Testing Climate Models with CLARREO: Feedbacks and Equilibrium Sensitivity

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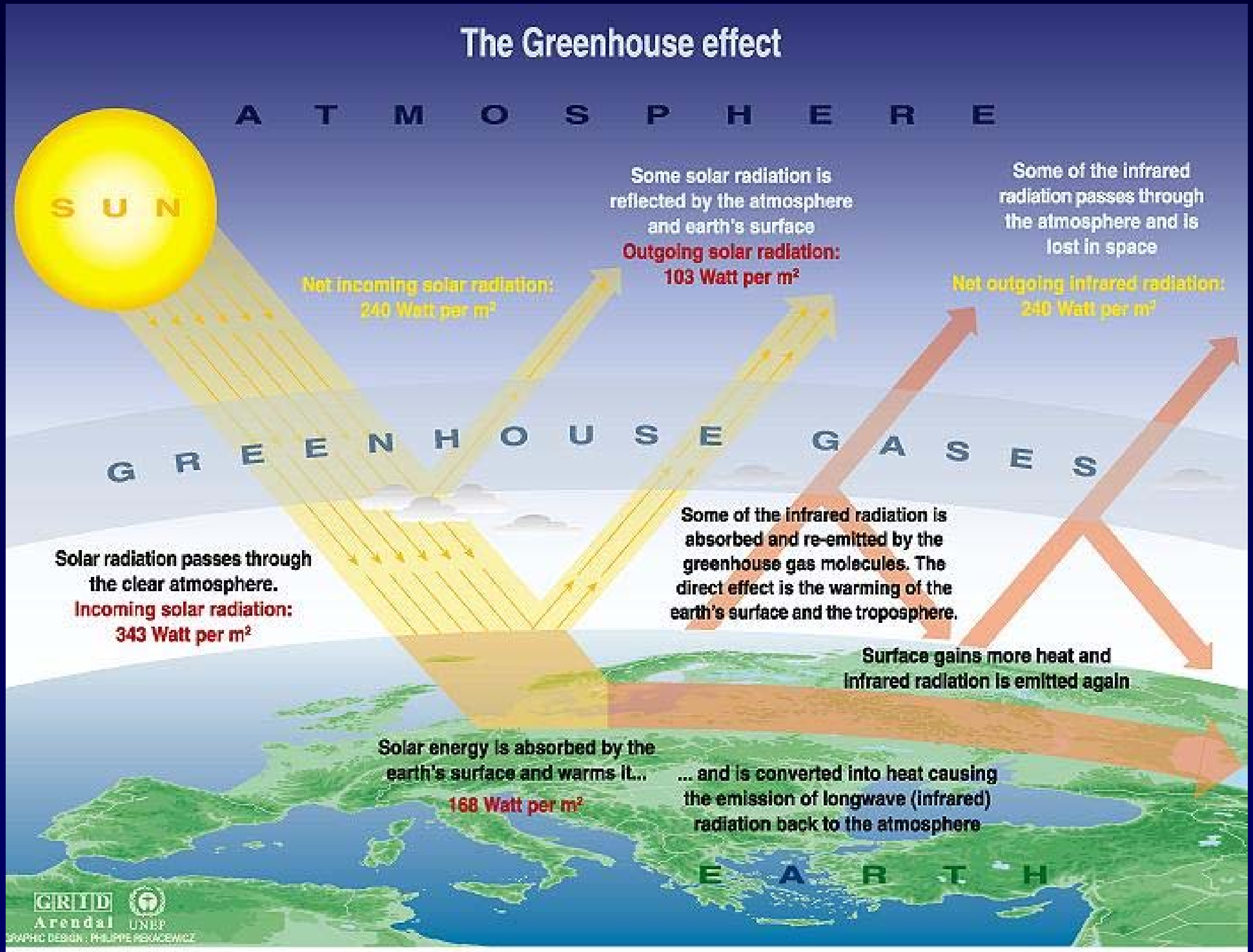
Talk Outline

- Feedbacks and Equilibrium Sensitivity
- Climate OSSE
  - Optimal Methods/Multi-pattern regression
  - Response: GPS Radio Occultation (RO)
  - Feedbacks: Clear-sky Thermal IR Spectra
- Discussion

Climate Feedback



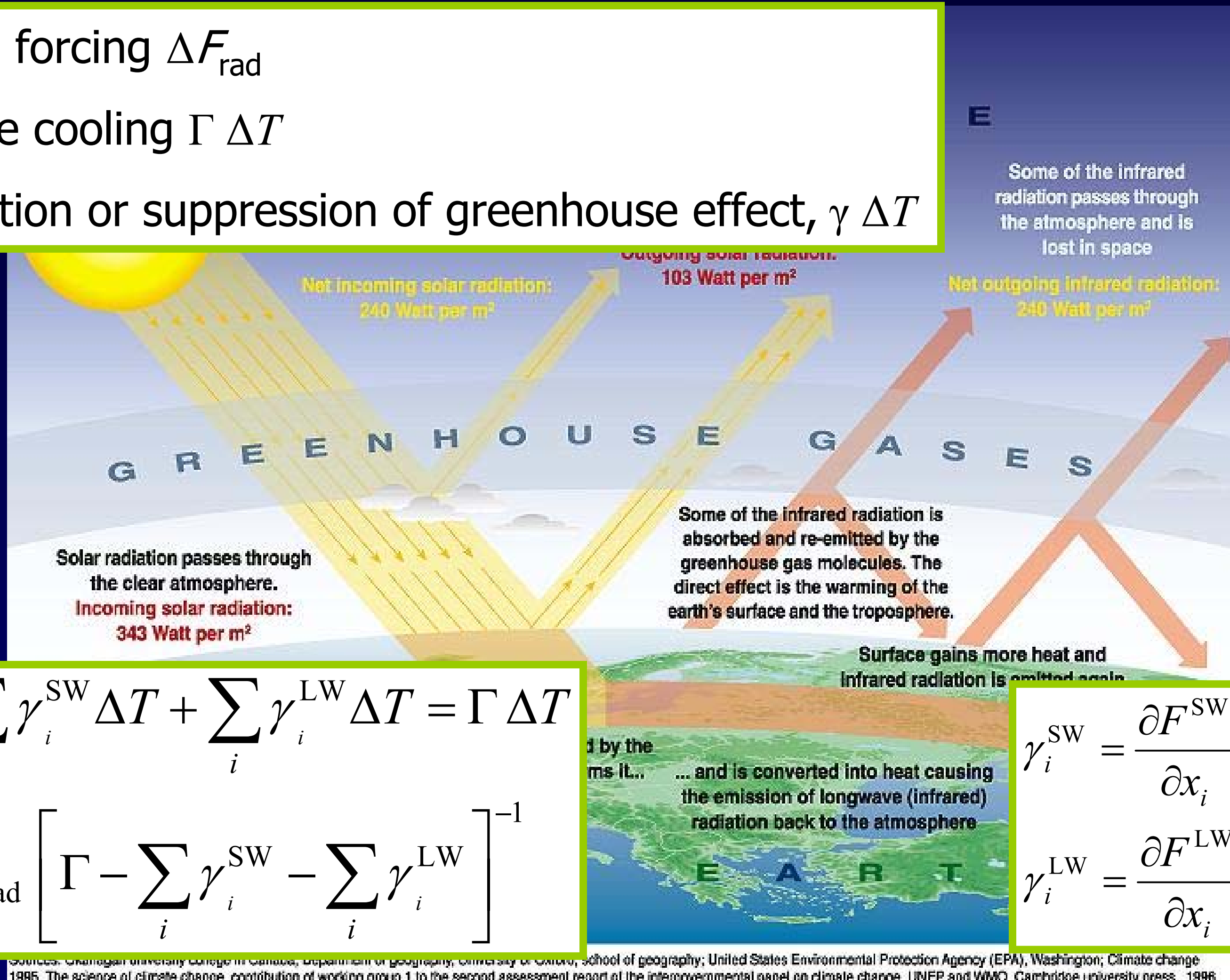
Sources: Okanagan university college in Canada, Department of geography, University of Oxford, school of geography; United States Environmental Protection Agency (EPA), Washington; Climate change 1995, The science of climate change, contribution of working group 1 to the second assessment report of the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

Climate Feedback (2)

Radiative forcing ΔF_{rad}

Longwave cooling $\Gamma\,\Delta T$

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



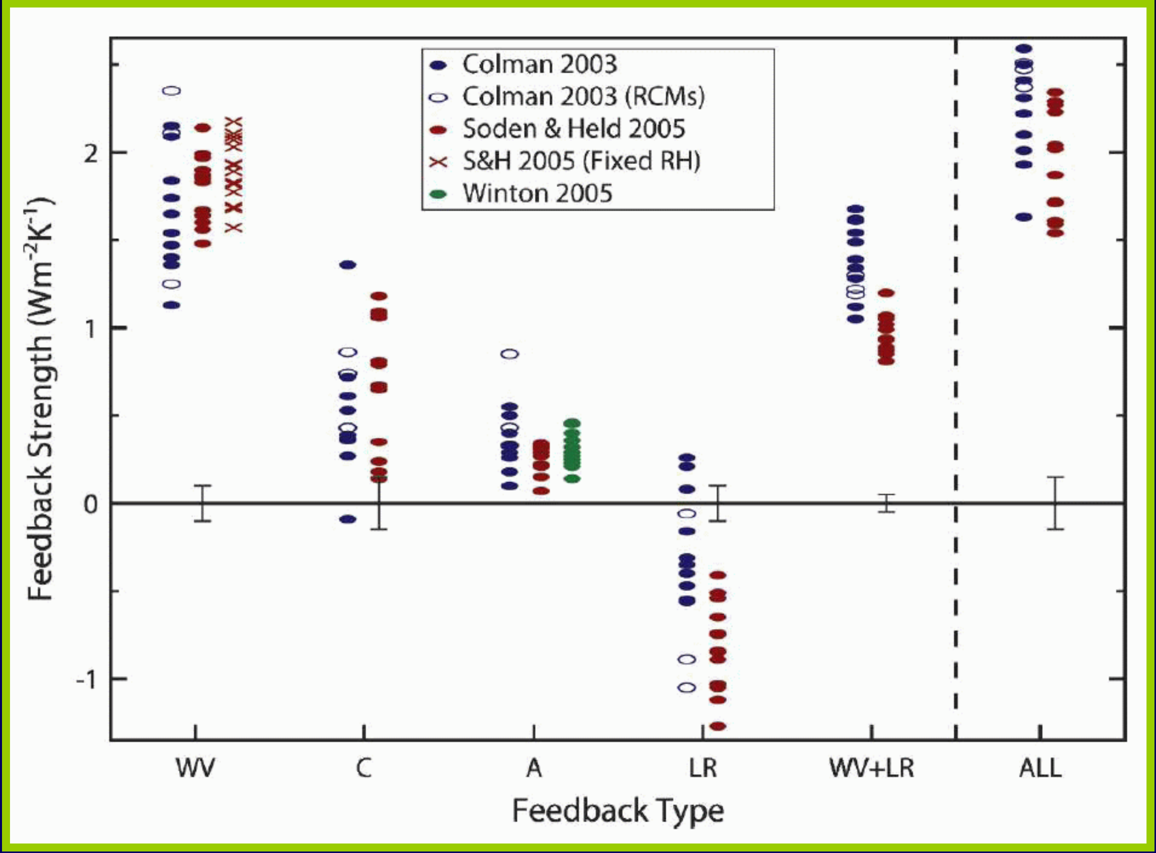
$$\Delta F_{\text{rad}} + \sum_i \gamma_i^{\text{SW}}\,\Delta T + \sum_i \gamma_i^{\text{LW}}\,\Delta T = \Gamma\,\Delta T$$

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

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

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

Feedback Uncertainty



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

Feedbacks and Climate Prediction

Hansen, J. et al., 1985: Climate response times: Dependence on climate sensitivity and ocean mixing. *Science*, **229**, 857-859.

$$s \equiv \frac{T(2\times \mathrm{CO}_2) - T(1\times \mathrm{CO}_2)}{F_{\text{radiative}}(2\times \mathrm{CO}_2) - F_{\text{radiative}}(1\times \mathrm{CO}_2)}$$

$$= \left(\Gamma - \sum_{\mathrm{i}} \gamma_i^{\text{longwave}} - \sum_{\mathrm{i}} \gamma_i^{\text{shortwave}} \right)^{-1}$$

$$\beta = \left(s \times \rho C_{\text{ocean}} d \right)^{-1}$$

$$\frac{dT}{dt} = \beta s \left(\Delta F_{\text{imbalance}} \right) = \beta \left(s\, \Delta F_{\text{radiative}} - \Delta T \right)$$

$$T(t) = T_0 + \beta s \int_0^t \Delta F_{\text{rad}}(t')\, e^{-\beta(t-t')}\, dt'$$

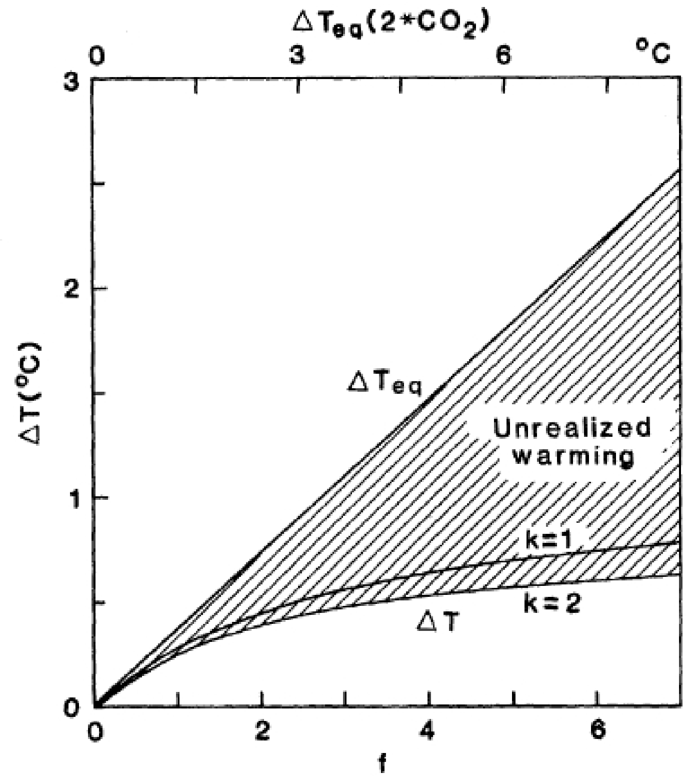


Fig. 2. Ocean surface warming (ΔT) and the equilibrium warming (ΔT_{eq}) due to CO_2 added to the atmosphere in the period 1850 to 1980 for the 1-D box diffusion ocean model as a function of f or $\Delta T_{eq}(2 * CO_2)$.

