Societally relevant multi-year climate predictions

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U.S. DEPARTMENT OF ENERGY
Office of Science
Biological and Environmental Research
Regional and Global Model Analysis

Workshop on Societally-Relevant Multi-Year Climate Predictions

Lisa did groundbreaking work in climate science and climate services. She was a pioneer in seasonal climate forecasting, and led key research on El Niño and La Niña. *Her commitment to ensuring that climate information was accessible and meaningful to decision makers across the globe* cannot be overstated

--press release from IRI

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--press release from IRI

Matt Newman's invitation to Lisa to give a keynote talk on **societally relevant initialized Earth System predictions:**
"Can we (and if so, how do we) push the seasonal prediction horizon well beyond its current 6-9 months, ideally **out to at least 2 years**, keeping in mind that (to justify the inevitable expense) such **forecasts need to produce information that is of real use — hence the "societally relevant" part of the workshop title".**

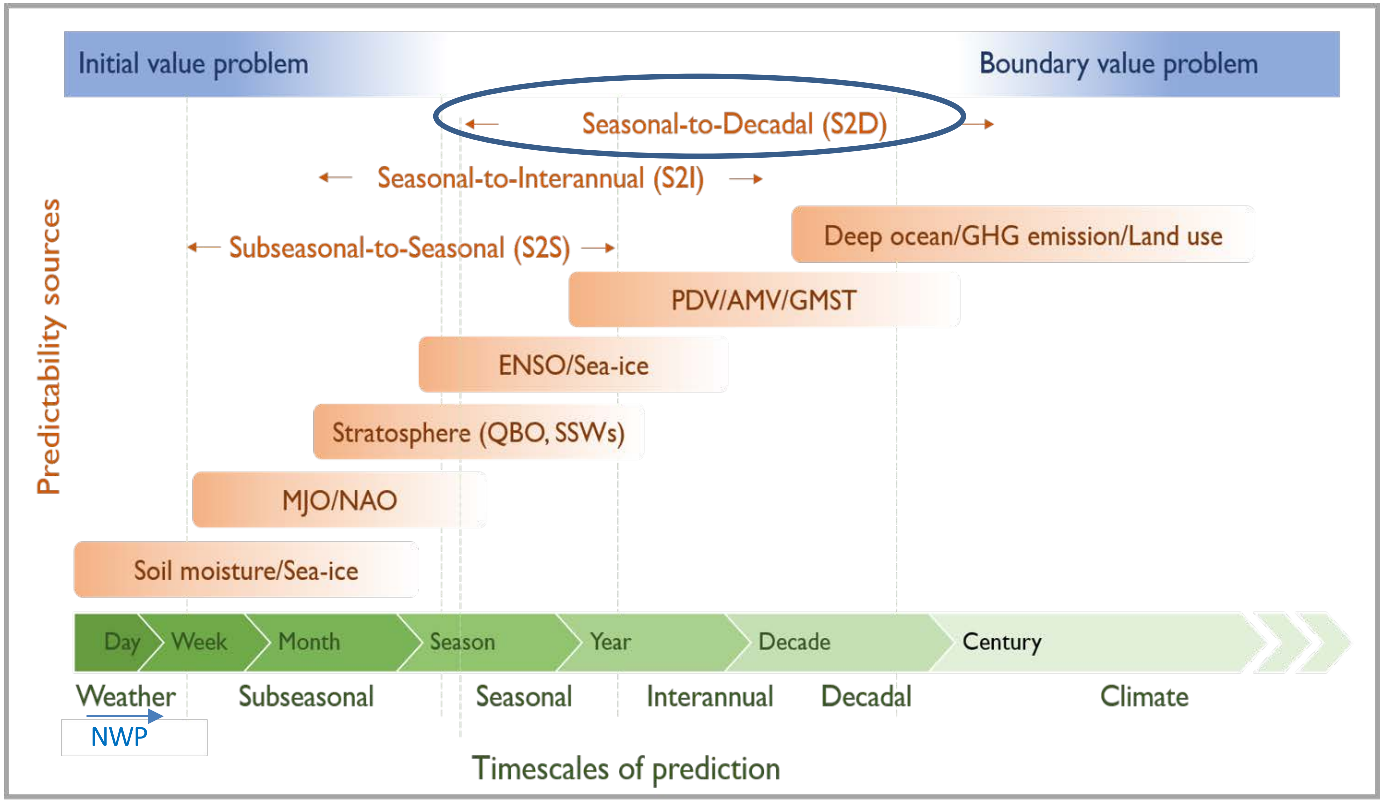
[information of "real use" indicates the **need for skillful and thus credible predictions**]

Lisa's response**:**

"There are few to no examples of people trying to use long term predictions currently. I would like to suggest **an overview of what's been demonstrated on predictability (or not) of climate variability beyond the next 3-12 months**…and the ability to **capture longer term phenomenon, such as trends and decadal variability".**

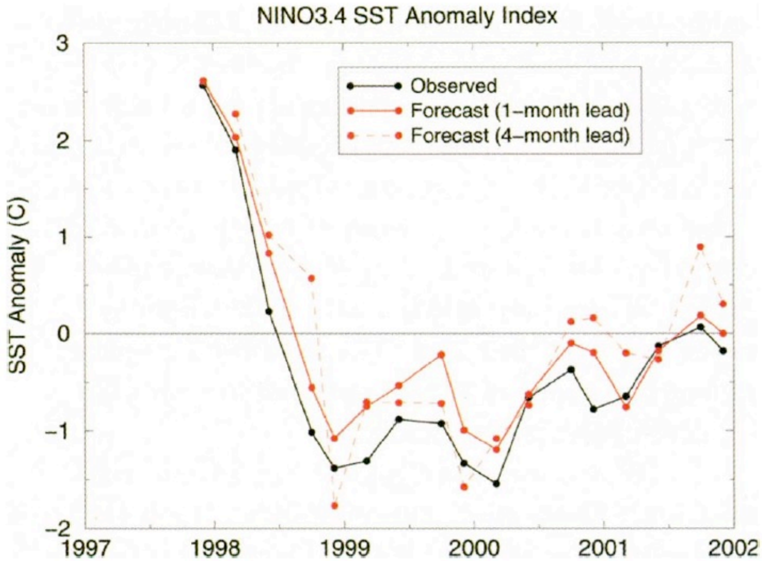
[interpretation: seasonal to decadal (S2D) climate predictions]

“predictability of climate variability beyond the next 3-12 months…to capture longer term phenomenon, such as trends and decadal variability”:
The “seasonal to decadal” (S2D) timescale



S2S timescale (~ 2 weeks to 2 months), S2I timescale (~2 to 12 months), S2D timescale (~ 3 months to ten years)

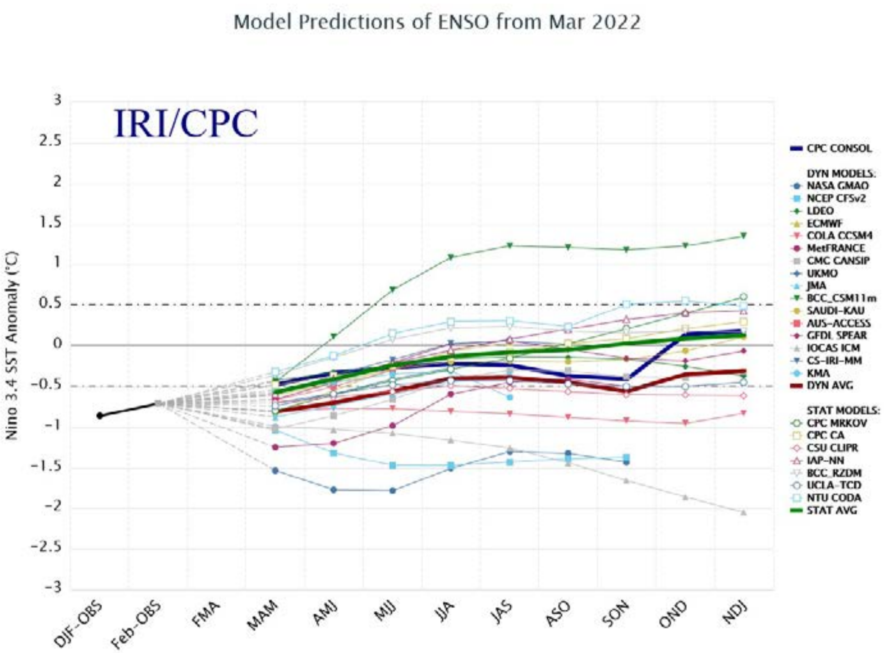
(Meehl et al., 2021: Initialized Earth system prediction from subseasonal to decadal timescales, *Nature Reviews Earth and Environment)*



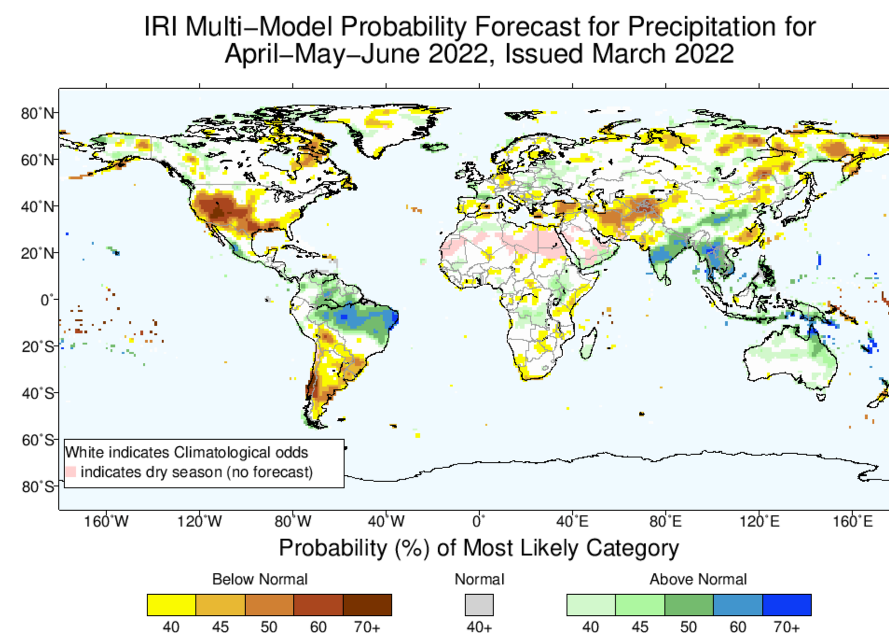
Goddard et al., 2003, BAMS

Lisa’s legacy at IRI: seasonal climate predictions for stakeholder communities

With the rise of initialized predictions on S2D timescales, Lisa connected with that community to bring to bear her expertise on initialized prediction on shorter timescales relevant for longer timescales



Seasonal prediction based on NOAA’s North American Multi-Model Ensemble Project (NMME), initialized predictions from 6 modeling centers



https://iri.columbia.edu/our-expertise/climate/forecasts/seasonal-climate-forecasts/

A 2008 session of the Aspen Global Change Institute (AGCI) formulated the first-ever coordinated set of decadal climate prediction experiments for the CMIP5 experimental design (convened by Meehl, Goddard, Stouffer, Murphy)

Article in Bull. Amer. Meteorol. Soc., 2009 describing outcomes of AGCI session

ARTICLES

DECADAL PREDICTION

Can It Be Skillful?

BY GERALD A. MEEHL, LISA GODDARD, JAMES MURPHY, RONALD J. STOUFFER, GEORGE BOER, GOKHAN DANABASOGLU, KEITH DIXON, MARCO A. GIORGETTA, ARTHUR M. GREENE, ED HAWKINS, GABRIELE HEGERL, DAVID KAROLY, NOEL KEENLYSIDE, MASAHIDE KIMOTO, BEN KIRTMAN, ANTONIO NAVARRA, ROGER PULWARTY, DOUG SMITH, DETLEF STAMMER, AND TIMOTHY STOCKDALE

A new field called "decadal prediction" will use initialized climate models to produce time-evolving predictions of regional climate that will bridge ENSO forecasting and future climate change projections.

AGCI session in 2011 convened by Goddard, Meehl and Kirtman assessed progress in S2D prediction and produced two papers

BAMS, 2014

DECADAL CLIMATE PREDICTION

An Update from the Trenches

BY GERALD A. MEEHL, LISA GODDARD, GEORGE BOER, ROBERT BURGMAN, GRANT BRANSTATOR, CHRISTOPHE CASSOU, SUSANNA CORTI, GOKHAN DANABASOGLU, FRANCISCO DOBLAS-REYES, ED HAWKINS, ALICIA KARSPECK, MASAHIDE KIMOTO, ARUN KUMAR, DANIELA MATEI, JULIETTE MIGNOT, RYM MSADEK, ANTONIO NAVARRA, HOLGER POHLMANN, MICHELE RIENECKER, TONY ROSATI, EDWIN SCHNEIDER, DOUG SMITH, ROWAN SUTTON, HAIYAN TENG, GEERT JAN VAN OLDENBORGH, GABRIEL VECCHI, AND STEPHEN YEAGER

The rapidly evolving field of decadal climate prediction, using initialized climate models to produce time-evolving predictions of regional climate, is producing new results for predictions, predictability, and prediction skill.

