Decadal prediction: pain and potential

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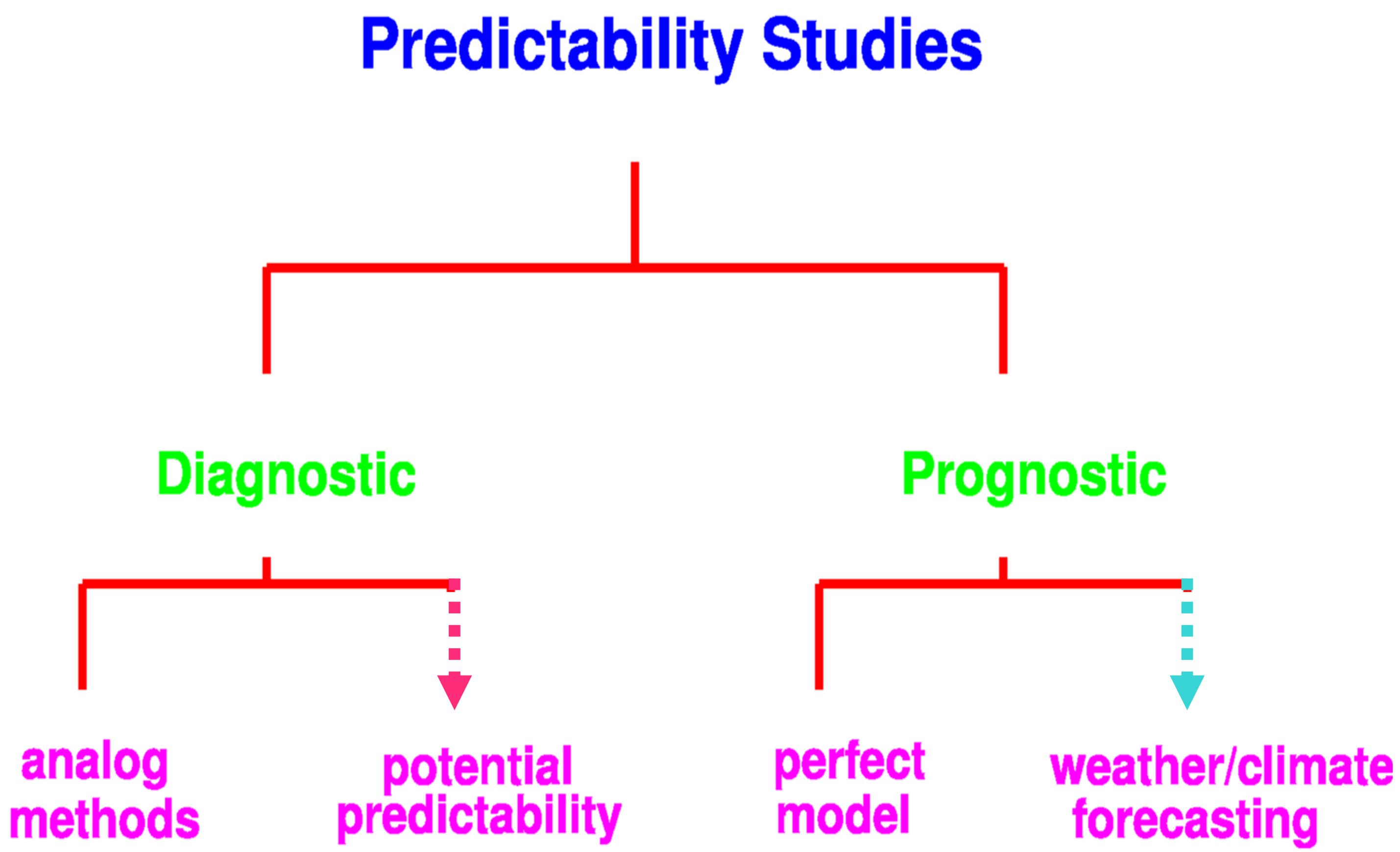
Topics

- Potential predictability and skill
- Realizing the potential
  - Initialization and integrations
  - Bias correction
  - Some basic results
- What have we learned


Predictability Studies
Diagnostic
Prognostic
analog methods
potential predictability
perfect model
weather/climate forecasting

Predictability and prediction

- predictability
  - a characteristic of a *physical system* itself
  - a measure of the *rate of separation* of *initially close* states
  - indicates the *possibility of prediction*
- prognostic predictability studies
  - typically use model to simulate “rate of separation”
  - presumption that the model “similar enough” to real system
  - model is not perfect but code characterizes it “perfectly”
- *forecast skill*
  - characterized by *error growth* rate, decorrelation, or other measure (rate of separation of actual and predicted states)
  - indicates the current *ability to predict*
- *potential predictability*
  - analysis of variance measure
  - identifies regions where *long timescale variance* is a useful fraction of the total
  - meant to indicate that prediction is *potentially possible*
  - *upper limit* of skill (if known from observations)

How do we determine the *predictability* and *forecast skill* of the system on decadal timescales?

- Prognostic perfect model predictability studies
  - Griffies and Bryan (1997)
  - Boer (2000)
  - Collins (2002)
  - Collins et al. (2006)
  - Latif et al., (2006)
  - Branstator et al. (2010)
  - and others
- Diagnostic potential predictability studies
  - Boer (2000, 2004)
  - Pohlmann et al. (2004)
  - Predicate (2004…)
  - Boer and Lambert (2008)
  - and others
- Investigations of forecast skill
  - Smith et al. (2008)
  - Keenlyside et al. (2008)
  - Pohlmann et al. (2009)
  - CMIP5/IPCC (2013)


and decadal prediction
Climate Change 2013
The physical and biophysical basis

Decadal predictability and prediction

- potential predictability p
  - skill measures and *p*
  - multi-model estimates of *p*
- CCCma DHFP (decadal historical forecasting project)
  - approach
  - “bias correction”
  - forecast skill
- implications

Statistics of the ***internally generated*** component

- Model control runs - no external forcing
- Variable X is expressed as

$$X = \mu + \chi + x$$

- μ is the mean
- χ is the long timescale *internally generated* component, presumed to be at least partially predictable
- x is the short timescale *"noise"* component which is unpredictable on the timescale considered

- Associated variances are

$$\sigma^2_X = \sigma^2_\chi + \sigma^2_x$$

- Potential predictability variance fraction (*ppvf*) is

$$p = \sigma^2_\chi / \sigma^2_X = \sigma^2_\chi / (\sigma^2_\chi + \sigma^2_x)$$

Potential predictability statistics

- Internally generated variability
  - Observations: $X = \mu + \chi + x$
  - Forecasts: $Y = \nu + \psi + y$

- Statistics
  - variances: $\sigma^2_X = \sigma^2_\chi + \sigma^2_x$

    $\sigma^2_Y = \sigma^2_\psi + \sigma^2_y \Rightarrow \sigma^2_\psi + \sigma^2_y/N$ for ensemble mean

  - potential predictability variance fractions (ppvf)

    $p_\chi = \sigma^2_\chi / \sigma^2_X$ for observations

    $p_\psi = \sigma^2_\psi / \sigma^2_Y$ for model

    $\Rightarrow 1$ with $\sigma^2_y/N \Rightarrow 0$ for large ensemble-average

  - covariances: $\mathrm{cov}(XY) = \sigma_\chi \sigma_\psi R_{\chi\psi}(\tau)$

    for $R_{\chi\psi}(\tau)$ the correlation of χ, ψ at forecast range τ

Connection of *p* with skill

- Correlation skill

$r_{XY}(\tau) = \mathrm{cov}(XY)/\ \sigma_X \sigma_Y$

$= \sigma_\chi \sigma_\psi R_{\chi\psi}(\tau)/\ \sigma_X \sigma_Y = (p_\chi\, p_\psi)^{1/2} R_{\chi\psi}\ (\tau)$

$\Rightarrow\ p_\chi R_{\chi\psi}\ (\tau)$

- for "good model" ($\sigma_\chi = \sigma_\psi$, $\sigma_x = \sigma_y$) single forecast

$\Rightarrow p_\chi^{\ 1/2} R_{\chi\psi}\ (\tau)$

- large ensemble-mean forecast ($\sigma^2_{\ y}$ /N => 0, p_ψ => 1)

$\Rightarrow p_\chi^{\ 1/2}$ for a "perfect" model with (p_ψ, $R_{\chi\psi} = 1$)

- Other skill measures also depend on *p*
  - Mean square error m

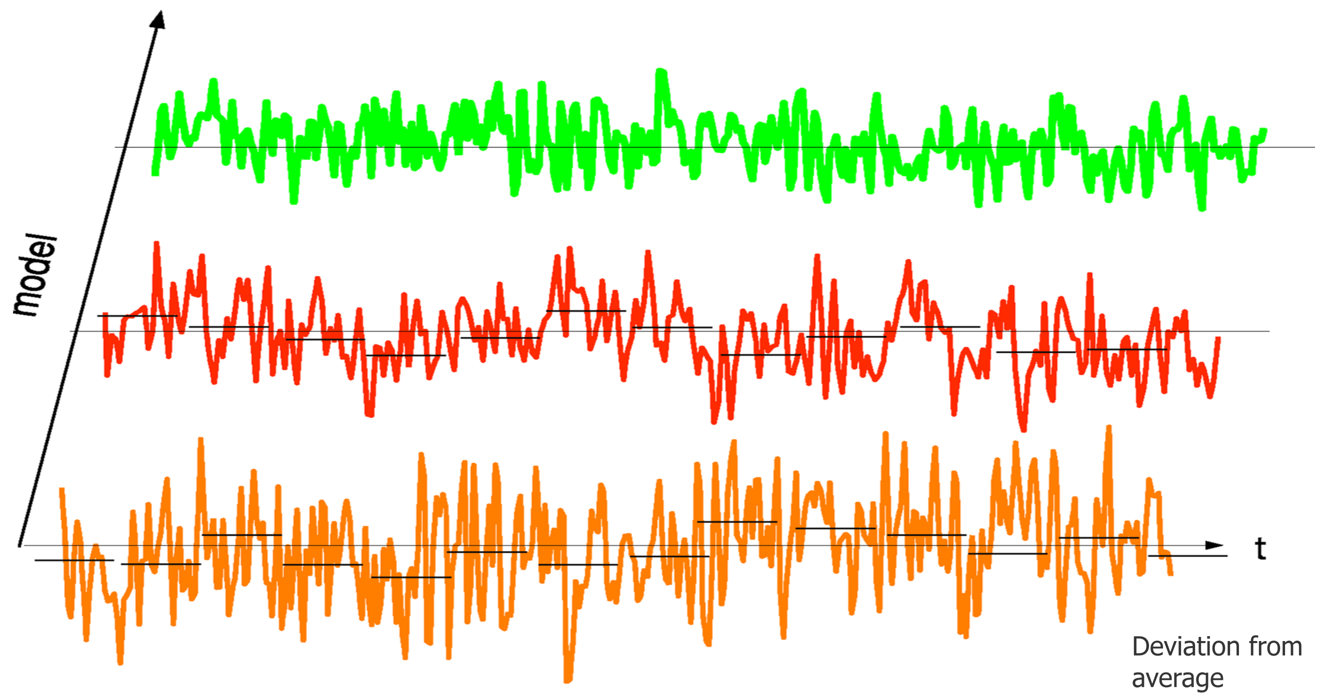
$m_{XY}(\tau) = \sigma^2_{\ \chi} + \sigma^2_{\ \psi} - 2\,\sigma_\chi \sigma_\psi R_{\chi\psi}\ (\tau) + (\sigma^2_{\ x} + \sigma^2_{\ y})$

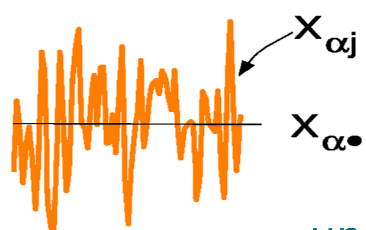
$=> 2\sigma^2_X(1 - p_\chi R_{\chi\psi}\ (\tau))$ for good model single forecast

