill remains low.

Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

ARTICLE OPEN

Robust skill of decadal climate predictions

D. M. Smith[1], R. Eade[1], A. A. Scaife[1,2], L.-P. Caron[3], G. Danabasoglu[4], T. M. DelSole[5], T. Delworth[6], F. J. Doblas-Reyes[3,7], N. J. Dunstone[1], L. Hermanson[1], V. Kharin[8], M. Kimoto[9], W. J. Merryfield[8], T. Mochizuki[10], W. A. Müller[11], H. Pohlmann[11], S. Yeager[4] and X. Yang[6]

Smith et al. (2019, 10.1038/s41612-019-0071-y)

Table 1. Forecast systems and ensemble sizes

Forecast Centre	Model	Initialised ensemble size	Uninitialized ensemble size	References
Barcelona Supercomputing Center, Spain	EC-EARTH	5	10	89,90
Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada	CANCM4	10	10	91
Geophysical Fluid Dynamics Laboratory, USA	CM2	10	10	92
Met Office Hadley Centre, UK	HADCM3 (ANOMALY INITIALISATION)	10		93
Met Office Hadley Centre, UK	HADCM3 (FULL FIELD INITIALISATION)	10	10	93
University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC5	6	3 (1 for precipitation and MSLP)	94,95
Max Planck Institute for Meteorology, Germany	MPI-ESM-LR	10	3	96
National Center for Atmospheric Research, USA	CESM1.1	10	10	35
	Total	71	56 (54 for precipitation and MSLP)	

"Residual method" applied to large multi-model CMIP6 ensemble reveals robust skill enhancement associated with initialization for: surface temperature, precipitation, and pressure.

Suggests AMOC/AMV the source of added predictability. Limited evidence of PDV skill/skill improvement.

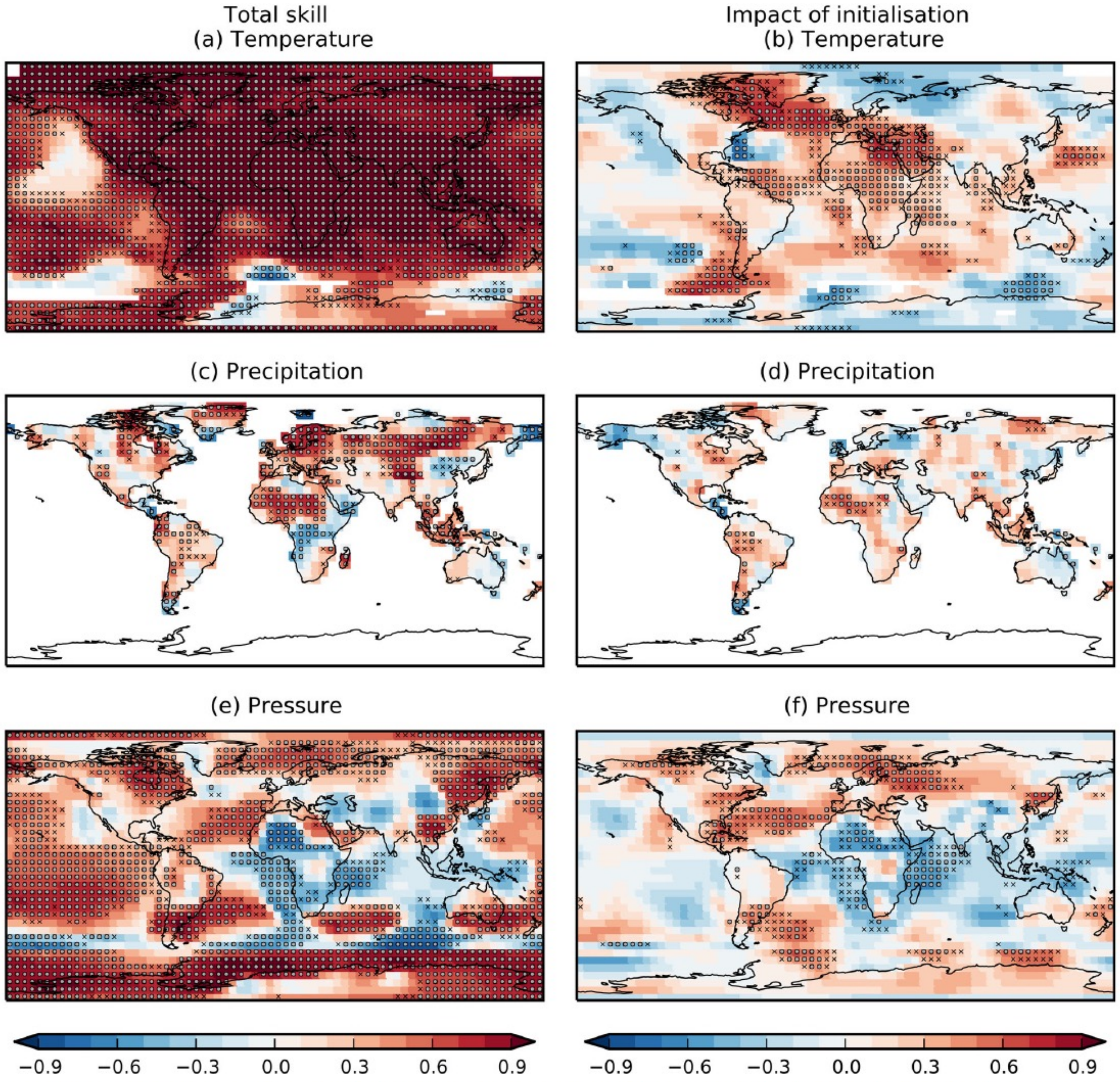
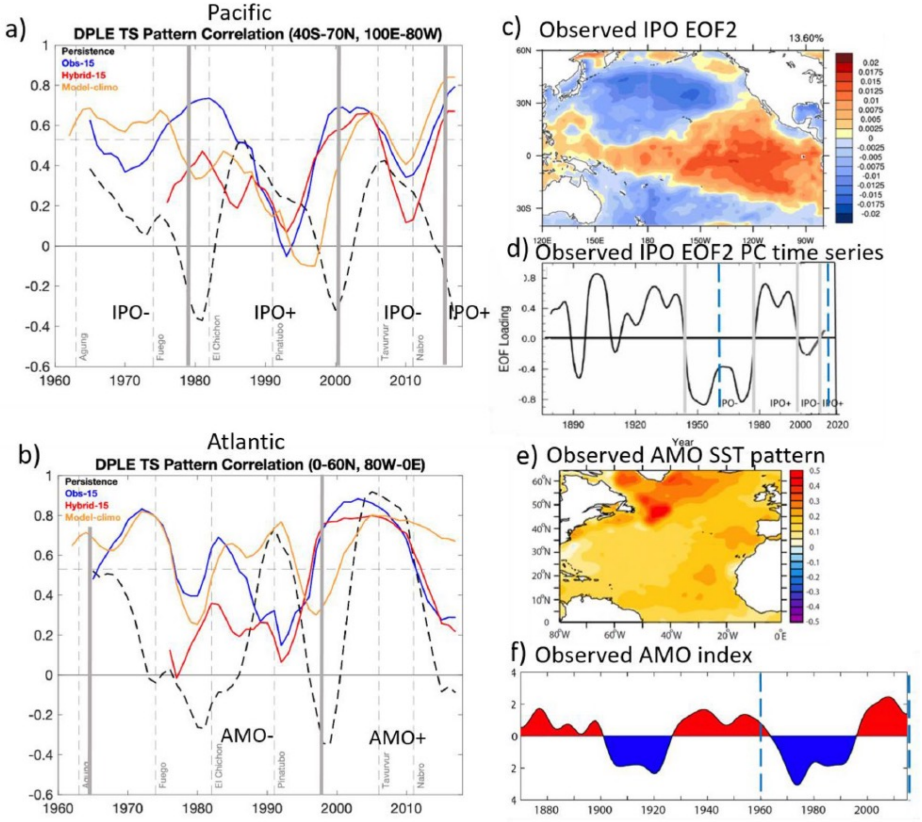
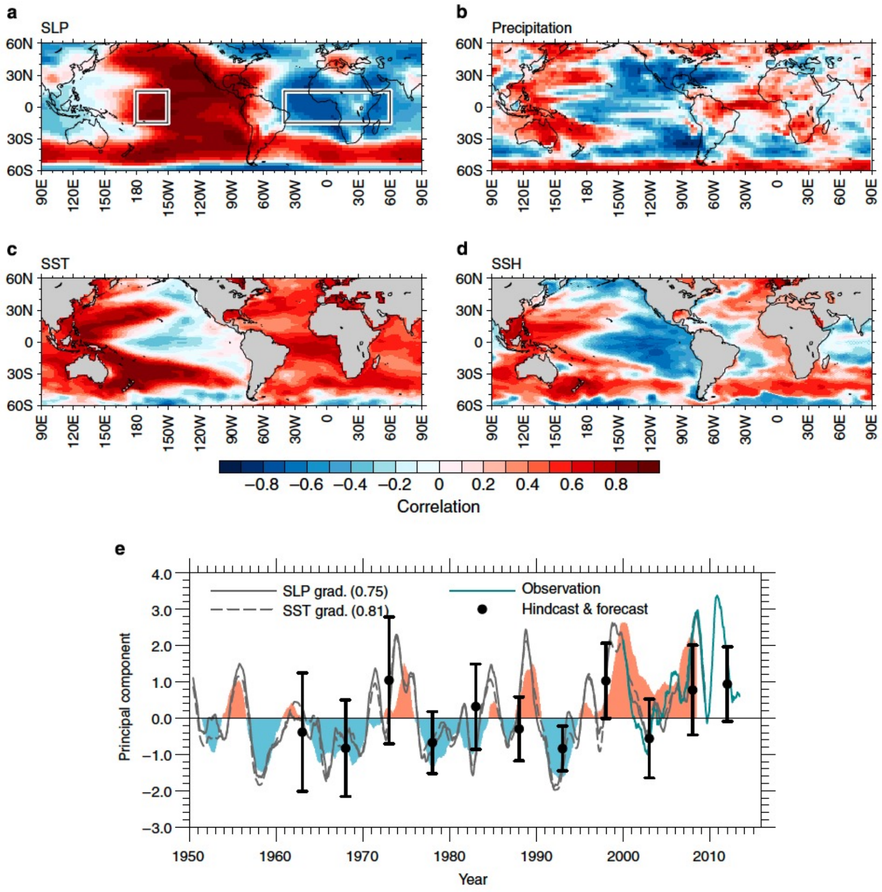


Fig. 3 Robust skill of decadal predictions. **a** Correlation between year 2–9 initialised ensemble mean forecasts and observations for near-surface temperature. **b** The impact of initialisation computed as the ratio of predicted signal arising from initialisation divided by the total predicted signal (where positive/negative values show improved/reduced skill, see Methods). **c**, **d** As (**a**, **b**) but for precipitation. **e**, **f** As (**a**, **b**) but for mean sea level pressure. Stippling shows where correlations with observations (**a**, **c**, **e**) and of residuals (**b**, **d**, **f**) are significant (crosses and circles show 90 and 95% confidence intervals, respectively)

Is PDV predictable?



Meehl et al. (2022, 10.1007/s00382-022-06272-7)



Chikamoto et al. (2015, 10.1038/ncomms7869)

- DP systems show generally low detrended/residual correlations in the eastern Pacific
- There is some evidence, however, that IPO transition events can be skillfully predicted and that predicted Pacific SST anomaly patterns beat persistence forecasts (Meehl et al. 2015, 2016, 2022). Pattern correlations appear degraded by large volcanic events (e.g. Pinatubo).
- Evidence of multiyear prediction skill for tropical trans-basin variability in at least one system (Chikamoto et al. 2015).

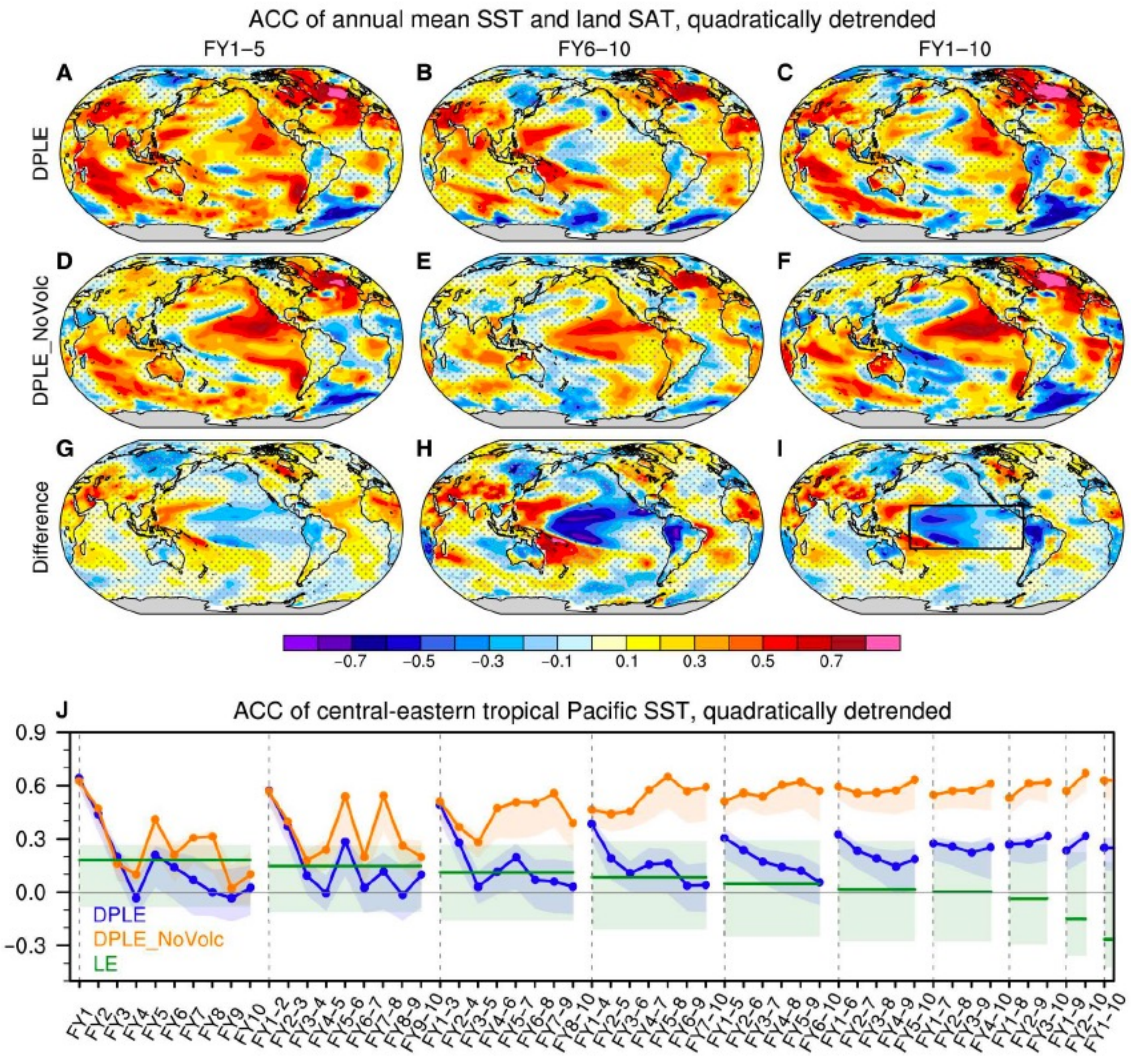
Is PDV predictable?

