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Testing Climate Models Using GNSS Occultation and Infrared Spectra

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Occultations for Probing Atmosphere and Climate III
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Outline

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- NRC Decadal Survey of NOAA and NASA: CLARREO
  - Problems with previous observational efforts
  - Climate Absolute Radiance and Refractivity Observatory: Establishing climate record & testing climate models
- SI Traceability and Climate Benchmarking
- Testing Climate Models: Information Content
- Climate Feedbacks
- Optimal Detection
  - GNSS Occultation
  - Infrared Radiance Spectra
- Summary

NRC Decadal Survey

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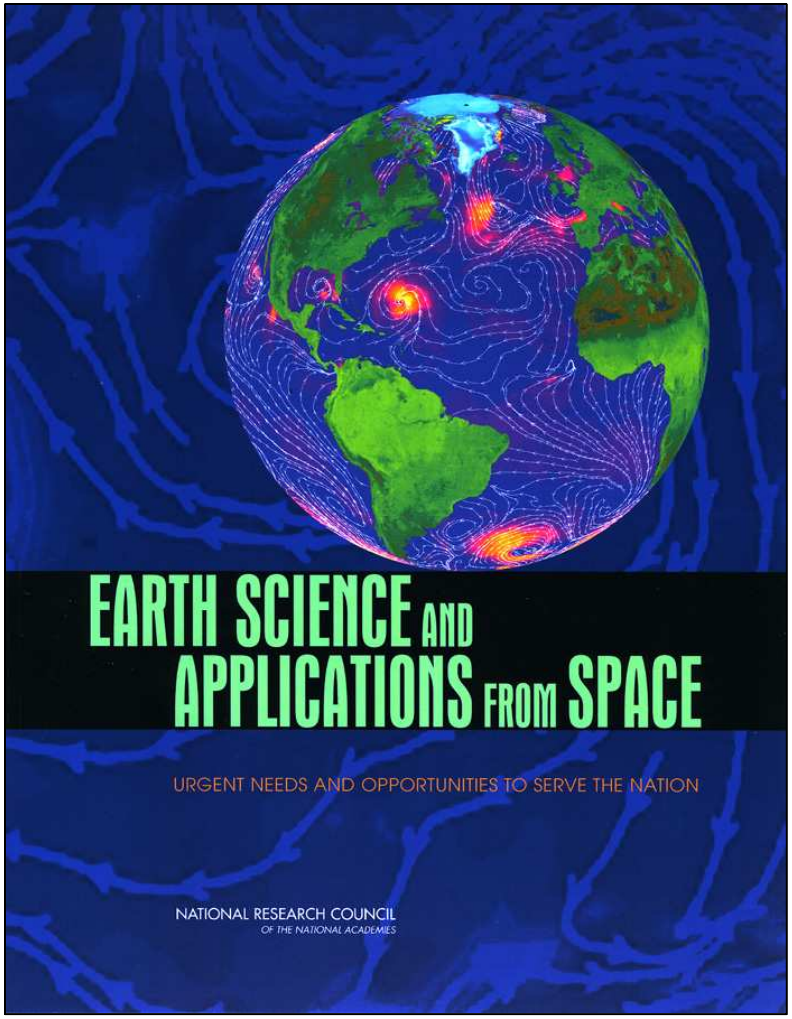
"The nation continues to lack an adequate foundation of climate observations that will lead to definitive knowledge about how climate is changing and will provide a means to test and systematically improve climate models." – NRC Decadal Survey of NOAA and NASA (2006)

"The Climate Absolute Radiance and Refractivity Observatory (CLARREO) will provide a benchmark climate record that is global, accurate in perpetuity, tested against independent strategies that reveal systematic errors, and pinned to international standards." – NRC Decadal Survey Recommendations (2007)

(1) Thermal infrared radiance;
(2) Incident and reflected solar radiation;
(3) GNSS radio occultation;
(4) Accurate broadband radiance (NOAA).



CLARREO Conceptually

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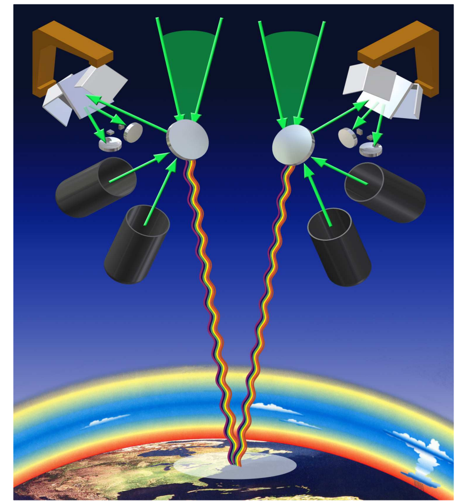
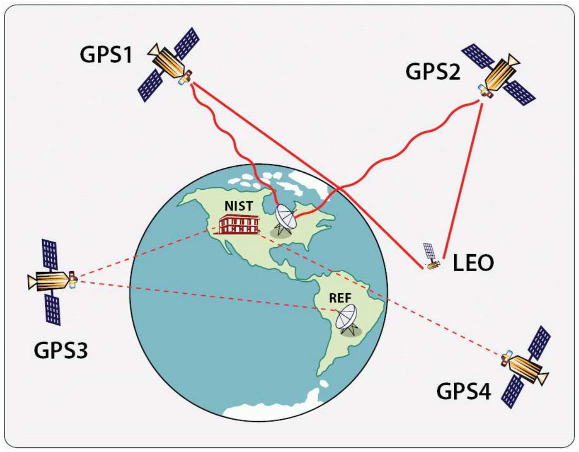
GNSS radio occultation measurements