  - Mean square skill score M

$M_{XY}(\tau) => 2p_\chi R_{\chi\psi}\ (\tau) - 1$ for good model single forecast

Multi-model *estimate* of *internally generated* long timescale potential predictability p_χ





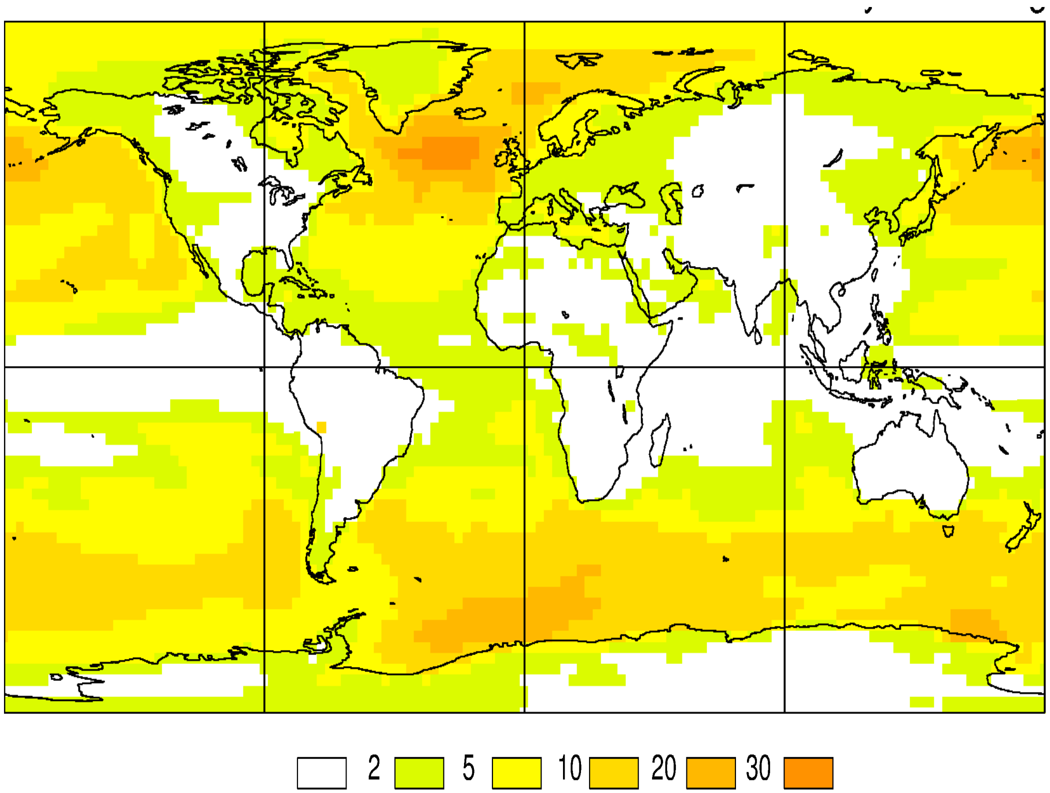
$$X(t) = X_{\alpha\bullet} + (X_{\alpha j} - X_{\alpha\bullet})$$

$$\sigma^2 = \sigma^2_\chi + \sigma^2_x$$

unbiased estimates
statistical *stationarity*

Temperature: potential predictability of *internally generated* variability $p_\chi = \sigma^2_\chi/\sigma^2$ (%) for *decadal means (CMIP3 multi-model control runs)*

- Ratio of long timescale to total variance
- MME provides stability of statistics: *ppvf* in white areas <2% and/or not significant at 98% level
- Long timescale predictability found mainly over oceans
- Some incursion into land areas but modest *ppvf* (*denominator* is large)



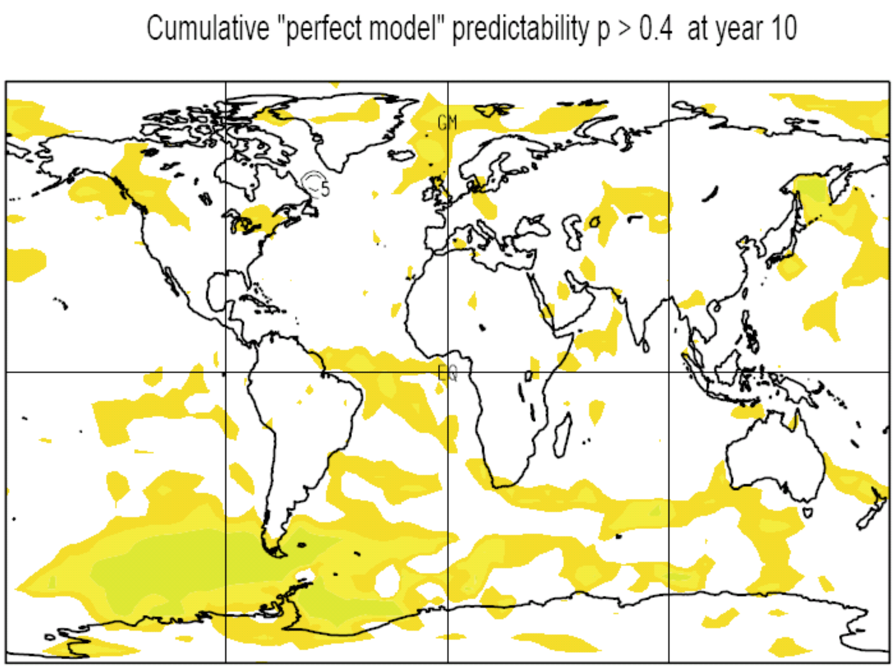
Control simulations

Boer and Lambert, 2008

Long-timescale prognostic predictability study

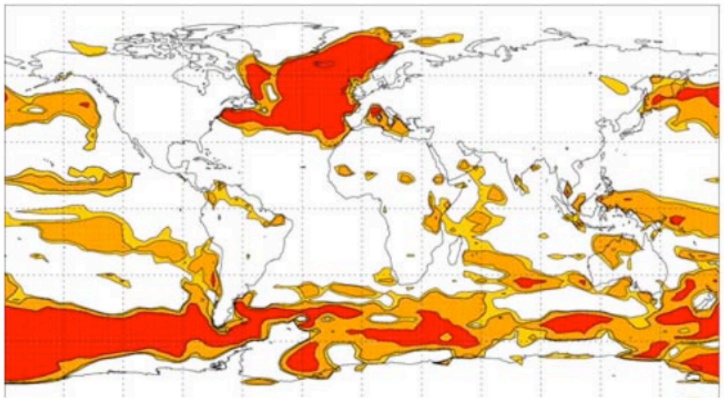
- Initial "perfect model" predictability estimates from CCCma model
- Only 3-member ensemble

Decadal ***perfect model*** predictability

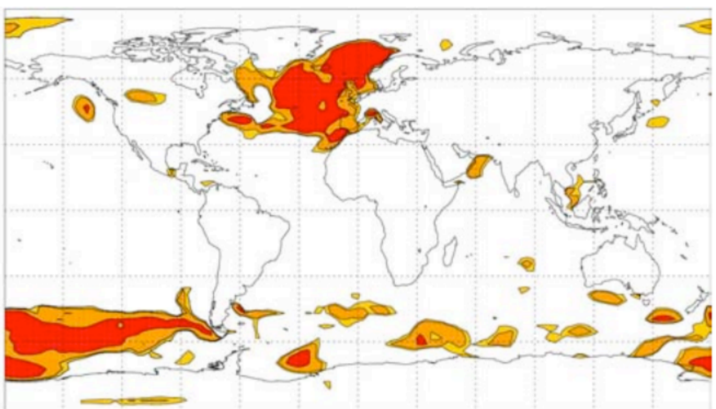


Boer,2000: Clim Dyn

years 1-5

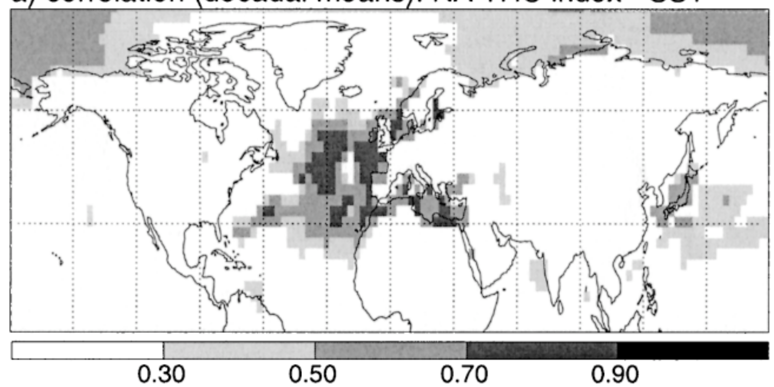


years 6-10

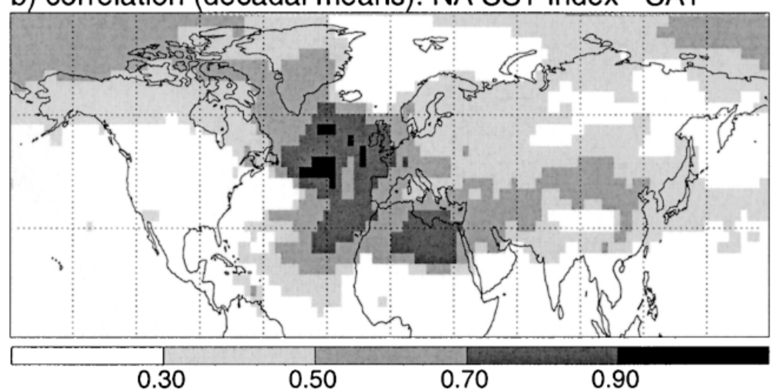


perfect model
predictability measure

a) correlation (decadal means): NA THC index - SST



b) correlation (decadal means): NA SST index - SAT

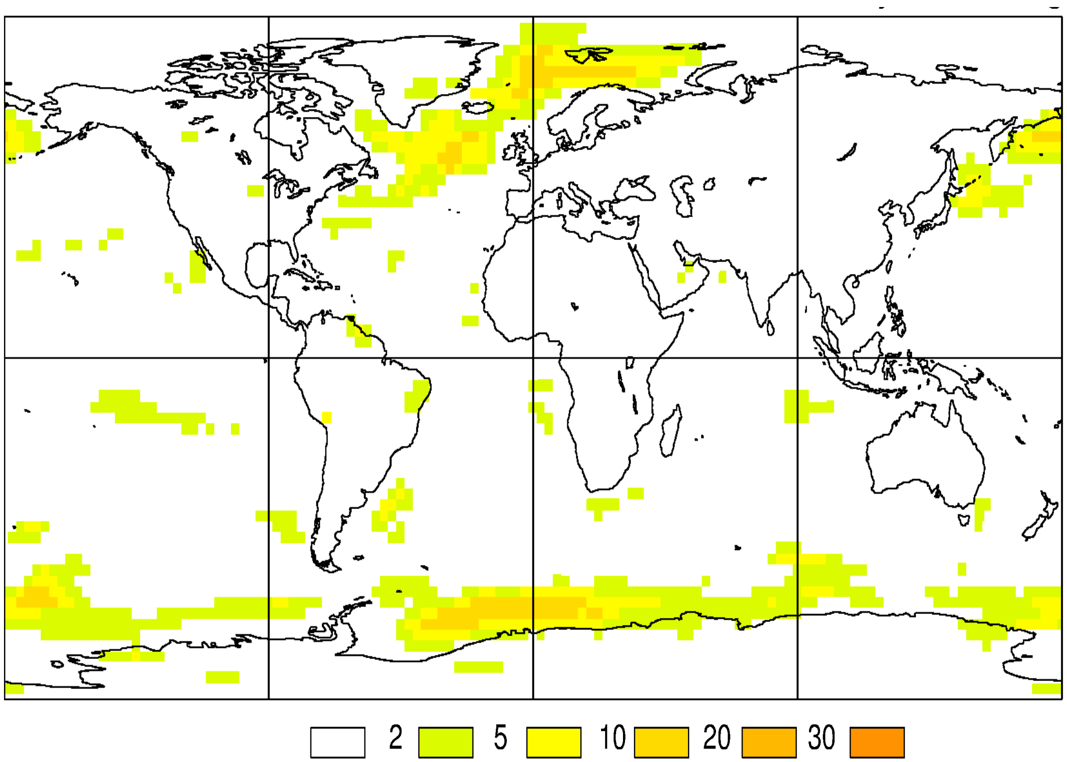


North Atlantic

Pohlmann et al. 2004

Precipitation: potential predictability of internally generated variability $p_\chi = \sigma^2_\chi/\sigma^2$ (%) for decadal means