- PDV skill appears to be degraded in many DP systems by an incorrect model response to volcanic forcing (tropical Pacific skill increases when forcing is withheld):

Timmreck et al. (2015, 10.1002/2015GL067431)
Ménégoz et al. (2018, 10.1088/1748-9326/aac4db)
Wu et al. (2023, 10.1007/s00382-022-06272-7)

- Wu et al. (2023) results suggest there is latent potential to predict PDV that is insensitive to AMV skill.

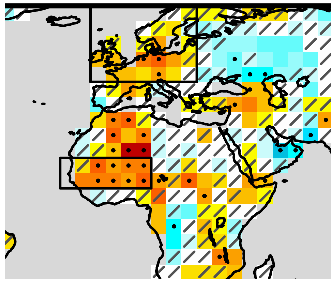
- High-resolution might help (see my talk on Thursday).



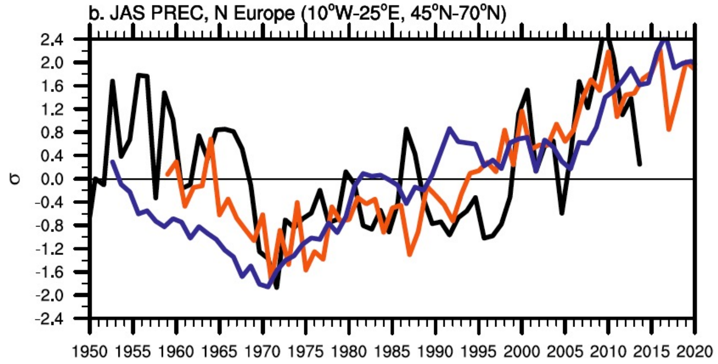
Wu et al. (2023, 10.1007/s00382-022-06272-7)

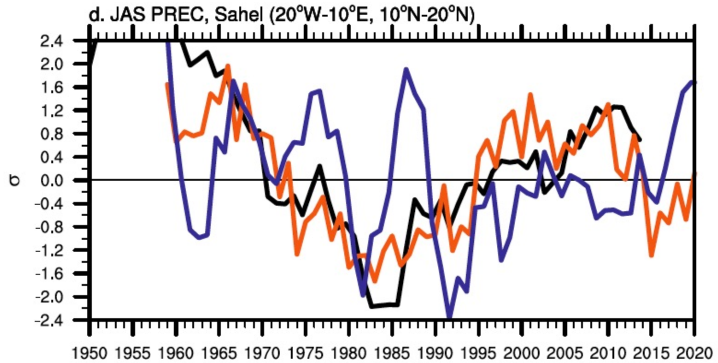
Predicting AMV Impacts: Land Precipitation

Single model large ensemble (DPLE) shows significant skill and benefit of initialization for two regions known to be impacted by AMV. Little benefit of ensemble size > 20.

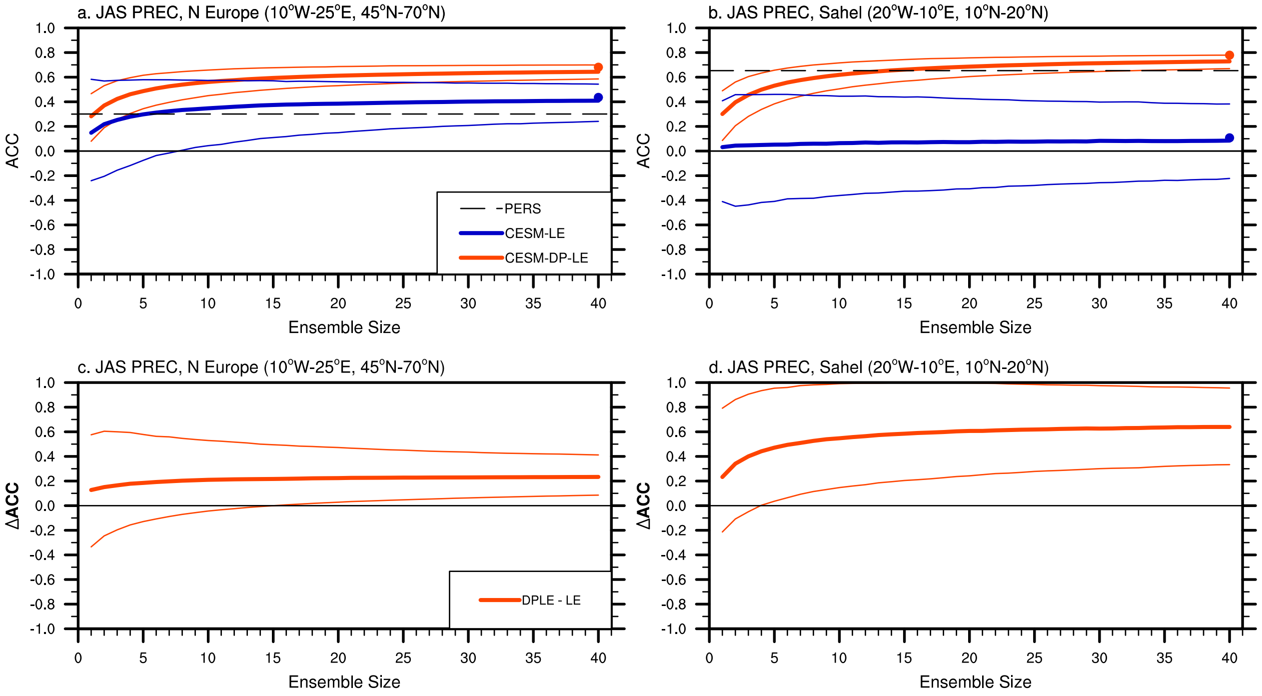


Lead Years 3-7:





OBS
Uninitialized
DPLE

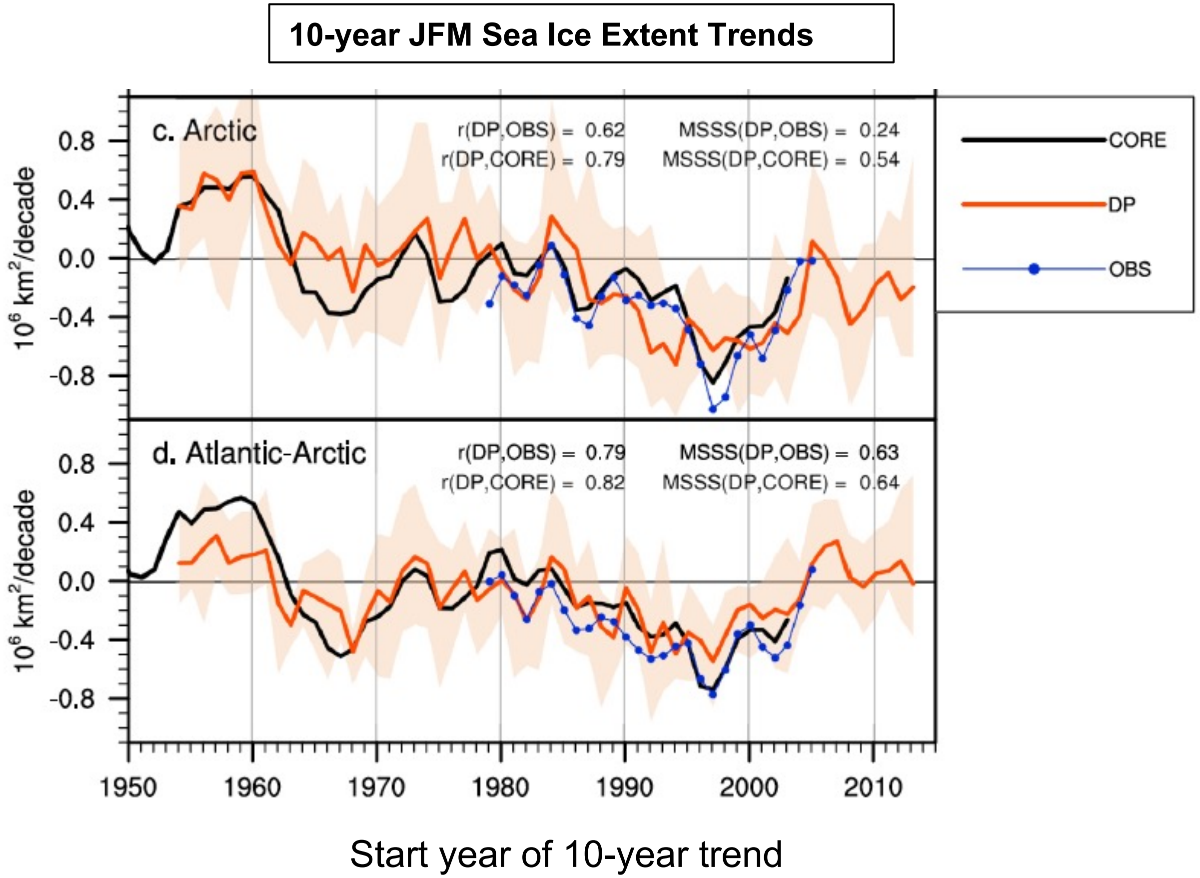


Yeager et al. (2018, 10.1175/BAMS-D-17-0098.1)

Predicting AMV Impacts: Sea Ice

Yeager et al. (2015, 10.1002/2015GL065364)

- 10-member CESM1-DP
- Predictable decadal changes in N. Atlantic ocean thermohaline circulation (THC) strength & northward heat transport (related to low-frequency NAO buoyancy forcing) translates into predictable changes in the rate of Arctic winter sea ice decline.
- Rapid sea ice decline in 1990s was associated with THC spinup, & ongoing and future THC spindown (weak NAO forcing after 1997) will result in a slowdown in the rate of Arctic winter sea ice loss.



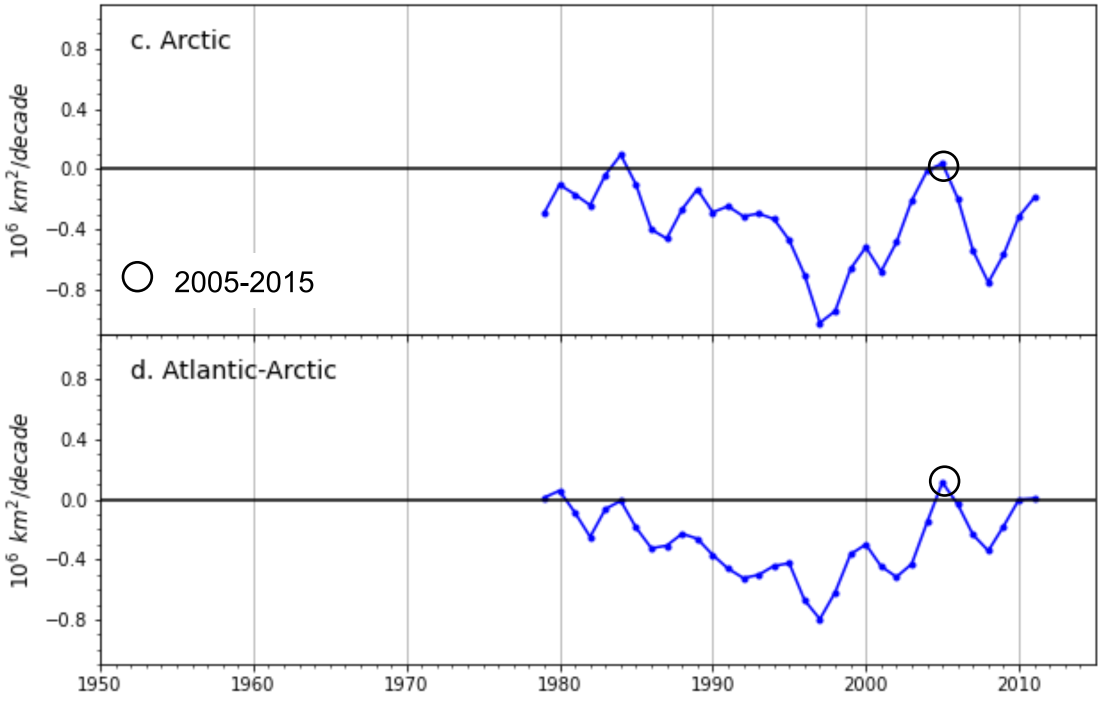
The CESM Decadal Prediction Large Ensemble: Forecasting decadal trends in the North Atlantic and Arctic

Predicting AMV Impacts: Sea Ice

Yeager et al. (2015, 10.1002/2015GL065364)