Absolute spectrally resolved radiance in the thermal infrared

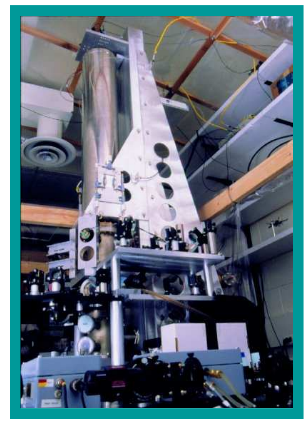
Solar irradiance: Incident and reflected

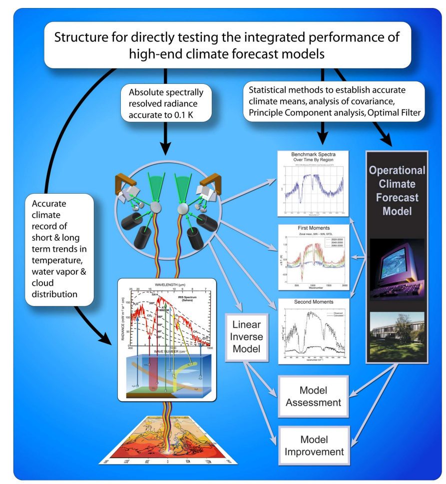


GPS Occultation: The Time Standard



- GNSS occultation is tied to ground-based atomic clock standards by double-differencing technique.
- NIST F1 measures time with fractional error of 1.7•10-15 (as of 1999).





Southwest Research Institute

SSEC

University of Maryland

Information Content

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Benchmark Measurement

- Traceable to international standards
- Minimize sampling error

Benchmark Simulation

- Simulate trends in observable as produced by different models
- Compare commonalities and differences between model predictions
- Apply optimal methods

Climate Uncertainty

- Shortwave forcing
- Longwave forcing
- Climate feedbacks & processes
- Sensitivity & meteorology

"Climate OSSE" Results

- Detection time and accuracy requirements
- Fingerprint: How to use data to test models
- How measurement constrains climate predictability

Optimal Detection

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I. **Electrical Engineering**: Weight the data so as to minimize the error associated with the fitted coefficients (North and Kim 1995):

$$\mathbf{y} = a\mathbf{f} + d\mathbf{n}$$

$$a = \left(\sum_{\mu} \frac{\langle \mathbf{e}_\mu, \mathbf{f} \rangle^2}{\lambda_\mu} \right)^{-1} \sum_{\mu} \frac{\langle \mathbf{e}_\mu, \mathbf{f} \rangle \langle \mathbf{e}_\mu, \mathbf{y} \rangle}{\lambda_\mu}$$

II. **Statistical**: Assemble the Bayesian evidence function given a model for the data (Hasselmann 1993, Leroy 1998):

$$d\mathbf{n} \sim N(\mathbf{y} - a\mathbf{f}, \mathbf{N})$$

$$a = \underbrace{(\mathbf{f}^T \mathbf{N}^{-1} \mathbf{f})^{-1} \mathbf{f}^T \mathbf{N}^{-1}}_{\text{fingerprint}} \mathbf{y}$$