-MME provides "some" significant areas of precipitation
-Much less potentially predictable than temperature
- Little incursion into land areas
- Precipitation predictability a weakened version of temperature predictability at these timescales



21st Century decadal potential predictability

- Variable now has forced component

$$X = \mu + \Theta + \chi + x$$

with associated variances

$$\sigma^2 = \sigma^2_\Theta + \sigma^2_\chi + \sigma^2_x$$

- Θ is long timescale *externally forced* variability
- χ is long timescale *internally generated* variability
- x is short timescale *unpredictable "noise"* variability
- statistics pooled across models

- Potential predictability variance fraction now has two components

$$p = (\sigma^2_\Theta + \sigma^2_\chi)/\sigma^2 = p_\Theta + p_\chi$$

Forced plus internally generated case

- Variability
  - Observations: $X = \mu + \Theta + \chi + x$
  - Forecasts: $Y = \nu + \Phi + \psi + y$

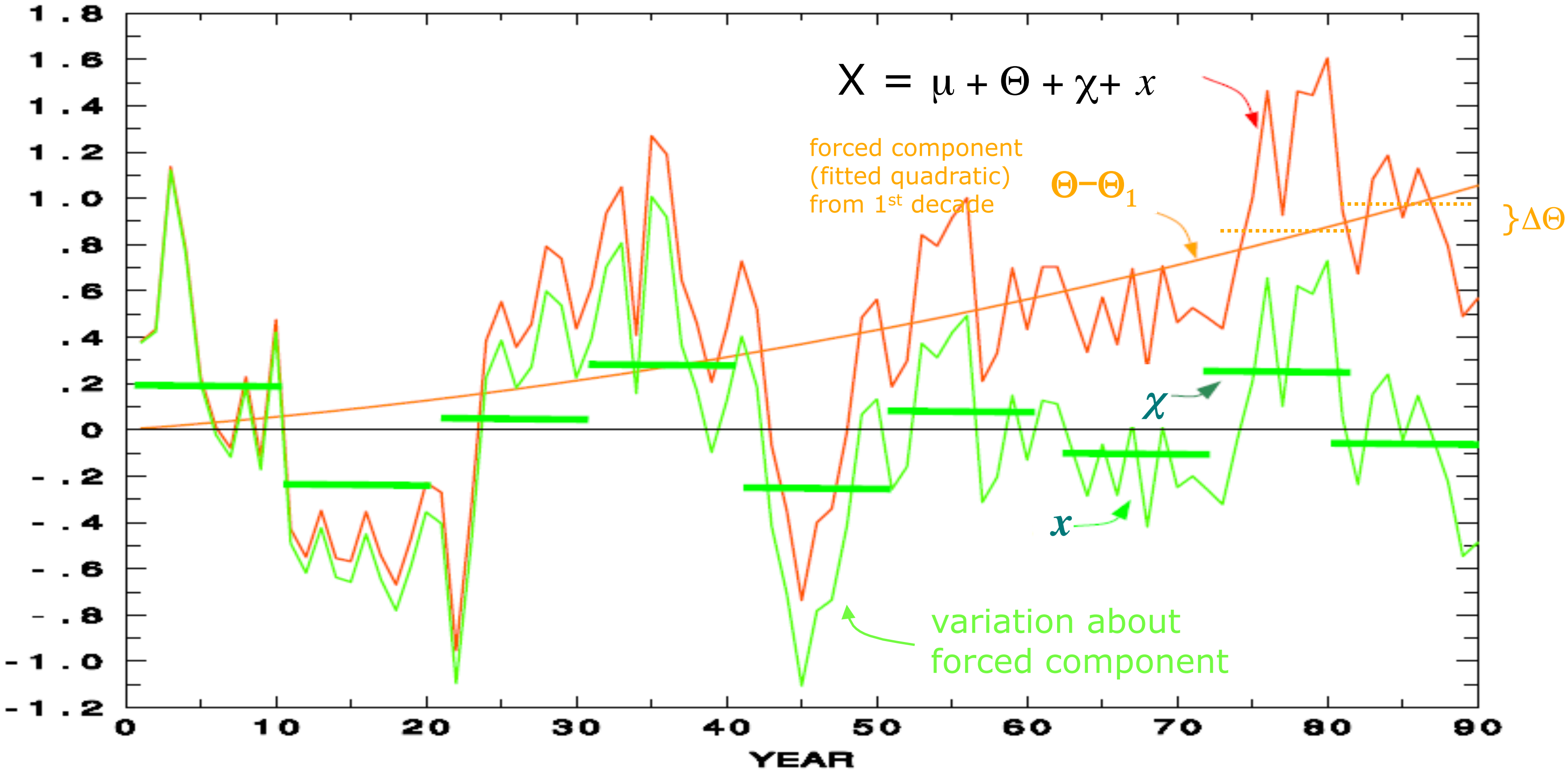
- Statistics:
  - variances: $\sigma^2_X = \sigma^2_\Theta + \sigma^2_\chi + \sigma^2_x$
    $\sigma^2_Y = \sigma^2_\Phi + \sigma^2_\psi + \sigma^2_y$
  - potential predictability for *forced* and *internally generated* components
    $p_X = (\sigma^2_\Theta + \sigma^2_\chi)/\sigma^2_X = p_\Theta + p_\chi$ for observations
    $p_Y = (\sigma^2_\Phi + \sigma^2_\psi)/\sigma^2_Y = p_\Phi + p_\psi$ for model
  - Correlation skill
    $r_{XY}(\tau) = \sigma_\Theta \sigma_\Phi R_{\Theta\Phi}(\tau)/\sigma_X \sigma_Y + \sigma_\chi \sigma_\psi R_{\chi\psi}(\tau)/\sigma_X \sigma_Y$
    $= (p_\Theta p_\Phi)^{1/2} R_{\Theta\Phi}(\tau) + (p_\chi p_\psi)^{1/2} R_{\chi\psi}(\tau)$

    $\Rightarrow p_\Theta^{\,1/2} R_{\Theta\Phi}(\tau) + p_\chi^{\,1/2} R_{\chi\psi}(\tau)$ for "good model, large-ensemble" forecast

    - forced contribution favoured
      - $R_{\Theta\Phi} = 1$ for linear trend
      - σ^2_Θ large hence p_Θ large for skill over a long forecast period (1961-2010)
      - applies also to forecasts

21st century temperature at a point

- forced component from 1st decade

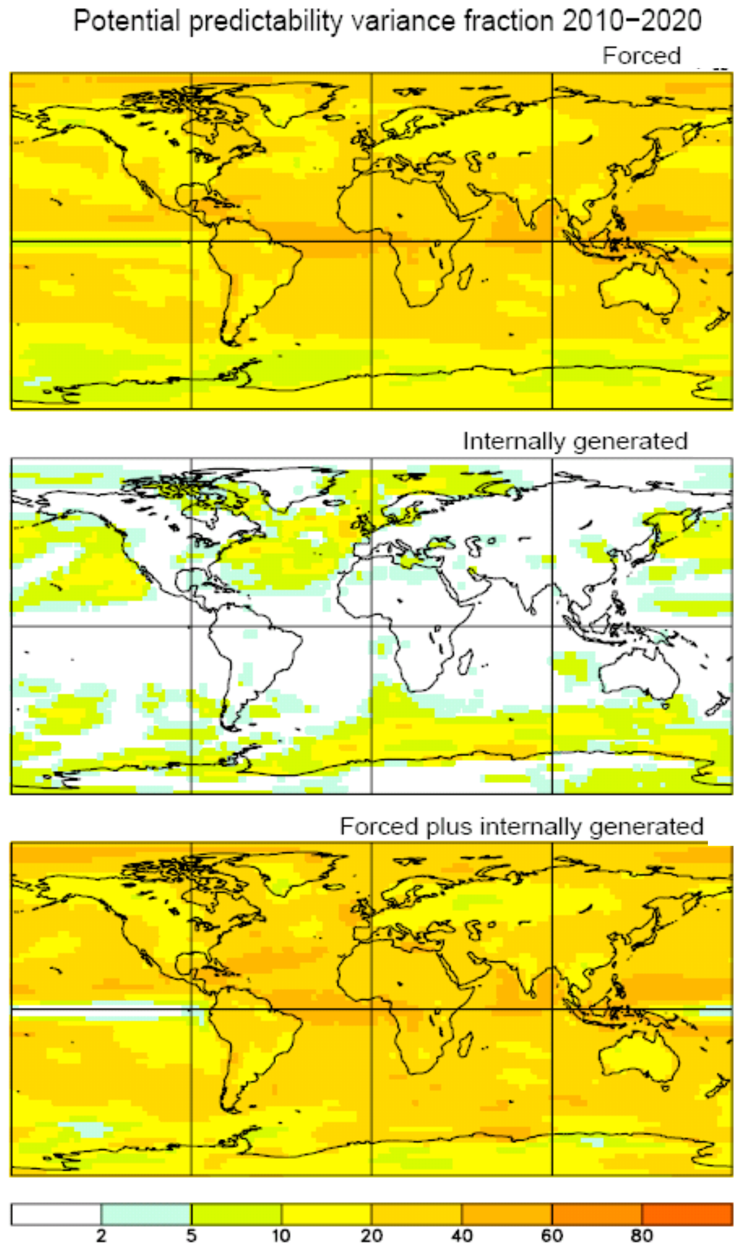


$$\sigma_1^{\,2} = \sigma^2_{\Theta 1} + \sigma^2_{\chi} + \sigma^2_{x} \quad \text{multi-decade}$$

$$\sigma_\Delta^{\,2} = \sigma^2_{\Delta\Theta} + \sigma^2_{\chi} + \sigma^2_{x} \quad \text{next-decade}$$

MME (CMIP) *next decade* potential predictability of Temperature for the 21st century

- $p_\Theta = \sigma^2_\Theta/\sigma^2$
  - *forced component* large over land
  - but *discounted* because noise is large
- $p_\chi = \sigma^2_\chi/\sigma^2$
  - internally generated component
  - largest over high latitude oceans
- $p = p_\Theta + p_\chi$
  - *low, mid-latitude land*
  - *oceans excluding equatorial Pacific*