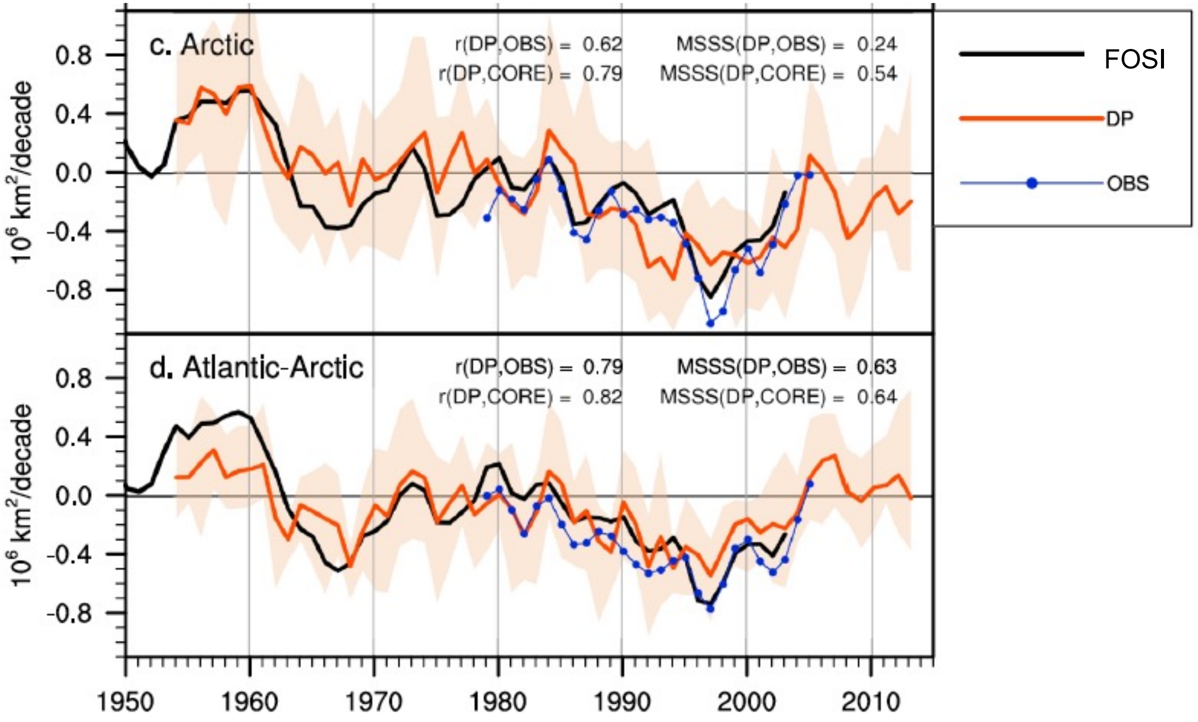
How accurate was the forecast?

10-year Observed Trends extended through 2011-2021



Start year of 10-year trend

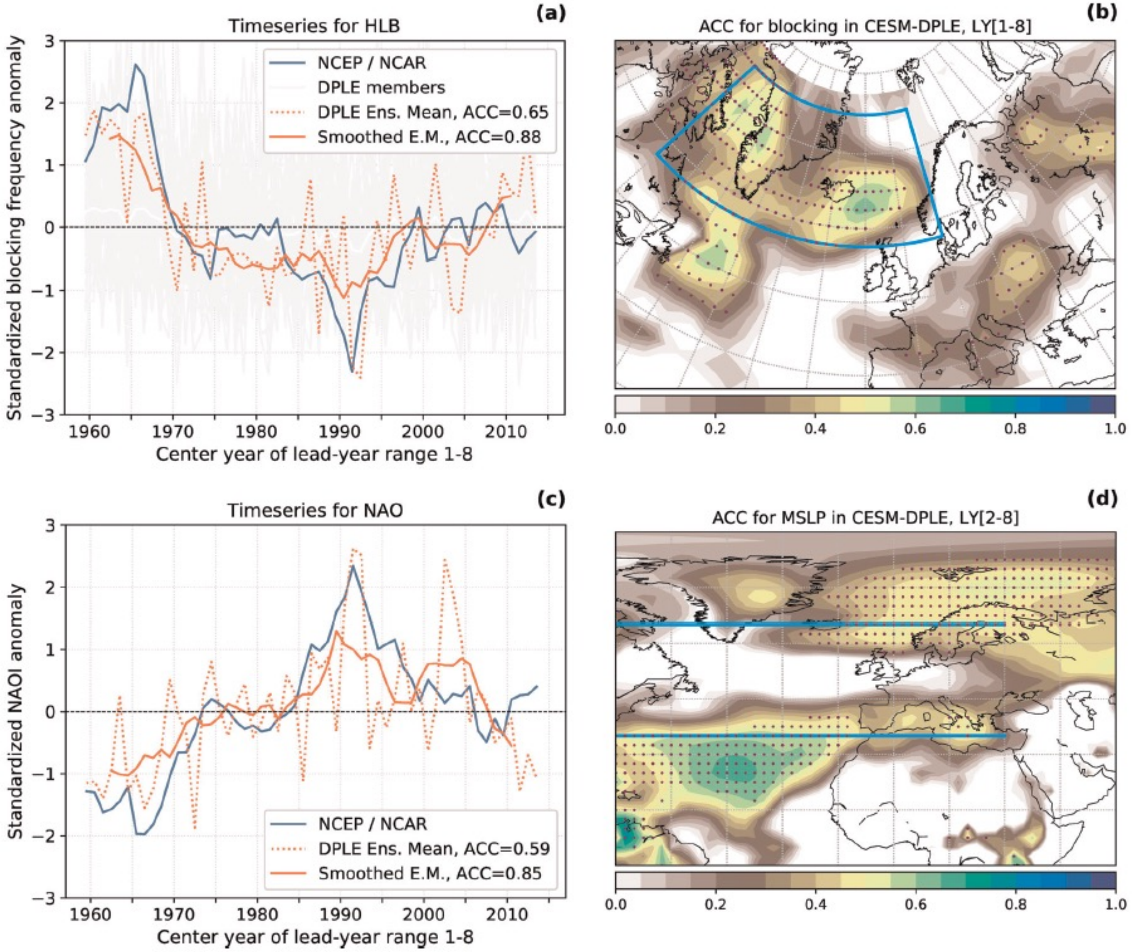
10-year JFM Sea Ice Extent Trends



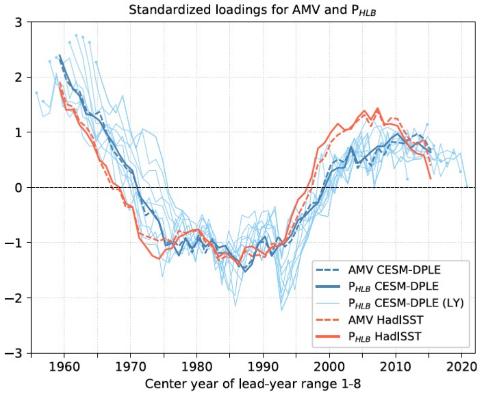
Start year of 10-year trend

Predicting AMV Impacts: NAO

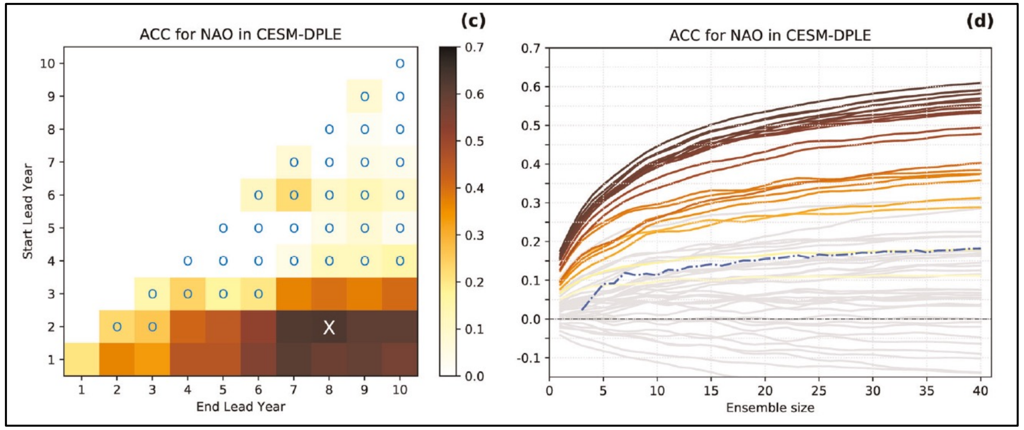
- CESM-DPLE exhibits skillful decadal prediction of winter NAO & winter blocking frequency:



- Skill was related to skillfully predicted AMV:



- Evidence of signal-to-noise paradox (RPC>5):

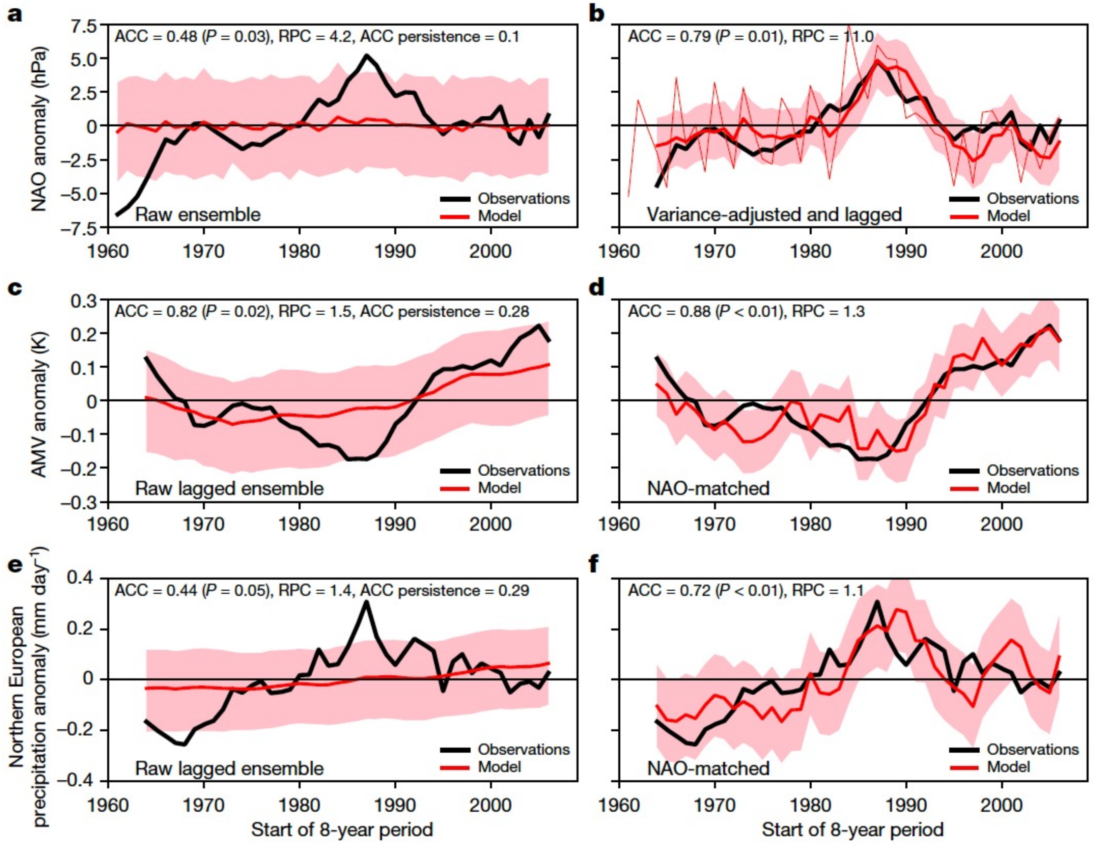


Athanasiadis et al. (2020, 10.1038/s41612-020-0120-6)

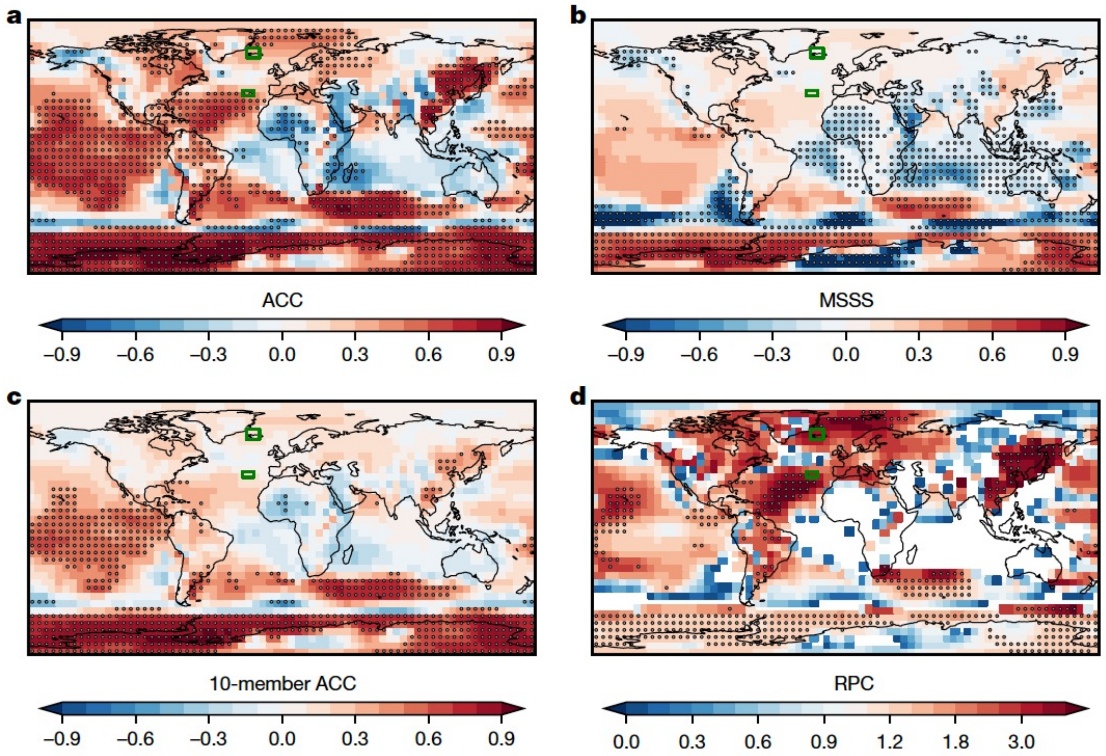
Predicting AMV Impacts: NAO

North Atlantic climate far more predictable than models imply

Smith et al. (2020, 10.1038/s41586-020-2525-0)