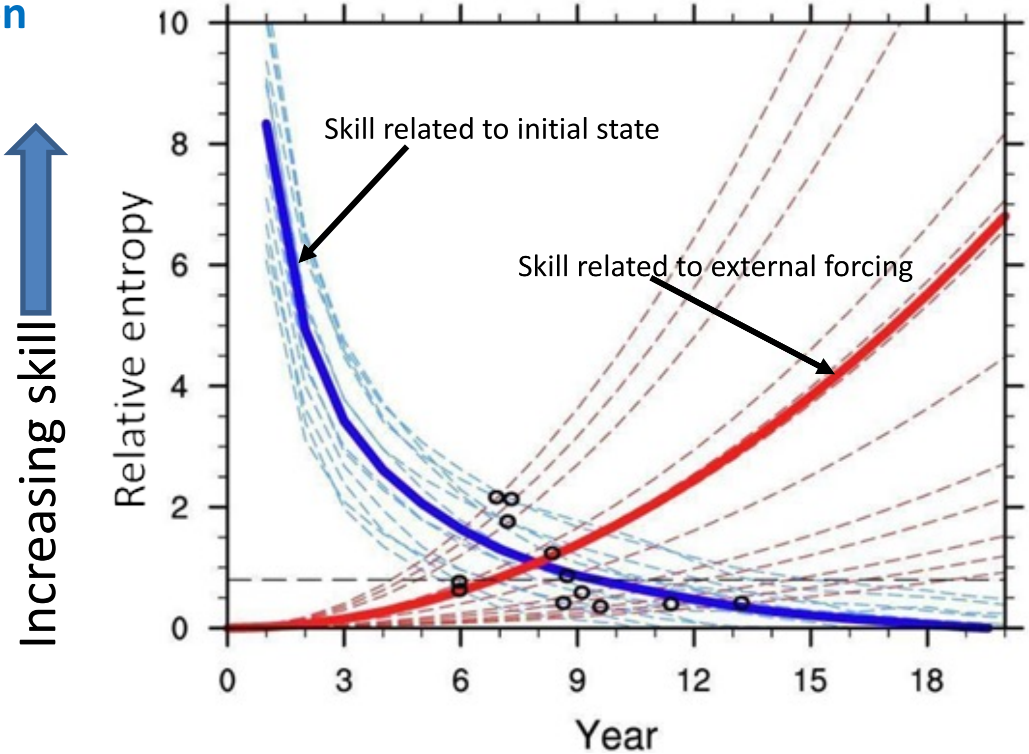
Cli. Dyn. 2013

Clim Dyn (2013) 40:245–272
DOI 10.1007/s00382-012-1481-2

A verification framework for interannual-to-decadal predictions experiments

L. Goddard · A. Kumar · A. Solomon · D. Smith · G. Boer · P. Gonzalez · V. Kharin · W. Merryfield · C. Deser · S. J. Mason · B. P. Kirtman · R. Msadek · R. Sutton · E. Hawkins · T. Fricker · G. Hegerl · C. A. T. Ferro · D. B. Stephenson · G. A. Meehl · T. Stockdale · R. Burgman · A. M. Greene · Y. Kushnir · M. Newman · J. Carton · I. Fukumori · T. Delworth

Prediction skill can come from the initial state or external forcing, and depends on the time scale and region



(dashed lines indicate uncertainty measured from 12 CMIP5 models; black circles indicate when decreasing skill from the initial state crosses over increasing skill from external forcing, for upper 300m ocean layer, North Atlantic, horizontal black dashed line indicates 90% significance level) (Branstator and Teng, 2012).

Model error, bias and drift

Compute anomalies from model to compare to obs for skill measures:

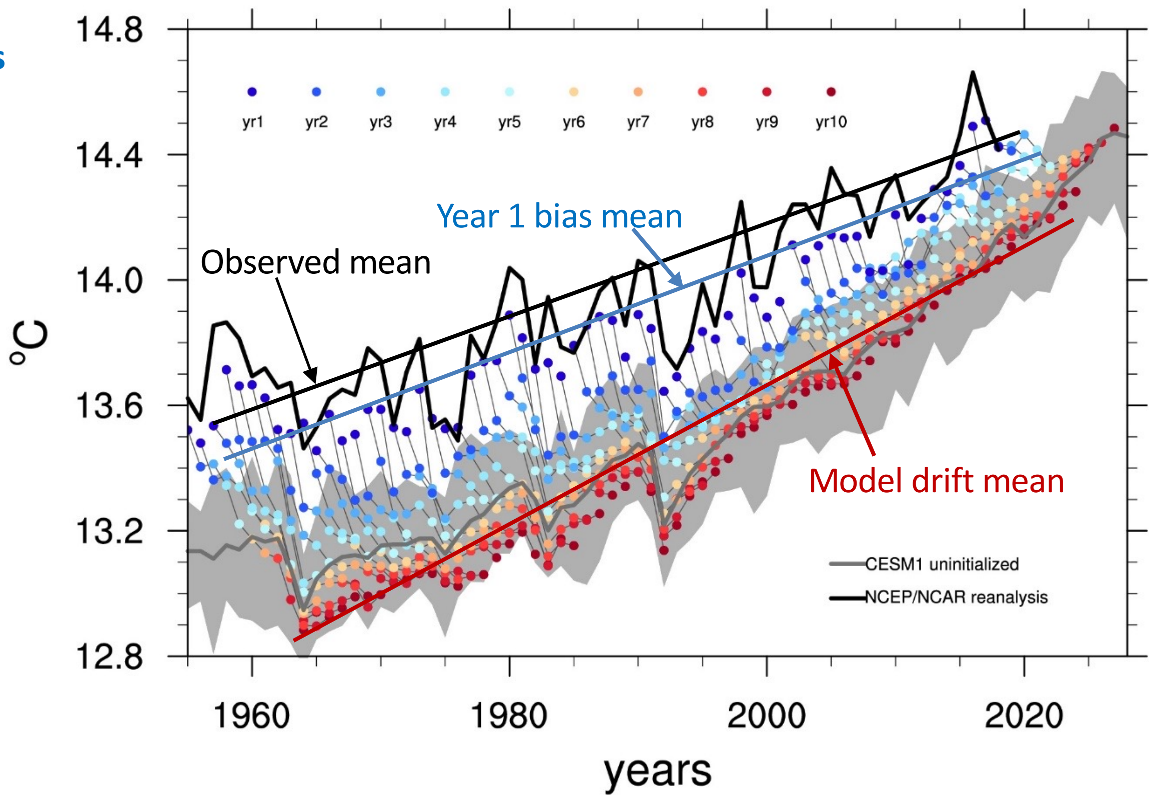
--drifted prediction minus long-term mean of model drift

--drifted prediction minus mean of previous 15 years model drift

--bias adjusted prediction minus observation mean

--time-evolving bias adjustment

--de-trend everything



CESM1 LE and DPLE Global ANN TAS

Trends in climatology are less of a problem for shorter timescales:

S2S: 1999-2016 (18 yrs)

S2I (NMME): 1981-2010 (30 yrs)

S2D (DPLE): 1954-2015 (62 yrs)

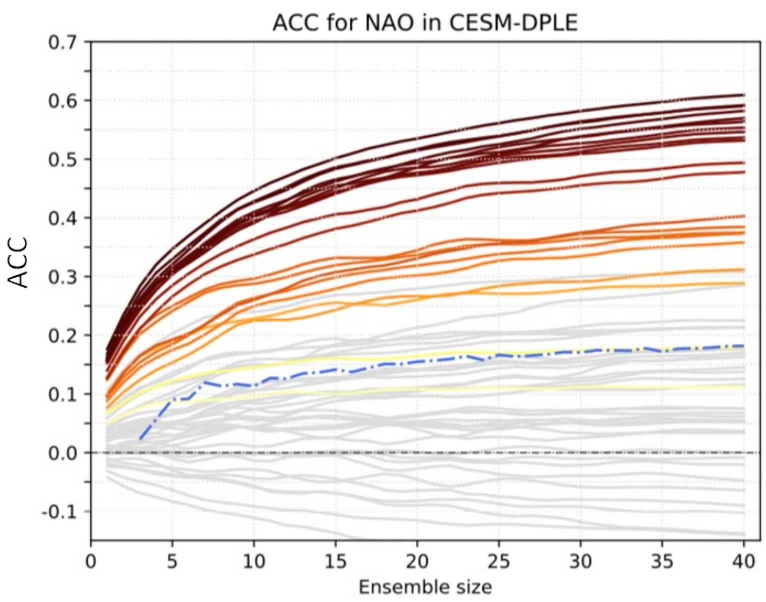
(Meehl, Teng, Smith, Yeager, Merryfield, Doblas-Reyes, and Glanville, 2022, Cli. Dyn.)

Science challenge: the "signal to noise paradox" and the need for more ensemble members

S2D predictions: NAO prediction skill, each line indicates a different lead year range: the more ensemble members, the higher the skill
(colored lines corresponding to statistically significant correlations for longer lead year ranges, with largest ACC values of 0.6 with 40 members for lead year ranges for an average of years 2 to 8)

Blue dash-dot line is the mean model prediction of one of its own ensemble members that has lower skill than the model predicting observations: the "signal to noise paradox"
(Athanasiadas et al., 2020, npj Clim. Atmos. Sci.)

b)



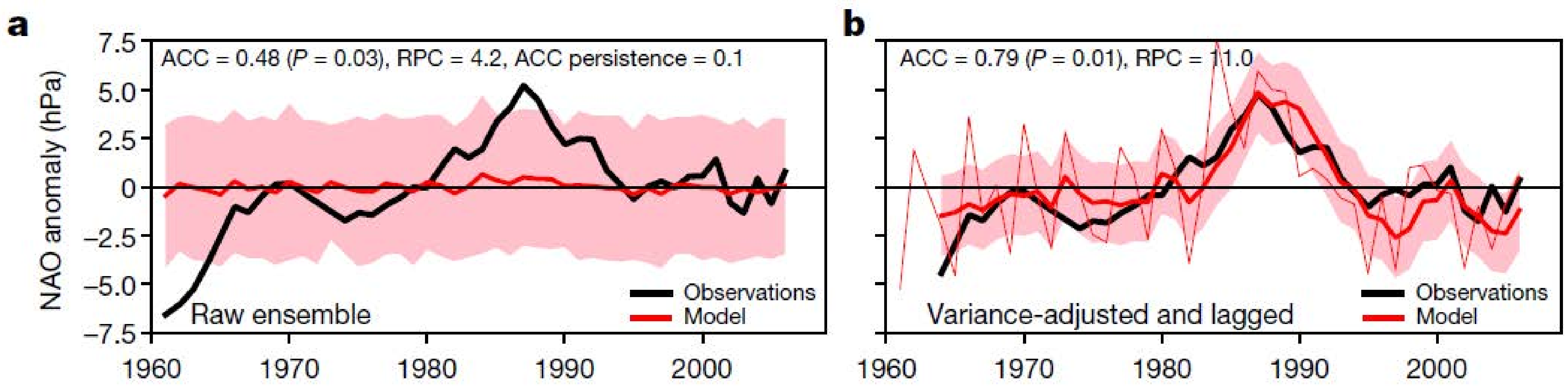
"ensemble predictions using climate models generally show higher correlation with observed variability than with their own simulations, and higher correlations with observations than would be expected from their small signal-to-noise ratios" (Scaife and Smith, 2018)

"the signal-to-noise ratio can be too small in climate models, requiring a very large ensemble to extract the predictable signal" (Smith et al., 2019)

The signal to noise paradox implies that there is a predictable signal from initialized hindcasts, giving a **positive correlation** with observations

But the **magnitude of the signal is very small and the noise is large**, such that the signal-to-noise ratio in the model is very small, and measures that include amplitude of the signal are small (e.g. MSSS)

Methods have been proposed to boost the signal by adjusting the variance to be close to observations, but the question remains as to **why the signals in the models are so small**?



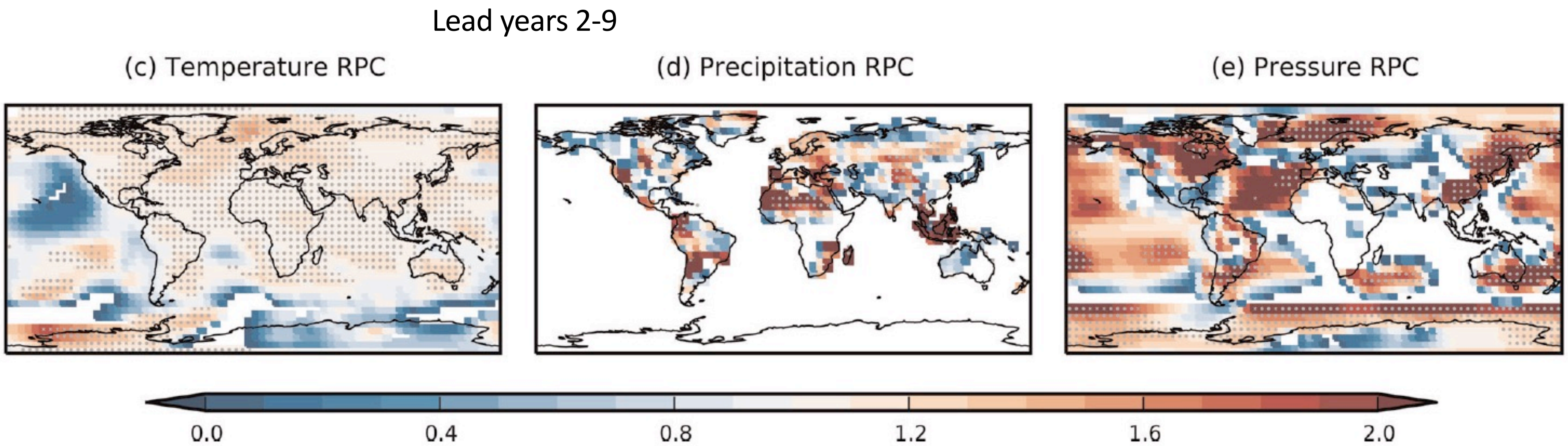
NAO index hindcasts, lead years 2-9, 1960-2005,
5 CMIP5 and 8 CMIP6 models

(Smith et al., 2020, Nature)

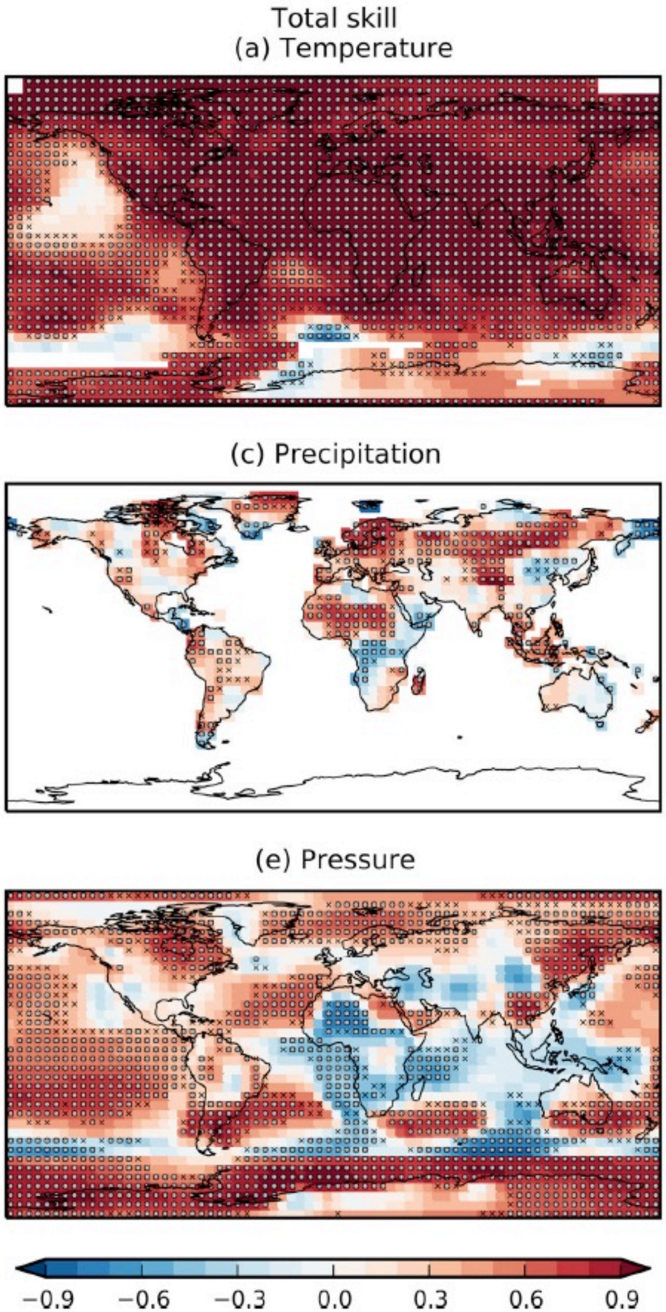
S2D: How widespread is the signal to noise paradox (i.e. predictable model phenomena smaller than observed)?