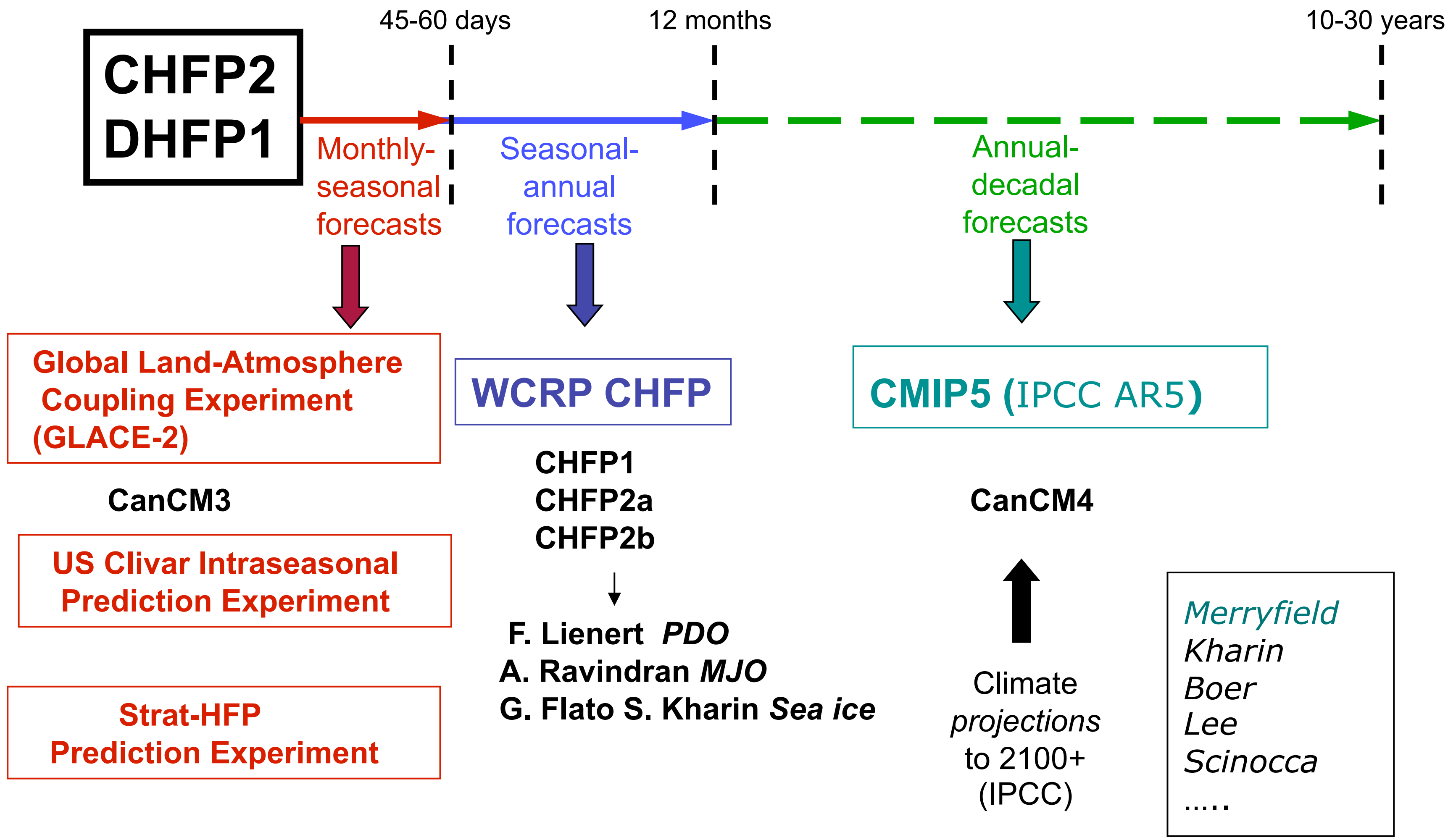
Boer, 2010

- In light of the potential predictability:
  - what are current "forecast skill" levels?
  - do they reflect the "potential predictability"?

Decadal predictability and prediction

- potential predictability
  - skill measures and *p*
  - multi-model estimates of *p*
- CCCma's DHFP (decadal historical forecasting project)
  - approach
  - "bias correction"
  - forecast skill
- implications

CCCma (seamless) Predictions



CanCM4 model components

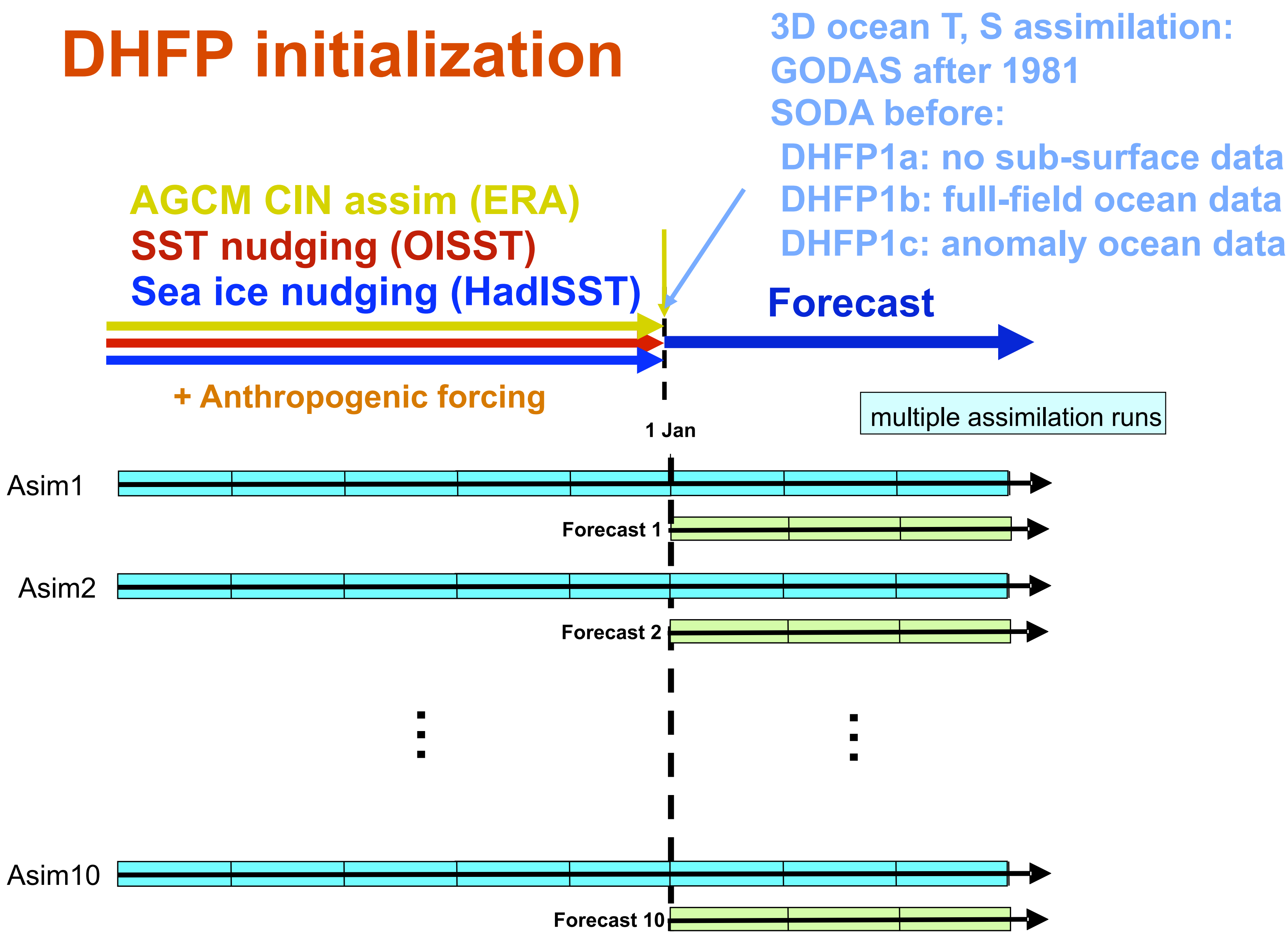
- AGCM and OGCM new since AR4
- **CanAM4**
  - T63/L35
  - new shallow convection, radiation, aerosols…
  - includes "natural" volcanic & solar forcings
- **CanOM4**
  - 1.41°×0.94°× L40 (Δz~10m near surface)
  - GM stirring, KPP + tidal vertical mixing, anisotropic viscosity
  - solar penetrative heating according to climatological chlorophyll
- Earth-system version CanESM2 used for long-term AR5 simulations

Decadal Historical Forecasting Project

		DHFP1A	DHFP1B	DHFP1C
Model		**CanCM4 (AGCM4+OGCM4)**		
Initialization	atmos	**IRU/CIN assim**		
	ocean	**Nudge to SST**	**+2Dvar assim with S-correction (full field)**	**+2Dvar assim with S-correction (anomaly)**
	sea ice	**Nudge to obs.**		
Ensemble members		**10**		
Commencing dates		**1st Jan each year**		
Forecast duration		**10 years**		
Retrospective period		**1961 (every 5 years) 2010 (completed for 1a, 1b, 1c)** **1979 (every year) 2010 (1b only, completed)** **1961 (every year) 1978 (1b only, in progress)**		

DHFP1N: ensemble of 10 uninitalized “freecasts”

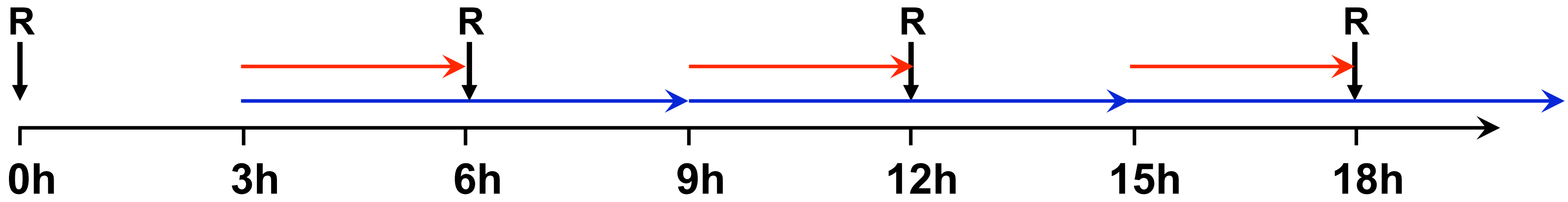
DHFP initialization



DHFP Atmospheric Data Assimilation

Incremental Reanalysis Update (IRU) assimilation:

- run model freely for 3h ("forecast")
- difference with reanalysis → "centered" increments $\Delta\mathbf{x}^a$
- rewind, rerun for 6h, adding analysis increments as forcing to model equations: $\boxed{\frac{d\mathbf{x}}{dt} = M(\mathbf{x}) + h(t)\Delta\mathbf{x}^{\mathbf{a}}}$



* To better reflect observational uncertainties in ensemble, "dial back" assimilation → ***constant incremental nudging (CIN)***