Climate OSSE: The Science of a Benchmark

Benchmark Measurement

- Traceable to international standards
- Minimize sampling error

Climate OSSE

- Simulate trends in observable as produced by different models
- Explore information content with various contravariant fingerprints

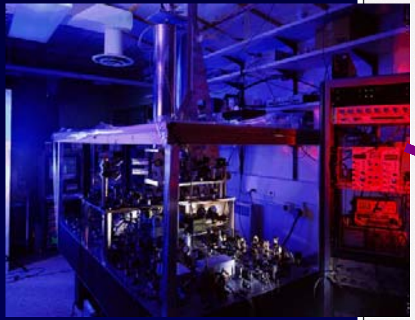
Climate Uncertainty

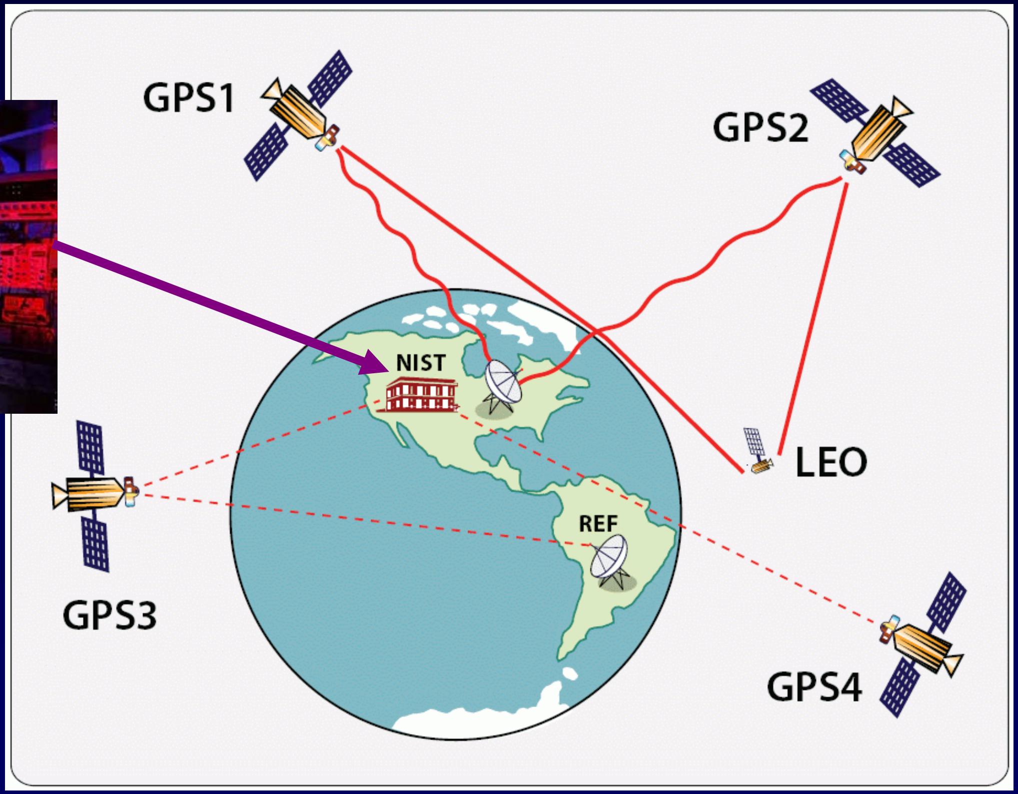
- Shortwave forcing
- Longwave forcing
- Climate feedbacks & sensitivity

Climate OSSE Results

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

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.

Optimal Fingerprinting/Multi-pattern Regression

We are limited by the naturally occurring inter-annual variability of the climate system…so optimize.

Find signal amplitudes ($\boldsymbol{\alpha}_m$) and uncertainty ($\boldsymbol{\Sigma}_\alpha$) in a data set ($\mathbf{d}$) according to the signals' patterns ($\mathbf{s}_i$) against a background of natural variability, the eigenvectors and eigenvalues of which are $\mathbf{e}_\mu$ and λ_μ.

$$\begin{aligned}\boldsymbol{\alpha}_m &= \mathbf{G}^{-1}\mathbf{h} \\ \boldsymbol{\Sigma}_\alpha &= \mathbf{G}^{-1}\end{aligned}$$

$$\begin{aligned}h_i &= \sum_{\mu=1}^{k} \lambda_\mu^{-1} \langle \mathbf{e}_\mu, \mathbf{s}_i \rangle \langle \mathbf{e}_\mu, \mathbf{d} \rangle \\ G_{i,j} &= \sum_{\mu=1}^{k} \lambda_\mu^{-1} \langle \mathbf{e}_\mu, \mathbf{s}_i \rangle \langle \mathbf{e}_\mu, \mathbf{s}_j \rangle\end{aligned}$$

GPS Radio Occultation

- Refractivity

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

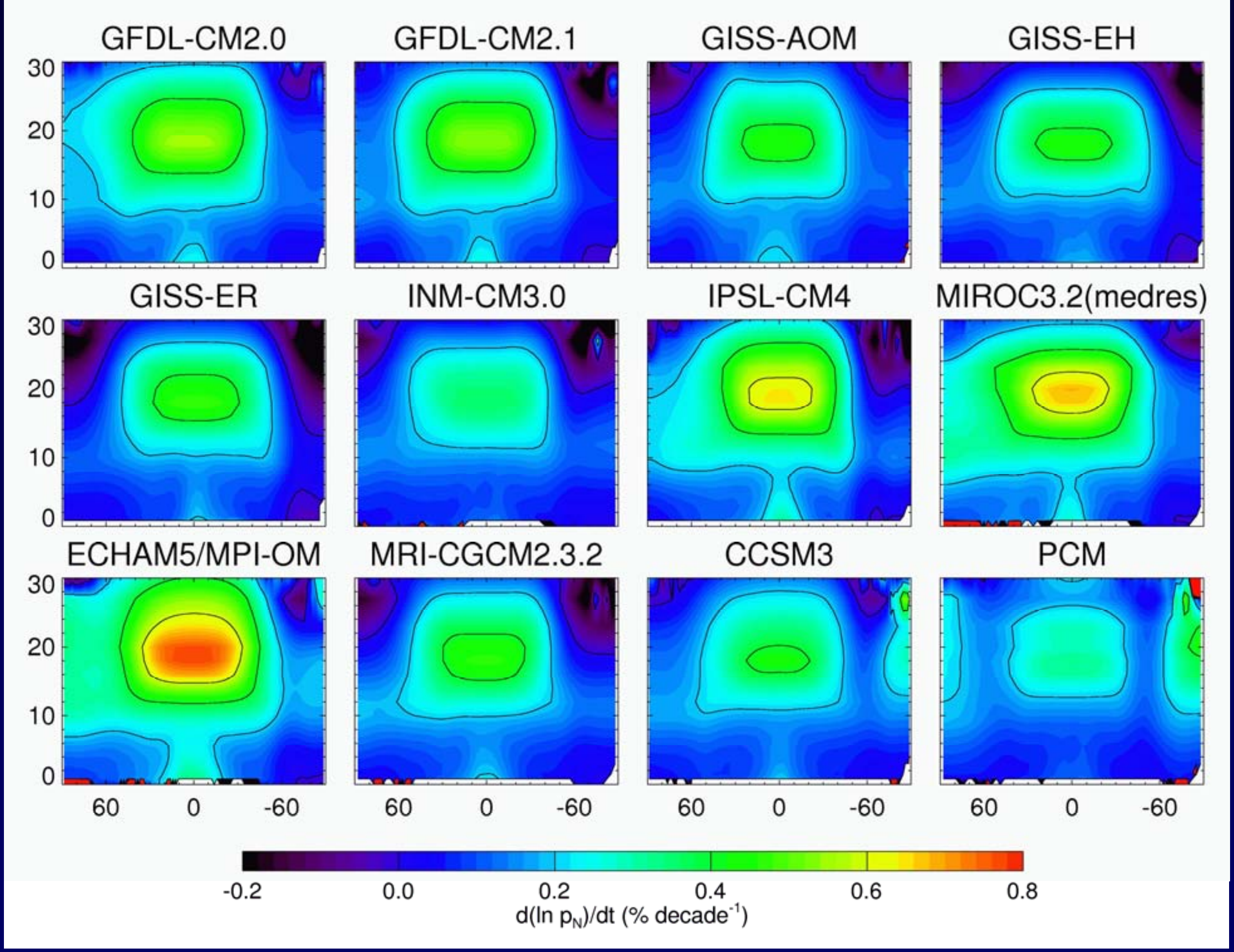
- "Dry" pressure

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

- Geopotential height

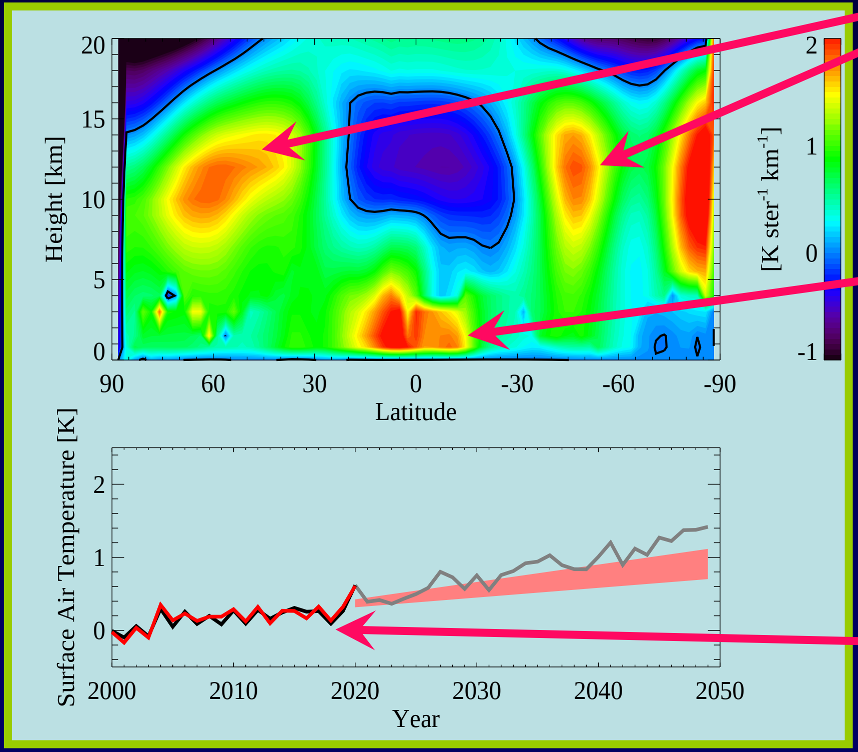
$$h = \left[(\Phi(\mathbf{r}) - \frac{1}{2}\Omega^2 r_s^2) - (\Phi - \frac{1}{2}\Omega^2 r_s^2)_\mathrm{msl}\right]/\,g_0$$

GPS RO Dry Pressure Tendency



How Does GPS RO Test GCMs?

