II.2.1 Potential Predictability of Current and Future Climates

II.2.2 Prognostic predictability from ensembles of coupled model simulations

Bill Merryfield
CCCma

Predictability Studies

- Climate dynamics can be characterized as having two components:

> **'Signal': dynamics *deterministic*, potentially predictable**
>
> **'Noise' : dynamics *random*, unpredictable**

- In *diagnostic* predictability studies the variability of the climate system is partitioned into these two components,

  → *potentially predictable variance fraction* = $\sigma^2_{Pred}/\sigma^2_{Total}$ ***"ppvf"***

- *Prognostic* predictability studies look at rates of divergence from neighboring initial conditions

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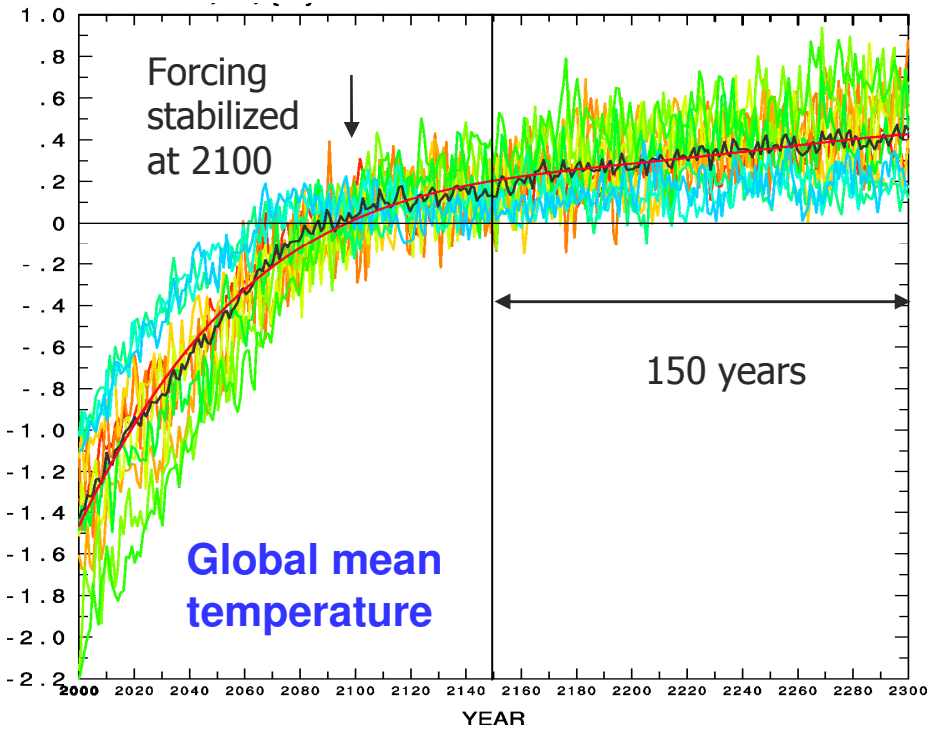
  → *potentially predictable variance fraction* = $\sigma^2_{Pred}/\sigma^2_{Total}$ ***"ppvf"***
- *Prognostic* predictability studies look at rates of divergence from neighboring initial conditions
- Functions of *time scale, region, climate variable*…

Potential predictability in a warmer world

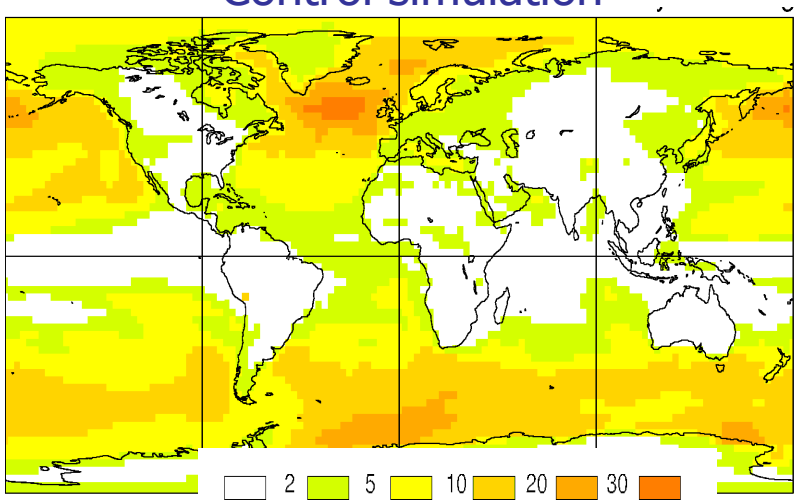
Boer, J. Climate accepted

- Consider B1/Stabilization Scenario
- Forcing stabilizes in 2100, consider 2150-2300
- 11 CMIP3 simulations
- Remove long term adjustments by fitting low-order polynomial

