Multi-Year Predictability and Prediction

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Why Study Multi-year Prediction?

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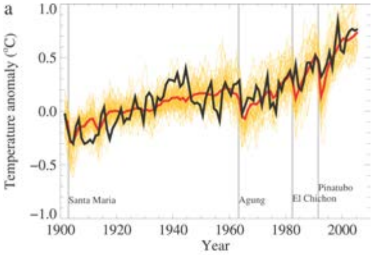
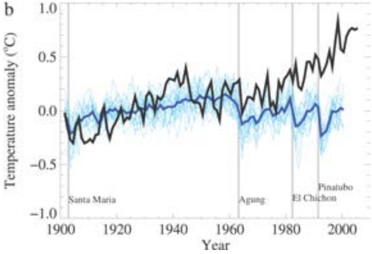
Predictions are critical tests of our understanding of the climate system.

Forced Predictability



Models using both natural and anthropogenic forcing



Models using only natural forcings

IPCC-AR4, fig. 9.5

Evidence of Unforced Multi-year Predictability

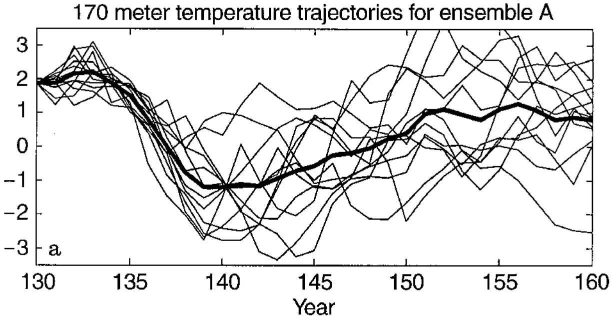


Figure: Trajectories of leading principal component of 170m ocean temperature simulated by GFDL model; from Griffies and Bryan (1997).

Claims of Multi-Year Predictability in Stationary Models

- Latif and Barnett (1994, Science)
- Grötzner et al. (1999, J. Climate)
- Boer (2000, Climate Dyn.)
- Delworth and Mann (2000, Climate Dyn.)
- Collins (2002; Climate Dynamics)
- Collins and Sinha (2003; Geophys. Res. Letters)
- Pohlmann et al. (2004; J. Climate)
- Latif et al. (2004; J. Climate)
- Boer and Lambert (2008; Geophys. Res. Letters)
- Branstator et al. (2011; J. Climate)

Percent of Predictable Variance of Decadal Mean 2m-Temperature

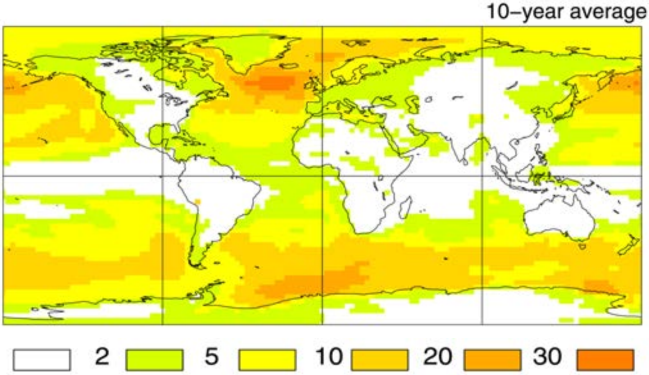


Figure: Boer and Lambert (2008)

Challenges in Predicting the Real Climate System

- Forced Predictability
  - accurate predictions of anthropogenic and natural forcing
  - accurate predictions of the response to climate forcing.
- Unforced Predictability
  - accurate observations of the subsurface ocean
  - construct initial conditions without "shock" or "drift"
  - different models imply different levels of predictability

Dynamical Predictions (Keenlyside et al. 2008)