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

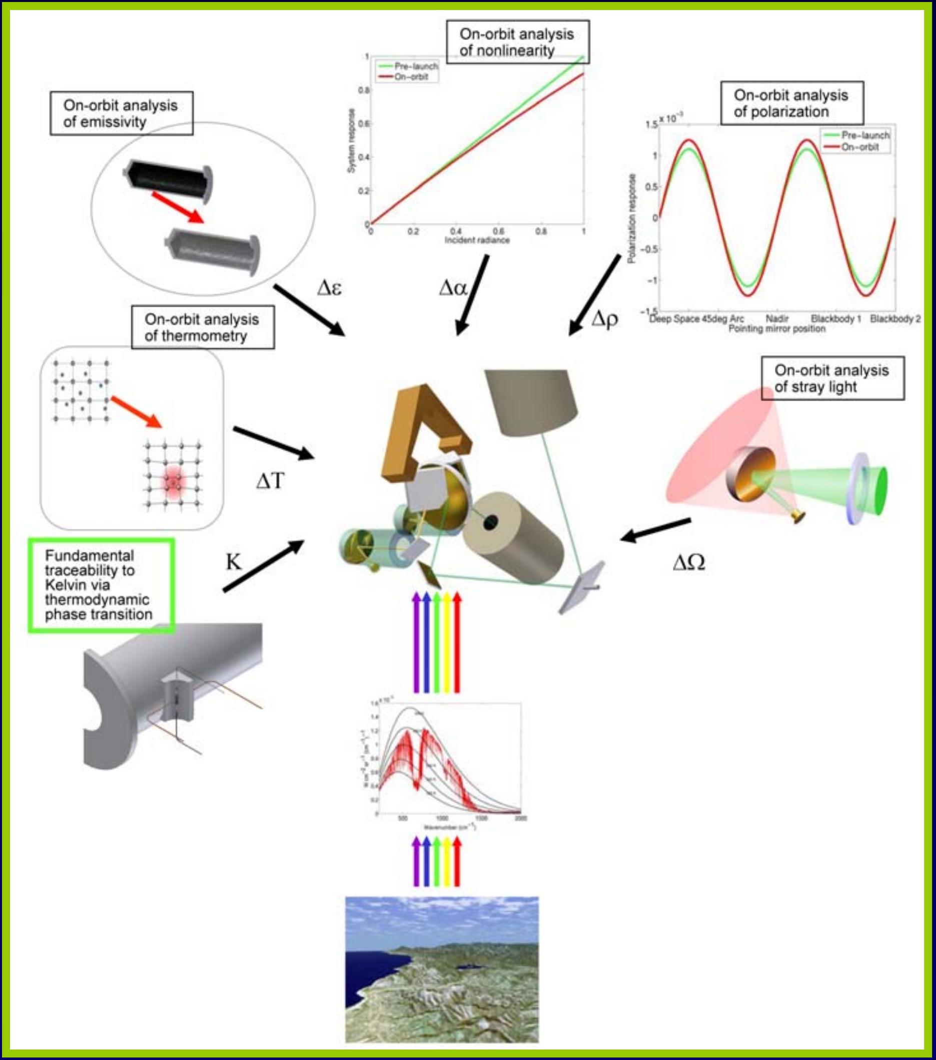


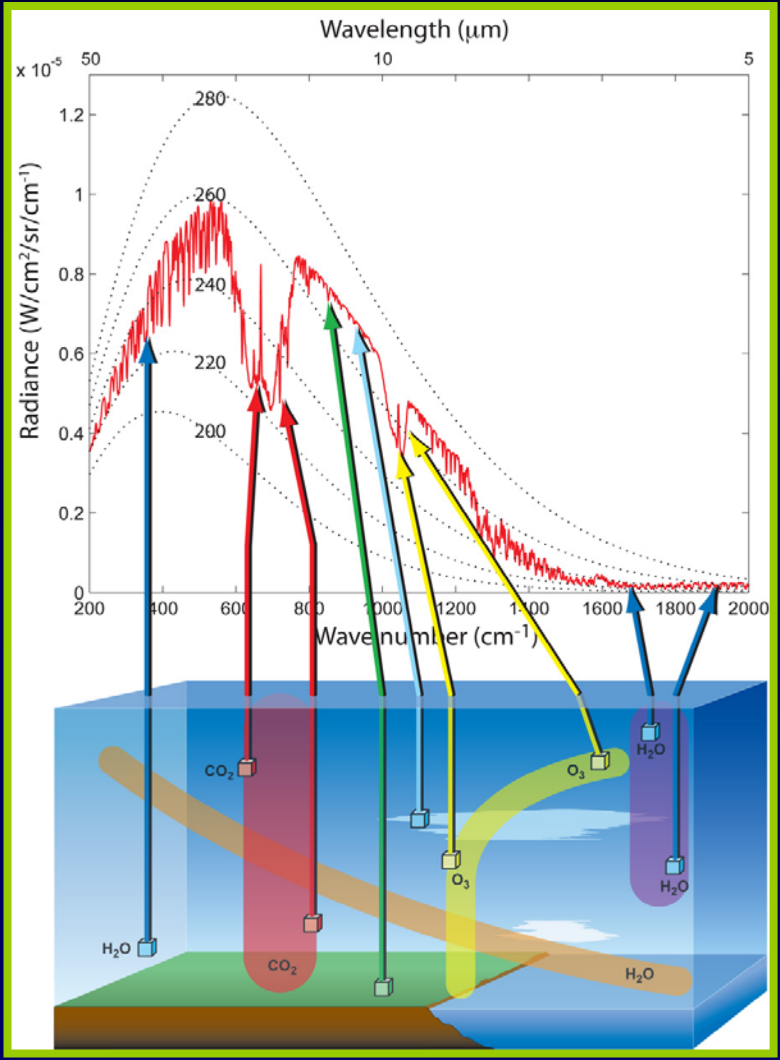
Poleward migration of jet streams

Increased ITCZ humidity

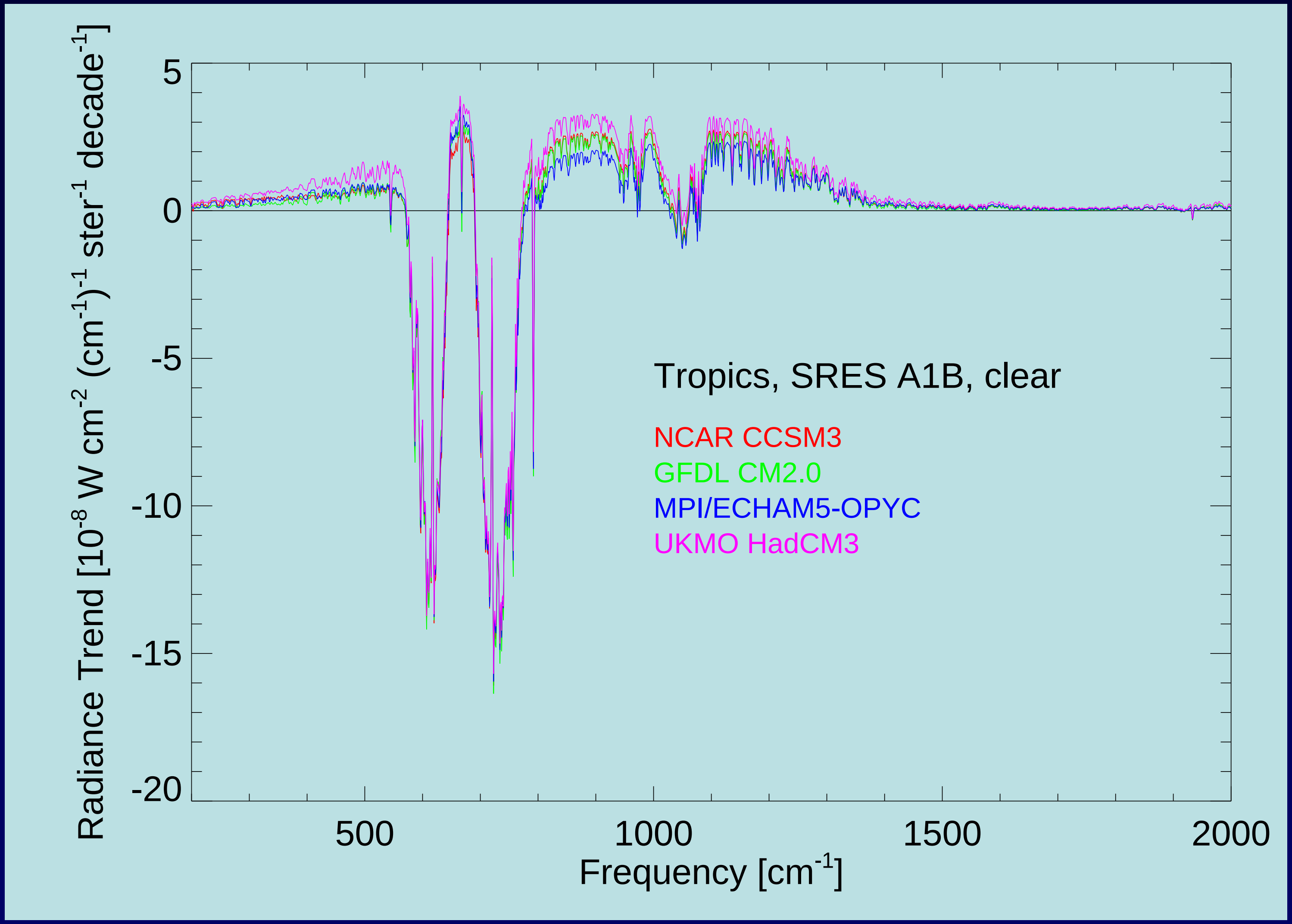
Near perfect tracking of global average surface air temperature

Thermal Infrared Spectra

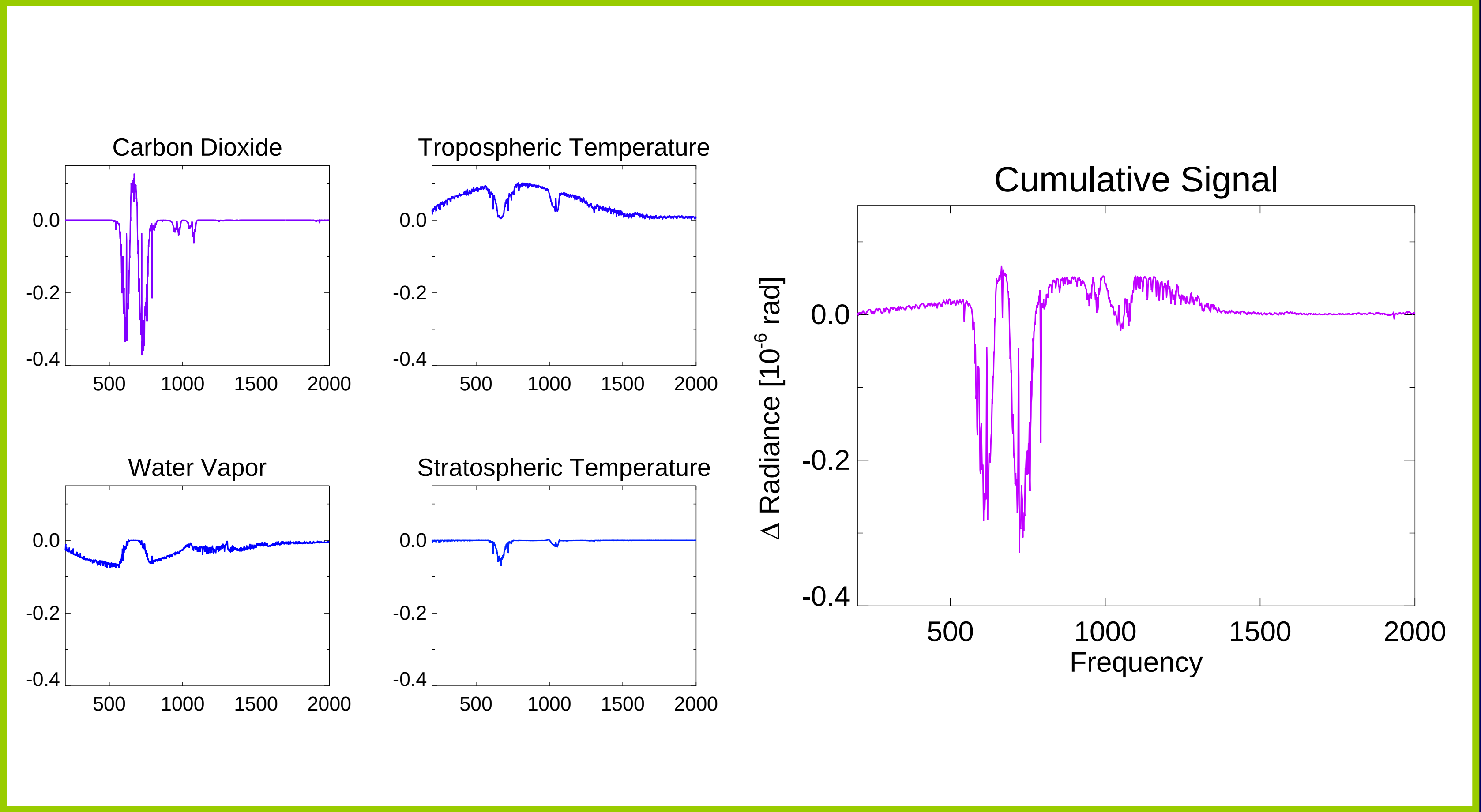




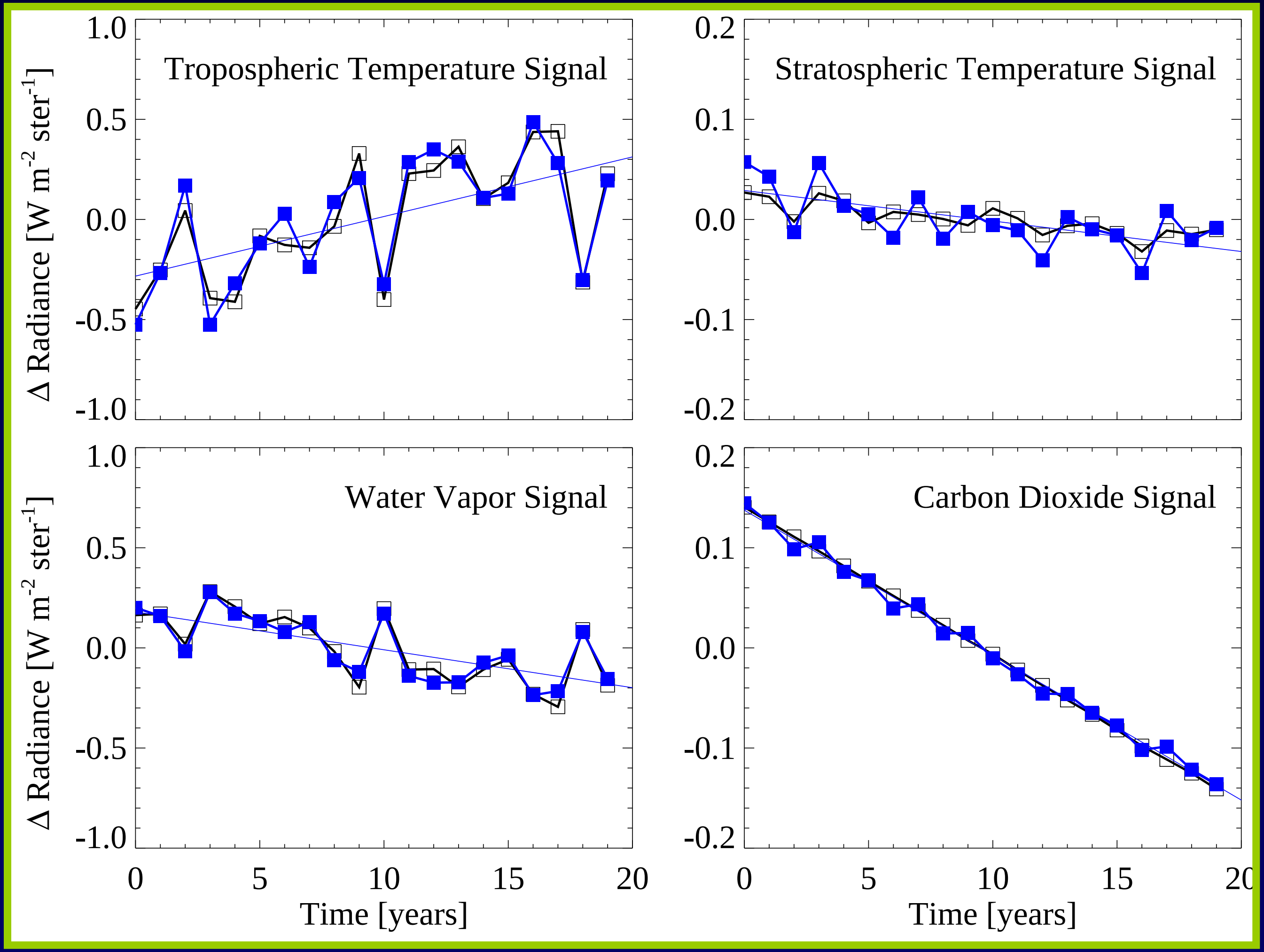
Thermal Infrared Spectra (2)



How Does Spectral IR Test GCMs?



