Radio Occultation Data: Its Utility in NWP and Climate Fingerprinting*

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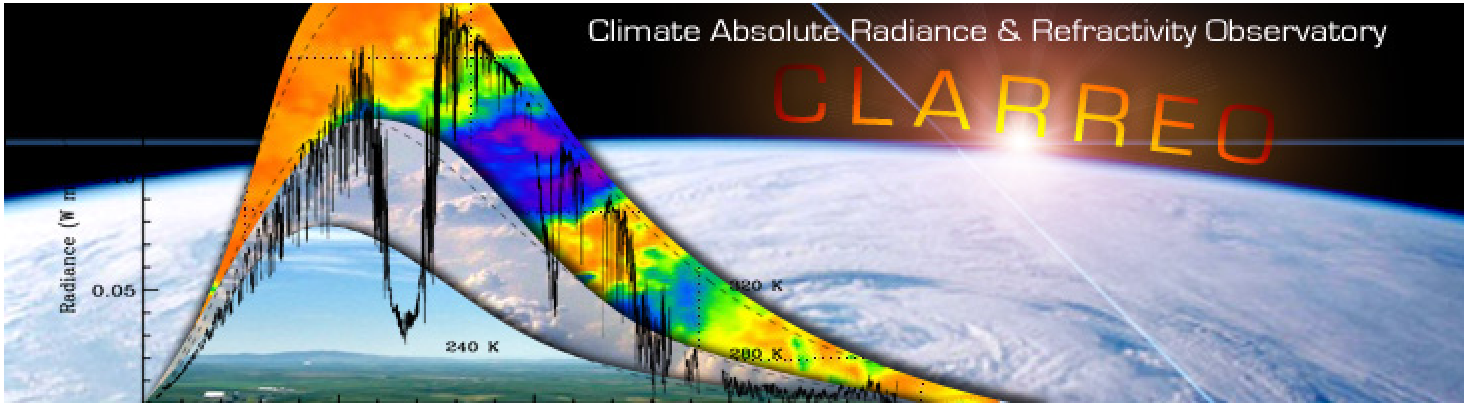
Diagnosis of Forecasting and Data Assimilation Systems
European Centre for Medium-Range Weather Forecasts
Reading, England

7-10 September 2009

*Not so much about NWP; perhaps a little about monitoring the infrared spectrum.



Two satellites in true polar orbit

Launch: ~2015

Mission concept review: February 2010

Project Scientist: Dave Young

Science Team Lead: Bruce Wielicki

Outline

- CLARREO and testing climate models
  - Climate benchmarking and climate benchmark data types
  - Information content: Scalar prediction
  - Requirements on accuracy
- Climate benchmark 1: Radio occultation
  - The sounding technique and its traceability
  - Retrieval
  - Information content
- Climate benchmark 2: High-resolution infrared spectra
  - Information content
  - Joint RO and IR information content
- Summary and discussion

Climate Benchmarks

"CLARREO addresses three key societal objectives: 1) the essential responsibility to present and future generations to put in place a benchmark climate record that is global, accurate in perpetuity, tested against independent strategies that reveal systematic errors, and pinned to international standards; 2) the development of an operational climate forecast that is tested and trusted through a disciplined strategy using state-of-the-art observations with mathematically-rigorous techniques to systematically improve those forecasts to establish credibility; and 3) disciplined decision structures that assimilate accurate data and forecasts into intelligible and specific products that promote international commerce as well as societal stability and security."

— The NRC Decadal Survey of NOAA and NASA, 2007

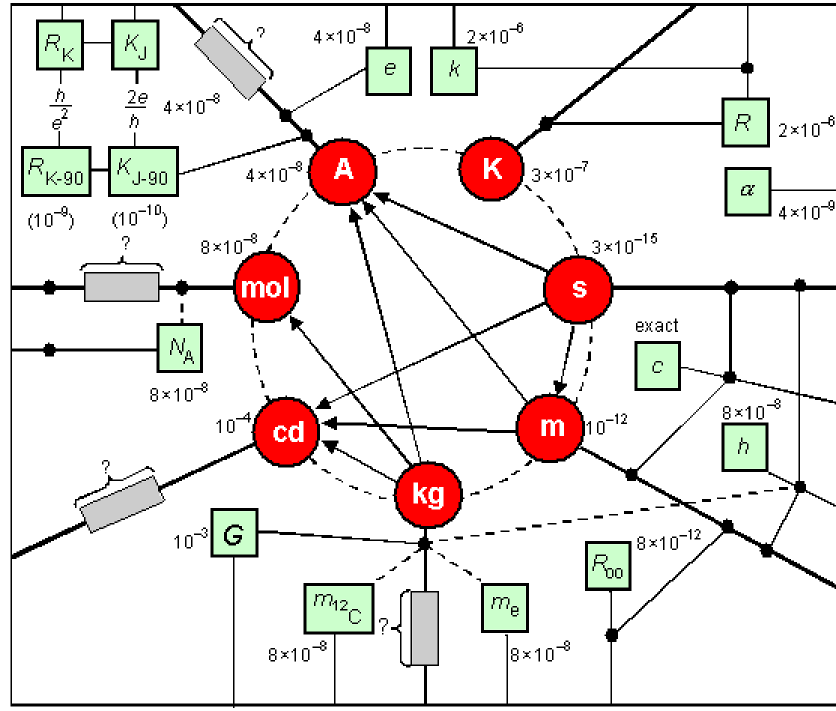
- CLARREO = Climate Absolute Radiance and Refractivity Observatory
- "Accurate in perpetuity" = Data can be used by all future generations with or without gaps in timeseries
- "International standards" = SI traceability, certainty that you've measured what you said you measured
- "Tested against independent strategies that reveal systematic error" = Determine error bars empirically
- "Mathematically rigorous techniques" = Bayesian methods, optimal detection

SI Traceability

The International Vocabulary of Basic and General Terms in Metrology (ISO 1993):

6.10 Traceability

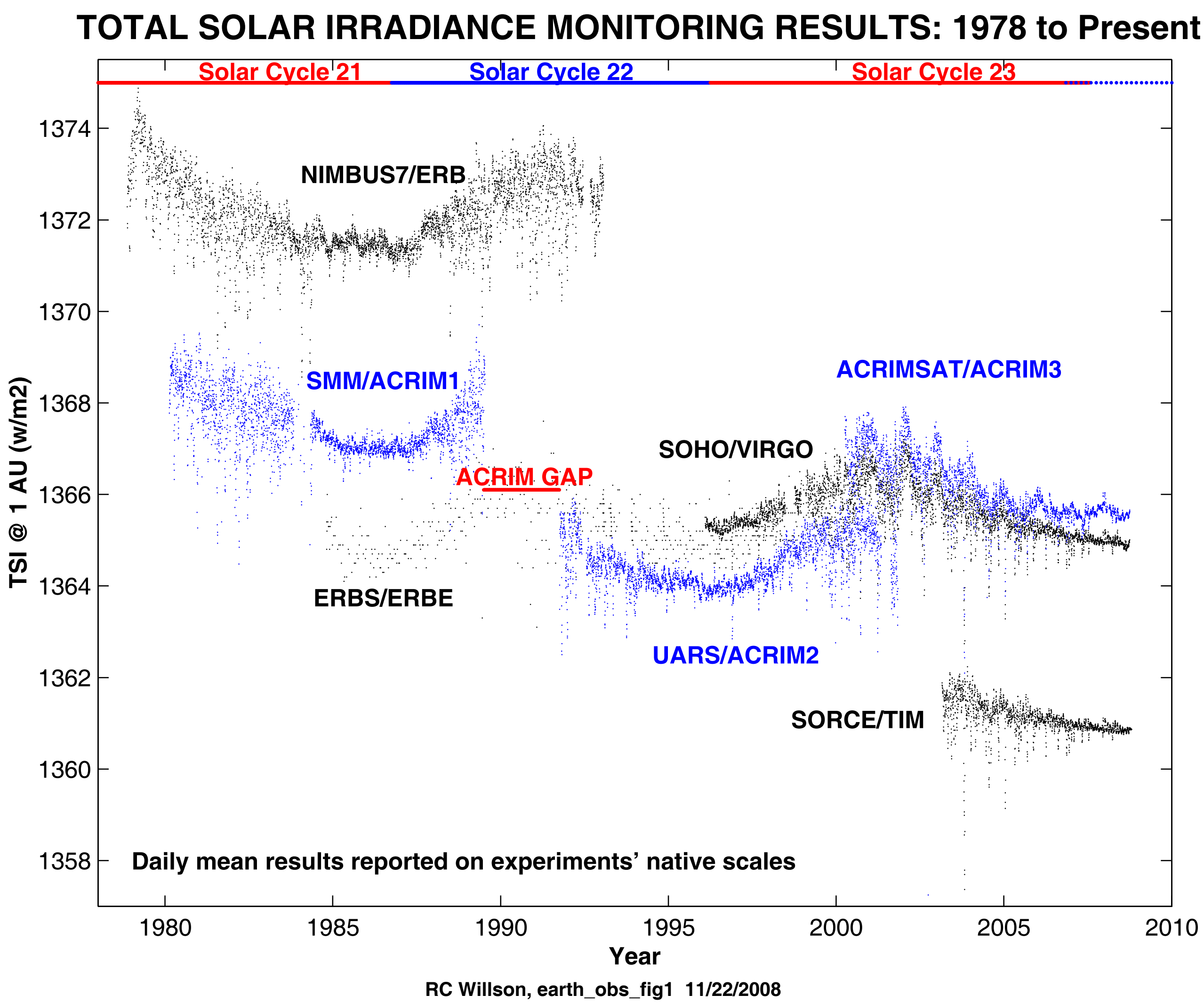
Property of the result of a measurement or the value of a standard whereby it can be related to stated references, usually national or international standards, through an unbroken chain of comparisons all having stated uncertainties.



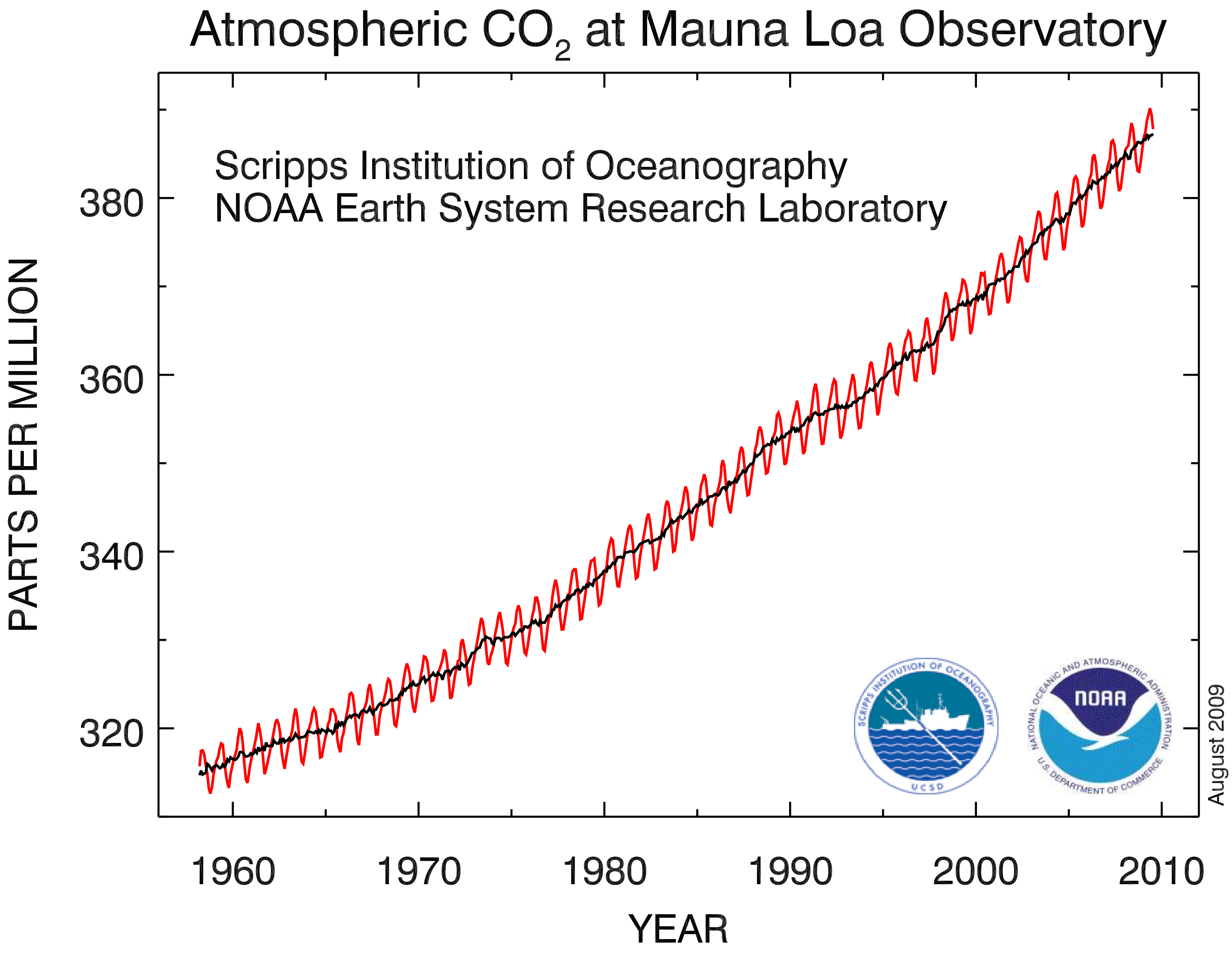
Source-based traceability: Reproduce the unit of the observation by means of physical laws (e.g., blackbodies & Planck equation)

Detector-based traceability: Reproduce the definition of the unit by means other than that of operational observation (e.g., electrical substitution)

Interruptions in record



Interruptions in record, resolved



Information content: "Climate OSSE"

Benchmark Measurement

- Traceable to international standards
- Minimize sampling errors, systematic and random

Climate OSSE

- Simulate trends in observable as produced by different models
- Explore information content for various climate scalars

Climate Uncertainty

- Shortwave forcing
- Longwave forcing
- Climate feedbacks & sensitivity

Climate OSSE Results

- Detection time and accuracy requirements
- How measurement constrains climate predictability
- Relative redundancy with other benchmark data types

Scalar detection

- Find underlying trends in arbitrary "climate" variables given climate benchmark data
- Confidence levels must reflect influence of natural variability and inability to relate observations and climate variables (model uncertainty).
- Connect to optimal detection and attribution work.

- **Solution:** Two levels of Bayesian inference.
  1) Inference for trends in climate variable conditioned on a single model,
  2) Inference for most probable model in an ensemble of climate models.