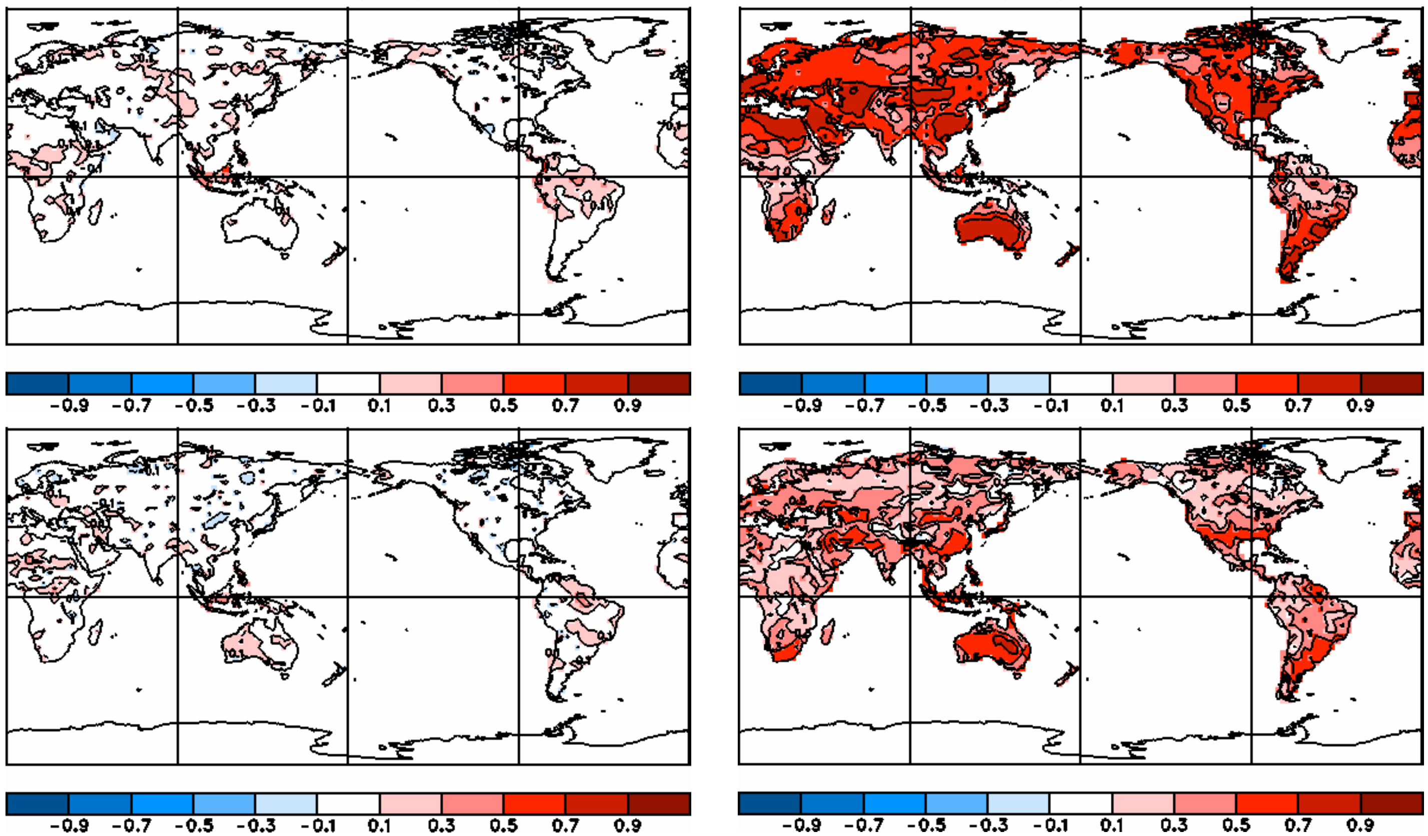
Benefits of IRU/CIN

- accurate AGCM initialization
    - essential for 1st month skill
- ensemble generation
- better land initialization
- better ocean initialization/ background state for assimilation

Due to "seeing" atmospheric forcing leading up to forecast

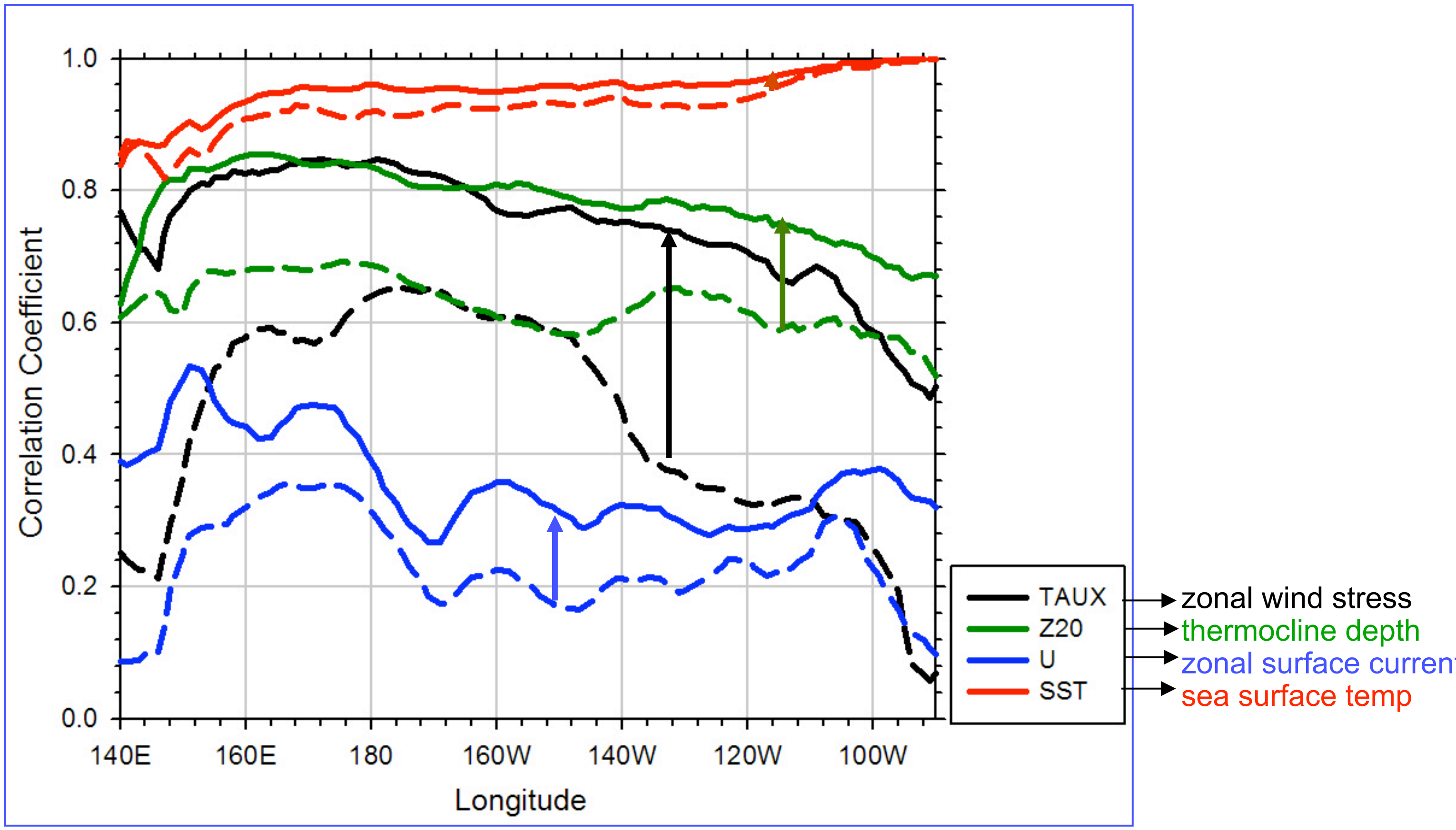
Impacts of AGCM assimilation on land initialization

Correlation of assimilation run vs Guelph offline analysis



Impacts of AGCM assimilation on ocean initialization vs nudging to SST

Correlations vs obs in equatorial Pacific (5S→ 5N)



SST nudging + IRU — — — — SST nudging only

Some initial results

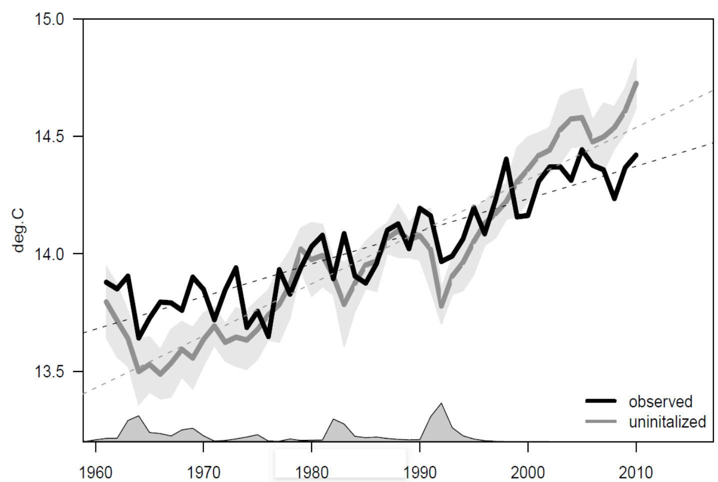
- *drift correction*
- results for
  - temperature
  - sea ice
  - MOC

Drift/bias correction

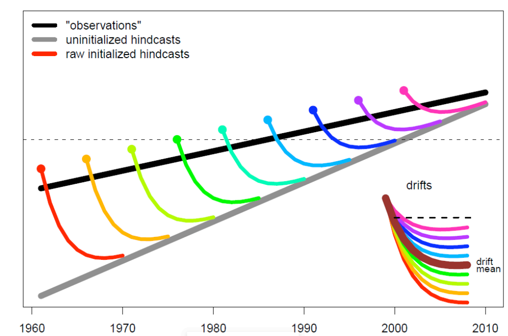
- models "drift" from the initial state toward model climate which differs from the observed
  - $Y(t_j,\tau)$ the forecasts with t_j the start times and τ the forecast range and $X(t_j,\tau)$ the corresponding observations
- the average "drift" is
  - $\Delta(\tau) = Y(\cdot,\tau) - X(\cdot,\tau)$ where the "dot" is the average over all the available start times t_j
- however, there are difficulties if there is a lack of stationarity in which case $\Delta = \Delta(t_j,\tau)$

Drift/bias correction and trend

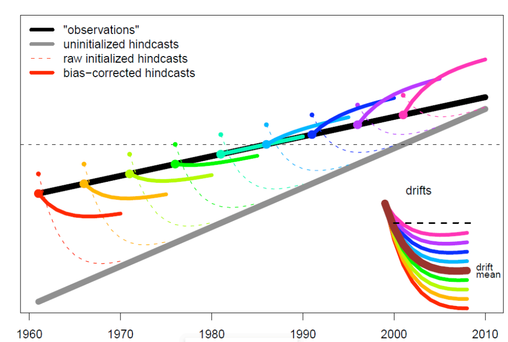
Global mean temperature



Schematic model drifts



Schematic model drifts - bias correction

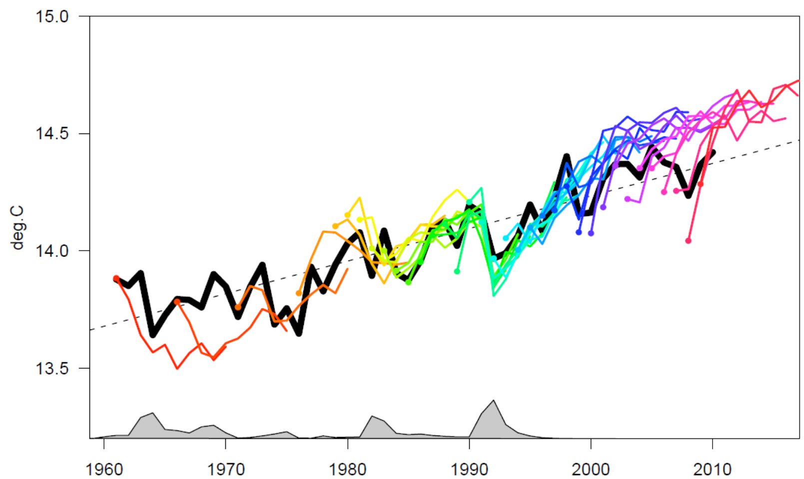


“standard” anomaly bias correction introduces systematic behaviour when model and observed trends are different

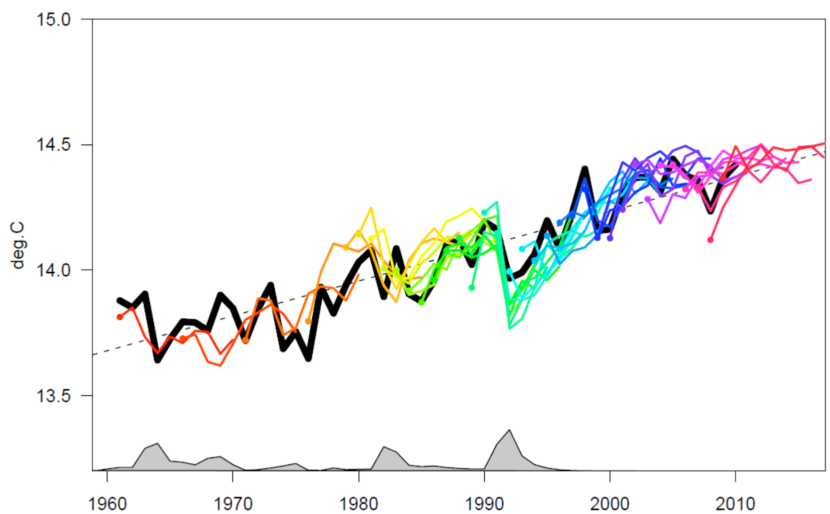
(S. Kharin)