Calculate the ratio of predictable components (RPC);

higher RPC (darker red) above 1 indicates larger signal-to-noise paradox



(Smith et al 2019)



More ensemble members are better to refine the small predictable signal

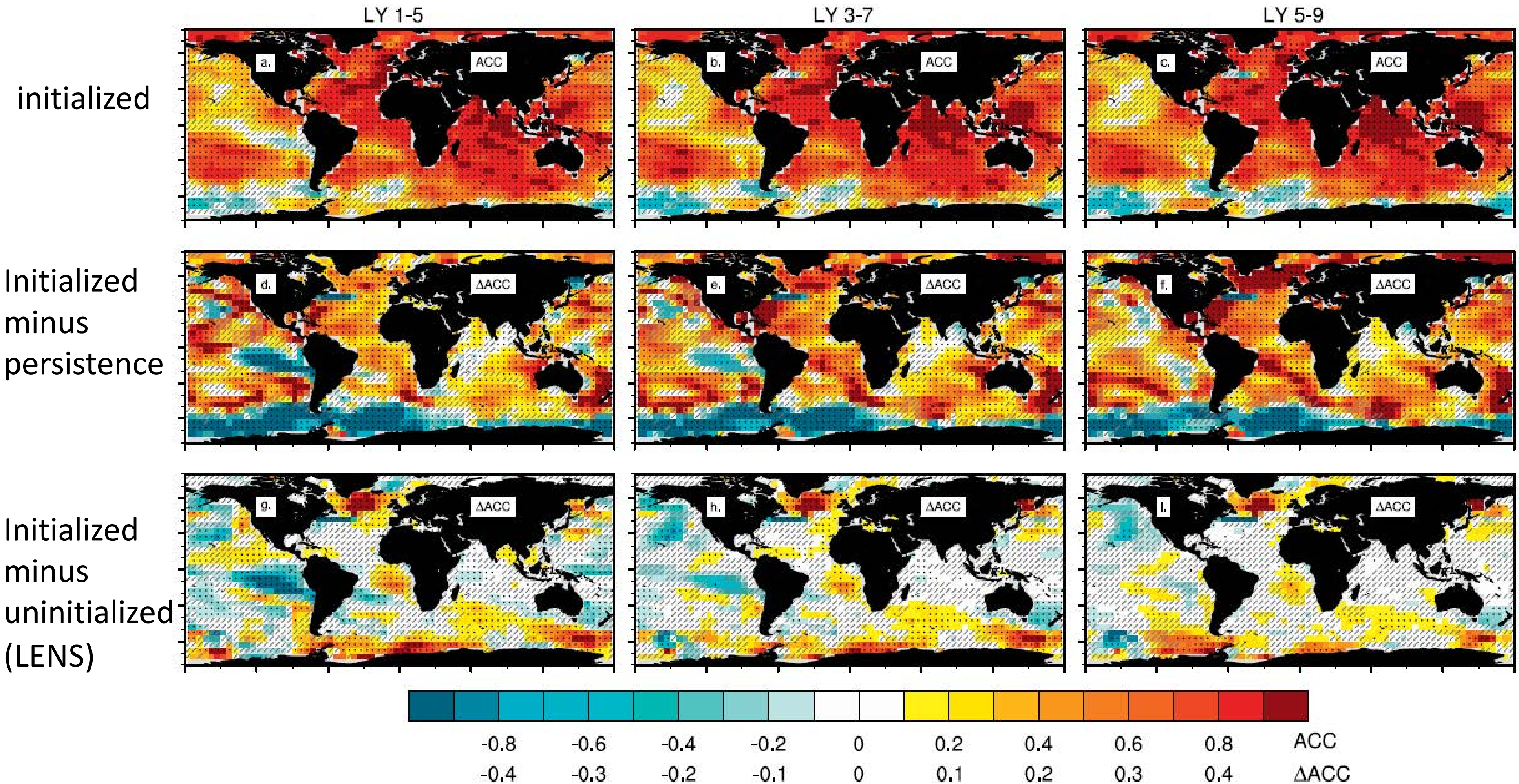
Multi-model ensemble, 7 models, from CMIP5

Correlation for lead year 2-9 initialized hindcasts

(Smith et al., 2019, jpj Clim. Atmos. Sci.)

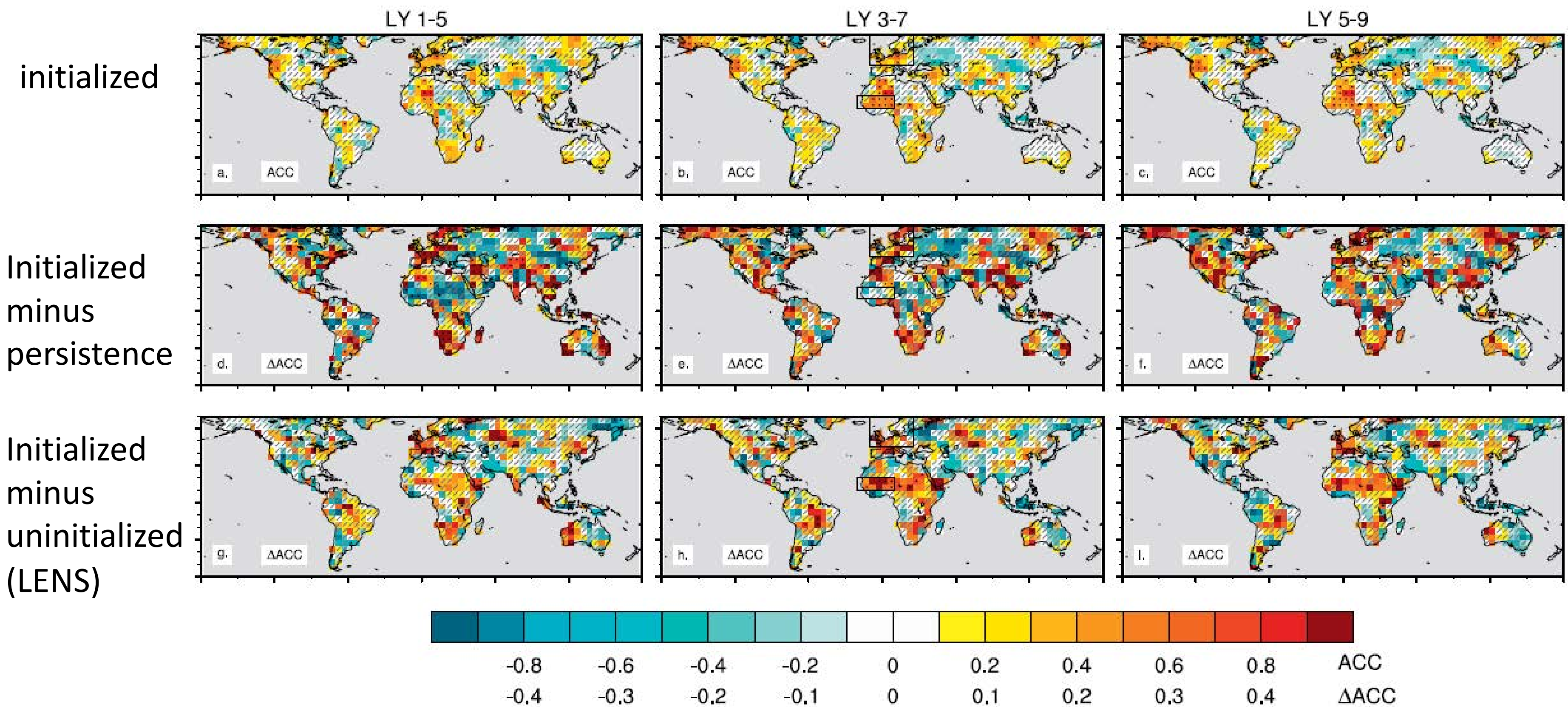
More ensemble members from a single model
Decadal Prediction Large Ensemble (DPLE) with CESM1
SST

(Yeager et al., 2018, BAMS)

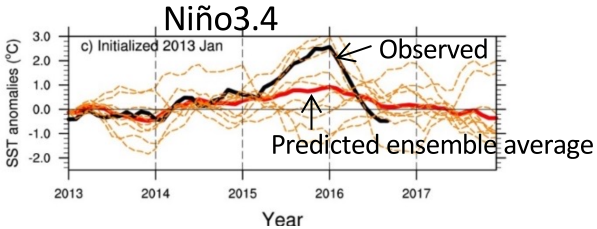


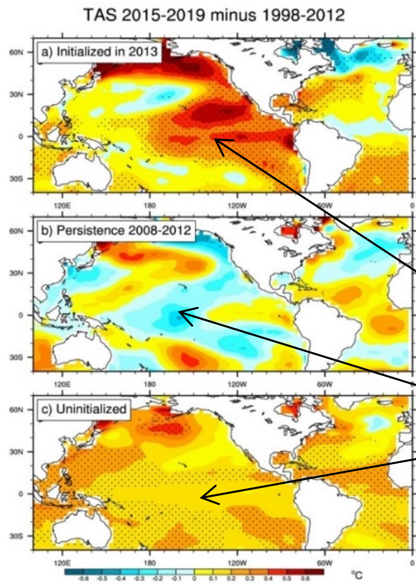
More ensemble members from a single model
Decadal Prediction Large Ensemble (DPLE) with CESM1
Precipitation

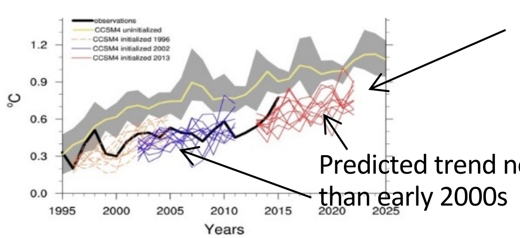
(Yeager et al., 2018, BAMS)



Some indications of predictive skill for large decadal transitions suggests the possibility of forecasts of opportunity







Published initialized prediction for IPO transition to positive ~2015 using CCSM4

Model initialized in 2013 predicted small warming in 2014 followed by larger El Niño in 2015-2016

Physical basis for prediction skill: build-up of off-equatorial western Pacific ocean heat content is a necessary condition for an El Niño event to trigger a decadal timescale IPO transition (Meehl, Teng, Capotondi, Hu, *Cli. Dyn*., 2021)

Prediction (initialized in 2013) for years 3-7 (2015-2019) shows transition to positive phase of the IPO different from persistence or uninitialized

Predicted transition to positive IPO produces global temperature trend for 2013-2022 of +0.22±0.13°C/decade, nearly 3 times larger than 2001-2014 trend of +0.08±0.05°C/decade during previous negative phase of IPO

(Meehl, G.A., A. Hu, and H. Teng, 2016, *Nature Comms.*)

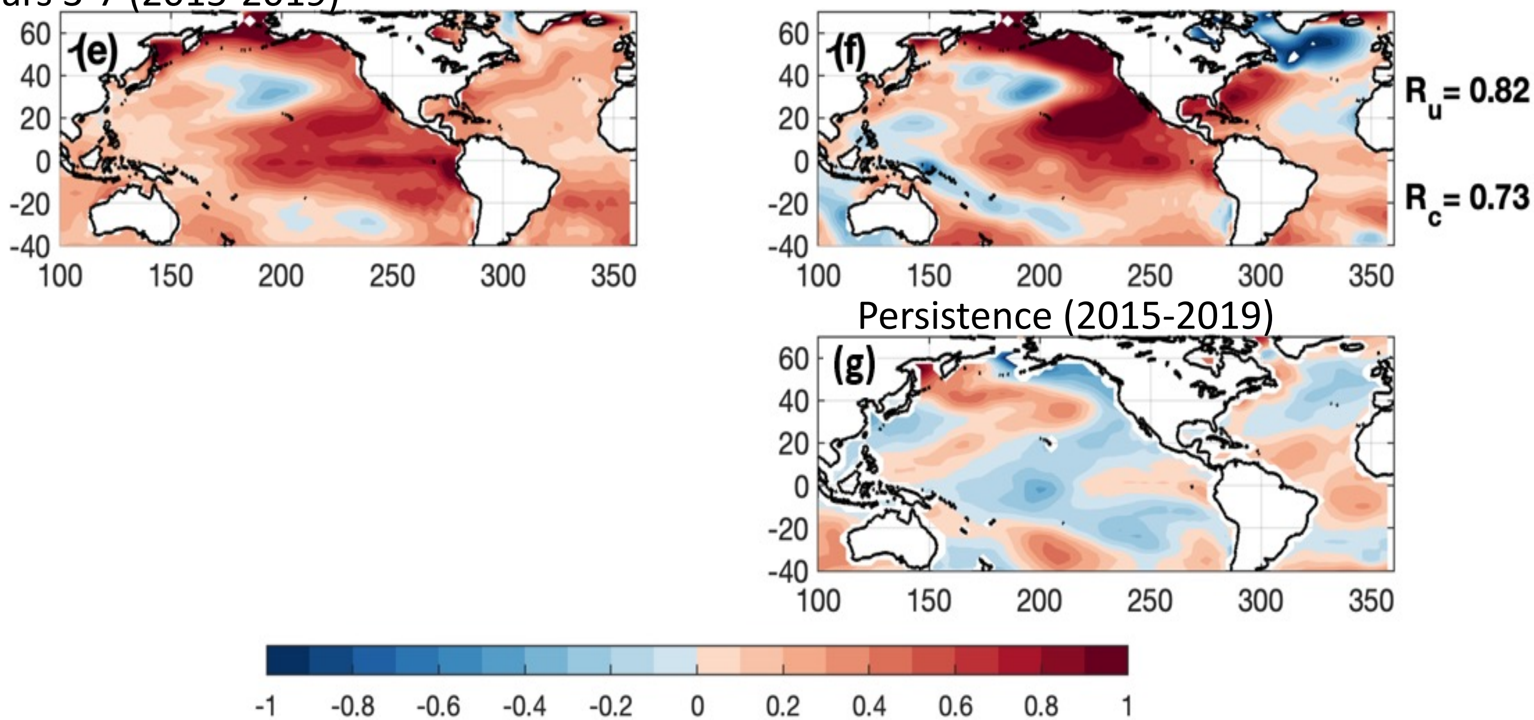
Verification for Meehl et al. (2016) prediction

