Testing Climate Models with GPS Radio Occultation

Stephen Leroy
Harvard University, Cambridge, Massachusetts

18 June 2008

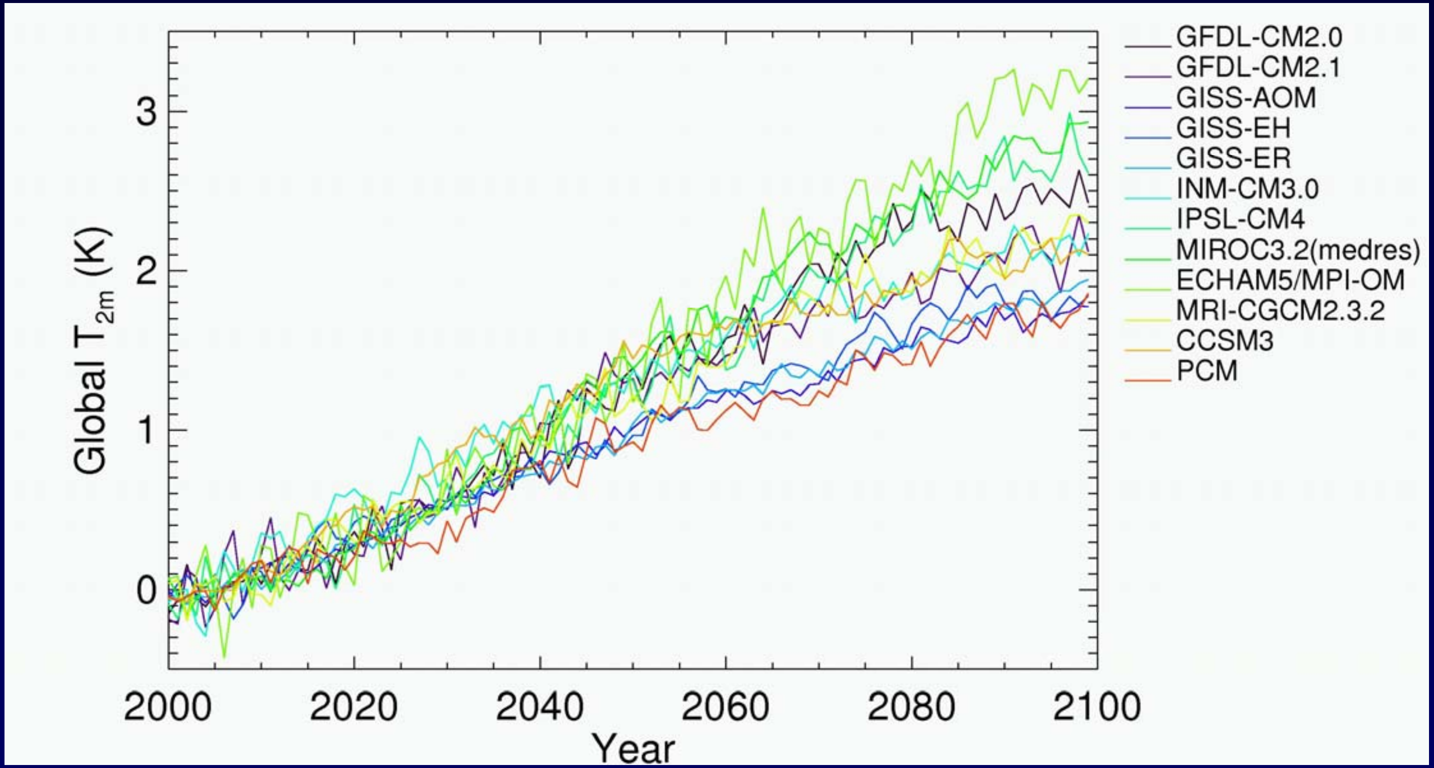
Talk Outline

- Motivation
  - Uncertainty in climate prediction
  - Fluctuation-dissipation in climate
- Optimal fingerprinting for GPS radio occultation
- Generalized scalar prediction
  - Surface air temperature
  - GPS radio occultation
- Discussion