Applied Scalar Prediction



Summary

- Trends in GPS radio occultation data bear strongly on global average surface air temperature.
- Trends in the outgoing longwave spectrum can be used to monitor longwave forcing and constrain all longwave feedbacks observationally. Optimization in space necessary to reduce detection times.
- Work in progress includes simulations in cloudy skies and shortwave trends.

Backup Slides

Applied Scalar Prediction

Find signal amplitudes (***α****ₘ*) and uncertainty (**Σ**$_\alpha$) in a data set (**d**) according to the signals' patterns (**s**$_i$) against a background of natural variability, the eigenvectors and eigenvalues of which are **e**$_\mu$ and λ_μ.

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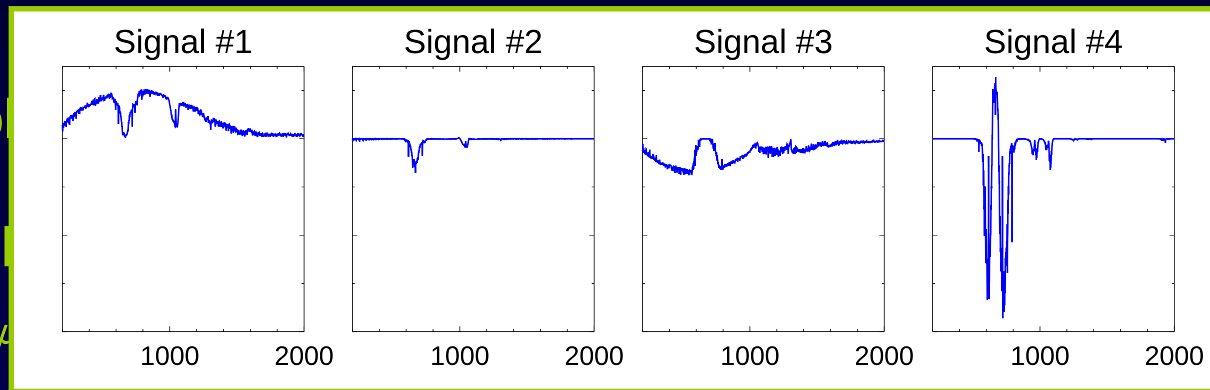

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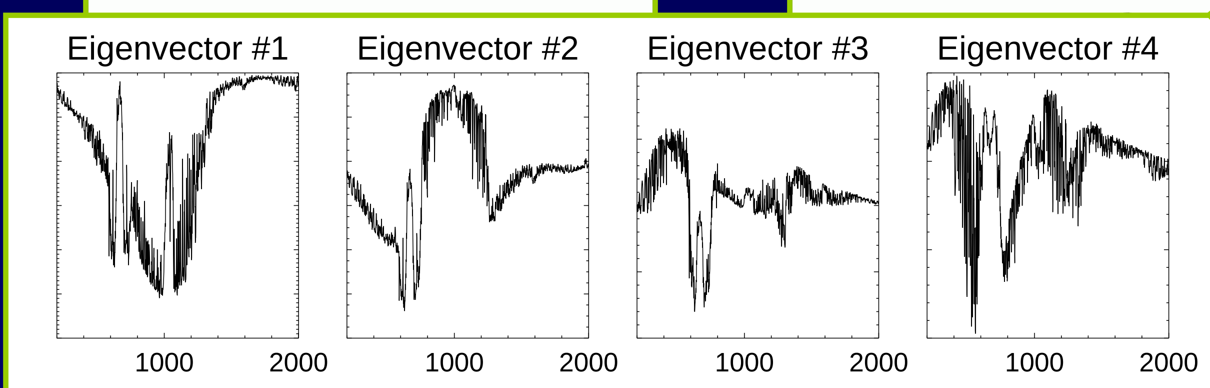
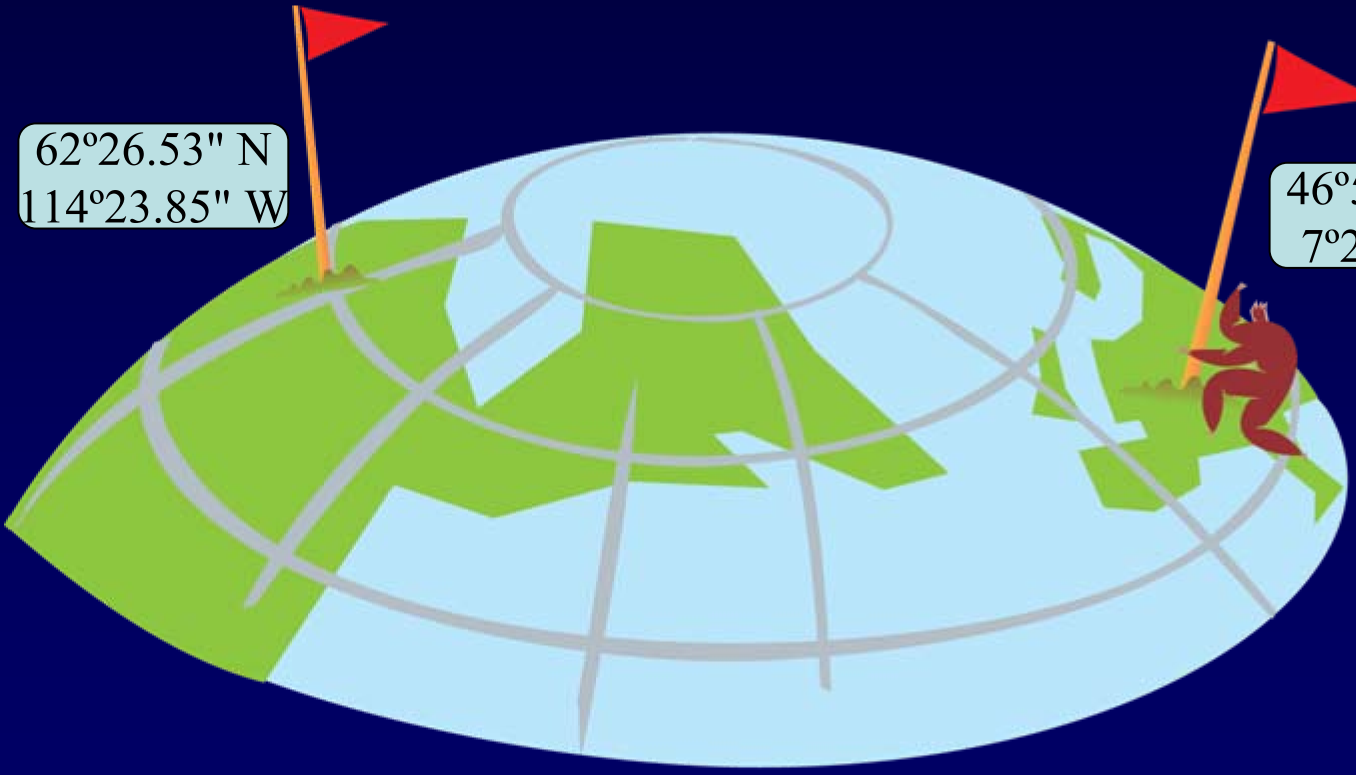


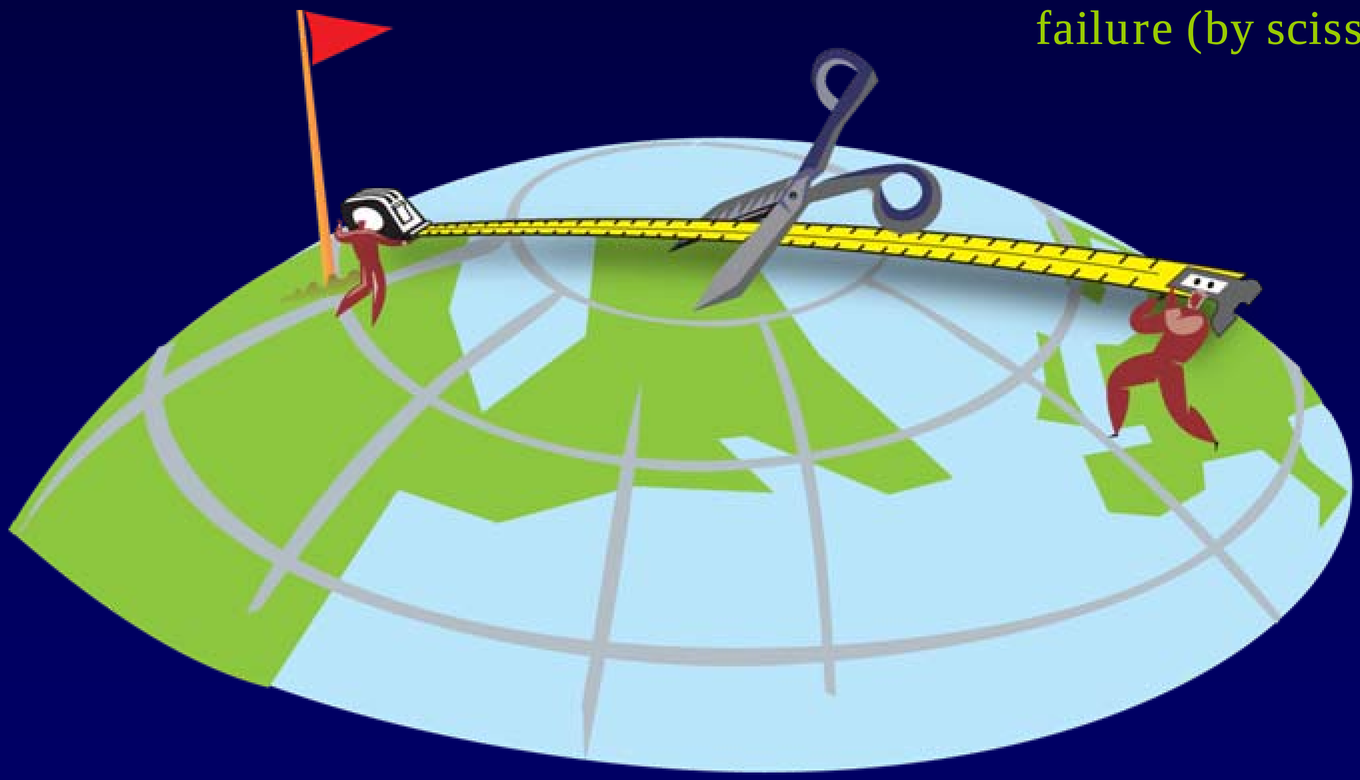
The Climate Benchmark

$$d = R_e \cos^{-1}\left[\cos(\lambda_2 - \lambda_1)\cos\phi_1 \cos\phi_2 + \sin\phi_1 \sin\phi_2\right]$$
$$= 6816.74 \text{ km}$$

- Lat-lon grid is standardized
- Uncertainty derived from independent tests

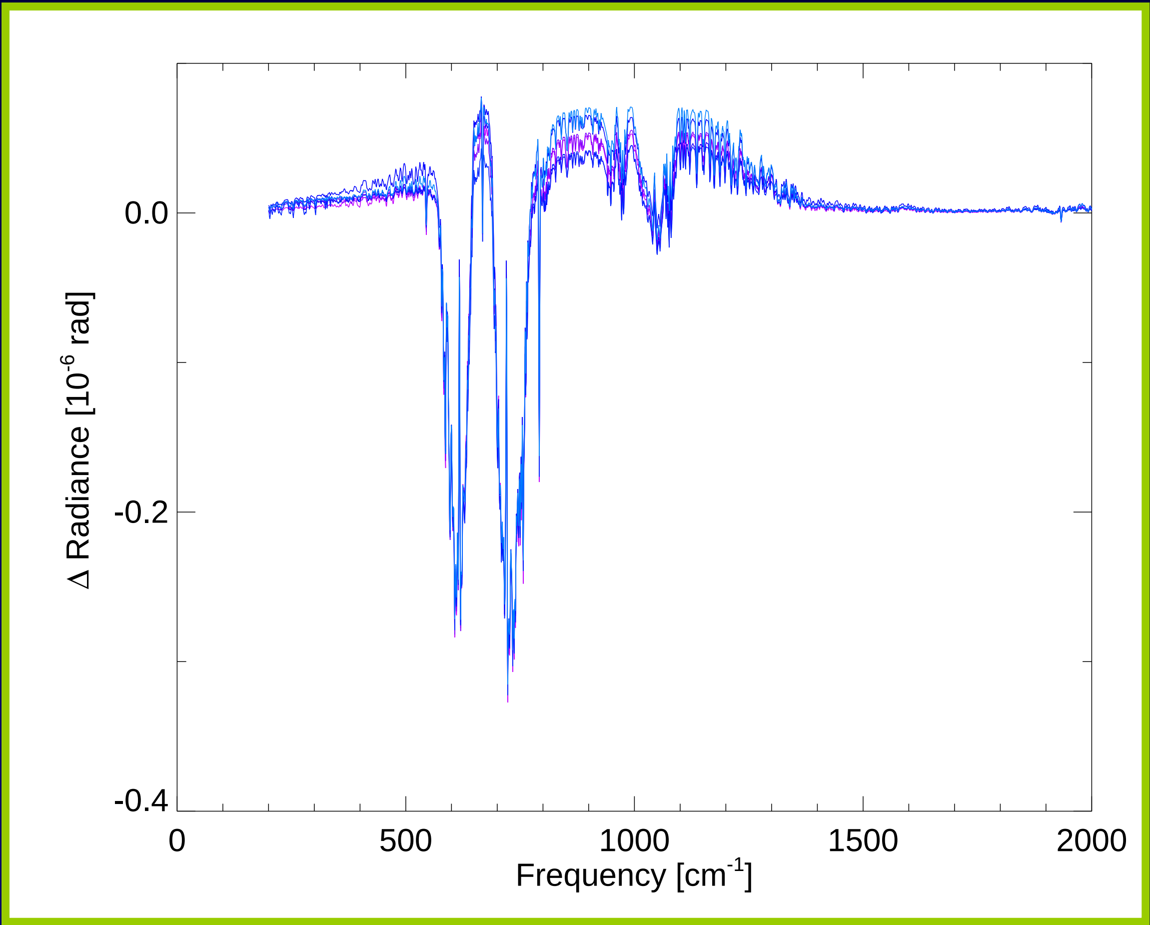


How Not to Monitor Climate…



- Tape measure calibration is unstandardized
- Tape measure subject to failure (by scissors)

How Does Spectral IR Test GCMs?