From Decadal Prediction Large Ensemble (DPLE with CESM1) initialized in 2013 for years 3-7 (2015-2019) shows transition to positive phase of the IPO different from persistence

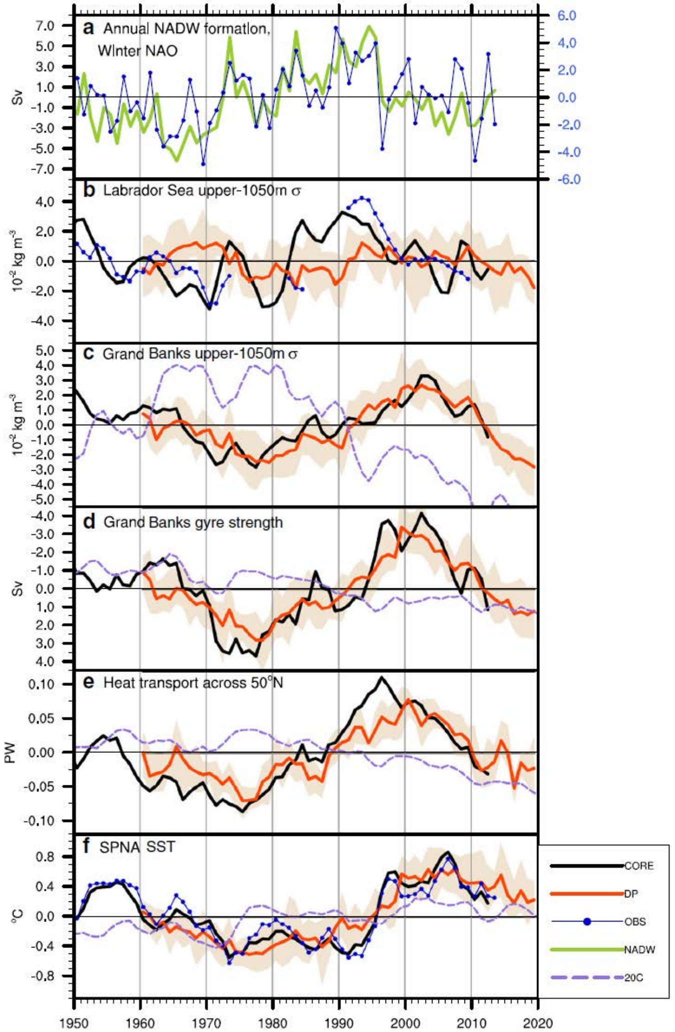
DPLE prediction initialized 2013 for lead years 3-7 (2015-2019)

Observations (2015-2019)

Persistence (2015-2019)



(Meehl, G.A., H. Teng, D. Smith, S. Yeager, W. Merryfield, F. Doblas-Reyes, and A.A. Glanville, 2022, Climate Dynamics)



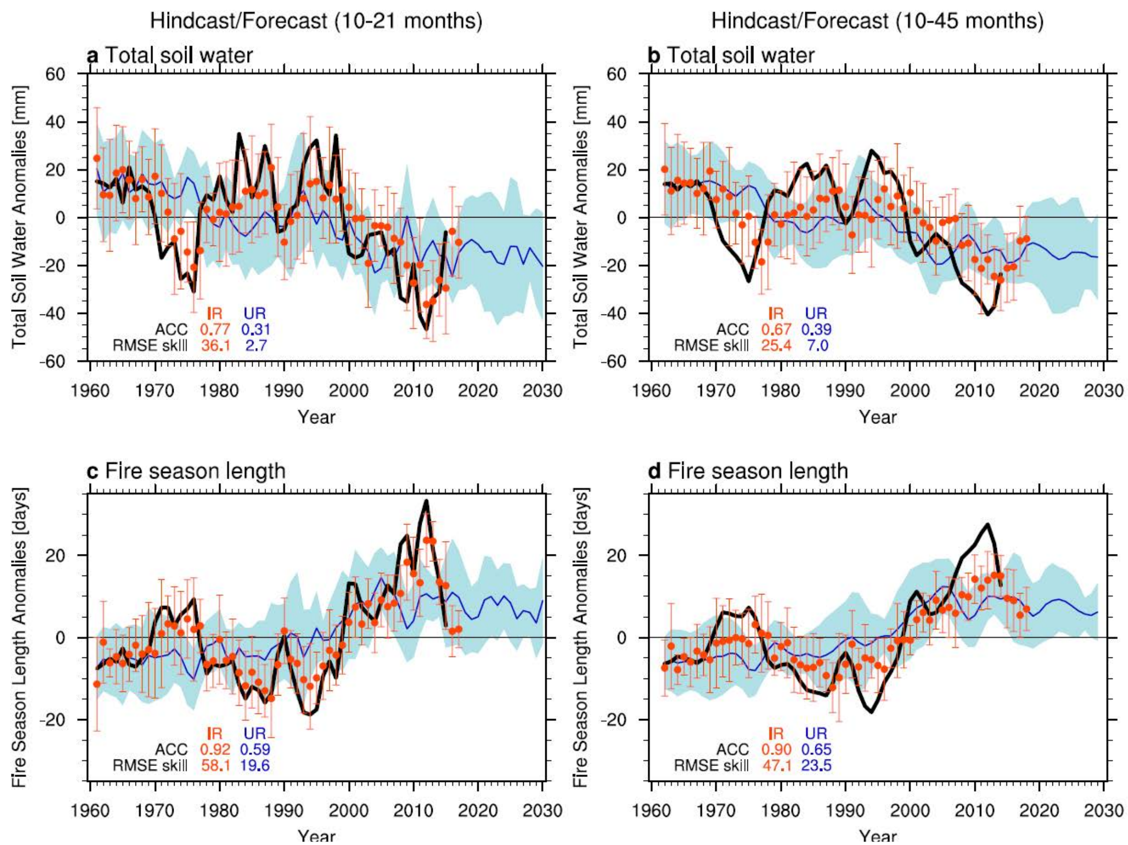
AMOC (buoyancy-forced thermohaline circulation) contributes to sub-polar North Atlantic SST predictive skill

(Yeager et al., 2015; Yeager and Robson, 2017)

Initialized predictions (lead 5-7 year average, red line, DPLE) compared to "observations" (CORE-forced ocean-sea-ice) and uninitialized (blue dashed)

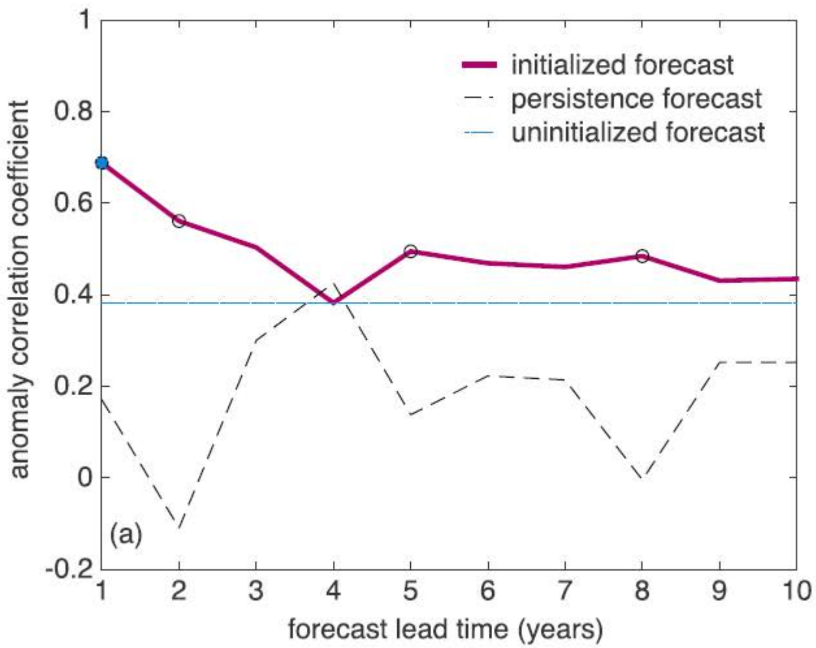
Skillful prediction of total soil water and fire season length over southwestern U.S. in CESM1 (Chikamoto et al 2017)

Uninitialized: blue
Initialized predictions: red
“observed”= black
(ocean data assimilation run)

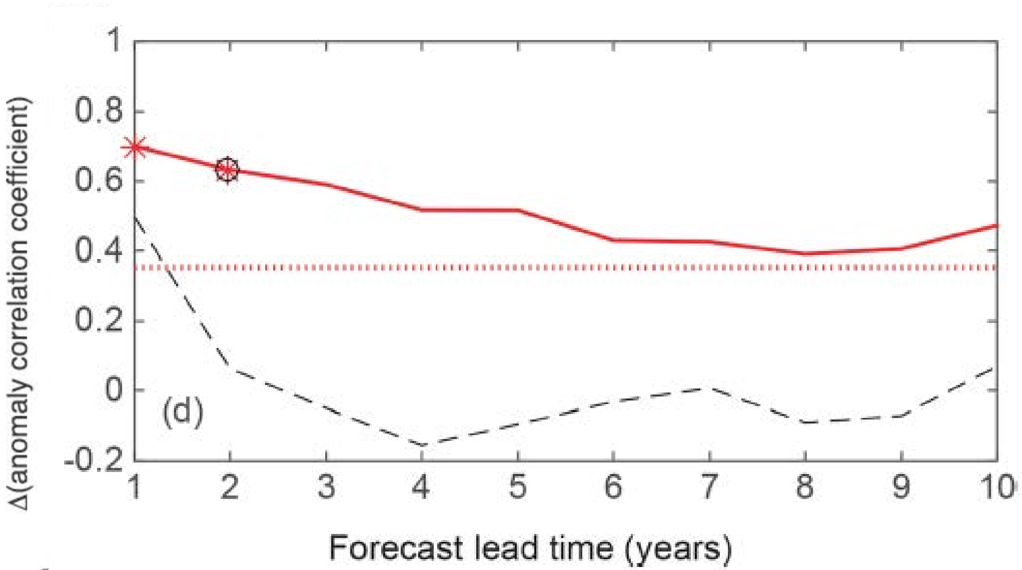


S2D: Some quantities other than SST in DPLE show skill:

Globally integrated net ecosystem production



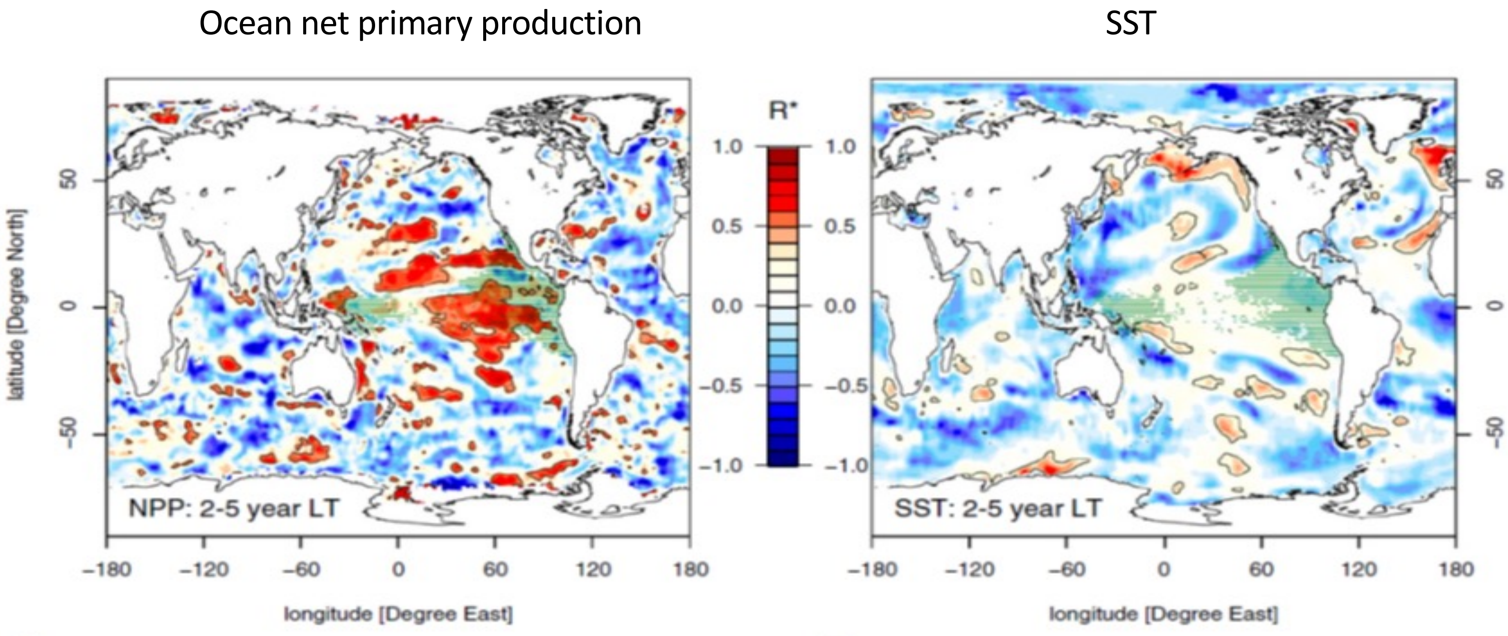
Globally integrated CO2 flux



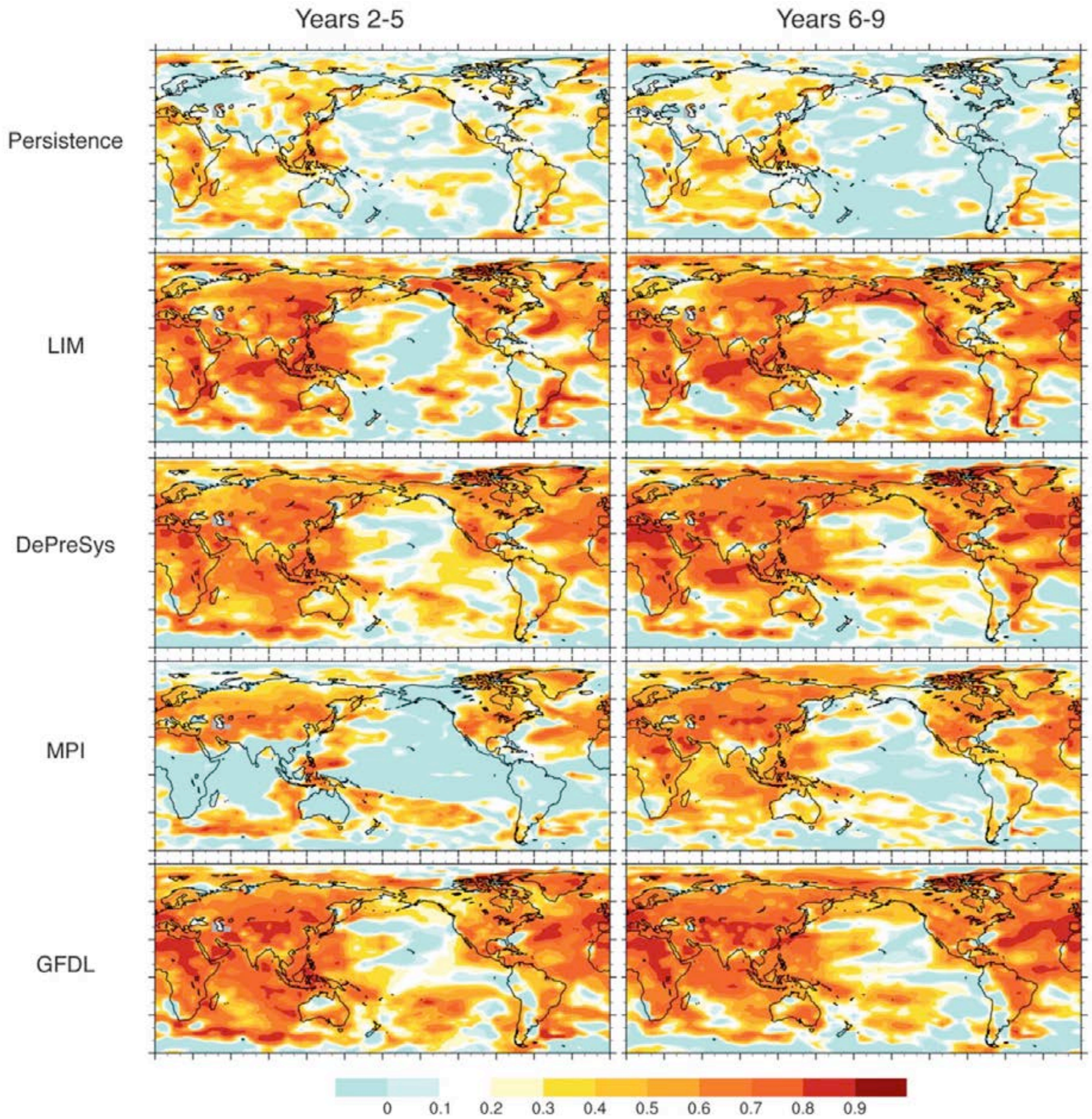
(Lovenduski et al., 2019a,b)

S2D prediction skill for ocean net primary production in the tropical eastern Pacific is greater than for SST

Skill at years 2-5 lead time of the hindcasts over the 10 y of SeaWiFS period (Seferian et al., 2014)



S2D predictions by means other than Earth System models: Linear Inverse Models (LIMs)



A linear inverse model (LIM) shows skill comparable to Earth System models on S2D timescales

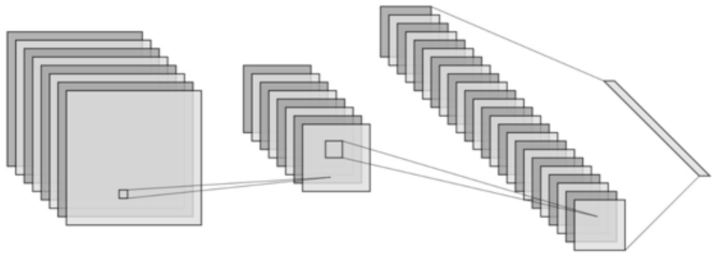
Predictions initialized yearly from 1960-2000
(local anomaly correlation; darker red indicates more skill)

(Newman, 2013, J. Climate)

S2D prediction with machine learning and investigation of prediction skill with Explainable AI

Step 1: Train ML

- Physically relevant upstream fields (SSTs, OLR).



S2S/S2D Prediction

- Modes of variability (MJO, ENSO).
- Impacts (temperature, precipitation).

Generate heatmaps (saliency maps, layer-wise relevance propagation (LRP)) using input fields (e.g., Barnes et al. 2020) to identify regions/processes that contribute to prediction skill.

Step 2:

Explainable AI

Work led by Maria Molina (NCAR)

Examples of current outreach initialized S2D prediction efforts:

Several national efforts will be described later in the workshop

WCRP Grand Challenge on Near-Term Climate Prediction

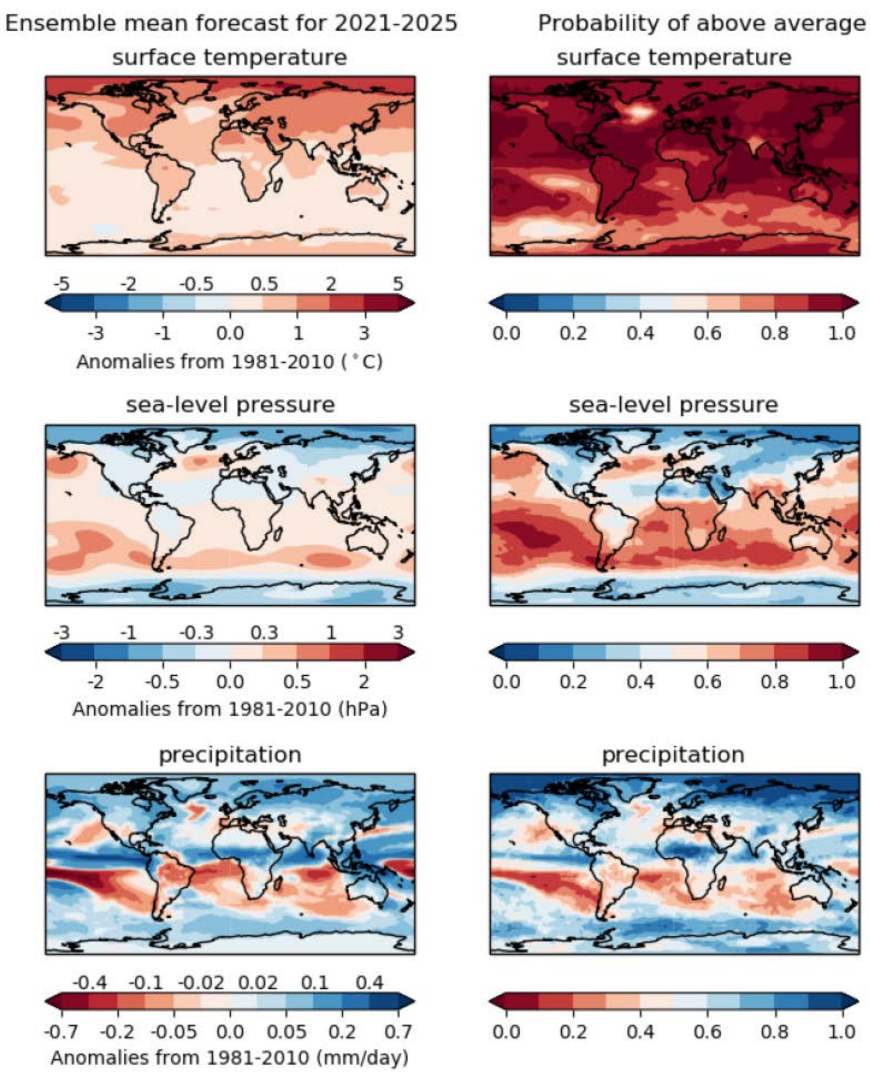
The Grand Challenge on Near-Term Climate Prediction will support research and development to improve multi-year to decadal climate predictions and their utility to decision makers.

It will furthermore support the development of organizational and technical processes for future routine provision of decadal prediction services that can assist stakeholders and decision-makers.

https://www.wcrp-climate.org/gc-near-term-climate-prediction

WMO Lead Centre for Annual-to-Decadal Climate Prediction

The Lead Centre for Annual-to-Decadal Climate Prediction collects and provides hindcasts, forecasts and verification data from a number of contributing centres worldwide.



Multi-model predictions from 11 groups

https://hadleyserver.metoffice.gov.uk/wmolc/

Conclusions

Initialized climate prediction spans the continuum of timescales from S2S, S2I and S2D
--Focus of this workshop is S2D

As skill from initial state drops off after a few years, skill from external forcing picks up

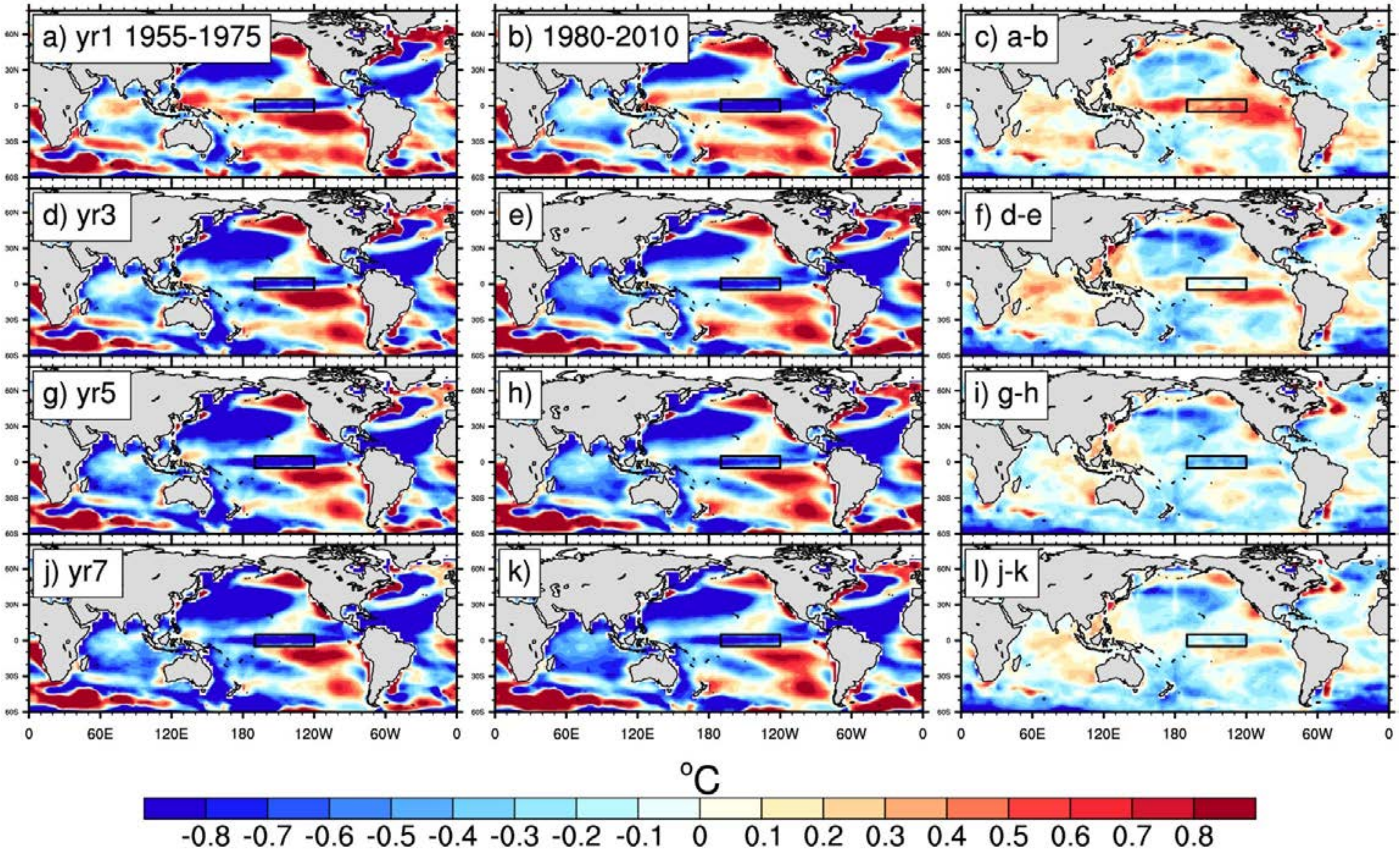
Usefulness of predictions beyond 2 years depends on skill and credibility of predictions; that depends on increased physical understanding the processes we're trying to predict and reducing model error

Earth System model predictions are being complemented by other tools such as LIMs and ML/AI

More ensemble members are better (signal to noise paradox)
Science question: why are model-predicted S2D signals much smaller than observed?

Biogeochemistry may be more predictable than SST in some cases (e.g. net ecosystem production, CO2 flux, ocean net primary production)

DPLE SST bias and drift due to model error

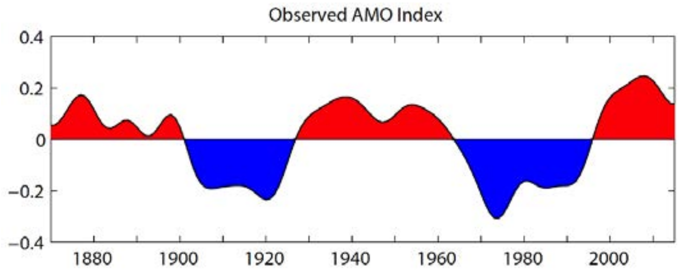


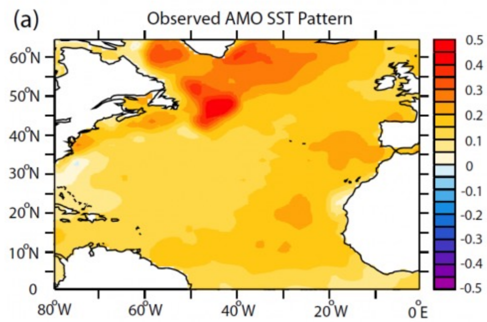
(Meehl,Teng, Smith, Yeager, Merryfield, Doblas-Reyes, and Glanville, 2022, Cli. Dyn.)