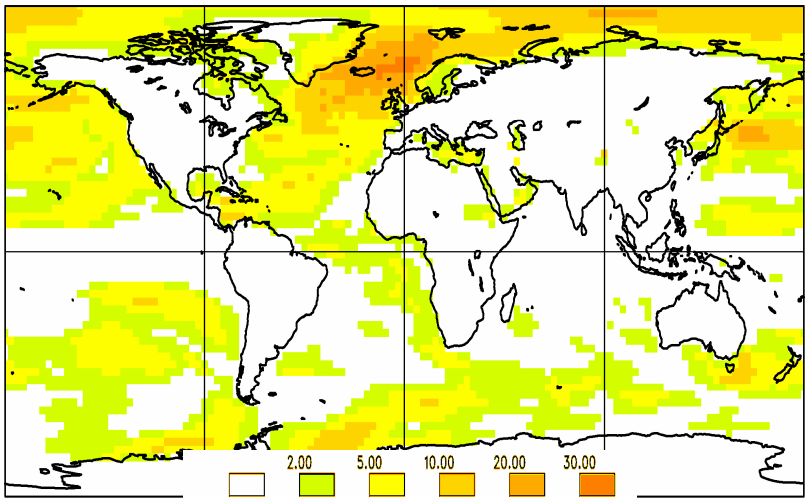


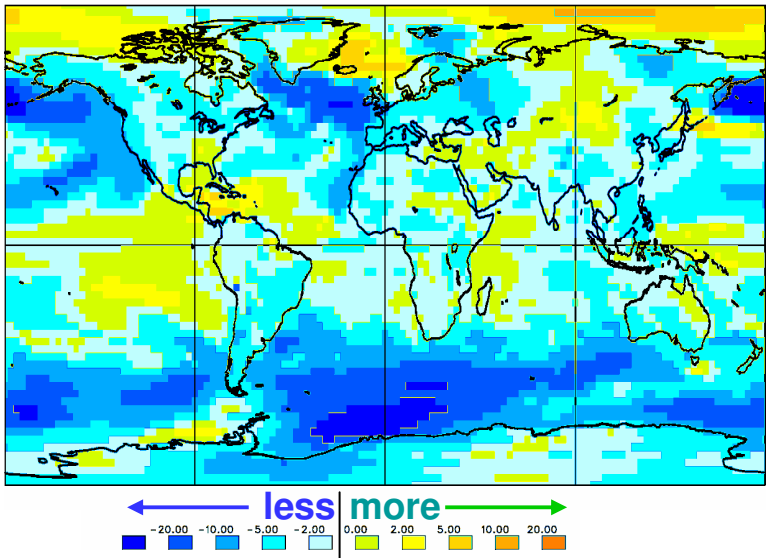
Decadal ppvf (%) for Temperature

Control simulation

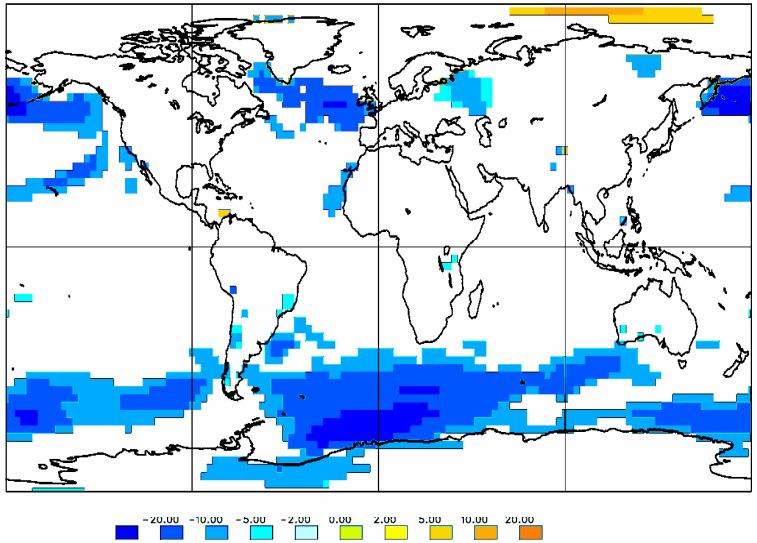


B1 stabilization





Difference in warmer world