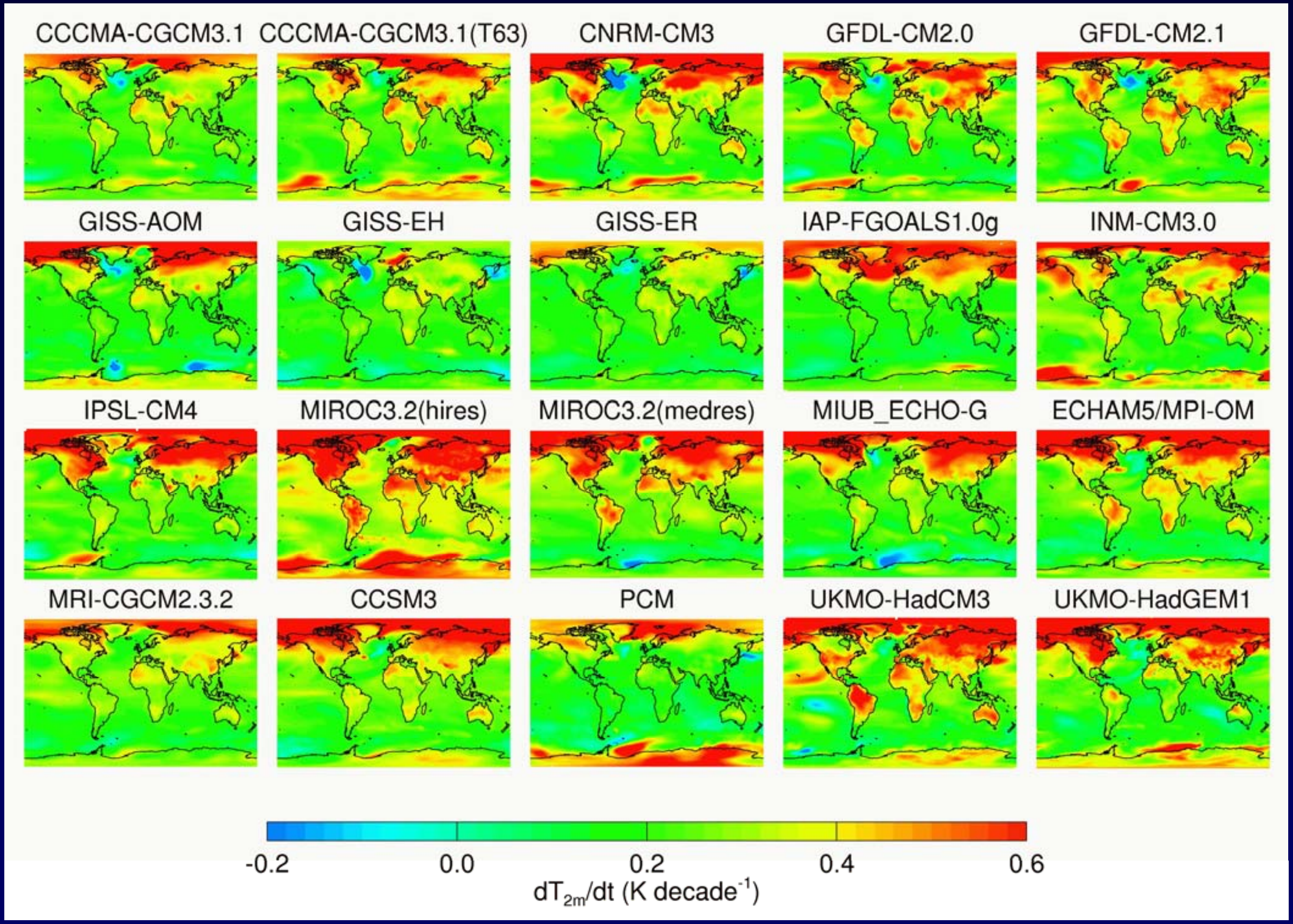
Three Questions

- Is the climate warming?
- Are humans responsible for some part of the warming?
- Can we predict future warming?

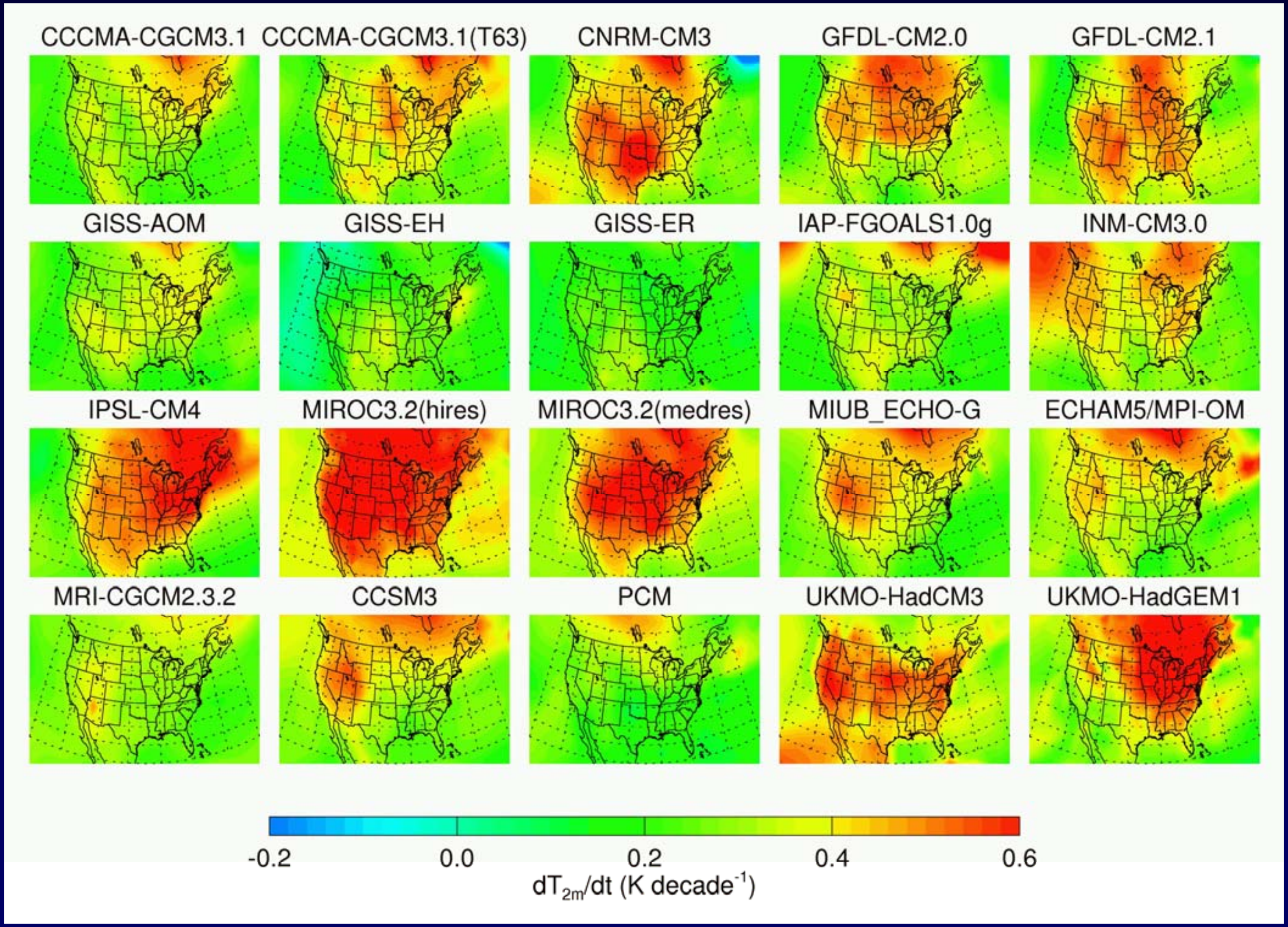
Surface Air Temperature



Surface Air Temperature



Surface Air Temperature



Fluctuation-Dissipation Theorem

$$\mathbf{u}(t) = \int_{-\infty}^{t} \mathbf{U}(t-t')\,\mathbf{U}(0)^{-1}\,\delta\mathbf{f}(t')\,dt'$$

Future trends in the climate can be related to lagged covariances, or second moments, of the climate system. (Leith, *J. Climate*, 1975)