Skill for DJFM Sea Level Pressure (FY2-9):

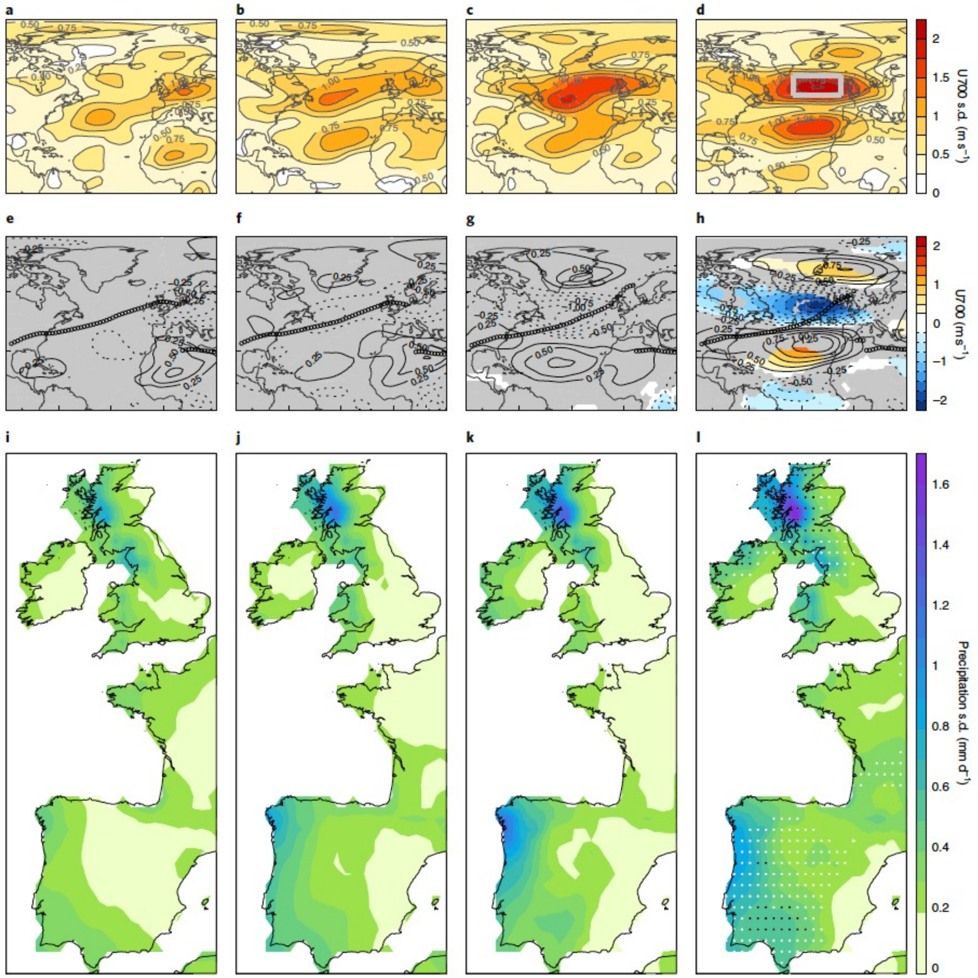


- CMIP5 & CMIP6 multi-model analysis (169 ensemble members → 676 by lagging)
- NAO decadal prediction is skillful, but models severely underestimate the predictable signal (RPC=11), implying that NAO impacts are not well predicted (but potentially could be, by developing more realistic systems or using post-processing techniques like "NAO-matching").

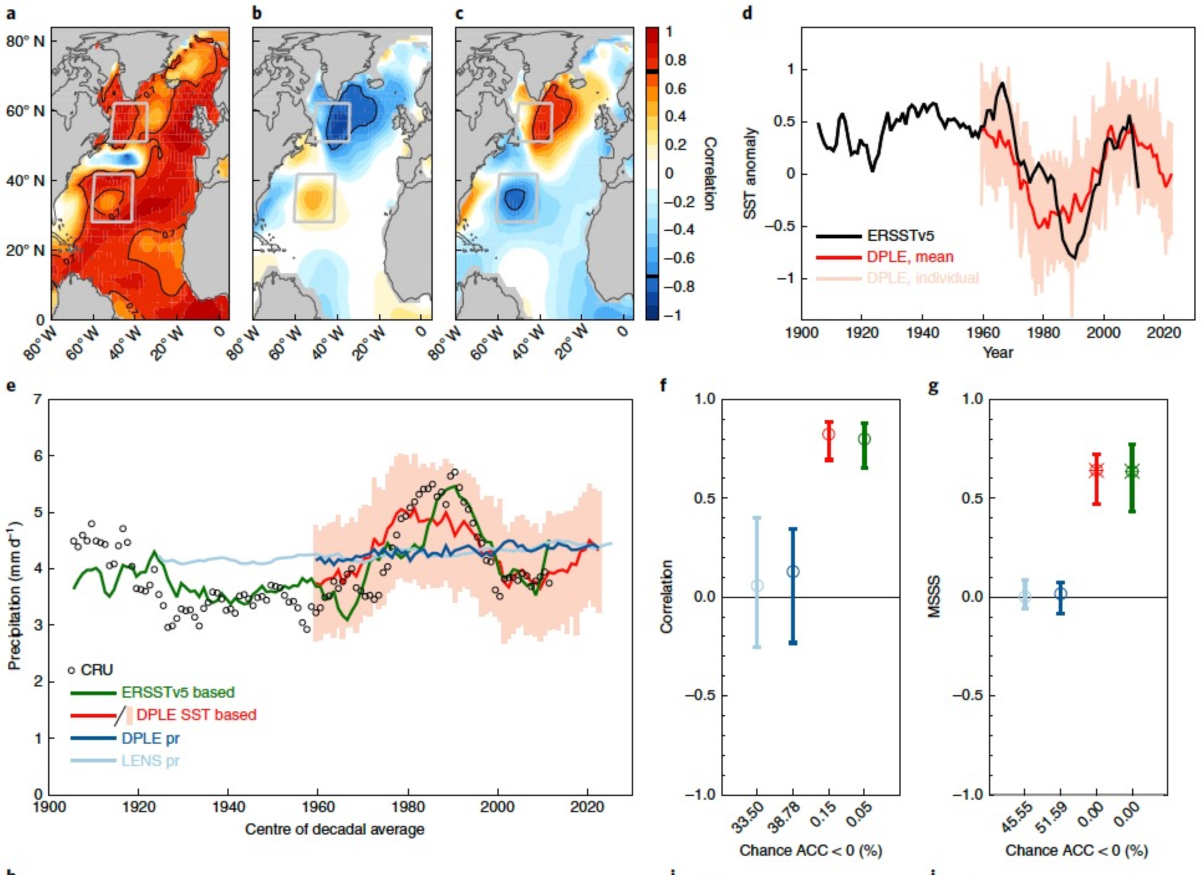
Predicting AMV Impacts: N. Atlantic Jet Shifts

Simpson et al. (2019, 10.1038/s41561-019-0391-x)

- AMV drives low-frequency U700 variability that peaks in March with corresponding precip variations in Scotland/Portugal:

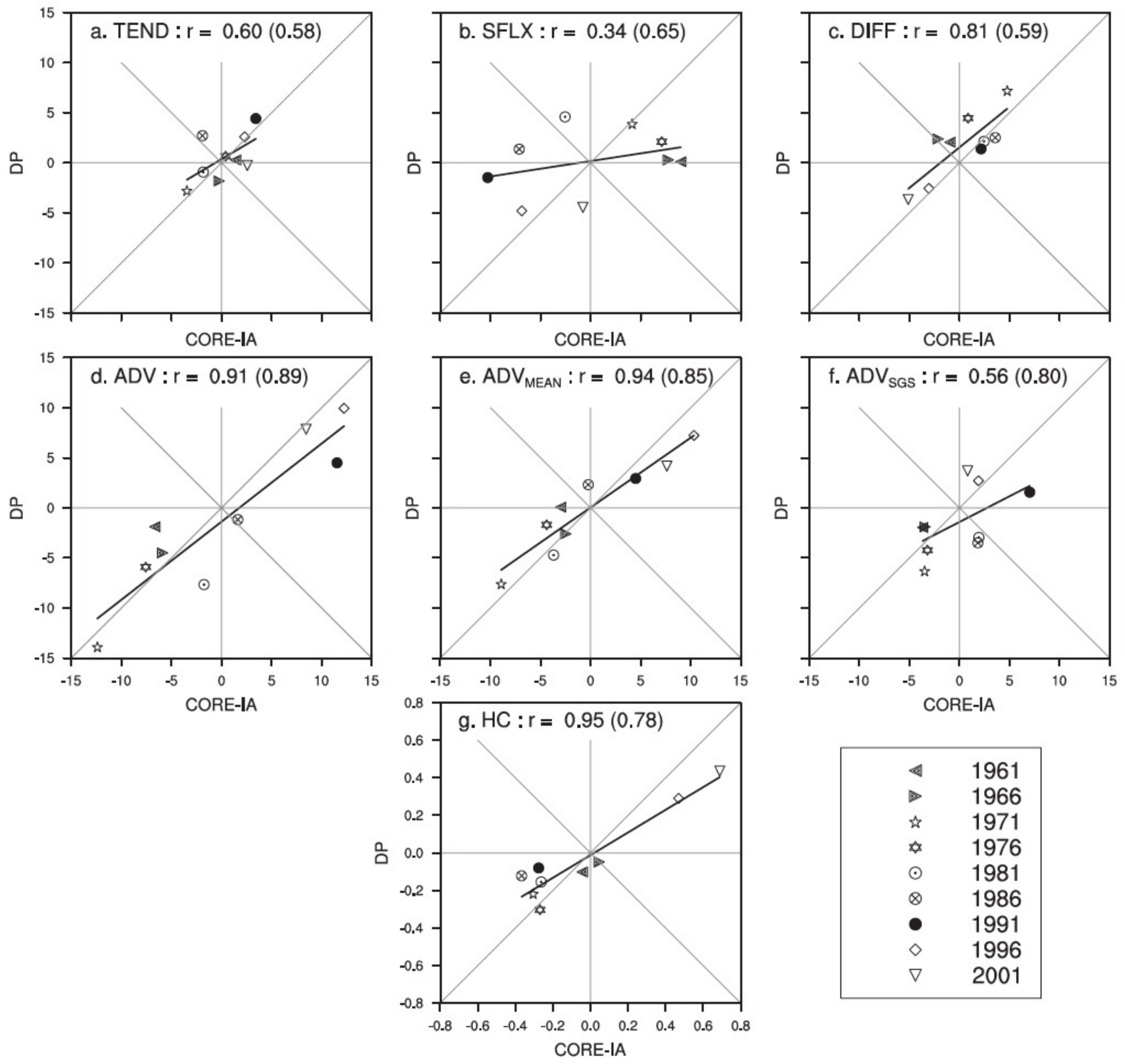


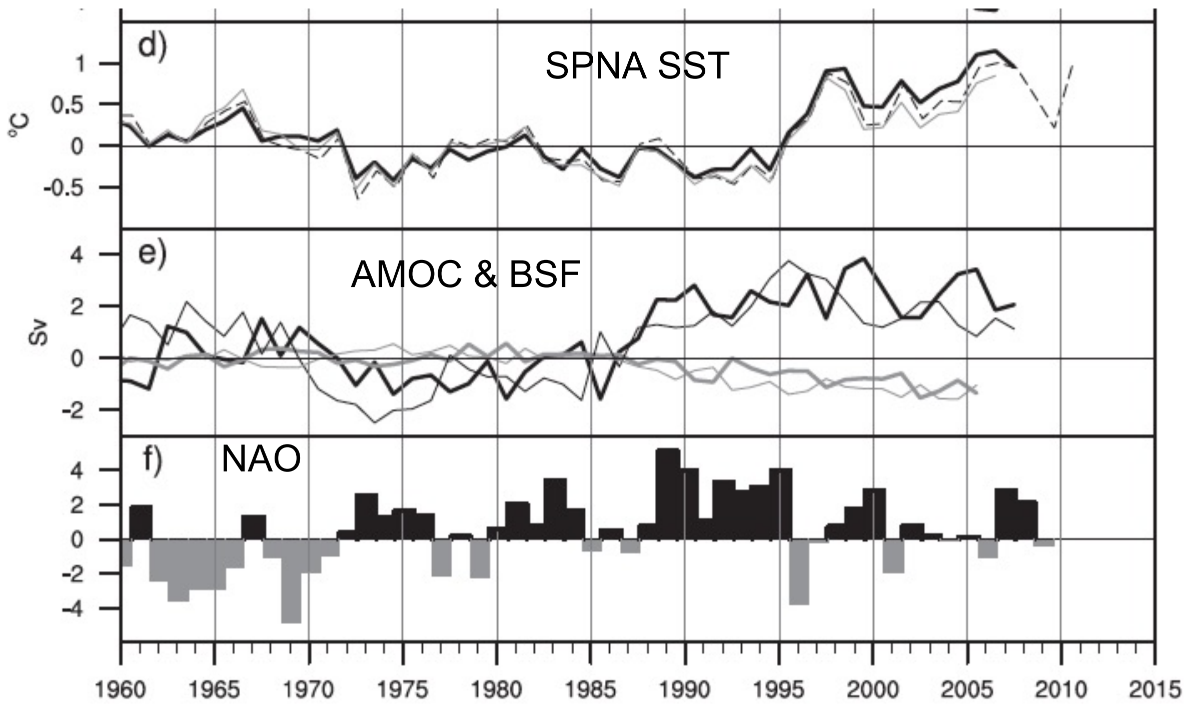
- Skillful prediction of Scotland & Portugal March precip is possible through combined dynamical-statistical approach:



III. The Role of AMOC

AMV Predictability Mechanisms



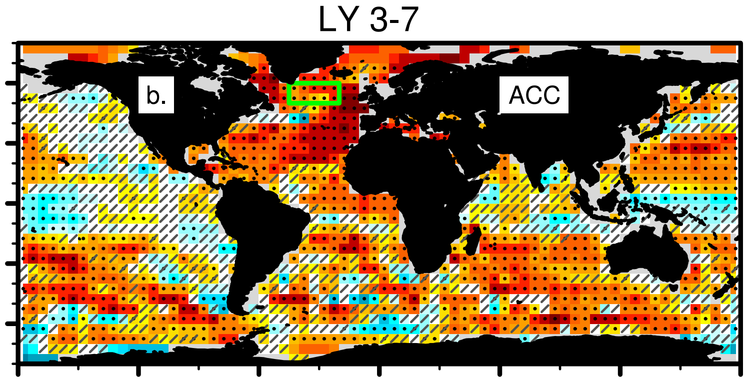


Yeager et al. (2012, 10.1175/JCLI-D-11-00595.1)

Invoking “AMOC” as the source of prediction skill in the Atlantic builds on large body of past modelling work (Delworth et al. 1993; Griffies & Bryan 1997; Keenlyside et al. 2008; etc).