Where confidence bands *don't* overlap

Decadal potential predictability of 21st Century climate

Boer (2009) submitted

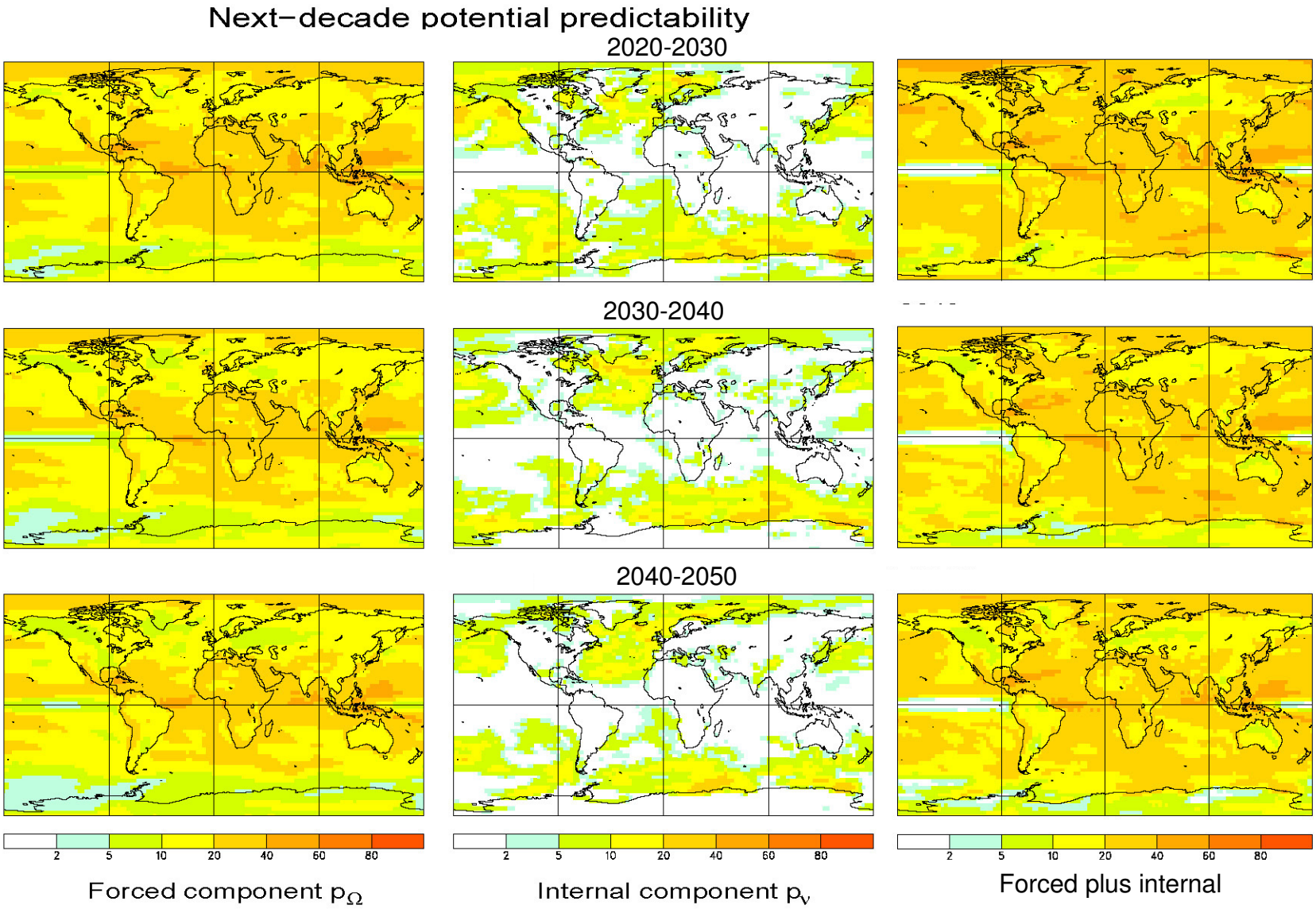
- Decadal climate variations are superimposed on warming trend
- Decompose variance as

