

Changes in the decadal potential predictability of the coupled system with global warming

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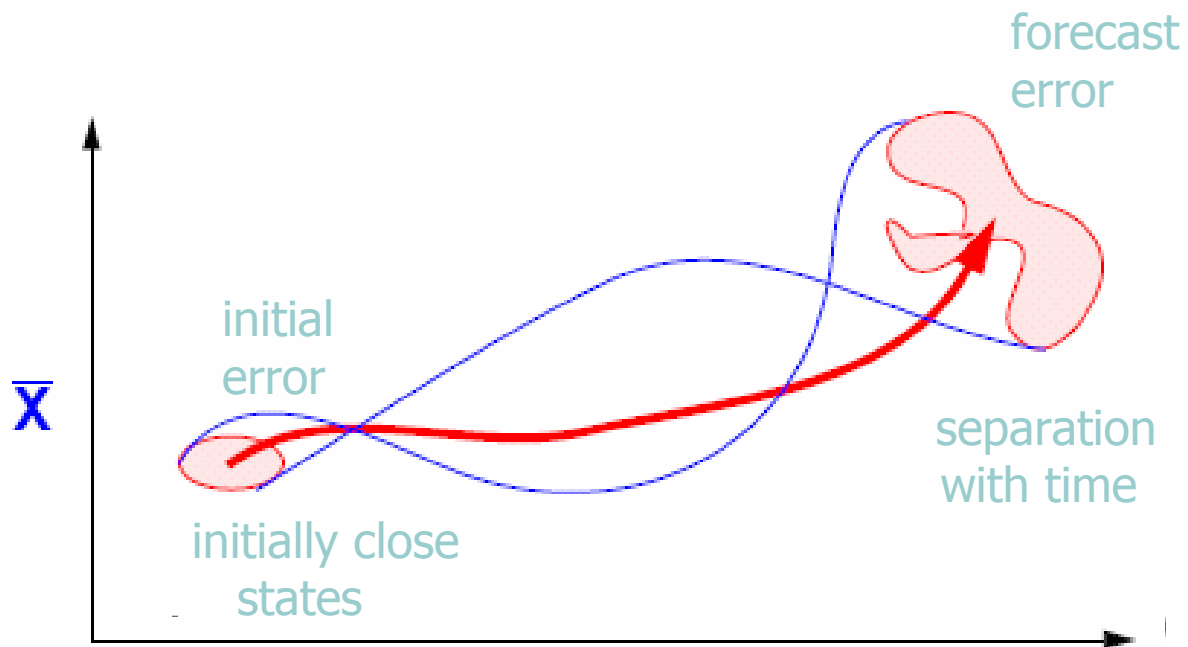
Environment Canada

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Topics

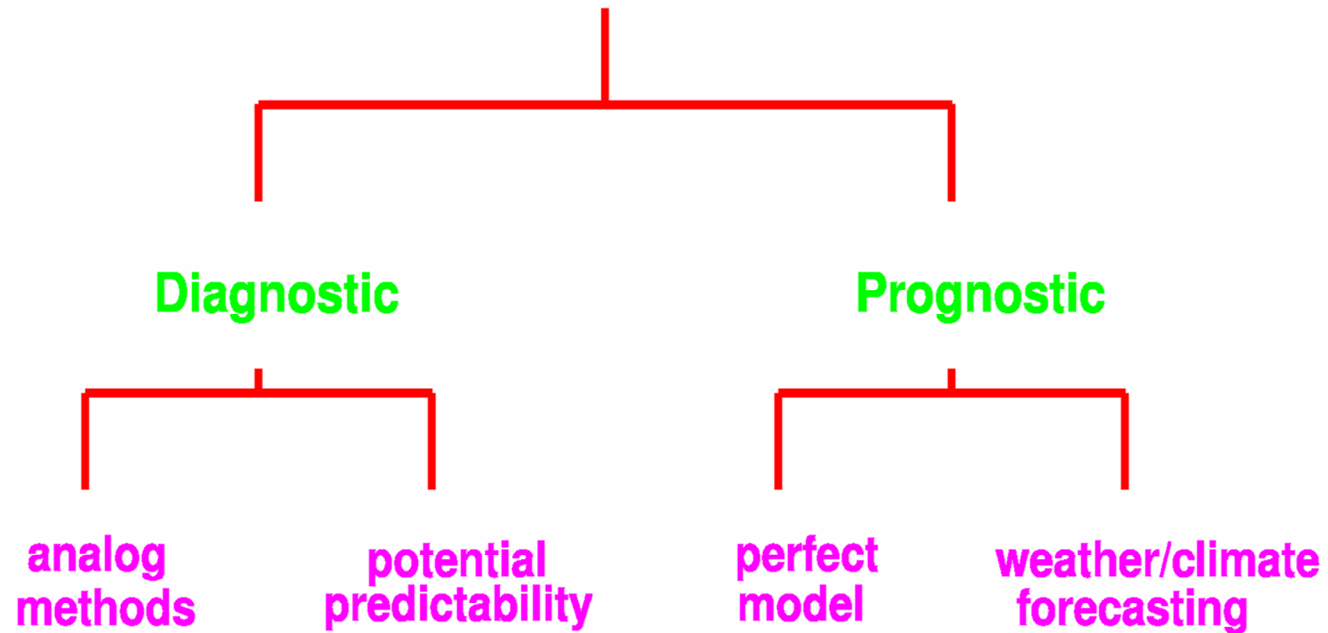
- Approaches to long-timescale predictability
- MIPs and multi-model ensembles (MMEs)
- Decadal potential predictability results for temperature and precipitation
- Potential predictability change in a warmer world
- Summary