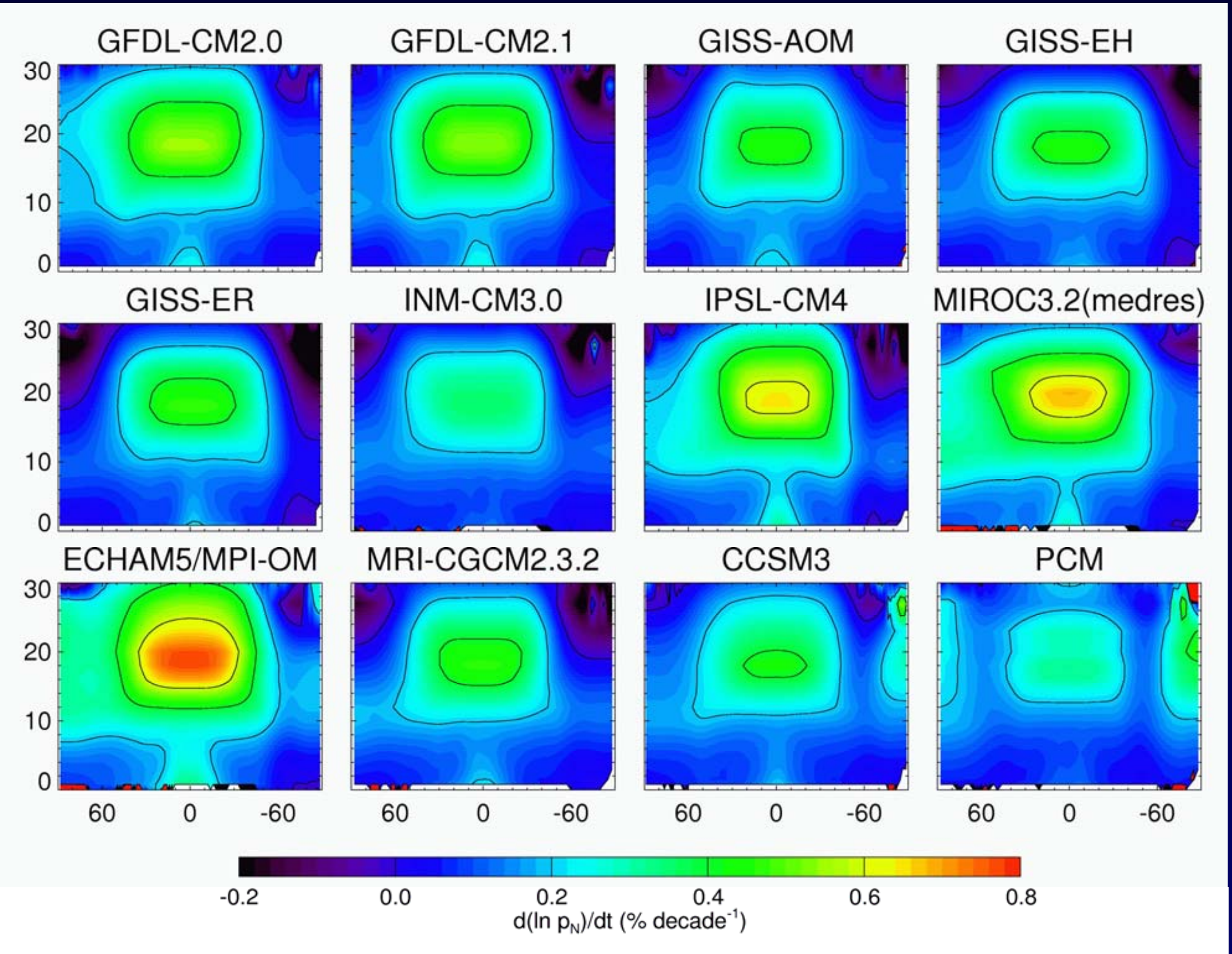
Climate model testing should favor comparison of second moments and trending between model and data over comparison of mean state.

Testing by Trending

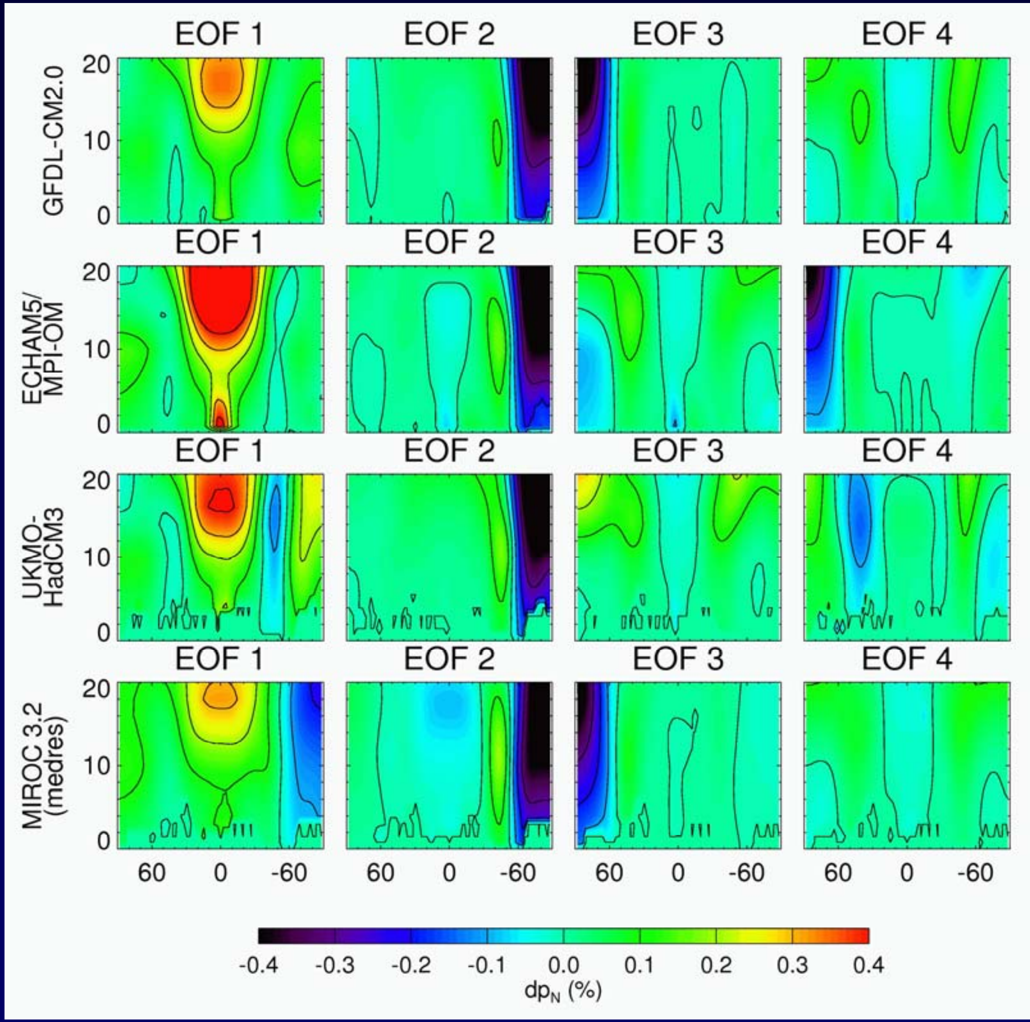
Before we have enough data…

- What signal is expected to emerge above natural variability first?
- Consider correlations in year-to-year natural variability.
- Optimal fingerprinting will tell us what to look for first and approximately how long it will take.