Trends in Log-Dry Pressure

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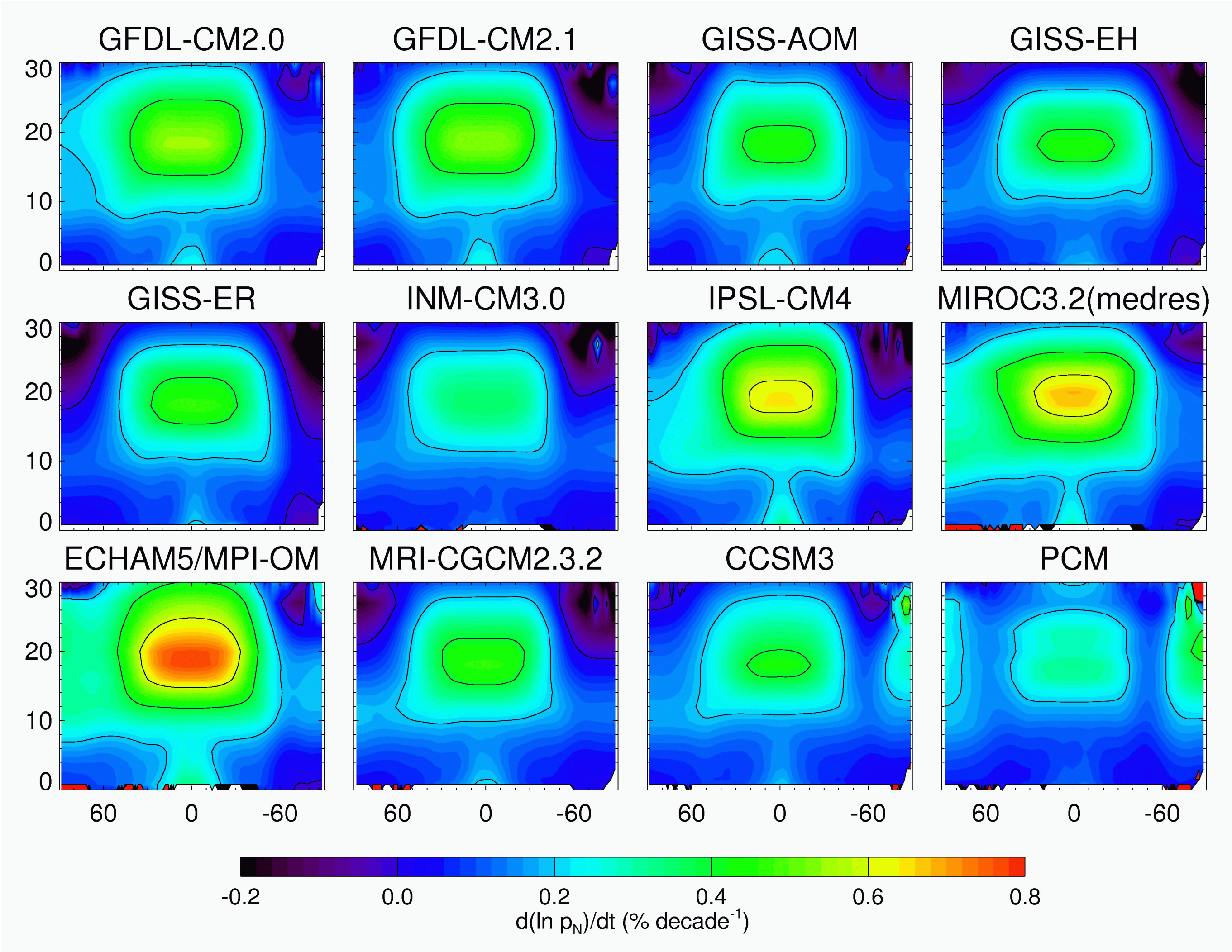

Optimal Fingerprints

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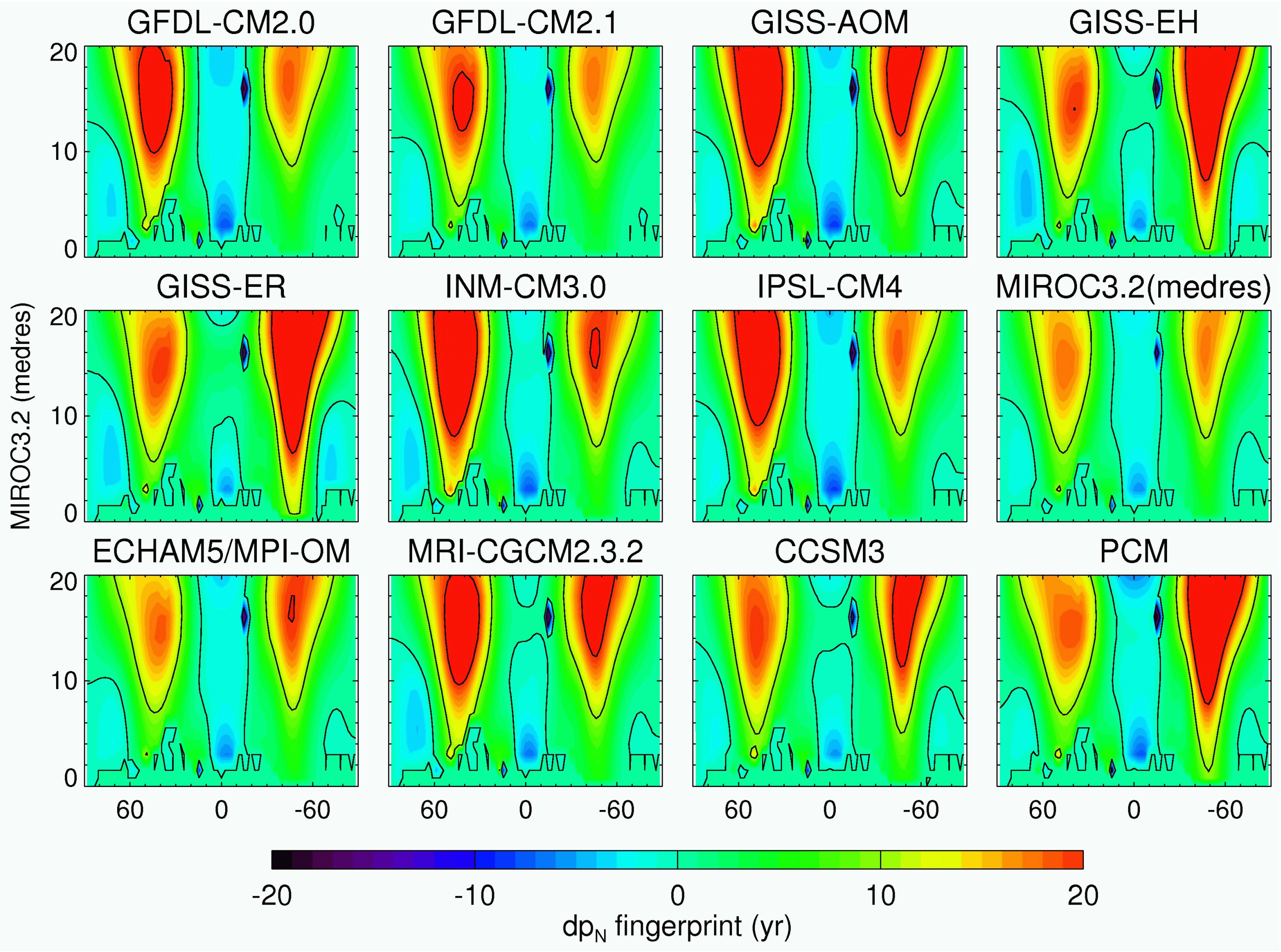