First level of inference

Solve for trends in climate scalar, no prior

$$\frac{d\mathbf{d}}{dt} = \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \frac{d\alpha}{dt} + \frac{d}{dt} d\mathbf{n} \qquad \frac{d}{dt} d\mathbf{n} \sim N(\mathbf{0}, \mathbf{\Sigma}_{d\mathbf{n}/dt})$$

Trend in data

Model of data

Trend in climate scalar

Postfit residuals

<u>Error:</u>
Observation error
Natural variability

Compare…

$d\mathbf{d}/dt$ to $(\boldsymbol{d} - \boldsymbol{y})$, difference between data and forecast

$d\mathbf{g}/d\alpha$ to $\mathbf{K}$, linear forward model

$d\alpha/dt$ to $\delta\boldsymbol{x}$, analysis increment

$\mathbf{\Sigma}_{d\mathbf{n}dt}$ to $\mathbf{O}$, observation error

First level of inference

Solve for trends in climate scalar, no prior

$$\frac{d\mathbf{d}}{dt} = \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \frac{d\alpha}{dt} + \frac{d}{dt} d\mathbf{n} \qquad \frac{d}{dt} d\mathbf{n} \sim N(\mathbf{0}, \mathbf{\Sigma}_{d\mathbf{n}/dt})$$

Trend in data

Model of data

Trend in climate scalar

Postfit residuals

<u>Error:</u>
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Natural variability

Compare…

$d\mathbf{d}/dt$ to $(\mathbf{d} - \mathbf{y})$, difference between data and forecast

$d\mathbf{g}/d\alpha$ to $\mathbf{K}$, li

$d\alpha/dt$ to $\delta\mathbf{x}$, a

$$\frac{d\alpha}{dt} = \left(\left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i}' \mathbf{\Sigma}^{-1}_{d\mathbf{n}/dt} \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \right)^{-1} \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i}' \mathbf{\Sigma}^{-1}_{d\mathbf{n}/dt} \frac{d\mathbf{d}}{dt}$$

$\mathbf{\Sigma}_{d\mathbf{n}dt}$ to $\mathbf{O} + \mathbf{F}$, observation + forecast error

First level of inference

Solve for trends in climate scalar, no prior

$$\frac{d\mathbf{d}}{dt} = \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \frac{d\alpha}{dt} + \frac{d}{dt} d\mathbf{n} \qquad \frac{d}{dt} d\mathbf{n} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{d\mathbf{n}/dt})$$

Trend in data

Model of data

Tr
clima

Postfit residuals

Error:
Observation error
Natural variability

$$G_{ij} = \sum_{\mu} \frac{\langle \mathbf{e}_\mu, \mathbf{s}_i \rangle \langle \mathbf{e}_\mu, \mathbf{s}_j \rangle}{\lambda_\mu}$$

$$\mathbf{h} = \sum_{\mu} \frac{\langle \mathbf{e}_\mu, \mathbf{s}_i \rangle \langle \mathbf{e}_\mu, d\mathbf{d}/dt \rangle}{\lambda_\mu}$$

$$\frac{d\alpha}{dt} = \mathbf{G}^{-1}\mathbf{h}$$

Compare…

$d\mathbf{d}/dt$ to $(\mathbf{d} - \mathbf{y})$, difference be

$d\mathbf{g}/d\alpha$ to $\boldsymbol{K}$, li

$d\alpha/dt$ to $\delta\mathbf{x}$, a

$\boldsymbol{\Sigma}_{d\mathbf{n}dt}$ to $\mathbf{O} + \mathbf{F}$, observation +

$$\frac{d\alpha}{dt} = \left(\left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \right. \quad {}_{dt} \frac{d\mathbf{d}}{dt}$$

Second level of inference

Weight posterior $P(d\alpha/dt \mid d\mathbf{d}/dt)$ by evidence for data and model $P(d\mathbf{d}/dt \mid M_i)$ for an ensemble of models, and sum over models.

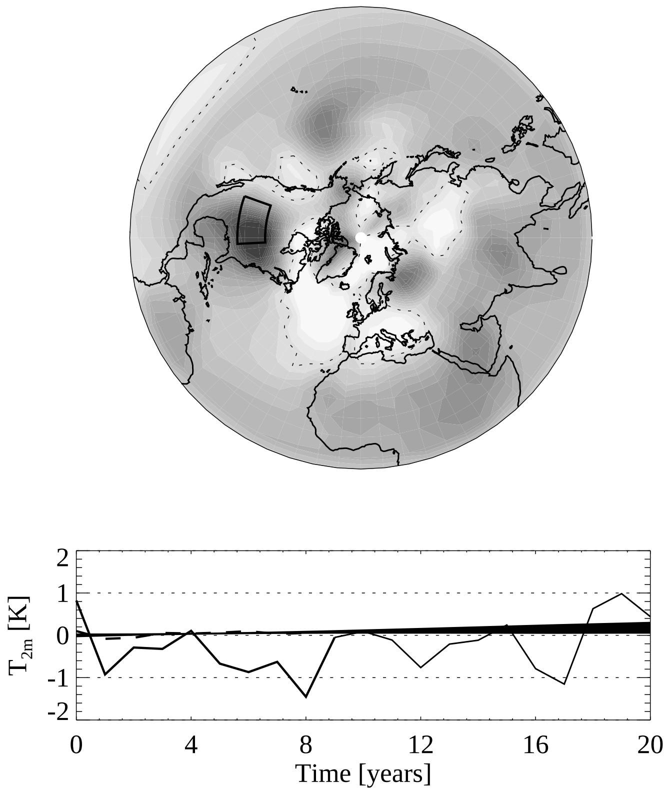
$$\frac{d\mathbf{g}}{d\alpha} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{d\mathbf{g}/d\alpha})$$

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_{d\mathbf{n}/dt} + (d\alpha/dt)^2\, \boldsymbol{\Sigma}_{d\mathbf{g}/d\alpha}$$

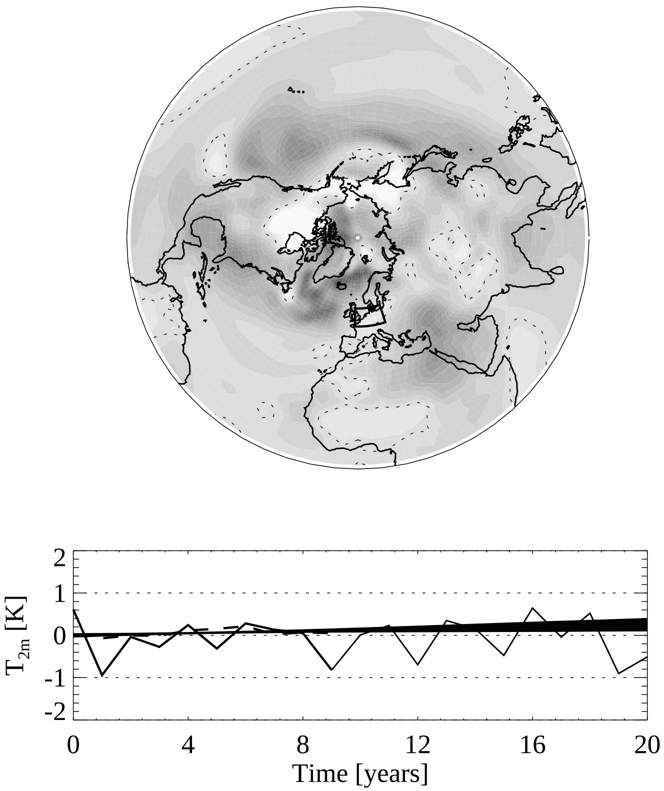
$$\frac{d\alpha}{dt} = \left(\left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i}' \boldsymbol{\Sigma}^{-1} \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \right)^{-1} \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i}' \boldsymbol{\Sigma}^{-1} \frac{d\mathbf{d}}{dt}$$

Scalar prediction: Examples

Central U.S. based on NH surface air temperature



Northern Europe based on NH surface air temperature



Requirements on accuracy

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}_{d\mathbf{d}/dt} + \boldsymbol{\Sigma}_{d\mathbf{n}/dt} + (d\alpha/dt)^2\, \boldsymbol{\Sigma}_{d\mathbf{g}/d\alpha}$$

$$\sigma_{\mathrm{obs}}^2 \tau_{\mathrm{obs}} << \sigma_{\mathbf{n}}^2 \tau_{\mathbf{n}}$$

Accuracy requirements are directly related to natural variability in observation space. You don't want inaccuracy to augment detection times too much more than natural variability already does.

Longer missions generally require more stringent accuracy requirements.

Accuracy requirements completely unrelated to expected trends!

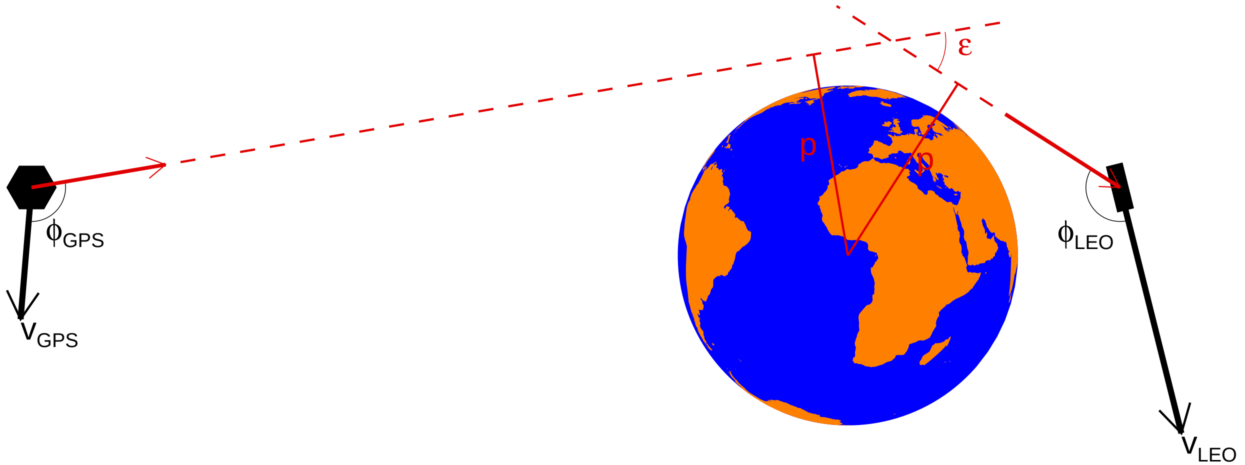
Leroy, Ohring, Anderson, 2009: *J. Climate*.

Optimal fingerprinting: Conclusions

- Optimal fingerprinting is the same as variational assimilation, but
  - Observations are long-term changes in observable
  - No prior (forecast, background)
  - Forward operator is model-projected climate change
- Scalar prediction
  - Relates trends in accurate data types to a projected trend in a user-selected scalar
  - Weights against natural variability and uncertainty in relationships

GNSS Radio Occultation

$$-\frac{dL}{dt} = \lambda \Delta \nu = v_{\mathrm{GPS}} \cos \phi_{\mathrm{GPS}} + v_{\mathrm{LEO}} \cos \phi_{\mathrm{LEO}}$$



GNSS Radio Occultation (2)

- Orbit determination and clock correction, GPS and LEO: dL/dt
- Diffraction (and multipath) inversion: $\varepsilon(p)$

$$U(p) = \frac{1}{4\pi} \iint_S \left\{ U \frac{\partial}{\partial n} \left(\frac{e^{iks}}{s} \right) - \frac{e^{iks}}{s} \frac{\partial U}{\partial n} \right\} dS$$

- Inversion for refractivity: $N(r)$

$$\ln n(p) = \frac{1}{\pi} \int_p^\infty \frac{\varepsilon(p')\, dp'}{\sqrt{p'^2 - p^2}}$$

Kursinski, E.R., G.A. Hajj, J.T. Schofield, R.P. Linfield, and K.R. Hardy, 1997: Observing Earth's atmosphere with radio occultation measurements using the Global Positioning System. *J. Geophys. Res.*, **102**, 23429-23465.

Hajj, G.A., E.R. Kursinski, W.I. Bertiger, L.J. Romans, and S.S. Leroy, 2002: A technical description of atmospheric sounding by GPS occultation. *J. Atmos. Solar-Terr. Phys.*, **64**, 451-469.

Gorbunov, M.E., H.H. Benzon, A.S. Jensen, M.S. Lohmann, and A.S. Nielsen, 2004: Comparative analysis of radio occultation processing approaches based on Fourier integral operators. *Radio Sci.*, **39**, doi:10.1029/2003RS002916.

GNSS Radio Occultation (3)

- Refractivity

$$N = (n-1)\times 10^6 = (77.6\,\mathrm{K\,hPa^{-1}})\frac{p}{T} + (363\times 10^3\,\mathrm{K^2\,hPa^{-1}})\frac{p_\mathrm{w}}{T^2}$$

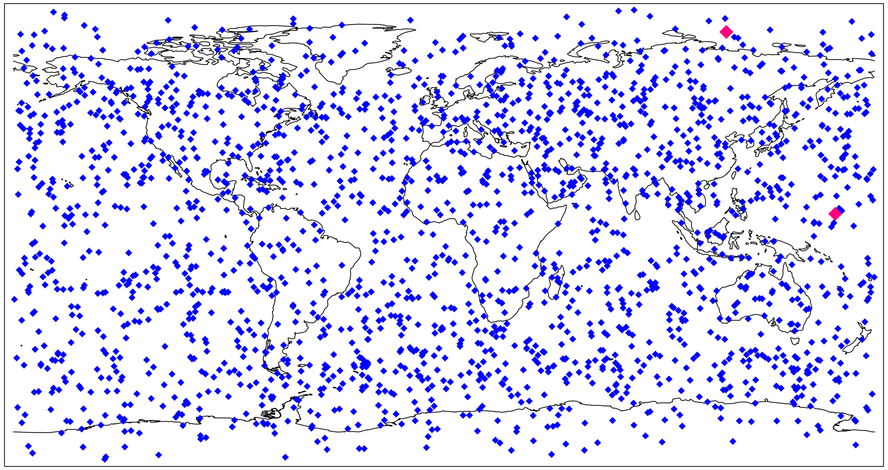
- "Dry" pressure

$$p_d(h) = (4.402\times 10^{-4}\,\mathrm{hPa\ m^{-1}})\int_h^\infty N\,dh \cong p(h) + (7521\,\mathrm{K})\int_0^{p(h)} \frac{q\,dp}{T}$$