Bias removal vs trend adjustment

Bias-adjusted decadal hindcasts



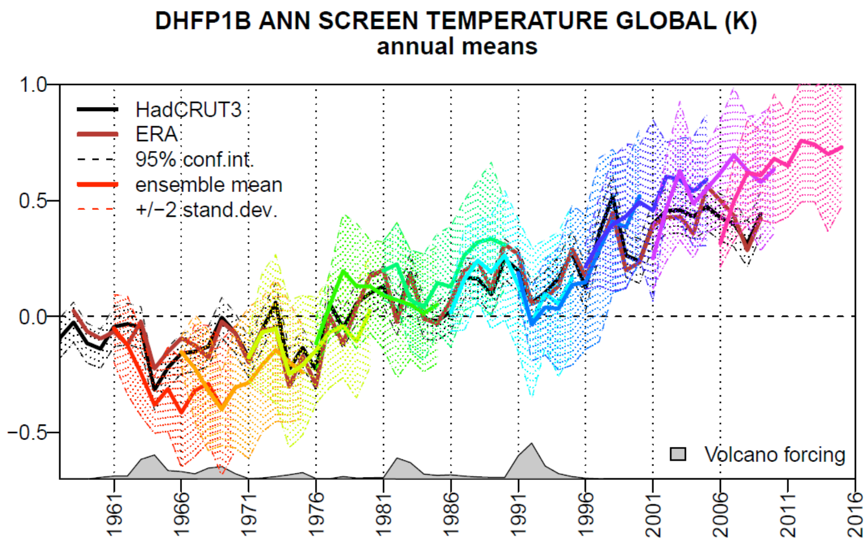
Trend-adjusted decadal hindcasts

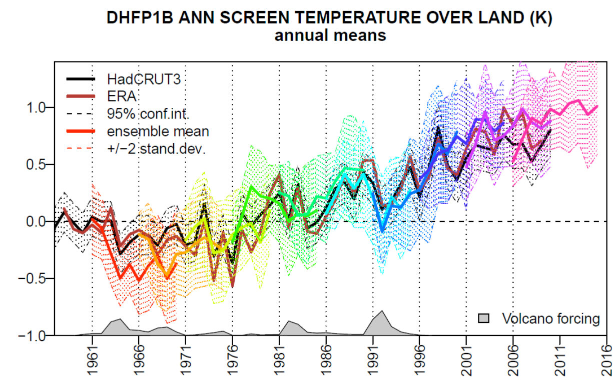


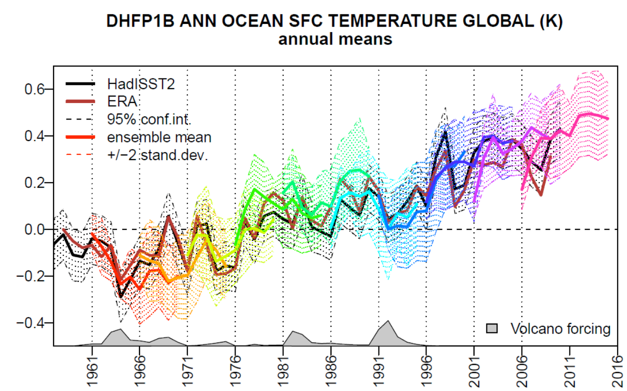
Drift/bias correction

- Generally need "correction" to make predictions useful (as in SIP)
- Non-stationarity/lack of cases adds difficulties
  - desirable to correct for "trend" but lack of data likely precludes this locally
  - serious risk of overfitting if you do anything other than basic bias correction
    - this can make "corrected" CMIP5 results untrustworthy and perhaps misleading
  - very little data involved in the standard CMIP5 case:
    - for forecasts every 5 years only 10 cases
    - ensembles and multi-model approaches don't help – still only 10 cases
    - forecasts every year would help (although they are not independent)

Some initial results for Temperature

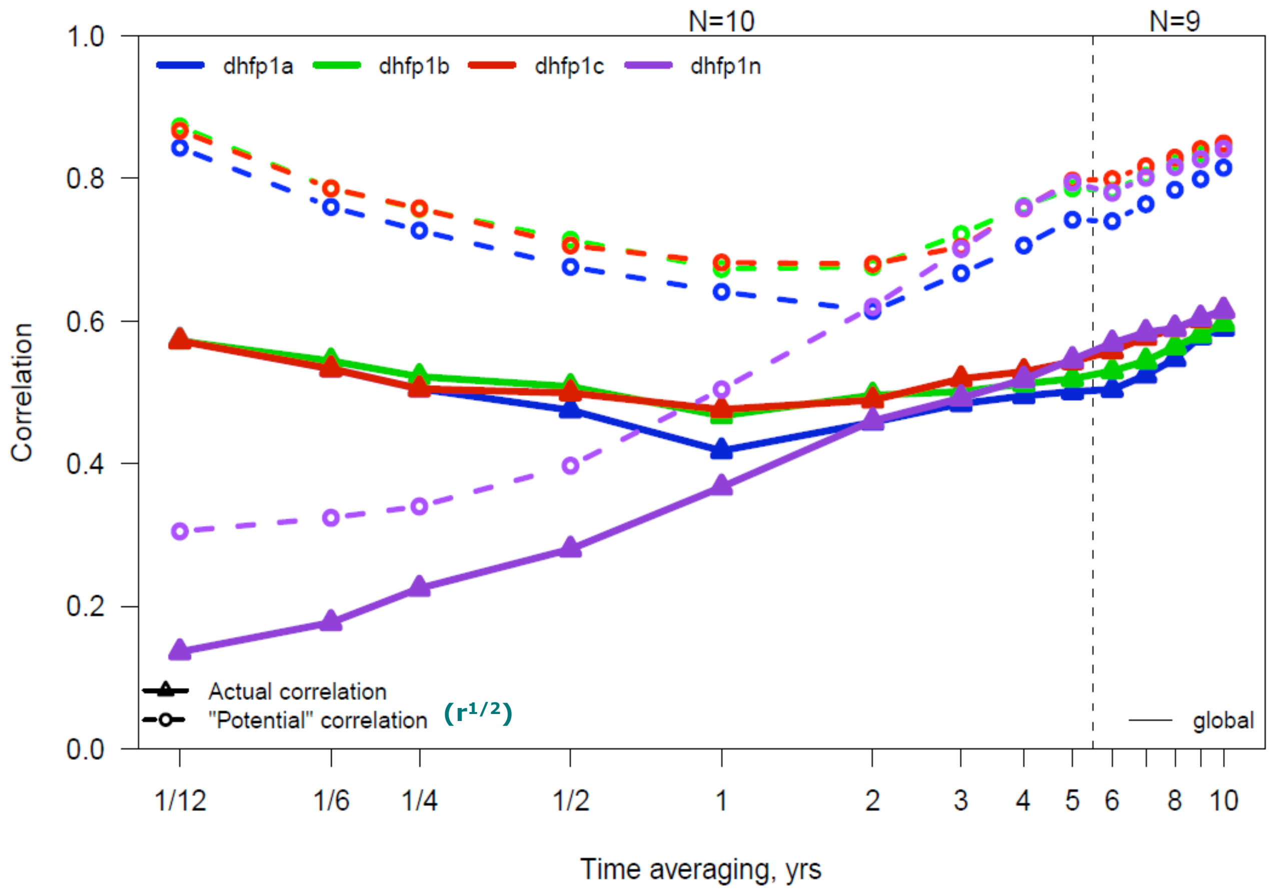






basic bias correction
10 cases

Temperature: global mean of correlation coefficient



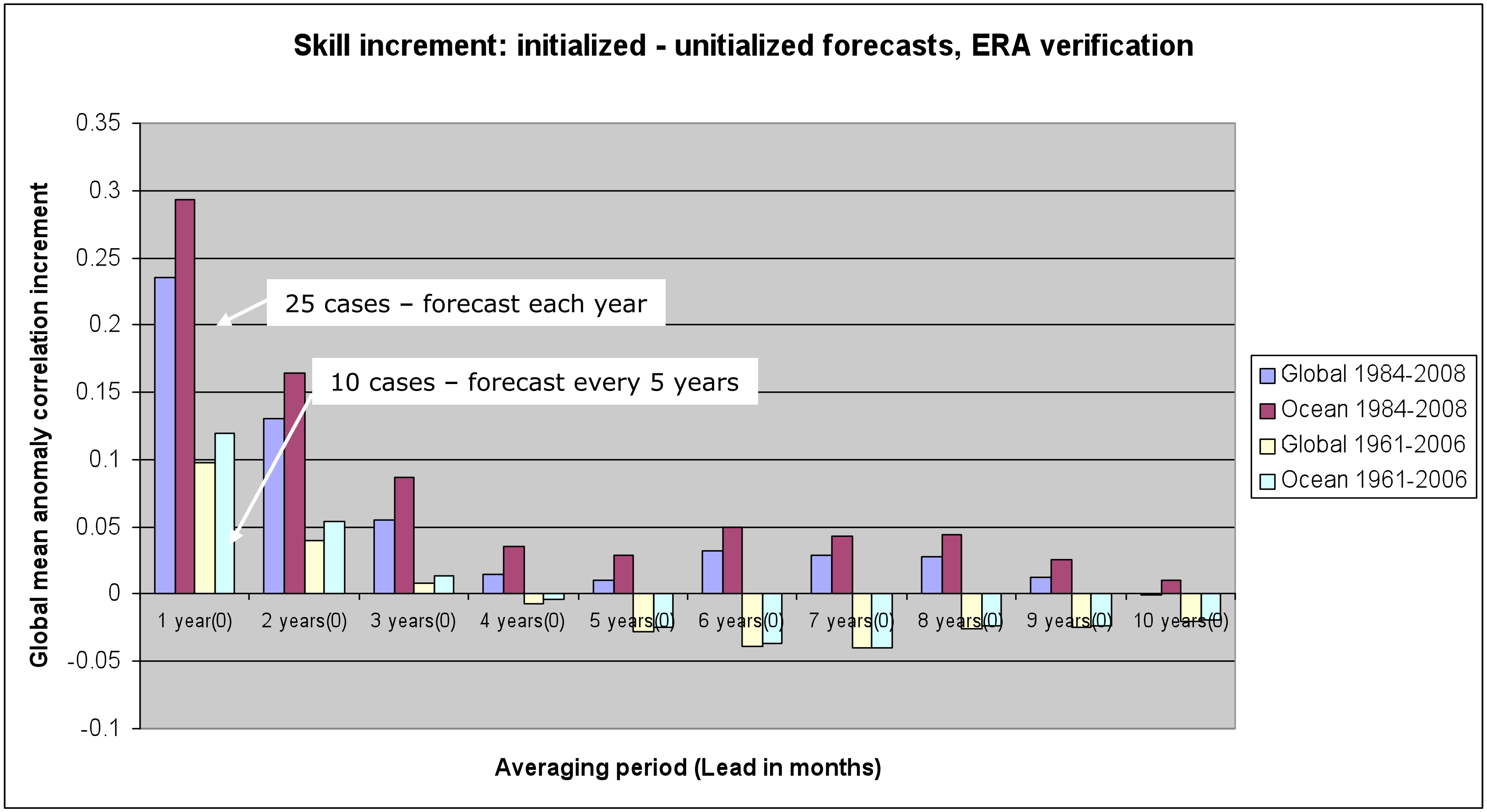
DHFP1a – surface forcing of ocean
DHFP1b – full field ocean initialization
DHFP1c – anomaly initialization of ocean
DHFP1n – uninitialized

basic bias correction
10 cases

- initial loss of skill for monthly, seasonal, annual averages
- subsequent increase in skill for longer averages from forced component
- initialized forecasts have improved skill compared to uninitialized
  - for averages of a month to ~3-4 years
- $r^{1/2} \sim p$ measure of "potential" correlation