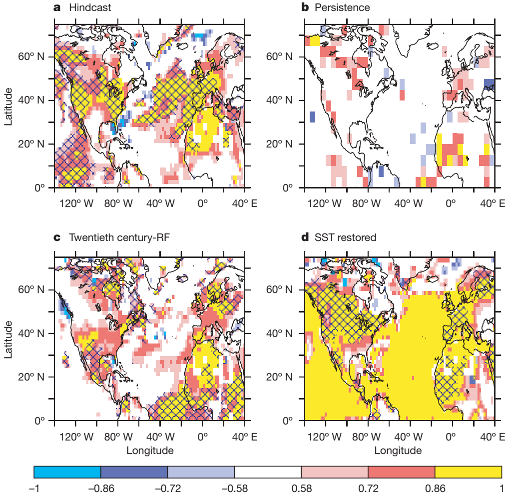
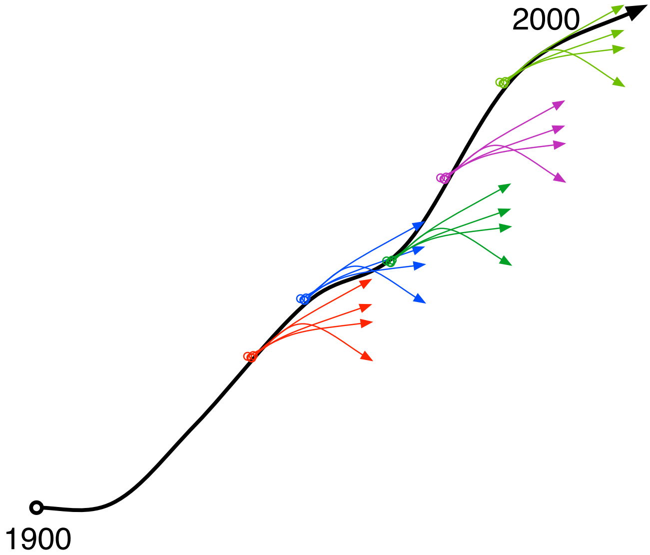
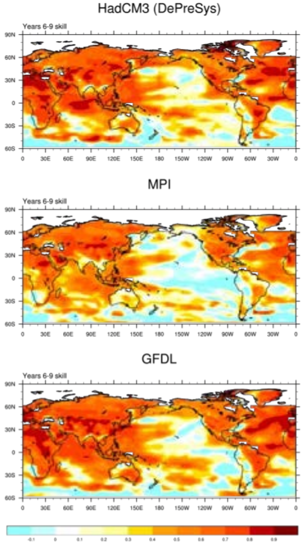


Figure: Correlation skill in predicting observed 10-year mean surface temperature anomalies a decade in advance for 9 ICs during 1955-2005.

CMIP5 Decadal Hindcast Experiments



Skill of CMIP5 Decadal Predictions



from fig. 2 of Newman (2012)

Empirical Predictions

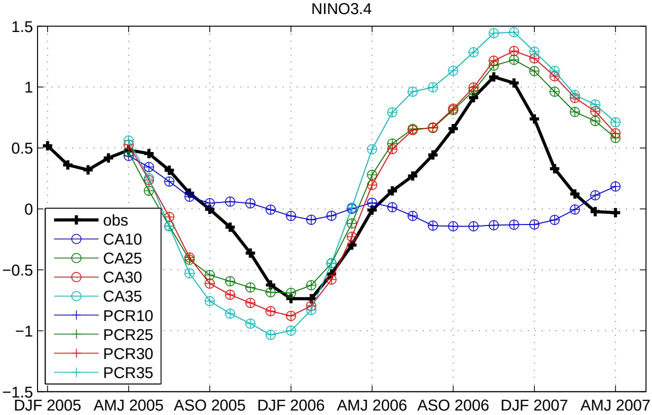
- Empirical predictions avoid many of the problems faced by dynamical models. For example:
  - They avoid "initialization shock" and "climate drift".
  - They do not require a dynamically complete state vector.
- Empirical predictions are easier than dynamical predictions
- On decadal time scales, much predictability comes from slowly varying anomalies, which can be predicted by empirical models.
- Predictability of linear models can be diagnosed in ways that nonlinear models cannot.

Models in Empirical Decadal Prediction

persistence	$x_{t+\tau} = x_t$
pointwise regression	$x_{t+\tau} = \beta_\tau x_t$
linear inverse model (LIM)	$\mathbf{x}_{t+\tau} = \mathbf{L}^\tau \mathbf{x}_t$
multivariate linear regression	$\mathbf{x}_{t+\tau} = \mathbf{L}_\tau \mathbf{x}_t$
constructed analogue	$\mathbf{x}_{t+\tau} = \sum_{n \in \text{training}} w_n \mathbf{x}_{n+\tau}$

Surprise!

Standard implementations of the constructed analogue method give forecasts that are the same as linear regression.