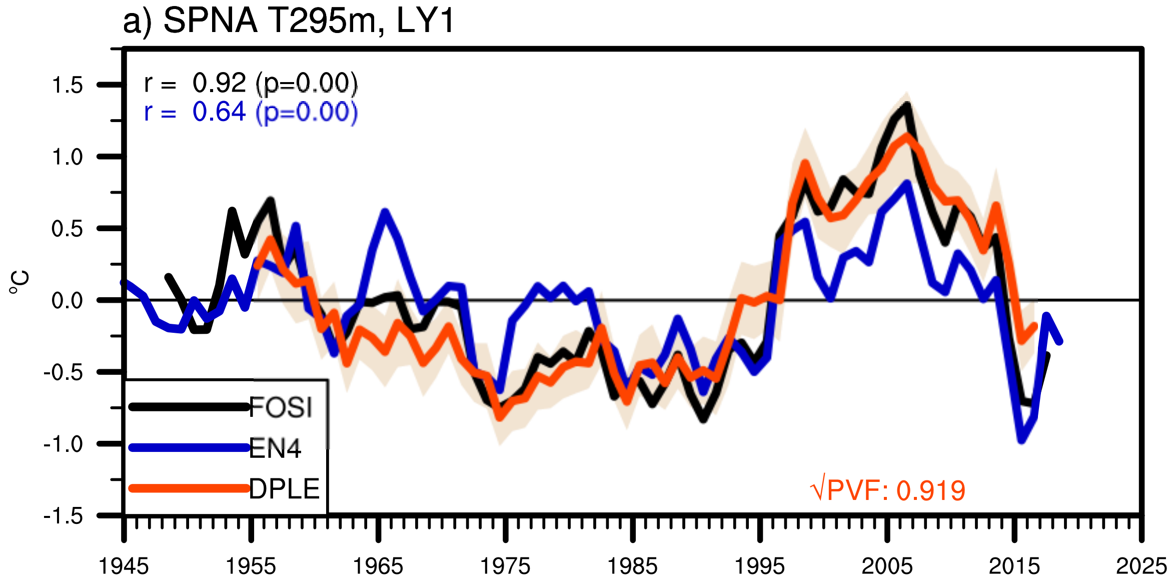
Difficult to verify DP mechanisms given lack of long ocean observations, so state reconstructions are used as truth.

SPNA Upper Ocean Heat Content (295m)



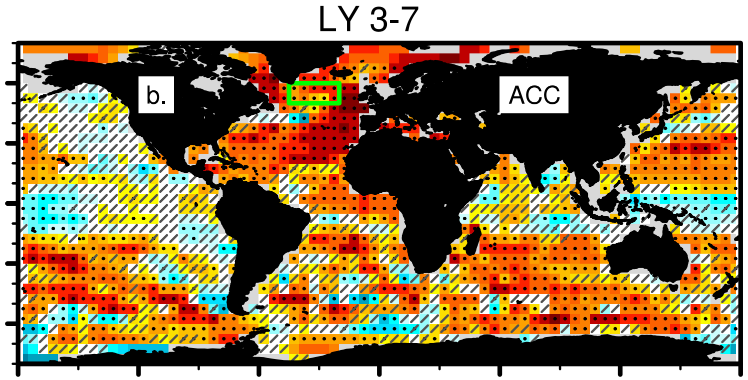
SPNA box: 45°W-20°W, 50°N-60°N

- Remarkably stable high skill in SPNA



Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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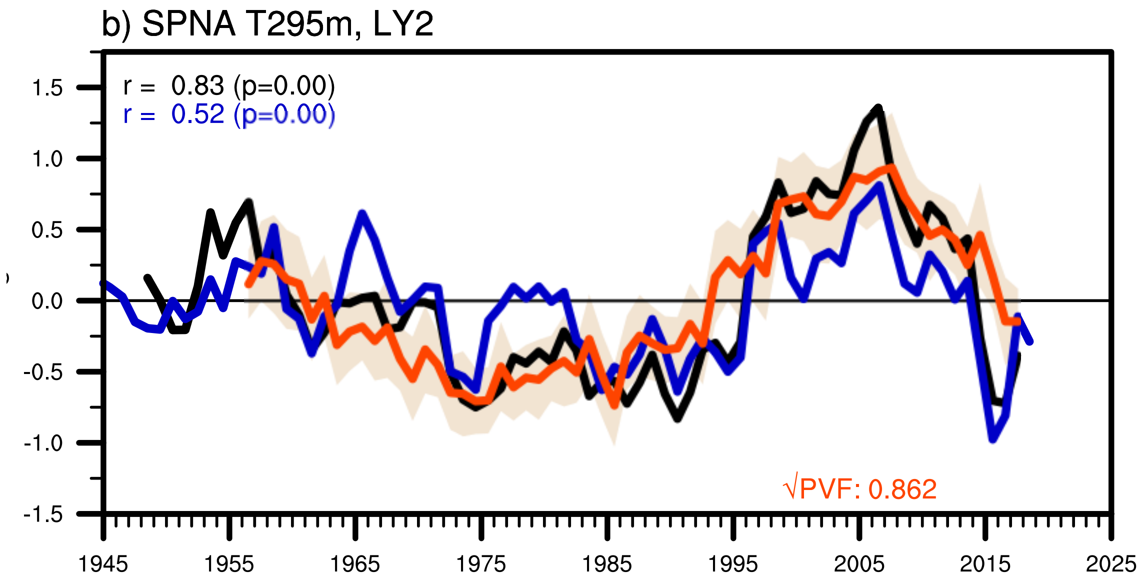
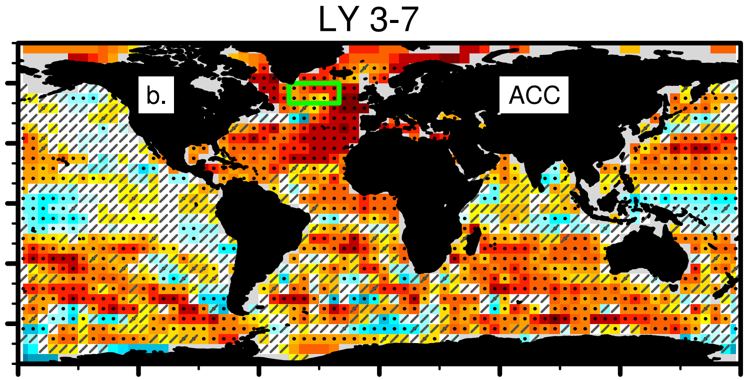


Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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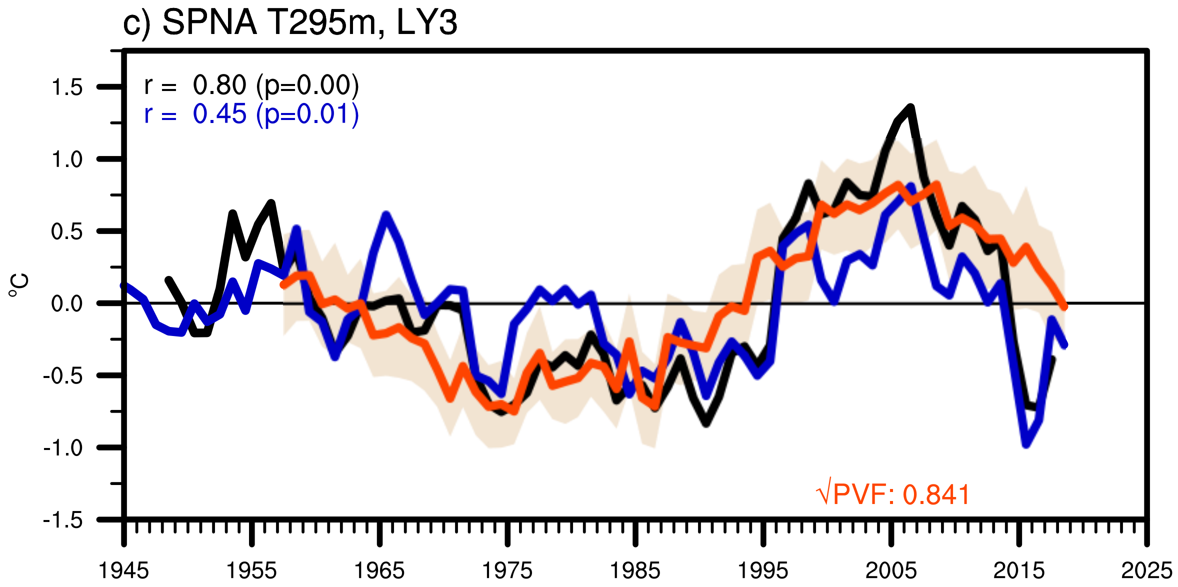
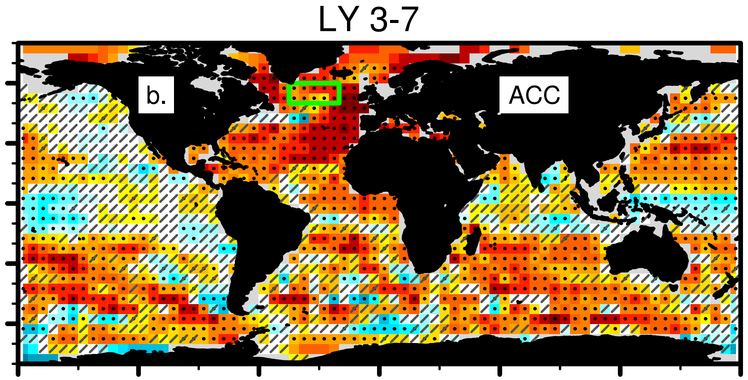


Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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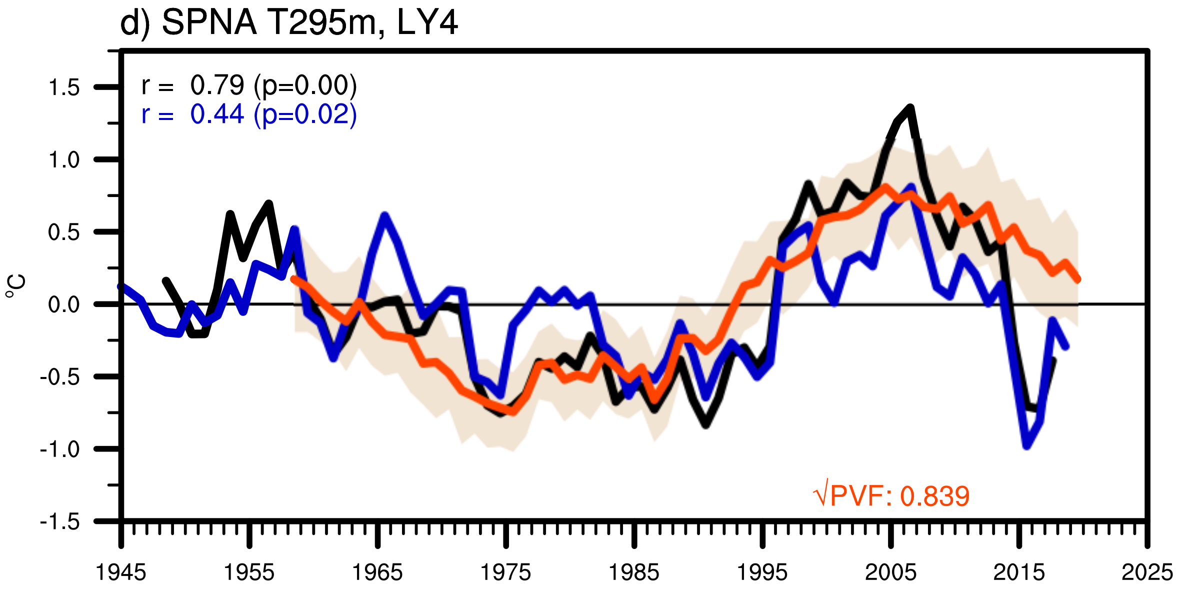
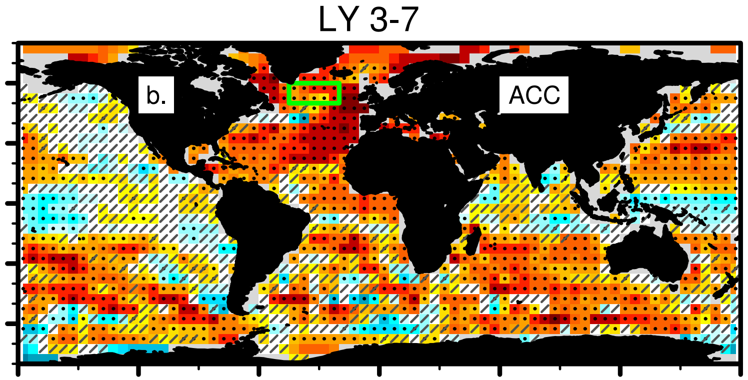


Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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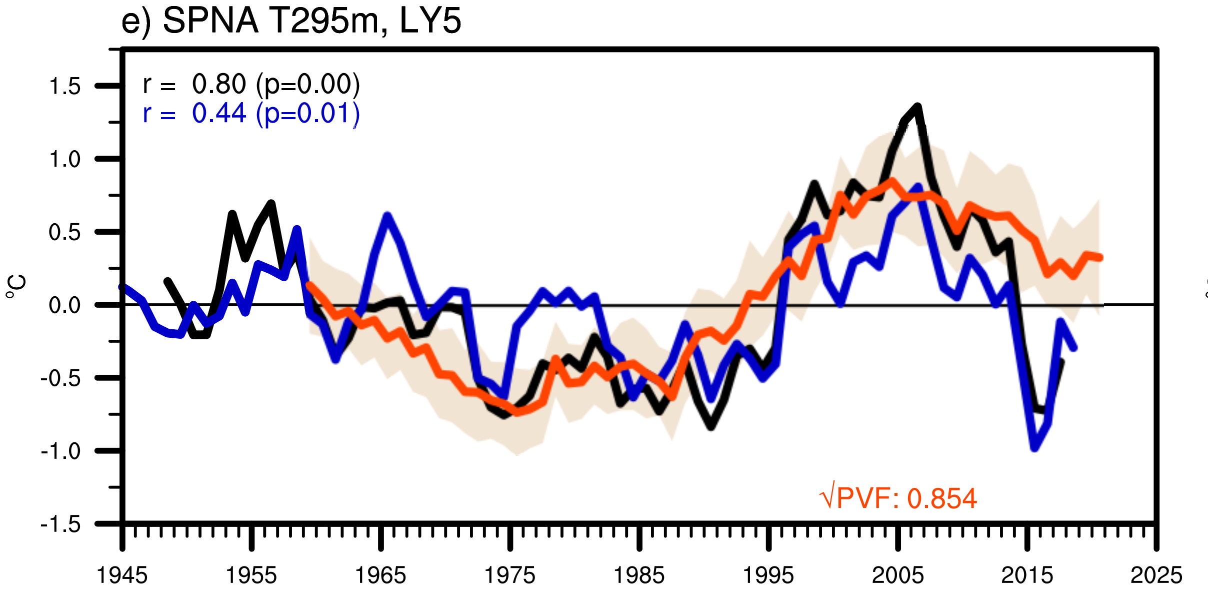
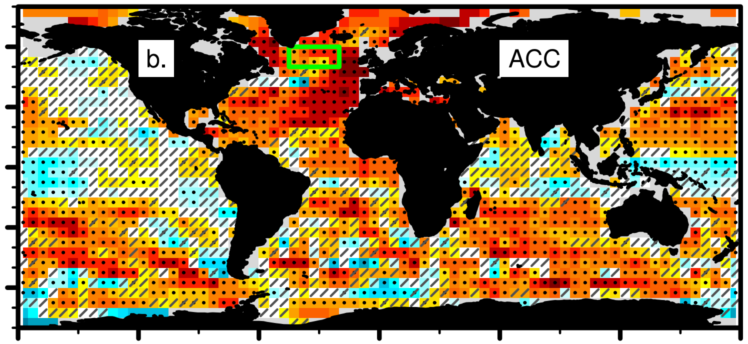


Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)

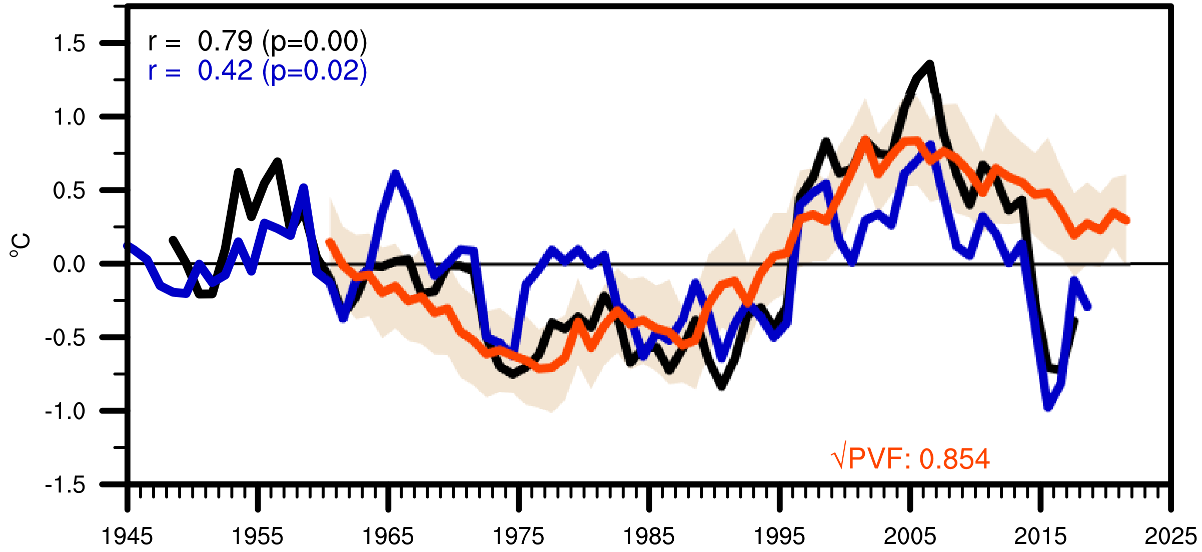
LY 3-7



SPNA box: 45°W-20°W, 50°N-60°N

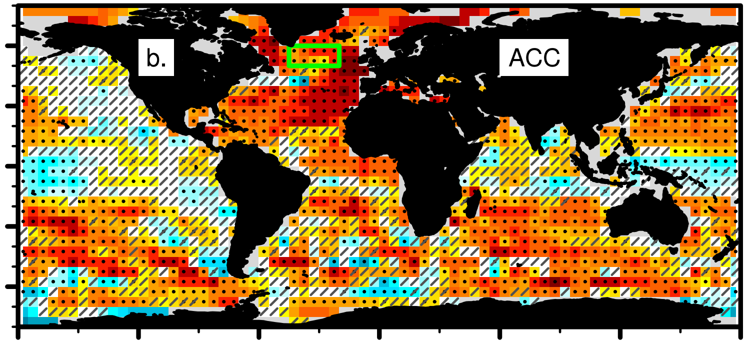
- Remarkably stable high skill in SPNA

f) SPNA T295m, LY6



Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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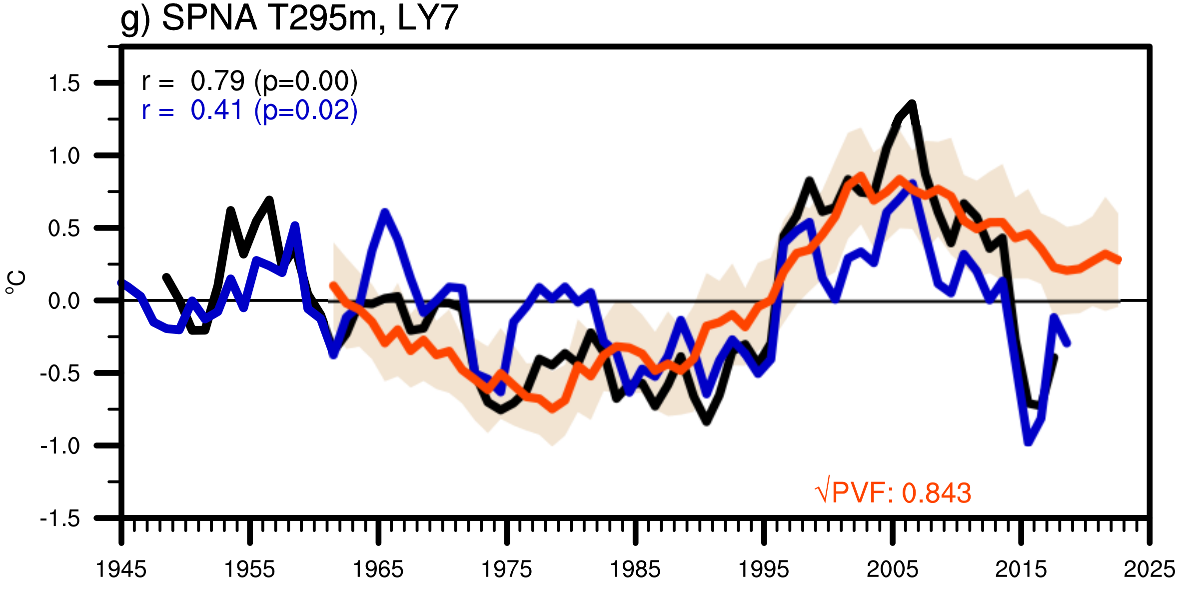
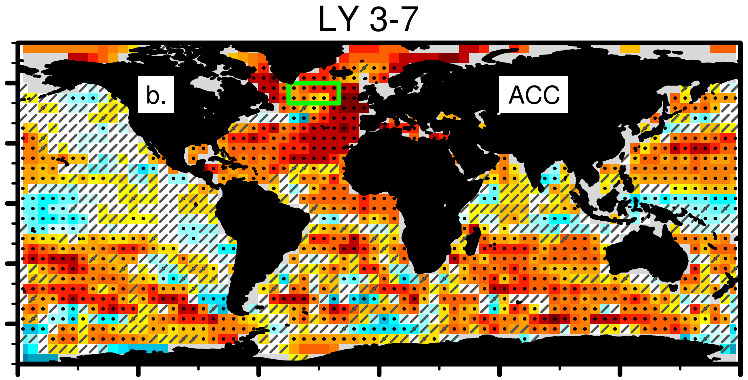


Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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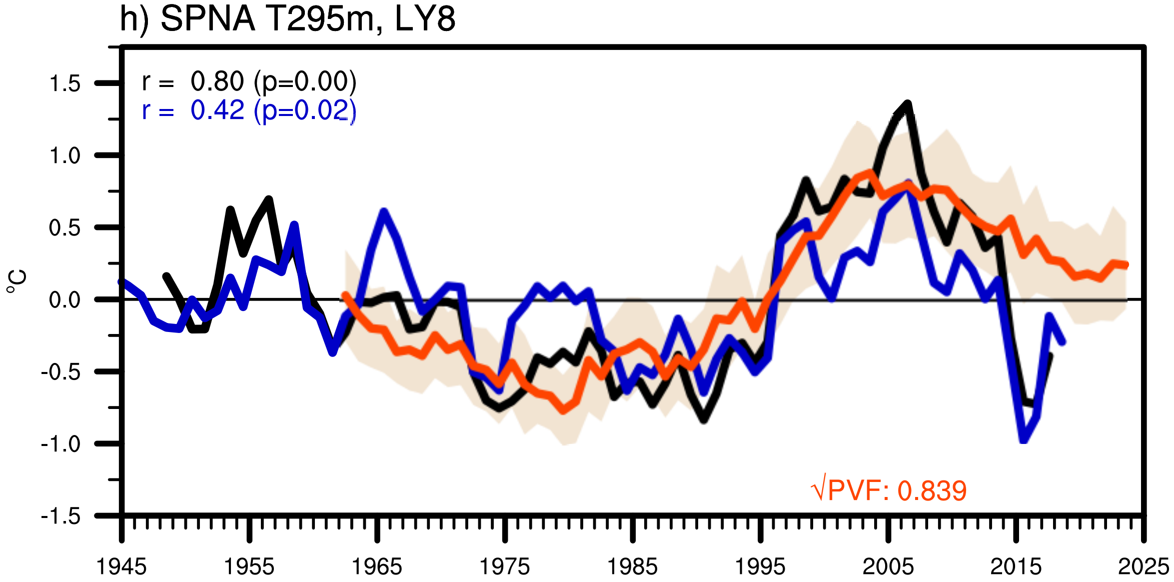
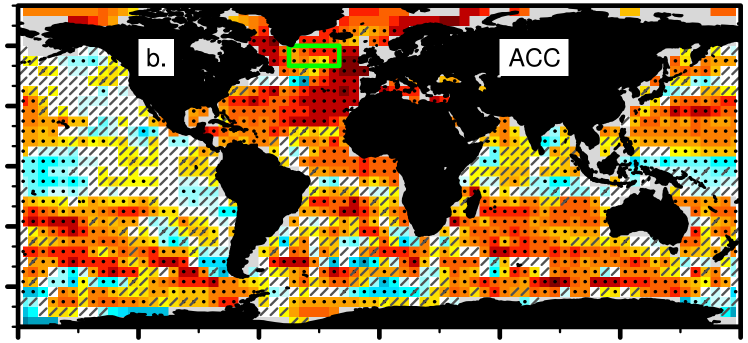


Yeager (2020, 10.1007/s00382-020-05382-4)

SPNA Upper Ocean Heat Content (295m)



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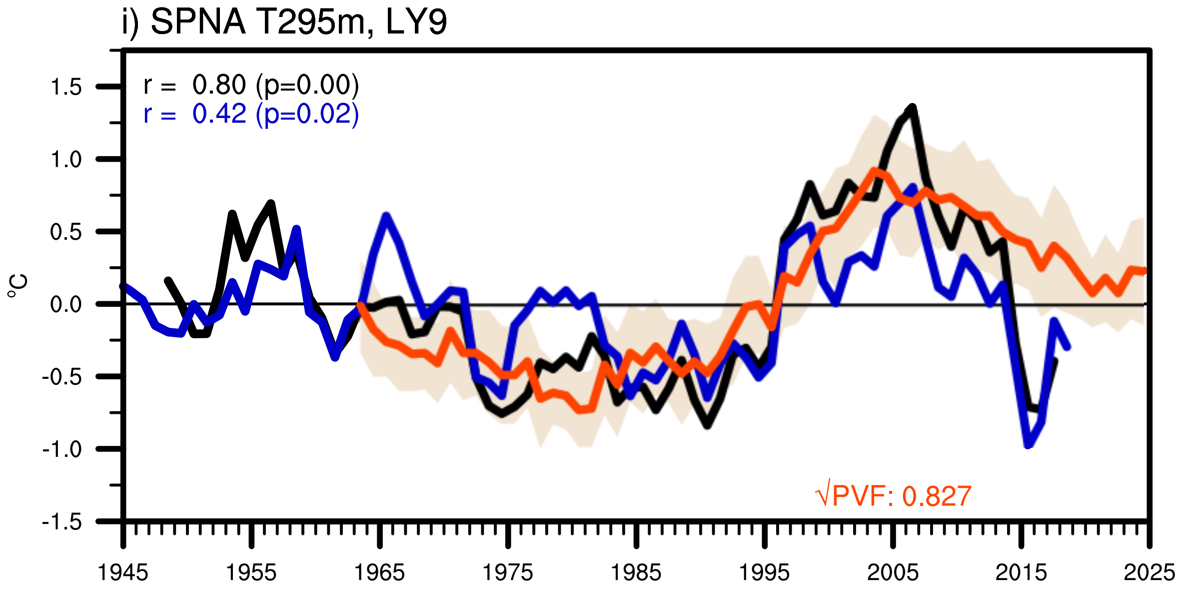