Classical predictability



Sensitive dependence on initial conditions

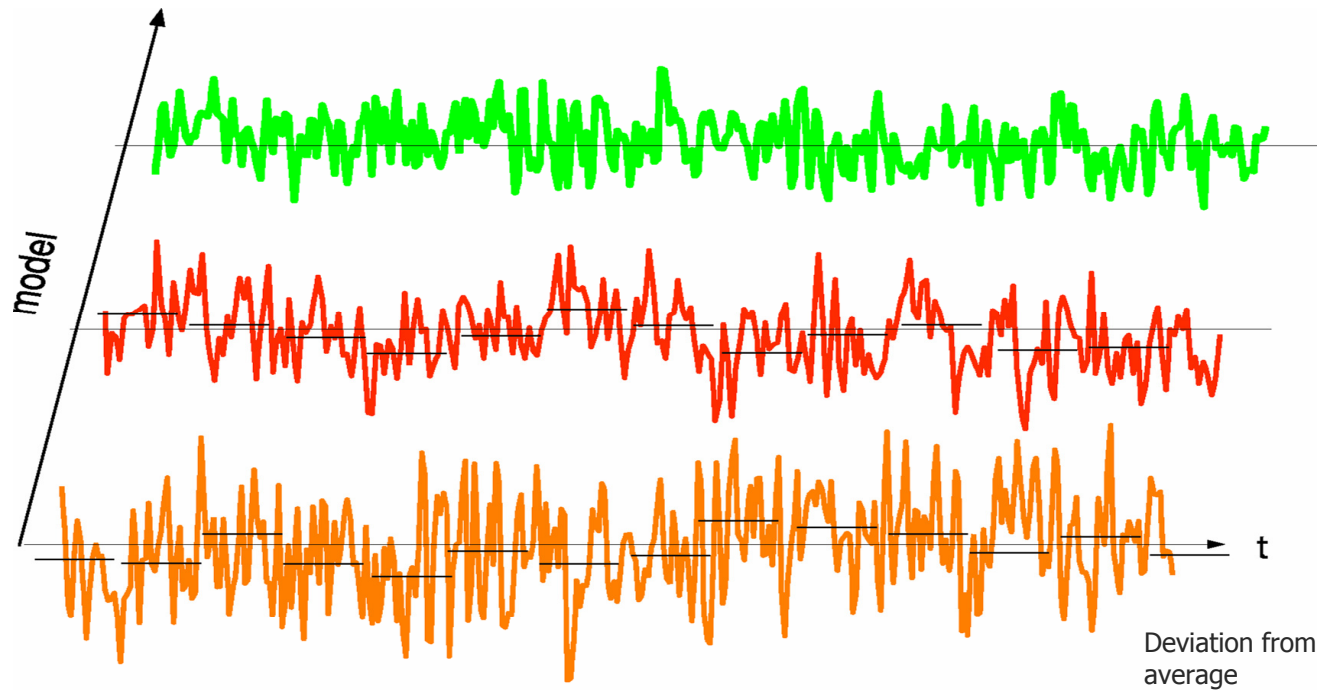
Predictability Studies



Predictability approaches

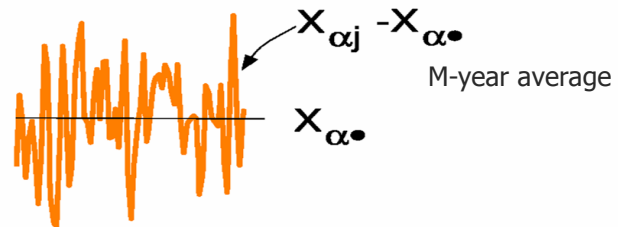
- *Classical predictability*
 - measures the average rate of separation of initially close states
 - prognostic or diagnostic
- *Potential predictability*
 - looks for the existence of deterministic long timescale variability
 - presumes this variability is “potentially” predictable with enough knowledge

Long timescale variability



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

$$S^2 = S_v^2 + S_\varepsilon^2$$



Potential predictability

- Analysis looks for:
 - long timescale variability at each point
 - not simply the residue of averaging
 - of sufficient magnitude to be of interest
- Presumption is that this variability is at least “potentially” predictable with enough knowledge
- Location and nature of the potential predictability should suggest mechanisms and processes

Approach

- Need suitable statistical tests and approaches
- Require lots of “observations” for statistical confidence
- Aim for geographic distribution of the *potential predictability variance fractions* (ppvf)
- We take a *multi-model ensemble approach* using CMIP3 data (IPCC AR4)

CMIP3 MME Approach

- Consider CMIP3 results as a sample from the population of models “produced with current knowledge”
- Ensemble approach – pool the statistics
 - provides more data
 - allows better estimation of population parameters
 - provides an “expert” consensus
- Simulations include:
 - unforced control simulations
 - A1B and B1 climate change scenarios
 - stabilization integrations

Statistical model

- Statistical model is

$$X = \Omega + v + \varepsilon$$

with associated variances

$$\sigma^2 = \sigma^2_{\Omega} + \sigma^2_v + \sigma^2_{\varepsilon}$$

- Ω is long timescale *externally forced* variability *if present* (we generally *don't* consider now)
- v is long timescale *internally generated* variability (*this* is what we are interested in)
- ε is short timescale *unpredictable "noise"* variability

- Potential predictability variance fraction is

$$p = (\sigma^2_{\Omega} + \sigma^2_v) / \sigma^2 = p_{\Omega} + p_v$$

Statistics

$$X_i = X_{(\alpha-1)M + j} = X_{\alpha j}$$

$$i = 1 \dots NM$$

$$\alpha = 1 \dots N$$

$$j = 1 \dots M$$

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

$$X_{\alpha \bullet} = \frac{1}{M} \sum_{j=1}^M X_{\alpha j}$$

is M-year average

$$S^2 = S_{\Omega}^2 + S_V^2 + S_{\varepsilon}^2 = \overline{X^2}$$

$$= \overline{P_{\alpha}^2} + \overline{(X_{\alpha \bullet} - P_{\alpha})^2} + \overline{(X_{\alpha \bullet} - X_{\alpha j})^2}$$

$$P_{\alpha} = \sum_{k=1}^K a_k p_k(\alpha)$$

is orthogonal
polynomial fit

Long TS
forced
(if present)

Long TS
internally
generated

Short TS
noise

Statistics are pooled across models in multi-model case

Variance estimates

$$\hat{\sigma}_{\varepsilon}^2 = \left(\frac{M}{M-1} \right) S_{\varepsilon}^2$$

$$\hat{\sigma}_{\mathbf{v}}^2 = \left(\frac{N}{N-K} \right) S_{\mathbf{v}}^2 - \left(\frac{1}{M-1} \right) S_{\varepsilon}^2$$

$$\hat{\sigma}_{\Omega}^2 = S_{\Omega}^2 - \left(\frac{K}{N-K} \right) S_{\mathbf{v}}^2$$

Potential predictability variance fraction (*ppv*)