Occultation Dry Pressure



Dry Pressure EOFs



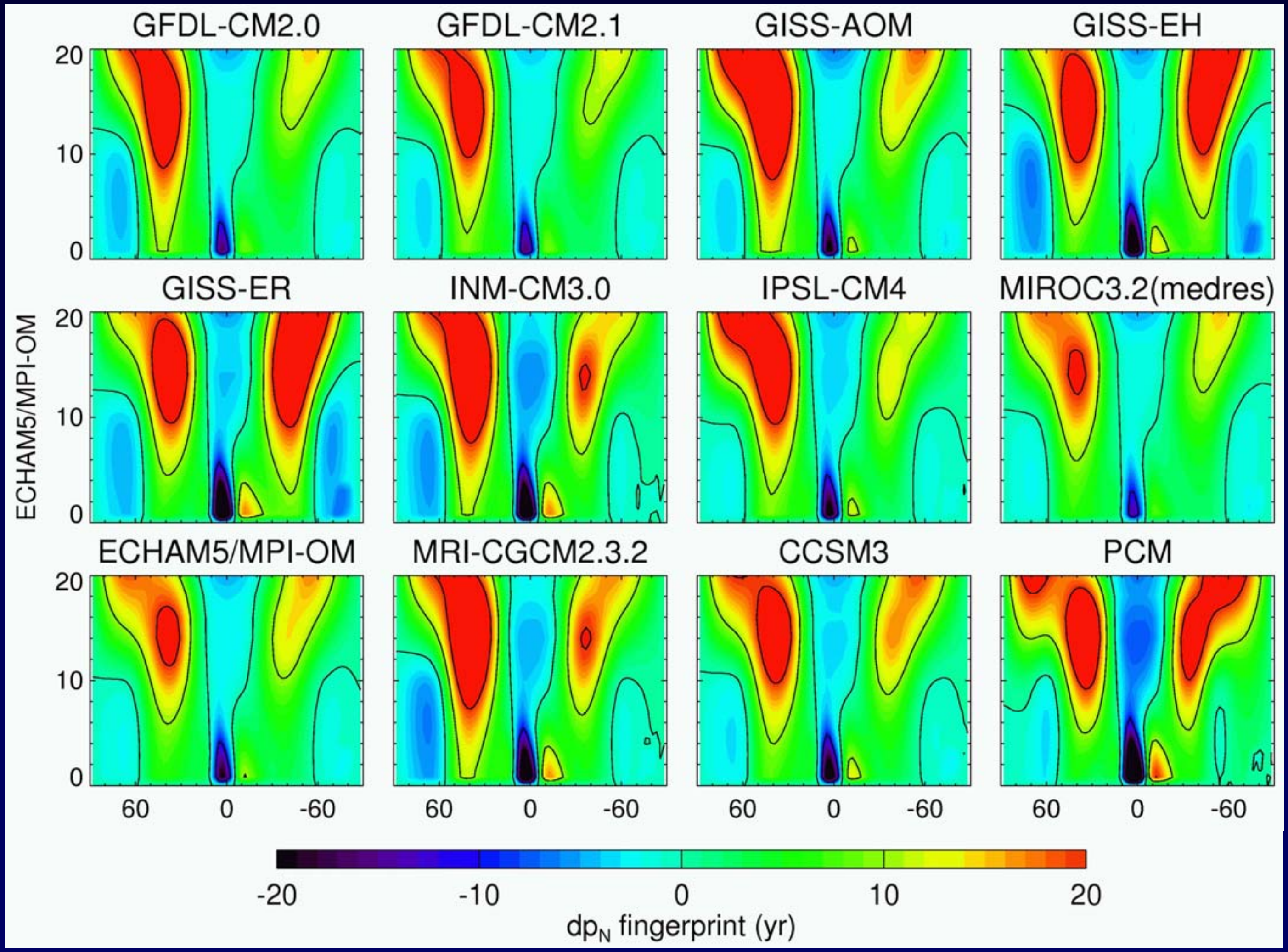
ENSO

Southern Annular Mode

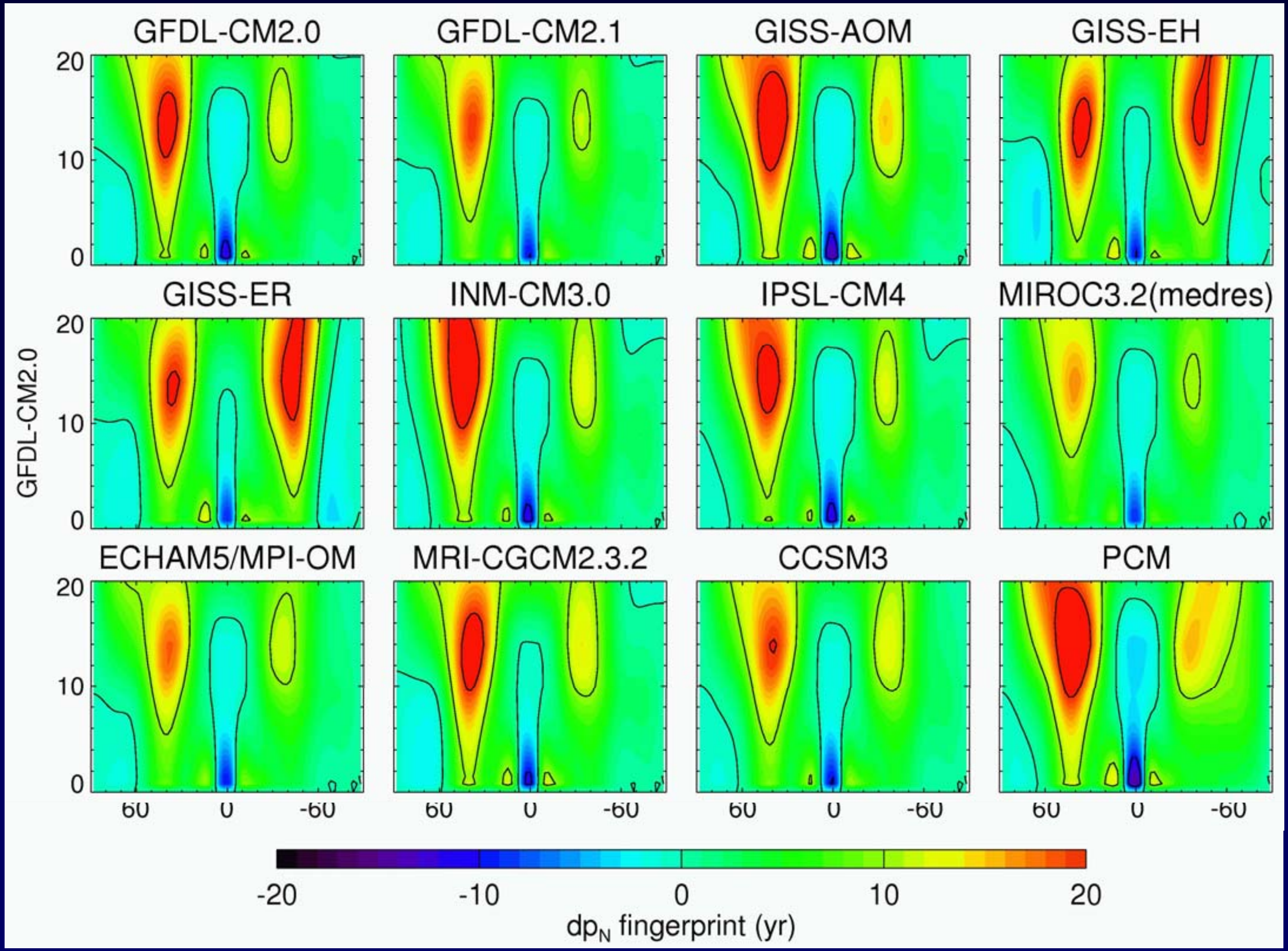
Northern Annular Mode

Symmetric Jet Migration (Hadley Circulation?)