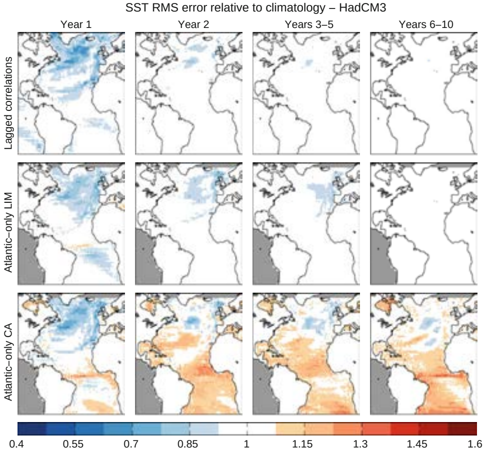
Tippett and DelSole (2012)

Skill of Constructed Analogue for NINO3.4

EOFs	10	25	30	35
correlation (CV)	0.51	0.29	0.22	0.12
variance fraction (CV)	0.51	1.18	1.66	2.45

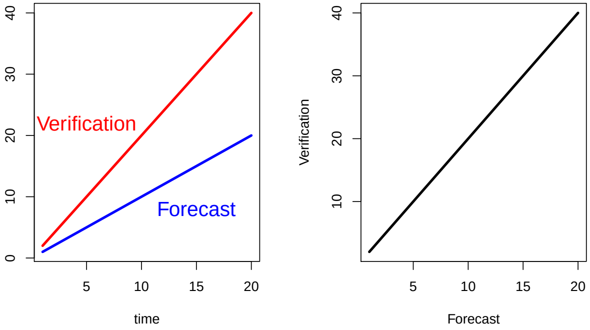
forecasts made in the beginning of July for the following March-May average (lead-8) of the NINO34 index during the period 1955-2003.

Predictions of Simulated SST (Hawkins et al. 2011)



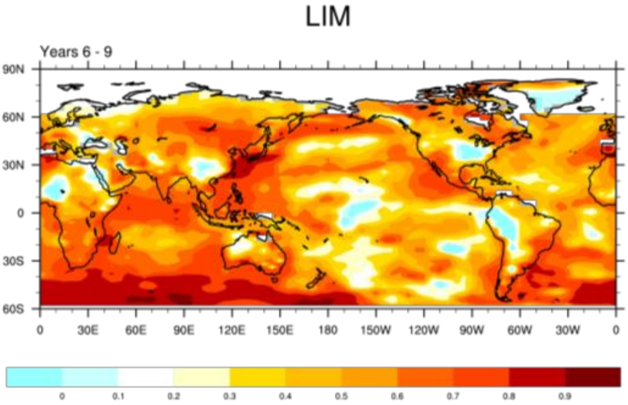
- **L** estimated from 7 EOFs of 140 years pre-industrial control.
- CA estimated 140 years of PiCNTRL, all grid points
- 10-year prediction based on preceding 140 year training data.
- Predictability of Pacific SST limited to under two years.

Correlation Skill



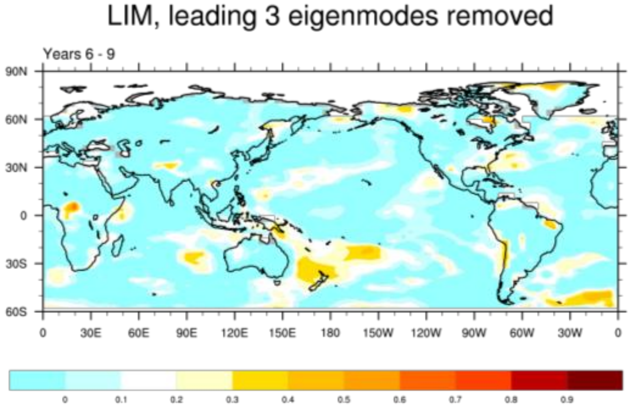
Correlation skill is 1 (perfect!). MSE grows quadratically with time.

Multi-Year Predictions of Observed SST (Newman 2012)



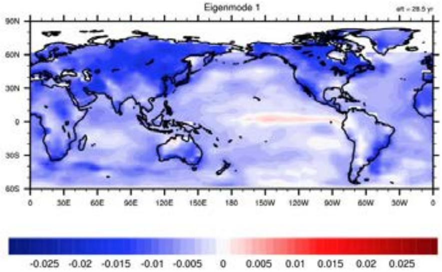
- correlation skill of surface temperature for leads 6-9 years
- 8, 6, 6 EOFs of IndoPacific, Atlantic, land surface temperature
- **L** from 1yr lagged 1900-2009 HadISST data ("observations").
- Leave-10-out cross validation.