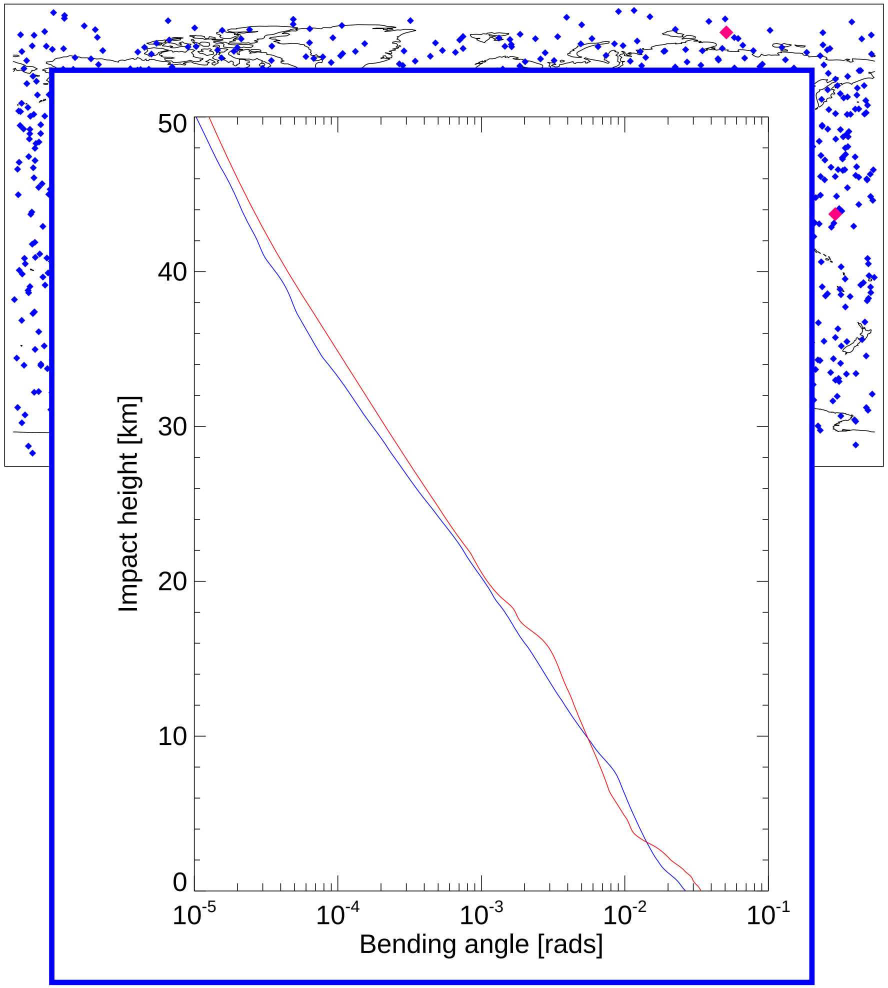
- Geopotential height

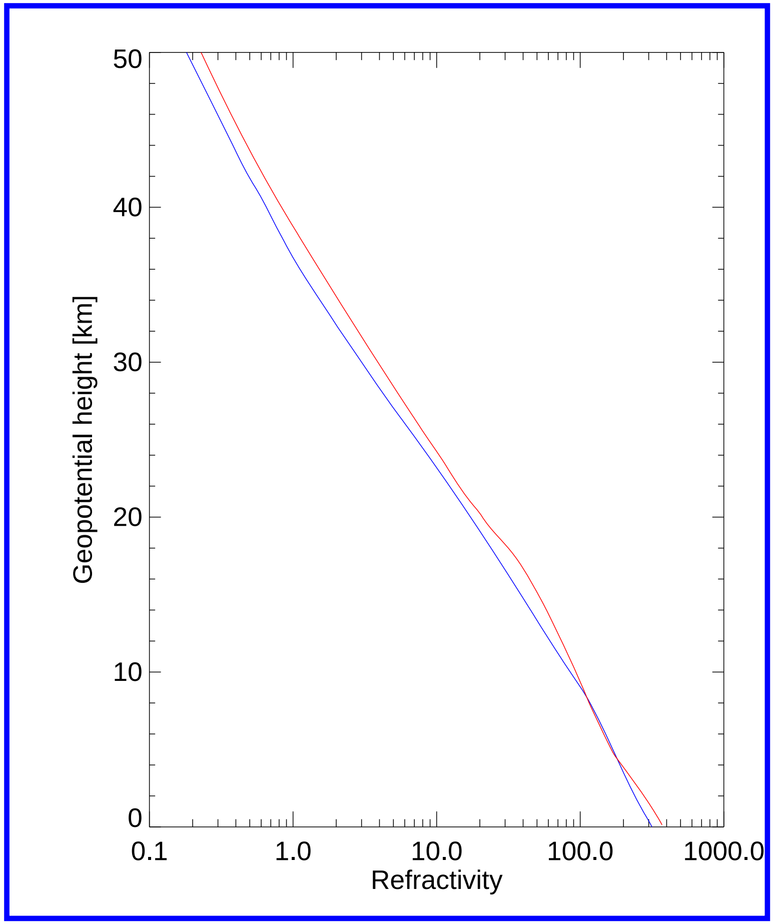
$$h = \left[(\Phi(\mathbf{r}) - \frac{1}{2}\Omega^2 r_s^2) - (\Phi - \frac{1}{2}\Omega^2 r_s^2)_\mathrm{msl} \right] / g_0$$

Radio occultation products

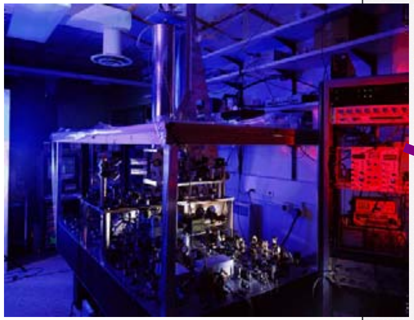


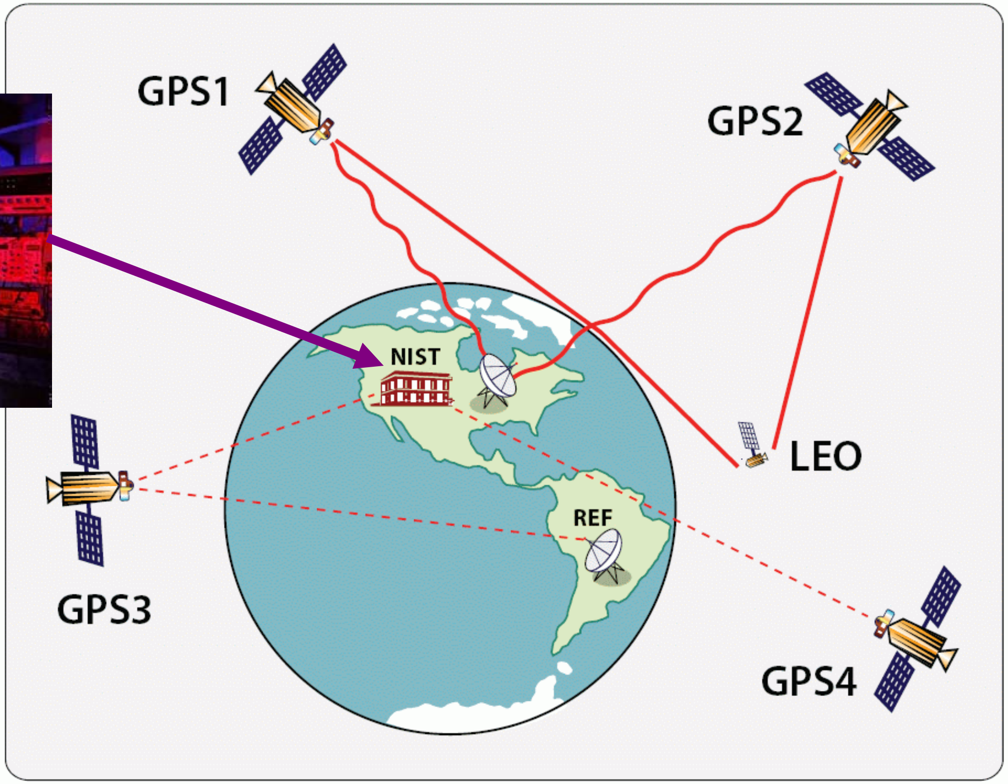
Radio occultation products





Calibration: Double Differencing





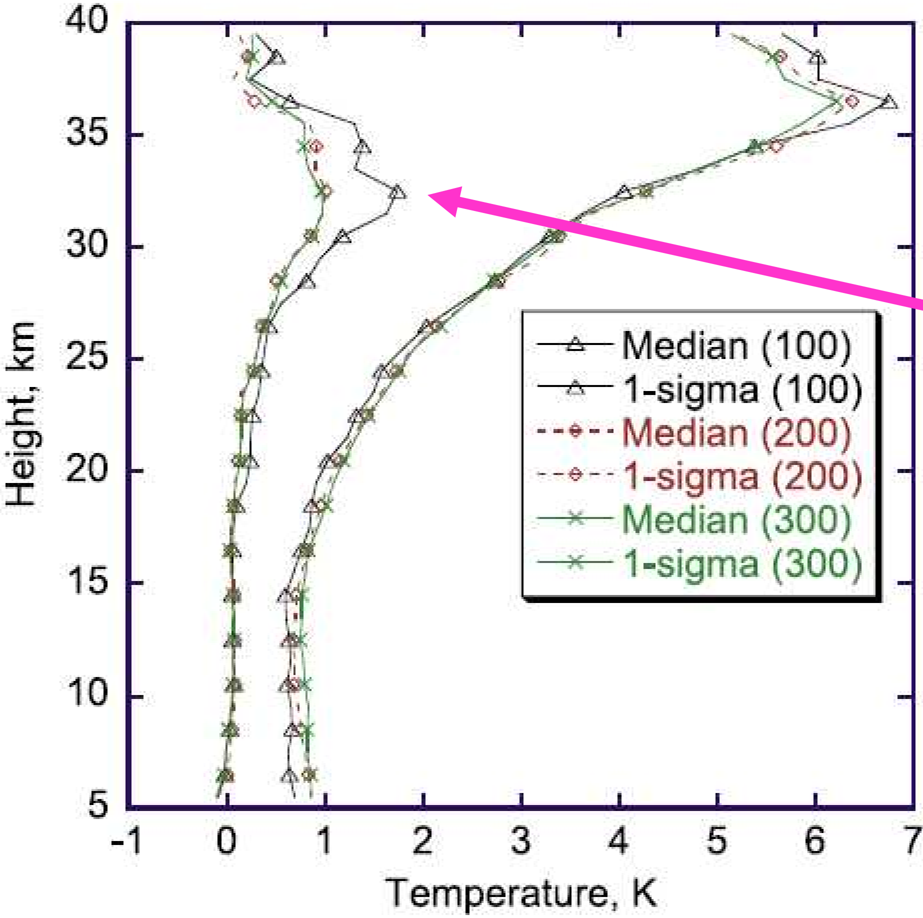
Hardy, K.R., G.A. Hajj, and E.R. Kursinski, 1994: Accuracies of atmospheric profiles obtained from GPS occultations. *Int. J. Sat. Comm.*, **12**, 463-473.

Verifying a Benchmark

- **Reproducible standards:** An SI traceable observable should be reproducible by anyone, anywhere, anytime.
  - Test: Collocated radio occultation soundings from independent satellites should produce identical measurements to within observation error. If not, there is an unaccounted break in SI traceability.
- **Accurate trend reproduction:** Uniform application of a retrieval algorithm should produce an accurate trend.
  - Test: Measure trends in refractivity as produced by independent retrieval centers. Disagreement indicates poorly understood uncertainty or poorly understood data type.

Verifying a Benchmark: Test 1

Reproducibility: Comparing CHAMP to SAC-C



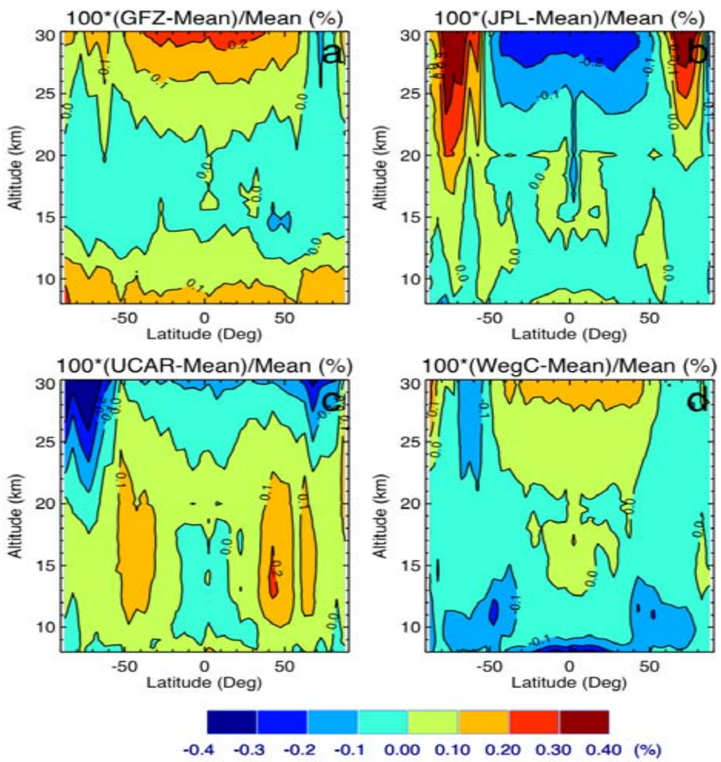
Hajj et al., *J. Geophys. Res.*, 2004.

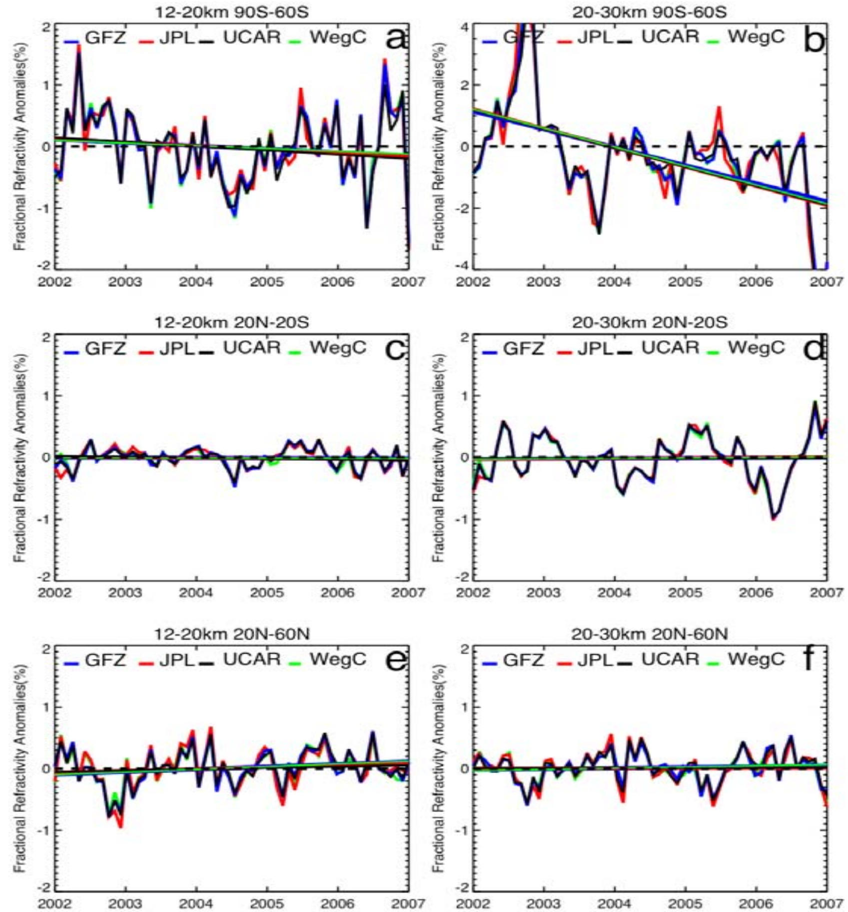
Possible break in traceability?

Verifying a Benchmark: Test 2

Robust trends

Ho et al., *J. Geophys. Res.*, In Press.