(S. Kharin)

Temperature: global mean of correlation



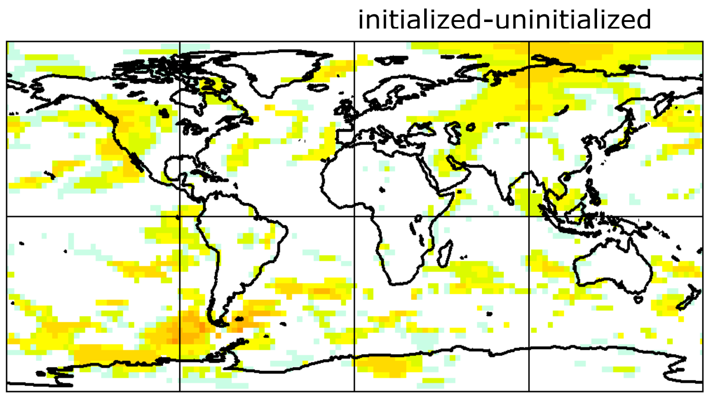
- improvement of initialized forecasts over uninitialized freecasts for *25 cases* compared to CMIP5's *10 cases*
- also get better scores verifying against GISS1200

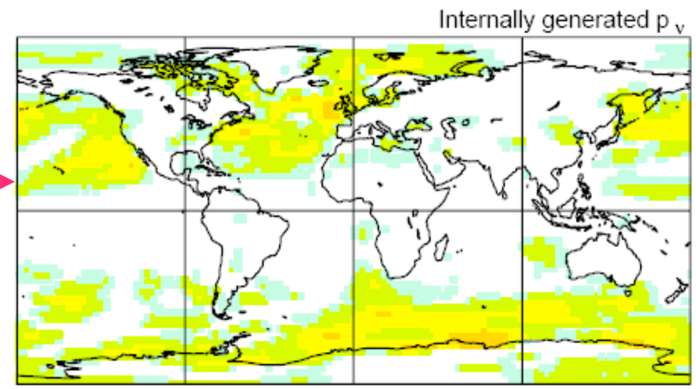
Correlation score for temperature vs multi-model *p*

(only roughly related to the internal component)

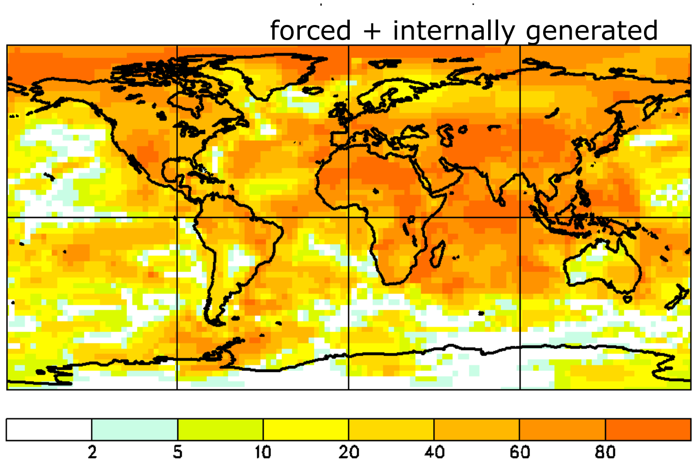
δr^2

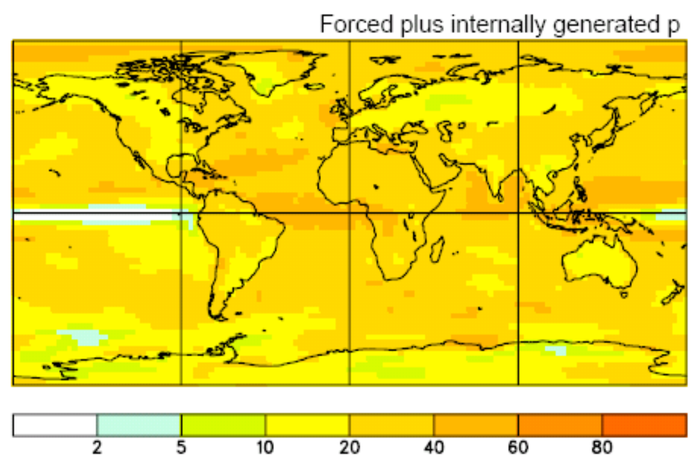
note only
>0 plotted





r^2

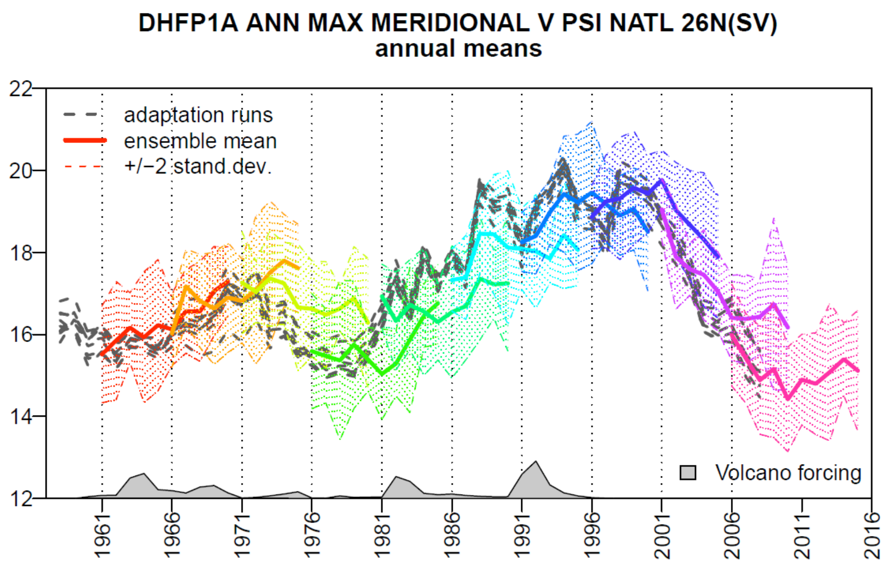




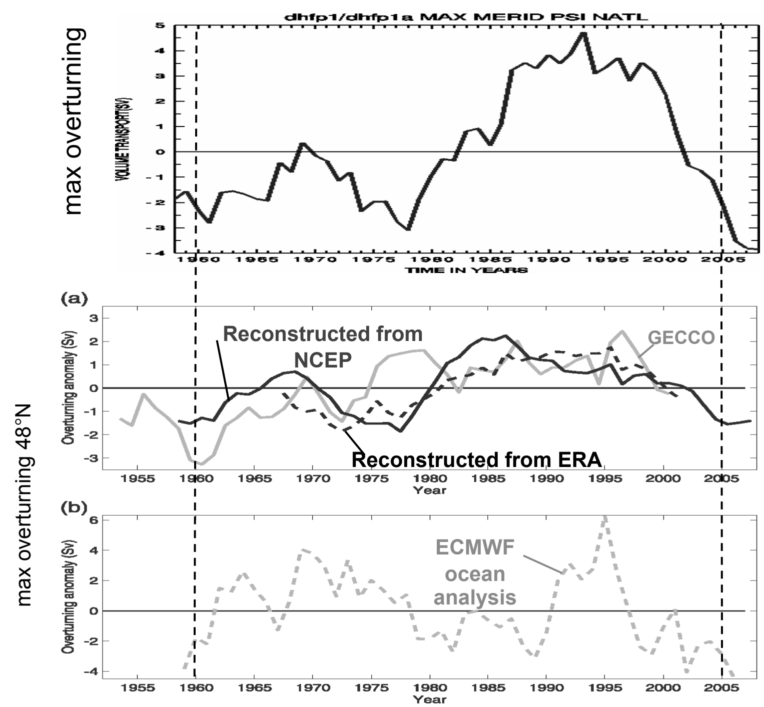
(some agreement between r^2 and p)