2σ Detection Times

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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

In the Thermal Infrared…

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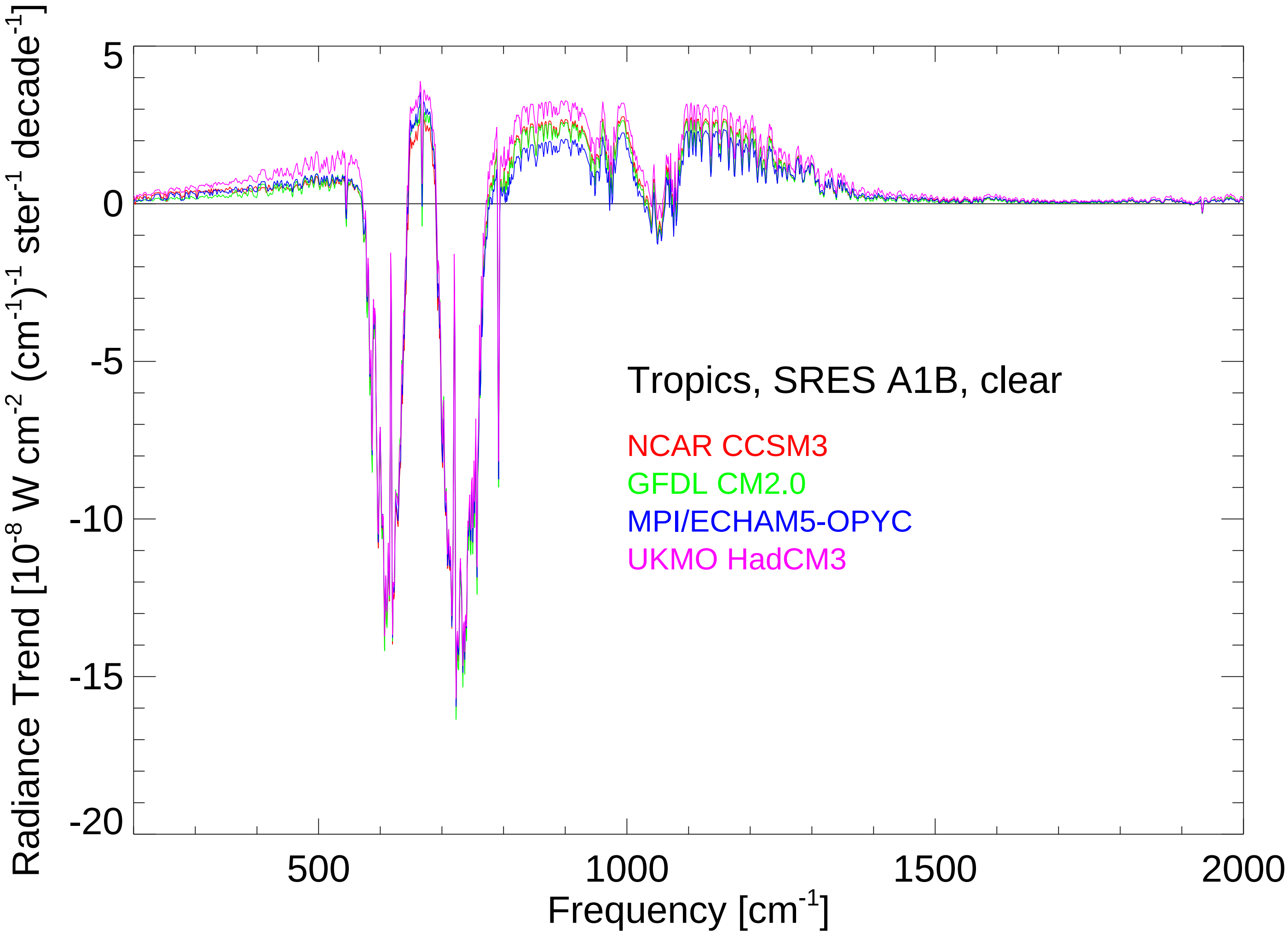