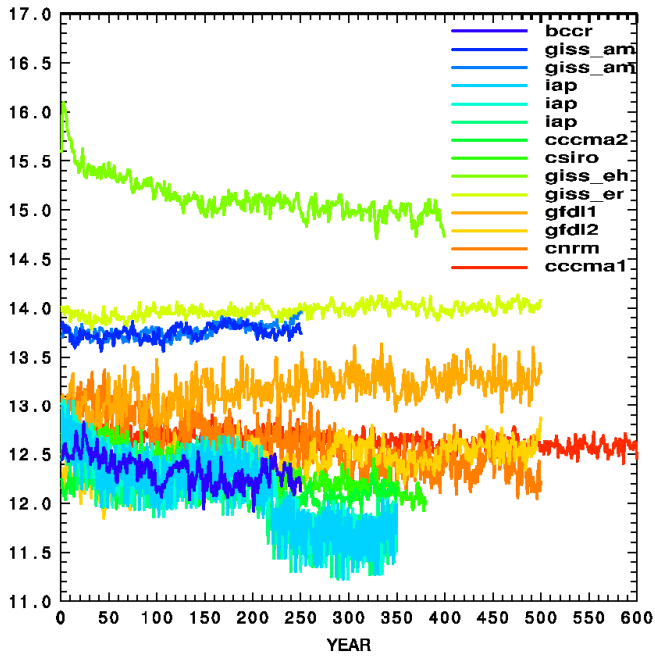
- we *consider here* the internally generated component $p_v = \sigma_v^2 / \sigma^2$
- test for hypothesis $p_v = 0$, hope to reject - i.e. potential predictability is *not* zero
- estimate confidence interval $p_l < p_v < p_u$
- is $p_v = \sigma_v^2 / \sigma^2$ big enough to be of interest?
 - ratio of variances *makes sense*
 - but small p_v *due to large* σ^2 allows correlation skill to exist

Apply to CMIP3 control climates

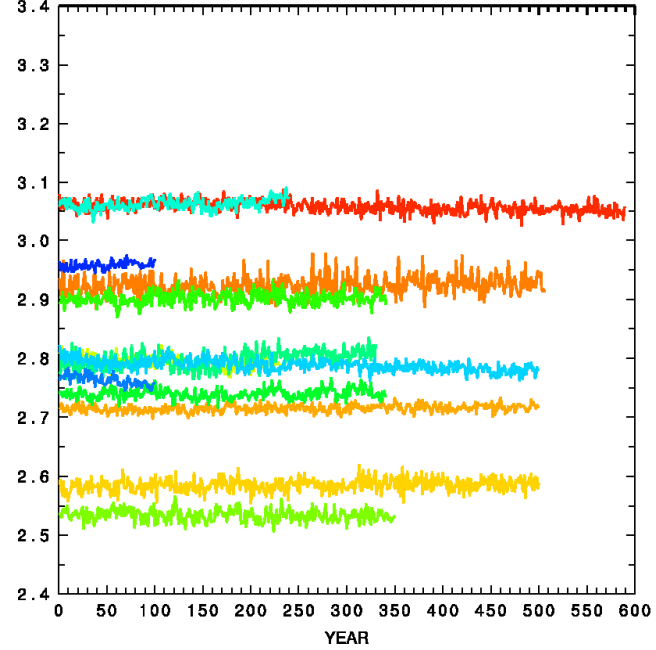
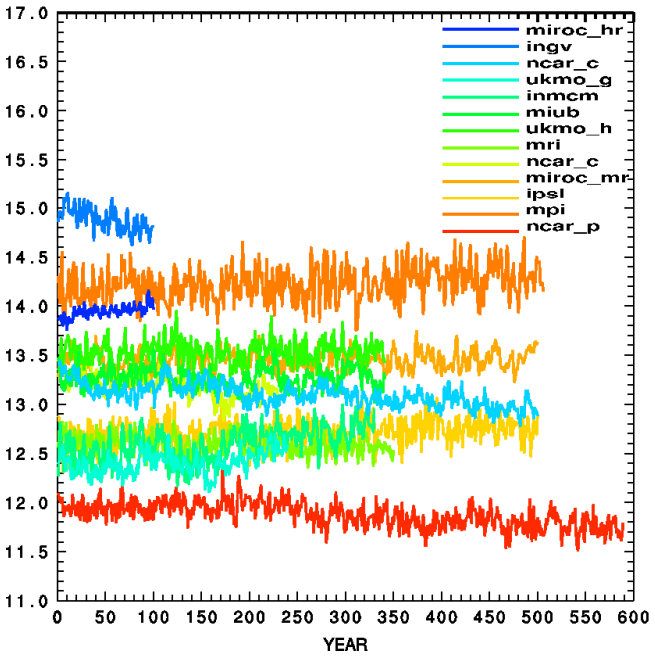
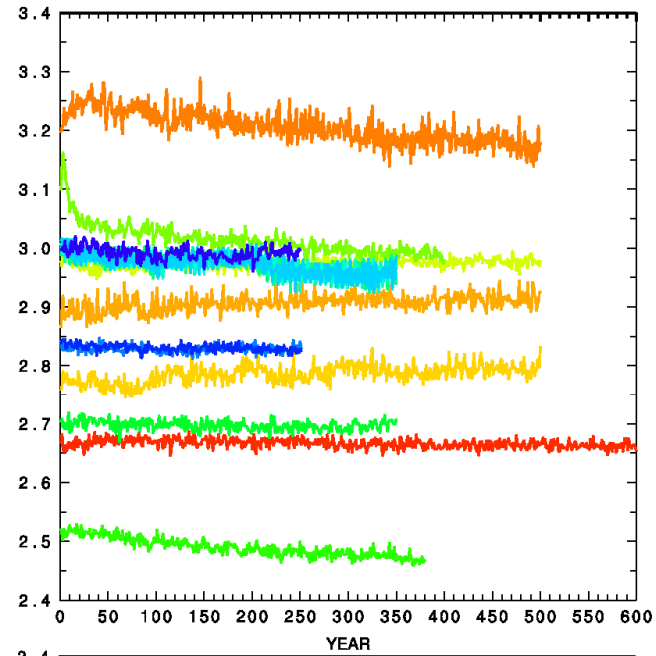
- (intended to be) equilibrium climate
- no external forcing – then *internally generated* ppvf is $p_v = \sigma_v^2 / \sigma^2$
- results from 27 models are available
- simulations lengths from 100 to 1000 years
- consider surface air temperature and precipitation (the two main climate parameters)

Time series of global annual means

Temperature (C)



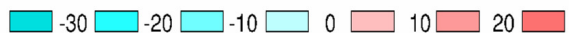
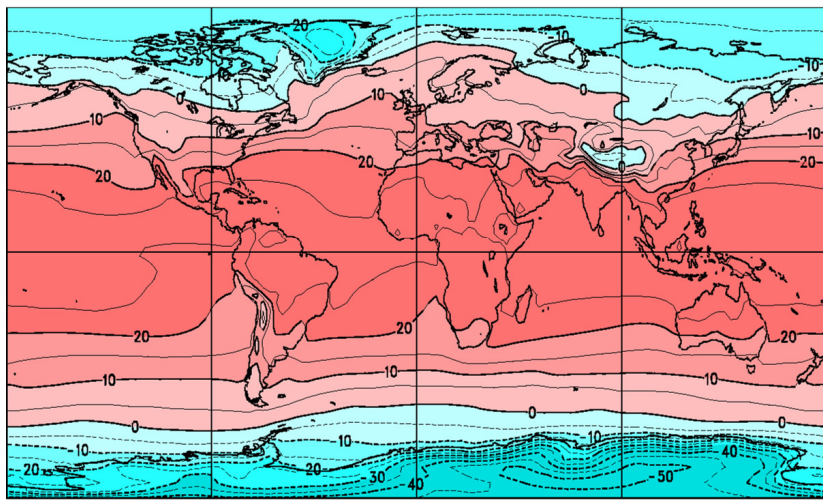
Precipitation (mm/day)