What phenomena are we trying to predict?

S2D:

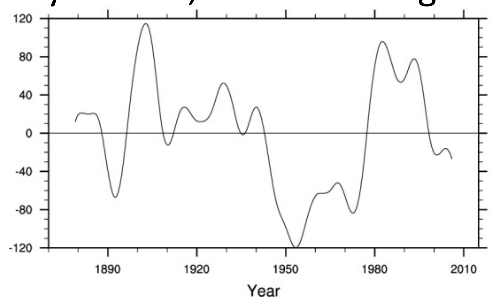
For the Atlantic: the Atlantic Multidecadal Oscillation (AMO) now generically referred to as Atlantic Multidecadal Variability (AMV)

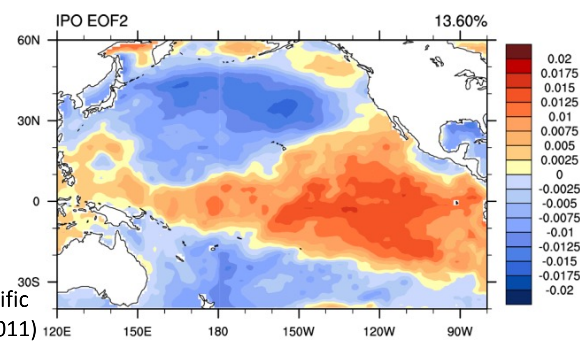




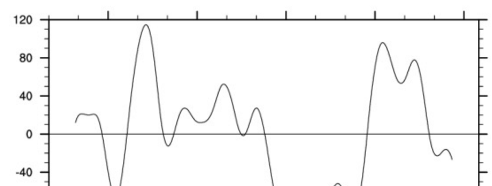
detrended 10-year low-pass filtered annual mean area-averaged SST anomalies over the North Atlantic basin (0N-65N, 80W-0E), using HadISST 1870-2015 (e.g. Trenberth and Shea, 2006)

For the Pacific: the Interdecadal Pacific Oscillation (IPO) and Pacific Decadal Oscillation (PDO); both are very closely related, and are now generically referred to as Pacific Decadal Variability (PDV)





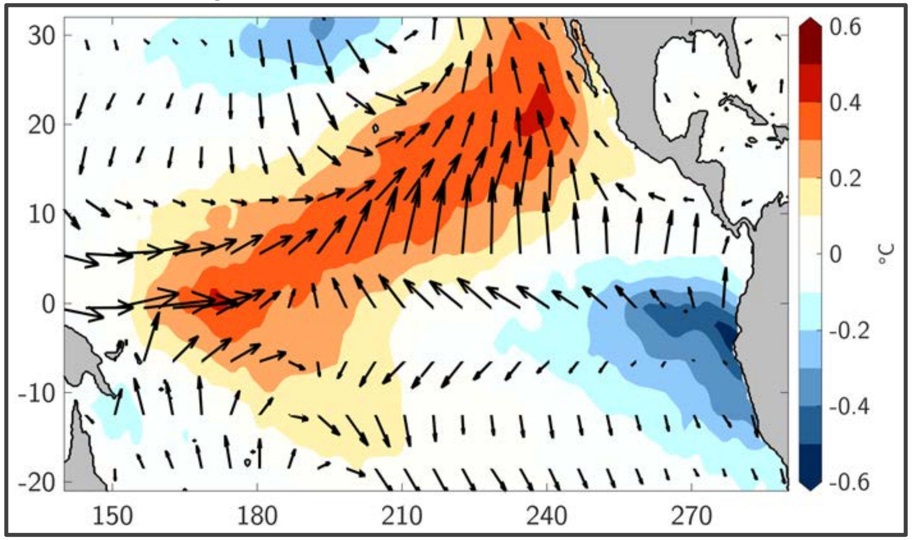
2nd EOF of low-pass filtered annual mean area-averaged SST anomalies over the Pacific basin (40S-60N, 120E-80W), using HadISST 1870-2015, (e.g. Meehl and Arblaster, 2011)



S2D:

For the Pacific: Pacific Meridional Mode (PMM) and North Pacific Gyre Oscillation (NPGO)
(Amaya, 2019; DiLorenzo et al., 2008; Vimont et al., 2014)

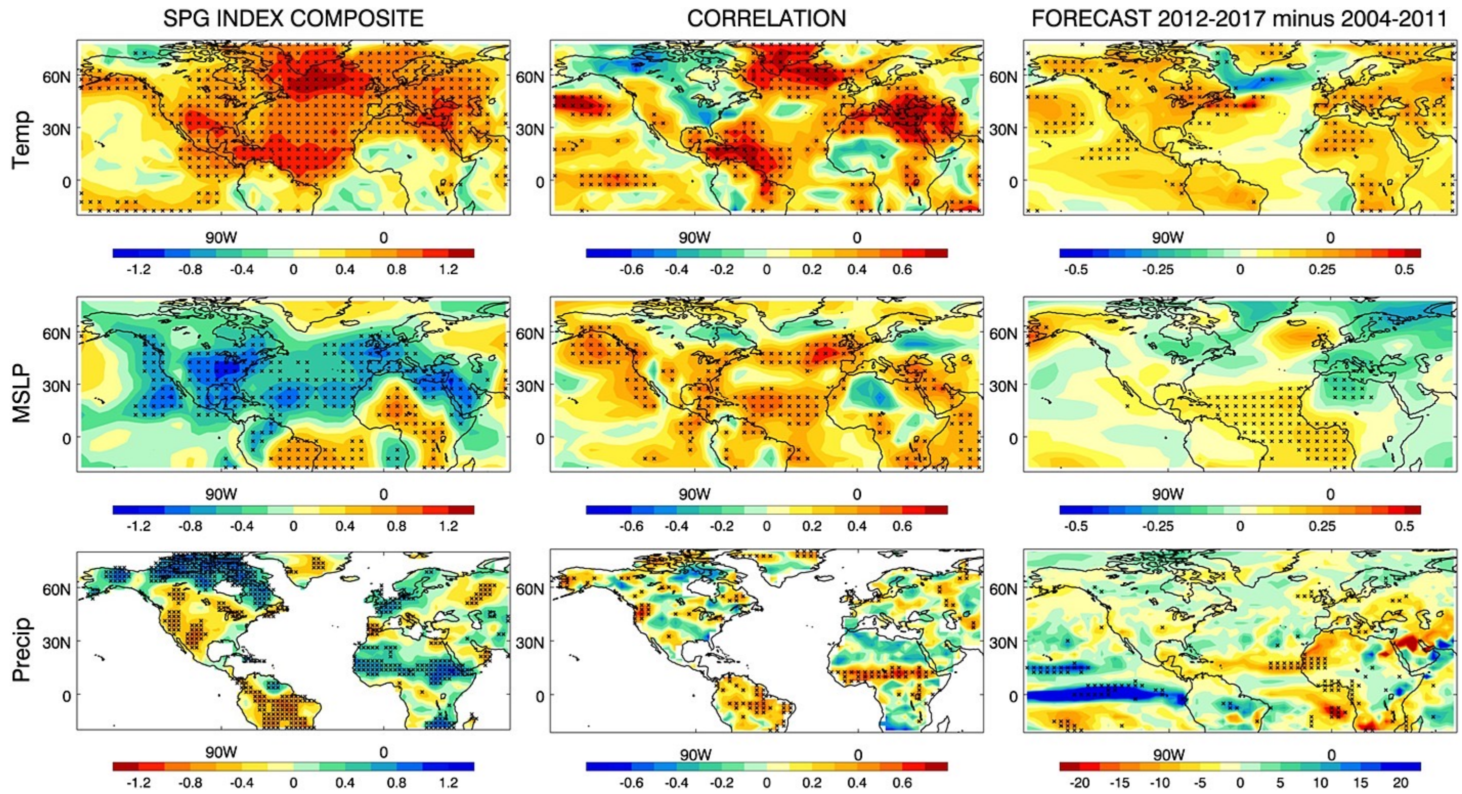
Pacific Meridional Mode



For the Indian Ocean:
Decadal variability exists and is being explored regarding mechanisms and connections to the Atlantic and Pacific (Han et al., 2014; Abram et al., 2020; Nieves et al., 2015)

Decadal variability in the tropical Pacific is associated with decadal ENSO modulation (Okumura et al., 2017)

Skillful predictions of subpolar gyre SST can lead to better predictions of other quantities in the Atlantic region (Hermanson et al., 2014)



variability associated with SPG changes (in SST) diagnosed from composite differences in (June, July, and August) between warm and cold SPG decades

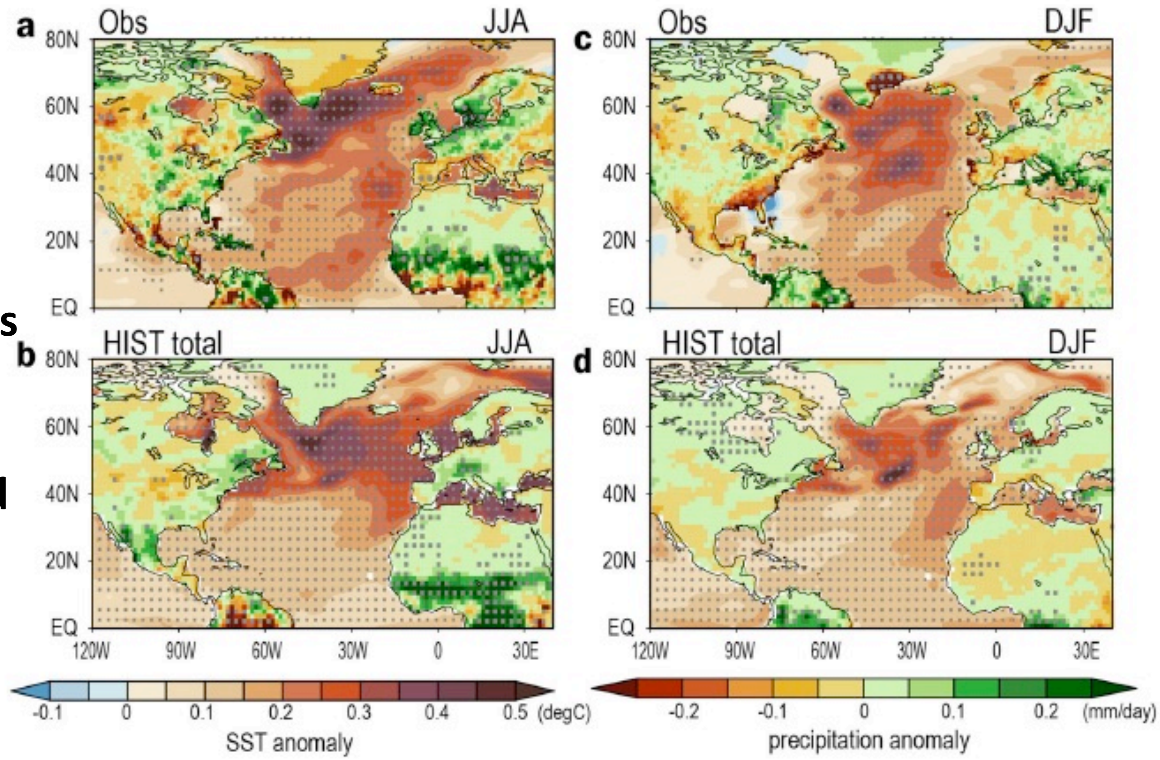
--warm SPG is associated with a warm northern Tropical Atlantic, warm mainland US, and warm European temperatures, especially in the eastern Mediterranean, and lower surface pressure on average. There is also a low pressure over western Europe, which is colocated with a signal for wet summers.

--The rainfall pattern in the tropical Atlantic regions indicates a northward shift of the Intertropical Convergence Zone (ITCZ), consistent with increased hurricane numbers

Role of aerosol forcing, as opposed to internal variability, in producing AMV could introduce skill in initialized S2D predictions

(e.g. Booth et al., 2012; Watanabe and Tatebe, 2019, shown here)

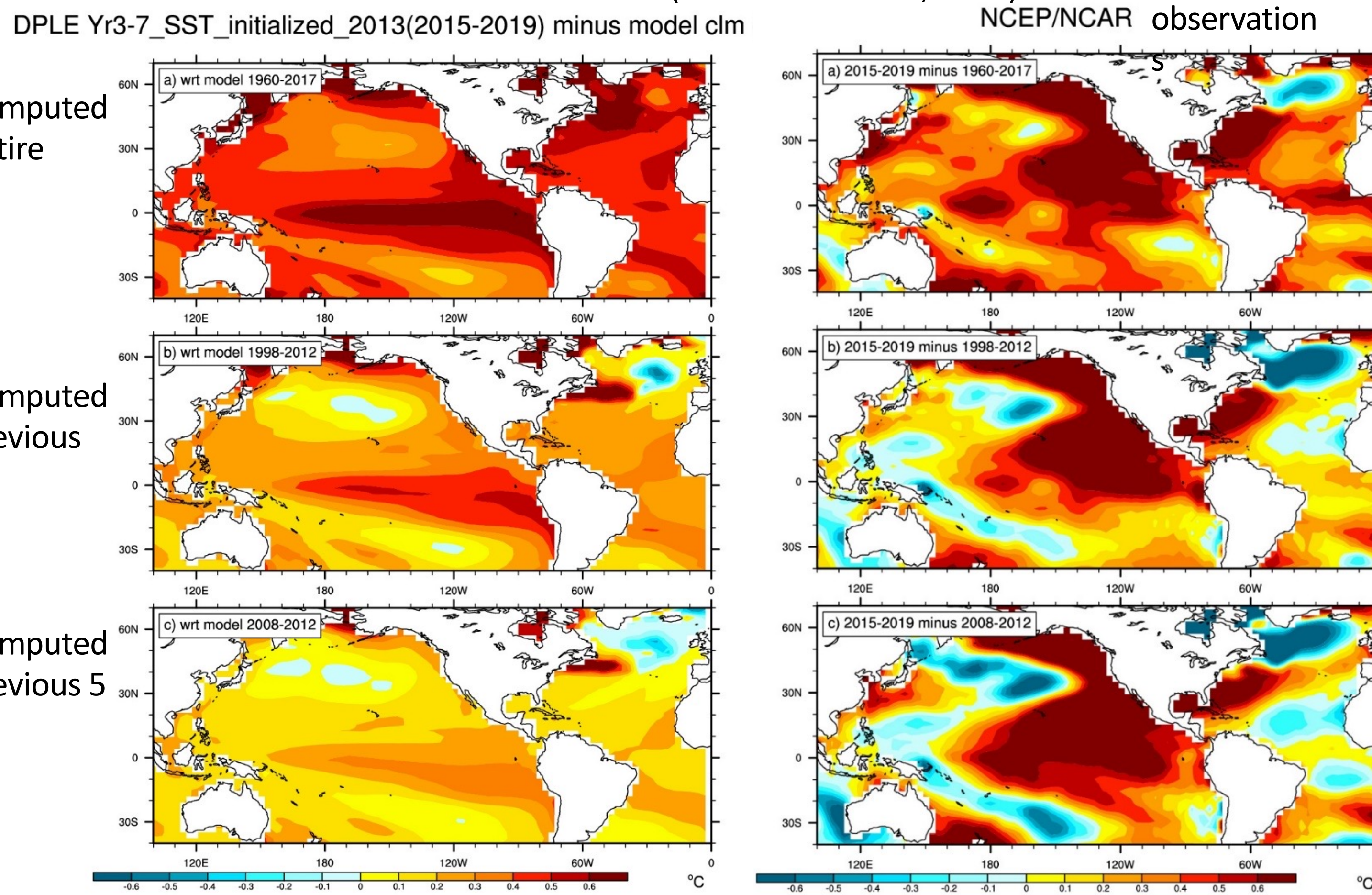
SST and precipitation regressed against low frequency AMV index shows externally-forced model-simulated patterns (HIST, bottom) similar to observed patterns (Obs, top)



and models. Since the correlation squared is the fraction of variance that is predictable, the RPC can be computed as the correlation skill for predicting the observations divided by the average correlation skill for predicting individual model members (where the square root has been taken for convenience). The expected value of the rpc should equal one for a perfect forecasting system; values greater than one are symptomatic of the signal-to-noise paradox where the real world is more predictable than models. The RPC for decadal predictions of the NAO is 6, compared to 2 or 3 for seasonal and annual