$$\sigma^2 = \sigma^2_\Omega + \sigma^2_\nu + \sigma^2_\varepsilon$$

externally forced component — **internal variability component** — **"noise"**

- B1 scenario 2001-2100
- CMIP3 $\rightarrow$ 35 simulations/18 models
- Examine decadal *forced* and *internal* ppvf

$$\sigma^2_\Omega / \sigma^2 \qquad \sigma^2_\nu / \sigma^2$$



→ these predictabilities should characterize decadal forecasts*

*to extent models are reliable

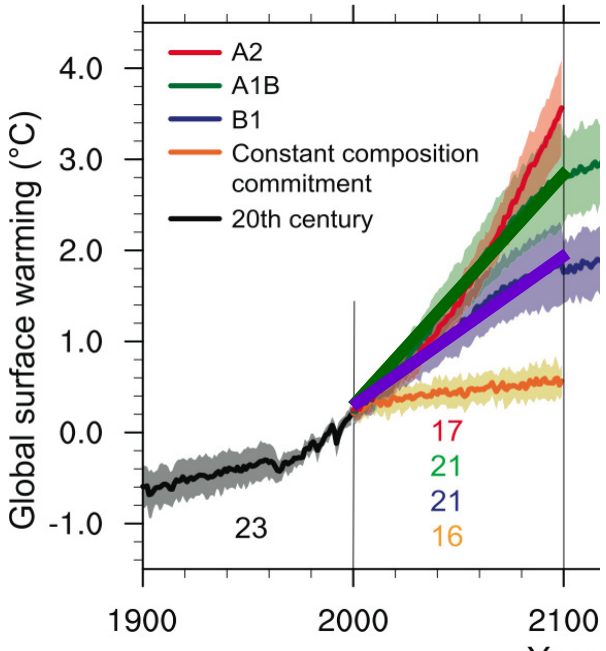
Likelihood and predictability of cooling episodes in a warming climate

W. Merryfield and Ajayamohan Ravindran

- Decadal forecasts from Kiel & Hadley Centre predict near-term *cooling,*
- *How likely is it that the next N years will be cooler than the last N years?* → probability P_N
- Approach:
  - diagnose P_N directly from CMIP3 output*:

    B1 : 20 models, 48 runs, **4800 years**
    A1B: 12 models, 12 runs, **1200 years**

  - apply statistical models



***courtesy S. Lambert**

Relate cooling probability to mean trend, internal variability

- Consider $p(\Delta T_N)$ for *differences* between successive N-year means

- If $p(\Delta T_N)$ is Gaussian then $p \propto \exp - \dfrac{(\Delta T_N - \overline{\Delta T_N})^2}{2\sigma_N^2}$

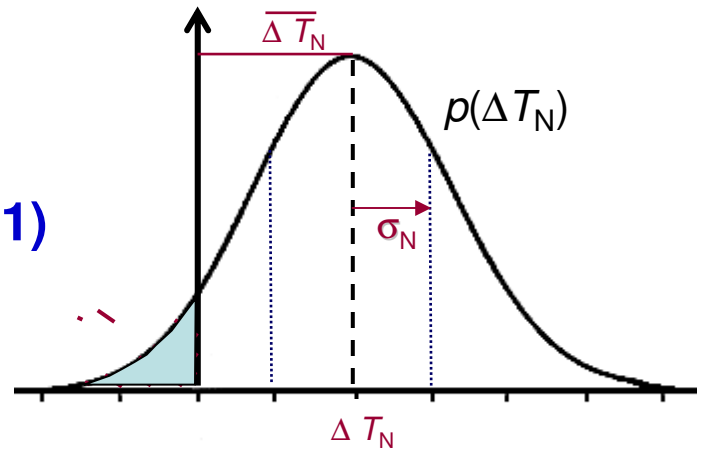
mean trend

internal variability

- Cooling probability P_N corresponds to probability of $\Delta T_N < 0$

$$P_N = \int_{-\infty}^{0} p(\Delta T_N) d(\Delta T_N)$$

$$= \tfrac{1}{2}[1 + \mathrm{erf}(-\overline{\Delta T_N} / \sigma_N \sqrt{2})] \quad (1)$$