Yeager (2020, 10.1007/s00382-020-05382-4)

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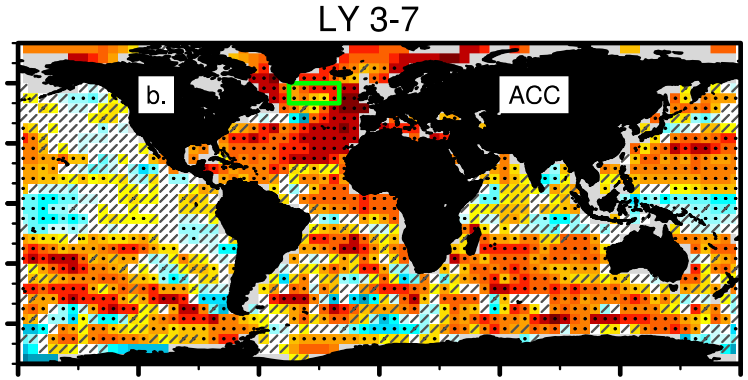

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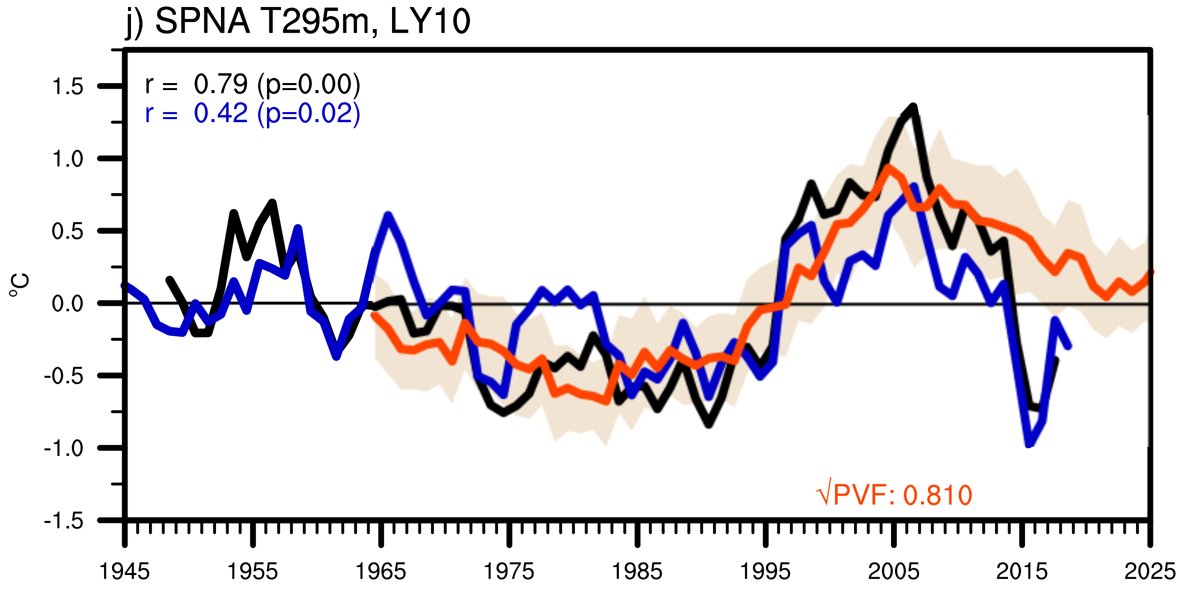


Yeager (2020, 10.1007/s00382-020-05382-4)

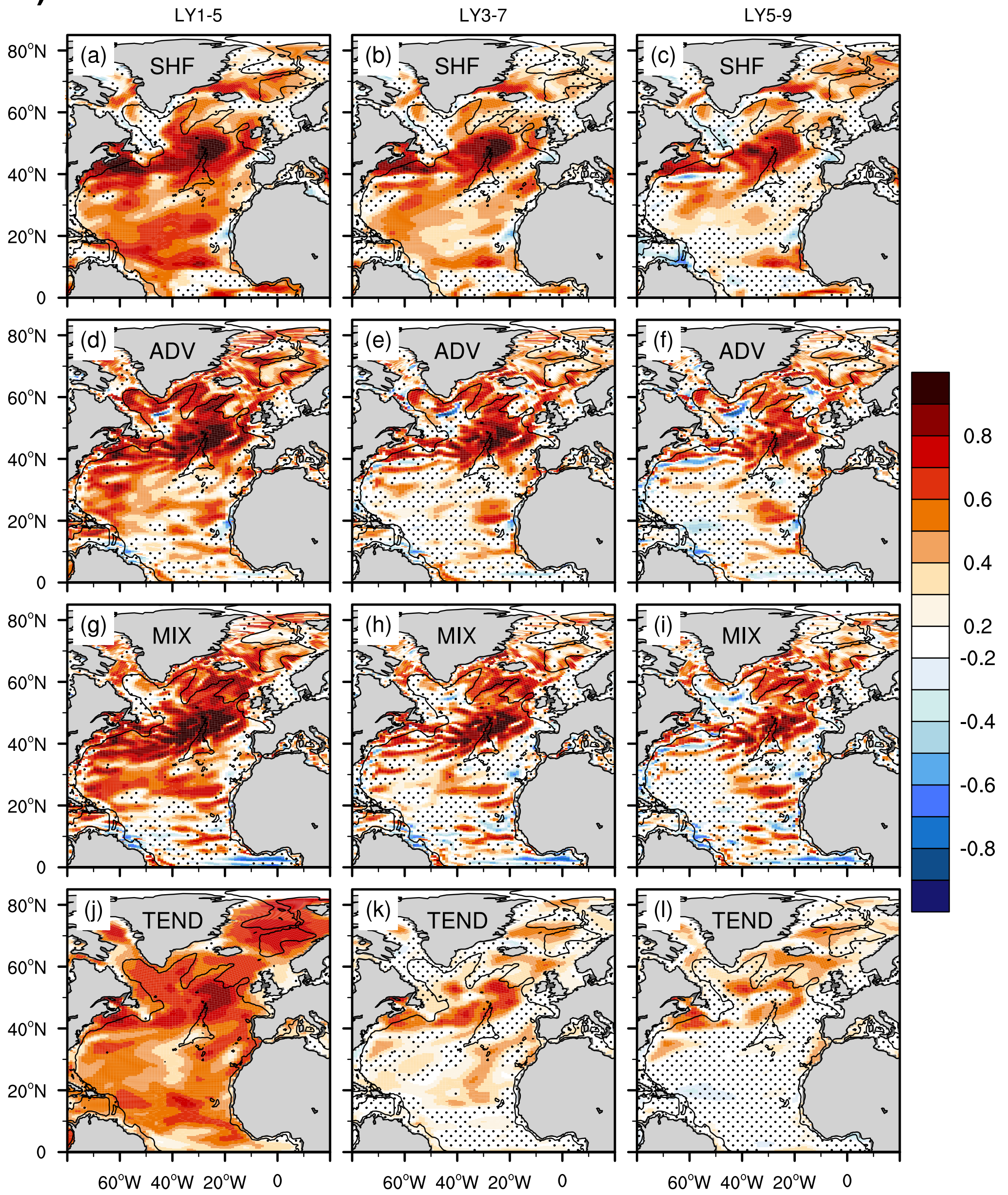
AMV Predictability Mechanisms

- 295m upper ocean heat budget predictability:
  TEND = ADV + SHF + MIX

- Advective heat convergence (ADV) is the dominant term in the multiyear upper ocean heat budget along the NAC into the central/eastern SPNA in FOSI.

- High ADV skill is the key to high UOHC decadal prediction skill in the SPNA.

r(DPLE,FOSI):



Yeager (2020, 10.1007/s00382-020-05382-4)

AMV Predictability Mechanisms

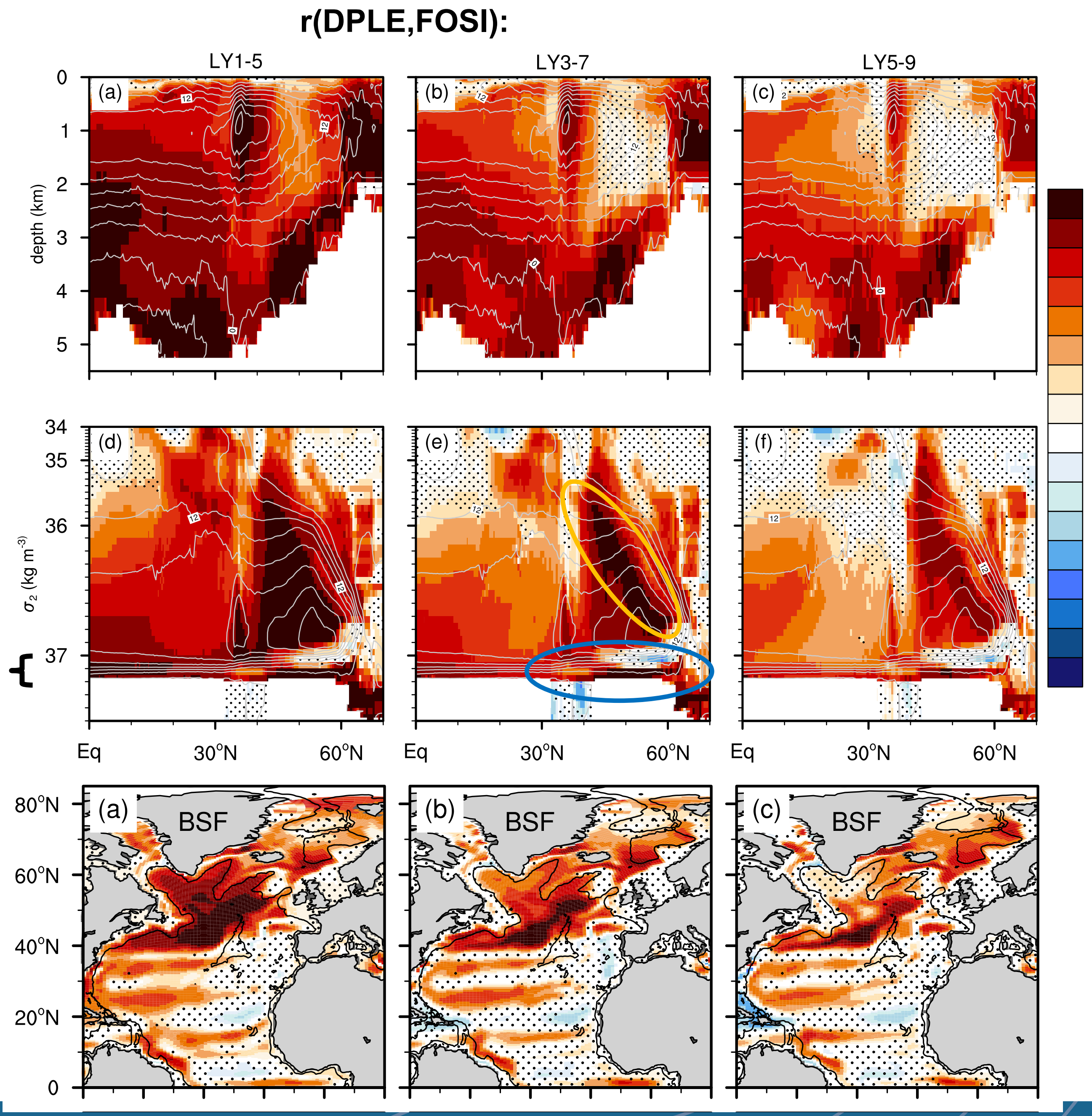
What explains predictable advective heat convergence in SPNA?