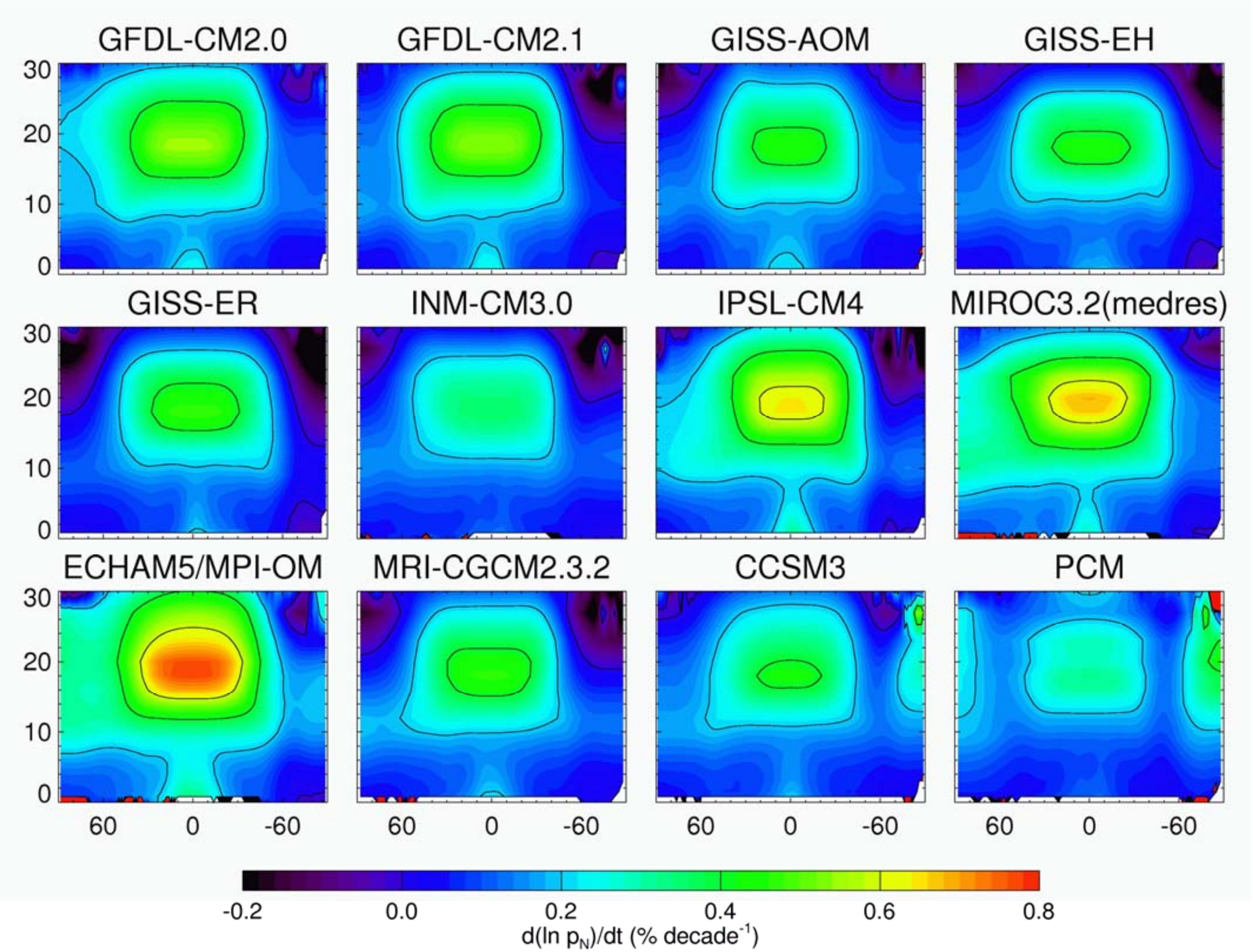




Verifying a Benchmark: Conclusions

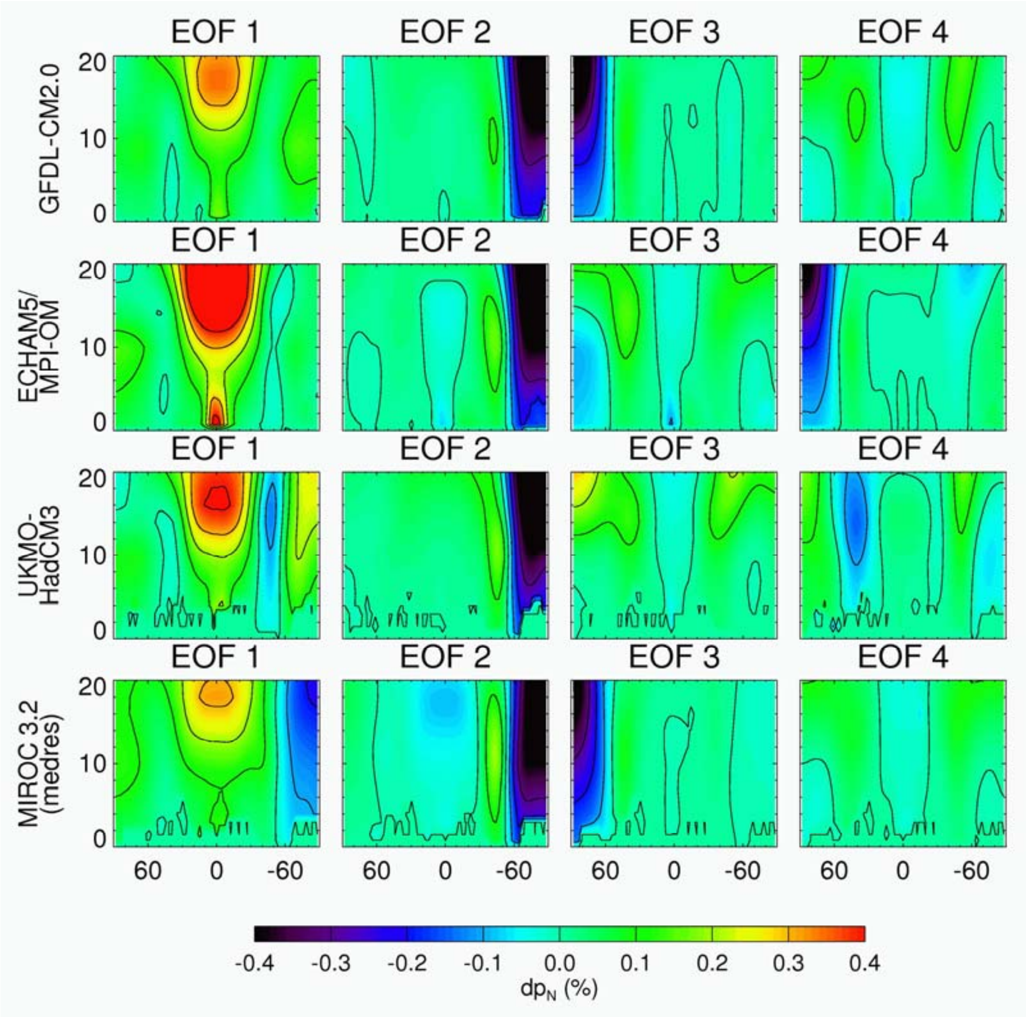
- RO is a strong benchmark (< 0.1 K) in its sweet spot, 8-20 km. Apparent break in traceability in the stratosphere, possibly due to local multi-path in either CHAMP or SAC-C.
- RO is a strong benchmark in its sweet spot, with four independent centers producing identical trends in refractivity. ***Not to be considered statistically significant climate trends!***

GNSS RO Dry Pressure Tendency



Leroy et al., *J. Geophys. Res.,* 2006.

Dry Pressure EOFs



ENSO

Southern Annular Mode

Northern Annular Mode

Symmetric Jet Migration (lagged response to ENSO)

First level of inference

Solve for trends in climate scalar,
no prior

$$\frac{d\mathbf{d}}{dt} = \left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \frac{d\alpha}{dt} + \frac{d}{dt} d\mathbf{n} \qquad \frac{d}{dt} d\mathbf{n} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{d\mathbf{n}/dt})$$

Trend in data

Model of data

Tr
clima

Postfit residuals

<u>Error:</u>
Observation error
Natural variability

$$G_{ij} = \sum_\mu \frac{\langle \mathbf{e}_\mu, \mathbf{s}_i \rangle \langle \mathbf{e}_\mu, \mathbf{s}_j \rangle}{\lambda_\mu}$$

$$\mathbf{h} = \sum_\mu \frac{\langle \mathbf{e}_\mu, \mathbf{s}_i \rangle \langle \mathbf{e}_\mu, d\mathbf{d}/dt \rangle}{\lambda_\mu}$$

$$\frac{d\alpha}{dt} = \mathbf{G}^{-1}\mathbf{h}$$

Compare…

$d\mathbf{d}/dt$ to $(\boldsymbol{d} - \mu)$, difference be

$d\mathbf{g}/d\alpha$ to $\boldsymbol{K}$, li

$d\alpha/dt$ to $\delta\mathbf{x}$, a

$\boldsymbol{\Sigma}_{d\mathbf{n}dt}$ to $\mathbf{O} + \mathbf{F}$, observation +

$$\frac{d\alpha}{dt} = \left(\left.\frac{d\mathbf{g}}{d\alpha}\right|_{M_i} \right. \quad {}_{dt} \; \frac{d\mathbf{d}}{dt}$$

Decomposing Optimal Detection

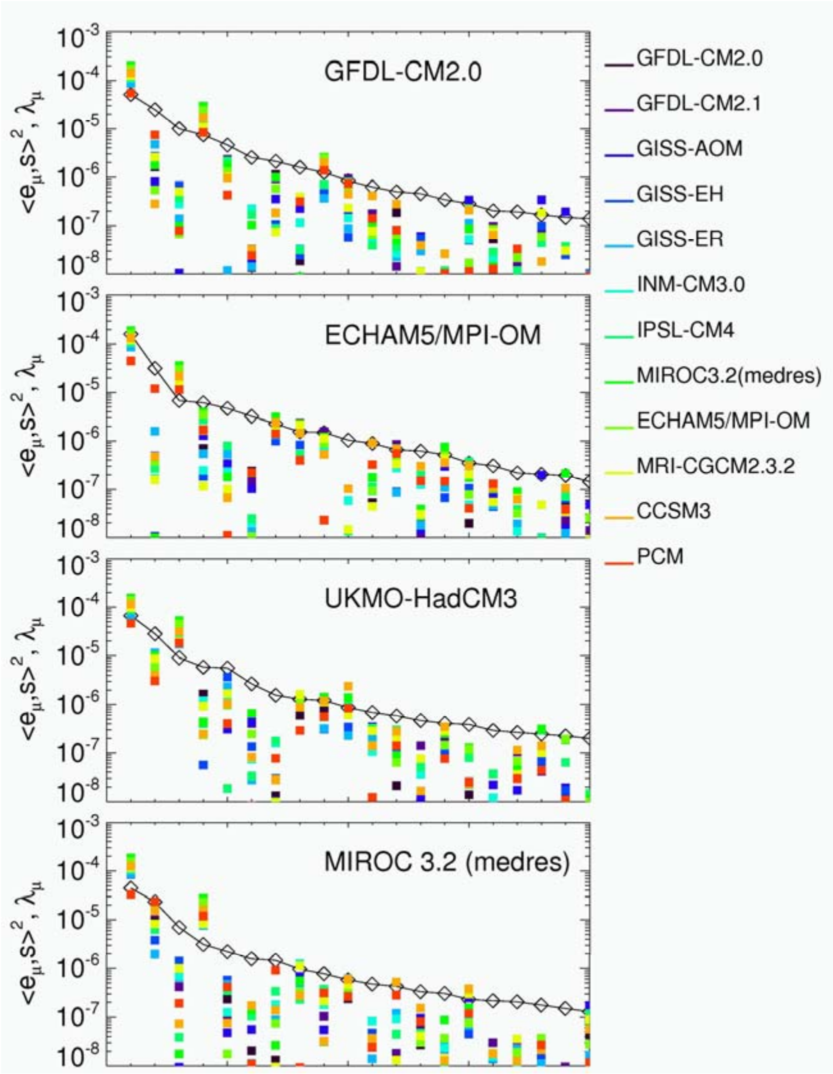
Open diamonds: Natural variability eigenvalues

Filled squares: Signals' projections onto EOFs

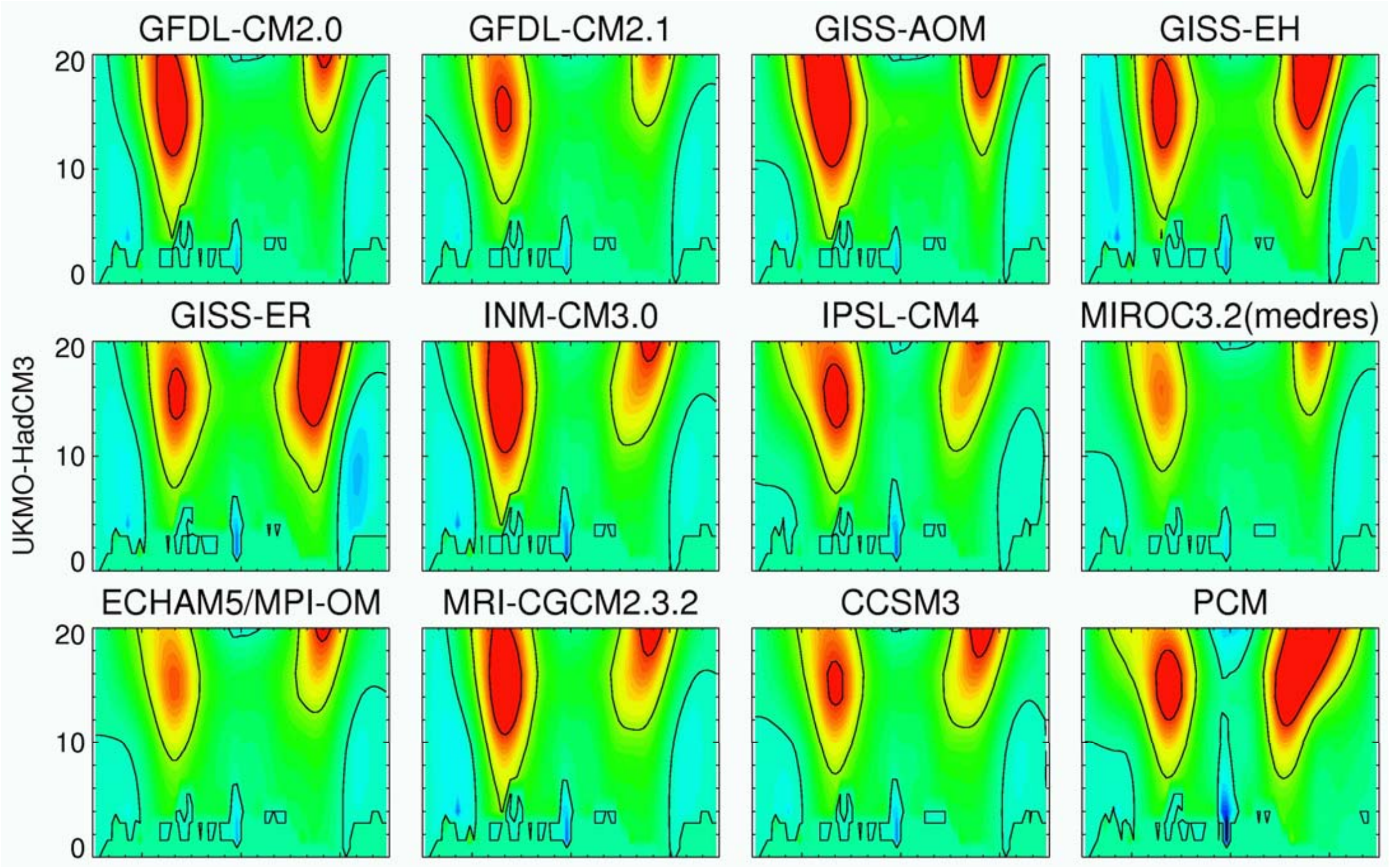
12 models for signal shape **s**

4 models prescribe natural variability **N**

The higher the filled squares are with respect to the eigenvalues, the more that mode will contribute to detection (and increase the SNR).