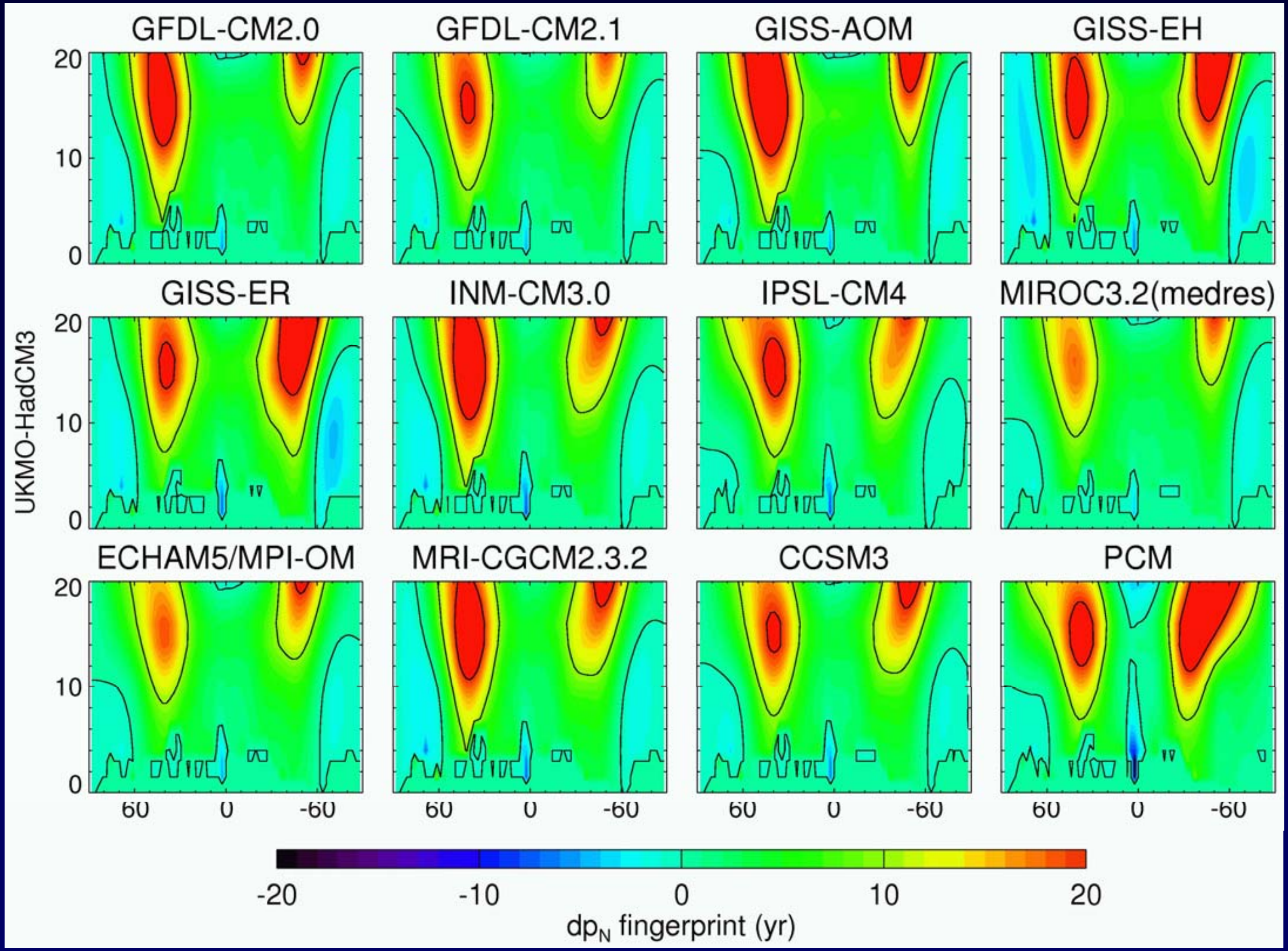
Fingerprints



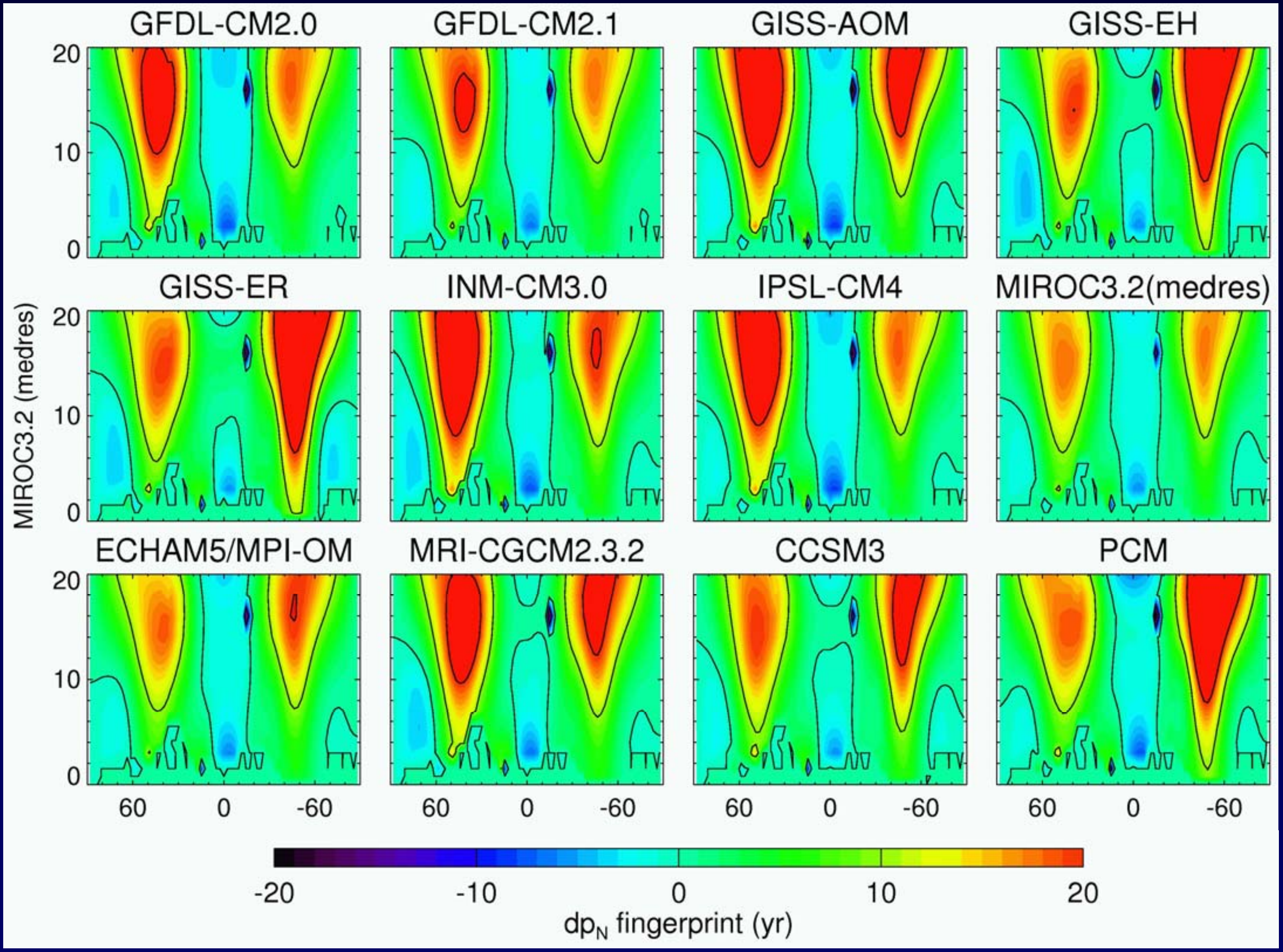
Fingerprints



Fingerprints



Fingerprints



95% Detection Times

Model	GFDL CM2.0 (yrs)	ECHAM5 / MPI-OM (yrs)	UKMO-HadCM3 (yrs)	MIROC3.2 (medres) (yrs)	Tropospheric Expansion (m $decade^{-1}$)
GFDL-CM2.0	8.67	9.05	8.29	6.63	11.02
GFDL-CM2.1	7.88	8.65	7.57	6.21	12.86
GISS-AOM	10.53	11.54	10.47	8.38	9.67
GISS-EH	10.41	11.74	10.77	8.50	9.12
GISS-ER	10.89	12.70	11.07	9.32	8.79
INM-CM3.0	9.98	11.23	9.79	8.15	10.71
IPSL-CM4	9.29	10.02	8.95	7.36	10.54
MIROC 3.2(medres)	7.09	7.47	6.83	5.39	13.04