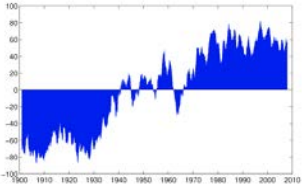
Diagnosis of LIM Predictability (Newman 2012)



$$\mathbf{x}_{t+\tau} = \mathbf{L}^{\tau}\mathbf{x}_t = \sum_k \lambda_k^{\tau}\mathbf{u}_k\left(\mathbf{v}_k^T\mathbf{x}_t\right)$$

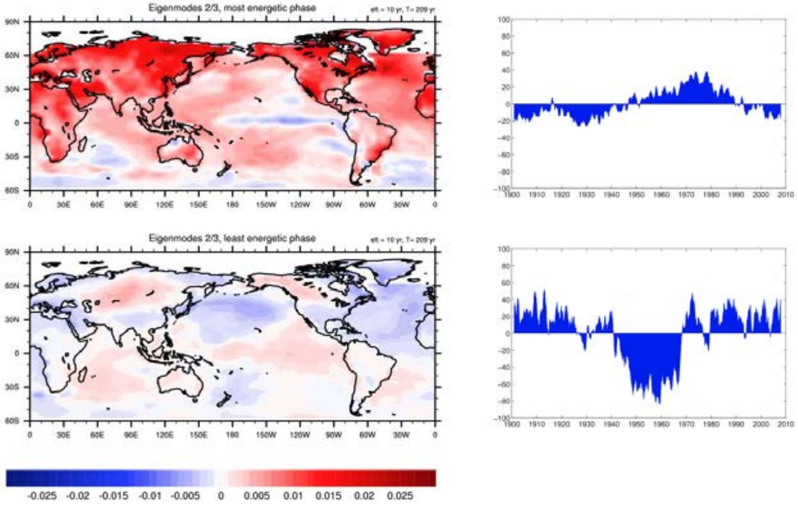
Least Damped Eigenmode of LIM (Newman 2012)





"Secular trend pattern"

Second Least Damped Eigenmode of LIM (Newman 2012)



most energetic phase: Atlantic decadal variability
least energetic phase: PDO when ENSO is removed

Empirical Decadal Predictions

- Newman (2007)
- Kruger and von Storch (2010)
- Hawkins et al. (2011)
- Zanna (2012)
- Newman (2012)
- DelSole, Jia, and Tippett (2012)

DelSole, Jia, and Tippett (2012)

Fit $\mathbf{L}_\tau$ to pre-industrial control runs, then predict observations.

- $\mathbf{L}_\tau$ is determined independently of observations (no artificial skill).
- Lots of data available (1500 years for training and verification)
- Regression model has skill only to the extent that dynamical models capture the correct space-time structure of observed variability.
- Regression model fitted to 20 EOFs from 8 CMIP5 control runs

Predictions of Observed SST (DelSole, Jia, Tippett 2012)

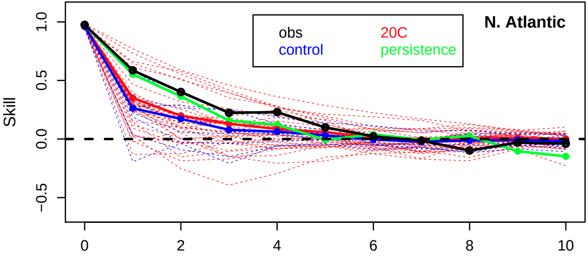
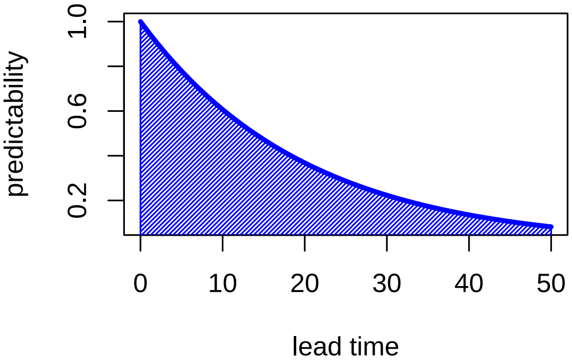


Figure: Skill for observed **unforced** N. Atlantic SST during 1910-2004.