Climate Feedback

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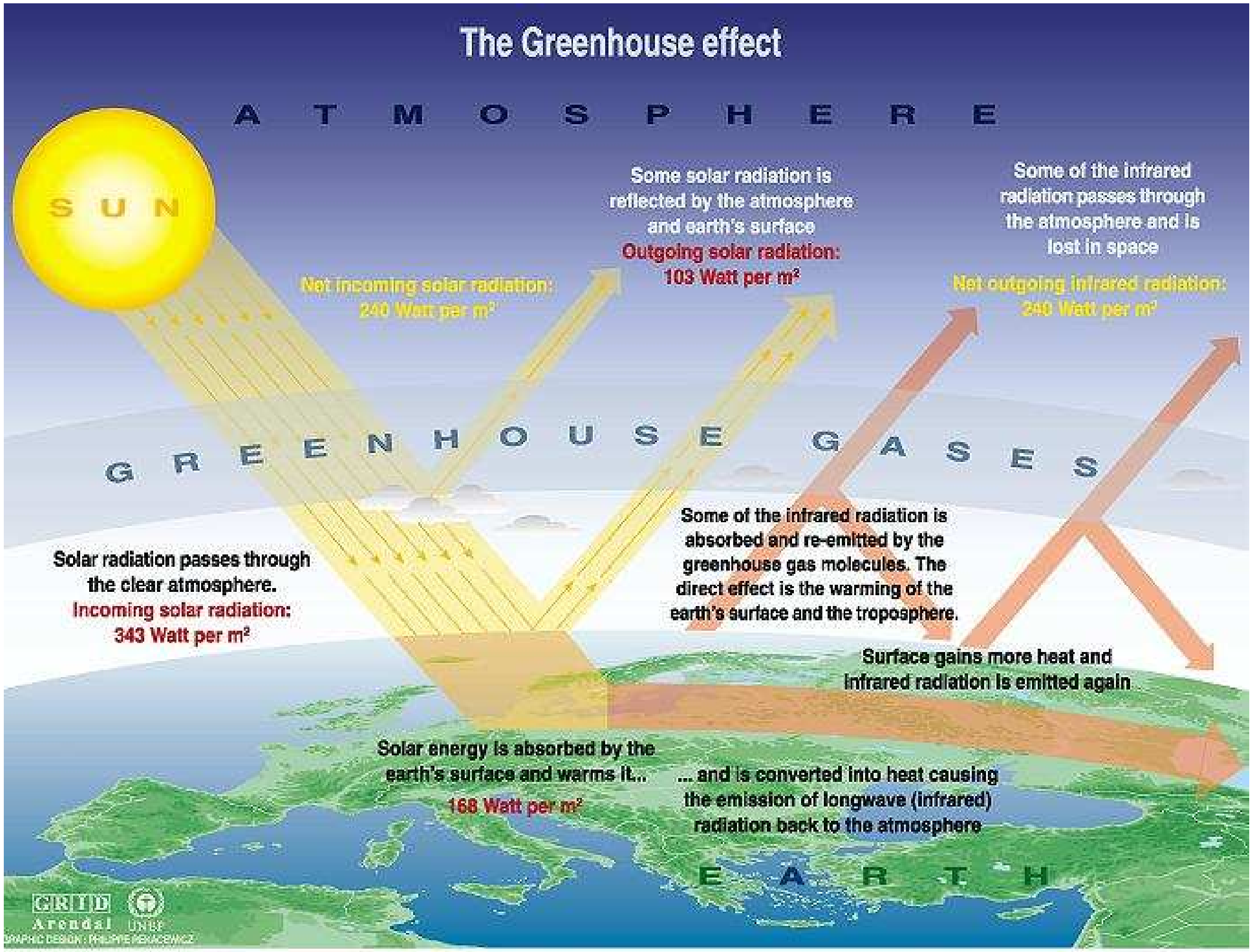

Sources: Okanagan university college in Canada, Department of geography, University of Oxford, school of geography; United States Environmental Protection Agency (EPA), Washington; Climate change 1995, The science of climate change, contribution of working group 1 to the second assessment report of the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