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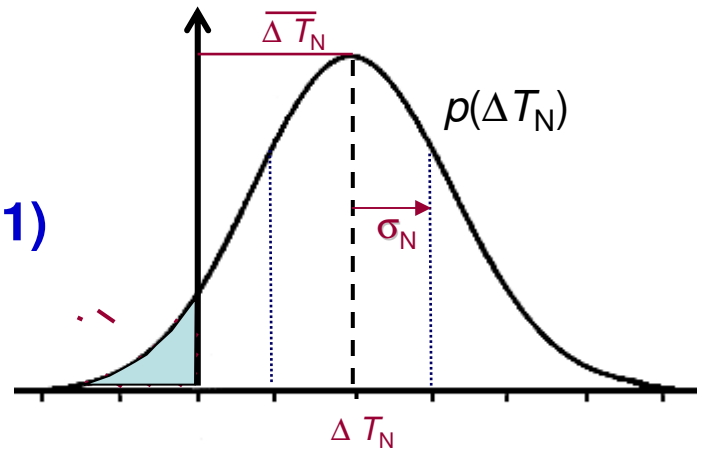


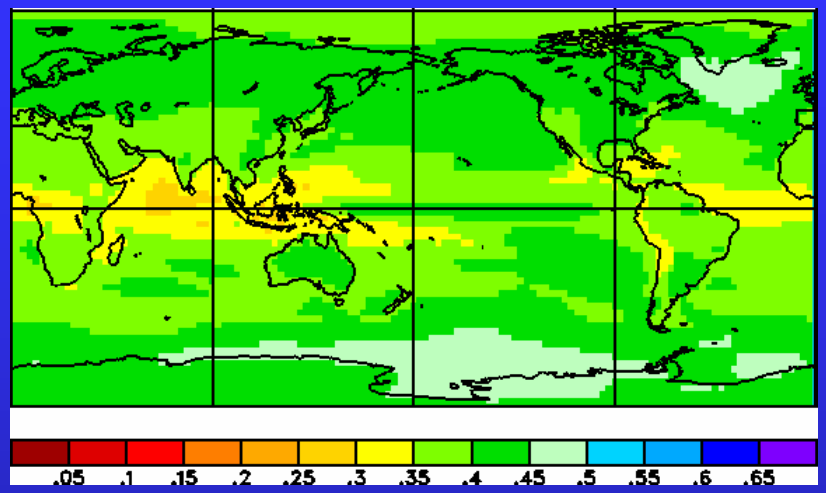
→ ***P_N large** where ΔT_N **small** or σ_N **large***

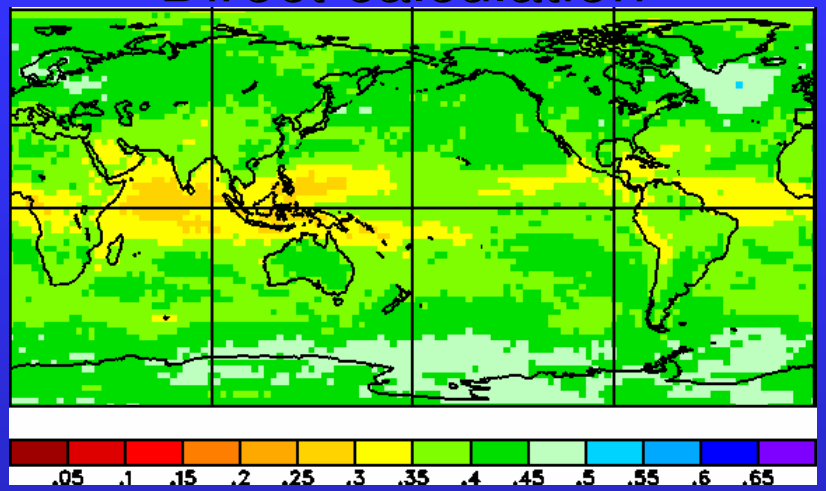
Multi-model P_N (B1)

From (1)