ECHAM5/MPI-OM	7.78	8.16	7.45	5.87	12.34
MRI-CGCM2.3.2	9.95	11.70	9.92	8.35	10.68
CCSM3	8.87	9.62	8.68	6.80	11.97
PCM	12.69	12.32	11.95	8.45	7.27

How does this test climate models?

- Compare jet stream migration rate produced by models and to observed rate.
- Compare thermal expansion of troposphere, especially in tropics, produced by models to observed rate.
- Host of other GPS RO observables, e.g. tropopause height and temperature, to compare.

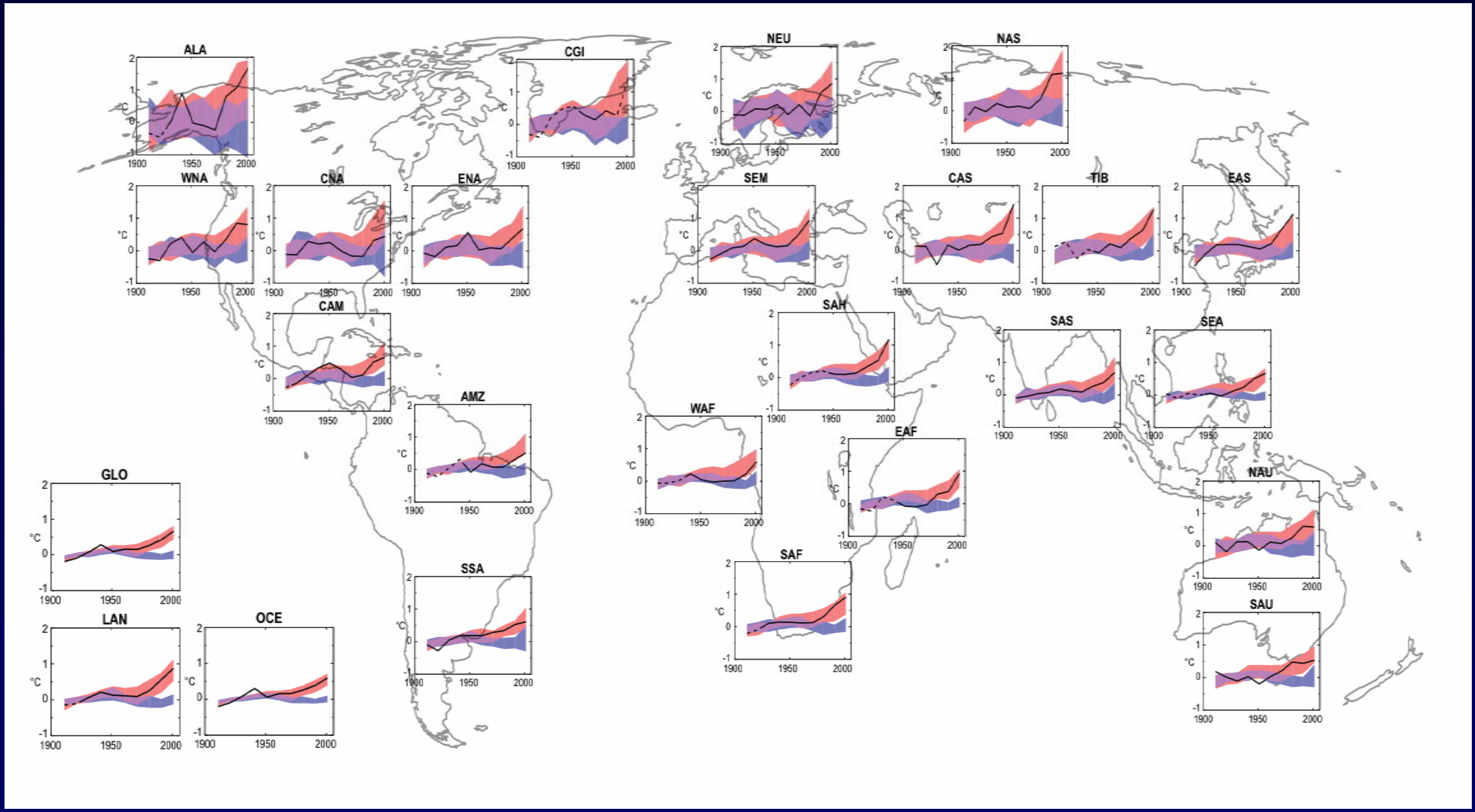
- Unanswered: What is it about climate prediction that we've improved?