Climate Feedback

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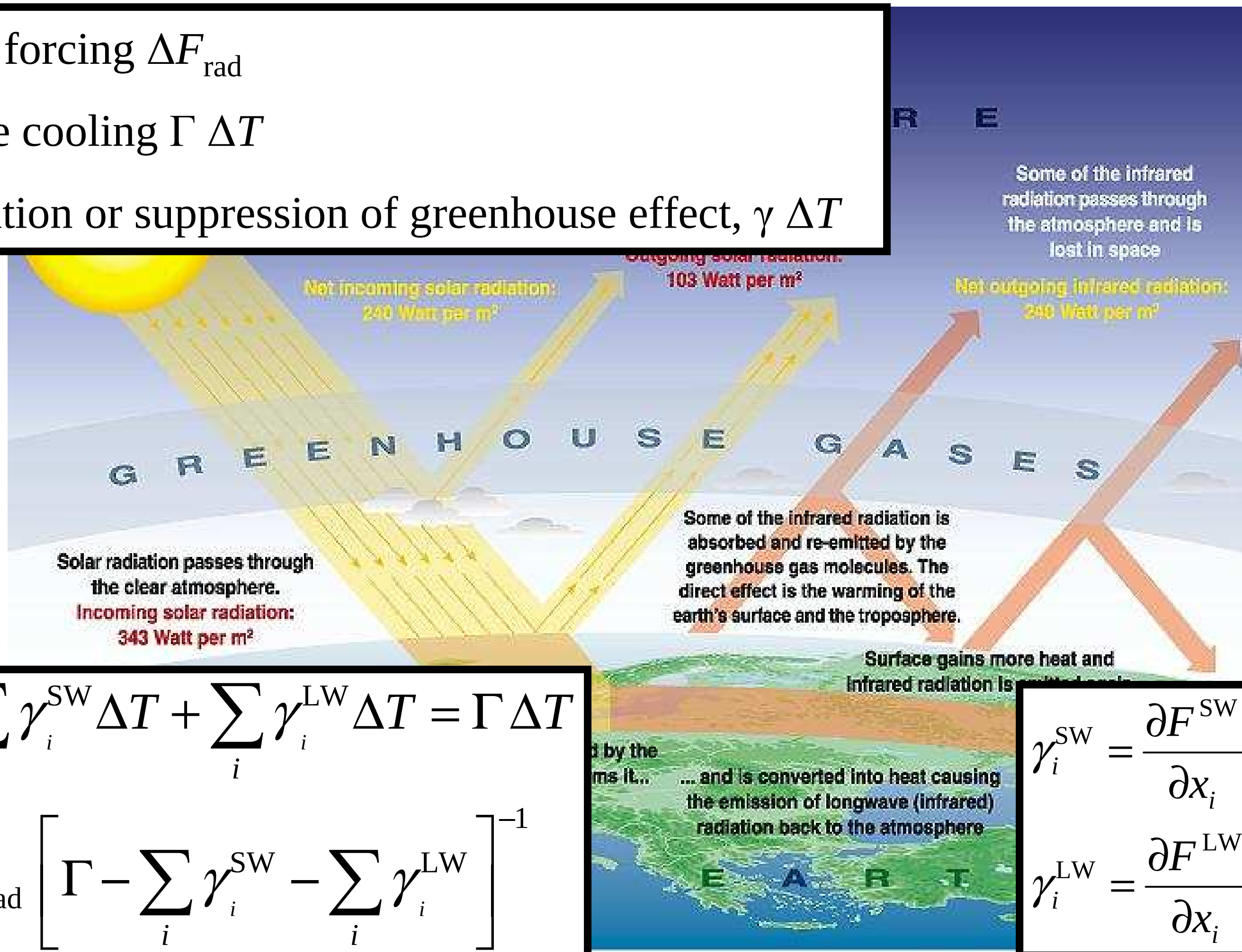
Radiative forcing ΔF_{rad}

Longwave cooling $\Gamma\ \Delta T$

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



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.