Optimal fingerprints

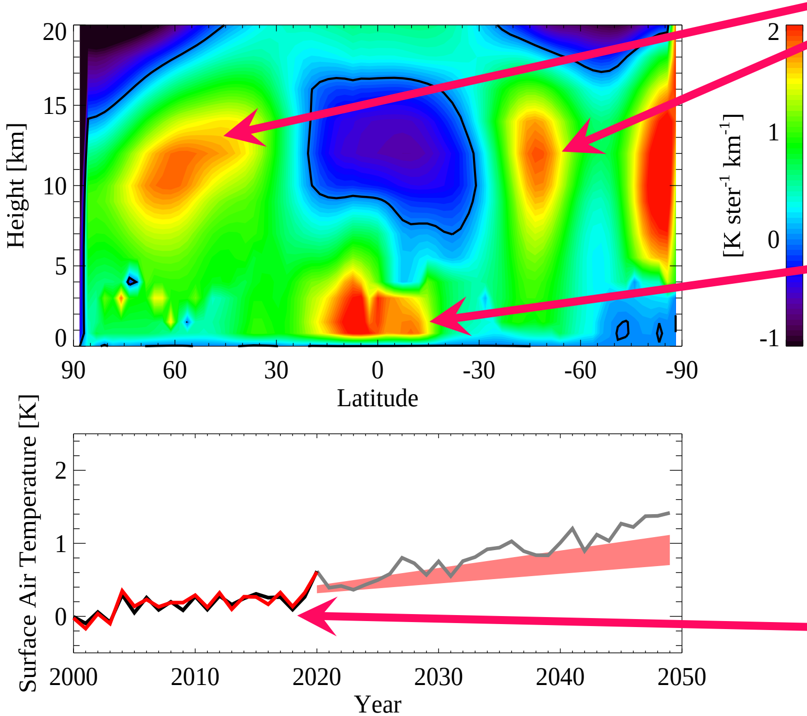


Detection times

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 GNSS RO Test GCMs?

α = global average surface air temperature, $\boldsymbol{d}$ = GPS RO dry pressure [height]

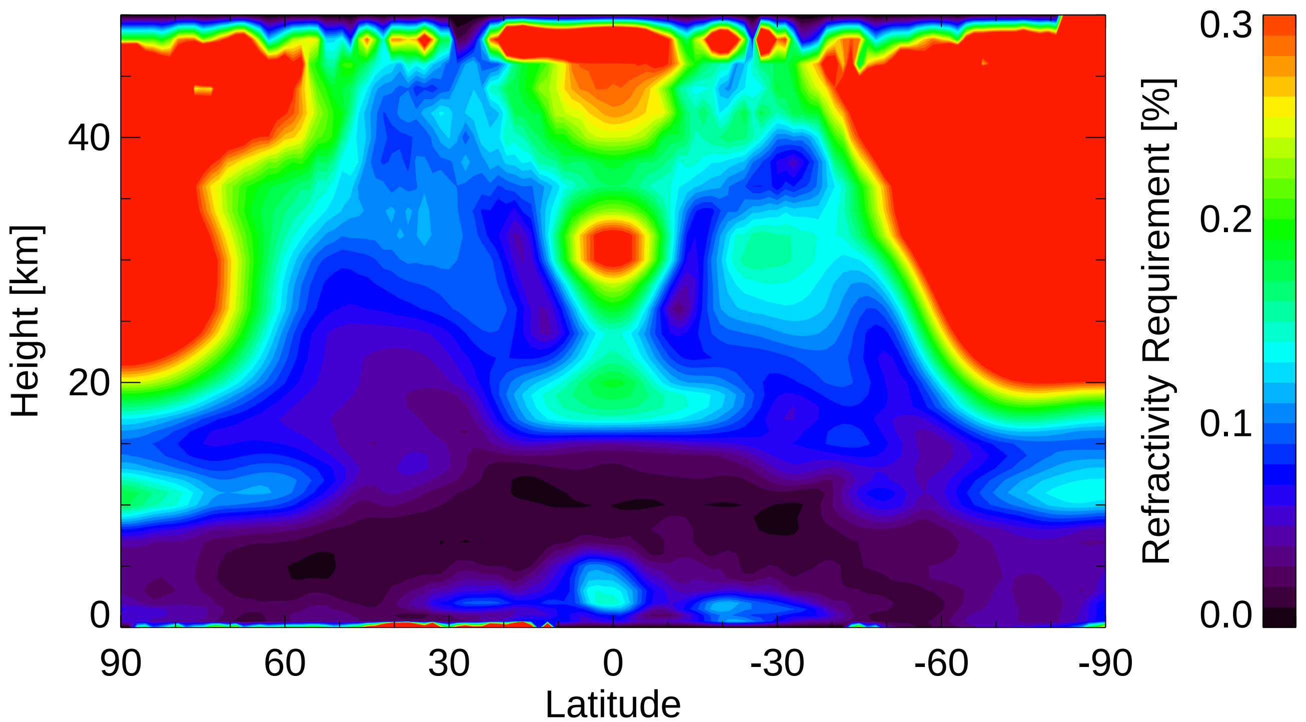


Poleward migration of jet streams

Increased tropical humidity

Near perfect tracking of global average surface air temperature

GNSS RO Accuracy Requirements



Nonoptimal Trends

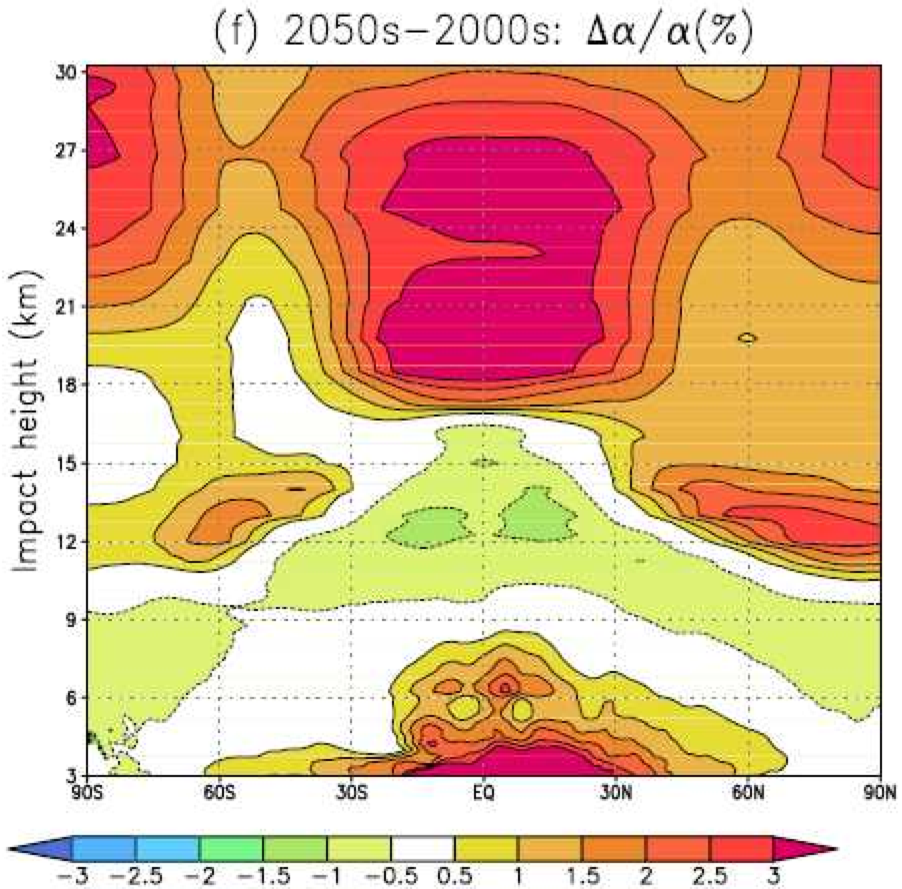


Table 1. Bending Angle Trends and Detection Times at the Equator for Three Selected Altitudes

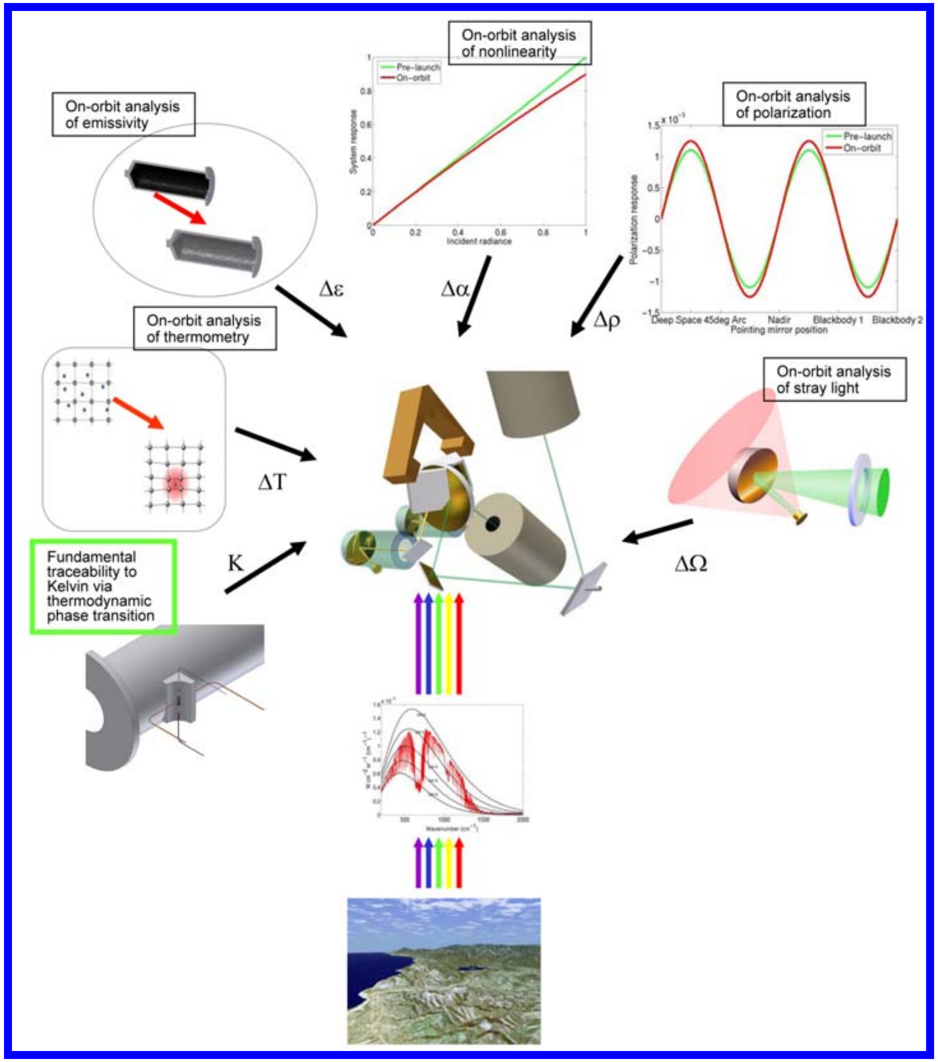
Impact Height, km	Trend, ω_0, 10^{-6} rads/year	Variability of Noise, σ_N, 10^{-6} rads	Autocorrelation of Noise φ	Detection Time n*, years	95% Confidence Interval, years
12	−0.92	9.45	0.58	16.3	(14.6, 18.2)
20	1.09	9.20	0.68	16.0	(13.6, 18.7)
26	0.41	2.04	0.55	10.6	(9.4, 11.7)

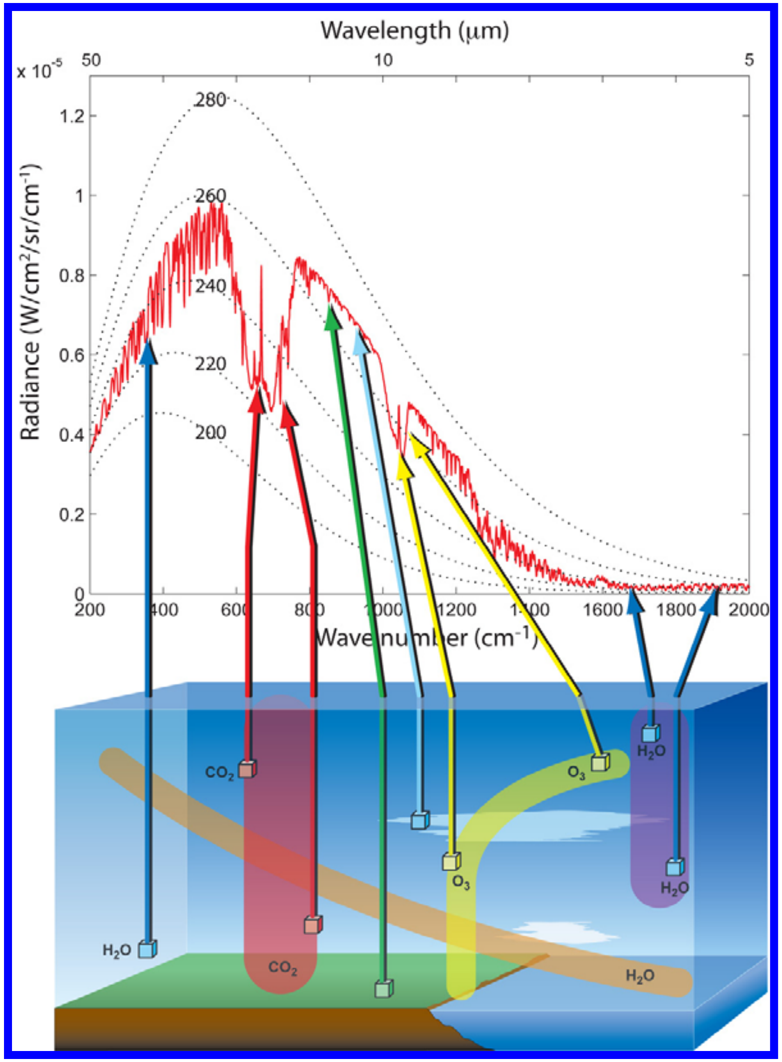
Ringer and Healy, *Geophys. Res. Lett.,* 2008.