Need for Attribution at Regional Scale

"The extent to which temperature changes at sub-continental scales can be attributed to anthropogenic forcings, and the extent to which it is possible to estimate the contribution of greenhouse gas forcing to regional temperature trends, remains a topic for further research....Robust detection and attribution are inhibited at the grid box scales because it becomes difficult to separate the effects of the relatively well understood large-scale external influences on climate...from each other and from local influences that may not be related to these large-scale forcings." --- IPCC AR4 (p. 697)

"[Rosenzweig et al.] make the case using what is known as the 'joint attribution' approach. They first show that the observed correspondence between impacts and warming would be very unlikely to occur if patterns of temperature change were the result of natural climate variability. They then argue that human influence has a role because observed large-scale climate change can be attributed to human influence on the climate system…These points emerge from Rosenzweig and colleagues' meta-analysis of the large literature on impacts, which involved synthesizing the results from studies of diverse types of system. This is probably the only available way of broadly linking impacts to climate change at global scales." --- Hegerl and Zwiers, *Nature*, 2008.

Scalar Prediction



Hegerl et al., IPCC AR4 Chapter 9

Bayesian Climate Prediction

Following Min & Hense, Raisanen & Palmer, Giorgi & Mearns:

$$P(d\alpha/dt \mid D, M) \propto \sum_i P(d\alpha/dt \mid m_i)\; p(m_i \mid D_{\text{mean state}}, D_{\text{trend}})$$

1. Models are rated according to their ability to hind-cast trends and produce an accurate mean state.
2. A weighted average of their predictions is formed, the weights being Bayesian posterior probabilities from the first step.

Bayesian Ensemble Prediction Theory

- Fluctuation-dissipation theorem suggests strong relationships between trends and second moments of climate, not mean state.
- Overall (transient) sensitivities of models might vary, but patterns of change are more robust.

$$P(d\alpha/dt \,|\, D, M) \propto \sum_i p(d\alpha/dt \,|\, D, m_i)\; p(m_i)$$

$$\forall m_i : \frac{d\mathbf{d}}{dt} = \left.\frac{d\mathbf{d}}{d\alpha}\right|_{m_i} \frac{d\alpha}{dt} + \frac{d}{dt}\delta\mathbf{n}$$

Generalized Scalar Prediction

$$\mathbf{F} = \left(\boldsymbol{\Sigma}_{\mathrm{var}} + \boldsymbol{\Sigma}_{d\mathbf{d}/d\alpha}\right)^{-1}\mathbf{S}\ \left[\overline{\mathbf{S}}^T\left(\boldsymbol{\Sigma}_{\mathrm{var}} + \boldsymbol{\Sigma}_{d\mathbf{d}/d\alpha}\right)^{-1}\overline{\mathbf{S}}\right]^{-1}$$

$$\mathbf{s}_i = d\mathbf{d}/d\alpha_i\,,\quad \boldsymbol{\Sigma}_{d\mathbf{d}/d\alpha} = \sum_{i,j}\left\langle \frac{d\alpha_i}{dt}\frac{d\alpha_j}{dt}\delta\mathbf{s}_i\delta\mathbf{s}_j^T\right\rangle_{\mathrm{models}}$$

$$\frac{d\boldsymbol{\alpha}}{dt} = \frac{d}{dt}\left(\mathbf{F}^T\mathbf{d}(t)\right)$$

Extrapolate from the past, searching for external indicators that are…

- **Physically robust**—there is significant agreement between models that the indicator’s trend is strongly related to the target scalar’s trend, and
- **Naturally quiet**—they are associated with minimal naturally occurring inter-annual variability.

Generalized Scalar Prediction

$$\mathbf{F} = \left(\boldsymbol{\Sigma}_{\text{var}} + \boldsymbol{\Sigma}_{d\mathbf{d}/d\alpha}\right)^{-1}\mathbf{S}\left[\bar{\mathbf{S}}^T\left(\boldsymbol{\Sigma}_{\text{var}} + \boldsymbol{\Sigma}_{d\mathbf{d}/d\alpha}\right)^{-1}\bar{\mathbf{S}}\right]^{-1}$$

“Contravariant fingerprint”

$$\mathbf{s}_i = d\mathbf{d}/d\alpha_i\,, \quad \boldsymbol{\Sigma}_{d\mathbf{d}/d\alpha} = \sum_{i,j}\left\langle \frac{d\alpha_i}{dt}\frac{d\alpha_j}{dt}\,\delta\mathbf{s}_i\,\delta\mathbf{s}_j^T \right\rangle_{\text{models}}$$

“Fingerprint”