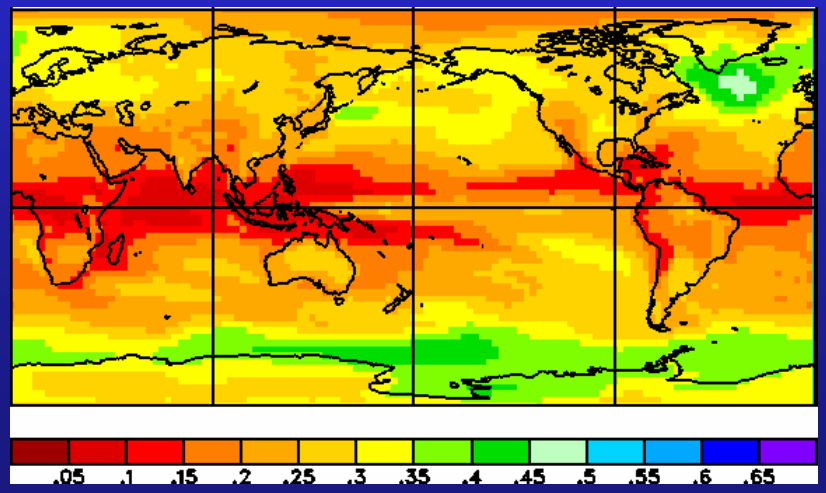
Direct calculation

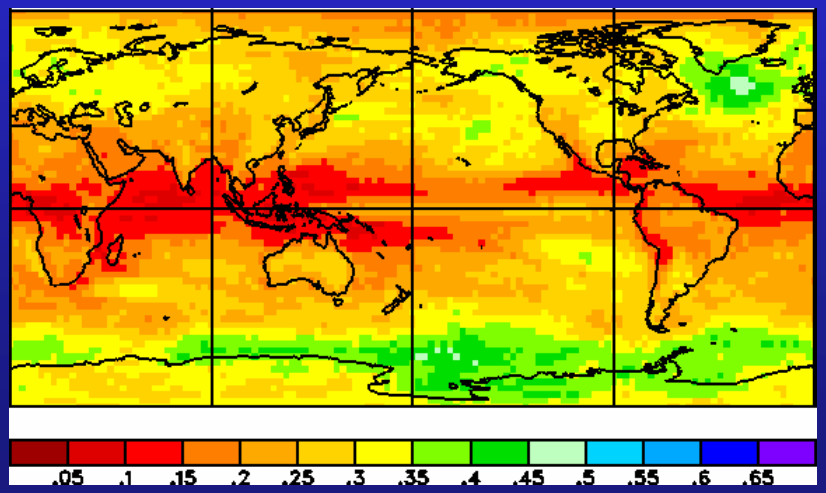
N=5





N=10





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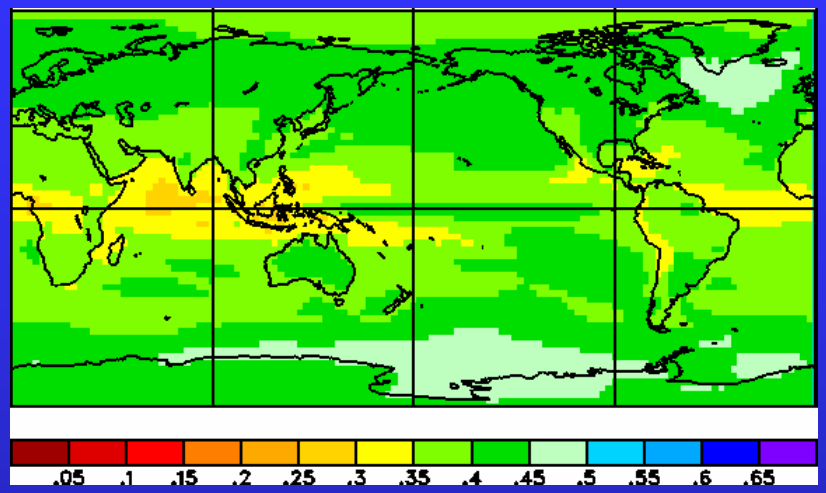
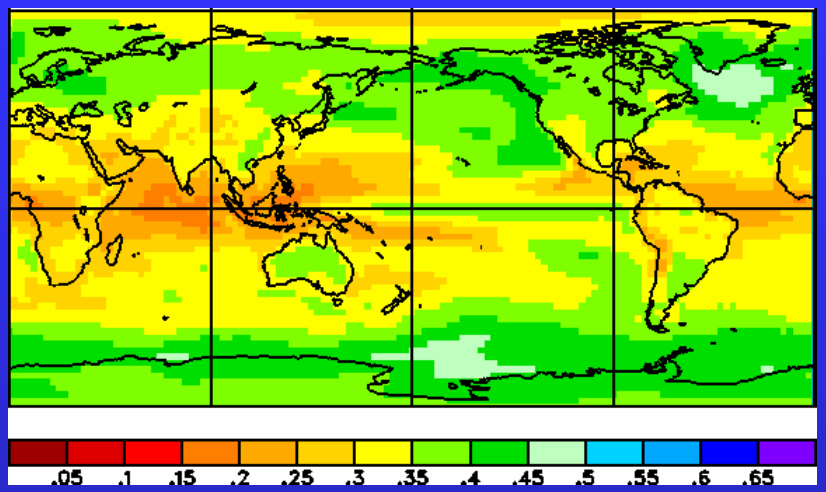