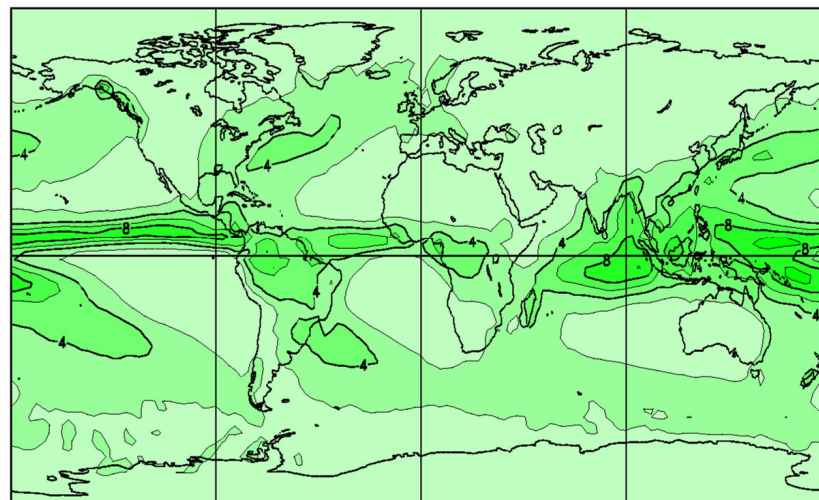
Long-term annual means

Observations

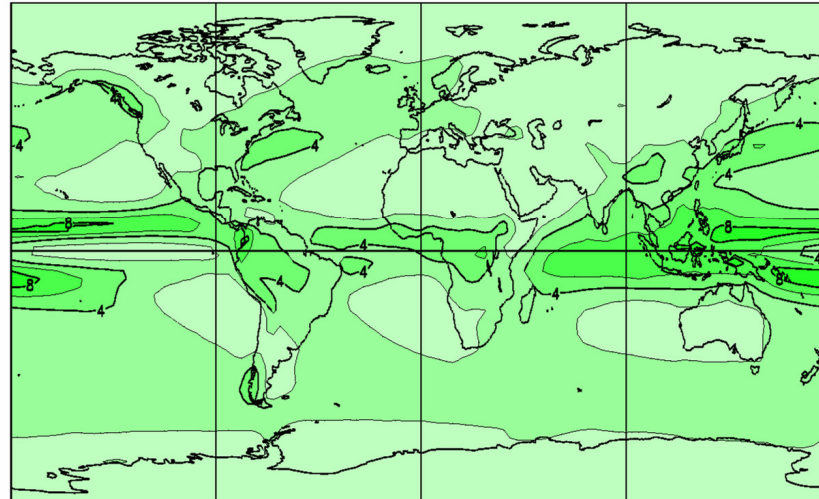
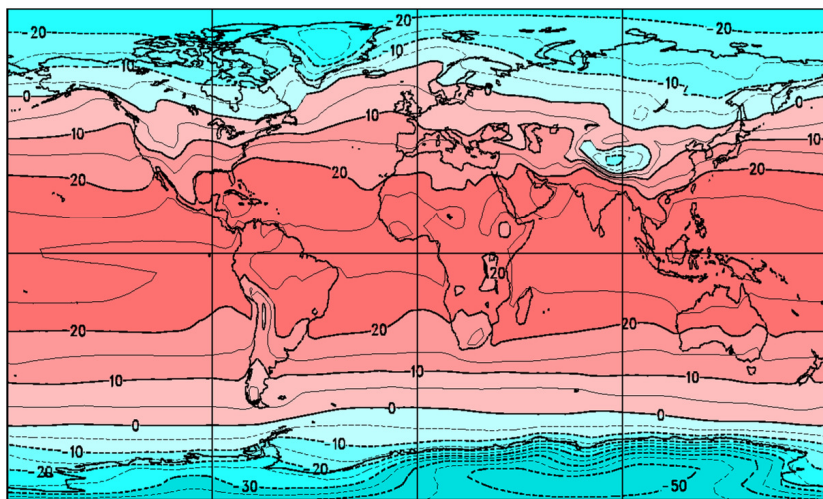
Temperature



Precipitation



Multi-model ensemble mean

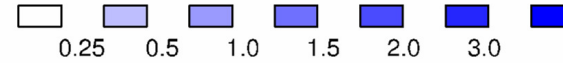
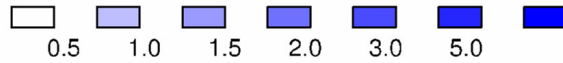
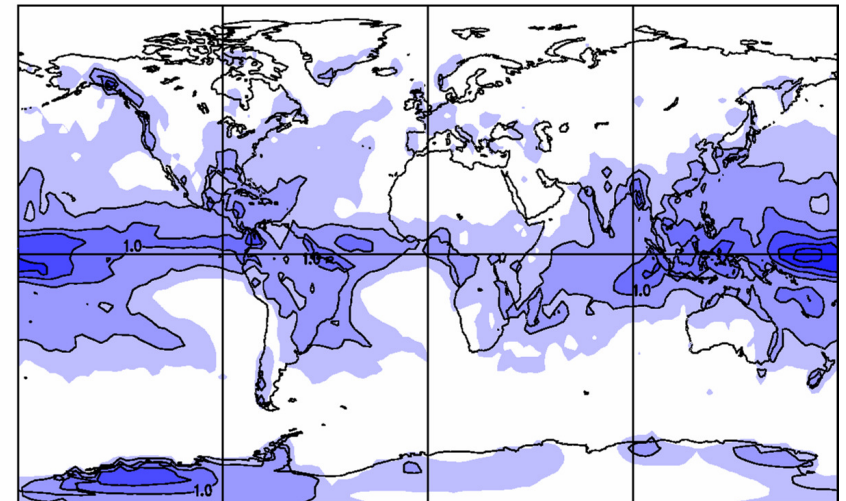
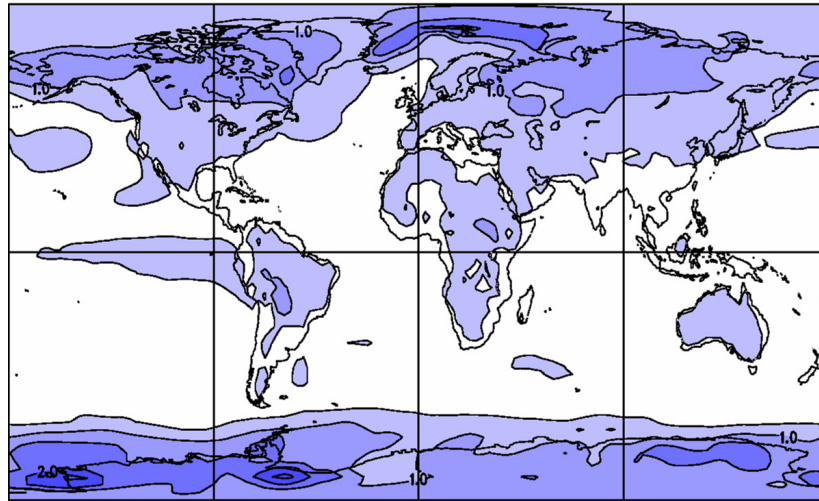