- AMOC($\boldsymbol{\sigma}_2$) skill in the warm, salty upper limb related to skill in the cold, fresh lower limb

★ Predictable near-surface advective heat convergence *derives from* highly predictable abyssal water mass thickness & bottom flow anomalies

- The Mechanism:

Slow interior propagation of LSW thickness anomalies that drive predictable SSH anomalies at intergyre latitudes (buoyancy-driven gyre)



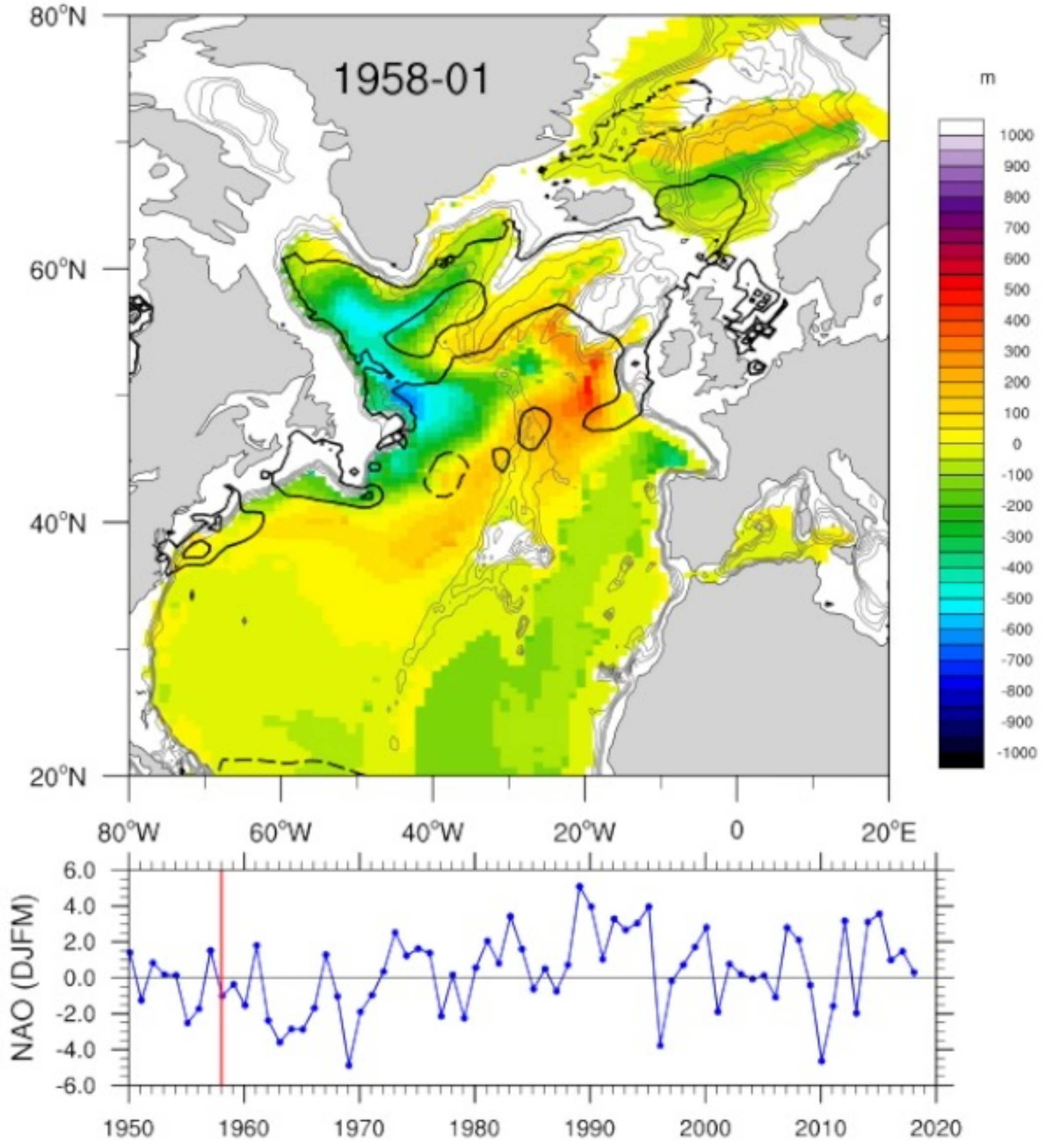
Yeager (2020, 10.1007/s00382-020-05382-4)

Link between LSW thickness and near surface advection in FOSI

Color:
dLSW thickness anomaly

Contours:
SSH anomalies (5-year low pass filtered), contour interval = 2cm

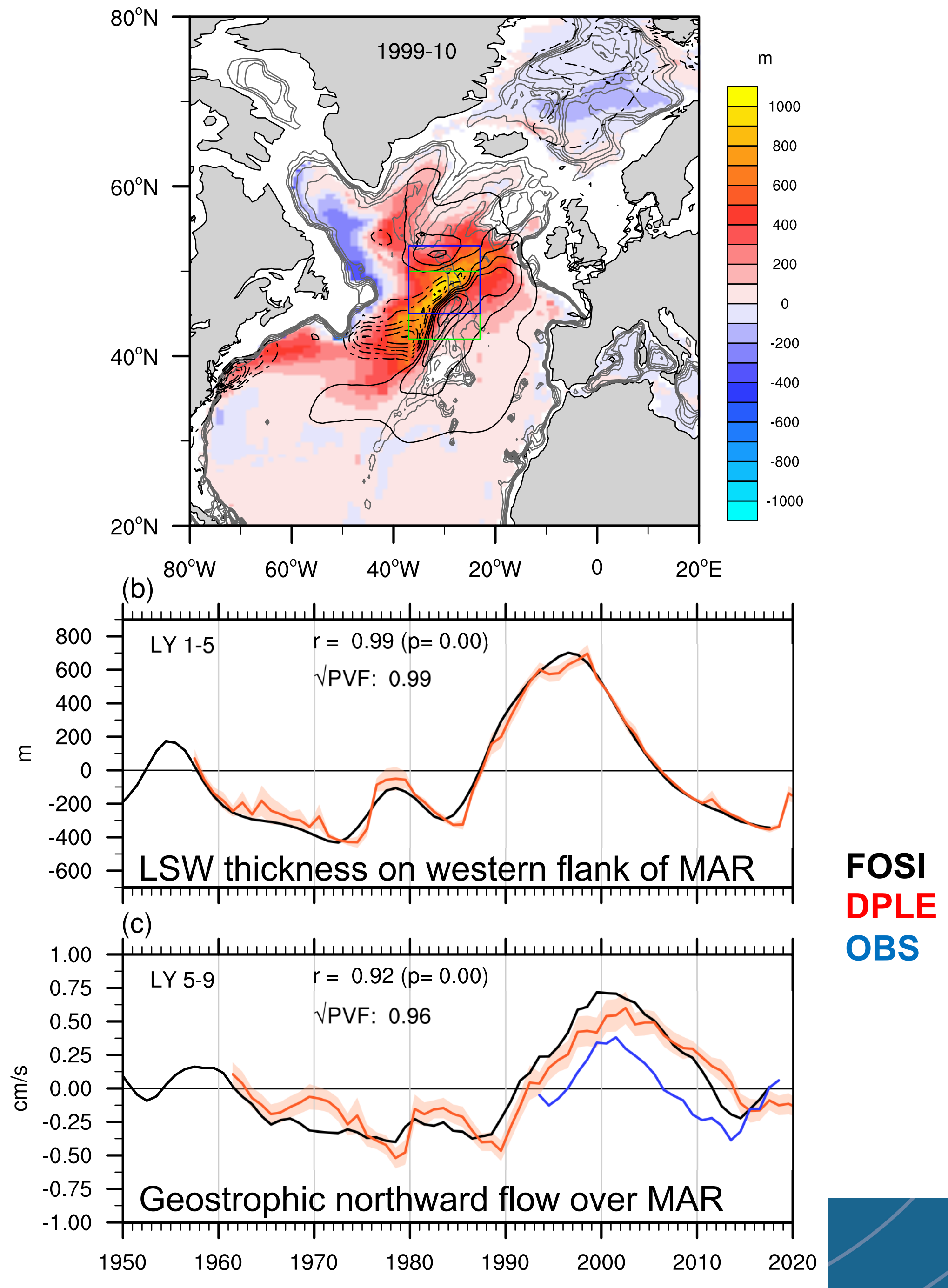
Time series:
Winter NAO index



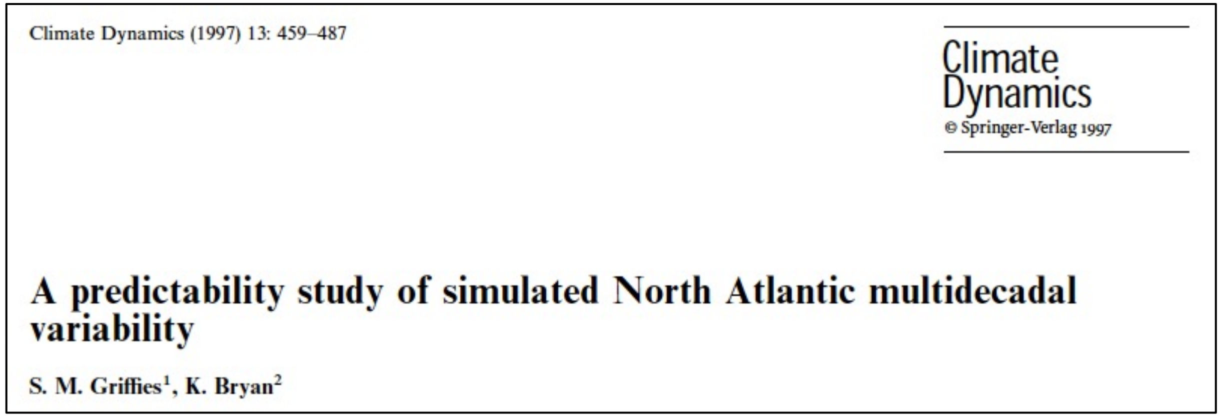
Yeager (*Clim Dyn* 2020)

Skillful prediction of LSW thickness underpins skillful prediction of AMOC Upper Limb

- Strong northward geostrophic surface flow anomalies over the MAR around year 2000 were associated with large LSW thickness anomalies (from early 1990s NAO forcing) that accumulated on the western flank of the MAR.
- Surface transport anomalies (∇SSH) exhibit high decadal predictability that reflects the exceptional predictability of abyssal layer thickness.

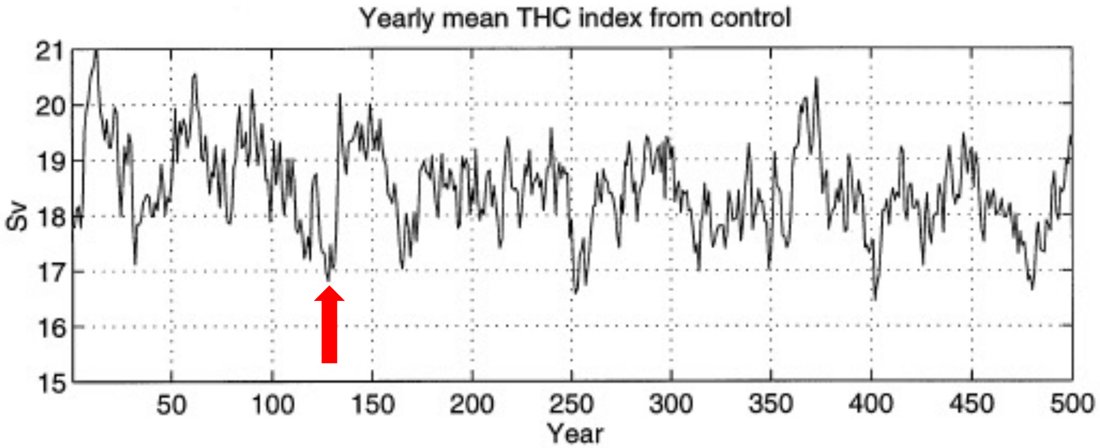


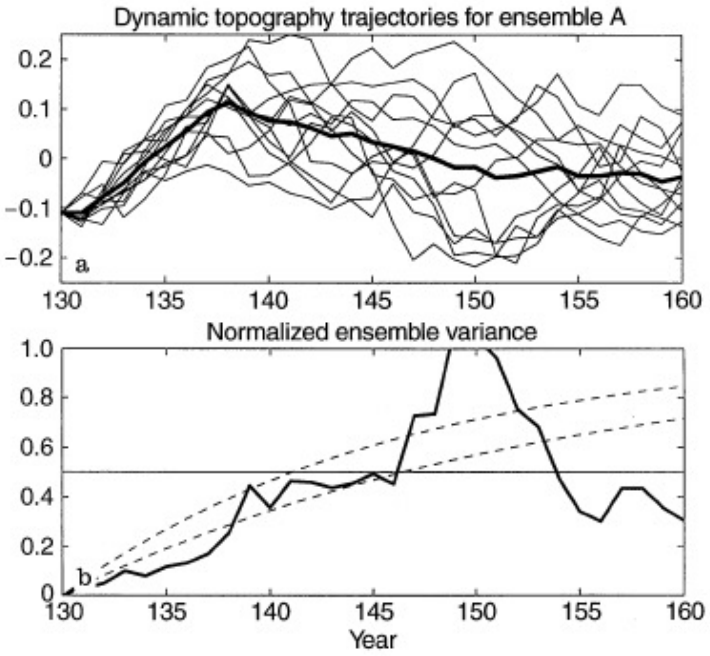
Yeager (*Clim Dyn* 2020)

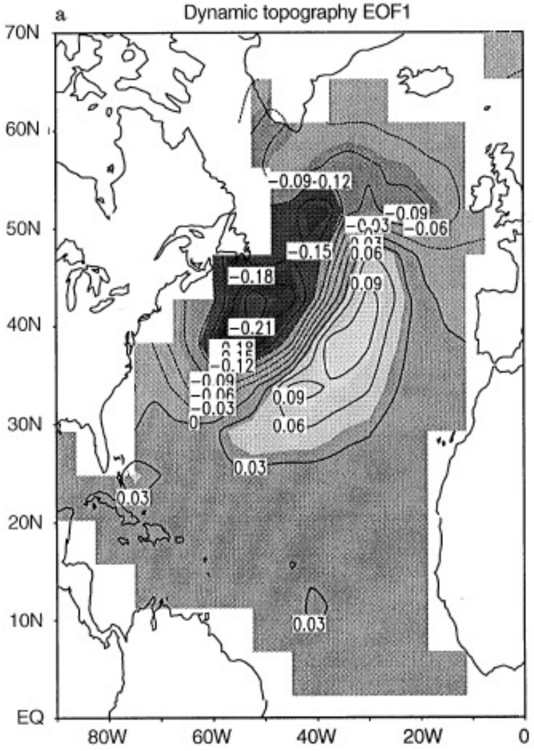

Climate Dynamics (1997) 13: 459–487
Climate Dynamics
© Springer-Verlag 1997

A predictability study of simulated North Atlantic multidecadal variability

S. M. Griffies[1], K. Bryan[2]







- Perfect model predictability in O(4°) GFDL model
- 12-member ensemble “A” initialized from year 130 of control run
- 10-20y predictability of EOF1 of N. Atlantic dynamic topography

Final Thoughts

- Large ensemble initialized decadal prediction has delivered more than most would have anticipated back in the 2000s in terms of refining our understanding of and capacity to predict regional environmental change years in advance.

- Robust evidence of capacity to predict AMV on decadal timescales (particularly subpolar AMV) along with wider impacts in the Atlantic sector.

- Pacific decadal prediction has proven less successful, but recent work suggests that skill could be improved.

- “Signal-to-noise paradox” identified in NAO predictions is a sign that systems underestimate predictable signals. This has important implications for climate modeling, generally, and suggests that further progress in decadal prediction is possible.

- AMV predictability derives from ocean thermohaline dynamics with memory residing in the deep ocean.