Red: Predict independent twentieth century runs
Blue: Predict independent pre-industrial control runs
Green: Persistence
Black: Predict observed **unforced** anomalies

Average Predictability Time (APT)



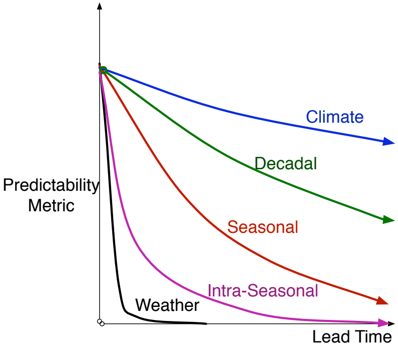
$$APT = 2 \int_0^\infty \left(\frac{\sigma^2_{clim} - \sigma^2_{forecast}(\tau)}{\sigma^2_{clim}} \right) d\tau$$

DelSole and Tippett (2009a, 2009b)

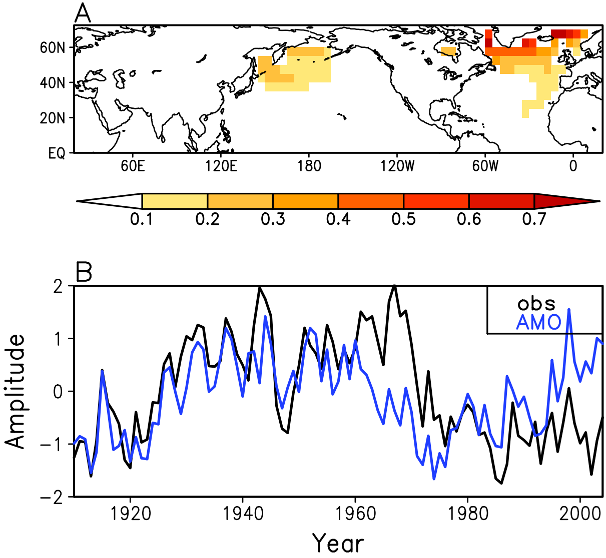
Decomposing Predictability

Find components that maximize APT (DelSole and Tippett 2009).

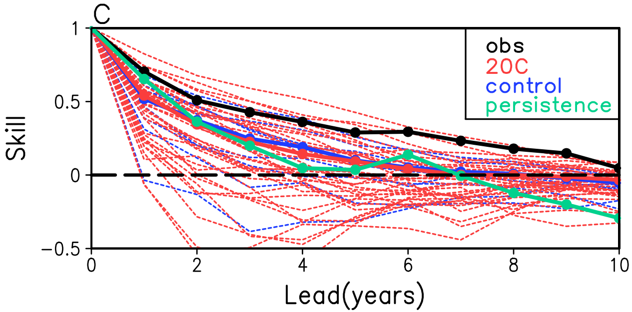
$$APT = 2\int_0^\infty \left(\frac{\sigma^2_{clim} - \sigma^2_{forecast}(\tau)}{\sigma^2_{clim}} \right) d\tau$$



Most Predictable Component in CMIP5 Pre-industrial Control Runs

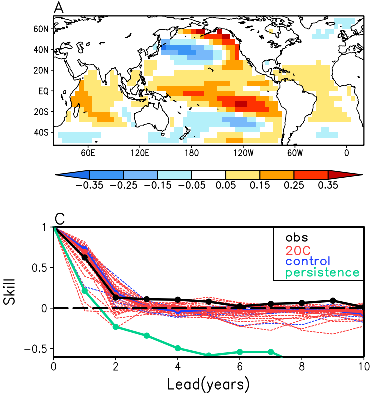


Skill in Predicting the Most Predictable Component in Observations (1910-2004).

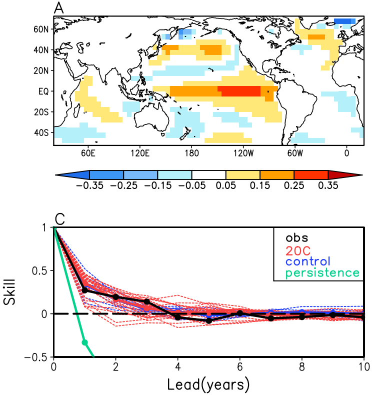


2nd and 4th Predictable Components

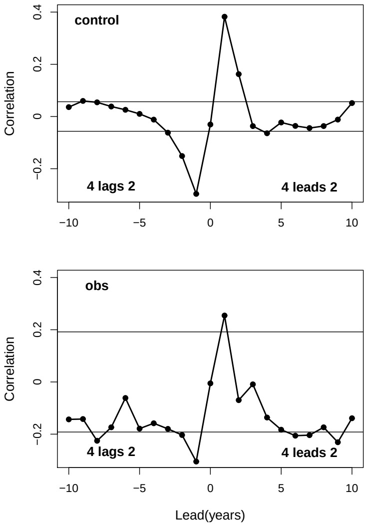
2nd PrC (PDO)