Standard Deviation of annual means

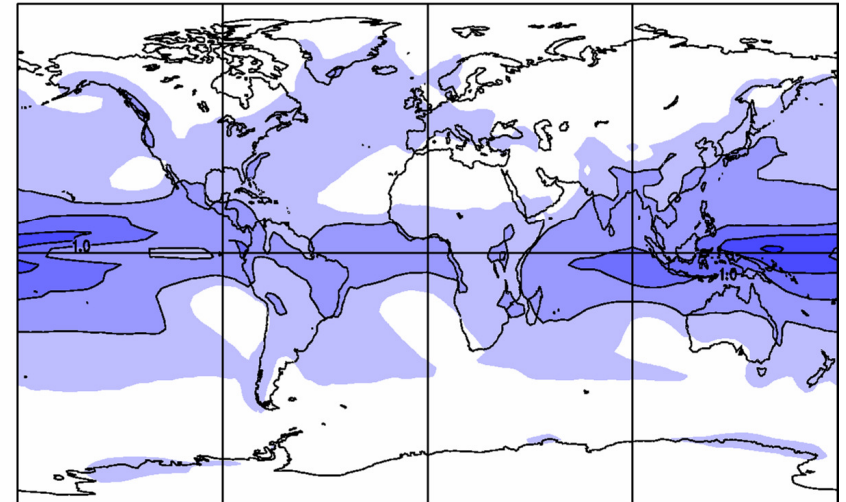
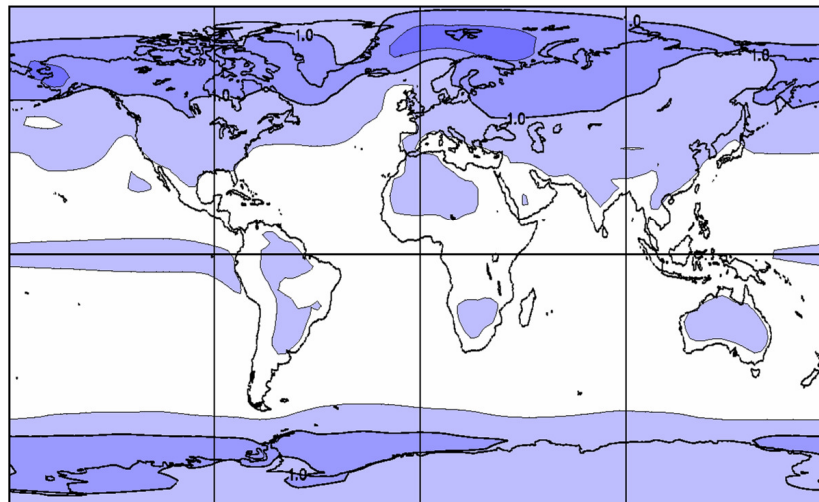
Temperature

Precipitation

Observations

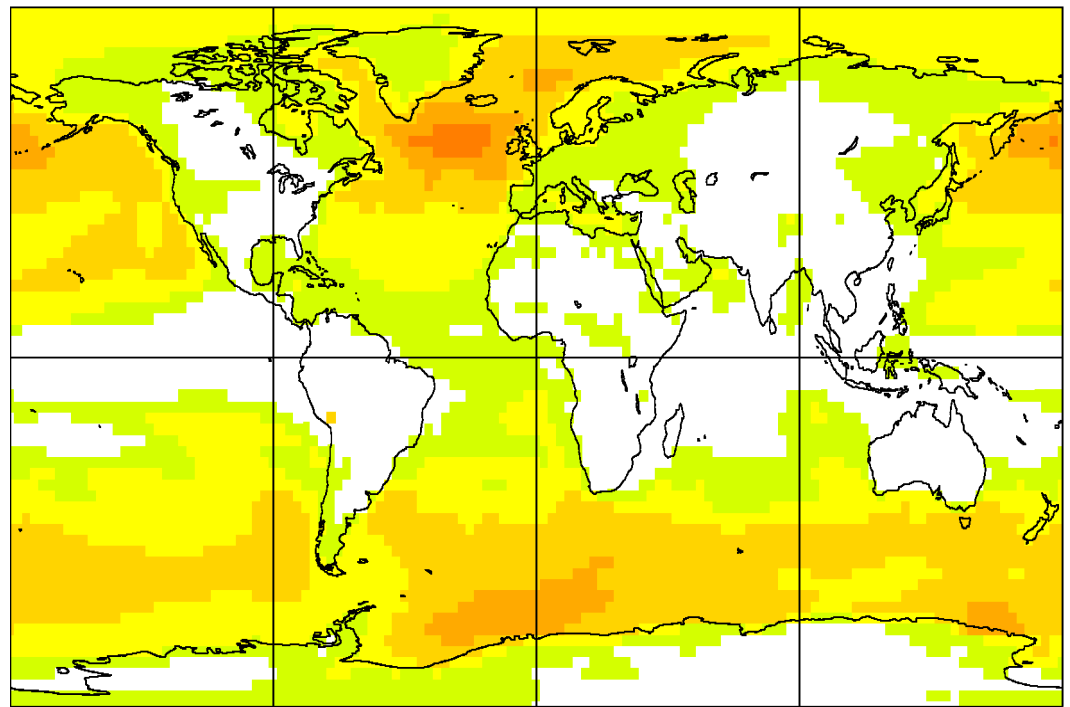


Multi-model ensemble



Temperature: potential predictability variance fraction $p_v = \sigma_v^2 / \sigma^2$ (%) for **decadal means**