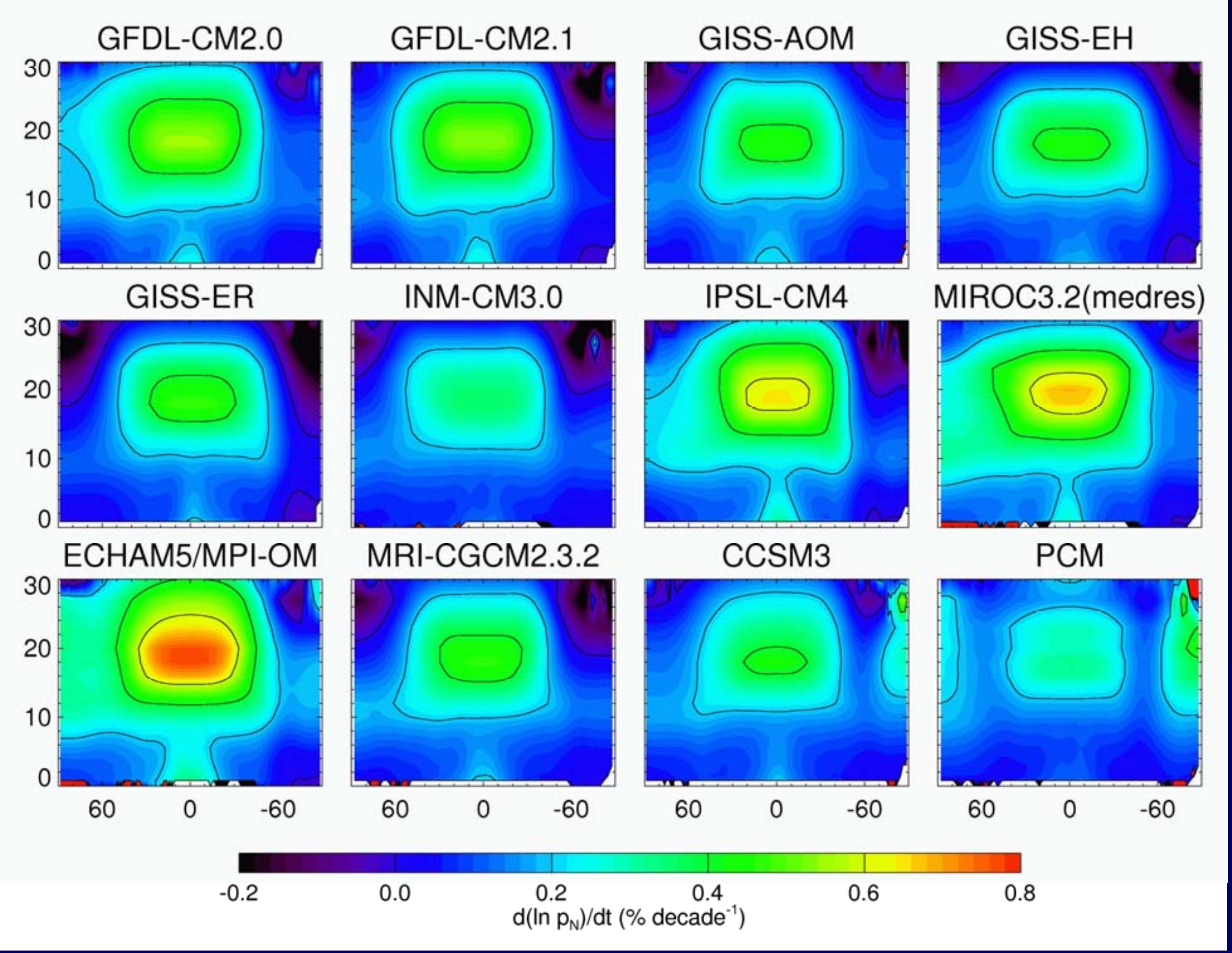
$$\frac{d\boldsymbol{\alpha}}{dt} = \frac{d}{dt}\left(\mathbf{F}^T\mathbf{d}(t)\right)$$

“Detectors”

Extrapolate from the past, searching for external indicators that are…

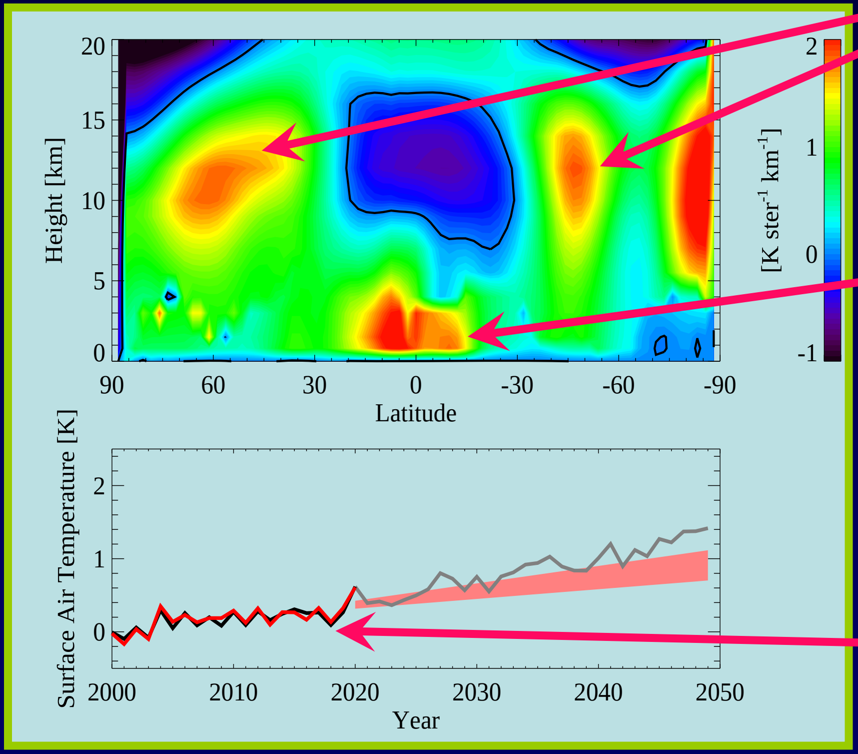
- **Physically robust**—there is significant agreement between models that the indicator’s trend is strongly related to the target scalar’s trend, and
- **Naturally quiet**—they are associated with minimal naturally occurring inter-annual variability.

GPS RO Dry Pressure Tendency



How Does GPS RO Test GCMs?

α = global average surface air temperature, ***d*** = GPS RO dry pressure [height]



Poleward migration of jet streams

Increased ITCZ humidity

Near perfect tracking of global average surface air temperature

Conclusions

- Trends GPS RO can be used to test models by (1) migration of maximum wind, (2) thermal expansion of troposphere. Because of one-to-one relationships between GPS RO variables, little is gained by trending a different GPS RO variable.
- GPS RO can be used to constrain climate prediction in the same way as global average surface air temperature. GPS RO is truly global and highly calibrated.
- A whole host of variables can be trended, such as tropopause height and temperature, stratospheric temperature, but it is not clear whether such tests are useful or are independent of those mentioned above.