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

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

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

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

Infrared Spectral Signals

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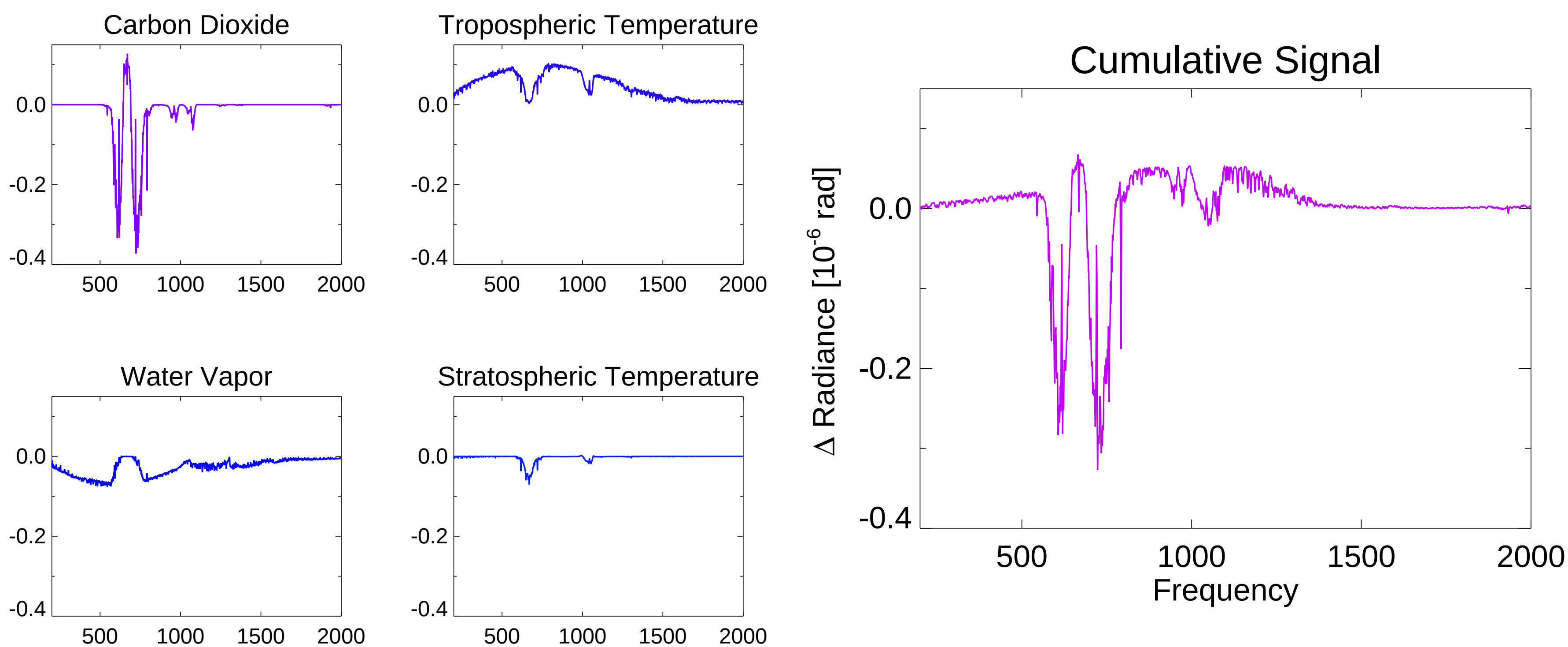
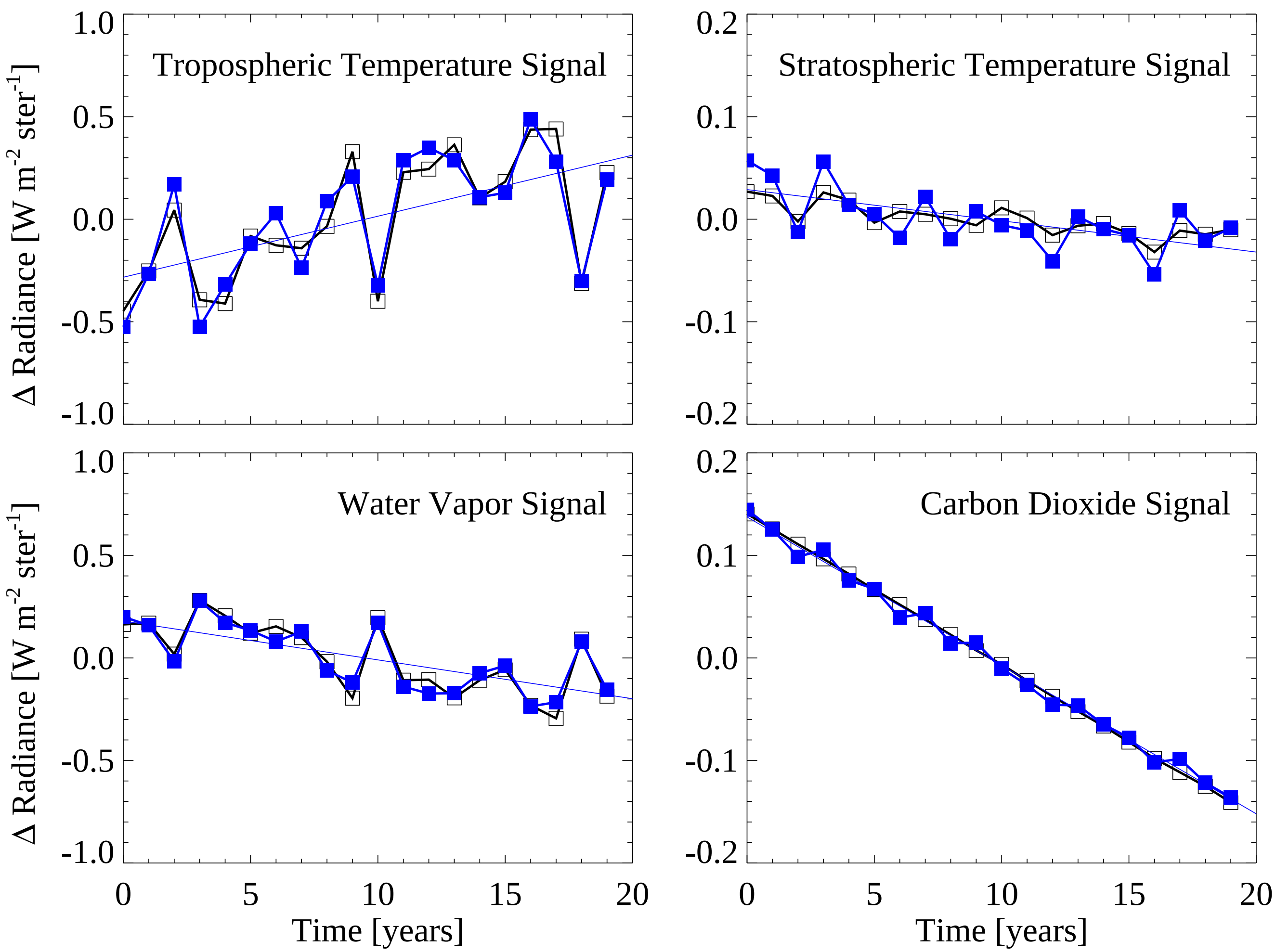
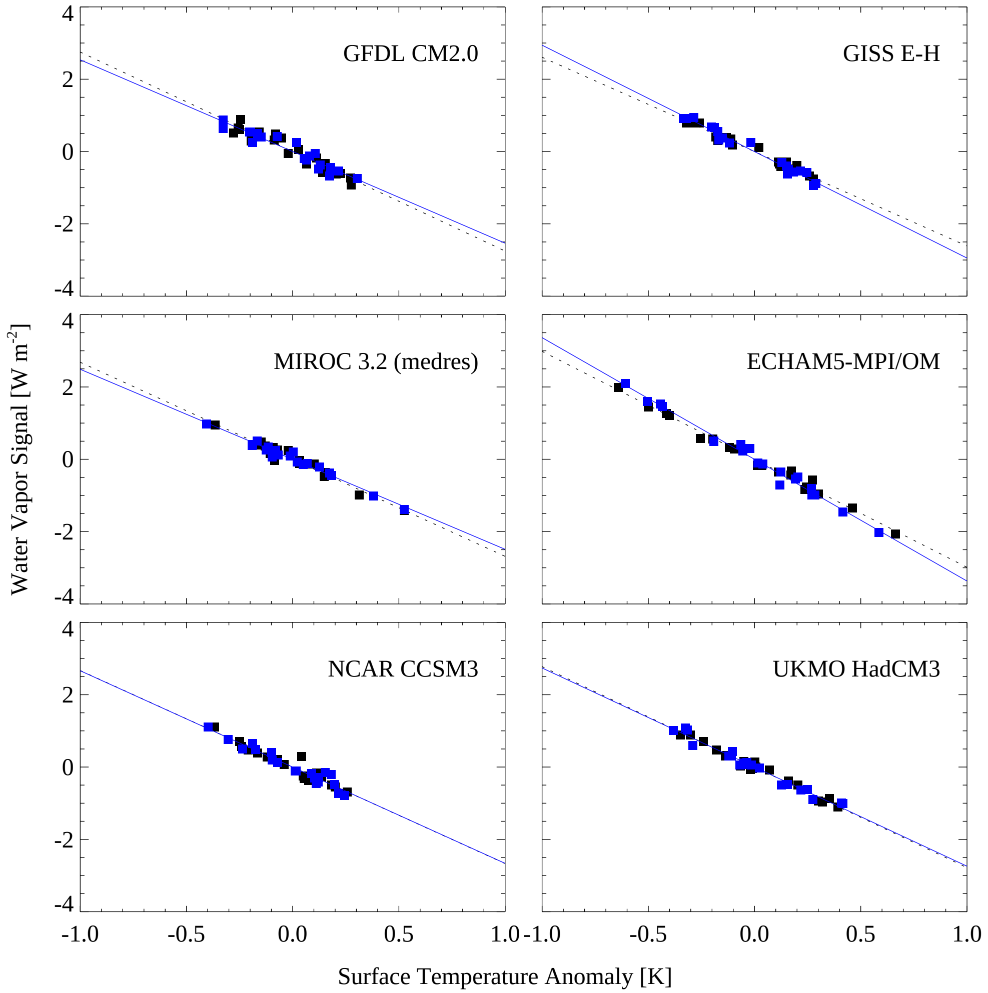