Computing anomalies for verification—the issue of trends

Prediction initialized in 2013 for IPO transition in 2015-2019 (after Meehl et al., 2016)



observation s

Anomalies computed relative to entire climatology

Pcorr =+0.8 8

Anomalies computed relative to previous 15 years

+0.70

Anomalies computed relative to previous 5 years

+0.62

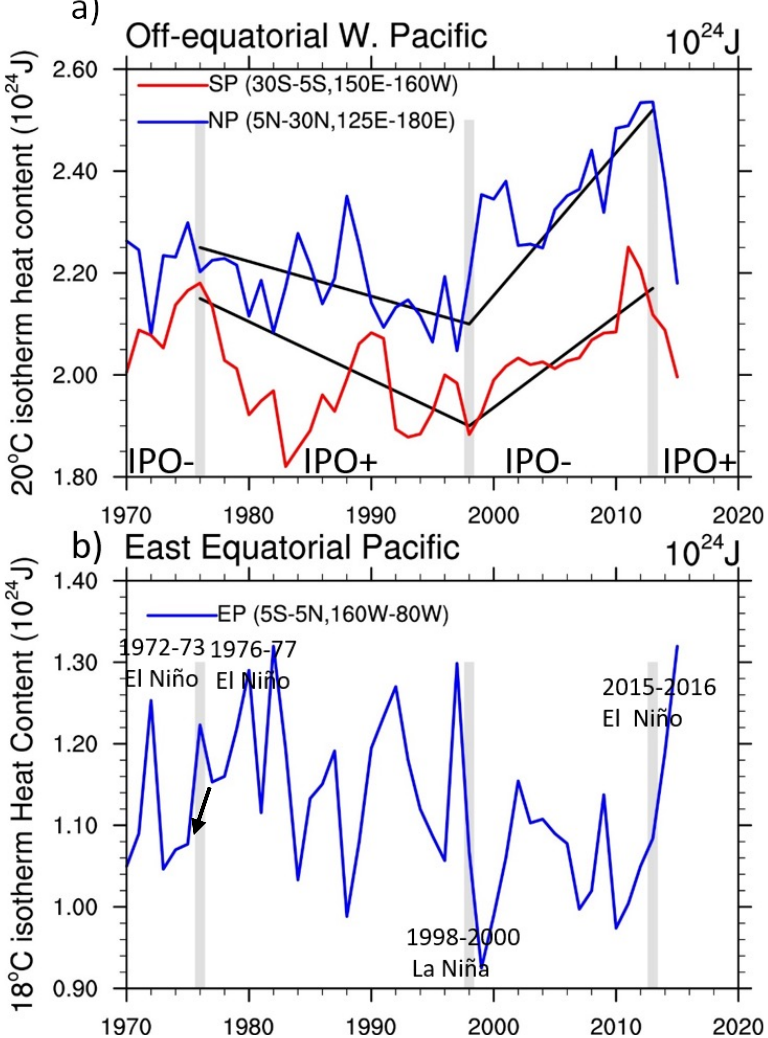
Initialized Earth System prediction presumes:

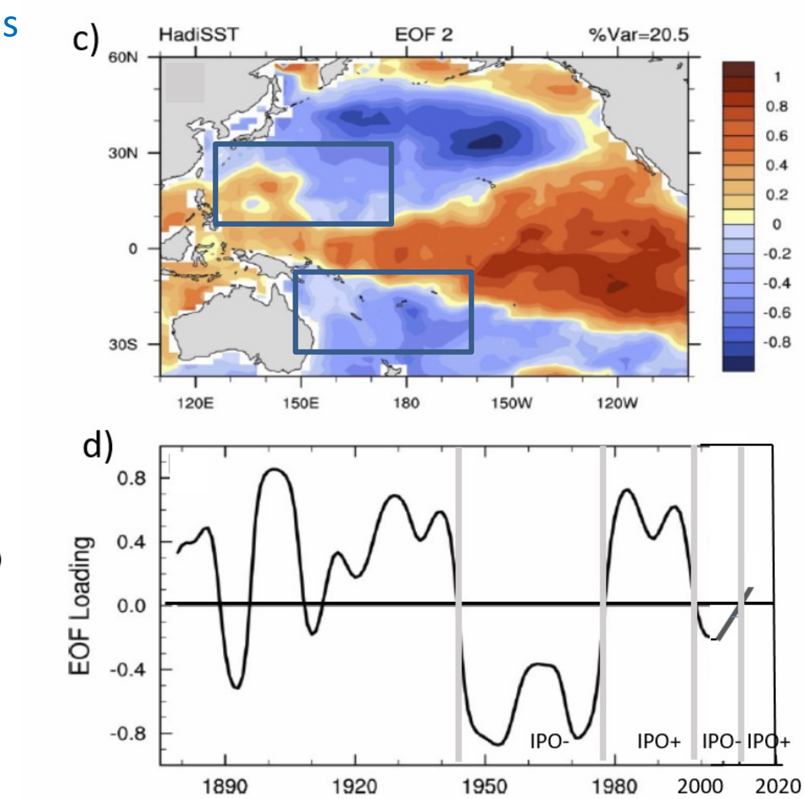
There are internal processes, with physical mechanisms that produce them, that could provide potential predictability in initialized predictions

Initialized hindcasts can provide insights into such physical processes and can point to analyses to increase physical understanding

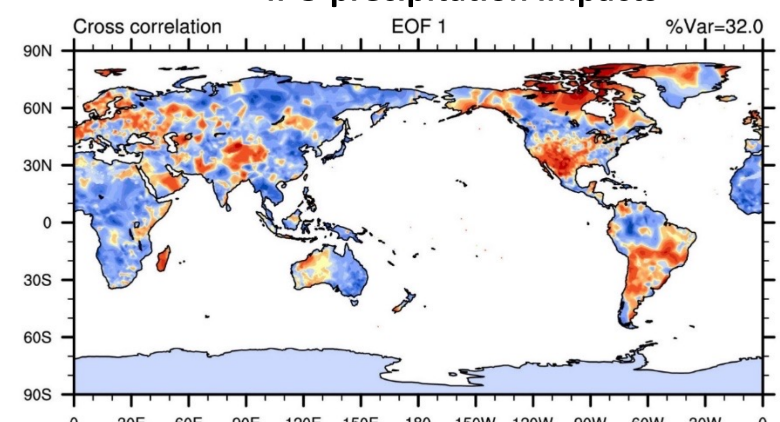
A candidate: low frequency tropical-midlatitude air-sea interaction for the Interdecadal Pacific Oscillation (IPO) (e.g. Meehl and Hu, 2006; Farneti et al., 2014)

Decadal Prediction Large Ensemble (DPLE) Forced Ocean and Sea Ice (FOSI) ocean initial states





IPO precipitation impacts



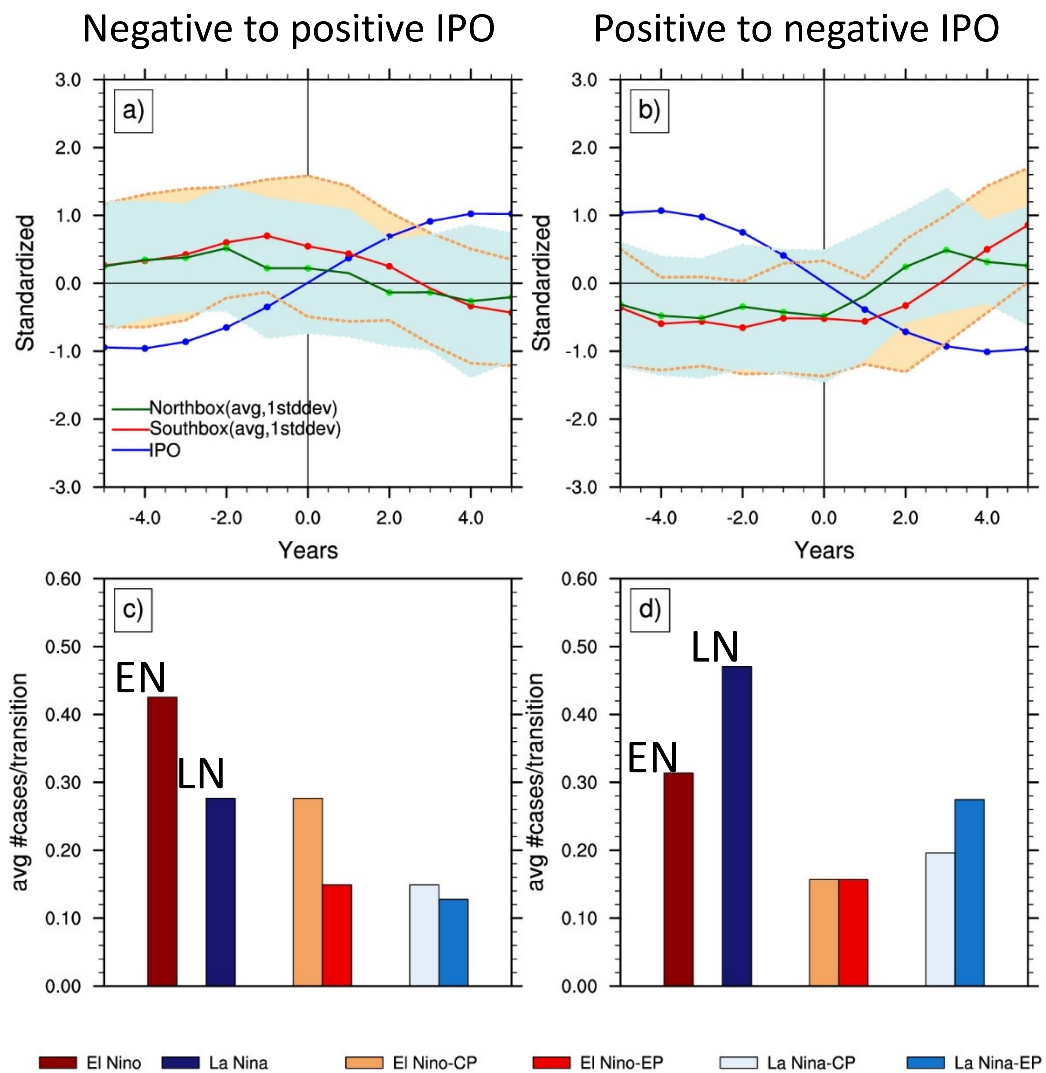
IPO correlated with observed low pass filtered precipitation (1901-2000; Meehl and Hu, 2006, J. Clim.)