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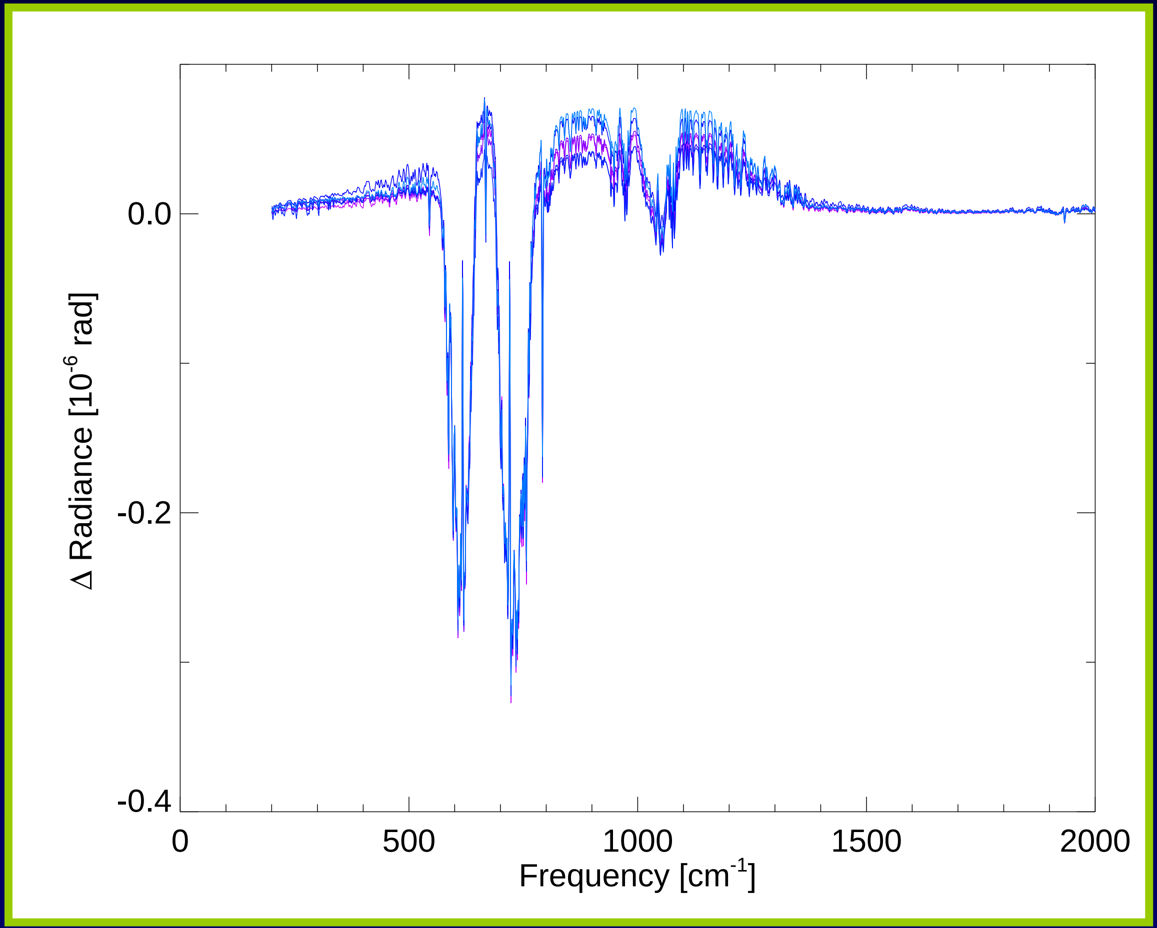

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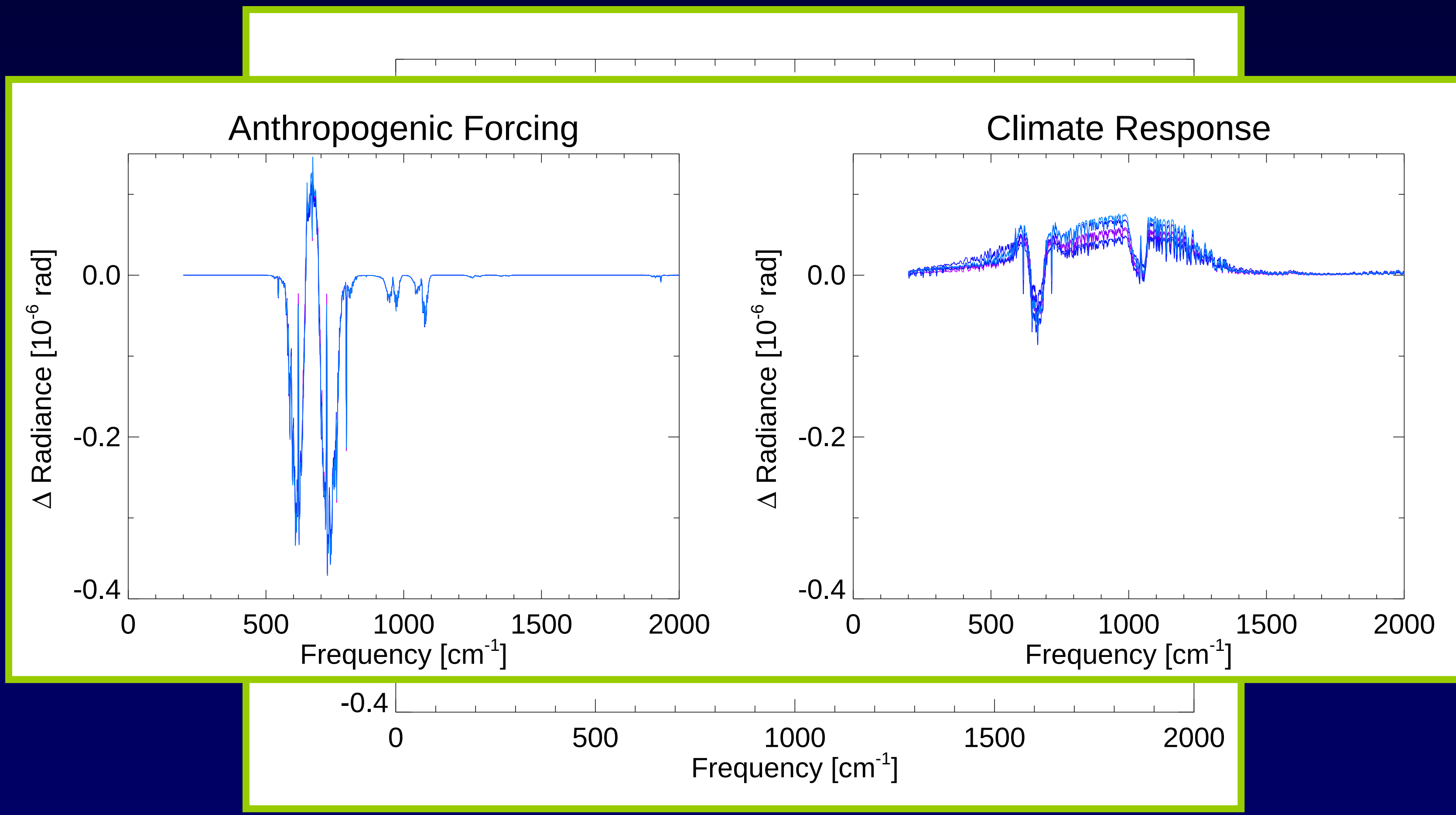
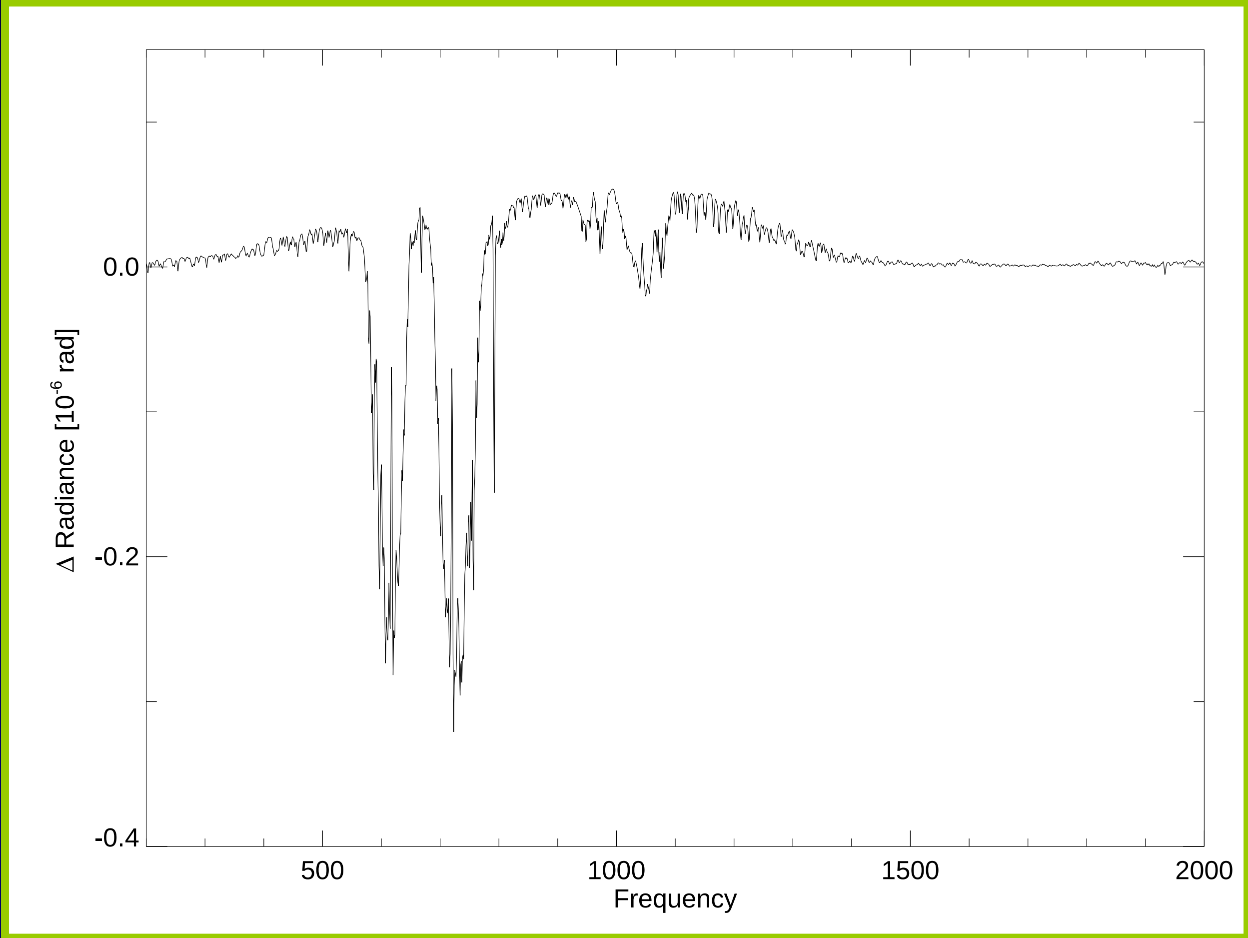


How Does Spectral IR Test GCMs? (3)



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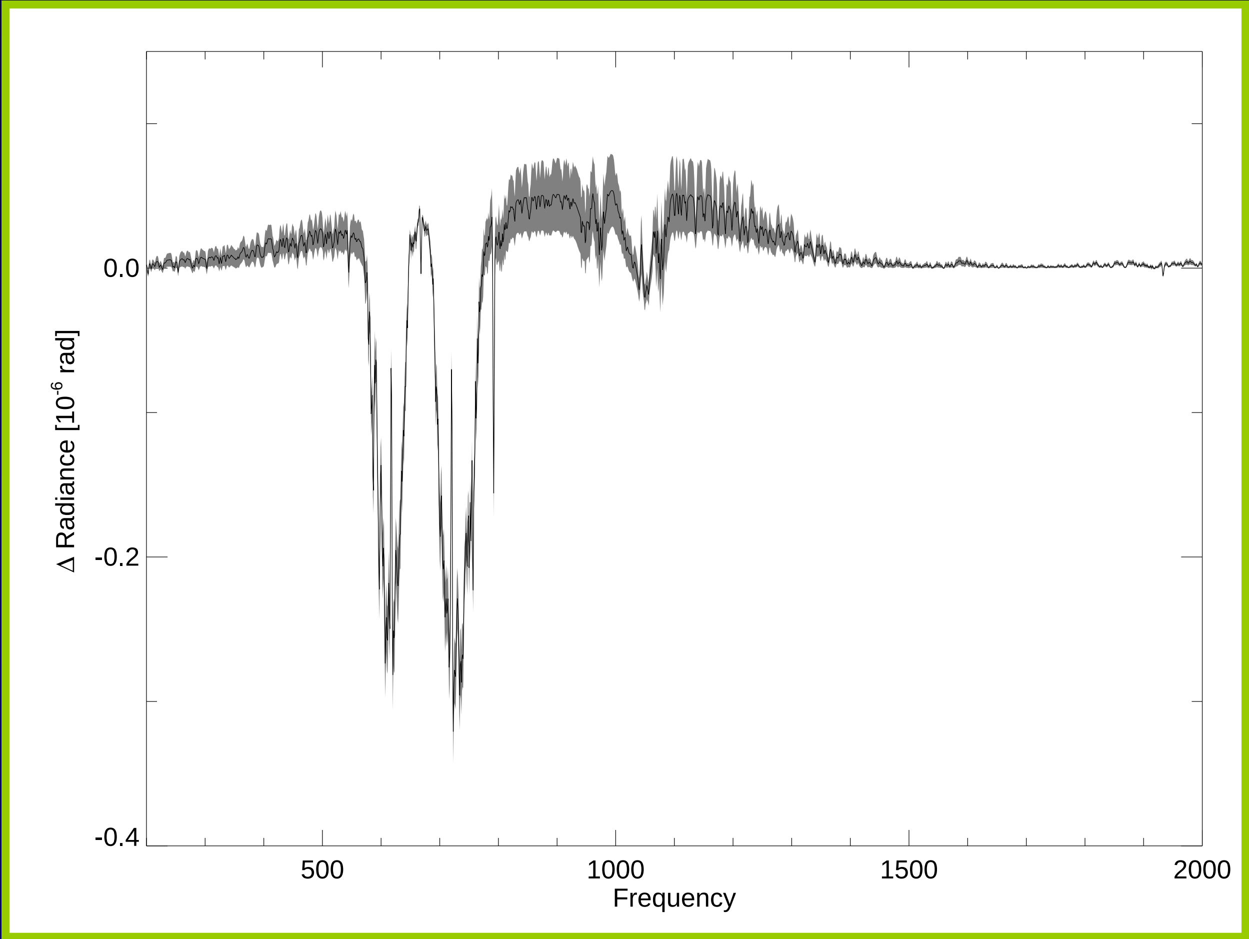