Climate trends: Summary

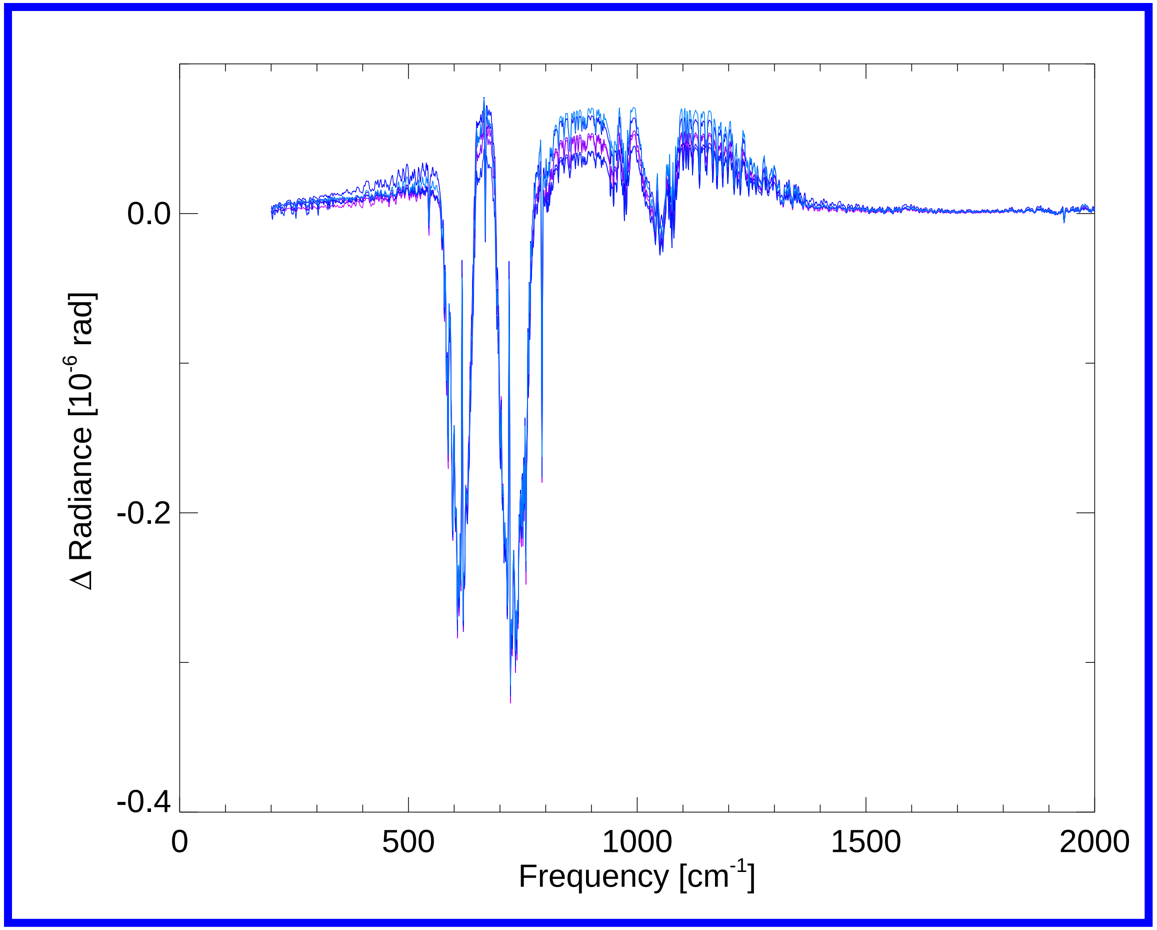
- First signal to emerge is poleward migration of baroclinic zones. Possibly jet streams as well. Detection time is ~ 10 years, corresponding to a 10-m thickening of troposphere.
- Trends in bending angle have similar detection times but first detect expansion of tropical troposphere.
- Relating RO data to surface air warming yields a very different optimal fingerprint.

Spectral thermal infrared

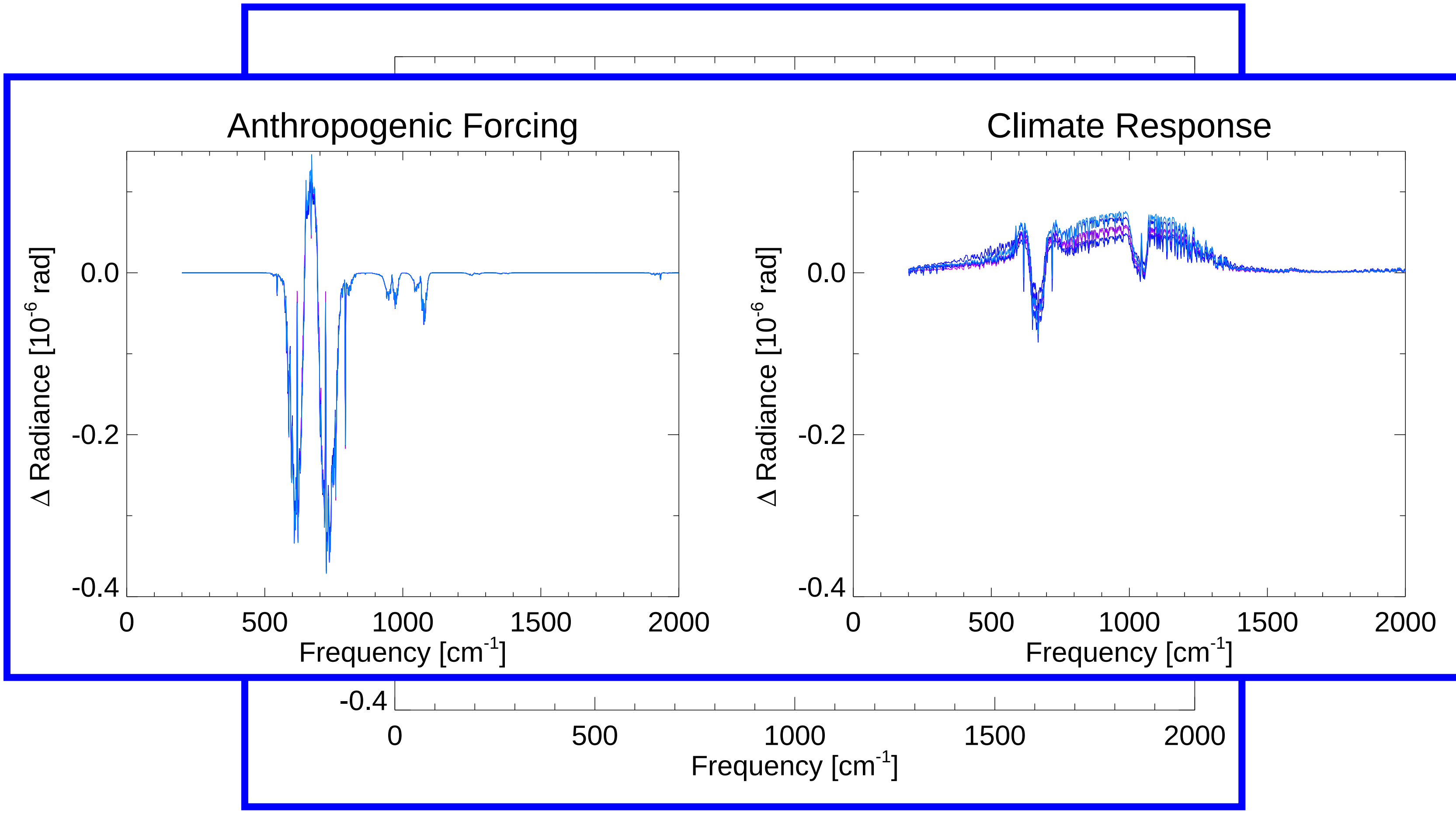




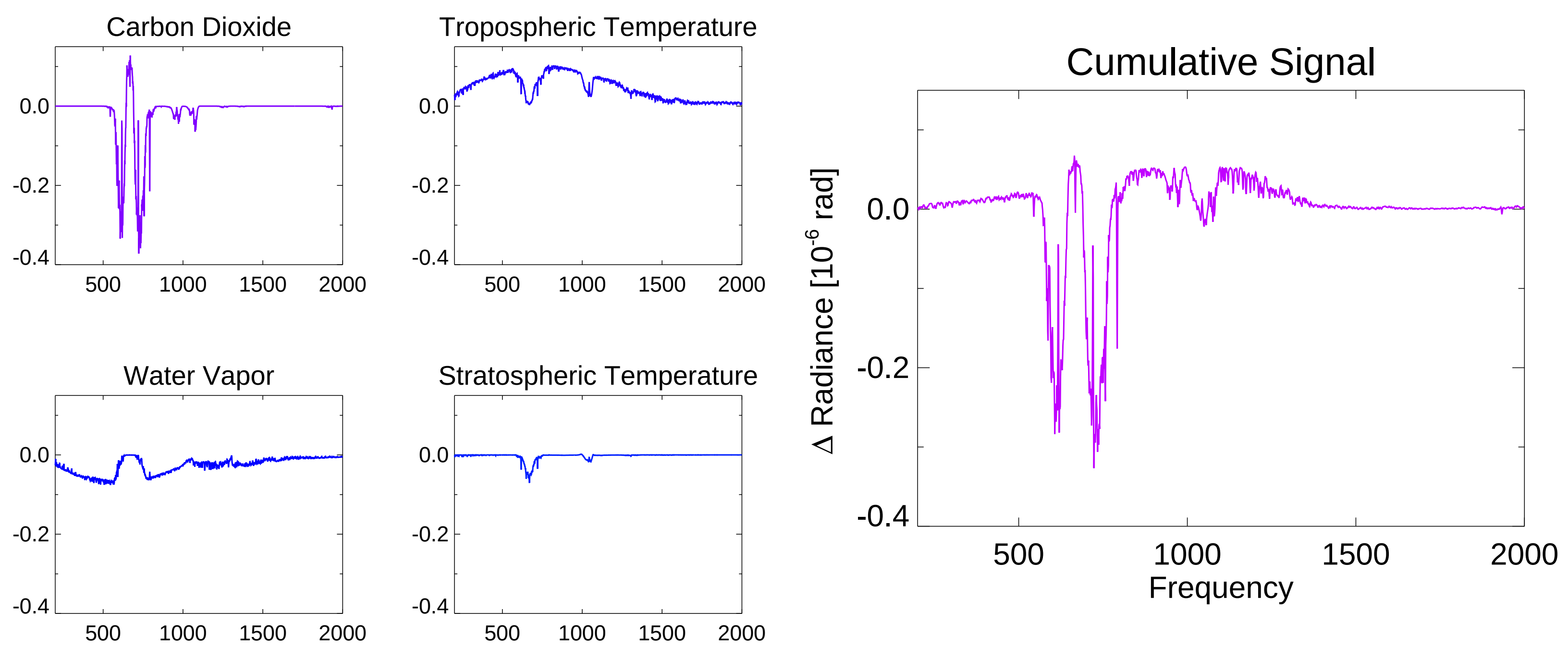
Thermal infrared spectra fingerprints



Thermal infrared spectra fingerprints

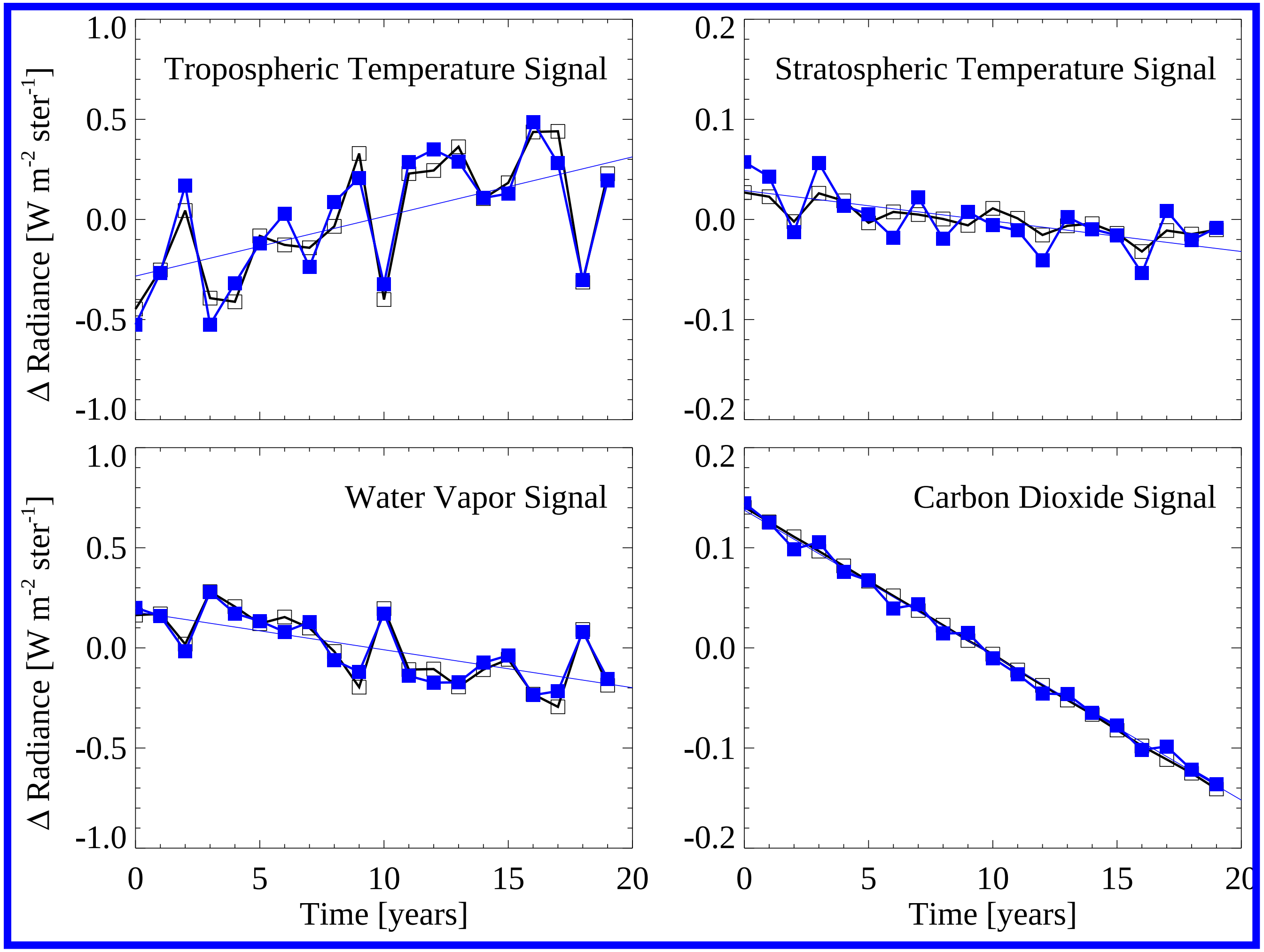


How Does Spectral IR Test GCMs?



Leroy et al., *J. Climate,* 2009b.