Multi-model P_N (A1B)



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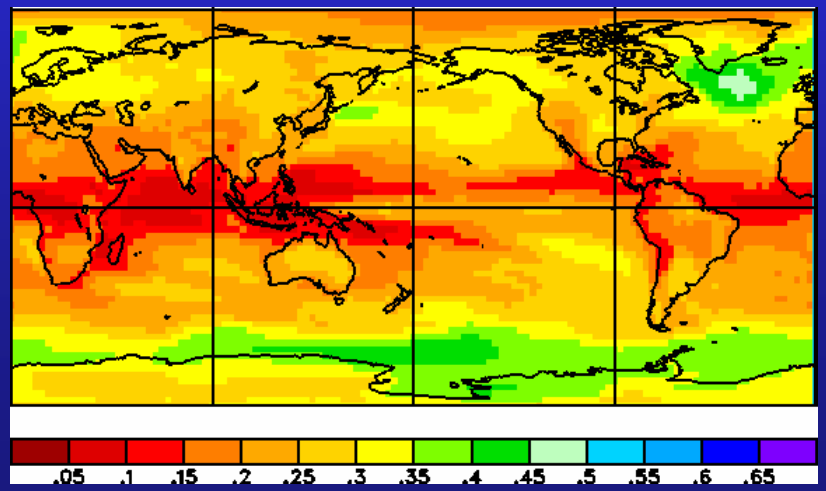

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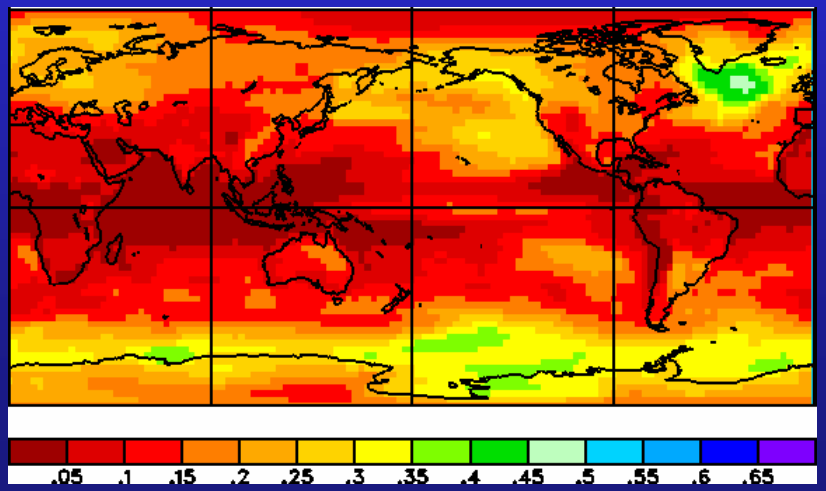


Global mean T: Modeled vs Observed

	B1		P_N from (1)
N	$\overline{\Delta T_N}$	σ_N	
5	0.081	0.081	15.8%
10	0.164	0.071	1.0%

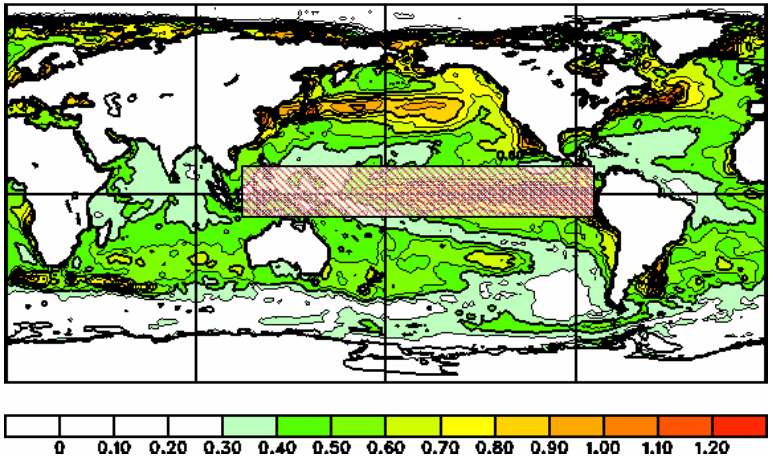
	GISS		P_N from (1)	HadCRUT3		P_N from (1)
N	$\overline{\Delta T_N}$	σ_N		$\overline{\Delta T_N}$	σ_N	
5	0.079	0.046	4.3%	0.079	0.057	8.3%
10	0.159	0.011	0.0%	0.158	0.009	0.0%