Off-equatorial ocean heat content in the tropical western Pacific appears to provide the conditions for ENSO events to trigger an IPO transition

(Meehl, Hu, Teng, 2016, *Nature Communications*)

Off-equatorial ocean heat content appears to reach a necessary (but not sufficient) threshold (~0.5 standard deviations) prior to an ENSO event that provides the sufficient condition for a transition

In the year of an IPO transition from negative to positive, there is a better chance of an El Niño event
(and better chance of a La Niña event from positive to negative IPO)



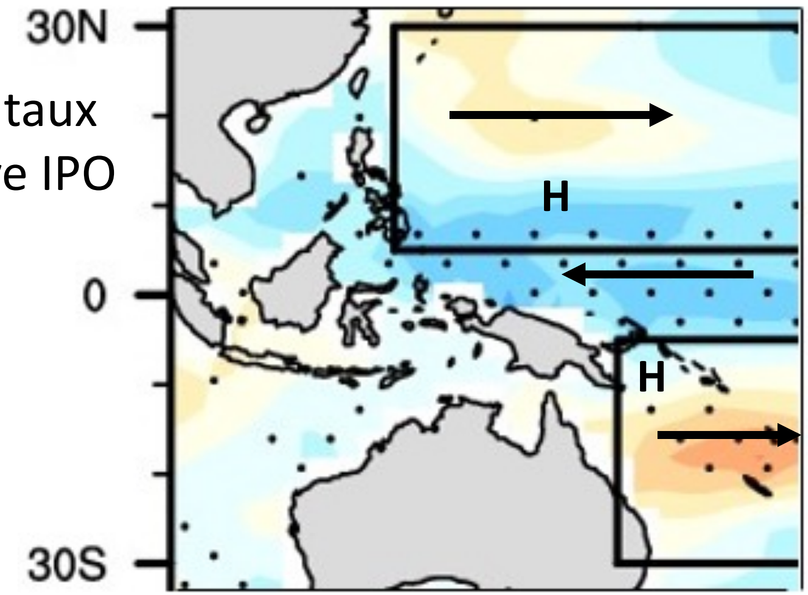
(El Niño: April-March Niño3.4 > +0.5°C for 5 consecutive overlapping 3 month seasons)

(events per IPO transition)

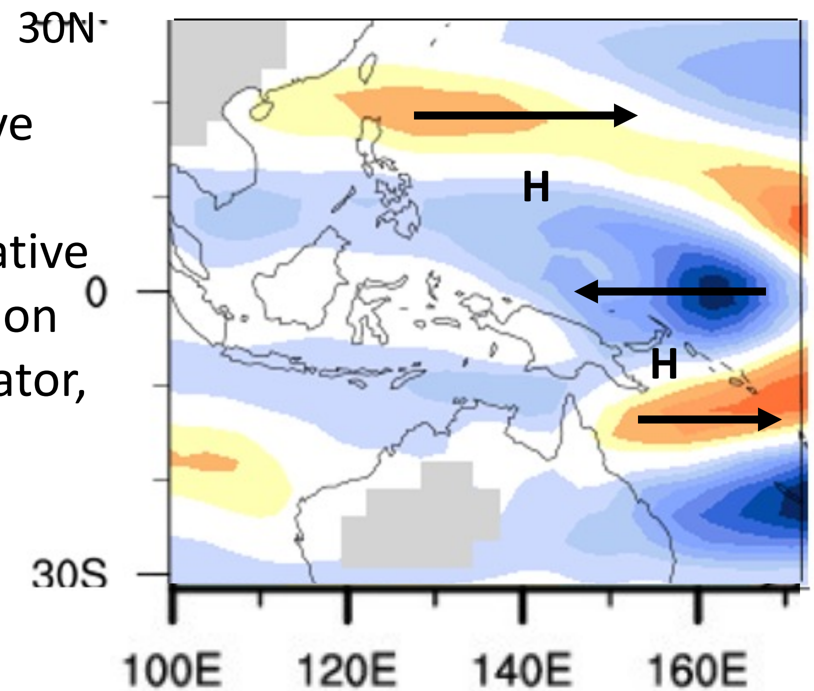
Meehl, G.A., , H. Teng, A. Capotondi, and A. Hu 2021, *Climate Dynamics*, doi: 10.1007/s00382-021-05784-y

Negative convective heating anomaly near 165E can produce u-component wind stress anomalies in off-equatorial western Pacific to sustain ocean heat content anomalies

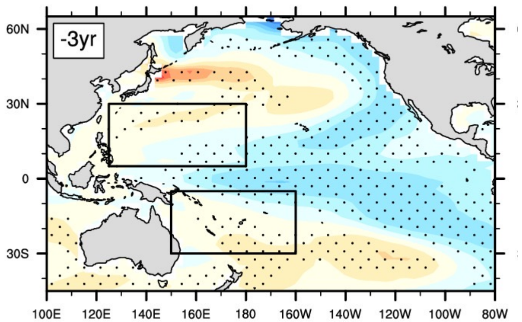
Year -4 composite taux negative to positive IPO transition



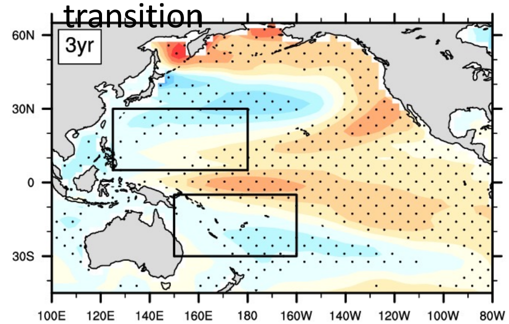
Negative convective heating anomaly (representing negative SST and precipitation anomalies) at equator, 165E



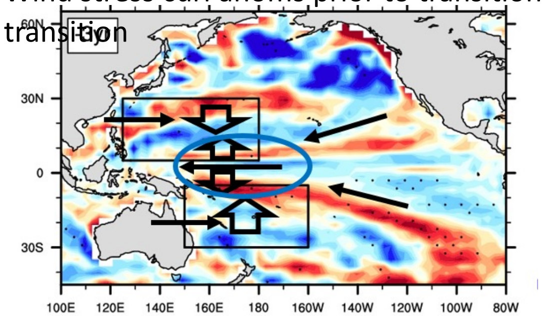
Negative IPO SST anomalies prior to transition



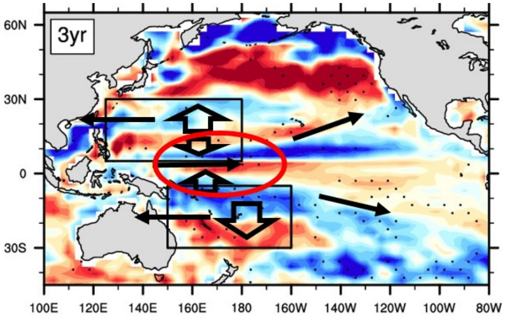
Positive IPO SST anomalies after transition



Wind stress curl anoms prior to transition



Wind stress curl anoms after

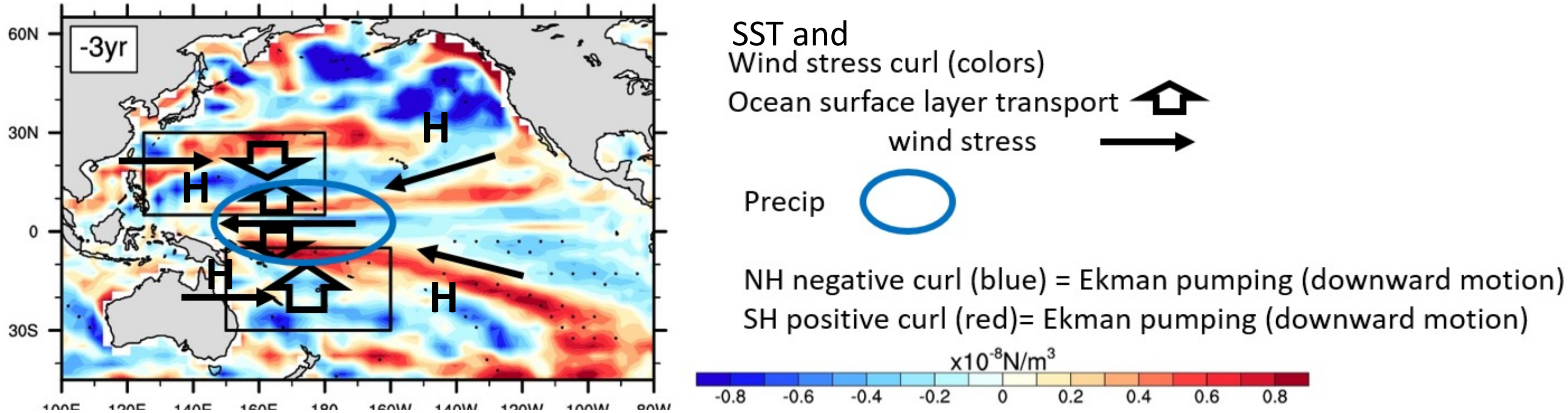


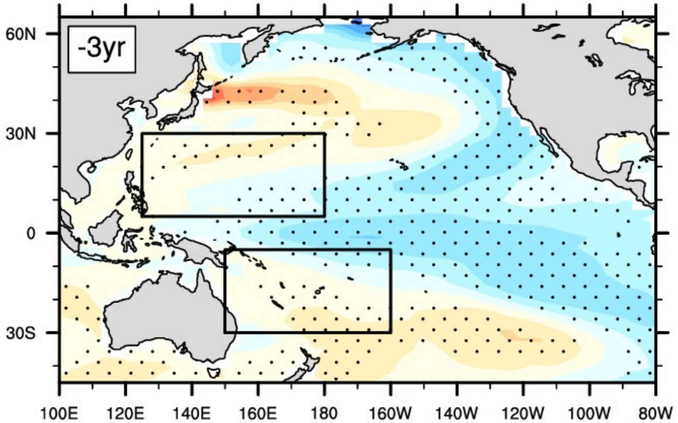
Composites from CESM1 long PI control run

(Meehl, Teng, Capotondi, and Hu, 2021, Cli. Dyn.)

The build-up of decadal timescale upper ocean heat content in the off-equatorial western tropical Pacific from ocean heat divergence from equatorial western Pacific maintained by convective heating anomalies and off-equatorial surface winds from a Gill-type response

Ocean heat convergence into western equatorial Pacific from westerly anomaly near-equatorial surface winds associated with El Niño activity then sustain anomalously warm western and central Pacific SSTs from positive precipitation and convective heating anomalies, a Gill-type response and wind stress curl anomalies that continue to feed warm water into the near-equatorial western Pacific.





-3yr: persistent easterly anomaly equatorial surface winds and negative SST precipitation and convective heating anomalies in the western eq. Pacific

--Gill-type response and cyclonic circulations to the northwest and southwest with easterly wind stress anomalies near 20°N and 15°S

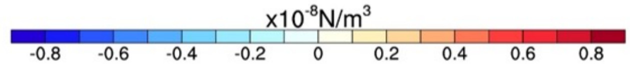
-- wind stress curl anomalies (negative near 15°N, positive near 10°S) and consequent negative vertical motions in the upper ocean produce accumulation of heat content and convergence of warmer water into the off-equatorial western Pacific.

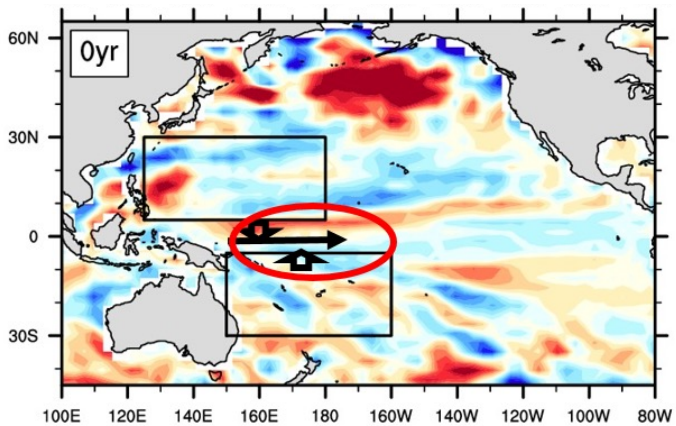
--stronger Trades in eastern tropical Pacific from anomalous high pressure in North and South Pacific from negative convective heating anomalies in equatorial central Pacific produce ocean Rossby waves that propagate slowly to the west, and NPMM and SPMM-type SST patterns

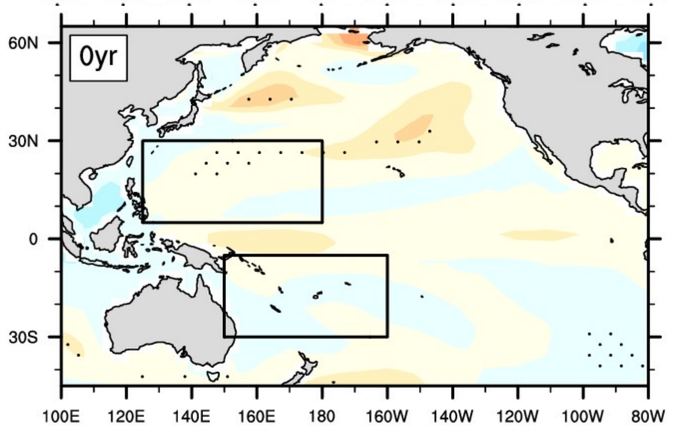
SST and
Wind stress curl (colors)
Ocean surface layer transport
wind stress

Precip

NH negative curl (blue) = Ekman pumping (downward motion)
SH positive curl (red)= Ekman pumping (downward motion)





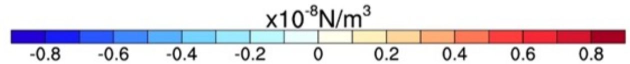


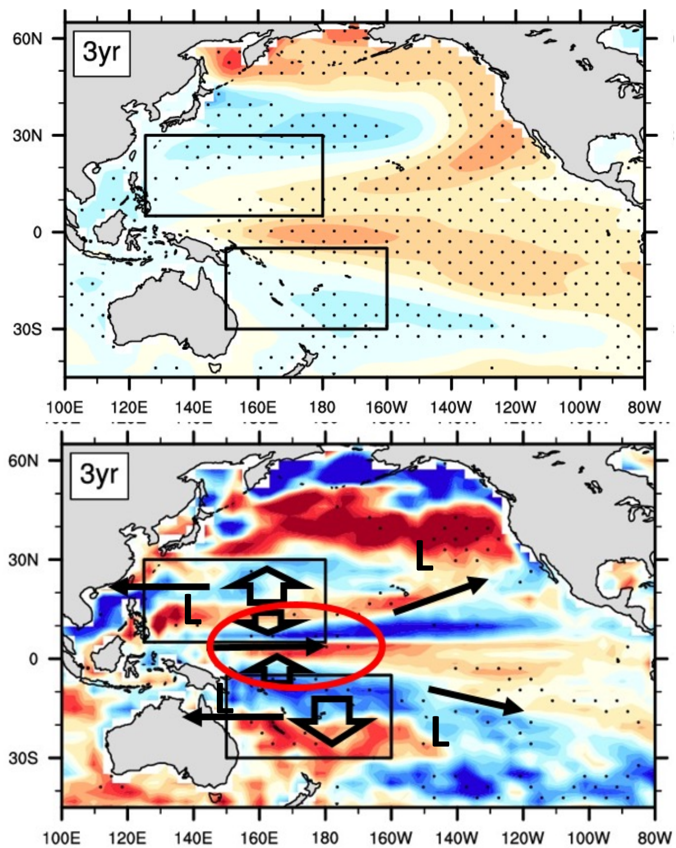
0yr: westerly anomaly surface winds in tropical western Pacific with ENSO activity, consequent positive wind stress curl near 5N and negative wind stress curl near 5S initiates heat convergence into equatorial Pacific with positive SST anomalies appear in western equatorial Pacific; positive heat content anomalies propagate from the western to eastern equatorial Pacific producing a flatter, more El Niño-like thermocline over several years even with interannual variability superimposed.

SST and
Wind stress curl (colors)
Ocean surface layer transport
wind stress

Precip

NH negative curl (blue) = Ekman pumping (downward motion)
SH positive curl (red)= Ekman pumping (downward motion)





+3yr: positive SST and convective heating anomalies in western equatorial Pacific and Gill-type response with the easterly anomalies near 15-20°N and 15-20°S, wind stress curl anomalies (positive near 15°N, negative near 10°S) and consequent positive vertical motions in the upper ocean produce depletion of heat content and ongoing convergence of warmer water into the equatorial Pacific.

--and so on, to produce an IPO transition from positive to negative several years later.