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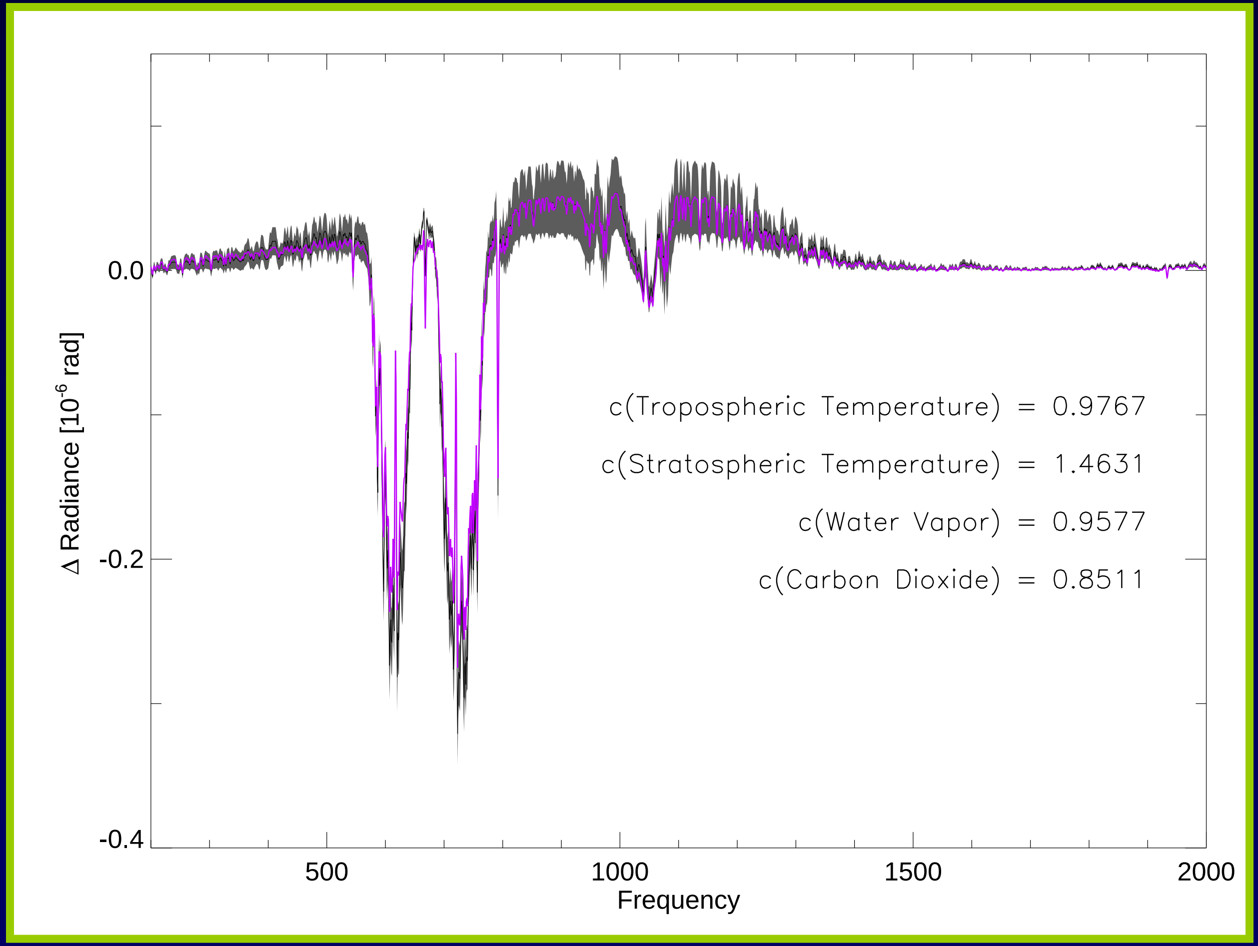

Water Vapor-Longwave Feedback Precision After 20 Years

	Linear Trend Analysis ($W\ m^{-2}\ K^{-1}$)		Correlation Analysis ($W\ m^{-2}\ K^{-1}$)	
	Truth	Data	Truth	Data
GFDL CM2.0	3.30 ± 1.85	3.20 ± 1.85	2.75 ± 0.20	2.53 ± 0.18
GISS E-H	2.63 ± 0.81	2.95 ± 0.62	2.61 ± 0.10	2.94 ± 0.12
MIROC3.2	2.81 ± 0.85	2.53 ± 0.62	2.68 ± 0.13	2.49 ± 0.10
ECHAM5	3.14 ± 1.60	3.53 ± 1.81	2.98 ± 0.08	3.36 ± 0.10
CCSM3	2.80 ± 0.92	2.81 ± 0.91	2.66 ± 0.17	2.66 ± 0.16
HadCM3	3.10 ± 1.48	2.65 ± 1.15	2.78 ± 0.09	2.74 ± 0.11

…scales as $(\Delta t)^{-3/2}$

…scales as $(\Delta t)^{-1/2}$

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	Linear Trend Analysis ($W\ m^{-2}\ K^{-1}$)		Correlation Analysis ($W\ m^{-2}\ K^{-1}$)	
	Truth	Data	Truth	Data
GFD[illegible]	[illegible]	[illegible]	[illegible]	[illegible].18
GISS[illegible]	[illegible]	[illegible]	[illegible]	[illegible].12
MIR[illegible]	[illegible]	[illegible]	[illegible]	[illegible].10
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HadCM3	3.10 ± 1.48	2.65 ± 1.15	2.78 ± 0.09	2.74 ± 0.11

Optimization: Little as of yet, but inclusion of the spatial dimension should yield substantial improvement.

…scales as $(\Delta t)^{-3/2}$

…scales as $(\Delta t)^{-1/2}$

Accuracy Requirements, Detection Times

- With observations traceable to international standards, one evaluates the uncertainty (accuracy) of individual measurements in a timeseries.
- Any timeseries of climate data includes both natural variability with standard deviation σ_v, timescale τ_v, and measurement uncertainty (σ_m and τ_m).

With a timeseries of length Δt, the uncertainty in the determination of the slope determination is

$$\delta m^2 = 12\,(\Delta t)^{-3}\left(\sigma_v^2 \tau_v + \sigma_m^2 \tau_m\right)$$

Leroy, S.S., J.G. Anderson, and G. Ohring, 2008: Climate signal detection times and constraints on climate benchmark accuracy requirements. *J. Climate*, **21**, 841-846.

Measurement Uncertainty & Detection Times

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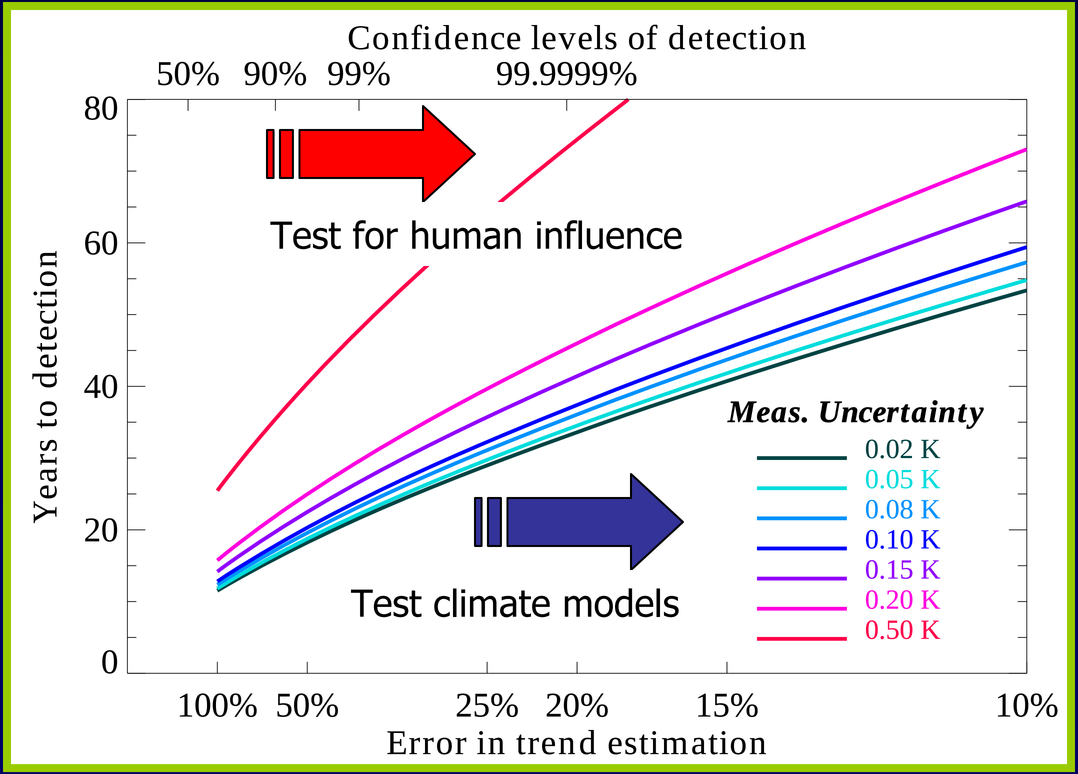


Global temperature at 500 hPa

Three satellites, 6-year lifetime.

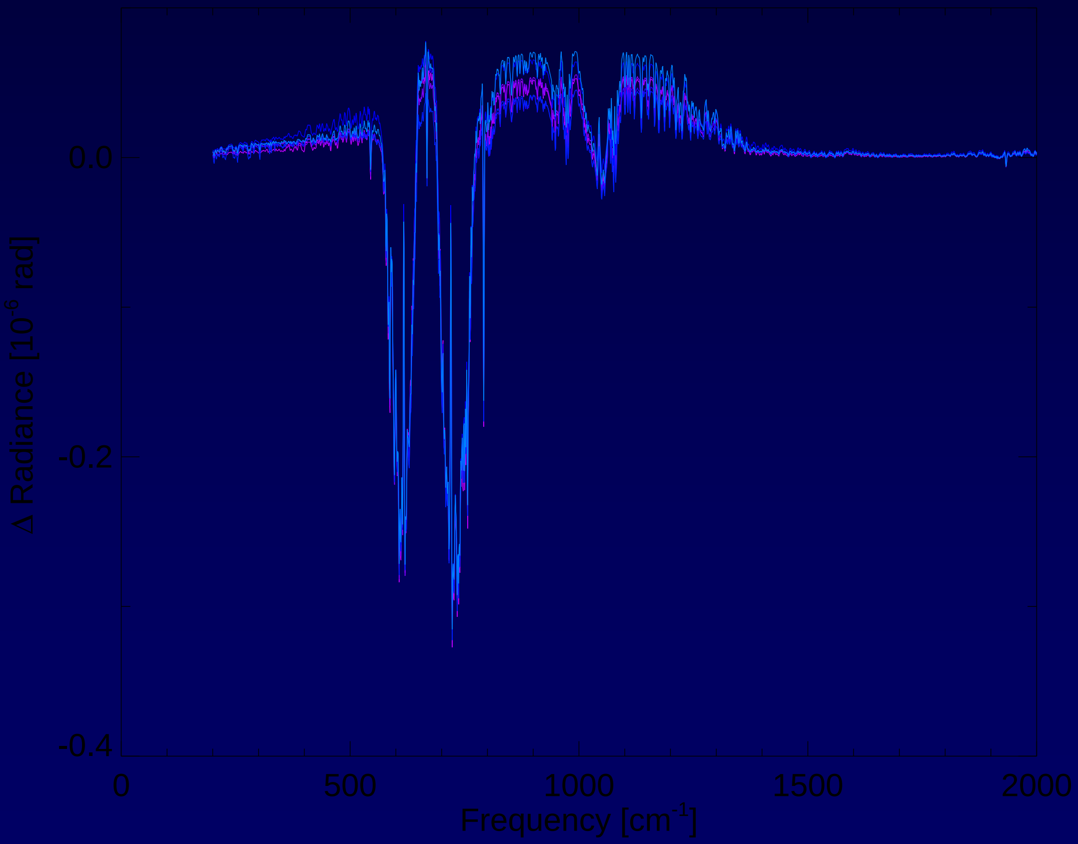
Natural variability: 0.18 K, 1.54 year correlation time (UKMO HadCM3), Trend: ~0.2 K decade^{-1}.

Optimization has the effect of lowering the entire family of curves.