- Ratio of “predictable” 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 $ppvf$
- Unforced internally generated long timescale variability

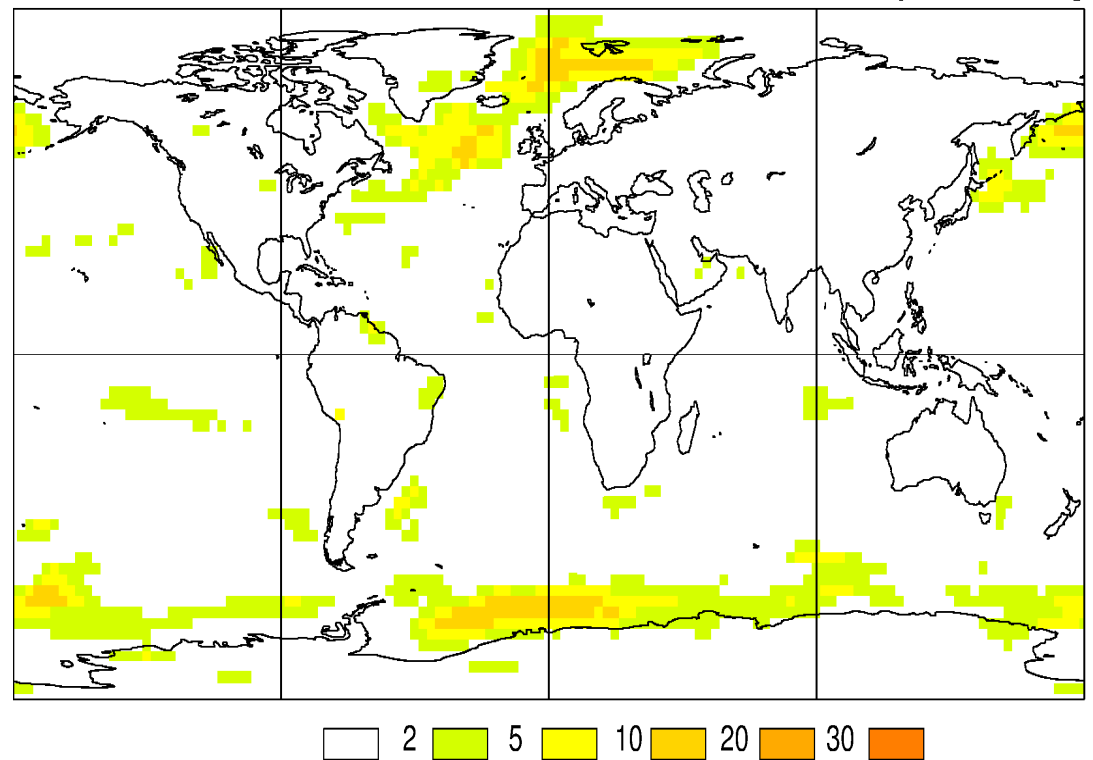


2 5 10 20 30 30

Control simulations

Precipitation: potential predictability variance fraction $p_v = \sigma^2_v / \sigma^2$ (%) 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

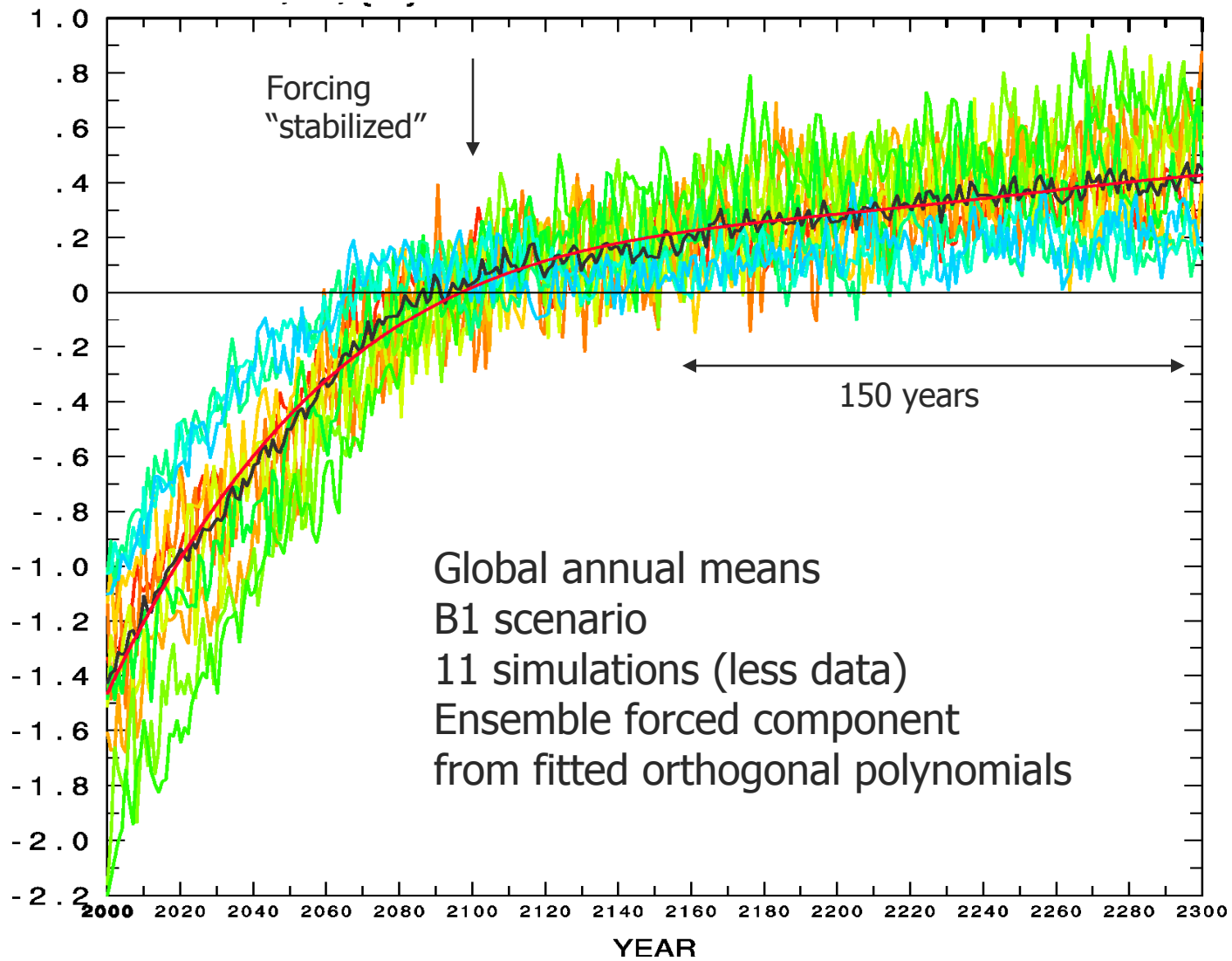


Control simulations

Potential predictability in a warmer world

- B1/Stabilization Scenario
- period is from 2000 to 2300
- GHG concentrations and aerosol loadings increase to 2100 then are constant (stabilized)
- less data: only 11 simulations for full data period