Applied Scalar Prediction (2)

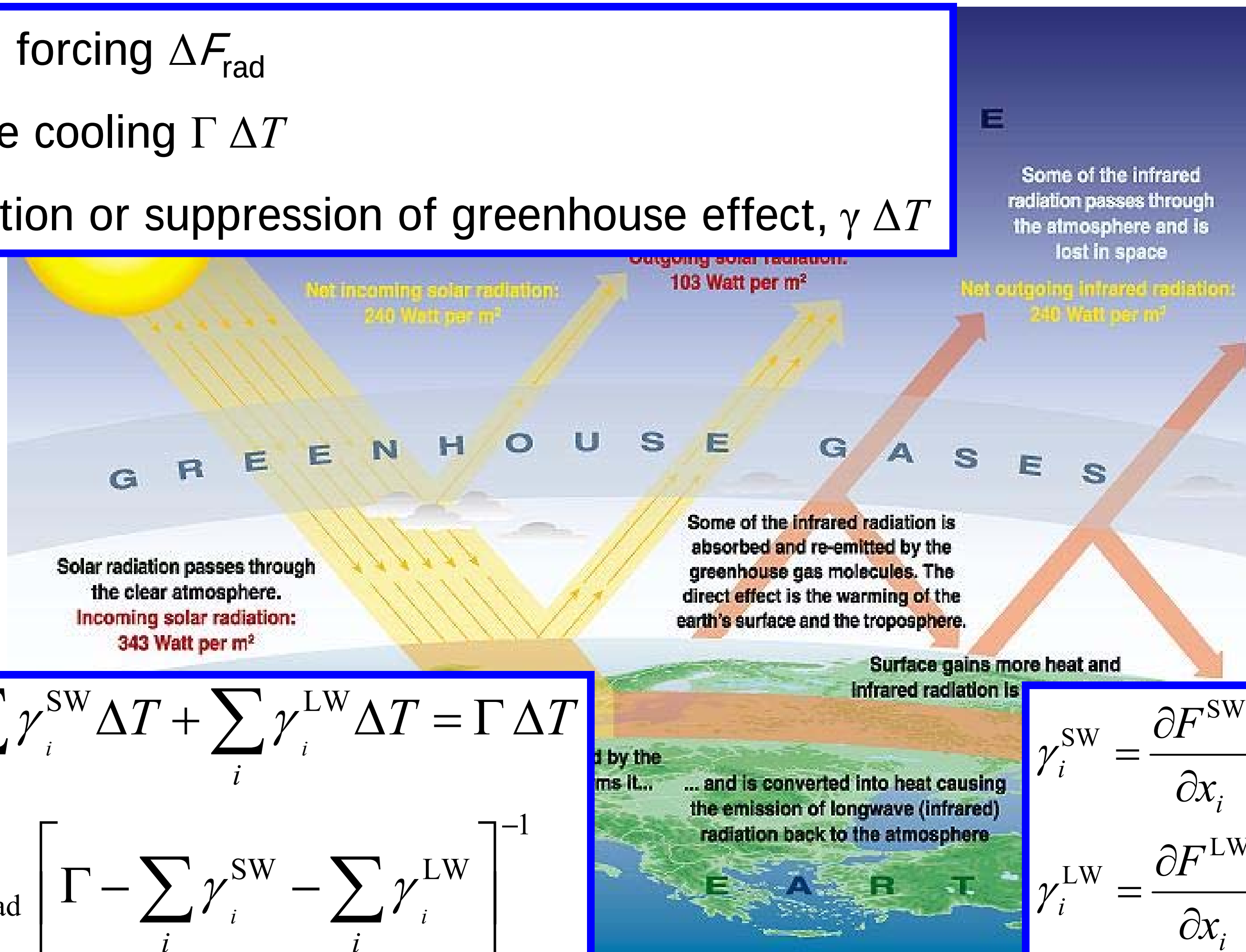


Climate Feedback

Radiative forcing ΔF_{rad}

Longwave cooling $\Gamma\, \Delta T$

Amplification or suppression of greenhouse effect, $\gamma\, \Delta T$



$$\Delta F_{\text{rad}} + \sum_i \gamma_i^{\text{SW}} \Delta T + \sum_i \gamma_i^{\text{LW}} \Delta T = \Gamma\, \Delta T$$

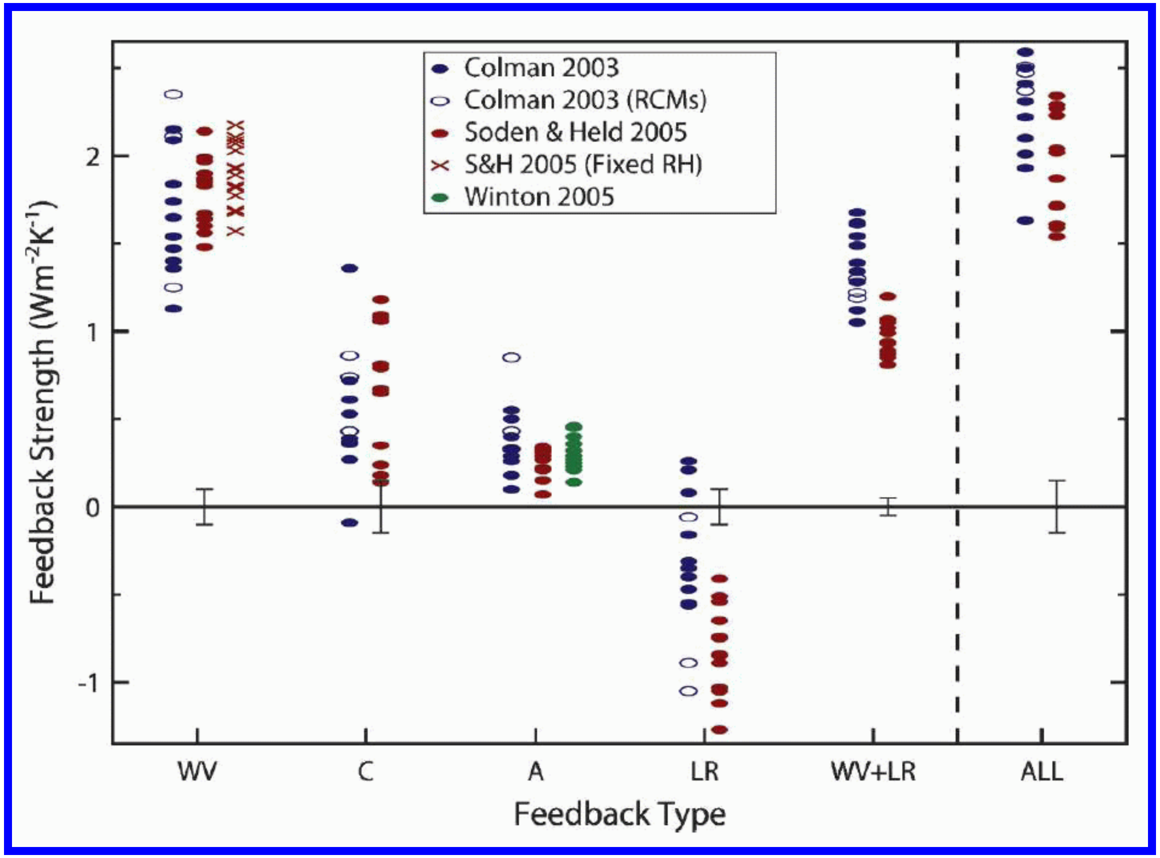
$$\Delta T = \Delta F_{\text{rad}} \left[\Gamma - \sum_i \gamma_i^{\text{SW}} - \sum_i \gamma_i^{\text{LW}} \right]^{-1}$$

$$\gamma_i^{\text{SW}} = \frac{\partial F^{\text{SW}}}{\partial x_i} \frac{dx_i}{dT}$$

$$\gamma_i^{\text{LW}} = \frac{\partial F^{\text{LW}}}{\partial x_i} \frac{dx_i}{dT}$$

Sources: ... school of geography; United States Environmental Protection Agency (EPA), Washington; Climate change 1995, The science of climate change, contribution of working group 1 to the second assessment report of the intergovernmental panel on climate change, UNEP and WMO, Cambridge university press, 1996.

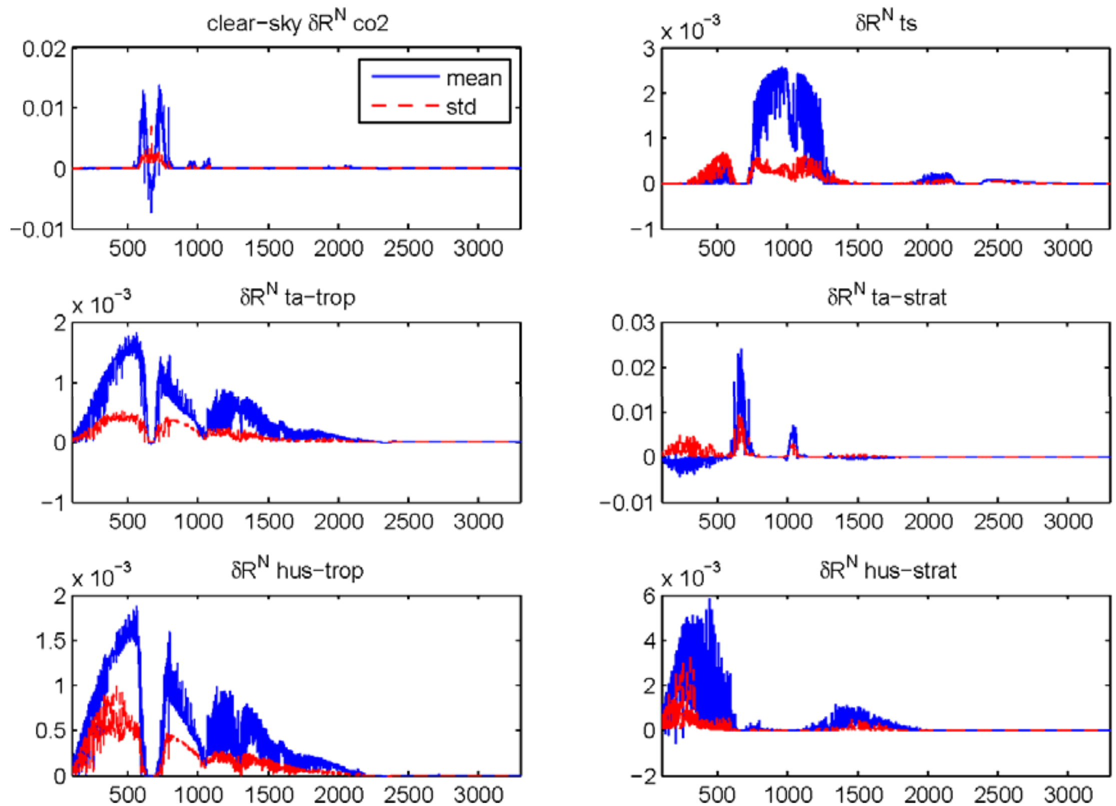
Feedback Uncertainty



Bony, S., et al., 2006: How well do we understand and evaluate climate change feedback processes? *J. Climate,* **19**, 3445-3482.

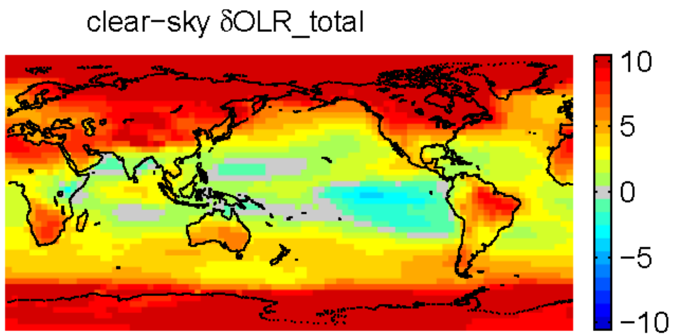
Longwave feedbacks: Clear sky

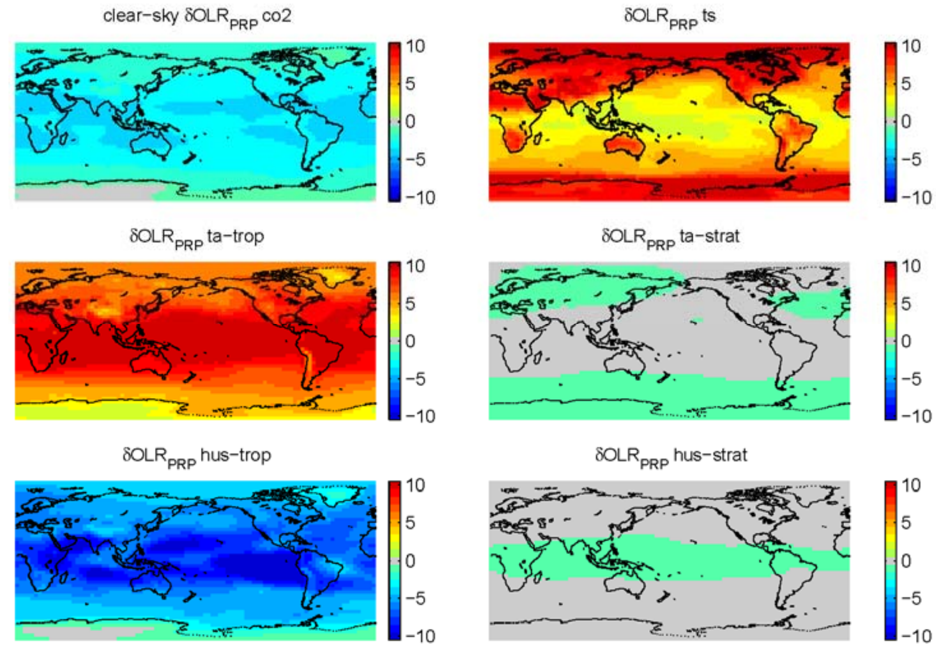
- From Cloud Feedback Model Intercomparison Project (CFMIP)
- Spectral fingerprints from equilibrium doubling of CO_2
- Spectral fingerprints computed by partial radiative perturbation (PRP)
- First, clear-sky fingerprinting; then, all-sky fingerprinting
- Discover whether we have enough information in “absolute” data to constrain radiative feedbacks and ultimately equilibrium sensitivity.



Longwave feedbacks: Clear-sky (2)

Longwave response to doubling of CO_2, W m^{-2}

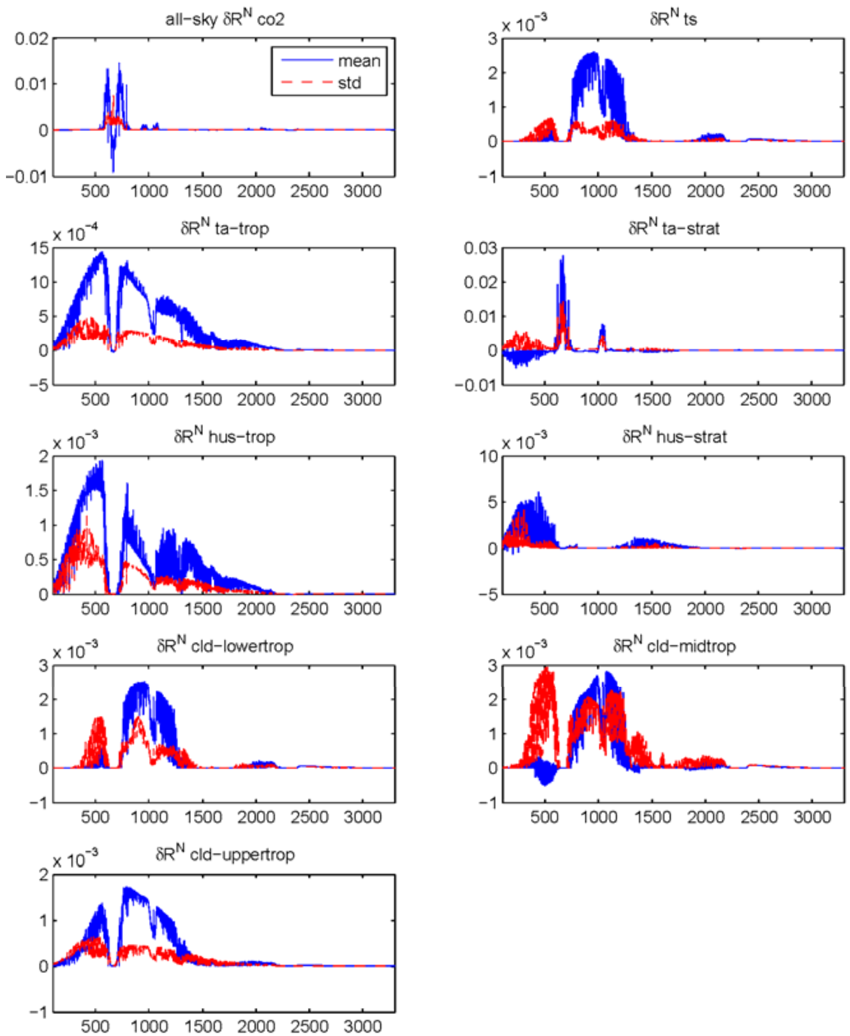




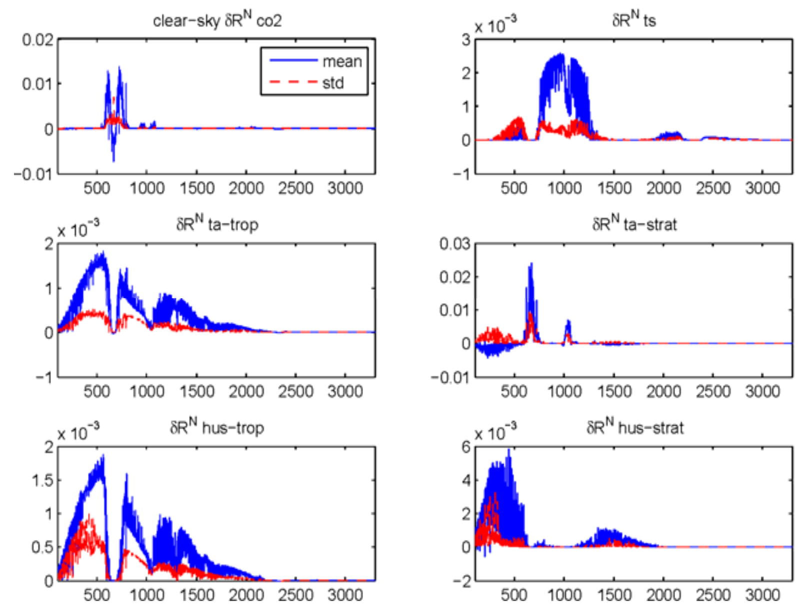
Longwave feedback components, W m^{-2}

Yi Huang et al., *J. Geophys. Res.*, In Review.