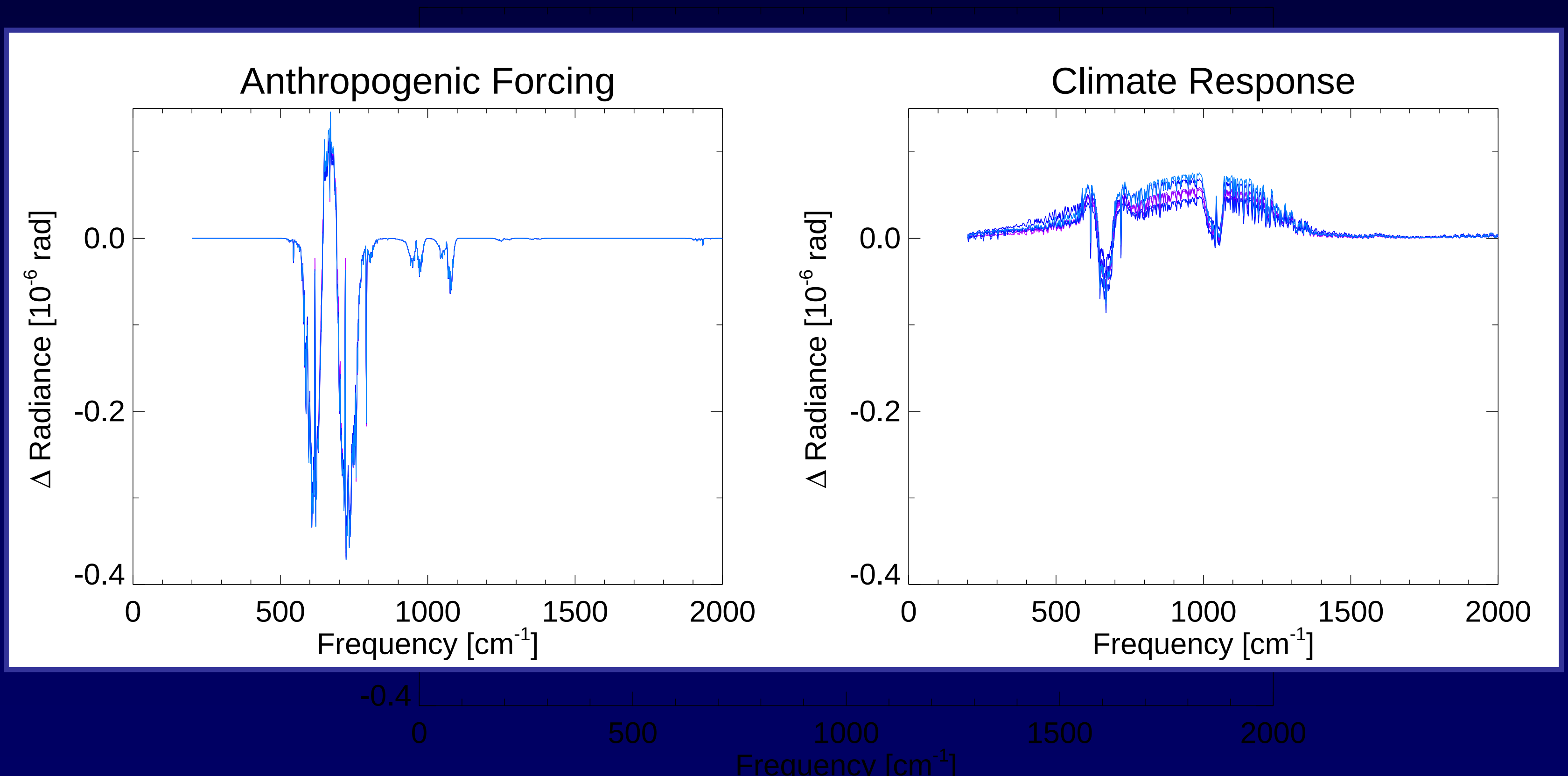
Discussion: Next Steps

- All-sky conditions
  - Explore potential for optimization: expand into spatial dimension
  - Cloud Feedback Model Intercomparison Project
  - Potentially GISS E-R in perturbed physics ensemble
  - *Fast forward model for radiance (AER's OSS)*
- Anticipated results
  - Information content in far infrared (100-300 cm^{-1})
  - Information content as a function of spectral resolution
  - Information content in joint GPS RO – Spectral IR data vector
  - Accuracy requirements
- Shortwave OSSE
  - Separating response (clouds) from forcing (aerosol)
  - Exploring necessary dimensionality: observation → SW↑
  - Accuracy requirements

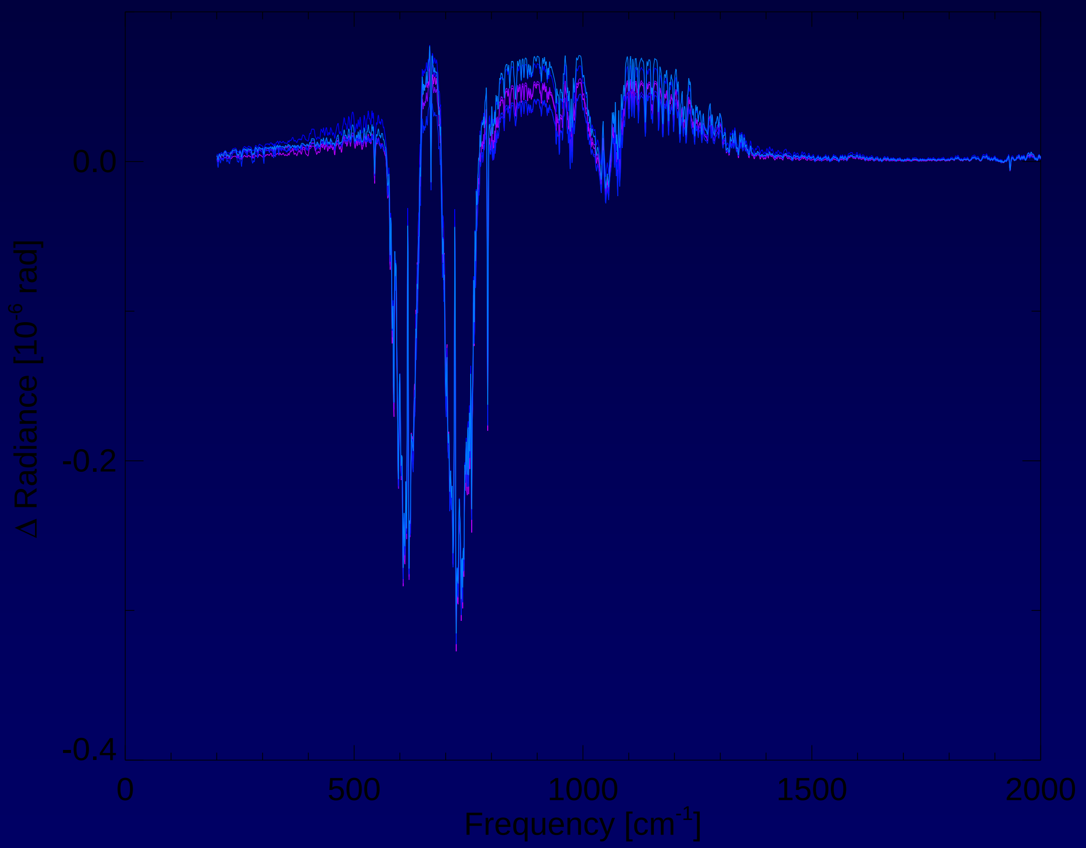
Model-predicted Trends in the IR



Model-predicted Trends in the IR



Deconstructing the IR Signal



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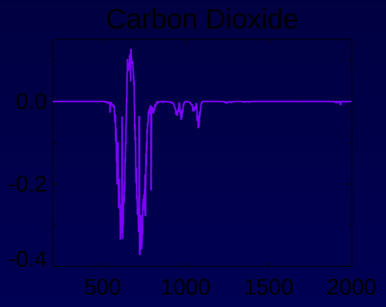

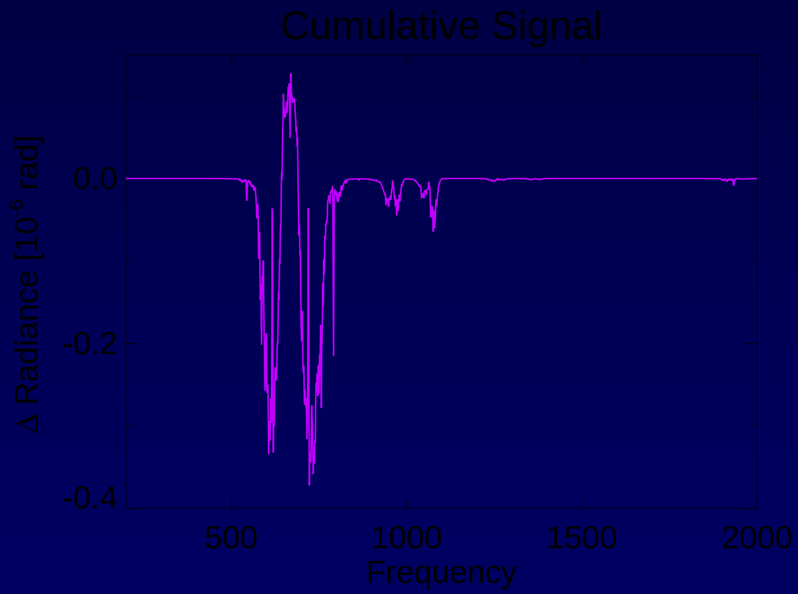

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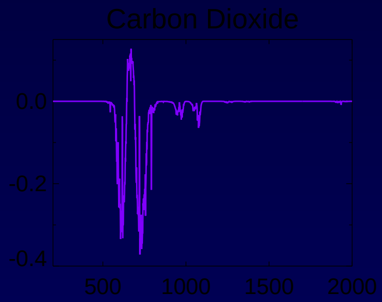

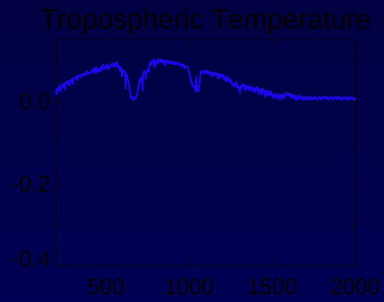

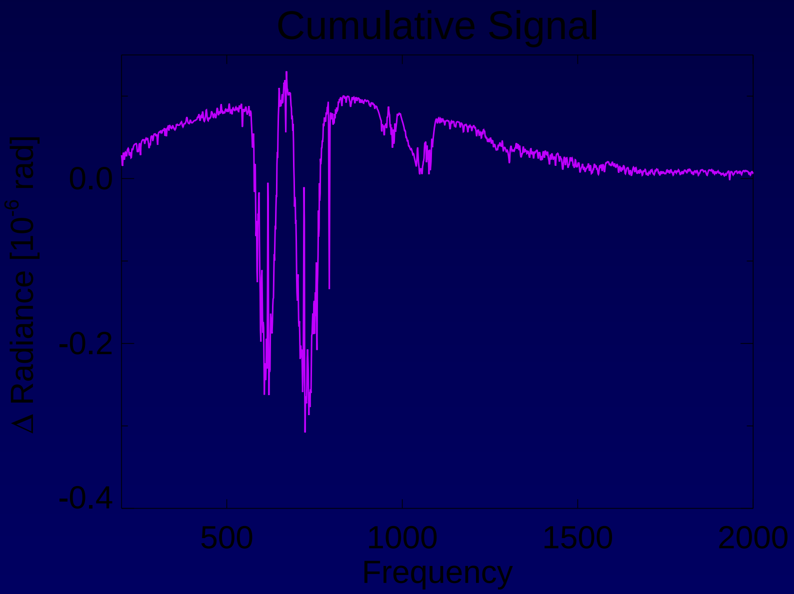

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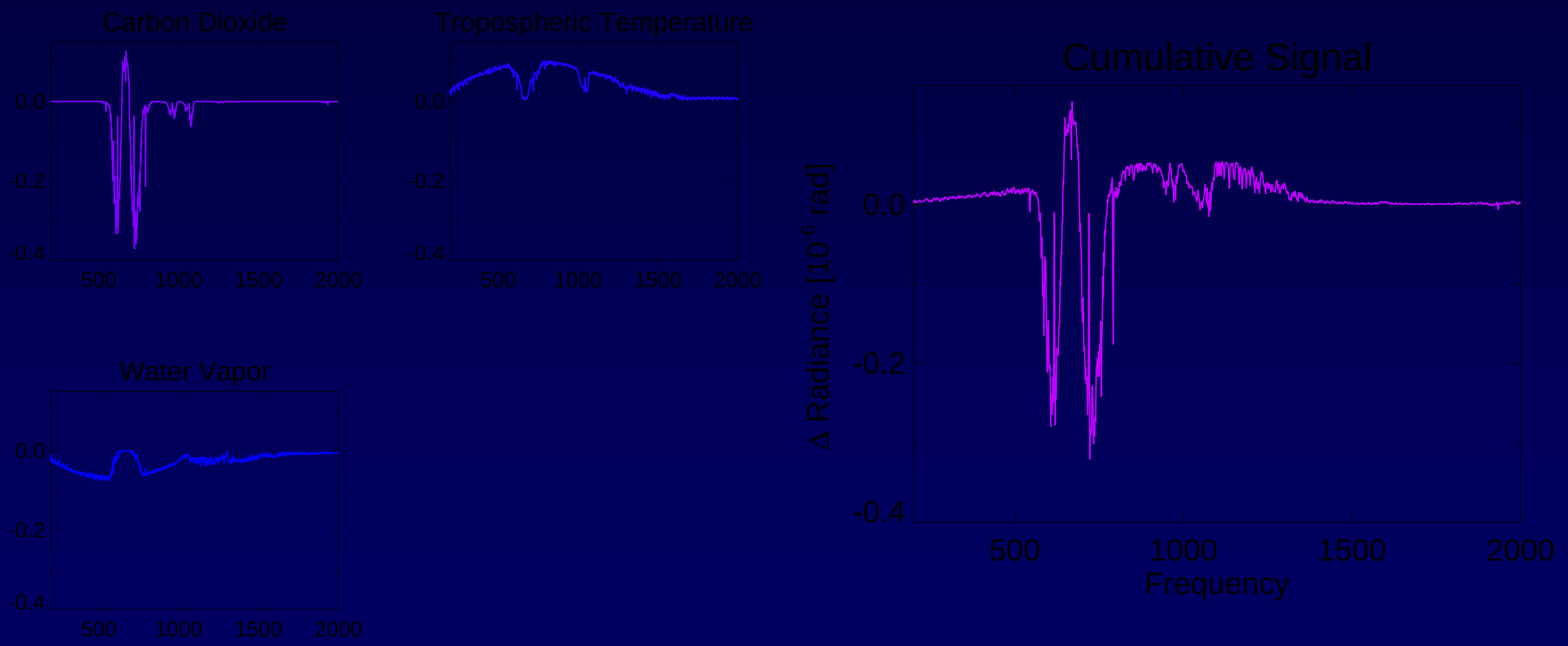