Temperature (C)



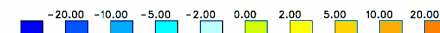
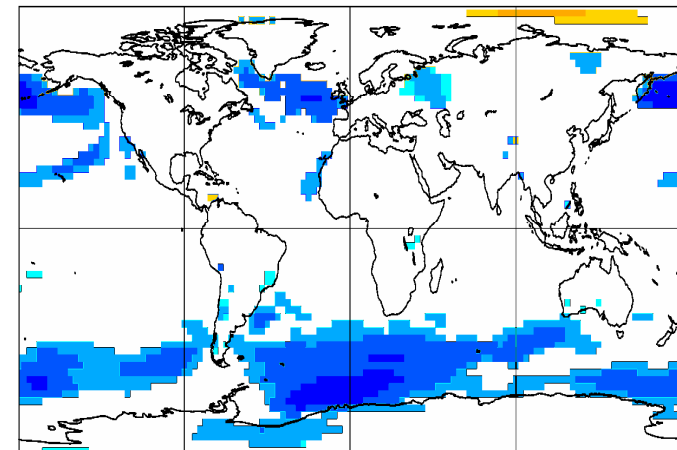
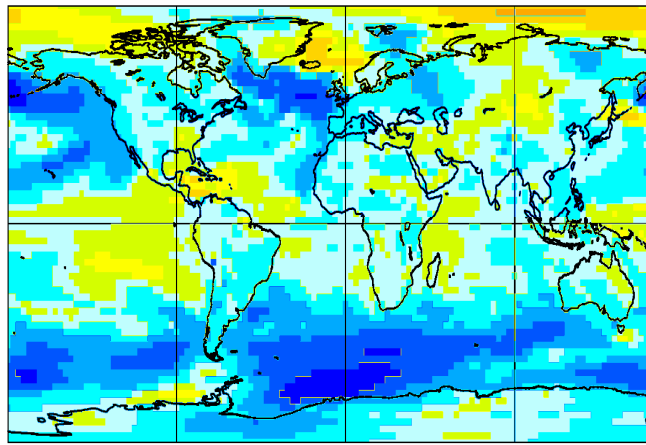
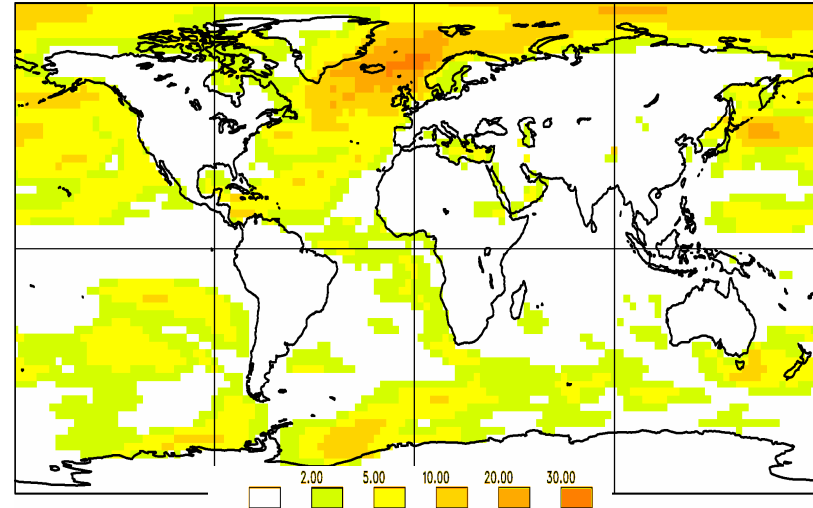
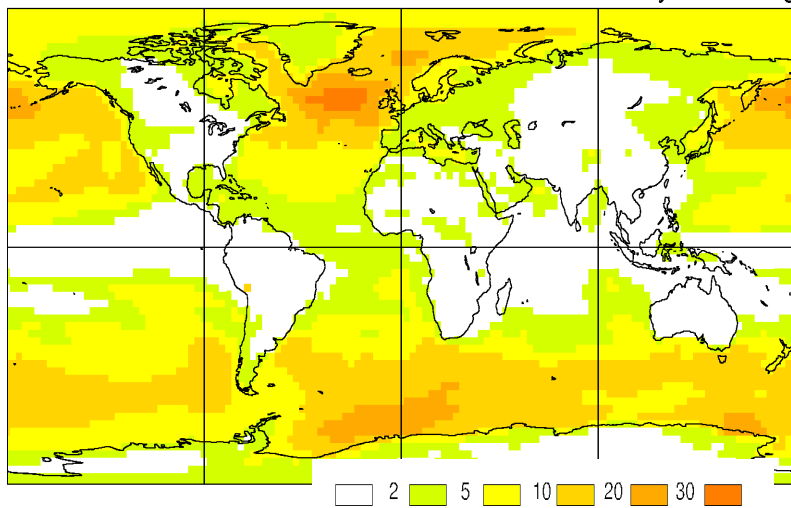
Potential predictability in a warmer world (stabilization case)

- last 150 years of stabilization simulations
- remove *trend* at each point
- estimate *internally generated* potential predictability p_v in warmer world
 - estimate *change* from control case