$\Rightarrow$ rate of warming similar to B1, but less variability (esp decadal)

Regional impacts of air-sea coupling on climate variability and predictability

Ajayamohan Ravindran, W. Merryfield, S. Kharin, G. Boer

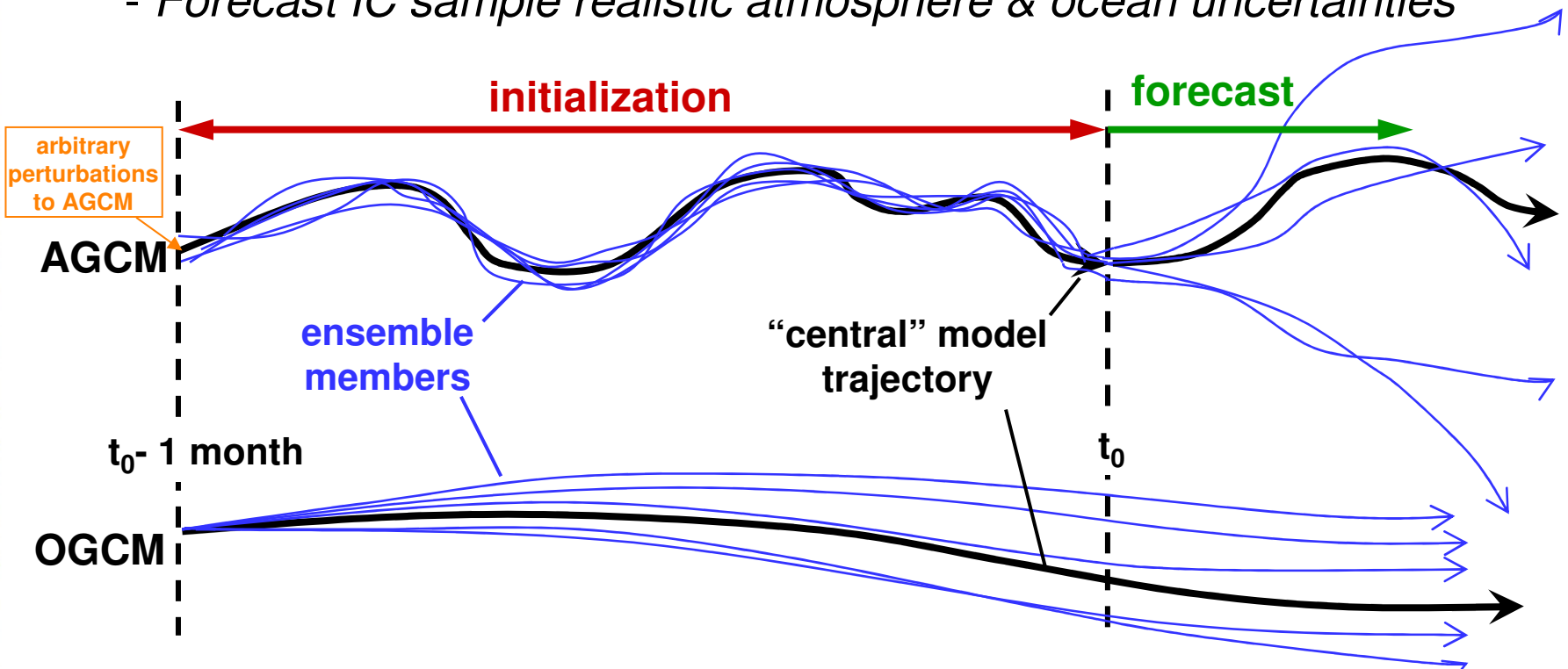
- Examine climate variability and potential predictability when atmosphere sees only *climatological* SSTs in specified regions:



- Ravindran afternoon talk…

II.2.2 Prognostic Predictability from coupled model ensembles

- Aim: “perfect model” predictability experiment based on large (~100-member) ensemble of coupled model integrations
- Take advantage of new initialization technique: incremental analysis updates (IAU):
  - AGCM assimilates “central” model run for ~1 mon prior to fcst
  - *Forecast IC sample realistic atmosphere & ocean uncertainties*



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