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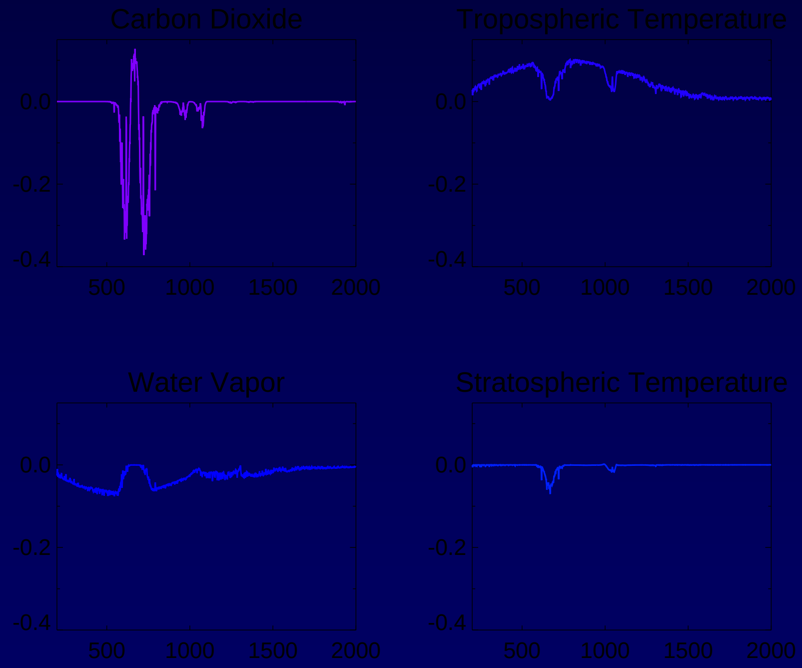

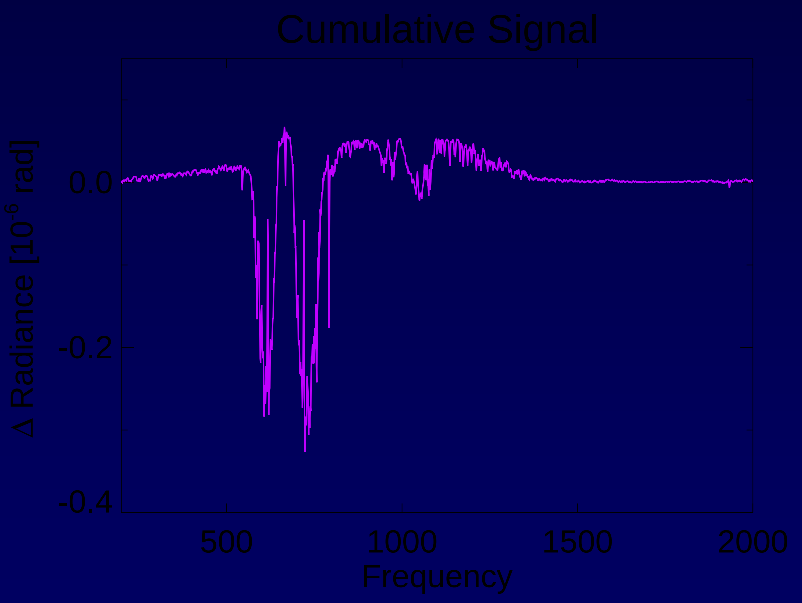

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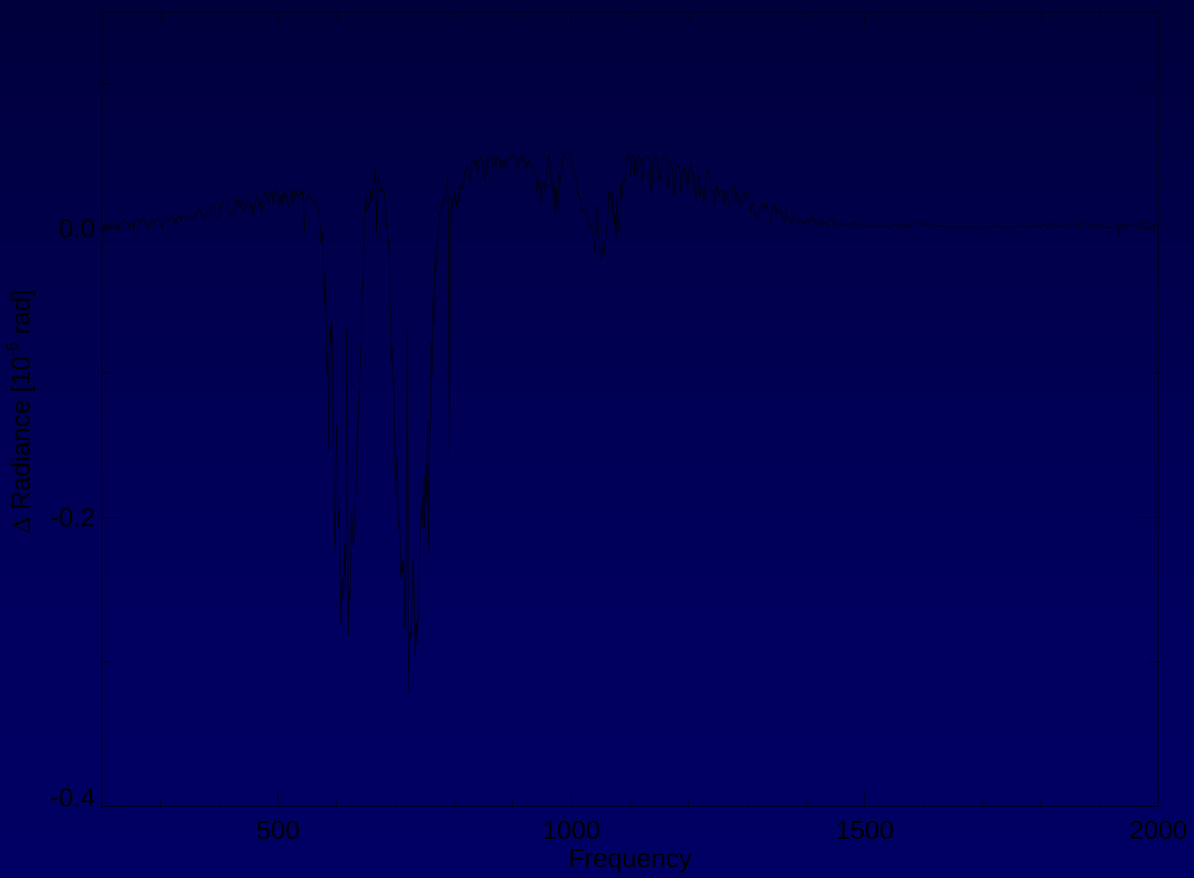

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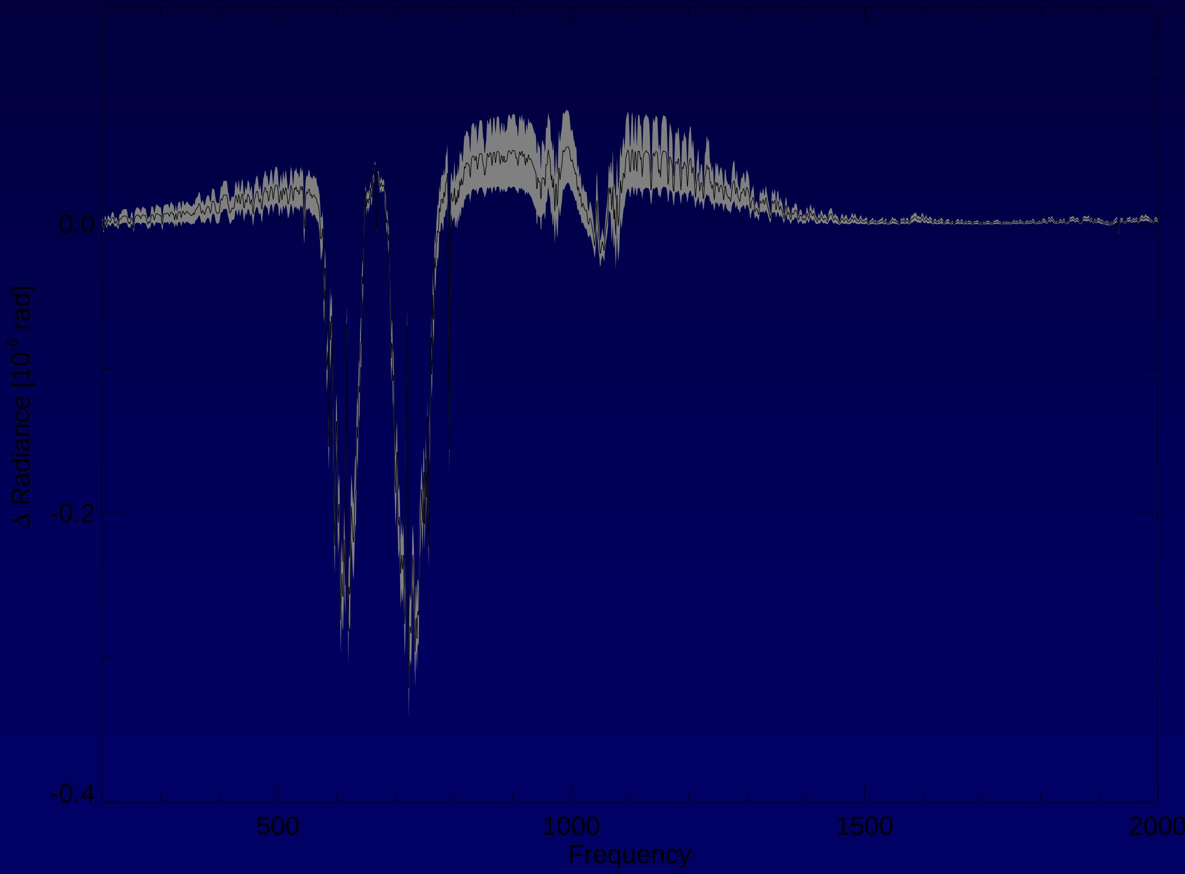

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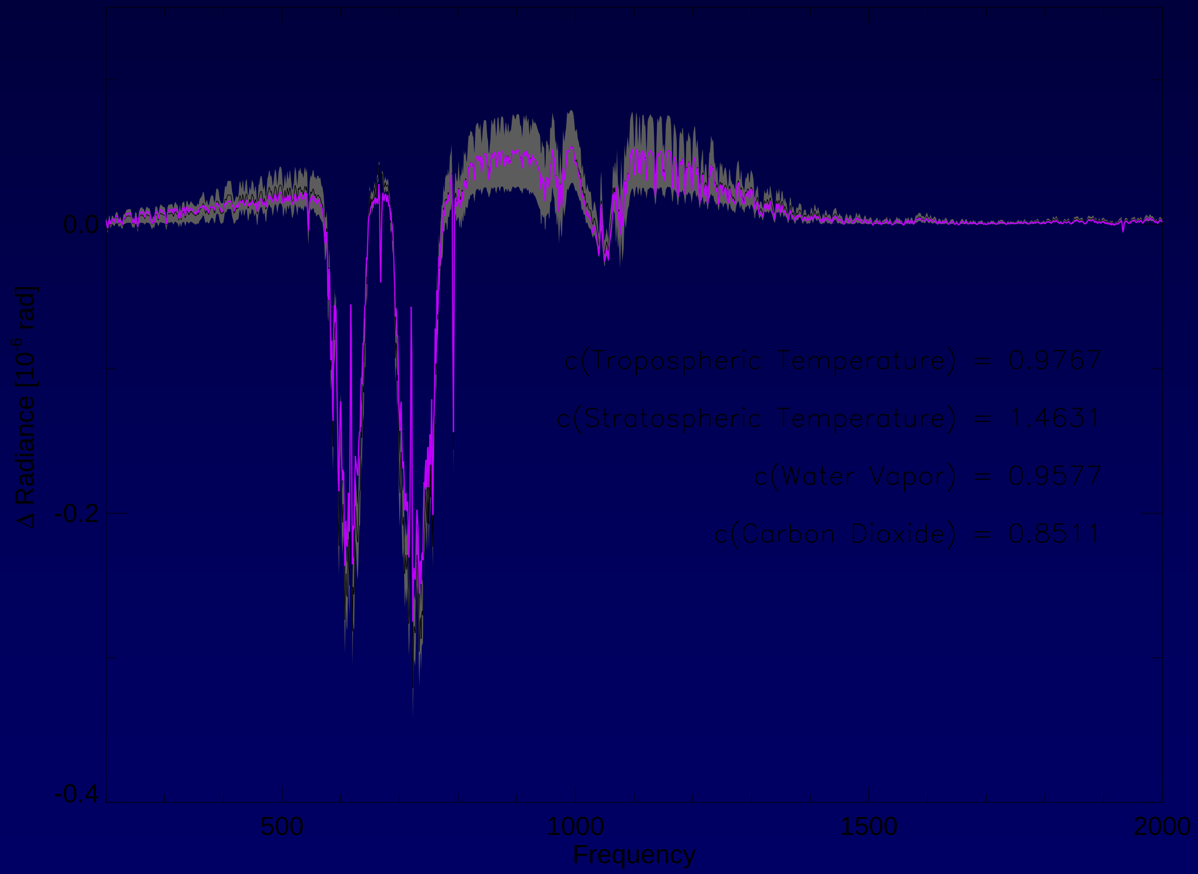

… which is Optimal Fingerprinting

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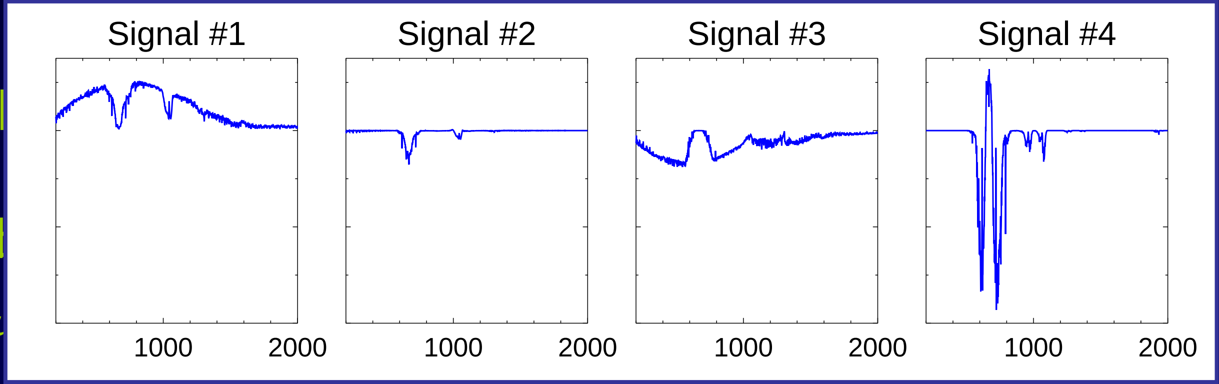

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