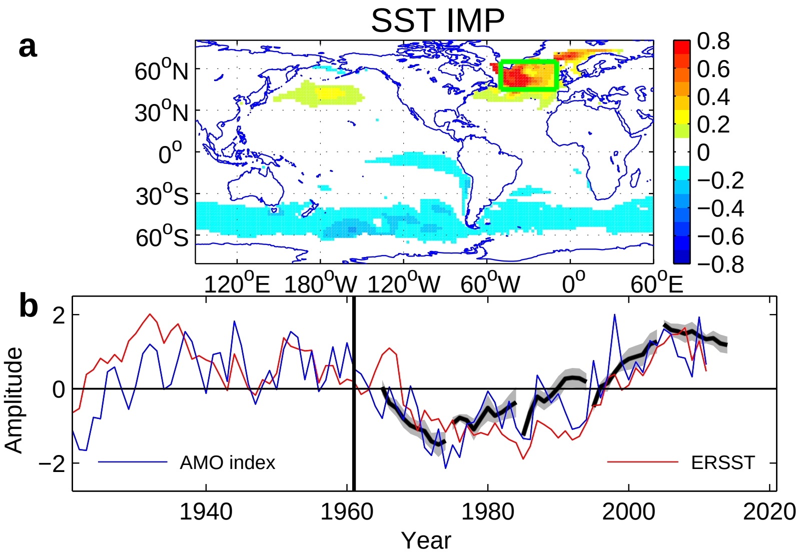
4th PrC



Coupling between 2nd and 4th Predictable Components



Decadal Experiments with GFDL Model (Yang et al. 2012)



Can the IMP and forced response be distinguished?

Fingerprinting Method

Fit observed annual average SST to

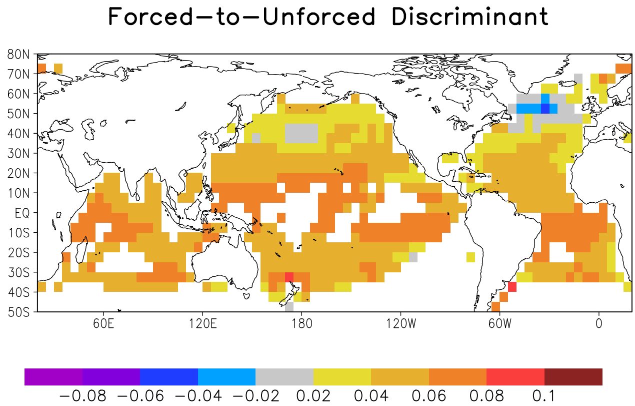
$$\underbrace{T_{obs}(x,y,t)}_{\textit{Observed}} = \underbrace{a_{for}(t)\,T_{for}(x,y)}_{\textit{Forced Response}} + \underbrace{a_{imp}(t)\,T_{imp}(x,y)}_{\textit{Internal Pattern}} + \underbrace{w(x,y,t)}_{\textit{Random Noise}}$$

Detection: Test hypothesis $a_{for}(t) = 0$.

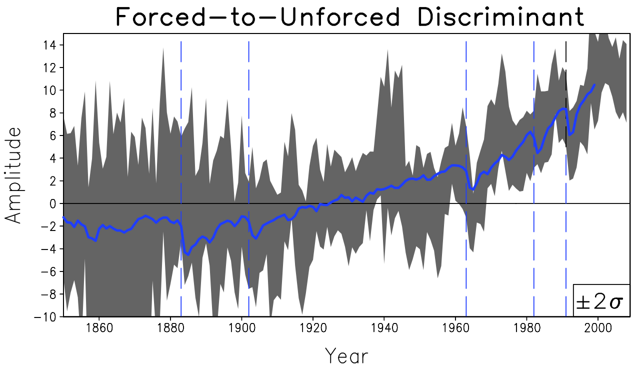
Attribution: Test hypothesis $a_{for}(t) =$ predicted amplitude.