basic bias correction
10 cases

MOC



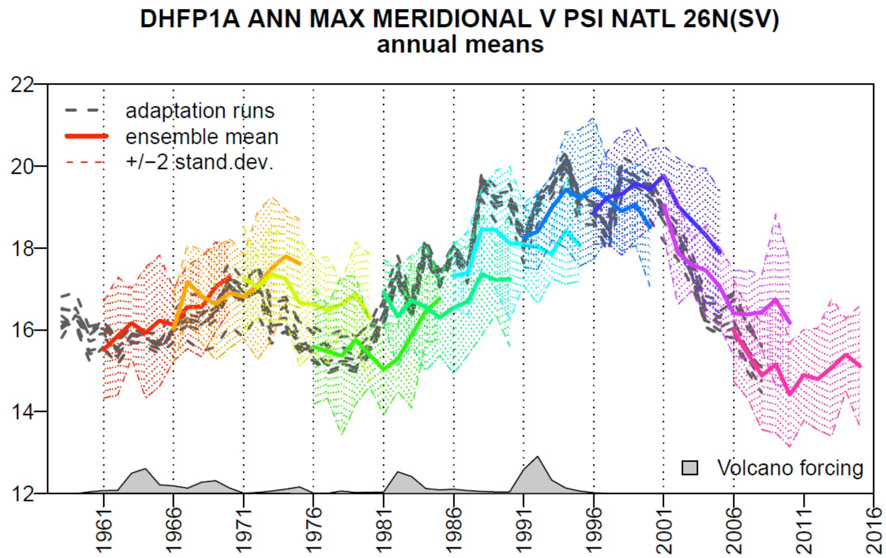
1a:no subsurface ocean data



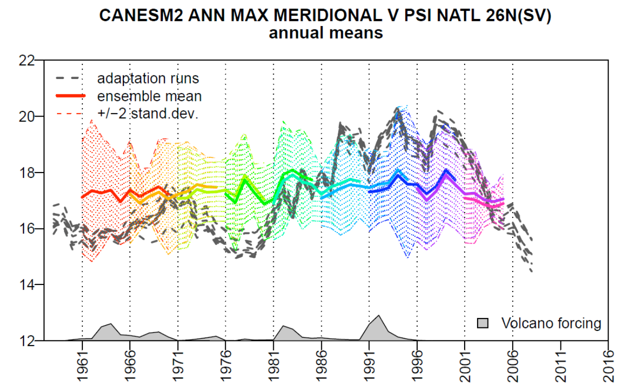
MOC estimates
Grist *et al. JClim* 2009

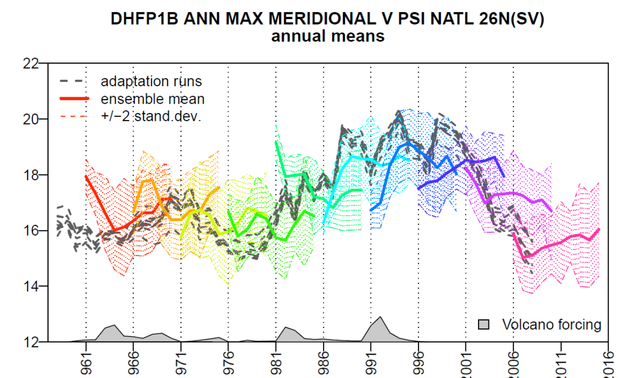
MOC

no subsurface ocean data



free running model



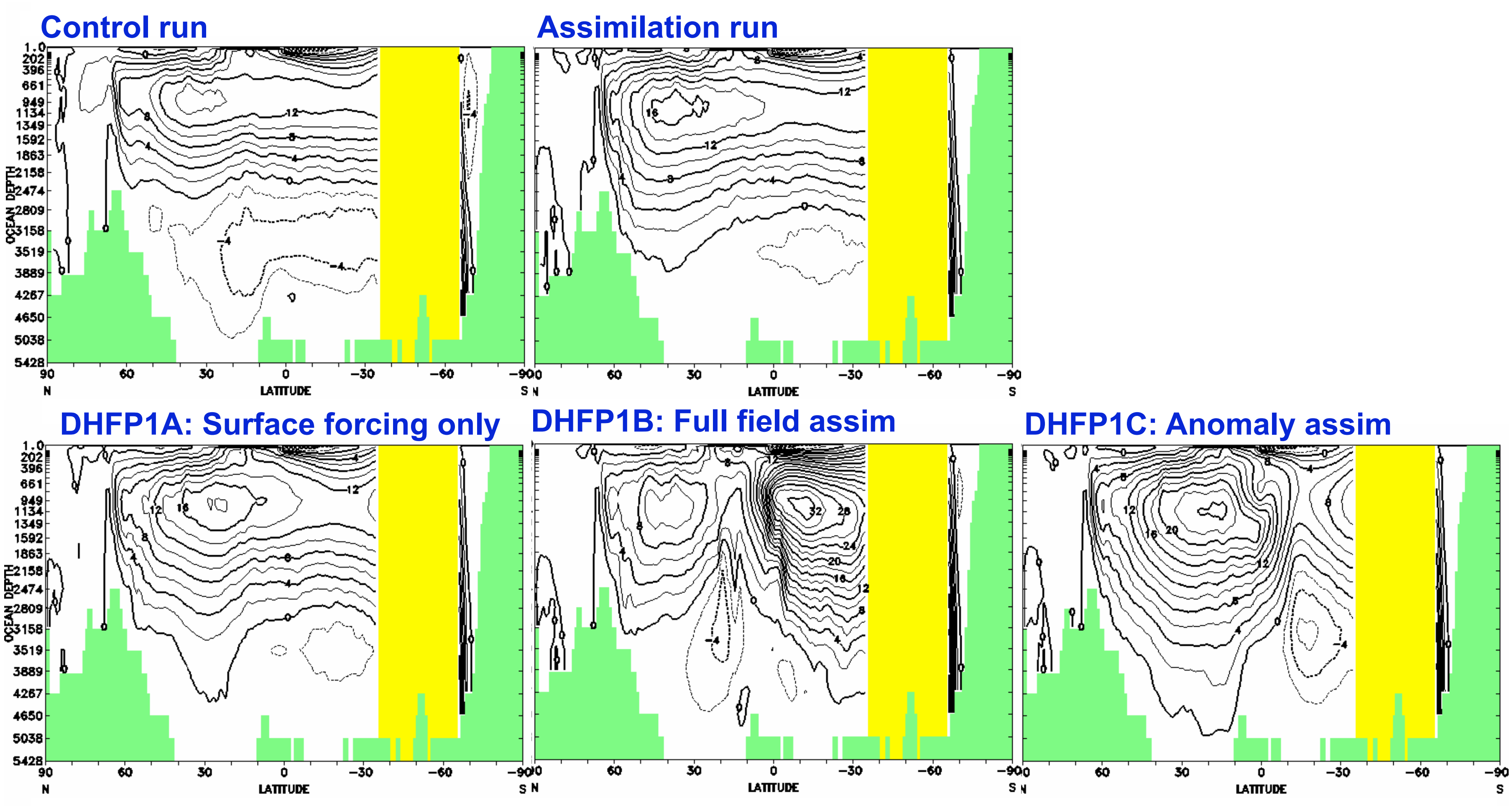


initialization uses subsurface ocean information

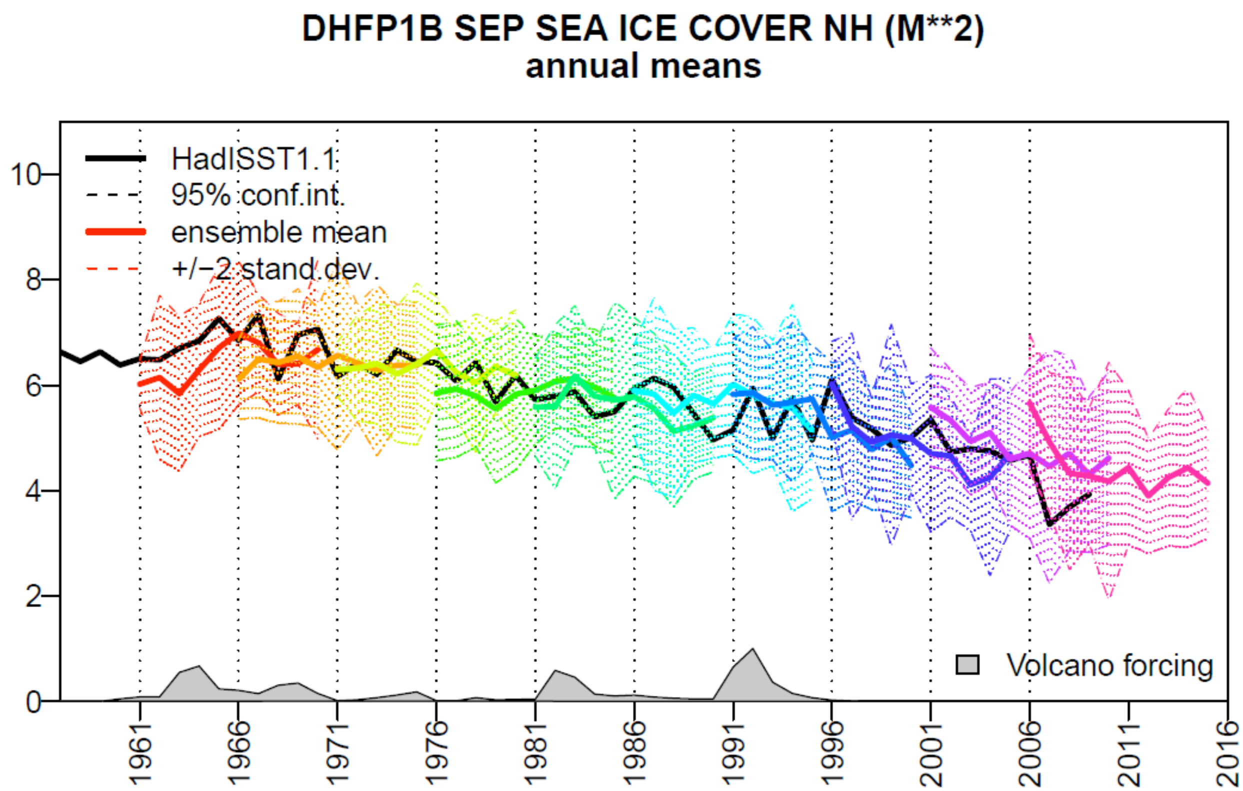
- ensemble of uninitialized simulations lack MOC variation
- surface forcing introduces MOC variation (but how realistic?)
  - MOC subsequently well predicted
- initialization with ocean information affects result, perhaps detrimentally

North Atlantic Overturning

Control run 10 year mean vs assimilation & forecast 1981 means (1st year of forecast)



Sea-ice


DHFP1B SEP SEA ICE COVER NH (M**2)
annual means
HadISST1.1
95% conf.int.
ensemble mean
+/−2 stand.dev.
Volcano forcing
0
2
4
6
8
10
1961
1966
1971
1976
1981
1986
1991
1996
2001
2006
2011
2016

Summary

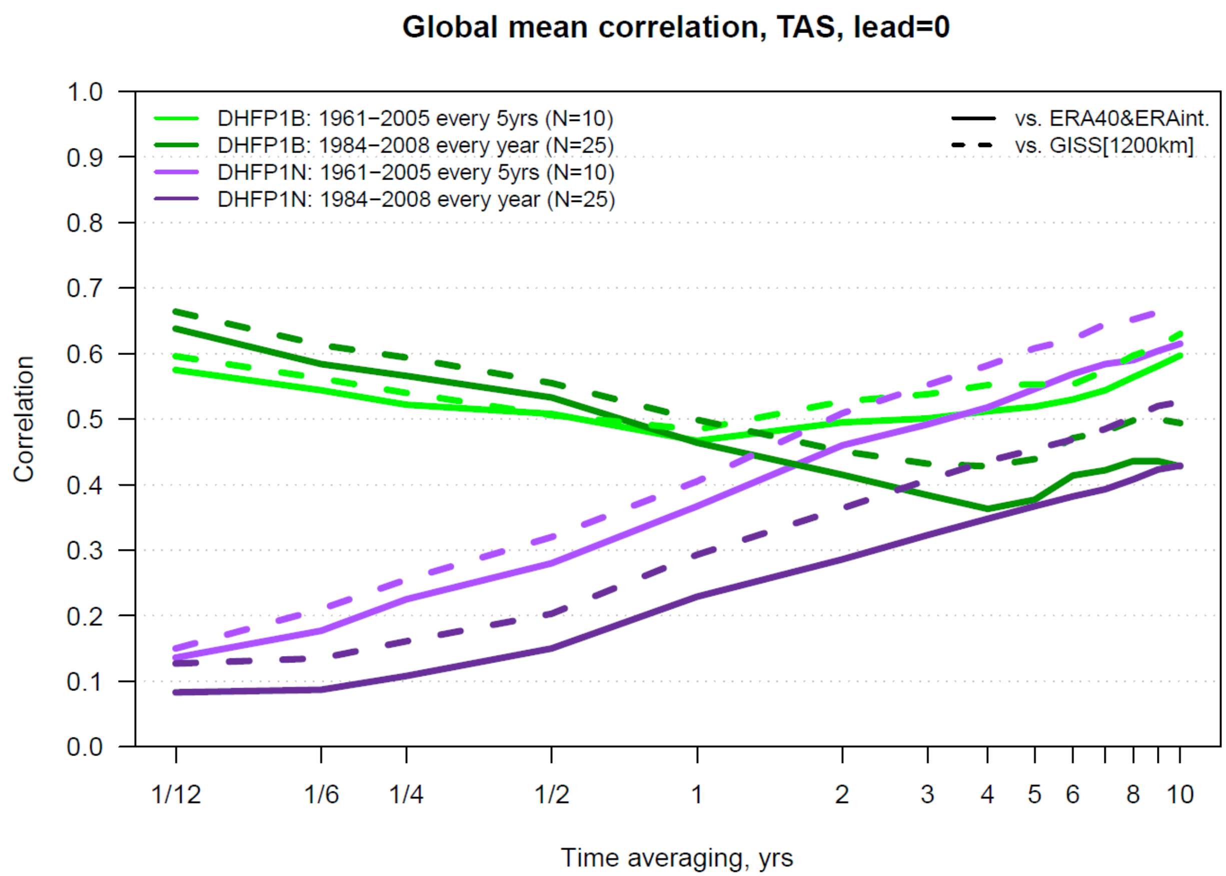
- Potential predictability measures give an indication of skill limits
- Skill from forced component apparent; skill from initialized/internally generated component generally “weak”
  - skill mainly for temperature
  - perhaps sea ice, MOC
- General lack of cases a problem
  - only 10 cases for CMIP5 forecasts every 5 years
  - multi-model approaches can increase ensemble size but not cases
  - need decadal forecasts every year at minimum (underway)
- Bias correction and skill assessment aspects
  - non-stationarity a problem
  - need more cases for stable statistics
  - statistical approaches need great care

end of presentation

Drift/bias correction

- Generally need "correction" to make predictions useful (as in SIP)
- Non-stationarity adds difficulties
  - desirable to correct for "trend" but lack of data likely precludes this locally
  - serious risk of overfitting if you do anything other than basic bias correction
    - this can make "corrected" CMIP5 results untrustworthy and perhaps misleading
- Very little data involved in the standard CMIP5 case:
  - for forecasts every 5 years only 10 cases
  - ensembles and multi-model approaches don't help – still only 10 cases
  - forecasts every year would help (although they are not independent)
- Implications
  - need forecasts initiated every year for better statistical stability
  - only "basic" bias corrected CMIP5 results made available?
  - what of bias correction for RCM driving fields?
  - statistical aspects in general need considerable care

Results depend on number of forecasts and verification



- better scores for:
  - larger sample (predictions every year)
  - GISS as reference data (smoother?)