Decadal potential predictability p_v for *Temperature*

Control simulation

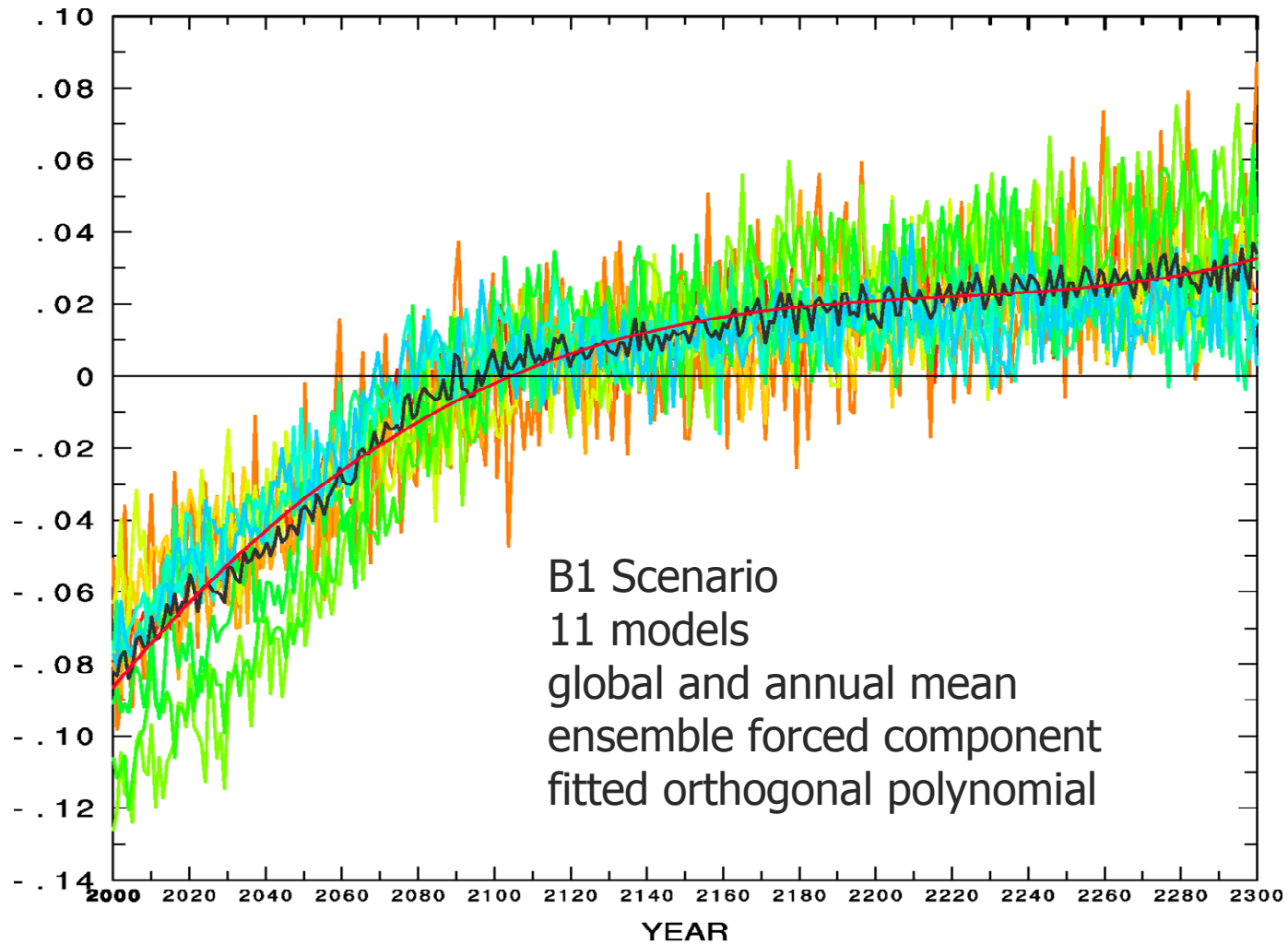
B1 stabilization scenario



Difference in warmer world

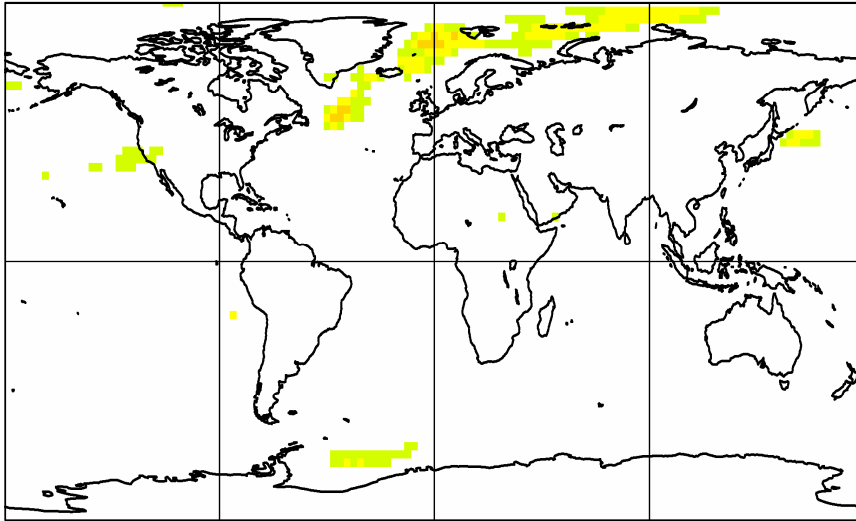
Where confidence bands *don't* overlap

Precipitation (mm/day)



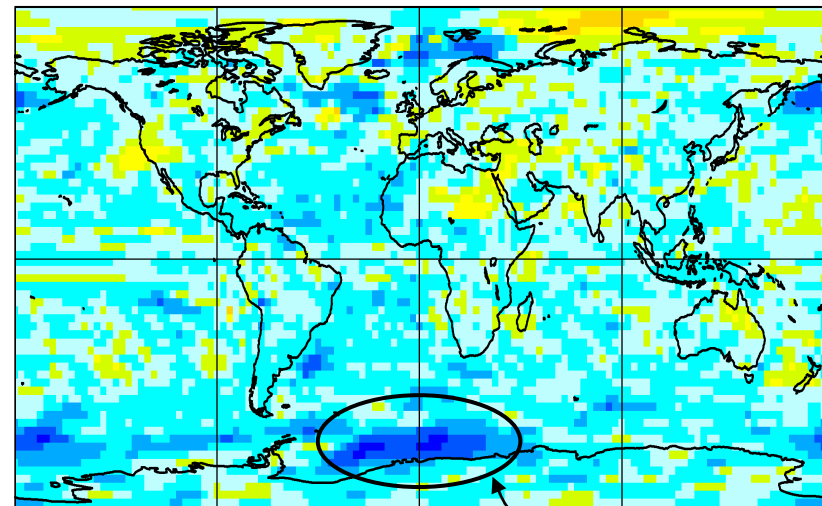
Warmer world: decadal potential predictability for Precipitation

Decadal ppvf



Given the enhanced hydrological cycle, rather an anticlimax

Difference from control



MME *decadal* potential predictability of temperature and precipitation

- “hot spots” over extratropical oceans for both temperature and precipitation
- precipitation considerably less potentially predictable than temperature
- comparatively little potential predictability over land and tropical oceans
- predictability found for regions/processes where surface connects to deeper ocean
- potential decadal predictability *decreases* in warmer world

The challenges of potential predictability

- to identify the mechanisms associated with regions of high potential predictability
- to understand the lack of potential predictability over land and tropical oceans
- to test potential predictability results by means of (multi-model) prognostic decadal predictions

End of presentation