Forced-to-Unforced Discriminant

Find the pattern $T_{for}(x,y)$ that maximizes detectability in models (Jia and DelSole 2012).



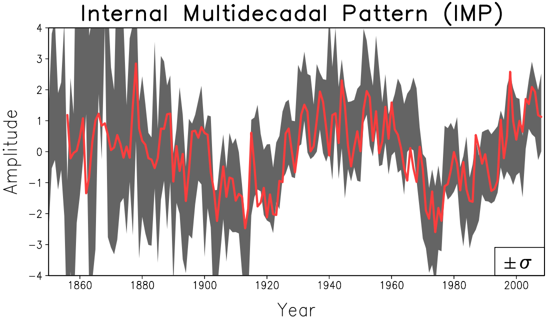
Forced Pattern



shaded area: 95% confidence interval of forced pattern in observations.

blue line: Ensemble mean amplitude of forced pattern in models

Project Most Predictable Pattern Onto Observations



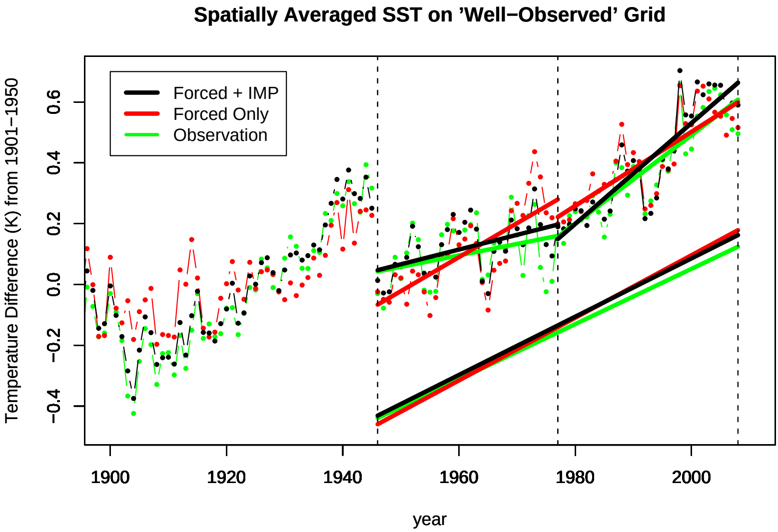
shaded area: 66% confidence interval of IMP in observations.

red line: Observed Atlantic Multidecadal Oscillation (AMO) index.

Unforced climate models naturally simulate a multi-decadal component very similar to the AMO.

DelSole, Tippett, and Shukla (2011)

Global Mean Sea Surface Temperature



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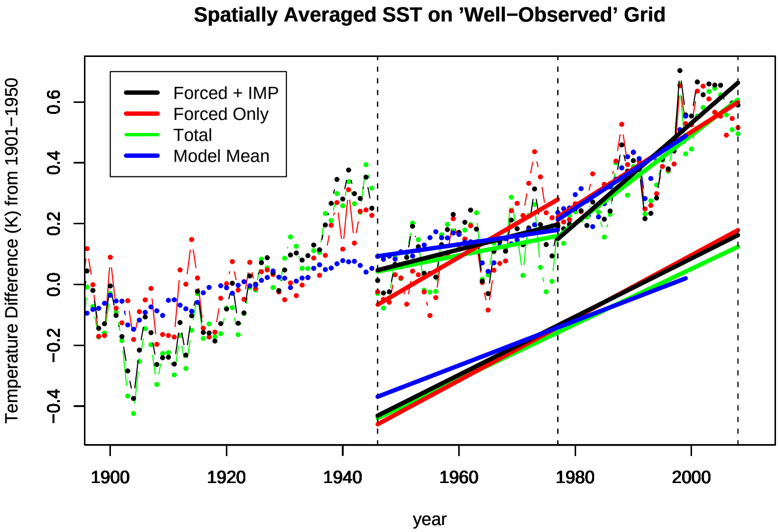

Summary

- Both dynamical and empirical models can skillfully predict SSTs on multi-year time scales.
- Linear models can be decomposed into components that explain skill.
- Unforced climate models naturally simulate a multi-decadal component very similar to the AMO.
- Empirical model derived from dynamical models show skill of predicting certain components of annual mean SST up to 9 years.
- Recent decadal predictions show hindcast skill in N. Atlantic.