Component OLR Timeseries



Anomaly Analysis



Water Vapor-Longwave Feedback Precision After 20 Years

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	Linear Trend Analysis ($W\ m^{-2}\ K^{-1}$)		Anomaly 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 $(\Delta t)^{-1/2}$

Summary & Discussion

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- Climate benchmarks of CLARREO can constrain longwave climate feedbacks, radiative forcing by well-mixed greenhouse gases, climate response.
- Linear trend analysis:
  - Longer than 20 yrs required to place strong constraints on feedbacks (tropical).
  - 10 yrs required to place strong constraints on radiative forcing (global).
  - Global-scale feedbacks? Cloud feedbacks?
- Anomaly analysis:
  - Just 10 yrs required to place strong constraints on feedbacks (tropical).
  - Probably not applicable to global scales.
- Both GNSS radio occultation and infrared spectral monitoring necessary likely necessary: resolve cloud-surface temperature ambiguity in infrared.

Pertinent Publications

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Leroy, S.S., J.A. Dykema, and J.G. Anderson, 2006: Climate benchmarking using GNSS occultation. OPAC2, 287-301.

Leroy, S.S., J.G. Anderson, and J.A. Dykema, 2006: Testing climate models using GPS radio occultation: A sensitivity analysis. *J. Geophys. Res.*, **111**, D17105, doi:10.1029/2005JD006145.

Leroy, S.S., J.G. Anderson, and G. Ohring, 2007: Climate signal detection times and constraints on climate benchmark accuracy requirements. *J. Climate*, in press.

Leroy, S.S., J.G. Anderson, J.A. Dykema, and R.M. Goody, 2007: Testing climate models using thermal infrared spectra. *J. Climate*, in press.

See ftp://ftp.arp.harvard.edu/pub/leroy/