Longwave feedbacks: All-sky

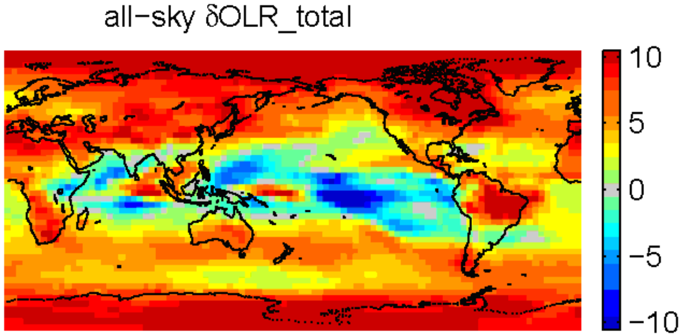


Clear-sky fingerprints

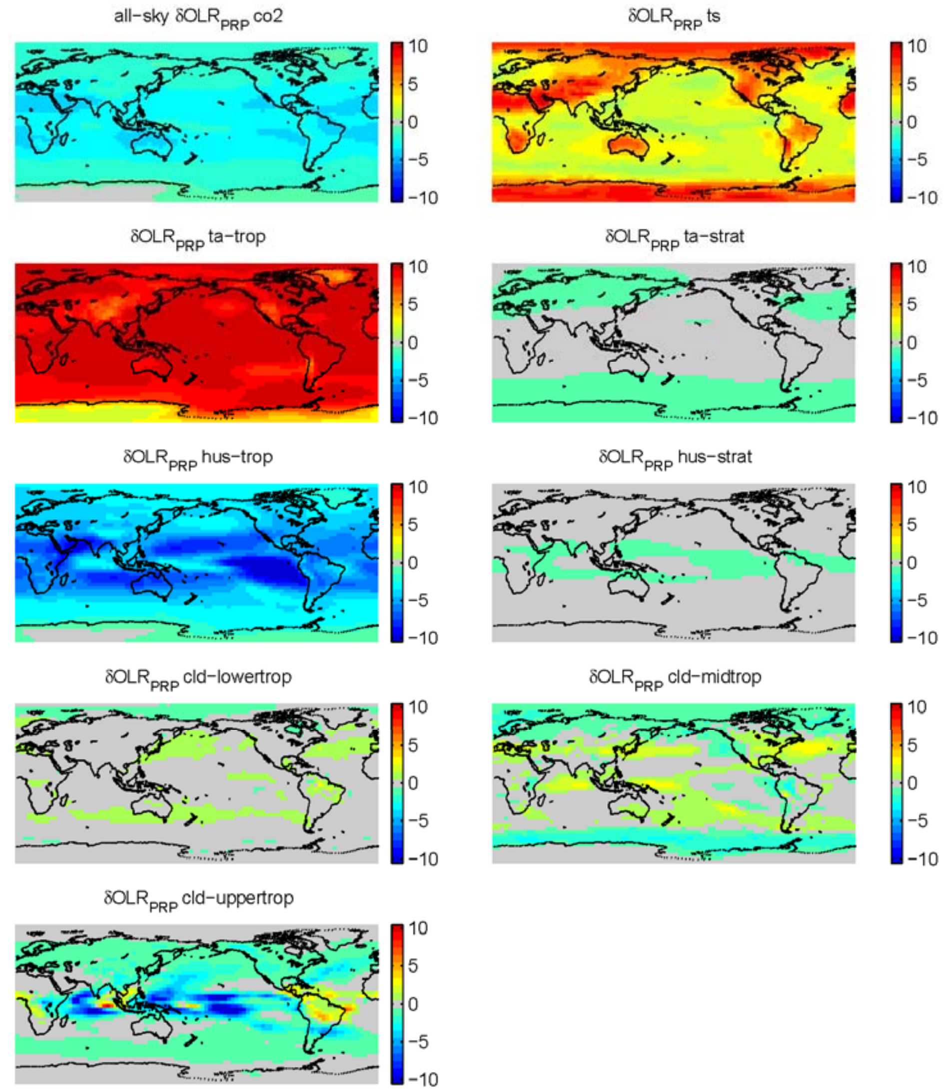


Longwave feedbacks: All-sky (2)

Longwave response to doubling of CO_2, W m^{-2}

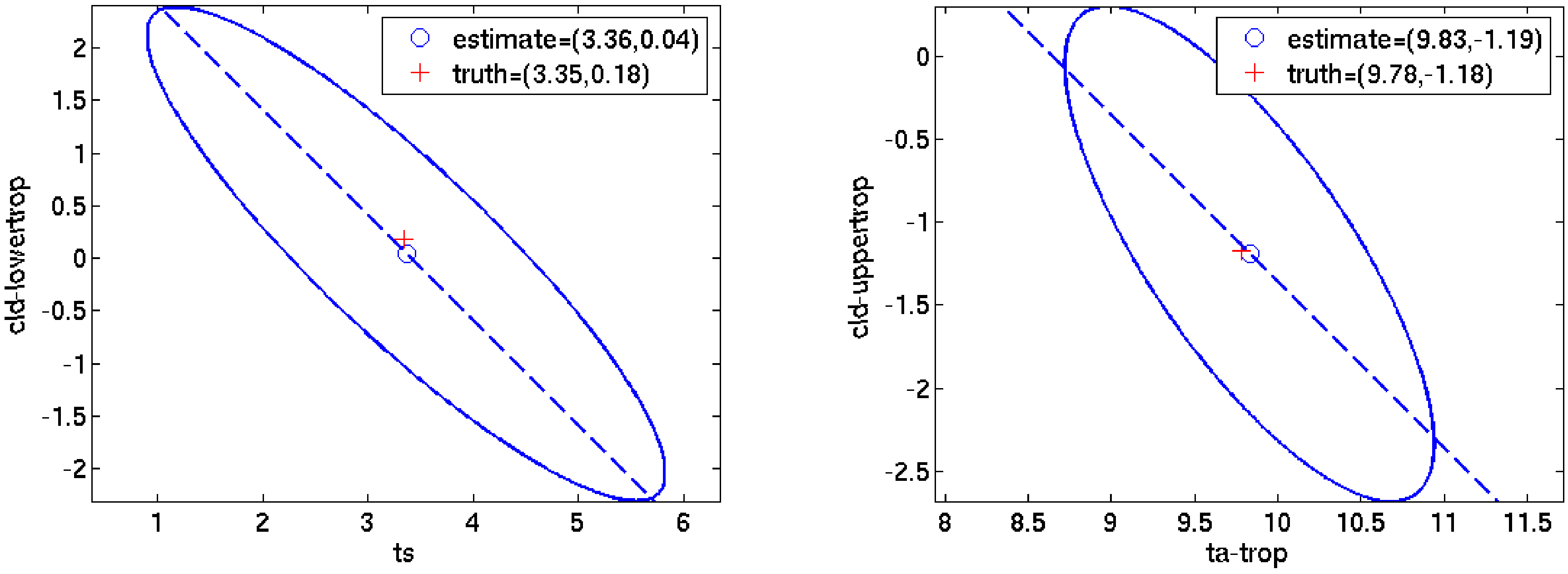


Longwave feedback components, W m^{-2}



All-sky degeneracies

Degenerate signals: It is difficult to identify unambiguously some pairs of feedbacks because the convolution of climate response with observation forward model produces signatures that can be very similar.

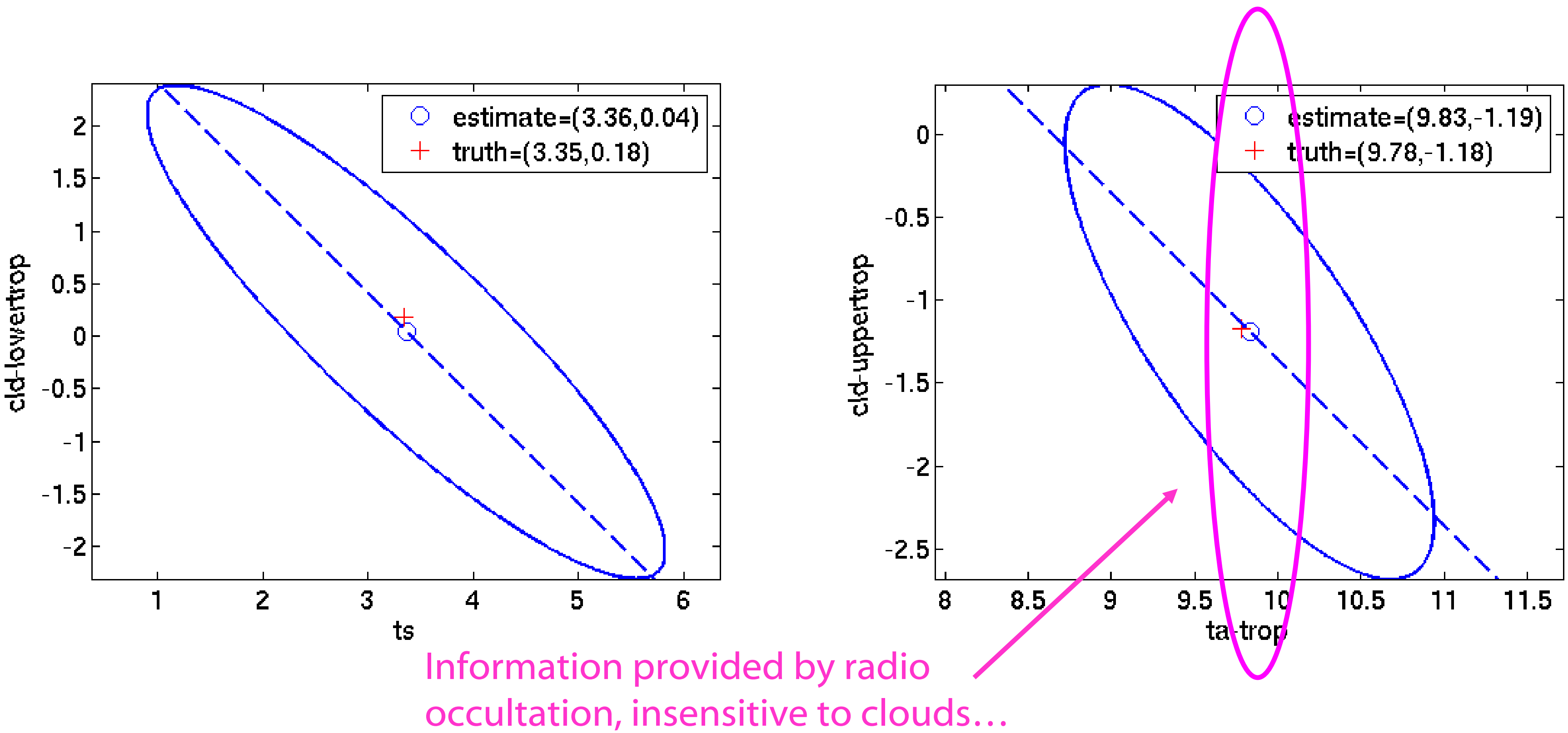


All-sky degeneracies

Global mean OLR change	PRP W m^{-2}	Optimal detection	
		Regional	Merged
δOLR (CO_2)	-2.73	-2.72 ± 0.12	-2.72 ± 0.12
δOLR (T_{strat})	-0.47	-0.46 ± 0.19	-0.46 ± 0.19
δOLR (q_{trop})	-4.99	-4.94 ± 0.77	-4.94 ± 0.77
δOLR (q_{strat})	-0.27	-0.26 ± 0.13	-0.26 ± 0.13
δOLR ($T_{surface}$)	3.35	3.36 ± 2.47	3.42 ± 0.78
δOLR ($Cloud_{low}$)	0.18	0.04 ± 2.35	
δOLR ($Cloud_{mid}$)	0.07	0.08 ± 0.19	8.70 ± 0.68
δOLR ($Cloud_{high}$)	-1.18	-1.19 ± 1.49	
δOLR (T_{trop})	9.78	9.83 ± 1.11	
χ^2		1.10	1.11

Joint infrared-radio occultation information?

Degenerate signals: It is difficult to identify unambiguously some pairs of feedbacks because the convolution of climate response with observation forward model produces signatures that can be very similar.



Monitoring the infrared spectrum: Summary

- Clear sky: Information content clearly constrains the longwave radiative feedbacks of the climate.
- All-sky: Information content can constrain longwave radiative feedbacks but with ambiguities
- Detection times for regional feedbacks too long to be of use. Optimization in spatial dimension should yield more useful detection times.
- Jointly considering GNSS RO and infrared spectrum information content should resolve ambiguities in longwave feedbacks.

Summary and discussion

- Climate benchmarking provides a way to monitor climate that is insensitive to breaks in time series.
  - Must be accomplished through traceability to international standards.
  - Accurate reproducibility
  - Trends independent of retrieval algorithm
- Climate projection: Important diagnostics for climate projection depend on the "climate scalar" of interest
  - Regions (components) of low natural variability
  - Regions (components) that have well understood relationships to climate scalar of interest
- Detection times are 10-14 years. Optimization in space probably necessary for strong tests of climate models.
  - GNSS RO sees poleward migration of baroclinic zones in first detection
  - Thermal infrared spectra provide information for direct determination of longwave feedbacks (half of equilibrium climate sensitivity). GNSS RO can enable resolution of longwave feedback ambiguities.
- **Ultimately, data will be assimilated into reanalyses. Must assure that climate benchmark data anchors the reanalysis so that inferred long-term trends in geophysical variables reflect advantages of climate benchmarking.**